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Scenario-driven flood resilience assessment and critical node identification for urban road networks

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Abstract: Urban flooding driven by extreme rainfall is growing in both frequency and severity. As the carrier of evacuation, rescue, and repair operations during floods, the road network is a lifeline on which urban disaster response depends. Most existing assessments, however, build on a single flood scenario, and critical nodes are identified mainly by topological importance, with actual flood exposure seldom considered jointly. This study uses the observed hyetographs of three extreme storms to drive pluvial flood simulations of the same urban road network, building flood evolution scenarios that span short-duration concentrated, multi-peak intense, and long-duration persistent rainfall patterns. A failure–reopening rule converts hourly water depths into dynamic resilience curves, from which five metrics are extracted, namely threshold-crossing times, resilience trough, recovery time, resilience loss, and fragmentation amplification ratio. A two-criterion method then identifies critical nodes by combining structural importance with flood exposure, and reinforcement replay tests its effectiveness. The three scenarios produce three distinct resilience processes, from instantaneous collapse–rebound, through oscillatory collapse, to sustained suppression. The scenario with the deepest trough does not suffer the largest resilience loss, so no single metric can characterize the whole process. Most of the topologically important nodes sit on roads that stay dry during the floods, and reinforcing by topology alone barely improves resilience. Local inundation is amplified into network-wide connectivity loss, with every 1% of failed nodes at the trough resulting in an approximate 3% loss in network performance. Reinforcing 1000 two-criterion critical nodes (1.6% of the network) cuts resilience loss by 22.3%–28.4% across the three scenarios, more than 5 times the reduction of structure-only selection and more than 23 times that of network-wide random selection. These results reveal how rainfall pattern, terrain, and network topology jointly shape road network

flood resilience, and provide a testable quantitative basis for prioritizing flood-proofing reinforcement under limited budgets.

Keywords: urban road network; flood resilience; resilience loss; critical node identification; rainfall scenario; flood-proofing reinforcement

1 Introduction

Pluvial flooding driven by extreme rainfall is striking large cities with growing frequency and intensity. The road network carries evacuees, relief supplies, and repair crews during a flood; it is the spatial backbone on which other critical infrastructure recovers. In the Zhengzhou storm of 20 July 2021 and the Beijing storm of July 2023, widespread road inundation severely delayed emergency response. Road network resilience under urban flooding has become an active research field [1]. Yet flood-proofing budgets are limited, and there is still no comparable, rankable, quantitative basis for deciding which nodes deserve reinforcement most.

How floods disrupt road traffic has been quantified at the link and the network scale. At the link scale, studies have established speed–depth decay relations and critical-depth closure rules, coupled them with hydrological models to project traffic disruption under climate change, and tested the instability limits of vehicles and pedestrians in floodwater [2-4]. Network-scale evidence has accumulated more recently: travel delays and detour costs grow nonlinearly with inundation extent, and the reachable area of emergency services shrinks rapidly in the rising stage of a storm [5,6]. Losses of transit and job accessibility concentrate in low-income neighborhoods, and commuting disruption can spread across an entire metropolitan network [7,8]. In contrast, the indirect costs of traffic disruption have long been left out of flood-loss assessments, and systematic city-scale methods remain incomplete [9]; flood-risk mapping of road assets, meanwhile, has been extended to the continental scale [10].

Measures of network resilience have developed along two threads, process and structure, and the two are converging [11]. The process thread stems from the resilience-triangle framework: resilience is no longer a static capacity to resist, but the full trajectory of performance degrading and then recovering over time. Assessment thus shifted from vulnerability to performance curves, and this idea was later brought into flood resilience analysis of urban road networks [12,13]. The structure thread asks when a network disintegrates as a whole: even local inundation can trigger sudden, large-scale failure of a road network, a

critical behavior repeatedly verified under floods combined with targeted attacks and compound failures [14-16]. Percolation frameworks and their diffusion-type variants have further served to characterize flood vulnerability, track the spread and recession of surface water, and identify traffic-flow bottlenecks [17-19]. Other work found that the largest connected component does not always capture flood losses and that percolation criticality applies only within limits; it turned instead to the accessibility of key locations [20]. The convergence of the two threads has produced multi-dimensional assessments combining function with topology, and hour-by-hour accessibility analysis during inundation [21-23].

On the application side, the literature follows two routes: identifying critical nodes before disasters and organizing recovery after them. Identification is anchored in topological centrality. Degree and betweenness have long been the default yardsticks of importance, and percolation centrality further folds a node's percolation state into the betweenness framework [24]. Stress tests probe such rankings from the consequence side, either closing road sections one by one across a large network and measuring importance by the loss of network efficiency [25], or assessing performance losses of the Swiss road network under flood and debris-flow scenarios with vulnerability and functional-loss functions [26]. Recent work also prioritizes which stress-test scenarios to simulate, avoiding exhaustive computation [27]. Recovery research addresses repair organization after disruption: one line evaluates the repair process with metrics such as the largest connected component and compares recovery strategies through Monte Carlo simulation [28]. Later work optimizes repair sequencing under uncertain repair durations [29], or allocates repair resources among damaged components under budget constraints [30]; deep reinforcement learning has recently been used to generate post-earthquake and post-flood repair sequences [31], and a quantum-driven framework has appeared for scheduling network restoration [32]. The two routes act at different stages, one ranking reinforcement before the disaster and the other scheduling repairs and resources after it, but both start from a ranking of component importance.

Existing research explains well how floods cause road failures and offers many ways to measure network resilience. Three key questions, however, still lack direct evidence. First, how does the resilience of one road network diverge under different real storm hyetographs? The controlling effect of rainfall spatio-temporal structure on urban hydrological response is well documented [33,34], but comparative assessments that fix the network and vary only the observed hyetograph are still missing [1,14-16,20]; in

existing results it is hard to tell whether resilience differences come from network structure or from rainfall pattern. Second, how is local ponding amplified into network fragmentation and dynamic resilience loss? A cross-storm measure linking inundation extent to connectivity loss is lacking, and the recovery phase is usually approximated by prescribed recovery functions or repair-scheduling models [29,30], with no direct tie to the physics of water recession. Third, with limited resources, how should structural importance and actual flood exposure be combined to find the nodes truly worth reinforcing? Identification studies commonly assume that topologically important components also matter most for disaster resilience [1,24,25]; whether this holds under flooding is rarely tested.

To address these questions, this study performs scenario-driven resilience assessment and critical node identification on the real road network within Chengdu's ring expressway. Specifically, we fix the network and vary only the rainfall: three observed extreme hyetographs with sharply different temporal structures drive hourly inundation, failure, and reopening of the same network, with a zero-rainfall tail appended to obtain a natural-recession recovery phase. On this basis we examine how the resilience process diverges with rainfall pattern. Next, we extract from the resilience curves a dynamic resilience metric system covering degradation, collapse, and recovery, and use the fragmentation amplification ratio to quantify how inundation extent converts into connectivity loss. Finally, we propose a two-criterion critical node identification method that merges structural importance with persistent flood exposure, and test its effectiveness through reinforcement comparisons across selection strategies. The remainder of the paper is organized as follows: Section 2 presents the methods; Section 3 describes the study area, data, and scenarios; Section 4 reports results; Section 5 discusses mechanisms and limitations; Section 6 concludes.

2 Methods

We propose SDRI, a method for Scenario-driven Dynamic Resilience assessment and two-criterion critical node Identification of road networks. Its framework (Fig. 1) has four layers. The flood evolution layer takes the modeled road network and the observed hyetographs as parallel inputs, and generates flood evolution scenarios of three distinct rainfall types through 2-D hydrodynamic simulation. The dynamic resilience layer converts the hourly depth fields into hourly failures and reopenings by the failure–reopening rule, producing dynamic resilience curves and the metric system. The identification layer screens the top k critical nodes within the persistent-exposure pool by a structural and an exposure

criterion. The reinforcement layer applies the reinforcement assumption to the selected nodes, replays the three scenarios, quantifies the gain by the resilience-loss reduction, and outputs the reinforcement priority. The following four subsections expand each layer in turn.

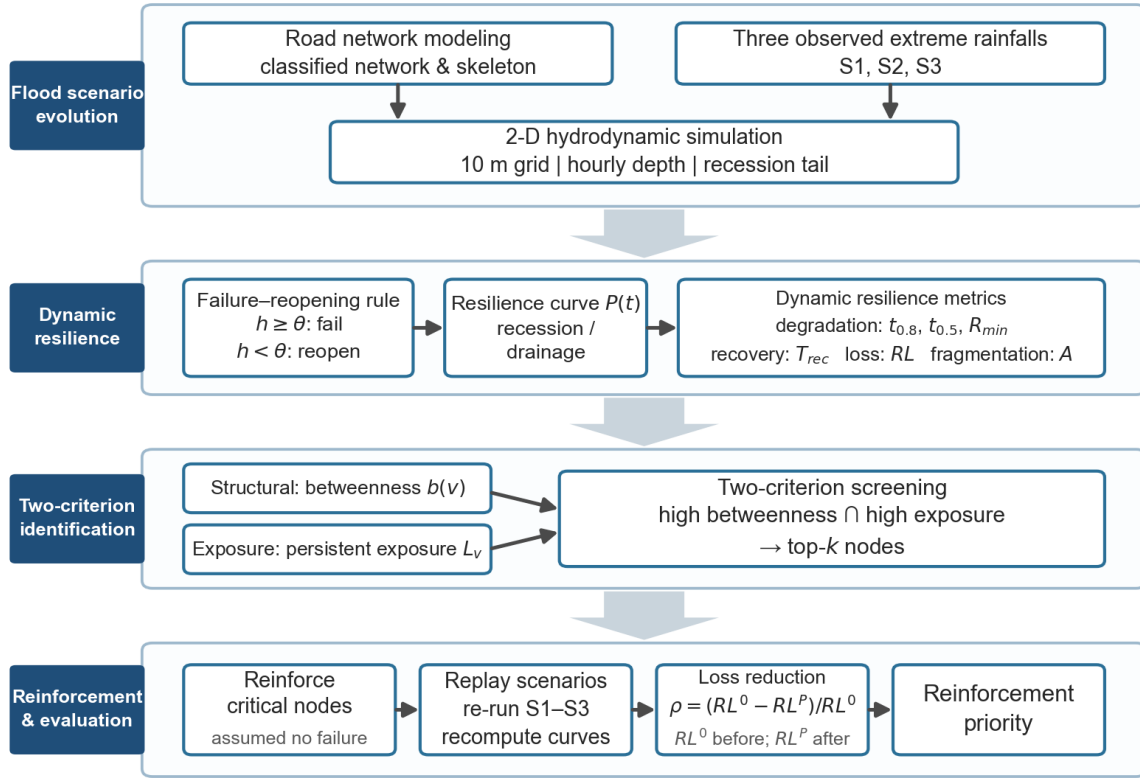


Fig. 1 Method framework

2.1 Construction of flood evolution scenarios

Scenario modeling has three parts: the exposed road network, the rainfall hazard, and the failure–reopening rule. The road network comes from OpenStreetMap: Class I (motorway/trunk/primary), Class II (secondary), and Class III (tertiary) roads and their connections form an undirected graph $G = (V, E)$ with segment length as edge weight. Its largest connected component serves as the analysis skeleton, with node set V_c and size N_0 . Bridge, tunnel, and layer tags in the road data then split the nodes into five vertical types: elevated, bridgehead, underpass, underpass link, and ground. The failure rule uses these types.

The hazard is the hourly hyetographs of three observed extreme storms, applied to the same study area. A 2-D hydrodynamic model turns them into hourly depth fields. After each storm ends, the simulation continues with zero rainfall so that ponded water recedes through drainage and outflow; the

recovery phase thus emerges from the depth process itself, with no prescribed performance trajectory. Section 3.2 details the three storms, the river boundary, and the model settings.

The failure–reopening rule takes the critical water depth for motor vehicles. Let $h_v^s(t)$ denote the depth at node v in scenario s at hour t ; the failed node set is

$$F_s(t) = \{v \in V_c \setminus V_{elev} : h_v^s(t) \geq \theta\}, \theta = 0.3 \quad (1)$$

where $F_s(t)$ is the failed node set of scenario s at hour t ; V_{elev} is the set of elevated nodes, whose decks sit above ground ponding and do not fail; and θ is the failure threshold. At a depth of 0.3 m, water reaches the exhaust height of most passenger cars and driving is no longer safe; link-scale depth–speed studies likewise treat 0.3 m as the upper limit for safe driving and close the road at this depth [2]. We therefore set $\theta = 0.3$ m. A node reopens once its depth falls back below θ ; failure and reopening are judged hour by hour. An elevated node itself never fails, but when all its bridgehead nodes are flooded, the elevated section disconnects from the main network and drops out of the largest connected component, so the blocking of access ramps is captured by the network structure automatically. Underpasses are mostly open sunken roadways: their depressions are already part of the terrain data, and water pooling in them is simulated directly by the hydrodynamic model.

2.2 Dynamic resilience metric system

Failed nodes and their incident edges are removed from the skeleton, and network performance is measured by the node share of the largest connected component of the remaining subgraph, giving the dynamic resilience curve:

$$P_s(t) = \frac{|C_{max}(V_c \setminus F_s(t))|}{N_0} \quad (2)$$

where $P_s(t)$ is the network performance of scenario s at hour t and $C_{max}(\cdot)$ is the node set of the largest connected component of the induced subgraph; the vertical bars denote set size. Connectivity is a necessary condition for travel; this measure involves no travel demand or flow assignment and is a conservative proxy for carrying capacity. The whole resilience process is read off this curve through five metrics: threshold-crossing times, resilience trough, recovery time, resilience loss, and fragmentation amplification ratio. They are presented in four groups below, followed by the drainage setting of the recovery phase.

(1) Degradation and collapse. Characterized by the family of threshold-crossing times and the trough:

$$t_x^s = \min\{t: P_s(t) < x\}, R_{min}^s = \min_t P_s(t) \quad (3)$$

where t_x^s is the first hour at which performance falls below level x , with x taken as 0.8 and 0.5 (some scenarios never fall below 0.5, hence a family of thresholds rather than a single half-performance indicator); R_{min}^s is the trough performance, reached at hour t_{min}^s . The cumulative hours spent below a given level are excluded from the metric system: under natural recession none of the three scenarios climbs back above 0.8 within the assessment window (storm duration plus 96 h after rain end, hereafter), so this count merely equals the window length minus the crossing time. It carries no information about recovery and varies with simulation length, so it is not comparable across scenarios.

(2) Recovery. Measured by the time needed to climb from the trough back to a given performance level:

$$T_{rec}^s(x) = \min\{t \geq t_{min}^s: P_s(t) \geq x\} - t_{min}^s \quad (4)$$

where $T_{rec}^s(x)$ is the recovery time to level x and t_{min}^s is the trough hour; when the level is not reached within the assessment window, the value is recorded as not reached.

(3) Whole-process measure. The resilience loss, the area enclosed between the performance curve and the ideal level:

$$RL_s = \sum_{t=1}^{T_s+96} [1 - P_s(t)] \quad (5)$$

where RL_s is the resilience loss of scenario s (dimensionless performance times hours) and T_s is its storm duration. The three storms last 73, 72, and 80 h; ending the window uniformly at 96 h after rain end keeps the scenarios comparable. Resilience loss reflects both how deep performance falls and how long it stays low, and serves as the primary measure for comparing reinforcement effects.

(4) Fragmentation amplification ratio. Quantifies how strongly inundation is converted into connectivity loss:

$$A_s(t) = \frac{1-P_s(t)}{f_s(t)}, f_s(t) = \frac{|F_s(t)|}{N_0} \quad (6)$$

where $A_s(t)$ is the amplification ratio and $f_s(t)$ is the failed share of the skeleton. If failures removed only the failed nodes themselves, the ratio would equal 1; the excess comes from surviving nodes cut off in blocks from the largest connected component, that is, from topological fragmentation.

Drainage setting of the recovery phase. After the rain stops, the urban drainage system takes over, drawing down the water at the remaining ponded nodes at an equivalent linear rate:

$$\tilde{h}_v^s(t) = \max \left\{ h_v^s(t) - \frac{q_p}{1000} (t - T_s)^+, 0 \right\} \quad (7)$$

where $\tilde{h}_v^s(t)$ is the equivalent depth with drainage, q_p is the equivalent drainage rate, and $(t - T_s)^+$ means the term acts only after rain end. China's standard for waterlogging control allows a 24-h design storm to be drained within 24 h [35]; the drainage rate then equals the design storm depth divided by 24 h. We take $q_p = 10$ mm/h, equivalent to removing a 240-mm design storm in 24 h; the technical code for urban flooding prevention likewise requires ordinary areas to draw urban river levels down to the design level within 24 h after a storm [36], the same order of time. Drainage capacity is a fixed property of the local drainage system, set by local standards rather than by the storm, so all three scenarios use the same rate. This rate and the base drainage during rainfall represent two operating conditions of one drainage system (Section 3.2). This emergency-drainage setting is used throughout as the primary setting; the pure natural-recession curve without drainage is shown alongside as the no-drainage lower bound.

2.3 Two-criterion critical node identification

The structural criterion is length-weighted betweenness centrality:

$$b(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \quad (8)$$

where $b(v)$ is the weighted betweenness of node v (hereafter weighted betweenness); σ_{st} is the number of length-weighted shortest paths from node s to node t ; and $\sigma_{st}(v)$ is the number of them passing through v . The sum runs over all ordered node pairs in the skeleton, normalized by $2/[(N_0 - 1)(N_0 - 2)]$ and computed exactly. Hop-count betweenness is distorted by the chained subdivision of open road data, whereas the length-weighted version is invariant to subdivision and is the standard choice for road networks; we use it throughout.

The exposure criterion is persistent exposure across scenarios, the minimum of a node's flooded hours over the three scenarios:

$$L_v = \min_s \sum_t \mathbf{1} [h_v^s(t) \geq \theta] \quad (9)$$

where L_v is the persistent exposure of node v (elevated nodes never fail, so their exposure is 0).

Taking the minimum keeps only nodes that get flooded under every storm used, decoupling the criterion from any single storm used. Two-criterion identification then ranks the nodes within the persistent-exposure pool $\{v: L_v \geq 1\}$ by weighted betweenness $b(v)$ and takes the top k as the two-criterion list. The 55 river-crossing bridge nodes whose coordinates fall on river cells, and whose depths therefore reflect channel flow rather than street ponding, are excluded from all selection strategies to keep the comparison fair. The baseline budget is $k = 1000$, about 1.6% of the skeleton, a round number for ease of statement, and k is swept from 250 to 4000 (Section 4.3). To describe where a node sits functionally in the network, nodes are further grouped by betweenness percentile and degree into four roles: hubs (top 10% betweenness, degree at least 4), bridges (top 10%, degree at most 3), secondary (10–30%), and peripheral (the rest).

2.4 Flood-proofing reinforcement and effect evaluation

Reinforcement replay sets the selected critical nodes to flooded-but-functional, approximating flood-proofing works (specific engineering measures are beyond the scope of this paper). It assumes that local works do not alter the domain-wide flood field, and replays the dynamic resilience curves on the hourly depths of the three scenarios. The primary measure of effect is the resilience-loss reduction:

$$\rho = \frac{RL_s^0 - RL_s^P}{RL_s^0} \quad (10)$$

where ρ is the resilience-loss reduction, and RL_s^0 and RL_s^P are the resilience losses of the unreinforced baseline and the reinforced network. Section 4.3 gives the selection strategies and budget settings used for comparison.

3 Study area, data, and scenarios

3.1 Road network modeling

The study area is the region enclosed by Chengdu's ring expressway and its adjacent roads, about 600 km². The terrain tilts gently from northwest to southeast, and the Fu, Sha, Qingshui, and Jiang'an rivers cross the city: a typical plain megacity core. Parsing OpenStreetMap yields 29608 Class I, 17850 Class II, and 23556 Class III segments, 71014 in total with a length of 5583 km, and 64540 nodes. The largest connected component covers 64479 nodes (99.9%) and serves as the analysis skeleton (Table 1).

Fig. 2 relates the classified network to the terrain. Ground elevation falls gently from northwest to southeast, with a 2nd–98th percentile range of about 482–541 m. Micro-terrain shows a statistically significant spatial correspondence with recorded flood-prone sites [37], and this terrain base controls where residual inundation and persistent exposure occur (Section 4.1). Among the skeleton nodes, 9831 are elevated (15%; on Class I roads, elevated segments reach 39%), 2747 are bridgeheads, 488 are underpass nodes clustered into 91 underpass sections, 452 are underpass links, and the remaining 50961 are ground nodes. By the rule of Section 2.3, the functional roles comprise 863 hubs, 5585 bridges, 12896 secondary, and 45135 peripheral nodes; Fig. 3(a) maps the roles and Fig. 3(b) the vertical types.

Table 1 Road network data and vertical types of the study area

Item	Value	Item	Value
Class I segments	29608	Total length	5583 km
Class II segments	17850	Total nodes	64540
Class III segments	23556	Analysis skeleton	64479 (99.9%)
Elevated nodes	9831 (15%)	Bridgehead nodes	2747
Underpass nodes	488 (91 sections)	Underpass-link nodes	452
Hubs / bridges	863 / 5585	Secondary / peripheral	12896 / 45135

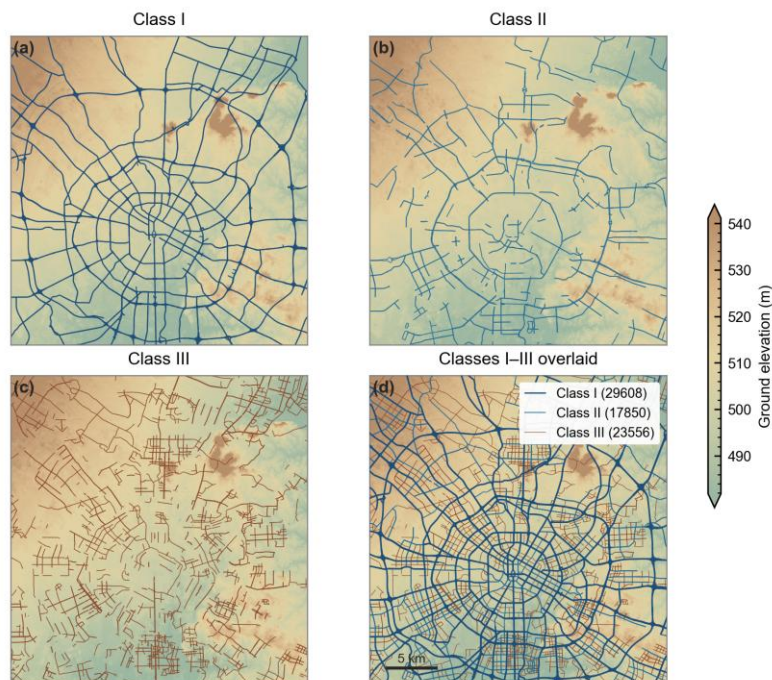


Fig. 2 Classified road network and terrain: (a) Class I; (b) Class II; (c) Class III; (d) Classes I–III overlaid (base map: DEM ground elevation; segment counts in the legend; scale bar in (d); all panels share the same extent)

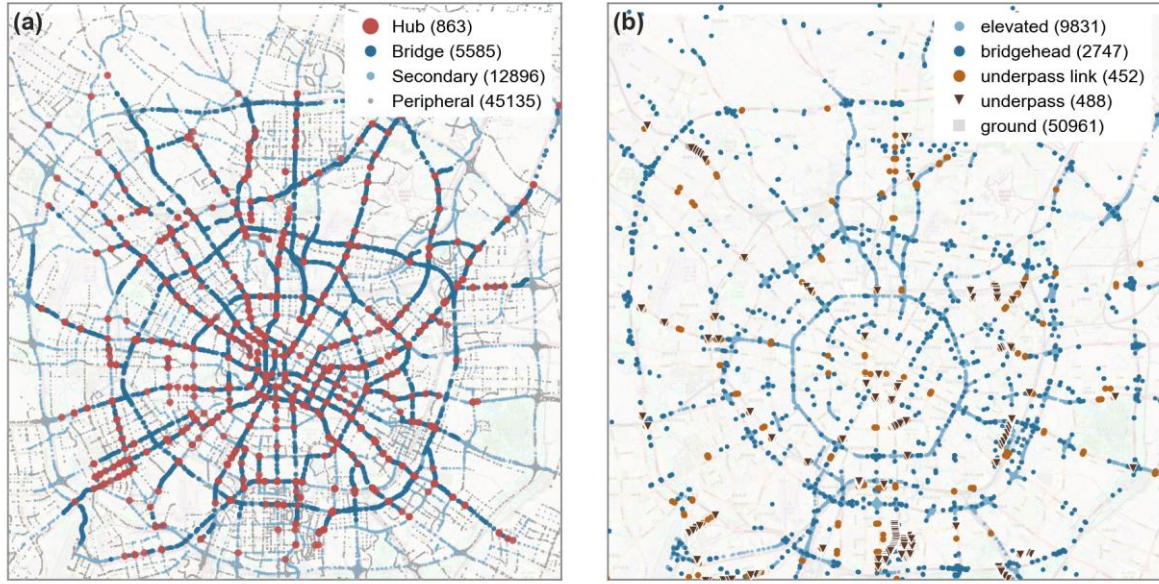


Fig. 3 Functional roles and vertical types of network nodes: (a) functional roles under the weighted-betweenness rule (node counts in parentheses); (b) vertical types (ground nodes form the light-grey background network and are not drawn individually)

3.2 Simulation of the flood process

The simulation takes three inputs: rainfall, river flow, and terrain. For rainfall, the three scenarios apply the single-station hourly hyetographs of three observed extreme storms to the same study area and network, so that the network is held fixed while only the rainfall varies. S1 is the record of the Chengdu 8·16 storm of 2020 at the urban representative station (Yongxing Dashu); S2 and S3 transplant the records of the Zhengzhou 7·20 national station and the Beijing 23·7 observatory (Table 2, Fig. 4). S2 and S3 are transplanted hyetographs used to build a rainfall-pattern spectrum with widely different durations and concentrations; they do not reconstruct the Zhengzhou or Beijing flood events, and all conclusions are confined to the three rainfall patterns used. The three storms form a gradient from short and concentrated to long and persistent: S2 is short-duration concentrated (766.2 mm in 72 h, peak 201.9 mm/h); S1 is multi-peak intense (542.3 mm in 73 h, peak 70.3 mm/h); S3 is long-duration persistent (only 237.7 mm in 80 h, peak 25.7 mm/h). Their total rainfalls are in the ratio of about 3.2:2.3:1 and their peak intensities about 7.9:2.7:1; the two rankings agree. Duration and peak count also differ across the storms and are uncontrolled variables that come with the patterns (Section 5).

268 **Table 2 The three rainfall scenarios (S2 and S3 are transplanted hyetographs, not event reconstructions)**

Scenario	Prototype and station	Duration (h)	Rainfall (mm)	Peak (mm/h)	Pattern	Tail (h)
S1	Chengdu 8·16, Yongxing Dashu station	73	542.3	70.3	multi-peak intense	96
S2	Zhengzhou 7·20, national station	72	766.2	201.9	short-duration concentrated	96
S3	Beijing 23·7, observatory	80	237.7	25.7	long-duration persistent	120

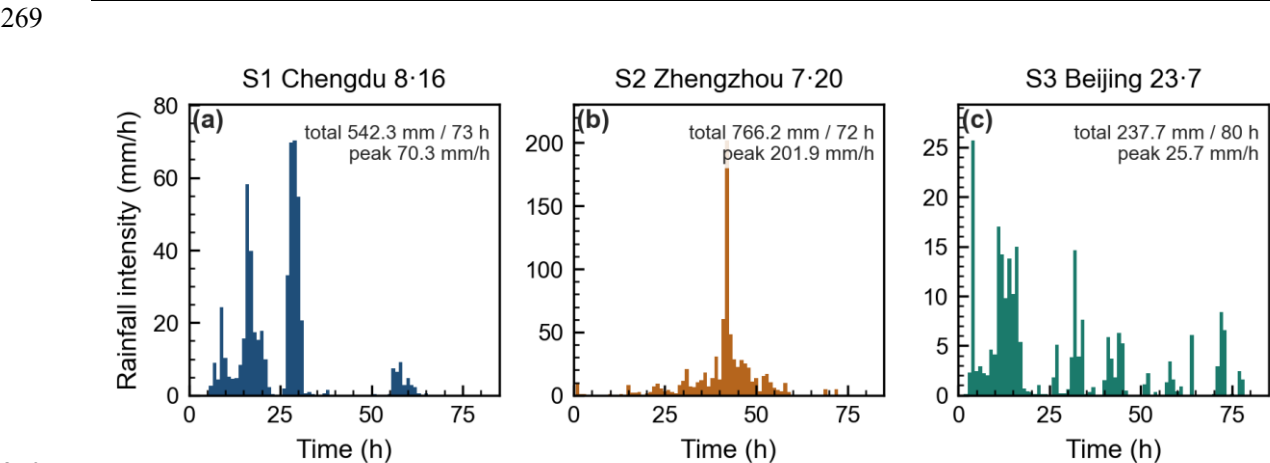


Fig. 4 Hourly hyetographs of the three storms: (a) S1; (b) S2; (c) S3

For river flow, the four main rivers of the area (Fu, Jiang'an, Qingshui, and Sha) are rasterized from the river vector data into the computation grid (Fig. 5), simulating a flood peak passing through during the storm. River discharge rises and falls in step with rainfall intensity, reaching the 50-yr design flows at full capacity in the peak period (Fu 240 m³/s, Jiang'an 220 m³/s, Qingshui 125 m³/s, Sha 80 m³/s) and overflowing along the banks. River cells receive no base drainage, representing high river stages that prevent street runoff from draining into the channels. For terrain, a digital elevation model (DEM) describes ground elevation and the local depressions of underpasses (Section 3.1, Fig. 2).

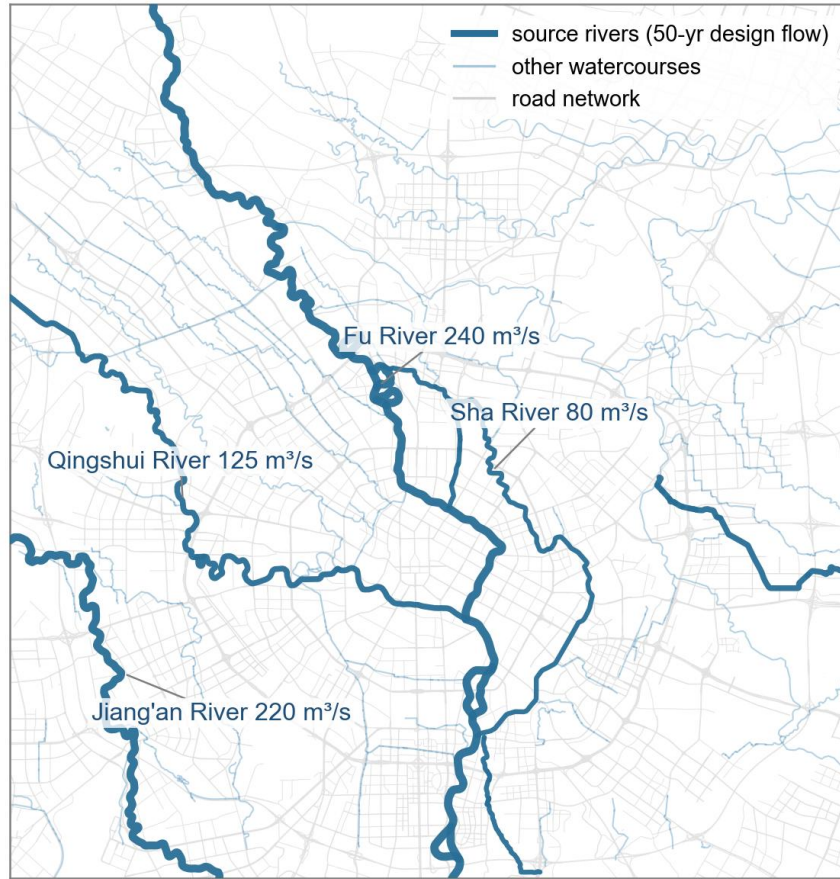


Fig. 5 Rivers of the study area and the 50-yr design flows of the four source rivers (bold: source rivers, each with several reaches and the label on the main reach; thin lines: other watercourses; light grey: road network)

Inundation is computed by a self-implemented 2-D hydrodynamic model based on the local inertial approximation of the shallow-water equations [38-39]: 10-m grid, Manning coefficient 0.04, base drainage 1.0 mm/h (0 on river cells), depth capped at 5 m, and critical-outflow open boundaries. The model is driven by hourly rainfall and outputs the domain-wide depth field every hour. The 1.0 mm/h is the domain-equivalent net drainage while the sewer system is surcharged during the storm; after rain end, the drainage switches to the Eq. (7) setting of $q_p = 10$ mm/h, representing the sewer system restored to normal operation plus emergency pumping. The two values describe one drainage system under two operating conditions, not a change in drainage capacity. Each network node takes the simulated depth of the 10-m cell containing its coordinates. After the rain stops, the simulation continues with zero rainfall (96 h for S1 and S2, 120 h for S3) so that ponded water recedes through drainage and outflow.

The model is validated against the observed Chengdu 8·16 storm. For the five flood-prone sites in the study area with field survey records, Table 3 compares the observed and simulated maximum depths: the simulated/observed ratios lie between 0.77 and 2.67, all within one order of magnitude, and all five sites

pond visibly in the simulation. The simulation is biased high overall (4 of 5 ratios above 1), consistent with applying a single-station hyetograph to the whole domain: this is equivalent to uniform rainfall peaking everywhere at once, more extreme than the real spatial distribution. The implication is that failure extents and metric values err on the severe side; the bias falls mainly on absolute values rather than on comparisons across scenarios.

Table 3 Order-of-magnitude validation of the hydrodynamic model against the Chengdu 8·16 storm

Surveyed flood-prone site	District	Observed max depth (m)	Simulated max depth (m)	Sim/Obs
Mingshu Xincun	Longquanyi	0.50	0.83	1.66
Fengshu St.– Chenglong Ave.	Jinjiang	1.30	1.49	1.15
Chengkang Road	Chenghua	0.35	0.27	0.77
Chengfei Hospital	Qingyang	0.40	0.83	2.07
Dashi South Rd.– Randengsi Rd.	Wuhou	0.15	0.40	2.67

3.3 Spatio-temporal failure evolution across scenarios

Fig. 6 shows the spatio-temporal failure patterns. Columns 1 and 2 are failed-network snapshots at the degradation stage (when performance first falls below 0.8) and at the resilience trough, with the intact network faded to light grey, failed segments in red, and the failed share f and performance P annotated. The two snapshot times are also marked on the resilience curves of Fig. 7 as open and filled circles. Column 3 maps the cumulative failed hours over the whole run.

Three observations follow. First, the three scenarios are more alike than different in spatial pattern: failures are not scattered at random but cluster along the rivers and in low-lying areas. At the degradation stage, failures first appear along the rivers and at underpasses; by the trough they have grown into patches, covering most of the ground network in the city core in S2, less in S1, and mainly the low-lying pockets in S3. Second, the annotated f and P reveal the amplification from failure to connectivity loss: at the trough, S1 has 18.9% of nodes failed but performance down to 0.334, S2 22.9% against 0.290, and S3 10.4% against 0.638; the connectivity loss is about three times the failed share (quantified in Section 4.1). Third, cumulative failed hours separate the three rainfall types: S1 floods a large area for a long time, with long-duration nodes across the whole domain; S2 floods an area comparable to S1, but most nodes fail only

briefly and the long-duration nodes survive only in the low-lying residual ponds; S3 floods the smallest area, yet most of its flooded nodes are long-duration ones, a pattern of sustained local suppression (the full runs are 169, 168, and 200 h).

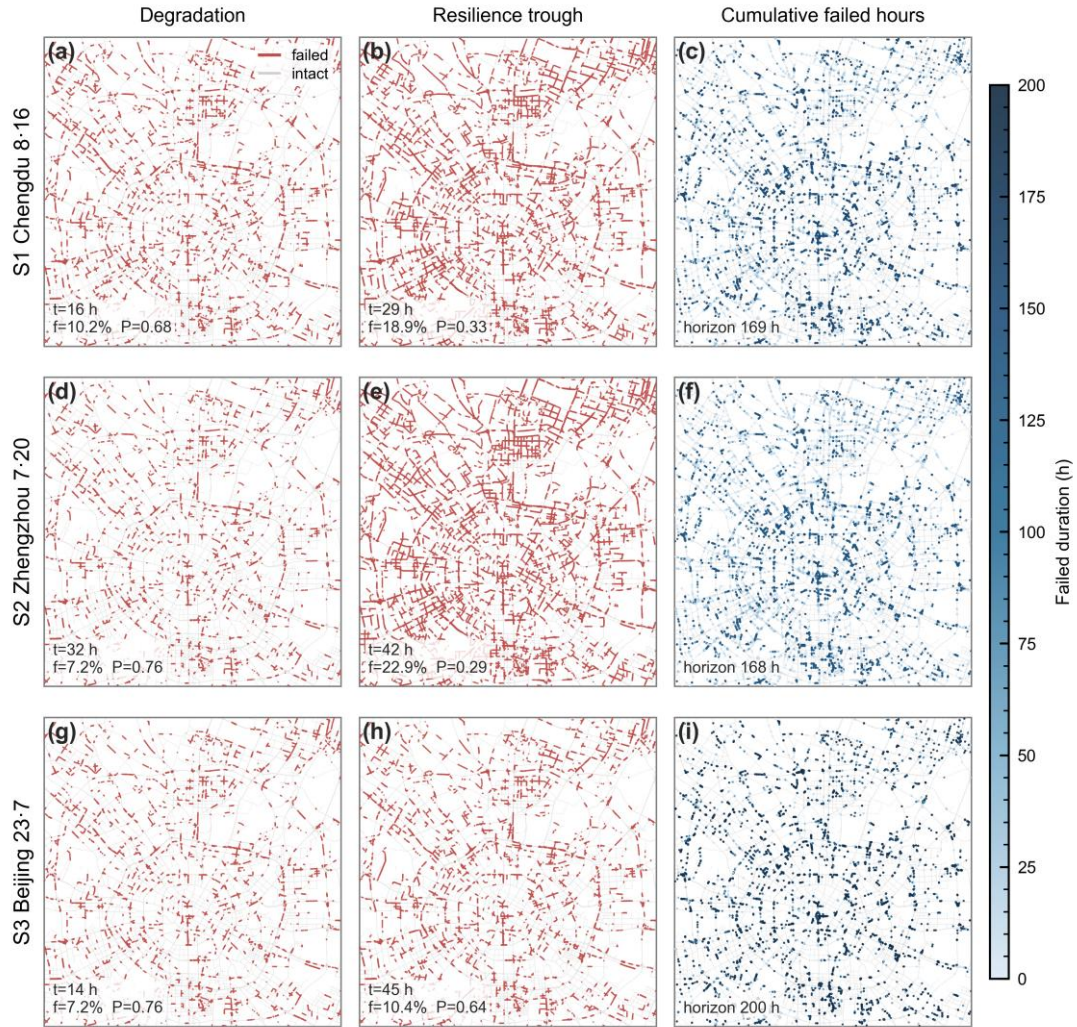


Fig. 6 Spatio-temporal failure patterns of the three scenarios: each row is one scenario; columns 1–2 are failed-network snapshots at the degradation stage and at the resilience trough (red: failed segments; f: failed share of the skeleton; P: network performance); column 3 is cumulative failed hours (whole run including the zero-rain tail)

Fig. 7 gives the full dynamic resilience curves; the open and filled circles correspond to the two snapshot columns of Fig. 6.

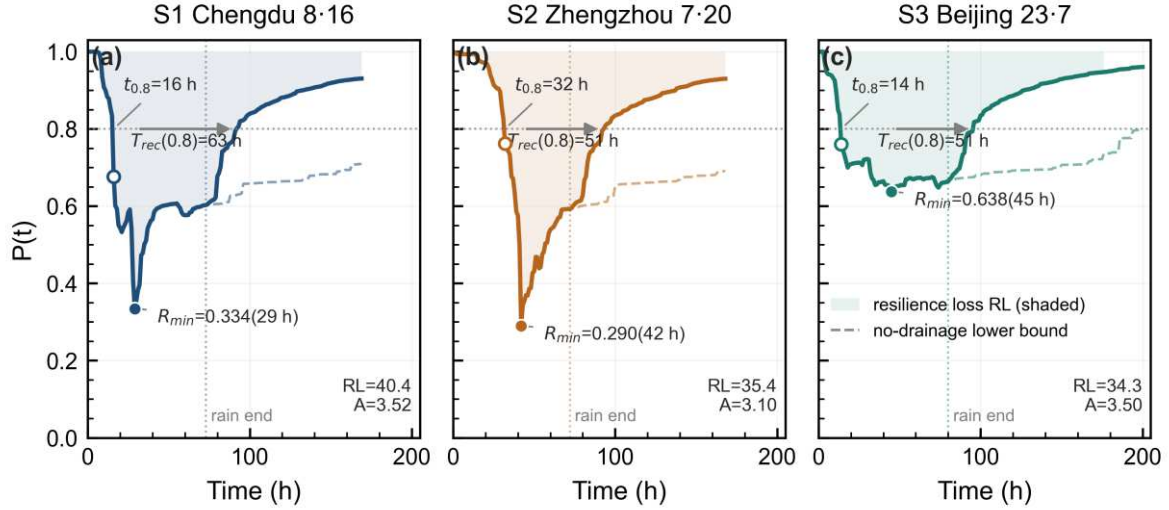


Fig. 7 Dynamic resilience curves with metric annotations: (a) S1; (b) S2; (c) S3 (solid: emergency-drainage primary setting; thin dashed: no-drainage lower bound; scenario colors as elsewhere; shaded area: resilience loss RL of the primary setting; horizontal dotted line: $P = 0.8$; vertical dotted line: rain end; open and filled circles: the snapshot times of Fig. 6)

4 Results and analysis

4.1 Three-type differentiation of the resilience process

The resilience curves of Fig. 7 show three qualitatively different processes under the three rainfall patterns; Tables 4 and 5 list the metrics. S2 is instantaneous collapse–rebound: performance collapses to the trough of 0.290 at hour 42 during the peak-intensity period, and has already rebounded to 0.591 by rain end. S1 is oscillatory collapse: it crosses 0.5 earlier ($t_{0.5} = 28$ h), reaches a trough of 0.334 at hour 29, and its descent fluctuates repeatedly as successive rain peaks arrive. S3 is sustained suppression: performance never falls below 0.5 and the trough is only 0.638 (hour 45), yet it crosses 0.8 the earliest (14 h) and stays suppressed between 0.64 and 0.68 until rain end. Trough depth follows the same order as peak intensity and total rainfall: deepest in S2, then S1, then S3.

The metric system exposes the failure of any single indicator. Ranked by trough, S2 is the most severe; ranked by resilience loss, the ranking shifts and S1 has the largest RL (40.4, versus 35.4 for S2 and 34.3 for S3), because S1 collapses earlier and stays low longer, accumulating more loss than the deeper but fast-rebounding S2. The total window differs slightly with storm duration (168–176 h); S3 has the longest window yet the smallest RL, so this ranking is robust to the difference. Depth of fall and cumulative loss thus give two conflicting severity rankings, and either alone would misread the disaster. The fragmentation amplification ratio reveals the conversion mechanism: at the trough, A is 3.52, 3.10, and 3.50 for the three scenarios, meaning that every 1% of the skeleton that fails costs about 3% of network performance, and

this factor is nearly the same across the rainfall types. The excess comes from surviving nodes cut off in blocks when channels are severed. This accounts for the bulk of flood-induced network loss, and it is also why reinforcing a small number of key nodes can return benefits far beyond their share of the network.

On recovery, under the primary setting the three scenarios need 63, 51, and 51 h to climb from the trough back to 0.8, and by 96 h after rain end they reach 0.931, 0.930, and 0.947, when 2318, 2358, and 1688 nodes are still ponded at 0.3 m or more. These residual nodes sit in terrain depressions, with a median depth of about 0.9 m and an upper quartile above 1.6 m: deep water that only forced pumping can remove. Without added drainage, the residual counts would rise to 6417, 6539, and 5607, and none of the scenarios would return to 0.8 within the assessment window. The bottleneck of post-storm reopening therefore lies not in the early recession but in the deep ponds of the tail. The residual sets overlap strongly across scenarios (intersection-over-union 0.852 under natural recession): the persistent ponding pattern is set mainly by the terrain, which underpins the cross-scenario stability of the exposure criterion.

Table 4 Dynamic resilience metrics of the three scenarios ($\theta = 0.3$ m, emergency drainage $q_p = 10$ mm/h; RL and residual counts at rain end +96 h; A at the trough)

Scenario	$t_{0.8}$ (h)	$t_{0.5}$ (h)	Trough Rmin (hour)	P at rain end +96 h	Resilience loss RL (h)	Fragmentation A	Residual flooded nodes
S1	16	28	0.334 (29 h)	0.931	40.4	3.52	2318
S2	32	41	0.290 (42 h)	0.930	35.4	3.10	2358
S3	14	not crossed	0.638 (45 h)	0.947	34.3	3.50	1688

Table 5 Time to recover from the trough to performance level P (P as defined in Eq. (2); assessment window = rain end +96 h)

Scenario	Setting	Recovery to P = 0.5	Recovery to P = 0.6	Recovery to P = 0.8
S1	Emergency drainage (primary)	6 h	17 h	63 h
S1	Natural recession (lower bound)	6 h	17 h	not reached
S2	Emergency drainage (primary)	15 h	32 h	51 h
S2	Natural recession (lower bound)	15 h	37 h	not reached
S3	Emergency drainage (primary)	0 h	0 h	51 h
S3	Natural recession (lower bound)	0 h	0 h	not reached

4.2 Two-criterion identification results

Fig. 8(a) places all skeleton nodes on the structure–exposure plane. The two dashed lines are the thresholds of the two-criterion rule: the horizontal line b^* is the lowest weighted betweenness within the two-criterion list, and the vertical line $L^* = 1 \text{ h}$ is the entry bar of the persistent-exposure pool. They divide the nodes into four groups: the two-criterion critical nodes ($k = 1000$) in the upper right; betweenness-only nodes (5957), structurally important but not flooded under all three storms; exposure-only nodes (6376), heavily flooded but structurally minor; and the rest in the lower left. Because the threshold lies close to the vertical axis, Fig. 8(b) zooms into the 0–5 h band marked by the dashed box; the y-axis is logarithmic with a zero band, where zero-betweenness nodes are drawn as they are rather than being replaced by a substitute value. The exposure axis shows vertical strips at some durations, an artifact of hourly discretization: nodes in the same depression tend to flood and drain in the same hours. This affects neither ranking nor selection; the maximum possible exposure is bounded by the shortest full run (S2, 168 h).

In Fig. 8(a) the structural threshold is back-derived from the budget k , so the upper-right count always equals k ; whether the two criteria are independent must be judged by evidence that does not depend on k . Correlating the exposure hours of every skeleton node with its weighted betweenness gives a rank correlation of only about 0.03, essentially uncorrelated: the structurally important nodes and the

persistently flooded nodes are, to a large extent, two different sets of nodes. Under natural recession, the three-scenario intersection of residual ponding contains 5573 persistently deep-flooded nodes, occupying 8%–12% of each functional role: exposure does not concentrate in any particular role.

Fig. 8(c) maps the three node classes, with the two-criterion nodes drawn on top. The two-criterion nodes line the important passages of the flooded corridors, covering key water-crossing roads of the core and the periphery. The betweenness-only nodes concentrate on the radial and ring corridors; only 17% of them are elevated or bridgehead nodes, while the other 83% are ground nodes that simply sit on higher ground and stay dry during the floods. The exposure-only nodes scatter over the low-lying periphery, mostly deep-ponding ends of minor roads. Along several radial and ring corridors the two-criterion and the betweenness-only nodes alternate: the two classes are not spatially separated; the mismatch lies in which nodes are picked within the same corridor. The two criteria carry independent information and must be used together; whether the combination works is tested by the reinforcement comparison in the next subsection.

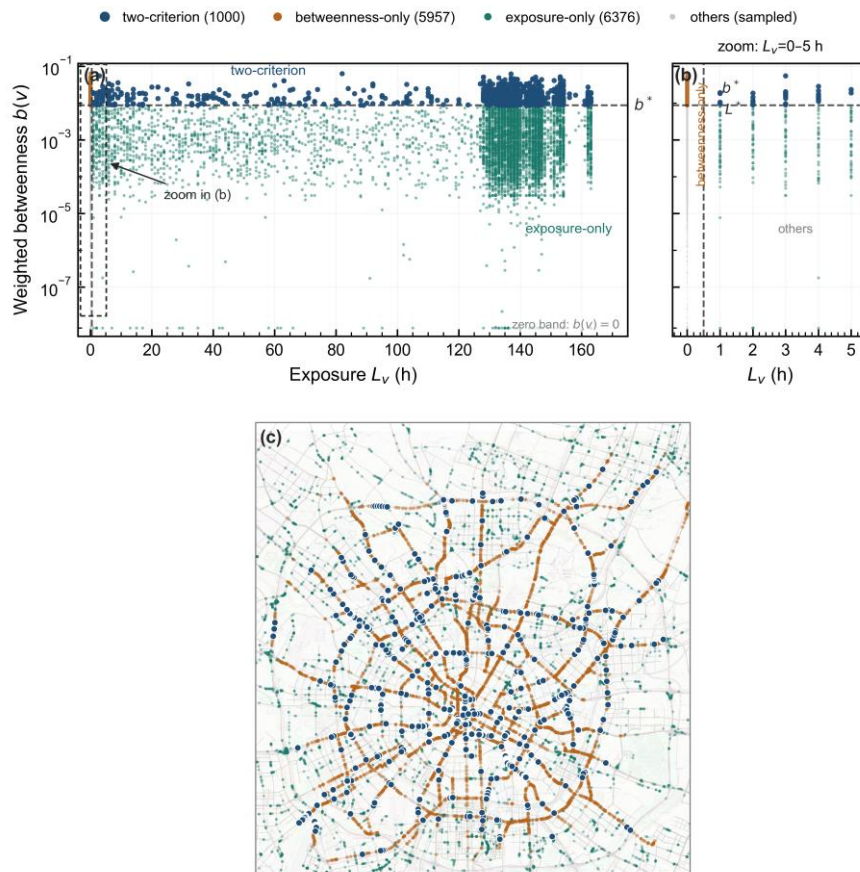


Fig. 8 Two-criterion critical node identification: (a) the structure–exposure plane (horizontal dashed line: structural threshold b^* , the lowest weighted betweenness within the list; vertical dashed line: exposure threshold L^* placed between

the 0 and 1 h columns, nodes with $L_v \geq 1$ h enter the pool; dashed box: zoom area; logarithmic y-axis, zero-betweenness nodes in the bottom zero band); (b) zoom of the 0–5 h threshold band; (c) spatial distribution of the three node classes (two-criterion nodes on top, other classes faded, grey sampled nodes not all drawn)

4.3 Reinforcement replay and comparison of strategies

Reinforcement replay compares five ways of choosing nodes under the same budget k ; the only difference is which k nodes are chosen. Two-criterion selection follows Section 2.3, ranking the persistent-exposure pool (the floodable, non-elevated nodes inundated under all three storms) by weighted betweenness. Structure-only selection takes the top k by weighted betweenness across the whole network, flooded or not; exposure-only selection ranks the pool by flooding severity (persistent exposure, then cumulative flooded hours, then peak depth), ignoring structure. Pool random draws k nodes at random from the same pool, and network random from all floodable nodes; both are averaged over 5 draws. The baseline budget is $k = 1000$ (Section 2.3), swept from 250 to 4000. Fig. 9 maps the selections of the four deterministic-and-random strategies at $k = 1000$ (the sampling range of pool random is the pool itself, shown in Fig. 8(c)): two-criterion selection covers the choke points of the flooded corridors; structure-only concentrates on the dry backbone core; exposure-only leans to the peripheral depressions; network random scatters evenly.

Fig. 10 shows the replay results. In terms of resilience-loss reduction ρ , two-criterion selection reaches 25.3%, 22.3%, and 28.4% in S1, S2, and S3, above 22% in every scenario. Exposure-only reaches 18.2%–26.0%, close to but below two-criterion. Structure-only manages only 2.7%–4.0% and network random about 1%; two-criterion exceeds them by factors of 5 and 23 or more. The direct reason structure-only fails is that only 15%–31% of its selected nodes are ever inundated: over two thirds of the budget goes to nodes that never flood.

Putting two-criterion beside pool random isolates the value of the ranking itself. Drawing 1000 nodes at random from the same pool yields ρ of only 9.7%–16.0%, whereas ranking the pool by betweenness reaches 22.3%–28.4%, roughly a doubling; and pool random in turn beats network random by a factor of 10 or more in every scenario. In other words, first targeting the nodes that will flood contributes most of the benefit, and ranking those nodes by structural importance nearly doubles it again. Exposure-only comes close to two-criterion because it also ranks within the pool, only by flooding severity; it lifts the collapse trough less than the betweenness ranking does (0.012–0.056 versus 0.053–0.114).

The budget sweep (Fig. 10d, e) shows that the advantage of two-criterion selection has a budget threshold. At $k = 250$ it reaches only 3.2%, below exposure-only at 6.0% (pool random 1.7%): with a very small budget, the betweenness ranking concentrates the reinforced nodes on a few backbone corridors, where they are likely adjacent and mutually redundant. From $k = 500$ on, two-criterion overtakes (14.6% versus 9.9% for exposure-only) and stays ahead as the budget grows, reaching 66.0% in the worst scenario at $k = 4000$, while structure-only still delivers only 19.5%. For practice, below a budget of about 500 nodes one should select by exposure severity; from that scale on, use the two-criterion list. The trough gain $\Delta R_{\min}$ is smallest in S2 (0.053): with over ten thousand nodes failing simultaneously in its peak period, point-wise reinforcement can do little about the instantaneous collapse depth, and its value lies more in shortening the low-performance period and speeding up recovery.

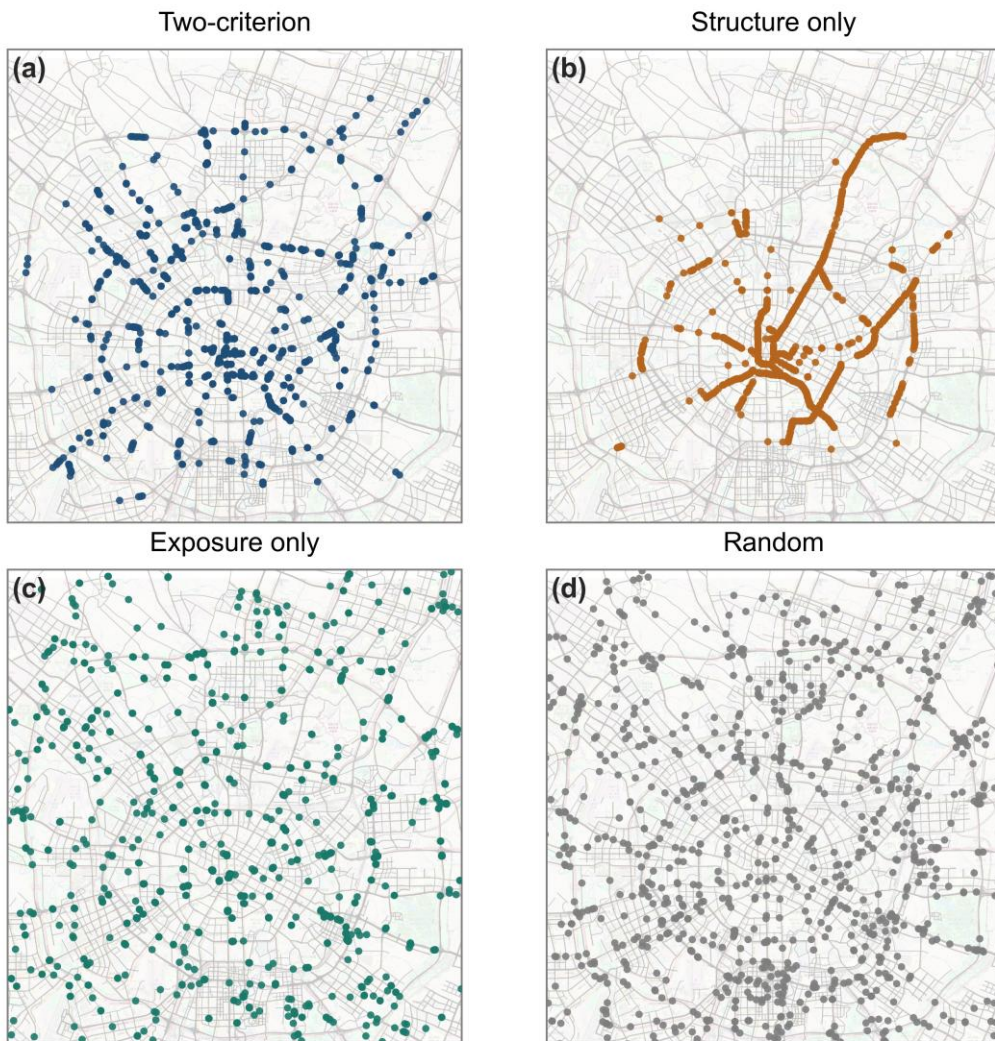


Fig. 9 Spatial distribution of four selection strategies ($k = 1000$): (a) two-criterion; (b) structure only; (c) exposure only; (d) random

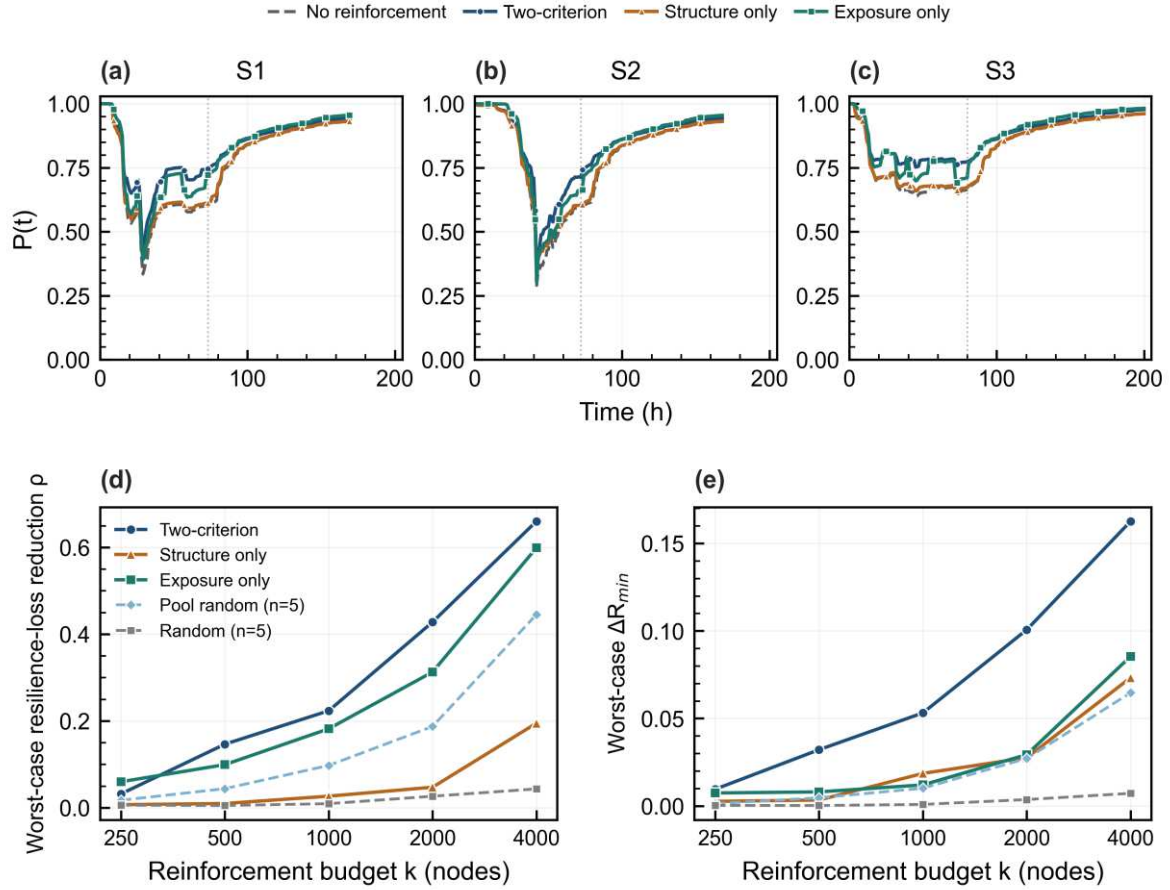


Fig. 10 Reinforcement replay: (a–c) dynamic resilience curves of the three scenarios under each strategy at $k = 1000$ (vertical dotted line: rain end; the random strategies enter (d)(e) as 5-run means); (d) worst-case resilience-loss reduction ρ and (e) worst-case trough gain versus budget.

5 Discussion

(1) The resilience process diverges with the temporal structure of rainfall, and total rainfall alone cannot explain it. The same network shows clearly different resilience processes under the three rainfall types, and S2, with the largest total rainfall, does not suffer the largest resilience loss. Within the three patterns used, total rainfall alone cannot explain the resilience ranking; the temporal structure of rainfall and the ponding dynamics it induces cannot be ignored. Persistent rainfall is low in intensity but lasts long, producing wide but shallow ponding that suppresses the network for a long time without sudden collapse. Concentrated rainfall pushes a large number of nodes over the threshold within a short time, fragmenting the network and crashing performance, which then rebounds visibly once the shallow ponding drains. Multi-peak rainfall sits in between, with second dips as later peaks arrive.

The controlling effect of rainfall spatio-temporal structure on urban hydrological response is well documented [33,34]; this study shows that the control propagates to the functional level of the road

network. Urban flood management should therefore not judge traffic impact by total rainfall alone, but combine the rainfall pattern with collapse depth, low-performance duration, and recovery speed. Under persistent rainfall, the main concern is prolonged, widespread travel restriction; under concentrated rainfall, it is short-lived collapse, with the useful feature that performance rebounds quickly once shallow ponding drains. Both the degradation and the recovery phases here are generated by the flow physics: degradation from hourly inundation, recovery from water recession plus the standard-derived drainage rate, with no prescribed performance trajectory [29,30].

(2) Network topology determines how strongly local inundation is amplified into connectivity loss. Local inundation does not stay local: it can be amplified by the topology into system-wide connectivity loss. At the trough, the fragmentation amplification ratio is about 3 in all three scenarios, so the connectivity loss far exceeds the directly flooded extent: flooded nodes not only drop out themselves but sever key channels, cutting off large blocks of dry roads from the largest connected component. This agrees with percolation studies in which local failures trigger sudden large-scale disintegration [14]; here the effect is quantified by a single ratio that can be compared across rainfall types. Two engineering implications follow. Judging traffic impact only by flooded nodes or flooded mileage may systematically underestimate the real loss; conversely, protecting the few nodes that hold the network together promises a system-level return far beyond their share of the network.

(3) The mismatch between structural importance and flood exposure determines which nodes to reinforce first. High-betweenness nodes mostly sit on roads that stay dry during the floods; only 17% of the betweenness-only nodes are elevated or bridgehead nodes, the rest sitting on backbone roads on higher ground. The persistently flooded nodes, in turn, mostly sit at the network's edge with limited structural roles. The two dimensions are nearly uncorrelated: topological centrality describes a node's role in the network structure, but is not a proxy for its protective value under flooding, and centrality-based importance rankings cannot simply be carried over to flood protection [14,24].

Reinforcement replay confirms that the two criteria complement each other, and the pool-random control separates their contributions: the exposure gate lifts ρ from about 1% to about 10%, and ranking within the pool by betweenness nearly doubles it again, the net contribution of the structural criterion. Two-criterion selection beats structure-only, exposure-only, and both random controls for budgets of $k \geq$

500, not because it is the most extreme on either single dimension, but because its nodes satisfy both conditions at once: easily reached by the flood, and prone to amplifying network loss once failed. When the failure threshold varies within 0.25–0.40 m, the two-criterion list overlaps the baseline list by 892–942 of every 1000 nodes; when the drainage rate varies within 5–20 mm/h, the list is unchanged (selection does not depend on the drainage setting). Under both sweeps ρ stays within 21.5%–31.2%, so the conclusions are robust to the two settings. Compared with centrality-based identification [24], this method makes the actual flood exposure from hydrodynamic simulation an explicit filter; compared with post-disaster repair sequencing [29,30], it answers the pre-disaster question of reinforcement priority under a limited budget, and the two are complementary. For planning practice, flood-proofing priorities should not copy the centrality list; they should go first to nodes that combine high flood exposure with high structural importance, with the ranking basis chosen by the available budget.

6 Conclusions

Facing the problem of ranking flood-proofing reinforcement of urban road networks under a limited budget, this paper proposes SDRI, a method for scenario-driven dynamic resilience assessment and two-criterion critical node identification. The method drives hourly inundation, failure, and reopening of one road network with three observed extreme hyetographs, builds a dynamic resilience metric system on the resilience curves, identifies critical nodes by a structural and an exposure criterion, and tests effectiveness by reinforcement replay under different selection strategies. The overall finding is that road network flood resilience is shaped jointly by rainfall temporal structure, terrain, and network topology; a purely topological view can neither evaluate resilience completely nor guide reinforcement reliably. The main conclusions follow.

(1) The same road network exhibits three types of resilience process under the three rainfall patterns: instantaneous collapse–rebound, oscillatory collapse, and sustained suppression. The trough is deepest under the short-duration concentrated pattern (0.290), followed by the multi-peak intense pattern (0.334) and the long-duration persistent pattern (0.638); yet the largest resilience loss belongs to the multi-peak pattern, which collapses earlier and stays low longer (40.4, versus 35.4 and 34.3). Depth of fall and cumulative loss rank severity inconsistently, so resilience assessment must extract from the dynamic curve a metric system covering degradation, collapse, and recovery, rather than rely on any single indicator.

(2) Inundation is amplified into connectivity loss through topological fragmentation, by a factor of 3.10–3.52 at the trough, about 3 and stable across rainfall types. The mechanism is that flooded nodes sever channels and surviving nodes drop out of the largest connected component in blocks, so the bulk of the connectivity loss does not come from the flooded segments themselves. The residual ponding sets overlap strongly across scenarios (three-scenario intersection-over-union 0.852 under natural recession, Section 4.1); under this study's setting of fixed terrain and equivalent base drainage, the persistent ponding pattern is decided mainly by the terrain, which underpins the cross-scenario stability of the exposure criterion.

(3) Structural importance and flood exposure are clearly mismatched, and pure topological centrality cannot guide flood-proofing on its own. A node's exposure hours and weighted betweenness are nearly uncorrelated: high-betweenness nodes mostly sit on roads that stay dry, with only 17% of the betweenness-only nodes elevated or bridgehead, the rest sitting on backbone roads on higher ground. Structural importance converts into resilience value only when combined with flood exposure.

(4) Reinforcing two-criterion critical nodes yields the highest and most robust returns at medium budgets and above. Reinforcing 1000 two-criterion nodes, 1.6% of the 64479-node skeleton, cuts resilience loss by 22.3%–28.4% across the three scenarios, more than 5 times structure-only selection (2.7%–4.0%) and more than 23 times network random. Pool random reaches only 9.7%–16.0%, about half of the two-criterion figure: the difference is the net contribution of the structural ranking. The benefit comes both from keeping passages through the flooded zone open during the storm and from reinforced nodes no longer dropping out of the network for long periods, lifting the whole recovery phase. The advantage holds from $k = 500$ onward and grows with the budget, reaching 66.0% in the worst scenario at $k = 4000$. At the very small budget of $k = 250$, however, selecting by exposure severity beats the two-criterion list, so the cut-off length of the list should match the budget rather than be truncated arbitrarily. The two-criterion list thus provides a direct basis for flood-proofing priorities under limited budgets.

The scientific message can be summarized as one chain of evidence: flood exposure causes local failures; local failures are amplified by topological fragmentation into network-level connectivity loss; and the temporal shape of that loss is controlled by the rainfall structure. The key to road network flood-proofing therefore lies not in the topologically most important nodes, but in the few nodes where structural

importance and flood exposure meet. This chain links hydrological processes, network structure, and protection decisions into a quantitatively testable whole and provides a methodological basis for resilience-oriented flood-proofing of urban road networks.

This study has four limitations. First, performance is measured by connectivity, without travel demand or flow assignment; the results reflect basic reachability at the structural level rather than full traffic-operation resilience. Failure is judged at nodes, so a long road flooded only in its middle with both ends dry is not counted as failed, which may underestimate the failure extent. Second, the drainage system is generalized: base drainage is a domain-equivalent constant, post-rain drainage is the equivalent linear recession of Eq. (7), and neither sewers nor pumping stations are modeled explicitly; a 10-m grid also cannot resolve roadbeds and side ditches. The sensitivity sweeps cover the failure threshold and the post-rain drainage rate, but not the base drainage during rainfall. As a result, the flooded duration of shallow segments is overestimated and residual ponding concentrates in deep terrain depressions, so absolute durations should not be read as real-world values, and the exposure criterion is used only for cross-scenario relative ranking. Third, reinforcement uses the idealized flooded-but-functional setting, without engineering cost or implementation constraints, and without the feedback of displaced water raising water levels in nearby depressions; the reported resilience-loss reductions are potential upper bounds for a given budget. Fourth, the conclusions rest on one urban network and three storms; the cross-scenario stability of the exposure criterion is derived from the three storms used for screening, and whether the list transfers to unscreened rainfall patterns is untested. Future work will add flow assignment to approach traffic-operation resilience, refine the drainage and reinforcement representation with sewer, pumping, and cost data, and extend to more cities and rainfall patterns to test whether the two-criterion rule and the roughly threefold fragmentation amplification carry over.

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Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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