

A dynamic modeling framework for metro network resilience assessment and improvement under extreme rainstorm disasters

Yangyang Meng^{1,2} (✉)

¹ The Hong Kong Polytechnic University Shenzhen Research Institute, Shenzhen 518057, China

² Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hong Kong 999077, China

✉ Corresponding author. E-mail: yangyang.meng@polyu.edu.hk

Received: September 7, 2026; Revised: October 19, 2026; Accepted: October 28, 2026

© The Author(s) 2026.

Abstract: Extreme rainstorms can severely disrupt metro systems through station inundation, passenger-flow redistribution, secondary overloads, and prolonged service disruption. Despite advances in metro vulnerability and resilience research, hazard exposure, direct disruption, passenger rerouting, and load-induced degradation are often modeled separately, while resilience assessment rarely integrates infrastructure availability, transport efficiency, and satisfied passenger demand. Recovery is also commonly treated as an external schedule rather than a feedback process, although station reopening may redistribute flows and trigger renewed overload. To address these limitations, this study develops a dynamic modeling framework for metro network resilience assessment and

improvement across the disruption–recovery process. The metro system is represented as a time-dependent weighted network integrating rainstorm hazard, rainfall-triggered station failures, passenger rerouting, flow-induced cascading degradation, network-state evolution, performance evaluation, and recovery intervention. System performance is measured using a composite indicator of passenger service ratio, network efficiency, and station availability, while resilience is characterized through stage-based capacities and cumulative performance loss. For resilience improvement, resource-constrained recovery decisions are formulated, and a stability-screened performance-gain strategy that prioritizes stations by marginal benefit is compared with a no-intervention reference scenario. An illustrative application to a simplified Shenzhen Metro subnetwork under a normalized rainstorm scenario reproduces the progression from direct failures to cascading disruption, performance deterioration, and recovery. Sensitivity analyses further show consistent and interpretable responses to variations in station-capacity buffers, direct-failure thresholds, and recovery budgets. The framework provides a computationally tractable and transferable basis for dynamic resilience analysis, and practical recovery planning in rainstorm-exposed metro systems.

Keywords: Metro network resilience; Extreme rainstorms; Cascading failure; Dynamic performance assessment; Resilience improvement

1 Introduction

Metro systems are essential components of urban transportation because they provide high-capacity, energy-efficient, and reliable mobility services. However, their predominantly underground configuration, dense passenger flows, and strong dependence on transfer stations make them particularly susceptible to extreme rainstorms and urban flooding (Guan et al., 2024; Yang et al., 2025; Zhang et al., 2025). Rainwater intrusions may directly interrupt station operations, damage

equipment, restrict passenger access, and force temporary station closures (Jiao et al., 2023). More importantly, the effects of localized disruption can spread through the network: passengers affected by failed stations or routes may shift to alternative paths, increasing the loads of the remaining stations and potentially causing further functional degradation (He et al., 2025; B. Zhao et al., 2022). Metro resilience under extreme rainstorms must therefore be understood as a dynamic network-level process rather than simply the sum of isolated station failures.

Infrastructure resilience generally refers to the ability of a system to withstand disruption, maintain essential functions, and restore its performance over time (Xu et al., 2024). In metro networks, this process involves several interrelated stages, including the absorption of the initial hazard impact, the response to subsequent network degradation, and the restoration of transport services (Gao et al., 2024; Wu et al., 2024). Static vulnerability and robustness indicators can identify structurally important stations or estimate performance under a predefined disruption, but they provide limited information about how passenger demand, station functionality, network connectivity, and recovery actions interact over time. Dynamic modeling is consequently needed to represent the complete performance trajectory from the pre-disaster state to disruption and recovery (He et al., 2025).

Existing studies on rainstorm-affected metro systems can be broadly classified into three research streams. The first focuses on hazard exposure and direct physical impacts. Hydrodynamic simulation, geographic analysis, vulnerability indicators, and scenario-inference methods have been applied to identify stations exposed to flooding and estimate the consequences of water intrusion (Li et al., 2025; Liang et al., 2026; Liang & Guan, 2025; Zhang et al., 2025). These studies improve the physical representation of rainstorm hazards but often treat station failure as the final outcome. The subsequent effects of station closure on passenger movements and network-level service performance are not always explicitly represented.

The second research stream examines metro-network vulnerability and cascading failure. Complex-network models commonly assess connectivity, network efficiency, or giant-component size under

random or targeted station attacks. More recent studies have incorporated passenger demand, station capacity, and route-choice behavior to represent flow redistribution following disruption (Guo et al., 2025; Meng & Zhao, 2026; Sun et al., 2022; J. Zhao et al., 2026). These developments show that a relatively small number of station failures can produce disproportionate service losses when disrupted passengers are redirected toward capacity-constrained parts of the network. Nevertheless, many models use predefined attacks, static passenger demand, or a single disruption stage. Relatively few studies jointly describe hazard-induced failures, endogenous flow-related degradation, cross-period state dependence, and the complete resilience trajectory.

The third-stream concerns resilience improvement and post-disaster recovery. Existing approaches prioritize failed stations according to centrality, vulnerability, criticality, marginal performance contribution, or optimization objectives. Dynamic network-flow and repair-allocation models have also demonstrated the importance of linking infrastructure states, redistributed flows, and limited recovery resources (Du et al., 2024; Huang et al., 2026; B. Zhao et al., 2022). However, recovery is frequently applied to a fixed damaged network without fully examining whether restored connectivity creates new flow concentrations (C. Xu & Xu, 2024). Restoring a topologically important station may attract substantial passenger demand and unintentionally overload other stations. Therefore, recovery priority should account not only for the immediate performance benefit but also for the stability of the resulting network state (Tan et al., 2024).

Despite substantial progress, an integrated and transferable framework connecting the assessment and improvement stages remains limited. Three gaps are particularly relevant. First, rainstorm hazards, direct station failure, passenger redistribution, and flow-induced degradation are often modeled separately. Second, resilience is frequently evaluated using either topological or passenger-oriented indicators, making it difficult to represent physical availability, network efficiency, and demand satisfaction simultaneously. Third, the feedback between recovery decisions and subsequent network-state evolution is not always incorporated, particularly when a restoration action may itself

trigger renewed overload. Addressing these gaps requires a unified framework in which hazard impacts, network operation, performance evaluation, and intervention decisions are updated iteratively. Accordingly, this study aims to develop a dynamic and transferable modeling framework for assessing and improving metro-network resilience under extreme rainstorm disasters. The framework follows the process: *Rainstorm hazard* $\rightarrow$ *Direct station failure* $\rightarrow$ *Passenger redistribution* $\rightarrow$ *Flow-induced degradation* $\rightarrow$ *Performance loss* $\rightarrow$ *Intervention and recovery*.

The main contributions of this study are summarized as follows.

- A unified dynamic process is established to connect rainstorm hazard, direct station failure, passenger-flow redistribution, flow-induced degradation, network-state evolution, performance loss, intervention, and recovery. This process enables disruption propagation and post-disaster restoration to be represented within a consistent time-dependent framework.
- A multidimensional resilience-measurement system is developed by integrating topological, operational, and passenger-service functionality. Normalized network efficiency, station availability, and passenger service ratio are combined to characterize system performance, while stage-based indicators quantify absorptive, response, and recovery capacities as well as cumulative resilience loss.
- A resilience-improvement approach is proposed under limited recovery resources. The stability-screened performance-gain rule sequentially identifies beneficial recovery actions and excludes interventions that may generate additional overload failures, thereby linking recovery decisions with subsequent network-state evolution.
- The framework is demonstrated using a simplified real-world metro subnetwork and evaluated through parameter-sensitivity analysis. The results confirm its computational feasibility and sensitivity to capacity, hazard, and recovery conditions. Because the model is formulated using general network, demand, hazard, and intervention inputs, it can be transferred to other metro systems after appropriate data preparation and parameter calibration.

The framework is demonstrated using a simplified four-line Shenzhen Metro subnetwork. The application is intended to verify model computability, illustrate the progression from direct failure to performance restoration, and examine sensitivity to key parameters. It is not intended to reproduce a specific historical rainstorm or conduct a comprehensive comparison of recovery strategies.

2 Overall Dynamic Modeling Framework

2.1 Problem Definition and Modeling Assumptions

The metro system is represented as a graph $G = (V, E)$, where V and E denote the sets of stations and rail connections, respectively. The analysis horizon is divided into discrete time periods to characterize the multi-day evolution of the system. For each station i , $R_{i,t}$ denotes its rainstorm-hazard intensity at time t , while $x_{i,t} \in [0, 1]$ represents its functional state, ranging from complete failure to normal operation. Passenger demand is described by a time-dependent origin–destination matrix $D^t = d_{od}^t$.

At each time step, the rainstorm may cause initial station failures or functional degradation. Passengers affected by these disruptions are redistributed over the remaining operational network. The resulting increase in passenger loads may exceed the effective capacities of other stations and cause further performance degradation. Recovery or improvement measures are then implemented subject to budget and resource constraints, after which station states and network performance are updated. This process is repeated throughout the analysis horizon to capture the interactions among rainstorm hazards, station failures, passenger-flow redistribution, and recovery interventions.

The model aims to: (1) quantify the dynamic resilience trajectory of the metro network during disruption and recovery, and (2) identify effective intervention strategies for reducing cumulative performance loss. Several assumptions are adopted for model tractability. First, the physical network topology and nominal capacities remain unchanged during the analysis period, while service availability is determined by station states. Second, rainstorm impacts are modeled primarily through

station failures, and a rail connection becomes unavailable if its associated stations cannot provide service. Third, disrupted passengers select feasible alternative paths according to a predefined route-choice rule, while passengers who cannot complete their journeys are treated as unsatisfied demand. Fourth, station degradation may occur when redistributed passenger demand exceeds effective capacity. Finally, recovery actions require limited time and resources, and external infrastructure dependencies are represented implicitly through station failure and recovery parameters. These assumptions provide a general and transferable basis for the subsequent dynamic resilience assessment and improvement models.

2.2 Metro Network and State Representation

The metro system is modeled as a weighted graph $G = (V, E, W)$, where each node $i \in V$ represents a station and each edge $(i, j) \in E$ represents a direct rail connection between two adjacent stations. Station attributes include nominal service capacity C_i^0 , passenger demand, transfer function, and rainstorm exposure. Edge attributes may include travel time, distance, and nominal transport capacity. The normal network topology is described by the adjacency matrix A .

The functional state $x_{i,t} = 1$ indicates normal operation, $x_{i,t} = 0$ indicates complete failure, and $0 < x_{i,t} < 1$ indicates degraded operation. Its effective capacity is consequently defined as $C_{i,t} = x_{i,t} C_i^0$.

The continuous state variable provides a general representation that permits partial station functionality. In the illustrative application, station states are restricted to $x_{i,t} \in [0,1]$, representing operational and unavailable conditions, respectively. Restored stations return to full functionality ($x_{i,t} = 1$). Intermediate functionality levels and partial restoration are not implemented in the present application.

The time-dependent network state is denoted by $\mathbf{X}_t = (x_{1,t}, x_{2,t}, \dots, x_{|V|,t})$. Correspondingly, the effective adjacency matrix can be expressed as $\mathbf{A}_t = \text{diag}(\mathbf{X}_t) \mathbf{A} \text{diag}(\mathbf{X}_t)$, which reflects the reduced availability of stations and their associated connections under disruption.

Passenger-flow conditions are represented by the station load q_i^t and the load ratio $\rho_{i,t} = q_{i,t}/C_{i,t}$. A station operates within its available capacity when $\rho_{i,t} \leq 1$, whereas $\rho_{i,t} > 1$ indicates overload and possible flow-induced degradation. The system state is therefore jointly characterized by station functionality, effective network connectivity, passenger-flow distribution, and recovery status. Its evolution can be generally written as $\mathbf{X}_{t+1} = \mathcal{F}(\mathbf{X}_t, \mathbf{H}_t, \mathbf{D}_t, \mathbf{Y}_t)$, where $\mathbf{H}_t$, $\mathbf{D}_t$, and $\mathbf{Y}_t$ denote the rainstorm hazard, passenger demand, and intervention decisions, respectively. This representation provides the common state basis for the subsequent failure, flow-redistribution, resilience-assessment, and recovery models.

2.3 Framework Architecture and Modeling Workflow

The proposed framework integrates rainstorm-induced disruption, passenger-flow adjustment, network-state evolution, resilience assessment, and intervention decision-making within a unified dynamic process. As shown in Fig. 1, the main workflow is summarized as *Rainstorm hazard* $\rightarrow$ *Initial failures* $\rightarrow$ *Passenger-flow redistribution* $\rightarrow$ *Cascading effects* $\rightarrow$ *State evolution* $\rightarrow$ *Resilience assessment* $\rightarrow$ *Intervention and recovery*.

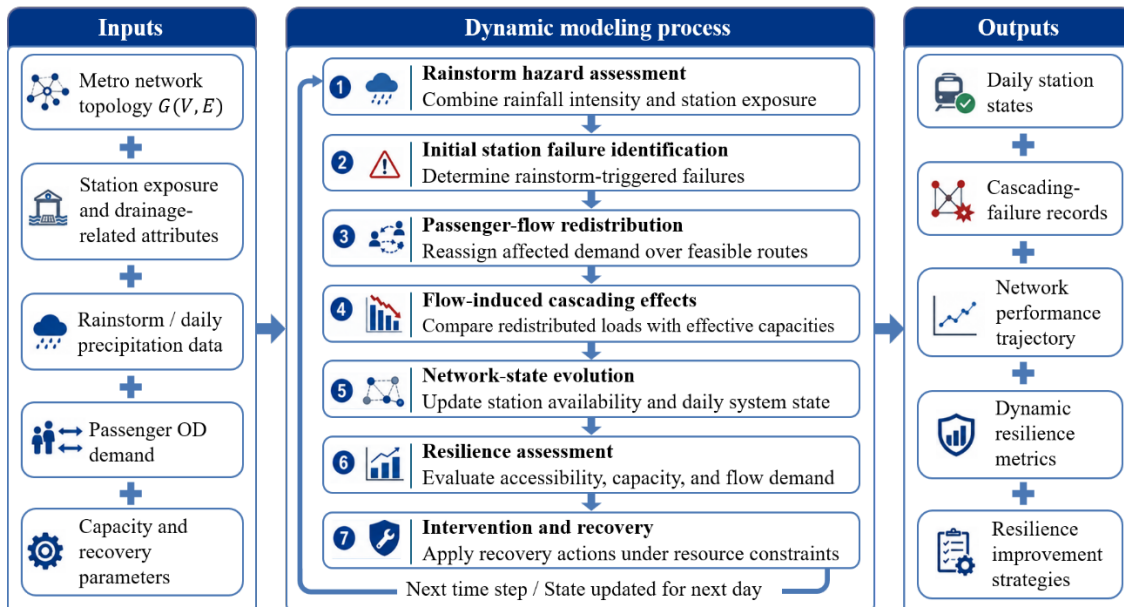


Fig. 1 The proposed framework and modeling workflow.

At each time step, the spatially and temporally varying rainstorm hazard is first mapped to station-level failure or degradation. Passenger demand affected by unavailable stations and connections is then redistributed over feasible alternative routes. The redistributed flows change station load ratios and may induce additional functional degradation when effective capacities are exceeded. Based on these changes, the network state is updated, and its performance loss is quantified in terms of connectivity, accessibility, transport capacity, and satisfied passenger demand.

Intervention and recovery measures are subsequently introduced to improve the network state under resource constraints. The updated state becomes the initial condition for the next time step, allowing the framework to reproduce the multi-period evolution of disruption and recovery. By iteratively linking the assessment and improvement processes, the framework supports both the evaluation of dynamic resilience trajectories and the comparison of alternative resilience-enhancement strategies.

3 Dynamic Resilience Assessment Model

3.1 Rainstorm-Induced Station Failure

(1) Station exposure assessment

To capture the spatial heterogeneity of stations under rainstorm conditions, a station-level exposure index was developed based on three attributes: the number of station entrances, lowland susceptibility, and drainage condition. The number of entrances reflects the potential access points through which surface runoff may enter the station. Lowland susceptibility describes the tendency of a station area to accumulate water, considering elevation, local depression, terrain slope, and proximity to water bodies. Drainage condition represents the local capacity to discharge stormwater, which is associated with impervious surface coverage, permeable land availability, and historical waterlogging records.

The preliminary exposure value of station i was defined as Eq. (1), where n_i denotes the number of station entrances, l_i represents the lowland-susceptibility level, and d_i is the drainage-capability level. Both l_i and d_i were scored on ordinal scales from 1 to 5. Higher values indicate greater lowland

susceptibility and better drainage capability, respectively. Since a higher drainage-capability score indicates better drainage performance, the term $6 - d_i$ was used to transform drainage capability into drainage deficiency. Therefore, stations with poorer drainage conditions obtain larger exposure values. The coefficients of 0.25, 0.40, and 0.35 were adopted as illustrative settings for the present application rather than empirically calibrated estimates. To make the exposure values comparable across stations, the raw exposure scores were rescaled to the range $[0, 1]$ with $\tilde{E}_i = \frac{E_i^* - E_{\min}^*}{E_{\max}^* - E_{\min}^*}$, where $E_{\min}^*$ and $E_{\max}^*$ are the minimum and maximum raw exposure scores among all stations.

$$E_i^* = 0.25n_i + 0.40l_i + 0.35(6 - d_i) \quad (1)$$

(2) Station Hazard Modeling

Daily rainfall was spatially matched to each metro station according to station coordinates. Because rainfall magnitude and station exposure are measured on different scales, rainfall values were first normalized over all station-day observations during the simulation period with $\tilde{R}_{i,t} = \frac{R_{i,t} - R_{\min}}{R_{\max} - R_{\min}}$, where $R_{i,t}$ is the rainfall intensity assigned to station i on day t , and $R_{\min}$ and $R_{\max}$ denote the minimum and maximum rainfall values across all stations and days.

The station-level hazard index $H_{i,t}$ was then calculated by combining normalized rainfall intensity and normalized station exposure as Eq. (2), where $\alpha = 0.6$ and $\beta = 0.4$. Rainfall was assigned a larger weight because it acts as the direct external trigger of station disruption, while station exposure reflects the local susceptibility of each station to rainfall impacts. Since both components were normalized, $H_{i,t}$ also ranged from 0 to 1.

$$H_{i,t} = \alpha\tilde{R}_{i,t} + \beta\tilde{E}_i \quad (2)$$

(3) Rainfall-Triggered Failure

A threshold-based rule was used to determine whether a station was directly disrupted by rainfall.

The direct failure state of station i on day t was expressed as $F_{i,t}^R = \begin{cases} 1, & H_{i,t} \geq \theta \\ 0, & H_{i,t} < \theta \end{cases}$, where $\theta = 0.6$ is

the hazard threshold. If $F_{i,t}^R = 1$, station i is regarded as an initial rainfall-induced failed station and is removed from the available metro network before passenger-flow redistribution. Stations with $H_{i,t} < \theta$ remain operational at the beginning of the simulation day, but they may still fail later due to overload propagation. In this way, the model explicitly distinguishes direct failures triggered by rainfall from secondary failures generated by cascading processes.

3.2 Passenger-Flow Redistribution and Flow-Induced Functional Degradation

(1) Network Representation and Benchmark State

The metro system was abstracted as an undirected weighted network $G = (V, E)$. The weight of each edge was defined by the corresponding interstation travel time, so that passenger routing could be modeled based on the minimum travel-time principle. For interchange stations, different lines were integrated into the same network node, allowing transfer functions to be represented within the topological structure. No additional transfer-time penalty was applied when passengers changed lines at a shared interchange node. Transfer walking and waiting times were therefore not explicitly modeled in the illustrative application. This simplification may affect the relative attractiveness of alternative routes and the resulting passenger-flow distribution.

A pre-disaster network state was established as the benchmark condition. Under this baseline scenario, daily origin–destination demand was assigned to the intact metro network to obtain reference station loads, network efficiency, and system performance. These benchmark values served two purposes: first, they provided the basis for estimating station capacity; second, they were used as reference values for normalizing performance loss during the disruption process.

(2) Passenger Demand Rerouting under Station Failures

Once rainfall-induced or cascade-induced station failures occurred, the failed stations were excluded from the operational network. At cascade iteration k on day t , the remaining available network was expressed as $G_t^{(k)} = G \setminus F_t^{(k)}$, where $F_t^{(k)}$ is the set of failed stations at iteration k . Passenger demand was then reassigned on $G_t^{(k)}$. For each OD pair, if both the origin and destination remained

operational and at least one feasible path existed between them, the demand was allocated to the shortest travel-time path. Otherwise, the corresponding demand was treated as unserved.

The redistributed load of station i at iteration k was calculated as $L_{i,t}^{(k)} = \sum_{o,d} q_{od,t} I(i \in p_{od,t}^{(k)})$, where $q_{od,t}$ denotes the travel demand between origin o and destination d on day t , $p_{od,t}^{(k)}$ is the selected shortest path in the available network, and $I(\cdot)$ is an indicator function. The load was assigned to all stations located along the selected path, including the origin, destination, and intermediate transfer stations.

As presented in Algorithm 1, this rerouting process was repeated after each update of the failed-station set. Therefore, newly failed stations could immediately alter available paths, change passenger-flow distribution, and modify station loads in the next cascade iteration. In this way, the model captured the dynamic coupling between station closures, passenger rerouting, and load redistribution.

Algorithm 1 Passenger-flow redistribution on the available metro network

Input: Full metro network G ; failed-station set $F_t^{(k)}$; daily OD demand Q_t ; edge travel times w_{ij} .

Process:

1. Construct the available network:

$$G_t^{(k)} \leftarrow G \setminus F_t^{(k)}.$$

2. Initialize:

$$L_{i,t}^{(k)} \leftarrow 0, \text{ for all } \forall i \in V(G_t^{(k)});$$

$$D_t^{\text{served}} \leftarrow 0;$$

$$D_t^{\text{lost}} \leftarrow 0.$$

3. For each OD pair $(o, d, q_{od,t}) \in Q_t$ with $q_{od,t} > 0$:

- a. If o and d belong to $V(G_t^{(k)})$ and an available path exists, find the minimum travel-time path:

$$p_{od,t}^{(k)} \leftarrow \arg \min_{p \in \mathcal{P}_{od}(G_t^{(k)})} \sum_{(i,j) \in p} w_{ij}.$$

b. Update the served demand:

$$D_t^{served} \leftarrow D_t^{served} + q_{od,t}.$$

c. For each station $i \in p_{od,t}^{(k)}$, update its passenger load:

$$L_{i,t}^{(k)} \leftarrow L_{i,t}^{(k)} + q_{od,t}.$$

d. Otherwise, update the lost demand:

$$D_t^{lost} \leftarrow D_t^{lost} + q_{od,t}.$$

4. Calculate the service ratio:

$$S_t \leftarrow \frac{D_t^{served}}{D_t^{served} + D_t^{lost}}.$$

5. Return $L_{i,t}^{(k)}$, D_t^{served} , D_t^{lost} , and S_t .

Output: Station loads $L_{i,t}^{(k)}$; served demand D_t^{served} ; lost demand D_t^{lost} ; service ratio S_t .

(3) Flow-Induced Functional Degradation

Station capacity was estimated from the benchmark passenger load. Specifically, the capacity of station i was defined as $C_i = \max[(1 + \delta) \cdot L_i^0 \varepsilon]$, where L_i^0 is the benchmark load of station i , $\delta = 0.20$ is the capacity-buffer coefficient, and $\varepsilon = 10^{-6}$ is a small positive value used to avoid zero capacity for stations with no benchmark passenger load. This setting implies that each station can accommodate up to 120% of its normal passenger load before functional degradation occurs.

At each cascade iteration, the redistributed load was compared with station capacity. If an operational station received a load greater than its capacity, it was regarded as overloaded and was added to the newly failed-station set: $\Delta F_t^{(k)} = \{i \in V \setminus F_t^{(k)} \mid L_{i,t}^{(k)} > C_i\}$.

Consistent with the binary implementation described in *Section 2.2*, an overloaded station transitions from an operational state to an unavailable state and is excluded from subsequent passenger routing

until restored. Here, overload-induced failure denotes operational unavailability, which does not necessarily imply physical damage.

The failed-station set was then updated as $F_t^{(k+1)} = F_t^{(k)} \cup \Delta F_t^{(k)}$. After the update, the available network was reconstructed, passenger demand was reassigned, and station loads were recalculated. This iterative procedure continued until no additional overloaded stations were identified, namely $\Delta F_t^{(k)} = \emptyset$, or until the maximum number of cascade iterations was reached. The final converged failure set represented the resulting functional state of the metro network for that simulation day.

3.3 Multi-Day Network-State Evolution

To represent the temporal evolution of metro disruptions under a prolonged rainstorm event, the simulation was conducted over multiple consecutive days, covering the pre-disaster benchmark, the disaster period, and the subsequent recovery stage. At the start of each simulation day, the initial failure set was determined by combining two sources of disruption: unresolved failures inherited from the previous day and newly triggered rainfall-induced failures on the current day. This daily initial failure set was defined as $F_t^{(0)} = F_{t-1}^{carry} \cup F_t^R$, where F_t^R denotes rainfall-induced failures on day t , and F_{t-1}^{carry} represents stations that remained unavailable after the previous day. Daily passenger demand and rainfall conditions were then applied, and the cascade model was iterated to convergence.

The multi-day simulation framework was developed to capture the temporal interdependence among rainfall-triggered disruptions, endogenous overload propagation, and delayed station recovery. The model comprises two coupled loops. The inner loop represents the within-day cascading process: failed stations are removed from the operational network, passenger flows are reassigned through feasible shortest paths, station loads are recalculated, and newly overloaded stations are identified and incorporated into the failure set. This iterative process continues until no additional overload-induced failures occur or the maximum number of cascade iterations is reached. The outer loop governs the day-to-day evolution of the network state. At the beginning of each time step, unresolved

failures inherited from the preceding step are combined with newly triggered rainfall-induced failures. Rainfall-induced and flow-induced failures are assigned different minimum failure durations to distinguish direct hazard impacts from overload-related operational disruptions. During designated recovery steps, stations that have satisfied their minimum failure durations and are no longer subject to an active direct hazard are eligible for intervention. Eligible stations are evaluated sequentially using the stability-screened performance-gain rule under the recovery resource constraint. Accepted recovery actions take effect within the current time step, before the final passenger-flow reassignment and cascade calculation. Once the updated network state has stabilized, station states, failure types, station loads, and network performance indicators are recorded. Accordingly, the reported performance P_t represents the stabilized post-intervention state at time step t . Failure-duration counters are then updated, and unresolved failures are carried forward to the next time step. This design enables the model to describe not only daily cascading failures, but also failure accumulation, delayed restoration, repeated overload, and non-monotonic recovery trajectories over the entire disaster–recovery period.

3.4 Network Performance and Resilience Quantification

(1) System performance indicators

To describe the time-varying functionality of the metro network, three complementary indicators are adopted, including passenger service availability, network efficiency, and station availability. The passenger service ratio is defined as the proportion of total daily OD demand that can still be accommodated by the operational network with Eq. (3), where D_t^{served} denotes the passenger demand that can be assigned to feasible paths at time t , and D_t^{total} is the total passenger demand. OD trips involving failed origins, failed destinations, or disconnected station pairs are regarded as unserved demand.

$$S_t = \frac{D_t^{served}}{D_t^{total}} \quad (3)$$

Network efficiency η_t is used to characterize the travel-time accessibility among available stations

with $\eta_t = \frac{1}{n_t(n_t-1)} \sum_{\substack{i,j \in V_t \\ i \neq j}} \frac{1}{d_{ij,t}}$, where V_t is the set of available stations, n_t is its size, and $d_{ij,t}$

represents the shortest travel time between stations i and j at time t . For station pairs that are not mutually reachable, their contribution to the summation is set to zero. The normalized network efficiency E_t is then given by Eq. (4), where η_0 is the benchmark efficiency under normal operating conditions.

$$E_t = \frac{\eta_t}{\eta_0} \quad (4)$$

The station availability ratio U_t is expressed as Eq. (5), where N is the total number of stations in the metro network. Based on the above indicators, the overall system performance at time t is calculated as Eq. (6). In this illustrative application, equal weights are adopted as a transparent reference setting to demonstrate the framework without assigning priority to any performance dimension. In practical applications, the weights can be adjusted to reflect local operational objectives and stakeholder priorities. Thus, P_t jointly reflects the network's ability to serve passenger demand, maintain efficient connectivity, and preserve physical station availability.

$$U_t = \frac{n_t}{N} \quad (5)$$

$$P_t = \frac{(S_t + E_t + U_t)}{3} \quad (6)$$

(2) Stage-based resilience assessment

The resilience process is divided into three stages: absorption, response, and recovery. The absorption stage describes the ability of the metro network to withstand the initial impact of the rainstorm hazard. The response stage represents the further degradation of system performance after the initial disruption, while the recovery stage captures the extent to which the system performance is restored after reaching its lowest level.

Let P_0 denote the pre-disaster benchmark performance, P_I the system performance immediately after the first impact, P_{min} the minimum performance observed during the disruption period, and P_f the final performance at the end of the simulation horizon. This stage-based description enables the resilience process to be interpreted from three perspectives: initial resistance, disruption severity, and post-disaster restoration.

(3) Resilience metrics

The absorptive capacity indicator A is defined as Eq. (7). A larger value of A indicates that the network can retain a higher proportion of its normal performance under the initial disaster impact. The value of A is bounded within $[0,1]$.

$$A = \frac{P_I}{P_0} \quad (7)$$

The response capacity indicator Q is calculated as Eq. (8), and this indicator measures the degree to which the system avoids further performance decline after the first impact. A higher Q suggests a milder subsequent degradation process.

$$Q = \frac{P_{min}}{P_I} \quad (8)$$

The recovery capacity indicator C is defined as Eq. (9), and this metric represents the recovered proportion of the total recoverable performance gap. A value of $C = 1$ indicates that the system has returned to the benchmark performance level, whereas $C = 0$ means that no net recovery has been achieved from the minimum-performance state. When $P_0 = P_{min}$, C is assigned a value of 1.

$$C = \frac{P_f - P_{min}}{P_0 - P_{min}} \quad (9)$$

The cumulative resilience loss is calculated by aggregating the performance deficits over the entire observation period with Eq. (10), where T is the number of time steps. Since this metric accumulates performance loss over time, it is not limited to the interval $[0, 1]$.

$$Re_{loss} = \sum_{t=1}^T \max(0, P_0 - P_t) \quad (10)$$

The overall resilience index is further defined as Eq. (11). This index indicates the proportion of ideal cumulative performance that is preserved during the study period. Finally, the vulnerability index is given by Eq. (12). Higher values of A , Q , C and Re imply stronger metro network resilience, whereas higher values of Re_{loss} and V indicate greater disruption and vulnerability.

$$Re = 1 - \frac{Re_{loss}}{TP_0} \quad (11)$$

$$V = 1 - Re \quad (12)$$

4 Dynamic Resilience Improvement Model

4.1 Resilience-Improvement Intervention Scenarios

Two scenarios are considered to evaluate the effect of recovery intervention: (i) a no-intervention reference scenario and (ii) a representative stability-screened performance-gain-based recovery scenario. Both scenarios are simulated under identical hazard, passenger-demand, capacity, and network-state conditions, ensuring that differences in system performance can be attributed to the implemented recovery actions.

(i) Under the no-intervention scenario, no failed station is actively restored during the analysis period. Accordingly, the recovery decision variables satisfy $y_{i,t} = 0$ for all stations and time steps. Failed stations remain unavailable according to the specified state-evolution rules, while passenger-flow redistribution, possible flow-induced failures, and network performance are continuously recalculated. This scenario provides a counterfactual reference for quantifying the benefits of intervention.

(ii) Under the stability-screened performance-gain-based scenario, eligible stations are evaluated sequentially according to their marginal contribution to system performance. At each selection step, a candidate station is temporarily restored, after which passenger flows, station loads, and possible

flow-induced failures are recalculated. The candidate is accepted only when its restoration produces a positive performance gain without generating additional overload failures. Among all acceptable candidates, the station with the largest marginal gain is selected. The temporary network state is then updated, and the evaluation is repeated until the recovery budget is exhausted or no further acceptable candidate is available.

The comparison between these two scenarios is intended to demonstrate whether the proposed improvement model can identify stable and beneficial recovery actions and quantify their effects on the resilience trajectory. It does not aim to provide a comprehensive comparison of alternative recovery strategies.

4.2 Recovery Decision Formulation

Let $s \in \{0, R\}$ denote the intervention scenario, where $s = 0$ represents the no-intervention reference scenario and $s = R$ represents the stability-screened performance-gain-based recovery scenario.

Under the reference scenario, no recovery action is implemented as $y_{i,t}^0 = 0, \forall i \in V, t = 1, \dots, T$.

For the recovery scenario, let $\mathcal{E}_t^R$ denote the set of stations eligible for intervention at time t . A disrupted station is considered eligible when it remains unavailable from the preceding time step, is not subject to an active direct hazard impact, and has satisfied its minimum required failure duration.

The binary recovery variable is defined as Eq. (13).

$$y_{i,t}^s = \begin{cases} 1, & \text{if station } i \text{ is selected and accepted for recovery at time } t, \\ 0, & \text{otherwise.} \end{cases} \quad (13)$$

The selected recovery set is $\mathcal{R}_t = \{i \in \mathcal{E}_t^R : y_{i,t}^R = 1\}$. Recovery decisions are subject to the resource constraint with $\sum_{i \in \mathcal{E}_t^R} k_i y_{i,t}^R \leq B_t$, where k_i is the resource requirement for restoring station i , and B_t is the available intervention budget at time t . If a unit recovery cost is assumed for all stations, the constraint can be simplified as $|\mathcal{R}_t| \leq B_t$.

For each eligible candidate station i , let $\tilde{\mathbf{X}}_t^{R,i}$ denote the temporary post-restoration state obtained by restoring station i . Passenger demand is then redistributed, and the flow-induced failure process is recalculated until a stable trial state $\hat{\mathbf{X}}_t^{R,i}$ is reached as $\hat{\mathbf{X}}_t^{R,i} = \mathcal{F}(\tilde{\mathbf{X}}_t^{R,i}, \mathbf{H}_t, \mathbf{D}_t)$.

The marginal performance gain associated with candidate station i is defined as $\Delta P_{i,t}^R = P_t(\hat{\mathbf{X}}_t^{R,i}) - P_t(\mathbf{X}_t^R)$. Let $\mathcal{C}_{i,t}^S$ denote the set of additional overload failures generated after the temporary restoration of station i . The set of acceptable recovery candidates is then defined as $\mathcal{A}_t^R = \{i \in \mathcal{E}_t^R \setminus \mathcal{R}_t : \Delta P_{i,t}^R > 0, \mathcal{C}_{i,t}^R = \emptyset\}$.

The station selected at each decision step is $i^* = \arg \max_{i \in \mathcal{A}_t^R} \Delta P_{i,t}^R$. After station i^* is accepted, the temporary network state is updated, and the marginal gains of the remaining candidates are recalculated. This procedure continues until the recovery budget is exhausted or no acceptable candidate remains.

4.3 Intervention-Driven Network-State Updating

Once the recovery decisions have been determined, the accepted intervention actions are applied to the network. Let $x_{i,t}^s$ denote the functional state of station i before intervention under scenario s . For full restoration, the post-intervention state is expressed as $\tilde{x}_{i,t}^s = x_{i,t}^s + y_{i,t}^s(1 - x_{i,t}^s)$.

Thus, a selected station is restored to its normal functional level, whereas the states of unselected stations remain unchanged. Under the no-intervention scenario, $y_{i,t}^0 = 0$, and therefore $\tilde{x}_{i,t}^0 = x_{i,t}^0$.

When partial restoration is considered, the state update can be generalized as $\tilde{x}_{i,t}^s = \min\{1, x_{i,t}^s + \delta_{i,t} y_{i,t}^s\}$, where $\delta_{i,t}$ denotes the functional improvement provided by the intervention. The resulting post-intervention network state is denoted by $\tilde{\mathbf{X}}_t^s = (\tilde{x}_{1,t}^s, \tilde{x}_{2,t}^s, \dots, \tilde{x}_{|V|,t}^s)$.

The restored stations and their associated connections are then reintroduced into the operational network. Passenger demand is reassigned over the updated feasible paths, after which station loads, capacity utilization, and possible flow-induced failures are recalculated. The resulting network state is given by $\mathbf{X}_{t+1}^s = \mathcal{F}(\tilde{\mathbf{X}}_t^s, \mathbf{H}_t, \mathbf{D}_t)$, $s \in \{0, R\}$.

For the recovery scenario, $y_{i,t}^R = 1$ only when the candidate action has produced a positive performance gain and passed the stability-screening condition specified in *Section 4.2*. Nevertheless, the restored station may experience renewed degradation in subsequent time steps if hazard conditions or passenger demand change.

4.4 Integrated Assessment–Improvement Process

The assessment and improvement components are coupled through a closed-loop procedure comprising intervention decision-making, dynamic network simulation, resilience evaluation, and intervention decision updating: *Intervention decision* $\rightarrow$ *Dynamic network simulation* $\rightarrow$ *Resilience evaluation* $\rightarrow$ *Next-period decision updating*.

For the no-intervention scenario, the recovery decision vector is fixed as $\mathbf{Y}_t^0 = \mathbf{0}$. For the representative recovery scenario, the intervention decision is determined by $\mathbf{Y}_t^R = \pi_R(\mathbf{X}_t^R, \mathbf{H}_t, \mathbf{D}_t, \mathcal{E}_t^R, B_t)$, where π_R denotes the stability-screened performance-gain decision rule. Based on the current network state, this rule evaluates eligible stations, applies the resource constraint, and selects recovery actions that provide positive and operationally stable performance improvements. Following the intervention decision, the network state is updated.

The simulation recalculates network connectivity, passenger-flow redistribution, station loads, flow-induced failures, and system performance. The resulting state and resilience indicators provide the information required to determine the intervention decision for the next time step. Repeating this procedure over the analysis horizon generates two performance trajectories: $\{P_t^0\}_{t=1}^T$ and $\{P_t^R\}_{t=1}^T$.

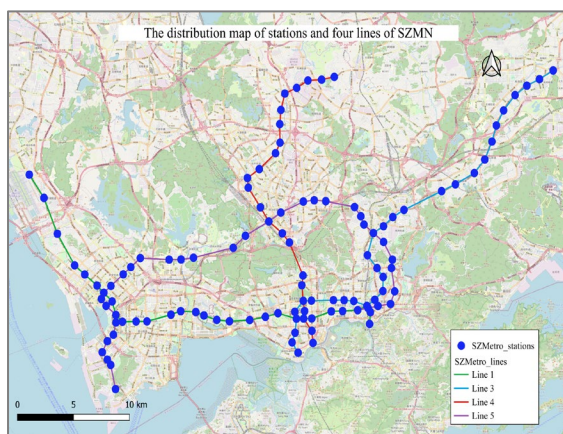
The intervention effect at time t can be measured as $\Delta P_t = P_t^R - P_t^0$. The overall resilience improvement and reduction in cumulative performance loss are respectively calculated as $\Delta Re = Re^R - Re^0$ and $\Delta Re_{\text{loss}} = Re_{\text{loss}}^0 - Re_{\text{loss}}^R$. Comparing the two scenarios makes it possible to determine whether the representative recovery intervention reduces performance loss, accelerates restoration, and improves overall network resilience. This comparison is intended to demonstrate the

operation of the integrated assessment–improvement framework rather than provide a ranking of multiple recovery strategies.

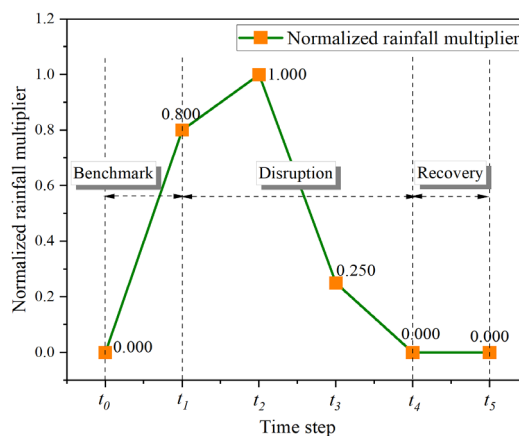
5 Illustrative Application

5.1 Study Network, Data, and Parameter Setting

A four-line subnetwork of the Shenzhen Metro was adopted to demonstrate the proposed framework. The illustrative network comprises Lines 1, 3, 4, and 5, which provide major east–west and north–south connections and contain several important interchange stations. This selection provides a manageable network with multiple interchange relationships and alternative routes, allowing passenger redistribution, overload propagation, and intervention-driven recovery to be demonstrated and interpreted. As shown in Fig. 2(a), the resulting network includes 112 unique stations, 117 rail sections, and 9 interchange stations. The numbers of stations on Lines 1, 3, 4, and 5 are 30, 31, 23, and 37, respectively, with interchange stations counted on each connected line. The travel time of an adjacent-station section ranges from 2.28 to 3.06 min, with a mean value of approximately 2.68 min.



(a)



(b)

Fig. 2 Illustrative network and rainstorm scenario. (a) Topology of the Shenzhen Metro four-line subnetwork, with interchange stations highlighted; (b) temporal multipliers of the generic normalized rainstorm scenario.

The network topology, station locations, interchange relationships, and section travel times were extracted from the available Shenzhen Metro dataset, using a network configuration corresponding to September 2023. The original OD matrix consisted of observed passenger demand obtained from data provider, with a reference period of September 6–11, 2023. Only OD pairs whose origins and destinations are both located within the selected subnetwork were retained, resulting in 12,432 directed OD pairs. The benchmark OD demand was proportionally adjusted using a scaling factor of 0.9784, preserving the average demand per station of the original network. The resulting total benchmark demand is approximately 1.69×10^6 passenger trips. To isolate the effects of network disruption and recovery, the same benchmark OD matrix was used throughout the illustrative simulation. Passenger routing is restricted to these lines, and only OD pairs with both endpoints inside the subnetwork are retained. Excluding other lines limits the available diversion routes and may affect passenger redistribution and overload propagation. The numerical results therefore describe the selected subnetwork under the specified inputs rather than the complete Shenzhen Metro system.

Station exposure was calculated using entrance counts, lowland-susceptibility scores, and drainage-capability scores compiled from online open-source data, and was normalized to $[0, 1]$. Rainfall data for 6–11 September 2023 were obtained from the Open-Meteo Historical Weather API to construct the spatial rainfall pattern for the illustrative scenario. Rather than reproducing a specific historical rainstorm, a generic six-step hazard scenario was constructed using the spatial pattern of the available rainfall data. The normalized rainfall at station i and time t was defined as $R_{i,t} = m_t R_i^{\text{spatial}}$, where R_i^{spatial} is the station-level rainfall index and $(m_0, m_1, m_2, m_3, m_4, m_5) = (0, 0.8, 1.0, 0.25, 0, 0)$.

As illustrated in Fig. 2(b), t_0 represents the benchmark state, t_1 – t_3 describe the disruption process, and t_4 – t_5 represent the recovery stage. The hazard index was calculated as $H_{i,t} = 0.6R_{i,t} + 0.4E_i$, where E_i is the normalized station exposure. A station was considered directly affected when $H_{i,t} \geq$

0.6. Station capacity was specified as 1.2 times its benchmark load, and a station was considered overloaded when its load ratio $\rho_{i,t}$ exceeded 1. The cascading-failure calculation was limited to 20 iterations within each time step. Direct rainstorm-induced and flow-induced failures were assigned minimum durations of two and one time steps, respectively. During the recovery stage, no more than two eligible stations could be restored per time step. Recovery actions were selected using the stability-screened performance-gain rule, under which a candidate station was accepted only when its restoration improved network performance without generating additional overload failures. The complete parameter settings are summarized in Table 1.

The application is intended to demonstrate the computational procedure and dynamic behavior of the framework rather than to reproduce an actual rainstorm event or provide a fully calibrated assessment of the Shenzhen Metro system.

Table 1 Main simulation parameters

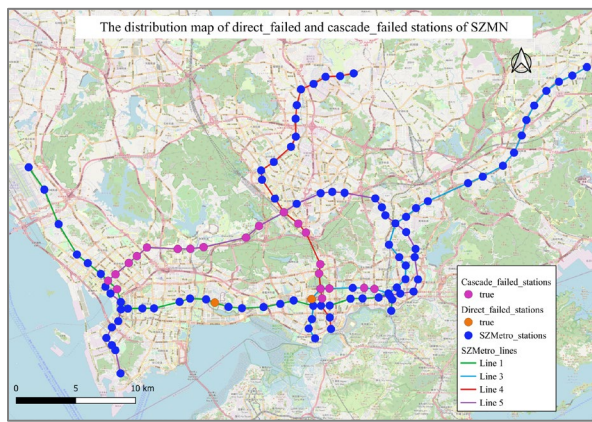
Parameter	Value
Rainfall weight	$\alpha = 0.6$
Station-exposure weight	$\beta = 0.4$
Direct-failure threshold	$\theta = 0.6$
Capacity buffer	20%
Overload threshold	$\rho_{i,t} = 1.0$
Recovery budget	$B_t = 2$

5.2 Cascading Failure and Performance Degradation

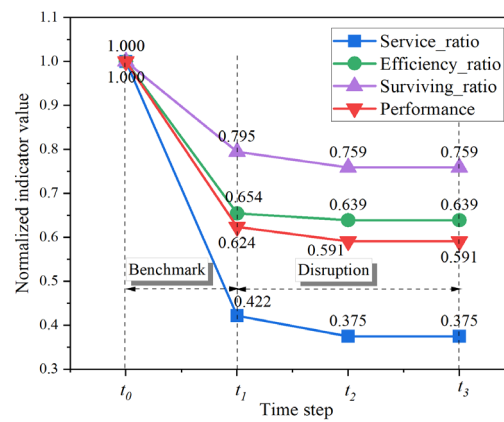
The dynamic failure process was simulated over the benchmark and disruption stages (t_0-t_3), and the relevant results are shown in Table 2. At t_0 , all 112 stations were operational, and the service, efficiency, station-availability, and composite-performance ratios were equal to 1. Under the constructed rainstorm scenario, the first direct failure occurred at t_1 , when the hazard indices of Window of the World and Futian exceeded the failure threshold (As shown in Fig. 3(a)).

Table 2 Dynamic failure and performance evolution before recovery

Time step	Active direct failures	New direct failures	New flow-induced failures	Total failed stations	S_t	E_t	U_t	P_t
t_0	0	0	0	0	1.0000	1.0000	1.0000	1.0000
t_1	2	2	21	23	0.4217	0.6545	0.7946	0.6236
t_2	6	4	0	27	0.3749	0.6392	0.7589	0.5910
t_3	0	0	0	27	0.3749	0.6392	0.7589	0.5910



(a)



(b)

Fig. 3 Dynamic cascading failure and performance degradation. (a) Spatial distribution of directly failed and flow-induced failed stations at t_1 ; (b) temporal evolution of the service ratio, efficiency ratio, station-availability ratio, and composite network performance over t_0 – t_3 .

Although only two stations failed directly at t_1 , their removal altered the available travel paths and caused passenger demand to be redistributed over the remaining network. Before overloaded stations were removed, system performance remained at 0.9691. However, the redistributed flows caused 21 additional stations to exceed their available capacities. After one cascade iteration, the number of unavailable stations increased to 23, and no further overload failures occurred. The stabilized service ratio, efficiency ratio, and station-availability ratio declined to 0.4217, 0.6545, and 0.7946, respectively, resulting in a composite performance of $P_{t_1} = 0.6236$. The closures of *Window of the World* and *Futian* interrupted direct connections along Lines 1 and 3, respectively. Although the

remaining 110 stations were initially still connected, affected passenger flows had to use alternative routes. The resulting redistribution concentrated loads on alternative corridors, including Lines 4 and 5 and their connecting interchanges. Under the assumed 20% capacity buffer, 21 additional stations exceeded their capacities and became unavailable. This amplification reflects the interaction between interrupted line connections, passenger rerouting, and limited reserve capacity.

At t_2 , six stations were directly exposed above the hazard threshold. Because two of them had already failed at t_1 , the number of newly generated direct failures was four. No additional flow-induced failures occurred at this time step, and the total number of unavailable stations increased from 23 to 27. As shown in Fig. 3(b), the service ratio further declined to 0.3749, while the composite network performance reached its minimum value of 0.5910. At t_3 , the rainstorm intensity dropped below the direct-failure threshold. Nevertheless, the previously failed stations remained unavailable because their required failure durations had not ended and no recovery intervention had yet been implemented. Consequently, network performance remained at the minimum level.

The results show that functional degradation was substantially greater than the proportion of physically unavailable stations. At t_1 , approximately 79.5% of the stations remained operational, but only 42.2% of passenger demand could still be served. This difference indicates that the loss of a limited number of structurally or functionally important stations can disrupt a much larger share of passenger trips through network disconnection and flow redistribution. The simulated process therefore demonstrates the ability of the framework to capture the transition from localized direct failures to network-wide performance degradation.

5.3 Recovery and Resilience Improvement

A representative recovery scenario was implemented at t_4 and t_5 to demonstrate the intervention component of the framework. At each recovery time step, no more than two eligible stations could be restored. Candidate stations were evaluated sequentially using the stability-screened performance-gain rule. An intervention was accepted only when it generated a positive marginal performance gain

without inducing additional overload failures. A no-intervention scenario was retained as the reference case. The related results can be found in Fig. 4(a) - (b).

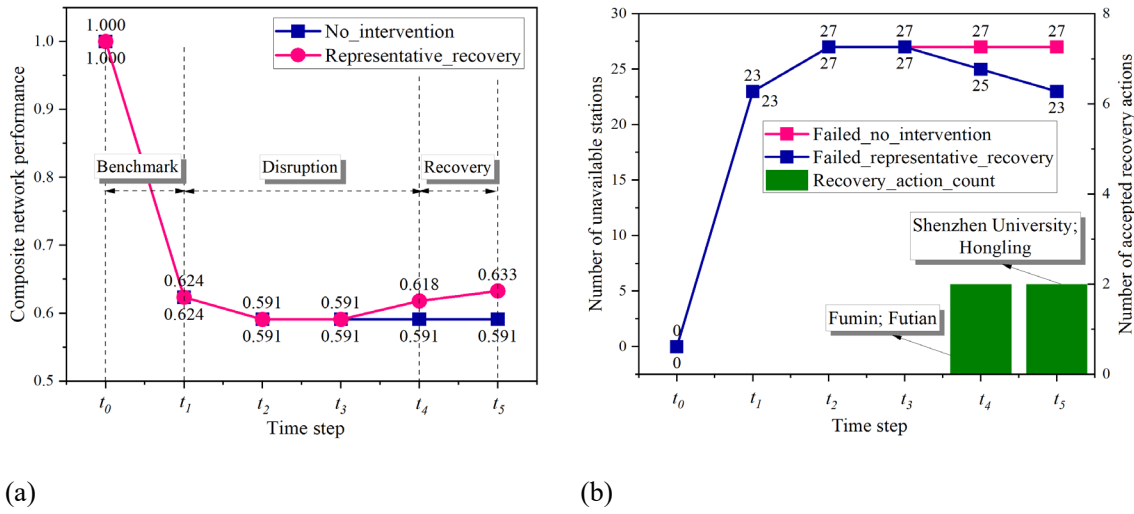


Fig. 4 Intervention-driven network recovery and resilience improvement. (a) System-performance trajectories under the no-intervention and representative-recovery scenarios; (b) changes in the number of unavailable stations and the timing of accepted recovery actions over t_0 – t_5 .

At t_4 , *Fumin* and *Futian* were selected for recovery. Their marginal performance gains were 0.0186 and 0.0085, respectively. Restoring these stations reduced the number of unavailable stations from 27 to 25 and increased the composite system performance from 0.5910 to 0.6181. At t_5 , *Shenzhen University* and *Hongling* were subsequently restored, providing additional marginal gains of 0.0081 and 0.0067. The final number of unavailable stations decreased to 23, while system performance increased further to 0.6330. None of the accepted recovery actions generated additional flow-induced failures.

The recovery process improved all three system-performance components. Between t_3 and t_5 , the service ratio increased from 0.3749 to 0.4358, the normalized network efficiency increased from 0.6392 to 0.6684, and the station-availability ratio increased from 0.7589 to 0.7946. The amount of served passenger demand increased from approximately 6.34×10^5 to 7.37×10^5 trips. By contrast, system performance remained at 0.5910 throughout t_4 and t_5 in the no-intervention scenario.

As summarized in Table 3, the representative recovery scenario increased the final performance from 0.5910 to 0.6330. The recovery-capacity indicator reached 0.1026, and the overall resilience index increased from 0.6646 to 0.6761. Meanwhile, cumulative resilience loss decreased from 2.0124 to 1.9433 (as shown in Table 4). The relatively low recovery-capacity value indicates that restoration remained partial within the limited simulation horizon and recovery budget. Nevertheless, the results demonstrate that the proposed framework can identify feasible interventions, update network states, and quantify their effects on the resilience trajectory.

Table 3 Intervention-driven performance restoration

Time step	Restored stations	Failed stations	S_t	E_t	U_t	P_t
t_3	None	27	0.3749	0.6392	0.7589	0.5910
t_4	<i>Fumin, Futian</i>	25	0.4144	0.6631	0.7768	0.6181
t_5	<i>Shenzhen University, Hongling</i>	23	0.4358	0.6684	0.7946	0.6330

Table 4 Resilience outcomes with and without intervention

Scenario	A	Q	C	Re_{loss}	Re	V
No intervention	0.6236	0.9477	0.0000	2.0124	0.6646	0.3354
Representative recovery	0.6236	0.9477	0.1026	1.9433	0.6761	0.3239

5.4 Sensitivity and Framework Validation

A one-at-a-time sensitivity analysis was conducted to examine whether the main simulation results respond consistently to changes in key model parameters. Three parameters were considered: the station-capacity buffer, the direct-failure threshold, and the recovery budget. The capacity buffer varied from 10% to 30%, the hazard threshold from 0.55 to 0.65, and the recovery budget from one to three stations per time step. All other parameters were maintained at their baseline values.

As shown in Table 5, increasing the capacity buffer reduced the total number of flow-induced failures from 25 to 16 and decreased the maximum number of unavailable stations from 31 to 22.

Correspondingly, the resilience index increased from 0.6368 to 0.6900. This result is consistent with the expectation that greater reserve capacity enables the network to accommodate more redistributed passenger demand.

Table 5 Sensitivity of failure and resilience outcomes to key parameters

Parameter	Value	Direct failures at t_2	New induced failures	flow- Maximum failed stations	P_{min}	P_f	Re
Capacity buffer	0.10	6	25	31	0.5304	0.6181	0.6368
	0.20*	6	21	27	0.5910	0.6330	0.6761
	0.30	6	16	22	0.5995	0.6596	0.6900
Failure threshold	0.55	19	21	37	0.5092	0.6232	0.6420
	0.60*	6	21	27	0.5910	0.6330	0.6761
	0.65	2	21	23	0.6236	0.7028	0.7106
Recovery budget	1	6	21	27	0.5910	0.6181	0.6722
	2*	6	21	27	0.5910	0.6330	0.6761
	3	6	21	27	0.5910	0.6530	0.6808

Note: *Baseline parameter setting.

The direct-failure threshold had a substantial influence on disruption severity. When the threshold decreased from 0.65 to 0.55, the number of directly affected stations at the peak-hazard step increased from 2 to 19, while the minimum system performance decreased from 0.6236 to 0.5092. The corresponding resilience index declined from 0.7106 to 0.6420. Thus, lower hazard tolerance produced more extensive direct disruption and a larger performance deficit.

Increasing the recovery budget did not change the minimum performance because intervention began after the network had reached its lowest state. However, it improved the subsequent restoration trajectory. When the recovery budget increased from one to three stations per time step, final performance increased from 0.6181 to 0.6530, and the resilience index increased from 0.6722 to 0.6808.

The sensitivity results exhibit consistent directional behavior: stronger station capacity and hazard tolerance mitigate network degradation, whereas greater recovery resources improve post-disruption restoration. Although the numerical results remain dependent on parameter assumptions, the framework consistently reproduces the expected sequence of direct failure, flow-induced degradation, performance loss, and intervention-driven recovery. The application therefore supports the computational validity and internal consistency of the proposed framework, rather than providing an empirically calibrated assessment of a specific Shenzhen rainstorm event.

6 Discussion

The illustrative application shows that metro-network disruption under extreme rainstorms cannot be explained by direct station failures alone. Under the adopted scenario, two directly affected stations generated 21 additional flow-induced failures after passenger redistribution. Although approximately 79.5% of stations remained operational at t_1 , only 42.2% of passenger demand could be served. This difference indicates that station availability, network connectivity, and passenger-flow redistribution must be evaluated jointly.

The results also demonstrate the importance of considering network stability during recovery. Restoring a station changes available routes and may redirect excessive passenger demand toward capacity-constrained stations. Therefore, topological importance alone does not guarantee an effective recovery action. The stability-screened performance-gain rule accepts an intervention only when it improves network performance without generating additional overload failures. In the illustrative application, restoring four stations increased final performance from 0.5910 to 0.6330 and reduced cumulative resilience loss, although full recovery was not achieved within the limited recovery period.

The sensitivity analysis further shows that greater capacity buffers and higher direct-failure thresholds reduce disruption severity, whereas a larger recovery budget mainly improves post-

disaster restoration. This finding suggests that proactive measures, including station protection, operational reserve capacity, and passenger-routing preparation, are as important as post-disaster recovery resources. Methodologically, the framework provides a unified representation of hazard impact, passenger redistribution, network-state evolution, performance loss, and intervention-driven recovery.

Methodologically, the proposed framework links rainstorm hazards, station failures, passenger redistribution, network-state evolution, multidimensional performance assessment, and recovery decisions within a unified time-dependent process. In contrast to static robustness measures, it captures both the amplification of localized disruptions and the feedback effect of intervention on subsequent network states. The simultaneous use of passenger service, network efficiency, and station availability also provides a more complete representation of metro functionality than any single indicator. For metro operators, the framework can support scenario testing, identification of vulnerable network states, and preliminary evaluation of recovery actions under resource constraints. Transferring the framework to another metro system requires local network, travel-time, passenger-demand, and hazard inputs. Particular attention should be given to calibrating exposure scores and hazard–failure thresholds, station capacities or capacity buffers, and failure-duration and recovery-resource parameters. Route-choice assumptions and performance-indicator weights may also be adapted to local conditions. Transferability therefore concerns the integrated modeling structure, while the numerical settings used in this illustrative application remain context specific.

However, several limitations remain. The application uses a simplified four-line network, scaled OD demand, a generic rainstorm scenario, uniform capacity buffers, and deterministic shortest-path assignment. The numerical results should therefore be interpreted as an illustration of framework computability rather than an empirical reconstruction of a specific disaster. Future research may incorporate observed operational data, calibrated hazard–failure relationships, behavior-based passenger rerouting, heterogeneous recovery resources, and full-scale metro networks. The

framework can also be extended to represent more complex cascading-failure mechanisms and learning-based recovery strategies, enabling adaptive intervention decisions under dynamically changing hazard and network conditions.

7 Conclusions

This study developed a dynamic modeling framework for assessing and improving metro-network resilience under extreme rainstorm disasters. The framework integrates rainstorm-hazard characterization, direct station failure, passenger-flow redistribution, flow-induced functional degradation, multi-period network-state evolution, resilience quantification, and recovery intervention. System performance is evaluated jointly through passenger service availability, normalized network efficiency, and station availability, while the resilience process is characterized in terms of absorption, response, recovery, and cumulative performance loss.

The framework was demonstrated using a simplified four-line Shenzhen Metro subnetwork containing 112 stations and 117 rail sections. Under the illustrative rainstorm scenario, two initial direct failures induced 21 additional flow-related failures, and composite system performance declined from 1.0000 to a minimum of 0.5910. The representative stability-screened recovery intervention restored four stations without generating further overload failures, increasing final performance to 0.6330. Compared with the no-intervention scenario, the resilience index increased from 0.6646 to 0.6761, while cumulative resilience loss decreased from 2.0124 to 1.9433. Sensitivity results further confirmed that the model responds consistently to changes in capacity buffers, failure thresholds, and recovery budgets.

The main contribution of this study is a transferable framework that links disruption assessment and resilience improvement within a unified dynamic process. Rather than reproducing a specific historical disaster, the illustrative application confirms the framework's computability and its ability to represent the progression from localized hazard impacts to network-wide degradation and intervention-driven restoration. The framework provides a methodological basis for future full-scale

applications involving more complex cascading failures, calibrated operational data, and adaptive or learning-based recovery strategies.

Acknowledgements

This work is supported by the National Natural Science Foundation of China (Grand No. 72304126).

We thank the editors and reviewers for the valuable comments.

Declaration of competing interests

The authors have no competing interests to declare that are relevant to the content of this article.

References

- Du, Q., Zong, X., Li, Y., Guo, X., Ye, Z., Li, S., & Bai, L. 2024. Resilience optimization of bus-metro double-layer network against extreme weather events. *Transportation Research Part D: Transport and Environment*, **135**: 104378.
- Gao, W., Lu, Y., Wang, N., Cheng, G., Qiu, Z., & Hu, X. 2024. Measurement and prediction of subway resilience under rainfall events: An environment perspective. *Transportation Research Part D: Transport and Environment*, **136**: 104479.
- Guan, X., Yu, F., Xu, H., Li, C., & Guan, Y. 2024. Flood risk assessment of urban metro system using random forest algorithm and triangular fuzzy number based analytical hierarchy process approach. *Sustainable Cities and Society*, **109**: 105546.
- Guo, C., Tang, J., Hong, J., Lu, Q., Wu, H., & Wei, R. 2025. Resilience assessment of urban bus-metro system to floods under future climate change. *Transportation Research Part D: Transport and Environment*, **148**: 104925.
- He, R., Zhang, L., & Tiong, R. L. K. 2025. Responding of metro stations to upcoming floods: To close or to protect? *Reliability Engineering & System Safety*, **256**: 110683.

- Huang, L., Liu, Z., Yu, C., & Yan, B. 2026. Resilience-Oriented Recovery Optimization of Metro Systems Under Extreme Rainfall-Induced Urban Flooding Disruptions. *Sustainability*, **18** (5): 2597.
- Jiao, L., Zhu, Y., Huo, X., Wu, Y., & Zhang, Y. 2023. Resilience assessment of metro stations against rainstorm disaster based on cloud model: A case study in Chongqing, China. *Natural Hazards*, **116**(2): 2311–2337.
- Li, Q., Ni, T., Li, L., Wen, H., & Xu, J. 2025. A probabilistic GIS-based framework for urban flood risk assessment in Chengdu metro network. *Scientific Reports*, **15**(1): 43526.
- Liang, C., & Guan, M. 2025. Increasing flood hazards threaten metro system resilience under climate and demographic changes. *Sustainable Cities and Society*, **133**: 106890.
- Liang, C., Guan, M., Guo, K., Yu, D., & Yin, J. 2026. Dynamic flood risk modeling in urban metro systems considering station configuration. *Reliability Engineering & System Safety*, **266**: 111760.
- Meng, Y., & Zhao, X. 2026. Extreme Rainstorm-Induced Cascading Vulnerability in Cross-Border Metro Networks: A Modeling Framework for Shenzhen-Hong Kong. *Proceedings of the International ISCRAM Conference*, **23**: 1-14.
- Sun, R., Zhu, G., Liu, B., Li, X., Yang, Y., & Zhang, J. 2022. Vulnerability Analysis of Urban Rail Transit Network considering Cascading Failure Evolution. *Journal of Advanced Transportation*, **2022**: 1–16.
- Tan, E., Ma, X., Du, Y., & Zhang, Z. 2024. Enhancing urban metro system resilience under disruptive events through multi-agent reinforcement learning. *Journal of Transportation Safety & Security*, **16**(10): 1184–1211.
- Wu, J., Ma, L., Guo, F., Chen, K., & Fang, W. 2024. An MCDM-GIS framework for assessing flooding resilience of urban metro systems. *International Journal of Disaster Risk Reduction*, **113**: 104824.

- Xu, C., & Xu, X. 2024. A two-stage resilience promotion approach for urban rail transit networks based on topology enhancement and recovery optimization. *Physica A: Statistical Mechanics and Its Applications*, **635**: 129496.
- Xu, P., Lu, Q., Feng, T., Li, J., Li, G., & Xu, X. 2024. Resilience analysis of metro stations integrating infrastructures and passengers. *Reliability Engineering & System Safety*, **252**: 110467.
- Yang, X., Zhang, X., Li, S., Tian, Y., Tan, C., Ding, S., Kalonji, G., & Xu, L. 2025. Increasing urban flooding facing metro system: Evidence from Internet media records in China from 2001 to 2021. *International Journal of Disaster Risk Reduction*, **124**: 105551.
- Zhang, D.-M., Bai, H., Zheng, C.-Z., Huang, H.-W., Ayyub, B. M., & Cao, W.-J. 2025. Extreme rainfall induced risk mapping for metro transit systems: Shanghai metro network as a case. *Reliability Engineering & System Safety*, **262**: 111234.
- Zhao, B., Tang, Y., Wang, C., Zhang, S., & Soga, K. 2022. Evaluating the flooding level impacts on urban metro networks and travel demand: Behavioral analyses, agent-based simulation, and large-scale case study. *Resilient Cities and Structures*, **1**(3): 12–23.
- Zhao, J., Liang, Q., & Guo, J. 2026. Dynamic evolution of metro network vulnerability: Shifting mechanisms under cascading failures. *Reliability Engineering & System Safety*, **275**: 112755.