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# Resilience analysis of urban cyber-physical-social systems: Insights from the 2023 Beijing rainstorm

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A R T I C L E I N F O

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A B S T R A C T

Modern cities function as complex cyber-physical-social (CPS) systems where digital networks, physical infrastructure, and human society are deeply interconnected. This study develops an integrated analytical framework to quantify urban CPS resilience considering their interdependences during extreme weather events, using the 2023 Beijing rainstorm as a case. We collect and analyze multi-dimensional data representing each system: communication outage data (cyber), transportation infrastructure performance (physical), and nightlight intensity (social). Through resilience triangle analysis and system dynamics modeling using differential equations, we quantify the bidirectional interdependences among these systems and their collective response to disruptions. We reveal distinct vulnerability and recovery patterns across the three systems. Physical infrastructure serves as a foundational component that significantly influences both cyber and social functions, showing asymmetric interdependences. Through intervention analysis, we demonstrate that early and coordinated actions across multiple systems yield synergistic resilience benefits that exceed individual system improvements. This research advances urban resilience theory by providing empirical quantification of cross-system dependences and offers practical guidance for integrated resilience planning.

## 1. Introduction

Modern cities represent complex cyber-physical-social (CPS) systems where digital networks, physical infrastructure, and human society function as deeply interconnected components [1]. This integration has fundamentally transformed how urban systems operate, respond to disruptions, and recover from extreme events. In contemporary urban environments, cyber systems manage physical infrastructure and coordinate social responses through information, communication, and digital networks, as shown in Fig. 1. These cyber components—including telecommunications, control systems, and digital services—have become an essential system in modern cities, transmitting critical information and enabling coordinated responses during both normal operations and disruption situations. Cyber threats—including cyberattacks, malware, and data breaches—can compromise physical infrastructure control systems and disrupt social services [2–4]. Physical systems, containing transportation networks, power grids, water supply, and built environments, provide the operational foundation for cyber information while enabling social activities through infrastructure and facilities. Physical threats such as infrastructure aging, structural failures, and natural hazards can damage communication networks and alter social interaction patterns [1,5–9]. Social systems, encompassing human behaviors (e.g., mobility), policy contexts, and social interactions [10–12], reflect the utilization and adaptation patterns of cyber and physical systems. Social disruptions, including public health emergencies, policy changes and human errors, can transform infrastructure utilization patterns and digital service demands [13–17].

Cities have witnessed the complex interdependences and vulnerabilities among cyber, physical and social systems during extreme events [18,14,16]. During Hurricane Sandy in 2012, damage to power infrastructure led to widespread outages and telecommunications failures, severely disrupting public services and community functions [19–21]. More recently in July 2023, Beijing experienced an unprecedented rainstorm with some areas receiving over 500 mm of precipitation. This extreme weather event caused widespread disruption across cyber, physical, and social systems [17]. Disconnected transportation infrastructure impeded repairmen and equipment from accessing disrupted communication facilities, while communication outages prevented residents from accessing critical information and requesting assistance. These cascading failures across system boundaries reveal a fundamental

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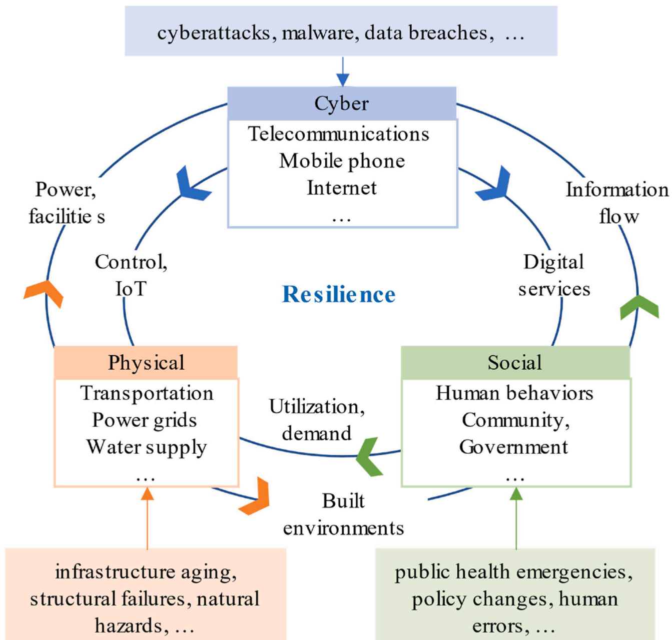



**Fig. 1.** Urban CPS systems.

characteristic of modern urban environments: the interconnected nature of cyber, physical, and social systems creates complex vulnerability pathways where disruptions propagate bidirectionally.

While system interdependences introduce vulnerabilities through potential cascading failures, they simultaneously present opportunities for enhancing system resilience through coordinated strategies [22]. Preparation and reinforcement of individual systems can decrease the probability of failure during disruptions and enable adaptive responses across interconnected domains. For example, pre-strengthening transportation infrastructure can maintain mobility networks during extreme events, facilitating the movement of resources to repair disrupted cyber components [23,24]. Simultaneously, functioning transportation systems help maintain social activities by allowing continued mobility for essential purposes [25]. Such positive interaction effects highlight the potential for strategic interventions that leverage system interdependences to enhance overall urban resilience.

Current approaches to urban resilience often treat cyber, physical, and social systems as separate domains with limited interaction [26–30]. These siloed approaches fail to capture the cascading failures and interdependent recovery processes that characterize real-world urban disruptions. Despite growing recognition of these interdependences, quantitative methodologies that holistically assess resilience across CPS systems with empirical evidences remain significantly underdeveloped [31–33].

To overcome the single-system approach limitations, this study develops an integrated analytical framework that quantifies resilience across interdependent cyber, physical, and social systems in urban contexts. The framework firstly integrates multi-dimensional data to represent system performances. According to system performances, statistical regression is used to identify initial disruption points and establish normal operational baselines for each system. Then, using mathematical curve fitting, resilience triangle is employed to measure standardized resilience that enables cross-system comparisons. Moreover, the system dynamics with coupled differential equations is applied in the framework to quantify inter-system dependences. Using the 2023 Beijing rainstorm as a case, we empirically demonstrate how this framework quantifies the bidirectional interdependences among cyber, physical, and social systems.

The main contributions of this study are as follows.

Methodological innovations: (1) We develop an integrated analytical framework that bridges cyber, physical, and social dimensions of urban resilience under extreme weather conditions, quantifying cross-system dependences and their impacts on collective resilience outcomes.

Empirical insights: (2) Unlike conceptual frameworks, our model uses empirical data to quantify specific dependence strengths. The model enables analysis of how varying interdependence levels influence system performance during both disruption and recovery phases, providing specific quantitative parameters for understanding system interactions in extreme events.

Practical significance: (3) Through systematic intervention analysis using our interdependence model, we generate specific actionable strategies for urban resilience planning. These insights offer practical guidance for resource allocation and intervention prioritization in urban disaster management.

The subsequent sections of this study are organized as follows. Relevant studies are surveyed in Section 2. The methods developed in this study are detailed in Section 3, with an accompanying illustration of the basic data and study areas. The results and discussions are presented in Sections 4 and 5, respectively. Section 6 concludes the study and highlights future research directions.

## 2. Literature review

Urban resilience—the ability of cities to resist disruptions and recover from the loss within reasonable temporal and economic constraints—has become increasingly important as urban areas face mounting challenges from extreme weather events, technological failures, and other hazards [34–36]. This section reviews individual system resilience and approaches towards CPS resilience in urban contexts.

### *2.1. Individual system resilience*

Substantial research has focused on single-domain approaches, examining cyber, physical, and social systems in isolation despite their inherent interconnectedness in modern urban environments. This section examines resilience within cyber, physical, and social systems independently, providing the foundation for understanding their interdependences and integrated behavior.

Cyber resilience encompasses the ability of information and communication technology systems to resist and recover from adverse conditions, attacks and failures while maintaining essential functions [26,37,38]. As urban infrastructure increasingly relies on digital control systems, cyber resilience has become critical for maintaining societal functions during extreme events. Cyber systems usually demonstrate network structure, allowing for information exchanging through communication links [39]. Based on the network structure, quantification approaches for cyber system resilience typically employ network-based metrics such as connectivity, service accessibility, and path redundancy [40–42]. Additionally, information transmission capability—measured by metrics such as delivered packets—commonly serves as a key performance indicator for cyber system resilience assessment [43–46].

Physical system resilience focuses on built infrastructure—including transportation networks, energy systems, water supply, and buildings—and their ability to withstand and recover from disruptions while maintaining adequate service levels [47–53]. Given that many infrastructure systems exhibit network topology, network-based metrics representing connectivity, betweenness, and redundancy are commonly used to measure infrastructure network resilience [54–61]. Beyond topological characteristics, physical infrastructure resilience is also evaluated through structural integrity indicators [62–65]. For example, Liu et al. [66] developed fragility models to quantify probabilistic relationships between hazard intensity and expected damage levels of bridges through cumulative distribution functions. The structure damage of physical infrastructure would influence their operational services.

Therefore, service-related indicators are often used to assess physical resilience, such as service flow (e.g., traffic flow, delivered power, supplied water) and service quality measures (e.g., travel time for transportation network, voltage stability for power infrastructure) [67–70].

Social system resilience addresses the capacity of communities, organizations, and governments to anticipate, absorb, adapt to, and recover from disruptive events while maintaining social cohesion, economic activity, and public well-being [71,29]. Social cohesion metrics typically include trust levels, interaction intensity, and civic engagement [72,73]. Socioeconomic status reflects the social resilience through measures like income, household savings, and employment rates [74–76]. While social resilience can be indicated by activity-based indicators include mobility patterns, nightlight intensity, mobile phone activity, and business operations [77,11,78–80]. Public well-being aspects of social resilience consider accessibility to critical services, such as healthcare, education and food supply [81–84]. Mental well-being of the public during the disaster represents the social resilience, including measurements of concern, sentiment, community support and belonging [85–87].

These domain-specific studies have advanced our understanding of resilience within individual systems. However, individual system approaches fundamentally fail to capture the complex interdependences that characterize real-world resilience challenges. Modern cities function as integrated cyber-physical-social (CPS) systems where disruptions in one domain inevitably cascade into others, necessitating more holistic resilience analytical frameworks that can account for these cross-system interactions.

### 2.2. Toward integrated CPS resilience

Recognition of single-system approach limitations has prompted the emergence of cyber-physical-social (CPS) systems as a conceptual framework for understanding urban resilience. Unlike traditional perspectives that treat cyber, physical, and social domains as separate entities, CPS resilience acknowledges their fundamental interdependence and the cascading effects that propagate across domain boundaries during extreme events [88,89]. Current approaches to analyzing CPS interdependence in urban resilience can be categorized into qualitative and quantitative methods.

#### 2.2.1. Qualitative analysis

Cascading-perspective and network-based methods provide conceptual analyses of interdependence among systems. Cascading-perspective methods focus on failure propagation across systems, viewing the failure of one system as the triggering cause of failures in others [88,90]. For example, in human -physical systems, human errors can cause physical system failures [4]. Similarly, physical infrastructure failures can trigger cyber blackouts in power systems [15], while Wang et al. [91] investigated how cyberattacks compromised physical port systems. Although these studies have recognized cascading failures among cyber, physical and social systems, they did not explicitly examine the bidirectional nature of interdependence itself.

Network-based approaches have been employed to model CPS interdependence, with hypernetworks being particularly prominent for establishing integrated system representations [92]. Hypernetworks conceptualize CPS interdependence by establishing connections between different system components, typically from the perspectives of geographical proximity or logical relationships [93–95]. For instance, Cavallaro et al. [96] developed a social-physical network where hyperedges represent relationships between residents in social sub-networks and physical streets based on building-street adjacencies. While Zhao et al. [17] constructed a hypernetwork where the hyperedges include residents' phone calls to urban management administrations, and the subsequent administrative processes for infrastructure improvement. While hypernetwork approaches offer valuable conceptual frameworks for understanding system interdependences, they face significant limitations when applied to general urban systems. Most notably, these models often rely on scenario-specific information flows or geographic adjacencies that lack generalizability across diverse urban contexts. Furthermore, establishing logical topologies becomes increasingly complex when considering the full spectrum of technologies, infrastructure types, and social contexts present in modern cities. In essence, not all systems are suitable or convenient to be modeled as network structures.

#### 2.2.2. Quantitative analysis

Compared to qualitative analysis, system dynamics (SD) modeling offers a flexible and generalizable approach to quantifying system interdependence, capturing feedback loops, multiple factors, heterogeneous temporal scales, and nonlinear behaviors [97–99]. SD can quantify system interdependence through parameters derived from mathematical equations, an approach that has shown promise in CPS resilience research. For example, Li et al. [100] developed an SD model to evaluate urban flood resilience, capturing interdependences among economic, social, infrastructure, and information systems through curve-fitting parameters. Yabe et al. [101] evaluated urban resilience across interdependent socio-physical systems using mobility and water supply data following Hurricane Maria. They captured bidirectional relationships between social and physical systems through differential equations, with equation parameters quantitatively reflecting the system interdependence. Differential equations provide a promising pathway for data-driven SD by mathematically representing both the rates of change in system variables and the causal relationships between them [102–104].

Current SD-based CPS resilience studies still face critical limitations that significantly constrain their practical applicability. First, data collection challenges lead to reliance on static datasets. CPS resilience studies based on SD typically rely on numerous variables with complex relationships [105,106], creating significant data collection challenges. Researchers often address these challenges by using static, open-source datasets or government reports [107,108]. For instance, Li et al. [100] utilized statistical yearbooks and national development reports for variables like hospital beds, disposable income, and mobile phone users. While valuable, such data represent static system states and struggle to capture temporal evolution during disruption events. This limitation prevents researchers from observing how systems actually respond to and recover from disruptions, forcing reliance on assumptions rather than empirical observations. Second, subjective relationship specifications undermine the model credibility. In the absence of theoretical frameworks or empirical data, relationships among variables are frequently established based on researcher experience or expert opinion [31,32]. Such approaches are inherently limited by subjectivity, and the established relationships remain difficult to validate empirically. These limitations highlight the critical need for data-driven SD approaches that can overcome these constraints [33].

### 2.3. Research gaps

Our review of existing literature reveals following critical research gaps that our study address. First, integration of CPS systems is limited in resilience frameworks. While significant progress has been made in understanding resilience within individual cyber, physical, and social domains, frameworks that conceptualize and quantify resilience across these systems in an integrated manner remain underdeveloped. Our research directly addresses this gap by developing a comprehensive framework that views cyber, physical, and social systems as fundamentally interconnected components of urban resilience. Second, empirical quantification of system interdependences is insufficient. Existing approaches to modeling system interdependences often rely on qualitative frameworks or expert opinions rather than empirical data, limiting their ability to capture real-world system behaviors during disruption events. Our study overcomes this limitation through a data-driven approach that quantifies interdependences using empirical observations from an actual extreme weather event.

## 3. Methods

This study develops a framework to analyze cyber-physical-social (CPS) resilience as illustrated in Fig. 2. The framework presents an integrated approach that bridges system boundaries by simultaneously capturing the performance dynamics of interconnected CPS systems in urban contexts through empirical data. This data-driven methodology synthesizes heterogeneous data sources into a cohesive analytical structure, allowing for evidence-based quantification of interdependences rather than relying on conceptual or qualitative assumptions. We use Beijing 2023 rainstorm as a case to demonstrate the framework's practical application. Performances of cyber, physical and social systems can be represented by related datasets, serving as primary inputs for resilience indicator and system interdependences. Empirical performance metrics are employed to establish baseline normal status for each system, enabling the identification of deviation starting points. This approach addresses the challenge of differentiating natural fluctuations and actual disruption impacts. A comparative resilience quantification technique is developed using standardized resilience triangles that allows for cross-system comparisons despite inherently different performance metrics. This standardization enables meaningful integration of cyber, physical, and social resilience measures. Bidirectional system interdependences are modeled using differential equations within a system dynamics framework, quantifying not only the magnitude but also the directionality of system influences. This mathematical formulation captures the complex feedback mechanisms operating between urban subsystems during extreme events and response phases. The following subsections detail the methodology.

### 3.1. Study area and data preprocessing

This study focuses on the southwest region of Beijing, China, which experienced severe precipitation from July 29th to August 1st, 2023 (Fig. 3). To capture pre-disruption baseline conditions, disruption impacts, and recovery trajectories, our data collection period extended from July 20th to August 20th, 2023.

The data preprocessing procedure is illustrated in Fig. 4. Communication outages, transportation infrastructure performance and nightlight intensity were selected as proxies for cyber, physical and social systems respectively. The selection of these proxy indicators was based on three criteria: the data availability, representative capacity and interdependence relationships among systems.

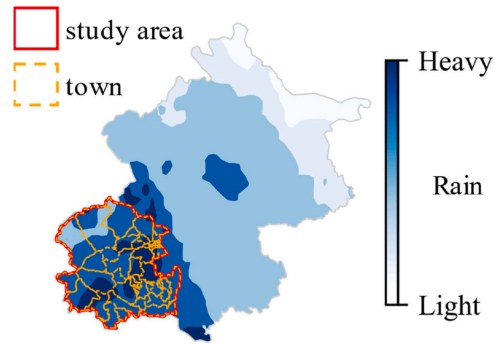



**Fig. 3.** Beijing administrative district and study area.

The communication service coverage directly represents the connectivity of the cyber system and its capacity to facilitate information exchange across urban systems. This characteristic makes it particularly suitable for analyzing how cyber system disruptions cascade into physical operations and social activities. Transportation infrastructure serves as an ideal physical system proxy because it acts as a foundational enabler for both cyber and social system functions [56]. Road and rail networks facilitate the physical movement of repair crews, equipment, and materials necessary for restoring disrupted cyber components, while simultaneously enabling population mobility that sustains social activities. Nightlight intensity provides a spatially explicit, temporally continuous proxy for human activity patterns and economic functioning [78]. It reflects the cumulative outcome of social system adaptations to cyber and physical disruptions. For instance, both communication outages and transportation disruptions influence nightlight intensity when businesses close, residents evacuate, or economic activities cease.

Cyber system is represented by the status of communication across towns in study area. Communication service completeness was tracked through official reports and news sources [109–114]. For each town in the study area, we recorded the communication outage starting date ($t_b$) and the complete recovery date ($t_e$). The communication recovery process of every town was modeled using a linear assumption. Specifically, the communication service coverage rate ($c_i^0(t)$) of town $i$ at time $t$ is formulated as:

$$c_i^0(t) = \begin{cases} 1 & \text{if } t < t_b \quad \text{or} \quad t \geq t_e \\ 0 & \text{if } t = t_b \\ c_i(t_b) + (c_i(t_e) - c_i(t_b))\dfrac{t - t_b}{t_e - t_b} & \text{if } t_b < t < t_e \end{cases} \tag{1}$$

Eq. (1) implies that at outage starting date $t_b$, there is no

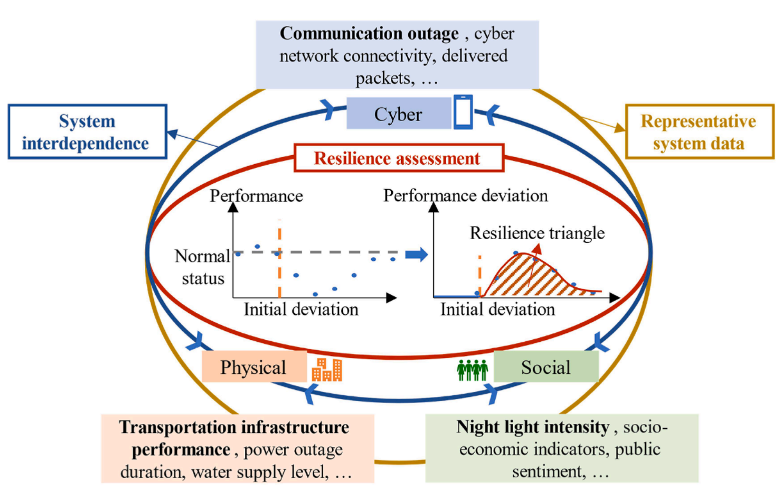



**Fig. 2.** Framework of CPS resilience (Bold indicators denote those implemented in the case study; non-bold indicators represent potential candidates).

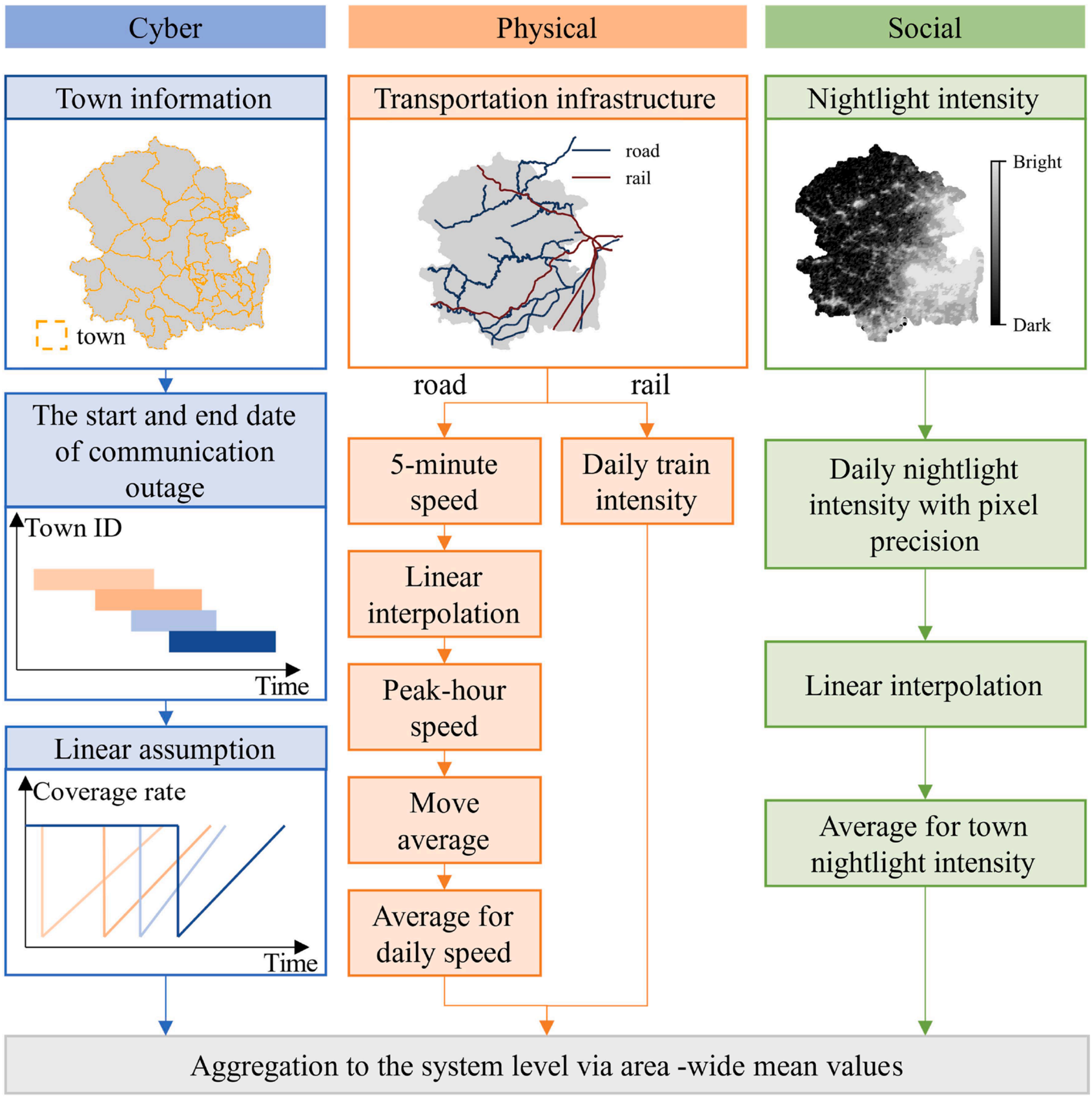



**Fig. 4.** Data preprocessing.

communication service cross the town (i.e., $c_i^0(t_b) = 0$). While before and after the disruption, the service coverage rate is 1. From $t_b$ to $t_e$, the service is assumed to gradually recover from 0 to 1 with a linear rate.

Transportation infrastructure for physical system in the study area (Fig. 4) includes 28 national and provincial highway roads and 14 railways, which were either directly damaged by the rainstorm or geographically adjacent to the affected segments. The geospatial data of studied road and rail infrastructure were collected from the OpenStreetMap [115]. For road segments, the raw data of five-minute average speed were obtained from the Baidu Map API. Linear interpolation was applied to fill missing values. We specifically focus on extracting peak-hour speeds to accurately represent repetitive operational conditions. Two critical time windows, morning (7:00–9:00) and evening (17:00–19:00) rush hours, were considered. To isolate long-term speed trends and mitigate daily fluctuation effects, a moving average method with a one-week window was applied to the 5-minute peak-hour speed data. The resulting road speed were averaged daily and denoted as $p_{j,road}^0(t)$ for road segment $j$ at time $t$, maintaining consistency with data representing other systems. For railways, daily train intensity, defined as the daily count of trains operating on each railway, was used to represent railway performance. Operating train data were collected from China Railway Map and official notifications posted by Beijing West Railway Station's Weibo account. The train intensity on railway $k$ at time $t$ was denoted as $p_{k,rail}^0(t)$.

Social system is represented by the nightlight intensity (Fig. 4), which serves as a proxy for human activity patterns [79]. The nightlight data were obtained from NASA LAADS [116], which provides global daily Gap-Filled Lunar BRFD-Adjusted Nighttime Lights at 500 m × 500 m resolution. The raw data are in pixel format. Linear interpolation was applied to the pixel-level nightlight intensity to fill missing values. These pixel values were then aggregated to the town-level according to the spatial pixel-town correspondence. The nightlight intensity of town $i$ at time $t$ is denoted as $s_i^0(t)$.

### 3.2. Resilience quantification

#### 3.2.1. Deviation detection and normal status determination

We statistically identify initial deviation points ($t_d$)—the moment when system performance begins to significantly deviate from normal operation status due to disruption. For each system representative data series ($c_i^0(t)$, $p_{j,road}^0(t)$, $p_{k,rail}^0(t)$ and $s_i^0(t)$), we determined the initial deviation time point $t_d$ by running multiple single-variate linear regressions.

Taking the cyber system as an example, define the deviation starting point detection dataset as $\mathscr{D}(w) = \{(0,\ c_i^0(0)),\ (1,\ c_i^0(1)),\ \ldots,\ (w,\ c_i^0(w))\}$, where $w \in \{0, 1, \ldots, T^{\text{End}}\}$ is the potential starting point. $T^{\text{End}}$ is the end of the rainstorm event. For each linear regression on $\mathscr{D}(w)$, we computed the corresponding slope coefficient $k_w$ with respect to time and p-value for significance. The initial deviation point $t_d$ was then identified as:

$$t_d = \min\{t \mid \forall\ w \geq t,\ k_w \neq 0 \text{ significantly}\} \tag{2}$$

Eq. (2) represents that the deviation start point is identified as the time after which regression slopes consistently and significantly (p-value<0.05) deviate from zero. This approach ensures a statistically significant trend of system deviation from normal status rather than random fluctuation, increasing the reliability of subsequent resilience measurements.

The normal status for each system was established by averaging basic performance data ($c_i^0(t)$, $p_{j,road}^0(t)$, $p_{k,rail}^0(t)$ and $s_i^0(t)$) from the start of the study period to the initial deviation point. Taking the cyber system as an example, the normal cyber status for town $i$ is identified as $\overline{c}_i = \sum_0^{t_d} c_i(t) / t_d$. Following this approach, we derived normal road, rail and social status, denoted as $\overline{p}_{j,road}$, $\overline{p}_{k,rail}$ and $\overline{s}_i$, respectively.

### 3.2.2. Performance deviation calculation and normalization

The performance deviation of cyber system $c_i(t)$ was calculated as the relative difference from its established normal status. For the cyber system in town $i$, this is formulated as:

$$c_i(t) = \begin{cases} 0, & t \leq t_d \\ \left| \dfrac{c_i^0(t) - \overline{c}_i}{\overline{c}_i} \right|, & t > t_d \end{cases} \tag{3}$$

This methodology assumes that cyber system does not deviate from the normal status prior to the initial deviation point ($t_d$), i.e., $c_i(t) = 0$, $\forall\ t \leq t_d$.

The performance deviation of cyber system at time $t$ in the whole study area was derived by averaging across all studied towns:

$$\overline{c}(t) = \sum_{i \in \mathscr{N}} c_i(t) / |\mathscr{N}| \tag{4}$$

where $\mathscr{N}$ is the set of all individuals in cyber system.

Following this approach, we calculated performance deviations for road infrastructure ($\overline{p}_{road}(t)$), rail infrastructure ($\overline{p}_{rail}(t)$) and social system ($\overline{s}(t)$), respectively. The overall performance deviation of physical system $\overline{p}(t)$ was derived by weighted integration of road and rail infrastructures:

$$\overline{p}(t) = \theta_1 \overline{p}_{road}(t) + \theta_2 \overline{p}_{rail}(t) \tag{5}$$

where $\theta_1$ and $\theta_2$ are the weights of road and rail infrastructures, respectively.

For cross-system comparability, we normalized the performance deviations by their maximum values:

(6)

where $c(t)$, $p(t)$ and $s(t)$ denote normalized performance deviation of cyber, physical and social systems, respectively.

### 3.2.3. Mathematical curve fitting for performance evolution

To capture the evolution patterns of system performance and enable analytical solutions for interdependence analysis, we fitted mathematical curves to the normalized performance deviations ($c(t)$, $p(t)$ and $s(t)$). Based on preliminary analysis of deviation patterns, we selected system-specific functional forms. Cyber system was fitted with an exponential decay function, reflective of rapid initial impact followed by gradual recovery:

$$C(t) = h_c \exp\left(-a_c(t - b_c)\right) \tag{7}$$

Physical and social systems were fitted with asymmetric Gaussian functions that can accommodate different rates of performance loss and recovery:

$$P(t) = \begin{cases} h_p G(t; a_p, \sigma_{p,1}), & \text{if } t \leq a_p \\ h_p G(t; a_p, \sigma_{p,2}), & \text{if } t > a_p \end{cases} \quad S(t) = \begin{cases} h_s G(t; a_s, \sigma_{s,1}), & \text{if } t \leq a_p \\ h_s G(t; a_s, \sigma_{s,2}), & \text{if } t > a_p \end{cases} \tag{8}$$

where $G(t; a, \sigma) = \exp\left(\frac{-(t-a)^2}{2\sigma^2}\right)$ is the gaussian function. The capital letters $C(t)$, $P(t)$, $S(t)$ represents the fitted values for the cyber, physical, and social system deviations, respectively. Note that the exponential and gaussian functions only return positive values for any $t$, which make them suitable to fit the absolute performance deviation.

Model parameters ($h_c$, $a_c$, $b_c$, $h_p$, $a_p$, $\sigma_{p.1}$, $\sigma_{p.2}$, $h_s$, $a_s$, $\sigma_{s.1}$ and $\sigma_{s.2}$) were calibrated using the Least Squares method to minimize the difference between actual ($c(t)$, $p(t)$ and $s(t)$) and fitted performance deviations ($C(t)$, $P(t)$ and $S(t)$). Compared to the actual deviation, the fitting curves, on the one hand, allow for smoother interpolation between discrete data points [117], on the other hand, enable analytical solutions for interdependences among cyber, physical and social systems.

For the purpose of description simplicity, the fitting curves ($C(t)$, $P(t)$ and $S(t)$) for normalized performance deviation are referred to as "deviation" in the following part of the article.

### 3.2.4. Resilience triangle calculation

We quantified resilience using the resilience triangle concept—a well-established approach that measures the cumulative performance deviation over time [118,98,119,120]. Mathematically, the resilience triangle is defined by the area between the normal performance level and the actual performance curve (Fig. 5) during and after a disruption [118,121,105,98,83,119].

The area of the resilience triangle serves as an inverse indicator of resilience (smaller area corresponds to lower deviations and thus higher resilience):

$$V_F = \int_u^v F(w) dw / (v - u) \tag{9}$$

where $F(w) \in \{C(w), P(w), S(w)\}$ is any performance deviation curve. Let the resilience triangle areas for cyber, physical, and social systems be $V_c$, $V_p$, and $V_s$, respectively. Parameters $u$ and $v$ represent the beginning and end of the study period.

The resilience of integrated CPS system was quantified as the average of individual system measures:

$$V = \left(V_c + V_p + V_s\right) / 3 \tag{10}$$

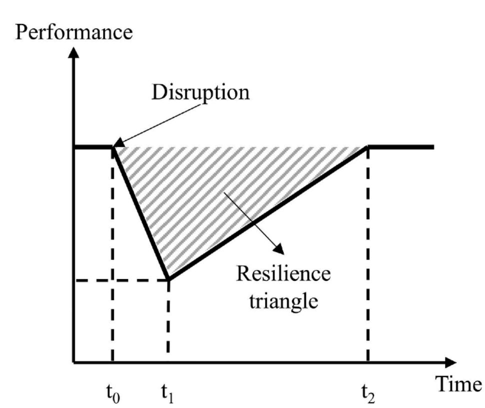



**Fig. 5.** Resilience triangle.

### 3.3. Interdependence among CPS systems

#### 3.3.1. Differential equation-based system dynamics

Urban CPS systems exhibit both self-dependence and cross-system influences during disruption and recovery phases. We use system dynamics (SD) to investigate the interdependences among cyber, physical and social systems, providing the underlying mechanism that drive observed patterns described in Eq. (7)-(8). The SD model is developed through coupled differential equations:

$$\frac{dC}{dt} = C(1-C) + \alpha_c \frac{C}{C+\tau_c} + \beta_c C^2 P + \gamma_c C(1-C)S \quad \frac{dP}{dt} = \alpha_p CP + \beta_p P + \gamma_p SP + \tau_p \quad \frac{dS}{dt} = \alpha_s CS + \beta_s PS + \gamma_s S + \tau_s \tag{11}$$

This formulation of Eq. (11) was inspired by the research of Yabe et al. [101], who explored the recovery dynamics of socio-physical systems. Parameters in this formulation captures both self-dependence and cross-system influences, as detailed in Table 1. These parameters were calibrated by Least Squares method using data from deviation of cyber ($C(t)$), physical ($P(t)$) and social ($S(t)$) systems. The calibration minimized the differences between terms on both sides of the equations in Eq. (11) for each individual system. Parameter significance was assessed using $t$-test statistics, and parameters with p-value$<0.05$ were considered statistically significant.

Given the initial values of deviation across cyber, physical and social ($C(0)$, $P(0)$ and $S(0)$) systems, the performances of these systems will evolute following the pattern modeled by the SD. Based on the SD, we investigated the influences of inter-system dependence and external intervention on the systems' performances.

Eq. (12) demonstrates the model to investigate the influences of inter-system dependence parameters on systems' performances.

$$X(t+\Delta t;\Omega) = X(t;\Omega) + \Delta t \times dX(t;\Omega)/dt \tag{12}$$

, where $\Omega = \left[\alpha_c,\ \beta_c,\ \gamma_c,\ \alpha_p, \beta_p,\ \gamma_p,\ \alpha_s,\ \beta_s, \gamma_s\right]^T$ represents the system dependence parameters, $X(t;\Omega) = [C(t;\Omega), P(t;\Omega), S(t;\Omega)]^T$ represents the system deviation vector with parameters $\Omega$. By systematically varying system dependence parameters ($\Omega$) while maintaining identical initial conditions across systems, we explored both individual and combined influences of interdependence relationships on system resilience.

We developed an intervention analysis framework to assess how targeted improvements in one or more systems could enhance overall resilience. As illustrated in Fig. 6, interventions were applied at time $t'$. Before $t'$, system performance followed the original evolution pattern from initial values $C(0)$, $P(0)$ and $S(0)$. At time $t'$, performance deviation in the targeted system was reduced from $C(t')$ to $(1-\mu)C(t')$, where $\mu \in [0,1]$ represented the intervention effectiveness. Lower deviation corresponds to better performance and higher resilience. After $t'$, performance of cyber, physical and social systems evolute as established differential equations in Eq. (11) with modified initial values of $(1-\mu)C(t')$, $P(t')$ and $S(t')$.

Such intervention framework enables us to examine the impact of intervention timing (early, mid-term, late), the degree of improvement (minor, moderate, major), and the single- versus multi-system interventions (e.g., cyber-physical, cyber-social, physical-social, cyber-physical-social).

**Table 1**
Parameters in SD model.

| Denotation | Abbreviation | Description |
|---|---|---|
| Self-dependence (dimensionless) | | |
| $\alpha_c$ | C-C | Cyber-Cyber dependence. Cyber system depends on its own characteristics. |
| $\beta_p$ | P-P | Physical-Physical dependence. Physical system depends on its own characteristics. |
| $\gamma_s$ | S-S | Social-Social dependence. Social system depends on its own characteristics. |
| Inter-system dependence (dimensionless) | | |
| $\beta_c$ | C-P | Cyber-Physical dependence. Cyber system depends on physical system. |
| $\gamma_c$ | C-S | Cyber-Social dependence. Cyber system depends on social system. |
| $\alpha_p$ | P-C | Physical-Cyber dependence. Physical system depends on cyber system. |
| $\gamma_p$ | P-S | Physical-Social dependence. Physical system depends on social system. |
| $\alpha_s$ | S-C | Social-Cyber dependence. Social system depends on cyber system. |
| $\beta_s$ | S-P | Social-Physical dependence. Social system depends on physical system. |
| Constant terms | | |
| $\tau_c$, $\tau_p$, $\tau_s$ | | Constant variables of cyber, physical and social systems, respectively. |

## 4. Results

### 4.1. Temporal performance evolution

Fig. 7 presents performance deviation across cyber-physical-social (CPS) systems during the 2023 Beijing rainstorm event, with higher deviation values indicating lower resilience. The cyber system (Fig. 7a) demonstrated remarkable initial resistance, maintaining normal operations during the first two days of the rainstorm (July 29–30). On the third day (July 31), however, it experienced an abrupt disruption, followed by a rapid recovery trajectory of mean and maximum deviations. Notably, the zero minimum deviation indicates that some towns maintained uninterrupted communication throughout the entire event, while others experienced significant service deviation. This spatial heterogeneity suggests localized vulnerabilities within the communication network, which may be influenced by complex interactions among precipitation exposure, infrastructure conditions, and topographic factors [122–124]. The rapid recovery pattern observed in the cyber system points to effective adaptation mechanisms, likely through deployment of temporary service provisions and efficient repair actions.

The physical infrastructure system (Fig. 7b) exhibited immediate vulnerability from the first day of the rainstorm. In the following days, the deviation increased, indicating the disruptions in physical systems lasted and spread. The deviations revealed highly heterogeneous disruption levels across different infrastructure components. While some elements remained relatively functional, others experienced severe performance deviation. Unlike the cyber system, physical infrastructure showed persistent high deviation levels even after cyber and social systems had substantially recovered, indicating prolonged recovery requirements. In fact, transportation infrastructure experienced fundamental structural damage during the rainstorm event, requiring extensive repairs and investment for complete recovery. For example, several critical national and provincial roads were disrupted and did not fully recover until June 2024[1], 10 months after the rainstorm. Additionally, the Fengtai-Shacheng railway required more than one year to restore passenger train service[2].

The social system (Fig. 7c) demonstrated an intermediate response pattern, with moderate initial deviation compared to the cyber and physical systems. Distinctively, the social system exhibited a more gradual response curve with prolonged deviation increments and an extended plateau phase at peak disruption. This pattern reflects the complex adaptive nature of social activities, where people progressively

[1] https://www.mot.gov.cn/xinwen/jiaotongyaowen/202512/t20251226_4186287.html

[2] https://www.thepaper.cn/newsDetail_forward_29287961

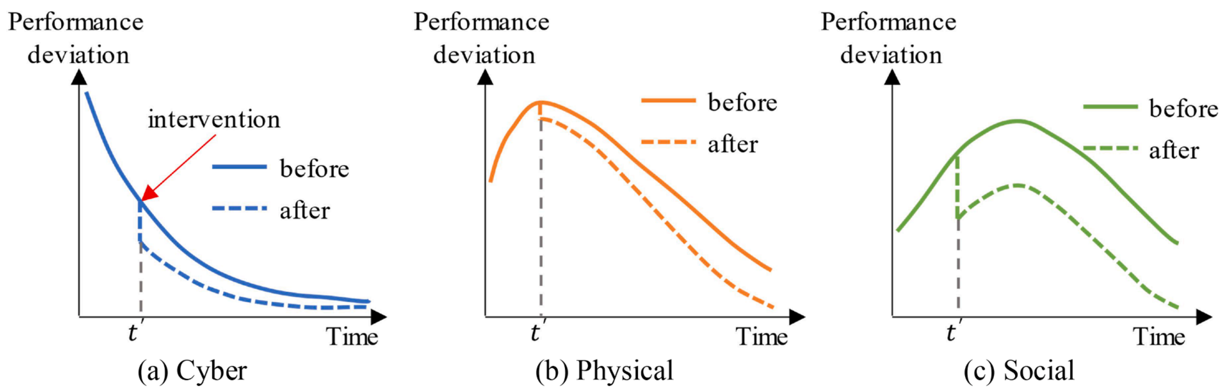



**Fig. 6.** Illustration of external intervention.

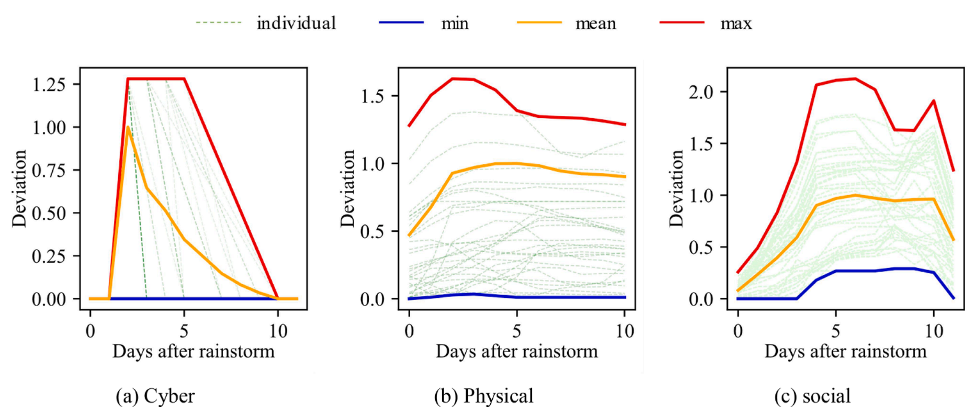



**Fig. 7.** Performance deviation (Normalized by mean deviation of each system).

adjust behaviors and expectations in response to changing conditions. The recovery trajectory of the social system positioned between the rapid cyber recovery and the prolonged physical infrastructure restoration, dropped to moderate deviation levels by the end of the study period.

The mean deviations of individual system were used to measure the resilience and construct the differential equation. Fig. 8 presents the mathematical fitting of mean deviation patterns and corresponding resilience triangles across the three systems. The cyber system performance deviation followed an exponential decay pattern (Fig. 8a), characteristic of systems with rapid response capabilities and effective repair mechanisms. Both physical and social systems exhibited asymmetric Gaussian patterns (Fig. 8b and Fig. 8c), reflecting complex disruption-recovery dynamics. All fitted models accurately captures system performance evolution with $R^2$ values exceeding 0.9, validating the selected mathematical formulations for subsequent interdependence analysis.

Fig. 8d shows the resilience triangle values of cyber, physical, social and average systems. The calculation period spans from July 31 (two days after the rainstorm onset when the cyber system began experiencing disruption) to August 8 (10 days post-rainstorm onset when the cyber system recovered), focusing specifically on the response phase rather than long-term recovery. The cyber system demonstrated the lowest triangle value (highest resilience), attributable to its rapid recovery capabilities despite significant initial disruption. Conversely, the physical system exhibited the highest triangle value (lowest resilience), reflecting its severe performance deviation and minimal recovery during the study period. The social system presented an intermediate resilience profile, with triangle values positioned between the cyber and physical systems.

### 4.2. System interdependence dynamics

Fig. 9 reveals highly heterogeneous interdependence patterns among cyber, physical and social systems. The physical system emerges as a foundational component with substantial influences on both cyber and social systems, as evidenced by the high dependence parameters (C-P: 1.14, S-P: 0.84). This finding suggests the critical role of physical

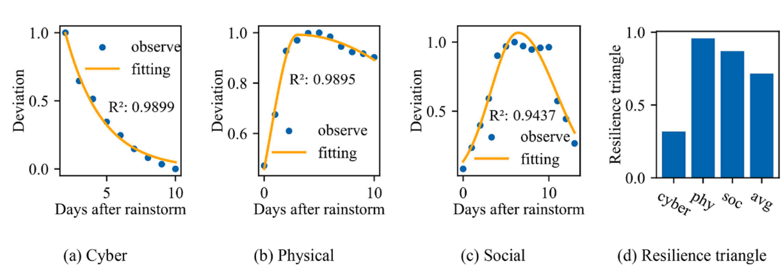



**Fig. 8.** Deviation fitting and resilience triangle.

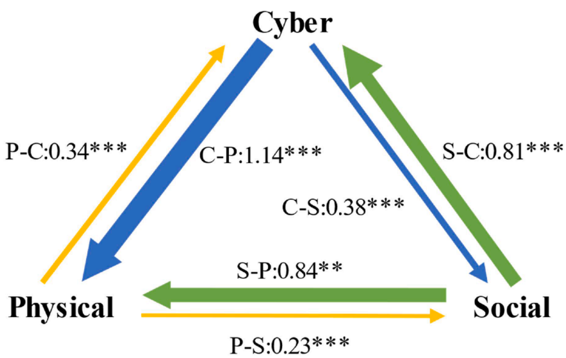



**Fig. 9.** Interdependence parameters across systems (***$p<0.001$, **$p<0.01$).

infrastructure as the operational backbone for both communication networks and social activities. Particularly during extreme events, transportation systems enabled repair crew mobility, equipment deployment, and population movement. During Beijing rainstorm, only after disrupted roads were cleared and repaired could repair resources, personnel and equipment be transported into the affected areas[3]. Subsequently, communication services and social activities can begin to recover. The relatively high dependence of cyber and social systems on physical infrastructure highlights the potential for cascading vulnerability when physical systems were disrupted.

Notably, the reverse dependences—physical-cyber (P-C: 0.34) and physical-social (P-S: 0.23)—were substantially lower, revealing a fundamental asymmetry in the interdependence pattern. This pattern suggests that while physical infrastructure strongly influences cyber and social functions, its own operation and recovery are less dependent on communication networks or social dynamics. This asymmetry likely stems from the inherent characteristics of physical infrastructure, which primarily relies on structural integrity, material conditions, and specialized technical interventions during recovery phases. In fact, as many road segments and railways were structurally damaged during Beijing rainstorm, communication networks and social dynamics contributed minimally to infrastructure restoration. Instead, the most critical resources required were personnel, equipment and materials to repair the damaged infrastructure[4].

The interdependence between cyber and social systems exhibited an unbalanced bidirectional relationship (C-S: 0.38, S-C: 0.81), indicating an asymmetric dependence where communication networks strongly facilitated social coordination while social activities had more limited influence on communication coverage. With the rapid evolution of information technologies, the proliferation of smartphones, social media platforms, and real-time communication applications has fundamentally transformed how people organize, share information, and respond to extreme events. The substantial penetration of digital technologies into daily social functions has made social activities increasingly depend on digital connectivity. This relationship becomes particularly critical during disaster recovery when rapid information flow enables more effective community response. For example, during the initial days of 2023 Beijing rainstorm, several countries were isolated from the outside world due to communication outages. Panic and anxiety gripped the affected communities. When communication services were restored, residents were able to report their safety and local conditions to the outside, which alleviated societal worry considerably[5]. Conversely, the weaker C-S relationship (0.38) reflects that communication restoration was primarily driven by technical and logistical constraints rather than immediate social demand[6]. While social activity levels may influence restoration priorities, the physical limitations of infrastructure repair, equipment availability, and coordinated restoration protocols constrain how directly social activities can influence communication coverage expansion.

The whole study period was further divided into adaptation and recovery stages. The recovery stage refers to the period when all cyber, physical and social systems exhibited recovery trajectories with decreasing deviation levels. The adaptation stage represents the remaining period, during which at least one system had not entered recovery. Interdependence parameters were additionally examined for these two stages, with results presented in Table 2.

During the adaptation stage, parameter values were largely similar to those of the entire period. C-P dependence remained the most significantly influential category, demonstrating the cyber system's strong reliance on physical infrastructure during initial adaptation. However, S-P dependence, which was influential over the entire period, exhibited weak influence during adaptation. This pattern can be attributed to the ability of people to identify alternative routes during the adaptation stage, thereby reducing immediate dependence on physical system status.

In the recovery stage, C-P and S-P remained the two most influential parameters, consistent with the overall pattern. However, S-P dependence emerged as the dominant relationship during this phase. Once alternatives cannot satisfy social needs, social activity recovery became unavoidably dependent on physical system restoration. With substantial infrastructure remaining unrepaired, social activities were significantly constrained by physical system limitations.

The sensitivity analysis reveals heterogeneity across different stages. While the analytical framework can be applied to individual stages using the same procedures, stage-specific analysis is beyond the scope of this study. Our primary focus remains on the integrated analysis of the entire study period. Therefore, subsequent analyses examine only the complete period rather than individual stages.

We systematically evaluated how varying levels of interdependence influence system performance, as shown in Fig. 10. Low and Medium levels represent 10% and 5% reduction in dependences, respectively. High level represents the initial dependence level. This design treats the observed interdependence as the baseline because it reflects realistic system coupling under actual disaster conditions. Examining reductions allows evaluation of potential decoupling strategies, providing more practical insights for resilience planning. For any dependence category, as interdependence strength increased from low to high levels, performance deviation consistently increased while recovery periods extended. This pattern was observed across all three systems, confirming that stronger system coupling amplifies the propagation of disruption effects while potentially impeding recovery processes. This interdependence mechanism represents a double-edged sword for resilience planning. On one hand, recovery in one system can facilitate improvements in dependent systems through positive feedback. On the other hand, disruptions can cascade more severely through highly interdependent systems, magnifying overall performance deviation.

**Table 2**
Sensitivity of interdependence parameter.

| Stage | C-P | C-S | P-C | P-S | S-C | S-P |
|---|---|---|---|---|---|---|
| Whole | 1.14*** | 0.38*** | 0.34*** | 0.23*** | 0.81*** | 0.84** |
| Adaptation | 1.06*** | 0.51*** | 0.35*** | 0.23*** | 1.07 | 0.20*** |
| Recovery | 0.86*** | 0.00*** | 0.06*** | 0.01*** | 0.39*** | 1.94*** |

[3] https://www.zgjtb.com/2023-08/07/content_369029.html
[4] https://www.mot.gov.cn/xinwen/jiaotongyaowen/202512/t20251226_4186287.html
[5] https://www.beijing.gov.cn/ywdt/zwzt/fxjzhfcj/cjmhjy/202308/t20230806_3216794.html
[6] https://finance.sina.com.cn/jjxw/2023-08-01/doc-imzesqvw8286190.shtml

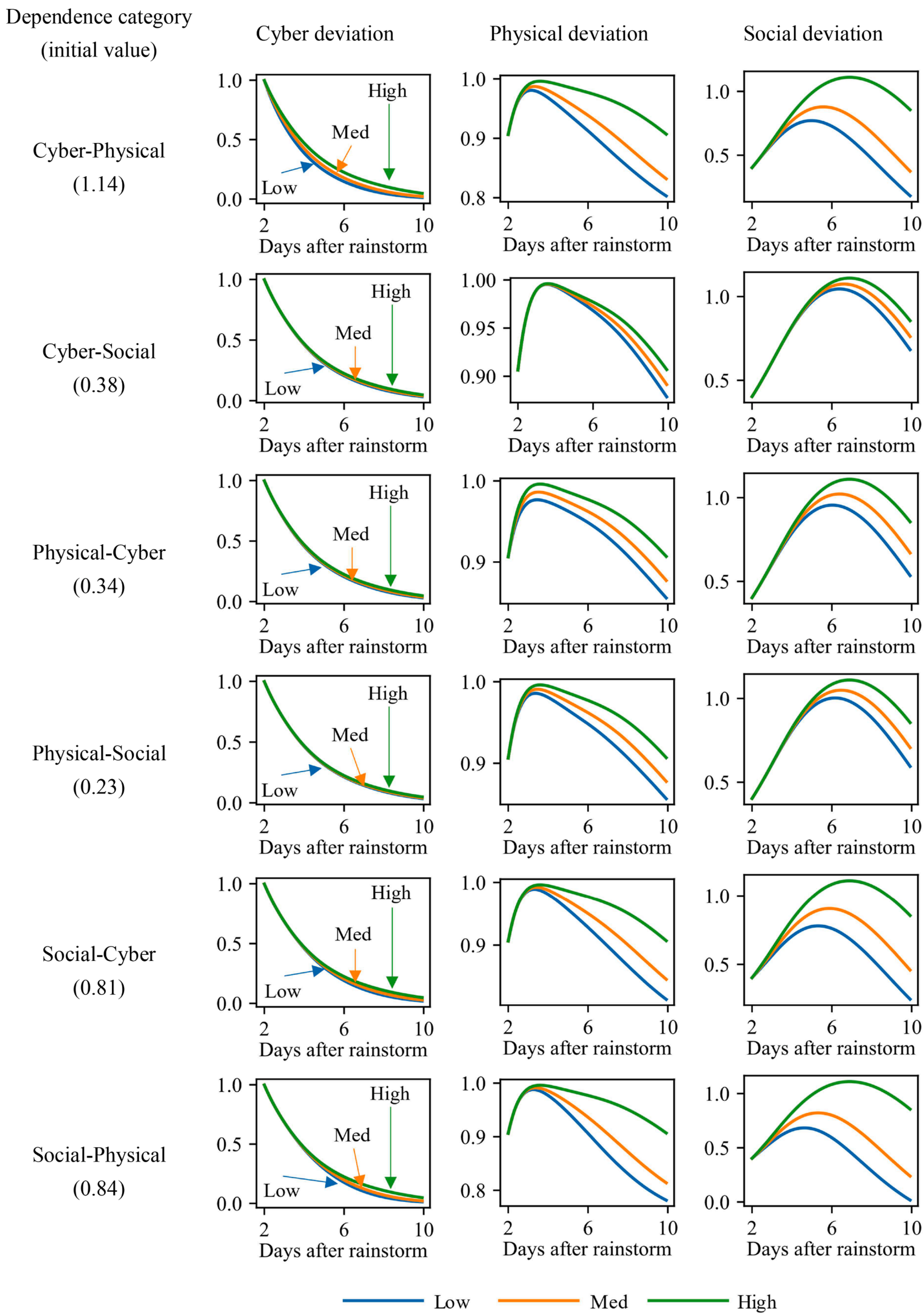
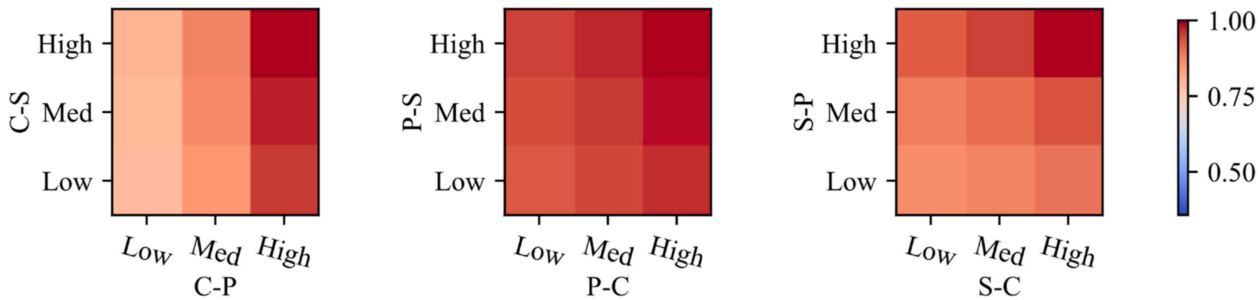
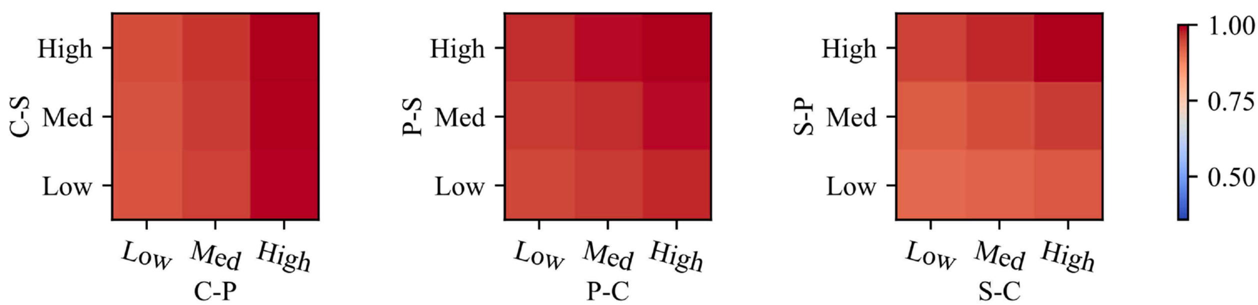



**Fig. 10.** Dependence parameters and their influences. (Low and Medium levels represent 10% and 5% reduction in dependences, respectively. High level represents the initial dependence level.).

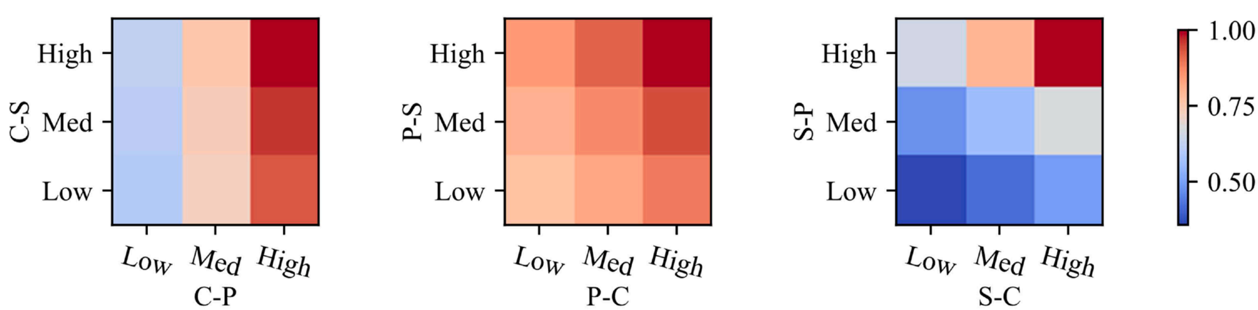
Fig. 11 illustrates the combined influence of dependences on resilience triangle values across all three systems. Elevated dependence levels exhibit a positive correlation with the expansion of the resilience triangle, a relationship that persists when accounting for combined influence of dependences. The cyber system demonstrated highest sensitivity to physical dependences (C-P). The physical system showed balanced and relatively low sensitivity to both cyber and social dependences. While the social system was most responsive to physical



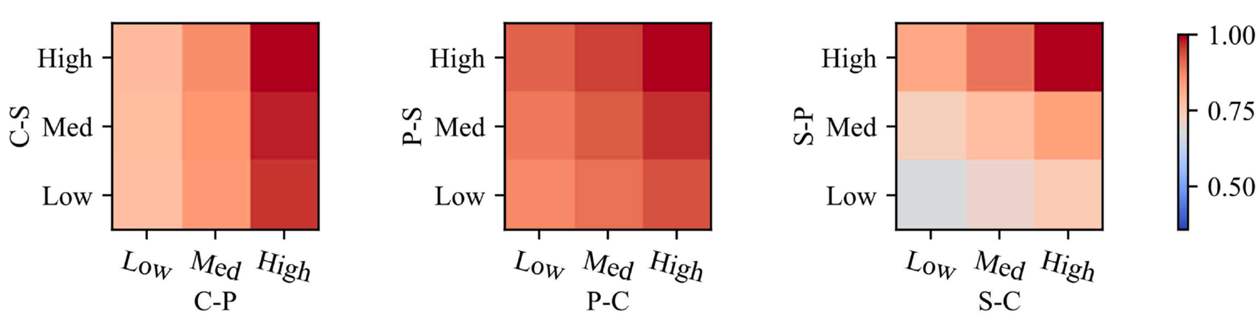

(a) Relative resilience triangle of cyber system




(b) Relative resilience triangle of physical system




(c) Relative resilience triangle social system




(d) Average relative resilience triangle

**Fig. 11.** Combined influence of dependences on system resilience (The color bar represents the ratio of current resilience triangle to the initial resilience triangle. Low and Medium levels represent 10% and 5% reduction in dependences, respectively. High level represents the initial dependence level.).

dependences (S-P). When considering the integrated CPS system, the social-physical dependence (S-P) emerged as the most influential parameter for overall urban resilience. These sensitivity patterns offer critical insights for prioritizing resilience enhancement strategies. From a risk mitigation perspective, reducing dependences with higher sensitivity (particularly C-P and S-P) would most effectively limit cascading failures. Conversely, from a recovery optimization standpoint, accelerating the restoration of systems with high dependence parameters would generate greatly positive spillover effects across the integrated urban system.

### *4.3. Intervention analysis*

#### *4.3.1. Influence of individual system intervention*

Fig. 12 reveals patterns in the relationship among intervention timing, improvement degrees and system resilience outcomes when the intervention was applied on individual system. Across all systems, earlier interventions combined with greater improvement degrees consistently yielded superior resilience outcomes (smaller resilience triangles). Conversely, late interventions with minor improvements produced the least favorable outcomes, highlighting the critical importance of both intervention timing and improvement degrees.

The cyber system exhibited the most significant resilience improvements when interventions targeted its own systems directly (Early-Major cyber intervention, Fig. 12a). This finding suggests that despite interdependence effects, cyber resilience depends substantially on characteristics of its own system such as redundancy and repair resources. The cyber system's more rapid recovery capability compared to other systems likely contributes to its heightened responsiveness to direct interventions.

The physical system exhibited a notably narrower range of resilience triangle improvement compared to other systems (Fig. 12b), indicating inherent recovery constraints that may require more substantial and sustained interventions to achieve significant resilience enhancement.

The social system (Fig. 12c) displayed a unique pattern, achieving substantial resilience improvements regardless of which system received the intervention. This finding highlights the exceptional adaptability of social systems and their capacity to leverage improvements in dependent systems. The social system's adaptive capacity enables it to reconfigure activities and priorities in response to changing infrastructure and communication conditions, creating multiple pathways for resilience enhancement.

When analyzing the integrated CPS system (Fig. 12d), the results demonstrate a balanced responsiveness across all intervention scenarios, reflecting the composite nature of the coupled system. The integrated system exhibits moderate resilience improvements that fall between the individual system responses. This average pattern suggests coordinated enhancement of all three subsystems simultaneously to require significant and effective improvements of the integrated system.

#### *4.3.2. Influence of system synergy*

Our analysis of multi-system interventions (Fig. 13) revealed powerful synergistic effects that exceeded the individual system improvements. Coordinated interventions across all three systems (cyber-physical-social) consistently produced the greatest resilience benefits, substantially outperforming both single-system and dual-system interventions across all timing scenarios and improvement magnitudes.

The cyber and social systems exhibit significant synergistic responses, particularly evident in reduction of resilience triangle when combined with other systems. The physical system demonstrates enhanced resilience when integrated with cyber and social interventions. However, the physical resilience enhancement is limited with relatively stable performance even with multi-system interventions. This pattern suggests extra efforts to be exerted on the physical system to obtain significant resilience improvement. The gap between single-system and multi-system interventions widens in early intervention scenarios, particularly in cyber system. Late interventions show compressed synergistic benefits, suggesting that delayed coordination limits the potential for cross-system reinforcement.

These synergistic effects demonstrate that the interconnected nature of urban systems creates opportunities for magnified resilience benefits when interventions are strategically coordinated across system boundaries. Rather than treating cyber, physical, and social systems as isolated domains, our findings strongly support integrated approaches to urban resilience that leverage system interdependences as amplifiers of positive intervention effects.

## 5. Discussion

### *5.1. Methodological advances*

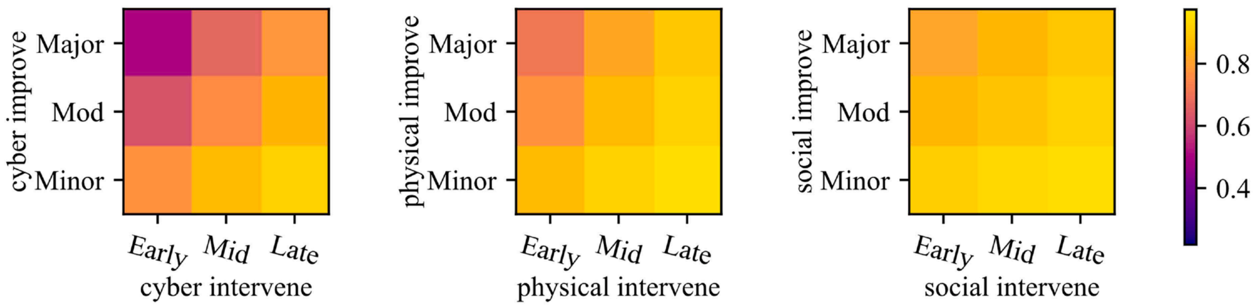
The integrated analytical framework proposed in this study provides a systematic, data-driven approach to quantify the complex interdependences among cyber, physical, and social systems during extreme events. This framework offers several distinct advantages over existing approaches. First, it enables the empirical measurement of cross-system dependences through mathematical modeling rather than relying on conceptual models or expert opinions [93,15]. Second, the framework's standardized resilience triangle methodology allows for meaningful comparisons across inherently different systems, facilitating integrated resilience assessment. Third, by incorporating differential equations within a system dynamics model, our approach captures both the magnitude and directionality of influence between systems. The asymmetric dependences observed between systems align with prior findings of Yabe et al. [101] and Klammler et al. [102], yet our model advances this understanding by extending the analysis from coupled dual systems to three interconnected cyber, physical and social systems. Finally, our findings support previous work demonstrating the benefits of early intervention [125,126,25,24] and cross-system coordination [127], providing a practical tool for policymakers to evaluate and prioritize resilience investments across multiple interdependent systems.

The application of this framework to the 2023 Beijing rainstorm demonstrates its analytical power in a real-world context. The Beijing case study provided a unique opportunity to track the performance evolution of interconnected urban systems under extreme stress, revealing distinct vulnerability and recovery patterns. The data-driven analysis quantified how disruptions propagated across system boundaries and identified critical dependence pathways that influenced overall urban resilience. These empirical findings from the Beijing case study not only validate our methodological approach but also generate actionable insights for enhancing urban resilience against future disruptions.

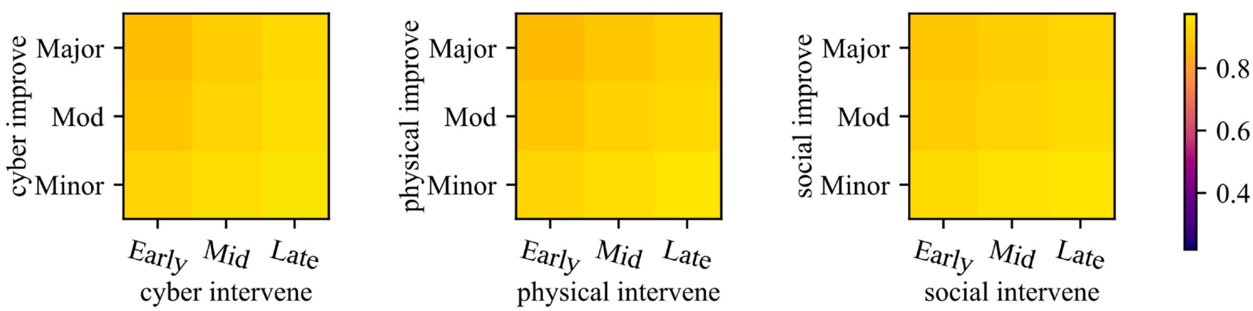
### *5.2. Practical recommendations for urban resilience planning*

1) Prioritize physical infrastructure resilience

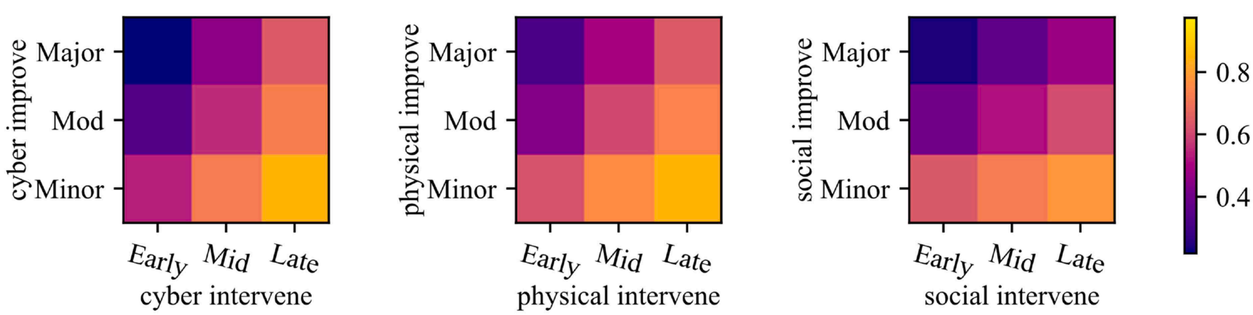
Our findings reveal that resilience of physical infrastructure relied primarily on intrinsic characteristics rather than on interactions with other dependent systems (low parameter value with P-C: 0.34, P-S: 0.23). These low parameter values indicate that physical infrastructure repair cannot rely heavily on communication-assisted information or social coordination. Communication networks and social systems are often disrupted simultaneously with physical infrastructure, limiting their effectiveness in supporting infrastructure restoration. Consequently, recovery strategies of physical system should be capable of operating autonomously, and remain effective under communication-constrained conditions. Moreover, the physical system demonstrated the lowest resilience among the three systems, constraining overall urban resilience despite relatively higher resilience levels in cyber and social systems. Given the foundational role of physical systems, strengthening physical infrastructure should be a priority in resilience planning [128,125,25,129,24]. We recommend: (1) structural



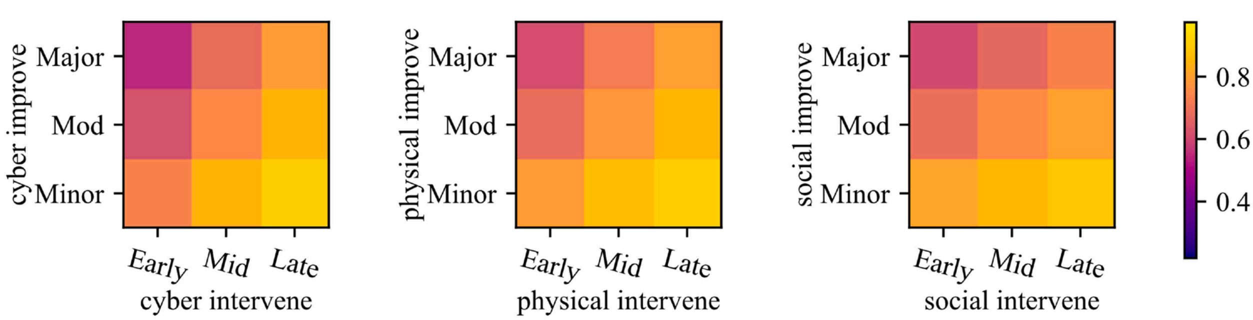

(a) Relative resilience triangle of cyber system




(b) Relative resilience triangle of physical system




(c) Relative resilience triangle of social system




(d) Relative resilience triangle of integrated CPS system

**Fig. 12.** Relative resilience triangle from system improvement (Early, Mid-term and Late interventions represent intervention at the beginning, 10% and 20% of the study period, respectively. Minor, Moderate and Major improvements represent 10%, 20% and 30% deviation reductions, respectively. The color bar represents the ratio of current resilience triangle to the initial resilience triangle. The labels of x-axis and y-axis represent the target system that the intervention was conducted on.).

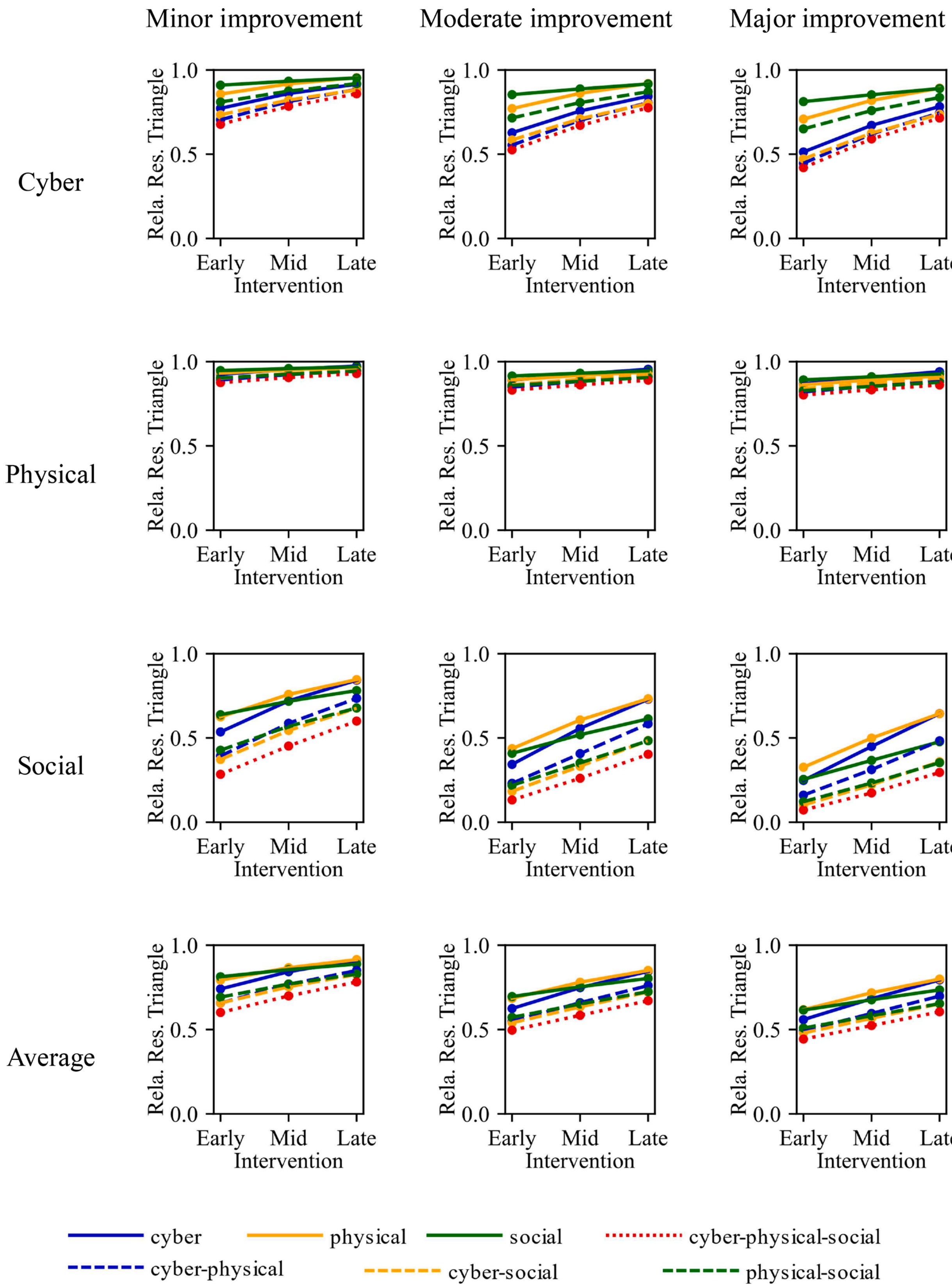



**Fig. 13.** Synergistic effects (The legends represent target systems that the intervention was conducted on).

reinforcements and higher design standards that incorporate future climate projections and historical data; (2) strategic redundancy planning that preserves critical functions during partial system failures; and (3) development of rapid repair capabilities with pre-positioned resources and trained personnel. These measures would create positive effects throughout interdependent urban systems, increasing the returns on resilience investments.

2) Implement strategic decoupling

Our analysis of dependence influences (Fig. 10 and Fig. 11) reveals that reducing the dependence between systems, particularly those with high sensitivity (C-P and S-P), can limit cascading failures during disruptions. Cities can implement targeted decoupling mechanisms that activate during disruptions. This might involve developing emergency operation capabilities for critical systems and establishing backup mechanisms that can function independently.

The observed effective deployment of emergency communication systems during the Beijing rainstorm represents an example of such strategic decoupling. The 2023 Beijing rainstorm induced widespread communication blackouts across multiple towns, compounded by road obstructions that hindered the deployment of repair equipment and personnel. To address this, portable satellite backpacks and unmanned aerial vehicles (UAVs) were used in affected areas to provide temporary communication services. These actions enabled trapped residents to report safety to their friends and family while providing real-time situational data to authorities [130]. This dual functionality not only reduced public anxiety but also enhanced administrative capacity for disaster assessment and targeted intervention.

Future resilience planning should systematically identify critical services and develop autonomous operational capabilities that can function independently when primary systems fail [131]. This includes: 1) expanding low-altitude logistics networks, particularly the number of available unmanned aerial vehicles, flight endurance and ability of drone operators; and 2) developing community-based resilience hubs with independent power, communication, and essential service capabilities (e.g., activating satellite communication service during disruptions, and mobile power sources).

3) Prepare and response early

The analysis of intervention demonstrates that early interventions consistently yielded better resilience outcomes across all systems compared to mid-term or late interventions (Fig. 12). This finding supports the growing consensus in disaster management that pre-disaster investment in resilience yields significantly higher returns than post-disaster recovery efforts [125,126,25,24]. Additionally, this finding emphasizes the value of rapid response during the initial phase of disruption. Preparedness and rapid response call for scientific planning, high quality of infrastructure and facilities, development of detection and warning systems, sufficient resource backup, and regular emergency exercises. Such measures enable more fluid, anticipatory adaptation to emerging disruptions.

4) Adopt cross-system coordination

The synergistic effects observed in multi-system interventions, particularly the superior performance of CPS coordinated interventions, demonstrate the importance of integrated approaches to urban resilience (Fig. 13). This empirical evidence suggests that resilience planning should transcend traditional sector boundaries, establishing coordination mechanisms across cyber, physical, and social domains to maximize resilience outcomes. The management and administration departments should overall allocate the resources across cyber, physical and social systems while coordinating the personnel and resources in an integrated manner [127]. Such coordination can focus on the greater interests of the entire city, rather than individual interests of specific domains and organizations.

### *5.3. Limitations and future research*

Several limitations should be acknowledged, which point to future research directions. First, the selected proxy indicators to represent systems, while appropriate for capturing functional interdependences during extreme weather, struggle to capture the full multidimensional characteristics of each domain, and affect the interpretation and generalizability of findings. In future research, incorporating additional indicators to represent urban systems (such as internet service for cyber system, buildings for physical systems, and mental well-being for social system) would enhance model robustness.

Second, results are derived from the specific case in Beijing, with a specific extreme rainfall event and a phase with several days after the disaster. Interdependence patterns may vary across hazard types (e.g., earthquakes, power outages) and different urban layouts. While long-term adaptation and feedback loops may exhibit different dynamics. Future research can apply the framework to multiple cities and disasters to examine contextual variability; and integrate longer longitudinal datasets to explore evolving interdependence patterns.

Third, this study adopts an aggregate, system-level perspective that averages individual performance to quantify interdependences among cyber, physical, and social systems. However, this approach does not reveal the underlying influence mechanism at the individual level. Future research could complement our system-level findings by developing spatially explicit models that identify the determinants of individual-level heterogeneity, enabling more geographically targeted resilience planning strategies.

## 6. Conclusions

As cities worldwide face increasing threats from climate change-related extreme weather events, understanding the complex dynamics of interdependent urban systems becomes critical for building comprehensive resilience. This study developed an integrated analytical framework to quantify resilience and interdependences across interconnected cyber, physical, and social systems in urban contexts, using the 2023 Beijing rainstorm as a case study. Key findings include:

- Cyber, physical, and social systems exhibit distinct vulnerability and recovery patterns when faced with external shocks.
- The quantification of interdependence parameters revealed asymmetric relationships among these three systems, with physical infrastructure emerging as the foundational component that significantly influences both cyber and social functions.
- The intervention analysis demonstrated two key principles for effective resilience enhancement: (1) preparation and early interventions, and (2) multi-system coordination.

By capturing the bidirectional interdependences between cyber, physical, and social systems, this study offers urban planners and disaster management professionals a powerful tool for understanding complex system interactions and insights for resilience strategy in planning and emergency response.

Although this study focuses on the 2023 Beijing rainstorm, the analytical framework is transferable to other cities and hazard scenarios due to its reliance on data-driven foundation. When appropriate data capturing system performance evolution are available, this approach can be applied to different types of disruptions with suitable adaptations. For example, fitting curves can be tailored to match the performance patterns of different proxy indicators. While this study employs exponential and Gaussian functions, other scenarios may require linear, polynomial, or logarithmic functions depending on observed performance dynamics. Comparative studies across multiple urban contexts, disaster types, and policy environments represent an important direction for future research to validate, refine, and extend the generalizability of the interdependence patterns identified in this work.

## CRediT authorship contribution statement

**Wenxin Ma:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Baichuan Mo:** Writing – review & editing, Methodology, Conceptualization. **Ruimin Li:** Writing – review & editing, Project administration, Investigation, Funding acquisition.

## 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.

## Acknowledgements

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## Data availability

Data will be made available on request.

## References

[1] Bhandari P, Boyle C, Gong J, Law KMY, Creighton D. Ongoing transformation of critical infrastructure systems as cyber-physical-human systems. In: Proceedings of 2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC); 2021. p. 3342–7.
[2] Abdellaoui S, Dumitrescu E, Escudero C, Zamai E. Monitoring cyberthreats in railway systems: a hybrid framework for detecting stealthy data tampering attacks. Reliab Eng Syst Saf 2026;266:111747.
[3] DiMase D, Collier ZA, Heffner K, Linkov I. Systems engineering framework for cyber physical security and resilience. Environ Syst Decis 2015;35:291–300.
[4] Duan S, Ayyub Bilal M. Assessment methods of network resilience for cyber-human-physical systems. ASCE-ASME J Risk Uncertain Eng Syst A: Civ Eng 2020;6:03119001.
[5] Gu B, Liu J, Chen J. Scenario-based strategies evaluation for the maritime supply chain resilience. Transp Res D: Transp Environ 2023;124:103948.
[6] Kurmankhojayev D, Tan H, Chen A. A methodological foundation for proactive disruption mitigation in transport networks: integrating route similarity and elastic demand in stochastic user equilibrium-based link criticality analysis. Reliab Eng Syst Saf 2025;261:111084.
[7] Wang Y, Ye Z, Jia X, Liu H, Zhou G, Wang L. Flood disaster chain deduction based on cascading failures in urban critical infrastructure. Reliab Eng Syst Saf 2025;261:111160.
[8] Zhang D-M, Bai H, Zheng C-Z, Huang H-W, Ayyub BM, Cao W-J. Extreme rainfall induced risk mapping for metro transit systems: shanghai metro network as a case. Reliab Eng Syst Saf 2025;262:111234.
[9] Zhong J, Zhang H, Miao Q. Enhancing aircraft reliability with information redundancy: a sensor-modal fusion approach leveraging deep learning. Reliab Eng Syst Saf 2025;261:111068.
[10] Chatzikyriakidis G, Makris N, Vu T. Quantification of community resilience to natural hazards by tracking cell-phone GPS location data. Reliab Eng Syst Saf 2026;266:111738.
[11] Hong B, Bonczak BJ, Gupta A, Kontokosta CE. Measuring inequality in community resilience to natural disasters using large-scale mobility data. Nat Commun 2021;12:1870.
[12] Valinejad J, Mili L. Cyber-physical-social model of community resilience by considering critical infrastructure interdependencies. IEEE Internet Thing J 2023;10:17530–43.
[13] Wang W, Lai X, Sun Y. Explore human-factor impacts on the occurrence of general aviation accidents. Reliab Eng Syst Saf 2026;267:111900.
[14] Xi H, Nelson JD, Hensher DA, Hu S, Shao X, Xie C. Evaluating travel behavior resilience across urban and rural areas during the COVID-19 Pandemic: contributions of vaccination and epidemiological indicators. Transp Res A: Policy Pract 2024;180:103980.
[15] Xu L, Guo Q, Sheng Y, Muyeen SM, Sun H. On the resilience of modern power systems: a comprehensive review from the cyber-physical perspective. Renew Sustain Energy Rev 2021;152:111642.
[16] Yao Y, Guo Z, Huang X, Ren S, Hu Y, Dong A, Guan Q. Gauging urban resilience in the United States during the COVID-19 pandemic via social network analysis. Cities 2023;138:104361.
[17] Zhao Z, Zhou X, Zheng Y, Meng T, Fang D. Enhancing infrastructural dynamic responses to critical residents' needs for urban resilience through machine learning and hypernetwork analysis. Sustain Cities Soc 2024;106:105366.
[18] Wang J, Huang J, Yang H, Levinson D. Resilience and recovery of public transport use during COVID-19. Npj Urban Sustain 2022;2:18.
[19] Kwasinski A. Hurricane sandy effects on communication systems. The University of Texas at Austin; 2012.
[20] Qu K, Yao W, Tang HS, Agrawal A, Shields G, Chien SI, Gurung S, Imam Y, Chiodi I. Extreme storm surges and waves and vulnerability of coastal bridges in New York City metropolitan region: an assessment based on Hurricane Sandy. Nat Hazards 2021;105:2697–734.
[21] Xiao J, Zhang W, Huang M, Lu Y, Lawrence WR, Lin Z, Primeau M, Dong G, Liu T, Tan W, Ma W, Meng X, Lin S. Increased risk of multiple pregnancy complications following large-scale power outages during Hurricane Sandy in New York State. Sci Total Environ 2021;770:145359.
[22] Dui H, Guo W, Xia W, Wu S. Digital twin-based resilience analysis and emergency maintenance with generative AI of smart urban metro systems. Reliab Eng Syst Saf 2026;265:111537.
[23] Johansen C, Tien I. Probabilistic multi-scale modeling of interdependencies between critical infrastructure systems for resilience. Sustain Resilient Infrastruct 2018;3:1–15.
[24] Zou Q, Chen S. Enhancing resilience of interdependent traffic-electric power system. Reliab Eng Syst Saf 2019;191:106557.
[25] Wei X, Wang M, Meng Q. Vulnerability assessment and reduction for intermodal freight transportation networks. Reliab Eng Syst Saf 2024;245:109969.
[26] AlHidaifi SM, Asghar MR, Ansari IS. A survey on Cyber resilience: key strategies, research challenges, and future directions. ACM Comput Surv 2024;56:1–48.
[27] Liu W, Shan M, Zhang S, Zhao X, Zhai Z. Resilience in Infrastructure systems: a comprehensive review. Buildings 2022;12:759.
[28] Ma R, Dong H, Han Q, Du X. Resilience modeling of transportation infrastructure and network based on the semi-markov process considering resource dependency. Reliab Eng Syst Saf 2025;261:111159.
[29] Saja AMA, Teo M, Goonetilleke A, Ziyath AM. An inclusive and adaptive framework for measuring social resilience to disasters. Int J Disaster Risk Reduct 2018;28:862–73.
[30] Zhang Q, Lin S, Sun X, Feng D. Seismic vulnerability assessment method of overhead contact systems based on numerical simulation. Reliab Eng Syst Saf 2026;267:111903.
[31] Khanmohammadi S, Farahmand H, Kashani H. A system dynamics approach to the seismic resilience enhancement of hospitals. Int J Disaster Risk Reduct 2018;31:220–33.
[32] Wang N, Wu M, Yuen KF. Modelling and assessing long-term urban transportation system resilience based on system dynamics. Sustain Cities Soc 2024;109:105548.
[33] Yabe T, Rao PSC, Ukkusuri SV, Cutter SL. Toward data-driven, dynamical complex systems approaches to disaster resilience. Proc Natl Acad Sci 2022;119:e2111997119.
[34] Gonçalves LAPJ, Ribeiro PJG. Resilience of urban transportation systems. Concept, characteristics, and methods. J Transp Geogr 2020;85:102727.
[35] Nair R, Avetisyan H, Miller-Hooks E. Resilience Framework for ports and other intermodal components. Transp Res Rec 2010;2166:54–65.
[36] Wan C, Yang Z, Zhang D, Yan X, Fan S. Resilience in transportation systems: a systematic review and future directions. Transp Rev 2018;38:479–98.
[37] Alhidaifi SM, Asghar MR, Ansari IS. Cyber resilience quantification: a probabilistic estimation model for IT infrastructure. Reliab Eng Syst Saf 2026;265:111473.
[38] Araujo MS, Machado BA, Passos FU. Resilience in the context of cyber security: a review of the fundamental concepts and relevance. Appl Sci 2024;14:2116.
[39] Cui G, Huang N, Meng F, Song Z, Cao Z. A GCN-based availability analysis method for mobile network with spatial–temporal effect awareness. Reliab Eng Syst Saf 2026;267:111879.
[40] Batista AdS, Santos ALD. A survey on resilience in information sharing on networks: taxonomy and applied techniques. ACM Comput Surv 2024;56:302.
[41] Kuikka V, Rantanen H. Resilience of Multi-layer communication Networks. Sensors 2023;23:86.
[42] Masud MT, Keshk M, Moustafa N, Turnbull B, Susilo W. Vulnerability defence using hybrid moving target defence in Internet of Things systems. Comput Secur 2025;153:104380.
[43] AlHidaifi SM, Asghar MR, Ansari IS. Towards a Cyber Resilience Quantification framework (CRQF) for IT infrastructure. Comput Netw 2024;247:110446.
[44] Galiardi M, Gonzales A, Thorpe J, Vugrin E, Fasano R, Lamb C. Cyber resilience analysis of SCADA systems in nuclear power plants. In: Proceedings of the 2020 International Conference on Nuclear Engineering collocated with the ASME 2020 Power Conference; 2020, V002T008A003.
[45] Li X, Xu QM, Chen CL, Yang B, Jiang YL, Zhu SY, Guan XP. Robust CyberPhysical Co-planning for multienergy ship operation under multidimensional uncertainties. IEEE Trans Transp Electrif 2024;10:7852–61.
[46] Song Z, Skuric A, Ji K. A recursive watermark method for hard real-time industrial control system cyber-resilience enhancement. IEEE Trans Autom Sci Eng 2020;17:1030–43.
[47] Almaleh A. Measuring resilience in smart infrastructures: a comprehensive review of metrics and methods. Appl Sci 2023;13:6452.
[48] Cocco G, Spacone E, Brando G. Seismic vulnerability assessment of urban areas made of adobe buildings through analytical and numerical methods: the case study of the historical center of Cusco (Peru). Int J Disaster Risk Reduct 2024;112:104786.
[49] D'Ayala DF, Paganoni S. Assessment and analysis of damage in L'Aquila historic city centre after 6th April 2009. Bull Earthq Eng 2011;9:81–104.
[50] Ferreira TM, Vicente R, Mendes da Silva JAR, Varum H, Costa A. Seismic vulnerability assessment of historical urban centres: case study of the old city centre in Seixal, Portugal. Bull Earthq Eng 2013;11:1753–73.
[51] Rapone D, Brando G, Spacone E, De Matteis G. Seismic vulnerability assessment of historic centers: description of a predictive method and application to the case study of scanno (Abruzzi, Italy). Int J Archit Herit 2018;12:1171–95.
[52] Simões AG, Bento R, Lagomarsino S, Cattari S, Lourenço PB. Seismic assessment of nineteenth and twentieth centuries URM buildings in Lisbon: structural features and derivation of fragility curves. Bull Earthq Eng 2020;18:645–72.
[53] Xu K, Liu J, Li Z. Vulnerability assessments of global liner shipping network based on extended coupled map lattices. Reliab Eng Syst Saf 2025;264:111306.
[54] Bi W, MacAskill K, Schooling J. Old wine in new bottles? Understanding infrastructure resilience: foundations, assessment, and limitations. Transp Res D: Transp Environ 2023;120:103793.

[55] Hong L, Ouyang M, Xu M, Hu P. Time-varied accessibility and vulnerability analysis of integrated metro and high-speed rail systems. Reliab Eng Syst Saf 2020;193:106622.
[56] Li R, Yang R, Shi Y, Liu J, Chen B. Hierarchy of urban road networks from a scaling law perspective. Cities 2025;166:106215.
[57] Lu Z-H, Wang X-W, Liu L, Zhang X-Y, Li C-Q. An efficient method for network connectivity reliability computation considering correlation of components. Reliab Eng Syst Saf 2025;257:110805.
[58] Ma W, Liu Z, Zheng C, Baikejuli M, Li R. Assessing and improving multi-perspective redundancy at segment level in multimodal transportation networks. Reliab Eng Syst Saf 2026;265:111630.
[59] Sugiura S, Kurauchi F. Isolation vulnerability analysis in road network: edge connectivity and critical link sets. Transp Res D: Transp Environ 2023;119:103768.
[60] Wen T, Gao Q, Chen Y-w, Cheong KH. Exploring the vulnerability of transportation networks by entropy: a case study of Asia–Europe maritime transportation network. Reliab Eng Syst Saf 2022;226:108578.
[61] Zhong H, Lei M, Gu Y. Vulnerability assessment in inland waterway transportation network for hazardous materials amid demand: a case of the pearl river delta. Reliab Eng Syst Saf 2025;262:111204.
[62] Harle SM, Sagane S, Zanjad N, Bhadauria PKS, Nistane HP. Advancing seismic resilience: focus on building design techniques. Structures 2024;66:106432.
[63] Hua W, Ye J, Ye J. Resilience assessment and seismic risk assessment of reticulated shell structures considering multiple uncertainties. Structures 2023;55:1584–94.
[64] Lan YC, Xu J, Zhong J, Li Y. Seismic fragility and resilience assessment of large-span cable-stayed bridges under multi-support ground motions with non-Gaussian characteristics. Earthq Eng Struct Dyn 2024;53:4310–33.
[65] Li S-Q, Chen P-C, Zheng L-L, Zhang C, Qin P-F, Milani G. Seismic failure and risk estimation of reinforced concrete bridges considering fatigue and seismic intensity measures. Reliab Eng Syst Saf 2026;267:111854.
[66] Liu Z, Li S, Guo A, Li H. Comprehensive functional resilience assessment methodology for bridge networks using data-driven fragility models. Soil Dyn Earthq Eng 2022;159:107326.
[67] Chi Y, Xu Y, Ding T. Coordinated VAR planning for voltage stability enhancement of a wind-energy power system considering multiple resilience indices. IEEE Trans Sustain Energy 2020;11:2367–79.
[68] Ma W, Lin S, Ci Y, Li R. Resilience evaluation and improvement of post-disaster multimodal transportation networks. Transp Res A: Policy Pract 2024;189:104243.
[69] Sang M, Ding Y, Bao M, Li S, Ye C, Fang Y. Resilience-based restoration strategy optimization for interdependent gas and power networks. Appl Energy 2021;302:117560.
[70] Zhang H, Zhao X, Wang J, Huang R. Dynamic port resilience assessment in the maritime network: modeling flow evolution and cascading failure. Reliab Eng Syst Saf 2026;267:111927.
[71] Moya J, Goenechea M. An approach to the unified conceptualization, definition, and characterization of social resilience. Int J Env Res Public Health 2022;19:5746.
[72] Jia X, Chowdhury M, Prayag G, Hossan Chowdhury MM. The role of social capital on proactive and reactive resilience of organizations post-disaster. Int J Disaster Risk Reduct 2020;48:101614.
[73] Zhang XA, Sung YH. Communities going virtual: examining the roles of online and offline social capital in pandemic perceived community resilience-building. Mass Commun Soc 2023;26:539–65.
[74] Godfrey-Wood R, Flower BCR. Does guaranteed employment promote resilience to climate change? The case of India's Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA). Dev Policy Rev 2018;36:O586–604.
[75] Ramezani R, Farshchin A. Urban resilience and its relationship with Urban poverty. J Urban Plan Dev 2021;147:05021042.
[76] Tang LY, Liu CC, Wang Y. Unveiling the role of social networks: enhancing rural household livelihood resilience in China's Dabie Mountains. J Geogr Sci 2025;35:335–58.
[77] Hadjielias E, Christofi M, Tarba S. Contextualizing small business resilience during the COVID-19 pandemic: evidence from small business owner-managers. Small Bus Econ 2022;59:1351–80.
[78] Li R, Dong L, Zhang J, Wang X, Wang W-X, Di Z, Stanley HE. Simple spatial scaling rules behind complex cities. Nat Commun 2017;8:1841.
[79] Li Y, Hao S, Han Q, Guo X, Zhong Y, Zou T, Fan C. Study on urban economic resilience of Beijing, Tianjin and Hebei based on night light remote sensing data during COVID-19. Sci Remote Sens 2024;9:100126.
[80] Podesta C, Coleman N, Esmalian A, Yuan F, Mostafavi A. Quantifying community resilience based on fluctuations in visits to points-of-interest derived from digital trace data. J R Soc Interface 2021;18:20210158.
[81] Aghababaei M, Koliou M. An agent-based modeling approach for community resilience assessment accounting for system interdependencies: application on education system. Eng Struct 2022;255:113889.
[82] Egamberdiev B. Social capital effects on resilience to food insecurity: evidence from Kyrgyzstan. J Int Dev 2024;36:435–50.
[83] Li S, Zhou Y. Integrating equity and efficiency into urban logistics resilience under emergency lockdowns. Transp Res E: Logist Transp Rev 2024;183:103446.
[84] Pei S-S, Zhai C-H, Hu J, Wang Z-Q, Xie L-L. Resilience assessment and enhancement of interdependent transportation-healthcare system: a spatial accessibility approach. Transp Res D: Transp Environ 2024;128:104090.
[85] Ntontis E, Drury J, Amlôt R, Rubin GJ, Williams R, Saavedra P. Collective resilience in the disaster recovery period: emergent social identity and observed social support are associated with collective efficacy, well-being, and the provision of social support. Br Journa Soc Psychol 2021;60:1075–95.
[86] Wang B, Loo BPY, Zhen F, Xi G. Urban resilience from the lens of social media data: responses to urban flooding in Nanjing, China. Cities 2020;106:102884.
[87] N., L.N.S. Wang K, Mihunov V. Correlating Twitter use with disaster resilience at two spatial scales: a case study of Hurricane Sandy Ann GIS 2023;29:1–20.
[88] Arghandeh R, von Meier A, Mehrmanesh L, Mili L. On the definition of cyber-physical resilience in power systems. Renew Sustain Energy Rev 2016;58:1060–9.
[89] Zhou Y, Yu FR, Chen J, Kuo Y. Cyber-physical-social systems: a State-of-the-art survey, challenges and opportunities. IEEE Commun Surv Tutor 2020;22:389–425.
[90] Wang J, Huang Y. An edge load cascading failure model and vulnerability analysis of coupled critical infrastructure networks: considering functional and geographical interdependency. Reliab Eng Syst Saf 2026;266:111719.
[91] Wang S, Wang H, Ma X, Han Y, Xue G, Zhang L, Li Y. Resilience analysis and recovery strategy for interdependent automated container port networks under cascading failures. Reliab Eng Syst Saf 2026;265:111495.
[92] Li X, Li W, Wang N. Resilience-oriented optimal allocation of renewable energy source capacity in cyber-physical power systems. Reliab Eng Syst Saf 2026;265:111505.
[93] Dagnas R, Barbeau M, Garcia-Alfaro J, Yaich R. Resilience assessment of multi-layered cyber-physical systems. In: Proceedings of 2024 IFIP Networking Conference (IFIP Networking); 2024. p. 634–9.
[94] Doostmohammadian M, Rabiee HR, Khan UA. Cyber-Social Systems: modeling, inference, and optimal design. IEEE Syst J 2020;14:73–83.
[95] Qiujie W, Hao X, Hong T, Zhenxing L, Fei Y, Mohamed MA. Enhancing pre-disaster resilience of distribution networks considering temporal characteristics of typhoon disasters and cyber-physical collaborative control. Reliab Eng Syst Saf 2026;268:111954.
[96] Cavallaro M, Asprone D, Latora V, Manfredi G, Nicosia V. Assessment of urban ecosystem resilience through hybrid social–physical complex networks. Comput-Aided Civ Infrastruct Eng 2014;29:608–25.
[97] Croope SV, McNeil S. Improving resilience of critical infrastructure systems postdisaster: recovery and mitigation. Transp Res Rec 2011;2234:3–13.
[98] Goldbeck N, Angeloudis P, Ochieng WY. Resilience assessment for interdependent urban infrastructure systems using dynamic network flow models. Reliab Eng Syst Saf 2019;188:62–79.
[99] Ouyang M, Pan Z, Hong L, He Y. Vulnerability analysis of complementary transportation systems with applications to railway and airline systems in China. Reliab Eng Syst Saf 2015;142:248–57.
[100] Li W, Jiang R, Wu H, Xie J, Zhao Y, Song Y, Li F. A system dynamics model of urban rainstorm and flood resilience to achieve the sustainable Development goals. Sustain Cities Soc 2023;96:104631.
[101] Yabe T, Rao PSC, Ukkusuri SV. Resilience of interdependent urban socio-physical systems using large-scale mobility data: modeling recovery dynamics. Sustain Cities Soc 2021;75:103237.
[102] Klammler H, Rao PSC, Hatfield K. Modeling dynamic resilience in coupled technological-social systems subjected to stochastic disturbance regimes. Environ Syst Decis 2018;38:140–59.
[103] Liu J, Shao Z, Wang W. Resilience assessment and critical point identification for urban water supply systems under uncertain scenarios. Water 2021;13:2939.
[104] Valinejad J, Mili L. Cyber–Physical–Social model of community resilience by considering critical infrastructure interdependencies. IEEE Internet Thing J 2023;10:17530–43.
[105] Ding Y, Chen S, Zheng Y, Chai S, Nie R. Resilience assessment of China's natural gas system under supply shortages: a system dynamics approach. Energy 2022;247:123518.
[106] Lara DVR, Pfaffenbichler P, Rodrigues da Silva AN. Modeling the resilience of urban mobility when exposed to the COVID-19 pandemic: a qualitative system dynamics approach. Sustain Cities Soc 2023;91:104411.
[107] Li G, Kou C, Wang Y, Yang H. System dynamics modelling for improving urban resilience in Beijing, China. Resour Conserv Recycl 2020;161:104954.
[108] Yin H, Xiao R, Fei X, Zhang Z, Gao Z, Wan Y, Tan W, Jiang X, Cao W, Guo Y. Analyzing “economy-society-environment” sustainability from the perspective of urban spatial structure: a case study of the Yangtze River delta urban agglomeration. Sustain Cities Soc 2023;96:104691.
[109] Beijing-Communications-Administration. Communication has recovered in all villages in Fangshan and Mentougou, https://bjca.miit.gov.cn/xwdt/gzdt/art/2023/art_96007918f83643589aa34af22922dd53.html; 2023.
[110] Beijing-Daily. Operators have opened up multiple emergency communication vehicles to the affected residents. https://www.beijing.gov.cn/ywdt/zwzt/fxjzhfcj/cjmhjy/202308/t20230807_3216824.html; 2023.
[111] CNR. Mentougou District of Beijing, mobile communication services were disrupted in five towns and power supply was cut off in some areas. Emergency repair and rescue efforts are now underway with great urgency. https://china.cnr.cn/gdgg/20230801/t20230801_526356812.shtml; 2023.
[112] People's-Post-and-Telecommunications-Daily. Beijing Fangshan communication emergency rescue chronicle | on august 8th, 29 villages were restored to communication. https://www.cnii.com.cn/rmydb/202308/t20230809_494312.html; 2023.
[113] The-People's-Goverment-of-Beijing-Municipality. Mobile phone signals have been restored in all 147 villages affected by the disaster in Mentougou. https://www.beijing.gov.cn/ywdt/zwzt/fxjzhfcj/cjmhjy/202308/t20230809_3218617.html; 2023.

[114] Xinhuanet. The communication in Mentougou district and Fangshan district of Beijing is being restored. https://www.xinhuanet.com/info/20230802/ebfa67e765d34f0cbf95d68c46c553ad/c.html; 2023.
[115] OpenStreetMap. https://www.openstreetmap.org/; 2024.
[116] LAADS. VIIRS/NPP gap-filled lunar BRFD-adjusted nighttime lights daily L3 Global 500m linear lat lon grid. https://ladsweb.modaps.eosdis.nasa.gov/search/order/1/VNP46A2–5000,VNP46A2–5200; 2023.
[117] Cimellaro GP, Reinhorn AM, Bruneau M. Framework for analytical quantification of disaster resilience. Eng Struct 2010;32:3639–49.
[118] Bruneau M, Chang S, Eguchi R, Lee G, O'Rourke T, Reinhorn A, Shinozuka M, Tierney K, Wallace W, Winterfeldt D. A framework to quantitatively assess and enhance the seismic resilience of communities. Earthq Spectra 2003;19:733–52.
[119] Serdar MZ, Koç M, Al-Ghamdi SG. Urban Transportation Networks Resilience: indicators, disturbances, and assessment methods. Sustain Cities Soc 2022;76:103452.
[120] Zhang L, Chen T, Liu Z, Yu B, Wang Y. Analysis of multi-modal public transportation system performance under metro disruptions: a dynamic resilience assessment framework. Transp Res A: Policy Pract 2024;183:104077.
[121] Cats O, Koppenol G-J, Warnier M. Robustness assessment of link capacity reduction for complex networks: application for public transport systems. Reliab Eng Syst Saf 2017;167:544–53.
[122] Huang J, Wen H, Zhou X, Xiao J. Is there difference in landslide susceptibility model based on explainable artificial intelligence from the perspective of slope units with different scales? Reliab Eng Syst Saf 2026;266:111701.
[123] Niu C, Zhang T, Nair DJ, Dixit V, Murray-Tuite P. Link-level resilience analysis for real-world networks using crowd-sourced data. Int J Disaster Risk Reduct 2022;73:102893.
[124] Yichi Z, Hanping Z, Haoyue Q, Jinfan L. Dynamic assessment of postdisaster road network vulnerability using crowdsourced traffic data. Transp Res D: Transp Environ 2024;126:104021.
[125] Koks EE, Rozenberg J, Zorn C, Tariverdi M, Vousdoukas M, Fraser SA, Hall JW, Hallegatte S. A global multi-hazard risk analysis of road and railway infrastructure assets. Nat Commun 2019;10:2677.
[126] Peng Q, Bakkar Y, Wu L, Liu W, Kou R, Liu K. Transportation resilience under Covid-19 uncertainty: a traffic severity analysis. Transp Res A: Policy Pract 2024;179:103947.
[127] Huizenga S, Oldenhof L, van de Bovenkamp H, Bal R. Governing the resilient city: an empirical analysis of governing techniques. Cities 2023;135:104237.
[128] Artime O, Grassia M, De Domenico M, Gleeson JP, Makse HA, Mangioni G, Perc M, Radicchi F. Robustness and resilience of complex networks. Nat Rev Phys 2024;6:114–31.
[129] Xu X, Chen A, Xu G, Yang C, Lam WHK. Enhancing network resilience by adding redundancy to road networks. Transp Res E: Logist Transp Rev 2021;154:102448.
[130] The-People's-Goverment-of-Beijing-Municipality. Satellite backpack stations, life-saving throw devices! these equipment functioned in restoring communication in the disaster area. https://www.beijing.gov.cn/ywdt/zwzt/fxjzhfcj/cjmhjy/202308/t20230807_3216827.html; 2023.
[131] Li G, Zhang D, Bie Z. An analytical method for reliability and resilience evaluation of power distribution systems with mobile power sources. Reliab Eng Syst Saf 2026;267:111817.