

Article

Fire Emergency Response Resilience in Interdependent Road–Water–Command Systems: A Bayesian Network Analysis

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Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and or methodology.

- This study conceptualizes urban fire response resilience as an emergent property of an interdependent road–water–command system, integrating physical infrastructure and organizational command capacities within a unified systems framework.
- It advances systems methodology by combining an 18-node Bayesian network with multi-state resilience outcomes, scenario inference, intervention simulation, and bootstrap validation based on 200 urban fire cases.

What are the main findings and/or the implications of the main findings?

- Command capacity is the most influential individual subsystem and can partially compensate for simultaneous road and water constraints, but it cannot fully substitute for adequate physical infrastructure.
- Coordinated improvements in fire lane access, water pressure and coordination, unified command, and alarm dispatch increase effective response from 34% to 50%, reduce high disruption severity from 42% to 32%, and raise high response resilience from 17% to 25%.

Abstract

Urban fire emergency response depends on the coordinated functioning of road access, firefighting water supply, and command systems. This study develops an 18-node Bayesian network to assess Response Resilience in interdependent road–water–command systems using 200 coded urban fire emergency cases. The model links 12 observable conditions to Road Capacity, Water Capacity, and Command Capacity, which jointly influence Response Effectiveness and Response Disruption Severity; these outcomes subsequently determine Response Resilience. Baseline inference indicates a 34% probability of effective response, a 42% probability of high Disruption Severity, and a 17% probability of high resilience. Scenario analysis shows that weak Command Capacity produces the most adverse single-subsystem outcome, while strong Command Capacity partially offsets simultaneous road and water constraints. Sensitivity analysis identifies Fire Lane Availability, Water Pressure, Water Coordination, Unified Command, Resource Mobilization, and Alarm Dispatch as influential nodes. The integrated intervention increases the effective response rate to 50%, reduces high Disruption Severity to 32%, and raises high resilience to 25%. A 1000-replication bootstrap supports the sampling stability of the principal estimates and intervention effects. The findings provide probabilistic decision support for coordinated urban fire–Response Resilience improvement.



Academic Editors: Golam Kabir,
Niamat Ullah Ibne Hossain and
Yasser Almoghathawi

Received: 23 June 2026

Revised: 25 July 2026

Accepted: 30 July 2026

Published: 1 August 2026

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Keywords: fire emergency response; response resilience; Bayesian network; infrastructure interdependence; road–water–command systems; intervention simulation

1. Introduction

Urban fire emergencies are no longer isolated safety incidents managed solely within the boundary of firefighting operations. In dense, complex cities, a major fire may simultaneously affect road accessibility, water supply, situational information, emergency command, medical assistance, and evacuation support [1,2]. The effectiveness of fire emergency response therefore depends not only on the availability of fire brigades but also on the coordinated functioning of road, water supply, and command subsystems. Once one subsystem is disrupted, such as blocked fire lanes, insufficient firefighting water, delayed situational information, or fragmented command coordination, the overall response system may experience service degradation and varying levels of response disruption.

This problem is particularly important in the context of interdependent critical infrastructure systems. Urban emergency response relies on physical infrastructure, including transportation networks, water supply systems, and building fire protection facilities, as well as command-related organizational arrangements, including situational information transmission, Alarm Dispatch, Resource Mobilization, and on-site coordination. These components do not operate independently [3,4]. Road accessibility determines whether firefighting and rescue forces can arrive in time; water supply support affects the ability to control the initial fire; and situational information shapes command decisions, resource matching, and coordinated response. Fire emergency Response Resilience is therefore an emergent property of an interdependent socio-technical system [5,6].

Existing studies on fire safety and emergency response have provided valuable insights into fire risk assessment, fire station location, evacuation simulation, emergency resource allocation, and fire prevention governance. However, several limitations remain. First, many studies focus on individual components of the response system, such as station coverage, building fire safety, or evacuation behavior, while paying insufficient attention to the functional interdependencies among road system conditions, water supply support, and command system capacity. Second, conventional fire risk analyses often emphasize static risk factors and final accident consequences. However, they are less able to explain how subsystem constraints jointly alter Response Effectiveness and the severity of operational disruption. Third, Response Effectiveness and Response Resilience are not always clearly distinguished, even though short-term task performance does not necessarily imply that core response functions can be maintained, adapted, or restored under disturbance. Fourth, probabilistic fire response studies often simplify disruption and resilience into binary outcomes, thereby obscuring differences among functional degradation levels ranging from limited to severe. A probabilistic framework that distinguishes these response stages and evaluates the stability of its estimates is therefore needed.

To address these gaps, this study develops a Bayesian network model for assessing fire emergency Response Resilience in interdependent road–water–command systems. Bayesian networks are suitable for representing uncertain and conditionally dependent relationships among multiple infrastructure and organizational factors [7,8]. In the proposed model, observable road, water supply, and command system conditions determine three subsystem capacities, which jointly influence Response Effectiveness and Response Disruption Severity. These two response process outcomes subsequently determine Response Resilience. The model therefore distinguishes immediate operational performance from the broader capacity to maintain or restore core response functions under disruption. It

also enables the posterior probabilities of an effective response, high Disruption Severity, and high Response Resilience to be updated under alternative subsystem constraints and intervention settings.

The central research question is how do road, water supply, and command system conditions jointly shape Response Effectiveness, Disruption Severity, and Response Resilience during major urban fire emergencies? Three related questions are examined:

- (1) How do individual and compound subsystem constraints alter the posterior distributions of the three principal response outcomes?
- (2) To what extent can strong Command Capacity compensate for simultaneous road and water supply constraints?
- (3) Which node-level interventions generate the greatest and most stable improvements in fire emergency Response Resilience?

To answer these questions, this study constructs an 18-node Bayesian network using 200 coded major urban fire emergency response cases. The model comprises twelve input nodes, three subsystem capacity nodes, one response performance node, one process outcome node, and one final resilience outcome node. Response Disruption Severity and Response Resilience are represented using three ordered states to retain variation in the degree of functional disturbance and recovery. The model is applied to baseline inference, scenario-based inference, one-way sensitivity analysis, targeted intervention simulation, and a 1000-replication bootstrap stability assessment.

This study makes three contributions. First, it advances the conceptualization of fire emergency Response Resilience by distinguishing subsystem capacities, immediate Response Effectiveness, Disruption Severity, and final Response Resilience within an interdependent socio-technical framework. This distinction clarifies why an operationally effective response does not necessarily constitute a highly resilient response when functional disruption remains substantial. Second, it strengthens the methodological basis of probabilistic fire response analysis by calibrating an 18-node Bayesian network with 200 coded cases, introducing three-state outcome variables, documenting the coverage of all theoretically possible parent-state configurations, and assessing the sampling stability of the principal estimates through 1000 bootstrap replications. Third, it provides differentiated decision support evidence by comparing road, water supply, command, and integrated intervention pathways. Rather than identifying a single universally dominant factor, the analysis shows how technical and organizational improvements generate complementary effects on Response Effectiveness, disruption control, and resilience.

The remainder of this paper is organized as follows. Section 2 reviews the literature on fire emergency response, interdependent critical infrastructure systems, and Bayesian network-based resilience assessment. Section 3 introduces the research design, case selection, node definitions, coding criteria, network structure, probability calibration, inference settings, and bootstrap procedure. Section 4 presents the baseline inference, scenario-based inference, key node sensitivity analysis, targeted intervention simulation, and bootstrap stability results. Section 5 discusses the theoretical interpretation and practical implications of the findings. Section 6 concludes the study and outlines its limitations and directions for future research.

2. Literature Review and Theoretical Framework

2.1. Fire Emergency Response and Urban Infrastructure Interdependence

Fire emergency response is a time-sensitive process involving alarm reception, dispatch, arrival, suppression, evacuation, medical assistance, and site control [9]. Existing studies have examined fire station location, response time, resource allocation, evacuation behavior, and building-level fire safety, providing important insights into the operational

determinants of fire response performance [10,11]. However, in dense urban environments, effective fire response is rarely determined solely by firefighting resources. It increasingly depends on the coordinated functioning of road system conditions, water supply support, and command system capacity.

Urban fires often occur in complex spatial settings, such as high-rise buildings, old residential communities, commercial complexes, industrial warehouses, and densely populated neighborhoods. In these contexts, fire response may be constrained by road accessibility, traffic conditions, water supply capacity, continuity of situational information, availability of fire protection facilities, and evacuation support [12,13]. Blocked fire lanes may delay rescue vehicles, insufficient Water Pressure may weaken initial suppression, and delayed situational information may reduce the accuracy of command decisions. These conditions suggest that fire emergency response should be understood as a system-level process supported by interdependent urban subsystems.

Road accessibility, water supply support, and command system information processing are particularly important for fire emergency response. Road systems determine whether firefighting and rescue forces can arrive within an effective response window. Water supply systems affect whether fire spread can be controlled at the initial stage. Situational information transmission within the command system connects fire scene conditions with command decisions, Alarm Dispatch, Resource Mobilization, and multi-agency coordination [14]. If any of these conditions is disrupted, the response process may shift from rapid control to delayed, fragmented, or prolonged operation.

At the same time, physical infrastructure alone cannot guarantee effective response. Unified Command, timely Alarm Dispatch, and Resource Mobilization shape how available infrastructure and emergency resources are used. Unified Command can reduce coordination delays, Alarm Dispatch can accelerate response activation, and Resource Mobilization can compensate for local shortages [15–18]. Therefore, fire emergency Response Resilience depends on the joint functioning of road system support, water supply support, and command system capacity.

From this perspective, Response Disruption Severity may emerge from the interaction of multiple subsystems rather than from a single isolated deficiency. Road constraints, insufficient water supply, delayed situational information, weak command coordination, delayed Alarm Dispatch, and inadequate Resource Mobilization may reinforce one another and exacerbate response delays, initial control difficulties, evacuation disorder, resource mismatches, or operational interruptions. Accordingly, this study treats fire emergency response as an interdependent socio-technical process. It uses the road–water–command logic to construct a Bayesian network model of Response Effectiveness, Response Disruption Severity, and Response Resilience.

2.2. Resilience of Interdependent Critical Infrastructure Systems

Critical infrastructure systems provide essential services for urban safety, economic activity, and social order. Road systems, water supply systems, emergency response services, and command systems are often analyzed as separate sectors, but their functions become closely coupled during major emergencies. A disruption in one system may affect the performance of other systems and produce cascading consequences [19,20]. Therefore, resilience research has shifted from protecting single infrastructure components to assessing interdependent systems and their capacity to withstand, adapt to, and recover from disruptions [21].

The concept of resilience emphasizes a system's ability to maintain core functions under disturbance and to recover after performance degradation. In the context of critical infrastructure systems, resilience is often associated with robustness, redundancy, resource-

fulness, rapidity, and adaptive capacity [22]. These attributes are particularly relevant to fire emergency response. A resilient response system should not only limit the severity of response disruption but also maintain access routes, ensure fire suppression water, activate command functions, mobilize resources, and restore effective response operations under changing conditions.

Fire emergency response provides a typical scenario for examining interdependent infrastructure resilience. When a major fire occurs, road networks support the movement of fire engines, ambulances, and emergency personnel [23]; water supply systems support fire suppression; and command systems support the transmission of situational information, Alarm Dispatch, Resource Mobilization, and on-site coordination. These systems are functionally linked during the response process. If road access is blocked, firefighting forces may arrive late; if water supply is insufficient, initial suppression may become difficult; if situational information is delayed or incomplete, command decisions and resource matching may become less effective. The resilience of fire response systems therefore depends on whether Road Capacity, Water Capacity, and Command Capacity can maintain sufficient functional continuity under stress.

At the same time, infrastructure resilience is not only about roads or water supply. In socio-technical systems, physical infrastructures and command-related organizational arrangements jointly determine response performance [24]. Road and water supply-related disruptions can be mitigated by strong Command Capacity, timely Resource Mobilization, and effective Alarm Dispatch [25,26]. For example, when road accessibility is reduced, Traffic Control and alternative routes may reduce response delay; when local water supply is insufficient, alternative water sources and water supply coordination may compensate for the shortage; when fire scene information is incomplete, Unified Command and timely Alarm Dispatch may improve situational awareness and resource matching. These mechanisms show that Command Capacity can play a compensatory role under technical constraints.

Based on this understanding, this study treats fire emergency Response Resilience as the final outcome of interdependent technical and organizational response processes. Road Capacity, Water Capacity, and Command Capacity jointly influence both Response Effectiveness and Response Disruption Severity, which subsequently determine Response Resilience. This perspective provides a system-level basis for assessing how road constraints, water supply constraints, and command system conditions jointly shape fire emergency Response Resilience [27].

2.3. Bayesian Network Analysis for Fire Emergency Response Resilience

Bayesian network analysis provides a useful method for modeling complex systems characterized by uncertainty, conditional dependence, and incomplete information. A Bayesian network represents variables as nodes and probabilistic dependencies as directed links [28]. Compared with deterministic models, it can describe how the probability of an outcome changes when new evidence is observed [29]. This feature is particularly relevant to fire emergency response, where decision makers often need to evaluate evolving situations with limited, uncertain, and fragmented information.

In fire emergency response, uncertainty exists throughout the response process. Road accessibility, Fire Lane Availability, water supply support, situational information, Unified Command, Alarm Dispatch, and Resource Mobilization may all change as the event unfolds. These factors are not independent. For example, road constraints may delay the arrival of emergency forces, insufficient water support may increase the probability of initial control difficulty, and delayed or incomplete situational information may weaken command decisions and resource matching. A Bayesian network can capture these conditional

relationships and provide a structured framework for inferring the likelihood of different levels of Response Disruption Severity under alternative evidence combinations [30].

Bayesian networks are also suitable for resilience assessment because they can connect system conditions, process states, and outcome variables within a single probabilistic framework [31]. In the context of fire emergency response, road system, water supply, and command system conditions can be modeled as input nodes; Road Capacity, Water Capacity, and Command Capacity can be modeled as subsystem capacity nodes; Response Effectiveness can be modeled as a response performance node; Response Disruption Severity can be modeled as a process outcome node; and Response Resilience can be modeled as the final resilience outcome node. This structure allows us to examine not only whether a given factor is important, but also how changes in one condition may propagate through the response system and affect the final resilience outcome.

Another advantage of Bayesian network analysis is its ability to support scenario inference and intervention comparison. Once the network structure and conditional probability tables are established, different evidence can be entered into the model to simulate alternative response situations [32]. For example, the model can estimate how the probabilities of an effective response, high Disruption Severity, and high Response Resilience change when Road Capacity, Water Capacity, or Command Capacity is constrained [33]. It can also assess whether strong Command Capacity can partially compensate for constraints in road and water supply. In this way, Bayesian inference provides decision support evidence for identifying priority intervention nodes.

Based on the above discussion, this study constructs a Bayesian network model to assess fire emergency Response Resilience from an interdependent road–water–command system perspective. Road, water supply, and command system conditions are used to represent the main input dimensions. These conditions determine Road Capacity, Water Capacity, and Command Capacity, which jointly influence both Response Effectiveness and Response Disruption Severity. Response Effectiveness and Response Disruption Severity subsequently determine Response Resilience. The conceptual framework of this study is shown in Figure 1.

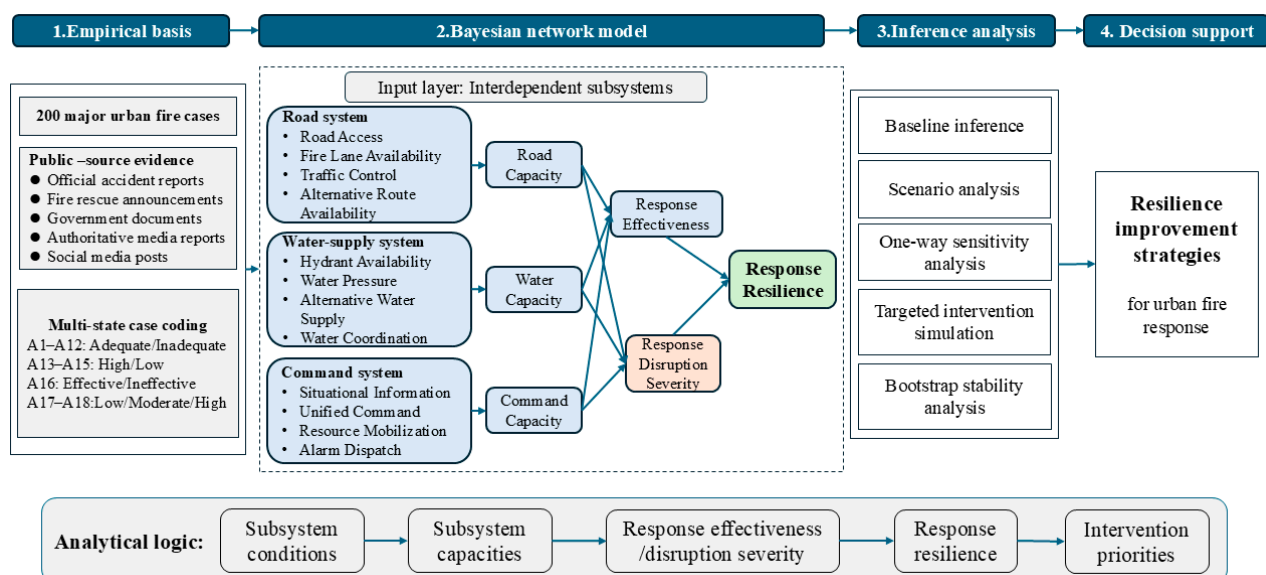


Figure 1. Research framework of Bayesian network analysis.

3. Materials and Methods

3.1. Research Design and Analytical Framework

This study adopts a Bayesian network-based research design to assess fire emergency Response Resilience in interdependent road–water–command systems. The analytical premise is that fire emergency response depends on the coordinated functioning of physical infrastructure and organizational command arrangements. Road system conditions affect the accessibility and movement of emergency forces; water supply conditions determine the continuity and adequacy of fire suppression support; and command system conditions shape situational awareness, Alarm Dispatch, Resource Mobilization, and interorganizational coordination. These observable subsystem conditions first determine Road Capacity, Water Capacity, and Command Capacity, which subsequently influence Response Effectiveness and Disruption Severity. Response resilience is treated as the final system-level outcome jointly determined by Response Effectiveness and Response Disruption Severity.

The research design consists of six steps. First, major urban fire emergency cases are collected from official accident investigation reports, fire and rescue service announcements, local government documents, authoritative media reports, and other publicly available evidence. Second, the variables are identified according to the road–water–command framework, producing an 18-node Bayesian network comprising 12 input nodes, three subsystem capacity nodes, one response performance node, one process outcome node, and one final resilience outcome node. Third, the cases are coded according to predefined binary and ordinal coding rules. The input nodes, subsystem capacity nodes, and Response Effectiveness use two-state coding, whereas Response Disruption Severity and Response Resilience use three-state coding. Fourth, the fixed network structure is specified based on theoretical relationships among subsystem conditions, capacities, response processes, and resilience outcomes, after which the prior probabilities and conditional probability tables are estimated from the coded data. Fifth, baseline inference, scenario-based inference, one-way sensitivity analysis, and targeted intervention simulation are conducted to examine how subsystem constraints and node-level improvements affect the posterior probabilities of Response Effectiveness, Disruption Severity, and Response Resilience. Sixth, a nonparametric bootstrap analysis based on 1000 resampled datasets is performed to evaluate the sampling stability of the baseline estimates and the integrated intervention effects. The resulting analytical framework follows a “subsystem conditions–subsystem capacities–response effectiveness and Disruption Severity–response resilience–intervention priorities” logic. It supports both diagnostic inference under adverse subsystem conditions and decision-oriented comparison of alternative resilience improvement strategies.

3.2. Case Selection and Data Sources

This study uses a database of 200 major urban fire emergency response cases that occurred in mainland China between 2010 and 2025 as the empirical basis for Bayesian network modeling. The unit of analysis is a specific fire emergency response case rather than a city, province, or year. Each case represents a distinct fire emergency event for which sufficient information was available to reconstruct the principal infrastructure conditions, command arrangements, response processes, and response outcomes. The cases were selected according to three principles: they had to occur in urban or urbanized settings; contain identifiable response process information, such as dispatch, arrival, suppression, evacuation, water supply, command coordination, Resource Mobilization, or on-site disposal; and be supported by traceable public sources. Cases that only reported casualties, property losses, or fire causes without sufficient response process information were excluded.

To improve comparability and diversity, the final case database covers multiple fire scenarios, including high-rise residential fires, commercial building fires, industrial and warehouse fires, public service facility fires, restaurant or gas-related fires, electric bicycle-related fires, and community-level fires. This diversity improves the empirical coverage of heterogeneous response conditions and supports comparison across different combinations of subsystem constraints.

Data were collected from official accident investigation reports, fire and rescue service announcements, local government documents, authoritative media reports, and publicly available visual materials. Official accident investigation reports were used as the primary evidence source whenever available because they generally provide the most detailed accounts of fire causes, response processes, operational deficiencies, and accountability findings. Fire and rescue service announcements and local government documents were used to identify dispatch, arrival, suppression, command coordination, Resource Mobilization, and on-site disposal processes. In contrast, authoritative media reports, images, and videos were used as supplementary evidence for road obstruction, evacuation conditions, water supply constraints, and observable response difficulties. Where evidence differed across sources, official investigation reports and fire and rescue service announcements were assigned the highest priority. In Appendix A, Table A1 presents 10 representative cases illustrating the temporal, geographical, and scenario diversity of the database.

3.3. Bayesian Network Nodes and Coding Rules

The Bayesian network nodes were designed according to the interdependent road–water–command framework developed in the previous sections. To represent the fire emergency response process in a structured, interpretable manner, the model includes 18 nodes: 12 input nodes, 3 subsystem capacity nodes, 1 response performance node, 1 process outcome node, and 1 final resilience outcome node. The 12 input nodes represent observable case-level conditions within the road, water supply, and command systems. Road Capacity, Water Capacity, and Command Capacity summarize the joint functional states of the three subsystems; Response Effectiveness represents operational performance during the response process; Response Disruption Severity describes the degree of operational disturbance; and Response Resilience represents the final system-level outcome.

The road system module contains Road Access, Fire Lane Availability, Traffic Control, and Alternative Route Availability, which jointly determine Road Capacity. The water supply module contains Hydrant Availability, Water Pressure, Alternative Water Supply, and Water Coordination, which jointly determine Water Capacity. The command system module contains situational information, Unified Command, Resource Mobilization, and Alarm Dispatch, which jointly determine Command Capacity. Road Capacity, Water Capacity, and Command Capacity subsequently influence both Response Effectiveness and Response Disruption Severity, while Response Effectiveness and Response Disruption Severity jointly determine Response Resilience.

The input nodes and subsystem capacity nodes represent different analytical levels. The input nodes describe directly observable case-level conditions, whereas Road Capacity, Water Capacity, and Command Capacity are derived subsystem-level states summarizing the joint functioning of multiple inputs. For example, Fire Lane Availability captures the condition of dedicated emergency access at the incident site. In contrast, Road Capacity represents the overall ability of the road subsystem to support emergency arrival and movement under the combined effects of road access, Fire Lane Availability, Traffic Control, and Alternative Route Availability. Similar distinctions apply to the water supply and command modules.

The model combines binary and ordinal multi-state coding. The input nodes A1–A12 were coded as Adequate or Inadequate; the subsystem capacity nodes A13–A15 were coded as High or Low; and Response Effectiveness was coded as Effective or Ineffective. To retain greater variation in the principal outcome variables, Response Disruption Severity and Response Resilience were each represented by three ordered states: Low, Moderate, and High. Response Effectiveness refers to whether the operational tasks of emergency response were implemented effectively under the observed subsystem conditions. By contrast, Response Resilience refers to the broader capacity of the response system to maintain or restore its core functions under disruption. An effective response therefore does not necessarily imply high resilience when Disruption Severity remains substantial.

The three-state classifications of Response Disruption Severity and Response Resilience were assigned according to predefined, evidence-based criteria. Response Disruption Severity was evaluated based on the extent, duration, and operational consequences of response delay, difficulty in suppression, evacuation disorder, resource mismatch, and command or disposal interruption. A Low state represented limited and localized disturbance without sustained interruption of core response activities; a Moderate state represented observable degradation or temporary interruption that constrained response performance but did not cause widespread functional breakdown; and a High state represented multiple, prolonged, or cascading disturbances that substantially disrupted emergency operations. Response Resilience was evaluated according to the continuity, adaptation, and restoration of core response functions. A High state indicated that essential response functions were maintained or rapidly restored through coordination, redundancy, or resource adjustment; a Moderate state indicated temporary functional degradation followed by partial or delayed recovery; and a Low state indicated prolonged or extensive loss of core response functions with limited capacity for timely adaptation or restoration. The classifications were based on the overall pattern of process evidence rather than on casualty or economic loss outcomes alone.

The coding process followed three principles. First, node states were assigned based on observable evidence contained in the case materials rather than inferred solely from the final accident consequences. Second, official accident investigation reports and fire and rescue service announcements were prioritized when evidence differed across sources. Third, cases with insufficient or ambiguous evidence for the core nodes were conservatively coded only when the available evidence supported a clear classification; otherwise, they were excluded from the final database. The definitions, analytical roles, and state classifications of all nodes are presented in Table 1.

Table 1. Bayesian network nodes and states.

Symbol	Node	System	Node Type	State
A1	Road Access	Road system	Input node	Adequate/Inadequate
A2	Fire Lane Availability	Road system	Input node	Adequate/Inadequate
A3	Traffic Control	Road system	Input node	Adequate/Inadequate
A4	Alternative Route Availability	Road system	Input node	Adequate/Inadequate
A5	Hydrant Availability	Water supply system	Input node	Adequate/Inadequate
A6	Water Pressure	Water supply system	Input node	Adequate/Inadequate
A7	Alternative Water Supply	Water supply system	Input node	Adequate/Inadequate
A8	Water Coordination	Water supply system	Input node	Adequate/Inadequate
A9	Situational Information	Command system	Input node	Adequate/Inadequate
A10	Unified Command	Command system	Input node	Adequate/Inadequate
A11	Resource Mobilization	Command system	Input node	Adequate/Inadequate
A12	Alarm Dispatch	Command system	Input node	Adequate/Inadequate
A13	Road Capacity	Subsystem capacity layer	Derived intermediate node	High/Low
A14	Water Capacity	Subsystem capacity layer	Derived intermediate node	High/Low

Table 1. Cont.

Symbol	Node	System	Node Type	State
A15	Command Capacity	Subsystem capacity layer	Derived intermediate node	High/Low
A16	Response Effectiveness	Response process layer	Response performance node	Effective/Ineffective
A17	Response Disruption Severity	Response process layer	Process outcome node	Low/Moderate/High
A18	Response Resilience	Resilience outcome layer	Final outcome node	Low/Moderate/High

3.4. Bayesian Network Structure and Probability Calibration

The Bayesian network structure was constructed according to the road–water–command framework and the node definitions presented in Section 3.3. Because the case dataset is limited and the purpose of this study is to represent a theory-driven mechanism of fire emergency Response Resilience, the network links were specified manually before parameter learning rather than automatically discovered from data. This design ensures that the directed links remain consistent with the theoretical logic of subsystem interdependence, response process effectiveness, and resilience outcomes.

The network consists of three subsystem modules, two parallel response process nodes, and one final resilience outcome node. Within the subsystem capacity layer, A1–A4 jointly determine Road Capacity, A5–A8 jointly determine Water Capacity, and A9–A12 jointly determine Command Capacity. At the response process level, Road Capacity, Water Capacity, and Command Capacity jointly influence both Response Effectiveness and Response Disruption Severity. Response Resilience is specified as the final outcome jointly determined by Response Effectiveness and Response Disruption Severity. This structure allows subsystem constraints to affect resilience through two distinct pathways: deterioration in operational effectiveness and escalation in Disruption Severity. The final network structure is shown in Figure 2.

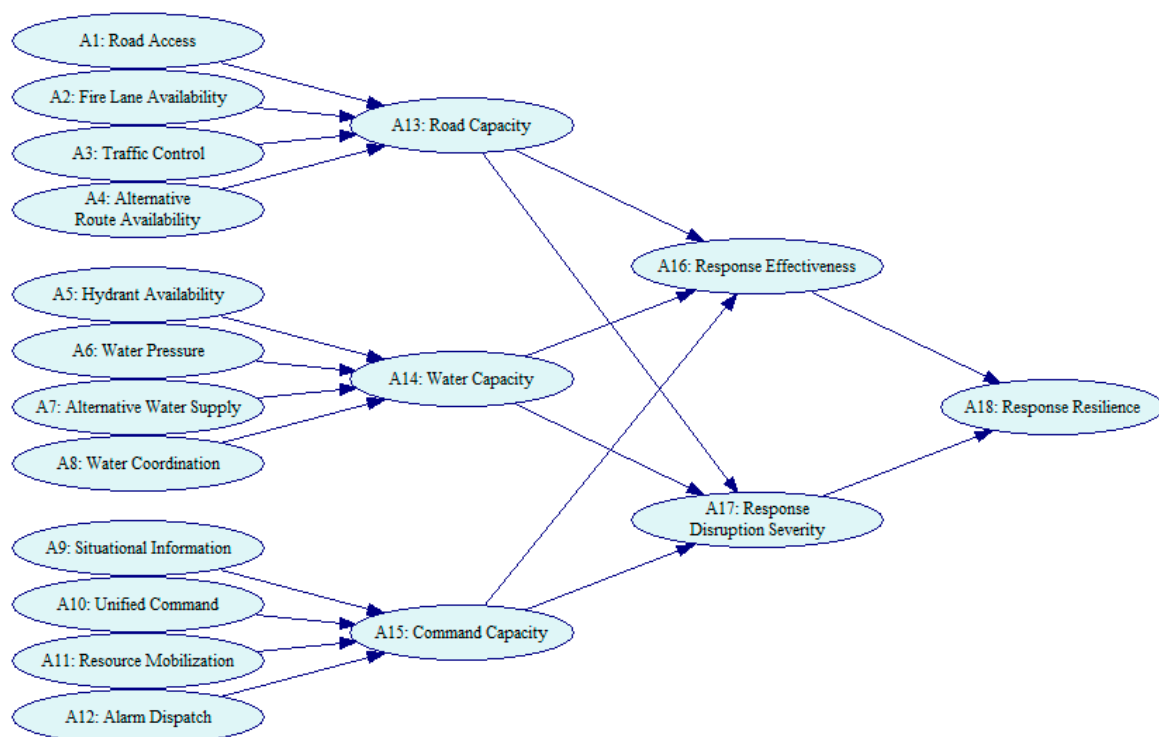


Figure 2. Bayesian network structure for fire emergency Response Resilience.

The joint probability distribution of the Bayesian network can be factorized according to the directed links among the nodes. The joint distribution can be expressed as

$$P(A1, A2, \dots, A18) = \prod_{i=1}^{18} P(A_i | Pa(A_i)), \quad (1)$$

where $Pa(X_i)$ denotes the set of parent nodes of X_i . The 12 input nodes are treated as root nodes, with their prior probabilities estimated from coded cases. In contrast, the probabilities of the subsystem capacity, response process, and resilience outcome nodes are represented through conditional probability tables.

The size of each conditional probability table depends on the number and state structure of its parent nodes. Road Capacity, Water Capacity, and Command Capacity each have four binary parent nodes, resulting in $2^4 = 16$ parent-state configurations. Response Effectiveness and Response Disruption Severity each have three binary subsystem capacity parents, resulting in $2^3 = 8$ configurations. Response Resilience has one binary parent, Response Effectiveness, and one three-state parent, Response Disruption Severity, resulting in $2 \times 3 = 6$ parent-state configurations.

Probability calibration followed a case-based parameter-learning strategy under the fixed network structure. The prior probabilities of A1–A12 were estimated from the observed marginal frequencies of the Adequate and Inadequate states. The conditional probability tables of A13–A18 were estimated from the observed parent–child state frequencies in the 200-case database. All theoretically possible parent-state configurations were represented: all 16 configurations were covered for each subsystem capacity node, eight for Response Effectiveness and Response Disruption Severity, and six for Response Resilience. The number of observations per configuration ranged from 7 to 22 for Road Capacity, 8 to 23 for Water Capacity, 5 to 33 for Command Capacity, 17 to 37 for Response Effectiveness and Response Disruption Severity, and 19 to 64 for Response Resilience. Thus, no conditional probability row was based on a zero-frequency parent configuration, although some configurations remained less frequent than others.

Parameter learning was performed in GeNIe under the fixed network structure using Bayesian parameter estimation with a uniform Dirichlet prior and an equivalent sample size of 1. This weakly informative prior introduced a small pseudo-count across the possible states of each child node, thereby preventing zero-probability entries in conditional probability tables while allowing the observed case frequencies to dominate the estimates. The same state definitions, prior specification, and parameter-estimation settings were applied to the full-sample model and all 1000 bootstrap replications. No conditional probability entry was manually adjusted after parameter learning. Table 2 summarizes the parent nodes, configuration coverage, and the probability calibration procedure for each node category.

Table 2. Parent-state coverage and probability calibration strategy.

Node Type	Nodes	Parent Nodes	Parent-State Coverage in the 200-Case Dataset	Probability Calibration Procedure
Input nodes	A1–A12: Adequate/Inadequate	None	Each input node contained 200 observations, and both states were represented.	Prior probabilities were estimated from the observed marginal state counts using Bayesian parameter estimation with a uniform Dirichlet prior and an equivalent sample size of 1.

Table 2. Cont.

Node Type	Nodes	Parent Nodes	Parent-State Coverage in the 200-Case Dataset	Probability Calibration Procedure
Subsystem capacity node	A13 Road Capacity: High/Low	A1, A2, A3, A4	All 16 theoretically possible parent-state combinations were represented; each combination contained 7–22 cases.	The conditional probability table was estimated from the observed Road Capacity state counts under each road system parent-state combination, using a uniform Dirichlet prior with an equivalent sample size of 1.
Subsystem capacity node	A14 Water Capacity: High/Low	A5, A6, A7, A8	All 16 theoretically possible parent-state combinations were represented; each combination contained 8–23 cases.	The conditional probability table was estimated from the observed Water Capacity state counts under each water supply parent-state combination, using a uniform Dirichlet prior with an equivalent sample size of 1.
Subsystem capacity node	A15 Command Capacity: High/Low	A9, A10, A11, A12	All 16 theoretically possible parent-state combinations were represented; each combination contained 5–33 cases.	The conditional probability table was estimated from the observed Command Capacity state counts under each command system parent-state combination, using a uniform Dirichlet prior with an equivalent sample size of 1.
Response performance node	A16 Response Effectiveness: Effective/Ineffective	A13, A14, A15	All 8 theoretically possible parent-state combinations were represented; each combination contained 17–37 cases.	Conditional probabilities were estimated from the observed Effective and Ineffective response counts under each subsystem capacity combination, using a uniform Dirichlet prior with an equivalent sample size of 1.
Process outcome node	A17 Response Disruption Severity: Low/Moderate/High	A13, A14, A15	All 8 theoretically possible parent-state combinations were represented; each combination contained 17–37 cases.	Conditional probabilities for Low, Moderate, and High Disruption Severity were estimated from the observed state counts under each subsystem capacity combination, using a uniform Dirichlet prior with an equivalent sample size of 1.
Final outcome node	A18 Response Resilience: Low/Moderate/High	A16, A17	All 6 theoretically possible parent-state combinations were represented; each combination contained 19–64 cases.	Conditional probabilities for Low, Moderate, and High Response Resilience were estimated from the observed state counts under each combination of Response Effectiveness and Response Disruption Severity, using a uniform Dirichlet prior with an equivalent sample size of 1.

3.5. Bayesian Inference and Robustness Analysis

After the network structure and probability parameters were established, the model was used for baseline inference, scenario-based inference, one-way sensitivity analysis, targeted intervention simulation, and bootstrap stability assessment. Across these analyses, the principal outcome indicators were the posterior probabilities of an Effective response, High Disruption Severity, and High Response Resilience, denoted as $P(A16 = \text{Effective})$, $P(A17 = \text{High})$, and $P(A18 = \text{High})$, respectively. Baseline inference was conducted with-

out entering additional evidence and was labeled S0 in the scenario analysis and I0 in the intervention analysis.

Scenario-based inference was used to examine the effects of subsystem constraints and command compensation. Six scenarios were considered. S0 represented the baseline state without additional evidence; S1 set Road Capacity to Low; S2 set Water Capacity to Low; S3 set Command Capacity to Low; S4 simultaneously set Road Capacity and Water Capacity to Low; and S5 set Road Capacity and Water Capacity to Low while setting Command Capacity to High. S1–S3 were designed to compare individual subsystem constraints; S4 represented compound technical constraints; and S5 examined whether strong Command Capacity could compensate for simultaneous road and water supply limitations. Before each scenario was implemented, all previously entered evidence was cleared. The network structure and probability parameters were not relearned between scenarios.

A one-way sensitivity analysis was conducted by setting each of the 12 input nodes to Inadequate while leaving all other nodes unobserved. For A1–A4, the posterior probability of Road Capacity being High was recorded; for A5–A8, the probability of Water Capacity being High was recorded; and for A9–A12, the probability of Command Capacity being High was recorded. In every test, the posterior probabilities of A16 = Effective, A17 = High, and A18 = High were also obtained. Node influence was evaluated by comparison with the baseline state. A node was considered more influential when its deterioration produced a larger reduction in effective response or a larger increase in high Disruption Severity, or when it led to higher resilience. Only one input node was entered as evidence in each test, and all evidence was cleared before the next test was conducted.

Targeted intervention simulation was then conducted using the nodes identified as relatively influential in the sensitivity analysis. Four targeted intervention scenarios were compared with the I0 baseline condition. I1 represented a road system intervention by setting A2 Fire Lane Availability to Adequate. I2 represented a water supply intervention by setting A6 Water Pressure and A8 Water Coordination to Adequate. I3 represented a command system intervention by setting A10 Unified Command and A12 Alarm Dispatch to Adequate. I4 represented an integrated intervention by simultaneously setting A2, A6, A8, A10, and A12 to Adequate. For each intervention, the changes in the three principal posterior probabilities were calculated relative to I0 and expressed in percentage points rather than relative percentage changes. The network parameters remained unchanged across I0–I4.

Finally, a nonparametric bootstrap procedure with 1000 replications was conducted to assess the sampling stability of the principal probability estimates and intervention effects. In each replication, 200 cases were sampled with replacement from the original 200-case database [34]. The network structure was held fixed, while the prior probabilities and conditional probability tables were re-estimated from the resampled dataset. The baseline probabilities of A16 = Effective, A17 = High, and A18 = High were recorded for each bootstrap model. The I4 integrated intervention was then entered, and its changes relative to the corresponding bootstrap baseline were calculated. The full-sample estimates, bootstrap means, standard deviations, and percentile-based 95% confidence intervals were used to evaluate the stability of the main findings.

4. Results

4.1. Baseline Bayesian Inference

Baseline Bayesian inference was conducted without entering any additional evidence into the model. Based on the prior probabilities and conditional probability tables estimated from the 200 coded fire emergency cases, the analysis generated the unconditional probability distribution of the interdependent road–water–command system. This baseline

state serves as the reference for subsequent scenario-based inference, one-way sensitivity analysis, targeted intervention simulation, and bootstrap stability analysis. The baseline inference results are presented in Figure 3.

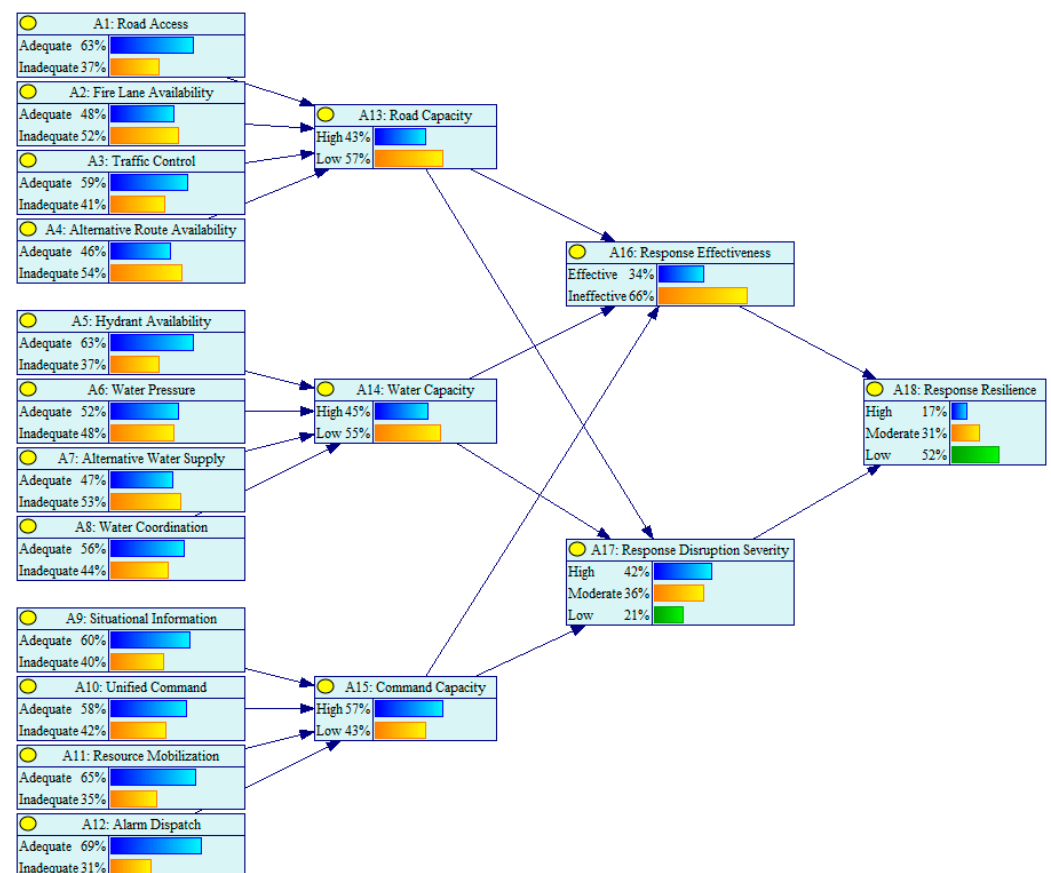


Figure 3. Baseline posterior probability distributions of the Bayesian network. Note: Percentages may not sum to 100% due to rounding.

As shown in Figure 3, the probabilities of Road Capacity and Water Capacity being High are 43% and 45%, respectively, while the probability of Command Capacity being High is 57%. At the response process level, the probability of Response Effectiveness being Effective is 34%, whereas the probability of an Ineffective response is 66%. The probabilities of High, Moderate, and Low Response Disruption Severity are 42%, 36%, and 21%, respectively. High and Moderate disruption therefore account for approximately 78% of the baseline distribution, indicating that operational constraints and response interruptions are common across the selected major fire emergency cases.

For the final outcome node, the probabilities of High, Moderate, and Low Response Resilience are 17%, 31%, and 52%, respectively. The probability of High Response Resilience is substantially lower than the probability of an Effective response, supporting the distinction between Response Effectiveness and resilience: an effective response does not necessarily indicate that the system can maintain or restore its core functions under substantial disruption. Overall, the baseline results reveal relatively constrained road and water capacities, a comparatively stronger Command Capacity, a high prevalence of moderate-to-high disruption, and a limited probability of high fire emergency Response Resilience.

4.2. Scenario-Based Bayesian Inference

Scenario-based Bayesian inference was conducted to examine how subsystem constraints and command compensation affect outcomes in fire emergency response. Six

scenarios were considered. S0 represents the baseline state without additional evidence; S1–S3 set Road Capacity, Water Capacity, and Command Capacity to Low, respectively; S4 simultaneously sets Road Capacity and Water Capacity to Low; and S5 retains these two technical constraints while setting Command Capacity to High. For each scenario, the posterior probabilities of Effective response, High Disruption Severity, and High Response Resilience were recorded, as reported in Table 3.

Table 3. Baseline and scenario inference results.

Scenario	Evidence Setting	Response Effectiveness P (A16 = Effective)	Response Disruption Severity P (A17 = High)	Response Resilience P (A18 = High)
S0	No evidence	34%	42%	17%
S1	Road Capacity = Low	25%	49%	13%
S2	Water Capacity = Low	21%	50%	11%
S3	Command Capacity = Low	17%	58%	9%
S4	Road Capacity = Low Water Capacity = Low	13%	58%	8%
S5	Road Capacity = Low Water Capacity = Low Command Capacity = High	20%	46%	11%

Compared with the baseline state, both road and water system constraints produce unfavorable shifts in probability. When Road Capacity is set to Low in S1, the probability of A16 = Effective decreases from 34% to 25%, the probability of A17 = High increases from 42% to 49%, and the probability of A18 = High decreases from 17% to 13%. The adverse effect is stronger under the water supply constraint in S2, where the corresponding probabilities change to 21%, 50%, and 11%, respectively. These results indicate that limited Water Capacity has a greater negative effect than limited Road Capacity, particularly by weakening Response Effectiveness and reducing the probability of high resilience.

Among the single-subsystem constraint scenarios, command weakness produces the most unfavorable results. In S3, setting Command Capacity to Low reduces the probability of an Effective response to 17%, increases the probability of High Disruption Severity to 58%, and decreases the probability of High Response Resilience to 9%. The compound technical constraint scenario produces an even lower overall response performance. Under S4, where both Road Capacity and Water Capacity are Low, the probability of Effective response falls to 13%, and the probability of High resilience falls to 8%. However, the probability of High Disruption Severity remains at 58%. These findings suggest that command weakness is the most influential individual subsystem constraint, whereas simultaneous road and water constraints create the most adverse combined outcome.

The command compensation scenario further demonstrates Command Capacity's coordinating role. When Command Capacity is set to High under simultaneous road and water constraints in S5, the probability of Effective response increases from 13% in S4 to 20%, the probability of High Disruption Severity decreases from 58% to 46%, and the probability of High Response Resilience increases from 8% to 11%. Nevertheless, the S5 results do not return to baseline levels, indicating that strong Command Capacity can partially mitigate but cannot fully substitute for adequate road and water supply support. As visualized in Figure 4, the scenario results collectively show a consistent pattern: subsystem constraints reduce Response Effectiveness and Response Resilience while increasing disruption severity, whereas stronger Command Capacity provides a measurable compensatory effect under compound technical constraints.

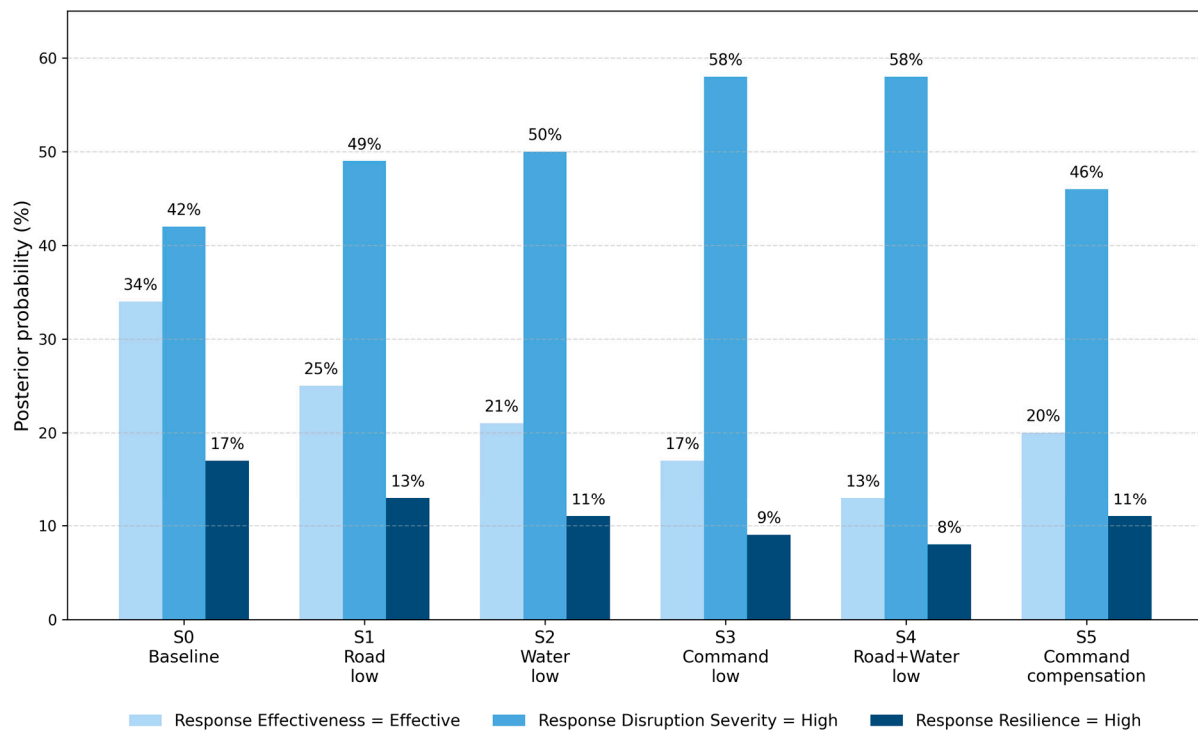


Figure 4. Scenario-based Bayesian inference results.

4.3. Key Node Sensitivity Analysis

A one-way sensitivity analysis was conducted to identify the input conditions that exert the greatest influence on fire emergency response outcomes. Each of the 12 input nodes was set to Inadequate, while all other nodes remained unobserved and the network parameters remained unchanged. The resulting posterior probabilities were compared with the baseline values of 34% for A16 = Effective, 42% for A17 = High, and 17% for A18 = High. For each test, Table 4 also reports the probability that the corresponding subsystem capacity node remains in the High state.

Table 4. One-way sensitivity results for input nodes.

Test	Node Set to Inadequate	P (Subsystem Capacity = High)	P (A16 = Effective)	P (A17 = High)	P (A18 = High)
T1	Road Access	A13: 32%	31%	44%	16%
T2	Fire Lane Availability	A13: 30%	31%	44%	16%
T3	Traffic Control	A13: 33%	32%	44%	16%
T4	Alternative Route Availability	A13: 34%	32%	44%	16%
T5	Hydrant Availability	A14: 33%	31%	44%	16%
T6	Water Pressure	A14: 32%	30%	45%	15%
T7	Alternative Water Supply	A14: 38%	32%	44%	16%
T8	Water Coordination	A14: 30%	30%	45%	15%
T9	Situational Information	A15: 44%	30%	46%	15%
T10	Unified Command	A15: 42%	29%	46%	15%
T11	Resource Mobilization	A15: 43%	29%	46%	15%
T12	Alarm Dispatch	A15: 41%	29%	47%	15%

Within the road system, setting any individual node to Inadequate reduced Road Capacity and produced moderately unfavorable downstream changes. Fire Lane Availability generated the largest reduction in Road Capacity, with the High-state probability declining from the baseline value of 43% to 30%. Under this condition, the probability of Effective response decreased to 31%, the probability of High Disruption Severity increased to 44%, and the probability of High Response Resilience decreased to 16%. Road Access produced similar downstream effects, while Traffic Control and Alternative Route Availability had slightly smaller effects on Response Effectiveness. These results indicate that Fire Lane Availability is a particularly important determinant of road system capacity, although the individual road factors have relatively limited effects on the final resilience outcome.

The water supply results show greater differentiation among the four input nodes. When Water Coordination was set to Inadequate, the probability of Water Capacity being High declined from 45% to 30%, the lowest value among the water system tests. Water Pressure produced a similar downstream effect: both Water Pressure and Water Coordination reduced the probability of Effective response to 30%, increased High Disruption Severity to 45%, and reduced High resilience to 15%. By comparison, Hydrant Availability and Alternative Water Supply produced smaller changes, with the latter retaining a 38% probability of High Water Capacity. This pattern suggests that reliable pressure and effective coordination are more consequential for maintaining continuous firefighting water support than the availability of a single hydrant or an alternative source alone.

The command system nodes produced the largest overall changes in the response outcomes. Setting situational information to Inadequate reduced the probability of High Command Capacity from 57% to 44%. In contrast, the corresponding probabilities of Effective response, High Disruption Severity, and High resilience changed to 30%, 46%, and 15%, respectively. Unified Command and Resource Mobilization further reduced Effective response to 29%. Alarm Dispatch had the lowest probability of high Command Capacity (41%) and the highest probability of severe disruption (47%). Although several command nodes produced identical rounded values for effective response and high resilience, their collective effects were consistently stronger than those observed for most road and water system inputs.

Overall, the sensitivity results indicate a hierarchical pattern in which command system conditions generally exert the strongest influence on Response Effectiveness and Disruption Severity, followed by water supply conditions and road system conditions. Fire Lane Availability, Water Pressure, Water Coordination, Unified Command, Resource Mobilization, and Alarm Dispatch constitute the most influential group of input nodes. Among them, Alarm Dispatch shows the strongest adverse effect on High Disruption Severity, whereas Water Coordination produces the largest reduction in water system capacity.

4.4. Intervention Scenario Analysis

Based on the one-way sensitivity results, targeted intervention scenarios were designed to evaluate whether improving selected input nodes could strengthen fire emergency response performance and resilience. I0 represents the baseline state without additional evidence. I1 sets Fire Lane Availability to Adequate; I2 sets Water Pressure and Water Coordination to Adequate; I3 sets Unified Command and Alarm Dispatch to Adequate; and I4 simultaneously implements all five interventions. For each scenario, the posterior probabilities of A16 = Effective, A17 = High, and A18 = High were compared with the baseline values of 34%, 42%, and 17%, respectively. The results are reported in Table 5.

Table 5. Posterior probabilities under targeted intervention scenarios.

Scenario	Evidence Setting	P (A16 = Effective)	P (A17 = High)	P (A18 = High)	Change in P (A18 = High)
I0 Baseline	No evidence	34%	42%	17%	-
I1 Road intervention	A2 = Adequate	37%	40%	18%	+1 pp
I2 Water intervention	A6 = Adequate; A8 = Adequate	41%	38%	20%	+3 pp
I3 Command intervention	A10 = Adequate; A12 = Adequate	39%	37%	20%	+3 pp
I4 Integrated intervention	A2, A6, A8, A10, and A12 = Adequate	50%	32%	25%	+8 pp

The road system intervention yields only a limited improvement. Under I1, the probability of Effective response increases from 34% to 37%, the probability of High Disruption Severity decreases from 42% to 40%, and the probability of High Response Resilience increases from 17% to 18%. By comparison, the water supply intervention generates a greater improvement. When Water Pressure and Water Coordination are both set to Adequate in I2, the effective response increases to 41%, the High Disruption Severity decreases to 38%, and the High Response Resilience increases to 20%. These results indicate that improving Fire Lane Availability contributes to response performance, but maintaining sufficient Water Pressure and coordinated water support produces broader downstream benefits.

The command system intervention produces a different but complementary effect. Under I3, setting Unified Command and Alarm Dispatch to Adequate increases the probability of Effective response to 39%, reduces High Disruption Severity to 37%, and increases High Response Resilience to 20%. Compared with I2, the water intervention produces a larger increase in effective response, whereas the command intervention produces a larger reduction in severe disruption. Both scenarios increase the probability of high resilience by 3 percentage points, suggesting that improvements in water supply and command strengthen resilience through distinct operational mechanisms.

The integrated intervention produces the strongest overall effect. Under I4, the probability of Effective response increases to 50%, representing a 16-percentage-point improvement over the baseline. At the same time, High Disruption Severity decreases to 32%, a reduction of 10 percentage points, while High Response Resilience increases to 25%, an improvement of 8 percentage points.

As illustrated in Figure 5, these changes are substantially larger than those generated by any single-system intervention. The results therefore indicate that coordinated improvements in Fire Lane Availability, Water Pressure, Water Coordination, Unified Command, and Alarm Dispatch create cumulative benefits across the response process. Nevertheless, the probability of high resilience remains at 25%, indicating that targeted improvements can substantially strengthen but cannot eliminate the constraints associated with major urban fire emergencies.

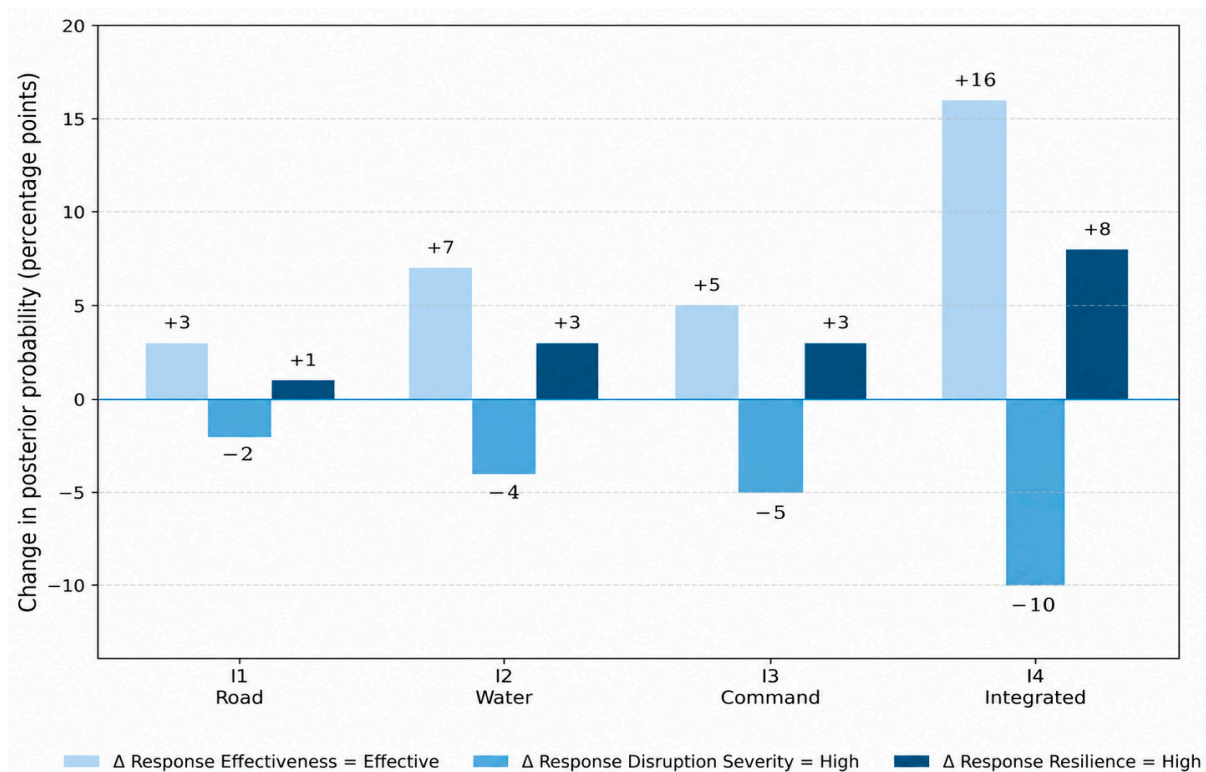


Figure 5. Changes in posterior probabilities relative to the baseline state.

4.5. Bootstrap Stability Analysis

To assess the sampling stability of the estimated probabilities and intervention effects, a nonparametric bootstrap analysis was conducted using 1000 resampled datasets. In each iteration, 200 cases were drawn with replacement from the original 200-case dataset. The Bayesian network structure was held constant, while the prior probabilities and conditional probability tables were re-estimated using the resampled data. For each bootstrap model, the baseline probabilities of Response Effectiveness being Effective, Response Disruption Severity being High, and Response Resilience being High were recorded. The posterior probability changes produced by the integrated intervention scenario (I4) were then calculated relative to the baseline state of the corresponding bootstrap model. Table 6 reports the full-sample estimates, bootstrap means, standard deviations, and percentile-based 95% confidence intervals.

Table 6. Bootstrap stability of baseline probabilities and integrated-intervention effects.

Indicator	Full-Sample Estimate	Bootstrap Mean	SD	95% CI
Baseline P (A16 = Effective)	33.7%	33.8%	3.3 pp	27.6–40.4%
Baseline P (A17 = High)	42.4%	42.2%	3.5 pp	35.5–49.3%
Baseline P (A18 = High)	17.0%	17.0%	2.5 pp	12.1–21.9%
I4 ΔP (A16 = Effective)	+16.4 pp	+16.3 pp	3.0 pp	+11.0–+22.7 pp
I4 ΔP (A17 = High)	−10.8 pp	−10.7 pp	2.5 pp	−15.9–−6.1 pp
I4 ΔP (A18 = High)	+7.7 pp	+7.7 pp	1.8 pp	+4.6–+11.6 pp

As shown in Table 6, the bootstrap means were highly consistent with the estimates obtained from the full dataset. The full-sample probabilities for A16 = Effective, A17 = High, and A18 = High were 33.7%, 42.4%, and 17.0%, respectively, while their bootstrap means were 33.8%, 42.2%, and 17.0%, respectively. The corresponding 95% confidence intervals were 27.6–40.4% for Effective response, 35.5–49.3% for High Disruption Severity, and 12.1–21.9% for High Response Resilience. These results indicate that the baseline probability estimates remained reasonably stable across repeated changes in the case sample.

The integrated intervention also showed consistent effects across the bootstrap replications. Relative to the baseline state, I4 increased the probability of Effective response by an average of 16.3 percentage points, with a 95% confidence interval of 11.0–22.7 percentage points. It reduced the probability of High Disruption Severity by an average of 10.7 percentage points, with a 95% confidence interval of 15.9 to 6.1 percentage points. The probability of High Response Resilience increased by an average of 7.7 percentage points, with a 95% confidence interval of 4.6–11.6 percentage points. None of the confidence intervals for the intervention effects included zero, and the direction of all three effects remained unchanged across the 1000 bootstrap samples. The bootstrap results therefore support the sampling stability of the main baseline estimates and the conclusion that coordinated intervention across the road, water supply, and command systems produces a robust improvement in fire emergency Response Resilience.

5. Discussion

5.1. Fire Emergency Response Resilience as an Interdependent Road–Water–Command System

The results support the argument that fire emergency Response Resilience should be understood as an emergent property of an interdependent road–water–command system rather than as the outcome of a single firefighting component. Critical infrastructure research has long emphasized that the performance of one subsystem depends on the operational states of other connected subsystems and that disruptions may propagate through functional, physical, informational, and organizational interdependencies [35]. The baseline inference shows that the probabilities of High Road Capacity and High Water Capacity are 43% and 45%, respectively, while the probability of High Command Capacity is 57%. At the response level, the probability of an Effective response is only 34%, whereas the probabilities of High and Moderate Response Disruption Severity are 42% and 36%. The final resilience distribution is similarly unfavorable, with probabilities of 17%, 31%, and 52% for High, Moderate, and Low Response Resilience, respectively. These results indicate that major urban fire emergencies commonly involve varying degrees of functional degradation generated by the interaction of infrastructure constraints and organizational response conditions.

The network structure further clarifies how this interdependence operates. Road Capacity, Water Capacity, and Command Capacity jointly influence both Response Effectiveness and Response Disruption Severity, which, in turn, determine Response Resilience through two parallel response pathways. Road Capacity affects whether emergency forces and equipment can reach and operate at the incident site; Water Capacity determines whether fire suppression operations can be sustained; and Command Capacity shapes the use and coordination of information, personnel, and physical resources. The three-state specification of Disruption Severity also shows that response disturbance is not simply present or absent. High and moderate disruption together account for approximately 78% of the baseline distribution, indicating that fire emergencies frequently involve varying degrees of delay, difficulty with suppression, evacuation disorder, resource mismatch, or operational interruption rather than complete system failure alone.

The distinction between Response Effectiveness and Response Resilience is particularly important. The probability of an Effective response is 34%, while the probability of High Response Resilience is only 17%. Response Effectiveness captures whether immediate operational tasks are performed effectively. In contrast, Response Resilience additionally reflects whether core response functions can absorb disturbance, adapt to changing conditions, and recover after functional degradation. This distinction is consistent with system resilience research, which treats resilience as a multidimensional capacity that extends beyond short-term operational performance or reliability [36]. A response may therefore achieve partial operational effectiveness without demonstrating High resilience when disruption remains substantial or functional recovery is delayed. The scenario results reinforce this system-level interpretation: constraints in any of the three subsystem capacities reduce Effective response and High resilience while increasing High Disruption Severity. Fire emergency Response Resilience therefore depends on coordinated technical and organizational support rather than on the isolated strengthening of firefighting resources.

5.2. Command Capacity as a Compensatory Mechanism Under Technical Constraints

A key finding of this study is the probabilistic compensatory role of Command Capacity under technical constraints. Among the single-subsystem constraint scenarios, setting Command Capacity to Low produces the most unfavorable combination of response outcomes: the probability of an Effective response falls from 34% to 17%, the probability of High Response Disruption Severity rises from 42% to 58%, and the probability of High Response Resilience declines from 17% to 9%. These changes suggest that Command Capacity is not merely an administrative support condition. It performs an integrative function by connecting situational information, response activation, Resource Mobilization, and interorganizational coordination with the physical capacities of the road and water supply systems. This interpretation accords with crisis management research emphasizing cognition, communication, coordination, and control as interdependent functions required for effective action under uncertainty [37].

The comparison between S4 and S5 provides more direct evidence of this compensatory role. When Road Capacity and Water Capacity are both set to Low in S4, the probability of an Effective response falls to 13%, the probability of High Response Disruption Severity reaches 58%, and the probability of High Response Resilience declines to 8%. When Command Capacity is subsequently set to High under the same technical constraints in S5, the probability of an Effective response increases to 20%, the probability of High Response Disruption Severity decreases to 46%, and the probability of High Response Resilience rises to 11%. Thus, stronger Command Capacity improves Effective response by 7 percentage points, reduces High Disruption Severity by 12 percentage points, and increases High resilience by 3 percentage points relative to S4.

This compensatory effect can be interpreted through several operational mechanisms. Unified Command can reduce fragmentation among firefighting, traffic management, water supply, medical, and local government actors. Timely Alarm Dispatch can accelerate response activation, while Resource Mobilization can compensate for localized shortages in personnel, vehicles, equipment, or water support. Command coordination can also facilitate adaptive adjustments, such as rerouting emergency vehicles, organizing alternative water supplies, reallocating resources, and revising evacuation arrangements when initial response conditions deteriorate. Research on emergency communication networks similarly shows that pre-existing interorganizational communication and boundary-spanning relationships are important for coordination and decision-making during multi-agency emergencies [38].

However, Command Capacity should not be interpreted as a complete substitute for physical infrastructure. Even under S5, the probability of Effective response remains below the baseline level, the probability of High Disruption Severity remains above the baseline, and the probability of High resilience reaches only 11%. The sensitivity analysis also indicates that no single command input independently determines the final outcome. Unified Command, Resource Mobilization, and Alarm Dispatch form the most influential group of command system inputs, with Alarm Dispatch producing the largest increase in high Disruption Severity when set to Inadequate. The findings therefore support a bounded interpretation: Command Capacity can coordinate and partially compensate for technical deficiencies, but sustained resilience still requires adequate road access and firefighting water support.

5.3. Priority Intervention Pathways for Improving Urban Fire Emergency Response Resilience

The sensitivity and intervention results provide differentiated priorities for improving urban fire emergency Response Resilience. Within the road system, Fire Lane Availability produces the largest reduction in High Road Capacity when set to Inadequate, lowering its probability from 43% to 30%. The corresponding intervention in I1 increases the probability of an Effective response by 3 percentage points, reduces High Response Disruption Severity by 2 percentage points, and increases High Response Resilience by 1 percentage point. Although these improvements are smaller than those produced by the water and command interventions, they confirm that unobstructed emergency access remains a basic condition for timely arrival and operational deployment. Urban fire governance should therefore strengthen routine fire lane inspections, illegal parking control, community-level access management, and emergency traffic clearance arrangements.

Water supply resilience should focus not only on the physical availability of hydrants but also on the functional reliability and coordination of water support. Water Pressure and Water Coordination produce greater downstream effects than Hydrant Availability and Alternative Water Supply in the one-way sensitivity analysis. When both nodes are set to Adequate in I2, the probability of an Effective response rises from 34% to 41%, the probability of High Response Disruption Severity decreases from 42% to 38%, and the probability of High Response Resilience increases from 17% to 20%. These findings indicate that installed firefighting water facilities do not automatically translate into effective suppression capacity. Regular pressure testing, hydrant maintenance, emergency water transfer planning, information sharing, and joint exercises between fire and water supply departments are necessary to convert physical water resources into usable operational capacity.

Command system improvement should emphasize rapid activation and coordinated resource use. In I3, setting Unified Command and Alarm Dispatch to Adequate increases the probability of an Effective response to 39%, reduces the probability of High Response Disruption Severity to 37%, and raises the probability of High Response Resilience to 20%. Compared with the water intervention, the command intervention produces a smaller increase in effective response but a larger reduction in severe disruption. This difference suggests that the two intervention pathways operate through complementary mechanisms: water support primarily strengthens sustained suppression performance, whereas command intervention reduces fragmentation, delayed activation, and operational interruption. In practice, command system improvement should include clear authority allocation, accurate alarm classification, interoperable communication, real-time resource tracking, and integrated on-site coordination.

The integrated intervention produces the greatest improvement across all three response indicators. When Fire Lane Availability, Water Pressure, Water Coordination, Unified Command, and Alarm Dispatch are simultaneously set to Adequate, the probabil-

ity of an Effective response increases from 34% to 50%, the probability of High Response Disruption Severity decreases from 42% to 32%, and the probability of High Response Resilience increases from 17% to 25%. These changes—+16, −10, and +8 percentage points, respectively—are substantially larger than those produced by any single-system intervention. This result is consistent with the argument that traditional crisis management measures are insufficient for tightly coupled infrastructure systems and should be complemented by resilience-oriented preparation across organizational and technical boundaries [39]. It also corresponds to resilience frameworks that emphasize the joint development of absorptive, adaptive, and restorative capacities rather than reliance on a single protective measure [40]. Related principal-agent research on rainstorm early-warning responses further indicates that clear authorization, incentive alignment, and supervision mechanisms can strengthen the timely implementation of emergency actions by local governments [41]. The findings therefore support a cross-system improvement strategy in which access, water support, response activation, and organizational coordination are strengthened together.

Nevertheless, the integrated intervention does not eliminate all resilience constraints. Under I4, the probability of Low Response Resilience remains at 40%, indicating that improvements in five priority nodes cannot fully resolve the uncertainty and complexity associated with major urban fires. The bootstrap analysis strengthens confidence in the comparative intervention conclusion: the 95% confidence intervals for the I4 changes in Effective response, High Disruption Severity, and High resilience do not include zero, and the direction of each effect remains stable across 1000 resampled datasets. These results provide evidence of sampling stability rather than proof of causal effects or external predictive validity. Accordingly, the intervention findings should be interpreted as probabilistic decision support evidence for prioritizing coordinated resilience measures. At the same time, their effectiveness should be further evaluated using larger datasets and implementation-based evidence.

6. Conclusions

This study examined fire emergency Response Resilience from the perspective of interdependent road–water–command systems. Based on 200 coded major urban fire emergency response cases, an 18-node Bayesian network was constructed to integrate observable subsystem conditions, Road Capacity, Water Capacity, Command Capacity, Response Effectiveness, Response Disruption Severity, and Response Resilience within a unified probabilistic framework. The results show that fire emergency Response Resilience is not determined by a single firefighting resource or infrastructure factor but emerges from the joint functioning of physical access, fire suppression water, command coordination, dispatch timeliness, and Resource Mobilization.

The empirical inference results provide three main findings. First, the baseline inference indicates a relatively high probability of response disruption and a relatively low probability of high resilience in major urban fire emergencies. Second, scenario-based inference shows that road constraints, water supply constraints, and command weakness all reduce Response Effectiveness and weaken resilience outcomes, with command weakness producing the most unfavorable result. The command compensation scenario further suggests that strong Command Capacity can partially offset the negative effects of road and water supply constraints. Third, the sensitivity analysis identifies Fire Lane Availability, Water Pressure, Water Coordination, Unified Command, Resource Mobilization, and Alarm Dispatch as the most influential group of input nodes. The intervention analysis further shows that coordinated improvement of five selected road, water supply, and command

system nodes produces the strongest increase in effective response and high resilience and the largest reduction in high Disruption Severity.

This study contributes to fire emergency management and infrastructure resilience research by providing a probabilistic approach for analyzing how interdependent urban subsystems shape response outcomes under uncertainty. It also suggests that urban fire governance should shift from fragmented capacity building toward integrated road–water–command system enhancement. Nevertheless, this study has two limitations. First, the case database was constructed from publicly available sources with varying levels of detail, and several parent-state configurations contained relatively few observations despite Dirichlet smoothing. Second, the theoretically specified network and bootstrap analysis support conditional inference and sampling stability but do not establish causal relationships or external predictive validity; future research should therefore validate the model using independent datasets and real-time operational records. Third, Response Disruption Severity integrates several forms of operational disturbance, including response delay, initial suppression difficulty, evacuation disorder, resource mismatch, and operational interruption. Although this integrated measure preserves model parsimony, it may obscure their differentiated relationships with road, water, and command constraints; future studies with larger datasets could model these disruption mechanisms as separate nodes.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/systems14080899/s1>, Table S1: Complete fire emergency case registry, source records, and A1–A18 Bayesian network coding; README: dataset structure, source hierarchy, record-linkage procedure, variable definitions, operational coding criteria, and validation information.

Author Contributions: Conceptualization, R.C. and J.L.; methodology, R.C. and M.L.; data curation, R.C. and M.L.; formal analysis, R.C.; software, R.C. and M.L.; validation, R.C., M.L. and J.L.; investigation, R.C. and M.L.; writing—original draft preparation, R.C.; writing—review and editing, R.C., M.L. and J.L.; visualization, R.C.; supervision, J.L.; project administration, J.L.; Funding acquisition, J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Science and Technology Plan Project of the National Fire and Rescue Administration (Grant No. 2025XFLR27).

Data Availability Statement: The complete case-level dataset, source records, A1–A18 coding results, and the accompanying README are provided in the Supplementary Materials.

Acknowledgments: The authors would like to thank Xuanyu Zhang for his valuable assistance with data verification and discussions during the revision of the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Representative fire emergency cases and main data sources (10 of 200 cases).

Case ID	Fire Emergency Case	Year	Location	Scenario Type	Main Data Sources
C1	Jiale yuan roadside shop fire	2024	Xinyu, Jiangxi	Mixed commercial–residential building	Accident investigation report; government notices; mainstream media reports
C2	Mingshang Xiyuan residential building fire	2024	Nanjing, Jiangsu	High-rise residential building; electric bicycle-related fire	Official investigation notice; fire rescue information; media reports

Table A1. Cont.

Case ID	Fire Emergency Case	Year	Location	Scenario Type	Main Data Sources
C3	Jiuding Building fire	2024	Zigong, Sichuan	Commercial complex/building fire	Government investigation report; official notices; media reports
C4	Yingcai School dormitory fire	2024	Fangcheng, Henan	School dormitory fire	Accident investigation report; government notices; media reports
C5	Changfeng Hospital fire	2023	Beijing	Hospital fire	National accident investigation report; government notices; media reports
C6	Fuyang Barbecue Restaurant gas explosion and fire	2023	Yinchuan, Ningxia	Urban restaurant; gas explosion and fire	National accident investigation report; government notices; media reports
C7	Kaixinda Trading Company fire	2022	Anyang, Henan	Industrial and commercial premises	National accident investigation report; government notices; media reports
C8	Jixiangyuan high-rise residential fire	2022	Urumqi, Xinjiang	High-rise residential building	Government press conference transcript; official notices; media reports
C9	Yanhu Community market gas explosion and fire	2021	Shiyan, Hubei	Urban market/community space	Provincial accident investigation report; government notices; media reports
C10	Li's Wedding Dream City fire	2021	Changchun, Jilin	Commercial photography base/building fire	Provincial accident investigation report; official news release; media reports

Note: The complete list of 200 cases, source records, and node-level coding results is provided in Supplementary Table S1.

References

- Li, Q.; Deng, Y.; Liu, C.; Zeng, Q.; Lu, Y. Modeling and analysis of subway fire emergency response: An empirical study. *Saf. Sci.* **2016**, *84*, 171–180. [\[CrossRef\]](#)
- Liu, Q.; He, R.; Zhang, L. Simulation-Based Multi-Objective Optimization for Enhanced Safety of Fire Emergency Response in Metro Stations. *Reliab. Eng. Syst. Saf.* **2022**, *228*, 108820. [\[CrossRef\]](#)
- Schweikert, A.E.; L'Her, G.F.; Deinert, M.R. Simple Method for Identifying Interdependencies in Service Delivery in Critical Infrastructure Networks. *Appl. Netw. Sci.* **2021**, *6*, 44. [\[CrossRef\]](#)
- Cantelmi, R.; Di Gravio, G.; Patriarca, R. Reviewing Qualitative Research Approaches in the Context of Critical Infrastructure Resilience. *Environ. Syst. Decis.* **2021**, *41*, 341–376. [\[CrossRef\]](#) [\[PubMed\]](#)
- Mentges, A.; Halekotte, L.; Schneider, M.; Demmer, T.; Lichte, D. A Resilience Glossary Shaped by Context: Reviewing Resilience-Related Terms for Critical Infrastructures. *Int. J. Disaster Risk Reduct.* **2023**, *96*, 103893. [\[CrossRef\]](#)
- Fuggini, C.; Solari, C.; De Stefano, R.; Bolletta, F.; De Maio, F.V. Assessing Resilience at Different Scales: From Single Assets to Complex Systems. *Environ. Syst. Decis.* **2023**, *43*, 693–707. [\[CrossRef\]](#)
- Schneider, M.; Halekotte, L.; Comes, T.; Lichte, D.; Fiedrich, F. Emergency Response Inference Mapping (ERIMap): A Bayesian Network-Based Method for Dynamic Observation Processing. *Reliab. Eng. Syst. Saf.* **2025**, *255*, 110640. [\[CrossRef\]](#)
- Rathnayaka, B.; Robert, D.; Adikariwattage, V.; Siriwardana, C.; Kuligowski, E.; Setunge, S.; Amaratunga, D. Novel Methodology for Resilience Assessment of Critical Infrastructure Considering the Interdependencies: A Case Study in Water, Transportation and Electricity Sector. *Int. J. Disaster Risk Reduct.* **2025**, *119*, 105271. [\[CrossRef\]](#)
- Mukhopadhyay, A.; Pettet, G.; Vazirizade, S.M.; Lu, D.; Jaimes, A.; El Said, S.; Baroud, H.; Vorobeychik, Y.; Kochenderfer, M.J.; Dubey, A. A Review of Incident Prediction, Resource Allocation, and Dispatch Models for Emergency Management. *Accid. Anal. Prev.* **2022**, *165*, 106501. [\[CrossRef\]](#) [\[PubMed\]](#)

10. Shahparvari, S.; Fadaki, M.; Chhetri, P. Spatial Accessibility of Fire Stations for Enhancing Operational Response in Melbourne. *Fire Saf. J.* **2020**, *117*, 103149. [[CrossRef](#)]
11. Cao, R.F.; Lee, E.W.M.; Xie, W.; Gao, D.L.; Chen, Q.; Yuen, A.C.Y.; Yeoh, G.H.; Yuen, R.K.K. Development of an Agent-Based Indoor Evacuation Model for Local Fire Risks Analysis. *J. Saf. Sci. Resil.* **2023**, *4*, 75–92. [[CrossRef](#)]
12. Baik, J.; Murray, A.T. Emergency Response Planning: A Framework to Assess Hydrant–Structure Access. *Trans. GIS* **2024**, *28*, 2412–2424. [[CrossRef](#)]
13. Figueroa, V.E.; Murray, A.T.; Funk, T. Supporting Fire Response: Advanced Spatial Data Analytics for Hydrant Access Assessment. *Trans. GIS* **2024**, *28*, 2559–2573. [[CrossRef](#)]
14. Kox, T.; Lüder, C. Impacts as Triggers for Weather-Related Decision Making: Observations at the Berlin Fire Brigade Control and Dispatch Center. *Int. J. Disaster Risk Sci.* **2021**, *12*, 610–615. [[CrossRef](#)]
15. Liu, J.; Dong, C.; An, S. Integration and Modularization: Research on Urban Cross-Regional Emergency Cooperation Based on the Network Approach. *Int. J. Disaster Risk Reduct.* **2022**, *82*, 103375. [[CrossRef](#)]
16. Liu, J.; Fu, Z.; Song, Y.; Ma, R.; Zhao, Z. How to Improve the Effectiveness of the Cooperation Networks of Emergency Science Communication for Public Health Emergencies. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 1449. [[CrossRef](#)]
17. Müller, R.; Graf, B.; Ellwart, T.; Antoni, C.H. How Software Agents Can Help to Coordinate Emergency Response Teams: Adaptive Team Performance Comparing Manual and Automated Team Communication. *J. Bus. Psychol.* **2023**, *38*, 1121–1137. [[CrossRef](#)]
18. Gooding, K.; Bertone, M.P.; Loffreda, G.; Witter, S. How Can We Strengthen Partnership and Coordination for Health System Emergency Preparedness and Response? Findings from a Synthesis of Experience across Countries Facing Shocks. *BMC Health Serv. Res.* **2022**, *22*, 1441. [[CrossRef](#)] [[PubMed](#)]
19. Mottahedi, A.; Sereshki, F.; Ataei, M.; Nouri Qarahasanlou, A.; Barabadi, A. The Resilience of Critical Infrastructure Systems: A Systematic Literature Review. *Energies* **2021**, *14*, 1571. [[CrossRef](#)]
20. Lin, I.-C.; Yağan, O.; Joe-Wong, C. Dynamic Coupling Strategy for Interdependent Network Systems Against Cascading Failures. *IEEE Trans. Netw. Sci. Eng.* **2023**, *10*, 2265–2282. [[CrossRef](#)]
21. Sathurshan, M.; Saja, A.; Thamboo, J.; Haraguchi, M.; Navaratnam, S. Resilience of Critical Infrastructure Systems: A Systematic Literature Review of Measurement Frameworks. *Infrastructures* **2022**, *7*, 67. [[CrossRef](#)]
22. Rathnayaka, B.; Robert, D.; Adikariwattage, V.; Siriwardana, C.; Meegahapola, L.; Setunge, S.; Amaratunga, D. A Unified Framework for Evaluating the Resilience of Critical Infrastructure: Delphi Survey Approach. *Int. J. Disaster Risk Reduct.* **2024**, *110*, 104598. [[CrossRef](#)]
23. Sun, J.; Bathgate, K.; Pan, S.; Zhang, Z. Network-Based Method for Assessing Multi-Modal Transportation Network Vulnerability to Cascading Failures. *Sustain. Anal. Model.* **2024**, *4*, 100034. [[CrossRef](#)]
24. Gebhard, T.; Sattler, B.J.; Gunkel, J.; Marquard, M.; Tundis, A. Improving the Resilience of Socio-Technical Urban Critical Infrastructures with Digital Twins: Challenges, Concepts, and Modeling. *Sustain. Anal. Model.* **2025**, *5*, 100036. [[CrossRef](#)]
25. Liu, J.; Dong, C. Understanding the Complex Adaptive Characteristics of Cross-Regional Emergency Collaboration in China: A Stochastic Evolutionary Game Approach. *Fractal Fract.* **2024**, *8*, 98. [[CrossRef](#)]
26. Sydnes, M.; Kjeve, M.; Sydnes, A.K. Interorganizational Coordination during Emergencies and Crises. *Int. J. Disaster Risk Reduct.* **2025**, *121*, 105310. [[CrossRef](#)]
27. Kong, J.; Zhang, C.; Simonovic, S.P. Optimizing the Resilience of Interdependent Infrastructures to Regional Natural Hazards with Combined Improvement Measures. *Reliab. Eng. Syst. Saf.* **2021**, *210*, 107538. [[CrossRef](#)]
28. Hanea, A.M.; Christophersen, A.; Alday, S. Bayesian Networks for Risk Analysis and Decision Support. *Risk Anal.* **2022**, *42*, 1149–1154. [[CrossRef](#)] [[PubMed](#)]
29. Sahlin, U.; Helle, I.; Perepolkin, D. “This Is What We Don’t Know”: Treating Epistemic Uncertainty in Bayesian Networks for Risk Assessment. *Integr. Environ. Assess. Manag.* **2021**, *17*, 221–232. [[CrossRef](#)] [[PubMed](#)]
30. Cai, Y.; Golay, M.W. A Dynamic Bayesian Network-Based Emergency Decision-Making Framework Highlighting Emergency Propagations: Illustrated Using the Fukushima Nuclear Accidents and the COVID-19 Pandemic. *Risk Anal.* **2023**, *43*, 480–497. [[CrossRef](#)] [[PubMed](#)]
31. Caetano, H.O.; Desuó Neto, L.; Fogliatto, M.S.S.; Maciel, C.D. Resilience Assessment of Critical Infrastructures Using Dynamic Bayesian Networks and Evidence Propagation. *Reliab. Eng. Syst. Saf.* **2024**, *241*, 109691. [[CrossRef](#)]
32. Tong, Q.; Gernay, T. Resilience Assessment of Process Industry Facilities Using Dynamic Bayesian Networks. *Process Saf. Environ. Prot.* **2023**, *169*, 547–563. [[CrossRef](#)]
33. Sun, J.; Bathgate, K.; Zhang, Z. Bayesian Network-Based Resilience Assessment of Interdependent Infrastructure Systems under Optimal Resource Allocation Strategies. *Resilient Cities Struct.* **2024**, *3*, 46–56. [[CrossRef](#)]
34. Garre, A.; Fernández, P.S.; Truchado, P.; Simón-Andreu, P.J.; Lindqvist, R.; Allende, A. The Use of Bayesian Networks and Bootstrap to Evaluate Risks Linked to the Microbial Contamination of Leafy Greens Irrigated with Reclaimed Water in Southeast Spain. *Microb. Risk Anal.* **2022**, *22*, 100234. [[CrossRef](#)]

35. Rinaldi, S.M.; Peerenboom, J.P.; Kelly, T.K. Identifying, Understanding, and Analyzing Critical Infrastructure Interdependencies. *IEEE Control Syst. Mag.* **2001**, *21*, 11–25. [[CrossRef](#)]
36. Hosseini, S.; Barker, K.; Ramirez-Marquez, J.E. A Review of Definitions and Measures of System Resilience. *Reliab. Eng. Syst. Saf.* **2016**, *145*, 47–61. [[CrossRef](#)]
37. Comfort, L.K. Crisis Management in Hindsight: Cognition, Communication, Coordination, and Control. *Public Adm. Rev.* **2007**, *67*, 189–197. [[CrossRef](#)]
38. Kapucu, N. Interagency Communication Networks During Emergencies: Boundary Spanners in Multiagency Coordination. *Am. Rev. Public Adm.* **2006**, *36*, 207–225. [[CrossRef](#)]
39. Boin, A.; McConnell, A. Preparing for Critical Infrastructure Breakdowns: The Limits of Crisis Management and the Need for Resilience. *J. Contingencies Crisis Manag.* **2007**, *15*, 50–59. [[CrossRef](#)]
40. Francis, R.; Bekera, B. A Metric and Frameworks for Resilience Analysis of Engineered and Infrastructure Systems. *Reliab. Eng. Syst. Saf.* **2014**, *121*, 90–103. [[CrossRef](#)]
41. Ma, R.; Liu, J.; An, S. Early Warning Response to Rainstorm: Designing a Model with Incentive and Supervision Mechanisms Based on the Principal–Agent Theory. *Int. J. Disaster Risk Reduct.* **2024**, *111*, 104683. [[CrossRef](#)]

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