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From Snow and Ice Warnings to Road Traffic System Resilience: A Bayesian Network Analysis of Preparedness and Response Pathways

Jida Liu †, Zheng Fu, Yuhang Yan † and Rui Cheng *

School of Management, Harbin Institute of Technology, Harbin 150001, China; liujida@hit.edu.cn (J.L.); 19b910024@stu.hit.edu.cn (Z.F.); 26b910077@stu.hit.edu.cn (Y.Y.)
* Correspondence: chengrui@stu.hit.edu.cn
† These authors contributed equally to this work.

Highlights

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

- Develops a 15-node Bayesian network that models how snow and ice warnings relate to risk assessment, interagency coordination, and operational actions in winter road systems.
- Assesses initial traffic continuity, loss containment, and recovery separately across 27 scenarios that vary in disruption severity, road network vulnerability, and maintenance resource availability.

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

- Under severe disruption, high road network vulnerability, and moderate resources, advance deployment showed the strongest association with initial traffic continuity, while sustained response showed the strongest associations with loss containment and recovery.
- Across levels of road network vulnerability, greater maintenance resource availability was more strongly associated with better recovery under mild disruption than under severe disruption.

Abstract

Snow and ice warnings support winter road operations, but their relationships with preparedness, response, and traffic resilience remain unclear. Using 760 practitioner assessments from five cities in northeastern China, a 15-node Bayesian network was developed in this study that integrates five categories: hazard and baseline conditions, warning attributes, organizational mechanisms, preparedness and response actions, and resilience outcomes. Dirichlet-smoothed probability tables were used to support inference across 27 environmental scenarios and nine-node comparisons under three contexts. Posterior sampling quantified uncertainty, while sensitivity analyses examined prior and network specifications. Shared five-fold record-level cross-validation compared the Bayesian network, random forest, and class-prior benchmark. Under high disturbance and vulnerability with moderate resources, high versus low preventive deployment was associated with a 14.4-percentage-point higher probability of high initial continuity. Corresponding contrasts for response implementation were 51.3 percentage points for high loss containment and 42.2 for high recovery. Resource–recovery contrasts were larger under low disturbance. Both models outperformed the benchmark, while moderate recovery was the hardest recovery state to classify. These findings distinguish advance preparation from sustained

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Academic Editors: Francesco Rouhana and Amvrossios C. Bagtzoglou

Received: 21 October 2026
Revised: 12 November 2026
Accepted: 14 November 2026
Published: 18 November 2026

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implementation across winter road service stages and support the post-event assessment of warning-to-action processes.

Keywords: snow and ice; road traffic resilience; Bayesian network; early warning; emergency preparedness; emergency response; random forest

1. Introduction

Snow accumulation and road icing place simultaneous pressures on road safety, traffic continuity, and winter maintenance. Research on winter road conditions identifies interdependencies among weather variables, maintenance operations, pavement friction, and collisions, indicating that safety outcomes depend on both hazardous conditions and their operational management [1]. When critical routes are affected and alternative routes are limited, disruption can restrict access to essential services and emergency transport. Continued snowfall or persistent icing can prolong these constraints and require repeated operational adjustments. Research using naturalistic driving data further highlights the need to account for weather-dependent lane-changing behavior when evaluating traffic safety and operations [2]. The system-level challenge is to preserve essential traffic services while maintaining acceptable safety conditions.

Winter-road service is particularly vulnerable where a small number of links carry essential traffic. Bridges, steep grades, and shaded segments may ice under conditions that leave nearby roads passable. If a key link has few viable alternatives, local disruption can propagate to scheduled bus services, emergency trips, and freight movements. The relevant performance question is how much service remains available and for how long. A treatment decision that preserves access on one priority corridor may still leave substantial losses elsewhere in the network. The operating problem also changes over the course of the event. Ahead of impact, the main decisions concern which roads to monitor, where to position vehicles and materials, and when to apply preventive treatment. During the event, incoming information may require reallocating crews or changing traffic controls. During recovery, the emphasis shifts to clearing persistent restrictions, restoring regular routes, and checking that service remains stable. This sequence motivates separate outcomes for continuity, containment, and recovery.

Early warnings offer opportunities to prepare equipment and materials, undertake preventive treatment, and coordinate traffic management before hazardous conditions develop. However, the availability of warning information does not establish whether these opportunities are used effectively. Protective action research distinguishes warning reception and comprehension from subsequent decisions and behavioral responses [3]. Organizational road traffic response introduces additional dependencies because meteorological services, traffic authorities, maintenance agencies, and road operators possess different information, responsibilities, and resources. A warning may be received without generating a shared assessment of priority road sections, and response measures may be initiated without sufficient deployment or sustained implementation. These potential discontinuities make it necessary to examine the processes connecting warning information with operational action and traffic functionality.

In this study, initial traffic continuity, loss containment, and recovery are investigated using 760 retained questionnaire records from practitioners in five cities in northeastern China. Its framework distinguishes hazard and baseline conditions, warning attributes, organizational mechanisms, preparedness and response actions, and resilience outcomes. The analysis compares conditional outcome probabilities and evaluates internal predictive performance against a random forest and a class-prior baseline. Two questions guide the

study: How do the three outcomes vary across disturbance, vulnerability, and resource levels? How do their conditional distributions differ across warning, organizational, and action states?

The contribution of this study is to connect warning and operational evaluations to distinct phases of road service in a single conditional model. In the remainder of the paper, the framework is developed in Section 2, while Section 3 describes the survey, model, and evaluation. Sections 4 and 5 present and interpret the results, and Section 6 concludes.

2. Literature Review and Theoretical Framework

2.1. Road Traffic System Resilience Under Snow and Ice Conditions

Bayesian network studies have examined disruption resilience in urban rail systems and long-term resilience in urban transportation systems [4,5]. A broader review of urban rail transit resilience also distinguishes multiple resilience abilities and assessment approaches [6]. This study applies phase-specific measures to winter road operations during a particular snow or ice experience. Resilience concerns how systems maintain essential functions and recover from disruption. Bruneau et al. [7] distinguish functional outcomes, including robustness and recovery rapidity, from enabling attributes such as resourcefulness and redundancy. In transportation research, Serdar et al. [8] review resilience indicators, disturbance categories, and assessment methods, highlighting the importance of specifying performance dimensions and their temporal scope. Network structure must also be considered alongside the services it supports. Morelli and Cunha [9] assess urban road network vulnerability using travel distribution under flooding, illustrating the importance of evaluating functional consequences rather than connectivity alone. Ganin et al. [10] further demonstrate that normal operating efficiency does not necessarily imply resilience to disruption.

Snow and ice introduce distinctive operational constraints through changing weather and pavement conditions. Malin et al. [11] show that accident risk under adverse road and weather conditions varies across road types, indicating that hazard effects depend partly on the operating context. Freistetter et al. [12] model snowy and icy road surfaces and driving conditions in Finland, Norway, and Sweden, demonstrating their spatial and seasonal variation under climate change. Karsisto and Lovén [13] examine the assimilation of vehicle-based surface temperature observations into road weather forecasts, illustrating the value of road-specific observations for characterizing hazardous conditions. Hu et al. develop an infrared–visible multimodal detection algorithm for urban traffic safety perception under degraded visual conditions. This work complements road-weather observation research by addressing the quality of information available for identifying traffic participants and local operating conditions [14]. Accordingly, in this study, disturbance intensity is characterized through the severity, extent, and duration of hazardous road conditions, while distinguishing it from the road network's pre-existing susceptibility.

Event-based studies support an examination of traffic functionality as hazardous conditions evolve. Yao et al. [15] integrate traffic forecasting, percolation-based robustness assessment, and congestion propagation modeling to examine local and network-level traffic resilience during a historical snowstorm. Their analysis connects evolving traffic conditions with opportunities for proactive intervention. Evidence from other weather hazards also highlights the importance of representing the degree of functional disruption. Pregnolato et al. [16] develop a depth disruption function linking floodwater depth to vehicle speed, moving beyond a binary representation of roads as either fully operational or blocked. Although the flood-specific relationship cannot be transferred directly to snow and ice, the study provides a methodological basis for distinguishing physical hazard conditions from their consequences for traffic performance. Shao et al. integrate spatiotemporal

traffic information and weather descriptions in a large-language-model framework for cross-city and cross-scenario traffic-speed fore-casting under abnormal weather. Their focus on traffic-state prediction complements the present study's examination of how warning information, organizational processes, and response actions relate to successive stages of traffic resilience [17].

Resilience metrics based on performance over time distinguish the depth of the initial loss, the duration of degraded service, and the subsequent rate of recovery [18,19]. A single aggregate value can conceal whether a road system maintained essential trips early, limited the spread of disruption, or restored its ordinary service quickly. The measures used here represent these dimensions through separate questions. An assessment of initial continuity concerns whether core travel and priority trips continued. Loss containment concerns the extent and spread of disruption. Recovery concerns the speed, completeness, and stability of restoration.

Vulnerability and resilience are related through the availability of alternative links and the capacity to respond after disruption [20]. Redundancy can protect essential service at onset, but it does not specify how quickly crews can treat affected roads or restore routes. Conversely, a network with few alternatives can suffer large initial losses yet recover after the affected sections become passable. Transport resilience models that include preparedness and recovery actions under budget and service constraints clarify why the availability of resources and their use are separate analytical questions [21]. Road-condition modeling provides a complementary perspective on maintenance needs. Pan et al. develop a diffusion-based digital twin that represents road distress evolution, maintenance interventions, and environmental disturbances [22]. Such models characterize the physical condition of infrastructure, while event-based resilience assessment examines the traffic services maintained and restored during disruption. Bringing these perspectives together helps distinguish infrastructure condition, operational demand, and service performance.

2.2. From Snow and Ice Warnings to Preparedness and Coordinated Response

Early warning effectiveness depends on the connection between risk information and response capacity. Neußner [23] reviews natural hazard warning practices worldwide and identifies substantial variation in alert terminology, levels, colors, and symbols, highlighting challenges for consistent interpretation. Potter et al. [24] identify research gaps in impact-based forecasting and warning, including the integration of data and models, communication, evaluation, and implementation. These studies indicate that warning effectiveness requires more than producing accurate forecasts: information must also be understandable, operationally relevant, and connected to arrangements for action.

Warning design and recipient response represent related but distinct concerns. Taggart and Wilke [25] develop a coherent framework linking hazard likelihood and severity to warning levels, providing a basis for consistent warning generation and evaluation. From a recipient perspective, Taylor et al. [26] experimentally examine how likelihood, impact severity, and warning format affect risk judgments, trust, and protective action intentions. Sadiq et al. [27] further review public alert and warning research, emphasizing the roles of message characteristics, recipient populations, and dissemination methods.

Organizational response introduces additional dependencies among agencies with different responsibilities and resources. Hu et al. review empirical emergency management network research, examining network formation, structural properties, and performance [28]. Bodin et al. develop a diagnostic framework for collaborative responses to compound emergencies, distinguishing actors, interaction venues, and required functions [29]. In the Chinese context, Liu and Dong examine cross-departmental emergency coordination across central, provincial, and municipal governments, highlighting differ-

ences in coordination networks and resource sharing under multiple risks [30]. Liu et al. analyze cooperation networks for emergency science communication during COVID-19, examining how organizational relationships vary across emergency phases [31]. Dong et al. use a stochastic evolutionary game model to examine interactions among government, scientists, and the public in emergency science communication [32]. Liu et al. [33] examine emergency technology innovation under technological and emergency-management uncertainties, emphasizing the alignment of technological capabilities with emergency needs and feedback from practical application. Lu et al. [34] analyze collaborative forest fire rescue systems in China, highlighting the complementary roles of local, reinforcement, and social rescue organizations and the importance of resource coordination and information sharing. Together, these studies provide a basis for examining whether information exchange, responsibility allocation, and coordination arrangements are aligned with operational tasks.

Winter maintenance research provides a more direct operational perspective. Matthews et al. describe the co-production of climate services for a Canadian road authority, illustrating how weather and climate information can inform winter maintenance decisions at different timescales [35]. Mohammadi et al. model plowing, salting, and combined maintenance efforts across Norway's state road network using weather and non-weather variables, linking environmental conditions to operational requirements [36]. Najar et al. examine winter maintenance fleet configurations and treatment strategies under climatic uncertainty, emphasizing the importance of matching resources and practices to changing conditions [37]. Together, these studies highlight the need to consider both the information available to road authorities and the operational capacity required to act on it. Resource availability establishes what personnel, equipment, and materials can be used, while deployment and treatment decisions determine how that capacity is applied.

The operational value of a warning also depends on whether it can inform decisions within the available time. Accuracy concerns whether the warned locations, timing, and severity correspond to subsequent conditions. Timeliness concerns whether information arrives early enough for preparation and is updated as conditions change. Receipt concerns whether the relevant staff and partner organizations obtain the information, while actionability concerns whether the message identifies priority locations and offers feasible guidance. These attributes address different potential obstacles between warning provision and operational action. A widely received message may leave crews uncertain about which road segments require treatment, while specific advice may arrive too late to support advance deployment. A related information-to-action perspective appears in autonomous driving. Ma et al. integrate perception, cognition, and behavior within a feedback framework for vehicle–environment interaction. At the organizational level considered here, the corresponding analytical question concerns how warning information is interpreted and translated into coordinated operational action [38].

Operational studies further distinguish the availability of resources from their deployment and use. Real-time information can inform treatment decisions as conditions change [39]. Urban snow plow routing and fleet-sizing studies identify constraints on covering a service area with limited vehicles, materials, and time [40,41]. Infrastructure protection and recovery scheduling studies address complementary decisions concerning protective actions before disruption and the execution and sequencing of restoration afterward [42,43]. In power-system restoration, Wang et al. examine the coordinated use of multi-port mobile emergency vehicles and other restoration resources while accounting for post-disaster transport constraints. This provides a complementary infrastructure perspective on how resource mobility and coordinated deployment shape the feasibility of recovery operations [44]. This literature provides a basis for distinguishing advance preparation, the timing of response initiation, and the coverage and continuity of subsequent work.

These operational dimensions may relate differently to the maintenance of essential traffic services at onset, the containment of disruption during an event, and the restoration of service afterward.

2.3. Bayesian Networks for Analyzing Warning–Response–Resilience Relationships

Structured safety research highlights the importance of examining relationships across system levels. Fan et al. organize urban air mobility safety through a matrix framework that identifies cross-level risk propagation and mitigation interdependencies. For winter-road operations, this systems perspective motivates examining environmental conditions, organizational processes, and operational actions jointly [45]. Bayesian networks provide a probabilistic framework for representing conditional dependencies and updating outcome distributions as evidence becomes available. Kaikkonen et al. [46] review their application in environmental risk assessment, emphasizing the integration of different knowledge sources and the explicit representation of uncertainty. Kitson et al. [47] review Bayesian network structure-learning algorithms, including constraint-based, score-based, and hybrid approaches. These studies support the use of Bayesian networks to examine interconnected conditions while making the assumptions underlying network construction explicit. Constantinou et al. [48] examine how different forms of prior knowledge influence causal structure learning, demonstrating the importance of how domain knowledge is incorporated. In a separate large-scale evaluation, Constantinou et al. [49] investigate structure-learning performance under noisy data, showing why algorithmic results obtained under ideal conditions may not transfer directly to imperfect observational datasets. These findings support the use of theory-informed restrictions and empirical assessment.

Transparent reporting and application-specific evaluation are also essential. Barons et al. [50] propose reporting standards covering the information needed to understand and reproduce Bayesian network studies, including model development and validation. Adams et al. [51] illustrate a participatory Bayesian network approach to resilience assessment, combining stakeholder knowledge, baseline data, and future scenarios to examine interactions within a river catchment system, demonstrating how conditional scenario analysis can support the examination of interconnected pressures and resources. Traffic state studies describe how disruption evolves, while warning studies examine how information is communicated and interpreted. The link between these research strands is addressed in this study by comparing how warnings, organizational processing, and successive actions relate to each stage of winter road performance under comparable environmental conditions.

Figure 1 summarizes the study design, linking the study constructs and retained questionnaire codes to the fixed archived network and subsequent analyses. The five variable categories provide a conceptual basis for questionnaire design and interpretation of the graph.

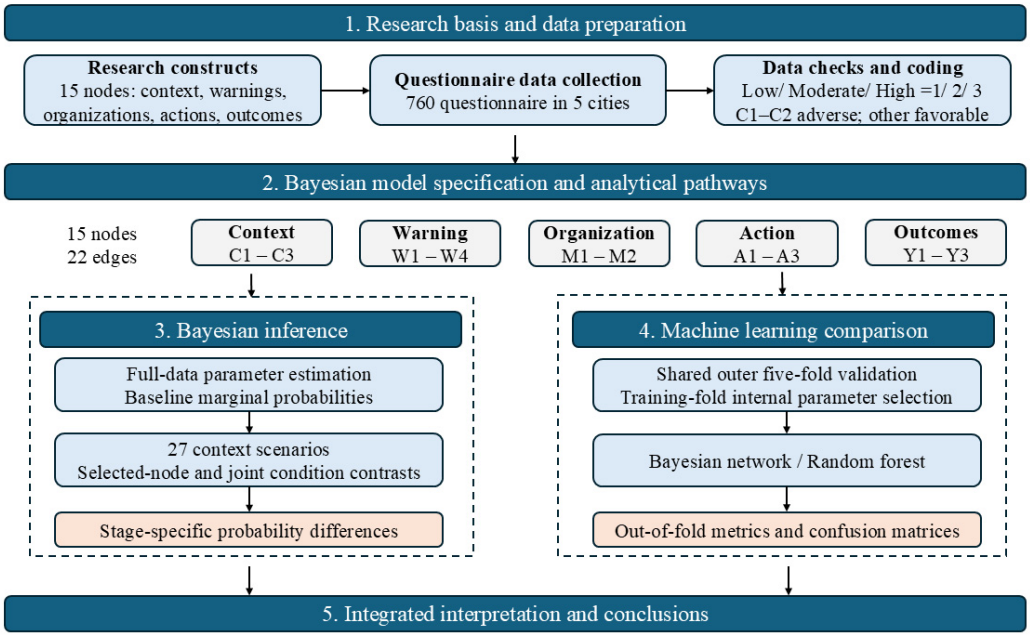


Figure 1. Research framework.

3. Materials and Methods

3.1. Research Design and Data Collection

A questionnaire design was adopted to examine the relationships among snow and ice warnings, organizational processes, response actions, and road traffic resilience. Each respondent evaluated a specified snow and ice event within a defined road network or management jurisdiction. Event-referenced questions are intended to anchor retrospective judgments, while recognizing that recall and inference can affect survey responses [52]. The questionnaire was administered from January to July 2026 among relevant personnel in five cities in northeastern China: Harbin, Daqing, Changchun, Mudanjiang, and Jiamusi. The target groups included traffic police officers, property management personnel, emergency management department staff, frontline sanitation workers, community staff, and bus drivers, as well as road maintenance personnel, snow and ice removal crews, public transport dispatchers, and meteorological warning service personnel. Eligibility required direct experience of the selected event within the relevant road network or management jurisdiction.

The questionnaire begins with eligibility and background questions, including city, role, event cues, and road or service area. The measurement section uses five-level agreement responses and offers a "do not know" option. Table 1 maps the three-item blocks to the modeled variables.

The analysis used the three ordered states recorded for each construct (1 = Low, 2 = Moderate, 3 = High). Higher states indicate more intense disturbance or greater vulnerability for C1 and C2, respectively, and more favorable conditions or performance for the remaining constructs. Table 1 maps the questionnaire items to the modeled variables. Risk assessment covers hazard locations, expected traffic consequences, and treatment priorities, while coordination covers information exchange, role clarity, and joint work.

The analytical unit is one retained respondent assessment. The analysis file contains 760 records and 15 coded node variables, with a state recorded for every node in each record. The respondents evaluated roads, routes, or areas familiar to them through their work, so each record represents an assessment of a particular operating setting. Warning ratings concern information available to respondents through channels such as messages, calls,

work groups, or formal systems. The completeness of the retained node codes does not establish the completeness of the original questionnaire responses.

Table 1. Variables and questionnaire items.

Node	Construct	Category	Questionnaire Items and Content	Recorded States
C1	Initial snow and ice disturbance intensity	Hazard conditions	9–11. Severity, extent, and duration of hazardous road snow and ice conditions.	Low/Moderate/High
C2	Road-network vulnerability to snow and ice	Hazard conditions	12–14. Susceptibility arising from ice-prone sections and limited alternative routes.	Low/Moderate/High
C3	Winter maintenance resource availability	Hazard conditions	15–17. Personnel, equipment, and treatment materials available before the event.	Low/Moderate/High
W1	Road snow and ice warning accuracy	Warning	18–20. Accuracy of warned hazard locations, timing, and severity.	Low/Moderate/High
W2	Road snow and ice warning timeliness	Warning	21–23. Adequacy of warning lead time and update timeliness.	Low/Moderate/High
W3	Warning receipt by response organizations	Warning	24–26. Extent of actual warning receipt among key response actors.	Low/Moderate/High
W4	Snow and ice warning actionability	Warning	27–29. Clarity and feasibility of location-specific operational guidance.	Low/Moderate/High
M1	Snow and ice risk assessment adequacy	Organizational mechanisms	30–32. Adequacy of hazard interpretation, traffic impact assessment, and priority setting.	Low/Moderate/High
M2	Interagency coordination for snow and ice response	Organizational mechanisms	33–35. Alignment of information, responsibilities, and operational arrangements.	Low/Moderate/High
A1	Preventive deployment adequacy for snow and ice control	Preparedness and response actions	36–38. Adequacy of resource deployment and preventive treatment before hazardous conditions develop.	Low/Moderate/High
A2	Snow and ice response initiation timeliness	Preparedness and response actions	39–41. Timeliness of initiating required road treatment and traffic management measures.	Low/Moderate/High
A3	Snow and ice response implementation adequacy	Preparedness and response actions	42–44. Coverage, completion, and continuity of required response measures.	Low/Moderate/High

Table 1. *Cont.*

Node	Construct	Category	Questionnaire Items and Content	Recorded States
Y1	Initial traffic functional continuity	Resilience outcomes	45–47. Maintenance of essential traffic services during initial disruption.	Low/Moderate/High
Y2	Traffic service loss containment during snow and ice	Resilience outcomes	48–50. Limitation of traffic service losses and their spread during sustained disruption.	Low/Moderate/High
Y3	Traffic functional recovery after snow and ice	Resilience outcomes	51–53. Speed, extent, and stability of essential traffic service restoration.	Low/Moderate/High

3.2. Bayesian Network Specification and Estimation

The primary analysis fixed all 22 directed edges to the archived 15-node specification (Figure 2).The network structure was modeled in GeNIe Modeler (version 4.0 Academic).

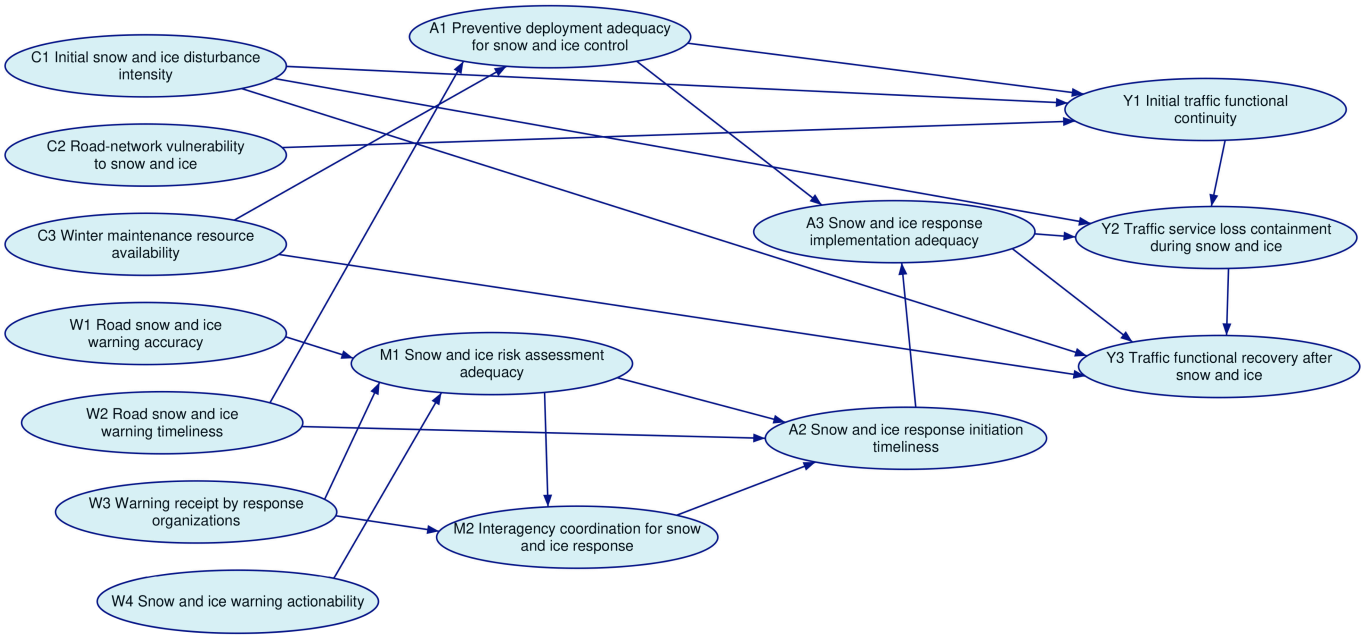


Figure 2. Bayesian network structure.

Table 2 lists the incoming edges and their operational interpretation. C1–C3 and W1–W4 are root nodes. This study fitted categorical tables for every node, including C1.

Let $X1$, $X2$, ..., $X15$ denote the study variables and $Pa(X_i)$ the parents of node X_i. Equation (1) gives the standard Bayesian network factorization [53].

$$P(X1, X2, \ldots, X15) = \prod_{i=1}^{15} P(X_i|Pa(X_i)) \quad (1)$$

For a node without parents, its factor is the marginal distribution. Each row of a conditional probability table (CPT) corresponds to one parent-state configuration j for node i. For child state k, let n_{ijk} denote the number of records in which node i is in state k and its parents are in configuration j, and let α_{ijk} denote the corresponding Dirichlet prior pseudocount. Following Heckerman et al. [53], we used Dirichlet–multinomial conjugacy to update the prior, yielding the posterior parameter $\alpha_{ijk} + n_{ijk}$ for state k. We used the posterior mean as the point estimate of the conditional probability [54]. Equation (2) gives

this estimate, and Equations (3) and (4) define the total observed count and total prior pseudocount in its denominator.

$$\hat{p}_{ijk} = \left(n_{ijk} + \alpha_{ijk}\right) / \left(N_{ij} + A_{ij}\right) \quad (2)$$

In the denominator of Equation (2), N_{ij} is the total observed count for parent-state configuration j, and A_{ij} is the total prior pseudocount for the same configuration. Both totals are obtained by summing over the three states of the child node [55]:

$$N_{ij} = \Sigma_k \, n_{ijk} \quad (3)$$

$$A_{ij} = \Sigma_k \, \alpha_{ijk} \quad (4)$$

Each CPT row represents one parent-state configuration; four three-state parents yield 81 configurations. The primary model used a symmetric Dirichlet prior with 0.5 pseudo counts per child state and parent configuration. Point estimates used posterior-mean CPTs, with uniform probabilities for unobserved configurations. Child-state counts were tabulated for all configurations, including empty ones. Sensitivity analyses used pseudo counts of 0.1, 1, and 2 on the primary graph and 0.5 on a reduced graph without the Y2-to-Y3 edge.

Table 2. Network edges and operational rationale.

Child	Parents	Operational Rationale
A1	C3, W2	Available assets make advance deployment feasible. Timely warning gives crews time to stage assets.
Y1	C1, C2, A1	Disturbance imposes immediate load. Vulnerability limits alternatives. Deployment represents readiness at onset.
M1	W1, W3, W4	Accuracy informs assessment. Reach makes information available to relevant units. Usability helps units interpret local priorities.
M2	W3, M1	Shared receipt supports communication. Risk assessment informs allocation of responsibilities.
A2	W2, M1, M2	Timeliness determines decision time. Risk assessment identifies needs. Coordination supports mobilization.
A3	A1, A2	Advance staging provides operational readiness. Activation precedes sustained execution.
Y2	C1, A3, Y1	Disturbance persists during operations. Implementation represents service protection. Initial continuity describes the starting state.
Y3	C1, C3, A3, Y2	Disturbance and resources constrain recovery. Implementation represents completed work. Containment indicates the extent of accumulated disruption.

Pointwise 95% model-based credible intervals were calculated from the 2.5th and 97.5th percentiles of estimates obtained using 1500 posterior CPT draws per specification. Both terms of each contrast used the same sampled CPTs within each draw.

Inference was conditioned on specified evidence, summed over unobserved variables, and normalized by the evidence probability. Baseline inference used no evidence. Context-only scenarios were conditioned on C1–C3, while expanded scenarios added warning, organizational, or action evidence. Matching record counts are reported separately from model-based conditional probabilities.

3.3. Bayesian Inference and Predictive Validation

Baseline inference used no conditioning evidence. The 27 environmental scenarios formed the complete combination of the three states of C1, C2, and C3. The analysis

compared High versus Low for all nine warning, organizational, and action nodes under three contexts, specified as (C1, C2, C3): (High, High, Moderate), (Low, Low, Moderate), and (Moderate, Moderate, Moderate). Additional comparisons contrasted joint High states of W2, A1, and A3 and their subsets with single-node High conditions in the adverse context. Equation (5) subtracts the reference probability from the comparison probability.

$$\Delta_\gamma = P(Y = High \mid C,\ E_1) - P(Y = High \mid C,\ E_0) \quad (5)$$

Equation (5) defines the study's contrast between two conditional distributions with the same context and different evidence. Multiplication by 100 expresses the contrast in percentage points. C denotes the environmental context, and E_1 and E_0 are the comparison and reference evidence.

Five-fold record-level cross-validation used the same shuffled outer splits for the Bayesian network, random forest, and class-prior baseline. Both models used the twelve non-outcome nodes, including response-stage assessments, with all three outcomes withheld together. Model parameters were refitted within each training fold, and three-fold inner validation selected Dirichlet smoothing and random forest hyperparameters by log loss. The baseline assigned training-fold class proportions to each held-out record, while both fitted models used the same input information.

Macro-F1 averages the three class-specific F1 scores, balanced accuracy averages class recalls, log loss evaluates the probability assigned to the observed state, and multiclass Brier score measures squared error across the probability vector. Fold means and standard deviations for macro-F1, balanced accuracy, and log loss were reported separately from pooled out-of-fold metrics, including class recall and Brier scores.

4. Results

4.1. Baseline Bayesian Inference

Baseline inference used the refitted parameters of the fixed network without entering evidence. Figure 3 presents the marginal probabilities of Low, Moderate, and High for all fifteen nodes.

Figure 3 presents the baseline marginal probabilities of the fifteen nodes without conditioning on evidence. These distributions summarize the fitted model's overall profile and provide a reference for subsequent scenario comparisons. They distinguish the environmental setting, warning performance, organizational and operational assessments, and three resilience outcomes.

The environmental profile combines relatively pronounced disturbance and vulnerability with predominantly Moderate maintenance resources. High snow and ice disturbance intensity (C1) was the most probable state at 40.6%, compared with 33.4% for Moderate and 25.9% for Low. Road network vulnerability (C2) was concentrated in the Moderate and High states, at 38.5% and 37.6%, respectively. Maintenance resource availability (C3) was most likely Moderate (42.9%), while Low and High had similar probabilities of 26.9% and 30.3%. These distributions describe the background against which warning and response performance are assessed.

Warning receipt (W3) had a more favorable distribution than the other warning attributes. Its High-state probability reached 59.6%, whereas the corresponding probabilities were 36.4% for warning accuracy (W1), 38.5% for warning timeliness (W2), and 33.9% for warning actionability (W4). Accuracy (W1) and actionability (W4) were most likely Moderate, while timeliness (W2) was more evenly distributed across the three states. Thus, favorable receipt was more prevalent in the fitted baseline than favorable timing, accuracy, or actionable guidance. This distinction indicates why receipt alone provides an incomplete description of warning performance.

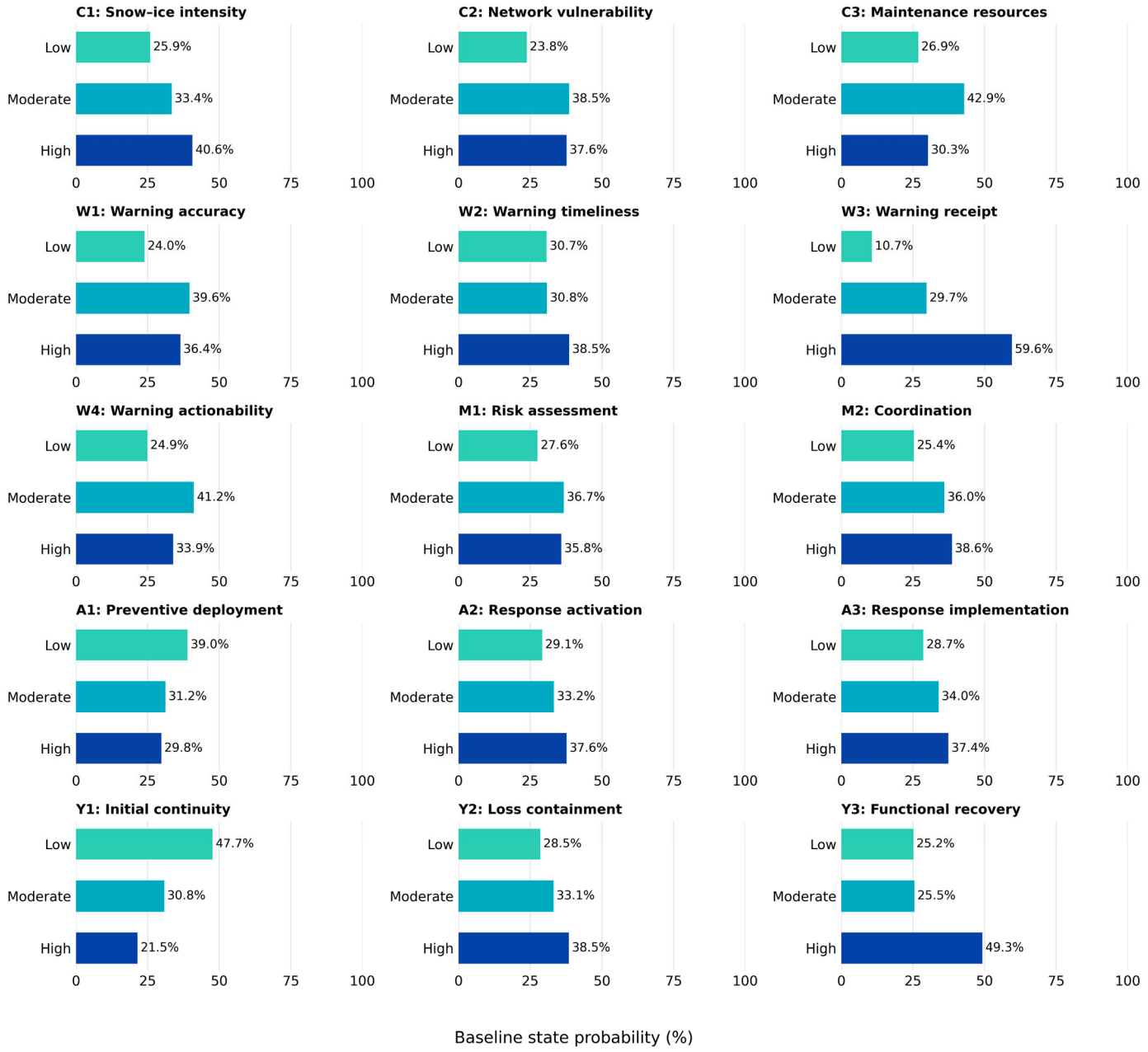


Figure 3. Baseline state probabilities.

Organizational assessments were concentrated around Moderate and High performance. Risk assessment adequacy (M1) had similar probabilities for these states, at 36.7% and 35.8%, while interagency coordination (M2) was slightly more likely to be High (38.6%) than Moderate (36.0%). The action nodes showed a clearer distinction between advance preparation and subsequent response. Preventive deployment adequacy (A1) was most likely Low (39.0%), with a High-state probability of 29.8%. In contrast, High was the most probable state for response initiation timeliness (A2) and response implementation adequacy (A3), at 37.6% and 37.4%, respectively. This profile shows that favorable evaluations of starting and sustaining response were more common than favorable evaluations of advance deployment, supporting their separate examination in the scenario analysis.

The resilience outcomes also differed substantially. Initial traffic functional continuity (Y1) was most likely Low (47.7%), and its High-state probability was only 21.5%. Traffic service loss containment (Y2) was more evenly distributed, with probabilities of 28.5%, 33.1%, and 38.5% for Low, Moderate, and High. Traffic functional recovery (Y3) had the

highest probability of favorable performance: High accounted for 49.3%, while Low and Moderate accounted for 25.2% and 25.5%. The baseline therefore portrays initial continuity (Y1) less favorably than containment (Y2) or recovery (Y3).

4.2. Scenario-Based Bayesian Inference

All 27 combinations of C1, C2, and C3 occurred in the retained data, with 5–71 records per combination. The recovery CPT contained 81 possible parent configurations, two unobserved and 21 with one to four observations. Table 3 reports resource contrasts across disturbance and vulnerability levels.

Table 3. Resource-related outcome contrasts.

C1/C2	Outcome	Difference (pp)	95% CrI Lower (pp)	95% CrI Upper (pp)
1/1	Y1	0.0	−8.2	7.7
1/1	Y2	3.4	1.2	5.8
1/1	Y3	21.1	5.4	36.6
1/2	Y1	1.9	−6.8	10.5
1/2	Y2	3.7	0.9	6.5
1/2	Y3	21.1	5.6	36.4
1/3	Y1	4.6	−4.9	14.1
1/3	Y2	1.7	−1.7	4.6
1/3	Y3	21.4	6.1	36.7
2/1	Y1	2.1	−6.5	10.5
2/1	Y2	2.5	0.5	4.8
2/1	Y3	7.8	−7.4	22.3
2/2	Y1	0.8	−4.4	6.8
2/2	Y2	2.4	0.8	4.4
2/2	Y3	8.3	−6.7	22.6
2/3	Y1	4.9	−0.1	11.9
2/3	Y2	3.3	1.5	5.4
2/3	Y3	8.8	−6.5	22.4
3/1	Y1	7.8	−1.6	18.0
3/1	Y2	3.0	0.7	5.6
3/1	Y3	5.6	−6.9	19.2
3/2	Y1	4.9	0.0	10.5
3/2	Y2	3.0	1.3	4.9
3/2	Y3	6.0	−6.6	19.3
3/3	Y1	4.7	0.6	9.8
3/3	Y2	3.3	1.6	5.2
3/3	Y3	6.3	−6.5	19.5

Note: CrI = credible interval; pp = percentage points. Codes 1–3 denote Low, Moderate, and High. Limits are pointwise 95% model-based credible intervals.

Table 3 reports differences in the probabilities of High outcomes between High and Low maintenance resources (C3), with disturbance intensity (C1) and network vulnerability (C2) held fixed within nine contexts. The estimated resource contrasts for High recovery (Y3) were 21.1–21.4 percentage points at Low disturbance and 5.6–6.3 points at High disturbance across vulnerability levels. Resource contrasts for loss containment (Y2) were smaller, ranging from 1.7 to 3.7 percentage points. For initial continuity (Y1), most credible intervals included zero, indicating uncertainty in the direction of the resource-related differences.

For recovery (Y3), all three pointwise 95% credible intervals were above zero under Low disturbance, whereas they spanned zero under High disturbance. Figure 4 presents the estimated probabilities of High outcomes across the 27 environmental configurations.

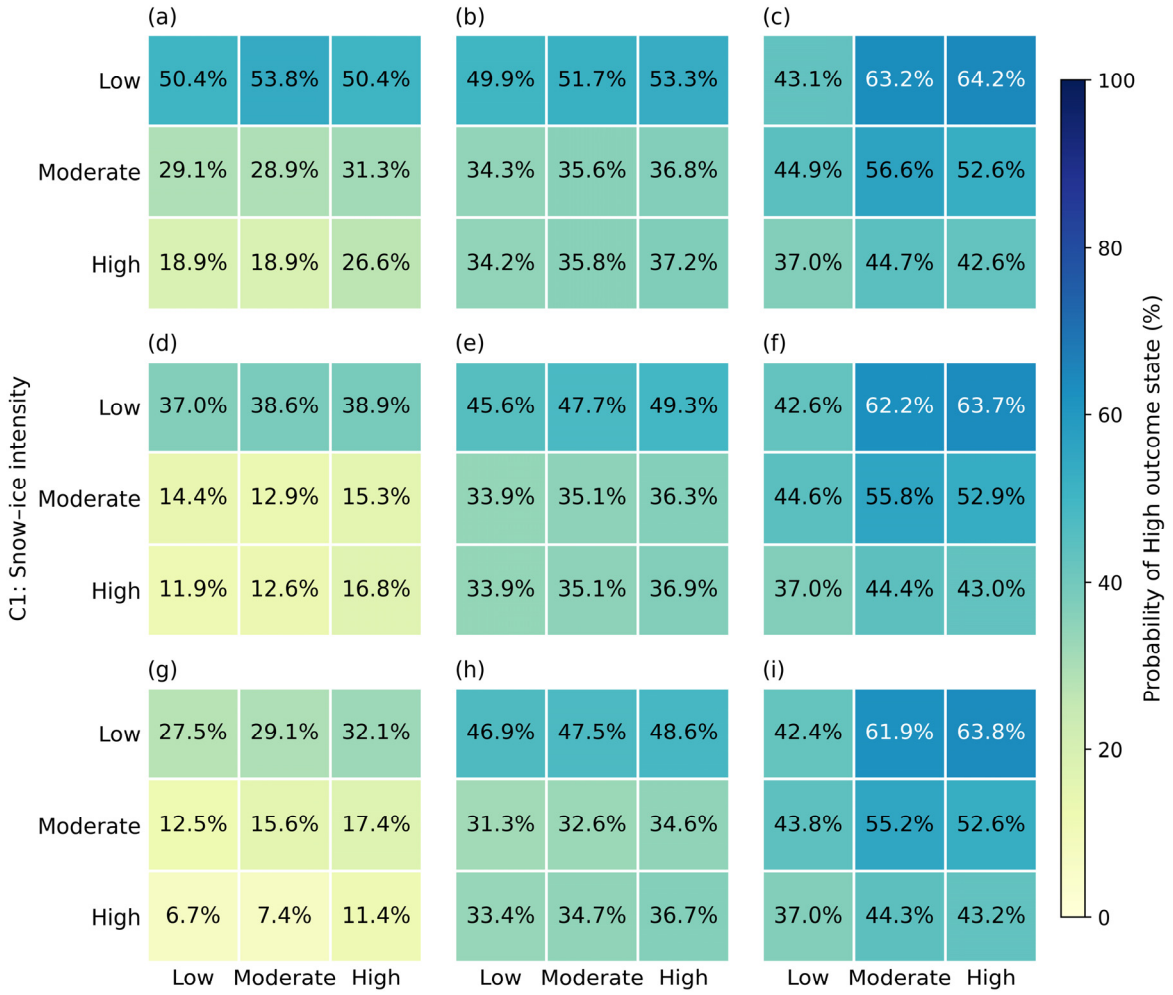


Figure 4. Environmental scenario probabilities. Panels (**a**–**c**), (**d**–**f**), and (**g**–**i**) correspond to Low, Moderate, and High road network vulnerability (C2), respectively. From left to right, the panels in each row show initial continuity (Y1), loss containment (Y2), and functional recovery (Y3). Within each panel, rows represent snow–ice intensity (C1), columns represent maintenance resource availability (C3), and cells show the probability that the corresponding outcome is High.

Figure 4 organizes the environmental scenarios by road network vulnerability (C2), with panel rows representing Low, Moderate, and High vulnerability. Panel columns show initial continuity (Y1), loss containment (Y2), and recovery (Y3). Within each panel, rows represent disturbance intensity (C1), columns represent maintenance resource availability (C3), and cell values indicate the probability of the corresponding outcome being High.

Initial continuity (Y1) showed pronounced differences across disturbance and vulnerability levels. With vulnerability (C2) and resources (C3) fixed at Low, the probability of High Y1 decreased from 50.4% under Low disturbance (C1) to 29.1% under Moderate and 18.9% under High disturbance. Under High vulnerability and Low resources, the corresponding probabilities were 27.5%, 12.5%, and 6.7%. Vulnerability-related differences were also evident: with disturbance and resources fixed at Low, High Y1 declined from 50.4% to 37.0% and 27.5% as vulnerability increased. Thus, favorable initial continuity became less probable under more adverse weather and network conditions.

Resource-related patterns differed across outcomes. Under High disturbance (C1) and High vulnerability (C2), the probabilities of High initial continuity (Y1), loss containment (Y2), and recovery (Y3) were 6.7%, 33.4%, and 37.0% with Low resources (C3),

compared with 11.4%, 36.7%, and 43.2% with High resources. Recovery displayed larger resource-related differences under Low disturbance. For example, under Low vulnerability, High Y3 increased from 43.1% with Low resources to 63.2% with Moderate and 64.2% with High resources. The resource pattern did not uniformly increase: under Moderate disturbance and High vulnerability, the corresponding recovery probabilities were 43.8%, 55.2%, and 52.6%.

Overall, the scenarios distinguish the environmental profiles of the three resilience outcomes. Initial continuity (Y1) was particularly unfavorable when disturbance and vulnerability were both High, remaining at 11.4% even with High resources. Loss containment (Y2) showed smaller resource-related differences, while recovery (Y3) displayed a stronger resource association under Low disturbance.

4.3. Key-Node Sensitivity and Response Strategy Analysis

To examine how warning attributes, organizational mechanisms, and response actions relate to resilience under adverse conditions, this section presents a comparison of all nine nodes with disturbance intensity (C1) and network vulnerability (C2) fixed at High and maintenance resources (C3) at Moderate. Each node was separately assigned High and Low, while the remaining non-context nodes were unobserved. Table 4 reports the resulting differences in High-outcome probabilities and their pointwise 95% credible intervals.

Table 4. Node contrasts under adverse conditions.

Node	Outcome	Difference (pp)	95% CrI Lower (pp)	95% CrI Upper (pp)
W1	Y1	0.0	0.0	0.0
W1	Y2	0.5	0.2	0.9
W1	Y3	0.4	0.1	0.9
W2	Y1	2.6	0.1	6.2
W2	Y2	4.5	2.6	6.8
W2	Y3	3.9	1.8	6.3
W3	Y1	0.0	0.0	0.0
W3	Y2	1.1	0.5	1.9
W3	Y3	0.9	0.4	1.7
W4	Y1	0.0	0.0	0.0
W4	Y2	0.3	0.1	0.6
W4	Y3	0.3	0.1	0.5
M1	Y1	0.0	0.0	0.0
M1	Y2	1.8	0.7	3.2
M1	Y3	1.6	0.5	3.0
M2	Y1	0.0	0.0	0.0
M2	Y2	4.0	2.1	6.2
M2	Y3	3.4	1.4	5.7
A1	Y1	14.4	2.0	29.2
A1	Y2	11.4	6.3	17.0
A1	Y3	9.8	4.6	15.6
A2	Y1	0.7	0.0	1.7
A2	Y2	10.0	5.7	14.7
A2	Y3	8.4	3.9	13.8
A3	Y1	2.4	0.0	5.5
A3	Y2	51.3	38.2	62.6
A3	Y3	42.2	21.2	60.5

Preventive deployment (A1) showed the largest estimated contrast for initial continuity (Y1), at 14.4 percentage points. Response implementation (A3) showed the largest contrasts for loss containment (Y2) and recovery (Y3), at 51.3 and 42.2 percentage points, respectively.

The corresponding A1 contrasts for Y2 and Y3 were 11.4 and 9.8 points, while the A3 contrast for Y1 was 2.4 points. This pattern distinguishes the stronger association of advance deployment with initial continuity from that of sustained implementation with containment and recovery. Figure 5 displays the conditional probabilities underlying these comparisons.

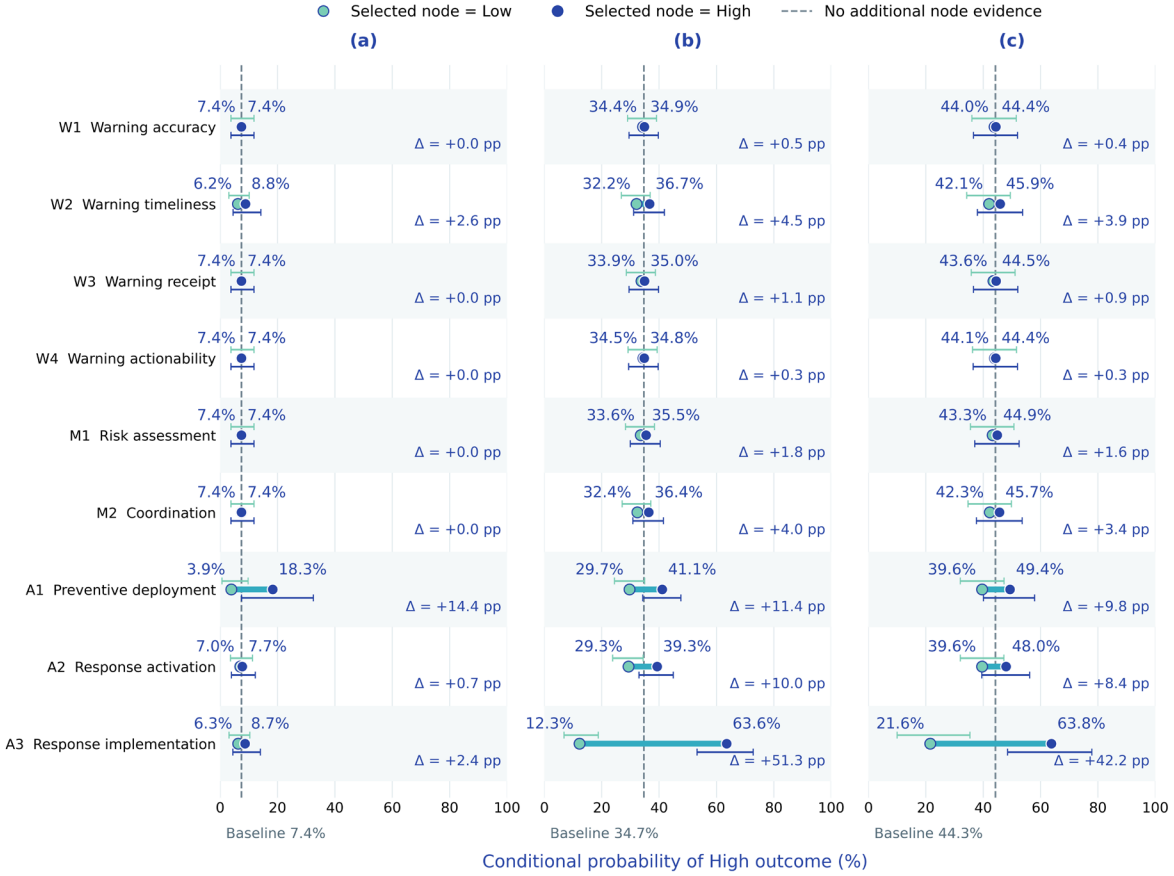


Figure 5. Conditional outcome probabilities under adverse conditions. Panels (**a**), (**b**), and (**c**) show the probabilities of High initial continuity (Y1), loss containment (Y2), and functional recovery (Y3), respectively. All estimates condition on High snow–ice intensity (C1), High road network vulnerability (C2), and Moderate maintenance resource availability (C3). Each row compares the probabilities when the selected node is Low and High. The dashed line shows the baseline probability without additional evidence on the selected node. Whiskers show pointwise 95% credible intervals, and Δ is the High-minus-Low difference in percentage points.

Among warning attributes, timeliness (W2) showed the largest estimated contrasts, at 2.6, 4.5, and 3.9 percentage points for Y1, Y2, and Y3, respectively. Warning accuracy (W1), receipt (W3), and actionability (W4) showed smaller contrasts for Y2 and Y3. Among organizational mechanisms, coordination (M2) showed contrasts of 4.0 and 3.4 points for Y2 and Y3, compared with 1.8 and 1.6 points for risk assessment (M1). Response initiation timeliness (A2) showed larger contrasts of 10.0 and 8.4 points for these outcomes. The zero contrasts between W1, W3, W4, M1, or M2 and Y1 reflect conditional independence relationships in the specified network.

The joint High condition for warning timeliness (W2), preventive deployment (A1), and response implementation (A3) was also compared with High A3 alone. The estimated differences were 9.6, −2.3, and 0.2 percentage points for Y1, Y2, and Y3, respectively. The joint condition showed a larger increment in initial continuity, while the loss-containment and recovery estimates remained close to those under High implementation alone. The credible intervals for the Y2 and Y3 differences included zero.

Across the five fitted specifications, the adverse-context A3–Y3 contrast ranged from 32.4 to 47.5 percentage points. Its direction remained positive, while its magnitude varied with prior smoothing and the recovery graph.

4.4. Predictive Performance Comparison with Machine Learning

To assess internal predictive performance, the Bayesian network (BN) was compared with a random forest (RF) and a class-prior baseline using shared five-fold record-level cross-validation. Both fitted models used the same twelve non-outcome variables to predict the three resilience outcomes. Table 5 summarizes macro-F1, balanced accuracy, and log loss as means and standard deviations across the five outer folds.

Table 5. Cross-validation performance.

Panel A. Macro-F1			
Outcome	**Model**	**Mean**	**SD**
Y1	Class-prior baseline	0.217	0.007
Y2	Class-prior baseline	0.184	0.015
Y3	Class-prior baseline	0.230	0.010
Y1	Bayesian network	0.395	0.061
Y2	Bayesian network	0.506	0.032
Y3	Bayesian network	0.429	0.037
Y1	Random forest	0.383	0.030
Y2	Random forest	0.488	0.045
Y3	Random forest	0.407	0.027
Panel B. Balanced accuracy			
Outcome	Model	Mean	SD
Y1	Class-prior baseline	0.333	0.000
Y2	Class-prior baseline	0.333	0.000
Y3	Class-prior baseline	0.333	0.000
Y1	Bayesian network	0.414	0.045
Y2	Bayesian network	0.513	0.033
Y3	Bayesian network	0.462	0.043
Y1	Random forest	0.416	0.023
Y2	Random forest	0.497	0.047
Y3	Random forest	0.441	0.028
Panel C. Log loss			
Outcome	Model	Mean	SD
Y1	Class-prior baseline	1.044	0.025
Y2	Class-prior baseline	1.094	0.011
Y3	Class-prior baseline	1.022	0.027
Y1	Bayesian network	1.003	0.034
Y2	Bayesian network	0.980	0.030
Y3	Bayesian network	0.924	0.023
Y1	Random forest	0.990	0.019
Y2	Random forest	1.001	0.032
Y3	Random forest	0.927	0.021

Note. Mean and standard deviation (SD) summarize the five outer folds.

Both fitted models outperformed the class-prior baseline across the three outcomes on macro-F1, balanced accuracy, and log loss. BN achieved higher mean macro-F1 than RF for initial continuity (Y1), loss containment (Y2), and recovery (Y3), with scores of 0.395, 0.506, and 0.429 compared with 0.383, 0.488, and 0.407, respectively. For Y2 and Y3, BN also achieved higher mean balanced accuracy and lower mean log loss. For Y1, RF had slightly

higher mean balanced accuracy and lower mean log loss. The relative performance of the two models therefore varied by outcome and evaluation criterion.

Figure 6 presents the pooled out-of-fold confusion matrices. Rows represent observed states and columns represent predicted states; diagonal percentages indicate class-specific recall.

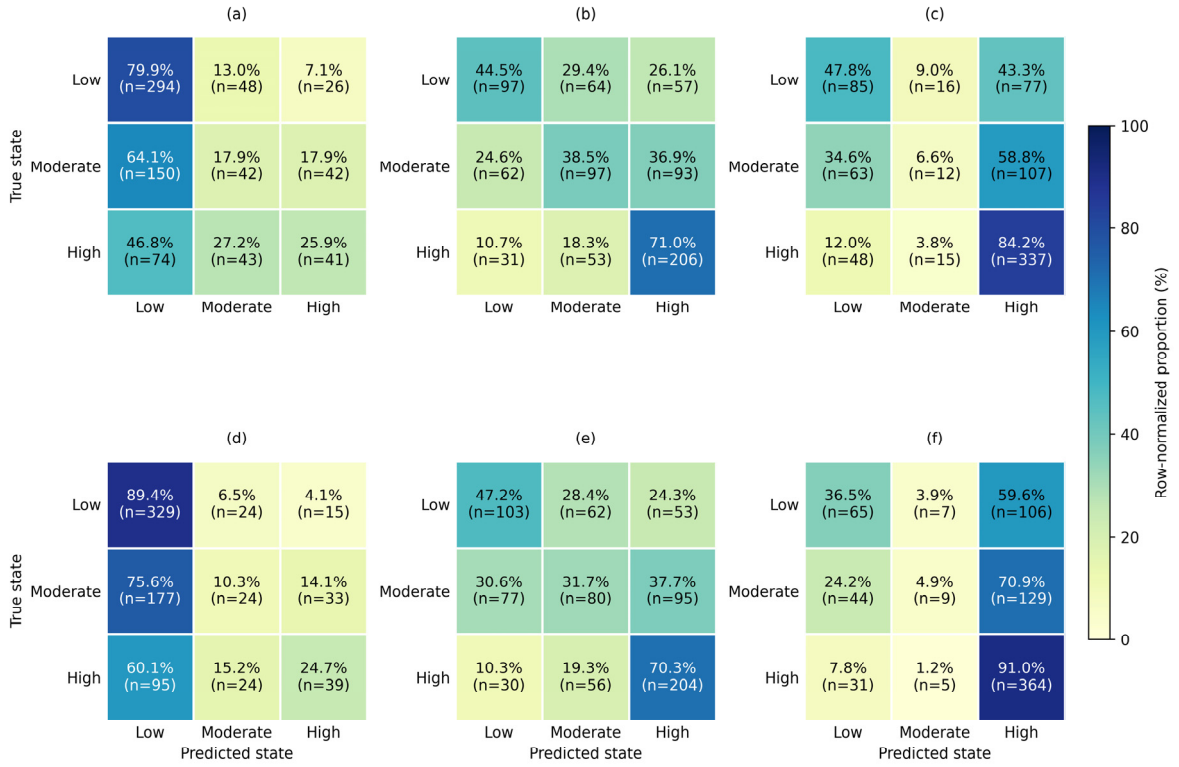


Figure 6. Predictive confusion matrices. Panels (**a**–**c**) show the Bayesian network results, and panels (**d**–**f**) show the random forest results. From left to right, the panels in each row correspond to initial continuity (Y1), loss containment (Y2), and functional recovery (Y3). Within each panel, rows represent observed states and columns represent predicted states. Cells show row-normalized percentages with counts in parentheses. Diagonal percentages indicate class-specific recall.

For initial continuity (Y1), both models identified Low states more successfully than Moderate or High states. Low-state recall was 79.9% for BN and 89.4% for RF, whereas Moderate-state recall was 17.9% and 10.3%, respectively. High-state recall was also limited, at 25.9% for BN and 24.7% for RF. The models therefore tended to assign more favorable continuity assessments to the Low category.

Loss containment (Y2) showed a more balanced classification profile. High-state recall was similar across models, at 71.0% for BN and 70.3% for RF. BN identified Moderate containment more successfully, with recall of 38.5%, compared with 31.7% for RF. Nevertheless, intermediate containment remained more difficult to identify than High containment.

Recovery (Y3) displayed the strongest contrast between High and Moderate recognition. High-state recall reached 84.2% for BN and 91.0% for RF, while Moderate-state recall was only 6.6% and 4.9%, respectively. Among observed Moderate records, 58.8% were classified as High by BN and 70.9% by RF. Thus, the relatively favorable aggregate recovery scores coexisted with substantial confusion between partial and High recovery, identifying intermediate-state recognition as a principal limitation of both models.

5. Discussion

5.1. Stage-Specific Patterns of Traffic Resilience

The results highlight different operational demands across initial continuity, loss containment, and recovery. Initial continuity concerns the services that remain available when hazardous conditions first affect roads. Loss containment concerns the extent and spread of disruption during sustained exposure, while recovery concerns the restoration of service as conditions improve. The differing outcome profiles therefore direct attention to distinct features of winter-road performance. This phase-specific interpretation extends performance-over-time approaches to resilience by distinguishing the preservation of essential service, the management of ongoing disruption, and subsequent restoration.

The scenario results show that initial continuity (Y1) is particularly unfavorable under high disturbance and high network vulnerability. An operational explanation lies in the concentration of essential trips on critical road sections. Ice on a bridge, a steep grade, or a poorly connected corridor can interrupt priority movements even when much of the surrounding network remains passable. Limited alternative routes increase the service consequences of these local restrictions, consistent with transport vulnerability research emphasizing both network structure and functional accessibility. The persistence of a low High-continuity probability under adverse conditions, including 11.4% with High resources, highlights the importance of where disruption occurs and which services depend on the affected links.

The resource–recovery pattern can be interpreted through the relationship between available capacity and maintenance workload. The estimated recovery contrasts were 21.1–21.4 percentage points under Low disturbance and 5.6–6.3 points under High disturbance. Under less demanding conditions, available personnel, vehicles, and materials can be allocated across a more manageable set of treatment tasks. Severe or persistent icing can increase the area requiring treatment, the frequency of repeat operations, and the time needed to reach and service affected sections. Consequently, the same nominal resource level can correspond to different operational capacity relative to demand.

Taken together, these findings suggest that winter-road resilience depends on the alignment of environmental demands, network characteristics, and operational capacity across service stages. Initial continuity draws attention to vulnerable links and essential movements, while containment and recovery draw attention to the coverage and continuity of maintenance operations.

5.2. Implications for Warning and Response Management

The contrasting associations of preventive deployment (A1) and response implementation (A3) emphasize the importance of distinguishing readiness before disruption from work delivered during an event. The advance positioning of crews, vehicles, and treatment materials concerns whether priority locations can receive attention before access deteriorates. Sustained implementation concerns whether required measures cover affected locations, are completed, and continue as conditions evolve. The larger A1 contrast for initial continuity (Y1), together with the larger A3 contrasts for loss containment (Y2) and recovery (Y3), supports the separate evaluation of these operational dimensions. Management reviews can accordingly distinguish the adequacy of advance arrangements from the coverage and continuity of subsequent operations.

The warning results further emphasize the steps between receiving information and organizing a response. Warning accuracy (W1) concerns the correspondence between forecast and experienced conditions, timeliness (W2) concerns the time available for decisions, receipt (W3) concerns access to information, and actionability (W4) concerns its operational relevance and feasibility. Risk assessment (M1) and coordination (M2) address

how organizations interpret this information, establish priorities, and arrange joint work. Within the specified network, warning attributes are connected to resilience outcomes through organizational and action nodes, so their conditional contrasts also reflect this modeled structure. The practical implication is to examine the complete information-to-action process, including receipt, local interpretation, dispatch decisions, and execution.

The joint-condition comparison adds an outcome-specific perspective to these arrangements. Joint High timeliness (W2), deployment (A1), and implementation (A3) corresponded to a higher initial continuity probability than High implementation alone, while the loss-containment and recovery estimates remained close to the implementation-only condition. This pattern is consistent with the distinct timing of advance readiness and sustained work: arrangements made before impact are particularly relevant to service at onset, whereas continued operations concern the management and clearance of disruption already present. Joint warning and response arrangements can therefore be evaluated against explicit service objectives, such as maintaining emergency access, containing disruption across adjoining routes, or restoring stable transit operations.

These evaluations also require a clear distinction between operational activity and traffic outcomes. Completing treatment tasks and maintaining service are related but separate assessments. Weyrich et al. compared behavioral intentions in scenario-based experiments with warning responses observed in real time [56], providing a methodological reference for examining questionnaire-based assessments alongside behavior during actual events. Because both were reported retrospectively by the same respondents, recall and a tendency toward consistent ratings may contribute to their association.

5.3. Predictive Performance and Scope of Model Use

The Bayesian network provides a framework for examining warning, organizational, operational, and environmental assessments alongside three stages of traffic resilience. Its principal use is to compare outcome distributions under specified evidence configurations and organize post-event assessment around distinct service objectives. Separating initial continuity, loss containment, and recovery allows the analysis to distinguish conditions associated with maintaining essential movements from those associated with managing ongoing disruption and restoring service. Because the inputs include assessments of actions undertaken during an event, the current model is most directly applicable to retrospective evaluation.

Predictive performance provides a complementary assessment of model applicability. Both the Bayesian network and random forest outperformed the class-prior baseline, while identifying Moderate recovery remained difficult. Class-specific metrics reveal differences that aggregate scores can conceal [57], and probability-based evaluation provides additional information about the predicted distributions. The validation results concern held-out respondent assessments under record-level splitting. Event and jurisdiction identifiers were unavailable for grouping the retained records, so assessments of the same disruption may have appeared in both training and test sets. Shared event conditions can produce optimistic estimates of performance for new disruptions [58,59]. The results therefore provide a reference for internal prediction and identify intermediate recovery as a priority for model refinement.

Further development can align measurement, validation, and information availability with the intended application. Measuring recovery speed, completeness, and stability separately would help distinguish operational profiles currently combined within the Moderate category. Event- or jurisdiction-grouped validation, followed by evaluation across different cities and winters, would assess transfer to new operating settings. Prospective applications would also require inputs available at the relevant decision time. A stage-

specific extension could update outcome probabilities as warning information, deployment status, and implementation records become available, connecting the current retrospective framework with operational assessment as an event unfolds.

6. Conclusions

The analysis distinguished initial traffic continuity, loss containment, and recovery in winter road operations. The estimated resource–recovery contrast was larger under low disturbance than under high disturbance. The recovery estimates also varied with prior and network specification.

In the adverse context, higher preventive deployment corresponded to higher estimated initial continuity, and higher response implementation corresponded to higher loss containment and recovery. Joint favorable conditions showed different increments across the three outcomes. These patterns support examining preparation and execution separately in post-event reviews.

The main empirical contribution is the joint analysis of five groups of variables and three service stages with a common probabilistic model. The sensitivity results show why recovery warrants particular attention to the choice of prior and recovery dependencies. The prediction comparison, in turn, identifies Moderate recovery as an especially difficult state to classify. Together, these results support phase-specific assessment and motivate follow-up measurements that distinguish warning receipt from actionability, early deployment from sustained work, and partial restoration from stable recovery.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/systems14111480/s1, Dataset S1: Data used to analyze road traffic system resilience under snow and ice warnings.

Author Contributions: Conceptualization, J.L., R.C. and Y.Y.; methodology, R.C. and Y.Y.; data curation, J.L. and R.C.; formal analysis, J.L. and R.C.; software, R.C. and Z.F.; validation, Z.F. and J.L.; investigation, Y.Y., R.C. and Z.F.; writing—original draft preparation, J.L., Y.Y., Z.F. and R.C.; writing—review and editing, J.L., Y.Y., Z.F. and R.C.; 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 National Key R&D Program of China (2024YFB2605300).

Informed Consent Statement: Informed consent was obtained from all participants included in the study.

Data Availability Statement: Supplementary Materials provide the coded analysis dataset and questionnaire.

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

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