



AI-Based Multi-Criteria Risk Assessment for Civil Infrastructure Under Extreme Environmental Hazards [†]

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Abstract

This study presents a proof-of-concept framework for multi-criteria assessment of civil-infrastructure risk under extreme environmental hazards. The framework combines fuzzy transformation, the Analytic Hierarchy Process (AHP), and a specified artificial intelligence (AI)-assisted weight-calibration module. It considers five dimensions: structural performance, environmental exposure, functional importance, emergency-response capacity, and maintenance condition. Quantitative indicators are normalized according to whether they increase or reduce risk, whereas qualitative indicators are converted using explicit fuzzy membership functions. The methodological contribution is a transparent separation between indicator processing, expert-derived AHP weighting, and optional data-driven calibration. The optional calibration module is specified to use projected gradient descent while maintaining non-negative, normalized weights. Because no historical outcome dataset or expert panel was available, the module was not trained or tested, and no improvement in predictive performance is claimed. The illustrative reinforced-concrete bridge calculation produced a Comprehensive Risk Index (CRI) of 0.686 (approximately 0.69), corresponding to the High Risk category. Sensitivity analysis showed that the High Risk classification remained unchanged when the two dominant dimension weights were varied by up to $\pm 30\%$ and the remaining weights were proportionally renormalized. The application is therefore presented as a reproducible proof of concept rather than an external demonstration. The framework can support future infrastructure maintenance prioritization and climate-resilience planning once it is calibrated and tested using independent asset data.

Keywords: AI-assisted calibration; bridge safety; extreme environmental hazards; infrastructure risk assessment; sustainability



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1. Introduction

Civil infrastructure systems underpin transportation, water supply, energy distribution, and emergency services. Climate change, rapid urbanization, and asset aging are increasing their exposure to floods, typhoons, extreme rainfall, heatwaves, landslides, and earthquakes. These hazards can cause direct damage, prolonged service disruption, and cascading socioeconomic losses. Climate-adaptation asset-management research therefore

emphasizes connecting hazard exposure, asset condition, service criticality, and intervention planning within a single risk-management process [1,2].

Infrastructure failures under extreme environmental conditions can also produce long-term environmental and social consequences and distribute risk inequitably. SDG 9 and SDG 13 call for resilient infrastructure and effective climate adaptation [3]. Accordingly, civil and environmental engineering requires risk-assessment methods that are transparent, reproducible, and capable of supporting defensible investment priorities [2,3].

Traditional infrastructure risk assessment relies heavily on expert judgment, deterministic safety factors, and historical experience [4–6]. Although these approaches remain useful, they have important limitations in complex multi-hazard settings. Expert evaluations can be subjective and difficult to reproduce; deterministic methods do not readily represent climate variability, interacting hazards, or system interdependencies; and single-domain assessments may overlook the combined influence of structural condition, environmental exposure, service criticality, emergency response, and maintenance. These limitations weaken the basis for risk-informed infrastructure management.

AI methods can support infrastructure assessment through data-driven pattern recognition, condition prediction, and decision support [7–9]. In parallel, multi-criteria decision-making (MCDM) methods such as AHP provide a structured means of evaluating alternatives against conflicting criteria. Recent applications demonstrate that MCDM can prioritize preventive actions in roadway projects [10] and evaluate interacting water-related hazards in complex mining transitions [11]. These studies support multi-dimensional criteria but also show that model transparency and uncertainty treatment remain essential.

Conventional AHP nevertheless depends on subjective pairwise comparisons, and inconsistent judgments can produce unstable weights. Fuzzy logic can represent linguistic assessments and imprecise boundaries [11,12]; for example, a recent drainage-infrastructure model integrated hydraulic performance, technical condition, and operational condition into actionable maintenance recommendations [13]. Entropy-weighted fuzzy comprehensive evaluation has likewise been used to reduce dependence on subjective weighting in safety-risk identification [14]. However, many studies still use AI, fuzzy logic, and MCDM as separate tools rather than as transparently separated components of an integrated framework.

Existing infrastructure-risk studies also tend to emphasize either structural condition or hazard exposure. Few studies combine physical condition, environmental stress, functional importance, emergency-response capacity, and maintenance quality in one quantitative model. Climate-adaptation asset risk management [1], fuzzy multi-criteria drainage assessment [13], preventive-measure prioritization [10], entropy-weighted fuzzy evaluation [14], and integrated disaster-risk-reduction/MCDM analysis [11] collectively indicate the value of combining heterogeneous evidence. However, a transferable framework that calibrates expert-derived weights against observed outcomes remains underdeveloped.

To address these gaps, this study develops a transparent proof-of-concept framework for assessing civil-infrastructure risk under extreme environmental hazards. It integrates five dimensions—structural performance, environmental exposure, functional importance, emergency-response capacity, and maintenance condition. Quantitative indicators are normalized according to risk direction, whereas qualitative indicators are mapped to numerical scores using defined fuzzy membership functions. AHP establishes initial weights; an optional AI-assisted module is specified only as a future calibration protocol for use when suitable historical outcomes are available.

The main contributions of this study are as follows:

- (1) A transparent fuzzy–AHP architecture that separates expert weighting from optional future data-driven calibration.

- (2) A complete indicator hierarchy that identifies data type, risk direction, and aggregation rules for structural, environmental, functional, emergency-response, and maintenance factors.
- (3) A reproducible CRI calculation and sensitivity procedure for comparing infrastructure risk under multi-hazard conditions.
- (4) An explicit statement of evidence scope: the bridge application demonstrates the calculation but does not constitute empirical validation.

An illustrative bridge case study demonstrates the computational procedure and evaluates sensitivity to weight changes. The example is not based on an expert survey or an independently demonstrated historical failure dataset. Accordingly, the results are interpreted only as proof of concept and as a basis for future empirical testing.

2. Materials and Methods

2.1. Framework Architecture

This study establishes a multi-criteria framework for assessing civil-infrastructure risks under extreme environmental hazards. The demonstrated procedure integrates fuzzy transformation and AHP, while a separate AI-assisted calibration protocol is specified for possible future use. It comprises four stages:

1. **Risk indicator system construction;**
2. **Data normalization and fuzzy transformation;**
3. **Optional AI-assisted weight calibration when suitable historical outcomes are available;**
4. **Comprehensive Risk Index (CRI) calculation.**

The objective is to transform heterogeneous quantitative and qualitative evidence into a consistent risk index that supports infrastructure management and resilience planning.

2.2. Risk Indicator System

Drawing on research on infrastructure safety, climate adaptation, disaster-risk reduction, and multi-criteria assessment [1,10,11,13,14], the framework considers five major risk dimensions:

1. **Structural Performance (SP):** Material degradation, structural integrity, load-bearing capacity, and damage accumulation.
2. **Environmental Exposure (EE):** Flooding intensity, seismic hazard level, extreme rainfall, and climate-induced stresses.
3. **Functional Importance (FI):** Traffic volume, service criticality, socioeconomic impact, and network connectivity.
4. **Emergency-Response Capacity (ER):** Accessibility, rescue efficiency, emergency preparedness, and response time.
5. **Maintenance Condition (MC):** Inspection frequency, maintenance quality, repair strategies, and management effectiveness.

Together, these dimensions represent the physical, environmental, functional, and managerial factors that shape infrastructure risk under extreme hazards. Their integration is consistent with recent frameworks that combine asset condition, hazard exposure, service consequences, and intervention priorities [1,10,11,13].

For reproducibility, Table 1 defines the complete indicator hierarchy used in the proof-of-concept application. The table distinguishes quantitative from qualitative inputs and identifies whether increasing values increase risk (cost-type) or decrease risk (benefit-type). In an operational deployment, agencies may replace these indicators only if the definition, unit, direction, and data source are documented.

Table 1. Complete indicator hierarchy, data type, and risk direction.

Dimension	Sub-Indicator	Data Type	Risk Direction
Structural performance (SP)	Strength/capacity loss	Quantitative	Increasing risk
	Maximum crack width	Quantitative	Increasing risk
	Reinforcement-corrosion severity	Qualitative	Increasing risk
	Observed damage condition	Qualitative	Increasing risk
Environmental exposure (EE)	Design flood depth or scour demand	Quantitative	Increasing risk
	Extreme-rainfall intensity	Quantitative	Increasing risk
	Peak ground acceleration	Quantitative	Increasing risk
	Thermal/moisture exposure class	Qualitative	Increasing risk
Functional importance (FI)	Average daily traffic	Quantitative	Increasing risk
	Detour length/time	Quantitative	Increasing risk
	Network criticality	Qualitative	Increasing risk
	Essential-service dependency	Qualitative	Increasing risk
Emergency response (ER)	Emergency response time	Quantitative	Increasing risk
	Emergency-route redundancy	Quantitative	Decreasing risk
	Emergency accessibility	Qualitative	Decreasing risk
	Preparedness level	Qualitative	Decreasing risk
Maintenance condition (MC)	Inspection interval	Quantitative	Increasing risk
	Preventive-maintenance coverage	Quantitative	Decreasing risk
	Maintenance quality	Qualitative	Decreasing risk
	Repair effectiveness	Qualitative	Decreasing risk

Within each dimension k , normalized sub-indicator values z_{kj} are aggregated as $D_k = \sum_j \alpha_{kj} z_{kj}$, where $\alpha_{kj} \geq 0$ and $\sum_j \alpha_{kj} = 1$. Equal sub-indicator weights ($\alpha_{kj} = 0.25$) are used in this proof-of-concept because no defensible empirical or expert-derived sub-indicator weights were available. The dimension weights are then applied to D_k in the CRI calculation.

2.3. Data Normalization and Fuzzy Transformation

To make heterogeneous indicators comparable, all inputs are converted to dimensionless risk-oriented values in $[0, 1]$. The two branches below ensure that a larger normalized value always represents greater risk. Values outside the documented calibration range are clipped to $[0, 1]$; the lower and upper bounds must be obtained from an engineering limit or a stated reference population.

2.3.1. Min–Max Normalization for Quantitative Indicators

For quantitative indicator i , risk-oriented min–max normalization is defined as:

$$z_i = \begin{cases} \frac{x_i - x_{\min,i}}{x_{\max,i} - x_{\min,i}}, & \text{increasing – risk indicator,} \\ \frac{x_{\max,i} - x_i}{x_{\max,i} - x_{\min,i}}, & \text{decreasing – risk indicator.} \end{cases}$$

where x_i is the observed value and $x_{\min,i}$ and $x_{\max,i}$ are the documented lower and upper reference bounds. If $x_{\max,i} = x_{\min,i}$, the indicator must be omitted or assigned using a prespecified engineering rule; division by zero is not permitted.

The decreasing-risk branch prevents beneficial attributes, such as emergency-route redundancy or preventive-maintenance coverage, from being incorrectly treated as risk-increasing variables.

2.3.2. Fuzzy Transformation for Qualitative Indicators

Qualitative indicators are rated on a five-level linguistic scale and mapped to triangular fuzzy numbers: Very Low = (0.00, 0.00, 0.25); Low = (0.00, 0.25, 0.50); Moderate = (0.25, 0.50, 0.75); High = (0.50, 0.75, 1.00); and Very High = (0.75, 1.00, 1.00). For an increasing-risk indicator, the label describes risk severity, and the defuzzified centroid c is used directly ($z = c$). For a decreasing-risk benefit-type indicator, the label describes attribute performance, and the risk-oriented value is reversed ($z = 1 - c$). Thus, Very Low preparedness or maintenance quality produces high risk, whereas Very High preparedness or maintenance quality produces low risk [13,14].

For a triangular fuzzy number $\tilde{A} = (l, m, u)$, the membership function is expressed as:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < l \\ \frac{x-l}{m-l}, & l \leq x \leq m \\ \frac{u-x}{u-m}, & m \leq x \leq u \\ 0, & x > u \end{cases}$$

Each triangular fuzzy number (l, m, u) is defuzzified using the centroid $c = (l + m + u)/3$. The centroids for Very Low, Low, Moderate, High, and Very High are 0.0833, 0.2500, 0.5000, 0.7500, and 0.9167, respectively. For the left-shoulder Very Low set ($l = m$) and right-shoulder Very High set ($m = u$), the zero-denominator branch of the general membership equation is omitted, and membership at the shared endpoint is defined as 1. The final risk-oriented value is clipped to $[0, 1]$ before aggregation.

2.4. AHP-Based Weight Determination

AHP is used to determine the relative importance of the risk indicators.

2.4.1. Construction of Pairwise Comparison Matrix

For each risk dimension, a pairwise comparison matrix $\mathbf{A} = [a_{ij}]$ is constructed:

$$\mathbf{A} = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ \frac{1}{a_{12}} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & \dots & 1 \end{bmatrix}$$

where a_{ij} denotes the importance of indicator i relative to indicator j , assessed using Saaty's 1–9 scale [4].

2.4.2. Weight Vector Estimation

The normalized row geometric-mean method is applied to estimate the weight vector $w = (w_1, w_2, \dots, w_n)$ [4]:

$$w_i = \frac{\left(\prod_{j=1}^n a_{ij}\right)^{1/n}}{\sum_{k=1}^n \left(\prod_{j=1}^n a_{kj}\right)^{1/n}}$$

2.4.3. Consistency Verification

The consistency of each judgment matrix is verified using the **Consistency Ratio (CR)**:

$$CR = \frac{CI}{RI}$$

where

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

where $\lambda_{\max}$ is the maximum eigenvalue of the matrix and RI is the random consistency index. A matrix is considered acceptably consistent when $CR < 0.10$.

2.4.4. Reproducibility and Expert-Elicitation Requirements

A full empirical AHP study should report the number and disciplines of experts, inclusion criteria, elicitation mode, individual pairwise matrices, aggregation method, row geometric means, normalized initial weights, $\lambda_{\max}$, Consistency Index, and Consistency Ratio for every matrix. No expert panel was convened for the present proof-of-concept application. The prescribed dimension weights (SP 0.30, EE 0.27, FI 0.18, ER 0.13, and MC 0.12) are scenario inputs rather than empirically elicited estimates. Therefore, no expert profile or empirical consistency statistic is claimed. The general AHP equations are retained to define how future applications should derive and verify initial weights.

2.5. Optional AI-Assisted Weight Calibration Protocol

The AI-assisted module is an optional future calibration protocol for applications with an asset-level historical dataset containing indicator vectors and observed continuous risk outcomes. It was neither trained nor evaluated in the present proof-of-concept study. This distinction avoids conflating a specified algorithm with an empirically demonstrated model.

For future empirical implementation, assets should be divided into mutually exclusive training, validation, and independent test sets (illustrative proportions: 60%, 20%, and 20%). With a continuous observed risk outcome, the single calibration objective is:

$$\min_{\mathbf{w} \in \Delta_5} \mathcal{L}(\mathbf{w}) = \frac{1}{N_{\text{train}}} \sum_{i \in \text{train}} \left[y_i - \sum_{k=1}^5 w_k D_{ik} \right]^2 + \lambda \|\mathbf{w} - \mathbf{w}^{(0)}\|_2^2, \quad \Delta_5 = \left\{ \mathbf{w} : w_k \geq 0, \sum_{k=1}^5 w_k = 1 \right\}.$$

Here, y_i is the observed outcome, D_{ik} is the normalized score of dimension k for asset i , $\mathbf{w}^{(0)}$ is the prescribed AHP weight vector, and $\lambda = 0.01$ is the default regularization coefficient. Calibration is performed only on the training set; the validation set is used for model selection, and the independent test set is reserved for final performance reporting.

Projected gradient descent is specified with a learning rate of 0.01, a maximum of 1000 iterations, and a stopping tolerance of 10^{-6} for the change in the single loss function above. Projection onto the probability simplex Δ_5 after each update guarantees non-negative weights that sum to one. These settings are reproducible defaults, not empirically optimized values. Future studies should report the dataset, random seed, missing-data treatment, final hyperparameters, convergence history, and independent test-set performance.

2.6. Comprehensive Risk Index Formulation

The overall infrastructure risk level is quantified using the **Comprehensive Risk Index (CRI)**:

$$CRI = \sum_{i=1}^n w_i \cdot x_i$$

where w_i is the prescribed weight of the i -th dimension, x_i (equivalently D_i in the dimension-level formulation) is its normalized risk-oriented score, and $n = 5$ in the present framework.

The CRI ranges from 0 to 1 and is classified into four levels:

- **Low Risk:** $CRI < 0.30$.
- **Moderate Risk:** $0.30 \leq CRI < 0.60$.
- **High Risk:** $0.60 \leq CRI < 0.80$.
- **Very High Risk:** $CRI \geq 0.80$.

2.7. Computational Procedure

The proposed framework is implemented using the following procedure:

1. Establish the multi-dimensional infrastructure risk indicator system.
2. Normalize quantitative indicators and fuzzify qualitative indicators.
3. Construct AHP pairwise comparison matrices and compute initial weights.
4. Perform CR consistency verification.
5. If suitable historical outcomes are available, optionally calibrate the dimension weights using the protocol in Section 2.5.
6. Compute the Comprehensive Risk Index (CRI).
7. Classify the infrastructure risk level and identify dominant risk contributors.

3. Results

3.1. Case Description

A medium-span reinforced-concrete bridge in a multi-hazard environment is used as an illustrative scenario. The assumed bridge carries more than 35,000 vehicles per day, has been in service for over 25 years, and exhibits cracking, reinforcement corrosion, and concrete spalling. These values are scenario inputs assembled to demonstrate the calculations; they are not presented as observations from a named bridge or as an independently audited inspection dataset.

The site is exposed to typhoon-induced rainfall, flooding, thermal stress, and moderate seismic activity. Dense surrounding development also constrains emergency access. Although routine inspections and maintenance have been performed, budgetary and operational limitations have restricted the intensity of intervention. The case therefore illustrates the combined influence of structural deterioration, hazard exposure, service importance, emergency-response constraints, and maintenance condition.

3.2. Baseline Risk Evaluation Results

The five dimension scores were not obtained from field measurements or model training. They are assumed, risk-oriented scenario inputs. Table 2 lists the four sub-indicator scores for each dimension in the same order as Table 1 and shows their equal-weight aggregation ($\alpha_{kj} = 0.25$). The prescribed dimension weights (SP 0.30, EE 0.27, FI 0.18, ER 0.13, and MC 0.12) sum to one and were not optimized by the untrained AI-assisted module.

Table 2. Assumed sub-indicator risk scores and equal-weight dimension calculations.

Dimension	Assumed Risk-Oriented Scores, in Table 1 Order	Equal-Weight Calculation	Dimension Score D_k
SP	0.82, 0.76, 0.80, 0.74	$(0.82 + 0.76 + 0.80 + 0.74)/4$	0.780
EE	0.78, 0.76, 0.72, 0.70	$(0.78 + 0.76 + 0.72 + 0.70)/4$	0.740
FI	0.70, 0.64, 0.68, 0.62	$(0.70 + 0.64 + 0.68 + 0.62)/4$	0.660
ER	0.58, 0.50, 0.48, 0.52	$(0.58 + 0.50 + 0.48 + 0.52)/4$	0.520
MC	0.60, 0.54, 0.52, 0.54	$(0.60 + 0.54 + 0.52 + 0.54)/4$	0.550

The prescribed dimension weights, weighted contributions, and baseline CRI are summarized in Table 3.

The CRI is calculated directly from the displayed values: $(0.78 \times 0.30) + (0.74 \times 0.27) + (0.66 \times 0.18) + (0.52 \times 0.13) + (0.55 \times 0.12) = 0.6862$. It is reported as 0.686 (approximately 0.69) and classified as High Risk under the thresholds in Section 2.6. Structural performance and environmental exposure make the largest weighted contributions in this illustrative scenario.

Table 3. Prescribed dimension weights and baseline CRI for the illustrative scenario.

Risk Dimension	Dimension Score D_k	Prescribed Weight	Weighted Contribution
Structural Performance (SP)	0.78	0.30	0.2340
Environmental Exposure (EE)	0.74	0.27	0.1998
Functional Importance (FI)	0.66	0.18	0.1188
Emergency Response (ER)	0.52	0.13	0.0676
Maintenance Condition (MC)	0.55	0.12	0.0660
Total CRI	—	—	0.6862 $\approx$ 0.69

3.3. Evidence Status and Scope of the Application

Table 4 separates the components demonstrated numerically from those that remain specified for future empirical validation.

Table 4. Evidence status of the framework components.

Framework Component	Evidence in This Study	Interpretation
Indicator processing and CRI AI-assisted calibration	Numerically demonstrated Algorithm specified; not trained	Reproducible proof of concept Requires historical outcome data

This proof-of-concept demonstrates indicator transformation, dimension aggregation, CRI calculation, risk classification, and sensitivity analysis. It does not demonstrate that AI calibration improves accuracy, stability, or generalizability. Those claims require a documented historical dataset, a clearly defined outcome, and independent test data.

Accordingly, the earlier claim of an 18–25% reduction in weight variance has been removed because this manuscript does not contain repeated assessments or the underlying calculations. Future evaluations should define stability as, for example, the mean coefficient of variation of criterion weights across repeated elicitation rounds or bootstrap samples, and should report the baseline value, calibrated value, sample size, and uncertainty interval.

3.4. Sensitivity Analysis

Sensitivity analysis varies one dominant weight at a time. If the target weight w_i is multiplied by factor f , the other weights are proportionally renormalized as $w_j' = w_j(1 - fw_i)/(1 - w_i)$, $j \neq i$, so that all weights remain non-negative and sum to one. Dimension scores are held fixed, and the CRI is recomputed as $\sum_k w_k' D_k$. Factors $f = 0.70, 0.80, 0.90, 1.00, 1.10, 1.20$, and 1.30 correspond to -30% through $+30\%$ perturbations.

The sensitivity calculations in Table 5 use the procedure stated above. Across the tested perturbations, the CRI remains within the High Risk category. This result shows local classification stability for the stated scenario and fixed dimension scores; it does not establish predictive reliability or robustness to measurement, model, or hazard uncertainty.

Table 5. Sensitivity of the CRI to one-at-a-time weight perturbations with proportional renormalization.

Weight Change	CRI (SP Adjusted)	CRI (EE Adjusted)
−30%	0.6741	0.6802
−20%	0.6782	0.6822
−10%	0.6822	0.6842
Baseline	0.6862	0.6862
+10%	0.6902	0.6882
+20%	0.6942	0.6902
+30%	0.6983	0.6922

4. Discussion

4.1. Interpretation of Dominant Risk Contributors

Structural performance (SP) and environmental exposure (EE) are the two largest contributors to the bridge's CRI of 0.69. This result reflects the interaction between asset aging and intensifying hazards. Material deterioration, including reinforcement corrosion, cracking, and concrete spalling, reduces structural capacity, while extreme rainfall, flooding, and thermal stress can accelerate deterioration and increase the likelihood of service disruption.

The importance of environmental exposure is consistent with climate-adaptation asset-management approaches that link hazard characterization, vulnerability, consequence, and treatment selection [1]. It also complements multi-criteria studies in drainage and water-related hazard management, which show that infrastructure condition and environmental loading should be evaluated jointly rather than in isolation [11,13].

The contribution of functional importance (FI) emphasizes that risk is not determined solely by the probability of physical failure. A bridge that carries high traffic volumes can generate substantial indirect losses and network disruption when its service is interrupted. This consequence-oriented interpretation is consistent with multi-criteria preventive-action frameworks for roadway infrastructure [10].

4.2. Scope of the Optional AI-Assisted Weight Calibration

The proof-of-concept calculation shows how prescribed dimension weights affect the CRI; it does not compare a trained AI-AHP model against conventional AHP. A valid comparison would require the same independently observed outcomes for both methods, predefined performance metrics, and a held-out test set. This manuscript therefore makes no claim that AI calibration lowers risk or improves predictive performance.

No repeated expert assessments or bootstrap samples were available to quantify weight stability. The unsupported 18–25% improvement claim has therefore been removed. Future work should report a clearly defined stability metric, the number of repetitions, baseline and calibrated values, and uncertainty intervals.

Conceptually, fuzzy logic and AI calibration address different sources of uncertainty. Fuzzy transformation represents imprecision in qualitative inputs [13,14], whereas data-driven calibration can update initial weights when reliable historical outcomes are available. In the present study, only the fuzzy transformation and CRI calculation are demonstrated; the calibration module remains a specified research protocol.

4.3. Sensitivity and Robustness of the Risk Model

The CRI remains in the High Risk category when the SP and EE weights are perturbed by up to $\pm 30\%$ using proportional renormalization. This finding is limited to the stated scenario, fixed dimension scores, and one-at-a-time weight changes.

The analysis demonstrates local classification stability but does not address uncertainty in indicator measurement, hazard projections, fuzzy parameters, correlations among hazards, or model structure. A global uncertainty analysis and independent asset data are required before operational decisions are based on the framework.

The results also show that structural performance remains the largest contributor while environmental exposure materially affects the overall risk. This finding supports the integration of climate-adaptation considerations into inspection, maintenance, and rehabilitation planning [1].

4.4. Engineering Implications for Bridge Management

The findings have several implications for bridge management. First, agencies should prioritize preventive maintenance and timely rehabilitation of deteriorated components.

Interventions addressing corrosion, fatigue cracking, drainage deficiencies, and material degradation can reduce both failure likelihood and lifecycle cost.

Second, the contribution of environmental exposure supports climate-adaptive measures such as flood-resilient foundations, improved drainage, scour protection, and materials suited to projected temperature and moisture conditions. Adaptation actions should be selected through a risk-based asset-management process that links projected hazards to asset criticality and feasible interventions [1].

Third, including emergency-response capacity highlights the need for coordination between infrastructure agencies and emergency-management authorities. Improved access planning, real-time monitoring, warning protocols, and response coordination can reduce consequences even when the hazard itself cannot be prevented. MCDM-based prioritization can help decision makers compare such preventive measures when cost, time, complexity, and expected effectiveness conflict [10].

4.5. Sustainability and Policy Implications

The framework supports SDG 9 and SDG 13 [3] by identifying the factors that most strongly influence infrastructure risk and by providing a quantitative basis for prioritizing maintenance, retrofitting, and adaptation investments.

Integrating structural, environmental, functional, emergency-response, and maintenance dimensions in a single index can strengthen infrastructure governance. The approach is consistent with the broader movement toward multi-criteria and resilience-based planning, in which heterogeneous evidence is synthesized into transparent intervention priorities [1,10,11,13,14].

Future data-driven calibration could incorporate sensor observations, inspection databases, remote sensing, and digital-twin outputs [8,9,15]. With appropriate empirical validation and data governance, these sources could support periodic or near-real-time updates to infrastructure risk estimates.

4.6. Limitations and Future Research Directions

This study is a proof-of-concept application rather than an empirical demonstration. It uses one illustrative bridge scenario, prescribed dimension weights, equal within-dimension sub-indicator weights, and no historical outcome dataset or expert panel. Consequently, the study cannot establish predictive accuracy, improved weight stability, transferability, or network-level effectiveness. The sensitivity analysis addresses only local weight perturbations and does not propagate all sources of uncertainty.

Future research should (1) elicit AHP judgments from a documented multidisciplinary expert panel; (2) compile asset-level indicator and outcome data; (3) train the calibration module using predefined settings and asset-level data splits; (4) compare calibrated and conventional models on an independent test set; (5) report discrimination, calibration, error, and stability metrics with uncertainty intervals; and (6) validate the framework across multiple assets, hazards, and regions.

5. Conclusions

This study developed a proof-of-concept framework that combines fuzzy indicator transformation, AHP weighting, and a specified AI-assisted calibration module for civil-infrastructure risk assessment under extreme environmental hazards. The revised method explicitly identifies indicator type and direction, defines fuzzy parameters and aggregation rules, and separates demonstrated calculations from components requiring future empirical evaluation.

The illustrative bridge scenario produced a CRI of 0.6862, reported as 0.686 (approximately 0.69), and therefore a High Risk classification. Structural performance and environmental exposure made the largest weighted contributions. The arithmetic and classification are consistent with the values displayed in Table 3.

The AI-assisted calibration algorithm is specified using projected gradient descent and simplex constraints, but it was not trained because no historical outcome dataset was available. Accordingly, no improvement in weight stability or predictive performance is claimed. The one-at-a-time sensitivity analysis showed that the scenario remained in the High Risk category under $\pm 30\%$ perturbations of the two dominant weights.

For engineering practice, the framework provides a transparent basis for comparing maintenance, rehabilitation, and disaster-mitigation priorities. The results emphasize preventive treatment of structural deterioration and explicit consideration of climate-related exposure in bridge inspection and adaptation planning.

From a policy perspective, the framework supports SDG 9 and SDG 13 [3] by connecting risk evidence to resilience-oriented investment decisions. Its multi-dimensional structure can help agencies explain why particular assets or interventions receive priority under constrained budgets.

The principal limitations are the illustrative single-asset scenario, prescribed weights, absence of an expert panel and historical outcome dataset, and incomplete uncertainty propagation. Independent multi-asset demonstration is required before the framework can be used for predictive or operational decision-making.

In summary, this framework provides a transparent and reproducible computational structure for future empirical investigation. Its present contribution is methodological and proof-of-concept; its predictive performance and practical reliability remain to be established using documented expert judgments and independent infrastructure data.

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