Developing an Integrated Climate Disaster Risk Framework for Critical Infrastructure Resilience Planning

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ABSTRACT

Climate change and the increasing frequency of natural hazards pose growing challenges to the resilience of critical infrastructure. However, climate and disaster risks are often assessed in isolation, limiting their effectiveness for infrastructure planning and constraining the ability to capture risk interactions, cascading effects, and spatial variability across interconnected systems. This study aimed to develop an integrated risk analysis model that simultaneously incorporates climate change and disaster risks to support critical infrastructure resilience planning. A mixed-methods approach was applied using a case study in Masbagik and Pringgasela Districts, East Lombok Regency, Indonesia. The analysis combined risk matrix assessment, GIS-based exposure analysis, and multi-criteria decision analysis (MCDA) using climate data, disaster records, spatial datasets, and inventories of five critical infrastructure sectors. The results showed integrated risk index values ranging from 0.67 to 0.83, with water supply, drainage, and road infrastructure consistently identified as the most critical systems. Scenario-based mitigation simulations indicated potential risk reductions of up to 40% at the district level, while integrated assessment reduced estimated annual losses by approximately 34% compared to separated analyses. However, the framework is constrained by data availability and does not fully capture long-term adaptive dynamics. The findings demonstrate that climate and disaster risks interact through reinforcing, cascading, and cumulative mechanisms, significantly shaping infrastructure vulnerability. The study contributes an interaction-based risk framework that extends conventional additive risk models into a system-level analytical approach, providing a spatially explicit decision-support tool for resilient and sustainable infrastructure planning.

Keywords: Climate–disaster risk, Critical infrastructure, Infrastructure resilience, Integrated risk analysis.

1. INTRODUCTION

Climate change and natural hazards are fundamentally reshaping global infrastructure risk profiles, impacting economic and social stability. Empirical evidence shows that climate-driven flooding increasingly disrupts transport networks, where losses in road connectivity propagate systemic impacts on urban mobility and regional economies [1]. At the same time, persistent post-disaster infrastructure damage across diverse national contexts indicates that conventional reconstruction practices remain insufficient to ensure long-term resilience under intensifying hazards [2]. Structural failures of bridges subjected to combined flood and seismic actions further demonstrate how multi-hazard interactions can amplify disruptions across transport systems, generating disproportionate socio-economic losses [3]. Comparable vulnerabilities are observed in power systems, where climate-related hazards expose the limitations of single-hazard fragility models [4]. Moreover, cascading failures across interdependent infrastructure systems, together with evolving human mobility responses during disasters, highlight the need for system-level perspectives that move beyond asset-based risk assessments [5], [6], particularly as sustainable and green infrastructure gains prominence in enhancing urban resilience under compound global stresses [7].

Infrastructure failures from combined climate hazards and disasters pose profound risks to public safety and development. Globally, the growing intensity and frequency of extreme events have revealed how localized infrastructure damage can rapidly trigger cascading failures across interconnected systems, disrupting essential services such as transportation, electricity, water supply, and sanitation [5], [8]. Evidence from large-scale hydrometeorological disasters indicates that damage to roads and bridges can destabilize traffic networks and obstruct emergency access at regional scales, thereby amplifying social vulnerability [9]. At the asset level, non-linear hydraulic responses of bridges under extreme flooding conditions critically influence transport system reliability, often exceeding expectations derived from linear damage assumptions [10]. Furthermore, compound climate events, such as heatwaves coinciding with power outages, expose escalating cross-sector risks with severe implications for urban health and safety, underscoring the societal consequences of infrastructure interdependence under climate stress [11].

Developing regions face fragmented risk assessments that neglect these coupled climate-disaster effects. Empirical studies on transport networks show that flood-induced disruptions are often assessed through isolated indicators of road connectivity, in which inundation depth and network topology explain losses in robustness but remain disconnected from cross-sectoral impacts and longer-term urban dynamics [1]. Although planning quality and policy integration have been empirically linked to improved preparedness, such dimensions are rarely operationalized alongside quantitative risk models, resulting in limited consistency between analytical outputs and planning instruments [12]. Conventional urban risk models further struggle to incorporate rapid urban growth as a driver of future exposure, frequently treating socio-spatial change as static despite its proven influence on evolving risk trajectories [13]. Meanwhile, evidence from utility systems demonstrates that service disruption, rather than asset damage, better reflects real impacts on households, yet this perspective remains weakly embedded in infrastructure planning workflows [8]. Persisting methodological and operational gaps thus risk reinforcing misaligned investments and undermining long-term resilience under compound climate–disaster pressures [11].

Previous studies establish a valuable but fragmented scientific foundation. Network-based analyses of transport systems consistently demonstrate that flood impacts on road connectivity depend more on topological position than on the extent of physical damage, highlighting systemic vulnerability within infrastructure networks [1], [14]. In parallel, indicator-based urban risk studies show that risk levels emerge from the interaction between asset exposure and social vulnerability, offering valuable planning insights but often relying on simplified aggregation schemes that obscure system dynamics [15]. Other strands emphasize institutional dimensions, indicating that integrated planning frameworks correlate with improved preparedness, although such approaches remain weakly coupled with quantitative risk metrics [12]. More recent multi-network and system-of-systems models advance the field by capturing cascading failures and service disruptions across sectors. Yet, their data-intensive nature and modeling assumptions constrain their transferability [5], [8]. Studies on compound events and interconnected energy systems further reveal non-linear risk amplification under climate extremes, underscoring persistent limitations of single-hazard models [11], [16]. This context highlights the need for frameworks combining spatial, systemic, and multi-criteria decision perspectives.

A critical conceptual limitation remains unaddressed: existing frameworks view risk as an additive outcome of hazard, exposure, and vulnerability, rather than a dynamic process of cross-system interactions. Consequently, prevailing models fail to explain how interacting risks reconfigure system vulnerability, alter dependencies, and cause emergent failure patterns. This gap limits current capabilities to capture the mechanisms through which climate-disaster interactions propagate within infrastructure networks at local and regional planning scales.

Literature continues to struggle with capturing the integrated nature of infrastructure risks. Operational resilience frameworks have enhanced conceptual understanding, yet their quantitative operationalization for simultaneously addressing climate and disaster risks across infrastructure types remains unclear [17]. Hierarchical decision-making and stochastic resilience models demonstrate theoretical promise but struggle to accommodate long-term climate uncertainty and multi-hazard interactions in ways applicable to cross-sector planning [18], [19]. Emerging tools such as digital twins provide real-time operational insights, though their integration with system-wide climate–disaster risk analysis remains underdeveloped [20]. Likewise, advances in green–grey infrastructure synergies, social equity integration, dynamic recovery control, and economic loss modeling highlight critical resilience dimensions but remain fragmented within a unified analytical framework [21], [22], [23].

Unlike standard management frameworks (such as ISO 31000, ISO 55000, and PMBOK), the proposed framework explicitly captures interaction-driven risk dynamics across interconnected infrastructure systems. This unifies spatial exposure, multi-hazard interactions, and system-level vulnerability within a single structure. Accordingly, this study aims to develop an integrated climate–disaster risk analysis framework that systematically captures risk interactions, system-level vulnerability, and spatial differentiation to support infrastructure resilience planning at regional and local scales.

Theoretically, this study advances Infrastructure Resilience Theory by treating vulnerability as an emergent property of interacting cross-system risks. It enhances Integrated Risk Management by operationalizing risk as an interaction-driven process combining risk matrices, spatial analysis, and multi-criteria decision-making. Finally, it strengthens Sustainable Infrastructure Planning by embedding system-level risk interactions into actionable, planning-oriented prioritization tools.

2. METHODS

This study adopts a mixed-methods research design combining climate and disaster risk for critical infrastructure resilience planning. The approach integrates quantitative spatial analytical techniques with structured decision-support methods to ensure analytical rigor and planning relevance. The overall workflow consists of six sequential stages: (1) identification of infrastructure systems and hazards; (2) data acquisition and pre-processing; (3) hazard, exposure, and vulnerability assessment using a risk matrix; (4) spatial risk characterization via GIS; (5) prioritization using Multi-Criteria Decision Analysis (MCDA); and (6) synthesis into an Integrated Climate Disaster Risk Framework. Each stage is explicitly linked, allowing feedback and iterative refinement for consistency and replicability.

The study focuses on essential sectors: water supply, transportation, electricity, drainage, and health facilities. The empirical application is conducted in Masbagik District, East Lombok Regency, Indonesia, a region characterized by rapid urbanization, climate-sensitive livelihoods, and recurrent hydrometeorological hazards. The area was selected for its coexisting flood, drought, and extreme rainfall risks, alongside diverse urban and peri-urban infrastructure typologies. Spatial boundaries were defined at the district level to align with local planning instruments, data availability, policy relevance, and operational feasibility.

A standardized ordinal scale (1–5) ensured consistency in scoring likelihood and consequence across infrastructure categories. Risk scores were assigned based on historical hazard records, regional climate projections, and expert judgment involving local practitioners and planners. This approach ensures that both empirical evidence and contextual expertise are systematically incorporated into the risk assessment process.

The analysis employed computational and field-support equipment rather than material laboratory testing. Spatial analysis was conducted using standard GIS platforms (ArcGIS/QGIS) with raster and vector capabilities. High-performance desktop computers (Intel i7, 16–32 GB RAM, dedicated GPUs) handled spatial overlays and multi-layer risk modeling. Field data collection utilized handheld GPS devices with sub-meter accuracy for asset geolocation and verification, while standard office software was used for database management, MCDA computation, and documentation.

A purposive sampling strategy was applied to select infrastructure assets based on functional importance, service coverage, and emergency response roles. Primary data were collected via structured field surveys to verify asset locations, conditions, and operational features. Secondary data sources included climate projections, disaster records, topographic maps, land-use data, and institutional infrastructure inventories. Climate and disaster variables (e.g., rainfall intensity, drought indices, flood extent) were derived from regional datasets and standardized to a common spatial reference system and temporal scale before analysis.

Following a structured analytical protocol instead of laboratory experiments, hazards were first classified into climate-related (extreme rainfall, drought) and disaster-related (flooding) categories. Second, exposure was quantified based on the spatial overlap between assets and hazard-prone areas. Third, vulnerability indicators were defined for each infrastructure type, incorporating physical condition, redundancy, and service dependency. These components were then combined using a risk matrix where likelihood and consequence levels were systematically scored on ordinal scales.

The risk matrix served as the initial analytical layer, translating hazard likelihood and impact severity into semi-quantitative risk categories based on historical data, climate projections, and expert judgment. GIS analysis was then applied to spatially visualize and refine these estimates through overlay, buffering, and proximity analysis, intersecting hazard maps, exposure layers, and asset locations into spatial risk indices. Subsequently, MCDA prioritized infrastructure systems and mitigation actions using criteria like risk level, criticality, population served, recovery importance, and intervention feasibility. Criteria weights were determined through expert judgment and normalized, involving X experts from civil engineering, infrastructure planning, and disaster risk management. Weighting consistency was verified using a consistency ratio approach, and a weighted linear combination approach computed composite priority scores for transparent asset ranking.

The Integrated Risk Index (IRI) was calculated as:

$$IRI = {}^{(HxExV)}\!\big/_{max(HxExV)}$$

where H represents hazard likelihood, E represents exposure, and V represents vulnerability. All variables were normalized to ensure comparability across infrastructure categories. This formulation enables risk to be represented as an interaction-driven measure rather than a simple additive construct.

Model calibration was conducted through iterative adjustment of risk matrix thresholds and MCDA weights to ensure alignment with observed conditions and expert expectations—validation involved cross-checking analytical results against historical disaster impacts and documented service disruptions. Sensitivity testing was performed by varying key parameters, such as hazard likelihood scores and criteria weights, to evaluate the robustness of prioritization outcomes. Consistency between spatial risk patterns and known high-impact areas was used as an additional validation measure.

Descriptive statistical analysis summarized risk scores, spatial distributions, and priority rankings. Uncertainty was addressed through scenario-based analysis testing alternative hazard intensities and weighting schemes, while potential error sources—such as spatial data resolution mismatches and subjective MCDA weighting—were documented. Error propagation was minimized through data normalization, consistency checks, and transparent assumptions. Relying on secondary data and non-intrusive field observations, data collection focused on infrastructure condition, hazard exposure, and service dependency without gathering personal or sensitive individual data. Institutional data adhered to data-sharing agreements, and the research strictly followed ethical principles of transparency, accountability, and responsible data use.

Despite its integrative design, the methodology has limitations. Reliance on available spatial and climate data may constrain resolution and accuracy in data-scarce contexts, and expert judgment introduces subjectivity to MCDA weighting despite mitigation through sensitivity analysis. Furthermore, the framework emphasizes current and near-future risks, potentially overlooking long-term socio-economic transformations. Nevertheless, it provides a replicable, systematic approach for integrating climate and disaster risks into infrastructure resilience planning, offering a robust foundation for future application in other regions.

3. RESULTS AND DISCUSSION

This section presents the empirical results of the integrated climate and disaster risk analysis conducted for critical infrastructure systems in Masbagik and Pringgasela Districts, East Lombok Regency. The results follow the sequential analytical workflow, beginning with integrated risk characterization, spatial differentiation, infrastructure vulnerability ranking, mitigation performance, and model robustness. All findings were derived from the combined application of the risk matrix, GIS-based exposure analysis, and multi-criteria decision analysis (MCDA). The study covered five categories of critical infrastructure: water supply, the main road network, electricity network, drainage infrastructure, and health facilities. For each category, an integrated risk index was calculated by aggregating hazard likelihood, spatial exposure, and vulnerability scores. The resulting index ranged from 0.67 to 0.83 across infrastructure types and districts, indicating moderate to very high levels of integrated climate–disaster risk within the study area. These values suggest that infrastructure risk is not uniformly distributed, but varies systematically across sectors and spatial contexts, reflecting differences in system function, exposure, and vulnerability configurations.

Table 1. Integrated Climate–Disaster Risk Indices for Critical Infrastructure

No.	Critical Infrastructure Type	Dominant Climate Risk	Dominant Disaster Risk	Climate Risk Index	Disaster Risk Index	Integrated Risk Index*	Risk Level	Key Findings
1	Water Supply Infrastructure	Drought, extreme rainfall	Flooding, landslides	0.79	0.83	**0.81**	Very High	Water distribution systems are highly vulnerable to climate variability and structural failure during disaster events.
2	Main Road Network	Extreme rainfall, high temperature	Flooding, landslides	0.72	0.76	**0.74**	High	Pavement deterioration increases due to the combined effects of extreme rainfall and traffic loading.
3	Electricity Network	Heatwaves	Flooding, earthquakes	0.68	0.71	**0.70**	High	Energy supply disruptions intensify during extreme climate events.
4	Drainage Infrastructure	Extreme rainfall	Urban flooding	0.75	0.78	**0.76**	High	Drainage capacity is insufficient to accommodate increased rainfall intensity under climate change.
5	Health Facilities	Heatwaves	Earthquakes, flooding	0.65	0.69	**0.67**	Moderate–High	Emergency service continuity is at risk during multi-hazard events.

Table 1 summarizes the integrated risk indices for all infrastructure categories at both the study-area and district levels. Water supply infrastructure recorded the highest average integrated risk index (0.81), followed by drainage infrastructure (0.76) and the main road network (0.74). Electricity infrastructure and health facilities exhibited lower but still substantial indices of 0.70 and 0.67, respectively. At the district scale, Masbagik consistently showed higher integrated risk values than Pringgasela across all infrastructure categories, with differences ranging from 0.02 to 0.04. The most pronounced inter-district contrast was observed for water supply infrastructure, indicating a stronger convergence of hazard exposure and vulnerability in Masbagik. Conceptually, this pattern suggests that integrated risk emerges from the compounding alignment of multiple risk dimensions within specific spatial contexts rather than from a single dominant factor.

GIS-based spatial analysis revealed distinct exposure patterns across infrastructure types and districts. In Masbagik, high-risk zones for water supply and drainage infrastructure were concentrated in densely populated areas and market centers, while in Pringgasela, elevated risk levels for road infrastructure were associated with hilly terrain and agricultural access corridors. Electricity infrastructure risk was spatially dispersed, with localized concentrations in low-lying areas across both districts. Health facilities exhibited moderate spatial clustering, primarily influenced by proximity to flood-prone zones. The consistency between mapped exposure patterns and numerical risk indices confirms that the integrated index captures spatially differentiated risk configurations rather than producing abstract, location-independent scores.

A comparative analysis of infrastructure vulnerability rankings further highlighted systematic differences between districts. As shown in Table 3, water supply infrastructure in Masbagik ranked as the most vulnerable system, followed by drainage infrastructure. In contrast, in Pringgasela, the main road network had the highest vulnerability score. Electricity infrastructure displayed similar vulnerability levels across districts. The clustering of high vulnerability scores above 0.75 for top-ranked infrastructure indicates that vulnerability is structurally embedded in the functioning of key systems and their service dependencies. These vulnerability rankings provide a direct basis for prioritizing infrastructure investments, enabling planners to allocate resources to systems with the highest combined exposure and vulnerability.

Table 2. Climate–Disaster Risk Interaction Patterns and Their Implications for Infrastructure Resilience

Risk Interaction Pattern	Description	Impacts on Infrastructure	Resilience Implications
Reinforcing Risks	Climate change increases the frequency and intensity of disaster events	Increased structural and functional failures of infrastructure systems	Requires adaptive and flexible infrastructure design
Cascading Risks	Disruption in one infrastructure system triggers failures in interconnected systems.	Domino effects across public service networks	Integrated system-based resilience approaches are required
Cumulative Risks	Repeated exposure to extreme climate conditions and disaster events over time	Progressive reduction in infrastructure service life and performance	Life-cycle–based planning and maintenance strategies are necessary

Table 3. Most Critical and Vulnerable Infrastructure Systems

Rank	Infrastructure Type	Vulnerability Score (MCDA)	Dominant Vulnerability Factors	Priority Category
1	Water Supply Infrastructure	0.86	Climate dependency and extensive service coverage	Highest Priority

2	Drainage Infrastructure	0.82	Direct exposure to extreme rainfall	High Priority
3	Main Road Network	0.79	Multi-hazard exposure	High Priority
4	Electricity Network	0.74	Sensitivity to heatwaves and flooding	Medium Priority
5	Health Facilities	0.71	Emergency service disruption risk	Medium Priority

The interaction between climate and disaster risks was examined by classifying interaction patterns (Table 2). Three dominant interaction types were identified: reinforcing, cascading, and cumulative interactions. Reinforcing interactions were observed when repeated climate extremes coincided with disaster events, resulting in elevated integrated risk scores. Cascading effects emerged through service dependencies, where disruption in one infrastructure category corresponded with increased risk in dependent systems. Cumulative impacts were reflected in infrastructure categories with repeated exposure histories, resulting in higher vulnerability scores and reduced service-life indicators. These patterns indicate that integrated risk is shaped by temporal and functional interdependencies rather than by isolated hazard events.

Table 4. Mitigation Priorities and Estimated Risk Reduction by District

Infrastructure Type	Local Mitigation Strategies	Mitigation Type	Estimated Risk Reduction — Masbagik	Estimated Risk Reduction — Pringgasela
Water Supply Infrastructure	Source diversification (deep wells and watershed conservation), pipeline network rehabilitation, mini reservoirs	Structural & Non-structural	**40%**	**34%**
Drainage Infrastructure	Increased capacity of market drainage channels and green infrastructure (infiltration systems)	Structural & Nature-based	**37%**	**30%**
Main Road Network	Slope geotechnical reinforcement, road drainage systems, and alternative evacuation routes	Structural	**30%**	**36%**
Electricity Network	Elevation of equipment, system redundancy, and surge protection	Non-structural	**28%**	**30%**
Health Facilities	Hybrid-fuel backup generators and alternative service locations	Non-structural	**25%**	**29%**

Table 5. Impact of Integrated Risk Assessment on Potential Economic Losses

Assessment Approach	Estimated Annual Loss Reduction — Masbagik	Estimated Annual Loss Reduction — Pringgasela
Separate Risk Analysis	Baseline (0%)	Baseline (0%)
Integrated Risk Analysis	Reduced by ~36%	Reduced by ~32%
Study-area Average (combined)	Reduced by ~34%	—

The prioritized mitigation results derived from MCDA are presented in Table 4. Scenario-based simulations showed that water supply and drainage infrastructure in Masbagik and road infrastructure in Pringgasela achieved the highest relative reductions in integrated risk. Electricity and health facilities exhibited lower but consistent reductions across districts. These variations indicate that mitigation effectiveness differs across infrastructure types, reflecting differences in adaptability and system constraints. Importantly, mitigation outcomes were evaluated against integrated risk indices, enabling direct comparison of intervention performance across sectors. The mitigation results can be translated into phased infrastructure programs, supporting planning decisions on budgeting, scheduling, and system upgrades.

The aggregated impact of integrated risk analysis on potential economic losses is summarized in Table 5. Under baseline conditions, with separate climate and disaster risk assessments, no reduction in estimated annual losses was observed. In contrast, the integrated risk framework yielded substantial decreases at both the district and study-area levels. The estimated risk and loss reductions were derived from scenario-based simulations within the integrated framework, where mitigation measures were modeled as reductions in exposure and vulnerability parameters. These simulations were calibrated using historical disruption data and validated against observed trends in infrastructure performance. This outcome suggests that integrated assessment enables the identification of intervention strategies that remain obscured under fragmented analytical approaches.

Model validation results demonstrated strong correspondence between modeled high-risk zones and historical records of infrastructure disruption, with spatial congruence exceeding 80% across infrastructure categories. Sensitivity analysis further indicated that integrated risk rankings remained stable across moderate variations in hazard likelihood and MCDA weights. Together, these results suggest that the framework produces robust and reliable outputs suitable for planning-oriented applications. Overall, the results demonstrate that integrated climate–disaster risk levels for critical infrastructure in Masbagik and Pringgasela are consistently high, spatially differentiated, and shaped by interacting risk processes. These findings provide a comprehensive empirical basis for examining how integrated risk manifests across infrastructure systems and districts.

Building on these results, the discussion interprets how the observed patterns advance understanding of system-level vulnerability in critical infrastructure. By integrating climate hazards, disaster processes, and infrastructure vulnerability within a single analytical framework, the study demonstrates that infrastructure risk cannot be adequately represented through additive or sectoral approaches. Instead, risk emerges as a process driven by interactions across hazards, systems, and spatial contexts.

The identification of reinforcing, cascading, and cumulative interaction patterns represents a central contribution of this study. While these patterns were observed empirically in Masbagik and Pringgasela, they can be interpreted as generic mechanisms of systemic risk formation in interdependent infrastructure networks rather than as context-specific anomalies. Reinforcing interactions occur when climate variability intensifies the impacts of disaster events, consistent with compound-risk mechanisms reported by Stone et al. [11]. Cascading interactions reflect functional dependencies across infrastructure systems, aligning with system-of-systems perspectives articulated by Mühlhofer et al. [5]. Cumulative interactions capture the progressive degradation of infrastructure performance under repeated stress, as discussed by Chester et al. [2]. Together, these mechanisms provide a coherent conceptual framework for understanding how integrated risk evolves over time and across interconnected systems.

The integrated risk index developed in this study represents more than a composite metric; it operationalizes a conceptual shift from additive to interaction-driven risk assessment. Unlike conventional indices that aggregate hazard, exposure, and vulnerability as independent components, the integrated index captures how these dimensions align and reinforce each other spatially and functionally. This reconceptualization advances Infrastructure Resilience Theory by framing vulnerability as an emergent system property shaped by interacting risks rather than as a static attribute of individual assets. The spatial differentiation observed between Masbagik and Pringgasela further illustrates the importance of context in shaping system-level vulnerability. Similar infrastructure categories exhibited different risk rankings across districts despite exposure to comparable hazard types. This finding extends previous work by Tachaudomdach et al. [1], who emphasized the role of network topology, by demonstrating that spatial configuration interacts with climate and disaster processes to reconfigure system vulnerability. Consequently, resilience planning cannot rely on uniform design standards or generic risk rankings, but must account for localized interaction structures.

Mitigation prioritization results highlight the practical value of integrated risk analysis for decision-making. The observed differences in mitigation effectiveness across infrastructure types indicate that resilience interventions must be tailored to system characteristics and interaction mechanisms. This finding aligns with Integrated Risk Management principles by linking risk identification directly to prioritization rather than treating mitigation as a separate planning stage. Compared with scenario-based optimization studies such as Liu et al. [18], the present framework provides a more transparent pathway from risk assessment to planning decisions by embedding mitigation within the same analytical structure. From a construction management perspective, the identified mitigation priorities can be translated into actionable programs, including phased infrastructure upgrades, cost allocation strategies, and risk-informed scheduling. For instance, high-risk infrastructure systems can be prioritized in capital investment planning, while medium-risk systems can be incorporated into maintenance and rehabilitation programs. The reduction in estimated economic losses further underscores the conceptual significance of integration. As shown by Dulin et al. [21], neglecting cascading effects leads to an underestimation of losses. By explicitly linking loss reduction to integrated risk indices, this study demonstrates that interaction-aware assessment enables more effective resource allocation, thereby strengthening Sustainable Infrastructure Planning.

The robustness of the framework, as evidenced by validation and sensitivity analysis, supports its applicability beyond the immediate case study. Generalization should be understood in theoretical rather than deterministic terms. While specific risk values are context-dependent, the mechanisms of interaction, the formation of system-level vulnerability, and the prioritization logic are transferable to other regional infrastructure systems with comparable interdependencies. Several limitations remain. The framework focuses on present and near-term risk conditions and does not explicitly model long-term socio-economic adaptation or behavioral change, as noted by Yabe et al. [6]. In addition, data availability may constrain application in regions with limited spatial or climate records. These limitations indicate that the framework should be extended through dynamic modeling and the use of broader datasets in future research.

In synthesis, this study contributes to civil engineering and infrastructure resilience research in three distinct ways. Conceptually, it reframes infrastructure risk as an interaction-driven process shaped by reinforcing, cascading, and cumulative mechanisms. Methodologically, it provides an operational framework that integrates risk matrix analysis, GIS-based exposure modeling, and MCDA within a coherent structure. Practically, it demonstrates how integrated risk assessment can support targeted mitigation and reduce potential losses. Together, these contributions advance the theoretical and practical foundations of integrated climate–disaster risk analysis for critical infrastructure resilience planning.

4. CONCLUSIONS

This study successfully developed an integrated risk analysis model incorporating climate change and disaster risks into critical infrastructure resilience planning, demonstrating that infrastructure risk arises from the interaction of hazard likelihood, spatial exposure, and systemic vulnerability rather than isolated assets. Scientifically, the study advances Infrastructure Resilience Theory, Integrated Risk Management, and Sustainable Infrastructure Planning by proving that integrated assessments produce more stable, spatially coherent, and reproducible risk characterizations than conventional, separated approaches. Methodologically, it establishes a replicable mixed-methods framework combining risk matrices, GIS-based exposure analysis, and MCDA within a unified workflow. Practically, these findings provide actionable implications for civil engineering and infrastructure planning, directly linking risk indices and spatial planning instruments to local government tools like engineering design documents (DED), cost estimations (BOQ), and budgeting frameworks without requiring significant additional resources. Future research should focus on integrating cost-benefit analysis, piloting the framework in real projects, and embedding it into digital planning systems.

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