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Natural Hazards, Critical Infrastructure Systems, and Resilience Enhancement: A Structured State-of-the-Art Review and a Synthesis-Based Rapid Assessment Framework

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Abstract: Critical infrastructure systems (CISs) are increasingly exposed to natural hazards whose impacts are amplified by infrastructure interdependence, urban complexity, and the growing prevalence of compound and cascading events. Existing research provides valuable insights into individual hazards, infrastructure components, modelling methods, and resilience metrics, but these insights remain difficult to translate into preliminary decision support because they are organized across different hazard types, sectors, analytical scales, and decision contexts. This article presents a structured state-of-the-art review of natural hazards, CIS impacts, and resilience enhancement. A two-pathway review strategy was adopted. A Web of Science core search was used to characterize the bibliometric landscape and identify WoS-sourced core synthesis studies, while a targeted anchor-search pathway was used to verify foundational concepts, hazard mechanisms, methodological approaches, resilience frameworks, and authoritative institutional sources. The review clarifies the conceptual distinction among dependencies, interdependencies, compound hazards, cascading failures, service disruption, and resilience; synthesizes cross-hazard infrastructure impact mechanisms; compares major method families for hazard-impact and resilience assessment; and develops a synthesis-derived rapid resilience assessment framework for preliminary screening and prioritization under constrained data and time conditions. The synthesis indicates that future CIS resilience assessment would benefit from moving beyond isolated asset-damage analysis toward integrated workflows that link hazard loading, component vulnerability, network functionality, service consequences, recovery capacity, uncertainty, and feasible intervention choices. The article contributes a more transparent evidence-source structure, an evidence-to-decision bridge, and a bounded decision-oriented framework for organizing future research and practical resilience screening.

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1. Introduction

1.1 Background

Critical infrastructure systems (CISs) support the continuous provision of essential services and are fundamental to public safety, economic activity, emergency response, and social continuity. In urban and regional settings, electric power, water and wastewater, transportation, and communication and information and communication technology (ICT) systems are closely coupled through physical, cyber, geographic, organizational, and functional links. Damage or operational degradation in one system can therefore affect not only the directly exposed assets, but also dependent services, emergency access, repair logistics, and community functionality (Field et al. 2012).

Natural hazards remain a major source of risk to CISs (IPCC 2021; IPCC 2023). Earthquakes, floods, storm surges, hurricanes, typhoons, tsunamis, landslides, heatwaves, wildfires, and snow- and ice-related extremes can damage infrastructure components, disrupt network connectivity, reduce service capacity, and delay restoration. These impacts are increasingly difficult to interpret through single-hazard or single-asset perspectives because hazard drivers, infrastructure dependencies, urban exposure, and social service demands interact across spatial and temporal scales (Kossin et al. 2020; Schotten et al. 2024; Wells et al. 2022).

In this review, resilience is treated as an analytical construct for evaluating how CISs withstand, absorb, recover from, and adapt to disruptive hazard events. This framing moves the discussion from damage description alone toward service continuity, recovery trajectories, cross-sector dependencies, and decision support for prioritizing mitigation and restoration actions under uncertainty.

1.2 Critical infrastructure, dependencies, interdependencies, and cascading processes

A defining characteristic of CISs is that they operate through multiple forms of dependency and interdependency. A dependency is a directional relation in which the operation of one infrastructure relies on another infrastructure, resource, or service. An interdependency is a coupled relation in which two or more infrastructures mutually influence performance or recovery. This distinction is analytically important because it affects how disruptions propagate, how restoration actions are prioritized, and how system-level resilience is interpreted (Rinaldi et al. 2001; Duenas-Osorio and Vemuru 2009; Ouyang 2014).

Infrastructure interdependencies are a source of both operational efficiency and systemic vulnerability. Under routine conditions, they support coordinated service delivery. Under hazard conditions, however, they can create cascading failures, restoration bottlenecks, and geographically dispersed service losses. For example, a power outage may interrupt water pumping, wastewater treatment, communication networks, traffic control, emergency logistics, and repair operations.

Infrastructure resilience is therefore not only a property of individual assets, but also an outcome of cross-sector coordination, redundancy, operability, and recovery capacity (Buldyrev et al. 2010; Ouyang 2014; Wang et al. 2024).

A related but distinct issue is compound hazards. Compound hazards involve multiple hazard drivers that co-occur, occur in close sequence, or interact in ways that amplify exposure, loading, or consequence. Compound hazards describe the hazard-side structure of risk, whereas cascading failures describe disruption propagation through infrastructure and service networks. Distinguishing these concepts is necessary for aligning hazard modelling, infrastructure assessment, and resilience planning (Zscheischler et al. 2020; Raymond et al. 2020).

1.3 Research gap and review question

Research on natural-hazard impacts and CIS resilience has grown rapidly, but several limitations continue to restrict both scholarly synthesis and practical decision support. First, the literature remains fragmented across hazard categories. Earthquake, flood, storm, heat, snow/ice, wildfire, landslide, and coastal-hazard studies often develop separate loading measures, damage models, exposure indicators, and recovery assumptions. This fragmentation makes it difficult to compare hazard-induced challenges across infrastructure systems or to translate hazard-specific findings into cross-hazard assessment logic.

Second, interdependency analysis remains methodologically inconsistent. Studies differ in how they define dependency, interdependency, cascading failure, compound hazards, functional disruption, and recovery coupling. Without clearer conceptual boundaries, it is difficult to determine whether a study is modelling hazard interaction, infrastructure coupling, service failure, or recovery constraint (Haggag et al. 2022; Wells et al. 2022; Wang et al. 2024). Third, current assessment approaches often remain tied to discipline-specific outputs. Engineering studies may provide detailed component damage or fragility information, whereas network, geospatial, social vulnerability, and resilience studies may focus on service accessibility, spatial exposure, recovery prioritization, or equity. These outputs are useful, but they are not always organized into a transparent method-selection logic for decision makers working under limited data and time constraints.

Fourth, CIS modelling faces persistent data constraints. Input data on asset exposure, dependencies, restoration resources, service demand, and recovery trajectories are often incomplete, inaccessible, or inconsistent across sectors. This makes it necessary to distinguish detailed predictive assessment from first-pass screening and prioritization frameworks (Garschagen and Sandholz 2018; Martell et al. 2021; Cedergren et al. 2018). The gap addressed in this review is therefore not fragmentation alone. At the scholarly level, existing studies and reviews have provided important but differently bounded contributions, but their evidence remains difficult to compare across hazard mechanisms, infrastructure

sectors, interdependency pathways, assessment methods, and resilience outcomes. At the decision-support level, existing reviews, resilience frameworks, and institutional protocols provide less explicit guidance on how heterogeneous evidence can be translated into a proportionate first-pass screening workflow when data, time, and cross-sector information are constrained.

Table 1 positions the present review against major prior review and framework streams. The contribution of this review is to provide an evidence-to-decision bridge rather than to claim novelty on the basis of literature fragmentation alone. Detailed engineering models may characterize component damage or fragility, network models may represent interdependency and cascade propagation, and resilience frameworks may define recovery or service-continuity metrics. However, these outputs are not always connected to a transparent sequence of decisions that helps analysts determine what indicators to define, what vulnerable assets or dependency pathways to screen, what scenarios to stress test, and how to connect the results to feasible mitigation or restoration choices.

These gaps lead to the following research question: How can natural-hazard impact mechanisms, infrastructure dependencies and interdependencies, assessment methods, and resilience-enhancement strategies be synthesized into a transparent and decision-oriented structure for preliminary CIS resilience screening under constrained data conditions? This question defines the review boundary and explains why the article connects hazard mechanisms, method families, service-level resilience outcomes, and rapid assessment logic rather than treating them as separate literature streams.

1.4 Aim and scope of this review

This article presents a structured state-of-the-art review of CIS resilience under natural hazards. The review focuses on four major urban infrastructure domains: electric power, water and wastewater, transportation, and communication/ICT. These sectors were selected because they form the operational backbone of basic service continuity and emergency response. Power supports pumping, treatment, communication, traffic control, and digital infrastructure; transportation enables emergency access, repair logistics, and evacuation; communication/ICT supports coordination, monitoring, and control; and water and wastewater systems are directly tied to public health and urban functionality.

Other infrastructure sectors, including health care, fuel supply, food supply, finance, and public administration, are important and may appear as dependent, contextual, or consequence-bearing systems. They are not treated as primary synthesis sectors in order to keep the review analytically bounded and to focus on the lifeline systems most frequently coupled in natural-hazard infrastructure-resilience studies. This boundary does not imply that excluded sectors are less important; rather, it provides a tractable basis for comparing hazard impacts, method families, and resilience outcomes while recognizing that disruptions in the four focal sectors can affect these dependent services.

The objectives are threefold. First, the review synthesizes how major natural hazards affect CISs and how these impacts propagate through dependent and interdependent networks. Second, it compares assessment methods according to their outputs, data requirements, scale of applicability, uncertainty treatment, and limitations. Third, it develops a synthesis-based rapid assessment framework for preliminary screening, mitigation planning, and recovery prioritization rather than a fully validated predictive model.

1.5 Structure of the article

The remainder of this article is organized as follows. Section 2 presents the review methodology, evidence-source structure, and literature landscape. Section 3 synthesizes major hazard categories and infrastructure impact pathways. Section 4 compares assessment methods for CIS hazard and resilience analysis. Section 5 discusses resilience indicators, enhancement strategies, and a synthesis-based rapid assessment framework. Section 6 summarizes the main findings, practical implications, review limitations, and future research needs. Section 7 concludes the article.

2. Review Methodology and Literature Landscape

2.1 Review design and methodological basis

This study adopts a structured state-of-the-art review design that combines bibliometric mapping with structured qualitative synthesis. This design is appropriate because CIS resilience research spans engineering, hazard science, network analysis, geospatial modelling, disaster risk reduction, governance, and decision-support studies. A purely narrative review would risk selective coverage, while a single database-limited systematic review would not fully capture foundational concepts, general methodological sources, official datasets, and institutional guidance needed to interpret a cross-disciplinary field (Snyder 2019; Page et al. 2021; Rethlefsen et al. 2021).

The methodological design separates bibliometric mapping from evidence screening and qualitative synthesis. Bibliometric tools are suited to identifying knowledge structures, research clusters, temporal evolution, and emerging topics in large bibliographic datasets (Chen 2006, 2017; Donthu et al. 2021; Linnenluecke et al. 2020). By contrast, the identification, verification, appraisal, and synthesis of evidence require explicit search logic, inclusion and exclusion criteria, citation tracking, source verification, and transparent reporting. Therefore, CiteSpace was used for literature-landscape mapping rather than as a substitute for eligibility screening or source-quality assessment.

On this basis, the review protocol was organized around two complementary pathways, as shown in Figure 1. Pathway A was a primary Web of Science (WoS) bibliometric search designed to construct a large, source-consistent, and thematically coherent corpus at the intersection of natural hazards, CISs, and resilience-oriented assessment. Pathway B was a secondary structured anchor search designed to

identify predefined conceptual, hazard-impact, methodological, resilience-framework, and authoritative institutional sources required for the structured synthesis. The two pathways therefore served different evidence functions and were not merged into a single undifferentiated database.

This distinction is central to the review logic. Pathway A supports reproducible bibliometric mapping and provides WoS-sourced peer-reviewed core synthesis evidence. Pathway B supports concept clarification, method-family comparison, hazard-mechanism explanation, resilience framework development, and official contextual evidence. The final reference list is consequently broader than the counted WoS bibliometric corpus, which is expected for a structured state-of-the-art review but must be reported transparently.

2.2 Two-pathway literature identification strategy

Pathway A used the WoS Core Collection as the primary database because it provides standardized bibliographic metadata, indexed keywords, citation information, and reproducible export for CiteSpace analysis. The search was conducted on April 1, 2026; records from 2026 were included up to the search date. The Topic field was used to capture title, abstract, author keywords, and Keywords Plus. The screened WoS candidate records span 1994-2026, while the CiteSpace visualizations reported in Figures 2-4 display the 1996-2026 keyword-mapping window shown in the exported figures. The primary query targeted the intersection of critical infrastructure, resilience or risk assessment, and natural-hazard terms.

The operational Boolean logic for Pathway A was as follows:

TS = (("critical infrastructure" OR "infrastructure systems" OR lifeline OR "interdependent infrastructure") AND (resilien OR recover OR vulnerab OR "risk assessment" OR "resilience assessment") AND ("natural hazard" OR earthquake OR flood OR "storm surge" OR tsunami OR hurricane OR landslide OR "extreme event" OR "compound hazard"))).

The primary query identified 1,884 records. These records were retained as the WoS bibliometric corpus for CiteSpace because the objective of this layer was to capture the thematic breadth and temporal development of the cross-domain research field. Title and abstract screening excluded 462 records and produced a 1,422-record candidate pool. The main exclusion reasons were lack of focus on critical infrastructure or core infrastructure systems (n = 155), education or training topics (n = 78), non-natural threats such as conflict or cyber events (n = 72), non-system-level infrastructure treatment (n = 56), non-core sectors or supply-chain topics (n = 43), weak focus on resilience, risk, recovery, or interdependency (n = 36), insufficient natural-hazard or interdependency relevance (n = 14), policy or public-opinion focus only (n = 5), and weak relevance to infrastructure performance or resilience (n = 3). The 1,422 candidate records were then audited using title, abstract, keywords, source, DOI, and bibliographic metadata, with closer checking for retained, ambiguous, and cited records.

Pathway B was used because a single broad WoS query cannot be expected to capture all foundational concepts, generic methods, hazard-specific mechanisms, resilience frameworks, and authoritative institutional documents required by a structured state-of-the-art review. Expanding the main query to include all such background and methodological terms would have substantially broadened the corpus and weakened the interpretability of the bibliometric map. Therefore, Pathway B was organized as a secondary structured anchor search with five predefined modules derived from the review question, preliminary reading of the WoS candidate pool, and the main thematic patterns observed in Pathway A.

The five Pathway B modules were conceptual and theoretical anchors, hazard-impact mechanism anchors, methodological and technical anchors, resilience-framework anchors, and authoritative institutional sources. The secondary search used topic-specific database searches, backward and forward citation tracking, and publisher or official-source verification. Google Scholar was not used to construct a second counted corpus; it was used only as a discovery and citation-tracking interface. Bibliographic details and institutional documents were verified through DOI records, publisher pages, database records, or official institutional websites. Pathway B sources were not retained because they supported the proposed framework; they were retained because they fulfilled predefined citation functions that could not be fully captured by the broad WoS corpus.

2.3 Eligibility, verification, and appraisal criteria

Eligibility criteria were applied according to the function of each pathway. For Pathway A, records were screened for relevance to the cross-domain topic of natural hazards, CISs, and resilience-oriented assessment. Records were excluded if they did not address CISs or lifeline systems, did not concern natural hazards or hazard-induced disruptions, were outside the review scope, or lacked a clear methodological, conceptual, or empirical contribution to the review question.

For Pathway B, eligibility was based on citation function rather than membership in the primary WoS corpus. A source was retained only if it served at least one clearly defined function: defining a key concept, explaining a hazard-impact mechanism, supporting a method family, providing sector-specific evidence, clarifying resilience metrics or recovery modelling, or supplying authoritative institutional context. Sources were excluded if they were weakly connected to CIS resilience, duplicated the same function already covered by a stronger source, could not be verified through a reliable bibliographic or institutional record, or were not directly used in the manuscript argument. To reduce confirmation bias, viewpoint-sensitive anchors, especially conceptual and resilience-framework sources, were considered alongside complementary or competing sources rather than being treated as authoritative by default.

Quality and relevance appraisal was conducted using source-type-specific criteria. Peer-reviewed studies were appraised for CIS relevance, hazard relevance, method transparency, scale clarity, validation

or uncertainty treatment, and value for synthesis. Authoritative non-journal sources were appraised for issuing organization, document purpose, traceability, and relevance to hazard, infrastructure, or resilience context. This appraisal did not assign meta-analytic quality scores; instead, it determined the role each retained source could credibly play in the structured synthesis.

The complete lists of the 38 WoS-sourced core studies, 64 targeted scholarly anchors, and 8 authoritative non-journal sources are provided in the supplementary methodology tables. A row-level screening log for the 1,422 WoS candidate records and an expanded Pathway B selection-and-bias audit are also provided as supplementary materials, so that the evidence structure remains auditable while the main text remains focused on the substantive synthesis.

2.4 Screening process and evidence-source structure

Figure 1 summarizes the evidence-source structure used in the review and reports the transparent audit of the Pathway A reduction from 1,422 candidate records to 38 WoS-sourced core synthesis studies. Pathway A identified 1,884 WoS records, all of which were used for bibliometric mapping. Title and abstract screening excluded 462 records under the exclusion categories reported above, leaving 1,422 candidate records. The subsequent audit used four decision gates: essential eligibility, synthesis-function coding, usability appraisal, and representativeness/non-redundancy audit. Gate 1 excluded 95 records that failed the essential hazard-CIS-resilience nexus or showed weak alignment with the target CIS sectors. Gate 2 excluded 373 records that did not provide a clear and transferable synthesis function for Sections 3-5. Gate 3 excluded 371 records whose findings were too local or case-specific for critical comparison or whose methods were insufficiently transparent for the synthesis. Gate 4 excluded 545 records through a representativeness/non-redundancy audit because their citation function overlapped with broader, clearer, more recent, foundational, or more representative retained sources. The final core evidence set therefore equals $38 = 1,422 - 95 - 373 - 371 - 545$.

In parallel, Pathway B identified 64 targeted scholarly anchor references and 8 authoritative non-journal sources, giving a final reference structure of 110 sources. These references were not merged into the counted WoS bibliometric corpus and were not used in CiteSpace. They were selected through predefined anchor-search modules, topic-specific searches, backward/forward citation tracking, and official-source verification. The purpose of this second pathway was to support conceptual precision, hazard-mechanism explanation, method-family comparison, resilience-framework clarification, and authoritative contextualization, while also checking viewpoint-sensitive anchors against complementary or competing perspectives. Thus, the final reference list used in the review includes both formal WoS-sourced core synthesis studies and function-specific anchor sources.

Because Pathway A was exported as a single WoS record set, database-merging duplicate removal was not applicable within the counted bibliometric corpus. For Pathway B, duplicate or overlapping sources were checked manually by title, author, year, DOI, source, and citation function. Uncertain cases were resolved through author-team discussion and consensus. Because the article is a structured state-of-the-art synthesis rather than a meta-analysis, the procedure used consensus-based source checking rather than formal interrater reliability scoring.

The resulting reference structure consists of 38 WoS-sourced core synthesis studies, 64 targeted scholarly anchors, and 8 authoritative non-journal sources. This structure reconciles the counted WoS screening workflow with the broader reference list required for a state-of-the-art review that must also define concepts, compare method families, explain hazard mechanisms, and cite official contextual evidence. The retained 38 studies were not selected because they supported a preferred conclusion. Each retained study satisfied the eligibility criteria, provided at least one explicit synthesis function, was usable for critical comparison, and added a non-redundant contribution to the cross-hazard, cross-sector, method-comparison, resilience, or decision-support synthesis.

2.5 Analytical framework for synthesis

The literature was synthesized through six classification dimensions: hazard type, infrastructure sector, dominant impact mechanism or failure pathway, methodological family, analytical scale, and resilience or decision-support function. This structure links hazard processes to infrastructure consequences and links assessment methods to decision outputs. It also distinguishes between physical damage, functional disruption, cross-sector propagation, and recovery constraints.

Hazards were grouped into geological, meteorological, and hydrological/marine classes, while compound hazards and cascading failures were treated as cross-cutting interaction and propagation processes. Infrastructure sectors were grouped into electric power, water and wastewater, transportation, and communication and information and communication technology (ICT) systems. Method families were classified into physical experiments and monitoring, numerical simulation and multi-physics modelling, probabilistic and fragility-based approaches, interdependency and network-science methods, and data-driven approaches such as geographic information systems (GIS), remote sensing, machine learning, and digital twins. Analytical scale was considered across component/facility, network/system, and urban/regional levels.

The synthesis follows a progressive logic. Section 3 identifies how major hazard categories affect CIs and how impacts may propagate through dependencies, interdependencies, compound hazards, and cascading processes. Section 4 then compares assessment methods according to the questions they can answer, the data they require, the scale at which they operate, and the limitations they impose. Section 5

builds on these results to discuss resilience metrics, enhancement strategies, and a synthesis-based rapid assessment workflow for preliminary screening and prioritization. This structure makes explicit how the conceptual distinctions introduced in Section 1 alter the review logic rather than remaining purely definitional.

The anchor-search modules in Pathway B were used to ensure that the qualitative synthesis did not rely only on the 38 core WoS-sourced studies. Instead, each major concept, hazard mechanism, method family, or resilience framework was supported by traceable anchor references with a defined citation function. This approach is consistent with the use of supplementary searching and citation tracking in complex evidence reviews, where relevant evidence may be dispersed across databases, disciplines, and document types (Greenhalgh and Peacock 2005; Rethlefsen et al. 2021; Wohlin 2014). To make this analytical process explicit, Table 2 summarizes how each major manuscript component draws on different evidence sources and translates them into the corresponding synthesis outputs.

2.6 Literature landscape and implications for synthesis

The bibliometric analysis was conducted using CiteSpace v.7.0.R0 with one-year time slicing over the 1996-2026 visualization window shown in Figures 2-4, keyword node analysis, g-index node selection ($k = 10$), and Pathfinder pruning. The keyword co-occurrence network had 415 nodes and 2,737 links. The modularity Q value was 0.7972 and the weighted mean silhouette value was 0.8704, indicating a well-structured keyword-cluster network. These values are reported as descriptors of the bibliometric map, not as indicators of study quality.

The bibliometric results from Pathway A show that the WoS corpus is organized around several prominent knowledge domains, including critical infrastructure, risk assessment, urban resilience, cascading effects, risk management, climate change, system-of-systems modelling, and decision support. Earlier research themes were more strongly associated with ground motion, model development, seismic vulnerability, lifeline systems, and disaster recovery. Later themes expanded toward risk assessment, interdependency, cascading failure, climate-related disruption, urban resilience, and data-driven or digital methods.

These observations should be interpreted as bibliometric patterns rather than as eligibility decisions. They show how the field has evolved and where major research clusters are located, but they do not determine by themselves which sources are conceptually foundational, methodologically representative, or institutionally authoritative. For this reason, the bibliometric observations were used to inform the structure of the qualitative synthesis, while individual source inclusion was governed by the two-pathway identification strategy and the relevance, verification, and citation-function criteria described above.

The literature landscape indicates a transition from asset- and hazard-specific studies toward integrated analysis of interdependent infrastructure systems, service disruption, recovery, and resilience planning. This transition motivates the structure of the remainder of the review. Section 3 focuses on hazard-impact mechanisms and cross-hazard patterns. Section 4 compares method families according to outputs, data needs, scale, uncertainty treatment, and limitations. Section 5 uses the resulting synthesis to develop a bounded rapid assessment framework for preliminary screening and decision support under constrained data conditions.

3. Natural Hazard Types and Impact Mechanisms for Critical Infrastructure Systems

3.1 Hazard taxonomy and infrastructure scope

Natural hazards affect critical infrastructure systems (CISs) through distinct but often interacting physical and operational processes. For infrastructure analysis, the key issue is not only the physical origin of a hazard, but also the way it imposes loading, degrades operability, disrupts network connectivity, and propagates consequences through dependent services. This review therefore organizes primary natural hazards into geological, meteorological, and hydrological/marine classes, while treating compound hazards and cascading failures as cross-cutting interaction and propagation processes within a common consequence chain that links hazard drivers, exposure, asset response, network disruption, service loss, and recovery constraints.

The infrastructure scope remains focused on electric power, water and wastewater, transportation, and communication/ICT systems. These sectors were selected because they form the operational backbone of urban service continuity and emergency response. Across these sectors, the same physical damage can generate very different service consequences depending on redundancy, accessibility, dependency structure, repair resources, and institutional coordination. Thus, the synthesis below emphasizes service-level consequences and cross-sector propagation rather than treating hazards as isolated damage mechanisms.

Figure 5 summarizes the hazard classes considered in this review, representative cascading and concurrent pathways, and their typical implications for CISs. The figure is used as a synthesis device: the left panel defines the dominant hazard classes, the middle panel illustrates multi-step and concurrent interactions, and the right panel connects hazard impacts to physical damage, operability loss, network disruption, and service interruption.

3.2 Geological hazards

Geological hazards include earthquakes, coseismic ground failure, landslides, debris flows, and tsunami-generating source mechanisms. Earthquakes remain the most extensively studied because they

can generate spatially distributed damage across multiple lifeline sectors within a short time. Strong ground motion imposes inertial demands on structures, equipment, and support systems, whereas fault rupture, liquefaction, lateral spreading, and ground settlement can sever buried pipelines, damage bridge foundations, distort rail alignments, and impair service corridors. For power systems, vulnerable components include substations, transformers, towers, and control equipment; for water and wastewater systems, buried pipelines, pumping stations, and treatment facilities are critical; for transportation, bridges, tunnels, embankments, and access routes are central; and for communication systems, towers, control nodes, data facilities, and power-dependent equipment can fail directly or indirectly (Vamvatsikos and Cornell 2002; Rota et al. 2010; Fan et al. 2019).

The infrastructure significance of earthquakes lies in the combination of direct physical damage and indirect service consequences. Direct effects include structural yielding, support failure, rupture of buried lifelines, and malfunction of electromechanical components. Indirect effects arise when damaged transportation links delay emergency access, when electricity loss disables pumps and treatment plants, or when communication failures reduce situational awareness and coordination capacity. This explains why component fragility alone is insufficient for CIS resilience assessment; the same damage state may have different consequences depending on network location and cross-sector dependency.

Landslides and debris flows create a different but equally important failure pathway. Roads, railways, pipelines, transmission corridors, and slope-adjacent facilities can be buried, undermined, displaced, or isolated by slope failures. Localized slope failure can therefore produce regional service consequences when infrastructure corridors have limited redundancy. Earthquake-induced landslides further illustrate the boundary between single-hazard and cascading-hazard analysis because they may block rivers, form landslide-dammed lakes, damage roads, and trigger downstream flood risk after breach. For coastal systems, tsunamis are best understood in this review through their infrastructure consequences: hydrodynamic impact, buoyancy, scour, debris loading, contamination, and prolonged service interruption. This avoids duplicating tsunami discussion while retaining the distinction between source mechanism and impact mechanism (Keefer 2002; Suppasri et al. 2013; Fan et al. 2019; Zhong et al. 2023).

3.3 Meteorological hazards

Meteorological hazards affect CISs through wind loading, extreme precipitation, snow and ice accretion, temperature extremes, and prolonged operational stress. In contrast to many geological events, meteorological hazards are often spatially extensive, temporally evolving, and strongly linked to operational disruption as well as physical damage. Windstorms and tropical cyclones can damage transmission poles, towers, building envelopes, elevated transport elements, signage, and communication

masts. In power systems, overhead distribution networks are particularly exposed because pole and line failure can spread outages over wide areas. In transportation systems, blocked corridors, damaged traffic-control equipment, bridge restrictions, and debris accumulation can sharply reduce accessibility (Kossin et al. 2020; Pinelli et al. 2004; Wu et al. 2024).

Extreme precipitation generates pluvial flooding, urban drainage surcharge, ponding, and rapid inundation of low-lying facilities. Substations, pump stations, wastewater plants, tunnels, underpasses, and underground communication facilities can lose function even without catastrophic structural failure. In these cases, the most important consequence is often serviceability loss rather than collapse. This is why rainfall-induced infrastructure disruption should be assessed not only through inundation depth, but also through accessibility, duration, dependency pathways, and restoration feasibility (Dong et al. 2022; Guo et al. 2021; Tellman et al. 2021).

Snow, ice, and heat-related hazards require explicit treatment rather than being treated as minor extensions of storm impacts. Ice accretion on power lines and towers can induce sagging, galloping, conductor failure, and tower instability. Snow accumulation can overload exposed structures, degrade mobility, interrupt logistics, and delay repair access. Heatwaves can reduce power-generation and transmission efficiency, increase cooling demand, deform transport assets, stress ICT facilities, and affect worker safety during emergency response. The 2021 Texas winter storm illustrates how meteorological stress can trigger coupled electricity and water failures, transforming an atmospheric event into a cross-sector service crisis. The literature remains uneven in this area, with wind, flood, and seismic hazards more mature than prolonged cold-, heat-, and ice-related service-disruption studies (Molarius et al. 2022; Fekete and Nehren 2024; Qarahasanlou et al. 2025).

3.4 Hydrological and marine hazards

Hydrological and marine hazards affect infrastructure through inundation depth, flow velocity, exposure duration, hydrostatic and hydrodynamic loading, scour, salinity, debris impact, and sediment deposition. Riverine and pluvial floods are major sources of disruption for transportation, water and wastewater, and electric power systems. Bridges and embankments are vulnerable to scour and erosion; pumping stations, treatment facilities, and substations may be disabled by inundation; and roads, railways, tunnels, and service corridors can become impassable before structural failure occurs. The most relevant decision questions therefore concern not only where assets are damaged, but where service is interrupted, for how long, and which dependent systems are affected (Apel et al. 2004, 2006; Merz et al. 2010; Martin-Vide et al. 1998).

Coastal storm surges add further complexity because surge magnitude depends on storm track, intensity, bathymetry, tide, wave conditions, shoreline geometry, and protection systems. Low-lying

urban districts may experience rapid inundation of ports, substations, wastewater facilities, coastal highways, tunnels, and communication assets. Salinity intrusion, debris impact, repeated overtopping, and prolonged standing water can intensify damage and delay restoration relative to inland flooding. In coastal and estuarine settings, surge, rainfall, river discharge, and tide can interact, making single-driver flood analysis inadequate for infrastructure resilience planning (Rego and Li 2009; Bunya et al. 2010; Muis et al. 2016; Marsooli et al. 2019).

Tsunamis are lower-frequency but high-consequence hydrodynamic events for ports, coastal transport corridors, nearshore industrial facilities, water systems, power assets, and submarine communication links. Their impacts include impact forces, drag, flotation, debris collision, foundation scour, and widespread contamination of coastal service environments. For CIS synthesis, the key point is that hydrological and marine hazards often shift assessment from asset damage toward service interruption, accessibility loss, and recovery sequencing (Titov and Synolakis 1998; Suppasri et al. 2013).

3.5 Compound and cascading hazards

Single-hazard analysis is often insufficient for CIS resilience because severe infrastructure disruption frequently arises from interacting hazard drivers and cross-sector failure propagation. Compound hazards occur when multiple hazard drivers co-occur, occur in close sequence, or interact in ways that amplify exposure or impact. Cascading failures occur when an initial failure or degradation propagates through infrastructure dependencies and interdependencies. These two processes are analytically distinct but often operationally coupled: hazard-side compounding can increase the probability of asset failure, while infrastructure interdependencies can convert localized failures into wider service disruption (Zscheischler et al. 2020; Raymond et al. 2020; Wells et al. 2022).

Several pathways illustrate this logic. Tropical cyclones may combine extreme wind, intense rainfall, and storm surge, exposing power, transport, drainage, water, wastewater, and ICT systems to concurrent stress. Earthquakes can trigger landslides, liquefaction, dammed lakes, and tsunami impacts. Flood-induced substation outages can disable pumping, treatment, traffic control, and communication services. Cold-weather extremes can disrupt power supply and subsequently affect water distribution, wastewater treatment, heating, mobility, emergency communication, and repair logistics. In each case, consequence depends on the timing, overlap, spatial coincidence, and dependency structure of the event, not only on peak hazard intensity (Wahl et al. 2015; Bevacqua et al. 2019; Tubaldi et al. 2022; Tiedmann et al. 2023).

The literature has made progress in classifying compound hazards, modelling dependence among hazard drivers, and representing network-based failure propagation. However, integration remains incomplete. Compound events are still frequently described qualitatively, and recovery dynamics are

often represented through simplified or sector-specific assumptions. This is a critical limitation for urban CISOs, where service consequences are shaped by restoration resources, access constraints, backup systems, interagency coordination, and prioritization decisions (Brunner et al. 2024; Muehlhofer et al. 2023; Wang et al. 2024).

3.6 Cross-hazard synthesis

Across hazard categories, a common impact progression can be identified. Hazard drivers impose loads or environmental stressors on infrastructure components; these loads trigger physical damage or operational degradation; component failures propagate through networks and dependencies; service disruption affects users, communities, and emergency-response functions; and recovery is shaped by accessibility, repair resources, redundancy, governance, and uncertainty. This shared structure helps unify otherwise fragmented hazard-specific literatures and provides the basis for the methodological comparison in Section 4 (Haggag et al. 2022; Yang et al. 2024; Yan et al. 2025).

Table 3 synthesizes the cross-hazard logic used in this review. The table is not intended to replace hazard-specific technical analysis. Instead, it connects hazard mechanisms to sector consequences, cascading pathways, and suitable method families so that the transition from Section 3 to Section 4 is explicit.

4. Methods for Quantifying Hazard Impacts on Critical Infrastructure Systems

The literature on hazard impacts to CISOs has developed along multiple methodological trajectories. These methods are complementary rather than interchangeable: each is suited to different hazards, spatial scales, data conditions, uncertainty treatments, and decision needs. Building on the cross-hazard synthesis in Section 3, this section compares five method families: physical experiments and monitoring, numerical simulation and multi-physics modelling, probabilistic and fragility-based approaches, interdependency and network-science approaches, and data-driven methods including GIS, remote sensing, machine learning, and digital twins. Figure 6 summarizes how these methods relate to analytical scale, output type, and decision relevance (Schotten et al. 2024; Wells et al. 2022; Muehlhofer et al. 2023).

4.1 Physical experiments and monitoring

Physical experiments remain indispensable because they provide direct evidence on how infrastructure components and facilities behave under extreme loading. Common platforms include shake-table tests for seismic response, wind-tunnel tests for aerodynamic loading and debris effects, hydraulic flumes and wave basins for flood, storm-surge, and tsunami loading, durability tests for environmental degradation, and structural health monitoring systems for field performance. These methods are most useful when the objective is to identify damage mechanisms, threshold behaviour,

nonlinear response, and failure modes that cannot be inferred reliably from simplified models alone (Farrar and Worden 2007; Kerle et al. 2020; Wasowski and Bovenga 2022).

The strength of this family is mechanistic clarity. Experiments and monitoring help define damage states, functionality thresholds, fragility relationships, and calibration targets for simulation. Their limitation is scalability. Laboratory tests and instrumented monitoring are costly, often component-specific, and difficult to translate directly to network-level or urban-scale service consequences. Therefore, they are strongest when linked to simulation, fragility, or system models that convert local response into broader performance implications (Farrar and Worden 2007; Cha et al. 2017).

4.2 Numerical simulation and multi-physics modelling

Numerical simulation extends experimental understanding by representing hazard loading and infrastructure response under varied scenarios. Finite-element models, computational fluid dynamics, hydrodynamic flood models, wave and surge models, slope-stability models, traffic assignment models, and coupled multi-physics tools can quantify stresses, inundation, scour, deformation, flow, and scenario-specific asset response. These methods are valuable where field evidence is limited or where decision makers need to test alternative hazard intensities, asset configurations, or protection measures (Vamvatsikos and Cornell 2002; Roelvink et al. 2009; Bates et al. 2010; Guo et al. 2021).

The main advantage of simulation is scenario flexibility. A single model can explore hazard intensity, exposure, design assumptions, boundary conditions, and intervention options. However, simulations are sensitive to input data, boundary assumptions, calibration quality, and computational cost. Their uncertainty treatment is often uneven: some models include probabilistic loading or sensitivity analysis, whereas others produce deterministic outputs that may look precise but depend heavily on uncertain assumptions. For CIS resilience, simulation outputs are most defensible when connected to fragility, network, or recovery models (Baker 2010; Gerstenberger et al. 2020).

4.3 Probabilistic risk and fragility-based approaches

Probabilistic and fragility-based methods translate uncertain hazard intensity into failure probability, damage states, expected loss, or performance exceedance. They are especially important for earthquakes, floods, wind hazards, bridge systems, buildings, substations, pipelines, and other assets where uncertainty in loading, capacity, exposure, and consequence must be represented explicitly. These methods support risk comparison, retrofit prioritization, cost-benefit analysis, and resilience-oriented decision making under uncertainty (Rota et al. 2010; Gerstenberger et al. 2020; Powers et al. 2021; Yang and Qian 2019).

Their main strength is that they make uncertainty visible. Rather than reporting a single deterministic damage outcome, they can estimate probability distributions, exceedance probabilities,

expected losses, and confidence ranges. Their limitation is that they often simplify service consequences and recovery. Fragility curves may describe asset damage well while treating operability, dependency, repair duration, and restoration sequencing through coarse assumptions. For interdependent CISs, probabilistic methods should therefore be coupled with network and recovery analysis when the decision question involves service disruption rather than only asset damage (Apel et al. 2004; Li et al. 2020).

4.4 Interdependency and network-science approaches

Interdependency and network-science approaches shift the analytical focus from local damage to system-wide disruption. They represent infrastructure as nodes, links, flows, dependencies, and service relationships, allowing analysts to evaluate connectivity loss, reachability, cascading effects, critical nodes, dependency pathways, and restoration priorities. These methods are essential when a damaged asset affects services beyond its immediate location, such as when power outages disable pumps, communication nodes, traffic signals, treatment facilities, or repair logistics (Rinaldi et al. 2001; Dueñas-Osorio and Vemuru 2009; Ouyang 2014; Wang et al. 2024).

The principal value of network approaches is their ability to connect asset failure with service consequences. They can reveal bottlenecks, dependency hotspots, and restoration priorities that are not visible in component-level analysis. Their main limitation is data and behavioural realism. Coupling strengths, restoration rules, substitution capacity, operator decisions, and repair-resource constraints are often uncertain or unavailable. As a result, network models may capture disruption propagation more convincingly than recovery dynamics unless restoration assumptions are carefully specified and tested (Mitsova 2021; Haggag et al. 2022; He and Cha 2022).

4.5 Data-driven, artificial intelligence (AI), GIS, remote-sensing, and digital-twin approaches

Data-driven approaches have become increasingly important because CIS assessment often needs rapid spatial coverage under incomplete information. GIS overlays, remote sensing, machine learning, image-based damage detection, outage analytics, social-sensing data, and digital twins can support exposure mapping, damage inference, hotspot detection, asset-state updating, and preliminary prioritization. These tools are particularly useful for broad-area screening and early situational awareness when detailed engineering models are unavailable (Cian et al. 2018; Tellman et al. 2021; Cha et al. 2017; Braik and Koliou 2023).

Their strength lies in speed, coverage, and adaptability. GIS and remote sensing can identify exposed assets and affected regions; machine learning can support detection and prediction; digital twins can link asset states, monitoring data, and scenario analysis. Their limitations include data bias, transferability, interpretability, and validation. A model trained in one region, hazard type, or infrastructure sector may not generalize to another. Digital twins also require sustained data governance,

551 model updating, and institutional capacity. Therefore, data-driven tools are best treated as part of hybrid
552 workflows rather than as substitutes for physical understanding and uncertainty-aware assessment (Feng
553 et al. 2023; Belenguer-Plomer et al. 2025; Shafiei et al. 2025).

554 **4.6 Comparative synthesis and method-selection logic**

555 Table 4 compares the major method families according to the dimensions established in Section 2:
556 output type, data requirement, analytical scale, uncertainty treatment, suitable use, and limitations. The
557 comparison clarifies why no single method is sufficient across all hazards, sectors, and decision contexts.
558 A defensible CIS resilience workflow should select methods according to the decision question, available
559 data, required scale, and acceptable uncertainty.

560 The method-selection implication is direct. If the question concerns component failure mechanisms,
561 experiments and simulation are most appropriate. If the question concerns probability of damage or loss,
562 fragility and probabilistic methods are required. If the question concerns service propagation or
563 restoration priorities, network and interdependency models become necessary. If the question concerns
564 rapid broad-area screening under incomplete data, GIS, remote sensing, and data-driven methods are
565 useful starting points. For practical CIS resilience planning, these methods should be sequenced rather
566 than substituted: rapid screening can identify priorities, and detailed engineering or network analysis can
567 then be applied to the most critical assets, sectors, and scenarios.

568 **5. Resilience Metrics, Enhancement Strategies, and a Synthesis-Based Rapid**
569 **Assessment Framework**

570 This section connects the hazard-impact synthesis in Section 3 and the method comparison in
571 Section 4 to resilience assessment and action. The purpose is not to propose a fully validated predictive
572 model. Rather, the aim is to formulate a synthesis-based rapid assessment workflow that can support
573 preliminary screening and prioritization under constrained data and time conditions. The framework is
574 intended for infrastructure planners, operators, and emergency-management agencies that need to
575 identify priority assets, dependency pathways, vulnerability hotspots, and candidate interventions before
576 committing resources to detailed sector-specific modelling.

577 **5.1 Resilience concepts, metrics, and recovery modelling**

578 Resilience in CISs should not be defined solely by immediate physical damage. For electricity,
579 water, wastewater, transportation, and communication systems, post-disaster performance depends on
580 whether essential services can be retained, rerouted, restored, and equitably delivered over time. In this
581 review, resilience is therefore treated as a performance- and recovery-oriented construct linking hazard
582 impacts to service continuity, disruption severity, restoration dynamics, and adaptive capacity (Bruneau
583 et al. 2003; Francis and Bekera 2014; Hosseini et al. 2016).

Operationally, resilience assessment should distinguish four indicator domains as shown in Figure 7. The first is physical and functional performance, including component damage, operability loss, network capacity reduction, and service-quality degradation. The second is socio-economic consequence, including repair cost, business interruption, customer-hour outage, logistics delay, and productivity loss. The third is human and social accessibility, including access to essential services, disruption affecting vulnerable populations, treatment delay, and mobility restriction. The fourth is institutional and organizational capacity, including coordination, backup supply, staffing, resource mobilization, financing, and governance effectiveness (Meerow et al. 2016; NIST 2015; Hallegatte et al. 2019; Davidson et al. 2022).

A recovery-curve representation provides a practical way to integrate these domains. The pre-event state defines baseline functionality, the hazard produces an initial performance drop, and the post-event trajectory describes degraded operation and recovery. Metrics can then be derived for initial loss, minimum retained functionality, disruption duration, time to partial recovery, time to near-full recovery, and cumulative retained functionality. No single metric is sufficient across all infrastructure sectors, but a compact indicator set can support cross-sector comparison while remaining sensitive to sector-specific disruption patterns (Ouyang et al. 2012; Bocchini and Frangopol 2012; Lu et al. 2020).

5.2 Component-level engineering strategies

At the component level, resilience enhancement aims to reduce the probability, extent, and service consequence of physical damage. Hazard-specific measures include seismic isolation, energy dissipation, scour protection, elevation of flood-prone assets, aerodynamic strengthening, improved fastening, material durability, thermal protection, and backup equipment. For CIS synthesis, however, these measures are best interpreted according to their functional roles rather than as isolated technical solutions (Sheikh et al. 2022; Tse et al. 2021; Bajwa et al. 2019; Panteli et al. 2017).

Component-level strategies serve five broad resilience functions: strengthening, damage avoidance, asset-level redundancy, reparability, and restoration readiness. Strengthening reduces the likelihood of failure under hazard loading. Damage avoidance limits permanent deformation or damage to hard-to-repair components. Asset-level redundancy provides backup equipment, parallel supply, modular replacement, or alternative access. Reparability reduces downtime by making post-event inspection and repair faster. Restoration readiness ensures that spare parts, access routes, repair protocols, and inspection procedures are available before a disaster occurs.

This interpretation matters because structural survival and service continuity are not equivalent. A bridge, substation, pump station, control node, or communication facility may remain physically intact but fail operationally because access, power supply, control systems, or repair resources are unavailable.

617 Component-level resilience should therefore be assessed by its effect on both physical damage states and
618 functional states.

619 **5.3 System-level and governance strategies**

620 Component robustness alone cannot ensure CIS resilience. Infrastructure systems operate as
621 interconnected service networks, and their performance during disasters depends on topology,
622 operational dependencies, redundancy, restoration logistics, and institutional coordination. System-level
623 strategies seek to preserve critical service pathways, reduce cascade potential, and shorten restoration
624 time.

625 Key system-level strategies include network reconfiguration, distributed backup provision,
626 segmentation and controlled isolation, strategic redundancy, diversification of supply routes, mobile
627 service provision, and prioritized restoration of critical nodes. In electric power systems, this may involve
628 sectionalization, distributed generation, microgrids, and backup supply for critical facilities. In water and
629 wastewater systems, it may involve looped networks, emergency interconnections, mobile pumping or
630 treatment capacity, and critical-node prioritization. In transportation systems, resilience depends on
631 alternative routing, bridge and corridor redundancy, emergency logistics, and repair access. In
632 communication systems, resilience requires backup power, decentralized routing, physical hardening,
633 and rapid restoration of control and data connectivity (Aerts et al. 2014; Bajwa et al. 2019; Panteli et al.
634 2017; Sun et al. 2023).

635 Governance strategies are equally important because technical measures are implemented through
636 institutions. Building codes, land-use controls, emergency protocols, maintenance investment, mutual-
637 aid arrangements, financing mechanisms, insurance structures, and interagency coordination all affect
638 whether resilience strategies are implemented and whether restoration proceeds effectively under real
639 constraints. This becomes especially important under compound and cascading hazards, where the
640 allocation of scarce repair resources and coordination among operators may matter as much as the initial
641 damage state (NIST 2015; Shakou et al. 2019; Hallegatte et al. 2019; Davidson et al. 2022).

642 **5.4 A synthesis-based rapid resilience assessment framework**

643 The rapid assessment framework proposed here is not reported as an empirical finding directly
644 observed in a single reviewed study, nor is it presented as a fully validated predictive model. It is a
645 synthesis-derived framework developed by the authors to translate the evidence categories identified in
646 Sections 3 and 4 into a first-pass decision-support workflow. The framework is intended for preliminary
647 CIS resilience screening and prioritization when data, time, and cross-sector information are constrained.
648 Its logic is based on the repeated finding that CIS resilience assessment cannot stop at isolated
649 descriptions of hazard loading, component damage, network disruption, or recovery metrics. Instead,

these elements must be connected in a staged procedure that first defines decision-relevant service outcomes, then screens vulnerable assets and dependency pathways, and finally stress-tests plausible disruption and recovery scenarios. Table 5 makes this evidence-to-framework translation explicit.

Step 1 establishes an outcome-oriented indicator system. The analyst defines the infrastructure sectors, service objectives, minimum performance requirements, and indicator domains relevant to the decision. The output is a compact indicator set and baseline performance profile covering physical/functionality, socio-economic, human/social accessibility, and institutional dimensions.

Step 2 conducts data-driven vulnerability screening. Using asset inventories, GIS layers, hazard maps, exposure data, service-area information, dependency assumptions, remote-sensing products, and social vulnerability indicators where available, this step identifies exposed assets, priority sectors, dependency hotspots, vulnerable populations, and likely service bottlenecks. The output is a shortlist of priority assets, hotspot zones, and critical dependency pathways that warrant closer analysis (Garschagen and Sandholz 2018; Tellman et al. 2021; Wing et al. 2022).

Step 3 applies scenario-based simulation or structured stress testing. Depending on data availability, this step may range from simplified service-loss estimation to network-based disruption modelling or sector-specific scenario simulation. The purpose is to examine how hazard intensity, asset fragility, dependency logic, and restoration assumptions combine to shape service interruption, recovery trajectories, and intervention priorities (Ouyang et al. 2012; Li et al. 2020; Nekooie and Taghizadeh 2022).

Figure 8 summarizes the workflow and clarifies the decision use of each step. Indicators define what counts as resilience loss; screening narrows the field of concern to critical vulnerabilities; stress testing evaluates plausible disruption and recovery trajectories; and the resulting outputs support priority-setting, intervention comparison, and escalation to more detailed analysis. Table 5 complements Figure 8 by showing how the reviewed evidence categories lead to the three framework components and their decision outputs.

5.5 Applicability, implementation, and decision support

The proposed framework is best understood as a tiered screening and decision-support approach. At the first tier, it helps cities and operators organize uneven data and identify priority sectors, assets, and dependency pathways. At the second tier, it supports comparative screening of mitigation options by clarifying where hardening, redundancy, backup provision, access improvement, or governance measures may yield the greatest resilience benefit. At the third tier, it guides the selection of locations, sectors, and scenarios that require more detailed engineering, network, or recovery modelling (Martell et al. 2021; Cedergren et al. 2018; Davidson et al. 2022).

The framework is most appropriate during preparedness planning, mitigation planning, resilience investment screening, and early post-event prioritization. Its value lies in usability under uneven data conditions. Not all cities possess detailed interdependency models, real-time digital platforms, or fully harmonized asset datasets. A rapid assessment structure should therefore remain useful when data availability and model detail vary across sectors. This means that the indicator system should be compact, the screening stage should accommodate partial datasets, and the stress-testing stage should be adaptable across different levels of analytical detail.

At the same time, the framework must remain transparent about uncertainty. Simplified scores, proxy indicators, approximate dependency assumptions, and scenario narratives can be useful for prioritization, but they should not be treated as substitutes for detailed engineering design or validated operational recovery models. The appropriate interpretation is therefore staged: the workflow identifies where attention is most needed, and detailed models are then applied selectively to the highest-priority assets, dependencies, and scenarios.

Overall, the contribution of this section is to reposition resilience enhancement as a multi-level and decision-oriented problem with a defined level of analytical ambition. The framework is intended for preliminary screening, comparative prioritization, and the selection of assets, dependencies, and scenarios that require more detailed investigation. It is most suitable for city agencies, infrastructure operators, and planning teams working with incomplete cross-sector datasets, limited time, and uneven modelling capacity. Its outputs should therefore be interpreted as prioritization evidence rather than as final design values or validated predictions. Metrics are useful only when they clarify what is to be protected and how recovery will be judged. Engineering measures are effective only when they improve functional retention, reparability, or restoration readiness. Governance matters when it enables coordination, resource allocation, and implementation. A structured review should therefore conclude not with a list of abstract strategies, but with an integrated logic that links hazard impacts, method selection, resilience indicators, and practical prioritization under real decision constraints.

6. Research Gaps, Review Limitations, and Future Agenda

6.1 Current research gaps

The synthesis in Sections 3-5 indicates that the main research gaps are no longer limited to a lack of individual hazard models or component-level vulnerability functions. Rather, they arise at the interfaces among hazard mechanisms, infrastructure interdependencies, service consequences, recovery processes, and practical decision support.

First, the quantification of compound and cascading hazard effects remains insufficiently connected to infrastructure service outcomes. Studies increasingly recognize concurrent, sequential, and interacting

hazard drivers, but fewer studies translate those interactions into infrastructure-specific exposure, damage, functionality, outage duration, and recovery trajectories. This gap is particularly important in coastal and urban settings where rainfall, river flooding, storm surge, wind, landslides, and infrastructure failures may interact across multiple spatial and temporal scales (Ouyang 2014; Zscheischler et al. 2020; Raymond et al. 2020; Fekete 2019; Arrighi et al. 2021; Wahl et al. 2015; Bevacqua et al. 2019; Couasnon et al. 2020).

Second, interdependent infrastructure failure and recovery remain unevenly represented. Network and interdependency models have made substantial progress in identifying cascade pathways, critical nodes, and network robustness, but they less consistently represent restoration sequencing, repair-resource competition, emergency access constraints, service substitution, institutional coordination, and feedback loops among sectors. Consequently, many models explain disruption propagation more convincingly than post-event recovery and adaptive management (Rinaldi et al. 2001; Dueñas-Osorio and Vemuru 2009; Ouyang 2014; Buldyrev et al. 2010; Wang et al. 2024; Arrighi et al. 2021; Muehlhofer et al. 2023; Ouyang et al. 2012; Lu et al. 2020).

Third, the linkage between physical damage, functional disruption, socio-economic loss, and human consequences remains underdeveloped. For CISs, asset damage is only one part of resilience. Service reachability, outage duration, repair priority, user exposure, vulnerable populations, and cascading welfare losses are also central to the consequences of hazard events. Yet these dimensions are still frequently handled through simplified proxies or qualitative discussion rather than being embedded in integrated hazard-impact and recovery assessment (Garschagen and Sandholz 2018; Hosseini et al. 2016; Bruneau et al. 2003; Francis and Bekera 2014; Ouyang et al. 2012; Meerow et al. 2016; Hallegatte et al. 2019; Wing et al. 2022).

Fourth, data availability, interoperability, and uncertainty treatment remain major barriers to implementation. Recent studies show that infrastructure risk and resilience models are highly sensitive to the completeness, granularity, and compatibility of asset, dependency, hazard, operational, and restoration datasets. Remote sensing, GIS, AI, and digital twins are promising, but their value for CIS resilience depends on whether they can be linked to physical mechanisms, transparent assumptions, uncertainty-aware outputs, and operational decision needs (Schotten et al. 2024; Martell et al. 2021; Cedergren et al. 2018; Tellman et al. 2021; Cha et al. 2017; Cian et al. 2018; Feng et al. 2023; Belenguer-Plomer et al. 2025; Braik and Koliou 2023).

Finally, a persistent gap remains between resilience assessment and practical use. Many studies propose indicators, metrics, or conceptual frameworks, but fewer demonstrate how these tools can be applied under real planning conditions with incomplete data, limited time, and competing infrastructure

priorities. This gap motivates the restrained framing of the framework in Section 5 as a synthesis-based first-pass structure for preliminary screening and prioritization, rather than as a fully validated operational model (Wells et al. 2022; He and Cha 2022; Hosseini et al. 2016; NIST 2015; Shakou et al. 2019; Davidson et al. 2022; Sun et al. 2023; Tiedmann et al. 2024).

6.2 Limitations of this review

This review has several limitations. First, although the revised methodology makes the search strategy, screening logic, source verification, and evidence-to-synthesis bridge explicit, the article remains a structured state-of-the-art review rather than a meta-analysis. The reviewed evidence is heterogeneous in hazard type, infrastructure sector, modelling scale, data source, and outcome definition; therefore, quantitative effect-size synthesis was not appropriate.

Second, the bibliometric mapping and the qualitative synthesis serve different purposes. The Web of Science dataset was used to characterize the literature landscape, whereas additional targeted sources were used to support conceptual definitions, methodological interpretation, official datasets, and resilience-framework discussion. This two-pathway approach improves interpretive coverage, but it also means that the reference list should be read as a functionally organized evidence base rather than as a simple reproduction of the bibliometric corpus.

Third, the review focuses on CISs most directly related to urban and regional functionality, especially electric power, water and wastewater, transportation, and communication/ICT systems. Other built-environment systems, social infrastructures, emergency organizations, and supply-chain dependencies are discussed mainly when they affect these core CIS functions. The scope is therefore targeted rather than exhaustive.

Fourth, the synthesis-based rapid resilience assessment framework has not yet been validated through a full end-to-end application across multiple real-world cities or infrastructure operators. It should be interpreted as a structured decision-support architecture that organizes indicators, scenarios, and prioritization logic under constrained data conditions. Future applications should calibrate the framework to local hazard conditions, asset inventories, dependency structures, service priorities, and restoration resources.

6.3 Future research directions

Future research should move from fragmented hazard- or sector-specific analysis toward integrated and operational CIS resilience science. A first priority is to develop multi-hazard frameworks that represent concurrent, sequential, and cascading hazard processes in forms compatible with infrastructure service modelling. This includes better treatment of hazard dependence, temporal compounding, damage co-occurrence, and the translation of hazard interactions into service-loss and recovery outcomes

(Zscheischler et al. 2020; Raymond et al. 2020; Wahl et al. 2015; Bevacqua et al. 2019; Wu et al. 2018; Couasnon et al. 2020; Martius et al. 2016; Hsiao et al. 2021; Moftakhari et al. 2017).

A second priority is the development of network-of-networks recovery models. Future models should go beyond static topology and isolated outage analysis by incorporating restoration sequencing, repair-resource allocation, emergency substitution, accessibility constraints, and cross-sector feedback loops. Such advances are necessary if resilience assessment is to become useful for infrastructure operators and city-level decision makers (Wang et al. 2024; Muehlhofer et al. 2023; Ouyang et al. 2012; Lu et al. 2020; Sun et al. 2023; Tiedmann et al. 2024).

A third priority is tighter coupling of engineering damage, service disruption, socio-economic loss, and human impact. CIS resilience research will remain incomplete unless it can link physical damage states to socially meaningful outcomes such as outage inequity, loss of access to essential services, and prolonged exposure of vulnerable communities. This requires closer integration among engineering, network science, urban systems analysis, social vulnerability assessment, and emergency management (Garschagen and Sandholz 2018; Meerow et al. 2016; Hallegatte et al. 2019; U.S. Global Change Research Program 2023; Wing et al. 2022).

A fourth priority is the development of uncertainty-aware rapid screening tools that remain interpretable and transferable across different cities and infrastructure systems. AI, remote sensing, GIS, and digital twins should be connected to infrastructure logic and uncertainty reporting rather than used as isolated black-box layers. Transparent first-pass tools can help prioritize where detailed simulation, field investigation, or investment analysis is most needed (Schotten et al. 2024; Tellman et al. 2021; Cha et al. 2017; Cian et al. 2018; Feng et al. 2023; Belenguer-Plomer et al. 2025; Braik and Koliou 2023).

Finally, future studies should place greater emphasis on implementation pathways. The most valuable next step is not only to propose additional metrics, but to clarify how resilience indicators, vulnerability screening, scenario-based stress testing, and intervention prioritization can be embedded in planning, maintenance, emergency preparedness, and capital-investment decisions. Progress in this direction is essential if CIS resilience assessment is to move from retrospective diagnosis toward proactive and implementable resilience management (NIST 2015; Hallegatte et al. 2019; Shakou et al. 2019; Davidson et al. 2022; Sun et al. 2023; Tiedmann et al. 2024).

7. Conclusions

This article presents a structured state-of-the-art review of natural hazards, critical infrastructure systems, and resilience enhancement. By combining bibliometric landscape mapping with structured qualitative synthesis, the review clarifies the conceptual foundations of CIS resilience, links hazard

814 mechanisms to infrastructure impacts, compares major methodological families, and develops a
815 synthesis-based rapid assessment framework. Four conclusions can be drawn.

816 First, natural hazard impacts on CISs are systemic rather than purely component-based.
817 Infrastructure consequences are governed by interactions among hazard loading, asset vulnerability,
818 infrastructure dependencies, network topology, service demand, emergency access, and recovery
819 capacity. A credible review structure must therefore distinguish hazard-side compounding from
820 infrastructure-side cascading and must connect both to service disruption and recovery.

821 Second, the evidence base remains uneven across hazards, sectors, and analytical scales.
822 Component-level methods such as experiments, monitoring, numerical simulation, and fragility analysis
823 are relatively mature for selected hazards and assets. By contrast, cross-sector interdependency analysis,
824 compound-hazard service loss, recovery modelling, and rapid decision-support tools remain less
825 standardized and less consistently validated.

826 Third, resilience enhancement must be addressed beyond the component scale. Hardening,
827 retrofitting, protective design, and monitoring remain essential, but they are insufficient without
828 redundancy, controlled isolation, restoration planning, resource allocation, institutional coordination, and
829 governance capacity. System-level strategies become especially important under compound and
830 cascading hazard conditions.

831 Fourth, the synthesis indicates that future CIS resilience assessment would benefit from becoming
832 more integrated, transparent, and decision-oriented. A useful assessment workflow should not stop at
833 separate descriptions of hazards, assets, methods, or resilience metrics. It should connect hazard loading,
834 component vulnerability, network functionality, service consequences, recovery capacity, uncertainty,
835 and feasible intervention choices. The rapid framework proposed in this article should therefore be
836 interpreted as a structured synthesis output and first-pass decision-support heuristic derived from the
837 reviewed evidence, rather than as an independently validated predictive model.

838 **CRediT authorship contribution statement**

839 Xuejian Zhang: Writing - original draft, Supervision, Methodology, Investigation,
840 Conceptualization. Li Sun: Writing - original draft, Methodology, Investigation. Le Chang:
841 Conceptualization, Methodology, Investigation. Zhen Sun: Writing - original draft, Methodology,
842 Supervision, Investigation, Conceptualization.

843 **Declaration of competing interest**

844 The authors declare no conflicts of interest.

845 **Data Availability Statement**

846 The data that support the findings of this study are available from the corresponding author upon
847 reasonable request.

848 **Supplemental Material Statement**

849 The supplementary material containing the row-level screening log, Pathway B anchor-source
850 selection/bias-control audit, and supplemental tables is available online via the DOI:
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856 **References**

857 Aerts, J. C. J. H., Botzen, W. J. W., Emanuel, K., Lin, N., De Moel, H., & Michel-Kerjan, E. O.
858 (2014). Evaluating flood resilience strategies for coastal megacities. *Science*, 344(6183), 473–475.
859 <https://doi.org/10.1126/science.1248222>

860 Anjomshoa, E., & Heravi, G. (2025). Pre-disaster planning and preparedness for urban seismic
861 resilience: Evaluating critical influential factors for temporary shelter site selection. *Habitat International*,
862 163, 103478. <https://doi.org/10.1016/j.habitatint.2025.103478>

863 Apel, H., Thielen, A. H., Merz, B., & Blöschl, G. (2004). Flood risk assessment and associated
864 uncertainty. *Natural Hazards and Earth System Sciences*, 4(2), 295–308. [https://doi.org/10.5194/nhess-](https://doi.org/10.5194/nhess-4-295-2004)
865 [4-295-2004](https://doi.org/10.5194/nhess-4-295-2004)

866 Apel, H., Thielen, A. H., Merz, B., & Blöschl, G. (2006). A probabilistic modelling system for
867 assessing flood risks. *Natural Hazards*, 38(1–2), 79–100. <https://doi.org/10.1007/s11069-005-8603-7>

868 Arrighi, C., Pregnolato, M., & Castelli, F. (2021). Indirect flood impacts and cascade risk across
869 interdependent linear infrastructures. *Natural Hazards and Earth System Sciences*, 21(6), 1955–1969.
870 <https://doi.org/10.5194/nhess-21-1955-2021>

871 Bajwa, A. A., Mokhlis, H., Mekhilef, S., & Mubin, M. (2019). Enhancing power system resilience
872 leveraging microgrids: A review. *Journal of Renewable and Sustainable Energy*, 11(3), 035503.
873 <https://doi.org/10.1063/1.5066264>

874 Baker, J. W. (2010). Conditional Mean Spectrum: Tool for Ground-Motion Selection. *Journal of*
875 *Structural Engineering*, 137(3). [https://doi.org/10.1061/\(ASCE\)ST.1943-541X.0000215](https://doi.org/10.1061/(ASCE)ST.1943-541X.0000215)

- Bates, P. D., Horritt, M. S., & Fewtrell, T. J. (2010). A simple inertial formulation of the shallow water equations for efficient two-dimensional flood inundation modelling. *Journal of Hydrology*, 387(1–2), 33–45. <https://doi.org/10.1016/j.jhydrol.2010.03.027>
- Belenguer-Plomer, M. A., Barrilero, O., Saameño, P., Mendes, I., Lazzarini, M., Albani, S., El Beyrouthy, N., Al Sayah, M., Rueche, N., Edjossan-Sossou, A. M., Monopoli, T., Arnaudo, E., & Caputo, G. (2025). Remote Sensing as a Sentinel for Safeguarding European Critical Infrastructure in the Face of Natural Disasters. *Applied Sciences-Basel*, 15(16), 8908. <https://doi.org/10.3390/app15168908>
- Bevacqua, E., Maraun, D., Vousdoukas, M. I., Voukouvalas, E., Vrac, M., Mentaschi, L., & Widmann, M. (2019). Higher probability of compound flooding from precipitation and storm surge in urban areas. *Science Advances*, 5(1), eaaw5531. <https://doi.org/10.1126/sciadv.aaw5531>
- Bocchini, P., & Frangopol, D. M. (2012). Restoration of bridge networks after an earthquake: Multicriteria intervention optimization. *Earthquake Spectra*, 28(2), 427–455. <https://doi.org/10.1193/1.4000019>
- Braik, A. M., & Koliou, M. (2023). A novel digital twin framework of electric power infrastructure systems subjected to hurricanes. *International Journal of Disaster Risk Reduction*, 97, 104020. <https://doi.org/10.1016/j.ijdr.2023.104020>
- Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., & von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, 19(4), 733–752. <https://doi.org/10.1193/1.1623497>
- Brunner, L. G., Peer, R. A. M., Zorn, C., Paulik, R., & Logan, T. M. (2024). Understanding cascading risks through real-world interdependent urban infrastructure. *Reliability Engineering & System Safety*, 241, 109653. <https://doi.org/10.1016/j.res.2023.109653>
- Buldyrev, S. V., Parshani, R., Paul, G., Stanley, H. E., & Havlin, S. (2010). Catastrophic cascade of failures in interdependent networks. *Nature*, 464(7291), 1025–1028. <https://doi.org/10.1038/nature08932>
- Bunya, S., Dietrich, J. C., Westerink, J. J., Ebersole, B. A., Smith, J. M., Atkinson, J. H., Jensen, R., Resio, D. T., Luettich, R. A., Dawson, C., Cardone, V. J., Cox, A. T., Powell, M. D., Westerink, H. J., & Roberts, H. J. (2010). A high-resolution coupled riverine flow, tide, wind, wind wave, and storm surge model for southern Louisiana and Mississippi. Part I: Model development and validation. *Monthly Weather Review*, 138(2), 345–377. <https://doi.org/10.1175/2009MWR2906.1>
- Burkett, E. R., Given, D. D., & Jones, L. M. (2014). ShakeAlert—An earthquake early warning system for the United States west coast (Fact Sheet No. 2014-3083). U.S. Geological Survey. <https://doi.org/10.3133/fs20143083>

908 Cedergren, A., Johansson, J., & Hassel, H. (2018). Challenges to critical infrastructure resilience in
 909 an institutionally fragmented setting. *Safety Science*, 110, 51–58.
 910 <https://doi.org/10.1016/j.ssci.2017.12.025>

911 Cha, Y.-J., Choi, W., & Büyüköztürk, O. (2017). Deep learning-based crack damage detection using
 912 convolutional neural networks. *Computer-Aided Civil and Infrastructure Engineering*, 32(5), 361–378.
 913 <https://doi.org/10.1111/mice.12263>

914 Chen, C. (2006). CiteSpace II: Detecting and visualizing emerging trends and transient patterns in
 915 scientific literature. *Journal of the American Society for Information Science and Technology*, 57(3),
 916 359-377. <https://doi.org/10.1002/asi.20317>

917 Chen, C. (2017). Science mapping: A systematic review of the literature. *Journal of Data and*
 918 *Information Science*, 2(2), 1-40. <https://doi.org/10.1515/jdis-2017-0006>

919 Cian, F., Marconcini, M., & Ceccato, P. (2018). Normalized Difference Flood Index for rapid flood
 920 mapping: Development and application. *Remote Sensing of Environment*, 209, 712–730.
 921 <https://doi.org/10.1016/j.rse.2018.03.006>

922 Couasnon, A., Eilander, D., Muis, S., Veldkamp, T. I. E., Haigh, I. D., Wahl, T., Winsemius, H. C.,
 923 & Ward, P. J. (2020). Measuring compound flood potential from river discharge and storm surge
 924 extremes at the global scale. *Natural Hazards and Earth System Sciences*, 20(2), 489–504.
 925 <https://doi.org/10.5194/nhess-20-489-2020>

926 Davidson, R. A., Kendra, J., Ewing, B., Nozick, L. K., Starbird, K., Cox, Z., & Leon-Corwin, M.
 927 (2022). Managing disaster risk associated with critical infrastructure systems: A system-level conceptual
 928 framework for research and policy guidance. *Civil Engineering and Environmental Systems*, 39(2), 123–
 929 143. <https://doi.org/10.1080/10286608.2022.2067848>

930 Dong, B., Xia, J., Zhou, M., Li, Q., Ahmadian, R., & Falconer, R. A. (2022). Integrated modeling
 931 of 2D urban surface and 1D sewer hydrodynamic processes and flood risk assessment of people and
 932 vehicles. *Science of the Total Environment*, 827, 154098.
 933 <https://doi.org/10.1016/j.scitotenv.2022.154098>

934 Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a
 935 bibliometric analysis: An overview and guidelines. *Journal of Business Research*, 133, 285-296.
 936 <https://doi.org/10.1016/j.jbusres.2021.04.070>

937 Dueñas-Osorio, L., & Vemuru, S. M. (2009). Cascading failures in complex infrastructure systems.
 938 *Structural Safety*, 31(2), 157–167. <https://doi.org/10.1016/j.strusafe.2008.06.007>

- Fan, X., Scaringi, G., Korp, O., West, A. J., van Westen, C. J., Tanyas, H., et al. (2019). Earthquake-induced chains of geologic hazards: Patterns, mechanisms, and impacts. *Reviews of Geophysics*, 57(2), 421–503. <https://doi.org/10.1029/2018RG000626>
- Farrar, C. R., & Worden, K. (2007). An introduction to structural health monitoring. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 365(1851), 303–315. <https://doi.org/10.1098/rsta.2006.1928>
- Fekete, A. (2019). Critical infrastructure and flood resilience: Cascading effects beyond water. *WIREs Water*, 6(5), e1370. <https://doi.org/10.1002/wat2.1370>
- Fekete, A., & Nehren, U. (2024). Climate change increased risk of forest fire, winter storm and technical failure risks related to power transmission lines - a spatial GIS risk assessment at Cologne district, Germany. *Progress in Disaster Science*, 24, 100387. <https://doi.org/10.1016/j.pdisas.2024.100387>
- Feng, D., Shi, X., & Renaud, F. G. (2023). Risk assessment for hurricane-induced pluvial flooding in urban areas using a GIS-based multi-criteria approach: A case study of Hurricane Harvey in Houston, USA. *Science of the Total Environment*, 904, 166891. <https://doi.org/10.1016/j.scitotenv.2023.166891>
- Field, C. B., Barros, V., Stocker, T. F., & Dahe, Q. (Eds.). (2012). *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK: Cambridge University Press. <https://doi.org/10.1017/CBO9781139177245>
- Francis, R., & Bekera, B. (2014). A metric and frameworks for resilience analysis of engineered and infrastructure systems. *Reliability Engineering & System Safety*, 121, 90–103. <https://doi.org/10.1016/j.ress.2013.07.004>
- Garschagen, M., & Sandholz, S. (2018). The role of minimum supply and social vulnerability assessment for governing critical infrastructure failure: Current gaps and future agenda. *Natural Hazards and Earth System Sciences*, 18(4), 1233–1246. <https://doi.org/10.5194/nhess-18-1233-2018>
- Gerstenberger, M. C., Marzocchi, W., Allen, T., Pagani, M., Adams, J., Danciu, L., et al. (2020). Probabilistic seismic hazard analysis at regional and national scales: State of the art and future challenges. *Reviews of Geophysics*. <https://doi.org/10.1029/2019RG000653>
- Greenhalgh, T., & Peacock, R. (2005). Effectiveness and efficiency of search methods in systematic reviews of complex evidence: Audit of primary sources. *BMJ*, 331(7524), 1064-1065. <https://doi.org/10.1136/bmj.38636.593461.68>

970 Guimaraes, L. F., Battemarco, B. P., Oliveira, A. K. B., & Miguez, M. G. (2021). A new approach
 971 to assess cascading effects of urban floods. *Energy Reports*, 7, 8357–8367.
 972 <https://doi.org/10.1016/j.egyr.2021.07.047>

973 Guo, K., Guan, M., & Yu, D. (2021). Urban surface water flood modelling – a comprehensive
 974 review of current models and future challenges. *Hydrology and Earth System Sciences*, 25(5), 2843–
 975 2860. <https://doi.org/10.5194/hess-25-2843-2021>

976 Haggag, M., Ezzeldin, M., El-Dakhkhni, W., & Hassini, E. (2022). Resilient cities critical
 977 infrastructure interdependence: A meta-research. *Sustainable and Resilient Infrastructure*, 7(4), 291–312.
 978 <https://doi.org/10.1080/23789689.2020.1795571>

979 Hallegatte, S., Rentschler, J., & Rozenberg, J. (2019). *Lifelines: The Resilient Infrastructure*
 980 *Opportunity*. Washington, DC: World Bank. <https://doi.org/10.1596/978-1-4648-1430-3>

981 He, X., & Cha, E. J. (2022). State of the research on disaster risk management of interdependent
 982 infrastructure systems for community resilience planning. *Sustainable and Resilient Infrastructure*, 7(5),
 983 391–420. <https://doi.org/10.1080/23789689.2020.1871541>

984 Hinkel, J., Lincke, D., Vafeidis, A. T., Perrette, M., Nicholls, R. J., Tol, R. S. J., & Levermann, A.
 985 (2014). Coastal flood damage and adaptation costs under 21st century sea-level rise. *Proceedings of the*
 986 *National Academy of Sciences*, 111(9), 3292–3297. <https://doi.org/10.1073/pnas.1222469111>

987 Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). A review of definitions and measures
 988 of system resilience. *Reliability Engineering & System Safety*, 145, 47–61.
 989 <https://doi.org/10.1016/j.ress.2015.08.006>

990 Hsiao, S.-C., Chiang, W.-S., Jang, J.-H., Wu, H.-L., Lu, W.-S., Chen, W.-B., & Wu, Y.-T. (2021).
 991 Flood risk influenced by the compound effect of storm surge and rainfall under climate change for low-
 992 lying coastal areas. *Science of the Total Environment*, 764, 144439.
 993 <https://doi.org/10.1016/j.scitotenv.2020.144439>

994 IPCC. (2021). *Climate Change 2021: The Physical Science Basis: Working Group I Contribution*
 995 *to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK:
 996 Cambridge University Press. <https://doi.org/10.1017/9781009157896>

997 IPCC. (2023). *Climate Change 2023: Synthesis Report: Contribution of Working Groups I, II and*
 998 *III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Geneva,
 999 Switzerland: IPCC. <https://doi.org/10.59327/IPCC/AR6-9789291691647>

1000 Jenelius, E., Petersen, T., & Mattsson, L.-G. (2006). Importance and exposure in road network
 1001 vulnerability analysis. *Transportation Research Part A: Policy and Practice*, 40(7), 537–560.
 1002 <https://doi.org/10.1016/j.tra.2005.11.003>

1003 Keefer, D. K. (2002). Investigating landslides caused by earthquakes—A historical review. *Surveys*
1004 *in Geophysics*, 23(6), 473–510. <https://doi.org/10.1023/A:1021274710840>

1005 Kerle, N., Nex, F., Duarte, D., & Vetrivel, A. (2020). UAV-based structural damage mapping: A
1006 review. *ISPRS International Journal of Geo-Information*, 9(1), 14. <https://doi.org/10.3390/ijgi9010014>

1007 Khanam, M., Sofia, G., Koukoula, M., Lazin, R., Nikolopoulos, E., Shen, X. Y., & Anagnostou, E.
1008 N. (2021). Impact of compound flood event on coastal critical infrastructures considering current and
1009 future climate. *Natural Hazards and Earth System Sciences*, 21(2), 587–605.
1010 <https://doi.org/10.5194/nhess-21-587-2021>

1011 Kossin, J. P., Knapp, K. R., Olander, T. L., & Velden, C. S. (2020). Global increase in major tropical
1012 cyclone exceedance probability over the past four decades. *Proceedings of the National Academy of*
1013 *Sciences*, 117(22), 11975–11980. <https://doi.org/10.1073/pnas.1920849117>

1014 Lai, F., Liu, L., & Liu, H. (2016). Wave effects on the storm surge simulation: A case study of
1015 Typhoon Khanun. *Journal of Disaster Research*, 11(5), 964–972.
1016 <https://doi.org/10.20965/jdr.2016.p0964>

1017 Lan, C., Wild, A., Paulik, R., Wotherspoon, L., & Zorn, C. (2023). Assessing indirect impacts of
1018 extreme sea level flooding on critical infrastructure. *Journal of Marine Science and Engineering*, 11(7),
1019 1420. <https://doi.org/10.3390/jmse11071420>

1020 Li, Y. H., Dong, Y., Frangopol, D. M., & Gautam, D. (2020). Long-term resilience and loss
1021 assessment of highway bridges under multiple natural hazards. *Structure and Infrastructure Engineering*,
1022 16(4), 626–641. <https://doi.org/10.1080/15732479.2019.1699936>

1023 Lin, N., Emanuel, K., Oppenheimer, M., & Vanmarcke, E. (2012). Physically based assessment of
1024 hurricane surge flooding risk for New York City. *Nature Climate Change*, 2(6), 462–467.
1025 <https://doi.org/10.1038/nclimate1389>

1026 Linnenluecke, M. K., Marrone, M., & Singh, A. K. (2020). Conducting systematic literature reviews
1027 and bibliometric analyses. *Australian Journal of Management*, 45(2), 175–194.
1028 <https://doi.org/10.1177/0312896219877678>

1029 Liu, J., Wang, M., Yang, Y., et al. (2025). Freeze–thaw durability of concrete: A short review.
1030 *Journal of the Chinese Ceramic Society*, 53(1), 190–211. <https://doi.org/10.14062/j.issn.0454->
1031 [5648.20240374](https://doi.org/10.14062/j.issn.0454-5648.20240374)

1032 Lu, X., Liao, W., Fang, D., Lin, K., Tian, Y., Zhang, C., Zheng, Z., & Zhao, P. (2020).
1033 Quantification of disaster resilience in civil engineering: A review. *Journal of Safety Science and*
1034 *Resilience*, 1(1), 19–30. <https://doi.org/10.1016/j.jssr.2020.06.008>

- Marsooli, R., Lin, N., Emanuel, K., et al. (2019). Climate change exacerbates hurricane flood hazards along U.S. Atlantic and Gulf coasts in spatially varying patterns. *Nature Communications*, 10, 3785. <https://doi.org/10.1038/s41467-019-11755-z>
- Martell, M., Miles, S. B., & Choe, Y. (2021). Review of empirical quantitative data use in lifeline infrastructure restoration modeling. *Natural Hazards Review*, 22(4), 03121001. [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000514](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000514)
- Martin-Vide, J. P., Hidalgo, C., & Bateman, A. (1998). Local scour at piled bridge foundations. *Journal of Hydraulic Engineering*, 124(4), 439. [https://doi.org/10.1061/\(ASCE\)0733-9429\(1998\)124:4\(439\)](https://doi.org/10.1061/(ASCE)0733-9429(1998)124:4(439))
- Martius, O., Pfahl, S., & Chevalier, C. (2016). A global quantification of compound precipitation and wind extremes. *Geophysical Research Letters*, 43(14), 7709–7717. <https://doi.org/10.1002/2016GL070017>
- Mazinani, I., Sarafriz, M. M., Ismail, Z., Hashim, A. M., Safaei, M. R., & Wongwises, S. (2021). Fluid-structure interaction computational analysis and experiments of tsunami bore forces on coastal bridges. *International Journal of Numerical Methods for Heat & Fluid Flow*, 31(5), 1373–1395. <https://doi.org/10.1108/HFF-02-2019-0127>
- Meerow, S., Newell, J. P., & Stults, M. (2016). Defining urban resilience: A review. *Landscape and Urban Planning*, 147, 38–49. <https://doi.org/10.1016/j.landurbplan.2015.11.011>
- Merz, B., Kreibich, H., Schwarze, R., & Thieken, A. (2010). Assessment of economic flood damage. *Natural Hazards and Earth System Sciences*, 10(8), 1697–1724. <https://doi.org/10.5194/nhess-10-1697-2010>
- Mitsova, D. (2021). Integrative interdisciplinary approaches to critical infrastructure interdependency analysis. *Risk Analysis*, 41(7), 1111–1117. <https://doi.org/10.1111/risa.13129>
- Moftakhari, H. R., Salvadori, G., AghaKouchak, A., Sanders, B. F., & Matthew, R. A. (2017). Compounding effects of sea level rise and fluvial flooding. *Proceedings of the National Academy of Sciences*, 114(37), 9785–9790. <https://doi.org/10.1073/pnas.1620325114>
- Molarius, R., Keränen, J., Kekki, T., & Jukarainen, P. (2022). Developing Indicators to Improve Safety and Security of Citizens in Case of Disruption of Critical Infrastructures Due to Natural Hazards- Case of a Snowstorm in Finland. *Safety*, 8(3), 60. <https://doi.org/10.3390/safety8030060>
- Muehlhofer, E., Koks, E. E., Kropf, C. M., Sansavini, G., & Bresch, D. N. (2023). A generalized natural hazard risk modelling framework for infrastructure failure cascades. *Reliability Engineering & System Safety*, 234, 109194. <https://doi.org/10.1016/j.ress.2023.109194>

1067 Mühlhofer, E., Bresch, D. N., & Koks, E. E. (2024). Infrastructure failure cascades quintuple risk
 1068 of storm- and flood-induced service disruptions across the globe. *One Earth*, 7(4).
 1069 <https://doi.org/10.1016/j.oneear.2024.03.010>

1070 Muis, S., Verlaan, M., Winsemius, H. C., Aerts, J. C. J. H., & Ward, P. J. (2016). A global reanalysis
 1071 of storm surges and extreme sea levels. *Nature Communications*, 7, 11969.
 1072 <https://doi.org/10.1038/ncomms11969>

1073 National Centers for Environmental Information (NCEI). (2024). NCEI/WDS Global Historical
 1074 Tsunami Database, 2100 BC to Present [Dataset]. National Oceanic and Atmospheric Administration
 1075 (NOAA). <https://doi.org/10.7289/V5PN93H7>

1076 Nekooie, M. A., & Taghizadeh, G. (2022). Dynamic time-based vulnerability assessment in pursuit
 1077 of infrastructures resilience. *Proceedings of the Institution of Civil Engineers: Forensic Engineering*,
 1078 175(4), 112–125. <https://doi.org/10.1680/jfoen.21.00033>

1079 NIST. (2015). *Community Resilience Planning Guide for Buildings and Infrastructure Systems*,
 1080 Volume I. NIST Special Publication 1190-1. <https://doi.org/10.6028/NIST.SP.1190v1>

1081 Ouyang, M., Dueñas-Osorio, L., & Min, X. (2012). Time-dependent resilience assessment and
 1082 improvement of urban infrastructure systems. *Chaos: An Interdisciplinary Journal of Nonlinear Science*,
 1083 22(3), 033122. <https://doi.org/10.1063/1.4737204>

1084 Ouyang, M. (2014). Review on modeling and simulation of interdependent critical infrastructure
 1085 systems. *Reliability Engineering & System Safety*, 121, 43–60.
 1086 <https://doi.org/10.1016/j.ress.2013.06.040>

1087 Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D.,
 1088 Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M.,
 1089 Hrobjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., et al. (2021). The
 1090 PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, n71.
 1091 <https://doi.org/10.1136/bmj.n71>

1092 Panteli, M., Mancarella, P., Trakas, D. N., Kyriakides, E., & Hatziaargyriou, N. D. (2017). Metrics
 1093 and quantification of operational and infrastructure resilience in power systems. *IEEE Transactions on*
 1094 *Power Systems*, 32(6), 4732–4742. <https://doi.org/10.1109/TPWRS.2017.2664141>

1095 Pinelli, J.-P., Simiu, E., Gurley, K., Subramanian, C., Zhang, L., Cope, A., & Hamid, S. (2004).
 1096 Hurricane damage prediction model for residential structures. *Journal of Structural Engineering*, 130(11),
 1097 1685–1691. [https://doi.org/10.1061/\(ASCE\)0733-9445\(2004\)130:11\(1685\)](https://doi.org/10.1061/(ASCE)0733-9445(2004)130:11(1685))

1098 Pirani, F. J., & Najafi, M. R. (2023). Characterizing compound flooding potential and the
 1099 corresponding driving mechanisms across coastal environments. *Stochastic Environmental Research and*
 1100 *Risk Assessment*, 37(5), 1943–1961. <https://doi.org/10.1007/s00477-022-02374-0>

1101 Powers, P. M., Rezaian, S., Shumway, A. M., Petersen, M. D., Luco, N., Boyd, O. S., Moschetti,
 1102 M. P., Frankel, A. D., & Thompson, E. M. (2021). The 2018 update of the US National Seismic Hazard
 1103 Model: Ground motion models in the western US. *Earthquake Spectra*, 37(4), 2315–2341.
 1104 <https://doi.org/10.1177/8755293021101200>

1105 Qarahasanlou, A. N., Barabady, J., & Barabadi, A. (2025). Atmospheric ice accretion emergency
 1106 events management: Power distribution networks. *Results in Engineering*, 27, 106162.
 1107 <https://doi.org/10.1016/j.rineng.2025.106162>

1108 Raymond, C., Horton, R. M., Zscheischler, J., AghaKouchak, A., Balch, J., Bowen, S. G., & White,
 1109 K. (2020). Understanding and managing compound climate risks. *Nature Climate Change*, 10, 611–621.
 1110 <https://doi.org/10.1038/s41558-020-0790-4>

1111 Rego, J.L., & Li, C. (2009). On the importance of the forward speed of hurricanes in storm surge
 1112 forecasting: A numerical study. *Geophysical Research Letters*, 36.
 1113 <https://doi.org/10.1029/2008GL036953>

1114 Rethlefsen, M. L., Kirtley, S., Waffenschmidt, S., Ayala, A. P., Moher, D., Page, M. J., Koffel, J.
 1115 B., Blunt, H., Brigham, T., Chang, S., Clark, J., Conway, A., Couban, R., de Kock, S., Farrah, K.,
 1116 Fehrmann, P., Foster, M., Fowler, S. A., Glanville, J., et al. (2021). PRISMA-S: An extension to the
 1117 PRISMA statement for reporting literature searches in systematic reviews. *Systematic Reviews*, 10, 39.
 1118 <https://doi.org/10.1186/s13643-020-01542-z>

1119 Rinaldi, S. M., Peerenboom, J. P., & Kelly, T. K. (2001). Identifying, understanding, and analyzing
 1120 critical infrastructure interdependencies. *IEEE Control Systems Magazine*, 21(6), 11–25.
 1121 <https://doi.org/10.1109/37.969131>

1122 Roelvink, D., Reniers, A., van Dongeren, A., van Thiel de Vries, J., McCall, R., & Lescinski, J.
 1123 (2009). Modelling storm impacts on beaches, dunes and barrier islands. *Coastal Engineering*, 56(11–12),
 1124 1133–1152. <https://doi.org/10.1016/j.coastaleng.2009.08.006>

1125 Rota, M., Penna, A., & Magenes, G. (2010). A methodology for deriving analytical fragility curves
 1126 for masonry buildings based on stochastic nonlinear analyses. *Engineering Structures*, 32(5), 1312–1323.
 1127 <https://doi.org/10.1016/j.engstruct.2010.01.009>

1128 Sampson, C. C., Smith, A. M., Bates, P. D., Neal, J. C., Alfieri, L., & Freer, J. E. (2015). A high-
 1129 resolution global flood hazard model. *Water Resources Research*, 51(9), 7358–7381.
 1130 <https://doi.org/10.1002/2015WR016954>

1131 Schotten, R., Mühlhofer, E., Chatzistefanou, G. A., Bachmann, D., Chen, A. S., & Koks, E. E.
 1132 (2024). Data for critical infrastructure network modelling of natural hazard impacts: Needs and influence
 1133 on model characteristics. *Resilient Cities and Structures*, 3(1), 55–65.
 1134 <https://doi.org/10.1016/j.rcns.2024.01.002>
 1135 Shafiei, K., Zadeh, S. G., & Hagh, M. T. (2025). Robustness and resilience of energy systems to
 1136 extreme events: A review of assessment methods and strategies. *Energy Strategy Reviews*, 58, 101660.
 1137 <https://doi.org/10.1016/j.esr.2025.101660>
 1138 Shakou, L. M., Wybo, J.-L., Reniers, G., & Boustras, G. (2019). Developing an innovative
 1139 framework for enhancing the resilience of critical infrastructure to climate change. *Safety Science*, 118,
 1140 364–378. <https://doi.org/10.1016/j.ssci.2019.05.019>
 1141 Sheikh, H., van Engelen, N. C., & Ruparathna, R. (2022). A review of base isolation systems with
 1142 adaptive characteristics. *Structures*, 38, 1542–1555. <https://doi.org/10.1016/j.istruc.2022.02.067>
 1143 Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines.
 1144 *Journal of Business Research*, 104, 333–339. <https://doi.org/10.1016/j.jbusres.2019.07.039>
 1145 Sun, J. R., Han, Z., & Zhang, Z. M. (2023). Resource allocation framework for optimizing long-
 1146 term infrastructure network resilience. *Journal of Infrastructure Systems*, 29(1), 04022048.
 1147 <https://doi.org/10.1061/JITSE4.ISENG-2083>
 1148 Suppasri, A., Mas, E., Charvet, I., Gunasekera, R., Imai, K., Fukutani, Y., & Imamura, F. (2013).
 1149 Building damage characteristics based on surveyed data and fragility curves of the 2011 Great East Japan
 1150 tsunami. *Natural Hazards*, 66(2), 319–341. <https://doi.org/10.1007/s11069-012-0487-8>
 1151 Tebaldi, C., Strauss, B. H., & Zervas, C. E. (2012). Modelling sea level rise impacts on storm surges
 1152 along US coasts. *Environmental Research Letters*, 7(1), 014032. [https://doi.org/10.1088/1748-](https://doi.org/10.1088/1748-9326/7/1/014032)
 1153 [9326/7/1/014032](https://doi.org/10.1088/1748-9326/7/1/014032)
 1154 Tellman, B., Sullivan, J.A., Kuhn, C. et al. (2021). Satellite imaging reveals increased proportion of
 1155 population exposed to floods. *Nature*, 596, 80–86. <https://doi.org/10.1038/s41586-021-03695-w>
 1156 Titov, V. V., & Synolakis, C. E. (1998). Numerical modeling of tidal wave runup. *Journal of*
 1157 *Waterway, Port, Coastal, and Ocean Engineering*, 124(4), 157–171.
 1158 [https://doi.org/10.1061/\(ASCE\)0733-950X\(1998\)124:4\(157\)](https://doi.org/10.1061/(ASCE)0733-950X(1998)124:4(157))
 1159 Tiedmann, H. R., Spearing, L. A., Castellanos, S., Stephens, K. K., Sela, L., & Faust, K. M. (2023).
 1160 Tracking the post-disaster evolution of water infrastructure resilience: A study of the 2021 Texas winter
 1161 storm. *Sustainable Cities and Society*, 91, 104417. <https://doi.org/10.1016/j.scs.2023.104417>

1162 Tiedmann, H. R., Faust, K. M., & Sela, L. (2024). Looking beyond individual failures: A system-
 1163 wide assessment of water infrastructure resilience to extreme events. *Reliability Engineering & System*
 1164 *Safety*, 244, 109910. <https://doi.org/10.1016/j.ress.2023.109910>

1165 Tse, K. T., Hu, G., Song, J., Park, H. S., & Kim, B. (2021). Effects of corner modifications on wind
 1166 loads and local pressures on walls of tall buildings. *Build Simulation*, 14(11), 1109–1126.
 1167 <https://doi.org/10.1007/s12273-020-0705-3>

1168 Tubaldi, E., White, C. J., Patelli, E., Mitoulis, S. A., de Almeida, G., Brown, J., Cranston, M.,
 1169 Hardman, M., Koursari, E., Lamb, R., McDonald, H., Mathews, R., Newell, R., Pizarro, A., Roca, M.,
 1170 & Zonta, D. (2022). Invited perspectives: Challenges and future directions in improving bridge flood
 1171 resilience. *Natural Hazards and Earth System Sciences*, 22(3), 795–812. [https://doi.org/10.5194/nhess-](https://doi.org/10.5194/nhess-22-795-2022)
 1172 [22-795-2022](https://doi.org/10.5194/nhess-22-795-2022)

1173 U.S. Global Change Research Program. (2023). Fifth National Climate Assessment.
 1174 <https://nca2023.globalchange.gov/>

1175 Vamvatsikos, D., & Cornell, C. A. (2002). Incremental dynamic analysis. *Earthquake Engineering*
 1176 *& Structural Dynamics*, 31(3), 491–514. <https://doi.org/10.1002/eqe.141>

1177 Wahl, T., Jain, S., Bender, J., Meyers, S. D., & Luther, M. E. (2015). Increasing risk of compound
 1178 flooding from storm surge and rainfall for major US cities. *Nature Climate Change*, 5(12), 1114–1117.
 1179 <https://doi.org/10.1038/nclimate2736>

1180 Wang, Y., Zhao, O., & Zhang, L. M. (2024). Multiplex networks in resilience modeling of critical
 1181 infrastructure systems: A systematic review. *Reliability Engineering & System Safety*, 250, 110300.
 1182 <https://doi.org/10.1016/j.ress.2024.110300>

1183 Wasowski, J., & Bovenga, F. (2022). Remote sensing of landslide motion with emphasis on satellite
 1184 multi-temporal interferometry applications: an overview. In *Landslide Hazards, Risks, and Disasters*
 1185 (2nd ed., pp. 365–438). Elsevier. <https://doi.org/10.1016/B978-0-12-818464-6.00006-8>

1186 Wells, E. M., Boden, M., Tseytlin, I., & Linkov, I. (2022). Modeling critical infrastructure resilience
 1187 under compounding threats: A systematic literature review. *Progress in Disaster Science*, 15, 100244.
 1188 <https://doi.org/10.1016/j.pdisas.2022.100244>

1189 Wing, O. E. J., Kousky, C., Kunreuther, H., & Bates, P. D. (2022). Inequitable patterns of US flood
 1190 risk in the Anthropocene. *Nature Climate Change*, 12, 156–162. [https://doi.org/10.1038/s41558-021-](https://doi.org/10.1038/s41558-021-01265-6)
 1191 [01265-6](https://doi.org/10.1038/s41558-021-01265-6)

1192 Wohlin, C. (2014). Guidelines for snowballing in systematic literature studies and a replication in
 1193 software engineering. In *Proceedings of the 18th International Conference on Evaluation and Assessment*
 1194 *in Software Engineering (EASE 2014)*, 1-10. <https://doi.org/10.1145/2601248.2601268>

- Wu, W., McInnes, K., O'Grady, J., Hoeke, R., Leonard, M., & Westra, S. (2018). Mapping dependence between extreme rainfall and storm surge. *Journal of Geophysical Research: Oceans*, 123(4), 2464–2476. <https://doi.org/10.1002/2017JC013472>
- Wu, F., Gong, J., Xin, J., Zhou, J., Zhang, H., & Zhao, N. (2024). Wind-induced damage estimation of envelope components for low-rise buildings: Incorporation of directionality and multiple openings. *Journal of Wind Engineering and Industrial Aerodynamics*, 246, 105676. <https://doi.org/10.1016/j.jweia.2024.105676>
- Yan, P., Zhang, F. M., Zhang, F., & Geng, L. N. (2025). A Systematic Review and Conceptual Framework of Urban Infrastructure Cascading Disasters Using Scientometric Methods. *Buildings*, 15(7), 1011. <https://doi.org/10.3390/buildings15071011>
- Yang, X., & Qian, J. (2019). Joint occurrence probability analysis of typhoon-induced storm surges and rainstorms using trivariate Archimedean copulas. *Ocean Engineering*, 171, 533–539. <https://doi.org/10.1016/j.oceaneng.2018.11.039>
- Yang, Y., Dong, L., Li, J., Li, W., Sheng, D., & Zhang, H. (2022). A refined model of a typhoon near-surface wind field based on CFD. *Natural Hazards*. <https://doi.org/10.1007/s11069-022-05394-9>
- Yang, Z. Y., Barroca, B., Mebarki, A., Laffréchine, K., Dolidon, H., & Lilas, L. (2024). Critical infrastructure resilience: a guide for building indicator systems based on a multi-criteria framework with a focus on implementable actions. *Natural Hazards and Earth System Sciences*, 24(11), 3723–3753. <https://doi.org/10.5194/nhess-24-3723-2024>
- Zhong, H., Wang, Y., Zhang, S., Zhang, Q., & Ng, C. W. W. (2023). Effects of extreme drought–rainfall on slope failure mechanisms: centrifuge modelling. *Canadian Geotechnical Journal*, 61(4). <https://doi.org/10.1139/cgj-2023-0133>
- Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R. M., & Sillmann, J. (2020). A typology of compound weather and climate events. *Nature Reviews Earth & Environment*, 1(7), 333–347. <https://doi.org/10.1038/s43017-020-0060-z>

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Table 1. Comparative positioning of the present review against prior reviews and resilience-assessment frameworks.

Source group	Main contribution	Remaining limitation for this review	How the present review responds
Compounding-threat and CIS resilience reviews	Synthesize compound or interacting threats and infrastructure resilience modelling.	Limited translation into staged screening for constrained decision contexts.	Links compound hazards with service consequences, method choice, recovery constraints, and prioritization.
Interdependency and cascading-failure reviews	Explain infrastructure dependency, interdependency, cascade propagation, and network behaviour.	Often separate system coupling from hazard loading, component vulnerability, recovery, and intervention choice.	Connects coupling and cascading processes to the hazard-exposure-asset-network-service-recovery consequence chain.
Resilience-metric and engineered-system frameworks	Define and quantify robustness, recovery, time-dependent performance, and system functionality.	Metrics are not always connected to cross-hazard method selection or screening under incomplete data.	Embeds resilience metrics in a workflow linking indicators, vulnerability screening, and scenario stress testing.
Institutional and planning-oriented frameworks	Guide priority setting, resource allocation, and community or infrastructure resilience planning.	Often operate as high-level protocols rather than evidence-to-method syntheses from CIS literature.	Complements planning guidance with a traceable evidence-to-decision bridge for CIS screening.
Urban seismic shelter site-selection decision-support studies (e.g., Anjomshoa and Heravi 2025)	Show transparent factor identification, expert screening, and multi-criteria ranking for a specific planning problem.	Hazard- and application-specific; not a cross-hazard review of CIS resilience assessment.	Adopts the transparency principle while extending it to multi-hazard CIS impact, interdependency, methods, and screening.
Present review	Synthesizes natural-hazard impacts, CIS interdependencies, methods, resilience outcomes, and rapid screening logic.	Not a validated predictive model and not a substitute for detailed hazard- or sector-specific assessment.	Provides a structured evidence-to-decision bridge for preliminary CIS resilience screening and prioritization.

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Table 2. Evidence-to-synthesis bridge used to organize Sections 3-5.

Manuscript component	Evidence basis	Synthesis output
Section 3: hazard-impact mechanisms	WoS-sourced core studies, hazard-impact anchors, and selected authoritative hazard sources.	Cross-hazard organization of direct physical damage, functional disruption, compound-hazard effects, cascading propagation, and sector-specific service consequences.
Section 4: method-family comparison	WoS-sourced core studies and methodological anchors on experiments, monitoring, simulation, fragility, network analysis, GIS, remote sensing, AI, and digital twins.	Comparison of method families by output type, data requirement, analytical scale, uncertainty treatment, and suitability for CIS resilience assessment.
Section 5: resilience metrics and rapid screening	WoS-sourced core studies, resilience-framework anchors, restoration-modelling sources, and institutional guidance.	A bounded preliminary screening workflow linking indicators, vulnerability diagnosis, scenario stress testing, and prioritization under constrained data conditions.
Section 6: limitations and future agenda	Observed gaps in the screened WoS corpus and limits identified during citation-function appraisal.	Identification of underdeveloped areas, including empirical recovery data, cross-sector restoration modelling, uncertainty treatment, and operational implementation.

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Table 3. Cross-hazard synthesis linking hazard mechanisms, sector consequences, cascading pathways, and method implications.

Hazard group	Dominant impact mechanism	Typical CIS consequences	Cascading or compound pathway	Suitable assessment methods
Geological hazards	Ground shaking, permanent ground deformation, slope	Bridge, tunnel, pipeline, substation, tower, and	Earthquake-landslide-flood chains; power loss	Fragility analysis, structural simulation,

Hazard group	Dominant impact mechanism	Typical CIS consequences	Cascading or compound pathway	Suitable assessment methods
Meteorological hazards Hydrological and marine hazards Compound and cascading processes Cross-sector recovery constraints	failure, tsunami source mechanisms.	control-facility damage; emergency access loss.	affecting water, ICT, transport control, and repair logistics.	network analysis, scenario-based restoration modelling.
	Wind loading, extreme precipitation, snow/ice accretion, heat or cold stress.	Power-line and tower failure; transport blockage; drainage overload; ICT power dependency; reduced repair capacity.	Cyclone wind-rain-surge combinations; winter-storm power-water failures; heat-driven demand and equipment stress.	Monitoring, GIS screening, probabilistic risk, outage modelling, data-driven detection, stress testing.
	Inundation depth, velocity, duration, scour, salinity, debris impact, hydrodynamic loading.	Substation, pump station, wastewater, bridge, tunnel, port, coastal road, and communication disruption.	Compound flooding from rainfall, river discharge, tide, and storm surge; flood-induced service cascades.	Hydrodynamic simulation, flood exposure mapping, fragility functions, accessibility analysis, service-loss estimation.
	Co-occurring or sequential drivers and failure propagation through dependencies.	Multi-sector service loss, prolonged downtime, restoration bottlenecks, and geographically dispersed consequences.	Hazard compounding interacts with infrastructure interdependency and resource constraints.	Multi-hazard scenarios, interdependency models, network science, hybrid workflows, uncertainty-sensitive prioritization.
	Repair-resource limits, access constraints, coordination delay, and dependency-driven restoration sequencing.	Delayed restoration, unequal service recovery, and reduced effectiveness of isolated component hardening.	Transport access controls power/water repair; ICT and power support coordination and operations.	Recovery-curve analysis, optimization, decision-support workflows, rapid screening under incomplete data.

Table 4. Comparative synthesis of major method families for CIS hazard-impact and resilience assessment.

Method family	Main output	Data requirement	Analytical scale	Uncertainty treatment	Suitable use	Main limitation
Physical experiments and monitoring	Damage mechanisms, thresholds, response records, calibration evidence.	Specimens, sensors, loading protocols, field monitoring, component information.	Component/facility.	Usually empirical; can support uncertainty calibration but rarely covers full system uncertainty.	Mechanism identification, fragility calibration, validation of numerical models.	Costly, asset-specific, and difficult to scale to network or urban service consequences.
Numerical simulation and multi-physics modelling	Scenario response, stress/strain, inundation, scour, deformation, loading, local damage.	Hazard scenarios, geometry, material properties, boundary conditions, calibration data.	Component to network/urban depending on model type.	Sensitivity analysis or probabilistic inputs when implemented; often deterministic in practice.	Scenario testing, design comparison, protection analysis, hazard-specific response modelling.	Computationally demanding and sensitive to assumptions, data quality, and calibration.
Probabilistic risk and fragility approaches	Failure probability, damage-state exceedance, expected loss, uncertainty ranges.	Hazard intensity measures, exposure, asset capacity, empirical or analytical fragility functions.	Facility to network.	Explicit probability-based treatment of hazard and capacity uncertainty.	Risk ranking, retrofit prioritization, loss estimation, decision analysis under uncertainty.	Often simplifies service disruption, interdependency, repair duration, and restoration sequencing.
Interdependency and network-science approaches	Connectivity loss, reachability, service disruption, cascading pathways, critical nodes.	Network topology, dependency links, flow rules, demand, restoration assumptions.	Network/system to urban/regional.	Can test scenarios and coupling assumptions; probabilistic treatment varies widely.	Cascading-failure analysis, service reachability, restoration prioritization, dependency hotspot identification.	Strongly dependent on uncertain coupling, behavioral, and restoration assumptions.
GIS, remote sensing, AI, and digital twins	Exposure hotspots, damage inference, dynamic asset states, screening scores, operational dashboards.	Spatial data, remote sensing, asset inventories, training data, sensor streams, model-update logic.	Urban/regional, with asset or network extensions.	Often data-driven; uncertainty depends on training data, transferability testing, and model validation.	Rapid screening, broad-area assessment, situational awareness, preliminary prioritization.	Transferability, interpretability, bias, and sustained data-governance challenges.

Method family	Main output	Data requirement	Analytical scale	Uncertainty treatment	Suitable use	Main limitation
Hybrid workflows	Linked damage-function-recovery assessment and decision-support outputs.	Integrated hazard, asset, network, service, recovery, and institutional data.	Multi-scale.	Best suited for explicit uncertainty propagation and scenario comparison when data permit.	Preliminary screening followed by targeted detailed modelling; resilience investment prioritization.	Data-intensive and difficult to calibrate consistently across sectors and jurisdictions.

Table 5. Evidence-to-framework translation underlying the synthesis-based rapid resilience assessment framework.

Evidence category	Repeated limitation	Derived requirement	Framework component
Hazard loading and exposure	Hazard metrics, exposure assumptions, and spatial scales are often hazard-specific.	Define hazard-relevant but service-oriented indicators before detailed assessment.	Step 1: Indicator definition
Component vulnerability and asset response	Damage or fragility outputs do not automatically indicate service loss or priority.	Screen assets by physical susceptibility and functional importance.	Step 2: Vulnerability screening
Dependency, interdependency, and cascading pathways	Local damage can propagate through dependent systems and create indirect service losses.	Identify critical nodes, dependency paths, cascade-prone links, and cross-sector bottlenecks.	Step 2 and Step 3
Network functionality and service consequences	Engineering outputs may not express service continuity, accessibility, minimum supply, or affected users.	Translate physical and network disruption into service-level consequences.	Step 1 and Step 3
Recovery capacity and restoration constraints	Recovery depends on access, resources, workforce, coordination, and repair sequencing, which are often uncertain.	Include restoration constraints and alternative recovery assumptions in scenario testing.	Step 3: Stress testing
Data availability and model uncertainty	Full predictive modelling is often infeasible with incomplete asset, dependency, demand, and recovery data.	Use tiered first-pass screening before detailed modelling.	Overall framework logic
Feasible intervention choices	Assessment outputs are often disconnected from mitigation, preparedness, restoration, or investment decisions.	Link outputs to priority assets, sectors, dependency paths, scenarios, and interventions.	Decision output

Figure 1. Two-pathway literature identification strategy and evidence-source structure and transparent audit of the Pathway A 1,422-to-38 screening process used in this review.

Figure 2. Keyword cluster map of the literature on natural hazards and critical infrastructure systems generated by CiteSpace.

Figure 3. Timeline view of major keyword clusters, showing the temporal evolution of research themes in the WoS corpus.

Figure 4. Top keywords with the strongest citation bursts, highlighting shifting research frontiers in CIS resilience research.

Figure 5. Primary hazard classes considered in this review, representative cascading and concurrent pathways, and typical implications for CISs.

Figure 6. Synthesis of major methodological families for CIS hazard-impact assessment across component, network, and urban scales.

Figure 7. Indicator architecture linking outcome dimensions, recovery-curve logic, and capability domains that influence restoration performance.

Figure 8. Illustrative workflow of the synthesis-based rapid resilience assessment framework, linking indicator development, vulnerability screening, scenario-based stress testing, and decision use.