

ResiliGrid: An AI-Enabled Framework for Infrastructure Resilience and Cascading-Failure Intelligence

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Abstract: Critical infrastructure systems such as roads, bridges, healthcare facilities, power assets, water facilities, and emergency shelters form an interconnected system of systems. A disruption affecting one asset can propagate through physical, geographic, cyber, or logical dependencies and reduce the availability of essential services. This paper reviews research spanning geographic information systems (GIS), infrastructure digital twins, interdependent-network modeling, machine learning for predictive maintenance, and accessibility-aware disaster response. Twelve studies were selected for a focused literature synthesis and compared with respect to methods, findings, limitations, and relevance to integrated infrastructure resilience. The review identifies four recurring gaps: departmental data fragmentation, weak coupling between asset-level prediction and network topology, the computational burden of high-fidelity cascade simulation, and limited representation of downstream public accessibility. In response, the paper proposes ResiliGrid, a lightweight decision-support architecture that combines open geospatial data, a GIS-oriented digital twin, supervised machine-learning models, directed dependency graphs, rule-based cascade simulation, and an interpretable resilience score. The proposed system is deliberately positioned as a proof-of-concept framework rather than a replacement for structural, hydraulic, or electrical engineering solvers. Its primary contribution is the integration of complementary techniques into a single operational pipeline suitable for experimentation on a defined pilot area. Because the present work does not report a controlled empirical evaluation of the prototype, quantitative performance claims are treated as future validation objectives.

Keywords: critical infrastructure; infrastructure resilience; cascading failures; digital twins; GIS; predictive maintenance; machine learning; network analysis; accessibility; decision support

I. INTRODUCTION

Urban infrastructure is increasingly characterized by strong functional and spatial coupling. Roads and bridges provide access to hospitals and shelters; electrical systems support water treatment and healthcare operations; and communication and control systems coordinate many of these services. Consequently, the operational state of one asset may affect the performance of assets belonging to other sectors. The literature commonly describes this environment as an interconnected or interdependent system of systems.

Conventional asset-management practices, however, are frequently organized by sector. Transportation agencies, utility operators, healthcare organizations, and public-works departments may maintain separate inventories and condition records. This fragmentation makes it difficult to determine not only whether an individual asset is likely to fail, but also what services may be disrupted if that failure occurs. The problem becomes more consequential during floods, structural deterioration, utility out ages, and other hazards in which failures can propagate across infrastructure boundaries.



The literature provides mature techniques for individual parts of this problem. GIS supports spatial asset inventories; digital twins provide virtual representations of physical assets; network models describe dependencies and cascading effects; machine learning can support condition and failure prediction; and accessibility models quantify the effect of network disruption on access to services. The central question addressed in this paper is therefore not whether these techniques exist, but how they can be composed into a practical, interpretable infrastructure-resilience workflow.

A. Problem Definition

The problem considered in this study is the lack of a lightweight cross-sector decision-support framework that can combine asset condition, spatial exposure, infrastructure dependencies, predicted failure likelihood, and downstream service accessibility. A useful framework should answer questions of the following form: if a bridge becomes unavailable, which transport links are affected, which critical facilities lose access, which dependent utilities may be disrupted, and which assets should receive inspection or maintenance priority?

B. Contributions

- A focused synthesis of twelve studies across five technical themes relevant to infrastructure resilience.
- A comparative analysis of the reviewed methods and their limitations from the perspective of integrated municipal decision support.
- A literature-derived architecture linking spatial data, digital-twin concepts, machine learning, dependency graphs, cascade simulation, and resilience scoring.
- An explicit identification of assumptions, scope boundaries, and validation requirements for the proposed ResiliGrid prototype.

II. LITERATURE REVIEW METHODOLOGY

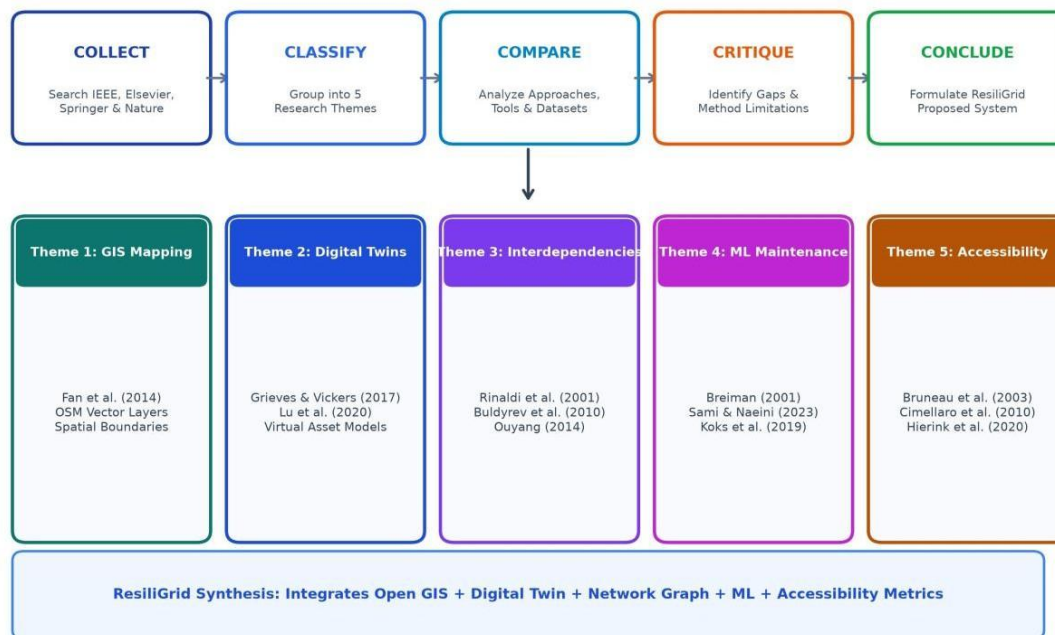


Fig. 1. Literature-review methodology and thematic pillars used to organize the review.

The source manuscript used a five-stage Collect–Classify–Compare–Critique–Conclude (5C) workflow. The search strategy targeted major scholarly repositories and used Boolean combinations around critical infrastructure,



interdependency, cascading failure, digital twins, GIS, predictive maintenance, machine learning, healthcare accessibility, network analysis, and OpenStreetMap. Studies were retained when they were peer-reviewed journal articles, recognized conference papers, or authoritative book chapters with direct mathematical, algorithmic, or spatial relevance to public infrastructure. Highly specialized sensor-hardware studies and administrative or governance papers without computational models were excluded.

The final source set contained twelve studies. The thematic taxonomy grouped them into five pillars: (1) traditional GIS and spatial infrastructure cataloging, (2) digital twins for infrastructure management, (3) infrastructure interdependencies and cascading failures, (4) machine learning for predictive maintenance and risk prediction, and (5) accessibility-aware emergency response and quantitative resilience.

A. Review Scope and Boundaries

- Infrastructure classes considered by the proposed prototype: roads, bridges, hospitals, power facilities, water facilities, and emergency shelters.
- Spatial data source: OpenStreetMap and public municipal GIS layers.
- Maintenance histories and sensor telemetry in the prototype are simulated rather than presented as live measurements.
- The intended deployment scope is a defined pilot zone rather than a national or metropolitan-scale operational system.
- The proposed analytics are decision-support mechanisms and are not presented as legal, structural-safety, or emergency-command directives.

III. THEMATIC REVIEW OF RELATED WORK

A. GIS and Spatial Infrastructure Cataloging

GIS provides the spatial foundation for representing infrastructure assets and their geographic relationships. The reviewed OpenStreetMap literature indicates that open spatial data can provide useful urban geometry and semantic tagging, while also highlighting limitations in completeness and the absence of operational fields such as condition, age, maintenance history, and interdependency metadata. Therefore, an open map can serve as the geometry layer of an infrastructure registry but cannot by itself function as a resilience-intelligence system. [11]

B. Digital Twins for Infrastructure Management

Digital-twin research extends static spatial representation by maintaining a virtual representation of a physical asset and linking it to state information and analytical processes. The reviewed bridge-oriented work demonstrates how inspection data, geometric models, and maintenance information can be integrated for asset-level monitoring. A limitation relevant to ResiliGrid is that many digital-twin implementations focus on individual assets or asset classes. The proposed framework instead treats the digital representation as a multi-infrastructure spatial environment in which assets can participate in dependency and accessibility analysis. [5], [6]

C. Infrastructure Interdependency and Cascading Failure

Rinaldi et al. provide a foundational taxonomy distinguishing physical, cyber, geographic, and logical interdependencies. Buldyrev et al. demonstrate, using coupled-network theory, how interdependent systems can undergo cascading collapse after localized failures. Ouyang's review compares empirical, agent-based, system-dynamics, and network-based approaches and highlights the trade-off between physical fidelity, computational cost, and interpretability. For a lightweight municipal prototype, directed graph models provide a practical abstraction in which nodes represent assets or services and edges represent dependency relationships. [2]–[4]

D. Machine Learning for Predictive Maintenance

Random Forests provide a robust ensemble-learning baseline for structured tabular prediction and offer useful interpretability through feature importance. More recent review literature on machine learning for cascading failure



analysis shows that ML can complement conventional physical and simulation-based approaches, particularly where large monitoring datasets are available. For ResiliGrid, tree-based supervised models are proposed as computationally modest baselines for asset-risk classification. Their use should not be interpreted as evidence that they universally outperform deep learning or physics-based models; model selection must ultimately depend on the available data, task, and validation results. [7], [8]

E. Accessibility and Quantitative Resilience

Accessibility analysis adds a service-oriented dimension to infrastructure resilience. Disaster-accessibility studies show that changes in road conditions can substantially alter travel time to functional healthcare facilities. This motivates the inclusion of route availability and service-access indicators alongside structural or asset-level measures. The 4R framework of robustness, redundancy, resourcefulness, and rapidity provides a conceptual basis for resilience assessment, while time-dependent formulations quantify changes in system functionality and recovery. [1], [9], [10], [12]

IV. COMPARATIVE SYNTHESIS

Table 1 condenses the twelve studies reviewed in the source manuscript. The table is intentionally compact for a publication layout; detailed bibliographic information is provided in the reference list.

TABLE I: COMPARATIVE SYNTHESIS OF THE TWELVE REVIEWED STUDIES

Ref.	Primary Theme	Approach	Principal Relevance	Key Limitation
[1]	Resilience	4R framework recovery curves	Conceptual basis for resilience measurement	Originally developed around seismic resilience; not an integrated software system
[2]	Interdependency	Taxonomy of infrastructure coupling	Defines physical, cyber, geographic, and logical dependencies	Conceptual taxonomy; does not itself provide a graph implementation
[3]	Cascading failure	Percolation on coupled networks	Formal basis for cascade propagation	Idealized network assumptions differ from municipal infrastructure
[4]	Interdependent systems	Comparative modeling review	Supports network-based modeling as a practical abstraction	Topological models omit detailed physical flow constraints
[5]	Digital twin	Bridge inspection and maintenance DT	Demonstrates asset-level digital representation	Focused on bridge assets rather than cross-sector dependencies
[6]	Digital twin	Cyber-physical systems concept	Provides conceptual foundation for digital-twin architecture	High-level framework rather than municipal implementation
[7]	Machine learning	Random Forest ensemble	Supports robust tabular predictive modeling	Requires appropriate domain features and labeled data
[8]	ML and cascades	Survey of ML methods	Connects ML with cascading-failure analysis	Focuses on power systems rather than multi-sector municipal networks
[9]	Accessibility	Geospatial healthcare-access modeling	Shows how disruption changes service accessibility	Accessibility model depends on spatial data quality and travel assumptions
[10]	Resilience	Analytical resilience quantification	Provides formal basis for functional degradation/recovery measures	Detailed formulations can require extensive data
[11]	GIS / OSM	Spatial quality	Supports use of OSM as a	Open data may lack operational



		assessment	geometry source	condition and maintenance information
[12]	Hazard risk	Multi-hazard geospatial risk analysis	Supports combining asset attributes with hazard exposure	Global analysis does not directly provide local cascade decision support

V. RESEARCH GAPS IDENTIFIED

The cross-theme synthesis reveals four gaps that are especially relevant to a practical, integrated resilience platform.

- Cross-sector data fragmentation. Asset inventories and condition records are often maintained independently, limiting system-level visibility.
- Weak coupling between predictive maintenance and network consequences. Asset-level failure probability does not automatically describe downstream service loss.
- High computational and data requirements of high-fidelity simulation. Detailed physics-based or enterprise-scale models may be impractical for lightweight pilot deployments.
- Insufficient representation of public accessibility. Structural survival alone does not capture whether people can still reach hospitals, shelters, or other essential services.

VI. RESILIGRID: PROPOSED INTEGRATED FRAMEWORK

Based on the literature synthesis, ResiliGrid is proposed as a modular web-based decision-support framework. Its purpose is to connect five classes of information that are commonly treated separately: spatial infrastructure data, asset condition, hazard exposure, interdependency structure, and service accessibility.

A. Five-Layer Architecture

Layer 1 — Data Collection: OpenStreetMap road and facility data, municipal GIS layers, and simulated asset-condition records.

Layer 2 — GIS and Digital Twin: PostgreSQL/PostGIS for spatial storage, GeoPandas for spatial processing, and Leaflet.js for interactive representation.

Layer 3 — Analytics: Criticality, vulnerability, and predictive-maintenance calculations using structured asset features and tree-based ML models.

Layer 4 — Resilience Intelligence: Directed dependency graphs, rule-based cascade propagation, and unified resilience scoring.

Layer 5 — Decision Support: Web dashboard, maps, cascade visualization, maintenance prioritization, and exportable reports.



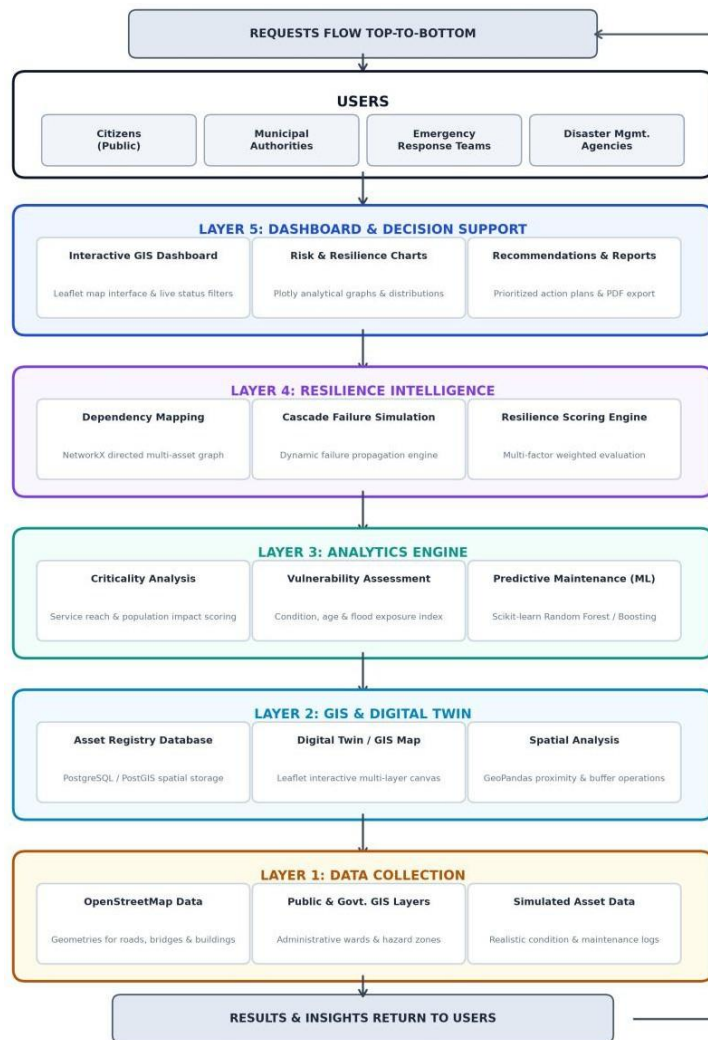


Fig. 2. Five-layer architecture of the proposed ResiliGrid platform.

B. End-to-End Workflow

The intended operational sequence is: (1) collect infrastructure data; (2) construct the spatial digital representation; (3) compute asset criticality; (4) estimate vulnerability; (5) predict maintenance or failure risk; (6) construct the dependency network; (7) simulate disruptions; (8) calculate resilience scores; (9) generate recommendations; and (10) support planning decisions. This sequence turns heterogeneous infrastructure records into a common decision-support workflow.



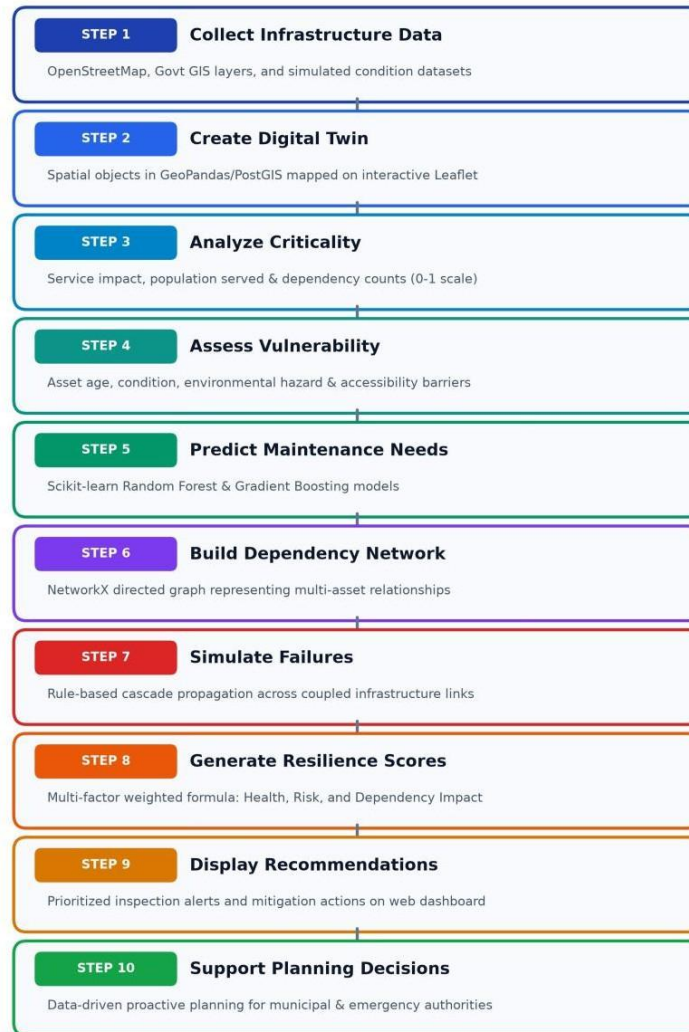


Fig. 3. End-to-end operational workflow from data collection to planning decisions.

C. Cascade-Failure Abstraction

The prototype uses a directed graph $G=(V,E)$, where V represents infrastructure assets or services and E represents a directed dependency. A failure event marks one or more nodes unavailable. Rules then propagate the disruption through dependent nodes according to edge semantics and threshold conditions. The approach is intentionally abstract: it seeks rapid, explainable what-if analysis rather than a numerically exact hydraulic, structural, or electrical simulation.



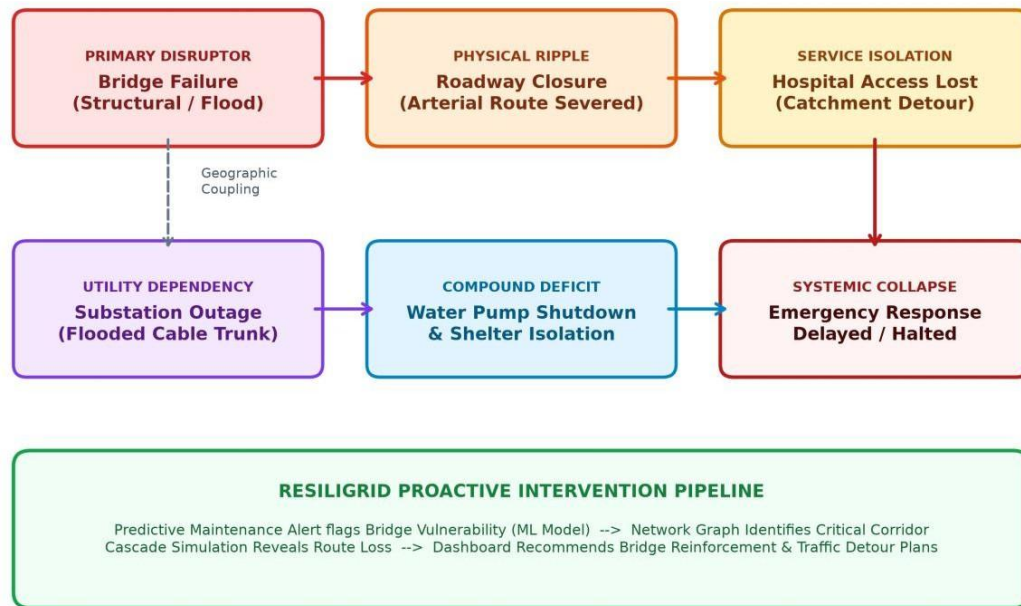


Fig. 4. Example cascade-failure sequence across transport, healthcare, and utility services.

D. Multi-Factor Resilience Score

$$R = 100 \times [w_1 H + w_2 (1 - C \cdot V) + w_3 (1 - D)]$$

Here, $H \in [0,1]$ denotes normalized asset health; $C \in [0,1]$ denotes criticality; $V \in [0,1]$ denotes vulnerability; $D \in [0,1]$ denotes downstream dependency impact; and w_1, w_2, w_3 are non-negative weights satisfying $w_1 + w_2 + w_3 = 1$. The source manuscript proposes baseline values $w_1 = 0.30$, $w_2 = 0.40$, and $w_3 = 0.30$. These weights should be treated as prototype defaults rather than empirically validated constants.

- Asset health (H) may combine age, condition indicators, defect frequency, and predictive-maintenance outputs.
- Criticality (C) may incorporate population served, service coverage, and dependency counts.
- Vulnerability (V) may combine hazard exposure, material/condition attributes, and accessibility barriers.
- Dependency impact (D) represents the fraction or weighted importance of downstream services affected by asset failure.



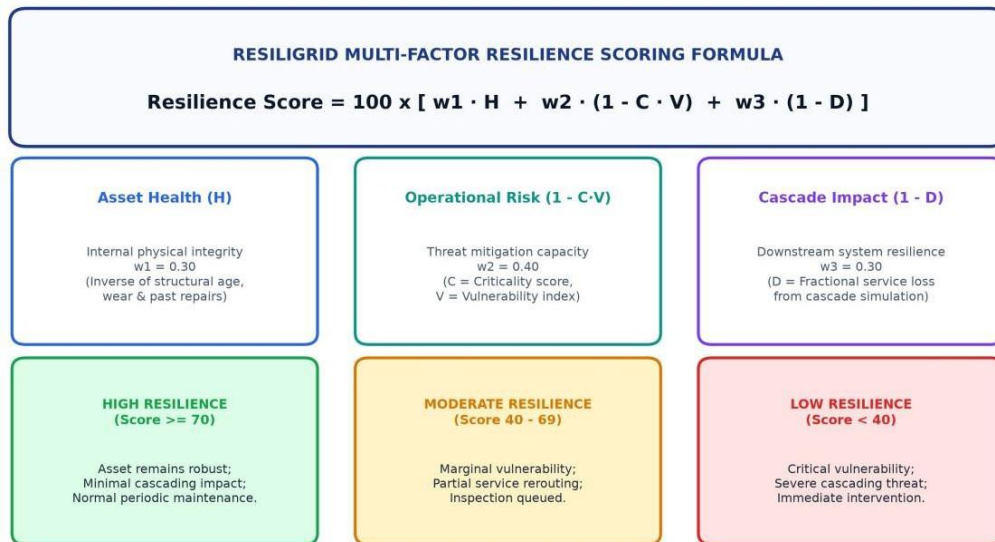


Fig. 5. Multi-factor resilience score and illustrative operational classification bands.

E. Prototype Technology Stack

The proposed implementation uses OpenStreetMap for open spatial data; PostgreSQL/PostGIS for spatial storage; GeoPandas for spatial operations; Leaflet.js for mapping; Scikit-learn for Random Forest and Gradient Boosting baselines; NetworkX for directed dependency graphs; and Flask or FastAPI with HTML, CSS, JavaScript, and Plotly for the decision-support interface.

VII. DISCUSSION

The main value of the proposed framework is architectural rather than algorithmically novel in isolation. Each component already has substantial precedent in the literature, but the review indicates a practical opportunity to connect them into a single pipeline. The combination is particularly relevant for pilot deployments where data, computation, and engineering expertise are limited.

The framework also exposes an important distinction between prediction and resilience. A high probability of failure does not necessarily imply high systemic risk: a redundant asset with several alternative routes may have less consequence than a moderately degraded asset that serves as a single point of failure. Conversely, an asset with acceptable structural health may become operationally vulnerable when exposed to a flood or when dependent infrastructure is already impaired. A useful decision-support system therefore needs to consider both asset state and network position.

Accessibility is similarly consequential. If a bridge failure increases the travel time to a hospital beyond an operational threshold, the effect is a service-access failure even if the hospital itself remains physically intact. Incorporating accessibility therefore shifts resilience assessment from an asset-centric view toward a service-centric view.

VIII. LIMITATIONS AND THREATS TO VALIDITY

- The review is focused on twelve selected studies and should not be interpreted as an exhaustive systematic review of the entire infrastructure-resilience literature.
- The prototype uses open spatial data and simulated condition/telemetry data; therefore, real-world predictive accuracy has not been established.



- The proposed resilience weights and classification thresholds are design choices requiring calibration against engineering judgment and empirical outcomes.
- The rule-based cascade model abstracts away detailed physical flows and may therefore produce different results from high-fidelity engineering simulators.
- OpenStreetMap completeness and positional/semantic accuracy vary geographically and temporally; operational deployment requires data-quality assessment and cross-validation.
- No controlled baseline comparison, cross-validation study, sensitivity analysis, or field evaluation is reported in the present manuscript. These are required before making quantitative performance claims.

IX. FUTURE RESEARCH AND VALIDATION

- Evaluate the framework on a defined pilot zone using a documented dataset and compare predicted risk rankings against expert or historical maintenance records.
- Perform sensitivity analysis on the resilience-score weights and investigate uncertainty propagation from spatial data and ML predictions into final rankings.
- Compare rule-based cascade results with established network or domain-specific simulation baselines.
- Integrate real-time IoT/structural-health-monitoring data when reliable telemetry is available.
- Investigate satellite remote sensing for flood and post-event damage mapping.
- Evaluate graph neural networks and other learned graph models only after establishing strong tabular and rule-based baselines.
- Develop dynamic evacuation and emergency-route optimization under time-varying road closures.
- Assess scalability from a pilot zone to larger municipal and regional networks.

X. CONCLUSION

This paper reviewed twelve studies spanning GIS, digital twins, interdependent infrastructure networks, machine learning, and accessibility-aware resilience analysis. The synthesis indicates that the individual technical components needed for infrastructure resilience intelligence are well established, but they are often applied within separate disciplinary or asset-specific boundaries. Four recurring gaps—data fragmentation, weak coupling between asset prediction and network consequence, computational burden, and limited accessibility representation—motivate an integrated approach.

ResiliGrid is proposed as a lightweight framework that connects these components through a common spatial registry, digital-twin representation, predictive analytics layer, dependency graph, cascade engine, and explainable resilience score. The framework is intentionally positioned as a proof-of-concept research platform. Its scientific value will depend on future empirical validation using real or well-documented benchmark data, quantitative comparison with baselines, sensitivity analysis, and evaluation by domain experts. Thus, the present manuscript establishes the literature-based rationale and technical architecture for the system while clearly separating proposed methodology from experimentally demonstrated results.

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