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Review

Resilience of road networks to natural hazards: A systematic literature review

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ABSTRACT

Road networks are essential to societal functioning yet remain highly vulnerable to natural hazards and cascading disruptions. This study presents a systematic review of road network resilience, synthesizing resilience metrics, assessment methods, and research gaps. Following the PRISMA 2020 guidelines, 109 peer-reviewed studies published between 2010 and 2025 were analyzed from the ScienceDirect, Scopus, and Web of Science databases. The results indicate that resilience assessment is primarily based on topology-based, functional performance-based, and hybrid metrics, with 31% of studies focusing on robustness and 25% emphasizing vulnerability and preparedness, while only 4% adopt fully integrated resilience frameworks. Methodologically, conventional approaches dominate the literature, including network analysis (24%), GIS-based methods (15%), and uncertainty modeling techniques (15%), alongside traffic assignment, traffic simulation, and agent-based modeling. In contrast, emerging approaches such as graph neural networks, deep reinforcement learning, digital twins, and hybrid data-driven frameworks are applied in no >14% of the reviewed studies, indicating limited but increasing adoption. Despite methodological progress, persistent gaps remain, including limited link-level analysis, inadequate modeling of spatial and temporal traffic dynamics, weak predictive and real-time capability, and insufficient consideration of multi-hazard scenarios. The study highlights the need for integrated frameworks combining machine learning with analytical and simulation-based methods to enhance dynamic resilience assessment and support proactive decision-making.

1. Introduction

1.1. Background and motivation

In engineering, the concept of resilience is commonly employed to assess a system's capacity to endure disruptions and recover efficiently [1,2]. Resilience comes from the Latin word “*risilio*”, meaning the ability to recover to the original condition after disruption [3]. Resilience is a process or characteristic before, during, and post-disruption of a system [4]. A resilient infrastructure features robust physical systems that can adapt and perform effectively under changing conditions without overly conservative design. This approach minimizes the need for redesign, maintenance, refurbishment, reconstruction, or demolition during its lifecycle, promoting greater sustainability [5,6].

Transport infrastructures like roads, railways, bridges, tunnels etc. are vulnerable to natural and man-made disasters in different countries across the globe [7–9]. Road networks are crucial for society to function effectively. The supply of resources and services like food distribution, energy supply, and medical services relies on these networks. Therefore, ensuring the resilience of road traffic is vital for maintaining the overall functioning of society [4]. However, road networks are exposed to traffic closure or limitations due to multi-hazards like earthquakes, landslides, tsunamis, volcano debris and flooding [10]. Among these hazards, landslides pose a significant threat to road infrastructure, with impacts generally categorized into two main types: one involves soil sliding down from mountainous regions, while the other concerns the sliding of road embankments [11,12]. As a result, these slides can cause either partial or complete damage to roads, leading to interruptions or complete shutdowns of road services [13]. Also, flooding is one of the most devastating disaster types in road networks. When flooding occurs, it often leads to road closures or reduced capacity by depositing debris such as mud, rocks, and vegetation on the roadway, obstructing traffic flow. Additionally, the force of floodwaters can scour bridge abutments, weakening their structural integrity and compromising safety. Unbound

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pavement layers are also vulnerable, as water erosion can wash away base materials, leading to pavement deformation and failure. Assessing the resilience of road networks to flooding is essential for ensuring a robust and reliable transportation system. A resilient transport system not only enhances safety and reduces disruptions but also supports economic stability and community recovery in the face of hazards [14].

Similarly, earthquakes can have a significant impact on road networks and bridges, causing extensive damage and disruption to transportation systems. The shaking and ground motion during an earthquake can lead to road failures, landslides, bridge collapses, and other structural damages. This can result in road closures, detours, traffic congestion, and delays in emergency response efforts. As a consequence, those disasters may result in serious socio-economic side effects. For instance, on May 12, 2008, an earthquake struck Wenchuan, China, resulting in significant damage to roads and other critical infrastructure. This disaster led to 1434 fatalities and 331 missing persons [3]. Years later, on September 24, 2008, and August 8, 2010, heavy rainfall and mudslides further impacted the region, exacerbating the already damaged roads and infrastructure. In 2015, another earthquake in Gorkha, Nepal, caused hundreds of landslides, resulting in severe damage to roads that had to be closed for five months [15]. On February 6, 2023, Turkey was hit by two earthquakes measuring 7.8 and 7.5 on the Richter scale [16]. The recent seismic activity has caused widespread damage to key infrastructures, such as the railway system, roads, water supply, and power facilities. As per the reports from the Turkish Transport Ministry, a total of 1275 km of railway tracks have suffered extensive destruction or have been completely demolished. This includes the collapse of 446 bridges, 6161 culverts, and 175 tunnels [17]. The estimated cost of damage to roads, power lines, and water supply infrastructure is approximately $6.4 billion [18]. Also, a 2016 earthquake in central Italy damaged 12 bridges, two of which were historic, and disrupted the road networks [19]. Moreover, earthquakes proceed in a series of events, starting with faulting and ground shaking that trigger secondary impacts like liquefaction, and tsunamis, landslides and rockfalls, fires, and possibly floods when dams or river embankments are damaged. These secondary effects then lead to further damages and losses [20]. For example, bridges and highway structures in areas with shallow groundwater levels or near bodies of water may be vulnerable to earthquake-induced liquefaction effects. Events such as liquefaction of saturated sand-like materials, cyclic softening or failure of clay-like materials, and lateral spreading can lead to substantial harm to these structures [21].

Also, high-intensity earthquakes commonly cause landslides, often due to the increased water pressure in correspondence to the sliding surface, and rockfalls in mountainous areas [22]. Slides can also occur to embankments, and even single blocks can obstruct a road segment as a whole or single lanes of the road segments. Furthermore, earthquake-induced fires (EIFs) are among the most destructive secondary hazards following seismic events, exacerbating damage to urban infrastructure [23]. According to historical data, earthquakes in San Francisco (1906), Kanto, Japan (1923), Mexico City (1987), and Hokkaido, Japan (2003) caused devastating fires in urban areas [24–26]. Earthquake-induced fires can cause significant damage to bridges and road networks. These transportation systems are often integrated with electrical lines and gas pipelines, which are vulnerable to seismic activity. When an earthquake occurs, ruptures in gas lines or electrical short circuits can ignite fires, exacerbating structural damage to road infrastructure. Such secondary disasters can hinder emergency response efforts and lead to prolonged disruptions in transportation networks [24].

Generally, the cases of Wenchuan, China; Gorkha, Nepal; Turkey; and Italy highlight the importance of ensuring road networks resilience both during and after disasters in order to enhance the overall resilience of critical infrastructure. Policy makers and road authorities work to provide resilient and uninterrupted functionalities of road networks [27] using specific tools for rapid response and for long-term policymaking.

Different researches has been conducted on multi-hazard effect assessments over infrastructures, including INFRARISK, which is reliable stress test framework for critical European transport infrastructure to analyze the response of networks to extreme hazard events [28], and the European INTACT project (FP7) studied the impacts of extreme weather on critical infrastructures, assessing their resilience and vulnerability under climate change [29]. However, these projects focus on fragility analysis during hazards, but still road networks analysis was not addressed, and it needs detailed investigations.

In recent times, there has been a notable shift in the focus of road authorities, governments, and policymakers towards enhancing the resilience of infrastructures rather than solely safeguarding them [30], and [31]. Extensive studies have been conducted to address the resilience of road infrastructures in the face of both natural disasters and man-made disruptions. These studies encompass various aspects related to the resilience of road transport systems, including preparedness before, response during, and recovery after the occurrence of disruptions. Researchers have employed diverse simulations and innovative methods to bolster the resilience of transport systems against multiple hazards, including traffic simulation [32], GIS [33], network analysis [34], fragility analysis [35], and machine learning. However, there is a significant need to organize and consolidate these research findings and insights to effectively inform future strategies and studies. Systematically reviewing the current state-of-the-art technologies, innovative methods, and strategies implemented by different countries to enhance the resilience of road networks against multiple hazards is crucial.

By synthesizing and evaluating existing research, this study provides a comprehensive understanding of the current landscape and identifies key areas for improvement and further development. This comprehensive review will serve as a valuable resource for road authorities, governments, researchers, and policymakers as they work towards enhancing the resilience of road networks in the face of an increasingly unpredictable environment. Furthermore, this research aligns with global resilience frameworks by supporting the Sendai Framework's Priority 4, "Enhancing disaster preparedness for effective response and to "Build Back Better" in recovery, rehabilitation and reconstruction" and advancing Sustainable Development Goal 9 (SDG 9) through enhancing the resilience of road networks.

1.2. Objectives and research questions

The aim of this paper was to perform a systematic literature review focusing on the current state of the art in road networks resilience for hazards. Specifically:

- investigating the current state of the art in road networks resilience for natural hazards.
- identifying the resilience metrics used to measure the resilience of road networks.
- assessing technologies and innovative methods used to assess and enhance the resilience of the road networks.
- identifying gaps and future improvements.

Also, the key research questions are:

1. How is the current state of the art in the resilience of road networks?
2. What are commonly used resilience metrics to measure the resilience of road networks?
3. What emerging technologies and innovative methods are currently being used to enhance road networks' resilience, and how effective are they?
4. What are the key areas for improvement in future research on road networks resilience?

2. Review methodology

To achieve the objective of this study, the PRISMA 2020 [36] methodology was employed. The data sources utilized in this research were ScienceDirect, Scopus, and Web of Science. The key search terms used were "road networks", "TRANSPORTATION* NETWORKS", "RESILIENCE*", "ROBUSTNESS", "HAZARD", "NATURAL DISASTER", and "MULTI HAZARD". These words were selected to address all possible papers to achieve the aim of this review. The search strategy combined the following terms: ("road networks" OR "transportation* networks") AND ("resilience*" OR "robustness") AND ("natural disaster" OR "hazard" OR "multi-hazard"). The selection of search terms was directly aligned with the objectives of the study. Because the review focuses on resilience at the network scale, the terms "road networks" and "transportation networks" were included to ensure the retrieval of studies addressing system-wide performance rather than asset-specific analyses. To capture how networks respond to and withstand external shocks, the keywords "resilience" and "robustness" were employed, reflecting complementary dimensions of network performance under stress. Finally, the terms "natural disaster," "hazard," and "multi-hazard" were added to specifically target studies that investigate disruptive events, enabling the review to encompass the full spectrum of hazard types considered in resilience assessments. This combination of terms was therefore designed to identify publications addressing road networks resilience, thereby aligning directly with the objectives of the study. This review examines peer-reviewed articles published between 2010 and 2025 to assess the recent progress in resilience research. By focusing on this recent period, the analysis captures meaningful shifts in methodology in road networks resilience assessment. This approach not only addresses gaps in earlier literature but also provides a timely perspective on emerging best practices in resilience assessment.

In addition, the study selection process employed the criteria in Table 1 as a filter, applied systematically at the title, abstract, and full-text screening stages to ensure relevance.

As depicted in Fig. 1, the initial search across the three databases yielded 3623 publications. Following the removal of duplicate entries and the exclusion of non-English records, 2613 publications remained eligible for preliminary screening. Then after applying the eligibility criteria specified in Table 1 during the title, abstract, and full paper review further narrowed the selection to 107 studies. An additional 2 relevant publications were identified through snowballing, resulting in a final dataset of 109 studies subjected to detailed examination. Screening was conducted by a single author following predefined inclusion and exclusion criteria, with careful adherence to minimize potential bias. These studies were systematically analyzed in terms of their methodological approaches, the hazard types addressed, and the resilience metrics employed.

Table 1
Inclusion and exclusion criteria used in this study.

Criterion Type	Category	Description
Inclusion	Publication Date	Articles published between 2010 and 2025.
	Publication Type	Peer-reviewed research articles (primary studies).
	Topic & Focus	Focus on road networks resilience under natural hazards.
	Methodological Content	Must include resilience metrics, assessment methods, or enhancement strategies with a clear, detailed methodology.
Exclusion	Language	Articles published in any language other than English.
	Document Type	Literature reviews, conference abstracts, opinion pieces, or studies without a full paper available.
	Scope of Infrastructure	Studies addressing single elements (e.g., a specific bridge) without network-level analysis or relevance.
	Network Type	Papers focusing on other transport networks (e.g., rail, maritime, aviation) or multi-modal studies where road networks are not the primary focus.
	System Interdependence	Studies centered on interdependent infrastructure (e.g., road-power-water networks) where road resilience is not separately analyzable.
	Conceptual Focus	Papers centered explicitly on vulnerability without a substantive link to resilience concepts (assessment or enhancement).

2.1. Yearly distribution of studies

As shown in Fig. 2, the annual distribution of studies from 2010 to 2025, comprising a total of 109 publications, exhibits a noticeable upward trajectory over the observed period. The initial years (2010–2016) were characterized by a phase of limited productivity, with annual publication counts remaining low. A gradual increase in output commenced from 2017 onward, transitioning into a period of marked acceleration during the subsequent five-year interval (2020–2025). Within this latter timeframe, annual publication frequency rose substantially from 14 to a peak of 20 in the most recent year. This pronounced and sustained increase indicates a substantial expansion of research activity in the field. Although the count for the current year is provisional, its notably high level further suggests the continuation of a strong growth trend in scholarly output.

2.2. Geographical distribution of papers

The analysis of 109 publications reveals a highly concentrated geographical distribution of empirical research on road network resilience, with a pronounced skew toward developed economies and a single major developing nation. As detailed in Fig. 3, developed countries collectively account for the largest share of case studies at 55.9 % (61 papers). This corpus is overwhelmingly dominated by the United States, which alone constitutes 29.4 % (32 papers) of the total literature. Other significant contributors within this group include Italy (7.3 %, 8 papers), while numerous other developed nations (e.g., Germany, France, Australia, Japan, and Canada) are represented by only one or two papers each, each constituting 0.9 % to 1.8 % of the total.

In contrast, developing countries represent 35.7 % (39 papers) of the sample. However, this aggregate figure is heavily skewed by the exceptional contribution of China, which represents 23.9 % (26 papers) of all studies and over half (66.6 %) of the developing world's share. Excluding China, the remaining developing regions encompassing vast and often highly vulnerable areas in South Asia, Southeast Asia, Africa, the Middle East, and Latin America are represented by only 11.9 % (13 papers) of the literature. Many of these countries, such as Bangladesh, Haiti, Nepal, and Indonesia, are represented by a single paper each (0.9 %). A notable 8.3 % (9 papers) of studies employ hypothetical or non-spatial models and are excluded from this geographical classification.

This distribution underscores a critical empirical bias: the evidence base for road network resilience is predominantly built upon contexts in high-capacity, developed economies and China. Consequently, resilience frameworks, models, and metrics may lack validation and transferability to the institutional, financial, and multi-hazard contexts of the underrepresented developing world, where infrastructure vulnerability is often most acute. Addressing this geographical research deficit is essential for developing inclusive and globally relevant resilience principles.

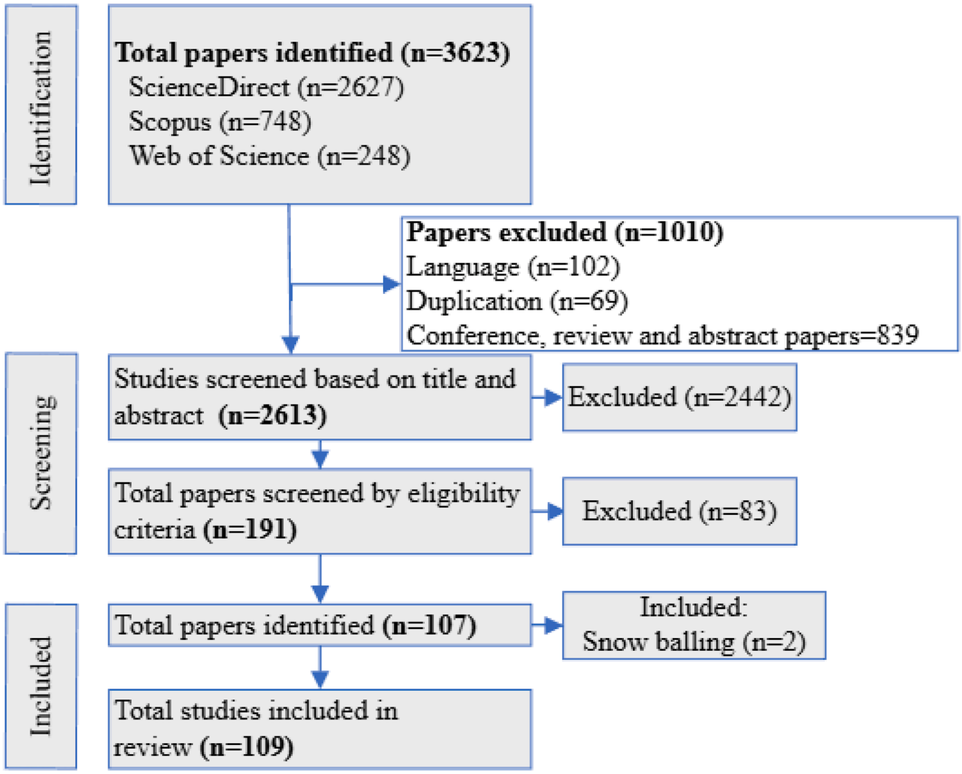

Fig. 1. PRISMA 2020 flowchart showing the study selection process, from the initial identification of 3623 records to the final inclusion of 109 studies on road network resilience under natural hazards.

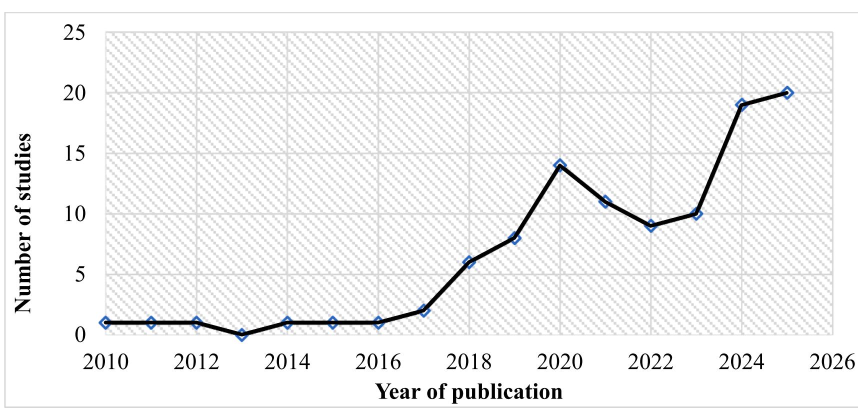

Fig. 2. Number of papers analyzed in this study with corresponding year of publication.

3. Results

3.1. Definition and state of the art of road networks resilience for natural hazards

In the context of road networks, there is no overall agreement in the definition and specific measure of the resilience to natural hazards [37]. The measured resilience of the road networks is the result of the resilience of the links and all the networks during and after hazards. Resilience during a hazard implies the robustness of the infrastructure, and it is commonly measured through its fragility by considering the magnitude of the hazard and the robustness of the infrastructure. In post-hazard, the resilience of the road networks is focused on search and rescue, the recovery process, and the management of the transportation after hazards. Therefore, the transport network is resilient when the performance of the road networks is not reduced due to the disruption. In order to measure the resilience, different metrics exist, as detailed below in section 3.4. Commonly, robustness, resilience, and vulnerabilities are used interchangeably by different researchers. However, it is important to note that there are firm distinctions among these concepts.

In different studies the concept of vulnerability was considered differently; there are no common consensuses [38]. However, commonly, vulnerability refers to the susceptibility of a transport system to disruptions as a consequence of a hazardous event or as the threats that can compromise its functionality, safety, or effectiveness. It involves identifying weaknesses, gaps, or potential points of failure within the system that could be exploited or lead to failures under adverse conditions. Vulnerability assessment helps in understanding the system's reaction to different hazards and enables the implementation of mitigation measures to enhance its resilience and robustness [39]. Whereas robustness is the ability to resist and maintain its position after hazards [32].

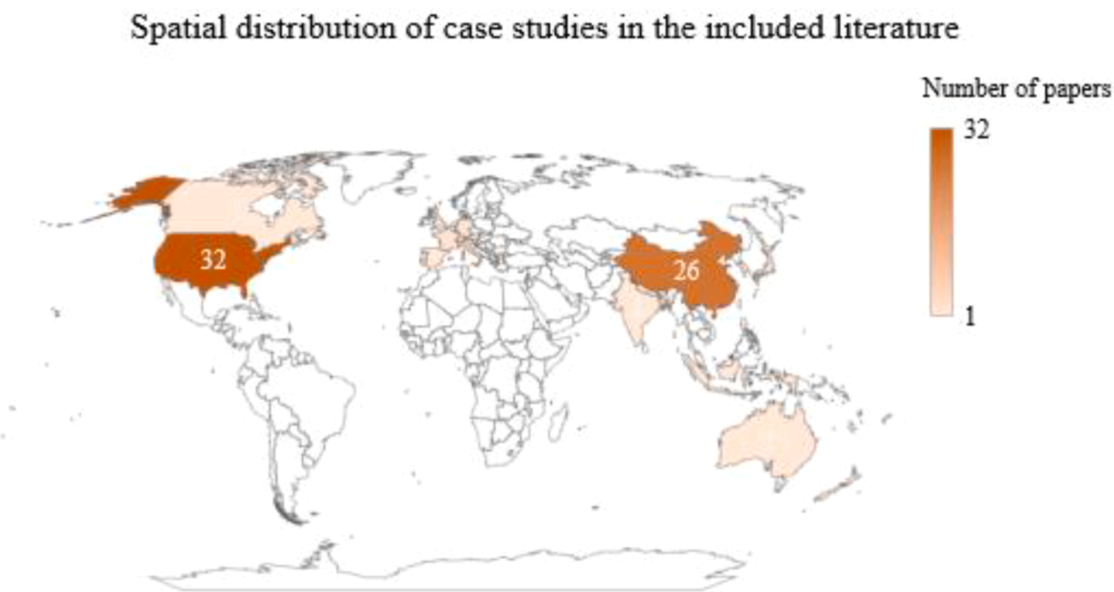

Fig. 3. Geographical distribution of the case study area of included studies.

The resilience of a road networks refers to its capacity to withstand external disruptions, absorb shocks, and restore its original functions, features, and layout following an incident that impacts certain nodes or routes within the network, such as a sudden and severe event like a natural disaster or traffic collision [3].

Fig. 4 illustrates the resilience curve of road networks under hazard conditions. Initially, resilience declines as the hazard strikes, but the subsequent recovery depends on factors such as resource availability, road redundancy, and the severity of the impact. In general, resilience is determined by both the system's robustness (its ability to withstand disruption) and the efficiency of its restoration mechanisms.

3.2. Resilience components in road networks

As shown below in Fig. 5, the analysis of 109 papers revealed that robustness (31.2 %) and vulnerability/preparedness (24.8 %) were the most frequently addressed components, followed by recovery (22.0 %). Interconnected terms, such as redundancy/robustness, appeared in 18.3 % of studies, while fully integrated frameworks covering all resilience components were rare (3.7 %). Robustness reflects the network's capacity to withstand hazards without significant loss of function, whereas recovery is typically evaluated through dimensions such as rapidity, resourcefulness, and adaptability, emphasizing strategies like optimization, rerouting, and restoring network functionality.

This result indicates that the literature focuses primarily on core attributes, particularly robustness and vulnerability/preparedness, while highlighting a lack of comprehensive frameworks that address the full spectrum of resilience.

3.3. Hazard types

In this study, the distribution of hazard types across the reviewed literature was systematically analyzed. Of the total 109 studies included, earthquake-related research represents the largest proportion, accounting for approximately 39 % of the sample, as illustrated in Fig. 6. This is followed by heavy rain/ snowstorm/winter storm, which accounts for 25 %, and flood-related studies, making up about 18 %. The predominance of earthquake, flooding, and snowstorm research highlights a clear scholarly focus on sudden-onset seismic and hydrological events, which are typically associated with immediate, high-impact consequences. In contrast, other hazard types, including landslides, hurricanes, wildfires, volcanic eruptions, and sea level rise are substantially underrepresented, suggesting potential gaps in the literature. This imbalance may reflect both the relative visibility and perceived

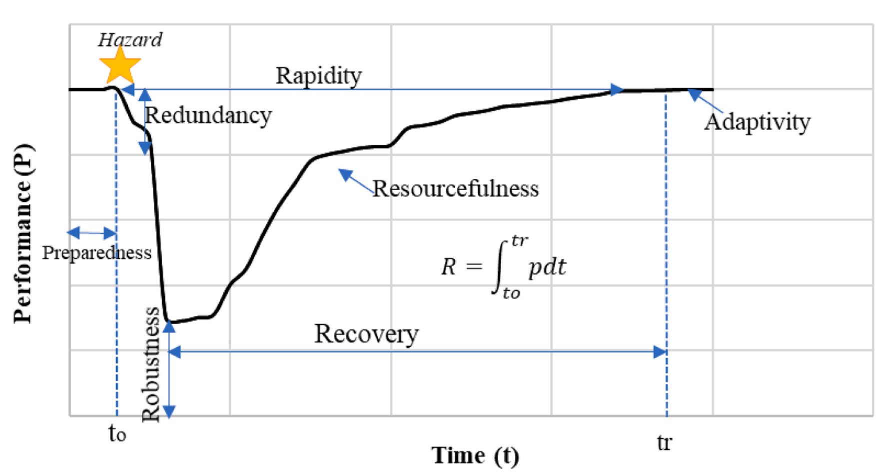

Fig. 4. Resilience curve showing the temporal evolution of network performance, and identifying the main concepts related to resilience [40,41].

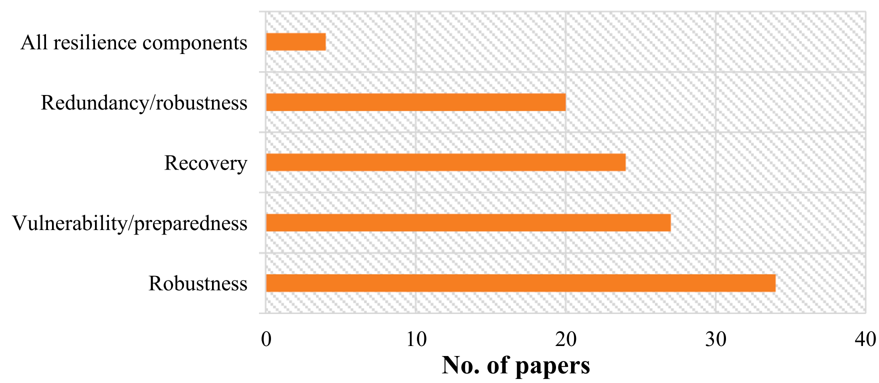

Fig. 5. Resilience components considered in the reviewed studies.

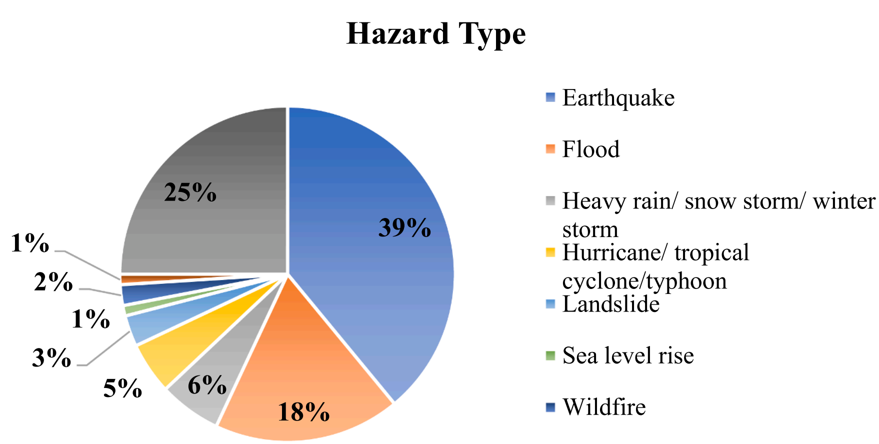

Fig. 6. Hazard distribution in the studies that are considered in this study.

severity of certain hazards, as well as challenges in studying slower onset or less frequent events, underscoring the need for more diversified hazard research to inform comprehensive risk management strategies.

3.4. Resilience metrics in road networks

Resilience metrics are quantitative measures used to evaluate a road network's ability to withstand, adapt to, and recover from disruptions. These metrics assess different aspects of resilience, including structural integrity, operational performance, and recovery efficiency [1]. Generally, the commonly used metrics in the previous studies are topology-based metrics, functional metrics and hybrid metrics.

Table 2 summarizes the resilience metrics used to measure the resilience of road networks conducted by different authors considered in this review in the last five years. The table highlights three primary categories of resilience metrics used in road network assessments, i.e., road topology-based, functional performance-based, and hybrid approaches.

Table 2
Resilience metrics.

Metric category	Example Metrics	Studies /Authors
Road topology-based	Centrality measures (betweenness, closeness), degree of nodes, redundancy, shortest path length, connectivity	[42–44,37,3,16,9,45–50]
Functional performance-based	Travel time, traffic flow, capacity, road user cost, accessibility, vehicle hours traveled, economic loss due to delay	[33,32,51–73]
Hybrid (topology + functional)	Combined network centrality and traffic dynamics, robustness indices, vulnerability index, resilience curves	[74,1,75–80]

The subsequent section presents a discussion of each resilience metric.

1. Road Topology-Based Metrics

Topological metrics, including centrality measures (betweenness, closeness), node degree, redundancy, and shortest path length are primarily used to evaluate the resilience of road networks [42–44]. Studies by [42,43,47] have explored the vulnerability and connectivity of road networks under hazardous conditions using topological resilience metrics. Their work provides valuable insights into how network accessibility and connectivity affect overall resilience, highlighting the importance of road link redundancy and link location for network performance. However, these studies predominantly adopt a static, topological perspective. Consequently, they are limited in their consideration of critical dynamic factors such as traffic flow patterns, temporal variations in demand, recovery processes, and spatial heterogeneity across regions, all of which are fundamental to shaping true network resilience [57].

2. Functional Performance-Based Metrics

Functional metrics, including travel time, traffic flow, capacity, congestion index, and economic loss due to delay ([33,51,62,32]) focus on operational performance. These are particularly relevant during and post-hazard, as they measure the immediate and prolonged impacts of disruptions. However, the studies often neglect the topological aspects of the network, making them insufficient for long-term resilience planning [58]. It also remains limited in considering the spatial-temporal dynamics of traffic and the real-time data.

3. Hybrid Metrics

Hybrid approaches combine topological and functional metrics, such as network centrality with traffic dynamics, efficiency indices, and resilience curves [27,68]. These provide a more comprehensive assessment, capturing both topological and operational resilience. However, traffic dynamics and its application across all phases of disaster management (pre-, during-, and post-hazard) are still evolving, with few studies explicitly addressing temporal resilience variations [75,77].

A holistic resilience assessment framework should integrate metrics that span all three phases, ensuring a continuous evaluation of road networks performance before, during, and after disruptions. Dynamic resilience modeling that adapts to real-time hazard impacts and recovery processes is needed.

3.5. Common and emerging methods in road networks resilience

This section examines the methodologies employed by researchers to assess road network resilience. It highlights how assessment techniques have evolved over time, transitioning from well-established methods to more innovative approaches. Fig. 7 illustrates the commonly used and emerging methods in the evolution of road network resilience assessment, with bubble size indicating the frequency of each method in the reviewed literature. Network analysis is the most frequently applied approach, appearing in 26 papers, followed by geographic information systems (GIS) and uncertainty modeling, each used in 16 studies. In contrast, emerging techniques are less prevalent, appearing in only a limited number of publications.

a) Common Methods

Table 3 summarizes the common methods used in road networks resilience analysis, along with a list of studies published between 2010 and 2025. These methods largely rely on well-established analytical approaches such as graph theory, network connectivity measures, travel time reliability, uncertainty measures, and efficiency-based indicators. They provide a structured means to evaluate how road networks absorb disruptions and maintain functionality under stress. Unlike emerging methods, which increasingly integrate advanced technologies such as big data analytics, machine learning, and simulation-based modeling, the common methods are more traditional and widely applied, offering consistency and comparability across studies.

The following section presents a comprehensive overview of the common / traditional methods utilized in road networks resilience.

Table 3
Common methods used to evaluate the resilience of road networks.

Method	Authors/Studies
Geographic information system (GIS)	[33,81,55,16,54,57,60,27,34,10,82–87].
Network Analysis	[3,16,9,45,46,1,80,33,34,50,10,80,83,88–90,84,91–94,86,95–98].
Uncertainty Modeling	[79,99,51,42,69–71,100–108].
Traffic Assignment	[37,56,53,52,65,66,64,57,109–119].
Traffic Simulation	[78,32,63,47,120–122,96,123–125].
Agent-Based Modelling (ABM)	[75,38].

1) Network Analysis

Network analysis is the preferred method for studying complex network systems in engineering, particularly in analyzing the capacity of nodes and links. Modeling networks is commonly used to assess the resilience of transportation systems. Representing systems through networks allows for simplified estimations of system performance, which is usually manageable in terms of computational complexity [9]. Therefore, the common methods used in road networks resilience for hazards are:

a. Dijkstra's Algorithm

According to [126], there are two common algorithms to find the shortest path in the road networks. Those are Moore and Dijkstra's algorithms, both of them discussed by using convenient node-oriented notation. The difference between them is the selection of nodes. Dijkstra's is good as compared with large networks. Dijkstra's algorithm was used by different researchers to evaluate the resilience of road networks. A weighted graph $G=$ (V, E), where:

V- set of nodes.

E – set of links, each with a non-negative weight.

b. Complex network theory

Unlike simple networks such as lattices or random graphs, a complex network displays unique features that are characteristic of real-world systems [127]. Currently, complex network theory is experiencing rapid growth within the fields of physics, mathematics, and computer

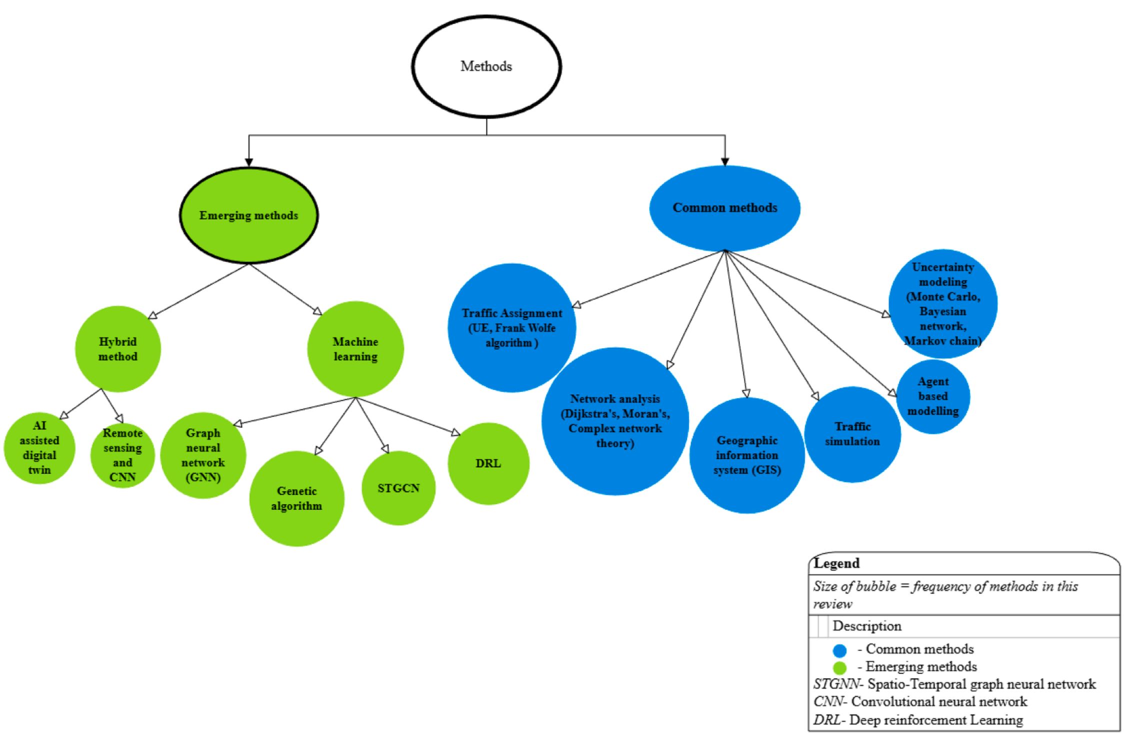

Fig. 7. Methods used to assess road networks' resilience in the studies analyzed in this review.

science. In recent years, the analysis of transportation systems as complex networks has attracted considerable attention within the research community. Complex network theories have been employed to examine the topologies of road networks [128].

Different types of metrics are used to measure the properties of the network. Those are the degree of centrality (betweenness, closeness, and eigenvector), degree of distribution, transitivity, clustering, and paths. Degree centrality is the most basic measure of centrality in a network; it is the degree of a node, i.e., the number of links it has, and it is sometimes referred to as degree centrality. Also, it was used to identify the significant node in the network [129]. The degree of nodes is calculated as:

$$Ki = \sum_{j=1}^{n} Aij, \tag{1}$$

Where: $Ki-$ degree of node i,

Aij adjacency matrix of the network.

Analyzing transportation networks using complex network theory is highly advantageous for researchers, service providers, and policymakers. This approach helps in translating the network structure and characteristics of transportation systems into real-world scenarios, particularly about the geographical features of specific regions. By utilizing methods such as centralities, significant nodes and components of the network can be identified, while assessing resilience, robustness, and vulnerability provides a thorough understanding of network performance. Complex network theory also aids in evaluating the growth and evolution of transportation networks over time and space, making it an essential tool for keeping pace with the rapidly changing world [130].

[37] and [3] demonstrate how complex network theory can identify critical nodes and links in transportation networks that are most vulnerable to disruptions or most essential for maintaining system functionality. The approach is particularly powerful, as [9] shows, in modeling cascading failure scenarios where localized disruptions propagate through network interdependencies. Despite these strengths, complex network theory applications face several limitations [9] points out that many complex network theory models incorporate simplifying assumptions that may not fully capture the operational realities of transportation systems, potentially leading to inaccurate vulnerability assessments. Furthermore, while complex network theory excels in static network analysis, [3,46], and [79] note significant challenges in adapting these methods for real-time dynamic analysis of evolving network conditions, and [1] indicates a significant limitation in predicting the potential scenarios. In addition, the computational complexity of this approach also grows substantially with network size, potentially limiting its practical application for large-scale regional analyses.

2) Geographic Information System (GIS) Modeling

Geographic Information Systems (GIS) are a fundamental tool for spatial analysis in infrastructure resilience studies, offering powerful capabilities for visualizing and assessing transportation networks under various disruption scenarios. As demonstrated by [33] and [81], GIS enables researchers to integrate multiple geospatial datasets, including road networks, land use patterns, and environmental factors, to conduct comprehensive vulnerability assessments. The system's strength lies particularly in its ability to support Multi-Criteria Decision Making (MCDM), as studied by [55] and [54], where it facilitates the weighting and analysis of diverse risk factors affecting infrastructure performance. However, GIS faces notable limitations in dynamic analysis contexts. As noted by [27] and [16], traditional GIS approaches are inherently static, requiring integration with other methodologies like traffic simulation or machine learning for real-time assessment capabilities. Furthermore, the effectiveness of GIS-based analyses is heavily contingent on data quality and availability. A study by [34], highlighting significant challenges in developing regions where geospatial data may be incomplete or outdated.

3) Traffic Assignment

Traffic assignment models, including user equilibrium, system optimal, Dijkstra, and Frank-Wolfe, are used to evaluate the road networks' resilience. A study by [27,56,64,57,109,110], and others applied this method to evaluate the functional resilience of the road networks.

Traffic assignment models, such as User Equilibrium (UE), system optimal assignment (SOA) and the Frank-Wolfe algorithm, play a critical role in evaluating the resilience of road networks. These models simulate how traffic flows respond to network conditions, disruptions, or capacity changes, allowing researchers to quantify the network's ability to maintain functionality under stress.

A substantial body of literature has demonstrated the effectiveness of traffic assignment–based approaches in assessing the functional resilience of road networks [37] applied the Model for Assignment and Regional Policy Evaluation (MARPLE) to evaluate regional network performance under disruption, while [56] employed a system-optimal assignment (SOA) framework to capture network-wide efficiency losses. User equilibrium (UE)–based formulations remain the most widely adopted, as evidenced by studies such as [53,64] and [52], which explicitly model travelers' route choice responses to capacity reductions and demand fluctuations. Solution algorithms, particularly the Frank–Wolfe method, have been extensively used to operationalize these models [65] and [57], while alternative formulations, such as the non-equilibrium probability random (NEPR) model proposed by [66], relax equilibrium assumptions to better capture transient traffic dynamics. Similarly, additional empirical studies have applied traffic assignment frameworks to assess transportation network vulnerability, performance degradation, and recovery under disruption scenarios such as link failures, demand surges, and natural hazards ([109,116–119] employed traffic assignment frameworks to examine network responses to disruptions such as link closures, demand surges, and natural hazards. Collectively, these studies underscore the central role of traffic assignment models in advancing resilience-oriented transportation network analysis. A key strength of these approaches lies in their ability to capture network-wide traffic redistribution and quantify resilience through interpretable performance indicators, including travel time increases, accessibility losses, and reductions in network connectivity under stressed conditions. In addition, traffic assignment models provide a robust basis for identifying critical links and nodes, supporting infrastructure investment prioritization and the evaluation of mitigation strategies. However, these methods also present limitations, as they often rely on simplified traveler behavior assumptions (e.g., static or deterministic route choice), require detailed and high-quality demand and network data, and may inadequately represent dynamic congestion propagation and post-disruption recovery processes. As a result, their applicability can be constrained when assessing real-time resilience or adaptive traveler responses during extreme events.

4) Uncertainty Model

Uncertainty is a fundamental characteristic of road networks resilience assessment, arising from unpredictable hazard occurrences, variability in traffic behavior, infrastructure fragility, and human decision-making during disruptions. Because both the timing and severity of hazards and the resulting road networks response cannot be known deterministically, several studies have incorporated probabilistic and stochastic modeling to better capture real-world uncertainty. Monte Carlo simulation is one of the most widely used approaches. For example, [99] applied Monte Carlo methods to simulate debris flow, landslide, rockfall, and snowstorm scenarios, allowing the authors to explore a wide distribution of possible impacts on traffic flow and travel time [52] combined Monte Carlo simulation with Latin Hypercube Sampling to quantify uncertainty in earthquake intensity and bridge fragility, linking the variability of seismic hazards directly to changes in overall network performance. Similarly, [51] used Monte Carlo simulation to evaluate the probabilistic reliability of road connectivity under earthquake-induced building collapse, enabling the assessment of multiple possible failure configurations that could not be captured through deterministic modeling [42] also used Monte Carlo analysis to identify bottleneck road sections by estimating the probability of failure and congestion under varying earthquake scenarios [100] used Monte Carlo simulation to assess the consequences of random single-road and multiple-road disruptions, emphasizing its value in modeling uncertainty in road redundancy and failure likelihood.

Other studies have adopted Bayesian approaches to explicitly model uncertainty through conditional dependencies among variables [79] constructed a Bayesian network using expert-derived Conditional Probability Tables (CPTs) to represent how different functional and infrastructural indicators influence overall transport system resilience under uncertain conditions. This probabilistic framework allowed the authors to capture interdependencies that would be difficult to express through deterministic equations. Likewise, [69] applied a dynamic Bayesian network to characterize long-term uncertainty in transportation safety, capacity, environmental impacts, and affordability across multiple cities. Their approach enabled the inclusion of temporal uncertainty, showing how transport system performance evolves probabilistically over time rather than in fixed deterministic trajectories. Together, these studies demonstrate that probabilistic modeling, whether through Monte Carlo simulation or Bayesian networks, plays a crucial role in addressing the inherent uncertainties present in road networks resilience analysis.

5) Traffic Simulation

Traffic simulation is a commonly used method for analyzing traffic dynamics at different levels and scenarios. Also, it is classified into three categories: microscopic, mesoscopic, and macroscopic analysis. Software tools such as SUMO and PTV VISUM are commonly used to study traffic dynamics in road networks. For instance, a study conducted by [32] utilized PTV Visum software to simulate traffic flow dynamics.

Traffic simulation methodologies offer valuable insights into infrastructure resilience by enabling detailed scenario testing under various disruption conditions [125] and [96] illustrate how these tools can model both microscopic (individual vehicle) and macroscopic (aggregate flow) behaviors, providing comprehensive assessments of system performance under stress. The flexibility of traffic simulation is particularly evident in studies by [121,122,96], and [32], where it has been successfully applied to evaluate evacuation route efficiency and congestion management strategies during emergencies. However, the effectiveness of traffic simulation is heavily dependent on proper calibration, with [63] emphasizing how inaccurate parameter settings can lead to misleading results. The computational demands of high-fidelity simulations present another significant challenge, particularly when modeling large urban networks or complex interaction scenarios. Additionally, while modern simulation approaches incorporate stochastic elements to better represent real-world conditions, [47] argue that fully capturing the unpredictability of human behavior and decision-making during disruptions remains an ongoing challenge.

Furthermore, in road networks resilience, traffic flow and demand are highly dynamic and vary temporally, depending on hazard severity and extent. However, existing studies ([32,47,121,63]) have not adequately considered the dynamic nature of traffic during restoration. Instead, they treated traffic as static and assumed road links were completely blocked.

6) Agent-Based Modelling (ABM)

Agent-based models extend beyond simply simulating mechanical movement to also incorporate the independent decision-making capabilities of agents. Typically, agents in these systems act in real-time rather than following a predetermined script. They begin with basic local rules and gradually develop into more intricate adaptive behaviors through interactions with neighboring agents. This process results in the emergence of system dynamics within the environment [131]. Agent-based modeling (ABM) is frequently utilized in the field of transportation systems, often incorporating traffic simulations such as SUMO and VUSIM [132]. In road networks analysis, agent-based modelling is effective for considering different agents like traffic dynamics, hazards, and road networks [75].

Studies by [75] and [38] demonstrate how ABM can capture the nuanced decision-making processes of individual actors from drivers to emergency responders and simulate how these micro-level interactions generate emergent system-level patterns. This capability makes ABM particularly valuable for studying evacuation dynamics and urban mobility during disruptions, as shown by [132]. The methodology's flexibility allows researchers to customize agent behaviors and rules to match specific study contexts, from routine traffic conditions to extreme disaster scenarios. However, ABM applications face notable limitations, particularly regarding computational requirements, often requiring the use of HPC systems [75] highlight how model complexity and runtime increase dramatically with the number of agents, potentially making large scale simulations impractical. The sensitivity of results to agent behavior rules presents another challenge, requiring careful design and validation to ensure realistic outcomes. Perhaps most significantly, as [38] discuss, validating ABM outputs against real-world observations remains difficult due to data limitations and the inherent unpredictability of human behavior during disruptive events.

b) Emerging Methods

Table 4 describes the emerging methods in road networks resilience assessments with the corresponding authors of the studies analyzed here.

The following section discusses emerging technologies used to assess the resilience of road networks. Moreover, methods such as genetic algorithms, graph neural networks, and deep reinforcement learning, classified broadly as machine learning techniques, are summarized and examined in detail. However, this review identifies a notable scarcity of detailed studies concerning the application of digital twin and remote sensing technologies in the assessment of road networks resilience, indicating a promising avenue for future research.

1) Machine Learning Algorithm

According to [133] and [68], machine learning algorithms excel at identifying complex, non-linear relationships in road networks performance data that traditional statistical methods might miss.

These techniques are particularly valuable for dynamic resilience modeling across all phases of road network performance from pre-disruption vulnerability assessment to post-disruption recovery analysis. The adaptive nature of machine learning models, as discussed by [77] and [61], allows for continuous improvement as new data becomes available, making them increasingly accurate for scenario prediction.

Among the most effective and commonly used approaches are genetic algorithms (GAs) and graph convolutional neural network-based deep reinforcement learning (GCN-DRL). Genetic algorithms are used for optimization of the recovery process [133,76,57,44], while GCN-DRL is utilized to capture complex spatial relationships within transportation networks, enabling dynamic decision-making in uncertain scenarios [77,68]. In addition, Graph Neural Networks (GNNs) can effectively model multi-class vehicle traffic assignment by capturing complex interdependencies between heterogeneous vehicle types, travel demand patterns, and network topology [143]. This capability allows for more realistic resilience assessments under multi-hazard scenarios where different vehicle classes exhibit varying vulnerability and recovery behaviors. According to [61], temporal decomposition-based dynamic multi-granularity graph neural network (TD2MG2NN) is effective in considering topological and temporal dynamics of the

Table 4
Emerging methods.

Methods	Authors/Studies
Genetic algorithm	[133,76,57,44,58,72]
Surrogated ANN	[85,134,135]
Graph neural network (GNN)	[68,61,77,136,137,73]
GNN with deep reinforcement learning (DRL)	[77,68,58]
GNN-assisted digital twin	[138–140]
GCN coupled with remote sensing	[141,142]

system. However, the practical deployment of these data-driven techniques, particularly machine learning models like GCN-DRL, introduces a set of constraints. Their remarkable effectiveness in applications like traffic flow management during disruptions is dependent on robust real-time data streams.

2) Artificial Intelligence (AI)-assisted Digital Twin

This method is an emerging technology; only one paper is available using digital twins in road infrastructure resilience. A study by [139] assesses the resilience of transport networks by using GNN-assisted network digital twin (NDT). The study concluded that this method is effective in considering both topological resilience and the temporal dynamics of traffic. However, the study indicates the challenges of twin positioning and synchronization. Besides, the study shows this methodology is a promising method to solve the limitations of traditional methods by considering both the topological and functional metrics in dynamic conditions. Furthermore, [140] conducted a study on the application of digital twins in urban resilience. The result shows that digital twins help improve urban resilience by integrating real-world data, simulating disasters virtually, and applying the insights to disaster prevention.

3) GNN-assisted remote sensing

AI-assisted remote sensing is effectively used in the transportation stream for different purposes. According to [141], GNN coupled with satellite images was used to infer road attributes. The study concluded that using this method is effective in classifying images and predicting and identifying the attribute's road.

3.6. *Critical discussion and hybrid approaches*

Several studies have employed hybrid methods to assess the resilience of road networks, enabling a more comprehensive representation of resilience across multiple phases, including preparedness, response, recovery, and adaptation, as well as across diverse performance metrics. For instance, [144] integrated traffic simulation with graph theory to capture both operational dynamics and topological properties of networks; [115] combined traffic assignment models with network analysis to evaluate system-wide performance under disruption; and [123] employed traffic simulation alongside GIS to spatially analyze network vulnerability and recovery. Similarly, [86] utilized network analysis and GIS to assess structural resilience, while [85] and [82] incorporated GIS with machine learning techniques, such as artificial neural networks (ANN) and genetic algorithms (GA), to enhance predictive and optimization capabilities. In addition, a study by [135] employs a hybrid framework that integrates graph-theoretic metrics, traffic simulation, and machine learning. To address the high computational burden of this integrated approach, the authors adopt a surrogate artificial neural network (ANN) model, which approximates simulation outputs and substantially improves computational efficiency while preserving predictive accuracy.

These studies collectively demonstrate that hybrid approaches are effective in capturing a wide range of disruption scenarios and analytical frameworks of transportation resilience. In addition, hybridization mitigates the inherent limitations of individual methods by leveraging their complementary strengths. For example, machine learning models offer strong predictive performance and pattern recognition capabilities but typically require large, high-quality datasets for training. Traffic simulation, on the other hand, allows for the explicit modeling of disruption and recovery scenarios and can generate synthetic data under controlled conditions, thereby supporting data-driven methods when empirical data are scarce. Consequently, hybrid methodologies provide a robust and flexible framework for road network resilience assessment, improving both analytical depth and practical applicability.

Generally, Table 5 provides a comparative synthesis of methodological approaches used in previous studies to assess road network resilience across different disaster management phases. The table highlights key trade-offs between data requirements, validation practices, reliability characteristics, and practical applicability. GIS-based and topology-driven network analysis methods dominate pre-hazard assessments due to their low to medium data requirements and high computational reliability; however, their validation is largely limited to structural and spatial consistency, offering limited representation of traffic dynamics and recovery processes. Traffic assignment and simulation-based approaches provide higher functional validity by explicitly modeling demand redistribution, congestion propagation, and post-disaster recovery, though their reliability depends on calibration quality and input assumptions. Uncertainty modeling techniques, including Monte Carlo simulation, Bayesian networks, and Markov-based models, play a critical role in improving both validation and reliability by explicitly representing variability in hazards, infrastructure damage, and traffic demand. These methods enhance the robustness of resilience estimates, particularly under incomplete or uncertain information. Recent advances in machine learning and AI-based approaches, such as graph neural networks and deep reinforcement learning, enable adaptive and real-time resilience assessment across all disaster phases but face significant data, computational, and financial barriers.

Recent studies indicate that surrogate modeling ([135,85,134]) and AI-assisted digital twin frameworks can partially overcome these limitations by approximating computationally expensive traffic simulations with trained meta-models. Such surrogate models retain high predictive accuracy while significantly reducing runtime and resource requirements, enabling broader application of advanced resilience assessment techniques, particularly in resource-constrained or data-limited contexts.

Overall, no single method is universally optimal; instead, hybrid and surrogate-assisted approaches provide the most balanced trade-off between validation, reliability, and practicality, especially for large-scale networks and resource-constrained contexts.

3.7. *Key areas for future improvement*

In this section, the identified research gaps and potential future areas of study are carefully examined and discussed. This analysis aims to highlight opportunities for further investigation and contribute to the advancement of knowledge in the field.

Research on road networks resilience has advanced considerably. Despite significant progress, several important limitations remain. Many studies [49,1] focus on network-level resilience, often treating links uniformly and assuming constant geometric or operational characteristics. In reality, link attributes such as lane width, gradient, and pavement condition vary significantly, influencing whether a segment remains partially functional, or completely blocked during disruptions. Despite their critical role, link-level dynamics and their impact on overall network resilience remain underexplored.

Studies like [52,32,76], and [51] indicate that road resilience assessments tend to rely on static, pre- and post-disruption comparisons, with limited attention to the spatial-temporal dynamics of traffic flow during disruption and recovery. This omission is critical, as the real-time processes of traffic rerouting, congestion propagation, and emergency response routing are essential for accurately modeling recovery and predicting cascading failures. This gap becomes even more problematic when considering compound events: for example, an earthquake that triggers landslides along multiple corridors, or flooding that weakens bridge structures while simultaneously cutting detour routes [74]. Such multi-hazard chains are far less studied than single-event scenarios, despite their prevalence in real-world disasters.

Another underexplored dimension is the integration of emerging transport technologies. As [145] suggests, autonomous and connected vehicles could principally adapt routes in real time to reduce recovery delays. Despite this potential, the integration of such emerging technologies remains an underexplored dimension in resilience assessment.

A study by [1] evaluates the resilience of road networks by using

Table 5
Summary of methods used for road network resilience assessment, including validation, reliability, data requirements, and practical limitations.

Method	Type of Data Used	Resilience Metric	Data requirement level	Phase	Validation	Reliability	Strengths	Limitations
GIS (Geographic Information Systems) [16,54,57,60,27,34,10,82,83]	Spatial data (road networks, bridges, tunnels, hazard zones)	Connectivity, accessibility, exposure mapping	Medium	Pre-hazard (Preparedness)	Validated mainly through consistency with historical hazard footprints and infrastructure exposure maps; limited functional validation against observed traffic impacts.	High reliability due to deterministic spatial analysis and low sensitivity to stochastic variation.	Effective for spatial visualization and hotspot identification; integrates multi-layer data (e.g., hazard intensity maps and road networks).	Cannot model traffic dynamics or behavioral response; static analysis without real-time adaptation.
Network Analysis (Graph Theory, Dijkstra, Complex Networks) (e.g. [33,34,50,84,91–94,86,95–98])	Road topology (nodes, edges, node and edge features)	Redundancy, centrality, shortest path, connectivity loss	Low	Pre-hazard (Preparedness)	Validation typically limited to theoretical soundness or comparison among network metrics; rarely validated using empirical traffic or post-disaster performance data.	High reliability due to deterministic computations; results are stable under similar network representations.	Computationally efficient for static networks; identifies critical nodes and links.	Ignores traffic flow, evacuation behavior, demand redistribution, and dynamic hazard evolution; limited realism.
Agent-Based Modeling (ABM) (e.g. [75,38])	Road topology, traffic data, hazard data, behavioral rules	Evacuation efficiency, traffic flow, recovery time	High	During & Post-hazard (Response, Recovery)	Often validated through scenario replication, comparison with evacuation drills, or alignment with observed behavioral patterns; empirical validation remains limited in large-scale cases.	Moderate reliability; sensitive to behavioral assumptions and stochastic agent interactions, often improved via sensitivity analysis.	Captures human decision-making and interactions among vehicles, infrastructure, and hazards.	Requires high-resolution behavioral data; computationally intensive for large populations.
Uncertainty Modeling (Monte Carlo, Bayesian Networks, Markov Chains) (e.g. [102–108])	Damage probability, hazard intensity, traffic demand distributions	Performance variability, robustness under uncertainty, recovery probability	Low-high	All phases	Validation achieved by comparing probabilistic outputs with historical damage distributions or expert judgment; enhances realism by explicitly representing uncertainty.	High reliability when sufficient simulation runs or probabilistic convergence criteria are applied.	Explicitly accounts for uncertainty in hazards, damage, and demand; improves robustness of resilience estimates.	Requires probabilistic data assumptions; results depend on quality of input distributions.
Traffic Assignment Models (UE, The Folk-Wolfe algorithm) (e.g. [64,57,109–112])	Origin–destination demand, network capacity, travel cost	Accessibility loss, travel time increase, network efficiency	Medium	During & Post-hazard	Validated through equilibrium consistency and, in some cases, comparison with observed rerouting patterns or baseline traffic conditions.	High reliability for deterministic equilibrium solutions; reduced reliability when demand assumptions are uncertain.	Captures demand redistribution and user response to disruptions; computationally efficient for large networks.	Limited representation of congestion dynamics and adaptive behavior during extreme disruptions.
Traffic Simulation (Microscopic / Macroscopic) [32,47,121,122,96,123,124].	Traffic volume, speed, travel time, travel cost	Travel time, rerouting success, traffic flow	High	During & Post-hazard (Response, Recovery)	Frequently validated against observed traffic data, baseline calibration, or scenario comparison; strong functional validity.	Moderate reliability; sensitive to calibration parameters and demand assumptions, often improved through Monte Carlo or sensitivity testing.	Dynamically models congestion propagation and recovery; allows testing of mitigation strategies.	High data and calibration requirements; computationally demanding.
Machine Learning (GNN, DRL, GA) [68,61,77,136,77,68,58]	Road topology, real-time traffic data, hazard data	Optimal rerouting, recovery cost, traffic flow, topological robustness	Extremely high	All phases	Validation depends strongly on training data representativeness and external testing; some studies validate against simulation outputs or historical disruption patterns.	Variable reliability; improves with large datasets and cross-validation, but may degrade in data-scarce contexts.	Captures nonlinear interactions; enables adaptive and real-time decision-making; effective for cascading failure prediction.	Requires large datasets, high computational capacity, and remains difficult to interpret for decision-makers.

both network analysis and traffic simulation. They remain limited in addressing real-time monitoring and predictive analytics, which could enable operators to anticipate bottlenecks, simulate alternative recovery strategies, and take proactive measures before disruptions escalate into full network paralysis. In addition, studies like [61], and [77] highlights the potential of real-time monitoring and predictive analytics, made possible through machine learning, is largely untapped in operational resilience frameworks, resulting in approaches that remain reactive rather than proactive. Furthermore, digital twin is an emerging technology and it is best in simulating the transport system for large scale and in detail [146]. As a dynamic digital replica of the real environment, it is highly effective for monitoring the real-time dynamics of a road networks during hazards. When integrated with artificial intelligence (AI), its capability is enhanced, enabling it to effectively predict future scenarios and significantly contribute to road networks resilience [138]. However, this specific application remains under-investigated, presenting a critical area for future research.

Generally, addressing these gaps will require a shift toward multi-scale, data-rich, and adaptive modeling approaches that integrate asset-level detail, temporal dynamics, multi-hazard interactions, emerging technologies, and interdependent infrastructure networks. Therefore, such a framework enables resilience strategies that genuinely reflect the complex realities of road networks under threat.

4. Conclusion

This systematic review highlights the current state of the art in road networks resilience under multiple and cascading hazards. This paper collects the commonly used resilience metrics to measure in road networks. The review synthesizes key resilience metrics and innovative methodologies, revealing that most studies overlook the dynamic and adaptive nature of road networks under cascading hazards. In addition, the prevalent use of graph theory, including Dijkstra's algorithm, complex network methods, and other methods was used to analyze the resilience of road networks. However, they are limited in dynamic behavior analysis and future prediction of resilience. Furthermore, machine learning, like Graph Convolutional Networks (GCNs) and deep reinforcement learning (DRL), present a promising approach for capturing spatial dependencies, dynamic behavior of traffic in time and road links and optimization of the recovery process. Future research should prioritize integrating dynamic modeling techniques, real-time data, and multi-hazard interactions to enhance resilience assessments. Addressing these gaps will enable more robust infrastructure planning and adaptive strategies for improving road networks resilience in the face of increasing climate and disaster risks.

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CRediT authorship contribution statement

Yohannes Sisay Zeleke: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Maurizio Tira:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Chiara Scaini:** Writing – review & editing, Supervision, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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