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# Integrating structural and social vulnerability for equitable bridge maintenance prioritisation ☆

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## ABSTRACT

As bridge infrastructure ages worldwide, managers face increasingly scarce resources for maintenance and rehabilitation. However, state-of-the-art prioritisation approaches rely on subjective weighting schemes that focus predominantly on structural conditions whilst neglecting social equity considerations. To address these limitations, this study introduces a novel methodology that integrates bridge structural and social vulnerability, incorporates data-driven weighting, includes subsidence susceptibility, and complements the assessment with economic, maintenance, and monitoring evaluations. The method develops a multi-dimensional Bridge Vulnerability Index that enhances traditional metrics with subsidence susceptibility, spaceborne monitoring availability, economic resilience, and inspection burden indicators. Using Principal Component Factor Analysis for objective weighting, these indicators are aggregated across three dimensions: network criticality, damage susceptibility, and adaptive capacity. The relationship between bridge and social vulnerability is then examined through bivariate mapping, creating a county-level socio-structural vulnerability framework for administrative-level resource prioritisation. Applied to 22,298 Californian bridges across 58 counties, the methodology highlighted several Northern California counties as exhibiting the highest compounded vulnerability scores within the framework, where poor bridge conditions coincide with resource constraints and elevated social vulnerability. These findings reveal how traditional approaches prioritising structural health and network importance may inadvertently perpetuate infrastructure-related social disparities by overlooking communities where failures would have the greatest societal impact. Notably, the strong correlation between social vulnerability and good monitoring availability presents immediate opportunities for deploying MT-InSAR technology to support equitable infrastructure management. The framework thus provides transportation agencies with a tool for more equitable resource allocation for enhancing infrastructure resilience while addressing community needs.

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## 1. Introduction

Bridges provide critical transport functionalities in modern societies. Many of these structures, especially in Europe and the US, were constructed during distinct periods of intensive development: the late 19th century during industrialisation and railway expansion, the 1930s during economic recovery programmes (such as the New Deal in the US), and the post-World War II era of the 1960s, coinciding with private transport growth [1,2]. Consequently, a significant portion of existing bridge infrastructure is now approaching or has exceeded its design life. This ageing infrastructure challenge is further compounded by climate change effects, which are expected to increase the frequency of structural issues [3,4]. Additionally, increased freight traffic means bridges must carry weight and volume loads higher than originally anticipated [2]. As a result, many bridges require urgent repair or rehabilitation. Given these pressures and often scarce maintenance resources, bridge managers face significant challenges in prioritising interventions [3]. Therefore, systematic bridge preservation strategies are needed that can help stakeholders effectively prioritise interventions for their bridge inventory.

Agencies managing bridge portfolios often employ performance-based metrics, such as condition or health indices, to identify structures requiring urgent repairs, with specific methodologies varying internationally [5–8]. These methodologies can be broadly categorised into four approaches [5]. The most prevalent approach applies expert-determined weights to structural and operational data, offering a straightforward framework that primarily utilises qualitative data to capture damage degree, severity, and importance for maintenance planning. However, weight assignment remains subjective when assessing how individual element conditions affect overall structural performance. Ratio-based methods compare current structural conditions against the original state, weighing individual elements by their failure cost for thorough evaluation. Nevertheless, data collection is resource-intensive, and failure cost estimation can be problematic. The component-worst-condition approach uses the poorest-condition component as a proxy for the entire structure's rating, effectively identifying high-risk bridges during extreme events, yet fails to provide a comprehensive overview of overall deterioration. Qualitative element-level inspection methods provide descriptive ratings indicating damage extent, severity, and element importance to indicate intervention urgency, though such ratings may lack sufficient granularity for effective prioritisation. These methods are sometimes combined when calculating final health indicators to avoid individual pitfalls, but some of the constraints still remain.

One of the drawbacks of the state-of-the-art bridge assessment metrics is that weights used to assign relative importance to assessment parameters rely heavily on expert opinion and engineering judgement [5]. Transportation agencies predominantly utilise subjective expert-based weights in their assessments [5,9–11], frequently determined through multi-criteria decision-making techniques such as the Analytic Hierarchy Process [9,12]. However, organising in-person workshops to gather expert opinions presents logistical challenges [12]. Furthermore, whilst expert-based weights may enhance the legitimacy of proposed indices, they can introduce bias, wherein higher weights are allocated to politically favoured factors or inequitable criteria are selected [5,13,14]. Therefore, more objective weighting approaches are needed. Data-driven weighting methods, including those based on machine learning algorithms or statistical models, offer alternatives that operate independently of expert judgement [14–16]. Specifically, Principal Component Analysis (PCA) and Factor Analysis (FA) enable the development of data-driven variance-based weights that effectively capture the greatest variation in datasets [14,17].

Beyond subjective weighting limitations, current methodologies primarily focus on structural condition and network relevance whilst relying predominantly on visual survey data, but fail to account for non-technical performance aspects such as operational, maintenance, resilience, or financial considerations that are integral to bridge restoration strategy implementation [5,9,18–20]. Remotely sensed data could provide more frequent updates and reduce uncertainty about bridge structural performance, thus improving decision-making reliability [20]. However, both non-technical metrics and remote sensing data have restricted availability to bridge stakeholders compared to commonly used survey-based databases, making implementation in codes and engineering practice challenging. Therefore, more comprehensive bridge assessment approaches are needed that account for additional performance dimensions using datasets easily accessible to bridge stakeholders.

Importantly, bridge assessment methodologies tend to neglect community impacts, despite calls made over 20 years ago for need-based, data-driven approaches to transportation project funding that reflect community concerns rather than relying solely on traditional cost–benefit analysis [13]. Research has confirmed correlations between poor transportation provisions and high social vulnerability, where inadequate infrastructure limits access to educational, economic, and social opportunities, perpetuating cycles of inequality and leading to social exclusion, whilst investments in transport infrastructure can reduce income inequalities by improving access to employment and education [21–23]. Furthermore, studies reveal correlations between community socioeconomic characteristics and disaster-related hardship, with socially vulnerable communities, including those with higher poverty rates, larger proportions of ethnic minorities, elderly, disabled, or economically disadvantaged populations, experiencing more disruptions from natural hazards, reduced disaster resilience, increased post-disaster mental health risks, longer recovery times, and limited access to support mechanisms after disaster [24–27]. Specifically regarding bridges, research demonstrates that structures in poor condition and those with vertical height restrictions are more frequently found in disadvantaged communities, indicating that these populations often face restricted access [28,29].

Recognising that infrastructure failures do not affect all populations equally, growing attention has been drawn to infrastructure resilience strategies that account for social vulnerability across four equity dimensions: demographic, spatial, procedural, and capacity, whilst procedural equity remains under-explored [30]. Frameworks propose incorporating social equity to guide infrastructure investments towards high-poverty areas with limited mobility [27]. However, research emphasises that whilst much attention has been given to technical infrastructure resilience, far less focus has been placed on how infrastructure failures disproportionately affect socially vulnerable populations, highlighting that assessing socially differentiated vulnerabilities is essential for effective disaster risk management and policy development [30,31]. Therefore, maintenance prioritisation strategies must extend beyond traditional economic assessment to include social equity considerations [24,28]. Nevertheless, despite emerging frameworks for social equity in infrastructure resilience, research on practical methods for incorporating social vulnerability into bridge vulnerability assessment for equitable prioritisation remains sparse and has yet to be implemented in frameworks used by national- or state-level managing agencies. Consequently, there is a need for methodologies that systematically integrate social vulnerability considerations into bridge vulnerability assessment frameworks.

The existing frameworks primarily focus on flood-related hazards [32,33] or those caused by torrential rainfall [34]. However, whilst water-related hazards are the leading cause of bridge failures [35–37], they represent only one category of threats. Land subsidence, recognised as a significant geo-hazard affecting numerous locations globally [38], also has the potential to cause major damage to bridge structures [39,40], but remains largely overlooked in assessment frameworks. Therefore, there is a need for novel methodologies that integrate both social vulnerability considerations and comprehensive hazard assessment, including subsidence susceptibility, into unified bridge vulnerability metrics.

Whilst the majority of transportation infrastructure resilience research has historically disregarded equity dimensions [41], recent studies have increasingly examined equity integration into transportation asset management. These include network-level approaches for disaster response [41], multi-objective optimisation frameworks balancing economic, environmental, and social aspects [42], and multi-criteria decision support systems for bridge rehabilitation [32]. However, those existing equity-oriented frameworks exhibit important limitations for systematic bridge maintenance prioritisation. Several studies quantify equity through social costs of interventions, primarily increased travel time, detours, and accident costs during maintenance or following bridge failure [43,44], rather than assessing the baseline social vulnerability of communities served by bridge infrastructure. Others employ expert-based weighting schemes such as fuzzy Analytic Hierarchy Process [44] that remain susceptible to subjective bias, or focus on specific hazard types such as floods [32] whilst neglecting broader vulnerability dimensions. Furthermore, these approaches often address either network-level optimisation or individual project assessment, without providing administrative-level frameworks suitable for regional resource allocation decisions. Therefore, several gaps remain in the context of bridge maintenance prioritisation and must be addressed for more comprehensive and socially equitable vulnerability assessment: (1) proposing methods for data-driven and unbiased weighting of vulnerability index components; (2) expanding metrics to account for non-technical aspects of bridge vulnerability using easily accessible datasets; (3) integrating social vulnerability into assessment frameworks; and (4) extending hazard consideration to include subsidence. This research addresses these identified gaps by developing an integrated administrative unit-level bridge vulnerability assessment framework.

The proposed methodology begins with a systematic literature review to identify metrics commonly used in bridge health assessment. These metrics are then enhanced with novel indicators, including subsidence susceptibility, spaceborne monitoring availability, economic pressure from bridge replacement costs relative to county resources, and inspection burden assessment. Then, the expanded metrics are organised into nine sub-indicators across three dimensions, network criticality, damage susceptibility, and adaptive capacity, with objective weights derived through data-driven analysis. These weighted sub-indicators are aggregated to create a composite bridge vulnerability metric, which is subsequently integrated with social vulnerability measures to produce a comprehensive socio-structural vulnerability assessment at the county level. The framework is applied to bridges in California, selected for its significant bridge portfolio, subsidence exposure, varied social vulnerability, and comprehensive data availability on bridge structural condition, subsidence, and social indicators.

The remainder of this paper is organised as follows. Section 2 provides a literature review of bridge assessment metrics with a focus on the US context. Section 3 explains the conceptual framework and specific methodological steps, followed by Section 4, which presents the county-level bridge vulnerability metric. Section 5 critically discusses the results and methodological constraints, with conclusions provided in Section 6. Through the proposed new approach for bridge assessment, the study seeks to support more equitable and effective prioritisation of state funding for bridge rehabilitation and maintenance, ultimately enhancing infrastructure resilience whilst addressing community needs.

## 2. Case study

Bridges are critical elements of transportation networks, yet a significant proportion of US structures are affected by ageing, with approximately 45% already exceeding their design life [45]. Consequently, in 2024, 168 million trips were taken daily across bridges in poor structural condition [45]. More than one-third of American bridges require major repair work or replacement, with necessary repairs estimated to cost over 400 billion dollars [46]. Meanwhile, almost half of the 623,000 bridges in the US are in “fair” condition, meaning that as they continue to age, they might be downgraded to “poor” in the near future [45]. This situation presents an opportunity for bridge management agencies, as rehabilitating these bridges is more cost-effective than preserving or replacing structures once their condition has deteriorated to “poor” [45]. Nevertheless, based on 2021 estimates, at current investment rates, it will take nearly 50 years to complete the necessary repairs, while ongoing deterioration will overwhelm the system [47]. Therefore, an effective bridge maintenance prioritisation in the US is crucial.

The American state transportation agencies are typically responsible for their bridge maintenance and rehabilitation prioritisation programmes [9]. A comprehensive literature review was conducted to identify metrics included in bridge health assessments, as summarised in Table 1. The review revealed that almost all methodologies consider the physical condition of bridges, while most evaluate the asset importance to the network along with structural capacity and serviceability. Few approaches examine vulnerability to hazards, primarily focusing on water-related risks. Some methodologies consider the financial implications of failure or rehabilitation cost-effectiveness, though only one correlates these costs with the economic conditions of affected communities.

Whilst the importance of social equity considerations is acknowledged by administrative bodies, with the US government proposing the Justice40 Initiative to ensure disadvantaged communities receive 40% of federal spending on clean transportation and the US Department of Transportation issuing an Equity Action Plan calling for data-driven equity assessment [48,49], the majority of currently employed prioritisation frameworks neglect the community needs and potential impacts of bridge closure or failure.

This study applies the methodology specifically to California, as it provides a suitable case study for this research, allowing for addressing all identified methodological gaps. First, the state employs expert-based weighting systems in bridge assessment, making it relevant for the evaluation of data-driven alternatives [50]. Second, California's comprehensive infrastructure databases enable integration of non-technical assessment metrics. Third, significant variation in social vulnerability across counties facilitates equity analysis. Finally, the state faces substantial land subsidence due to groundwater extraction [51,52], which can adversely impact critical infrastructure [39,40,51,53]. Notably, whilst the American National Risk Index excludes subsidence assessment due to insufficient data [54,55], this data gap has recently been addressed through the development of a California-wide subsidence map [56], providing a valuable opportunity to investigate state-wide subsidence impacts on bridges.

## 3. Methods

This paper presents a novel methodology for assessing the socio-structural vulnerability of bridges at the administrative unit level. The term "vulnerability" varies considerably across different research contexts and disciplines [68,69]. Therefore, this study introduced the "Bridge Vulnerability Index (BVI)" to describe a composite index indicating that the bridge infrastructure within a county is in poor condition, characterised by structural and operational deficiencies and consequently requiring increased maintenance and rehabilitation investment. Similarly, the term "socio-structural vulnerability" was used to represent an integrated index that combines BVI with social vulnerability measures, thereby enabling the identification of counties that warrant prioritised resource allocation.

The methodology comprised three primary phases. First, a methodology for constructing the BVI for county-level bridge assessment was developed. The BVI evaluated three critical dimensions of bridge vulnerability: the bridge's network criticality, its susceptibility to structural and hazard-induced damage, and the county's systemic capacity to manage bridge deterioration. The BVI methodology involved the following steps: identification of appropriate metrics, derivation of county-level sub-indicators, selection of data sources and pre-processing of datasets, calculation of data-driven weights for each sub-indicator, and aggregation of these sub-components into a composite indicator. Second, social vulnerability was assessed using a publicly available, state-of-the-art dataset [70]. Finally, the interrelationships between BVI and social vulnerability were examined with a map that illustrated integrated socio-structural vulnerability.

### 3.1. Conceptual framework for bridge vulnerability assessment

In order to establish the conceptual framework, this research first identified the metrics most commonly employed for bridge condition and criticality assessment through a comprehensive literature review of currently used approaches for bridge health assessment in the US, summarised in Table 1. This analysis revealed that the commonly applied metrics can be broadly categorised into two dimensions: network criticality and damage susceptibility, as presented in Table 2. Variables classified as network criticality measure how essential the bridge is to the transportation network by assessing traffic conditions, bridge redundancy through detour length, and strategic importance to the transportation system. The damage susceptibility dimension commonly evaluates the structural condition of the bridge through assessment of the structure itself, examination of the deck condition, and analysis of weight or safe load restrictions. Additionally, susceptibility to damage caused by water-related hazards is frequently considered in existing frameworks. However, as discussed in Section 2, California is significantly affected by ground subsidence, a hazard omitted by current approaches. Therefore, in this study, subsidence susceptibility was incorporated as an additional assessment metric to extend state-of-the-art methods. Unlike other damage susceptibility indicators that rely on structural assessments, subsidence susceptibility can be directly quantified using measured subsidence rates, given their established impact on structural integrity [71].

This study aims to extend the bridge vulnerability metrics to account for the economic aspects of bridge maintenance. The analysis of the state-of-the-art approaches in Table 1 revealed that while several of them incorporate metrics related to maintenance costs or funding availability, methodologies vary considerably, as accurate cost estimation presents significant challenges [5]. To overcome those limitations and develop a universally applicable and readily implementable method, this study employed the estimated replacement cost for "poor" bridges, which is a metric widely utilised by state transportation agencies for decision-making processes [72], and could be employed for estimation of potential county-level economic losses when bridge replacement becomes necessary [73]. However, recognising that California counties vary substantially in size and financial resources, these costs were standardised relative to each county's GDP, thereby creating a metric that effectively assesses a county's economic resilience to potential bridge replacement expenditures.

A critical component in obtaining the majority of metrics used for bridge condition assessment is the inspection process, which must be conducted by qualified bridge inspectors. Nevertheless, numerous state transportation agencies, including the California Department of Transportation (Caltrans), report significant shortages of construction inspection personnel [74]. To address this constraint, the proposed framework incorporated an assessment of inspection burden through two key indicators: inspection frequency (where inspection intervals shorter than the standard biennial requirement indicate increased workload demands) and elapsed time since last inspection, which facilitates identification of bridges with overdue inspections. This approach acknowledged the practical resource limitations faced by bridge management agencies.

**Table 1**

Summary of metrics used for bridge assessment frameworks used in the USA (some components have been summarised or omitted for the sake of simplification; for a comprehensive understanding of each component, the reader should refer to the original references); Metrics that repeat most often between methods are written in italics. Note: FHWA — Federal Highway Agency, ADT — Average Daily Traffic, ADTT — Average Daily Truck Traffic, Waterway adequacy — relates to the probability of overtopping during flooding, NHS — National Highway System, Inventory rating — relates to safe load level.

| Name | Structural health | Network importance | Hazard vulnerability | Capacity & serviceability | Funding related | Other | Weighting | Reference |
|---|---|---|---|---|---|---|---|---|
| Bridge and Culvert Sensitivity Index | *Superstructure and Substructure condition* | *ADT, ADTT, Detour length, NHS* | *Waterway adequacy, Scour susceptibility* | *Deck condition*, Channel condition | – | Structure length | Subjective | Van Dyke et al. [11] |
| Good-Fair-Poor rating by FHWA | *Superstructure and Substructure condition* | – | – | *Deck Condition* | – | – | Subjective classification into three classes based on the lowest of the considered ratings | KYTC Staff [57],Department of Transportation (DOT) [58] |
| Sufficiency Rating by FHWA | *Superstructure and Substructure condition* | *ADT, Detour length*, STRAHNET | *Waterway adequacy* | *Deck condition, Inventory Rating*, Vertical Clearance, Underclearance, Deck geometry, Number of lanes, Width, Structural Evaluation, Approach Road Alignment etc. | – | – | Subjective weighting given by the guide | Office of Engineering Bridge Division Bridge Management Branch [59] |
| Functionally Obsolete by FHWA (no longer used) | – | – | *Waterway adequacy* | Underclearance, Deck Geometry, Structural Evaluation, Approach Road Alignment | – | – | Subjective binary assessment — if any of the ratings is below an agreed value, the bridge is classified as not meeting current design guidelines | KYTC Staff [57] |
| Structurally Deficient by FHWA (no longer used) | *Superstructure and Substructure condition* | – | *Waterway adequacy* | *Deck Condition* | – | – | Subjective binary assessment — if any of the ratings is below an agreed value, the bridge is classified as structurally deficient | KYTC Staff [57] |
| Arizona DOT | *Superstructure and Substructure condition, Presence of fracture in critical elements* | *ADT, ADTT, Detour length*, Functional classification | *Waterway adequacy, Scour susceptibility* | *Deck condition, Weight restrictions*, Vertical Clearance, Underclearance, Operating Rating, Width, Roadway alignment | Projects partially funded externally receive additional points | Age, whether bridge is structurally deficient or functionally obsolete, Sufficiency rating, Elevation | Subjective scoring with weights depended on component values given by guide | Gibson et al. [9],AECOM [60],Yang and Eberhart [61] |
| California Bridge Health Index | Element-level condition assessment | – | – | – | Failure cost and element condition are combined to calculate a health index as the ratio of current to initial element value | – | Subjective weights | Shepard and Johnson [50] |
| Colorado DOT | Structure condition | Mobility | *Scour susceptibility* | Safety | Economic factors | | Model-based data analytics based scoring | Gibson et al. [9] |
| Connecticut DOT | *Superstructure and Substructure condition* | – | – | *Deck condition, Inventory Rating* | – | Includes the sufficiency rating also in the equation, so some variables are considered twice | Subjective | Bureau of Engineering and Construction Division of Bridges [62] |
| Iowa Risk-Based Prioritisation | *Superstructure and Substructure condition, Presence of fracture in critical elements* | *ADT, ADTT, Detour length*, Functional classification, *NHS*, Type of service under bridge | *Waterway adequacy* | *Deck condition, Inventory Rating*, Under clearance, Number of lanes, Channel condition, Deck protection, Design load, Skew angle, Lane width | – | Age, length of maximum span | Subjective weights proposed in paper | Neubauer [63] |
| Kentucky Enhanced Bridge Prioritisation Index | Health Index/NBI condition rating, Presence of fracture in critical elements | *ADT, ADTT, Detour length, NHS*, Emergency route designation, School bus route | *Scour susceptibility* | *Weight restrictions*, Vertical clearance, Horizontal clearance | – | Age, frequency of inspections, the existence of fatigue-prone details | Analytic Hierarchy Process used to assign weights so that they are based on stakeholders/experts knowledge | Gibson et al. [9] |

(*continued on next page*)

Additionally, remote sensing monitoring can be used to aid inspectors in data collection and provide more frequent measurements, thereby reducing uncertainty about bridge structural health [20]. In response to this capability, this study integrated the availability of remote sensing monitoring, specifically Multi-Temporal Interferometric Synthetic Aperture Radar (MT-InSAR), into the assessment metrics to allow prioritisation of bridges lacking spaceborne measurement coverage for earlier intervention, as their structural health cannot be continuously monitored, necessitating more proactive problem identification and resolution

**Table 1** (*continued*).

| Name | Structural health | Network importance | Hazard vulnerability | Capacity & serviceability | Funding related | Other | Weighting | Reference |
|---|---|---|---|---|---|---|---|---|
| Kentucky Truss Bridge Rehabilitation | *Superstructure and Substructure condition* | – | – | *Deck condition*, Channel condition | Potential for rehabilitation assessing if capacity, geometry, and safety can be improved cost effectively | Age, Historic significance, Uniqueness of bridge type and its specific features | Subjective weights | Peiris and Harik [64] |
| Massachusetts DOT | Condition Loss and Change in Health Index of all bridge elements | *ADT*, *Detour length*, Roadway classification | – | *Load restrictions*, Deck geometry deficiency | – | – | Subjective weights given by manual | Gibson et al. [9],Pollack et al. [65] |
| Minnesota DOT Bridge Scoring | *Superstructure and Substructure condition*, *Presence of fracture in critical elements* | *Detour length*, Traffic volume, Heavy commercial traffic, Highway classification | *Scour susceptibility* | *Deck Condition* | – | Bridge length and area, deck remaining service life, fracture criticality | Subjective scoring guide given by agency | Gibson et al. [9],Minnesota Department of Transportation [66] |
| Ohio Bridge Condition Index | *Superstructure and Substructure condition* | *ADT* | – | *Deck condition*, *Weight restrictions*, Number of lanes, Speed limits | Agency and user costs | Structure type, # of spans | Subjective weights proposed in paper | Fereshtehnejad et al. [10] |
| Ohio DOT | Element-level assessment of key structural elements | *ADT*, Functional classification | – | – | Local share (i.e. non-state funding) | Economic stress (i.e. unemployment rate in the region) | Subjective weights given by manual | Gibson et al. [9] |
| Virginia DOT | *Superstructure and Substructure condition*, *Presence of fracture in critical elements* | *ADT*, *ADTT*, *Detour length*, Functional classification, *NHS*, Corridor of Statewide Significance | *Waterway adequacy*, *Scour susceptibility*, Seismic susceptibility | *Deck Condition*, *Weight restrictions*, Vertical Clearance, Number of lanes, Deck width, Approach width | Cost-effectiveness score | Presence of fatigue-prone elements | Subjective scoring and weighting as per guide | Gibson et al. [9],VDOT [67] |

strategies. MT-InSAR employs satellite radar images acquired by spaceborne SAR sensors that actively emit electromagnetic waves and measure the backscatter signal to provide amplitude and phase measurements in the form of a complex SAR image [75,76]. Interferometric processing of paired images generates an InSAR product that can be used to detect temporal changes and quantify movement in the investigated period between the two acquisitions [77,78]. Through the processing of multiple interferogram stacks, MT-InSAR can be used to measure temporal displacement, enabling monitoring of bridges for indications of thermal expansion, ageing-related deformation, or subsidence-induced movement, facilitating early detection of bridge deterioration, providing frequent updates regarding structural health, and consequently reducing uncertainty surrounding bridge structural conditions [79–83]. MT-InSAR has proven to be an effective solution for monitoring bridge displacement due to subsidence [84], with studies demonstrating that it provides valuable information about Californian subsidence patterns, enabling authorities to prioritise repairs of critical infrastructure before significant capacity loss occurs [51]. However, MT-InSAR measurements are only provided for point-like targets, called Persistent Scatterers (PSs), which are pixels of the SAR image that maintain stable reflective properties over time [85,86]. Therefore, despite offering wide coverage and free data availability with the European Sentinel-1 satellite constellation [87], which could provide a cost-effective complementary assessment methodology, MT-InSAR's applicability may be constrained by the reflective properties of certain structures [88]. Still, it is possible to estimate its availability for specific bridge assets [83,88]. Consequently, this study incorporated MT-InSAR availability assessment as an adaptive capacity metric to enable targeted intervention strategies based on monitoring capability.

These three additional aspects of bridge assessment: county economic resilience to potential replacement costs, inspection resource burden, and spaceborne monitoring availability, collectively represent the resources (or constraints thereof) available to mitigate or manage the consequences of bridge deterioration or failure. Within this framework, this dimension was classified as 'adaptive/coping capacity', drawing upon established conceptual frameworks from disaster risk reduction and climate change vulnerability research [68,89]. The incorporation of adaptive capacity would enhance bridge assessment frameworks by recognising that effective bridge management requires not only understanding the criticality and susceptibility dimensions previously discussed, but also the systemic capacity to respond to identified vulnerabilities through economic, operational, and technological means.

### *3.2. Development of Bridge Vulnerability Index (BVI) sub-indicators*

Once identified, the metrics describing bridge vulnerability were consolidated into three distinct dimensions of BVI: network criticality, damage susceptibility, and adaptive capacity (see Fig. 1). This structured approach enhanced communication clarity and facilitated a more nuanced assessment of factors influencing county-level vulnerability.

The first aspect of bridge assessment, network criticality described in Table 3, was quantified as a composite of three components: traffic load intensity (proportion of bridges experiencing high daily traffic or significant freight volumes), strategic significance (percentage of structures that are part of the National Highway System), and detour impact (proportion of bridges where failure would necessitate significant re-routing).

Damage susceptibility evaluation comprised three components (see Table 4): structural vulnerability (based on superstructure and substructure condition ratings and the presence of fracture in critical elements), capacity constraints (identified through poor deck

**Table 2**
Summary of metrics used in this study to assess bridge vulnerability. The currently commonly used variables (marked in italics) only describe the criticality of the bridge to the network and its damage susceptibility. Moreover, only susceptibility to water-related hazards is considered. Therefore, this study adds data on subsidence susceptibility and adaptive capacity to assess the vulnerability of bridges more comprehensively.

| Network criticality | Damage susceptibility | Adaptive capacity |
|---|---|---|
| *ADT* | *Superstructure condition* | Monitoring availability |
| *ADTT* | *Substructure condition* | Inspection frequency |
| *Detour length* | *Presence of fracture in critical elements* | Time since last inspection |
| *NHS* | *Deck condition* | Bridge Replacement Cost |
| | *Inventory rating/Weight restrictions* | County's GDP |
| | *Waterway adequacy* | |
| | *Scour susceptibility* | |
| | Subsidence susceptibility | |

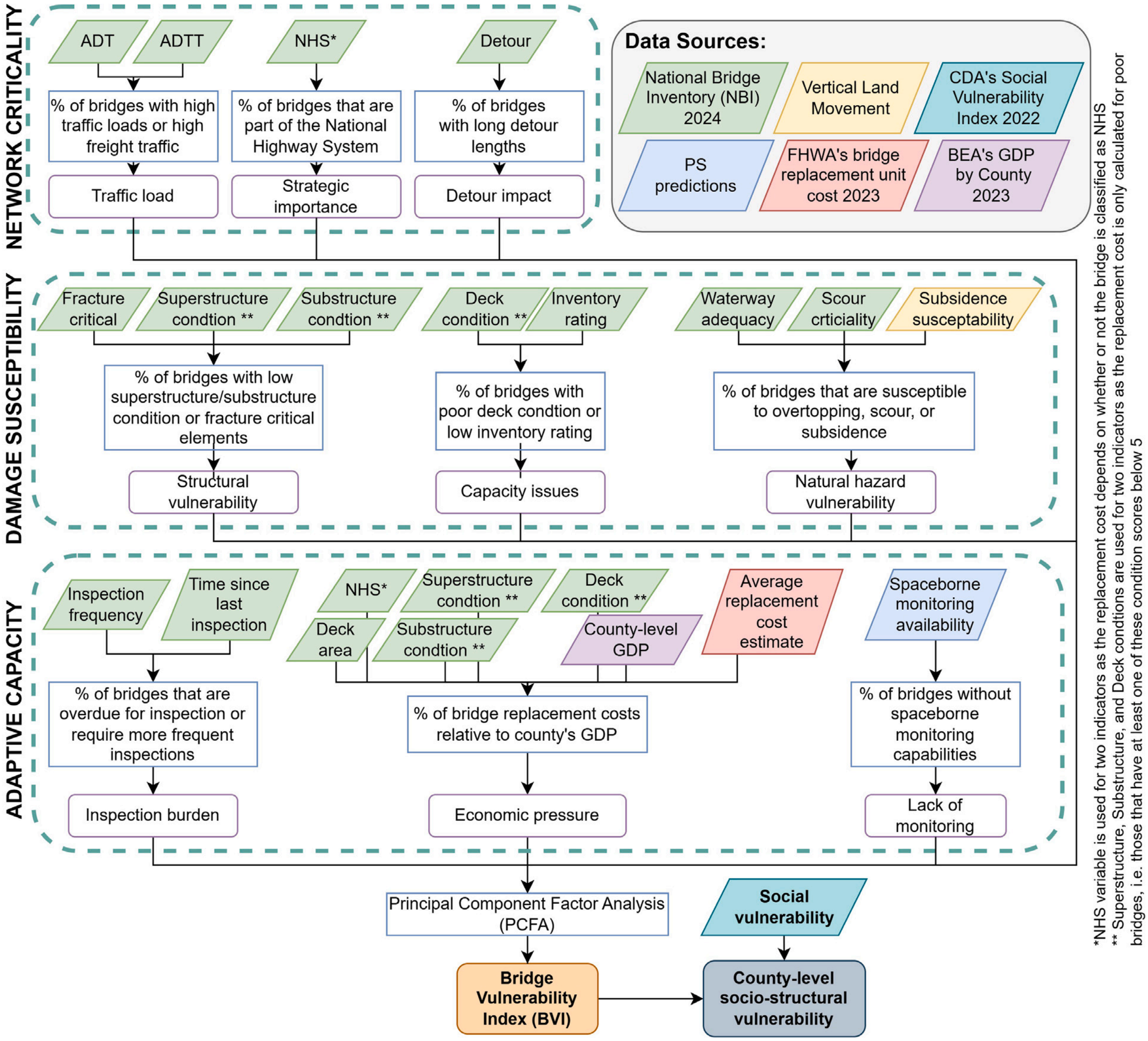



**Fig. 1.** Methodology flowchart.

**Table 3**
Network criticality assessment framework measuring the criticality of the bridge for the network.

| Metric | Description and purpose | Variable (Type) - Data source | Threshold | Reason for threshold |
|---|---|---|---|---|
| Traffic load | Share of bridges with high traffic loads or high freight traffic to assess the volume of traffic flow | ADT (Continuous) - National Bridge Inventory (NBI) [90] Item 29 | ADT > 25,000 | The thresholds used for categorisations of ADT in bridge health indicators vary significantly between methodologies. When considering the numbers used for the highest vulnerability threshold, values range from 5000 in [11], through 6500 in [61], 10,000 in [63], to 25,000 in [67]. As the case study in this paper focuses on California, which has relatively high traffic volumes, the threshold uses 25,000, representing approximately the 75th percentile of the input data. |
| | | ADTT (Continuous) - NBI Item 109 | ADTT > 0.15 | The threshold for ADTT as a share of the ADT is only explicitly mentioned in [61], where it takes a value of 0.15 for the highest vulnerability category. Moreover, AASHTO's guidelines for bridge design instruct engineers to assume the following fractions of trucks in traffic: 0.2 for rural interstate roads, 0.15 for urban interstate and other rural roads, and 0.1 for other urban roads [91]. Therefore, this study assumes 0.15 as the threshold. |
| Strategic importance | Share of bridges that are part of the National Highway System to assess relative importance of bridges within a highway network | NHS (Binary) - NBI Item 104 | NHS = True | Commonly used by other frameworks [9,11,63,67] |
| Detour impact | Share of bridges with long detour lengths to measure the impact a bypass would cause | Detour length (Continuous) - NBI Item 19 | Detour > 15 miles | Similarly to ADT, the detour threshold varies considerably between methodologies. The NBI sufficiency rating assigns considerable 3%–5% reductions only if the detour exceeds approximately 85 miles [59]. At the other extreme is the threshold applied in [67], where the highest vulnerability is assigned when the detour exceeds 8.5 miles. Other studies use values such as 15 miles, 20 miles, and 30 miles as their threshold for high vulnerability categories [11,60,63]. Considering that most Californian bridges have low detours due to dense road networks, this paper uses the 15-mile threshold. |

condition or suboptimal inventory ratings indicating reduced safe load thresholds), and natural hazard susceptibility (vulnerability to overtopping, scour, or subsidence).

For adaptive capacity assessment, shown in Table 5, three factors were examined: inspection burden (proportion of bridges requiring above-standard inspection frequency or currently overdue for assessment), economic pressure (county-level replacement cost for all poor-condition bridges as a percentage of county GDP, representing its financial capacity to address critical infrastructure deficiencies), and spaceborne monitoring availability (identifying bridges lacking access to remote sensing capabilities for early detection of structural deterioration).

To develop sub-indicators which represent the proportion of county-level bridges meeting vulnerability criteria, specific thresholds for each input metric were established, as detailed in Tables 3–5. The threshold determination process varied in complexity across metrics. For certain variables, threshold selection was unambiguous — either because of consensus in the literature or the binary nature of the variable itself. However, for several metrics, existing assessment frameworks exhibit considerable variation in threshold values. In these instances, expert judgement was applied to establish appropriate thresholds while rigorously evaluating their impact on our final assessments through Monte Carlo uncertainty and sensitivity analysis, as described in Section 3.6. This approach ensured that while subjective decisions were necessary for threshold selection, their influence on our results was systematically quantified for robust bridge vulnerability classification.

### *3.3. Data acquisition and pre-processing for bridge assessment*

To conduct a comprehensive assessment of California bridge vulnerability, this study integrated multiple complementary datasets. This approach was taken to capture the three dimensions of the BVI identified in the conceptual framework. The National Bridge Inventory (NBI) for the year 2024 was selected as the primary data source for bridge characteristics [90], as it provides standardised information collected by the Federal Highway Administration (FHWA) for all US bridges exceeding 6 m (20 ft) in length on public roads [101,102]. Tunnels and culverts, which are not of interest for this study, were removed from the NBI dataset, leaving 22,298 bridges out of the total 25,848 assets for investigation.

Several preprocessing operations were necessary to ensure data quality and consistency of the NBI dataset, based on the Recording and Coding Guidelines, which provide specifications about the bridge records [59]. When assessing superstructure condition,

**Table 4**
Damage susceptibility assessment framework measuring susceptibility of bridges to structural and environmental hazards.

| Metric | Description and purpose | Variable (Type) - Data source | Threshold | Reason for threshold |
|---|---|---|---|---|
| Structural vulnerability | Share of bridges with low superstructure/substructure condition or fracture critical elements to measure structural vulnerability | Presence of fracture in critical elements (Binary) - NBI Item 92A | Fracture Critical = True | Commonly used by other frameworks [9,60,61,63,66,67,67] |
| | | Superstructure condition (Ordinal) - NBI Item 59 | Rating ≤ 4 | This threshold on superstructure/substructure/deck condition is used for assigning NBI structurally deficient status and NBI poor condition rating [9,57–59]. It is also commonly used by other grading systems [9,11,66] |
| | | Substructure condition (Ordinal) - NBI Item 60 | Rating ≤ 4 | |
| Capacity issues | Share of bridges with poor deck condition or low inventory rating to indicate a need for present or future restrictions on the number or weight of vehicles crossing the bridge | Deck condition (Ordinal) - NBI Item 58 | Rating ≤ 4 | See above |
| | | Inventory rating (Continuous) - NBI Item 66 | Rating < 10.8 | The lowest threshold of inventory rating used in the NBI structural evaluation is 10.8, which also equals approximately one-third reduction in load capacity in sufficiency rating calculations [59]. Similarly, in [62], inventory rating is included in prioritisation calculations, and 10.8 would result in approximately 30% reduction of one of the elements of the equation. Therefore, this is the threshold used in this study. |
| Natural hazard vulnerability | Share of bridges that are susceptible to overtopping, scour, or subsidence to assess structures' vulnerability to natural hazards | Waterway adequacy (Ordinal) - NBI Item 71 | Rating ≤ 3 | The NBI structurally deficient classification uses ≤ 2 thresholds whilst the functionally obsolete classification uses ≤ 3 [57]. The NBI sufficiency rating assigns the largest reduction of 4% when this metric is ≤ 3, 2% when it is 4, and 1% when it is 5 [59]. When the method focuses on hydraulic-related risks, a threshold of ≤ 4 might be used [11]. In this paper, the ≤ 3 threshold is used, as the Coding Guidelines indicate it represents occasional significant delays on principal roads [59]. |
| | | Scour criticality (Ordinal) - NBI Item 113 | Rating ≤ 3 | When considering hydraulic-related risks, a ≤ 4 threshold can be used [11]. Other methods use the following scour vulnerability weights: 0.5 if equal to 4, 0.75 if equal to 3, and 1 if ≤ 2 [67]. In this paper, a threshold of ≤ 3 was used, as the Coding Guidelines state that this means the bridge is scour critical [59]. |
| | | Subsidence susceptibility (Ordinal) - California Vertical Land Movement [56,92] | Absolute vertical velocity > 10 mm/year | The threshold for assessing whether a structure is affected by displacement varies between studies. When considering Line of Sight velocity, some set it as low as 2-5 mm/year [93,94], some consider a structure unstable if the change in displacement rate between consecutive acquisitions is at least 10 mm/year [95], and some establish an early-warning threshold when maximum deformation velocity is 15 mm/year [96]. When considering landslides, a threshold on velocity projected alongside slope can be set as low as 2 mm/year [97]. In other studies, a structure is classified as high risk if maximum vertical settlement velocity exceeds 10 mm/year [98]. Due to a lack of consensus on this threshold, this study uses 10 mm/year and investigates the impact of different values through a sensitivity study, starting with 4 mm/year, as lower values might be below the uncertainty of the source data. |

deck condition, and waterway adequacy for the damage susceptibility dimensions of BVI, bridges recorded as 'N' (indicating no superstructure, no deck, or not over water, respectively) were considered not vulnerable in the respective category. For natural hazard vulnerability, scour criticality ratings were categorised as follows: bridges rated 'N' (not over water) or 'T' (tidal waters) were considered not vulnerable based on their low-risk classification in the guidelines. Conversely, bridges rated 'U' (unknown foundation not evaluated for scour) or '6' (scour calculations not yet completed) were assigned the highest scour vulnerability. Data gaps were identified in 878 bridges (less than 4% of the database): 870 entries lacked Average Daily Truck Traffic (ADTT) information required for the traffic load sub-indicator, and 282 entries were missing inventory ratings needed for capacity assessment. Some bridges had missing data for both indicators. To maintain conservative vulnerability estimates, the study applied a worst-case scenario approach, assigning the lowest condition ratings to all missing data entries.

**Table 5**
Adaptive capacity assessment framework evaluating maintenance and economic factors.

| Metric | Description and purpose | Variable (Type) - Data source | Threshold | Reason for threshold |
|---|---|---|---|---|
| Lack of monitoring | Share of bridges without spaceborne monitoring capabilities to indicate higher need for in-person inspection or installation of additional in-situ sensors | Spaceborne monitoring availability (Ordinal) - Followed method from [83,88] | ≤0.4 | Bridges with monitoring availability below this threshold are deemed poor monitoring targets. |
| Inspection burden | Share of bridges that are overdue for inspection or require more frequent inspections to indicate a higher burden on inspectors and agencies caring for bridges | Overdue for inspection, calculated based on the time of the last inspection and inspection frequency (Binary) - NBI Items 90 & 91 | Time till next inspection ≤ 0 | If a bridge requires immediate inspection or is overdue for inspection, the burden on inspectors/agency is increased. |
| | | Inspection frequency (Continuous) - NBI Item 91 | Inspection frequency < 24 months | 24 months is the standard inspection frequency [59]. Therefore, if a bridge requires inspection more frequently than the standard biannual schedule, it increases the burden on the inspectors/agency. |
| Economic pressure | Share of bridge replacement costs relative to county's GDP to show how much of the county funds would be required to address all the critical bridges | Poor bridges replacement cost, calculated based on the NHS, bridge condition, Deck Area, and Average Replacement Cost, relative to county's GDP (Continuous) - NBI Items 58-60, 104 & Deck Area, California Counties Data File (for GDP) [99], FHWA 2023 (for bridge replacement cost) [100] | N/A | No threshold required as value already a ratio. |

While NBI provides an indication of bridge susceptibility to water-related hazards such as scour and overtopping, it does not assess subsidence susceptibility. Therefore, this study incorporated a displacement magnitude assessment into the bridge vulnerability metric using California-wide InSAR-based Vertical Land Motion (VLM) datasets published in [56,92]. The VLM dataset is created using Sentinel-1 imagery at 90 m resolution and employs data from both satellite viewing angles (i.e. ascending and descending) together with sparse data from Global Navigation Satellite System (GNSS) for North-South motion information, to decompose for three-dimensional land motion, i.e. East-West, North-South and vertical. The VLM estimates are validated against GNSS datasets, and accuracy over regions with linear motion is reported to be below 2 mm/year. For this study, several processing steps were applied to the published dataset. First, only the vertical component was considered, as its magnitude was considerably higher than horizontal and north-south displacements. Second, interpolation was applied to the VLM dataset to fill missing data pixels and ensure coverage over all bridges not covered by the original data due to loss of coherence over water or vegetated areas. After interpolation, only one bridge was missing data, and following the conservative worst-case approach taken with the NBI dataset, the highest vertical displacement, indicating the highest subsidence susceptibility, was assumed. Finally, the bridge centrelines were identified using the Open Street Map (OSM) [103] dataset and the method described in [83], and the maximum displacement value along each bridge line was extracted to serve as the baseline for subsidence susceptibility calculations.

The process for assessing each structure's spaceborne monitoring capabilities comprised two steps. First, predictions of PS availability were generated using a pre-trained machine learning model with Sentinel-1 long-term coherence and OSM-based infrastructure maps as inputs, as described in [88] and using the coherence data by [104]. This process created a dataset containing the predicted count of PS per approximately 90 by 90 metre pixel. The second step assigned a spaceborne monitoring class to each bridge. To account for varied PS availability across different bridge sections, each bridge centreline was divided into five segments. For each segment, two statistics were calculated: the proportion of pixels containing at least one PS and the average PS density. These statistics were used to assign a segment-level PS availability class, which was then aggregated to a bridge-level value using a weighted mean approach. Finally, PS availability was adjusted by Sentinel-1 data availability based on the acquisition plans [105] to account for variations in acquisition frequency across different locations, despite the mission's global coverage. This process yielded a spaceborne monitoring class for each bridge, following the methodology detailed in [83].

To quantify the economic burden of bridge replacement on county finances, this study employed FHWA's 2023 bridge replacement unit cost dataset [100], which provides average replacement cost per deck area differentiated by state and National Highway System (NHS) classification. The methodology focused on bridges classified as "poor condition", i.e., those with deck, superstructure, or substructure condition ratings of four or below [9]. Using NBI data on bridge NHS classification and deck area, combined with appropriate FHWA cost estimates, the study calculated replacement costs for each poor-condition bridge within every county. These cumulative replacement costs were then normalised against each county's 2023 GDP [99] to create a ratio representing the economic impact on county finances, where higher values indicate a greater financial pressure of addressing critical infrastructure deficiencies.

Following data preprocessing, the study calculated the proportion of bridges meeting high vulnerability criteria for each category using thresholds detailed in Table 3 for the three network criticality sub-indicators, in Table 4 for the three damage susceptibility sub-indicators, and in Table 5 for the three adaptive capacity sub-indicators. Consequently, nine sub-indicators were generated for each county. The economic pressure sub-indicator required no threshold application as it was already expressed as a ratio. This process yielded a dataset with 58 counties and nine variables, which were subsequently processed to derive data-driven weights and construct the composite BVI.

### *3.4. Principal Component Factor Analysis (PCFA) for bridge vulnerability sub-indicator weights estimation*

To avoid subjective weighting and create data-driven weights for combining the identified sub-indicators into the bridge vulnerability metric, this study employed variance-based methods, specifically Principal Component Factor Analysis (PCFA). This approach was taken to ensure that the composite indicator reflected the inherent data structure rather than arbitrary weighting decisions. PCFA combines FA and PCA methodologies. FA comprises statistical methods designed to identify underlying variables, called factors, that explain correlation patterns among original variables in a multivariate dataset [106]. PCA serves as the factor extraction method within PCFA, creating uncorrelated variables termed principal components whilst maximising retained variance from the original data [14,17,107–109]. Following factor extraction, these factors undergo rotation to enhance interpretability by simplifying the factor structure [14]. Subsequently, weights for sub-indicators can be derived using the factor loadings, with each weight representing the proportion of total variance explained by a given factor [14].

This study selected PCFA based on its established effectiveness across multiple domains related to vulnerability assessment. The method is widely employed for composite indicator development in social science applications such as the Social Vulnerability Index [110–113] and the Human Development Index [114]. It is also applied in natural hazards research for community vulnerability and resilience assessment [115,116], flood vulnerability, with some frameworks incorporating social aspects [117–122], and household-level resilience to food insecurity [123]. Moreover, within civil engineering-related studies, PCFA is utilised to derive metrics such as resilience indices for road transport networks [124], infrastructure vulnerability measures [33], or vulnerability assessments of heritage churches [125]. Furthermore, these techniques can be used when integrating different vulnerability dimensions, as demonstrated in studies of socio-ecological vulnerability [126] or socioeconomic and infrastructural vulnerability to cyclones [127]. Building upon this established methodological foundation, this study applied PCFA to derive objective, data-driven weightings for combining sub-indicators, ensuring methodological independence from stakeholder perspectives and enabling application across diverse geographical contexts where comparable data is available.

The PCFA implementation required systematic data pre-processing to satisfy methodological assumptions. The application of thresholds to create the nine sub-indicators for the 58 counties yielded a favourable 6.4:1 case-to-variable ratio that exceeded the minimum 5:1 requirement for reliable PCFA results [14]. Given PCFA's sensitivity to multivariate outliers, the study calculated robust Mahalanobis distances for all observations to identify counties that deviated significantly from the multivariate centroid [109,128]. Counties identified as multivariate outliers were temporarily excluded from the PCFA procedure to prevent factor structure distortion. To address univariate outliers and skewed distributions, which introduce excessive variability that can distort PCFA results [14,129], this study implemented a twofold approach. Recognising that univariate outliers in this dataset represented legitimate but highly skewed observations rather than measurement errors, the interquartile range (IQR) method was employed for outlier identification, with values exceeding the upper boundary ($Q3 + 1.5 \times IQR$) replaced by the boundary value. No outliers were identified below the lower boundary. To address skewness, Yeo-Johnson transformations were applied to variables with skewness coefficients exceeding 1.0 [130]. The sensitivity of results to these preprocessing decisions was systematically evaluated through Monte Carlo simulations. Finally, all sub-indicators were standardised to achieve zero mean and unit variance, ensuring balanced variable influence in the analysis [14].

The dataset's appropriateness for PCFA was systematically validated through multiple statistical tests. The correlation matrix was examined to confirm significant inter-variable correlations ($p< 0.05$), a prerequisite for meaningful factor extraction. Relationship linearity was assessed through scatter plot analysis. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was calculated to ensure values exceeded 0.6 (preferably 0.8) for reliable factor analysis [14,131]. Finally, Bartlett's test of sphericity confirmed that the correlation matrix differed significantly from an identity matrix ($p< 0.05$), validating the appropriateness of the factor analytic approach [109].

Following data preprocessing, the PCFA process began with determining the optimal number of factors to retain. While multiple established criteria exist, such as the Kaiser criterion (retaining factors with eigenvalues exceeding one) and scree plot analysis (identifying variance inflexion points) [14], this study adopted the variance-explained criterion to ensure comprehensive data representation. Thus, a sufficient number of factors to collectively explain at least 80% of the total variance were retained, balancing model complexity with information retention. To assess the robustness of this threshold choice, the study systematically evaluated the impact of alternative variance thresholds on weight calculation through a Monte Carlo simulation.

After component extraction, varimax rotation was applied to enhance the results' interpretability. This orthogonal rotation technique transforms factor axes to distribute variance more evenly across principal components whilst creating clearer loading patterns by maximising individual sub-indicator loadings on specific factors [14]. This approach facilitates a more straightforward interpretation of the underlying factor structure.

The study evaluated factor extraction quality through two key metrics. Communalities were examined to assess the proportion of variance in each sub-indicator explained by the extracted factors, with higher values indicating more comprehensive representation [132]. Additionally, residual correlations were analysed to quantify remaining inter-indicator correlations not captured by the retained factors, with lower residual values suggesting more effective factor extraction [106]. These diagnostics ensured that the factor solution adequately represented the underlying data structure.

### 3.5. Aggregation of sub-indicators to a composite Bridge Vulnerability Index

The final PCFA stage involved constructing weights from the rotated factor loadings to create the composite BVI. Following factor rotation, each factor was normalised by squaring the factor loadings and dividing by the explained variance, yielding the proportion of variance explained by each variable within a given factor [14]. Two established approaches exist for aggregating factor loadings into final weights. The simplified approach calculates weights using only the highest squared factor loading for each sub-indicator, multiplied by the corresponding explained variance ratio, then scaled to sum to unity. Whilst straightforward and interpretable, this method disregards sub-indicator contributions to secondary factors. Therefore, to capture the full complexity of variable relationships, this study employed the comprehensive approach [133]. This methodology first generates intermediate components for each extracted factor by multiplying sub-indicators by their corresponding rotated loadings and summing these products. These intermediate components are then synthesised into the final composite indicator using weights proportional to each factor's contribution to total explained variance. This approach ensures that all meaningful variable-factor relationships are incorporated into the final measurement. The sensitivity of results to aggregation method choice was assessed through a Monte Carlo simulation.

Following weight derivation, the study applied all data transformations (outlier capping, non-linear transformations, and standardisation) to the complete dataset, using transformation parameters calculated exclusively from the multivariate outlier-free subset. This approach prevented extreme values from influencing the transformation process. The PCFA-derived factor weights were then applied to all 58 counties, including previously excluded multivariate outliers, to generate final BVI values. This methodology preserved the integrity of the factor structure derived from the cleaned dataset while ensuring comprehensive geographical coverage in the final bridge assessment.

### 3.6. Uncertainty and sensitivity analysis of Bridge Vulnerability Index

To evaluate the robustness of the BVI and assess the impact of methodological decisions, this study implemented comprehensive uncertainty and sensitivity analyses. The analysis addressed two primary uncertainty sources: threshold decisions during sub-indicator derivation and methodological choices within the PCFA procedure.

The study employed Monte Carlo analysis to quantify composite indicator robustness and evaluate uncertainty source impacts on final results [14,134]. The approach involved uncertainty analysis, which assessed how uncertainty propagated through the composite indicator construction process, and sensitivity analysis, which quantified how specific uncertainty sources contributed to variance in the final result [14,134]. To comprehensively evaluate uncertainty source impacts, the sensitivity analysis utilised first-order and total-effect Sobol's indices with quasi-random sampling. The first-order indices quantify individual input factor impacts, whilst the total-effect indices capture both individual effects and interaction effects between factors on the composite indicator [134–137]. Each analysis employed 4098 iterations with Saltelli sampling to enable robust calculation of Sobol's indices.

The first analysis examined threshold selection impacts, focusing on decisions that, whilst informed by literature, contained inherent subjectivity. The investigation incorporated five variables identified in Tables 3 and 4 as exhibiting varied values across literature: Average Daily Traffic (ADT) and subsidence susceptibility (uniform distributions within ranges identified in the literature review), detour length (log-normal distribution with parameters derived from the values identified in the literature), and waterway adequacy and scour criticality (discrete distributions reflecting categorical nature). Although threshold variations directly affected only three sub-indicators, the resulting changes in data distribution generated entirely different weight sets, consequently altering the final composite indicator values across all counties.

The second analysis assessed the robustness of PCFA implementation decisions. This evaluation encompassed: random exclusion of individual sub-indicators to test structural stability, variable thresholds for Mahalanobis distance-based multivariate outlier exclusion, alternative outlier handling approaches (including different capping strategies and skewness thresholds), varied variance thresholds affecting the number of retained components, and aggregation method selection (simplified versus comprehensive approaches) [14]. Table 6 provides comprehensive details of all parameters tested across both uncertainty and sensitivity analyses, enabling full reproducibility of the robustness assessment methodology.

### 3.7. Social vulnerability assessment

To assess social vulnerability, this study utilised the county-level Social Vulnerability Index (SVI) published by the Centres for Disease Control and Prevention (CDC) in 2022 [70]. The SVI represents a state-of-the-art, regularly updated dataset that serves as an operational diagnostic tool in disaster management decision-making across the United States and forms a core component of frameworks such as FEMA's National Risk Index [111]. The SVI is constructed from American Community Survey data across four established dimensions of social vulnerability [70,138]. These dimensions comprise: socioeconomic status (incorporating unemployment, education, poverty, housing cost, and health insurance indicators), household characteristics (encompassing age structure, single parenting, English language proficiency, and disability prevalence), racial and ethnic minority status (covering ethnicity), and housing type and transportation (including housing structure quality, overcrowding, and vehicle access). This study selected the SVI based on several methodological advantages: its regular updates maintain temporal relevance, and its widespread adoption by federal agencies provides validation of its operational utility [111]. Although some researchers have raised critiques regarding specific aspects of the index [139–141], its established role in federal disaster management and free accessibility made it the most appropriate choice for this analysis, supporting potential policy implementation.

**Table 6**
Monte Carlo sensitivity analysis parameters.

| Parameter | Analysis 1: Threshold sensitivity | Analysis 2: PCFA sensitivity |
|---|---|---|
| *Threshold Parameters* | | |
| ADT Threshold | Varied: Uniform (5000, 25,000) | Fixed: 25,000 |
| Detour Threshold (miles) | Varied: Log-normal (8.5, 85), median=15.0 | Fixed: 15 |
| Waterway Evaluation Threshold | Varied: Discrete {2, 3, 4} | Fixed: 3 |
| Scour Criticality Threshold | Varied: Discrete {2, 3, 4} | Fixed: 3 |
| Displacement Threshold | Varied: Uniform (4, 15) | Fixed: 10 |
| *PCFA Parameters* | | |
| Outlier Capping | Fixed: True | Varied: Discrete {True, False} |
| Skew Threshold | Fixed: 1.0 | Varied: Uniform (0, 2) |
| Variance Threshold | Fixed: 0.8 | Varied: Uniform (0.7, 0.9) |
| Aggregation Method | Fixed: Complex | Varied: Discrete {Simplified, Complex} |
| Mahalanobis Threshold | Fixed: 97.5 | Varied: Uniform (95, 100) |
| Indicator Dropping | Fixed: None | Varied: Discrete (either a complete set used or a random single exclusion of a sub-indicator) |

Note: In Analysis 1, PCFA parameters were held constant while threshold parameters were varied. In Analysis 2, threshold parameters were held constant while PCFA parameters were varied.

### *3.8. Integrated socio-infrastructure vulnerability of bridges at an administrative level*

The final methodological stage involved developing an approach to integrate social and bridge vulnerability at the county level, creating a framework designed to facilitate socially equitable resource prioritisation for bridge rehabilitation and maintenance. Rather than combining these distinct dimensions into a single composite metric, an approach that previous research has shown can yield misleading results, this study employed a bivariate mapping methodology [33]. This methodology avoids oversimplification of complex vulnerability relationships while preserving proper interpretation of component indicators and maintaining the ability to assess different vulnerability aspects within a unified framework [33].

To implement the bivariate mapping approach, both BVI and SVI were classified into three equal-interval categories: low (0–0.33), medium (0.33–0.66), and high (0.66–1). This classification scheme generated nine possible combinations, each represented through a distinct colour in the bivariate map. The resulting visualisation enabled straightforward identification of each county's socio-structural bridge vulnerability profile, facilitating recognition of areas where compounding vulnerabilities exist or where targeted interventions might yield the greatest social benefit. This approach could provide decision-makers with a nuanced understanding of vulnerability patterns whilst avoiding the information loss inherent in single composite indicators, thereby supporting more informed and equitable infrastructure investment decisions.

## 4. Results

This section presents the results of applying the methodology outlined in Section 3 to California's bridge infrastructure dataset. The analysis proceeds through four stages: first, examination of the bridge dataset and derived sub-indicators; second, presentation of PCFA results and the composite BVI, including uncertainty and sensitivity analyses; third, assessment of social vulnerability and its relationships with bridge sub-indicators; and finally, integration of bridge assessment and social vulnerability dimensions to create county-level socio-structural vulnerability profiles.

### *4.1. Bridge dataset and sub-indicators*

The NBI bridge database provides data for over 22,000 bridges. Fig. 2 illustrates the distribution of those bridges across counties. Los Angeles County, with over 3000 bridges, has the highest number of structures, while many less populated counties, particularly in the northern and eastern regions, maintain significantly smaller bridge portfolios.

The nine sub-indicators used for bridge assessments are presented in Fig. 3. Traffic load is highest in urbanised areas, particularly around San Francisco and Los Angeles. Strategic importance follows a similar pattern, with Southern California and San Francisco demonstrating high importance while the northern portion of the state exhibits low strategic significance. Conversely, detour impact displays an inverse spatial distribution, with the most substantial detours occurring in Northern California.

Structural vulnerability varies between counties. However, counties previously identified with high traffic and strategic importance demonstrate notably fewer structural issues. Capacity issues are predominant in the northern and northeastern regions of the state. Notably, San Francisco is also significantly affected by capacity problems. Natural hazard vulnerability is higher in the north of California compared to the southern regions. Subsidence primarily affects the central part of the state [92], so it does not appear to significantly impact vulnerability to natural hazards. Therefore, water-related hazards appear to have the dominant effect on the vulnerability to natural hazards.

The inspection burden map identifies several counties with a substantial proportion of bridges either overdue for inspection or requiring frequent inspections. Notably, out of those identified counties, only San Bernardino County has a relatively high number

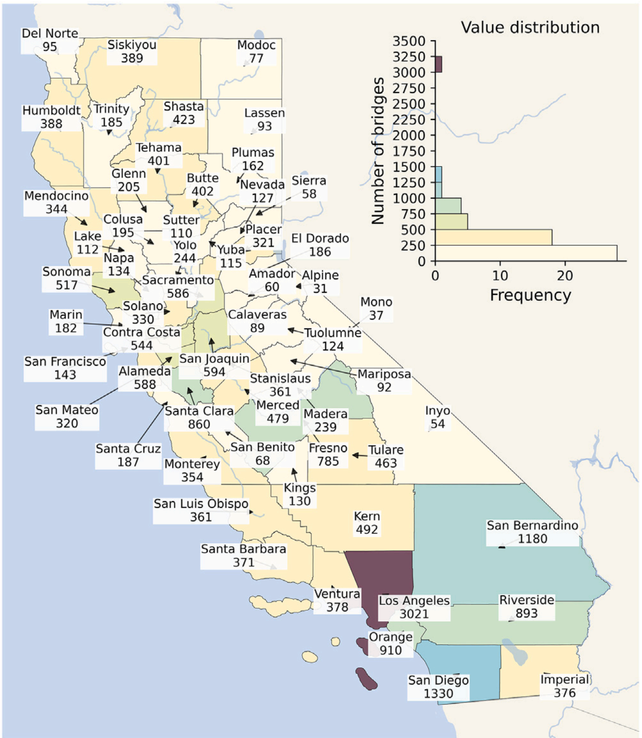



**Fig. 2.** Map of California with county-level count of bridges.

of bridges. The other three counties with high inspection burdens, Del Norte, Mono, and Lassen, maintain relatively small bridge portfolios of 95, 37, and 93 bridges, respectively. Regarding economic pressure, three counties stand out: Glenn, Tehama, and Sierra. Finally, analysis of spaceborne monitoring availability reveals that northern California has the largest proportion of bridges that cannot be monitored from space.

### 4.2. Principal component factor analysis results

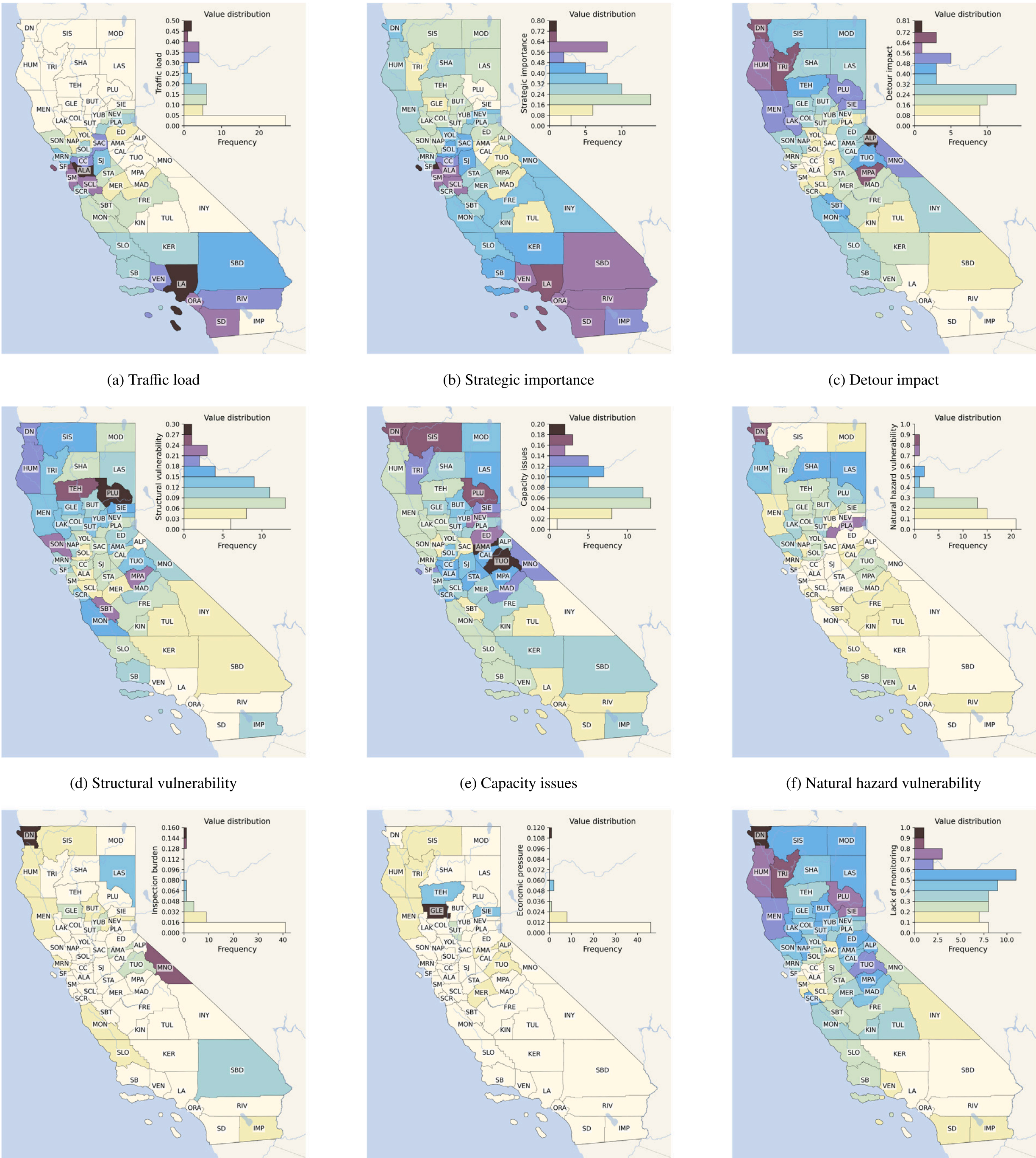
First, based on the robust Mahalanobis distance, variables exceeding the 97.5 percentile were temporarily removed from the dataset. Two counties met this criterion: Del Norte and Glenn. Subsequently, univariate outliers were identified based on the interquartile range as those exceeding the upper boundary defined as the third quartile (Q3) plus 1.5 times the interquartile range (IQR), a standard statistical threshold for outlier detection. The following variables were affected: detour impact, structural vulnerability, natural hazard vulnerability, inspection burden, and economic pressure, with 1, 1, 4, 3, and 4 outliers, respectively. These outlying values were capped at $Q3 + 1.5 * IQR$. Two variables with skewness exceeding one were identified: inspection burden and economic pressure. The Yeo-Johnson transformation was applied to improve the normality of these distributions.

Following data preprocessing, statistical tests were conducted. The Kaiser–Meyer–Olkin (KMO) measure was 0.81, and Bartlett's Test yielded a p-value below .05, indicating the dataset's suitability for PCFA. Examination of the correlation matrix (Fig. 4) revealed significant correlations between the variables, further confirming the suitability of the data set for PCFA.

The PCA was employed to determine which components should be retained for subsequent FA. Table 7 summarises the loadings for individual indicators extracted through PCA. Based on the proportion of total variance explained (see Table 8), four components were retained as they collectively accounted for over 80% of the total variance. These selected components were then subjected to rotation to distribute the loadings more evenly among factors.

Table 9 shows factor loadings after the rotation and scaling to a unity sum. The first factor primarily accounts for network criticality (i.e., traffic load, strategic importance, and detour impact) along with monitoring and economic aspects. Capacity issues predominantly influence the loadings of the second factor. The third factor is primarily loaded on inspection burden, while structural and natural hazard vulnerability constitute the main loadings for the fourth factor. Notably, some sub-indicators, while having a primary loading on one factor, demonstrate significant secondary loadings on others, for example, monitoring availability loads at 0.18 on the first factor and 0.12 on the fourth factor. This pattern underscores the importance of employing the comprehensive aggregation approach described in Section 3.5.

Analysis of communalities in Table 9, i.e. the proportion of variance captured by the factors, reveals that most sub-indicators have approximately 80% or more of their variance explained. However, two sub-indicators, namely detour impact and economic




(a) Traffic load (b) Strategic importance (c) Detour impact

(d) Structural vulnerability (e) Capacity issues (f) Natural hazard vulnerability

(g) Inspection burden (h) Economic pressure (i) Lack of monitoring

**Fig. 3.** County-level sub-indicators used for bridge infrastructure assessment.

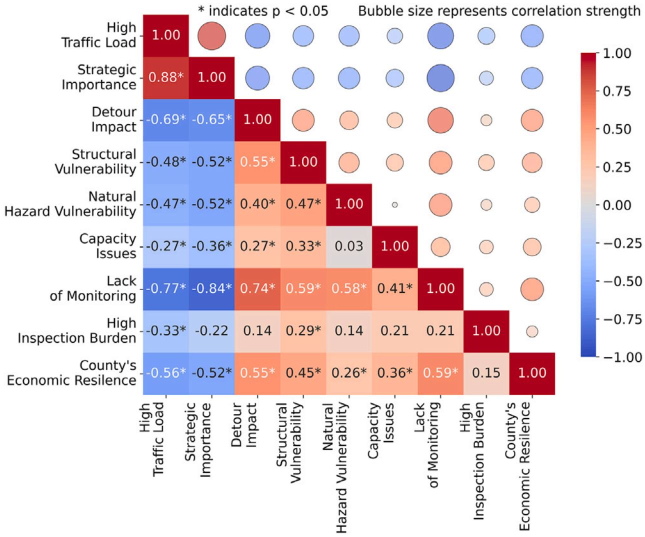



**Fig. 4.** Correlation matrix of transformed and scaled data prepared for PCFA.

**Table 7**
Component loadings for individual indicators extracted with PCA.

| | PC 1 | PC 2 | PC 3 | PC 4 | PC 5 | PC 6 | PC 7 | PC 8 | PC 9 |
|---|---|---|---|---|---|---|---|---|---|
| Traffic load | −0.40 | 0.07 | −0.06 | 0.43 | 0.16 | 0.05 | 0.29 | 0.47 | −0.56 |
| Strategic importance | −0.41 | 0.10 | 0.03 | 0.21 | 0.36 | 0.05 | 0.39 | −0.09 | 0.70 |
| Detour impact | 0.37 | −0.12 | −0.18 | −0.13 | 0.26 | −0.52 | 0.62 | −0.20 | −0.19 |
| Structural vulnerability | 0.33 | 0.06 | 0.15 | 0.59 | 0.44 | −0.32 | −0.46 | −0.02 | 0.05 |
| Capacity issues | 0.21 | 0.67 | −0.33 | 0.37 | −0.44 | 0.06 | 0.16 | −0.22 | 0.03 |
| Natural hazard vulnerability | 0.28 | −0.48 | 0.35 | 0.43 | −0.20 | 0.45 | 0.30 | −0.24 | −0.04 |
| Inspection burden | 0.15 | 0.52 | 0.76 | −0.23 | 0.11 | 0.06 | 0.18 | 0.09 | −0.10 |
| Economic pressure | 0.32 | 0.14 | −0.34 | −0.17 | 0.56 | 0.64 | −0.02 | 0.00 | −0.09 |
| Lack of monitoring | 0.42 | −0.09 | −0.08 | 0.01 | −0.18 | −0.02 | 0.13 | 0.79 | 0.37 |

**Table 8**
Eigenvalues of individual indicators before and after rotation.

| Principal component | Initial total eigenvalue | % of total variance | % cumulative | Extractions sums of squared loadings | % of total variance | % cumulative | Rotation sums of squared loadings | % of total variance | % cumulative |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 4.87 | 0.53 | 0.53 | 4.87 | 0.53 | 0.53 | 3.51 | 0.46 | 0.46 |
| 2 | 1.08 | 0.12 | 0.65 | 1.08 | 0.12 | 0.65 | 1.28 | 0.17 | 0.63 |
| 3 | 0.94 | 0.10 | 0.75 | 0.94 | 0.10 | 0.75 | 1.10 | 0.14 | 0.77 |
| 4 | 0.67 | 0.07 | 0.83 | 0.67 | 0.07 | 0.83 | 1.68 | 0.22 | 1.00 |
| 5 | 0.58 | 0.06 | 0.89 | – | – | – | – | – | – |
| 6 | 0.45 | 0.05 | 0.94 | – | – | – | – | – | – |
| 7 | 0.32 | 0.03 | 0.97 | – | – | – | – | – | – |
| 8 | 0.17 | 0.02 | 0.99 | – | – | – | – | – | – |
| 9 | 0.08 | 0.01 | 1.0 | – | – | – | – | – | – |
| Total | 9 | 1 | – | 7.57 | 0.83 | – | 7.57 | 1 | – |

pressure, exhibit somewhat lower communalities. While this could be addressed by retaining additional factors, the comprehensive coverage of most sub-indicators rendered the current values suitable for analysis. This assessment is supported by the residuals plot in Fig. 5, which indicates that the unaccounted inter-indicator correlations are minimal, suggesting an appropriate number of retained components.

### *4.3. Bridge vulnerability index*

Weights derived through PCFA were applied to the sub-indicators in order to construct the BVI illustrated in Fig. 6. The map clearly distinguishes counties with significantly poorer bridge portfolios from their counterparts. Del Norte County, which exhibited elevated values across multiple sub-indicators, emerged as the region with bridge infrastructure in the poorest condition.

**Table 9**
Rotated factor loadings for individual indicators extracted with PCA and Varimax normalised rotation. Explained variance is the amount of variance explained by each factor, and the explained/total is the explained variance divided by the total cumulative variance of the four factors. The second part of the table shows the loading when scaled to a unity sum. The last column lists the communality of each sub-indicator.

| | Factor loading | | | | Squared factor loading (scaled to unity sum) | | | | Communality |
|---|---|---|---|---|---|---|---|---|---|
| | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 1 | Factor 2 | Factor 3 | Factor 4 | |
| Traffic load | −0.89 | −0.01 | −0.26 | −0.22 | 0.23 | 0.00 | 0.06 | 0.03 | 0.91 |
| Strategic importance | −0.85 | −0.11 | −0.13 | −0.33 | 0.20 | 0.01 | 0.02 | 0.07 | 0.86 |
| Detour impact | 0.78 | 0.16 | −0.02 | 0.29 | 0.17 | 0.02 | 0.00 | 0.05 | 0.72 |
| Structural vulnerability | 0.31 | 0.42 | 0.16 | 0.70 | 0.03 | 0.14 | 0.02 | 0.29 | 0.79 |
| Capacity issues | 0.21 | 0.91 | 0.11 | 0.02 | 0.01 | 0.65 | 0.01 | 0.00 | 0.89 |
| Natural hazard vulnerability | 0.32 | −0.16 | 0.03 | 0.86 | 0.03 | 0.02 | 0.00 | 0.44 | 0.86 |
| Inspection burden | 0.11 | 0.11 | 0.98 | 0.09 | 0.00 | 0.01 | 0.88 | 0.00 | 1.00 |
| Economic pressure | 0.71 | 0.37 | −0.02 | 0.04 | 0.15 | 0.11 | 0.00 | 0.00 | 0.65 |
| Lack of monitoring | 0.79 | 0.23 | 0.06 | 0.45 | 0.18 | 0.04 | 0.00 | 0.12 | 0.88 |
| Explained variance | 4.87 | 1.08 | 0.94 | 0.67 | – | – | – | – | – |
| Explained/total | 0.53 | 0.12 | 0.10 | 0.07 | – | – | – | – | 0.83 |

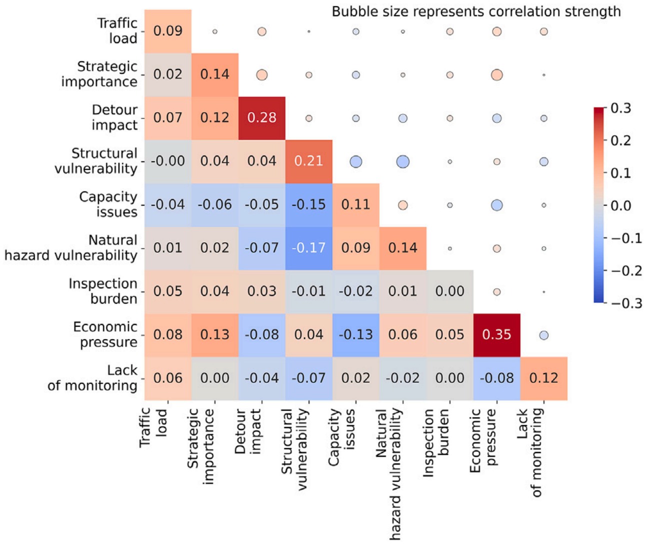



**Fig. 5.** Residual inter-indicator correlations not accounted by the retained factors.

Notably, counties characterised by high network criticality, such as San Francisco or Los Angeles, did not show correspondingly high composite metrics, as their performance on other constituent sub-indicators demonstrated comparatively low values.

Fig. 7 illustrates which components of the BVI, i.e., network criticality, damage susceptibility, or adaptive capacity, had the greatest influence on the final composite indicator. As anticipated, urbanised areas surrounding San Francisco and Los Angeles are predominantly affected by network criticality. Damage susceptibility and adaptive capacity are distributed among counties without exhibiting a clear pattern.

### 4.4. Uncertainty and sensitivity analysis of the composite BVI

The impact of methodological choices in the BVI construction was thoroughly analysed through a Monte-Carlo-based uncertainty and sensitivity analysis. First, the thresholds set on the bridge metrics in sub-indicator creation were investigated. Fig. 8(a) shows that while many counties exhibit low variation in the results, for some of them the change in thresholds causes a significant deviation in results. While this means that the BVI of some counties is less robust, the sensitivity analysis in Figs. 8(b) and 8(c) highlights that the threshold set on scour criticality has the most significant impact on this uncertainty.

The plots in Fig. 9(a) show that the decisions taken during PCFA have a much greater impact on variability than the threshold choices. The Sobol's indices in Figs. 9(b) and 9(c) show that the main contribution to variability is caused by the random exclusion of an indicator.

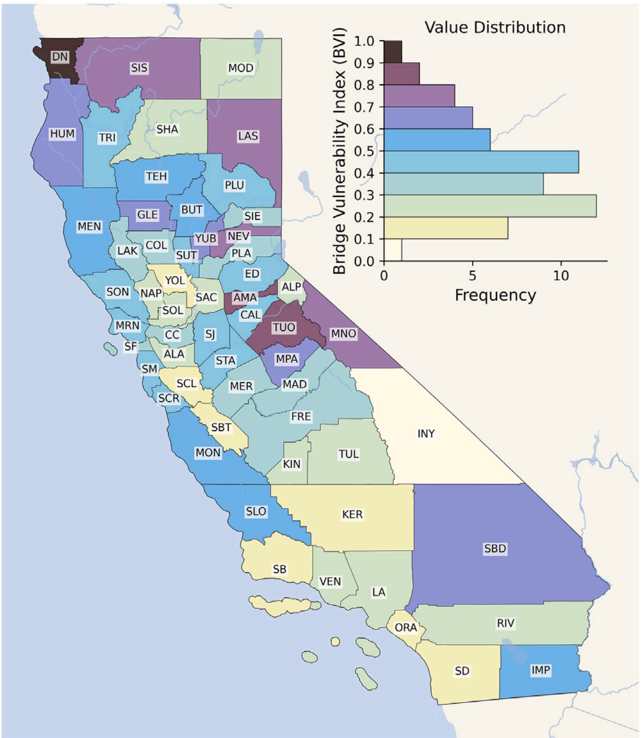



**Fig. 6.** County-level BVI.

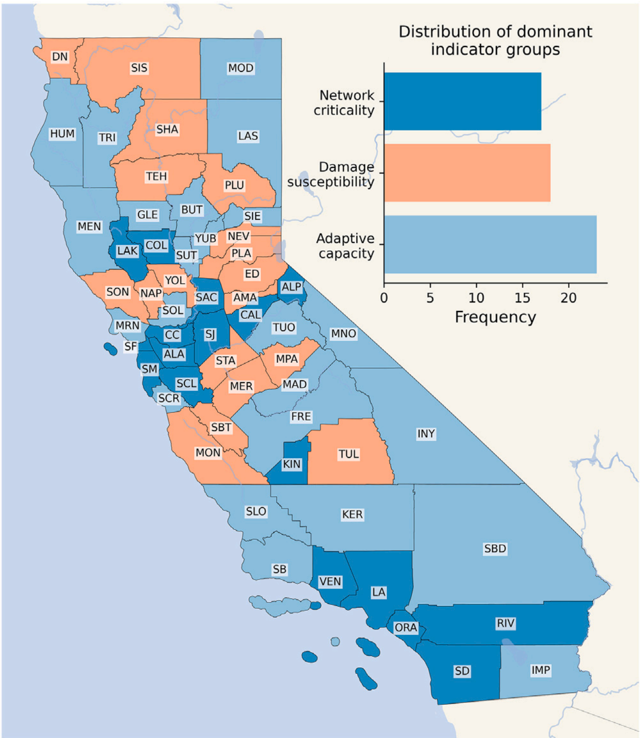
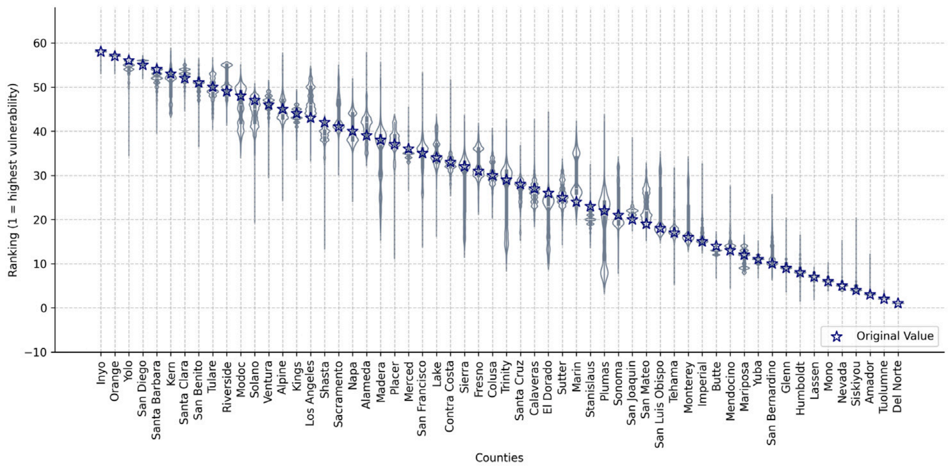
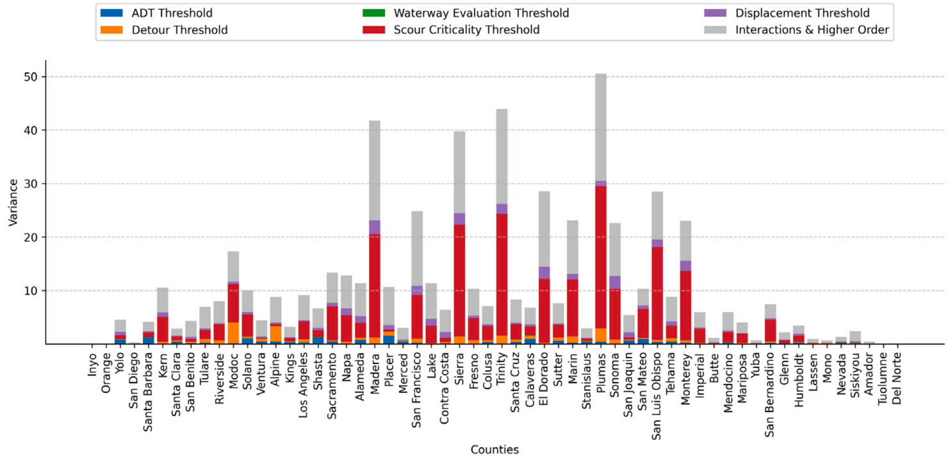


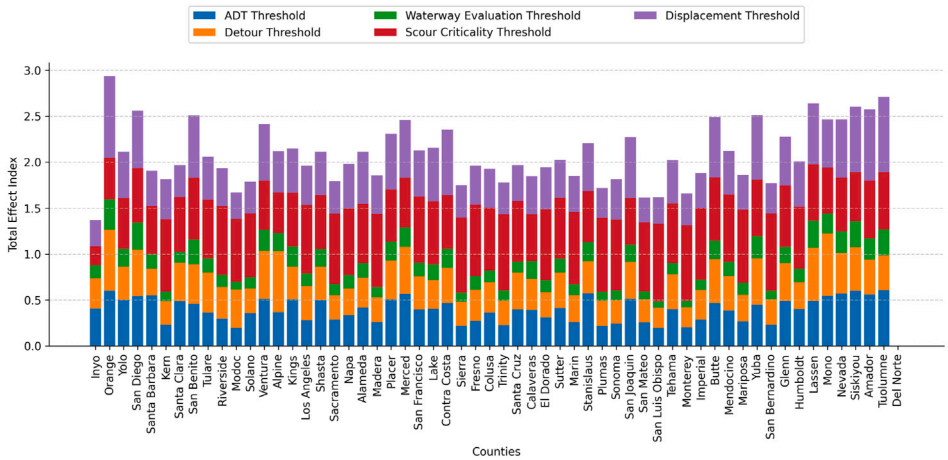

**Fig. 7.** The map shows which part of the BVI, network criticality, damage susceptibility, or adaptive capacity, had the dominant effect on the final value of the index.




(a) Uncertainty analysis of the sub-indicators thresholds. Counties are ranked by vulnerability, with one representing the highest vulnerability and 58 the lowest.

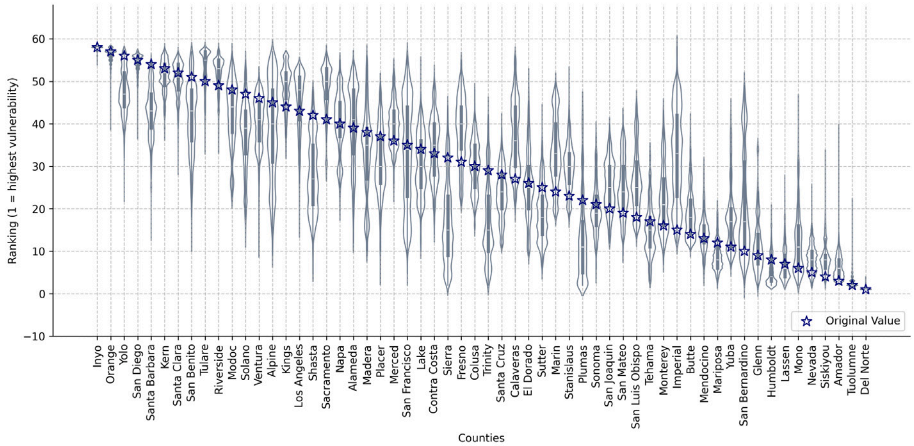



(b) First-order Sobol's indices allowing for a sensitivity analysis of the sub-indicators thresholds.

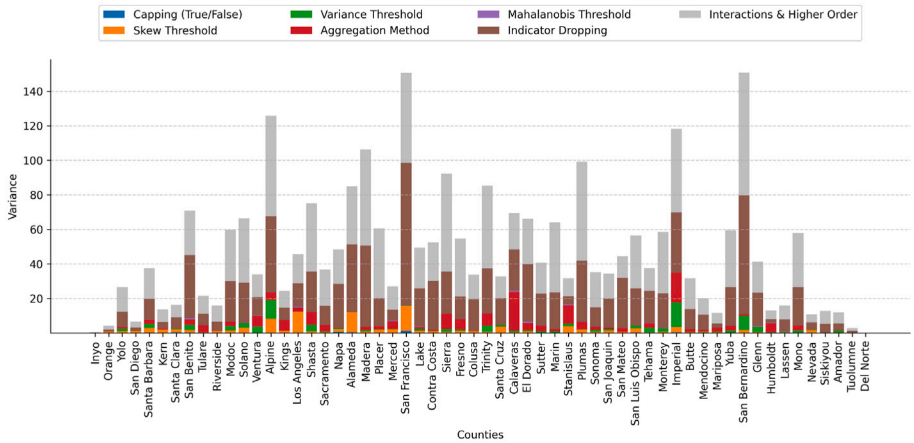



(c) Total-effect Sobol's indices allowing for a sensitivity analysis of the sub-indicators thresholds

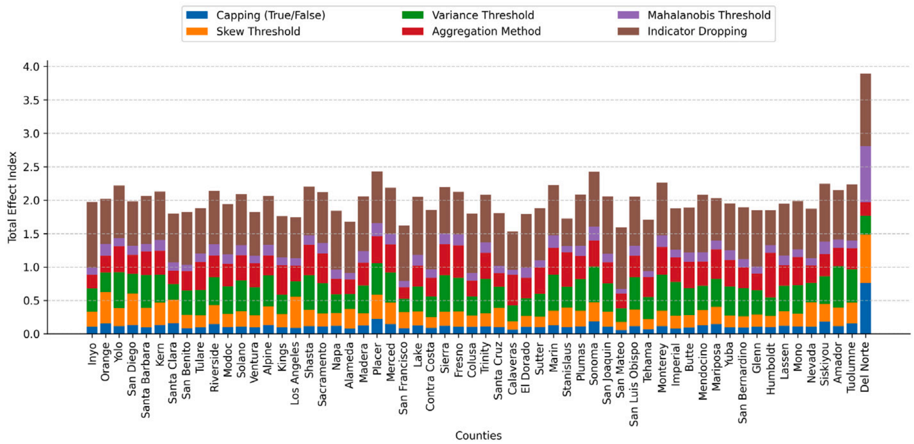
**Fig. 8.** Results of Monte Carlo analysis with varying sub-indicators thresholds.




(a) Uncertainty analysis of the PCFA assumptions. Counties are ranked by vulnerability, with one representing the highest vulnerability and 58 the lowest.




(b) First-order Sobol's indices allowing for a sensitivity analysis of the PCFA assumptions.




(c) Total-effect Sobol's indices allowing for a sensitivity analysis of the PCFA assumptions.

**Fig. 9.** Results of Monte Carlo analysis with varying parameters of PCFA.

### 4.5. Social vulnerability index

The Social Vulnerability Index (SVI) used in this study comprises variables grouped into four themes: socioeconomic status, household characteristics, racial and ethnic minority status, and housing type and transportation. While Fig. 11 maps the composite SVI at the county level, Fig. 10 displays the spatial distribution of each of these four thematic components, offering insight into the drivers of vulnerability in different regions.

Fig. 11 presents the SVI across California counties, showing that the highest levels of social vulnerability are concentrated in the San Joaquin Valley, notably in Fresno, Tulare, Kern, and Madera counties. These socioeconomic conditions are also reflected in Fig. 10, where counties in the San Joaquin Valley score consistently high across all four social vulnerability components. Outside the San Joaquin Valley, Los Angeles and San Bernardino Counties also exhibit extensive areas of high vulnerability. This is supported by the indicator groups in Fig. 10, where both counties score high on the racial and ethnic minority status dimension, as well as on housing and transportation stress, such as overcrowding or lack of vehicle access.

Figs. 12 and 13 further show that the racial and ethnic minority status component of social vulnerability has the strongest and most consistent statistically significant correlations with bridge vulnerability indicators. The relationship with strategic importance is positive, indicating that counties with higher proportions of ethnic minority populations are more likely to host bridges that are critical to the transportation network. In contrast, negative correlations are observed between racial and ethnic minority status and several condition-related indicators, including structural vulnerability and capacity issues, as well as the lack of spaceborne monitoring.

### 4.6. Integrated socio-structural vulnerability of bridges

Fig. 14 presents the integrated assessment of bridge and social vulnerabilities. To facilitate interpretation, both vulnerability indices were categorised into three levels based on their values (0–0.33, 0.33–0.66, 0.66–1). The spatial analysis reveals distinctive regional patterns: areas surrounding San Francisco and eastern California exhibit medium bridge vulnerability coupled with low social vulnerability. Counties further north, including Glenn, Mendocino and adjacent territories, as well as southeastern regions such as Stanislaus, Merced and Fresno, demonstrate similar levels of the BVI but noticeably higher social vulnerability. Conversely, Los Angeles County, which maintains California's largest bridge portfolio, and its neighbouring counties, present relatively robust bridge infrastructure despite experiencing high social vulnerability. The northern extremities of California, encompassing Del Norte, Siskiyou, Humboldt and Lassen counties, are characterised by the highest BVI alongside relatively high social vulnerability. Notably, no county was classified within the highest vulnerability category for both bridge and social dimensions simultaneously.

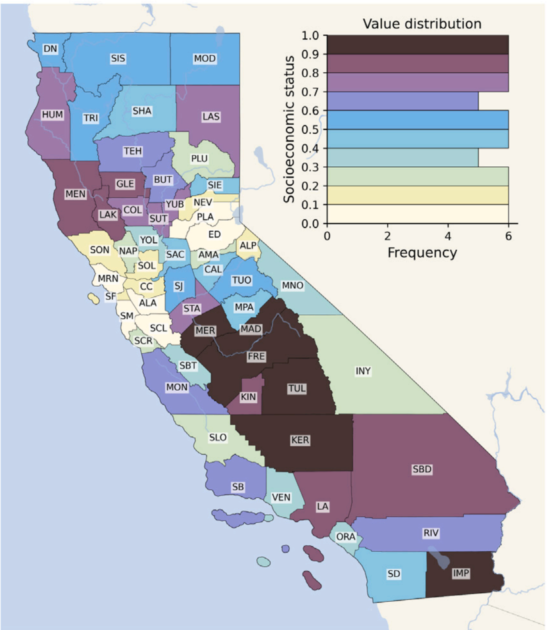
The bivariate framework enables prioritisation refinement within bridge vulnerability categories through integration of social dimensions. This is most consequential within the medium BVI category, where substantial social vulnerability variation exists, and resource allocation trade-offs are most acute. For example, as shown in Table 10, San Mateo County ranks 19th in BVI (medium vulnerability), whilst Merced County ranks 36th in BVI (also medium vulnerability, near the bottom of this tier). Assessed purely on structural grounds, San Mateo would receive priority over Merced given its higher BVI ranking. However, San Mateo exhibits low social vulnerability, whilst Merced exhibits high social vulnerability. The bivariate framework suggests prioritising Merced despite its lower BVI ranking, recognising that bridge failures would impose disproportionate consequences on populations with limited adaptive capacity.

### 4.7. Benchmarking against traditional prioritisation approaches

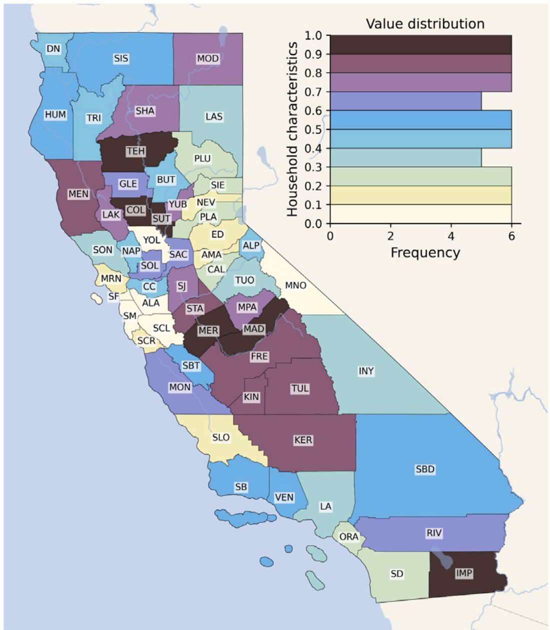
To compare the BVI to current bridge management practices, county rankings derived from the methodology proposed for this study were benchmarked against those based on the county-level percentage of poor bridges weighted by deck area. This metric is employed by the Federal Highway Administration in the Bridge Formula Program funding allocation, with 75% of federal funds distributed proportionally to states based on the cost of replacing bridges in poor condition [142]. While this federal metric operates at the state level, it provides the most appropriate benchmark for comparison as it represents the established methodology driving actual funding allocation decisions.

Table 10 presents all 58 California counties ranked by BVI alongside their traditional rankings. The comparison revealed substantial and systematic differences in county prioritisation. Only one county (San Bernardino) appeared in both top 10 priority lists. Del Norte County ranks first in BVI due to high detour impact, capacity issues, natural hazard vulnerability, severe inspection burden, and lack of spaceborne monitoring, yet it ranks 49th traditionally with relatively few structurally deficient bridges. Conversely, Los Angeles County ranks 2nd for poor bridge replacement costs but 43rd in BVI. This is because, despite this county having one of the highest traffic loads and strategic importance scores, it scored low for detour, structural vulnerability, and across the adaptive capacity dimension, which substantially reduces its overall BVI score.

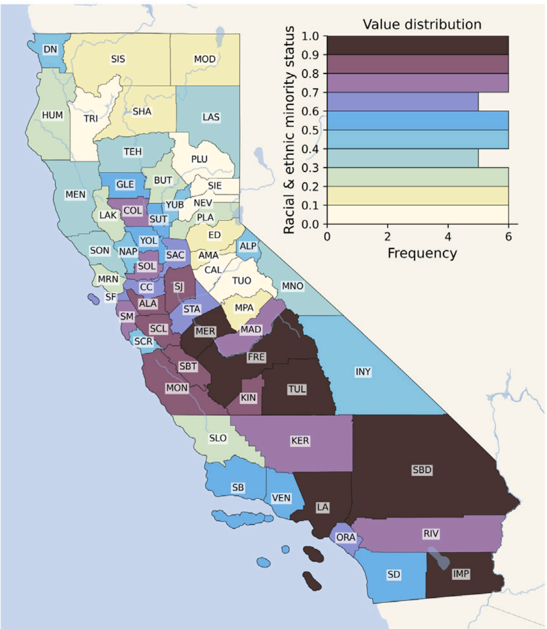
The divergence between structural and socio-structural priorities, previously illustrated through the bivariate analysis in Section 4.6, is further magnified when benchmarking against traditional condition-based approaches in Table 10. For instance, under the traditional FHWA metric, San Mateo County ranks 1st, indicating the highest structural deficiency in the state. However, the BVI framework reclassifies it to the 19th due to its high adaptive capacity. When the 'Low' social vulnerability identified in the bivariate map is also considered, the contrast with counties like Merced becomes acute. While Merced ranks lower than San Mateo in traditional structural terms, its 'High' social vulnerability suggests that infrastructure failures there would have disproportionately severe societal consequences. This comparison demonstrates that traditional approaches, by overlooking both adaptive capacity and social equity, prioritise resources towards robust, wealthy communities (like San Mateo) at the expense of highly vulnerable populations (like Merced).



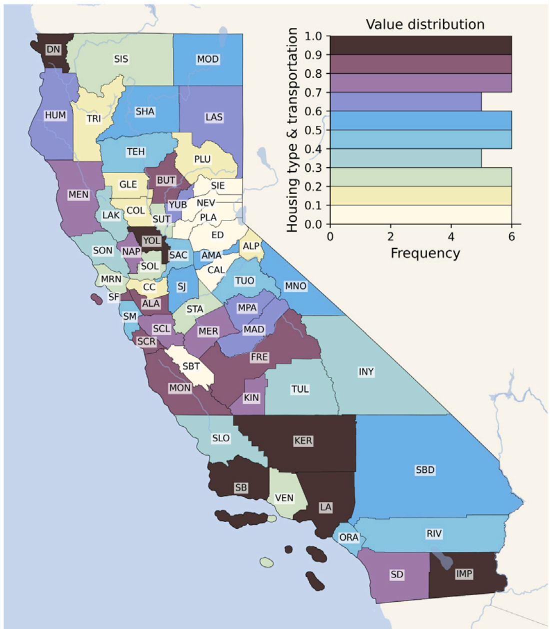

(a) Socioeconomic status




(b) Household characteristics




(c) Racial & ethnic minority status




(d) Housing type & transportation

**Fig. 10.** Social vulnerability components.

## 5. Discussion

This paper presents a novel method for assessing bridge vulnerability and integrating it with social vulnerability measures. The methodology constructs the BVI as an aggregation of nine sub-indicators that comprehensively describe network criticality, damage susceptibility and adaptive capacity of structures. This approach extends traditional methods by incorporating subsidence susceptibility and assessing systemic resources available to mitigate potential bridge failure. The weights for each sub-indicator were determined using PCFA, which enables data-driven weight creation independent from stakeholders' judgment. Therefore, the

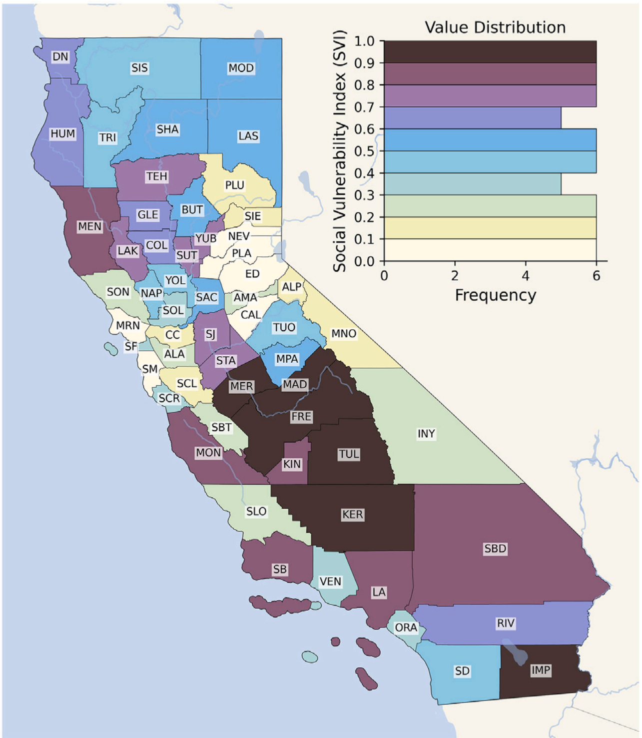



**Fig. 11.** Social Vulnerability Index (SVI).

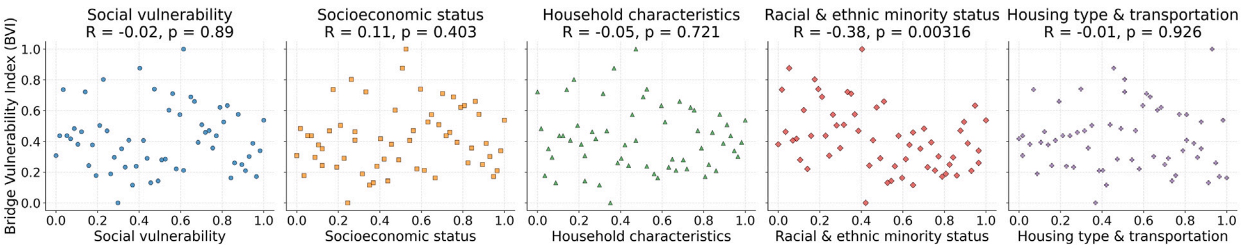



**Fig. 12.** Scatter plot of all components of social vulnerability vs bridge vulnerability metric.

proposed method advances state-of-the-art approaches that primarily rely on subjective stakeholder weights and capture only the network criticality and damage susceptibility of bridges. This comprehensive approach allows the assessment of a bridge's criticality to the network and the potential impact of structural and environmental risks, as well as the evaluation of maintenance and economic factors. The socio-structural county-level bridge network vulnerability was presented as a bivariate map, facilitating straightforward identification of administrative units with the highest vulnerability.

Several observations regarding the spatial distribution of sub-indicators should be discussed. The highest detour impact observed in Northern California likely stems from the region's less dense road network, as evidenced by the considerably lower bridge count, which necessitates longer detours when bridges are closed. However, counties with short detour distances often have high traffic loads, so future studies could explore incorporating detour time rather than distance, as travel delays may be substantial even for geographically short detours due to traffic congestion.

Interestingly, counties with high traffic and strategic importance demonstrated low structural vulnerability, potentially attributable to higher investments in bridge rehabilitation based on cost-benefit analyses. This same reasoning may explain the high capacity issues in the northern part of California. However, this explanation fails to account for the significant capacity issues in San Francisco, highlighting that even bridges in relatively good structural condition may suffer from poor deck condition and safe load restrictions, consequently impacting traffic, as heavy goods vehicles might need to avoid these structures.

The relatively low contribution of subsidence susceptibility to the natural hazard vulnerability indicator might be attributed to bridges being situated outside the most severely affected areas. Still, it should be noted that only the vertical displacement was considered, and further studies could be extended by using the horizontal and north-south displacements. Conversely, the significant

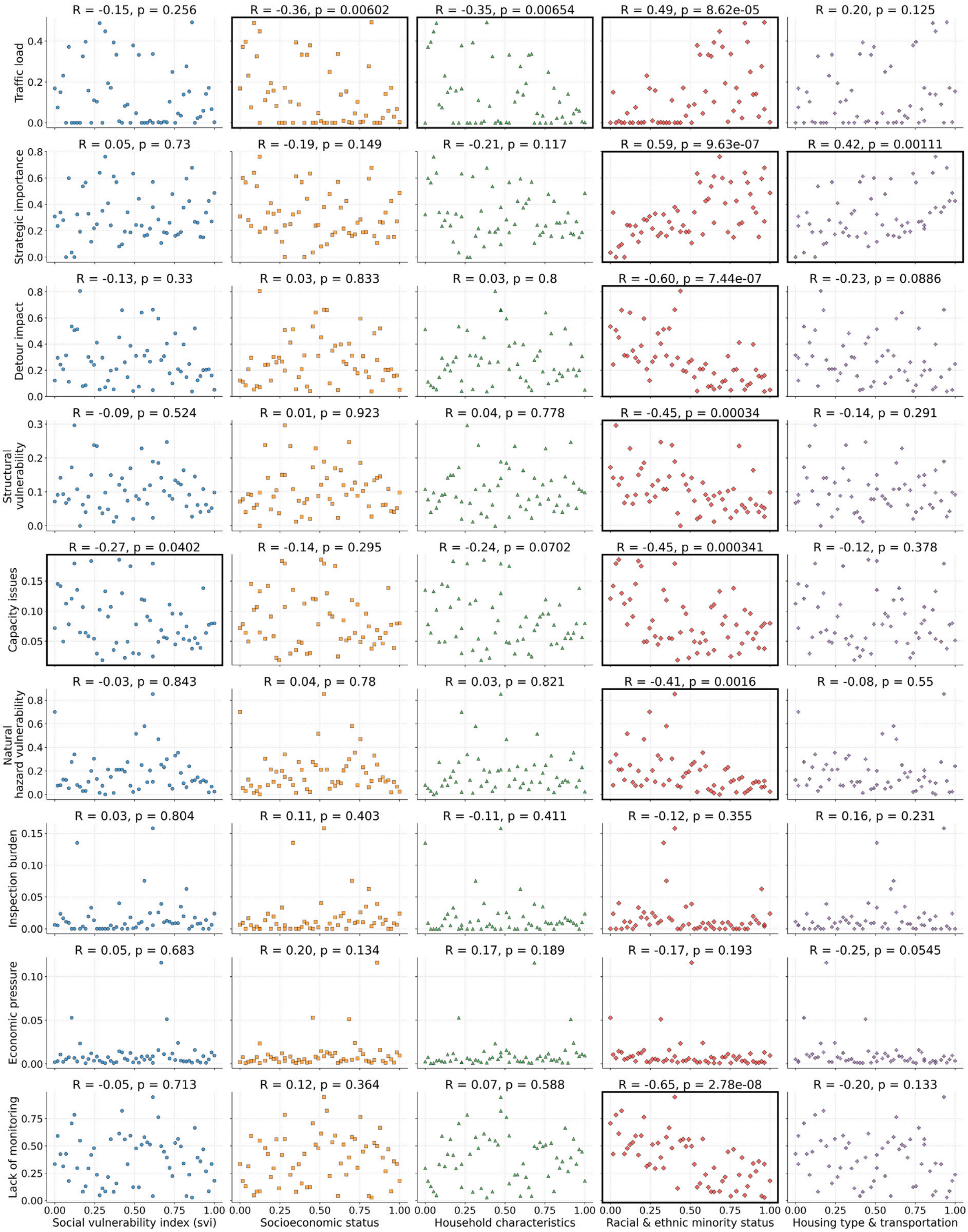



**Fig. 13.** Scatter plot of components of social vulnerability vs components of bridge assessment (in box those that have $p < 0.05$).

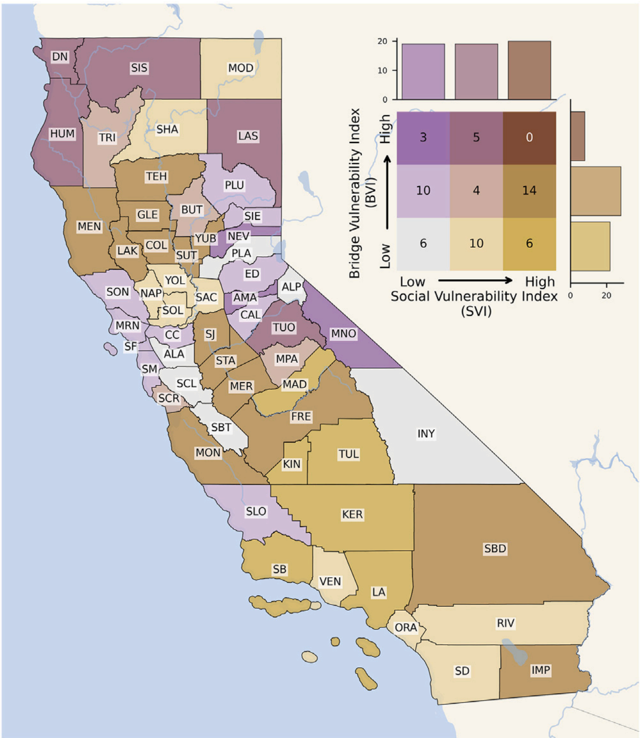



**Fig. 14.** A bivariate choropleth map illustrating the spatial distribution of bridge vulnerability and social vulnerability indices across counties, emphasising their cumulative effect in selected regions. Both vulnerability measures were classified into three equal intervals (0–0.33, 0.33–0.66, and 0.66–1.00). The accompanying legend quantifies the number of counties within each categorical combination, whilst adjacent histograms depict the frequency distribution of each vulnerability type, facilitating interpretation of their respective spatial patterns and potential correlation.

impact of water-related hazards on the BVI could be explained by terrain configurations that render these areas more susceptible to flooding, overtopping and scour damage.

It is noteworthy that even counties with very small bridge portfolios might experience difficulties in ensuring timely inspections and may face high inspection burdens. Counties exhibiting high economic pressure typically demonstrate relatively low overall GDP and medium-to-high structural vulnerability, potentially indicating a substantial proportion of deteriorating bridges. Consequently, even with modest bridge portfolios, the replacement of deteriorating bridges could impose significant strain on these counties' economic resources.

The significant proportion of bridges lacking spaceborne monitoring in northern California may result from low urbanisation in these regions, as MT-InSAR technology functions more effectively in urban areas, coupled with bridges being situated in more heavily vegetated terrain. To sum up, whilst the spatial distribution of sub-indicators varies considerably, many demonstrate peak values in the northern part of the State. This pattern is subsequently reflected in the BVI, which exhibits high values in this region. However, these results should be interpreted with caution. The concentration of high vulnerability scores in Northern California may partially reflect an artefact of the aggregation process. These rural counties often score highly across multiple distinct sub-indicators: detour impact (due to sparse road networks), inspection burden (due to small agency sizes), and lack of monitoring, which, when combined, elevate the composite score. While this highlights genuine operational and logistical challenges, it represents a different type of vulnerability than the high-consequence, high-traffic risks found in metropolitan areas. Therefore, the 'highest vulnerability' designation should be understood as reflecting a compounded lack of system redundancy and adaptive resources, rather than necessarily indicating an imminent risk of structural collapse.

The thresholds selected for creating sub-indicators have a critical influence on the composite indicator. Whilst some thresholds were readily identifiable based on the literature review, others required informed decisions due to a lack of consensus. In particular, certain thresholds required regional calibration to ensure meaningful discrimination within California's specific context. For instance, the ADT threshold of 25,000 vehicles/day was selected because lower values used in other states (5000–10,000) would classify the majority of California bridges as high-traffic, failing to meaningfully distinguish structures experiencing elevated stress. California's transportation network is characterised by substantially higher baseline traffic volumes than more rural states, necessitating a higher threshold to identify bridges with genuinely elevated exposure. Future applications of this methodology to other regions should reassess threshold appropriateness based on local traffic characteristics to ensure adequate discrimination within the assessed population. To evaluate the impact of these choices, threshold values were assessed through Monte Carlo simulation. The sensitivity

**Table 10**
Comparison of county bridge prioritisation using traditional condition-based metrics versus comprehensive Bridge Vulnerability Index (BVI). Traditional ranking uses a poor bridge replacement cost percentage (weighted by deck area), which forms the basis of the FHWA Bridge Formula Program funding allocation. Arrows indicate direction of priority change: ↑ = higher priority under BVI than traditional approach; ↓ = lower priority under BVI. BVI and SVI categories: Low, Medium, High vulnerability.

| County | Traditional Rank | BVI Rank | Priority Shift | BVI Category | Social Vulnerability |
|---|---|---|---|---|---|
| **Del Norte** | 49 | 1 | 48 ↑ | High | Medium |
| **Tuolumne** | 38 | 2 | 36 ↑ | High | Medium |
| **Amador** | 43 | 3 | 40 ↑ | High | Low |
| **Siskiyou** | 42 | 4 | 38 ↑ | High | Medium |
| **Nevada** | 36 | 5 | 31 ↑ | High | Low |
| **Mono** | 56 | 6 | 50 ↑ | High | Low |
| **Lassen** | 52 | 7 | 45 ↑ | High | Medium |
| **Humboldt** | 25 | 8 | 17 ↑ | High | Medium |
| **Glenn** | 16 | 9 | 7 ↑ | Medium | High |
| **San Bernardino** | 8 | 10 | 2 ↓ | Medium | High |
| **Yuba** | 46 | 11 | 35 ↑ | Medium | High |
| **Mariposa** | 51 | 12 | 39 ↑ | Medium | Medium |
| **Mendocino** | 30 | 13 | 17 ↑ | Medium | High |
| **Butte** | 37 | 14 | 23 ↑ | Medium | Medium |
| **Imperial** | 23 | 15 | 8 ↑ | Medium | High |
| **Monterey** | 26 | 16 | 10 ↑ | Medium | High |
| **Tehama** | 18 | 17 | 1 ↑ | Medium | High |
| **San Luis Obispo** | 22 | 18 | 4 ↑ | Medium | Low |
| **San Mateo** | 1 | 19 | 18 ↓ | Medium | Low |
| **San Joaquin** | 6 | 20 | 14 ↓ | Medium | High |
| **Sonoma** | 17 | 21 | 4 ↓ | Medium | Low |
| **Plumas** | 50 | 22 | 28 ↑ | Medium | Low |
| **Stanislaus** | 13 | 23 | 10 ↓ | Medium | High |
| **Marin** | 27 | 24 | 3 ↑ | Medium | Low |
| **Sutter** | 24 | 25 | 1 ↓ | Medium | High |
| **El Dorado** | 40 | 26 | 14 ↑ | Medium | Low |
| **Calaveras** | 48 | 27 | 21 ↑ | Medium | Low |
| **Santa Cruz** | 33 | 28 | 5 ↑ | Medium | Medium |
| **Trinity** | 53 | 29 | 24 ↑ | Medium | Medium |
| **Colusa** | 45 | 30 | 15 ↑ | Medium | High |
| **Fresno** | 31 | 31 | 0 | Medium | High |
| **Sierra** | 54 | 32 | 22 ↑ | Medium | Low |
| **Contra Costa** | 3 | 33 | 30 ↓ | Medium | Low |
| **Lake** | 47 | 34 | 13 ↑ | Medium | High |
| **San Francisco** | 12 | 35 | 23 ↓ | Medium | Low |
| **Merced** | 15 | 36 | 21 ↓ | Medium | High |
| **Placer** | 35 | 37 | 2 ↓ | Low | Low |
| **Madera** | 32 | 38 | 6 ↓ | Low | High |
| **Alameda** | 4 | 39 | 35 ↓ | Low | Low |
| **Napa** | 28 | 40 | 12 ↓ | Low | Medium |
| **Sacramento** | 14 | 41 | 27 ↓ | Low | Medium |
| **Shasta** | 34 | 42 | 8 ↓ | Low | Medium |
| **Los Angeles** | 2 | 43 | 41 ↓ | Low | High |
| **Kings** | 41 | 44 | 3 ↓ | Low | High |
| **Alpine** | 57 | 45 | 12 ↑ | Low | Low |
| **Ventura** | 21 | 46 | 25 ↓ | Low | Medium |
| **Solano** | 11 | 47 | 36 ↓ | Low | Medium |
| **Modoc** | 55 | 48 | 7 ↑ | Low | Medium |
| **Riverside** | 20 | 49 | 29 ↓ | Low | Medium |
| **Tulare** | 39 | 50 | 11 ↓ | Low | High |
| **San Benito** | 44 | 51 | 7 ↓ | Low | Low |
| **Santa Clara** | 7 | 52 | 45 ↓ | Low | Low |
| **Kern** | 10 | 53 | 43 ↓ | Low | High |
| **Santa Barbara** | 19 | 54 | 35 ↓ | Low | High |
| **San Diego** | 5 | 55 | 50 ↓ | Low | Medium |
| **Yolo** | 29 | 56 | 27 ↓ | Low | Medium |
| **Orange** | 9 | 57 | 48 ↓ | Low | Medium |
| **Inyo** | 58 | 58 | 0 | Low | Low |

analysis revealed that the scour criticality threshold had the most significant influence on results. This threshold classifies bridge foundations using a scale where: level two indicates extensive scour occurrence detected during field reviews; level three means foundations are determined to be unstable based on calculated scour conditions; and level four denotes foundations that are stable according to calculations but require protective actions based on field reviews [59].

The uncertainty analysis of the scour threshold provides valuable insights for bridge management agencies, revealing that many bridges currently exist in borderline conditions. When the threshold increases from three to four, more bridges are deemed vulnerable, causing increased vulnerability. Counties such as Solano, which present with sensitivity distributions below the baseline value, likely contain numerous bridges currently rated at level four that are at risk of deteriorating to the more critical level three, thereby increasing future vulnerability. Conversely, when the threshold becomes more restrictive, i.e., changes from three to two, the vulnerability can decrease. Counties such as Marin, which have sensitivity distributions above the baseline value, probably contain many bridges currently at level three that could deteriorate to the critical level two in the near term.

The prominence of scour criticality in the sensitivity analysis reflects broader challenges in bridge scour management. Whilst periodic visual inspection remains standard practice for most transport authorities, this approach may be insufficient due to reliance on expert opinion, necessary assumptions, and potentially incomplete knowledge of subsurface conditions [143,144]. Consequently, various risk-informed methodologies have been developed to support decision-making, ranging from traditional risk-based frameworks incorporating hydrological modelling and scour depth calculations [145] to machine learning-based approaches [146]. Recent applications include risk-informed scour assessment employing Analytic Hierarchy Process to prioritise in-person inspections based on regional, structural, hydro-geological, and flood risk characteristics [147], as well as network-level scour risk management frameworks [148]. Notably, one recent study has integrated equity considerations with deep learning-based algorithms that account for ageing, flood-induced degradation, and social vulnerability [146], demonstrating convergence towards the equity-oriented approach advocated in this research.

Beyond visual inspection, direct measurement of scour depth through submerged instrumentation faces significant practical limitations: high installation and operational costs, vulnerability to flood-induced debris impacts, and challenges in data interpretation [144]. These constraints have motivated the development of indirect monitoring approaches based on changes in structural dynamic behaviour, which offer practical advantages including accessibility for sensor placement above water level and reduced maintenance requirements [144]. Furthermore, emerging research demonstrates that InSAR techniques can detect precursor signs of structural failures due to scour [149,150], reinforcing the value of integrating spaceborne monitoring availability into vulnerability assessment and providing a cost-effective pathway for routine surveillance of scour-critical bridges.

Uncertainty and sensitivity analysis of methodological choices implemented during PCFA revealed several important findings. First, randomly excluding individual indicators had the greatest influence on composite indicator variability. This finding confirms that all selected sub-indicators contributed meaningfully to the analysis without redundancy, validating the indicator selection process. Second, while the Mahalanobis distance threshold set to the 97.5th percentile for multivariate outlier exclusion was somewhat conservative, it identified only two counties whose extreme value combinations could potentially distort the factor structure. Additionally, the Monte Carlo sensitivity analysis confirmed that varying this threshold between the 95th and 100th percentiles has minimal impact on final rankings. These counties were reintegrated for the final BVI calculation, ensuring no geographical areas were excluded from the assessment.

The analysis of social vulnerability and its correlations to the BVI sub-indicators revealed interesting patterns. The concentration of high social vulnerability in the San Joaquin Valley counties reflects areas characterised by persistent poverty, limited access to essential services, and reliance on low-wage or seasonal employment, which are traits common to rural, agricultural regions with long-standing structural disadvantages. The observed high vulnerability in Los Angeles and San Bernardino Counties demonstrates how, in urbanised contexts, social vulnerability is driven by high population density, ethnic disparities, and housing insecurity, particularly in outer suburbs and historically marginalised neighbourhoods. The analysis illustrates how different underlying socioeconomic conditions, such as rural economic hardship and urban inequality, manifest in distinct yet comparably high levels of social vulnerability across California. The finding that racial and ethnic minority status shows the strongest correlations with bridge vulnerability indicators reveals important equity implications. The positive relationship with strategic importance may reflect the presence of large, historically underserved urban populations relying on essential infrastructure. However, the negative associations with condition-related indicators suggest that in counties with higher minority populations, bridges tend to be in worse condition, face more restrictions, and are overdue for inspection, pointing to patterns of infrastructure neglect or delayed maintenance. Together, these relationships highlight a structural inequity: while bridges in these communities may be strategically vital, they are also more likely to be degraded or insufficiently maintained, reinforcing systemic vulnerabilities. This aligns with findings by [30], who identified distributional-demographic inequities, particularly along racial and income lines, as a key dimension of infrastructure resilience research, yet often under-examined in practice.

The substantial divergence between BVI and traditional rankings observed in the benchmarking analysis highlights systematic limitations of current prioritisation practice. While condition-based metrics effectively identify bridges requiring structural intervention, they implicitly assume that structural deficiency alone determines investment urgency, overlooking factors such as network dependencies, hazard exposure, and capacity to manage deterioration. This omission has significant implications: counties like Del Norte, which face elevated vulnerability across multiple dimensions, receive minimal priority under current approaches until structural problems manifest, by which point interventions become reactive and costly. Conversely, counties with extensive structural deficiencies but strong adaptive capacity may receive disproportionate resources despite their ability to manage risks effectively through existing monitoring systems, economic resources, and network redundancy. Several limitations constrain this comparison. The FHWA metric operates at the state level for federal funding allocation rather than the county level, and longitudinal data on actual bridge failures or service disruptions that could empirically validate either approach remain unavailable. Nevertheless, the divergence supports the BVI's methodological contribution: integrating dimensions beyond structural condition enables identification of vulnerabilities that current fund allocation practice systematically overlooks. The persistence of these methodological gaps is further evidenced by the federal transition from the NBI (1995 guidelines) to the updated Specifications for the National Bridge Inventory (SNBI) framework [59,101]. While modernising data collection standards, SNBI maintains exclusive focus on structural and operational metrics without social vulnerability provisions. This demonstrates that the integration of equity considerations into bridge performance evaluation, as proposed in this study, addresses a fundamental gap that persists even in contemporary assessment systems.

While care is taken to identify suitable metrics and state-of-the-art open-source datasets for sub-indicator selection, these sources present several limitations. The NBI is a well-established and easily available data source. However, finding publicly accessible data covering other global regions with comparable detail is challenging, limiting the methodology's international applicability. Moreover, NBI exclusively considers bridges exceeding 6 m (20 ft) in length, thereby omitting information about numerous shorter structures, particularly pedestrian and cycling bridges, which likely exhibit substantially worse conditions than their larger counterparts [151]. Furthermore, whilst NBI constitutes an invaluable information resource due to its extensive spatial coverage and granular detail [102], it is susceptible to errors, such as incorrect bridge coordinates [152]. Additionally, many NBI scores derive from visual inspections, which introduce significant variability in ratings due to inspector subjectivity [153].

The Bridge Replacement Unit Costs methodology, despite its simplicity and common usage among state transportation agencies, suffers from reliability issues precisely because of this simplification [72]. Additionally, whilst GDP serves as a reasonable approximation of a county's resources, it may not accurately reflect funds specifically available for bridge rehabilitation. This limitation stems from the complex funding structure of bridge maintenance: approximately half of NBI bridges are federally owned, with the remainder under local government jurisdiction and a small proportion belonging to other institutions such as tribal authorities [154]. Whilst federal funds contribute significantly, states retain authority to determine rehabilitation priorities [155], and local entities can apply for additional funding programmes [154]. Consequently, the methodology could benefit from a more comprehensive assessment of available funding and its economic impact at the local level. However, the BVI framework is agnostic to the specific economic capacity metric employed: where detailed budget data, federal funding allocations, or other financial indicators are available, these can replace GDP without requiring methodological changes. The use of GDP enables global applicability through consistent, standardised data availability, while the framework remains flexible to incorporate region-specific financial metrics where available.

Regarding monitoring technologies, whilst MT-InSAR is not yet routinely employed for bridge monitoring in California, Californian entities such as the California Department of Water Resources already utilise spaceborne monitoring for land subsidence measurements [51]. Thus, implementing such technology for regular bridge inspection would constitute a relatively straightforward extension of existing practices. The correlation analysis between monitoring availability and infrastructure characteristics reveals important patterns. Counties experiencing high inspection burdens typically exhibited limited spaceborne monitoring availability, suggesting a mismatch between resource constraints and availability of complementary technological solutions. However, counties maintaining large bridge portfolios had good monitoring availability, indicating that MT-InSAR implementation in these areas could yield substantial benefits for managing extensive infrastructure networks. Furthermore, the observed negative correlation between lack of monitoring and both strategic importance and traffic load variables suggests that bridges critical to the transportation network possess relatively good visibility from space, highlighting the benefit of using spaceborne monitoring.

Notably, the analysis showed important equity-related correlations with monitoring availability. Counties in the San Joaquin Valley and southern California, which exhibit high social vulnerability, demonstrated relatively good monitoring availability. This finding suggests that spaceborne monitoring could serve as a cost-effective tool for enhancing structural health assessment in these socially vulnerable areas. The negative correlation between lack of monitoring and ethnic minority populations further underscores this potential, revealing that disadvantaged communities often have bridges with good observability from space. These results emphasise MT-InSAR's capacity to support more equitable bridge maintenance practices. Nevertheless, the method employed in this work to estimate MT-InSAR availability, whilst providing a reasonable first approximation, assesses PSs availability at a roughly $90 \times 90$ m pixel level, potentially misclassifying bridges as visible when measurement points actually represent reflections from surrounding structures. Furthermore, it is worth emphasising that remote sensing-based monitoring will not eliminate the necessity for in-person surveys, but rather could provide an additional and more frequent data source to complement traditional inspection methods.

The weights for the BVI sub-indicators are developed through PCFA. This approach enables the derivation of data-driven weights that are independent from potentially biased expert judgment and allows for their determination even when facing a shortage of available experts. However, the PCFA approach generates weights based on correlations between sub-indicators, which might not accurately represent the underlying relationships in the phenomena being investigated [128,156]. A particular consideration is whether certain variables might reflect outcomes of deterioration rather than independent vulnerability factors, which could introduce unintended feedback loops in the assessment. However, examination of the indicators in this framework reveals that most represent independent factors rather than consequences of deterioration. Spaceborne monitoring availability is determined primarily by bridge geometry and material reflectivity. These characteristics remain stable regardless of structural condition, as radar backscatter properties are unaffected by deterioration processes. Similarly, inspection burden in the California dataset appears predominantly influenced by systemic resource constraints: counties exhibiting elevated inspection burden typically maintain smaller bridge portfolios, which, considering known staffing shortages in transportation agencies [74], suggests that inspector availability rather than condition-driven demand determines inspection frequency patterns. Moreover, within a resource allocation framework, inspection burden represents a legitimate driver of vulnerability regardless of its underlying causes: counties requiring more frequent inspections face greater resource demands that must be addressed through funding prioritisation. Other indicators in the framework, such as traffic volumes, detour length, or hazard exposure, represent external factors independent of structural outcomes. Whilst these concerns do not appear to compromise the current application, future implementations should carefully examine whether dataset-specific characteristics might introduce such feedback relationships between vulnerability indicators and deterioration outcomes. Additionally, PCFA only measures relative vulnerabilities between locations and does not inform about absolute levels of vulnerability [118]. PCFA results depend heavily on methodological choices. Whilst most of these choices are investigated through uncertainty and sensitivity analysis, several remain unexamined. For instance, selecting PCA as the method for factor extraction, rather than alternatives such as maximum likelihood, significantly impacts the assigned weights [14]. Moreover, whilst we propose the use of Mahalanobis distance, interquartile range and Yeo-Johnson transformations to address outliers and skewed distributions, robust PCA could potentially be employed to avoid such issues altogether [157]. Although PCA-related methods for composite indices have been criticised in the literature [156], they remain straightforward and readily applicable approaches for simplifying multivariate datasets and providing useful indicators for decision-makers. In future research, machine learning techniques could be investigated as alternatives for creating composite indices [158]. Similarly, whilst composite indices themselves have faced criticism, they continue to offer valuable solutions for simplifying complex constructs and presenting insights to stakeholders [159].

The aggregation of bridge vulnerability metrics into nine sub-indicators is methodologically essential for conducting PCFA, which requires variables to be measured on interval, ratio, or ordinal scales, whereas the original metrics comprised diverse data types [14]. Moreover, PCFA's reliability depends critically upon maintaining appropriate sample-to-variable ratios. The aggregation into sub-indicators enables achievement of the recommended proportions whilst preserving the substantive information contained within the original metrics. This intermediate aggregation step therefore strengthens both the statistical robustness and interpretative value of the composite vulnerability index. Nevertheless, as with any aggregation procedure, this methodological approach may result in information loss through the inevitable reduction of granular, bridge-specific data to administrative unit-level indicators. Consequently, further research could explore alternative data-driven methods, such as machine learning-based approaches, that are not constrained by the PCFA requirements.

The bivariate mapping approach used to combine BVI with SVI has important methodological limitations as an equity assessment tool. The methodology identifies spatial coincidence of structural and social vulnerability but does not capture procedural equity dimensions (meaningful community participation in infrastructure prioritisation decisions) or temporal dynamics (how vulnerability and resource allocation patterns evolve over time). Additionally, the county-level aggregation may also mask intra-county disparities where vulnerable populations are spatially concentrated. These limitations mean the assessment provides a screening tool for identifying counties with compounded socio-structural vulnerability rather than a comprehensive equity evaluation. Nevertheless, the approach offers a practical framework for systematically incorporating social considerations into infrastructure prioritisation at the administrative scale, where resource allocation decisions occur.

To operationalise the proposed framework within real-world decision-making contexts, it should be recognised that asset management is fundamentally constrained by budget availability and maintenance requirements. While structures posing immediate public safety risks must always take precedence regardless of socioeconomic context, the substantial inventory of bridges in poor condition requiring non-emergency intervention necessitates prioritisation. Therefore, the framework developed in this study could serve as a decision-support tool for administrative-level resource allocation. Rather than replacing traditional assessments, the method operationalises equity by identifying counties with compounded structural and social vulnerabilities that warrant prioritised funding. For instance, when a state agency must distribute budget among multiple districts, the framework highlights regions where high structural deficiency coincides with low adaptive capacity. This approach navigates the trade-off between efficiency and equity by ensuring that funding distribution accounts for the disproportionate societal impacts of network failure in communities lacking the systemic resources to cope with service disruptions.

Whilst this methodology was applied to California due to its significant social equity challenges and natural hazard impacts on bridge infrastructure, it is important to acknowledge that California represents one of the world's most economically prosperous regions. Given adequate data availability, future research should extend this methodology to regions with greater economic constraints, where the compounding effects of social vulnerability and deteriorating bridge infrastructure may be more pronounced. Such global applications would enable identification of true vulnerability hotspots where limited adaptive capacity exacerbates infrastructure-related social risks, potentially revealing more critical intervention priorities than those identified within California's relatively resource-rich context.

Finally, the county-level socio-structural vulnerability index provided by this study can be employed to inform decisions regarding allocating funds for bridge rehabilitation and maintenance in a socially equitable manner. The county-level aggregation aligns with network-level maintenance planning principles, as the objective is to improve the performance of entire transportation networks rather than merely individual structures [160]. However, the method does not highlight individual bridges that could be problematic, which represents a limitation for targeted interventions. Furthermore, in counties with small bridge portfolios (common in Northern California), aggregating metrics into percentages can result in high variance, where a small number of deficient bridges disproportionately influences the final index score. Additionally, the county-level aggregation raises concerns about the ecological fallacy, as aggregate vulnerability patterns may not accurately reflect the spatial co-location of vulnerable bridges with vulnerable populations within counties. The framework, therefore, serves as a screening tool for identifying administrative regions warranting prioritised attention and closer examination. Nevertheless, the presented methodology offers a valuable tool for stakeholders and decision-makers by identifying critical counties that possess bridge portfolios with not only a significant proportion of deteriorating structures, but also high social vulnerability within the region. To render the prioritisation process even more comprehensive, future work could incorporate environmental justice considerations [118] and finer-scale spatial analysis where data availability supports sub-county assessment.

## 6. Conclusions

This study successfully integrates bridge vulnerability metrics with social vulnerability to assess county-level priorities for bridge maintenance and inform equitable resource allocation decisions. The research makes several key methodological contributions. First, it extended traditional bridge assessment frameworks by incorporating subsidence susceptibility as a novel damage factor. Second, it introduced adaptive capacity as a third vulnerability dimension in the bridge prioritisation framework, encompassing economic resilience, inspection burden, and monitoring capability. Third, the data-driven weighting approach through PCFA eliminated subjective bias in indicator aggregation. Finally, the proposed method employed a bivariate mapping technique to highlight distinct characteristics of social and structural vulnerability whilst enabling integrated assessment.

The framework's application to California suggests that counties in Northern California exhibit the highest levels of compounded vulnerability effects as defined by the proposed index, where poor bridge conditions coincide with operational constraints and elevated social vulnerability. Conversely, the state's two most populated regions, which would typically receive priority in traditional infrastructure assessments, demonstrate markedly different vulnerability patterns. The San Francisco Bay Area exhibits bridges in moderate condition categories alongside low social vulnerability, whilst the Los Angeles metropolitan area, despite maintaining the state's largest bridge portfolio, is characterised by bridges in very good structural condition, but experiences high social vulnerability levels. These findings demonstrate that traditional bridge prioritisation approaches, which typically focus on structural condition and traffic volumes, may inadequately address social equity concerns and potentially perpetuate infrastructure-related disparities. The results suggest that prioritising solely based on structural deficiency or traffic density could overlook regions where bridge failures would disproportionately impact socially vulnerable populations, whilst simultaneously over-investing in areas with robust adaptive capacity despite structural challenges. Moreover, the study found a strong correlation between high social vulnerability and good spaceborne monitoring availability, highlighting the benefit of deploying MT-InSAR where it could most effectively support equitable infrastructure management.

Beyond resource allocation, this methodology supports broader infrastructure equity goals by providing transparent, evidence-based prioritisation criteria. The framework's transferability to other regions, given adequate data availability, offers potential for addressing global infrastructure vulnerability hotspots where social and structural vulnerabilities compound and create critical intervention needs.

## CRediT authorship contribution statement

**Dominika Malinowska:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kristina Petrova:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Pietro Milillo:** Writing – review & editing, Methodology, Conceptualization. **Cormac Reale:** Writing – review & editing, Methodology, Conceptualization. **Chris Blenkinsopp:** Writing – review & editing, Methodology, Conceptualization. **Giorgia Giardina:** Writing – review & editing, Supervision, Resources, Methodology, Funding acquisition, 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.

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## Data availability

Data will be made available on request.

## References

[1] C.C. Caprani, J. De Maria, Long-span bridges: analysis of trends using a global database, Struct. Infrastruct. Eng. 16 (1) (2020) 219–231, http://dx.doi.org/10.1080/15732479.2019.1639773.

[2] D. Proske, Bridges, in: The Collapse Frequency of Structures: Bridges - Dams - Tunnels - Retaining Structures - Buildings, Springer International Publishing, Cham, 2022, pp. 31–50, http://dx.doi.org/10.1007/978-3-030-97247-9_3.

[3] A. Mondoro, D.M. Frangopol, L. Liu, Bridge adaptation and management under climate change uncertainties: A review, Nat. Hazards Rev. 19 (1) (2018) http://dx.doi.org/10.1061/(ASCE)NH.1527-6996.0000270.

[4] Q. Wang, K. Liu, M. Wang, E. Koks, H. Wang, Exposure of global rail and road infrastructures in future record-breaking climate extremes, Earth's Futur. 12 (1) (2024) e2023EF003632, http://dx.doi.org/10.1029/2023EF003632.

[5] S. Chase, Y. Adu-Gyamfi, A. Aktan, E. Minaie, Pennoni Associates Incorporated, Synthesis of National and International Methodologies Used for Bridge Health Indices, Tech. Rep. FHWA-HRT-15-081, Federal Highway Administration (FHWA), 2016, pp. 1–44, URL https://rosap.ntl.bts.gov/view/dot/34775.

[6] A.A. Chávez, J. Gonzalez-Libreros, C. Wang, G. Sas, Bridge condition index: A review of methodologies used in bridge management systems, in: Bridge Maintenance, Safety, Management, Digitalization and Sustainability, CRC Press, 2024, pp. 1130–1137.

[7] J.C. Matos, V. Nicoletti, J. Kralovanec, H.S. Sousa, F. Gara, M. Moravcik, M.J. Morais, Comparison of condition rating systems for bridges in three European countries, Appl. Sci. 13 (22) (2023) 12343, http://dx.doi.org/10.3390/app132212343.

[8] C. Iacovino, Z.I. Turksezer, P.F. Giordano, M.P. Limongelli, A survey of bridge condition rating systems, in: C. Pellegrino, F. Faleschini, M.A. Zanini, J.C. Matos, J.R. Casas, A. Strauss (Eds.), Proceedings of the 1st Conference of the European Association on Quality Control of Bridges and Structures, Springer International Publishing, Cham, 2022, pp. 14–22, http://dx.doi.org/10.1007/978-3-030-91877-4_2.

[9] B. Gibson, C. Van Dyke, S. Palle, R. Griffith, D. Kreis, Bridge Project Prioritization, Tech. Rep., Kentucky Transportation Center, 2022, http://dx.doi.org/10.13023/ktc.rr.2022.08.

[10] E. Fereshtehnejad, J. Hur, A. Shafieezadeh, M. Brokaw, Ohio bridge condition index: Multilevel cost-based performance index for bridge systems, Transp. Res. Rec.: J. Transp. Res. Board 2612 (2017) http://dx.doi.org/10.3141/2612-17.

[11] C. Van Dyke, T. Jerin, N. Albright, B. Blandford, E. Lammers, D. Kreis, Rapid diagnostic framework for assessing bridge and culvert sensitivity to hydraulic forcing, Nat. Hazards Rev. 22 (2) (2021) 04021006, http://dx.doi.org/10.1061/(ASCE)NH.1527-6996.0000452.

[12] S.S. Wakchaure, K.N. Jha, Determination of bridge health index using analytical hierarchy process, Constr. Manag. Econ. 30 (2) (2012) 133–149, http://dx.doi.org/10.1080/01446193.2012.658075.

[13] R.B. Kulkarni, D. Miller, R.M. Ingram, C.-W. Wong, J. Lorenz, Need-based project prioritization: Alternative to cost-benefit analysis, J. Transp. Eng. 130 (2) (2004) 150–158, http://dx.doi.org/10.1061/(ASCE)0733-947X(2004)130:2(150).

[14] OECD and European Union and Joint Research Centre - European Commission, Handbook on Constructing Composite Indicators: Methodology and User Guide, OECD, 2008, http://dx.doi.org/10.1787/9789264043466-en.

[15] Q.O. Abiona, M.H. Head, Determination of bridge elements' weights using the random forest algorithm, J. Perform. Constr. Facil. 39 (1) (2025) 04024056, http://dx.doi.org/10.1061/JPCFEV.CFENG-4885.

[16] Q.O. Abiona, M.H. Head, Y. Yoon, Bridge element weights based on data-driven model with artificial neural networks, in: Structures Congress 2023, American Society of Civil Engineers, New Orleans, Louisiana, 2023, pp. 106–119, http://dx.doi.org/10.1061/9780784484777.011.

[17] M. Greenacre, P.J.F. Groenen, T. Hastie, A.I. D'Enza, A. Markos, E. Tuzhilina, Principal component analysis, Nat. Rev. Methods Prim. 2 (1) (2022) 100, http://dx.doi.org/10.1038/s43586-022-00184-w.

[18] M.A. Zanini, F. Faleschini, J.R. Casas, State-of-research on performance indicators for bridge quality control and management, Front. Built Environ. 5 (2019) http://dx.doi.org/10.3389/fbuil.2019.00022.

[19] J. Matos, S. Fernandes, M.Q. Tran, Q.T. Nguyen, E. Baron, S.N. Dang, Developing a comprehensive quality control framework for roadway bridge management: A case study approach using key performance indicators, Appl. Sci. 13 (13) (2023) 7985, http://dx.doi.org/10.3390/app13137985.

[20] A. Mandić Ivanković, A. Strauss, H. Sousa, European review of performance indicators towards sustainable road bridge management, Proc. Inst. Civ. Eng. - Eng. Sustain. 173 (3) (2020) 109–124, http://dx.doi.org/10.1680/jensu.18.00052.

[21] I. Josa, A. Aguado, Infrastructure, innovation and industry as solutions for breaking inequality vicious cycles, IOP Conf. Ser.: Earth Environ. Sci. 297 (1) (2019) 012016, http://dx.doi.org/10.1088/1755-1315/297/1/012016.

[22] K. Lucas, Transport and social exclusion: Where are we now? Transp. Policy 20 (2012) 105–113, http://dx.doi.org/10.1016/j.tranpol.2012.01.013.

[23] E. Hooper, S. Peters, P. Pintus, To what extent can long-term investments in infrastructure reduce inequality? J. Infrastruct. Policy Dev. 2 (2) (2018) 193–225, http://dx.doi.org/10.24294/jipd.v2i2.858.

[24] N. Coleman, A. Esmalian, A. Mostafavi, Equitable resilience in infrastructure systems: Empirical assessment of disparities in hardship experiences of vulnerable populations during service disruptions, Nat. Hazards Rev. 21 (4) (2020) 04020034, http://dx.doi.org/10.1061/(ASCE)NH.1527-6996.0000401.

[25] J. Cuthbertson, F. Archer, A. Robertson, J. Rodriguez-Llanes, A socio-health approach to improve local disaster resilience and contain secondary crises: A case study in an agricultural community exposed to bushfires in Australia, Prehospital Disaster Med. 38 (1) (2023) 3–10, http://dx.doi.org/10.1017/s1049023x22002436.

[26] S.C. Ganz, C. Duan, C. Ji, Socioeconomic vulnerability and differential impact of severe weather-induced power outages, PNAS Nexus 2 (10) (2023) http://dx.doi.org/10.1093/pnasnexus/pgad295.

[27] S. Dhakal, L. Zhang, Integrating social equity and vulnerability with infrastructure resilience assessment, in: Construction Research Congress 2022, American Society of Civil Engineers, Arlington, Virginia, 2022, pp. 299–309, http://dx.doi.org/10.1061/9780784483954.031.

[28] C.A. Gandy, D.E. Armanios, C. Samaras, Social equity of bridge management, J. Manag. Eng. 39 (5) (2023) 04023027, http://dx.doi.org/10.1061/JMENEA.MEENG-5265.

[29] S.H. Jones, D.E. Armanios, Methodological framework and feasibility study to assess social equity impacts of the built environment, J. Constr. Eng. Manag. 146 (11) (2020) 05020016, http://dx.doi.org/10.1061/(ASCE)CO.1943-7862.0001914.

[30] N. Coleman, X. Li, T. Comes, A. Mostafavi, Weaving equity into infrastructure resilience research: a decadal review and future directions, Npj Nat. Hazards 1 (1) (2024) 1–19, http://dx.doi.org/10.1038/s44304-024-00022-x.

[31] M. Garschagen, S. Sandholz, The role of minimum supply and social vulnerability assessment for governing critical infrastructure failure: current gaps and future agenda, Nat. Hazards Earth Syst. Sci. 18 (4) (2018) 1233–1246, http://dx.doi.org/10.5194/nhess-18-1233-2018.

[32] N. Mohamadiazar, A. Ebrahimian, A. Azizinamini, Equitable prioritization of bridge rehabilitation projects using a spatial multi-criteria decision support framework, Transp. Res. Rec. (2024) 03611981241254110, http://dx.doi.org/10.1177/03611981241254110.

[33] C. Wehbe, H. Baroud, Limitations and considerations of using composite indicators to measure vulnerability to natural hazards, Sci. Rep. 14 (1) (2024) 19333, http://dx.doi.org/10.1038/s41598-024-68060-z.

[34] C.-H. Hsieh, J.-L. Su, C.-M. Feng, Disaster risk analysis of highway bridges from vulnerability perspective, Proc. East. Asia Soc. Transp. Stud. 2011 (2011) http://dx.doi.org/10.11175/eastpro.2011.0.1.0, 1–1.

[35] M.V. Biezma, F. Schanack, Collapse of steel bridges, J. Perform. Constr. Facil. 21 (5) (2007) 398–405, http://dx.doi.org/10.1061/(ASCE)0887-3828(2007)21:5(398).

[36] J. Zhang, Y. Li, Y. Si, B. Peng, F. Xiao, S. Luo, L. He, A low-grade road extraction method using SDG-DenseNet based on the fusion of optical and SAR images at decision level, Remote. Sens. 14 (12) (2022) 2870, http://dx.doi.org/10.3390/rs14122870.

[37] D. Smith, Bridge failures, Proc. Inst. Civ. Eng. 60 (3) (1976) 367–382, http://dx.doi.org/10.1680/iicep.1976.3389.

[38] T. Davydzenka, P. Tahmasebi, N. Shokri, Unveiling the global extent of land subsidence: The sinking crisis, Geophys. Res. Lett. 51 (4) (2024) e2023GL104497, http://dx.doi.org/10.1029/2023GL104497.

[39] C. Zhang, K. Wu, S. Huang, L. Li, X. Rao, Study on the simulation of bridge deformation in a mining subsidence area, Sci. Rep. 15 (1) (2025) 529, http://dx.doi.org/10.1038/s41598-024-84220-7.

[40] A. Nettis, V.M. Di Mucci, S. Ruggieri, G. Uva, Seismic fragility and risk assessment of isolated bridges subjected to pre-existing ground displacements, Soil Dyn. Earthq. Eng. 194 (2025) 109335, http://dx.doi.org/10.1016/j.soildyn.2025.109335.

[41] M. Arabi, S. Gerasimidis, C. Barchers, J. Oke, Resilience in multilayer transportation infrastructure networks: A review and conceptual framework for equity-based assessment, Sustain. Resilient Infrastruct. 9 (6) (2024) 616–639, http://dx.doi.org/10.1080/23789689.2024.2344909.

[42] S. Arezoumand, O. Smadi, Equity in transportation asset management: A proposed framework, Algorithms 17 (7) (2024) 305, http://dx.doi.org/10.3390/a17070305.

[43] D.M. Frangopol, Y. Dong, S. Sabatino, Bridge life-cycle performance and cost: Analysis, prediction, optimisation and decision-making, Struct. Infrastruct. Eng. 13 (10) (2017) 1239–1257, http://dx.doi.org/10.1080/15732479.2016.1267772.

[44] J. Peng, Y. Yang, H. Bian, J. Zhang, L. Wang, Optimisation of maintenance strategy of deteriorating bridges considering sustainability criteria, Struct. Infrastruct. Eng. 18 (3) (2022) 395–411, http://dx.doi.org/10.1080/15732479.2020.1855215.

[45] ASCE, 2025 Report Card for America's Infrastructure - A Comprehensive Assessment of America's Infrastructure, Tech. Rep., American Society of Civil Engineers (ASCE), 2025.

[46] ARTBA, Annual Bridge Report, Tech. Rep., American Road & Transportation Builders Association (ARTBA), 2024.

[47] ASCE, 2021 Report Card for America's Infrastructure, Tech. Rep., American Society of Civil Engineers (ASCE), 2021.

[48] J. Biden, Tackling the climate crisis at home and abroad, 2021.

[49] U.S. Department of Transportation, Department of transportation equity action plan update (docket no. DOT–OST–2023–0087), 2023.

[50] R.W. Shepard, M.B. Johnson, California bridge health index: A diagnostic tool to maximize bridge longevity, investment, TR News 215 (2001).

[51] C.E. Jones, T.G. Farr, Z. Liu, M.M. Miller, Measuring subsidence in california and its impact on water conveyance infrastructure, in: V. Singhroy (Ed.), Advances in Remote Sensing for Infrastructure Monitoring, Springer International Publishing, Cham, 2021, pp. 211–226, http://dx.doi.org/10.1007/978-3-030-59109-0_9.

[52] C.C. Faunt, J.A. Traum, S.E. Boyce, W.A. Seymour, E.R. Jachens, J.T. Brandt, M. Sneed, S. Bond, M.F. Marcelli, Groundwater sustainability and land subsidence in California's central valley, Water 16 (8) (2024) 1189, http://dx.doi.org/10.3390/w16081189.

[53] M.M. Miller, C.E. Jones, S.S. Sangha, D.P. Bekaert, Rapid drought-induced land subsidence and its impact on the California aqueduct, Remote Sens. Environ. 251 (2020) 112063, http://dx.doi.org/10.1016/j.rse.2020.112063.

[54] C. Zuzak, M. Mowrer, E. Goodenough, J. Burns, N. Ranalli, J. Rozelle, The national risk index: establishing a nationwide baseline for natural hazard risk in the US, Nat. Hazards 114 (2) (2022) 2331–2355, http://dx.doi.org/10.1007/s11069-022-05474-w.

[55] C. Zuzak, A. Sheehan, E. Goodenough, A. McDougall, C. Stanton, P. McGuire, M. Mowrer, B. Roberts, J. Rozelle, National Risk Index Technical Documentation, Tech. Rep., Federal Emergency Management Agency, Washington, DC, 2025.

[56] M. Govorcin, Variable vertical land motion for sea level rise projections, 2024, http://dx.doi.org/10.5281/zenodo.11154177.

[57] KYTC Staff, Kentucky Bridge Inspection Procedures Manual, Tech. Rep., Kentucky Transportation Cabinet (KYTC), 2023.

[58] Department of Transportation (DOT), National Performance Management Measures; Assessing Pavement Condition for the National Highway Performance Program and Bridge Condition for the National Highway Performance Program, Tech. Rep., Federal Highway Administration (FHWA), 2017.

[59] Office of Engineering Bridge Division Bridge Management Branch, Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges, Tech. Rep. FHWA-PD-96-001, U.S. Department of Transportation Federal Highway Administration, 1995.

[60] AECOM, ADOT Planning to Programming Scoring Guidebook, Tech. Rep., Arizona Department of Transportation (ADOT), 2020.

[61] P.-S. Yang, D. Eberhart, Bridge Group Bridge Preservation Program Manual, Tech. Rep., Arizona Department of Transportation, 2016.

[62] Bureau of Engineering and Construction Division of Bridges, Local Bridge Program Manual, Tech. Rep., Connecticut Department of Transportation, 2019.

[63] S. Neubauer, Risk-based prioritization and multi-objective optimization for LongTerm network-level preservation planning of bridges in iowa, in: 11th International Bridge and Structure Management Conference, 2017, pp. 1–6.

[64] A. Peiris, I. Harik, Truss Bridge Rehabilitation Prioritization, Tech. Rep. KTC-18-13/SPR15-503-1F, Kentucky Transportation Center, 2019, http://dx.doi.org/10.13023/ktc.rr.2018.13.

[65] S. Pollack, F. DePaola, L. Dunlavy, J. Lovejoy, D. Mohler, J.M. Pourbaix, J.B. Mullan, S. Silveira, Recommendations for MassDOT Project Selection Criteria, Tech. Rep., Project Selection Advisory Council Report to the Legislature, 2015.

[66] Minnesota Department of Transportation, Trunk Highway Bridge Improvement Program Chapter 152, Tech. Rep., Minnesota Department of Transportation, 2016.

[67] VDOT, State of Good Repair (SGR) Program Bridge Prioritization Formula, Tech. Rep., Virginia Department of Transportation (VDOT), 2024.

[68] United Nations Office for Disaster Risk Reduction, Hazard Definition and Classification Review: Technical Report, Tech. Rep., United Nations, Geneva, Switzerland, 2022, http://dx.doi.org/10.24948/2020.03.

[69] A.M. Dewan, Hazards, risk, and vulnerability, in: Floods in a Megacity: Geospatial Techniques in Assessing Hazards, Risk and Vulnerability, in: Springer Geography, Springer Netherlands, Dordrecht, 2013, pp. 35–74, http://dx.doi.org/10.1007/978-94-007-5875-9_2.

[70] CDC, SVI data & documentation download, 2024, URL https://www.atsdr.cdc.gov/place-health/php/svi/svi-data-documentation-download.html.

[71] Y. Chen, L. Shu, T.J. Burbey, Composite subsidence vulnerability assessment based on an index model and index decomposition method, Hum. Ecol. Risk Assess.: An Int. J. 19 (3) (2013) 674–698, http://dx.doi.org/10.1080/10807039.2012.691405.

[72] M.J. Whelan, T.L. Cavalline, P. Phillips, C. Rice, Improving Replacement Cost Data for NCDOT Highway Bridges, Tech. Rep. FHWA/NC/2017-09, University of North Carolina at Charlotte. Department of Civil and Environmental Engineering, 2019, URL https://rosap.ntl.bts.gov/view/dot/53594.

[73] Y. Zhang, B.M. Ayyub, J.F. Fung, Projections of corrosion and deterioration of infrastructure in united states coasts under a changing climate, Resilient Cities Struct. 1 (1) (2022) 98–109, http://dx.doi.org/10.1016/j.rcns.2022.04.004.

[74] J. Kasan, A. Ream, C. Pasma, M. LaViolette, N. Richards, HDR, 2023 Bridge Construction Practices Peer Exchange Report, Tech. Rep. FHWA-HIF-24-060, Federal Highway Administration (FHWA), 2024.

[75] J.C. Curlander, R.N. McDonough, Synthetic aperture radar: systems and signal processing, in: Wiley Series in Remote Sensing, Wiley, New York, 1991.

[76] R. Bamler, P. Hartl, Synthetic aperture radar interferometry, Inverse Problems 14 (4) (1998) R1, http://dx.doi.org/10.1088/0266-5611/14/4/001.

[77] P. Rosen, S. Hensley, I. Joughin, F. Li, S. Madsen, E. Rodriguez, R. Goldstein, Synthetic aperture radar interferometry, Proc. IEEE 88 (3) (2000) 333–382, http://dx.doi.org/10.1109/5.838084.

[78] J. Biggs, T.J. Wright, How satellite InSAR has grown from opportunistic science to routine monitoring over the last decade, Nat. Commun. 11 (1) (2020) 3863, http://dx.doi.org/10.1038/s41467-020-17587-6.

[79] M. Crosetto, L. Solari, M. Mróz, J. Balasis-Levinsen, N. Casagli, M. Frei, A. Oyen, D.A. Moldestad, L. Bateson, L. Guerrieri, V. Comerci, H.S. Andersen, The evolution of wide-area DInSAR: From regional and national services to the European ground motion service, Remote. Sens. 12 (12) (2020) 1–20, http://dx.doi.org/10.3390/RS12122043.

[80] F. Van Leijen, Persistent Scatterer Interferometry based on Geodetic Estimation Theory (Ph.D. thesis), Delft University of Technology, 2014.

[81] E. Farneti, N. Cavalagli, M. Costantini, F. Trillo, F. Minati, I. Venanzi, W. Salvatore, F. Ubertini, Remote sensing satellite data and progressive collapse analysis for structural monitoring of multi-span bridges, in: P. Rizzo, A. Milazzo (Eds.), in: European Workshop on Structural Health Monitoring, vol. 254, Springer International Publishing, Cham, 2023, pp. 377–386, http://dx.doi.org/10.1007/978-3-031-07258-1_39, Series Title: Lecture Notes in Civil Engineering.

[82] V. Macchiarulo, P. Milillo, C. Blenkinsopp, C. Reale, G. Giardina, Multi-temporal InSAR for transport infrastructure monitoring: Recent trends and challenges, Proc. Inst. Civ. Eng.: Bridg. Eng. (2021) http://dx.doi.org/10.1680/JBREN.21.00039/ASSET/IMAGES/SMALL/JBREN.21.00039-F10.GIF.

[83] D. Malinowska, P. Milillo, C. Reale, C. Blenkinsopp, G. Giardina, Global geo-hazard risk assessment of long-span bridges enhanced with insar availability, Nat. Commun. 16 (1) (2025) 9048, http://dx.doi.org/10.1038/s41467-025-64260-x.

[84] K. DePrekel, E.H. Bouali, T. Oommen, Monitoring the impact of groundwater pumping on infrastructure using geographic information system (GIS) and persistent scatterer interferometry (PSI), Infrastructures 3 (4) (2018) 57, http://dx.doi.org/10.3390/infrastructures3040057.

[85] A. Ferretti, C. Prati, F. Rocca, Nonlinear subsidence rate estimation using permanent scatterers in differential SAR interferometry, IEEE Trans. Geosci. Remote Sens. 38 (5) (2000) 2202–2212, http://dx.doi.org/10.1109/36.868878.

[86] A. Ferretti, C. Prati, F. Rocca, Permanent scatterers in SAR interferometry, IEEE Trans. Geosci. Remote Sens. 39 (1) (2001) 8–20, http://dx.doi.org/10.1109/36.898661.

[87] R. Torres, P. Snoeij, D. Geudtner, D. Bibby, M. Davidson, E. Attema, P. Potin, B. Rommen, N. Floury, M. Brown, I.N. Traver, P. Deghaye, B. Duesmann, B. Rosich, N. Miranda, C. Bruno, M. L'Abbate, R. Croci, A. Pietropaolo, M. Huchler, F. Rostan, GMES sentinel-1 mission, Remote Sens. Environ. 120 (2012) 9–24, http://dx.doi.org/10.1016/j.rse.2011.05.028.

[88] D. Malinowska, P. Milillo, K. Briggs, C. Reale, G. Giardina, Coherence-based prediction of multi-temporal insar measurement availability for infrastructure monitoring, IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. (2024) 1–22, http://dx.doi.org/10.1109/JSTARS.2024.3449688.

[89] J.J. McCarthy, O.F. Canziani, N.A. Leary, D.J. Dokken, K.S. White (Eds.), Climate change 2001: Impacts, adaptation, and vulnerability, in: Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge Univ. Press, Cambridge, UK, 2001.

[90] U.S. Department of Transportation, Federal Highway Administration, 2024 - download NBI ASCII files - national bridge inventory - bridge inspection - safety inspection - bridges & structures - federal highway administration, 2024, URL https://www.fhwa.dot.gov/bridge/nbi/ascii2024.cfm.

[91] AASHTO, AASHTO LRFD Bridge Design Specifications (8th Edition), Tech. Rep., American Association of State Highway and Transportation Officials (AASHTO), 2017.

[92] M. Govorcin, D.P.S. Bekaert, B.D. Hamlington, S.S. Sangha, W. Sweet, Variable vertical land motion and its impacts on sea level rise projections, Sci. Adv. 11 (5) (2025) eads8163, http://dx.doi.org/10.1126/sciadv.ads8163.

[93] V. Macchiarulo, P. Milillo, C. Blenkinsopp, G. Giardina, Monitoring deformations of infrastructure networks: A fully automated GIS integration and analysis of insar time-series, Struct. Health Monit. 21 (4) (2022) 1849–1878, http://dx.doi.org/10.1177/14759217211045912.

[94] L. Solari, A. Barra, G. Herrera, S. Bianchini, O. Monserrat, M. Béjar-Pizarro, M. Crosetto, R. Sarro, S. Moretti, Fast detection of ground motions on vulnerable elements using Sentinel-1 InSAR data, Geomatics Nat. Hazards Risk 9 (1) (2018) 152–174, http://dx.doi.org/10.1080/19475705.2017.1413013.

[95] F. Raspini, S. Bianchini, A. Ciampalini, M. Del Soldato, L. Solari, F. Novali, S. Del Conte, A. Rucci, A. Ferretti, N. Casagli, Continuous, semi-automatic monitoring of ground deformation using Sentinel-1 satellites, Sci. Rep. 8 (1) (2018) 1–11, http://dx.doi.org/10.1038/s41598-018-25369-w.

[96] A. Nettis, V. Massimi, R. Nutricato, D.O. Nitti, S. Samarelli, G. Uva, Satellite-based interferometry for monitoring structural deformations of bridge portfolios, Autom. Constr. 147 (2023) 104707, http://dx.doi.org/10.1016/J.AUTCON.2022.104707.

[97] D. Infante, D. Di Martire, D. Calcaterra, P. Miele, A. Scotto di Santolo, M. Ramondini, Integrated procedure for monitoring and assessment of linear infrastructures safety (I-pro MONALISA) affected by slope instability, Appl. Sci. 9 (24) (2019) 5535, http://dx.doi.org/10.3390/app9245535.

[98] P. Ma, Y. Zheng, Z. Zhang, Z. Wu, C. Yu, Building risk monitoring and prediction using integrated multi-temporal insar and numerical modeling techniques, Int. J. Appl. Earth Obs. Geoinf. 114 (2022) 103076, http://dx.doi.org/10.1016/J.JAG.2022.103076.

[99] U.S. Bureau of Economic Analysis (BEA), Gross domestic product by county and metropolitan area, 2023, 2025, URL https://www.bea.gov/news/2024/gross-domestic-product-county-and-metropolitan-area-2023.

[100] U.S. Department of Transportation, Federal Highway Administration, Bridge replacement unit costs 2023 - bridge tables - national bridge inventory - bridge inspection - safety inspection - bridges & structures - federal highway administration, 2024, URL https://www.fhwa.dot.gov/bridge/nbi/sd2023.cfm.

[101] Federal Highway Administration, Specifications for the National Bridge Inventory, Tech. Rep. FHWA-HIF-22-017, U.S. Department of Transportation, 2022.

[102] S.B. Chase, E.P. Small, C. Nutakor, An in-depth analysis of the national bridge inventory database utilizing data mining, GIS and advanced statistical methods, in: Transportation Research Circular, 2000, pp. C–6/1–17.

[103] OpenStreetMap contributors, Planet dump, 2025, retrieved from https://planet.osm.org, Available at: https://www.openstreetmap.org. (Accessed 3 March 2025).

[104] J. Kellndorfer, O. Cartus, M. Lavalle, C. Magnard, P. Milillo, S. Oveisgharan, B. Osmanoglu, P.A. Rosen, U. Wegmüller, Global seasonal Sentinel-1 interferometric coherence and backscatter data set, Sci. Data 9 (1) (2022) 1–16, http://dx.doi.org/10.1038/s41597-022-01189-6.

[105] ESA, Sentinel-1 acquisition plans, 2025, Available at: https://sentinels.copernicus.eu/copernicus/sentinel-1/acquisition-plans. (Accessed 3 March 2025).

[106] R. Cudeck, 10 - exploratory factor analysis, in: H.E.A. Tinsley, S.D. Brown (Eds.), Handbook of Applied Multivariate Statistics and Mathematical Modeling, Academic Press, San Diego, 2000, pp. 265–296, http://dx.doi.org/10.1016/B978-012691360-6/50011-2.

[107] K. Pearson, LIII. On lines and planes of closest fit to systems of points in space, Lond. Edinb. Dublin Philos. Mag. J. Sci. 2 (11) (1901) 559–572, http://dx.doi.org/10.1080/14786440109462720.

[108] H. Hotelling, Analysis of a complex of statistical variables into principal components, J. Educ. Psychol. 24 (6) (1933) 417–441, http://dx.doi.org/10.1037/h0071325.

[109] I. Jolliffe, Principal component analysis, in: Springer Series in Statistics, Springer-Verlag, New York, 2002, http://dx.doi.org/10.1007/b98835.

[110] S.L. Cutter, B.J. Boruff, W.L. Shirley, Social vulnerability to environmental hazards, Soc. Sci. Q. 84 (2) (2003) 242–261, http://dx.doi.org/10.1111/1540-6237.8402002.

[111] S.L. Cutter, The origin and diffusion of the social vulnerability index (SoVI), Int. J. Disaster Risk Reduct. 109 (2024) 104576, http://dx.doi.org/10.1016/j.ijdrr.2024.104576.

[112] D.B. Karakoc, K. Barker, C.W. Zobel, Y. Almoghathawi, Social vulnerability and equity perspectives on interdependent infrastructure network component importance, Sustain. Cities Soc. 57 (2020) 102072, http://dx.doi.org/10.1016/j.scs.2020.102072.

[113] Y. Zhao, R. Paul, S. Reid, C. Coimbra Vieira, C. Wolfe, Y. Zhang, R. Chunara, Constructing social vulnerability indexes with increased data and machine learning highlight the importance of wealth across global contexts, Soc. Indic. Res. (2024) http://dx.doi.org/10.1007/s11205-024-03386-9.

[114] D. Lai, Principal component analysis on human development indicators of China, Soc. Indic. Res. 61 (3) (2003) 319–330, http://dx.doi.org/10.1023/A:1021951302937.

[115] P.M. Johnson, C.E. Brady, C. Philip, H. Baroud, J.V. Camp, M. Abkowitz, A factor analysis approach toward reconciling community vulnerability and resilience indices for natural hazards, Risk Anal. 40 (9) (2020) 1795–1810, http://dx.doi.org/10.1111/risa.13508.

[116] J. Smits, J. Huisman, The GDL vulnerability index (GVI), Soc. Indic. Res. 174 (2) (2024) 721–741, http://dx.doi.org/10.1007/s11205-024-03399-4.

[117] I. Ajtai, H. Ştefănie, C. Maloş, C. Botezan, A. Radovici, M. Bizău-Cârstea, C. Baciu, Mapping social vulnerability to floods. a comprehensive framework using a vulnerability index approach and PCA analysis, Ecol. Indic. 154 (2023) 110838, http://dx.doi.org/10.1016/j.ecolind.2023.110838.

[118] L. Chakraborty, H. Rus, D. Henstra, J. Thistlethwaite, D. Scott, A place-based socioeconomic status index: Measuring social vulnerability to flood hazards in the context of environmental justice, Int. J. Disaster Risk Reduct. 43 (2020) 101394, http://dx.doi.org/10.1016/j.ijdrr.2019.101394.

[119] H. Chang, A. Pallathadka, J. Sauer, N.B. Grimm, R. Zimmerman, C. Cheng, D.M. Iwaniec, Y. Kim, R. Lloyd, T. McPhearson, B. Rosenzweig, T. Troxler, C. Welty, R. Brenner, P. Herreros-Cantis, Assessment of urban flood vulnerability using the social-ecological-technological systems framework in six US cities, Sustain. Cities Soc. 68 (2021) 102786, http://dx.doi.org/10.1016/j.scs.2021.102786.

[120] I. Török, Qualitative assessment of social vulnerability to flood hazards in Romania, Sustainability 10 (10) (2018) 3780, http://dx.doi.org/10.3390/su10103780.

[121] A. Roldán-Valcarce, D. Jato-Espino, C. Manchado, P.M. Bach, M. Kuller, Vulnerability to urban flooding assessed based on spatial demographic, socio-economic and infrastructure inequalities, Int. J. Disaster Risk Reduct. 95 (2023) 103894, http://dx.doi.org/10.1016/j.ijdrr.2023.103894.

[122] T. Wu, Quantifying coastal flood vulnerability for climate adaptation policy using principal component analysis, Ecol. Indic. 129 (2021) 108006, http://dx.doi.org/10.1016/j.ecolind.2021.108006.

[123] K. Boudt, M. d'Errico, H.A. Luu, R. Pietrelli, Interpretability of composite indicators based on principal components, J. Probab. Stat. 2022 (1) (2022) 4155384, http://dx.doi.org/10.1155/2022/4155384.

[124] R.A.H. El Rashidy, S. Grant-Muller, A composite resilience index for road transport networks, Proc. Inst. Civ. Eng. - Transp. 172 (3) (2019) 174–183, http://dx.doi.org/10.1680/jtran.16.00139.

[125] I. Turbay, P. Ortiz, R. Ortiz, Statistical analysis of principal components (PCA) in the study of the vulnerability of heritage churches, Procedia Struct. Integr. 55 (2024) 168–176, http://dx.doi.org/10.1016/j.prostr.2024.02.022.

[126] D.J. Abson, A.J. Dougill, L.C. Stringer, Using principal component analysis for information-rich socio-ecological vulnerability mapping in southern africa, Appl. Geogr. 35 (1–2) (2012) 515–524, http://dx.doi.org/10.1016/j.apgeog.2012.08.004.

[127] J. Mazumdar, S.K. Paul, Socioeconomic and infrastructural vulnerability indices for cyclones in the eastern coastal states of India, Nat. Hazards 82 (3) (2016) 1621–1643, http://dx.doi.org/10.1007/s11069-016-2261-9.

[128] M. Nardo, M. Saisana, A. Saltelli, S. Tarantola, Tools for Composite Indicators Building, Tech. Rep., Joint Research Centre - European Commission, 2005.

[129] M. Kuhn, K. Johnson, Data pre-processing, in: Applied Predictive Modeling, Springer, New York, NY, 2013, pp. 27–59, http://dx.doi.org/10.1007/978-1-4614-6849-3_3.

[130] J.F. Hair, W.C. Black, B.J. Babin, R.E. Anderson, Multivariate Data Analysis, eighth ed., Cengage, Andover, Hampshire, 2019.

[131] H.F. Kaiser, J. Rice, Little jiffy, mark iv, Educ. Psychol. Meas. 34 (1) (1974) 111–117, http://dx.doi.org/10.1177/001316447403400115.

[132] M. Tavakol, A. Wetzel, Factor analysis: a means for theory and instrument development in support of construct validity, Int. J. Med. Educ. 11 (2020) 245–247, http://dx.doi.org/10.5116/ijme.5f96.0f4a.

[133] G. Nicoletti, S. Scarpetta, O. Boylaud, Summary Indicators of Product Market Regulation with an Extension to Employment Protection Legislation, Tech. Rep. OECD Economics Department Working Papers No. 226, OECD, 2000, http://dx.doi.org/10.1787/215182844604.

[134] M. Saisana, A. Saltelli, S. Tarantola, Uncertainty and sensitivity analysis techniques as tools for the quality assessment of composite indicators, J. R. Stat. Soc. Ser. A: Stat. Soc. 168 (2) (2005) 307–323, http://dx.doi.org/10.1111/j.1467-985X.2005.00350.x.

[135] I.M. Sobol, Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates, Math. Comput. Simulation 55 (1) (2001) 271–280, http://dx.doi.org/10.1016/S0378-4754(00)00270-6.

[136] A. Saltelli, Making best use of model evaluations to compute sensitivity indices, Comput. Phys. Comm. 145 (2) (2002) 280–297, http://dx.doi.org/10.1016/S0010-4655(02)00280-1.

[137] A. Saltelli (Ed.), Global Sensitivity Analysis: the Primer, John Wiley, Chichester, England Hoboken, NJ, 2008, http://dx.doi.org/10.1002/9780470725184.

[138] B.E. Flanagan, E.W. Gregory, E.J. Hallisey, J.L. Heitgerd, B. Lewis, A social vulnerability index for disaster management, J. Homel. Secur. Emerg. Manag. 8 (1) (2011) http://dx.doi.org/10.2202/1547-7355.1792.

[139] S. Rufat, E. Tate, C.T. Emrich, F. Antolini, How valid are social vulnerability models? Ann. Am. Assoc. Geogr. 109 (4) (2019) 1131–1153, http://dx.doi.org/10.1080/24694452.2018.1535887.

[140] B. Flanagan, E. Hallisey, J.D. Sharpe, C.E. Mertzlufft, M. Grossman, On the validity of validation: A commentary on rufat, tate, emrich, and antolini's "how valid are social vulnerability models?", Ann. Am. Assoc. Geogr. 111 (4) (2020) em–i–em–vi, http://dx.doi.org/10.1080/24694452.2020.1857220.

[141] S. Rufat, E. Tate, C.T. Emrich, F. Antolini, Answer to the CDC: Validation must precede promotion, Ann. Am. Assoc. Geogr. 111 (4) (2020) em–vii–em–viii, http://dx.doi.org/10.1080/24694452.2020.1857221.

[142] U.S. Department of Transportation, - Revised Apportionment of Fiscal Year (FY) 2022 Highway Infrastructure Program Funds for the Bridge Formula Program Pursuant to the Infrastructure Investment and Jobs Act, FHWA Notice N 4510.867, Federal Highway Administration, 2022.

[143] M. Pregnolato, L.J. Prendergast, P.J. Vardanega, P.F. Giordano, M.P. Limongelli, Risk-based bridge scour management: A survey, in: Bridge Maintenance, Safety, Management, Life-Cycle Sustainability and Innovations, CRC Press, 2021, http://dx.doi.org/10.1201/9780429279119-91.

[144] L.J. Prendergast, K. Gavin, A review of bridge scour monitoring techniques, J. Rock Mech. Geotech. Eng. 6 (2) (2014) 138–149, http://dx.doi.org/10.1016/j.jrmge.2014.01.007.

[145] A.M. Bento, A. Gomes, T. Viseu, L. Couto, J.P. Pêgo, Risk-based methodology for scour analysis at bridge foundations, Eng. Struct. 223 (2020) 111115, http://dx.doi.org/10.1016/j.engstruct.2020.111115.

[146] A. Taherkhani, W. Mo, E. Bell, F. Han, Towards equitable infrastructure asset management: scour maintenance strategy for aging bridge systems in flood-prone zones using deep reinforcement learning, Sustain. Cities Soc. 114 (2024) 105792, http://dx.doi.org/10.1016/j.scs.2024.105792.

[147] M.N. Abdel-Mooty, M. Sasidharan, M. Herrera, A.K. Parlikad, J. Schooling, W. El-Dakhakhni, P. Coulibaly, Strategic assessment of bridge susceptibility to scour, Reliab. Eng. Syst. Saf. 251 (2024) 110334, http://dx.doi.org/10.1016/j.ress.2024.110334.

[148] M. Sasidharan, A.K. Parlikad, J. Schooling, Risk-informed asset management to tackle scouring on bridges across transport networks, Struct. Infrastruct. Eng. 18 (9) (2022) 1300–1316, http://dx.doi.org/10.1080/15732479.2021.1899249.

[149] L. Zhou, X. Li, Y. Pan, J. Ma, C. Wang, A. Shi, Y. Chen, Deformation monitoring of long-span railway bridges based on SBAS-InSAR technology, Geod. Geodyn. 15 (2) (2024) 122–132, http://dx.doi.org/10.1016/j.geog.2023.07.005.

[150] S. Selvakumaran, S. Plank, C. Geiß, C. Rossi, C. Middleton, Remote monitoring to predict bridge scour failure using interferometric synthetic aperture radar (InSAR) stacking techniques, Int. J. Appl. Earth Obs. Geoinf. 73 (2018) 463–470, http://dx.doi.org/10.1016/j.jag.2018.07.004.

[151] Pennsylvania Transportation Advisory Committee, Local Small Bridges A Pennsylvania Transportation Advisory Committee Policy Study, Tech. Rep., Pennsylvania Department of Transportation, 2021.

[152] C.A. Gandy, X. Kang, N. Ritsch, D.E. Armanios, Evaluating geospatial accuracy for equity analyses: A case study of the U.S. national bridge inventory, Transp. Eng. 13 (2023) 100198, http://dx.doi.org/10.1016/j.treng.2023.100198.

[153] B.A. Graybeal, B.M. Phares, D.D. Rolander, M. Moore, G. Washer, Visual inspection of highway bridges, J. Nondestruct. Eval. 21 (3) (2002) 67–83, http://dx.doi.org/10.1023/A:1022508121821.

[154] R.S. Kirk, W.J. Mallett, Highway Bridge Conditions: Issues for Congress, Tech. Rep. R47194, Congressional Research Service, 2022, URL https://www.congress.gov/crs-product/R44459.

[155] R.S. Kirk, W.J. Mallett, Highway Bridge Conditions: Issues for Congress, Tech. Rep. R44459, Congressional Research Service, 2020.

[156] M. Mazziotta, A. Pareto, Use and misuse of PCA for measuring well-being, Soc. Indic. Res. 142 (2) (2019) 451–476, http://dx.doi.org/10.1007/s11205-018-1933-0.

[157] M. Hubert, P.J. Rousseeuw, K. Vanden Branden, ROBPCA: A new approach to robust principal component analysis, Technometrics 47 (1) (2005) 64–79, http://dx.doi.org/10.1198/004017004000000563.

[158] F. Yarveysi, A. Alipour, H. Moftakhari, K. Jafarzadegan, H. Moradkhani, Block-level vulnerability assessment reveals disproportionate impacts of natural hazards across the conterminous United States, Nat. Commun. 14 (1) (2023) 4222, http://dx.doi.org/10.1038/s41467-023-39853-z.

[159] F. Booysen, An overview and evaluation of composite indices of development, Soc. Indic. Res. 59 (2) (2002) 115–151, http://dx.doi.org/10.1023/A:1016275505152.

[160] D.M. Frangopol, M. Liu, Maintenance and management of civil infrastructure based on condition, safety, optimization, and life-cycle cost, Struct. Infrastruct. Eng. 3 (1) (2007) 29–41, http://dx.doi.org/10.1080/15732470500253164.