Vulnerability analysis in complex networks under a flood risk reduction point of view

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The measurement and mapping of transportation network vulnerability to natural hazards constitute subjects of global interest for a sustainable development agenda and as means of adaptation to climate change. During a flood, some elements of a transportation network can be affected, causing the loss of lives. Furthermore, impacts include damage to vehicles, streets/roads, and other logistics services - sometimes with severe economic consequences. The Network Science approach may offer a valuable perspective considering one type of vulnerability related to network-type critical infrastructures: the topological vulnerability. The topological vulnerability index associated with an element is defined as reducing the network's average efficiency due to removing the set of edges related to that element. In this paper, we present the results of a systematic literature overview and a case study applying the topological vulnerability index for the highways in Santa Catarina (Brazil). We produce a map considering that index and areas susceptible to urban floods and landslides. Risk knowledge, combining hazard and vulnerability, is the first pillar of an Early Warning System and represents an important tool for stakeholders of the transportation sector in a disaster risk reduction agenda.

KEYWORDS

disasters, transportation, vulnerability, floods, graphs, complex networks, systematic literature mapping

1 Introduction

In a global change scenario, some climatic and extreme weather events are expected to increase in frequency and intensity and cause more social and economic impacts in several sectors, such as transportation systems and urban mobility. As presented in several papers in literature, the cost of repairing transport assets after either an urban flood or landslide represents a significant percentage of the total damage cost of several recent disasters around the world [1]; [2]; [3]; [4] and in Brazil [5]; [6]; [7].

To mitigate those impacts, evaluating the risk associated with disasters and the best ways to deal with them is necessary. Disaster risk reduction is aimed at preventing new and reducing existing disaster risks and managing residual risk, all of which contribute to strengthening resilience and achieving sustainable development [8].
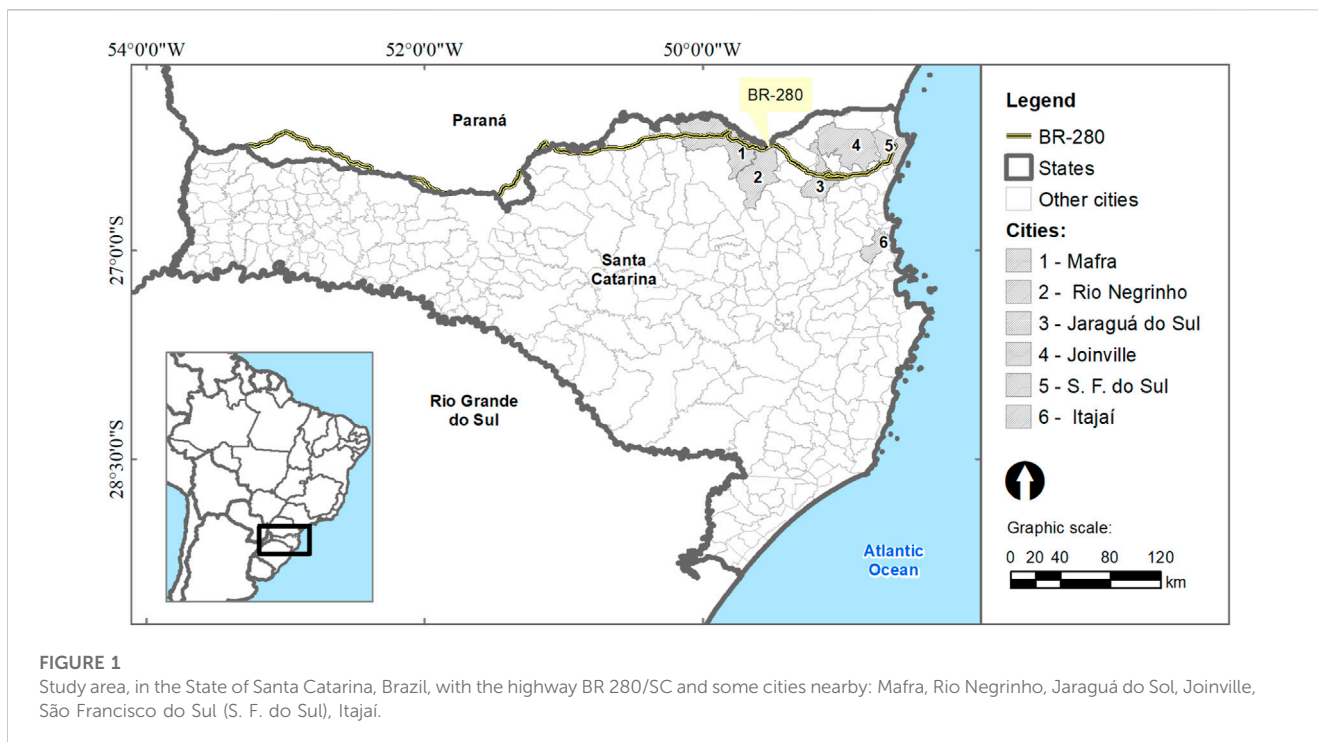
FIGURE 1
Study area, in the State of Santa Catarina, Brazil, with the highway BR 280/SC and some cities nearby: Mafra, Rio Negrinho, Jaraguá do Sol, Joinville, São Francisco do Sul (S. F. do Sul), Itajaí.

For disaster risk reduction, vulnerability is a key concept. There are several types and meanings for vulnerability. According to [9], vulnerability represents "the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impact of a natural hazard (an extreme natural event or process)". The UN Office for disaster risk reduction also includes assets and systems as subjects to vulnerability: "The conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards" [8].

The transportation systems' literature also has different meanings for vulnerability [10]. For example, [11] suggested that network vulnerability should be understood as "susceptibility to incidents that can result in considerable reductions in road network serviceability", and [12] understood network vulnerability as the extent of a failure to impact the original purpose of the system.

Vulnerability is a key idea in Network Science as well. Due to its generality in representing the system topology (relation among the elements on the system), Network Science approaches have been applied to a huge number of very different areas [13]. Section 2.3 presents a Systematic Literature Mapping of papers related to road networks, disasters, and network vulnerability. The listed works are predominantly from 2020, published in interdisciplinary and transport journals. The most frequent type of disasters and data origin are flooding/landsliding and USA/China.

This paper presents a formulation for a vulnerability index based on the efficiencies of the system of networks. It aims to locate the most vulnerable links in a transportation network and assess whether these links are susceptible to hazards and disruptions. The idea is presented as a case study on a set of highways mapped based on vulnerability index and disaster susceptibility data.

2 Materials and methods

2.1 Study area

Brazil is among the ten countries most affected by weather-related disasters in the last 20 years [8]. Santa Catarina state, located in the Brazilian Southern region (Figure 1), is particularly affected by disasters - there is an annual mean of 64 damage records triggered by hydrological processes, such as floods in Santa Catarina municipalities [14]. The maximum value was achieved in 2008 when the material losses summed almost 1 billion US dollars [14].

[14] pointed out that there were 1,344 records of disasters from 1980 to 2010 in Santa Catarina. High numbers of registers in summer and spring are associated with severe storms [14]. Between 1995 and 2014, the municipalities produced 2,704 official documents to report damages and/or losses due to disasters in the State. The documents are often related to rainfall, especially flash floods (907 records).

According to the last census track (2010), 295 municipalities and more than 6 million inhabitants are in the State of Santa Catarina. The State's HDI - Human Development Index - is 0.774, the third in the Brazilian HDI ranking [15]. Despite the high socio-economic indicators for municipalities from Santa Catarina state, many communities are at risk in those places due to characteristics of land occupation [16,17]. The mountainous relief on the east side determined the human settlement in the fluvial plains, areas naturally prone to floods. Moreover, industrialization and economic growth attracted many people to the regions and induced environmental interventions, such as deforestation, landfill, and irregular constructions [16, 17].

The susceptible flood areas used in this study were mapped by the Brazilian Geological Survey (CPRM) based on a database of previous occurrences and *in situ* evaluation of physical characteristics [18].
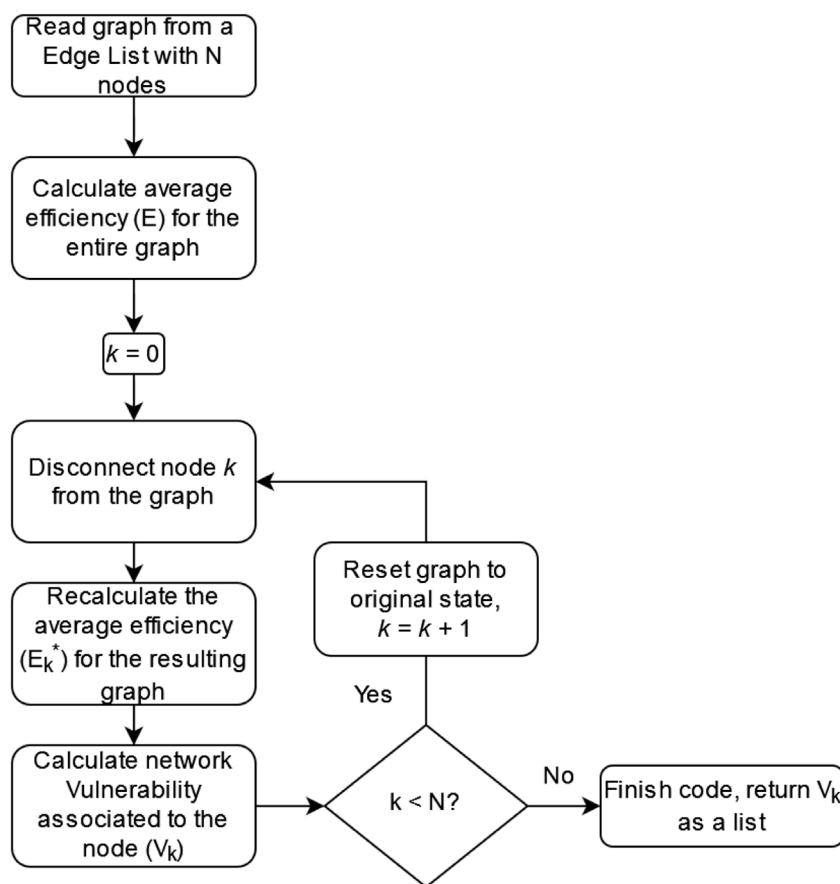
FIGURE 2
Diagram explaining the process to calculate the vulnerability index in a graph.

2.2 Topological vulnerability

Several topological measures can be extracted from a network and used to analyze the modeled phenomena or processes - see [19]. One of these simple and important indexes is the shortest path length d_{ij} between two nodes i and j, defined as the smallest number of links from i to j, among all the possible paths between i and j. On the other hand, the efficiency e_{ij} in the communication between nodes i and j can be defined as inversely proportional to the shortest path length between them. The average efficiency E of the network G is the average of all e_{ij}, considering all pairs of nodes. The topological vulnerability index of an element k in a network G, V_k, is thus given by

$$V_k = \frac{E - E_k^{\star}}{E}, \qquad (1)$$

where $E_k^{\star}$ is the efficiency of the network when the element k is inaccessible: all its edges are removed. The first paper considering the pointwise vulnerability index was that of [20], based on two relevant previous works: [21,22].

Calculating the vulnerability is illustrated in Figure 2. We start by reading our dataset, then calculate the average efficiency E) for the entire graph and disconnect each node k individually to calculate the vulnerability V_k associated with this node.

According to [23], network models are typically aspatial: the emphasis has been on topological interactions, not their geography. More details about space-related properties in Network Science can be found in [24]; [25].

Here, we use the concept and tools of a (geo) graph, a network in a geographical space. Recently, this approach was applied for a mobility network analysis [26] and for a rainfall network analysis [27]. In this paper, we represent a set of highways as a network, calculate the topological vulnerability index of its elements and show them on a map. We highlight the spacial location of the most vulnerable element to combine this information with the locations most susceptible to either floods or landslides.

2.3 Systematic literature mapping

This section presents a systematic literature mapping papers on road networks, natural hazards, and network vulnerability. We collected manuscripts from Google Scholar using the following search protocol: "(graph OR network) AND (transport OR roads OR highways OR streets) AND (disaster OR flood OR flooding OR landslide) AND (vulnerability)". The aim is to identify gaps and trends in literature and position our contributions regarding the state-of-the-art.

TABLE 1 Results of the systematic literature mapping.

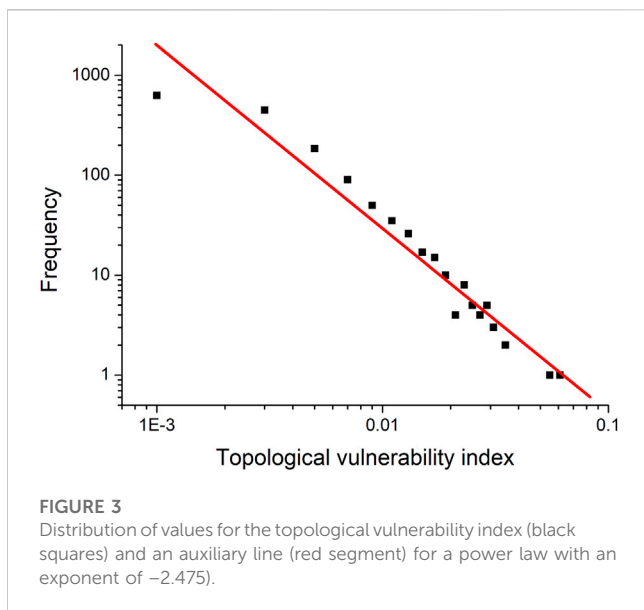| Paper	Citations	Journal type	Country of the data	Context of "vulnerability"	Network type	Disaster type	Metric "vulnerability"
[28]	119	Geography	England	graph	road network	natural disaster	vulnerability
[29]	605	Transport	No Country	graph	road system	natural disaster	vulnerability
[30]	12	interdisciplinary	China	transport	urban road network	natural disaster	vulnerability
[53]	21	interdisciplinary	Swedish	disaster	streets	flooding	closeness
[31]	45	interdisciplinary	United Kingdom	transport	road network	landslide	vulnerability
[32]	20	Transport	United States	transport	road network	storm surge flooding	susceptibility
[2]	159	interdisciplinary	No Country	transport	road/railway	multi-hazard	vulnerability
[33]	17	interdisciplinary	China	graph	urban rail transit	vehicle breakdown	vulnerability
[34]	9	interdisciplinary	Spain	transport	road network	flooding	vulnerability
[10]	25	interdisciplinary	Austrian	graph	road network	landslide	susceptibility
[35]	119	Transport Geography	England	graph	road network	flooding	vulnerability
[36]	18	interdisciplinary	United States	transport	road networks	flooding	susceptibility
[37]	1	Geology	Laos	disaster	road network	landslide	vulnerability
[38]	28	interdisciplinary	No Country	disaster	rural vulnerability	flooding	vulnerability
[39]	7	Transport	United Kingdom	transport	streets	natural disaster	vulnerability
[54]	4	Transport	Poland	transport	transport network urban	flooding	vulnerability
[40]	9	interdisciplinary	China	transport	highway	flooding	vulnerability
[41]	8	interdisciplinary	China	disaster	highway	landslide	susceptibility
[42]	14	Transport	United States	graph	transportation network	landslide	vulnerability
[43]	14	Environmental Science	United States	graph	road network	flooding	vulnerability
[44]	1	interdisciplinary	France	graph	transportation network	traffic Jam	vulnerability
[45]	13	Transport	Brazil	disaster	road network	flooding	vulnerability
[46]	0	interdisciplinary	Portugal	transport	road transport network	flooding	vulnerability

We selected the first forty papers and, as a cut-off criterion, we discarded those whose abstracts and titles deviated from the subject. In chronological publication order, we ended up with twenty-three articles grouped according to Table 1.

Regarding networks, Roads (highways) are the most frequent, followed by streets (urban networks). Nearly all papers quantify vulnerability with the network metric of the same name. The context of the word "vulnerability" relates more often to transport and graphs, with only a few cases associated with disasters.

In particular, we mention the top three cited papers: [29] provide a review of problems in transport systems around the globe, [2] bring a global view of multiple disasters, and [35] investigate the vulnerability of transport networks from British data. They all explore the problem under different scales: global and country-level.

Some future research directions that the set of papers present: mapping of critical segments (roads) and the creation of susceptibility indexes to build catastrophe models in response to extreme events such as flooding and severe wind storms; mapping landslides incidence and; how severe and frequent the phenomena is becoming [31]. The literature also lacks a detailed assessment of how climate transformations impact transport systems [34].

Here, we quantify links' vulnerability in a transportation network and susceptibility to hazards and disruptions. We showed that the most well-cited works deal with a similar problem but at a country and global level, whereas we address it from a state-level perspective. Table 1 presents only one paper with Brazilian data but with a different interpretation of the word

FIGURE 3
Distribution of values for the topological vulnerability index (black squares) and an auxiliary line (red segment) for a power law with an exponent of −2.475.

"vulnerability" and a different scale for the network construction. It shows that our work fills a literature gap.

3 Results and discussion

Using the (geo) graph approach, we represent the set of highways as a network. For the Santa Catarina State case study area, the road network presents 1,536 nodes/road segments and 2,101 directed edges/connections between road segments.

The topological vulnerability index is used to assess the potential impact of disruptions in a transportation network. In the context of the current analysis, this index's distribution was highly inhomogeneous. It is demonstrated in Figure 3, where the distribution is shown on a double logarithmic scale. Using Clauset's method [47], the power law fitting to the distribution resulted in an exponent of $\alpha = 2.475$.
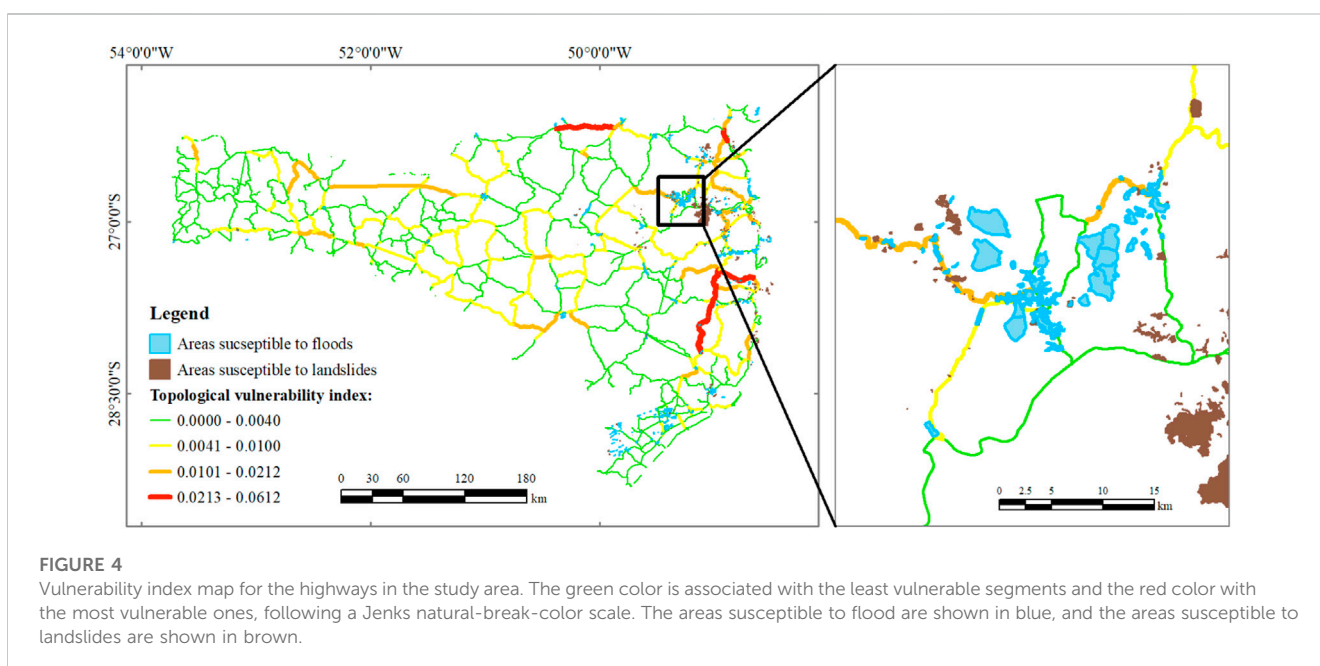
This finding suggests that the vulnerability of transportation networks is not evenly distributed, with some highways being significantly more vulnerable than others. Specifically, most highways have a low to moderate vulnerability (see Figure 4, segments in green and yellow), while a small subset is highly vulnerable (see Figure 4, segments in red). It indicates that efforts to enhance the resilience of transportation networks should be focused on the most vulnerable highways to ensure the most significant impact in reducing the risk of disruptions.

Another important question is about where the most vulnerable elements are, particularly whether they are close to the areas most susceptible to floods. Figure 4 shows the topological vulnerability index map for all highways in the study area. The four classes (colors in Figure 4) correspond to Low Vulnerability, Moderate Vulnerability, High Vulnerability, and Extremely High Vulnerability.

In the subset of the study area in Figure 4, it is possible to see some elements with a high topological vulnerability index close to urban areas susceptible to flood. In this area, in the cities of Rio Negrinho and Mafra, the BR-280 highway crosses the river. This area is marked by several records of floods in the rainy season (susceptibility component), which makes traffic in the region unfeasible (impact).

The highway BR-280 is one of the most important in Santa Catarina state, playing an important role in transporting goods to the ports of São Francisco do Sul and Itajaí (Figure 1). It also promotes the interconnection link between important regional cities, such as Joinville and Jaraguá do Sul. Thus, this highway has a large flow of people and goods.

Considering vulnerability (as a topological index) and susceptible areas, this representation is an important tool for

FIGURE 4
Vulnerability index map for the highways in the study area. The green color is associated with the least vulnerable segments and the red color with the most vulnerable ones, following a Jenks natural-break-color scale. The areas susceptible to flood are shown in blue, and the areas susceptible to landslides are shown in brown.

stakeholders from the transportation sector concerning climate change, disaster risk reduction, and sustainable development agenda. Risk Knowledge, combining hazard and vulnerability, is the first pillar of an Early Warning System (EWS) [8]. Also, the transportation sector represents direct and indirect economic losses: the destruction of physical assets and the decline in economic value. In this work, the suggested representation adds knowledge about the potential losses to the disaster risk assessment.

4 Conclusion

In this paper, we represented the set of highways from our study area as a network and calculated the topological vulnerability index. Using the (geo) graphs approach [26]; [27], it was possible to represent the results in a Geographical Information System.

In our case study, in the south region of Brazil, there are some elements with a vulnerability index of approximately 5% - therefore, a flood impairing the traffic on this highway's element can reduce the efficiency of this transportation network by approximately 5%. Also, elements with high topological vulnerability index are close to urban flood areas, for example, in Mafra and Rio Negrinho, where the BR-280 highway crosses the Negrinho River. This area is marked by several records of floods in the rainy season (susceptibility component), which makes traffic unfeasible in the region (impact). In the State of Santa Catarina, there is a heavy flow of people and goods, with important national and international ports and airports.

The topological vulnerability index associated with an element of a network (in our case, a highway segment) is a measure quantifying how the system reacts to damage on this element. Although it is a measure associated with the element, the topological vulnerability index contains information about the dynamics throughout the network [48]. The disaster triggering is local, but its impacts can be extended to a wider region. The topological vulnerability index captures this relation, and it is possibly the most important feature of this index.

According to the Sendai Framework for Disaster Risk Reduction 2015–2030, one of the most important documents in the Disaster Risk Reduction (DRR) guidelines, there is one global target related to "Substantially reduce disaster damage to critical infrastructure and disruption of basic services" [49]. Many critical infrastructures (such as roads) are of network type and can be modeled using the Network Science approach [13]. The topological vulnerability index is a network measure particularly interesting in the context of critical infrastructures. Developing a vulnerability map to disasters and their impacts on infrastructures is also aligned with the 2030 Agenda for Sustainable Development, particularly with the Sustainable Development Goals 9, 11, and 13, related to Infrastructures, Intelligent Cities, and Climate [50].

Mapping risk areas is an indispensable step to doing better urban planning and lessening the risk of disasters. This mapping can create a risk reduction plan, define priority areas for attention in the municipalities, make recommendations for works on infrastructure, and prepare municipal master plans. The mapping of risk areas for Santa Catarina follows the guidelines established by GIDES Project [51], which is a partnership between Brazil and Japan to strengthen the National Strategy for Integrated Management of Risks and Disasters. The project's goal is to reduce the risks of disasters through non-structural preventive actions. The main results are improving assessment systems and risk mapping, warnings, and urban planning for disaster prevention.

A possible extension for this investigation is to draft risk scenarios considering other components, such as the dynamic exposure (daily traffic on each highway) and other kinds of vulnerability, for example, one based on traffic engineering parameters or the coverage of meteorological sensors [52].

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://github.com/gioguarnieri/highways-vulnerability.

Author contributions

LS—Conceptualization, Methodology, Project Administration, Writing GS—Methodology, Writing TG—Methodology, Writing AJ—Methodology, Writing LL—Conceptualization, Methodology, Writing RR—Methodology, Writing RB—Methodology, Writing CO—Methodology, Writing VF—Methodology, Writing IS—Conceptualization, Review Editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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