

HYDROGEOLOGICAL RISK ASSESSMENT OF EXISTING BRIDGE PORTFOLIOS THROUGH AN INDEX-BASED APPROACH

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Abstract

In recent years, several collapses of existing bridges have highlighted the need for rapid risk analysis methods to support infrastructure managers in the prioritisation of detailed assessments and, where necessary, the implementation of risk mitigation actions. Among other natural perils, hydraulic and geological hazards, particularly floods, scour, and landslides are primary causes of bridge failure, compounding risks in multi-hazard scenarios. The frequency and intensity of extreme weather events has also increased due to climate change, overstraining existing infrastructure and exposing it to multiple hydrogeological risks. This study presents a quantitative, index-based methodology for risk assessment and prioritisation of existing bridge portfolios, focusing on flood, scour and landslide hazards. The proposed methodology integrates structural vulnerability, exposure, and the consequences of failure into a multi-hazard, hydrogeological risk indicator. Single-hazard indices are developed separately for flood/scour and landslide hazards, accounting for key factors such as bridge geometry, material properties, environmental conditions, and surrounding topography. These indices are then combined to facilitate a comparative analysis across bridge portfolios. The methodology is applied to a case-study portfolio of roadway bridges in northern Italy, generating a risk-based ranking that identifies critical structures requiring immediate attention or further detailed assessment. The results are analysed and discussed, highlighting the influence of the considered hazards and corresponding variables on the final risk prioritisation, providing infrastructure managers with a quantitative tool for large-scale bridge risk assessment and prioritisation, enabling risk-targeted maintenance and mitigation strategies.

Keywords: Multi-hazard risk assessment, existing bridges, risk indicators, risk-based ranking, comparative analysis.

1 INTRODUCTION

Bridge risk management plays a fundamental role in ensuring the safety and functionality of transport infrastructure. All around the world, especially in Italy, the backbone of the existing road infrastructure dates back to the Second World War, meaning that many bridges are 50 years old or more. Their natural ageing, combined with recently observed collapses [1], has highlighted the need for assessment and, if necessary, intervention. However, limited resources necessitate a rational prioritisation approach to assist decision-makers in identifying critical structures, especially when managing large bridge portfolios [2]. Traditional prioritisation methods primarily rely on index evaluations that assess structural health based on the condition of individual components [3]. While effective for identifying structural damage, these methods often overlook functional aspects such as capacity, traffic volume, and clearance, which are crucial for assessing overall risk [4]. To address these limitations, risk-based prioritisation methodologies have been developed to consider structural integrity, safety, maintenance requirements, and potential failure consequences [5].

Several studies have statistically shown that bridge collapses often result from either natural or human-related events [6]. Between 1989 and 2000, 503 bridge failures occurred in the United States of America, with floods (33%) and scour (16%) accounting for nearly half of the incidents. Additional causes included supervision mistakes (13%), collisions (12%), overload (11%), fires (3%), and earthquakes (2%) [6]. Between 1900 and 2023, 16,535 natural hazard-related disasters were recorded globally, 19% of which involved multiple hazards. Flood-landslide interactions were the most common (33%), followed by earthquakes triggering landslides and tsunamis [7]. Recognising these risks, several countries have established national guidelines for assessing and mitigating the impacts of bridge-related hazards, particularly those related to hydraulic events such as flooding, scour, and debris impact.

Based on the above, a prioritisation procedure must be risk-based and deployable on a large scale, given the typically high number of bridges to manage. Additionally, to create a ranking of bridges based on their criticality, it is essential to use a quantitative approach. Conversely, if a qualitative risk approach were to be used, as is the case in most international standards [4, 8], identifying critical bridges would not be immediate, making in-depth evaluations more difficult.

Building upon the work described in [2], this study proposes a multi-hazard risk-based prioritisation methodology applicable at a territorial scale, accommodating both low- and high-data availability scenarios.

The risk level is quantified through indices ranging from 0 to 1, incorporating uncertainties. These indices are combined into a global indicator that provides a comparative risk assessment between bridges, facilitating prioritisation without establishing absolute hazard-related risks.

A portfolio of 44 bridges in northern Italy was analysed using the proposed method. Single-hazard risk indices (I_{Hj}) were calculated for traffic loading, landslides, and hydraulic events. These were then combined into multi-hazard risk indicators (I_{MHi}) using established combination methods [2]. To account for uncertainties, the Statistical Design of Experiments (DoE) methodology was applied, followed by Monte Carlo simulations to generate statistical distributions of multi-hazard risk indicators for each bridge. Additionally, a quantitative classification system with five Multi-Hazard Risk-Based Priority Classes (MRPCs) was developed, considering statistical thresholds to distinguish relative risk levels among the portfolio bridges. Finally, the bridges were ranked by comparing the prescribed percentile of their multi-hazard risk indicators with established thresholds, using either mean or upper-tail percentiles to ensure appropriate risk perception.

2 SIMPLIFIED QUANTITATIVE METHODS FOR INDEX-BASED RISK ASSESSMENT OF EXISTING ROAD BRIDGES

The assessment of existing roadway bridges requires efficient and scalable methodologies capable of evaluating various hazards, including traffic, landslide, and hydraulic. Simplified quantitative approaches provide a practical framework for assessing the risks posed by these perils through the integration of hazard, vulnerability, and exposure components. Such models enable the prioritisation of bridges based on their relative risk levels, facilitating targeted maintenance and mitigation efforts.

The following sections describe the methodologies applied to assess different risk types, including road traffic risk (Section 2.1), landslide risk (Section 2.2), and hydraulic risk (Section 2.3). Each approach employs a weighted multi-factor model to produce standardised risk indices, allowing for consistent comparisons across bridge portfolios.

2.1 Road traffic risk assessment

According to [12], a weighted multi-factor average model is used to assess road traffic-related risk. This approach integrates the three main components - hazard (H), vulnerability (V), and exposure (E) - by assigning specific weights to each element and combining them as shown in Eq. (1):

$$PR = 0.2 H + 0.4 V + 0.4 E \quad (1)$$

H , V , and E are quantified using multi-parametric equations that consider various specific parameters for each analysed bridge. Specifically, hazard is quantified based on the frequency of commercial vehicles per lane (H_{CT}), while vulnerability is evaluated through five key parameters: year of construction (V_{YC}), static scheme (V_{SS}), largest span length (V_{LL}), number of spans (V_{NS}), and deck material (V_{DM}). Additionally, the vulnerability component includes the bridge condition (V_D), which accounts for deterioration effects due to structural ageing and insufficient maintenance [2]. This is evaluated using the United Kingdom Bridge Condition Index (UK-BCI) approach [4]. The exposure component is in turn estimated using parameters that consider average daily traffic (E_{AT}), detour length (E_{DL}), mean span length (E_{ML}), entity bypassed (E_{EB}), and road category (E_{RC}). Such parameters are quantified through a sub-parameter ranging between 0 and 1, determined based on specific thresholds [12].

2.2 Landslide risk assessment

Following the work described in [13], a linear regression technique is used to analyse the relationship between H , V , and E in order to define the Index of Attention for landslide hazard. The study [13] converted the qualitative priority method outlined in the Italian Guidelines (LG20, [8]) into a quantitative approach, where the Class of Attention (CoA) is transformed into the Index of Attention (IA). Specifically, the Index of Attention for landslide risk (IA_l) is determined using the Eq. (2):

$$IA_l = \sum_i a_i I_i + \sum_{i,j} a_{ij} I_i I_j + a \quad (2)$$

where $i, j = H, V$, and E , while the weighting factors (a_i) are shown in Table 1. In this way, the landslide risk components (i.e., H , V , and E) are first evaluated accounting for the parameters proposed by LG20 [8]. A preliminary index is associated with each of them: I_H , I_V , and I_E , respectively. These indices can assume integer values from 1 to 5, corresponding to the Low (L), Medium-Low (M-L), Medium (M), Medium-High (M-H), and High (H) classes proposed by LG20 [8]. Various parameters are considered and classified into primary and secondary

categories [8]. Hazard is assessed by analysing slope instability, considering factors such as magnitude, velocity, and the landslide's state of activity. Additionally, uncertainties in predictive models and the presence of mitigation measures are also evaluated, as they can influence the overall hazard assessment. The vulnerability component is determined by examining the characteristics of the infrastructure, i.e., the bridge's properties (e.g., material, static scheme) and the type of foundations used. Another key aspect is the spatial of interaction between the landslide and the structure, which can significantly impact the level of vulnerability. Finally, exposure is linked to average daily traffic and the span length of the bridge. Furthermore, additional factors, such as the availability of alternative routes, the type of bypassed entity (e.g., natural ground, water body, built-up areas, road), and the failure consequences of the infrastructure are considered, as they can influence the potential impacts of a landslide event.

Parameters	Weights [-]
a_H	0.487
a_V	0.262
a_E	0.263
a_{HH}	0.00286
a_{VV}	-0.004
a_{EE}	0
a_{HE}	-0.00286
a_{HV}	0.002
a_{EV}	0
a	0.118

Table 1: Weighting factors values for the landslide Index of Attention evaluation.

2.3 Hydraulic risk assessment

To strengthen the application of the LG20 [8], a novel semi-quantitative risk model is proposed to assess hydraulic actions. According to [9-12], a Hydraulic Risk Indicator (I_{HYD}) is computed as a weighted combination of H , V , and E , with weights of 0.2, 0.4, and 0.4, respectively (Eq. 3). This approach emphasises the significance of both the structural susceptibility of the bridge and its environmental context. Each component is subdivided into three subcategories: Local Scour (LS, Eq. 6), General & Contraction Scour (GS, Eqs. 7-8) and Vertical Clearance & Drag/Lift Forces (CF, Eqs. 9-10).

$$I_{HYD} = 0.2 H_{hyd} + 0.4 V_{hyd} + 0.4 E_{hyd} \quad (3)$$

$$H_{hyd} = (H_{CF} + H_{GS} + H_{LS}) / 3 \quad (4)$$

$$V_{hyd} = (V_{CF} + V_{GS} + V_{LS}) / 3 \quad (5)$$

$$V_{LS} = (V_{OA} + V_{SA}) / 2 \quad (6)$$

$$V_{GS} = (V_{SH} + V_{FT} + V_{BR}) / 3 \quad (7)$$

$$H_{GS} = (H_{FV} + H_{RM} + H_{OW}) / 3 \quad (8)$$

$$V_{CF} = (V_{OS} + V_{OW} + V_{SF}) / 3 \quad (9)$$

$$H_{CF} = (H_{FP} + H_{FV} + H_D) / 3 \quad (10)$$

The hydraulic risk model is based on a structured set of parameters, each associated with a predefined scoring scale to represent its contribution to the overall vulnerability of a bridge to flood-related events. For instance, the flood return period (H_{FP}) reflects the probability of occurrence of extreme events, with more frequent floods (e.g., 50-year return period) being assigned a lower score (i.e., 0.25), and rare, more severe events (e.g., 500-year) being assigned the highest score (i.e., 1). Similarly, flow velocity (H_{FV}) is categorised from low (< 1 m/s) to high (> 3 m/s), with increasing scores reflecting a higher hydraulic threat. Debris and floating material (H_D) are also considered for their potential to obstruct flow and impact structures; minimal presence scores 0.25, while significant accumulation scores 1.

The obstruction shape factor (V_{OS}) distinguishes between lenticular (i.e., 0.3) and rectangular shapes (i.e., 0.7), acknowledging the resistance differences. The obstruction-to-flow width ratio (V_{OW}), a geometric relationship between the structure and the channel, is another critical factor: wider obstructions relative to the channel width result in higher scores (up to 1). Parameters like the soffit-to-flood height ratio (V_{SF}) capture the available clearance under the bridge; smaller clearances (e.g., $h_S/h_F \leq 1.25$) indicate higher risk and are thus score higher. The riverbed material (H_{RM}) ranges from rock (i.e., 0) to highly erodible materials like sand or silt (i.e., 1), reflecting the susceptibility to scour.

Historical performance is incorporated through the scour history of the bridge (V_{SH}), where the absence of scour evidence yields a low score (i.e., 0.25), while documented severe scour raises it to 1. The foundation type and depth (V_{FT}) also influence risk: deep foundations (piles/caissons) score lower (i.e., 0.25), while shallow ones are more vulnerable (score 1). The scour-to-foundation depth ratio (d_S/d_F) directly quantifies the severity of potential scour (H_{SF}), ranging from < 0.6 (score 0) to ≥ 1.2 (score 1). Lastly, the model considers obstruction orientation (V_{OA}) — structures aligned with the flow are less risky (i.e., 0.25), while those that are perpendicular are more prone to flow impacts (i.e., 1.0) — and sediment/debris accumulation (V_{SA}), where increasing likelihood also raises the assigned score. All these parameters are combined, to enable a multi-dimensional evaluation of hydraulic risk at the bridge level. The hazard and vulnerability indicators are averaged within each subcategory (Eq. 3-10) to form composite scores used in the I_{HYD} calculation (Eq. 3). Finally, the exposure component of hydraulic risk is defined according to the approach outlined in [12] for seismic hazard.

3 PROPOSED RISK-BASED PRIORITY INDEX

The individual risk indices (I_{Hj}) described above (see Sections 2.1, 2.2 and 2.3), each of them related to the j -th hazard, are combined to obtain an overall multi-hazard risk indicator (I_{MH}), similarly to what was carried out in [2]. To this end, three combinations are considered:

- i) a quadratic combination of the individual risk indices, normalised with respect to the number of considered hazards (N_H) (Eq.11);
- ii) a weighted sum of the individual risk indices, thus considering the possibility of using different weighting factors (C_{Hj}) (Eq.12);
- iii) a quadratic combination of the individual risk indices with their associated C_{Hj} values, normalised with respect to their square root (Eq.13).

$$I_{MH} = \sqrt{\frac{\sum_j I_{Hj}^2}{N_H}} \quad (11)$$

$$I_{MH} = \frac{\sum_j C_{Hj} I_{Hj}}{\sum_j C_{Hj}} \quad (12)$$

$$I_{MH} = \sqrt{\frac{\sum_j (C_{Hj} I_{Hj})^2}{\sum_j C_{Hj}^2}} \quad (13)$$

The weighting factors (C_{Hj}) can be assigned to each risk indicator following different rationales, e.g., according to the level of knowledge [2] of the required input, naturally implying that different expert judgments (or, similarly, needs of decision-makers) might lead to the assumption of different weights for each hazard. Alternatively, weighting factors can be defined through other approaches such as, for instance, multi-criteria analysis [2]. Regardless of the assignment criterion, the aim behind the use of the C_{Hj} factors is to reproduce the relative contribution of each single-hazard risk to the overall risk against multiple hazards.

The highest weight was attributed to the road traffic risk indicator (i.e., $C_G = 1$), due to its high likelihood of occurrence, when compared to the other hazards (as also assumed by the Italian guidelines), while C_L and C_{HY} were set to 0.5 of landslide and hydraulic risks, respectively. In the following Sections, the single-hazard risk indices associated with traffic, landslide, and hydraulic hazards are designated as I_G , I_L , and I_{HY} , respectively.

4 CASE STUDY APPLICATION

4.1 Description of case study

The described multi-hazard risk assessment methodology was applied to a portfolio of 44 real bridges located in Northern Italy, specifically in the Lombardy region, a critical area for national transportation. These structures, predominantly constructed during the 1960s, exhibit diverse typologies in terms of static schemes, materials, and span configurations, providing a representative sample for evaluating ageing infrastructure. The portfolio consists of isostatic (23%) or hyperstatic (77%) structural schemes, primarily designed as simply supported spans of reinforced concrete slabs. The bridge lengths vary from 6 to over 8 m, with single-span configurations representing the vast majority (97%). Reinforced concrete (RC) is the prevailing deck material (91%), ensuring robustness but requiring systematic assessment for degradation phenomena such as carbonation-induced reinforcement corrosion.

From a functional perspective, these bridges support significant traffic volumes, with average daily traffic (ADT) exceeding 34,000 vehicles per lane, including a substantial portion of heavy commercial transport. In some cases, the commercial traffic (CT) reaches 1,665 vehicles per day, imposing high cyclic loads that could contribute to structural fatigue over time. Seismic vulnerability is uniform across the region, with expected peak ground acceleration (PGA) around to 0.05 g for a return period (T_r) of 475 years. Most structures are founded on Type C soil. Given the absence of viable alternative routes, these bridges serve as indispensable nodes within the regional and national mobility network. Any functional impairment would generate severe logistical and economic repercussions, emphasising the urgency of proactive maintenance and strategic interventions to enhance durability and load-bearing capacity.

4.2 Simulation-based priority ranking for multi-hazard risk assessment

The quantitative methods described in the previous sections were thus applied to evaluate the single-hazard risk indices, i.e., those related to structural and road traffic risk (I_G), landslide risk (I_L), and hydraulic risk (I_{HY}). The quantification of the road traffic index was conducted for two options of the state of conservation of the bridge, namely the average (*Avg*) and critical (*Crit*) state based on the defects of all bridge components [12]. The average state is an overall picture of the bridge condition through a weighted indicator, obtained considering the state of conservation of each element and considering its importance for bridge safety. On the other hand, the critical state associates the bridge condition with the worse condition among the critical elements for the bridge health [2]. For the selected portfolio, in the absence of data from visual inspections, the level of damage was evaluated using the UK-BCI method [12], assuming a defect score (DS_{UK-BCI}) value of 50 to define the average condition and 25 for the critical condition, obtaining $I_{G,Avg}$ and $I_{G,Crit}$, respectively.

Regarding the evaluation of the landslide (I_L) and hydraulic (I_{HY}) risks, some input parameters required to define each single-hazard index are unknown. Furthermore, when a given input parameter was unknown for one bridge, it was unknown for all bridges. Therefore, the unknown input parameters were considered as statistically independent random variables (RVs). Values of those RVs were simultaneously changed according to the statistical Design of Experiments (DoE) method to obtain, for each bridge in the portfolio, a statistical distribution of the multi-hazard risk indicator (I_{MH}). In such a way, the level of epistemic uncertainty associated with limited knowledge on selected bridges was quantified, accounting for the influence of different rationales and refinement levels of the adopted methods for calculation of single-hazard indices [2]. A summary of the unknown input parameters considered in this study is shown in Table 2.

Hazard	Random variables	Distribution adopted	No. of realisations
Landslide	Susceptibility	Discrete uniform	5
	Flow velocity	Discrete uniform	3
	Riverbed material	Discrete uniform	4
	Obstruction to flow width ratio	Discrete uniform	4
Hydraulic	Scour history of bridge	Discrete uniform	3
	Flood return period	Discrete uniform	3
	Sediments/debris accumulation	Discrete uniform	3
	Scour to foundation depth ratio	Discrete uniform	5
	Soffit to flood height ratio	Discrete uniform	4

Table 2: Random variables used for the DoE method.

Subsequently, three multi-hazard risk indicators, I_{MH1} to I_{MH3} , were calculated according to the procedure described in Section 3. Specifically, Eq. (11) was used to combine $I_{G,Avg}$, I_L , and I_{HY} to obtain I_{MH1} , while Eq. (12) and Eq. (13) were applied to obtain I_{MH2} and I_{MH3} , respectively, using $I_{G,Crit}$ instead. The procedure resulted in a statistical distribution of each multi-hazard risk indicator, derived from 97200 realisations per bridge (all possible combinations of the nine RVs considered in Table 2).

The statistical distributions of the different I_{MH} are shown in the box plots of Figure 1, defined by the mean (μ_i), and the 25th and 75th percentiles. Moreover, the mean (μ_{IMHi}) and

standard deviation (σ_{IMHi}) of the probability distribution associated with the entire bridge portfolio were evaluated.

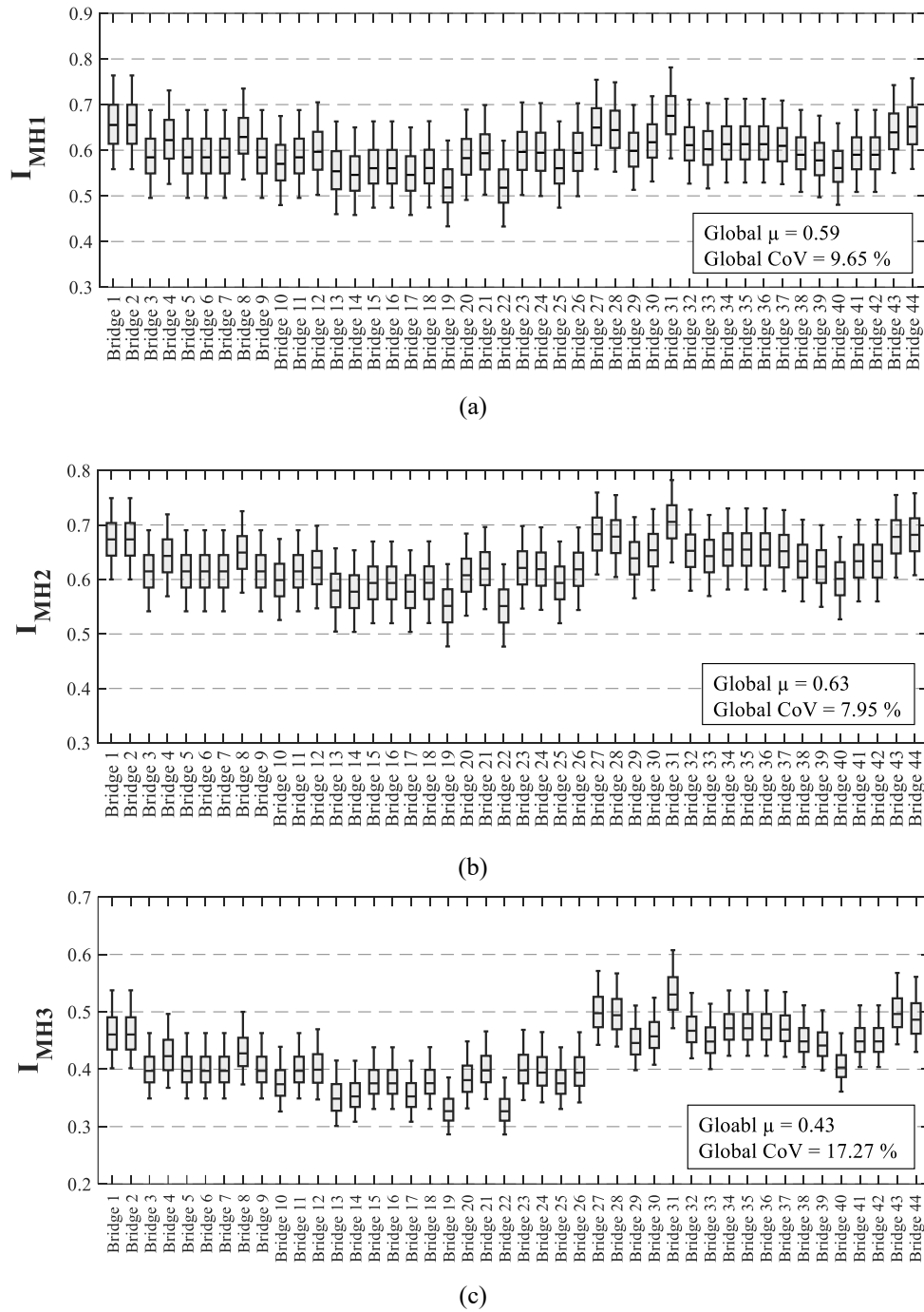


Figure 1: Distribution of multi-hazard risk indices according to the DoE method: (a) I_{MH1} , (b) I_{MH2} and, (c) I_{MH3} .

The most noticeable distinction lies in their inter-bridge mean values: I_{MH2} has the highest mean ($\mu_{IMH2} = 0.63$), followed by I_{MH1} ($\mu_{IMH1} = 0.5$), while I_{MH3} has the lowest ($\mu_{IMH3} = 0.43$). This suggests that the methodology used to compute I_{MH3} results in lower overall risk assessments compared to the other two indicators. Another important difference is the variability of the distributions. I_{MH3} shows the highest dispersion, with an inter-bridge coefficient of variation

(CoV_{IMH3}) of 17.3%, meaning that its values fluctuate significantly across different bridges. In contrast, $IMH1$ and $IMH2$ exhibit lower variability, with CoVs of 9.7% and 8.0%, respectively. This indicates that $IMH3$ is more sensitive to input variations, whereas $IMH1$ and $IMH2$ appear to be more stable. Looking at how these indicators behave across the different bridges, $IMH1$ and $IMH2$ display multi-hazard indicators closer to each other, with only moderate fluctuations. In turn, $IMH3$ exhibits more pronounced bridge-to-bridge variations, with some bridges showing noticeably lower values than others. This suggests that the method used to compute $IMH3$ amplifies differences between bridges, making it more responsive to variations in input parameters. As a result, in this study, the $IMH3$ was selected for defining a priority-based relative risk ranking.

4.3 Statistics-based classification of bridges

For priority ranking purposes, two different statistics of the intra-bridge distribution of the multi-hazard risk indicator are considered, namely, one based on the mean (μ_i) and the other based on the mean plus two standard deviations ($\mu_i + 2\sigma_i$). The latter is motivated by the high importance of upper tails in risk-based prioritisation. Based on the results presented in Section 4.2, for each multi-hazard risk indicator $IMHi$ ($i = 1, \dots, 3$) statistical thresholds are proposed via mean (μ_{IMHi}) and standard deviation (σ_{IMHi}) of the probability distributions related to the entire bridge portfolio [2]. Each k -th bridge is then assigned to a risk-based prioritisation class by comparing a statistical value (x_k) of the intra-bridge distribution of $IMHi$ to the adopted portfolio-related thresholds. Specifically, the mean value (μ_i) or an upper-tail percentile (e.g., $\mu_i + 2\sigma_i$) of $IMHi$ might be used to derive the relative level of risk for each bridge with respect to that of the portfolio. This approach allows the definition of five multi-hazard risk-based priority classes (MRPCs). After that a statistical value x_k is assumed, the MRPCs are defined as follows:

- Low MRPC if $0 \leq x_k < \mu_{IMHi} - 2\sigma_{IMHi}$.
- Medium-Low MRPC if $\mu_{IMHi} - 2\sigma_{IMHi} \leq x_k < \mu_{IMHi} - \sigma_{IMHi}$.
- Medium MRPC if $\mu_{IMHi} - \sigma_{IMHi} \leq x_k < \mu_{IMHi} + \sigma_{IMHi}$.
- Medium-High MRPC if $\mu_{IMHi} + \sigma_{IMHi} \leq x_k < \mu_{IMHi} + 2\sigma_{IMHi}$.
- High MRPC if $x_k \geq \mu_{IMHi} + 2\sigma_{IMHi}$.

Figure 2 shows the output when $IMH3$ is used according to μ_i and $\mu_i + 2\sigma_i$. The results highlight the impact of incorporating uncertainty into the multi-hazard risk assessment of bridges. When the priority ranking is evaluated using μ_i , the overall risk classification appears lower, with no bridges falling into the High MRPC and the majority being classified as Medium. However, when the assessment includes $\mu_i + 2\sigma_i$, accounting for epistemic uncertainty, the distribution of risk levels shifts significantly. In particular, five bridges that were previously in the Medium-High MRPC are now classified as High MRCP, while 11 bridges move from Medium to Medium-High, and four bridges shift from Medium-Low to Medium. This demonstrates that incorporating uncertainty leads to more conservative risk classifications, increasing the number of bridges that would require higher priority for intervention.

Overall, these findings suggest that relying solely on the mean may underestimate relative risk levels, whereas considering uncertainty provides a potentially safer prioritisation strategy for maintenance and mitigation efforts.

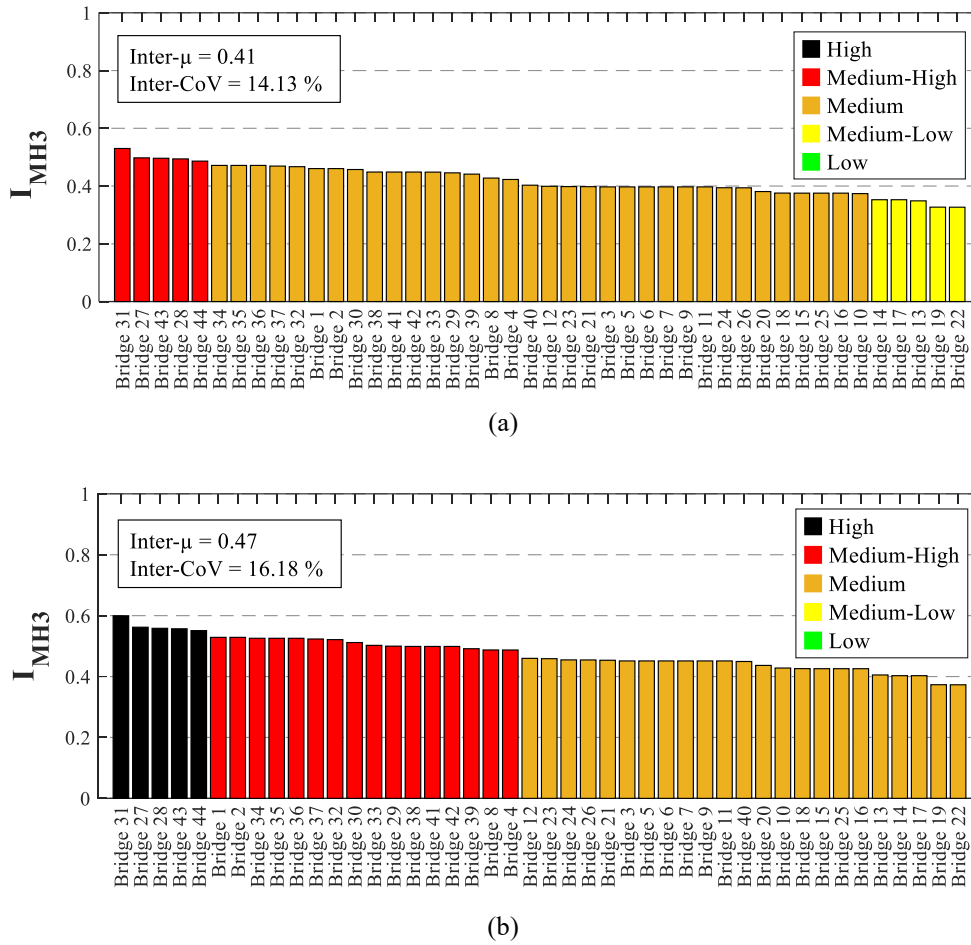


Figure 2: Multi-hazard risk-based ranking and classification of bridges according to the statistical thresholds and I_{MH3} : output based on (a) μ_i and (b) $\mu_i + 2\sigma_i$.

5 CONCLUSIONS

This study proposed a multi-hazard risk assessment framework for prioritising road bridge portfolios using an aggregated multi-hazard risk indicator (I_{MH}). The method was applied to a portfolio of 44 highway bridges in Lombardy, Italy, accounting for hazards related to road traffic (I_G), landslides (I_L), and hydraulic (I_{HY}) actions. Three alternative formulations (I_{MH1} , I_{MH2} , and I_{MH3}) were developed by combining single-hazard risk indices. To enhance accuracy, structural degradation was included in condition-based evaluations of traffic-related risk. Specifically, two measures of structural degradation (average and critical) were considered according to the UK-BCI method.

Uncertainty in input parameters was addressed using a design of experiments approach, allowing for a probabilistic representation of each I_{MH} . Among the tested indicators, I_{MH3} demonstrated the highest variability and sensitivity outcomes, making it the preferred choice in this study, considering the risk-based prioritisation purpose.

The bridges were classified into five risk-based priority classes (MRPCs) adopting both deterministic and statistical thresholding methods. The results showed that using statistical thresholds based on the mean (μ_i) and standard deviation (σ_i) of I_{MH} provides a more representative classification. The selection of the threshold $\mu + 2\sigma_i$ was found to enhance sensitivity to

inspection data while reducing the likelihood of overlooking high-relative risk bridges, highlighting the effectiveness of a statistically driven multi-hazard risk assessment for bridge prioritisation.

The relative nature of I_{MH} does not allow to quantify absolute consequences that may be associated with the future occurrence of hazards, while the relative risk level of each bridge may change with the size of the bridge portfolio under study.

Future research could further improve the framework by incorporating additional hazards, such as explosion, fire and vehicle impact actions, and by refining hybrid methods that integrate qualitative guidelines with quantitative parameters for more robust risk management.

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REFERENCES

- [1] G.M. Calvi, M. Moratti, G.J. O'Reilly, N. Scattarreggia, R. Monteiro, D. Malomo, P.M. Calvi, R. Pin-ho. Once upon a Time in Italy: The Tale of the Morandi Bridge. *Structural Engineering International*, **29**, 198–217, 2019.
- [2] L.A. Grieco, N. Scattarreggia, R. Monteiro, F. Parisi. An index-based multi-hazard risk assessment method for prioritisation of existing bridge portfolios. *International Journal of Disaster Risk Reduction*, **14**, 2024.
- [3] S. Bianchi, F. Biondini. Bridge Condition Assessment Using Supervised Decision Trees. *EUROSTRUCT*, **200**, 1108–1116, 2022.
- [4] Federal Highway Administration (2016). *Synthesis of National and International Methodologies Used for Bridge Health Indices*. No. FHWA-HRT-15-081, US.
- [5] E. Sheils, A. O'Connor A., D. Breysse, F. Schoefs, S. Yotte. Development of a two-stage inspection process for the assessment of deteriorating infrastructure. *Reliability Engineering and System Safety*, **95**, 182–194, 2010.
- [6] L. Deng, W. Wang, Y. Yu. State-of-the-Art Review on the Causes and Mechanisms of Bridge Collapse. *Journal of Performance Construction Facility*, **30**, 2016.
- [7] R. Lee, C.J. White, M.S. Gani Adnan, J. Douglas, M.D. Mahecha, F.E. O'Loughlin, E. Patelli, A.M. Ramos, et al. Reclassifying historical disasters: From single to multi-hazards. *Science of The Total Environment*, **912**, 2024.
- [8] Ministry of Infrastructure and Transportation. *Linee guida per la classificazione e gestione del rischio, la valutazione della sicurezza ed il monitoraggio dei ponti esistenti*, Parere CSLPP n. 88/2019, Rome, Italy, 2020.
- [9] M. Pregnolato, P.F. Giordano, D. Panici, L. J. Prendergast, M. P. Limongelli. A comparison of the UK and Italiano national risk-based guidelines for assessing hydraulic actions on bridges. *Structure and Infrastructure Engineering*, **20**, 117–130, 2022.
- [10] H. Takano, M. Pooley. New UK guidance on hydraulic actions in highway structures and bridges. *Bridge Engineering*, **174**, 231–238, 2021.

- [11] M. Pregnolato, P.F. Giordano, L. J. Prendergast, P. J. Vardanega, M. P. Limongelli. Comparison of risk-based methods for bridge scour management. *Sustainable and Resilient Infrastructure*, **8**, 514-531, 2023.
- [12] S. Hamidpour, N. Scattarreggia, R. Nascimbene, R. Monteiro. A risk-based quantitative approach for priority assessment of ageing bridges accounting for deterioration, *Structure and Infrastructure Engineering*, 1-16, 2024.
- [13] C. Ormando, V. Lucaferri, A. Giocoli, P. Clemente, G. Buffarini, A. Tofani (2024). Index of Attention for a Simplified Condition Assessment and Classification of Bridges. *Infrastructures*.