A procedure for bridge visual inspections prioritisation in the context of preliminary risk assessment with limited information

Andrea Meoni[a], Enrique García-Macías[b], Ilaria Venanzi[a] and Filippo Ubertini[a]

[a]Department of Civil and Environmental Engineering, University of Perugia, Italy
[b]Department of Structural Mechanics and Hydraulic Engineering, University of Granada, Spain

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Abstract
Visual inspections represent the most resource-expensive operation in bridge management systems (BMSs). Consequently, their planning cannot be limited to the results of risk assessments, which are often performed under incomplete or uncertain information, but operating costs should also be accounted for. In this light, this paper presents a new methodology to prioritise visual inspections in BMSs based on risk condition and operating cost assessment. Framed in a context of limited information, the methodology exploits an information gain criterion to tackle potential uncertainties in the risk classification, so enabling to optimize the potential outcomes of the inspection plan. The proposed approach is conceived to be implemented in Geographical Information Systems (GISs) to facilitate the construction of intuitive risk maps and inspection plans. The effectiveness of the framework is demonstrated through its application to a simulated bridge stock whose risk condition was evaluated through the new guidelines for bridge risk classification and management recently adopted in Italy. The presented results highlight the benefits of simultaneously considering bridge risk conditions and inspection costs in defining the inspection plan, hence the usefulness of information theory to prioritise visual inspections. Limitations and future improvements of the proposed prioritisation method have also been highlighted and discussed.

KEYWORDS
Bridges; Geographical information system; Information gain; Prioritisation; Risk assessment; Visual inspections

1. Introduction

Recent tragic collapses like the I-35 W Mississippi river in 2007 or the Genoa bridge in 2018 have revealed the fundamental challenge posed by ageing civil infrastructure and the need to prioritise its management in the political agenda. A remarkable evidence of this is the last Infrastructure Report Card recently released in 2021 by the American Society of Civil Engineers (ASCE), which detected that 7.5% of the more than 600,000 American highway bridges are in poor conditions and estimated the nation's backlog of bridge repair at $123 billion (**CivilEngineersASCE2021**). The EU-funded BRIME project in 2001 revealed a similar picture across the European highway bridges, with deficiency rates among the surveyed countries ranging between 26 and

CONTACT Andrea Meoni. Email: andrea.meoni@unipg.it

39% (**woodward2001bridge**). This has promoted the publication of a multitude of technical standards worldwide in the last two decades (**Moreu2018**). These comprise from the first Structural Health Monitoring (SHM) guide in 2001 by the ISIS Canada Research Network (**ISIS2001**), until the last guidelines on the assessment and management of risk conditions of bridges and viaducts published by the Italian Ministry of Infrastructure and Transport in 2020 (**LLGGPonti**).

Risk is commonly formulated as the probabilistic product of three main components, namely hazard, vulnerability, and exposure (**ferrier2003hazards**; **grunthal2006comparative**; **omenzetter2014prioritisation**; see also **UNDRO1977**). A comprehensive evaluation of the risk condition requires the systematic combination of parameters involved in these three contributions according to the prescriptions of a certain standard. Bridges and viaducts are often subjected to numerous risk sources during their service life, e.g. structural (**frangopol2014structural**; **sacconi2021life**), seismic (**messore2020life**; **torti2022life**), landslides (**farzam2018susceptibility**; **pang2022probabilistic**), and hydraulic risks (**pregnolato2022comparison**; see also **tung1982optimal**). Especially in the context of structural and seismic risks, the structural performance is highly dependent on the presence of defects and pathologies, which may occur both during construction and service stages. As a result, the available information related to structural defectiveness often highly influences the evaluation processes prescribed by risk assessment standards for bridges and viaducts. In this context, visual inspections represent the most widely adopted Non-Destructive Evaluation (NDE) technique in routine inspections of bridges and viaducts (**lee2015bridge**; **zanini2017bridge**; see also **campbell2020benchmark**) to assess surface defects and disruptions in structural elements. Depending on the typology of the bridge/viaduct to be inspected and the surrounding environment, different inspection strategies can be adopted. For instance, visual inspections can be carried out from the ground level, by using an under-bridge platform, or by means of Unmanned Aerial Vehicles (UAVs), that is drones equipped with high-resolution cameras (**hallermann2014visual**). In common practice, the planning of visual inspections is usually borne by management authorities according to the inspection frequency prescribed by standards and the outcomes of past risk assessments. As it is well known, visual inspections are the most resource-intensive operations for management authorities due to their high recurrence over time and the large number of structures to be assessed in BMSs (**phares2001reliability**). It follows that their planning should not only be designed according to the risk condition of the bridge stock, but also the operating costs for their execution should be accounted for to enable a proper allocation of financial resources. Moreover, given the large amount of data involved in risk assessment procedures, a common situation in practice regards the lack of information as well as the need to dynamically update in time some parameters in the evaluations (**nettis2020rpas**). This circumstance may lead to delays in the establishment of risk conditions of bridges and viaducts to the detriment of the subsequent decision-making process by the management authority (**abdallah2021comprehensive**). In light of these considerations, the prioritisation of visual inspections can be a challenging task affected by myriad factors. Given its key role in BMS, the development of easily implementable inspection planning approaches accounting for the uncertain nature of information included in risk assessment procedures appears crucial. This is particularly critical for management authorities responsible for large bridge inventories. This is the case of ANAS (National Autonomous Roads Corporation) in Italy, which manages about 18,000 bridges located throughout the more than 32,000 km long Italian road network (**ANASwebsite**).

Several methodologies have been proposed in the literature to define inspection priorities within a stock of bridges and viaducts based on the evaluation of risk conditions. These approaches aim to define effective inspection plans based on the evaluation of the failure probability determined for a structural component or the entire bridge/viaduct (**reising2014risk**). Damage modes and deterioration models are typically considered to determine the failure probability within a reference time period (**torti2022monitoring**), while concepts from information theory are frequently employed to quantify the information gained from the execution of different inspection activities. **washer2014proposed** proposed a methodology to tune the inspection interval for a given bridge based on risk evaluations by an expert panel and meaningful structural and non-structural features, such as the year of construction, structural typology, loading conditions, defectiveness, the importance of the road network, and surrounding environment. **nasrollahi2015estimating** presented an inspection prioritisation method based on the statistical analysis of historical condition data over 20 years of routine inspections conducted on concrete, steel, and prestressed concrete bridges. The outcomes from that analysis made it possible to define the probability of a bridge or a bridge typology deteriorating from good to poor condition over a reference period, so allowing tailoring the inspection intervals. **yang2018probabilistic** presented an approach to design optimal inspection/repair plans with the lowest expected life-cycle cost suitable for structures subjected to fatigue cracking, such as, among others, bridges, and viaducts. Their approach exploits the Bayesian decision theory to minimise the posterior expected life-cycle cost and the value of information criterion to assess the contributions from different inspection strategies. Similarly, **liu2019utility** developed a risk-based inspection prioritisation algorithm emphasizing the importance of inspections based on information obtained from fatigue crack prognosis. In that work, the inspection results were characterized in probabilistic terms and used to update the prior distribution of fatigue damage. This allowed extracting the information gained from the inspection as the variation of the posterior with respect to the prior distribution. Those authors also investigated the variation in time of the information gain to analyze the decision maker's attitude and preference towards certain inspection outcomes using the utility theory. **santos2022improvement** proposed a prioritisation approach leveraging on the use of a deterioration model and a neural network for the simulation of different damage scenarios involving a bridge or a bridge typology. The outcomes from their analysis permitted the definition of the periodicity of the inspection activities within a bridge inventory and their prioritisation.

The present work proposes a new methodology to prioritise visual inspections of bridges and viaducts based on the evaluation of risk conditions and inspection costs in the context of limited information. In contrast to the approaches mentioned above, this methodology is primarily conceived to resolve the issues related to the planning of visual inspections of bridges/viaducts within a framework apt to operate in synergy with the existing standards for bridge risk assessment. Furthermore, the proposed methodology exploits concepts from the information theory to tackle potential uncertainties in risk assessment and subsequent inspection prioritisation. Overall, the proposed inspection prioritisation approach is ready to be applied by bridge owners and managers, even though it has to be acknowledged that the chronic lack of extensive bridge inspection databases at global level significantly complicates scientific progress in the optimal management of bridge inventories. The organization of the paper is as follows. Section 2 overviews the proposed methodology and its theoretical foundations. Section 3 presents the case study used to exemplify the practical application of the developed prioritisation algorithm. Section 4 presents the obtained results and, finally, Section 5 closes the paper with the main conclusions drawn from this work.

2. Methodology

Visual inspections are periodically carried out on bridges and viaducts during their lifetime to detect and assess defects and disruptions affecting their structural components and, therefore, their structural integrity depending on the defect typology and entity (**zanini2017bridge**). The outcomes from visual inspections are commonly processed through expert judgments or the prescriptions provided by a certain selected standard, to assign a defect level to every asset under examination that concisely expresses its condition state (**santarsiero2021italian**). This information is then used to carry out preliminary risk evaluations of the assets, the results of which can be used to critically prioritise the next activities predicted in the decision-making process defined by a management authority, such as the execution of in-depth inspections and maintenance/retrofit interventions. In the context of bridge rating through visual inspections, the risk of the i-th bridge/viaduct in the stock is often formally defined through a discrete random variable, R^i, as follows:

$$R^i = f(H^i, V^i, E^i) = f(Y^i), \tag{1}$$

where $H^i = \{h_1^i, ..., h_n^i\}$ collects a finite number of n hazard discrete variables attributed to the considered bridge/viaduct. Similarly, $V^i = \{v_1^i, ..., v_m^i\}$ and $E^i = \{e_1^i, ..., e_k^i\}$ encapsulate m-vulnerability and k-exposure discrete variables, respectively, such that $Y^i \in \mathbb{R}^{n+m+k}$. The nature of these variables depends on the type of risk being assessed. However, in the context of structural and seismic risk, the defect level resulting from a visual inspection is commonly included among the variables in V^i most influencing the vulnerability of the asset.

2.1. Inspection priority score

A general flowchart of the proposed methodology is illustrated in Figure 1. The method has been conceived to be implemented in a Geographical Information System (GIS), which allows the processing and mapping of a broad variety of georeferenced data. The main motivation of such a framework is to provide infrastructure managers with an intuitive tool to prioritise inspections at a regional scale, find risk patterns within dense stocks of bridges and viaducts, and optimize logistic operations.

The proposed methodology comprises three main stages, namely data collection (i), processing (ii), and analysis (iii). The data collection stage (i) involves the systematic collection and storage of the main structural and non-structural features of each bridge/viaduct in the considered stock in the GIS database. These may include, among others, the construction date, materials, structural typology, the number of spans, and inspection strategy. Additional data strictly depends on the standard adopted in the BMS to carry out the risk evaluation. Secondly, the data processing stage (ii) involves the implementation of algorithms to assess the risk condition and the inspection cost from the previously acquired structural and non-structural features in the GIS framework. At this stage, the methodology operates with basic knowledge of the bridges in the network, thereby it is common that the assessment suffers from considerable uncertainty. The minimization of this uncertainty typically requires the acquisition of numerous pieces of information about the particular assets in the network, which may be difficult to determine without thorough on-site inspections and the analysis of physical and digital archives. In this context of limited information, the analysis stage of the proposed methodology (iii) is designed as a two-step procedure. In the first place, a preliminary risk assessment of the bridges/viaducts in the network is conducted on a probabilistic basis. To do so, the risk assessment is conducted by processing sets of simulated data representing all possible scenarios covering the missing information according to the provisions of the selected standard. The outcome of this first step is the definition of probabilistic distributions of the risk classes of the bridges in the network. Afterwards, the second step involves a refinement of the risk evaluation of the bridges according to the potential information gain that on-site inspections and archival investigations may provide to the classification. To this aim, the information gain criterion, later outlined in Section 2.4, is adopted. The simultaneous consideration of the risk conditions and operating costs for the execution of visual inspections ensures the achievement of a comprehensive and informed planning of the inspection activities. Compared to prioritisation approaches based solely on the outcomes from risk assessments, the proposed approach has the main advantage of allowing inspection priorities to be set between bridges and viaducts under similar risk conditions by considering operating costs as an additional discriminating factor for planning inspection activities. Furthermore, especially in the case of limited economic resources for carrying out visual inspections, this combined approach allows to study the economic consequences related to the choice of different inspection strategies and to define the inspection plan accordingly. Given the different nature of risk and operating cost assessments, a dimensionless index, named Inspection Prioritisation Score (IPS), is introduced to rank structures within a bridge inventory. Let us consider a bridge stock of N structures, which are scored according to their inspection priority as:

$$IPS^i = F_{\mathrm{R}}^i + \left(1 - F_{\mathrm{I}}^i\right), \tag{2}$$

where terms F_{R}^i and F_{I}^i are called the *Risk Factor* and the *Inspection Factor* of the i-th bridge in the stock, respectively. Term F_{R}^i accounts for the risk condition of the asset in such a way that the higher the risk, the higher the value of F_{R}^i and thus the inspection priority. Similarly, F_{I}^i encapsulates the influence of the expenses related to the visual inspection of the asset on the prioritisation process, yet its implementation in Equation (2) reduces the inspection priority as the operating costs increase. Overall, the higher the IPS value of a bridge/viaduct, the higher its inspection priority over the other structures included in the inventory. On this basis, the proposed methodology gives priority to visual inspections of the bridges/viaducts most at risk, whose inspection requires limited operating costs. In addition, the approach primarily prioritises the visual inspection of the assets that have never been inspected over those whose defectiveness is known, e.g. from past inspection activities, but has to be periodically updated within a reference period that is commonly defined by the adopted standard/guidelines for bridge risk assessment (e.g. one year). The priority order of visual inspections resulting from the application of the proposed methodology is therefore intended to be valid within that reference period. When a new reference period begins, the defectiveness of every asset is considered obsolete, hence a new cycle of visual inspections must be carried out. In this circumstance, the proposed methodology can be adopted to define a second inspection plan refined through the information gathered in the previous inspection cycle. The IPS offers a compact scalar easily implementable in GIS environments, allowing rendering risk maps and inspection plans at a regional level by implementing the Kriging method later described in Section 2.5. The outcome of this process is a set of informative maps that intuitively highlight risk conditions and inspection priorities within the stock of bridges and viaducts under assessment. A detailed description of the procedures adopted to evaluate F_{R}^{i} and F_{I}^{i} under the assumption of limited information is provided hereafter. Assuming that both F_{R}^{i} and F_{I}^{i} are defined within a range of variability comprised between 0 and 1, and that $F_{\mathrm{R}}^{i} = 1$ indicates an asset that is anticipated to be under critical risk conditions, while $F_{\mathrm{I}}^{i} = 1$ points out an asset whose visual inspection requires high effort to be conducted, the IPS can range between 0 and 2 according to Equation (2). In particular, an IPS equal to 2 indicates an asset under expected critical risk conditions that can be inspected with low or negligible efforts, while an IPS equal to 0 is attributed to an asset under low or negligible risk conditions but requiring high efforts to be inspected.

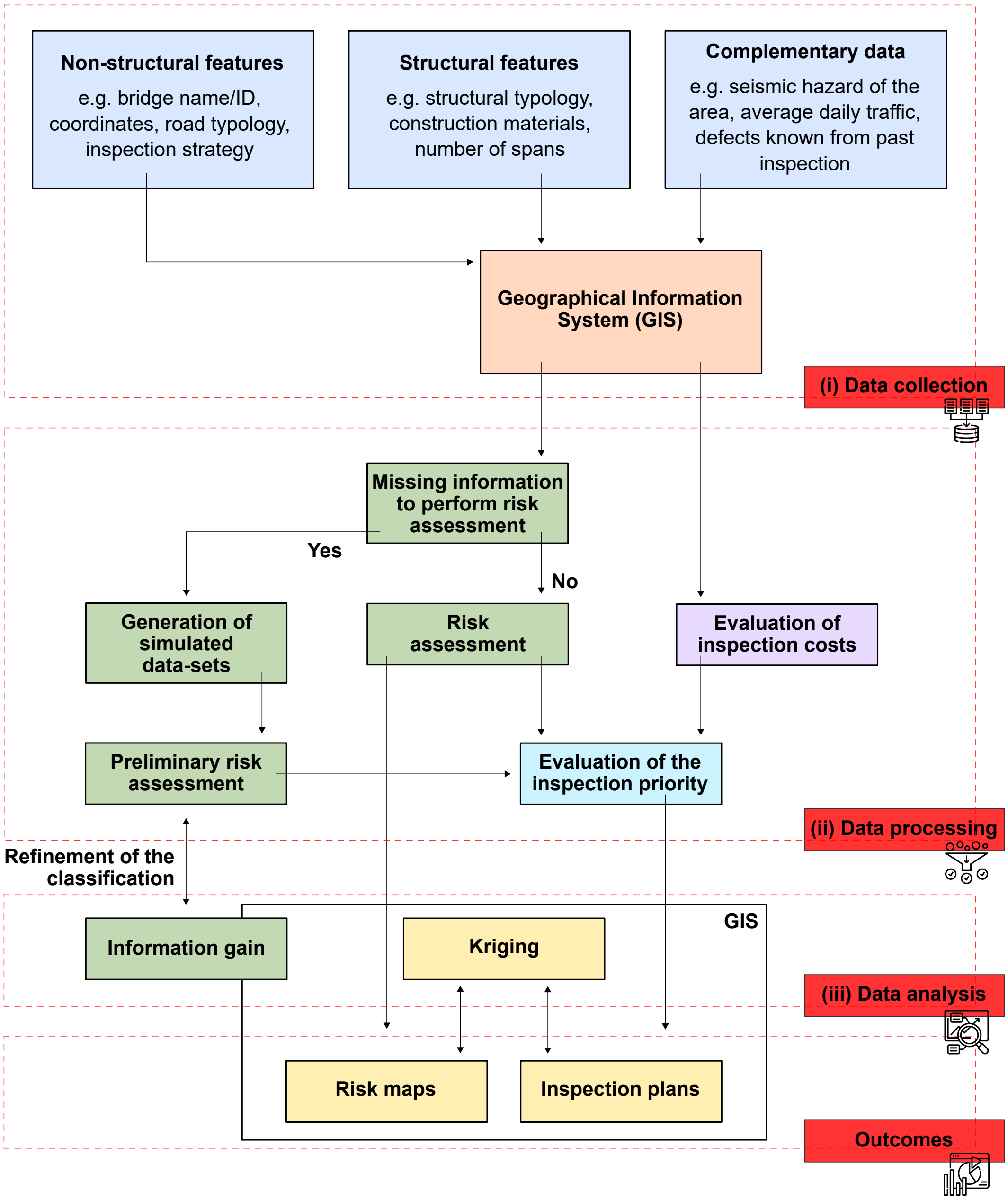


Figure 1. General flowchart of the proposed methodology to prioritise inspection activities in BMSs based on risk conditions and inspection costs in the context of limited information.

2.2. Preliminary risk assessment

In the context of limited information to fully conduct the assessment of a certain risk condition of a bridge/viaduct (e.g. structural, seismic, landslides, and hydraulic risk) according to the provisions of a selected standard, the proposed methodology preliminarily estimates the risk through a Monte Carlo Simulation (MCS) approach. To do so, let us consider that only n parameters are available for the bridge under assessment, $K_i = \{k_i\}$, $i \in \{1, \ldots, n\} \,|\, K_i \subseteq Y$ (Equation (1)). These will typically include a set of general descriptors of the structure that are known before conducting any specific inspection, such as the construction material, structural typology, number of spans, and more. These known parameters are systematically combined with m unknown terms, $U_j = \{u_j\}$, $j \in \{1, \ldots, m\} \,|\, U_j \subseteq Y$ (Equation (1)), by MCS to obtain a probabilistic definition of the risk condition. In the MCS, the unknown factors are assumed discretely distributed and equiprobable (uniform distributions), that is $P\left[u_j = x^{(i)}\right] = p\left(x_j^i\right) = p_x$, $i = 1, \ldots, n_{u_j}$, with x_j^i being an arbitrary value among n_{u_j} possible options for u_j. In this light, the MCS simplifies the analysis of all possible combinations between the known factors and the unknowns as:

$$K_1 \times ... \times K_n \times U_1 \times ... \times U_m = \{(k_1, ..., k_n, x_1^i, ..., x_m^i) \,|\, \forall i \in n_{u_j}\}, \tag{3}$$

which amounts to a total of $\prod_{j=1}^{m} n_{u_j}$ combinations. Considering the lack of specific studies to determine the probability distributions of the parameters involved in bridge risk assessment procedures, assuming unknown terms as discretely distributed and equiprobable in MCS represents an effective simplification to obtain preliminary estimates of the risk conditions of the assets for the timely prioritisation of inspection activities within bridge inventories. Certainly, realistic distributions for the unknown terms, e.g. derived from literature works or real data-sets, can be considered in MCS to obtain more accurate estimates of the risk conditions of the assets. It is also worth stressing that the adopted MCS approach assumes that all random variables in the model are independent. Consequently, potential correlations between the variables in the selected risk assessment process have to be modelled appropriately to avoid under- or over-estimates of the risk.

Assuming that the adopted standard classifies the considered risk condition according to t discrete risk levels, $R = \{r_1, ..., r_t\}$, the iterative processing of the simulated data-sets results in a discrete probability distribution of the risk classification by computing the frequency of each risk level, that is $P\,[R = r_j] = p(r_j)$ with $\sum_{j=1}^{t} p(r_j) = 1$. The algorithm attributes the risk level, $r = r_p$, corresponding to the maximum probability value in the obtained distribution, $p(r_p) = \max\{p(r_1), \ldots, p(r_t)\}$, to the bridge/viaduct under evaluation. Accordingly, the higher the occurrence probability $p(r_p)$, which represents the confidence level of the estimation, the higher the reliability of the assessment. It follows that the so-determined risk level will not be affected by any uncertainty if all the information required in the assessment process is available (i.e. $p(r_p) = 1$, and $p(r_k) = 0$, $\forall k \neq p$). In the context of uncertain risk assessment, F_{R}^i for the i-th bridge/viaduct in the stock can be calculated as the weighted average of the risk levels attributed to the structure for all the l risk conditions for which it has been assessed, that is:

$$F_{\mathrm{R}}^i = \frac{\sum\limits_{j=1}^{l} w_{\mathrm{R}}(r_{p,j}) \cdot p^i(r_{p,j})}{\sum\limits_{j=1}^{l} p^i(r_{p,j})}, \tag{4}$$

where term $w_{\mathrm{R}}(r_{p,j})$ indicates the weighting factor associated with the risk level attributed to the bridge/viaduct for the l-th risk condition, when the risk classification provided by the adopted standard/guidelines is expressed through qualitative descriptors (e.g. high, medium, low risk). Such factors encapsulate the economical/societal costs related to every risk condition, in such a way that the largest values will be assigned to those conditions representing severe risks to the integrity of the stock (e.g. risk of collapse, complete disruption of the network). It follows that, in case of semi-qualitative risk classifications (e.g. 1=high risk, 0.5=medium risk, 0=low risk), term $w_{\mathrm{R}}(r_{p,j})$ may represent the numerical value associated to the risk level r_p determined for the l-th risk condition. In Equation (2), F_{R}^i is a scalar varying from 0 to 1, with values close to one denoting a higher inspection priority due to more critical risk conditions. Such a range of variability of F_{R}^i can be achieved through an appropriate definition of the weighting factors included in its formulation, as exemplified later in Section 3.

2.3. Inspection costs and Inspection Factor

The operating costs of visual inspections can vary according to the structural features of the bridge/viaduct under examination. Important features include for instance the construction material, structural typology, number of spans, height of the piers, and more. These factors determine the required inspection strategy (techniques, number of operators, auxiliary platforms, etc.) and the related costs. The proposed inspection prioritisation algorithm accounts for these aspects by means of three cost factors associated with every asset in the bridge inventory. These include cost factors w_{CM}, w_{ST}, and w_{IS} encapsulating the costs related to the construction material, structural typology, and inspection strategy, respectively. Typically, specific mathematical rules for the computation of cost factors $\{w_{\mathrm{CM}}, w_{\mathrm{ST}}, w_{\mathrm{IS}}\}$ can be easily established by the inspection manager according to previous experience. Depending on the case, cost factors can be either expressed in currency or by means of numerical coefficients whose values increase with the economic resources/efforts required to conduct the inspection of the asset. Sample suggestions for their formulation will be later reported in Section 3.

Once the previously introduced cost factors are assigned to all the assets in the considered bridge stock, these can be rated according to three non-dimensional scoring factors C_{CM}, C_{ST}, and C_{IS}. An additional factor, C_{NS}, is also introduced to consider the number of spans in the prioritisation process. Let us denote w_{CM}^i, w_{ST}^i, and w_{IS}^i the cost factors assigned to the i-th bridge/viaduct in the stock under assessment. On this basis, scoring factors C_{CM}^i, C_{ST}^i, C_{NS}^i, and C_{IS}^i can be readily computed as:

$$\begin{cases} C_{\mathrm{CM}}^i = & \frac{w_{\mathrm{CM}}^i}{\max\limits_i\{w_{\mathrm{CM}}^i\}}, \\ C_{\mathrm{ST}}^i = & \frac{w_{\mathrm{ST}}^i}{\max\limits_i\{w_{\mathrm{ST}}^i\}}, \\ C_{\mathrm{NS}}^i = & \frac{s^i}{\max\limits_i\{s^i\}}, \\ C_{\mathrm{IS}^i} = & \frac{w_{\mathrm{IS}}^i}{\max\limits_i\{w_{\mathrm{IS}}^i\}}, \end{cases} \tag{5}$$

where s^i denotes the number of spans of the i-th bridge/viaduct. Scoring factors have the main advantage of normalizing the operating costs related to each category. Such a normalization can be performed by considering subsets of assets included in the bridge inventory to improve the impact of cost evaluations in the prioritisation process. As an example, scoring factors can be computed for the subset of bridges/viaducts that have never been inspected by determining the maximum values of terms $w_{\mathrm{CM}}, w_{\mathrm{ST}}, w_{\mathrm{IS}}$, and s among those associated to the assets belonging to this subset, instead of considering those of all the assets in the bridge inventory. On this basis, the so-called Inspection Factor, F_{I}^{i}, is defined as:

$$F_{\mathrm{I}}^{i} = C_{\mathrm{CM}}^{i} \cdot C_{\mathrm{ST}}^{i} \cdot C_{\mathrm{NS}}^{i} \cdot C_{\mathrm{IQ}}^{i}, \tag{6}$$

in such a way that higher values will be obtained in cases where visual inspections require a greater effort to be conducted by the management authority.

Term C_{IQ}^{i} in Equation (6) represents the contribution due to the quality of the selected inspection strategy and can be related to C_{IS}^{i}, in the absence of specific studies by the authors, through the following relationship (**mori1994maintaining**):

$$C_{\mathrm{IQ}}^{i} = C_{\mathrm{IS}}^{i}(1-\beta_{\min})^{20}, \tag{7}$$

with $\beta_{\min}$ being a numerical coefficient accounting for the minimum damage intensity on the considered structure detectable by visual inspection. It is assumed that the damage intensity can vary from zero to one indicating no damage and fully developed damage, respectively. Therefore, according to Equation (7), the cost stemming from the visual inspection increases non-linearly as the requirements on the minimum detectable damage intensity raise. As proposed by Frangopol and co-authors (**frangopol1997life**), the quality of visual inspection techniques can be defined in statistical terms through a certain detectability function, $d(\beta)$. Assuming a cumulative normal distribution for $d(\beta)$ as a standard, $\beta_{50\%}$ the median of the distribution (damage intensity with 50% probability of being detected), and σ its standard deviation, the limits in the distribution encapsulating 99.7% of the probability can be defined as:

$$\beta_{\min} = \beta_{50\%} - 3\sigma, \tag{8}$$

$$\beta_{\max} = \beta_{50\%} + 3\sigma. \tag{9}$$

In this light, the detectability function can be simplified to a truncated cumulative normal distribution as follows:

$$d(\beta) = \begin{cases} 0, & \text{if } 0 \leq \beta \leq \beta_{\min}, \\ \Phi\left(\dfrac{\beta - \beta_{50\%}}{\sigma}\right), & \text{if } \beta_{\min} < \beta \leq \beta_{\max}, \\ 1, & \beta > \beta_{\max}, \end{cases} \tag{10}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. In this work, the quality of a visual inspection is associated with the number of operators involved in the inspection activity and their experience. These factors can be embodied in terms $\beta_{50\%}$ and σ by assuming that their value decreases when the inspection is conducted by a more experienced operator or by several operators at the same time. It is worth noting that the quality of visual inspections can be influenced by several human factors (**see2012visual**). These include, among others, the search pattern and inspector-paced approach (**drury2002good**), the age of the operators and their training experience (**megaw1979eye**; **see2015visual**), the possibility of consultation between operators (**hillman1976value**), and the environmental conditions under which visual inspections are carried out (**moore2001reliability**), such as the ambient lighting and air temperature. Determining the contribution of human factors to visual inspection quality is often a challenging task. As an example, several literature works have demonstrated that the inspection quality can increase, decrease, or remain constant with varying operators' experience (**campbell2021human**; see also **megaw1979factors**). Nonetheless, it is assumed in this work that the quality of visual inspections increases with the number of employed operators and their experience. This certainly represents a simplification which is however deemed as acceptable based on the experience of the authors to keep the computation of the term C^i_{IQ} simple but effective for prioritisation purposes. In Equation (2), term F^i_{I} can vary from 0 to 1 depending on the contributions of C^i_{CM}, C^i_{ST}, C^i_{NS}, C^i_{IS}, and $\beta_{\min}$, yet in the majority of cases $0 \leq F^i_{\mathrm{I}} < 1$. This is because $F^i_{\mathrm{I}} = 1$ when $w^i_{\mathrm{CM}} = \max\limits_i \left\{w^i_{\mathrm{CM}}\right\}$, $w^i_{\mathrm{ST}} = \max\limits_i \left\{w^i_{\mathrm{ST}}\right\}$, $w^i_{\mathrm{IS}} = \max\limits_i \left\{w^i_{\mathrm{IS}}\right\}$, $s^i = \max\limits_i \left\{s^i\right\}$, and $\beta_{\min} = 0$, where this last condition, indicating that defects of any entity can be detected on the i-th asset by performing visual inspections, appears rather difficult to achieve in real applications.

2.4. Information gain as a metric for prioritisation of inspection tasks

The risk level attributed to a bridge/viaduct according to the approach described in Section 2.2 can be refined until certain reliability of the assessment is reached through the estimation of the unknown terms involved in the evaluation process. This typically involves surveying physical and digital archives, e.g. for the purpose of retrieving certain design data, as well as performing visual inspections to determine the defectiveness of the structures. The conscious planning of these activities according to the potential knowledge of the actual condition of the assets that may be gained from their execution is a task of crucial importance for management authorities. This becomes even more important in the case of visual inspections, which are costly activities both in terms of time and financial resources. In this regard, the proposed methodology exploits the information gain criterion, later introduced in this section, to aid management authorities in establishing priority rules for retrieving missing information and minimise delays in the whole decision-making process. The information gain criterion is used in the proposed methodology to identify, among the unknown parameters in the selected risk assessment process, those whose determination would add the highest informative contribution to the risk classification of the considered asset. It follows that, in the context of visual inspections, the information gain criterion is adopted to quantify the potential informative contribution that conducting the inspection of a bridge, and thus determining its level of defectiveness, would add to its risk classification. In this sense, when applied to multiple assets, the information gain criterion can be used to identify bridges whose visual inspection is characterized by a higher informative contribution, i.e. those bridges for which the determination of the defect level leads to significant improvements in their risk classification. Hence, the inspection plan can be refined by prioritising the inspection of the assets with maximum potential information gain, as exemplified in Figure 2.

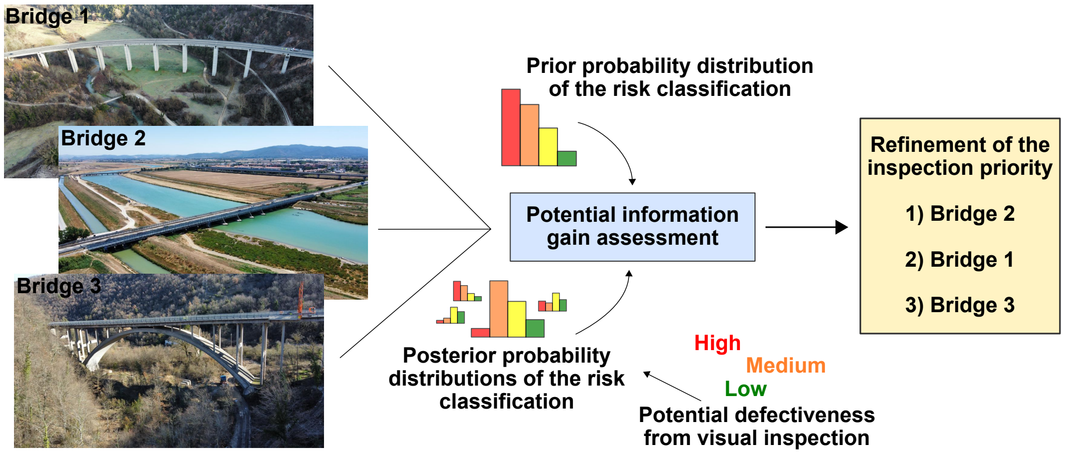


Figure 2. Exemplification of the use of the information gain to refine the priority of visual inspections in a bridge inventory based on the potential information content that their execution would add to the risk classification of the assets.

Information gain expresses the amount of information acquired about the properties of a certain class or stochastic process after collecting a new realization. In information theory, the Kullback-Lieber divergence (**kullback1959information**; see also **kullback1951information**), also called relative entropy, represents a common approach to computing the information gain. It is a divergence score implemented in the proposed methodology to measure the information gained in moving from the prior probability distribution, $p\,(r\,|\,I)$, of the random variable r, which represents the risk of a considered asset, obtained from the systematic combination of a certain set of available information, I, to a posterior probability distribution of the risk, $p\,(r\,|\,y, I)$, when a new piece of information y is introduced in the risk assessment process (e.g. the defect level of the asset). The prior probability distribution of the risk r can be obtained by processing the information available for the considered asset according to the MCS approach described in Section 2.2. Similarly, the posterior probability distribution can be obtained by adding the new piece of information y to the data-set of the considered asset, hence by carrying out simulations of risk classifications with the same MCS approach. The risk assessment classes to be evaluated according to the provisions of a certain selected standard can be usually described through discrete probability distributions. In this light, the Kullback-Lieber divergence in its discrete form can be expressed as follows (**mackay2003information**):

$$D_{KL}\left[p\,(r\,|\,y, I)\;\|\;p\,(r\,|\,I)\right] = \sum_r p\,(r\,|\,y, I)\log\left(\frac{p\,(r\,|\,y, I)}{p\,(r\,|\,I)}\right). \tag{11}$$

A relative entropy equal to zero indicates that the compared distributions are identical in terms of information content, hence the added piece of information y does not affect the risk classification of the considered asset. Conversely, values of the relative entropy greater than zero denote a certain gain in the information content due to the introduction of the observation y. When a second observation z is introduced in the risk assessment process (e.g. the year of construction of the asset), the posterior probability distribution becomes $p\,(r\,|\,y, z, I)$. The latter can be compared with the prior probability distribution, $p\,(r\,|\,I)$, or with $p\,(r\,|\,y, I)$, which can act as a reference distribution, to compute the information gain corresponding to the new piece of information z. In the context of risk evaluation, therefore, such a criterion can be used as a variable selection method to optimize the retrieval of missing information in the assessment process, by prioritising the retrieval of those parameters that can add a higher information content to the risk classification.

Considering that the defectiveness of a structure, D, can be usually described through n discrete defect levels prescribed by a certain selected standard, $D = \{d_1, ..., d_n\}$, and assuming these as equiprobable outcomes from the inspection of a given bridge, the potential information gain associated with the execution of the inspection activity is as follows:

$$\begin{gathered} \mathbb{E}(D_{KL}\left[p\left(r \mid D, I\right) \parallel p\left(r \mid I\right)\right]) = \\ D_{KL}\left[p\left(r \mid d_1, I\right) \parallel p\left(r \mid I\right)\right] a_1 + ... + D_{KL}\left[p\left(r \mid d_n, I\right) \parallel p\left(r \mid I\right)\right] a_n, \end{gathered} \tag{12}$$

where $a_1 =, ..., = a_n$ and $\sum_{i=1}^{n} a_i = 1$. Note that this definition evaluates the expected information gain from all the possible outcomes that a visual inspection may provide to the risk classification. Therefore, in the context of visual inspections, the potential information gain can be used as a metric to prioritise the inspections whose execution would add a higher informative contribution to the risk classification of the corresponding bridges, hence to revise the inspection plan accordingly. A practical application of the information gain analysis has been later exemplified with numerical examples in Section 4.2.

2.5. Ordinary Kriging to render informative maps at a regional level

Managing risk conditions and inspection priorities on a regional scale is a task of the utmost importance, especially for management authorities responsible for large bridge inventories. In this context, the proposed methodology exploits Kriging procedures to spatially interpolate the discrete outcomes obtained for every bridge/viaduct within the stock under examination, such as the risk level and inspection order. This results in macro-level illustrative maps that intuitively provide preliminary estimates of risk conditions and inspection priorities for bridges and viaducts geographically located in the vicinity of the examined assets, as exemplified in Figure 3. The so-determined estimates certainly do not represent the actual risk or inspection priorities of all the assets in the macro-area under consideration. However, the Kriging interpolator can provide estimates of the interpolated parameter with an acceptable degree of reliability, also considering that bridges and viaducts on the same road network or on neighbouring networks usually share similar characteristics, such as the year of construction, structural typology, average daily traffic, and others, and therefore similar risk conditions and inspection priorities. Bridge owners and managers can exploit the obtained macro-level illustrative maps, to be included in a GIS supporting the BMS, to identify areas with similar bridge risk conditions and inspection demands, which may be indicative of common geographical/regional/administrative drivers, and thus to properly allocate financial resources at a regional scale accordingly.

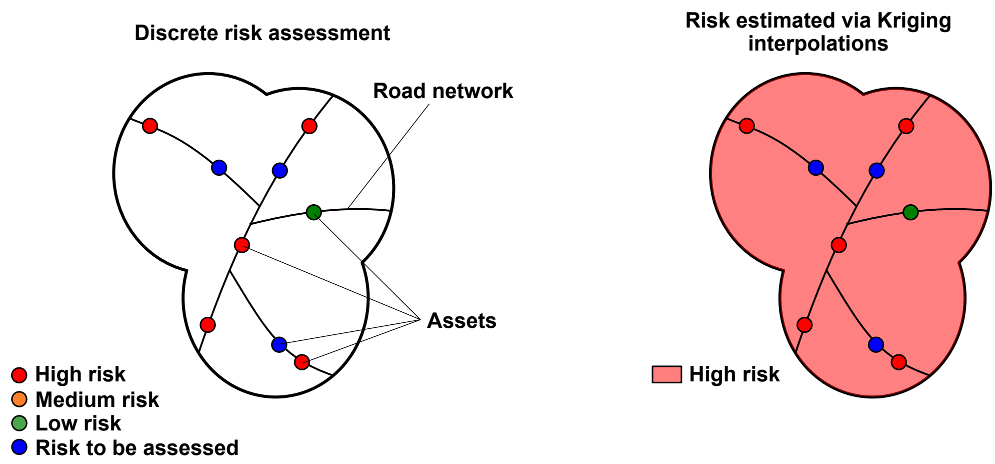


Figure 3. Exemplification of the use of Kriging interpolations to preliminary estimate the risk conditions of bridges and viaducts within a certain geographical area (note that at the level of a single bridge, risk conditions may differ from those shown on the macro-level illustrative map obtained from the Kriging interpolator).

Kriging procedures are spatial interpolation methods commonly used in Geostatistics (**kleijnen2017kriging**; see also **oliver1990kriging**). In general, a Kriging model allows the interpolation of an unknown multi-dimensional random function $z(x)$ within a certain design space $\mathbb{D}$ (i.e. $x \in \mathbb{D}$) when only a set of n function evaluations $z(x_i)$, $i = 1, \ldots, n$, are available. A semivariogram is used to model the spatial correlation between the interpolation points and the known function evaluations. This approach allows the interpolation of the function by means of certain weighting factors affecting the known function evaluations. In this work, the Ordinary Kriging (OK) method (**cressie1988spatial**) is adopted to perform spatial interpolation of the risk classes and inspection priorities at a regional scale. The method assumes that the mean of the interpolating function, yet unknown, is constant throughout the interpolation domain $\mathbb{D}$. This results in better estimations at the interpolating points when only a limited number of known values are available to train the Kriging model, as it will be the case when applied for the interpolation of the outcomes from the proposed methodology. In this light, the OK approach estimates the value of $z(x_0)$ at an arbitrary interpolation point x_0 as follows (**cressie2015statistics**):

$$z(x_0) = \sum_{i=1}^{n} \lambda_i z(x_i), \quad \text{with} \quad \sum_{i=1}^{n} \lambda_i = 1, \tag{13}$$

where $\{\lambda_i\}_{i=1}^{n}$ are weighting factors derived from a semivariogram model selected to obtain an unbiased estimate with minimal error variance. The expression in Equation (13) is considered the best linear unbiased estimate (BLUE) of $z(x_0)$. A generic formulation of a semivariogram model can be expressed as a spatial correlation function between two points $z(x)$ and $z(x+h)$ as:

$$\gamma(h) = \frac{1}{2}\mathrm{Var}\left[z(x) - z(x+h)\right] = \frac{1}{2}\mathbb{E}\left[\left(z(x) - z(x+h)\right)^2\right], \tag{14}$$

with h denoting the spatial distance (often referred to as lag distance) between the considered points. In this light, after defining a certain spatial correlation model to represent the semivariogram, it is possible to fit the weighting factors $\{\lambda_i\}_{i=1}^{n}$ by minimizing the variance errors of the Kriging prediction through a certain prediction method (refer to **montero2015spatial** for further details).

3. Application case study

This section presents an application case study conceived to demonstrate the effectiveness of the proposed methodology in prioritising visual inspections within a stock of bridges based on risk and operating costs evaluations in a context of limited information. Firstly, the standard adopted to evaluate the risk conditions of the stock is presented in Section 3.1. Then, Section 3.2 describes in detail the simulated stock of structures and the available information for the definition of the inspection plan.

3.1. The Italian Guidelines for bridge risk classification and management

The Italian Guidelines for risk classification and management, safety assessment, and monitoring of existing bridges (**LLGGPonti**) recently released by the Italian Ministry of Infrastructures and Transport in 2020 have been chosen in this application case study as the reference standard to assess the risk condition. The Standard proposes a multilevel approach for bridge risk classification and management consisting of six levels of analysis as shown in Figure 4 (**LLGGPonti**). The assessment of the risk condition falls within the first three analysis levels prescribed by the Italian Guidelines. Firstly, Level 0 is devoted to the construction of the database collecting information about the bridges and viaducts under evaluation. Then, Level 1 is aimed at estimating the defect level of the structures through the execution of visual inspections, and, finally, Level 2 combines the information gathered in the previous levels to determine the attention class or preliminary risk level of each bridge/viaduct in the network. The attention class can be high (critical risk level), medium-high, medium, medium-low, and low, as the risk level of the structure decreases. These classes are assigned according to the potential existence of risks related to structural-foundational factors, as well as to seismic, hydraulic, and landslide risks. Each of these risk conditions is evaluated through the systematic combination of parameters characterising the hazard, vulnerability, and exposure of the structure under analysis. An overall attention class is then attributed to every bridge/viaduct according to predefined logic rules that combine the attention classes obtained for the analysed risk conditions. Based on this initial assessment of the attention class, the Italian Guidelines prescribe different actions (Levels 3, 4, and 5) for further deepening into the knowledge of bridges/viaducts and managing their risk condition (interested readers may refer to reference (**LLGGPonti**) for further details). For instance, the Guidelines determine the frequency with which visual inspections must be carried out on a structure during its lifetime to monitor modifications in its defect level. The defectiveness of bridges/viaducts represents a key parameter for the evaluation of the structural-foundational and seismic attention classes. Therefore, a particular focus is put on the consideration of these risk conditions for setting inspection priorities in the proposed methodology. The defect level, which can be high, medium-high, medium, medium-low, and low (a high defect level indicates the potential incipient failure of the bridge/viaduct), is dependent on whether the structural-foundational or seismic risk is assessed. This is because the Standard assumes that some structural elements may exhibit defects that are particularly critical for the assessment of structural-foundational attention class, yet less influential in seismic risk, and vice versa. In the absence of specific pathologies, the defect level attributed to a bridge/viaduct will be the same for both risk conditions. It is important to remark that, while the Italian Guidelines impart specific indications to process the outcomes from visual inspections to assign a defect level to a structure, no specific guidance on the prioritisation of visual inspections between bridges subjected to the same risk level is provided.

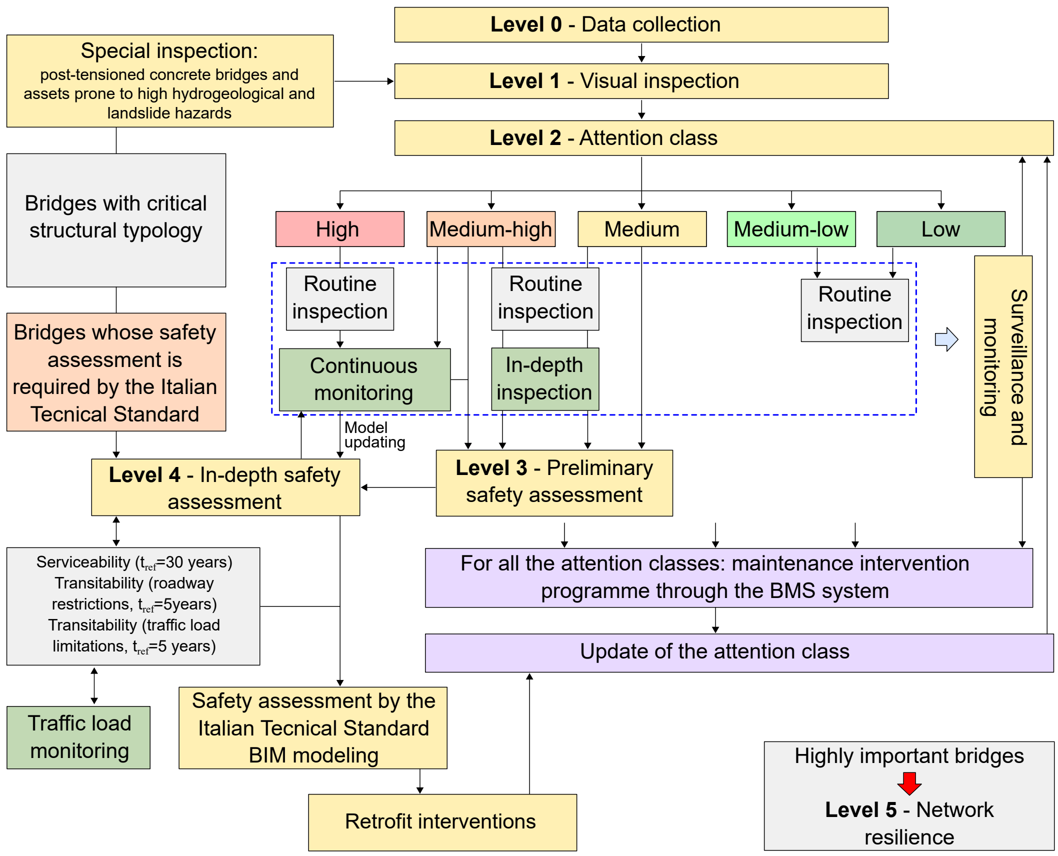


Figure 4. Flowchart of the multilevel approach for bridge risk classification and management proposed by the Italian Guidelines (translated from **LLGGPonti**).

3.2. Simulated bridge stock

A sample stock of bridges located in Umbria, a region of central Italy, has been considered in the practical application of the proposed methodology. It is worth pointing out that the sample stock consists of bridges simulated on the basis of the authors' experience, whose structural and non-structural features are, however, representative of real scenarios but not related to specific real bridges. Figure 5 shows the geographical position of the twenty-five structures composing the inventory and labelled from A to Y. The analysed bridges are evenly distributed throughout Umbria and serve both the main and secondary road networks. The QGIS software (**QGIS_software**) has been adopted to manage and process the geostatistical data of the considered stock. The prioritisation algorithm previously introduced in Section 2.1 has been implemented in this GIS environment by means of a plug-in written in Python language. Moreover, the Smart-Map plug-in (**pereira2022smart**) has been used to perform Kriging spatial interpolations (a linear semivariogram model and the k-nearest neighbors method have been considered to perform interpolations).

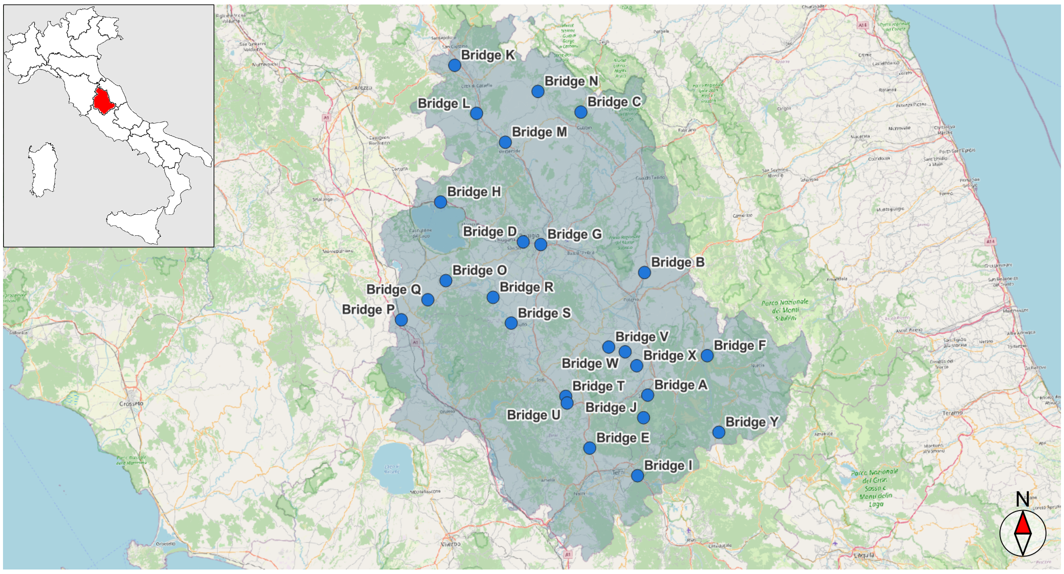


Figure 5. Map from QGIS showing the geographical position of the bridges composing the sample stock considered in the practical application of the proposed inspection prioritisation methodology.

Tables A1 and A2 gather the available information on the stock under assessment. Specifically, for every bridge included in the stock, Table A1 collects the data required by the Italian Guidelines for the evaluation of the structural-foundational attention class, while Table A2 reports additional information required by the Standard for the assessment of the seismic attention class. This latter table also illustrates the strategy chosen to conduct the visual inspection of each asset in the network. Basic structural features such as the construction material, structural typology, static scheme, and the number of spans have been assumed to be known in the simulated data-set. Similarly, a value of the peak ground acceleration (with 10% probability of exceedance in 50 years for hard ground sites) has been attributed to every bridge in the asset according to the national seismic hazard map (**ntc2018**). Common issues encountered in the practical application of the Italian Guidelines are the lack of documentation on the design of structures and specific on-site traffic flow surveys. That is in particular the case of many bridges constructed in the 20th century, located in road networks of minor importance, as well as bridges whose management responsibility has been transferred from one authority to another over time. In order to define a representative data-set, pieces of information including, among others, date of construction, adopted design code, geometrical features, traffic statistics, and soil category, have been assumed to be missing for some structures within the inventory. Along with this information, the defect level has also been hypothesised to be unknown for some bridges. This circumstance may be representative of those assets for which the inspection and the subsequent assignment of the defect level have not yet been carried out given the recent adoption of the Italian Guidelines.

Tables 1 and 2 provide the weighting and cost factors adopted for the computation of the Inspection Prioritisation Score (IPS) in Equation (2). Specifically, Table 1 illustrates the weighting factors involved in the computation of F_{R} and related to the assessment of the structural-foundational and seismic risks. A greater impact on the prioritisation of inspection activities has been given to the outcomes obtained from the assessment of the structural-foundational attention class compared to those obtained from the seismic class. This is because the former evaluation accounts for the common operating conditions of the structures. To compute F_{I}, Table 2 collects the cost factors assigned to the bridges of the sample stock based on their construction material, structural typology, and the selected inspection strategy. The values of the factors have been defined according to the Authors' experience in recent years in performing visual inspections of bridges and viaducts, as well as considering the bridge typologies included in the sample stock under examination. In particular, the assignment of the cost factors related to the construction materials and structural typologies took into account the most commonly observed defects and the number of structural components per span to be inspected. As an example, the highest value of the cost factor related to the construction materials has been assigned to steel bridges, since the inspection of this bridge typology usually involves checking a large number of structural elements and connection systems (welds and bolts) that may experience damage (Figure 6(a)). Conversely, the lowest value of the cost factor has been attributed to masonry bridges, since the inspection of this typology usually requires less effort. In these cases, defects/pathologies often develop in a limited number of structural components involving large portions of the structure, which usually facilitates the inspection activities (Figure 6(b)). The cost factors related to the structural typology have been assigned in a similar fashion, namely associating a greater value of the cost factor to those structural typologies for which a higher inspection effort is expected. For instance, a lower cost factor has been assigned to continuous box girder bridges (Figure 7(a)) compared to multi-span simply supported configurations (Figure 7(b)) since the number of structural components to be checked is usually considerably lower. Finally, the cost factors stemming from the inspection strategy have been attributed according to whether an external platform is required or the visual inspection can be performed from the ground level (Figure 8). Assuming the inspections are conducted by a qualified operator, a value equal to 0.015 has been considered for $\beta_{50\%}$, while the standard deviation has been set to $\sigma = 0.1\beta_{50\%}$ (i.e. a coefficient of variation of 10%). It follows that a value of $\beta_{\min}$ equal to 0.01 has been assumed for every bridge in the stock.

Table 1. Weighting factor assigned to every class of attention obtainable from the assessment of the structural-foundational and seismic risks.

Class of attention (risk level)	Structural-foundational attention class – w_{R}	Seismic attention class – w_{R}
High	1.2	0.8
Medium-high	1.0	0.6
Medium	0.8	0.4
Medium-low	0.6	0.2
Low	0.4	0.1

Table 2. Cost factors assigned to the bridges of the sample stock according to their construction material, structural typology, and inspection strategy.

Construction material	w_{CM}	Structural typology	w_{ST}	Inspection strategy	w_{IS}
Steel (Figure 6(a))	1.0	Simply supported truss beam (Figure 6(a))	1.0	Platform (Figure 8(b))	1.0
Reinforced concrete	0.6	Simply supported beam (Figure 7(a))	0.6	Ground level (Figure 8(a))	0.2
Post-tensioned/Prestressed concrete (Figure 7(b))	0.5	Continuous box beam (Figure 7(b))	0.4		
Masonry (Figure 6(b))	0.2	Arch (Figure 6(b))	0.2		

(a)

(b)

Figure 6. Examples of bridges built with different construction materials: (a) pictures from the visual inspection of a simply supported truss beam bridge; (b) photos taken during the visual inspection of masonry arch bridges.

(a)

(b)

Figure 7. Examples of bridges built with different structural typologies: (a) pictures from the visual inspection of a continuous box beam bridge; (b) photos taken during the visual inspection of a simply supported beam bridge.

(a) (b)

Figure 8. Examples of different strategies for performing visual inspections on bridges: (a) inspection carried out from the ground level; (b) inspection performed by means of the use of an external platform.

4. Results

This section illustrates the outcomes obtained by applying the proposed methodology to the considered case study. In light of the previously reported information, the analyses consisted of three consecutive steps. Namely, (i) preliminary definition of an inspection plan for the bridge stock in a context of limited information; (ii) sample analysis of the use of the information gain criterion; (iii) update and refinement of the obtained inspection plan on the basis of the outcomes from the information gain analysis.

4.1. Visual inspection priorities

Following the methodology previously outlined in Section 2, the inspection plan has been defined on the basis of the information available for the considered stock of bridges. Table B1 collects the class of attention determined for every bridge in the examined inventory for both the structural-foundational and seismic risk conditions together with the corresponding confidence levels expressed as the associated probability (in percentage). In general, the more information is available, the more reliable is the obtained risk evaluation. This is for instance the case of Bridges D, F, and G, which exhibit confidence levels in the assessments of 100% (number of performed MCSs for every asset: 1), as also shown in Figures 9(a)-(f). Note that 100% confidence level is possible when some discrete variables critically determining the attention class are known (random errors affecting such variables are not considered). A clear example of this aspect is the case of Bridge C, for which accurate risk evaluations, presented in Figures 9(g) and (h), are obtained even in the absence of knowledge about certain parameters whose informative contribution can be inferred to be low compared to that of the known features (number of performed MCSs: 270). On the other hand, despite the data-set available for Bridge R is rather complete, the risk evaluations obtained for that bridge appear quite uncertain (number of performed MCSs: 2700), as pointed out by Figures 9(i) and (j). Note for instance that the probability associated with the structural-foundational class of that bridge is only 27.41%, thus requiring additional insights to achieve a more reliable assessment of its attention class. This circumstance leads to the conclusion that the informative contribution of the set of data available for Bridge R is rather limited. It is worth stressing, however, the fact that the proposed methodology made it possible to carry out a preliminary evaluation of the attention classes even in the case of bridges characterised by limited information, as it is the particular case, among others, of Bridges B, M, and N (number of performed MCSs for every asset: 648000). Figure 10(a) depicts the maps rendered in QGIS to illustrate the risk conditions of every bridge in the sample stock after the preliminary assessment. In this figure, the larger the size of the marker, the higher the confidence level attributed to the risk evaluations.

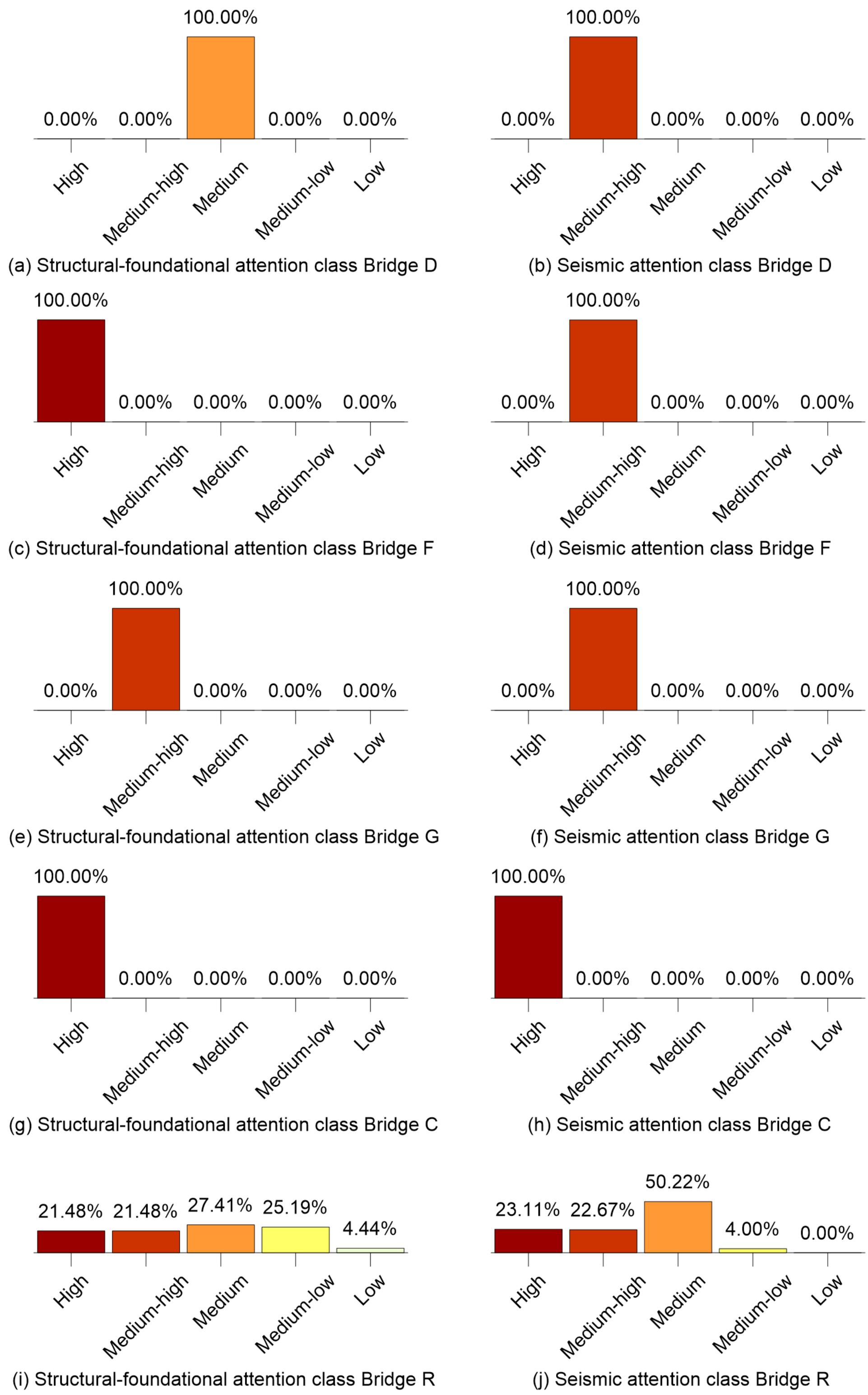
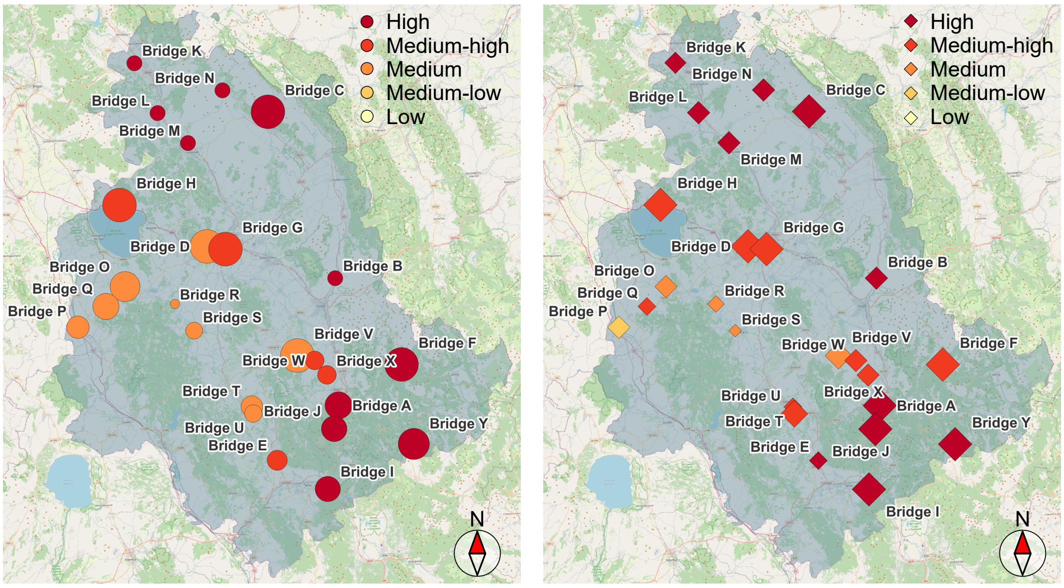


Figure 9. Examples of histograms obtained from the preliminary assessment of the structural-foundational and seismic risks of some of the bridges included in the sample stock: (a) structural-foundational attention class of Bridge D; (b) seismic attention class of Bridge D; (c) structural-foundational attention class of Bridge F; (d) seismic attention class of Bridge F; (e) structural-foundational attention class of Bridge G; (f) seismic attention class of Bridge G; (g) structural-foundational attention class of Bridge C; (h) seismic attention class of Bridge C; (i) structural-foundational attention class of Bridge R; (j) seismic attention class of Bridge R.



(a) (b)

Figure 10. Maps from QGIS illustrating the risk conditions of the bridge inventory after the preliminary assessment (the larger the marker in the maps, the higher the corresponding confidence level): (a) structural-foundational attention class; (b) seismic attention class.

Table 3 presents the F_{R}, F_{I}, IPS, and inspection priority order obtained for the bridges in the sample stock. A graphical illustration of the resulting inspection plan can be also visualized in QGIS, as shown in Figure 11. It is worth stressing that the simultaneous consideration of risk conditions and operating costs makes it possible to prioritise visual inspections among bridges classified under the same risk level or sharing similar structural features. To mention some examples, note that the inspection priorities of Bridges B and N exceed those for Bridges M and L, despite being characterised by similar risk conditions. Similarly, despite demanding similar inspection efforts, Bridges C, H, Q, and U have gained different inspection priorities according to their risk conditions.

Table 3. F_{R}, F_{I}, IPS, and inspection order obtained for the bridges comprised in the sample stock.

Label	F_{R}	F_{I}	IPS	Inspection order
Bridge B	0.961	0.082	1.879	1
Bridge N	0.961	0.082	1.879	2
Bridge K	0.966	0.136	1.830	3
Bridge S	0.629	0.009	1.620	4
Bridge M	0.961	0.409	1.552	5
Bridge R	0.541	0.003	1.538	6
Bridge L	0.961	0.818	1.143	7
Bridge C	1.000	0.012	1.988	8
Bridge J	0.973	0.008	1.965	9
Bridge Y	0.992	0.029	1.963	10
Bridge A	0.978	0.024	1.954	11
Bridge I	0.971	0.020	1.951	12
Bridge F	0.900	0.082	1.818	13
Bridge G	0.800	0.008	1.792	14
Bridge H	0.800	0.012	1.788	15
Bridge X	0.782	0.001	1.781	16
Bridge W	0.782	0.001	1.781	17
Bridge E	0.906	0.196	1.710	18
Bridge Q	0.719	0.012	1.707	19
Bridge T	0.709	0.008	1.701	20
Bridge U	0.679	0.012	1.667	21
Bridge D	0.700	0.039	1.661	22
Bridge O	0.629	0.006	1.623	23
Bridge V	0.622	0.001	1.621	24
Bridge P	0.500	0.006	1.494	25

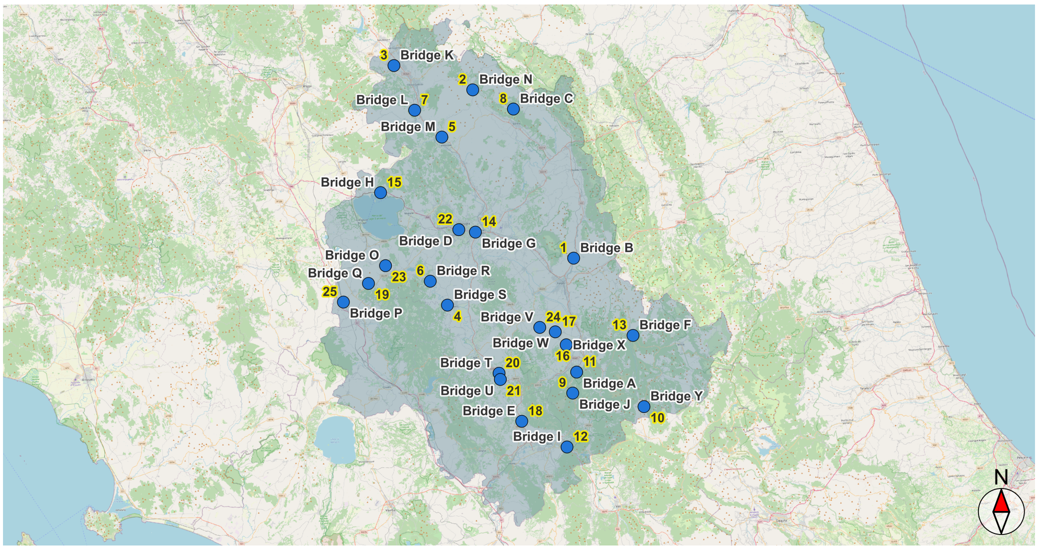


Figure 11. Map from QGIS illustrating the inspection plan determined for the bridge inventory.

Finally, Figure 12 shows the illustrative maps rendered in QGIS and obtained by spatially interpolating the attention class and inspection order attributed to every bridge included in the inventory. These maps offer a macro-level information tool useful for infrastructure managers to obtain preliminary estimates of the risk conditions and inspection priorities within the macro-area under their responsibility. As an example, Figures 12(a) and (b) intuitively show that in the northern, eastern, and south-eastern areas of the Umbria region, bridges are mostly characterised by a high structural-foundational and seismic attention class, although it is worth remembering that at the local level the risk of a certain bridge could be different. Likewise, Figure 12(c) highlights the existence of clusters of bridges with a similar inspection priority. This sort of analysis can be particularly useful for infrastructure managers and political agencies to strategically allocate human and economic resources to perform visual inspections. Note that a continuous map is purposely considered in this paper for its immediate visual interpretability, although it is obvious that bridge risks are spatial discrete variables.

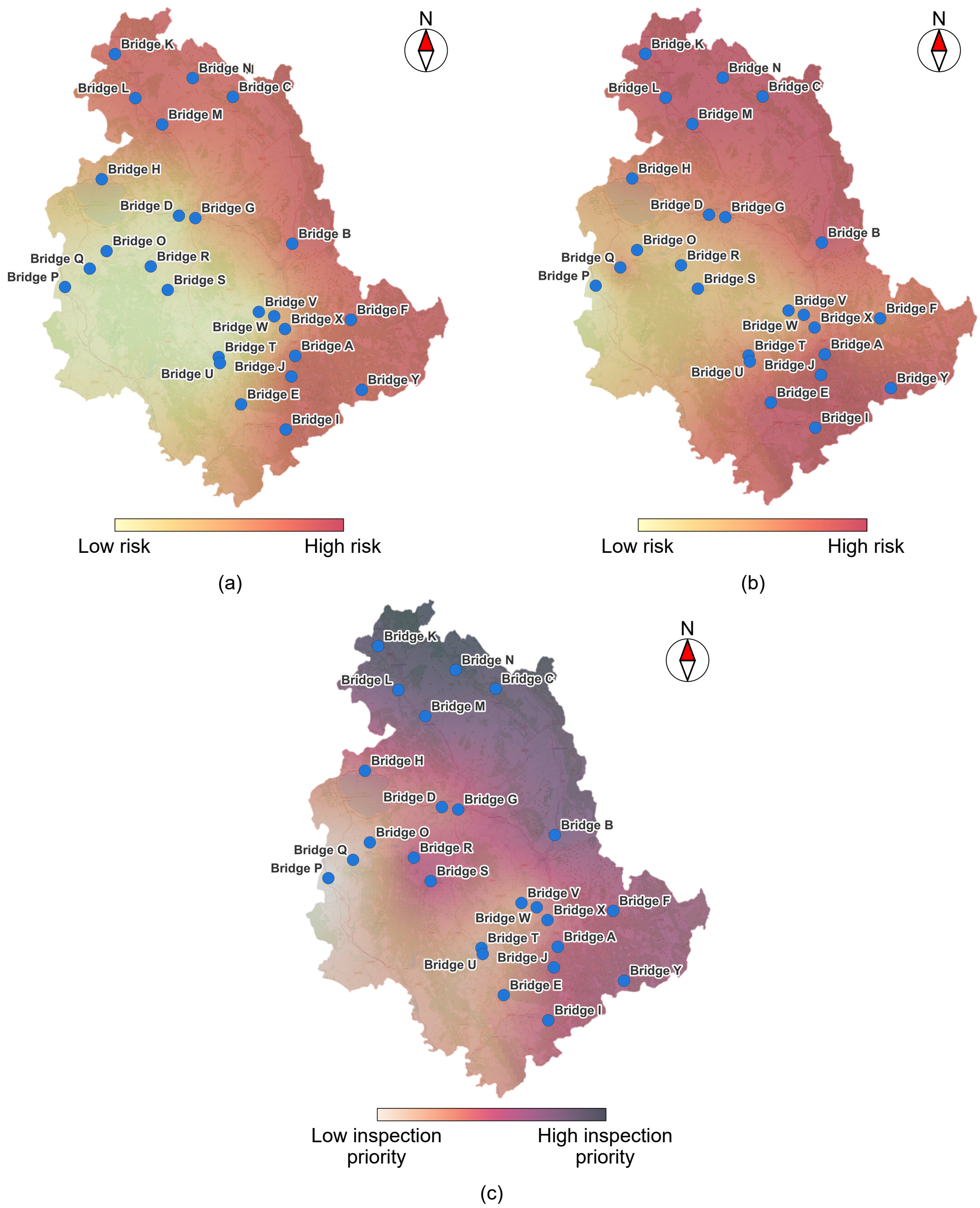


Figure 12. Illustrative maps showing the outcomes from Kriging interpolations: (a) structural-foundational attention class; (b) seismic attention class; (c) inspection plan.

4.2. Information gain analysis

4.2.1. Application to a single asset

To exemplify the use of the information gain analysis when applied to a single asset, Bridge B with limited available information has been further analysed. Tables 4 and 5 collect the results obtained by carrying out the analysis of the preliminary assessment of the structural-foundational and seismic attention classes of this bridge, respectively.

Both tables report in the first row the prior probability distribution of the respective risk classification obtained from the preliminary classification carried out in the previous section. Each subsequent row shows the posterior probability distributions obtained for the respective risk classification by introducing, one at a time, the unknown pieces of information (e.g. year of construction $\leq$ 1945, span length $>$ 25 m, medium defect level, and the others) in the risk assessment process. The value of the information gain computed for each investigated parameter is also reported in these tables, thus providing an intuitive quantification of the informative contribution that the knowledge on each parameter would add to the preliminary risk classification of Bridge B. A practical exemplification illustrating the computation of the information gain assuming the addition of details regarding the year of construction of Bridge B (y = year of construction $\leq$ 1945) to its risk classification is reported below:

$$D_{KL}\left[p\left(r \mid y, I\right) \parallel p\left(r \mid I\right)\right] = 42.89 \log\left(\frac{42.89}{45.26}\right) + 12.30 \log\left(\frac{12.30}{21.12}\right) + \\ + 32.96 \log\left(\frac{32.96}{27.42}\right) + 9.18 \log\left(\frac{9.18}{4.94}\right) + 2.67 \log\left(\frac{2.67}{1.26}\right) = 4.80. \tag{15}$$

The assessment of the information gain results in Tables 4 and 5 highlights that the defect level is the most influential parameter among the investigated factors. The information gain is particularly significant when the defect level assumes its limit values, namely when a high/low defect level is hypothesised in the risk evaluation process. In particular, risk assessments with no uncertainty (confidence level of 100%) are obtained when the defect level of Bridge B is assumed high – this circumstance corresponds to an information gain of approximately 79 in the case of the structural-foundational attention class and of about 39 in the context of the seismic risk assessment. On the other hand, the hypothesis of low defectiveness leads to a medium structural-foundational attention class associated with a confidence level of about 59% and an information gain of approximately 59. The same hypothesis results in a medium-high seismic attention class with a probability of about 54% and an information gain of around 42. Hence, these results evidence that an inspection confirming the defect level of Bridge B to be low would lead to a decrease of two levels with respect to the preliminary structural-foundational risk evaluation (from high to medium attention class), and of one level compared to the initial assessment of the seismic risk of Bridge B (from high to medium-high attention class). Furthermore, the obtained outcomes also indicate that the information contribution associated with the defectiveness of Bridge B slightly affects more the assessment of its structural-foundational attention class than that of its seismic attention class. In fact, given a certain defect level, a higher value of the information gain is generally obtained in the context of the structural-foundational attention class than in the seismic risk assessment, with the exception of the medium-high defect level for which the opposite applies. Other parameters that, albeit to a minimal extent compared to the defect level, influence the structural-foundational attention class of Bridge B are the year of construction (maximum information gain of about 6 if Bridge B would be built after 1985 without seismic criteria), the traffic load category (maximum information gain of approximately 12 if Bridge B was classified in traffic load category E), the average daily vehicle traffic (maximum information gain of about 4 if Bridge B was affected by high average vehicle traffic), and the importance of the crossed entity (maximum information gain of about 4 if Bridge B crossed a main road, an urban context or a river of significant importance). Similarly, the average daily vehicle traffic (maximum information gain of about 7 if Bridge B was affected by high average vehicle traffic) and the importance of the crossed entity (maximum information gain of about 7 if Bridge B crossed a main road, an urban context or a river of significant importance) are factors whose assumption also influences the determination of the seismic attention class of the considered asset to a modest extent. Overall, the results obtained from the information gain analysis point out that the preliminary risk assessment of Bridge B can be markedly refined through the determination of its structural defectiveness. Parameters with low informative contribution can be also adopted for this purpose, yet it might be necessary to combine several of them to achieve a satisfactory refinement of the preliminary risk classification. It is also worth emphasising how the information gain analysis can aid bridge managers in intuitively excluding a priori the retrieval of certain unknown parameters whose potential informative contribution to the risk evaluation process is negligible; these are those characterized by an information gain equal to zero.

Table 4. Information gain in the structural-foundational attention class of Bridge B.

	Probability distribution					
	High [%]	Medium-high [%]	Medium [%]	Medium-low [%]	Low [%]	Information Gain
Bridge B (prior probability distribution)	45.26	21.12	27.42	4.94	1.26	-
Year of construction $\leq$ 1945	42.89	12.30	32.96	9.18	2.67	4.80
1945 < Year of construction < 1980	36.22	24.78	31.74	5.78	1.48	1.68
Year of construction $\geq$ 1985 (lack of seismic criteria)	56.22	23.89	18.41	1.33	0.15	5.74
Year of construction $\geq$ 1985 (seismic criteria)	43.78	17.11	31.26	6.22	1.63	0.89
15 m $\leq$ span length < 25 m	45.26	21.12	27.42	4.94	1.26	0.00
Span length > 25 m	45.26	21.12	27.42	4.94	1.26	0.00
High defect level	100.00	0.00	0.00	0.00	0.00	**79.27**
Medium-high defect level	85.74	8.76	5.25	0.25	0.00	**37.65**
Medium defect level	28.71	43.83	26.23	1.23	0.00	**16.06**
Medium-low defect level	8.70	36.54	46.24	6.91	1.61	**32.56**
Low defect level	3.15	16.48	59.38	16.30	4.69	**59.02**
Traffic load category A	55.06	26.98	16.73	1.23	0.00	7.42
Traffic load category B	48.77	27.72	21.04	2.47	0.00	3.90
Traffic load category C	42.47	25.37	26.17	5.68	0.31	1.09
Traffic load category D	40.00	18.15	32.96	7.16	1.73	1.58
Traffic load category E	40.00	7.41	40.18	8.15	4.26	11.92
High average daily vehicle traffic	49.89	25.26	23.74	1.11	0.00	4.30
Medium average daily vehicle traffic	44.78	21.59	28.52	4.37	0.74	0.19
Low average daily vehicle traffic	41.11	16.52	30.00	9.33	3.04	3.30
High average daily commercial vehicle traffic	49.04	23.30	23.7	3.11	0.85	0.99
Medium average daily commercial vehicle traffic	45.26	21.89	26.78	5.04	1.03	0.04
Low average daily commercial vehicle traffic	41.48	18.18	31.78	6.67	1.89	1.12
High importance of the crossed entity	49.89	25.26	23.74	1.11	0.00	4.30
Medium importance of the crossed entity	44.78	21.59	28.52	4.37	0.74	0.19
Low importance of the crossed entity	41.11	16.52	30.00	9.33	3.04	3.30
Road alternatives	43.19	19.06	28.77	6.96	2.02	0.74
Lack of road alternatives	47.34	23.19	26.07	2.91	0.49	0.98
Seismic criteria	43.78	17.11	31.26	6.22	1.63	0.89
Lack of seismic criteria	45.56	21.93	26.65	4.68	1.18	0.04
Strategic road	45.26	21.12	27.42	4.94	1.26	0.00
Non-strategic road	45.26	21.12	27.42	4.94	1.26	0.00
Soil category A/B	45.26	21.12	27.42	4.94	1.26	0.00
Soil category C/D/E	45.26	21.12	27.42	4.94	1.26	0.00
Topographic category T1/T2/T3	45.26	21.12	27.42	4.94	1.26	0.00
Topographic category T4	45.26	21.12	27.42	4.94	1.26	0.00

Table 5. Information gain in the seismic attention class of Bridge B.

	Probability distribution					
	High [%]	Medium-high [%]	Medium [%]	Medium-low [%]	Low [%]	Information Gain
Bridge B (prior probability distribution)	67.28	28.27	4.45	0.00	0.00	0.00
Year of construction $\leq$ 1945	67.28	28.28	4.44	0.00	0.00	0.00
1945 < Year of construction < 1980	67.28	28.28	4.44	0.00	0.00	0.00
Year of construction $\geq$ 1985 (lack of seismic criteria)	67.28	28.28	4.44	0.00	0.00	0.00
Year of construction $\geq$ 1985 (seismic criteria)	67.28	28.28	4.44	0.00	0.00	0.00
15 m $\leq$ span length < 25 m	67.28	28.28	4.44	0.00	0.00	0.00
Span length > 25 m	67.28	28.28	4.44	0.00	0.00	0.00
High defect level	100.00	0.00	0.00	0.00	0.00	**39.63**
Medium-high defect level	100.00	0.00	0.00	0.00	0.00	**39.63**
Medium defect level	55.56	43.61	0.83	0.00	0.00	**6.88**
Medium-low defect level	55.56	43.61	0.83	0.00	0.00	**6.88**
Low defect level	25.28	54.17	20.55	0.00	0.00	**41.92**
Traffic load category A	67.28	28.28	4.44	0.00	0.00	0.00
Traffic load category B	67.28	28.28	4.44	0.00	0.00	0.00
Traffic load category C	67.28	28.28	4.44	0.00	0.00	0.00
Traffic load category D	67.28	28.28	4.44	0.00	0.00	0.00
Traffic load category E	53.35	32.36	14.29	0.00	0.00	8.67
High average daily vehicle traffic	83.00	16.50	0.50	0.00	0.00	7.45
Medium average daily vehicle traffic	67.33	29.50	3.17	0.00	0.00	0.23
Low average daily vehicle traffic	51.50	38.83	9.67	0.00	0.00	6.06
High average daily commercial vehicle traffic	67.28	28.28	4.44	0.00	0.00	0.00
Medium average daily commercial vehicle traffic	67.28	28.28	4.44	0.00	0.00	0.00
Low average daily commercial vehicle traffic	67.28	28.28	4.44	0.00	0.00	0.00
High importance of the crossed entity	83.00	16.50	0.50	0.00	0.00	7.45
Medium importance of the crossed entity	67.33	29.50	3.17	0.00	0.00	0.23
Low importance of the crossed entity	51.50	38.83	9.67	0.00	0.00	6.06
Road alternatives	59.78	33.44	6.78	0.00	0.00	1.41
Lack of road alternatives	74.78	23.11	2.11	0.00	0.00	1.67
Seismic criteria	67.28	28.28	4.44	0.00	0.00	0.00
Lack of seismic criteria	67.28	28.28	4.44	0.00	0.00	0.00
Strategic road	74.78	23.11	2.11	0.00	0.00	1.67
Non-strategic road	59.78	33.44	6.78	0.00	0.00	1.41
Soil category A/B	59.03	34.03	6.94	0.00	0.00	1.67
Soil category C/D/E	72.78	24.44	2.78	0.00	0.00	0.85
Topographic category T1/T2/T3	65.44	29.56	5.00	0.00	0.00	0.09
Topographic category T4	72.78	24.44	2.78	0.00	0.00	0.85

4.2.2. Application to multiple assets

In light of the results obtained for Bridge B, the information gain analysis has been then applied to the remaining bridges of the stock whose defectiveness has not yet been assessed according to the Italian Guidelines (Bridges K, L, M, N, R, and S), by focusing the attention on the informative contribution of the defect level. Tables 6 and 7 collect the obtained results for structural-foundational and seismic attention classes, respectively. The assessment of the obtained values of the information gain remarks the high informative contribution possessed by the defect level in both the evaluated risk conditions. As in the case of Bridge B, risk assessments with a confidence level of 100% are obtained under the assumption that the defect level of the considered assets is high. In this circumstance, however, it is important to note that the informative contribution associated with the high defect level tends to be quite different among the cases under analysis. For instance, considering the structural-foundational attention class, the assumption of a high defect level for Bridge K results in an information gain of about 79, while the same hypothesis leads to an information gain of around 161 in the case of Bridge S. A similar consideration also applies to the other defect levels. More in detail, looking anew at the structural-foundational attention class, equal values of the information gain have been determined for Bridges K, L, M, and N; this is because these assets share similar structural and non-structural features influencing the risk condition under examination (these assets belong to the simply supported RC bridge typology). The information gain analysis has provided equal outcomes for Bridges L, M, and N even in the case of the seismic attention class, yet slightly different results have been obtained for Bridge K. This is because the former assets are multi-span bridges, whereas Bridge K has a single span. Similar observations can also be made while evaluating the information gain determined for Bridges R and S; these two bridges, in particular, differ from the others in terms of the structural typology and the construction material (bridges R and S are masonry arch bridges), while they differ from each other in terms of pieces of information like the period of construction (Bridge R is older than Bridge S) and the number of spans (Bridge R is a single span bridge while Bridge S is a multi-span bridge). Overall, the obtained results suggest that performing a visual inspection on a certain bridge, and thus determining its level of defectiveness, can provide a different informative contribution to its risk classifications depending on the typology and the known structural and non-structural features of the asset under investigation.

Table 6. Information gain of the defect levels in the structural-foundational attention class of Bridges K, L, M, N, R, and S.

	Probability distribution					
	High [%]	Medium-high [%]	Medium [%]	Medium-low [%]	Low [%]	Information Gain
Bridge K/L/M/N (prior probability distribution)	45.26	21.12	27.42	4.94	1.26	-
High defect level	100.00	0.00	0.00	0.00	0.00	79.27
Medium-high defect level	85.74	8.76	5.25	0.25	0.00	37.65
Medium defect level	28.71	43.83	26.23	1.23	0.00	16.06
Medium-low defect level	8.70	36.54	46.24	6.91	1.61	32.56
Low defect level	3.15	16.48	59.38	16.30	4.69	59.02
Bridge R (prior probability distribution)	21.48	21.48	27.41	25.19	4.44	-
High defect level	100.00	0.00	0.00	0.00	0.00	153.80
Medium-high defect level	7.41	81.48	11.11	0.00	0.00	90.71
Medium defect level	0.00	25.93	74.07	0.00	0.00	78.52
Medium-low defect level	0.00	0.00	25.93	62.96	11.11	66.43
Low defect level	0.00	0.00	25.93	62.96	11.11	66.43
Bridge S (prior probability distribution)	20.00	10.37	50.37	17.04	2.22	-
High defect level	100.00	0.00	0.00	0.00	0.00	160.94
Medium-high defect level	0.00	25.93	74.07	0.00	0.00	52.33
Medium defect level	0.00	25.93	74.07	0.00	0.00	52.33
Medium-low defect level	0.00	0.00	77.78	22.22	0.00	39.69
Low defect level	0.00	0.00	25.93	62.96	11.11	82.96

Table 7. Information gain of the defect levels in the seismic attention class of Bridges K, L, M, N, R, and S.

	Probability distribution					
	High [%]	Medium-high [%]	Medium [%]	Medium-low [%]	Low [%]	Information Gain
Bridge K (prior probability distribution)	63.94	29.12	6.80	0.14	0.00	-
High defect level	100.00	0.00	0.00	0.00	0.00	44.72
Medium-high defect level	92.59	7.27	0.14	0.00	0.00	23.65
Medium defect level	55.56	43.61	0.83	0.00	0.00	8.06
Medium-low defect level	50.51	45.37	4.12	0.00	0.00	6.14
Low defect level	21.07	49.35	28.89	0.69	0.00	45.54
Bridge L/M/N (prior probability distribution)	67.28	28.27	4.45	0.00	0.00	-
High defect level	100.00	0.00	0.00	0.00	0.00	39.63
Medium-high defect level	100.00	0.00	0.00	0.00	0.00	39.63
Medium defect level	55.56	43.61	0.83	0.00	0.00	6.88
Medium-low defect level	55.56	43.61	0.83	0.00	0.00	6.88
Low defect level	25.28	54.17	20.55	0.00	0.00	41.92
Bridge R (prior probability distribution)	23.11	22.67	50.22	4.00	0.00	-
High defect level	100.00	0.00	0.00	0.00	0.00	146.49
Medium-high defect level	7.78	48.89	43.33	0.00	0.00	22.71
Medium defect level	7.78	48.89	43.33	0.00	0.00	22.71
Medium-low defect level	0.00	7.78	82.22	10.00	0.00	41.38
Low defect level	0.00	7.78	82.22	10.00	0.00	41.38
Bridge S (prior probability distribution)	24.44	32.78	37.78	5.00	0.00	-
High defect level	100.00	0.00	0.00	0.00	0.00	140.89
Medium-high defect level	16.67	83.33	0.00	0.00	0.00	71.37
Medium defect level	2.78	38.89	58.33	0.00	0.00	25.94
Medium-low defect level	2.78	38.89	58.33	0.00	0.00	25.94
Low defect level	0.00	2.78	72.22	25.00	0.00	80.17

4.3. Updating of the inspection priorities

Results obtained from the information gain analysis carried out in Section 4.2 are exploited to update and refine the preliminary inspection plan determined in Section 4.1.

The updating of the inspection plan consists of revising the inspection priorities following the addition of new pieces of information in the risk assessment process. For instance, let us assume that Bridge B has recently undergone maintenance works to repair defects detected in past inspection activities. In this circumstance, a hypothetical management authority could make assumptions about the defectiveness of Bridge B, based on the support of this evidence, to substantially revise the preliminary risk classifications of the asset, and thus its inspection priority over the remaining structures of the stock. Reasonably assuming a low defect level for Bridge B, hence considering this new piece of information in its data-set, a medium structural-foundational attention class (initially this attention class was high), with a confidence level of about 59%, and a medium-high seismic attention class (even this attention class was initially evaluated as high), associated with a confidence level of about 54%, are attributed to the asset. In light of that, the F_{R} determined for Bridge B decreases from a value of 0.961 to 0.705 as reported in Table 8, which also shows the updated inspection plan. The knowledge of the defect level of Bridge B also leads to a modification of the value of the F_{I} from 0.082 to 0.018. This is because Bridge B is now included in the subset of structures for which the defect level has been already evaluated according to the Italian Guidelines (from Bridge C to Bridge P in Table 8), hence the operating costs for its visual inspection has been revised with respect to the features of this group of bridges according to Equation (6). Overall, the inspection order of Bridge B decreases by nineteen positions compared to the preliminary inspection plan. Modifications made in the inspection plan also reflect in the preliminary assessment of the bridge inventory at a regional scale. Figure 13 reports the illustrative maps obtained by spatially interpolating the attention classes and inspection order determined for the bridges in the stock under the assumption of knowing the defect level of Bridge B. Maps of the structural-foundational and seismic attention class, reported in Figures 13(a) and (b) respectively, show marked modifications in the risk conditions of the stock compared to Figures 12(a) and (b). Particularly, the updated versions of these illustrative maps point out that the eastern area of the Umbria region, where Bridge B is located, is reclassified to low/moderate risk conditions. Similarly, the map interpolating the inspection priority order, shown in Figure 13(c), intuitively highlights the changes introduced in the updated inspection plan compared to Figure 12(c). It is worth remembering that, at the level of a single bridge, risk conditions and inspection priorities may differ from those shown on the macro-level illustrative maps.

Table 8. F_{R}, F_{I}, IPS, and inspection order determined for the bridges in the sample stock once gained information on the defect level of Bridge B.

Label	F_{R}	F_{I}	IPS	Inspection order
Bridge N	0.961	0.082	1.879	1
Bridge K	0.966	0.136	1.830	2
Bridge S	0.629	0.009	1.620	3
Bridge M	0.961	0.409	1.552	4
Bridge R	0.541	0.003	1.538	5
Bridge L	0.961	0.818	1.143	6
Bridge C	1.000	0.012	1.988	7
Bridge J	0.973	0.008	1.965	8
Bridge Y	0.992	0.029	1.963	9
Bridge A	0.978	0.024	1.954	10
Bridge I	0.971	0.020	1.951	11
Bridge F	0.900	0.082	1.818	12
Bridge G	0.800	0.008	1.792	13
Bridge H	0.800	0.012	1.788	14
Bridge X	0.782	0.001	1.781	15
Bridge W	0.782	0.001	1.781	16
Bridge E	0.906	0.196	1.710	17
Bridge Q	0.719	0.012	1.707	18
Bridge T	0.709	0.008	1.701	19
Bridge B	**0.705**	**0.018**	**1.687**	**20**
Bridge U	0.679	0.012	1.667	21
Bridge D	0.700	0.039	1.661	22
Bridge O	0.629	0.006	1.623	23
Bridge V	0.622	0.001	1.621	24
Bridge P	0.500	0.006	1.494	25

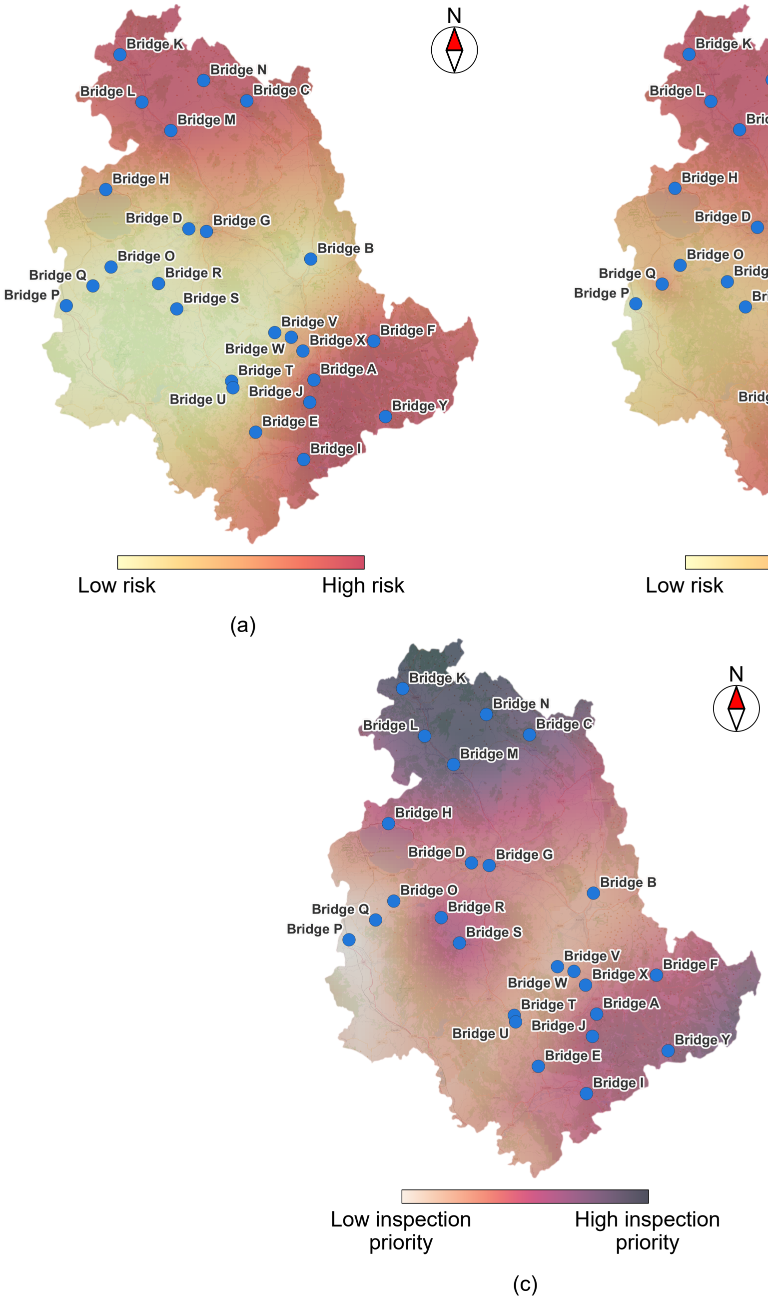
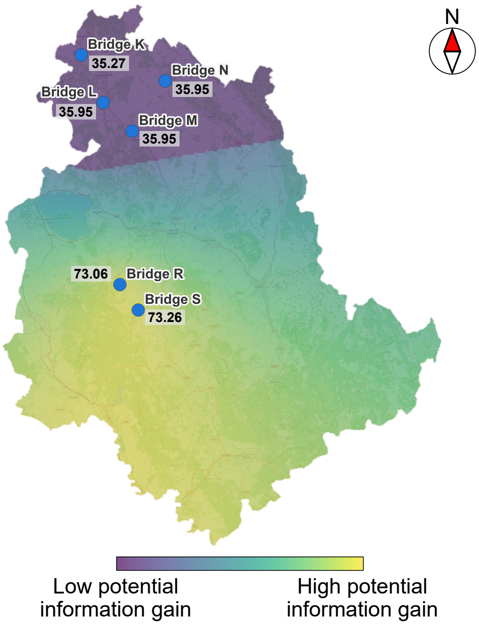


Figure 13. Illustrative maps showing the outcomes from Kriging interpolations under the assumption of knowing the defect level of Bridge B: (a) structural-foundational attention class; (b) seismic attention class; (c) inspection plan.

The potential amount of information that can be gained by inspecting one asset rather than another has been considered to refine the updated inspection plan. The analysis has been carried out on the subset of bridges whose structural defectiveness has not yet been assessed according to the Italian Guidelines, i.e. Bridges K, L, M, N, R, and S. Table 9 reports the potential information gain of the visual inspection in the structural-foundational and seismic attention classes of the considered subset of bridges. The highest values of this metric have been obtained for Bridges R and S; specifically, their inspection has a potential information gain of about 91 and 77, respectively, in the case of the structural-foundational attention class and of around 55 and 69, respectively, for the seismic attention class. The inspection of the other assets has a potential information gain of around 45 in the case of the structural-foundational attention class, hence of about 26/27 considering the seismic attention class. The obtained results thus indicate that the visual inspection of Bridges R and S will potentially make a more significant informative contribution to the refinement of the preliminary risk classification of the stock than the inspection of Bridges K, L, M, and N. Accordingly, the management authority can decide to prioritise the visual inspection of Bridges R and S over the other assets. In this case, such a decision is also supported by the fact that the inspection costs computed for Bridges R and S are lower than those of Bridges K, L, M, and N, as indicated by the respective value of F_{I} collected in Table 8. The potential information gain computed for the structural-foundational and seismic attention classes can be further averaged to obtain a synthetic metric to rate bridges to be inspected and thus to facilitate the refinement of the inspection plan. In this view, Figure 14(a) intuitively points out the inspection priorities within the considered subset of bridges at a regional scale based on the outcomes from the applied information theory (a high potential average information gain corresponds to a high inspection priority), while Figure 14(b) shows the refined inspection plan.

Table 9. Potential information gain of the visual inspection in the structural-foundational and seismic attention classes of Bridges K, L, M, N, R, and S.

Label	Potential Information Gain (structural-foundational attention class)	Potential Information Gain (seismic attention class)	Potential average Information Gain
Bridge K	44.91	25.62	35.27
Bridge L	44.91	26.99	35.95
Bridge M	44.91	26.99	35.95
Bridge N	44.91	26.99	35.95
Bridge R	91.18	54.93	73.06
Bridge S	77.65	68.86	73.26



(a)

Label	Potential average Information Gain	*IPS*	Inspection order
Bridge S	73.26	1.620	1
Bridge R	73.06	1.538	2
Bridge N	35.95	1.879	3
Bridge M	35.95	1.552	4
Bridge L	35.95	1.143	5
Bridge K	35.27	1.830	6

(b)

Figure 14. Refinement of the inspection plan through the information gain analysis: (a) Illustrative map obtained through the Kriging interpolation of the potential average information gain; (b) refined inspection plan.

5. Conclusions

Visual inspections are widely used by bridge owners and managers to obtain a preliminary screening of superficial defects and disruptions affecting the structures under their supervision. The outcomes of these inspection activities assume also a role of the utmost importance in the estimation of the vulnerability of the assets in risk assessment procedures. Due to their recurrence over time and the large number of bridges that are typically involved in BMSs, visual inspections are usually resource-intensive operations for management authorities. Consequently, the planning of inspection activities cannot be limited to inputs from risk assessments (bridges with a higher risk level have priority for inspection), as it is often prescribed in standards for bridge risk assessment and management, but should also take operating costs into account. In addition, in common practice, bridge owners often find it difficult to complete risk assessments due to a lack of data, a circumstance that can lead to delays in the definition of the inspection plans as well as to the incorrect prioritisation of the inspection activities.

To address these challenges, the paper has proposed a new methodology to prioritise visual inspections in bridge inventories based on the assessment of risk conditions and operating costs in the context of limited information. The prioritisation algorithm proposed in this work has been conceived to be implemented in GIS frameworks to assist management authorities in the systematic collection of data and the intuitive interpretation of the obtained results, providing risk maps and inspection plans. The proposed methodology prioritises visual inspections within a bridge inventory through the computation of the IPS, that is a scalar index determined for every bridge in the examined stock, whose value depends on the contributions of the F_{R} and F_{I}. Term F_{R} accounts for risk conditions of bridges and viaducts and consists of calculating the weighted average of the preliminary risk levels attributed to a bridge for all the risk conditions for which it has been assessed. The methodology evaluates risk conditions according to the provisions of the adopted standard by the bridge management authority. Specifically, to circumvent the potential lack of data, a MCS approach is used to estimate the risk level and its corresponding confidence level to be attributed to every bridge in the inventory. Similarly, F_{I} encapsulates the operating costs of visual inspections through different terms accounting for meaningful structural features of the bridge to be inspected and the selected inspection strategy. Both F_{R} and F_{I} have been conceived to include in their definition specific weighting coefficients for the fusion of risk and operating cost factors. From the information theory, the information gain criterion is implemented in the proposed methodology to mitigate uncertainties affecting the preliminary risk evaluations, hence to critically update and revise priorities defined in the inspection plan. Lastly, the OK interpolator is considered in the approach for the definition of illustrative maps providing macro-level informative contributions for the management of bridge inventories at a regional scale.

For demonstration purposes, the proposed methodology for bridge inspection prioritisation has been implemented in a GIS software and applied to a simulated data-set from a bridge network composed of twenty-five bridges with different structural features. Limited information has been assumed to be available for some of the structures comprised in the examined stock, while the Italian Guidelines for risk classification and management, safety assessment, and monitoring of existing bridges have been adopted to evaluate the risk conditions of the inventory. Values of the weighting and cost factors contained in the IPS metric have been suggested on the basis of the Authors' experience in bridge inspections. The proposed application case study has exemplified the definition of the inspection priorities based on the information initially available for the considered bridge inventory, as well as the update and revision of the preliminary inspection plan through the application of the information theory. The obtained results have highlighted (i) the benefits of simultaneously considering bridge risk conditions and inspection costs when defining the inspection plan, (ii) the effectiveness of the proposed approach for carrying out risk evaluations in the context of limited information, (iii) the use of the information gain as a metric to optimize the retrieval of missing information in the risk assessments and, consequently, to critically revise the inspection priorities, and, finally, (iv) the employment of the Kriging interpolator for the definition of illustrative maps expressing clear informative contents at a regional scale.

Overall, the proposed methodology for bridge inspection prioritisation results in a simple yet effective tool for bridge owners and managers, with solid theoretical foundations and characterised by high interoperability in GIS environments. The possibility of determining inspection priorities under the simultaneous consideration of multiple risk conditions, as well as by the possibility of setting weighting and cost factors included in the IPS based on the needs and attitude of each management authority, also highlight the broad scalability of the proposed procedure. Although the application case study provided a first demonstration of the effectiveness of the proposed prioritisation approach, its application to real bridge inventories and diverse real-world scenarios could provide significant insights to improve the methodology and reduce the uncertainty related to assumptions. In this regard, future studies may concern the implementation of realistic probability distributions for the unknown terms in risk assessments, a more accurate evaluation of the cost factor expressing the inspection quality through the consideration of further human factors, the introduction of additional prioritisation parameters such as the detour length of each bridge, as well as further implementations of information theory and decision-making concepts. It is therefore highly desirable that more extensive bridge inspection databases will be available in the future to the scientific community to further test and possibly improve the proposed inspection prioritisation method.

Disclosure statement

The Authors declare no conflict of interest.

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6. Appendices

Appendix A. Simulated bridge stock

Table A1. Known features of the sample stock for the assessment of the structural-foundational attention class in accordance with the Italian Guidelines (please note that for some parameters the range of variability is provided by the Italian Guidelines).

	Hazard		Vulnerability						Exposure			
Label	Traffic load category	Average daily commercial vehicle traffic	Construction material	Structural typology	Year of construction	Design code	Maximum length of the spans [m]	Defect level	Average daily vehicle traffic	Average length of the spans [m]	Road alternatives	Importance of the crossed entity
Bridge A	A		Post-tensioned/Prestressed concrete	Simply supp. beam			30	Medium-High		30	Yes	Medium
Bridge B			Reinforced concrete	Simply supp. beam								
Bridge C	E		Reinforced concrete	Simply supp. beam			25	High		25	Yes	Low
Bridge D	A	800	Post-tensioned/Prestressed concrete	Simply supp. beam	1945-1980	B	22	Medium	10000	22	Yes	High
Bridge E	A		Post-tensioned/Prestressed concrete	Simply supp. beam	1945-1980 ≥1985			Medium-Low			Yes	Medium
Bridge F	A	500	Steel	Simply supp. truss beam	≥1985	B	40	Medium-High	5000	40	Yes	Medium
Bridge G	A	800	Post-tensioned/Prestressed concrete	Continuous box beam	1945-1980	B	35	Medium	10000	35	Yes	High
Bridge H	A	800	Post-tensioned/Prestressed concrete	Simply supp. beam	1945-1980	B	35	Medium	10000	35	Yes	Medium
Bridge I	A	500	Post-tensioned/Prestressed concrete	Simply supp. beam	1945-1980 ≥1985		30	Medium-High	5000	30	Yes	High
Bridge J	A		Post-tensioned/Prestressed concrete	Simply supp. beam	1945-1980 ≥1985		30	Medium-High		30	Yes	Low
Bridge K			Reinforced concrete	Simply supp. beam			35			35		
Bridge L			Reinforced concrete	Simply supp. beam			35			35		
Bridge M			Reinforced concrete	Simply supp. beam								
Bridge N			Reinforced concrete	Simply supp. beam								
Bridge O	B		Reinforced concrete	Simply supp. beam	≥1985	B	25	Low		25	Yes	Low
Bridge P	A		Reinforced concrete	Simply supp. beam	≥1985	C	22	Low		22	Yes	Low
Bridge Q	A		Reinforced concrete	Simply supp. beam	≥1985	B	25	Low		25	Yes	Low
Bridge R	A		Masonry	Arch	≤1945	A	10			10	Yes	
Bridge S	A		Masonry	Arch	1945-1980	B	15			15	Yes	
Bridge T	A		Post-tensioned/Prestressed concrete	Continuous box beam	1945-1980 ≥1985			Medium-Low			Yes	Low
Bridge U	A		Post-tensioned/Prestressed concrete	Simply supp. beam	1945-1980 ≥1985			Medium-Low			Yes	Low
Bridge V	A		Masonry	Arch	≤1945	A	10	Medium		10	Yes	Low
Bridge W	A		Masonry	Arch	1945-1980	B	10	Medium		10	Yes	High
Bridge X	A		Masonry	Arch	≤1945	A	15	Medium		15	Yes	High
Bridge Y	A		Reinforced concrete	Simply supp. beam				Medium-High			Yes	High

Table A2. Additional known features of the sample stock for the assessment of the seismic attention class in accordance with the Italian Guidelines and strategies selected to perform visual inspections (please note that for some parameters the range of variability is provided by the Italian Guidelines).

Label	Hazard			Vulnerability			Exposure	Inspection strategy
	Peak ground acceleration	Topographic category	Soil category	Static scheme	Seismic Criteria	Number of spans	Strategic road	
Bridge A	0.22	T1		Isostatic		6	Yes	Ground
Bridge B	0.24			Isostatic		3		Ground
Bridge C	0.22	T1		Isostatic		2	Yes	Ground
Bridge D	0.18	T1	B	Isostatic	No	10	Yes	Ground
Bridge E	0.16	T1		Isostatic	No	10	Yes	Platform
Bridge F	0.25	T2	A	Isostatic	No	1	Yes	Platform
Bridge G	0.20	T1	B	Iperstatic	No	3	Yes	Ground
Bridge H	0.16	T1	C	Isostatic	No	3	Yes	Ground
Bridge I	0.17	T1		Isostatic	No	5	Yes	Ground
Bridge J	0.20	T1		Isostatic	No	2	Yes	Ground
Bridge K	0.22			Isostatic		1		Platform
Bridge L	0.22			Isostatic		6		Platform
Bridge M	0.22			Isostatic		3		Platform
Bridge N	0.23			Isostatic		3		Ground
Bridge O	0.15	T1	A	Isostatic	No	1	Yes	Ground
Bridge P	0.14	T1	A	Isostatic	Yes	1	Yes	Ground
Bridge Q	0.15	T1		Isostatic	No	2	Yes	Ground
Bridge R	0.16			Iperstatic	No	1	Yes	Ground
Bridge S	0.16		B	Iperstatic	No	3	Yes	Ground
Bridge T	0.16	T1		Iperstatic		3	Yes	Ground
Bridge U	0.16	T1		Isostatic		3	Yes	Ground
Bridge V	0.20	T1		Iperstatic	No	1	Yes	Ground
Bridge W	0.22	T1		Iperstatic	No	2	Yes	Ground
Bridge X	0.22	T1		Iperstatic	No	1	Yes	Ground
Bridge Y	0.25	T1		Isostatic		1	Yes	Platform

Appendix B. Visual inspection priorities

Table B1. Attention classes with the corresponding confidence levels obtained from the preliminary assessment of the structural-foundational and seismic risks of the bridges included in the sample stock.

Label	Structural-foundational attention class (risk level)	Confidence level [%]	Seismic attention class (risk level)	Confidence level [%]
Bridge A	High	80.56	High	100.00
Bridge B	High	45.26	High	67.28
Bridge C	High	100.00	High	100.00
Bridge D	Medium	100.00	Medium-High	100.00
Bridge E	Medium-High	59.72	High	53.33
Bridge F	High	100.00	Medium-High	100.00
Bridge G	Medium-High	100.00	Medium-High	100.00
Bridge H	Medium-High	100.00	Medium-High	100.00
Bridge I	High	75.00	High	100.00
Bridge J	High	76.00	High	100.00
Bridge K	High	45.26	High	63.94
Bridge L	High	45.26	High	67.28
Bridge M	High	45.26	High	67.28
Bridge N	High	45.26	High	67.28
Bridge O	Medium	88.89	Medium	66.67
Bridge P	Medium	66.67	Medium-Low	66.67
Bridge Q	Medium	77.78	Medium-High	53.33
Bridge R	Medium	27.41	Medium	50.22
Bridge S	Medium	50.37	Medium	37.78
Bridge T	Medium	64.44	Medium-High	53.33
Bridge U	Medium	52.11	Medium-High	80.00
Bridge V	Medium	100.00	Medium	80.00
Bridge W	Medium-High	55.56	Medium-High	66.67
Bridge X	Medium-High	55.56	Medium-High	66.67
Bridge Y	High	92.59	High	100.00