Abstract (150 – 200 words)

Flood-induced scour is the principal cause of bridge failure worldwide. Nevertheless, bridge scour risk assessment is still based on visual inspections, which may be affected by human errors and cannot be performed during flood peaks. This problem, together with the simplifications in scour estimation, might cause misclassification of the bridge scour risk, unnecessary bridge closures or recourse to avoidable scour mitigation measures. Structural health monitoring systems allow overcoming these issues, providing bridge managers with more accurate information about scour, thus supporting them in taking optimal management decisions.
This paper illustrates the development of an SHM- and event-based classification system for bridge scour management, which extends and complements current risk rating procedures by incorporating the various sources of uncertainty characterising the scour estimation, and information from different sensors. The proposed system is based on a probabilistic framework for scour risk estimation and can be used to provide transport agencies with a real-time scour risk classification of bridges under a heavy flood event. The system is applied to a bridge network located in South-West Scotland under a heavy flood scenario and information from heterogeneous sources are considered for updating the knowledge of scour. It is shown that integrating scour monitoring data leads to an overall uncertainty reduction that is reflected in a more accurate scour risk classification, thus helping transport agencies in prioritising bridge inspections and risk mitigation actions.

Keywords chosen from ICE Publishing list
Bridges; sensors; risk & probability analysis.

Introduction

Bridge scour is the erosion and removal of material from the bed of streams around bridge foundations due to the action of fast flowing water. The scour process is classified according to the circumstances and structures that have caused it, and in general the following types of scour need to be considered at a bridge site: (i) degradation scour, (ii) constriction scour and (iii) local scour.

In the United Kingdom, according to van Leeuwen and Lamb (2014), scour has caused 138 bridge collapses in 1846-2013. In the United States, it has been recognised as the number one cause of bridge failure with an average annual rate of 22 failures or bridges being closed due to a partial collapse (Briaud et al., 2007). A review of bridge collapses in the US in the 1990s carried out by Wardhana and Hadipriono (2003) has shown that the combined figure of 266 flood/scour-related cases constitutes the most dominant bridge failure cause (53% of the total cases of failures). Furthermore, the UK Climate Change Risk Assessment has identified scour bridge failures as one of the principal climate change risks for the transport sector (Thornes et al., 2012).

Current approaches for bridge scour risk management in the UK rely on a classification of bridges based on estimates of their scour risk, which is used by transport agencies for prioritising and planning inspections and scour risk mitigation measures. The risk assessment is based on an essentially deterministic approach, with a prefixed flood scenario (e.g., according to a standard used in the UK, the scour depth must be assessed by considering a flood flow corresponding to a return period of 200 years) and disregarding the various uncertainties that may characterise the problem (Tubaldi et al., 2017, Pizarro and Tubaldi, 2019, Pizarro et al. 2020, Maroni et al., 2020a). Visual inspections play a major role in risk assessments, also during extreme events. However, they may provide unreliable estimates of scour and of its effects (Megaw, 1979), also considering the difficulties in visually monitoring the riverbed erosion around foundations during an extreme flood event. In fact, no direct or indirect measure of the actual scour depth enters the scour risk assessment until water levels have receded so that inspectors can safely carry out checks.

Hence, current scour risk management approaches could be improved (i) by adding a more explicit consideration of the various sources of uncertainty that affect the problem, thus enabling the shift from a deterministic to a probabilistic evaluation of the scour risk, and (ii) by integrating the quasi-real-time observations from different types of sensors in the risk assessment, allowing the reduction of the uncertainty in the scour risk estimates, and thus helping bridge operators in taking the optimal decisions concerning bridge scour risk management.

Structural health monitoring (SHM) sensors can significantly help to support risk mitigation strategies and decision-making processes under flood events (Farrar and Worden, 2007), by allowing measuring more precisely the extent of scour at bridge foundations. However, alongside the development of SHM scour systems, there is a need for techniques to handle the data obtained from them and provide bridge owners and managers with useful information for optimal management of bridge scour.

In this paper, a monitoring-based classification system is developed for road bridge scour management during a flood event, which extends and complements current scour risk rating procedures of UK transport agencies. The proposed system is based on a more fair and accurate bridge assessment of the scour risk that reflects the uncertainties characterising the problem and allows the integration of observation from different sources of information (e.g., gauging stations and scour probes) in the decision-making process. The proposed classification system can be used to develop a SHM-based decision support system (Cappello et al., 2016; Verzobio et al., 2018), helping transport agencies to make more informed decisions regarding scour risk management of bridges.

The rest of the paper is structured as follows. Section 2 presents the scour risk classification procedure currently followed by transport agencies in the UK, whereas Section 3 illustrates how the proposed classification system can complement the current rating of bridges at scour risk. Section 4 describes the application of the developed system to a case study and discusses the achieved outcomes. The paper ends with a conclusion and future works section.

2. Current procedures for scour risk assessment and management

National transport agencies in the UK, such as Transport Scotland (TS) or Network Rail (NR), carry out the assessment of the scour risk at highway and railway structures in accordance with the Procedure BD 97/12 (Highways Agency, 2012) and the EX2502 Procedure (HR Wallingford, 1993), respectively. In these procedures, the scour depth under a hypothetical 200-year return period is used to categorise the bridge asset and prioritize risk mitigation interventions. TS classification consists of five classes of risk while *NR* classification has six classes, and bridges with the highest priority fall into class 1 in both procedures. When a bridge is categorised into category 1 or 2, it is considered at high scour risk for both agencies.

The input parameter in TS's classification (Figure 1(a)) is the relative scour depth D_R, that is, the ratio between the total scour depth D_T and the foundation depth D_F. The total scour depth D_T is defined as the sum of constriction, D_C, and local scour depth, D_L, of which the BD97/12 provides the estimation formulas starting from an assessment flow (i.e., the flow corresponding to a return period of 200 years). Furthermore, a priority factor P_F enters the risk rating to account for several factors, such as the history of scour problems *H*, the type of foundation *F,* riverbed material *M*, type of river T_R and the bridge importance (i.e., vehicle traffic volume) *V* and it is quantified as:

$$P_F = F \cdot H \cdot M \cdot T_R \cdot V.$$

1.

For instance, if *PF* = 2, the scour risk classes are defined by the value of D_R as follows: Class 5 for $D_R \leq 1$, Class 4 for $1 < D_R \leq 1.5$, Class 3 for $1.5 < D_R \leq 2.3$, Class 2 for $2.3 < D_R \leq 3.5$, and Class1 for $D_R > 3.5$.

[Figure 1a & 1b]

The scour risk classification carried out by NR is performed according to the graph reported in Figure 1(b), which provides a priority rating for the considered bridge according to total scour and foundation depth. The chart shows different curves depending on the foundation depth D_F, consequently, even if the graph's axis related to scour depth is flipped with respect to TS chart, the two classification methods are equivalent because both transport agencies use D_R to categorise the bridge risk of scour. Alternatively, Equation 1 may be used to calculate the preliminary priority rating *ppr*:

$$\mathbf{ppr} = 15 + \ln\left[\frac{D_T - D_F}{D_F} + 1\right] = 15 + \ln\left[\frac{D_T}{D_F}\right]$$

2.

where D_T/D_F is the relative scour depth D_R. Then, the preliminary priority rating *ppr* is corrected by summing the variable *TR* to obtain the priority rating shown in Figure 1(b). Variable *TR* can lie between -1 and 0 and considers the type of watercourse, the bank stability and how susceptible the structure is to extreme weather events (i.e., flashiness).

By manipulating and plotting Equation 1 as in Figure 2, the scour risk classes for railway bridges managed by NR can be defined by the value of D_R as follows: Priority 6 for $D_R \leq 0.14$, Priority 5 for $0.14 < D_R \leq 0.37$, Priority 4 for $0.37 < D_R \leq 1$, Priority 3 for $1 < D_R \leq 2.8$, Priority 2 for $2.8 < D_R \leq 7.0$ and Priority 1 for $D_R > 7.0$. This priority class definition considers TR=0, thus giving the preliminary priority factor equal to the priority factor.

[Figure 2]

These procedures for scour risk assessment have some limitations and drawbacks. For instance, the formulas used for scour depth assessment are based on lab experiments and the assumption that the designed flood acts over an infinite duration (Pizarro et al., 2020). Conversely, real flood events are characterised by different hydrograph magnitude and duration. Therefore, high-flow events (i.e., corresponding to a high-water level) may not necessarily result in the development of a significant scour hole, especially if they have a short duration. This often results in significant overestimation of the scour depths developing in bridges (Johnson et al., 2015). For instance, the reader could appreciate the comparisons between the scour depths developed in bridges in Cumbria under storm and the estimates according to BD 97/12 formulas shown in Mathews and Hardman (2017). Scour estimated according to the DMRB design memorandum BD 97/12 and actual scour depths observed at bridges after Storm Desmond in Cumbria (Szoenyi et al., 2015) have shown that the first may be significantly biased on the conservative side (Mathews and Hardman, 2017). Moreover, bridges are exposed to sequences of events, each potentially contributing to scouring. Thus, their safety could be jeopardised by the progressive accumulation of the excavations under multiple events with low return period (i.e., low-water level) occurring in sequence (Tubaldi et al., 2017), as was the case of the Lamington viaduct (Rail Accident Investigation Branch, 2016).

Flint et al. (2017) outlined that the risk of failure due to scour cannot be directly related to only one designed flood scenario and its corresponding return period T_R. Their review of 35 historical bridge collapses in the US (16 failures due to scour) show highly dispersed flow return periods for scour-induced collapses, ranging between one to more than 1,000 years. Interestingly, most of the analysed bridge collapsed under events with T_R lower than 200 years, i.e., the return period usually adopted for scour bridge design, thus highlighting the problem of accumulation of scour over several floods (Flint et al., 2017).

Furthermore, transport agencies rely on visual inspections to identify the bridges that may be at risk of scour (Transport Scotland, 2018; Network Rail, 2017). The inspections are carried out at regular intervals or after major flood events, by involving scuba divers for underwater inspections of bridge foundations. For instance, TS undertakes two types of examination: a General Inspection, which occurs at each bridge every two years, and a Principal Inspection, which is carried out every six years (Transport Scotland, 2018). The first type of inspection includes the visual check of structure's footings to establish whether scour is present, and the riverbed material is soft due to scour and re-deposition while the Principal Inspection is a more detailed survey of the structure including an underwater examination of the foundation and the soil underneath, which records the bed profile, scour holes, any areas of deposition and the presence of debris (such as trees) that may cause blockage, the diversion of water or local scour. However, after a particularly heavy flood event, a scour examination and scour assessment are usually coordinated before the usual inspection schedule if there is a concern for the bridge state (Transport Scotland, 2018).

These inspections are time-consuming, costly and cannot be carried out during the peak of the flood, when the risk of scour is the highest, but only after the flood has receded. This again occurs because these procedures and maintenance plans do not consider the temporal evolution of the scour process. For example, in the case of live-bed scour condition, bed material may be partially redeposited in the scour hole when the flood event finishes (Hamill, 1999). Thus, a scour measurement carried out at the end of a flood may not record the maximum scour that occurred during the event as the scour hole might have partly filled during the recession stage (Melville and Coleman, 2000).

In summary, these limitations in the scour risk assessment procedures might cause a misclassification of the bridge scour risk and even result in unnecessary bridge closure as a precautionary action for many days, thus resulting in significant downtime.

3. Proposed SHM-based classification system for scour risk management

This section illustrates the proposed classification system for bridge scour risk management during or after a flood event, incorporating: (i) the various sources of uncertainty inherent to the hydrological and hydraulic parameters as well as the models employed for evaluating the scour depth at a bridge, and (ii) information from different type of sensors, leading to an uncertainty reduction. The proposed system uses the probabilistic framework for bridge scour hazard assessment presented in Maroni et al. (2020a), where it was observed that information from scour sensors at a monitored location allows a reduction of uncertainty in the scour depth estimation also at the unmonitored ones. The work presented here constitutes a continuation of the study initiated by the authors in that previous paper. The focus of this contribution is to quantify how the uncertainty in the scour estimates affects bridge risk classification under a flood scenario and how observations from SHM systems can improve it.

For this purpose, two alternative monitoring data are used within the BN and investigated, by measuring how the information they provide can enhance the accuracy of the scour risk classification during a flood event. The monitoring strategy considers both the water level measurements upstream of the bridges and the scour recordings at one bridge location, where scour probes are installed. The correlation between the scour depths at various locations, as described by the Bayesian Network, is used to update the scour estimates at unmonitored locations.

Two risk classifications are proposed and compared, one considering no observations, the other one based on the monitoring strategy described above. The concept of information entropy (Shannon, 1948) is used to quantify the uncertainty of the classification outcome (i.e., probability of falling in the different classes), and to evaluate how the monitoring data improve the classification.

The system is illustrated by considering a small bridge network of road bridges in South-West Scotland, therefore, the methodology presented in the next section considers only the scour risk classification performed by TS using the Procedure BD97/12.

3.1 SHM-based classification of bridge risk

Maroni et al. (2020a) developed a probabilistic framework for updating the scour depths at any location of a bridge network given the data from scour sensors installed only at critical locations. The logic underpinning the proposed framework is that the correlation between the scour depths at different locations can be used to extend the information from the monitored pier of a bridge to the other piers of the same bridge and to other bridges. The correlation stems from the models used to estimate scour depths, which are the same for any bridge. Consequently, the scour estimation at every pier is affected by the same correlated error.

The proposed framework is based on a Bayesian Network (BN) modelling approach (Jensen and Nielsen, 2007) where the BN is developed based on the Procedure BD 97/12 (Highway Agency, 2012) to assess the scour risk of TS road bridges. Starting from the river hydraulic characteristics (such as river flow Q), the depth of flow upstream of the bridge y_U is evaluated, followed by the calculation of the two components of scour, constriction scour (D_C) and local scour (D_L), both contributing to the total scour depth D_T. For the details about the definition of each model, each employed probability distribution and each error, reference can be made to Maroni et al. (2020a). Figure 3 illustrates the BN developed in Maroni et al. (2020a) for the problem of scour assessment at a every bridge pier of the considered case studies. The BN includes the scour estimation of a bridge network consisting of three bridges, each with their piers. The three correlated model uncertainties (i.e., e_m, $e_{vB,c}$ and e_{DL} in Figure 3) allow the BN to extend information gained from the scour monitoring system to each sub-network (i.e., unmonitored bridges) because the models used to estimate scour depths are the same for any bridge.

[Figure 3]

Two forms of inference are performed (Ben Gal, 2007). Firstly, the BN is used to predict the a-priori probability density function (pdf) of the scour depth under an extreme flood event. For this purpose, samples of the root nodes generated with a Monte-Carlo approach from their respective prior pdfs, are propagated through the BN to the child nodes up to the one representing the scour total depth. It is worth mentioning that this predictive analysis is performed without any observations entering the BN. On the other hand, by performing Bayesian learning, information from the scour sensors is used to update the a-priori estimates of the root nodes and the BN scour depth at any location of the bridge network.

The posterior pdf of the total scour depth resulting from Bayesian learning is then used to classify the bridge performance under an extreme event. The same classification scheme used by TS is considered here (see Figure 1), with the relative scour depth D_R discriminating among the risk classes. However, in the BD 97/12 a deterministic approach is employed, based on a nominal value of the scour depth at the bridge pier under a hypothetical flood scenario (i.e., the one with a return period of 200 years), yielding a unique identified class for the bridge. On the other hand, the output of the proposed approach is the event-based bridge probability of being in a particular risk class. Thanks to the use of monitoring data and the BN-based probabilistic framework, it is indeed possible to increase the knowledge of the scour estimates, thus reducing the uncertainty in the classification.

Figure 4 illustrates an example of the risk classification, using only the relative scour distribution obtained “a priori” (i.e., without observations entering the BN), and using the posterior distribution considering monitoring data (Figure 4(a)). For a given value of the priority factor (e.g., P_F=2 in Figure 4), the probability $P_{(i)}$ of being in a particular class i is computed based on the cumulative distribution function (cdf) of the relative scour depth (Figure 4(b)) as:

$$P_{(i)} = F_{D_R}\left(\bar{D}_R^{(i)}\right) - F_{D_R}\left(\bar{D}_R^{(i+1)}\right)$$

3.

where $F_{D_R}\left(\bar{D}_R^{(i)}\right)$ is the cdf calculated with the minimum value of D_R associated with the class i, and $F_{D_R}\left(\bar{D}_R^{(6)}\right) = 0$.

[Figure 4a & 4b]

The a-priori distribution of the scour depth is characterised by a significant dispersion, which is the effect of the uncertainties considered in the BN (i.e., those concerning the flow discharge and the hydrological and hydraulic models). This results for the example of Figure 4 in comparable values of the probability of the bridge being in class 2, 3, or 4, and very small probability of being in the two other classes (1 and 5).

Information from monitoring systems is expected to significantly reduce the uncertainty in the scour estimation, thus allowing for a more precise identification of the distribution of D_R and, in turn, of the scour risk (blue bars in Figure 5). Based on the updated pdf of D_R, the bridge most probably falls in class 5, with a small possibility of being in class 4 and a negligible probability of being in the other classes (Figure 5). In this example, the bridge can be classified by the transport agency based on the most probable class (i.e., class 5). The updated classification can be used by transport agencies to make more-informed decisions concerning bridge closure, traffic management, and for prioritizing scour mitigation interventions.

[Figure 5]

The concept of information entropy (Shannon, 1948) is used to quantify the uncertainty in the risk classification and the uncertainty reduction stemming from the application of the proposed monitoring strategy. The information entropy *H* associated to the classification with and without the monitoring data is evaluated using Shannon's equation:

$$H(X) = -\sum_{i=1}^{n} \mathrm{P}(x_i) \log \mathrm{P}(x_i)$$

4.

where *X* is the risk classification, P(x_i) is the probability of being in a particular class *i* for the considered risk classification *X* and log is the logarithm with base 10.

The most uncertain case, that is, the a-priori risk classification (e.g., red bars in Figure 5, with similar probabilities of falling into the five risk classes), is expected to be the one with the greatest entropy. On the other hand, the posterior risk classification (e.g., blue bars in Figure 5, with only a state very likely to be attained), is expected to be characterised by a lower entropy.

4. Case study

The proposed scour risk classification is applied to the same case study presented in Maroni et al. (2020a). This consists in a small bridge network, consisting of bridges managed by TS in south–west Scotland. The bridges cross the same river (River Nith) and only one pier of Bridge 1 is instrumented with a scour monitoring system. The installed system includes two dielectric probes equipped with electromagnetic sensors able to observe changes in the permittivity of the medium around bridge foundations, thus detecting riverbed erosion and refill. Sensors can also discriminate the permittivity values between air and water, and, therefore, use to measure the water level as well (Maroni et al., 2020b). One probe is installed on the upstream face of the left pier to detect total scour, whereas the other is installed in the centre of the river to detect degradation and contraction scour.

Three bridges, which have experienced significant scour event in the past, are chosen from the TS database:

- Bridge 1: A76 200 Nith bridge in New Cumnock (Figure 6). It is a 3-span (9.1m, 10.7 m and 9.1 m) stone-masonry arch bridge, with two piers in the riverbed.

  [Figure 6a & 6b]
- Bridge 2: A76 120 Guildhall bridge in Kirkconnel (Figure 7). It is a 3-span (8.8m, 11.3 m and 11.3 m) masonry arch bridge, with one pier in the riverbed.

  [Figure 7a & 7b]
- Bridge 3: A75 300 Dalscone bridge in Dumfries (Figure 8). It is a 7-span (spans of 35 m and two of 28 m) steel-concrete composite bridge, with one pier in the riverbed.

  [Figure 8a & 8b]

The foundation depth D_F is unknown for the first two bridges (i.e., they were built in the 18th century); therefore, a depth of 1 m is assumed in the calculation of the relative scour depth D_R. The Dalscone bridge is founded on deep foundation (i.e., sheet piling); according to BD 97/12, D_F is the underside of the pilecap in the case of a piled foundation, which for the Dalscone Bridge is 3 meters below the riverbed (D_F=3 m). Moreover, a riprap apron is installed at the piers of this bridge to protect them against the scour. The Procedure BD97/12, in its Level 1 Assessment, specifies that the presence of scour protections in good condition automatically categorised the bridge at no risk of scour (i.e., class 5). Therefore, in the presented scour risk classification system, the Dalscone bridge is studied before the installation of the scour protection so that a scour risk class can be computed.

The priority factor PF is equal to 1.6 for the first two bridges (i.e., Foundation type factor F=1, History of scour problem factor H=1.5, Foundation material factor M=1, Type of river factor T_R=1.2, and Importance factor V=0.9) and to 1.2 for Dalscone bridge (i.e., F=0.75 since the bridge is founded on piled foundation). Therefore, the scour risk classes are defined differently for the three bridges as shown in Table 1.

Table 1. Scour risk classes defined according to the value of D_R for the three case studies

	A76 200 Nith bridge	**A76 120 Guildhall bridge**	**A75 300 Dalscone bridge**
		Relative sour depth	
Class 5	$D_R \leq 1$	$D_R \leq 1$	$D_R \leq 1$
Class 4	$1<D_R \leq 1.8$	$1<D_R \leq 1.8$	$1<D_R \leq 2.1$
Class 3	$1.8<D_R \leq 2.9$	$1.8<D_R \leq 2.9$	$2.1<D_R \leq 3.8$
Class 2	$2.9<D_R \leq 5.3$	$2.9<D_R \leq 5.3$	$3.8<D_R \leq 7.9$
Class 1	$D_R >5.3$	$D_R >5.3$	$D_R >7.9$

5. Results

Figure 9 shows the results of application of the procedure for the scour risk classification proposed in Section 3. In particular, the first column compares the prior and posterior probability density functions of the scour depth at the unmonitored pier foundation of the A76 200 Nith bridge (the scour at pier 1 is directly monitored) and at the foundations of the other two unmonitored ones. These distributions are the results of the application of the BN (Maroni et al., 2020a) and the mean μ and standard deviation σ of prior and posterior distributions of the total scour depth D_T are shown in Table 2.

Table 2. Mean and standard deviation of prior and posterior distribution of the total scour depth D_T

Observation source	**Nith Bridge**		**Guildhall Bridge**		**Dalscone Bridge**	
	Pier 2		**Pier 1**		**Pier 1**	
	μ [m]	**σ [m]**	**μ [m]**	**σ [m]**	**μ [m]**	**σ [m]**
None (prior)	1.992	0.762	2.297	0.798	1.855	0.752
Probe+gauging stations	0.452	0.172	0.985	0.212	0.897	0.219

The BN calculates the prior estimations starting from log-normal distributions of the water discharge based on the gauging station data of the last ten years collected by the Scottish Environmental Protection Agency (SEPA). Peak water flow values recorded at gauging stations, simulating a heavy flood scenario, and observation from scour sensors at the first pier of Bridge 1, are then used to update the scour estimates (i.e., blue posterior pdf in Figure 9). The prior risk classification is uncertain: the first two bridges had similar probabilities to fall into class 2, 3, 4 or 5 while Dalscone Bridge, being founded on deep foundations (D_F is higher than the one assumed for the first two bridges), had two predominant risk classes where to be categorised (i.e., Class 4 and 5), but the classification was still uncertain. Following the procedure BD 97/12, with the classification based on the mean value of the scour depth estimated under a 200-year flood discharge, the bridges would fall into category 2, 3, and 5, respectively (i.e., black bars in Figure 9, right graphs). Instead, according to the prior risk classification that incorporates the inherent uncertainties of the scour estimation, the most probable risk categories for the three bridges are 3, 3, and 5, respectively.

[Figure 9a, 9b & 9c]

Figure 9 also shows how incorporating information from monitoring sensors into the BN allows estimating the scour risk during the flood event. The SHM-based risk classification is indeed more explicit because of the uncertainty reduction thanks to scour monitoring data. (e.g., σ passes from 0.76 to 0.201 on average). By simulating a high-flow rate event (i.e., water level upstream the Bridge 1 assumed equal to 1.879 m) and assuming a measured total scour depth at the first pier of Bridge 1 equal to 0.45m, the second pier (i.e., not monitored) is assigned to category 5 (Figure 9(a)). The correlation existing between the scour depths at different locations achieves a reduction of uncertainty even at unmonitored bridges. This reduction is reflected in the scour risk estimation: Bridge 3 is classified in the lowest risk class (Figure 9(c)), while Bridge 2 has around the same probability to be categorised in risk class 5 or 4 (Figure 9(b)). For this latter bridge, there is not a clear classification because the mean value of D_T is 0.98 m, very close to the hypothesized foundation value D_F (1 m). Consequently, the numerical method used to solve the BN has evaluated the relative scour depth D_R greater than 1 in several simulations of the algorithm. This has led the method to classify the bridge within class 5 and 4 because this latter class is defined by values of relative scour falling within the interval $1 < D_R \leq 1.8$.

The calculated entropy (shown in Table 3) confirms that the risk classification calculated with no observations (i.e., with the prior pdf of the scour depth) provides the highest value of entropy and, in turn, the more uncertain classification. Incorporating the information from monitoring data generally results in a reduction of uncertainty, which is reflected in a lower value of the entropy compared to the prior. Obviously, the entropy decrease is highest for the bridge that is monitored directly with the scour probes. However, it is also quite significant for the other cases.

Table 3. Information entropy for the three scour risk classifications shown in Figure 9 according to the corresponding monitoring approach

Entropy (*H*)	**Nith Bridge**	**Guildhall Bridge**	**Dalscone Bridge**
	Pier 2	**Pier 1**	**Pier 1**
None (prior)	0.537	0.576	0.344
Probes+gauging stations	0.013	0.303	0

The outcomes of this analysis suggest that a monitoring- and event-based risk classification could effectively help transport agencies in facilitating decision making during flood events and reduce potential misclassification errors.

6. Conclusions

This paper presents an SHM- and event-based classification system for bridge scour risk management during or after an extreme flood event. It is based on a Bayesian network (BN) approach for evaluating bridge scour risk and for updating it based on the available observations. The risk classification accounts for the relevant sources of uncertainty characterising the problem and integrates real-time measurements from in-river and structural health monitoring (SHM) sensors in the decision-making process. It leads to a fairer probabilistic classification of the scour risk and quantifies the benefits of monitored data in terms of uncertainty reduction.

A small network consisting of three bridges at risk of scour managed by Transport Scotland in south–west Scotland is presented to illustrate the application of the proposed risk rating system. Information from water levels recorded upstream of the bridges by SEPA, and the scour depth recorded by two dielectric probes installed at one bridge pier are used within the developed monitoring-based scour risk classification system to update the probabilistic distribution of scour at monitored and unmonitored locations. The information entropy associated with the a-priori and a-posteriori risk classifications is used to evaluate the uncertainty reduction stemming from the monitored data.

The study outcomes exhibit that, starting from an uncertain prior risk classification (i.e., all the three bridges have similar probabilities to fall into multiple classes because no observation are considered into the BN), the integration of monitoring data leads to an overall reduction of uncertainty that is reflected in the proposed scour risk classification.

The overall uncertainty reduction given by the investigated monitoring strategy (i.e., gauging stations and scour dielectric probes) is significant, and it is reflected in the risk classification and, in turn, in the computed entropy. Under the considered flood scenario, Bridge 1 and Bridge 3 clearly fall into class 5, whereas Bridge 2 can be classified in either Class 5 or 4 (i.e., it has a negligible probability of being in the riskier classes).

The proposed classification provides information that can be of paramount importance for bridge scour risk ranking and decision-making in the aftermath of an extreme flood event. It could also help transport agencies in minimising "false positives" in bridge scour risk assessment, thus reducing the times that bridges are closed unnecessarily as a precautionary action, and directing reactive inspections according to a more accurate scour risk classification.

Future studies will aim to produce a more complete decision support system for bridge management, using measurement-informed scour thresholds to trigger bridge closure to traffic under heavy floods.

References

Ben Gal I (2007) Bayesian Networks, in *Encyclopedia of Statistics in Quality & Reliability* (Ruggeri F, Faltin F and Kenett R(ed)). John Wiley & Sons, Chichester, UK.

Briaud J-L, Brandimarte L, Wang J and D'Odorico P (2007) Probability of scour depth exceedance owing to hydrologic uncertainty. Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards **1(2)**: 77–88.

Cappello C, Zonta D and Glišić B (2016) Expected utility theory for monitoring-based decision making. Proceedings of IEEE **104(8)**: 1647–1661.

Farrar CR and Worden K (2007) An introduction to structural health monitoring. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences **365(1851)**: 303–315.

Flint MM, Fringer O, Billington SL, Freyberg D and Diffenbaugh NS (2017) Historical Analysis of Hydraulic Bridge Collapses in the Continental United States. Journal of infrastructure systems **23(3)**: 04017005–16.

Hamill L (1999) *Bridge Hydraulics*. E & FN Spon, London, UK.

Highway Agency (2012) The Assessment of Scour at and Other Hydraulic Actions at Highway Structures - Procedure BD97/12. Vol. 3 of Design manual for roads and bridges. The Stationery Office Ltd, London, UK.

HR Wallingford (1993) Hydraulic Aspects of Bridges - Assessment of the Risk of Scour. Report EX 2502. HR Wallingford Ltd., Wallingford, UK.

Jensen FV and Nielsen TD (2007) *Bayesian networks and decision graphs*, second edn. Information Science and Statistics, Springer, Berlin, Germany.

Johnson PA, Clopper PE, Zevenbergen LW and Lagasse PF (2015) Quantifying Uncertainty and Reliability in Bridge Scour Estimations. Journal of Hydraulic Engineering **141(7)**: 04015013.

Maroni A, Tubaldi E, Val DV, McDonald H and Zonta D (2020a) Using Bayesian networks for the assessment of underwater scour for road and railway bridges. Structural Health Monitoring, 2020, doi: 10.1177/1475921720956579.

Maroni A, Tubaldi E, Ferguson NS, Tarantino A, McDonald H and Zonta D (2020b) Electromagnetic sensors for underwater scour monitoring. Sensors, **20(15)**: 4096.

Mathews R, and Hardman M (2017) Lessons learnt from the December 2015 flood event in Cumbria, UK. Proceedings of the Institution of Civil Engineers-Forensic Engineering, **170(4)**: 165-178.

Megaw ED (1979) Factors affecting visual inspection accuracy. Applied Ergonomics **10(1)**: 27–32.

Melville BW and Coleman SE (2000) *Bridge Scour*. Water Resources Publication, Highland Ranch, Colorado, USA.

Network Rail (2017) Scotland Adverse and Extreme Weather Plan. Network Rail, Glasgow, UK.

Pizarro A, Manfreda S and Tubaldi E (2020) The Science behind Scour at Bridge Foundations: A Review. Water **12(2)**: 374–26.

Pizarro A and Tubaldi E (2019) Quantification of Modelling Uncertainties in Bridge Scour Risk Assessment under Multiple Flood Events. Geosciences **9**: 445–15.

Rail Accident Investigation Branch (2016) Structural failure caused by scour at Lamington viaduct, South Lanarkshire 31 December 2015. Report 22/2016. Rail Accident Investigation Branch, Department for Transport, Derby, UK.

Shannon CE (1948) A mathematical theory of communication. The Bell System Technical Journal **27(3)**: 379-423. doi: 10.1002/j.1538-7305.1948.tb01338.x.

Szoenyi M, May P and Lamb R (2015) Flooding in Cumbria after Storm Desmond. Zurich Insurance Group, Zurich, Switzerland, JBA Trust, North Yorkshire, UK.

Thornes J, Rennie M, Marsden H and Chapman L (2012) Climate Change Risk Assessment for the Transport Sector. Department for Environment, Food and Rural Affairs, London, UK.

Transport Scotland (2018) Scour Management Strategy and Flood Emergency Plan. Transport Scotland, Glasgow, UK.

Tubaldi E, Macorini L, Izzuddin BA, Manes C and Laio F (2017) A framework for probabilistic assessment of clear-water scour around bridge piers. Structural Safety **69**: 11–22.

van Leeuwen Z and Lamb R (2014). Flood and scour related failure incidents at railway assets between 1846 and 2013. Project W13 – 4224. JBA Trust Limited 2014, Skipton, UK.

Verzobio A, Tonelli D, Bolognani, D et al. (2018) Monitoring-based Decision Support System for optimal management of Colle Isarco Viaduct. In *Proceedings of SPIE 10600, Health Monitoring of Structural and Biological Systems XII*, p. 106002C.

Wardhana K and Hadipriono FC (2003) Analysis of recent bridge failures in the United States. Journal of performance of constructed facilities **17(3)**: 144–150.

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Figure 1. Scour risk classification performed by (a) TS (Highway Agency, 2012) and (b) NR (HR Wallingford, 1993)

Figure 2. Definition of the NR's priority scour risk classes according to the value of relative scour depth. Red line defines the categories considered at high scour risk (Priority class 1 and 2).

Figure 3. BN for scour estimation developed for the case study in Maroni et al. (2020a). Q: water flow; y_U: depth of flow upstream the bridge; $v_{B,C}$: scour threshold velocity; d: bed material grain size; $D_{C,ave}$: average depth of constriction scour; y_B: depth of flow below the bridge; $D_{C,pier}$: depth of constriction scour at the pier; e_x and ${}^{(i)}e_x$: model uncertainties applied to the estimation models

Figure 4. (a) Probability density function, and (b) cumulative density function of prior and posterior relative scour depth provided by BN with corresponding risk classes (*PF* = 2)

Figure 5. Example of prior and posterior risk class classification from the proposed system

Figure 6. (a) A76 200 Nith bridge and (b) bridge elevation

Figure 7. (a) A76 120 Guildhall bridge and (b) bridge elevation

Figure 8. (a) A75 300 Dalscone bridge and (b) Bridge elevation

Figure 9. Scour risk classification of the three bridges making up the case study: (a) Pier 2 of Nith Bridge, (b) Pier 1 of Guildhall bridge and (c) Pier 1 of Dalscone bridge