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The science-policy interface of risk-based freshwater and marine management systems: From concepts to practical tools

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Abstract

Maintaining the current state of ecosystem services from freshwater and marine ecosystems around the world is at risk. Cumulative effects of multiple human pressures on ecosystem components and functions are indicative of residual pressures that “fall through” the cracks of current industry sector management practices. Without an understanding of the level of residual pressures generated by these measures, we are unlikely to reconcile the root causes of ecosystem effects to improve these management practices to reduce their residual pressures. In this paper, we present a new modelling framework that combines a qualitative and quantitative assessments of the effectiveness of the measures used in the daily operations of industry sectors to predict their residual pressure that is delivered to the ecosystem. The predicted residual pressure can subsequently be used as an input variable for ecosystem models. We combine the Bow-tie analysis of the measures with a Bayesian belief network to quantify the effectiveness of the measures and predict the residual pressures.

Keywords: effectiveness; compliance; Bow-tie analysis; Bayesian Belief Network; cumulative effects

1. Introduction

The interface between science and policy eventually needs to operationalize ecosystem-based approaches to management (Gavaris, 2009; Murawski, 2007; Cormier et al., 2017) so as to carry into effect policy objectives. Formalizing and defining the science-policy interface within a management system or even among management systems is a key challenge in achieving sustainable development while maintaining the current state of ecosystems (Creed et al., 2016; Gluckman, 2016). Human activities and their demands for ecosystem services generate pressures that can cause physical changes, chemical interferences as well as biological and ecological disturbances within marine and freshwater ecosystems (Halpern et al., 2008; Allan et al., 2013). Cumulative effects assessment has been the hallmark approach to unravel the complex pressure-effect relationships and inform mitigation strategies to reduce them (Ban et al, 2010; Andersen et al., 2015; Jones, 2016; Stelzenmüller, et al., 2018). However, mitigation strategies are most often focused on reducing the effects (Mangano and Sara, 2017) and seldom consider or integrate an assessment of the effectiveness of the management measures implemented to reduce the pressures at their sources (Katsanevakis et al., 2011; ICES, 2014; Elliott et al., 2017).

One strategy for identifying how pressures are managed is by analysing the management system of policies, processes, and procedures that are implemented to reduce the pressures (ISO, 2009). Performance of such a system is a measure of the degree to which policy objectives are being achieved (ISO, 2005) such as the effectiveness of current mitigation strategies in reducing environmental effects (Batista et al., 2015). In addition to compliance and external factors (Girling, 2013; Green, 2015), performance relies significantly on the effectiveness of so called operational controls (e.g. procedures, tasks, maintenance, repairs) that are implemented in the daily operations on the ground (Anthony and Dearden, 1980). In this operational context, effectiveness is the extent to which controls can produce their expected result or outcome. Lack of performance could be attributed to either the effectiveness of the controls or the legislation and policies that are intended to regulate the phenomenon in question (Cormier et al., 2017). For example, best management practices that are meant to reduce sediment input to watercourses are designed to operate effectively within certain boundary conditions (Cooke et al., 2015). Thus, despite proper installation and maintenance, residual amounts of sediment still reach the watercourse. Based on the effectiveness of a given control design, we are of the view that the collective residual materials, substances or wastes released to the environment can represent significant pressures to sensitive aquatic ecosystems. This implies that controls implemented as regulatory requirements or best management practices are inadvertently contributing to cumulative environmental effects despite the requirements and objectives stipulated in legislation and policy (Sardà et al., 2014; Jones, 2016; Cormier et al., 2017).

Outside the influence of natural or climate driven processes, we call 'residual pressures' the pressures that are generated by the residual materials, substances or wastes as a result of the level of effectiveness of the controls that are implemented in the daily operations of industry sectors. Without the capability of estimating the level of the residual pressures, we are unlikely to reconcile the root causes of disturbances to ecosystems with the management practices for addressing those disturbances and ultimately, the performance of their management systems in achieving environmental objectives. We use the Bow-tie analysis (IEC/ISO, 2009) and a Bayesian Belief Network (Badreddine and Amor, 2013) as an approach to predict the residual pressure. This approach provides a predicted residual pressure that would serve as an input variable to ecosystem models. In this paper, we tested this approach in two distinct case studies being 1) nutrient loading in the Great Lakes, and 2) sea-floor integrity of the North Sea. Based on these two case studies, we identify knowledge and data gaps and reflect on lessons learned from implementing such an approach.

2. Materials and Methods

We use the Bow-tie analysis to develop a qualitative model of the controls implemented to reduce a pressure generated from the activities of multiple sectors. We then use a Bayesian belief network model (Marcot et al. 2006) to predict the residual pressure based on the integration of the effectiveness of each control, the implementation compliance of the controls and external factors that could undermine the effectiveness of the controls. Here, we are using the predicted residual pressure as an indicator of the effectiveness of the management system of controls implemented to reduce an initial pressure instead of predicting the ecosystem effects. A description of the data manipulation, model application and predicted total residual pressure loads for the two case studies are provided in the Supplementary Material section.

In the case study for the Laurentian Great Lakes, the analysis is conducted on farming best management practices implemented to reduce phosphorus as a result of their activities. The case study was conducted within the boundaries of the Grand River Watershed of Lake Erie considered as a priority area for enhanced management of phosphorus. The Bow-tie analysis identified the sequence of controls of each farming practice implemented to reduce and prevent phosphorus from reaching Lake Erie. Based on the Bow-tie structure of the controls, a Bayesian belief network was developed to quantify the effectiveness of each controls and predict the residual amount of phosphorus that could potentially reach Lake Erie.

In the case study for the North Sea, the analysis was conducted on marine spatial management controls implemented to reduce abrasion and selective extraction of the seafloor as a result of fish trawling, aggregate mining, gas extraction, and anchoring. The case study was conducted within the boundaries of the German Exclusive Economic Zone given that bottom trawling is considered as causing significant impact on the demersal ecosystem. The Bow-tie analysis was used to identify the controls that restrict fishing activities to reduce abrasion to the seafloor. The Bayesian belief network was then used to quantify the effectiveness of the fishing restrictions and predict the residual amount of abrasion in the German Exclusive Economic Zone.

2.1 Controls assessment technique: Bow-tie analysis

As one of the controls assessment techniques of IEC/ISO 31010 (IEC/ISO, 2009), the Bow-tie analysis is primarily a diagrammatic representation of the controls implemented within a cause-event-consequence pathway in the presence of a source of risk (Figure 1). The technique was developed by the petrochemical industries to assess the prevention and mitigation measures needed to avoid catastrophic events as a result of a failure of their operational controls (Lewis and Hurst 2005; Cockshott 2005). The technique is currently used in wide variety of industries dealing with health and safety risks (Saud et al. 2014; van Thienen-Visser et al. 2014; Abimbola et al. 2014). In an ecosystem context, the technique has been adapted to the analysis of legislation and policies (Creed et al. 2016; Elliott et al. 2017; Kishchuk et al. 2018).

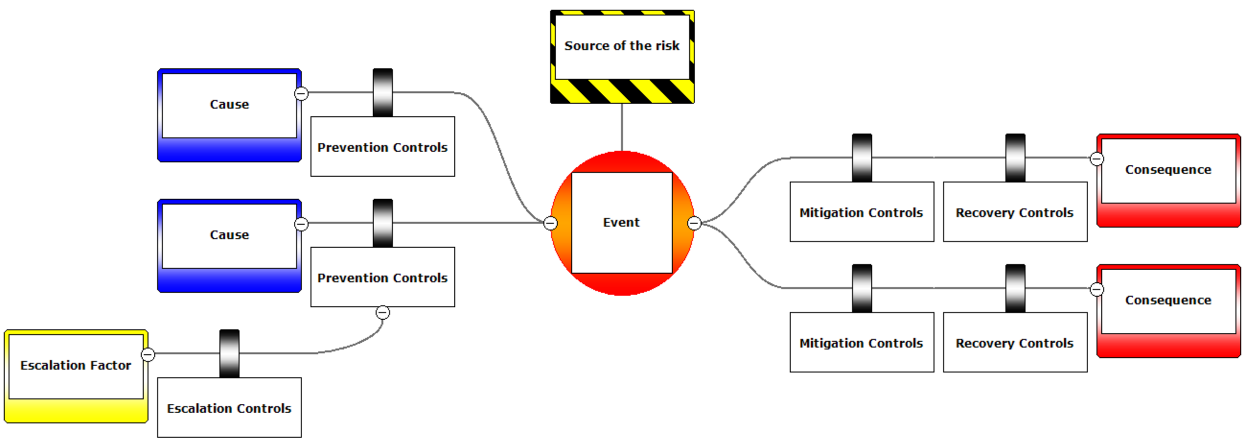

Figure 1: Bow-tie structure (BoxTieXP adaptation of IEC/ISO 31010).

The basic structure of the Bow-tie identifies the causes of an event in the presence of a source of risk and the consequences of that event when it occurs. Prevention controls are intended to reduce the likelihood of an event; mitigation controls are intended to reduce the magnitude of the consequences of an event and recovery controls are used to recover from the consequences that could not be mitigated. Escalation factors are external factors that can undermine the effectiveness of any of the prevention, mitigation or recovery controls. They require additional escalation controls to reduce the effects of the escalation factor on their effectiveness. This technique is a qualitative assessment of the prevention controls to prevent the event, the mitigation and recovery controls to reduce the consequences and the escalation controls to reduce the effect of escalation factors on controls.

In this example Bow-tie analysis (Figure 2), we focused on the prevention controls that would be implemented to reduce the initial pressure loads generated by the operational activities of multiple sectors. Conceptually, Figure 2 shows two management systems of prevention controls that are used for Activity 1 and Activity 2. Activity 1 has two prevention controls and Activity 2 has one prevention control that are used independently to reduce their respective initial pressure down to a combined total residual pressure load. Ecosystem effects would be the consequence of the total residual pressure load. Natural pressures can also contribute directly to the total residual pressure load as a consequence of natural processes, thus, by-passing the prevention controls for Activity 1 and Activity 2. The effects of climate change could also be included using this diagrammatic approach. The dotted lines between the natural pressures and the total residual pressure implies that prevention controls cannot be used to reduce natural pressures. Only mitigation and recovery controls could be used to reduce the consequences in terms of ecosystem effects. Given the focus on the effectiveness of the prevention controls and the integration of compliance and escalation factors, we did not consider the mitigation and recovery controls that could be implemented to further reduced ecosystem effects. The intent of the Bow-tie diagram is to represent the management system of the prevention controls, and to develop a Bayesian Belief Network that could then predict the total residual pressure load. Conceptually, the left side of the Bow-tie represents the management system and the right side of the Bow-tie represents the ecosystem. BowTieXP (v 9.0.10.0W; CGE Risk Management Solutions) is the software that is used to develop Bow-tie diagrams. From this point on, we use the terms prevention controls as the operational controls to reflect the Bow-tie standard definition for controls on the left side of the Bow-tie.

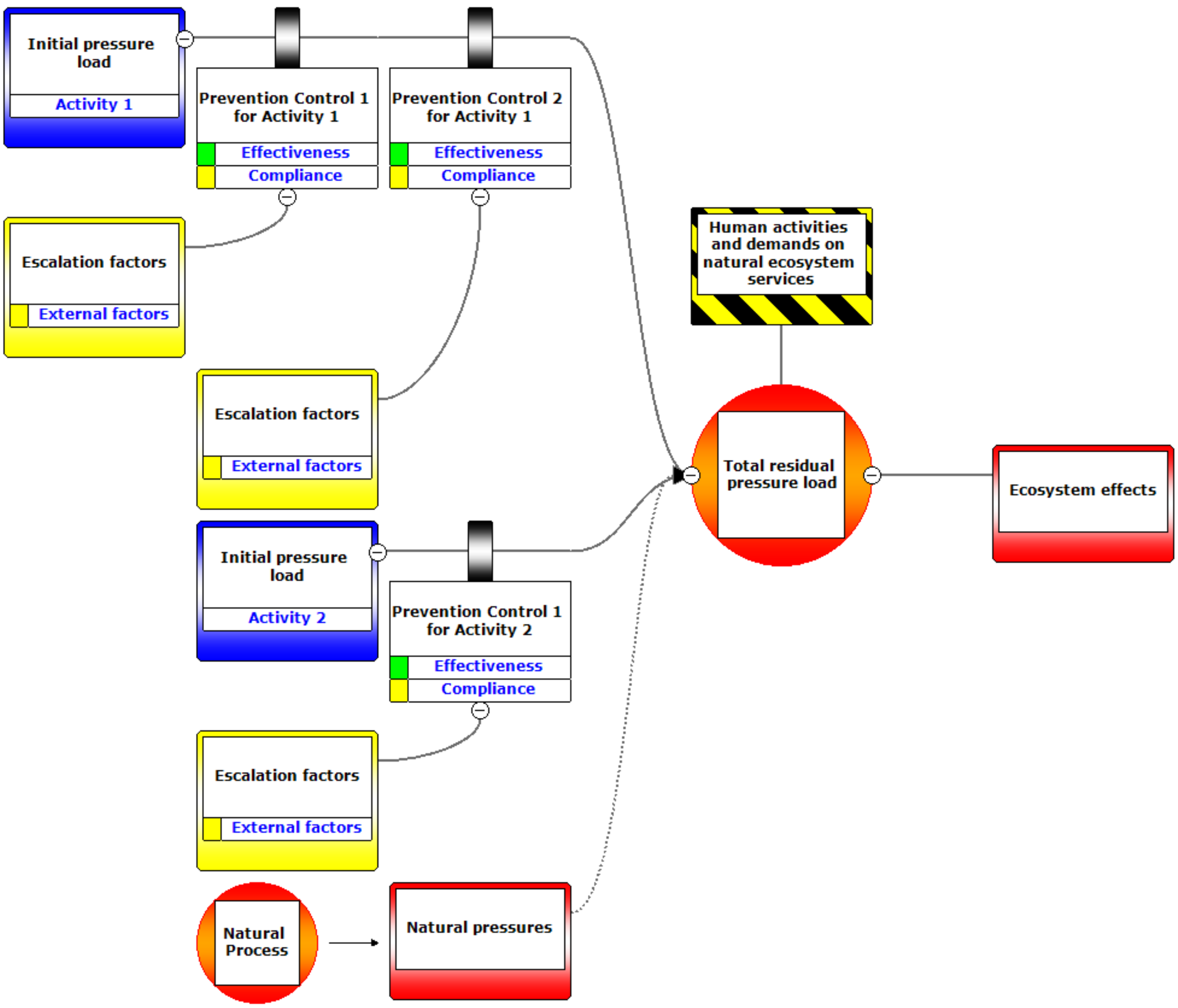

Figure 2: Schematic Bow-tie representation of a management system for measures for each initial pressure load.

2.2 Bayesian belief network

Bayesian belief networks are used to provide a quantitative approach to the Bow-tie analysis (Bobbio, et al. 2001). Specifically, Bayesian approaches are used to uncover the complex conditional dependencies between the cause-event-consequence pathways, and to assess the effectiveness and compliance of the controls (Badreddine and Amor, 2013). As probabilistic models, Bayesian belief networks are also used to assess the performance of alternative management strategies (Varis et al., 1990; Marcot et al., 2006; Nyberg et al., 2006; Stelzenmüller et al., 2015). In brief, Bayesian belief networks are based on two structural model components: (1) a directed acyclic graph that denotes dependencies and independencies between the model's variables (referred to as nodes) and (2) conditional probability tables denoting the strengths of the links in the graph (McCann, 2006). The directed acyclic graph consists of a structured set of nodes that represent the modelled system. Assumed as cause-effect relationships between the system variables, directed arrows represent the statistical dependencies between the different nodes. Each arrow starts in a parent node and ends in a child node. The graph is acyclic and, therefore, no feedback arrows from child nodes to parent nodes exist. The directed acyclic graph can either be developed by experts, based on the understanding of the system being modelled or can be learned by empirical observation.

The Bayesian belief network replicates the left side of the Bow-tie diagram of prevention controls for each activity (Figure 3). Based on the elements of the Bow-tie diagram, a node is used to represent the activity that generates the initial pressure load and the residual pressure of each prevention control combined into the total residual pressure load. The residual pressure of each prevention control is based on a performance node that integrates the effectiveness of the control with the compliance and escalation factor nodes. The output of the total residual pressure load becomes an input into a node to predict ecosystem effects. Nodes are also assigned for the natural processes that are contributing natural pressures to the total residual pressure load. Netica (v4.16; Norsys Software Corp) is the software that is used to develop Bayesian belief network.

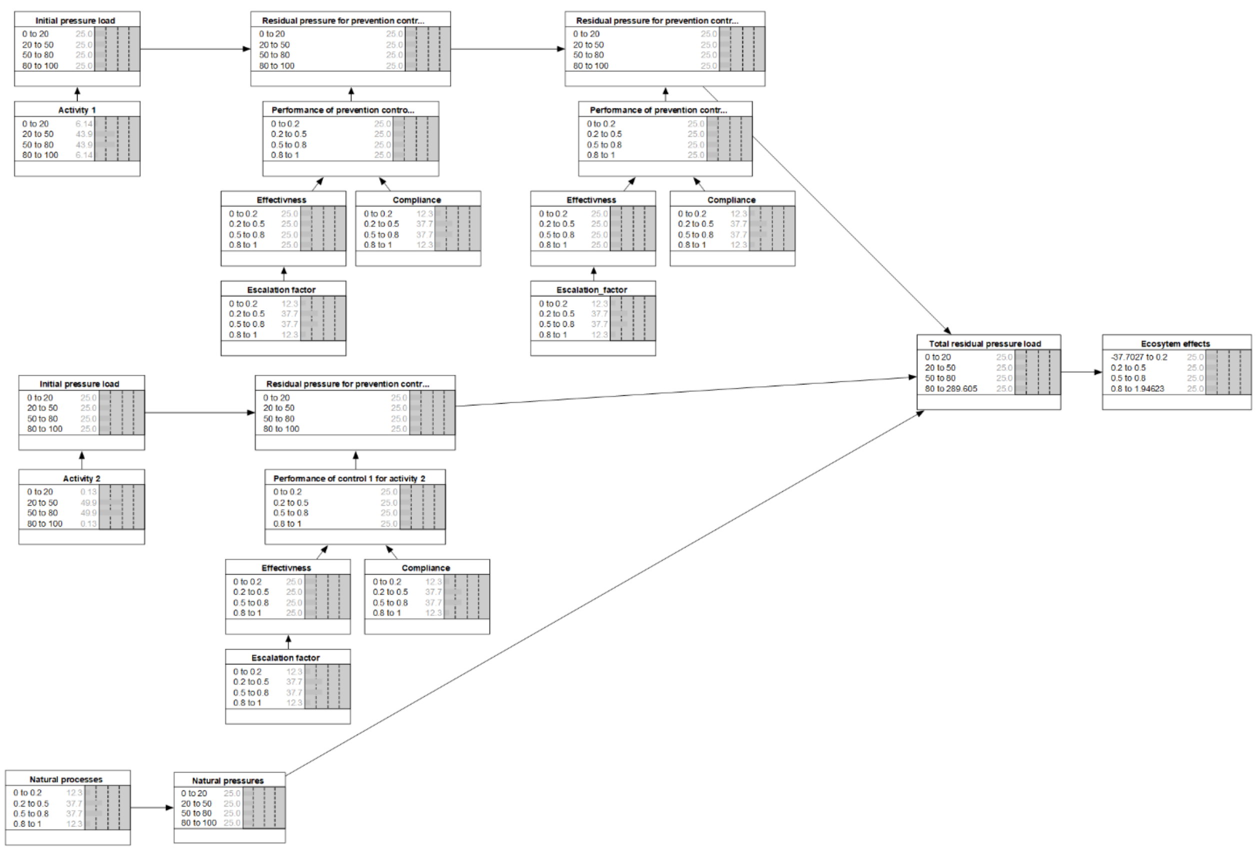

Figure 3: Bayesian belief network model of the left side of the Bow-tie diagram (see Figure 2).

3. Results

We find that the Bow-tie and Bayesian belief network combined models can be used to analyse the effectiveness of different management systems of prevention controls regardless of the ecosystem setting. The case studies demonstrate that the models can be used for either freshwater or marine ecosystems because the analysis assesses the effectiveness of the prevention controls in reducing the pressures generated by the activities and not the ecosystem effects. As mentioned above, the predicted total residual pressures load can then be used in ecosystem models to assess effects.

The Laurentian Great Lakes case study integrates the spatial distribution of the prevention controls along the hydrological pathways of phosphorus loading to the Lake Erie Basin. Prevention controls such as nutrient application management and contour cropping reduce farm sources of phosphorus, while vegetative filter strips reduce the phosphorus runoff to the watercourse. The hydrology of the catchment basin also plays an important role in understanding the temporal scale between the release of the phosphorus and it reaching the watercourse. The application of phosphorus does not immediately result in the phosphorus load found in the Great Lakes such as a latent residual pressure of dissolved reactive phosphorus (Igras, 2016). The effectiveness of the prevention controls used to reduce the sediments inadvertently increased the dissolved reactive phosphorus reaching the Great Lakes. This modelling approach is able to identify the "hidden costs" of achieving total phosphorus objectives based on soil conservation in terms of increasing the dissolved reactive phosphorus load reaching Lake Erie. It also suggests the need to rethink the current strategy in order to achieve dissolved reactive phosphorus objectives.

The North Sea case study integrates the effectiveness of fishing restriction areas as the prevention controls to reduce abrasion in these area. Although data from different sources were summarized into a single metric to quantify the abrasion pressures from different activities, the analysis was able to single out compliance as the key factor that is potentially undermining the effectiveness of the fisheries restriction areas. As a prevention control, these areas are effective in reducing abrasion as long as operators do not cross the boundaries of the restricted areas. The results of the case study show that the fishing restriction in the Natura 2000 sites reduces the total residual pressure load by only 3%, suggesting only marginal improvements for the demersal fish communities. When non-fishing activities are excluded from both the baseline and future scenario, the expected total residual pressure load is only reduced by 0.7% indicating a negligible overall impact on the ecosystem components at the case study scale.

The case studies demonstrate that combining the Bow-tie analysis and Bayesian belief network approach provided a valuable tool to assess the effectiveness of prevention controls implemented within different operational contexts and predict the total residual pressure load. However, the approach was limited by the data availability needed to define the respective probability distribution for each node of the Bayesian belief network.

4. Discussion

4.1 Matching the scales of the sources of the pressure and ecosystem effects

The Bow-tie/Bayesian belief network models must capture the inherent spatial and temporal properties of the pressure-effect pathways. There may be significant separation between where and when the initial pressure load is occurring, the prevention controls are being implemented, the total residual pressure load is being released and the resulting ecosystem effects. Each side of the Bow-tie demarks two spatial and temporal pathways of risk. The left side of the Bow-tie represents the boundary of the sources of the pressures while the right side of the Bow-tie represents the ecological boundary of the ecosystem effects. Each application of the Bow-tie/Bayesian belief network models will be constrained by a unique set of spatial and temporal scales that will determine the appropriate data inputs for the analysis. In some cases, the pressure and the effect will be co-located and contemporaneous (e.g., fishing restriction areas example), while in other cases, the pressure is remote from the effect and the time lags may be significant (e.g., phosphorus loading in Lake Erie).

This is an important consideration for managers and stakeholders when they face the need to address ecosystem effects. They must be able to identify the right pressure source to improve the prevention control of the right activity which may not be located at the same time and place as the effects (Jones, 2016). Depending on the spatial and temporal scales of the cause and effect pathways, they must also understand that the improvements may take several years before monitoring detects a reduction in the ecosystem effects (Stelzenmüller et al., 2018).

4.2 Accounting for all sources of the pressure and their management measures

All human activities that contribute to a pressure within the spatial boundary of the ecosystem effects have to be accounted for (Jones, 2016). In most cases, this implies that trans-boundary sources of the pressure and their jurisdictional management system must also be included in the analysis. Without this information, the total residual pressure load delivered to the ecosystem and the potential ecosystem effects will likely be underestimated. Given that the Bow-tie/Bayesian belief network approach is focused on the prevention controls, the analysis must also include all the prevention controls used to reduce the initial pressure load of each activity. In our case studies, the expected outcomes of the prevention controls is a total residual pressure load needed to reduce the likelihood of ecosystem effects.

From the Great Lakes case study, we learned that the use of the best management practices indirectly increased dissolved reactive phosphorus loads reaching the lake, even though phosphorus management traditionally favours soil conservation to achieve total phosphorus reduction objectives (Scavia et al., 2014). The Bow-tie/Bayesian belief network analysis identifies a key misunderstanding that often occurs in most management context. Initially developed to conserve soils, the recurrence of eutrophication in the Great Lakes gave the impression that the best management practices no longer appear to be working. At the time these were developed, however, they were not designed to reduce dissolved reactive phosphorus. They were primarily soil conservation measures. The Bow-tie/Bayesian belief network analysis shows that the phosphorus loads reaching the lake follows two phosphorus pathways dependent on the movement of sediments and water. More importantly, the analysis confirms that soil conservation is effective at reducing total phosphorus and not effective at reducing dissolved reactive phosphorus.

In the North Sea case study, the fishing restrictions within the marine protected area have the potential to effectively reduce abrasion if not eliminate changes to the integrity of the seafloor (Pedersen et al., 2009). A spatial prevention control that restricts or prohibits all activities that cause physical changes to the seafloor simply removes the sources of the risks and thus is 100% effective. This case study confirms that non-compliance can undermine the effectiveness of a marine protected area implemented as a prevention control. The Bow-tie/Bayesian belief network analysis identified the different abrasion loads generated by each the activity and their contribution to the residual abrasion load in the restricted areas. This demonstrates the usefulness of the Bow-tie/Bayesian belief network approach to identify the activities that need the most attention from an enforcement perspective.

In addition to accounting for all the operational sources of the pressure, natural pressures also need to be accounted for to avoid underestimating the total residual pressure loads. Ecosystem effects can be exacerbated by natural processes as well as the effects of climate change (Elliott et al., 2015) despite the implementation of effective prevention controls. Based on a better understanding of the pressures generated by natural processes, managers and stakeholders would be informed of the need for mitigation strategies to address ecosystem effects instead of pursuing futile improvements to prevention controls used in the daily operations of industry sectors. Prevention controls can only reduce the pressures generated by operational activities. They cannot control the pressures generated by natural processes or the effects of climate change.

4.3 Sequencing the controls to reflect the management system

The implementation sequence of the prevention controls may be dictated by management and operational constraints (de Dianous et al., 2006) as reflected in case studies in terms of location of the sources of the pressure and the pathways of effects at the ecosystem scale. The total residual pressure load predicted by the Bow-tie/Bayesian belief network model is mathematically the same regardless of the sequence of the measures. In practice, however, prevention controls are implemented to reflect the spatial and temporal sequence of their intermediate and incremental reduction of the initial pressure loads. The Great Lakes case study is an example of such a sequence where the initial phosphorus loads are reduced through the implementation of best management practices to reduce the phosphorus load along the hydrological pathways from the sources of the phosphorus in the catchment basin to the release into the lakes. The function of each prevention control reduces the particulate phosphorus load starting with the agricultural activities through the pathways by which the particulate phosphorus reaches the lakes.

4.4 Ensuring coherence and consistency of data

The Bow-tie/Bayesian belief network model can be used in two ways. There may be cases where only the total residual pressure load is known instead of the initial pressure load for each activity. In these cases, the initial pressure load would have to be estimated for each activity in order to analyse effectiveness of the prevention controls. Alternatively, there may be cases where the total residual pressure load is known only for specific ecosystem components. For such cases, the Bow-tie/Bayesian belief network model would be used to 'back-calculate' a potential distribution of the initial pressure loads for each activity based on the performance levels of their respective management systems. In either situation, the Bow-tie/Bayesian belief network model could be used to explore where best to adjust the prevention controls if the total residual pressure load is above threshold levels to avoid ecosystem effects. However, in many cases, baseline data on the spatial and temporal distribution of human activities and their initial pressure loads are not readily available. In these cases, expert elicitation would be needed to populate the conditional probability tables of the respective nodes of the Bayesian belief network model.

Compliance data and effectiveness studies to be used for this framework must provide predicted pressure reductions including the posterior probability distribution of such predictions to encapsulate the uncertainties for the Bow-tie/Bayesian belief network model. Due to the lack of coherence and consistency in the data used for the Bayesian belief network nodes for compliance and effectiveness, we used standardized probability distributions to reflect the states of the respective Bayesian belief network nodes. This allowed us to reflect changes in the total residual pressure load even though the data sets came from different sources (ICES, 2015). Hence, both case studies used extensive manipulation of very different data sources to generate the parameters for the Bayesian belief network model (ICES, 2016).

Escalation factors are external to the span of controls of the management system and can include any external influence such as trends or stochastic natural processes. Natural processes can reduce the effectiveness or cause the failure of a specific prevention control or can amplify the total residual pressure load directly. Although we included escalation factors in the Bow-tie/Bayesian belief network model, we were not able to include specific factors in the case studies due to a lack of data. In addition, the potential ecosystem effects predicted by ecosystem models should reflect the inherent vulnerabilities and sensitivities of the ecosystem component to the specific pressure being analysed. As with the previous section, data were not readily available or structured for such an analysis.

5 Conclusion

This paper puts a spotlight on key challenges of working at the science-policy interface, particularly when considering the operational context of ecosystem-based approaches to the management of the daily activities of the sectors operating in a given area. Our modelling approach shifts the focus from the assessment of ecosystem effects, to an assessment of the effectiveness of the prevention controls in reducing the pressures and ultimately their effects. Regardless of the results of any assessment, managers and stakeholders need to understand the root causes of ecosystem effects to identify where improvements are needed in the management of their respective activities. The Bow-tie/Bayesian belief network approach helps identify issues related to effectiveness, compliance or external factors that may be undermining the overall performance of the management system of policies, processes and procedures used to achieve objectives. It also helps identify changes in activities and pressures that may fall outside the span of prevention controls that were developed and implemented. The Bow-tie/Bayesian belief network approach addresses a much needed concern of any regulator when approving the conditions to allow a project to go ahead after an environmental assessment or for allocating the spatial and temporal distribution controls in a marine planning exercise.

Using international risk management standards and techniques such as the Bow-tie analysis can provide the harmonized definitions and processes that can improve the understanding of the risks and how the risks could be managed to achieve an objective. The Bow-tie diagram is particularly useful for communicating and engaging managers, stakeholders and scientists, providing transparency in the understanding of the risks within the context of a policy. The Bow-tie/Bayesian belief network approach does not simplify the complexities of the management system and the ecosystem. It simply structures the complexity to systematically analyse the causes and consequences of risk within a management system.

As an important extension to the qualitative aspect of the Bow-tie analysis, the Bayesian belief network provides an important quantitative interface to assess the effectiveness of the prevention controls in relation to ecosystem models used to predict effects. The Bayesian belief network explicitly integrates the operational uncertainties of the management system of prevention controls with the scientific uncertainties of modelling ecosystem responses to the pressures. In data-poor situations, the Bayesian belief network allows for expert elicitation to populate the nodes and conditional probabilities while providing a platform for future updates to the model as new scientific and technical knowledge become available.

Nonetheless, these case studies confirmed that the structure of the Bow-tie/Bayesian belief network model is transferable to any management system as well as ecosystem type and scale. The combination of Bow-ties and Bayesian belief networks also operationalizes adaptive management approaches to identify ineffective management strategies and their controls and to improve the management system to reduce or prevent cumulative effects caused by human activities.

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