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# Implementing Bayesian networks for ISO 31000:2018-based maritime oil spill risk management: State-of-art, implementation benefits and challenges, and future research directions

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ABSTRACT

The risk of a large-scale oil spill remains significant in marine environments as international maritime transport continues to grow. The environmental as well as the socio-economic impacts of a large-scale oil spill could be substantial. Oil spill models and modeling tools for Pollution Preparedness and Response (PPR) can support effective risk management. However, there is a lack of integrated approaches that consider oil spill risks comprehensively, learn from all information sources, and treat the system uncertainties in an explicit manner. Recently, the use of the international ISO 31000:2018 risk management framework has been suggested as a suitable basis for supporting oil spill PPR risk management. Bayesian networks (BNs) are graphical models that express uncertainty in a probabilistic form and can thus support decision-making processes when risks are complex and data are scarce. While BNs have increasingly been used for oil spill risk assessment (OSRA) for PPR, no link between the BNs literature and the ISO 31000:2018 framework has previously been made. This study explores how Bayesian risk models can be aligned with the ISO 31000:2018 framework by offering a flexible approach to integrate various sources of probabilistic knowledge. In order to gain insight in the current utilization of BNs for oil spill risk assessment and management (OSRA-BNs) for maritime oil spill preparedness and response, a literature review was performed. The review focused on articles presenting BN models that analyze the occurrence of oil spills, consequence mitigation in terms of offshore and shoreline oil spill response, and impacts of spills on the variables of interest. Based on the results, the study discusses the benefits of applying BNs to the ISO 31000:2018 framework as well as the challenges and further research needs.

## 1. Introduction

Global trade largely relies on international maritime transport: an estimated 80 per cent of the volume of world trade is seaborne and international maritime transport has been projected to continue growing in the coming decades (UNCTAD 2019). While significant improvements have been made in terms of maritime safety (UNCTAD 2019; Hassler, 2011; Haapasaari and Dahlbo 2014; Hänninen and Rytkönen 2006; Knudsen and Hassler, 2011; Lagring et al., 2012; Mitchell 1994; Ringbom 2018), the risk of a large-scale oil spill remains significant. It is well known that there are many different definitions of risk (Aven 2012). For example, the ISO 31000:2018 risk management standard defines risk as

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the “effect of uncertainty on objectives” (ISO 2018), while, e.g. Aven and Renn (2009) define the term as “uncertainty about and severity of the consequences (or outcomes) of an activity with respect to something that humans value”. Here, we do not suggest any specific definition for risk.

In this article, we focus on studies that have mainly analyzed oil spill risk in terms of the uncertainty about the occurrence of an oil spill in the marine environment, and the related environmental, economic, human-health, and socio-cultural consequences. The severity of consequences is a highly value-laden concept requiring additional scientific procedures and the topic is out of the scope of this paper. The environmental as well as the socio-economic impacts could be substantial in the case of a large-scale oil spill from maritime transport, as evidenced by historic accident cases such as Prestige (Spain), Erika (France), and Exxon Valdez (United States) (e.g. Garza-Gil et al., 2006; Miraglia 2002; Kontovas et al., 2010; Peterson et al., 2003).

Oil spill models and modeling tools help both the researchers and end-users (decision-makers, wider audience) to gain a deeper understanding of oil spills, their assessment, and management. Oil spill models for pollution preparedness and response (PPR) planning and decision-making (i.e. models addressing the accident occurrence, the response effectiveness, and the ecological, economic, health, and socio-cultural impacts of oil spills) can provide response operators and risk managers with valuable information to support 1) effective response operations and tactical planning, and 2) strategic (long-term) planning for response concerning, e.g. the dimensions of response resources, guiding the mobilization of resources, and prioritizing protection areas and strategies.

Oil spill models and approaches for PPR can generally be categorized as ex post studies, which are oil spill specific studies conducted after a spill has already taken place, and ex ante approaches that are based on modeled simulations to estimate the possible oil trajectories and the final impacts (Nelson and Grubesic 2018). For reviews on oil spill models and their use in supporting response globally, see e.g. Spaulding (1988), Spaulding (2017), ASCE (1996), Reed et al. (1999), and Afenyo et al. (2015). Widely used models for predicting fate and trajectory of spilled oil include, e.g. OSCAR (Reed et al., 1995), SIMAP (French-McCay 2004; French-McCay et al., 2004), and the General National Oceanic and Atmospheric Administration Operational Modeling Environment (GNOME) (Beegle-Krause et al., 2001). In addition, several models have been developed to assess the environmental (e.g. COWI 2007; French-McCay et al., 2004; Kingston, 2002; Olita et al., 2012) and socio-economic impacts (e.g. Wirtz and Liu, 2006; Wirtz et al., 2007; Nelson et al., 2015), as well as oil spill response effectiveness (e.g. Fingas 2011; Li et al., 2014; Ventikos et al., 2004).

However, limited attention has been paid to uncertainty in maritime transport risk analysis (Merrick and van Dorp 2006; Goerlandt and Montewka 2015a; Kelangath et al., 2012) and in other maritime modeling contexts (Li et al., 2016; Sepp Neves et al., 2015; Sebastião and Guedes Soares 2007; Spaulding 2017). In general, the existing models are deterministic and designed for operational planning or for testing different scenarios and they rarely assess risks *per se*, i.e. they do not provide information about the uncertainties (probabilities) and consequences of particular scenarios. Therefore, models do not describe how well we know what may happen or what were the consequences, and neither do they offer basis to judge which parameters should be known more precisely by additional scientific effort.

Yet, oil spill risks can be considered as systemic and complex risks characterized by high levels of uncertainty as well as ambiguity, i.e. the differing understandings and perceptions of risks, as well as societal values (Aven and Renn 2010). While various definitions exist for uncertainty in decision-making contexts (Döll and Romero-Lankao 2017; Kwakkel et al., 2016; van Asselt and Rotmans, 2002; Walker et al., 2003) and in modeling (Hamilton et al., 2019; Refsgaard et al., 2007; Regan et al. 2002, 2003), uncertainty is often classified as epistemic and stochastic or ontological uncertainty (Walker et al., 2003). Epistemic uncertainty (caused by limited knowledge) related to oil spills is high, since large-scale oil spills are rare and data related to e.g. site specific accident statistics and the environmental conditions/factors are often scarce. Still, deterministic models typically rely on past information (historical data and statistics), i.e. require large amounts of data for parameterization and the number of parameters is easily high compared to available observations. Similarly, ontological uncertainty, which refers to the inherent, natural variability of human and/or natural systems, is high in the model input data. However, deterministic models provide only point estimates or expected values, and do not express or evaluate the uncertainties related to, e.g. assessing the trajectory of the oil in operational oil combating decision-making (Li et al., 2016). Further, complex risks are generally rife with ambiguity, but ambiguity can also occur in cases where risks are “simple” and uncertainty is low (Aven and Renn 2010). Previous studies propose that uncertainty in oil spill risk analysis needs to be better addressed and clearly presented (Mazaheri et al., 2016) and that uncertainty treatment should be applied as a validity criterion for quantitative risk analysis (Aven and Heide, 2009; Goerlandt et al., 2017a).

Further, there is a lack of common methodology for oil spill risk assessments (Sepp Neves et al., 2015): commonly accepted methods are important since oil spill risks are often a transnational problem and require international cooperation in terms of response operations and contingency planning (Laine et al., 2018; Sepp Neves et al., 2015). Recently, comprehensive risk management approaches for planning and preparing for oil spill incidents have increasingly been advocated (IMO 2010; Laine et al., 2018; Sepp Neves et al., 2015). The ISO 31000:2018 International Standard on Risk Management (ISO 2018) provides guidelines for integrated risk management for all types of organizations and is therefore in essential role in communication of academia and industry. The use of the ISO 31000:2018 standard has also been suggested as a suitable basis for the evaluation of Pollution Preparedness and Response (PPR) risk management (Laine et al., 2018) and for dealing with uncertainties when assessing oil spill risks (Sepp Neves et al., 2015) in industry activities. As the main focus has been on industry activities, there is a need to improve the link of the academic scientific work to the ISO 31000:2018 standard.

In recent years, Bayesian networks (BNs, also known as belief networks, Jensen 1996; Pearl 1988) have been increasingly applied in OSRA (e.g. Helle 2015; Hänninen 2015; Lehikoinen 2014; Mazaheri 2017; Nevalainen 2019a; Valdez Banda 2017; Venesjärvi 2015; and references listed in section 4.1.). Bayesian networks offer a flexible modeling approach for risk management as outlined by the ISO 31000:2018 standard/or OSRA. Bayesian networks are well suited for evaluating complex systems where uncertainty is high as they express uncertainty in terms of probability distributions. Despite the increasing interest in BNs for OSRA, there has previously been no analysis on how such models can be used to implement the ISO 31000: 2018 standard. We provide a systemic analysis of the use of BN-based oil spill risk assessment (OSRA-BN) models for pollution preparedness and response (PPR) planning and decision-making, i.e. models addressing the accident occurrence, the response effectiveness, and the ecological, economic, health, and socio-cultural impacts of oil spills. The aim of this paper is, therefore, to analyze how the existing OSRA-BNs models can be aligned with the ISO 31000:2018 framework by offering a flexible approach to integrate various sources of probabilistic knowledge. This paper, however, does not aim to explicitly evaluate the benefits and challenges of the ISO 31000: 2018 standard for oil spill risk assessment and management.

The paper is structured as follows. First, the need for a comprehensive oil spill risk management framework is outlined in Section 2, and the ISO 31000:2018 risk management standard and the Bayesian approach to treating uncertainty are introduced. Section 3 describes the methods used in the study. We performed a literature review of BN models for OSRA for maritime transportation activities, with relevance for pollution preparedness and response (PPR) planning and decision-making. Section 4 then presents the results of the literature review and provides an overview of how Bayesian OSRA models can be applied to the ISO 31000:2018 risk management framework. This is followed by a discussion (Section 5) on the potential and challenges related to the approach, as well as a summary of further research needs. Section 6 is left for conclusions.

## 2. The need for a comprehensive risk management framework

### *2.1. The ISO 3100:2108 framework for oil pollution preparedness and response*

Even though there are various interests in using the risk assessment tools, risk is commonly defined as a combination of the probability of an event and the related negative consequences (Burgman 2005; Jardine et al., 2003; UNISDR 2009; USEPA 1998). Risk assessment is a vital part of the risk management process. Various guidelines and frameworks exist, e.g. for environmental risk assessment (EFSA 2020; OECD 2013; USEPA 1998; IRGC 2017) as well as for assessing risks related to shipping (such as the Formal Safety Assessment (FSA) developed by the International Maritime Organization (IMO)). While the terminology, scope, and elements vary among the different operational guidelines, the assessment and management process is typically described as an iterative one that aims to identify the optimal management action to reach justified balance between expected utilities (e.g. production and carrying oil) and potential negative impacts (e.g. oil spills).

However, the conventional risk management approaches, such that predominantly rely on the traditional, two-dimensional, risk definition, may not be the most suitable for assessing systemic risks characterized by complexity, high levels of uncertainty, and ambiguity (Aven and Renn 2010; ; Döll and Romero-Lankao 2017; Sperotto et al., 2017). Therefore, comprehensive risk management approaches based on stakeholder participation are needed, where the various sources of risk, the system interactions, as well as uncertainties related to the system, are considered in a systematic and iterative manner (Assmuth and Hilden 2008; Pollino and Hart 2008). Likewise, the need for new and integrated ways to assess and manage oil spill risks is increasingly highlighted due to the systemic and complex nature of the risks (IMO 2010; Davies and Hope 2015; Laine et al., 2018; Sepp Neves et al., 2015). Fig. 1 (based on Chang et al., 2014) presents a framework for classifying oil spill response and the short and long-term environmental, economic, human health, and socio-cultural impacts. Fig. 1 illustrates the complexities of oil spill risks as well as the interactions between the elements. When moving from short term operational policy support to long term strategic and directive decisions, the role and methodological basis of probabilistic advice changes (Barton et al., 2012).

In terms of oil spills, the use of the ISO 31000:2018 risk management framework has recently been suggested as a suitable basis for the comprehensive evaluation of PPR risk management (Laine et al., 2018; Sepp Neves et al., 2015). The ISO 31000 Risk Management standard (ISO 2009) was first published in 2009, and updated in 2018 (ISO 2018). Experts from different backgrounds contributed to developing the standard (ISO 2009). The standard is mainly followed by industry players, but it is flexible and is not industry or sector specific.

The standard defines risk management as “coordinated activities to direct and control an organization with regard to risk”, where risk is defined as the “effect of uncertainty on objectives” (ISO 2018). The ISO 31000:2018 definition differs from other risk definitions in traditional risk assessments (Aven 2012; Burgman 2005), as risk is not only defined in terms of the probabilities of negative or undesirable outcomes, but the focus is on uncertainty management. The focus of this paper, however, is not on the various risk definitions, rather, we explore the flexibility of Bayesian networks as a tool to provide relevant knowledge for oil spill risk assessment and management.

The standard comprises the risk management principles, framework, and process (ISO, 2018). The framework provides guidance on how risk management processes can be integrated in a specific organizational setting, i.e. into the activities and functions of an organization. The ISO 31000:2018 risk management process is considered as an iterative process including the following steps: 1) defining the scope, context, criteria, 2) risk assessment (including risk identification, risk analysis, and risk evaluation), 3) risk treatment, 4) recording and reporting, 5)

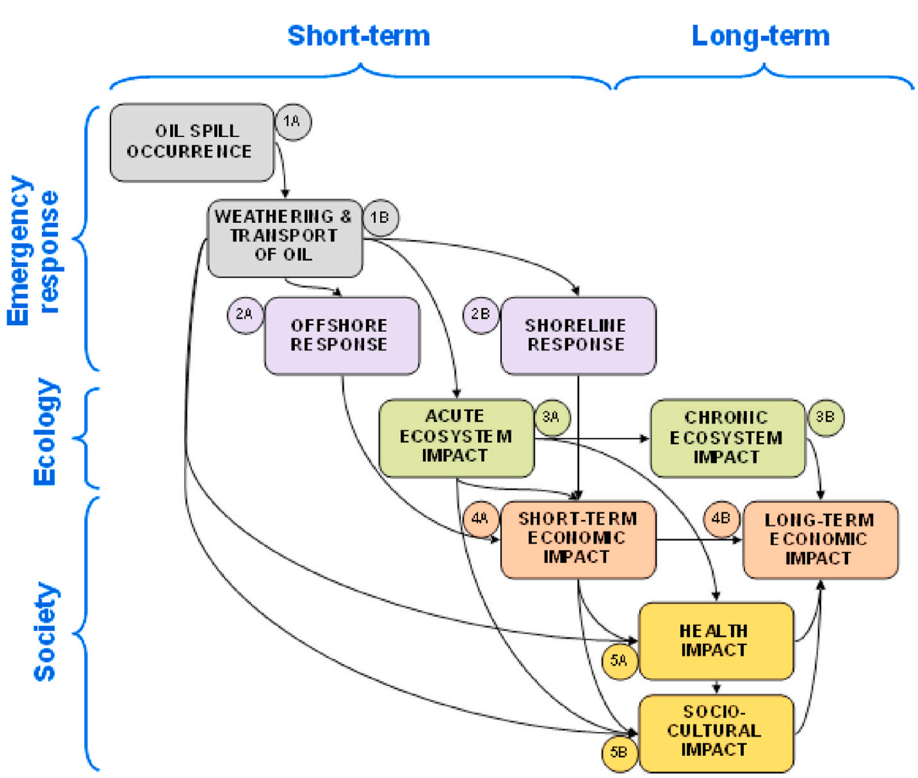


**Fig. 1.** Framework for classifying oil spill response and short and long-term consequences in PPR context. Grey boxes (1 A, 1 B) indicate oil spill occurrence and fate; purple boxes (2 A, 2 B) oil spill response effectiveness; green boxes (3 A, 3 B), ecosystem impacts; orange boxes (4 A, 4 B) economic impacts; yellow boxes (5 A, 5 B) health and socio-cultural impacts. Adapted from Chang et al. (2014). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

**Table 1**
Risk management framework and examples of OSRA-BNs and their applicability (Adapted from ISO 2018).

| | Definition in the context of oil spills | Examples of OSRA-BNs and their applicability |
|---|---|---|
| Scope, context, criteria | Defining the objectives and decisions that need to be made, specifying the time frame and the geographical scope of the study, the sources of risks, the nature and type of potential consequences, as well as the type of the assessment method to be used. | Context specific risk models for the Baltic Sea (e.g. Lecklin et al., 2011). |
| Risk assessment | **Risk identification** refers to identifying and defining the assessment endpoints (e.g. impacts on ecosystems, habitats or species), the potential sources of oil pollution (causes of events), the variables contributing to oil spill occurrence and/or the impacts of a spill (after it has occurred), and the dependencies between those variables. **Risk analysis** includes quantifying the system and the dependencies between the system variables in order to, e.g. estimate impacts in an area, the likelihood of actually polluting vulnerable areas, or the effectiveness of oil spill response measures. **Risk evaluation** includes the consideration, comparison, and prioritization of reduction alternatives based on the results of risk analysis. | Identifying the ecological impacts of dispersants to seabirds in the North Sea, German Bight (Liu and Callies 2019); assessing the economic impacts of oil spill on commercial fisheries in the Great Australian Bight (Pascoe 2018). Quantifying oil outflows from collision (Goerlandt and Montewka 2014b; Montewka et al., 2015); quantifying the ecological impacts of oil in the Baltic Sea (Helle et al., 2011, 2016; Lecklin et al., 2011) Evaluating response effectiveness (Helle et al., 2011; Lehikoinen et al., 2013b) and cost-benefit (Helle et al., 2015b) or cost-effectiveness of response measures (Montewka et al., 2013). |
| Risk treatment | The formulating and selecting of risk treatment options, planning and implementing risk treatment, assessing the effectiveness of the treatment, deciding whether the remaining risk is acceptable, and if not acceptable, taking further actions (e.g. reconsider objectives and/or carry further analysis to gain a better understanding of the risk). | BNs inform which treatment to implement as they allow for assessing risks, e.g. the effectiveness of response measures with the use of decision nodes (e.g. Helle et al., 2015; Lehikoinen et al., 2013a). |
| Recording and reporting | Recording and reporting is necessary in order to communicate risk management activities and outcomes, provide information for decision-making and wider policy activities, improve risk management activities, and support interaction with stakeholders. | The visual nature of BNs serves as a way of structuring information in a systemic manner, i.e. it records information from various sources; Strength of Evidence (SoE) can further support reporting and recording (e.g. Lu et al., 2019). |
| Monitoring and review | Monitoring and review refers to assessing the need for modifying risk treatment options. In terms of risk assessment, monitoring and review of risk models is necessary for examining how well the models represent the system in the light of new information or changes in the system. | BNs can be easily updated as new evidence becomes available; BNs can build on previous models (e.g. the work by Lehikoinen et al., 2013b builds on a previous study by Lecklin et al. (2011)). |
| Communication and consultation | Communication and consultation refer to communicating results of risk assessments to stakeholders such as the industry, insurance companies, or national and international response authorities. | Visual risk diagrams and causal networks, such as BNs, can support risk communication; BNs can be combined, e.g. with GIS (Jolma et al., 2014); BNs can facilitate stakeholder deliberation (Goerlandt and Reiniers 2017; Parviainen et al., 2019). |

monitoring and review, and 6) communication and consultation (Table 1).

The eight risk management principles refer to the underlying values and considerations that are commonly seen as the best practices in risk management: e.g. risk management should be structured and comprehensive, inclusive, dynamic, iterative, and based on the best available information (ISO, 2018). Hence, risk management needs to be based on information that is factual, timely, relevant, accurate and understandable. Risk assessments should utilize both historical and current information, and future scenarios should also be included. (ISO, 2018). These principles should be integrated in the organization's risk management framework and process (ISO, 2018).

### 2.2. Bayesian networks (BNs) as a tool for evaluating uncertainty and identifying decision options

Bayesian networks (Jensen, 1996; Pearl 1988) are increasingly used to evaluate uncertain and complex systems. They build on the subjectivist Bayesian approach, which, in comparison to the frequentist approach in statistics, expresses the personalist view of probability (Aven and Reniers 2013; Gelman et al., 2013) and allows the use of probability distributions, which is not possible in classical statistics. Whereas the frequentist approach is based on induction, the Bayes' theorem enables two-way reasoning, i.e. from cause to effect and vice versa (Jensen, 1996; Pearl, 1998; Pearl and MacKenzie 2018). The diagnostic use, from the effect back to potential causes, enables learning from uncertain evidence.

Bayesian networks help to conceptualize complex systems and describe uncertainty in probabilistic terms. In BNs, different types of variables can be included in the same network, e.g. sources of risks, the uncertainties related to the risks, and the system endpoints, as well as the interaction between the variables. Bayesian networks are often depicted as directed acyclic graphs (DAGs) with nodes and arcs, where the nodes represent random variables and the arcs the probabilistic dependencies between the variables (Fig. 2). A detailed description of BNs can be found, e.g. from Jensen (1996) or Jensen and Nielsen (2007).

Conditional probability tables (CPTs) are used to quantify BNs. The quantification requires the defining of possible values to each variable and assigning conditional probabilities for the strength of the relationships, i.e. the dependencies, between the variables. CPTs contain information of the probabilities of a given state of a child node given the state of its parent nodes and, therefore, they also describe the quality of knowledge, i.e. uncertainties. In addition, BNs can be applied even when data are scarce as the dependencies can be quantified using different types of data, information, and knowledge (i.e. new experimental data, empirical or theory-based models, existing publications, statistics), including expert elicitation, which may be crucial when considering actions that have not yet been tested in practice.

Finally, BNs can be used as decision support tools by including

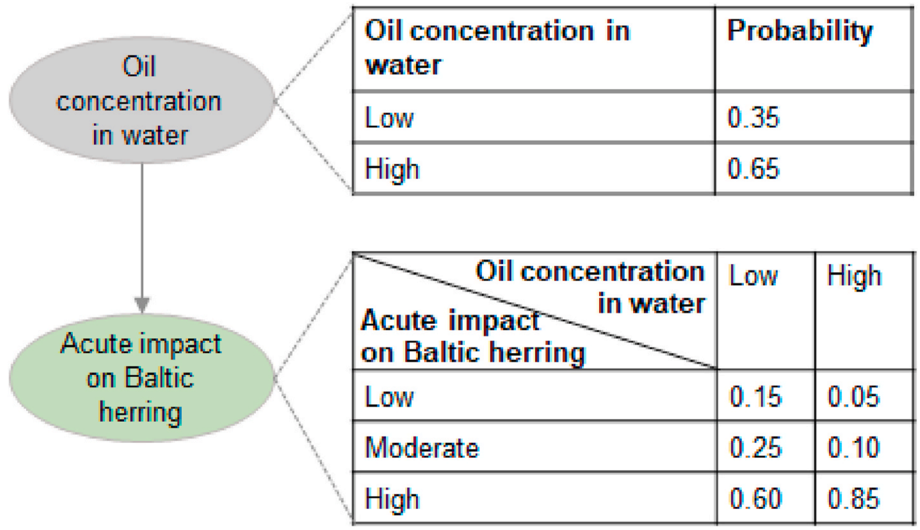


**Fig. 2.** A simplified example of a directed acyclic graph in the context of an oil spill. The nodes represent variables and the arrows linking the variables indicate that the state of the receiving 'child' node (acute impact on Baltic herring) is conditionally dependent on the state of the originating 'parent' node (oil concentration in water). The graph is quantified with the use of conditional probability tables.

distinctive decision and/or utility nodes in the network and effectively embedding the models in a decision analysis context. Bayesian networks with decision and/or utility nodes are generally referred to as influence diagrams (IDs). Decision and utility nodes can also be associated with cost-benefit analysis, which enables comparing the actions also in economic terms. Further, IDs can be used to assess, for instance, the value-of-information, i.e. whether knowing the state of a certain variable would change the expected value of a given decision (Raiffa and Schlaifer, 2000; Helle et al., 2015).

## 3. Methods

We performed a literature review in order to gain insight in the utilization of OSRA-BN models for pollution preparedness and response (PPR) planning and decision-making, and to assess the suitability of the models to the implementation of the ISO 31000:2018 framework. The review focused on BN models for oil spill risks from maritime transportation activities, with relevance for pollution preparedness and response (PPR) planning and decision-making. In particular, we focused on articles presenting BN models that analyze the occurrence of oil spills, consequence mitigation in terms of offshore and shoreline oil spill response, and the impacts of spills on ecosystem and other variables of interest. Articles that discuss the use of BN models for this purpose, e.g. presenting a conceptual approach, or discussing the challenges in developing those, were included as well.

We applied a rigorous and traceable process to identify the relevant literature, based on recommendations by Van Wee and Banister (2016). We used the following steps to identify the relevant literature. First, a search was made in the Web of Science Core Collections (WoSCC) abstract database. All combinations from the following three sets of keywords were used: {"marine" OR "maritime" OR "shipping"} AND {"model" OR "approach"} AND {"oil"} AND {"Bayesian"}. Second, we inspected the title and abstract of the results to screen relevant articles, i.e. that the articles focused on maritime transport oil spill risks and that the information was related to oil spill response. The selected articles were used to construct an initial dataset. Finally, we used backward and forward snowballing to identify further articles, i.e. the reference lists in the articles in the dataset were inspected, and Web of Science was used to search for articles citing these articles. The search was performed in June 2019, leading to a final dataset of 39 articles.

## 4. Results

### 4.1. Review results

The review shows an increased use of BNs for PPR: Figure S1 (Appendix 1) shows a temporal evolution of the number of publications (by country) using BN for PPR. The first article on using BN modeling as an approach for quantifying oil spill risks, response, and ecological impacts, was published in 2005 b y Juntunen et al. (2005). Thereafter, there was an increased interest in the approach from 2009 onwards, with a slowly increasing trend thereafter. It is seen that by far most contributions originate from Finland (31 publications) (Fig. S1). There was an early interest in Estonia (3 publications), and more recent interest in the approach in Canada (4 publications) (Fig. S1). Other countries where BNs have been used for oil spill risk related modeling for pollution preparedness and response include Australia, the United States of America, Norway, Germany, Poland, and Sweden. In this analysis, full counting is applied, i.e. where an article is co-authored by authors affiliated with institutions from different countries, each country is counted for that publication.

BNs have been applied to gain understanding of various aspects of oil spill response and impacts as defined in the framework by Chang et al. (2014), see Fig. 1. Table 2 gives an overview of the articles in the database. It is seen that by far most models explicitly address the oil spill occurrence itself. Most models consider variables considering the size and type of oil (1 A) only as starting points to understand response or impacts, which are the main focus of the models. However, some models are dedicated specifically to provide accurate probabilistic estimates of oil outflow sizes in collision (Goerlandt and Montewka 2014b) or grounding (Montewka et al., 2015) accidents, conditional to traffic and impact conditions. A significant number of models also includes variables related to weathering and transport of oil (1 B), to explicitly account for the extent of the area affected by oil, given the sea and meteorological conditions.

Often, the models quantify the probabilities through expert judgment (Juntunen et al., 2005; Lecklin et al., 2011), but some models (Helle et al., 2011; Lu et al., 2019) use oil drift models as a basis for quantification in one part of the model.

The assessment of offshore response effectiveness (2 A) has been an important use for the developed BN models, e.g. Aps et al. (2010), Helle et al. (2011), Lehikoinen et al. (2013b), Liu and Callies (2019), and Lu et al. (2019). However, shoreline response (2 B) has been included in

**Table 2**
Analysis of OSRA-BN models for oil spill PPR according to framework of Fig. 1. Color coding: Grey (1 A, 1 B): oil spill occurrence and fate; Purple (2 A, 2 B): oil spill response effectiveness; Green (3 A, 3 B): ecosystem impacts; Orange (4 A, 4 B): economic impacts; Yellow (5 A, 5 B): health and socio-cultural impacts. CA = presentation of conceptual approach |D = discussion on BNs for OSRA for oil spill PPR.

| | | Emergency response | | | | Ecology | | Society | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **No.** | **Reference** | **1A** | **1B** | **2A** | **2B** | **3A** | **3B** | **4A** | **4B** | **5A** | **5B** | **CA** | **D** |
| **1** | Juntunen et al. 2005 | ■ | ■ | ■ | | ■ | ■ | | | | | | |
| **2** | Kuikka et al. 2005 | | | | | ■ | ■ | | | | | | ■ |
| **3** | Aps et al. 2009a | | | | | ■ | | | | | | | |
| **4** | Aps et al. 2009b | | | ■ | | ■ | | | | | | | |
| **5** | Klemola et al. 2009 | ■ | ■ | ■ | | ■ | | | | | | ■ | |
| **6** | Aps et al. 2010 | | | ■ | | ■ | | | | | | | |
| **7** | Helle et al. 2011 | ■ | ■ | ■ | | ■ | | | | | | | |
| **8** | Jolma et al. 2011 | ■ | ■ | | | | | | | | | ■ | |
| **9** | Kuikka et al. 2011 | | | | | | | | | | | | ■ |
| **10** | Lecklin et al. 2011 | ■ | ■ | ■ | | ■ | ■ | | | | | | |
| **11** | Lehikoinen et al. 2012 | ■ | ■ | | | ■ | | | | | | ■ | |
| **12** | Venesjärvi 2012 | ■ | | | | ■ | ■ | | | | | | |
| **13** | Kuikka et al. 2013 | | | | | | | | | | | | ■ |
| **14** | Lehikoinen et al. 2013a | | | | | | | | | | | | ■ |
| **15** | Lehikoinen et al. 2013b | ■ | ■ | ■ | | | | | | | | | |
| **16** | Montewka et al. 2013 | ■ | ■ | ■ | ■ | | | ■ | | | | | |
| **17** | Goerlandt and Montewka 2014a | ■ | | | | | | | | | | | |
| **18** | Goerlandt and Montewka 2014b | ■ | | | | | | | | | | | |
| **19** | Jolma et al. 2014 | ■ | ■ | | | ■ | | | | | | | |
| **20** | Khan et al. 2014 | ■ | ■ | | | ■ | | ■ | | ■ | | ■ | |
| **21** | Rahikainen et al. 2014 | ■ | ■ | | | ■ | | | | | | | |
| **22** | Davies and Hope 2015 | | | ■ | | | | | | | | ■ | |
| **23** | Goerlandt and Montewka 2015b | ■ | | | | | | | | | | | |
| **24** | Helle et al. 2015 | ■ | | ■ | ■ | | | ■ | | | | | |
| **25** | Lehikoinen et al. 2015 | ■ | ■ | ■ | | | | | | | | | |
| **26** | Montewka et al. 2015 | ■ | | | | | | | | | | | |
| **27** | Helle et al. 2016 | ■ | ■ | | | ■ | | | | | | | |
| **28** | Valdez Banda et al. 2016 | ■ | | | | | | | | | | | |
| **29** | Goerlandt 2017 | ■ | | | | | | | | | | | |
| **30** | Goerlandt et al. 2017b | ■ | ■ | ■ | | | | | | | | ■ | |
| **31** | Nevalainen et al. 2017 | | | | | | | | | | | ■ | |
| **32** | Rahikainen et al. 2017 | ■ | | | | ■ | | | | | | | |
| **33** | Pascoe 2018 | ■ | ■ | | | ■ | ■ | ■ | ■ | | | | |
| **34** | Afenyo et al. 2019 | ■ | ■ | ■ | | | | ■ | ■ | ■ | ■ | | |
| **35** | Fahd et al. 2019 | ■ | | | | ■ | | | | | | | |
| **36** | Liu and Callies 2019 | ■ | ■ | ■ | | ■ | | | | | | | |
| **37** | Lu et al. 2019 | ■ | ■ | ■ | | | | | | | | | |
| **38** | Nevalainen et al. 2019b | | | | | | | | | | | | ■ |
| **39** | Parviainen et al. 2019 | | | | | | | | | | | ■ | |
| | **Total** | **31** | **19** | **16** | **3** | **22** | **7** | **6** | **3** | **3** | **2** | **8** | **4** |

only a handful of models (Helle et al. 2011, 2015; Montewka et al., 2013).

In terms of impacts, most models focus on assessing the acute impacts (3 A) of oil to specific marine or coastal species, e.g. Aps et al. (2009a), Aps et al. (2009b), Helle et al. (2011) and Rahikainen et al. (2017), while some models also address long-term impacts (3 B) to certain species (Lecklin et al., 2011; Venesjärvi 2012; Pascoe 2018). Economic impacts, especially acute ones (4 A) such as the direct costs related to offshore oil combating and shoreline clean-up (Helle et al., 2015b; Montewka et al., 2013), have been considered. Long-term economic impacts (4 B) have been evaluated significantly less often, and if so in a more exploratory sense (Afenyo et al., 2019; Pascoe 2018). Human health impacts (5 A) and socio-cultural impacts (5 B), have been included in exploratory and more conceptual models (Afenyo et al., 2019; Parviainen et al., 2019), but no advanced quantifications have been performed.

A significant number of articles provides a conceptual approach (CA), i.e. presenting the idea of using BN models for oil spill impact and response management. These may involve the use of BNs as real-time environmental decision support systems during an oil spill response (Davies and Hope 2015), using BNs alongside other modeling approaches (Klemola et al., 2009), presenting the idea as a new solution for a specific geographical area (Khan et al., 2014), or presenting a new use case for BNs in a pollution preparedness and response context. An example of the latter is the model by Parviainen et al. (2019), which uses influence diagrams based on the logic of BNs to study how different stakeholders frame oil spill risks. In this work, however, the strength of the probabilistic dependencies between variables was not quantified. Also, Nevalainen et al. (2017) lays out a conceptual approach to analyze the ecological impacts of oil spills in the Arctic marine environment without quantifying the model parameters.

A final cluster of articles provides discussions on the development and use of BNs for oil spill occurrence, response, and impacts. For instance, Kuikka et al. (2011) describe challenges in developing BNs, particularly in interdisciplinary research teams. Kuikka et al. (2013) discuss the use of BNs as learning systems, both in terms of using the models as a tool to understand the value of information about particular system aspects which are uncertain at the time of the model development, as well as in terms of using the outputs of a model as inputs for further models with different aims. Further, Nevalainen et al. (2019b) apply BNs in sensitivity analysis related to the index approach developed to estimate the vulnerability of Arctic biota to oil spills.

### 4.2. Defining scope, context, criteria

As the review results demonstrate (section 4.1), OSRA-BNs have been increasingly applied for PPR depicting complex systems and covering the uncertainties related to the occurrence of oil spills, their magnitude, the effectiveness of various response measures, as well as possible ecological, economic, health, and socio-cultural impacts.

Context-specific oil spill risk assessments are important (ISO, 2018). Risk models need to consider the specific context of the risks: the nature of spill risks varies by region due to differences in the type of shipping, the physical features of the marine environment, regulations and policy measures, and varying economic, social, and cultural context. For example, models assessing the oil-induced impacts to ecosystems in other marine environments may not be applicable in the low-saline, brackish, water conditions of the Baltic Sea (Lecklin et al., 2011). As noted in Section 4.1, so far, the OSRA-BN studies have mostly focused on the Baltic Sea.

Further, the ISO 31000:2018 framework emphasizes stakeholder participation in defining the scope, context, and criteria of risk assessments (ISO, 2018). Especially in the case of complex risks, where defining the system variables is difficult and the causal interactions between the variables are highly uncertain, reaching a consensus on the model structure might be challenging and alternative model structures are possible, often due to differing views about the key causalities. BNs can be used for exploring different scenarios as well as the multiple perspectives and dimensions (e.g. economic, social, and environmental) of risk, which can then be either integrated within the same network or assessed separately. For example, Parviainen et al. (2019) provided a conceptual approach for building qualitative influence diagrams to examine how different stakeholders perceive and identify oil spill risks caused by offshore oil industry operations in the Norwegian Barents Sea. BNs require the quantification of the system, and the influence diagrams built in the study could be further quantified. Fully quantified BNs can be used to promote informed discussion on tradeoffs or to calculate the optimal tradeoffs between different objectives (see section 4.3.3).

### 4.3. Risk assessment

#### 4.3.1. Risk identification

Risk identification includes deciding on the system end points, i.e. what is at risk. Once risks are identified, BNs can help to conceptualize complex systems as well as describe the different possible interactions between the variables and the system endpoints in a probabilistic manner (section 2.2). In terms of oil spill risks, with the use of BNs, Liu and Callies (2019) studied the use of dispersants and the ecological impacts of dispersants to seabird distributions in the North Sea, German Bight. The system included several variables related to e.g. the oil type, season, drift paths to target areas, currents, and the ecological impacts. Pascoe (2018) applied BNs to explore the economic impacts of a potential oil spill on commercial fisheries in the Great Australian Bight. The model captured several key biophysical and economic factors to identify the system and the potential economic consequences for different fisheries (both wild-catch fisheries and aquaculture).

Studies by Lecklin et al. (2011) and Helle et al. (2011) were the first to identify risks to assess the ecological impacts of a potential oil spill in the Baltic Sea using BNs. Lecklin et al. (2011) identified risks to assess the biological acute and long-term impacts to Baltic Sea marine and coastal species using BNs. The study also ranked species sensitivity to oil. Helle et al. (2011) identified the risks to six different species in order to assess the impacts of an oil spill to the different parts of the ecosystem in the Gulf of Finland.

Further, Nevalainen et al. (2017; 2019) proposed the use of BNs to identify risks in order to assess the biological impacts of oil spills on different functional groups in Arctic waters. Previous research on oil spill risks in the Arctic also investigated the biophysical and socio-economic impacts with the use of BNs (Afenyo et al., 2019) and qualitative influence diagrams (Parviainen et al., 2019). Afenyo et al. (2019) developed a comprehensive probabilistic model, named as the Socio-Economic Impact Model for the Arctic (SEMA), which was used to identify risks to assess the social, economic, and biophysical impacts (in terms of costs) of an oil spill due to shipping activity in the Arctic.

#### 4.3.2. Risk analysis

Following the ISO 31000:2018 standard, risk identification is followed by risk analysis, where, in a BN application context, the aim is to quantify the system and the relationships between the system variables using conditional probabilities. BNs are useful for risk analysis. Oil spill risk analysis is often challenging due to lack of observational data. As noted earlier (section 2.2), BNs allow for the integration of different types of knowledge sources. In addition, expert elicitation is often used for constructing BNs in the cases where statistical data, publications for meta-analysis or simulation models are not available.

For example, in their study on the biological impacts of a potential oil spill in the Baltic Sea, Lecklin et al. (2011) used already published studies and expert elicitation in order to quantify the biological impacts as well as the recovery potential of a selected group of organisms. In addition, BNs can be combined with deterministic simulations models, e.g. Helle et al. (2016) studied the effects of an oil spill caused by different tanker accident scenarios to threatened species and habitats in the Northern Baltic Sea using BNs. The study (ibid.) combined a BN describing tanker accidents and uncertainties related to them, probabilistic maps showing the movement of oil, and a database of threatened species and habitats.

Risk analysis includes a comprehensive overview of uncertainties (ISO 2018). BNs are designed to handle and communicate uncertainties explicitly (section 2.2). Bayesian models estimating oil outflows from collision (Goerlandt and Montewka 2014b) and grounding (Montewka et al., 2015) accidents have provided a way for assessing the uncertainties related to the size of outflows when only limited data regarding e.g. ship design or the specific accident scenario is available. In the study by Valdez Banda et al. (2016), BNs have been quantified for sea ice conditions. The study (ibid.) primarily focused on accident prevention measures for ship collision occurrence, but also provided estimates of oil spill sizes conditional to navigation conditions, i.e. gave estimates of the likely oil spill sizes in different accident scenarios, which is useful in a PPR context.

Further, Helle et al. (2011) applied BNs to describe uncertainties related to the effectiveness of oil combating from an ecological perspective in the Baltic Sea. Helle et al. (2016) further illustrated the uncertainties related to the environmental impacts of oil spills in their study on the effects of an oil spill caused by different tanker accident scenarios to threatened species and habitats in the Northern Baltic Sea.

#### 4.3.3. *Risk evaluation*

BNs with decision and/or utility nodes can be used for comparing the effectiveness of different measures and decision alternatives (section 2.2). When evaluating oil spill risks, BNs have been used to compare the effectiveness of different oil combating methods on the risk level and to evaluate what is the potential of a response system to reduce the amount of oil in the water. For example, Liu and Callies (2019) have evaluated the benefits of using dispersants in oil combating in the German Bight.

Most of the response models have focused on the Baltic Sea (Helle et al., 2013; Juntunen et al., 2005; Lehikoinen et al., 2013b; Lu et a. 2019; Montewka et al., 2013). For example, Juntunen et al. (2005) compared the effectiveness of different oil combating strategies in order to assess the effects of oil spills on the ecosystem of the Gulf of Finland. In the Baltic Sea, the response needs to be rapid and effective. In the case of an accident, oil spill response would rely on mechanical clean-up as according to the HELCOM agreement, the use of chemical dispersants or in-situ burning is not recommended in the Baltic sea (HELCOM 2001). Collecting the oil before it reaches the shore is considered vital to protect the coastal ecosystems. However, for example in the Gulf of Finland, effective oil spill response is challenging since the Gulf is narrow and oil would reach the shores fast, i.e. within some days or even in some hours (e.g. in the case of a grounding). Similarly, oil response in the archipelagos of the Baltic Sea would be complicated as, e.g. the navigation of clean up vessels in the narrow inlets would be difficult (Montewka et al., 2013).

The existing Bayesian models highlight the uncertainties that relate to the assessment of the response effectiveness (Helle et al., 2011; Lehikoinen et al., 2013b) and the costs and benefits of oil spills (Helle et al., 2015b) or the cost-effectiveness of different response measures (Montewka et al., 2013). Using different scenarios, Helle et al. (2011) demonstrated that the effects of different oil combating strategies are difficult to predict as their efficiency is strongly dependent on the environmental conditions, which are stochastic and where impacts are highly uncertain. The model included three oil combating options (mechanical recovery offshore, dispersants, and oil deflection booms) and several variables representing the uncertainty related to the accident, behavior of spilled oil, environmental conditions, efficiency of oil combating, and biological effects. The deployment time of the booms, an important restriction for the operational oil combating, was not included as a random variable, but it was still taken into account when calculating the proportion of the populations that can be safeguarded by booms. Similarly, when assessing the optimal placement of combating vessels, Lehikoinen et al. (2013b) found that environmental variables, e.g. wave height and wind speed, make the effectiveness of response operations highly uncertain.

Winter period and ice cover would significantly reduce response effectiveness. Most of the existing BN response models, however, have excluded winter season with ice, as the conditions differ significantly from open sea. Recent research on mechanical recovery in sea ice conditions in the Baltic Sea by Lu et al. (2019) provided a comprehensive model on oil spill recovery under different sea ice and atmospheric conditions, for different oil types, accident locations, spill sizes and port locations.

Considering the high levels of uncertainty related to response effectiveness, the role of preventive actions has been highlighted: preventive actions can also be more cost-efficient than response measures (Helle et al. 2011, 2015; Hänninen 2014; Haapasaari and Dahlbo 2014).

### 4.4. *Risk treatment*

Risk treatment refers to actions and the implementation of measures to reduce the probability of an oil spill and to mitigate the consequences based on risk assessment (section 2.1). BNs do not have a direct role in risk treatment, i.e. in the implementation of treatment measures in practice. The OSRA-BNs, however, demonstrate the need for action: BNs inform risk treatment as they allow for assessing risks and the effectiveness of response measures with the use of decision nodes (e.g. Helle et al., 2015; Lehikoinen et al., 2013a).

OSRA-BNs also imply that risk treatment measures need to pay careful attention to uncertainties: as shown in the previous sections (e.g. sections 4.3- 4.3.3), the existing BN models for Baltic Sea demonstrate that the uncertainties related to oil spill occurrence, response effectiveness and the environmental impacts are high. BNs also support iterative and participatory risk treatment (see e.g. sections 4.2, 4.6, and 5.2).

### 4.5. *Recording and reporting*

Recording and reporting of oil spill risks need to embody the principles underlying risk management, such as transparency, the use of best available knowledge, a structured approach, and inclusiveness (section 2.1). The systematic and visual nature of BNs serves as a way of structuring the information, i.e. it records information from various sources. When developing BNs, documenting the information behind the conditional probability tables and the variables needs to be carried out in a systematic manner. For example, in the study of Valdez Banda et al. (2016) and Lu et al. (2019), the information has been provided in the appendix of the journal articles. Strength of Evidence (SoE) assessment, which refers to the qualitative assessments of the quality of the evidence underlying the BNs, can also be utilized to further support systematic and transparent recording and reporting. For example, Lu et al. (2019) included an SoE assessment for the quantified uncertainty measures in a BN model assessing response effectiveness in winter conditions, and Goerlandt and Montewka (2014b) provided a qualitative uncertainty and bias assessment related to oil outflows.

### 4.6. *Monitoring and review*

BNs can be easily updated once new information and evidence (e.g. observations, field data, model results) becomes available, which facilitates monitoring and review. BNs can also be used as a basis for new models. For example, the oil dispersion model (including probability estimates of the amount of spilled oil, evaporation of oil, length of oiled coastal water, type of the accident, and leakage stop) developed by Juntunen et al. (2005) has later been applied to other models to estimate, e.g. the ecological impacts of oil spills (Lecklin et al., 2011; Helle et al., 2011). Similarly, the work of Lecklin et al. (2011) has later been used to develop other, more specific, ecological impact models (Helle et al., 2011) as well as response models (Lehikoinen et al., 2013b).

### 4.7. Communication and consultation

Visual risk diagrams and causal networks, such as BNs, can support risk communication. SoE assessments can further improve communication on uncertainties (Lu et al., 2019). The models can also be combined with user-friendly interfaces, e.g. Geographic Information Systems (GIS) for spatial risk assessments (Jolma et al., 2014; Helle et al., 2016), which supports the use of BNs as communication tools. In a broader sense, risk diagrams also make the possible conflicting views over risks explicit and facilitate stakeholder deliberation, and finally, can help in selecting appropriate risk management measures as well as ranking them (Goerlandt and Reniers 2017; Parviainen et al., 2019). Hence, it is recommended to use BNs alongside other visualization tools to maximally facilitate communication.

## 5. Discussion

The ISO 31000:2018 standard provides a comprehensive framework for contextualizing, assessing, evaluating, and treating risks. In Section 4, an overview is given of how the existing probabilistic BNs can support the implementation of ISO 31000:2018-based maritime oil spill risk management. The work suggests that BNs have several useful features for oil spill risk management and can serve as a valuable tool for implementing the ISO 31000:2018 principles and process.

The benefits of OSRA-BNs over alternative modeling approaches include features such as the possibility to comprehensively represent complex systems in a graphical fashion and the flexibility in using various knowledge sources (both quantitative and qualitative information). Further, BNs are especially valuable for treating uncertainty as they explicitly express uncertainty between system variables in the form of probability distributions. Overall, BNs for OSRA can support and improve iterative and participatory management approaches that are based on continuous learning processes.

### 5.1. BNs for ISO 31000:2018 risk management

OSRA-BNs can help the implementation of the ISO 31000:2018 risk management principles in practice. OSRA-BNs effectively facilitate conceptualizing complex systems. In BNs, different types of variables can be included in the same network, e.g. sources of risks, the uncertainties related to the risks, and the system endpoints. The causal and visual structure allows for evaluating the interactions in a structured and systematic manner. BBN can be used also in a diagnostic manner, i.e. updating the probabilities of causes by observing the state of impacts. This may be very useful in case specific analysis, i.e. after an accident.

The use and integration of both qualitative and quantitative information from different knowledge domains ensures that BNs are based on best evidence that is factual, timely, and relevant. The use of different knowledge forms, such as expert elicitation, to identify system variables and to quantify the cause-effect relationships between the system variables allows for risk analysis even when quantitative data are lacking or scarce, which makes the approach especially suitable for context-specific oil spill modeling, where region-specific data are often limited. BNs can also be easily customized for specific contexts as, e.g. existing general models can be modified with region specific information.

OSRA-BNs also allow for risk evaluation, i.e. for comparing management actions and identifying the optimal measures to minimize risks. For example, the effectiveness and/or cost-efficiency of alternative response measures can be compared by adding new decision and utility nodes to a BN and by assigning fixed distributions to input variables and testing how the probability distributions of the output variables change as a response to this. The results, i.e. the outcome variables, are expressed as probability distributions, which provides a basis for a probabilistic assessment of risks where uncertainty, e.g. related to achieving the desired outcome, is expressed in an explicit manner. In sum, BNs can help decision-makers to realistically evaluate the chances (likelihood) of achieving the desired result/outcome as well as the uncertainties associated with it. The effective calculus of discrete probabilities enables the use of the model to interactively learn from the case.

Further, OSRA-BNs support iterative and adaptive management. BNs use previous knowledge (e.g. models and expert knowledge) effectively as the modular structure of BNs allows for modifying and updating previous oil spill models by adding new information/nodes: this supports continuous learning processes. BNs also assist iterative modeling as they allow for updating the prior information as new evidence becomes available. The probability distribution narrows as new knowledge accumulates and uncertainty about the phenomenon and the parameters decreases.

### 5.2. BNs and OSRA

Risk management approaches need to take into consideration the complexity of oil spill risks, the high levels of uncertainty, as well as ambiguity. The overview in Section 4 indicates that existing OSRA-BNs are valuable for understanding systemic risks, such as oil spill risks. Notably, OSRA-BNs can improve and support risk communication about uncertainties as well as stakeholder participation. The role of stakeholder participation throughout the modeling process is increasingly emphasized in the management of complex risks (ISO 2018; Aven and Renn 2010): stakeholder participation can enhance the legitimacy of decision-making, support effective implementation of models, and promote social learning (Aven and Renn 2010; Shrader-Frechette 1991; Stern and Fineberg 1996).

The graphical form of BNs allows the communication of uncertainty and risks in an understandable way to decision makers and other stakeholders. The users can easily identify the main sources of uncertainty affecting in the model as well as where uncertainty can be reduced. Communication about uncertainties is especially important when the results are used to inform public policy, as decision-makers and managers need to be informed about the possible outcomes and base their decisions on robust quantitative estimates (Sperotto et al., 2017). However, the end-users might not be aware of the uncertainties involved in modeling results, or the risk assessment results expressed as point estimates may seem definitive if the limitations in data and the inadequacies of the models are not communicated appropriately (Merrick and Van Dorp 2006; Goerlandt and Montewka 2015a). Therefore, uncertainties need to be understood also by the non-scientific community in order to avoid misjudged information as well as to prevent overconfidence in management responses (Uusitalo 2007). Accounting for the uncertainties include in models is important as it can strengthen the acceptance of model outputs as well as the implementation of risk treatment options based on the outputs. In sum, if uncertainties are left untreated and are poorly communicated, the models may, contrary to their purpose, hamper effective risk management (Uusitalo et al., 2015).

Participatory approaches based on visual risk diagrams, such as BNs, can provide better understanding of how risks and risk control options are defined and prioritized by different stakeholders (Haapasaari et al., 2015; Parviainen et al., 2019). Involving stakeholders in the modeling processes and in identifying, analyzing, and evaluating risks ensures inclusive risk management that is considerate of human and cultural factors. Participation of stakeholders can be seen as especially important during the first phase of the process as setting the scope and context for risk assessment and management, i.e. framing of the risk, defines the rest of the management process (Brugnach et al., 2011; Döll and Romero-Lankao 2017; Parviainen et al., 2019).

Regional stakeholder committees can support the participation of stakeholders in assessing regional oil spill risks (Haapasaari et al., 2015). Such committees can provide an arena for discussing risk perceptions, the tolerability of risks and the costs of reducing them, as well as the development and use of decision support tools. The use of BNs can provide an effective method to explore how different stakeholders perceive and prioritize risks and risk control options. The use of full probability distributions can support discussions over acceptable risks that is informed by science. Indeed, rather than aiming to accurately quantify risks and uncertain systems, Rae and Alexander (2017) propose that risk assessments should primarily be seen as a means of describing uncertainties. A similar view is expressed by Goerlandt and Reniers (2018), who suggest that risk models and assessments are better understood as non-predictive artefacts, which serve as a basis for reflection and discussion, rather than as tools for accurate measurement. In sum, participatory OSRA-BNs can support knowledge co-production, enable experimentation between a range of stakeholders, and finally, enable social learning (Parviainen et al., 2019).

The challenges related to the use of BNs in environmental modeling have been extensively discussed by several authors (Aguilera et al., 2011; Düspohl et al., 2012; Phan et al., 2016; Pollino and Henderson, 2010; Uusitalo, 2007). The main challenges include, e.g. the high level of expertise needed for model development, the labor-intensive process of model development, the limited capacity of BNs in dealing with continuous variables, and the growing computational effort when modeling complex systems. As with models in general, BNs can also oversimplify the system, as it is not always possible to include all (potentially) relevant factors in a model. This may lead to overly optimistic outcomes. The major drawbacks related to the use of BNs in oil spill risk assessment and management, however, include their limited capacity to represent temporal and spatial dynamics (temporal developments cannot be easily represented), the limitations of expert elicitation (Rae and Alexander 2017), and the difficulty of performing a quantitative validation of model results (Goerlandt et al., 2017a,b).

To deal with temporal and spatial dynamics, BNs can be combined with e.g. GIS for spatial risk assessment (Helle et al., 2016; Jolma et al., 2014). Combining BN models with user-friendly interfaces, such as GIS, helps to visualize outputs and also support the use of BNs as communication tools. Further, Dynamic Bayesian Networks (DBNs) can be used for representation of risk through time and space (Pollino and Henderson, 2010). Both methods, however, are relatively time-consuming and require extensive expertise for developing models.

### 5.3. Knowledge gaps and future work

Most of the current work focuses on the environmental impacts of oil spill accidents in the Baltic Sea: only few OSRA-BN models exist for other sea areas. Limited attention has been paid to identifying and assessing environmental risks in sea ice conditions. New risks, such as the use of liquefied natural gas (LNG) or biofuels and their impact on the environment should be further explored.

Research on other than the environmental impacts of oil spills remains exploratory. Models assessing the economic impacts focus on comparing the cost-benefit or cost-effectiveness of different prevention and response measures (Helle et al., 2015; Montewka et al., 2013). Similarly, further research is needed on the socio-cultural as well as health impacts of oil spills. In terms of risk analysis, i.e. the quantification of BNs, further attention should be paid on the limitations of expert elicitation. Combining the views of multiple experts and/or other relevant stakeholders may help in overcoming biases. Improving methods for the quantitative validation of results is also needed. For analysing future risks, it might be useful to combine different types of models to achieve a more complete picture of a system change, such as the effects of an oil spill on the ecosystem, and the uncertainties related to the process (Laine et al., 2018; Uusitalo et al., 2016). Combining different models (deterministic, probabilistic, etc.) and types of risk assessments (quantitative, qualitative, participatory, etc.) could contribute to a more nuanced, transparent, and deeper understanding of oil spill risks and the uncertainties related to the risks and risk management.

For risk evaluation, most of the models focus on the Baltic Sea. The existing BN models for the Baltic Sea often combine some of the aspects of oil spill risk pollution preparedness and response. However, the models are not comprehensively integrated (e.g. combine the estimation of oil fate and potential trajectory with the assessment of oil spill response effectiveness or with potential impacts) and even if they are integrated, it is not necessarily optimal as the models are typically developed for specific conditions and/or policy questions. Further, most OSRA-BNs exclude winter conditions: the existing models for ice covered waters focus on prevention measures for ship collision occurrence and on mechanical recovery.

While expert knowledge has been used for developing BN models, the existing models have not included a wider range of societal stakeholders in constructing and developing the risk models. Most of the OSRA-BNs focus on quantifying risks and the system dependencies, however, BNs can also be applied to explore stakeholder perceptions (Haapasaari et al., 2012; Kuikka and Varis, 1997; Varis and Kuikka 1997; Parviainen et al., 2019). More research is needed on how well stakeholders understand the BNs approach, how to effectively facilitate knowledge sharing and social learning, and what factors enable successful stakeholder deliberation.

We have provided an overview of existing OSRA-BN models and their use, but the overall framework provided is only a suggested approach for how the models can be integrated in the ISO 31000:2018 structure. Naturally, the ISO 31000: 2018 risk management framework and the suggested approach for integrating BNs in the ISO framework is open for discussion and requires testing and possible adjustments. For example, Aven and Ylönen (2019) argue that the strong focus on industry standards, such as the ISO 31000, in risk management may pose a threat to the development of risk science. Therefore, further research is needed to explore and test how OSRA-BNs can contribute to different risk management frameworks, such as the guidelines provided by the Society for Risk Analysis (SRA 2018), which are based on work by scientific organizations. However, as noted by Aven and Ylönen (2019), both industry-based standards and scientific-based guidance are needed to support the development and enhancement of risk science.

## 6. Conclusion

This study provides a global review of the OSRA-BNs models for pollution preparedness and response and systematically analyses how the models can help to implement the ISO 31000:2018 risk management framework in practice. The study also offers insight into the use of BNs in oil spill risk assessment and management at a broader level, and suggests various avenues for future research.

The study indicates that OSRA-BNs can help to support many of the ISO 31000:2018 principles and that the models are especially useful for risk analysis and evaluation, as well as communication. OSRA-BNs represent complex systems in a visual, easily understandable, manner, and can utilize various knowledge sources (both quantitative and qualitative information). Explicit treatment of uncertainty as well as communication about uncertainty is a vital part of the assessment and management of complex risks. BNs express uncertainty between system variables in the form of probability distributions in a visual manner, which aids risk communication. We also discuss the challenges related to OSRA-BNs. We suggest that transparent methods that allow also for qualitative descriptions of risks and the system uncertainties are needed to complement the current quantitative risk assessment models.

Finally, BNs for OSRA can support participatory management approaches that are based on continuous learning processes. We suggest that OSRA-BNs can help to explore possible conflicting views over risks, facilitate collaborative problem framing, and promote social learning. In sum, we suggest that BNs aid robust decision making even in the case of systemic and multi-layered risks, such as oil spill risks. However, as participatory approaches do not necessarily lead to more inclusive decision-making, further research is needed to study the “why”, “how”, and "who" in participatory modeling.

## Author contribution

Tuuli Parviainen: Conceptualization, Investigation, Writing - original draft, Visualization.: Floris Goerlandt: Formal analysis, Writing - review & editing, Visualization.; Inari Helle: Writing - review & editing, Visualization.: Päivi Haapasaari: Conceptualization, Writing - review & editing, Supervision.: Sakari Kuikka: Conceptualization, Supervision, Funding acquisition.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2020.111520.

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