



A Bayesian Network risk model for assessing oil spill recovery effectiveness in the ice-covered Northern Baltic Sea

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ARTICLE INFO

Keywords:

Risk analysis

Oil spill

Recovery effectiveness

Sea ice

Maritime safety

Marine pollution

ABSTRACT

The Northern Baltic Sea, as one of the few areas with busy ship traffic in ice-covered waters, is a typical sea area exposed to risk of ship accidents and oil spills in ice conditions. Therefore, oil spill capability for response and recovery in this area is required to reduce potential oil spill effects. Currently, there are no integrated, scenario-based models for oil spill response and recovery in ice conditions. This paper presents a Bayesian Network (BN) model for assessing oil spill recovery effectiveness, focusing on mechanical recovery. It aims to generate holistic understanding and insights about the oil spill-to-recovery phase, and to estimate oil recovery effectiveness in representative winter conditions. A number of test scenarios are shown and compared to get insight into the impact resulting from different oil types, spill sizes and winter conditions. The strength of evidence of the model is assessed in line with the adopted risk perspective.

1. Introduction

Oil spills of different sizes have occurred in open waters, causing marine pollution. Accordingly, oil spills comprise an active area of research in various disciplines, such as biological, chemical, and physical science, as well as engineering and operations research (Murphy et al., 2016). The geographical focus of oil spill research mostly covers the North Atlantic, the North Pacific and, in recent years, the Gulf of Mexico as well (Murphy et al., 2016). Lee et al. (2015) conducted an expert panel review on crude oil release and identified high-priority research needs, including the need to better understand spills in regions such as the Arctic, oil spill effects on the ecosystem, and spill response and prevention. Meanwhile, with the development of shipping routes in the Arctic – see, e.g., Beveridge et al. (2016), Stoddard et al. (2016), and Aksenov et al. (2017) – concerns about marine safety and oil spills in ice conditions have received greater attention in recent years (EPPR, 2015). For instance, Knol and Arbo (2014) addressed the Norwegian case from a pan-Arctic perspective, Afenyo et al. (2016b) focused on a fugacity model of accidental oil release, Goerlandt et al. (2017a) analyzed navigational accidents in ice, and Zhang et al. (2017) focused on the safety of escort operations in Arctic ice-covered waters. The Northern Baltic Sea is one of the busiest ship traffic areas in which

shipping occurs in ice conditions. The Gulf of Finland (GOF), part of the Northern Baltic Sea, is recognized as one of the most transited maritime areas in the world (Kuronen et al., 2009). About 80% of Finnish imports and exports are transported through the Northern Baltic Sea (Asplund and Malmberg, 2011). Winter conditions usually begin in mid-November in the Bay of Bothnia and between mid-December and early January in the Gulf of Finland and Sea of Bothnia, and last until mid-April in the Gulf of Finland and the beginning of May in the Bay of Bothnia (Jalonen et al., 2005). However, there is also a possibility that the length of the ice season may be significantly shorter in the future (Höglund et al., 2017). In this area, oil transportation has increased steeply in the last decade (Brunila and Storgård, 2012; Kujala et al., 2009; Rosqvist et al., 2017). Therefore, this traffic density poses an increasing risk of accidents and oil spills in ice (Valdez Banda et al., 2015a, b; Goerlandt et al., 2017b).

An oil spill in ice conditions has some features in common with a spill in open waters. However, ice conditions require considering more complex conditions and factors, as shown in Fig. 1. In general, oil behavior after a spill in ice conditions consists of two main parts: weathering and transport. Weathering means the change in the physical and chemical composition of oil, involving evaporation, emulsification, biodegradation, dissolution and photo-oxidation. Transport represents

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<https://doi.org/10.1016/j.marpolbul.2018.12.018>

Received 21 May 2018; Received in revised form 11 December 2018; Accepted 11 December 2018

Available online 22 January 2019

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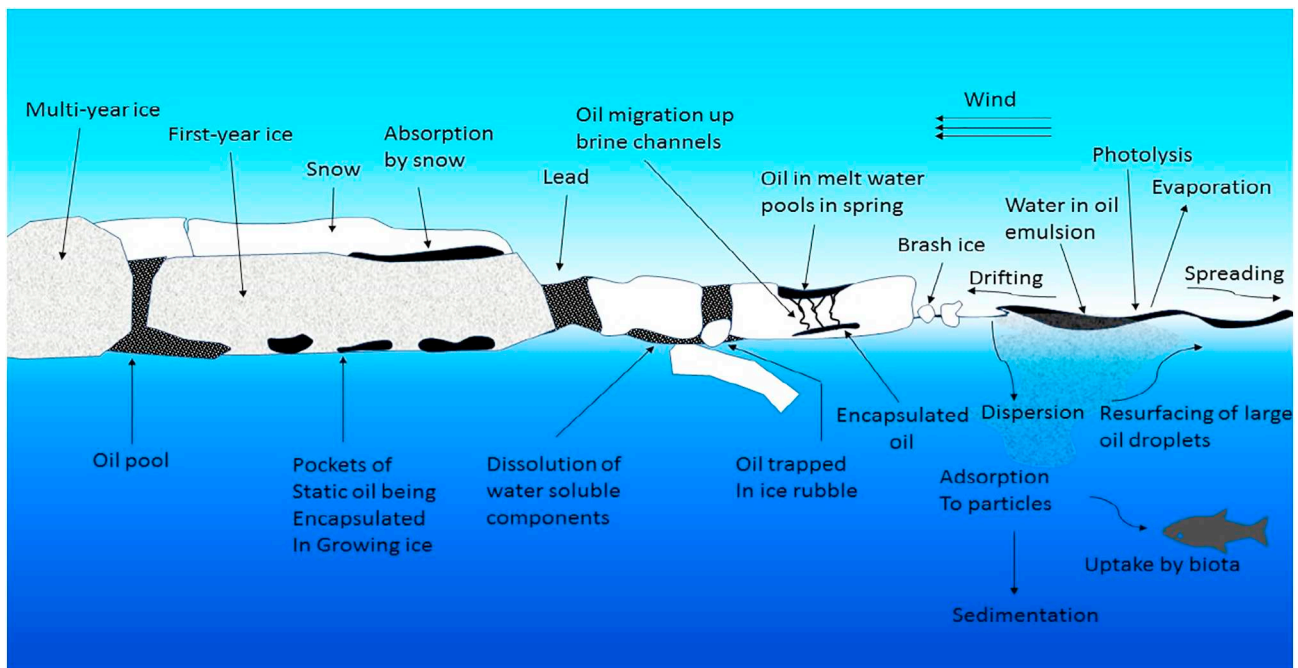


Fig. 1. Weathering and transport process in ice and at ice edge. (After EPPR (2015).)

the movement of oil, including dispersion, advection, spreading, sedimentation and encapsulation (Afenyo et al., 2016a). Different models have been developed to estimate oil behavior in ice conditions. Extensive research efforts have been conducted concerning oil spills and response in ice-covered waters, such as in SINTEF JIP and Arctic Response Technology (ART) JIP (Sørstrøm et al., 2010; ART, 2012). SINTEF JIP drafted a generic Oil Spill Response Guide (OSRG), giving recommendations for response measures in ice-covered waters (Sørstrøm et al., 2010). ART JIP further consolidates the extensive knowledge base on the topics of dispersants, environmental effects, trajectory modeling, remote sensing, mechanical recovery, and in-situ burning (ART, 2017). In addition, some research has focused solely on recovery equipment (Nordvik, 1999; Nuka, 2007; Lamor, 2017; Jensen and Mullin, 2003). EPPR (2017) has performed research regarding oil spill response in the Arctic region; however, this only focused on the response viability of the deployment of different recovery options (including in-situ burning, mechanical recovery, and dispersants) in corresponding Arctic environments. Lehtikoinen et al. (2013) developed a model for oil spill recovery estimation, but it is limited to open water conditions in the Northern Baltic Sea. BSEE developed a set of online response system planning calculators for mechanical recovery (ERSP), in-situ burning (EBSP), and surface-applied dispersants (EDSP). However, these are also for open sea conditions only. Currently, there is no model available to systematically assess oil spill response and recovery effectiveness in ice conditions.

The objective of this paper is to generate a holistic, scenario-based understanding of the oil spill-to-recovery phase, focusing on modeling the effectiveness of mechanical recovery of oil in ice conditions. This is done by developing a Bayesian Network (BN) model, from which the oil recovery effectiveness in ice-covered water can be estimated under different system-level scenarios. The exclusive focus on the mechanical recovery method stems from regionally agreed requirements covering the Northern Baltic Sea area, where the use of chemical agents and other non-mechanical means is restricted by a recommendation adopted by HELCOM (2001). A further scope restriction is the focus on Tier-3 oil spills (see, e.g., IMO, 2010; IPIECA and OGP, 2016), i.e., spills for which collaboration between countries is required. Such oil spills, should they occur, would result from accidents at open sea/ice areas.

Based on findings by Goerlandt et al. (2017a), collision accidents are the main potential accident type leading to spills in ice conditions.

The remainder of the paper is organized as follows. Section 2 describes the methodology for developing the BN. Section 3 presents the qualitative content and structure of the BN, based on the process described in Section 2. This BN is completed in Section 4 by introducing the evidence underlying the parameterization process. Section 5 shows the results. A discussion follows in Section 6. Section 7 presents the conclusions.

2. Methodology

The methodology applied in this article is summarized in Fig. 2. The framework in Fig. 2 is utilized to develop the risk model for assessing the effectiveness of oil spill response with mechanical recovery in the ice-covered Northern Baltic Sea. The oil recovery modeling applies an uncertainty-based risk perspective, which is described in detail in Section 2.1. Correspondingly, the modeling is divided into three stages: Background knowledge (BK), Consequences and their Quantified uncertainties (C-Q), and Strength of Evidence of the uncertainty measures (SoE). Background knowledge (BK) is a fundamental and essential part of risk modeling, consisting of the available evidence that provides an understanding of the system and knowledge about its functioning. This paper combines three approaches to obtaining background knowledge: a literature review, an excursion to an oil combating vessel and expert inputs. The process is described in more detail in Section 2.3.1, as well as in Lu et al. (2017). The use of the term ‘background knowledge’ in this article follows its specification in Aven (2013).

The consequences (C) and the uncertainty measures (Q) represent risk modeling and presentation, which in this paper is implemented using a BN approach, applied as a predictive, epistemic approach to risk analysis, see Apeland et al. (2002). The approach is illustrated in Section 2.2. The Strength-of-Evidence (SoE) assessment is not part of modeling as such, but is included since it is part of the adopted risk perspective, aimed at contextualizing the model in light of the strength of its underlying evidence, as recommended in state-of-the-art risk research (Aven, 2013; Goerlandt and Reniers, 2016). The evidence used in model parameterization is not presented in detail in this section, but

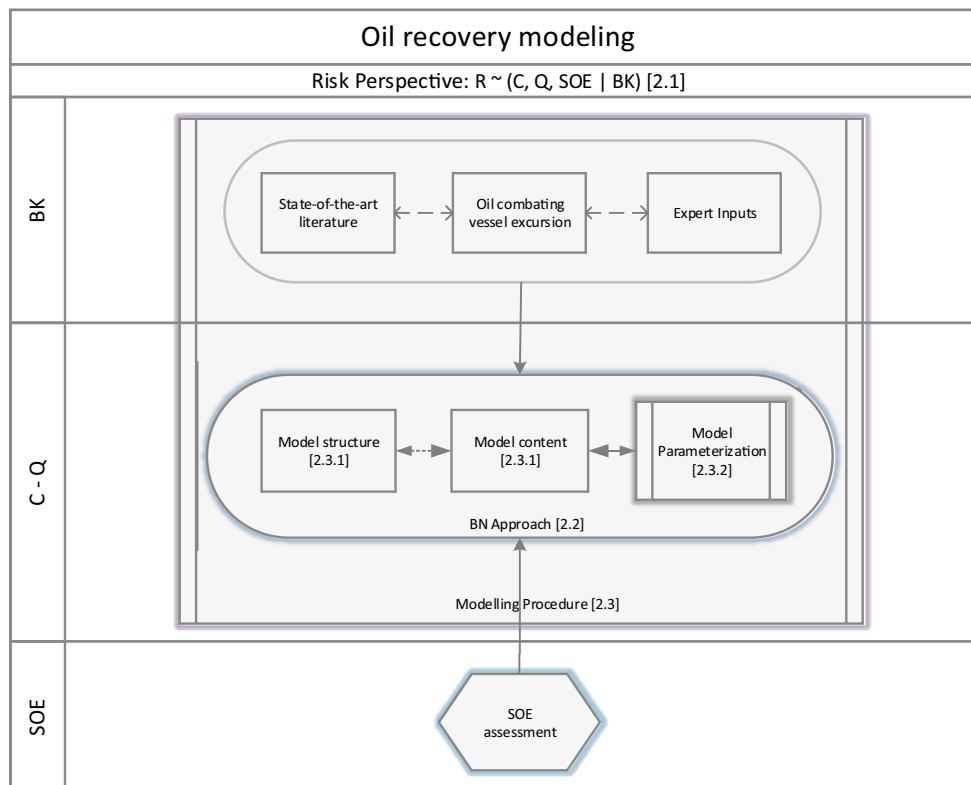


Fig. 2. Framework of the model development process, in line with the uncertainty-based risk perspective.

Note: C represents the consequences of the activity, Q a quantified measure of the uncertainties associated with this consequence, and SoE a qualitative description of the strength of evidence for the quantified uncertainty measure. BK is the background knowledge, to which the risk description is conditional.

←→ Parallel and interactive process; ←→ parallel and interactive process, big arrow side is the base; ↔ individual process and big arrow side is the base.

is clarified in Sections 3 and 4. SOE stands as a separate aspect for evaluating the model in Section 6.3.

2.1. Risk perspective

The modeling is established in the context of a risk analysis of oil spill response and recovery in the Northern Baltic Sea. Therefore, in order to make the risk model applicable and acceptable to end-users and stakeholders, the clarity of the adopted risk-theoretical basis is important for communicating risks and for setting the expectations of the model capabilities at an appropriate level. In the presented approach, risk is understood as the occurrence of certain specified consequences of the activity and associated uncertainties, in line with state-of-the-art risk research (Aven, 2013; Goerlandt and Reniers, 2016). Correspondingly, the risk perspective can be summarized as follows:

$$R \sim (C, Q, SoE \mid BK) \quad (1)$$

where C represents the consequences of the activity, Q a quantified measure of the uncertainties associated with this consequence, and SoE a qualitative description of the strength of evidence for the quantified uncertainty measure. BK is the background knowledge, to which the risk description is conditional. That is, risk is described here in terms of the consequences and uncertainties with the indication of strength of its underlying evidence, and all these are conditional to the background knowledge established.

2.2. Bayesian Network approach

BNs are relatively widely used tools for risk modeling and have been applied in many fields (Fenton and Neil, 2012), including maritime risk analysis (Lim et al., 2018; Aps et al., 2009; Helle et al., 2015). One feature of BNs is that they can present relatively complex problems and cope with uncertain and unobserved variables, i.e. variables which cannot be directly measured, while also having a graphical dimension. This makes BNs suitable for modeling complex problems, with the additional benefit of being able to incorporate different types of evidence

in the model construction. Meanwhile, BNs also align well with the risk perspective. The establishment of the structure of BNs is based on specific background knowledge, and the consequences are reflected as the quantified measure of the uncertainties by a finite number of mutually exclusive states and corresponding probabilities of occurrence. In addition, the visible graphical structure serves as a useful frame of reference to analyze the strength of evidence.

In mathematical terms, BNs represent a class of probabilistic graphical models, defined as a pair $\Delta = \{G(V,A), P\}$ (Koller and Friedman, 2009), where $G(V,A)$ is the graphical component and P the probabilistic component of the model. $G(V,A)$ is in the form of a directed acyclic graph (DAG), where the nodes represent the variables $V = \{V_1, \dots, V_n\}$ and the arcs (A) represent the conditional (in)dependence relationships between these. P consists of a set of conditional probability tables (CPTs) $P(V_i \mid Pa(V_i))$ for each variable V_i , $i = 1, \dots, n$ in the network. $Pa(V_i)$ signifies the set of parents of V_i in G : $Pa(V_i) = \{Y \in V \mid (Y, V_i) \in A\}$. A BN encodes a factorization of the joint probability distribution (JDP) over all variables in V (Goerlandt and Montewka, 2015):

$$P(V) = \prod_{i=1}^n P(V_i \mid Pa(V_i)) \quad (2)$$

In this work, a BN is used in a predictive, epistemic approach to scenario-based risk analysis, as described in Apeland et al. (2002). This means that the probabilities are either expressions of uncertainty based on available evidence, which can include non-informative (uniform) probability densities over variable states, when the intention is to obtain insights into the model output for specific scenarios.

2.3. Modeling procedure

2.3.1. Model content and structure

The modeling procedure for developing a BN is generally divided into two stages (Fenton and Neil, 2012). The first stage focuses mainly on model content and model structure, i.e., the variables that need to be included in the model and their mutual linkages, i.e., $G(V,A)$ in Section

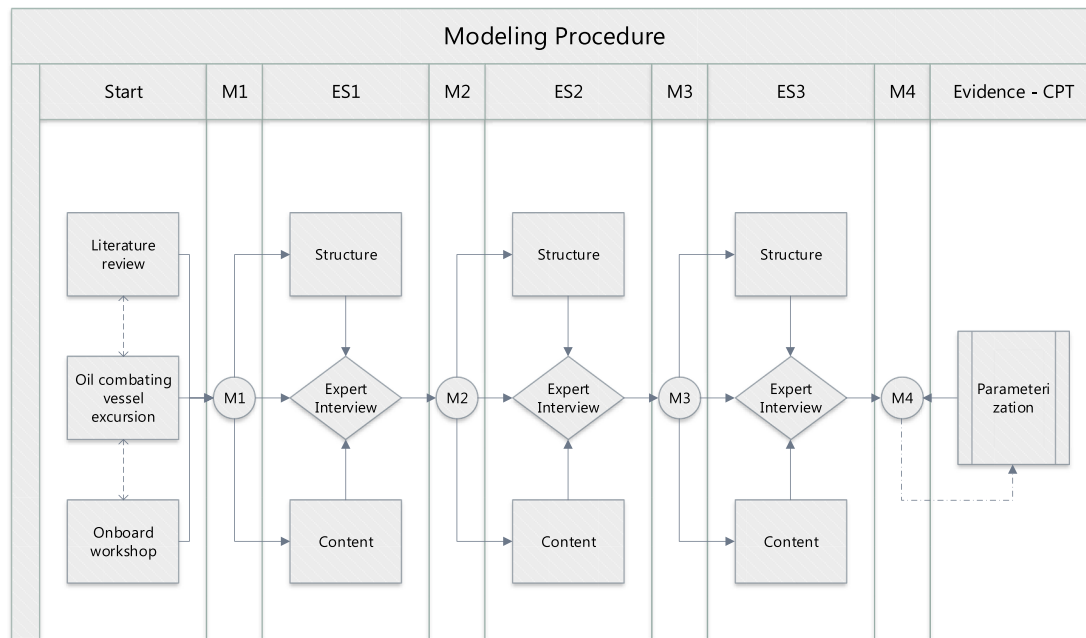


Fig. 3. Detailed BN modeling procedure in terms of model content and structure.

2.2. The second stage is referred to as model parameterization, which means the procedure for analyzing the available evidence and for converting this into probability distributions and conditional probability tables, populating the model content and structure with evidence-based quantities, i.e., P in Section 2.2.

As illustrated in Fig. 3, the modeling starts with exploring the background knowledge, and systemizing it for use as the basis for building an initial model. The development of the current model combines three parts: a literature review, an excursion to an oil combating vessel, including crew enquiry and interviews, and an onboard workshop with a pollution response expert from the Finnish Environment Institution (SYKE) and an expert in mechanical oil recovery equipment from VTT Technical Research Centre of Finland. These three parts are used to establish a comprehensive background to enable start building a model. The preliminary model (M1) is generated based on all the information obtained from the abovementioned sources. After the creation of the preliminary model, individual oil spill and response experts (from the Baltic Marine Environment Protection Commission (HELCOM), the South-East Finland University of Applied Sciences (XAMK), and LAMOR Oy) are invited and interviewed. This is done systematically, based on documented model information where each variable is allocated an ID card, showing the contents and definition of the variable and its links to other variables (parent node(s) and child node(s)). This ID card also includes the evidence base for including the variable in the model and for establishing their dependencies. Each interview follows the same interview process, executed by the first author. First, an overview of the whole model and all the variables is given to the expert, after which open discussions are held and comments recorded. Then, the interviewer and expert go through and discuss each variable ID card together with the visual BN model simultaneously on display, to check the links among them. Open discussions are held about each ID card. Finally, the overall model is reviewed, and suggested system-level modifications recorded. The expert sessions (ES1–3) at this stage focus on model content and structure. A tentative model is generated after each session, as shown in Fig. 3, where the next session is always based on the most recent tentative model.

2.3.2. Model parameterization

Model parameterization is a process that is relatively separate from the development of model content and structure. However, it is based

on the established model content and structure, as indicated by the dashed line in Fig. 3. Parameterization itself is a comprehensive process, symbolized as a special process block in Fig. 3. It includes the analysis of available evidence and discretization to probability distributions or conditional probability tables. This needs to be based on the established model content and structure, i.e., the qualitative part of the BN as shown in Fig. 4. Therefore, the next section presents the qualitative part of the BN, whereas model parameterization is introduced in Section 4.

3. Qualitative part of the BN model

The BN model is built up based on eight sub-models, as shown in Fig. 5. One of them is the sub-model for output, i.e., **Recovery Effectiveness**. The other seven represent the main bodies of the BN model, covering various interconnected clusters representing system and situational characteristics that affect recovery effectiveness: **Oil Spill**, **Response**, **Forcing Representative Scenarios**, **Weathering and Transport**, **Atmospheric Environment**, **Sea Ice Environment**, and **Recovery**.

The division of the BN sub-models is based on the general stage and process from oil spill to recovery. The **Oil Spill** sub-model represents the beginning of the oil spill and contains variables corresponding to oil spill-related characteristics that affect subsequent oil drifting conditions. When an oil spill occurs, oil spill response will start accordingly. The **Response** sub-model contains the essential elements to reflect the operability of a response vessel and the time required to arrive at the spill location in the ice conditions under each forcing representative scenario. The **Forcing Representative Scenarios** consist of representative sea ice and relevant forcing conditions for very mild, mild, average and severe winter seasons. Likewise, when the response vessel is traveling to the spot, the spilled oil is also in the process of weathering and transport under representative forcing scenarios. The **Weathering and Transport** sub-model gives the outcomes of oil behavior with variables important to oil recovery. When the response vessel arrives at the spill area, the recovery operation begins. Local atmospheric and sea ice environment conditions will affect the recovery operation. These aspects are considered in the sub-models **Atmospheric Environment** and **Sea Ice Environment**. The system elements connect to each other in a complex way. Recovery effectiveness is assessed in the **Recovery** sub-model by focusing on the external factors of the recovery

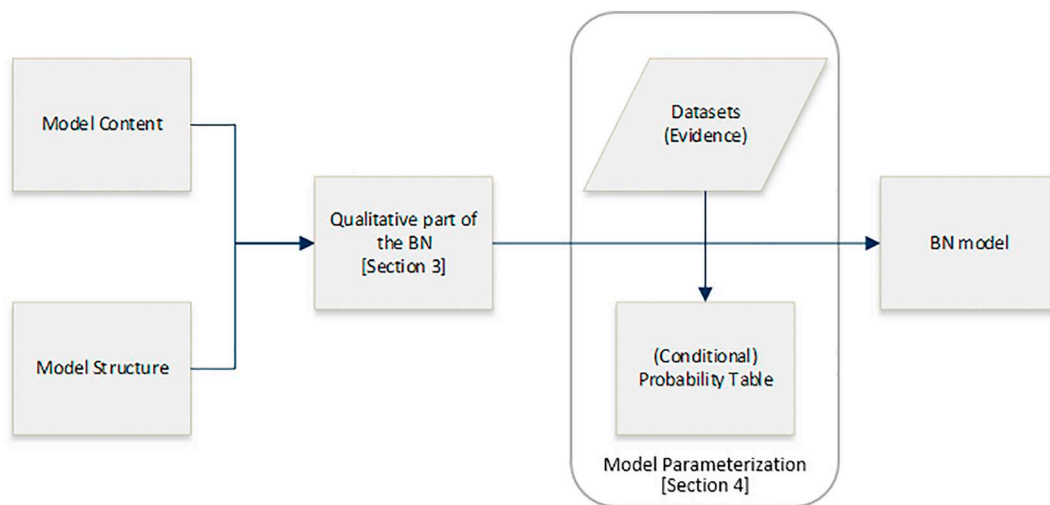


Fig. 4. Overall flowchart of building the BN model.

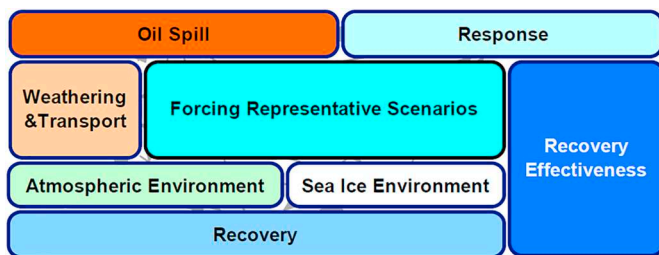


Fig. 5. BN sub-model structure, reflecting the general stage and process from oil spill to response and recovery. The detailed qualitative part of the BN model shown in Fig. 6.

system, i.e., environmental and operation conditions and the internal impactors affecting the recovery system, i.e., oil behavior and properties.

The complete BN model, including the model variables and their interconnections, is shown in Fig. 6. The parameters involved in each sub-model have the same color as the sub-models in Fig. 5. Tables 1 to 8 present the 35 model variables and their interpretations. The tables also show for each sub-model in which section of the article the evidence underlying the model construction is described.

4. Parameterization: converting the evidence to conditional probability tables in the Bayesian Network

This section focuses on the evidence and its parameterization to conditional probability tables (CPTs) in the developed BN. The available evidence can be divided into four categories as shown in Table 9: data obtained directly from measurements, data simulated by models, data elicited from experts by questionnaires, and data from published documents. Parameterization is defined as the procedure of utilizing, processing, and discretizing the evidence and translating it into conditional probability tables in the Bayesian Network model. Thus, the discretization creates the finite number of mutually exclusive states of the consequences, where corresponding probabilities are applied.

Here, the process of obtaining EV3 is referred to as expert elicitation, i.e., transforming experts' knowledge about a certain phenomenon into quantities, which are commonly used in the design and management of large, complex engineering projects (O'Hagan et al., 2006). This is organized with the expert from LAMOR Oy, who is responsible for oil recovery equipment, by means of a face-to-face discussion and answering the designed questionnaire.

The following subsections follow the sub-model divisions. In each

subsection, the evidence is first introduced, after which the parameterization of each variable is illustrated in detail. For the parent nodes, i.e., the nodes without any linkage to them from other nodes, e.g., *Forcing Representative Scenarios*, *Oil Type*, *Spill Size*, *Accident Location* and *Port Location*, uniform distributions are assigned in the parameterization process. In the final analysis and application of the BN model, the probability of each state of the above variables will be set to one in order to conduct a scenario-based study of that state condition.

4.1. Forcing Representative Scenarios

As shown in Fig. 6 and in Table 1, *Forcing Representative Scenarios* is a basis to calculate the oil drift, including factors such as representative ice cover, sea conditions and environmental forcing. To cover the oil spill and recovery behavior in different winter conditions, the 2007–08, 2008–09, 2009–10, and 2010–11 winter seasons are selected as representative scenarios for very mild, mild, average and severe winters. March 1 is selected as the representative oil spill date for each winter, because this usually corresponds to the period in which the maximum ice cover extent is reached in the area (Höglund et al., 2017). The four representative forcing scenarios are shown in Fig. 7, focusing on the ice concentration and average ice thickness. The discretization of the variable *Forcing Representative Scenarios* is [very mild, mild, average, severe]. Uniform distribution is assigned for forcing representative scenarios, as in Table 10.

4.2. Oil Spill

The *Oil Spill* sub-model describes the basic features of the oil spill scenario, using the variables *Oil Type*, *Spill Size* and *Accident Location*, as shown in Table 2. The discretization of the variable *Accident Location* is set as [A1 (24.85 Lon, 59.8 Lat) in the Gulf of Finland, A2 (22.5 Lon, 64.2 Lat) in the Bothnia Bay]. The variable *Spill Size* is discretized as [no spill, small (100 m³), medium (2000 m³), large (20,000 m³)]. The variable *Oil Type* is discretized as [gasoline, light diesel, medium crude oil, heavy crude oil]. Table 11 shows their properties. These parent nodes are initially set by uniform distribution. The probability tables are shown in Table 12.

4.3. Response

4.3.1. Vessel, Port Location, Response Vessel Operability

The *Response* sub-model contains the essential elements (defined in Table 6) to reflect the operability of a response vessel and the time to arrive at the spill location in the prevailing ice conditions. This study

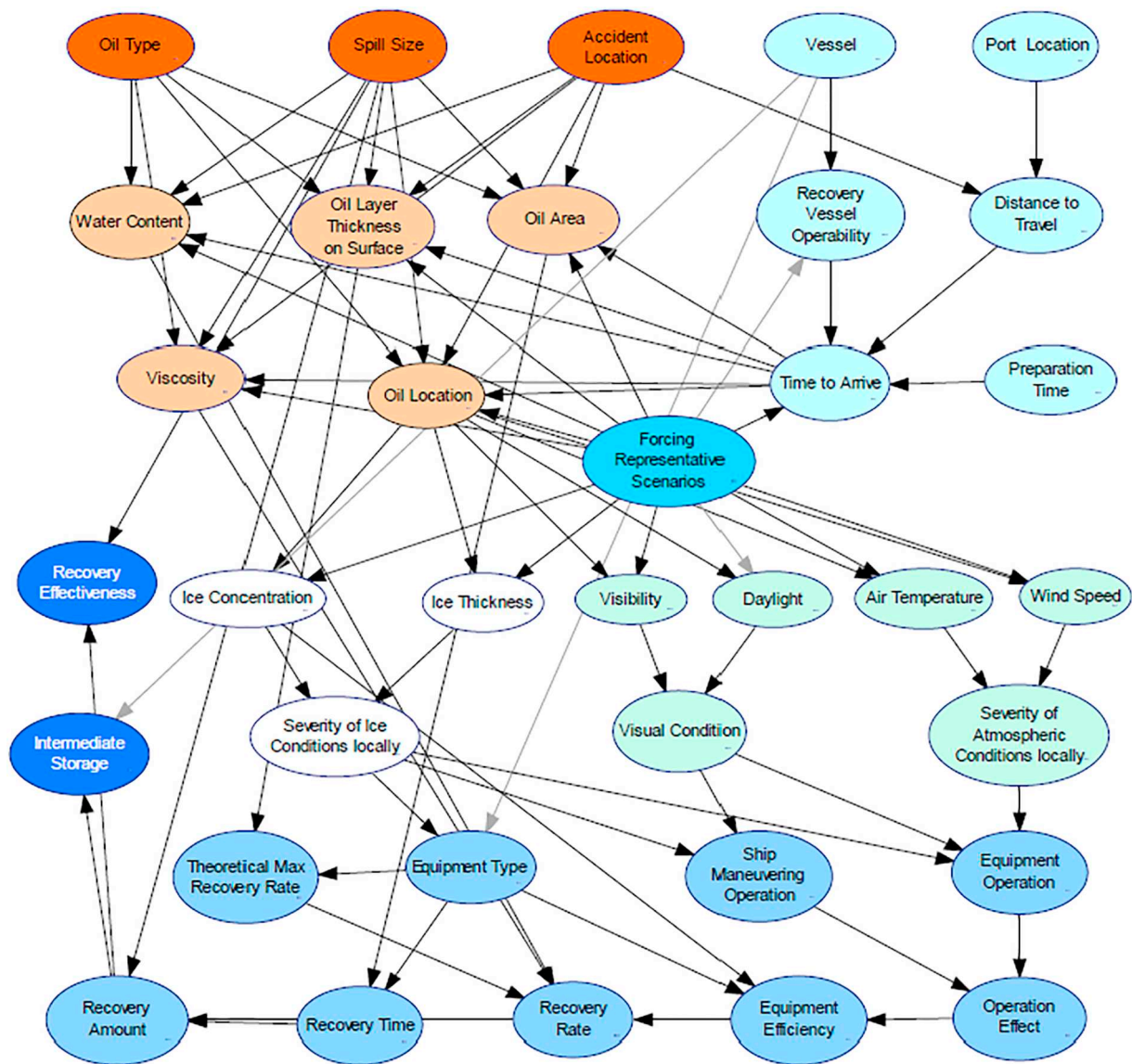


Fig. 6. Qualitative part of the BN model; the definition of each variable is shown in Tables 1–8.

Table 1
Variable information in *Forcing Representative Scenarios* sub-model.

Ab.	Variable	Interpretation	Unit	Ref. section
FRS	Forcing Representative Scenarios	Representative sea ice and relevant forcing conditions for very mild, mild, average and severe winter season	[–]	4.1

focuses on the analysis of a recovery vessel, for which the oil combating vessel Seili, operated by Meritaito (Lehikoinen et al., 2013), is selected. Therefore, the discretization of the variables *Vessel* and *Port Location* is limited, i.e., *Vessel*: [Seili, other]; *Port Location*: [Helsinki, Turku]. The

Table 2
Variable information in *Oil Spill* sub-model.

Ab.	Variable	Interpretation	Unit	Ref. section
OT	Oil Type	Classification of oil, defining physical and chemical properties of oil	[–]	4.2
OS	Spill Size	Amount of oil spilled	[m ³]	4.2
OAL	Accident Location	The geographical location where oil is released in the sea	[–]	4.2

variable *Vessel* is included in the BN, although the focus here is only on Seili to allow further extension of the model to other oil response vessels. Seili is considered to be able to navigate in 50 cm ice conditions according to the excursion observation, i.e., probability of *Response Vessel Operability* is set as one in this analysis. Probabilities are assigned to parent nodes, *Vessel* and *Port Location*, as shown in Table 13.

4.3.2. Distance

The variable *Distance* is measured from the port location to accident location by using the distance measurement tool in Google. The distances are [46 km, 211 km, 536 km, 756 km] respectively. The probability table is shown in Table 14.

For further use in time calculation, each distance is divided into

Table 3
Variable information in *Weathering & Transportation* sub-model.

Ab.	Variable	Interpretation	Unit	Ref. section
OV	Oil Viscosity	Oil viscosity, i.e., a fluid property	[cSt]	4.4.1
OLT	Oil Layer Thickness on surface	The thickness of the oil layer on surface after oil released to ice sea	[mm]	4.4.1
WC	Water Content	The water content contained in the spilled oil	[%]	4.4.1
OL	Oil Location	The geographical coordinate location of the drifted oil when the combating vessel arrives	[–]	4.4.3
OA	Oil Area	The area of the spread oil after spill	[m ²]	4.4.2

different groups based on the ice thickness variation on ice charts (SMHI Ice Service, n.d.) for March 1, for the different sea ice conditions corresponding to the representative forcing scenarios shown in Fig. 7. An ice thickness difference of 10 cm is used as a criterion to divide the route legs in ice to estimate the transit time.

4.3.3. Preparation Time

The conditional probability table for the variable *Preparation Time* is established based on expert elicitation, shown as in Table 15.

4.3.4. Time to Arrive

The route legs are obtained as described in Section 4.3.2, so the speed data is still needed to estimate the traveling time. The speed data is from an oil combating vessel ice trial held from March 13 to 16, 2017 (Rytönen et al., 2017). The data consists of records of ship propulsion power, speed and ice conditions, recorded at one-minute intervals. In reality, a response vessel will attempt to arrive at the oil spill location at the highest possible speed, and therefore the speed data is filtered by two criteria: 1) selecting the speed data with a propulsion power setting of over 80%; 2) selecting the speed records with the observation records of level ice or ridged ice. The speed distribution in corresponding ice conditions is summarized as shown in Table 16.

The time for the response vessel to arrive at the oil spill location (TA) is calculated by Eq. (3):

$$TA = \sum_{i=1}^n \frac{d_i}{v_i} + PT \quad (3)$$

where i is the division number of the distance legs as well as speed divisions; d is the distance of each leg; v is the speed in each ice condition; and n is the number of classifications of ice thickness, up to six in this study. PT is preparation time, as introduced in Section 4.3.3.

TA is limited to 168 h for CPT analysis, i.e., one week. When it is beyond one week, the response actions are considered to be too late according to experts, and a new strategy for dealing with the spilled oil should be planned accordingly. The discretization is [0–3 h, 3–6 h, 6–12 h, 12–24 h, 24–48 h, 48–72 h, 72–120 h, 120–168 h]. The CPT is too large to show here. It is based on the calculation from Eq. (3).

4.4. Weathering and Transport

Oil weathering and transport data is simulated by the SeaTrack Web model PADM, Particle Dispersion Model (Ambjörn et al., 2014), which includes the latest ice code improvements (Arneborg et al., 2017). PADM is a Lagrangian particle tracking model specialized in oil spill modeling. The oil being simulated is represented as a cloud of particles. Each particle represents a quantity of oil with a common set of properties, e.g., mass of oil and weathering status. These properties change

over time as oil evaporates and becomes emulsified, for instance. The trajectory of each particle is calculated in three dimensions based on currents, Stokes' drift, buoyancy and other processes relevant for oil spill spreading. PADM is forced by currents, water temperature, water density, ice concentration and ice thickness from a simulation with NEMO-Nordic (Pemberton et al., 2017) in which sea surface temperature, ice concentration and ice thickness were assimilated (Axell and Liu, 2016). PADM also uses winds from the atmospheric forcing of NEMO-Nordic, which comes from the EURO4M reanalysis data set (Dahlgren et al., 2016). Output from the NEMO-Nordic simulation and EURO4M is also used for the environment data and is further described in Section 4.5.

The oil spill drift simulation is based on the input information from the *Forcing Representative Scenarios* sub-model and *Oil Spill* sub-model, as described in Sections 4.1 and 4.2. Twenty-four scenarios are run for each winter spill date. The results are hourly-based outputs from the simulation, including the variables *Oil Layer Thickness*, *Oil Area*, *Viscosity*, *Water Content* and *Oil Location* (defined in Table 6) for the length of one month, i.e., the whole of March. Fig. 8 gives an example of simulation results of the oil location and area on surface for the four selected scenarios in Table 17. Other results for different spill locations, oil types and spill sizes are not shown for reasons of brevity. The parameterization process of relevant variables in the *Weathering and Transport* sub-model follows from Sections 4.4.1 to 4.4.3.

4.4.1. Oil Layer Thickness, Oil Viscosity and Water Content

Based on the simulated data, the mean oil layer thickness is calculated for each scenario each hour after the spill. The variable *Oil Layer Thickness* is discretized as [0–1 mm, 1–5 mm, 5–10 mm, 10–20 mm, 20–50 mm, 50–80 mm, 80–120 mm, 120–190 mm]. The CPT is filled according to Eq. (4):

$$CPT_OLT_nTA_j = \frac{\sum_{i=TA_j}^{TA_{j+1}} [OLT_n < OLT_i \leq OLT_{n+1}]}{TA_{j+1} - TA_j + 1} \quad (4)$$

where $CPT_OLT_nTA_j$ is the probability for *Oil Layer Thickness* group n at *Time to Arrive* period j , i.e., oil thickness from OLT_n to OLT_{n+1} and arrive time from TA_j to TA_{j+1} ; n is the discretization number of *Oil Layer Thickness*; j is the discretization number of *Time to Arrive*. OLT_i is the hourly mean oil layer thickness at the time i within the period from TA_j to TA_{j+1} .

The CPTs for the variables *Oil Viscosity* and *Water Content* are derived using a similar approach. The discretization of *Oil Viscosity* is [extremely small (< 5 cSt), small (5–100 cSt), medium (100–7500 cSt), large (> 7500 cSt)]. The discretization of *Water Content* is [0–30%, 30–60%, 60–100%].

Table 4
Variable information in *Sea Ice Environment* sub-model.

Ab.	Variable	Interpretation	Unit	Ref. section
IT	Ice Thickness	Thickness of ice in oiled region	[cm]	4.5.1
IC	Ice Concentration	The percentage of sea covered by ice in oiled region	[%]	4.5.1
SI	Severity of Ice Conditions locally	Combined factor of relevant ice variables indicating severity of ice	[–]	4.5.1

Table 5
Variable information in *Atmospheric Environment* sub-model.

Sub-model	Ab.	Variable	Interpretation	Unit	Ref. section
Atmospheric Environment	DL	Daylight	The light condition	[–]	4.5.3
	VI	Visibility	Visibility condition	[km]	4.5.3
	VC	Visual Condition	Combined factor indicating visual condition	[–]	4.5.3
	T	Air Temperature	Air temperature in the oiled region	[°C]	4.5.2
	WS	Wind Speed	Wind speed in the oiled region	[m/s]	4.5.2
	SA	Severity of Atmospheric Conditions locally	Combination of the relevant atmospheric variables	[–]	4.5.2

Table 6
Variable information in *Response* sub-model.

Sub-model	Ab.	Variable	Interpretation	Unit	Ref. section
Response	PL	Port Location	The port for the recovery vessel, where the recovery vessel will be equipped with the recovery equipment	[–]	4.3.1
	PT	Preparation Time	Time to install the oil recovery equipment and performing other preparations before commencing the recovery operation	[h]	4.3.3
	VE	Vessel	Specific recovery vessel	[–]	4.3.1
	RVO	Response Vessel Operability	Variable indicating whether or not the recovery vessel can navigate in the ice condition	[–]	4.3.1
	D	Distance	Distance between the accident location and the port of recovery vessel	[km]	4.3.2
	TA	Time of Arrival	Time for the recovery vessel to arrive at the accident location	[h]	4.3.4

Table 7
Variable information in *Recovery* sub-model.

Ab.	Variable	Interpretation	Unit	Ref. section
EO	Equipment Operation	The equipment operation by crew or oil combating people, which will influence the oil recovery effectiveness	[–]	4.6.2
SMO	Ship Maneuvering Operation	The maneuvering operation during oil combating in ice, which will affect the oil conditions in ice	[–]	4.6.2
OE	Operation Effect	Combined effect of ship maneuvering and equipment operation	[–]	4.6.2
E	Equipment Type	The oil recovery machine used on the vessel	[–]	4.6.1
EE	Equipment Efficiency	The efficiency of the machine under external environmental and operation impact, i.e., non-oil property related factors	[%]	4.6.2
TRR	Theoretical Maximum Recovery Rate	The maximum oil recovery rate in theory, considering the equipment capacity and the practical oil amount	[m ³ /h]	4.6.1
RR	Recovery Rate	True recovery rate in the real oil-ice conditions	[m ³ /h]	4.6.3
RT	Recovery Time	The time to sweep through the oil spill area once	[h]	4.6.3
RA	Recovery Amount	The amount recovered during the recovery time	[m ³]	4.6.3

Table 8
Variable information in *Recovery Effectiveness* sub-model.

Ab.	Variable	Interpretation	Unit	Ref. section
RE	Recovery Effectiveness	What percentage of the total oil spill size does the recovered oil account for	[%]	4.7
IS	Intermediate Storage	Is there any need to prepare the intermediate storage	[–]	4.7

Table 9
Classification of evidence used in the modeling and corresponding sections.

Abbreviation	Definition	Section
EV1	Data obtained directly from measurement	4.1, 4.3.2
EV2	Data simulated by models	4.1, 4.3.4, 4.4, 4.5.1, 4.5.2, 4.5.3, 4.6.2, 4.6.3
EV3	Data elicited from experts by questionnaires	4.3.3, 4.5.1
EV4	Published documents	4.2, 4.3.1, 4.6.1

4.4.2. Oil Area

The oil area is averaged for each hour and processed into a CPT, using a similar approach as for *Oil Layer Thickness* in Section 4.4.1. The difference is that when the oil layer thickness is extremely thin, the resulting oil area is huge. Here, an assumption is made that if *Oil Layer Thickness* is < 1 mm, it is practically impossible to perform recovery operations. Therefore, *Oil Area* is considered to be zero in the context of recovery. The discretization of the variable *Oil Area* is [0, 0–1e3, 1e3–5e3, 5e3–1e4, 1e4–5e4, 5e4–1e5, 1e5–1e6, 1e6+ m²].

4.4.3. Oil Location

The spatial grids are divided with size 0.5 in longitude and 0.25 in latitude for oil location information. Due to the state limit in the BN model, only the areas containing oil, based on the simulation result, are taken into account in the BN states. For all cases in the two oil spill locations, the grids are divided by the following combination of longitude and latitude: 1) Lon (24: 0.5: 27.5), Lat (59.5: 0.25: 60.5); 2) Lon (20: 0.5: 24.5), Lat (63.5: 0.25: 65). In total, there are 81 grid points. The CPT for the variable *Oil Location* is derived by using a similar approach as shown in Section 4.4.1 by detecting whether the oil location

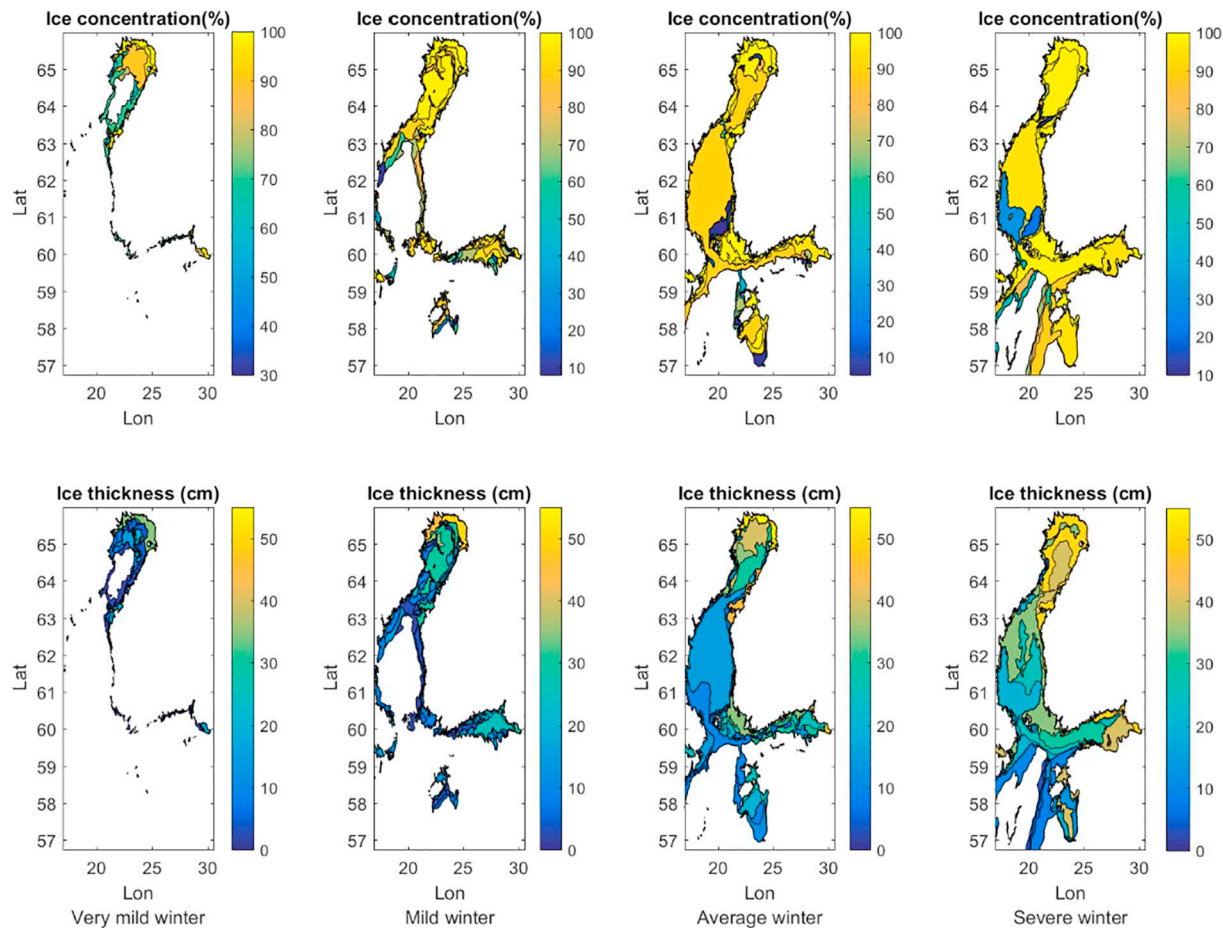


Fig. 7. Ice concentration and thickness condition of representative winter scenarios in 1 NM resolution (March 1).

Table 10
Probabilities of Forcing Representative Scenarios.

Forcing representative scenarios	P
Very mild winter	0.25
Mild winter	0.25
Average winter	0.25
Severe winter	0.25

Table 12
Probabilities of Accident Location, Spill Size and Oil Type.

Accident location	P	Spill size	P	Oil type	P
A1 Gulf of Finland	0.5	No spill	0.25	Gasoline	0.25
		Small	0.25	Light diesel	0.25
		Medium	0.25	Medium crude	0.25
A2 Gulf of Bothnia	0.5	Large	0.25	Heavy crude	0.25

Table 11
Initial oil properties. The properties change during the SeaTrack Web simulation as the oil gets weathered and volatile parts evaporate.

Oil type	Density (kg/m ³)	Viscosity (cSt)
Gasoline	700	0.5
Light diesel fuel	850	2.4
Light-medium crude	850	6.5
Heavy crude	990	5050

belongs to the relevant grid point.

4.5. Environment

With given forcing representative scenarios (Section 4.1) and information regarding oil location (Section 4.4.3), information concerning the prevailing environmental conditions of the oiled areas is obtained, which is relevant as input for the effectiveness of oil recovery operations. The environmental metadata includes sea ice data and

atmospheric data for March from 2008 to 2011. The parameters are defined in Tables 4 and 5. The ice parameters, ice thickness and ice concentration, are taken from the NEMO-Nordic simulation forcing the oil spill modeling (see Section 4.4), which has a horizontal resolution of 3.9 km and a time resolution of 1 h. The atmospheric parameters, visibility, two-meter air temperature and 10-meter winds, are taken from the UERO4M reanalysis dataset forcing the NEMO-Nordic simulation (see Section 4.4), which has a horizontal resolution of 22 km and a time resolution of 3 h. However, the winds are interpolated in space and time by the NEMO-Nordic model and are thus presented at the same apparent space and time resolution as the ice parameters.

4.5.1. Ice Thickness, Ice Concentration and Severity of Ice Condition locally

Ice thickness and ice concentration are processed using a similar approach as in Section 4.4.1. The first step is to combine the 3.9 km resolution data to the Oil Location grid (see Section 4.4.3) by taking the mean values inside the grid. The second step is to count the merged hourly data for March and obtain the probability for each state. The applied discretization for the variable Ice Thickness is [0–20 cm, 20–40 cm, 40–60 cm], while for the variable Ice Concentration, the

Table 13
Probabilities of Vessel, Port Location and Response Vessel Operability.

Vessel	P	Port location	P	Response vessel operability	P
Seili	1	Helsinki	0.5	Yes	1
Other	0	Turku	0.5	No	0

Table 14
Conditional probabilities of Distance.

Port location	Helsinki		Turku	
Accident location	A1 Gulf of Finland	A2 Gulf of Bothnia	A1 Gulf of Finland	A2 Gulf of Bothnia
46 km	1	0	0	0
211 km	0	0	1	0
536 km	0	0	0	1
756 km	0	1	0	0

Table 15
Probabilities of Preparation Time.

Preparation time	P
Up to 2 h	0.3
Up to 4 h	0.6
Up to 8 h	0.1

Table 16
Speed distribution in various ice thicknesses for Vessel Seili.

Ice thickness (cm)	0	10	20	30	40	50
Speed (kn)	12	10	8	6	5	3

discretization is [0–30%, 30–70%, 70–100%].

The variable *Severity of Ice Condition locally* combines the local ice data to reflect the severity of the conditions in which the oil recovery operation would be conducted, see Table 4. A similar judgment of the severity of the ice conditions for navigation in ice has also been developed by Valdez Banda et al. (2016). Based on the navigation ice severity condition and expert opinions elicited regarding the recovery operations, a synthesized description of the severity of ice conditions for oil recovery operations is formed, shown in Fig. 9. This is then converted into a CPT in the BN model for the variable *Severity of Ice Condition locally*.

4.5.2. Air Temperature, Wind Speed and Severity of Atmospheric Condition locally

The approach to converting air temperature and wind speed data to their relevant CPTs is similar to the process applied to the ice data, see Section 4.5.1. The only additional step for the wind speed is that the data contains two direction components that need to be integrated to get the actual wind speed. The variables *Air Temperature* and *Wind Speed* are discretized as follows: $[(-37)-(-20), (-20)-(-10), (-10)-0, 0-10^{\circ}\text{C}]$ and $[0-5, 5-10, 10-15\text{ m/s}]$, respectively.

The variable *Severity of Atmospheric Condition locally* is also a synthesized parameter, which combines wind and air temperature. The wind chill concept is used as the indication of the synthesized parameter. The calculation of the severity is according to Woodson and Tillman (1992):

$$T_{wc} = 13.12 + 0.625 \times T_a - 11.37 \times (3.6 \times W_s)^{0.16} + 0.3965 \times T_a \times (3.6 \times W_s)^{0.16} \quad (5)$$

where, W_s is wind speed, m/s; T_a is air temperature, $^{\circ}\text{C}$.

To eliminate the condition that wind chill number is higher than the actual air temperature, the minimum of the two values is always taken,

as in EPPR (2017). The severity in Table 18 is based on impact of wind chill (Woodson and Tillman, 1992).

4.5.3. Visibility, Daylight and Visual Condition

The data on visibility is transferred to a CPT using a similar approach as in Section 4.5.1. The discretization for the variable *Visibility* ([poor, medium, good]) refers to the classification of visibility condition ([favorable, marginal, not favorable]) in the system limit table for mechanical recovery (EPPR, 2017), where horizontal and vertical visibility criteria are described. Then, they are integrated into one value for the visibility in this model. The CPT for the variable *Daylight* is based on the sunrise and sunset time and has three states [day, twilight, night]. The variable *Visual Condition* (VC) has three states [poor, medium, good] and combines the other two parameters, *Visibility* (VI) and *Daylight* (DL), by Eq. (6), i.e., it takes the minimum value state of the two variables:

$$VC = \min(DL, VI) \quad (6)$$

The states are balanced as such to be comparable: day = good, twilight = medium and night = poor. Among them, poor < medium < good.

4.6. Recovery

Oil recovery in ice conditions is complex and there is very limited empirical data. Therefore, the process is modeled using an analytical approach. In particular, the influencing factors in the adopted analytical formulae are obtained through a questionnaire in expert elicitation. Other utilized data include published information on equipment recovery capabilities. Here, the recovery approach uses single recovery equipment at the stern of the vessel and the vessel navigates with stern ahead.

4.6.1. Equipment Type and Theoretical Maximum Recovery Rate

Three oil recovery equipment types suitable for ice conditions are selected for further modeling. They are Equipment A – oil recovery bucket 250, Equipment B – Arctic skimmer 125, Equipment C – Sternmax (Lamor, n.d.). According to the expert elicitation, the CPT for the variable *Equipment Type* is derived (Table 19).

The variable *Theoretical Maximum Recovery Rate* is calculated by:

$$TRR_i = \min(0.8 \times L_i \times v \times OLT, trr_i) \quad (7)$$

where TRR_i is the theoretical recovery rate of equipment i ; L_i is the length of equipment i ; v is recovery vessel speed, set as 0.5 kn according to excursion interview and exercise observation; OLT is oil layer thickness; trr_i is certificated recovery capability of equipment i . The discretization is [0, 0–11, 11–21, 21–37, 37–54, 54–67, 67–84, 84–92, 92–125, 125–140, 140–230 m³/h].

4.6.2. Equipment Operation, Ship Maneuvering Operation, Operation Effect and Equipment Efficiency

The discretization of the variables *Equipment Operation* (EO) and *Ship Maneuvering Operation* (SMO) is [poor, medium, good]. The determination of the CPTs is based on the following principle for each state:

$$EO \text{ or } SMO = \min(VC, SI, SA) \quad (8)$$

Similar to Eq. (6), here, light = good and severe = poor. Among them, poor < medium < good. VC is visual condition, SI is severity of ice conditions locally and SA is severity of atmospheric conditions locally.

The variable *Operation Effect* (OE) is a combination of EO and SMO and discretized as [poor, medium, good], where poor < medium < good. Eq. (9) is applied for each State to obtain the CPTs:

$$OE = \min(EO, SMO) \quad (9)$$

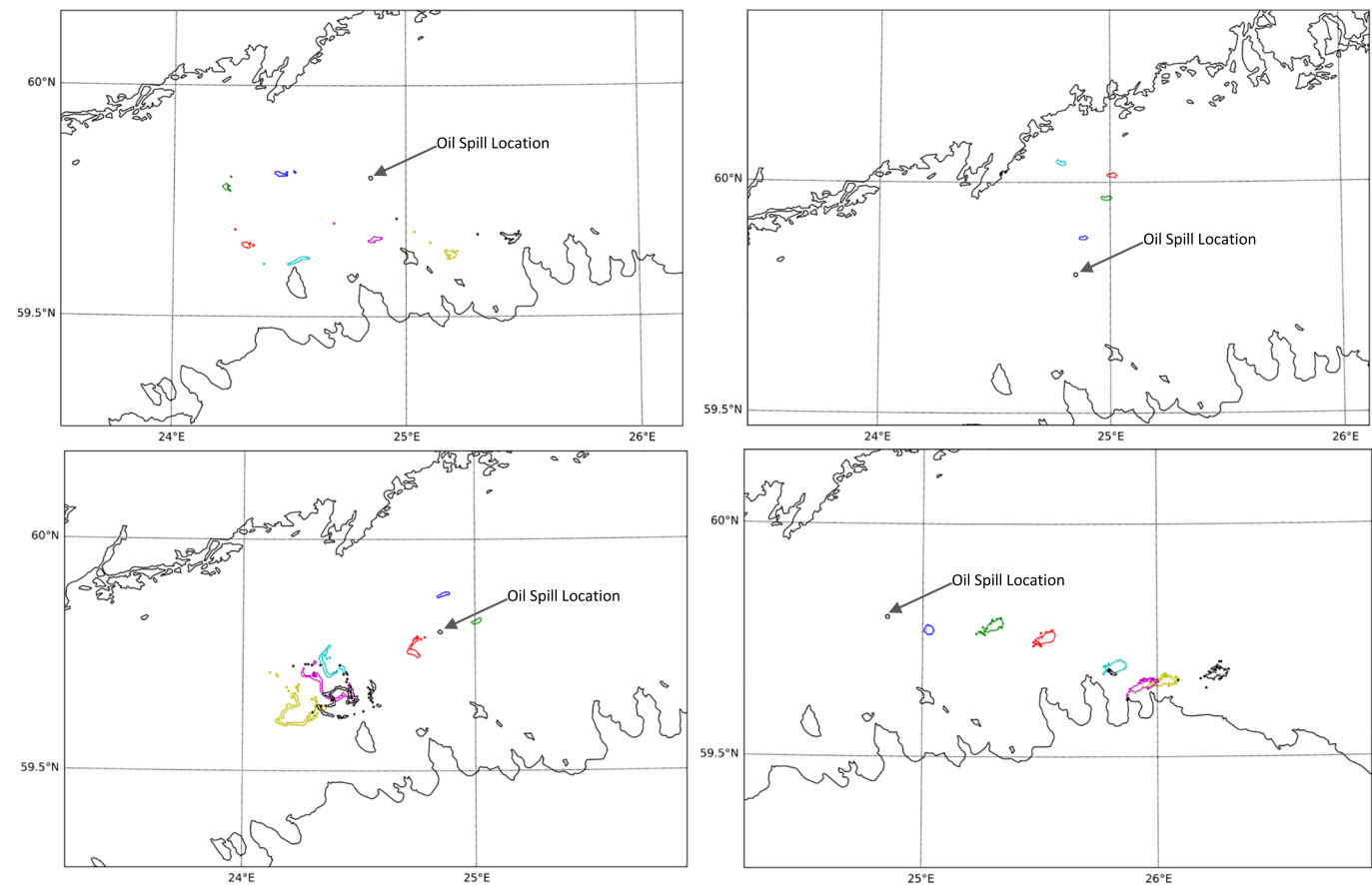


Fig. 8. Example of oil drift condition on sea/ice surface for 7 days, interval: 1 day, released on March 1, 2008 (left, top), 2009 (right, top), 2010 (left, bottom) and 2011 (right, bottom). 0 day after release: black; 1 day: blue; 2 days: green; 3 days: red; 4 days: cyan; 5 days: magenta; 6 days: yellow; 7 days: black. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 17
Oil spill scenarios for simulation plotted in Fig. 8.

Four spill dates	Spill location	Spill size	Oil type	Duration	Interval
March 1 2008/09/10/ 11	(24.85, 59.8)	20,000 m ³	heavy crude oil	7 day	1 day

Severity	Ice concentration (%)	Ice thickness (cm)
Severe	70–100	20–60
	30–70	40–60
Medium	70–100	0–20
	30–70	20–40
Light	30–70	0–20
	0–30	0–60

Fig. 9. Classification of severity of ice conditions in terms of ice concentration and ice thickness.

Table 18
Classification of severity of atmospheric condition.

Severity	Wind chill	Impact on human comfort
Light	(−13)–0	None, unpleasant
Medium	(−33)–(−13)	Possible frost nip
Severe	(< −50)–(−33)	Frostbite likely, exposed skin will freeze in 30 s

The variable *Equipment Efficiency* is discretized as [0–25%, 25–50%, 50–75%, 75–100%]. The calculation is based on expert judgment, i.e., *Equipment Efficiency* (EE) is considered to be under the influence of Ice Concentration (IC), Operation Effect (OE) and equipment effect, which is formulated as:

$$EE = (1 - IC \times c_{EI}) \times (c_{OE} \times c_{EO}) \quad (10)$$

where c_{OE} is the operation effect coefficient; $c_{OE} = 0.5$ if OE = poor, $c_{OE} = 0.7$ if OE = medium and $c_{OE} = 0.9$ if OE = good. c_{EO} is coefficient for equipment sensitivity to operation effect; $c_{EO} = 0.6$ if E = A or B, $c_{EO} = 0.8$ if E = C. c_{EI} is coefficient for equipment sensitivity to ice concentration; $c_{EI} = 0.4$ if E = A or B, $c_{EI} = 0.1$ if E = C. The coefficients are based on the expert elicitation. (A, B and C mean Equipment A, Equipment B and Equipment C, as in Section 4.6.1.)

4.6.3. Recovery Rate, Recovery Time and Recovery Amount

The recovery rate is also based on expert judgment, i.e., it is considered under the impact of two aspects: 1) equipment capability: *Theoretical Maximum Recovery Rate* (TRR), *Equipment Efficiency* (EE); 2) oil properties: *Water Content* (WC) and *Oil Viscosity* (OV), formulated as:

$$RR = TRR \times EE \times (1 - WC) \times c_{OV} \quad (11)$$

where c_{OV} is coefficient for oil viscosity. $c_{OV} = 0.1$ if OV is extremely small; $c_{OV} = 0.8$ if OV is small; $c_{OV} = 0.9$ if OV is medium; $c_{OV} = 0.6$ if OV is large.

The discretization of the variable *Recovery Rate* is [0, 0–2, 2–5, 5–10, 10–20, 20–30, 30–40, 40–50, 50–60, 60–70, 70–80, 80–90, 90–100, 100–110, 110–120, 120–140, 140–190, 190–230 m³/h].

The recovery time RT is calculated as:

Table 19
Probabilities of application of equipment type.

Severity of ice conditions locally	Light	Medium	Severe
Equipment A	0.33	0.20	0.1
Equipment B	0.33	0.13	0.1
Equipment C	0.34	0.67	0.8

Table 20
Recovery effectiveness for scenarios (Accident Location: A1; Port Location: Helsinki) (all the numbers are in percentage).

	VW			MW			AW			SW		
	S	M	L	S	M	L	S	M	L	S	M	L
GO												
RE1	100	100	100	100	100	100	100	100	100	13	6	0
RE2	0	0	0	0	0	0	0	0	0	87	93	51
RE3	0	0	0	0	0	0	0	0	0	0	1	0
RE4	0	0	0	0	0	0	0	0	0	0	0	0
RE5	0	0	0	0	0	0	0	0	0	0	0	0
RE6	0	0	0	0	0	0	0	0	0	0	0	49
LD												
RE1	100	100	100	100	100	8	100	100	100	13	0	0
RE2	0	0	0	0	0	0	0	0	0	87	99	51
RE3	0	0	0	0	0	0	0	0	0	0	1	0
RE4	0	0	0	0	0	0	0	0	0	0	0	0
RE5	0	0	0	0	0	0	0	0	0	0	0	0
RE6	0	0	0	0	0	92	0	0	0	0	0	49
MCO												
RE1	100	88	88	28	2	0	1	0	0	0	0	0
RE2	0	0	0	14	10	0	43	21	7	73	60	25
RE3	0	0	0	14	7	0	21	11	1	19	27	17
RE4	0	0	0	16	4	0	14	8	0	5	9	6
RE5	0	0	0	28	5	0	20	16	0	2	4	3
RE6	0	12	12	0	72	100	0	44	92	0	0	49
HCO												
RE1	0	0	0	0	0	0	0	0	0	0	0	0
RE2	31	68	30	31	68	30	28	61	29	56	70	53
RE3	33	25	13	33	25	13	30	27	14	26	19	10
RE4	21	6	3	21	6	3	22	9	3	11	7	5
RE5	14	1	1	14	1	1	20	4	1	6	5	3
RE6	0	0	53	0	0	53	0	0	53	0	0	29

Note: VW: very mild winter, MW: mild winter, AW: average winter, SW: severe winter; GO: gasoline, LD: light diesel, MCO: medium crude oil, HCO: heavy crude oil; S: small spill, M: medium spill, L: large spill; RE1–6: 0, 0–25%, 25–50%, 50–75%, 75–100%, other.

$$RT = \frac{OA}{L_{eff} \times v} \quad (12)$$

where, L_{eff} is effective length of recovery equipment, set as $0.8 \times L$, OA is oil area.

The discretization of the variable *Recovery Time* is [0, 0–1, 1–2, 2–4, 4–6, 6–10, 10–15, 15–20, 20–30, 30–60, 60–100, 100–200 h, other]. Recovery time is set to be under 200 h in the study due to the relatively unknown conditions involved in recovery operations lasting over 200 h. State “other” represents that condition, i.e., recovery time over 200 h.

The recovery amount RA is calculated as:

$$RA = RR \times RT \quad (13)$$

The states for the variable *Recovery Amount* are set as [0, 0–25, 25–50, 50–75, 75–100, 100–500, 500–1000, 1000–1500, 1500–2000, 2000–5000, 5000–10,000, 10,000–15,000, 15,000–20,000 m³, other]. The state “other” corresponds to the “other” state in the variable *Recovery Time*.

4.7. Recovery Effectiveness

The variable *Recovery Effectiveness* is divided into six states (0, 0–25%, 25–50%, 50–75%, 75–100%, other) according to the recovered oil percentage compared to the total spilled size. Zero means no oil recovered. “Other” corresponds to the “other” state in variable *Recovery Amount*. “Other” is actually the part which should be calculated for 0–100%, but when recovery time is over 200 h, it is not calculated for 0–100%. It is set as a separate state to represent the uncertainty involved in a long recovery operation. It is mutually exclusive to 0–100% states.

Intermediate Storage is a variable indicating whether arrangements will need to be made for additional storage based on the comparison between the estimated recovery amount and response vessel storage. It is not the focus of this paper; however, it is modeled as an indicator for oil spill response planning and preparedness when the model is applied.

5. BN model and results for various scenarios

The established BN model is applied by setting relevant conditions, i.e., input parameters, so that it very quickly provides an estimate of the recovery effectiveness in response to an accidental oil spill in the given scenarios. In the following sections, several scenarios are investigated through application of the model. The accident location is set as A1 and the port location as Helsinki.

Table 20 shows the recovery effectiveness probabilities for gasoline (GO), light diesel (LD), medium crude oil (MCO) and heavy crude oil (HCO) spills of small (S), medium (M) and large (L) sizes in different winter conditions: very mild winter (VW), mild winter (MW), average winter (AW) and severe winter (SW).

5.1. Recovery effectiveness for gasoline and light diesel spill

As seen in Table 20, gasoline spilled in location A1 in the Gulf of Finland is very difficult to recover by only using the mechanical recovery approach, i.e., using single recovery equipment at the stern of the vessel with the vessel navigating stern ahead (see Section 4.6), especially in very mild, mild and average winters. In severe winters, there is a high probability (87% for small spill, 93% for medium spill and 51% for large spill) to collect 0–25% of the spilled oil and a 1% probability to recover 25–50% of the oil in a medium-sized spill. However, when the oil spill size is large, the “other” state has almost the same probability as the 0–25% state. The “other” state means that the oil area is large and that it takes too much time to apply this recovery approach, and hence that the uncertainty is high.

Recovery effectiveness for light diesel is very similar as in the case of gasoline. The two differences are: 1) in mild winter, 92% probability moves from 0 recovery effectiveness to state “other” for a large spill; 2) in severe winter, 6% probability for 0 recovery effectiveness rises to 0–25% recovery effectiveness, making the probability for 0–25% recovery effectiveness 99%.

5.2. Recovery effectiveness for medium crude oil spill

As seen in Table 20, medium crude oil spills in location A1 (Gulf of Finland) are also difficult to recover in very mild winters with the mechanical recovery approach that this paper focuses on. In mild winters, it is more promising to recover a small-sized oil spill (14% probability of 0–25% and 25–50% recovery effectiveness, 16% probability of 50–75% recovery effectiveness and 28% probability of 75–100% recovery effectiveness). However, with the increase of spill size, the probability of recovery decreases and the “other” state dominates in large-sized spills. The size effect is similar for average winter

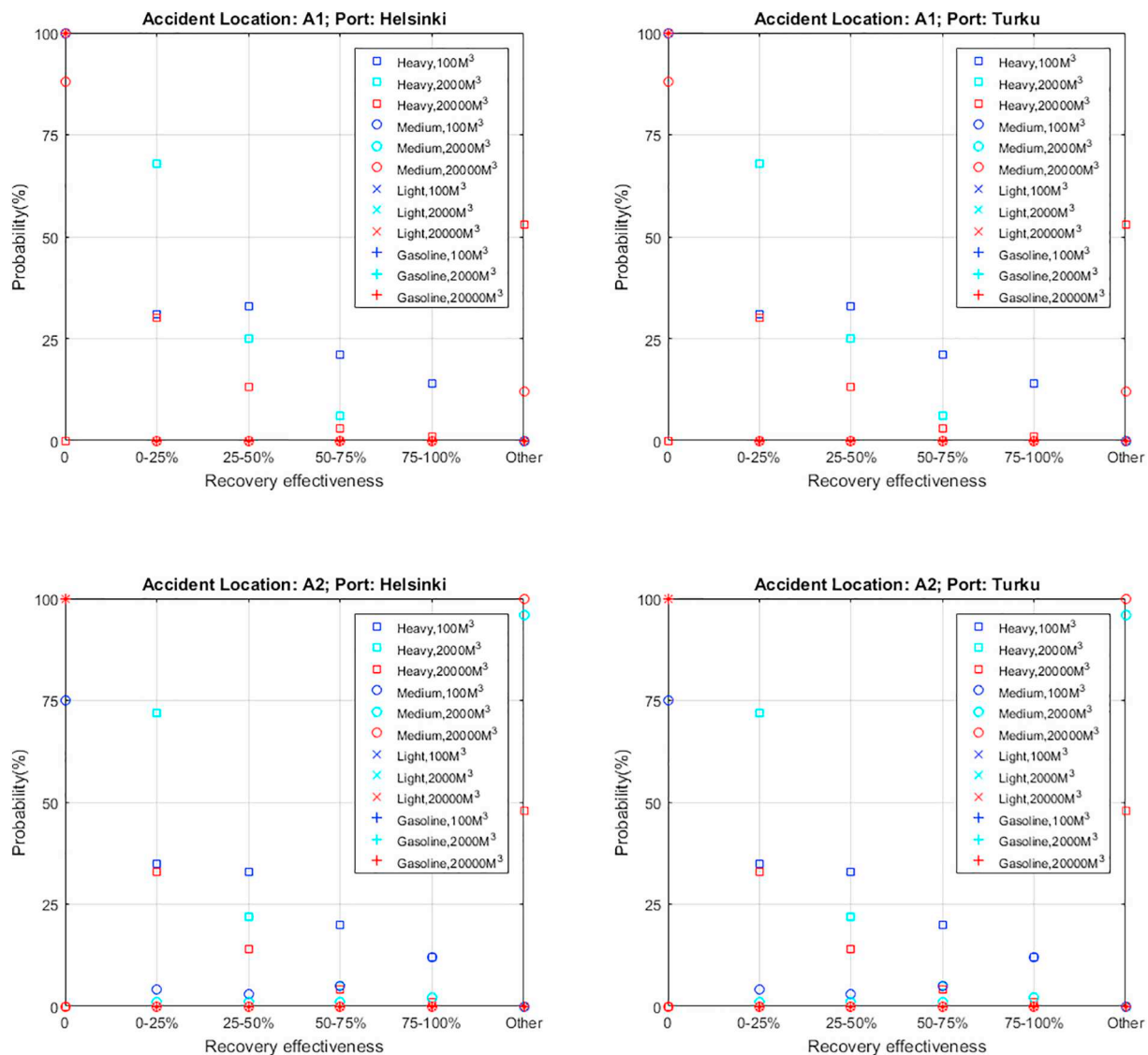


Fig. 10. Recovery effectiveness comparisons in terms of the variables: *Spill Size*, *Oil Type*, *Accident Location*, *Port Location*, in very mild winter.

conditions. In an average winter, there is a 43% probability to recover 0–25% of medium crude oil, 21% probability to recover 25–50% of oil, 14% probability to recover 50–75% of oil and 20% probability to get 75–100% of oil in the case of a small-sized spill. The probabilities for successful recovery of medium-sized spills decline to approximately half the values compared to the values for small-sized spills. In severe winter conditions, recovery effectiveness is better in general in the case of medium-sized spills.

5.3. Recovery effectiveness for heavy crude oil spill

As seen in Table 20, in the case of heavy crude oil spills, more oil can be collected in general. The probability that no oil can be recovered is zero for all conditions. Meanwhile, a very mild winter and mild winter do not make a difference to the recovery effect. However, in average winter conditions, the probability of recovering oil is higher than in the severe winter condition, except for in the case of a large oil spill. In the large oil spill scenario, “other” dominates the result for large oil spills in average winter conditions, while 0–25% recovery effectiveness dominates in a severe winter. Heavy crude oil has a similar trend as medium crude oil, i.e., with the increase in spill size, the probability of recovery decreases and the “other” state increases in

large-sized spills.

5.4. Overview of recovery effectiveness comparison

To provide an overview of the probability of oil recovery for all the scenarios, each state of the input parameters *Spill Size*, *Oil Type*, *Accident Location*, *Port Location* and *Forcing Scenario* is chosen in turn to set a scenario, and the corresponding results are obtained from the BN model. These results are shown in Figs. 10–13, which can also be used as reference to know the recovery effectiveness for different oil spills in different conditions.

Fig. 10 shows the results in very mild winter conditions. By comparing the left with the right part, it is seen that there is no significant difference between the two representative port locations in very mild winter conditions. By comparing the top with the bottom part, it is seen that accident location A2 makes the oil recovery of medium crude oil possible, i.e., the circles can be seen at different recovery effectiveness levels. A small drop is seen in the case of heavy crude oil recovery, which can be caused by the longer distance to travel to A2 compared with A1.

In very mild winter conditions, it is generally possible to recover heavy crude oil, but the probability decreases with the increase in the

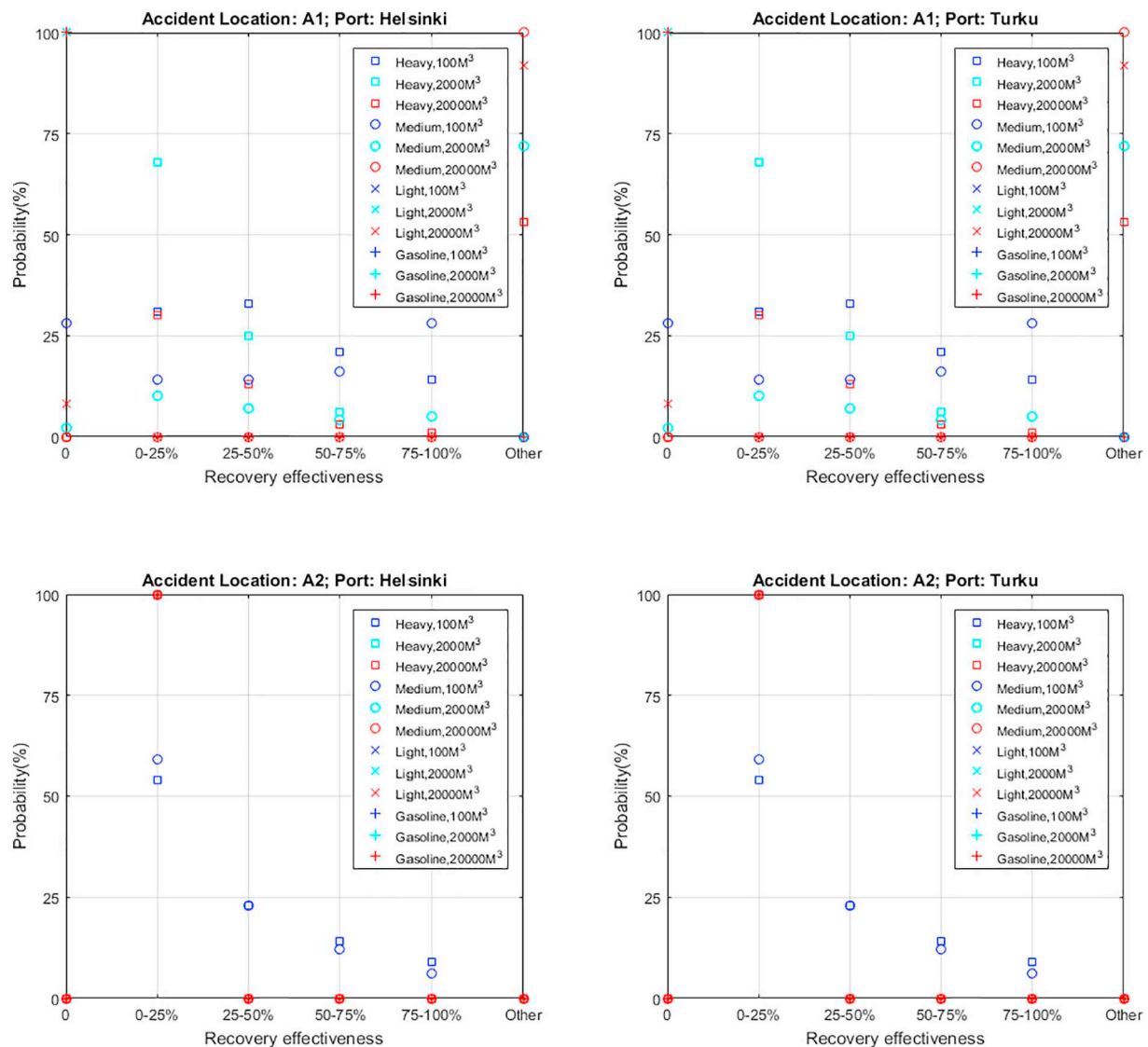


Fig. 11. Recovery effectiveness comparisons in terms of the variables: *Spill Size, Oil Type, Accident Location, Port Location*, in mild winter.

spill size.

Fig. 11 shows the results in mild winter conditions. As in the case of very mild winter conditions, port location has almost no effect on the results. However, different accident locations lead to quite different results. That said, the spills with the greatest potential for recovery involve heavy and medium crude oil in small and medium-size spills. The probability decreases with the increase in the spill size, and in position A2 it is only possible to recover a small spill.

Fig. 12 shows the results during an average winter. Port location has a small, but very limited effect. Accident location has quite a similar effect as in the mild winter condition. Therefore, general recovery effectiveness is quite similar as in mild conditions, with some small variations.

Fig. 13 shows the results in severe winter. The port and accident location effects are similar as in the case of other winter conditions. However, it is seen that severe winter conditions lower the probabilities of recovering heavy or medium crude oil in general. Meanwhile, it gives probabilities for recovering light diesel and gasoline at very low recovery effectiveness for accidents in position A1. In the case of position A2, a severe winter does not have an obvious effect. Similar results are seen in the case of mild and average winters, with a slightly > 50% probability for 0–25% recovery effectiveness, slightly > 20%

probability for 25–50% recovery effectiveness and around 10% for 50–75% recovery effectiveness.

6. Discussion

6.1. Model results

Form the investigated variables, port location makes little difference to the results. The reason may be that the two ports are not far away from each other. Especially when traveling to position A1, the distance difference is small. When the ship needs to navigate to position A2, there is a small difference. However, the distance difference is not significant compared to the total distance to A2. Meanwhile, the ice conditions in A2 may already hinder the oil from spreading, and the time effect is weakened to some extent.

There are differences between accident locations, i.e., in the north, A2 (Bay of Bothnia), fewer oil types are recovered and effectiveness is lower. This can be linked to both the distance and the ice effect. A very mild winter is helpful to oil recovery in A2 (Bay of Bothnia), while a mild and average winter seems to result in somewhat higher recovery in A1 (Gulf of Finland). They may have a common reason, i.e., ice may stop the oil from spreading and ice that is not too heavy does not

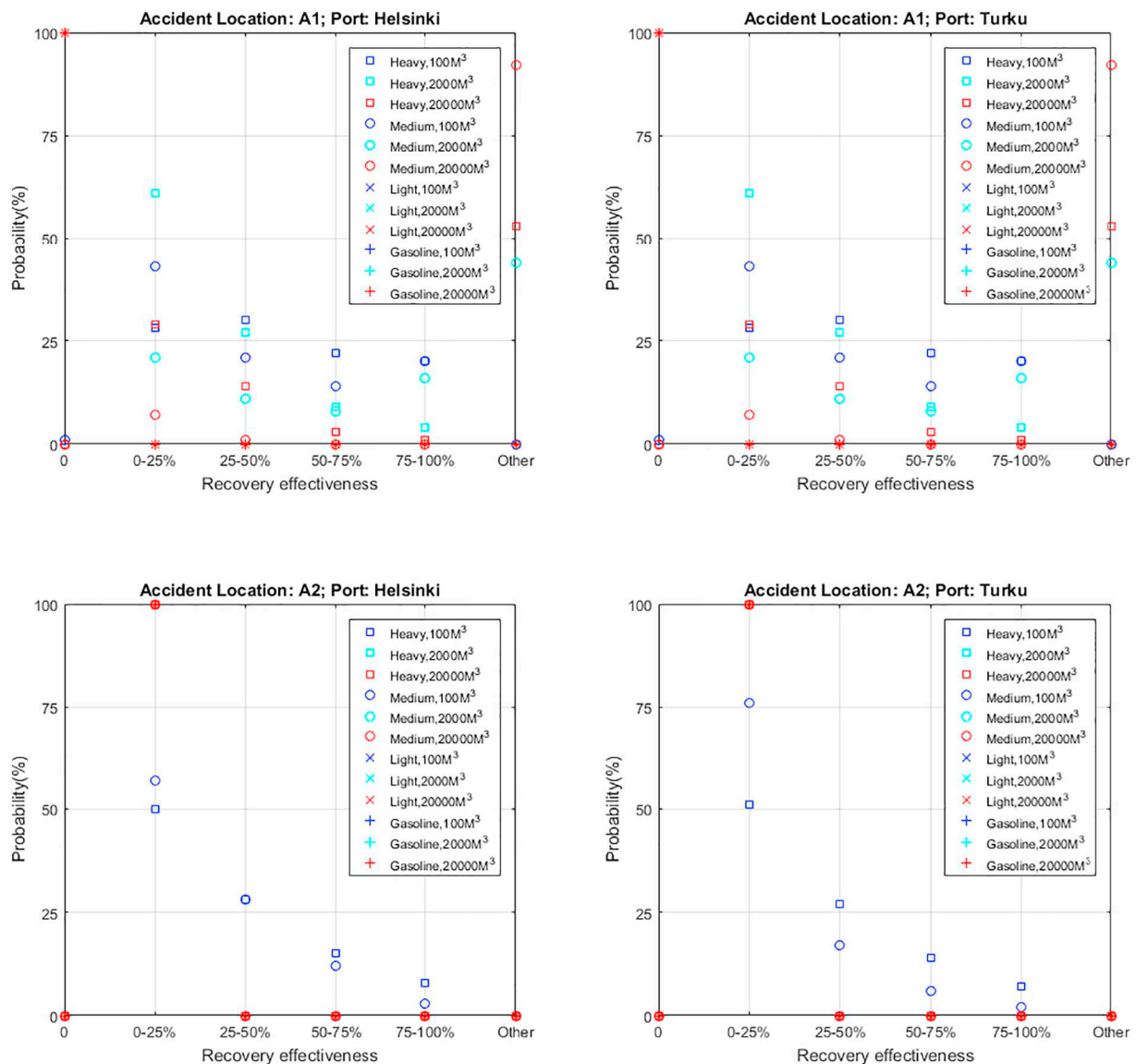


Fig. 12. Recovery effectiveness comparisons in terms of the variables: *Spill Size, Oil Type, Accident Location, Port Location*, in average winter.

disturb the recovery method described in this article. Therefore, combining the effects, these conditions may be helpful to oil recovery.

In addition, it is seen that heavy crude oil and medium crude oil in small or medium spill sizes have higher probabilities of recovery than gasoline and light crude oil. This trend corresponds to the observations made in the oil spreading simulation result (Section 4.4), as gasoline will spread quicker than heavy crude oil, and has higher evaporation rates.

6.2. Model limitations

The developed BN model provides systematic and comprehensive insight about oil spills and their recovery under different sea ice and atmospheric conditions, for different oil types, accident locations, spill sizes and port locations. However, the practical oil spill recovery system is very complex and tactical recovery operations can lead to differences in the recovery process. The scope of the developed model is to estimate recovery effectiveness using single mechanical recovery equipment, as

described in Section 4.6. Other possible tactical and technical approaches are not included in the modeling, e.g., the probability of using a boom or how to use the boom.

In the general modeling process, there are also some limitations:

1. The model uses limited scenarios, i.e., it uses March 1 in four different years to represent very mild, mild, average and severe winters; it uses two accident locations and one recovery vessel to conduct the case study in this article. However, some potential extensions, especially on more accident location and response vessels, are discussed in Section 6.4 Future work.
2. A subjective modeling choice of the bin size and numbers are made after investigating and observing the data trends in the discretization of the data into bins.
3. Model structure is developed based on literature and several rounds of discussion with experts, and it is unlikely that all possible dependencies are encoded. However, the simplification should provide sufficient realism in the dependencies for the purpose of gaining

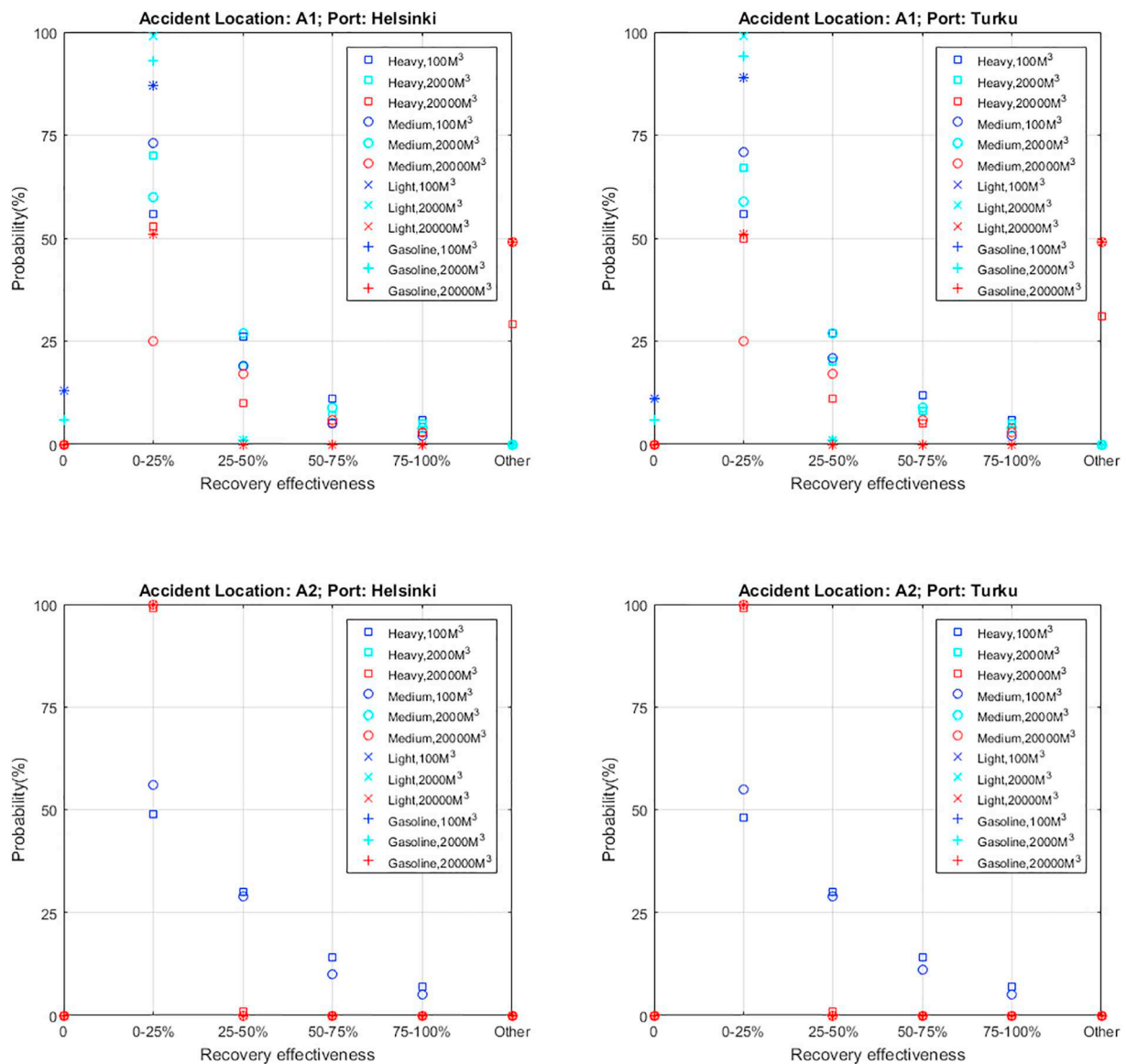


Fig. 13. Recovery effectiveness comparisons in terms of the variables: *Spill Size, Oil Type, Accident Location, Port Location*, in severe winter.

insight into the overall effectiveness.

- The variables *Forcing Representative Scenarios, Oil Type, Spill Size, Accident Location* and *Port Location* are assumed to have the same likelihoods, but the probabilities are only used to facilitate the variable as an assumption, as described in Section 6.3. The probability of the occurrence of these variables will be investigated in future work.

Meanwhile, there are some other specific limitations or assumptions, which are also reflected in SoE assessment in Section 6.3:

- Oil layer thickness used in the model is the averaged thickness of simulated oil particles for a certain area.
- Severity of ice conditions locally is based on judgments assessing ice concentration and ice thickness.
- Visual condition is based on the logic assumption and takes the worst condition from daylight and visibility at the recovery time.
- When estimating preparation time, it is assumed that no external conditions hinder this process. Preparation time mainly refers to onboard crew preparation.

- The theoretical max recovery rate is based on the assumed recovery vessel speed. Meanwhile, in the formulation of the equipment efficiency and recovery rate, coefficients provided by the recovery equipment expert are used.

6.3. Evaluation of the model

The model takes a wide range of evidence sources into consideration. As stated in Section 2.1, where the adopted risk perspective is introduced, it is important to assess any uncertainties concerning the evidence. In recent risk research, this assessment of the strength-of-evidence is an essential part of a risk analysis, see, e.g., Flage et al. (2014) and Goerlandt and Reniers (2016). The method suggested by Goerlandt and Reniers (2016) is adopted in this paper to conduct SoE analysis. The data, model, judgment and assumption criteria are also described in detail by Goerlandt et al. (2017b). Table 21 shows the results of the SoE assessment. Here, the discretization is divided into five color categories, representing the strength of evidence, as explained at the bottom of Table 21.

It should be noted that the CPTs for the variables *Forcing*

Table 21
Strength of evidence (SoE) assessment of the established BN model.

Variable	Section	Data				Ju	As	SoE
		Q	A	E	T			
Forcing Representative Scenario	4.1							-
Oil Type	4.2							-
Spill Size	4.2							-
Accident Location	4.2							-
Oil Viscosity	4.4.1							
Oil Layer Thickness	4.4.1							
Water Content	4.4.1							
Oil Location	4.4.3							
Oil Area	4.4.2							
Ice Thickness	4.5.1							
Ice Concentration	4.5.1							
Severity of Ice Conditions locally	4.5.1							
Daylight	4.5.3							
Visibility	4.5.3							
Visual Condition	4.5.3							
Air Temperature	4.5.2							
Wind Speed	4.5.2							
Severity of Atmospheric Conditions locally	4.5.2							
Port Location	4.3.1							-
Preparation Time	4.3.3							
Vessel	4.3.1							
Response Vessel Operability	4.3.1							
Distance	4.3.2							
Time of Arrival	4.3.4							
Equipment Operation	4.6.2							
Ship Maneuvering Operation	4.6.2							
Operation Effect	4.6.2							
Equipment Type	4.6.1							
Equipment Efficiency	4.6.2							
Theoretical Max Recovery Rate	4.6.1							
Recovery Rate	4.6.3							
Recovery Time	4.6.3							
Recovery Amount	4.6.3							
Not relevant		Low	Low-medium	Medium	Medium-high	High		

Note: Q - quality, A - amount, E - empirical validation, T - theoretical viability, Ju - judgment, As - assumption.

Representative Scenarios, Oil Type, Spill Size, Accident Location and Port Location are filled by assumed evenly distributed probabilities in the model. However, the probabilities are not used in the final analysis and application of the BN model, where certain states of the variables are chosen respectively for the scenario-based analysis. Therefore, the strength of evidence (SoE) of these five variables is not assessed in Table 21. However, the variables will be considered in future work (Section 6.4).

6.4. Future work

The outcomes show the capability of the model, identifying general trends in oil recovery in different accident locations, winter conditions and spill cases. However, as a limited case study, it may be insufficient as a basis for risk-informed decision-making concerning the need to make adjustments to oil spill response capabilities in Northern Baltic Sea winter conditions. Therefore, work on the following two aspects can be implemented to further develop and extend the current model: 1) the accident risk in terms of oil spill probability in different locations and for different oil types and sizes; 2) recovery fleet information and port information.

By integrating oil spill probabilities in different locations and for different oil types and sizes, the probable oil spill conditions can be determined so that comprehensive information about the estimated oil spill risk in winter conditions is available and can be integrated into the current model. Simultaneously, if information on the recovery vessel fleet and their port locations is available, it can be utilized to build a more complete response sub-model in light of the oil spill risks. In this way, the current model can be further developed in terms of oil spill and response sub-models so that the model can cover both information on oil spill risk and overall oil recovery fleet capability in the Northern Baltic Sea, leading to a fully implemented risk-based approach for oil spill preparedness and response.

Additionally, as in most existing maritime risk analysis models, the current manuscript does not include a validation of the developed risk model. This is a common limitation in risk analysis, with current ongoing research about appropriate methods to validate risk models (Goerlandt et al., 2017c). In future work, model validation tests, such as the ones applied in the framework proposed by Goerlandt and Montewka (2015), will be performed and the results reported.

7. Conclusion

In this paper, a Bayesian Network model for assessing oil spill recovery effectiveness in ice conditions has been presented. A systematic approach has been applied to establish the model content and structure by combining information from the literature, an excursion to an oil spill response vessel, and expert interviews. Various datasets are applied as evidence for parameterizing the probabilities in the model variables. The established BN model is able to estimate the recovery effectiveness for a range of scenarios, generating a holistic understanding and insights about the process from oil spill to recovery. It provides information to better understand the capabilities of the mechanical recovery approach, which is currently standard practice in the Northern Baltic Sea.

Simulated results and comparisons provide insights into the impact of different oil spill conditions (oil types, spill sizes and spill location) and winter conditions, and also account for specific attributes of the response vessel (port location). Identifying under which scenarios the recovery has high or low effectiveness contributes to better oil spill preparedness, as the identified gaps and weaknesses in the recovery system can be used to develop new recovery approaches. In future work, the model will be extended with information about the recovery fleet, ship traffic and ship accident conditions in the Northern Baltic Sea, and will thus be further used in strategic oil spill preparedness and response planning in this region for wintertime conditions.

Acknowledgements

The work in this paper has been performed as part of the BONUS STORMWINDS project. Funding has been received from BONUS (Art. 185), funded jointly from the European Union Seventh Framework Programme for research, technological development and demonstration, and from the Academy of Finland and the Swedish Research Council for Environment, Agricultural Sciences and Spatial Planning (FORMAS). The authors are also grateful to the experts who have contributed to this study. The contributions by the second author have been in part supported by funding received from the Ocean Frontier Institute, through the project 'Safe Navigation & Environmental Protection'. The authors are indebted to two anonymous reviewers, whose constructive comments have helped to improve a previous version of this article.

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