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Modeling the effectiveness of oil combating from an ecological perspective – A Bayesian network for the Gulf of Finland; the Baltic Sea

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ABSTRACT

Maritime traffic poses a major threat to marine ecosystems in the form of oil spills. The Gulf of Finland, the easternmost part of the Baltic Sea, has witnessed a rapid increase in oil transportation during the last 15 years. Should a spill occur, the negative ecological impacts may be reduced by oil combating, the effectiveness of which is, however, strongly dependent on prevailing environmental conditions and available technical resources. This poses increased uncertainty related to ecological consequences of future spills. We developed a probabilistic Bayesian network model that can be used to assess the effectiveness of different oil combating strategies in minimizing the negative effects of oil on six species living in the Gulf of Finland. The model can be used for creating different accident scenarios and assessing the performance of various oil combating actions under uncertainty, which enables its use as a supportive tool in decision-making. While the model is confined to the western Gulf of Finland, the methodology is adaptable to other marine areas facing similar risks and challenges related to oil spills.

1. Introduction

Economic growth has augmented the volume of sea traffic around the world, as maritime transportation is the most efficient way to ferry goods among countries. This trend has also negative side-effects such as accidental oil spills, which pose a threat to coastal ecosystems.

The Gulf of Finland (GOF), the easternmost part of the Baltic Sea, has many features that make it exceptional among the world's water bodies and also sensitive to oil spills. Due to low salinity (0–7‰), relatively short geological history and northern location the biota is a fairly species-poor mixture of marine and freshwater species capable of dealing with low temperatures and ice-cover in wintertime. The GOF is also an important migratory route for the arctic birds, and it harbors numerous conservation areas [1,2]. Nowadays, being one of the most heavily trafficked sea areas in the world and with over 12 million people inhabiting its drainage area [3], the GOF is suffering from serious environmental problems like eutrophication and invasive species [1].

A new major threat to this fragile ecosystem is the risk of a large-scale oil spill. The volume of oil transportation has increased substantially in the area during the last 15 years. In 2007, over 145 million tons of crude oil and refined products were transported via the GOF [4], and the volume is expected to be 250–300 million tons by year 2015 [5]. The drastic increase is mainly due to the construction and development of new terminals especially in Russia and Estonia [6]. In addition, the GOF is facing rapidly growing maritime cargo and passenger traffic. Although there have been major improvements in maritime safety [6], the risk of a major accident is evident. The worst-case scenario in the GOF is assumed to be a collision of two tankers, which can result in an oil spill of approximately 30 000 t of crude oil; if a tanker is lost due to sinking, explosion or intense fire, the resulting spill can be even larger [5]. An accident of this magnitude could have a devastating and long-lasting effect on the GOF ecosystem.

After an accident, effective oil combating can play an essential role in minimizing any harmful effects. At present oil combating in the GOF is based on mechanical recovery, which is in accordance with the recommendations of the Baltic Marine Environment Protection Commission [7]. However, the characteristics of the GOF make oil combating a challenging task. Since the GOF is narrow and shoreline is occupied by vast archipelago especially on the northern coast, the time window for response measures is very narrow. Furthermore, the wintertime ice-cover reduces the efficiency of combating.

It is essential to have extensive knowledge of the behavior and movement of drifting oil as well as of the ecological effects oil induces in order to mitigate the negative impacts oil spills may

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have. There is a large number of models that can be used for predicting the fate and trajectory of spilled oil (reviewed e.g. by ASCE [8] and Reed et al. [9]). While these models use fairly sophisticated ways to calculate the physical and chemical processes spilled oil undergoes, they seldom can be applied to assess the impacts on biota, and they usually do not include uncertainty estimates, i.e. impacts having low probability cannot be evaluated. The relatively few models focusing on the ecological effects of oil spills include models developed for birds [10], fur seals [11], sea otters [12] and intertidal invertebrates [13]. However, also a more comprehensive model combining the physical fate of spilled oil with ecological and economic impacts has been devised [14,15]. Although some of developed models include also oil combating options, they are mainly designed for operational or educational purposes, and thus their capability to assess the effectiveness of oil combating activities in a general environmental context is highly limited.

The aim of this paper is to present a probabilistic Bayesian network model that combines the behavior of oil, ecological effects and oil combating options, and which can be used to assess the effectiveness of different oil combating methods from an ecological perspective. Bayesian networks are graphical models that enable the assessment of different management decisions and thus help the decision-making under high uncertainty. First we provide a short introduction to the methodology and describe the structure of the model, after which we present a scenario that offers possibility to assess, how different decisions in oil combating in the GOF affect the state of the populations of interest. Finally we examine our results in the light of present oil combating practices.

2. Materials and methods

2.1. Bayesian networks

Bayesian networks (BNs, also known as belief networks [16]) are graphical models describing probabilistic relationships between a set of variables. Formally they are directed acyclic graphs (DAGs) with nodes and arcs. The nodes represent discretized random variables and arcs represent probabilistic dependencies between the variables. As they handle uncertainty explicitly, they are suitable for examining systems containing complex and uncertain interactions. BNs can be constructed as influence diagrams by including decision and/or utility nodes in the network, which further improves their use as decision tools. By choosing one decision option at a time one can examine the possible consequences of planned actions as the information is propagated through the network. For more detailed information, e.g. Jensen [17,18] offers an extensive presentation of the methodology related to BNs in general.

BNs originate from artificial intelligence research, and in addition to their use in e.g. medical [e.g. [19–21]] and social sciences [e.g. [22,23]], BNs are increasingly applied to solve problems concerning environmental issues and management [24–33]. As described above, they enable the assessment of different decision options and thus offer an effective and user-friendly tool for decision-making under uncertainty. This makes BNs applicable to oil spill management, seen as a field of environment management encountering very high uncertainty. BNs also allow the combination of information from different sources (e.g. simulation models, observed data and expert knowledge) with differing accuracies (quantitative or qualitative), and they are also able to cope with missing data and small datasets. However, there are also some issues that have to be taken into account when using them, e.g. their ability to handle continuous variables is limited, and they cannot operate with loop structures in the model. Uusitalo [34] offers a detailed review of the advantages and challenges of BNs in environmental problems.

2.2. Description of the model

The model includes three oil combating options and several environmental and biological variables, which are needed to describe the overall uncertainty related to the management problem (Fig. 1, Table 1). The combating options considered in the model are: (1) mechanical recovery offshore, (2) dispersants (i.e. chemicals that break up the oil slick into small dispersible droplets) offshore, and (3) oil deflection booms inshore, i.e. three combating options that can potentially be applied in the GOF during the ice-free period. Mechanical recovery and deflection booms are widely used in oil combating in the GOF today, whereas chemical dispersants have not been considered as a countermeasure since the 1980s. The latter were nevertheless included in the model because they are still seen as a possible combating option in situations where there are no other means to avoid e.g. severe losses of seabirds within endangered breeding colonies [7]. Yet, quantitative analyses on the subject in the GOF are lacking. They are however needed, if the rationale behind the management decision ought to be evaluated.

The model is a continuation of the work of Juntunen et al. [35], who studied the effects of different oil combating strategies (limiting the tanker size, stopping of oil leakage, mechanical and chemical combating offshore) on the ecosystem of the GOF. The present study widens the repertoire of combating options and focuses on a detailed ecological analysis with a realistic spatial scale, while the work of Juntunen et al. [35] presented an elaborate analysis of the leakage event and had a more general approach to the ecosystem effects.

The final outcome of the model is the probability distributions describing the decrease in the population sizes of selected species after an oil accident. The model includes six species: (1) the grey seal (*Halichoerus grypus*) and (2) the common eider (*Somateria mollissima*) representing mobile animals living in a close contact with both littoral zone and water surface, (3) the blue mussel (*Mytilus trossulus*) and (4) the Baltic herring (*Clupea harengus membras*) representing subsurface organisms, and (5) the prickly saltwort (*Salsola kali kali*) and (6) the scarab beetle *Aegialia arenaria* representing terrestrial species living onshore. The species were chosen so that they describe the effects of an oil spill on different parts of the ecosystem. In addition, they all can be considered important in the context of the GOF either on ecological, economic or conservational basis. Four first-mentioned species are fairly common in the GOF, whereas the latter two species are considered threatened in Finland [36].

Since the effectiveness of deflection booms is highly dependent on local conditions like the topography of the shore, the model is spatially confined to the Hankoniemi area (Fig. 2) in the western GOF to make the assessment and comparison of different combating methods more realistic. Due to geological as well as geographical reasons, an exceptional mixture of habitats can be found in Hankoniemi, including e.g. rocky shores, groves, seashore meadows, leas and dunes. As the peninsula is a continuation of the Salpausselkä end moraine, long sandy beaches and underwater reefs, i.e. habitats absent from elsewhere in Finland, are also present. The uniqueness of habitats is expressed also via biodiversity, and Hankoniemi can the seen as a “hot spot” of biodiversity in the GOF, especially when considering endangered species.

The occurrence data of the common eider, the grey seal, the prickly saltwort and the scarab beetle *Aegialia arenaria* in the Hankoniemi area were retrieved from the databases of the Finnish Environment Institute and delineated by experts if needed. Since the exact occurrence data of the Baltic herring and the blue mussel do not exist, the occurrence for the former was assumed to cover sea areas deeper than 1 m (spring and summer) and 10 m (autumn), and for the latter the sea areas that were 0–20 m deep.

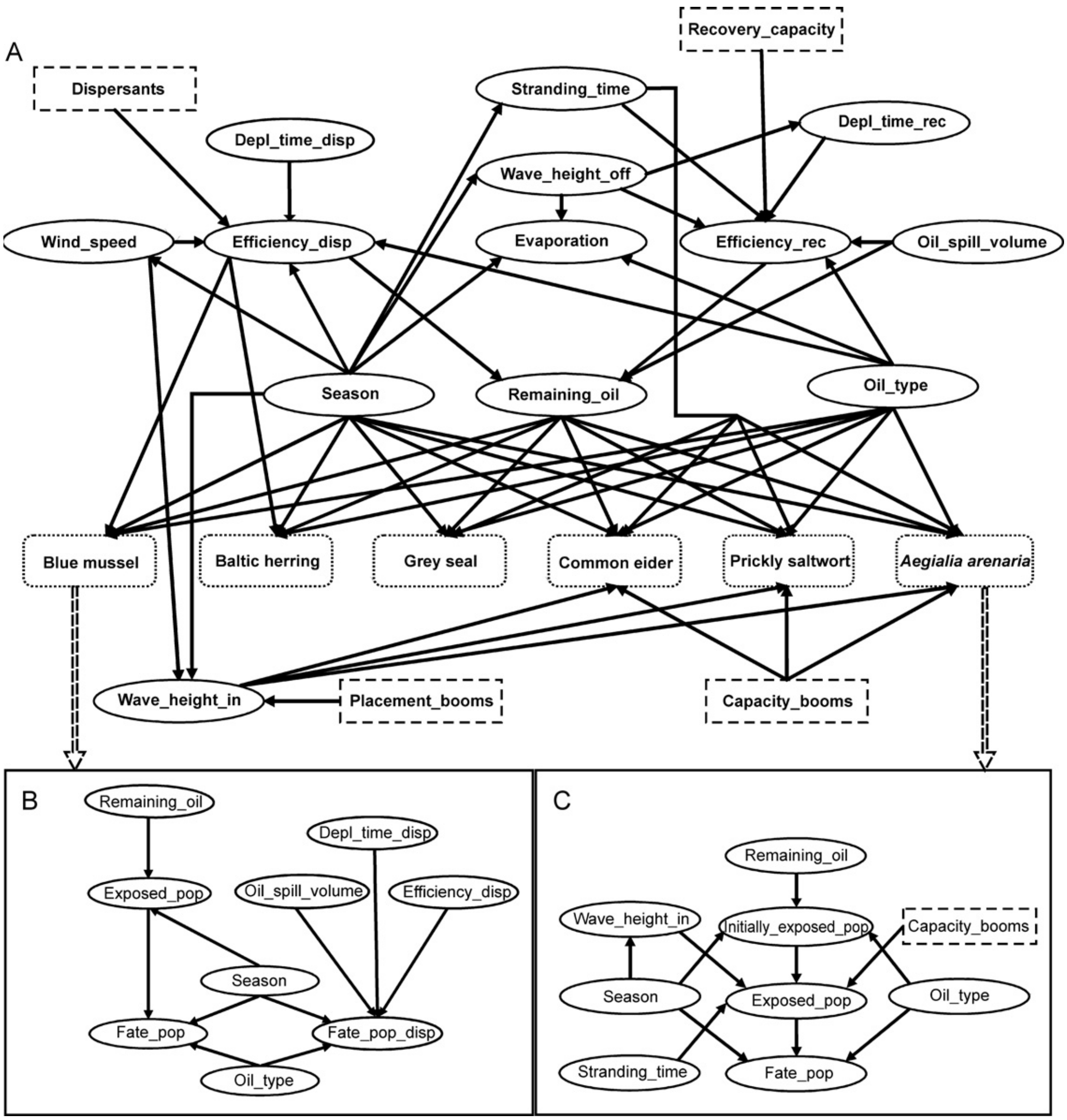

Fig. 1. A simplified graphical representation of the model. A. The general structure of the model. Squares: decision variables; ellipses: random variables; rounded squares: a group of variables related to a species. B. A set of variables related to subsurface species exposed to dispersed oil, i.e. the blue mussel and the Baltic herring. C. A set of variables related to species that can be safeguarded by oil booms, i.e. the common eider, the prickly saltwort and the scarab beetle *Aegialia arenaria*. The grey seal has a similar set of variables except variables **Capacity_booms**, **Exposed_pop** and **Wave_height_in** are absent. In addition, the common eider is in reality divided in three subgroups representing individuals living in different parts of the archipelago, i.e. the inner and the outer archipelago and the open sea, as these populations differ in how they can be protected by oil booms. In B and C, only the variables directly linked to species-specific variables are shown.

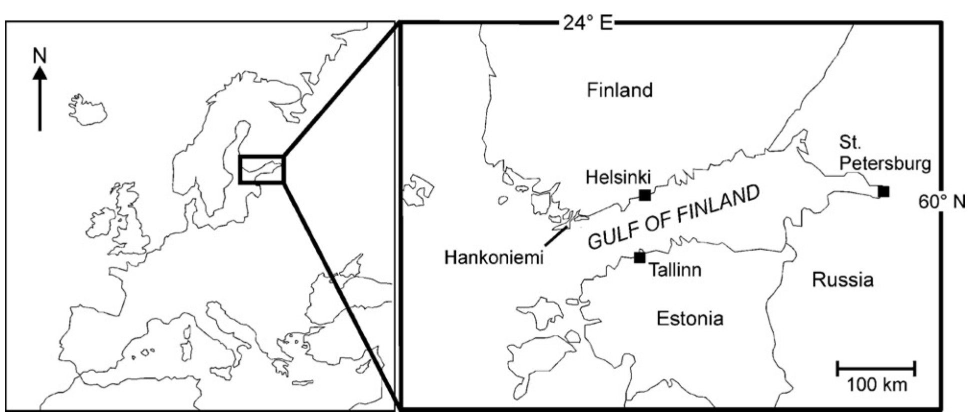

Fig. 2. The location of the Gulf of Finland and the Hankoniemi area.

Table 1
The type and the states of the variables. R: random variable, D: decision variable.

Variable category	Variable	Type	States
Accident	Oil_spill_volume (t)	R	0–1000, 1000–5000, 5000–10000, 10–25000, 25–50000, >50000
	Oil_type	R	Light, medium, heavy
Behavior of oil	Evaporation (%)	R	0–33, 33–67, 67–100
	Stranding_time (h)	R	0–48, 48–96, 96–144, 144–192, 192–240, >240
Environmental conditions	Season	R	Spring, summer, autumn
	Wave_height_off (m)	R	0–1, 1–2, 2–3, >3
	Wave_height_in (m)	R	0–1, 1–2, 2–3, >3
	Wind_speed (m/s)	R	0–5, 5–10, 10–15, 15–20, >20
Efficiency of oil combating	Depl_time_disp (d)	R	1, 2, 3, ≥4
	Depl_time_rec (d)	R	2, 3, 4, ≥5
	Dispersants	D	No, Yes
	Efficiency_disp (%)	R	0–5, 5–10, 10–15, 15–20, 20–30, 30–50, 50–70, 70–100
	Efficiency_rec (%)	R	0–10, 10–20, 20–30, . . ., 70–80, 80–90, 90–100
	Recovery_capacity	D	Year 2007, year 2010, year 2015
	Remaining_oil (t)	R	0–500, 500–1000, 1000–2000, . . ., 4000–5000, 5000–7500, 7500–10000, 10000–15000, . . ., 45000–50000, >50000
	Capacity_booms (m)	D	Year 2007, year 2010
	Placement_booms	D	Present, IUCN, Public
Biological effects	Exposed_pop (for all species) (%)	R	0–20, 20–50, 50–80, 80–100
	Fate_pop (%)	R	0–20, 20–50, 50–80, 80–100
	Fate_pop_disp (for the blue mussel and the Baltic herring) (%)	R	0–20, 20–50, 50–80, 80–100
	Initially_exposed_pop (for all species) (%)	R	0–10, 10–20, 20–30, . . ., 70–80, 80–90, 90–100

The structure of the model and the prior distributions and conditional probabilities between the variables were defined mainly by using literature and expert knowledge. The oil spill drifting model SPILLMOD 2.0 (described by Ovsienko [37]) and the software system Geoinformatica [38] were used along with the occurrence data of species to create the probability distributions for the exposure of species to drifting oil. Geoinformatica platform was also used to calculate the conditional probability distributions for inshore wave height. For some variables like the efficiency of oil combating simple functions were developed by using literature and expert knowledge. In addition, to make the evaluation of the effects of dispersed oil on species easier, a separate BN was constructed to describe the dispersion and the concentration changes of underwater oil. The BN models were constructed with Hugin Educational 6.8 and Hugin Researcher 6.2 software [39].

2.3. Description of the variables

The variables in the model can be grouped into five categories: the variables related to the (1) accident, (2) behavior of spilled oil, (3) prevailing environmental conditions, (4) efficiency of oil combating, and (5) biological effects.

2.3.1. Variables related to the accident

The variables describing the accident are **Oil_spill_volume** and **Oil_type** (Table 1). The prior distribution for the variables was derived from the model developed by Juntunen et al. [35].

2.3.2. Variables related to the behavior of spilled oil

The behavior of spilled oil is described with the variables **Evaporation** and **Stranding_time**. Evaporation is usually considered the most important weathering process and the only one that removes oil completely from the aquatic system [e.g. [40]]. The conditional probability distribution for the variable was derived from Juntunen et al. [35].

Stranding_time describes how rapidly oil reaches the shoreline after the spill, and the conditional probabilities were gained from oil spill trajectory data provided by the Finnish Environment Institute. The data consisted of over 6500 oil spill trajectories that were calculated with the oil spill program SPILLMOD. Each trajectory represents the movement of the centre of mass of a 1000 t oil slick within 10 days after the spill. The trajectory number 1 represents an oil spill happening in the first hour of the spring, the trajectory number 2 an oil spill happening in the second hour of the spring etc. Thus one season, i.e. a three-month period, includes approximately 2160 different trajectories. The wind and current data used in the computation represented the prevailing hydrometeorological conditions in the GOF in the year 1996. The spill location used in the calculation (N59°36′00″, E23°10′00″) was chosen to be close to the intersection of two routes, the main west–east passage in the GOF and the deep-water channel leading to the harbor of Hanko thus realistically representing an oil accident taking place in the western GOF. Each trajectory included in the analysis embodied information about the time it takes for the slick to hit the shoreline for the first time after the accident.

2.3.3. Variables related to environmental conditions

The variables describing environmental conditions at the time of the accident include **Season**, **Wind_speed**, **Wave_height_off** and **Wave_height_in**. The variable **Season** has three states: spring (Mar.–May), summer (Jun.–Aug.) and autumn (Sep.–Nov.). Winter was left out, as at the present moment there does not exist any oil spill package capable of predicting reliably the movement of oil in ice conditions in the GOF. The prior distribution for the variable was gained from the accident statistics of HELCOM [41–45]. The prior distribution for **Wind_speed** was elicited from wind statistics of the Finnish Meteorological Institute (the monitoring station Hanko Jussarö (N59°46′0″, E22°57′0″), years 1971–2000). **Wave_height_off** describes the significant wave height offshore in the GOF, and the prior distribution was taken from wave buoy measurements carried out by the Finnish Institute of Marine Research [46].

Wave_height_in describes the wave height inshore, i.e. wave height that deflection booms encounter when they are used to safeguard certain species/habitats. The wave environment depends strongly on the exposure of these habitats, and the wave height is substantially smaller e.g. in sheltered inner archipelago than in the seaward side of islets located in outer archipelago. Since buoy measurement data inshore in the GOF is lacking, the conditional probability table for the variable was calculated using a technique described by Ekebom et al. [47]. The method takes into account the wind speed and the fetch length, i.e. the length of open water over which a given wind blows. The fetch length data (provided by the University of Turku) consisted of fetch lengths representing 48 directions (i.e. at 7.5° intervals) calculated for points covering the Finnish coastline at 10 m intervals. To produce a conditional distribution for the wave height that oil booms encounter when placed in a certain manner in the Hankoniemi area, the following procedure was applied: (1) The alternative locations of oil booms (depending on the species and the strategy applied to place the booms, see the decision variable **Placement_booms**) were digitized on the map, (2) The fetch length data points belonging to a buffer zone extending 50 m from the booms were selected, (3) The fetch lengths of the selected points were reduced to represent eight compass directions, and (4) The distributions of wave heights were calculated by combining the fetch length data and the wind data for each eight directions.

2.3.4. Variables related to the efficiency of oil combating

In the model, mechanical recovery is considered to benefit all species by diminishing the amount of spilled oil in the environment. Dispersants are assumed on the one hand to help species living on shore and in close contact with the water surface, but on the other hand to pose a threat to subsurface species. Deflection booms inshore are considered applicable to safeguard species living in the mainland and in the inner archipelago, i.e. the common eider, the prickly saltwort and the scarab beetle *Aegialia arenaria*.

A decision variable **Recovery_capacity** describes mainly the number of recovery vessels capable of recovering oil offshore. The decision options include the year 2007 capacity and the capacities for years 2010 and 2015 assuming that the proposed investments in the GOF will actualize [5]. **Depl_time_rec** represents the time that it takes from 80% of the available vessels to reach the area. The prior distribution for the variable was derived from Juntunen et al. [35]. **Dispersants** is a decision variable describing the decision to use or not to use dispersant application. **Depl_time_disp** describes the time it takes that the chemicals are sprayed onto the oil slick. Since there is no preparedness to use chemicals in the Gulf of Finland at the present moment (e.g. there are no stockpiles of combating chemicals neither in Finland, Estonia nor Sweden [48]), the prior distribution for the variable was unfeasible to define. Thus the variable was given a uniform marginal distribution, i.e. each state was estimated to be as probable as another.

Efficiency_rec as well as **Efficiency_disp** were estimated by simple functions calculating the percentage of oil removed from water surface. The maximum efficiency of mechanical recovery was assumed to be dependent on the volume of oil spill, whereas the maximum efficiency of dispersants was set to 35% (see e.g. Fingas et al. [49] and Fingas [50] concerning the efficiency of dispersants in brackish water). The logic of the calculation, adopted from Juntunen et al. [35], is presented in Fig. 3. **Remaining_oil** describes the amount of floating oil (t) after evaporation and offshore oil combating actions.

The variables related to the efficiency of deflection booms near shoreline are decision variables **Capacity_booms** and **Placement_booms**. The former has two options, the capacity of coastal booms for year 2007 and 2010 [51], and the latter has three options for the placing of booms: the present contingency plans ("Present"), to safeguard threatened species living on shore in Hankoniemi (excluding birds and seals) ("IUCN") and to safeguard species traditionally considered highly sensitive to oil spills by the public like birds and seals ("Public"). As the use of coastal booms have certain limitations (e.g. anchoring of booms in deep water is unfeasible), the populations living in outer archipelago and offshore were considered to be out of reach of this kind of safeguarding.

2.3.5. Variables related to the biological effects

Initially_exposed_pop describes the percentage of the population that becomes exposed to the spilled oil if no safeguarding actions are taken inshore. The conditional probability tables for the variable for all six species were gained by using the following steps:

1) Over 6500 oil spill trajectories were calculated with the oil spill program SPILLMOD (see Section 2.3.2 *Variables related to the behavior of spilled oil*).
2) The trajectories were reduced to describe only the drifting of oil before the slick hits the shore for the first time, i.e. the re-heading of the slick to the open sea was not considered.
3) A buffer zone representing the width of the slick was added to the trajectory data. The width was calculated by using the formula introduced by Lehr et al. [52], re-written by Chao et al. [53]. In the calculation, the density of sea water was set to 1.008 kg/l and the densities of light, medium and heavy oil were assumed to be 0.8 kg/l, 0.9 kg/l and 0.975 kg/l, respectively.
4) The percentage of the initially exposed population was gained by first calculating the intersection area of the modified trajectory data (from step 3) and the digitized occurrence data of the species (the latter being transformed to a circle), and then proportioning this area to all Hankoniemi occurrences of the species. The probability distribution for the species to become exposed to oil was achieved by going through in a similar manner every trajectory from March to November (ca 6500 trajectories).

Exposed_pop, i.e. the percentage of the population exposed to oil after the safeguarding actions near the shore have been conducted, is estimated with an equation, which takes into account the capacity and the placement of booms, the wave height the booms encounter (i.e. the wave height near), the stranding time of oil (i.e. how much there is time to place the booms properly) and the behavior of the species.

Fate_pop_disp describes the decrease in the population size of a subsurface species, if dispersants are used in oil combating. Since the variable depends on several factors, an additional BN illustrating the dispersion of oil was developed to help the evaluation of biological effects. The model describes first the spreading of oil afloat and, after dispersants have been applied, the dispersion and mixing of the subsurface plume of dispersed oil. The computation of the horizontal dispersion of oil was calculated in two phases. At first, the spreading of oil on the water surface was calculated with the equation by Lehr et al. [52]. The second phase i.e. the horizontal mixing of underwater oil was calculated with the formula of Carter and Okubo (1965, cited in e.g. Peeters et al. [54]), which takes into account both diffusion and shear stress. The vertical mixing of oil droplets was calculated by assuming that oil droplets disperse into the depth of $1.5 \times$ wave height within first 2 h [55] and into the depth of the Ekman layer within 48 h. After 48 h, the dispersion of droplets continues as a slow diffusion process until the thermocline, halocline or seabed is reached. In the BN, the concentration of dispersants and dispersed oil as well as the magnitude of underwater plume are assessable for the time-steps of 2 h, 48 h, 96 h and 240 h after the deployment of dispersants. The exact parameters used in the computation are available from the authors by request.

Fate_pop is the final outcome of the model and describes the decrease in the population size of the species of interest. The estimation of the biological effects was made following the logic in [35] and Lecklin et al. (in preparation). The magnitude of negative impacts is dependent on three factors: season, oil type and the proportion of the population that becomes exposed to oil. All

$$g_1(\text{season}) = \begin{cases} 0.8, & \text{if season} = \text{spring} \\ 1, & \text{if season} = \text{summer} \\ 0.9, & \text{if season} = \text{autumn} \end{cases}$$

$$g_3(\text{wind speed}) = \begin{cases} 0.1, & \text{if wind speed} < 5\,\text{m/s} \\ 0.9, & \text{if wind speed} = 5\text{–}10\,\text{m/s} \\ 1, & \text{if wind speed} = 10\text{–}15\,\text{m/s} \\ 0.5, & \text{if wind speed} = 15\text{–}20\,\text{m/s} \\ 0.25, & \text{if wind speed} > 20\,\text{m/s} \end{cases}$$

$$\mathbf{Eff_{DISP} = g_1(season) \times g_2(deployment\ time) \times g_3(wind\ speed) \times g_4(oil\ type) \times 35\ \%}$$

$$g_2(\text{deployment time}) = \begin{cases} 1, & \text{if deployment time} \le 1\,\text{d} \\ 0.6, & \text{if deployment time} = 2\,\text{d} \\ 0.1, & \text{if deployment time} = 3\,\text{d} \\ 0.05, & \text{if deployment time} \ge 4\,\text{d} \end{cases}$$

$$g_4(\text{oil type}) = \begin{cases} 1, & \text{if oil type} = \text{light} \\ 0.33, & \text{if oil type} = \text{medium} \\ 0.033, & \text{if oil type} = \text{heavy} \end{cases}$$

Fig. 3. An example of the logic used when creating functions for certain variables. The estimation of the coefficients for season was mainly based on Hayes et al. [70], for deployment time NRC [71], Hayes et al. [70], Nordvik [72] and Nordvik [73], for wind speed Fingas [50] and ITOPF [74], and for oil type Hayes et al. [70].

species except the blue mussel are assumed to be more vulnerable to oil exposure in spring and/or summer than in autumn, i.e. in the reproduction or growth period [e.g. [56]]. Subsurface organisms are assumed to suffer more gravely from light and thus acutely more toxic oils than from heavy and smothering oils, and littoral organisms vice versa [e.g. [57]]. For subsurface populations the calculation differs slightly depending on whether dispersant are used or not.

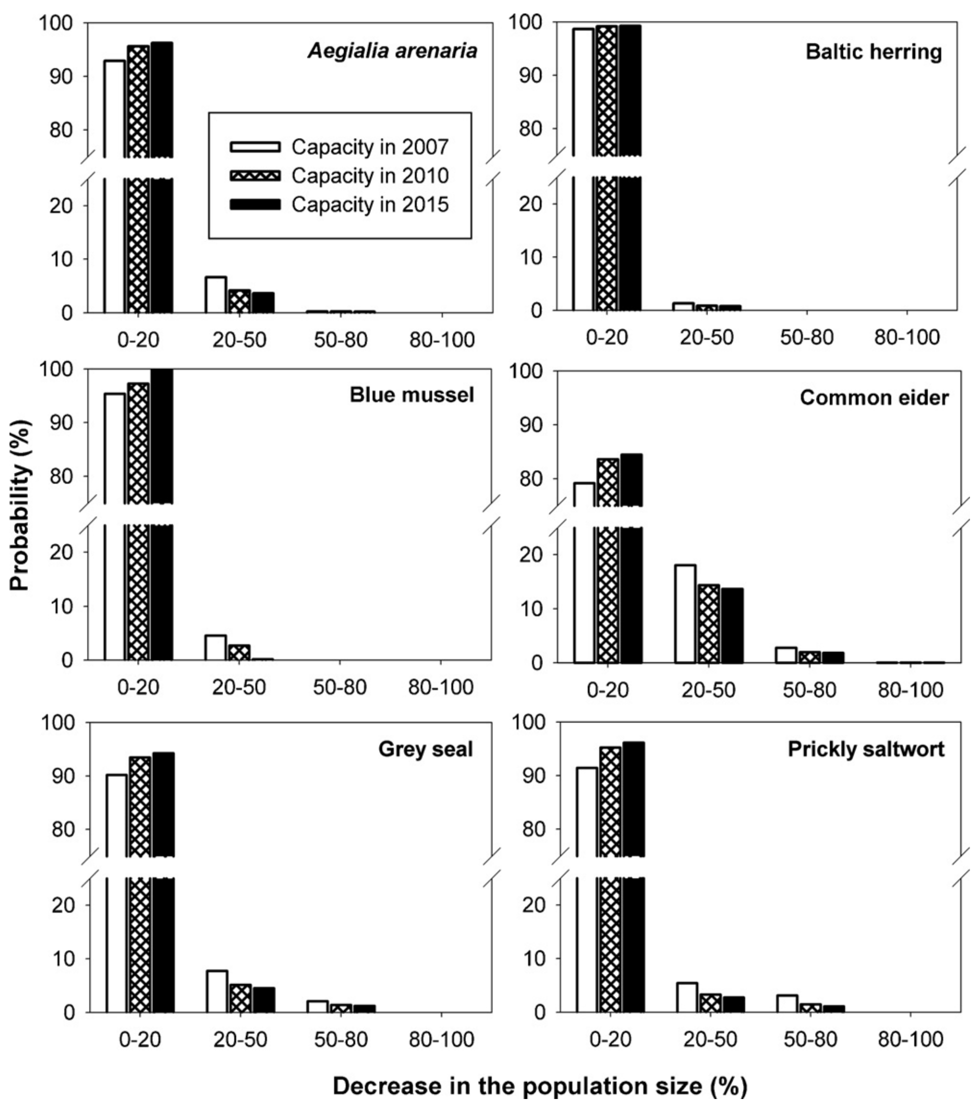

Fig. 4. The effect of different mechanical recovery capacities on the fate of species. Notice the breaks in the *y*-axes.

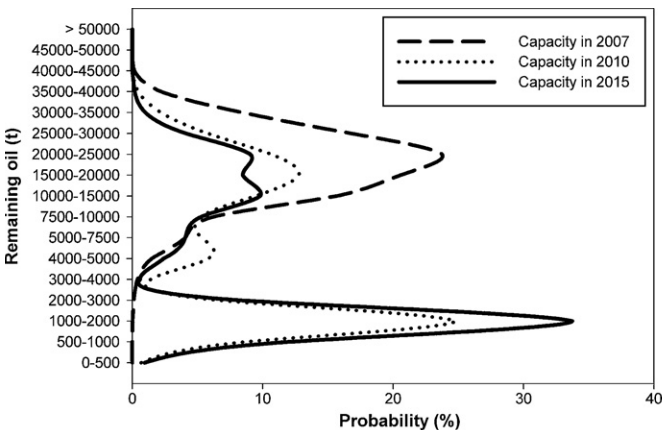

Fig. 5. The effect of the mechanical recovery capacity on the amount of oil afloat. The increments in recovery capacity shift the probability distribution towards smaller volumes of remaining oil. At the same time, however, the distribution changes from unimodal to bimodal as with higher recovery capacities the effect of the stranding time, which has a bimodal conditional probability distribution in spring and autumn, becomes more apparent. With present capacity, the time for recovering spilled oil does not matter that much as the capacity is so low in any case. With larger capacities, a longer time available for recovery has a potential to increase the overall recovery efficiency.

3. Results

The model can be used to examine the effects of different oil combating decisions in any combination of oil spill volume, oil type and season. We demonstrate the functioning of the model by using one oil spill scenario. The chosen scenario represents an accident happening in springtime and resulting in a 25,000–50,000 t oil spill of medium crude oil, which is a realistic worst-case scenario in the present situation.

In the scenario, with present combating capacity (year 2007) and methods, the common eider encounters the greatest loss: there is over 20% probability that the Hankoniemi population will decrease 20% at minimum as a result of the exposure to oil within 10 days after the accident (Fig. 4). This would mean the death of at least 1800–2000 individuals. Also the grey seal, the scarab beetle *Aegialia arenaria* and the prickly saltwort are probable to suffer from noticeable losses. For subsurface species the losses are probably only negligible.

3.1. Mechanical recovery

When the capacity of mechanical recovery is increased, the probability for larger losses decreases with all species. However, the shifts are only minor (Fig. 4), although the increase in capacity may become manifested in the amount of the remaining oil (Fig. 5). Yet, even though high efficiencies are possibly to achieve in optimal conditions by increasing the capacity of mechanical recovery, it is important to notice that the conditions are rarely optimal. The effectiveness of recovery is highly dependent on the prevailing environmental conditions, especially on wave height (Fig. 6). Even with the highest capacity (year 2015) and the time for mechanical recovery set to the maximum (>240 h), the efficiency of recovery drops drastically when wave height increases. With the present capacity, the probability that less than 10% of the spilled oil is mechanically recovered is almost 85% when wave height at open sea exceeds 3 m.

3.2. Dispersants

Dispersants have a 2-fold effect in the chosen scenario: the model estimates an increase in the probability of the Baltic herring and the blue mussel to suffer from oil, and at the same time they diminish the probability of negative impacts in other than subsurface species (Fig. 7). However, both the negative impact on the blue mussel and the positive impact on species living on shore (i.e. dispersants capacity to diminish the amount of floating oil) are only minute.

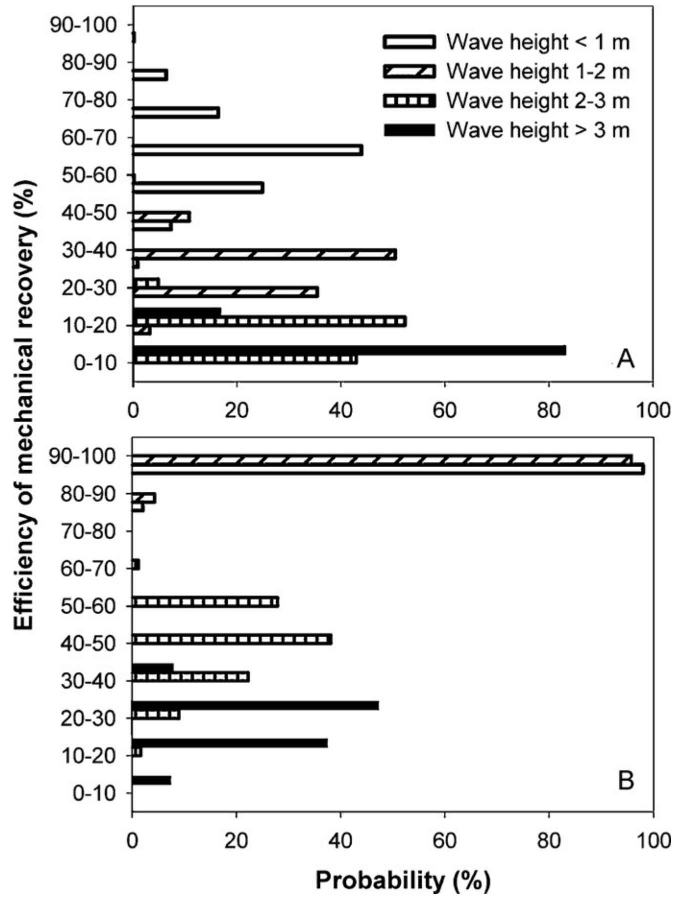

Fig. 6. The effect of wave height on the efficiency of mechanical recovery. A. Capacity for year 2007. B. Capacity for year 2015.

The reason for the Baltic herring to be more vulnerable to dispersant application than the blue mussel stems from the differences in species' occurrences as well as in physiology. Even though spring is the spawning time for most of the Baltic herring populations living in the GOF and the individuals migrate to shallow shores, fish are abundant also in the open sea, where the concentrations of dispersed oil are the highest. As the blue mussel inhabits the rocky bottoms mainly at the depth of 0–10 m, the concentrations of dispersed oil they encounter are assessed to be much lower than at the open sea. In addition, bivalves are able to temporarily escape hostile environmental conditions like toxic substances by closing their valves [e.g. [58]].

The smallness of the positive effect that dispersants have on the species living on shore is directly linked to their weak capacity to diminish the amount of remaining oil afloat. This is mainly due to the inefficiency of modern dispersants in low salinity conditions [e.g. [49,50]].

3.3. Deflection booms inshore

Oil combating actions taking place in shore include decisions about the capacity of booms and the grounds for their placement. It seems that the increase in capacity does not have a major effect on the fate of species, although a slight increase in the probabil-

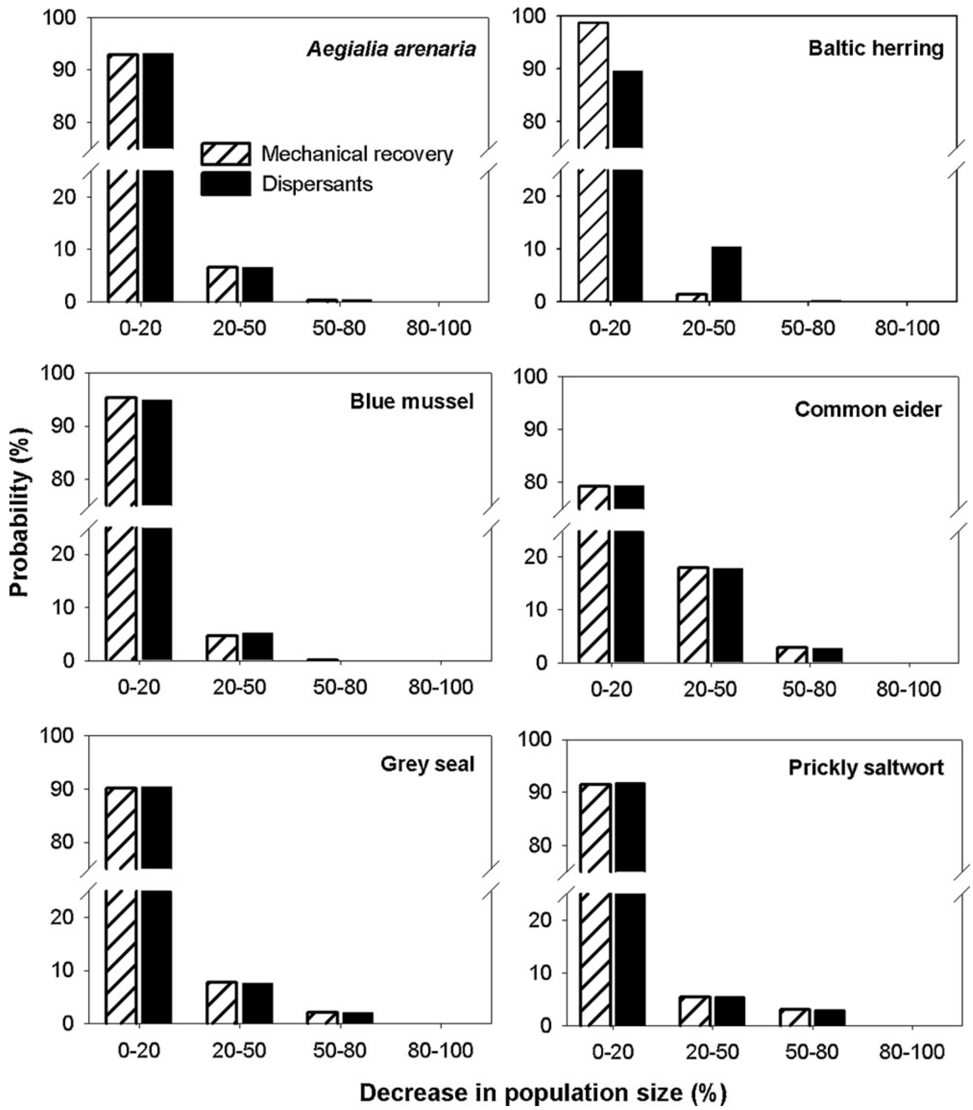

Fig. 7. The effect of dispersants on the fate of species. Dispersants are assumed to be spread within 24 h after the accident, and applied along with mechanical recovery. Notice the breaks in the *y*-axes.

ity towards the smallest loss can be detected. The insignificance of the effect is due to the insufficiency of proposed investments in combating equipment. The model suggests that the placement of booms has more distinctive effect: the scarab beetle *Aegialia arenaria* and the prickly saltwort benefit when available booms are placed according to "Present" or "IUCN" manner compared to "Public". With the common eider the results are more minute: the species benefits only slightly when the booms are placed in compliance with "Public", i.e. the practice favouring birds and seals.

Although these effects are rather minor, they become clearer if the initially exposed population is large, e.g. 50–60% of the population (Fig. 8). Then the benefits are evident, especially for *Aegialia arenaria* and the prickly saltwort. For the common eider, however, the effect seems to be only moderate even in this case. This is partly explained by the fact that the species inhabits also the outer archipelago, where they are more exposed to rough seas than in inner archipelago, and where the performance of deflection booms is highly limited. The main reason is, however, related to the behavior of species. As a highly mobile animal, the common eider is difficult to safeguard by oil booms, because they may change their location rapidly and unexpectedly. As a matter of fact, the effectiveness of oil booms is even lower in summer and autumn, when the nesting is over and the female individuals are able to move more freely.

4. Discussion

The model suggests that a large oil accident taking place in the western GOF would have diverse effects in the light of the six species included in the model. The decrease in the population size would be the greatest in the case of the common eider and the least in the Baltic herring.

Although the probability that the populations of the scarab beetle *Aegialia arenaria* and the prickly saltwort would decrease >20% is less than 10%, their status as threatened species emphasizes the importance of efficient protection. Small populations are vulnerable to extinction due to the stochastic variations in genetic, demographic and environmental factors [e.g. [59,60]]. Thus, even minor reductions in already small populations may have severe consequences.

The results are interesting in the light of oil spill management. The model suggests that oil combating in the GOF should rely on mechanical recovery and inshore protection instead of chemical combating. However, as mechanical combating can be strongly

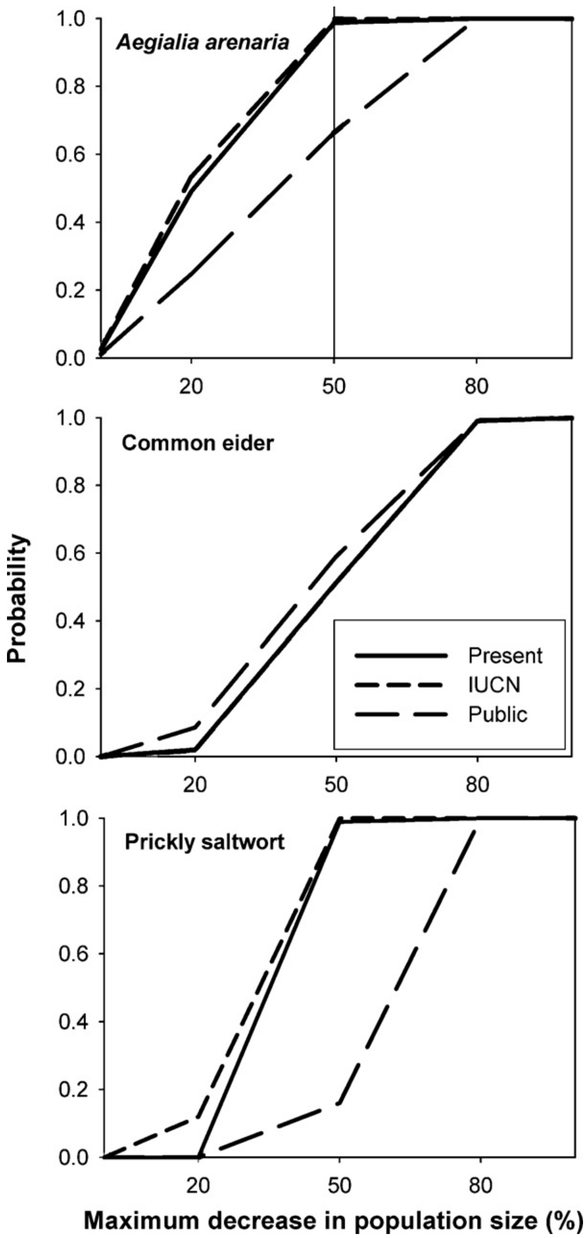

Fig. 8. The effect of different strategies for placing oil booms in shore. The more the curve is leftward, the higher the risk. E.g. the probability that the decrease of the population size of *Aegialia arenaria* is not more than 50% is almost 1 with "Present" and "IUCN" practices. However, if the practice is "Public", the probability is only 0.67.

affected by environmental conditions, even large investments in recovery capacity do not ensure successful protection of biological resources. This highlights the importance of measures that reduce the risk of accidents taking place (e.g. education of the crews).

The model demonstrates that the effects of the different oil combating strategies are difficult to predict, owing to the large uncertainties related to many variables. E.g. the evaporation of oil is a variable loaded with high uncertainty, even if the type of oil is known. This effect may be strengthened by the rather coarse discretization of some variables in the model: as there are only few classes in a discrete variable, information about minor changes is lost. Yet, despite rather low prediction power, it is important to realise that the model probably reveals the reality: the sweep of oil combating is a complex process with many uncertainties and it may indeed be impossible to exactly predict, what will happen after an oil accident. For humans, it may be hard to include all uncertainty in reasoning, and the human mind has e.g. limited capacity to handle conditional probabilities over more than one or two dimensions [61]. This means that the "fog of uncertainty" may be much thicker than decision makers realise, i.e. the correlatives of decisions do not appear in a deterministic cause-effect manner.

The output of the model suggests that the increase in recovery capacity does not necessarily become manifested in the fate of exposed species. Albeit logical, the procedure of calculating the initially exposed populations may underestimate the exposure of the populations. As described earlier, the calculation of the variable is based on the assumption that oil is spilled instantly. In reality, the spill is seldom instantaneous; exceptions are spills resulting from e.g. intense explosions. Oil may keep leaking from the wreck for hours, even for days, depending e.g. on environmental conditions and oil combating actions. As oil is carried away from the wreck by wind and currents, the forming slick may be dozens of kilometres long. If the direction of wind changes before the slick reaches the shoreline, the result may be dozens or hundreds of kilometres of polluted coastline. To be able to evaluate the exposure of species in a more realistic way, a more inclusive oil drift model should be used. Within the Baltic Sea several such models are in use, including Seatrack Web [62] and PISCES [63]. However, these software systems are mainly designed for forecasting the movement of oil either in real or scenario-type situations, and their ability to produce reliable probability estimates on oil drifting is limited.

It is also important to notice that the method used to estimate the drifting of oil does not encompass all uncertainty. As it is not feasible to model an oil spill occurring at every point in the GOF, our solution is to demonstrate the model by assessing uncertainty related to one spill location. We feel that this approach is justified, as our main interest is to compare different oil spill combating options.

The model is, to our knowledge, the first attempt to evaluate the ecological impacts of dispersant application in the GOF systematically and quantitatively. Although Juntunen et al. [35] included dispersants in their study, the effectiveness of dispersants e.g. to reduce the amount of floating oil was not considered explicitly. Nevertheless, it is important to recall that our assessment covers only accidents happening in the open sea, and only two subsurface species are included in the model. Negative impacts would certainly be more prominent if the dispersants were applied in more shallow areas, where the circulation and dilution capacity of water is more limited. There are also substantial differences in tolerance limits for dispersants and dispersed oil between species; even within a single species group, the differences in tolerance limits may be 1000-fold, and in addition to taxonomic status, the toxicity estimates are significantly affected by other variables such as lifestage, exposure duration, and temperature [[64] and references therein]. In addition, the dispersion of oil is calculated in a fairly coarse manner. The circulation of water masses in the GOF is a highly complex phenomenon with a wide spectrum of dynamic patterns, from small-scale turbulence and meso-scale eddies to basin-wide circulation [65,66]. To reliably assess the fate of dispersed oil, these processes should be taken into account in a more detailed way. This would require the use of 3D hydrodynamic models, the development of which is still underway.

The way to handle uncertainty is an evident virtue of the model. Classic oil spill models are deterministic by nature, and although some models offer a possibility to include uncertainty to models, e.g. GNOME [67] and ADIOS2 [68], it is important to notice that varying some input parameters or input data do not produce any justified quantitative estimates of uncertainty. French McCay et al. [14] included uncertainty by running different scenarios in stochastic mode, and some models are able to produce probabilistic maps (e.g. Statmap [69]). However, BNs enable the inclusion of uncertainty in every step of the process as all variables are represented by probability distributions.

The structure of the model is universal, and thus adaptable also to other coastal sea areas threatened by oil spills. Nevertheless, when the model is applied to other areas the probability tables linked to the variables must be updated. This can be done with various sources of information. For some variables such as wind speed and wave height, the relevant probability distributions can easily be obtained e.g. from statistics. Other variables like the efficiencies of mechanical recovery and dispersants are very dependent on local conditions such as available combating resources and water salinity. However, also these variables can be updated with literature, models and/or local expert knowledge, depending on the context. Updating is thus not limited to the methods presented in this paper.

The model offers a promising starting point to further studies on the ecological impacts of oil spills and on the efficiency of different management decisions related to oil combating in the GOF. Yet, a model is always a simplistic description of a complex system, and it is thus recommended that the results here are discussed with care. Fortunately, because the information within BNs can be updated easily, the model can be updated as the knowledge related to oil combating in the GOF accumulates.

5. Conclusions

The BN model presented in this paper introduces a novel approach to assess the effectiveness of different oil combating methods from an ecological perspective. While the model still needs adjustments to be fully applicable in a strategic oil spill management, the benefits of the approach, such as the explicit handling of uncertainty, are evident. Hence, we strongly encourage BNs to be applied in oil spill management.

The results suggest that the efficiency of oil combating in the GOF is highly dependent on prevailing environmental conditions and can be severely limited in many ways. Even though additional capacity clearly enhances the effectiveness, mechanical recovery is still highly susceptible e.g. to rough sea states. Dispersants, on the contrary, seem to be ineffective in all conditions. Hence, applying dispersants in the GOF does not seem reasonable as their benefits are only minute; on the other hand, they do not seem to have devastating negative impacts even on underwater species. Safeguarding species by oil booms near shoreline appears to be a promising option for oil combating, as their capability to protect species is clearly supported by the model. However, as demonstrated with the common eider, it is crucial to apply booms in situations, where the probability of advantages is high: there is no use to allocate limited resources to protect species that do not benefit from activities.

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