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Index-based approach for estimating vulnerability of Arctic biota to oil spills

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Abstract. Risk of an Arctic oil spill has become a global matter of concern. Climate change induced opening of shipping routes increases the Arctic maritime traffic which exposes the area to negative impacts of potential maritime accidents. Still, quantitative analyses of the likely environmental impacts of such accidents are scarce, and our understanding of the uncertainties related to both accidents and their consequences is poor. There is an obvious need for analysis tools that allow us to systematically analyze the impacts of oil spills on Arctic species, so the risks can be taken into account when new sea routes or previously unexploited oil reserves are utilized. In this paper, an index-based approach is developed to study exposure potential (described via probability of becoming exposed to spilled oil) and sensitivity (described via oil-induced mortality and recovery) of Arctic biota in the face of an oil spill. First, a conceptual model presenting the relevant variables that contribute to exposure potential and sensitivity of key Arctic marine functional groups was built. Second, based on an extensive literature review, a probabilistic estimate was assigned for each variable, and the variables were combined to an index representing the overall vulnerability of Arctic biota. The resulting index can be used to compare the relative risk between functional groups and accident scenarios. Results indicate that birds have the highest vulnerability to spilled oil, and seals and whales the lowest. Polar bears' vulnerability varies greatly between seasons, while ice seals' vulnerability remains the same in every accident scenario. Exposure potential of most groups depends strongly on type of oil, whereas their sensitivity contains less variation.

Key words: Arctic; exposure potential; functional group; index; oil spill; sensitivity; sensitivity analysis; uncertainty; vulnerability.

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Introduction

As the climate change is extending the ice-free period in the Arctic, intensifying maritime traffic is increasing the risk of an oil spill (AMAP 2010, Ho 2010, Carson and Peterson 2016). Oil spills are considered the most significant threat to Arctic seas posed by maritime traffic (Arctic Council 2009), but assessing the potential environmental impacts related to such accidents is difficult due to scarce empirical data (AMAP 1998, Nevalainen et al. 2017). Some of the impacts can be assessed using oil spill models such as SIMAP (French-McCay 2004) and OSCAR (Reed et al. 1995), but generally these models have limitations in Arctic context. They typically require detailed spatiotemporal data on, for example, weather, currents, and species abundance, which limit their use to those regions and species in the Arctic for which enough data exist (French-McCay et al. 2018, Wilson et al. 2018). The models also generally assume the biota to have the same vulnerability throughout the year which can be particularly problematic in the Arctic characterized by strong seasonality. Furthermore, the models do not generally consider the recovery potential of biota. Moreover, the models have limited ability to account for uncertainty which is a significant shortcoming especially in the Arctic where the underlying uncertainties are typically great (Emmerson and Lahn 2012). In addition to the abovementioned models, some Arctic oil spill response planning tools include estimates of impacts to environment (Wenning et al. 2018). However, such methodologies have been mainly developed for the most data-rich parts of the Arctic such as the Norwegian Arctic continental shelf and the U.S. Alaskan region (Aurand and Essex 2012, DNV-GL 2014, Robinson et al. 2017). For majority of the Arctic, such methods and detailed enough data are not available.

Still, better understanding of the ecological impacts of oil spills would help to prepare for their environmental and socioeconomic consequences, to minimize the risks where possible, and to guide the targeting of conservation and other management measures. As there are limited data on oil spill impacts in the Arctic, the existing information should be exploited as efficiently as possible. One concrete solution to tackle the problem of scarce data is to develop an index describing the risk the spilled oil poses to marine species: An index is a convenient way of compiling a score from different variables from variety of data sources with varying level of precision. It is therefore a practical method to be used when studying the oil spill impacts in the Arctic where data are limited and scattered. Such an approach has been used in oil impact studies, for example, by King and Sanger (1979) for marine oriented birds of northern North America, Williams et al. (1994) for seabirds of North Sea, and Helle et al. (2016) for threatened habitat types and species of the northern Baltic Sea. Index-based approaches have also been developed to support oil combating. For instance, Ihaksi et al. (2011) developed an index system covering both ecological values and biota's ability to benefit from safeguarding measures to prioritize areas in coastal oil combating. Perhaps the most widely used index in oil spill research is the Environmental Sensitivity Index (ESI; Petersen et al. 2002), where the coastline is mapped based on physical properties, biological resources sensitive to oil, and human activities that the spilled oil may impact. However, ESI is region-specific and does not rank biological resources quantitatively. Moreover, a few indices using rather detailed habitat information have been published describing the sensitivity of certain Arctic or sub-Arctic areas (Stjernholm et al. 2011, Environment Canada 2015, Clausen et al. 2016). However, extrapolating the existing indices to the whole Arctic would be difficult or impossible as often the accurate information on habitats and their physical characteristics in the true Arctic is lacking.

In this paper, a new index-based approach to assess the risk oil spills pose to Arctic biota is presented. First, a conceptual model describing how Arctic biota is affected by spilled oil is built, the structure of which is based on an extensive literature review. The conceptual model consists of (1) variables affecting the probability of contact if oil is spilled, such as feeding and breeding habitats and biotas' ability to avoid oil; (2) variables affecting the probability of death once oiled, such as the robustness of the thermoregulation system and individual's tolerance to toxins; and (3) variables affecting populations' recovery potential such as reproduction efficiency and distributional patterns. Second, a probability distribution is assigned for each variable under different accident scenarios describing their effect on the overall exposure potential (described via probability of becoming exposed to spilled oil) and the overall sensitivity (described via oil-induced mortality and recovery). The vulnerability index is then calculated as a combination of the overall exposure potential and sensitivity. Lastly, sensitivity analysis is performed to study how the uncertainty in the model outputs can be divided into different sources of uncertainty in the model inputs.

This novel approach integrates a vast amount of published knowledge into an easily understandable index which allows for a practical-orientated way to assess the vulnerability of Arctic biota to oil spills. The approach explicitly accounts for uncertainty related to both lack of data and natural variation, as the index is presented as a probability distribution instead of a single value, which, in general, has been the custom in the Arctic risk assessments so far (AMAP/CAFF/SDWG 2013, Hauser et al. 2018). Moreover, the process of assigning the index is highly transparent, as every step of the process is carefully reported instead of presenting just the final results. Furthermore, the index presented in this paper is the first one built for the true Arctic. True Arctic is characterized by harsh climatic conditions, and it maintains some of its ice cover throughout the year. Due to difficult weather conditions, true Arctic has been studied considerably less than sub-Arctic and temperate areas. True Arctic has partly different biota compared to sub-Arctic areas, and as it is fully covered by ice during winter, many species are forced to winter in warmer areas. Characterization of the true Arctic is loosely based on TRBNRC (2014).

The paper is structured as follows: First, a brief overview of the Arctic oil spill risk assessment is given, and the conceptual model is presented. Then, the logic of how the existing knowledge was compiled into probabilistic estimates of vulnerability of key Arctic functional groups is demonstrated. Next, a summary of the results is presented, and lastly, the results are discussed, the biggest knowledge gaps are underlined, and recommendations for future research are given.

Overview of the Approach

In this section, overview of and general motivation behind the index approach are given. A detailed description of how the index was formed is given in *Materials and Methods*.

Conceptual model

To study how Arctic biota is affected by oil, we built a conceptual model describing the most important variables contributing to their vulnerability (Fig. 1). The model structure was based on literature (most importantly AMAP 2010, AMAP/CAFF/SDWG 2013, Nevalainen et al. 2017), and the final output of the model is an index describing the vulnerability of a given functional group to spilled oil (see *Overview of the approach: Functional groups*). The index does not describe absolute impact (e.g., the percentage of the population lost due to an oil spill) but provides a semi-quantitative estimate of the vulnerability of the functional groups. The time span is not strictly limited, as the reasonable study period depends on a functional group. For example, the smaller the animal, the faster their recovery (Kaiser et al. 2011).

Vulnerability consists of two components (sub-indices): overall exposure potential and overall sensitivity (Fig. 1). Exposure potential describes the probability of an individual to get into contact with spilled, and it depends on both the habitat use and behavior of the individuals. Sensitivity describes the probability of death due to the contact with oil and the probability of a population recovering from that death: It takes into account both the acute mortality, chronical impacts of oiling, and a population's ability to replace the dead individuals through reproduction and migration (modified from Lee et al. 2015 and references therein).

The overall exposure potential and overall sensitivity were estimated by using 23 variables describing relevant characteristics of functional groups. Overall exposure potential consists of 10 variables related to use of habitat, behavior, and offspring exposure potential, whereas overall sensitivity includes 13 variables related to physical and chemical sensitivity, recovery potential, and offspring sensitivity (Fig. 1, Table 1). Some of the variables were considered separately for adults and offspring: Use of habitat, use of ice, flocking tendency, escape capability, thermoregulation system, size, and tolerance to toxins were assumed to differ between offspring and adults at least under some accident scenarios for some functional groups. The rest of the variables would have a similar distribution for adults and offspring (partly due to lack of information to distinguish between them), and therefore, we chose not to assess them separately for offspring.

The variables, sub-indices (overall exposure potential and overall sensitivity), and vulnerability index have four possible states: high, medium, low, and none. Sub-indices' values were calculated based on the values of their parent variables (variables from where an arrow points to a sub-index), and vulnerability index values were calculated based on the values of the sub-indices. Further, instead of assigning one certain state for each variable for a given functional group, we allowed for uncertainty and used probability distributions to describe the relative likelihoods of these four states. As an example, with variable grooming, high state was

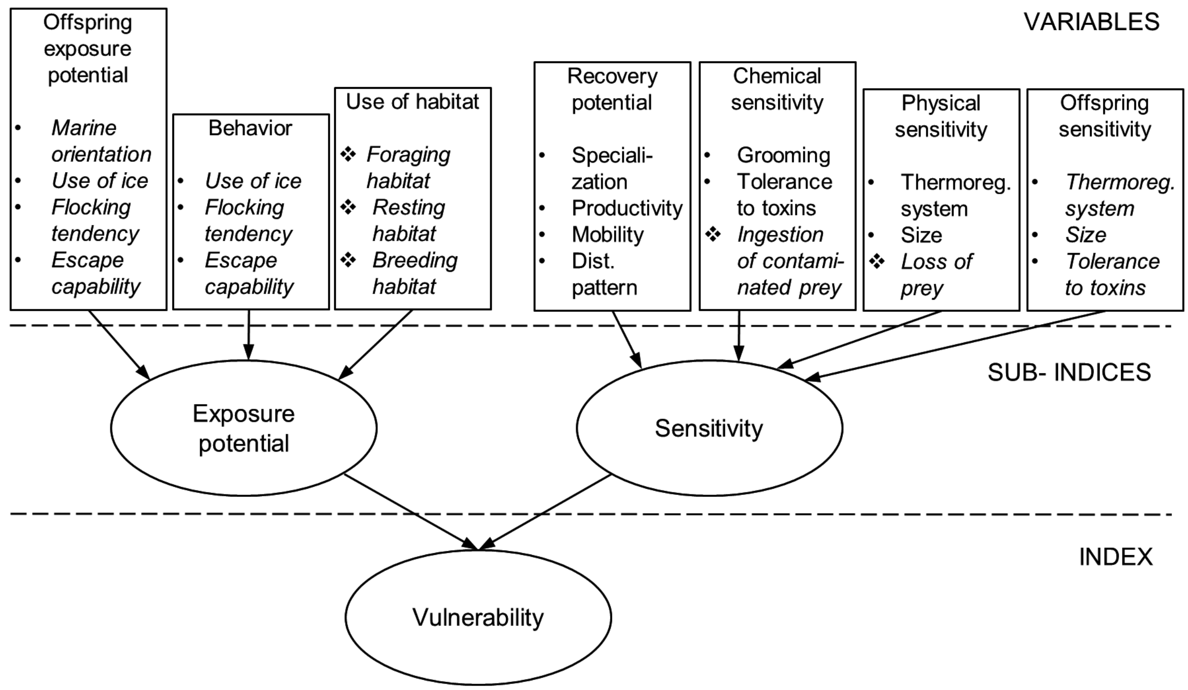

Fig. 1. The conceptual model presenting the variables affecting overall exposure potential, overall sensitivity, and vulnerability of Arctic functional groups. Each variable has four possible states: high, medium, low, and none, over which we assigned a probability distribution that describes the relative likelihood of the states. For some of the variables, the probability distribution varies depending on the type of oil spilled (indicated with star bullet) and for some depending on the timing of an accident (indicated with italic font). The rest have the same probability distribution under every accident scenario. For a detailed description of the variables, see Table 1, and for detailed calculations of overall exposure potential, overall sensitivity, and vulnerability, see *Materials and Methods: Overall exposure potential and sensitivity*.

associated with diligent, medium with occasional, low with not likely, and none with physically impossible grooming (Table 1). We assessed the probability for each of these states—and similarly for other variables. The probability distributions were assigned based on literature (and quantitative data if such were available), and essentially, they consist of expert assessment made by the first author and reviewed and if necessary revised by other others (Appendix S1). The probability distribution of overall exposure potential and overall sensitivity was then calculated based on the probability distributions of the variables affecting them, and the probability distribution of vulnerability index was calculated based on the probability distribution of overall exposure potential and overall sensitivity (for more detailed description, see *Materials and Methods: Overall exposure potential and sensitivity*). Definitions of each variable affecting exposure potential and sensitivity can be found from Table 1 (formed based on AMAP 2010 and AMAP/CAFF/SDWG 2013), and the logic behind forming the states of each variable can be found from Appendix S1.

As the majority of the variables contributing to overall exposure potential and overall sensitivity depend on the type of oil and timing of the accident, also the sub-indices vary accordingly (Fig. 1). Generally, light oils are more toxic and less adhering than heavier oils (TRBNRC 2003, Lee et al. 2015), which affects both the chemical and physical lethality of the oils. Moreover, oil type affects the fate of oil and thus exposure potential of biota. For instance, the heavier the oil, the more quickly it sinks to the seafloor thus exposing benthic fauna to the adverse effects of oil. Season affects the sensitivity especially by

Table 1. Definitions of the variables and their possible states in the conceptual model.

Variable	Definition	High state	Medium state	Low state	None state	Main source of uncertainty
Foraging habitat	Where does an average individual feed? *Note that the exposure potential state for a habitat varies depending on an oil type*	Extra heavy: seafloor Heavy: shore Medium: surface Light: surface	Extra heavy: – Heavy: surface Medium: water column/shore Light: water column	Extra heavy: surface/water column Heavy: water column/seafloor Medium: seafloor Light: seafloor	Land, high cliffs, pack ice (not on the edge)	Natural variation on foraging habitat of a species and fate of oil. Lack of data to estimate these
Resting habitat	Where does an average individual rest? *Note that the exposure potential state for a habitat varies depending on an oil type*	Extra heavy: seafloor Heavy: shore Medium: surface Light: surface	Extra heavy: – Heavy: surface Medium: water column/shore Light: water column	Extra heavy: surface/water column Heavy: water column/seafloor Medium: seafloor Light: seafloor	Land, high cliffs, pack ice (not on the edge)	Natural variation on resting habitat of a species and fate of oil. Lack of data to estimate these
Breeding habitat	Where does an average individual have their offspring? *Note that the exposure potential state for a habitat varies depending on an oil type*	Extra heavy: seafloor Heavy: shore Medium: surface Light: surface	Extra heavy: – Heavy: surface Medium: water column/shore Light: water column	Extra heavy: surface/water column Heavy: water column/seafloor Medium: seafloor Light: seafloor	Land, high cliffs, pack ice (not on the edge)	Natural variation on breeding habitat of a species and fate of oil. Lack of data to estimate these
Use of ice (both adults and offspring)	How does an average individual use ice?	Openings in ice	Under ice	On ice (close to the edge)	None	Natural variation on use of ice of a species and fate of oil. Lack of data to estimate these
Flocking (both adults and offspring)	Does an average individual spend time in large groups?	Forms large, dense aggregations	Forms smaller, less dense groups	Mostly solitary	Solitary and territorial	Natural variation in flocking behavior, and lack of field observations
Escape (both adults and offspring)	Will an average individual escape if oil is spilled in its habitat?	No escape or avoidance behavior	Able to avoid oil in immediate environment	Leaves the oiled area	Avoids ships	Lack of field observations on behavior of species
Offspring: marine orientation	Where an average offspring individual is located? *Note that the exposure potential state for a habitat varies depending on an oil type*	Extra heavy: seafloor Heavy: shore Medium: surface Light: surface	Extra heavy: – Heavy: surface Medium: water column/shore Light: water column	Extra heavy: surface/water column Heavy: water column/seafloor Medium: seafloor Light: seafloor	Land, high cliffs, pack ice (not on the edge)	Natural variation on use of habitat of a species and fate of oil. Lack of data to estimate these
Thermoregulation system (both adults and offspring)	What kind of thermoregulation system an average individual has?	Fur/feathers	Short fur and blubber	Thick skin and blubber	Ectothermic	Lack of field observations of experienced hypothermia from cold regions
Loss of prey	Will the main food source(s) of the group disappear (die or escape) because of oil?	Main prey likely to die or escape, specific diet	Some prey may die or escape, more versatile diet	Main prey not likely to die or escape, opportunistic diet	N/A	Lack of field observations of escaping and dying of species and limited knowledge on Arctic food webs
Size (both adults and offspring)	What is the physical size of an average individual?	Will get stuck, drown, or suffocate	Oil may temporally slow down or lead to exhaustion	Oil not likely to physically slow down	N/A	Lack of data on importance of size on oil spill impacts
Grooming	Does an average individual groom itself to keep clean?	Grooms diligently	Grooms occasionally	Not likely to groom	Physically incapable to groom	Lack of data on grooming behavior when oiled

(Table 1. Continued.)

Variable	Definition	High state	Medium state	Low state	None state	Main source of uncertainty
Tolerance to toxins (both adults and offspring)	How well can an average individual tolerate toxins?	Impaired reproduction or death	Non-lethal harm on individual level	Mostly reversible	N/A	Lack of laboratory data
Ingestion of contaminated prey	Will the main food source(s) get oiled and will an average individual eat the oiled food?	Main prey accumulates toxins or is slowed down but not killed by oil	Varied diet, some prey may accumulate toxins or be slowed down by oil	Main prey is likely to die if oiled	N/A	Lack of data on species feeding behavior when their food is oiled, natural variation in diets
Specialization	How are the individuals able to adapt to a new environment?	Philopatric	Requires certain kind of environment to survive	Opportunist	N/A	Lack of data on adaptability of species especially in the Arctic
Productivity	How efficient the individuals are at reproducing?	High age of maturity, have few offspring infrequently	Breed and wean once a year, a few offspring	Large number of offspring, often breed throughout the year	N/A	Lack of data on how oil may affect productivity especially in the Arctic
Mobility	Are the individuals able and willing to travel to new areas?	Not able to travel	Able to travel moderate distances but prefers to stay in relatively small area	Able to travel great distances	N/A	Lack of data on species willingness to travel to new areas, and how oil may affect it
Distributional pattern	How densely are the subpopulations located?	Scattered	Everywhere in low densities	Everywhere in high densities	N/A	Lack of data from the true Arctic, natural variation

Notes: Note that the higher the state, the higher the exposure potential or the sensitivity of the functional group. See Appendix S1 for more detailed description of defining the states high, medium, low, and none. – indicates not assessed.

determining the presence and development stage of offspring, which are generally considered more sensitive to oil than adults (Malins 1977, Carls et al. 1999, AMAP 2010). Season affects exposure potential most notably by exchanging use of habitat. For example, a species may spend spring nesting on ground and the other seasons mostly in water. In addition, season guides the ice coverage, which affects both the fate of oil and the habitat of many species thus changing their exposure potential.

Functional groups

The developed index deals with functional groups instead of individual species. The reason is twofold: Firstly, the variety of functional groups is likely to affect the functioning of an ecosystem more than the number of species within it (Allaby 2010), and secondly, this is a practical simplification in the Arctic, where comprehensive species-level data are often lacking (Nevalainen et al. 2017). The studied groups are shown in Table 2, and they are loosely based on Nevalainen et al. (2017). It should be noted that we use the term functional group to refer to a group that is formed not only based on ecological characteristics but also considering the expected vulnerability of each group: how and on what timescale spilled oil is likely to affect them. For example, a group with fur or feathers is more likely to suffer from hypothermia if oiled than a group with thick, blubbery skin that repels oil. Moreover, for example groups' habitat use and feeding behavior affect whether they are likely to get into physical contact with freshly spilled oil or are more likely to experience longer-term, chronical impacts through food web. The groups do not cover all Arctic species but include the species that are most likely to be exposed to and affected by spilled oil.

Accident scenarios

Exposure potential, sensitivity, and vulnerability of Arctic biota were assessed separately for four seasons (spring, summer, fall, and winter) and for four oil types (extra heavy, heavy, medium, and light oil) leading to 16 different

Table 2. Definitions of the functional groups studied.

Functional group	Example species/genera	Oil spill relevant characteristics
Polar bear	Polar bear (*Ursus maritimus*)	Feeds especially on ice seals. May stay on land during summer in which case may have opportunistic diet. Low reproduction efficiency. Denning when giving birth (usually far from water). Cubs stay with mother for years. Migratory, solitary, and possibly philopatric. Fur-covered
Ice seals	Ringed seal (*Pusa hispida*), harp seal (*Pagophilus groenlandicus*)	Feeds on fish and crustaceans. Low reproduction efficiency, generally one cub per female per year. Relatively solitary but may aggregate when breeding. Feeds and breeds on, near or under ice. Migrates following prey and optimal ice conditions. Short, thick fur and blubber
Bottom-feeding seals	Walrus (*Odobenus rosmarus*), bearded seal (*Erignathus barbatus*)	Dives food from seafloor, most importantly bivalves (which may accumulate toxins). Low reproduction efficiency. May form massive aggregations. Migratory. Patchy distributions due to limited diving ability and patchy food sources. Tough skin and blubber
Other seals	Harbor seal (*Phoca vitulina*)	Similar to ice seals but breeds and rests on shore, and feeds mostly on pelagic fish and crustaceans
Toothed whales	Beluga whale (*Delphinapterus leucas*), narwhal (*Monodon monoceros*)	Feeds mainly on schooling fish and crustaceans. Low reproduction efficiency and late maturity. Calves nursed for up to two years. Sociable and gregarious, forms massive aggregations during summer. During other seasons relatively solitary. Migratory. May avoid ships
Baleen whales	Bowhead whale (*Balaena mysticetus*), northern minke whale (*Balaenoptera acutorostrata*)	Feeds on zooplankton. Low reproduction efficiency and late maturity. Calves nursed for a year. Relatively solitary, travel and feed alone or in small pods. May avoid ships
Omnivorous birds	Glaucous gull (*Larus hyperboreus*), Glaucous-winged gull (*Larus glaucescens*)	Opportunistic feeder: eats everything from (mainly schooling) fish and crustaceans to bird eggs and carcasses. Nests on land relatively close to water in colonies, lays 2–4 eggs per year. Migratory. Feathers
Diving piscivorous birds	Common murre (*Uria aalge*), thick-billed murre (*Uria lomvia*)	Feeds mainly on schooling fish. Breeds on cliffs and can form massive aggregations. Lays single egg per year. Migratory. Feathers
Surface piscivorous birds	Northern fulmar (*Fulmarus glacialis*), arctic tern (*Sterna paradisaea*)	Feeds mainly on schooling fish. Nests on land or islands relatively close to water in colonies, lays 1–3 eggs per year. Migratory. Feathers
Benthivorous birds	Common eider (*Somateria mollissima*), king eider (*Somateria spectabilis*)	Feeds mainly on benthic invertebrates. Nests on land in colonies relatively close to water. Lays 2–7 eggs per year. Migratory. Feathers
Diving planktivorous birds	Least auklet (*Aethia pusilla*), little auk (*Alle alle*)	Feeds mainly on water column crustaceans. Breeds in large colonies on cliffs. Lays single egg. Migratory. Feathers
Surface planktivorous birds	Leach's storm petrel (*Oceanodroma leucorhoa*), fork-tailed storm petrel (*Oceanodroma furcata*)	Feeds on zooplankton in surface waters. Breeds in colonies on cliffs or rocky islands. Lays single egg. Migratory. Feathers
Pelagic fish	Polar cod (*Boreogadus saida*), navaga (*Eleginus nawaga*)	Feeds mainly on zooplankton. High reproduction efficiency. Highly mobile as adults. Habitat may differ during different life stages. Juveniles and eggs highly sensitive. Ectothermic
Cryopelagic fish	Polar cod (young), arctic cod (*Arctogadus glacialis*)	Feeds and breeds near the underside of surface ice cover. High reproduction efficiency. Habitat may differ during different life stages. Juveniles and eggs highly sensitive. Ectothermic
Forage fish	Capelin (*Mallotus villosus*), herring	Feeds on plankton in water column. High reproduction efficiency. Highly mobile as adults. Forms massive aggregations. Habitat may differ during different life stages. Juveniles and eggs highly sensitive. Ectothermic
Demersal fish	Sculpins, plaice, flounders, eelpouts	Feeds on benthic invertebrates. High reproduction efficiency. Mobile but stay near the seabed as adults. Habitat may differ during different life stages. Juveniles and eggs highly sensitive. Ectothermic
Surface water invertebrates	Notably crustaceans	Feeds on plankton in surface waters. High reproduction efficiency. Mobility varies between species. Habitat may differ during different life stages. Ectothermic

(Table 2. Continued.)

Functional group	Example species/genera	Oil spill relevant characteristics
Ice-associated invertebrates	Crustaceans, nematodes	Feeds on plankton under ice. High reproduction efficiency. Remains in or under ice: relatively sessile. Ectothermic
Water column invertebrates	Notably crustaceans	Feeds on plankton in water column. High reproduction efficiency. Mobility varies between species. Found everywhere in water body. Ectothermic
Benthic invertebrates	Mollusks, crustaceans, annelids, echinoderms	Feeds on plankton on seafloor. High reproduction efficiency. Adults mostly sessile, juveniles' mobility varies. Habitat may differ during different life stages. Ectothermic

combinations of spill-specific factors, that is, accident scenarios. The seasons were classified according to Kaiser et al. (2011) and Aune et al. (2018). Spring (approximately from March to June) was defined as the season when days get longer and warmer, and ice starts to melt. Increase in light and temperature results to massive algae blooms that serve as a base of the food web. Many migratory species arrive to the Arctic, and open water sites are biological hotspots. During summer (approximately from July to September), many species have their offspring. Ice has mainly melted, but ice floes are still found. Autumn (approximately from October to November) starts when days get shorter, and sea begins to refreeze. Migratory species start the migration toward their wintering grounds. Winter (approximately from December to February) is dark and cold, and the sea is mostly covered by ice. The number of species and the level of primary production are low compared to the highly productive summer. Nevertheless, biological activity is found in Arctic waters throughout the year and some species may even be present at higher numbers during winter compared to other seasons (Aune et al. 2018). We assume that at least some species of each functional group may be present in the Arctic throughout the year although for example the number of bird species may be particularly low compared to the breeding period.

Oil types differ both in their likely fate and in lethality, which depend on a number of processes that may vary considerably in space and time. We formed four general oil type groups (similarly to ITOPF 2014) that we believe to represent the variety of potential fates and environmental consequences of different oils possibly shipped in the Arctic with reasonable accuracy (Table 3, modified from Nevalainen et al. 2018). In general, the lighter the oil, the better it mixes to and dissolves in water, whereas the heavier the oil, the more it smears the shoreline or sinks to the seafloor. The dispersed oil can be highly toxic, while the heavier, more solid oil causes especially physical harm to biota.

In short, extra heavy oils are assumed to sink to the seafloor after being spilled and form thick, sticky layers that can remain in nature for particularly long time. Heavy oils float as thick, sticky slicks that adhere to shorelines and ice and may end up under ice. Medium oils float as thin slicks that can also adhere shorelines and ice but less compared to heavy oils due to their faster dispersion and evaporation rates. Medium oil may also end up under ice. Light oils spread rapidly to very thin slicks that evaporate relatively quickly, and they are not likely to adhere to shoreline or

Table 3. Potential fates and main source(s) of mortality of the oil type categories studied in this paper.

Oil type	Fate: seafloor	Fate: shore/ice	Fate: surface/ water column	Fate: under ice	Lethality: physical	Lethality: chemical
Extra heavy (API below 10)	x		x		x	
Heavy oil (API from 22.3 to 10)		x	x	x	x	
Medium oil (API from 31.1 to 22.3)		x	x	x	x	x
Light oil (API higher than 31.1)			x	x		x

ice. However, they may end up under ice. The oil types and the weathering processes were defined based on Fingas and Hollebone (2003), TRBNRC (2003), Afenyo et al. (2016), and Fingas (2016). It should be noted that the presented classification does not cover the temporal changes in the chemical composition of the spilled oil explicitly. In other words, it does not take into account that, for instance, after weathering the sunken oil residues can have different chemical composition than the original fresh oil. However, as the intensity of weathering depends on both environmental conditions (such as winds and ice coverage) and characteristics of the oil (such as the portion of asphaltenes and resins), the inclusion of such temporal aspect would be unfeasible in this context.

Materials and Methods

Data collection

Both the structure of the conceptual model and the probability distributions of the variables were based on an extensive literature review consisting of scientific and gray literature. The literature was searched from databases such as Scopus and Web of Science using keywords such as Arctic, oil, oil spill, polar bear, and ringed seal. The search was limited to literature published in English. Knowledge on oil spill impacts on Arctic species has increased during recent years (Bejarano et al. 2017, Aune et al. 2018, Camus and Smit 2019), but the amount of field data in particular is still low compared to temperate regions. Therefore, literature from temperate regions was used as a complementary source of information where necessary. See Appendix S2 for detailed description on which references were used to determine which distribution.

Functional group-specific estimates and uncertainty in them

As stated earlier, each variable had four possible states, high, medium, low, or none, and we used probability distributions to describe the uncertainty related to the impact size (e.g., 50% chance of a variable having high impact on overall exposure potential and 50% chance of it having a medium impact would equal to a probability distribution of 0.5, 0.5, 0, 0). The main source(s) of uncertainty behind these distributions are summarized in Table 1. All the information collected during literature review was compiled into probability distributions following the procedure summarized in Fig. 2 and explained in detail in Appendix S1. The probability distributions were assigned by first assessing the most data-rich cases. This included both variables for which (for some functional groups) the probability distributions could be calculated from quantitative data such as tolerance to toxins (Appendix S1) and variables that by definition could be defined without any uncertainty such as thermoregulation system. Next, the variables with less but some (qualitative) information were analyzed. For some of these variables (for some functional groups), there were enough qualitative data to form a probability distribution. As an example, flocking tendency of many birds has been documented accurately and often enough to infer the suitable probability distribution even if quantitative data were not available. There were also variables for which there were no data at all to support the assessment, and for those, a uniform distribution was assigned. As an example, use of ice of many groups has not been documented. Lastly, there were variables for which there were some qualitative data available but not enough to form a distribution. Those variables were compared to other, data-richer functional groups, life stages, and accident scenarios to form the rest of the estimates (Fig. 2). As an example, if there were data on escape capability of water column invertebrates, we could, with reasonable certainty, assume the escape capability of surface invertebrates to resemble it. Since

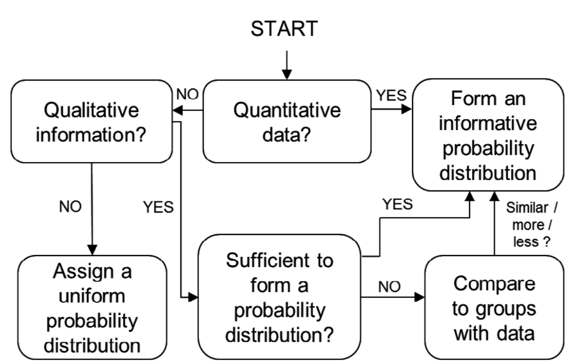

Fig. 2. The steps followed in assigning the probability distributions.

no data were available to suggest a specific weighting system for calculating the sub-indices, equal weights were used to all variables suggesting they contribute to overall exposure potential and sensitivity equally much.

The assessment yielded altogether 7360 separate probability distributions (20 functional groups, 10 variables affecting exposure potential, 13 variables affecting sensitivity, 4 oil types, and 4 seasons). All distributions together with a citation to literature used to form them can be found in Appendix S2, and the logic for assigning the probabilities for all of the variables affecting exposure potential and sensitivity can be found from Table 1, Fig. 2, and Appendix S1.

Overall exposure potential and sensitivity

The individual variables were treated additively when calculating the overall exposure potential and sensitivity. The reason was that each variable can be thought to more or less independently increase the chances of a species to encounter oil (exposure potential) or to die because of oil (sensitivity). For example, whether a species encounters oil in the foraging habitat is independent from whether it encounters it in resting habitat (even though the likelihood to encounter oil in these two habitats would be the same if the habitats are the same). Hence, the effects to the overall exposure potential (and overall sensitivity) are essentially additive.

In order to form the probability distributions of overall exposure potential and overall sensitivity, 1000 samples were first drawn from the probability distribution of each variable affecting the overall exposure potential (10 variables) and overall sensitivity (13 variables). High state was scored as 3, medium as 2, low as 1, and none as zero. The samples were summed up pointwise, and the results were classified according to the following criteria: If the sum was zero, it was classified as none (value 0), a sum of 1–10 for exposure potential (1–13 for sensitivity) was classified as low (value 1), 11–20 (14–26) as medium (value 2), and 21–30 (27–39) as high (value 3). Then, the values of the sums (1000 pcs of 0, 1, 2, or 3) were distributed to corresponding classes (none, low, medium, or high). Thereby, the overall exposure potential and sensitivity correspond to rounded up average of individual variables. If, for example, all variables affecting exposure potential would be at low state, the score would be 10 and the overall exposure potential would therefore be classified as low. However, if one of the variables would be at medium state while the rest were low, the score would be 11 and the overall exposure potential classified as medium.

The effects of total exposure potential and total sensitivity on vulnerability are multiplicative. Therefore, even if total exposure potential was 1 (i.e., an animal was oiled for certain) but sensitivity was zero, vulnerability would also be zero. In biological terms, this means that if sensitivity to oil is equal to zero, an animal suffers no ill consequences, even when oiled. Hence, vulnerability was calculated by sampling 1000 values of overall exposure potential and overall sensitivity from their respective distributions (calculated as described above) and multiplying these pointwise to produce a distribution for vulnerability. If the product was zero, then vulnerability was classified as none, one as low, 2–5 as medium, and 6–9 as high. This corresponds to rounded up geometric mean of exposure potential and sensitivity. Due to geometric mean, the relative change in vulnerability is constant for equal size relative changes in exposure potential and sensitivity. Further, rounding the means up can be seen to promote precaution, as we aim to avoid underestimating the risk.

Sensitivity analysis of model variables and indices

Sensitivity analysis (note that here sensitivity does not refer to species' sensitivity to oil) studies the relative importance of different input factors (here the 23 variables affecting the overall exposure potential and sensitivity) on the model output. It is used for, for example, studying how the uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model's inputs. We created seven summative variables: habitat use, behavior, offspring exposure potential, physical sensitivity, chemical sensitivity, recovery potential, and offspring sensitivity and studied how their probability distributions change due to changes in the distributions of the variables affecting them (Fig. 1; Appendix S3). The probability distributions of the summative variables were formed as follows. For instance, if all three variables affecting habitat use would be at low state, the habitat use would be classified as low.

If one of the variables would be at medium state while the rest were low, the habitat use would be classified as medium similar to calculation of overall exposure potential and sensitivity (*Materials and Methods: Overall exposure potential and sensitivity*). The reason for studying the summative variables instead of the overall exposure potential and overall sensitivity was mainly technical: Calculating the sensitivity of a conditional network with more than 20 variables would be computationally very challenging (the conditional probability table of overall sensitivity has over billion columns). As all the summative variables have 3–4 variables affecting them and they all contribute to overall exposure potential or sensitivity equally much, we believe the results indicate sufficiently well the variables effect on the overall exposure potential and sensitivity, and not much information is lost when studying the summative variables. We also studied the relative importance of season and oil type on the outputs by treating them as input variables (with uniform distributions) that affect some of the variables (Fig. 1).

The sensitivity analysis was conducted by turning the conceptual model (Fig. 1) and the probability distributions (Appendix S2) into a Bayesian network using software GeNIe (BayesFusion LLC 2018). GeNIe estimates sensitivity of a model output by calculating a complete set of derivatives of the posterior probability distributions over the output variables over each of the numerical parameters affecting them (for a more detailed description of the calculations, see Kjællrulff and van der Gaag 2000). In simple terms, outcomes of a model (e.g., distribution of habitat use) are recalculated altering the inputs (distributions of variables affecting the output) to determine the impact of the input on the output. This increases the understanding of the relationship between input and output variables. More precisely, the measure of sensitivity is the value of the (first order) derivative of the probability of the selected state of the output with respect to the probability of the selected state of an input in question. If the derivative is large, then small deviation in probability distribution of the input may lead to large difference in the probability distribution of the output.

When performing the sensitivity analysis, GeNIe changes the probability of each state of each input variable by $\pm 10\%$ at a time (and complements the other states accordingly) and records the change in probability of each state of the output variable (here high, medium, low, and none). In this paper, we report two kind of derivatives: maximum derivative and average derivative. Each state of each output variable has a derivative (with respect to each state of each input variable): Maximum derivative is the highest of them, and average derivative is their calculated average.

Results

Exposure potential, sensitivity, and vulnerability

In general, exposure potential differs between the key Arctic functional groups and accident scenarios (Fig. 3). Polar bear and ice seals seem to have the lowest exposure potential, and especially, polar bear's probability of encountering oil during summer is low compared to the other groups. Exposure potential of all mammals and birds vary to some extent between seasons, but for most groups there is more variation between oil types. Whales, most birds, and non-demersal fish and invertebrates have the highest exposure potential to light or medium oil, whereas demersal biota has highest exposure potential to extra heavy oil. Exposure potential of fish and invertebrates varies substantially between oil types, while the exposure potential of some groups such as benthivorous and omnivorous birds has relatively little variation with relatively little uncertainty between accident scenarios. Exposure potential of non-demersal fish and invertebrates exhibits highest uncertainty when considering all the accident scenarios. There is also high uncertainty in the exposure potential of polar bears during summer and of toothed whales to medium or light oil during spring, summer, and autumn. In general, fish and invertebrates seem to be the groups with highest exposure potential but their relative order depends on the type of oil. Most groups have either medium or high exposure potential under all accident scenarios, and low exposure potential is only reached by some mammals and birds under some accident scenarios.

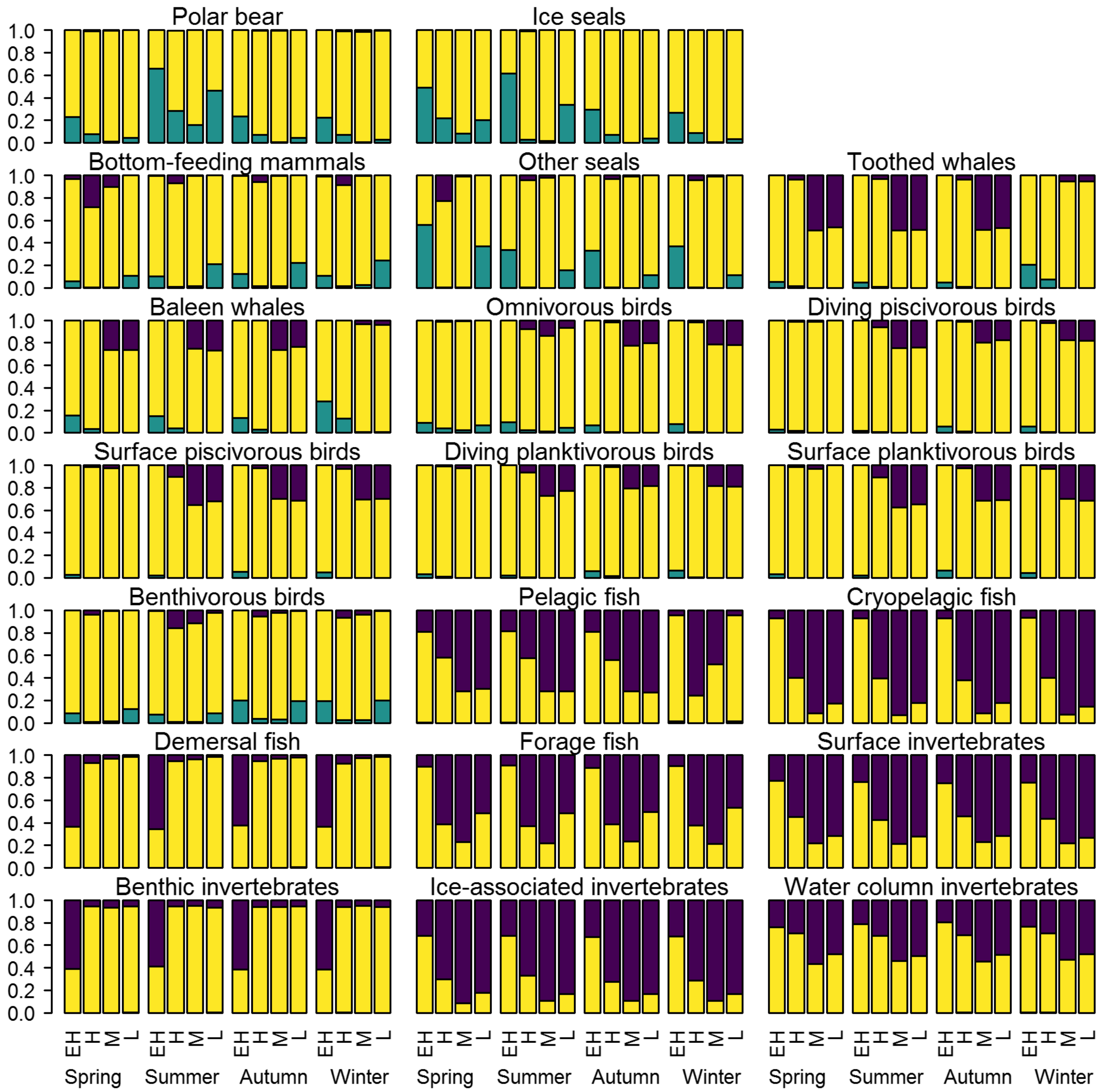

Fig. 3. Exposure potential of the functional groups under different accident scenarios. On the *x*-axis, EH, H, M, and L refer to extra heavy, heavy, medium, and light oil, respectively. The *y*-axis presents the probability of exposure potential being at a certain state: High is dark purple, medium is yellow, and low is blue.

Sensitivity differs less between the functional groups (Fig. 4) and accident scenarios than exposure potential (Fig. 3). Polar bears and birds are the most sensitive groups with their close to certain high sensitivity, while the rest of the groups have similar, almost constant medium, sensitivity. Polar bears are slightly less sensitive during summer than during other seasons, and most birds and bottom-feeding mammals are somewhat more sensitive during spring than during other seasons. The omnivorous birds are the least sensitive and benthivorous birds the most sensitive groups of birds. For the rest of the groups, there is basically no variation between accident scenarios, and the results include very little uncertainty. All groups have either medium or high sensitivity under every accident scenario.

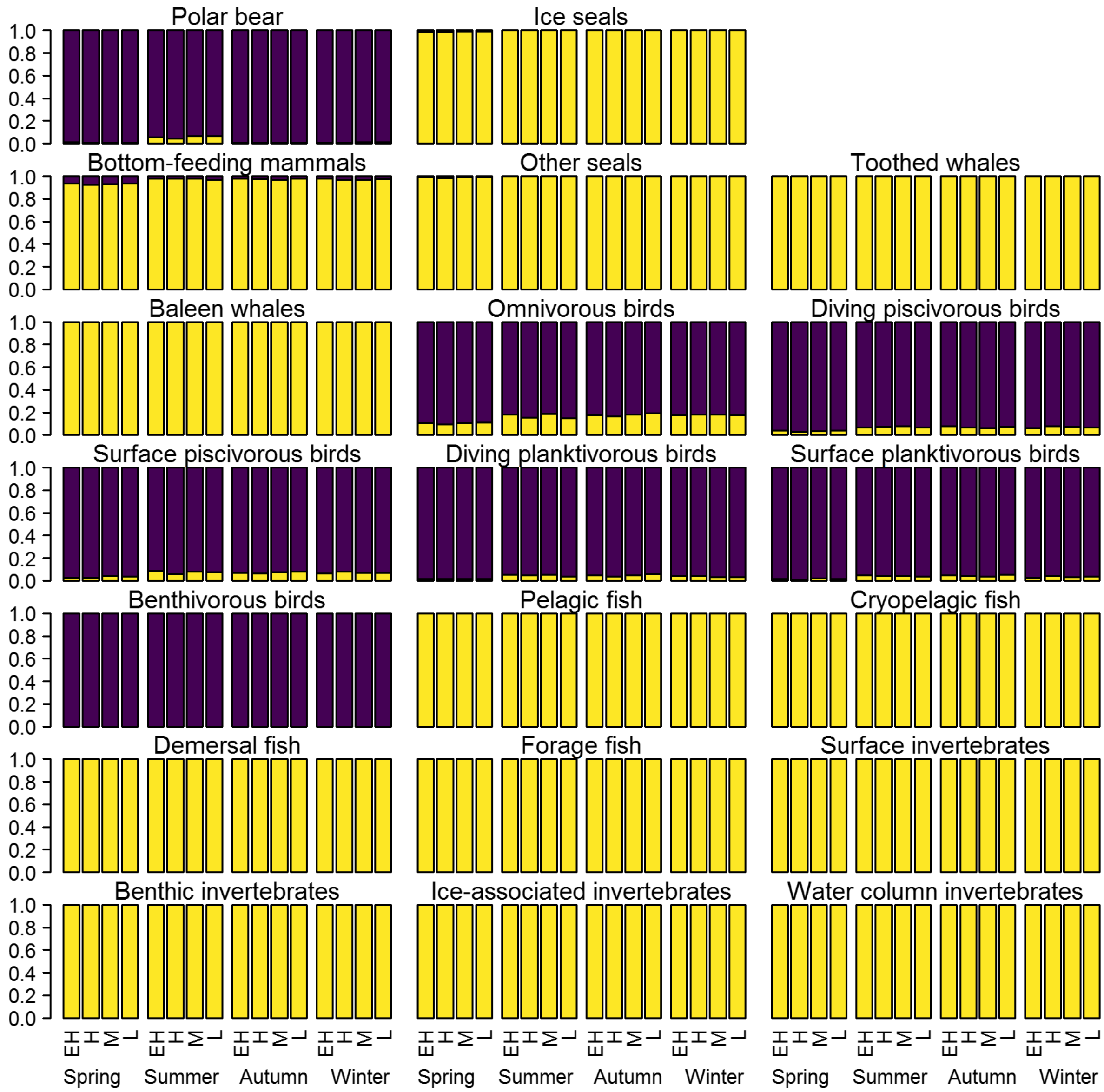

Fig. 4. Sensitivity of the functional groups under different accident scenarios. On the x-axis, EH, H, M, and L refer to extra heavy, heavy, medium, and light oil, respectively. The y-axis presents the probability of exposure potential being at a certain state: High is dark purple and medium is yellow.

Similar to exposure potential, vulnerability differs between the functional groups and accident scenarios, albeit the differences are smaller than with the exposure potential (Fig. 5). Birds have the highest vulnerability. Omnivorous birds have slightly lower vulnerability than other birds, and the vulnerability order of the rest of the birds depends on the accident scenario. For example, planktivorous birds are more vulnerable to medium and light oils than piscivorous birds. Polar bears rank second after birds. During summer, polar bears' vulnerability is lower than during other seasons, but it also contains more uncertainty. Ice seals have the lowest vulnerability: medium under every accident scenario. The rest of the mammals have mostly medium vulnerability with occasional high vulnerability depending on the accident scenario. For example, toothed whales' vulnerability is equally likely to be medium or high to light or medium oils. Fish and invertebrates have most variation in their vulnerability between oil types (but no variation between seasons). For example, vulnerability of demersal fish and benthic invertebrates is most likely high to extra heavy oil, and medium with high certainty to other oil types. Cryopelagic fish have nearly certain medium vulnerability to extra heavy oil and nearly certain high vulnerability to medium oil. Ice-associated invertebrates have the highest and benthic invertebrates the lowest vulnerability of the invertebrates under all accident scenarios. The

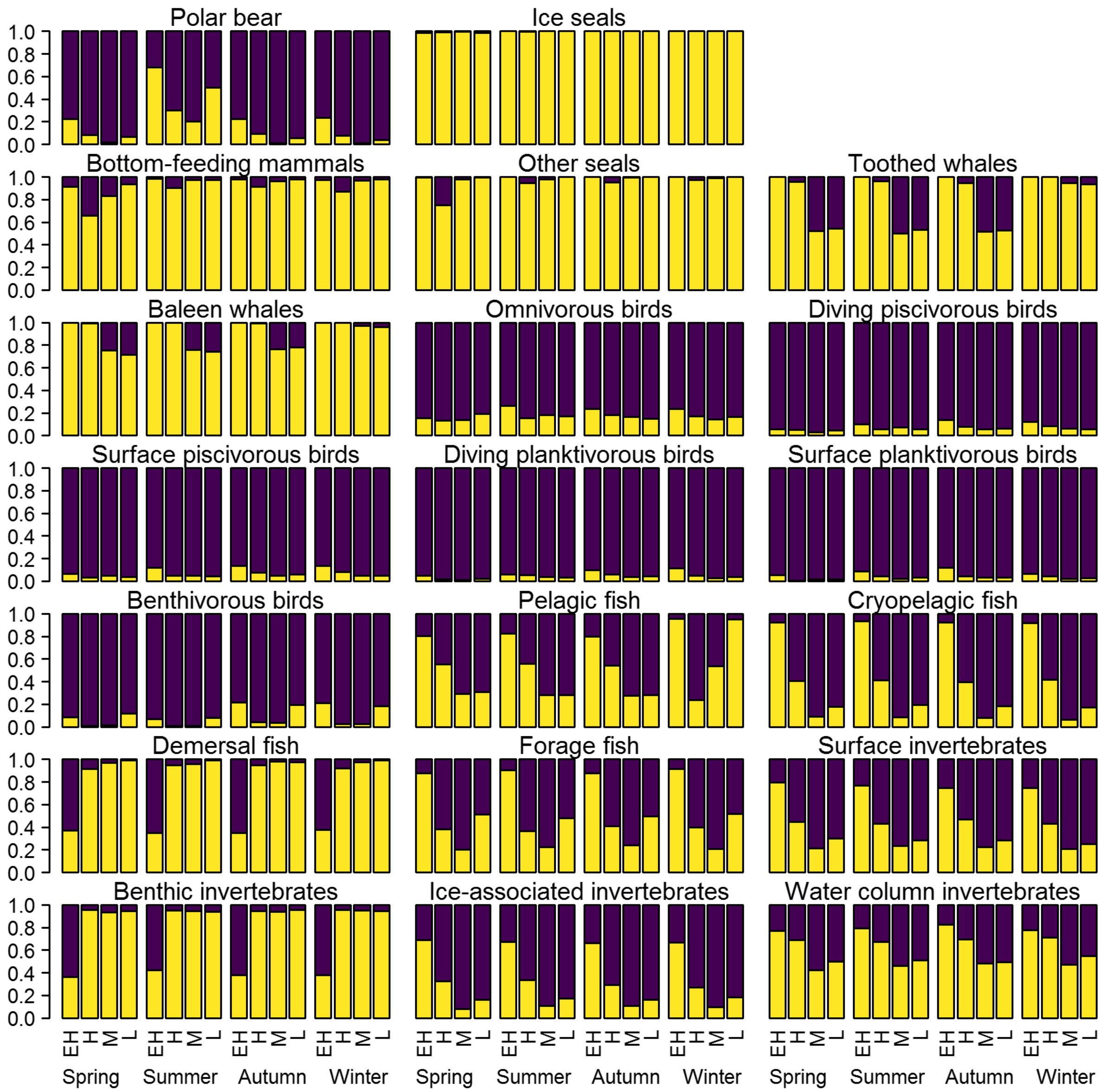

Fig. 5. Vulnerability of the functional groups under different accident scenarios. On the x-axis, EH, H, M, and L refer to extra heavy, heavy, medium, and light oil, respectively. The y-axis presents the probability of exposure potential being at a certain state: High is dark purple and medium is yellow.

uncertainty associated with vulnerability resembles that of exposure potential as it is highest for non-demersal fish and invertebrates. Depending on the accident scenario, there is also significant uncertainty in vulnerability results of polar bears, toothed whales, demersal fish, and benthic invertebrates. All groups have either medium or high vulnerability under every accident scenario.

Sensitivity of model outputs

The results of the sensitivity analysis vary greatly between functional groups (Appendix S3). However, for all functional groups, habitat use is the most sensitive variable to the changes in its input probability distributions, and it is particularly sensitive to changes in season and oil type (Appendix S3: Fig. S1). Although behavior is clearly less sensitive to changes in its inputs compared to habitat use, behavior of polar bears, ice seals, and toothed whales is sensitive to changes in season (Appendix S3: Fig. S2). Offspring exposure potential of mammals, birds, and fish is relatively sensitive to changes in, for example, escape capability in addition to season and oil type, whereas invertebrates' offspring exposure potential is not sensitive to changes in any of their input distributions (Appendix S3: Fig. S3).

In general, the output variables related to sensitivity of biota are less sensitive to changes in their input variables than the outputs related to exposure potential. Polar bears' physical sensitivity is somewhat sensitive to season, baleen whales' to loss of prey, and omnivorous birds' to size (Appendix S3: Fig. S4). Output variable chemical sensitivity of some functional groups is sensitive to changes in the distribution of tolerance to toxins, but for most groups, such as ice seals and benthivorous birds, chemical sensitivity is just slightly or not at all sensitive to changes in its input distributions (Appendix S3: Fig. S5). Similarly, recovery potential of all functional groups has relatively low sensitivity to changes its input variable distributions (Appendix S3: Fig. S6). Recovery potential of forage fish is sensitive to changes in mobility and polar bears' to changes in specialization, but in general, many groups are not sensitive to changes in any inputs related to recovery potential. Ice seals' and bottom-feeding mammals' offspring sensitivity is sensitive to changes in season; otherwise, also offspring sensitivity of all functional groups is not sensitive to changes in its input variables (Appendix S3: Fig. S7).

Discussion

Interpretation of the results

The main objective of the study was to compile the existing knowledge on oil spill impacts on marine animals, and to apply that knowledge to assess the vulnerability of Arctic biota. This was done by developing a novel vulnerability index. The method proved to be functional at drawing the present knowledge into a semi-quantitative form, as the results agree with the previous understanding of the likely oil spill impacts, meaning that the knowledge was not lost, for example, in discretization of the variables or calculus (the significance of which is discussed later in this section). For example, birds are believed to be one of the groups most affected by spilled oil (French-McCay 2004, AMAP 2010, Lecklin et al. 2011), whereas seals and whales are believed to be relatively unharmed by oil (French-McCay 2004, AMAP 2010). This was also seen in our results. Further, the study enhanced the understanding of how season and oil type affect the overall vulnerability. Season appeared to have particularly significant impact on exposure potential (and therefore vulnerability) of polar bears, and vulnerability of many functional groups was notably affected by the type of oil. As an example, groups living or feeding on seafloor have significantly higher vulnerability to extra heavy oil than other oil types, whereas groups inhabiting the upper parts of water column have the highest vulnerability to light oil. For many of the functional groups studied, these are the first estimates of their exposure potential, sensitivity, and vulnerability (see Nevalainen et al. 2018, for estimates on seals, anatids, and seabirds obtained through expert elicitation). Moreover, in this study we moved from previous, mostly qualitative estimations of oil spill impacts toward semi-quantitative ones paying special attention to associated uncertainties. Here, we highlight the most important results.

Our results show that birds have the highest vulnerability. Albeit they do not have the highest exposure potential, they are very sensitive (nearly certain high under all accident scenarios), and therefore, their vulnerability is high, too. Benthivorous birds seem to have slightly lower exposure potential when compared to other bird groups, and omnivorous birds have somewhat lower sensitivity than other birds. The relative order of vulnerability of birds depends on an accident scenario, but omnivorous birds seem to always have lower vulnerability than other birds. They have highly opportunistic diet and may therefore be less likely to get into physical contact with oil while foraging for food and to consume oiled food. Moreover, their breeding colonies are typically located on high cliffs, where the oil is unlikely to reach them. Benthivorous birds may spend less time in water compared to the more marine birds: For example, eiders may prefer to rest on land. On the other hand, marine birds are used to flying long distances to find food, so oil in their habitat does not automatically harm them. It has also been suggested that oil on water surface may prevent seabirds from locating schooling fish (Irons 1996), which may furthermore lower their exposure potential. In our results, the difference between bird groups is explained mostly by differing use of habitat and the fate of their main prey(s) after an oil spill.

Polar bears are also often believed to be at high risk from oil spills (AMAP 2010). In our results, polar bears have the highest vulnerability right after birds. However, our results also suggest that polar bears may be significantly less at risk during summer, which is the most active season for Arctic shipping. This may be of practical significance for the protection of polar bears. However, it is worth noting that there is significantly more uncertainty in the polar bears' habitat use (including use of ice) and diet during summer compared to other seasons (Appendix S2), and this may, at least partly, explain the lesser exposure potential, sensitivity, and vulnerability.

Vulnerability of whales has been studied relatively little compared to many other functional groups. Our results suggest that generally toothed whales face higher risk than baleen whales, but there is some variation between accident scenarios. Both whale groups have similar sensitivity, but toothed whales have higher exposure potential especially related to medium or light oil during breeding season (from spring to autumn). Explanatory factors include toothed whales' larger group sizes and their tendency to gather in estuaries (Reeves and Kenney 2003, Luque and Ferguson 2009, Heide-Jørgensen and Wiig 2014) making them more vulnerable to oil spills. In our results, the main differences between the whale groups arise from differing pod size and distributional patterns.

Also seals have been studied relatively little from oil spill point of view, but the general understanding is that they are relatively unharmed by spilled oil (AMAP 2010, Nevalainen et al. 2018). Our results agree with this understanding. The differences between ice seals and other seals were minor: Other seals have slightly higher exposure potential, and therefore, vulnerability. Sensitivity of the both groups are always medium. Moreover, our results suggest that the vulnerability of seals is only marginally higher during spring when they have their offspring. Even though offspring are undoubtedly more sensitive than adults during the time they have soft, fluffy hair, their exposure potential is low as they stay on ice or on land away from water. However, it is still possible that an oil spill during breeding season would cause indirect harm to seal populations for example through changes in the food web even if the individuals would not end up in direct contact with oil (AMAP 2010).

All studied fish and invertebrate groups have similar, that is, medium sensitivity, but their exposure potential differs greatly depending on the type of oil. For demersal fish and benthic invertebrates, the exposure potential is the highest with extra heavy oil. However, with other oil types their exposure potential is significantly lower than that of other fish and invertebrates. For non-demersal fish and invertebrates, the exposure potential is highest with medium oil. The reason is that medium oil is likely to disperse to water column in greater amounts than other oil types. The differences between oil types are particularly high for fish and invertebrates associated with ice, as the exposure potential of these groups depends strongly on the fate of oil, that is, whether the oil ends up under ice or not.

There is less uncertainty in the results regarding sensitivity than exposure potential. Most groups have close to 1 probability of having either medium or high sensitivity. This is partly explained by the characteristics of the variables affecting sensitivity. For example, thermoregulation system, grooming tendency, and size of individuals are well-known biological facts, and therefore, the assigned estimates did not include much uncertainty. This in turn led to little or no uncertainty in the overall sensitivity. However, it should be noted that similar vulnerabilities and sensitivities do not mean that the groups were assigned similar probability distributions for each (if any) variable. As an example, pelagic fish and toothed whales have similar overall sensitivity even though the probability distributions of their variables differ greatly (Appendix S2). To mention a few, their size, distributional pattern, and loss of prey are very different. When considering all the accident scenarios, the highest uncertainty is associated with the results of non-demersal fish and invertebrates. This is mostly explained by natural variation. Fish and some invertebrates are highly mobile and can, for example, spawn in different parts of the water body, feed under ice or in openings in ice, or be nowhere near ice. Therefore, many of these groups were assigned several uniform distributions to describe this variability, which led to relatively high uncertainty in their exposure potential and vulnerability. Some of the uncertainty might be removed by dividing the groups into smaller ones based on, for example, taxonomy or more restricted habitats such as estuary, distance to coastline, or the preferred water depth. However, such categorization could require more detailed data to be collected from the Arctic.

Sensitivity analysis

Sensitivity analysis revealed that even minor changes in the probability distributions of the input variables could lead to different outputs. The results suggest that forecasting vulnerability could be more accurate, if we had a better understanding on timing of an accident and the type of oil spilled, as many of the outputs are highly sensitive to changes in probability distributions of season and oil type. When applying the method, for instance, in oil spill contingency planning, it is possible to narrow down uncertainty by producing separate estimates for different oil types and seasons. However, in upper-level strategic planning we typically aim at getting a comprehensive picture on the risk, which requires that all possible combinations of oil types and seasons are taken into account. It is therefore important to study not only the consequences of oil spills but also the characteristics of Arctic maritime accidents.

Moreover, the results are particularly sensitive to changes in the distributions of use of ice, resting and breeding habitat, and tolerance to toxins. It is worth noting that these are not variables that generally were assigned a uniform distribution (Appendix S2). In other words, the model output is not automatically most sensitive to the most uncertain variables. Still, an analyst can compare the variables that cause most changes in the model output to the amount of data available and estimate how easily new data can be obtained. For example, changes in the probability distribution of breeding habitat cause relatively large changes in the outputs and collecting data on them would be relatively easy through fieldwork, expert elicitation, or participatory science. However, it should also be taken into account that data collection should ideally focus on variables in which uncertainty is not mostly explained by natural variation. From this point of view, breeding habitat would not be a top priority. Instead, for example, escape capability of fishes and invertebrates causes relatively large changes in the outputs and would be relatively easy to study in a laboratory. Toxicity of oil to fishes and invertebrates has been studied widely (Albers 1998), but their behavior in oiled environment has received little attention. As another example, physical sensitivity is sensitive to changes in loss of prey but collecting data on it would be expensive and demanding or would require use of detailed ecosystem models (see, e.g., Ainsworth et al. 2018 for using ecosystem model Atlantis in evaluating the population-level impacts of the Deepwater Horizon oil spill). However, no such ecosystem model has yet been calibrated for the true Arctic as they require vast amount of data. Simpler population models exist (Ohlberger and Langangen 2015, de Vries et al. 2018) but only for few Arctic species. Moreover, such models are generally deterministic and hence, as discussed before, ill-suited for the Arctic where uncertainties are generally great (Emmerson and Lahn 2012).

The results of the sensitivity analysis can also guide us in the further model development. As an example, the model outputs are currently very sensitive to changes in season and oil type. Therefore, it could be justifiable to consider building separate models for different seasons and oil types. Conceptualizing our thinking separately for each season and oil type could potentially reveal some new variables and relationships between them that were now overlooked when aiming for a general description.

We performed a simple sensitivity analysis where only the effect of varying one model input at a time while keeping the others fixed was studied. This kind of one-at-a-time sensitivity analysis has been criticized (Saltelli and Annoni 2010) as it does not detect the presence of interactions between variables. It would be possible to conduct a more sophisticated sensitivity analysis by moving from single to multiple parameters (Chan and Darwiche 2004). Here, however, the simplified approach seemed suitable, as the outputs considered were additive functions of the inputs and, hence, the model did not include interactions between the inputs in the studied level. It should also be noted that if a model is representing reality poorly, determining the sensitivity of an individual parameter in the model does not add to our understanding of reality (Pilkey and Pilkey-Jarvis 2007) and it is important to update the model when new data come available.

In general, exposure potential, sensitivity, and vulnerability of all the groups were mostly assessed to be either high or medium. This reflects the justification for the functional groups to study: We only focused on groups that are believed to suffer most from spilled oil (AMAP 2010, Lecklin et al. 2011, AMAP/CAFF/SDWG 2013, Nevalainen et al. 2017). It is, however, worth noting that the groups were chosen based on the current knowledge and, hence, with new knowledge it could become justifiable to add new groups into analysis. The results also reflect more or less the chosen assumption that the overall exposure potential and overall sensitivity depend additively with equal weights (independent equal effects) on the variables affecting them and that vulnerability depends multiplicatively (joint effect) on overall exposure potential and overall sensitivity (loosely based on Nevalainen et al. 2017, 2018). It can also be argued that the classification of the states was somewhat arbitrary as, for example, the sum of 11–20 equaling to the state medium could result from many different combinations of variable states. Hence, apparent future development points would be to consider alternative weightings for the variables and possible finer resolution for classifying the sub-indices and vulnerability. Moreover, rounding upwards the sum and geometric mean when setting the index state can be seen as precautious approach. The precautionary principle has been widely adopted in environmental research, and it has been characterized as methods that should be taken when an activity raises a threat to either human health or the environment, even when some causal relationships are not fully understood (Raffensperger and Tickner 1999). However, our discretization may lead to overly precautious estimates compared to finer scale discretization of risk classes, but we leave these considerations for future studies.

Benefits and drawbacks of the approach

The developed method has three clear advantages: (1) It integrates a vast amount of published knowledge into an easily understandable index; (2) it takes uncertainty explicitly into account by using probabilistic approach; and (3) as the index consists of separate variables that are assessed independently, the process is transparent, the functioning of the index can be easily examined, and the index can be updated relatively easily. These are all widely recognized properties of good practice in expert-based assessments (Cooke 1991, O'Hagan et al. 2006, Cooke and Goossens 2008, French 2011, Dias et al. 2018).

The most challenging part of the study was turning qualitative knowledge into quantitative estimates. The method we developed eased this work as there were clear rules how to assign the distributions, and the process was transparent and easily reproducible for every group and accident scenario. We believe that with modification the method can also be used with other (data-poor) study topics. As an example, it could be used for assessing vulnerability of biota in temperate regions by removing the use of ice variable (given the temperate region was ice-free) and by considering different functional groups. It could even be used as a base for assessing impacts of other pollutants such as different toxins, if they behave similarly when released into environment.

Although we found the method to work well, it also has some limitations that need to be recognized. As there are little hard data on variables affecting exposure potential and sensitivity of Arctic biota, the authors had to make a number of judgement calls. Even though all these choices, such as what variables to include in the analysis, how the states of those variables should be formed, and what probabilities to assign for each state, were made based on literature, and every step of the study was documented accurately, there is still room for unintentional biases typical for studies based mainly on expert assessments (Kuhnert et al. 2010). To mention a few, possible sources of such biases include overconfidence and anchoring effect. Overconfidence may arise if the authors underestimate the uncertainties related to the topic (Kynn 2008, Speris-Bridge et al. 2010), whereas anchoring effect can cause bias if the authors start their estimations with initial estimates and then fail to adjust the following estimates sufficiently therefore anchoring their answers too strongly to the first estimate (Tversky and Kahneman 1974, Dias et al. 2018). We aimed to minimize the anchoring effect by cross-checking the probability distributions: After assigning the initial probability distributions, we checked them carefully for several times and in varying order comparing them to each other (between groups, life stages, and accident scenarios) to reduce the possibility for mistakes and to check that the probability distributions followed the logic of the definitions of categories (Table 1). We aimed at reducing possible overconfidence by documenting uncertainty accurately and transparently. Overconfidence can also be reduced by assessing probability distributions instead of single values (Haran et al. 2010). Bias could also be reduced by relying on external experts to either form or review the probability distributions (similarly to, for example, Lecklin et al. 2011). However, expert elicitation study by Nevalainen et al. (2018) suggested that finding and engaging experts to assess the exposure potential and sensitivity of the studied functional groups is very challenging. Therefore, the index relies on the extensive literature review and the expertise of the authors, and the credibility of the results was studied through sensitivity analysis. For comprehensive descriptions of different biases and some solutions to tackle them, see Cooke (1991) and O'Hagan et al. (2006), and for topic-specific challenges, see Nevalainen et al. (2018).

The explicit handling of uncertainty is a clear advantage of our approach. Burgass et al. (2017) underlined that environmental indices are being produced increasingly, but they often lack uncertainty estimates. It is important to account for the uncertainties and to present them as transparently as possible as decision-makers are increasingly interested to understand the uncertainties of the models (O'Hagan 2012). Identification and quantification of major sources of uncertainty is also relevant from the research point of view, as it helps to focus future research on topics that would benefit most from new knowledge. There are many sources of uncertainty in oil spill risk assessment, and the method developed in this paper has aimed at including the uncertainty estimates in a transparent way. It should be noted that in this study we did not make a difference between uncertainty originating from the lack of knowledge and from natural variability related to, for example, the behavior of organisms (Clark 2005, Merz and Thieken 2005, Kiureghian and Ditlevsen 2009, Kuikka et al. 2014, for distinguishing between natural variation and lack of knowledge as a source of uncertainty). For example, if an individual's habitat use varies within season (not only between seasons), it was assigned a relatively wide probability distribution. Additionally, limited knowledge resulted in wide distributions, the most extreme case being uniform distribution over all states. The number of uniform distributions assigned for the functional groups ranged from 0 (polar bears, ice seals, and piscivorous and planktivorous birds) to 4 (bottom-feeding mammals). As an example, out of the four uniform distributions of bottom-feeding mammals, only one (offspring size) is clearly due to lack of data as we assess the body size in terms of probability of drowning once oiled and such studies have not been conducted for bottom-feeding mammals. The rest of the variables with uniform distributions (distributional pattern and use of ice of both adults and offspring) are due to natural variation, and further research would not necessarily change the distributions. We have reported our estimation of the sources of uncertainty for each variable, and future research could focus on the variables where the uncertainty arises from lack of data, including, for example, escape capability and tolerance to toxins.

The paper aimed at simplifying a very multidimensional problem so that assessing the vulnerability of Arctic biota would be possible based on the knowledge we already have. Still, more data are needed. Several variables were assigned a uniform distribution, and new data on them could change the results. In addition, even though the conceptual model includes the most important variables affecting the vulnerability of biota according to our current understanding, there might be unknown unknowns that we will not discover until an accident happens. The conceptual model aimed at including both longer-term impacts and impacts via food web in addition to the direct impacts of an oil spill. Still, our understanding of the longer-term impacts is particularly poor (AMAP 2010). Moreover, to assess the longer-term impacts we should also consider the persistence of oil but we currently lack the means of estimating it. Arctic food webs are known relatively well (Hobson and Welch 1992, Budge et al. 2008, Kaiser et al. 2011, Hop and Gjøsæter 2013, Kortsch et al. 2018), but the impact of spilled oil on food web dynamics has hardly been studied. The few existing empirical and theoretical studies have concentrated only on few species or very simplified food chains (Bowyer et al. 1994, Christiansen and George 1994, Hjermann et al. 2007). If more empirical data become available, both the conceptual model and the probability distributions (and their relative weights) can be updated. The index built in this study is merely a step on the way toward a comprehensive understanding of the vulnerability of Arctic biota.

Applicability of the method

When moving from general descriptions to location-specific risk assessments, we need knowledge on the environment dependent fate of oil and species distributions (Nevalainen et al. 2017, 2018). Such data combined with the developed vulnerability index can produce detailed knowledge on overall oil spill impacts. Nonetheless, even without the spatial knowledge the current work allows us to compare different seasons and oil types and suggests that regulation of the shipping time and type of oil shipped can be relevant for ecosystem risk management. However, no accident scenario seemed to be more harmful than others when considering all the functional groups since the groups differ greatly both in their use of habitat and behavior and are therefore harmed to varying degrees by different accidents: The most dangerous scenario for one group may be the safest one for another. If conservation measures are to be targeted at a certain group based on, for example, endangerment or economic importance, our results suggest that the type of oil shipped may have a great contribution to the risk management.

It is worth noting that not all the studied accident scenarios are equally likely to realize. For example, few oil types fall into the category of extra heavy oils, but we still included them in the analysis to get a more complete picture of the potential effects of variety of oil types. Moreover, the carriage and use of heavy fuel oil in the Arctic may be prevented in near future (Prior and Walsh 2018). Lastly, Arctic oil spill response is an increasingly studied topic (Wenning et al. 2018) and the improving preparedness may decrease the risk the spilled oil poses to environment in the future. Nevertheless, proactive preventative measures to minimize the risk are also needed, and the oil spill impacts can be controlled by managing when, where, what kind, and how much oil is shipped.

Conclusions

A number of complex processes affect the overall harm caused by an oil spill. The index-based approach presented in this paper introduces simplifications and neglects some processes altogether but is rather meant for understanding the most important variables contributing to species' exposure potential and sensitivity in the oil spill risk context. Further, it is the first attempt to transparently compare the functional groups of the Arctic to each other while taking into account the great uncertainties related to the topic. In the future, results can be combined with oil spill models and species distribution models to enable spatial Arctic risk analyses. Such analyses could concretely benefit conservation of Arctic as shipping routes could be designed based on the spatially and temporally varying risk, and in case of an accident, possible oil combating resources could be allocated to areas with highest ecological risk. The future research should also consider different values related to oil spills—economical, ethical, and conservational to mention a few. Such values could also contribute to the weights of variables used in this study and benefit the exploitation of the current results in conservation work: Is the death of a polar bear equally bad as the death of a fish?

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