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Citation for the original published paper (version of record):
Amir Heidari, P., Arneborg, L., Lindgren, F. et al (2019). A state-of-the-art model for spatial and stochastic oil spill risk assessment: A case study of
oil spill from a shipwreck. Environment International, 126: 309-320.
http://dx.doi.org/10.1016/j.envint.2019.02.037

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Environment International 126 (2019) 309–320

Contents lists available at ScienceDirect

Environment International

journal homepage: www.elsevier.com/locate/envint

A state-of-the-art model for spatial and stochastic oil spill risk assessment: A case study of oil spill from a shipwreck

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ARTICLE INFO

Handling Editor: Hefa Cheng

Keywords:
Oil spill
Shipwreck
Risk assessment
Probabilistic approach
Uncertainty

ABSTRACT

Oil spills are serious environmental issues that potentially can cause adverse effects on marine ecosystems. In some marine areas, like the Baltic Sea, there is a large number of wrecks from the first half of the 20th century, and recent monitoring and field work have revealed release of oil from some of these wrecks. The risk posed by a wreck is governed by its condition, hazardous substances contained in the wreck and the state of the surrounding environment. Therefore, there is a need for a common standard method for estimating the risks associated with different wrecks. In this work a state-of-the-art model is presented for spatial and stochastic risk assessment of oil spills from wrecks, enabling a structured approach to include the complex factors affecting the risk values. A unique feature of this model is its specific focus on uncertainty, facilitating probabilistic calculation of the total risk as the integral expected sum of many possible consequences. A case study is performed in Kattegat at the entrance region to the Baltic Sea to map the risk from a wreck near Sweden. The developed model can be used for oil spill risk assessment in the marine environment all over the world.

1. Introduction

Environmental risks in a marine environment can arise from a variety of natural and anthropogenic sources. One important risk source, which has raised concerns during decades, is oil. Since oil pollution can result in variety of ecological and socio-economic impacts (Alló and Loureiro, 2013; Cirer-Costa, 2015; Price, 1998), it is necessary to plan for minimizing the risk of oil spill from human activities. Major sources of oil spill in marine waters are natural seepage, industrial and urban run-off from land, offshore production and shipping (Farrington and McDowell, 2004; GESAMP, 2007; Lindgren et al., 2016). On average, 1,250,000 tons of oil are released annually into the marine environment from sea-based sources GESAMP, 2007. Another source of oil pollution is leaking shipwrecks (Landquist et al., 2014; Michel et al., 2005, Rytkönen, 2017, Tornero & Hanke, 2016). The number of shipwrecks, (non-tank vessels of at least 400GRT and tankers of at least 150 GRT), worldwide in marine waters is estimated to be > 8600 (Michel et al., 2005), and some of these wrecks still contain considerable amounts of oil. The amount of petroleum products in the wrecks is estimated to be 2.5–20.4 million tons (Landquist et al., 2017a). Since > 75% of the wrecks date back to World War II and have been underwater for > 70 years (Michel et al., 2005), corrosion in the steel structures could be well developed and ultimately cause leaks or even structural collapse (Landquist et al., 2014; Masetti, 2012).

The Baltic Sea is a brackish inland sea, which due to its northerly geographical location, limited water exchange and long residence time is vulnerable to oil spills (Bernes, 2005). Considering the importance of the threat from oil spills in this region, remote sensing (RS) methods have been extensively utilized for on-time detection of oil spills (Bulycheva et al., 2015, 2016; Kostianoy et al., 2004, 2006, 2014; Uiboupin et al., 2008). Among these methods, Satellite Synthetic Aperture Radar (SAR) is known as the most effective tool (Migliaccio et al., 2008, 2015, 2018a, 2018b). Recent monitoring and field work have revealed release of oil from some of the shipwrecks in the Baltic Sea region (Hac, 2017; Hac et al., 2014; Rogowska, et al., 2010; Svensson, 2010).

Generally oil spill events can be divided into large (macro) and small (micro) spills (Sardi et al., 2017). Large oil spills, from shipping disasters (Jewett et al., 1999) and marine oil well blowouts (Valentine et al., 2014), affect biota differently than small but frequent discharges

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https://doi.org/10.1016/j.envint.2019.02.037
Received 17 October 2018; Received in revised form 12 February 2019; Accepted 15 February 2019
Available online 27 February 2019

from shipping and urban/industrial run off (Camphuysen, 2007; Liu et al., 2016; Liubartseva et al., 2015; Renner & Kuletz, 2015). The effects can range from acute toxic to sub-lethal (Bejarano & Michel, 2016; Beyer et al., 2016; Chen et al., 2017; Han et al., 2018; Kim et al., 2017; Langangen et al., 2017; Rekadwad & Khobragade, 2015; Silva et al., 2009; Zhang et al., 2019). Large oil spills result in, for example, narcotic effects, oxygen deficiency, hindering of sunlight transfer to the water, and seabirds' hypothermia (Lindgren et al., 2016; Troisi et al., 2016). In addition to acute effects, they can also cause long-term impacts on marine ecosystems (Arzaghi et al., 2018; Frometa et al., 2017; Girard & Fisher, 2018; Nevalainen et al., 2018; Sardi et al., 2017; Yang et al., 2018). Unlike large oil spills, small spills usually lead to only chronic and long-term effects (Camphuysen, 2007; Frometa et al., 2017; Klotz et al., 2018; Lindgren et al., 2012; Yuxin Liu et al., 2019; Silva et al., 2009; Szczybelski et al., 2018; Troisi et al., 2016; Xie et al., 2018). Lindgren et al. (2012) studied the ecological effects of low concentrations of poly aromatic hydrocarbons (PAHs) on benthic ecosystems and concluded that even low concentrations of PAH can have pronounced effects on meiofaunal and bacterial communities. Hence, both large and small oil spills can be of ecological significance.

Depending on the cause of oil spill from a wreck, the spill can be continuous, or instantaneous (Hassellöv, 2007). In addition to rate of spill from a shipwreck, there are other uncertainties associated with the environmental risk posed by it: Is there still oil present in the wreck and in what volumes? When will an oil spill occur? What receptors will be affected by a potential release? (Landquist et al. 2017a). By evaluating and presenting the nature and extent of uncertainties, risk assessment can provide the decision-maker a realistic picture of the possible outcomes (Jolma et al., 2014). The final results can, for example, be presented using a probability density function (PDF) of risk, illustrating the included uncertainties.

Risk is commonly defined as a combination of probability of a negative event, its consequences and the uncertainty related to both (Jolma et al., 2014). In the context of oil spill risk assessment, it can be expressed as the combination of the probability that a particular spill event will occur and the magnitude of the consequences of that spill (Etkin et al., 2017; Ji et al., 2011). Both spill probability and spill consequence have some degree of uncertainty, which leads to uncertainty in the final risk value of oil spill. Probability of an oil spill scenario is usually estimated based on historical data and/or expert elicitation (Abascal et al., 2015; Amir-Heidari & Raie, 2018; Landquist et al., 2016). Considering a sunken ship, oil spill is assumed to occur due to activities that have the potential to damage the wreck. Wreck-specific and site-specific conditions will have an influence on the degree of impact of the hazardous activities. Furthermore, the wreck must still contain oil (Landquist et al., 2017b). Considering these uncertain factors, a PDF can be derived for describing the uncertainty in the probability of a spill. The uncertainty in the consequences/impacts of oil spills can be quantified by simulation. Trajectory modeling can be used to predict the behavior of oil in the environment, and the relative spatial and temporal extent of potential consequences (Bejarano & Mearns, 2015; Liu et al., 2011; MacFadyen et al., 2011; Zodiatis et al., 2016). The circumstances of a spill, including source, cause to the spill, the oil type involved, amount and rate of spillage, location of the spill, and the season in which the spill occurs are examples of factors that affect the impacts of a spill (Etkin et al., 2017; Frazão Santos et al., 2013). To account for uncertainties in these factors, the calculation of the impact should be based on trajectory modeling of the integral expected sum of a large range of possible spill scenarios (Abascal et al., 2010; Al Shami et al., 2017; Amir-Heidari & Raie, 2018; Barker, 1999; Goldman et al., 2015; Guo, 2017; Lee & Jung, 2015; Nelson & Grubesic, 2017; Sepp Neves et al., 2015).

Although regulations with regard to oil spills do exist, there is still a lack of efficient decision support tools for oil spill risk management (Li et al., 2014). A comprehensive framework for shipwreck risk assessment (VRAKA) has previously been presented by Landquist et al. (2016). The research presented in this paper complements the previous work (Landquist et al. 2014, 2016, 2017a, 2017b) by using an advanced oil transport model. In this research, a model is presented for quantification of the oil spill risk by considering uncertainties in both the probability of a spill and the consequences of such an event. In the context of spatial risk assessment, a spill source usually poses different risks to several receptors in different locations. Considering a specific spill source, the aggregated risk can thus be expressed as the sum of risks posed by the source to different receptors. The proposed methodology in this research makes it possible to rank different spill sources based on the aggregated risk posed by each source. A case study is performed to map the oil spill risk from a wreck in Kattegat and to evaluate the applicability of the presented model.

2. Theoretical background

Considering an environmental accident, risk assessment can be performed in different stages: before the accident, during the accident and after the accident (Jiang et al., 2012). Before the accident, a probabilistic risk assessment (PRA) is performed based on hypothetical scenarios to help decision-makers to identify high-risk receptors. In this research and in this section, the focus is on PRA.

The common approach in the recent research on probabilistic oil spill risk assessment is calculation of oiling probability/likelihood (Al Shami et al., 2017; Depellegrin and Pereira 2016; Goldman et al. 2015; Guillen et al. 2004; Guo, 2017; Lee and Jung 2015; Nelson et al. 2015; Sepp Neves et al. 2015). Considering a potential spill source, oiling probability/likelihood for a receptor describes the chance that in the event of an oil spill, the receptor will be exposed to oil. Several software models have also been presented for estimation of oiling probability (Applied Science Associates, 2017; NOAA, 2000; Price et al., 2003; SINTEF, 2014; Smith et al., 1982). The clearest explanation of the traditional approach for calculation of oiling probability is presented by Goldman et al. (2015). They performed a stochastic study in the Mediterranean Sea using MEDSLIK to quantify the oiling probability in different locations. In Goldman et al. (2015), the oiling probability resulting from a spill source is defined based on pollution indicator $I(x, y, T, \omega)$, which is calculated for different hypothetical scenarios (iterations) with different inputs (for example, different start-times):

$$I(x,y,T,\omega) = \begin{cases} 1 & max\{\{C(x,y,t,\omega)\}: t < T\} > 0 \\ 0 & otherwise \end{cases}, \tag{1}$$

where, $C(x, y, t, \omega)$ is the concentration of oil at a cell centered at longitude x and latitude y at time step t, resulting from an iteration ω. For an iteration ω, the concentration of oil in a cell is calculated several times during a simulation period T, and $I(x, y, T, \omega)$ indicates whether the maximum concentration of oil in at least one of the calculations is > 0, or not. If the maximum concentration exceeds 0, at least once, it will be 1, otherwise it will be 0. If this process is repeated for all scenarios in a spill source (E), the oiling probability can be defined as:

$$P_E(x,y,T) = \frac{\sum_{\omega \in E} I(x,y,T,\omega)}{\sum_{\omega \in E} 1} \tag{2}$$

where, $P_E(x, y, T)$ is the oiling probability at a cell centered at longitude x and latitude y, calculated based on simulation of a number of hypothetical spills (iterations) in source E; each simulation for a period of T. This approach statistically makes sense.

The traditional approach described above is based on a binary “on or off” (or “0 or 1”) philosophy; once the maximum concentration is above 0, the scenario is counted as a significant, and there is no difference between, for example, concentration of 1 and concentration of 1000. The “on or off” philosophy is still used today in models, such as NOAA TAP (NOAA, 2000).The difference in NOAA TAP is that the criteria of comparison has been changed from 0 to LOC (level of concern); this means that the scenarios with maximum concentrations greater than LOC are regarded as significant.

In addition to oiling probability, Goldman et al. (2015) have also tried to define a parameter for representation of the retention time of oil in different areas, which is good for measuring the exposure to oil. Lee and Jung (2015) and Al Shami et al. (2017), beside the oiling likelihood, have considered the first impact time of the oil slick, as well.

The more specific methods developed for risk assessment of wrecks have some important limitations. After scrutinizing 9 major shipwreck risk assessment methods and comparing them with the ISO 31000 risk management standard (International Standardization Organization, 2009), Landquist (2016) concluded that there was no comprehensive standard method for risk assessment of shipwrecks. Most of the developed methods for shipwreck risk assessment are qualitative (Landquist et al., 2013; Landquist, 2016). In this research, a new model is presented that combines the oil spill probability (Landquist et al., 2017a, 2017b) and a quantification of the consequences in terms of potential oiling. Hence, provided is a fully quantitative model for shipwreck risk assessment.

3. Methodology

The methodology of this research can be divided into three main parts. The first part is related to quantification of spill probability using expert elicitation and Bayesian updating in a fault tree analysis (FTA) framework, and the second part is related to quantification of the potential oiling impact in different areas by stochastic simulation. In the third part, the estimated probability and impact are combined to calculate the quantitative risk of oiling. The risk of a spill scenario to a receptor is calculated according to the following general formula:

$$R = P \times E \times S \tag{3}$$

where, R is the risk, P is the probability of the spill scenario, E is the exposure of the receptor to oil, and S is the sensitivity index of the receptor. The term $E \times S$ represents the potential oiling impact. The presented methodology in this research is general, but in the following, it is described with a focus on oil spill from shipwrecks.

3.1. Quantification of the release probability

When defining a scenario of oil spill from a wreck, it is essential to estimate the probability of occurrence for the specific scenario. Because of the individual conditions of each wreck, the probability of release differs from wreck to wreck (Landquist et al., 2014). Previously, a method (VRAKA) was developed for quantification of the probability of release based on fault tree analysis (FTA), integrating site-specific data and expert judgments by means of Bayesian updating (Landquist et al. 2014, 2016, 2017a, 2017b). This method is here adopted for estimation of probability of release in quantitative oil spill risk assessment.

The first step in the VRAKA method is to identify potential hazardous events that may cause damage to the wreck and release of oil. For each hazardous event, a rate is estimated to describe how often the specific event (release cause) is assumed to occur. This rate is site-specific and typically estimated from existing information by the risk assessor. The generic probability of an opening in the hull or tank due to each of the hazardous events is estimated by use of expert elicitation. The details of the expert elicitation methodology to obtain input probabilities were described by Landquist et al. (2017a). Included in the method is furthermore the possibility to estimate if hazardous substances are still contained in the wreck. These three variables are then combined in the FTA to estimate the generic annual probability of discharge for a wreck (Landquist et al., 2014). The specific fault tree developed for shipwrecks is shown in Fig. 1.

The eight hazardous events included in the model (left branch of Fig. 1) are the ones identified as the most likely causes of an opening in the wrecks. These events have been identified based on a literature review and brainstorming sessions (Landquist et al., 2014). Each event (i) is assigned an occurrence rate ($\lambda_{occurence,\ i}$) and a conditional probability of opening given the event ($P_{opening|event,\ i}$). The rate is a frequency, and it describes how often the event occurs per year. The conditional probability represents how likely one occurrence of the specific event is to cause an opening in the hull or the tank. The rate of each event causing an opening in the wreck is calculated as:

$$\lambda_{opening,i} = \lambda_{occurence,i} \times P_{opening|event,i} \tag{4}$$

Assuming exponential rates, the probability of each event causing an opening in the wreck within a time frame t is:

$$P_{opening,i} = 1 - e^{-\lambda_{opening,i} \times t} \tag{5}$$

When the opening probabilities are calculated, they can be used to calculate the total probability of opening, using the Boolean formula for an OR-gate (left branch of Fig. 1):

$$P_{opening} = 1 - \prod_{i} (1 - P_{opening,i}) \tag{6}$$

With a similar method, the probability of presence of oil in the wreck is calculated (the right branch of the Fig. 1), and finally in the last step, the probability of discharge of oil is estimated using Boolean formula for an AND-gate:

$$P_{discharge} = P_{opening} \times P_{oil\ exists\ in\ wreck} \tag{7}$$

To account for the uncertainty in the expert knowledge, the conditional probabilities are estimated as probability distributions, not point values. More specifically, the conditional probabilities are modeled using Beta distribution, which enables a mathematically formal Bayesian updating of the previous knowledge as new hard data becomes available (Landquist et al., 2014, 2017b). The prior generic information is updated when site-specific indicator information is available for a specific wreck. After all the updated probability distributions for the FTA nodes are prepared for a specific wreck, the input to FTA is complete and the calculation of the posterior probability of discharge can be started. The inputs to the fault tree model are distributions, and Monte Carlo simulation is employed to calculate the probability of the top event. This way the output will be a set of many probability values which can be represented by a distribution function, which indicates the uncertainty in the probability of oil spill. For more complex studies, specially where there are dependencies among spill casual factors, Bayesian Networks (BNs) can be employed for estimating the probability of occurrence of oil spill (Cai et al., 2012; Cai et al., 2013a, 2013b; Meng et al., 2018).

3.2. Quantification of the oiling impact

The impact of an oil spill scenario on a receptor can be determined in terms of exposure of the receptor to oil pollution. The exposure is a function of both the concentration of oil and the time for which the receptor is affected (Lamine and Xiong, 2013). In this research, a Lagrangian particle tracking model is used and a new formula is presented to integrate the oiling probability and the exposure to oil in a single parameter, mean exposure (*ME*). The development of this formula is described in the following.

Suppose that there are only one source and one receptor. A total of n spill scenarios with different start-times are simulated. According to the traditional approach of calculation of oiling probability (described with Eqs. (1) and (2)) the oiling probability in the receptor is:

$$P = \frac{\sum_{i=1}^{N} B_i}{N} \tag{8}$$

where N is the number of simulated scenarios and B_i is a Boolean indicator which is 1 if the scenario i leads to a maximum concentration of greater than zero, or 0 if the scenario i leads to a maximum concentration of zero. According to the frequentist interpretation of

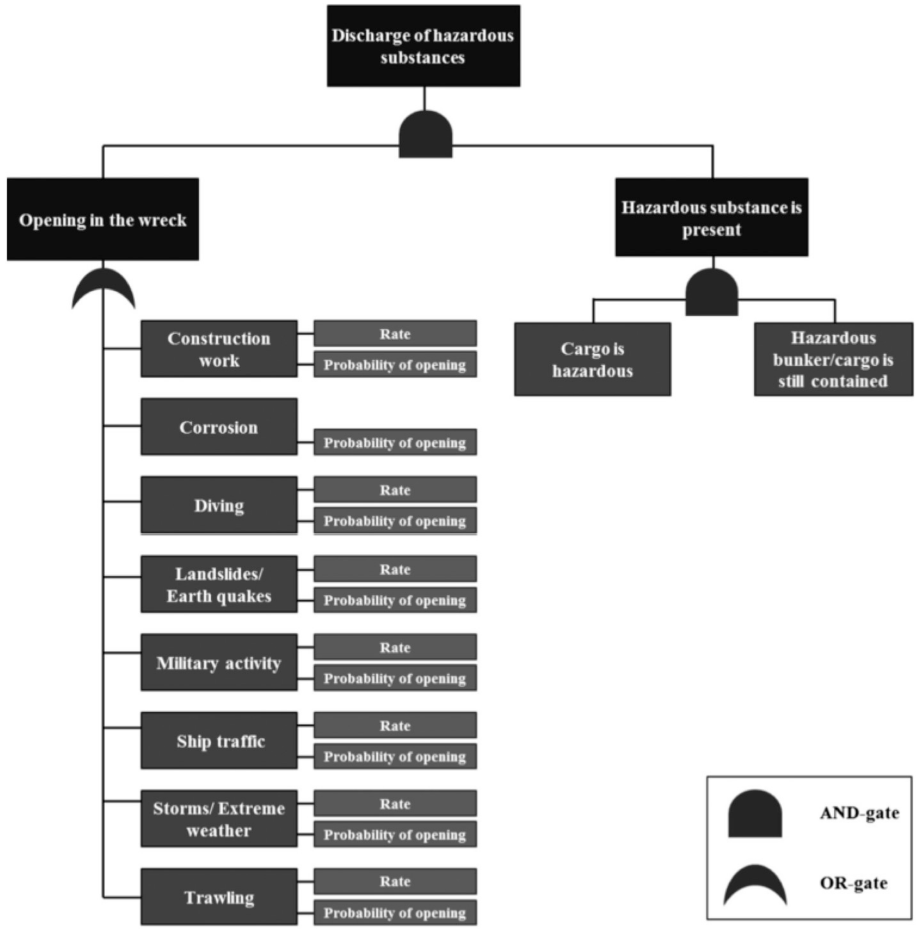

Fig. 1. The fault tree structure for modeling of release from a wreck (Reprinted from Landquist et al. (2014) with permission from Elsevier).

probability, this is a correct definition of oiling probability. According to our new approach, the Boolean indicator B_i in Eq. (8) is weighed by an 'exposure' factor, or mean concentration factor (MCF [kg m^{-2}]), to define a new parameter:

$$ME = \frac{\sum_{i=1}^{N} B_i \times MCF_i}{N} \tag{9}$$

where ME [kg m^{-2}] is mean exposure for the receptor ($0 < ME < \infty$). In a Lagrangian trajectory modeling framework, the mean concentration factor, MCF_i, for an oil spill scenario i is defined as:

$$MCF_i = \frac{\sum_{j=1}^{n} m_j}{n \times A} \tag{10}$$

where A is the receptor area, and m_j is the total mass of Lagrangian elements located within the receptor area at time t_j, which is summed over n times distributed uniformly between the release time, tr_i, and the end of simulation $tr_i + T$. MCF_i is an estimation of time weighted oil concentration in the receptor, and it can be considered as a parameter representing 'exposure to oil'. Similarly, in the human health field, ACGIH (American Conference of Governmental Industrial Hygienists, 2017) proposed the time weighted average threshold limit value (TLV_{TWA}) as a parameter to regulate the safe exposure to hazardous materials in the workplace (American Conference of Governmental Industrial Hygienists, 2017). Since MCF_i is either a positive number or zero, in Eq. (9), the Boolean indicator B_i can be absorbed to MCF_i. Therefore, this equation can be re-written as:

$$ME = \frac{\sum_{i=1}^{N} MCF_i}{N} \tag{11}$$

Hence, to calculate ME for a spill source and a receptor, we should define a sufficient number of hypothetical scenarios with different input variables (for example, different start-times). After simulation of each scenario i, a MCF_i is calculated for the receptor. The average of all MCF_i values is the ME for the receptor. It is clear that in this quantitative approach, the ME has the unit of MCF (or, concentration of oil). This new formula (Eq. (11)) is an alternative to the "on or off" approach, described earlier. Based on mean exposure, the mean oiling impact from source i to receptor j (MI_{ij}) is calculated by:

$$MI_{ij} = ME_{ij} \times S_j \tag{12}$$

where, ME_{ij} is the potential mean exposure of receptor j as a result of spills in source i; and S_j is the sensitivity index of the receptor j. If S_j is defined as a dimensionless index, MI_{ij} will have the unit of ME (or oil concentration).

3.3. Quantification of the oiling risk

For risk mapping purpose, where each receptor area is assigned a single mean risk value, the average risk from a wreck i to a receptor j ($\overline{R_{ij}}$) can be formulated as:

$$\overline{R_{ij}} = \overline{P_i} \times MI_{ij} \tag{13}$$

where $\overline{P_i}$ is the mean probability of release in wreck i. Based on this relation, the quantitative risk will have the unit of MI (or, oil concentration). Similarly, for uncertainty analysis purpose, where the distribution of the output risk is required, the distribution of risk from a source i to a receptor j (R_{ij}) is obtained by:

$$R_{ij} = P_i \times I_{ij} \tag{14}$$

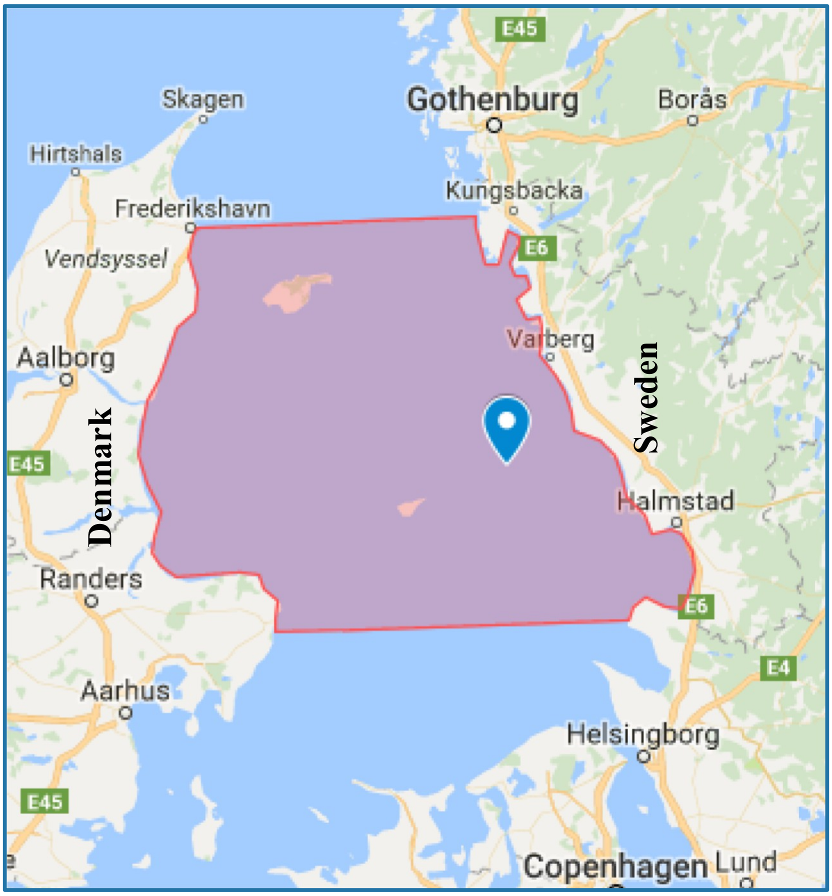

Fig. 2. The area of study in the Kattegat (the study area is highlighted and the blue mark's tip indicates the location of the wreck Altnes; Map from Google. For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.) (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

where, P_i is the distribution of the propability of release in source i, and I_{ij} is the distribution of oiling impact for the receptor j resulted from simulation of many spill scenarios in the source i ($I_{ij} = MCF_{ij} \times S_j$). This step is implemented through Monte Carlo simulation.

4. Case study

To test the developed model for sunken ships risk assessment, a case study is performed in Kattegat, which is a regional sea that connects the Baltic Sea to the North Sea. In the following, the details of the study area, the used inputs, and other details are described.

4.1. The geographical domain of the study

The study area is Kattegat (see Fig. 2). Kattegat is a shallow sea between Denmark and Sweden in northern Europe, situated just north of the Danish straits, which are the main constrictions between the Baltic and the North Sea. The sea has a mean depth of about 23 m but is shallower on the Danish side and up to 100 m deep within trenches on the Swedish side. Tides are weak, but there are relatively large volume fluxes back and forth through the straits driven by sea level and air pressure differences (Gustafsson, 2000). These fluctuating currents are superposed on a mean estuarine circulation where brackish Baltic water flows northward and mixes with more saline North Sea water. The water column is stratified with inflowing North Sea water at the bottom and outflowing less saline water at the surface. The case study object is the shipwreck Altnes, indicated by a blue mark in Fig. 2.

4.2. The temporal domain of study and inputs

Considering the restriction in computational time, limited access to sensitivity maps and high volume of the input met-ocean data, the temporal domain of the case study is limited to the fall of 2016, from September to November (3 months). The most important factors which have temporal variation are the sensitivity map of the area under study and the met-ocean data. For the sensitivity map of the Kattegat, the result of the BRISK (Sub-regional risk of spill of oil and hazardous substances in the Baltic Sea) project is used (Admiral Danish Fleet HQ, 2012). The sensitivity map of the area has been presented for four seasons, separately. The resolution of each sensitivity map is $2km \times 2km$. This means that the whole area is divided into some $2km \times 2km$ cells and a sensitivity index has been assigned to each cell. The sensitivity map of the area under study for fall is indicated in Fig. 3. This map consists of 3615 cells, and the sensitivity index ranges from 1 (low sensitivity) to 5 (very high sensitivity). The sensitivity index of each cell has been determined based on indicators describing the environmental value of it. These indicators are related to the vulnerability of coastal habitats, flora, fish, birds, marine mammals, etc. (Admiral Danish Fleet HQ, 2012).

The 3D current data for this study are modeled using the model NEMO-Nordic (Hordoir et al., 2015; Pemberton et al., 2017), based on NEMO (Nucleus for European Modeling of the Ocean) version 3.6. It is the operational oceanographic forecast model for the North Sea and the Baltic Sea at the Swedish Meteorological and Hydrological Institute (SMHI) since 2017. In the present version, the resolution of the current data is 1 h in time, about 4 km in horizontal space and 3 m in vertical space. The wind data are from the High Resolution Limited Area Model (HIRLAM) with 11 km horizontal resolution and 3 h temporal resolution, but for this study interpolated to the ocean model resolution of 4 km and 1 h, respectively. The monthly mean patterns of the sea surface current and wind in fall 2016 are shown in Fig. 4. In addition to advection by the sea current and wind, the wave can also affect the transport of the spilt oil (Weisberg et al., 2017). To account for the effect of turbulent diffusion by wave, a diffusion coefficient of

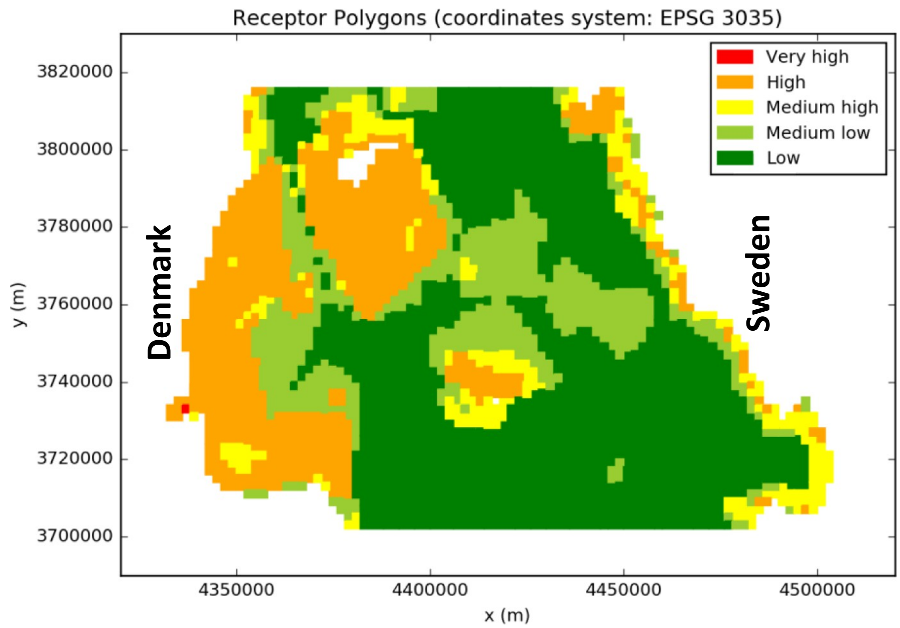

Fig. 3. The sensitivity map of the area under study in fall (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

100,000 cm^2/s is defined in the model (Zelenke et al., 2012).

4.3. Probability estimation details

The VRAKA model (described in Section 3.1) is employed to estimate the probability of release of oil from the wreck Altnes. According to the specific conditions of this wreck, the rate of hazardous events and the updated conditional probabilities are derived. The 5th, 50th and 95th percentiles of Beta distributions of annual probability of release per hazardous activity are shown in Fig. 5. These distributions are the inputs for the left-hand side branch of the fault tree presented in Fig. 1. Based on field data, the probability of the presence of oil (right-hand side branch of the fault tree) is assumed to be 1.

It should be noted that in this research, the time frame in Eq. (5) is assumed 1 year (t = 1). Therefore, the directly calculated probability is the annual probability of release. By assuming that the probability of release in 4 seasons is equal and independent, the seasonal probability of release is estimated by dividing the annual probability by 4. The seasonal probability is used for risk calculations of fall season in this research.

4.4. Impact estimation details

The amount of the oil contained in the wreck Altnes has been estimated to be 21–28 m^3. For simulation of impacts in this preliminary case study, the spill volume is assumed to be equal to the maximum oil

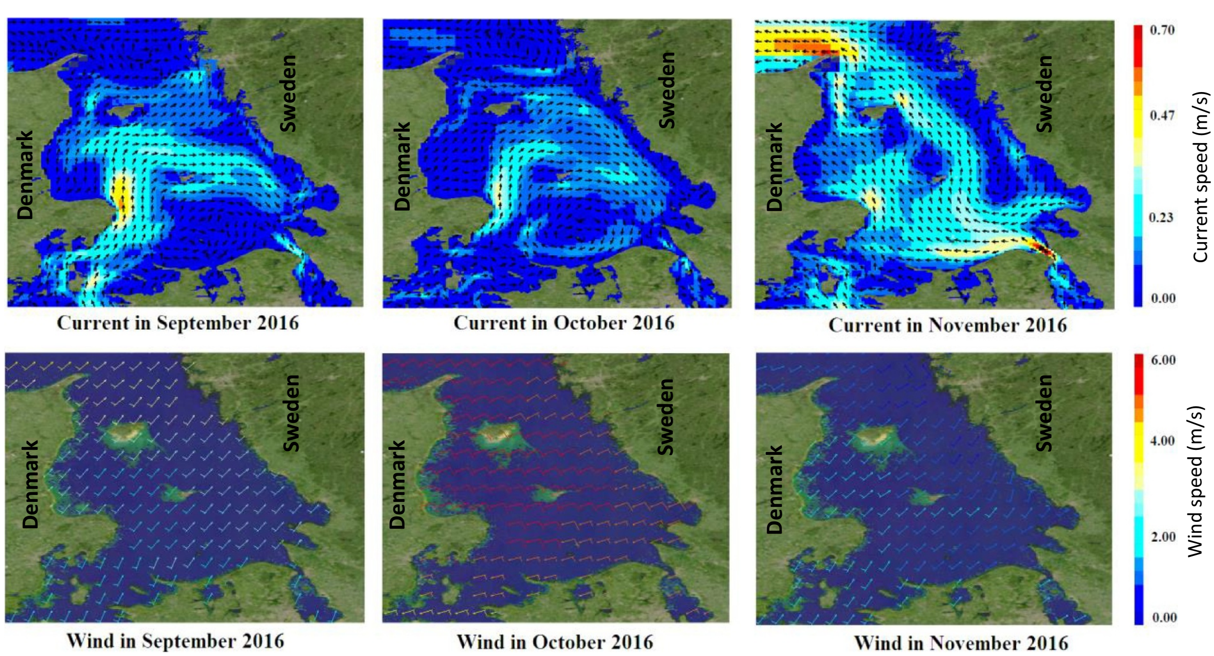

Fig. 4. The monthly mean pattern of the sea surface current and wind in the Kattegat (Sep. to Nov. 2016) (The maps are generated using the online visualization tool provided in http://marine.copernicus.eu. For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

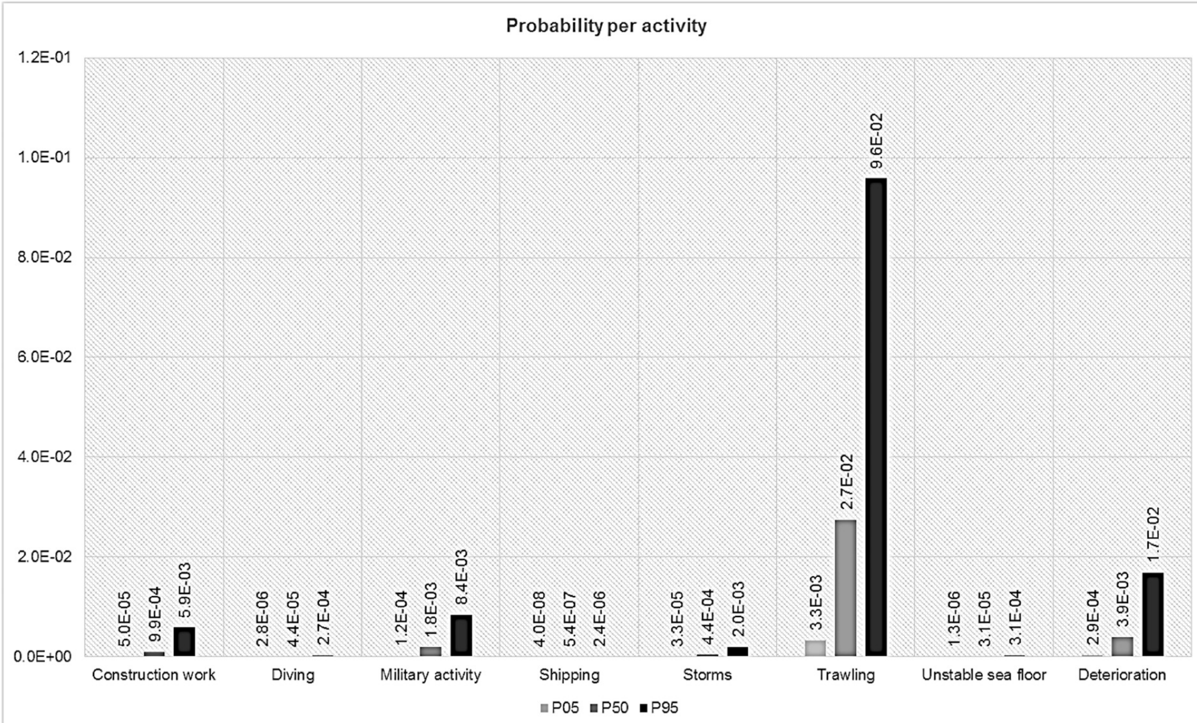

Fig. 5. The annual probability of release per activity (5th, 50th and 95th percentiles of the Beta distribution have been presented for each activity).

inventory in the wreck (= 28 m^3). For more advanced simulations, the spill volume should be considered as a distribution, not a point value (Amir-Heidari & Raie, 2018). The oil type in Altnes is heavy fuel oil (HFO) with an API gravity of 19.69. The depth of the wreck is about 36 m, and the trajectories are modeled as 3D plumes using General NOAA Operational Modeling Environment (GNOME) (Zelenke et al., 2012). The weathering of the spilt oil is also taken into account by defining four natural processes in the model: evaporation, natural dispersion, sedimentation and emulsification. These weathering processes are modeled using NOAA's ADIOS®, which models how different types of oil undergo physical and chemical changes in the marine environment (Lehr et al., 2002; NOAA, 2018).

For defining the hypothetical spills from the wreck, 50 random start times are selected in fall 2016, by random sampling from a uniform probability density function. The simulation or tracking time for each trajectory is set to 15 days. It is assumed that after 15 days, the released oil is cleaned up by natural weathering processes and emergency response. The release from the wreck is supposed to be continuous, and for each start time, 10 iterations with different release durations are simulated. The release durations are selected randomly, from the triangular distribution T (1, 15, 10) days. This distribution is selected based on regional experts' opinion. Totally 50 × 10 = 500 hypothetical spill scenarios are modeled.

To define the receptor areas and to reduce the number of receptor polygons, an algorithm is developed to merge the adjacent small $2km \times 2km$ cells which have the same sensitivity indices in Fig. 3. The lower the number of receptor polygons, the shorter the computational time. By merging algorithm, finally, 389 polygons are produced for spatial risk assessment (See Fig. 6(a)).

In the post processing of the trajectories for calculation of *MCF*, the time between consequent measurements of mass of Lagrangian elements in each receptor area (averaging time) is set to 12 h. With the simulation time of 15 days, 30 measurements are carried out for each polygon in each scenario. Considering 500 scenarios, 389 polygons and 30 measurements, totally 500 × 389 × 30 = 5835000 measurements are carried out in this case study. The computations are performed in parallel model using the computer cluster of Swedish National Infrastructure for Computing (SNIC).

5. Results and discussion

The result of the Monte Carlo simulation for estimation of the probability of release, i.e. spill from the wreck Altnes in fall is presented in Fig. 7 (a). The mean probability of spill based on this distribution is 0.0115 (indicated with red dashed line).

The spatial distribution of the mean exposure (*ME*) in the study area is indicated in Fig. 6 (b). From this figure, it is clear that considering the integral sum of 500 spill scenarios in Altnes in fall, the mean exposure of the eastern shore (west coast of Sweden) to potential spilt oil is considerably higher than that of the western shore (east coast of Denmark). Areas with high *ME* experience higher concentration and/or higher retention times of oil slicks. Therefore, based on the result, in most of the hypothetical spill scenarios in fall 2016, oil slicks have had a tendency to move toward the Swedish coast and reside a relatively longer time near the shoreline. Areas adjacent to the wreck and areas around the island Anholt in the vicinity of the wreck also experience high *ME*. The *ME* map reveals the general hydrodynamic status of the marine environment under study. From Fig. 6(b) it is clear that if oil slicks move toward the coast, the near-shore areas experience higher concentration and/or retention time of oil. This is because the coast acts as a 'mirror boundary'. The oil particles pass from the near-shore region and reach to the boundary, and they again return to the water and pollute the near-shore region. This reveals the fact that near-shore waters may experience higher effects in the event of an oil spill. The sticking of oil parcels to the shoreline in GNOME can be customized by the parameter 'refloat half-life' (Zelenke et al., 2012). This parameter empirically describes the adhesiveness of the spilt oil to the shoreline. It is the number of hours in which half of the Lagrangian elements on a given shoreline are expected to be removed and entered to water if there is an offshore wind or diffusive transport. In this study this parameter is set to 6 h.

The exposure map in Fig. 6(b) is based on the fall season of only

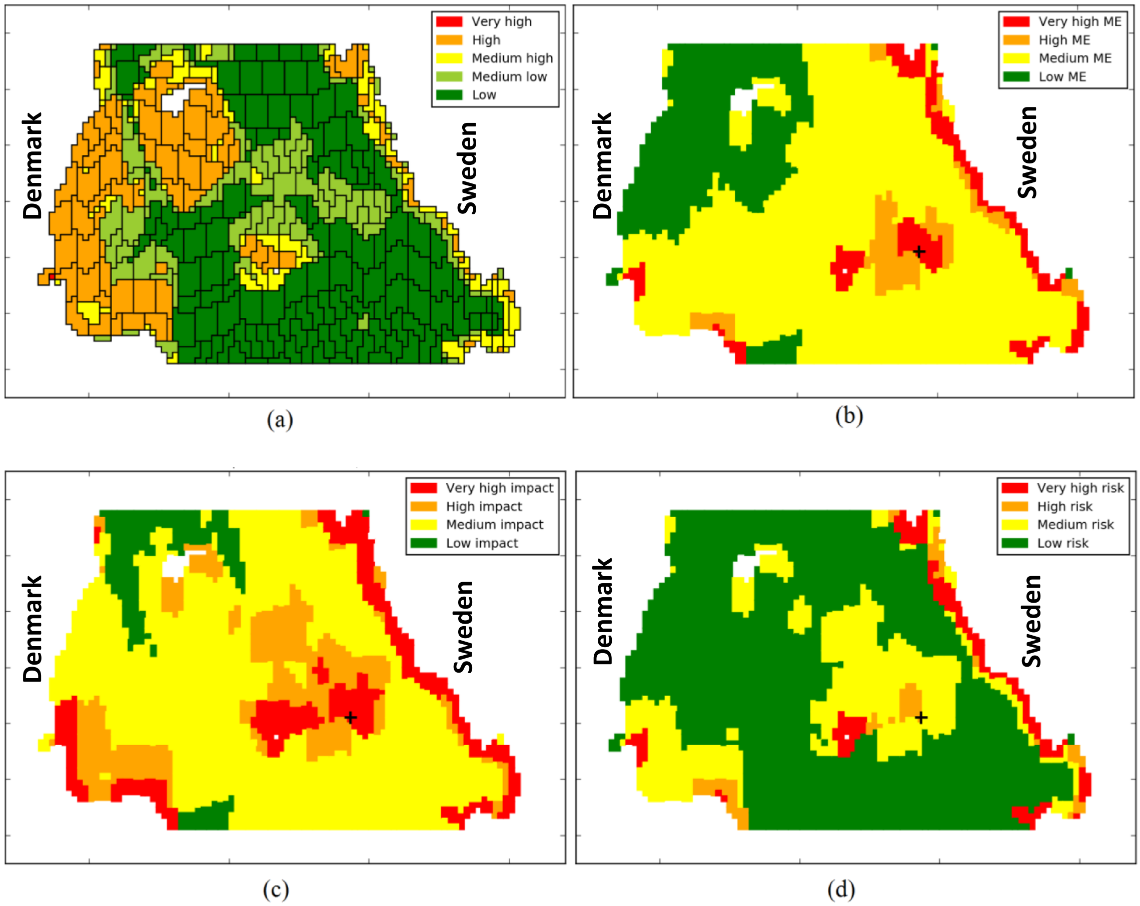

Fig. 6. Spatial risk assessment maps. (a) The final receptor polygons with their sensitivity classes for fall, (b) The mean exposure (*ME*) map for fall (*ME* > 1000 g/km^2: very high, 500 g/km^2 < *ME* < 1000 g/km^2: high, 100 g/km^2 < *ME* < 500 g/km^2: medium, *ME* < 100 g/km^2: low), (c) The mean impact (*MI*) map for fall (impact > 1000 g/km^2: very high, 500 g/km^2 < impact < 1000 g/km^2: high, 100 g/km^2 < impact < 500 g/km^2: medium, impact < 100 g/km^2: low), (d) The Mean risk map for fall (risk > 50 g/km^2: very high, 20 g/km^2 < risk < 50 g/km^2: high, 5 g/km^2 < risk < 20 g/km^2: medium, risk < 5 g/km^2: low). The limits in (a), (b) and (c) are arbitrary chosen. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2016. To obtain a more reliable map of mean exposures for the fall season, one would need to include more years to take into account year-to-year variability. To represent present climate one would need in the order of 10–30 years. Analysis of wind data from the meteorological station Niddingen somewhat north of the wreck for the period 1995 to 2017 shows that the fall of 2016 has more NE and less SW winds than

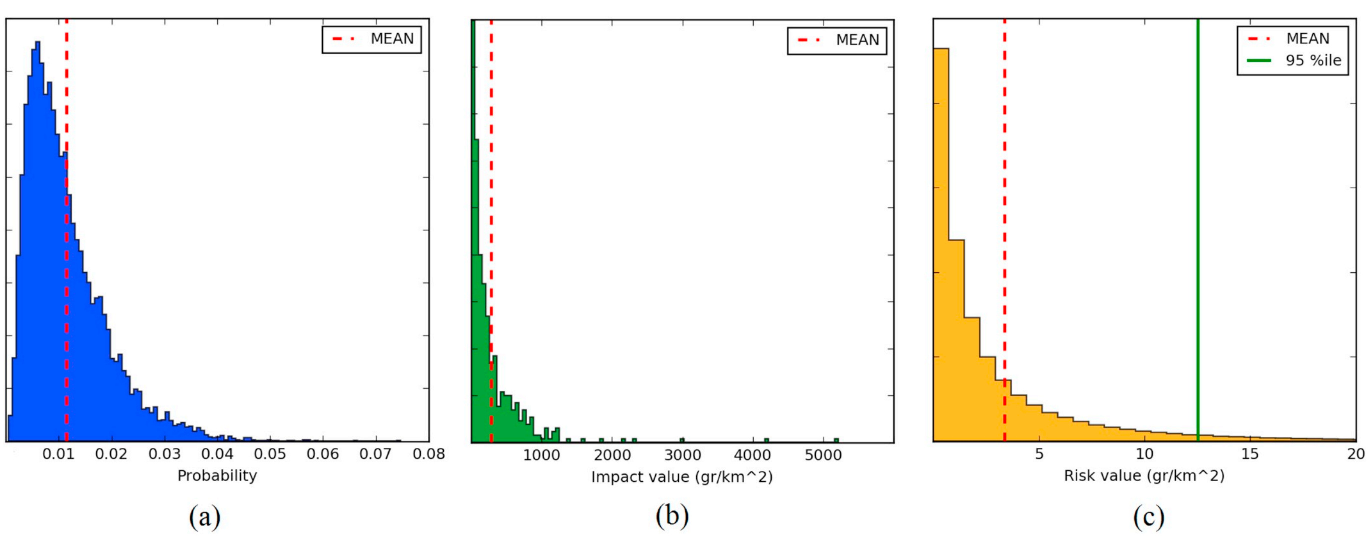

Fig. 7. The results of stochastic assessment of the risk posed by the wreck Altnes to a sample polygon. (a) PDF of probability of spill in Altnes in fall, (b) PDF of impact to the sample polygon, (c) PDF of the risk to the sample polygon. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the average for all falls. For example, the occurrence of winds in the sector 45° - 90° is 18% in 2016 and only 11% on average. Therefore Fig. 6(b) probably underestimates the ME values for the Swedish west coast and overestimates them for the Danish east coast. Because of the limitation of input data and computational time, and considering the purpose of this study, i.e. evaluation of the developed model, the temporal domain of this case study is limited to a short period of time.

According to Eq. (12), *ME* and the sensitivity index of a receptor are multiplied to derive the mean oil impact (*MI*) for that. To derive the mean impact map, the *ME* map (Fig. 6(b)) is combined with the sensitivity map (Fig. 6 (a)). The result is shown in Fig. 6(c). The philosophy behind the mean impact map is that beside the potential mean exposure to oil (*ME*), it should be considered how sensitive (or vulnerable) an area is to oil. Inherent sensitivity of each receptor is combined with the level of potential threat to it to estimate the potential impact. Areas with higher *ME* and higher sensitivity are expected to experience higher impacts. Considering the sensitivity map (Fig. 6(a)) and *ME* map (Fig. 6(b)), it is clear that the Swedish west coast and parts of the Danish coast have both high sensitivity and high *ME*. Therefore, as indicated in Fig. 6(c), in the case of a spill in fall season these areas are expected to experience higher impact.

As discussed before, the probability of oil release in different wrecks is different. To be able to compare the threat of one wreck with others, the 'impact' parameter should be converted to 'risk'. According to Eq. (13), this is accompanied by combining impact and probability of spill. To derive the average risk map for the area under study, the mean probability of spill in Altnes ($\overline{P} = 0.0115$) is multiplied by the average impact map (Fig. 6(c)). The result is presented in Fig. 6(d). From this figure, it is obvious that the very high risk areas are all near to the shoreline (near a coast or island). The risk level is not necessarily proportional to the proximity to the wreck because there are some areas far from the wreck with very high risk, and on the other hand, there are some low risk areas which are very close to the wreck. The main ecosystem components in the area of study are benthic species, birds, fish, and marine mammals (e.g. harbor porpoise and harbor seal). Considering the spatial distribution of physical features in the Kattegat Sea (HELCOM, 2019) and based on the produced risk map (Fig. 6 (d)), the main environmental resources at risk are breeding, moulting, wintering and staging areas for birds, spawning and nursery areas for fish, stone reefs (along the Swedish rocky shores), sandy beaches (along the Danish shores), seagrass meadows (mostly around the islands), shallow inlets and bays, underwater sandbanks and protected areas.

As described in Section 3.3, beside average risk for each receptor site, it is possible to derive the risk distribution for each of the receptors for uncertainty analysis purpose (see Eq. 14). As discussed, in this work 500 hypothetical spill scenarios with different inputs are simulated, and in each of these scenarios an *MCF* is calculated for each of the receptor polygons. Therefore, there are 500 *MCF*s for each polygon. These can be represented by a distribution. If the *MCF* distribution of a polygon is multiplied by its sensitivity index, an impact distribution is derived for it. For example, the impact distribution for a sample polygon is shown in Fig. 7 (b). To derive the risk distribution for this sample polygon, the PDF of probability of spill from the wreck (Fig. 7 (a)) is multiplied by the PDF of the impact to this polygon (Fig. 7 (b)). This is realized by Monte Carlo simulation. The output of simulation with 1,000,000 iterations is indicated in Fig. 7 (c). According to the risk distribution for the sample polygon, the mean risk is 3.18 g/km^2, the 95th percentile is 11.9 g/km^2 and the maximum risk is 346 g/km^2 (risks > 98th percentile have not been shown in Fig. 7 (c)). The large difference between the maximum risk and the 95th percentile of the risk distribution reveals the uncertain nature of the oil spill risk, and the importance of identification of the extreme risk values and worst case scenarios for the receptor sites of the interest, based on simulation. Depending on the purpose, the decision making in oil spill risk management can be based on mean risk, 95th percentile risk, maximum risk, or other statistics.

In oil spill risk assessment, a focus should be on aggregation of risks, according to a rational basis. The aggregation can be performed both in time and in space. For example, in the case study of this research, the risk is calculated only for fall season. To have a complete picture of the risk in the area of the study, the same procedure should be repeated for the three other seasons, and the total risk (*TR*) for each receptor should be calculated as:

$$TR = risk_{spring} + risk_{summer} + risk_{fall} + risk_{winter} \quad (15)$$

The reason for dividing the entire time frame to four seasons is seasonality in the sensitivity map of the area; there is one sensitivity map for each season. Beside aggregation in time, the aggregation of oil spill risk can be also performed in spatial domain. For example, to derive the aggregated risk (*AR*) from a wreck, the total risk posed by the wreck to different receptors in different locations should be summed:

$$AR = \sum_{i} TR_i \quad (16)$$

where, TR_i is the total risk from the wreck to the receptor *i* (See Eq. (15)).

In this research, an advanced method of oil spill probability estimation (VRAKA) is combined with an advanced Lagrangian trajectory model (GNOME) to present a fully quantitative methodology for spatial and stochastic risk assessment of oil spill from shipwrecks. With this methodology, it is possible to prioritize different wrecks based on their aggregated risk levels. Prioritization of wrecks is important, because remediation and control efforts should be focused on high risk wrecks. If a limited amount of budget is available for remediation of sunken ships, it should be allocated to wrecks with the highest aggregated risk levels, first. The aggregated risk can be also useful in advanced risk assessment and decision analysis of potential actions, such as cost-benefit analysis (CBA).

6. Conclusion

A new model is presented for spatial and stochastic oil spill risk assessment. As a case study, the risk of oil spill from a shipwreck in Kattegat is assessed using the developed model. The probability of spill from the wreck is estimated using expert elicitation and Bayesian updating in a FTA framework. For each receptor, the mean probability ($\overline{P}$) of spill from the wreck is multiplied by the potential mean impact (*MI*) of oiling to derive the average oil spill risk posed by the wreck to the receptor. Then, a risk map is generated based on the average risks to different receptors. Beside the average risk map, the PDF of the oil spill risk for each receptor is also derived. The PDF of the risk, describing the uncertainty associated with the risk value, is needed to provide a comprehensive picture of the risk a receptor is exposed to. The PDF for the risk is here based on uncertainties in both the probability of spill occurrence and the spill impact.

The result of case study of the wreck Altnes in Kattegat indicates that, in the fall of 2016, the eastern coast (Swedish shoreline) receives the highest level of risk, compared to other regions. This is related to the pattern of the wind and sea current (See Fig. 4) and the spatial distribution of sensitive environmental endpoints (See Fig. 3) in the study area. The risk (PDF, see Fig. 7 (c)) for a sample polygon is also derived to indicate the capability of the developed model for complete uncertainty quantification. To provide a more detailed model, the case study should be based on met-ocean data of more years (e.g. 10–30 years) to take into account interannual variability in the pattern of the wind and sea current in the area of study.

The most important strengths of the developed model are that it is fully quantitative holistic by considering a chain of events. Using this comprehensive model, three important factors are considered together in oil spill risk assessment: (1) the characteristics of the spill source, which is considered in both estimation of the oil spill probability and simulation of its impacts, (2) the dynamic pattern of the environmental forcing elements (wind and sea current) that is considered in simulation of the oiling impacts, and (3) the spatial distribution of environmental/natural resources, which is taken into account by considering the *ESI* map of the area of study. Therefore, the approach used here is an integrated and holistic approach where the whole chain of events from contaminant release to the end-point is taken into account. Another important advantage of the developed model is that it explicitly accounts for uncertainties and, using this model, it is possible to perform sensitivity analyses of the uncertainty contribution from input parameters to the outcome uncertainties. Furthermore, with the developed model, it is possible to sum the risk of oil spill in different seasons to calculate the total risk to each of the receptors. In addition, since each spill source (e.g. a wreck) threatens several receptors in different locations, it is also possible to sum the total risk posed by a source to different receptors to derive the aggregated risk posed by a specific source. By deriving the aggregated risk value for different sources, it is possible to rank and prioritize them based on the environmental risk they pose.

Some of the input data to the presented model is based on expert judgments. This is common in risk assessments when, for example, historical data is limited. The results of the model may depend on the level of experience and expertise of the expert team utilizing the model. However, a Bayesian approach is used to in a mathematically formal manner integrate subjective and hard data. The model is developed to be generic, i.e. possible to be used with any arbitrary temporal and spatial domain all over the world.

Acknowledgement

This project has been funded by Sharif University of Technology, and Chalmers Area of Advance Transport. The authors appreciate the Office of Response and Restoration of US NOAA and Swedish Meteorological and Hydrological Institute (SMHI) for sharing their experience in trajectory modeling. The authors also acknowledge the Baltic Marine Environment Protection Commission (HELCOM) for providing the sensitivity map of the study area. Special thanks to Prof. Rickard Bensow for coordination of access to Swedish National Infrastructure for Computing (SNIC).

References

Abascal, A.J., Castanedo, S., Medina, R., Liste, M., 2010. Analysis of the reliability of a statistical oil spill response model. Mar. Pollut. Bull. 60 (11), 2099–2110. https://doi.org/10.1016/j.marpolbul.2010.07.008.

Abascal, A.J., Castanedo, S., Minguez, R., Medina, R., Liu, Y., Weisberg, R.H., 2015. Stochastic Lagrangian Trajectory Modeling of Surface Drifters Deployed during the Deepwater Horizon Oil Spill. In Thirty-Eighth AMOP Technical Seminar (Pp. 77–91) Ottawa, ON.

Admiral Danish Fleet, H.Q., 2012. Sub-Regional Risk of Oil and Hazardous Substances in the Baltic Sea (BRISK): Environmental Vulnerability.

Al Shami, A., Harik, G., Alameddine, I., Bruschi, D., Garcia, D.A., El-Fadel, M., 2017. Risk assessment of oil spills along the Mediterranean coast: a sensitivity analysis of the choice of hazard quantification. Sci. Total Environ. 574, 234–245. https://doi.org/10.1016/j.scitotenv.2016.09.064.

Alló, M., Loureiro, M.L., 2013. Estimating a meta-damage regression model for large accidental oil spills. Ecol. Econ. 86, 167–175. https://doi.org/10.1016/j.ecolecon.2012.11.007.

American Conference of Governmental Industrial Hygienists. (2017). TLV® - chemical substances introduction. Retrieved November 29, 2017, from http://www.acgih.org/tlv-bei-guidelines/tlv-chemical-substances-introduction

Amir-Heidari, P., Raie, M., 2018. Probabilistic risk assessment of oil spill from offshore oil wells in Persian Gulf. Mar. Pollut. Bull. 136, 291–299. https://doi.org/10.1016/j.marpolbul.2018.07.068.

Applied Science Associates. (2017). SIMAP. Retrieved November 13, 2017, from http://asascience.com/software/simap/

Arzaghi, E., Abbassi, R., Garaniya, V., Binns, J., Khan, F., 2018. An ecological risk assessment model for Arctic oil spills from a subsea pipeline. Mar. Pollut. Bull. 135 (August), 1117–1127. https://doi.org/10.1016/j.marpolbul.2018.08.030.

Barker, C. H. (1999). The NOAA trajectory analysis planner: TAP II. In oceans '99. MTS/IEEE. Riding the crest into the 21st century. Seattle, USA: IEEE.

Bejarano, A.C., Mearns, A.J., 2015. Improving environmental assessments by integrating species sensitivity distributions into environmental modeling: examples with two hypothetical oil spills. Marine Pollution Bulletin Journal 93, 172–182. https://doi.org/10.1016/j.marpolbul.2015.01.022.

Bejarano, A.C., Michel, J., 2016. Oil spills and their impacts on sand beach invertebrate communities: a literature review. Environ. Pollut. 218, 709–722. https://doi.org/10.1016/j.envpol.2016.07.065.

Bernes, C. (2005) Change beneath the surface: an in-depth look at Sweden's marine environment. English translation: M. Naylor. ISBN: 91-620-1246-0.

Beyer, J., Trannum, H.C., Bakke, T., Hodson, P.V., Collier, T.K., 2016. Environmental effects of the Deepwater Horizon oil spill: a review. Mar. Pollut. Bull. 110 (1), 28–51. https://doi.org/10.1016/j.marpolbul.2016.06.027.

Bulycheva, E.V., Krek, A.V., Kostianoy, A.G., Semenov, A.V., Joksimovish, A., 2015. Oil pollution of the southeastern Baltic Sea by satellite remote sensing data and in-situ measurements. Transport and Telecommunication 16 (4), 296–304. https://doi.org/10.1515/ttj-2015-0027.

Bulycheva, E.V., Krek, A.V., Kostianoy, A.G., Semenov, A.V., Joksimovich, A., 2016. Oil pollution in the southeastern Baltic Sea by satellite remote sensing data in 2004-2015. Transport and Telecommunication 17 (2), 155–163. https://doi.org/10.1515/ttj-2016-0015.

Cai, B., Liu, Y., Liu, Z., Tian, X., Dong, X., Yu, S., 2012. Using Bayesian networks in reliability evaluation for subsea blowout preventer control system. Reliab. Eng. Syst. Saf. 108, 32–41. https://doi.org/10.1016/j.ress.2012.07.006.

Cai, B., Liu, Y., Fan, Q., Zhang, Y., 2013a. Application of Bayesian networks to reliability evaluation of software system for subsea blowout preventers. International Journal of Control and Automation 6 (1), 47–60.

Cai, B., Liu, Y., Liu, Z., Tian, X., Zhang, Y., Ji, R., 2013b. Application of Bayesian networks in quantitative risk assessment of subsea blowout preventer operations. Risk Anal. 33 (7), 1293–1311. https://doi.org/10.1111/j.1539-6924.2012.01918.x.

Camphuysen, C. J. (2007). Chronic oil pollution in Europe, a status report. Retrieved from http://www.ifaw.org/sites/default/files/Chronic oil pollution in Europe_0.pdf.

Chen, C.-C., Tew, K.S., Ho, P.-H., Hsieh, H.-Y., Meng, P.-J., 2017. The impact of two oil spill events on the water quality along coastal area of Kenting National Park, southern Taiwan. Mar. Pollut. Bull. 124 (2), 974–983. https://doi.org/10.1016/j.marpolbul.2017.02.034.

Cirer-Costa, J.C., 2015. Tourism and its hypersensitivity to oil spills. Mar. Pollut. Bull. 91 (1), 65–72. https://doi.org/10.1016/j.marpolbul.2014.12.027.

Depellegrin, D., Pereira, P., 2016. Assessing oil spill sensitivity in unsheltered coastal environments: a case study for Lithuanian-Russian coasts, South-eastern Baltic Sea. Mar. Pollut. Bull. 102 (1), 44–57. https://doi.org/10.1016/j.marpolbul.2015.12.005.

Etkin, D.S., French McCay, D., Horn, M., Landquist, H., Hassellov, I.-M., Wolford, A.J., 2017. Quantification of oil spill risk. In: Spill, Oil (Ed.), Science and Technology Second. Gulf Professional Publishing, Edmonton, pp. 72–183.

Farrington, J. W., & McDowell, J. E. (2004). Mixing Oil and Water,Tracking the sources and impacts of oil pollution in the marine environment. Oceanus, 42(3), 1–4. https://doi.org/10.1037/cou0000094.

Frazão Santos, C., Michel, J., Neves, M., Janeiro, J., Andrade, F., Orbach, M., 2013. Marine spatial planning and oil spill risk analysis: finding common grounds. Mar. Pollut. Bull. 74 (1), 73–81. https://doi.org/10.1016/j.marpolbul.2013.07.029.

Frometa, J., DeLorenzo, M.E., Pisarski, E.C., Etnoyer, P.J., 2017. Toxicity of oil and dispersant on the deep water gorgonian octocoral Swiftia exserta, with implications for the effects of the Deepwater Horizon oil spill. Mar. Pollut. Bull. 122 (1–2), 91–99. https://doi.org/10.1016/j.marpolbul.2017.06.009.

GESAMP (Joint group of experts on the Scientific Aspects of Marine Environmental Protection). (2007). Estimates of oil entering the marine environment from sea-based activities. Reports and studies GESAMP (Vol. 75). London.

Girard, F., Fisher, C.R., 2018. Long-term impact of the Deepwater Horizon oil spill on deep-sea corals detected after seven years of monitoring. Biol. Conserv. 225 (November 2017), 117–127. https://doi.org/10.1016/j.biocon.2018.06.028.

Goldman, R., Biton, E., Brokovich, E., Kark, S., Levin, N., 2015. Oil spill contamination probability in the southeastern Levantine basin. Mar. Pollut. Bull. 91 (1), 347–356. https://doi.org/10.1016/j.marpolbul.2014.10.050.

Guillen, G., Rainey, G., Morin, M., 2004. A simple rapid approach using coupled multivariate statistical methods, GIS and trajectory models to delineate areas of common oil spill risk. J. Mar. Syst. 45 (3–4), 221–235. https://doi.org/10.1016/j.jmarsys.2003.11.006.

Guo, W., 2017. Development of a statistical oil spill model for risk assessment. Environ. Pollut. 230, 945–953. https://doi.org/10.1016/j.envpol.2017.07.051.

Gustafsson, B.G., 2000. Time-dependent modeling of the Baltic entrance area. 1. Quantification of circulation and residence times in the Kattegat and the Straits of the Baltic sill. Estuaries 23 (2), 231–252. https://doi.org/10.2307/1352830.

Hac, B., 2017. Ammunition Risks and Wrecks in the Baltic Sea. In Wrecks as Environmental Risks: The Legal Framework Helsinki, Finland.

Hac, B., Szefler, K., Nowak, J., Gajewski, Ł., Rudowski, S., Kałas, M., 2014. Hazard of Seabed Contamination by Oil Products from Motor Shipwrecks Based on the Example of the Stuttgart Shipwreck. In 1st Meeting of the The HELCOM Expert Group on Environmental Risks of Hazardous Submerged Objects Szczecin, Poland.

Han, Y., Nambi, I.M., Clement, T.P., 2018. Environmental impacts of the Chennai oil spill accident – a case study. Sci. Total Environ. 626, 795–806. https://doi.org/10.1016/j.scitotenv.2018.01.128.

Hassellöv, I.-M. (2007). Förstudie om vraksanering. Gothenburg, Sweden: Alliance for Global Sustainability (AGS).

HELCOM. (2019). Helcom Map And Data Service. Retrieved January 1, 2019, from http://maps.helcom.fi/website/mapservice/?datasetID=720bab94-aad9-47ae-bef7-a9a24865e6e0

Hordoir, R., Axell, L., Loptien, U., Dietze, H., Kuznetsov, I., 2015. Influence of Sea Level Rise on the Dynamics of Salt Inflows in the Baltic Sea. Journal of Geophysical Research, Oceans, pp. 6653–6668. https://doi.org/10.1002/2014JC010299.Received.

International Standardization Organization. (2009). ISO 31000: Risk Management-

Principles and Guidelines.
Jewett, S.C., Dean, T.A., Smith, R.O., Blanchard, A., 1999. “Exxon Valdez” oil spill: impacts and recovery in the soft-bottom benthic community in and adjacent to eelgrass beds. Mar. Ecol. Prog. Ser. 185, 59–83. https://doi.org/10.3354/meps185059.
Ji, Z.-G., Johnson, W.R., Li, Z., 2011. Oil spill risk analysis model and its application to the Deepwater Horizon oil Spill using historical current and wind data. In: Liu, Y., Macfadyen, A., Ji, Z.-G., Weisberg, R.H. (Eds.), Monitoring and Modeling the Deepwater Horizon Oil Spill: A Record-Breaking Enterprise. vol. 195. American Geophysical Union, Washington, DC, pp. 227–236. https://doi.org/10.1029/GM195.
Jiang, J., Wang, P., Lung, W. seng, Guo, L., & Li, M., 2012. A GIS-based generic real-time risk assessment framework and decision tools for chemical spills in the river basin. J. Hazard. Mater. 227–228, 280–291. https://doi.org/10.1016/j.jhazmat.2012.05.051.
Jolma, A., Lehikoinen, A., Helle, I., Venesjärvi, R., 2014. A software system for assessing the spatially distributed ecological risk posed by oil shipping. Environ. Model. Softw. 61, 1–11. https://doi.org/10.1016/j.envsoft.2014.06.023.
Kim, T.-G., Opaluch, J., Moon, D.S.-H., Petrolia, D.R., 2017. Natural resource damage assessment for the Hebei Spirit oil spill: an application of Habitat Equivalency Analysis. Mar. Pollut. Bull. 121 (1–2), 183–191. https://doi.org/10.1016/j.marpolbul.2017.05.064.
Klotz, P., Schloss, I.R., Dumont, D., 2018. Effects of a chronic oil spill on the planktonic system in San Jorge Gulf, Argentina: a one-vertical-dimension modeling approach. Oceanography 31 (4), 81–91.
Kostianoy, A.G., Lebedev, S.A., Litovchenko, K.T., Stanichny, S.V., Pichuzhkina, O.E., 2004. Oil Spill Monitoring in the Southeastern Baltic Sea. In First US-Baltic International Symposium. Klaipeda, Lithuania.
Kostianoy, A., Litovchenko, K., Lavrova, O., Mityagina, M., Bocharova, T., Lebedev, S., ... Pichuzhkina, O., 2006. Operational Satellite Monitoring of Oil Spill Pollution in the Southeastern Baltic Sea: 1.5 Years Experience. In IEEE US/EU Baltic International Symposium Klaipeda, Lithuania.
Kostianoy, A.G., Lavrova, O.Y., Mityagina, M.I., Solovyov, D.M., Lebedev, S.A., 2014. Satellite monitoring of oil pollution in the southeastern Baltic Sea. In: Kostianoy, A.G., Lavrova, O.Y. (Eds.), Oil Pollution in the Baltic Sea. Springer-Verlag, Berlin Heidelberg, pp. 125–153. https://doi.org/10.1007/978-3-642-38476-9.
Lamine, S., Xiong, D.Q., 2013. Guinean environmental impact potential risks assessment of oil spills simulation. Ocean Eng. 66, 44–57. https://doi.org/10.1016/j.oceaneng.2013.04.003.
Landquist, H., 2016. Environmental Risk Assessment of Shipwrecks – Model Development and Application. CHALMERS UNIVERSITY OF TECHNOLOGY.
Landquist, H., Hassellöv, I.M., Rosén, L., Lindgren, J.F., Dahllöf, I., 2013. Evaluating the needs of risk assessment methods of potentially polluting shipwrecks. J. Environ. Manag. 119, 85–92. https://doi.org/10.1016/j.jenvman.2012.12.036.
Landquist, H., Rosén, L., Lindhe, A., Norberg, T., Hassellöv, I.-M., Lindgren, J.F., Dahllöf, I., 2014. A fault tree model to assess probability of contaminant discharge from shipwrecks. Mar. Pollut. Bull. 88, 239–248.
Landquist, H., Rosén, L., Lindhe, A., Hassellöv, I.-M., 2016. VRAKA—A probabilistic risk assessment method for potentially polluting shipwrecks. Frontiers in Environmental Science 4, 1–14.
Landquist, H., Norrman, J., Lindhe, A., Norberg, T., Hassellöv, I.-M., Lindgren, J.F., Rosén, L., 2017a. Expert elicitation for deriving input data for probabilistic risk assessment of shipwrecks. Mar. Pollut. Bull. 125 (1-2), 399–415.
Landquist, H., Rosén, L., Lindhe, A., Norberg, T., Hassellöv, I.M., 2017b. Bayesian updating in a fault tree model for shipwreck risk assessment. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2017.03.033.
Langangen, Ø., Olsen, E., Stige, L.C., Ohlberger, J., Yaragina, N.A., Vikebø, F.B., ... Hjermann, D., 2017. The effects of oil spills on marine fish: implications of spatial variation in natural mortality. Mar. Pollut. Bull. 119 (1), 102–109. https://doi.org/10.1016/j.marpolbul.2017.03.037.
Lee, M., Jung, J.-Y., 2015. Pollution risk assessment of oil spill accidents in GarorimBay of Korea. Marine Pollution Bulletin Journal 100, 297–303. https://doi.org/10.1016/j.marpolbul.2015.08.037.
Lehr, W., Jones, R., Evans, M., Simecek-Beatty, D., Overstreet, R., 2002. Revisions of the ADIOS oil spill model. Environ. Model Softw. 17 (2), 191–199. https://doi.org/10.1016/S1364-8152(01)00064-0.
Li, P., Chen, B., Li, Z., Zheng, X., Wu, H., Jing, L., Lee, K., 2014. A Monte Carlo simulation based two-stage adaptive resonance theory mapping approach for offshore oil spill vulnerability index classification. Mar. Pollut. Bull. https://doi.org/10.1016/j.marpolbul.2014.06.036.
Lindgren, J.F., Hassellöv, I., Dahllöf, I., 2012. Meiofaunal and bacterial community response to diesel additions in a microcosm study. Mar. Pollut. Bull. 64 (3), 595–601. https://doi.org/10.1016/j.marpolbul.2011.12.014.
Lindgren, J.F., Wilewska-Bien, M., Granhag, L., Andersson, K., Eriksson, K.M., 2016. Discharges to the sea. In: Andersson, K., Brynolf, S., Lindgren, J.F., Wilewska-Bien, M. (Eds.), Shipping and the Environment: Improving Environmental Performance in Marine Transportation. Springer-Verlag, Berlin Heidelberg. https://doi.org/10.1007/978-3-662-49045-7.
Liu, Y., Weisberg, R.H., Hu, C., Zheng, L., 2011. Tracking the Deepwater Horizon oil spill: a modeling perspective. EOS Transactions 92 (6).
Liu, X., Guo, M., Wang, Y., Yu, X., Guo, J., Tang, C., ... Li, B., 2016. Assessing pollution-related effects of oil spills from ships in the Chinese Bohai Sea. Mar. Pollut. Bull. 110 (1), 194–202. https://doi.org/10.1016/j.marpolbul.2016.06.062.
Liu, Y., Liu, Y., Li, N., Lou, Y., Zhao, X., 2019. Effect of oil spill stress on fatty acid stable carbon isotope composition of Ulva pertusa. Sci. Total Environ. 649, 1443–1451. https://doi.org/10.1016/j.scitotenv.2018.08.377.
Liubartseva, S., De Dominicis, M., Oddo, P., Coppini, G., Pinardi, N., Greggio, N., 2015. Oil spill hazard from dispersal of oil along shipping lanes in the southern Adriatic and northern Ionian seas. Mar. Pollut. Bull. 90 (1–2), 259–272. https://doi.org/10.1016/j.marpolbul.2014.10.039.
MacFadyen, A., Watabayashi, G.Y., Barker, C.H., Beegle-Krause, C.J., 2011. Tactical modeling of surface oil transport during the Deepwater Horizon spill response. In: Liu, Y., MacFadyen, A., Ji, Z.-G., Weisberg, R.H. (Eds.), Monitoring and Modeling the Deepwater Horizon Oil Spill: A Record-Breaking Enterprise. American Geophysical Union, Washington, DC.
Masetti, G., 2012. A Geo-Database for Potentially Polluting Marine Sites and Associated Risk Index. University of New Hampshire.
Meng, X., Chen, G., Zhu, G., Zhu, Y., 2018. Dynamic quantitative risk assessment of accidents induced by leakage on offshore platforms using DEMATEL-BN. International Journal of Naval Architecture and Ocean Engineering 11 (1), 1–11. https://doi.org/10.1016/j.ijnaoe.2017.12.001.
Michel, J., Gilbert, T., Etkin, D.S., Urban, R., Waldron, J., Blocksidge, C.T., 2005. Potentially Polluting Wrecks in Marine Waters. In International Oil Spill Conference. Miami, USA.
Migliaccio, M., Nunziata, F., Gambardella, A., 2008. Polarimetric Signature for Oil Spill Observation. In IEEE/OES US/EU-Baltic International Symposium, Tallinn, Estonia.
Migliaccio, M., Nunziata, F., Buono, A., 2015. SAR polarimetry for sea oil slick observation. Int. J. Remote Sens. 36 (12), 3243–3273.
Migliaccio, M., Nunziata, F., Buono, A., 2018a. SAR Polarimetry for Effective Sea Oil Slick Observation. In Dragon 4 Mid-term Results Symposium Xian, China.
Migliaccio, M., Nunziata, F., Buono, A., 2018b. SAR Polarimetry for Effective Sea Oil Slick Observation. In 7th IEEE/OES Baltic Symposium Klaipėda, Lithuania.
Nelson, J.R., Grubesic, T.H., 2017. A repeated sampling method for oil spill impact uncertainty and interpolation. International Journal of Disaster Risk Reduction 22, 420–430. https://doi.org/10.1016/j.ijdrr.2017.01.014.
Nelson, J.R., Grubesic, T.H., Sim, L., Rose, K., Graham, J., 2015. Approach for assessing coastal vulnerability to oil spills for prevention and readiness using GIS and the Blowout and Spill Occurrence Model. Ocean Coast. Manag. 112, 1–11. https://doi.org/10.1016/j.ocecoaman.2015.04.014.
Nevalainen, M., Helle, I., Vanhatalo, J., 2018. Estimating the acute impacts of Arctic marine oil spills using expert elicitation. Mar. Pollut. Bull. 131 (April), 782–792. https://doi.org/10.1016/j.marpolbul.2018.04.076.
NOAA, 2000. TAP II User Manual.
NOAA. (2018). ADIOS | Automated Data Inquiry for Oil Spills. Retrieved June 29, 2018, from https://response.restoration.noaa.gov/oil-and-chemical-spills/oil-spills/response-tools/adios.html
Pemberton, P., Löptien, U., Hordoir, R., Höglund, A., Schimanke, S., Axell, L., Haapala, J., 2017. Sea-ice evaluation of NEMO-Nordic 1.0: a NEMO–LIM3.6-based ocean–sea-ice model setup for the North Sea and Baltic Sea. Geosci. Model Dev. 10, 3105–3123.
Price, A.R.G., 1998. Impact of the 1991 Gulf War on the coastal environment and ecosystems: current status and future prospects. Environ. Int. 24 (1/2), 91–96.
Price, J.M., Johnson, W.R., Marshall, C.F., Ji, Z.-G., Raineyà, G.B., 2003. Overview of the Oil Spill Risk Analysis (OSRA) model for environmental impact assessment. Spill Science & Technology Bulletin 8 (5), 529–533. https://doi.org/10.1016/S1353-2561(03)00003-3.
Rekadwad, B.N., Khobragade, C.N., 2015. A case study on effects of oil spills and tar-ball pollution on beaches of Goa (India). Mar. Pollut. Bull. 100 (1), 567–570. https://doi.org/10.1016/j.marpolbul.2015.08.019.
Renner, M., Kuletz, K.J., 2015. A spatial-seasonal analysis of the oiling risk from shipping traffic to seabirds in the Aleutian archipelago. Mar. Pollut. Bull. 101 (1), 127–136. https://doi.org/10.1016/j.marpolbul.2015.11.007.
Rogowska, J., Wolska, L., Namieśnik, J., 2010. Impacts of pollution derived from ship wrecks on the marine environment on the basis of s/s “Stuttgart” (Polish coast, Europe). Sci. Total Environ. 408, 5775–5783.
Rytkönen, J., 2017. Environmental Threats from Wrecks: The Point of View of the Environmental Authorities. In Wrecks as Environmental Risks: The Legal Framework Helsinki, Finland.
Sardi, A.E., Renaud, P.E., Morais, G.C., Martins, C.C., da Cunha Lana, P., Camus, L., 2017. Effects of an in situ diesel oil spill on oxidative stress in the clam Anomalocardia flexuosa. Environ. Pollut. 230, 891–901. https://doi.org/10.1016/j.envpol.2017.07.040.
Sepp Neves, A.A., Pinardi, N., Martins, F., Janeiro, J., Samaras, A., Zodiatis, G., De Dominicis, M., 2015. Towards a common oil spill risk assessment framework - adapting ISO 31000 and addressing uncertainties. J. Environ. Manag. 159, 158–168. https://doi.org/10.1016/j.jenvman.2015.04.044.
Silva, S.J., Carman, K.R., Fleeger, J.W., Marshall, T., Marlborough, S.J., 2009. Effects of phenanthrene- and metal-contaminated sediment on the feeding activity of the harpacticoid copepod, Schizopera knabeni. Arch. Environ. Contam. Toxicol. 56 (3), 434–441. https://doi.org/10.1007/s00244-008-9197-3.
SINTEF. (2014). The OSCAR model. Retrieved November 13, 2017, from https://www.sintef.no/globalassets/upload/materialer_kjemi/faktaark/environment/oscar-fact.pdf
Smith, R.A., Slack, J.R., Wyant, T., Lanfear, K.J., 1982. The oilspill risk analysis model of the U.S. Geological Survey. Retrieved from http://pubs.usgs.gov/pp/1227/report.pdf.
Svensson, E., 2010. Potential Shipwreck Pollution in the Baltic Sea - Overview of Work in the Baltic Sea States (35pp). Swedish Maritime Administration (Ref 09-02375).
Szczybelski, A.S., Kampen, T., Vromans, J., Peeters, E.T.H.M., van den Heuvel-Greve, M.J., van den Brink, N.W., Koelmans, A.A., 2018. Avoidance tests as a tool to detect sublethal effects of oil-impacted sediments. Environ. Toxicol. Chem. 37 (6), 1757–1766. https://doi.org/10.1002/etc.4129.
Tornero, V., Hanke, G., 2016. Identification of marine chemical contaminants released from sea-based sources. Luxembourg. https://doi.org/10.2788/258216.
Troisi, G., Barton, S., Bexton, S., 2016. Impacts of oil spills on seabirds: unsustainable impacts of non-renewable energy. Int. J. Hydrog. Energy 41 (37), 16549–16555.

https://doi.org/10.1016/j.ijhydene.2016.04.011.
Uiboupin, R., Raudsepp, U., Sipelgas, L., 2008. Detection of Oil Spills on SAR Images, Identification of Polluters and Forecast of the Slicks Trajectory. In IEEE/OES US/EU-Baltic International Symposium, Tallinn, Estonia.
Valentine, D.L., Fisher, G.B., Bagby, S.C., Nelson, R.K., Reddy, C.M., Sylva, S.P., Woo, M.A., 2014. Fallout plume of submerged oil from Deepwater Horizon. Proc. Natl. Acad. Sci. U. S. A. 111 (45), 15906–15911. https://doi.org/10.1073/pnas.1414873111.
Weisberg, R.H., Zheng, L., Liu, Y., 2017. On the movement of Deepwater Horizon oil to northern gulf beaches. Ocean Model. 111, 81–97. https://doi.org/10.1016/j.ocemod.2017.02.002.
Xie, Y., Zhang, X., Yang, J., Kim, S., Hong, S., Giesy, J.P., ... Khim, J.S., 2018. eDNA-based bioassessment of coastal sediments impacted by an oil spill. Environ. Pollut. 238, 739–748. https://doi.org/10.1016/j.envpol.2018.02.081.
Yang, Z., Shah, K., Laforest, S., Hollebone, B.P., Lambert, P., Brown, C.E., ... Goldthorp, M., 2018. A study of the 46-year-old arrow oil spill: persistence of oil residues and variability in oil contamination along Chedabucto Bay, Nova Scotia, Canada. J. Clean. Prod. 198, 1459–1473. https://doi.org/10.1016/j.jclepro.2018.07.112.
Zelenke, B., O'Connor, C., Barker, C., Beegle-Krause, C.J., Eclipse, L., 2012. General NOAA Operational Modeling Environment (GNOME). Technical Documentation, Seattle.
Zhang, B., Matchinski, E.J., Chen, B., Ye, X., Jing, L., Lee, K., 2019. Marine oil spills—oil pollution, sources and effects. In: Sheppard, C. (Ed.), World Seas: an Environmental Evaluation (Second Edi, pp. 391–406). Elsevier Ltd.. https://doi.org/10.1016/B978-0-12-805052-1.00024-3.
Zodiatis, G., De Dominicis, M., Perivoliotis, L., Radhakrishnan, H., Georgoudis, E., Sotillo, M., ... Mancini, M., 2016. The Mediterranean decision support system for marine safety dedicated to oil slicks predictions. Deep-Sea Research Part II: Topical Studies in Oceanography 133, 4–20. https://doi.org/10.1016/j.dsr2.2016.07.014.