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Probability of a ship becoming beset in ice along the Northern Sea Route – A Bayesian analysis of real-life data

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ABSTRACT

Ships operating in ice-infested Arctic waters are exposed to a range of ship-ice interaction related hazards. One of the most dangerous of these is the possibility of a ship becoming beset in ice, meaning that a ship is surrounded by ice preventing it from maneuvering under its own power. Such a besetting event may not only result in severe operational disruption, but also expose a ship to severe ice loading or cause it to drift towards shallow water. This may cause significant structural damage to a ship and potentially jeopardize its safety. To support safe and sustainable Arctic shipping operations, this article presents a probabilistic approach to assess the probability of a ship becoming beset in ice. To this end, the proposed approach combines different types of data, including Automatic Identification System (AIS) data, satellite ice data, as well as data on real-life ship besetting events. Based on this data, using a hierarchical Bayesian model, the proposed approach calculates the probability of a besetting event as a function of the Polar Ship Category of a ship, sea area, and the distance travelled in the prevailing ice concentration. The utility of the proposed approach, e.g. in supporting spatiotemporal risk assessments of Arctic shipping activities as well as Arctic voyage planning, is demonstrated through a case study in which the approach is applied to ships operating in the Northern Sea Route (NSR) area. The outcomes of the case study indicate that the probability of besetting is strongly dependent on the Polar Ship Category of a ship and that the probability increases significantly with higher ice concentrations. The sea area, on the other hand, does not appear to significantly affect the probability of besetting.

1. Introduction

1.1. Background

Maritime activity in the Arctic is increasing due to multiple factors. For a start, the Arctic holds some of the world's largest remaining oil and gas reserves (Gautier et al., 2009). Today, the extraction of these resources generates a significant volume of so-called destination-Arctic shipping, i.e. the shipping of cargo from the Arctic to non-Arctic destination. Over the next decades, driven by new oil and gas developments such as the Arctic LNG 2 project, this type of shipping is expected to increase significantly (Total S.A., 2019). *trans*-Arctic shipping is another type of Arctic shipping in which cargo is transported between non-Arctic destinations through Arctic waters. In comparison with a conventional non-arctic route, trans-Arctic shipping might offer a range of advantages, perhaps the most important of which is savings in distance. For instance, for shipping between Northern Europe and the Far East, in comparison with the conventional route through the Suez channel, trans-Arctic shipping along the Northern Sea Route (NSR) offers an up to 40% shorter distance. Because such savings in distance could potentially be translated into significant savings in transport time, costs, and emission, the use of the NSR is being promoted by among others China

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and Russia (Serkez et al., 2018). A third factor driving Arctic maritime activity is a strong interest in Arctic cruises and tourism (Wright, 2018).

Despite recent advances in science and technology, Arctic maritime activity is still a risky endeavour, subject to multiple hazards including sea ice, icing, low temperatures, darkness, remoteness, the lack of relevant crew experience, and difficult weather conditions (IMO, 2015). Among the ship-ice interaction related hazards, one of the most dangerous is the risk of a ship becoming beset in ice. Beset in ice means that a ship is surrounded by ice preventing it from maneuvering under its own power. Naturally, such a besetting event might cause significant operational disruption and delays (Turnbull et al., 2019). In the worst case, a besetting event might cause structural damage and jeopardize the safety of a ship by exposing it to severe ice loading or cause it to drift towards shallow water. Such besetting related risks and uncertainties are considered a major challenge for commercial Arctic shipping (Guy, 2006; Marken et al., 2015).

In addition to a ship's ice-going capability, numerous external factors may contribute to the probability of a ship becoming beset in ice, including the prevailing ice thickness and concentration, the occurrence of pressured ice conditions, and the degree of ice ridging (e.g. ridge thickness or height, ridge density) (Kubat et al., 2012). The ice conditions (e.g. occurrence of pressured ice), depend in turn on factors such as the speed and direction of the prevailing wind and sea currents, as well as on the presence of geographical boundaries such as a shoreline. Due to the stochastic interaction between these factors, ice besetting events occur stochastically.

To support safe and sustainable Arctic shipping operations, this article presents a probabilistic approach to assess the probability of a ship becoming beset in ice. The presented approach is based on research addressing the following research questions: Is it feasible to obtain new and relevant information to support the assessment of the probability of besetting events by combining Automatic Identification System (AIS) data, satellite ice data, and real-life data on ice besetting events? If so, what does the obtained data indicate about the probability of a ship becoming beset in ice?

Our approach is applicable to any ice-infested sea area for which relevant data is available. However, in this study, we apply our approach to sea areas along the Northern Sea Route (NSR), including the Kara Sea, the Laptev Sea, and the East Siberian Sea. The considered Arctic shipping related data covers the period 2013–2017.

1.2. Related studies

Previous studies on ship ice besetting events have mainly been related to ship operations in the Baltic Sea and the Canadian Arctic. Kubat et al. (2012) studied two separate ship ice besetting events in the Canadian Arctic to identify and specify critical besetting criteria, among others. One of the besetting events involved a general cargo ship, the other involved a tanker. For the studied besetting events, the study specified besetting criteria in terms of lateral ice pressure [kN/m] and prevailing ridge height [m]. Turnbull et al. (2019) studied two specific ice besetting events experienced by an individual ice-breaking bulk carrier operating in the Labrador Sea in the Canadian Sub-Arctic. Specifically, the study analysed the role of factors that may have contributed to the occurrence of the besetting events, including the ship's distance to the nearest coastline, the prevailing wind conditions (e.g. wind speed and wind direction relative to the nearest coastline), sea currents, and ice conditions (e.g. ice concentration and thickness, ice floe size). The outcome of their analysis suggests that the primary cause of the two studied besetting events was the presence of large ice floes (the majority of the floes present during the besetting events were greater than 6 km in diameter) in combination with the presence of wind and sea currents. Although the studies by Kubat et al. (2012) and Turnbull et al. (2019) both provide valuable insights into the topic of ship ice besetting, it appears difficult to generalize their applicability to other types of ships and operations.

Montewka et al. (2015) presented a probabilistic Bayesian Belief Networks based approach for the prediction of a ship's performance in dynamic sea ice. Their approach combines two full-scale datasets: AIS data describing the real-life performance of an unassisted bulk-carrier operating on the Baltic Sea in difficult ice conditions, and a numerical description of the ice field in which the ship operated. Multiple factors contributing to the probability of a besetting event are considered, including level ice thickness, ice concentration, degree of ice ridging, rafted ice characteristics, and ice compression, among others. Another Bayesian Belief Networks based approach was presented by Fu et al. (2016). In their study, the probability of a ship becoming beset in ice along the NSR is assessed considering navigation data from an individual ship operating along the NSR, as well as expert knowledge. They found that the most important factors influencing the probability of the studied ship becoming beset in ice are ice concentration, wind speed, and sea temperature, followed by ice thickness, ship speed, visibility, and engine power. A limitation of both of the above-mentioned Bayesian Belief Networks based approaches is that they are validated only for the studied ships and operating conditions.

An alternative to data-based approaches is presented by Kuuliala et al. (2017). In their approach, the probability of a ship becoming beset in ice when operating through a ridge field is assessed using a transit simulation-based approach in which individual geometrical features of a ridge field (e.g. ridge sail heights, ridge keel depths, and ridge spacings) are assumed to follow specific distributions. During a simulation, different ridge fields are generated stochastically by drawing random numbers from the distributions. The probability of a ship becoming beset in ice is then obtained by dividing the number of simulation runs in which a ship gets stuck in ridges by the total number of simulation runs. Given enough statistical data based on which the topography of an ice field can be accurately modelled, this approach appears effective. However, for application over extensive distances along the NSR, the effectiveness of the approach is questionable primarily due to the limited availability of up-to-date and reliable statistics on ice field geometries in the area (Bergström et al., 2017). Also, the approach depends on empirical formulations for ship-ice ridge field resistance, which are not validated for all types of ships and operations.

Issues related to ship besetting in ice have also been studied by model scale testing. For instance, Külaots et al. (2013) conducted ice tank tests to study the resistance of an ice-going general cargo ship operating in a compressive ice channel. Among others, they found that the presence of broken ice rubble has a great influence on the total resistance of the studied ship, and that it therefore may affect the probability of the ship getting stuck in ice.

Some previous studies have demonstrated that AIS data can be used to study ice navigation operations. For example, Kotovirta et al. (2009) and Lensu and Goerlandt (2019) used AIS data for route optimization in ice-covered waters, Winther et al. (2014) used AIS data to model emissions from Arctic shipping, and Goerlandt et al. (2017) and Valdez Banda et al. (2016) used AIS data for the analysis of winter navigation-related accidents in the Baltic Sea. Moreover, Sormunen et al. (2018) and Similä and Lensu (2018) used AIS data for the analysis of real-life speed of ships engaged in ice navigation on the Baltic Sea. However, there are no earlier studies on besetting events along NSR and our work is the first to provide holistic analysis of besetting events and AIS data over several Polar Ship Categories and ship routes.

2. Materials and methods

2.1. Compiling data on Arctic shipping operations

Data on the distance and time that different types of vessels operate in different ice conditions and regions was extracted through a specific process outlined in Fig. 1. The subtasks of this extraction process are described in the following.

The process starts by defining the *User input* in terms of the period, region, and vessel type(s) to be considered in the analyses. Based on the

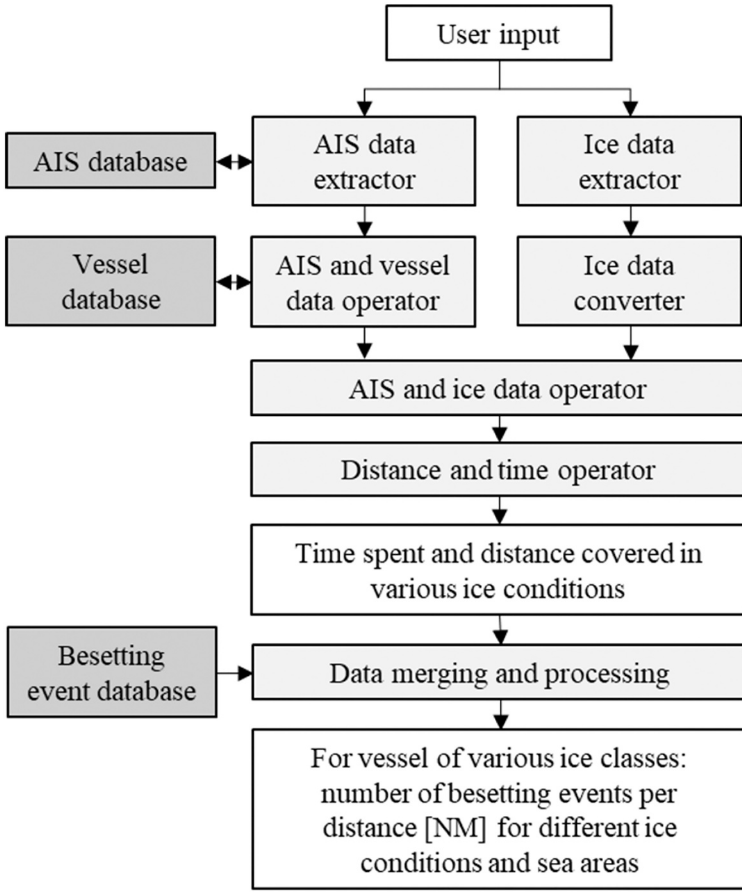

Fig. 1. The general process for compiling data on Arctic shipping operations and besetting events. The grey boxes denote databases, light grey boxes denote data processing steps and white boxes denote user defined inputs and outputs of the processes.

user input, relevant AIS data is extracted from an *AIS database* by *AIS data extractor* sub-process. The *AIS database* includes AIS data collected from the Norwegian Coastal Administration (2019). For this study, we extracted AIS data covering the whole Arctic region over the studied period 2013–2017. The contents of AIS data are presented in Sec. 2.1.1. For each vessel included in the selected AIS data, based on the vessel's MMSI number, the *AIS and vessel data operator* searches a *Vessel database* for additional vessel-specific data (e.g. ship type, ice class, and gross tonnage). *The vessel database* includes data from MarineTraffic (2019), RS (2019), and DNV GL (2019). For the defined region and period, the *Ice data extractor* extracts relevant satellite ice data from an external database with *Satellite ice data* in the form of ice charts determined based on measurements by the CryoSat-2 satellite (Francis et al., 2010). Additional information on the ice data used in this study is presented in Section 2.1.2. Utilizing a color detection method that identifies pixels in an image that matches a specified color or color range, the *Ice data converter* converts extracted ice charts into data matrices containing information on ice concentration. Based on the selected and processed ice and AIS data, for all considered vessel (AIS) coordinates, the *AIS and ice data operator* determines the presence of sea ice in a binary fashion as 'ice' or 'no ice'.

The *Distance and time operator* calculates both the elapsed time as well as the great-circle distance between consecutive AIS positions by the Haversine formula. All coordinate points where a vessel's speed over ground is non-zero are considered. In some cases, this means that the interval between consecutive AIS signals from a ship is as low as 3 s, resulting in a high number of calculations. However, the consideration of all data points is warranted as it minimizes the calculation error for ships operating in areas with locally varying ice conditions. As an outcome of these calculations, ships' time spent and distance travelled in various ice concentrations is obtained. In the *Data merging and processing* step, this data is then merged with data from the *Besetting event database,* which is described in Sec. 2.1.3. As an outcome of this step, a data matrix is obtained that contains information on the total distance (NM) travelled by ships of different categories in different ice concentrations and sea areas, as well as the corresponding number of besetting events.

2.1.1. *AIS data*

The International Convention for the Safety of Life at Sea (SOLAS) requires Automatic Identification System (AIS) to be fitted on all ships larger than 300 GT and all passenger ships built on or after the 1st of July 2002 (IMO, 2019a, 2019b). AIS is a ship communication and tracking system originally developed as a collision-avoidance system. The system is based on the Global Positioning System (GPS) and Very High Frequency (VHF) technology. A vessel fitted with an AIS system sends out frequent AIS signals, each of which contains a set of data as listed by Table 1.

2.1.2. *Ice data*

The ice data used in this study originate from Cavalieri et al. (1996), updated yearly). These data are generated from brightness temperature data derived from satellite measurements. Specifically, the data originate from the following sensors: the Nimbus-7 Scanning Multichannel Microwave Radiometer (SMMR), the Defence Meteorological Satellite Program (DMSP) —F8, —F11 and —F13 Special Sensor Microwave/Imagers (SSM/Is), and the DMSP-F17 Special Sensor Microwave Imager/Sounder (SSMIS) (Cavalieri et al., 1996, updated yearly). The data indicate the daily average sea ice concentrations (the percentage of ocean area covered by sea ice) and they are provided in binary format at a grid cell size of 25 × 25 km. According to Cavalieri et al. (1992), the

Table 1
Contents of AIS-data (MarineTraffic, 2019).

Type of data	Description
Maritime mobile service identity (MMSI)	A nine-digit unique identification number used in radio communication to identify ships
AIS navigational status	E.g., "at anchor", "under way using engine(s)", "not under command", etc.
Rate of turn	Right or left (0 to 720° per minute)
Speed over ground (SOG)	Speed [knots] of the ship over ground at given time
Position coordinates	Latitude/Longitude - up to 0.0001 min accuracy
Course over ground (COG)	Course of the ship over ground at given time relative to true north (up to 0.1° relative to true north)
True heading	0 to 359°
Bearing at own position	0 to 359°
Coordinated Universal Time (or UTC)	Data and time of the ship in the format [YYYY]-[MM]-[DD] [hh]:[mm]:[ss]

accuracy of the measurements varies depending on sea ice conditions. In general, the accuracy of total sea ice concentration is within $+/-$ 5% in winter and $+/-$ 15% in the Arctic during summer when melt ponds are present on the sea ice.

2.1.3. Besetting event database

The considered data on ship ice besetting events cover 58 besetting events that occurred in the NSR area in the period 2013–2017. Most of the data originate from NSRA (2020), which provides publicly available information on the movements of vessels in the NSR area. Additional information on individual besetting events were obtained from the Russian maritime news site Mortrans.info (2020). Potential duplicate data were removed. In general, the applied data on besetting events can be considered reliable as most of it originates from icebreaker logbooks. However, some uncertainty arises from individual cases where it is not clear whether a ship is beset in ice, or if it has simply stopped at sea (e.g. to wait for icebreaker assistance).

2.1.4. Ice class categories

Different ice class standards are determined by different maritime administrations and classification societies. In this study, along the lines of the Polar Code (IMO, 2015), ships are divided into three Polar Ship Categories (A - C) based on their ice class. The Polar Class standards are determined as per IACS (2016). Other ice classes and their equivalency to the Polar Class standards are determined as per Table 2 along the lines of Nyseth and Bertelsen (2014), Traficom (2017), and DNV GL (2020).

2.3. Statistical analysis

We analysed the besetting event data with a hierarchical statistical model using the Bayesian approach (Gelman et al., 2013). The Bayesian approach for data analysis is model-based so that we first build a model that describes the process behind the besetting events and then use probability calculus to summarize the information that the data contains about the model parameters in terms of a posterior probability distribution. The benefit of the Bayesian approach is that it explicitly quantifies the uncertainties in the model parameters, conditional on observed data and model assumptions, and allows us to predict the probability of besetting for ships operating in different ice conditions. With these predictions, we can then, among others, compare the risk that a ship becomes beset along various navigation routes.

Table 2
Equivalency of Polar Ship Categories used in the study to Polar Classes and other ice classes.

Polar ship category	Polar class (PC)	Roughly equivalent ice classes
Category A	PC 1–5	Icebreaker9, Icebreaker8, Icebreaker7, Icebreaker6, LL1, LL2, LL3, Arc7, Arc6, ULA
Category B	PC 6–7	E3, E4, Arc5, Arc4, UL, LU5, IAA, A1, 1A, 1A Super, L1
Category C	Below PC 7	E2, E, Ice1, Ice2, Ice3, L4, L3, L2, 1D, 1C, IB, B, DNV ICE-10 IB

We built the model using the classical exponential model for event distribution, which has been used for ship and traffic accident modelling for example in McCullagh and Nelder (1989). That is, we assumed that the rate of besetting events of a ship of Category c (see Table 2) is described by a besetting rate parameter $\lambda_c(x,a) > 0$ which equals the expected number of besetting events when a ship of Category c travels a unit distance (nautical mile) in ice concentration x and sea area a. We discretized the sea ice concentration into ten classes $\{0-10\%, 10-20\%, \ldots, 90-100\%\}$. Due to the properties of the exponential model, the probability that a ship of Category c becomes beset within a distance $d(x,a)$ in ice conditions x in sea area a is

$$\pi(d,x,a,c) = Pr(\text{besetting}|d(x,a),\lambda_c(x,a)) = 1 - e^{-d(x,a)\times\lambda_c(x,a)}$$

so that the probability increases with distance and goes towards 100% (see Fig. 5). The underlying assumption in the exponential model is that besetting events are mutually independent and that they occur continuously along the shipping route at a rate given by $\lambda_c(x)$. Further, the model is memoryless so that the probability of a besetting event along a specific distance does not depend on whether a besetting event occurred over an earlier distance. We modelled the rate parameter with a log-linear model

$$log\lambda_c(x) = \tilde{\lambda}_c + \beta_c x + \delta_a$$

where $\tilde{\lambda}_c$ is the log baseline rate corresponding to 0–10% ice concentration, β_c is the Polar Ship Category specific weight for ice concentration and δ_a is the sea area-specific adjustment to the log rate. The area-specific adjustment accounts for possible differences between sea areas in the besetting rate that cannot be accounted for by ice concentration; these could be, for example, navigational or environmental factors that would increase or decrease the probability of a besetting event. Hence, the besetting rate increases exponentially with ice concentration, and the rate of increase depends on a ship's Polar Ship Category.

Since we apply the Bayesian approach to model inference, we give prior distributions for the model parameters. Both the log baseline rate and the Polar Ship Category -specific linear weights were given hierarchical Gaussian priors such that

$$\tilde{\lambda}_c \sim N(\mu_\lambda, \sigma_\lambda^2)$$

where $\mu_\lambda \sim N(0,10)$ and $\sigma_\lambda^2 \sim \text{Student} - t_+(\nu = 4, \mu = 0, s^2 = 2)$, and

$$\beta_c \sim N(\mu_\beta, \sigma_\beta^2)$$

where $\mu_\beta \sim N(0,10)$ and $\sigma_\beta^2 \sim \text{Student} - t_+(\nu = 4, \mu = 0, s^2 = 2)$. These hierarchical priors provide shrinkage for the log baseline rates and linear weights towards a common mean of all Polar Ship Categories. The parameter μ_λ corresponds to the average log besetting rate for all vessel categories in ice concentration 0–10% and μ_β corresponds to the average effect of increasing ice concentration over all vessel categories. The vague Gaussian priors with large variance encode prior ignorance on the actual value of the parameters but if prior information on besetting rates was available, we could give them informative priors as well. The sea area-specific adjustment was modelled as a zero mean random effect with

$$\delta_a \sim N(0, \sigma_a^2)$$

where $\sigma_a^2 \sim \text{Student} - t_+(\nu = 4, \mu = 0, s^2 = 1)$.

The exponential distribution implies Poisson distribution for the number of besetting events within a given distance (McCullagh and Nelder, 1989). Hence, the model for the number of besetting events is

$$y(c,x,a) \sim \text{Poisson}(d(c,x,a) \times \lambda_c(x,a))$$

where $y(c,x,a)$ is the total number of besetting events and $d(c,x,a)$ the total distance travelled by ships of Category c in ice concentration x in sea area a. Given the data on besetting events (Section 2.1) and setting $\lambda_c(x) = e^{\widetilde{\lambda_c}+\beta_c x+\delta_a}$ into above equation we can calculate the posterior distribution for the model parameters with density function

$$p\left(\beta,\lambda,\delta,\sigma_\beta^2,\sigma_\lambda^2,\sigma_a^2,\mu_\lambda,\mu_\beta|y,d\right)$$
$$\propto p\left(\beta,\lambda,\sigma_\beta^2,\sigma_\lambda^2,\mu_\lambda,\mu_\beta\right)\prod_c\prod_x\prod_a \text{Poisson}\left(y(c,x,a)\,|d(c,x,a)\times e^{\widetilde{\lambda_c}+\beta_c x+\delta_a}\right)$$

where $\boldsymbol{y}$ and $\boldsymbol{d}$ collect all the data on the number of besetting events and distances travelled in different ice conditions, $\beta = [\beta_A,\beta_B,\beta_C]$ and $\lambda = \left[\widetilde{\lambda}_A,\widetilde{\lambda}_B,\widetilde{\lambda}_C\right]$ are the vectors of Polar Class Category-specific parameters for Polar Ship Categories $c \in \{A,B,C\}$ and δ is a vector of sea area-specific random effects. The posterior distribution was estimated by using the Markov chain Monte Carlo (MCMC, (Gelman et al., 2013)). We used R (R Core Team, 2017) and the Stan probabilistic programming language (Carpenter et al., 2017) to conduct the sampling.

The posterior distribution for the model parameters induces posterior distribution for the besetting probability parameter, with density function $p(\pi(d,x,c,a)|\boldsymbol{y},\boldsymbol{d})$, for a ship of Polar Ship Category c when it travels distance $d(x,a)$ in ice conditions x in sea area a. This posterior distribution summarizes the information (with explicit uncertainty estimates) about besetting probability contained in our data. After obtaining MCMC samples from the posterior distribution for the model parameters we estimated the posterior distribution of the besetting probability with Monte Carlo by using the posterior samples of $\widetilde{\lambda}_c$, β_c and δ_a. In order to illustrate the extension of the model to practical risk analysis, we calculated the besetting probability for five commercial traffic routes in the Kara Sea (Liu and Kronbak, 2010) under the typical ice conditions in three different seasons: spring, summer, and fall. Winter was excluded from these predictions since commercial transport traffic in winter is currently negligible. The seasons are not always straightforward to define in the Artic context so we followed the definition of Helle et al. (2020). They analysed environmental oil spill risks in the Kara Sea and defined the seasons based on the ecological processes relevant to the Arctic so that they are meaningful entities from the ecological point of view. Hence, we defined spring as March–June, summer as July–September, and autumn as October–November.

In the supplementary material, we provide the data and an RMarkdown document and its pdf output implementing all the analyses and results presented in this work.

3. Results

3.1. Extracted data

Following the process described in Sec. 2.1, data on Arctic shipping operations were extracted for the period 2013–2017. The obtained data, which are summarized in Fig. 2, indicate the annual cumulative distance within the NSR area for ships of various Polar Ship Category. Annual cumulative distances are further split between total distance in open water and total distance in ice. Distance in ice refers to operations in ice-infested waters with an ice concentration above 5%.

Based on the data the following can be concluded. Firstly, in general, ship operations within the NSR area show growing trend. Secondly, the annual distance that ships travel in ice tends to increase with the Polar Ship Category so that the largest distance is covered by ships of Category A. Thirdly, ships of a higher Polar Ship Category tend to operate in ice of a higher concentration than ships of a lower category (see supplementary material for details). As shown in the supplementary material, for all Polar Ship Categories, the number of besetting events increased with increasing ice concentration.

3.2. Statistical analysis

Posterior distributions for the model parameters are presented in Fig. 3. As per Fig. 3A, the log baseline rate (log rate at ice concentration 0–10%, $\widetilde{\lambda}_c$) of besetting events is higher for ships of a lower Polar Ship Category. As per Fig. 3B, for all ship categories, the rate of besetting events increases with higher ice concentration, but the increase is faster for ships of lower Polar Ship Category. These findings indicate that the lower the Polar Ship Category, the higher the probability that a ship experiences a besetting event. As per Fig. 3C, there is no noticeable difference in besetting event rates between the Laptev Sea, the Kara Sea and the East Siberian Sea.

The above findings are also reflected in Fig. 4, which presents predictions for the expected number of besetting events for different Polar Ship Categories and ice concentrations. The expected number of ice besetting events per 1000 NM is the highest for ships of Category C and lowest for ships of Category A, with an approximately 10-fold increase between consecutive categories. Fig. 4 also presents the raw besetting rates as calculated from the data. These match considerably well with the central 95% posterior probability intervals of the model predictions for category B and C ships, indicating that the model fits these data well. Most of the raw besetting rates of Category A ships are zero, for which reason many of them are at the boundaries of or outside the central 95% posterior interval of the predicted besetting rate.

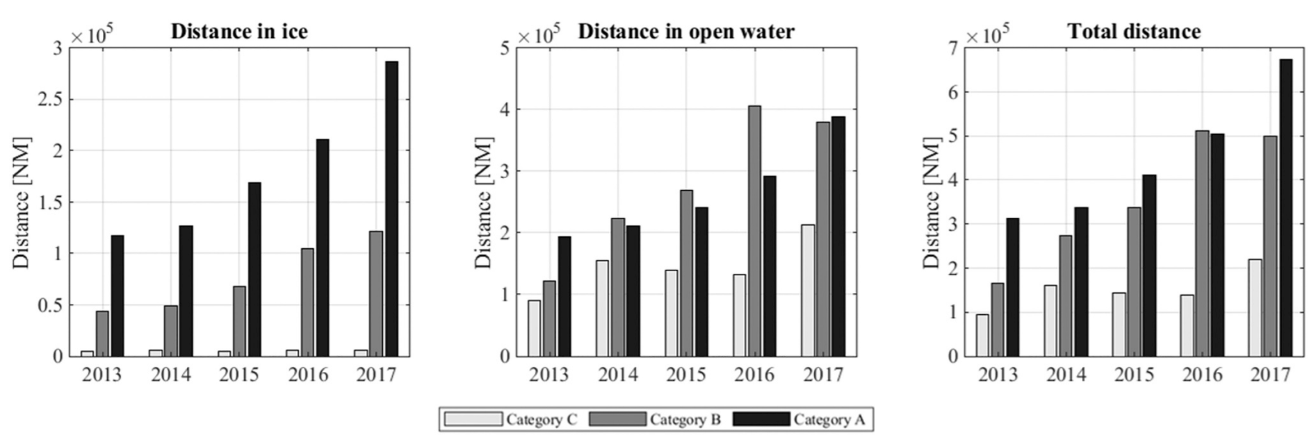

Fig. 2. Cumulative distance covered (NM) along the NSR in 2013–2017 by ships of various polar class categories. Distance in ice refers to operations in ice-infested waters with an ice concentration above 5%.

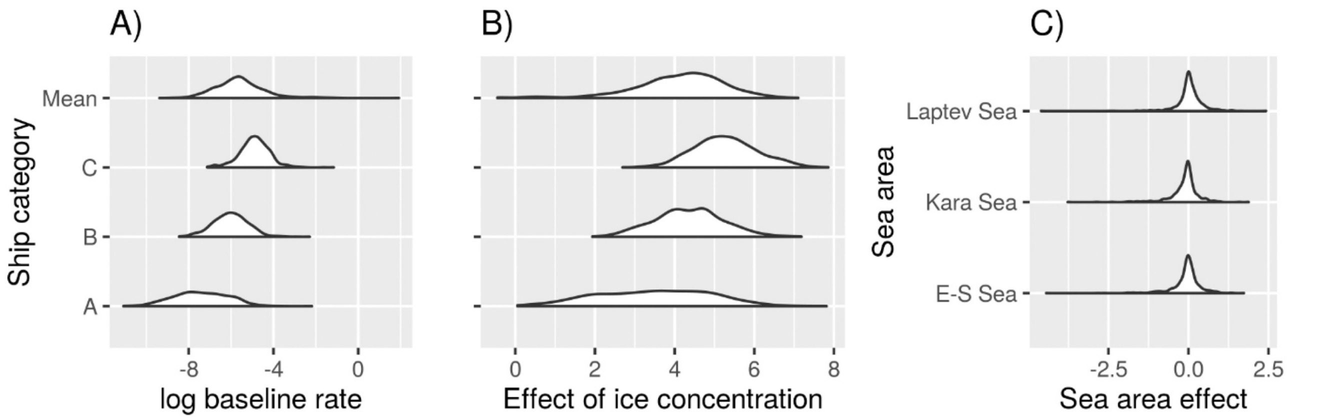

Fig. 3. Posterior distributions of model parameters. A) The posterior distributions of the log baseline rate (log rate at ice concentration 0–10%, $\widetilde{\lambda}_c$) for each of the Polar Ship Categories as well as for the mean over the three categories (μ_λ). B) The posterior distributions of the effect of ten percentage units increase in ice concentration to the log rate (β_c) for each Polar Ship Category as well as their mean (μ_β). C) The effect of the sea area to the log rate where *E*-S Sea denotes the East-Siberian Sea.

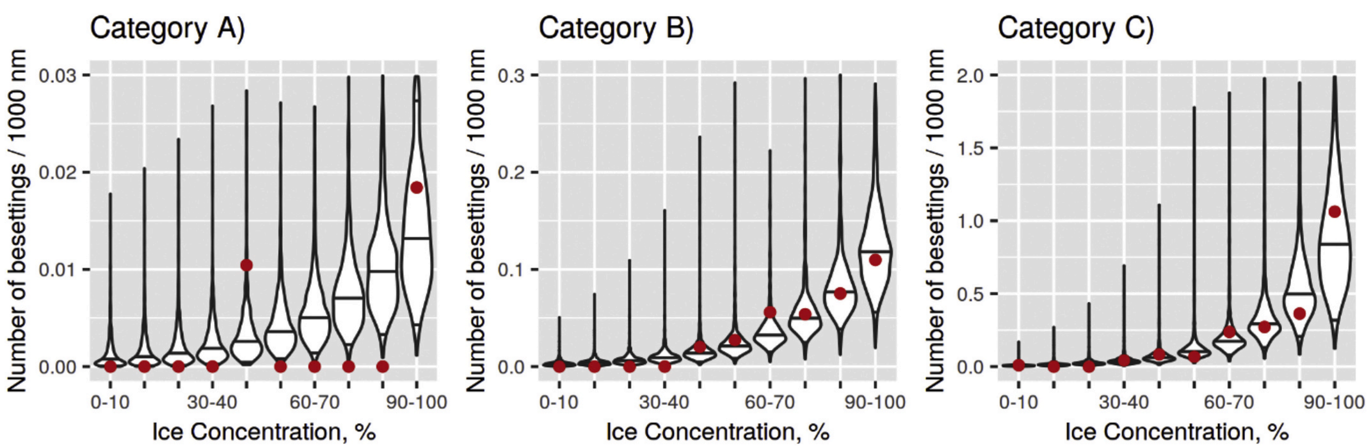

Fig. 4. Frequency of besetting events as a function of ice concentration for different Polar Ship Categories. The violin plots show the shape of the posterior predictive distribution and the horizontal lines show the median and central 95% probability interval of the posterior distribution. The red dots show the raw besetting rates as determined directly from the data.

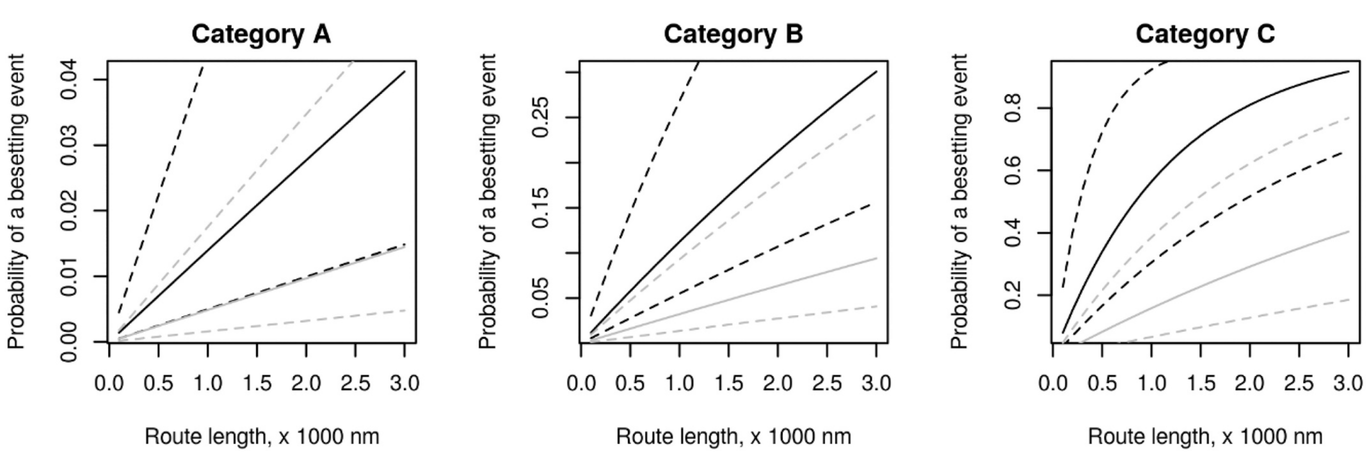

Fig. 5. The probability of a besetting event as a function of distance travelled in 60–70% (grey lines) and 90–100% (black lines) ice concentration. The solid line shows the posterior mean and the dashed lines the central 95% posterior probability interval for π.

Based on the above findings, in Fig. 5 we determine the probability of a besetting event (π) as a function of a ship's distance travelled in ice of two different concentrations: 60–70% and 90–100%. Other ice concentrations are considered in the supplementary material. The probability of a besetting event is significantly dependent on a ship's Polar Ship Category. For example, for a distance of 3000 NM, the probability of a besetting event for a ship of Category C is approximately three times higher than that for a ship of Category B, and approximately 20 times higher than that for a ship of Category A.

In our case study, we used the above-calculated probabilities to predict the probability of a besetting event for five commercial traffic routes on the Kara Sea and for three different seasons: spring (March-June), summer (July-September) and autumn (October-November). As per the results presented in Fig. 6 (Category A ship) and Section 3 in the supplementary material (Category B and C ships), the probability of a besetting event may vary significantly between different routes and seasons. The probabilities follow ice concentration being the highest in spring and the lowest in summer. In autumn the probabilities are higher in coastal than in open sea region.

4. Discussion

The proposed approach differs fundamentally from previously proposed approaches to assess the probability of ship besetting in ice, including Kubat et al. (2012), Montewka et al. (2015), Fu et al. (2016), (Montewka et al., 2018) and Turnbull et al. (2019). Instead of aiming to determine a detailed model validated for a small number of real-life besetting events, the approach aims to determine a rough but general assessment of the probability of a besetting event. As such, the approach is thought to be useful, especially for the planning of Arctic maritime operations (e.g. to roughly assess the operational uncertainty) and risk assessment. This is relevant, for instance, in the context of the Polar Code (IMO, 2015), which requires an Operational Assessment to be carried out for ships operating in the Arctic. The Operational Assessment should include a risk model considering potential accident scenarios. As per IMO (2015), the frequency and consequences of different accident scenarios can be assessed based on available data and expert judgement. The approach proposed in this article may support this process. Also, the presented data collection approach in which AIS data, satellite ice data, ship data, and accident data are collected and merged is new and applied for the first time in this study. We believe that the approach is not only relevant for the assessment of the probability of ice besetting but that it could also be applied for a range of purposes related to the analysis of winter navigation systems and operations.

The strength of our approach is that the analyses are primarily based on readily available (even though somewhat laboriously collectable) data. However, this poses some limitations to our approach. First, the AIS and ship data include important information on several factors such as the speed, position, and technical characteristics of ships. However, they do not include any information on how ships are operated (e.g. the competency of their crew). Second, in the present study, the considered technical characteristics of ships are limited to the Polar Ship Category. Other information related to a ship's ice-going capability (e.g. hull form, machinery power, propulsion system) is not considered. Third, the satellite ice data provide information on the prevailing ice concentration in an area, but they do not include any information on other important sea ice characteristics such as ice thickness, ice ridging, and the possible presence of compressive ice. The occurrence of compressive ice, in turn, depends among others on the prevailing wind and sea currents, which are also not considered in the present study. Fourth, the applied besetting data is based on real-life events and can be considered reliable. However, it does not include details on the exact circumstances around a besetting event. Also, because the data is historical, it does not consider the possible effects of new ship technology and navigation support systems.

Hence, additional variables such as ice thickness, ice type, and wind can be considered in future studies, if the needed data are possible to obtain directly, or to derive from other data. The consideration of additional variables may result in somewhat different results. For instance, for a given ice concentration range (e.g. 90–100%), the severity of the overall ice conditions might vary significantly depending on, among others, the ice thickness and level of ice ridging. If we consider operation in a specific ice concentration range, it is probable that ships of, for instance, Category A operate on average in overall worse ice conditions than ships of Category C. This means that if we would consider the overall operating conditions instead of simply ice concentration, differences between the obtained besetting rates of ships of different Polar Ship Categories would likely change.

We did not account for possible errors in the data itself in our study. As mentioned in Sec. 2.1.3, concerning the besetting data, in some cases

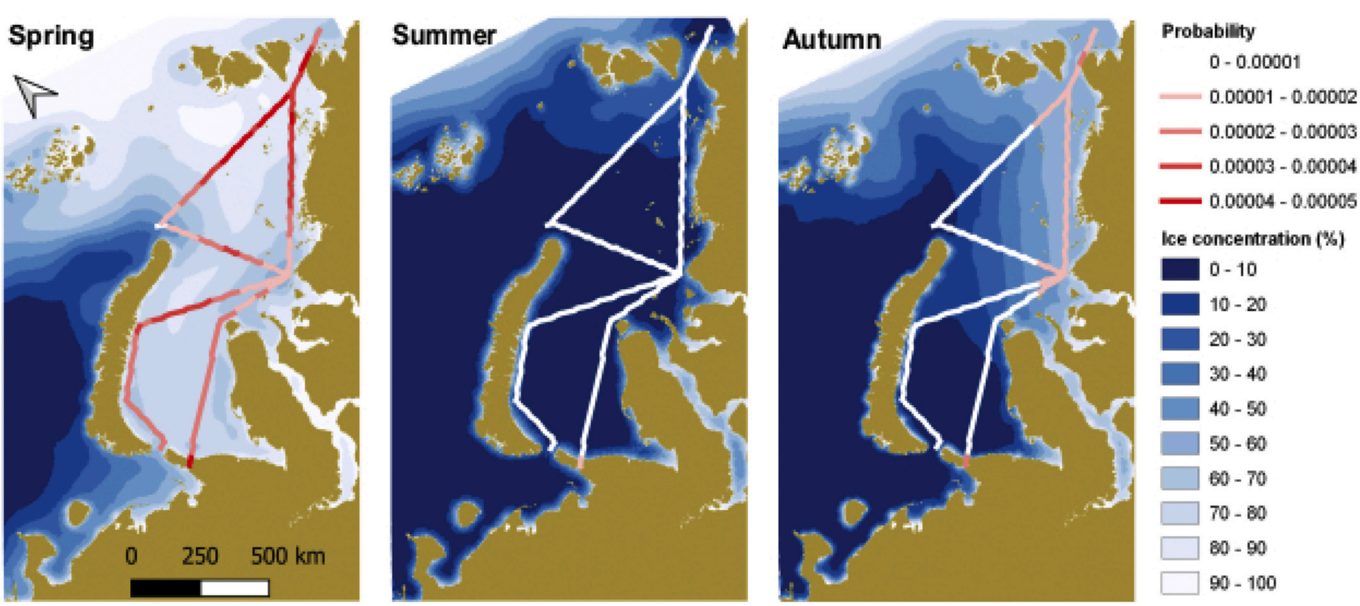

Fig. 6. The expected probability of besetting for a Category A ship along different navigation routes in the Kara Sea in spring (March-June), summer (July-September) and autumn (October-November). Assumed ice concentration values were determined as the mean ice concentration for the season as in Helle et al. (2020). See the supplementary material for similar figure for Category B and C ships.

it is unclear whether a ship has simply stopped (e.g. to wait for icebreaker assistance) or if it is beset in ice. This uncertainty arises from a lack of details in the available data on the movements of the ships in the NSR area (NSRA, 2020). Furthermore, in boundary areas between open water and ice, the variation in ice concentration as determined by the satellite data is very significant. This is likely due to the relatively large grid resolution of 25x25km. As a result, for a ship that has got beset in an open water-ice boundary area, it is difficult to precisely determine the ice concentration in which the ship got stuck. As a simplification, we assumed that ships got stuck in the highest ice concentration occurring within a 25x25km grid cell. Because of these considerations, one future development area should be to quantify the effects of errors in ice concentration data and extend our Bayesian modelling approach towards robust models that are not sensitive to them.

We believe that the developed approach and the presented results can be applied in several ways. An obvious application area is risk analysis and risk management related to Arctic shipping. Risk is typically defined as the product of the probability and the consequences of an accidental event (e.g. besetting). Hence, a comprehensive assessment of the risk of besetting events would also require the assessment of the related consequences including, for example, human casualties, economic losses, structural damages and, through the latter, environmental pollution. Even though quantification of such potential consequences is challenging, posing restrictions to risk assessment, the spatially and temporally explicit besetting probability predictions (Fig. 6) can directly be used for comparing the safety and risks (relative to constant consequences) between different operation areas and times.

An especially important application area for our approach is Arctic oil spill risk assessment. Structural damages due to a besetting event can further lead to leaks of bunker or cargo oil. As oil spills can have devastating and long-lasting impacts to the Arctic marine and coastal ecosystems, they are considered the most significant environmental threat from Arctic shipping activities (Arctic Council, 2009). A proactive approach for managing such risks calls for comprehensive oil spill risk assessment, which should take into account two spatially and temporally varying components: the probability of accidents and the extent of damages caused by the spilled oil (e.g. Frãzao Santos, 2013; Helle et al., 2016; Nevalainen et al., 2017; Nevalainen et al., 2019). Our analysis affords data for the quantification of the former component and hence, when combined with the information on the latter, i.e. the socio-economic and environmental resources at risk (see, e.g., Helle et al., 2020), support the implementation of oil spill risk assessment in the Arctic. Further, the results can be used to plan the spatial allocation of resources and activities related to, for instance, search and rescue (SAR) and oil spill response operations in the Arctic. Hence, the analysis provides useful information for marine spatial planning (MSP), an activity deemed necessary in the Arctic to support the management of spatially and temporally varying demands on marine areas presented by different users (Edwards and Evans, 2017).

5. Conclusions

For ships operating in ice-infested waters, the risk of becoming beset in ice is a hazard with potentially serious safety, environmental and economic consequences. Therefore, the risk of besetting must be carefully considered in the planning of any Arctic voyage or operation. However, this is challenging as a typical besetting event is the result of an interaction between multiple factors, many of which are stochastic by nature. In this study, we have presented a novel data-based approach to predict the probability of besetting events. Specifically, we have demonstrated that it is feasible to obtain new and relevant ice besetting related data by merging data from four existing databases: Automatic Identification System (AIS) data, satellite ice data, ship data, and real-life data on ice besetting events. Specifically, by merging this data, it becomes possible to determine, among others, the distance that ships of different Polar Ship Categories operate in different ice conditions during a year, as well as the corresponding ice besetting frequencies. Moreover, by feeding the obtained raw data into a hierarchical Bayesian model, we found the following: Firstly, the probability of a besetting event is strongly dependent on a ship's Polar Ship Category so that it is higher for ships of a lower category. For instance, over a distance of 3000 NM in 90–100% ice concentration, the probability of a Category A ship to become beset is 0.04. The corresponding probabilities for ships of Category B and Category C are 0.3 (7.5 times higher) and 0.9 (22.5 times higher), respectively. Secondly, for all ships, the probability of a besetting event increases quickly with higher ice concentration. For instance, if the ice concentration increases from 60 to 70% to 90–100%, the probability of a Category A ship to become beset in ice over a distance of 3000 NM increases from 0.015 to 0.04 (+167%). The corresponding figures for ships of Category B and Category C are 0.1 to 0.3 (+200%) and 0.4 to 0.9 (+125%), respectively. Thirdly, within the considered region (i.e. the NSR area), the sea area does not appear to significantly affect the probability of besetting.

The utility of the proposed approach is demonstrated in a case study in which the probability of besetting is calculated for five different routes on the Kara Sea and three different seasons. As per the outcome of the case study, the probability of a besetting event may vary significantly between different routes and seasons. As demonstrated by the case study, the presented approach may directly support the planning and risk management of Arctic maritime voyages and operations.

Data availability

We provide the data and an RMarkdown document implementing all the analyses and results presented in this work in the Supplementary material.

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Declaration of Competing Interest

The authors do not have competing interests to state.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.coldregions.2021.103238.

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