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REVIEW

Not all maps are equal: Evaluating approaches for mapping vessel collision risk to large baleen whales

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Abstract

1. A growing and increasingly globalised human population, requiring the movement of goods and commodities, is placing increasing demands on the maritime industry, resulting in a concurrent increase in global shipping activities. This has consequences for the marine environment, particularly for species vulnerable to the impacts of vessel traffic. For example, vessel collisions can result in sub-lethal or fatal injuries for marine mammals, whilst vessel noise can cause acoustic masking that effectively reduces an animal's listening space, potentially impacting their communication, navigation and foraging capacity.
2. While a number of parallel approaches to mapping collision risk to large whales have arisen, these methods vary in their focus, usually on either co-occurrence, collision probability, or probability of mortality. However, little attention has been given to the implications of methodological choice and data selection on subsequent risk predictions.
3. To assess differences between these approaches, we used a standardised input dataset comprised of telemetry-point data from tagged bowhead whales, and satellite-based Automated Identification System (AIS) data of spatial vessel movements covering the Davis-Baffin Arctic Marine Area. We applied this data to eight different, previously published analyses for deriving areas of vessel risk.
4. We found that the choice of risk mapping approach affected the location, and total area, identified as 'high risk', and that more computationally complex approaches did not necessarily equate to different predictions. There was considerable variation in the total area of 'high risk' predicted within each map (range = 20–42,246 km^2).

5. *Synthesis and Applications*. The results underscore the importance of methodological transparency, informed data selection and careful interpretation when predicting collision risk. We provide practical recommendations for enhancing transparency when predicting risk, and discuss choice of approach suitable for different situations or management applications. It is critical that managers and policy makers are aware of the implications of applying different approaches when interpreting risk evaluation outputs.

KEYWORDS
collision, marine mammal, maritime traffic, risk mapping, strike, vessel risk, whale

1 | INTRODUCTION

Global seaborne trade has increased fourfold since 1992 (Tournadre, 2014), with shipping now responsible for the movement of over 80% of all the worlds trade (UNCTAD, 2023). However, the ongoing expansion in maritime traffic is threatening large marine megafauna, particularly baleen whales (Pirotta et al., 2019). Threats from vessels can be simultaneously direct, in-direct and cumulative, and may occur for example via vessel-related pollution (i.e. degradation of habitat, environmental contamination, ingestion of toxins), via vessel-presence resulting in modification or disturbance of behaviour (i.e. leading to disruption to life processes, reduced fitness, habitat fragmentation), and/or via physical harm (i.e. injury or mortality through collision with a vessel) (Blair et al., 2016; Lundin et al., 2018; van der Hoop et al., 2014). For several large whale species and populations, vessel strike is one of the leading causes of mortality (e.g. Moore et al., 2021; Sèbe et al., 2023), and thus efforts to understand and mitigate this risk are urgently required to ensure global conservation goals to protect the planet and life within it (such as the UN Sustainable Goal 14: Life Below Water) do not continue to directly conflict with global trade and economic progress.

Understanding and mitigating the relative level of risk that vessels pose to whales is an issue academics, marine managers and conservationists have been grappling with for decades (Laist et al., 2001). There are a variety of techniques utilised to predict and understand the risk vessels pose, including post-mortem analysis for cause of death, analysis of bodily scarring to predict near-miss events, observations of vessel-whale avoidance (e.g. Arregui et al., 2019; George et al., 2017; Grossi et al., 2021) and using vessel and whale distribution data to predict spatio-temporal overlap and consequent likelihood of strike at certain speeds, or by certain vessel types (Silber et al., 2021). The latter approach of using spatial models to predict strike risk has been commonly applied to help inform the conservation and management of several endangered populations including North Atlantic right whales (*Eubalaena glacialis*), blue whales (*Balaenoptera musculus*), Bryde's whales (*Balaenoptera brydei*) in the Hauraki Gulf and sperm whales (*Physeter macrocephalus*) in the Mediterranean (Conn & Silber, 2013; Constantine et al., 2015; Rockwood et al., 2020; van der Hoop et al., 2014). The outputs of such studies have then subsequently been used to inform vessel management measures (e.g. slowdowns, movement of shipping lanes [e.g. Bay of Fundy (Vanderlaan et al., 2008)]) to mitigate the risk of collisions occurring in areas identified as being high risk (Conn & Silber, 2013; Redfern et al., 2013; Rockwood et al., 2020).

When it comes to predicting risk of whale-vessel collision, a simple but effective and commonly used approach, is to predict the likelihood of whales and vessels overlapping in space and/or time (*co-occurrence*). Additional complexity can be added by also considering the likelihood of the whale occurring near to or within the vessel strike zone (i.e. *close encounters*, *strike-zone events*) and further, the likelihood that the co-occurrence results in a *collision*. Finally, approaches may also predict the likelihood that a collision results in a sub-lethal or lethal injury of the whale (probability of *lethality risk*, aka PLETH (Vanderlaan & Taggart, 2007)) (for a summary of definitions, see table 1 in Keen et al., 2023). Hereafter, we will refer to all the aforementioned approaches as collective ways to map '*vessel risk*', though we acknowledge that for this work, vessel risk here infers the risk associated with potential collisions, and we do not consider other vessel-related risks such as noise, disturbance or pollution.

Globally a number of different computational approaches for estimating vessel risk have been developed, each differing in their complexity, software utilised and often the input data they require (e.g. type of vessel data (usually Automatic Identification System data), type of species coverage data (e.g. species presence, distribution)). Some studies only include certain vessel types (e.g. those recognised as posing the greatest risk due to variables related to size or speed [e.g. cargo ships or high-speed ferries (Ritter, 2010)]), while other approaches may consider *all* vessel traffic to pose an inherent risk of collision, and as such evaluate cumulative risk and do not necessarily take into account factors that likely result in some vessels being more lethal than others (e.g. Silber et al., 2021). The different approaches and constraints placed on vessel speed or type will have a significant impact on the areas predicted to be 'high risk', yet no study has evaluated how the selection and application of approaches for modelling the likelihood of collision may be affecting the consequent risk outputs (and subsequent management decisions). To explore how different approaches can affect the output predictions, we applied different pre-published methodologies to a consistent, standardised whale and vessel dataset. This allowed us to compare the variation in output risk predictions, as well as the resources and time required to replicate each respective method. The findings of this work should provide those tasked with predicting and reducing risk (including researchers, managers, eNGOs and consultancies) with information on which approach may be most suitable for their needs (including the size of area to be evaluated) and resources (e.g. data available), alongside a better understanding of how their choice of approach may influence the consequent levels of relative vessel risk predicted and areas identified in the output maps.

2 | METHODS

The aim of this study is to explore how the utilisation of different approaches to evaluating vessel risk will influence the size and location of the 'high risk' areas identified and to evaluate to what extent predictions agree upon which areas pose a higher risk. To do this, we follow eight pre-published methods, which follow three different broad approaches to mapping vessel risk: co-occurrence, strike risk and mortality risk. The methods are taken from seven peer-review publications (Halliday et al., 2022; Keen et al., 2023; Nichol et al., 2017; Redfern et al., 2020; Smith et al., 2020; Wiley et al., 2011; Williams & O'Hara, 2010) and one report (Vaes & Druon, 2013), all of which explicitly used Automated Identification System (AIS) data to predict vessel-related risk to one or more species of baleen whales. These approaches were selected for reproduction and comparison within the present study as they each represent a unique method for mapping vessel risk to marine megafauna, and whilst the underlying methods are different, the outputs of each respective approach were developed with the same primary goal; to be used to inform vessel-related management and risk mitigation within their respective study area. Further, the approaches represent many of the most up-to-date techniques used to map vessel risk, as well as an example of an approach that has previously been used within international level reporting on this topic (i.e. Vaes & Druon, 2013). Therefore the approaches replicated within this study comprehensively represent the variety of different methods currently utilised to map vessel risk.

We apply each of the methods to our identical input dataset, which consists of AIS vessel data within the Davis-Baffin Arctic Marine Area (AMA) (CBMP),[1] and telemetry data from the Eastern Canada-Western Greenland population of bowhead whales (*Balaena mysticetus*).

As this study was a desk-based study, applying pre-published datasets to multiple different methodologies, we did not require appropriate licences or permits for fieldwork, or ethical approval.

[1]https://geo.abds.is/geonetwork/3fefa587-6801-4dfc-9565-1e26fb296219/api/records/54294151-9e15-4457-8a44-df2c0ec5ada5.

2.1 | Case study dataset

2.1.1 | Case study: Whale data

This study utilises previously collected, processed and published telemetry point data to represent bowhead whale distribution within the Davis-Baffin AMA (Chambault et al., 2018; Fortune et al., 2020; Halliday et al., 2022; Matthews et al., 2020; Yurkowski et al., 2019) (for a summary of the data, including the relevant ethics, licence and permitting information, see the Supporting Information).

Modelled daily points were extracted for only months July to November, corresponding with the months of highest vessel activity (see Section 2.1.2). This resulted in a subset of 4400 modelled daily points, from 2002 to 2016 (see Figure S1). The data from these months suggests bowhead whale distribution is focused around the western portion of the Davis-Baffin AMA, particularly areas closer to Baffin Island (Figure 1a).

Vessel risk mapping methods tend to use predictions of density within a study area (i.e. via a density surface model or species distribution model), rather than using raw data or predicted presence as point data. To replicate this, we developed a bowhead whale probable density estimation layer using the July to November subset of bowhead whale modelled telemetry point data, using the ArcGIS Pro Kernel Density tool (method = geodesic, output cell values = densities, area units = square kilometres, output cell size = 0.003). It was this probable density layer that we used as our whale input data for each respective approach (Figure 1b). The area covered by the kernel density whale layer was from then on considered to be our 'study area', with corresponding vessel information extracted from the same area, as described below.

2.1.2 | Case study: Vessel data

Regulation 19 of The International Convention for the Safety of Life at Sea (SOLAS) states that vessels >300 tonnes on international voyages, or >500 tonnes in national waters, are legally required to operate an AIS. Other vessels may also fit AIS voluntarily. In Canadian waters (which encompass part of the study area), additional laws outline that vessels >150 tonnes with >12 passengers on international voyages should also operate an AIS. An AIS unit transmits identification and positional information, which can be received by other vessels, and terrestrial or satellite AIS receivers, usually within line of sight (~50 km). The data is used in real-time for navigational safety and collision avoidance, but can also be used to map AIS vessel traffic and density. For this study, decoded satellite Automatic Identification System (S-AIS) vessel position data within the Davis-Baffin AMA were provided by Spire Global LLC (formerly Exact Earth Ltd).

From the S-AIS, we used positional AIS messages (1–3, 18, 27) which provide information on vessel identity, position,

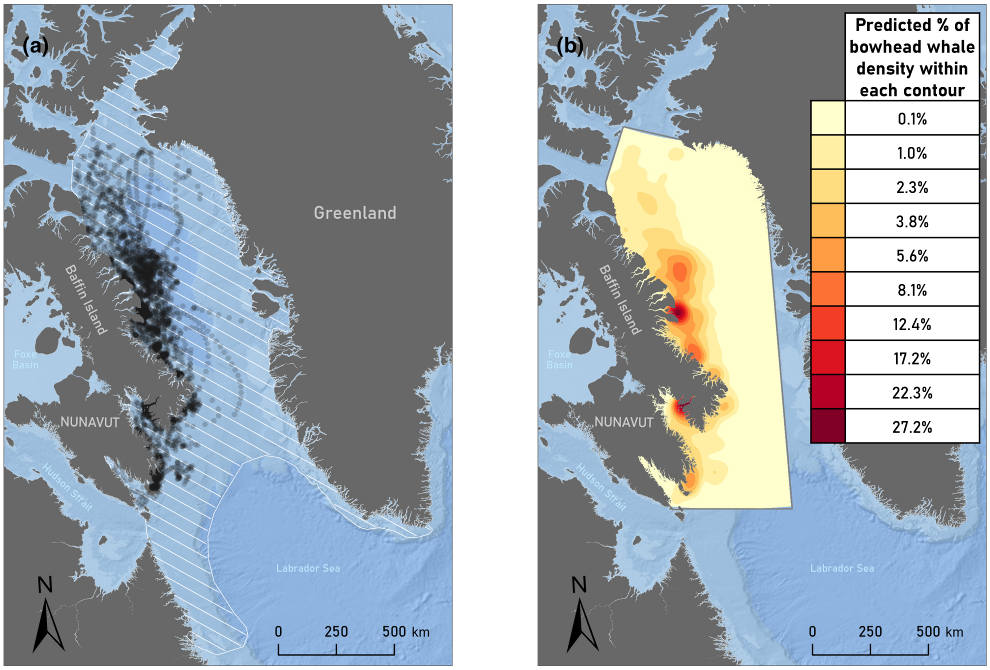

FIGURE 1 Whale case study dataset. (a) Processed daily-modelled telemetry locations of tagged bowhead whales within the Davis-Baffin Arctic Marine Area (cross hatched area). (b) Kernel density estimate of bowhead whale telemetry locations. The scale outlines the predicted proportion of bowhead whale density within each contour (i.e. the darkest red contour is predicted to hold 27.2% of the total density of bowhead whales within the study area, for this period).

speed, heading, rate of turn and navigational status. As we have just outlined, the limitation of AIS data is that it is not mandatory to be broadcast by all vessels operating in the region (including smaller non-commercial traffic), meaning that some vessel activity within the study area may not be captured within the AIS dataset. However, according to the Canadian Coast Guard, the vast majority of ships in Arctic Canada utilise AIS for safety and navigation support and as a result, we trust that the AIS data for this area is representative of the majority of vessels utilising this waterway.

Exploratory analysis of the AIS data encompassing 2019 confirmed that the presence of AIS vessel traffic in the study area corresponds with the timeframe where this waterway is navigable due to sea ice, with the highest vessel traffic within the AMA in July to November (when sea ice coverage is at its lowest). During other months of the year, sea ice extent and thickness restrict access and safe navigation, and thus the volume of AIS vessel traffic is substantially lower. Consequently, we extracted AIS data for only those months with the greatest intensity of vessel traffic (01 July to 30 November 2019).

AIS data from the entire Davis-Baffin AMA (Figure 2a) was then restricted to only include data collected within the case study area (delineated by the predicted kernel density distribution of bowhead whales). This resulted in 4,472,030 AIS data points, which represented the vessel data for input into subsequent analysis (Figure 2b,c).

3 | COMPARISON OF APPROACHES TO VESSEL RISK MAPPING

The vessel and whale data layers (as point data and kernel density, respectively) were then applied to the eight-vessel risk mapping approaches to allow for direct comparison of the outputs. The approaches are summarised below and in Table 1, with greater detail provided in the Supporting Information (including the corresponding workflow). Depending on method, we used ArcGIS Pro 2.9.2 and/or RStudio 2023.09.1 (R Core Team, 2023).

Following each respective method, we produced a vessel risk map and categorised risk within each map by 'Natural Breaks (Jenks)', using 10 classes. Natural breaks (Jenks), also known as the Jenks optimisation method, is a data classification method that divides features into classes that maximise the difference between each class (by grouping similar values together in a way that minimises each classes average deviation from the class mean, whilst also maximising each classes deviation from the means of the other classes) (Chen et al., 2013). To compare the spatial coverage and locations of high risk areas predicted by each respective method, we extracted the top two 'high risk' classes for comparison.

A log-linear model was used to explore whether the size of the AIS data subset had an effect on predicted areas of 'high risk' (a log transformation was used to account for an outlier within the results, regarding the total area of 'high risk' predicted).

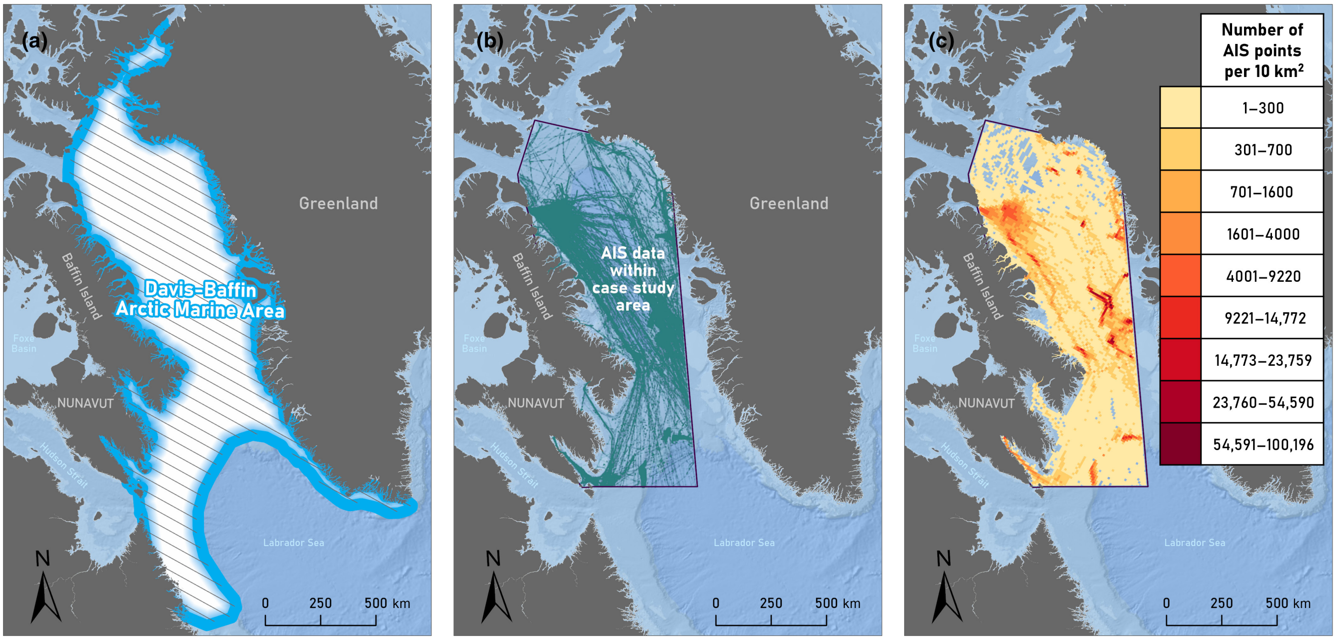

FIGURE 2 (a) Initial area of interest: Davis-Baffin Arctic Marine Area, (b) satellite AIS data within the case study area (AIS data July to November 2019), (c) density of AIS data points, represented within a 10×10 km^2 grid (n.b. AIS point data was the raw input data used for each approach (not density)).

3.1 | Approach A: Mapping co-occurrence

3.1.1 | Method A1: Redfern et al. (2020)

This method uses a subset of AIS data (only ships ≥80 m in length and speeds ≥2.5 knots) to summarise the cumulative distance travelled by vessel traffic each year, and the average distance travelled per day, in a 10×10 km^2 grid. The mean daily kilometres of vessel traffic per grid cell are then multiplied by the predicted number of whales per grid cell to present a metric of vessel risk.

3.1.2 | Method A2: Williams and O'Hara (2010)

A subset of AIS data (only moving ships ≥20 m, or, ships engaged in towing or pushing anything >20 m (other than fishing gear) with a combined length of >45 m. Yachts <30 m and fishing vessels <24 m and 150 tonnes excluded) is used to generate the total number of uniquely identifiable vessels per grid cell per hour as an index of vessel intensity. This is then multiplied with a whale density estimate grid using an 'Inverse Distance Weighting' function to get a metric of predicted co-occurrence per 5×5 km^2 grid cell.

3.1.3 | Method A3: Keen et al. (2023)

This method develops a grid of the number of times a vessel and a whale occur in the same cell, using 1×1 km^2 grids of vessel traffic and whale density. This approach has R code available to aid replication ('shipstrike' (Keen, 2023)).

3.2 | Approach B: Mapping strike and/or lethality risk

3.2.1 | Method B1 (collision) and B2 (mortality): Keen et al. (2023)

Building upon the prediction grids described in Method A3, avoidance rates (by both vessels, and/or whales) are incorporated, with data on whale dive depths distribution (gained from telemetry data), to infer the time a whale might spend in the 'strike-zone' (i.e. 1 or 1.5 times the draught of the vessel). This is used to predict collision (Method B1) and mortality rate (Method B2) for only ships >180 m long. For collision rate, the number of predicted strike zone events per grid cell is scaled according to an avoidance metric, which is based on vessel speed (Method B1). For mortality rate, this is further scaled using an equation generated from a 'Probability of Lethality' (PLETH) regression curve, which estimates the likelihood that a vessel at a certain speed will cause a fatal injury. Keen et al. (2023) use the PLETH equation described in Kelley et al. (2021).

3.2.2 | Method B3: Nichol et al. (2017)

This method bins a subset of AIS data (excluding vessel speeds <5 knots or >40 knots) into speed categories (e.g. 5–10 knots), and then represents each category as vessel density within a 1×1 km^2 grid. To predict the relative probability of vessel strike, the method then estimates the likelihood that whales and vessels occupy the same grid cell, and then advances this by also considering the risk that a

TABLE 1 Comparative approaches for predicting vessel risk to baleen whales.

Approach	Vessel categories and speed included	How is vessel traffic represented?	How is vessel risk estimated?
Co-occurrence	Method A1: *Co-occurrence* Redfern et al. (2020) Species: fin, humpback and blue whale		
	Type: Ships >80 m Speeds: Speed over ground ≥2.5 knots	Summarised cumulative distance travelled by ships within a grid cell. Grid Size: 10 × 10 km^2 Approx. study area: 350,000 km^2	By multiplying the predicted number of whales by the mean daily kilometres of vessel traffic within a grid cell. PLETH curve used: NA
	Method A2: *Co-occurrence* Williams and O'Hara (2010) Species: fin, humpback and killer whale		
	Type: Ships >20 m, and ships engaged in towing or pushing any vessel or object more than 20 m, that had a combined length of more than 45 m. Exclude yachts <30 m and fishing vessels <24 m and 150 tonnes. Speed: 'Only moving ships' (here, we used >2.7 knots to replicate this method)	Vessel data were reduced to one uniquely identifiable vessel observation per hour, per cell. The total number of uniquely identifiable vessels (i.e. MMSI numbers) per grid cell was used as an index of vessel intensity. Grid Size: 5 × 5 km^2 Approx. study area: 100,000 km^2	By multiplying gridded predicted whale density estimates with the nearest value of shipping intensity, using an Inverse Distance Weighting function which takes into account the average values of neighbouring cells. PLETH curve used: NA
	Method A3: *Co-occurrence* Keen et al. (2023) Species: fin and humpback whale		
	Type: Length 5–500 m, beam >2 m, draft no more than half the reported length. Types: • Cargo >180 m • Fishing <60 m • Other <40 m • Other >100 m • Other 40–100 m • Passenger >180 • Pleasure <40 m • Sailing <40 m • Towing <50 m • Tug <50 m Speed: >3 knots and <40 knots	AIS data for each vessel class was categorised as day or night and mapped onto a grid. For each grid cell, a table was developed for each month–diel period (e.g. nighttime in July), with associated vessel data for each vessel that crossed the cell in that time period. Vessel crossings through a grid cell were simulated 10,000 times, with crossing randomly sampled from the bootstrapped distribution. Grid Size: 1 × 1 km^2 Approx. study area: 3000 km^2	Risk is described as the number of times a vessel and whale occur in the same 1 × 1 km^2 grid cell. PLETH curve used: NA
Strike and/or lethality risk	Method B1: *Collision Rate* Keen et al. (2023) Species: *as Method A3*		
	Subset of Method A3 data that only included vessels >180 m. Type: Length 180-500 m, beam >2 m, draft no more than half the reported length. Types: • Cargo >180 m • Other >100 m • Passenger >180 Speed: Speeds >3 knots and <40 knots	*As Method A3*	By scaling potential collision events within the vessel strike zone (i.e. 1.5× vessel draught) stochastically, taking into account avoidance and vessel speed, to predict rates of collision. To replicate, we use strike zone as 1.5× vessel draught, and P(Collision) as 1.0 (i.e., worst-case scenario: no avoidance by whale or vessel). PLETH curve used: NA
	Method B2: *Mortality Rate* Keen et al. (2023) Species: *as Method A3*		
	As Method B1	*As Method A3*	The probability of a collision being lethal is calculated using a stochastic approach, as a function of vessel speed based on the PLETH equation. PLETH curve used: Kelley et al. (2021)

TABLE 1 (Continued)

Vessel categories and speed included	How is vessel traffic represented?	How is vessel risk estimated?
Method B3: *Relative risk of vessel strike and lethal injury* Nichol et al. (2017) Species: Fin and humpback whale		
Type: Only: Cargo (container, bulk), tanker, passenger (cruise ships, ferries), tug, towing, fishing, pleasure vessels Speed: Speeds >5 knots and <40 knots	AIS data is split into four speed categories (5–10, 10–15, 15–20 and 20–40 knots), and then each category is gridded as an average number of ships per hour, during the study period. Grid Size: $1 \times 1\,km^2$ Approx. study area: $80{,}000\,km^2$	Gridded vessel density layers are multiplied by the median speed of each vessel speed category, which is in turn then used to predict the probability of lethal strike. This value is multiplied by the likelihood of encounter between a whale and a vessel within a given grid cell, to give a relative risk value. PLETH curve used: Conn and Silber (2013)
Method B4 *Vessel strike risk* Vaes and Druon (2013) Species: Fin whale		
Type: All, no vessel categories excluded Speed: >5 knots, and 'impossible speeds filtered out'. To replicate, we use speeds <40 knots.	Vessel traffic density is calculated as the length of vessel transect within a given grid cell per day. Grid Size: $4.6 \times 4.6\,km^2$ Approx. study area: $1{,}200{,}000\,km^2$	The formulation of risk of vessel strike is adapted from Tregenza et al. (2000), where the number of collisions is a function of vessel width, whale length, length of vessel transect within a given area, whale density, and the speed of the vessel relating to the likelihood of lethality (i.e. PLETH curve). PLETH curve used: Vanderlaan and Taggart (2007)
Method B5: *Vessel Strike Risk* Halliday et al. (2022) Species: Bowhead whale		
Type: • Bulk carriers • Container ships • Cruise ships • Ferries • Fishing vessels • Government vessels (including coast guard ships, ice breakers, and other research ships) • Navy vessels • Pleasure craft (private yachts, sailboats, small boats, and other recreational boats) • Tanker ships • Tugboats Speed: Speeds >1 knot and <40 knots	Vessel density is calculated separately, for each vessel class they calculate the mean number of vessel tracks per grid cell per month to gain a monthly vessel density value for each grid cell. Grid Size: $10 \times 10\,km^2$ Approx. study area: $6{,}500{,}000\,km^2$	The density of bowhead whales (as normalised bowhead whale density per cell) is first multiplied by vessel density per cell, to gain a measure of overlap for each vessel class and grid cell. This value is then corrected by vessel speed per vessel class, to account for higher average vessels speeds resulting in greater lethal strike risk. PLETH curve used: Vanderlaan and Taggart (2007)
Method B6: *Relative Expected Fatality of a whale from the risk of a vessel strike* Smith et al. (2020) Species: Humpback whale		
Type: Class 'A' cargo, tanker and passenger vessels ≥80 m in length Speed: >0.4 knots	Point data converted to tracks (by MMSI), and then density is gridded as distance travelled per grid cell. Grid Size: 1×1 and $50 \times 50\,km^2$ Approx. study area: $230{,}000\,km^2$	A relative risk of vessel strike calculated by multiplying vessel and whale density grids with the mean vessel beam per grid cell, and the probability of a lethal whale strike given the mean vessel speed for each grid cell. PLETH curve used: Conn and Silber (2013)

(Continues)

TABLE 1 (Continued)

Vessel categories and speed included	How is vessel traffic represented?	How is vessel risk estimated?
Method B7: *PLETH within a study area* Wiley et al. (2011) Species: No whale data used. However, the study area is the Stellwagen Bank National Marine Sanctuary, and is seasonal habitat for North Atlantic right, humpback, and fin whales.		
Type: Ships >295 metric tons Speed: Not stated, presume all speeds included	For each grid cell, the mean speed of each vessel transit is calculated, and then input into a speed/lethality curve to predict the probability of lethality of that transit in that cell. The probabilities for each cell are then averaged to present the likelihood of a fatal collision in that grid cell. Grid Size: 1 × 1 min (1.85 × 1.85 km^2) Approx. study area: 2181 km^2	The probability of lethality per vessel transit across each grid cell is calculated using the mean speed of each vessel transit. These values are then summed to give the mean probability of lethality per grid cell. PLETH curve used: Pace and Silber (2005)

Note: 'Probability of lethality' (PLETH) refers to the logistic regression equation used to estimate the likelihood that a vessel at a certain speed will cause a fatal injury.

strike would be lethal given the average speed of vessels travelling through each grid cell, using the PLETH curve described by Conn and Silber (2013). The probability of encounter within each grid cell, and the PLETH within each grid cell, are then multiplied to gain the relative risk of lethal collision.

3.2.3 | Method B4: Vaes and Druon (2013)

This method builds on work presented in Tregenza et al. (2000) and considers the width of the vessel, whale length, whale density and habitat preferences, whale time at the surface, and PLETH of strike at set speeds (using the PLETH equation presented in Vanderlaan and Taggart (2007)). Daily traffic density (which is calculated as the length of vessel transect within a given cell per day) and mean speed is plotted into a 4.6 × 4.6 km^2 grid, using a subset of AIS data (only speeds >5 knots, excluding 'impossible speeds'). From this, daily risk estimates are calculated, and then summed to calculate risk over a given period (e.g. monthly).

3.2.4 | Method B5: Halliday et al. (2022)

A subset of AIS data (speeds <1 knot and >40 knots excluded) are grouped by vessel class, and converted into tracks to calculate the number of times each individual vessel crossed a 10 × 10 km^2 grid cell per month, and the mean speed per vessel class per grid cell per month. A whale density layer is then multiplied with each vessel class density layer, to identify overlap. Overlap is then corrected by average speed per vessel class, per cell, using the Vanderlaan and Taggart (2007) PLETH equation.

3.2.5 | Method B6: Smith et al. (2020)

A subset of AIS point data (only cargo, tanker and passenger vessels, >80 m; only speeds >0.4 knots) are converted to tracks for each unique vessel, and then gridded to summarise the distance travelled per 1 × 1 km^2 grid cell. This is then multiplied with a grid of whale density, with the average vessel beam (width) per grid cell, and with the average probability of lethal strike per grid cell based on the average vessel speed for each grid cell (using the Conn and Silber (2013) PLETH equation) to quantify the total relative risk per grid cell. Relative risk was also calculated at the scale of a 50 × 50 km^2 grid, to explore trends at a regional scale.

3.2.6 | Method B7: Wiley et al. (2011)

This method is used for areas where densities are expected to be high throughout and/or areas that are recognised as being important to multiple whale species (here, for the Stellwagen Bank National Marine Sanctuary (USA)), and therefore does not require whale density data. A subset of AIS data (only vessels >295 tonnes) is used to generate each grid cell's overall PLETH (using the Pace and Silber (2005) PLETH curve), based on average speed through each 1 × 1 min grid (1.85 × 1.85 km^2) grid cell.

4 | RESULTS

Application of the eight different methods resulted in the production of 11 output maps identifying areas of vessel-related risk for evaluation (Figure 3). There were more output maps produced than methods followed because one method used more than one grid size for risk prediction (Smith et al., 2020), and another followed a stepwise approach to risk mapping, which resulted in three risk maps (Keen et al., 2023).

4.1 | Area(s) identified as very high risk

All 11 maps identified waters east of the Clyde River and Isabella Bay (including the Ninginganiq (Isabella Bay) National Wildlife Area) as an

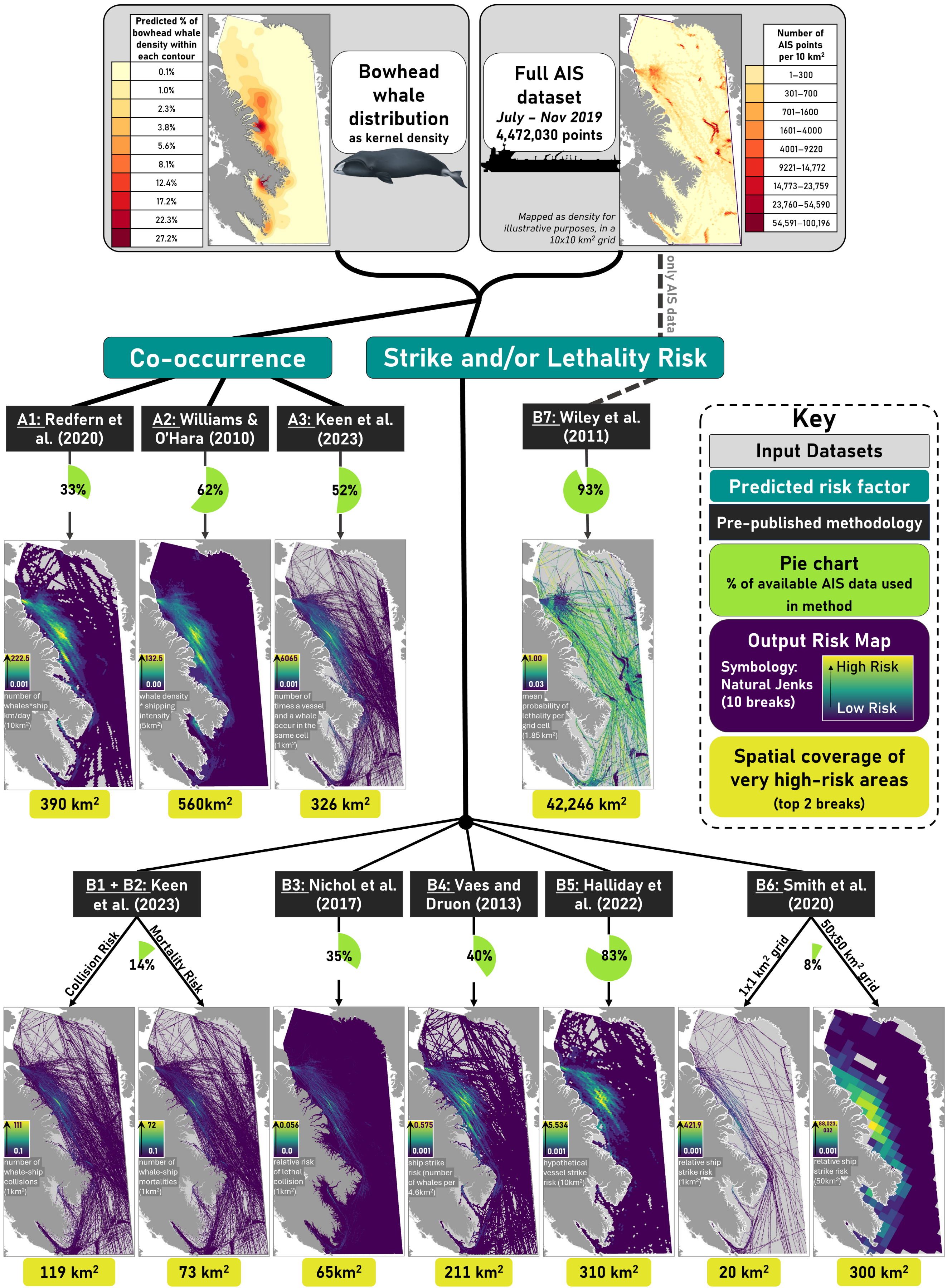
Predicted % of bowhead whale density within each contour
0.1%
1.0%
2.3%
3.8%
5.6%
8.1%
12.4%
17.2%
22.3%
27.2%
Bowhead whale distribution
as kernel density
Full AIS dataset
July – Nov 2019
4,472,030 points
Mapped as density for illustrative purposes, in a 10x10 km² grid
Number of AIS points per 10 km²
1–300
301–700
701–1600
1601–4000
4001–9220
9221–14,772
14,773–23,759
23,760–54,590
54,591–100,196
only AIS data
Co-occurrence
Strike and/or Lethality Risk
A1: Redfern et al. (2020)
A2: Williams & O'Hara (2010)
A3: Keen et al. (2023)
B7: Wiley et al. (2011)
33%
62%
52%
93%
222.5
0.001
number of whales*ship km/day (10km²)
132.5
0.00
whale density * shipping intensity (5km²)
6065
0.001
number of times a vessel and a whale occur in the same cell (1km²)
1.00
0.03
mean probability of lethality per grid cell (1.85 km²)
390 km²
560km²
326 km²
42,246 km²
Key
Input Datasets
Predicted risk factor
Pre-published methodology
Pie chart
% of available AIS data used in method
Output Risk Map
Symbology: Natural Jenks (10 breaks)
High Risk
Low Risk
Spatial coverage of very high-risk areas
(top 2 breaks)
B1 + B2: Keen et al. (2023)
B3: Nichol et al. (2017)
B4: Vaes and Druon (2013)
B5: Halliday et al. (2022)
B6: Smith et al. (2020)
Collision Risk
Mortality Risk
14%
35%
40%
83%
1x1 km² grid
8%
50x50 km² grid
111
0.1
number of whale-ship collisions (1km²)
72
0.1
number of whale-ship mortalities (1km²)
0.056
0.0
relative risk of lethal collision (1km²)
0.575
0.001
ship strike risk (number of whales per 4.6km²)
5.534
0.001
hypothetical vessel strike risk (10km²)
421.9
0.001
relative ship strike risk (1km²)
88,023.032
0.001
relative ship strike risk (50km²)
119 km²
73 km²
65km²
211 km²
310 km²
20 km²
300 km²

FIGURE 3 Output maps of eight different vessel risk mapping approaches, predicting risk (as co-occurrence, strike, or lethality risk) to bowhead whales, using vessel (AIS) data collected in 2019 and bowhead whale data collected between 2002 and 2016. Risk is predicted on a scale of low relative risk (navy) to high relative risk (yellow) for each map (note, the respective scale and units are overlaid, but the scale, values and break points are relative to each individual map (and as such, the scale and values for each output should not be directly compared). Instead, the maps should be used to visualise similarities and differences between geographic areas of high and low (relative) predicted risk). Pie charts represent the proportion of the full AIS dataset used in that respective methodology. Spatial coverage estimates (in yellow boxes) indicate the area predicted as highest risk by that respective methodology, identified by top 2 (of 10) classes through Natural Breaks (Jenks). The dotted line to Method B7 represents this approach only using AIS data as input data. Bowhead illustration by Uko Gorter.

area of higher vessel risk for bowhead whales (Figure 3; Figure S2). This geographic area was very clearly highlighted as posing the highest risk in comparison to the remainder of the study area by 10 of the 11 maps (all methods except Method B7). These same 10 maps also identified the area east of Pond Inlet as an area of elevated vessel risk. Furthermore, from the visual comparison of the final outputs, it appears that these 10 maps were in broad agreement that the majority of the remainder of the study area posed a substantially lower risk to bowhead whales (represented by dark blue colouration, rather than 'high risk' areas in yellow) (Figure 3).

To further quantify the similarities between location and total area of 'high risk', we isolated and mapped the highest risk areas (identified by extracting the top two (out of 10) risk classes per map, identified by Natural Breaks (Jenks)). There was considerable variation in the total area of 'high risk' predicted within each map (range = 20–42,246 km^2, mean = 4056 km^2, median = 300 km^2; Figure 3; Table 2). Method B7 predicted the most expansive total area that was in 'high risk' (42,246 km^2). This estimate was an order of magnitude higher (and thus arguably an outlier) compared to the 'high risk' areas predicted by the other 10 maps, which had more comparable areas of 'high risk' (range = 20–560 km^2, mean = 237 km^2, median = 256 km^2).

To understand the overlap in the geographic coverage of the areas each map identified as 'high risk', we calculated the frequency that the same 'high risk' area (1 × 1 km^2) co-occurred within multiple risk maps (i.e. count of overlap) (Figure 4). The 11 maps identified no ubiquitous 'high risk' areas. The most frequently co-occurring area of high risk was identified within 7 of the 11 maps, yet this area of 'high risk accordance' only extended over 2 km^2 of the 884,190 km^2 study area (i.e. >0.0002% of the study area) (Figure 4). Despite areas of highest risk showing little geographic commonality, many of the risk maps did identify the same general areas of elevated risk (Figure 4b,c).

4.2 | Grid size

The two maps produced by Method B6 provide an opportunity to explore the effect of grid size on the consequent total area identified as 'high risk', as the method maps risk at both a 1 × 1 and 50 × 50 km^2

TABLE 2 Table comparing the total subset of vessel data (AIS) used by each respective vessel risk mapping approach, and the total area of predicted 'high risk'.

Method		Total AIS points used within each respective method data subset Total count, and % used of total data available		Total area predicted to be 'high risk'
Total data available		4,472,030		884,190 km^2
Approach				
Co-occurrence	Method A1 Redfern et al. (2020)	1,492,646	33%	390 km^2
	Method A2 Williams and O'Hara (2010)	2,755,322	62%	560 km^2
	Method A3 *Co-occurrence* Keen et al. (2023)	2,307,400	52%	326 km^2
Strike and/or lethality risk	Method B1 *Collision* Keen et al. (2023)	620,778	14%	119 km^2
	Method B2 *Mortality* Keen et al. (2023)	*As B1*	*As B1*	73 km^2
	Method B3: Nichol et al. (2017)	1,555,320	35%	65 km^2
	Method B4 Vaes and Druon (2013)	1,794,069	40%	211 km^2
	Method B5 Halliday et al. (2022)	3,716,717	83%	310 km^2
	Method B6: Smith et al. (2020)	361,615	8%	1 × 1 km^2 grid = 20 km^2 50 × 50 km^2 grid = 300 km^2
	Method B7: Wiley et al. (2011)	4,165,776	93%	42,246 km^2

Abbreviation: AIS, Automated Identification System.

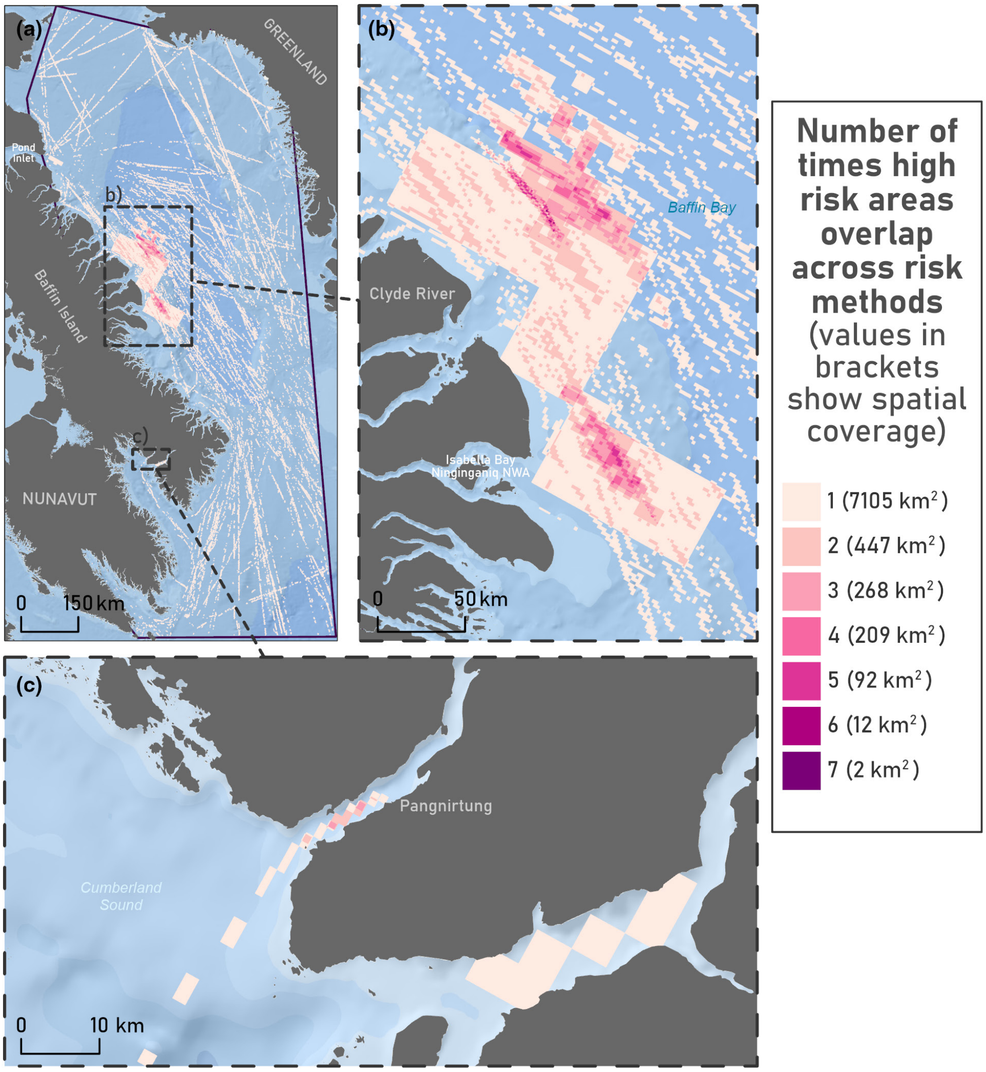

FIGURE 4 Choropleth map demonstrating the number of times there is overlap between the high risk areas identified by 11 different vessel risk mapping outputs, which each predicted spatial coverage of vessel-related risk to bowhead whales, for (a) the entire study area, (b) the waters east of the Clyde River and (c) waters of Cumberland Sound.

scale. Replicating this method with our case study data results in a $20\,km^2$ area of 'high risk' when adopting a $1\times1\,km^2$ grid, but a $300\,km^2$ area of 'high risk' when using a $50\times50\,km^2$ grid (Figure 3). Importantly, the areas predicted as 'high risk' do not geographically overlap for these outputs (Figure S3). The smaller grid size output map highlights only the constrained waterways of Pangnirtung as 'high risk', whilst the output map with the larger grid size identifies the more open waters of Baffin Bay, to the east of the Clyde River, as 'high risk'.

4.3 | Proportion of AIS data used compared to full dataset

None of the approaches used 100% of the AIS data points available within the input dataset (Figure 3; Tables 1 and 2). All used a subset of the data, the exact configuration varied according to vessel speed (e.g. setting upper and/or lower speed over ground (SOG) thresholds), and/or by only including certain vessel types within the analysis. Consequently, the total proportion of AIS data used compared to the full dataset available varied from 8% to 93% (average = 47% of available AIS data used). The proportion of AIS data used from the total subset available had a significant impact on the total 'high risk' area predicted (log-linear model; $r^2=0.57$, $df=10$, $F=11.9$, $p\geq0.005$).

4.4 | Processing time

The time taken to prepare the subset of input data and replicate each method varied from 1 working day to 1 month (Table S1), though it should be noted that times will be variable depending on the users computing power, and as such, these results are presented as a general guide. Whilst some methods, especially

Methods A3, B1 and B2, did require substantial time commitments for coding and numerous processing steps, a high proportion of time was attributed to the model processing time in either ArcGIS Pro or R. The long processing times are likely in part attributable to the high volume of input AIS data (due to relatively large spatial/temporal coverage).

5 | DISCUSSION

This comparative study sheds light on the importance of understanding the implications of the choice of a methodological approach for evaluating vessel risk for large baleen whales. We show how the choice of approach can affect both the geographic distribution and the extent of the areas predicted to be of highest risk for baleen whales. In addition, we demonstrate that several approaches predicted effectively very similar areas of risk (geographically and total volume). Given the similarity between those outputs, but the contrasting time, hardware capabilities and technical expertise required to complete each one, it raises the question, are more computationally complex or time-consuming analyses necessary given the approach outputs are very similar to less computationally intensive, and ultimately more time-effective approaches? This work should provide managers, policy makers and researchers with the means to identify which approach would be most suitable for their particular data, locale and species, along with the available time-frame for analysis and technical expertise and hardware available, whilst also providing some insight into how the implementation of different approaches will affect the nuance in interpreting their respective predictions of vessel risk.

When interpreting the vessel risk maps produced for this study, it is important to acknowledge that we have no information on which approach and output map best reflects the real-world presence of collision risk. In other words, we do not have comprehensive data on vessel strikes of bowhead whales within the study area during the study period. As we do not know which approach output is closest to the 'truth' we must instead consider the commonalities between the predicted areas of 'high risk' and consider the most appropriate input data and approach that likely reflects the real-world risk of collisions occurring. It is important to note here, that it is currently unlikely that any study area, irrespective of geographic location, will have the corresponding data to ground truth predictive vessel risk maps for their own respective area (e.g. Félix & Van Waerebeek, 2005; Peel et al., 2018; Ransome et al., 2021), and so having output maps from multiple approaches, as presented here, may be beneficial for decision makers, at least until we have a better grasp on which approach provides the most accurate real-world reflection. Improved strike and near-miss reporting for all vessel types (including exact locational data, speed of travel and outcome for the whale) (Winkler et al., 2020), along with a deepened understanding of vessel-whale avoidance behaviours (by both skippers and whales) (e.g. Gende et al., 2019; Szesciorka et al., 2019), and details from necropsies of all potential vessel-struck whales to confirm cause of death and severity and type of injury (e.g. Arregui et al., 2019; Campbell-Malone et al., 2008; Sierra et al., 2014), are all examples of complementary methods that could contribute to building a better understanding of vessel-related risk and refinement of predictive risk mapping approaches.

5.1 | Variability in approaches to vessel risk mapping

The eight pre-published methods used by this study predict vessel risk in one of three ways; by predicting co-occurrence (i.e. overlap in space (not always temporal)), by predicting risk of strike, and finally, by predicting the likelihood that a strike is fatal. Maps of co-occurrence highlight areas where vessel strikes are most likely to occur, based on overlap of usage areas, though maps of risk of co-occurrence assume that if whales and vessels are in the same area at the same time, there is risk. These types of maps usually do not reflect the effects of potential avoidance by the whale or the vessel operator (e.g. Gende et al., 2019), and will also usually not take into account whether the whale and vessel overlap in 3D space (i.e. dive patterns of animals; the whale may be at depth, and thus not within the 'strike zone' of the vessel) (e.g. Calambokidis et al., 2019; Caruso et al., 2021; Owen et al., 2016; Soldevilla et al., 2017; Stepanuk et al., 2021). Co-occurrence maps can then be used alongside additional predictions (i.e. the probability that a strike is lethal based on vessel speed and/or the probability of encounter between a vessel and a whale based on vessel speed (Gende et al., 2011; Vanderlaan & Taggart, 2007)), in order to predict the potential outcome of a collision should it occur (i.e. strike risk, probability of lethality).

Each approach should be interpreted with care, particularly with consideration to the type of vessel risk that is being predicted (e.g. co-occurrence vs. risk of fatal strike) and with the nuances and associated limitations of each approach in mind. Risk maps are often a 'quick-to-use' approach providing quick-to-read visual information of 'high' versus 'low' risk areas, yet hasty interpretation may mean insufficient time and care is given to understanding and correctly interpreting the underlying approach (Lahr & Kooistra, 2010; Szigeti-Pap et al., 2023). Also, readers may not have the technical knowledge to understand the complexities between risk-mapping approaches, and what this means for interpretation of the associated output risk maps (Lahr & Kooistra, 2010). This can lead to misinterpretation through direct comparison of risk maps, when comparisons may not always be appropriate or meaningful (e.g. comparison of high co-occurrence areas vs. areas of high risk of fatal strike).

To this end, the work presented here highlights that despite each approach ultimately mapping a different type of vessel-related risk (i.e. co-occurrence vs. strike risk), the output maps produced can often, but not always, be similar in terms of the geographic area predicted as 'high risk', and the total area of predicted 'high risk' (e.g. Methods A1, A2, B4 and B5 (Figure 3)). However, a standardised approach to vessel risk mapping, or the presentation of results, will aid interpretation for managers and policy makers (for example, clarity on what type of risk has been mapped (and the data used to inform

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this), clarity on how 'high risk' areas have been defined, clarity on interpretation and caveats to each approach, consistent presentation of co-occurrence *and* strike risk).

5.2 | Risk-mapping resource demands: Computational power, technical expertise and time

Whilst hard to quantify, it is important to note when comparing the risk-based approaches presented here, that there are practicalities relating to the availability of resources that make some approaches more or less straightforward to replicate. This is an important real-world consideration for those seeking to map vessel risk, particularly those with restrictive time or funding budgets, and so is worthy to note.

There was significant variation in the amount of time it took to interpret and replicate each method, varying from days to months. The practitioner who replicated each methodology for this work has extensive expertise with both software used (ArcGIS Pro and R), experience processing large AIS datasets, and familiarity with modelling and evaluating risk. This likely aided the time taken to undertake some of the methods, but all of these factors should be considered when choosing which approach is most suitable for a particular set of circumstances. Hardware capabilities will also have a large effect on the time taken to replicate some methods, with some steps of analyses taking ~2 weeks per step due to the high volume of data processing and computational power (i.e. Methods A3, B1 and B2). The processing duration will vary depending on the size of the study area (this case study was extensive (~800,000 km^2)) and any temporal constraints (in this instance, we considered a 5-month period). For this study, we had a relatively large area and time window to consider, which resulted in a high volume of corresponding AIS data to be processed (4,472,030 points) and significant hardware requirements. Smaller geographical study areas, and/or shorter study windows, may result in quicker computer processing times.

5.3 | Mapping risk at a scale appropriate to the study area

We found that the spatial coverage of the area predicted as 'high risk' was notably different, depending on the grid size applied to the data. When comparing outputs of the same input data and approach, but with different grid sizes applied, smaller gridding (1×1 km^2) allowed for the identification of risk in coastal, narrow (4 km wide) constrained waterways, whilst larger 50×50 km^2 gridding did not identify 'high risk' within the same narrow waterway, and instead only predicted 'high risk' in open waters (see Figure S3). Therefore, larger grid scales may limit an approach's capacity to determine risk in more spatially constrained areas (e.g. along coastlines, within estuaries and waterways). This is because cells that cover coastal or spatially constrained areas will contain proportionally less input data when gridded at larger scales (as a large proportion of the grid cell area may be over land) compared to cells that have input data available throughout the cell, and as such direct comparison is inappropriate. We therefore suggest for study areas that overlap with land and/or contain geographically constrained waterways, that smaller grid sizes are more suitable.

We also found that the total area of predicted 'high risk' is highly affected by the size of gridding applied to the data. This was clear when comparing the resulting 'high risk' areas of Method B6, where identical input data and methodology predicted a 20 km^2 area of 'high risk' when using a 1×1 km^2 grid, but a 15-fold increase in predicted area of 'high risk' (300 km^2 area) when using a 50×50 km^2 grid (Figure 3). Similarly, Blondin et al. (2020) found that coarser temporal resolutions tended to produce outputs that overestimated risk. The appropriate grid size and data resolution for any given approach will depend on the respective study area, input dataset and the 'requirements of usage' for the output risk maps (e.g. vessel management schemes and marine protected area planning) (see Amoroso et al. (2018) and Kroodsma et al. (2018) for a discussion on the importance of spatial resolution when predicting impact footprints). To this end, we must also be mindful of the realities of designing and informing any management measures or policy that vessel risk predictions may inform. It is also important to consider the scale that any vessel-based management measures would be undertaken (i.e. movement of vessel lanes and lane displacement). For example, would vessel-based management measures such as a slow-down of cargo ships be practical on a 1×1 km^2 scale, or would a more appropriate area of identified risk and thus management be at a 5×5 or 10×10 km^2 scale?

Further, the distribution of the species at risk (here, marine mammals) are also commonly used as input data for many vessel-related risk approaches (e.g. noise exposure modelling), yet, depending on approach, this data will also highly affect the predicted areas of 'high risk' identified (see Blondin et al. (2020) for further discussion related to the resolution of input marine mammal data). The reliability of knowledge related to species distribution, and the likelihood of any population(s) of interest remaining precisely in those areas, should also be considered when choosing an appropriate grid size for analysis, as well as when interpreting the accompanying risk maps.

5.4 | Vessel risk maps that do not input whale distribution data produce very different predictions of 'high risk' areas, but may be appropriate for some scenarios

Identifying and comparing areas where the input datasets appear to be whale- or vessel-dense is helpful to aid comprehension and interpretation of the output risk maps produced. For example, in our input case study dataset, the input AIS data show marked vessel-dense areas dispersed throughout the study area (Figure 2), but the input whale data predict high bowhead whale densities in the western portion of the study area (Figure 1). In other words, 'whale-dense' and 'vessel-dense' areas did not always overlap in the input datasets. Interestingly, one study, Method B7 only uses vessel data as input data and does not include any input or metric of whale distribution. This is because the original study was conducted over an area that is predicted to be homogeneously 'whale-dense'. However, when we replicated this approach for our respective study area, where the distribution of bowhead whales is predicted to be heterogeneous, the resulting map predicts that the total area of high vessel risk to bowhead whales ~75 times larger than any of the other approaches. Also, this approach mainly bases risk predictions on the average vessel speed in each grid cell, estimating higher risk (here, the likelihood of lethality) in cells that have vessels transiting at higher speeds, on average, and predicting lower risk where vessels were idling or slower, on average. Subsequently, the 'high risk' areas span much of the study area, including many cells where bowhead whales are predicted to be absent or in low numbers, and so arguably this approach may be less appropriate and overestimate risk, given the approach's assumption that whales are evenly distributed throughout the area. However, for study areas that assume reasonably even distribution of whales throughout (e.g. if study area includes designated critical habitat, a designated important marine mammal area (IMMA), feeding or calving grounds), then this method may be most suitable and could be used to generate monthly maps, to explore how risk in an area varies over smaller temporal windows to inform implementation of seasonally explicit vessel management measures (as highlighted by Wiley et al., 2011). Furthermore, if this method is appropriate for a study area, it has the additional benefit that the volume of input data required is reduced to only AIS data (i.e. no whale input data required).

All studies other than Method B7 utilised both vessel *and* whale data within their respective methodologies. These approaches all predicted areas of high vessel-related risk that overlapped with areas of predicted high bowhead whale density (Figure 3). Unlike Method B7, these approaches did not identify areas of high vessel density as equating to high vessel risk, unless it was a corresponding area of high whale density.

5.5 | The importance of the choice of vessel data subset

For our case study, the smaller the AIS data subset used, the smaller the predicted area of high vessel risk. This is a significant point for managers to consider, as it highlights how the outputs can be influenced to produce smaller (or larger) areas of high predicted risk. However, the pattern found within our case study dataset may not necessarily apply to all geographic scenarios (e.g. along spatially constricted waterways).

Ultimately, the choice of a subset of AIS data should be undertaken using a considered process, and with sufficient justification for each constraint being introduced. Exclusion of speeds based on certain thresholds should, where possible, be based on evidence that collisions at those speeds are inconsequential (i.e. no injury or harm) for the species being considered (e.g. Kelley et al., 2021). Similarly, exclusion of certain vessel types should be based on evidence that the likelihood of collisions with these vessel types is minimal, and if collisions do occur, that they are inconsequential. Instead, many methods included only those vessel types with an evidence base that collisions with these types of vessels are likely to be lethal or injurious to whales (i.e. cargo vessels and tankers). However, the absence of a weight of evidence with regard to collisions with other vessel types is not evidence of the absence of risk. Whilst evidence is limited for some vessel types (e.g. due to underreporting, likelihood of observation of strike occurring), there is a growing body of evidence that smaller vessels can also be lethal or injurious (Kelley et al., 2021). Consequently, placing constraints on vessel types introduced into vessel risk modelling based on current relatively limited evidence of strike events is problematic, and if used within current approaches such as those in this study, could lead to the underestimation of risk through exclusion of 'strike data deficient' vessel types from these approaches (e.g. smaller fast-moving vessels). We therefore reiterate that careful consideration of inclusion and exclusion criteria for vessel speeds and types is imperative to avoid underestimation of risk.

5.6 | The selection of the appropriate probability of lethality regression curve

Vessel speed at the time of collision has an impact on the likelihood that the strike will be injurious or fatal (Conn & Silber, 2013; Kelley et al., 2021; Pace & Silber, 2005; Vanderlaan & Taggart, 2007). As such, six of the eight methods utilised vessel speed information from within the AIS data to inform their risk mapping. This was incorporated within each respective method using an equation generated from a 'Probability of Lethality' (PLETH) regression curve. PLETH curves estimate the likelihood that a strike from a vessel travelling at a certain speed will cause a fatal injury, and are most commonly generated based on historical vessel strike records, where the record includes the vessel speed at the time of collision and the collision outcome (i.e. injury or fatal). There are currently a number of published PLETH equations available, with four different equations used within the six methods that did consider speed as a metric of risk. Two methods used the PLETH equation presented in Vanderlaan and Taggart (2007), two used Conn and Silber (2013), whilst one approach used Pace and Silber (2005) and one used Kelley et al. (2021) (Table 1). The earliest PLETH curve (Pace & Silber, 2005) was generated using data from 53 strike records for 'all large whales', predicting a 50% chance of death or serious injury at 10.5 knots, increasing to 90% at 17 knots. Two years later, Vanderlaan and Taggart (2007) published a similar PLETH equation using 47 historical strike records of primarily baleen whales, predicting the probability of lethality to approach 100% when vessels are travelling over 15 knots. Conn and Silber (2013) then used an updated version of the same dataset used to generate the two prior PLETH equations, adding an extra 38 strike records. Notably, several of the new observations of serious injury were at lower speeds (2 to 5.5 knots), which allowed for improvement in reliability of the PLETH equation at lower speeds, which had previously been cited as being a particular area of uncertainty. Kelley et al. (2021) advanced PLETH research further by considering the relative forces that arise during a strike (i.e. the mechanical stresses placed on whales due to vessel type, size, speed and location of collision). Kelley et al. (2021) found that speeds that led to 50% PLETH varied by vessel type and tonnage (e.g. 6.6 knots for a 45-tonne fishing boat, 4.7 knots for a 311-tonne ship and 4.5 knots for a 30,000-tonne ship). Consequently, PLETH at 10 knots varied somewhat depending on vessel type (69%, 83% and 85%, respectively) (Kelley et al., 2021). They also showed how the location of a strike along the whales' body affected the likelihood of lethality. The work presented by Kelley et al. (2021) highlights both that constraining vessel risk models to only include vessels based on their length likely excludes vessel types that do still pose a risk (as discussed in the previous section), and importantly, that not all vessel speeds are equal; vessel type and tonnage affects the speed at which it becomes lethal. This nuance is not captured in the previously published PLETH equations and is in part captured by the PLETH equation published by Kelley et al. (2021), who rather than illustrate the probability of lethality at a certain speed, plot the probability of lethality in relation to the maximum compression stress incurred during a strike (which is back calculated based on a number of vessel metadata, including its collision speed amongst additional metrics).

Although the literature and nuance within PLETH equations are advancing with increasing knowledge of vessel strike events, currently there is no particular equation that is prioritised for use. The way each PLETH equation weights risk at different speeds will ultimately affect the locations predicted as 'high risk', which, like the choice of approach, will further contribute to potential dissimilarities in the risk map outputs. Whilst this study compared risk-mapping approaches, it would be similarly valuable to quantify and visualise how the choice of PLETH equation utilised may affect the predicted areas of risk within the output maps. Until such information is available, it is important when interpreting risk maps to consider the underlying PLETH equation that has been employed, and its associated assumptions. We also recommend, where and when the data allow, that species- and vessel-specific PLETH equations be developed, which will hugely aid vessel risk mapping efforts. As the equations are based on strike records, this will require improved reporting of strikes for all vessel types.

5.7 | Caveats of mapping vessel risk

It may seem obvious, but it is essential here to also acknowledge the inherent importance that the input data itself plays in the risk mapping process. The best approach for a circumstance can be selected, but if the input data is incomplete, incorrect or out of date, then the maps produced will also be incomplete, incorrect or outdated. Therefore, it must be reiterated that the best available data should always be used for both whales and vessels. If there are seasonal patterns to the presence of either in the area of interest, then this should be considered (for example, summer vessel traffic is not necessarily relevant to whales that migrate through the area in winter). If other data is used as a proxy (e.g. older datasets of whale distribution with more up-to-date vessel data) then the effect this will have on risk map interpretation should be thoroughly laid out for map viewers.

An overarching problem affecting all approaches is the increasing awareness that AIS data rarely, if ever, reflects actual vessel activity in a given area. This is because regulation with regards to transmission of AIS data from the International Maritime Organisation (IMO) only requires vessels over a certain size and tonnage to transmit AIS (see Methods). Therefore, many vessel types (e.g. recreational speed boats, small fishing vessels) are not legally required to transmit AIS, and as such, are missing from AIS datasets (e.g. Hermannsen et al., 2019; Serra-Sogas et al., 2021). The vessel types typically missing from AIS datasets do pose a risk to whales (Kelley et al., 2021), and therefore should be included in risk mapping efforts. However, this is challenging given the lack of any data allowing inclusion into such methods, though methods to include non-AIS vessels in risk mapping are emerging (Mayaud et al., 2024). Until non-AIS vessels are included in vessel risk maps then there will be some level of underestimation of risk in any areas where non-AIS vessels are present.

6 | CONCLUSIONS

We demonstrate here that the choice of approach to mapping the direct risk of vessels to whales (co-occurrence, collision, mortality), including the data input, can affect the areas deemed as 'high risk'. In the worst-case scenario, the selection of an approach that results in inaccurate outputs and under- or over-estimation of risk could result in the misplaced designation of vessel-related management measures which do not aid whale conservation efforts. Whilst the current data on strikes in our study location do not allow us to identify which approach provides the best approximation of 'real world risk', the work presented here clearly highlights the importance of careful consideration of the choice of approach and data subset. We show these choices have substantial implications for the risk maps produced, and thus any subsequent management or policy decisions arising from the consequent outputs.

AUTHOR CONTRIBUTIONS

Emily L. Hague led the investigation, formal analysis, visualisation and writing of the first draft. Lauren H. McWhinnie conceived the idea for the manuscript, acquired funding and supervised the work. William D. Halliday, Jackie Dawson, Steven H. Ferguson, Brent G. Young and Mads P. Heide-Jørgensen provided data for the case study used. All authors contributed to the editing and review of the manuscript, and approved the final version of the manuscript.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

Workflow and code to replicate each methodology are available within the Zenodo repository https://doi.org/10.5281/zenodo.13769540 (Hague, 2024).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Data S1: Supporting Information, including summary of bowhead whale data, and workflows to replicate the methods.

Data S2: Adapted code to replicate Methods A3, B1 and B2.

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