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Ship-strike forecast and mitigation for whales in Gitga'at First Nation territory

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ABSTRACT: As marine traffic increases globally, ship strikes have emerged as a primary threat to many baleen whale populations. Here we predict ship-strike rates for fin whales *Balaenoptera physalus* and humpback whales *Megaptera novaeangliae* in the central territorial waters of the Gitga'at First Nation (British Columbia, Canada), which face increases in existing marine traffic as well as new liquified natural gas (LNG) shipping in the next decade. To do so, we utilized Automatic Identification System (AIS) databases, line-transect surveys, shore-based monitoring, whale-borne tags, aerial drone-based focal follows, and iterative simulations. We predict that by 2030, whale encounters will triple for most vessel types, but the change is most extreme for large ships (length >180 m) in prime whale habitat, in which co-occurrences will increase 30-fold. Ship-strike mortalities are projected to increase in the next decade by 2.3× for fin whales and 3.9× for humpback whales, to 2 and 18 deaths yr^{-1}, respectively. These unsustainable losses will likely deplete both species in the coastal region of BC. Models indicate that the largest single source of mortality risk in 2030 will be from the LNG Canada project. Of the mitigation options we evaluated, a 10 knot speed ceiling for all large ships is potentially effective, but the best measure for guaranteed mitigation would be seasonal restrictions on LNG traffic. While certain data gaps remain, particularly with respect to humpback whales, our predictions indicate that shipping trends within Gitga'at waters will impact whale populations at regional levels. We provide our analysis in the R package 'shipstrike'.

KEY WORDS: Ship strike · Fin whale · Humpback whale · Kitimat Fjord System · Liquified natural gas · LNG · Gitga'at First Nation · Marine traffic

1. INTRODUCTION

As marine vessel traffic continues to increase globally, its consequences for ocean ecosystems are of growing concern (Jägerbrand et al. 2019). Whale populations are particularly vulnerable to marine traffic, since they are acoustically sensitive, dependent upon the sea surface for air, depleted by the recent era of commercial whaling, and exposed to many other anthropogenic threats (Schoeman et al. 2020).

Whales can be impacted by chronic exposure to the noises and dangers of marine traffic in multifarious

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ways (Erbe et al. 2019). The most direct and acute threat is collisions, often referred to as 'ship strikes' (Erbe et al. 2020), though even small vessels are capable of inflicting fatal wounds upon large whales (Kelley et al. 2021). Scoping the impact of ship strikes upon whale populations is difficult due to the many variables and stochastic processes involved (Martin et al. 2016, Redfern et al. 2020), but recent estimates indicate that ship-strike mortalities of large baleen whales are already occurring at unsustainable rates along the US west coast (Rockwood et al. 2017, 2020). That region is one of the few in the world for which adequate data exist to estimate ship-strike mortality rates throughout an exclusive economic zone (EEZ), and it serves as an indication that ship-strike rates may be similarly severe along other industrializing coasts (Rockwood et al. 2017).

The ship-strike threat is particularly acute when traffic rates increase within established whale habitat (Crum et al. 2019), especially in areas deemed critically important because they attract a disproportionate share of a whale population for a prolonged period into a relatively small area compared to the rest of its range. Critical habitats present opportunities for effective and resource-efficient protection, but any perturbations introduced within their borders, including shipping, can also have outsized effects (Williams et al. 2009). This is the scenario developing within the Gitga'at First Nation (British Columbia, Canada), whose marine territory (Fig. 1) has experienced 3 simultaneous trends that we shall explore in this study: (1) the repatriation and/or increased use by whales of a historically important whale foraging area, leading to the shortlisting of Gitga'at territory as critical habitat for several Canadian Pacific stocks (fin whales *Balaenoptera physalus*, Nichol & Ford 2012; humpback whales *Megaptera novaeangliae*, DFO 2010; northern resident killer whale *Orcinus orca*, Ford 2006; and Bigg's killer whale, Ford et al. 2013); (2) increases in commercial and recreational traffic associated with the Inside Passage and the nearby port of Kitimat (Heywood 2016); and (3) a series of fuel shipping projects for Kitimat that, when completed, would multiply large ship traffic within Gitga'at waters by more than an order of magnitude (Keen et al. 2022). These fuel projects have placed the otherwise remote Gitga'at community at the center of a national debate about Canada's energy futures (e.g. Thompson 2016), imposing difficult decisions upon Gitga'at leadership.

To navigate the stewardship–development decision space, managers of Gitga'at waters — and any coastal area facing such pressures, as well as those charged with species recovery—need actionable information about the risks posed by marine traffic. Ideally, those risks would be framed in concrete terms connected directly to actual outcomes, e.g. the predicted number of collisions or mortality events (Martin et al. 2016, Keen et al. 2022). However, achieving such specificity is not yet feasible for most study areas, since such analyses require a depth of local knowledge on whale abundance, habitat use, seasonality, travel pattern, dive behavior, etc., that remains rare in cetacean science. Without those details, risk must instead be framed in relative terms, i.e. identifying areas with the highest degree of spatiotemporal overlap between whales and vessels (Redfern et al. 2019). Relative risk is still valuable, since it helps managers focus their resources upon high-priority areas, but it can be difficult to leverage in high-stakes management decisions with concrete economic repercussions (Crum et al. 2019). Relative risk frameworks also make it difficult to assess tradeoffs and to evaluate potential opportunities for mitigation, since the benefits of measures such as ship-speed reduction are not easily quantified using metrics of spatial or temporal overlap (Martin et al. 2016, Rockwood et al. 2020). However, even with the necessary details in hand to transcend relative metrics and predict concrete outcomes, analytical approaches for doing so remain inaccessible and/or infeasible for many research groups.

Fortunately, the same data gaps that preclude impact assessments of marine traffic in other areas are shrinking in Gitga'at waters. Partially in response to the shipping projects proposed for the region, Gitga'at territory is now one of the best-studied large-whale habitats in the Canadian Pacific, particularly with respect to humpback whales (Ashe et al. 2013, Keen et al. 2017, Wray & Keen 2020, Wray et al., 2021, O'Mahony 2021), fin whales (Nichol et al. 2018, Hendricks et al. 2021, Keen et al. 2021), their ecological interactions (Keen 2017a,b, 2018, Keen & Qualls 2018, Qualls 2019), their acoustic habitat (Heywood 2016, Pilkington et al. 2018, Hendricks et al. 2018, 2019, 2021), and the area's oceanography (Shan et al. 2020 and references therein). Moreover, whale ship-avoidance behaviors have been studied in similar habitats in southeast Alaska (Gende et al. 2011), and studies elsewhere in the northeast Pacific continue to shed light on aspects of whale behavior relevant to ship-strike risk, such as patterns in dive behavior (Calambokidis et al. 2019, Keen et al. 2019). That research has led in turn to insights on the transferability of such findings to models for less-studied

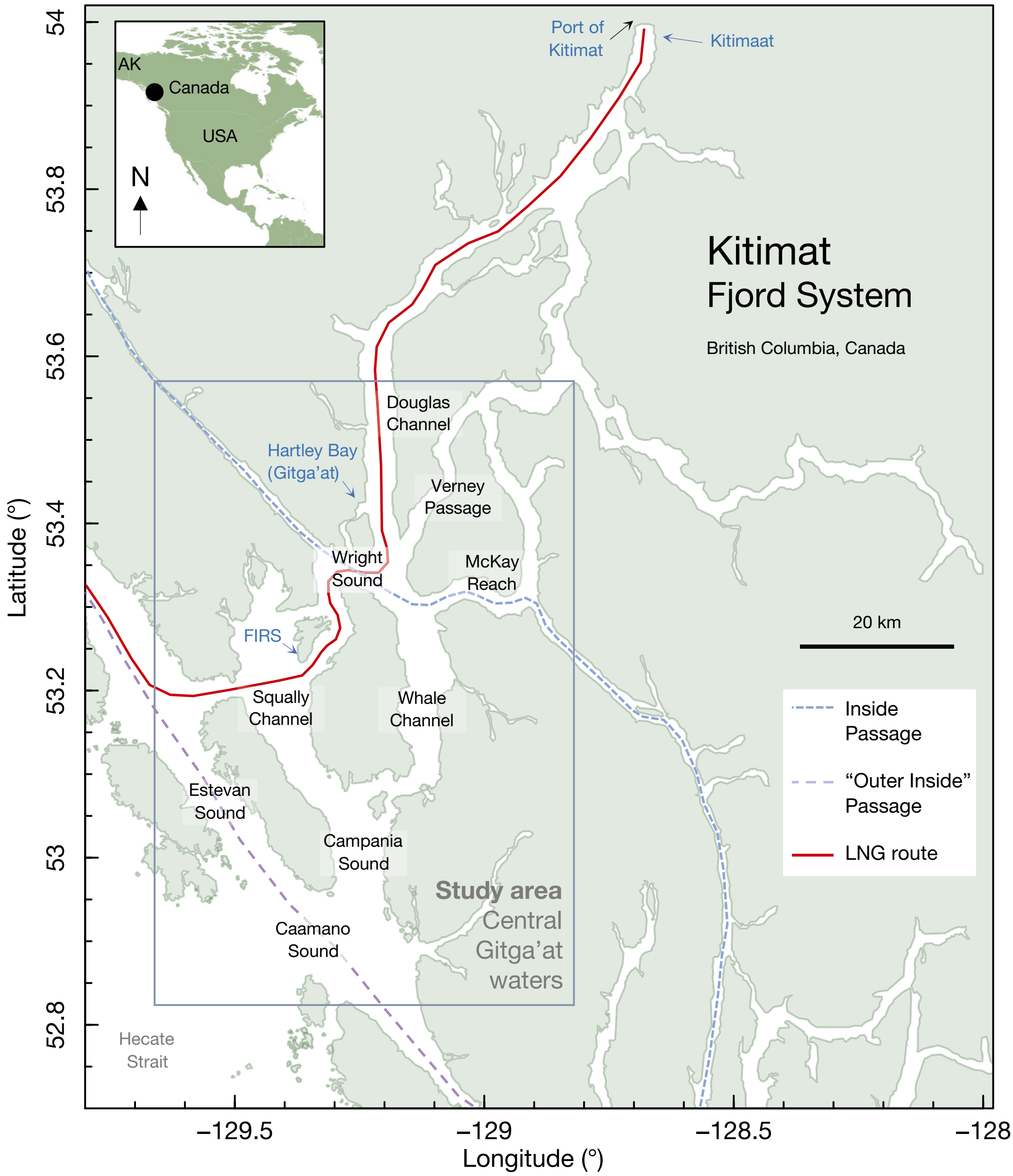

Fig. 1. The study area in central Gitga'at waters, within the Kitimat Fjord System (British Columbia, Canada), with current and proposed traffic routes indicated. Waterways and the research station (FIRS: Fin Island Research Station) mentioned within the main text are shown. Inset rectangle represents the area for which whale–vessel interactions were modeled in this study

regions (Rockwood et al. 2017, Keen et al. 2022). While certain data gaps still remain, the past decade of research has brought an outcomes-oriented ship-strike assessment within reach for Gitga'at waters.

Our goal here is to predict rates of whale–vessel interactions in central Gitga'at territory, both currently and in 2030, by which time all liquified natural gas (LNG) shipment projects currently approved for the port of Kitimat will be fully operational. We restrict our focus to fin whales and humpback whales, the only 2 baleen whale species that occur regularly within Gitga'at waters (Ford 2014, Towers et al. 2022). Both species are of cultural and economic importance to the Gitga'at (Gitga'at First Nation 2017).

Globally, fin whales were once the most numerous baleen whale (Christensen 2006) before being taken in greater numbers than any other whale species by commercial whalers (Aguilar 2009), reducing the worldwide population by approximately 70 % (Cooke

2018). Many stocks appear to be in the process of recovery (Cooke 2018), though fin whales are now considered the species most often struck by vessels worldwide (Laist et al. 2001). The British Columbia (BC) population remains severely depleted, but the recent discovery of sizable numbers far offshore has prompted a status reassessment from 'Threatened' to 'Special Concern' and a subsequent process for downlisting the species under Canada's Species At Risk Act (SARA), which has not been concluded as of this writing (COSEWIC [Committee on the Status of Endangered Wildlife in Canada] 2019). Ship-strike risk has been assessed for fin whales off Vancouver Island (Nichol et al. 2017), as well as in the California Current System further south, where fin whale mortalities from ship strikes are occurring at unsustainable rates (Rockwood et al. 2017). No assessment yet exists for northern BC waters, where 400 fin whales occur over the continental shelf waters and coastal areas of Queen Charlotte Sound and Hecate Strait (Nichol et al. 2018). Roughly a quarter of those individuals exhibit high interannual site fidelity to the fjord waters of Gitga'at territory, which is noteworthy as an atypical habitat for an otherwise offshore and oceanic species (Keen et al. 2021). Commercial whaling records indicate that Gitga'at waters were used historically as well, suggesting its long-term importance to the inshore contingent of the Canadian Pacific stock, which appears to practice limited interchange, if any, with the fin whales occurring far offshore (Nichol et al. 2018, COSEWIC 2019, Wright et al. 2021).

The humpback whale is currently the most numerous baleen whale in the Canadian Pacific, including its mainland inlets, and is managed as a stock of 'Special Concern' (Williams & Thomas 2007, FOC 2010). Similar to other coastal areas, humpback whales have increased dramatically in Gitga'at waters in the last 2 decades (Ashe et al. 2013, Wray et al. 2021). These whales belong to the Northern BC–Southeast Alaska feeding aggregation, the vast majority of which migrate to Hawaiian waters during the boreal winter breeding season (Barlow et al. 2011). While this population increased quickly after the cessation of commercial whaling (Barlow et al. 2011), that recovery appears challenged according to several indicators, including (1) recent declines in calving rate, both within Gitga'at waters (Wray & Keen 2020) and elsewhere (Neilson & Gabriele 2019, Cartwright et al. 2019); (2) ship-strike models from the California Current System, which predict that humpback mortality rates are twice the sustainable limit (Rockwood et al. 2017); (3) increased rates of entanglement along the US west coast (Ingman et al. 2021); and (4) unusual mortality events in Alaska in the past decade (Savage 2017).

In addition to predicting whale–vessel interaction rates and ship-strike rates for these 2 species, our final goal is to evaluate the efficacy of various mitigation measures for reducing shipping impacts on whales within Gitga'at waters, with a particular focus on large-ship traffic. We carry out this analysis using an updated version of the open-source R package 'shipstrike' (Keen et al. 2022), which makes the replication of our analysis feasible for Gitga'at waters and other areas as well.

2. MATERIALS AND METHODS

We adapted the ship-strike impact assessment framework outlined by Keen et al. (2022), which we summarize here, then detail in the subsections below. To predict whale–vessel interaction rates (see Table 1 for definitions), we first prepared spatial grids of vessel traffic, density surface models of whale density, and seasonal models of whale abundance to predict the number of times in which a vessel and a whale occur in the same square km (hereafter, a 'co-occurrence'). Second, co-occurrences were scaled by a 'close-encounter' rate, i.e. the rate at which a vessel and whale are expected to intersect in time and horizontal space assuming no avoidance measures are taken. The close-encounter rate is estimated using simulations that draw upon size and travel patterns for both vessel and whale. Third, close encounters were scaled according to vessel draft and whale depth distribution, which we inferred using whale-borne time-depth-recording tags, to estimate the number of 'strike-zone events', i.e. the times in which the whale and vessel will collide unless avoidance measures are taken. These 3 interaction rates — co-occurrences, close encounters, and strike-zone events — were estimated for all documented marine traffic and projected shipping, ranging from small pleasure craft to LNG carriers >300 m in length.

Next, rates of collision and mortality were predicted for large ships (>180 m) only, in order to match the source data underlying the best-available whale–ship avoidance models in the literature (Gende et al. 2011). Strikes from smaller vessels certainly introduce sub-lethal and lethal risks (Kelley et al. 2021), but given the highly variable and poorly understood dynamics of whale–vessel avoidance, we limited our focus to vessel size classes for which empirical models exist. To predict collisions, we scaled strike-zone

Table 1. Definitions and data requirements for the whale–vessel interactions and impacts predicted in this study. AIS: Automatic Identification System

Stage of analysis	Category	Definition	Spatial scale	Data requirements
Interaction rates	Co-occurrences	Number of times a vessel and whale occur in the same km^2, assuming no avoidance	1 km^2	- AIS data (real or simulated) - Whale density surface
	Close encounters	Number of co-occurrences that lead to horizontal overlap, assuming no avoidance	Horizontal meters (ignoring depth)	- AIS data (real or simulated) - Distributions for whale dimensions, speed, and travel pattern (for day and night, if possible)
	Strike-zone events	Number of close encounters during which the whale is expected to occur within the vessel strike zone based on its draft, assuming no avoidance	Meters, in 3 dimensions	- Vessel draft distribution - Whale depth distribution (i.e. share of time spent shallower than depth bins 0–max. draft)
Impacts	Collisions	Number of strike-zone events that result in a ship strike after accounting for avoidance	Whale–ship contact	Either (1) a constant P(Avoidance), or (2) a model of P(Avoidance) ~ vessel speed
	Mortalities	Number of collisions that result in whale death	Whale–ship contact	Either (1) a constant P(Lethality), or (2) a model of P(Lethality) ~ vessel speed

events according to an avoidance rate that was modeled as a function of vessel speed (Gende et al. 2011, Rockwood et al. 2017). Finally, the number of collisions were scaled by the lethality rate, which we also modeled using equations from the ship-strike literature (Kelley et al. 2021), to estimate the number of whale mortalities resulting from large ships.

2.1. Marine traffic

2.1.1. Present-day traffic. The year 2019, the latest full year of 'normal' traffic prior to the onset of the COVID-19 pandemic, was used to characterize 'present-day' marine traffic within the central waters of the Gitga'at First Nation, in the lower Kitimat Fjord System (KFS) of mainland British Columbia, Canada (Fig. 1). Vessel traffic in 2019 was represented by archived data from the Automatic Identification System (AIS). In sheltered Canadian waters, AIS is a mandatory requirement for all carrier ships >300 gross tonnage, all passenger ships >500 gross tonnage, any commercial vessel >20 m in length, any vessel >8 m in length with 12 or more passengers, and all towing vessels >8 m in length (Government of Canada 2020). In addition, many vessels that do not meet these requirements voluntarily participate in the AIS network. AIS transmissions from participating vessels are collected by coastal stations and satellites, and contain data regarding the unique identifier, position, speed-over-ground (hereafter, 'speed'), course, dimensions, draft, and type of the vessel. Note that, since AIS is not mandatory for small non-commercial vessels, its use as a characterization of marine traffic inherently underestimates the impact of small-vessel traffic in Gitga'at waters.

AIS records from 2019 were provided to us as decimated records with a median of 86 s between transmissions (mean = 121 s, SD = 145 s; Canadian Coast Guard 2019). These data include 1 871 873 location fixes within the entire KFS. Of these, 229 452 valid records of 992 unique vessels come from our study in the lower KFS (52.8 to 53.55° N, 129.68 to 128.66° W). Invalid records were filtered out by only keeping location fixes within the study area with speed between 3 and 40 knots, length-overall (hereafter 'length') between 5 and 500 m, beam width (hereafter 'beam') of at least 2 m, and with drafts of no more than half the reported length. If beam data were missing, it was inferred based on a beam:length ratio of 0.125:1 (after Marsh 2013). If draft data were missing, it was inferred using a draft:length ratio of 0.05:1 (Marsh 2013). Remaining records were inspected visually to ensure that vessel paths never crossed islands.

For this analysis, the 21 vessel types represented within this dataset (Table S1 in the Supplement at www.int-res.com/articles/suppl/n051p031_supp.pdf) were pooled into 10 categories (Table 2) such that the vessels in each class shared a similar length and

Table 2. Summary of 2019 AIS traffic in central Gitga'at waters for the 10 vessel types used in this study

Vessel type	ID	Transits		Speed (knots)			Length (m)				Beam (m)				Draft (m)			
		n	d^{-1}	Mean	SD	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
Cargo >180 m	38	94	0.26	13.1	1.4	17.1	193	7	180	200	31	1	28	33	9.5	1.7	6.0	11
Fishing <60 m	305	822	2.25	8.4	3.2	32.2	20	7	6	54	6	2	1	15	1.4	1.1	0.4	10
Other <40 m	70	565	1.55	11.5	7.2	39.2	23	9	6	40	6	2	2	10	1.8	1.4	0.3	8
Other >100 m	23	378	1.04	16.0	3.4	23.0	142	18	116	179	23	3	4	29	5.3	1.1	3.0	10
Other 40–100 m	46	340	0.93	9.5	2.6	16.6	57	14	42	100	13	3	7	22	3.9	1.3	2.0	6
Passenger >180 m	6	73	0.20	17.4	3.4	23.3	259	39	197	301	32	2	28	36	7.8	0.4	7.0	8
Pleasure craft <40 m	263	1123	3.08	8.1	3.8	37.5	16	5	7	37	5	1	1	14	0.9	0.7	0.4	9
Sailing <40 m	117	426	1.17	6.0	1.3	12.6	14	4	8	35	4	1	1	8	0.7	0.3	0.4	3
Towing <50 m	74	738	2.02	8.0	1.9	21.7	29	9	6	41	9	2	2	12	4.1	1.7	0.3	7
Tug <50 m	61	835	2.29	7.3	1.8	13.9	22	8	11	41	7	2	4	22	3.0	1.8	0.6	6

speed profile (Figs. S1 & S2). Some types were split according to troughs in their length and/or speed distributions (e.g. pleasure craft were split into those <40 m and those >40 m), or to match the minimum length cutoff of 180 m for collision/mortality predictions. Pooling vessel types improved sample sizes for analysis and eased interpretability of results. Three catch-all categories, 'Other 40–100 m', 'Other >40 m' and 'Other >100 m', were used to capture rare vessel types with characteristics that did not fit well with other categories, as well as to capture vessels with anomalous length/speed characteristics. For example, only a few pleasure craft were longer than 40 m, so these were pooled into 'Other 40–100 m' so that the 'Pleasure craft' category only contained vessels less than 40 m.

To prepare AIS data for the ship-strike assessment, vessel traffic for each class was summarized using a 1 km^2 spatial grid. To do so, each date for each unique vessel within the AIS record was interpolated such that location fixes were <0.25 km apart. The solar angle at each location fix was determined using the package 'oce 2.7.1' (Kelley & Richards 2022) in R 4.0.2 (R Core Team 2020) according to location and timestamp. Each fix was labeled as daytime or nighttime using a threshold solar angle of −12 degrees for nautical dusk/dawn (after Calambokidis et al. 2019). These fixes were then mapped onto the spatial grid. For each grid cell, we prepared a table for each month–diel period (e.g. nighttime in July) with the length, beam, draft, and speed for each vessel that crossed the cell. Note that the same vessel could occur on this table more than once if it crossed the grid cell on separate dates. In this way, each grid-cell table represented a prevalence-weighted synopsis of vessel traffic within its respective 1 km^2.

2.1.2. Predicted AIS traffic in 2030. To predict rates of traffic in 2030, we used AIS records available to us from 2014, 2015, 2018, and 2019 (Canadian Coast Guard 2019) to establish simple linear models of annual changes in km transited by each vessel type separately. We then used those models to predict 2030 traffic rates. Note that trends in vessel classes for which AIS usage may be voluntary depending on route and passenger load, e.g. pleasure craft <20 m (Government of Canada 2020), may reflect changes in both the fleet size as well as rates of AIS adoption. To account for the disruption of the COVID-19 pandemic, we assumed that 2022 traffic rates were equal to those in 2019 (i.e. no net change in traffic rates during the 2 pandemic years of 2020 and 2021), and adjusted the linear models accordingly.

2.1.3. Simulated LNG Canada traffic in 2030. Once fully operational by 2030, the LNG Canada project will bring 350 calls by LNG carriers (LNGC) to the Kitimat Terminal each year, therefore introducing 700 additional transits of the study area (TERMPOL 2015). The route taken by incoming and outgoing ships will be the same (Fig. 1), and calls are expected to be distributed evenly throughout the year. No daily schedule for the timing of calls is available at this time. Each transiting LNGC will be accompanied by 1 escort tug >35 m in length (TERMPOL 2015). Beam and draft details for these tugs were not provided.

LNGCs for this project will come from the fleets of Shell, Kogas, Mitsubishi, and China National Petroleum Corporation. The fleet characteristics (length, beam, draft) differ for each company, but range from 286 to 298 m in length, 41 to 46 m in beam width, and 11.5 to 12 m in draft (Table S4). LNG Canada reports that safe operating speeds for these vessels range from 4 to 19.5 knots, with full maneuverability at 12 to 14 knots and effective 'dead slow' ahead of 6 knots. The stated intention of LNG Canada is to travel <10 knots within KFS whale habitat, but they also acknowledged that speed will be determined on a per-transit basis by pilots according to conditions and port schedules, and that maneuverability will take precedence over slow transit speeds.

Based on this information, we simulated traffic for the LNG Canada project as follows: incoming transits were randomly distributed throughout the year with only 1 allowed per calendar day, and outgoing transits were scheduled for the day following each incoming transit. For each transit, the coordinates of the proposed route were modified slightly in order to emulate realistic route variation. This was done using error terms drawn from a random normal distribution (mean = 0°, SD = 0.002°). A random start time was assigned to the beginning of the track, and the simulated LNGC was assigned a length, beam, and draft (drawn randomly from Table S4), as well as a speed. Since exact speeds are unknown but will vary by navigation conditions and schedule, we allowed the average speed of each LNGC transit to vary uniformly between 8 (slightly greater than effective 'dead slow' ahead) and 14 knots (full maneuverability). Based upon start time and speed, timestamps and sun angles along the route were determined. These transits were then mapped onto the 1 km^2 spatial grid of the study area and categorized as daytime or nighttime traffic for their respective month, similar to the 2019 AIS analysis above. This was repeated for all LNGC transits (n = 700). These transits were then duplicated to represent escort tugs accompanying the LNGCs, for a total of 1400 transits. All escort tugs were given the same dimensions: 35 m length, 5.2 m beam (based on the empirical mean beam:length ratio of 0.15 in 2019 tugs), and 3 m draft (based on the mean for 2019 tugs).

2.1.4. Simulated Cedar LNG traffic in 2030. The Cedar LNG project will bring up to 50 additional LNGC calls (100 transits) to the port of Kitimat every 7 to 10 d (Stantec Consulting 2019). The route of these carriers is the same as the LNG Canada project, and at least 1 escort tug will be assigned to each LNGC, but details are not publicly available regarding fleet dimensions or speed regime during transit. To simulate the shipping activities for this project, we drew ship dimensions from the LNG Canada fleet specifications and assigned each transit a random speed between 8 and 14 kn.

2.1.5. Simulated total traffic in 2030. Total marine traffic activity in 2030 was predicted by combining all predictions of AIS traffic in 2030 with the addition of traffic from both LNG projects.

2.2. Fin whales

2.2.1. Whale density. Within the context of a shipping impacts assessment, whale density (whales km^{-2}) represents the probability that a whale will be present within a square kilometer as a vessel transits. We estimated fin whale density from design-based line-transect sampling surveys conducted during June to September in 2013 to 2015, in which standard distance sampling methodologies (Buckland et al. 2001) were used to survey marine mammals aboard a 12 m motorsailer along pre-planned tracklines (see Keen et al. 2021, 2017, or Keen 2017b for detailed methods). This effort (3596 km of trackline surveyed within the KFS; Table S5) yielded 42 fin whale detections with valid perpendicular distance estimates and associated sighting conditions (Fig. S6).

To estimate density from these sightings, we selected the detection function using standard methods with the R package 'Distance' (Miller et al. 2019). To optimize model fit, a half-normal model key was used and the furthest 10% of sightings were excluded (right-truncation distance 2.0 km; Gerrodette & Forcada 2005). The base model was compared to additional models in which Beaufort sea state, year, and waterway were added as covariates in a forward stepwise procedure adapted from Barlow (2016) and Bradford et al. (2021): each candidate covariate was added to the model one at a time, the model AIC score was compared to that of the base model, and the model with the lowest AIC was kept for the next round of model-fitting. Covariates were added until the AIC no longer improved, and all models within 2 AIC scores of the lowest AIC were considered best-fitting. If multiple models were best-fitting, the most parsimonious (i.e. fewest parameters) was kept (Table S6, Fig. S7).

The detection function was then passed to a density surface modeling routine (R package 'dsm'; Miller et al. 2022), in which transect effort was chopped into discrete 5 km segments (n = 712) and the number of whales counted along each segment was modeled based upon latitude and longitude (combined in a single 'te' smoother), as well as several candidate covariates in a generalized additive model (GAM) framework. The distribution family for this model was chosen from 3 standard options (quasi-poisson, negative binomial, and tweedie) using quantile-quantile and residual plots. In the case of fin whales, candidate covariates were limited to fixed physiographic features — mean seafloor depth along the transect and the range in seafloor depths within 1 km of the transect (Fig. S8) — since (1) sightings were too few to model seasonally dynamic spatial trends, and (2) previous research has not found strong evidence of broad changes in fin whale distribution within the fjord system (Keen et al. 2018, 2021). These covariates were checked for collinearity, and were then added with spline smoothing in a forward stepwise model-fitting procedure, as described above. The best-fitting model was used to estimate density for the same 1-km^2 grid used to summarize vessel traffic.

Variance in our estimates of the detection function and density surface was estimated using a bootstrapping routine with 1000 iterations (adapted from Bradford et al. 2021 and references therein). In each iteration, survey segments were re-sampled with replacement, the detection model was re-fit, as was the density surface model, and the density surface was predicted and saved. This process resulted in 1000 bootstrapped density estimates, which were distributed around the original best estimate, for each 1 km^2 grid cell. This set of density surfaces was used for both 2019 and 2030 impact predictions, since the most recent time series for the Gitga'at-area population does not indicate an increasing or decreasing trend and it is not feasible to predict any future changes in habitat use (Keen et al. 2021).

2.2.2. Seasonal abundance trends. The survey effort underpinning the above density estimates was temporally coarse and limited to late June until early September. To produce a better estimate of seasonal trends, we used daily shore-based surveys carried out between early May and late October in 2017 to 2021 from Fin Island Research Station (FIRS), which is located on the proposed tanker route near the center of the study area (Fig. 1).

Survey methods are detailed in Keen et al. (2021); briefly, a team of trained observers conducted 20 min scans for marine mammals and vessel traffic on an hourly basis between 07:00 and 12:00 h and between 16:00 and 20:00 h, with additional midday scans as glare and wind permitted. The 220° vantage from Fin Island, with approximately 200 km^2 of central Squally Channel in view (Fig. 1), was surveyed using a combination of 25-power tripod-mounted binoculars (Big Eyes), 20–60× tripod-mounted spotting scope (Zeiss), and 7 × 50 handheld Fujinon binoculars. Effort and sighting conditions were documented with detail, and only scans with >10 km visibility were used in this analysis.

Biweekly fin whale counts from 2017 to 2021 (n = 45) were used to model relative fin whale abundance as a function of day of the year using a GAM framework with the R package 'mgcv' (Wood 2011), in which fin whale counts were modeled with a negative binomial error distribution using minutes of search effort as an offset (log transformed). The predicted fin whale encounter rate for each month of the research season (May to October) was estimated by averaging predictions across days in each month. These predictions were then scaled such that their mean value between June 1 and September 1 (the seasonal window of line-transect sampling effort) was equal to 1.0. In this way, the predictions could then be used to scale the density surface such that it reflected our best-available spatially explicit estimate of fin whales in Gitga'at waters within any given month.

Note that this model did not predict encounter rates outside of the research season, but fin whales have been documented within Gitga'at waters during all months of the year (Hendricks et al. 2021, Keen et al. 2021). Based on those records and the authors' collective field experience in this study area as well as the trends reported in Hendricks et al. (2021) and Keen et al. (2021), we approximated the relative abundance of fin whales for November to April as follows: we estimated November abundance to be 20% of October abundance, December to be 20% of November abundance, and January to be 20% of December abundance. Likewise, April abundance was 20% of May abundance, March was 20% of April abundance, and February was the mean of estimates for January and March.

This modeling routine was then iterated using a bootstrap procedure, in which biweekly counts were resampled with replacement to produce a distribution of abundance estimates for each month that reflects the variability of both fin whale abundance and the uncertainty of our sampling and modeling methods.

2.2.3. Close-encounter rate. Rates of close-encounter, i.e. the fraction of square kilometer co-occurrences that lead to an imminent collision assuming no avoidance, were estimated using the simulation method presented in detail in Keen et al. (2022). Briefly, iterative simulations were used to determine the fraction of times in which a vessel of a certain size and speed and a whale of a certain size, speed, and travel pattern overlap in horizontal space and time within a circular 1 km^2 area under a null expectation of no avoidance. With each iteration, vessel and whale size/speed parameters are randomly sampled from parameter distributions defined by prior research (Table 3), so that the resulting distribution of encounter rate estimates successfully

Table 3. Body morphology and movement values to parameterize vessel encounter rate models for fin whales and humpback whales. Minimum and maximum values were used to define truncated normal distributions. Sources: [1] Keen et al. (2021), [2] Hendricks et al. (2021), [3] Gregr et al. (2000). UAS: unmanned aerial system

Parameter		Fin whale		Humpback whale	
		Value	Source	Value	Source
Length (m)	Mean	20	[1]	11.85	UAS flights in this study
	SD	1.65	[1]	1.32	Inferred from Gaussian based on mean, SD, & max.
	Min.	10	[1]	8.25	Inferred from Gaussian based on mean, SD, & max.
	Max.	26	[1]	15.5	Max. female in catch record in [3]
Width:length ratio	(constant)	0.207	[1]	0.330	UAS flights in this study
Day speed (m s^{-1})	Mean	1.14	[2]	0.58	UAS flights in this study
	SD	0.44	[2]	0.26	UAS flights in this study
	Min.	0.27	[2]	0.04	UAS flights in this study
	Max.	2.22	[2]	1.43	Max. speed in this study plus 1 SD
Night speed (m s^{-1})	Mean	1.81	[2]	0.71	Scale day speed by fin whale night:day speed ratio
	SD	0.57	[2]	0.21	Scale mean by fin whale CV
	Min.	0.55	[2]	0.08	Scale day min. speed by fin whale night:day ratio
	Max.	3.04	[2]	1.96	Scale day max. speed by fin whale night:day ratio
Day track variability (deg. min^{-1})	Mean	0.81	[2]	0.81	Assumed same as fin whale
	SD	1.33	[2]	1.33	Assumed same as fin whale
Night track variability (deg. min^{-1})	Mean	1.50	[2]	1.50	Assumed same as fin whale
	SD	1.39	[2]	1.39	Assumed same as fin whale

captures the variability inherent to the process. Fin whale body measurement distributions were inferred from a previous photogrammetry study using unmanned aerial systems (UAS; Keen et al. 2021), and travel patterns were inferred from acoustically localized tracks (Hendricks et al. 2021). Both studies occurred within Gitga'at waters.

Since speed and travel patterns of rorqual whales are known to vary by diel period (i.e. day or night; Calambokidis et al. 2019, Keen et al. 2019, Hendricks et al. 2021), spatially explicit encounter-rate distributions must be prepared separately for each vessel–species–diel scenario. To accommodate this, each transit that occurs during a given diel period contributes a set of values (length, beam, and speed) for every 1 km^2 grid cell intersected by the transit, such that the vessel parameter distribution represents a spatially weighted expectation. The close-encounter rate distribution was prepared for each scenario using 100 iterations, in which each iteration used 100 simulation runs to estimate the probability of a close encounter.

For 2019 AIS data, we checked within each vessel class for monthly patterns in vessel size and speed. Strong seasonal patterns may require that encounter-rate distributions be prepared for each month separately, particularly if those patterns change during months of high whale abundance, and such processing would be computationally intensive. We found (1) an increase in passenger ship lengths for the period of May to October, and (2) an increase in pleasure craft size and speed for the same set of months (Figs. S3 & S4). To account for these seasonal trends, we estimated encounter rates across vessel types separately for May to October and November to April.

In some coastal regions, there are distinct geographic patterns in the size and speed of vessels within a single vessel class (e.g. cargo ships within nearshore speed-reduction zones vs. unrestricted offshore routes). There may also be regional heterogeneity in whale size, speed, and/or directionality (e.g. foraging grounds vs. migration routes). In those cases, separate encounter rate distributions ought to be produced for each region separately. We decided this was not necessary for the Gitga'at study area, given its small area and the fact that its waterways are similarly confined within the fjord system. Therefore, for a single vessel class–season–diel period scenario, a single encounter rate distribution was produced for the entire study area.

2.2.4. Surface rate. The rate at which fin whales occur within the near-surface 'strike zone' is a function of both vessel draft and whale dive depth (Friedlaender et al. 2009, 2013, Calambokidis et al. 2019, Keen et al. 2019). Fin whale depth distribution in the KFS was inferred from dive data for 7 individuals studied in August 2013 and August to September 2014 (Nichol et al. 2018) using satellite-linked SPLASH10 tags (Wildlife Computers; Table S9, Figs. S9 & S10). Details of deployment and tag data processing are provided in Nichol et al. (2018) as well as in our Supplement.

A depth distribution for each tag record was prepared by determining the proportion of depth samples occurring above various depth cutoffs. Proportions were calculated for 0 to 210 m (the maximum recorded dive was 209 m) in half-meter increments (Fig. S11). The proportions for all tags were averaged at each depth bin to produce a mean and SD value for the proportion of time spent. This process was carried out for daytime and nighttime samples separately, based on the sun altitude for each timestamp determined using the R package 'oce' (Kelley & Richards 2022), and these 2 depth distributions were carried forward into the ship-strike impacts analysis.

2.2.5. Interaction rates. We used the parameter distributions above to estimate whale interaction rates for each combination of traffic scenario (e.g. AIS-transmitting traffic in 2030), vessel class (e.g. passenger ships >180 m), waterway (e.g. Squally Channel), species (i.e. fin whale), month (e.g. July), and diel period (e.g. nighttime). For each scenario, the following stochastic routine was carried out 1000 times.

The 1 km^2 grid cells crossed by all vessel transits were counted to enumerate the opportunities for vessel–whale co-occurrence. Those grid cells were used to reference the whale density surface in subsequent steps, and the number of cells intersected by transits offers an estimate of traffic intensity in the area. However, since vessels do not bisect grid cells perfectly and will travel the exact same route in future years, the cell count has to be scaled stochastically in order to produce a prediction of the actual distance transited. To carry out this scaling, we simulated a vessel transiting a square 1 × 1 km space with randomly selected entry and exit points along its perimeter, calculated the distance traveled within the space, and repeated this simulation 10000 times to produce a distribution (mean = 0.527 km, SD = 0.248 km). This distribution was then sampled for each grid cell transited, and the drawn distance was compared to a random-uniform value between 0 and 1. If that value was greater than the drawn distance, its respective grid cell was removed from the set. The number of grid cells kept thus represented a stochastic estimate of the number of potential co-occurrence events, as well as a stochastic sample of grid cells from which to estimate whale density in the next step. For each potential co-occurrence, a whale density was randomly drawn from the distribution of bootstrapped density estimates corresponding to that grid cell. If this density was larger than a randomly drawn value from a uniform distribution between 0 and 1, a co-occurrence event was logged.

In that event, we tested for a close-encounter event using a similar stochastic approach by comparing a second random-uniform value between 0 and 1 to a random draw from the encounter-rate distribution of the scenario. In the event of a close encounter, we tested for a 'strike-zone event' as follows: A vessel draft was randomly drawn from the spatially weighted distribution of vessel drafts for this scenario. The depth distribution model for the whale was used to determine the mean and SD of the probability that the whale is occurring shallower than this draft. A value was drawn from a Gaussian distribution with those mean and SD parameters to obtain the probability that the whale is occurring within the near-surface strike zone, and this was compared to a random-uniform draw as above. Following Rockwood et al. (2017), we tested 2 strike-zone scenarios, one in which the depth of the strike zone was equivalent to the draft of the vessel, and a second in which strike zone depth was 1.5× vessel draft to account for hydraulic suction from the hull and propellers (Silber et al. 2010).

2.2.6. Collision rate. For ships >180 m, strike-zone events were scaled stochastically by an avoidance model in order to predict rates of collision. Avoidance response is perhaps the least understood component of whale–ship interactions, in part because such behavior is likely to vary in unknown ways across species, behavioral states, times of year, and vessel type, as well as the fact that avoidance can be attempted by both the whale and the vessel (Rockwood et al. 2017). Fin whales have been shown to exhibit changes in behavior near smaller vessels (Jahoda et al. 2003) and ferry traffic (David et al. 2022), but the efficacy of such responses for avoidance has not been quantified.

To account for these knowledge gaps, we predicted outcomes under 3 potential avoidance scenarios (after Rockwood et al. 2017). In the first, we assumed no avoidance at all (i.e. the worst-case scenario). In the second scenario, we used a constant 55% avoidance (adopted from McKenna et al. 2015 and Rockwood et al. 2017). In the third scenario, avoidance was modeled as a low-slope logistic function of vessel speed, developed by Gende et al. (2011) based upon humpback whale interactions with cruise ships in Glacier Bay, Alaska (USA), and implemented in collision rate assessments by Rockwood et al. (2017) among others (Fig. S12):

$$P(\text{Collision}) = 0.90/(1 + e^{-0.20(\text{Vessel speed} - 11.8)}) \quad (1)$$

where 0.90 is the maximum probability of collision, P(Collision), −0.20 reflects a representative large-ship draft of 20 m, and 11.8 knots is the threshold speed in the logistic function.

2.2.7. Lethality rate. In the event of a collision, we tested for a mortality event using the same stochastic approach applied to the probability of lethality, which also remains a poorly understood component of ship-strike science (Kelley et al. 2021). Nearly all data on lethality rates come from studies of other species, mainly the North Atlantic right whale *Eubalaena glacialis* (Conn & Silber 2013), and many ship-strike studies extrapolate the regressions for that species to others (e.g. Nichol et al. 2017, Rockwood et al. 2017, 2020, 2021, Kelley et al. 2021). We adapted such conventions for our analysis here. The probability of collision lethality, P(Lethal), was treated as a function of vessel speed based on the following equation from Kelley et al. (2021), who used biophysical models to find that the commonly used model from Conn & Silber (2013) underestimates the lethality of ships (Fig. S12):

$$P(\text{Lethal}) = 1.0/(1 + e^{-[-1.241 + 0.271(\text{Vessel speed})]}) \quad (2)$$

2.2.8. Outcome forecasts. After predicting rates of interactions, collisions, and mortalities, the result is a set of posterior distributions of the predicted number of each event for a given vessel–channel–month–diel scenario. To produce forecasts based on these results, we combined and summarized them in 3 ways:

1. Cumulative outcomes for a given traffic scheme (e.g. 2019 AIS traffic) were estimated by summing the interactions across all vessel types, months, and diel periods for each of the 1000 iterations. This returned a distribution of predictions, i.e. a posterior, for each interaction type (co-occurrence, close encounter, etc.). The 95% CIs were estimated based upon the 2.5% and 97.5% quantiles. Additionally, the value at the 0.20 quantile of the posterior was used to indicate a minimum prediction with 80% confidence (e.g. 'We predict an 80% chance of at least 1 collision annually.'), which is a common and intuitive confidence threshold in conservation management statistics (Wade 2000, NMFS 2016).

2. Posterior quantiles were also used to report the percent chance of various outcome severities. For example, the chance of at least 2 mortality events occurring in a single year is the proportion of the mortality posterior at or greater than 2. Similarly, the chance of no mortality event at all is the proportion of zeroes in the posterior.

3. To estimate the share of risk by vessel class, i.e. the proportional contribution of each vessel class to a set of predicted outcomes, we used a 1000 iteration bootstrapping procedure which we describe here using co-occurrence events as an example outcome: For each iteration, the annual number of co-occurrences attributable to each vessel class was predicted based on the sum of single random draws from its co-occurrence posterior for each channel–month–diel scenario. The share of co-occurrences for each vessel class was calculated by dividing their co-occurrences by the total number of co-occurrences across all vessel classes. Once this process was repeated for 1000 iterations, the mean of this distribution was treated as the predicted share. The same approach was used to estimate the share of risk by waterway, the share of risk by month, and the share of risk by diel period.

2.2.9. Potential biological removal. Our next step was to compare our mortality predictions to an estimate of potential biological removal (PBR) — i.e. the maximum number of non-natural deaths that can sustainably occur on an annual basis — for Canadian Pacific fin whales. Estimates of PBR are based on the product of 3 parameters (Eq. 3): a minimum population estimate (N_{min}), defined as the 20% quantile of the log-normal distribution of the abundance estimate (NMFS 2016), a maximum rate of population increase (R_{max}), and a recovery factor (F_r) (NMFS 2016). We used the default values of R_{max} (0.08) and F_r (0.5) recommended for a depleted cetacean stock (NMFS 2016).

$$\text{PBR} = 0.5\, N_{min}\, F_r\, R_{max} \quad (3)$$

We first estimated PBR for the entire BC EEZ in order to place local Gitga'at-area outcomes within the context of federal mechanisms of stock protection (i.e. Canada's SARA). To do this, we used published results from 2018 line-transect surveys operated by Canada's Department of Fisheries and Oceans (N = 2893; 95% CI = 2171–3855; CV = 0.15; Wright et al. 2021). Second, given that rates of interchange between the inshore and offshore BC populations appear low but remain unknown (COSEWIC 2019), we calculated PBR for that survey's North Coast sector only (Queen Charlotte Sound, Hecate Strait, Dixon Entrance, and coastal inlets including Gitga'at First Nation waters; N = 161; 95% CI = 64–407; CV = 0.50). Third, we estimated PBR for the coastal population south of Dixon Entrance, including Gitga'at waters, which was assessed using mark–recapture analysis by Nichol et al. (2018) (N = 405; 95% CI = 363–469; CV = 0.60).

2.3. Humpback whales

The humpback whale analysis mirrored that of fin whales above, with the following exceptions.

2.3.1. Density and seasonality. Humpback whales are more numerous in the fjord system. Line-transect survey effort in 2013 to 2015 yielded 419 sightings for use in modeling the detection function and the density surface (Table S5). This sample size allowed us to account for the seasonally dynamic distribution of humpback whales within the KFS. Unlike fin whales, whose distribution within the study area appears to be seasonally stable (Keen et al. 2018), humpback whales are known to shift their distribution from the southwestern outer channels of the KFS to the northeastern interior channels as summer transitions to fall (Keen et al. 2017). This trend was captured in the density surface model via an additional candidate covariate that included an interaction term for Latitude, Longitude, and Day of Year. This covariate was selected in the best-fitting model (Table S11), which allowed us to produce a separate density surface for each survey month (June to September). This was fortunate, given that the seasonally dynamic distribution of this species prevented us from using FIRS shore-based surveys to model the seasonal curve of humpback abundance, since apparent density within the FIRS viewshed is not always correlated with fjord-wide abundance. Instead, the monthly density surface models for June to September were used without scaling. As with fin whales, densities for months without survey effort were assumed using the same scaling regime (October abundance was 20% of September abundance, November was 20% of October, etc.), and the same set of density surfaces was used for 2019 and 2030 due to recent uncertainty in local humpback population trends (Wray & Keen 2020).

2.3.2. Close-encounter rates. In encounter-rate simulations, humpback whale dimensions were derived from UAS footage from Gitga'at waters in 2019 (Table S7). Data collection and analysis followed the same methods as for fin whales, which are based on established methods in Dawson et al. (2017) and detailed in Keen et al. (2021) as well as in our Supplement. UAS footage was also used to characterize daytime swim speeds based upon the timestamp and geospatial coordinates of each photograph still centered over a whale. Mean swim speed was estimated for each individual for which photographic stills were separated by at least 60 s, and the distribution of mean speeds across individuals was used to define a truncated normal distribution of swim speeds (Tables 3 & S8).

To estimate nighttime swim speeds for humpback whales, for which we have no data, the daytime speed distribution was scaled by the day:night ratio of speeds observed for fin whales in Gitga'at waters (Hendricks et al. 2021; Table 3). We also lacked data on humpback whale track variability. Given that the encounter rate is not sensitive to this parameter (Keen et al. 2022), we used the fin whale values in their place (Table 3).

2.3.3. Remaining parameters. No regional data on humpback whale dive behavior was available for our study, so we used the locally derived fin whale depth distribution for humpback whales as well. Tag data from the California Current corroborate that humpback whales practice a similar diel pattern in dive behavior and surface use, though their depth distribution is shallower on average than fin whales (Calambokidis et al. 2019), meaning that our estimate of humpback whale depth distribution can be considered a best-case scenario for overlap with the near-surface strike zone. The same avoidance and lethality scenarios were used for both fin whales and humpback whales, since (1) a study specific to fin whale avoidance does not yet exist, and (2) the same models are regularly applied to several species in the ship-strike literature (e.g. Nichol et al. 2017, Rockwood et al. 2017).

2.3.4. PBR. We estimated humpback whale PBR for the entire BC EEZ based upon abundance estimates from 2018 line-transect surveys (N = 7030; 95% CI = 5733–8620; CV = 0.10; Wright et al. 2021), then again for the North Coast sector of those surveys (N = 1816; 95% CI = 1403–2351; CV = 0.13).

2.4. Mitigation measures

We then used the methods above to evaluate various candidate measures for mitigating large ship traffic (>180 m) within Gitga'at waters in 2030 and beyond. We focused upon 4 categories of mitigation pertaining to speed reductions, transit rescheduling, and seasonal moratoria.

Category 1: speed reduction measures — We considered 2 scenarios: (1a) LNG traffic is restricted to 7–9 knots (this mitigation measure was cited as a possibility by LNG Canada; TERMPOL 2015); and (1b) in addition to the 7 to 9 knots restriction for LNG traffic, all other large ship traffic (>180 m) is restricted to speeds of 10 knots or less (this is a common reduction target in ship-strike impact studies; Rockwood et al. 2020).

Category 2: rescheduling transits to daytime only — By rescheduling transits to daytime only, we avoid the nighttime periods during which whales occur in shallow waters more frequently (Calambokidis et al. 2019, Keen et al. 2019). Two scenarios were considered here: (2a) only LNG traffic are required to comply; and (2b) LNG as well as all large ship (>180 m traffic) are made to comply.

Category 3: rescheduling LNG traffic — In this category, we explored the effect of rescheduling LNG traffic such that the timing of transits changes but there is no change in the volume of product transported. Three scenarios were considered: (3a) all transits during 1 month are rescheduled to occur throughout the remaining months instead; (3b) 2 months are rescheduled; and (3c) 3 months are rescheduled. In each scenario, rescheduling was tested for each candidate month window, and the window yielding the greatest mitigation efficacy was selected. For example, for Scenario 3b, rescheduling was applied to January and February first, then February and March, then repeated for every month until December and January.

Category 4: seasonal moratorium in LNG traffic — This category was carried out similar to the previous one: (4a) 1 month of transits is eliminated without rescheduling; (4b) 2 months; (4c) 3 months. In each scenario, the moratorium was applied to each month window and the most efficacious window was selected.

We did not investigate alternative route designs, since (1) the route already represents the shortest possible path through the study area, and (2) previous fuel-trafficking projects have determined that the only alternative route (along the eastern shore of Gil Island, in Whale Channel) is not safe for large-ship navigation (Enbridge 2010).

To quantify the efficacy of a mitigation measure, we used the reduction in the predicted number of mortalities, expressed in both absolute and proportional terms. In this mitigation analysis, total 2030 traffic (AIS + LNG Canada + Cedar LNG) was treated as the baseline, the strike zone was defined as 1.5× vessel draft, and the probabilities of collision and lethality were a function of vessel speed.

2.5. Forecast validation

Ship-strike models cannot be validated empirically, but the feasibility of model predictions can be evaluated statistically by determining the likelihood of an observation under the assumption that the ship-strike model is true. In our case, a ship-strike mortality has never been observed in the study area to our knowledge, even during the decade that preceded the pandemic (2010 to 2019) in which monitoring effort was particularly thorough in the months of June to September. To find the probability of a decade of null observations according to our forecast models, we used 2015 AIS data (Canadian Coast Guard 2019) to serve as a representative traffic year for the monitoring decade of 2010 to 2019, and estimated whale–vessel interaction rates in that year using the methods described above. We then developed an iterative simulation in which, for each iteration, a decade of outcomes was generated by drawing from the 2015 mortality posterior 10 times (using months June to September only) and taking the sum of those draws. This was repeated 10000 times, and the proportion of iterations with no mortality represents the likelihood of our actual decade of observations under 2 assumptions: (1) that our ship-strike model is accurate, and (2) that all whale mortalities are observed without fail.

If this validation exercise reports that the probability of our decade of observations is very low, that result could be attributable to (1) inaccurate models, (2) strikes going unnoticed, or (3) some mixture of the two. To understand how poor our strike detection rate (SDR) would have to be in order for our models to be plausible by conventional statistical standards, we carried out a secondary validation analysis as follows: the simulation exercise above was repeated, but this time each realized strike had the opportunity to be 'missed' by the simulation according to a candidate SDR. This simulation was run for 100 candidate SDRs ranging from 0.01 to 1.00. The SDR value that raised the probability of our null observation above 0.05 was treated as an indication of how poor our SDR would have to be in order for the accuracy of our models to be plausible.

3. RESULTS

3.1. Marine traffic

3.1.1. Present-day traffic. AIS-transmitting marine traffic occurs in all channels of the KFS study area,

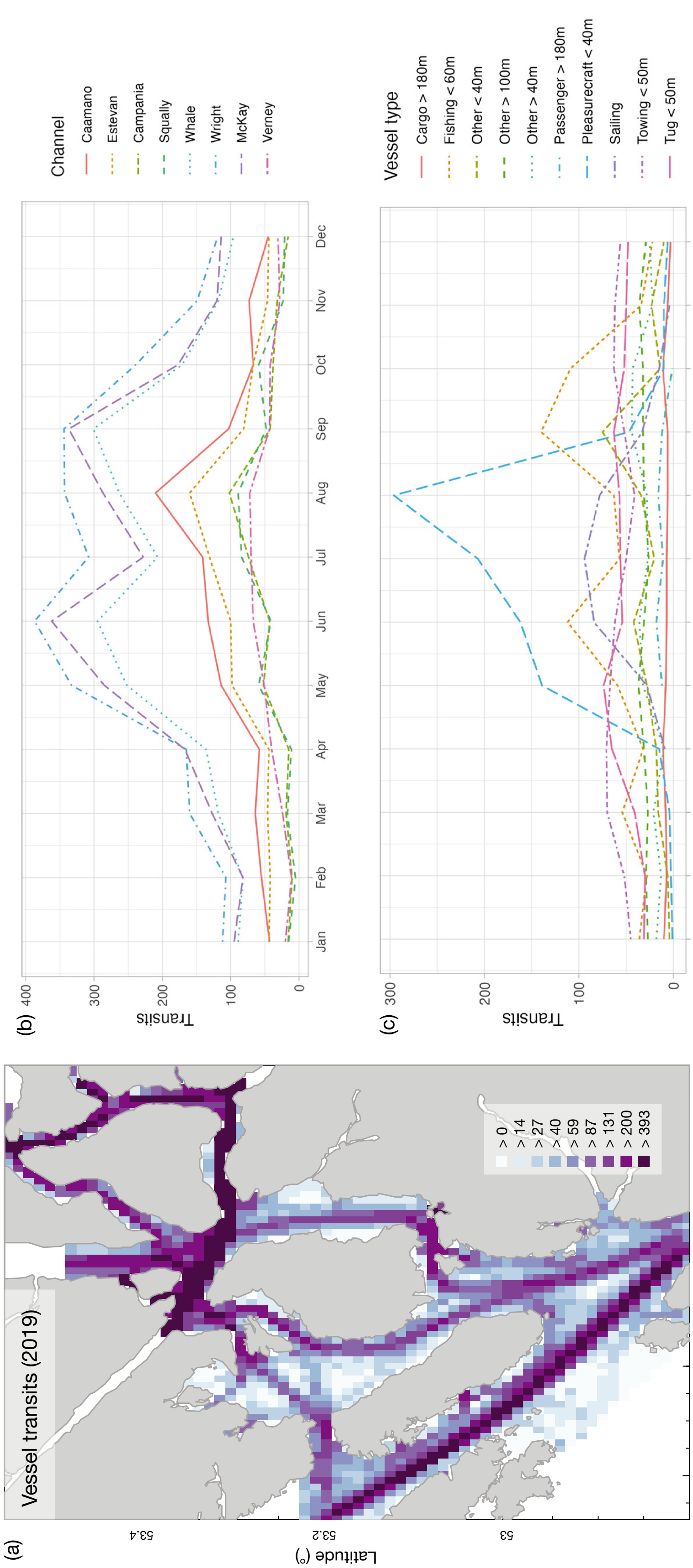

Fig. 2. Marine traffic within the study area in the lower Kitimat Fjord System during 2019, based upon archived Automatic Identification System (AIS) data. (a) All AIS-transmitting traffic (spatial grid of 1 km^2), (b) monthly activity in each waterway (see Fig. 1 for orientation to waterway names), and (c) monthly activity of the 10 vessel types used in this study

with the most occurring in (1) Wright Sound, at the intersection of the Inside Passage and routes to Kitimat through Douglas Channel; (2) McKay Reach and northern Whale Channel, also due to Inside Passage activity; and (3) Caamaño Sound, at the intersection of the outer Inside Passage and routes into the fjord system (Fig. 2a,b). The least-transited waterways year-round are Campania Sound, Squally Channel, and Verney Passage (Fig. 2a,b).

Traffic along the Inside Passage (McKay Reach and Wright Sound) is highest in summer and fall, with peaks in June and September (Fig. 2b). The most common AIS-reporting vessel classes in these waters are, in descending order: commercial fishing vessels <60 m, pleasure craft <40 m, and tug and towing vessels <50 m (Fig. S15). Caamaño Sound traffic peaks in August, and consists predominantly of tug and towing vessels, 'Other' uncategorized vessels >40 m, fishing vessels <60 m, and pleasure craft <40 m (Figs. 2b,c & S15). Traffic occurs predominantly during daylight hours for most of the year (Figs. S13 & S14).

In 2019, AIS recorded only 7 transits from ships self-reporting as a 'tanker' (Table S1). For vessels >180 m, 167 transits were logged in the study area, split roughly evenly between cruise ships (n = 73 transits) and cargo ships (n = 94 transits). Squally Channel, a waterway of interest in this study due to its habitat suitability for fin whales, also sees peak AIS traffic in August, with the most common vessel class being pleasure craft <40 m (Figs. 2b,c & S15). In this waterway, there were only 23 transits by vessels >180 m (19 cruise ship transits, 4 cargo ship transits; Table S2).

3.1.2. Projected traffic in 2030. Linear models of AIS data from

2014, 2015, 2018, and 2019 predict that traffic will increase for 9 of the 10 vessel types, the exception being 'Other' vessels <40 m (Fig. S5). Among those types, the average rate of increase as of 2019 is 9.9% yr^{-1} (Table S3). The greatest proportional increase is occurring in sailing craft (19% yr^{-1} as of 2019), cargo ships and pleasure craft (each 15% yr^{-1}), and fishing vessels <60 m (12% yr^{-1}). Assuming that these trends mirror those for vessels without AIS, and that these trends resume after the pandemic years of 2020 to 2021, total km transited by non-LNG vessels will increase by 56% between 2019 and 2030 (Table S3). Based on these trends, the 700 additional transits from LNG carriers will increase large-ship traffic in the study area 2.7× above the 2030 baseline expectation, and 4.2× above the 2019 baseline. Within the prime fin whale habitat of Squally Channel, where humpback whales are also common, LNG traffic will increase large-ship traffic above 2030 and 2019 baselines by 20× and 30×, respectively.

3.2. Whales

3.2.1. Density and seasonality. Fin whale density for June to September was modeled best using seafloor depth, seafloor range, and a spatial coordinate interaction term as covariates (AIC improvement upon second-best fit model = 104; 54% deviance explained; Table S10, Fig. S16). This model estimated an average summertime fin whale density of 0.014 whales km^{-2} (95% CI = 0–0.118; Table S11). It predicted fin whale absence in Estevan Sound and the interior-most waterways of the study area, very low densities in lower Whale Channel (<0.00001 whales km^{-2}) and lower Wright Sound (<0.00017 whales km^{-2}), relatively high densities in Caamaño Sound and Campania Sound (0.022–0.024 whales km^{-2}), and the highest density in Squally Channel (0.031 whales km^{-2}; Fig. 3, Table S11). The seasonal regression model (26% deviance explained; day of year coefficient $p = 0.0007$; Table S13) indicated that peak fin whale abundance occurs in August, but wide confidence intervals allow for this peak to occur between mid-June and late September (Fig. 4).

Humpback whale density for June to September was modeled best using the explanatory variables of seafloor depth, seafloor depth range, and an interaction term with latitude, longitude, and day of year that captured the seasonal shift in their distribution within the fjord system (AIC improvement upon second-best fit = 14; 51% deviance explained; Table S10,

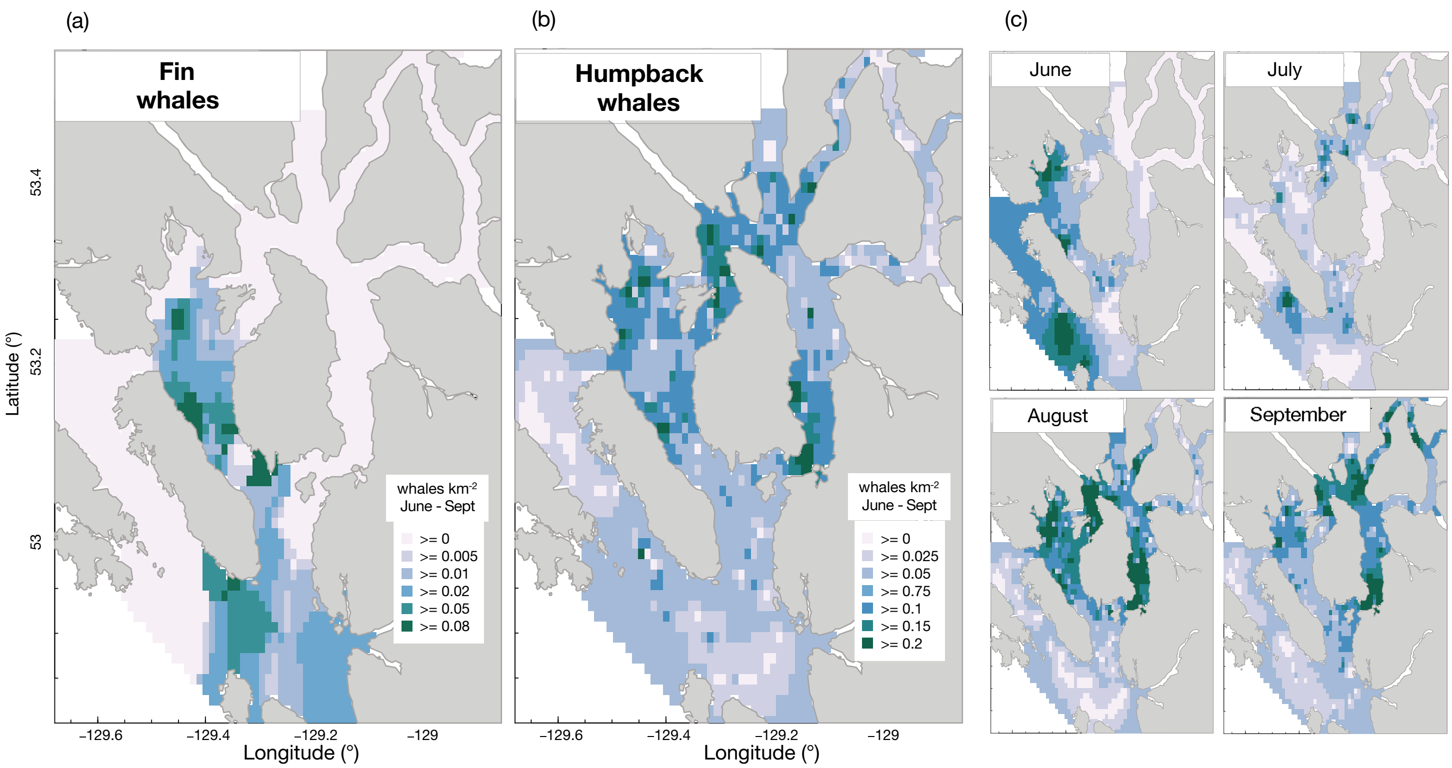

Fig. 3. Spatially explicit density estimates (whales km^{-2}) for (a) fin whales, June to September, (b) humpback whales, June to September, and (c) humpback whales in each of those months. Note different color scales for the 2 species. Based on line-transect analyses of 2013–2015 surveys

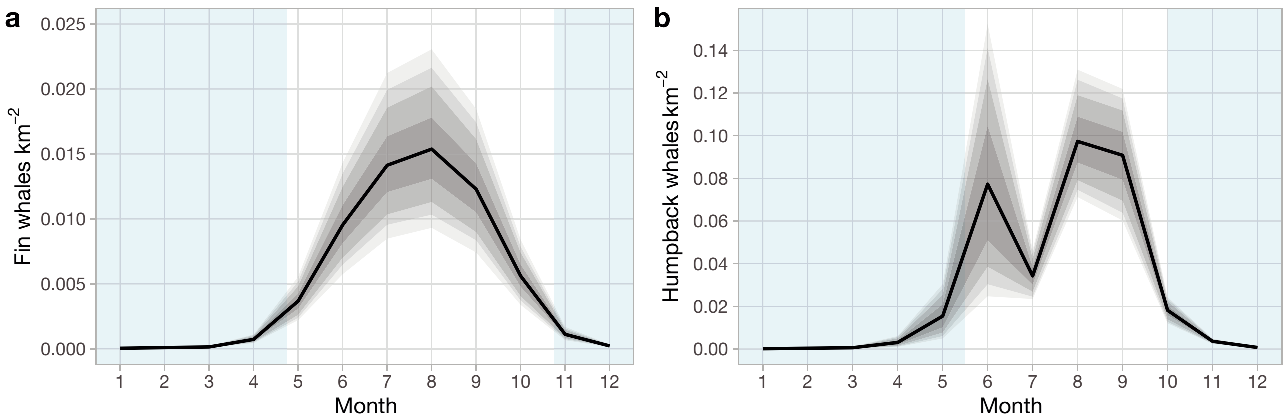

Fig. 4. Seasonal models of average spatial density (whales km^{-2}) for (a) fin whales, based on line-transect surveys scaled by a relative seasonal abundance curve fit to biweekly encounter rates from shore-based surveys in Squally Channel, and (b) humpback whales, based on monthly line-transect surveys throughout the study area. Shaded ribbons denote CI based on posterior quantiles (from outside in: 95%, 90%, 80%, 50%). (Black lines) median prediction in each month; (blue shaded regions) months that are estimated instead of modeled, as no systematic survey data are available (see Section 2.2.2 for details)

Figs. 3 & S16). Average summertime density within the study area was 0.079 whales km^{-2} (95% CI = 0.01–0.223), with highest densities in Wright Sound (0.117 whales km^{-2}, 0.007–0.308), the busiest waterway for marine traffic, followed by Whale Channel (0.113 whales km^{-2}, 0.023–0.298) and Squally Channel (0.110 whales km^{-2}, 0.025–0.251; Table S12). Between early June and the September peak in annual humpback abundance (Fig. 4), the region of highest whale density shifted from Caamaño Sound, Estevan Sound, and Squally Channel (mean densities of 0.119–0.132 whales km^{-2}) to Wright Sound, Whale Channel, and Verney Passage (0.154–0.165 whales km^{-2}), respectively (Table S12).

3.2.2. Close-encounter rates. Close-encounter rates, i.e. the share of co-occurrences that will result in collision if the whale is in the near-surface strike zone and avoidance is not attempted, were higher for larger vessels (Table S14, Fig. S17). Of all current traffic, cruise and cargo ships were associated with the highest close-encounter rates (fin whales: 0.05, 95% CI 0.02–0.11; humpback whales: 0.05, 95% CI 0.01–0.10), and fin whale rates were higher than those for humpback whales across vessel types. In 2030, the highest close-encounter rates will be associated with LNG tankers (e.g. for fin whales, mean 0.09, 95% CI 0.04–0.14; Table S14, Fig. S17).

Table 4. Predictions of whale–vessel interaction rates for all vessel types in each traffic scheme. Table 1 provides definitions of interactions. 2030 AIS predictions are based on linear trends in 2014–2019 marine traffic for each vessel type. 80% Conf.: the 20% percentile of posterior distributions, indicating an 80% confidence that the result is at or above the displayed value. LNG: liquified natural gas

Traffic	Interactions	Fin whales				Humpback whales			
		Mean	Median	95% CI	80% Conf.	Mean	Median	95% CI	80% Conf.
2019 AIS only	Co-occurrence	509	509	471–549	488	5959	5961	5820–6099	5887
	Close encounter	13.6	14	8–19	10	120	120	102–138	111
	Strike-zone event	3.1	3	1–6	2	26	25	17–34	21
	(1.5× draft)	3	3	0–6	2	26	25	18–34	21
2030 AIS only	Co-occurrence	866	856	802–912	827	9428	9428	9222–9638	9322
	Close encounter	22.8	23	16–31	19	185	185	164–209	173
	Strike-zone event	4.9	5	2–9	3	39	39	29–50	34
	(1.5× draft)	5.0	5	2–9	3	39	39	30–49	34
2030 AIS + LNG	Co-occurrence	1013	1014	954–1074	981	11375	11373	11154–11590	11262
	Close encounter	31.1	31	23–40	26	265	265	239–292	251
	Strike-zone event	8.3	8	4–13	6	74	73	60–88	66
	(1.5× draft)	8.5	8	4–14	6	73	73	59–87	66

3.2.3. Surface rates. Dive tag analysis indicates that fin whales practice a strong diurnal pattern in their depth distribution: at night, fin whales spend 90% (SD = 13%) of their time shallower than 30 m, compared to 63% (SD = 7%) during the day (Table S15, Fig. S18). Most nighttime activity (59%, SD = 15%) occurs at 10 m depth or less, with 41% (SD = 16%) occurring shallower than 5 m. However, even during the day, fin whales occur at 5 m depth or less a quarter of the time (mean = 26%, SD = 5%).

3.3. Whale–vessel interaction rates

We estimate that in 2019, AIS traffic occurred within 1 km^2 grid cells containing fin whales 509 times (95% CI 471–549; Table 4). Co-occurrences with humpback whales were more common by an order of magnitude, at 5959 times (95% CI 5820–6099). Roughly a quarter of these co-occurrences (27% for fin whales, 23% for humpbacks) were associated with AIS-transmitting pleasure craft <40 m, and less than 10% were associated with large ships

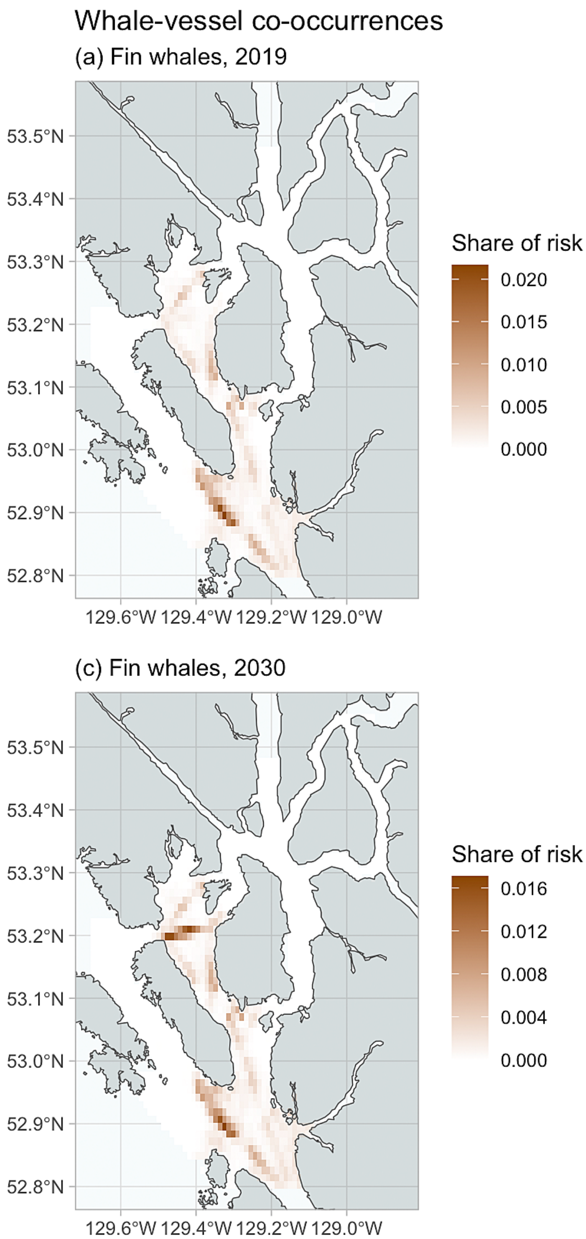

Fig. 5. Whale–vessel co-occurrence predictions in 2 years and 2 traffic schemes: (a,b) 2019, all AIS traffic and (c,d) 2030, projected AIS traffic + liquified natural gas (LNG) traffic for (a,c) fin whales and (b,d) humpback whales. Each grid cell is colorized according to its relative share of the total co-occurrences predicted for the study area. Note that color scales differ for each panel

>180 (9% for fin whales, 5% for humpbacks; Tables 4, S16 & S17). For fin whales, we estimate that these co-occurrences would have resulted in 14 close encounters (95% CI 8–19) and 3 strike-zone events (95% CI 0–6), i.e. imminent collisions if not avoided (Table 4). For humpback whales, we estimate 120 close encounters (95% CI 102–138) and 26 strike-zone events (95% CI 18–34) if not avoided.

Interaction rates peaked in August for both species (Table S19, Figs. S28 & S29), but the geography of risk differed in that Caamaño Sound (i.e. the outer Inside Passage) harbored the greatest vessel interaction risk for fin whales, while Wright Sound (i.e. the Inside Passage proper) posed the greatest risk for humpbacks (Table S18, Figs. 5, S26 & S27). Daytime traffic was by far a greater contributor to risk than nighttime traffic, though strike-zone events were disproportionately common at night due to the diel dive behavior of whales (Table S20, Figs. S 30 & S31). Scaling vessel draft by 1.5× did not increase the rounded number of strike-zone events (Table 4).

In 2030, by which time LNG ships will become operational in addition to an increase in general marine traffic, we predict that co-occurrence rates will double for both fin whales (mean 1013; 95% CI 954–1074) and for humpback whales (mean 11375, 95% CI 11 154–11 590; Table 4). Strike-zone events will triple (fin whales: mean 8, 95% CI 4–14; humpback whales: 74, 95% CI 60–88). Three and 35 of these strike-zone events, respectively, will be attributable to LNG traffic (Table S16). By 2030, the geography of co-occurrence risk will have shifted such that Squally Channel will hold the largest share of risk for both species (Fig. 5c,d). We provide complete details on interaction rate results in Tables S16–S19 and Figs. S19–S31.

3.4. Collisions and mortalities

For 2019, our models indicate an 80% chance that no fin whale mortalities occurred (median expectation 1 collision/mortality, 95% CI 0–2), but that at least 2 humpback whale mortalities occurred (median 4, 95% CI 1–7; Table 5). Three-quarters of this collision risk came from cruise ships (74% for fin whales, 78% for humpback whales), and

Table 5. Predicted rates (yr^{-1}) of collision and mortality for each vessel class (>180 m) and each whale species in Gitga’at waters. 2030 AIS predictions are based on linear trends in 2014–2019 marine traffic for each vessel type. 80% Conf.: the 20% percentile of posterior distributions, indicating an 80% confidence that the result is at or above the displayed value. Results pertain to scenarios in which strike zone is 1.5× ship draft and the probability of collision is a function of ship speed

Traffic	Outcome	Fin whales				Humpback whales			
		Mean	Median	95% CI	80% Conf.	Mean	Median	95% CI	80% Conf.
2019 AIS only	Collision	0.77	1	0–2	0	3.89	4	1–8	2
	Mortality	0.74	1	0–2	0	3.70	4	1–7	2
2030 AIS only	Collision	1.33	1	0–3	0	6.93	7	3–12	5
	Mortality	1.29	1	0–3	0	6.55	6	3–11	4
2030 AIS + LNG	Collision	2.68	3	0–6	1	20.18	20	13–28	16
	Mortality	2.44	2	0–5	1	18.02	18	12–25	14

Table 6. Share (%) of collision and mortality risk attributable to each vessel type, in 2019 and in 2030. Results pertain to scenarios in which strike zone is 1.5× ship draft and the probability of collision is a function of ship speed. –: ship type was not included in the prediction year

Ship type	Share (%) of collision risk				Share (%) of mortality risk			
	Fin whales		Humpback whales		Fin whales		Humpback whales	
	2019	2030	2019	2030	2019	2030	2019	2030
Cargo >180 m	26	11	22	11	41	14	39	14
Passenger >180 m	74	39	78	41	59	20	51	22
LNG Canada tug	–	24	–	23	–	30	–	30
LNG Canada tankers	–	20	–	19	–	29	–	27
Cedar LNG tug	–	3	–	3	–	4	–	3
Cedar LNG tankers	–	4	–	5	–	4	–	4

the remainder from cargo ships (Table 6). Collision/mortality risk was highest for fin whales in Caamaño Sound, Campania Sound, and South Squally Channel (Fig. 6a), which is similar to the co-occurrence geography for this species (Fig. 5a). In contrast, humpback whale collision/mortality risk occurred throughout the study area (Fig. 6b).

In 2030, we predict that increases in AIS traffic alone will not lead to more fin whale mortalities, but humpback whale mortalities will be doubled (80% confidence of at least 4, median 6, 95% CI 3–11; Table 5). After including LNG traffic, we predict a total of 2 fin whale mortalities per year (95% CI 0–5, 80% confidence of at least 1) and 18 humpback whale mortalities (95% CI 12–25, 80% confidence of at least 14; Table 5). Of these, 1 fin whale death (95% CI 0–3) and 10 humpback whale deaths (95% CI 5–16) are estimated to be due to LNG Canada ship traffic (Table S21), with Cedar LNG contributing 0 (95% CI 0–1) and 1 (95% CI 0–4) death, respectively

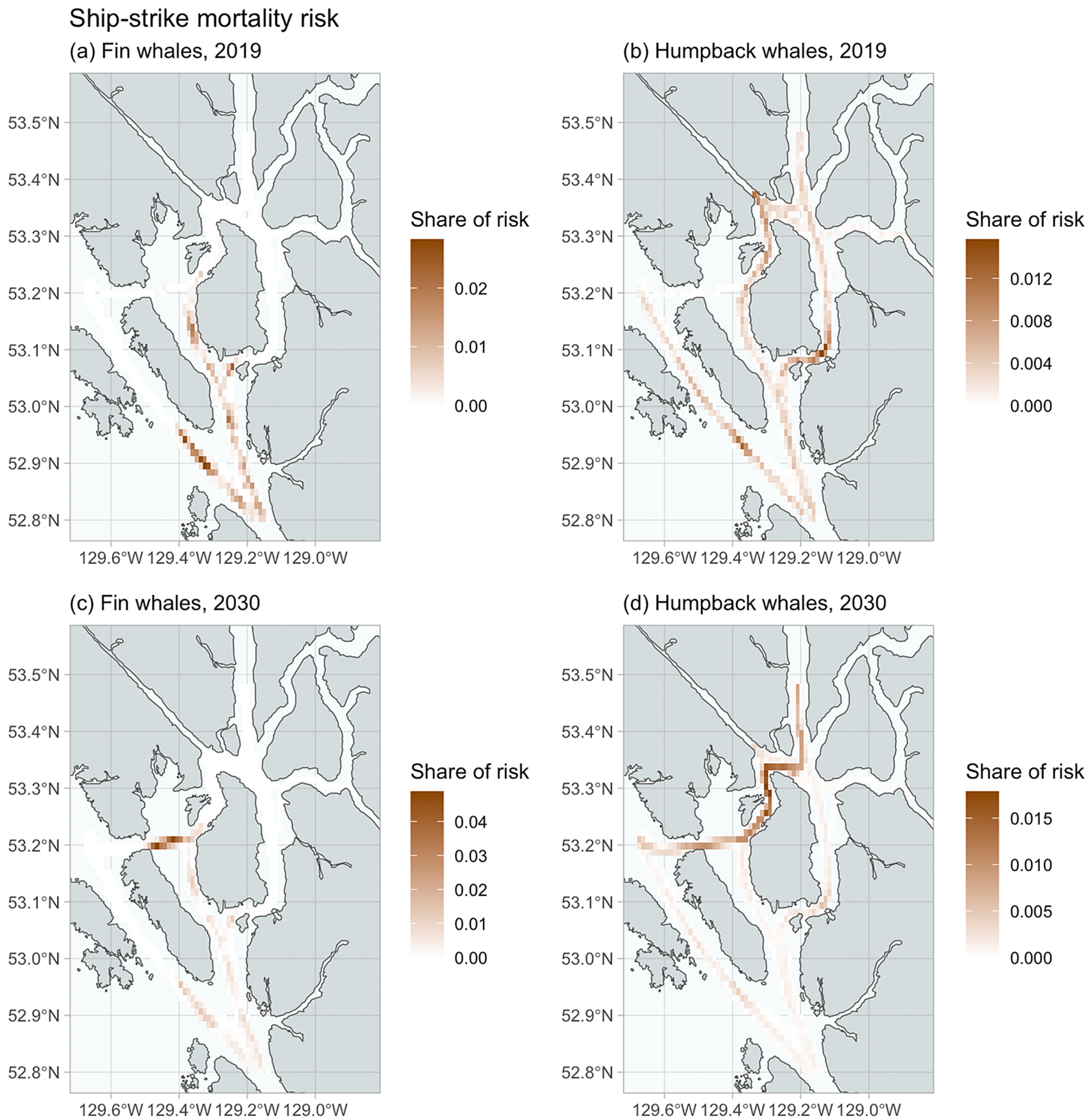

Fig. 6. Mortality predictions in 2 years and 2 traffic schemes: (a,b) 2019, all AIS large ships >180 m and (c,d) 2030, project AIS large ships >180 m + LNG ships for (a,c) fin whales and (b,d) humpback whales. Each grid cell is colorized according to its relative share of total mortalities predicted for the study area, assuming the strike zone is 1.5× ship draft and that the probability of collision is a function of ship speed. Note that color scales differ for each panel

Table 7. Chances of various impact severities in terms of collisions and mortalities for fin whales and humpback whales, due current and project traffic. For example: for fin whales, the chances of at least 4 mortalities in 2019 is only 2 %, but increases to 31 % when LNG projects are operational in 2030. 2030 AIS predictions are based on linear trends in 2014–2019 marine traffic for each vessel type. Results pertain to scenarios in which strike zone is 1.5× ship draft and the probability of collision is a function of ship speed

Species	Chance (%) of …	Collisions 2019 (AIS)	Collisions 2030 (AIS)	Collisions 2030 (AIS + LNG)	Mortalities 2019 (AIS)	Mortalities 2030 (AIS)	Mortalities 2030 (AIS + LNG)
Fin whale	Zero	33	14	4	38	19	6
	At least 1	67	86	96	62	81	94
	At least 2	33	55	84	27	46	76
	At least 3	11	27	65	8	21	53
	At least 4	3	12	42	2	9	31
	At least 5	1	5	24	0	3	17
Humpback whale	Zero	0	0	0	0	0	0
	At least 1	100	100	100	100	100	100
	At least 2	100	100	100	100	100	100
	At least 3	100	100	100	98	100	100
	At least 4	98	100	100	95	100	100
	At least 5	96	100	100	91	100	100

(Table S21). Of all traffic from ships >180 m, LNG traffic is expected to contribute 48 and 53 % of the mortality risk for fin whales and humpback whales, respectively (Tables 5 & 6). These predictions for 2030 represent a 2.3× and 3.9× increase in mortality risk for fin whales and humpback whales, respectively (Table 8).

The addition of LNG traffic is expected to change the spatial distribution of mortality risk for both species (Fig. 6c,d, Table S23). For fin whales, mortality risk will shift from Caamaño Sound (the waterway with greatest risk in 2019) to north Squally Channel, where the LNG route crosses the waterway (Fig. 6c). Likewise, mortality risk for humpback whales will become concentrated along the LNG tanker route in Wright Sound, Lewis Passage, and Squally Channel (Fig. 6d). The addition of LNG traffic will also increase the proportion of predicted mortality risk in August, increasing from 27 to 29 % for fin whales and from 30 to 35 % for humpback whales (Table S24, Fig. S35).

These results are based upon models in which avoidance was treated as a function of ship speed, but those predictions were generally equal to models in which *P*(Avoidance) was treated as a constant of 0.55 (Table S21). In a worst-case scenario of no avoidance, by 2030 we expect 4 fin whale mortalities per year (95 % CI 1–8) and 37 humpback whale mortalities (95 % CI 28–48).

We provide complete details on collision and mortality predictions in Tables S21–S26 and Figs. S32–S36.

3.5. PBR

Our models indicate that by 2030, ship-strike mortalities of fin whales within central Gitga'at waters alone (mean expectation of 2 to 3 mortalities per year, Table 5) will meet PBR for the inshore population of fin whales in Queen Charlotte Sound and Hecate Strait (PBR = 2–3 whales). We have 80 % confidence that mortalities will exceed PBR for the North Coast sector of the BC EEZ (PBR = 1 whale). PBR for the entire Canadian Pacific population is 15 to 16 whales. In 2030, we predict that mortalities within central Gitga'at waters will represent 13 % of this EEZ PBR, despite the region comprising only 0.3 % of the EEZ total area.

Similarly for humpback whales, we also have 80 % confidence that ship-strike mortalities (mean prediction of 18 per year, Table 5) will exceed PBR for the North Coast sector of Canadian Pacific abundance (PBR = 10–11 whales), and will contribute more than 50 % of PBR for the entire EEZ (PBR = 34–35 whales).

3.6. Mitigation measures

Of all mitigation scenarios considered for 2030, speed restrictions <10 knots for all large ships >180 m, including non-LNG traffic, are most effective at reducing mortality risk (Table 8, Fig. 7). For fin whales, in fact, this mitigation measure returns risk to 2019 levels, and is even more efficacious than a 3 mo mora-

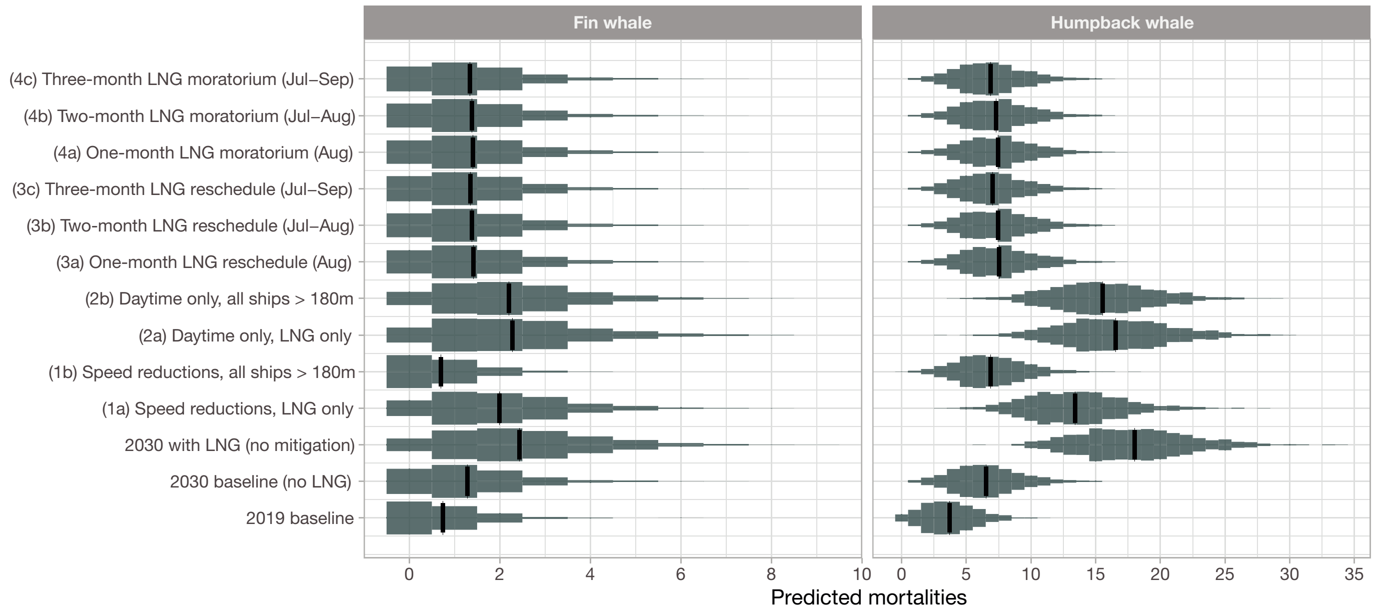

Fig. 7. Posterior distributions of ship-strike mortalities, in number of whale individuals, from large ships (>180 m) predicted for fin whales and humpback whales in Gitga'at waters under various mitigation scenarios, compared to baseline expectations both currently and in 2030. Distributions are represented as unsmoothed violin plots; (black lines) mean of each posterior. Results pertain to scenarios in which the strike zone is 1.5× ship draft and the probability of collision is a function of ship speed. See Section 2.4 for a description of the mitigation categories

torium on LNG traffic. The effect is less dramatic for humpback whales, but still manages to erase the risk imposed by LNG traffic in 2030 and is still comparable in efficacy to a 3 mo LNG moratorium. These predictions hinge upon several assumptions: (1) that fin whales exhibit similar avoidance behavior to humpback whales; (2) that their avoidance of LNG traffic is similar to that of the cruise ship traffic upon which

Table 8. Mean ship-strike mortality rates (95% CI) predicted for fin whales and humpback whales under various mitigation scenarios, compared to baseline (unmitigated) expectations in 2019, 2030 (no LNG), and 2030 (with LNG). For each mortality, its percent difference from each baseline scenario is provided. For example, applying speed restrictions to LNG traffic will result in fin whale mortalities that are 169% higher than the 2019 baseline, 54% higher than the 2030 baseline without LNG traffic present, 18% lower than the 2030 baseline in which LNG traffic is present and unmitigated. Results pertain to scenarios in which strike zone is 1.5× ship draft and the probability of collision is a function of ship speed

Category	Scenario	Fin whales				Humpback whales			
		Mortalities	Baseline change (%)			Mortalities	Baseline change (%)		
			2019	2030	2030 LNG		2019	2030	2030 LNG
Baseline	2019	0.7 (0–2)	0	−43	−70	3.7 (1–7)	0	−44	−79
	2030	1.3 (0–3)	74	0	−47	6.6 (3–11)	77	05	−64
	2030 (LNG)	2.4 (0–5)	230	89	0	18.0 (12–25)	387	175	0
2030 mitigation									
Speed reductions	LNG only	2.0 (0–5)	169	54	−18	13.4 (8–20)	263	105	−26
	All ships >180 m	0.7 (0–2)	−5	46	−71	6.9 (3–11)	86	5	−62
Daytime-only transits	LNG	2.3 (0–5)	208	77	−7	16.5 (10–24)	347	153	−8
	All ships >180 m	2.2 (0–5)	197	71	−10	15.5 (9–22)	320	137	−14
LNG rescheduling	One month (Aug)	1.4 (0–4)	92	10	−42	7.5 (3–14)	104	15	−58
	Two months (Jul–Aug)	1.4 (0–4)	88	8	−43	7.5 (3–14)	101	14	−59
	Three months (Jul–Sep)	1.4 (0–4)	84	5	−44	7.0 (3–13)	90	7	−61
LNG moratorium	One month (Aug)	1.4 (0–4)	91	9	−42	7.5 (3–14)	102	14	−59
	Two months (Jul–Aug)	1.4 (0–4)	85	6	−44	7.3 (3–13)	97	11	−60
	Three months (Jul–Sep)	1.3 (0–4)	81	4	−45	6.9 (3–13)	86	5	−62

avoidance models were based in Gende et al. (2011); (3) that speed restrictions would be enforced; and (4) that speed restrictions would be safe for navigation, given reduced maneuverability within the narrow fjord waterways. Given these unknowns, the next-best mitigation measures need to be considered as well.

The next-most efficacious mitigation measures after speed restrictions are seasonal rescheduling and moratoria, with the 3 mo scenarios yielding the greatest reduction in risk (Table 8, Fig. 7). A 3 mo moratorium effectively eliminates the impact of LNG traffic in 2030 (only 4–5% increase for both species; Table 8). However, due to the trends in existing traffic, a 3 mo LNG moratorium still allows for an 81 and 86% increase in mortality risk for fin whales (mean expectation of 1–2 deaths) and humpback whales (6–7 deaths), respectively (Table 8). In contrast, the least efficacious mitigation measure we evaluated is restricting transits to daylight hours only, which reduces mortality risk by only 10 to 14% when applied to all large-ship traffic (Table 8, Fig. 7).

Note that due to the confluence of peak whale abundance and peak AIS traffic in August, multimonth windows for rescheduling/mitigation LNG traffic are only marginally more effective than single-month measures. For example, the risk reduction of a 3 mo LNG moratorium is only 10 to 20% better than a 1 mo reduction (Table 8, Fig. 7). Furthermore, moratoria are only marginally more effective than transit rescheduling; for example, cancelling LNG transits in July to September yields a 45% reduction in fin whale mortality risk, while rescheduling those transits uniformly to within October to June yields a 44% reduction. For all rescheduling and seasonal moratorium scenarios, centering the mitigation window in August produces the best outcomes (Figs. S39 & S40), assuming that seasonal patterns of habitat use do not shift in 2030.

3.7. Ship-strike model validation

Our validation analysis indicates that, if we assume that our models are correct and that we have achieved perfect detection of all ship strikes (i.e. no strike has gone unobserved in the decade of 2010 to 2019), the probability of our having never observed a strike in the study area is extremely low: 0.004 for fin whales and 0.000 for humpback whales (Figs. S37 & S38). For our models to be statistically plausible at the 0.05 alpha level, we would need to miss 51% of fin whale strikes and 83% of humpback whale strikes. These results are discussed in Section 4.2.

4. DISCUSSION

This study presents the first full-fledged ship-strike assessment for Gitga'at waters, made possible thanks to decades of long-term study in the area by several teams including the Gitga'at themselves. Our models predict a steep increase in whale mortalities for Gitga'at waters in the coming decade, reaching rates that exceed sustainable anthropogenic removal for BC coastal waters. While baseline trends in all large-ship traffic contribute to these risks, the largest single source of mortality risk in 2030 — for both fin whales and humpback whales — will be LNG Canada traffic. The introduction of LNG shipping will concentrate mortality risk in the month of August and in the waterways of Squally Channel (for both species) and Wright Sound (for humpback whales). We predicted these outcomes in a framework that can be utilized in other well-studied areas using the R package 'shipstrike'.

4.1. Limitations

Our analysis navigated several data limitations, some of which are inherent to all ship-strike studies. First and foremost, our collision and mortality predictions pertain only to large ships >180 m, since empirical models of avoidance for smaller ships are not yet available to our knowledge, even though vessels as small as 30 m are known to pose lethal risks to large whales (Kelley et al. 2021). Furthermore, our assessment of marine traffic is based upon AIS, which (1) indicates annual trends that may not necessarily persist in the decade to come, due to finite limitations such as port capacity, and which (2) only monitors small-vessel traffic from mariners who voluntarily participate in the network. The fleet of small craft that currently goes unmonitored can produce significant ambient noise (Parsons et al. 2021) and pose injury risks to whales that are potentially fatal (Kelley et al. 2021, Serra-Sogas et al. 2021). Our shore-based surveys in Squally Channel document high levels of small recreational vessel traffic in summer months (authors' unpubl. data), but the impacts of such traffic on whale safety and habitat quality remain poorly understood (Parsons et al. 2021). This means that our predictions may be taken as conservative estimates of whale–ship interactions and impacts within Gitga'at waters. Future ship-strike analyses using our framework could be improved by (1) using AIS traffic rates to estimate the number of vessels not transmitting (Serra-Sogas et al. 2021) and (2) refining traffic extrapolations by accounting for trends in both vessel transits as well as vessel length.

A second knowledge gap common to all ship-strike literature to date is the dynamics of whale–vessel avoidance. The avoidance model commonly used in ship-strike studies (e.g. Gende et al. 2011, Nichol et al. 2017, Rockwood et al. 2017), and which we used here, is based upon humpback whale reactions to cruise ships in coastal Alaska (USA). It is not known how well these models transfer to other areas or other species. The fin whale is a species that is less familiar to coastal mariners and more difficult to track thanks to its speed, dive duration, and tendency to dive without presenting its fluke (Ford 2014). Recent studies offer insights into the behavioral responses of these species to nearby traffic (Jahoda et al. 2003, David et al. 2022, Currie et al. 2023), but we still do not know to what extent those responses serve to avoid collision. Another unknown is the tendency of whale species to avoid shipping lanes at larger spatiotemporal scales than an imminent collision. For example, in areas with a steady stream of traffic, such as the Inside Passage route through Wright Sound, it is possible that whales are staying out of the main thoroughfare, but our density surface models are too coarse-scale to detect this form of avoidance. We also do not know to what extent — if at all — such area-avoidance strategies would be used for traffic schemes that are far less frequent, e.g. twice-daily transits by a large LNG carrier. These data gaps could lead to over- or underestimation of ship-strike impacts, depending on their details. Focused study of whale–vessel avoidance dynamics — at multiple scales — is a pressing research priority.

Third, our understanding of fin whale depth distribution is based upon a small sample of individuals (n = 6) for relatively short durations (1–20 d) in only 2 months (August and September). While there is ample precedent for small sample sizes in tag-based studies of dive behavior (Friedlaender et al. 2009, 2013, Calambokidis et al. 2019, Keen et al. 2019), and while the dive depth distributions we ascertained are similar to those reported in previous studies (Rockwood et al. 2017, Keen et al. 2019, Calambokidis et al. 2021), we highlight the value of continued tagging efforts throughout the coastal zone of northern British Columbia, across multiple seasons, and for various demographic group types (e.g. mother–calf pairs).

Other data limitations were specific to the Gitga'at study area. Our models relied upon assumptions about wintertime whale abundance and also assumed that whale density and distribution have remained unchanged since our line-transect surveys in 2015. Moreover, the probabilistic structure of our models do not allow whale density to change for subsequent iterations in response to a predicted mortality, nor is it understood how much time passes before the population is replenished by immigrating individuals. However, these whale populations are both (1) in the process of recovery and (2) experiencing unprecedented anthropogenic impacts, resulting in interannual and seasonal trends for the coming decade that are impossible to predict. Moreover, recent sightings of fin whales in Wright Sound, Whale Channel, south Douglas Channel, and McKay Reach (authors' unpubl. data, A. Dundas pers. comm.) indicate that fin whale range may be shifting and/or expanding further into Gitga'at waters. While we have not observed notable trends in whale abundance since 2015, we highlight the importance of repeating systematic surveys of Gitga'at territory at regular intervals, with special focus upon fine-scale effort in Squally Channel and Wright Sound, as well as expanding survey effort into winter and early spring, then updating our ship-strike models accordingly.

We also lacked several locally derived sources of data for humpback whales, particularly their depth distribution, nighttime travel pattern, and directional variability in both day and night. This study addressed several previous data gaps in a preliminary manner, such as daytime travel speeds and the morphometrics of Gitga'at-area humpback whales, but including more samples from other months and waterways will be valuable on those fronts as well. Keen et al. (2022) indicate that estimates of the close-encounter rate are insensitive to whale morphometrics or travel pattern parameters, which makes these data gaps admissible until they can be addressed by subsequent research. Dive depth distributions from Calambokidis et al. (2019) indicate that humpback whales spend more time nearer to the surface than fin whales do during both day and night, which suggests that our predictions of humpback whale strike-zone events — and hence collisions and mortalities — are conservative.

Finally, our comparison of ship-strike rates to PBR limits may not properly reflect the demographic composition of the whale populations using Gitga'at waters. There is evidence that Gitga'at fin whales may be younger than elsewhere in the northeast Pacific (Keen et al. 2021), and the Gitga'at humpback whale population is socially structured in a way that may indicate underlying genetic structure (O'Mahony 2021, Wray et al. 2021), and such factors can exacerbate the population-level ramifications of anthropogenic mortality in a given locale (NMFS 2016).

4.2. Strike detection rates and model validation

As with all ship-strike studies, model validation is hindered by the many uncertainties inherent to strike detection in the field. The vast majority of whale–vessel collisions go unobserved or unreported globally (Williams et al. 2011). On one hand, it may be argued that strikes in Gitga'at waters are less likely to go unnoticed, given the high monitoring intensity by researchers and the Gitga'at community. On the other hand, the characteristics of the study area may make such observations less likely for several reasons: (1) the steep shoreline walls of the fjord system are not conducive to stranding (Olson et al. 2020), thus increasing the odds that a struck-and-killed whale would sink or be carried out of the area; (2) the freshwater lens within the fjordic waters of the study area (Keen 2017b) decreases whale buoyancy and may increase the chances of sinking or remaining sunk (Moore et al. 2020); (3) the seaward flow of the upper water column of the fjord (Shan et al. 2020) is liable to carry an immobilized whale out of the study area, decreasing the odds that it would be observed; and (4) hazardous seasonal weather limits vessel-based monitoring to a window of only 4 to 5 mo, during which several weeks of effort are lost to bouts of rain, fog, and storms. Moreover, the poor visibility during those weather days increases the chances of strikes, with the ironic outcome that strikes are most likely when monitoring effort is lowest.

These factors combine to suggest that a vessel collision within the study area could easily go unnoticed, and that missing several collisions over the course of a decade may still be more likely than not. This conclusion is in line with the results of our validation routine, which indicate that we would need to be missing some strike events — or, in the case of humpback whales, most strikes — in order for our models to be plausible. Given the considerations above, we do not see a plausibility issue with the fin whale ship-strike model results. Humpback whale predictions, however, may require further investigation. Such low strike-detection rates would certainly be feasible if a substantial portion of whales sink soon after being struck or are carried out of the area on the bulbous bows of ships; indeed, these considerations may be enough to provide the poor strike detection required for our models to be plausible. However, it is also possible that there are forms of avoidance behavior that are not being captured by our models in full, such as chronic avoidance of the busy Inside Passage traffic route, as hypothesized above. Clearly, focused studies are needed to help us constrain our models of whale–ship avoidance and strike-detection rates.

4.3. Management and mitigation

Despite these limitations, our results can still inform the management of marine traffic in Gitga'at waters in the years to come, particularly in the case of fin whales with ship-strike models that are better supported by locally derived data, a better defined primary range within Gitga'at waters, and a protection status that may soon change (COSEWIC 2019). Our models highlight (1) that Squally Channel and Wright Sound will become areas of concentrated mortality risk by 2030, (2) that August will be the peak month of risk, (3) that mortality risk will come from all large traffic, not just LNG carriers, and (4) that speed reductions can be a highly effective form of mitigation measure, especially when applied to all large ship traffic—assuming that our avoidance models are reasonable, and that the speed reductions are feasible and adequately enforced. If mitigation measures can only be applied to new LNG traffic, seasonal mitigation (1 to 3 mo windows of rescheduling or moratoria in the late summer) is the measure with the greatest promise and least uncertainty. These measures would likely go further if they were combined (e.g. speed restrictions for all large ship traffic in addition to seasonal rescheduling of LNG transits) and/or complemented by other strategies, such as establishing real-time alert systems to aid mariners in avoiding collisions with whales. We also note that the acoustic dimension of the whale–vessel interactions predicted in this study deserves focused investigation, particularly within relatively quiet waterways, such as Squally Channel, which face dramatic changes in ambient noise in the decade to come (Quijano & Ramsey 2022).

4.4. The 'mixed blessing' of critical habitat

Our results highlight the vulnerability of important whale habitat to trends in marine traffic. We report whale densities in Gitga'at waters that are significantly higher than elsewhere. Fin whales here (mean 0.014 whales km^{-2}) are twice as common as the EEZ average (0.007; Wright et al. 2021), 7× that of the North Coast (0.002; Wright et al. 2021, but note that this study did not sample the Kitimat Fjord System thoroughly), and 5× that off of Vancouver Island (0.003; Nichol et al. 2017). Within the prime fin whale habitat of Squally Channel, mean density is 4×, 15×, and 10× that of said regions, respectively. Similarly, humpback density within Gitga'at waters (0.079) is 5×, 3×, and 6× that of the entire EEZ (0.016; Wright et al. 2021), the North Coast (0.025; Wright et al. 2021), and off Vancouver Island (0.014; Nichol et al. 2017), respectively. These differences highlight the value of Gitga'at waters for Canadian Pacific whales, the opportunities for effective and spatially efficient conservation in this area, and, conversely, the vulnerability inherent to such important places. This is the 'mixed blessing' of critical habitat described in Williams et al. (2009).

While we have named several research priorities above for the years to come, we conclude by emphasizing that the importance of this habitat and the threats facing it have long been known and are increasingly well established. With this study we have endeavored to frame those threats in actionable terms that allow proposed mitigation measures to be considered in a concrete way. To start addressing these issues, managers and industry need not hold out for further analysis. We know enough now to act.

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LITERATURE CITED

Aguilar A (2009) Fin whale: *Balaenoptera physalus*. In: Perrin WF, Würsig B, Thewissen JWG (eds) Encyclopedia of marine mammals, 2nd edn. Elsevier, Amsterdam, p 433–437

Ashe E, Wray J, Picard CR, Williams R and others (2013) Abundance and survival of Pacific humpback whales in a proposed critical habitat area. PLOS ONE 8: e75228

Barlow J (2016) Cetacean abundance in the California Current estimated from a 2008 ship-based line-transect survey. NOAA-Tech Memo-NMFS-SWFSC-456

Barlow J, Calambokidis J, Falcone EA, Baker CS and others (2011) Humpback whale abundance in the North Pacific estimated by photographic capture-recapture with bias correction from simulation studies. Mar Mamm Sci 27: 793–818

Bradford AL, Oleson EM, Forney KA, Moore JE, Barlow J (2021) Line-transect abundance estimates of cetaceans in U.S. waters around the Hawaiian Islands in 2002, 2010, and 2017. US Department of Commerce, NOAA Tech Memo-NMFS-PIFSC-115

Buckland S, Anderson D, Burnham D, Laake J, Borchers D, Thomas L (2001) Introduction to distance sampling: estimating abundance of biological populations. Chapman & Hill, New York, NY

Calambokidis J, Lahbusch JA, Szesciorka AR, Southall BL, Cade DE, Friedlaender AS, Goldbogen JA (2019) Differential vulnerability to ship strikes between day and night for blue, fin, and humpback whales based on dive and movement data from medium duration archival tags. Front Mar Sci 6:543

Canadian Coast Guard (2019) Automatic identification system data 2019 for Hartley Bay region. Data file retrieved from Ocean Networks Canada, Victoria, BC

Cartwright R, Venema A, Hernandez V, Wyels C, Cesere J, Cesere D (2019) Fluctuating reproductive rates in Hawaii's humpback whales, *Megaptera novaeangliae*, reflect recent climate anomalies in the North Pacific. R Soc Open Sci 6:181463

Christensen LB (2006) Reconstructing historical abundances of exploited marine mammals at the global scale. MSc thesis, University of British Columbia, Vancouver, BC

Conn PB, Silber GK (2013) Vessel speed restrictions reduce risk of collision-related mortality for North Atlantic right whales. Ecosphere 4:art43

Cooke JG (2018) *Balaenoptera physalus*. The IUCN Red List of Threatened Species 2018:e.T2478A50349982. https://dx.doi.org/10.2305/IUCN.UK.2018-2.RLTS.T2478A50349982.en (accessed 18 August 2022)

COSEWIC (Committee on the Status of Endangered Wildlife in Canada) (2019) COSEWIC assessment and status report on the fin whale, *Balaenoptera physalus*, Atlantic population and Pacific population, in Canada. COSEWIC https://epe.lac-bac.gc.ca/100/201/301/weekly_acquisitions_list-ef/2020/20-41/publications.gc.ca/collections/collection_2020/eccc/CW69-14-428-2019-eng.pdf

Crum N, Gowan T, Krzystan A, Martin J (2019) Quantifying risk of whale–vessel collisions across space, time, and management policies. Ecosphere 10:e02713

Currie JJ, Stack SH, Kaufman GD (2023) Modelling whale-vessel encounters: the role of speed in mitigating collisions with humpback whales (*Megaptera novaeangliae*). J Cetacean Res Manag 17:57–64

David L, Arcangeli A, Tepsich P, Di-Meglio N and others (2022) Computing ship strikes and near miss events of fin whales along the main ferry routes in the Pelagos Sanctuary and adjacent west area, in summer. Aquat Conserv 32:442–456

Dawson SM, Bowman MH, Leunissen E, Sirguey P (2017) Inexpensive aerial photogrammetry for studies of whales and large marine animals. Front Mar Sci 4:366
DFO (Fisheries and Oceans Canada) (2010) Recovery strategy for the North Pacific humpback whale (*Megaptera novaeangliae*) in Canada (draft). FAO Canada, Ottawa
Enbridge (2010) Volume 8A: overview and general information — marine transportation; Volume 8B: environmental and socio-economic assessment (ESA) — marine transportation. Enbridge Northern Gateway Project Sec. 52 Application. Northern Gateway Piplines, Calgary
Erbe C, Marley S, Schoeman RP, Smith JN, Trigg LE, Embling CB (2019) The effects of ship noise on marine mammals — a review. Front Mar Sci 6:606
Erbe C, Smith JN, Redfern JV, Peel D (2020) Editorial: impacts of shipping on marine fauna. Front Mar Sci 7:637
Ford JKB (2006) An assessment of critical habitats of resident killer whales in waters off the Pacific Coast of Canada. DFO Can Sci Advis Sec Res Doc 2006/072
Ford JKB (2014) Marine mammals of British Columbia. Royal BC Museum, Victoria, BC
Ford JKB, Stredulinsky EH, Towers JR, Ellis GM (2013) Information in support of the identification of critical habitat for transient killer whales (*Orcinus orca*) off the west coast of Canada. DFO Can Sci Advis Sec Res Doc 2012/155
Friedlaender AS, Hazen EL, Nowacek DP, Halpin PN and others (2009) Diel changes in humpback whale *Megaptera novaeangliae* feeding behavior in response to sand lance *Ammodytes* spp. behavior and distribution. Mar Ecol Prog Ser 395:91–100
Friedlaender AS, Tyson RB, Stimpert AK, Read AJ, Nowacek DP (2013) Extreme diel variation in the feeding behavior of humpback whales along the western Antarctic Peninsula during autumn. Mar Ecol Prog Ser 494:281–289
Gende SM, Hendrix AN, Harris KR, Eichenlaub B, Nielsen J, Pyare S (2011) A Bayesian approach for understanding the role of ship speed in whale-ship encounters. Ecol Appl 21:2232–2240
Gerrodette T, Forcada J (2005) Non-recovery of two spotted and spinner dolphin populations in the eastern tropical Pacific Ocean. Mar Ecol Prog Ser 291:1–21
Gitga'at First Nation (2017) State of the Gitga'at ocean report 2015–2016. Public version. https://coastfunds.ca/wp-content/uploads/2017/01/state-of-the-gitgaat-ocean.pdf (accessed on 18 August 2022)
Government of Canada (2020) Navigation safety regulations (SOR/2020-216). https://laws-lois.justice.gc.ca/eng/regulations/SOR-2020-216/FullText.html (accessed on 19 August 2022)
Gregr EJ, Nichol L, Ford JKB, Ellis G, Trites AW (2000) Migration and population structure of northeastern Pacific whales off coastal British Columbia: an analysis of commercial whaling records from 1908–1967. Mar Mamm Sci 16:699–727
Hendricks B, Wray JL, Keen EM, Alidina HM, Gulliver TA, Picard CR (2018) Automated monitoring and analysis of marine mammal vocalizations in coastal habitats. 2018 OCEANS – MTS/IEEE Kobe Techno-Oceans (OTO), Kobe, p 1–10
Hendricks B, Wray JL, Keen EM, Alidina HM, Gulliver TA, Picard CR (2019) Automated localization of whales in coastal fjords. J Acoust Soc Am 146:4672–4686
Hendricks B, Keen EM, Shine C, Wray JL, Alidina HM, Picard CR (2021) Acoustic tracking of fin whales: habitat use and movement patterns within a Canadian Pacific fjord system. J Acoust Soc Am 149:4264–4280
Heywood EI (2016) Ambient noise in the Kitimat Fjord System. MSc thesis, Duke University, Durham, NC
Ingman K, Hines E, Mazzini PLF, Rockwood RC, Nur N, Jahncke J (2021) Modeling changes in baleen whale seasonal abundance, timing of migration, and environmental variables to explain the sudden rise in entanglements in California. PLOS ONE 16:e0248557
Jägerbrand AK, Brutemark A, Svedén JB, Gren IM (2019) A review of the environmental impacts of shipping on aquatic and nearshore ecosystems. Sci Total Environ 695:133637
Jahoda M, Lafortuna L, Sciara DI (2003) Mediterranean fin whale's (*Balaenoptera physalus*) response to small vessels and biopsy sampling assessed through passive tracking and timing of respiration. Mar Mamm Sci 19: 96–110
Keen EM (2017a) Aggregative and feeding thresholds of sympatric rorqual whales within a fjord system. Ecosphere 8:e01702
Keen EM (2017b) Whales of the rainforest: habitat use strategies of sympatric rorqual whales within a fjord system. PhD thesis, University of California, San Diego, CA
Keen EM, Qualls KM (2018) Respiratory behaviors in sympatric rorqual whales: the influence of prey depth and implications for temporal access to prey. J Mammal 99: 27–40
Keen EM, Wray J, Meuter H, Thompson KL, Barlow JP, Picard CR (2017) 'Whale wave': shifting strategies structure the complex use of critical fjord habitat by humpbacks. Mar Ecol Prog Ser 567:211–233
Keen EM, Wray J, Pilkington JF, Thompson KL, Picard CR (2018) Distinct habitat use strategies of sympatric rorqual whales within a fjord system. Mar Environ Res 140: 180–189
Keen EM, Scales KL, Rone BK, Hazen EL, Falcone EA, Schorr GS (2019) Night and day: diel differences in ship strike risk for fin whales (*Balaenoptera physalus*) in the California current system. Front Mar Sci 6:730
Keen EM, Pilkington J, O'Mahony ÉN, Thompson KL and others (2021) Fin whales of the Great Bear Rainforest: *Balaenoptera physalus velifera* in a Canadian Pacific fjord system. PLOS ONE 16:e0256815
Keen EM, Hendricks B, Shine C, Wray J, Picard CR, Alidina HM (2022) A simulation-based tool for predicting whale-vessel encounter rates. Ocean Coast Manage 224:106183
Kelley D, Richards C (2022) oce: analysis of oceanographic data. R package version 1.7-2. https://CRAN.R-project.org/package=oce
Kelley DE, Vlasic JP, Brillant SW (2021) Assessing the lethality of ship strikes on whales using simple biophysical models. Mar Mamm Sci 37:251–267
Laist DW, Knowlton AR, Mead JG, Collet AS, Podesta M (2001) Collisions between ships and whales. Mar Mamm Sci 17:35–75
Marsh MB (2013) Length-beam ratio. M.B. Marine Design. http://marine.marsh-design.com/content/length-beam-ratio (accessed 5 February 2022)
Martin J, Sabatier Q, Gowan TA, Giraud C and others (2016) A quantitative framework for investigating risk of deadly collisions between marine wildlife and boats. Methods Ecol Evol 7:42–50
McKenna MF, Calambokidis J, Oleson EM, Laist DW, Gold-

bogen JA (2015) Simultaneous tracking of blue whales and large ships demonstrates limited behavioral responses for avoiding collisions. Endang Species Res 27: 219–232

Miller DL, Rexstad E, Thomas L, Marshall L, Laake JL (2019) Distance sampling in R. J Stat Softw 89:1–28

Miller DL, Rexstad E, Burt L, Bravington MV, Hedley S, Ferguson M, Kelly N (2022) dsm: density surface modelling of distance sampling data. R package version 2.3.2. https://CRAN.R-project.org/package=dsm

Moore MJ, Mitchell GH, Rowles TK, Early G (2020) Dead cetacean? Beach, bloat, float, sink. Front Mar Sci 7:333

Neilson JL, Gabriele CM (2019) Glacier Bay & Icy Strait humpback whale population monitoring: 2018 update. National Park Service Resource Brief, Gustavus, AK

Nichol LM, Ford JK (2012) Information relevant to the assessment of critical habitat for blue, fin, sei and north Pacific right whales in British Columbia. DFO Can Sci Advis Sec Res Doc 2011/078

Nichol LM, Wright BM, O'Hara P, Ford JKB (2017) Risk of lethal vessel strikes to humpback and fin whales off the west coast of Vancouver Island, Canada. Endang Species Res 32:373–390

Nichol LM, Abernethy RM, Wright BM, Heaslip S and others (2018) Distribution, movements and habitat fidelity patterns of fin whales (*Balaenoptera physalus*) in Canadian Pacific waters. DFO Can Sci Advis Sec Res Doc 2017/004

NMFS (National Marine Fisheries Service) (2016) Guidelines for preparing stock assessment reports pursuant to the 1994 amendments to the Marine Mammal Protection Act. www.fisheries.noaa.gov/national/marine-mammal-protection/guidelines-assessing-marine-mammal-stocks (accessed August 2022)

O'Mahony ÉN (2021) Baleen whale exhaled breath condensate as a minimally invasive source of DNA for conservation genetics and kinship analysis. MSc(Res) thesis, University of St. Andrews

Olson JK, Aschoff J, Goble A, Larson S, Gaydos JK (2020) Maximizing surveillance through spatial characterization of marine mammal stranding hot spots. Mar Mamm Sci 36:1083–1096

Parsons MJG, Erbe C, Meekan MG, Parsons SK (2021) A review and meta-analysis of underwater noise radiated by small (<25 m length) vessels. J Mar Sci Eng 9:827

Pilkington JF, Stredulinsky E, Abernathy R, Ford JKB (2018) Patterns of fin whale (*Balaenoptera physalus*) seasonality and relative distribution in Canadian Pacific waters inferred from passive acoustic monitoring. DFO Can Sci Advis Sec Res Doc 2018/032

Qualls KM (2019) Drivers of euphausiid abundance and biomass in the Kitimat Fjord System, BC Canada. MSc thesis, Oregon State University, Corvallis, OR https://ir.library.oregonstate.edu/concern/graduate_thesis_or_dissertations/j67318750

Quijano JE, Ramsey EH (2022) Ships, whales, and acoustics in Gitga'at Territory initiative. Vessel noise study: ARTEMIS modelling and validation. Document 02830, Version 2.0. Technical report by JASCO Applied Sciences for WWF-Canada

R Core Team (2020) R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna

Redfern JV, Moore TJ, Becker EA, Calambokidis J and others (2019) Evaluating stakeholder-derived strategies to reduce the risk of ships striking whales. Divers Distrib 25:1575–1585

Redfern JV, Becker EA, Moore TJ (2020) Effects of variability in ship traffic and whale distributions on the risk of ships striking whales. Front Mar Sci 6:793

Rockwood RC, Calambokidis J, Jahncke J (2017) High mortality of blue, humpback and fin whales from modelling of vessel collisions on the U.S. West Coast suggests population impacts and insufficient protection. PLOS ONE 12:e0183052

Rockwood RC, Adams J, Silber G, Jahncke J (2020) Estimating effectiveness of speed reduction measures for decreasing whale-strike mortality in a high-risk region. Endang Species Res 43:145–166

Rockwood RC, Adams JD, Hasting S, Morten J, Jahncke J (2021) Modeling whale deaths from vessel strikes to reduce the risk of fatality to endangered whales. Front Mar Sci 8:649890

Savage K (2017) Alaska and British Columbia large whale unusual mortality event summary report. NOAA Protected Resource Division, Juneau, AK

Schoeman RP, Patterson-Abrolat C, Plön S (2020) A global review of vessel collisions with marine animals. Front Mar Sci 7:292

Serra-Sogas N, O'Hara PD, Pearce K, Smallshaw L, Canessa R (2021) Using aerial surveys to fill gaps in AIS vessel traffic data to inform threat assessments, vessel management and planning. Mar Policy 133:104765

Shan S, Hannah CG, Wu Y (2020) Response of sea level to tide, atmospheric pressure, wind forcing and river discharge in the Kitimat Fjord System. Estuar Coast Shelf Sci 246:107025

Silber GK, Slutsky J, Bettridge S (2010) Hydrodynamics of a ship/whale collision. J Exp Mar Biol Ecol 391:10–19

Stantec Consulting (2019) Project description summary: Cedar LNG Liquefaction and Export Terminal. Revision 0 (August 30, 2019). Stantec Consulting, Edmonton

TERMPOL (Technical Review Process of Marine Terminal Systems and Transshipment Sites) (2015) TERMPOL review process on the LNG Canada Project, 1st edn, October 2015. TP 15287E Transport Canada, Marine Safety and Security, Ottowa, ON

Thompson C (2016) B.C. Supreme Court rules province failed to consult with First Nations on Enbridge. www.coastmountainnews.com/news/b-c-supreme-court-rules-province-failed-to-consult-with-first-nations-on-enbridge/ (accessed 16 August 2022)

Towers JR, Pilkington JF, Mason EA, Mason EV (2022) A bowhead whale in the eastern North Pacific. Ecol Evol 12:e8664

Wade PR (2000) Bayesian methods in conservation biology. Conserv Biol 14:1308–1316

Williams R, Thomas L (2007) Distribution and abundance of marine mammals in the coastal waters of British Columbia, Canada. J Cetacean Res Manag 9:15–28

Williams R, Lusseau D, Hammond PS (2009) The role of social aggregations and protected areas in killer whale conservation: the mixed blessing of critical habitat. Biol Conserv 142:709–719

Williams R, Gero S, Bejder L, Calambokidis J and others (2011) Underestimating the damage: interpreting cetacean carcass recoveries in the context of the Deepwater Horizon/BP incident. Conserv Lett 4:228–233

Wood SN (2011) Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric

generalized linear models. J R Stat Soc B 73:3–36
Wray J, Keen EM (2020) Calving rate decline in humpback whales (*Megaptera novaeangliae*) in northern British Columbia. Mar Mamm Sci 36:709–720
Wray J, Keen EM, O'Mahony ÉN (2021) Social survival: humpback whales (*Megaptera novaeangliae*) use social structure to partition ecological niches within proposed critical habitat. PLOS ONE 16:e0245409
Wright BM, Nichol LM, Doniol-Valcroze T (2021) Spatial density models of cetaceans in the Canadian Pacific estimated from 2018 ship-based surveys. DFO Can Sci Advis Sec Res Doc 2021/049 (Erratum: March 2022)

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