A probabilistic framework for evaluating ship strike hazard and the effectiveness of vessel speed reduction policies

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A thesis

submitted in partial fulfillment of the
requirements for the degree of

Master of Marine Affairs

University of Washington
2026

Committee:
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Program Authorized to Offer Degree:
School of Marine and Environmental Affairs

University of Washington

Abstract

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Ship strikes to whales are a threat to the recovery of threatened and endangered whale species. In Washington state, humpback whale (*Megaptera novaeangliae*) presence and vessel traffic are both increasing within federally designated humpback whale critical habitat, increasing the potential for collisions to occur. I estimated ship strike hazard in Washington humpback whale critical habitat, as well as potential hazard reductions under a Vessel Speed Reduction (VSR) policy using a ship strike model I developed. This model takes a probabilistic approach to quantifying hazard in the region and is largely driven by vessel characteristics and behaviors. I also modified a probability of lethality (PLETH) equation fit to empirical ship strike data by applying biological constraints which have not been previously incorporated in other models. I found that Washington humpback whale critical habitat is highly hazardous to humpback whales, particularly within the Strait of Juan de Fuca. I estimated that hazard could be reduced under a voluntary VSR policy by 9 to 22% across compliance rates of 50, 75, and 100%.

1. Introduction

Vessel strikes are among the top conservation issues facing whale populations, and mitigating the risk posed by vessel strikes is urgently required to fulfill global conservation goals and protect threatened and endangered whale populations (Hague et al., 2024). As the global shipping industry continues to grow (UNCTAD, 1991; 2025), and some whale populations begin to recover and reap the conservation benefits of post-whaling regulations (Best, 1993), it is imperative that we prepare for an increase in whale-vessel conflict. Dozens of whale strikes are reported each year in U.S. waters alone, but these documented strikes only represent a fraction of actual strikes. It is estimated that only 5 to 17% of strikes are reported; not only do strikes go unreported, they go unmitigated (Rockwood et al., 2017). A recent study conducted at the University of Washington found that fewer than 7% of the world's hotspots for whale-vessel collisions have mitigation measures in place (Nisi et al., 2024). Economic impacts are a barrier to implementing these measures, therefore the conservation benefits must be strong enough to warrant any economic or logistical strain. Due to the lack of empirical data on ship strikes, it is essential that we develop models that can accurately predict these conservation benefits in order to ensure the successful implementation of mitigation measures.

Ship strike risk models involve two essential components: an estimation of the likelihood of an encounter, and the probability that a given encounter will be lethal. The likelihood of an encounter is dependent on spatial overlap between whales and vessels. Co-occurrence, a measure of how often whales and vessels occur in the same area, is used as an estimate of encounter likelihood in several metrics (Keen et al., 2022; Redfern et al., 2020; Redfern et al., 2024). However, co-occurrence does not capture the effect of vessel speed on strike occurrence. Vessel speed is linked to the probability that a whale and vessel will be in close enough proximity for a strike to occur (Martin et al., 2016; Keen et al., 2022), which can be represented through encounter rate theory. Encounter rate is a function of the critical encounter radius, whale speed, and vessel speed; it estimates how frequently 1 whale and 1 vessel would exist within the critical strike radius if they were co-occuring in the same area (Martin et al., 2016). Rockwood et al. (2017, 2020, 2021) implement encounter rate theory as a component in a ship strike model that integrates multiple other mechanisms influencing collision risk, including avoidance behavior, vertical overlap between whales and vessel strike depth, the probability of lethality given a strike, and the spatial and temporal exposure of whales and vessels. Though this model captures many mechanistic components of a lethal ship strike, its accuracy depends on the quality of whale distribution and behavioral data. Therefore, a model that relies less on uncertain whale data, but still captures key mechanisms of ship strikes by focusing on the characteristics and behavior of vessels rather than whales, may improve the model's out-of-sample predictive accuracy.

The speed and size of a vessel influence collision outcomes, informing the probability that a given encounter will be lethal. Probability of lethality (PLETH) equations are a component of most ship strike models. The most commonly cited PLETH is Conn & Silber's (2013) curve, which fits a logistic regression to empirical data (n = 52) on documented ship strikes and their mortality outcome with speed as the predictor variable. The recently published Garrison et al. (2025) PLETH model uses an expanded dataset (n = 201) to model the relationship between vessel speed and size of ship strike lethality. In addition to speed as a predictor variable, vessels are classified into four discrete size categories, each associated with a size-specific effect. Furthermore, separate equations are provided for humpback whales and all other species, resulting in a total of eight PLETH curves under the same model formulation. This approach represents the current best available science for predicting ship strike mortality (Nisi, 2025), despite substantial uncertainty and several non-significant coefficients (Garrison et al., 2025).

The models discussed above are not only applied to assessments of baseline risk, but also estimations of risk reduction under management scenarios. Vessel speed reductions (VSRs) are the typical mitigation measure aimed at reducing ship strike risk due to the influence of speed on multiple mechanisms of strike risk, including strike occurrence, whale and vessel avoidance, and lethality (Conn & Silber, 2013; Gende et al., 2019; Vanderlaan & Taggart, 2007). Mandatory VSRs have been implemented seasonally as ship strike mitigation on the East Coast of the U.S. in response to north atlantic right whale mortalities (NOAA, 2026), and voluntary VSRs on the West Coast in California. The success of these policies in reducing ship strikes is difficult to measure directly because most incidents go undocumented (Gavigan, 2025), therefore, policymakers rely on modelled estimations. These estimates can be improved through more precise PLETH formulations, as well as the elimination of uncertain whale data such as modelled distribution and avoidance behavior estimates.

I developed a model that uses a probabilistic framework to analyze ship strike hazard through the lens of vessel behavior and characteristics that contribute to ship strike occurrence and severity. By framing the approach around observable vessel behavior and characteristics, reliance on speculative whale-centered data is reduced. Notably, my model does not require detailed whale distributional data. Furthermore, the PLETH model is reformulated to incorporate biologically realistic constraints, so that predicted lethality more closely reflects the physical dynamics of vessel strikes across the observed range of vessel speeds. This model provides a straightforward, constrained framework for ship strike analysis, particularly in evaluating potential effectiveness of mitigation strategies such as VSRs.

I apply my model to humpback whale critical habitat off the coast of Washington and estimate the risk reduction from implementing a voluntary VSR where boats are asked to travel at 10 knots or less in the region. Washington waters are summer feeding grounds for the CA-OR-WA humpback stock, which contains individuals from two federally-listed populations: the Mexico distinct population segment (DPS), which is listed as threatened, and the Central America DPS, which is listed as endangered under the Endangered Species Act (ESA)(80 FR 22304). Recent studies demonstrate that humpback presence is increasing yearly in Washington State (Calombokidis & Vanderzee, 2026; Miller, 2020), which is home to the 9th and 10th busiest container ports in the U.S., the Ports of Seattle and Tacoma (Supply Chain 24/7, 2025). Marine mammal stranding reports documented 31 lethal ship strikes in Washington between 2015 and 2024, 7 of which were humpback whales (NOAA Fisheries, 2025). In 2025, there were multiple reports of humpback whale strikes in the Salish Sea region: one strike from a ferry resulted in death, and another instance involving a whale watching vessel left a calf seriously injured (Durling, 2025; Greer, 2025). A broad-scale model of ship strike mortality along the U.S. West Coast Economic Exclusion Zone (EEZ) found that humpback whales have a high predicted mortality area along the coast of Washington (Rockwood et al., 2017). These authors did not include the highly trafficked Strait of Juan de Fuca in their analysis, which contains a traffic separation scheme (TSS) and associated shipping lanes which are the only commercial access point to the major ports of Seattle, Vancouver, and Tacoma. Rockwood et al. (2017) found that areas above the 90th percentile of predicted mortalities were largely concentrated around TSSs and shipping lanes; therefore, I expect that the Strait has a significant contribution to overall ship strike risk in Washington, which has not been accounted for in previous models. In addition to applying my model, I compare this framework to existing approaches, with particular emphasis on differences in predicted outcomes associated with a novel PLETH curve.

2. Materials and Methods

2.1. Data Collection

The study area is the Coastal Washington humpback whale critical habitat north of the Quinault Range Exclusion Zone (See Appendix I). I constructed a 1km² grid over the bounding box (-125.995, 47.2, -123.553, 48.506) and clipped it to the study area polygon, resulting in 7,027 grid cells. I collected 2024 vessel traffic data from within this grid for the months of June through October; since 2015, these are the only months that humpback whale strikes have been reported in the area and align with the months of most frequent humpback sightings. For vessel traffic data, I used the Automatic Identification System (AIS) data from NOAA's open source Marine Cadastre Hub (NOAA Office for Coastal Management, 2026).

AIS data comes from ships equipped with a transmitter that continuously reports various parameters, including the vessel's location, speed, size, status, and type. Mandatory AIS reporters are broken into two classes. Class A, which requires vessels to be equipped with long-range transmitters, includes self-propelled commercial vessels certified to carry more than 150 passengers, dredging vessels, vessels with hazardous cargo, and any other vessel outside of these categories that exceeds 65 feet (33 CFR §164.46); this class encompasses most commercial vessels. Class B is largely composed of recreational vessels. For the purposes of this study, I include only Class A AIS data. I filtered my AIS data to only include vessels with a status that indicated they were under way. I also filtered for observations with between 2 and 102.2 knots, and drafts greater than 0, as any values outside of these ranges are indicative of a reporting error (U.S. Coast Guard, n.d.). Though I included the entire valid reporting range for speed in my analysis, no vessels were observed to be going over 40 knots. Any observations with insufficient data were also removed. I then organized my dataset into transit tracks based on spatial and temporal relatedness. Observations with matching vessel identification numbers where gaps between observations did not exceed 10 minutes were linked into transit tracks. Each track was clipped into transit segments based on grid cell boundaries. For segments where there were multiple observations per grid cell, I considered the speed associated with that segment to be the mean speed of all contributing observations. Total distance for each segment is the planar distance between the transit's entrance and exit point in each grid cell.

2.2. Transit Hazard Index Framework

The Transit Hazard Index (THI) considers vessel characteristics and behaviors that contribute to ship strikes. THI is the product of three probabilities: the probability of ship + whale encounter in the *x-y* plane; the probability of encounter in the *z*-plane; and the probability a strike will be lethal given vessel speed and length (PLETH). It can be written mathematically as:

(Eq 1.1)

$$THI = (P(enc.\, in\, xy \mid Presence_j))\,(P(enc.\ in\, z \mid Draft_i,\ Presence_j))\,(P(lethality \mid Enc.,\ Speed_i,\ Length_i))$$

where enc. is abbreviated for encounter, presence indicates a whale is present in grid cell j, and THI is calculated for each transit segment i.

The probability of an encounter in the *x-y* plane is calculated as

(Eq. 1.2) $$1 - e^{-\lambda t_i}$$

Encounter rate (λ) measures the effect of whale and vessel speed and size on the frequency that the two would overlap within a critical radius, given a shared area. Encounter rate alone yields encounters per second given a single whale; treating encounter rate as a Poisson distribution, it can be converted into the probability of at least one encounter given a single whale during transit time *t*. This study follows a fixed-speed scenario for calculating encounter rate (Martin et al., 2016), applied in Rockwood et al., (2017), where

(Eq 1.3) $$\lambda = \frac{2r_c}{S} I(\overline{v}_m,\ v_b)$$

and r_c is the critical radius of encounter, S is area in meters squared, and monotonic function I integrates the relative velocity between one whale ($\overline{v}_m$) and one vessel (v_b) over all possible encounter angles. The critical radius of encounter is calculated as vessel width plus whale radius; humpback whale length is considered 13.5 m, and head width is 3.21 m, taken from mean values in Clapham & Mead, 1999. Whale velocity is considered the mean swim speed of humpback whales (0.94 m/s ± 0.36) from satellite tag data collected by McKenna et al., 2015 .

The probability of an encounter in the z-plane employs time-at-depth data for humpback whales from Rockwood et al. (2017), representing the cumulative percent of time spent in the water column from depths of 0 to 30 feet based on satellite tag data. Specifically, this term estimates the probability that a hypothetical whale and vessel will overlap in the z-plane, based on the cumulative amount of time a whale spends within strike depth. The strike depth is a function of a vessel's draft, which is defined as the depth of the vessel beneath the surface in meters. Strike depth is 1 to 2 times the vessel's draft due to propeller suction effect drawing whales towards the hull during an encounter (Silber et al., 2010). Therefore, I analyze results using strike depth multipliers x = 1, 1.5, and 2 and consider how this impacts the overall analysis.

I calculate the THI across all transit segments for each month to determine the status quo. Cumulative THI is used to identify regions of high hazard and is calculated per grid cell as:

(Eq. 1.4) $$1 - \Pi(1 - THI)$$

which yields the cumulative probability of at least one whale being struck in the area, given that a whale is present. I also calculate the mean THI within each grid cell to determine whether certain regions have vessels with higher-risk characteristics. To simulate the implementation of a 10 knot VSR in the study area, I randomly sampled non-compliant vessels to alter their speed to be 10 knots until the desired compliance rate was reached. Vessels travelling 10.5 knots or slower were considered compliant, consistent with similar voluntary VSR definitions of compliant. Simulated compliance rates are 50, 75, and 100%. To analyze the hazard reduction under each scenario, I calculate the percent change between the median THI across the whole study area at status quo and under each VSR compliance scenario. I report the average reduction across all months as the estimated hazard reduction under each compliance scenario.

2.3. PLETH

The PLETH equation developed for this study was estimated using observations from the ship strike dataset provided in the supplementary information for Garrison et al. (2025) which included vessel length, speed, and mortality outcome (n = 182). The data were modeled using a generalized linear model with a binomial distribution and logit link, with vessel speed and length included as predictors. Vessel length is included as a proxy for vessel size, which has been shown to influence mortality outcomes (Garrison et al., 2026, Kelley et al., 2021). To impose a biologically realistic lower bound on lethality, the model intercept was fixed at the logit equivalent of a 1% lethality probability:

(Eq 3.1) $$\text{logit}(0.01) = -4.59512$$

resulting in the fitted logistic function:

(Eq 3.2) $$g(v,l) = \text{logit}^{-1}(-4.59512 + 0.177415 * v_i + 0.029497 * l_i)$$

where v_i is vessel speed in knots, and l_i is vessel length in meters. Setting speed to 0 yields:

(Eq 3.3) $$g(0,l) = \text{logit}^{-1}(-\ 4.59512\ +\ 0.029497\ *\ l_i)$$

Because the effect of vessel length causes $g(0,l)$ to increase above 0.01 when $l > 0$, fitted probabilities were normalized to ensure a common baseline PLETH of 0.01 at zero vessel speed across all vessel lengths. The final PLETH function was therefore calculated as:

(Eq 3.4) $$PLETH\ =\ 0.01\ +\ 0.99\left(\frac{g(v,l) - g(0,l)}{1-g(0,l)}\right)$$

This normalization preserves the fitted effects of vessel speed and vessel length on lethality probability while ensuring that all vessel lengths share the same baseline PLETH of 0.01 at zero vessel speed.

2.4. Sensitivity analyses

Sampling uncertainty in THI inputs includes mean humpback whale swim speed (0.94 m/s ± 0.36) (Rockwood et al., 2017), as well as standard error associated with the coefficients of the PLETH model. To evaluate the effect of this uncertainty, I generated 1,000 Monte Carlo draws for each parameter and applied them to a simulated THI calculation for a representative observation drawn from my dataset with median vessel characteristics (Speed = 11.5 knots, Length = 199 m, Width = 32 m, Draft = 8.3 m). Furthermore, I test the effect of strike depth multiplier x being 1, 1.5, and 2 across all draws, resulting in 3,000 simulated THI values used to determine the median THI and range of the 95% confidence interval.

3. Results

3.1. Baseline conditions

Vessel traffic did not vary substantially month-to-month. There were an average of 720 monthly vessel transits through the study area. The average length, width, and draft of vessels was 195 m, 30 m, and 8 m, respectively. The average transit speed across all months was 11.6 knots. The distribution of transit tracks throughout the study area is shown in Figure 1. Whale presence, however, does vary each month, with the peak months being July through September (WDFW, n.d.). This trend is demonstrated in whale observation data for the region (Figure 2), though it is important to note that observational data is biased towards months when the most observers are present on the water. Whales are observed throughout the study area each month (Figure 3).

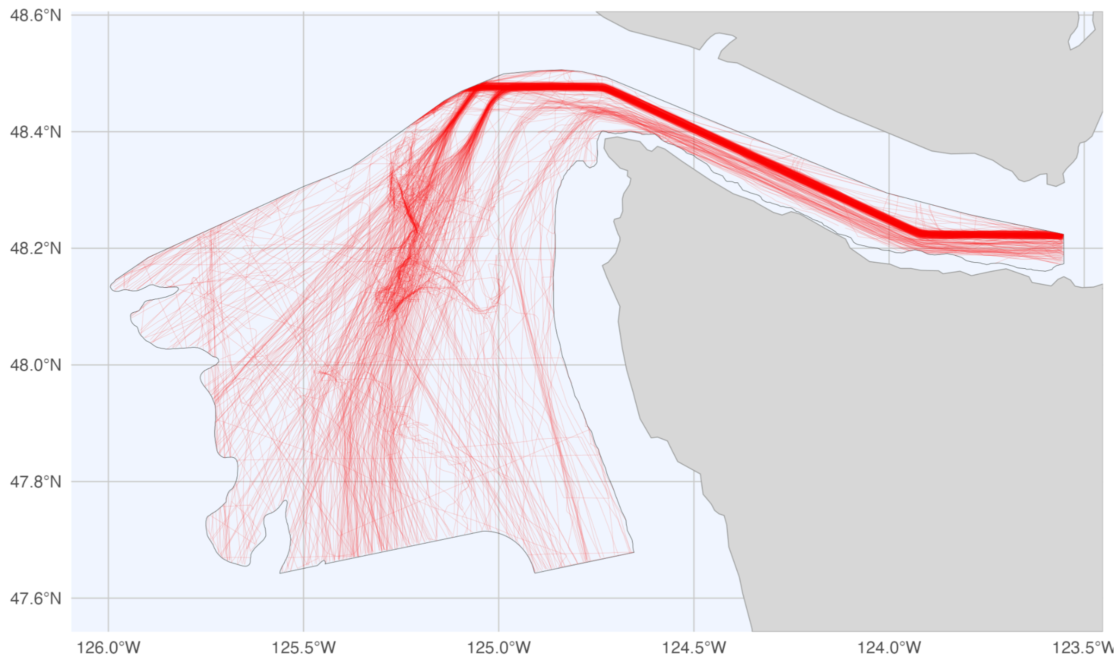


Figure 1. Transit tracks in the study area for the representative month of September (n = 754).

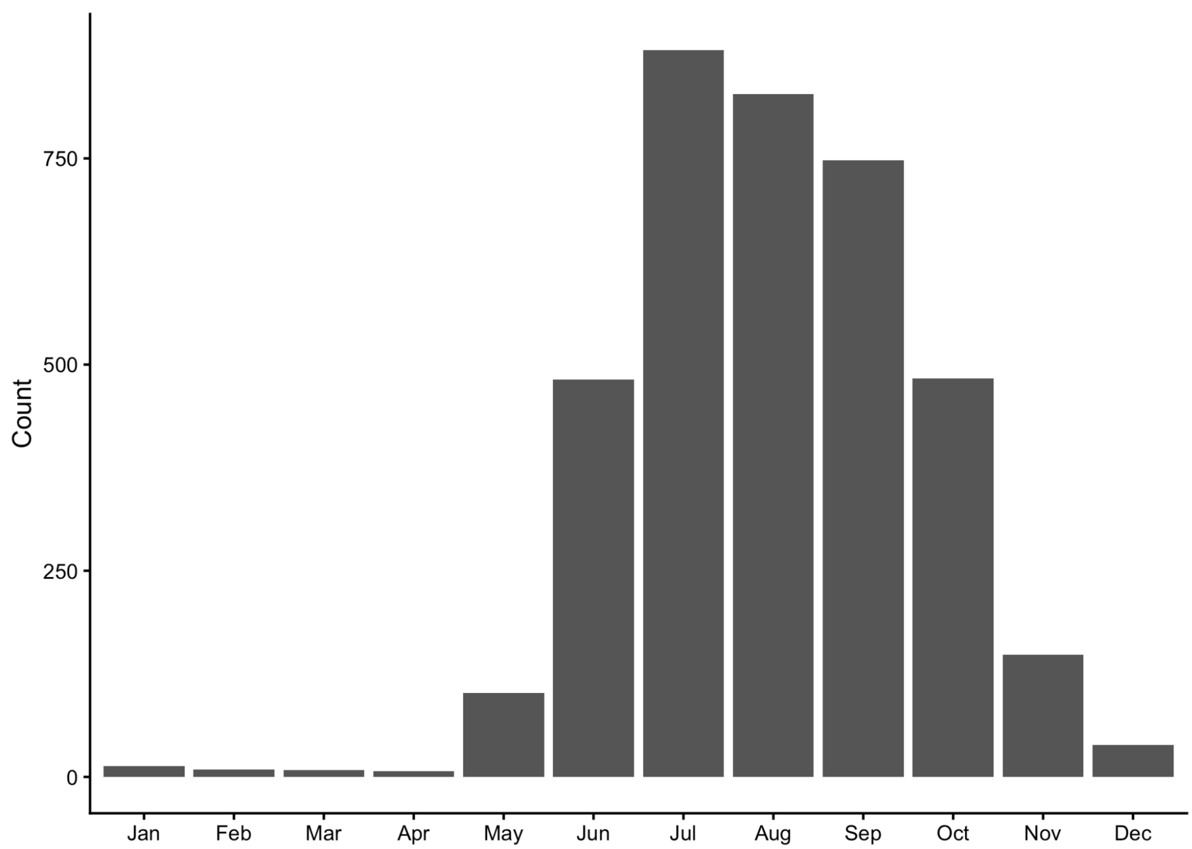


Figure 2. Number of humpback whale sightings in the study area by month, courtesy of Nisi et al., 2024.

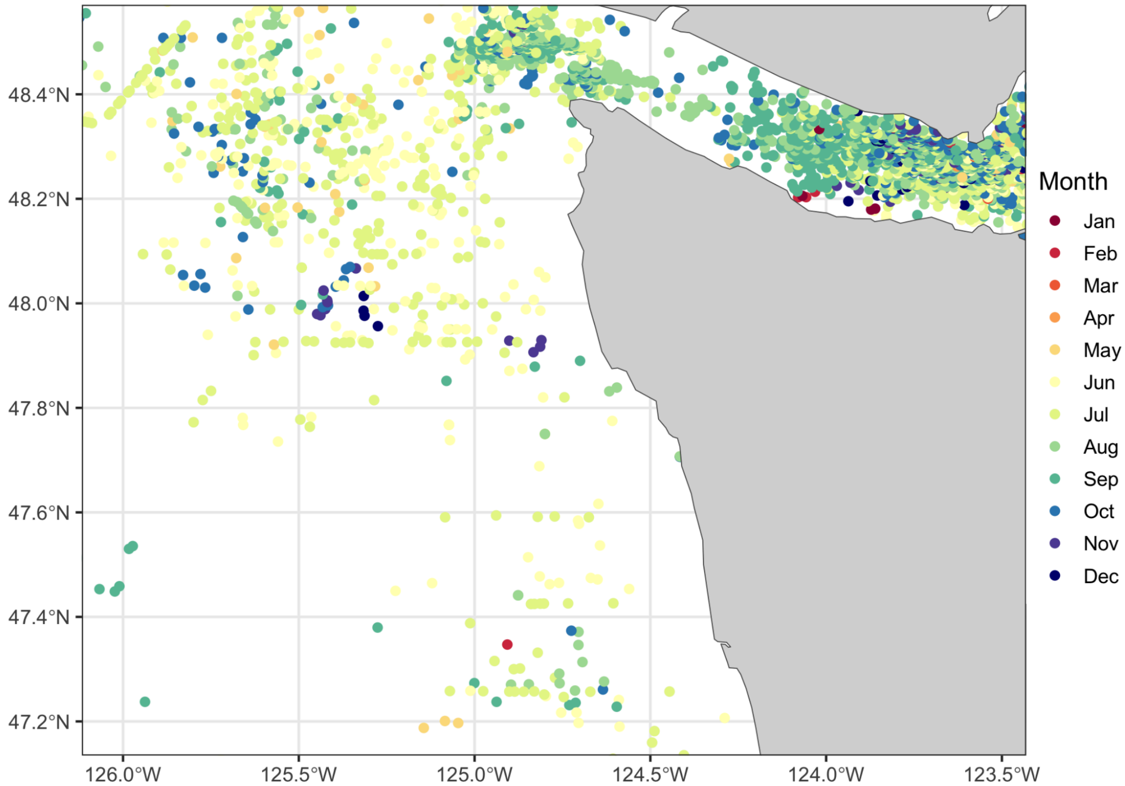


Figure 3. Locations of humpback whale sightings in the study area by month, courtesy of Nisi et al., 2024.

3.2. PLETH Analysis

The final PLETH curve was normalized from a generalized linear model fit to ship strike data (n = 182). The fitted model predicts nonzero lethality at zero vessel speed (Figures 4-5), which is not biologically realistic. After applying the baseline correction, the adjusted PLETH curve approaches zero lethality at low speeds while preserving the effects of the predictor variables across all values. The summary for the coefficients of the fitted model before normalization (Eq. 3.2) is shown in Table 1. The probability of a lethal vessel strike increases with vessel speed across both model formulations, supporting the findings of previous PLETH analyses (Conn & Silber, 2013; Vanderlaan & Taggart, 2006; Garrison et al., 2026). Furthermore, my adjusted PLETH model preserves high lethality for larger vessels across the majority of the speed range (Figure 4), consistent with findings from biophysical modeling (Kelley et al., 2021).

As expected, the adjusted PLETH curve predicts lower lethality at low speeds than both Conn & Silber (2013), and Garrison et al., (2026) (Figure 5). Similar to Garrison et al. 's curve, the predicted lethality for smaller vessels is lower than that estimated by Conn & Silber due to the introduction of vessel size as a predictor variable (Figure 5). In contrast to Garrison et al., the adjusted PLETH predicts much lower lethality for smaller vessels (Figure 5). Table 2 compares estimated mean PLETH values for the final model formulation for this study, Conn & Silber's (2013), and Garrison et al., (2026), along with the 95% confidence interval range.

Coefficient	Estimate	Std. Error	z-value	p-value
Speed	0.177415	0.013378	13.262	< 2e-16***
Length	0.029497	0.005705	5.171	2.33e-07***

Table 1. Logistic regression results for vessel strike lethality (PLETH) as a function of vessel speed and length. This table represents the results of the fitted model before normalization. Asterisks denote degree of significance.

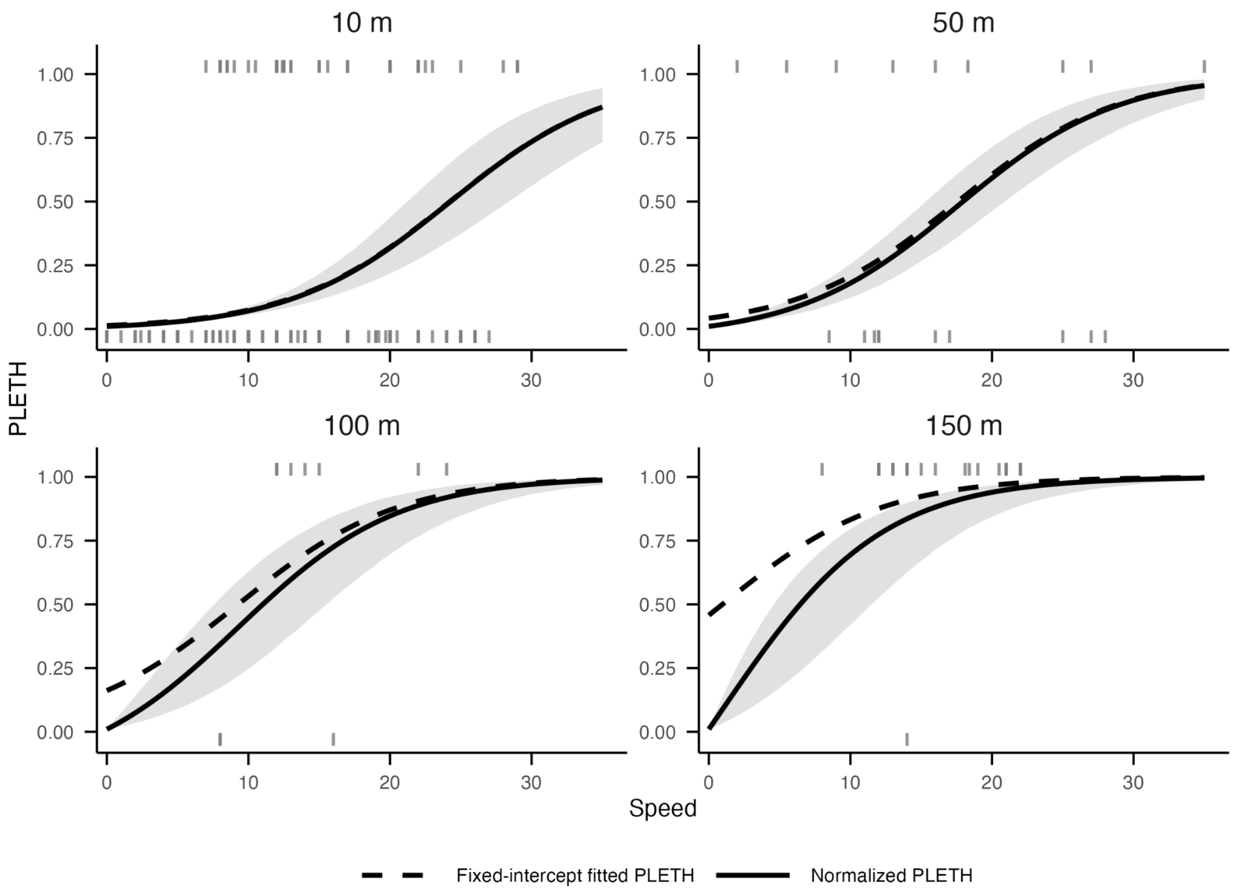


Figure 4. Normalized PLETH compared to fixed-intercept fitted PLETH. Gray ribbon represents the range of the 95% confidence interval. Gray dashes represent ship strike outcome data within each size range (10m: 0-25, 50m: >25-75, 100m: >75-125, 150m: >125-max value). Lines at y = 0 indicate that the whale survived, and lines at y = 1 indicate mortality.

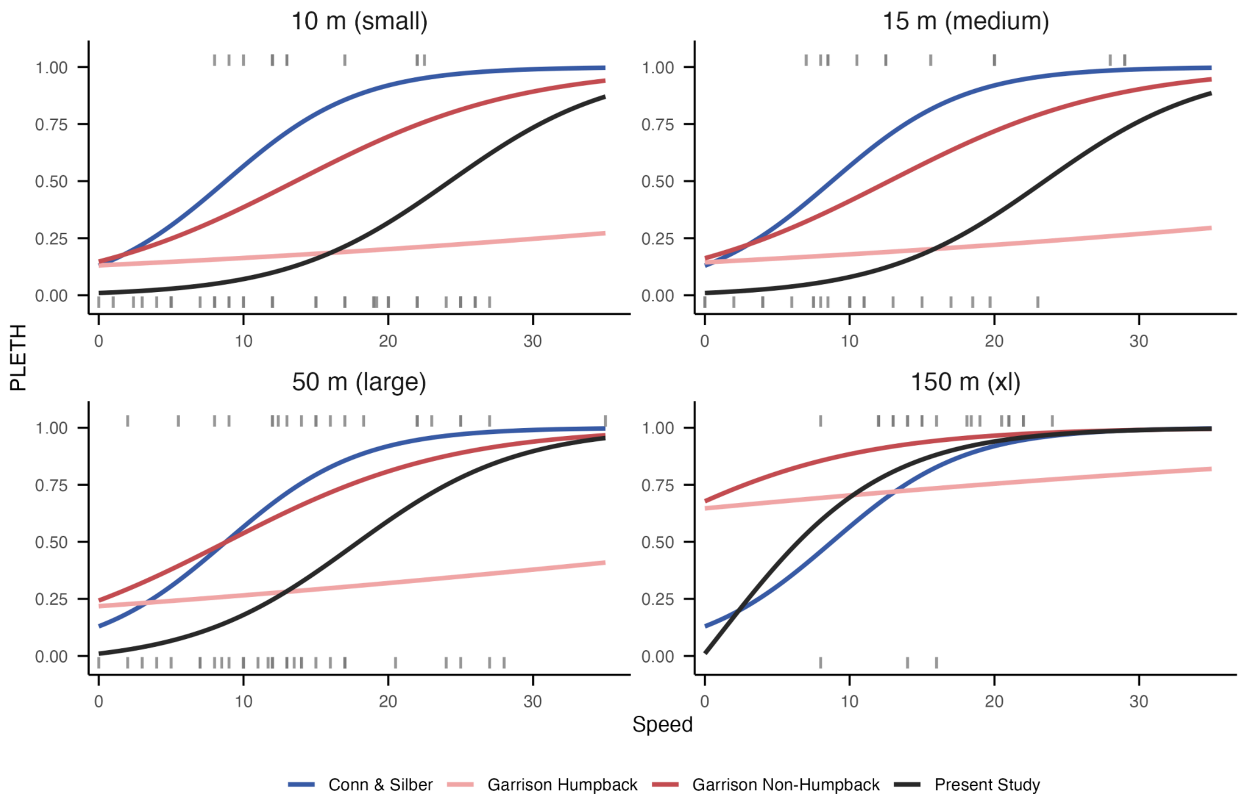


Figure 5. Comparison of present study to other published PLETH curves. Blue curve (Conn & Silber) only includes speed as a predictor variable. Red curves (Garrison et al.) include speed, length, and taxa as predictor variables. Hashes at 0 and 1 represent ship strike outcomes for the corresponding size category, where 0 indicates the whale survived and 1 indicates mortality.

Length	Study	Speed					
		5 kts	10 kts	15 kts	20 kts	25 kts	30 kts
-	Conn & Silber	0.306 (0.129 - 0.568)	0.567 (0.401 - 0.751)	0.795 (0.679 - 0.877)	0.920 (0.814 - 0.968)	0.972 (0.887 - 0.930)	0.990 (0.931 - 0.999)
10 m	Garrison et al.	0.250 (0.081- 0.558)	0.389 (0.183 - 0.644)	0.549 (0.318 - 0.760)	0.699 (0.430 - 0.877)	0.816 (0.510 - 0.950)	0.894 (0.569 - 0.982)
	Current Study	0.029 (0.025 - 0.032)	0.071 (0.056 - 0.089)	0.160 (0.115 - 0.216)	0.318 (0.218 - 0.436)	0.532 (0.374 - 0.685)	0.735 (0.569 - 0.857)
15 m	Garrison et al.	0.272 (0.095 - 0.571)	0.416 (0.216 - 0.649)	0.576 (0.369 - 0.760)	0.722 (0.486 - 0.877)	0.832 (0.561 - 0.950)	0.904 (0.615 - 0.982)
	Current Study	0.031 (0.028 - 0.036)	0.080 (0.064 - 0.100)	0.179 (0.133 - 0.240)	0.350 (0.252 - 0.468)	0.568 (0.422 - 0.711)	0.761 (0.611 - 0.874)
50 m	Garrison et al.	0.382 (0.152 - 0.681)	0.541 (0.320 - 0.747)	0.692 (0.501 - 0.835)	0.811 (0.616 - 0.920)	0.891 (0.682 - 0.969)	0.940 (0.727 - 0.989)
	Current Study	0.066 (0.046 - 0.096)	0.180 (0.122–0.256)	0.367 (0.264–0.478)	0.592 (0.462–0.714)	0.781 (0.663–0.870)	0.897 (0.817–0.946)
150 m	Garrison et al.	0.802 (0.445 - 0.953)	0.886 (0.660-0.969)	0.937 (0.799-0.982)	0.966 (0.871-0.992)	0.982 (0.909-0.997)	0.990 (0.930-0.999)
	Current Study	0.401 (0.181 - 0.527)	0.694 (0.430 - 0.792)	0.860 (0.682 - 0.914)	0.940 (0.845 - 0.965)	0.975 (0.932 - 0.986)	0.989 (0.970 - 0.995)

Table 2. Comparison of estimated PLETH values across different studies. Mean estimates are reported, as well as the range of the 95% confidence intervals.

3.3. THI analyses

The distribution resulting from my sensitivity analysis drawing 3,000 THI values had a median THI of 0.0114, with a 95% confidence interval (CI) ranging from 0.0088 to 0.0128 (Figure 6). To isolate the effect of strike depth multiplier x, I calculated THI for each x value for all baseline and VSR analyses (n = 24). On average there was a 7.15% difference between THI values where x = 1 and x = 1.5, a 5.27% difference from x = 1.5 and x = 2, and a 12.79% difference from x = 1 and x = 2. Unless otherwise specified, I report my THI analyses results using x = 1.5, representing the mid-range estimate.

Hazard is highly concentrated in the shipping lanes in the Strait of Juan de Fuca where vessel traffic is most dense (Figure 7). Normalizing the THI by vessel count shows a distinct contrast in per-transit hazard driven by the Olympic Coast Area to be Avoided, which is a voluntary measure which asks large vessels to reroute around the area (Figure 8). This pattern indicates that size plays a strong role in the level of hazard posed by a vessel. Mean THI is relatively high throughout the study area (Figure 8).

THI was analyzed under simulated 10 knot voluntary VSR scenarios each month under scenarios of 50%, 75% and 100% compliance (Table 3). Estimated hazard reduction is the average percent change between the median THI across the whole study area at status quo and under the compliance scenario across all months. At 50% compliance, estimated hazard reduction was 5.39%. At 75% compliance, estimated hazard reduction was 18.26%. At 100% compliance, estimated hazard reduction was 30.48%. At 100% compliance, mean speed across all transits was reduced by 2.4 knots on average. Figure 9 demonstrates how the VSR simulation shifts the distribution of THI values of the 90th percentile of high risk transits slightly closer to zero.

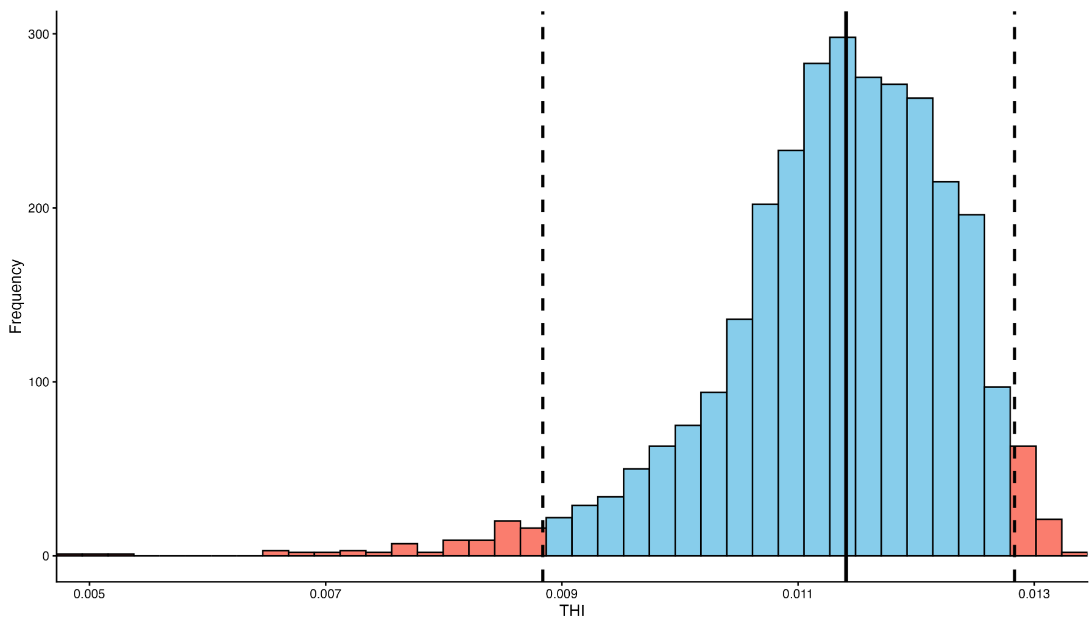


Figure 6. Frequency of THI values across draws (n = 3,000) for a case example with typical vessel characteristics. Blue indicates the middle 95% of simulated outcomes, red represents tail values outside the 95% confidence interval. Solid line denotes the median THI, dashed lines represent the range of the 95% confidence interval.

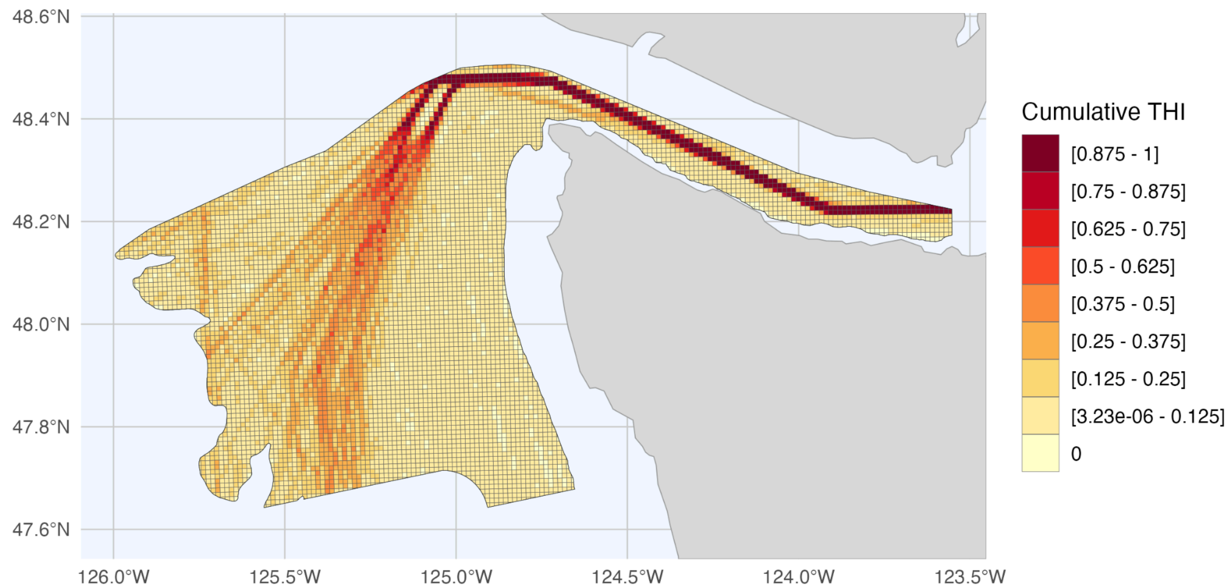


Figure 7. Cumulative THI in the study area, calculated as the sum THI across all transits. Data is from the month of September and is representative of all months across the study period.

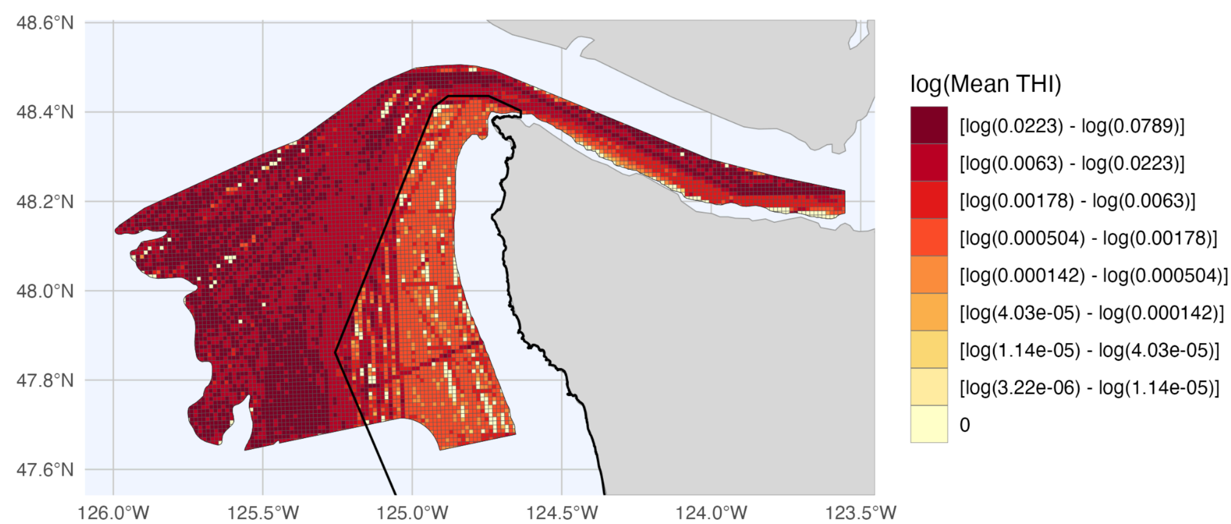


Figure 8. Mean THI for each grid cell in the study area (n = 7,027) for the month of September. Values greater than 0 are displayed on a logarithmic scale. Black polygon indicates the boundaries for the Olympic Coast National Marine Sanctuary Area to be Avoided.

Month	Percent THI Reduction at 50% Compliance	Percent THI Reduction at 75% Compliance	Percent THI Reduction at 100% Compliance
May	7.759841	22.42256	33.61888
June	5.355522	18.37623	30.59936
July	4.804762	17.14983	30.87247
August	7.305706	21.58678	35.61682
September	3.489409	15.81749	28.72868
October	3.639368	14.19837	23.46925

Table 3. Percent reduction in median THI across the whole study area for each month at various 10 knot VSR compliance rates.

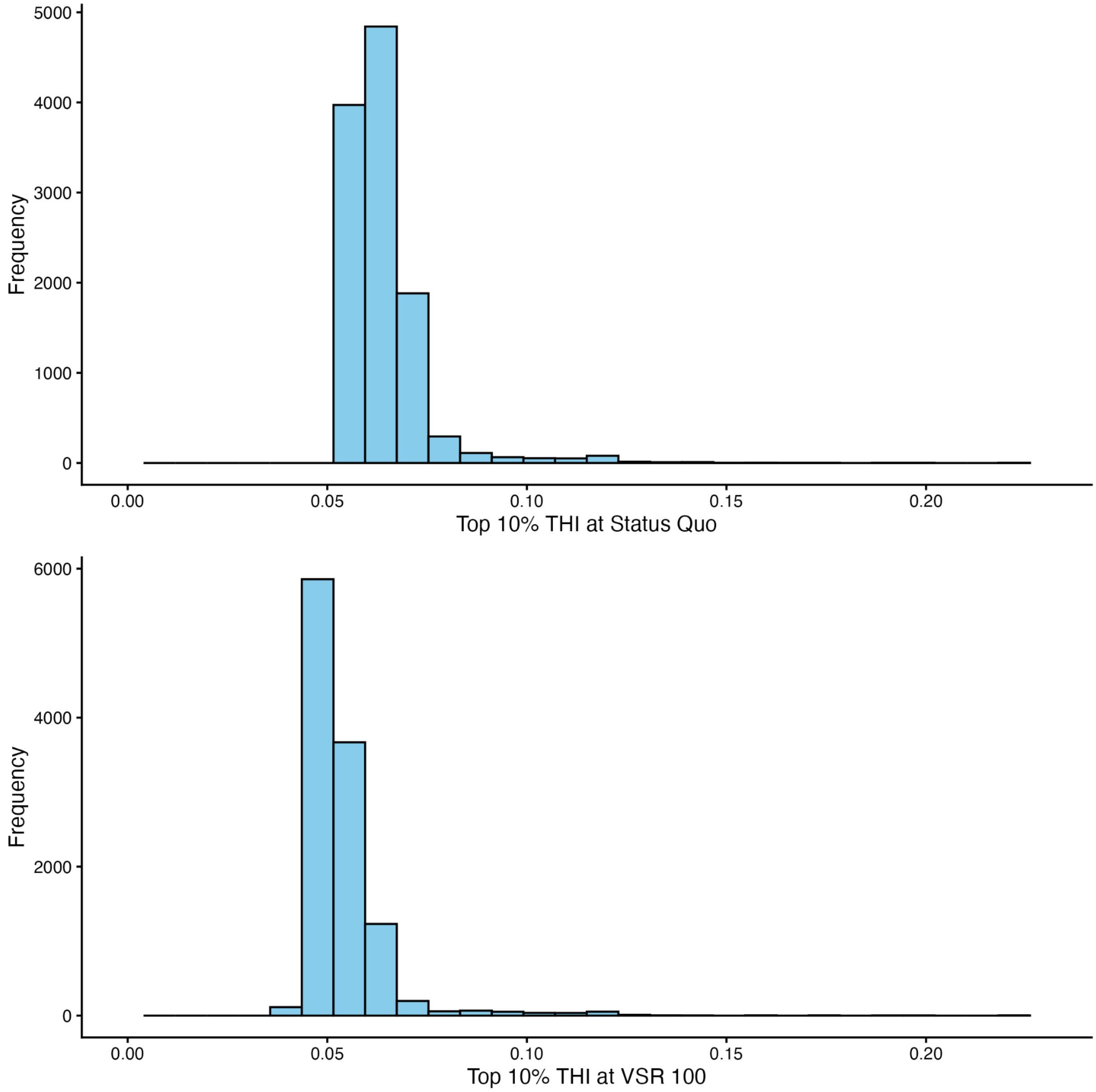


Figure 9. Frequency of THI values at status quo and under a 10 knot voluntary VSR at 100% compliance for the 90th percentile of hazardous transits for the month of September.

4. Discussion

The THI metric provides a vessel-based, probabilistic framework for estimating relative ship-strike hazard in the absence of explicit whale density estimates. THI may be applied to ship strike analysis to estimate baseline hazard posed by the characterization of vessel traffic without the need for inaccessible and often uncertain whale density estimates. Sensitivity analysis for the THI metric produced a tightly constrained 95% CI (0.0088-0.0128) with a left-skewed distribution for a representative vessel scenario, indicating that THI estimates fall within a narrow range and that parameter uncertainty is likely to produce a conservative estimate of hazard.

THI-based results produce similar estimated reductions from VSR scenarios compared to previous studies. Redfern et al., (2024) estimated an 18% reduction in risk using a co-occurrence based metric. Rockwood et al., (2021) also employs encounter rate theory, and estimated a maximum reduction of 30% at high cooperation levels, which matches my estimate for average reduction in hazard for 100% cooperation. The terms in Rockwood et al., (2021) which depend on speed are encounter rate, PLETH, and probability of avoidance. A limitation of the THI metric is it does not account for the effect of avoidance behavior; if avoidance behavior were considered, the probability of avoidance would be expected to be higher at lower speeds, meaning the hazard reduction estimates from THI are conservative as they do not account for this added conservation benefit. However, avoidance behavior of whales from vessels is poorly understood (Rockwood et al., 2017), and modelling avoidance relies on assumptions about whale response distance and avoidance dive rates, which have substantial variation (McKenna et al., 2015). Furthermore, humpback whales have demonstrated weak responses to vessel traffic (Dunlop et al., 2024; Laist et al., 2021; Wensveen et al., 2017). Due to variability in avoidance behavior, avoidance was not explicitly modeled.

The selection of a PLETH model also drives differences in results compared to other metrics. My corrective method for forcing PLETH to 0 at 0 speed introduced relatively steep changes around the commonly observed range of vessel speeds (5-15 kts), which contributes to large PLETH reductions even at small speed changes within that range. This behavior is consistent with Conn & Silber's (2013) model of PLETH based on speed alone. In contrast, Garrison et al.'s (2025) formulations have very high probabilities at very low speeds for large vessels, lessening the overall influence of speed in the model. Though the final Garrison et al., (2025) model was tested to be best fit to the data among several other model formulations, high probabilities of lethality (upwards of 50% for large vessels) at zero speed are difficult to reconcile with vessel strike mechanics. The PLETH model developed for this study represents a balance between statistical fit and biological reasoning, incorporating both empirical relationships from the data and constraints based on the underlying mechanics of vessel strikes. Although it is supported that large vessels may have relatively high probabilities of causing lethal strikes even at low speeds (Kelley et al., 2021), it is unlikely that a non-moving vessel would result in high lethality. Consequently, despite not strictly maximizing statistical fit to the available data, the PLETH curve developed in this study incorporates a biologically realistic boundary condition at zero vessel speed and is intended to better reflect the underlying mechanics of vessel-whale interactions.

PLETH estimates could be further improved with additional observations of large vessels; however, most ship strikes in large vessels go undetected, limiting the availability of such data. The data available to inform PLETH models are strongly skewed towards vessels under 50 meters in length, whereas the characterization of actual vessel traffic indicates that most commercial vessels are much larger (Garrison et al., 2025). Furthermore, for vessels over 100 meters, there are only 2 observations at speeds under 10 knots, likely due to limitations in the minimum speed at which they can operate (Maryland Sea Grant, n.d.). Consequently, empirical data alone provide limited support for estimating lethality probabilities for large vessels at low speeds, necessitating the incorporation of biologically and mechanically informed constraints.

As expected, cumulative THI is highest where there are the most vessels, which is in the Strait of Juan de Fuca. The stark contrast in cumulative THI values shown in Figure 3 indicates that vessel traffic density has the strongest influence on hazard. The baseline mean THI analysis found that most grid cell-level mean THI values fall within the range of 0.002 to 0.02; this value estimates the probability that a lethal collision occurs between one whale and one transit during its time spent in the grid cell. Although these values are low, as probability accumulates over multiple transits and multiple grid cells, the likelihood of a lethal encounter to the given whale increases substantially. For example, if an individual whale is exposed to 100 equivalent transit-segments with a lethal-strike probability of 0.005, the probability of at least one fatal event would be approximately $1-(1-0.007)^{100} \approx 0.5$, or a 50% chance of a lethal strike, assuming no successful strike avoidance.

Humpback whales come to Washington to feed, therefore, they are not travelling linearly across long distances, but rather swimming erratically in a localized area where food is most abundant (Millien et al., 2025). Data from Nisi et al., (2024) demonstrate that humpback whales are frequently observed in the Strait of Juan de Fuca (Figure 3); whales feeding in this area would be at a substantial risk of fatality given the very high exposure to shipping traffic. An average of 27 vessels transited through the Strait each day in September. In the THI analysis, these transits are clipped into transit-segments along the boundaries of $1km^2$ grid cells, resulting in a given whale's exposure to hundreds of transit segments each day within the Strait. Furthermore, the high traffic density and geographical constraints of the region would likely act as barriers to successful strike avoidance by both whales and vessels. This suggests the Strait of Juan de Fuca is a region of elevated ship strike risk.

Humpback whale critical habitat was designated after being identified as critically important to the conservation and recovery of the species (86 FR 21082). Yet, this crucial habitat is a hazardous area for whales in Washington. Numerous, large vessels transiting through a geographically constrained area such as the Strait of Juan de Fuca create the conditions that lead ship strikes, necessitating the implementation of mitigation measures to suppress human-caused mortalities.

I can conclude from my THI analysis that the implementation of a VSR in the study area would meaningfully reduce the hazard posed by vessels, and is therefore expected to lower the occurrence of ship strikes. Observed compliance rates for voluntary VSR programs along the U.S. West Coast range from approximately 59% to 85% (BlueWhalesBlueSkies, 2025; Vancouver Fraser Port Authority, 2025; QuietSound, 2025). Assuming similar levels of participation, a voluntary VSR in the study area could achieve hazard reductions within the range of 15–20%, despite requiring only modest reductions in mean vessel speed (approximately 2 knots). Given that my analyses produced similar results to other studies estimating VSR effectiveness, the literature demonstrates that reductions in ship strike risk from VSRs alone are constrained around 25%. However, the logistics of a more effective policy are challenging. Vessel density plays the biggest role in ship strike risk, and in a geographically constrained region such as the Strait of Juan de Fuca, reducing vessel density would not be feasible with major reductions in global shipping traffic. VSRs are the standard in ship strike mitigation because speed is a component of ship strike risk that policies can control. However, the degree to which speed can be reduced is also limited, because the minimum operating speed for large vessels is restricted due to a loss of maneuverability at speed below 10 knots (AMSA, n.d.). Furthermore, the average size of container ships has been steadily increasing, meaning VSR policies may only become more logistically challenging if this trend continues (Mevada, 2025).

Despite these limitations, the predicted hazard reduction from VSRs is still meaningful. My findings suggest that moderate compliance with voluntary measures can produce substantial reductions in vessel-related risk, supporting VSRs as a potentially effective and practical strategy for mitigating ship strike impacts on humpback whales.

Literature Cited

AMSA. (n.d.). *Safe vessel speeds.* Government of South Australia. https://marinesafety.sa.gov.au/your-safety-and-operations/safe_vessel_speeds

Best, P.B. (1993). Increased rates in severely depleted stocks of baleen whales. *ICES Journal of Marine Science, 50*(2), 169-186. https://doi.org/10.1006/jmsc.1993.1018

Blue Whales Blue Skies. (2025). *Results by VSR season.* https://bluewhalesblueskies.org/impact/#previous-results

Calambokidis, J. & Vanderzee, A. (2026, January 22). *Humpback whales of the Salish Sea.* Encyclopedia of Puget Sound. https://www.eopugetsound.org/article/humpback-whales-salish-sea

Clapham PJP, Mead J (1999) *Megaptera novaeangliae*. Mamm Species 63: 1–9.

Conn, P.B. & Silber, G.K. (2013). Vessel speed restrictions reduce risk of collision-related mortality for North Atlantic right whales. *Ecosphere, 4*(4),43.

Department of Commerce (2015). Endangered and Threatened Species; Identification of 14 Distinct Population Segments of the Humpback Whale (Megaptera novaeangliae) and Proposed Revision of Species-Wide Listing. *Federal Register, 80*(76).

Department of Commerce (2021). Endangered and Threatened Wildlife and Plants: Designating Critical Habitat for the Central America, Mexico, and Western North Pacific Distinct Population Segments of Humpback Whales. *Federal register, 86*(71).

Dunlop, R. (2024). Use of a behavioural response method to assess the risk of collision between migrating humpback whales and vessels. *Marine Pollution Bulletin, 199,* 115986.https://doi.org/10.1016/j.marpolbul.2023.115986

Durling, J. (2025, October 21). *Humpback calf being monitored after it was struck by Hullo Ferry in Vancouver.* The Williams Lake Tribune. https://wltribune.com/2025/10/21/humpback-calf-being-monitored-after-it-was-struck-by-hullo-ferry-in-vancouver/

Endangered Species Act, 16 U.S.C. § 1533, 1536, 1538 (1973)

Hague, E. L., Halliday, W. D., Dawson, J., Ferguson, S. H., Heide-Jørgensen, M. P., Serra Sogas, N., Gormley, K., Young, B. G., & McWhinnie, L. H. (2024). Not all maps are equal: Evaluating approaches for mapping vessel collision risk to large baleen whales. *Journal of Applied Ecology*, *00,* 1–18. https://doi.org/10.1111/1365-2664.14794

Garrison, L. P., Lisi, N. E., Gahm, M., Patterson, E. M., Blondin, H., & Good, C. P. (2025). The effects of vessel speed and size on the lethality of strikes of large whales in U.S. waters. *Frontiers in Marine Science, 11,* 1467387. https://doi.org/10.3389/fmars.2024.1467387

Gavigan, E. (2025, August 13). *20,000 whales are killed by ship strikes each year*. International Marine Mammal Project. https://savedolphins.eii.org/news/20-000-whales-are-killed-by-ship-strikes-each-year

Gende, S.M., Baken, V.J., Gabriele, C.M., Preston, R. & Hendrix, A.N. (2019). Active whale avoidance by large ships: components and constraints of a complementary approach to reducing ship strike risk. *Frontiers in Marine Science, 6*. https://doi.org/10.3389/fmars.2019.00592

Greer, D. (2025, October 28). *'Exceedingly rare': B.C. humpback's death may be first linked to whale-watch industry.* Times Colonist.

Keen, E. M., Mahony, É. O., Nichol, L. M., Wright, B. M., Shine, C., Hendricks, B., Meuter, H., Alidina, H. M., & Wray, J. (2023). Ship-strike forecast and mitigation for whales in Gitga'at first nation territory. Endangered Species Research, 51, 31–58. https://doi.org/10.3354/esr01244

Mevada, R. (20 November, 2025). *Why Container SHips Keep Getting Bigger – And When It Will Stop.* Medium. https://medium.com/@rudramevada15/why-container-ships-keep-getting-bigger-and-when-it-will-stop-dfe677083b01

Millien, V., Stafiej, N., Félix, F. & Guzman, H.M. (2025). Migratory behaviour of humpback whales in the southeastern Pacific under climate change. *Scientific Reports, 15.*

Nisi, A. C., Welch, H., Brodie, S., Leiphardt, C., Rhodes, R., Hazen, E. L., Redfern, J. V., Branch, T. A., Barreto, A. S., Calambokidis, J., Clavelle, T., Dares, L., de Vos, A., Gero, S., Jackson, J. A., Kenney, R. D., Kroodsma, D., Leaper, R., McCauley, D. J., Moore, S. E., Ovsyanikova, E., Panigada, S., Robinson, C. V., White, T., Wilson, J., & Abrahms, B. (2024). Ship collision risk threatens whales across the world's oceans. *Science, 386*(6626), 870-875. https://doi.org/10.1126/science.adp1950

Nisi, A.C. (2025). *Estimated reduction in whale ship-strike risk during the 2025 Protecting Blue Whales and Blue Skies voluntary vessel speed reduction program in California waters.* Blue Whales Blue Skies.

NOAA. (2026). *Reducing vessel strikes to North Atlantic right whales.* NOAA Fisheries. https://www.fisheries.noaa.gov/national/endangered-species-conservation/reducing-vessel-strikes-north-atlantic-right-whales

NOAA Fisheries. (2025, December 3). *West Coast Marine Mammal Stranding Network*. NOAA Fisheries. https://www.fisheries.noaa.gov/west-coast/marine-mammal-protection/west-coast-marine-mammal-stranding-network

Martin, J., Sabatier, Q., Gowan, T.A, Giraud, C., Gurarie, E., Calleson, C.S., Ortega-Ortz, J.G., Deutsch, C.J., Rycyk, A. & Kolslovsky, S.M. (2016). A quantitative framework for investigating risk of deadly collisions between marine wildlife and boats. *Methods in Ecology and Evolution, 7*(1), 42–50. https://doi.org/10.1111/2041-210X.12447

Maryland Sea Grant. (n.d.). Avoiding Ship Collisions https://www.mdsg.umd.edu/avoiding-ship-collisions

McKenna, M.F., Calambokidis, J., Oleson, E.M., Laist, D.W. & Goldbogen, J.A. (2015). Simultaneous tracking of blue whales and large ships demonstrates limited behavioral responses for avoiding collision. *Endangered Species Research, 27,* 219-232. doi: 10.3354/esr00666

QuietSound. (2025). *Results of 2024-2025 voluntary commercial vessel slowdown in Washington waters for the protection of southern resident killer whales* [Executive summary]. https://quietsound.org/wp-content/uploads/2025/08/2024-25-Slowdown-Report-Cover-Exec-Summary.pdf

Redfern, J.V., Becker, E.A. & Moore, T.J. (2020). Effects of variability in ship traffic and whale distributions on the risk of ships striking whales. *Marine Conservation and Sustainability, 6.* https://doi.org/10.3389/fmars.2019.00793

Redfern, J. V., Hodge, B. C., Pendleton, D. E., Knowlton, A. R., Adams, J., & Wiley, D. (2024). Estimating reductions in the risk of vessels striking whales achieved by management strategies. Biological Conservation, 144(9), 2377–2381. https://doi.org/10.1016/j.biocon.2023.110427

Rockwood, R.C., Calambokidis, J. & Jahncke, J. (2017). High mortality of blue, humpback and fin whales from modeling of vessel collisions on the U.S. West Coast suggests population impacts and insufficient protection. *PLOS One.* https://doi.org/10.1371/journal.pone.0183052

Rockwood, R. C., Adams, J., Silber, G., & Jahncke, J. (2020). Estimating effectiveness of speed reduction measures for decreasing whale-strike mortality in a high-risk region. *Endangered Species Research, 43,* 145–166. https://doi.org/10.3354/

Rockwood R.C., Adams, J.D., Adams, J., Hastings, S., Morten, J. & Jahncke, J. (2021). Modeling whale deaths from vessel strikes to reduce the risk of fatality to endangered whales. *Frontiers in Marine Science, 8*. https://doi.org/10.3389/fmars.2021.649890

Silber, G.K., Slutsky, J. & Bettridge, S. (2010). Hydrodynamics of a ship/whale collision. *Journal of Experimental Marine Biology and Ecology, 391*(1-2), 10-19. https://doi.org/10.1016/j.jembe.2010.05.013

UNCTAD (1991). *Review of maritime transport*. United Nations. https://unctad.org/webflyer/review-maritime-transport-1991

UNCTAD (2025). *Review of maritime transport*. United Nations.

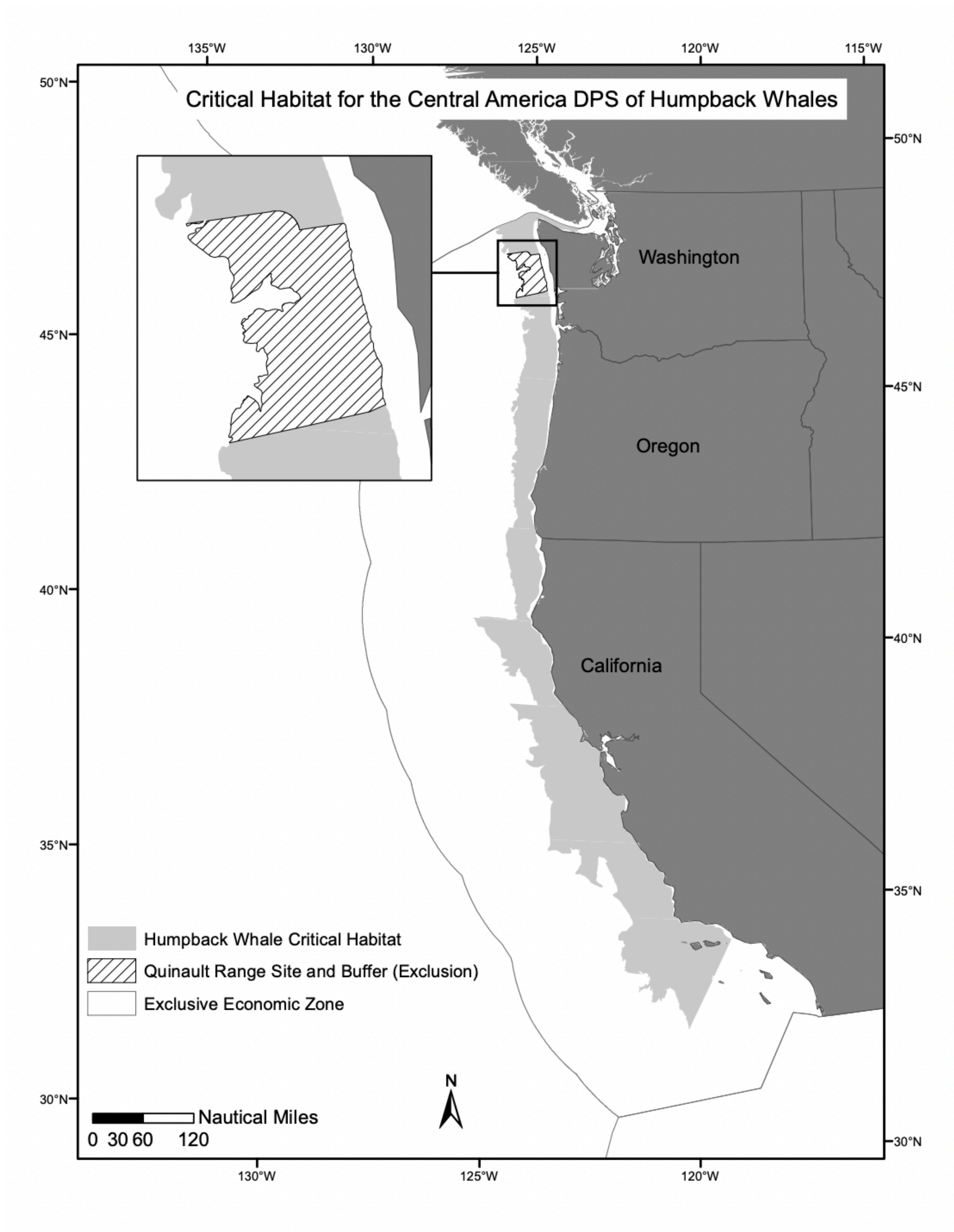
Vanderlaan, A.S.M. & Taggart, C. (2007). Vessel collisions with whales: The probability of lethal injury based on speed. *Marine Mammal Science, 23*(1), 144-156. https://doi.org/10.1111/j.1748-7692.2006.00098.x

Vancouver Fraser Port Authority. (2024). *2023 ECHO Program annual report.* Vancouver Fraser Port Authority.

WDFW. (n.d.) Humpback whale (*Megaptera novaeangliae*) https://wdfw.wa.gov/species-habitats/species/megaptera-novaeangliae

Wensveen, P.J., Kvadsheim, P.H., Lam, F.A., von Benda-Beckman, A.M., Silve, L.D., Visser, F., Curé, C., Tyack, P.L. & Miller, P.J.O. (2017). Lack of behavioural responses of humpback whales (*Megaptera novaeangliae*) indicate limited effectiveness of sonar mitigation. *Journal of Experimental Biology, 220*(22), 4150-4160. https://doi.org/10.1242/jeb.161232

Appendix



Appendix I. Humpback whale critical habitat in the U.S. West Coast, courtesy of NOAA fisheries.