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# Earth Observations Can Enable Cost-Effective Conservation of Eastern North Pacific Blue Whales: A Value of Information Analysis

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# About RFF



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# Abstract

We conduct an analysis to estimate the value of information (VOI) of Earth observations for prospective regulation of marine shipping to conserve Eastern North Pacific blue whales in the Exclusive Economic Zone of the United States. Outcomes are driven by differences across two data products that can be used to inform regulations to limit ship strikes. In the reference case, vessel speed limits depend on species distribution data from shipboard surveys. In the counterfactual case, speed limits depend on species distributions predicted by WhaleWatch, a federal data product incorporating information from several remote sensing technologies. The VOI is identified as the difference in costs to marine shipping operators under the reference and counterfactual cases for regulation of vessel speeds. We estimate that the annual VOI of WhaleWatch is US$21–332 million, depending on the conservation goals of the modeled regulation. Conserving more blue whales—averting more ship strikes—increases the VOI.

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# 1. Introduction

In the Pacific Ocean, blue whales are protected by the Endangered Species Act (ESA) [1] and the Marine Mammal Protection Act (MMPA) [2], which limit the number of whales killed by ships and other vessels and direct federal agencies to minimize the number of fatal encounters between blue whales and vessels that exceed these limits. To implement the ESA and MMPA, federal ocean managers must determine how many fatal encounters occur between whales and vessels. Historically, this has been challenging because observing whales in situ is expensive and data on fatal encounters is incomplete [3]. However, recent advances in remotely sensed data offer near-real-time information about where whales are in time and space—at a finer scale and with less error than in situ data. In this study, we quantify the socioeconomic benefits of using remotely sensed information instead of in situ observations to estimate the spatiotemporal distribution of endangered blue whales in the Eastern North Pacific (ENP) Ocean.

Our analysis demonstrates how applying remotely sensed data and information (RSDI) can reduce the cost of conserving blue whales under the ESA and MMPA by minimizing the economic impact of regulatory compliance for vessel operators. The improved information contributes to reducing spatial and temporal misassignment of limits on vessel transit speeds, particularly with monthly spatiotemporal probability estimates of whale densities and associated variables, in contrast to estimates based on in situ observations, which do not vary from month to month within each year.

Because this impact assessment is employed to estimate the value of information (VOI) that is not yet being used in a decision—in this case, the RSDI—it is an ex ante (or prospective) analysis. To quantify VOI, we must compare outcomes in two different states of the world: a "reference case" in which ocean managers take action based on in situ data and information (ISDI) currently available to them about whale and vessel encounters and a "counterfactual case" in which they take action using RSDI on these encounters. The difference in the societal value of the economic and environmental outcomes between these two information cases yields the VOI of RSDI in prospective ocean management decisions for conservation of ENP blue whales. Our assessment focuses on management decisions in the Exclusive Economic Zone of the United States (USEEZ) that is part of the ENP off the California, Oregon, and Washington coasts.[1]

The historical regulatory experience of the North Atlantic right whale provides background for how regulations might be informed by RSDI in the ENP [4]. In the northeast and southeast US coastal waters, vessels must slow down and keep a lookout for right whales [5]. In modeling an extension of this policy to the ENP for blue whales, we identify potential management areas where large commercial vessels must slow to 10 knots or less during times of the year when blue whales are likely to be in

[1] The US EEZ extends no more than 200 nautical miles from the territorial sea baseline [16].

the area. At the 10-knot limit, whales have more time to avoid a ship and a ship strike is less likely to be fatal. The right whale speed reduction rule is a mandatory regulation, which vessel operators can be fined for violating. We apply a similar regulation to estimate the cost to vessel operators of a vessel speed reduction (VSR) regulation for the ENP.

On both US coasts, ISDI and RSDI serves ocean management by helping decisionmakers identify when and where VSR could avert fatal encounters of vessels and blue whales. We find that RSDI enables more cost-effective management by improving estimates of such encounters. In particular, RSDI contributes more accurate and precise estimates of densities of blue whales by area and month. This improvement reduces the cost of any policy designed to protect blue whales from encounters with vessels; more accurate and precise estimates of fatal encounters allow decisionmakers to select less stringent restrictions on vessel speeds or paths, attaining the same conservation outcomes as with ISDI at lower costs to vessel owners.

More specifically, the policy objective we simulate is to achieve an expected reduction in whale deaths per year to meet the established annual Potential Biological Removal (PBR) at least cost.[2] The VOI of the RDSI is the difference in estimated costs of compliance borne by vessel operators under alternative regulations to reduce fatal encounters with blue whales: those informed by ISDI versus RSDI. The VOI in this decision context is equivalent to the monetary savings of relying on RSDI to choose a policy that ensures a sustainable blue whale stock at least cost.

In our analysis, the reference and counterfactual information cases are sets of ecological information from models of habitat suitability from ISDI [6] and RSDI [3]. Information describing vessel locations, characteristics, and behavior and ecological estimates of parameters for whale characteristics augment these models. Ocean management in the reference case is informed by ISDI and involves relatively coarse limits on vessel speed and routes to reduce mortality. Ocean management in the counterfactual (RSDI) case employs an improved statistical estimation of blue whale spatial density on a monthly basis that allows for finer limits on vessel speed and routes.

We estimate the VOI of RSDI in several steps. First, we employ ISDI and RSDI products to generate historical distributions of blue whales in the USEEZ over a common spatiotemporal scope. Next, we simulate interactions between marine mammals and vessels in a probabilistic model to find expected rates of fatal encounters for ENP blue whales. Finally, we simulate the VSRs implemented to meet an annual PBR in the reference (ISDI) and counterfactual (RSDI) cases.

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[2] The Potential Biological Removal (PBR) level is the maximum number of animals, not including natural mortalities, that may be removed from a marine mammal stock while allowing that stock to reach or maintain its optimum sustainable population [2].

Our results demonstrate that using RSDI to support policy to conserve ENP blue whales yields significant cost-savings relative to using only ISDI over a range of VSRs and thus has a positive VOI for a VSR conservation program for the US EEZ. This VOI increases with conservation objectives: savings are greater with greater reductions in estimated rates of fatal strikes.

# 2. Decision Context

While the blue whale is the largest living animal on Earth, it is challenging to determine how many are killed each year by vessel strikes. The observed annual vessel strike mortality rate was 0.4 whales for 2013–2017; unobserved strikes are difficult to estimate and could dwarf the observed rate [7,8]. Given no perfect information about the population of blue whales for conservation decisions, reducing uncertainty about vessel strikes would benefit ocean managers who protect endangered species listed under the ESA and regulate stocks under the MMPA.

From a regulatory perspective, the National Oceanic and Atmospheric Administration is responsible for managing the whale stock and enacting speed restrictions to protect marine species under the MMPA and ESA. This responsibility is the basis for the general objectives of the ESA and MMPA applied to the USEEZ. The ESA governs taking species that have an elevated risk of extinction to ensure that effects of threats are restricted to levels that allow recovery of the species to the point where it is no longer threatened or endangered [1]. Blue whales were listed as endangered under the 1969 Endangered Species Conservation Act and afforded continued protection under the ESA [8]. The goal of the MMPA is to protect marine mammal species by maintaining their population "stocks" as functioning elements of their ecosystem [2]; blue whales are considered a depleted and strategic stock under the MMPA [7].

# 3. Conceptual Framework

The conceptual framework for our analysis consists of (a) estimation of expected rates of fatal strikes using ISDI and RSDI, (b) development of a decision model to characterize how managers choose VSRs using expected rates of fatal strikes, (c) a strategy to estimate the costs to vessels of complying with the VSRs, and (d) a VOI estimate associated with the difference in costs of complying with a range of VSR alternatives using ISDI and RSDI.

## 3.1. Estimating Fatal Strikes

We estimate expected rates of fatal encounters between ENP blue whales and vessels with established marine science models. Martin et al. [9] estimate fatal strikes by location and period from location area; period duration; vessel time in transit, speed over ground, draft, length, and width; and whale density, speed over ground, depth, length, and width. Rockwood et al. [10] follow Martin et al. [9] to estimate fatal strikes for ENP blue whales. Conceptually, the quantification of fatal strikes in our analysis follows the approach taken in these previous studies. The expected number of fatal strikes for each area $i = 1, \ldots, I$, month $t = 1, \ldots, 12$, and vessel $v = 1, \ldots, V$ is given by

$$m_{i,t,v} = \mathrm{e}\left(\mathrm{w}_{i,t}, \tau_{i,t,v}(s^{vessel}{}_{i,t,v}), \Gamma^{whale}, \Gamma^{vessel}, s^{whale}\right) \cdot \theta^{strike} \cdot \theta^{fatal}(s^{vessel}{}_{i,t,v}), \quad (1)$$

where e is the expected number of whale–vessel encounters, which is a function of the density of whales ($\mathrm{w}_{i,t}$), vessel transit duration ($\tau_{i,t,v}$), the dimensions of whales and vessels ($\Gamma^{whale}$ and $\Gamma^{vessel}$), and velocities of whales and vessels ($s^{whale}$ and $s^{vessel}{}_{i,t,v}$); $\theta^{strike}$ is the probability of an encounter leading to a strike, which is assumed to be a constant; and $\theta^{fatal}$ is the probability that a strike is fatal, which is a function of vessel velocity.[3]

Summing over vessels and areas throughout the area of interest yields a regional monthly mean estimate of fatal strikes:

$$M(t) = \sum_{i,v} m_{i,t.v}\,, \text{for } t = 1, \ldots 12. \quad (2)$$

$M(t)$ informs regulatory cost estimates of VSR for conservation objectives. That is, higher expected rates of fatal strikes require greater speed reductions to attain conservation objectives and, in turn, impose greater costs on vessels.

[3] Specific functional forms for e(·) and $\theta^{fatal}(\cdot)$ are provided in Appendix A1.

## 3.2. Management Decision Model

The management decision relies on a critical threshold for annual blue whale mortality, which is the PBR. Under the MMPA, the PBR was last estimated at 1.23 whales per year [7]. However, because underlying data on aggregate mortality are uncertain, we can only estimate probabilistic fatalities. We define a management decision that seeks to attain the PBR with a risk tolerance such that it is not exceeded by a fixed percentage in month $t$ for the region. We assume that the decisionmaker incorporates the uncertainty associated with the mean of the probability density function of fatal vessel–whale collisions. To account for this preference, the decision uses an exceedance probability, which is the annual probability that expected mortalities will reach or exceed a given PBR. For example, including the uncertainty in expected blue whale mortality, the decisionmaker includes a 10 percent chance that anthropogenic mortality of a protected species would exceed the PBR. This exceedance probability can be expressed as

$$EP\big(M(t)\big) = Prob\big(PBR > \textstyle\sum_{i,.v} M(t)\big) \qquad t = 1, \ldots, 12, \tag{3}$$

where $EP\big(M(t)\big)$ is the monthly probability of exceeding the PBR.

Estimation of an exceedance probability, in turn, allows us to formalize a regional management decision and associated costs to vessel owners and operators. Specifically, let $d_{i,t}$ be a binary variable that equals 1 if the decisionmaker decides to restrict vessel speeds in area $i$ in month $t$ and equals 0 if the decisionmaker decides not to restrict vessel speed. The decisionmaker's problem is to choose $d_{i,t}$ for all $i$ and $t$ so as to minimize the total cost of speed restrictions while also maintaining the monthly exceedance probability below a certain level.

## 3.3. Cost of Management

For each regional set of decisions, the application of each case has a monthly cost proportional to VSR. Let $\bar{\tau}_{i,t,v}$ represent the time required for vessel $v$ to transit through area $i$ in month $t$ in the absence of speed restrictions. If $\tau^{+}_{i,t,v}$ is the additional transit time required to comply with a speed restriction, the total cost borne by commercial vessel operators and other vessel owners is given by

$$C\left(\left\{\{d_{i,t}\}_{i=1}^{I}\right\}_{t=1}^{12}\right) = \textstyle\sum_v \big[c_v \sum_{i,t}\big(\bar{\tau}_{i,t,v} + \tau^{+}_{i,t,v} d_{i,t}\big)\big], \tag{4}$$

where $c_v$ represents the cost associated with a unit of transit time by vessel $v$. For simplicity, we assume that $c_v$ does not vary with vessel speed, though in reality it may vary due to differences in fuel efficiency at different speeds. In addition, we do not include the cost of delayed arrival resulting from vessel speed restriction, nor do we account for changes in vessel routes and unrestricted vessel speeds.

Based on this setup, the decisionmaker solves the following constrained cost minimization problem:

$$\min_{\left\{\{d_{i,t}\}_{i=1}^{I}\right\}_{t=1}^{12}} \sum_v \left[c_v \sum_{i,t}\left(\bar{\tau}_{i,t,v} + \tau_{i,t,v}^{+} d_{i,t}\right)\right] \tag{5}$$
$$s.t. \quad EP\big(M(t)\big) \leq \overline{EP} \quad \text{for all } t = 1, \ldots 12,$$

where $\overline{EP}$ is the maximum exceedance probability that would be tolerated. The resulting values of $d_{i,t}$ represent the least-cost vessel speed restriction across space and time that meets the decisionmaker's tolerance of the exceedance probability.

## 3.4. VOI Analysis

The choice of which areas the decisionmaker will impose vessel speed restrictions on (i.e., the values of $d_{i,t}$) is driven by the best information available regarding whale density over time and space. To assess the information sources that can achieve cost-effective ocean management, we apply an impact assessment framework developed by the VALUABLES Consortium, a cooperative agreement between Resources for the Future and the National Aeronautics and Space Administration to measure and communicate the socioeconomic benefits of satellite information. The information cases are two sets of ecological information from models of habitat suitability based on ISDI [6] and RSDI [3]. The VOI is the difference in economic cost of compliance for vessel operators under regulations informed by the two information cases.

Formally, VOI is the difference in the expected vessel operating costs under each information case for different levels of program spatial extent (i.e., areas affected by regulatory decisions $d_{i,t}$, for all $i$ and $t$) for the reference and counterfactual cases:

$$VOI = C\left(\left\{\{d_{i,t}^{\mathrm{RSDI}}\}_{i=1}^{I}\right\}_{t=1}^{12}\right) - C\left(\left\{\{d_{i,t}^{\mathrm{ISDI}}\}_{i=1}^{I}\right\}_{t=1}^{12}\right), \tag{6}$$

where $d_{i,t}^{\mathrm{RSDI}}$ and $d_{i,t}^{\mathrm{ISDI}}$ represent regulatory decisions made under RSDI and ISDI, respectively.

Figure 1 summarizes our VOI analysis. The upper boxes reflect the data and information on which regulatory decisions are made in the reference (red shade) and counterfactual (blue shade) cases. The middle boxes describe the decisionmaker actions that are supported by the scientific information in the two cases. Finally, the lower boxes describe the different societal outcomes that arise through use of ISDI and RSDI. Our numerical analysis will characterize all three determinants of VOI—differences in information, decisionmaker actions, and societal outcomes under both cases.

**INFORMATION**

Predictions of blue whale distribution for each **month** by 25km$^2$ area based on **remote sensing** of tagged blue whales' distribution and environmental covariates.

These are of **low relative uncertainty**.

Predictions of blue whale distribution for each **season** by 25km$^2$ area based on **in situ** sightings of blue whales and direct measurements of environmental covariates.

These are of **high relative uncertainty**.

**DECISIONMAKER ACTIONS**

Scientists estimate fatal ship strikes of blue whales for each period and area to support rulemaking. Managers implement regulations to slow ships in **fewer** areas at greatest risk of fatal ship strikes during **a few critical months**.

Scientists estimate fatal ship strikes of blue whales for each period and area to support rulemaking. Managers implement regulations to slow ships in **more** areas at greatest risk of fatal ship strikes during the **full critical season**.

**OUTCOMES FOR PEOPLE AND THE ENVIRONMENT**

**Compliance with conservation policy at lower estimated fatal ship strikes**, conserving blue whales in the Eastern North Pacific at lower cost to vessel operators.

**Compliance with conservation policy at higher estimated fatal ship strikes**, conserving blue whales in the Eastern North Pacific at higher cost to vessel operators.

**Figure 1.** VALUABLES impact assessment framework is shown for blue whale regulation VOI.

# 4. Data

## 4.1. Blue Whale Distribution

### 4.1.1. Reference Case: ISDI

Becker et al. [6] collect and synthesize line-transect data on the spatial distribution of blue whales off California, Oregon, and Washington for July–December, 1991–2009. Data include sightings of blue whales and measurements of sea surface temperature, salinity, chlorophyll concentration, and water column temperature. For the reference case information in this analysis, we use estimates by Becker et al. [6] of mean and variance for densities of blue whales by month in contiguous areas of 625km$^2$ within the USEEZ. We impute these estimates to 2017, a recent representative year, through operations described later.

### 4.1.2. Counterfactual Case: RSDI

Hazen et al. [3] collect and synthesize satellite tracking and environmental data to identify the spatial and temporal distribution of blue whales in the ENP at a high resolution. The method for real-time environmental covariate data enables estimates of greater precision than nautical and aerial observation. The authors also capture interannual variation using near-real-time data. For the counterfactual case information in our analysis, we use estimates by Hazen et al. [3] of mean and variance for densities of blue whales by month over 2017 in contiguous areas of 625km$^2$ within the USEEZ.

### 4.1.3. Comparing Information in the Reference and Counterfactual Cases

The whale density information in the reference and counterfactual cases relies on different underlying data sources and methods. Table 1 lists the data that drive differences in whale density estimates between the two cases.

**Table 1. Data in Reference and Counterfactual Cases**

| Reference | Counterfactual | Data |
|---|---|---|
| ✓* | ✓** | Blue Whale Presence |
| | ✓ | Sea Surface Temperature (SST) |
| | ✓ | SST Variance |
| | ✓ | Sea Surface Height (SSH) |
| | ✓ | SSH Variance |
| ✓ | | Sea Surface Salinity |
| ✓ | | Mixed Layer Depth |
| ✓ | ✓ | Chlorophyll Concentration |
| | ✓ | Wave Energy |
| | ✓ | Wind Speed |
| | ✓ | Upwelling |
| ✓ | ✓ | Bottom Depth |
| ✓ | ✓ | Bottom Slope |
| | ✓ | Bottom Aspect |
| | ✓ | Bottom Rugosity |
| | ✓ | 2km Isobath Distance |

*Transect Surveys (1991–2008)

**Telemetry Time Series (1994–2008)

The common scope and output of the reference and counterfactual cases allow us to compare differences in estimated distributions of blue whales. We interpolate reference data to the geospatial definitions of the counterfactual data and then scale regional abundance in reference data to match that of the counterfactual data.

For each area defined in the counterfactual case, we find the area-weighted means for all intersecting areas defined by the reference case. The region is framed by the coastline and USEEZ boundary of the ENP. Areas intersecting boundaries are irregular in shape and area but functionally identical to regular areas. We next normalize regional abundance over the reference and counterfactual cases, transforming distributional statistics to preserve spatiotemporal distributions while matching the reference data to abundance estimates contemporaneous with the counterfactual data. Both intermediate steps—interpolating geometries and normalizing abundance—enable the direct comparison implicit in both data products' common output. Comparing the two data products reveals that the RSDI exhibits less uncertainty in whale densities than ISDI. Figure 2 captures this reduction in uncertainty by month and location for 2017, displaying coefficients of variation to normalize error by location. While the distribution of errors decreases in the counterfactual data in the high-abundance season of July–November, the distribution of errors in the reference data is constant, a consequence of the limited seasonal resolution imposed by ISDI.

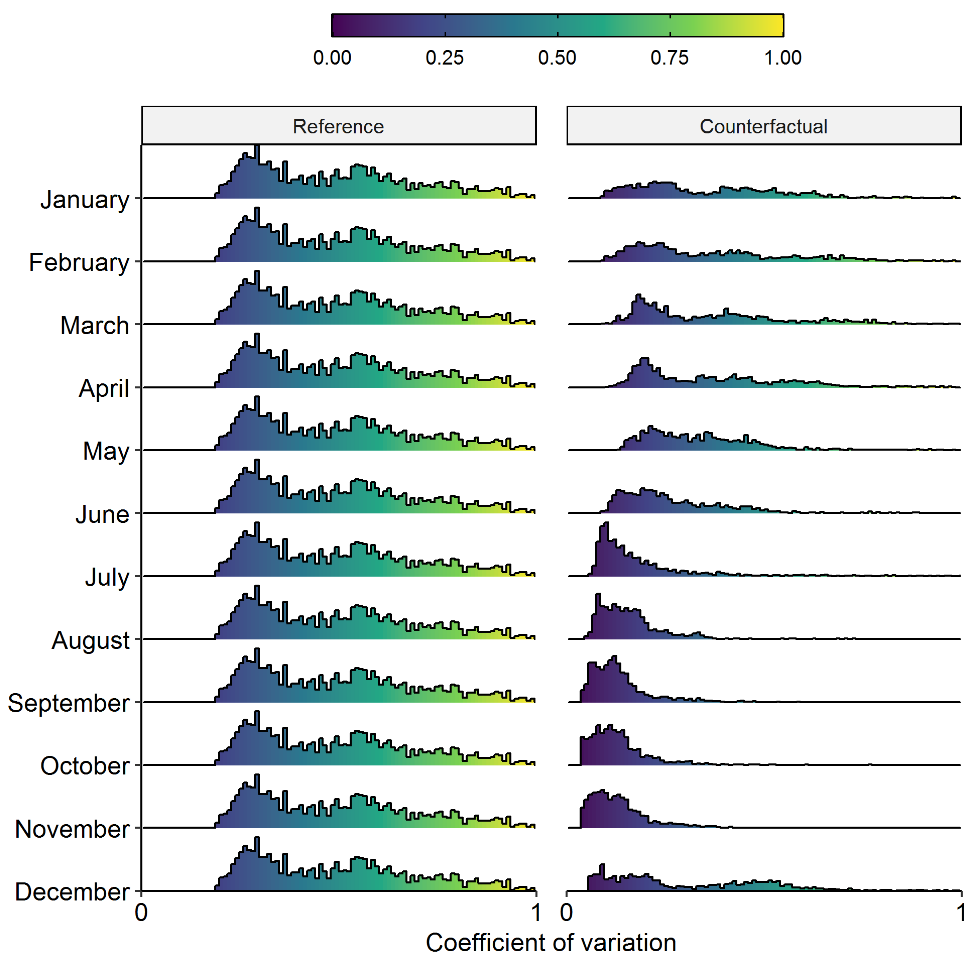


**Figure 2.** Distributions of coefficients of variation (CV) for the density of blue whales are estimated in each location and month for both information cases in 2017. Frequencies beyond 1.00 are not shown; these amount to 1.7 percent of locations, with respective maxima of 1.11 and 7.86 for the reference and counterfactual cases.

In estimating VOI contingent on differences between information cases, we also consider the hazard in selecting either model as a truth for rulemaking. First, we establish whether distributions statistically differ over the two cases. A Kolmogorov–Smirnov test shows that they are significantly different at $p < 0.01$ (Appendix A2). Given the distributions are different as a basis for decisionmaking, it is assumed that the ocean manager will choose to use the distribution that minimizes uncertainty. RSDI is of lower aggregate standard deviation than ISDI, and the aggregate cumulative distribution lies below the ISDI cumulative distribution. Both features suggest that RSDI meets first- and second-order stochastic dominance requirements [11]. In the reference case, the CVs are constant for the year, which has been noted as being unrealistic by Grossi and Kunreuther [12]. On the other hand, for the counterfactual case, the CVs vary month to month. The difference between the estimates is greatest in the times of the year when whales are more abundant in the ENP. For these reasons, the RSDI is the preferred model as a more reliable representation of the actual distribution of blue whales.

## 4.2. Blue Whale Abundance

We follow Hazen et al. [3] in imputing annualized abundance in the USEEZ from a central estimate by Calambokidis et al. [13]. Several estimates in different years are available, but this estimate continues to represent best available science [7]. Hazen et al. [3] estimate the proportion of abundance in the study area from the proportion of time tracked whales spent in and out of the study area in each month and then distribute corresponding numbers of blue whales over their study area within the ENP to estimate an explicit distribution. We leverage resulting model output available through institutional repositories[4] to estimate blue whale abundance in the USEEZ in each month. We also rescale the seasonal abundance implicit in estimates of distribution by Becker et al. [6] to match the abundance imputed by Hazen et al. [3]. Our adaptation of estimates of abundance and distribution enables interpretation of different data products as RSDI and ISDI with comparable scope and purpose.

Figure 3 illustrates the blue whale densities used as support for the reference and counterfactual spatial distributions in August 2017. Panel A illustrates the distribution under the reference case and Panel B shows the distribution for the counterfactual case. Figure 3 reveals clear differences between the reference and counterfactual spatial densities. The counterfactual case shows greater probabilities for whale occurrence farther out into the ocean and lower probabilities near shore. The reference case densities are distributed more uniformly in bands across the area, whereas RSDI exhibits a finer intermingling of different probabilities of densities. The reference case map also shows a higher probability cluster in areas near the Farallon Islands off the coast of San Francisco, whereas the map of counterfactual information does not. On the other hand, the counterfactual indicates greater whale density off the Oregon and Washington coasts.

[4] RSDI via oceanview.pfeg.noaa.gov/WhaleWatch/, ISDI via seamap.env.duke.edu/

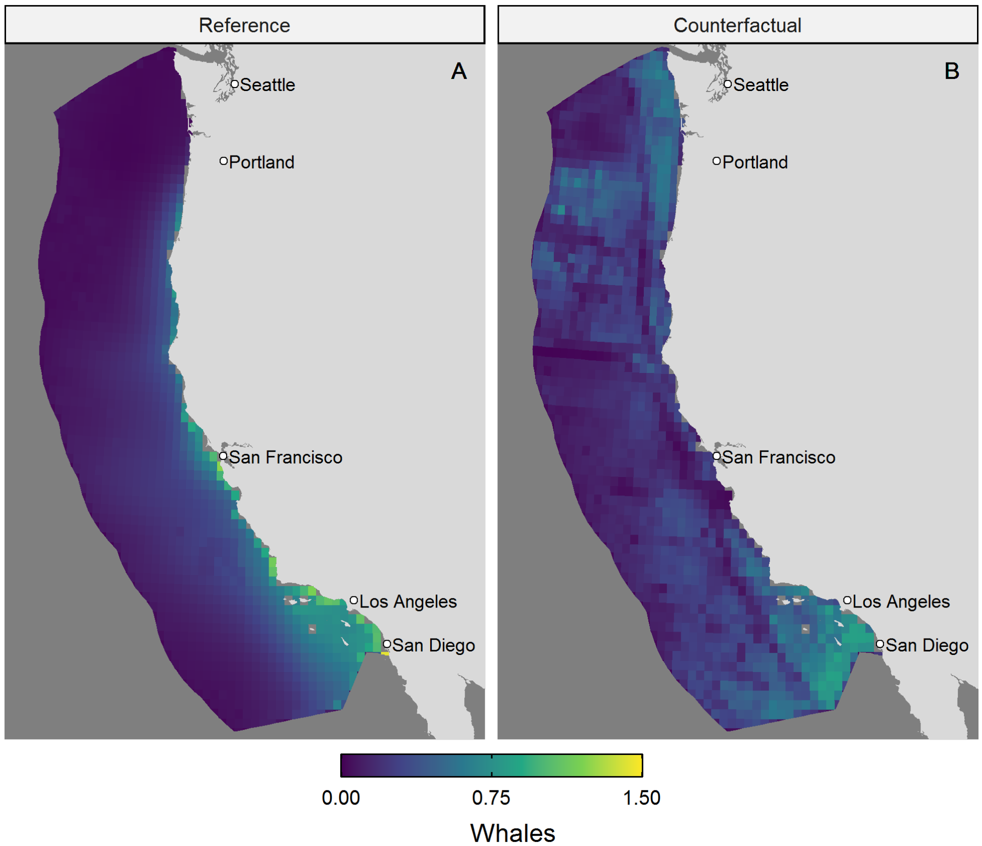


**Figure 3.** Distributions of blue whales are estimated with ISDI (Panel A) and RSDI (Panel B) along the US coast in the Eastern North Pacific in 2017. Each panel illustrates the annualized mean estimate of blue whales.

## 4.3. Other Blue Whale Parameters

Parameters for representative length, width, speed, and depths of blue whales follow Rockwood et al. [10]. These parameters support probabilistic modeling of physical interactions between blue whales and vessels, as replicated from Martin et al. [9] and Rockwood et al. [10].

## 4.4. Vessel Traffic

The Bureau of Ocean Energy Management and National Oceanic and Atmospheric Administration distribute vessel Automatic Identification System data [14] for each year, month, and Universal Transverse Mercator zone. Coastal receivers record regular, automated reports from vessels, enabling a high-resolution dataset of individual vessels' location, speed, width, length, draft, and type, among other characteristics.

The resulting unit of analysis for strike modeling is the time in transit at a mean speed over ground of a particular vessel in an area during a month, shown in hours (Figure 4A) and knots (Figure 4B). The transit time and speed enable our adaptation of methods for probabilistic modeling of physical interactions between blue whales and vessels as replicated from Martin et al. [9] and Rockwood et al. [10]. We join the Automatic Identification System data to the spatial definition of blue whale density data and summarize data by vessel, area, and month, preserving each vessel's length, width, draft, mean speed over ground, and time in transit for each area and month.

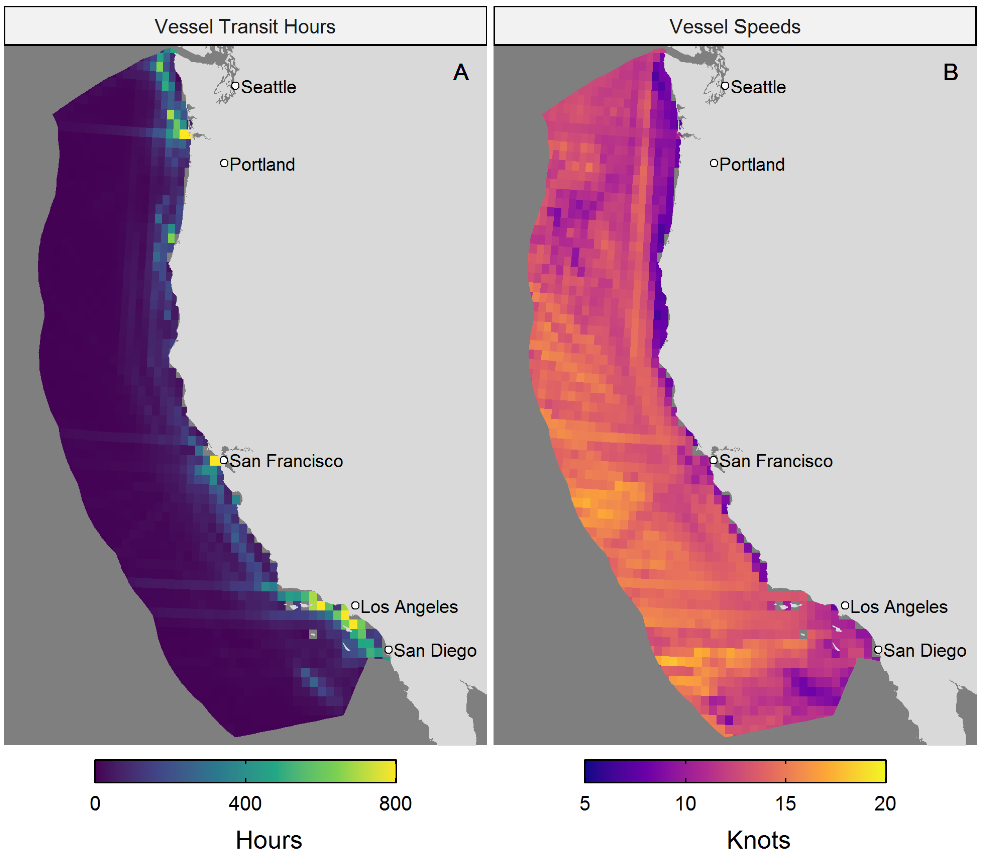


**Figure 4.** Vessel traffic in 2017 is illustrated by transit hours (Panel A) and speeds in knots (Panel B). Transit hours shown are mean monthly hours for each area. Speeds shown are annual means for each area. Scales for each panel omit outliers, notably including areas with major ports, vessels in transit at speeds of minimal concern for cetaceans, and a negligible number of vessels in transit at high speeds.

## 4.5. Vessel Operating Costs

Nathan Associates [15] summarize confidential federal data on operational costs per hour by categories of vessels to estimate costs of VSR for conservation of North Atlantic right whales. These data inform our estimates of costs to avert fatal strikes.

Specifically, we join these operational costs per hour by vessel type to the Automatic Identification System data, returning lower-bound costs of each vessel transit by time in transit, area, and period. With the assumption of nonadaptation by vessel operators, the only change to vessel operation is greater times in transit following speed reductions. This assumption is likely to lead to an overestimate of the absolute costs associated with VSR in both the reference and counterfactual cases, though the implications on the relative costs of VSRs imposed under the two cases is ambiguous. Accounting for the costs of adaptation by vessel operators would require obtaining additional logistical information and modeling to predict alternative routes, tasks that we leave for future research.

# 5. Results

## 5.1. Information on Estimated Fatal Strikes

Figure 5 illustrates the mean fatal blue whale strikes estimated for each location in the USEEZ in 2017. For both information cases, strikes cluster in key habitats for blue whales, where oceanographic conditions support higher densities, and where vessels transit at greater speeds or in greater numbers; both occur in the Santa Barbara Channel and off the Port of Los Angeles, as well as off the coast near Portland and Seattle. Panels A and B in Figure 5 show a small number of areas with critical distinctions between reference and counterfactual strike estimates.

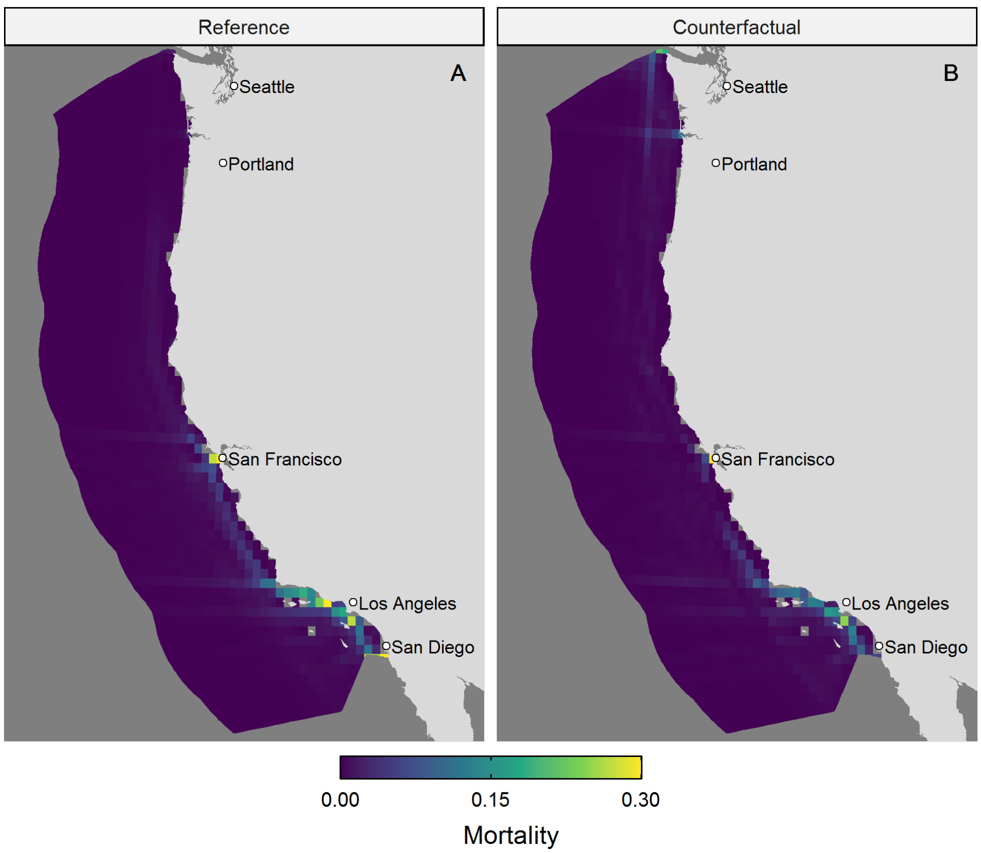


**Figure 5.** Fatal strikes of blue whales are illustrated for 2017. The scale shown indicates annualized mean estimates with respect to model error.

Closer inspection of the coastline between Los Angeles and San Francisco in Figure 6 demonstrates how the information cases diverge in several areas, especially in the Santa Barbara Channel: the counterfactual information (Panel B) suggests fewer fatal strikes occur in the Channel, incidental to predicting greater densities of blue whales offshore than the reference information (Panel A). That strikes are a function of both blue whale and vessel distributions allows vessel data to conceal substantial differences in spatial distributions of blue whales by information case.

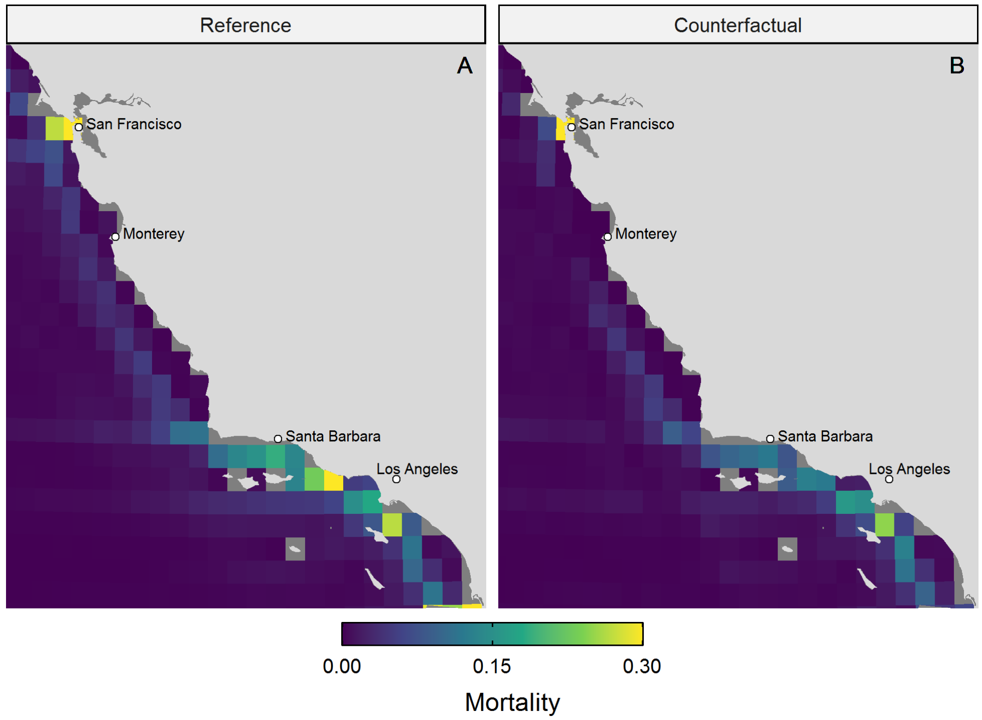


**Figure 6.** Fatal strikes of blue whales off critical areas of the California coast are shown for the reference (5A) and counterfactual (5B) cases in 2017. As in Figure 5, these are annualized mean estimates, with outliers off major ports scaled relative to surrounding areas.

There is uncertainty around the estimated mean fatal strikes illustrated in Figure 5. Table 2 lists regional means and standard deviations of fatal strikes in 2017. Notably, the ratio of mean and standard deviation for the counterfactual varies month to month and is smaller in the critical months of August, September, and October with the greatest density, unlike the ISDI, which varies little throughout the year. Where predicted fatal strikes depend on changes in estimated densities of blue whales and observed vessel transits in the counterfactual, in the reference case predicted fatal strikes depend only on variation in vessel transits.

**Table 2. Estimated Regional Means and Standard Deviations of Fatal Strikes by Month for 2017**

| Month | Fatal Strikes (Reference) | | Fatal Strikes (Counterfactual) | |
|---|---|---|---|---|
| | Mean | SD | Mean | SD |
| January | 0.0490 | 0.0004 | 0.0286 | 0.0001 |
| February | 0.0403 | 0.0003 | 0.0295 | 0.0001 |
| March | 0.0845 | 0.0007 | 0.0856 | 0.0004 |
| April | 0.2251 | 0.0019 | 0.2200 | 0.0010 |
| May | 0.5197 | 0.0044 | 0.4790 | 0.0018 |
| June | 1.2337 | 0.0106 | 0.8125 | 0.0023 |
| July | 1.6485 | 0.0125 | 0.9289 | 0.0015 |
| August | 2.5877 | 0.0202 | 2.1556 | 0.0025 |
| September | 2.3286 | 0.0263 | 1.6653 | 0.0017 |
| October | 1.9367 | 0.0193 | 1.2848 | 0.0011 |
| November | 0.8133 | 0.0073 | 0.5189 | 0.0004 |
| December | 0.2251 | 0.0017 | 0.1497 | 0.0003 |

## 5.2. Decisionmaker Actions

There are two components in determining an outcome for an ocean management policy: (1) a percent ranking of the 625 $km^2$ areas based on expected monthly fatal strikes and (2) the corresponding decisionmaker action or intervention.

A given area in a given month at a percent rank of zero or 100 has the lowest or highest expected value of fatal strikes, respectively. The fatal strike ranking for 2017 is shown in Figure 7 in Panels A (for ISDI) and B (for RSDI). ISDI has a consistently greater number of high-ranking areas along the coast north of Los Angeles, which suggests a greater number of fatal strikes and more speed regulation in those areas throughout the year. In the counterfactual case, RSDI supports prioritizing areas farther out in the ocean and in the southwest corner of the map off the coast of Los Angeles.

The corresponding decision and action or intervention is an application of a VSR to areas where a change in speed returns the greatest expected reduction in fatal strikes, which is based on the ranking described earlier. To achieve a specific mortality target, the ranking is used to identify grid locations for intervention as a decreasing function of expected fatal strikes. In addition, the differences in interventions between the information cases diminish with decreasing speed limits and increasing extent. The diminishing returns with speed limits reflect similarities in information. For example, a conservation objective of 10 fatal strikes (EP=0.9) eliminates the information cases' difference. On the other hand, the diminishing return with extent reflects that estimated fatal strikes occur with greater probabilities in a subset of areas; beyond those areas, speed limits return negligible or no benefits.

One way to characterize the decisionmaker action is to display the number of months a VSR would be expected to be enforced in each grid during a year. We illustrate the action in this way in Panels C and D of Figure 7. Differences in the spatial distribution of shaded areas across the reference and counterfactual grids illustrates the differences in the action; that is, differences in the number of months that a VSR is applied in each area in the ENP. The extent of months and areas is set to 10 percent to demonstrate the model process for site selection; varying extent for cost-effectiveness would also vary the proportion of areas and months selected for intervention. There are more areas and more applications with the reference case in 2017. These differences can be observed in Panels C and D (Figure 7) for the ENP off the Pacific Northwest coast, where the counterfactual case has higher rankings for intervention decisions, and off Monterey Bay, where the reference case has higher rankings.

The ranking maps provide the link to estimating the cost of the VSR with and without RSDI in Equation 5 and VOI in Equation 6.

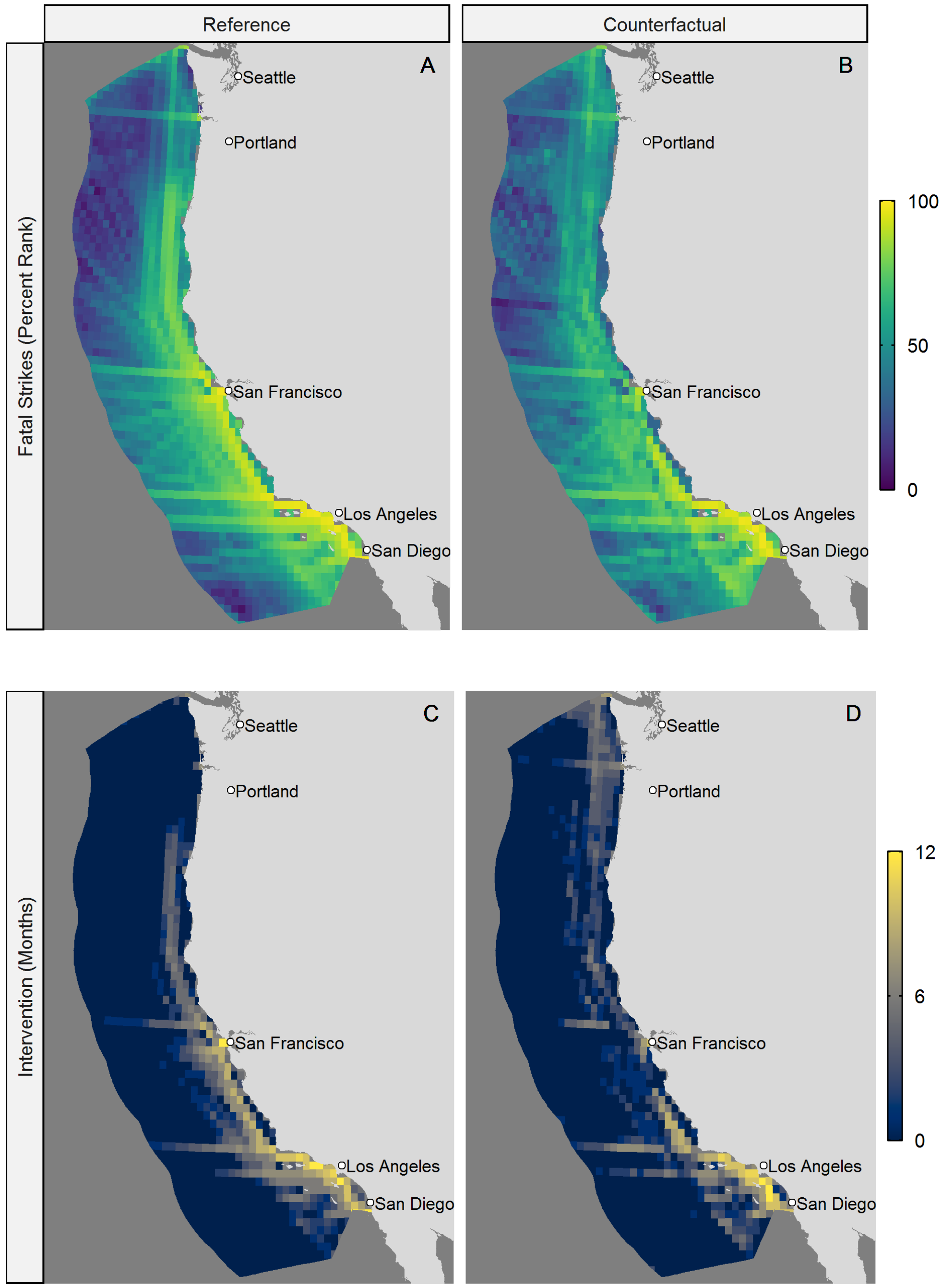


**Figure 7.** The percent ranking identifies priority areas for VSR in 2017—with 100 representing the highest-priority area and 0 representing the lowest-priority area—for the reference (Panel A) and counterfactual cases (Panel B). Panels C and D illustrate the corresponding number of months (0–12) a VSR is applied under ISDI and RSDI, subject to a VSR including the top 10 percent of opportunities for intervention in terms of areas over months. Appendix A3 illustrates key areas off the California coast for 2017.

## 5.3. Outcomes

We find that the counterfactual case information enables conservation of blue whales at a lower cost than the reference case information. The difference in cost is driven by differences in precision and spatial distribution of blue whales in the two cases, which means that different areas and different months are targeted for VSR when the decisionmaker uses ISDI and RSDI. Columns 1–6 of Table 3 describe the speed limit, spatial extent of regulation, and costs to vessel operators for several annual fatal strike targets when ISDI and RSDI are used for decisionmaking.

### Table 3. Target Levels of 2017 Fatal Strikes, Speed Limits, Spatial Extents of Regulation, Costs to Vessels, and VOI Associated with ISDI and RSDI

| Fatal Strikes (EP = 0.9) | Speed Limit (kn) | | Extent (%) | | Cost (US$M) | | RSDI VOI (US$M) |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | ISDI | RSDI | ISDI | RSDI | ISDI | RSDI | |
| **7.80** | 11.39 | 11.86 | 15.22 | 15.24 | 23 | 2 | 21 |
| **7.70** | 10.86 | 11.34 | 15.25 | 15.27 | 32 | 5 | 27 |
| **6.90** | 7.51 | 8.05 | 15.46 | 15.53 | 145 | 49 | 96 |
| **6.70** | 6.83 | 7.37 | 15.50 | 15.58 | 185 | 66 | 118 |
| **6.30** | 5.58 | 6.11 | 15.58 | 15.70 | 275 | 107 | 168 |
| **6.00** | 4.72 | 5.22 | 15.64 | 15.73 | 351 | 143 | 209 |
| **5.70** | 3.92 | 4.39 | 15.70 | 15.80 | 435 | 183 | 252 |
| **5.50** | 3.40 | 3.86 | 15.70 | 15.86 | 496 | 212 | 284 |
| **5.20** | 2.66 | 3.09 | 15.75 | 15.92 | 591 | 259 | 332 |

The results in Table 3 show that regulators using RSDI compared to ISDI can achieve a given target number of fatal strikes with less stringent speed limits (Columns 1 and 2) and smaller spatial extents of regulation (Columns 3 and 4). This outcome translates into lower costs on vessel operators when RSDI is used to achieve the same target number of fatal strikes (Columns 5 and 6). For example, the target of six fatal strikes slows vessels down to 4.72kn over 15.64 percent of the region in the reference case, whereas the restriction in the counterfactual impact is less severe, with a maximum speed of 5.22kn over 15.73 percent of the region. Lower speed limits and greater spatial extents of regulation would yield fewer mortalities. A mortality target of an expected 5.50 fatal strikes suggests in the reference case a speed limit of 3.40kn over 15.70 percent of the region, whereas the counterfactual requires a higher speed limit of 3.86kn over 15.86 percent of the region.

## 5.4. Value of RSDI

Based on the costs to vessel operators associated with different speed limits, we estimate the VOI of RSDI associated with a range of ocean management targets for fatal ship strikes. We define that VOI as the reduction in costs when decision makers use RSDI instead of ISDI to implement VSRs to attain the same target number of fatal strikes.

Columns 5 and 6 in Table 3 contain the costs to vessel operators under each information case, and Column 7 lists the VOI for the RSDI. Several patterns are apparent regarding VOI. It is larger for lower target numbers of fatal strikes; cost-savings of using RSDI are US$21 million for a target of 7.8 fatal strikes, rising to US$332 million for a target of 5.2 fatal strikes. Figure 8 illustrates the range of cost as curves for achieving different target levels of fatal strikes by type of information. The upper cost curve for the reference case (ISDI) is shown in light blue, and the lower curve for the counterfactual case (RSDI) is shown in dark blue. The vertical difference between the two curves can be interpreted as the VOI associated with different fatal strike targets.

The range of scenarios illustrates that the reference case overestimates the density of blue whales in areas of high vessel traffic relative to the counterfactual. This mismatch of status quo estimates indicates a positive VOI even without an intervention under the counterfactual case; interventions are only necessary for estimated rates of fatal strikes above the counterfactual status quo. That is, the reference case supports costly intervention, whereas the counterfactual supports none. Minimal targets and maximal costs for each information case are omitted from Figure 8. These extreme outcomes depend on functional forms that extend past meaningful or realistic estimates with lower speed limits.

Altogether, Figure 8 illustrates the magnitude and trend of VOI with attainment of decreasing targets for fatal strikes, showing both the substantial costs borne under the reference case and the opportunities for cost-effective intervention created by the counterfactual.

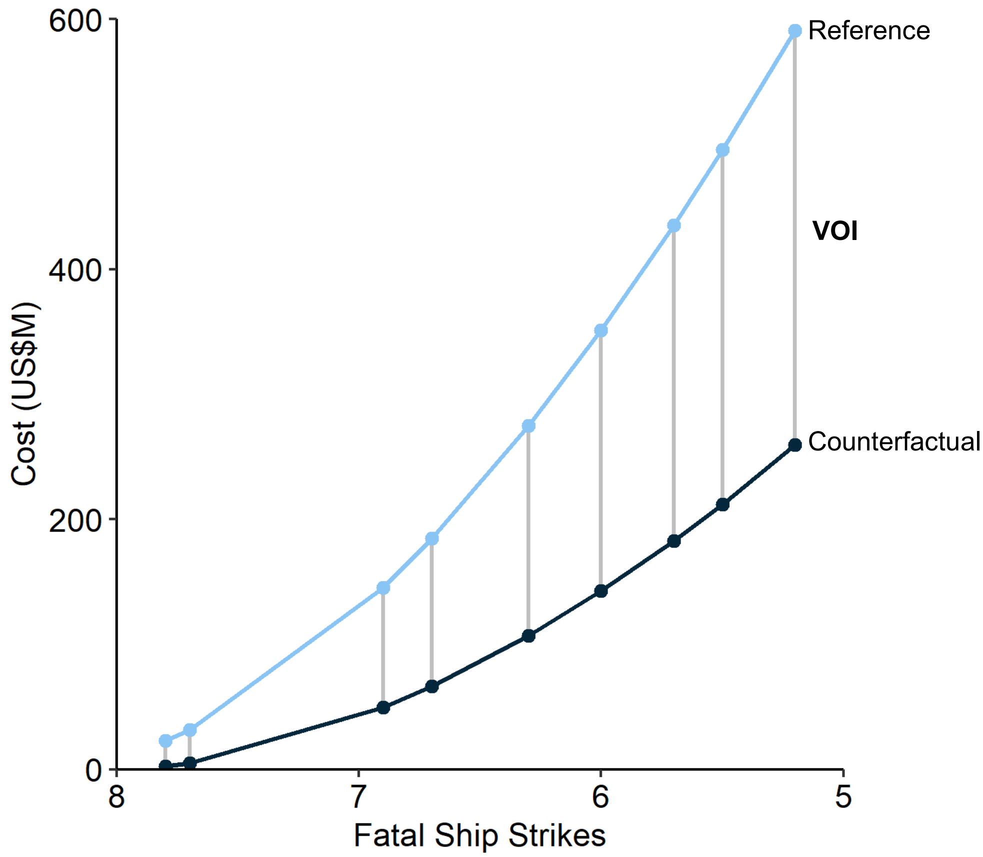


**Figure 8.** Cost of attaining various levels of target fatal strikes are shown for the reference (ISDI) and counterfactual (RSDI) cases.

# 6. Conclusion

In this paper, we estimate a VOI of scientific and monitoring data that supports the implementation of ocean management policy to conserve blue whales off the coast of the western United States. We estimate expected fatal strikes using an existing probabilistic model of animal–vessel interactions. We then compare the expected rate of mortality of blue whales to a PBR. We also compare expected fatal strikes to potentially achievable targets for fatal strikes with reference to existing models.

We model an ocean management policy in the ENP for blue whale conservation similar to policy for the North Atlantic right whale in effect since 2008. Costs to vessel operators are estimated for the same management policy under two different information cases, ISDI and RSDI. Estimated costs differ between regulations that employ shipboard ISDI versus WhaleWatch (RSDI). Results indicate a cost-savings in ocean management policy of US$21M–$332M in 2017, depending on the conservation objective. Our findings underline the importance of remote sensing data in effective policy to conserve endangered marine mammals and support growth in marine economies.

We abstract from several factors crucial to successful regulation to conserve blue whales, including logistical and navigational challenges for stakeholders (vessel owners, operators, and regulators) and stakeholders' compliance with present and future laws and regulations. Nonetheless, our VOI analysis illustrates the critical importance for science to inform policy.

Uncertainties in monitoring information impede policy to conserve blue whales subject to ship strikes, which are just one of several anthropogenic factors that affect cetaceans. We demonstrate the role of RSDI in minimizing those uncertainties through comparison to an ISDI product.

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# A1. Biophysical Model

We estimate expected rates of fatal encounters between cetaceans and vessels with established marine science models [9,10]. Martin et al. [9] estimate fatal strikes by location and period from location area; period duration; vessel time in transit, speed over ground, draft, length, and width; and whale density, speed over ground, depth, length, and width. Rockwood et al. [10] follow Martin et al. [9] to estimate fatal strikes for Eastern North Pacific blue whales. The expected number of fatal strikes conditional on the number of total strikes for each area *i*, period *t*, and vessel *v* is given by

$$m_{i,t,v} = \mathrm{p}_{1,\mathrm{i,t,v}}\mathrm{p}_{2,\mathrm{i,t,v}}\mathrm{p}_{3,\mathrm{i,t,v}} \tag{1}$$

$$\mathrm{p}_{1,\mathrm{i,t,v}} = \frac{4\mathrm{d}_{\mathrm{w,i,t,v}}t_{\mathrm{i,t,}v}}{\pi^{\frac{1}{2}}\left((\mathrm{l}_{\mathrm{w}}^2+\mathrm{w}_{\mathrm{w}}^2)^{\frac{1}{2}}+(\mathrm{l}_{\mathrm{v}}^2+\mathrm{w}_{\mathrm{v}}^2)^{\frac{1}{2}}\right)area_{\mathrm{i}}}\int_0^{2\pi}\left(1-\cos\theta\,\frac{(2v_{\mathrm{i,t,}v}v_{\mathrm{i,t,}w})}{(\mathrm{v}_{\mathrm{i,t,v}}^2+\mathrm{v}_{\mathrm{i,t,w}}^2)}\right) \tag{2}$$

$$\mathrm{p}_{2,\mathrm{i,t,v}} = (1-\mathrm{p}_{\mathrm{a,v}})(1-\mathrm{p}_{\mathrm{a,w}}) \tag{3}$$

$$\mathrm{p}_{3,\mathrm{i,t,v}} = \frac{1}{1+\mathrm{e}^{-(\beta_0+\beta_1\mathrm{v}_{\mathrm{i,t,v}})}}. \tag{4}$$

The variables $p_{1,i,t,v}$, $p_{2,i,t,v}$, $p_{3,i,t,v}$ represent vessel—whale encounters (Equation 2), total strikes (Equation 3), and fatal strikes (Equation 4), respectively. Encounters are a function of densities of whales *w*, vessel transit duration *t*, dimensions of whales and vessels *l* and w, area, and speeds of whales and vessels *s*—vessels' velocities and transit durations are the variables sensitive to policy intervention for this study. Strikes are a function of probabilities of encounters and probabilities of avoidance by whales and vessels $p_a$. Finally, fatal strikes are a function of velocities of vessels *v* and coefficients describing the nonlinear effect of vessel velocities on strike outcomes (Conn and Silber 2013). In Equations 1–4, subscripts *w* and *v* indicate parameters corresponding to blue whales (*w*) or a specific vessel *v*.

# A2. Kolmogorov-Smirnov Tests

| Month | Count (ISDI Mean | Count (RSDI Mean) | Count (ISDI SD) | Count (RSDI SD) | p-value |
|---|---|---|---|---|---|
| January | 15.85 | 21.07 | 0.22 | 0.18 | 0.00 |
| February | 14.21 | 19.68 | 0.20 | 0.18 | 0.00 |
| March | 25.71 | 35.10 | 0.36 | 0.36 | 0.00 |
| April | 69.09 | 94.95 | 0.96 | 0.94 | 0.00 |
| May | 142.74 | 192.67 | 1.97 | 1.83 | 0.00 |
| June | 363.48 | 480.77 | 5.00 | 3.00 | 0.00 |
| July | 482.47 | 631.81 | 6.64 | 2.56 | 0.00 |
| August | 699.00 | 910.77 | 9.78 | 3.59 | 0.00 |
| September | 635.92 | 813.89 | 8.76 | 2.48 | 0.00 |
| October | 525.66 | 675.25 | 7.23 | 1.87 | 0.00 |
| November | 244.70 | 290.98 | 3.42 | 0.85 | 0.00 |
| December | 70.68 | 96.07 | 0.97 | 0.47 | 0.00 |

**Table A2.1.** Distributions of p-values and Test Statistics by Month for Two-Sided Kolmogorov-Smirnov Tests of Difference in Distributions of Error over Estimates of Blue Whale Counts over the Full Study Area

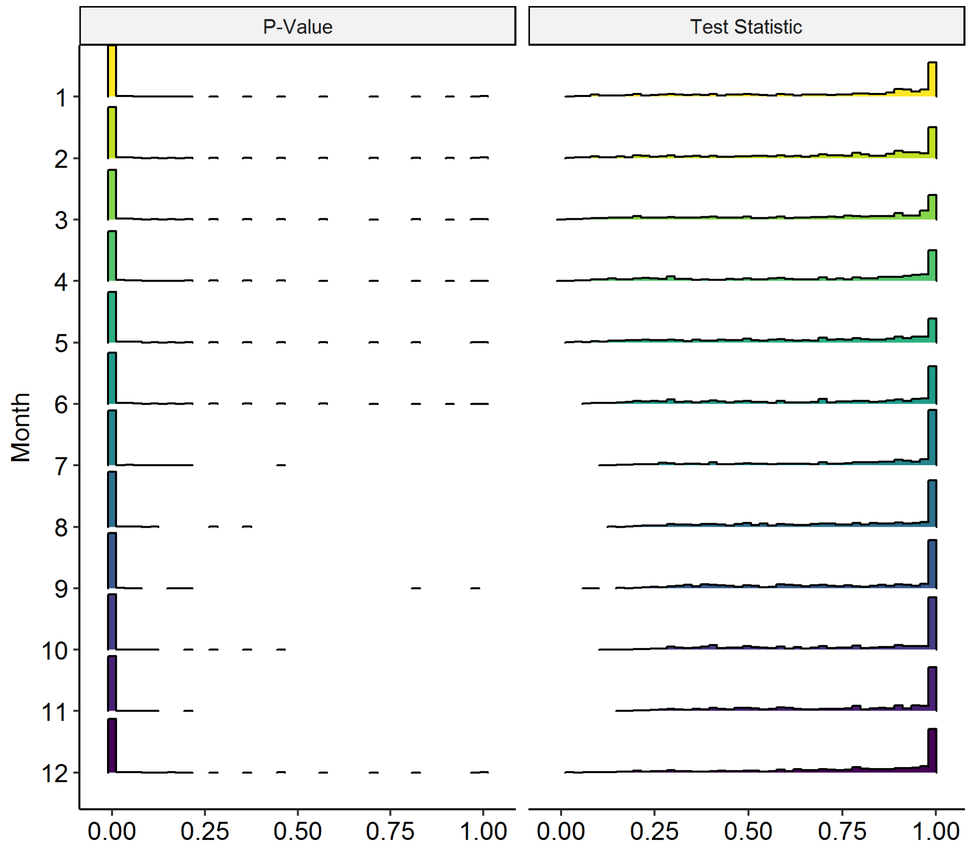


**Figure A2.1.** Distributions of *p*-values and test statistics are shown by month for two-sided Kolmogorov-Smirnov tests of difference in distributions of error over estimates of blue whale counts by area.

# A3. Supplemental Visualization

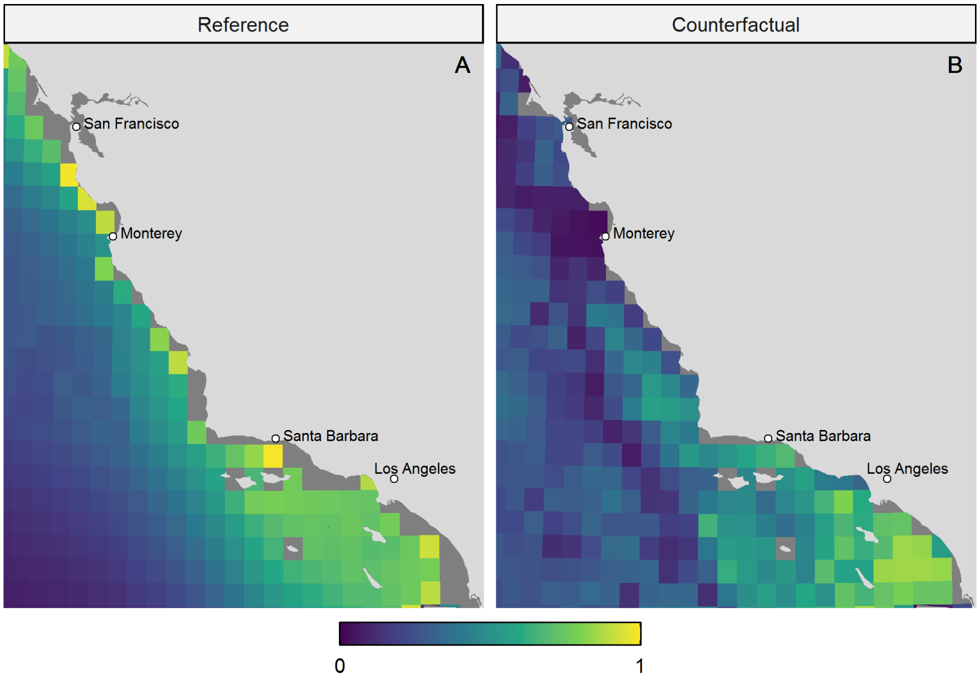


**Figure A3.1.** Distributions of blue whales are estimated with ISDI (Panel A) and RSDI (Panel B) in a subset of the study area. Each panel illustrates the annualized mean estimate of blue whales.

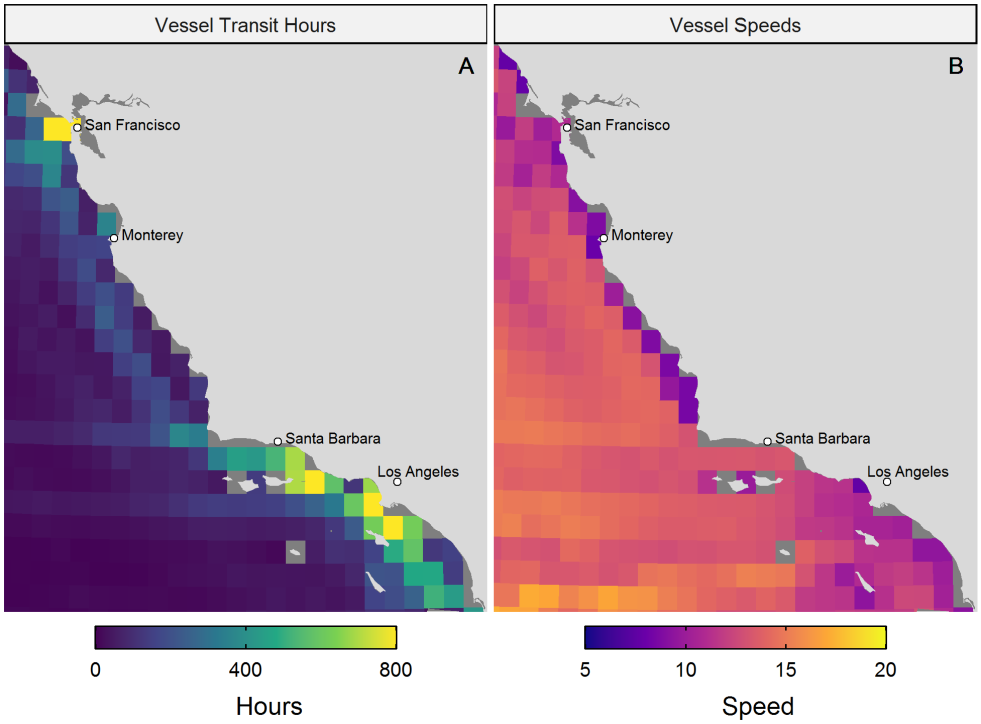


**Figure A3.2.** Vessel traffic in 2017 is illustrated by transit hours (Panel A) and speeds in knots (Panel B). Transit hours shown are mean monthly hours for each area. Speeds shown are annual means for each area. Scales for each panel omit outliers, notably including areas with major ports, vessels in transit at speeds of minimal concern for cetaceans, and a negligible number of vessels in transit at high speeds.

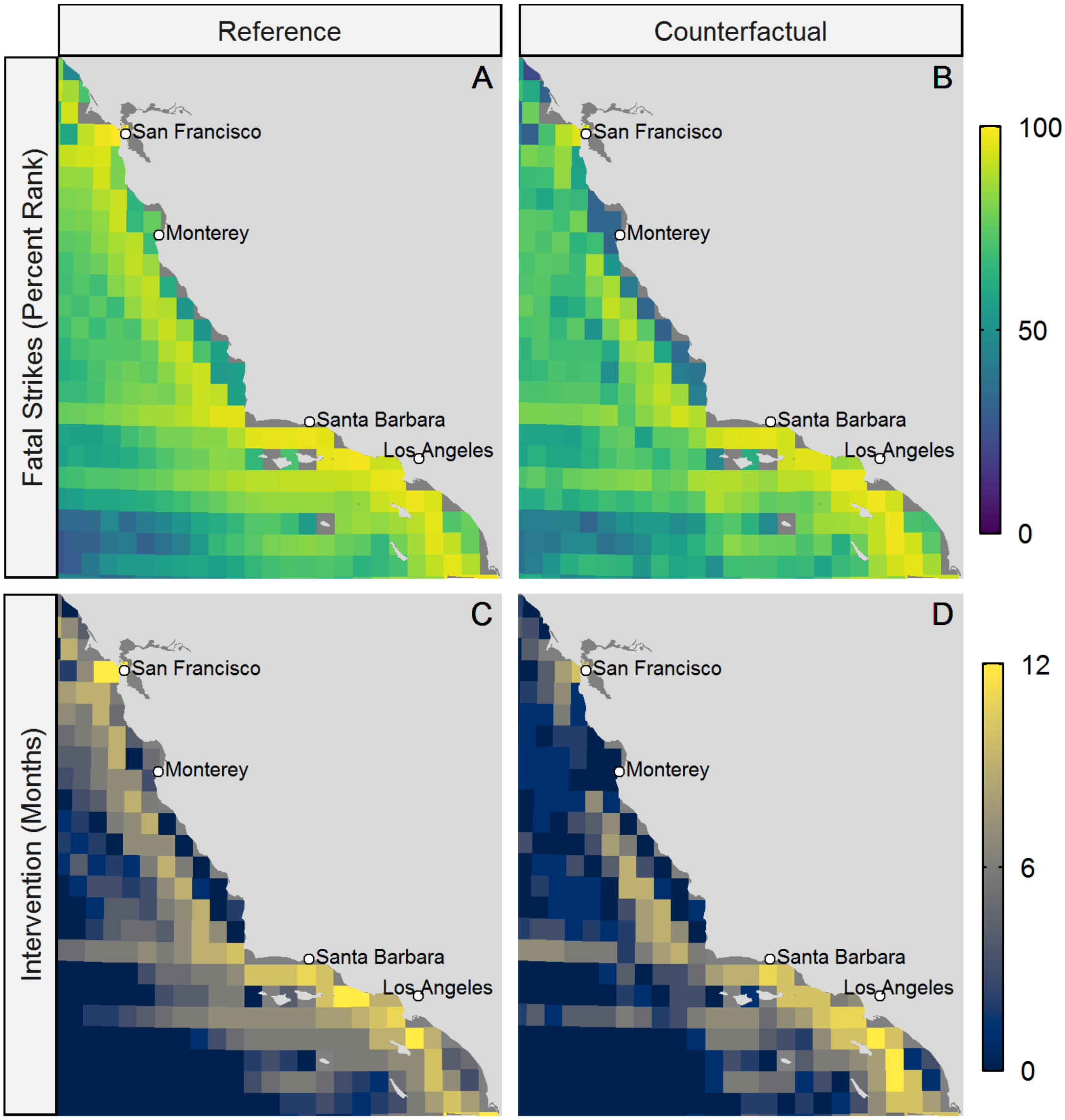


**Figure A3.3.** The percent ranking identifies priority areas for VSR in 2017—with 100 representing the highest-priority area and 0 representing the lowest-priority area—for the reference (Panel A) and counterfactual (Panel B) cases. Panels C and D illustrate the corresponding number of months (0–12) a VSR is applied under ISDI and RSDI, subject to a VSR including the top 10 percent of opportunities for intervention in terms of areas over months.

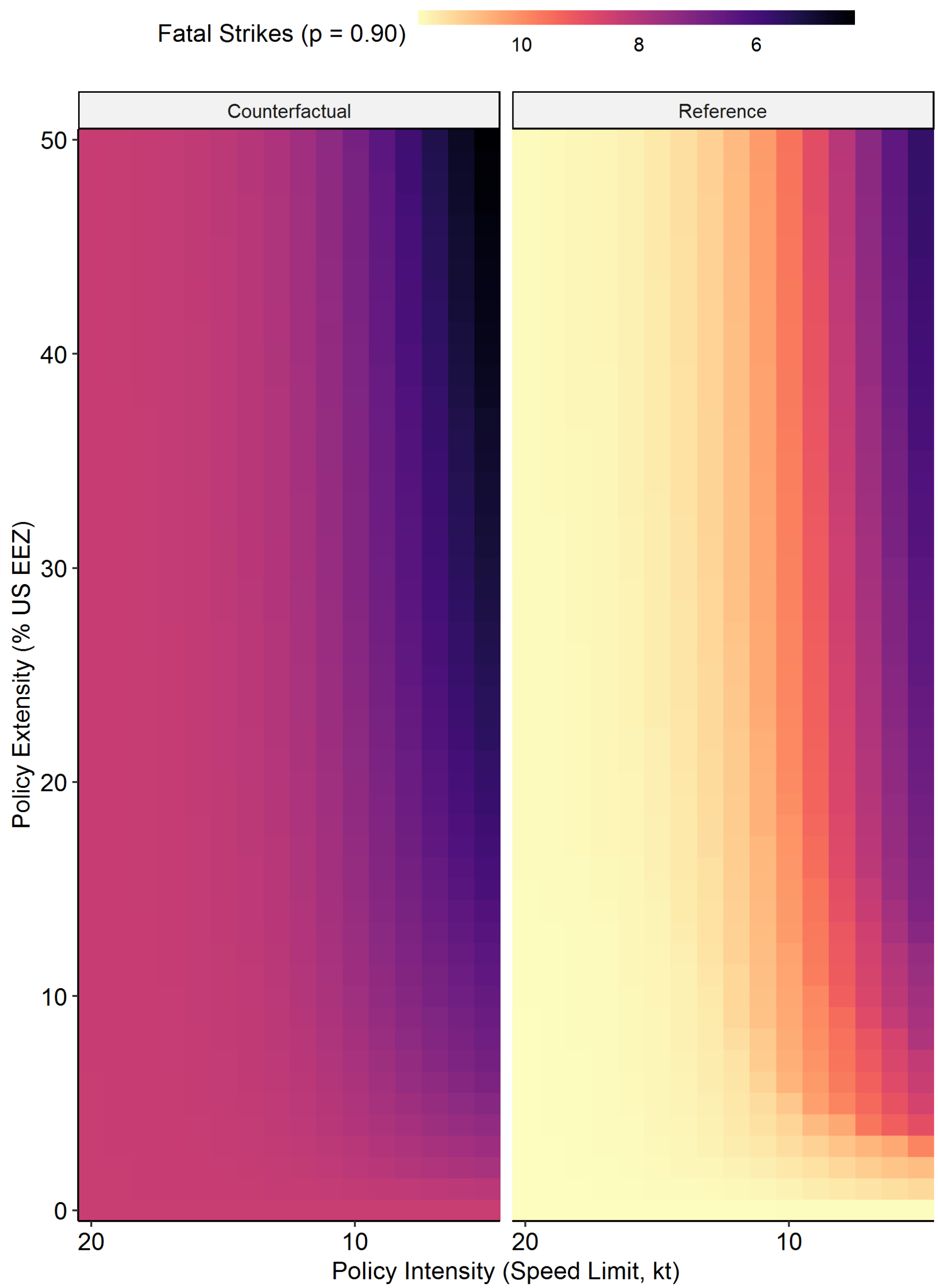


**Figure A3.4.** Mortalities of blue whales in fatal ship strikes are shown over sets of inputs to model policies.

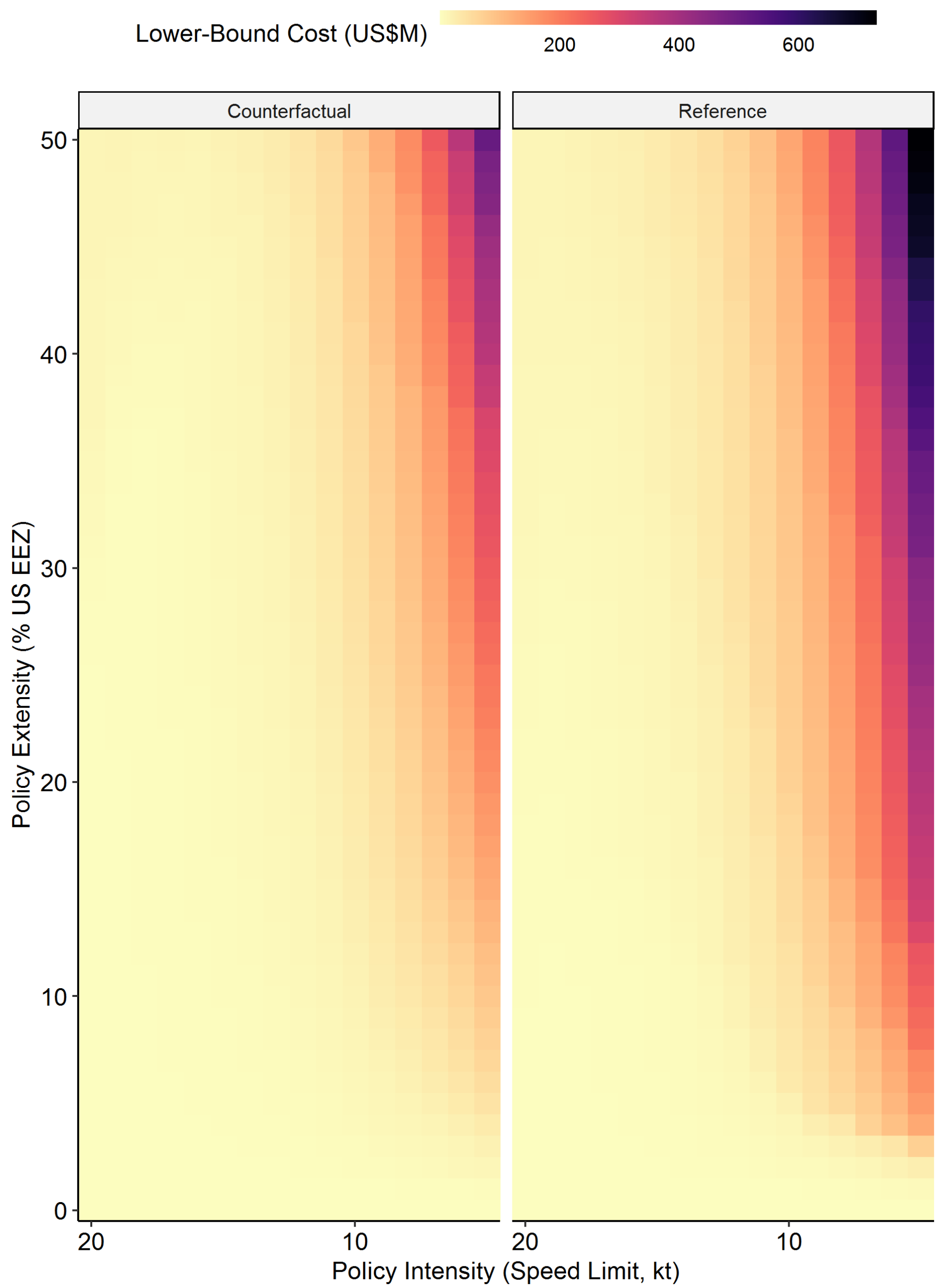


**Figure A3.5.** Costs of model policies are shown over sets of inputs.