Combining high temporal resolution whale distribution and vessel tracking data improves estimates of ship strike risk

Hannah Blondin[a,*], Briana Abrahms[b,c], Larry B. Crowder[a], Elliott L. Hazen[a,c,d]

[a] *Department of Biology, Hopkins Marine Station, Stanford University, 120 Ocean View Blvd., Pacific Grove, CA 93950, USA*
[b] *Center for Ecosystem Sentinels, Department of Biology, University of Washington, Seattle, WA 98195, USA*
[c] *Environmental Research Division, NOAA Southwest Fisheries Science Center, 99 Pacific St., Suite 255A, Monterey, CA 93940, USA*
[d] *University of California Santa Cruz, Department of Ecology and Evolutionary Biology, 130 McAllister Way, Santa Cruz, CA 95060, USA*

ARTICLE INFO

ABSTRACT

When assessing harmful human-wildlife interactions, researchers often attempt to calculate the risk that an interaction will occur. However, these analyses often quantify risk based on temporally static or spatially coarse measures of species distributions and human activity. As a result, risk estimates often do not reflect the dynamic nature of animal movement and anthropogenic uses of the environment. To illustrate the impacts of various temporal resolutions of data, we present a case study of blue whale (*Balaenoptera musculus*) ship strike risk in the U.S. Southern California Bight by combining predicted daily whale distributions with continuous vessel movement data. This represents the first effort to characterize blue whale ship strike risk by including the most recent high-resolution estimates of eastern Pacific blue whale distribution. We used these data to compare the ship strike risk models at varying temporal resolutions to address the effect of using coarser resolution input data. Our results show that it is critical to account for both dynamic patterns of human activity and species occurrences when assessing the risk of human-wildlife conflict. Analysis based on higher resolutions of potential interactions show greater variability in risk. Coarser resolution data mask variability in risk that may result from patchy conditions of blue whale habitat and/or variations in vessel traffic. We also demonstrate that coarser temporal resolutions lead to overestimations of risk. For highly mobile species subject to human-wildlife interactions such as blue whales, long-term environmental solutions depend on matching ecological data to human activity data at the most appropriate scale.

1. Introduction

Human-wildlife conflicts occur when anthropogenic uses of the environment and wildlife coincide in space and time (Nyhus, 2016). These interactions often result in adverse effects on either humans, wildlife, or both (Conover, 2002). Although human-wildlife conflicts can take various forms and result in varying degrees of severity and impact, the most serious conflicts result in population decline or extinction (Nyhus, 2016). Natural resource managers have attempted to mitigate these interactions through conflict management, but several barriers (e.g. lack of information and setting unattainable goals) can prevent effective negotiation of solutions and long-term successful management strategies (Redpath et al., 2013).

Identifying management strategies for highly mobile species that also account for environmental variability can be even more challenging, but is crucial to ecosystem health and sustainability (Maxwell et al., 2015). While marine ecosystems are dynamic in space and time, marine spatial management evolved from the largely static approaches used in terrestrial systems (Briscoe et al., 2016; Game et al., 2009). In contrast to traditional, static management approaches, dynamic management integrates near-real time data to guide the spatial and temporal distribution of management efforts to be more closely aligned with variability in the marine environment, species distributions, and resource use (Dunn et al., 2016; Maxwell et al., 2015). Consequently, there has been increasing effort to predict changing environmental conditions (Cai et al., 2014; Keeling et al., 2010), species distributions (Araujo and New, 2007; Jones and Cheung, 2015), and highly mobile species migrations (Anderson et al., 2013; Block et al., 2011; Hazen et al., 2013). However, for management schemes to be successful, they must rely on accurate information quantifying human activities within the same spatial and temporal scales as the natural resources being protected. Here we examine a case study involving blue whales
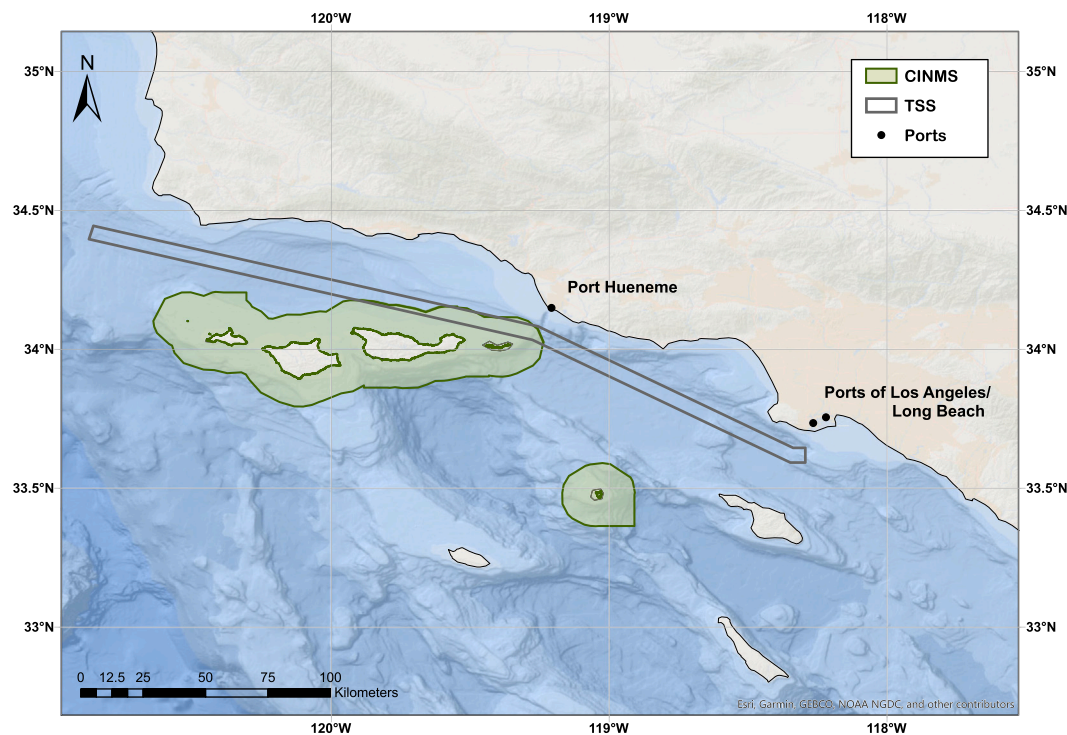
Fig. 1. Study area of the Southern California Bight displaying the Channel Islands National Marine Sanctuary (CINMS) and Transit Separation Scheme (TSS) boundaries leading to Ports of Los Angeles and Long Beach.

(*Balaenoptera musculus*) and ship strikes in the Southern California Bight, where there is a rare opportunity to match a new high-resolution species distribution model to fine scale vessel tracking data in space and time.

Global transportation networks continue to increase as technology accelerates and the human population continues to grow (Nyhus, 2016; Tournadre, 2014). As a result, transportation-related human-wildlife interactions are becoming more common and one of the most persistent forms of conflict (Conover, 2002). It is also one of the deadliest conflicts for both humans and wildlife (Nyhus, 2016). The collision between vessels and whales ('ship strikes') occur on a global scale and can cause injuries and fatalities in marine mammals (Pirotta et al., 2019). Because many marine mammal populations are still threatened as a result of historical whaling, even relatively low levels of mortality due to human interactions can have catastrophic impacts (Clapham et al., 1999). The total effect of ship strikes on whale populations is unclear, as reported whale-vessel collisions likely represent only a small percentage of strike occurrence due to low detection rates (Laist et al., 2001). While some management and legislative frameworks have reduced the number of ship strikes (Conn and Silber, 2013), most are voluntary and face low compliance, which have proven ineffective to mitigate the likelihood of ship strikes (van der Hoop et al., 2015). Because it is difficult for managers to accurately assess the magnitude of strike incidence to whale populations, researchers have aimed to characterize collision risk between whales and various vessel types (Rockwood et al., 2017; Abrahms et al., 2019; Keen et al., 2019).

When assessing ship strike risk for whales, studies typically predict species distributions by collating movement or observer data (Irvine et al., 2014; Hazen et al., 2017; Rockwood et al., 2017). However, to accurately predict the incidence of these potentially lethal interactions, it is critical to also account for patterns of shipping traffic (Moore et al., 2018; Keen et al., 2019). While density of vessel traffic is often acknowledged as an influential factor worthy of consideration (Dransfield et al., 2014; Hazen et al., 2017; Redfern et al., 2013), it is rarely analyzed at the same temporal and spatial scales as blue whale occurrence or distribution models. Estimated whale mortality due to cryptic

mortality events such as oil spills and ship strikes is estimated to be nearly ten-fold higher than is currently documented from carcass recoveries alone (Williams et al., 2011). Previous research has incorporated fine-scale vessel movement data, but has relied on static or seasonal blue whale distributions (Redfern et al., 2013; Rockwood et al., 2017) that do not account for the large amounts of variation in space use at finer timescales that are typical of highly mobile species (Abrahms et al., 2019). In fact, recent work has shown that coarse scales of spatial analysis can obscure estimates of overlap and risk (Kroodsma et al., 2018a, 2018b).

Recent advances in tracking technology, ecological modeling, and data science now allow unprecedented opportunity to use eco-informatics toward human-wildlife conflict management solutions such as ship strike mitigation (Hays et al., 2019; Hazen et al., 2018). An innovation in high-resolution predictions of daily blue whale habitat suitability (Abrahms et al., 2019) allows a direct comparison with globally available high-resolution vessel movement data (Kroodsma et al., 2018a; Moore et al., 2018). Here, we detail this case study to examine trends in overlap between blue whale habitat and shipping vessels at nested timescales to determine when and where blue whales are most at risk of ship strike in the Southern California Bight (SCB). We further examine the impact of the temporal resolutions of our data to explore consequent effects on risk estimation. Combining predicted daily whale distributions with continuous vessel movement data represents the first effort to characterize blue whale ship strike risk by including the newest and most high-resolution estimates of eastern Pacific blue whale distribution. We use these data to compare the ship strike risk models at varying temporal resolutions to address the effect of using coarser resolution input data.

2. Methods

2.1. Study area

We calculated blue whale risk of ship strike within the SCB (33° N to 35° N and 117° W to 121° W; Fig. 1). The SCB encompasses the Channel

Islands National Marine Sanctuary (CINMS) – an 3800 square kilometer region where dense patches of euphausiids provide a seasonally highly productive feeding area for blue whales (Fiedler et al., 1998; Širovic et al., 2015). The SCB also contains the Ports of Los Angeles and Long Beach, two of the world's busiest seaports (WSC, 2017). A shipping lane to these ports (i.e. Traffic Separation Scheme (TSS)) intersects with the CINMS which is considered important whale habitat (Calambokidis et al., 2019; Fiedler et al., 1998). Following implementation of the California Air Resources Board's Ocean-Going Vessels Fuel Rule (CARB rule) in 2009 and a narrowing of the TSS by the International Maritime Organization (IMO) in 2013, 40% of shipping vessels shifted their incoming and outgoing tracks south of the Channel Islands, outside the TSS (Moore et al., 2018). In this study, we analyzed data from the entire SCB for four years (2011, 2013, 2015, 2017) to represent a variety of both climatic conditions and spatial vessel behavior.

2.2. Blue whale habitat suitability

Abrahms et al. (2019) generated daily, year-round predictions of blue whale habitat suitability for each year from a dynamic ensemble species distribution model. The model relates daily satellite tracking data from 104 blue whales to daily surface and subsurface environmental data sourced from the California Current Regional Ocean Modeling System (CCROMS; Neveu et al., 2016; Moore et al., 2018). Habitat suitability ranged from 0 to 1, with 1 representing most suitable habitat. Abrahms et al. (2019) used extensive cross-validation on satellite tag data, as well as independent validation using the largest compilation of blue whale sightings to date to demonstrate a strong relationship between suitability and occurrence. Point biserial correlation with independent sightings data resulted in a *p*-value < 0.001 and the Area Under the Receiver-Operator Curve metric, which measures true-positive versus false-positive rates on a 0–1 scale, resulted in a score of 0.95. See Abrahms et al., 2019 for further detail on model performance evaluation. Daily spatial predictions of blue whale habitat suitability, used as a proxy for probability of occurrence for the purpose of this study (Elith and Leathwick, 2009; Guisan and Thuiller, 2005; Havron et al., 2017), were generated on a 10 × 10 km grid throughout the CCROMS domain to match the finest spatial resolution of the available environmental data. See Abrahms et al. (2019) for further detail.

2.3. AIS shipping data

We collected tanker and cargo AIS shipping data from the ship-tracking data housed on MarineCadastre.gov (www.marinecadastre.gov/AIS/data). Passenger vessels were excluded due to large inconsistencies in AIS usage over the study period. AIS records are pre-filtered to consistent time series at one observation per minute per vessel. We filtered data to include only observations with an AIS Status classified as 'underway using engine' to exclude points where vessels were anchored or otherwise not traversing. Observations within 3 nautical miles from the coastline and observations with speeds below 1 knot were also excluded from all analyses to prevent analysis on portions of tracks where vessels were anchored, closely approaching or sitting at port, or loading and unloading. Speed over ground was extracted from the raw AIS data and prepared for analyses by MarineCadastre.gov. We aggregated data at a daily time step and at a resolution of 10 × 10 kilometers, to match both the temporal and spatial resolution of the blue whale prediction model described above. Vessel density ranged from 0 to 1, with 1 representing the highest density raster cell.

We assessed spatial patterns of vessel speed within the study area with the 'raster' R package (Hijmans, 2019). We determined the number of unique vessel identification (i.e. MMSI) codes present in the study area during each day of the year. Daily vessel density was calculated via the number of unique voyages in each 10 × 10 kilometer grid cell each day.

2.4. Risk of interaction

We analyzed vessel and whale probability data at several nested time scales – daily, weekly, monthly, quarterly, and annually – to identify variation in interaction likelihood at each scale. We first calculated risk of interaction for each grid cell on a given day with Eq. (1):

$$Risk_{ti} = D(Vessel)_{ti} \times P(Whale)_{ti} \tag{1}$$

where $D(Vessel)_{ti}$ represents the density of vessels traveling over 10 knots within grid cell i on day t and $P(Whale)_{ti}$ represents blue whale probability of occurrence, as described above, for grid cell i on day t (adapted from Vanderlaan et al., 2009). This method resulted in a relative spatially explicit interaction risk index ($Risk_{ti}$). After calculation, $Risk_{ti}$ was rounded to the nearest tenth. By subsetting data to include only vessels traveling over 10 knots, we identified potential interactions that likely result in severe injury or fatality (Silber et al., 2010).

To evaluate the average risk over the entire spatial domain (n) per day, we used a spatially-weighted average (A_t). A_t is calculated as:

$$A_t = \sum_{i=1}^{n} (Risk_{ti}(W_{Risk_{ti}})) \tag{2}$$

W_{Riskti} represents the weight of $Risk_{ti}$ relative to all other $Risk$ values within the study area on day t (Eq. (2)). We determined weight (W_{Riskti}) by first calculating the area of each $Risk$ value in the study area (i.e. $Area_{Riskti}$) followed by the division of $Area_{Riskti}$ by the total study area ($Area_{total}$) detailed in Eq. (3):

$$W_{Risk_{ti}} = \frac{Area_{Risk_{ti}}}{Area_{total}} \tag{3}$$

Weight (W_{Riskti}) represents the total spatial area of $Risk_{ti}$ relative to the study area, such that a $Risk$ value with a larger spatial area is weighted more than a $Risk$ value with a smaller spatial area. A_t allows for a single average risk score to be calculated for the study area each day. As a result, we are able to compare average risk for the study area across each day included in the study. We used Mann–Whitney U nonparametric tests, as data were non-normally distributed, to assess the statistical differences in daily average risk ($n = 364$) by year.

We used Eqs. (1), (2), and (3) to calculate risk at the weekly, monthly, and quarterly temporal scale. However, prior to computation of risk in Eq. (1), daily rasters of blue whale probability of occurrence and vessel density were first averaged by week, month, and quarter for their respective assessments to explore the effects of reduced temporal resolutions. We completed all analyses in R version 3.6.1 (Core Team, 2018).

3. Results

3.1. Spatial patterns of risk

Differences in spatial concentrations of vessel activity emerged when risk rasters were averaged across each year. Vessel activity became more concentrated north of the Channel Islands over time (Fig. 2a-d). The four study years demonstrate a variety of vessel spatial patterns (Fig. 2a-d). Spatial areas of whale probability were largely consistent across the four years (Fig. 2i-l), however average whale probability was higher across a broader spatial area in 2015 (Fig. 2k). Spatially, risk does not vary much on finer temporal scales, and instead, risk followed a similar interannual spatial pattern to vessel activity, meaning that risk is largely driven by the vessel traffic distribution. Vessel activity, and subsequent risk, was most spatially concentrated in 2017 (Fig. 2p) and most diffuse in 2013 (Fig. 2n).

3.2. Daily patterns of risk

Each year followed a similar within-day time series trend, where the number of unique vessels per hour increased from hour 00:00 PST
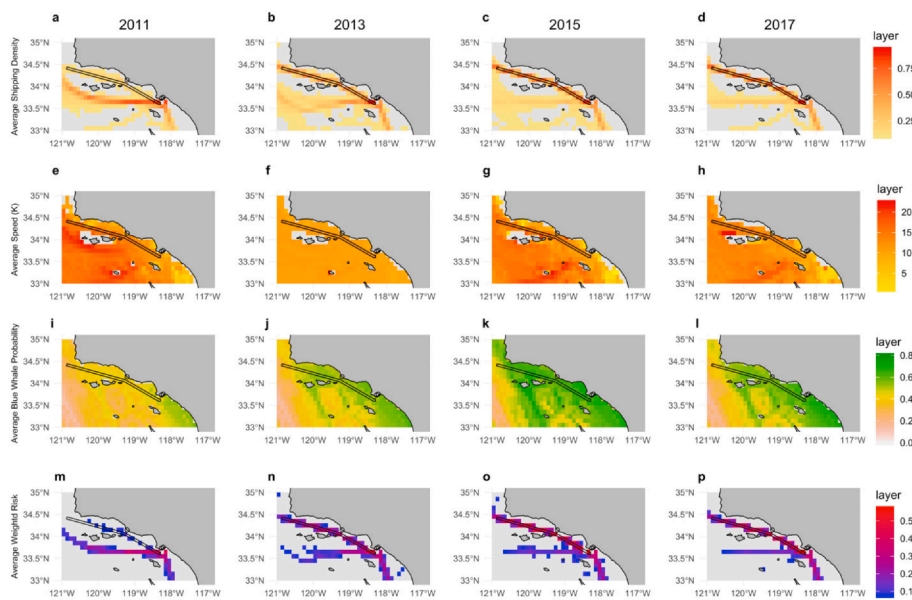
Fig. 2. Aggregation of daily results each of the four years of the study period highlighting interannual variability in spatial patterns of risk. Average daily vessel density in a) 2011, b) 2013, c) 2015, d) 2017. Average speed of a vessel track passing through grid cell *i* in e) 2011 f) 2013, g) 2015, h) 2017. Average daily blue whale habitat suitability, as a result of the dynamic daily ensemble model (Abrahms et al., 2019) in i) 2011 j) 2013, k) 2015, l) 2017. Average daily risk of interaction in m) 2011, n) 2013, o) 2015, p) 2017. Zero risk (usually due to a lack of vessel activity) is represented by gray cells.
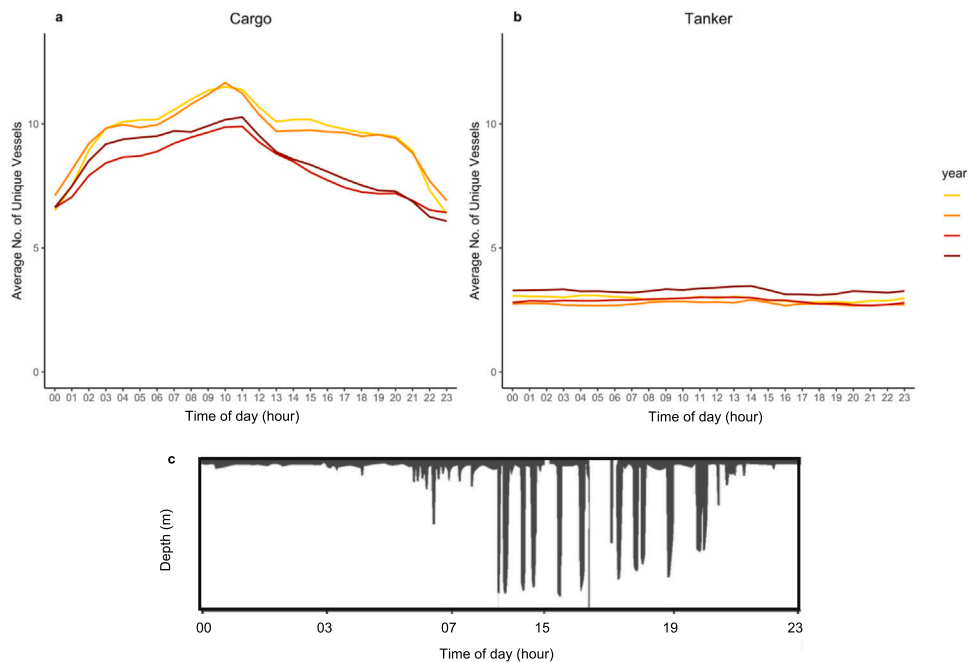

Fig. 3. Time series highlighting diel patterns of risk. Average number of unique vessels per hour traveling through the SCB for each year in the study for a) cargo vessels and b) tanker vessels. c) Time-depth dive profile for a blue whale tagged in the study region (reprinted from Friedlaender et al., 2015).

through 10:00–11:00 PST, followed by a slight decrease through 24:00 PST (Fig. 3a-b). Blue whale dive depth studies show strong diel patterns in time spent at the ocean surface, where they make consistent dives to depths of 100 to 300 m 07:00–20:00, followed by a period of surface behavior from 20:00 to 07:00 (Fig. 3e; Calambokidis et al., 2019; Friedlaender et al., 2015). Although we are unable to calculate risk at finer temporal scales than the blue whale distribution model (Abrahms et al., 2019), we can use these data to deduce that strike risk is likely higher at between hours of 20:00 and 07:00 when blue whales are spending the majority of their time at the surface.

3.3. Seasonal and interannual patterns of risk

The number of unique vessels per day was consistent throughout the annual cycle of each year (Fig. 4a-d). The median average speed and

interquartile range for both cargo and tanker vessels exceeded 10 knots for all four years of the study, however cargo vessels averaged higher speed than tanker vessels (Fig. A1). Although vessel activity was temporally consistent throughout the year, whale presence was not. In both 2011 and 2013, average daily whale probability in the SCB was low until April, when habitat suitability increased rapidly through the start of June. High blue whale probability continued through October, at which point it steadily declined through November (Fig. 4e-f). Anomalous conditions during the El Niño and marine heatwave of 2015 and warm water conditions of 2017 resulted in more variable habitat suitability in both years, and included periods of relatively high blue whale probability as early as March and as late as November (Fig. 4g-h).

Temporally, risk of interaction varied within and among years (Fig. 4i-l). Mimicking the temporal pattern of whale probability, 2011 and 2013 resulted in highest daily risk in July–October, reaching a
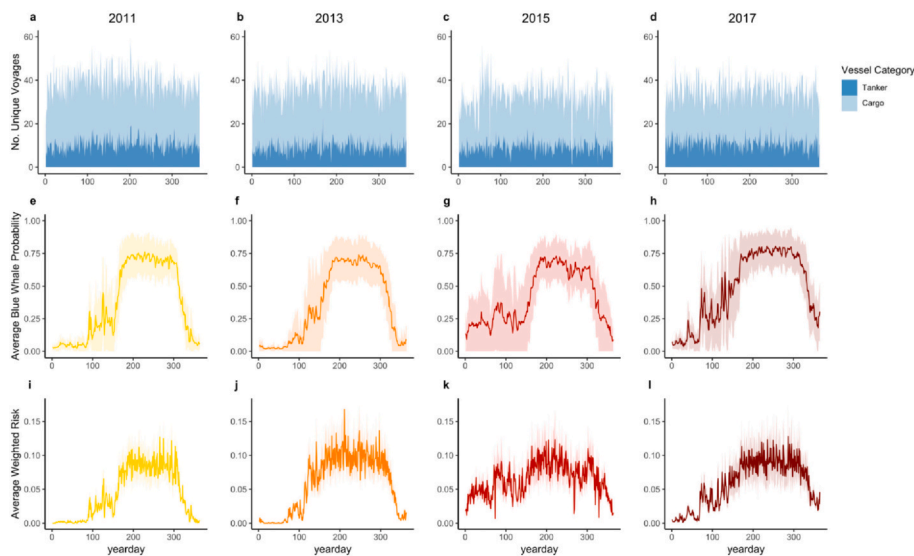
Fig. 4. Time series for each of the four years of the study period highlighting intra-annual variability in risk. Number of unique voyages in the SCB by year day in a) 2011, b) 2013, c) 2015, d) 2017. Average (spatial mean ± SD) blue whale habitat suitability in the SCB by yearday in e) 2011, f) 2013, g) 2015, h) 2017. Average risk (spatial mean ± SD) of blue whale-vessel interaction in i) 2011, j) 2013, k) 2015, l) 2017.

maximum relative risk in July and August (Fig. 4i-j). In 2015 and 2017, periods of high risk occurred as early as March and as late as November (Fig. 4k-l). In 2015, a spike in risk was calculated in March - due to both an increase in whale probability and an increase in vessel activity.

Average daily risk is represented as ratios rather than values with units as both whale habitat suitability and vessel traffic were first scaled from 0 to 1 prior to risk calculations using Eqs. (1), (2), and (3). Average daily risk was 4.3% in 2011, 5.7% in 2013, 6.5% in 2015 and 5.8% 2017 (Fig. 5). Mann-Whitney U tests revealed a statistically significant difference in risk between 2011 and 2013 ($p < .01$, $W = 53,802$), 2015 ($p < .01$, $W = 43,712$), and 2017 ($p < .01$, $W = 49,070$), and between 2015 and 2017 ($p < .05$, $W = 72,328$), but not between 2013 and 2015 ($p = .18$, $W = 62,480$) or 2013 and 2017 ($p = .76$, $W = 65,395$).
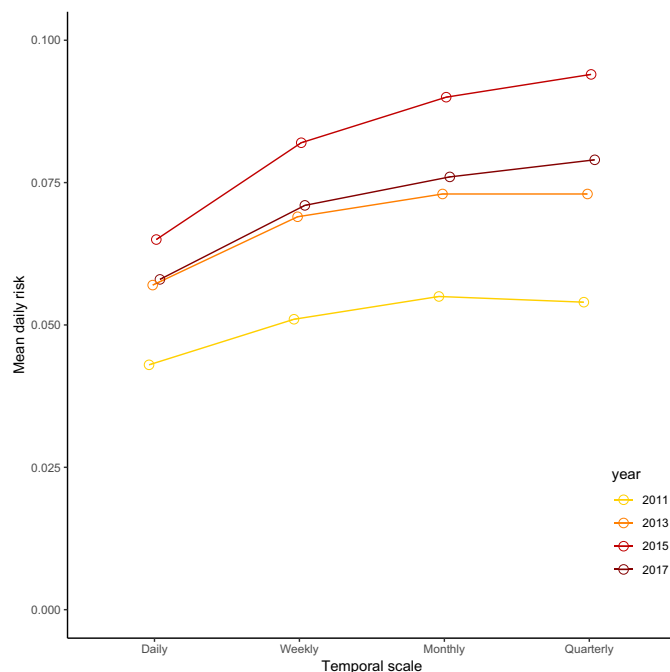
3.4. Effect of decomposing temporal resolutions

When risk was calculated at temporal scales coarser than daily, risk was overestimated (Fig. 5). In 2015, average daily risk was 9.4% when risk was calculated at a quarterly (i.e. seasonal) scale – a 44% increase when compared to when risk was calculated at a daily time step. Similar discrepancies exist among temporal scale calculations in 2011, 2013 and 2017.

4. Discussion

Our study integrates daily predictions of blue whale probability of occurrence with high resolution vessel tracking data for the first time to characterize ship strike risk via simultaneous ecological and socio-economic data matched in space at multiple temporal scales. While previous studies have begun to characterize blue whale ship strike risk using both species probabilities and vessel tracking data (Redfern et al., 2013, 2019; Rockwood et al., 2017), the use of static species distribution models may give the incorrect impression that overlap is consistent within a season or from year to year. While this may be true on average, this approach misses seasonal and interannual variability, as well as finer scale spatial patterns that occur both as a result of changes in the highly migratory species' habitat suitability as well as human behavior.

4.1. Evaluation of risk and potential conservation actions

The hourly analysis of vessel traffic indicated that shipping activity is more prevalent during the day, but still consistently occurs at night. As such, to address intra-day management options, managers can refer to blue whale diurnal behavioral patterns to estimate intra-day patterns in risk. Previous studies concluded that diving behavior in blue whales follows a consistent diurnal pattern where blue whales feed at shallower depths during dusk and spend the majority of time at the surface at night (Calambokidis et al., 2019; Friedlaender et al., 2015). These findings indicate that, similar to fin whales (Keen et al., 2019), ship strike risk would be highest during nighttime hours (19:00–06:00 PST), which poses a problem for visibility in terms of recognizing that an animal has been struck.

Previous studies indicated that strike risk is concentrated along major TSSs (Redfern et al., 2019; Rockwood et al., 2017), however our study specifies that areas outside the TSS are also important to consider when vessels alter their spatial behavior (sensu Keen et al., 2019). Changes in the spatial behavior of the shipping industry is often in response to new regulations (Moore et al., 2018). Continuous vessel

Fig. 5. Average daily risk of ship strike by temporal scale of analysis for 2011, 2013, 2015, and 2017.

movement data provided more spatially explicit results and better-informed risk intensity relative to studies which overlay habitat suitability models with static shipping lanes or other hypothetical measures of vessel traffic. Future studies would benefit from assessing vessel response, or lack thereof, to previously implemented regulations to predict response to potential future changes in policy such as shifts and extensions of the TSS or expansion of the area to be avoided (ATBA).

In contrast, predicted whale migratory behavior and their responses to interannual fluctuations in environmental conditions led to high temporal variability in their distributions both seasonally and interannually. Our results confirm that a "normal" climatic year (e.g. 2011, 2013) results in highest risk of strike during the months of June through October (Abrahms et al., 2019; Redfern et al., 2013), but also that average risk intensity was greater and extended over a longer portion of the annual cycle during an El Niño year (e.g. 2015).

Consequently, both whale habitat probability of occurrence predictions and rates of vessel activity are both important when considering overall interaction risk intensity on a daily, weekly, monthly, seasonal, or inter-annual scale. In 2007, more blue whale deaths due to ship strikes were reported than any other year on record. Blue whales were also more abundant in the Southern California Bight during 2007 than in previous years, particularly within shipping lanes where patches of krill were also present (Berman-Kowalewski et al., 2010). Positive El Niño/Southern Oscillation (ENSO) conditions were present in early 2007 (NOAA NCEI, 2008), which could indicate that higher reported rate of ship strikes were correlated with these anomalous environmental conditions. With projected increases in frequency of extreme El Niño events (Cai et al., 2014; Wang et al., 2017) and projected increases in vessel traffic to 2050 (Sardain et al., 2019), this trend may continue leading to an increase in daily risk.

4.2. Influence of temporal scale

Coarse resolution data mask spatial and temporal variability in risk that may result from patchy conditions of blue whale habitat and/or variations in vessel traffic. Further, coarser calculations of risk result in an overestimation of average risk (Table 1; Fig. 5) which could reduce the efficiency of management strategies and/or lead to the misallocation of limited conservation resources. At coarser temporal scales, variability in whale presence and vessel density within cells is dampened, meaning the mean at coarser time scales is skewed higher by outliers in whale presence and vessel density. The daily calculations of risk are more informative regarding both variability of calculated risk and of which cells more consistently display co-occurrence of human and whale activity and which cells contain anomalies of co-occurrence.

While exploring the impact of spatial resolution of input data was not considered in this study, it may be beneficial to consider in future studies. The Abrahms et al. (2019) SDM was developed using the finest spatiotemporal scale available for environmental data within the spatial domain (i.e. daily temporal resolution, 10 × 10 km spatial resolution). It is unknown how skillful SDMs would be at higher spatial resolution, however, Scales et al. (2017) showed that 3–100 km for a hypothetical blue whale SDM were all very similar in skill. Finer spatial scales may allow for greater separation between whale distribution and presence of risk.

Transportation related conflicts with megafauna are becoming increasingly common due to increased density of humans in marine and terrestrial environments (Nyhus, 2016; Pirotta et al., 2019; Conover, 2002; National Wildlife Research Center, 2007). Transportation related conflicts, including ship strike risk and traffic density, have even hindered recovery of endangered populations such as North Atlantic Right Whales and Southern Resident Killer Whales (Kraus et al., 2005; Lusseau et al., 2009). Areas where highly-variable oceanographic conditions influence the space and time use of the area by migratory animals, and human behavior (e.g. ship routing) is influenced by economic factors such as the SCB, it is important to consider human-wildlife conflict at a temporal resolution that captures these variabilities.

A recent study by Redfern et al. (2019) evaluates specific management options in our study area, such as adding a shipping lane to the SCB, expanding the whale area to be avoided, and reducing ship speeds – highlighting the importance of the risk assessment presented here to inform future management perspectives (Redfern et al., 2019). Rather than only focusing on the biophysical predictions of blue whale presence in the area, to optimize management measures, managers should likely consider both predicted whale density and predicted risk. For example, it may be preferable to prioritize areas of highest risk, which may differ than the areas of highest whale density. It further may be advantageous to prioritize the areas of high risk that have high whale density but fewer ships, rather than areas that have large numbers of ships but lower whale density, even if resulting risk is the same in both cases. Although dynamic management is more difficult to implement within the shipping industry due to economic costs (Lewison et al., 2015), a daily analysis in risk could indicate when strike risk crosses a "threshold" indicating that a management strategy, such as a mandatory slow down, needs to be activated within a specific area. Further, successful conflict management also depends on understanding the species-specific characteristics (e.g. foraging behavior, nocturnality) that can influence when and where these conflicts are likely to occur (Snow et al., 2015).

4.3. Data science and near-real time technology

Effective conservation and management rely on an accurate understanding of where and when threats to species occur. In the absence of continuous observations, we must rely on modeled distribution data to predict species occurrence (Elith and Leathwick, 2009). Dynamic, high spatiotemporal resolution species distribution models, such as the one used in this analysis offer a major advancement in the ability to predict and assess risk at relevant ecological scales (Abrahms et al., 2019). However, it is equally important to distill high-resolution socioeconomic data to refine patterns of human activity at multiple time scales. Continuous anthropogenic data can provide more spatially explicit results and better inform when and where human-wildlife conflict occurs. These methods can also be used to forecast human-wildlife interactions based on projected climatic conditions and policy implementations to ensure they are climate-ready (Hazen et al., 2018). Our study highlights the continuing need for the combination of human risk and animal space use via eco-informatics when assessing interactions between economic and ecological uses of the same environment to solve complex global environmental issues.

Table 1
Daily risk of ship strike by time scale averaged to each year with standard deviation.

Temporal scale	2011	2013	2015	2017
Quarterly	0.054 ± 0.048	0.073 ± 0.056	0.094 ± 0.028	0.079 ± 0.052
Monthly	0.055 ± 0.049	0.073 ± 0.057	0.09 ± 0.031	0.076 ± 0.049
Weekly	0.051 ± 0.046	0.069 ± 0.052	0.082 ± 0.029	0.071 ± 0.043
Daily	0.043 ± 0.037	0.057 ± 0.043	0.065 ± 0.024	0.058 ± 0.034

CRediT authorship contribution statement

Declaration of competing interest

Acknowledgements

Data accessibility

All spatial predictions from the habitat suitability model will be made publicly available upon acceptance. All AIS shipping data are available for download at https://www.marinecadastre.gov/ais/.

Appendix A. Supplementary data

Further information on vessel speeds over the four years included in the study (Appendix S1) will be made available online. This includes both average speed by vessel category (i.e. tanker and cargo) for each of the four years, as well as spatial representation of where vessel slow-downs below 10 knots most frequently occur. The authors are responsible for the content within these materials. Questions should be directed to the corresponding author. Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2020.108757.

References

Abrahms B, Welch H, Brodie S, Jacox MG, Becker EA, Bograd SJ, Irvine LM, Palacios DM, Mate BR, Hazen EL. 2019. Dynamic ensemble models to predict distributions and anthropogenic risk exposure for highly mobile species. Diversity and Distributions 25:ddi.12940.

Anderson, J.J., Gurarie, E., Bracis, C., Burke, B.J., Laidre, K.L., 2013. Modeling climate change impacts on phenology and population dynamics of migratory marine species. Ecol. Model. 264, 83–97.

Araujo, M., New, M., 2007. Ensemble forecasting of species distributions. Trends Ecol. Evol. 22, 42–47.

Berman-Kowalewski, M., et al., 2010. Association between blue whale (*Balaenoptera musculus*) mortality and ship strikes along the California coast. Aquat. Mamm. 36, 59–66.

Block, B.A., et al., 2011. Tracking apex marine predator movements in a dynamic ocean. Nature 475, 86–90.

Briscoe, D., Maxwell, S., Kudela, R., Crowder, L., Croll, D., 2016. Are we missing important areas in pelagic marine conservation? Redefining conservation hotspots in the ocean. Endanger. Species Res. 29, 229–237.

Cai, W., Borlace, S., Lengaigne, M., Van Rensch, P., Collins, M., Vecchi, G., ... England, M.H., 2014. Increasing frequency of extreme El Niño events due to greenhouse warming. Nature Climate Change 4, 111–116.

Calambokidis, J., Fahlbusch, J.A., Szesciorka, A.R., Southall, B.L., Cade, D.E., Friedlaender, A.S., Goldbogen, J.A., 2019. Differential vulnerability to ship strikes between day and night for blue, fin, and humpback whales based on dive and movement data from medium duration archival tags. Front. Mar. Sci. 6, 543.

Clapham, P.J., Young, S.B., Brownell, R.L., 1999. Baleen whales: conservation issues and the status of the most endangered populations. Mammal Rev. 29, 37–62.

Conn, P.B., Silber, G.K., 2013. Vessel speed restrictions reduce risk of collision-related mortality for North Atlantic right whales. Ecosphere 4 (4), 1–16.

Conover, M., 2002. Resolving Human-Wildlife Conflicts: The Science of Wildlife Damage Management. CRC Press.

Core Team, R., 2018. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.

Dransfield, A., Hines, E., McGowan, J., Holzman, B., Nur, N., Elliott, M., Howar, J., Jahncke, J., 2014. Where the whales are: using habitat modeling to support changes in shipping regulations within national marine sanctuaries in central California. Endanger. Species Res. 26, 39–57.

Dunn, D.C., Maxwell, S.M., Boustany, A.M., Halpin, P.N., 2016. Dynamic ocean management increases the efficiency and efficacy of fisheries management. Proc. Natl. Acad. Sci. U. S. A. 113, 668–673.

Elith, J., Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. Annu. Rev. Ecol. Evol. Syst. 40, 677–697.

Fiedler, P.C., Reilly, S.B., Hewitt, R.P., Demer, D., Philbrick, V.A., Smith, S., Armstrong, W., Croll, D.A., Tershy, B.R., Mate, B.R., 1998. Blue whale habitat and prey in the California Channel Islands. Deep-Sea Res. II Top. Stud. Oceanogr. 45, 1781–1801.

Friedlaender, A.S., Goldbogen, J.A., Hazen, E.L., Calambokidis, J., Southall, B.L., 2015. Feeding performance by sympatric blue and fin whales exploiting a common prey resource. Marine Mammal Science 31, 345–354.

Game, E.T., Grantham, H.S., Hobday, A.J., Pressey, R.L., Lombard, A.T., Beckley, L.E., Gjerde, K., Bustamante, R., Possingham, H.P., Richardson, A.J., 2009. Pelagic protected areas: the missing dimension in ocean conservation. Trends Ecol. Evol. 24, 360–369.

Guisan, A., Thuiller, W., 2005. Predicting species distribution: offering more than simple habitat models. Ecol. Lett. 8, 993–1009.

Havron, A., Goldfinger, C., Henkel, S., Marcot, B.G., Romsos, C., Gilbane, L., 2017. Mapping marine habitat suitability and uncertainty of Bayesian networks: a case study using Pacific benthic macrofauna. Ecosphere 8, e01859.

Hays, G.C., et al., 2019. Translating marine animal tracking data into conservation policy and management. Trends Ecol. Evol. 34, 459–473.

Hazen, E.L., et al., 2013. Predicted habitat shifts of Pacific top predators in a changing climate. Nat. Clim. Chang. 3, 234–238.

Hazen, E.L., et al., 2017. WhaleWatch: a dynamic management tool for predicting blue whale density in the California Current. J. Appl. Ecol. 54, 1415–1428.

Hazen EL et al. 2018. A dynamic ocean management tool to reduce bycatch and support sustainable fisheries. Science Advances 4:eaar3001.

Hijmans RJ. 2019. raster: Geographic Data Analysis and Modeling. R Package Version 2. 9-5. Available from https://cran.r-project.org/package=raster.

Irvine LM, Mate BR, Winsor MH, Palacios DM, Bograd SJ, Costa DP, Bailey H. 2014. Spatial and temporal occurrence of blue whales off the U.S. West Coast, with implications for management. PLoS ONE 9:e102959.

Jones, M.C., Cheung, W.W.L., 2015. Multi-model ensemble projections of climate change effects on global marine biodiversity. ICES J. Mar. Sci. 72 (3), 741–752.

Keeling, R.F., Körtzinger, A., Gruber, N., 2010. Ocean deoxygenation in a warming world. Annu. Rev. Mar. Sci. 2, 199–229.

Keen, E.M., Scales, K.L., Rone, B.K., Hazen, E.L., Falcone, E.A., Schorr, G.S., 2019. Night and day: diel differences in ship strike risk for fin whales (Balaenoptera physalus) in the California current system. Front. Mar. Sci. 6, 730.

Kraus, S.D., Brown, M.W., Caswell, H., Clark, C.W., Fujiwara, M., Hamilton, P.K., Kenney, R.D., Knowlton, A.R., Landry, S., Mayo, C.A., McLellan, W.A., 2005. North Atlantic right whales in crisis. Science 309 (5734), 561–562.

Kroodsma DA et al. 2018a. Tracking the global footprint of fisheries. Science (New York, N.Y.) 359:904–908.

Kroodsma DA et al. 2018b. Response to Comment on "Tracking the global footprint of fisheries." Science (New York, N.Y.) 361:eaat7789.

Laist, D.W., Knowlton, A.R., Mead, J.G., Collet, A.S., Podesta, M., 2001. Collisions between ships and whales. Marine Mammal Science 17, 35–75.

Lewison, R., Hobday, A.J., Maxwell, S., Hazen, E., Hartog, J.R., Dunn, D.C., ... Abecassis, M., 2015. Dynamic ocean management: identifying the critical ingredients of dynamic approaches to ocean resource management. BioScience 65 (5), 486–498.

Lusseau, D., Bain, D.E., Williams, R., Smith, J.C., 2009. Vessel traffic disrupts the foraging behavior of southern resident killer whales Orcinus orca. Endanger. Species Res. 6 (3), 211–221.

Maxwell, S.M., et al., 2015. Dynamic ocean management: defining and conceptualizing real-time management of the ocean. Mar. Policy 58, 42–50.

Moore, T.J., Redfern, J.V., Carver, M., Hastings, S., Adams, J.D., Silber, G.K., 2018. Exploring ship traffic variability off California. Ocean & Coastal Management 163, 515–527.

National Wildlife Research Center (US). Innovative Solutions to Human-wildlife Conflicts: National Wildlife Research Center Accomplishments, 2006. National Wildlife Research Center, 2007.

Neveu, E., Moore, A.M., Edwards, C.A., Fiechter, J., Drake, P., Crawford, W.J., Jacox, M.G., Nuss, E., 2016. An historical analysis of the California Current circulation using ROMS 4D-Var: system configuration and diagnostics. Ocean Model. 99, 133–151.

NOAA National Centers for Environmental Information. (2008). State of the Climate: El Niño/Southern Oscillation for Annual 2007, published online January 2008, retrieved from https://www.ncdc.noaa.gov/sotc/enso/200713.

Nyhus, P.J., 2016. Human–wildlife conflict and coexistence. Annu. Rev. Environ. Resour. 41, 143–171.

Pirotta, V., Grech, A., Jonsen, I.D., Laurance, W.F., Harcourt, R.G., 2019. Consequences of global shipping traffic for marine giants. Front. Ecol. Environ. 17 (1), 39–47.

Redfern, J.V., McKenna, M.F., Moore, T.J., Calambokidis, J., Deangelis, M.L., Becker, E.A., Barlow, J., Forney, K.A., Fiedler, P.C., Chivers, S.J., 2013. Assessing the risk of ships striking large whales in marine spatial planning. Conserv. Biol. 27, 292–302.

Redfern J V., Moore TJ, Becker EA, Calambokidis J, Hastings SP, Irvine LM, Mate BR, Palacios DM. 2019. Evaluating stakeholder-derived strategies to reduce the risk of ships striking whales. Diversity and Distributions:ddi.12958.

Redpath, SM, Young, J, Evely, A, Adams, WM, Sutherland, WJ, Whitehouse, A, ... Gutierrez, RJ, 2013. Understanding and managing conservation conflicts. Trends in ecology & evolution 28 (2), 100–109.

Rockwood CR, 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 12:e0183052.

Sardain, A., Sardain, E., Leung, B., 2019. Global forecasts of shipping traffic and biological invasions to 2050. Nature Sustainability 2, 274–282.

Scales, K.L., Hazen, E.L., Jacox, M.G., Edwards, C.A., Boustany, A.M., Oliver, M.J., Bograd, S.J., 2017. Scale of inference: on the sensitivity of habitat models for wide-ranging marine predators to the resolution of environmental data. Ecography 40 (1), 210–220.

Silber, G.K., Slutsky, J., Bettridge, S., 2010. Hydrodynamics of a ship/whale collision. J. Exp. Mar. Biol. Ecol. 391, 10–19.

Širovic, A., Rice, A., Chou, E., Hildebrand, J., Wiggins, S., Roch, M., 2015. Seven years of blue and fin whale call abundance in the Southern California Bight. Endanger. Species Res. 28, 61–76.

Snow, N.P., Porter, W.F., Williams, D.M., 2015. Underreporting of wildlife-vehicle collisions does not hinder predictive models for large ungulates. Biol. Conserv. 181, 44–53.

Tournadre, J., 2014. Anthropogenic pressure on the open ocean: the growth of ship traffic revealed by altimeter data analysis. Geophys. Res. Lett. 41, 7924–7932.

van der Hoop, J.M., Vanderlaan, A.S., Cole, T.V., Henry, A.G., Hall, L., Mase-Guthrie, B., ... Moore, M.J., 2015. Vessel strikes to large whales before and after the 2008 Ship Strike Rule. Conserv. Lett. 8 (1), 24–32.

Vanderlaan, A., Corbett, J., Green, S., Callahan, J., Wang, C., Kenney, R., Taggart, C., Firestone, J., 2009. Probability and mitigation of vessel encounters with North Atlantic right whales. Endanger. Species Res. 6, 273–285.

Wang, G., Wang, D., Trenberth, K.E., Erfanian, A., Yu, M., Bosilovich, M.G., Parr, D.T., 2017. The peak structure and future changes of the relationships between extreme precipitation and temperature. Nat. Clim. Chang. 7, 268–274.

Williams, R., Gero, S., Bejder, L., Calambokidis, J., Kraus, S.D., Lusseau, D., Read, A.J., Robbins, J., 2011. Underestimating the damage: interpreting cetacean carcass recoveries in the context of the Deepwater Horizon/BP incident. Conserv. Lett. 4, 228–233.

World Shipping Council (WSC), 2017. Top 50 World Container Ports. World Shipping Council. Available from. http://www.worldshipping.org/about-the-industry/global-trade/top-50-world-container-ports.