

Spring 2018

## Fishery Interaction Modeling of Cetacean Bycatch in the California Drift Gillnet Fishery to Inform a Dynamic Ocean Management Tool

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**FISHERY INTERACTION MODELING OF CETACEAN BYCATCH IN  
THE CALIFORNIA DRIFT GILLNET FISHERY TO INFORM A  
DYNAMIC OCEAN MANAGEMENT TOOL**

by

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B.A. June 2012, University of California Santa Cruz

A Thesis Submitted to the Faculty of  
Old Dominion University in Partial Fulfillment of the  
Requirements for the Degree of

MASTER OF SCIENCE

BIOLOGY

OLD DOMINION UNIVERSITY  
May 2018

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## ABSTRACT

# FISHERY INTERACTION MODELING OF CETACEAN BYCATCH IN THE CALIFORNIA DRIFT GILLNET FISHERY TO INFORM A DYNAMIC OCEAN MANAGEMENT TOOL

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Old Dominion University, 2018  
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Understanding the drivers that lead to interaction between target species in a fishery and marine mammals is a critical aspect in efforts to reduce bycatch. In the California drift gillnet fishery static management approaches and gear changes have reduced bycatch but neither measure ascertains the underlying dynamics causing bycatch events. To avoid further potentially drastic measures such as hard caps, dynamic management approaches that consider the scales relevant to physical dynamics, animal movement and human use could be implemented. A key component to this approach is determining the factors that lead to fisheries interactions. Using 25 years (1990-2014) of National Oceanic and Atmospheric Administration fisheries' observer data from the California drift gillnet fishery, we model the relative probability of bycatch (presence-absence) of four cetacean species in the California Current System (short-beaked common dolphin *Delphinus delphis*, northern right whale dolphins *Lissodelphis borealis*, Risso's dolphins *Grampus griseus*, and Pacific white-sided dolphins *Lagenorhynchus obliquidens*). Due to the nature of protected species bycatch, these are rare-events, which cause a large amount of absences (zeros) in each species' dataset. Using a data-assimilative configuration of the Regional Ocean Modeling System, we determined the capabilities of a flexible machine-learning algorithm to handle these zero-inflated datasets in order to explore the physical drivers of cetacean bycatch in the California drift gillnet fishery. Results suggest that cetacean bycatch probability has a complex relationship with the physical environment, with mesoscale variability acting as a strong driver. Through the modeling process, we observed varied responses to the range of sample sizes in the zero-inflated datasets, determining the minimum number of presences capable of building an accurate model. The selection of predictor variables and model evaluation statistics were found to play an important role in assessing the biological significance

of our species distribution models. These results highlight the statistical capability (and incapability) of modeling techniques to predict the complex nature driving fishery interaction of cetacean bycatch in the California drift gillnet fishery. By determining where fisheries interactions are most likely to occur, we can inform near real-time management approaches to reduce bycatch while still allowing fishermen to meet their catch quotas.

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## ACKNOWLEDGEMENTS

Thanks first and foremost to my advisor Sara Maxwell, I was lucky enough to have met her when I was an undergrad at the University of California Santa Cruz where she served as a wonderful mentor until ultimately becoming my graduate advisor 4.5 years later. She has been continually attentive of my development, both academically and personally, and always there to keep pushing me forward in my research. Thanks also to my amazing committee (Elliott Hazen and Holly Gaff), their expertise and guidance was immensely helpful in developing and crafting my research.

Thank you to the members of the Maxwell Lab (Tiffany Dawson, Jeri Wisman, and Tully Champagne-Maxwell). Especially Tiffany for showing me around Old Dominion University (ODU) and Norfolk when I first arrived. Thank you to Amanda Laverty for always being there to help with anything I needed, and always having eternal positivity and not letting me get down on things. And to my cohort in the Biological Sciences Department, I enjoyed our discussions and getting through classes together. Especially Gaya Gnanalingam for putting up with my visits when I needed a break.

Thanks to all my collaborators (Stephanie Brodie, Heather Welch, Elizabeth Becker, Kylie Scales, Mike Jacox, Steven Bograd, Rebecca Lewison, and Larry Crowder) for their assistance throughout this project. Especially Steph for all your help, you've made me much better at coding. Thanks to Karin Forney, Jim Carretta, Jeff Moore and Jay Barlow at NOAA's Southwest Fisheries Science Center for your expertise and taking the time to talk to me about modeling and cetaceans. Thanks to my mentors (Alexis Gutierrez and Kristy Long) during my Knauss Fellowship who gave me time whenever I needed it to work on my thesis. Thank you to James Murphy, Laura Koehn, and Emily Markowitz of my Knauss Fellowship class for help with edits, coding and sitting through practice runs of my defense.

Thank you to ODU, and the Biology Graduate Student Organization for funding and assistance throughout my time there. Especially, Danielle Achterfeld and Jen Ellis in the Biological Sciences Department. Thank you to Carly Thomas at Old Dominion University Research Foundation, who was so incredibly helpful whenever an issue arose.

Many thanks to the California Sea Grant College Program, Harold G. Marshall and Vivian J. Marshall scholarship, NOAA Bycatch Reduction Engineering Program and NASA Research Opportunities in Earth and Space Science for funding. This publication was prepared under California Sea Grant College Program Project #R/SSFS-04, through NOAA'S National Sea Grant College Program, U.S. Dept. of Commerce. The statements, findings, conclusions and recommendations are those of the author(s) and do not necessarily reflect the views of California Sea Grant, NOAA or the U.S. Dept. of Commerce.

## NOMENCLATURE

<i>AUC</i>	Area Under the receiver operating Curve
<i>BF</i>	Bag Fraction
<i>BRT</i>	Boosted Regression Tree
<i>BV</i>	Brunt-Väisälä frequency
<i>CCS</i>	California Current System
<i>Curl</i>	Wind stress curl
<i>DGN</i>	Drift Gillnet Fishery
<i>DOM</i>	Dynamic Ocean Management
<i>EA</i>	Environmental Assessment
<i>EEZ</i>	Exclusive Economic Zone
<i>PFMC</i>	Pacific Fisheries Management Council
<i>EKE</i>	Natural log of Eddy Kinetic Energy
<i>ESA</i>	Endangered Species Act
<i>GAM</i>	Generalized Additive Model
<i>HPPS</i>	High Priority Protected Species
<i>ILD</i>	Isothermal layer depth
<i>Lat</i>	Latitude
<i>LR</i>	Learning Rate
<i>LOF</i>	List of Fisheries
<i>Lunar</i>	Lunar illumination
<i>MBTA</i>	Migratory Bird Treaty Act
<i>MMPA</i>	Marine Mammal Protection Act
<i>MSA</i>	Magnuson-Stevens Fishery Conservation and Management Act
<i>NMFS</i>	National Marine Fisheries Service (NOAA Fisheries)
<i>NOAA</i>	National Oceanic and Atmospheric Administration
<i>NRT</i>	Near-Real Time
<i>RIR</i>	Regulatory Impact Review
<i>ROMS</i>	Regional Ocean Modeling System
<i>SDM</i>	Species Distribution Model

<i>SSH</i>	Sea Surface Height
<i>SSH_SD</i>	Standard deviation of Sea Surface Height
<i>SST</i>	Sea Surface Temperature
<i>SST_SD</i>	Standard deviation of Sea Surface Temperature
<i>SU</i>	Surface eastward velocity
<i>SUSTR</i>	Surface eastward wind stress
<i>SV</i>	Surface northward velocity
<i>SVSTR</i>	Surface northward wind stress
<i>SWFSC</i>	Southwest Fisheries Science Center
<i>TC</i>	Tree Complexity
<i>TSS</i>	True Skill Statistic
<i>VI</i>	Variable Importance
<i>Z</i>	Bathymetry
<i>Z_SD</i>	Rugosity
<i>ZINB</i>	Zero-Inflated Negative Binomial distribution
<i>ZIP</i>	Zero-Inflated Poisson distribution



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## CHAPTER 1

# FISHERY INTERACTION MODELING OF CETACEAN BYCATCH IN THE CALIFORNIA DRIFT GILLNET FISHERY TO INFORM A DYNAMIC OCEAN MANAGEMENT TOOL

## INTRODUCTION

Global development and human uses around the world have increased the impact upon the oceans. Marine ecosystems and their inhabitants face an ever-increasing number of threats (e.g. climate change, invasive species, pollution, resource extraction). Multiple studies have looked at the cumulative impact of human activities both around the world (Halpern et al. 2008) and within specific regions (Halpern et al. 2009, Teck et al. 2010, Maxwell et al. 2013). Along the west coast of the United States, these studies found that there are many areas of high impact and few areas of low impact (Halpern et al. 2009). When normalizing risks for multiple top predators (seabirds, sea turtles and marine mammals), these areas were generally distributed closer to shore than offshore (Maxwell et al. 2013). Specifically, the central coast of California and prominent headlands along the United States west coast were found to have high cumulative impacts for marine mammals (Maxwell et al. 2013). These anthropogenic threats can range from ocean acidification and climate change to commercial shipping and fishing interactions (Maxwell et al. 2013), with fisheries bycatch and climate change posing two of the greatest threats to marine vertebrates (Dayton et al. 1995, Lewison et al. 2004, Read et al. 2006, Hazen et al. 2013). Bycatch, the incidental capture of non-target marine species and undersized individuals of target species during fishing activities is an issue of ecological, moral and economic grounds (Dayton et al. 1995, Lewison et al. 2004, Read et al. 2006). This is a direct threat to the population survival of marine species and must be managed to ensure the continued existence of marine species worldwide (Read et al. 2006). Climate change represents an indirect threat because the impacts can occur through pathways such as prey resources, but the results can

have equally detrimental impacts to direct threats like bycatch (Hazen et al. 2013). Using data from the Tagging of Pelagic Predators dataset (4,300 electronic tags deployed on 23 marine species) and the output from a global climate model to 2100, Hazen et al. (2013) found that a 35% change in core habitat is possible for some marine species in the North Pacific. Similar to bycatch, this change in distribution can be accounted for by managers in order to ensure the continued existence of healthy stocks of marine species.

Bycatch is a direct threat that occurs at relatively shorter temporal and small spatial scales, compared to the indirect global threat of climate change. As a direct threat, the management of bycatch needs to happen in real-time with strategies that can adapt to the threat of climate change. Managing and mitigating the effects of bycatch and climate change necessitates an understanding of the drivers that influence both threats. Bycatch is the result of ecological (i.e. season, physical environment) and social factors (i.e. fishermen behavior) (Jannot and Holland 2013). There is a need to be able to quantify ecological aspects of bycatch species that influence their habitat selection, migration, and foraging behavior that lead to the temporal and spatial co-occurrence with target species (Dunn et al. 2011, Jannot and Holland 2013). To adequately manage the threat, approaches that incorporate oceanographic, ecological, and fishery variables at spatial and temporal scales relevant to bycatch species are needed (Soykan et al. 2008). However, the nature of bycatch and the marine environment adds complexity to the issue. Determining the drivers of bycatch can be difficult because the spatial and temporal distribution of bycatch species are confounded by the choices of the fishermen. In the marine environment, the horizontal and vertical distribution of species, whether target or non-target, is influenced by factors that can occur at different temporal scales (minutes to hours vs. days to months). Vertical distributions are often caused by events that occur on short temporal scales (i.e. diving or foraging), while horizontal distributions often occur on longer temporal scales (i.e. migration) (S. Brodie, personal communication, 2018). These complexities necessitate the need for flexible variables that can be forecast to anticipate the effects of climate change and are relevant to the species' ecology, oceanographic features of the study area, and behavior of the fishery (Forney 2000, Jannot and Holland 2013).

In the United States, there are four leading federal statutes that address fisheries bycatch, including that of large marine vertebrate species; the Endangered Species Act (ESA), Marine Mammal Protection Act (MMPA), Migratory Bird Treaty Act (MBTA), and the Magnuson-

Stevens Fishery Conservation and Management Act (MSA), all require assessment of bycatch species under their respective purview (NMFS 2011, Moore et al. 2009, Martin et al. 2015). Under these mandates, the National Oceanic and Atmospheric Administration's National Marine Fisheries Service (hereafter "NOAA Fisheries") is charged with the management of sustainable fisheries activities. As well as sustainable fisheries management, these mandates also authorize the use of federal fisheries observer programs (video or in-person) and/or logbooks to record and quantify catch (target) and bycatch (non-target) data (NMFS 2011, Eguchi et al. 2017). Monitoring first began nationwide in 1972 and currently 47 federal fisheries in the United States are covered by observers (NMFS 2013). However, observer coverage among fisheries is not uniform, with levels ranging from 5-100% in part due to regulatory mandates. For partial observer coverage fisheries (<100%), observers are assigned using either a random vessel-selection method or trip-selection method. Observer coverage levels are impacted by available funding, the number of active participants in the fishery, fishing conditions, boat size and berth space, management needs, and program goals (NMFS 2013). Specifically in relation to marine mammal bycatch, NOAA Fisheries is required by section 118 of the MMPA to publish a yearly List of Fisheries (LOF) which reflects up-to-date information on interactions between United States commercial fisheries and marine mammals. Each fishery on the LOF is classified into a category (I, II, or III) based on the amount of incidental mortality or serious injury of marine mammals. The classification determines if participants in a fishery are required to comply with MMPA regulations, including registration, observer coverage and take reduction plan requirements. Under this regulation, category I and II fisheries are required to carry fisheries observers if requested by NOAA Fisheries (Federal Register 2018).

In 1998 a National Bycatch Plan was established to guide research and management of bycatch, and in 2011 the first United States National Bycatch Report was released. The report calculated that in 2005, 1.2 billion pounds of fish bycatch was recorded, with total landings of just over 6 billion pounds (NMFS 2011). However, bycatch extends beyond just fish. In a similar time period the United States National Bycatch Report estimated the following large marine vertebrates bycatch: 1,887 marine mammals, 11,772 sea turtles, and 7,769 seabirds (NMFS 2011). Although significantly smaller numbers than fish bycatch, bycatch of large marine vertebrates is of greater concern due to their ecosystem importance as well as being long-lived, slowly reproducing species (Read et al. 2006). In the United States, large marine vertebrates are

often characterized as protected species and not targeted by fishermen due to regulatory restrictions. Therefore, catch of these animals is extremely low. However, assessment of protected species by fisheries managers can be difficult due to factors such as limited data, poorly defined management objectives and lack of quantitative bycatch reduction targets (Amande et al. 2012, Moore et al. 2013). Variable fisheries observer coverage rates also contribute challenges in estimating the level of bycatch that avoids negative population impacts (Moore et al. 2013). Additionally, these estimates may have unacceptably low precision and severe bias, especially in single-year estimates (McCracken 2004, Amande et al. 2012, Moore et al. 2013, Carretta and Moore 2014, Martin et al. 2015).

The California drift gillnet fishery (hereafter “California DGN fishery”) targeting broadbill swordfish (*Xiphias gladius*) currently exists in the productive waters of the California Current within the United States exclusive economic zone (EEZ), primarily off the coast of California, although fishing effort has historically taken place as far north as Washington state. Commercial fishing for swordfish and pelagic sharks on the United States west coast began as a harpoon fishery in the early 1900s targeting sharks before changing to primarily drift gillnets for both species in the late 1970s, with the transition to primarily swordfish occurring in 1985 (Hanan et al. 1993). During the years the fishery existed along the entire West Coast, the DGN fleet moved up and down the coast relative to oceanographic conditions, swordfish abundance and weather. While water temperature was still warm in the late summer, fishing effort was strongest in waters off southern Oregon to central California, and as water temperatures cooled, effort shifted southward in the fall and early winter (Hanan et al. 1993, Sepulveda et al. 2018). Along with seasonal oceanographic conditions, fishermen also determine fishing grounds based on bathymetric features. Temperature, salinity and turbidity fronts, as well as banks and escarpments are typically productive areas that concentrate prey for swordfish. Nets are set perpendicular to these fronts at dusk and allowed to drift until retrieved at dawn. One iteration of this process is considered a ‘set’. Due to the seasonal migratory pattern of swordfish and implemented seasonal management measures over 90% of recent fishing effort has occurred from August 15 through January 31 (Hanan et al. 1993, PFMC 2016).

The California DGN fishery is regulated by the Pacific Fishery Management Council (PFMC) and NOAA Fisheries West Coast Regional Office with regulations regarding procedures and equipment under both State laws (time/area closures, limited entry, mesh size, logbooks) and

Federal regulations (net depth, pingers, observers). The West Coast Regional Office is responsible for coordinating and enacting regulations put forth by the PFMC. Together, the PFMC and the West Coast Regional Office are charged with meeting environmental mandates (e.g., the ESA, MMPA) while also managing for ecologically and economically viable fisheries. Mandatory gear standards include a maximum net length 1,829 m, with stretched mesh size no less than 35.6 cm. Beginning in 1997, acoustic pingers (to deter cetaceans) and 36-foot net extenders were required to be attached to all nets (PFMC 2011, NMFS 2016). Fisheries observers were implemented in the fishery beginning in 1990 and have had an average coverage rate of ~18% over a 25-year period (1990-2014). The fishery is managed as a limited entry permit system, with the permit tied to an individual rather than vessel (Hanan et al. 1993, PFMC 2016). When the limited entry system first opened, 150 permits were issued, and the number quickly rose to 251 permits by 1986. Currently, numbers hover around 50. The sharp decline in actively held permits is attributed to increasing regulations to protect marine mammals, endangered sea turtles, and seabirds (PFMC 2016).

Historically classified as a category I or II fishery in the LOF, bycatch, especially marine mammals has been a significant regulatory issue in the California DGN fishery (NMFS). The incidental catch of protected species in the fishery has resulted in repeated legal action and widespread fishery closures, in response to regulation under the ESA and MMPA. Beginning in 1982, the California DGN fishery has been closed inside the entire United States west coast EEZ from February 1<sup>st</sup> to April 30<sup>th</sup>. As the target catch shifted over to swordfish, a closure to conserve common thresher sharks (*Alopias vulpinus*) was established in 1986 within 75 miles of mainland California between May 1<sup>st</sup> to August 14<sup>th</sup>. Two of the most recent and expansive time-area closures were implemented in 2001 to protect endangered leatherback (*Dermochelys coriacea*) and Pacific loggerhead (*Caretta caretta*) sea turtles. The larger time-area closure (the Pacific Leatherback Conservation Area) covers 548,785 km<sup>2</sup> between August 15<sup>th</sup> to November 15<sup>th</sup> (Fig. 1). A smaller time-area closure off the coast of Southern California was implemented to protect Pacific loggerhead sea turtles during a forecasted or concurrent El Niño event from June 1<sup>st</sup> to August 31<sup>st</sup>. Since the Pacific Leatherback Conservation Area was enacted, fishing effort has greatly reduced. With fishing grounds shifting to primarily southern Californian waters, effort has declined from 78 vessels in 2000 to 40 in 2004, and has remained under 50 vessels since then, with many boats not operating despite holding active permits (Federal



Register 2001, PFMC 2012).

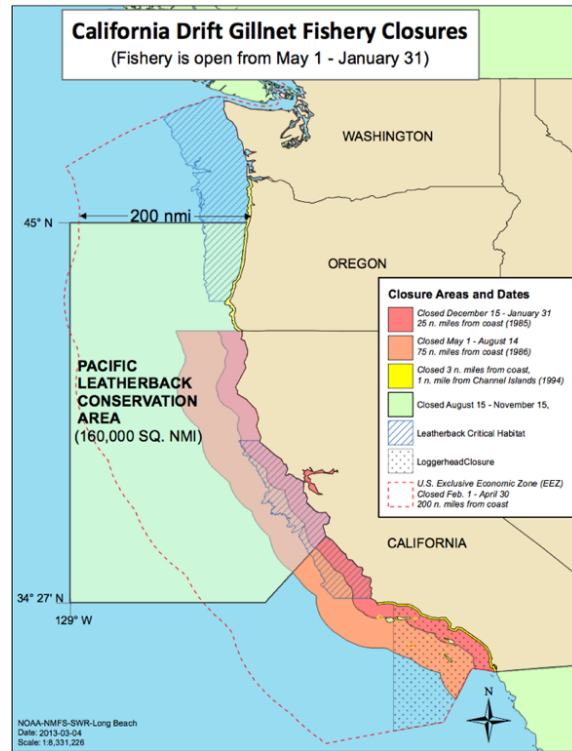


FIG. 1. Current time-area closures that are closed to fishing in the California drift gillnet fishery.  
Credit: NOAA

Although bycatch reduction measures in the fishery have greatly reduced the catch of non-target species (Carretta et al. 2017), the PFMC is still considering whether protected species mandates can be achieved while also reducing closures because of the negative economic impact closures are having on fishermen. In 2015, the PFMC recommended the implementation of “hard caps” in the California DGN fishery for five marine mammal species and four sea turtle species, all considered high priority protected species (HPPS). This regulation included a 2-year rolling period where individual caps would be established for the nine HPPS, and if any of the caps were reached the fishery would be shut down for the remainder of the year (NOAA 2001, PFMC

2012, NMFS 2015, PFMC 2016). Following the recommendation by the PFMC, NOAA Fisheries proposed the “hard caps” rule in 2016 and released a draft Environmental Assessment (EA), an Initial Regulatory Flexibility Analysis, and draft Regulatory Impact Review (RIR) and an ensuing public comment period. However, after the comment period closed and a final EA, Final Regulatory Flexibility Analysis, and final RIR were completed, NOAA Fisheries decided the proposed changes were not warranted and withdrew the rule in June 2017 (Federal Register 2001, 2017). The PFMC has also has set a goal of 100% observer coverage by 2018, whether by human observers or electronic monitoring (Federal Register 2001, PFMC 2012, NMFS 2015, PFMC 2016).

In the field of fisheries, bycatch of large marine vertebrates such as sea turtles, marine mammals, and seabirds are often considered rare-events (McCracken 2004). These events play an important but challenging role in ecological sciences, including in the management of protected species bycatch. Rare-events often are significant in a management or ecological context because they alter decision making or significantly affect populations despite low numbers, but discerning trends is usually difficult due to low sample sizes (Dixon et al. 2005). In relation to bycatch, rare events are significant to decision making because many of the bycatch species are protected species and thus necessitate legal action as stipulated by the ESA or MMPA (Moore et al. 2009). Protected species bycatch (e.g. marine mammals, sea turtles) in the California DGN fishery is considered a rare event because these are non-target species and thus catch of these species occur less than the target catch, swordfish. However, due to their life history and ecosystem function, bycatch of protected species are extremely problematic and must be mitigated.

In ecology, rare-event data are often in the form of binary presence/absence, counts of abundance, proportional occupancy rates or continuous population densities. In the case of presence/absence data especially, data sets are often defined by a large proportion of zero values, and often referred to as “zero-inflated” (Martin et al. 2005). A large number of zeros typically occur in ecological data sets for two reasons and are known as “true” and “false” zeros. “True zeros” arise due to the “real ecological effect of interest” (e.g. sampling a rare species, species was not present because of ecological processes or species does not inhabit entire suitable habitat by chance), and “false zeros” typically can occur due to non-detection when the species is in fact present or because of sampling errors during data collection (Cunningham and Lindenmayer

2005, Martin et al. 2005). Both types of “false zeros” need to be accounted for in analysis because failure to do so can cause bias in parameter estimates, however “true zeros” are of ecological importance because they contain information about species (e.g. species-environment relationships, habitat suitability and availability as well as preferences and distributions) (Martin et al. 2005, Lewin et al. 2010).

Fisheries data, especially catch and effort databases can have records of zero catch even though effort has occurred. This can particularly be true for less abundant species or bycatch species (Maunder and Punt 2004). Due to the large number of zeroes, a zero-inflated data set can lead to incorrect inferences if not modeled properly and also invalidate assumptions because the response variable contains more zeros than expected based on conventional statistical distributions (Maunder and Punt 2004, Cunningham and Lindenmayer 2005, Martin et al. 2005, Zuur et al. 2009, Webley et al. 2011). Historically, approaches to deal with additional zeros have included simply ignoring, eliminating, or grouping zero observations, as well as replacing the zeros with a small number, either by substitution or adding a constant (Maunder and Punt 2004). These approaches are very specific to a research question and cannot be widely applied; ignoring zeroes are only appropriate if a sampling malfunction (e.g. gear failure) could have led to the observed zero, grouping observations can be done if records are similar (e.g. same trip; daily into month), however grouping may result in a bias and/or loss of resolution, and taking the approach of replacing the zero or adding a small number must be taken with particular care (see Maunder and Punt 2004 for detailed explanation) but may not be appropriate as the model may be sensitive to the constant (Maunder and Punt 2004). However, these options may not be suitable for the goal of the analysis, and other methods that can handle zero observations must be used. One method is to model the zero-inflated variable that represents the probability a zero can come from using a zero-inflated distribution such as the zero-inflated Poisson (ZIP) distribution or the zero-inflated negative binomial (ZINB) distribution. Both distributions work with count data but ZIP models perform better when data is not overdispersed, while ZINB models function better when data is overdispersed (UCLA: Statistical Consulting Group). Another method is the use hurdle models where the zero and non-zero data are modeled with one model, and the count data are modeled with another. This method models the zero/non-zero data and count data as two different processes, allowing for different predictors to be used if one hypothesizes that one process leads to the zero/non-zero data and another leads to the amount of the non-zero data

(Dalrymple et al. 2003). When selecting the model type for zero-inflated data, the type of data (e.g. continuous, discrete) being analyzed is usually the determining factor. Continuous count data is often the more common data type, especially in fisheries where catch data is recorded as counts of individuals (Maunder and Punt 2004). Count data is most commonly modeled using a Poisson or negative binomial distribution. Both of these distributions assume the proportion of zeros is related to the non-zero values (i.e. a closed system where the catch of target and non-target species is not affected by outside processes) (Maunder and Punt 2004). However, in ecology this is unrealistic and zero-inflated distributions must be used. Both ZIP and ZINB assume the processes leading to zeros and non-zeros may not be the same (Maunder and Punt 2004). An extension of a Poisson distribution known as a Tweedie error distribution has also been successfully used to model continuous count data (Becker et al. 2016). This approach accounts for overdispersion in the response variable through a flexible parameterization technique that uses a Poisson-gamma distribution (Shono 2008, Miller et al. 2013, Scales et al. 2017b). Although becoming more frequent in the field of ecology, zero-inflated models have been primarily used in the social sciences, economics, etc. (Zuur et al. 2009). However, these models are best suited to model continuous count data, rather than discrete binary data sets. Binary data is usually modeled using a binomial distribution (Maunder and Punt 2004), but existing statistical modeling approaches do not handle zero-inflated binomial data well, and thus no one method is readily used. This problem is especially magnified as zero-inflated data sets often deal with rare-events when sample sizes may not be especially high which can lead to poor predictive power and under- or overestimation. Bycatch data from a fisheries observer dataset can often be characterized as zero-inflated and rare-event data because bycatch is a non-target species and thus infrequently caught. Zeros in this case would be ‘true zeros’ and would be due to a “real ecological effect of interest” such as a dynamic oceanographic environment, which may influence species distribution.

The California Current System (CCS), which stretches from British Columbia to Baja, is a seasonally dynamic region which carries cold water south and is strongly affected by El Niño events and the Pacific Decadal Oscillation (Lynn and Simpson 1987, Sherman and Hempel 2008, Fautin et al. 2010). Due to the physical size and dynamic environment of the CCS, the near-shore region can be divided into three distinct zones (NOAA 1988, Fautin et al. 2010). The northern and central zone, are characterized by physical and ecological processes (e.g. water temperature,

upwelling, freshwater inputs, bathymetry) (NOAA 1988, Fautin et al. 2010). Due to the orientation of the California coast, the CCS is further offshore in the southern zone, in an area known as the Southern California Bight. This area is a transition zone, where the warmer waters of the northern flowing Davidson Current and colder waters of the southern flowing CCS meet (NOAA 1988, Fautin et al. 2010). The Southern California Bight is an area of high species diversity, as it is the extreme limit of the range for many marine species (Fautin et al. 2010). Although certain regions of the CCS have stronger individual physical and ecological influences on species assemblage than others, a total of 38 marine mammals, 92 seabirds, and 912 fishes have been recorded in the entire CCS (Fautin et al. 2010). Along with an overall high species diversity, a wide group of marine vertebrates use the CCS for important parts of their life history (migration, foraging and breeding) (Block et al. 2011). TOPP tracked seven top-predator guilds (sharks, tunas, albatrosses, shearwaters, turtles, pinnipeds and rorqual whales) from 2000-2009 and found that many of these long-lived, K selected species use the CCS for seasonal north-south migrations, residency and foraging that may be “driven by oceanic processes, species-specific thermal tolerances and shifts in prey distributions” (Block et al. 2011). Additionally, many tagging and modeling studies have found marine vertebrates in the CCS to have pronounced spatial overlap (Barlow et al. 2009, Becker et al. 2012a, Feist et al. 2015, Hazen et al. 2017). Although teeming with marine life at all times of the year due to wide-ranging and diverse physical and ecological processes, these factors that congregate many species in the CCS can also increase their vulnerability to anthropogenic threats and extinction risk due to their life history traits (Halpern et al. 2009, Teck et al. 2010, Davidson et al. 2012, Feist et al. 2015).

Historically, spatial management of the ocean has largely revolved around regions with fixed management boundaries. However, the ocean is a dynamic environment where species and users move across boundaries. Dynamic ocean management (DOM) is method to conserve biodiversity for a healthy marine ecosystem while balancing anthropogenic threats (e.g. marine resource extraction and climate change), while being able to move in time and space to adeptly adapt to the shifting nature of the ocean and its users (Hobday et al. 2013, Lewison et al. 2015, Maxwell et al. 2015, Dunn et al. 2016). This management approach integrates biological, ecological, environmental, and socioeconomic data collected over multiple spatiotemporal scales (Scales et al. 2017b). This management approach is able to guide marine policy in areas where potentially harmful anthropogenic activities occur that also exhibit substantial temporal and

spatial variability in response to both oceanography and in the distribution of marine species (Becker et al. 2016). DOM is an efficient management approach that has shown increasing applicability in managing highly migratory and protected species (Maxwell et al. 2015), promoting fisheries sustainability (Howell et al. 2008, Hobday et al. 2010, Dunn et al. 2016). In a fishery such as the California DGN fishery which combines a dynamic physical environment with complex movement of target and non-target species and a non-discriminatory fishing method, a DOM approach that would bring near-real-time data to managers and users has potential to reduce bycatch, increase target catch and prepare the fishery for distribution changes from climate change.

Dynamic ocean management hinges on the ability to relate data on the physical environment of the ocean with the distribution of marine species in order predict key habitats, identify productive fishing grounds, and track how species shift through time (Hobday et al. 2013, Scales et al. 2017b). Species distribution models (SDMs) have become an increasingly common approach to gain insight on the distribution and environmental preferences of species (Elith and Leathwick 2009, Robinson et al. 2011). They combine observations of species occurrence or abundance with environmental data. SDMs have proven to be an effective tool primarily in the terrestrial realm but have been increasingly used to inform conservation planning, climate change adaptation, biosecurity (species invasion and disease), and testing principles of theoretical ecology in the marine environment (Robinson et al. 2011, Becker et al. 2012a, Becker et al. 2016, Scales et al. 2017a). Species occurrence and abundance records for marine SDMs can be obtained from systematic shipboard surveys, biologging sources, fisheries observer records and acoustic monitoring sources (Scales et al. 2017b). In the marine realm the spatial ecology of species is influenced by both static (e.g. depth) and dynamic (e.g. sea surface temperature) factors, at varying spatiotemporal scales (Redfern et al. 2006, Robinson et al. 2011, Becker et al. 2012b, Scales et al. 2017a). In order to explore these environmental drivers, a wide range of corresponding environmental data sources exist. Depending on spatiotemporal scale, SDMs can incorporate in situ measurements, satellite remotely sensed data, and more recently data assimilative ocean circulation models (Scales et al. 2017b). Remotely-sensed satellite data provides broad spatial coverage and are as effective at capturing species-environmental relationships as in situ data (Becker et al. 2016). However, remotely sensed satellite data has limitations; data gaps are present due to cloud cover, spatial and temporal resolution is not

uniform for all products and data can only be used for short-term forecasts (Becker et al. 2012a, Becker et al. 2016). Assimilative oceanographic models are increasingly being used in SDMs because they overcome some of the limitations of remotely sensed data (e.g. cloud cover, varying spatial and temporal resolution and coverage, surface measurements) (Becker et al. 2016, Scales et al. 2017a). Along with providing high-resolution data on the horizontal structure of the ocean, ocean circulation models provide spatiotemporal resolution of the vertical structure of the ocean, which has been shown to improve the accuracy of predictions in SDMs. With continued development of these modeled products, ocean circulation models are adept at overcoming the limitations of satellite data and have become increasingly used in SDM construction of broad-scale predictions of dynamic species distributions in near real time. (Becker et al. 2016, Scales et al. 2017a, Scales et al. 2017b, S. Brodie, personal communication, 2018).

The goal of this study is to explore the influence of the physical marine environment on the bycatch probability of cetacean species in the California DGN fishery using SDMs to inform a dynamic management tool, as well as other potential applications (e.g. marine spatial planning, Navy testing). To accomplish this we answered four questions (two ecological, and two statistical): 1) what are the physical drivers of cetacean bycatch in the California DGN fishery, and are they different than drivers of the target catch, swordfish; 2) how do habitat predictions compare to the ecology and known probability of these cetacean species; 3) how would the large proportion of zeros (absences) impact the model building process and performance of models; and 4) how small of a sample size would still yield an accurate model? Using presence-absence catch data for the four most common cetacean species caught as bycatch in the California DGN fishery, we used a robust parameterization process and multi-pronged model assessment approach to create habitat models using a data-assimilative ocean circulation model and compared the results to predictions of the target catch (Scales et al. 2017b, S. Brodie, personal communication, 2018) and to cetacean density predictions based off ship survey data (Becker et al. 2016). By determining where fisheries interactions are most likely to occur, we can integrate cetacean models to an existing dynamic management framework and move towards near-real-time fisheries management to reduce bycatch while still allowing fishermen to meet their quotas.

## METHODS

### *Fisheries Observer Data*

Fisheries-observer data for the California DGN fishery were obtained from the Southwest Fisheries Science Center (National Marine Fisheries Service, National Oceanographic and Atmospheric Administration). Fisheries' observer coverage began in 1990 and has averaged approximately 18% coverage through 2014 with 1,519 fishing trips observed and within those trips, 8,681 sets were observed (Fig. 2). Observer data covered a 25-year period (1990-2014) and included trip number, set number, set location, target and non-target catch, and soak time. Each trip in the California DGN fishery lasts approximately 10 days and consists of an average of 4-5 individual sets per trip. A "set" is the process of deploying the drift gillnet at dusk and hauling it back at dawn.

The catch and bycatch of the California DGN fishery includes many fishes (e.g. swordfish, bluefin tuna *Thunnus orientalis*, opah *Lampris regius*, sunfish *Mola mola*) and sharks (e.g. shortfin mako *Isurus oxyrinchus*, common thresher, blue *Prionace glauca*) as well as many protected species such as sea turtles (e.g. leatherback, loggerhead), cetaceans (e.g. baleen whales *Balaenoptera sp.*, common dolphins *Delphinus sp.*, beaked whales *Ziphiidae sp.*) and pinnipeds (e.g. California sea lions *Zalophus californianus*, northern elephant seals *Mirounga angustirostris*). Of all observed sets, there were 1,103 individual records of protected species bycatch, 677 of which were cetaceans of 26 different species. Cetacean species caught as bycatch are summarized in Table 1. For modeling purposes, the observer dataset was separated into presence/absence records for each individual cetacean species, as the bycatch of multiple individuals of the same species within a single set was rare.

### *Predictor Variables*

Dynamic Environmental Variables – To capture the physical environment, 12 dynamic environmental variables were extracted from daily fields of the California Current System (CCS) configuration of the Regional Ocean Modeling System (ROMS) (Table 2) (<http://oceanmodeling.ucsc.edu/ccsrt>, Neveu et al. 2016). ROMS variables were extracted at matching time and space for each set and were chosen over remotely-sensed data as the source of



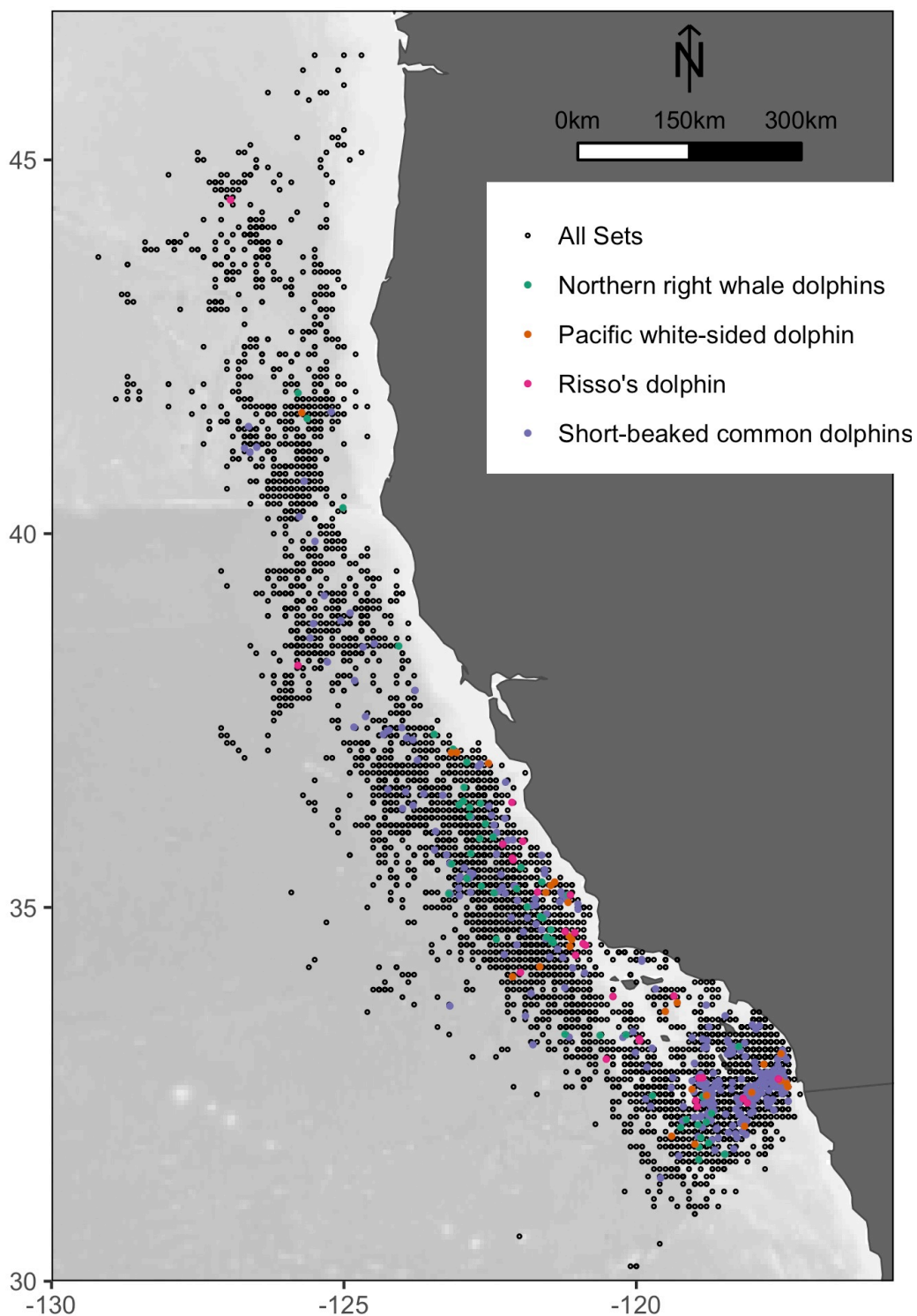


FIG. 2. Study area off the United States west coast. Location of observed fishing sets (black hollow points,  $n=8,681$ ) and cetacean bycatch events between 1990-2014: short-beaked common dolphins (purple points,  $n=309$ ), northern right whale dolphins (green points,  $n=54$ ), Risso's dolphins (pink points,  $n=27$ ), and Pacific white-sided dolphins (orange points,  $n=26$ ). Base map shows bathymetric features, shallower areas are denoted as lighter colors. Latitude and longitude of observed fishing sets has been rounded to one decimal place to comply with the signed non-disclosure agreement associated with this data.

TABLE 1. Total count (includes records when multiple of the same species were caught in the same set) of cetacean species bycatch as recorded by fisheries observers in the California drift gillnet fishery between 1990-2014.

Family	Common name	Scientific name	Count	IUCN designation
Balaenopteridae	Whale, Minke	<i>Balaenoptera acutorostrata</i>	4	Least Concern
Ziphiidae	Beaked Whale, Baird's	<i>Berardius bairdii</i>	1	Data Deficient
Balaenopteridae	Whale, Fin	<i>Balaenoptera physalus</i>	1	Endangered
Delphinidae	Dolphin, Unidentified Common	<i>Delphinus sp.</i>	21	NA
Delphinidae	Dolphin, Long-Beaked Common	<i>Delphinus capensis</i>	22	Data Deficient
Delphinidae	Dolphin, Short-Beaked Common	<i>Delphinus delphis</i>	385	Least Concern
Eschrichtidae	Whale, Gray	<i>Eschrichtius robustus</i>	4	Least Concern
Delphinidae	Dolphin, Risso's	<i>Grampus griseus</i>	35	Least Concern
Delphinidae	Whale, Short-finned Pilot	<i>Globicephala macrorhynchus</i>	14	Data Deficient
Physeteridae	Whale, Pygmy Sperm	<i>Kogia breviceps</i>	2	Data Deficient
Delphinidae	Dolphin, Northern Right Whale	<i>Lissodelphis borealis</i>	73	Least Concern
Delphinidae	Dolphin, Pacific White-sided	<i>Lagenorhynchus obliquidens</i>	36	Least Concern
Ziphiidae	Beaked Whale, Hubbs'	<i>Mesoplodon carlhubbsi</i>	5	Data Deficient
Balaenopteridae	Whale, Humpback	<i>Megaptera novaeangliae</i>	3	Least Concern
Ziphiidae	Beaked Whale, Stejneger's	<i>Mesoplodon stejnegeri</i>	1	Data Deficient
Delphinidae	Whale, Killer	<i>Orcinus orca</i>	1	Data Deficient
Phocoenidae	Porpoise, Dall's	<i>Phocoenoides dalli</i>	23	Least Concern
Physeteridae	Whale, Sperm	<i>Physeter macrocephalus</i>	10	Vulnerable
Delphinidae	Dolphin, Striped	<i>Stenella coeruleoalba</i>	1	Least Concern
Delphinidae	Dolphin, Bottlenose	<i>Tursiops truncatus</i>	4	Least Concern
Cetacea	Cetacean, Unidentified	<i>Cetacea</i>	2	NA
Delphinidae	Dolphin, Unidentified	<i>Delphinidae</i>	1	NA
Ziphiidae	Beaked Whale, Mesoplodont	<i>Mesoplodon sp.</i>	2	NA
Cetacean	Whale, Unidentified	<i>Cetacean whale</i>	2	NA
Ziphiidae	Beaked Whale, Cuviers	<i>Ziphius cavirostris</i>	21	Least Concern
Ziphiidae	Beaked Whale, Unidentified	<i>Ziphiidae</i>	3	NA

environmental data due to their coverage, resolution, and availability. The CCS ROMS configuration covers coastal waters to approximately 1000 km offshore (from the coast to 134°W) and extends from the Canadian border in the north to midway down the Baja Peninsula in the south (30° to 48°N), with a 0.1° (~10km) horizontal resolution and 42 vertical layers (Veneziani et al. 2009). In order to temporally cover the entire 25-year observer dataset, two ROMS datasets were combined: daily outputs of the 31-yr (1980-2010) historical reanalysis (Neveu et al. 2016) were combined with a near real-time (NRT) product (2010-present). Both ROMS datasets were compared to confirm consistency between variables. A correction factor was applied to the NRT variable of sea surface height (SSH) (+0.035 m) for continuity between both datasets (Scales et al. 2017b).

Many of the 12 dynamic variables chosen have been widely used in SDMs and were also considered for their relevance to cetacean distributions and fishery interactions (Soykan et al. 2014, Feist et al. 2015, Becker et al. 2016). These variables are believed to represent the biophysical environment that is responsible for the distribution of large marine vertebrates, and likely their prey. Additionally, some variables may act as proxies for unmeasured or unknown environmental factors, furthermore, distributions of these wide-ranging species may also be explained by other factors which are unknown (Reisinger et al. 2018). ROMS assimilates measured data from satellites and in-situ sources (ships, gliders, buoys...etc.) with the physical model to create cloud-free layers (Scales et al. 2017b). The modeled product allows a continuous three-dimensional view of the ocean and enables the use of water column variables such as Brunt-Väisälä frequency (BV) and isothermal layer depth (ILD). Inclusion of dynamic subsurface ROMS variables in SDMs have shown to improve model explanatory power and model predictive performance (S. Brodie, personal communication, 2018). ILD represents the depth of surface mixing and was established as the depth that was 0.5°C cooler than the sea surface temperature (Monterey and Levitus 1997). BV is indicative of upper water column stability and was averaged over the upper 200m of the water column (S. Brodie, personal communication, 2018). The standard deviation of SST and SSH, both proxies for mesoscale variability (fronts and eddies), were calculated over a 0.3° square (S. Brodie, personal communication, 2018). Eddy kinetic energy (EKE), another indicator of mesoscale variability was calculated from surface eastward (SU) and northward (SV) currents as:

$$EKE = \frac{1}{2} * (SU^2 + SV^2)$$

EKE was highly right skewed and was log transformed (Aviso altimetry, S. Brodie, personal communication, 2018).

TABLE 2. Regional Ocean Modeling System (ROMS) environmental variables used as predictors in species distribution models for cetacean bycatch species in the California drift gillnet fishery.

Description/Variable	Type	Unit	Spatial resolution	Temporal resolution	Source
Sea Surface Temperature (SST)	Dynamic	°C	0.1°	Daily	<a href="http://oceanmodeling.ucsc.edu/index.html">http://oceanmodeling.ucsc.edu/index.html</a>
Sea Surface Height (SSH)	Dynamic	m	0.1°	Daily	<a href="http://oceanmodeling.ucsc.edu/index.html">http://oceanmodeling.ucsc.edu/index.html</a>
Surface eastward velocity (SU)	Dynamic	ms <sup>-1</sup>	0.1°	Daily	<a href="http://oceanmodeling.ucsc.edu/index.html">http://oceanmodeling.ucsc.edu/index.html</a>
Surface eastward wind stress (SUSTR)	Dynamic	ms <sup>-1</sup>	0.1°	Daily	<a href="http://oceanmodeling.ucsc.edu/index.html">http://oceanmodeling.ucsc.edu/index.html</a>
Surface northward velocity (SV)	Dynamic	ms <sup>-1</sup>	0.1°	Daily	<a href="http://oceanmodeling.ucsc.edu/index.html">http://oceanmodeling.ucsc.edu/index.html</a>
Surface northward wind stress (SVSTR)	Dynamic	ms <sup>-1</sup>	0.1°	Daily	<a href="http://oceanmodeling.ucsc.edu/index.html">http://oceanmodeling.ucsc.edu/index.html</a>
Isothermal Layer Depth (ILD)	Dynamic	m	0.1°	Daily	<a href="http://oceanmodeling.ucsc.edu/index.html">http://oceanmodeling.ucsc.edu/index.html</a>
Brunt-Väisälä frequency (BV)	Dynamic	s <sup>-1</sup>	0.1°	Daily	<a href="http://oceanmodeling.ucsc.edu/index.html">http://oceanmodeling.ucsc.edu/index.html</a>
Wind stress curl (Curl)	Dynamic	Nm <sup>-2</sup>	0.5°	Daily	<a href="http://oceanmodeling.ucsc.edu/index.html">http://oceanmodeling.ucsc.edu/index.html</a>
Lunar illumination (Lunar)	Dynamic	%	0.1°	Daily	Lunar package for R (Lazaridis 2014)
Natural log of Eddy Kinetic Energy (EKE)	Dynamic	m <sup>2</sup> s <sup>-2</sup>	0.1°	Daily	Derived from zonal (su) and meridional (sv) geostrophic currents
Standard deviation of Sea Surface Temperature (SST_SD)	Dynamic	°C	0.3°	Daily	Calculated over a 0.3° square
Standard deviation of Sea Surface Height (SSH_SD)	Dynamic	m	0.3°	Daily	Calculated over a 0.3° square
Latitude (Lat)	Static	°N	native data resolution	-	-
Bathymetry (Z)	Static	m	0.1°	-	<a href="https://www.ngdc.noaa.gov/mgg/global/global.html">https://www.ngdc.noaa.gov/mgg/global/global.html</a>
Rugosity (Z_SD)	Static	z	0.3°	-	Calculated over a 0.3° square

*Static Variables* – In addition to the 12 dynamic variables, four static variables were also included in the habitat models (Table 2). Bathymetry was obtained at 0.1° resolution from ETOPO1 (Amante & Eakins, 2009; <https://www.ngdc.noaa.gov/mgg/global/global.html>). Rugosity (standard deviation of bathymetry) was calculated over a 0.3° square (S. Brodie, personal communication, 2018). To understand the drivers of fishery interaction, the proportion of lunar illumination ('lunar' package for R; Lazaridis 2014) corresponding to each set date was included as a predictor as swordfish, the target species of the California DGN fishery, are thought to respond their use of the water column to changing light conditions (Dewar et al. 2011). Latitude was also included as a predictor to account for unexplained spatial variance. Values for all static variables were extracted at matching time and space for each set location.

### *Species Distribution Models*

Probability of bycatch probability was assessed by modeling the relationship between cetacean bycatch events in the California DGN fishery and environmental predictors using boosted regression trees (BRTs). BRTs were fit using the 'gbm' (v.2.1.3) (Ridgeway 2017), and 'dismo' (v.1.1-4) (Hijmans et al. 2017) packages, following Elith et al. (2008) and Soykan et al. (2014). BRTs operate using machine-learning principles where many simple models are fit and combined for prediction. This is accomplished through two components: (1) decision tree algorithms are used to partition the predictors into similar response groupings and (2) boosting algorithms aim to improve predictive performance by adaptively combining decision trees (Elith et al. 2008). This ensemble method allows BRTs to be able to fit complex interactions between predictors and also have advantages over traditional regression methods in that BRTs are able to accommodate different types of predictor variables, missing values, outliers, collinearity and non-independence, and the inclusion of irrelevant predictors (De'ath and Fabricius 2000, Leathwick et al. 2006, De'ath 2007, Elith et al. 2008). Although no clear modeling framework was identified that could handle the binomial zero-inflated dataset, BRTs were favored over more commonly used additive regression techniques (e.g., generalized additive models) because of their flexibility to model the hypothesized complex interactions leading to cetacean bycatch in

the California DGN fishery. All data processing and analyses were carried out using R statistical computing (R 3.4.1; R Core Team 2013).

### *Subsetting And Parameter Selection*

The California DGN fishery observer dataset posed two main statistical questions, 1) how would the large proportion of zeros (absences) impact model building and performance, and 2) how small of a cetacean species presence number would still yield an accurate model. Initial data exploration was performed using the most abundant species in the dataset (short-beaked common dolphin,  $n=309$  presences) to understand the influence zero-inflation would have on the modeling process. When using presence-absence data for SDMs, Barbet-Massin et al. (2012) found that using the same number of pseudo-absences as available presences yielded the greatest predictive performance for machine-learning techniques. Building off this recommendation, we used 1:1 subsets of real absences relative to the number of presences, however because some presence sample sizes in the observer dataset were small we explored other subset ratios (2:1, 3:1...) as well as building models with the full set of absences. This method of subsetting would potentially improve the bycatch signal and reduce the size of a relatively large dataset and computing time which is a consideration during model building. During initial data exploration with the short-beaked common dolphin dataset, a 1:1 subset was found to have the strongest predictive metrics for this species. The 1:1 subset represents approximately 3.6% of absences relative to presences for short-beaked common dolphins; for the remaining species we used this number as a guide and started subsetting at numbers which would achieve approximately 3.6% of absences. The subsets were evaluated using three criteria: 1) we determined mean Area Under the receiver operating Curve (AUC) and deviance over 10 model iterations, 2) we ensured that all 10 models grew to at least 1000 trees, and 3) we ensured all 10 models converged. Parameterization of a BRT requires the tuning of the learning rate ( $lr$ ), tree complexity ( $tc$ ), and bag fraction ( $bf$ ), as well as the number of trees ( $ntrees$ ). For each subset of absences, a group of 90 candidate models with different parameter combinations were compiled (Table 3). All presence-absence models were built using a binomial (Bernoulli) distribution, and followed the model optimization procedures and tree optimization (`gbm.step`) as in Elith et al. (2008). This procedure uses 10-fold cross-validation (CV) to iteratively find the optimal number of trees relative to a fixed combination of BRT parameters. Finding the optimal model parameters is an

important component of BRT regularization in order to avoid overfitting (Elith et al. 2008). Model performance for each candidate model was assessed by comparing the average AUC score and average proportion of deviance explained over 10 iterations (Barbet-Massin et al. 2012). Parameter combinations were only considered if they grew the model to at least 1000 trees (Elith et al. 2008). Although not all parameter combinations converged, a total of 90 possible candidate models were tested for each subset.

TABLE 3. BRT tuning parameters tested for all cetacean species.

Modeling approach	Tuning parameters	Values
Boosted regression tree	Tree complexity (TC)	1, 2, 3, 4, 5
	Learning rate (LR)	0.05, 0.01, 0.005, 0.001, 0.0005, 0.0001
	Bag fraction (BF)	0.5, 0.6, 0.75
	Number of trees (ntrees)	1-15,000

The same candidate models for each subset were compared and the subset that produced models with the highest average AUC and deviance values was chosen. After the subset ratio was determined, the candidate model with the highest average AUC and deviance values that converged to at least 1000 trees over all 10 iterations was chosen as the parameter combination for the final BRT model.

To ascertain the model stability within each species dataset, a sensitivity analysis was undertaken using the set of parameters determined using the procedure above. Using this fixed set of parameters, a BRT was fit using a random selection of absences of the given subset ratio. This process was repeated 50 times, each time with a new random selection of absences. The number of trees, AUC and deviance values were recorded for each model run and the mean and standard deviation were calculated. If 90% (n=45) of all 50 model iterations converged, we assumed the parameter combination and dataset were stable enough to model the species bycatch probability.

### *Boosted Regression Tree Model Output*

Because the goal of this study was to predict bycatch probability in near real-time, and also support fisheries management, it was necessary to understand how accurate our predictions were in general, but also how the model is performing for predicting presences versus absences. To accomplish this, six metrics were used to evaluate model performance: (1) percent deviance explained; (2) AUC; (3) 75/25 cross validation; (4) True Skill Statistic (TSS); (5) false positive error rate; and (6) false negative error rate. Percent deviance explained is the proportion of variation explained by the model and is similar to the  $R^2$  value used in regression analysis. AUC is a threshold independent measure of model accuracy, a value of 1 would mean the model is predicting perfectly and a value of 0.5 would mean the model is predicting no better than chance (Fielding and Bell 1997). Araújo et al. (2005) recommends interpreting AUC values as: excellent  $AUC > 0.90$ ; good  $0.80 > AUC < 0.90$ ; fair  $0.70 > AUC < 0.80$ ; poor  $0.60 > AUC < 0.70$ ; fail  $0.50 > AUC < 0.60$ . An AUC value of  $>0.75$  is considered to be appropriate for conservation applications (Pearce and Ferrier 2000). To assess predictive capability of the models, 75/25 cross validation was performed where 75% of the dataset is randomly selected to run a training model, then the results are compared against the remaining 25% of the data. Ten iterations using different sets of randomly selected data were run. A confusion matrix was constructed using the confusionMatrix function from the 'caret' package (v. 6.0-77) (Kuhn et al. 2017) to calculate the TSS, false positive and negative error rates. TSS is a threshold dependent measure used in presence-absence predictions that assesses the overall accuracy of the predictive model. Values range from -1 to +1, where +1 indicates perfect accuracy and values of 0 or less indicate accuracy is no better than random (Allouche et al. 2006). Both TSS and AUC have been widely used in SDM evaluation, and the threshold dependent and independent approaches are often used in combination to evaluate predictive power (Elith et al. 2006b). TSS is the sum of sensitivity and specificity minus 1 ( $TSS = sensitivity + specificity - 1$ ). Sensitivity is the proportion of correctly predicted presences, and specificity is the proportion of correctly predicted absences. False positive error rate is the proportion of predicted bycatch that actually have zero reported bycatch, and is calculated by  $1 - sensitivity$ , and the false negative error rate is the proportion of zero predicted bycatch occurrence that actually have bycatch and is calculated by  $1 - specificity$



(Allouche et al. 2006). Binary transformations were performed using the threshold that minimized the difference between sensitivity and specificity. This threshold was found to produce the most accurate predictions and did not have an effect when used with rare species data, unlike the sensitivity – specificity sum maximizer (Manel et al. 2001, Jiménez-Valverde and Lobo 2007, Liu et al. 2011). Thresholds were calculated for each species using the ‘PresenceAbsence’ (v. 1.1.9) package (Freeman 2012).

To aid in understanding which predictor variables were important in predicting fishery interaction, variable importance (VI) scores were used (Soykan et al. 2014). Although relative, VI scores show the influence of each predictor variable used in the model. A random number (0-100) was also added as a predictor in the model fitting process to determine which predictors in the model were more important to fishery interaction than random (Soykan et al. 2014). Variable contributions were recorded during the 50-run sensitivity analysis and averaged to determine the final order of predictors based on relative influence. Variables that contributed less to the model than the random number were removed as a means to simplify the predictor set and avoid model overfitting. Partial dependence plots were also calculated for each predictor variable using the ‘pdp’ (v. 0.6 0) package (Greenwell 2017).

This approach of using multiple metrics to determine SDM performance was conceived in order to be able to fully assess how well models were performing in a rather extreme modeling situation: predicting probability of dynamic species using zero-inflated presence-absence data. Deviance explained (%) provides a metric of how well the model explains the data, while AUC, TSS, false positive error rate and false negative error rate are used to understand how well the model is performing at predicting presence/absence. All validation metrics were calculated as the average of 10 model iterations; with each iteration being unique because of the stochastic element of the bag fraction, which allows a random selection of data to each tree in the model building process.

### *Model Predictions*

Bycatch probability predictions were generated for each cetacean species SDM over a fall climatology (September, October November, December) of the whole 25-year observer dataset. SDMs were also used for three example days, 1 December 2005, 1 December 2012 and 1 December 2015, these days represent scenarios where upwelling was delayed, a neutral year and

a strong El Niño influence respectively. To estimate the uncertainty in the models of bycatch probability, standard deviation in daily predictions was calculated.

## RESULTS

Due to concerns in the fitting, validation and prediction phase of the Risso's and Pacific white-sided dolphin models, spatial predictions nor variable response curves will be described for these species. However, model results for both species as well as short-beaked common dolphin and northern right whale dolphin are presented below.

### *BRT Model Performance*

Throughout the 25-year time-period of the California DGN fishery observer dataset, fishing effort (number of sets) and distribution of effort both varied. Effort reduced over time and the distribution of effort mostly concentrated off the Central and Southern coasts of California over time (Fig. 2). The four most common cetacean species caught as bycatch were chosen for model building, with varying degrees of success in predictions. Short-beaked common dolphin (*Delphinus delphis*, n=309, Fig. 2) bycatch represented 3.55% of the total sets and a 1:1 ratio of absences to presences was found to produce the model with the best explanatory power and predictive performance (mean AUC and deviance over 10 runs) as well as being the most efficient subset computationally. All models converged and produced similar AUC and % deviance explained (AUC=  $0.90 \pm 0.02$ , % deviance explained =  $22.00 \pm 4.75$ ) during the 50-run sensitivity analysis for the 1:1 subset indicating the absence ratio was representative of the entire dataset and the subset dataset was stable. Higher ratios of absences relative to presences (e.g. 2:1, 3:1...etc.) showed a decrease in predictive capability as well as an increase in computing time. The fitted short-beaked common dolphin BRT showed good ability to predict bycatch occurrence, with an AUC value of  $0.89 \pm 0.01$  and explaining  $22.63\% \pm 1.74$  of the deviance in the data (Table 4). Using a 0.49 threshold, determined using the sensitivity-specificity minimizer, the results from the confusion matrix revealed moderately low false positive and false negative error rates (19.94% and 17.86% respectively). TSS had a value of  $0.62 \pm 0.02$  showing a correlation between observed and predicted values. The visual assessment of the predictive spatial model, comparing known bycatch locations with predicted bycatch occurrence over the same area, indicated good overlap.

TABLE 4. Final BRT parameters, model evaluation metrics (average over 10 iterations,) and absence/presence subset for each species.

Species	Parameter combination	AUC	Deviance explained (%)	TSS	False positive error rate (%)	False negative error rate (%)	75/25 cross validation	Absence subset
Short-beaked common dolphins (n=309)	TC = 5, LR = 0.001, BF = 0.75, ntrees= 2735	0.89 ± 0.01	22.63 ± 1.74	0.62 ± 0.02	19.94	17.86	AUC = 0.84 Deviance = 15.58%	1:1
Northern right whale dolphins (n=54)	TC = 5, LR = 0.0005, BF = 0.75, ntrees= 6070	0.98 ± 0.004	53.32 ± 3.35	0.88 ± 0.01	6.01	5.75	AUC = 0.96 Deviance = 45.06%	7:1
Risso's dolphins (n=27)	TC = 5, LR = 0.0005, BF = 0.75, ntrees= 1850	0.99 ± 0.005	54.58 ± 7.26	0.94 ± 0.06	2.48	13.33	AUC = 0.90 Deviance = 32.42%	35:1
Pacific white-sided dolphins (n=26)	TC = 5, LR = 0.0005, BF = 0.75, ntrees= 2650	0.98 ± 0.01	32.09 ± 7.85	0.82 ± 0.03	8.09	10.00	AUC = 0.87 Deviance = 24.45%	40:1

The second most frequently caught cetacean bycatch species, northern right whale dolphins (*Lissodelphis borealis*, n=54, Fig. 2), represented 0.62% of the total sets and a 7:1 ratio of absences to presences was found to produce the model with the best explanatory power and predictive performance (mean AUC and deviance, over 10 runs). All models converged and similar AUC and % deviance explained (AUC= 0.99 ± 0.005, % deviance explained = 50.59 ± 5.21) during the 50-run sensitivity analysis for the 7:1 subset indicating the absence ratio was representative of the entire dataset the subset dataset was stable. The AUC value for the fitted BRT had a score of 0.98 ± 0.004 and explained 53.32% ± 3.35 of the deviance in the data, indicating excellent predictive capabilities (Table 4). Using a 0.22 threshold, the model had a low false positive error rate and false negative error rate (6.01% and 5.75% respectively). The TSS had a value of 0.88 ± 0.01 showing a correlation between observed and predicted values. The visual assessment of the predictive spatial model, comparing known bycatch locations with

predicted bycatch occurrence over the same area, indicated good overlap. For northern right whale dolphins, smaller ratios of absences (e.g. 4:1, 5:1...etc.) caused overfitting (AUC=1) in the parameterization stage of the model building process as well as non-convergence of models, though computing time was shorter than the 7:1 subset.

Risso's dolphins (*Grampus griseus*, n=27, Fig. 2) represented 0.31% of the total sets, and a 35:1 ratio of absences to presences was found to produce the model with the best explanatory power and predictive performance (mean AUC and deviance, over 10 runs). Over 90% of models converged during the 50-run sensitivity analysis for the 35:1 subset indicating the absence ratio was representative of the entire dataset the subset dataset was relatively stable (AUC=  $0.98 \pm 0.01$ , % deviance explained =  $44.17 \pm 7.89$ ). The fitted BRT showed excellent ability to predict bycatch occurrence, with an AUC of  $0.99 \pm 0.005$  and explaining  $54.58\% \pm 7.26$  of the deviance in the data (Table 4). Using a 0.07 threshold, the model had a false positive error rate of 2.48%, and a false negative error rate of 3.70%. The TSS value of  $0.94 \pm 0.06$  showed a strong correlation between observed and predicted values.

Pacific white-sided dolphins (*Lagenorhynchus obliquidens*, n=26, Fig. 2) represented 0.29% of the total sets, and a 40:1 ratio of absences to presences was found to produce the model with the best explanatory power and predictive performance (mean AUC and deviance, over 10 runs). All models converged during the 50-run sensitivity analysis for the 40:1 subset indicating the absence ratio was representative of the entire dataset the subset dataset was stable (AUC=  $0.98 \pm 0.01$ , % deviance explained =  $37.10 \pm 7.96$ ). The fitted BRT had an AUC value of  $0.98 \pm 0.01$  indicating excellent ability to predict bycatch occurrence and explained  $32.09\% \pm 7.85$  of the deviance in the data (Table 4). The results from the confusion matrix showed relatively low false positive and false negative error rates (8.09% and 10.00% respectively), and a TSS value of  $0.82 \pm 0.03$  showed a strong correlation between observed and predicted values. Smaller absence ratios for Risso's dolphins and Pacific white-sided dolphins were both found to cause overfitting of candidate models during parameterization, as well as non-convergence of models in the 50-run sensitivity analysis and 75/25 cross-validation. Compared to short-beaked common dolphins and northern right whale dolphins, absence ratios for Risso's dolphins and Pacific white-sided dolphins were much more variable and had issues not converging during all stages of the model fitting process.

*Physical Drivers Of Short-Beaked Common Dolphin Bycatch*

The best-fit BRT model results for short-beaked common dolphin suggest a dynamic relationship between probability of bycatch and the physical environment, indicated by at least 75% of the variables consistently having a greater relative importance to the model than the random number (Table 5). Four variables were eliminated from the final model (natural log

TABLE 5. Relative importance for each environmental variable in short-beaked common dolphin species distribution model. Average % contribution over 50 model iterations. Variables below the Random Number were removed.

Variable	Contribution
Latitude	9.7%
Standard deviation of Sea Surface Temperature	8.6%
Sea Surface Height	8.1%
Sea Surface Temperature	7.8%
Brunt-Väisälä frequency	7.5%
Bathymetry	7.1%
Rugosity	5.7%
Isothermal Layer Depth	5.6%
Wind stress curl	5.2%
Standard deviation of Sea Surface Height	4.9%
Lunar illumination	4.5%
Surface eastward velocity	4.4%
Random number	4.4%
Natural log of Eddy Kinetic Energy	4.3%
Surface northward velocity	4.2%
Surface northward wind stress	4.1%
Surface eastward wind stress	3.9%

of EKE, surface northward velocity, surface eastward and northward wind stress). Among the 12 included predictors, measures of mesoscale variability including SSH, wind stress curl, rugosity and the standard deviation of SST, and SSH all had greater influence on the model than the random number. This suggests that mesoscale variability such as fronts and eddies are an

important determinant of short-beaked common dolphin bycatch. Variable response curves show how the probability of species presence is influenced by each predictor. The five most important variable responses are described, but response curves for all 12 final variables are included in Fig. 3. For short-beaked common dolphins, bycatch probability has a negative near-linear

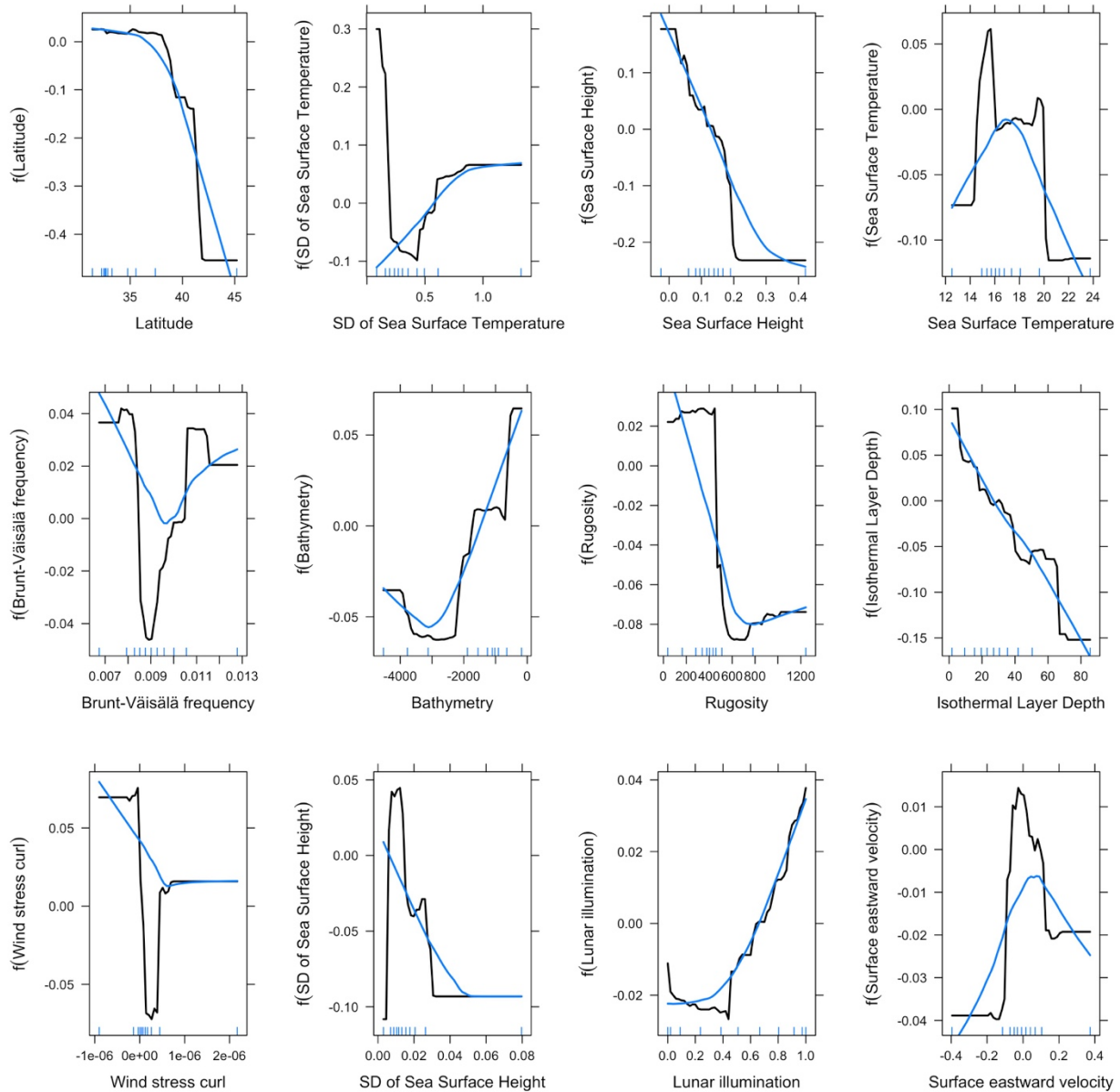


FIG. 3. Partial response curves for variables used in fitted short-beaked common dolphin BRT model. Blue line is a LOESS smoother.

correlation with latitude, a positive correlation with the standard deviation of sea surface temperature, a negative near-linear correlation with sea surface height, and complex non-linear correlations with sea surface temperature and Brunt-Väisälä frequency.

### *Physical Drivers Of Northern Right Whale Dolphin Bycatch*

The BRT model showed bycatch probability of Northern right whale dolphins was strongly influenced by a few specific components of the physical environment; over 33% of the predictors had greater influence on the model than chance (indicated by the random number) (Table 6). Latitude and rugosity were two of the more important predictors, with sea surface temperature and Brunt-Väisälä frequency also having notable influence. Variable response

TABLE 6. Relative importance for each environmental variable in northern right whale dolphin species distribution model. Average % contribution over 50 model iterations. Variables below the Random Number were removed.

Variable	Contribution
Latitude	15.1%
Rugosity	12.3%
Sea Surface Temperature	10.3%
Brunt-Väisälä frequency	8.7%
Sea Surface Height	7.1%
Bathymetry	6.3%
Isothermal Layer Depth	6.0%
Random Number	5.5%
Standard deviation of Sea Surface Height	5.0%
Surface northward velocity	4.3%
Lunar illumination	4.2%
Wind stress curl	3.8%
Surface northward wind stress	3.0%
Surface eastward wind stress	2.9%
Natural log of Eddy Kinetic Energy	2.2%
Standard deviation of Sea Surface Temperature	1.8%
Surface eastward velocity	1.4%



curves showed that bycatch probability has a negative correlation with latitude, a positive near-linear correlation with rugosity, a negative correlation with sea surface temperature, a negative near-linear correlation with Brunt-Väisälä frequency and sea surface height. The five most important variables are described, with the remaining variable response curves included in Fig. 4.

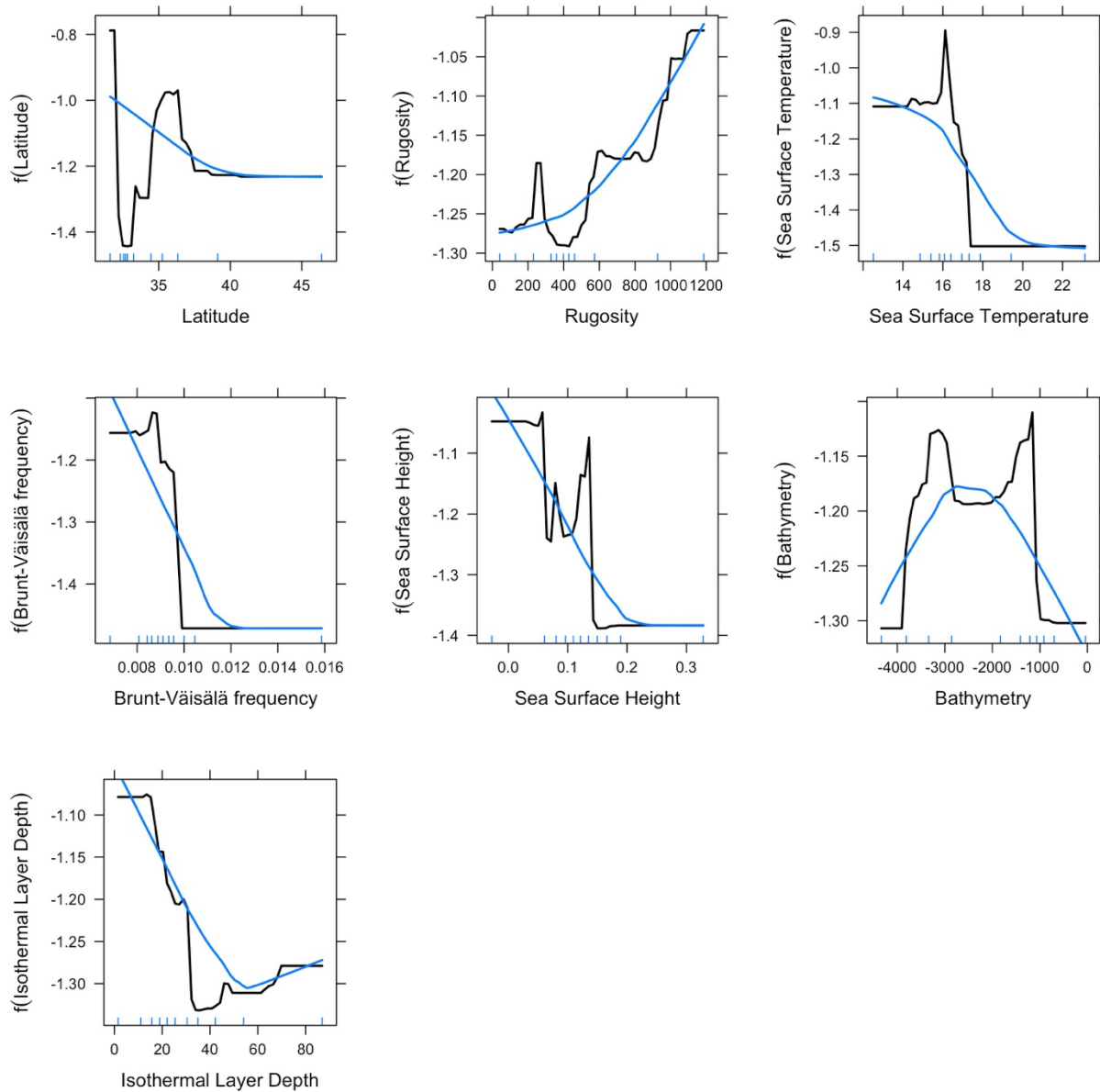


FIG. 4. Partial response curves for variables used in fitted northern right whale dolphin BRT model. Blue line is a LOESS smoother.

### *Spatial Predictions Of Bycatch Probability*

Predicted bycatch probability for the whole 25-year observer dataset revealed spatial differences between short-beaked common dolphins (Fig. 5) and northern right whale dolphins (Fig. 6). Short-beaked common dolphins were predicted to have the greatest bycatch probability in the Southern California Bight, with areas of high probability continuing offshore until about 40°N. Waters along and inshore of the continental shelf break had low bycatch probability. Inshore presence in the Southern California Bight and north past Point Conception is consistent with bycatch records, while offshore distribution has been observed during ship surveys (Becker et al. 2016). Northern right whale dolphins had the greatest bycatch probability in waters offshore of the Southern California Bight, north along the continental shelf break to the Gulf of the Farallones. Areas of low probability were primarily offshore waters as well as in the Southern California Bight. These predictions are consistent with both bycatch records from the California DGN fishery (Fig. 2) and ship survey observations (Becker et al. 2016). Comparison of bycatch occurrence between a year where upwelling was delayed (Fig. 5 and 6), a neutral year (Fig. 5 and 6) and a strong El Niño influence (Fig. 5 and 6), exhibited vast changes in bycatch probability for both species. In 2005 when upwelling was delayed, areas of high bycatch probability for short-beaked common dolphins were patchily distributed offshore and around the Southern California Bight, primarily south of 35° N. During this same period, northern right whale dolphins had the highest bycatch probability in waters south of the California Bight, all other areas had low bycatch probability. During the neutral year in 2012 short-beaked common dolphins bycatch probability was highest around Point Conception, but generally broadly distributed throughout the California EEZ in both inshore and offshore waters until 39° N. While bycatch of northern right whale dolphins had the greatest bycatch probability along the continental shelf break between Point Conception to the Gulf of the Farallones and in offshore waters south of Point Conception. Low probability was observed in offshore waters and in the Southern California Bight. The El Niño influence in 2015 caused bycatch probability to be patchily distributed offshore throughout the California EEZ for short-beaked common dolphins, while inshore waters and the Southern California Bight had areas of low probability. Bycatch probability for northern right whale dolphins was generally very low during this El Niño period,

with only a small area of elevated probability between Point Conception and Monterey Bay. Single day predictions during specific oceanographic events illustrate the dynamic distribution these animals have in relation to the physical environment.

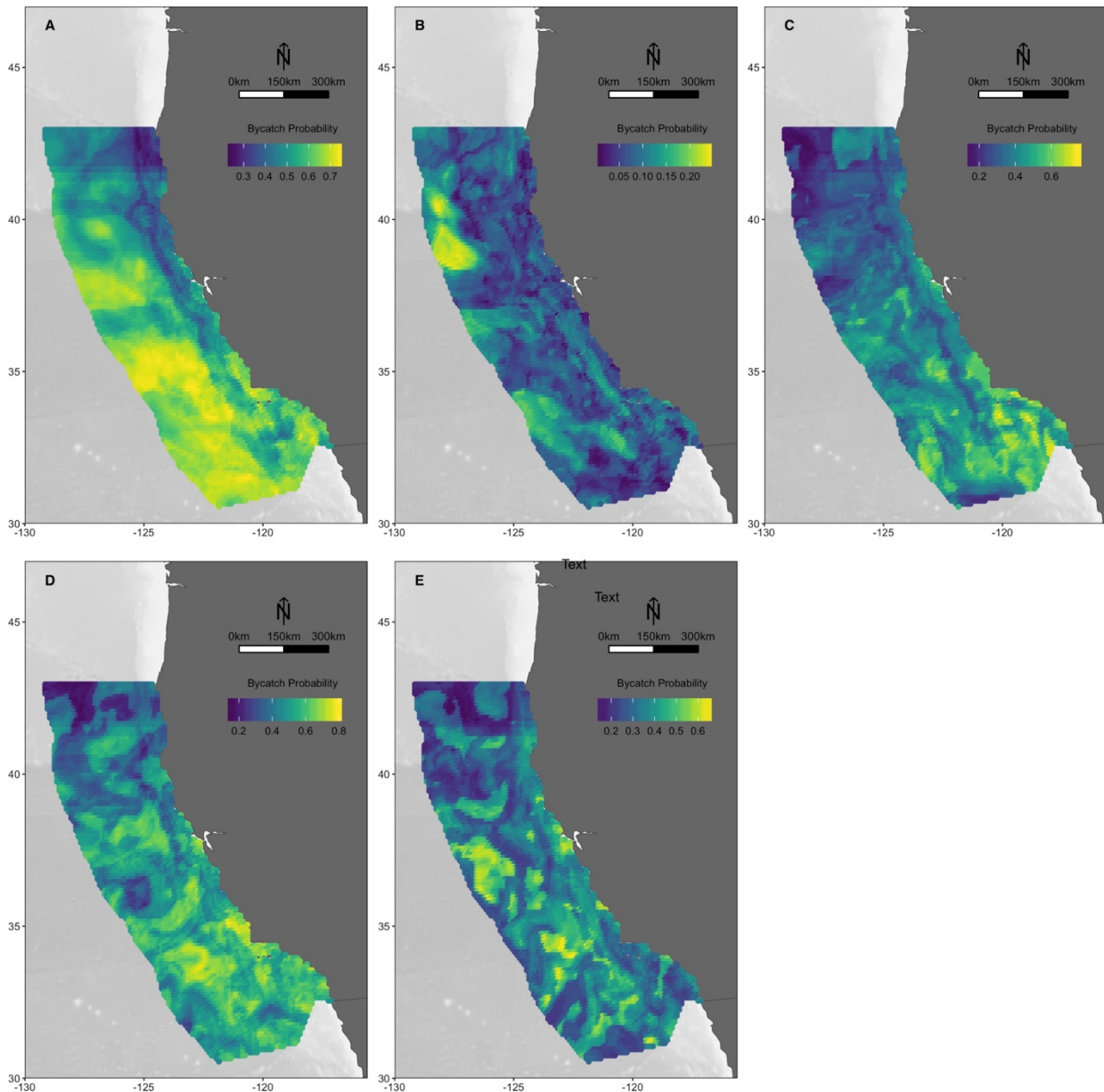


FIG. 5. Predicted short-beaked common dolphin bycatch probability over a 25-year period (1990-2014), mean (plot A), standard deviation (plot B), and three oceanographic scenarios: 1 December 2005, where upwelling was delayed (plot C), 1 December 2012, a neutral year (plot D), and 1 December 2015, an el Niño year (plot E). Base map shows bathymetric features, shallower areas are denoted as lighter colors.

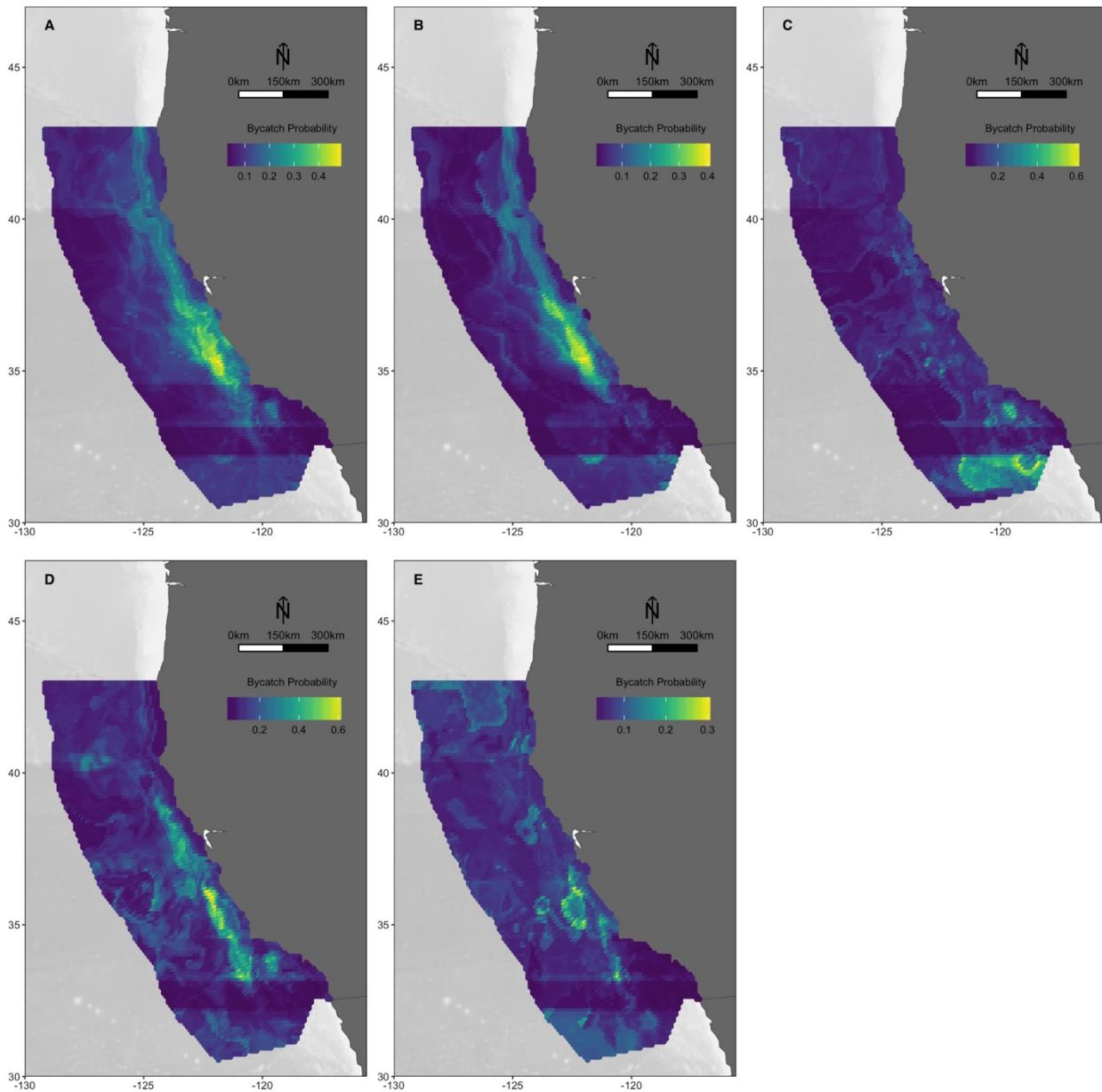


FIG. 6. Predicted northern right whale dolphin bycatch probability over a 25-year period (1990-2014), mean (plot A), standard deviation (plot B), and three oceanographic scenarios: 1 December 2005, where upwelling was delayed (plot C), 1 December 2012, a neutral year (plot D), and 1 December 2015, an el Niño year (plot E). Base map shows bathymetric features, shallower areas are denoted as lighter colors.

## DISCUSSION

The California DGN observer dataset provided presence/absence data on multiple cetacean species caught as bycatch over a 25-year time-period. The fishery-dependent data allowed us to explore the ecological drivers of bycatch and compare these to fishery-independent ship survey data to further our understanding of bycatch drivers. Bycatch probability showed complex relationships with the physical environment for both short-beaked common dolphins and northern right whale dolphins. Although both dolphin species inhabit different temperature ranges, responses to bathymetric features and foraging ecology are similar (Barlow and Forney 2007).

In addition to ecological questions, the observer dataset posed statistical challenges because it is a rare event, zero-inflated binomial dataset. We wanted to determine the minimal sample size that could be used to accurately predict a species' distribution and also understand how zero-inflation would impact certain steps of the modeling process, such as subset selection, parameterization, accuracy assessment, and threshold selection. Working with the four most commonly caught species in the dataset, we fit candidate models using 90 potential parameter combinations (Table 3), as well as testing different subsets of absences relative to presences. Using the multi-pronged approach of subsetting, parameterization, predictor set simplification and several model evaluation metrics (percent deviance explained, AUC, 75/25 cross validation, TSS, false positive error rate, and false negative error rate) we were able to successfully build and evaluate SDMs for four cetacean species. Through the modeling process we were able to develop a method to overcome the zero-inflated dataset and ascertain how models were responding to the range of small sample sizes. The short-beaked common dolphin and northern right whale dolphin models both showed strong predictive performance and explanatory power, with areas of spatial agreement and disagreement with known bycatch events and previously published habitat-based cetacean density models from ship survey data (discussed below; Becker et al. 2016). These results demonstrate that our subsetting approach was a successful method to handle the zero-inflated dataset and allowed accurate models to be built with relatively small sample sizes. Both of these models could have useful application to a near-real time tool to reduce fishery interaction or other marine utility. To determine how small of a sample size could be accurately modeled, we also built BRTs for Risso's (n=27) and Pacific white-sided dolphins

(n=26), which both had sample sizes smaller than short-beaked common dolphins (n=309) and northern right whale dolphins (n=54). We were successful in constructing models for these two smaller species, however there were concerns in the fitting, validation and prediction phases that cast doubt in the accuracy of these models, and their application to a near-real time dynamic management tool or other marine utility.

### *Unravelling Drivers Of Cetacean Bycatch In The California DGN Fishery*

Our results demonstrate the intricate relationship between cetacean distribution and the physical marine environment. Understanding these drivers of bycatch is an important consideration for fisheries managers as well as in the development of an dynamic management tool. The fishery-dependent California DGN observer dataset provides a unique opportunity to study the response that cetaceans have to dynamic and static environmental variables. These bycatch events are the result of cetacean species simultaneously inhabiting the same waters as the target catch (swordfish), possibly because of a similar ecological event (i.e. foraging), or a combination of ecological (i.e. area) and social factors (i.e. fishing behavior).

The two cetacean species used for the final models have known distributions in the CCS that differ from each other. Short-beaked common dolphins are classified as temperate species, generally found in southern and central California. BRT prediction showed areas of highest probability of bycatch are in the Southern California Bight as well as in offshore waters, which is consistent with the known distribution of the species; they have been shown to occupy both neritic and oceanic habitats (Forney and Barlow 1998, Barlow and Forney 2007, Pusineri et al. 2007). Northern right whale dolphins are a cold-temperate species, more commonly found in the northern California and Oregon-Washington regions (Barlow and Forney 2007). The higher predicted bycatch probability of northern right whale dolphins along the continental shelf break in waters off the coast of northern California is consistent with Barlow and Forney (2007) for the same area. Bathymetric variables were important predictors of bycatch probability for both species. Areas of higher bycatch probability for northern right whale dolphins were shown to be waters along the shelf break, which are known areas of upwelling (Huyer 1983). Similarly, short-beaked common dolphin bycatch probability was higher in the waters of the Southern California Bight, which is an area of complex seafloor topography. Bathymetric features and complex seafloor topographies are known aggregation sites for many predatory marine vertebrates

(Morato et al. 2010, Scales et al. 2017b). These areas are typically associated as upwelling regions, a defining characteristic of the highly-productive CCS. Steep bathymetric features cause cold, nutrient rich water to be brought up to the surface, which can aggregate common prey for dolphin species (Bearzi and Saylan 2011). Upwelling regions in the CCS have also been associated with higher-than-average regions of swordfish catch, the target catch of the California DGN fishery (Scales et al. 2017b).

The target catch of the California DGN fishery is well studied; recent papers by Scales et al. (2017b), S. Brodie, personal communication (2018) and Sepulveda et al. (2018) have examined the relative influence the physical environment has on the presence of swordfish along the United States west coast. Both Scales et al. (2017b) and S. Brodie, personal communication (2018) used the same fisheries observer dataset, ROMS dataset, and modeling framework (BRTs) as this study which presents an opportunity to compare the relative influence that environmental variables have on the distribution of target species swordfish and bycatch cetacean species. Scales et al. (2017b) compared the impact of modeled and remotely sensed environmental variables on swordfish presence and catch while S. Brodie, personal communication, (2018) investigated the influence of subsurface metrics on swordfish distribution. When comparing the relative influence environmental variables had on swordfish presence, SST, ILD, and bathymetry ranked in the top four for both papers with lunar illumination ranking 4<sup>th</sup> in Scales et al. (2017b), and Brunt-Väisälä frequency (BV) ranking 4<sup>th</sup> in S. Brodie, personal communication (2018); BV was not used in Scales et al. (2017b). When comparing those results to this study we see some similarities; SST and BV were ranked 4<sup>th</sup> and 5<sup>th</sup> respectively in relative contribution to the short-beaked common dolphin model (Table 4) and SST and BV were ranked 3<sup>rd</sup> and 4<sup>th</sup> respectively in relative contribution to the northern right whale dolphin model (Table 6). When comparing variable response curves from the study by S. Brodie, personal communication (2018) and this one, there were some similarities between swordfish and short-beaked common dolphin and northern right whale dolphin responses. Short-beaked common dolphins and swordfish both had elevated responses to sea surface temperature at 17° C, but response curves for neither short-beaked common dolphins or northern right whale dolphins were similar to swordfish. When comparing response curves for bathymetry, northern right whale dolphins and swordfish both exhibited similar responses as their variable response curves were similar in shape. However, both cetacean species had inverse responses to

isothermal layer depth compared to swordfish, and response curves had no similarities between species for Brunt-Väisälä frequency (S. Brodie, personal communication, 2018) (Fig. 4 and 5). These similarities and differences are likely attributed to the broad dynamic nature of swordfish, and the individual nature of both cetacean species to the physical environment (Barlow and Forney 2007, Sepulveda et al. 2018). Both cetacean models had latitude ranked as the most important variable, with short-beaked common dolphins having a greater response to more southern regions of waters along the California coast and northern right whale dolphins having a greater response to waters in more central regions along the California coast (Tables 4 and 5, Fig. 3 and 4). Although not a driver of bycatch specifically, latitude has a range-limiting effect for both species. In concert with SST and depth, latitude also acts as a proxy for different water masses and bathymetric features, two defining features of the CCS (Forney 2000). However, for northern right whale dolphins a trough can be seen at 32° N in the partial dependence plot (Fig. 4) and horizontal striping can be seen on the spatial predictions (Fig. 6) in the same area (32° N). This result is not biologically accurate and indicative of overfitting the predictor in this specific region. An interaction between sea surface temperature and latitude may be responsible for this. Results in this region should be interpreted with caution.

The similarities in environmental variable influences could be explained by the foraging behavior of both dolphin species and swordfish. Both dolphin species and swordfish are known to be opportunistic feeders, primarily on a range of mid-trophic-level pelagic species. Although both cetacean species have defined temperature ranges, short-beaked common dolphins are warm-temperate and northern right whale dolphins are cold-temperate, and thus have little spatial overlap, while swordfish are a cosmopolitan species (Nakamura 1985). Their wide temperature range and flexible foraging behavior allows swordfish to inhabit waters where both cetacean bycatch species occur (Nakamura 1985). When comparing spatial predictions of swordfish presence (Scales et al. 2017b, see Figure 5(c)) with short-beaked common dolphins bycatch probability, there is strong overlap in offshore waters between 31-38° N. However, short-beaked common dolphins have higher predicted bycatch probability in the Southern California Bight than swordfish. Comparison with the northern right whale dolphin prediction, shows an overlap between 35-40° N along the continental shelf break, but no offshore overlap. Both cetacean species' overlap with the target catch of California DGN fishery is indicative of



their habitat preferences as demonstrated by the physical drivers shown to be influential to both species, highlighting areas where spatial management may allow for reductions in bycatch.

### *Comparison To NOAA SWFSC Systematic Surveys*

Since 1949, NOAA's Southwest Fisheries Science Center (SWFSC) has conducted multidisciplinary systematic ship surveys to study the CCS ecosystem, including protected species abundance, distribution, and biology. The results from the ship surveys have been used in many studies (Barlow and Forney 2007, Barlow et al. 2009, Becker et al. 2010, Becker et al. 2012a, Becker et al. 2012b, Becker et al. 2016) that model the distribution and abundance of multiple cetacean species as well as inform protected species stock assessment reports (SARs) and other management practices (Barlow et al. 2009). The controlled sampling design of fishery-independent survey data provides a good comparison to fishery-dependent data to help determine ecological vs. fishing drivers of bycatch (Jannot and Holland 2013).

Many of the cetacean species observed on these surveys are cetacean species also caught as bycatch in the California DGN fishery. The SDMs constructed from this long-term dataset are well validated and are used in many management applications (Barlow et al. 2009). Although the systematic ship surveys and California DGN fishery vary in time and space, the SDMs using the fishery-independent survey data provides a robust reference to compare to the spatial predictions of bycatch probability for short-beaked common dolphins and northern right whale dolphins, as insight into the physical drivers of both species through variable response curve comparisons.

Becker et al. (2016) used cetacean sighting data collected in the CCS during the summer and fall (July through early December) of 1991, 1993, 1996, 2001, 2005, 2008, and 2009 to build habitat-based density models. These models were built using a generalized additive model (GAM) framework and a comparison between ROMS and remotely-sensed environmental data was conducted. Although some differences exist between the studies, response variable (count versus presence/absence), model framework (GAM versus BRT), and predictive outputs (density versus bycatch probability), a comparison still adds insight into the spatial and temporal distribution of the shared cetacean species. Multi-year average density predictions for short-beaked common dolphins from Becker et al. (2016) show the highest predicted densities (7 animals/km<sup>2</sup>) in the Southern California Bight, with more moderate predicted densities (0.4 - 0.8 animals/km<sup>2</sup>) offshore of Southern California to the United States exclusive economic zone

(EEZ) and north to the Mendocino Escarpment at 40° N. Predictions for northern right whale dolphins showed highest predicted densities (0.5 animals/km<sup>2</sup>) along the entire United States west coast continental shelf, with densities decreasing further offshore to the west and south. Densities varied (0.5-0.03 animals/km<sup>2</sup>) north of the Mendocino Escarpment at 40° N (Becker et al. 2016). These spatial predictions further the evidence that both cetacean species exhibit a broad spatial and temporal domain along the entire United States west coast.

Predicted bycatch probability of short-beaked common dolphins (Fig. 5) from the California DGN fishery observer dataset showed high probability south of 40° N, in both inshore waters primarily along Point Conception and into the Southern California Bight and offshore along the entire coast. Predicted short-beaked common dolphin density by Becker et al. (2016) (see Figure 2 (b)) shows very similar distribution, with highest densities in the Southern California Bight. However, there are slight differences in the magnitude between the predictions, the survey model shows highest predicted densities in the Bight whereas predicted bycatch probability is not as strong. Differences also exist offshore around 38° N, where the survey model shows higher predicted density. Predicted bycatch probability for northern right whale dolphins (Fig. 6) from the observer dataset showed highest probabilities north of 34° N, primarily along the continental shelf break. Ship survey-based density predictions of northern right whale dolphins by Becker et al. (2016) (see Figure 2 (g)) shows similar distribution, with highest densities predicted offshore of the Southern California Bight and primarily along the shelf edge before extending offshore at the Mendocino Escarpment (40° N). However, the ship survey-based prediction shows higher densities in waters south of Point Conception than the observer-based bycatch probability models, as well as greater densities offshore of the shelf break. These spatial differences for both species could be attributed to the underlying data in both models, temporal and spatial differences exist between the ship surveys and California DGN fleet, as do the methods of data collection. The sightings data from the ship survey covers a much broader area and has a greater coast-wide application than the observer data where most of the fishing in the California DGN fishery occurs in the Southern California Bight and in relatively near-shore waters.

As well as comparing spatial patterns between the ship survey and observer-based predictions, similarities and differences in habitat preferences can also be analyzed through variable response curves. For both models, the responses from short-beaked common dolphins

and northern right whale dolphins to three environmental variables can be compared. In the variable response curves from Becker et al. (2016, supplemental material), short-beaked common dolphins had a positive near-linear correlation to sea surface temperature, whereas the variable response curves for short-beaked common dolphins in this study showed a complex non-linear correlation. However, both variable curves had elevated responses to sea surface temperature at 17° C. In response to sea surface height, short-beaked common dolphins in both studies had negative correlations, but the response curve from the observer-based study had a much steeper line. The variable response curves for bathymetry showed different shape, though both had similar rises at -2900m. Northern right whale dolphins in both studies exhibited negative correlations to sea surface temperature, with similar breaks at 16° C. In response to sea surface height, northern right whale dolphins in both studies had negative correlations, but the shape of the responses was not similar. Variable response curves for bathymetry from both studies had non-linear correlations, with similar peaks at -2500m. Similar to comparing the spatial predictions in Becker et al. (2016) and this study, comparing the habitat preferences exhibited by short-beaked common dolphins and northern right whale dolphins provides a good reference for deciphering the physical drivers that may lead to fishery interaction.

#### *Which Ratio Of Absences Achieves The Most Accurate Model?*

There are many approaches that can be used to analyze zero-inflated datasets, ranging from excluding, eliminating, or grouping zero observations, replacing the zeros with a small number, or employing zero-inflated specific models (hurdle models, zero-inflated Poisson, and zero-inflated negative binomial) (Maunder and Punt 2004). However, these methods were not appropriate for this analysis because the cetacean records in the California DGN observer dataset were binary presence/absence records and hurdle models as well as zero-inflated models are best suited to model continuous count data. A binary response variable is typically modeled using a Bernoulli distribution, however issues during analysis can arise due to the imbalance of the dataset (Maunder and Punt 2004). This problem is especially magnified when zero-inflated data sets deal with rare-events where sample sizes may not be especially high; not only are counts generally low but overall presences are low with extreme numbers of zeros.

To successfully model the binomial and zero-inflated dataset, we adapted the findings of Barbet-Massin et al. (2012), which proposed guidelines on how many pseudo-absences should be

generated to build reliable SDMs. We took the approach of reducing the number of absences because we could not use specialized zero-inflated models which can handle the large number of zeros, and thus had to employ models that are typically used for normally distributed data. Although our data included real absences, rather than pseudo-absences, we started with the approach of using the same number of absences as available presences suggested for machine-learning techniques (Barbet-Massin et al. 2012). Beginning with the most common cetacean bycatch species, short-beaked common dolphins, we found that a 1:1 subset produced the best model in terms of explanatory power and predictive performance as well as having the fastest computing time. The 1:1 subset represents 3.55% of the absences of the entire dataset, given that this is a small number it indicates that the entire short-beaked common dolphin dataset has low variability. This could be owed to the fact that fishing effort primarily occurs during the same season (fall) each year, and this overcomes the dynamic environment of the California Current. With the other three species we found that regardless of BRT parameter combination, 1:1 absence ratios and ratios representing less than ~3.6% of the absences always overfit the BRT. Starting with at least ~3.6% of the absences for the other species, we used an iterative process to determine the best absence to presence ratio. We developed a set of criteria to find the optimal subset by balancing the smallest subset while still growing models to 1000 trees and having at least 90% (>45) of the model iterations converge during the sensitivity analysis. It became clear through the model building that there was a threshold for the number of absences that yielded a model with the best evaluation metrics without overfitting. Subsets less than the threshold would cause AUC values to increase, reaching 1 if the subset was too small, and explanatory power to decrease. A subset greater than the threshold would result in progressively lower predictive performance and explanatory power as the subset got larger. Based on this knowledge, we ultimately chose a 7:1 subset for northern right whale dolphins, 35:1 for Risso's dolphins and 40:1 for Pacific white-sided dolphins. Higher absence ratios for Risso's and Pacific white-sided dolphins can likely be attributed to the small number of presences.

With Risso's and Pacific white-sided dolphins, there was significantly more variability in the entire model fitting process than with short-beaked common dolphins and northern right whale dolphins. During the parametrization step for each species, the selected parameter combination always converged across all 10 iterations. However, during the 50-iteration sensitivity analysis with the chosen parameter combination, short-beaked common dolphins and northern right whale

dolphins did not have convergence issues while both Risso's and Pacific white-sided dolphins had greater variation in how many models would converge. Absence ratios smaller than 35:1 for Risso's and 40:1 for Pacific white-sided dolphins converged less than 90% of the time during the 50-iteration sensitivity analysis. Similar results were observed in the 75/25 cross validation where the two species with the smallest sample sizes had convergence issues. This can partly be owed to the naturally stochastic element of the bag fraction parameter in BRTs, which adds variability into the model building process, but may also be due to the small presence sample sizes. Studies analyzing minimum sample size have concluded that sample sizes  $< 30$  cannot be consistently modeled accurately (Wisz et al. 2008, Proosdij et al. 2016). Our approach of subsetting absences relative to presences resulted in accurate SDMs for the cetacean species with records of 309 and 54 presences, but the approach was not able to overcome samples with smaller sample sizes ( $n = 27$  and  $n = 26$ ) in the zero-inflated dataset.

### *How Low Can You Go?*

As the field of species distribution modeling has evolved, greater emphasis has been placed on enhancing knowledge of the model building process to improve model accuracy (i.e. sample size requirements, model fitting, accuracy assessment, threshold selection, and prediction) (Fourcade et al. 2018). Our dataset provided a unique opportunity to further this knowledge through the use of a fishery-dependent observer data, which was zero-inflated and contained records of both presence and absence of cetacean species caught as bycatch. Although our primary goal was to create SDMs to explore the ecological interactions that influenced bycatch for fisheries management applications, we also wanted to evaluate how minimal sample sizes would impact the modeling process. In addition to a unique subsetting approach and robust parameterization of all four models, we used a suite of six evaluation metrics. These metrics allowed us to evaluate both the accuracy of the model in terms of overall predictive capability, as well as accuracy in terms of specifically predicting presences and absences (Elith et al. 2006a).

We found that the BRT parameters (TC, LR, BF) responded similarly with all subset ratios of absences. For all species, larger tree complexities (4 or 5), smaller learning rates ( $< 0.001$ ), larger bag fractions (0.6 or 0.75) generally produced optimal models based on evaluation metrics (Table 4). These parameter combinations suggest that computationally the BRT was being pushed to its capacity in order to fit an accurate model. More complex trees

indicate that each regression tree that made up the BRT was relatively large, and the model was also allowing for 5-way interactions between variables (Elith et al. 2008). The slow learning rates can be tied to the higher tree complexity because the more complex trees allow for each tree to have relatively smaller contributions to the overall model, which allows for better prediction. The larger bag fractions indicate greater percentages of data were needed in each step to grow the regression trees. This introduces randomness into the model, which usually improves accuracy as well as decreasing computing time and overfitting (Elith et al. 2008).

To evaluate how small of a sample size could be modeled, it was necessary to understand how accurate our predictions were in general, but also how the models were performing in predicting presences versus absences, we evaluated models using AUC and percent deviance explained and also constructed confusion matrices for each species to determine TSS scores and false positive and negative error rates (Soykan et al. 2014). Both TSS and AUC have been widely used in SDMs to evaluate predictive power, and unlike the threshold independent approach of the AUC metric, TSS is threshold dependent (Elith et al. 2006b). To calculate the threshold for TSS, binary transformations were performed using the threshold that minimized the difference between sensitivity and specificity. This threshold was found to produce the most accurate predictions as opposed to fixed default threshold of 0.5 and was not affected when used with rare species data, unlike the sensitivity - specificity sum maximizer (Manel et al. 2001, Liu et al. 2005, Jiménez-Valverde and Lobo 2007, Liu et al. 2011).

Using the suite of evaluation metrics, we found that we could produce an accurate model for each species (Table 4). Through the modeling process we observed similar trends for all species in regard to the number of presences and absences used in model building; as sample size decreased the performance metrics generally increased as well as absence ratio. We also observed the threshold used to classify presences and absences in the confusion matrix decreased as sample size decreased. All models explained an acceptable amount of deviance in the dataset given the known ecology of these species and were accurate and stable in their predictions as indicated by the AUC scores during the sensitivity analysis and 75/25 cross validation results. We also predicted back over all sets in the observer dataset for each species to compare explanatory power versus predictive power. Models with larger sample sizes showed good overlap between areas of predicted bycatch and dense areas of known bycatch locations, however the overlap was not as strong in areas of less dense known bycatch location (Fig. 2, 5,

and 6). Overall, for species with smaller sample sizes, it was more difficult to discern the overlap between areas of predicted bycatch and areas of known bycatch due to the small sample sizes. When analyzing the spatial predictions for the entire California EEZ, short-beaked common dolphin and northern right whale dolphin predictions showed areas of overlap with the known distribution of each respective species per review of peer-reviewed research however there were also areas of disagreement – most commonly in areas with few known bycatch locations (Barlow and Forney 2007, Barlow et al. 2009, Becker et al. 2016). Specifically to short-beaked common dolphins, areas of greatest agreement between the predictions and known bycatch data occurred in the Southern California Bight (Fig. 2 and 5). The mean prediction differed along the continental shelf, where there is a significant amount of known bycatch locations, but also offshore where areas of high probability were in agreement with other studies (Becker et al. 2016) but where few known bycatch locations existed. Although the prediction of high bycatch probability offshore, differs from the known bycatch data, these results are supported by other studies (Becker et al. 2016), and may be caused by the modeled relationship with the physical environment. The mean northern right whale dolphin prediction showed strong agreement with known bycatch locations along the continental shelf break and in northern offshore waters, however the prediction had low probability offshore of the Southern California Bight where there is a clustering of known bycatch events (Fig. 2 and 6). This result may be caused by the influence of the latitude variable, where horizontal striping can be seen on the prediction and may cause a relationship that doesn't biologically exist. For both species, areas of high predicted probability that also overlap with a significant amount of known bycatch locations should be most trusted in this study, as the underlying data to support the prediction is strongest. Despite the portrayed accuracy of the models (Table 4), spatial predictions for the species with the fewest occurrences, Risso's dolphins and Pacific white-sided dolphins, were not deemed biologically accurate during consultation with experts (Becker and Forney, personal communication, 2018) and did not show an accurate representation of their known habitat when compared to SDMs built with systematic ship survey data (Becker et al. 2016).

Although all models showed strong ability (AUC and % deviance explained) to predict bycatch accurately and were supported by the results from the confusion matrix (TSS, false positive and false negative error rates) (Table 4), the results of the Risso's dolphin and Pacific white-sided dolphin spatial predictions brings into question why these common performance

metrics failed in a biological-sense. Given the results of the variable response curves for the species' modeled, we know their distribution is largely related to the complex physical environment. We attempted to capture this dynamic relationship through our selection of predictor variables as they were driven by the ecology of the cetacean bycatch species', the target catch in the fishery (swordfish) and the general oceanographic features of the study area. However, the inclusion of 16 predictor variables in the initial model fitting stage may have led to the difficulties encountered in the modeling process. Previous studies have noted that large numbers of predictor variables in relation to few occurrences can lead to model overfitting (Barry and Elith 2006, Breiner et al. 2015). In this case along with a large number of predictor variables, the fit between predicted values and actual data is deceptively good (Vaughan and Ormerod 2005, Breiner et al. 2015). Breiner et al. (2015), suggests a general rule of thumb that the number of occurrences should be 10 times larger than the number of predictors used for modeling. This supports our model results as the larger sample sizes were able to be modeled accurately, both statistically and biologically. In a complex environment like the California Current, is likely that large occurrence sizes are needed to match the number of predictor variables used to represent the environment. Animals that live in a more stable, homogeneous environment may be able to be modeled accurately at smaller occurrence numbers, with fewer predictors. We took careful biological consideration in our selection of relevant predictor variables as recommended by Fourcade et al. (2017), and also included a random number predictor to simplify the predictor set. However, the random number method did not have much influence for the two species with the smallest sample sizes, as it only eliminated one variable from the Risso's dolphin dataset and no predictors from the Pacific white-sided dolphin dataset. We hypothesize this is attributed to the weak bycatch signal due to the small sample sizes, as the model could not identify a clear relationship with the physical environment that drove bycatch probability. In a study investigating minimum sample sizes for SDMs by Proosdij et al. (2016), the absolute minimum of 13 for widespread species was highly dependent on the species' prevalence. However, this simulation took place in an ideal, balanced, orthogonal world. When the simulation took place in a real study area in Africa, the minimum for widespread species was 25, one fewer than our smallest sample size (Proosdij et al. 2016).

Previous studies have noted that the commonly used AUC statistic has many faults and should not be solely used to assess SDM performance (Lobo et al. 2008, Fourcade et al. 2018).



As such, we took recommended measures to carefully select variables according to the species' ecology, and only evaluated models in areas that we had underlying data for and incorporated alternative metrics such as sensitivity and specificity, but these steps were also not robust enough to decipher a biologically inaccurate model (Jiménez-Valverde 2014, Fourcade et al. 2018). Other recommendations such as splitting data into spatial blocks was not possible in this study due to small sample sizes (Fourcade et al. 2018). As supported by other studies, our findings are most likely attributed to modeling rare species (i.e. small sample sizes) and zero-inflated dataset (Bean et al. 2012, Breiner et al. 2015). When presences are low, evaluation metrics, like AUC, overestimate the performance of models (Lobo et al. 2008). However, further analysis should be undertaken to understand why these commonly used metrics to assess model explanatory and predictive power depicted a highly accurate model, but the spatial predictions did not portray results similar to known bycatch occurrence or sightings from systematic ship surveys. The results of the spatial predictions for Risso's dolphins and Pacific white-sided dolphins bycatch occurrence did not instill confidence that these SDMs could be applied in a management capacity or dynamic management tool. Although we took thorough measures to ensure proper validation and evaluation of models, limited sample sizes coupled with many predictor variables have been known to cause accuracy measures to be inflated and optimal thresholds for presence/absence more difficult to discern (Bean et al. 2012, Breiner et al. 2015). Our findings underscore the importance of accessing biological accuracy, not just statistical accuracy when evaluating model results.

#### *Use Of Fisheries Dependent Data In SDMs*

To adequately capture environmental preferences and distributions of wide-ranging protected marine species such as cetaceans, seabirds, sharks, turtles, pinnipeds and large migratory fishes, SDMs are commonly built using data from telemetry or survey sources (Elith and Leathwick 2009). These types of data give a presence-only vantage point of species distribution and are often used to estimate density, but pseudo-absences can also be used in order to model habitat use. However, telemetry and survey data can be costly data sources and are not always readily available. Fishery observer data on the other hand is required to be collected to some level in most fisheries for fishery management applications, and cost is usually the responsibility of NOAA fisheries and/or the fishing boat. These datasets typically provide large,

long-term data that has both catch and presence and absence data of target and non-target species. The availability of real absence data is a considerable benefit as these models can take on different complexion than presence-only or pseudo-absence studies.

Although there are many potential benefits of using fisheries observer data, bycatch – especially protected species bycatch – can be a rare event and pose modeling and inference challenges. This often precludes fishery dependent data from being used in SDMs, especially ones focused on the conservation of species rarely caught. However, fishery dependent observer data has been used in some instances in SDMs; Ward et al. (2015) modeled the co-occurrence of target and non-target species as a function of environmental variables in fisheries off the United States west coast that target pink shrimp. Minami et al. (2007) determined temporal trends in shark bycatch in the eastern Pacific Ocean purse-seine fishery for tunas. Carretta et al. (2017) used fisheries observer data to estimate bycatch of marine mammals, sea turtles and seabirds. Observer data is often best used for SDM construction when using the data of the target catch, as successfully demonstrated by Scales et al. (2017b) and S. Brodie, personal communication (2018). Although model construction using bycatch species is possible, emphasis should be put on commonly caught fish species rather than protected species as major statistical challenges can arise.

In our study we successfully demonstrated the model building process of two cetacean species commonly caught as bycatch in the California DGN fishery using a binomial zero-inflated observer dataset. Through this experience we suggest some points to consider for future studies which incorporate the use of fishery dependent data, especially zero-inflated data sets. In the United States, observer monitoring first began nationwide in 1972 and currently 47 fisheries in the United States are covered by observers (NMFS 2013). Observer data, which is freely available, offers a rich data source for a wide range of species and often contains many years of data, either in the form of counts or presence-absence. In addition to multi-species and long-term datasets, the data is collected by trained observers and provide records of target and non-target catch, and associated data. Observer data offers a unique vantage point for SDMs because the data is fishery dependent, and can yield insight into multi-species aggregations, fisheries interactions, hotspots and other socio-economic phenomena that may not observed with telemetry or survey data. However, when using a dependent data source, biases may occur in a dataset for several reasons. First, fishing is not random in time and space, fishermen often have

preferred fishing grounds and the emphasis on target and non-target catch must be considered. Observer data is restricted to the areas where a vessel fishes and thus is influenced by a human dimension which may add bias in the sampling process. Second, observer coverage is rarely 100% and level of coverage by trained observers may vary within a fishery, furthermore biases may exist in the vessel and trip-selection methods used to assign observers in fisheries that require less than 100% coverage, however this process is random and often computer generated. Finally, fishing behavior by vessel may vary depending if an observer is aboard or not (Ward et al. 2015). As with all data sources bias should be acknowledged and appropriately interpreted.

In our study, all of our cetacean datasets were zero-inflated and in our initial exploration we found that using the entire dataset in the SDMs would weaken the ‘bycatch signal,’ so we took the approach of subsetting. We successfully modeled two cetacean bycatch species with relatively small sample sizes but found limitations in model assessment when trying to model species with even smaller sample sizes. These challenges when using observer data should be considered during SDM construction, and inferences from the data should be made with caution. In regard to rare events (i.e. protected species), observer data has a limited but useful application. Bycatch of protected species continues to pose problems to the survival of many of these species’ populations, but SDMs, similar to the ones built in this study can yield insight into the interaction between non-target protected species and target species of the fishery (Guisan and Thuiller 2005, Guisan et al. 2013). Often complex relationships with the physical environment exist that can explain why or why not a species was present, and any additional insight into these relationships can inform fisheries management decisions. Although not a commonly used data type for protected species SDMs, we believe that fishery observer data provides a unique vantage point into the dynamic distribution of these species and accurate models can be constructed using these data.

## CONCLUSION

Maintaining sustainable seafood harvest and minimizing bycatch can be challenging in areas with high species overlap. In the California DGN fishery current static management approaches have partially reduced bycatch but have led to significant declines in fishing effort. However, hard caps have still been proposed for five marine mammal species. If met for any of these species, the fishery would shut down, this potential risk would be detrimental to the existence of the California DGN fishery. A change in management towards a dynamic management approach has the potential to reduce marine mammal bycatch and also increase target catch. Using 25 years (1990–2014) of NOAA fisheries' observer data from the California DGN fishery we attempted to model the probability of bycatch of the four most common cetacean bycatch species. Through this process we developed a unique approach that allowed us to successfully use a fishery-dependent rare-event zero-inflated binomial dataset. Here we illustrate the use of a data source that previously has not been used in SDM construction for protected species. Our results show exciting promise to examine the historical response of these cetacean species to their habitat, but also furthering the field of rare-event modeling for future studies using zero-inflated data. Further research could be conducted on different approaches to subsetting these types of datasets (i.e. quantifying how many sets of actual catch and bycatch and using that as a subset). Through a robust suite of evaluation metrics as well as visual comparisons with validated density models, we were able to ascertain that our models with the two smallest sample sizes were not biologically accurate and would not be appropriate for use in a dynamic management tool. As recent studies have noted the failures of popular evaluation metrics in the validation of SDMs, the results from this study underscore the importance of accessing biological accuracy, not just statistical accuracy when evaluating model results. Models for short-beaked common dolphins and northern right whale dolphins have potential application to a dynamic management tool. However, both of these models still require further validation to ensure the species–environment relationships hold true in different scenarios, whether in a changing climate or for alternative fisheries management approaches.

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### PEER-REVIEWED PUBLICATIONS

CL Conrath & NB Sisson (2018). Delayed discard mortality of the giant Pacific octopus, *Enteroctopus dofleini*, in the Gulf of Alaska cod pot fishery. *Fisheries Research*. 197, 10-14.

NB Sisson & MR Baker (2017). Feeding ecology of the Pacific sand lance (*Ammodytes personatus*) in the San Juan Archipelago. *Marine and Coastal Fisheries*. 9:1, 612-625.

SM Maxwell, MG Connors, NB Sisson and TM Dawson (2016). Potential Benefits and Shortcomings of Marine Protected Areas for Small Seabirds Revealed Using Miniature Tags. *Frontiers in Marine Science*. 3, 264.

### ORAL PRESENTATIONS

NB Sisson, K Scales, EL Hazen, EA Becker, SJ Bograd, S Brodie, H Welch, MG Jacox, RL Lewison, LB Crowder, and SM Maxwell. Fishery interaction modeling of cetacean bycatch in the California drift gillnet fishery to inform dynamic ocean management. 22<sup>nd</sup> Biennial Conference on the Biology of Marine Mammals, 2017, Canada.

NB Sisson, EA Becker, EL Hazen, SM Maxwell, K Scales, H Welch, S Brodie, SJ Bograd, MG Jacox, RL Lewison, LB Crowder. Using predictive models to help reduce marine mammal bycatch. Marine Mammal Mortality in Global Fisheries: Assessment, Mitigation, and Capacity Building Workshop. 22<sup>nd</sup> Biennial Conference on the Biology of Marine Mammals, 2017, Canada.