Modeling Shark Bycatch Mitigation Strategies in Longline Fisheries

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UNIVERSITY OF MIAMI

MODELING SHARK BYCATCH MITIGATION STRATEGIES IN LONGLINE FISHERIES

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This dissertation uses various modelling approaches to evaluate methods to reduce shark bycatch in the U.S. Atlantic pelagic longline and Gulf of Mexico (GOM) bottom longline fisheries. Combinations of environmental and gear variables are used to parameterize models to predict where and under what conditions bycatch occurs and propose bycatch mitigation strategies. All work uses NOAA NMFS observer datasets for U.S. commercial longline fleets operating in the Atlantic and/or Gulf of Mexico (GOM). Several statistical models are used to identify environmental conditions, regions and fishing methods that favor high bycatch of the overfished shortfin mako shark, *Isurus oxyrinchus,* based on the outputs of the delta-lognormal model and quantile regression of the upper quantiles. The results suggest that using the binomial portion of the delta-lognormal model, the probability of positive catch, to define a hot set basis for a "no fish" algorithm. Second, an individual based movement model is used to test three closure scenarios: stationary, seasonal, and moving weekly closures, for their ability to decrease shortfin mako incidental catch while minimizing the impact on the target fishery. Results suggest that any of the tested closures have potential to improve rebuilding when compared to the status quo. While the two moving closures give some reprieve to the population when compared to current fishing practices, the varying success and failure to surpass the stationary closure indicated that the time scale of a moving closure is very important, and a mismatch can dampen the benefits of the closure. The dissertation finishes with consideration of how to mitigate bycatch of 12 commonly caught shark species in the GOM reef bottom longline fishery including: blacknose, nurse, Atlantic sharpnose, scalloped hammerhead, sandbar, smooth dogfish, night, blacktip, silky, tiger, bigeye sixgill, and sevengill sharks. Catch rates of each species are modeled as a function of environmental and gear variables individually and all combined, as well as grouped by similar ecology. Gear and behavior variables were the most consistently retained in the best predictive models across all species and were the only variables with the potential to be used for a single rule that could decrease bycatch across all studied species. Patterns of environmental variables were only consistent across species with similar ecology and habitat. For both the shortfin mako shark and bottom longline examples, we found that environmental conditions and gear configurations can be used to predict shark bycatch well enough to suggest bycatch mitigation strategies that significantly reduce shark bycatch in longline fisheries; however, there are tradeoffs involved in minimizing bycatch of multiple species, and minimizing bycatch while not unduly restricting target species catch.

For Old Granny and Grampy Dude –
for teaching me to never stop learning

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CHAPTER 1: INTRODUCTION

The Problem of Bycatch

According to the National Bycatch Report (Karp et al. 2011), bycatch is the discarded catch of a living marine resource as a result of direct interaction with fishing gear. Because the gear is not selective enough to only catch the targeted species, fishing impacts more than just the target species. This becomes an additional source of mortality to these species which is of concern to their management, especially for species that may be overfished, endangered, or prohibited (Karp et al. 2011, Clarke et al. 2014). In the United States, reducing bycatch is one of the National Standards for fishery management under the Magnuson-Stevens Fishery Conservation and Management Act, and, for populations where bycatch is a substantial source of mortality, estimation of bycatch may be necessary to achieve the National Standards of using the best available science and ending overfishing (National Marine Fisheries Service 2020b). Recent efforts have used spatial models to predict bycatch rates (Cuevas et al. 2018, Stock et al. 2019, Stock et al. 2020). Circle hooks are used specifically to reduce the catch and mortality of bycatch species like marine mammals and sea turtles (Clarke et al. 2014). Depending on the type, configuration, and placement of longline gear, fisheries can have encounters with a variety of unintended species including turtles, marine mammals, sharks, and sea birds (Karp et al. 2011, Clarke et al. 2014).

For the purposes of this dissertation, I will define bycatch as any unintended catch regardless of retention or discard fate and focus on shark bycatch in longline fisheries. Shark species make up a substantial portion of the catch in longline fisheries and require an expanded definition because, while they may not be intended catch, some species are commercially valued and are therefore retained (Clarke et al. 2014). Shark life history is generally described by K-selection with late maturity, long gestation periods, few energetically demanding offspring, and a long lifespan when compared to bony fishes (Cortes 1998). This results in a low productivity making them particularly vulnerable to overfishing even at low levels of harvesting (Cortes 1998, 2002). The rate of exploitation exceeds shark productivity which is further complicated by the fact that mortality occurs even when sharks are not being targeted. Incidental shark catch is an important source of mortality that must be addressed in order to sustainably manage shark species (Karp et al. 2011, McCully et al. 2013, Clarke et al. 2014). While descriptive shark bycatch studies on longline fisheries in the North Atlantic are plentiful (Molina and Cooke 2012) there is a lack of modeling studies, studies exploring time and area closures, and studies that consider a large number of species at once (Molina and Cooke 2012).

Dissertation Approach

NOAA NMFS observer programs place observers on commercial vessels to monitor and record data on activities that affect living marine resources (National Marine Fisheries Service 2018). Observers collect information such as species composition of catch, individual fish length, weight, and otoliths, as well as data regarding gear used and fishing methods for each set (National Marine Fisheries Service 2018). While catch should be reported by each vessel in their logbooks, sharks are known to be under-reported (Clarke et al. 2014) and fishers not able to collect the same amount of data that an observer is capable of recording (Liggins et al. 1997, Suuronen and Gilman 2019). Observer data are considered to be the most reliable because observers are autonomous with no personal stake in the fishing outcomes and are able to directly view and record bycatch (Karp et al. 2011, National Marine Fisheries Service 2018, Suuronen and Gilman 2019). Observer coverage varies from year to year and from fishery to fishery depending on funding, legislation, and the number of commercial vessels registered to the fishery (Liggins et al. 1997, FAO 2002, Babcock et al. 2003, Bravington et al. 2003, Suuronen and Gilman 2019).

In this dissertation observer data will be used to predict shark bycatch rates and form mitigation strategies from those predictions. This is particularly difficult for sharks because preliminary analysis of longline observer datasets (Beerkircher 2016, National Marine Fisheries Service 2018) show that catch events are generally rare which leads to a lack of information from positive sets in addition to zero-inflation. Furthermore, while catch events may be rare in their occurrence, they can consist of substantial and significant numbers of sharks removed. The traditional approach to relative abundance estimation is to predict mean catch per unit effort (Cortes 2007, 2013, Thorson et al. 2015). The existence of rare, very high catch events suggests that fitting to the mean may not be the most appropriate method for prediction. If so, is there a viable alternative and does it outperform fitting to the mean?

Quantile regression is a method that allows for the fitting of a model to a desired quantile and is appropriate for abundance data with non-linear, non-symmetric, heterogenous scatter in response to a gradient (Koenker and Bassett 1978, Cade and Noon 2003, Anderson 2008, Fukunaga et al. 2016). Sets with low catch per unit effort (CPUE) and ultimately the resulting low mean CPUE, have less potential to tell us about the conditions that lead to high bycatch events. Chapter 2 of this dissertation will explore the predictive ability of quantile regression of the upper extreme to the traditional approach of modeling mean bycatch per set. Because high catch events are rare, it is expected that the traditional modelling approach of fitting to mean conditions will perform poorly when compared to the quantile regression modeling approach that is applied to the upper extreme. Models will be developed using both methods, then bycatch avoidance strategies built from those models will be tested for their efficacy. Models based on the first part of the time series will be applied to see how well they would have avoided shark bycatch in the second part of the time series. This will show which method is a better basis for bycatch mitigation and whether regulations based on existing data could be effective in reducing bycatch in the future. It is expected that the traditional modelling approach of fitting to mean conditions will perform poorly when compared to a modeling approach that is applied to the upper extremes

Time and area closures are a common approach to minimize bycatch. However, several sharks impacted by longline fisheries are highly migratory (Anadon et al. 2011, Campana et al. 2011, Jacoby et al. 2012, Carlson et al. 2014) going in and out of closed areas as well as in and out of management areas, moving between state managed areas as well as in and out of federally managed waters. Stationary time/area closures have been shown to have varying success in reducing the fishing mortality of highly migratory species (Little et al. 2009, Le Bris et al. 2013, Schofield et al. 2013, Maxwell et al. 2020). It is still unclear how to best design time/area closures for highly migratory species.

The problem of movement is further complicated by variation between species and even between individuals within the same species (Jorgensen et al. 2012, Papastamatiou et al. 2013, Vandeperre et al. 2014). The degree of variation between individuals requires a complex model. An individual-based population model (IBM) will provide the complexity needed to simulate the interaction between individuals and fisheries. An IBM is a method that uses information about individual "agents" (the lowest level of the system) and interactions between agents as the foundation of computer simulations (Grimm et al. 2005). Chapter 3 will develop an Individual Based Model (IBM), with individual sharks as the smallest unit, that models the seasonal movement of sharks following a preferred temperature signal (Humston et al. 2000). Alternative scenarios including stationary and moving closures based on the migratory pattern will be tested for their ability to reduce shark bycatch. I expect that a moving closure following the preferred temperature signal will be the effective closure design reducing incidental catch the most.

The poor selectivity and variety of gear configurations for longlines leads to encounters with several species at once. This creates an issue where we have several shark species interacting with a set simultaneously that must be concurrently managed and mitigated. Chapter 4 considers 12 commonly caught shark species at once. Statistical models are used to determine gear configuration, fisher activities, and environmental conditions that contribute to shark bycatch. Each species is modeled individually and all combined, as well as grouped by similar ecology. For each species or species group, we explore which combination of variables is retained in the best predictive model. We will look for patterns across species, across similar species, and across groups of species for common conditions that could become the basis of a mitigation strategy for all 12 sharks. We expect there to be a difference in variable retention and predictive pattern for species with different ecologies.

Species and Fisheries Studied

Chapters 2 and 3 will focus on the shortfin mako incidental catch in the U.S. pelagic longline fishery. In the Atlantic, shortfin makos are caught as bycatch in commercial longline fisheries targeting tunas and swordfish. They are assessed and monitored by the International Commission for the Conservation of Atlantic Tunas (ICCAT) and are one of the most commercially valuable sharks assessed (Levesque 2008). The population dynamics models used in the most recent stock assessment (Anonymous 2017b) and stock assessment update (Anonymous 2019a) found that the North Atlantic stock is overfished and experiencing overfishing. The ICCAT shark working group determined that the total shortfin mako catch needs to be reduced to less than 500t from the level of 3115 t in 2017 to end overfishing and eventually rebuild (Anonymous 2019a). These findings contributed to the 2019 Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) listing the shortfin mako under Appendix II (Anonymous 2019b). Shortfin mako are used as a case study because their distribution is shown to have high overlap with longline fleets (Queiroz et al. 2016, Queiroz et al. 2019), they are a highly migratory species that displays seasonal migrations (Casey and Kohler 1992, Abascal et al. 2011, Queiroz et al. 2016), and their population is overfished with an urgent need for rebuilding (Anonymous 2017b, 2019a).

The U.S. Gulf of Mexico (GOM) Reef Fish Bottom Longline fishery is comprised of Federally permitted commercial vessels that typically target groupers, *Epinephelus* spp., and snappers, *Lutjanus* spp. (Karp et al. 2011, Scott-Denton et al. 2011). Since 2006 a mandatory observer program jointly implemented by the GOM Fishery Management Council (GMFMC) and the National Marine Fisheries Service's (NMFS) Southeast Fisheries Science Center (SEFSC) has monitored the commercial reef fishery in the GOM. This fishery catches 27 species of sharks (Scott-Denton et al. 2011) ranging from the common and not overfished Atlantic sharpnose (Cortés 2009, National Marine Fisheries

Service 2020b) to the depleted (National Marine Fisheries Service 2020b) and CITES listed scalloped hammerhead (Rigby et al. 2019). Collectively, sharks make up a significant portion of catch and discards indicating a need for a reduction in encounters (Scott-Denton et al. 2011).

Scientific Objectives

This dissertation aims to explore if and how shark bycatch can be reliably predicted and how the predictions can be employed to reduce interactions with longline fisheries. This is approached by identifying conditions that describe bycatch interactions, using this information to develop several mitigation strategies, and assess the potential of proposed strategies. First, we focus on describing U.S. pelagic longline sets and determining what combination of conditions lead to particularly high shortfin mako incidental catch. Strategies are developed to give fishers a set of rules that will help them reduce interactions with shortfin mako by altering their configurations rather than specifying physical locations. Then we directly consider the highly migratory nature of some shark species by modeling shortfin mako migration patterns and developing strategies utilizing moving and stationary no-fish zones designed to eliminate effort in spaces that correspond to where we expect high densities of shortfin mako. Lastly, we expand our scope to see if patterns and strategies can be used for multiple species at once in the GOM bottom longline fishery. By exploring no-fish conditions, no-fish locations, and our ability to mitigate bycatch of multiple species at once this dissertation is expected to provide practical solutions and tools for management decisions.

CHAPTER 2: SHORTFIN MAKO HOT SETS-DEFINING HIGH BYCATCH CONDITIONS AS A BASIS FOR BYCATCH MITIGATION

Background

The shortfin mako, *Isurus oxyrinchus*, is a pelagic, migratory shark from the family Lamnidae. Like other Lamnid sharks, they are fast, active swimmers that can retain metabolically created heat (Maia et al. 2007). These sharks have a broad geographic distribution and are found throughout tropical and temperate regions in both hemispheres of the Atlantic, Pacific, and Indian Oceans (Casey and Kohler 1992, Abascal et al. 2011). They are sexually dimorphic; they have a similar growth rate until about age 11 (207cm fork length (FL), 212cm FL for males and females respectively) but females grow to a greater size than males (Natanson et al. 2006).

Shortfin mako sharks are highly migratory, long-lived sharks that are not known to aggregate. A conventional tag recapture study on the North Atlantic shortfin mako population by Casey and Kohler (1992) showed that shortfin makos make seasonal migrations, spending the winter months offshore. This has been further support by Queiroz et al. (2016) satellite tagging study that found shortfin makos moving further east into the pelagic habitat in the fall and winter. They have a preference for water temperatures 17-22°C and appear to move inshore when the continental shelf waters warm, beginning in April and May. More satellite tagging studies have revealed that shortfin makos tagged off the US are distributed across the continental shelf and pelagic habitats following seasonal movements north and south seemingly dictated by seasonal patterns in ocean productivity (Queiroz et al. 2016, Vaudo et al. 2017). Satellite tags also showed that individual sharks exhibit high variability in their movements with some making long-distance migrations south into oligotrophic waters (Vaudo et al. 2017). Shortfin mako sharks' distribution is shown to have high overlap with longline fleets (Queiroz et al. 2016, Queiroz et al. 2019).

In the Atlantic, shortfin makos are caught as bycatch in commercial longline fisheries targeting tunas and swordfish. In the U.S. they are fished recreationally in the Atlantic and Gulf of Mexico (Babcock 2013). They are assessed and managed by the International Commission for the Conservation of Atlantic Tunas (ICCAT) and are one of the most commercially valuable sharks (Levesque 2008). For the purposes of monitoring and assessment, the fishing grounds are divided by ICCAT into eleven geographical areas and extend from the Grand Banks to 5-10° south (Cortes 2013). The population dynamics models used in the most recent stock assessment (Anonymous 2017b) and stock assessment update (Anonymous 2019a) agree that the North Atlantic stock is overfished and experiencing overfishing. The ICCAT shark working group determined that the total shortfin mako catch needs to be reduced to less than 500t from the current level of 3115 t in 2017 to eliminate overfishing (Anonymous 2019a). These findings contributed to the 2019 Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) listing the shortfin mako under Appendix II (Anonymous 2019b). CITES aims to ensure that international trade does not threaten the survival of vulnerable species. Appendix II limits international trade for listed species and will require that fishing nations demonstrate that fishing the shortfin mako would not threaten their chances for survival (Anonymous 1973). ICCAT recommendations and a listing under CITES acknowledge that shortfin mako sharks are not productive enough to rebuild without intervention.

This work will look specifically at the US portion of the pelagic longline fishery where shortfin mako are considered a bycatch species. For the purposes of this study shortfin mako will be referred to as bycatch. The US Pelagic Observer Program started in

1992 and monitors the US pelagic longline fleet operating from Newfoundland to Brazil including the Caribbean and Gulf of Mexico (Beerkircher et al. 2004). The program is managed by the Southeast Fisheries Science Center and has covered about 5% (1992-2001) to 8% (2002-present) of the vessels operating in this fishery. Observers on selected vessels record information about gear configurations and the species, size, sex, dead/alive status, and the ultimate fate (kept or discarded) of fish caught (Beerkircher et al. 2004). Shark and ray bycatch comprises about 29% of the total longline catch (Beerkircher et al. 2004). Catches of shortfin mako sharks recorded by observers in the US pelagic longline fishery are typically zero, so the shortfin mako bycatch per set data are zero-inflated. When there is a positive shortfin mako bycatch, most of the time only 1 or 2 shortfin makos are caught per set. However, there are several events in the shortfin mako bycatch history that have caught upwards of 20 shortfin makos in one set. If we can identify the set of conditions that lead to sets with unusually high shortfin mako bycatch, hereafter referred to as “hot sets”, it may be possible to use this information to avoid high shortfin mako bycatch events and ultimately reduce the overall fishing mortality.

In this study, a generalized linear modeling (GLM) approach was used to predict mean shortfin mako bycatch per unit effort (CPUE), similar to the standardization methods used to generate abundance indices for past stock assessments (Cortes 2007, 2013, Thorson et al. 2015). Additionally, this study determined conditions favoring particularly high CPUE, where much of the fishing mortality occurs. Quantile regression was used to focus on the upper tail of the CPUE distribution, rather than the mean, to reveal what conditions predict higher CPUE. Quantile regression is a method appropriate for abundance data with non-linear, non-symmetric, heterogenous scatter in response to a gradient (Koenker and

Bassett 1978, Cade and Noon 2003, Anderson 2008, Fukunaga et al. 2016). It addresses the scatter by allowing the coefficients to differ for the different parts of the abundance distribution (Koenker and Bassett 1978). It has been used in ecology particularly to test whether environmental predictor variables predict areas of high or low abundance (Cade and Noon 2003, Anderson 2008, Fornaroli et al. 2016, Fukunaga et al. 2016). Application of quantile regression to the upper extreme allows the independent environmental variables to be viewed more easily as boundaries to suitable habitat (Fornaroli et al. 2015). Development of both model types involved a model selection process that included trying categorical and numerical methods as well generalized additive models (GAMs) with smoothers on the environmental variables in an attempt to improve model fit and performance.

The traditional delta-lognormal approach (predicted probability of positive shortfin mako bycatch multiplied by the predicted mean of the positive shortfin mako bycatch to get the overall predicted mean CPUE) is hypothesized to perform poorly compared to the quantile regression fit to the upper extreme when trying to predict hot sets. Quantile regression eliminates the need for a delta-lognormal approach and the difficulties in using zero-inflated data because the higher quantiles do not include zeros. For the purposes of determining conditions that favor a hot set, as opposed to standardized shortfin mako bycatch rates over time, quantile regression may be a better method. Sets with low CPUE (which are the overwhelming majority in this dataset) and ultimately the mean CPUE, have less potential to tell us about the combination of conditions that lead to high shortfin mako bycatch. There is also more flexibility in model fit because there is no assumption of a normal distribution and the error distribution does not need to be specified. This method may provide the tools necessary to best identify potential hot sets and design a bycatch mitigation strategy.

This paper will present several ways to identify environmental conditions, regions and fishing methods that favor shortfin mako bycatch based on the outputs of the delta-lognormal model and quantile regression of the upper quantiles. The analysis will then determine which definition of a hot set and model could be used as a dynamic “no fish” algorithm to avoid shortfin mako bycatch and lower fishing mortality. The ultimate objective is to determine whether identifying conditions that favor high shortfin mako bycatch has the potential to decrease shortfin mako fishing mortality substantially while maintaining catches of target species.

Methods

Data Preparation

Sea surface temperature (SST), sea surface height (SSH), and bathymetry (BATHY) were considered as environmental variables. Catch and effort data were obtained from the US pelagic longline observer program (1992-2016) (Beerkircher 2016), while weekly sea surface temperature composites (2003-2016) and daily sea surface height (1992-2012) (Ducet et al 2000) were downloaded from the NOAA CoastWatch satellite database and bathymetry was downloaded from the Scripps Institute of Oceanography Geodesy satellite database (Smith and Sandwell 1997, Tozer *et al.,* 2016). The shortfin mako bycatch dataset was reduced to those events in time for which environmental variables were available so there would be no null values. Environmental variable values were considered a match if the location was within 5 degrees in space and 15 days in time with the closest value in time and space ultimately being used. This resulted in a dataset spanning 2003 to 2012. All of the following analyses were conducted in R version 3.1.2 (R Development Core Team 2017) using the *mgcv* (Wood 2012), *quantreg* (Koenker and Hallock 2001), and *qgam* (Fasiolo et al. 2017) libraries.

Environmental conditions were considered within the delta-lognormal and quantile regression as explanatory variables along with gear variables including the number of hooks between floats, the use of light sticks, and fishing areas. All independent variables were considered as fixed factors. The fishing areas are based on those used by ICCAT (Cortes 2013). Some areas had too few observations and were combined (Table 2.1).

Model Goodness of Fit and Predictive Ability

To define preferred environmental conditions, presence/absence of shortfin mako shark was modeled as a function of the environmental and gear variables using a fixed effect GLM or a GAM (Manel et al. 2001, Boyce et al. 2002, Guisan et al. 2002, Elith et al. 2006, Palialexis et al. 2011). GLMs are extensions of linear models that allow for non-linearity and variability in variance through the use of link functions and a specified error distribution (Guisan et al. 2002) and GAMs work similarly but also allow a smoothing function to be used to model the relationship between the environmental variable and the response variable. In the delta-lognormal approach the proportion of positive shortfin mako bycatch assumes a binomial error distribution with a logit link, while the mean shortfin mako bycatch rate for positive observations assumes a lognormal error distribution (Maunder and Punt 2004, Ortiz and Arocha 2004). The predicted mean CPUE is then calculated as the probability of presence from the binomial model multiplied by the mean CPUE of positive catch from the lognormal model. Standard errors are calculated following the method of Lo et al. (1992). The variables year, fishing area, quarter, hooks between floats, and the use of lights were considered in all models. Gear variables (hooks between floats, lights) were included to account for variation due to changes in catchability. The exact methods of inclusion are discussed further in the coming text.

The quantile regression method analyzes patterns in the user-specified quantile rather than the mean and can be applied to the same kinds of explanatory variables as GLM and GAM including smoothed terms (Koenker and Bassett 1978). The *quantreg* R library fits to the specified quantile by minimizing the sum of the residuals distribution giving positive values a weight equal to the specified quantile and negative residuals a weight equal to 1 minus the quantile (Koenker and Bassett 1978, Cade and Noon 2003). The *qgam* library works to select the loss smoothness that minimizes the asymptotic mean square error of the estimated coefficient of the smoothed variable (Fasiolo et al. 2017). For this analysis, the interest was focused on particularly high values of CPUE; the 99th percentile was analyzed for the Akaike information criterion (AIC) best model by looking at different combinations of the environmental variables as numerical variables, including the interactions between all possible pairs in addition to quadratic terms for each variable, with the response variable being (log (CPUE + 1)). The gear variables, use of light sticks and hooks between floats, were also considered as gear differences that could influence shortfin mako bycatch rates even at the higher tails of the distribution (Table 2.1).

For both methods, the models were run with the variables as factors (factor levels provided in Table 2.1), continuous, and as a generalized additive model (GAM) (Guisan et al. 2002, Drexler and Ainsworth 2013, Gruss et al. 2014, Grüss et al. 2016) with smoothers on the environmental variables. GAMS are “semi-parametric” expansions of GLMs that are based on additive smoothing functions (Guisan et al. 2002). GAMs are data-driven and therefore require more data; however, they are better able to estimate spatial distribution over a broad area, potentially including areas that have not been sampled (Guisan et al. 2002, Gruss et al. 2014). The stepAIC() function was used to consider all variable combinations and select the best model for each method (i.e. presence/absence binomial, lognormal positive shortfin mako bycatch, quantile 99) based on the AIC. Variable coefficients for those expressed as factors are all presented as difference to the reference level except for fishing area, for which the intercept is suppressed by subtracting 1 in the equation which gives each area its own value. The same variables chosen in the quantile 99 regression were used when quantile regression was used for other quantiles.

Predictive ability was tested by training each AIC best model with the data from the first half of the time series (2003-2008) to see if shortfin mako bycatch could be predicted in the second half of the time series (2009-2012). GLM/GAM results were assessed using the root mean square error (RMSE), mean absolute error (MAE), r^2, and coverage estimates (Stow et al. 2009, Gruss et al. 2019). The coverage was determined by simulating CPUE values for 10000 random draws using the coefficients and their covariance matrix from the binomial and lognormal models fit to the training dataset. The simulated data was used to calculate a prediction interval with the upper and lower bounds representing the 2.5% and 97.5% quantiles of the simulated values for a 95% prediction interval. The coverage was estimated as the fraction of the real CPUEs calculated using the test data that were within the prediction interval (Gruss et al. 2019). A "perfect" model would have an RMSE and MAE equal to zero, an R^2 equal to 1, and coverage equal to the specified coverage of the prediction interval (e.g. 0.95 for a 95% interval).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(CPUE_i - \widehat{CPUE_\iota}\right)^2}{n}}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|CPUE_i - \widehat{CPUE_\iota}\right|}{n}$$

Table 2.1 Factor levels used for fishing area, hooks between floats, sea surface temperature, sea surface height, and bathymetry predictor variables used in the generalized linear model and quantile regression approaches to predict shortfin mako bycatch rates.

Variable (n=7609)	Number of Levels	Levels
Fishing Area GOM: 4565 NED: 315 NEC: 525 MAB: 1062 SAB: 309 CARFEC: 435 TUNNCASAR: 398	7	GOM (Gulf of Mexico) NED (Northeast Distant) NEC (Northeast Coastal) MAB (Mid-Atlantic Bight) SAB (South Atlantic Bight) CARFEC (Caribbean and Florida East Coast) TUNNCASAR (Tuna North, North Central Atlantic, and Sargasso
Quarter One: 1353 Two: 3214 Three: 1703 Four: 1339	4	1: January, February, March 2: April, May, June 3: July, August, September 4: October, November, December
Hooks Between Floats $min = 2.0$ $\bar{x} = 4.4 \pm 0.80$ $med = 4.0$ $max = 9.0$	5	<3 4 5 6 >7
Sea Surface Temperature (°C) $min = 8.085$ $\bar{x} = 24.403 \pm 3.654$ $med = 24.865$ $max = 32.695$	5	<15° 15°-<20° 20°-<25° 25°-<30° 30°-<35°
Sea Surface Height (m) $min = -0.3189$ $\bar{x} = 0.2308 \pm 0.227$ $med = 0.2183$ $max = 1.1137$	4	<0m 0m-<0.3m 0.3m-0.6m >0.6m
Bathymetry (m) $min = -8400$ $\bar{x} = -1993 \pm 1282.3$ $med = -1767$ $max = -41$	7	0m-<800m 800m-<1600m 1600m-<2400m 2400m-<3200m 3200m-<4000m 4000m-4800m >4800m

For the quantile regression method, the distribution of CPUE at the 0.95, 0.96, 0.97, 0.98, and 0.99 quantiles was estimated for the training and test data. Better specified models predicted quantiles close to those calculated empirically from the test data. They were also assessed using a pseudo-R^2 described by Koenker and Machado (1999). Pseudo-R^2 is similar to R^2 in that it is between 0 and 1 and is interpreted the same way as a measure of goodness of fit but it measures the local fit to the given quantile rather than the global fit. It does so using the weighted sum of the absolute residuals at the specified quantile (Koenker and Machado 1999). R^2 and pseudo-R^2 cannot be directly compared to each other. The pseudo-R^2 is a measure of the local goodness of fit dictated by the defined quantile while R^2 measures across the entire distribution (Koenker and Machado 1999) therefore, the pseudo-R^2 is used here only to compare across quantiles.

Models were evaluated for their potential as tools for developing bycatch mitigation strategies. To identify which model output was the most effective for identifying conditions where high shortfin mako bycatch occurs, each of the following definitions was considered as a cutoff in model predictions: the 95^{th}-99^{th} quantile of predicted CPUE is greater than some x value (quantile regression output), greater than y probability of presence (binomial output), and more than z predicted mean CPUE if present (lognormal output) where multiple values of x, y, and z were tried to find an optimal value (Table 2.2). The distribution of the fitted values for each model type fit to the entire original dataset were used as the foundation for cutoff values. Percentiles 95^{th}-99^{th} were calculated for the fitted values of each model type and treated as potential hot set cutoff values. As the quantile increases the cutoff value to be considered a hot set increases and less of the fishery would be closed if the hot set definition was used to avoid potential shark sets. Then each model was fit to the early half of the data (2003-2008; n=3985 sets). The sets with predicted catch higher than that of the specified quantile (x), high predicted probability of presence (y), or high predicted log positive shortfin mako bycatch (z), were classified as hot sets (Table 2.2). The total actual number of sharks caught in a hot set was calculated, as a measure of how many sharks could have been avoided if this hot set definition was used to avoid sets. Finally, since any bycatch avoidance strategy is designed based on past data and applied to future sets, the model is fit to the early data to predict the later data (2009-2012; n= 3624 sets) to identify hot sets in the same way and calculate how many sharks would be avoided if the hot sets were avoided.

Table 2.2 Tested models with their corresponding outputs and how those outputs are used to define hot sets, those that indicate high shortfin mako bycatch.

Model	Output	Definition of Hot Set
Quantile Regression	x= catch values that align with the 95^{th}-99^{th} percentiles	Predicted catch quantile > x
Binomial	y= probability of shortfin mako presence	Predicted probability of presence > y
Lognormal	z= catch if present	Predicted catch if present > z

Correlations between target species' catch rates and shortfin mako bycatch rates are very low, with a range of -0.021 to 0.124 for whole logbook and observer datasets and -0.002 to 0.145 for positive shortfin mako sets (Enric Cortes, SEFSC, Personal Communication) indicating that any reduction in fishing effort aimed at mitigating mako bycatch is an appropriate proxy for the reduction in target catch. The best model is considered to be the model that prevents the most shortfin mako shark bycatch for a 20% reduction in the number of longline sets. The choice of 20% is arbitrary, however, it was set to acknowledge that any reduction of fishing effort greater than 20% would lead to unacceptable levels of reduction in the target catch.

Development of an operational algorithm for avoiding bycatch

The best model was selected and subjected to further analysis to determine which variable(s) contributed most to determining hot sets vs not hot sets. The 20% closure cut off value corresponding to the best model trained by the early dataset was used to identify hot sets in the full dataset. This analysis was intended to make the algorithm operational by identifying combinations of gear and environmental variables that are associated with hot sets and so could be avoided in a potential bycatch mitigation strategy. First the later dataset was predicted using the predict.gam() function with the corresponding distribution and with type=”terms” to get the contribution of each variable to the final value for each set. The positive coefficients for each factor option of each categorical variable contribute to high probability of positive shortfin mako bycatch. Those variables imply conditions that favor shortfin mako bycatch. All variable contributions for hot and not hot sets were compared to narrow down the features that could be used to produce an operational algorithm that aims to maximize the identification of hot sets. To get further information the early dataset was put into a summary table showing the total number of hot sets and not hot sets fall under each combination of area, quarter, HBF (hooks between floats), and environmental variables using the ranges described in Table 2.1. Conditions that contained high proportions of hot sets were identified and combined with the information from the variable coefficient terms to develop potential mitigation strategies.

To determine the potential effectiveness of each proposed strategy, the strategy algorithms were each applied to the late data set. Individual sets that met those defined by the different algorithms were considered “no fish” sets that would have been avoided under that particular rule. The known shortfin mako bycatch values were then used to determine how many sharks would be avoided, how much of the fishery would be closed, how many hot sets are encompassed by the algorithm, and how many not hot sets are impacted by the rule(s). The best strategy is considered to be the one that encompasses the most hot sets and the least not hot sets impacted by the rule(s); i.e. maximizes the reduction in mako bycatch while minimizing the effort reduced impacted.

The estimates of the effects of the strategies on total mako shark bycatch assume the effort affected by the strategy is reduced to zero. In reality, it is more likely that the effort will be redistributed to areas/conditions that are not impacted by the closure or restriction. While developing a model of where fishing effort would be reallocated based on fisher economic decisions was beyond the scope of this study, some alternative estimates were made to approximate the range of possible effects of effort reallocation. This analysis assumes that a fisher can go to any open area and that they will redistribute effort proportionally with the existing distribution. The relocated sets were multiplied by the mean catch in that area and time in the late dataset to estimate the catch of relocated fishers. Total catch under the combined strategy and effort reallocation was then compared to the total catch of the late dataset if there were no mitigation strategy.

Results

In the US pelagic longline observer data, shortfin mako bycatch per set is generally low with a median of 0.0 and a mean of 0.67 ± 2.17 shortfin mako sharks. Most sets catch no shortfin mako sharks, or at most one or two (Figure 2.1). However, sets that catch one shortfin mako shark account for less than 18% of the total shortfin mako bycatch and sets that catch two or fewer shortfin mako account for less than 35% of the total shortfin mako bycatch (Figure 2.2). Sets with shortfin mako bycatches greater than four shortfin mako cumulatively account for over half of the total shortfin mako bycatch (Figure 2.2). This indicates that while high shortfin mako bycatch sets are rare, the number of shortfin mako caught during these uncommon events is a significant portion of the total shortfin mako bycatch.

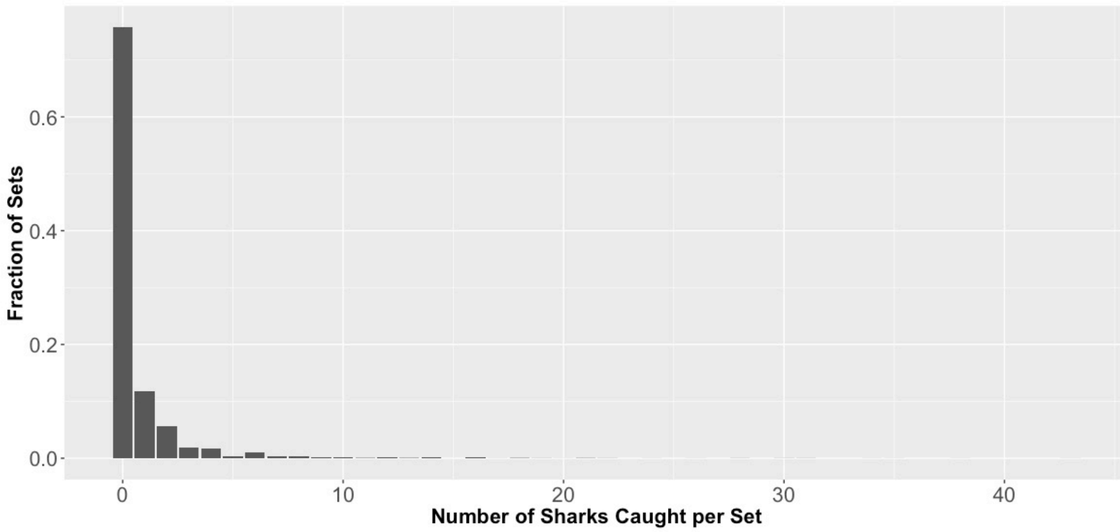


Figure 2.1 The fraction of all sets plotted against the number of shortfin mako sharks caught per set in the United States Pelagic Longline Observer Program (2003-2012).

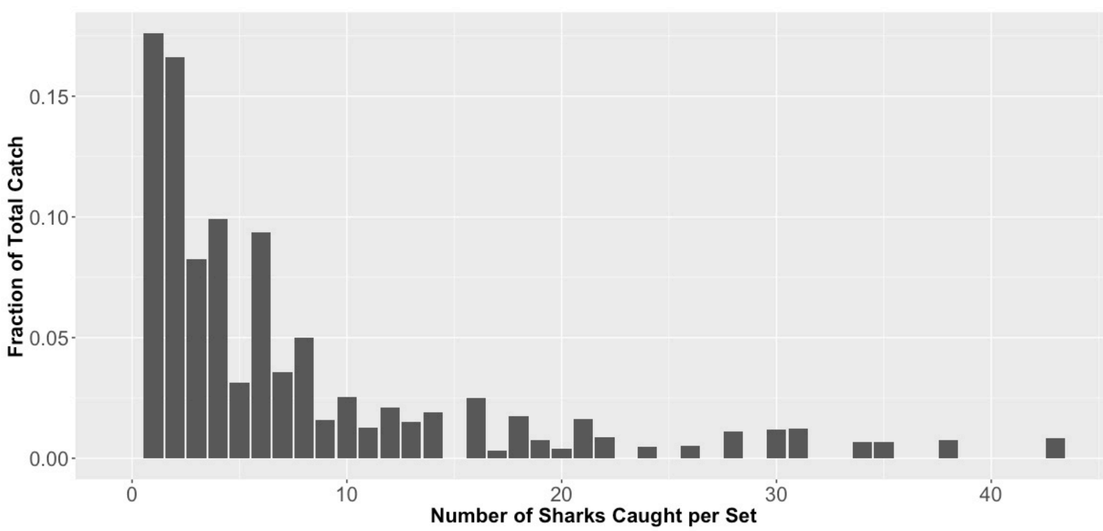


Figure 2.2 The fraction of the total shortfin mako bycatch against the number of sharks caught per set in the United States Pelagic Longline Oberserver Program (2003-2012).

Model Selection and Comparison of Environmental Variables

For the models fit to the complete dataset from 2003 to 2012, in all cases (lognormal GLM, binomial GLM, QR 99th percentile) the GAM with smoothers on the environmental variables had the lowest AIC value (Table 2.3) compared to models where the environmental variables were factors or numbers; GAM models were therefore used in all subsequent analyses. In addition, all environmental explanatory variables were found to be statistically significant ($p < 0.05$) and were retained. All environmental variables appear to be important regardless of which part of the distribution is assessed. The following final models were used:

Quantile Regression:

$$\log(CPUE + 1) \sim (Year + Fishing\ Area + Quarter + Use\ of\ Lights + Hooks\ Between\ Floats + s(SST) + s(SSH) + s(BATHY) - 1)$$

GLM:

$$Predicted\ Mean\ CPUE = (Probability\ of\ Positive\ Catch) \times (Mean\ Catch\ if\ Present)$$

where

$$Probability\ of\ Positive\ Catch: Presence \sim Year + Fishing\ Area + Quarter + Use\ of\ Lights + Hooks\ Between\ Floats + s(SST) + s(SSH) + s(BATHY) - 1\ )$$

$$Mean\ Catch\ if\ Present: \log(CPUE + 1) \sim (Year + Fishing\ Area + Quarter + Use\ of\ Lights + Hooks\ Between\ Floats + s(SST) + s(SSH) + s(BATHY) - 1)$$

The fishing area variable explains most of the variance in the probability of presence and the estimated CPUE if present (Table 2.4). Of the environmental variables, BATHY explains the most variance in the probability of presence (~2.3%) and the estimated CPUE if present (~7.1%) (Table 2.4). For the following results, we also ran QR models at the 95, 96, 97 and 98th percentiles as well as at 99th, using the same variables that were chosen by the AIC for the 99th percentile.

Table 2.3 Variables retained under each combination of model type and variable type with the corresponding Δ^{AIC} values within model type. Model types include a generalized linear model (GLM) lognormal, GLM binomial, and quantile regression (QR) at the 99th quantile. Variable types refer to how the environmental variables are treated: as factors, numbers, or as a generalized additive model (GAM) with smoothers.

Model Type	**GLM lognormal**			**GLM binomial**			**QR 99th Quantile**		
Variable Type	Factors	Numbers	GAM	Factors	Numbers	GAM	Factors	Numbers	GAM
ΔAIC	55	39	0	49	84	0	12511	12850	0
Year	X	X	X	X	X	X	X	X	X
Area	X	X	X	X	X	X	X	X	X
Quarter	X	X	X	X	X	X	X	X	X
Light sticks				X	X	X	X	X	X
HBF	X	X	X				X	X	X
SST	X	X	X	X	X	X	X	X	X
SSH	X	X	X	X		X	X	X	X
BATHY	X	X	X	X	X	X	X	X	X
SST^2	NA		NA	NA		NA	NA	X	NA
SSH^2	NA	X	NA	NA	X	NA	NA	X	NA
$BATHY^2$	NA	X	NA	NA	X	NA	NA	X	NA

Table 2.4 Fraction of deviance explained by each variable separately for the binomial and lognormal models.

Variable	**Binomial**	**Lognormal**
Year	0.008689	0.026056
Fishing Area	0.122025	0.088129
Quarter	0.004748	0.047321
Use of Light	0.012607	0.000777
HBF	0.001275	0.027355
SST	0.010889	0.014805
SSH	0.012525	0.022749
BATHY	0.022681	0.071169

Delta Lognormal

The RMSE and MAE values for the full delta-lognormal model are 2.87 and 1.01 respectively. Both measures are in units of difference and a perfect performance would have a value of zero, indicating that values further from zero have poor model adequacy. In addition, the model does not explain much of the variation in the data with an R^2 value of 0.17. However, this does not necessarily mean the model is poorly specified. While the coverage at 0.98 is not equal to the expected 0.95, it does not deviate far and is higher than expected indicating that the confidence intervals are slightly too wide but reasonable. The model appears to be appropriately specified but the gear and environmental variables used are lacking in their predictive ability.

Quantile Regression

The quantile regression models overall have good predictive ability for the upper extremes. All of the predicted upper quantiles consistently under-estimate the observed upper quantile indicating a potential bias but consistent and smooth estimators (Figure 2.3). The pseudo-R^2 values for the extreme quantiles are between 0.31 and 0.34 indicating similar variance explained with the value increasing with increasing quantile. Quantile regression of the upper quantiles appears to be appropriate for predictive purposes.

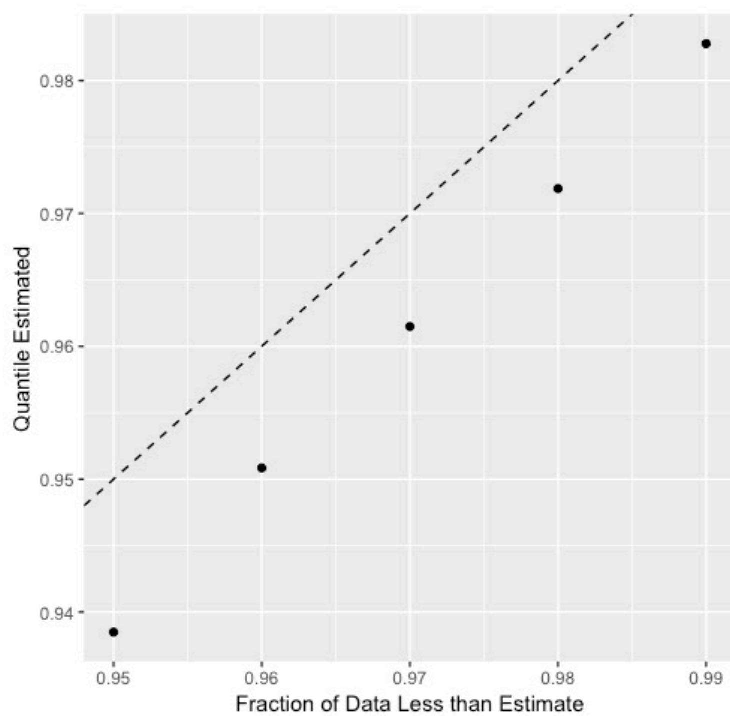


Figure 2.3 The estimated 95th-99th quantiles of the early 2003-2013 shortfin mako bycatches for models fit to the observer longline catch dataset plotted with the 1:1 line.

SST Across Models

The SST term appears to have a significant p-value for all models except at the 99th quantile (Tables A1-A7). All models perform poorly at extreme temperatures (SST < 10°C and SST > 32°C) and provide unreliable predictions due to insufficient data at these temperatures. Only predictions for SST between 10° and 32° C are considered. The shapes of the smoothing relationships are similar across models. They all have a general "U" shape (Figure 2.4) with the binomial model showing the most variation in the relationship between probability of positive shortfin mako bycatch and SST (Figure 2.4a). All models have the same minimum around 25-28°C and a local maximum at 15-20°C (Figure 2.3) The 95th-97th quantiles closely resemble the shape of the binomial model while the highest extremes are shaped more like the lognormal model (Figures 2.4b, 2.4c), which may be related to the fact that the mean shortfin mako bycatch when positive is influenced by very high shortfin mako bycatches. This indicates that there is a higher probability of positive shortfin mako bycatch and a higher predicted shortfin mako bycatch in 15-20°C colder waters.

SSH Across Models

The SSH term appears to be significant for all models except at the 98th and 99th quantiles (Tables A1-A7). All models perform poorly at the higher extreme of SSH (SSH > 0.9) and provide unreliable predictions due to insufficient data at these temperatures. Only predictions at SSH less than 0.9 and greater than -0.3 are considered. The 95th-97th quantiles (Figure 2.5c) have a bell shape similar to the lognormal model (Figure 2.5b) while the 98th and 99th quantiles more closely resemble a linear relationship with the estimated shortfin mako bycatch decreasing as SSH increases. The binomial model has the least variation with a fairly equal probability of positive shortfin mako bycatch across the sampled range of SSH (Figure 2.5a). All plots except the 98th and 99th quantiles show a global maximum around 0.1 with the binomial model suggesting a slightly lower global maximum at 0.0. This indicates that SSH has little influence on the probability of presence but there is a high estimated shortfin mako bycatch around an SSH of 0.0 across the distribution until the 98th quantile. At the highest extremes, the highest estimated shortfin mako bycatch is at the lowest SSH values.

BATHY Across Models

The BATHY term appears to be significant for all models (Tables A1-A7). All models perform poorly at very deep waters (BATHY < -6000m) and provide unreliable predictions due to insufficient data at these depths. Only predictions in waters shallower than 6000m are considered. All models show a similar pattern being fairly flat across depth with a sharp peak in shallower waters (<1000m). The most variation occurs in the binomial model (Figure 2.6a) with a small increase in the probability of presence below 3000m that does not appear in the quantiles and lognormal models (Figures 2.6b, 2.6c). Shortfin mako are a pelagic species so predicting a high probability of presence in deeper waters is expected. The high probabilities across models in the shallower waters is more unexpected as they are not known to be a coastal species.

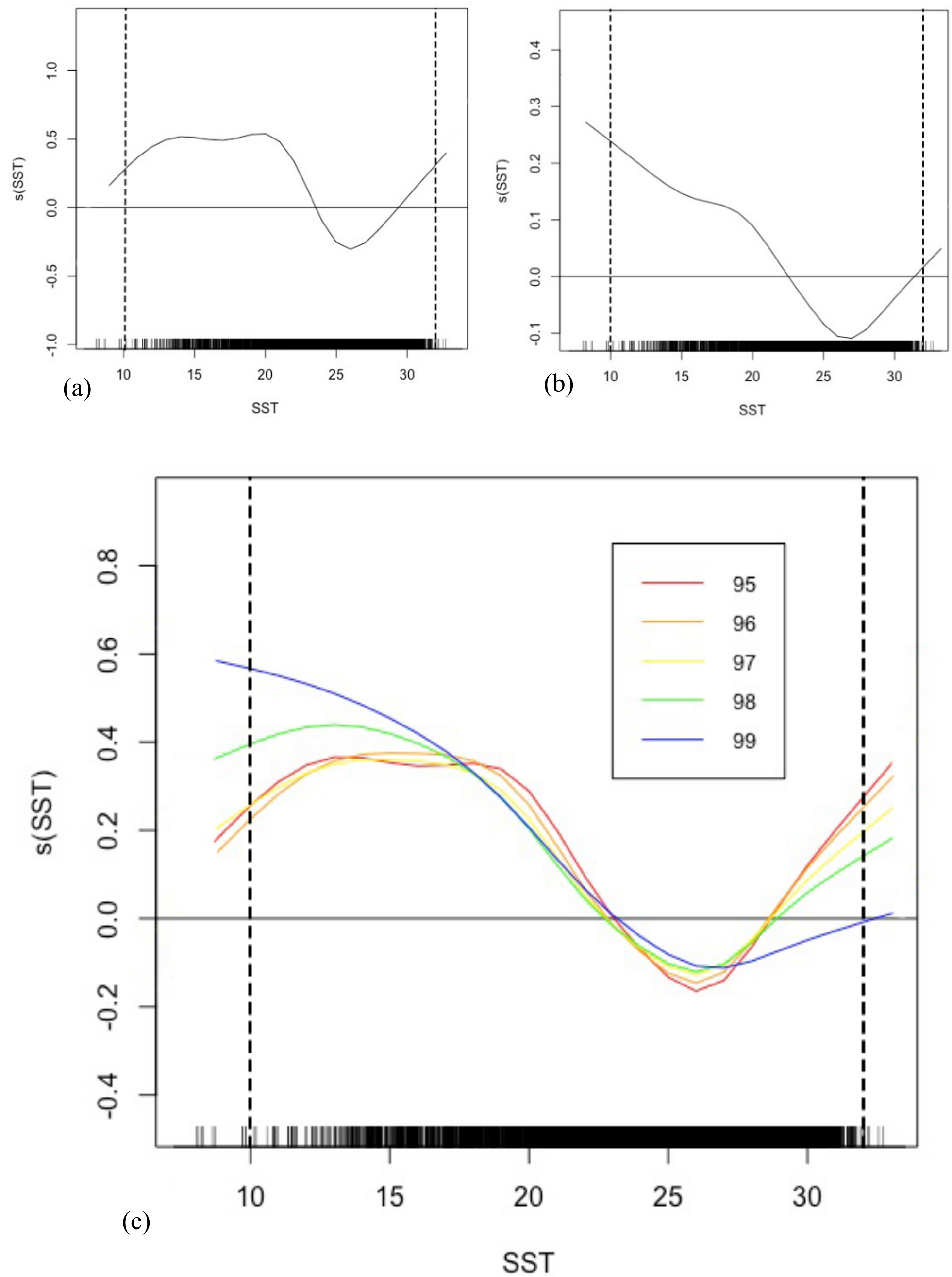


Figure 2.4 Smoothing curves for the sea surface temperature (SST) in degrees Celsius explanatory variable resulting from fitting the (a) binomial, (b) lognormal, and (c) quantile regression models to the 2003-2012 United States pelagic longline observer program. Density of data used to inform the model are displayed as a rug plot along the SST axis. All models perform poorly at extreme temperatures (SST < 10°C and SST > 32°C) and provide unreliable predictions due to insufficient data at these temperatures. Only predictions for SST between 10° and 32°C are considered.

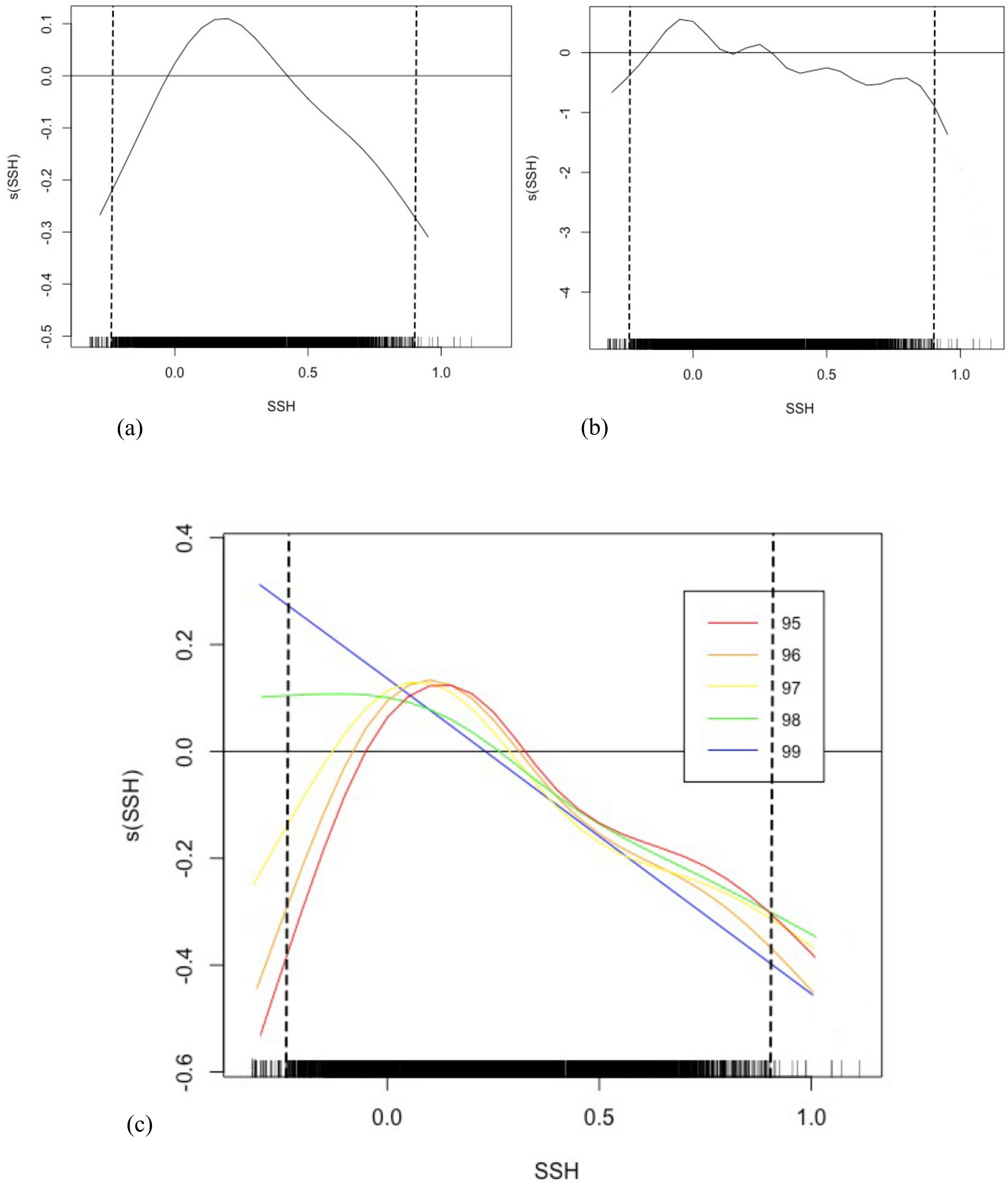


Figure 2.5 Smoothing curves for the sea surface height (SSH) explanatory variable resulting from fitting the (a) binomial, (b) lognormal, and (c) quantile regression models to the 2003-2012 United States pelagic longline observer program. Density of data used to inform the model are displayed as a rug plot along the SSH axis. All models perform poorly at the higher extreme of SSH (SSH > 0.8) and provide unreliable predictions due to insufficient data at these temperatures. Only predictions at SSH less than 0.8 are considered.

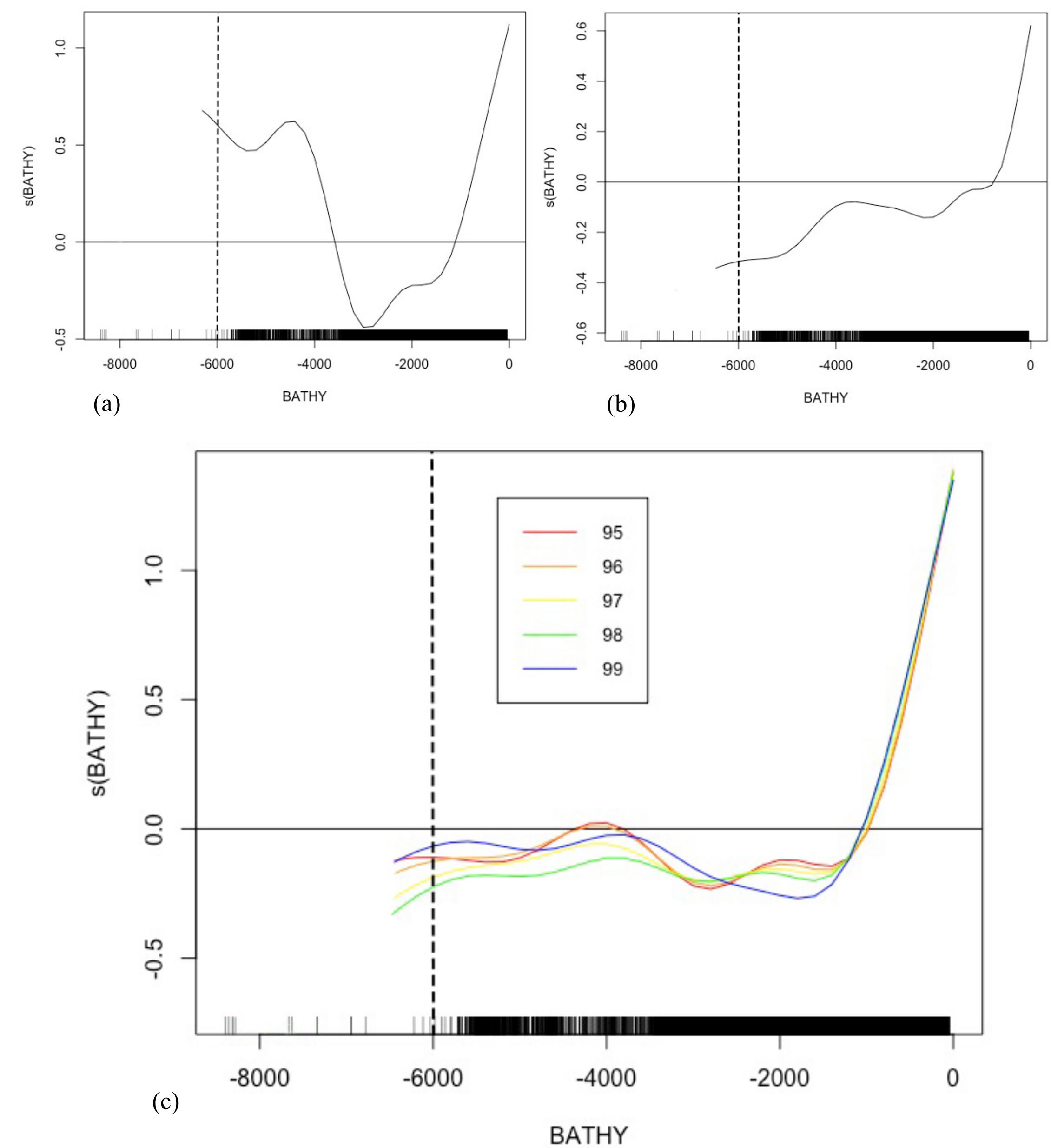


Figure 2.6 Smoothing curves for the bathymetry (BATHY) in meters explanatory variable resulting from fitting the (a) binomial, (b) lognormal, and (c) quantile regression models to the 2003-2012 United States pelagic longline observer program. All models perform poorly at very deep waters (BATHY < -6000m) and provide unreliable predictions due to insufficient data at these depths. Only predictions in waters shallower than 6000m are considered.

Model Comparison for Predicting Future Hot Spots

The delta-lognormal model fit to the early dataset has an RMSE equal to 3.32 and an MAE equal to 1.12, both slightly higher than the corresponding values from fitting to the entire dataset (RMSE=2.87, MAE=1.01). Furthermore, only about 11% of the variance is explained in this model. However, the model has a coverage of about 0.96, not far from the expected 0.95. The model appears to be appropriately specified but the gear and environmental variables used are lacking in predictive ability.

Quantile regression models overall have good predictive ability for the upper extremes. For all models the early data was predicted more accurately than the late data set as expected for a comparison between in-sample and out-of-sample prediction. Like the model fit to the entire dataset, this analysis consistently under-estimated the quantile (Figure 2.7). The estimation of the upper extremes explains increasingly more variance with the pseudo-R^2 of the 0.95 quantile about 0.32 up to the 0.99 quantile of about 0.35.

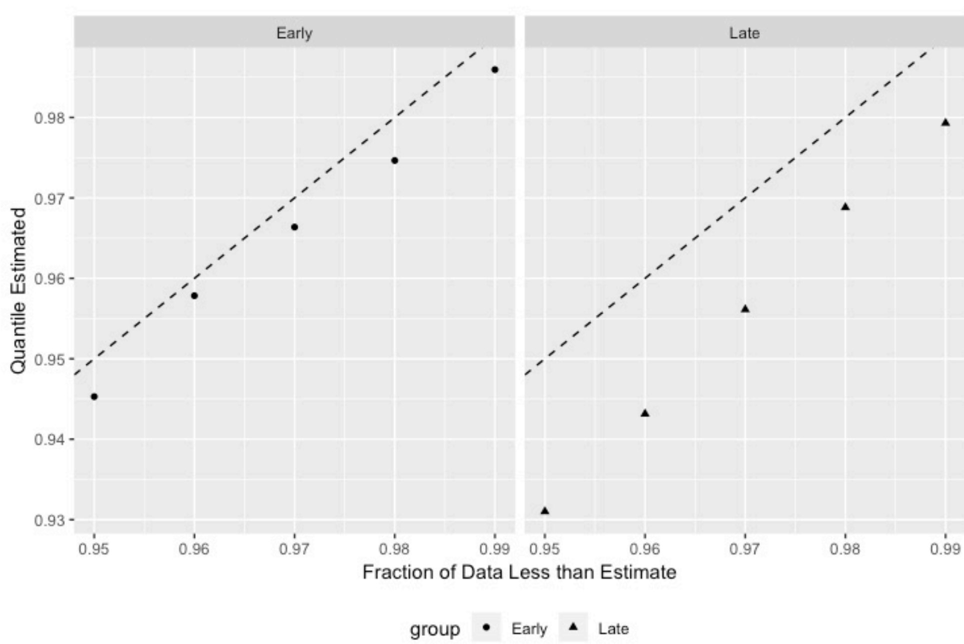


Figure 2.7 The estimated 95th-99th quantiles of the early (2003-2008) and late (2009-2012) shortfin mako bycatches for models fit to the early half (2003-2008) of the observer longline catch dataset.

For all models a higher cutoff corresponds to excluding fewer sets and therefore excluding a smaller percentage of the fishing effort. Potential cutoff values for the binomial model range from 0.14 to 0.95 predicted probability of a positive shortfin mako bycatch (Figure 2.8a). The following cutoff values, in number of sharks per set, represent closing 50% decreasing to 1% of the fishery for the lognormal and 95-99 quantile regression models respectively: 2.85-7.31, 2.90-24.4, 3.12-28.3, 3.42-33.9, 3.89-42.1, 5.06-57.5 (Figure 2.8b).

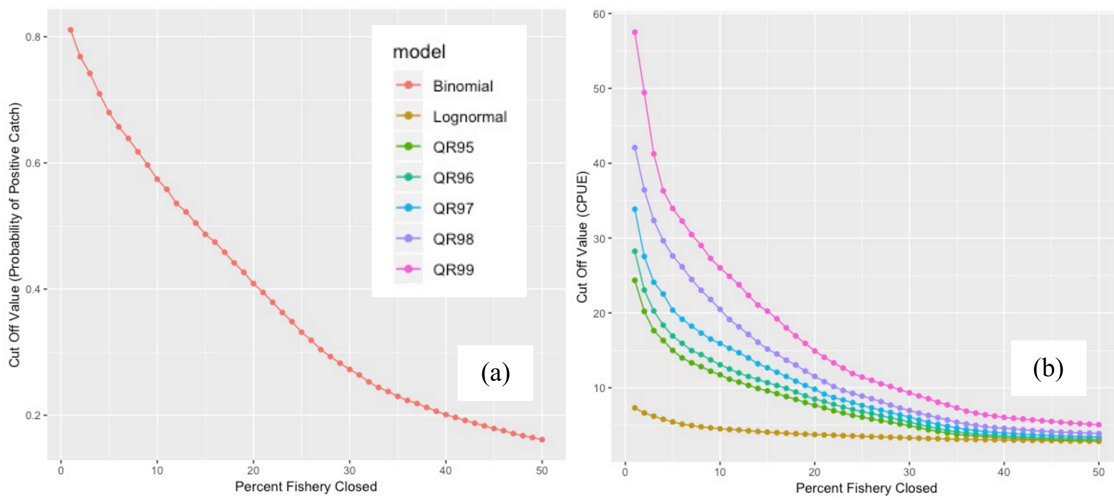


Figure 2.8 The hot set minimum cut off value for each model prediction used to determine sets that should not be fished at each percent of the fishery closed from 0% to 50% closure (a) binomial model probability of positive catch and (b)lognormal and 95-99 quantile catch per unit effort.

Management strategies are developed based on data from the past, and it is necessary to predict how much accuracy is lost when using that information to predict the performance of a bycatch reduction strategy into the future. To estimate the uncertainty involved in designing a bycatch avoidance strategy based on past data, fitted results for the "early" dataset are shown (Figures 2.9a, 2.10a). The "early" results show our performance with the best available knowledge while the "late" results show the effectiveness of the strategy applied into the future. Comparing the early and late results shows the degradation of accuracy when attempting to avoid future shortfin mako bycatches. Performance is measured as the number of shortfin mako sharks avoided per set and as the fraction of the total shortfin mako bycatch avoided in the given time period (Figures 2.9, 2.10).

When we closed more than 20% of the fishing effort (Figures 2.9, 2.10), all the models followed similar trends for both performance metrics. In the early scenario, when more than 20% of the fishery was closed, the quantile regression and binormal models generally agreed and performed equally well under both metrics (Figures 2.9a, 2.10a), while the lognormal model avoided fewer sharks per set (Figure 2.9a) and a smaller fraction of the total (Figure 2.10a). When we used the models to avoid future shortfin mako bycatches, while following a similar trend, there were large differences between the models' performance (Figures 2.9b, 2.10b). The binomial model performed the best and the 99^{th} quantile regression model performing the worst overall (Figures 2.9b, 2.10b).

Ideally, we would want to close as few sets as possible to avoid foregoing catch of target species. The rate of increase in the fraction of the total shortfin mako shark bycatch avoided per percent fishery closed is highest between closing 1% and 20% of the fishery (Figure 2.10). When closing less than 20% of the fishery there also appear to be more differences in the number of sharks avoided per set between the models (Figure 2.9). For the early dataset, the lognormal and quantile regression models all have a similar avoidance rate with the binomial model performing poorly only at very small closures in comparison to the lognormal (Figure 2.9a). However, from a 5%-20% closure the binomial model performs the best for both performance metrics. Predicting into the future (the late data), the quantile regression models perform very poorly with small closures. The binomial model has the highest shark avoidance rate (Figure 2.9b) and avoids the highest fraction of the total shortfin mako bycatch (Figure 2.10b) except at very low closure (<5%) where the lognormal model performs best. Overall, cut off values that correspond to closing about 20% of the fishery appears to best balance model performance and keeping as much of the fishery open as possible. The binomial model appears to best manage minimizing bycatch and impact on target catches. For example, in the late dataset 2644 shortfin makos were caught from 2009-2012. Using a mitigation strategy that avoids 20% of the sets, a strategy based on the binomial model results in avoiding 1638 sharks, about a 62% reduction in shortfin mako bycatch, while the lognormal model results in avoiding 1387 sharks, about a 52% reduction with the quantile regression models falling in between (Figure 2.9b). While these are both substantial reductions in bycatch, the binomial model is better at identifying high bycatch sets using past data.

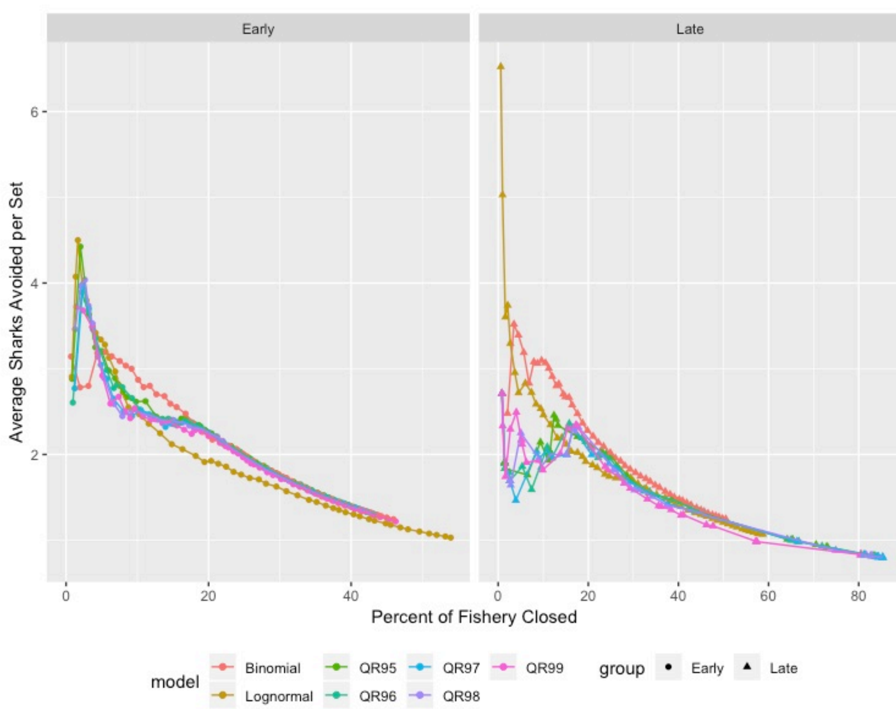


Figure 2.9 The average number of sharks avoided per set as a function of the percent of the fishery closed to fishing as determined by a binomial presence/absence GAM, a lognormal estimation of the mean shortfin mako bycatch if present, and quantile regression of the 95th to 99th quantiles for the early half (2003-2008) and the late half (2009-2012) of the dataset. All models were fit to the early half of the dataset.

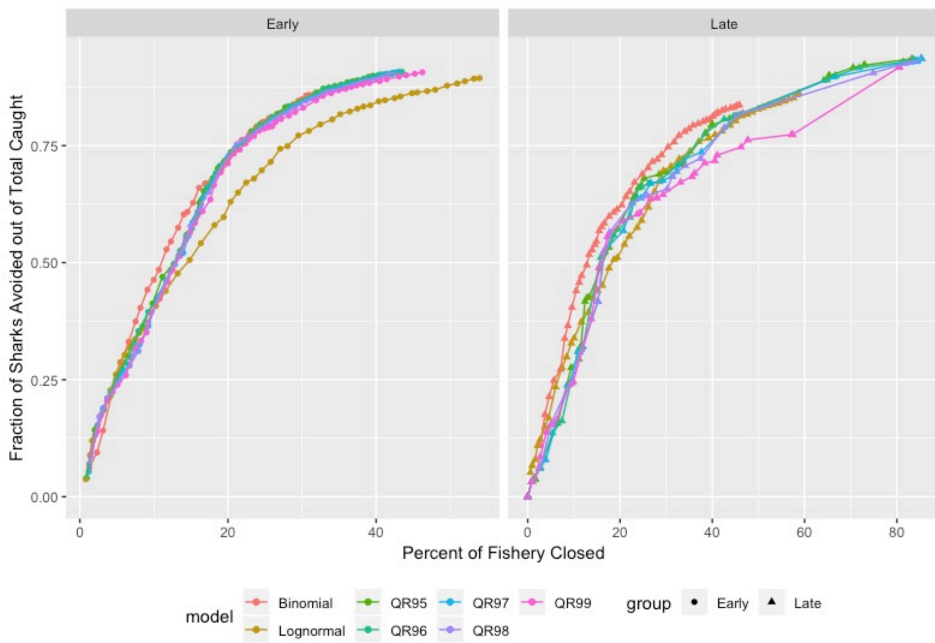


Figure 2.10 The fraction of shortfin mako sharks avoided out of the total shortfin mako bycatch in the time period as a function of the percent of the fishery closed to fishing as determined by a binomial presence/absence GAM, a lognormal estimation of the mean shortfin mako bycatch if present, and quantile regression of the 95th to 99th quantiles for the early half (2003-2008) and the late half (2009-2012) of the dataset. All models were fit to the early half of the dataset.

Using the binomial model to design a bycatch avoidance algorithm

Because the binomial model performed best at predicting hot sets, it was the only model considered for designing bycatch mitigation strategies. At a 20% closure binomial model identifies 725 of the 3624 sets in the time period as hot and avoids 1585 shortfin mako of the 2644 sharks caught 2009-2012 (about a 60% avoidance). Fishing area appears to be one of the strongest contributors, with many not-hot sets having a very strong negative area coefficient indicating that shortfin mako sharks are unlikely in those areas and hot sets having an area coefficient around zero. Yearly quarters one and two have very small positive coefficients close to zero indicating high probability of shortfin mako bycatch in that half of the year (Table 2.5). The use of lights favors a higher probability of positive shortfin mako bycatch (Table 2.5). The environmental variables vary more with positive and negative coefficients (Figure 2.11); however, all three variables have quite different distributions of coefficient values between hot and not hot sets (Figure 2.11). Because fishing area appears to be the strongest contributor, we focused on this variable.

Table 2.5 Coefficient values for each factor value of fishing area, quarter, use of lights, and hooks between floats and the mean coefficient values for hot sets and not hot sets.

N=3624	Coefficient Value	Hot Mean Coefficient Value (n = 725)	Not Hot Mean Coefficient Value (n = 2899)
Fishing Area	CARFEC: -0.970 GOM: -2.00 MAB: -0.345 NEC: 0.337 NED: -0.564 SAB: -1.62714 TUNNCASAR: -1.08	$\bar{x} = -0.183$ $median = -0.345$	$\bar{x} = -1.67$ $median = -2.00$
Quarter	Jan-Mar: 0.00 Apr-Jun: 0.00713 July-Sept: -0.525 Oct-Dec: -0.649	$\bar{x} = -0.424$ $median = -0.523$	$\bar{x} = -0.161$ $median = 0.00713$
Use of Lights	No: 0.00 Yes: 0.582	$\bar{x} = 0.491$ $median = 0.582$	$\bar{x} = 0.390$ $median = 0.582$
Hooks Between Floats	<3: 0.00 4: -0.294 5: -0.336 6: -0.645 >7: -1.56	$\bar{x} = -0.339$ $median = -0.337$	$\bar{x} = -0.347$ $median = -0.294$

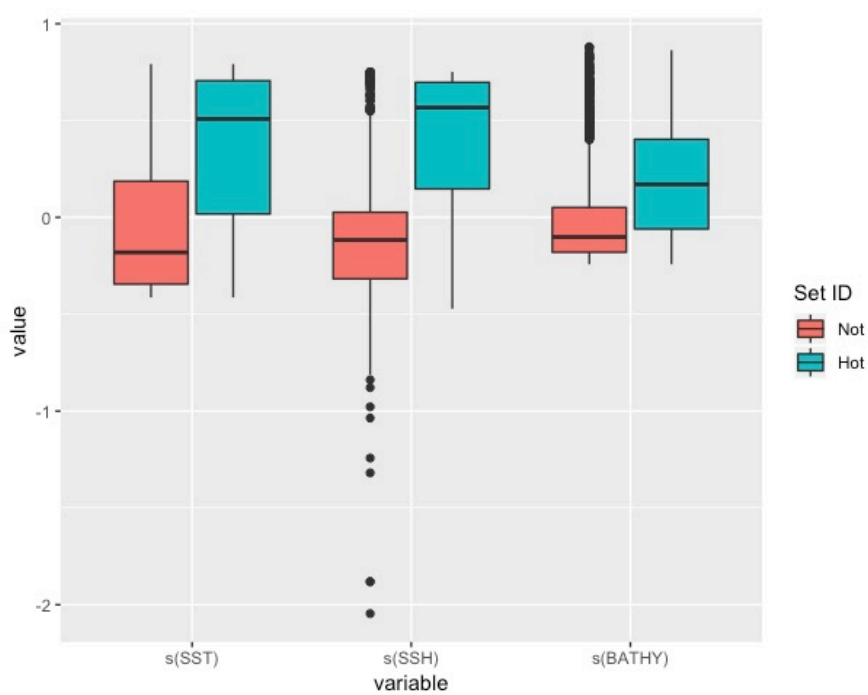


Figure 2.11 Coefficient values by environmental variable for prediction of the late dataset (2009-2012) using the binomial model fit to the early dataset (2003-2008).

Hot sets appear to occur mainly in the NEC (Northeast Coast) and MAB (Mid-Atlantic Bight) fishing areas together making up about 81% of the hot sets (about two thirds MAB and one third NEC) (Figure 2.12). While the next largest contributor, NED (Northeast Distant), only consists of about 12% of the hot sets (Figure 2.12), about 47% of the sets in NED are identified as hot (Figure 2.12). All of the sets in the GOM (Gulf of Mexico) are not hot, indicating that the GOM is not an area of concern when it comes to shortfin mako bycatch. Sets in the GOM represent 80% of all not hot sets. Like the GOM, the sets in the remaining areas are predominantly not hot with the CARFEC (Caribbean and Florida east coast), SAB (South Atlantic Bight), and TUNNCASAR (Tuna North, North Central Atlantic, and Sargasso) areas comprising of about 95%, 95%, and 81% not hot sets for each area, respectively (Figure 2.12).

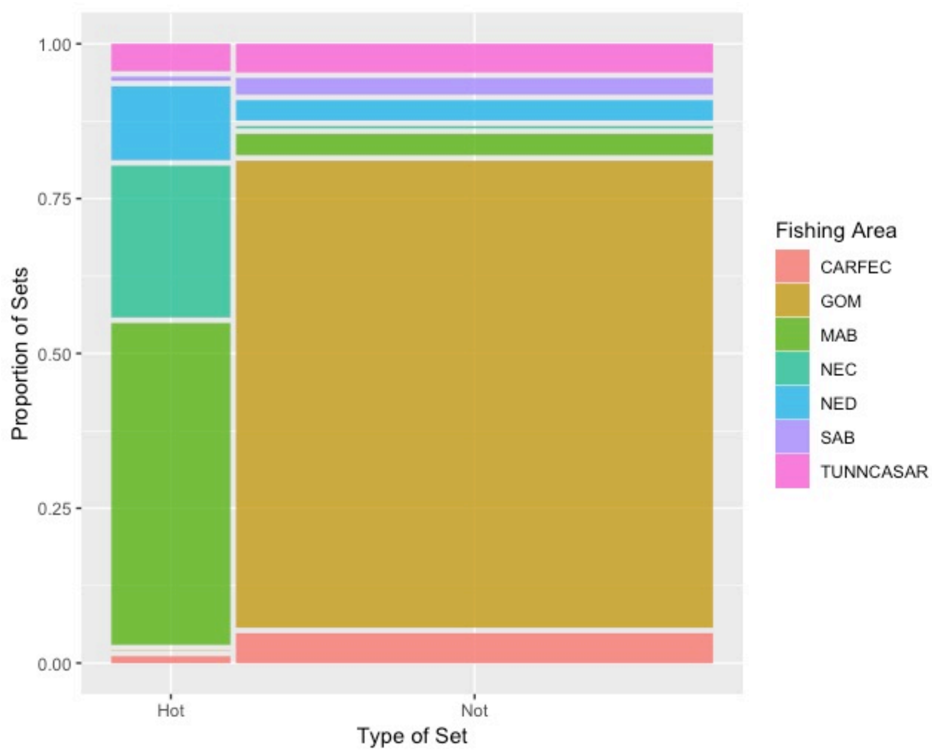


Figure 2.12 Mosaic plot showing the proportion of US Pelagic Longline Observer Program sets in the early dataset (2003-2008) that are categorized as hot or not hot by fishing area.

More in-depth analysis of the binomial model showed that hot sets are largely defined by fishing area and tend to occur in management areas NEC, MAB, and NED. These three areas make up about 25% of all the US observer longline sets from 2003 to 2012. Furthermore, hot sets in these areas have positive contributions from the environmental variable coefficients. To make this algorithm operational we could start by only applying options to these areas.

The most extreme mitigation strategy (Strategy 1) is to avoid all pelagic longline fishing in these three areas resulting in closing about 26% of the fished sets to avoid about 70% of the shortfin mako shark bycatch. When applied to the late dataset, this would close off 92% of all hot sets while placing restrictions on about 9% of the not hot sets in the entire US fishing grounds. A pattern in the early sets indicates that the use of lights had a very strong impact on whether a set was hot or not in these areas, particularly in MAB and NEC. For example, in MAB, NEC, and NED areas during the early data set, 91%, 98%, and 51% of the hot sets in each respective area used light sticks. A mitigation strategy (Strategy 2) would be to not allow the use of light sticks in these areas. When applied to the late dataset, this would close off 17% of all the fished sets to avoid 55% of the shortfin mako bycatch. Furthermore, this would close off 76% of all hot sets while placing restrictions on 2% of all not hot sets. The most complicated approach (Strategy 3) would be a strategy targeting hot sets specifically as much as possible. Based on the model fit to the early dataset, hot sets can be described by the following 19 combinations of conditions in the MAB, NEC, and NED fishing areas shown in Table 2.6. These conditions can be used operationally as a mitigation strategy. Fishers in any of the MAB, NEC, and MED fishing areas would not set in spots that meet any of the combinations of conditions that define hot sets. When all of the combinations are applied to the late dataset as a mitigation strategy, the entire set of rules closes about 17% of the fished sets and avoids about 47% of the total shortfin mako bycatch. This set of rules correctly restricts fishing on 79% of the hot sets in the combined MAB, NEC, and NED areas in addition to 73% of all hot sets over the entire US fishing grounds. Furthermore, the algorithm impacts 33% of the not hot sets in the combined MAB, NEC, NED areas and 3% of the total not hot sets. The individual results of each rule can be found in Table A8.

Table 2.6 Conditions that lead to high shortfin mako bycatch. In the application of Strategy 3 these combinations of conditions would avoid when fishing in the MAB (Mid-Atlantic Bight), NEC (Northeast Coastal), and NED (Northeast Distant) fishing areas. Unlisted combinations either have shown to have low shortfin mako bycatch or have no recorded effort in that area and time. The impact of fishing under those conditions is unknown based on the US Longline Observer data.

Area	Quarter	Lights	Hooks Between Floats	Sea Surface Height	Bathymetry (m)	Sea Surface Temperature (°C)
MAB	1	1	All	All	All	All
	2	0	5	[0.0-0.3]	<1600	[15-20]
		1	All	All	All	All
	3	0	4-6	≤0.0	<800	[20-25]
			5	≤0.0	<800	[25-30]
		1	All	All	All	All
	4	0	4-5	≤0.0	<1600	[20-25]
		1	All	All	All	All
NEC	2	1	All	All	All	All
	3	0	4	≤0.0	<2400	[20-25]
			5	≤0.0	(3200-4000)	[25-30]
		1	All	All	All	All
	4	1	All	All	All	All
NED	3	0	4	≤0.3	All	[20-25]
		1	4	≤0.0	<800	≤15
				≤0.3	All	[15-20]
			5	≤0.0	All	[15-20]
	4	1	4	<0.3	All	[15-20]
			5	<0.0	3200-4000	[15-20]

Estimated effect of best strategy

Strategy 2 appears to best balance the need to maximize the number of hot sets avoided and minimize the impact on fishers. Reallocation of effort in response to this strategy is assumed to either be a change in gear (switch to not using light sticks) or a spatial change to an area with no gear restrictions. If impacted fishers switched to not using light sticks in their current areas, they are estimated to avoid catching about 615 sharks based on the average catch for not using light sticks in each area (MAB, NEC, and NED) in the corresponding quarters, avoiding about a 23% of the total shortfin mako bycatch that would have been caught with no management strategy. If the fishers that would have used light sticks reallocated themselves spatially to the unimpacted areas, CARFEC, GOM, SAB, or TUNNCASAR, it is estimated that fishers would avoid catching about 1127 sharks based on the average catch in these areas in each quarter. Redistribution is space avoids 45% of the shortfin mako bycatch.

Discussion

In this paper we presented several ways to identify environmental conditions, regions and fishing methods that favor high shortfin mako bycatch based on the outputs of the delta-lognormal model and quantile regression of the upper quantiles. We found that using the binomial portion of the delta-lognormal model, the probability of positive catch was the best way to define a hot set basis for a "no fish" algorithm. Three potential mitigation strategies were designed based on the identification of hot sets in the early half of the dataset (1. minimal targeting: MAB, NEC, and NED completely closed to longline fishing, 2. intermediate targeting: no use of light sticks in MAB, NEC, and NED, 3. extreme targeting: rules for each combination of explanatory variables) and tested by applying them to the later half of the dataset. The results suggest that an intermediate strategy best balanced the need for flexibility over time, maximizing the number of hot sets avoided, and minimizing the impact on the target fishery.

The retention of all environmental variables in the lognormal, binomial, and quantile regression models contradicts our hypothesis that different parts of the distribution will be influenced by different environmental variables at least for the three variables considered. SST results are consistent with findings of shortfin mako tagging studies (Casey and Kohler 1992, Loefer et al. 2005, Abascal et al. 2011, Vaudo et al. 2017). However, for all models, the most important environmental variable is BATHY. Many catch events are located at or near the shelf edge in depths around 1500m or less which could account for a model predicting high shortfin mako bycatch in shallower waters in general. Also, this could be a result of catchability rather than abundance. Regardless of bottom depth, shortfin mako (Vaudo et al. 2016), usually stay above the thermocline (Anonymous 2019a) so that in shallower waters habitat compression might make them easier to catch. None of the gear or environmental variables explain much of the variation in CPUE regardless of the model.

When exploring the use of the different models to estimate the effect of not fishing under those conditions, all the models have the potential to reduce the total shortfin mako bycatch significantly with relatively small reductions in effort. The binomial model performed the best giving the highest avoidance rate per set and total number of sharks avoided at a given closure percentage. We hypothesized that quantile regression models would be more effective at identifying hot sets, but their performance overall is not as good as that of the binomial model. The quantile regressions had the lowest average number of sharks avoided per set and fell between the binomial and lognormal models in the fraction of total shortfin mako bycatch avoided.

In all cases the estimated number of sharks avoided for all approaches is expected to be an overestimate. All method results assume that the effort is completely removed. However, in reality, no set conditions would be replaced with sets in other locations that do not fall under the no set conditions that should have a lower probability of positive shortfin mako bycatch and therefore catch fewer shortfin makos. It is important to remember that avoiding a hot set does not bring the potential shortfin mako bycatch to zero, it reduces it based on the new conditions the fisher sets in. Following any of the methods will displace the bycatch from areas where the catch would be high to locations where the catch should be lower. A switch in gear was estimated to reduce catch by about 23% and a switch in spatial distribution was estimated to reduce catch by about 45%. These are promising numbers, but they are based on the proportional distribution of other fishers at the time and the corresponding mean catch. This gives us a rough idea of the performance under effort displacement.

While the performance of the binomial model may be surprising, as it is the simplest model tested, requiring and providing the least information, the successful use of presence/absence models in hot set analysis has been shown before (Phillips and Dudik 2008, Phillips and Elith 2010, McDonald et al. 2013, Stolar and Nielsen 2015). The binomial model has the potential to perform under limited data conditions, is less prone to bias caused by catchability, and can be more easily combined with multiple data sources (Gruss et al. 2014). Under the proposed bycatch mitigation strategies presented here, it is not necessary to accurately predict the shortfin mako bycatch but rather to accurately predict if the probability of shortfin mako bycatch of a particular set will be above the defined hot set threshold. This is similar to work done in Cuevas et al. (2018) where scientists used a scale of zero to one to describe the potential interaction between fishing effort and sea turtles. Areas with higher values indicated a higher potential for sea turtle bycatch. Again, it was not necessary to predict the sea turtle bycatch to mitigate interactions between sea turtles and the fishery.

Hot sets are found mostly in the MAB, NEC, and NED management areas, which allowed us to focus hot set criteria to a smaller area of the entire US fishing grounds. As expected, avoiding all longline fishing sets in these three areas avoids the most sharks (70%) and encompasses the most hot sets (92%) but has the greatest impact on not hot sets (9%). While this does support the idea of an area-based gear restriction, the amount of not hot sets impacted can be improved. We tried restricting the use of lights in the areas in addition to a very targeted approach requiring fishers to follow very specific rules with the idea that we could optimize the number of sharks avoided, hot sets avoided, and not hot sets impacted. It was surprising that Strategy 3, the most targeted towards avoiding hot sets, performed worse than just restricting lights. While both approaches close off about 17% of all fished sets, the targeted approach only encompasses 73% of all hot sets and avoids 46% of the shortfin mako bycatch compared to the 76% of all hot sets encompassed and 55% of the shortfin mako bycatch avoided by the restriction of using lights. Creating a targeted operational mitigation strategy from past data appears to be too specific to hold true when applied to the future.

Strategy 2 of closing the three areas to pelagic longline fishing entirely closes off too many opportunities for fishers to catch their intended target. Strategy 3 is so specific that it cannot hold up to uncertainty and changes over time. Strategy 2 is an intermediate approach that best balances the need for flexibility while substantially reducing the shortfin mako bycatch. Furthermore, this strategy would be much easier for fishers to follow as it is simple and straightforward. In addition, when the effort was reallocated, instead of assumed to be zero, the strategy still performed well, potentially avoiding up to 46% of the bycatch. Strategy 3 aims to target the hot sets and is very complicated with no benefit to the added complexity. From this analysis, Strategy 2, avoiding sets that use light sticks, could be the basis of an effective bycatch mitigation strategy. Sets that use light sticks are typically targeting swordfish (Clarke et al. 2014) but there have not been studies looking at the interaction between shark species and the use of light sticks on tuna longlines (Clarke et al. 2014).

This modeling exercise has shown that instances of high shortfin mako bycatch are important, impactful events that should be considered when assessing and managing the shortfin mako population. It is expected that avoiding these high shortfin mako bycatch sets would reduce the total mortality therefore complying with ICCAT recommendations (Anonymous 2017b, 2019a). The fishery data available to us combined with environmental data can be used to design effective shortfin mako bycatch mitigation strategies. Surprisingly, the binomial probability of positive shortfin mako bycatch model was the most effective in our tests and has allowed us to narrow down hot set areas and create several mitigation strategies. The full model allowed us to identify the combinations of gear and environmental variable values that have a high probability of positive shortfin mako bycatch and should therefore be avoided. This translated into an operational “no fish” mitigation strategy that is simple, straightforward, and easily understood and implemented by all stakeholders.

Closures based on conditions that favor high probability of shortfin mako bycatch rather than locations or seasons allow for management to adapt and follow variability in time as fisheries shift and change and as the effects of climate change take hold (Hazen et al. 2018). Even on smaller time scales, dynamic closures allow for management to respond to eddy and front formation and movement that is known to attract shark species (Block et al. 2002, Block et al. 2011, Rogers et al. 2015, Queiroz et al. 2016, Queiroz et al. 2019). These findings support that it is possible to have highly specific, dynamic, targeted management that hinders the longline fishery as little as possible if we can accurately identify conditions that favor shortfin mako presence and bycatch. The EcoCast models described by Hazen et al. (2018) showed that a dynamic closure required half the area to prevent bycatch numbers similar to a known seasonal closure thus achieving the same bycatch reduction with less reduction in fishing opportunity. The EcoCast models (Hazen et al. 2018) suggest closures by following suitable bycatch habitat and resulted in higher bycatch reduction rates at lower impediment to the fishery. Since correlations between target species' catch and shortfin mako bycatch rates are very low, the proposed algorithm for avoiding shortfin mako bycatch should operate similarly to the EcoCast models. The algorithm follows conditions that favor high shortfin mako bycatch, which are also areas with low target catch suggesting this algorithm could minimally reduce fishing opportunity similarly to the EcoCast models.

This study is limited by the data used. The US longline dataset is restricted to the western sub-population of the North Atlantic shortfin mako stock and should not be extrapolated to the entirety of the North Atlantic stock nor the South Atlantic stock. The range of the shortfin mako population extends beyond the US Exclusive Economic Zone and other countries' longline fleets operate and catch shortfin mako throughout their range. These have not been accounted for in this study. Inclusion of additional fleets and fishing operational variable could highlight additional shortfin mako bycatch hot sets or alter the distribution of shortfin mako bycatch hot sets across the whole north Atlantic fishery. In addition, this study did not include any fishery independent data, which could further inform the model on conditions that favor high numbers of shortfin mako which could translate to high CPUE. Despite the lack of variance explained by the gear and environmental variables, the models perform well enough at identifying hot sets to avoid half the shortfin mako bycatch with only a 20% reduction in effort and only a 17% reduction when converted to the recommended operational rule.

Future studies should explore the interaction between the use of light sticks and shortfin mako shark bycatch rates. Specifically, to better target high catch sets scientists should analyze what about the use of light sticks attracts the shortfin makos and leads to hot sets. Are there specific gear configurations, along with the use of lights, that increase the catchability of shortfin makos in the North Atlantic? As the correlation between swordfish catch and shortfin mako catch is low but the use of lights indicates the targeting of swordfish, what makes the difference between a high shortfin mako bycatch set and a high swordfish catch set? The results suggest that light sticks increase the catchability of shortfin mako in addition to the targeted swordfish. Spatial and temporal relative densities of swordfish and mako should be compared to determine when and where swordfish densities are high while mako densities are low to allow for the use of light sticks simultaneously decreasing shortfin mako bycatch and increasing swordfish catch. A more specific analysis of how the effort would be displaced, based on swordfish targeting and economics, should be explored to get a more detailed and accurate estimation of the true impact of the mitigation strategies (van Putten et al. 2012).

The binomial model presented here can be re-run as new information arises and provide managers with an updated operational set of conditions that should be avoided. New conditions can be tested in this same framework to evaluate tradeoffs and find optimal foundations for bycatch mitigation strategies. In its current form, this could be provided to managers for immediate consideration in potential policy. All information required for the fishers to follow any of the proposed strategies can be obtained from knowledge of their own gear and from the instruments they already use to locate suitable set sites.

The current stock will continue to decline until 2035 even under a zero TAC scenario according to the latest stock assessment conducted by ICCAT. This cannot be avoided, but if we can quickly start implementing effective measures to decrease shortfin mako bycatch we can help the population rebuild as quickly as possible and prevent further decline beyond 2035.

CHAPTER 3: POTENTIAL OF CLOSURE DESIGNS TO REDUCE SHORTFIN MAKO, *ISURUS OXYRINCHUS,* INCIDENTAL CATCH IN THE UNITED STATES PELAGIC LONGLINE FISHERY

Background

The shortfin mako, *Isurus oxyrinchus*, is a pelagic, migratory shark from the family Lamnidae. They are found throughout tropical and temperate regions in both hemispheres of the Atlantic, Pacific, and Indian Oceans (Casey and Kohler 1992, Abascal et al. 2011). Conventional and electronic tagging studies in the North Atlantic Ocean have shown that shortfin makos prefer water temperatures 15-22°C and follow seasonal migrations, spending fall and winters offshore in the pelagic habitat and the warmer months inshore over the continental shelf (Casey and Kohler 1992, Queiroz et al. 2016, Vaudo et al. 2017).

Commercial longline fishing gear consists of a long mainline with floats evenly spaced along the length. Between floats, gangions attach baited circle hooks to the mainline. The depth, soak time, and hook depth vary depending on the target species (Beerkircher et al. 2002, Clarke et al. 2014). Circle hooks are used specifically to reduce the catch and mortality of bycatch species like marine mammals and sea turtles(Clarke et al. 2014). Mako sharks' distribution is shown to have high overlap with longline fleets (Queiroz et al. 2016, Queiroz et al. 2019). In the Atlantic, shortfin makos are caught as incidental catch in commercial longline fisheries targeting tunas and swordfish. Shortfin mako are particularly unproductive while being highly susceptible to the fishery and experience high post capture mortality resulting in a large discrepancy between productivity and susceptibility to the fishery (Cortes et al. 2010). While they are not targeted, shortfin mako are considered to be one of the most important pelagic shark species affected by Atlantic Ocean pelagic longlines because they are listed as endangered on the

IUCN Red List (Rigby et al. 2019) and under Appendix II of Cites (Anonymous 1973) while being commercially valuable resulting in incidental catch being retained as well as discarded depending on regulations. The commercial value and conservation status of shortfin mako requires extra examination when considering management strategies.

Shortfin makos are assessed and managed by the International Commission for the Conservation of Atlantic Tunas (ICCAT) (Levesque 2008). The population dynamics models used in the most recent stock assessment (Anonymous 2017b) and stock assessment update (Anonymous 2019a) agree that the North Atlantic stock is overfished and experiencing overfishing. These findings contributed to the 2019 Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) listing the shortfin mako under Appendix II (Anonymous 2019b). CITES aims to ensure that international trade does not threaten the survival of vulnerable species. Appendix II limits international trade for listed species and requires that fishing nations demonstrate that fishing the shortfin mako would not threaten their chances for survival if they want to allow trade (Anonymous 1973). ICCAT recommendations and a listing under CITES acknowledge that mako sharks are not productive enough to rebuild without intervention.

Shortfin mako have a particularly low productivity, 0.31-0.60 per year (Cortés 2017), and a long generation time of 25-26 years (Cortés 2017). Harvest of such a slow growing, long lived species is likely to be unsustainable as the species may not be capable of compensating for the removal (Cortes 2002). ICCAT Recommendation 17-08 (Anonymous 2017a) instructs all parties to require vessels to cause the least amount of harm when releasing live shortfin mako. Furthermore, large vessels must release all shortfin makos regardless of whether the individual is alive or dead when brought to the boat. Smaller vessels may retain live shortfin makos provided they meet minimum size restrictions (Anonymous 2017a). Some shortfin makos are still retained by some fishers and this recommendation does not necessarily reduce shortfin mako interaction with fishing gear; those released alive are still subject to post-release mortality (Anonymous 2017b, 2019a). The current non-retention policy does not adequately mitigate these remaining sources of mortality enough to allow the population to recover. Projections performed during the 2017 and 2019 ICCAT stock assessments (Anonymous 2017b, 2019a) indicate that the population will continue to decline even under a complete non-retention policy (Courtney et al. 2017, Vaughan et al. 2019, Courtney and Rice 2020). A substantial reduction in total mortality is essential for population recovery to the point that it is not overfished nor experiencing overfishing (Anonymous 2019a). Chapter 2 of this dissertation found that a combination of area closures and gear restrictions have the potential to reduce incidental catch substantially by targeting management to maximize avoiding incidental catch hotspots. ICCAT projections and the results of Chapter 2 indicate that population recovery depends on shortfin makos having reduced interactions with fishing gear in the first place.

Here we explore a fishery closure as a potential strategy for incidental catch mitigation by way of reducing the interaction of shortfin makos with fishing gear. The previous dissertation chapter results suggest that high incidental catch events often happen in waters 15-20º and off the coast of north eastern North America (Chapter 2). Closures are implemented as defined areas in time and space where the species of interest cannot be fished with the idea that this will give the species a habitat free of fishing mortality allowing the population numbers to grow, functioning similarly to a marine protected area (MPA).

This study aims to determine if the implementation of a targeted longline closure can reduce shortfin mako incidental catch rates. Closures can be seasonal or all year as well as stationary or moving. A closure in the waters off the coast of north eastern North America would be stationary while a closure following the temperature would move with direct consideration of seasonal migration. Stationary MPAs have been shown to have varying success with reducing the fishing mortality of highly migratory species (Little et al. 2009, Le Bris et al. 2013, Schofield et al. 2013, Maxwell et al. 2020). This, combined with tagging study conclusions that shortfin makos migrate seasonally (Casey and Kohler 1992, Queiroz et al. 2016, Vaudo et al. 2017), suggests that mako movement could potentially follow a seasonal temperature signal. For these reasons, we hypothesize that a moving closure following the preferred temperature signal will be an effective closure design reducing incidental catch the most, allowing the population to rebuild while impacting the fishery the least.

This study aims to explore the potential of several closure simulation scenarios to reduce shortfin mako incidental catch in a fishery loosely resembling the U.S. pelagic longline fleet targeting tuna and swordfish. We will present several closure designs, stationary and moving, designed relative to this theoretical fishery and test which (if any) can best target high incidental catch events and reduce incidental catch rates the most when compared to the status quo of no closure. All scenarios are simulated and assessed for their ability to reduce shortfin mako incidental catch while minimizing the impact on a theoretical fishery.

Methods

An Individual Based Model (IBM), with individual sharks as the smallest unit, modeled the seasonal movement of sharks following a preferred temperature signal, aging, reproduction, and natural mortality, and fishing mortality. Fishing effort was distributed throughout the study space proportionally to the effort distribution of the US longline fleet. Individual fisher behavior is assumed to follow the distribution of the target species. For simplicity, fishing vessels were not modeled individually with an IBM but distributed in time and space consistent with the existing US pelagic longline fishery with modifications in accordance with the proposed closure scenarios, capturing the dynamics of the fishers' seasonal fleet movements. The base case scenario used this spatial distribution while the alternative scenarios reduced the effort in a closed area and re-distributed it proportionately to the remaining open areas while keeping the total effort constant. Alternative scenarios included changing the effort to 0 in the area corresponding to waters off of the north east coast of North America, making the effort=0 in preferred temperature areas seasonally, and making the effort=0 in preferred temperature areas weekly. The presentation of the methods of this study follows the ODD protocol published by Grimm et al. (2006) in which I will present an overview of the IBM, then the design concepts, and finish with model details.

Purpose

The purpose of this model is to use simulations to evaluate the potential of a stationary closure, based on incidental catch hotspots, and moving closure scenarios, based on following shortfin mako seasonal movements to increase the shortfin mako population to the point that rebuilding and recovery is possible under constant total fishing effort.

State Variables and Scales

The IBM has three hierarchical levels: individual, population, and environment. Individuals are all female and are described by state variables: shark number, age, reproductive ability, and location. The population consists of all of the living individuals grouped by age. The abiotic environment is characterized by its temperature as determined by the week number and location. The fishery is characterized by a distribution of fishing effort determined by week number and location.

Process Overview and Scheduling

This model has a weekly time step. Each week every surviving individual is allowed to age by one week and is then subjected to the rules governing natural mortality, movement, fishing mortality and reproduction, in that order (Figure 1).

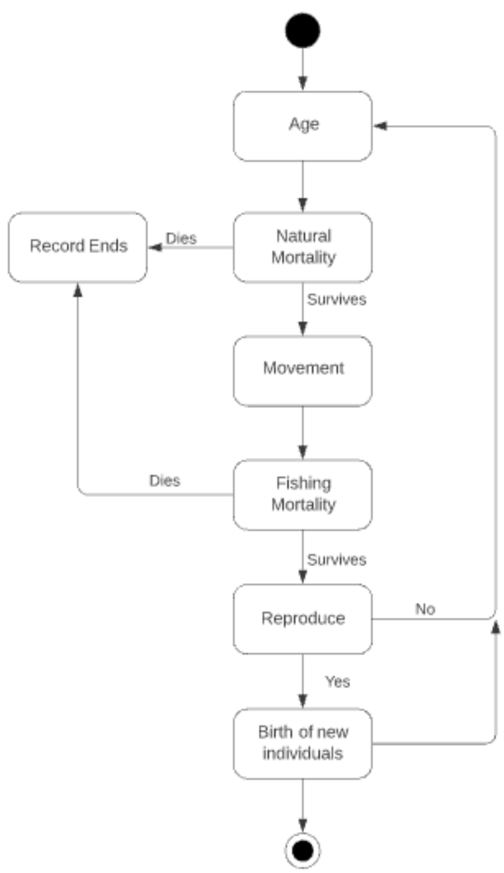


Figure 3.1 Flow chart of individual based model scheduling at each weekly time step.

Design Concepts

All modeling was performed using R (R Core Team 2019) and is an adaptation of the individual-based kinesis model described by Humston et al. (2000). The Humston et al. (2000) two dimensional model depicts movement of bluefin tuna following a temperature orthokinesis, with random speed change in response to temperature stimulus. Each individual can detect its current temperature and respond but cannot detect the surrounding temperature gradient and therefore knows only that it is in an unfavorable habitat, not knowing the location of more preferable temperature. The movement of an individual at any given time depends on the surrounding temperature and its location in the previous time step.

This study simplifies their model to one dimension where individuals can move around an arc (Figure 3.2) and the seasonal temperature signal (Figure 3.3) moves along the arc with time. This study follows an initial population of 1000 female individuals over 50 years. The temperature signal is mapped so that it corresponds to the waters off the east coast of the U.S. and is intended to resemble the Gulf Stream with theta=90° corresponding to the location 43.5336 latitude and -53.3961 longitude and theta=180°corresponding to 24.0849 latitude and -76.0994 longitude (Figure 3.2). Because the seasonal trends in this region follow a strong latitude and inshore/offshore gradient, this arc is able to capture the seasonal temperature trends in time and space with sufficient resolution. When exploring the potential of moving closures based on temperature, only one dimension is needed. Added spatial complexity would introduce additional assumptions and uncertainty unnecessarily in the context of the goals of this study. Individual sharks are completely independent and do not have any interaction. Multiple individuals can occupy the same theta location at any given time. The population is considered to be all living individuals at the end of that time step. All life history parameters are generally based on the statistical catch at age model from the 2017 ICCAT stock assessment (Anonymous 2017b). The fishery is based on the US pelagic longline fishery with total catch (retained, released alive, released dead, lost at surface, finned, and unknown) and effort data obtained from the US pelagic longline observer program (2003-2012) (Beerkircher 2016). During this period, there was no retention ban. As a result, when compared to current conditions, incidental catch during that time could have been either higher or about the same but with a higher retention. Projections performed in the 2019 stock assessment (Anonymous 2019a) showed that if catch remains similar, reducing retention does not decrease discard mortality enough to allow the population to rebuild. To focus on the potential effect of the proposed closures, this model does not include live releases and discard mortality and therefore depicts the worst-case scenario that every shark that encounters fishing gear dies.

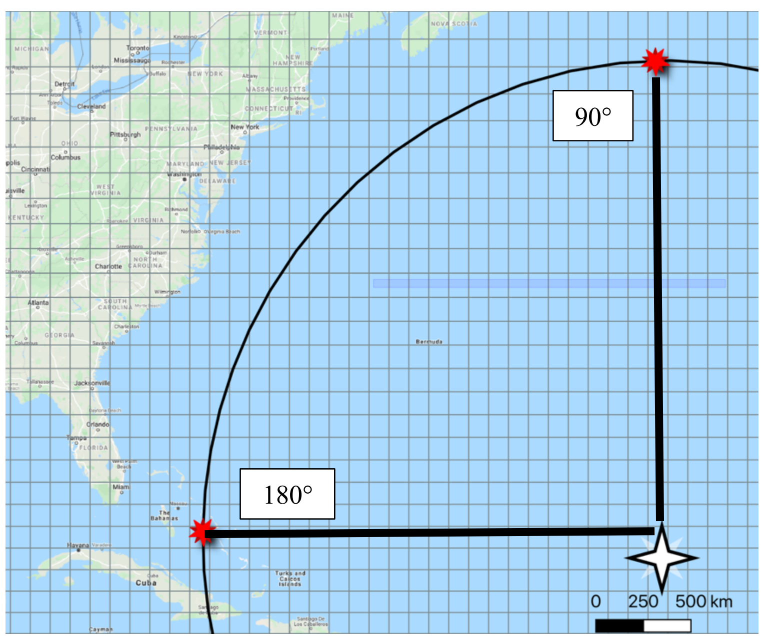


Figure 3.2 Mapping of the theoretical study space in real space. The theoretical study space is the one-dimensional angle along the depicted arc. This arc is meant to be a simplified depiction of the Gulf Stream.

Initialization

The initial population of 1000 individuals all have the same arbitrary starting velocity, 1 angular degree per day. The age for each individual is randomly assigned based on the proportion of the female population at age for year 2015, the terminal year in the stock synthesis 3 (SS3) run of the 2017 stock assessment (Anonymous 2017b, Courtney et al. 2017). The starting location is randomly drawn from a preliminary run of the base case scenario for 10 years. Each scenario is run 5 times with different starting locations and ages with the starting populations the same across scenarios.

Input

The temperature signal is centered on the preferred temperature, T_m, and shifts seasonally following a simple wave equation that mimics the sea surface temperature values of the Gulf Stream in the study area. The period of the cycle is one year (52 weeks) with Week 1 representative of the week of January 1 and Week 52 representative of the week of December 31 of an average year. The change in temperature with latitude and the change in temperature with time, T_s and T_a respectively, were determined through trial-and-error plotting of the equation so that in winter months the preferred temperature signal moves south and during summer months the signal moves further north mimicking the temporal temperature patterns of the Gulf Stream. Spatially, at any given time, the temperature increases as from north to south. The seasonal temperature signal on a weekly time step is described by the Equation 1 (Figure 3.3):

$$T_{t+1} = T_m + T_s \times \sin\frac{2\pi(\theta_{t+1} - 135)}{180} + T_a \times \sin\frac{2\pi\theta_{t+1}}{180} \times \cos\frac{2\pi t}{52} \qquad (1)$$

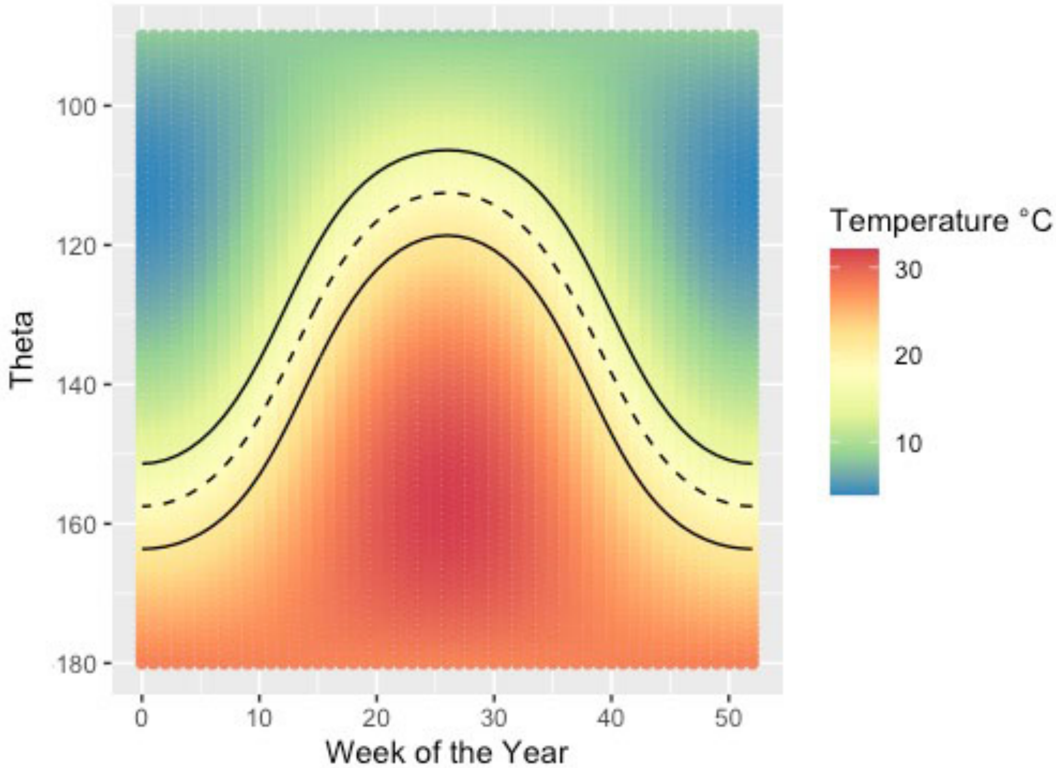


Figure 3.3 Weekly temperature signal along the modeled spatial arc (theta, where 90 is the northeast end and 180 is the south end) over one year with the preferred temperature, 18°C, shown with a dashed line and the preferred temperature range (15°C, 21°C) shown with solid lines. The theoretical study space is the one-dimensional angle, theta along an arc on a polar coordinate system.

Natural mortality M is constant, 0.08, while F varies in time and space following US pelagic longline effort and includes age dependent selectivity. The mean total F over the last 5 years of the SS3 simulations is 0.216 (Courtney et al. 2017). The spatial distribution of F was the same in all times steps and was based on a composite of US longline data from 2003-2012 to represent a typical recent year for this fleet. To distribute F spatially, catch and effort data were obtained from the US pelagic longline observer program (2003-2012) (Beerkircher 2016). Each haul was plotted with the arc and assigned to a 5° theta bin ranging 90-180°depending on where it fell along the arc (Figure 3.2) and assigned to a quarter of the year depending on the haul month; Jan.-Mar.= Quarter 1, Apr.-Jun.=Quarter 2, Jul.-Sept.=Quarter 3, Oct.-Dec.=Quarter 4. The number of hooks in each bin per quarter is defined as the aggregation of all of the hooks set in each bin for each quarter (Figure 3.4). Movement of sharks is restricted to only the study area so the effort outside of the study area is not considered. Total F is assumed to be proportional to total effort. The number of hooks for each theta bin in each quarter was divided by the highest number of hooks to determine relative effort. F for each area and time are proportional to the relative effort at that area and time.

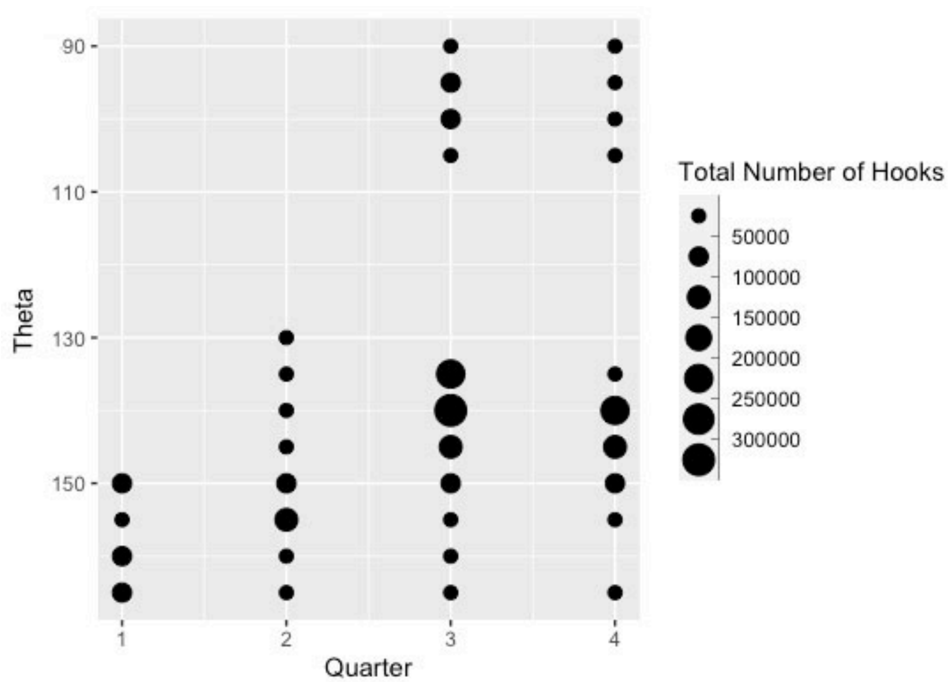


Figure 3.4 US pelagic longline hauls from 2003-2012 assigned to a 5° theta bin ranging 90 (northeast) -180° (south) and assigned to a quarter of the year depending on the haul month; Jan.-Mar.= Quarter 1, Apr.-Jun.=Quarter 2, Jul.-Sept.=Quarter 3, Oct.-Dec.=Quarter 4. The theoretical study space is the one-dimensional angle, theta along an arc on a polar coordinate system. The number of hooks in each bin per quarter is defined as the aggregation of all of the hooks set in each bin for each quarter. Bins without an assigned number of hooks indicate no data in that location and are subsequently set to zero hooks for further modeling.

All parameters regarding age structure, the instantaneous natural mortality rate (M), instantaneous fishing mortality rate (F), and reproduction (Table 3.1) are based on the stock synthesis (SS3) model performed during the 2017 ICCAT Shortfin Mako stock assessment (Anonymous 2017b, Courtney et al. 2017). However, the IBM is different in that it only includes the US fleet in the Northwest Atlantic while the SS3 model applies to the entire North Atlantic for multiple fleets. This study assumes that the F imposed by the US fleet in the Northwest Atlantic portion of the stock is comparable to that imposed by all fleets on the entire stock. The model focuses on only the NW Atlantic region to evaluate how much a single fleet could reduce its impact on mako sharks. In practice, rebuilding mako sharks would require that mortality be reduced throughout the North Atlantic by all the fleets that catch makos.

Simulation Scenarios

Simulation scenarios are designed to determine the best way to remove fishing mortality and allow the shortfin mako population to rebuild. Each scenario starts with the same population but is governed by different fishing mortality scenarios. The baseline scenario mimics the current fishing effort distribution and an absence of no-take zones. Fishing mortality is proportional to the spatial distribution of the sharks and the US longline fleet, as described above. Alternative scenarios aim to determine if a moving closure has more potential than a traditional stationary closure by testing three different options with varying degrees of movement in time and space. The stationary closure is based on incidental catch hotspots and moving closure scenarios are based on following shortfin mako seasonal movements. Treatment scenarios include 1) NE: a stationary no take zone that corresponds to the statistical reporting region that the US NMFS calls Northeast Distant (Cortes 2013), 2) Seasonal: no take zone that follows the preferred temperature signal quarterly and 3) Moving: no take zone that follows the weekly preferred temperature signal. The NE stationary closure follows the findings of Chapter 2 that concluded the NE region has a particularly high predicted probability of catching at least one mako and gear restrictions in this particular area of the fishery could significantly reduce shortfin mako incidental catch. The seasonal and moving scenarios both assume that shortfin mako migrations are based on temperature and use different time scales to capture the uncertainty in how this assumption can be applied temporally.

Submodels

Mortality

The natural survival of an individual shark is a Bernoulli random draw with the weekly probability of surviving natural mortality equal to S_m (Equation 2, Table 3.1).

$$S_m = e^{-(\frac{M}{52})} \tag{2}$$

where M is taken from SS3. SS3 uses data from all fleets throughout the North Atlantic and does not take space into account. The weekly probability of surviving fishing is a function of relative effort ($E_{\theta t}$) in a given theta bin and week and selectivity at age (S_a). As a result, to determine S_f (Equation 3), the E must be multiplied by a constant, f. This constant, f=13, was determined by trial and error to result in a total annual harvest rate across all ages comparable to the assessment results (harvest rate = 0.061) (Anonymous 2017b, Courtney et al. 2017).

$$S_f = e^{-(\frac{E_{\theta t} f S_a}{52})} \tag{3}$$

Individuals are subjected to fishing mortality depending on their theta, time of the year, and age-based selectivity (Figure 3.5). The fishing survival of an individual shark is a

Bernoulli random draw with the probability S_f. The age-based selectivity curve (S_a) is the double normal distribution used in the SS3 model runs for the US fleet (Anonymous 2017b).

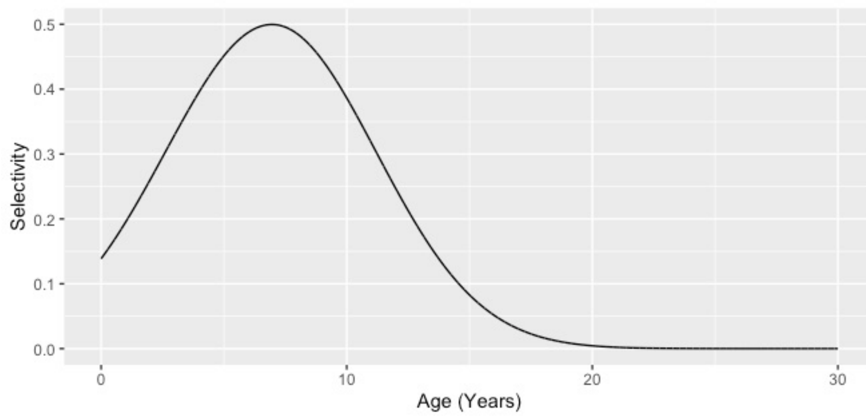


Figure 3.5 Selectivity at age following a double normal distribution with a mean of 6.96, standard deviation of ascending limb of 5.12, and standard deviation of descending limb of 4.99 (ICCAT 2017).

Reproduction

All sharks in the model are capable of reproducing regardless of age but the number of pups is determined by the fecundity curve resulting in immature sharks producing 0 pups while older mature sharks can produce several pups. This process results in an average of about 4 female pups per mature shark per year which is consistent with what we know of the biology (Mollet et al. 2000, Anonymous 2017b, Courtney et al. 2017). Each shark can reproduce once every year. At any time, t+1, given the individual did not reproduce in the current calendar year, each individual has an equal probability of reproducing based on the three-year reproduction cycle (1/3years/52days = 0.00641) and reproduction is an independent Bernoulli random draw. Those that do reproduce produce a number of pups specified by the equations in the SS3 models used in the 2019 Update to the Shortfin Mako Stock Assessment (Anonymous 2019a). Age is converted to fork length (cm) following the

Von Bertalanffy Growth Equation (VBGE) (Table 3.1) (Cortés 2017, Courtney et al. 2017), then converted to total length in meters (Table 3.1) (Cortés 2017, Courtney et al. 2017). The fraction mature (Mat), litter size (LS), and reproductive cycle (C) (Table 3.1) is used to calculate the deterministic annual pup production at age, LS*Mat/C. The total number of new sharks pupped in the time step is equal to the sum of the annual pup production at age for all individuals that undergo reproduction. The pups start at Age 0, have the same starting velocity and random component as the initial population, and inherit their location from their parent.

Movement

The location in angular degrees from 0 (θ) at each time t+1 is a function of the location at time t, velocity at time t, and a random component at time t (Equation 4). Velocity (V) at time t+1is a function of velocity at time t reduced by a decay factor (T_g) and a random component at time t (Equation 5). The decay factor is an indication of how much of the previous time step's velocity affects current movement. The surrounding temperature (T) at time t+1 is the value of the seasonal temperature function with the location of time t+1 and time t (Equation 1). The random change in degrees (r) at time t+1 is a function of the difference between the surrounding temperature at time t+1 and the preferred temperature (T_m), a random number (X) between -100 and 100 drawn from a uniform distribution, and the strength of temperature perturbations as the maximum amplitude of the random step in degrees per day (ss) (Equation 6). This model assumes that individuals can sense the temperature they are in but cannot sense temperature at a distance. The more preferable the local temperature, the smaller the random component, lowering the velocity. The less preferable the local temperature, the more random the response, increasing the velocity. Random behavior changes thus cause sharks on average to enter more favorable conditions.

$$\theta_{t+1} = \theta_t + V_t + r_t \tag{4}$$

$$V_{t+1} = T_g V_t + r_t \tag{5}$$

$$r_{t+1} = r_o \left[(T_{t+1} - T_m) \left(\frac{X \sim \cup (-100{,}100)}{100} \right) ss \right] \tag{6}$$

Simulation Scenarios

For all treatments, the fishing mortality is set to zero for a defined arc of the model's circle landscape that represents the no take zone. Fishing effort is relocated outside of the no-take zone. The number of hooks that were actually in the corresponding no take zone is relocated to the other areas proportional to the existing effort in those areas. In treatment scenario 1, NE closure, the defined arc does not change with time (Figure 3.6), while in treatment scenarios 2, Seasonal, and 3, Moving, the defined no-take arc changes in accordance with the preferred 15°-21°C preferred temperature signal within a 5-degree theta bin. The temperature at each location is averaged across 5-degree theta bins quarterly for the Seasonal scenario (Figure 3.7) and weekly for the Moving scenario (Figure 3.8). Any location with a seasonal or weekly average within the 15°-21°C preferred temperature signal is a no-take zone.

Treatment scenarios are compared to the base scenario and each other using population size over time, change in incidental catch over time, harvest rate, and fraction of effort displaced. The best strategy will reduce incidental catch while minimizing the displaced effort and by extension minimize the effects on catch of target species. Displaced effort is measured by the fraction of hooks affected by the closure when compared to fishing in the base case scenario.

Table 3.1 Definitions, units, and values of model parameters and variables.

Variable	**Definition**	**Value if Constant**
M	Natural mortality	0.08
S_m	Weekly probability of an individual shark surviving natural mortality	0.998
S_a	Fishing selectivity at age See Figure 3.5	Double normal distribution with mean 6.96, std dev of ascending limb 5.12, and std dev of descending limb 4.99
$E_{\theta t}$	Fishing relative effort at location theta and time t	
f	F Multiplier	13
S_f	Weekly probability of an individual shark surviving fishing	
L_{inf}	Asymptotic maximum length at which growth is 0 (cm)	350.6cm
k	Growth rate	0.064
t_o	Age at size zero (cm)	-3.09cm
LS	Mean litter size (number of males and females, sex ratio 1:1)	12.5
C	Reproductive Cycle (years)	3
T_t	Temperature at time t (°C)	
T_m	Preferred temperature (°C)	18°C
T_s	Spatial change in temperature with latitude (°C)	10°C
T_a	Amplitude of the seasonal temperature change (°C)	10°C
θ_t	Location along the arc at time t (angular degrees)	
T_g	Decay factor: indication of how much of the previous time step's velocity affects current movement	0.75
V_t	Velocity at time t (angular degrees/day)	
r_t	Random component at time t	
ss	Strength of temperature perturbations as the maximum amplitude of the random step (angular degrees/day)	4
Conversion Factors		
FL(cm)-TL(m)	Fork length (cm) to total length (m)	$TL_m=(FL_{cm}+1.7101)/0.9286/100$
TL(m)-Mat	Total length (m) to fraction mature; maturity ogive	Mat=1/(1+exp-(-27.81+9.332*TLm)

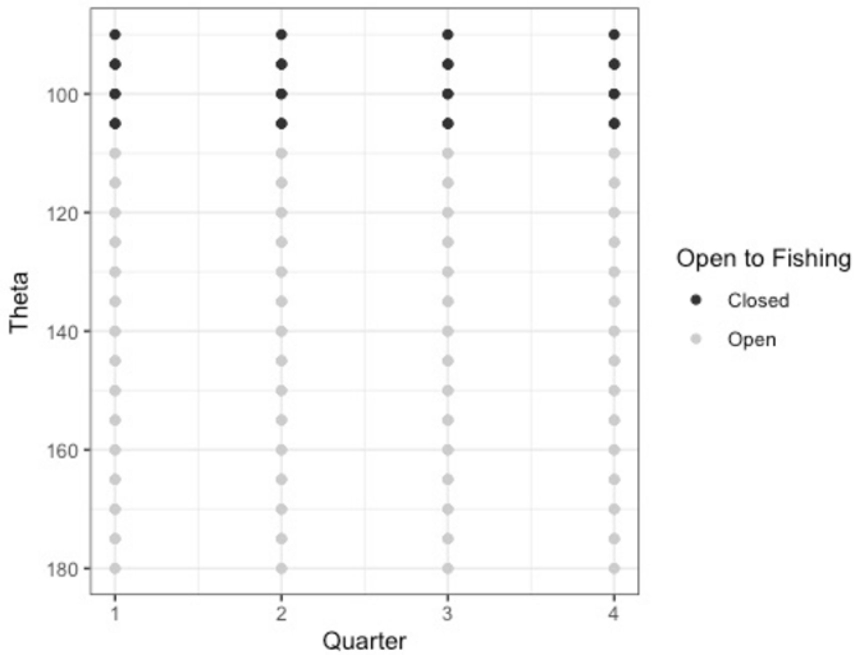


Figure 3.6 Northeast closure scenario with a stationary no take zone that corresponds to the statistical reporting region that the US NMFS calls Northeast Distant (Theta <110 across all quarters of the year). The theoretical study space is the one-dimensional angle, theta along an arc on a polar coordinate system.

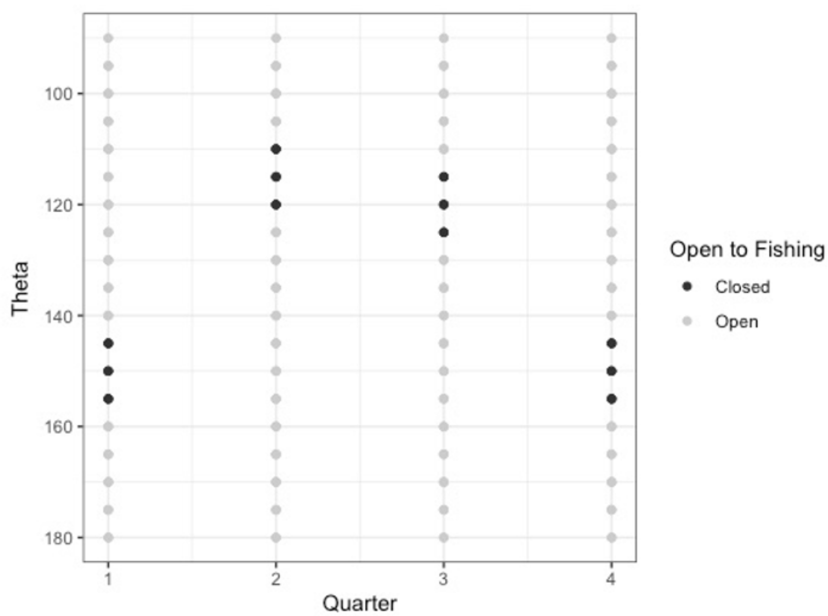


Figure 3.7 Seasonal closure scenario with the defined no-take arc locations changing in accordance with the preferred 15°-21°C preferred temperature signal within a 5-degree theta bin. The temperature at each location is averaged across 5-degree theta bins quarterly. The theoretical study space is the one-dimensional angle, theta along an arc on a polar coordinate system.

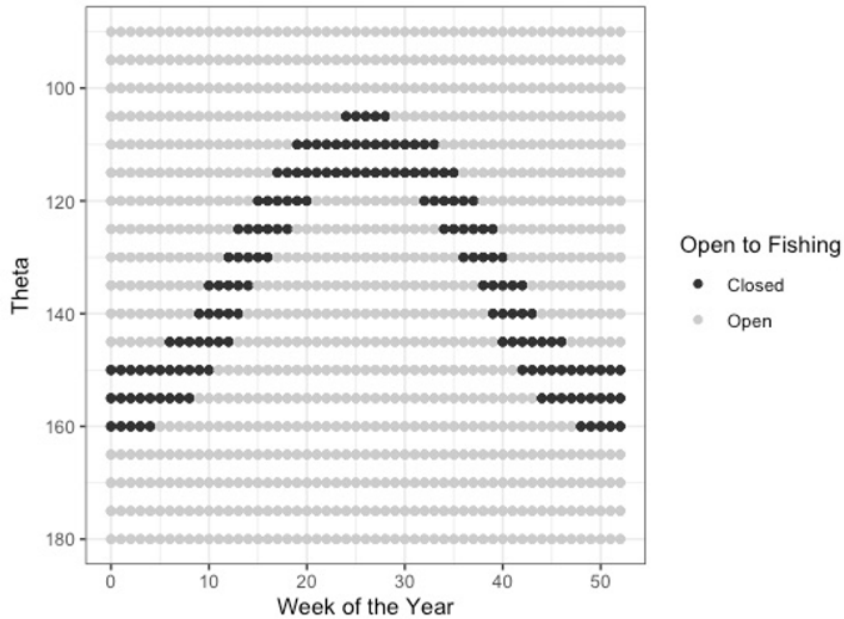


Figure 3.8 Moving closure scenario with the defined no-take arc locations changing in accordance with the preferred 15°-21°C preferred temperature signal within a 5-degree theta bin. The temperature at each location is averaged across 5-degree theta bins weekly. The theoretical study space is the one-dimensional angle, theta along an arc on a polar coordinate system.

Results

Effort and Shark Spatial Distributions

The scenarios result in very different areas being closed. The reduction in fishing effort by a closure is not proportional to the size of the area closed due to the patchy distribution of the fishery in time and space. For example, the NE scenario closed the entire NE region, theta 90-105, for all four quarters (Figure 3.6). However, when applied to the fishery the result is a closure in only the third and fourth quarters because the fishery does not exist in that area in the first two quarters (Figure 3.9) resulting in a displacement of about 13.6% of the total hooks annually (Table 3.2). The seasonal closure removed effort from the first and fourth quarters in theta 145-159 only (Figure 3.9) therefore displacing about 14.2% of the hooks (Table 3.2). The moving closure, which is coupled tightly to the temperature signal (Figure 3.8), most closely resembled the distribution of the fishery (Figure 3.9) resulting in the largest impact on the fishery causing about 17.5% of the hooks to be displaced (Table 3.2).

The shark population dispersed throughout the study area over the 50-year simulation (Figure 3.9). Throughout the simulation the individuals were symmetrically distributed north and south about the preferred temperature signal (Figure 3.9). Under the specified movement function the sharks took time to respond to the temperature signal causing the highest concentrations of individuals to lag behind the preferred temperature signal throughout each year (Figure 3.9). In the base case, areas of particularly high effort overlapped with areas of medium shark concentration. The NE scenario reallocated effort to an area with a comparable or slightly higher, concentration of sharks. The seasonal closure moved effort to a less concentrated area in the first quarter, but the reallocated effort encounters the lagging high concentration in Quarter 4 (Figure 3.9). The moving scenario reallocated effort for all four quarters and increased the effort in an area of higher shark concentration at the end of Quarters 1 and 4 (Figure 3.9).

Population Abundance and Structure

For all scenarios the total number of sharks started to rebuild over the first 10 years then decreased over the following 15 years (Figure 3.10). The SS3 projections in ICCAT (2019) show that the abundance of the mature population will decrease in the short term regardless of the total allowable catch, because overfishing of the immature animals in the recent past has left fewer sharks to age into the mature population. This study found the same short-term pattern with the mature population decreasing and continuing to go down before the recovery period started around year 25 and total population decreasing along with the mature population as the smaller mature population produced fewer pups (Figure 3.12).

The IBM had similar dynamics to the SS3 projections indicating that this model adequately captured the overall population dynamics while integrating the assumed seasonal spatial movement.

The population appeared to recover over the final 25 years for the NE and moving scenarios while the base and seasonal scenarios increased to a much lesser extent. While the seasonal scenario reached its previous peak, the base case never again reached the peak experienced in the first 10 years, and both scenarios decreased in the last 5-10 years of the simulations (Figure 3.10). The pup production followed a similar pattern to the total population, decreasing over the first 23 years, then increasing over the remainder of the simulation time frame (Figure 3.14). The base case and seasonal scenarios failed to recover over the last 25 years of the simulations (Figure 3.10, Table 3.2). The NE and the weekly moving closures both surpassed the status quo when rebuilding, did not decrease as much, and climbed to higher population numbers in the last 25 years than reached in the rebuilding period (Figure 3.10, Figure 3.11, Table 3.2). Over the later part of the simulation time frame the number of mature females and the number of pups increased (Figure 3.12, Figure 3.14) particularly for the NE and moving scenarios (Figure 3.13, Figure 3.15). Across all measured metrics, the seasonal closure scenario performed the most similarly to the base case.

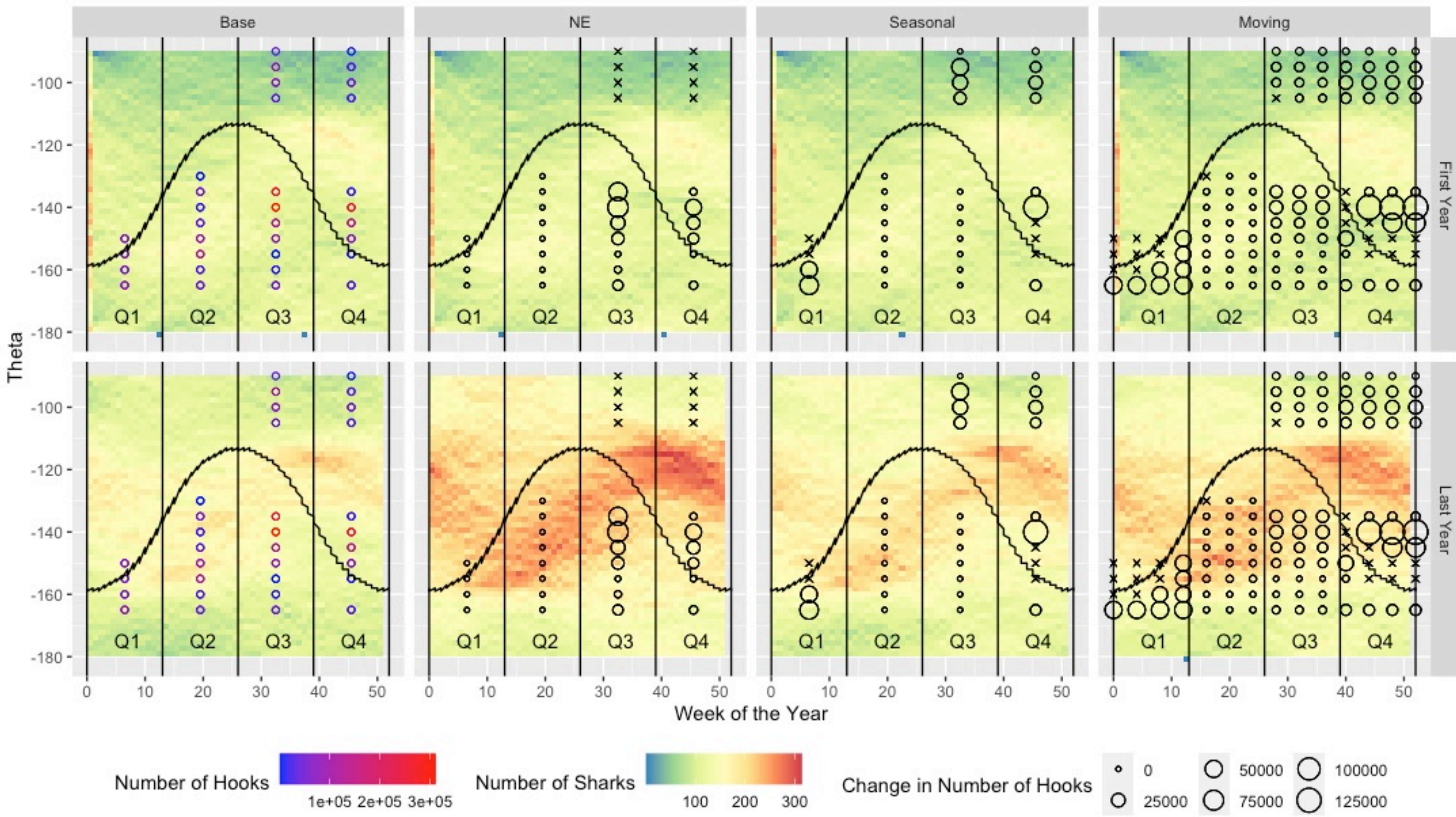


Figure 3.9 Distribution of individual shortfin mako sharks in the study space in the second and last years of the simulations for each closure scenario with the 18°C preferred temperature signal curve. The theoretical study space is the one-dimensional angle, theta along an arc on a polar coordinate system. The base case scenario shows the effort distribution in number of hooks. For the other three alternative closure scenarios, the effort is depicted as the increase in hooks when compared to the base case with locations where effort removed depicted with an "X."

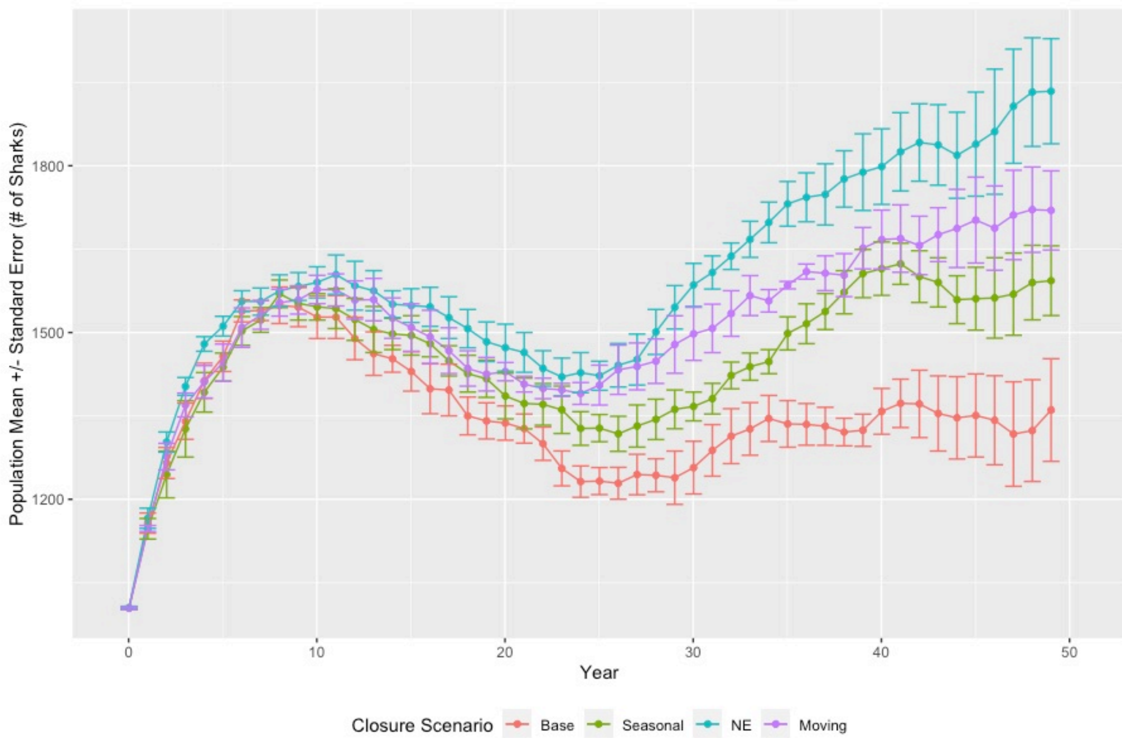


Figure 3.10 Mean total population in number of individual sharks for each closure scenario plus or minus standard error, across the 5 simulations, at each time step over the 50-year simulation time frame.

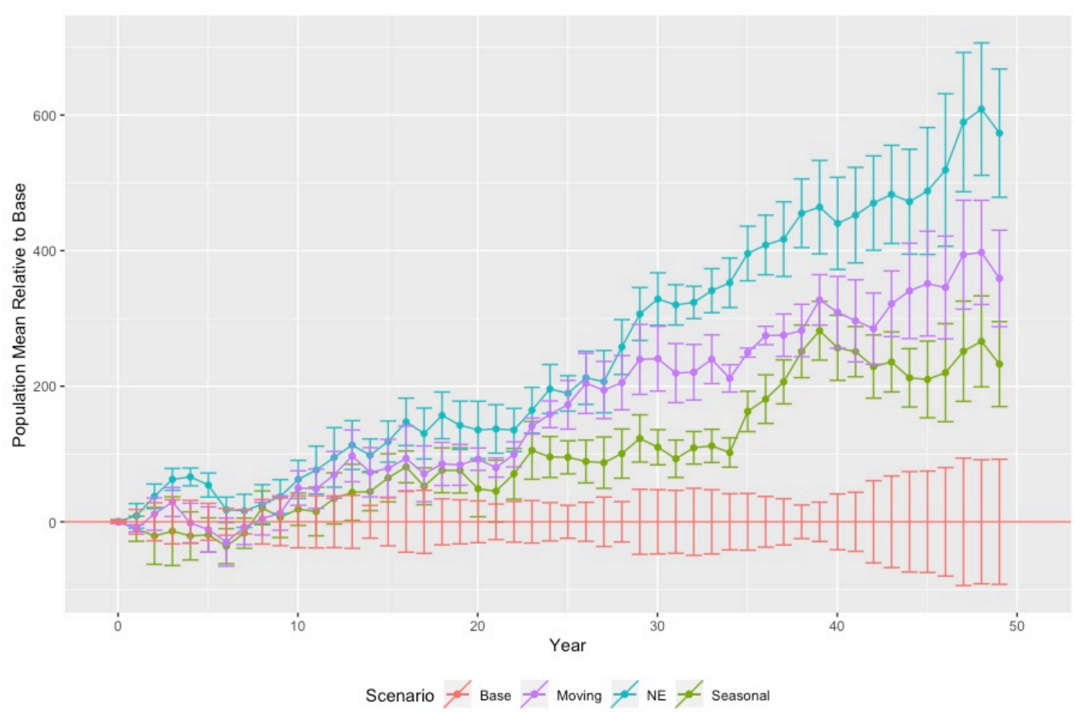


Figure 3.11 Mean total population in number of individual sharks for each closure scenario relative to the base case plus or minus standard error, across the 5 simulations, scenario, at each time step over the 50-year simulation time frame.

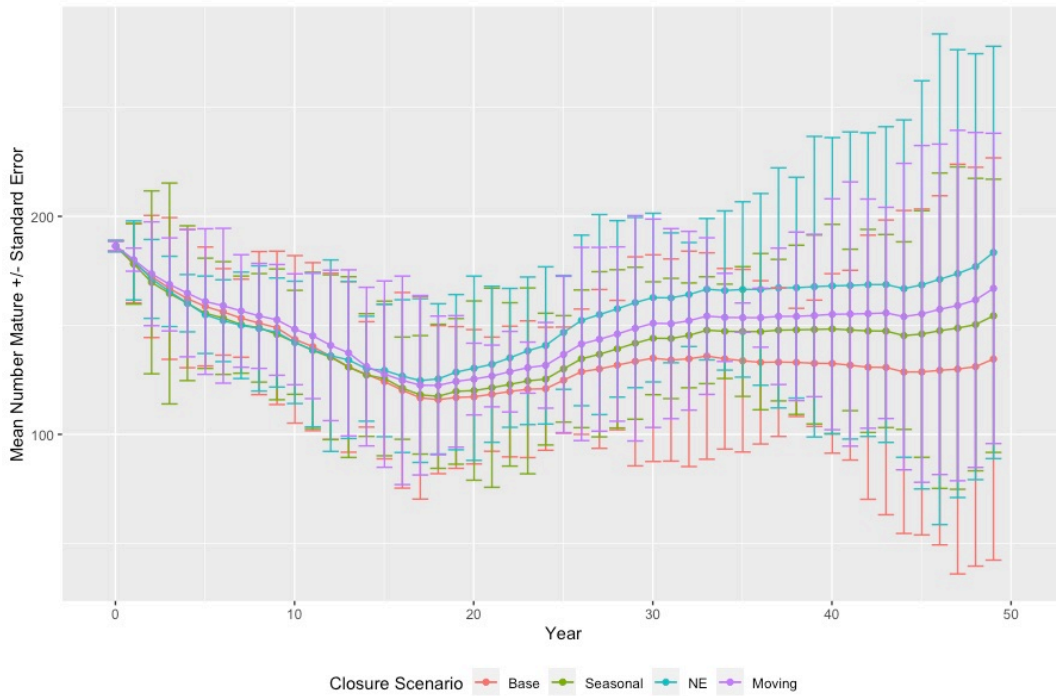


Figure 3.12 Mean number of mature individual sharks for each closure scenario plus or minus standard error, across the 5 simulations, at each time step over the 50-year simulation time frame.

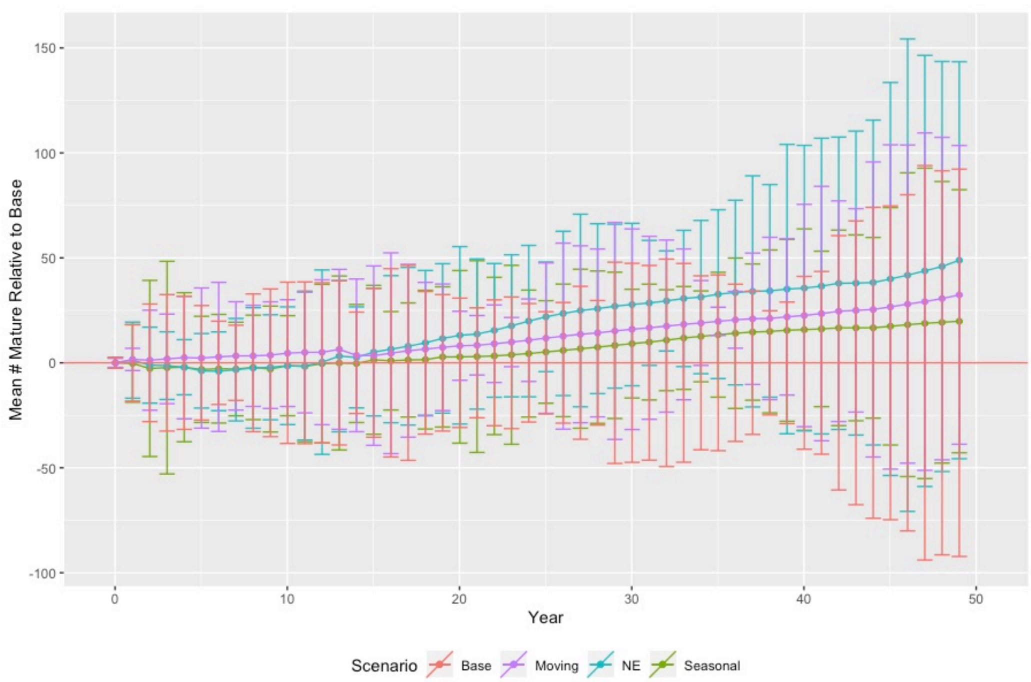


Figure 3.13 Mean number of mature individual sharks for each closure scenario relative to the base case scenario plus or minus standard error, across the 5 simulations, at each time step over the 50-year simulation time frame.

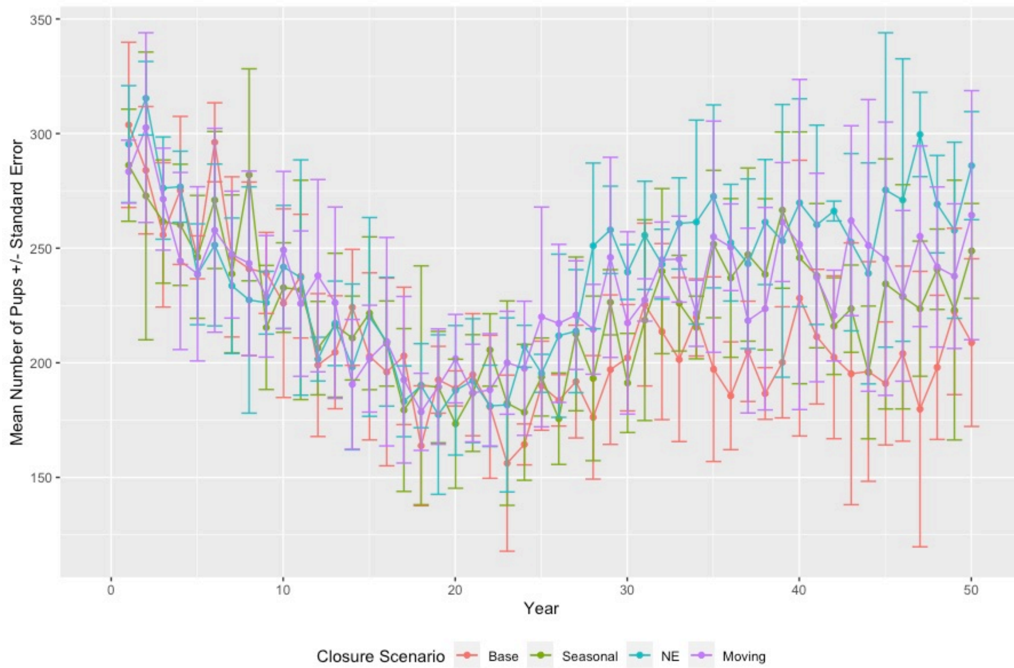


Figure 3.14 Mean number of individual shark pups for each closure scenario plus or minus standard error, across the 5 simulations, at each time step over the 50-year simulation time frame.

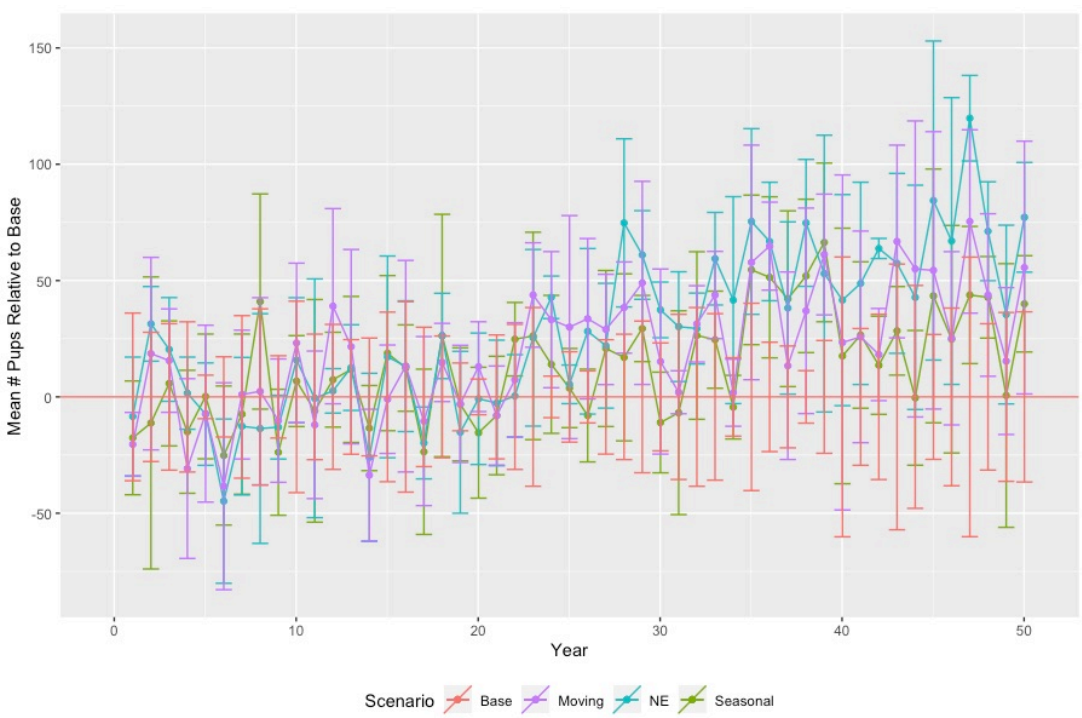


Figure 3.15 Mean number of individual shark pups for each closure scenario relative to the base case scenario plus or minus standard error, across the 5 simulations, at each time step over the 50-year simulation time frame.

Incidental Catch and Harvest

The base scenario exhibited higher shortfin mako incidental catch over the first 25 years while all of the alternative scenarios had higher shortfin mako incidental catch over the final 25 years (Figures 3.16, 3.17). The NE and moving alternative scenarios had a higher mean catch at the end of the simulation time frame because the total population was higher, so that catches increased (Figure 3.16, Table 3.2) even though the harvest rates for the northeast and moving scenarios were always lower than the base and seasonal scenarios (Figures 3.18, 3.19). Regarding catch, the seasonal scenario appears to bounce back and forth between whether it behaves more like the base case or more like the other two alternatives. The first half of the time series the seasonal scenario resembles the base case while over the later half of the time frame had values very similar to the other two alternatives cases for all of these metrics (Figures 3.16, 3.17, Table 3.2). However, the seasonal scenario harvest rate is consistently an intermediate between the base scenario and the other two alternatives (Figures 3.18, 3.19, Table 3.2).

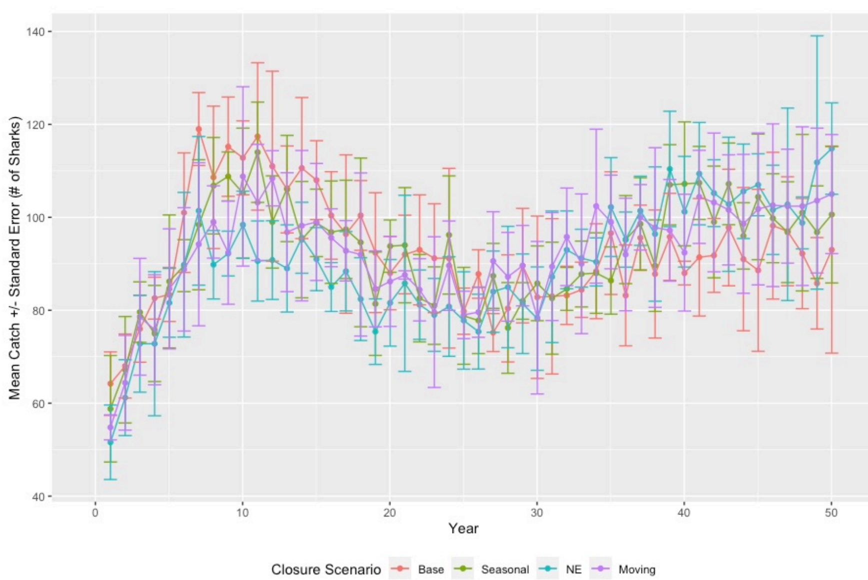


Figure 3.16 Mean number of individual sharks caught for each closure scenario plus or minus standard error, across the 5 simulations, at each time step over the 50-year simulation time frame.

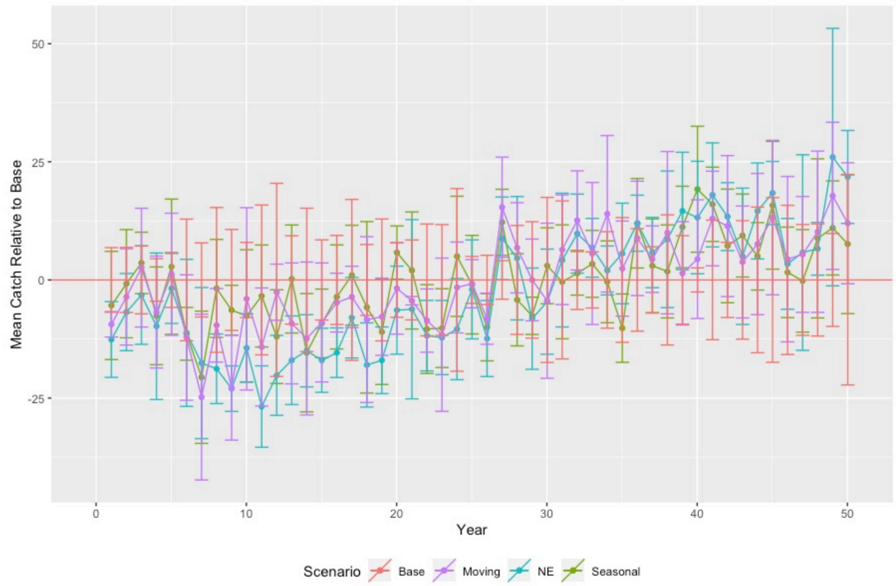


Figure 3.17 Mean number of individual sharks caught for each closure scenario relative to the base case scenario plus or minus standard error, across the 5 simulations, at each time step over the 50-year simulation time frame.

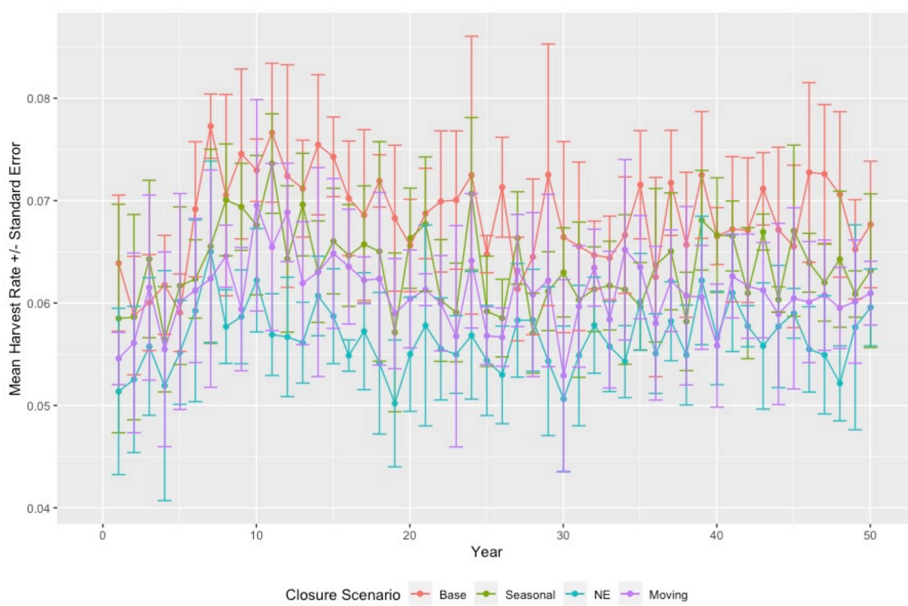


Figure 3.18 Mean harvest rate for each closure scenario plus or minus standard error, across the 5 simulations, at each time step over the 50-year simulation time frame.

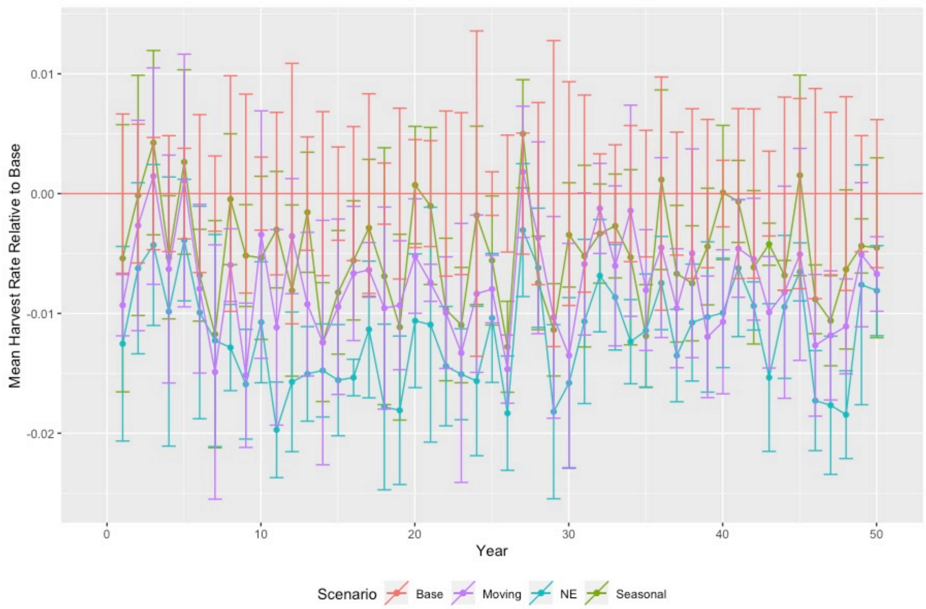


Figure 3.19 Mean harvest rate for each closure scenario relative to the base case scenario plus or minus standard error, across the 5 simulations, at each time step over the 50-year simulation time frame.

Table 3.2 Summary values by scenario where values relative to Year 1 are determined by subtracting the initial year value from the terminal year value.

	Base	**NE**	**Seasonal**	**Moving**
Fraction Effort Displaced	0	0.136	0.142	0.175
Population Relative to Year 1	356.0	929.0	588.6	715.6
Catch Relative to Year 1	28.8	63.2	41.8	50.2
Number Mature Relative to Year 1	-51.8	-2.9	-32.0	-19.4
Pup Production Relative to Year 1	-95.0	-9.4	-37.4	-19.0

Discussion

Overview of Findings

Results of our simulations indicate that no take scenarios in the north east and following a weekly temperature signal have the most potential for lowering shortfin mako incidental catch enough to allow the population to rebuild and recover. The current age structure causes the mature population to decrease before recovery under all scenarios. However, under the north east and moving scenarios, the population of mature individuals is able to recover to the point that pup production could overcome fishing pressures. The mature population increased, the pup production increased, allowing the whole population to increase to the point that catch also increased without increasing the harvest rate. Under the status quo, the mature population does not increase enough to allow the pup production to compensate adequately for fishing pressures.

Relationship to Other Studies

The moving closure was designed to be more targeted, protecting the species of interest without the drastic impact of a permanent closure. The NE permanent closure displaces the effort at all times while the moving scenario may displace more total effort, at any given time a much smaller area is impacted. While the moving scenario performed well, contrary to the starting hypothesis, it did not perform as well as the north east scenario at allowing the overall population to grow the most. The results are consistent with Chapter 2, this dissertation, which found that the waters off of the north eastern coast of North America is home to sets with particularly high shortfin mako incidental catch and imposing restrictions in this area has the potential to reduce incidental catch with minimal impact to the target fishery. This is also consistent with Queiroz et al. (2019) whose analysis of spatial overlap of shark species and longline fisheries showed that shortfin mako have a high risk of fishery exposure in the waters off of North East North America.

While the moving scenario displaces more total effort than the NE scenario the displacement does not yield a corresponding lower catch. Recent studies suggest that highly migratory species require dynamic spatial management without static boundaries (Hazen et al. 2018, Maxwell et al. 2020). The promising performance of the weekly moving scenario supports the idea that management should move with the animal. On the other hand, the seasonal scenario resulted in a population faring little better than the status quo of no restrictions. The comparatively poor performance of the seasonal scenario demonstrates the importance of properly matching the time scale of dynamic management to the needs of the species and that incorrect assumptions have the potential to drastically impact the population. From all three alternative scenarios we see that basing closures on shark location, as assumed by temperature preference, the most successful options are those with the least and the most focus on mako movement. The intermediate option appears to redistribute the effort in a way that increases the interaction between sharks and fishers, increasing catch.

The need for an all or nothing approach with regards to targeted management is consistent with Hazen et al. (2018), Maxwell et al. (2020) whose arguments for dynamic closures involve real-time monitoring of catches and updating of management. It is possible that the NE closure performed better than either of the moving closures reinforces that success is dependent on having the adequate information to manage at the correct scale (Schofield et al. 2013, Breen et al. 2015, Maxwell et al. 2020). Hazen et al. (2018), Maxwell et al. (2020) also stress that dynamic closures cannot address all issues and will not replace traditional stationary closures.

Caveats and research recommendations

This study assumes a closed system and is therefore limited to the US longline fleet and should not be extrapolated to the entire stock. It is unclear how connected the West Atlantic and East Atlantic subpopulations of the stock are and it is very possible that individual sharks migrate throughout the Atlantic basin spending significant portions of time outside of the study area (Queiroz et al. 2016, Anonymous 2019a). Furthermore, the study includes waters fished by other countries whose incidental catch, effort, and behavior are not considered.

Further research should focus on how fishers react to restrictions to more realistically estimate the impact of scenarios on fishers and their ability to catch their target species. Fishers would presumably shift their distribution based on the target species and not the distribution of shortfin mako. However, a review by van Putten et al. (2012) concluded that, while economic drivers are key determinants of behavior, other variables, such as habit, tradition, risk aversion, and reluctance to change are significant in the prediction of behavior. A model that explicitly included a range of socio-economic factors of individual fishers in the pelagic longline fishery could be combined with this model, or one similar, to more realistically model the effects of management on fisher behavior which in turn impacts shortfin mako incidental catch. This would give a more holistic analysis that would explicitly measure tradeoffs, especially applied to a non-target species.

As dynamic closures still remain promising, further research should also focus on more accurately predicting shortfin mako distribution, migration, and habitat use. Fishery independent movement data exists but not at the sample sizes necessary to meet statistical requirements. However, ICCAT (Anonymous 2017b, a, 2019a) has recommended more satellite tagging efforts, and as more data becomes available it will become sufficient to incorporate into a similar study. Specifically incorporating variation by life stage may allow for better targeting and minimal disruption to the fishery as juveniles make up the vast majority of incidental catch. Including fishery independent data, especially by life stage, will improve movement modeling and better inform the time and space scales necessary for effective dynamic management strategies.

Management Recommendations and Conclusions

The redistribution of effort in time and/or space has the potential to allow the mature population to increase and reproduce to the point that production surpasses catch, allowing the shortfin mako to rebuild and eventually recover. Even when the scale of the closure is poorly matched, closures decrease the catch in the short term enough to allow the population in the long term to grow to numbers higher than under current management. A management measure such as closure is needed to reduce interaction with the fishery; live release with some retention does not reduce mortality enough. This study supports the idea that areas with high probability of positive catch, like the waters off the north eastern coast of the US, should be avoided. Benefits are maximized when effort in these types of areas are eliminated, or at least reduced. A stationary closure is simpler and easier to implement and enforce than regulations that change, especially a management plan that changes weekly. However, dynamic closures should not be abandoned; better matched scenarios could be more successful and there is the possibility of the shark distribution shifting as the ocean experiences climate change. Fishery independent data collection should be pursued and as more information becomes available, dynamic management must be reconsidered. At this point, until more information to accurately and precisely match the time/space scale needed, a stationary closure is the most promising move forward of the kinds of closures tested.

CHAPTER 4: CONSIDERATION OF MULTIPLE COMMONLY CAUGHT SHARK SPECIES IN BYCATCH MITIGATION IN THE GULF OF MEXICO REEF BOTTOM LONGLINE FISHERY

Background

The U.S. Gulf of Mexico Reef Fish Bottom Longline fishery (GOMRBLL) is comprised of Federally permitted commercial vessels that typically target groupers, *Epinephelus* spp., and snappers, *Lutjanus* spp. (Karp et al. 2011, Scott-Denton et al. 2011). Since 2006 a mandatory observer program jointly implemented by the Gulf of Mexico Fishery Management Council (GMFMC) and the National Marine Fisheries Service's (NMFS) Southeast Fisheries Science Center (SEFSC) has monitored the commercial reef fishery in the Gulf of Mexico (GOM). NMFS observers were allocated to vessel-trips through several methods over the years including stratified random sampling, proportional (to effort) sampling, and voluntary cooperation (Scott-Denton et al. 2011, National Marine Fisheries Service 2018). Observers record information about the vessel, gear, and environment before each set and record the total time gear was in the water, condition of fish brought onboard, and fate of fish after release at the end of each set (Scott-Denton et al. 2011, National Marine Fisheries Service 2018). Analysis of observer data has shown that this fishery interacts with 27 species of sharks and collectively, sharks make up a significant portion of catch and discards indicating a need for a reduction in encounters (Scott-Denton et al. 2011).

In this particular fishery, shark species are considered bycatch and reduction of shark bycatch is necessary to meet legislative mandates under the Magnuson-Stevens Fishery Conservation and Management Act (Karp et al. 2011, National Oceanic and Atmospheric Administration 2016) that state that conservation and management measures must be in place to minimize bycatch. While not all of the species in this study are currently overfished or experiencing overfishing, sharks are particularly vulnerable to overfishing and being overfished due to their low productivity, slow growth, and late maturity coupled with increasing levels of exploitation (Cortes 1998, Baum and Myers 2004). The GOMRBLL fishery discards the majority of sharks encountered regardless of species, or condition of individuals caught (Scott-Denton et al. 2011). The high shark discards and the vulnerability of sharks makes shark bycatch reduction favorable regardless of the individual species' current status.

In this study we consider the 12 most commonly caught shark species (Table 4.1, Figure 1) including blacknose (*Carcharhinus acronotus*), nurse (*Ginglymostoma cirratum*), Atlantic sharpnose (*Rhizoprionodon terraenovae*), scalloped hammerhead (*Sphyrna lewini*), sandbar (*Carcharhinus plumbeus*), smooth dogfish (*Mustelus canis*), night (*Carcharhinus signatus*), blacktip (*Carcharhinus limbatus*), silky (*Carcharhinus falciformis*), tiger (*Galeocerdo cuvier*), bigeye sixgill (*Haxanchus nakamurai*), and sevengill (*Heptranchias perlo*). They are very different in terms of their ecology with some species being coastal while others are found in deeper waters off the continental shelf (Table 4.1). Some are highly migratory making pelagic movements, such as scalloped hammerhead (Wells et al. 2018), while others are reef associated, such as nurse (Carrier and Pratt 1998) and blacknose sharks (Compagno 1984). All species are in the family Carcharhinidae, except smooth dogfish, (Triakidae), bigeye sixgill and sevengill sharks (Hexanchidae).

In addition to ecological differences, these species vary greatly in their current status (Table 4.1), management, and protections. The status of nurse, night, silky, tiger, bigeye sixgill, and sevengill populations is unknown, but only bigeye sixgill, night, and sevengill sharks are prohibited in both recreational and commercial fisheries (National Marine Fisheries Service 2020b). Some shark populations that are not prohibited in the commercial fishery, sandbar (SEDAR 2016, 2017), blacknose (SEDAR 2012), and scalloped hammerhead (SEFSC Scientific Review), are overfished. While all three of these species have rebuilding plans, only the sandbar shark is no longer experiencing overfishing. Scalloped hammerhead sharks have additional protections including prohibition in the recreational fishery, and listing under CITES Appendix II (Anonymous 1973). A particular issue with smooth dogfish is that three species of *Mustelus* occur in the GOM and observer identification of the species is known to be unreliable (SEDAR 2015) which affects estimation of individual species' stock status. Reducing shark bycatch is important regardless of current stock status.

Although the observer program only covers about 1% of effort in this fishery (variable over time but 1% in 2018), it is a random sample, so the observer program can be used to evaluate which variables influence bycatch (National Marine Fisheries Service 2020a). Foster et al. (2017) studied the effect of soak time on targeted red grouper catch per set as well as bycatch per set of shark species in the GOMRBLL fishery. They found that reducing soak time could reduce shark bycatch per set with minimal reduction in target catch per set. Modification of fishing gear and deployment methods has the potential to alter catchability of non-targeted species. Furthermore, Molina and Cooke (2012) who reviewed trends in shark bycatch research found a lack in modeling studies and those that look at multiple species concurrently. Molina and Cooke (2012) argue that filling these gaps would help to formally experiment with mitigation strategies and identify which species are more susceptible and affected by interactions with the fishery. Several species commonly caught have an unknown status (Table 4.1).

Table 4.1 Summary of stock status and ecology group for shark species included in this study. Updated September 30, 2020.

Common Name	Scientific Name	Overfishing	Overfished	Ecology Group	Management Notes
Shark, Blacknose	*Carcharhinus acronotus*	Yes	Yes	Small Coastal	In year 8 of 30-year rebuilding program IUCN Red List: Near Threatened
Shark, Nurse	*Ginglymostoma cirratum*	Unknown	Unknown	Large Coastal	IUCN Red List: Data Deficient
Shark, Atlantic Sharpnose	*Rhizoprionodon terraenovae*	No	No	Small Coastal	IUCN Red List: Least Concern
Shark, Scalloped Hammerhead	*Sphyrna lewini*	Yes	Yes	Large Coastal	In year 8 of 10-year rebuilding plan Recreationally prohibited CITES Appendix II (2014) IUCN Red List: Critically Endangered
Shark, Sandbar	*Carcharhinus plumbeus*	No	Yes	Large Coastal	In year 16 of 66-year rebuilding plan IUCN Red List: Vulnerable
Shark, Smooth Dogfish	*Mustelus canis*	No	No	-	IUCN Red List: Near Threatened
Shark, Night	*Carcharhinus signatus*	Unknown	Unknown	Deep-water	Prohibited IUCN Red List: Vulnerable
Shark, Blacktip	*Carcharhinus limbatus*	No	No	Large Coastal	IUCN Red List: Near Threatened
Shark, Silky	*Carcharhinus falciformis*	Unknown	Unknown	Large Coastal	Listed under CITES Appendix II (2017) IUCN Red List: Vulnerable
Tiger	*Galeocerdo cuvier*	Unknown	Unknown	Large Coastal	IUCN Red List: Near Threatened
Bigeye Sixgill	*Hexanchus vitulus or Hexanchus nakamurai*	Unknown	Unknown	Deep-water	Prohibited IUCN Red List: Data Deficient
Sevengill	*Heptranchias perlo*	Unknown	Unknown	Deep-water	Prohibited IUCN Red List: Near Threatened

This study considers multiple individual species at once as well as grouping those individuals by size (small vs large) and habitats (coastal vs deep-water) with the aim of exploring gear modification and/or behavior modification based on environmental conditions that will reduce encounters for sharks as a whole. An optimal strategy to reduce shark bycatch per set would reduce catch per set of all shark species at the same time without reducing target species catch per set. However, it is expected that bycatch per set of sharks in different species groups will have different important explanatory variables and trends. Bycatch per set of species that are modeled individually is expected to have explanatory variables and trends similar to the other species within their group but different to species in other groups. We expect soak time and number of hooks in a set to be important explanatory variables with the same trends for all species and species groups because more hooks and more time in the water offers greater opportunity for catch per set in general. It is also expected that coastal and deep-water species and species groups will have opposing trends representing their preferred habitat. We expect there to be a difference in predictive pattern for small versus large species when it comes to hook size with large hooks predicting higher catch per set for large species and small hooks predicting higher catch per set for small species.

The purpose of this study is to determine what gear and/or environmental variables best predict shark catch per set for commonly caught shark species in the U.S. GOMRBLL fishery. We hope to propose mitigation strategies based on the results that aim to collectively reduce interaction of commonly caught shark species with GOMRBLL lines.

Methods

Catch per set, effort, gear, and environmental data was taken from the NOAA NMFS observer dataset for the GOMRBLL fishery 2009-2017 (National Marine Fisheries Service 2018). Only species that had at least one positive observation every year of the time series were analyzed. This resulted in a total of 12 shark species (Figure 4.5). Catch per set is defined as the number of individual sharks caught in a set regardless of whether or not it was retained. Effort is defined as one set, as opposed to the more common hours or hooks, based on unpublished research showing that sets is the best unit of effort for matching observer to logbook effort (Steven Smith, personal communication NOAA). CPUE by species (or group of species) was modeled as a function of environmental and gear variables using a generalized additive model (GAM) (Guisan et al. 2002). GAMs are extensions of linear models that allow for non-linearity and variability in variance through the use of link functions and a specified error distribution (Guisan et al. 2002) in addition to allowing a smoothing function to be used to model the relationship between the predictor variable and the response variable.

Delta-lognormal, delta-gamma, and negative binomial error distributions were explored, but the negative binomial distribution was ultimately used because it is most appropriate for data consisting of small counts that may be over-dispersed. Standard residual plots of equations with an integer response variable will have curved rows of residuals that correspond with the integer values of the y-variable, which would indicate model problems even if the model is correctly specified (Hartig 2017). To avoid misinterpreting residuals, we used the DHARMa R package (Hartig 2017) which uses a simulation-based approach to transform residuals into a standardized scale. New data are simulated from likelihood function of the fitted model, the empirical cumulative density function of the simulated data is calculated, and the residual is defined as the empirical density function's value at the value of the observed data. The DHARMa residuals compare the data to the expected distribution under a negative binomial distribution and if the model is properly specified, we expect residual distribution to be flat and uniformly distributed (Hartig 2017). Diagnostics plots of DHARMa residuals revealed that negative binomial was more appropriate than other distributions and adequate for all shark species (Figure A8). The negative binomial model was used in all further analysis to explore the selection of predictor variables.

Candidate environmental variables include year, season, location (latitude and longitude), and fishing depth (m), while the candidate gear variables include soak time (hrs), hook shape, hook size, and number of hooks set (Factor levels in Table 4.2, continuous variable distributions in Figures 4.1, 4.2, 4.3, and 4.4). Smoothers were placed on continuous variables and categorical variables were treated as fixed effects. Variable coefficients for those expressed as factors were all presented as difference to the reference level which is defined as the first level of the factor (Table 4.2).

$$CPUE \sim (Year + Season + te(Latitude, Longitude) + s(Depth) + s(Soak\ Time) + Hook\ Shape + Hook\ Size + s(Hooks\ Set)$$

Table 4.2 Factor levels used for season, hook shape, and hook size predictor variables considered in the generalized additive model approaches to predict commonly caught shark species' bycatch per set. *Refers to the reference level for each factor variable.

Variable (n=10,783 sets)	Number of Levels	Levels(n)
Year	8	2010 (1370)*
		2011 (2332)
		2012 (524)
		2013 (2134)
		2014 (860)
		2015 (655)
		2016 (1695)
		2017 (458)
Season	3	1: January, February, March, April (4784)*
		2: May, June, July, August (2798)
		3: September, October, November, December (3201)
Hook Shape	2	Offset (5004)*
		Straight (5779)
Hook Size	5	<=11 (432)*
		12 (653)
		13 (5728)
		14 (2216)
		>=15 (999)

The *dredge* function from the *MuMin* R package (Barton and Barton 2015) was used to test all possible variable combinations with the full model above. The Bayesian information criterion (BIC), maximum likelihood estimation and 10-fold cross validation were used to identify which combination of variables produced the best model performance balancing fitting and parsimony to optimize predictive ability. BIC was chosen specifically because it penalizes more complex models preventing over fitting (Schwarz 1978). Models with BIC determined weight greater than 0.01 were further considered as candidate models, where model weight w_i for model *i* was calculated from the difference in BIC Δ_i between model i and the best model as: $w_i = e^{-\Delta_i/2} / \sum e^{-\Delta_i/2}$ (Burnham and Anderson 2004). Cross validation of each candidate model was then used to determine the best predictive model of all candidate GAMS. A ten-fold cross validation procedure (Then et al. 2015) randomly allocated each data point to one of the ten folds. Nine tenths of the data were used for training while one tenth was used as the test dataset. GAM cross-validation results were assessed using the root mean square error (RMSE) and mean absolute error (MAE) calculated by comparing the CPUE predicted from the model fitted to the training dataset to the sets in the test dataset (Stow et al. 2009, Gruss et al. 2019). The best of several candidate models would have the smallest RMSE and MAE. These metrics can also be compared across models for different species to determine which species' CPUE can be predicted most accurately and precisely from the models. The equations are:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(CPUE_i - \widehat{CPUE_i}\right)^2}{n}}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|CPUE_i - \widehat{CPUE_i}\right|}{n}$$

where $CPUE_i$ refers to observed CPUE in the test dataset, $\widehat{CPUE_i}$ refers to CPUE predicted for the same set in the test dataset, and n is the number of sets in the test dataset. RMSE and MAE were calculated across all ten folds and the mean was used to select the best model.

The fitting and cross validation procedures were performed for the CPUE of each species individually, CPUE of all small coastal species, CPUE of all large coastal species (as defined by NMFS), CPUE of deep-water species, and CPUE of all species combined. Final models were selected based on the results of the BIC ranking and cross-validation. Retained variables and their fitted coefficients were compared across species and species groups to look for broad patterns that can be used to design mitigation strategies that influence as many species as possible at once.

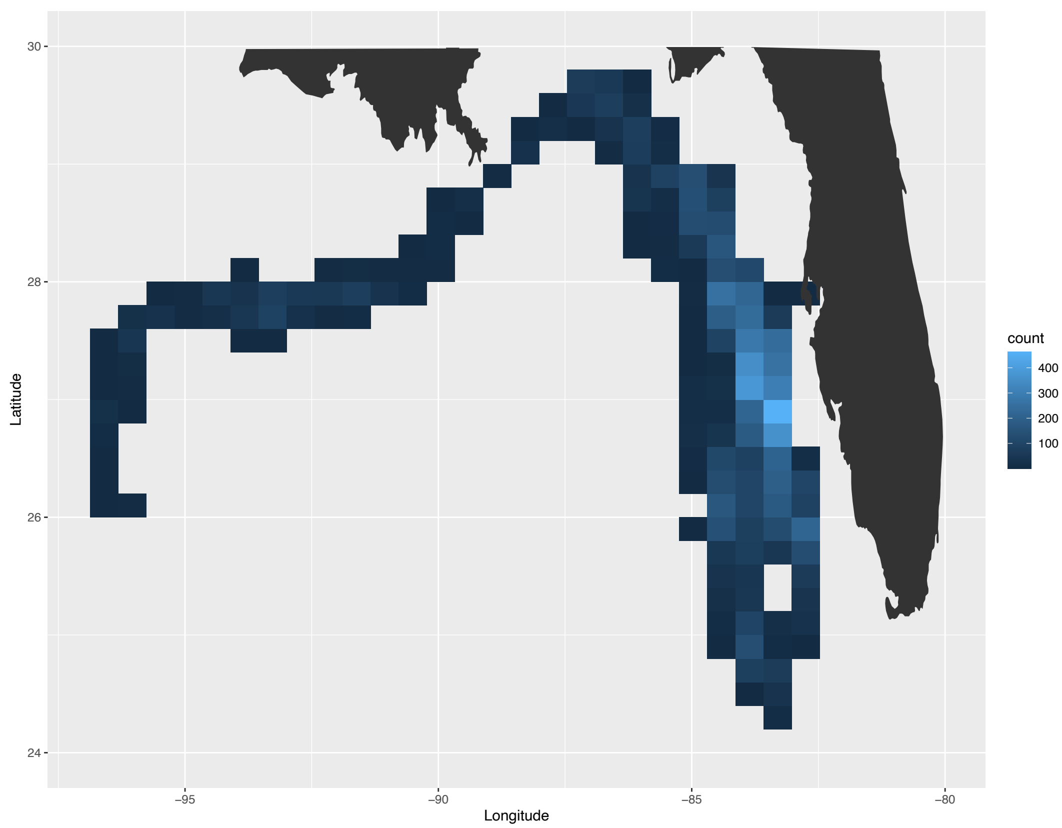


Figure 4.1 Number of observations in the Gulf of Mexico bottom longline fishery observer dataset for each combination of latitude and longitude.

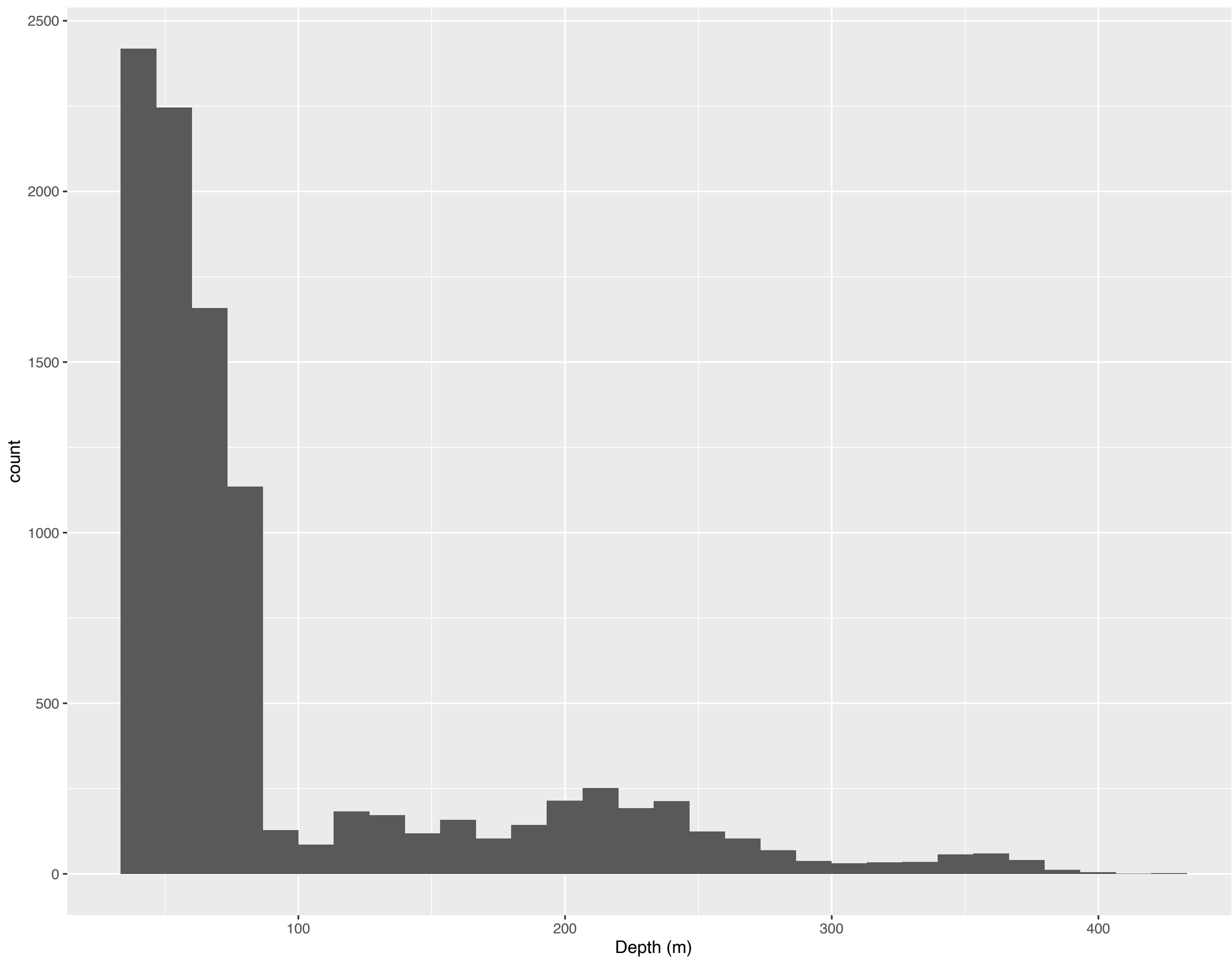


Figure 4.2 Distribution of the number of observations in the Gulf of Mexico bottom longline fishery observer dataset for fishing depth in meters.

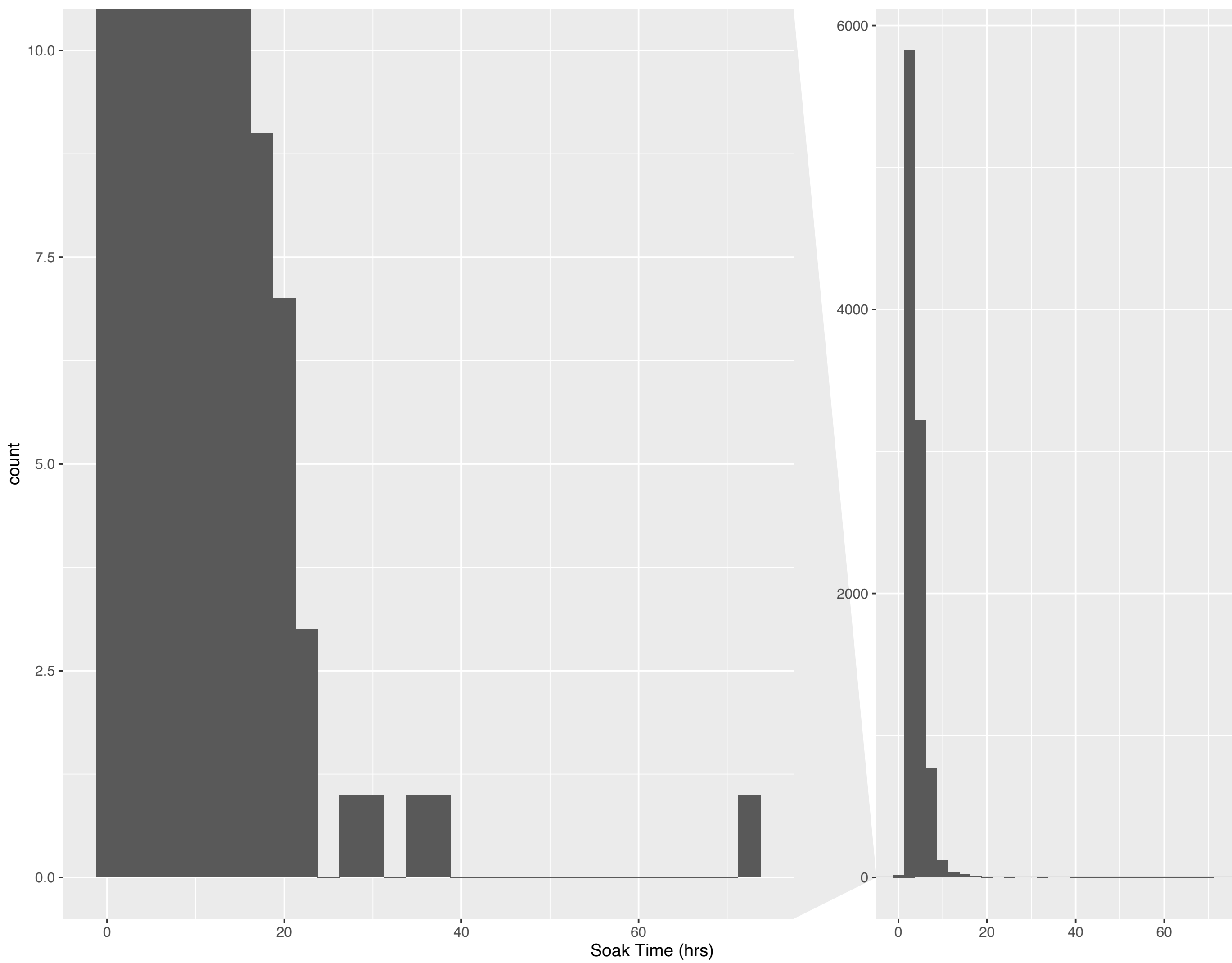


Figure 4.3 Distribution of the number of observations in the Gulf of Mexico bottom longline fishery observer dataset for soak time in decimal hours. To display the distribution at low counts the left graph displays the soak times with less than 10 observations.

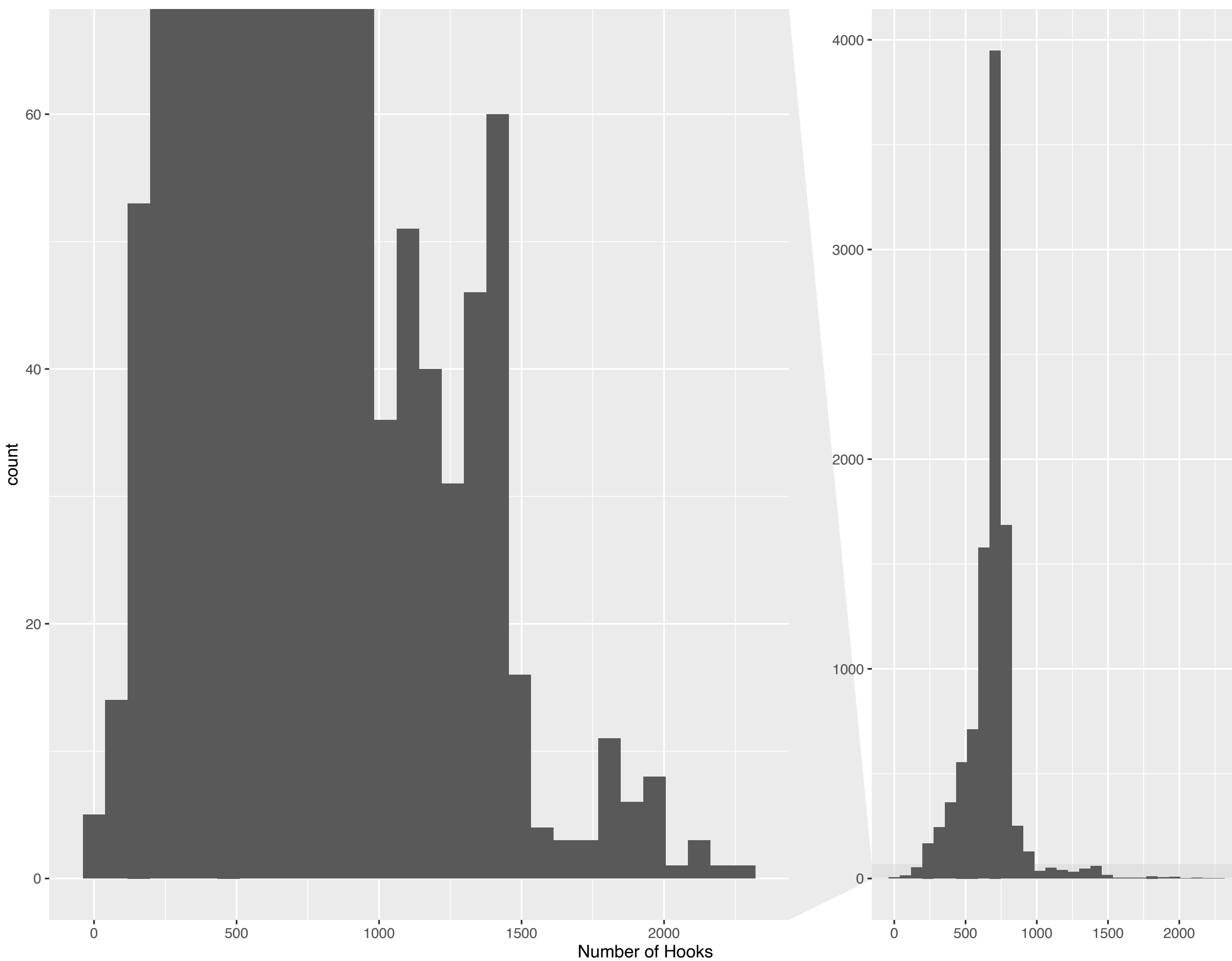


Figure 4.4 Distribution of the number of observations in the Gulf of Mexico bottom longline fishery observer dataset for number of hooks in a set. To display the distribution at low counts the left graph displays the number of hooks with less than 70 observations.

Results

Shark bycatch per set in the GOMRBLL fishery is primarily characterized by the following species, in order of decreasing total numbers encountered (Figure 4.5): Atlantic sharpnose sharks, smooth dogfish, blacknose sharks, tiger sharks, sandbar sharks, nurse sharks, silky sharks, scalloped hammerhead sharks, blacktip sharks, night sharks, bigeye sixgill, and sevengill sharks. Over two thirds, ~70%, of the most encountered species are made up of Atlantic sharpnose sharks and smooth dogfish.

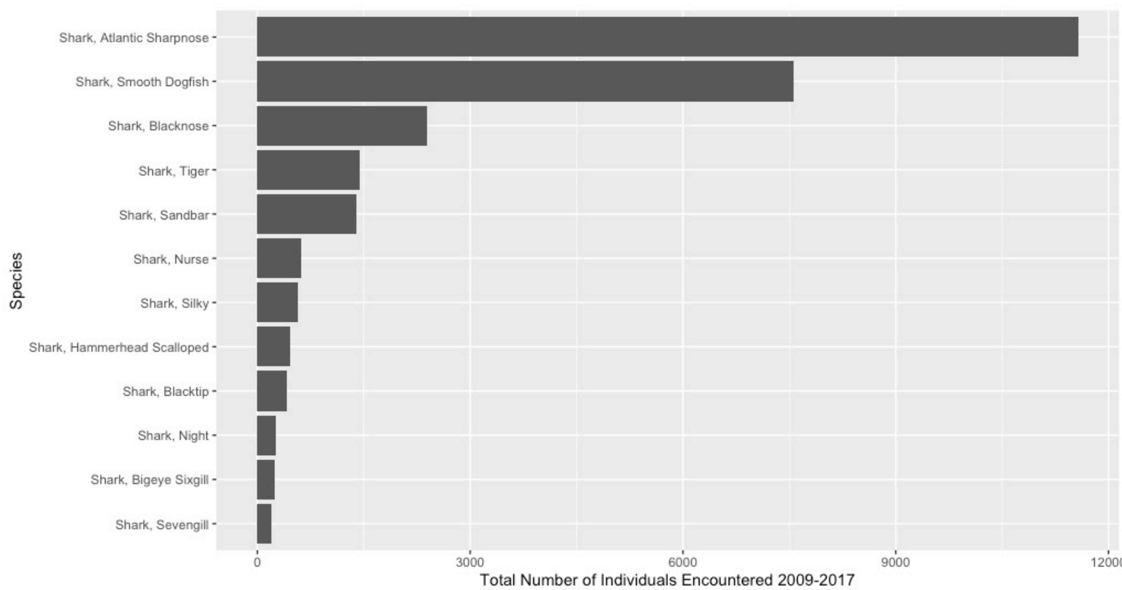


Figure 4.5 The total number of individuals encountered by observers in the Gulf of Mexico bottom longline fishery, 2009-2017, by species. Individuals encountered are defined as any shark that was hooked regardless of ultimate fate.

Model Consideration

All models with weight greater than 0.01 based on the BIC weight were considered to be candidate models and underwent a 10-fold cross validation procedure. This resulted in 41 total candidate models with the number per species/group varying. R^2 values ranged from 0.04 for the tiger shark to 0.46 for the smooth dogfish (Table 4.3). Of the 41 candidate models, 66% explained less than 10% of the variation in catch per set. All of the candidate models explain less than half of the variation in catch per set. Nurse and sandbar sharks only considered the BIC best model, which was therefore selected as the final model. Blacknose, Atlantic sharpnose, smooth dogfish, night, blacktip, tiger, small coastal combined, deep-water combined, and all species combined considered two models. Sevengill and large coastal sharks combined considered three potential models. Scalloped hammerhead, silky, and bigeye sixgill considered five models. When considering all 41 candidate models, hook size was the most commonly excluded variable (excluded from 71% of the considered models) followed by number of hooks set (excluded in 66%), hook shape (excluded from 61%), soak time and season (excluded in 56% each), latitude/longitude (excluded in 49%), and year (excluded in 29%) while depth was only excluded in 4 models (Table 4.3).

Final Model Selection

In all cases where more than one candidate model was being considered, the MAE values across candidate models were similar and the RMSE values were similar across candidate models within a species/species group. Candidate models within a species/species group therefore had similar predictive ability, so the BIC best model was selected as the final model for each species/species group. In the final 16 models, one per species or combined species, hook size was excluded the most, followed by hook shape, number of hooks set, and soak time, then season and latitude/longitude (Table 4.3). Year was excluded from four models while depth was only excluded from one model. All individual species in addition to large coastal, small coastal, and deep-water species excluded at least one variable, while all species combined was the only model to select the full model (Table 4.3). All individual deep-water species retained two variables with all retaining depth, night sharks additionally retaining season, bigeye sixgill sharks additionally retaining year, and sevengill sharks additionally retaining latitude/longitude (Table 4.3).

Year

Year was included in the best model for all the species groups and all individual species except smooth dogfish, night, blacktip, and sevengill sharks. Predicted catch per set rate patterns were variable over time with few long-term patterns (Table 4.3, Figure 4.6). The large coastal group appears to have an approximately 6-year cycle. Bigeye sixgill predicted catch per set declined from 2015 until the end of the time series in 2017. Blacknose and Atlantic sharpnose sharks had similar prediction patterns, which remain when they are combined for the small coastal species group (Figure 4.6). The deep-water species group is most strongly influenced by bigeye sixgill, which was the only individual species of the deep-water group that retained year in the final model. When all species were combined, the year effect was significantly dampened and appeared cyclical (Figure 4.6).

Season

Seven individual species, nurse, Atlantic sharpnose, scalloped hammerhead, sandbar, smooth dogfish, night, and silky sharks, and the small coastal species group, deep-water species group, and all species combined retained the season explanatory variable in the BIC best model (Table 4.3, Figure 4.7). For all of these species except sandbar, smooth dogfish, and silky sharks, Season 2, which corresponds with the summer months May-August, has a negative relationship with catch per set (Figure 4.7). Atlantic sharpnose, scalloped hammerhead, night, small coastals, large coastals, and all species combined had the highest predicted catch per set in Season 1, January-April (Figure 4.7). For sandbar sharks and smooth dogfish Season 2 had the highest predicted catch per set with Seasons

1 and 3 approximately equal for sandbar sharks (Figure 4.7). Nurse and silky sharks had the highest predicted catch per set in Season 3, September-December (Figure 4.7). The combined small coastal group followed the same pattern as Atlantic sharpnose; highest catch per set in Season 1 and lowest in Season 2. When all species are considered together, all three seasons had similar predicted catch per set.

Hook Shape

Atlantic sharpnose, sandbar, smooth dogfish, and blacktip sharks were the only individual species that retained hook shape as an explanatory variable in the BIC best model (Table 4.3, Figure 4.8). Both large coastal species and all combined species groups also retained hook shape as an explanatory variable. For all four species and the two species groups, models suggest that offset hooks catch more sharks per set than straight hooks (Figure 4.8).

Hook Size

Only blacknose, nurse, Atlantic sharpnose, small coastal, large coastal and all species combined retained hook size as an explanatory variable (Table 4.3, Figure 4.9). Generally, hook size is important for individual small coastal species and the small coastal group while hook size is significant for only one species of large coastal shark, the nurse shark, and predicting catch per set for the large coastal shark group (Figure 4.9). The patterns for small coastals and large coastals oppose with the highest estimated catch per set for large coastals predicted for size 14, the hook size that predicts the lowest estimated catch per set for small coastals (Figure 4.9). However, none of the individual species or species groups show a discernable pattern. Across all species and species groups there is no single hook size that would minimize shark bycatch rates. Sizes 12 and 13 neither maximize nor minimize predicted catch per set, thus this is an example of a possible option that balances all species at once.

Latitude/Longitude

For scalloped hammerhead, sandbar, night, tiger, bigeye sixgill, and deep-water species combined, latitude/longitude was not retained in the BIC best model (Table 4.3, Figure 4.10). Blacknose and nurse sharks have the lowest predicted catch per set between 26- and 28-degrees latitude in the western portion of the study area. This contrasts with smooth dogfish, blacktip, and sevengill sharks, which have their highest predicted catch per set in that same location (Figure 4.10). Smooth dogfish and silky sharks have their lowest predicted catch per set at and around the intersection of -82.5 degrees longitude 28 degrees latitude, which corresponds with Tampa Bay. When all the combined species groups are compared, they are very similar with an almost uniform prediction across the study latitudes and longitudes (Figure 4.10).

Depth

Silky shark was the only species that did not retain depth as an explanatory variable (Table 4.3, Figure 4.11). Blacknose, nurse, Atlantic sharpnose, sandbar, and blacktip sharks all had a decrease in predicted catch per set with increase in depth with high catch per set predicted in shallow waters. The combined small coastal species followed the same pattern. Night, bigeye sixgill and sevengill sharks had an increase in predicted catch per set with an increase in depth, high catch per set in deeper waters. The combined deep-water species followed the same pattern. Scalloped hammerhead, smooth dogfish, silky, tiger sharks, and all sharks combined had relatively little variation in predicted catch per set with depth but some peaks in shallower waters (Figure 4.11).

Soak Time

Blacknose, Atlantic sharpnose, sandbar, tiger, small coastal species grouped, large species grouped, and all species combined retained soak time as an explanatory variable (Table 4.3, Figure 4.12). All species/species groups except blacknose had an overall increasing trend in catch per set rate with increasing soak time (Figure 4.12). Blacknose had a different pattern with a dome-shaped pattern peaking between 5 and 10 hours soak time and soak times less than 4 hours and greater than 12 hours negatively associated with catch per set (Figure 4.12). The decrease in catch per set after 5 hours could be due to depredation by larger sharks.

Number of Hooks Set

Smooth dogfish, blacktip, silky, tiger, large coastal species grouped, deep-water species grouped, and all species combined retained the number of hooks set as an explanatory variable (Table 4.3, Figure 4.13). For every species/species group that retained the variable, there is a clear increase in catch per set with an increase in the number of hooks. Increasing the number of hooks in a set increases shark catch per set.

Table 4.3 Retained variables in models with BIC model weights greater than 0.01. Black boxes indicate the variable was not selected for while + indicates that the variable was selected for. * denotes species included in the combined small coastal sharks group, ** denotes species included in the combined large coastal sharks group, *** denotes species included in the combined deep-water sharks group, † denotes prohibited species.

Species	Hook Shape	Hook Size	Depth (m)	Num. Hooks Set	Soak Time (hrs)	Season	Latitude Longitude	Year	BIC	ΔBIC	R^2	logLik	Weight
Blacknose*		+	+		+		+	+	9052	0.000	0.1363	-4392	0.9619
		+	+	+	+		+	+	9059	7.008	0.1364	-4392	0.0289
Nurse**		+	+			+	+	+	3286	0.000	0.1247	-1509	0.9964
Atlantic Sharpnose*	+	+	+		+	+	+	+	20784	0.000	0.2601	-10174	0.9655
		+	+		+	+	+	+	20791	6.665	0.2589	-10182	0.0345
Scalloped Hammerhead**			+			+		+	2545	0.000	0.0733	-1191	0.6372
			+					+	2547	2.020	0.0714	-1201	0.2321
			+		+				2550	4.968	0.0713	-1202	0.0531
			+		+	+			2550	5.466	0.0730	-1192	0.0414
	+		+			+		+	2552	7.399	0.0734	-1190	0.0158
Sandbar**	+		+		+	+		+	6806	0.000	0.0656	-3295	0.9813
Smooth Dogfish	+		+	+		+	+		9609	0.000	0.4589	-4649	0.8970
	+		+				+	+	9613	4.529	0.4597	-4642	0.0932
Night†			+			+			1521	0.000	0.0637	-711	0.9459
	+		+			+			1527	6.172	0.0639	-709	0.0432
Blacktip**	+		+	+			+		1354	0.000	0.0983	-610	0.5699
			+	+			+		1355	0.653	0.0965	-620	0.4112
Silky**				+		+	+	+	3698	0.000	0.0539	-1706	0.5995
	+			+		+	+	+	3700	1.380	0.0546	-1703	0.3006
	+			+			+	+	3703	5.028	0.0518	-1717	0.0485

	+		+	+			+	+	3705	6.256	0.0547	-1702	0.0263
				+			+	+	3706	7.996	0.0508	-1723	0.0110
Tiger**			+	+	+			+	8000	0.000	0.0417	-3919	0.6234
			+		+			+	8001	1.219	0.0403	-3927	0.3390
		+	+		+			+	8007	7.103	0.0427	-3914	0.0179
Bigeye Sixgill†			+					+	1408	0.000	0.0821	-652	0.6785
			+		+				1411	3.080	0.0783	-673	0.1454
			+			+		+	1413	4.386	0.0834	-645	0.0757
			+						1415	6.587	0.0758	-686	0.0252
		+	+		+				1415	6.854	0.0812	-657	0.0220
		+	+					+	1416	8.012	0.0847	-637	0.0124
			+		+			+	1416	8.071	0.0834	-645	0.0120
Sevengill†			+				+		846	0.000	0.0800	-380	0.9698
	+		+				+		855	8.671	0.0802	-379	0.0127
Small Coastal*	+	+	+		+	+	+	+	23374	0.000	0.2957	-11471	0.9965
Large Coastal**	+	+	+	+	+		+	+	16144	0.000	0.1748	-7834	0.9431
	+	+	+		+		+	+	16150	5.651	0.1735	-7841	0.0559
Deep-water†			+	+		+		+	2908	0.000	0.1699	-1367	0.6290
			+			+		+	2909	1.129	0.1691	-1372	0.3577
All	+	+	+	+	+	+	+	+	42882	0.000	0.3819	-21170	0.7525
	+		+	+	+	+	+	+	42884	2.224	0.3795	-21190	0.2475

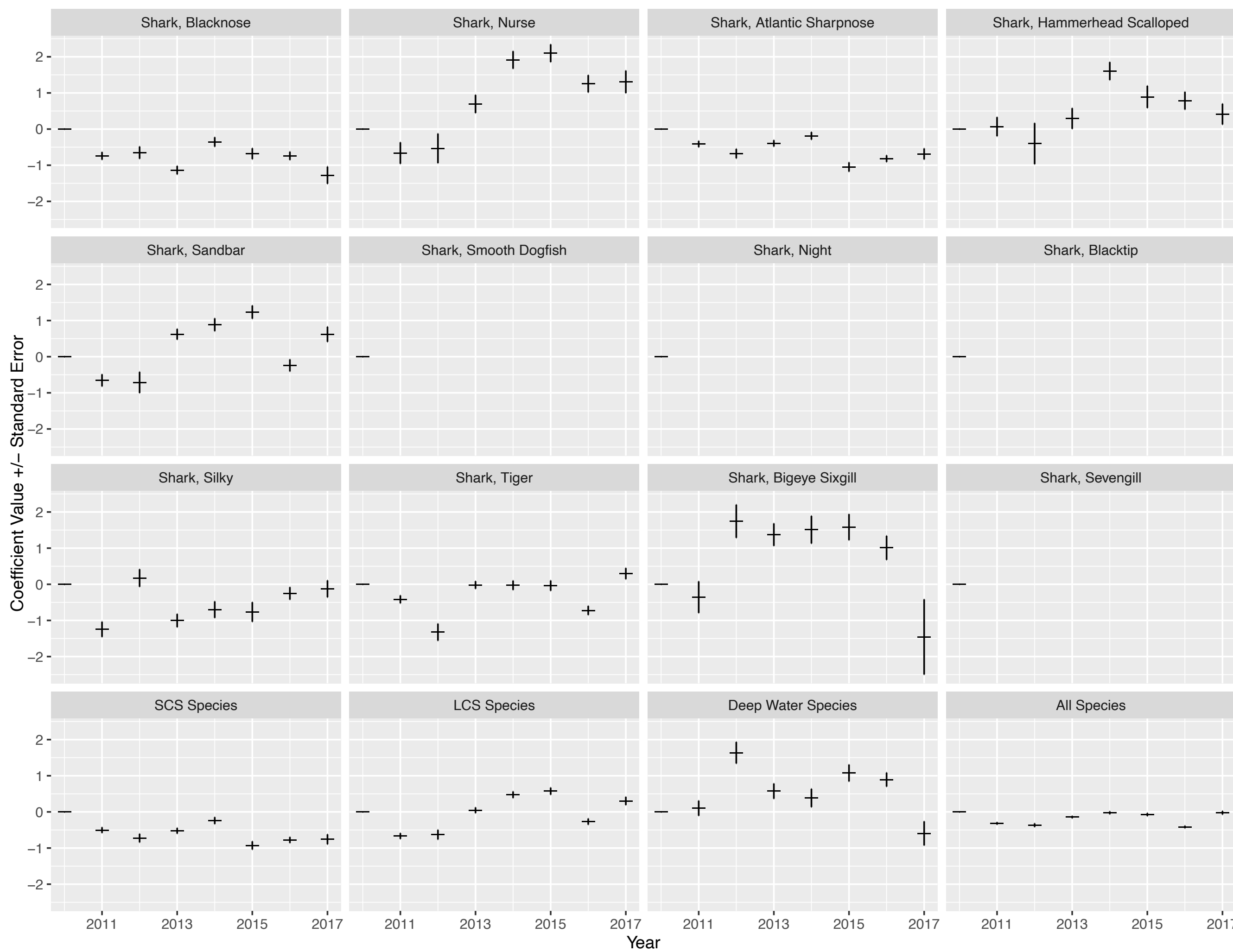


Figure 4.6 Year coefficient value plus/minus standard error as determined by the final generalized additive model for each corresponding species or species group. The first year is the reference value and species with only the reference value have a final model without this variable.

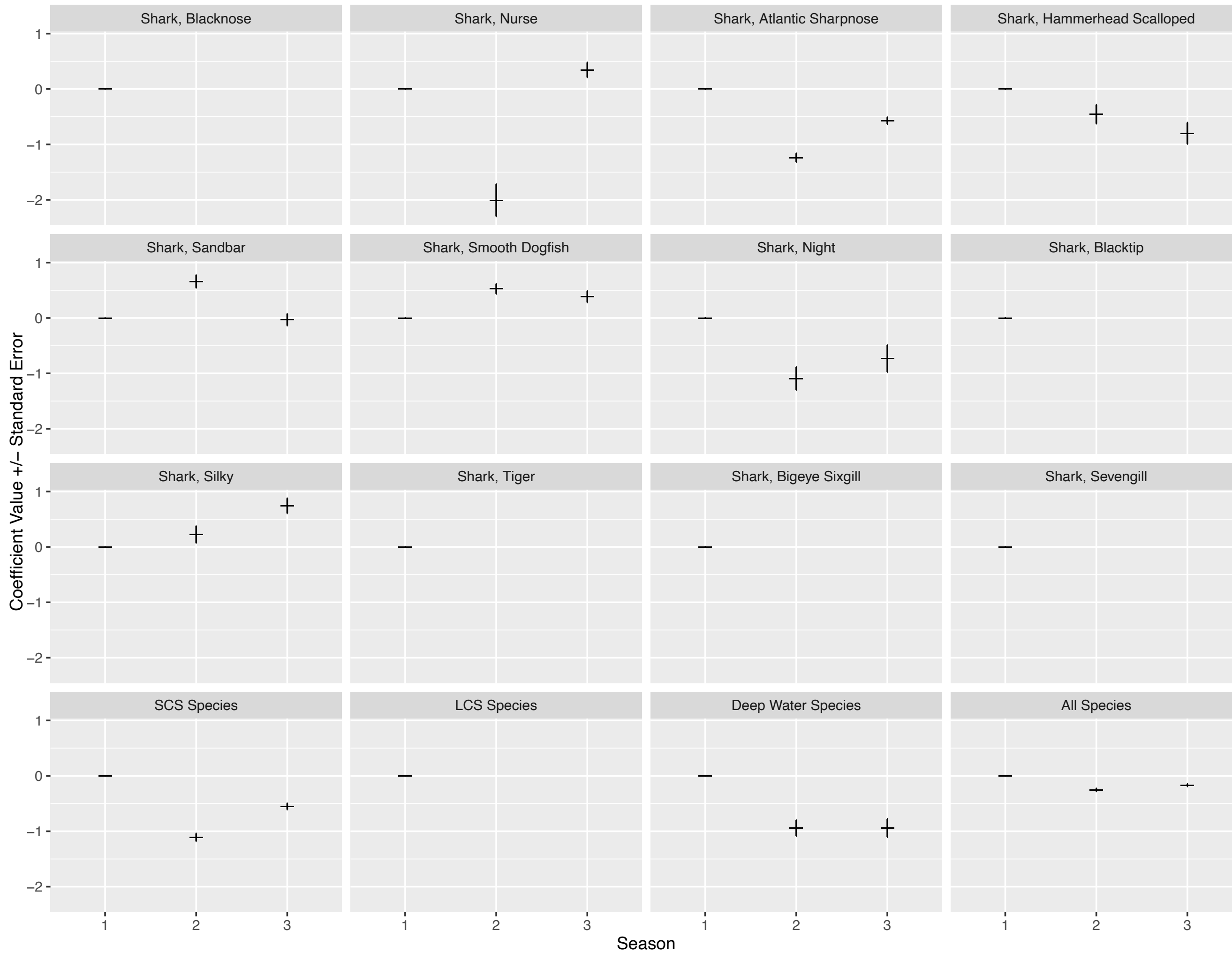


Figure 4.7 Season coefficient value plus/minus standard error as determined by the final generalized additive model for each corresponding species or species group. The first season is the reference value and species with only the reference value have a final model without this variable.

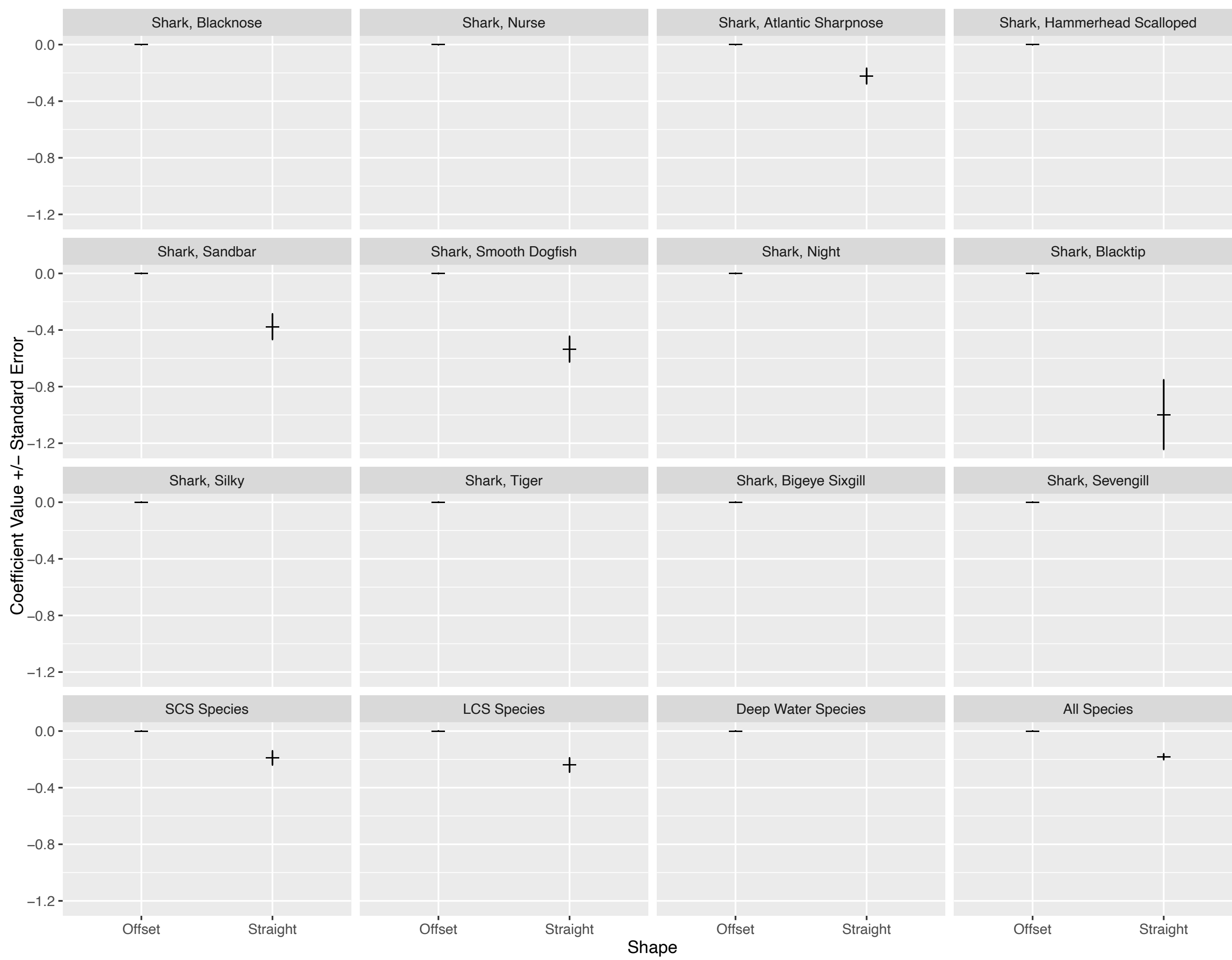


Figure 4.8 Hook shape coefficient value plus/minus standard error as determined by the final generalized additive model for each corresponding species or species group. Offset hook shape is the reference value and species with only the reference value have a final model without this variable.

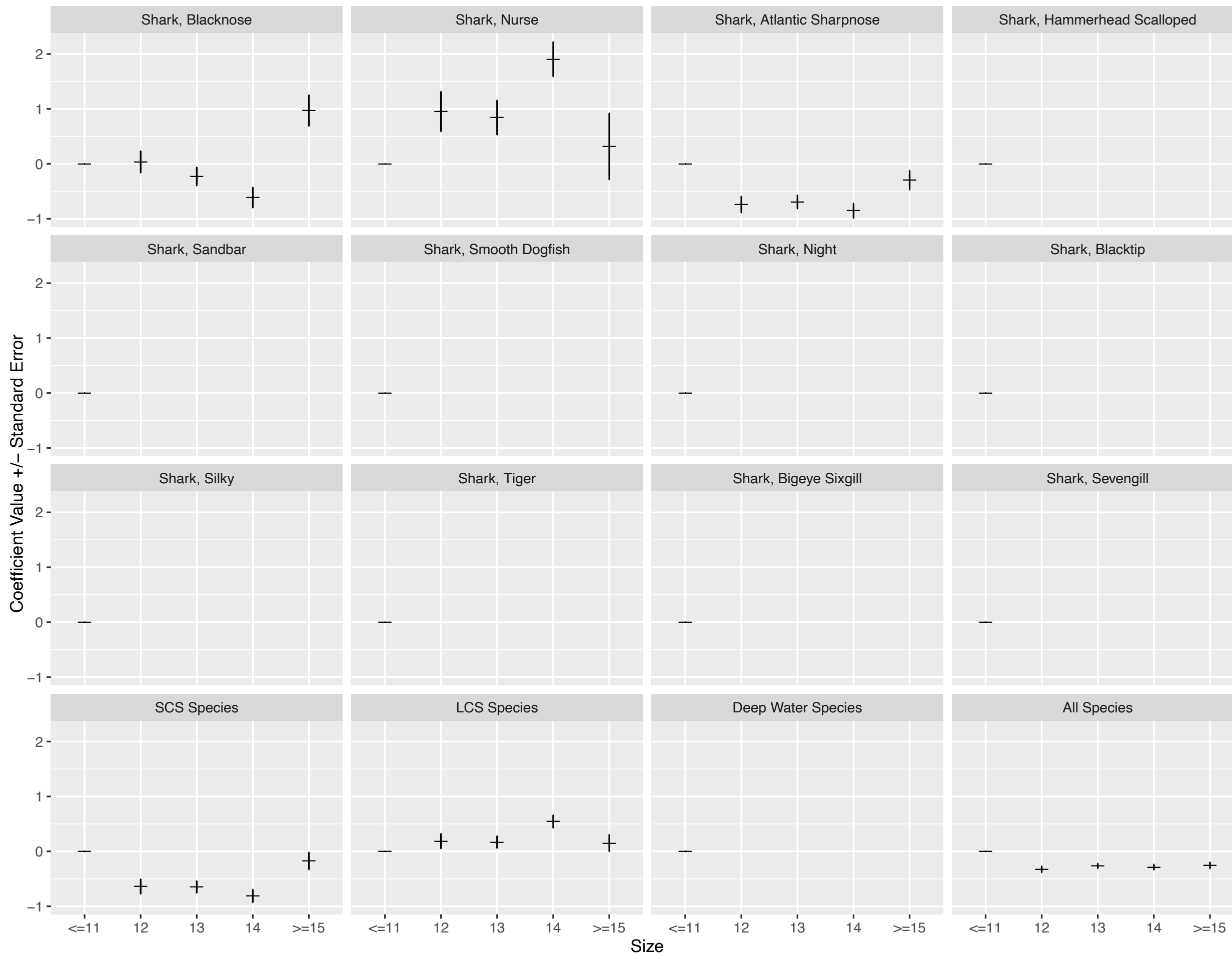


Figure 4.9 Hook size coefficient value plus/minus standard error as determined by the final generalized additive model for each corresponding species or species group. Hook size <=11 is the reference value and species with only the reference value have a final model without this variable.

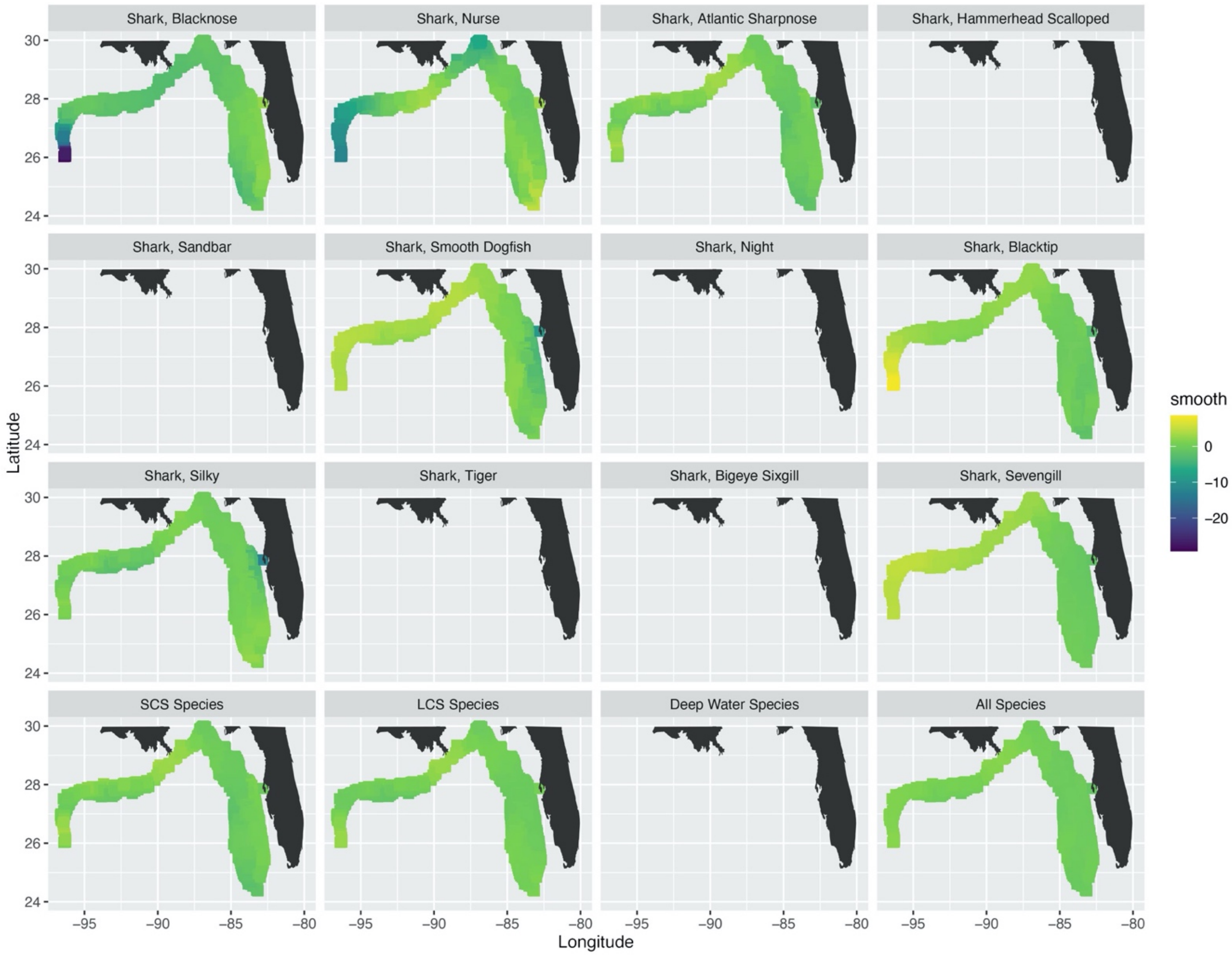


Figure 4.10 Smoothing values for the combination of latitude and longitude as determined by the corresponding generalized additive models for each species and species group. Species with no contours did not select for this variable.

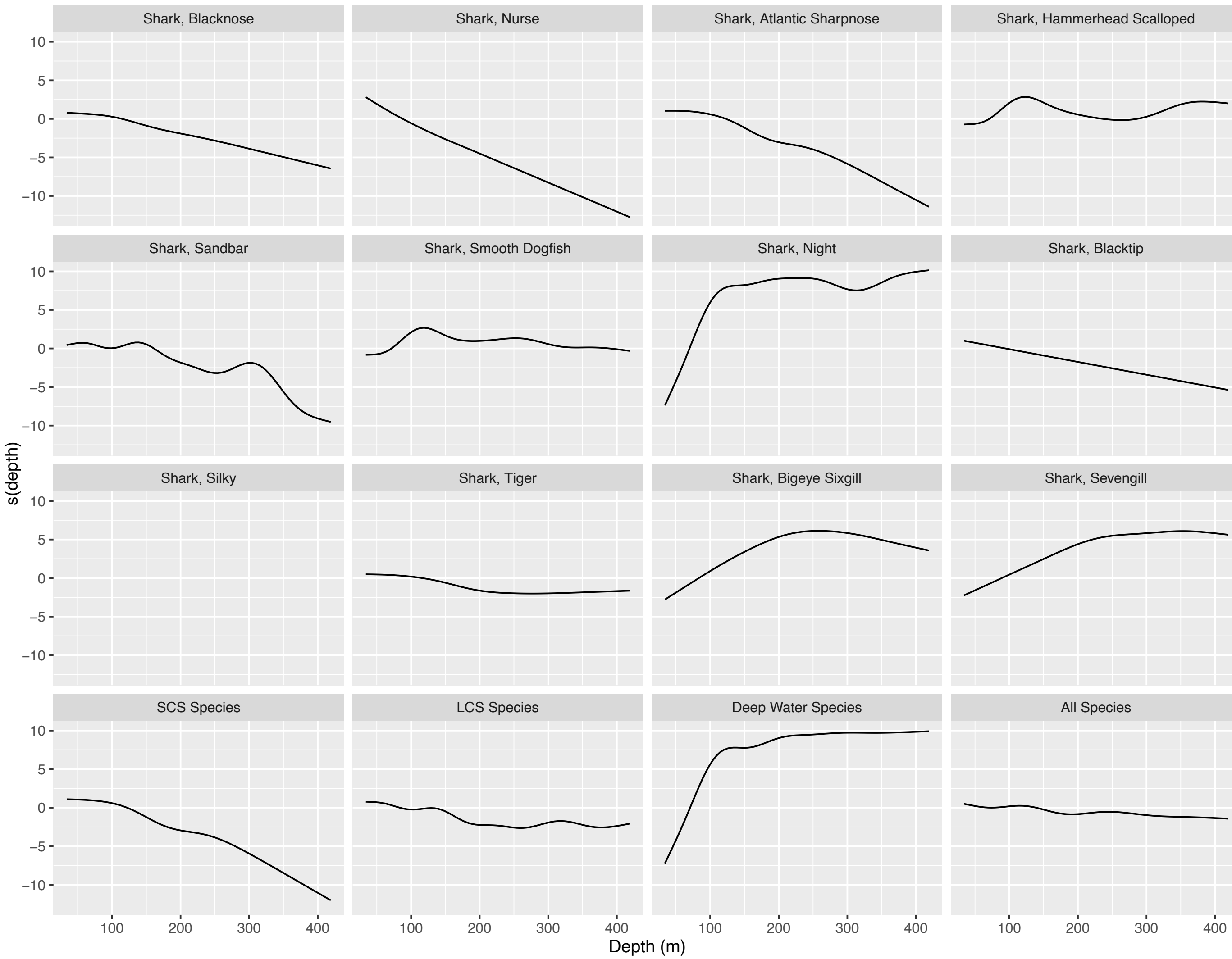


Figure 4.11 Depth smoothing values for depth 35m-420m as determined by the final generalized additive model for each corresponding species or species group. Species with no contours did not select for this variable.

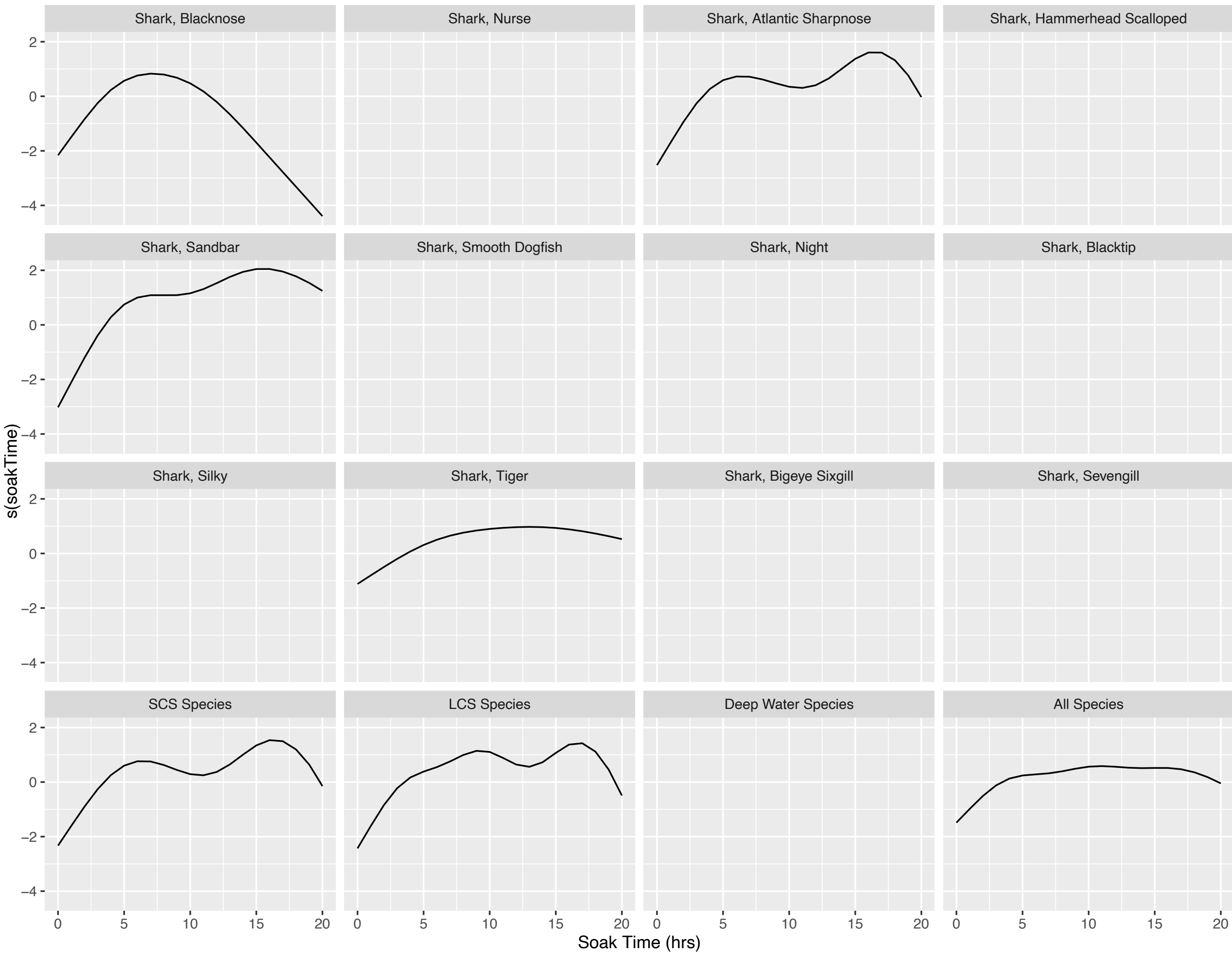


Figure 4.12 Soak time smoothing values for durations 0hrs-20hrs as determined by the final generalized additive model for each corresponding species or species group. Species with no contours did not select for this variable.

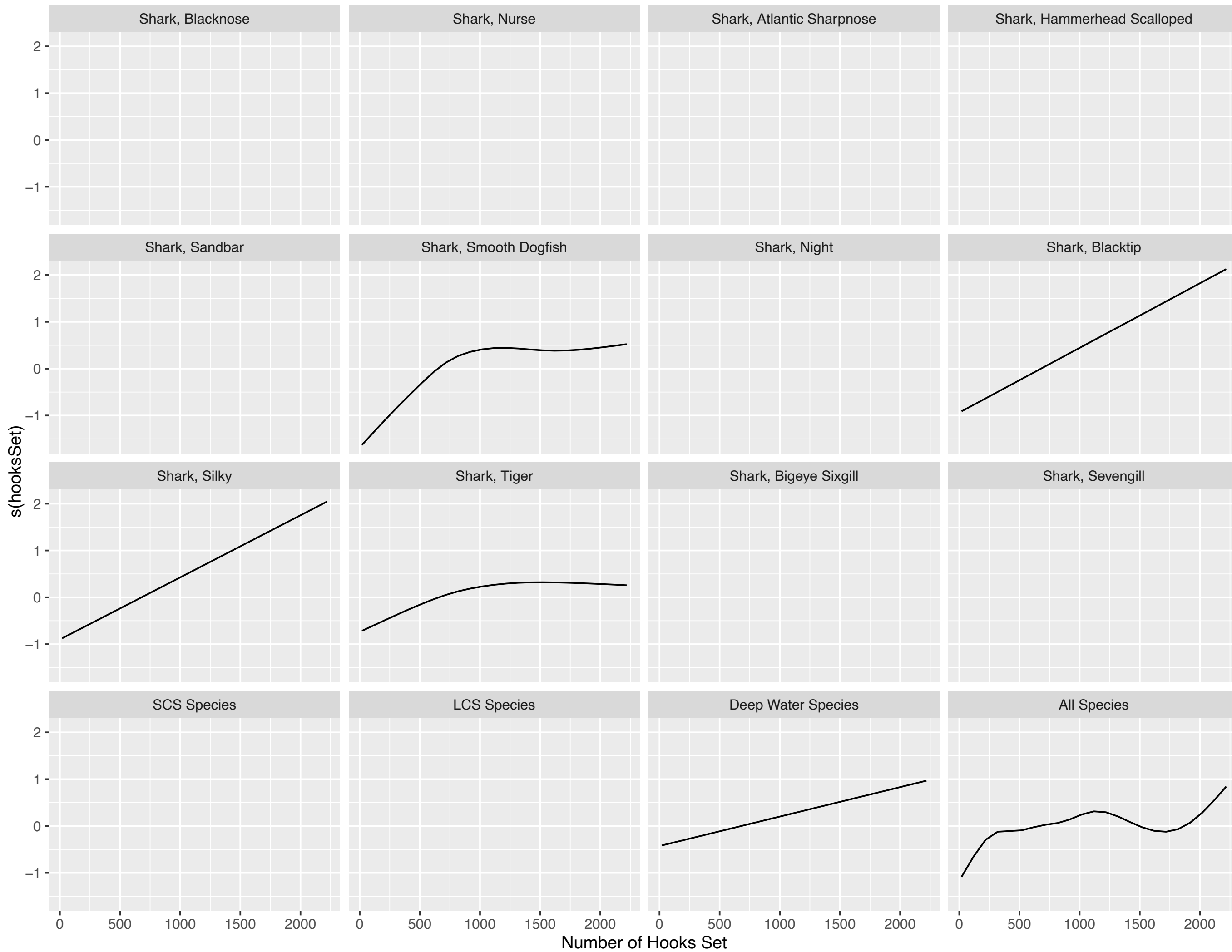


Figure 4.13 Number of hooks smoothing values for sets with 19hooks-2300 hooks as determined by the final generalized additive model for each corresponding species or species group. Species with no contours did not select for this variable.

Model Predictive ability

All species and species groups had MAE and RMSE values less than 2.7 and 5.3 (aside from 2 outlier RMSE values), respectively (Figures 4.14, 4.15). Blacknose, nurse, scalloped hammerhead, sandbar, night, blacktip, silky, tiger, and bigeye sixgill have MAE and RMSE values all less than 0.37 and 2, respectively. Sevengill had the smallest median MAE and RMSE values while all species combined had the highest median MAE and RMSE values. Combined species groups had higher median MAE and RMSE values than the individual species that comprise each corresponding species group. Deep-water species combined had relatively low median MAE and RMSE values of 0.1 and 4 respectively, when compared to the other combined species groups and had lower medians than blacknose, Atlantic sharpnose, sandbar, and tiger sharks. However, the deep-water species group contained the highest single MAE and RMSE values with an outlier over 20 and over 600, respectively. The large coastal species group had a lower median MAE than the small coastal species group which is reflected by the corresponding individual species MAE medians.

These MAE and RMSE values indicate that our ability to predict bycatch per set varies by species. Generally large coastal sharks are better predicted than small coastal sharks, deep-water species are better predicted than coastal species, and we have the worst predictive ability when all species are combined.

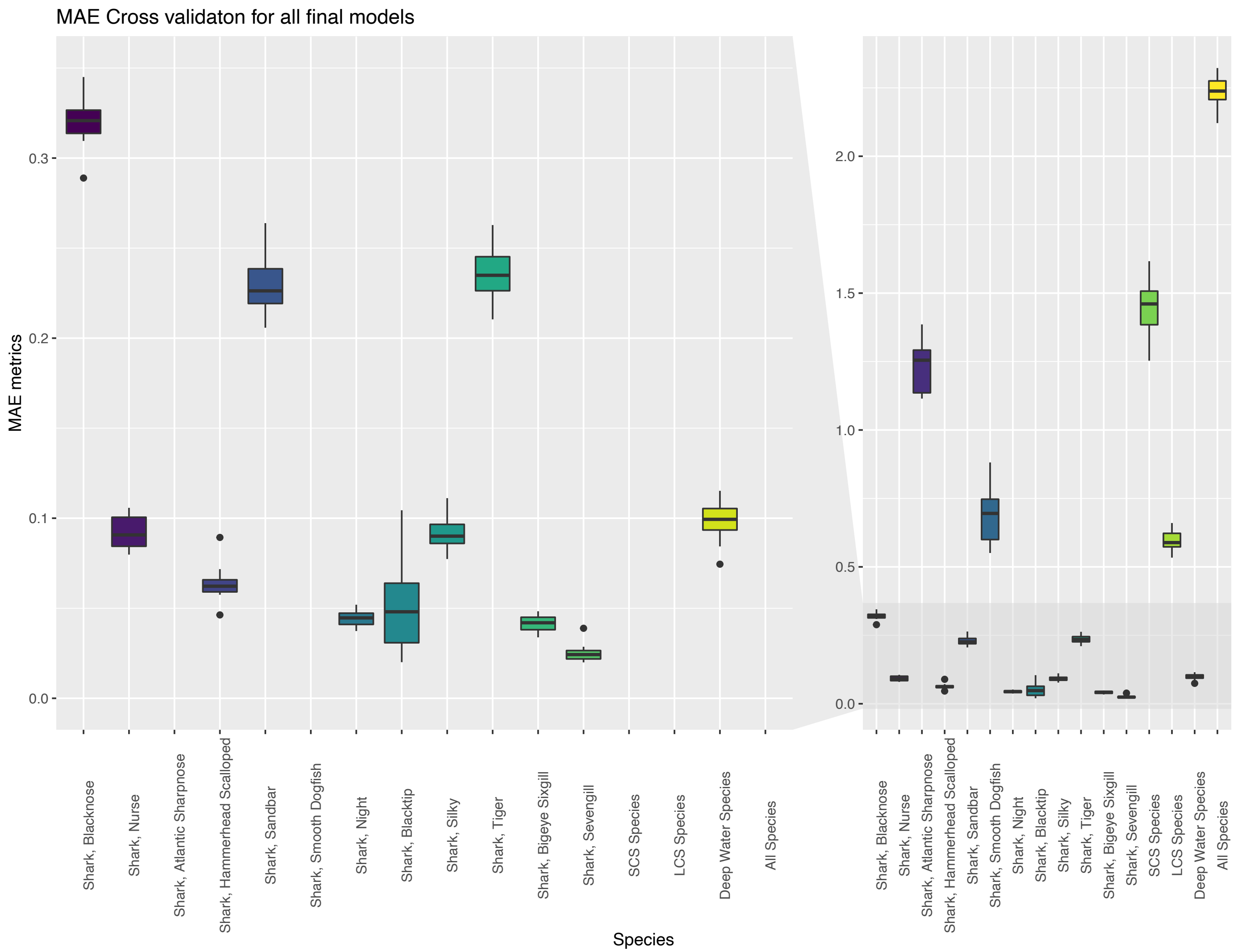


Figure 4.14 Boxplot of the mean absolute error (MAE) metric values from performing 10-fold cross validation on the final model of each species and species group. The graph to the left is zoomed in to depict values less than 0.4.

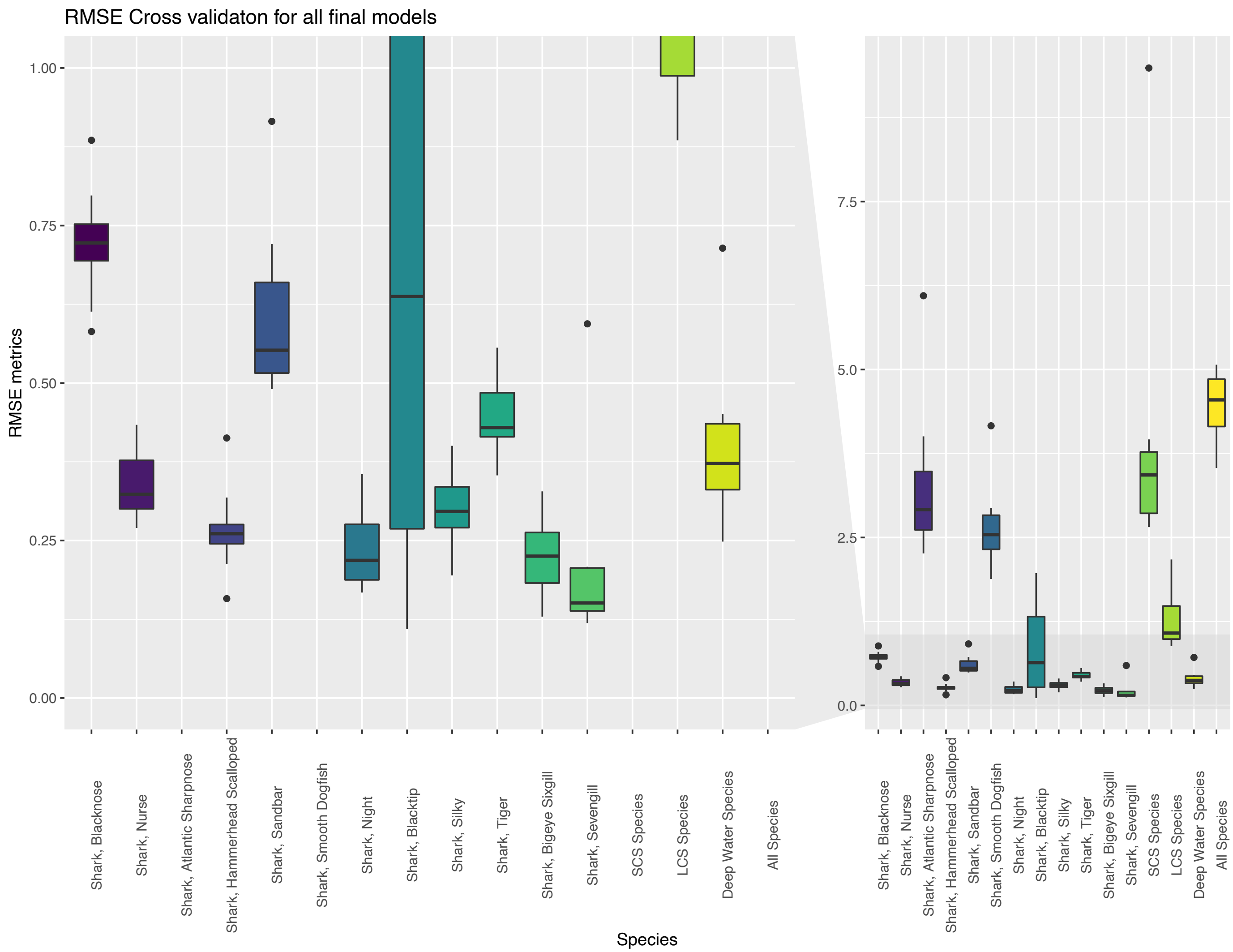


Figure 4.15 Boxplot of the root mean square error (RMSE) metric values from performing 10-fold cross validation on the final model of each species and species group. The graph to the left is zoomed in to depict values less than 5.

Discussion

Overview of Findings

All tested explanatory variables appear to have potential for predicting shark bycatch per set in the GOMRBLL fishery. It was expected that there would be differences across species and similarities within species groups. Findings from this study are largely consistent with other studies examining shark bycatch per set. We expected soak time and number of hooks to be retained with the same trends for all species and species groups. It was also expected that coastal and deep-water species and species groups would have opposing trends representing their preferred habitat. Lastly it was expected that there would be a difference in predictive pattern for small versus large species when it comes to hook size; smaller hooks catching smaller species and larger hooks catching larger species. In general, these patterns were seen as expected, although not all variables were retained for all species.

Environmental variables largely showed variation across species and groups of species while gear/behavior variables largely showed consistency across species and groups of species. Catch per set predicted by environmental variables was consistent with species'/species group's ecology. Coastal species are caught more in coastal locations with shallow waters while deep-water species are caught more in deep waters. No discernable yearly patterns are shown but some seasonal patterns within each year are apparent, which is fairly consistent across species and groups that retain the variable. Gear variables number of hooks and soak time all showed an increase in catch per set with an increase in each variable while hook shape was consistent across all species and groups. It was surprising that hook size did not clearly delineate between small and large species. However, habitat is a key source of differentiation between species and species groups while the use of straight hooks, in the water for less time appears to uniformly reduce shark bycatch per set. Interestingly, the magnitude of each variable's effect is largely lost when all species are combined even when the effects are consistent across species. Furthermore, the predictive ability of models is reduced when species are grouped and is the worst for all species combined.

Relationship to Other Studies

Foster et al. (2017) found that reducing soak time would reduce shark bycatch per set without affecting red grouper catch per set, supporting the patterns found in this study and suggesting that focusing on this variable would have minimal effect on target species catch per set. Further support is provided by the comprehensive global pelagic longline bycatch per set report of Clarke et al. (2014) which concludes that shark bycatch per set in the pelagic longline fishery can be determined by bait type, soak time, hook shape, leader length and material, depth, and special shark targeting gear. Clarke et al. analyzed the body of mitigation strategies based on these gear configurations and variables had varying results and suggests that bycatch does not necessarily correspond to the species typical habitat depth, contrary to the current study. This discrepancy could be due to the difference in the type of longline studied, pelagic versus bottom longline, and the difference in scope of the two studies. Clarke et al.'s (2004) study included large variation over a large spatial area that is a result of very broad spatial and species groupings whereas the GOMRBLL study was very restricted spatially and found that grouping of species can mask the effect of environmental variables.

A recent study by Driggers and Hannan (2019) looking at the relationship between Atlantic sharpnose catch per set and bait type found that mackerel baited hooks had higher catch per set than squid baited hooks. It is possible that combining this finding with the findings of the current study could be a way to mitigate the tradeoffs between trying to reduce the bycatch per set of multiple species simultaneously. For example, if deep-water species were prioritized, encouraging fishers to shift to shallower waters and bait their hooks with squid could allow avoidance of deep-water sharks while reducing catch per set of Atlantic sharpnose.

Caveats and Future Research

This study was limited in temporal and spatial scope. It may not be applicable in the western GOM or the Atlantic coast. Interannual effects could be more variable, or cyclical if analyzed over a longer time series. This study was also unable to consider more rarely caught species due to data limitations. As demonstrated in Chapter 2 of this dissertation with the shortfin mako, rare occurrence of catch per set events does not equate to insignificant catch per set. Shortfin mako are highly migratory species that move in and out of the area and are caught in this fishery rarely, with only 31 caught in 2009-2017. Shortfin mako are overfished and experiencing overfishing (Anonymous 2019a). Other rarely caught sharks, dusky, *Carcharhinus obscurus*, angel, *Squatina dumeril*, and smalltail, *Carcharhinus porosus*, caught 37, 7, and 4 times, respectively, are prohibited species. These species are good examples to demonstrate the need to effectively manage species with rare catch per set events.

Further research should directly examine tradeoffs and the consequences of prioritizing one shark group over another or attempting to balance the needs of multiple groups at once. Because the species caught as bycatch in this fishery vary in their status, productivity, and whether bycatch is an important source of mortality, a management strategy evaluation could be used to weigh the tradeoffs involved in mitigation bycatch for multiple species simultaneously. Booth et al. (2020) have recently proposed a mitigation hierarchy for sharks designed to help make science-based management decisions at the fishery level. Step 2 explores management measures that could potentially meet specified goals and quantitative targets and includes specific consideration of options for avoiding encounters and minimizing capture. Step 3 assesses the hypothetical effectiveness of management options including a technical assessment of the degree to which the method in question can reduce risk. One potential method for this is implementing some of these measures within the mitigation hierarchy for sharks proposed by Booth et al. (2020). This study could fit into Steps 2 and 3 of this hierarchy as part of a larger formal decision-making process.

The impact of any proposed mitigation in this study does not consider the impact to any other bycatch species. Suuronen and Gilman (2019) reviewed several recent studies on approaches to monitoring and managing discards. While changing gear selectivity, e.g., hook shape, is a common and effective strategy for minimizing capture, they found that there is no single gear selectivity option that will reduce interactions with all bycatch species. While the current study only looked at sharks while Suuronen and Gilman (2019) looked across the bycatch literature, the current study also found that there is no one solution that will reduce interaction with all bycatch species. Furthermore, this indicates that changing the hook shape to reduce shark bycatch may have unintended consequences for other bycatch species in this fishery. Tradeoffs and consequences for other species in the fishery should be incorporated in future studies.

Results from this study could be combined with information from the GOM shark bottom longline fishery that targets shark species, research surveys, and other fisheries that catch sharks as bycatch to better define the habitats of species with fewer data, less knowledge of ecology, and those that are rarely caught as bycatch but are more prevalent in other fisheries. At that point, there may be enough observations of rare species to allow for comparison with common species for potential tradeoffs and consequences. Will the consistency of hook shape, hook size, and soak time remain? If rare species are grouped together will the integrity of the individual species pattern be maintained, or will they need to be further grouped by habitat and/or size?

Recommendations and Final Conclusions

Considerations of species ecology coupled with management targeting fisher choice of gear and methodology have the potential to reduce shark bycatch per set in the GOMRBLL fishery. Species vary in which specific environmental and gear variables will mitigate their bycatch per set. However, there are indicators that are consistent across all species and groups including hook shape, number of hooks set, and soak time. Focusing on gear modifications is the only way I found to reduce catch per set of all 12 species at once. Encouraging the use of straight hooks, rather than offset, could reduce the catch per set of several shark species without negatively affecting other shark species. The number of hooks and amount of time the hooks are in the water should be minimized.

Environmental and location-based variables show more variation across species and appear to be consistent with the ecology of each species. A management plan to minimize shark bycatch per set would need to manage tradeoffs and prioritize some species over others. For example, depth is important for all but one species/species group, but the coastal species show a pattern in direct opposition to the deep-water species. The environmental variable that appears the most consistent across species is season. For seven species/species groups Season 1 has the highest predicted CPUE. A time closure that corresponds to Season 1 could move effort to times of the year when these sharks are less susceptible to catch per set. However, this would potentially be detrimental to sandbar, smooth dogfish, and silky sharks. Incentives that encourage more effort in Season 2 rather than Season 1 move effort onto the highest catch per set time for sandbar and smooth dogfish while encouraging more effort in Season 3 rather than Season 1 or 2 moves effort onto the highest catch per set time for silky shark but could be beneficial for scalloped hammerhead. For the environmental conditions, Hazen et al. (2018) EcoCast integrated models suggest that avoidance of multiple bycatch species is possible using fine time/area scales. A fine scale, real-time approach like EcoCast, that predicts occurrence of multiple species on a probability surface could be the best implementation of measures with inconsistent results across species. Applied measures can be chosen based on which shark species have the highest probability of being in a given location.

This study supports the importance of the observer program. While the observer program covers only about 1% of fishing effort (National Marine Fisheries Service 2020a), it remains the most accurate and reliable source of catch information (Suuronen and Gilman 2019). Observer programs collect data at the set level while logbooks often report at the trip level and tend not to include fine-scale gear and environmental data. These set level variables are shown to be important in predicting shark bycatch. Focusing on gear rather than environmental variables is the best apparent option to potentially reduce shark catch per set across commonly caught species. Other options based on environment and location force the acknowledgement of tradeoffs. Sharks as a group should not be lumped together as the signals become confounded and directly managing tradeoffs becomes impossible. At the very least, they should be analyzed in subgroups based on ecology; while predictive ability and magnitude of variable signals is reduced, the data requirements are minimized while still maintaining the integrity of the patterns for the species they represent.

CHAPTER 5: CONCLUSION

General Overview

This dissertation aimed to explore if and how shark bycatch can be reliably predicted and how such predictions can be employed to reduce interactions with longline fisheries. Two different longline fisheries, the U.S. Pelagic Longline (PLL) and Gulf of Mexico Reef Bottom Longline fishery (GOMRBLL), were explored to predict bycatch per unit effort. A focus on both single and grouped species that span across stock status, conservation needs, ecology, spatial movement, and size, allowed us to fill some of the gaps identified in shark bycatch mitigation research (Molina and Cooke 2012). Based on several quantitative modeling approaches, i.e. generalized linear models, generalized additive models, individual based models, delta lognormal distribution, and quantile regression, it can be concluded that environmental conditions and gear configurations can be used to predict shark bycatch well enough to suggest bycatch mitigation strategies that significantly reduce shark bycatch in longline fisheries.

Main Points

It was surprising that throughout the dissertation, simpler, intermediate strategies tended to perform better than those with more complicated structure. It was expected that specific methods and targeted mitigation strategies would most effectively predict bycatch rates, reduce bycatch, and minimally impact fishers. If mitigation could focus on particular catch events and particular conditions, we could target the problem and minimize unintended consequences. For example, the shortfin mako catch in the pelagic longline fishery is highly clumped and patchy, with many sets catching none or one shark while some sets catch over 50 individuals at once. If most sets are not contributing to the bycatch rates, a method which focuses only on sets contributing to high bycatch rates would in theory be better, in spite of the added complexity. However, this was not the case, quantile regression a more complicated method which can focus on high catch rates did not perform better than simpler methods. While all approaches appeared to reduce shark bycatch, through all three studies, more complex approaches, models, and mitigation strategies appear to overfit and be too rigid to deal with the inevitable variation over time. More complex models and strategies performed poorly by comparison, even when looking at more commonly caught species like the Atlantic sharpnose shark. Very simple and easy to implement operational strategies such as not using light sticks in a certain area, a stationary area closure, or using straight over offset hooks have the most potential to reduce shark bycatch rates.

Management can focus on broader trends across species with similar ecology. This finding, that comparatively minimal data are required for the development of promising bycatch mitigation strategies, offers optimism for other data limited species, which would include many sharks. While this study was limited in the number of species considered, it gives insight and a foundation for how to approach the bycatch problem for other overfished shark species, particularly those that are data limited. Findings suggest that more complicated strategies, like a moving closure, could be more effective but only if we have enough information to successfully capture spatio-temporal dynamics. There does not appear to be a buffer that allows for incorrect assumptions. Incorrect assumptions about such dynamics appear to lead to unintended impacts on the shark populations and fishers. The Hazen et al. (2018) EcoCast model for the U.S. west coast successfully models blue shark bycatch, along with two other bycatch species and the target species, in near real time suggesting that at fine scales and with enough information, bycatch mitigation can be improved. There is a dichotomy where over generalizing and more complete knowledge can yield positive results but having incomplete information that forces assumptions can potentially be worse if those assumptions are incorrect.

The results of this dissertation show promise for shark management in general. Adding detail and complexity may add realism, but this increases the number of parameters and need for more data (Plagányi 2007, Espinoza-Tenorio et al. 2012). Several species are data limited which can limit our ability to successfully manage them. This study shows that we can use simple models with few requirements. Furthermore, the inclusion of environmental factors in these models, takes a step toward ecosystem-based fisheries management (EBFM) via an ecosystem approach to fisheries management (EAFM). EAFM includes the addition of ecosystem factors, such as abiotic environmental factors, to a single species stock assessment to enhance our understanding of fishery dynamics (Patrick and Link 2015). This level of complexity balances the data requirements, uncertainty, and need for some degree of realism (Espinoza-Tenorio et al. 2012).

According to the updated terminology for classifying ecosystem models, based on their structure and purpose, by O'Farrell et al. (2017), all the models presented here could be considered to be strategic extensions of single-species models. Currently the incorporation of ecosystem factors in the stock assessment process is limited and viewed with caution due to data limitations (Christensen and Walters 2011, Patrick and Link 2015, O'Farrell et al. 2017). This study shows that for some shark species, the environmental data from the observer datasets are sufficient to develop bycatch reduction strategies and assess bycatch rates particularly when it comes to considering habitat features. This may also ring true for incorporating environmental factors into the development of abundance indices used in stock assessment process in the near future.

Limitations and Future Work

This study is limited to two U.S. fisheries operating in the Northwest Atlantic and the Gulf of Mexico and 13 species of sharks. While we attempted to represent the variation in shark species that interact with longlines, the results of this study may not be applicable to all U.S. longline fisheries and the sharks that encounter them. Furthermore, several of these species are highly migratory (Abascal et al. 2011, Block et al. 2011, Queiroz et al. 2016) and experience fishing pressures of other countries' fleets (Clarke et al. 2014, Queiroz et al. 2019). To comprehensively address the stock status and conservation issues that surround these species, all sources of fishing mortality must be considered. This study has shown the while we have the ability to capture patterns by grouping similar species, the impact of generalized bycatch reduction strategies is limited when compared to treating species separately.

Fisheries management could benefit from determining if this threshold of knowledge is persistent across species or groups of species. Further work could include predicting bycatch of a species with well-known dynamics and ecology modeled with the correct assumptions and again with incorrect assumptions. The efficacy of borrowing information from one species to another could be tested in the same framework by grouping two species that are known to be ecologically similar and then grouping two species that are known to be different. Comparing the model outputs to each other and what is known would show the consequences of an incorrect assumption, our ability to effectively use and implement information in a management context, and the appropriateness and hazards associated with grouping similar and dissimilar species.

The issue of tradeoffs could also be explored in a more encompassing ecosystem-based fisheries approach. This dissertation does not directly measure or model fisher behavior. Many of the results of proposed mitigation measures would be greatly influenced by fisher operational responses in space/time (including gear changes), however, this study made broad assumptions about such responses to get a rough idea of the effectiveness of mitigation measures. Future work could develop models that also simulate fisher decision making in longline fisheries. This could be achieved by linking a fisher decision module to the models presented in this dissertation, or to similar models. This would give additional information to management without requiring additional data and information about the shark species of interest although it would require more socioeconomic data about fisher decisions. Instead of adding complexity to the modeling of the sharks themselves, which has been shown to be potentially detrimental to bycatch reduction efforts, one could add complexity by incorporating fisher responses, thus eliminating some of the simplistic assumptions made. This would improve the assessment of the potential of these mitigation strategies and provide an additional measure of potential tradeoffs.

Final Thoughts

Shark management and conservation are challenged by our lack of ecological knowledge, the variation across species, and the fact that many are caught incidentally or as bycatch. No one method or strategy will affect all shark species that interact with longline gear. This study has shown that we have options even with our current lack of information for some species. Despite knowledge gaps there is enough information to use simple models and simple mitigation strategies to reduce shark bycatch while we obtain more data and knowledge. There will be tradeoffs and all shark species will not be equally helped or harmed. The literature and the studies presented in this dissertation suggest that once we surpass the knowledge threshold, reliable and consistent bycatch mitigation with consideration of target species is possible. Observer programs are vital to supplying the data needed to attempt bycatch mitigation and expansion, or some other method of improving data limitations, could yield optimal results. In the meantime, the information we currently have is enough to substantially reduce shark bycatch in longline fisheries.

REFERENCES

Abascal, F. J., M. Quintans, A. Ramos-Cartelle, and J. Mejuto. 2011. Movements and environmental preferences of the shortfin mako, Isurus oxyrinchus, in the southeastern Pacific Ocean. Marine Biology **158**:1175-1184.

Anadon, J. D., C. D'Agrosa, A. Gondor, and L. R. Gerber. 2011. Quantifying the spatial ecology of wide-ranging marine species in the Gulf of California: implications for marine conservation planning. Plos One **6**.

Anderson, M. J. 2008. Animal-sediment relationships re-visited: Characterising species' distributions along an environmental gradient using canonical analysis and quantile regression splines. Journal of Experimental Marine Biology and Ecology **366**:16-27.

Anonymous. 1973. Text of the Convention. Convention on International Trade in Endangered Species of Wild Fauna and Flora.

Anonymous. 2017a. Recommendation by ICCAT on the conservation of north atlantic stock of shortfin mako caught in association with ICCAT fisheries.*in* ICCAT, editor. ICCAT, iccat.int.

Anonymous. 2017b. Report of the 2017 ICCAT Shortfin Mako Assessment Meeting. Report, ICCAT.

Anonymous. 2019a. Report fo the 2019 shortfin mako shark stock assessment update meeting. ICCAT.

Anonymous. 2019b. Summary record of the fourth plenary session. Convention on International Trade in Endangered Species of Wild Fauna and Flora.

Babcock, E. A. 2013. Updated index of abundance for shortfin mako sharks from the U.S. marine recreational fisheries statistics survey. Report.

Babcock, E. A., E. K. Pikitch, and C. G. Hudson. 2003. How much observer coverage is enough to adequately estimate bycatch? , Oceana, oceana.org.

Barton, K., and M. K. Barton. 2015. Package 'MuMIn'. Version **1**:18.

Baum, J. K., and R. A. Myers. 2004. Shifting baselines and the decline of pelagic sharks in the Gulf of Mexico. Ecology Letters **7**:135-145.

Beerkircher, L. 2016. Southeast Pelagic Observer Program.

Beerkircher, L. R., D. W. Lee, and C. J. Brown. 2002. SEFSC pelagic observer program data summary for 1992-2000. NOAA Technical Memorandum NMFS-SEFC, NOAA.

Beerkircher, L. R., D. W. Lee, C. J. Brown, and D. L. Abercrombie. 2004. SEFSC pelagic observer program data summary for 1992-2002. NOAA Technical Memorandum NMFS-SEFC, NOAA.

Block, B. A., D. P. Costa, G. W. Boehlert, and R. E. Kochevar. 2002. Revealing pelagic habitat use: the tagging of Pacific pelagics program. Oceanologica Acta **25**:255-266.

Block, B. A., I. D. Jonsen, S. J. Jorgensen, A. J. Winship, S. A. Shaffer, S. J. Bograd, . . . D. P. Costa. 2011. Tracking apex marine predator movements in a dynamic ocean. Nature **475**:86-90.

Booth, H., D. Squires, and E. J. Milner-Gulland. 2020. The mitigation hierarchy for sharks: A risk-based framework for reconciling trade-offs between shark conservation and fisheries objectives. Fish and Fisheries **21**:269-289.

Boyce, M. S., P. R. Vernier, S. E. Nielsen, and F. K. A. Schmiegelow. 2002. Evaluating resource selection functions. Ecological Modelling **157**:281-300.

Bravington, M., C. Burridge, and P. Toscas. 2003. Design of observer program to monitor bycatch species in the Eastern Tuna and Billfish Fishery. Pages 1-25 *in* 16th Meeting of the Standing Committee on Tuna and Billfish.

Breen, P., P. Posen, and D. Righton. 2015. Temperate Marine Protected Areas and highly mobile fish: A review. Ocean & Coastal Management **105**:75-83.

Burnham, K. P., and D. R. Anderson. 2004. Multimodel inference: understanding AIC and BIC in model selection. Sociological Methods & Research **33**:261-304.

Cade, B. S., and B. R. Noon. 2003. A gentle introduction to quantile regression for ecologists. Frontiers in Ecology and the Environment **1**:412-420.

Campana, S. E., A. Dorey, M. Fowler, W. Joyce, Z. L. Wang, D. Wright, and I. Yashayaev. 2011. Migration pathways, behavioural thermoregulation and overwintering grounds of blue sharks in the Northwest Atlantic. Plos One **6**.

Carlson, A. E., E. R. Hoffmayer, C. A. Tribuzio, and J. A. Sulikowski. 2014. The use of satellite tags to redefine movement patterns of spiny dogfish (Squalus acanthias) along the US East Coast: implications for fisheries management. Plos One **9**.

Carrier, J. C., and H. L. Pratt. 1998. Habitat management and closure of a nurse shark breeding and nursery ground. Fisheries Research **39**:209-213.

Casey, J. G., and N. E. Kohler. 1992. Tagging studies on the shortfin mako shark (Isurus oxyrinchus) in the western North Atlantic. Australian Journal of Marine and Freshwater Research **43**:45-60.

Christensen, V., and C. J. Walters. 2011. Progress in the use of ecosystem modeling for fisheries management. Ecosystem Approaches to Fisheries: A Global Perspective:189-205.

Clarke, S., M. Sato, C. Small, B. Sullivan, Y. Inoue, and D. Ochi. 2014. Bycatch in longline fisheries for tuna and tuna-like species: a global review of status and mitigation measures. FAO fisheries and aquaculture technical paper **588**:1-199.

Compagno, L. 1984. Sharks of the world. An annotated and illustrated catalogue of shark species known to date. FAO Species Catalogue. Vol. 4. Part 2. Carcharhiniformes. UN Dev. Prog., FAO, Rome.

Cortes, E. 1998. Demographic analysis as an aid in shark stock assessment and management. Fisheries Research **39**:199-208.

Cortes, E. 2002. Incorporating uncertainty into demographic modeling: Application to shark populations and their conservation. Conservation Biology **16**:1048-1062.

Cortes, E. 2007. Chondrichthyan demographic modelling: an essay on its use, abuse and future. Marine and Freshwater Research **58**:4-6.

Cortes, E. 2013. Standardized catch rates of mako sharks from the U.S. Pelagic Longline Logbook and Observer Programs using a generalized linear mixed model. Report.

Cortés, E. 2009. Rhizoprionodon terraenovae. The IUCN Red List of Threatened Species 2009 **e.T39382A10225086**.

Cortés, E. 2017. Estimates of maximum population growth rate and steepness for shortfin makos in the North and South Atlantic Ocean. Collect. Vol. Sci. Pap. ICCAT **74**:1822-1829.

Cortes, E., F. Arocha, L. Beerkircher, F. Carvalho, A. Domingo, M. Heupel, . . . C. Simpfendorfer. 2010. Ecological risk assessment of pelagic sharks caught in Atlantic pelagic longline fisheries. Aquatic Living Resources **23**:25-34.

Courtney, D., E. Cortés, and X. Zhang. 2017. Stock synthesis (SS3) model runs conducted for North Atlantic shortfin mako shark. Collect. Vol. Sci. Pap. ICCAT **74**:1759-1821.

Courtney, D., and J. Rice. 2020. Example of a stock synthesis projection approach at alternative fixed total allowable catch (TAC) limits implemented for three previously completed north atlantic shortfin mako stock synthesis model runs. Collect. Vol. Sci. Pap. ICCAT **76**:78-114.

Cuevas, E., V. Guzman-Hernandez, A. Uribe-Martinez, A. Raymundo-Sanchez, and R. Herrera-Pavon. 2018. Identification of potential sea turtle bycatch hotspots using a spatially explicit approach in the Yucatan Peninsula, Mexico. Chelonian Conservation and Biology **17**:78-93.

Driggers, W. B., III, and K. M. Hannan. 2019. Efficacy of 2 common bait types in reducing bycatch of coastal sharks on bottom longline gear in the absence of choice. Fishery Bulletin **117**:189+.

Elith, J., C. H. Graham, R. P. Anderson, M. Dudik, S. Ferrier, A. Guisan, . . . N. E. Zimmermann. 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography **29**:129-151.

Espinoza-Tenorio, A., M. Wolff, M. H. Taylor, and I. Espejel. 2012. What model suits ecosystem-based fisheries management? A plea for a structured modeling process. Reviews in Fish Biology and Fisheries **22**:81-94.

FAO. 2002. Guidelines for developing an at-sea fishery observer programme. Food and Agriculture Organization of the United Nations Rome.

Fasiolo, M., Y. Goude, R. Nedellec, and S. N. Wood. 2017. Fast calibrated additive quantile regression. arXiv preprint arXiv:1707.03307.

Fornaroli, R., R. Cabrini, L. Sartori, F. Marazzi, S. Canobbio, and V. Mezzanotte. 2016. Optimal flow for brown trout: Habitat - prey optimization. Science of the Total Environment **566**:1568-1578.

Fornaroli, R., R. Cabrini, L. Sartori, F. Marazzi, D. Vracevic, V. Mezzanotte, . . . S. Canobbio. 2015. Predicting the constraint effect of environmental characteristics on macroinvertebrate density and diversity using quantile regression mixed model. Hydrobiologia **742**:153-167.

Foster, D. G., J. R. Pulver, E. Scott-Denton, and C. Bergmann. 2017. Minimizing bycatch and improving efficiency in the commercial bottom longline fishery in the Eastern Gulf of Mexico. Fisheries Research **196**:117-125.

Fukunaga, A., R. K. Kosaki, D. Wagner, and C. Kane. 2016. Structure of mesophotic reef fish assemblages in the northwestern Hawaiian Islands. Plos One **11**.

Grimm, V., U. Berger, F. Bastiansen, S. Eliassen, V. Ginot, J. Giske, . . . D. L. DeAngelis. 2006. A standard protocol for describing individual-based and agent-based models. Ecological Modelling **198**:115-126.

Grimm, V., E. Revilla, U. Berger, F. Jeltsch, W. M. Mooij, S. F. Railsback, . . . D. L. DeAngelis. 2005. Pattern-oriented modeling of agent-based complex systems: Lessons from ecology. Science **310**:987-991.

Grüss, A., E. A. Babcock, S. R. Sagarese, M. Drexler, D. D. Chagaris, C. H. Ainsworth, . . . T. T. Sutton. 2016. Improving the spatial allocation of functional group biomasses in spatially-explicit ecosystem models: insights from three Gulf of Mexico models. Bulletin of Marine Science **92**:000-000.

Gruss, A., M. Drexler, and C. H. Ainsworth. 2014. Using delta generalized additive models to produce distribution maps for spatially explicit ecosystem models. Fisheries Research **159**:11-24.

Gruss, A., J. F. Walter, E. A. Babcock, F. C. Forrestal, J. T. Thorson, M. V. Lauretta, and M. J. Schirripa. 2019. Evaluation of the impacts of different treatments of spatio-temporal variation in catch-per-unit-effort standardization models. Fisheries Research **213**:75-93.

Guisan, A., T. C. Edwards, and T. Hastie. 2002. Generalized linear and generalized additive models in studies of species distributions: setting the scene. Ecological Modelling **157**:89-100.

Hartig, F. 2017. DHARMa: residual diagnostics for hierarchical (multi-level/mixed) regression models. R package version 0.1 **5**.

Hazen, E. L., K. L. Scales, S. M. Maxwell, D. K. Briscoe, H. Welch, S. J. Bograd, . . . R. L. Lewison. 2018. A dynamic ocean management tool to reduce bycatch and support sustainable fisheries. Science Advances **4**.

Humston, R., J. S. Ault, M. Lutcavage, and D. B. Olson. 2000. Schooling and migration of large pelagic fishes relative to environmental cues. Fisheries Oceanography **9**:136-146.

Jacoby, D. M. P., E. J. Brooks, D. P. Croft, and D. W. Sims. 2012. Developing a deeper understanding of animal movements and spatial dynamics through novel application of network analyses. Methods in Ecology and Evolution **3**:574-583.

Jorgensen, S. J., N. S. Arnoldi, E. E. Estess, T. K. Chapple, M. Ruckert, S. D. Anderson, and B. A. Block. 2012. Eating or meeting? Cluster analysis reveals intricacies of white shark (Carcharodon carcharias) migration and offshore behavior. Plos One **7**.

Karp, W. A., L. L. Desfosse, and S. G. Brooke. 2011. U.S. National Bycatch Report. Page 508 *in* N. M. F. Service, editor., U.S. Department of Commerce.

Koenker, R., and G. Bassett. 1978. Regression Quantiles. Econometrica **46**:33-50.

Koenker, R., and K. F. Hallock. 2001. Quantile regression. Journal of Economic Perspectives **15**:143-156.

Koenker, R., and J. A. F. Machado. 1999. Goodness of fit and related inference processes for quantile regression. Journal of the American Statistical Association **94**:1296-1310.

Le Bris, A., A. Fréchet, and J. S. Wroblewski. 2013. Supplementing electronic tagging with conventional tagging to redesign fishery closed areas. Fisheries Research **148**:106-116.

Levesque, J. C. 2008. International fisheries agreement: Review of the International Commission for the Conservation of Atlantic Tunas case study - Shark management. Marine Policy **32**:528-533.

Liggins, G., M. Bradley, and S. Kennelly. 1997. Detection of bias in observer-based estimates of retained and discarded catches from a multi species trawl fishery. Fisheries Research **32**:133-147.

Little, L. R., A. E. Punt, B. D. Mapstone, G. A. Begg, B. Goldman, and N. Ellis. 2009. Different responses to area closures and effort controls for sedentary and migratory harvested species in a multispecies coral reef linefishery. ICES Journal of Marine Science **66**:1931-1941.

Lo, N. C. H., L. D. Jacobson, and J. L. Squire. 1992. Indexes of relative abundance from fish spotter data based on delta-lognormal models. Canadian Journal of Fisheries and Aquatic Sciences **49**:2515-2526.

Loefer, J. K., G. R. Sedberry, and J. C. McGovern. 2005. Vertical movements of a shortfin mako in the western North Atlantic as determined by pop-up satellite tagging. Southeastern Naturalist **4**:237-246.

Maia, A., N. Queiroz, H. N. Cabral, A. M. Santos, and J. P. Correia. 2007. Reproductive biology and population dynamics of the shortfin mako, Isurus oxyrinchus Rafinesque, 1810, off the southwest Portuguese coast, eastern North Atlantic. Journal of Applied Ichthyology **23**:246-251.

Manel, S., H. C. Williams, and S. J. Ormerod. 2001. Evaluating presence-absence models in ecology: the need to account for prevalence. Journal of Applied Ecology **38**:921-931.

Maunder, M. N., and A. E. Punt. 2004. Standardizing catch and effort data: a review of recent approaches. Fisheries Research **70**:141-159.

Maxwell, S. M., K. M. Gjerde, M. G. Conners, and L. B. Crowder. 2020. Mobile protected areas for biodiversity on the high seas. Science **367**:252-254.

McCully, S. R., S. Finlay, J. R. Ellis, and G. M. Pilling. 2013. Productivity and susceptibility analysis: application and suitability for data poor assessment of elasmobranchs in northern european seas. ICCAT Collective Volume of Scientific Papers **69**:1679-1698.

McDonald, L., B. Manly, F. Huettmann, and W. Thogmartin. 2013. Location-only and use-availability data: analysis methods converge. Journal of Animal Ecology **82**:1120-1124.

Molina, J. M., and S. J. Cooke. 2012. Trends in shark bycatch research: current status and research needs. Reviews in Fish Biology and Fisheries **22**:719-737.

Mollet, H. F., G. Cliff, H. L. Pratt, and J. D. Stevens. 2000. Reproductive biology of the female shortfin mako, Isurus oxyrinchus Rafinesque, 1810, with comments on the embryonic development of lamnoids. Fishery Bulletin **98**:299-318.

Natanson, L. J., N. E. Kohler, D. Ardizzone, G. M. Cailliet, S. P. Wintner, and H. F. Mollet. 2006. Validated age and growth estimates for the shortfin mako, Isurus oxyrinchus, in the North Atlantic Ocean. Environmental Biology of Fishes **77**:367-383.

National Marine Fisheries Service. 2018. Characterization of the US Gulf of Mexico and Southeastern Atlantic Otter Trawl and Bottom Reef Fish Fisheries: Observer Training Manual.

National Marine Fisheries Service. 2020a. National Observer Program FY 2018 Annual Report. NOAA Tech. Mem. NMFS-F/SPO-206.

National Marine Fisheries Service. 2020b. Status of Stocks. 3rd Quarter Update.

National Oceanic and Atmospheric Administration. 2016. National Standard Guidelines. Pages 71858-71904 *in* D. o. Commerce, editor. Magnuson-Stevens Act Provisions.

O'Farrell, H., A. Grüss, S. R. Sagarese, E. A. Babcock, and K. A. Rose. 2017. Ecosystem modeling in the Gulf of Mexico: current status and future needs to address ecosystem-based fisheries management and restoration activities. Reviews in Fish Biology and Fisheries **27**:587-614.

Ortiz, M., and F. Arocha. 2004. Alternative error distribution models for standardization of catch rates of non-target species from a pelagic longline fishery: billfish species in the Venezuelan tuna longline fishery. Fisheries Research **70**:275-297.

Palialexis, A., S. Georgakarakos, I. Karakassis, K. Lika, and V. D. Valavanis. 2011. Prediction of marine species distribution from presence-absence acoustic data: comparing the fitting efficiency and the predictive capacity of conventional and novel distribution models. Hydrobiologia **670**:241-266.

Papastamatiou, Y. P., C. G. Meyer, F. Carvalho, J. J. Dale, M. R. Hutchinson, and K. N. Holland. 2013. Telemetry and random-walk models reveal complex patterns of partial migration in a large marine predator. Ecology **94**:2595-2606.

Patrick, W. S., and J. S. Link. 2015. Myths that continue to impede progress in ecosystem-based fisheries management. Fisheries **40**:155-160.

Phillips, S. J., and M. Dudik. 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography **31**:161-175.

Phillips, S. J., and J. Elith. 2010. POC plots: calibrating species distribution models with presence-only data. Ecology **91**:2476-2484.

Plagányi, É. E. 2007. Models for an ecosystem approach to fisheries. Food & Agriculture Org.

Queiroz, N., N. E. Humphries, A. Couto, M. Vedor, I. Costa, A. M. M. Sequeira, . . . D. W. Sims. 2019. Global spatial risk assessment of sharks under the footprint of fisheries. Nature **572**:461.

Queiroz, N., N. E. Humphries, G. Mucientes, N. Hammerschlag, F. P. Lima, K. L. Scales, . . . D. W. Sims. 2016. Ocean-wide tracking of pelagic sharks reveals extent of overlap with longline fishing hotspots. Proceedings of the National Academy of Sciences of the United States of America **113**:1582-1587.

R Core Team. 2019. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

R Development Core Team. 2017. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Rigby, C. L., R. Barreto, J. Carlson, D. Fernando, S. Fordham, M. P. Francis, . . . H. Winker. 2019. Isurus oxyrinchus. The IUCN Red List of Threatened Species 2019 **e.T39341A2903170**.

Rogers, P. J., C. Huveneers, B. Page, S. D. Goldsworthy, M. Coyne, A. D. Lowther, . . . L. Seuront. 2015. Living on the continental shelf edge: habitat use of juvenile shortfin makos Isurus oxyrinchus in the Great Australian Bight, southern Australia. Fisheries Oceanography **24**:205-218.

Schofield, G., R. Scott, A. Dimadi, S. Fossette, K. A. Katselidis, D. Koutsoubas, . . . G. C. Hays. 2013. Evidence-based marine protected area planning for a highly mobile endangered marine vertebrate. Biological Conservation **161**:101.

Schwarz, G. 1978. Estimating the dimension of a model. The Annals of statistics **6**:461-464.

Scott-Denton, E., P. F. Cryer, J. P. Gocke, M. R. Harrelson, D. L. Kinsella, J. R. Pulver, . . . J. A. Williams. 2011. Descriptions of the U.S. Gulf of Mexico reef fish bottom longline and vertical line fisheries based on observer data. Marine Fisheries Review **73**:1.

SEDAR. 2012. SEDAR 29: HMS Gulf of Mexico Blacktip Shark. NOAA, North Charleston, SC.

SEDAR. 2015. SEDAR 39 Stock Assessment Report HMS Atlantic Smooth Dogfish Shark. SEDAR, North Charleston, SC.

SEDAR. 2016. Update assessment to SEDAR 21: HMS Dusky Shark. NOAA, North Charleston, SC.

SEDAR. 2017. SEDAR 54: HMS Sandbar Shark. NOAA, North Charleston, SC.

Stock, B. C., E. J. Ward, T. Eguchi, J. E. Jannot, J. T. Thorson, B. E. Feist, and B. X. Semmens. 2020. Comparing predictions of fisheries bycatch using multiple spatiotemporal species distribution model frameworks. Canadian Journal of Fisheries and Aquatic Sciences **77**:146-163.

Stock, B. C., E. J. Ward, J. T. Thorson, J. E. Jannot, and B. X. Semmens. 2019. The utility of spatial model-based estimators of unobserved bycatch. ICES Journal of Marine Science **76**:255-267.

Stolar, J., and S. E. Nielsen. 2015. Accounting for spatially biased sampling effort in presence-only species distribution modelling. Diversity and Distributions **21**:595-608.

Stow, C. A., J. Jolliff, D. J. McGillicuddy, S. C. Doney, J. I. Allen, M. A. M. Friedrichs, . . . P. Wallhead. 2009. Skill assessment for coupled biological/physical models of marine systems. Journal of Marine Systems **76**:4-15.

Suuronen, P., and E. Gilman. 2019. Monitoring and managing fisheries discards: New technologies and approaches. Marine Policy **116**:103554.

Then, A. Y., J. M. Hoenig, N. G. Hall, and D. A. Hewitt. 2015. Evaluating the predictive performance of empirical estimators of natural mortality rate using information on over 200 fish species. Ices Journal of Marine Science **72**:82-92.

Thorson, J. T., A. O. Shelton, E. J. Ward, and H. J. Skaug. 2015. Geostatistical delta-generalized linear mixed models improve precision for estimated abundance indices for West Coast groundfishes. Ices Journal of Marine Science **72**:1297-1310.

van Putten, I. E., S. Kulmala, O. Thebaud, N. Dowling, K. G. Hamon, T. Hutton, and S. Pascoe. 2012. Theories and behavioural drivers underlying fleet dynamics models. Fish and Fisheries **13**:216-235.

Vandeperre, F., A. Aires-da-Silva, J. Fontes, M. Santos, R. S. Santos, and P. Afonso. 2014. Movements of Blue Sharks (Prionace glauca) across Their Life History. Plos One **9**.

Vaudo, J. J., M. E. Byrne, B. M. Wetherbee, G. M. Harvey, and M. S. Shivji. 2017. Long-term satellite tracking reveals region-specific movements of a large pelagic predator, the shortfin mako shark, in the western North Atlantic Ocean. Journal of Applied Ecology **54**:1765-1775.

Vaudo, J. J., B. M. Wetherbee, A. D. Wood, K. Weng, L. A. Howey-Jordan, G. M. Harvey, and M. S. Shivji. 2016. Vertical movements of shortfin mako sharks Isurus oxyrinchus in the western North Atlantic Ocean are strongly influenced by temperature. Marine Ecology Progress Series **547**:163-175.

Vaughan, N., E. A. Babcock, and D. Courtney. 2019. Summary of intersessional work completed with the decision support tool (DST) to evaluate 2017 conservation measures recommended by ICCAT to reduce mortality for north atlantic shortfin mako. ICCAT Collective Volume of Scientific Papers **72**:337-345.

Wells, R. J. D., T. C. TinHan, M. A. Dance, J. M. Drymon, B. Falterman, M. J. Ajemian, . . . J. A. McKinney. 2018. Movement, behavior, and habitat use of a marine apex predator, the scalloped hammerhead. Frontiers in Marine Science **5**.

Wood, S. 2012. mgcv: Mixed GAM Computation Vehicle with GCV/AIC/REML smoothness estimation.

APPENDIX

This appendix includes supplementary information at more detail than was required for the main body of work. This includes model diagnostic plots, summaries of model fit, and the specific outcomes of each proposed "no-fish" rule explored as Strategy 3 in Chapter 2 (Figures A1-A7 and Tables A1-A7), as well as the residual plots for the models in chapter 4 (Figure A8).

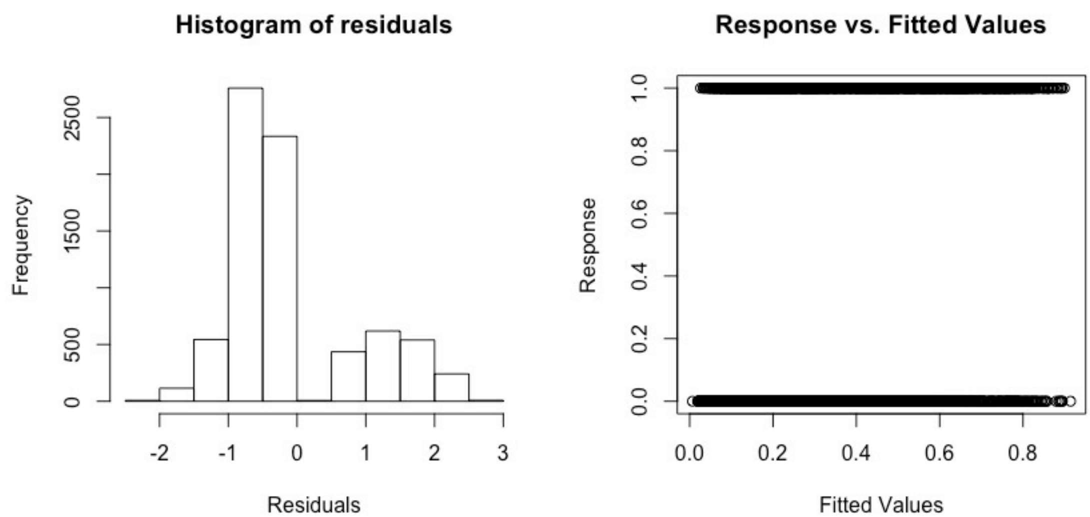


Figure A1 Diagnostic plots of the fitted binomial generalized additive model of the probability of shortfin mako positive catch. Presence ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1).

Table A1 Summary of the fitted binomial generalized additive model of shortfin mako positive catch. Presence ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1) where R-sq.(adj) = 0.211 and deviance explained = 18.7% (n = 7609). Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Coefficient	Estimate	Std. Error	Z value	Pr(>|z|)
YEAR2003	-1.81117	0.27173	-6.665	2.64E-11***
YEAR2004	-1.41412	0.26386	-5.359	8.35E-08***
YEAR2005	-1.48016	0.26479	-5.59	2.27E-08***
YEAR2006	-1.62276	0.26916	-6.029	1.65E-09***
YEAR2007	-1.68083	0.26191	-6.417	1.39E-10***
YEAR2008	-1.75802	0.25206	-6.974	3.07E-12***
YEAR2009	-1.35803	0.25345	-5.358	8.40E-08***
YEAR2010	-1.73951	0.24769	-7.023	2.17E-12***
YEAR2011	-1.19915	0.24139	-4.968	6.77E-07***
YEAR2012	-1.28531	0.25107	-5.119	3.07E-07***
Fishing_AreaGOM	-0.40909	0.19281	-2.122	0.03386*
Fishing_AreaMAB	0.82402	0.21111	3.903	9.49E-05***
Fishing_AreaNEC	1.15048	0.23866	4.821	1.43E-06***
Fishing_AreaNED	0.49359	0.31601	1.562	0.11831
Fishing_AreaSAB	0.2739	0.19935	1.374	0.16944
Fishing_AreaTUNNCASAR	-0.45602	0.23263	-1.96	0.04996*
QUARTER2	0.02255	0.10601	0.213	0.83155
QUARTER3	-0.06506	0.164	-0.397	0.6916
QUARTER4	-0.40603	0.13229	-3.069	0.00215**
Use_of_Light1	0.66664	0.08794	7.58	3.45E-14***
HBFfac>7	-0.42845	0.25707	-1.667	0.09559.
HBFfac4	-0.2442	0.15	-1.628	0.10351
HBFfac5	-0.2085	0.1631	-1.278	0.20111
HBFfac6	-0.41293	0.18856	-2.19	0.02853*
Smooth Terms	**edf**	**Ref.df**	**Chi.sq**	**p-value**
s(SST)	5.553	6.777	60.96	1.21E-10***
s(SSH)	8.413	8.897	48.14	8.45E-07***
s(BATHY)	7.579	8.447	139	<2e-16***

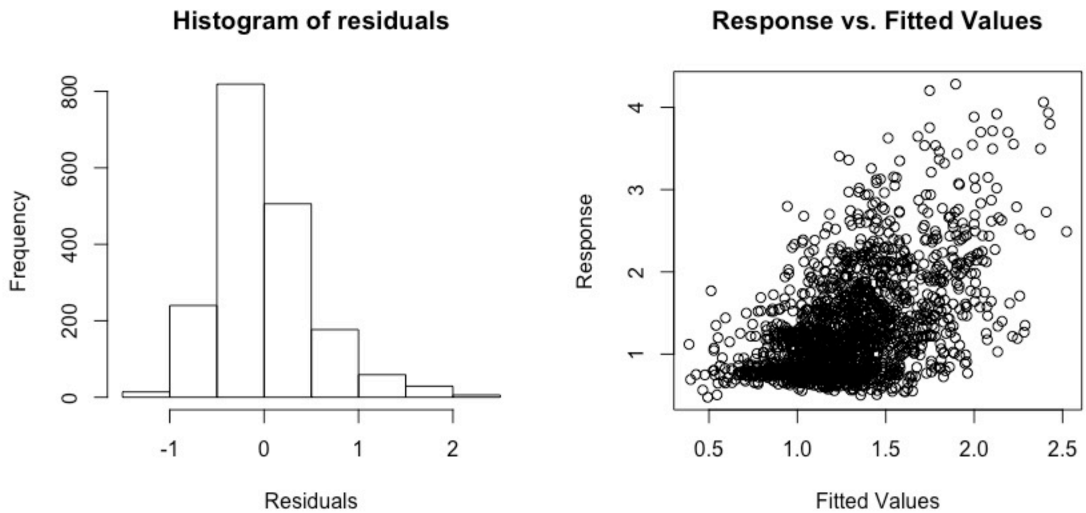


Figure A2 Diagnostic plots of the fitted gaussian generalized additive model of the mean shortfin mako catch if present. Log(Catch per Unit Effort) ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1).

Table A2 Summary of the fitted gaussian generalized additive model of the mean shortfin mako catch if present. Log(Catch per Unit Effort) ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1) where R-sq.(adj) = 0.267 and deviance explained = 86.4% (n = 1850). Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Coefficient	Estimate	Std. Error	t value	Pr(>|t|)
YEAR2003	1.608265	0.117104	13.734	<2e-16***
YEAR2004	1.836146	0.113401	16.192	<2e-16***
YEAR2005	1.617891	0.11478	14.096	<2e-16***
YEAR2006	1.733958	0.113002	15.345	<2e-16***
YEAR2007	1.585978	0.111945	14.167	<2e-16***
YEAR2008	1.492378	0.107312	13.907	<2e-16***
YEAR2009	1.675615	0.107885	15.532	<2e-16***
YEAR2010	1.582313	0.105744	14.964	<2e-16***
YEAR2011	1.710076	0.104103	16.427	<2e-16***
YEAR2012	1.710659	0.110038	15.546	<2e-16***
Fishing_AreaGOM	-0.097639	0.082141	-1.189	0.234725
Fishing_AreaMAB	0.421151	0.09252	4.552	5.67e-06***
Fishing_AreaNEC	0.34711	0.099767	3.479	0.000515***
Fishing_AreaNED	0.576055	0.124799	4.616	4.19e-06***
Fishing_AreaSAB	0.078126	0.086263	0.906	0.36523
Fishing_AreaTUNNCASAR	0.104057	0.10699	0.973	0.330888
QUARTER2	-0.023447	0.046342	-0.506	0.612954
QUARTER3	-0.225448	0.067566	-3.337	0.000865***
QUARTER4	-0.279354	0.053424	-5.229	1.90e-07***
Use_of_Light1	-0.002016	0.039814	-0.051	9.60E-01
HBFfac>7	-0.636156	0.107055	-5.942	3.36e-09***
HBFfac4	-0.430188	0.061748	-6.967	4.52e-12***
HBFfac5	-0.463346	0.065667	-7.056	2.43e-12***
HBFfac6	-0.510353	0.075097	-6.796	1.46e-11***
Smooth Term	**edf**	**Ref.df**	**F**	**p-value**
s(SST)	4.214	5.284	4.231	0.000651***
s(SSH)	3.484	4.461	6.114	6.2e-05***
s(BATHY)	7.702	8.582	16.294	<2e-16***

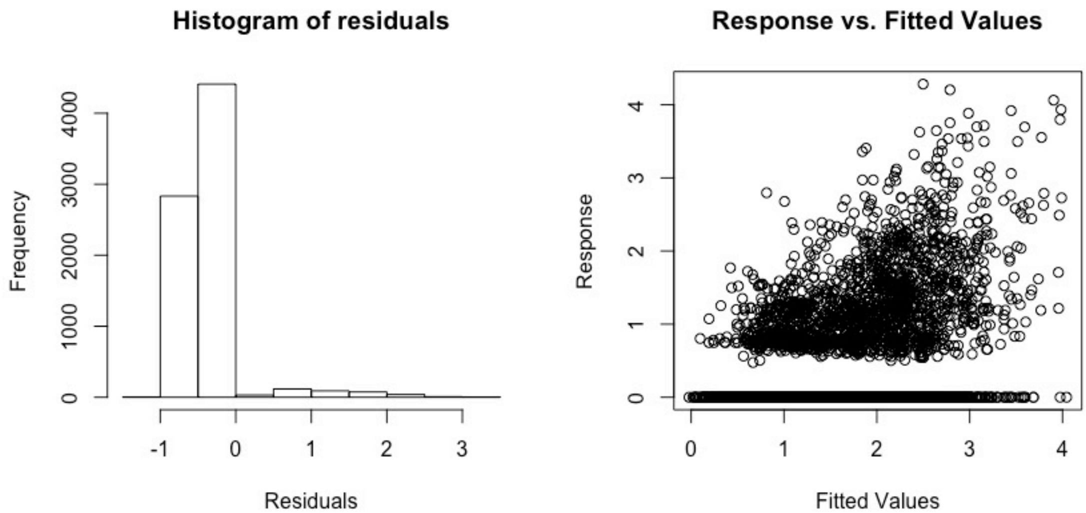


Figure A3 Diagnostic plots of the fitted generalized additive quantile regression of the 95th quantile shortfin mako catch. Log(Catch per Unit Effort) ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1).

Table A3 Summary of the fitted generalized additive quantile regression of the 95th quantile shortfin mako catch. Log(Catch per Unit Effort) ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1) where R-sq.(adj) = -0.174 and deviance explained = 74.3% (n = 7609). Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Coefficient	Estimate	Std. Error	z value	Pr(>|z|)
YEAR2003	1.51162	0.16911	8.939	<2e-16***
YEAR2004	1.66462	0.17205	9.675	<2e-16***
YEAR2005	1.54765	0.15211	10.175	<2e-16***
YEAR2006	1.68094	0.16534	10.166	<2e-16***
YEAR2007	1.46755	0.15508	9.463	<2e-16***
YEAR2008	1.37044	0.14278	9.598	<2e-16***
YEAR2009	1.58103	0.14684	10.767	<2e-16***
YEAR2010	1.35609	0.157	8.638	<2e-16***
YEAR2011	1.78405	0.14302	12.474	<2e-16***
YEAR2012	1.69187	0.15243	11.099	<2e-16***
Fishing_AreaGOM	-0.29491	0.11358	-2.596	0.009420**
Fishing_AreaMAB	0.80539	0.14074	5.723	1.05e-08***
Fishing_AreaNEC	0.87574	0.16825	5.205	1.94e-07***
Fishing_AreaNED	1.32178	0.20962	6.306	2.87e-10***
Fishing_AreaSAB	0.22373	0.14436	1.55	0.121169
Fishing_AreaTUNNCASAR	-0.10545	0.15079	-0.699	0.484348
QUARTER2	-0.01449	0.06751	-0.215	0.830069
QUARTER3	-0.30732	0.10169	-3.022	0.002509**
QUARTER4	-0.29625	0.07469	-3.966	7.30e-05***
Use_of_Light1	0.19419	0.04797	4.048	5.16e-05***
HBFfac>7	-0.49132	0.18714	-2.625	0.008655**
HBFfac4	-0.30698	0.09197	-3.338	0.000844***
HBFfac5	-0.2966	0.0996	-2.978	0.002902**
HBFfac6	-0.42799	0.12977	-3.298	0.000974***
Smooth Term	**edf**	**Ref.df**	**Chi.sq**	**p-value**
s(SST)	5.088	6.257	46.27	4.61e-08***
s(SSH)	3.881	4.912	25.24	0.000162***
s(BATHY)	7.155	8.101	251.5	<2e-16***

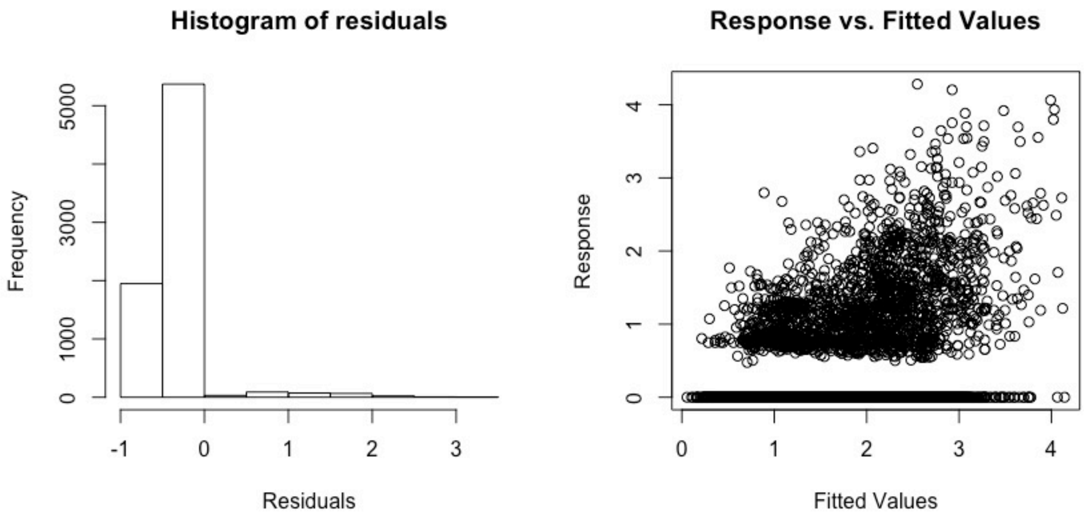


Figure A4 Diagnostic plots of the fitted generalized additive quantile regression of the 96th quantile shortfin mako catch. Log(Catch per Unit Effort) ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1).

Table A4 Summary of the fitted generalized additive quantile regression of the 96^{th} quantile shortfin mako catch. Log(Catch per Unit Effort) ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1) where R-sq.(adj) = -0.195 and deviance explained = 78.4% (n = 7609). Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Coefficient	Estimate	Std.Error	zvalue	Pr(>|z|)
YEAR2003	1.67356	0.18675	8.961	<2e-16***
YEAR2004	1.87321	0.19457	9.628	<2e-16***
YEAR2005	1.69254	0.18121	9.34	<2e-16***
YEAR2006	1.84958	0.18625	9.931	<2e-16***
YEAR2007	1.62597	0.18882	8.611	<2e-16***
YEAR2008	1.52825	0.17222	8.874	<2e-16***
YEAR2009	1.72553	0.17322	9.962	<2e-16***
YEAR2010	1.5413	0.1765	8.732	<2e-16***
YEAR2011	1.91045	0.17299	11.044	<2e-16***
YEAR2012	1.82577	0.18008	10.138	<2e-16***
Fishing_AreaGOM	-0.32195	0.12519	-2.572	0.010120*
Fishing_AreaMAB	0.76136	0.16267	4.68	2.86e-06***
Fishing_AreaNEC	0.82586	0.18851	4.381	1.18e-05***
Fishing_AreaNED	1.24035	0.23114	5.366	8.04e-08***
Fishing_AreaSAB	0.2917	0.17685	1.649	0.099056.
Fishing_AreaTUNNCASAR	-0.14092	0.175	-0.805	0.420674
QUARTER2	-0.02505	0.07546	-0.332	0.73993
QUARTER3	-0.32607	0.11431	-2.852	0.004338**
QUARTER4	-0.31824	0.08305	-3.832	0.000127***
Use_of_Light1	0.16531	0.05993	2.759	0.005806**
HBFfac>7	-0.52537	0.22141	-2.373	0.017655*
HBFfac4	-0.31271	0.11236	-2.783	0.005385**
HBFfac5	-0.29262	0.12027	-2.433	0.014974*
HBFfac6	-0.45047	0.1466	-3.073	0.002121**
Smooth Term	**edf**	**Ref.df**	**Chi.sq**	**p-value**
s(SST)	4.364	5.417	34.9	3.17e-06***
s(SSH)	3.403	4.33	16.19	0.0031**
s(BATHY)	6.844	7.862	192.06	<2e-16***

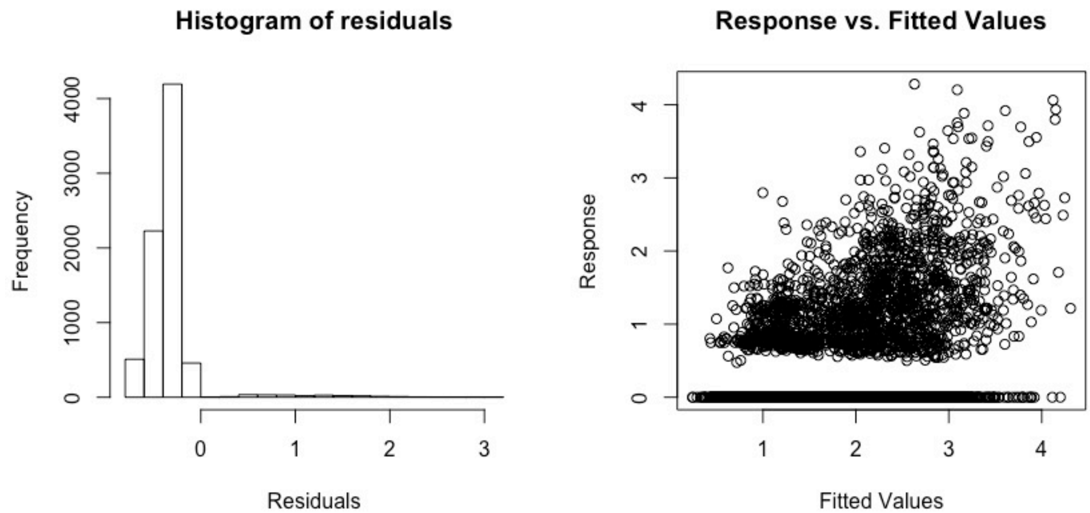


Figure A5 Diagnostic plots of the fitted generalized additive quantile regression of the 97th quantile shortfin mako catch. Log(Catch per Unit Effort) ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1).

Table A5 Summary of the fitted generalized additive quantile regression of the 97th quantile shortfin mako catch. Log(Catch per Unit Effort) ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1) where R-sq.(adj) = -0.233 and deviance explained = 82.8% (n = 7609). Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Coefficient	Estimate	Std. Error	z value	Pr(>|z|)
YEAR2003	1.87438	0.25317	7.404	1.33e-13***
YEAR2004	2.12243	0.23697	8.957	<2e-16***
YEAR2005	1.90358	0.25456	7.478	7.55e-14***
YEAR2006	2.04929	0.25053	8.18	2.84e-16***
YEAR2007	1.86001	0.25449	7.309	2.69e-13***
YEAR2008	1.77211	0.24228	7.314	2.59e-13***
YEAR2009	1.91522	0.24023	7.972	1.56e-15***
YEAR2010	1.75177	0.21566	8.123	4.56e-16***
YEAR2011	2.09955	0.23979	8.756	<2e-16***
YEAR2012	2.01412	0.24661	8.167	3.16e-16***
Fishing_AreaGOM	-0.35275	0.17006	-2.074	0.038059*
Fishing_AreaMAB	0.73614	0.20667	3.562	0.000368***
Fishing_AreaNEC	0.7635	0.23032	3.315	0.000916***
Fishing_AreaNED	1.21418	0.29346	4.137	3.51e-05***
Fishing_AreaSAB	0.34353	0.21958	1.564	0.117702
Fishing_AreaTUNNCASAR	-0.1449	0.21747	-0.666	0.505235
QUARTER2	-0.03943	0.0946	-0.417	0.676861
QUARTER3	-0.34614	0.14278	-2.424	0.015335*
QUARTER4	-0.31649	0.10574	-2.993	0.002762**
Use_of_Light1	0.10421	0.07292	1.429	1.53E-01
HBFfac>7	-0.50568	0.48659	-1.039	0.298698
HBFfac4	-0.32647	0.15784	-2.068	0.038612*
HBFfac5	-0.28877	0.16418	-1.759	0.078601.
HBFfac6	-0.5334	0.19329	-2.76	0.005787**
Smooth Term	**edf**	**Ref.df**	**Chi.sq**	**p-value**
s(SST)	3.864	4.795	19.079	0.00165**
s(SSH)	2.938	3.716	8.698	0.04691*
s(BATHY)	6.024	7.116	141.558	<2e-16***

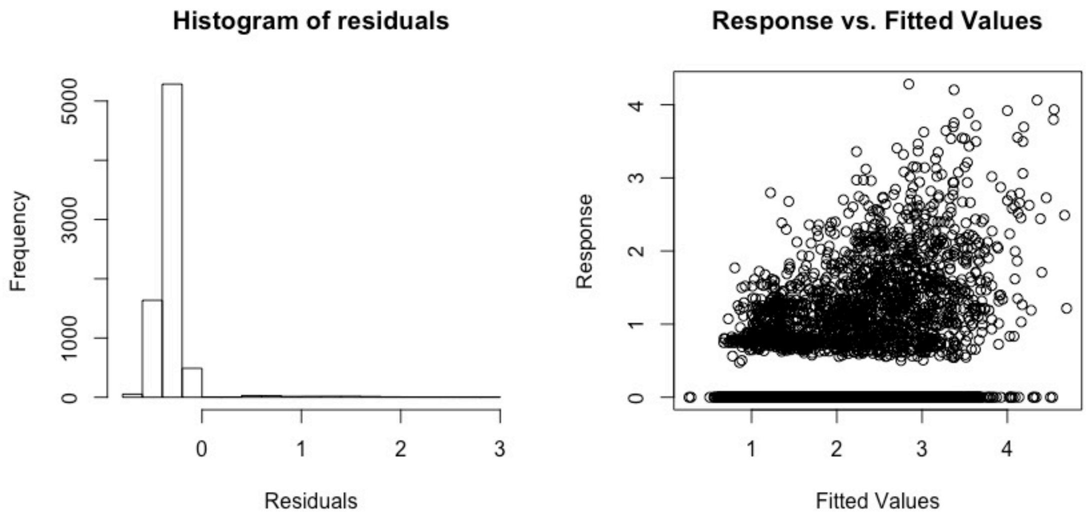


Figure A6 Diagnostic plots of the fitted generalized additive quantile regression of the 98th quantile shortfin mako catch. Log(Catch per Unit Effort) ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1).

Table A6 Summary of the fitted generalized additive quantile regression of the 98th quantile shortfin mako catch. Log(Catch per Unit Effort) ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1) where R-sq.(adj) = -0.37 and deviance explained = 87.7% (n = 7609). Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Coefficient	Estimate	Std. Error	z value	Pr(>|z|)
YEAR2003	2.13583	0.31383	6.806	1.01e-11***
YEAR2004	2.39832	0.28689	8.36	<2e-16***
YEAR2005	2.21849	0.32524	6.821	9.03e-12***
YEAR2006	2.32255	0.31015	7.489	6.96e-14***
YEAR2007	2.15547	0.30493	7.069	1.56e-12***
YEAR2008	2.10524	0.28494	7.388	1.49e-13***
YEAR2009	2.20917	0.29306	7.538	4.76e-14***
YEAR2010	2.02665	0.28278	7.167	7.67e-13***
YEAR2011	2.34548	0.29244	8.02	1.05e-15***
YEAR2012	2.26687	0.30442	7.447	9.58e-14***
Fishing_AreaGOM	-0.31565	0.17269	-1.828	0.067572.
Fishing_AreaMAB	0.78869	0.22077	3.572	0.000354***
Fishing_AreaNEC	0.83865	0.25011	3.353	0.000799***
Fishing_AreaNED	1.3716	0.38725	3.542	0.000397***
Fishing_AreaSAB	0.37609	0.21479	1.751	0.079946.
Fishing_AreaTUNNCASAR	-0.06949	0.32695	-0.213	0.831675
QUARTER2	-0.06538	0.12104	-0.54	0.589107
QUARTER3	-0.43111	0.18071	-2.386	0.017049*
QUARTER4	-0.32568	0.13102	-2.486	0.012930*
Use_of_Light1	0.06299	0.07485	0.842	4.00E-01
HBFfac>7	-0.57775	0.30224	-1.912	0.055930.
HBFfac4	-0.4412	0.20876	-2.113	0.034566*
HBFfac5	-0.38073	0.22167	-1.718	0.085886.
HBFfac6	-0.68643	0.27921	-2.459	0.013951*
Smooth Term	**edf**	**Ref.df**	**Chi.sq**	**p-value**
s(SST)	3.355	4.214	10.664	0.0357*
s(SSH)	2.038	2.612	3.902	2.60E-01
s(BATHY)	5.553	6.618	116.332	<2e-16***

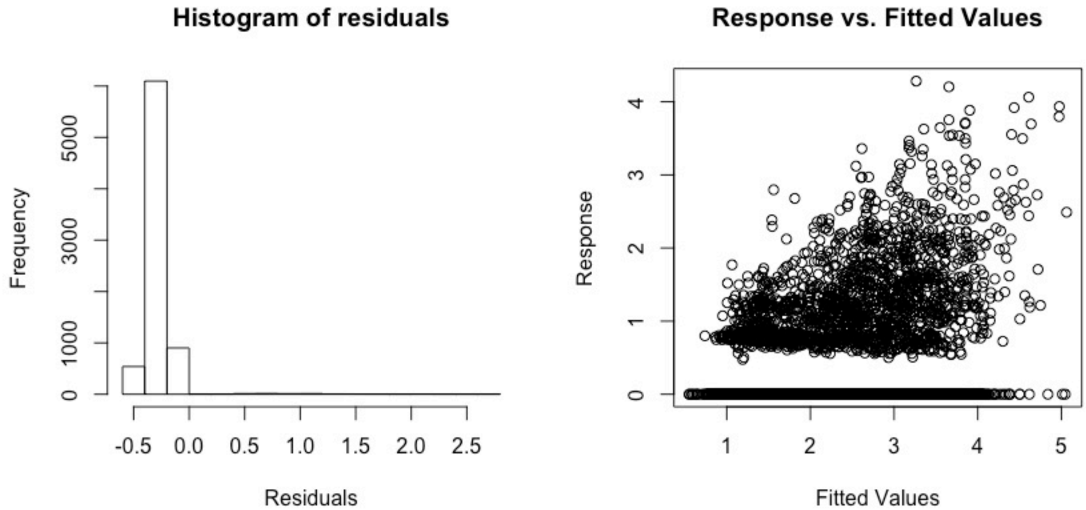


Figure A7 Diagnostic plots of the fitted generalized additive quantile regression of the 99th quantile shortfin mako catch. Log(Catch per Unit Effort) ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1).

Table A7 Summary of the fitted generalized additive quantile regression of the 99th quantile shortfin mako catch. Log(Catch per Unit Effort) ~ (Year + Fishing Area + Quarter + Use of Light + Hooks Between Floats + s(Sea Surface Temperature) + s(Sea Surface Height) + s(Bathymetry) - 1) where R-sq.(adj) = -0.502 and deviance explained = 93.2% (n = 7609). Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Coefficient	Estimate	Std. Error	z value	Pr(>|z|)
YEAR2003	2.446608	0.427188	5.727	1.02e-08***
YEAR2004	2.644425	0.395238	6.691	2.22e-11***
YEAR2005	2.630077	0.410091	6.413	1.42e-10***
YEAR2006	2.716223	0.389055	6.982	2.92e-12***
YEAR2007	2.413323	0.415862	5.803	6.51e-09***
YEAR2008	2.559711	0.393287	6.509	7.59e-11***
YEAR2009	2.519736	0.376568	6.691	2.21e-11***
YEAR2010	2.325321	0.370312	6.279	3.40e-10***
YEAR2011	2.643396	0.383187	6.898	5.26e-12***
YEAR2012	2.517404	0.398491	6.317	2.66e-10***
Fishing_AreaGOM	-0.223785	0.219029	-1.022	0.30692
Fishing_AreaMAB	0.884287	0.302457	2.924	0.00346**
Fishing_AreaNEC	0.736717	0.326992	2.253	0.02426*
Fishing_AreaNED	1.314825	0.417846	3.147	0.00165**
Fishing_AreaSAB	0.410903	0.244293	1.682	0.09257.
Fishing_AreaTUNNCASAR	0.008614	0.272204	0.032	0.97475
QUARTER2	-0.070257	0.135569	-0.518	0.60429
QUARTER3	-0.369058	0.223045	-1.655	0.09800.
QUARTER4	-0.388786	0.16411	-2.369	0.01783*
Use_of_Light1	0.093256	0.104602	0.892	3.73E-01
HBFfac>7	-0.89251	0.410706	-2.173	0.02977*
HBFfac4	-0.628367	0.285217	-2.203	0.02759*
HBFfac5	-0.539178	0.298366	-1.807	0.07075.
HBFfac6	-0.819812	0.32755	-2.503	0.01232*
Smooth Term	**edf**	**Ref.df**	**Chi.sq**	**p-value**
s(SST)	2.785	3.514	6.373	1.34E-01
s(SSH)	1.018	1.036	2.496	1.20E-01
s(BATHY)	4.484	5.369	88.004	<2e-16***

Table A8 Individual results of each rule of a potential operational strategy avoiding hot sets. Based on the binomial model fit to the early dataset, hot sets can be described by the following 19 combinations of conditions. These conditions can be used operationally as a mitigation strategy. Fishers in any of the MAB, NEC, and MED fishing areas would not set in spots that meet any of the combinations of conditions that define hot sets.

Area	Quarter	Lights	HBF	SSH	BATHY	SST	Num Sets Avoided	Num Sharks Avoided	Num Hot Sets Avoided	Num Not Hot Impacted
	1	1	all	all	all	all	26	131	22	4
		0	5	0-0.3	<1600	15-20	0	0	0	0
	2	1	all	all	all	all	68	90	42	26
			4-6	<0	<800	20-25	6	6	5	1
MAB		0	5	<0	<800	25-30	21	16	5	16
	3	1	all	all	all	all	57	74	30	27
		0	4-5	<0	<1600	20-25	2	4	2	0
	4	1	all	all	all	all	159	327	151	8
	2	1	all	all	all	all	53	101	51	2
			4	<0	<2400	20-25	1	0	1	0
NEC		0	5	<0	3200-4000	25-30	0	0	0	0
	3	1	all	all	all	all	164	383	163	1
	4	1	all	all	all	all	37	62	37	0
		0	4	<0.3	all	20-25	2	22	2	0
				<0	<800	<15	5	14	5	0
			4	<0.3	all	15-20	12	3	12	0
NED	3	1	5	<0	all	15-20	0	0	0	0
			4	<0.3	all	15-20	0	0	0	0
	4	1	5	<0	3200-4000	15-20	0	0	0	0
TOTAL							**613**	**1233**	**528**	**85**

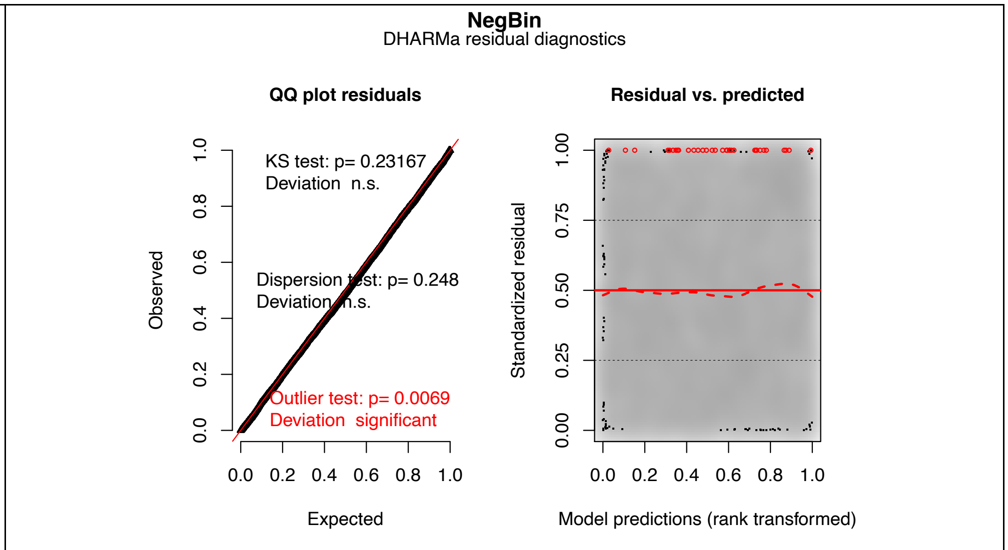
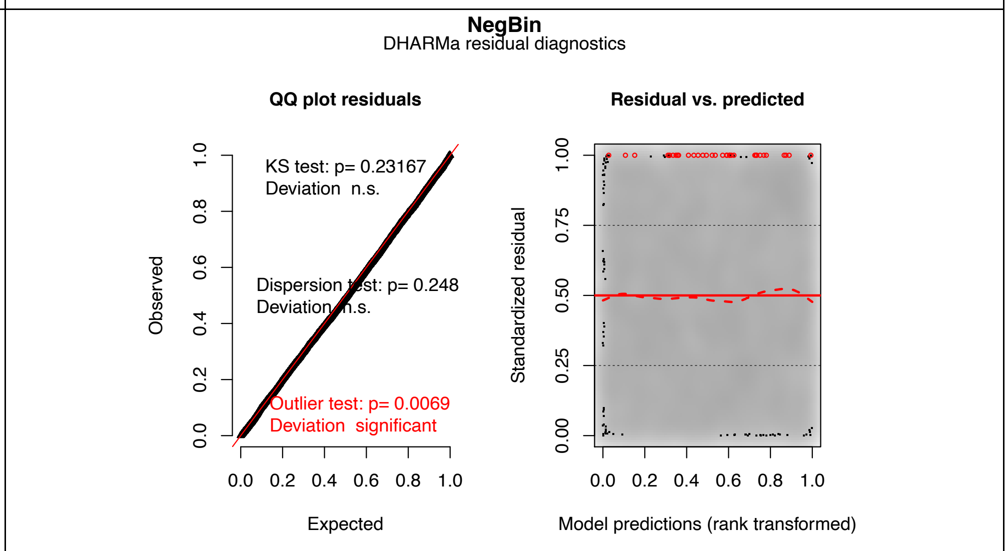
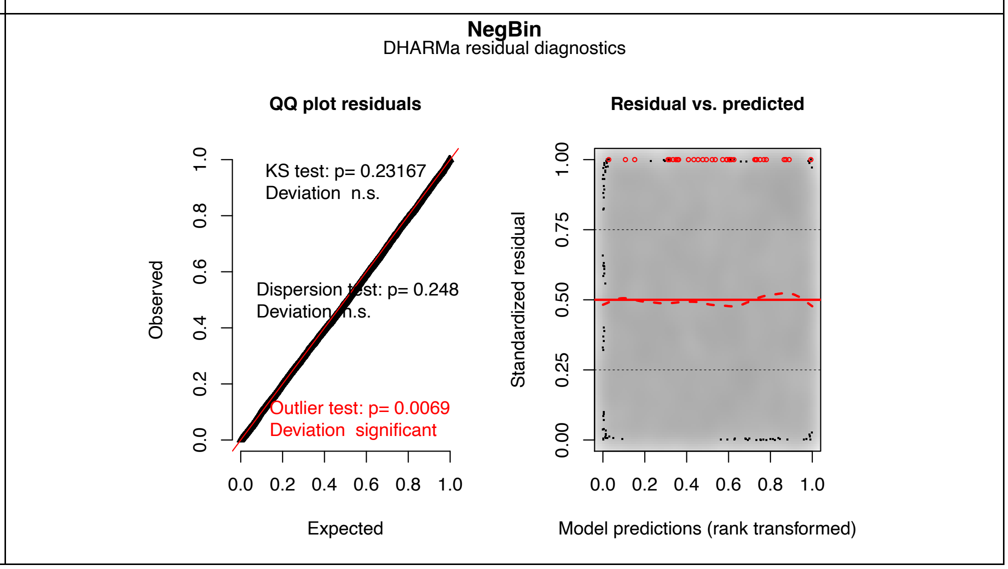
Blacknose	
Nurse	
Atlantic Sharpnose	

Figure A8 DHARMa residuals diagnostic plots by species/species group BIC best negative binomial model for the bycatch models in chapter 4 (Hartig 2017).

Figure A8 Continued DHARMa residuals diagnostic plots by species/species group BIC best negative binomial model for the bycatch models in chapter 4 (Hartig 2017).

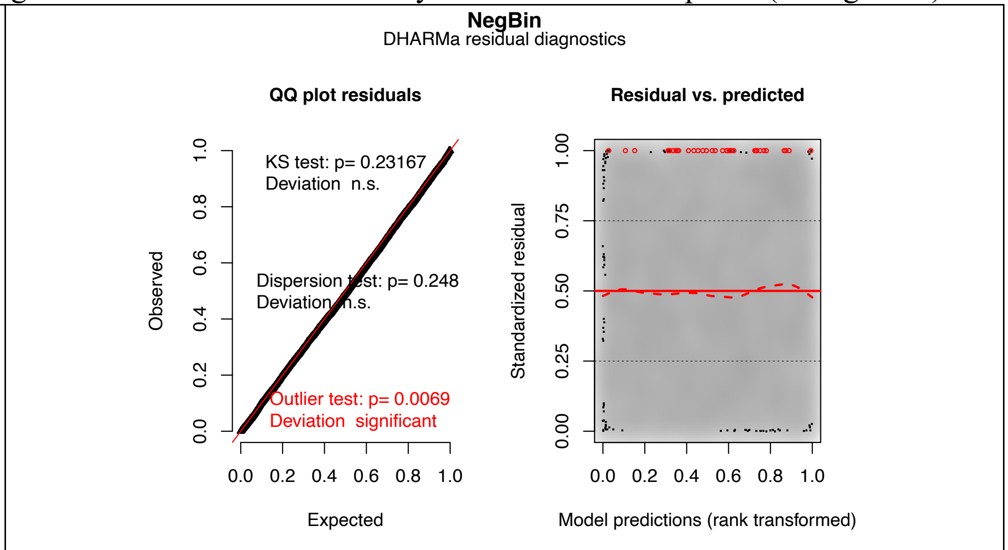
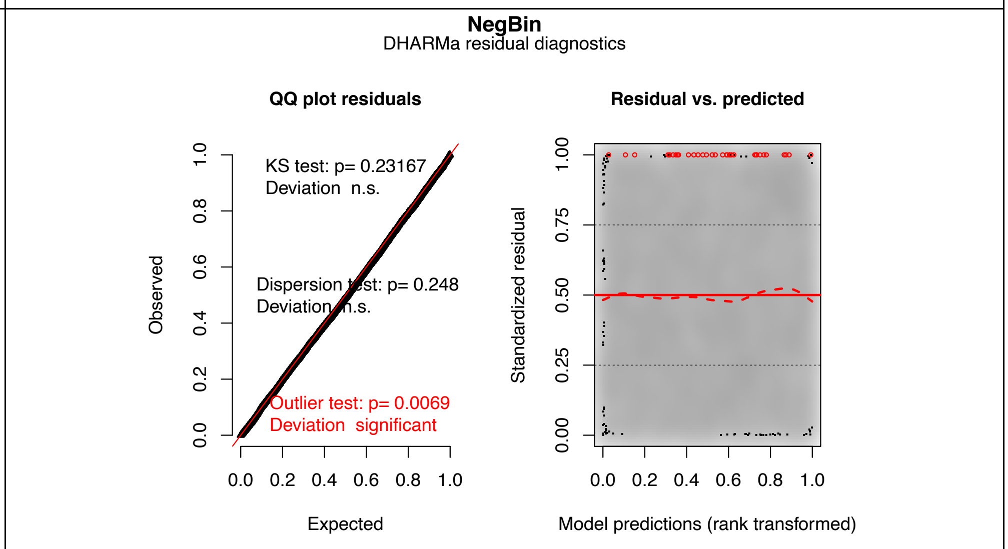
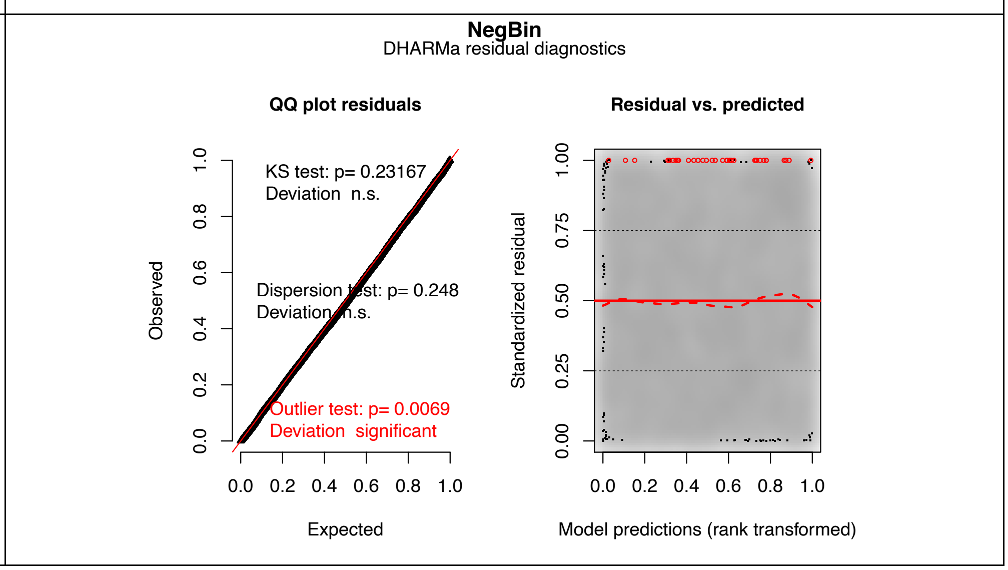
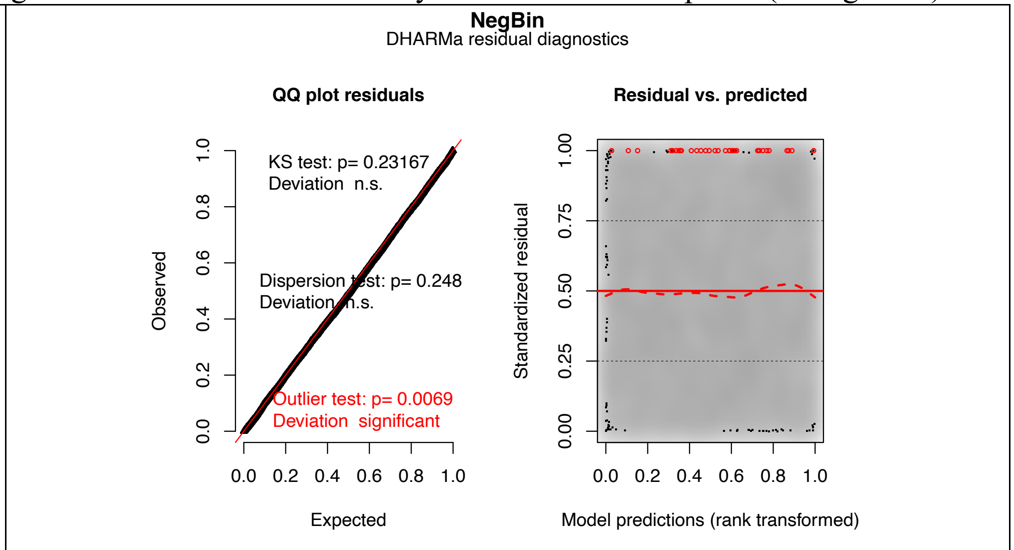
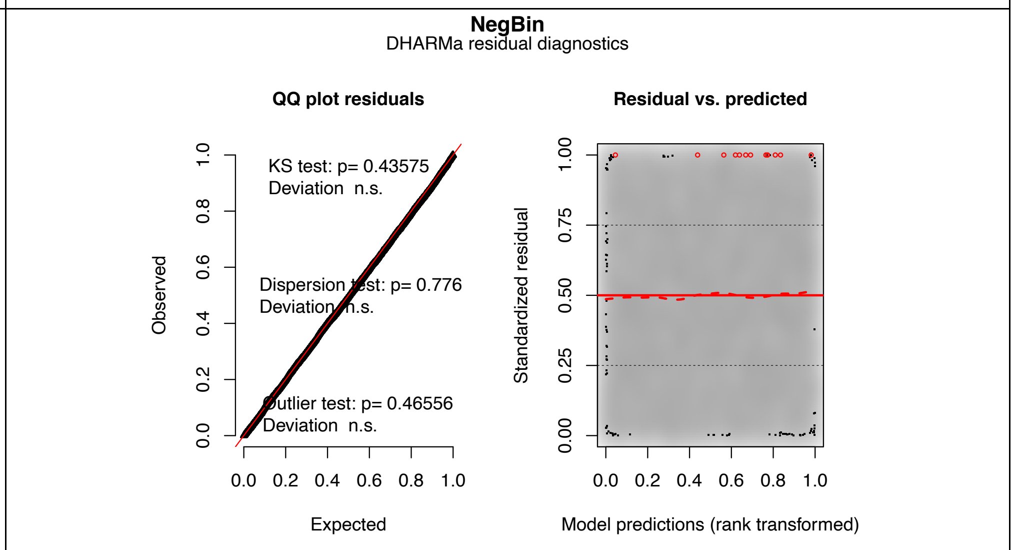
Scalloped Hammerhead	
Sandbar	
Smooth Dogfish	

Figure A8 Continued DHARMa residuals diagnostic plots by species/species group BIC best negative binomial model for the bycatch models in chapter 4 (Hartig 2017).

Night



Blacktip



Silky

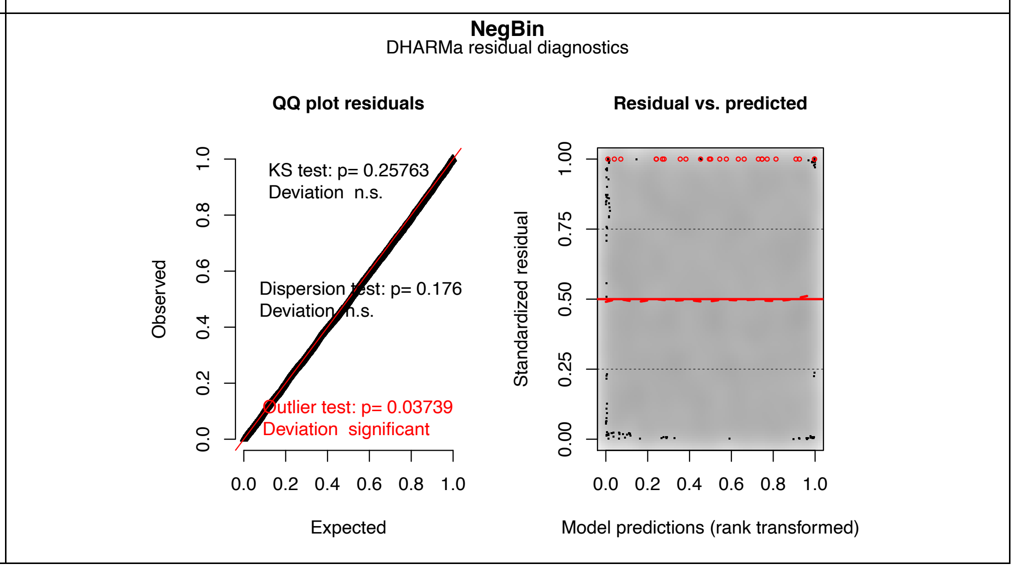
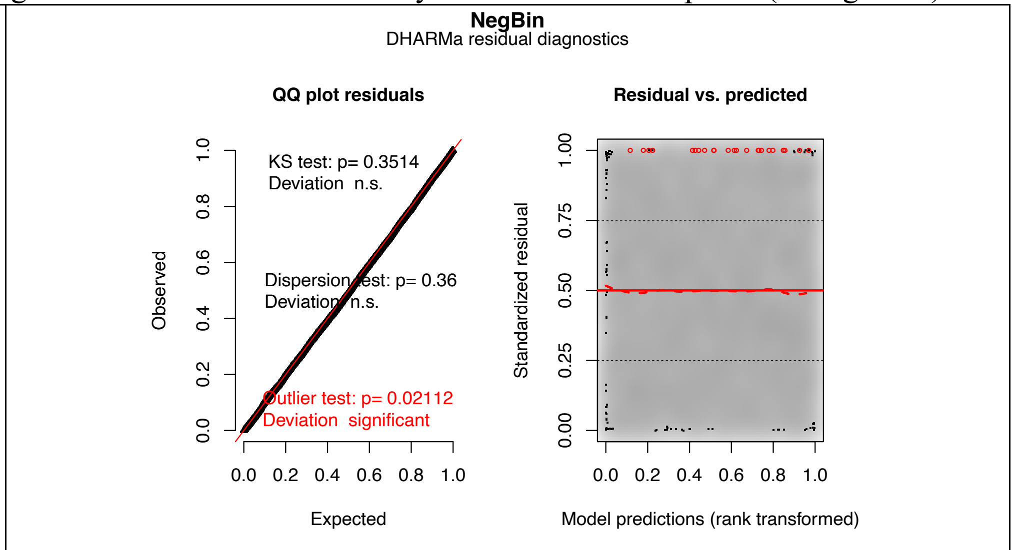
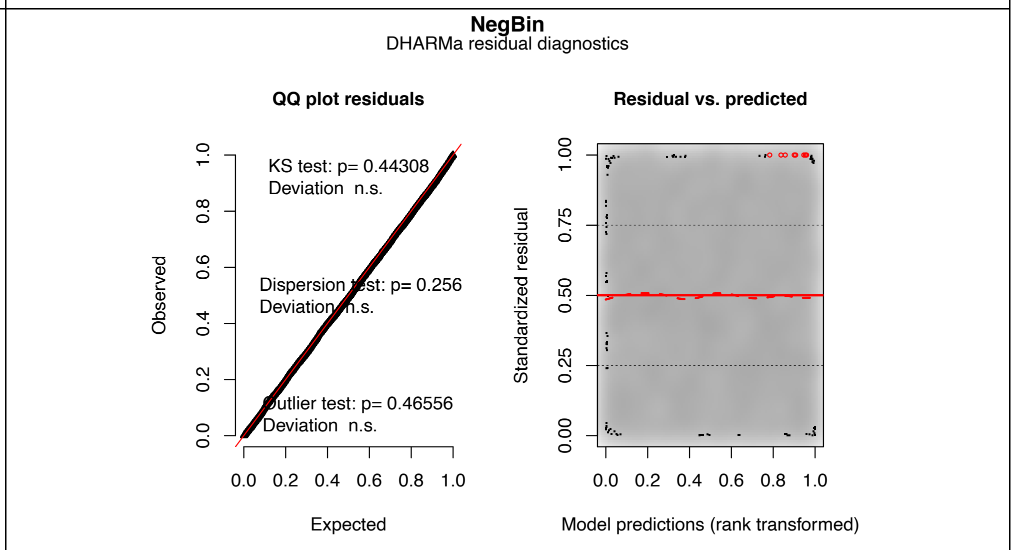


Figure A8 Continued DHARMa residuals diagnostic plots by species/species group BIC best negative binomial model for the bycatch models in chapter 4 (Hartig 2017).

Tiger



Bigeye Sixgill



Sevengill

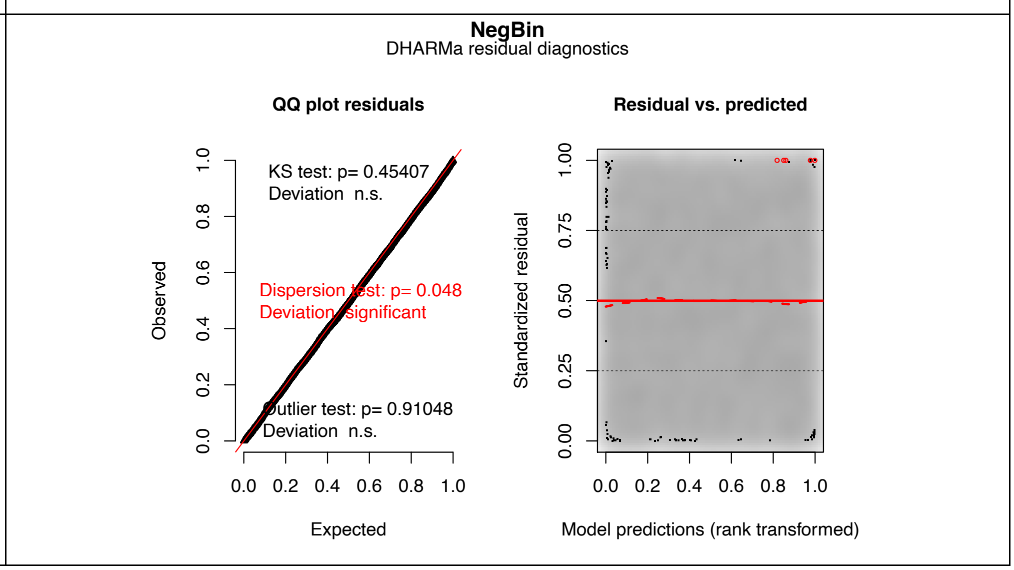
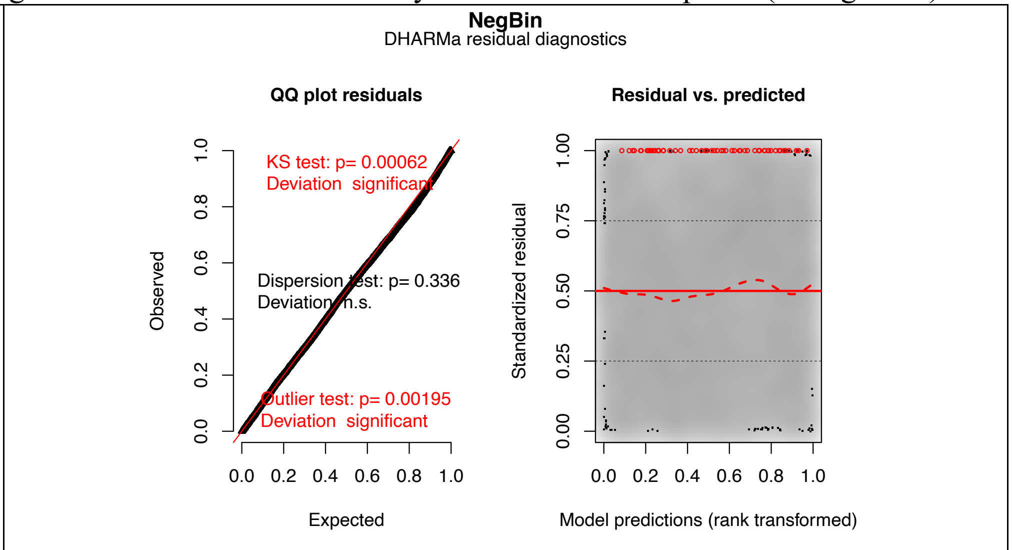
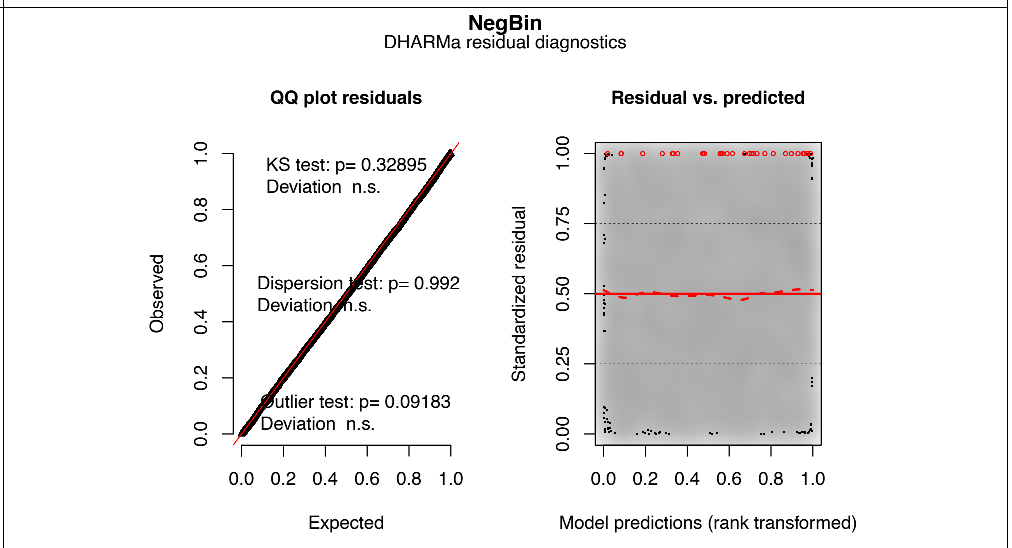


Figure A8 Continued DHARMa residuals diagnostic plots by species/species group BIC best negative binomial model for the bycatch models in chapter 4 (Hartig 2017).

Small Coastal



Large Coastal



Deep Water

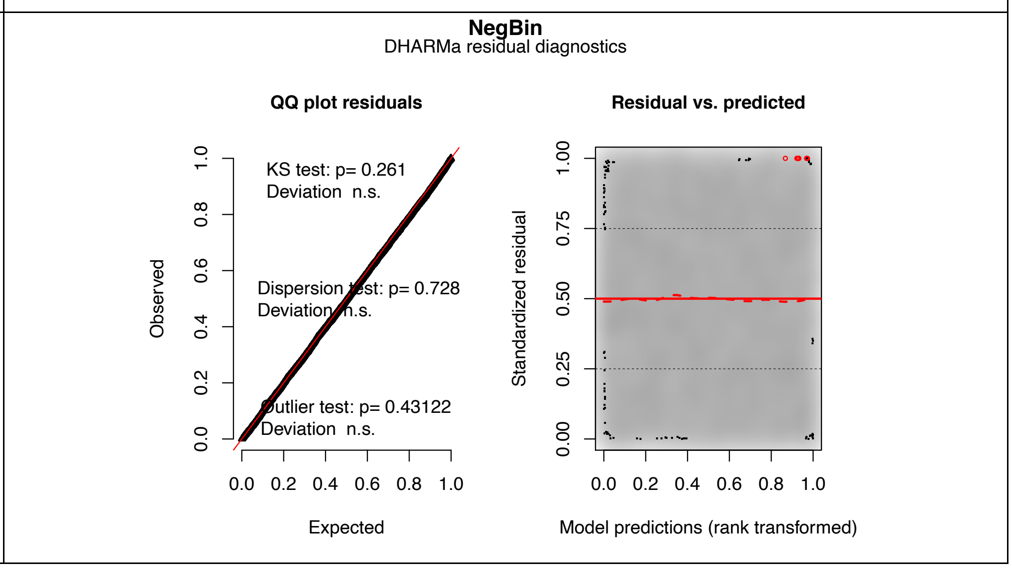


Figure A8 Continued DHARMa residuals diagnostic plots by species/species group BIC best negative binomial model for the bycatch models in chapter 4 (Hartig 2017).

All