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Monte Carlo simulation modelling of purse seine catches of silky and oceanic whitetip sharks

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Executive summary

This paper applies Monte Carlo simulation modelling to investigate the impacts of purse seine fisheries on silky and oceanic whitetip sharks under different scenarios of fishing effort on free schools and FAD- associated schools. Two scenarios were explored: the redistribution of effort on FADs to free schools; and, redistribution of free school sets to FAD sets. Probability distributions for school association and species specific shark presence were generated through standardisation of purse seine observer data. It was not possible to fit robust statistical models to non-zero catches. Therefore values were based upon the mean and standard deviation of non-zero catches identified by observers. Redistribution of effort from FADs to free schools resulted in substantial reductions in estimated catches of silky shark (by 83%) and oceanic whitetip shark (by 57%) compared to the 'status quo'. There was large uncertainty in total catch estimates due to low confidence in assumed estimates of non-zero shark catches.

1 Introduction

Recent stock assessments of silky shark (*Carcharhinus falciformis*; Rice and Harley, 2013) and oceanic whitetip shark (*Carcharhinus longimanus*; Rice and Harley, 2012) indicated that stocks were overfished and that overfishing was taking place. In response to concerns regarding stock status, the Western and Central Pacific Fisheries Commission (WCPFC) banned the retention of these species (WCPFC, 2011; WCPFC, 2013)). Furthermore WCPFC requested an analysis of observer data to determine factors that influence interactions between these species and longline gear, and the subsequent fate of affected individuals. On the basis of the analyses of Bromhead *et al.* (2013) and Caneco *et al.* (2014), WCPFC required longliners targeting tuna or billfish to choose between a ban on wire trace for branch and leader lines, or a ban on shark lines (WCPFC, 2014). Harley *et al.* (2015) used Monte Carlo simulation modelling to examine the potential impacts of different management measures on fishing related mortality of silky shark and oceanic whitetip shark resulting from interactions with longline gear.

In 2015, the WCPFC requested that Monte Carlo simulation modelling be used to examine the effects of purse seine fishing on fishing mortality of sharks when effort on associated (FAD) sets was re-distributed to unassociated sets. This paper presents the results for silky shark and oceanic whitetip shark. These are the two most common shark species recorded in the purse seine observer data, contributing 80 and 2.8% respectively of total recorded elasmobranchs (Table 1). The general Monte Carlo simulation modelling framework of Harley *et al.* (2015) was applied, modified where necessary for relevance to a purse seine context. Briefly, purse seine observer data were used to explore how school association influences catch rates of silky and oceanic whitetip sharks. These catch rate estimates were then used in simulations to determine the impact on catch of these species resulting from different scenarios of effort on drifting FADs, taking account of their likely spatial distribution.

Throughout the paper, sets on unassociated schools are referred to as free school sets, sets on schools associated with man-made FADs and drifting logs and other debris are referred to as FAD sets. Attempts have been made to ensure consistency in terminology and reporting with that used by Harley *et al*. (2015).

2 Methods

The analysis consisted of a number of steps which are outlined here, and expanded on in Sections 2.1 to 2.9:

- Exploratory analysis of available purse seine observer data to inform the analytical approach;
- Analysis of available purse seine observer data to estimate silky shark and oceanic whitetip shark catch rates by school association;
- Development of a process model of how silky and oceanic whitetip sharks interact with purse seine gear;
- Development of scenarios to reflect the redistribution of purse seine effort between association types;
- Development of spatial surfaces of purse seine effort by school association type;
- Adjustment of total effort to take account of the relative abundance of each species;
- Estimation of probability distributions for parameters of the process model;
- Comparison of outputs of Monte Carlo simulations for the scenarios considered.

2.1 Datasets used in the analysis

Two datasets were used for the analysis. The first was raised 1 X 1 ° purse seine effort data, used to generate spatial effort surfaces. The second was purse seine observer data, used to estimate catch rates for silky and oceanic whitetip sharks for purse seine sets by school association type. Both datasets were restricted to the equatorial region of the Western and Central Pacific Ocean (WCPO), i.e. 140°E to 150°W and 20°S to 20°N. Effort and observer data from archipelagic waters were excluded. The datasets were also filtered for free school, drifting FAD and natural drifting FAD sets, which accounted for 95 % of the total sets in the effort dataset. The two FAD set types were modelled separately, given different shark CPUE rates.

2.2 Exploratory data analysis

A potential concern is that the absence of recorded catch of sharks by observers may not necessarily reflect an absence of sharks in the catch, but could instead be due to sharks remaining undetected by observers e.g. due to relatively low volumes of shark catch compared to tuna catch by purse seiners. As an initial step, the potential for incomplete recording of purse seine catches of silky shark and oceanic whitetip shark by observers was explored by looking at presence/absence of recorded catch of these species for sets in which observer length frequency samples were available, and thus individuals must have been caught.

2.3 Estimation of shark catch rates by school association

Observer data for the period 2009 to 2015 were used to generate models of purse seine catch rates of silky shark and oceanic whitetip shark. Observer data pre-2009 were excluded to minimise potential for temporal shifts in shark recording within the modelled dataset.

Previous analyses of purse seine shark catch data have used two-stage models to account for the high proportion of sets with no shark catch, *e.g.* zero-inflated Poisson models of silky shark catch in the Indian Ocean (Amandè *et al.*, 2008) and delta-lognormal models of silky shark and oceanic whitetip shark catches in the WCPO (Lawson, 2011). Here we use a similar approach, modelling the presence/absence of shark catch separately to the numbers of shark caught when present.

Sharks of a given species were considered present if the observer recorded them in either numbers or weight. Shark catch was more commonly recorded in numbers rather than weight, so non-zero shark catch was modelled in terms of numbers. Records with non-zero shark catch weight but no catch number information were removed from the data set for the non-zero catch model, representing 4,882 of the 25,145 sets where silky shark were present and 165 of the 904 sets where oceanic whitetip shark were present. We therefore assume that the distribution of shark catches when recorded by weight is the same as for the larger data set recorded by number.

Explanatory variables used in models were:

- *year* and *quarter* – the year and quarter when the set took place, included as categorical variables;
- *association* - school association type;
- *SST* – sea surface temperature (Reynolds *et al.*, 2002);
- *chl* – AQUA/MODIS chlorophyll-a concentration[1];

and, for models of shark catch when present:

- *tuna* - the total tuna catch from the set.

All models were implemented in R (R Core Team, 2015).

2.3.1 Models for presence/absence of shark catch

Species-specific presence/absence of shark catch was modelled using logistic models with a logit link:

$$presence_{ij} \sim \text{Bernoulli}(\mu_{ij}),$$

$$\log\left(\frac{\mu_{ij}}{1-\mu_{ij}}\right) = \beta_0 + \beta_1 year_{ij} + \beta_2 quarter_{ij} + \beta_3 association_{ij}$$

$$+ f_1(SST_{ij}) + f_2(chl_{ij})$$

where $presence$ denotes whether sharks of a given species were observed, μ denotes the estimated probability that sharks of a given species were present, i and j subscripts denote observer trip and set number respectively and f_1 and f_2 were natural cubic splines. Presence/absence models were

[1] Accessed from: http://oceandata.sci.gsfc.nasa.gov/MODIS-Aqua/Mapped/Monthly/9km/chlor_a

fitted with Generalised Estimating Equations using the R package geepack (Højsgaard *et al.*, 2006) to account for correlated residuals. Working correlation structures were selected using the correlation information criterion (CIC; Hin & Wang, 2009). Exchangeable correlation structures within observer trips were selected for both silky shark and oceanic whitetip shark, *i.e.* residuals from the same observer trip were correlated, with a shared correlation parameter for all observer trips.

2.3.2 Models for shark catch when present

Candidate models of non-zero species-specific catch were also constructed using the R package gamlss (Rigby & Stasinopoulos, 2005). Lognormal, Poisson and negative binomial distributed residuals were tested, truncated using the R package gamlss.tr (Stasinopoulos & Rigby, 2016) to account for the fact that the response variable was conditioned on the presence of species-specific shark catch. However all candidate models struggled to fit to observed catches (*e.g.* Figure 8 for silky shark), and assumptions regarding residual distributions were violated. The specification of the (truncated) negative binomial model is provided here as an example for completeness, noting that explanatory variables for the various candidate models were equivalent:

$$number_{ij} \sim \mathrm{NBItr}(\mu_{ij}, \sigma)$$

$$\log(\mu_{ij}) = \beta_0 + \beta_1 year_{ij} + \beta_2 quarter_{ij} + \beta_3 association_{ij}$$

$$+ f_1(SST_{ij}) + f_2(chl_{ij}) + f_3(tuna_{ij})$$

where $number$ was the observed number of sharks caught of a given species, μ denotes the estimated number of sharks caught, $\mathrm{NBItr}(\mu_{ij}, \sigma)$ is a negative binomial truncated at zero distribution and f_1 to f_3 were natural cubic splines. Note that a log(effort) offset was theoretically included, but all records represented one set and thus the offset would equal zero.

It is important to note that Tweedie models have been used to model longline shark catch (*e.g.* Caneco, *et al.*, 2014; Shono, 2008), which allows zero and non-zero shark catches to be modelled simultaneously. However attempts to use Tweedie models in this study were unsuccessful with particularly poor fits to non-zero shark catches, as encountered with the candidate models of non-zero shark catch.

2.4 Development of the process model

The process model describes how silky shark and oceanic whitetip shark interact with purse seine fishing gear, and how different school association types impact on catch rates and subsequent mortalities. Almost all silky (97.6 %) and oceanic whitetip sharks (96.2 %) in the modelled dataset were recorded as dead at the point of capture. We therefore made the simplifying assumption that all individuals of these species were dead at the point of capture. Thus the process model consisted solely of the catch component.

A flow-chart summarising the model process is provided in Figure 1. The catch component required a spatial surface of purse seine effort by school association type (Section 2.5). This school association type effort surface was then weighted by a surface of species-specific relative abundance, so that for example FAD sets in an area of high shark species abundance would receive a higher weighting than an equal number of FAD sets in an area of low shark abundance (Section 2.7). The resulting adjusted (weighted) effort was then summed to provide the overall species-specific equatorial WCPO effort by school association. Catch was then estimated by applying this (school association specific) adjusted effort to the corresponding school association catch rates for that species (Section 2.8). Catch was then summed across school association types to give the total species-specific catch estimates for a given scenario.

2.5 Development of spatial surfaces of effort

Raised 1 x 1° purse seine effort data for 2012 to 2015 were used to generate the average annual number of sets within a 5 X 5° cell for a scenario representing the 'current' distribution of purse seine effort (called the 'Status Quo'), disaggregated by school association type. The range of years was chosen to best reflect the distribution of effort in recent years. Scenario-specific effort surfaces were then generated by modifying the Status Quo effort within each 5 x 5° cell. Note that the total effort within each 5 x 5 ° cell is equivalent for all three scenarios.

2.6 Scenarios examined for purse seine effort by association type

Three scenarios were examined in this study:

- *Status Quo* (SQ) - current levels of purse seine effort for each school association type, at a 5 x 5 ° cell spatial resolution;
- *No FAD* – Status Quo, but with drifting FAD and natural drifting FAD sets redistributed to free school sets within each 5 x 5 ° cell;
- *No FS* – Status Quo, but with all free school sets redistributed *pro rata* to drifting FAD and natural drifting FAD sets within each 5 x 5 ° cell.

By way of example, consider a grid cell for which the *Status Quo* effort was 160 sets, of which 32 (20%) were drifting FAD sets, 80 (50%) free school sets and 48 (30%) natural drifting FAD sets. The *No FAD* scenario effort would simply be 160 (100%) free school sets. The *No FS* scenario effort would be 64 (40%) drifting FAD sets and 96 (60%) natural drifting FAD sets, preserving the *Status Quo's* 2:3 ratio between drifting FAD and natural drifting FAD sets.

Natural drifting FAD sets (e.g. log sets) were treated equivalently to drifting FAD sets in scenarios to maintain consistency with the definition of FAD as outlined in WCPFC CMM 2009-02 (WCPFC, 2009). The *No FS* scenario was included as the natural counterpoint to the *No FAD* scenario, quantifying the potential 'extremes' of the range of shark catches in response to changes in drifting FAD and free school sets, under the assumptions made for natural drifting FAD sets.

2.7 Adjustment of effort to account for spatial relative abundance of sharks

Purse seine effort surfaces were adjusted to account for the fact that the level of shark catch for a given level of purse seine effort will be dependent on the relative abundance of the shark species in that location. For example, high effort in areas of low shark abundance will give a lower contribution to catches of sharks compared to the same level of effort in areas of high shark abundance. Relative abundance surfaces from Harley *et al.* (2015) were used for consistency with the Monte Carlo simulations for longline fisheries (Figure 9). The adjusted effort was then summed across the 5 x 5 ° cells to give a scenario specific total adjusted effort by school association type.

2.8 Parameterisation of the process model

School association and species specific probability distributions for shark presence were generated by predicting mean probability of shark presence where explanatory variables were held at reference levels, with standard errors generated from the variance-covariance matrix. Reference levels for explanatory variables were: *year* = 2014, *qtr* = 2, *SST* = 29, *chl* = 0.186. The reference levels for *SST* and *chl* were set at their respective means for the latitude bands with the highest relative abundance, i.e. -10 to -5°S and 5 to 10°N.

None of the candidate models of non-zero shark catch provided a robust and adequate fit to observations. Consequently school association and species specific probability distributions for non-zero shark catch (numbers) were assumed to be log-normally distributed, such that the mean and standard deviation of the logarithm of the distribution were equal to the mean and standard deviation of the observed non-zero catch.

Probability distributions for school association and species specific catch rates (numbers per set) were generated through parametric bootstrapping, by calculating the products of 100,000 samples drawn from the probability distributions of shark presence, and, numbers caught when present. This gave 100,000 estimates of overall catch rate. Probability distributions of school association and species specific catch rates were then constructed from these estimates, assuming a log-normal distribution such that the mean and standard deviation of the logarithm of the distribution were equal to the mean and standard deviation of the 100,000 catch rate estimates.

2.9 Monte Carlo simulations

Species specific Monte Carlo simulations were implemented in R (R Core Team, 2015). 100,000 draws were taken from catch rate probability distributions of the different school association types. These catch rate draws were then applied to (school association specific) adjusted effort to calculate school association specific catches for a given scenario. This allowed comparison of total catches of between scenarios, taking account of their uncertainty.

3 Results

3.1 Exploratory data analysis

Observers reported catch of silky shark (95%) and oceanic whitetip shark (88%) for the majority of sets with length frequency samples for these species. Examination of data from sets with length frequency samples and no catch data suggested that a substantial proportion of these apparent instances of non-recording of shark catches were in fact due to data entry errors, *e.g.* attributing length frequency samples to the set immediately before or after the set where sampling actually took place. On the basis of this investigation, non-reporting of shark species was ignored within the analysis.

3.2 Standardisation of bycatch rates

Silky shark

All explanatory variables in the silky shark presence/absence model were significant (Table 2). Plots of predicted probability of silky shark catch are provided in Figure 3. The probability of silky shark presence displayed no clear trend against year, though with some interannual variability. The probability of silky shark presence displayed a weak declining trend between quarters, and displayed a declining trend against sea surface temperature and cholorophyll-a concentration. The probability of silky shark presence was significantly lower for free school sets compared to sets on drifting FADs and natural drifting FADs. Furthermore, the probability of silky shark presence was significantly higher for sets on natural drifting FADs compared to drifting FADs.

Oceanic whitetip shark
All explanatory variables in the oceanic whitetip shark presence/absence model were significant, with the exception of cholorophyll-a concentration (Table 3). Plots of predicted probability of oceanic whitetip shark catch are provided in Figure 4. The probability of oceanic whitetip shark presence displayed a weakly increasing trend between 2012 and 2015, displayed no clear trend between quarters, and a declining trend against sea surface temperature. The probability of oceanic whitetip shark presence was significantly lower for free school sets compared to sets on drifting FADs and natural drifting FADs. There was no significant difference between probability of oceanic whitetip shark presence for sets on natural drifting FADs and drifting FADs.

3.3 Parameterisation of process model
The probability distributions for presence, non-zero catch numbers and overall catch rates of silky shark and oceanic whitetip shark are provided in Figure 5 to Figure 7. The hyper parameters for the school association specific catch rate probability distributions are provided in Table 4.

Overall catch rates were higher for silky shark than oceanic whitetip shark, due to both a higher probability of presence and higher numbers caught when present. In terms of within species comparisons between school association types, overall catch rates of silky shark were lowest for free school sets due to a significantly lower probability of presence. Overall catch rate distributions of silky shark for drifting FAD and natural drifting FAD sets overlapped, though mean catch rates of natural drifting FAD sets were higher due to a significantly higher probability of presence. Catch rate distributions of oceanic whitetip shark were also lowest for free school sets, due to a lower probability of presence. Catch rate distributions of oceanic whitetip shark were similar for drifting FAD and non-drifting FAD sets.

3.4 Monte Carlo simulations
The total adjusted number of sets by school association type and scenario are provided in Table 5. Redistributing drifting FAD and natural drifting FAD sets to free school sets resulted in an 83% and 57% reduction in median catch of silky shark and oceanic whitetip shark respectively, relative to the *status quo* (Table 6, Table 7 and Figure 10). Conversely, redistributing free school sets to drifting FAD sets resulted in a 168% and 113% increase in median catches of silky shark and oceanic whitetip shark respectively, relative to the *status quo*[2]. There was considerable uncertainty in model catch estimates with substantial overlap in the ranges of total catch estimated for each scenario. This uncertainty was principally a result of the diffuse probability distributions assumed for shark catch when present.

[2] We note that the redistribution assumption transferred free school sets to natural and man-made drifting FADs on a pro rata basis. Potentially all additional sets could be transferred to man-made drifting FADs alone. This would have a minimal effect on the increases seen for oceanic whitetip shark, but would result in slightly smaller increases for silky shark.

4 Discussion

The accuracy of the estimates of the absolute levels of total catch is dependent on accurate estimation of the magnitude of catch rates, whereas the accuracy of between-scenario catch comparisons is affected only by the relative magnitude of catch rates between school association types. As such, the estimates of absolute numbers of sharks caught should be treated with caution, particularly given the uncertainty in positive catch rate estimates. Therefore we concentrate on the relative impact of FAD/free school combinations, rather than the absolute estimates.

Monte Carlo simulations indicate that redistribution of effort from drifting FAD sets to free school would reduce purse seine catch of silky shark and oceanic whitetip shark, with average estimated reductions of 83% and 57% respectively if all sets on drifting FAD sets were redistributed.

Comparison of length frequency and catch data suggested a low prevalence of false negatives, *i.e.* recorded catch of zero when sharks were in fact caught. This approach was used as the length frequency sampling provides a means of determining, with high certainty, whether shark species were caught but not recorded by observers. However it is reasonable to expect that observers would be more likely to record catch of a species for a set if they have sampled the species for length frequency. As such, the estimates of false negatives likely represent lower bounds. Regardless, false negatives would only affect the relative changes in scenario specific shark catch if the rates of false negatives vary between school association types.

It was not possible to fit robust models to non-zero catch of silky and oceanic whitetip sharks. The inclusion of flexible latitude-longitude surfaces and vessel flag did not substantially improve model fits, suggesting that the lack of fit was not due to un-modelled spatial correlation or fleet effects. The explanatory variables used may have been inappropriate; it is possible that the lack of fit results from other missing explanatory variables, though it is not clear whether information would be available to include these variables if they were known. The lack of fit could also be explained, at least partially, by errors in recorded catch numbers.

Examination of residuals provided no indication in lack of fit of the presence/absence models against vessel flag. However, the exchangeable correlation structure selected for both silky shark and oceanic whitetip indicates variability in shark presence/absence between trips. This could reflect variable catch rates between vessels due to operational configurations, or variable detection rates of sharks by observers. It is important to note that the way in which bycatch species are handled and sorted by crew could have an impact on the accuracy of shark catch data recorded by observers. For example, on some sets observers may base shark bycatch estimates on separate piles of bycatch that have been sorted and retained, at least temporarily, on deck for later processing. This opportunity for comprehensive sampling would likely result in more accurate estimation of shark catch for the set, compared to a situation where sharks are dealt with as and when they are brought on board. In that case, shark catch will only have been recorded if the observer happened to notice the shark being handled by crew, which may be missed if the observer was undertaking other tasks. As such, variation in observed shark rates is also likely to be partially explained by between trip differences in the handling of sharks by crew.

WCPFC CMMs 2013-08 (WCPFC, 2013) and 2011-04 (WCPFC, 2011) implemented a ban on the retaining of silky and oceanic whitetip sharks from 1st July 2014 and 1st January 2013 respectively, as well as the requirement for vessels to release individuals in such a way as to cause as little harm as possible. In theory these measures may reduce the magnitude of silky and oceanic whitetip shark catch compared to the status quo estimates presented here, though research suggests this would require sharks to be released before the brailing process starts (Hutchinson *et al*., 2015). However, reductions in post-release mortality rates are unlikely to result in changes in the relative impacts of the different scenarios, unless there are differences in these rates between school association types.

Finally silky shark and oceanic whitetip shark are the two most prevalent shark species in purse seine catches, but may not be the shark species most at risk from interactions with purses seine fisheries due to differences between species in overall abundance and life history characteristics. However, it is unlikely that an equivalent analysis could be undertaken for other shark species due to the paucity of catch data.

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Table 1 Total number of individuals observed using all available purse seine observer data. Rows are provided for species or species groups that fall within WCPFC's key shark species (light blue fill), or elasmobranch species or species groups that accounted for more than 1 % of total elasmobranchs.

Species description	Species code	Individuals (% of total)
Silky shark	FAL	211,507 (79.8%)
Oceanic white-tip shark	OCS	7,417 (2.8%)
Whale shark	RHN	1,663 (0.6%)
Short finned mako shark	SMA	806 (0.3%)
Blue shark	BSH	662 (0.2%)
Scalloped hammerhead	SPL	84 (0%)
Bigeye thresher shark	BTH	80 (0%)
Great hammerhead	SPK	80 (0%)
Pelagic thresher shark	PTH	73 (0%)
Long finned mako shark	LMA	53 (0%)
Thresher shark (vulpinas)	ALV	45 (0%)
Smooth hammerhead	SPZ	26 (0%)
Winghead shark	EUB	1 (0%)
Mako sharks nei	MAK	425 (0.2%)
Thresher sharks nei	THR	133 (0.1%)
Hammerhead sharks nei	SPN	96 (0%)
Manta rays (nei)	MAN	6,224 (2.3%)
Devil manta ray (nei)	RMV	5,412 (2%)
Giant manta	RMB	5,193 (2%)
Sharks (nei)	SHK	17,662 (6.7%)
Others		7,289 (2.8%)
Total		**264,931**

Table 2 Significance of explanatory variables in the model of silky shark presence/absence.

Term	Df	χ^2	P(>|Chi|)
yy	6	250.5	< 2.2e-16
qtr	3	828.6	< 2.2e-16
association	2	9075.2	< 2.2e-16
ns(sst, df = 4)	4	14.2	0.006618
ns(chl, df = 4)	4	311.6	< 2.2e-16

Table 3 Significance of explanatory variables in the model of oceanic whitetip shark presence/absence.

Term	Df	χ^2	P(>|Chi|)
yy	6	25.784	0.000244
qtr	3	49.903	8.38E-11
association	2	248.439	< 2.2e-16
ns(sst, df = 4)	4	113.842	< 2.2e-16
ns(chl, df = 4)	4	9.208	0.056105

Table 4 Probability distributions and hyperparameters used in the process model (FS = free school; dFAD = man-made drifting FAD sets; ndFAD = natural drifting object sets). The parameters for mean (μ) and standard deviation (σ) are provided on the log-scale.

Species	Association	Distribution	µ	σ
Silky shark	FS	Lognormal	-2.33	0.979
Silky shark	dFAD	Lognormal	0.134	0.861
Silky shark	ndFAD	Lognormal	0.766	0.955
Oceanic whitetip shark	FS	Lognormal	-5.12	0.535
Oceanic whitetip shark	dFAD	Lognormal	-3.74	0.640
Oceanic whitetip shark	ndFAD	Lognormal	-3.28	0.948

Table 5 Adjusted effort (sets) by scenario, school association and species. FS = free school; dFAD = man-made drifting FAD sets; ndFAD = natural drifting object sets.

Species	Scenario	FS	dFAD	ndFAD	Total
Silky shark	SQ	22,838.2	8,971.2	1,637.7	33,447.1
Silky shark	No FAD	33,447.1	0.0	0.0	33,447.1
Silky shark	No FS	0.0	27,047.6	6,399.5	33,447.1
Oceanic whitetip shark	SQ	25,265.6	9,862.5	1,815.9	36,944.1
Oceanic whitetip shark	No FAD	36,944.1	0.0	0.0	36,944.1
Oceanic whitetip shark	No FS	0.0	29,825.9	7,118.2	36,944.1

Table 6 Overall catch of silky shark (numbers) for the status quo (SQ) and alternative scenarios (No FS = no free school sets; no FAD = no FAD sets).

	Percentile		
Scenario	0.10	0.50	0.90
SQ	9,092.6	19,425.1	43,424.3
No FS	21,919.0	51,998.0	125,550.0
No FAD	926.5	3,260.2	11,358.9

Table 7 Overall catch of oceanic whitetip shark (numbers) for the status quo (SQ) and alternative scenarios (No FS = no free school sets; no FAD = no FAD sets).

	Percentile		
Scenario	0.10	0.50	0.90
SQ	307.1	515.0	894.5
No FS	546.1	1,096.9	2,255.5
No FAD	111.5	220.3	440.0

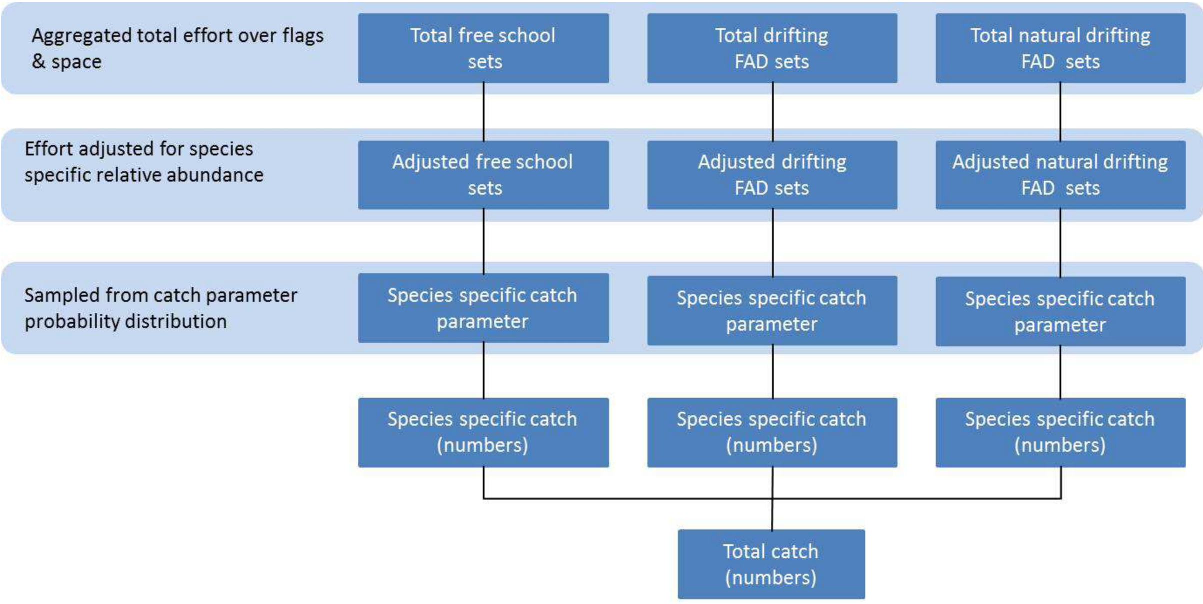

Figure 1 Schematic of the process model.

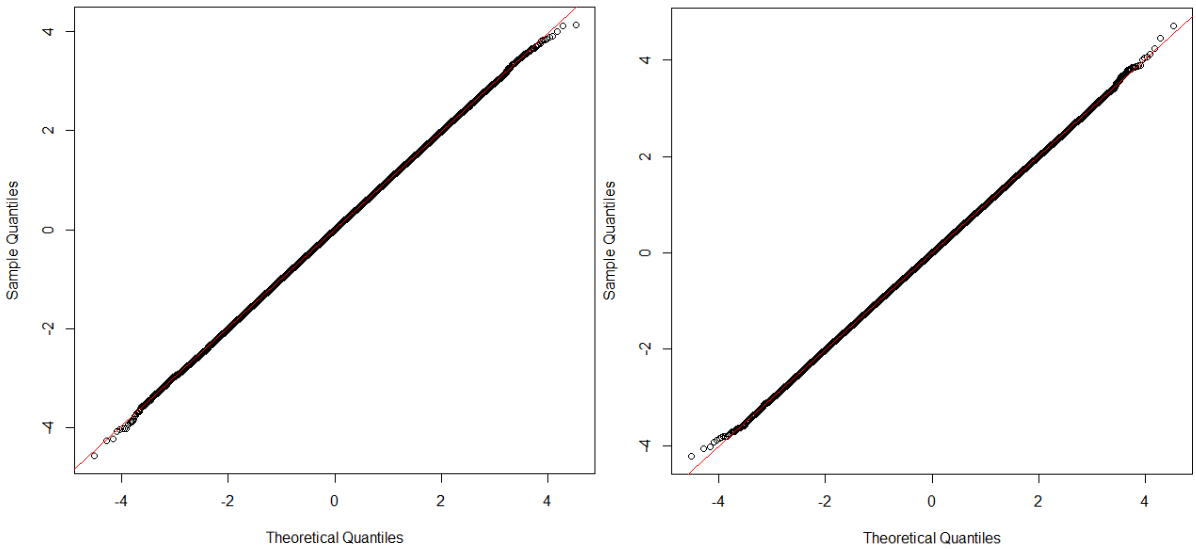

Figure 2 QQ plots of quantile residuals of presence/absence models for silky shark (left) and oceanic whitetip shark (right).

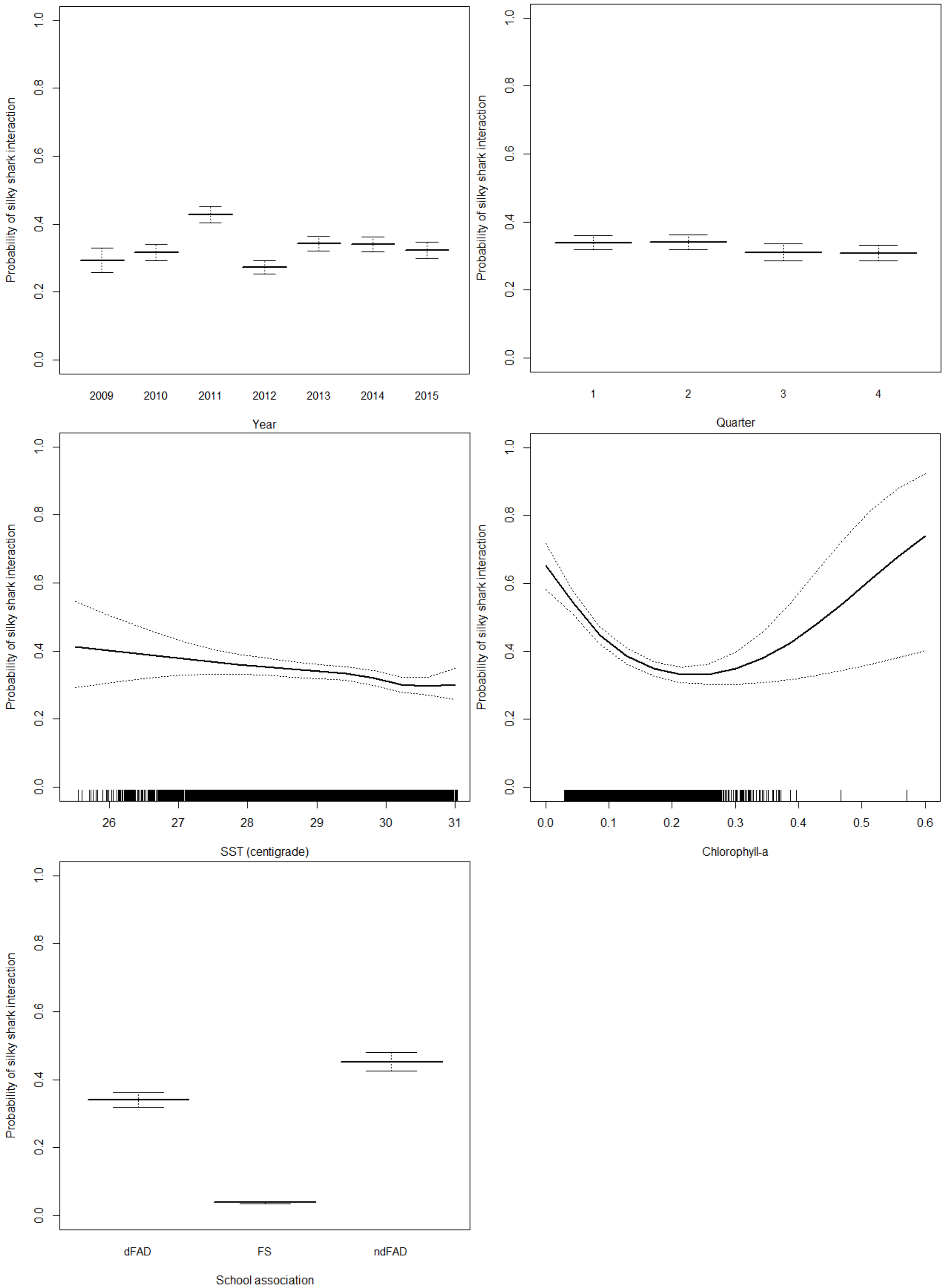

Figure 3 Predicted probability of silky shark presence against year (top left), quarter (top right), sea surface temperature (middle left), chloropyll-a concentration (middle right) and school association (bottom left). Confidence intervals include uncertainty from all model terms.

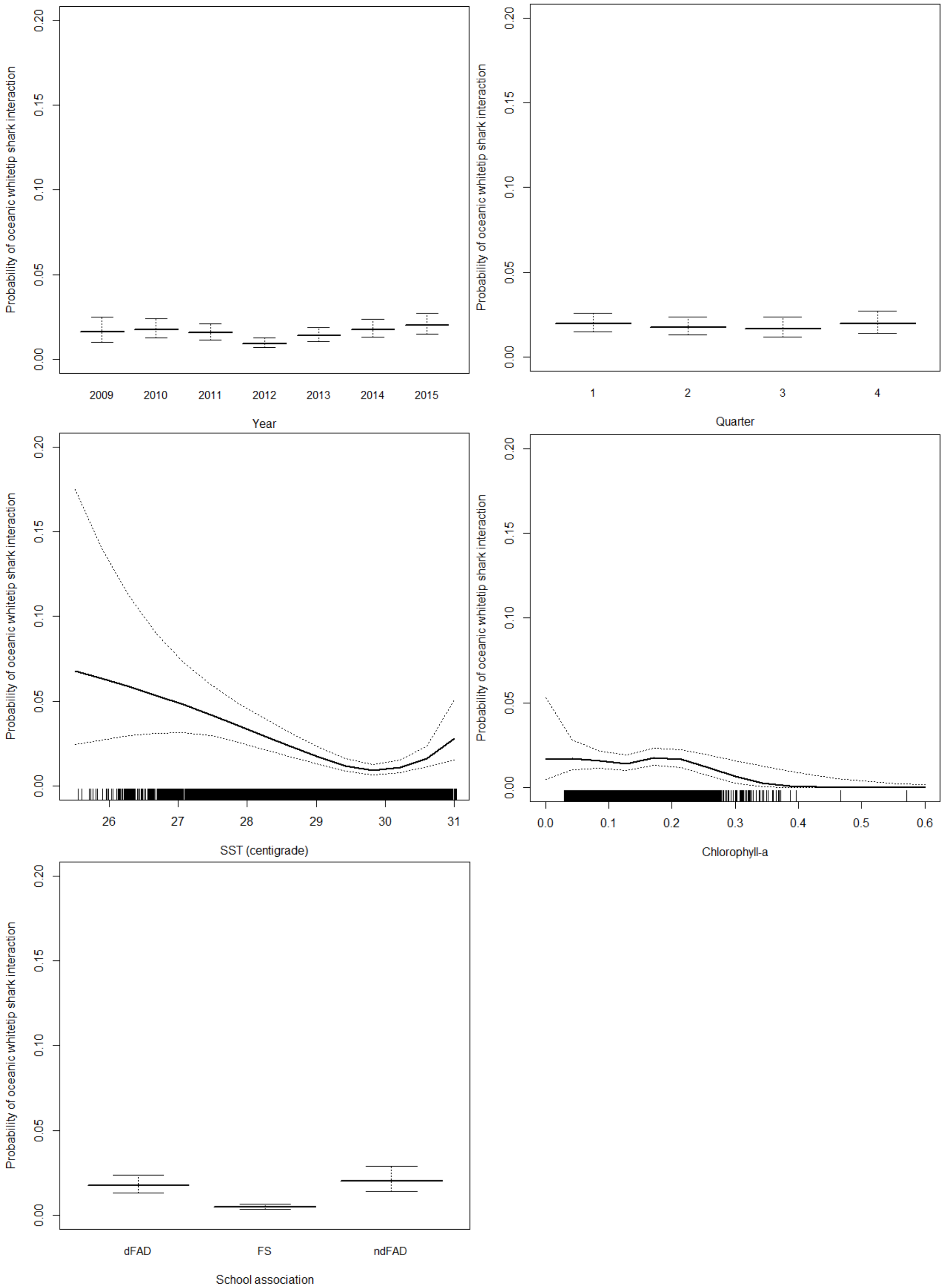

Figure 4 Predicted probability of oceanic whitetip shark presence against year (top left), quarter (top right), sea surface temperature (middle left), chloropyll-a concentration (middle right) and school association (bottom left). Confidence intervals include uncertainty from all model terms.

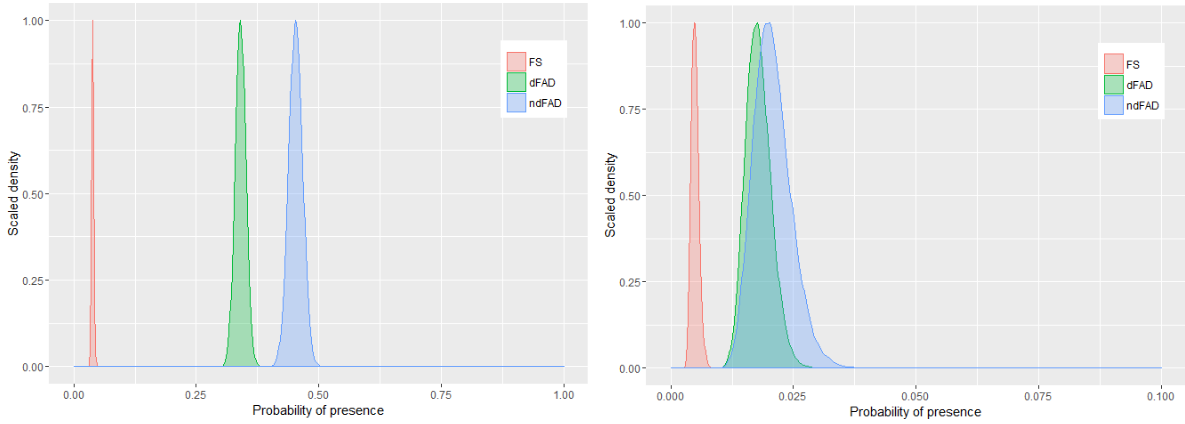

Figure 5 Probability distributions for presence of silky shark (left) and oceanic whitetip (right) catch for drifting FADs (dFAD), free schools (FS) and natural drifting objects (ndFAD) sets. Note that the range of the x-axis differs between the two panels.

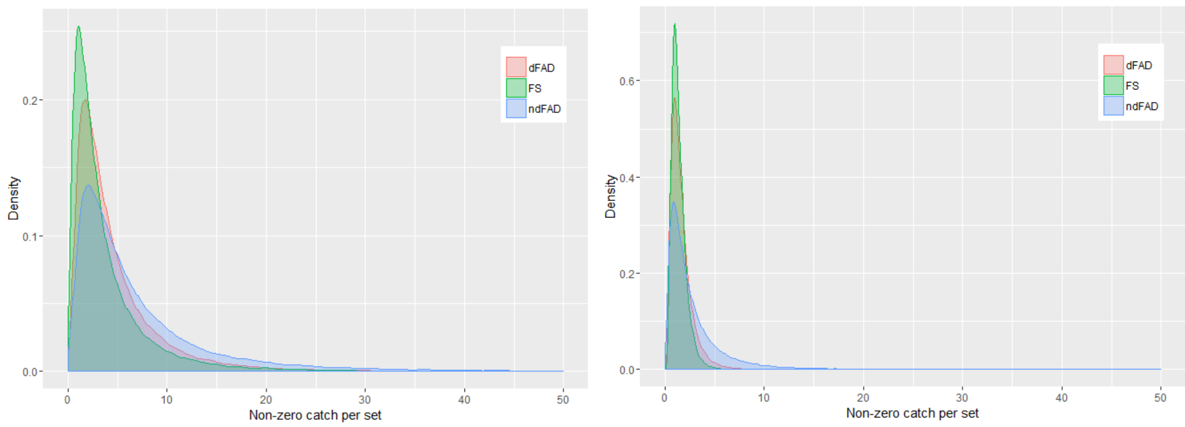

Figure 6 Probability distributions for non-zero catch per set of silky shark (left) and oceanic whitetip (right) for drifting FADs (dFAD), free schools (FS) and natural drifting objects (ndFAD) sets. Note different y-axis scales.

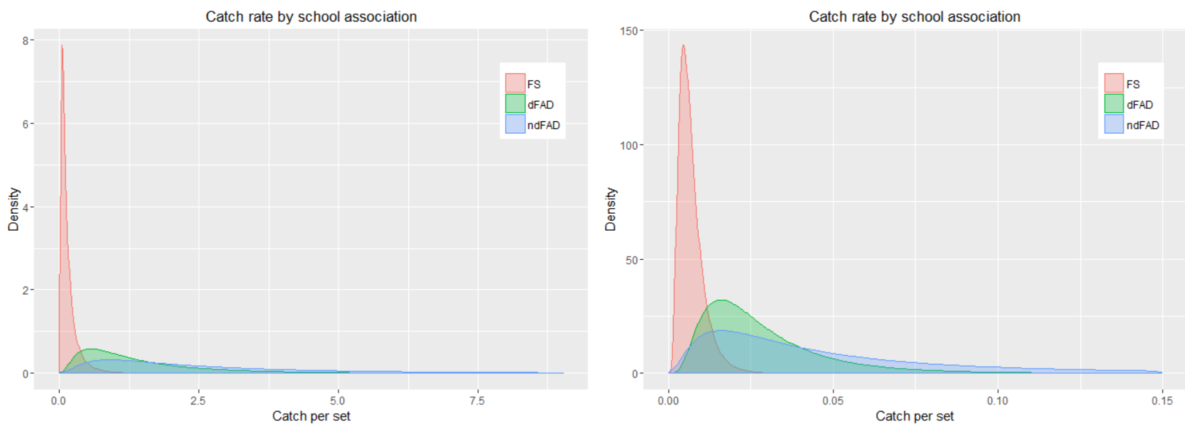

Figure 7 Sample distributions of catch rates (numbers per set) for silky shark (left) and oceanic whitetip (right). Note different y-axis scales.

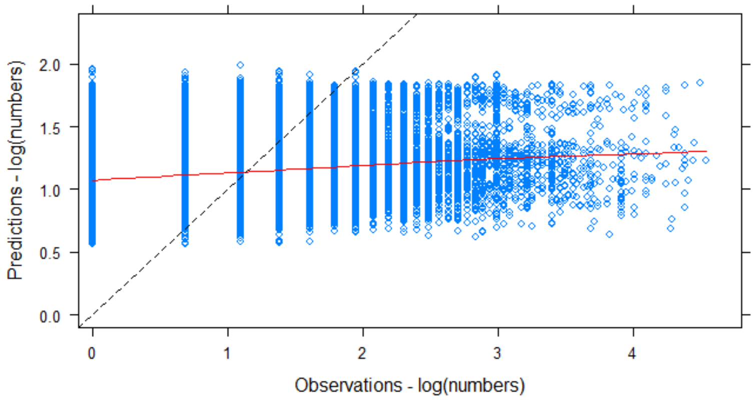

Figure 8 Predicted catch numbers when present of silky shark (log-scale) against observed catch numbers (log-scale), assuming residuals have a truncated negative binomial distribution. A loess smooth (red line) is included to provide a means of comparison between the average prediction for a given level of observed catch. Observed = predicted is provided for reference (broken black line).

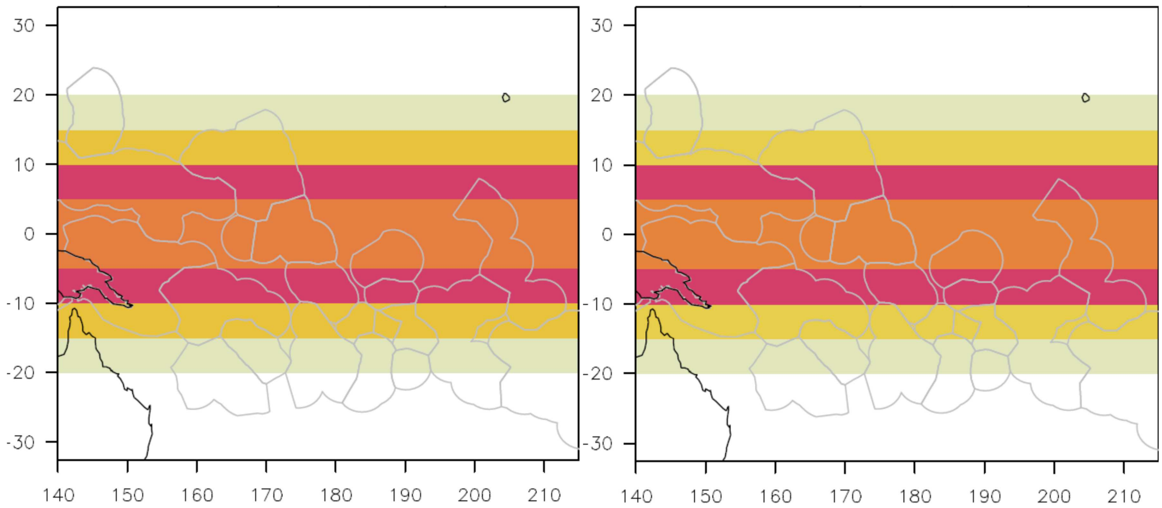

Figure 9 Relative abundance surfaces for silky shark (left) and oceanic whitetip shark (right), reproduced from Harley *et al.* (2015).

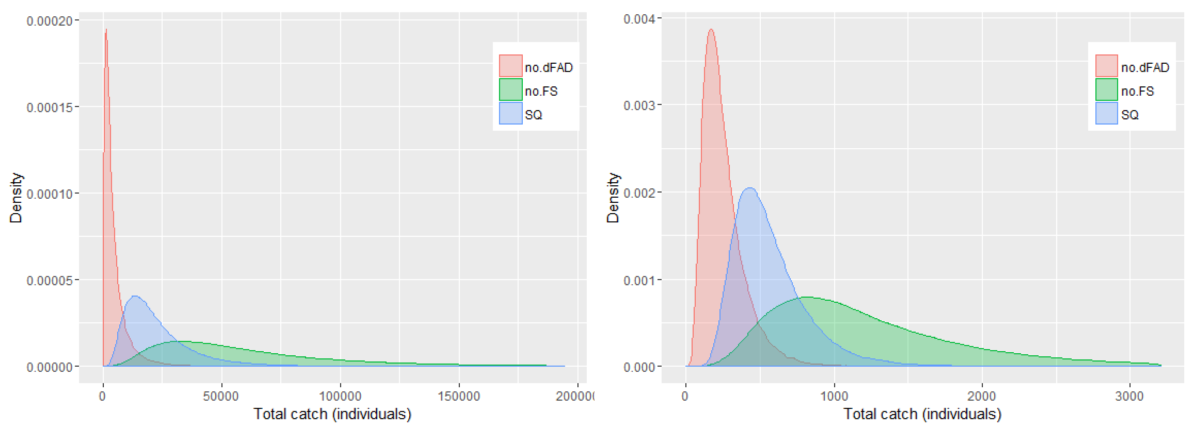

Figure 10 Total catch (numbers) of silky shark (left) and oceanic white tip (right) for the Status Quo (SQ) along with scenarios where all FS effort was redistributed to dFAD (no FS) and all dFAD effort was redistributed to FS and ndFAD (no dFAD).