SCIENTIFIC COMMITTEE
EIGHTH REGULAR SESSION

7–15 August 2012

Busan, Republic of Korea

Catch per unit effort of oceanic whitetip sharks in the Western and Central Pacific Ocean

---

WCPFC-SC8-2012/SA-IP-10

Joel Rice[1]

[1] Oceanic Fisheries Programme, Secretariat of the Pacific Community (SPC-OFP), Noumea, New Caledonia.

Catch per unit effort of oceanic whitetip sharks in the Western and Central Pacific Ocean

Summary

This paper follows from the indicator based analysis presented to the Western and Central Pacific Fisheries Commission (WCPFC) Scientific Committee (SC7, Clarke et al. 2011). Following a brief summary of exploratory data analysis, this report presents a Catch Per Unit Effort (CPUE) standardization for oceanic whitetip shark (*Carcharhinus longimanus*) taken in longline and purse seine fisheries based on observer data held by the Secretariat of the Pacific - Oceanic Fisheries Program (SPC-OFP).

The objectives were to produce multiple time series of standardized CPUE to be used as indices of abundance for use in the stock assessment. The sections of this report include a) a summary of the exploratory data analysis of oceanic whitetip shark (OCS) CPUE in the WCPO, b) presentation of the final standardized CPUE trends for oceanic whitetip sharks, c) model diagnostics, and d) a discussion of the quality of the available data and the relative strengths and weaknesses of the standardization procedures. This paper is prepared as an information paper to support the stock assessment presented to the scientific committee (Rice and Harley 2012) along with a study on alternate catch estimates (Rice 2012).

1 Introduction

This paper follows from the indicator based analysis presented to the Western and Central Pacific Fisheries Commission (WCPFC) Scientific Committee (SC7, Clarke et al. 2011). The developments presented here include additional analyses of the SPC data holdings for oceanic whitetip caught in longline and purse seine fisheries in the Western and Central Pacific Ocean (WCPO).

The framework for the analysis is to construct inputs for stock assessment based on an estimated catch and an index of abundance based on standardized catch per unit of effort (CPUE). The SPC longline observer database contains records from 1985 to recent years; however, oceanic whitetip sharks were not identified to species until 1995, hence the dataset used in this analysis spans the years 1995-2009[2]. Recent work by Clarke et al. (2011) noted gaps in observer data in terms time, space, reporting rate and identification with respect to sharks. Oceanic whitetip sharks are observed mainly in the equatorial waters in the purse seine fishery (Figure 1), and from about -25˚S to 25˚N in the longline fishery (Figure 2).

CPUE data for species such as sharks often have a large proportion of observations (or sets) with no catch, and also includes observations with large catches when areas of higher densities are encountered; this is typical of bycatch species (Ward and Myers, 2005). The signals from the nominal (observed catch/observed effort) CPUE data can be heavily influenced by factors other than abundance and therefore a procedure to standardize CPUE data is usually recommended to remove the influence of factors (other than change in abundance) that may cause variation or trends in the CPUE. Nominal CPUE data can be more variable than expected (i.e., over-dispersed), with many outlying data points from uncommonly high catch rates. These outlying data points can sometimes be a function of shark targeting.

[2] At the time of this analysis, there was insufficient 2010 longline observer records.

2 Methods

This analysis follows the work of Clarke et al. (2011, 2011b) and Walsh and Clarke (2011), but the regions for this study differ slightly. Because oceanic whitetip sharks are tropical species this led to the analysis being considered for one region, from 25˚S to 25˚N and bordered on the east and west by the WCPFC Statistical Area. A comprehensive overview of the observer logsheet data and a characterization of the fisheries in which oceanic whitetip sharks are caught is presented in Clarke et al. (2011). What follows is a summary of the methods used in this analysis.

2.1 Longline data preparation

The data were validated and trimmed (records with missing values for key explanatory variables removed) to include only relevant data from the species 'core' habitat. This was done to reduce the already excessive number of zeros in the data, i.e. zero catch where you would not reasonably expect to catch oceanic whitetip sharks. Environmental data about temperature, salinity, moon phase, and depth of the 27˚C isotherm downloaded from the GODAS database (GODAS 2011) were matched to the set by set observer data.

Because oceanic whitetip sharks are an epi-pelagic tropical species, all sets that occurred in water colder than 25˚C were discarded. This left 90% of the sets with a non-zero catch (Figure 2). The effect of the number of hooks between floats (a proxy for depth) was investigated independently and sets with greater than 30 hooks between floats were discarded, leaving 80% of the sets with non-zero catch (Figure 3). National affiliation of the fishing vessel was included in the data set, and only those nations that had greater than 100 sets since 1995 were used. The last variable that resulted in a culling of the data set was based on the non-zero CPUE for unidentified sets (sets where the target is marked as unidentified) as a function of national affiliation. Flagged vessels that had an average positive CPUE 3 times larger than the mean CPUE for all other nations combined were removed from the bycatch longline data under the premise that these vessels were targeting sharks.

Latitude and longitude were truncated to the nearest 1˚; this location information was used to calculate the association with a 5˚square (referred to hereinafter as cell). Date of set was used to calculate the year, month, quarter and trimester of the set. Set time was used to calculate the time category of the day in sixths starting at midnight. A non-target data set was created as a result of filtering data according to the above rules. A targeted data set was created in a similar manner. This was done under the premise that the factors leading to non-zero catch rates when targeting sharks would be different than factors that lead to non-zero catch rates when not targeting sharks.

Although a much smaller proportion of the overall dataset (6.5% of the sets), the targeting sets represent significant oceanic whitetip shark catch (47%). Therefore, the dataset was examined with respect to variables relating to whether sharks were the intentional target of the set. Oceanic whitetip shark CPUE was plotted as a function of variables relating to the use of shark lines, the use of shark bait, and shark targeting against the date of set (Figure 3). Inspection of these covariates led to the separation of shark-targeting sets and non-targeting (bycatch) sets. Shark targeting sets were deemed to be sets where the observer had marked that the set was intentionally targeting sharks of any species (i.e., whether shark bait or shark lines were used).

The results of these filtering rules are in Table 2.

2.2 Purse seine data preparation

The only restriction placed on the purse seine observer data was that the set occurred within the rectangle defined by 7˚N and -12˚S Latitude and 139˚W to 192˚E. The purse seine data was separated into two fisheries, one based on associated sets and one based on unassociated sets.

2.3 CPUE methodology

CPUE is commonly used as an index of abundance for marine species. However, it is important that raw nominal catch rates be standardized to remove the effects of factors other than abundance. Catch data for non-target species (sharks in particular) often contain a large number of sets with zero catch as well as sets with substantial catch. These phenomenon need to be explicitly modelled (Bigelow et al. 2002, Campbell 2004, Ward and Myers 2005, Minami et al. 2007).

Standardized CPUE series for all fisheries (bycatch and target longline; associate and unassociated purse seine fisheries) were developed using generalized linear models. For longline analyses, effort was defined as the number of hooks fished in a set. For purse seine analyses, effort was defined as a single set. It is notoriously difficult to come up with accurate estimates of the true effort that relates to a purse seine set (Punsly, 1987).

2.4 Overview of GLM Analyses

The filtered datasets were standardized using generalized linear models (McCullagh and Nelder 1989) using the software package R (www.r-project.org). Multiple error structures were tested including:

- The delta lognormal approach (DLN) (Lo et al. 1992, Dick 2006, Stefansson 1996, Hoyle and Maunder 2006): this approach is a special case of the more general delta method (Pennington, 1996, Ortiz and Arocha 2004), and uses a binomial distribution for the probability *w* of catch being zero and a probability distribution *f(y)*, where y was log(catch/hooks set) for non-zero catches. An index was estimated for each year, which was the product of the year effects for the two model components, $(1-w)*E(y|y \neq 0)$.

$$\Pr(Y=y)=\begin{cases} w, & y=0, \\ (1-w)\,f(y) & \text{otherwise} \end{cases}$$

- The negative binomial (Lawless 1987): typically more robust to issues of overdispersion (overdispersion can arise due to excess zeros, clustering of observations, or from correlations between observations) was also used. This model has been advocated as a model that is more robust to overdispersion than the Poisson distribution (McCullagh and Nelder 1991), and is appropriate for count data (Ward and Myers 2005), but does not expressly relate covariates to the occurrence of excess zeros (Minami et al. 2007).

- The quasi-Poisson: in which a dispersion parameter ϕ is estimated and corrected for to account for overdispersion was also used though this tends to produced larger standard errors and model misspecification when ϕ is large because the standard errors of the covariates are multiplied by $\sqrt{\phi}$.

- Mixture models such as the zero inflated Poisson (ZIP) and zero inflated negative binomial (ZINB) (Zuur et al. 2009, Cunningham and Lindenmayer 2005, Welsh et al. 2000): these models are useful for modelling counts of rare species when the number of zero observations is larger than expected. Zero inflated models are a process similar to the delta approach in which the presence or absence of the catch is modelled orthogonally to the size of the catch (Welsh et al. 2000), however unlike the delta approach the count data can include zeros. Zero counts can result from predator satiation, competition for hooks, or disinterest (called true zeros) as opposed to design errors, sampling errors, observer errors or zeros resulting from sampling outside the habitat range (called false zeros). The total probability of a zero count is then,

$$\Pr(Y_i = 0) = \Pr(False\ Zeros) + (1 - \Pr(False\ Zeros)) * \Pr(True\ Zeros)$$

Therefore, the probability distribution for the zero inflated Poisson is equal to:

$$\Pr(y_i = 0) = \pi_i + (1 - \pi_i) * e^{-\mu_i}$$

$$\Pr(y_i | y_i > 0) = (1 - \pi_i) * \frac{\mu^{y_i} {}_* e^{-\mu_i}}{y_i!}$$

Where y_i is the size of the catch of the i^{th} set, and distributed y_i ~ Poisson(μ_i) (μ_i is the mean of the Poisson distribution), and π_i is the probability of a false zero. The probability definition for the zero inflated negative binomial is similar,

$$\Pr(y_i = 0) = \pi_i + (1 - \pi_i) * \left(\frac{k}{\mu_i + k}\right)^k$$

$$\Pr(y_i | y_i > 0) = (1 - \pi_i) * \frac{\Gamma(y_i + k)}{\Gamma(k) * \Gamma(y_i + 1)} * \left(\frac{k}{\mu_i + k}\right)^k * \left(1 - \frac{k}{\mu_i + k}\right)^{y_i}$$

Where y_i is the size of the catch of the i^{th} set, and distributed y_i ~ *Negative Binomial* ($\mu_{i,}k$), and π_i is the probability of a false zero. Under this parameterization the mean of the negative binomial is μ and the variance is $\mu + \mu^2/k$. The main advantage of the zero inflated approach is that these techniques can model the overdispersion in both the zeros and the counts as opposed to just the counts (negative binomial), and they deal with over-dispersion better than other models (quasi Poisson) (Zuur et al. 2009).

Each model was fit to the data set independently and all variables used in the models were included as categorical factors except the response variables for catch and CPUE (owt and OWTCPUE variables, respectively) and the effort offset variable (hook_est). These variables were included in the model as continuous variables (Table 1). Model selection began with regression trees and piecewise ANOVA models for each model (De'ath and Fabricius, 2000; Zuur et al. 2009). The Akaike information criterion (AIC) was used as a metric to score the results and determine the final models for each data set, because criteria and model diagnostics resulted in different variables and different models were often selected for the different data sets.

2.5 2.5 Indices of abundance and Confidence Intervals

Multiple methods of calculating the indices of abundance and confidence intervals exist depending on the model type(Shono H. 2008, Maunder and Punt 2004). In this study estimates were calculated by predicting results based on the fitted model and a training data set that included each year effect and the mean effect for each covariate (Zuur et al. 2009). Confidence intervals were calculated as ±1.96* SE, where SE is the standard error associated with the predicted year effect term.

3 Results

For brevity we only describe the model results for the final model chosen for each data set. A comparison of the proportion of zeros, mean non-zero catch and the standardized CPUE for oceanic white tips in the longline and purse seine fleets is presented in Table 3.

3.1 Longline bycatch data series

The Zero Inflated Negative Binomial model was the selected model-type for the non-target longline dataset. The resulting standardized CPUE trend (Figure 4) contains the combined effects from two models, one that calculates the probability of a zero observation and one that estimates the count per year. The result from the model is the combined predicted level of the response variable, oceanic whitetip catch. The resulting standardized CPUE trend was plotted against the mean nominal trend (both relative to their maximum values). The standardized CPUE trend is similar to the mean nominal trend (Figure 4), with both trends declining since the late 1990s. The 95% confidence interval is widest in the late 1990's and smallest throughout the 2000's, reflecting the overall quality and quantity of the data through the time period.

The diagnostic results from the ZINB model (Figure 5), do not show any significant trends in the plots of the residuals against the model covariates (the left hand panel). The right hand panel shows the standard diagnostics of residuals vs. fitted, Pearson residuals vs. fitted, QQ plot and a histogram of the residuals. These model diagnostics plots show the expected departure from normality arising from a mixture model. The partial dependence plots (Figure 6) show the influence of the number of hooks between floats (hk_bt_flt) being constant across the range of data and the influence of the time of day increasing through the middle of the day (TIMECAT categories 3-6). A deviance table showing the contribution of the model components is presented in Table 4.

3.2 Target longline data series

The longline target data set was best fit using the delta lognormal approach. Initial attempts to model the target longline data with ZINB, ZIP or other models that attempt to explain the over-dispersion (i.e., excess zeros) resulted in a severe lack of fit. Both the nominal CPUE and the standardized CPUE that was based on the DLN model show a declining trend in oceanic whitetip shark CPUE during the 2000's (Figure 7) . Prior to the 2000's, both the nominal and standardized CPUE trends were characterized by large fluctuations in the values, which may be due to lack of sufficient data, or poor quality data. This is reflected in the larger confidence intervals prior to 2003.

The standard diagnostics of residuals vs. fitted, QQ plot, scale location plot, and the residuals vs. the leverage are shown in Figure 8. There were data points identified as having high leverage in the count data set (positive catches). However, it was deemed appropriate to include these data because large catches of oceanic whitetip sharks are not uncommon and was a filtering criteria for characterizing the target longline CPUE series as opposed to the bycatch longline CPUE series.

Partial dependence plots for the binomial and lognormal components of the target longline DLN model (Figures 9 and 10) show a different trend in the covariate describing the use of shark lines only. While inclusion of the 'sharkline' covariate increases the probability of capturing at least one oceanic whitetip shark (i.e., the 'sharkline' main effect had a positive impact on the catch rate in the binomial model), inclusion of 'sharkline' in the lognormal model (the count model) reduces the total number of expected oceanic whitetip caught, given that at least one was caught. This is most likely due to the mixed-shark /multi-species (shark and tuna) nature of many sets – when shark lines are employed sharks are often one of multiple targets. A deviance table showing the contribution of the model components is presented in Table 5.

3.3 Purse seine associated set data series

The observer data from the purse seine fleet is inherently difficult to standardize because there is no standard metric for effort. Further, oceanic whitetip sharks were only commonly identified to species since the early 2000's, therefore interpretation of the any standardized time series must be undertaken cautiously. A DLN standardized CPUE time series was quite similar to the mean nominal CPUE time series (Figure 11). Although the standard errors and confidence intervals on the standardized CPUE are quite large, the trends in the CPUE (standardized and nominal) are similar to each other and to the target and bycatch CPUE from the longline fleet (i.e., all show a trend with the highest values pre-2000 and subsequent declines in CPUE thereafter).

Despite the large confidence intervals, model behavior showed little departure from the standard assumptions for the binomial model (left hand side panel Figure 12), and a reasonable distribution of residuals for the lognormal model (right hand side panel Figure 12). Figure 13 shows the partial dependence plots for oceanic whitetip sharks caught in associated sets. The top panel is for the single covariate (apart from year) in the binomial model, and the bottom four panels are from the lognormal model. . A deviance table showing the contribution of the model components is presented in Table 6.

3.4 Purse seine unassociated set data series

A DLN standardized CPUE based on unassociated purse seine sets was similar to that for associated sets across the time series (highest prior to 2000 and then declining thereafter, Figure 14). The standardized CPUE was quite similar to the mean nominal CPUE; however, there were differences in the first two years of the time series. Despite the large confidence intervals, model behavior showed little departure from the standard assumptions for the binomial model (left hand side panel Figure 15), and a reasonable distribution of residuals for the lognormal model (right hand side panel Figure 15). The large confidence intervals are partly due to the deficient nature of the unassociated dataset (only approximately 250 records of oceanic whitetip catch in the unassociated data set). Figure 16 shows the partial dependence plots for oceanic whitetip sharks caught in unassociated sets. The four panels are from the lognormal model (only the index variable, the year effect, was included in the binomial model and so is not shown)..

4 Discussion

This paper has presented the standardized CPUE series for oceanic whitetip sharks in the western central Pacific Ocean based on observer data collected in the region over the years 1995- 2009. In late 2011 when the analysis was undertaken, there was insufficient longline observer data for 2010. These data are critical for both CPUE and catch inputs to the stock assessment therefore our analysis only goes through 2009. In the analyses described here, data was separated into two longline series (bycatch and target) and two purse seine series (unassociated and associated sets) from which a standardized CPUE series was generated for each.

All four standardized CPUE trends share the same general trend with the highest values prior to 2000 and a steep decline thereafter. Each standardized CPUE trend was also similar to the nominal data. Figure 1 showed that the data is coming from the same area in the ocean throughout the time series, except for some missing longline data from the Hawaiian Islands in 2005-2009. This suggests that the decline in standardized (and nominal) CPUE is not likely to be a factor of the lack of observations in the Hawaiian islands region but rather a result of an overall decline in oceanic whitetip CPUE. Including observer data from Hawaii would nonetheless improve the predictive power of these models. It would most likely not change the estimated trends as a separate analysis of Hawaiian data reveals similar trends (Walsh and Clarke 2011).

In addition to standardizing the CPUE trends from the longline and purse seine fishery, this analysis had the additional objective of assessing the strengths and weaknesses of the available data and to identify the main effects that are important to CPUE standardization for shark bycatch. The most important covariate in the longline CPUE standardization was vessel ("vesselname") for both target and bycatch data sets (Tables 4-5). Introduction of the vessel effect greatly increase the explanatory power of the models for the longline CPUE, although it did not greatly alter the standardized CPUE trend from the nominal trend. Vessel effects reflect multiple factors that are intrinsic to a fishing boat, including the intention and ability to effectively target a species. The standardization models considered in this study only account for the relative catchability among vessels and make no account for any change in the absolute fishing power over time. Potential changes in vessel characteristics, equipment, crew or captain may alter the vessel effect through time. Further research on better ways to model vessel catchability through time is recommended (e.g., see Wilberg et al. 2010).

Research into vessel catchability and effort in the purse seine fishery is also recommended. Attempts at including vessel effects in the purse seine CPUE standardization resulted in models that did not converge. The inclusion of a proxy for effort, such as the tonnage of skipjack caught, should also be investigated.

In the early time period, sharks were not commonly identified to species but rather as one 'shark' category. A back extrapolation of the undocumented shark community composition could be undertaken, although it would be inherently uncertain. There are many problems that would have to be overcome to do this including (but not limited to) changes in vessel catchability, targeting, changes in fishing behavior and natural fluctuations in the relative abundance and availability of the individual shark species with respect to each other and to their key prey.

Acknowledgements

This paper benefited from the help of Shelton Harley, Aaron Berger and Simon Hoyle.

5 Figures

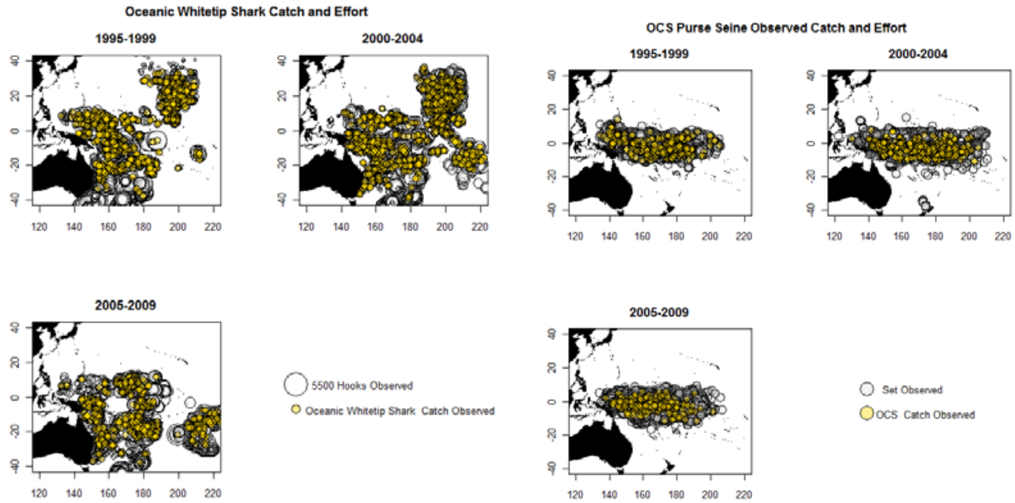

Figure 1. Oceanic whitetip shark catch and effort in the longline (left) and purse seine (right) fisheries by 5 year increments.

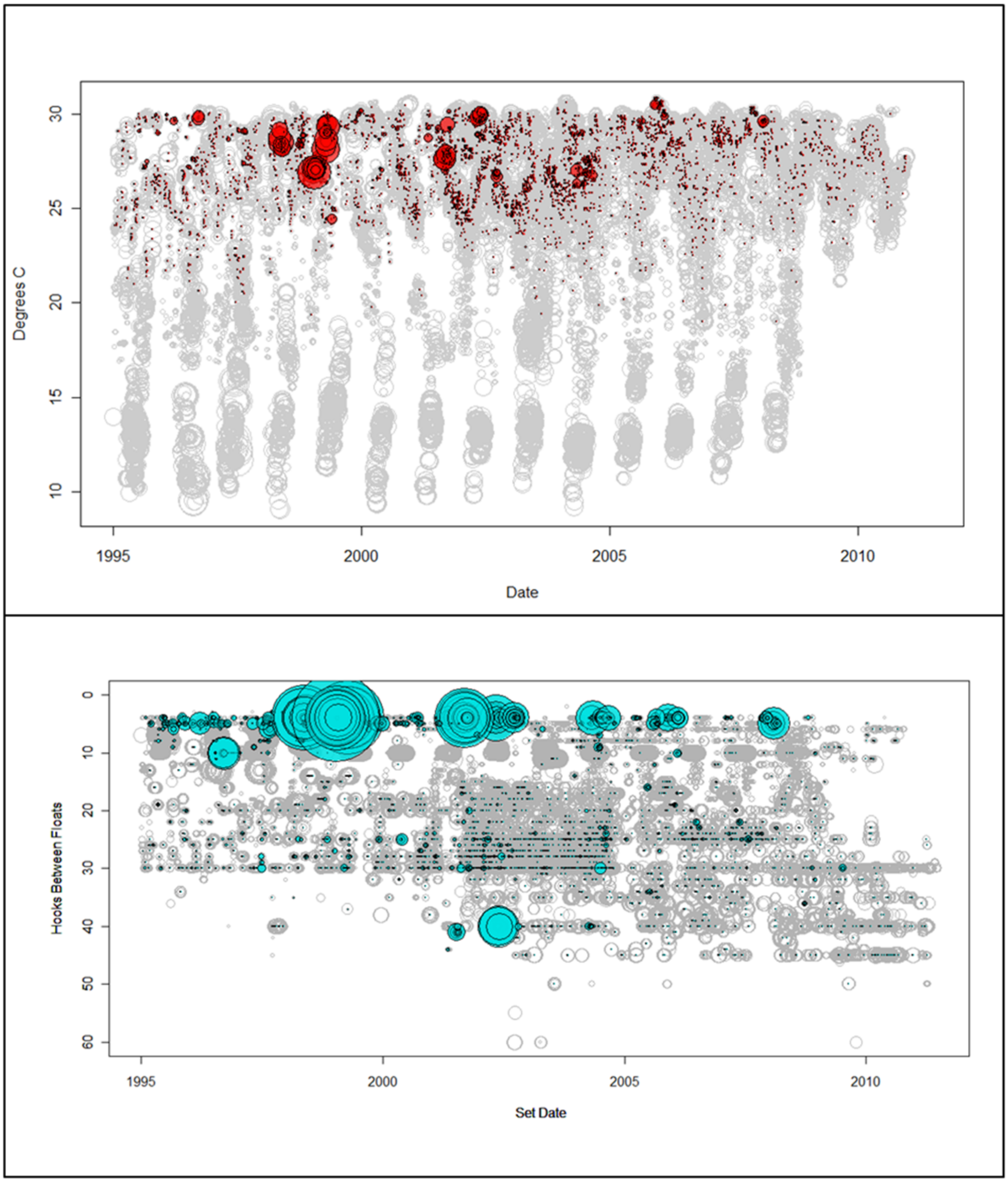

Figure 2. Longline CPUE for oceanic whitetip sharks as a function of time (x-axis) and degrees centigrade (top) and hooks between floats (bottom). Colored circles are scaled proportional to the maximum observed CPUE value. Grey circles are scaled proportional to the maximum number of hooks observed.

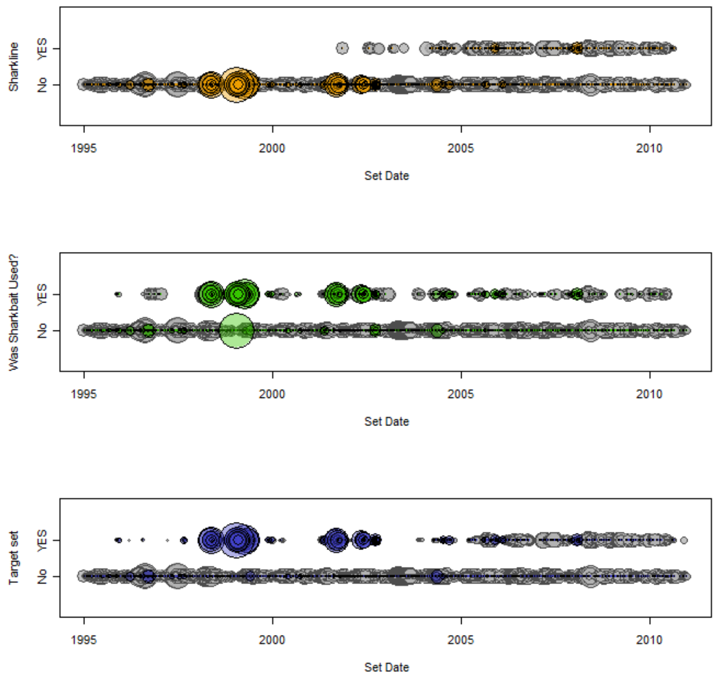

Figure 3. Longline CPUE for oceanic whitetip sharks as a function of time (x-axis) and whether: a shark line was used (top panel), shark bait was used (middle panel); or the set was intentionally targeting sharks (bottom panel). Grey circles are scaled proportional to the maximum number of hooks deployed.

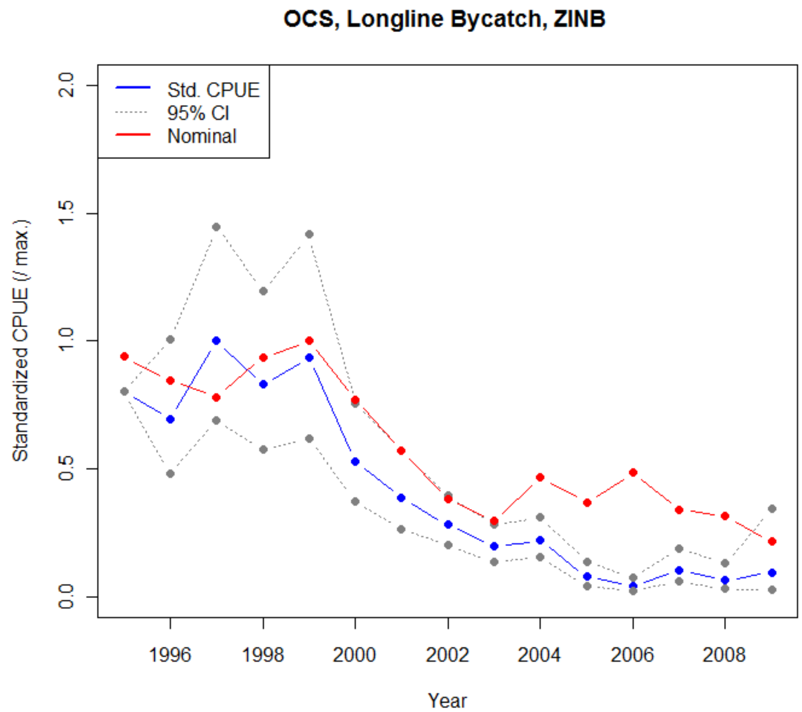

Figure 4. Nominal CPUE and standardized CPUE based on the ZINB model for oceanic whitetip sharks caught in the longline bycatch fishery.

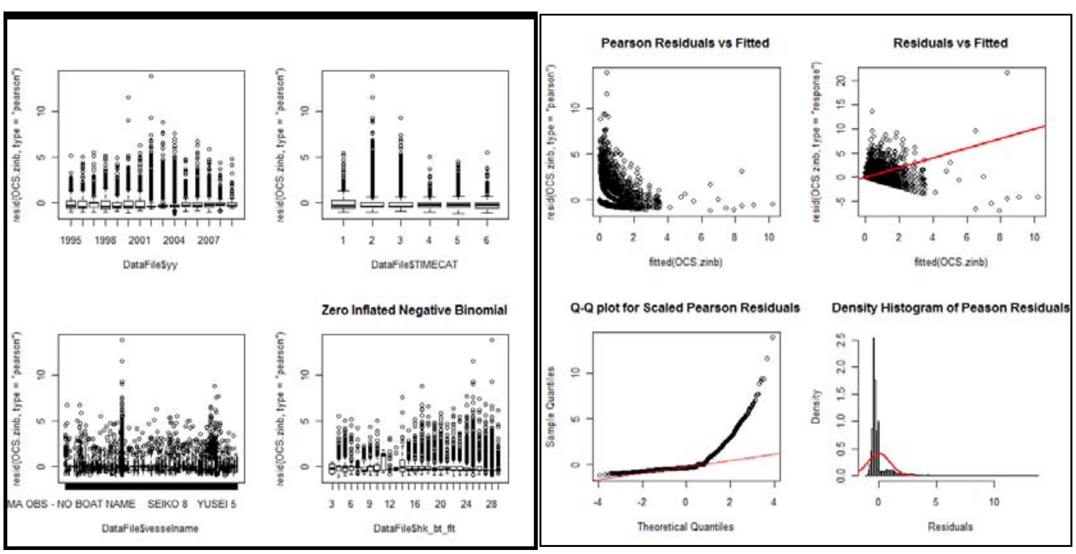

Figure 5. Diagnostic results from the ZINB model for oceanic whitetip sharks caught in the longline bycatch fishery. The left hand panel show the plots of the residuals against the model covariates, and the right hand panel shows the standard diagnostics of residuals vs. fitted, Pearson residuals vs. fitted, QQ plot and a histogram of the residuals. See table 1 for variable descriptions.

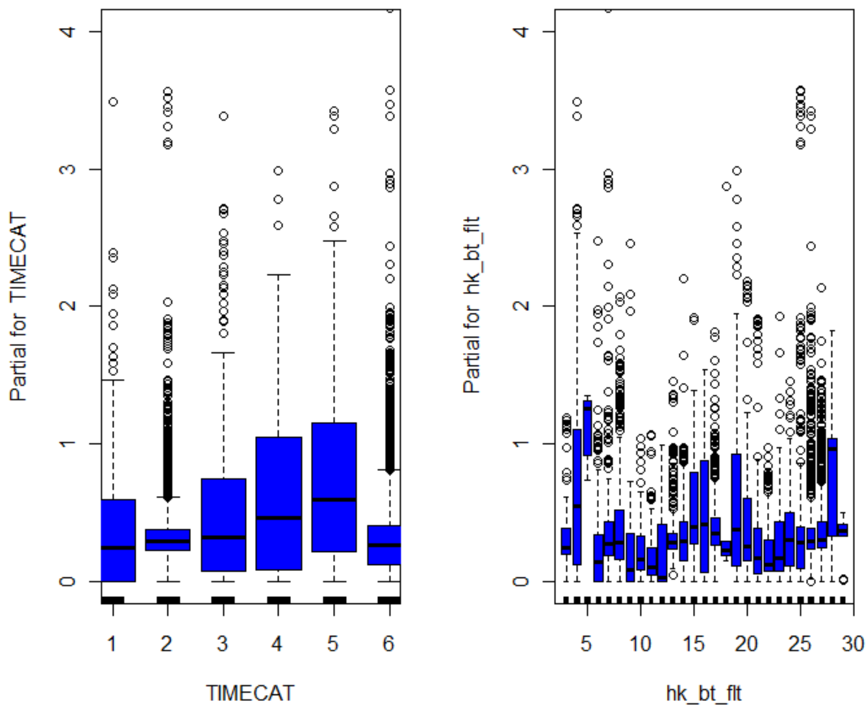

Figure 6. Partial dependence plots for the longline bycatch ZINB standardized model. This plot shows the impact of the main effects on the catch rate of oceanic whitetip in the bycatch longline fishery. Vessel name is omitted due to confidentiality. See table 1 for variable descriptions.

6

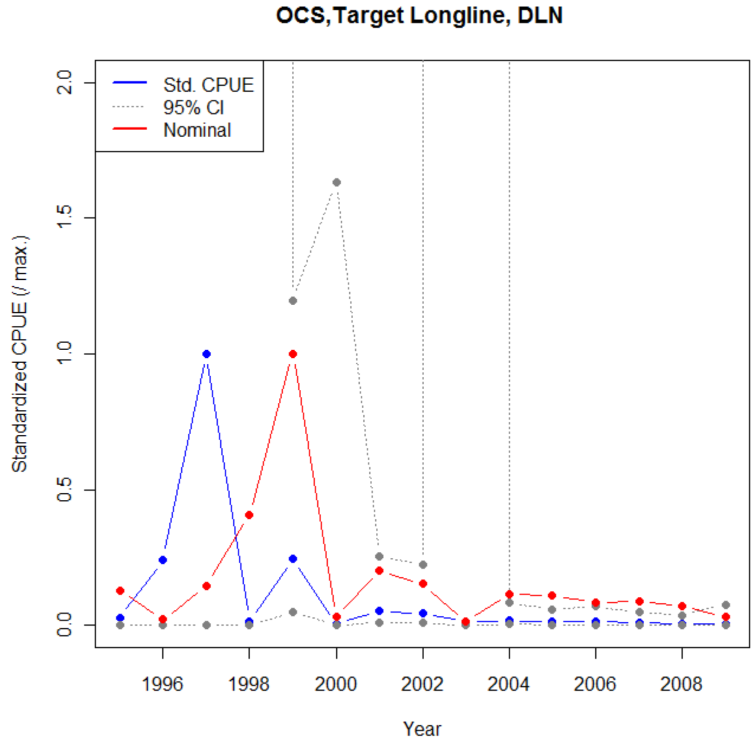

Figure 7. Nominal CPUE and standardized CPUE based on the DLN model for oceanic whitetip sharks caught in the longline target fishery.

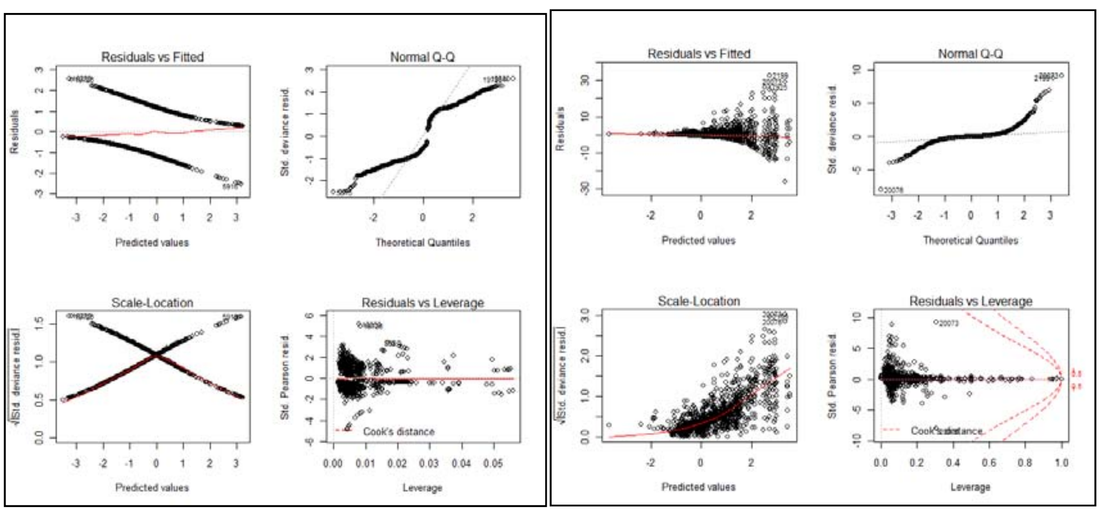

Figure 8. Diagnostic results from the DLN model for oceanic whitetip sharks caught in the longline target fishery. The left hand panel shows the diagnostics from the binomial component of the model; the right hand panel shows the diagnostics from the lognormal component of the model. Standard diagnostics of residuals vs. fitted, deviance residuals vs. fitted, QQ plot and a histogram of the residuals are shown for both components. See table 1 for variable descriptions.

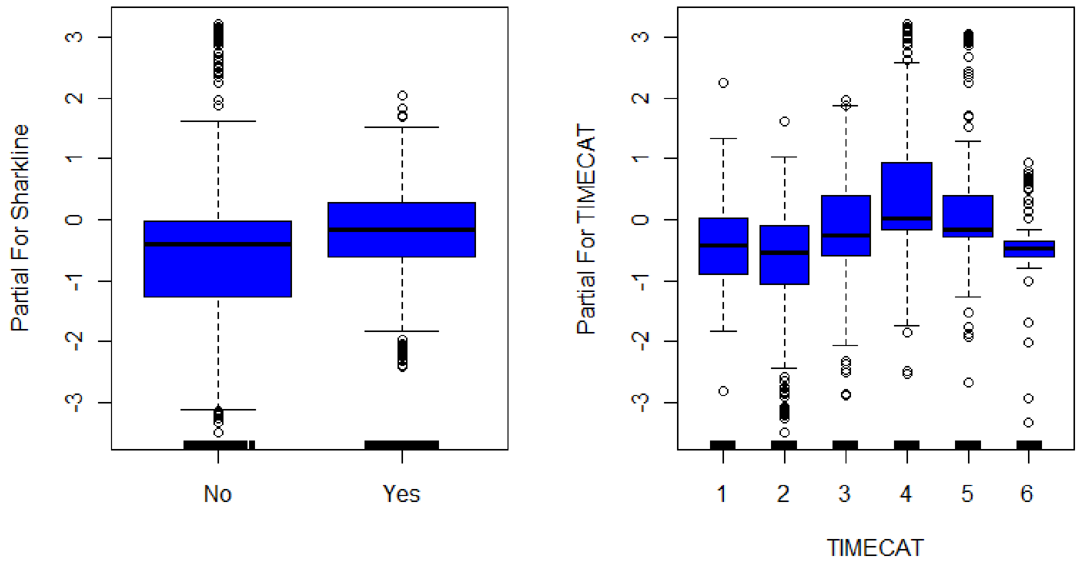

Figure 9. Partial dependence plots for the binomial component of the target longline DLN model. See table 1 for variable descriptions.

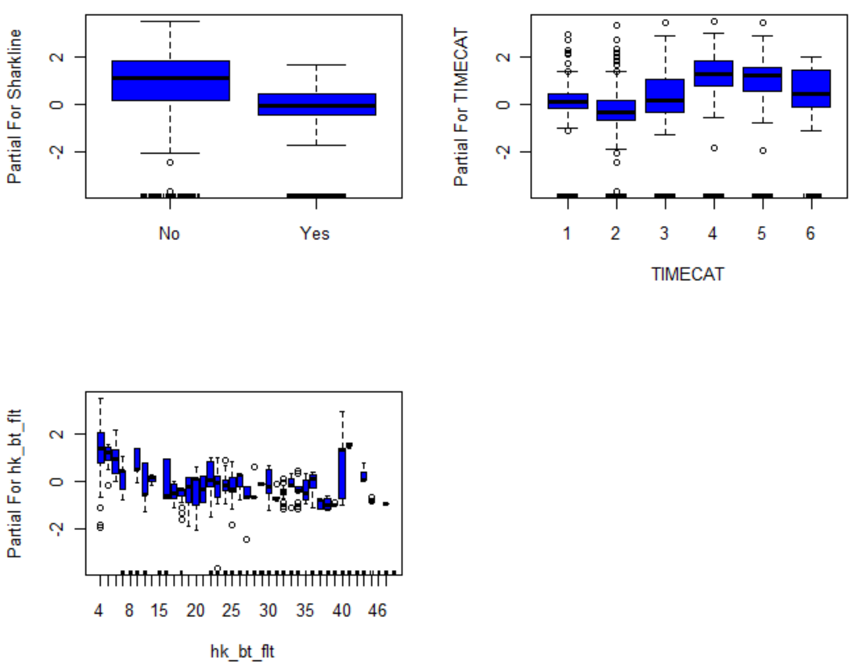

Figure 10. Partial dependence plots for the lognormal component of the target longline DLN model. See table 1 for variable descriptions.

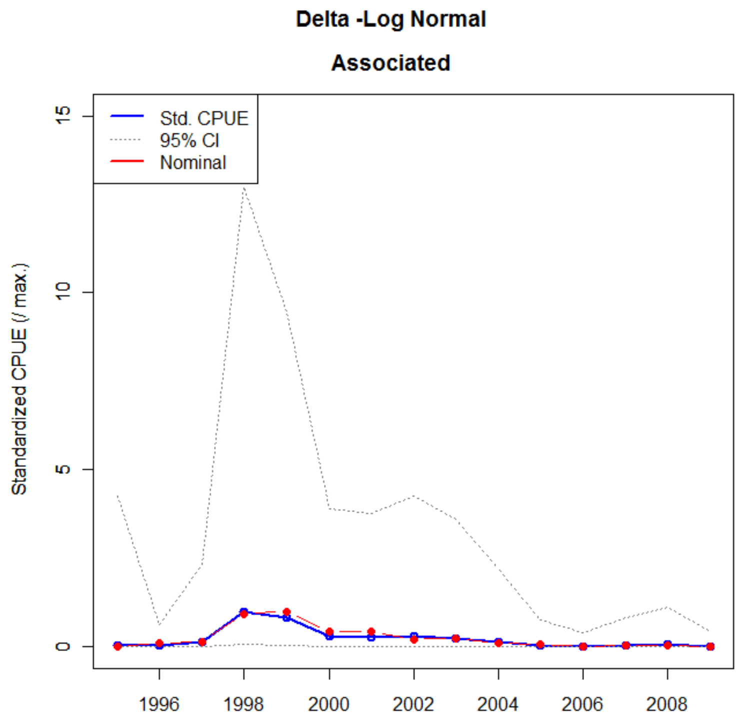

Figure 11. Nominal CPUE and standardized CPUE based on the DLN model for oceanic whitetip sharks caught in associated sets from the purse seine fishery.

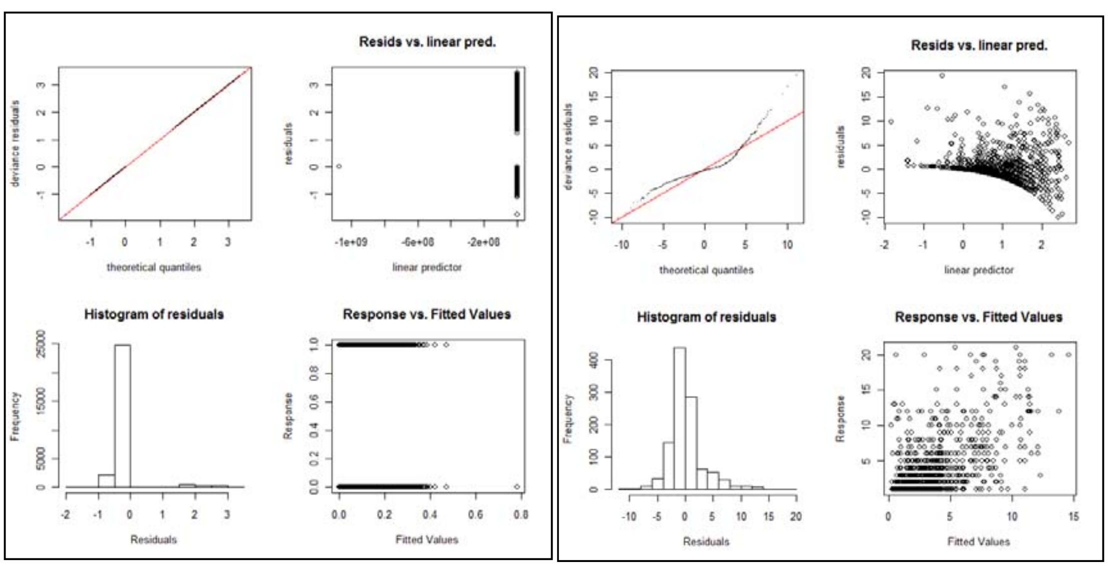

Figure 12. Diagnostic results from the DLN model on oceanic whitetip catches in the associated purse seine fishery, the left hand panel shows the diagnostics from the binomial component of the model; the right hand panel shows the diagnostics from the lognormal component of the model. Standard diagnostics of residuals vs. fitted, deviance residuals vs. fitted, QQ plot and a histogram of the residuals are shown for both components. See table 1 for variable descriptions.

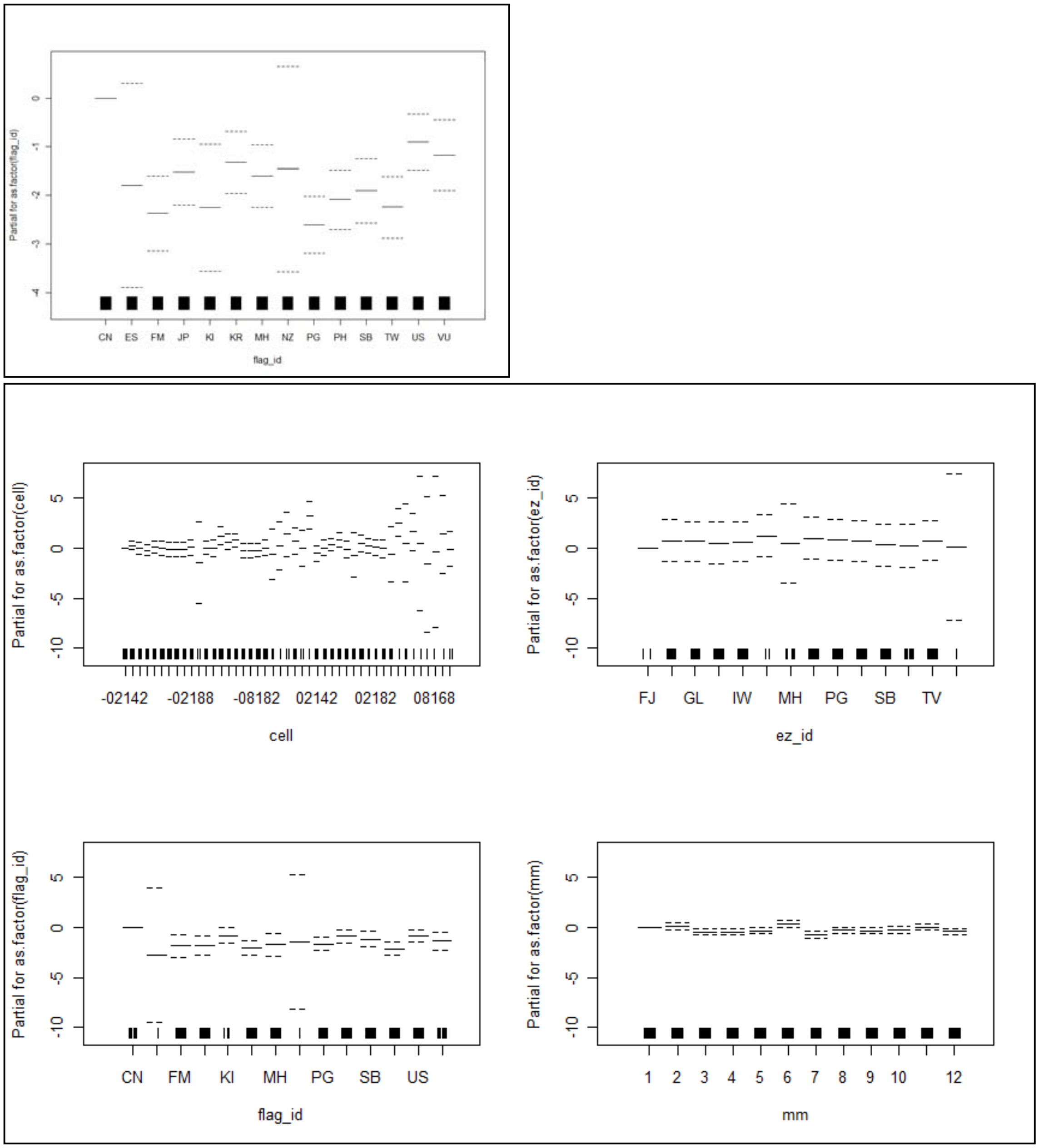

Figure 13. Partial dependence plots for oceanic whitetip sharks caught in purse seine associated sets; the top panel is for the single covariate (apart from year) in the binomial model, and the bottom four panels are from the lognormal model. See table 1 for variable descriptions.

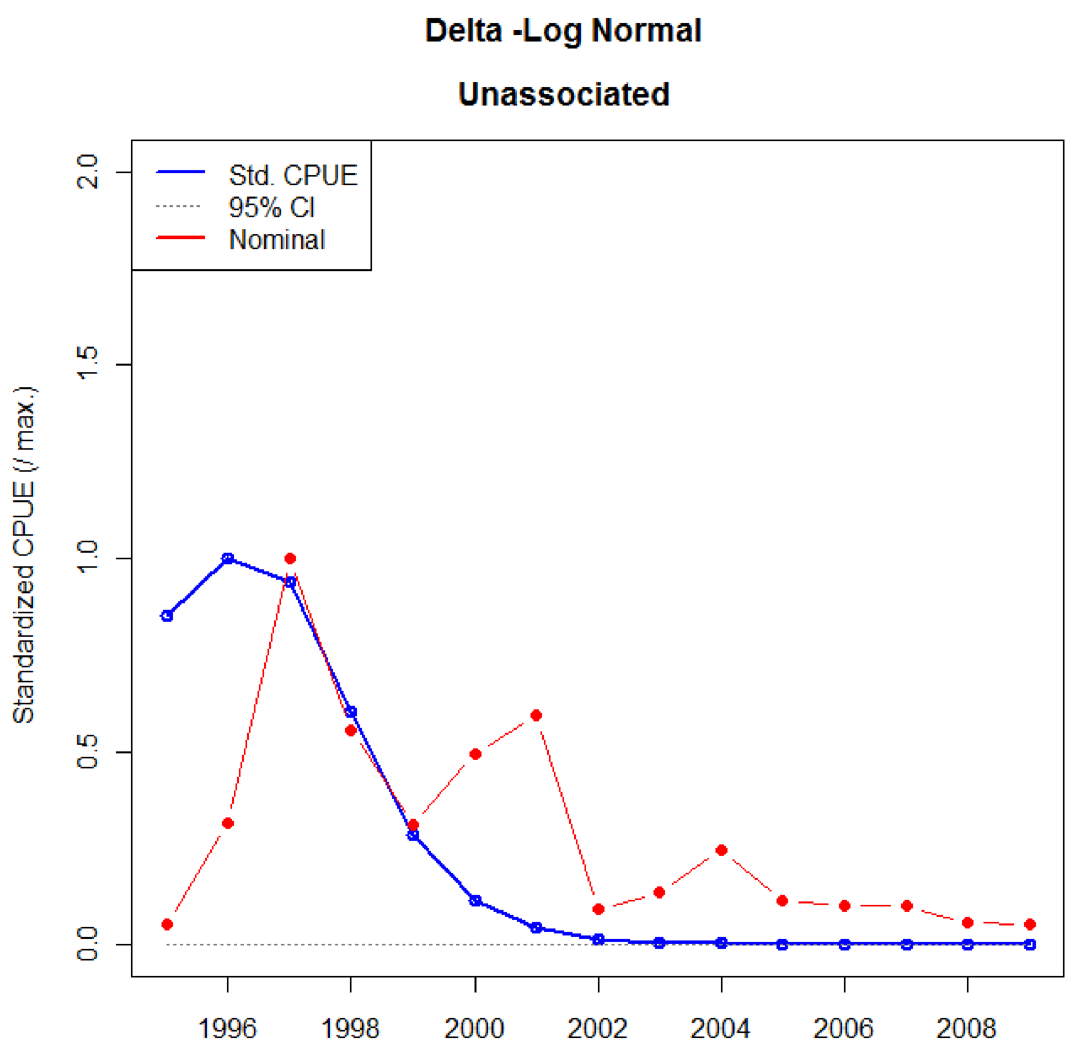

Figure 14. Nominal CPUE and standardized CPUE based on the DLN model for oceanic whitetip sharks caught in unassociated sets from the purse seine fishery. Note that he upper level of the confidence interval is off the scale of the plot.

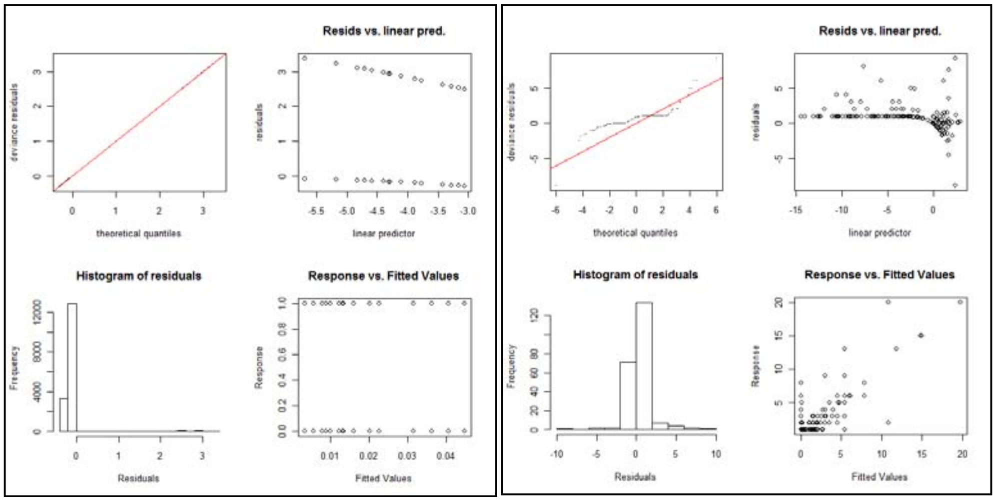

Figure 15. Diagnostic results from the DLN model on oceanic whitetip catches in unassociated sets in the purse seine fishery, the left hand panel shows the diagnostics from the binomial component of the model; the right hand panel shows the diagnostics from the lognormal component of the model. Standard diagnostics of residuals vs. fitted, deviance residuals vs. fitted, QQ plot and a histogram of the residuals are shown for both components. See table 1 for variable descriptions.

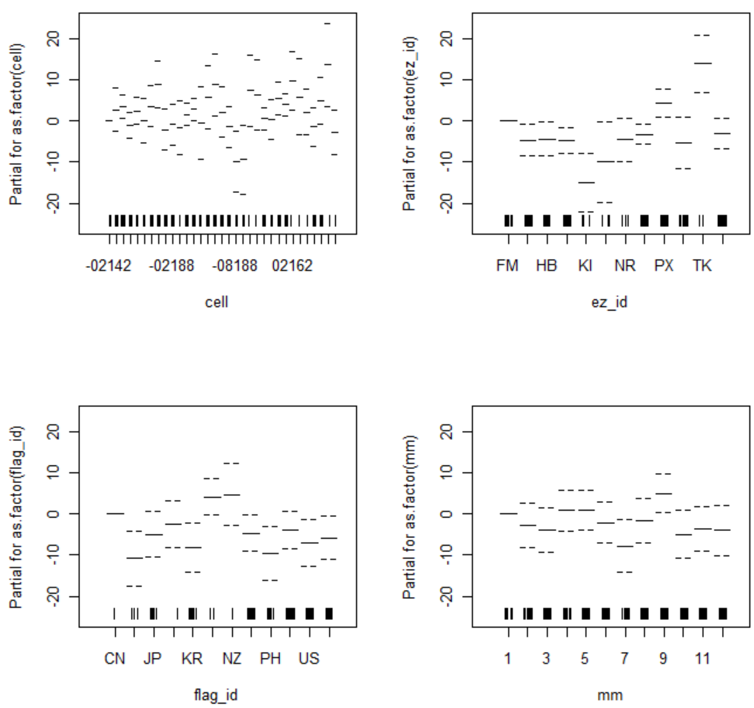

Figure 16. Partial dependence plots for oceanic whitetip sharks caught in purse seine unassociated; the four panels are from the lognormal model (the binomial model only had year effects). See table 1 for variable descriptions.

7 Tables

Table 1. Variables used in the CPUE standardization process

Predictor	Abbreviation	Type	Description
Number of oceanic whitetip sharks caught	owt	Continuous	Number of oceanic whitetip sharks caught per set
Oceanic whitetip shark CPUE	OWTCPUE	Continuous	Set specific catch rate in oceanic whitetip sharks/1000 hooks (Longline Only)
Year	yy	Categorical	1995-2010
Month	mm	Categorical	Month of the year (January- December)
Time category	timecat	Categorical	The sixth of the day that the set happened in, beginning at midnight.
Vessel Name	vesselname	Categorical	The name of the fishing vessel
Trip identification number	trip ID	Categorical	The unique trip identification number
Hooks between floats	hk_bt_flt	Categorical	The number of hooks between floats on the longline ((Longline Only)
Estimated Hooks	hook est	Continuous	The total number of estimated hooks fished (Longline Only)
Shark line	shkline	Categorical (Yes/No)	Were shark lines used (Y/N) (Longline Only)
Shark Bait	Sharkbait	Categorical (Yes/No)	Was shark bait used (Y/N) (Longline Only)
Exclusive Economic Zone	ez_id	Categorical	Which nations EEZ did the set take place
Vessel Flag	flag_id	Categorical	Which nation is the vessel flagged to
Sea Surface temperature	SST	Categorical	Degrees centigrade
5˚x5˚ cell	cell	Categorical	5˚ Latitude by 5˚ Longitude cell.

Table 2. Filtering Rules for the longline dataset

Filtering rules for the Bycatch data sets.

Number of Records	Number removed	Filtering Rule	Number of Oceanic Whitetip Sharks
35307	2467	remove sets marked as targeted sets	8337
34995	312	remove data from Flags w/ less than 100 sets	8201
19093	15902	remove sets with associated temperatures ≤ 25 degrees	6671
13274	5819	remove sets with >30 hooks between floats	4957
12567	707	remove sets with high CPUE where target is 'unidentified'	4841
12542	25	remove sets in 2010	4840

Filtering rules for the Target data sets.

Number of Records	Number removed	Filtering Rule			Number of Oceanic Whitetip Sharks
3775	33999	Keep Shark Bait, shark line or shark target of which			6407
		2467	Marked	*Target*	
		1935	Marked	*Sharkline*	
		1987	Marked	*Sharkbait*	

Table 3. Comparison of the proportion of zeros, mean non-zero catch and the standardized CPUE for oceanic white tips in the longline and purse seine fleets.

Data Source	Bycatch Longline				Target Longline				Associated Purse Seine				Un-Associated Purse Seine			
	% Positive Catch	Mean Annual	Std. Annual	Std. Error	% Positive Catch	Mean Annual	Std. Annual	Std. Error	% Positive Catch	Mean Annual	Std. Annual	Std. Error	% Positive Catch	Mean Annual	Std. Annual	Std. Error
1995	38.60	0.64	3.76	0.00	63.16	1.71	0.72	3E+05	1.53	0.02	0.05	2.18	0.61	0.01	4E-08	2E-04
1996	36.63	0.58	3.27	0.74	16.67	0.12	6.59	6E+19	2.30	0.11	0.03	0.30	1.45	0.04	5E-08	2E-04
1997	30.33	0.44	4.70	1.08	51.72	1.58	27.28	4E+20	3.98	0.30	0.15	1.13	1.54	0.22	5E-08	2E-04
1998	37.77	0.46	3.90	0.87	64.50	4.27	0.43	2E+05	10.87	1.02	1.02	6.21	3.62	0.07	3E-08	1E-04
1999	36.20	0.46	4.40	1.15	91.91	10.99	6.72	13.24	19.32	0.88	0.83	4.48	0.58	0.05	1E-08	6E-05
2000	33.09	0.44	2.49	0.54	14.06	0.26	0.19	22.63	17.21	0.35	0.32	1.86	0.97	0.04	6E-09	3E-05
2001	28.14	0.26	1.82	0.44	48.09	3.50	1.41	2.84	12.04	0.38	0.28	1.81	0.50	0.01	2E-09	1E-05
2002	18.63	0.14	1.32	0.27	36.66	1.33	1.22	2.48	4.45	0.32	0.30	2.06	1.06	0.03	8E-10	6E-06
2003	15.53	0.11	0.92	0.20	6.41	0.09	0.34	1E+08	4.26	0.22	0.25	1.74	0.39	0.01	3E-10	3E-06
2004	21.03	0.21	1.03	0.22	46.50	1.14	0.46	0.93	3.03	0.08	0.15	1.06	0.31	0.02	2E-10	2E-06
2005	17.80	0.16	0.36	0.14	52.63	1.07	0.34	0.65	1.81	0.06	0.04	0.37	0.63	0.02	8E-11	1E-06
2006	19.94	0.17	0.19	0.08	46.06	0.68	0.39	0.77	0.72	0.01	0.02	0.20	0.25	0.01	4E-11	6E-07
2007	16.48	0.15	0.49	0.20	52.94	0.75	0.26	0.53	1.48	0.03	0.04	0.40	0.56	0.01	1E-11	3E-07
2008	15.48	0.13	0.29	0.17	46.06	1.03	0.18	0.44	2.09	0.04	0.06	0.55	0.45	0.01	6E-12	1E-07
2009	12.02	0.09	0.44	0.60	42.86	0.28	0.15	0.96	0.39	0.01	0.01	0.21	0.30	0.01	2E-12	6E-08

Table 4. Model comparison for CPUE standardization using the zero inflated negative binomial model on oceanic whitetip shark bycatch in the longline fleet. Due to the mixture model the intercept only model is taken as the null model.

Predictor	Offset	Df	Deviance Explained	Resid. DF	Resid. Dev	P(>|Chi|)
intercept only	log(Hook_Est)	3		12539	20446.6	
~yy	log(Hook_Est)	31	952	12511	19494.6	<2.20E-16
~yy+TIMECAT	log(Hook_Est)	41	-74.6	12511	19569.2	5.45E-12
~yy+TIMECAT|YY	log(Hook_Est)	36	-23.4	12501	19592.6	3.09E-04
~yy+TIMECAT+ vesselname | yy	log(Hook_Est)	426	2035.2	12506	17557.4	<2.20E-16
~ yy + TIMECAT + vesselname | yy + hk_bt_flt	log(Hook_Est)	452	124.8	12116	17432.6	7.23E-15

Table 5. Model comparison for CPUE standardization using the binomial model on oceanic whitetip shark target CPUE in the longline fleet.

Binomial moddel

Predictor	Df	Deviance Explained	Resid. DF	Resid. Dev	P(>|Chi|)
NULL			3640	5420.6	
+ yy	15	594.57	3625	4826.1	< 2.2e-16
+TIMECAT	5	168.44	3620	4657.6	< 2.2e-16
+SHKLINE	1	86.02	3619	4571.6	< 2.2e-16

Lognormal

Predictor	Df	Deviance Explained	Resid. DF	Resid. Dev	P(>|Chi|)
NULL			1567	55610	
+ yy	15	14939	1552	40671	< 2.2e-16
+ hk_bt_flt	35	7278	1517	33393	0.09576
+ vesselnames	146	12496	1371	20898	< 2.2e-16
+TIMECAT	5	715	1366	20183	5.475e-09
+SHKLINE	1	40.4	1365	20142	0.098

Table 6. Model comparison for CPUE standardization using the DLN model on oceanic whitetip shark target CPUE in the associated purse seine fleet.

Binomial Model

	Df	Deviance Explained	Resid. DF	Resid. Dev	P(>|Chi|)
Intercept only			28055	9262.658	
+yy	10	1217.09	28045.1401	8045.568	<2.20E-16
+ flag_id	22	383.273	28033	7662.295	<2.20E-16

Lognormal Model

	Df	Deviance Explained	Resid. DF	Resid. Dev	P(>|Chi|)
Intercept only			1096	6133	
+yy	10	189.0	1086	5944	<2.02E-16
+cell	54	57.8	1042	5886	0.08142
+ez_id	67	27.0	1029	5859	0.01189
+flag_id	80	108.8	1016	5750	<2.02E-16
+mm	91	88.4	1005	5662	3.41E-14

Table 7. Model comparison for CPUE standardization using the DLN model on oceanic whitetip shark target CPUE in the unassociated purse seine fleet.

Binomial Model

	Df	Deviance Explained	Resid. DF	Resid. Dev	P(>|Chi|)
Intercept only			16407	2368.6	
+yy	6	134.4	16401	2234.2	<2.20E-16

Lognormal Model

	Df	Deviance Explained	Resid. DF	Resid. Dev	P(>|Chi|)
Intercept only			223	1093.8	
+yy	3	1.78	220	1092.02	0.1836
+cell	43	81.02	180	1011	0.0001333
+ez_id	54	44.98	169	966.02	4.88E-06
+flag_id	61	10.54	162	955.48	0.1603
+mm	68	65.88	155	889.6	1.00E-11

8 References

Bigelow K. A., Hampton J., & Miyabe N. (2002) Application of a habitat-based model to estimate effective longline fishing effort and relative abundance of Pacific bigeye tuna (*Thunnus obesus*). Fisheries Oceanography 11: 143-155.

Clarke, S. Harley, S. Hoyle and J. Rice (2011) An Indicator-based Analysis of Key Shark Species based on Data held by SPC-OFP . http://www.wcpfc.int/doc/eb-wp-01/indicator-based-analysis-key-shark-species-based-data-held-spc-ofp

Clarke, S., Yokawa, K. Matsunaga, H., Nakano, H. (2011b) Analysis of North Pacific Shark Data from Japanese Commercial Longline and Research/Training Vessel Records. WCPFC-SC7-EB-WP-04. Accessed online at http://www.wcpfc.int/doc/eb-wp-02/analysis-north-pacific-shark-data-japanese-commercial-longline-and-researchtraining-ves

Campbell R. A. (2004) CPUE standardisation and the construction of indices of stock abundance in a spatially varying fishery using general linear models. Fisheries Research 70: 209-227.

Cunningham, R.B., Lindenmayer, D.B. (2005). Modeling count data of rare species: some statistical issues. Ecology 86, 1135–1142.

De'ath G. & Fabricius K. E. (2000) Classification and regression trees: a powerful yet simple technique for ecological data analysis. Ecology 81: 3178-3192.

Dick E. J. Delta_glm. [1.7.2]. (2006) Santa Cruz, CA, USA, NOAA.

GODAS (2011) Data provided by the NOAA-ESRL Physical Sciences Division, Boulder Colorado from their Web site at http://www.esrl.noaa.gov/psd/, data accessed November 2011.

Hoyle S. D. & Maunder M. N. (2006) Standardisation of yellowfin and bigeye CPUE data from Japanese longliners, 1975-2004. IATTC Working Group on Stock Assessments. 6th Meeting, SAR-7-07.http://www.iattc.org/PDFFiles2/SAR-7-07-LL-CPUE-standardization.pdf . 2006.

Lawless, J.F. (1987) Negative binomial and mixed Poisson regression. Can. J. Stat. 15, 209–225.

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

Maunder, M.N., Punt, A.E. (2004) Standardizing catch and effort data: a review of recent approaches. Fish.Res. 70, 141 -159.

McCullagh P. & Nelder J. A. (1989) Generalized Linear Models. Chapman & Hall.

Minami, M. Lennert-Cody, C.E., Gao, W. , Román-Verdesoto, M. (2007) Modeling shark bycatch: the zero-inflated negative binomial regression model with smoothing. Fisheries Research 84: 210-221.

Ortiz, M., Arocha, F. (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. Fish. Res. 70, 275–297.

Pennington, M. (1996) Estimating the mean and variance from highly skewed marine data. Fish. Bull. 94, 498–505

Punsly R. (1987) Estimation of the relative annual abundance of yellowfin tuna, Thunnus albacares , in the eastern Pacific Ocean during 1970-1985. I-ATTC, LA JOLLA, CA.

Rice, J. (2012) Alternative catch time series for oceanic whitetip and silky sharks in the Western and Central Pacific Ocean. WCPFC-SC8-SA-IP-12.

Rice, J., and Harley, S. J. (2012). Stock assessment of oceanic whitetip sharks in the Western and Central Pacific Ocean. WCPFC-SC8-SA-WP-06.

Shono H. (2008) Confidence interval estimation of CPUE year trend in delta-type two-step model. Fisheries Science 74: 712-717.

Stefansson G. (1996) Analysis of groundfish survey abundance data: Combining the GLM and delta approaches. Ices Journal of Marine Science 53: 577-588.

Walsh, W. A., and S. C. Clarke. (2011) Analyses of catch data for oceanic whitetip and silky sharks reported by fishery observers in the Hawaii-based longline fishery in 1995−2010. Pacific Islands Fish. Sci. Cent., Natl. Mar. Fish. Serv., NOAA, Honolulu, HI 96822-2396. Pacific Islands Fish. Sci. Cent. Admin. Rep. H-11-10, 43 p. + Appendices.

Ward, P., Myers, R.A., (2005), Shifts in open –ocean fish communities coinciding with the commencement of commercial fishing. Ecology 86, 835-847.

Welsh, A.H., Cunningham, R.B., Chambers, R.L., 2000. Methodology for estimating the abundance of rare animals: seabird nesting on North East Herald Cay. Biometrics 56, 22–30.

Zuur, A.., Ieno, E.N., Walker, N.J., Saveliev, A.A., Smith, Graham, M.S. (2009) Mixed effects models and extensions in ecology with R. Springer, NY, NY.

9 Appendix 1 Summaries of the individual models.

Some estimates, e.g. vesselname, and area have been excluded due to either confidentially or space reasons.

Summary of the LL ZINB

```
Call:
zeroinfl(formula = owt ~ yy + TIMECAT + vesselname | yy + hk_bt_flt, data = DataFile, offset = log(hook_est), dist = "negbin")

Pearson residuals:
   Min     1Q  Median     3Q    Max
-1.0192076 -0.4245529 -0.3430724 -0.0001116 12.5448738

Count model coefficients (negbin with log link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   -5.709e+00 3.172e-01 -18.000 < 2e-16 ***
yy1996        4.029e-01 1.880e-01  2.143 0.032120 *
yy1997        3.108e-01 1.891e-01  1.644 0.100209
yy1998        3.917e-01 1.858e-01  2.108 0.035055 *
yy1999        3.928e-01 2.117e-01  1.856 0.063492 .
yy2000        -5.507e-02 1.813e-01 -0.304 0.761330
yy2001        -3.086e-01 1.973e-01 -1.564 0.117818
yy2002        -3.299e-01 1.730e-01 -1.907 0.056462 .
yy2003        -6.312e-01 1.841e-01 -3.429 0.000606 ***
yy2004        -8.126e-01 1.785e-01 -4.553 5.28e-06 ***
yy2005        -1.887e+00 2.931e-01 -6.439 1.20e-10 ***
yy2006        -2.433e+00 3.056e-01 -7.961 1.70e-15 ***
yy2007        -1.676e+00 2.959e-01 -5.665 1.47e-08 ***
yy2008        -2.087e+00 3.794e-01 -5.500 3.79e-08 ***
yy2009        -3.661e-01 6.624e-01 -0.553 0.580474
TIMECAT2      -5.569e-01 8.806e-02 -6.324 2.55e-10 ***
TIMECAT3      -5.607e-01 9.822e-02 -5.709 1.14e-08 ***
TIMECAT4      -3.682e-01 1.862e-01 -1.978 0.047943 *
TIMECAT5      -3.969e-01 1.379e-01 -2.879 0.003984 **
TIMECAT6      -2.024e-01 1.510e-01 -1.340 0.180332
Log(theta)    5.607e-01 1.102e-01  5.088 3.62e-07 ***

Zero-inflation model coefficients (binomial with logit link):
      Estimate Std. Error z value Pr(>|z|)
(Intercept) -6.418e+00 2.469e+04  0.000  0.9998
yy1996    5.736e-01 5.099e-01  1.125  0.2607
yy1997   -1.473e+01 9.919e+02 -0.015  0.9881
yy1998   -3.311e-02 5.452e-01 -0.061  0.9516
yy1999   -1.085e+00 1.052e+00 -1.031  0.3025
yy2000    5.571e-03 5.139e-01  0.011  0.9914
yy2001    1.189e-01 5.441e-01  0.219  0.8270
yy2002    1.058e+00 4.487e-01  2.359  0.0183 *
yy2003    1.133e+00 4.688e-01  2.418  0.0156 *
yy2004    4.627e-01 4.766e-01  0.971  0.3317
yy2005   -6.028e-01 8.472e-01 -0.711  0.4768
yy2006   -3.168e-01 7.784e-01 -0.407  0.6840
yy2007   -1.696e+00 2.071e+00 -0.819  0.4128
yy2008   -1.508e+01 1.425e+03 -0.011  0.9916
yy2009    1.243e+00 6.702e-01  1.855  0.0637 .
hk_bt_flt4 -9.520e+00 2.471e+04  0.000  0.9997
hk_bt_flt5 -1.405e+01 2.491e+04 -0.001  0.9996
hk_bt_flt6  6.275e+00 2.469e+04  0.000  0.9998
hk_bt_flt7 -1.355e+01 2.532e+04 -0.001  0.9996
```

```
hk_bt_flt8  5.020e+00 2.469e+04  0.000  0.9998
hk_bt_flt9 -1.005e+01 2.472e+04  0.000  0.9997
hk_bt_flt10 5.905e+00 2.469e+04  0.000  0.9998
hk_bt_flt11 -1.615e+01 3.242e+04  0.000  0.9996
hk_bt_flt12 6.425e+00 2.469e+04  0.000  0.9998
hk_bt_flt13 7.731e+00 2.469e+04  0.000  0.9998
hk_bt_flt14 -1.431e+01 2.535e+04 -0.001  0.9995
hk_bt_flt15 4.032e+00 2.469e+04  0.000  0.9999
hk_bt_flt16 3.673e+00 2.469e+04  0.000  0.9999
hk_bt_flt17 5.333e+00 2.469e+04  0.000  0.9998
hk_bt_flt18 4.693e+00 2.469e+04  0.000  0.9998
hk_bt_flt19 5.518e+00 2.469e+04  0.000  0.9998
hk_bt_flt20 5.334e+00 2.469e+04  0.000  0.9998
hk_bt_flt21 5.278e+00 2.469e+04  0.000  0.9998
hk_bt_flt22 4.867e+00 2.469e+04  0.000  0.9998
hk_bt_flt23 5.309e+00 2.469e+04  0.000  0.9998
hk_bt_flt24 5.325e+00 2.469e+04  0.000  0.9998
hk_bt_flt25 5.386e+00 2.469e+04  0.000  0.9998
hk_bt_flt26 5.296e+00 2.469e+04  0.000  0.9998
hk_bt_flt27 5.650e+00 2.469e+04  0.000  0.9998
hk_bt_flt28 5.647e+00 2.469e+04  0.000  0.9998
hk_bt_flt29 6.282e+00 2.469e+04  0.000  0.9998
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Theta = 1.7518
Number of iterations in BFGS optimization: 150
Log-likelihood: -8716 on 452 Df
>
```

SUMMARY OF THE DLN LL TARGET CPUE STNADAEDIZATION

```
summary(BinMod)

Call:
glm(formula = presabs ~ as.factor(yy) + as.factor(TIMECAT) +
  as.factor(SHKLINE), family = binomial, data = DataFile, offset = log(hook_est))

Deviance Residuals:
  Min   1Q Median   3Q   Max
-2.527 -1.036 -0.528  1.183  2.568

Coefficients:
         Estimate Std. Error z value Pr(>|z|)
(Intercept)     -7.41350  0.51355 -14.436 < 2e-16 ***
as.factor(yy)1996  -1.70612  0.70051 -2.436 0.014870 *
as.factor(yy)1997  -0.25952  0.60979 -0.426 0.670404
as.factor(yy)1998  0.32892  0.51705  0.636 0.524677
as.factor(yy)1999  1.94599  0.58077  3.351 0.000806 ***
as.factor(yy)2000  -2.15296  0.60399 -3.565 0.000364 ***
as.factor(yy)2001  -0.86860  0.50540 -1.719 0.085676 .
as.factor(yy)2002  -0.89171  0.49890 -1.787 0.073881 .
as.factor(yy)2003  -3.37206  0.67222 -5.016 5.27e-07 ***
as.factor(yy)2004  -0.74251  0.49745 -1.493 0.135538
as.factor(yy)2005  -0.90557  0.49731 -1.821 0.068613 .
as.factor(yy)2006  -1.33656  0.49994 -2.673 0.007508 **
as.factor(yy)2007  -1.07452  0.50275 -2.137 0.032573 *
as.factor(yy)2008  -2.06686  0.50704 -4.076 4.58e-05 ***
as.factor(yy)2009  -2.08998  0.51657 -4.046 5.21e-05 ***
as.factor(yy)2010  -3.27108  0.68678 -4.763 1.91e-06 ***
```

```
as.factor(TIMECAT)2 -0.30501  0.16707 -1.826 0.067909 .
as.factor(TIMECAT)3 0.06872  0.19218  0.358 0.720649
as.factor(TIMECAT)4 1.30628  0.18214  7.172 7.39e-13 ***
as.factor(TIMECAT)5 1.12684  0.19284  5.843 5.12e-09 ***
as.factor(TIMECAT)6 0.87238  0.26901  3.243 0.001183 **
as.factor(SHKLINE)1 1.05577  0.11758  8.979 < 2e-16 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

  Null deviance: 5420.6 on 3640 degrees of freedom
Residual deviance: 4571.6 on 3619 degrees of freedom
AIC: 4615.6

Number of Fisher Scoring iterations: 5

> summary(PosMod)

Call:
glm(formula = OWTCPUE ~ as.factor(yy) + as.factor(hk_bt_flt) +
  as.factor(vesselname) + as.factor(TIMECAT) + as.factor(SHKLINE),
  family = gaussian(link = "log"), data = PosDat)

Deviance Residuals:
  Min    1Q  Median    3Q   Max
-25.736  -0.718  -0.070  0.413  32.695

Coefficients: (6 not defined because of singularities)
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)             -1.926833 21.279894 -0.091 0.927866
as.factor(yy)1996           2.965346 21.501264  0.138 0.890328
as.factor(yy)1997           3.708936 21.928841  0.169 0.865715
as.factor(yy)1998           -0.586321  0.793797 -0.739 0.460260
as.factor(yy)1999           2.000755  7.596187  0.263 0.792290
as.factor(yy)2000           -0.298614  7.097902 -0.042 0.966448
as.factor(yy)2001           0.971004  7.604112  0.128 0.898410
as.factor(yy)2002           0.831436  7.606264  0.109 0.912973
as.factor(yy)2003           1.330473 13.548978  0.098 0.921790
as.factor(yy)2004           -0.194411  7.606024 -0.026 0.979612
as.factor(yy)2005           -0.447568  7.604119 -0.059 0.953073
as.factor(yy)2006           -0.082648  7.603161 -0.011 0.991329
as.factor(yy)2007           -0.626321  7.602386 -0.082 0.934353
as.factor(yy)2008           -0.406316  7.606454 -0.053 0.957407
as.factor(yy)2009           -0.570278  7.666859 -0.074 0.940717
as.factor(yy)2010           -0.664274 11.099929 -0.060 0.952288
as.factor(hk_bt_flt)5         4.230144 21.276091  0.199 0.842432
as.factor(hk_bt_flt)6         0.407576  5.297786  0.077 0.938688
as.factor(hk_bt_flt)7         0.294786 22.284572  0.013 0.989448
as.factor(hk_bt_flt)9         0.990241 22.651225  0.044 0.965136
as.factor(hk_bt_flt)10         1.503327 21.362710  0.070 0.943908
as.factor(hk_bt_flt)12         2.687200 22.655499  0.119 0.905601
as.factor(hk_bt_flt)16         1.925540 21.167994  0.091 0.927534
as.factor(hk_bt_flt)17         1.520796 21.348565  0.071 0.943220
as.factor(hk_bt_flt)18         2.481328 22.027212  0.113 0.910326
as.factor(hk_bt_flt)19         1.662830 21.370712  0.078 0.937992
as.factor(hk_bt_flt)20         0.980023 21.069542  0.047 0.962908
as.factor(hk_bt_flt)21         1.992182 21.240333  0.094 0.925288
as.factor(hk_bt_flt)22         1.169974 20.961042  0.056 0.955496
as.factor(hk_bt_flt)23         1.141863 20.981585  0.054 0.956607
as.factor(hk_bt_flt)24         0.735770 20.971260  0.035 0.972017
as.factor(hk_bt_flt)25         0.511126 20.970973  0.024 0.980559
```

```
as.factor(hk_bt_flt)26         0.127071 20.997823  0.006 0.995172
as.factor(hk_bt_flt)27         0.156340 20.876516  0.007 0.994026
as.factor(hk_bt_flt)28         0.913883 20.983710  0.044 0.965268
as.factor(hk_bt_flt)29         1.968703 21.074408  0.093 0.925586
as.factor(hk_bt_flt)30         1.383963 20.439128  0.068 0.946025
as.factor(hk_bt_flt)31         0.022076 21.067456  0.001 0.999164
as.factor(hk_bt_flt)32         0.212897 20.928357  0.010 0.991885
as.factor(hk_bt_flt)33         0.479589 20.870120  0.023 0.981670
as.factor(hk_bt_flt)34         0.521519 21.060595  0.025 0.980248
as.factor(hk_bt_flt)35        -0.363533 21.109758 -0.017 0.986263
as.factor(hk_bt_flt)36         0.598737 20.342956  0.029 0.976524
as.factor(hk_bt_flt)37        -0.352140 21.613028 -0.016 0.987003
as.factor(hk_bt_flt)38        -0.309560 14.207224 -0.022 0.982620
as.factor(hk_bt_flt)39         1.416553 22.875312  0.062 0.950632
as.factor(hk_bt_flt)40         0.037187  0.146798  0.253 0.800060
as.factor(hk_bt_flt)41        -0.946236  0.281049 -3.367 0.000782 ***
as.factor(hk_bt_flt)44        -1.642029  1.391269 -1.180 0.238111
as.factor(hk_bt_flt)45         2.609403 24.208147  0.108 0.914178
as.factor(hk_bt_flt)50         2.504042 24.567414  0.102 0.918831
as.factor(TIMECAT)2           -0.923223  0.156984 -5.881 5.12e-09 ***
as.factor(TIMECAT)3           -0.815370  0.148293 -5.498 4.57e-08 ***
as.factor(TIMECAT)4           -0.737861  0.142433 -5.180 2.55e-07 ***
as.factor(TIMECAT)5           -0.814360  0.142909 -5.698 1.48e-08 ***
as.factor(TIMECAT)6           -1.273627  0.243163 -5.238 1.88e-07 ***
as.factor(SHKLINE)1           0.529298  0.307006  1.724 0.084923 .
---
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 14.75657)

  Null deviance: 55610 on 1567 degrees of freedom
Residual deviance: 20142 on 1365 degrees of freedom
AIC: 8860.9

Number of Fisher Scoring iterations: 14
```

PURSE SEINE ASSOCIATED CPUE STANDARDIZATION

Binomial Model

```
Family: binomial
Link function: logit

Formula:
pos ~ s(yy) + as.factor(flag_id)

Parametric coefficients:
        Estimate Std. Error z value Pr(>|z|)
(Intercept)      -1.9860   0.2787 -7.125 1.04e-12 ***
as.factor(flag_id)ES -1.7950   1.0535 -1.704 0.088393 .
as.factor(flag_id)FM -2.3748   0.3856 -6.158 7.37e-10 ***
as.factor(flag_id)JP -1.5174   0.3409 -4.451 8.56e-06 ***
as.factor(flag_id)KI -2.2492   0.6525 -3.447 0.000566 ***
as.factor(flag_id)KR -1.3183   0.3196 -4.125 3.70e-05 ***
as.factor(flag_id)MH -1.6015   0.3227 -4.963 6.94e-07 ***
as.factor(flag_id)NZ -1.4589   1.0558 -1.382 0.167035
as.factor(flag_id)PG -2.6076   0.2950 -8.838 < 2e-16 ***
as.factor(flag_id)PH -2.0843   0.3046 -6.843 7.78e-12 ***
as.factor(flag_id)SB -1.9056   0.3285 -5.800 6.62e-09 ***
```

```
as.factor(flag_id)TW -2.2439   0.3170 -7.079 1.45e-12 ***
as.factor(flag_id)US -0.9018   0.2892 -3.118 0.001820 **
as.factor(flag_id)VU -1.1753   0.3607 -3.259 0.001119 **
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
   edf Ref.df Chi.sq p-value
s(yy) 8.842 8.992 543.9 <2e-16 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.0839  Deviance explained = 17.3%
UBRE score = -0.72526 Scale est. = 1     n = 28056
```

Lognormal Model

```
Formula:
owt ~ s(yy) + as.factor(cell) + as.factor(ez_id) + as.factor(flag_id) +
  as.factor(mm)

Parametric coefficients:
        Estimate Std. Error t value Pr(>|t|)
(Intercept)      0.77288  2.18520  0.354 0.723632
as.factor(ez_id)FM   1.56753  2.12431  0.738 0.460714
as.factor(ez_id)GL   0.71260  2.09896  0.340 0.734290
as.factor(ez_id)HB   0.16409  2.13588  0.077 0.938775
as.factor(ez_id)IW   1.26567  2.09702  0.604 0.546247
as.factor(ez_id)KI   0.65470  2.12240  0.308 0.757774
as.factor(ez_id)MH   0.10944  3.93426  0.028 0.977812
as.factor(ez_id)NR   1.55340  2.15549  0.721 0.471246
as.factor(ez_id)PG   1.92616  2.12564  0.906 0.365027
as.factor(ez_id)PX   0.86694  2.09836  0.413 0.679567
as.factor(ez_id)SB   1.46663  2.12001  0.692 0.489188
as.factor(ez_id)TK   0.44850  2.18140  0.206 0.837134
as.factor(ez_id)TV   0.87107  2.09177  0.416 0.677167
as.factor(ez_id)WF   0.81210  5.83299  0.139 0.889294
as.factor(flag_id)ES -1.72714  5.27088 -0.328 0.743212
as.factor(flag_id)FM -2.17013  0.92356 -2.350 0.018941 *
as.factor(flag_id)JP -1.45605  0.59538 -2.446 0.014598 *
as.factor(flag_id)KI -0.34996  0.55428 -0.631 0.527911
as.factor(flag_id)KR -2.29438  0.52452 -4.374 1.32e-05 ***
as.factor(flag_id)MH -1.08113  0.79712 -1.356 0.175247
as.factor(flag_id)NZ -1.18497  3.84529 -0.308 0.758010
as.factor(flag_id)PG -1.58544  0.41940 -3.780 0.000164 ***
as.factor(flag_id)PH -1.33894  0.42964 -3.116 0.001872 **
as.factor(flag_id)SB -0.32627  0.50068 -0.652 0.514748
as.factor(flag_id)TW -1.28915  0.41472 -3.108 0.001923 **
as.factor(flag_id)US -0.62715  0.40836 -1.536 0.124843
as.factor(flag_id)VU -1.41461  0.62418 -2.266 0.023598 *
as.factor(mm)2    -0.12173  0.23626 -0.515 0.606462
as.factor(mm)3    -0.47795  0.23453 -2.038 0.041773 *
as.factor(mm)4    -0.37962  0.22565 -1.682 0.092753 .
as.factor(mm)5    -0.20647  0.22215 -0.929 0.352858
as.factor(mm)6     0.13333  0.23801  0.560 0.575461
as.factor(mm)7    -0.90471  0.27057 -3.344 0.000851 ***
as.factor(mm)8    -0.61001  0.24441 -2.496 0.012694 *
as.factor(mm)9    -0.12216  0.22249 -0.549 0.583065
as.factor(mm)10    0.18879  0.21687  0.871 0.384186
as.factor(mm)11    0.11060  0.21378  0.517 0.605014
as.factor(mm)12    -0.26792  0.23375 -1.146 0.251926
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Approximate significance of smooth terms:
edf Ref.df F p-value
s(yy) 7.176 8.161 12.3 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.21 Deviance explained = 26.1%
GCV score = 29.344 Scale est. = 27.382 n = 1349

Purse Seine -Unassociated Sets

Binomial model

Family: binomial
Link function: logit

Formula:
pos ~ s(yy)

Parametric coefficients:
Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.55935 0.08679 -52.54 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
edf Ref.df Chi.sq p-value
s(yy) 5.555 6.71 120.2 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.00964 Deviance explained = 5.67%
UBRE score = -0.86303 Scale est. = 1 n = 16408

LOGNORMAL MODEL

Family: gaussian
Link function: log

Formula:
owt ~ s(yy) + as.factor(cell) + as.factor(ez_id) + as.factor(flag_id) +
as.factor(mm)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 6.61589 3.91305 1.691 0.092874 .
as.factor(ez_id)GL -4.77409 1.91905 -2.488 0.013901 *
as.factor(ez_id)HB -4.37541 2.05274 -2.131 0.034605 *
as.factor(ez_id)IW -4.83008 1.54195 -3.132 0.002068 **
as.factor(ez_id)KI -15.00331 3.49380 -4.294 3.06e-05 ***
as.factor(ez_id)MH -9.97387 4.93191 -2.022 0.044842 *
as.factor(ez_id)NR -4.62502 2.57962 -1.793 0.074913 .
as.factor(ez_id)PG -3.22703 1.18842 -2.715 0.007361 **
as.factor(ez_id)PX 4.35204 1.65901 2.623 0.009568 **
as.factor(ez_id)SB -5.27656 3.16004 -1.670 0.096956 .
as.factor(ez_id)TK 13.84874 3.47612 3.984 0.000103 ***
as.factor(ez_id)TV -3.09580 1.82532 -1.696 0.091862 .
as.factor(flag_id)FM -10.86906 3.39607 -3.200 0.001661 **
as.factor(flag_id)JP -4.95874 2.80444 -1.768 0.078975 .

```
as.factor(flag_id)KI  -2.41721  2.86911 -0.842 0.400791
as.factor(flag_id)KR  -8.24255  3.02478 -2.725 0.007160 **
as.factor(flag_id)MH  4.10168  2.21327  1.853 0.065727 .
as.factor(flag_id)NZ  4.73762  3.72517  1.272 0.205330
as.factor(flag_id)PG  -4.70791  2.22869 -2.112 0.036233 *
as.factor(flag_id)PH  -9.62881  3.31329 -2.906 0.004189 **
as.factor(flag_id)TW  -3.96529  2.31694 -1.711 0.088975 .
as.factor(flag_id)US  -7.03858  2.79677 -2.517 0.012850 *
as.factor(flag_id)VU  -5.78771  2.57685 -2.246 0.026097 *
as.factor(mm)2     -2.89378  2.68359 -1.078 0.282543
as.factor(mm)3     -3.85500  2.69409 -1.431 0.154443
as.factor(mm)4     0.80661  2.45636  0.328 0.743066
as.factor(mm)5     0.97166  2.42869  0.400 0.689645
as.factor(mm)6     -2.11289  2.51831 -0.839 0.402737
as.factor(mm)7     -7.77752  3.20375 -2.428 0.016329 *
as.factor(mm)8     -1.70619  2.71826 -0.628 0.531126
as.factor(mm)9     4.91973  2.35060  2.093 0.037960 *
as.factor(mm)10    -5.03720  2.92104 -1.724 0.086593 .
as.factor(mm)11    -3.59322  2.74059 -1.311 0.191734
as.factor(mm)12    -4.06617  3.05259 -1.332 0.184779
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
   edf Ref.df   F p-value
s(yy)  1   1 20.46 1.19e-05 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.504  Deviance explained = 59.8%
GCV score = 6.324 Scale est. = 4.4325  n = 224
```