CPUE Standardization for Oceanic Whitetip Shark, *Carcharhinus longimanus*, in the Hawaiian Longline Fishery during 1994−2019

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Abstract

This paper presents a standardization of catch per unit effort (CPUE) for the oceanic whitetip shark *Carcharhinus longimanus* taken by the Hawaii-based pelagic longline fishery during 1994–2019. This research was conducted because this species, once considered common in pelagic tropical waters of all major oceans, is now classified as ‘‘Threatened’’ under the U.S. Endangered Species Act (ESA) and “Critically Endangered” on the International Union for the Conservation of Nature (IUCN) Red List. Oceanic whitetip shark CPUE was standardized by application of a zero-inflated negative binomial model (ZINB) to data collected by the NOAA Pacific Islands Region Observer Program (PIROP). These analyses provided updated results based upon published work using data from 1995 to 2010 in which the ZINB model was determined to be appropriate for standardizing oceanic whitetip shark CPUE. This update has demonstrated that the ZINB model would converge over a longer time series, that the ZINB fit could be improved by including latitude, longitude, and sea surface temperature as covariates, and that use of the estimated marginal means (EMMs) was preferable to the ordinary marginal means (OMMs) to determine the temporal trend due to the unbalanced data set. Importantly, a decrease in CPUE on the order of 90% since the 1990s is a well-supported estimate, but the decrease was not linear throughout these years. Rather, the standardized CPUE decreased sharply during 2000–2005 while the fishery instituted two-sector management and the PIROP increased its fleet-wide coverage rates for the Hawaii longline fishery.

Introduction

As part of a collaborative research project with the Western Pacific Regional Fishery Management Council, we conducted alternative CPUE standardizations for several bycatch species taken by the Hawaiian pelagic longline fishery, including oceanic whitetip shark *Carcharhinus longimanus*. These CPUE standardization analyses entailed fitting alternative formulations of zero-inflated negative binomial (ZINB) models for each species. However, goodness-of-fit criteria and convergence patterns indicated that some of the ZINB models were not appropriate. This document presents the final CPUE standardization results using the best-fitting ZINB model for oceanic whitetip shark. We compare our final results with the previous CPUE standardization analysis for oceanic whitetip shark in the Hawaii longline fishery based on multimodel inference (Brodziak and Walsh 2013).

Methods

All statistical analyses were conducted with catch and operational data reported by the Pacific Islands Region Observer Program (PIROP) from February 1994 through December 31, 2019 (PIRO 2021). The initial compilation of Hawaii longline fishery data included 90,634 longline sets. This initial compilation of 90,634 longline sets was filtered to yield a data frame with 90,157 longline sets. A final series of data inspections led to the deletion of 18 more longline sets as likely observational errors. The reasons for all of these data deletions, including the 18 sets from the oceanic whitetip shark analyses conducted using 90,139 sets, are documented (Appendix A). All data preparation and computations were performed in R Version 4.3 (R Core Team 2020; Crawley 2013). This data preparation provided an improved basis for conducting CPUE standardization analyses to assess recent trends in the relative abundance of oceanic whitetip shark in the North Pacific Ocean.

Standardized CPUE time series are commonly used to draw inferences about the relative abundance of non-target species in the absence of full stock assessments (Brodziak and Walsh 2013). The CPUE standardizations for oceanic whitetip shark presented herein entailed fitting zero-inflated negative binomial (ZINB) models following previously published analytical methods (Brodziak and Walsh 2013; Walsh and Brodziak 2015). The ZINB model is a type of mixture model that is appropriate when data are characterized by a greater proportion of zero catches than expected under a standard discrete probability distribution (e.g., negative binomial) and the positive catches exhibit overdispersion (Zuur et al. 2009; 2012; Brodziak and Walsh 2013). Here the observations of extra zeros can be due to observational errors or due to longline sets occurring in low quality pelagic habitat for oceanic whitetip sharks.

We note that the ZINB model applied to standardize oceanic whitetip shark CPUE was a mixture model with two components. The first component was a binomial model, which measured the probability of observing a false or extra zero, denoted by π. The second component was a negative binomial count model with a mean catch rate parameter μ and an overdispersion parameter k that measured the probability of negative binomial zeros and positive catches (C) of oceanic whitetip shark. Thus, the ZINB model was comprised of a binomial and a non-negative count distribution for which a zero catch could occur as an extra zero with probability equal to π or as a negative binomially-distributed zero with probability equal to $1-\pi$. This compound structure determines the probabilities of a zero catch $C=0$ and a positive catch amount $C=c$ for $c>0$ as

(1)
$$\begin{aligned} \Pr(C=0) &= \pi + (1-\pi)\left(\frac{k}{k+\mu}\right)^k \\ \Pr(C=c \mid c>0) &= (1-\pi)\frac{(c+k)!}{k!(c+1)!}\left(\frac{k}{k+\mu}\right)^k\left(\frac{\mu}{k+\mu}\right)^c \end{aligned}$$

Given the zero-inflated negative binomial assumption, the expected catch C per hook was equal to the probability of not observing an extra zero times the mean catch rate parameter

(2)
$$E[C] = (1-\pi)\mu$$

and the variance of the catch was

(3) $$Var[C] = (1-\pi)\left(\mu + \frac{\mu^2}{k}\right) + \mu^2\left(\pi + \pi^2\right)$$

Under the ZINB model, the index of dispersion is always greater than unity and is a decreasing function of k and an increasing function of the extra zero probability with a variance to mean ratio (*VMR*) of

(4) $$VMR = 1 + \frac{\mu}{k} + \frac{\mu\pi(1+\pi)}{(1-\pi)}$$

In general, we note that the ZINB model can exhibit overdispersion for both the binomial process generating extra zeros and the positive count process.

Updating the ZINB standardization models for oceanic whitetip shark was important for two reasons. First, this species was long considered one of the most abundant pelagic sharks of tropical waters, but it is now officially classified as ''Threatened'' under the U.S. Endangered Species Act (ESA) and as "Critically Endangered" on the International Union for the Conservation of Nature (IUCN) Red List (Young and Carlson 2020). Therefore, fitting a revised ZINB model to update our published work (Brodziak and Walsh 2013) was an important priority for monitoring relative shark abundance. The second reason was to investigate whether we could improve the fit of a ZINB (i.e., a re-fit of the ZINB model throughout 1994–2019) by applying additional predictors to better explain the trends in longline CPUE.

We used the best-fitting ZINB model from Brodziak and Walsh (2013), or 2013 model, as the starting point for investigating whether the structure of the CPUE standardization model could be improved with additional predictors. To begin, standardized CPUE was fit using the best ZINB model structure as reported in Brodziak and Walsh (2013). Standardized CPUE values were predicted using both ordinary marginal means and estimated marginal means, a.k.a. least squares means (Searle et al. 1980, Lenth 2016). Here we note that Brodziak and Walsh (2013) used only ordinary marginal means (OMM) to predict standardized CPUE based on the assumption that the longline data were adequately balanced with respect to the relative number of longline sets observed for each combination of predictors. Upon further investigation, it became clear that this assumption was probably not adequately satisfied for the bycatch of oceanic whitetip in the Hawaii longline fishery. As a result, we changed the analytical approach for predicting standardized CPUE in these analyses and used estimated marginal means to predict the best estimates of standardized CPUE. Estimates of CPUE based on ordinary marginal means were also included for comparison. Here it is important to note that the EMM predictions accounted for the unbalanced nature of the longline data by giving equal weights to each observed cell, or combination of predictive factors and covariates. Thus, we began the CPUE standardization analyses by fitting the 2013 ZINB model to the updated longline data using estimated marginal means as the best analytical approach and also using ordinary marginal means for comparison with the 2013 analyses.

In the search for potential improvements to the CPUE standardization model, we used the initial model fitting results to refine the configuration of predictors in the ZINB model for oceanic whitetip shark (Walsh, Brodziak, and Fitchett 2021). The revised standardization models were identified using forward entry variable selection with the 2013 model as the null model, or starting point (Brodziak and Walsh 2013; Walsh and Brodziak 2016). Factor variables and covariates used in these analyses are described in the footnote[1], where factors in all R formula statements and model summary outputs are denoted by a suffix "F" and some covariate names are abbreviated. This usage is employed in all R formula statements and model summary results. The variables used to fit the ZINB models reflected the expected importance of temporal (annual, quarterly) and spatial (regions, latitude and longitude) effects, fishery sector effects that reflect the management regime, thermal effects as both a controlling and a directive factor (Fry 1971), and the effects of several operational longline fishing gear parameters.

When determining the best-fitting ZINB model with a revised set of predictors, it was important to note that there would be some confounding among potential explanatory variables in the CPUE standardization analyses. This confounding was partly due to differences in operational fishing practices between the shallow-set and deep-set fishery sectors. Therefore, to avoid use of overly complex models for analytical and predictive purposes, we applied a rule of thumb regarding the inclusion of model terms. This rule was that each factor variable or covariate that was included in the best-fitting ZINB model needed to reduce the AIC of the null model by at least 0.1% of the null AIC per degree of freedom. In comparison, for the 2013 standardization analyses, explanatory variables were required to reduce the absolute value of the fitted Akaike information criterion by at least 0.1% of the null model AIC (Brodziak and Walsh 2013; Walsh and Brodziak 2015), where the null model is the fitted model using only intercepts and an offset for hooks per set. Thus, in this updated standardization analysis, a similar but more rigorous standard was used to select predictors for the best-fitting model. The best-fitting, or base case standardization model was analyzed with the R package "emmeans"[2] to calculate the estimated marginal means for the best estimate of standardized CPUE, and also with the "predict" function to calculate the ordinary marginal means for comparison.

To begin the updated CPUE standardization analyses, we first summarize some descriptive statistics of oceanic whitetip shark catches during 1994−2019. We then describe the updated CPUE standardization analyses based on two fitted ZINB models. The first model is a simple update of the ZINB model used in the 2013 CPUE standardization fitted using the updated and filtered Hawaii longline observer data (Brodziak and Walsh 2013); this is the 2013 model. The second model is the best-fitting ZINB model that was identified based on our updated stepwise selection of explanatory variables using the variable selection criteria; this is the base case

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[1] Factor variables: Annual effects during 1994–2019 (Haulyr_F); quarterly effects (Quarter_F) follow the calendar; spatial effects (Region_F) follow Brodziak and Walsh (2013); fishery sectors (Sector_F) follow the Federal Register (2004); several operational parameters (e.g., hook and bait types) follow the Hawaii Longline Observer Field Manual (2017).
Covariates: SST denotes sea surface temperature (℃); Soak_Time denotes the soak duration (begin-set through end-haul); BS_Time denotes begin-set time.

[2] Available at: https://www.rdocumentation.org/packages/emmeans/versions/1.6.1

model. For both the 2013 and the base case models, we predicted standardized CPUE using EMMs to provide the best scientific information available and also predicted CPUE based on OMMs for comparison. The nominal CPUE of oceanic whitetip shark, expressed as sharks caught per 1000 longline hooks, was also calculated for comparison with the standardized CPUE time series. For comparison, we rescaled each of the CPUE time series to have an average value of unity during 1994−2019. We then compared the similarity of trends in the CPUE series using correlations and angular deviations and examined time trends using regression. Last, we included some information about the accuracy of self-reported shark catches in the commercial logbooks for the Hawaii longline fishery in response to changes in monitoring regimes. Here our purpose was to describe observed tendencies in self-reported logbooks that may be expected in other logbook data systems used to monitor threatened bycatch species.

Results

The summary of longline catch statistics showed that the bycatch of oceanic whitetip shark was primarily a rare event in the Hawaii longline fishery with a nominal CPUE of 0.053 sharks per 1,000 hooks deployed (Table 1). The total catch of oceanic whitetip shark during the study period was 9,501 sharks in a total of 90,139 longline sets. Of these, roughly 92% of the sets caught zero, 6% caught one and 2% caught multiple oceanic whitetip sharks. The average number of oceanic whitetip sharks caught per set was 0.11 sharks. Longline sets with zero reported catch increased from 86% in 1994 to 93% in 2019 while the percentage of sets with positive catches decreased by half, from 14% to 7% (Figure 1). Longline sets with multiple catches decreased from over 4% in 1994 to less than 1% in 2019. Thus, the long-term trends in oceanic whitetip shark catch statistics showed increases in longline sets with no catch and substantial decreases in longline sets with positive catch. Here we note that the nominal CPUE for the shallow-set sector was typically about 40% higher than for the deep-set sector. Most of the oceanic whitetip bycatch occurred on deep-sector longline sets targeting bigeye tuna (76%) while shallow-sector sets targeting swordfish accounted for about 19% of the catch. We also note that changes in the management regime for the longline fishery also had some effects on oceanic whitetip shark catches during two periods (1995–2000 and 2004–2006) when regulations for the shallow-set fishery changed (Walsh et al. 2009). Overall, the high proportion of zero catches of oceanic whitetip shark in the Hawaii longline sets supported the choice to apply a statistical mixture model comprised of zero-catch and positive catch components to standardize CPUE of this highly migratory shark (i.e., Lynch et al. 2012).

The results of fitting the 2013 model fitted to the updated longline data with standardized CPUE calculated using estimated marginal means are shown in Tables 2.1 and 2.2 and the associated model summaries are shown in Appendix B. The results of the 2013 model fitting based on estimated marginal means were similar to the results of the 2013 analysis by Brodziak and Walsh (2013) with all predictors being statistically significant (P<0.0001). However, the 2013 model showed an improved fit to the updated data. In particular, the 2013 model explained 21.2% of the AIC of the null model, an increase of 1.4% over the 2013 paper analysis, which was fit to longline data during 1995-2010 (Table 2.1 and Brodziak and Walsh (2013, Table A2)). The 2013 model also had higher percentages of AIC explained per degree of freedom than the 2013 paper analysis for each predictor, with the exception of the SST predictor in the counts model. Further, the 2013 model also had a lower overall median residual value of $\varepsilon_{med} = -0.16$ vs. a median residual of $\varepsilon_{med} = -0.20$ in the 2013 paper analysis. The standardized CPUE series for the 2013 model and the 2013 paper analysis (Table 2.2) were also significantly positively correlated $\left(\rho = 0.89,\ P < 0.0001,\ n = 16\right)$ although the series were based on different longline data sets and different marginal mean predictions. Similarly, when one compares the standardized CPUE series for the 2013 model based on EMM vs. OMM (Table 2.2), one finds that the CPUE series were also significantly positively correlated $\left(\rho = 0.91,\ P < 0.0001,\ n = 26\right)$. Overall, the update of the 2013 model based on EMM showed a long-term decreasing trend in standardized CPUE of oceanic whitetip shark (Table 2.2) that was similar to that based on OMM and also that reported in Brodziak and Walsh (2013).

The results of the variable selection to identify the best-fitting ZINB model are shown in Table 3.1 and the associated model summaries presented in Appendix B. The primary difference between the 2013 model and the base case model (i.e., best-fitting ZINB) was the inclusion of latitude and longitude as predictors in the counts component of the latter model (Table 3.1). The base case model converged with an AIC value (47086.8) that was 13438.9 units less than the null model AIC (60525.7). As expected, the fishery sectors, fishing regions, and SST exerted strong effects as indicated by the decreases in AIC and decreases per degree of freedom. The other factor variables and covariates investigated in the variable selection search (see Footnote 1, above) did not reduce the AIC sufficiently for retention in the model. Thus, the base case CPUE standardization model had an overall structure that was very similar to the 2013 model.

The effects of the various predictive variables on nominal catches of oceanic whitetip shark were visualized with scatterplot smoothers and boxplots (Figure 2) using the R package ggplot2 (Wickham 2016). The scatterplot smoother of the year effect or temporal trend (Figure 2a) showed high catch rate values during the early years (i.e., 1994–1999), followed by a steady decrease during 2000–2005. The boxplot of the region effect (Figure 2b) was characterized by the high catch values in Region 2, which includes the US Line Islands. The boxplot of the fishery sector effect (Figure 2c) showed that both the deep-set and shallow-set sectors showed low catch rate values. The scatterplot smoothers for latitude (Figure 2d), longitude (Figure 2e), and sea surface temperature (Figure 2f) together showed that the tropical waters southwest of the Hawaiian Islands with SST *ca*. 27° represented the preferred habitat of oceanic whitetip sharks in the fishing grounds of the Hawaii longline fleet, as expected (Brodziak and Walsh 2013). Overall, each of the predictors had a significant impact on either the presence (Figure 2, panels (a) and (f)) or the catch amount (Figure 2, panels (a) through (f)) of oceanic whitetip shark in the base case CPUE standardization model for oceanic whitetip shark. Overall, the graphs of the empirical relationships between the predictors and the oceanic whitetip catch per set showed that there were nonlinear spatial and temporal gradients in nominal longline CPUE of oceanic whitetip shark.

The standardized CPUE time series showed that there were temporal patterns in the estimated marginal means of oceanic whitetip CPUE in relation to other CPUE series. There was a highly significant positive Spearman correlation between standardized and nominal CPUE (Table 4 and Figure 3a). However, there were three years for which nominal CPUE fell outside the 95% confidence interval of standardized CPUE (1997, 1998, 2000) and it was apparent that the standardization model had a more substantial impact in the earlier years of the time series (Figure 2a). The standardized CPUE and the predicted CPUE series from the base case model using ordinary marginal means were also significantly positively associated, albeit with a lower correlation than for nominal CPUE (Table 4 and Figure 3b). In particular, the predicted CPUE series using OMMS fell outside the confidence interval of annual standardized CPUE in 10 out of 26 years suggesting that the treatment of the unbalanced nature of the longline fishery data was an important consideration in evaluating the relative abundances of oceanic whitetip shark using these data. The comparison of the standardized CPUE series with the standardized CPUE series based on the 2013 model showed that these series were very similar (Table 4 and Figure 3c) with a highly significant Spearman correlation ($r_S = 0.978$). There was also a significant negative Spearman correlation between the standardized CPUE series and the estimated series of false zero probabilities ($r_S = -0.418$, Figure 3d). This suggested that as relative abundance of oceanic whitetip shark and sets with positive catch declined over time that there could be a corresponding increase in either the chance of not observing a shark in preferred habitat or in the chance of not recording a shark observation. Last, we note that the application of estimated marginal means to predict standardized CPUE had a substantial impact on the variability of predicted CPUE (Figure 3e), where the coefficients of variation (CVs) of the ordinary marginal means were an order of magnitude higher than those based on estimated marginal means. Overall, we considered the standardized CPUE series to provide the best scientific information for measuring the trends in relative abundance in comparison to the other measures of abundance evaluated in this study.

The strength of the relationships between the standardized CPUE series from the base case model and the other abundance measures was evaluated with linear regression. The CPUE time series compared were the estimated marginal means from both the best-fitting model and the base case model, the ordinary marginal means from the best-fitting model, and from the nominal mean CPUE, along with the CV for each value (Tables 2.2 and 3.2). Here we note that the CV values associated with the nominal mean CPUE and the ordinary marginal means series were always greater than those from the marginal means CPUE series. Several aspects of the linear, or first order relationships between CPUE estimates were analyzed (Figure 4). The relationship between the nominal mean CPUE and the estimated marginal mean from the base case standardization model was linear and through the origin (i.e., an initial test for the intercept was non-significant), but there were apparent differences. For example, the estimated marginal means from the base case model from1997 and 1999 were considerably greater than the nominal mean CPUE values from those years. The two EMM series were collinear and passed through the origin, whereas the ordinary marginal means included a significant intercept term in the regression on the estimated marginal means. The estimated probability of false zeros did not vary significantly during 1994–2019 (Figure 4d). Also as noted above, the time series plots (Figure 4e) of standardized vs. nominal CPUE without confidence intervals illustrate the overall effects of the CPUE standardization, which were substantial in the early years of the longline catch rate time series.

Conclusions

Our revised standardization analyses have demonstrated that the zero-inflated negative binomial model for standardizing longline CPUE for oceanic whitetip shark presented by Brodziak and Walsh (2013) could be improved with a longer and more rigorously filtered data series and with improved analytical methods. The alternative models demonstrated that inclusion of latitude and longitude as linear predictors, in addition to the region as a factor, increased explanatory power. The SST was important in both components of the best-fitting model. Notably, the best-fitting model was a moderate revision of the published basic model (Brodziak and Walsh 2013), with latitude and longitude included in the counts model as well as with the application of estimated marginal means for standardized CPUE prediction.

We conducted additional evaluations of the approved PIROP longline data before attempting to refit the ZINB model to standardize CPUE of oceanic whitetip shark in this longline fishery during 1994–2019. This led to deletion of 18 longline sets (about 0.02% of the data), but these were highly improbable outliers. Thus, although the PIROP conducts detailed data checking procedures, additional data filtering and evaluations proved to be appropriate and indeed necessary.

The two primary analytical objectives of this project were met in full. First, the previously fitted ZINB model, developed by model selection (Brodziak and Walsh 2013), converged over this longer time series. Second, it was possible to improve the ZINB model fit by inclusion of latitude and longitude as covariates. Because both the filtered data frame and model object have been provided as deliverables, this CPUE standardization analysis could be updated periodically if so desired. Data preparation for such updates should be straightforward; the methods described in Appendix A could be applied to data collected during or after 2020, and the new data would then be appended to the present data frame.

The results include the fitting and comparisons of the base case and best case ZINB models, and application of the best case ZINB model to generate the EMM time series. These values were much less variable than the nominal mean CPUE values, and were better suited for application with unbalanced data.

The standardized and nominal CPUE trends were significant and negative during 1994–2019, whereas the regression of the probability of false zeros on years was not significant. We conclude that a decrease in CPUE of on the order of 90% since the 1990s is a well-supported estimate, but the decrease was not linear throughout these years. Rather, the standardized CPUE decreased sharply during 2000–2005 while the fishery instituted two-sector management and the PIROP increased its fleet-wide coverage rates for the Hawaii longline fishery.

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Table 1. Summary of descriptive catch statistics for oceanic whitetip shark taken by the Hawaiian longline fishery, including total numbers caught, nominal catch per unit effort (CPUE as measured by catch numbers per 1000 hooks), mean catch per set, percentage of sets with positive catches, as well as shark catches sorted by target species (SWO is swordfish, *Xiphias gladius* and BET is bigeye tuna, *Thunnus obesus*) and the deep- and shallow-set fishery sectors. All summaries were calculated using the best scientific information available consisting of the 90,139 observed longline sets from 1994 to 2019.

Total catch	Nominal mean CPUE	Mean catch per set	Percentage of positive catch sets	Percentages of catch relative to target species [3]		
				SWO	BET	Other
9,501	0.053	0.110	7.7%	19%	76%	5%

Nominal mean CPUE relative to target species		Nominal mean CPUE by fishery sector	
SWO	BET	Shallow	Deep
0.049	0.053	0.070	0.050

[3] "Other" denotes all other species that were primary or secondary targets (e.g., yellowfin tuna, blue marlin).

Table 2. Summary of the forward entry variable selection for the updated 2013 model fitted to PIROP data collected during 1994−2019 consisting of 90,139 longline sets, where df is degrees of freedom, ∆AIC is the change in AIC, ∆AIC per df is the change in AIC per degree of freedom and median residual is the median of the model residuals.

Zero-inflated negative binomial GLM

Parameter	**df**	**ΔAIC**	**ΔAIC per df**	**Median residual**
Counts Model				
Intercept	1	---	---	-0.25
Haul-end year	25	3894.4	155.8	-0.23
Fishing region	7	5162.6	737.5	-0.19
Fishery sector	1	1088.4	1088.4	-0.19
SST	1	421.2	421.2	-0.18
Zeros Model				
SST	1	2038.8	2038.8	-0.17
Haul-end year	25	246.3	9.9	-0.16

Null mixture model with two intercepts: Null AIC = 60525.7

Fitted 2013 model: AIC = 47674.1 and ΔAIC = 12851.6

Dispersion parameter for ZINB model: $\theta = 1.04$

Table 3. Relative abundance indices based on the rescaled CPUE standardization results for the 2013 model as well as rescaled nominal CPUE.

Year	2013 Ordinary Marginal Mean CPUE	2013 OMM CPUE CV	2013 Estimated Marginal Mean CPUE	2013 EMM CPUE CV	Scaled OMM Mean CPUE from 2013 Paper	Nominal Mean CPUE	Nominal CPUE CV
1994	1.190	1.62	1.505	0.18		1.602	2.97
1995	2.788	1.30	3.134	0.17	2.02	3.684	2.84
1996	2.305	1.26	2.594	0.16	1.82	3.206	2.55
1997	2.064	1.76	3.307	0.15	1.97	2.229	2.73
1998	2.421	1.36	1.619	0.24	2.07	2.724	2.46
1999	2.933	1.54	3.601	0.15	1.99	2.459	2.40
2000	1.739	1.32	0.995	0.19	1.19	1.535	2.99
2001	2.079	1.34	1.689	0.11	1.39	1.578	2.37
2002	1.204	1.32	1.272	0.09	0.77	0.940	3.09
2003	0.897	0.77	1.131	0.17	0.62	0.699	2.81
2004	0.961	1.23	0.200	0.23	0.67	0.778	3.47
2005	0.598	1.29	1.069	0.09	0.41	0.886	4.58
2006	0.382	1.44	0.362	0.27	0.26	0.281	4.40
2007	0.375	1.32	0.560	0.11	0.26	0.388	6.18
2008	0.187	1.43	0.352	0.14	0.13	0.182	6.30
2009	0.302	2.02	0.338	0.15	0.21	0.257	5.50
2010	0.295	1.73	0.325	0.17	0.21	0.286	5.61
2011	0.312	1.29	0.321	0.16		0.292	6.73
2012	0.219	1.84	0.172	0.18		0.158	6.06
2013	0.229	1.88	0.121	0.29		0.182	6.36
2014	0.405	1.71	0.184	0.21		0.268	4.43
2015	0.595	1.47	0.283	0.17		0.400	3.98

Year	2013 Ordinary Marginal Mean CPUE	2013 OMM CPUE CV	2013 Estimated Marginal Mean CPUE	2013 EMM CPUE CV	Scaled OMM Mean CPUE from 2013 Paper	Nominal Mean CPUE	Nominal CPUE CV
2016	0.548	1.14	0.316	0.16		0.379	3.84
2017	0.279	1.11	0.201	0.21		0.194	5.15
2018	0.257	1.62	0.147	0.23		0.163	6.07
2019	0.434	0.92	0.203	0.22		0.252	3.85
Average 1994-2019	1.000	1.42	1.000	0.18	1.000	1.000	4.22
Average 1994-1999	2.284	1.47	2.627	0.17	1.975	2.651	2.66
Average 2000-2004	1.376	1.20	1.057	0.16	0.927	1.106	2.95
Average 2005-2009	0.369	1.50	0.536	0.15	0.255	0.399	5.39
Average 2010-2014	0.292	1.69	0.225	0.20		0.237	5.84
Average 2015-2019	0.423	1.25	0.230	0.20		0.278	4.58

Table 4. Summary of the forward entry variable selection results for the base case ZINB model with latitude and longitude included in the counts component fitted to PIROP data collected during 1994−2019 consisting of 90,139 longline sets, where df is degrees of freedom, ∆AIC is the change in AIC, ∆AIC per df is the change in AIC per degree of freedom and median residual is the median of the model residuals.

Zero-inflated negative binomial GLM

Parameter	df	∆AIC	∆AIC per df	Median residual
Counts Model				
Intercept	1	---	---	-0.25
Haul-end year	25	3894.4	155.8	-0.23
Fishing region	7	5162.6	737.5	-0.19
Fishery sector	1	1088.4	1088.4	-0.19
Latitude	1	758.2	758.2	-0.18
Longitude	1	638.2	638.2	-0.18
SST	1	1238.5	1238.5	-0.16
Zeros Model				
SST	1	481.3	481.3	-0.16
Haul-end year	25	167.7	6.7	-0.16

Null mixture model with two intercepts: Null AIC = 60525.7

Base case model: AIC = 47086.8 and ∆AIC = 13438.9

Dispersion parameter for ZINB model: $\theta = 1.09$

Table 5. Rescaled CPUE standardization results for the base case model using EMM and OMM predictions along with the estimated time series of false zero probabilities.

Year	Estimated Marginal Mean CPUE	EMM CPUE CV	Ordinary Marginal Mean CPUE	OMM CPUE CV	Estimated Probability of False Zero
1994	1.482	0.20	1.209	1.73	0.49
1995	3.149	0.19	2.693	1.16	0.37
1996	2.602	0.18	2.261	1.15	0.36
1997	3.473	0.15	1.952	1.62	0.51
1998	1.738	0.24	2.379	1.34	0.40
1999	3.091	0.17	3.017	1.54	0.45
2000	0.958	0.20	1.681	1.23	0.35
2001	1.545	0.12	2.149	1.46	0.13
2002	1.227	0.11	1.227	1.38	0.03
2003	1.150	0.18	0.917	0.90	0.11
2004	0.199	0.28	0.985	1.29	0.27
2005	1.122	0.11	0.603	1.32	0.25
2006	0.404	0.28	0.391	1.55	0.31
2007	0.527	0.12	0.383	1.49	0.27
2008	0.397	0.14	0.190	1.41	0.43
2009	0.350	0.15	0.309	2.10	0.42
2010	0.334	0.18	0.302	1.88	0.53
2011	0.321	0.17	0.317	1.48	0.51
2012	0.201	0.19	0.220	1.88	0.56
2013	0.246	0.36	0.236	1.83	0.47
2014	0.249	0.25	0.414	1.81	0.50
2015	0.309	0.21	0.611	1.59	0.53
2016	0.330	0.19	0.564	1.26	0.52

Year	Estimated Marginal Mean CPUE	EMM CPUE CV	Ordinary Marginal Mean CPUE	OMM CPUE CV	Estimated Probability of False Zero
2017	0.238	0.23	0.284	1.22	0.48
2018	0.155	0.27	0.262	1.75	0.59
2019	0.204	0.26	0.445	1.02	0.38
Average 1994-2019	1.000	0.20	1.000	1.48	0.39
Average 1994-1999	2.589	0.19	2.252	1.42	0.43
Average 2000-2004	1.016	0.18	1.392	1.25	0.18
Average 2005-2009	0.560	0.16	0.375	1.57	0.34
Average 2010-2014	0.270	0.23	0.298	1.77	0.51
Average 2015-2019	0.247	0.23	0.433	1.37	0.50

Table 6. Matrix of Spearman rank correlations (in bold below diagonal) and angular deviations (in bold above diagonal) among the standardized CPUE series (Standardized EMM), the CPUE series based on the 2013 model using EMMs (Standardized 2013 EMM), the predicted CPUE series using OMMs (Standardized OMM), and the nominal CPUE series.

-----	**Standardized EMM**	**Standardized 2013 EMM**	**Standardized OMM**	**Nominal**
Standardized EMM CPUE	-----	**4.5°**	**18.5°**	**11.9°**
Standardized 2013 EMM	**0.98** $P < 0.0001$	-----	**17.6°**	**18.3°**
Standardized OMM	**0.76** $P < 0.0001$	**0.80** $P < 0.0001$	-----	**14.1°**
Nominal	**0.85** $P < 0.0001$	**0.86** $P < 0.0001$	**0.95** $P < 0.0001$	-----

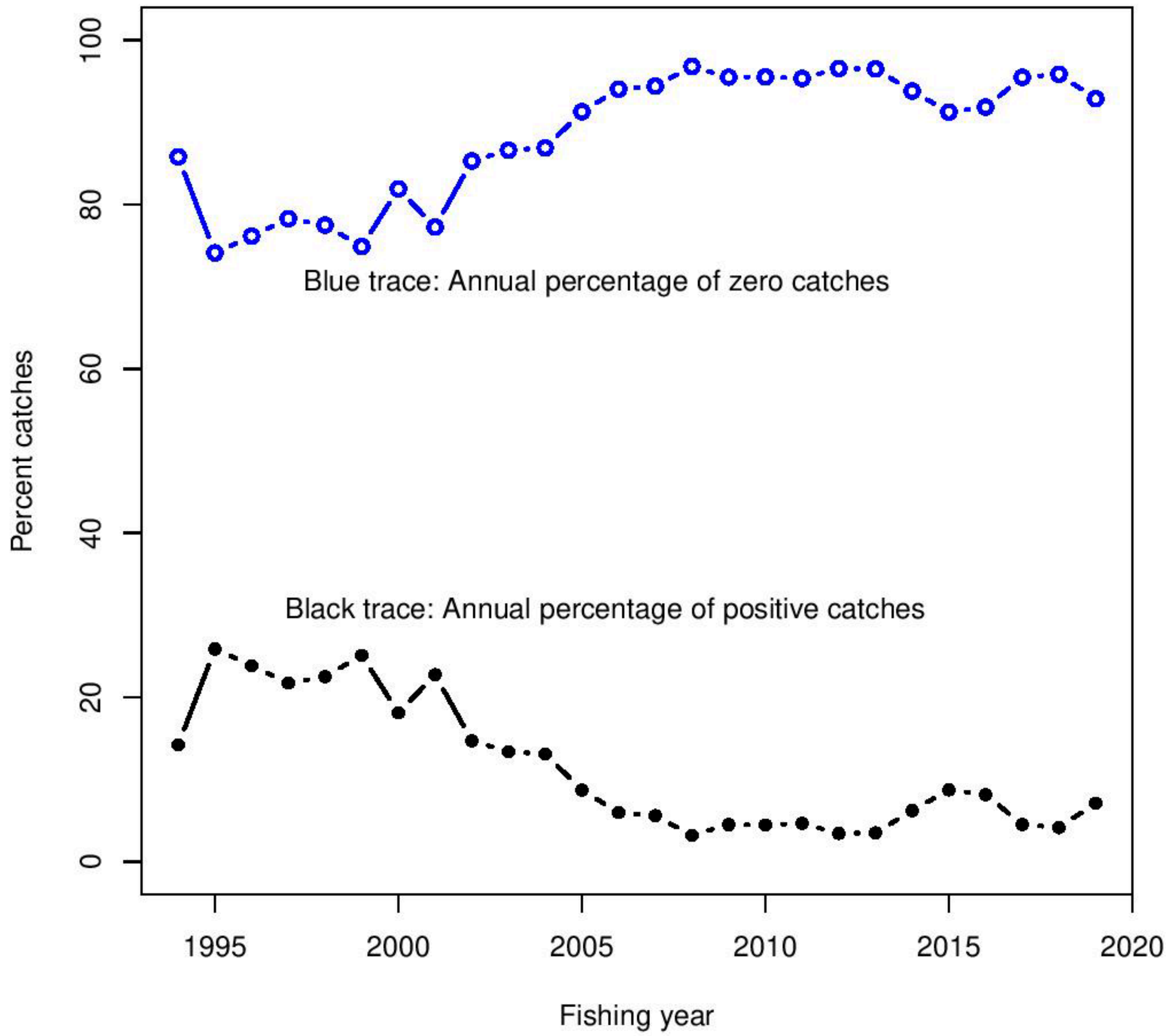
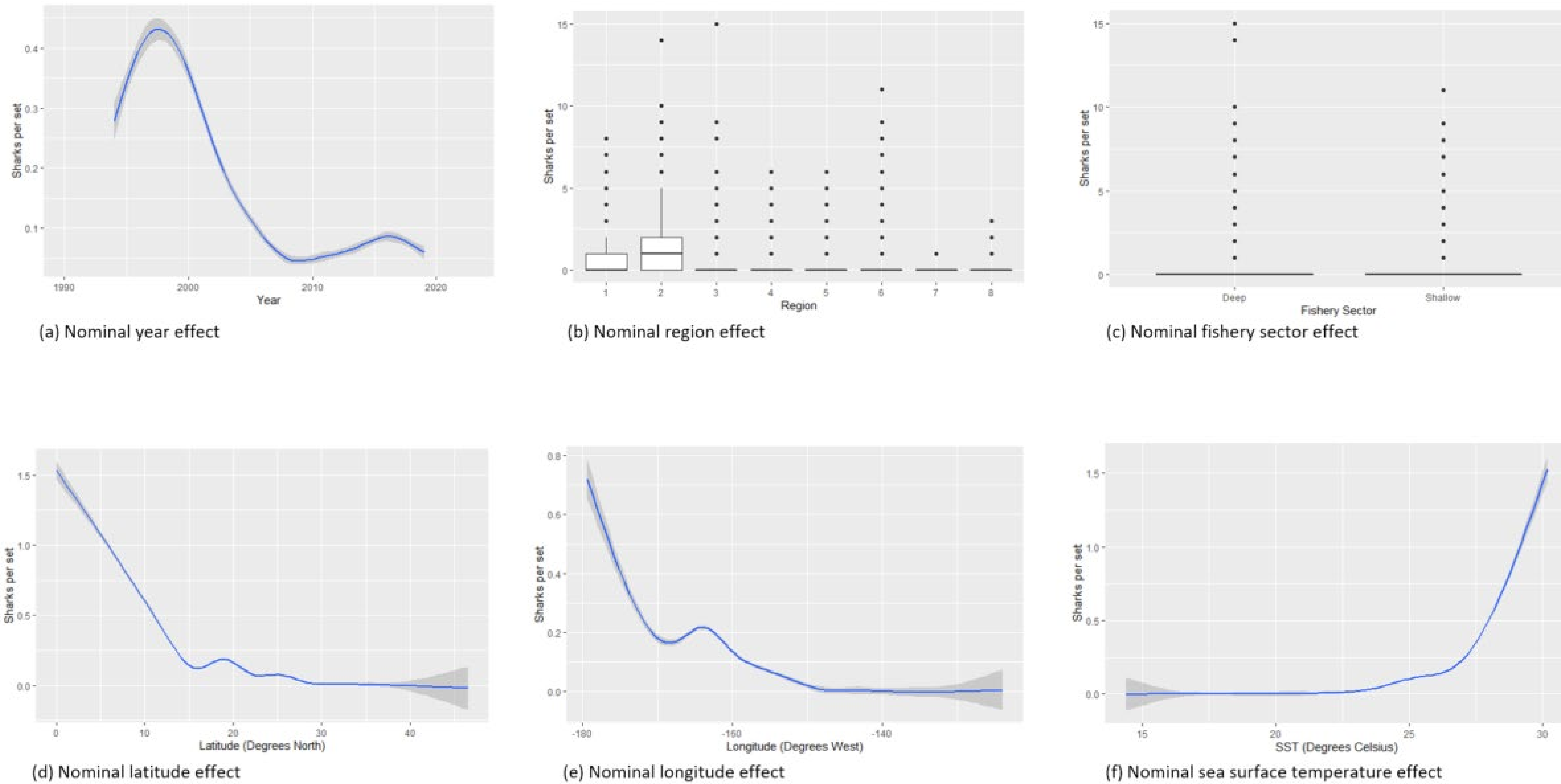


Figure 1. Trends of annual mean zero (open circles) and positive catches (solid circles) of oceanic whitetip sharks in the Hawaii longline fishery as reported by PIROP observers during 1994−2019.



(a) Nominal year effect
(b) Nominal region effect
(c) Nominal fishery sector effect
(d) Nominal latitude effect
(e) Nominal longitude effect
(f) Nominal sea surface temperature effect

Figure 2. Scatterplot smoothers or boxplots showing the effects of CPUE predictors on the nominal catch per set of oceanic whitetip shark in the Hawaii longline fishery during 1994-2019. Effects of CPUE predictors on nominal catch per set are: (a) year, (b) region, (c) fishery sector, (d) latitude, (e) longitude, (f) sea surface temperature.

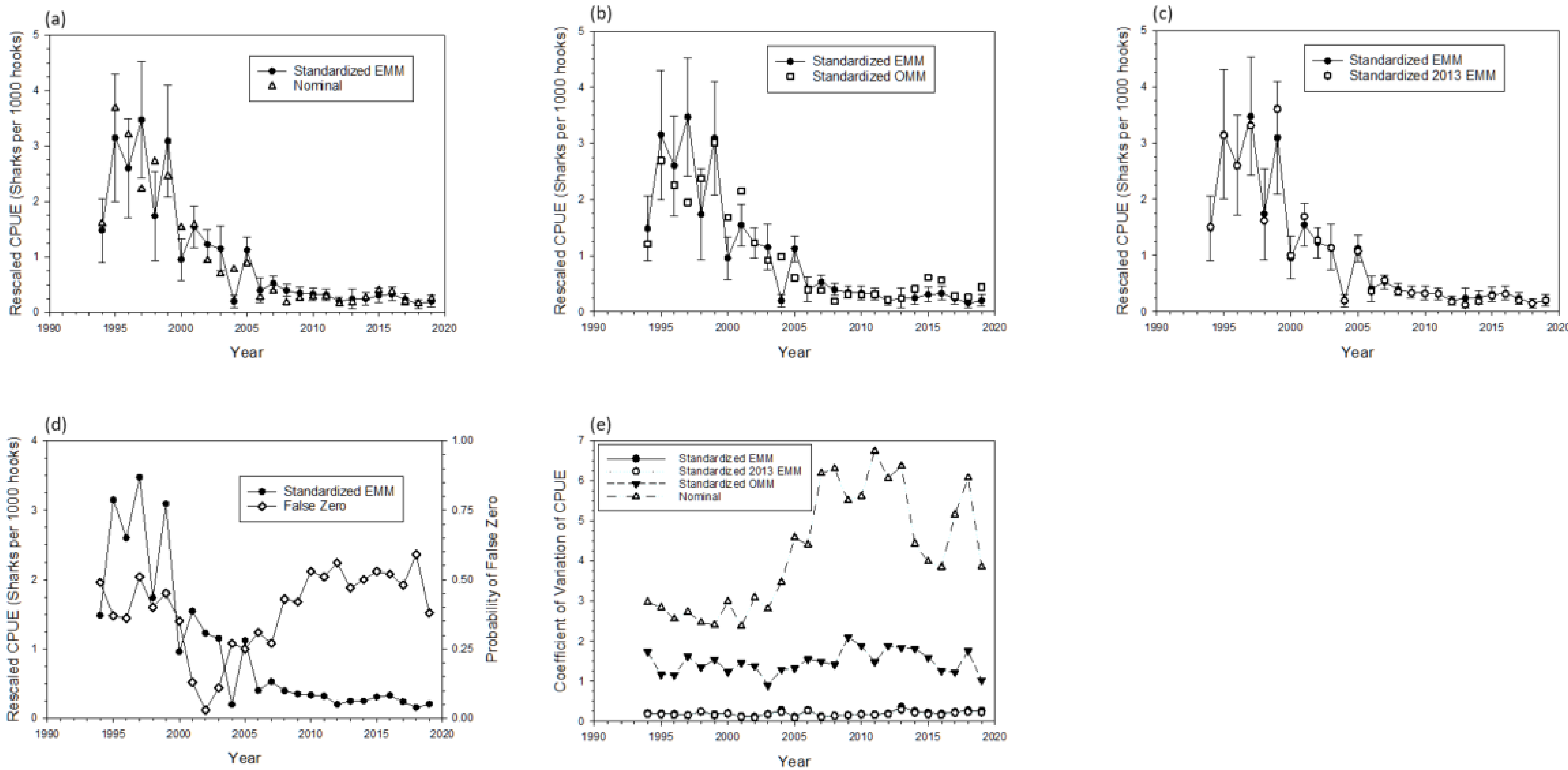
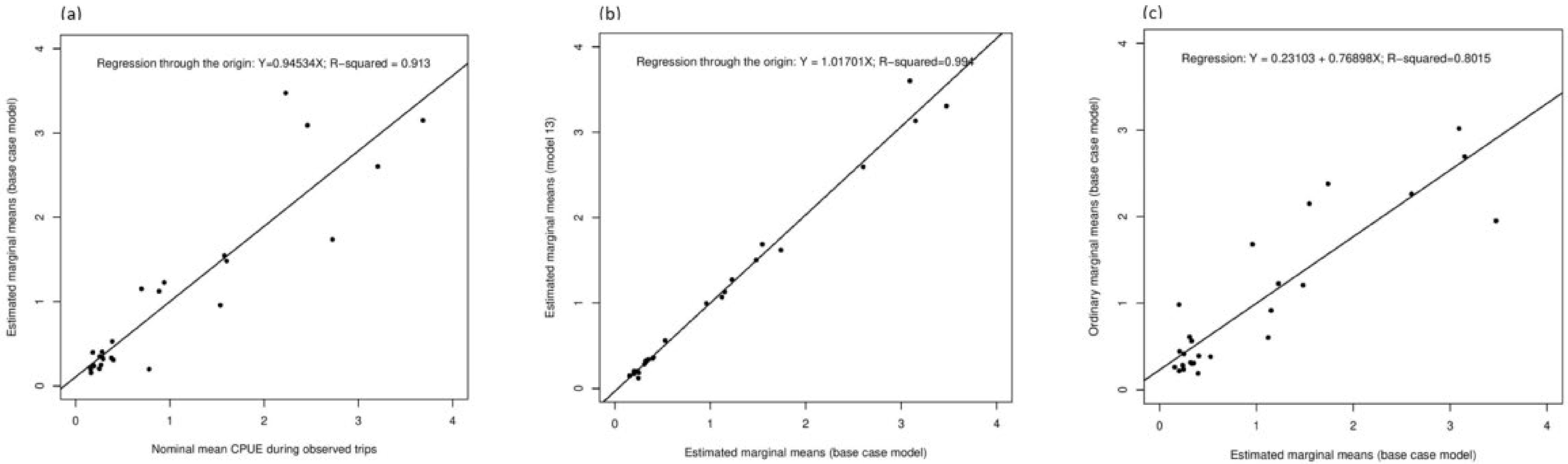


Figure 3. Plots of standardized CPUE with 95% confidence intervals vs. (a) nominal CPUE, (b) predicted standardized CPUE using ordinary marginal means, (c) standardized CPUE based on the 2013 model relative abundance and (d) the probability of a false zero, as well as (e) the comparison of the time series of annual coefficients of variation of standardized CPUE and other relative abundance indices.



Regression analysis

> Regression<-lm(EMM~Noml-1)

> summary(Regression)

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
EMM	0.94534	0.05831	16.21	8.95e-15 ***

Residual standard error: 0.4266 on 25 degrees of freedom

Multiple R-squared: 0.9131, Adjusted R-squared: 0.9097

F-statistic: 262.8 on 1 and 25 DF, p-value: 8.95e-15

Regression analysis

> Regression<-lm(EMM_Model_13~EMM-1)

> summary(Regression)

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
EMM	1.01701	0.01618	62.85	<2e-16 ***

Residual standard error: 0.1171 on 25 degrees of freedom

Multiple R-squared: 0.9937, Adjusted R-squared: 0.9935

F-statistic: 3950 on 1 and 25 DF, p-value: < 2.2e-16

Regression analysis

> Regression<-lm(OMM_MM_CPUE~EMM)

> summary(Regression)

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.23103	0.11086	2.084	0.048 *
EMM	0.76898	0.07811	9.845	6.66e-10 ***

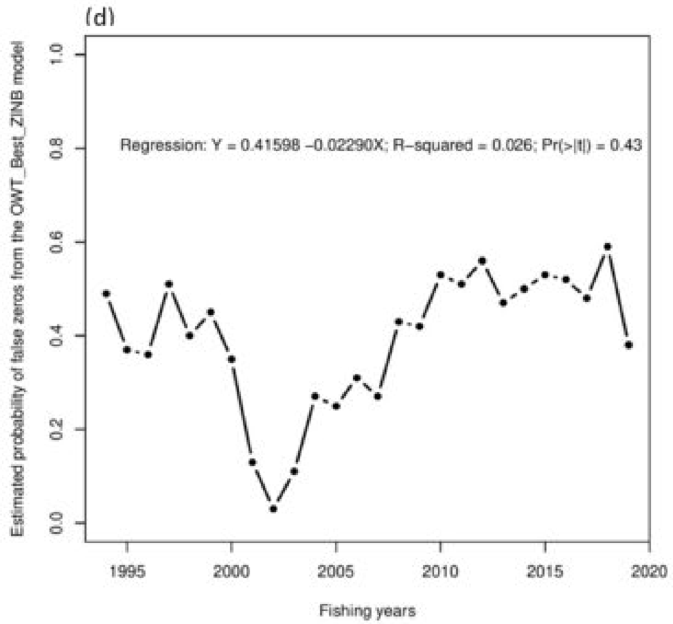
Residual standard error: 0.4011 on 24 degrees of freedom

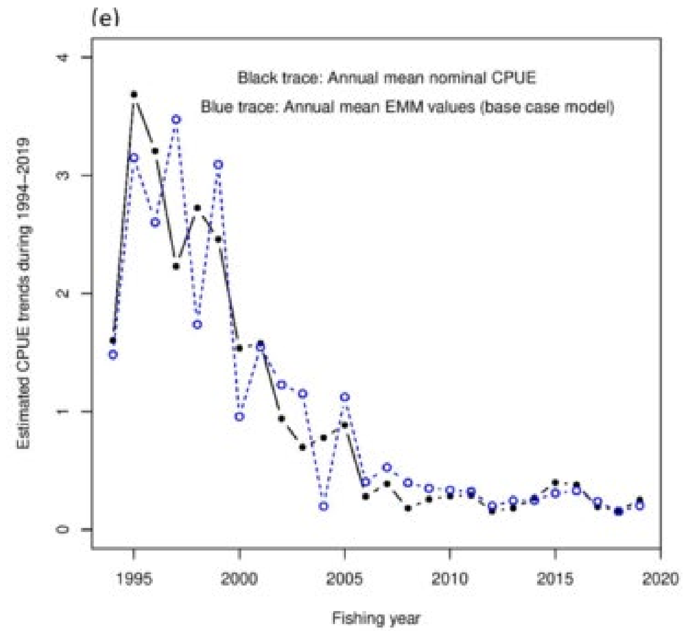
Multiple R-squared: 0.8015, Adjusted R-squared: 0.7933

F-statistic: 96.93 on 1 and 24 DF, p-value: 6.662e-10

Figure 4. Plots of the (a) estimated marginal means from the base case standardization model vs. the nominal mean CPUE, (b) estimated marginal means from the 2013 model vs. the base model marginal means CPUE, (c) ordinary marginal means vs. the estimated marginal means from the base case model, (d) the probability of a false zero, and (e) the nominal and standardized CPUE time series.

Figure 4 continued—





Regression Analysis

```
> Regression<-lm(FZ_prob~EMM)
> summary(Regression)
Coefficients:
             Estimate   Std. Error t value Pr(>|t|)
(Intercept)  0.41598    0.04052  10.266 2.94e-10 ***
EMM         -0.02290    0.02855  -0.802     0.43
Residual standard error: 0.1466 on 24 degrees of freedom
Multiple R-squared:  0.02612,   Adjusted R-squared:  -0.01446
F-statistic: 0.6436 on 1 and 24 DF,  p-value: 0.4303
```

Appendix A. Summary of some R language commands used in the preparation of data for CPUE standardization for oceanic whitetip shark.

Appendix A summarizes some of the procedures and associated R language commands used in preparing the Hawaii longline observer data. These data were used to fit the zero-inflated negative binomial models for oceanic whitetip shark *Carcharhinus longimanus* in the Hawaiian longline fishery during 1994−2019. Some noteable R language statements are in listed in **boldface.**

Initial data acquisition

Two sets of files were obtained from Mark Fitchett of the WPRFMC on September 2-3, 2020. These were operational and catch data EXCEL files (tab-delimited) for 1994 through 2019, named "HI LL Set Data 1994.csv", "HI LL Set Data 1995.csv", …,"HI LL Set Data 2019.csv". and "HI LL Catch Data 1994.csv", "HI LL Catch Data 1995.csv",…, "HI LL Catch Data 2019.csv".

Import into R for analytical processing

These annual EXCEL files were saved as plain text and read into R language data sets using the **read.csv** statement. Here are the read statements for 1994 data, for example:

catch_94<-read.csv("HI LL Catch Data 1994," **as.is=T, sep=** "**t**," and

set_94<-read.csv("HI LL Set Data 1994," as.is=T, sep= "**\t**."

There were 25 and 58 fields in the resulting catch and set data frames. The number of rows in the set data frame corresponded to the observations, which were the uniquely identified longline sets. This process was repeated until set and catch data frames for 1994−2019 had been prepared.

Data compilation

The annual set data with operational parameters were concatenated into vectors. Here is an example for 1994:

Hooks<-c(set_94NUM_HKS_SET,set_95NUM_HKS_SET…, set_19$NUM_HKS_SET);

Trip_ID<-c(set_94$TRIP_ID,set$95$TRIP_ID…, set_19$TRIP_ID).

These vectors were then combined to form a data frame:
Bycatch_DF<-data.frame(Hooks, TRIP_ID, …) .

The catch data were compiled differently because each fish is a separate record. To do so, a new field ("TRIP_SET") was created for use as a unique set identifier using the **paste** function: **TRIP_SET<-paste(DF$TRIP_ID,DF$SETNUM)**. This identifier was used with the **tapply** function to obtain the species-specific catch by counting the number of records:
junk<-catch_94[catch_94$SPECIES_COMMON_NAME=="Shark, Oceanic White-Tip,"]

OWT_94<-tapply(junk$ SPECIES_COMMON_NAME, junk$TRIP_SET,length).

Identifiers were again created using the paste function:
junk$TRIP_SET<-paste(junk$TRIP_ID,junk$SETNUM).

TRIP_SET_94<-tapply(junk$TRIP_SET,junk$TRIP_SET,unique).

The "**tapply**" function returns an array, which were converted to vectors, as follows:

OWT_94<-as.vector(as.array(OWT_94)), and

TRIP_SET_94<-as.vector(as.array(TRIP_SET_94)).

These annual vectors were concatenated so that data from all years were compiled:

OWT_Shark<-c(OWT_94,OWT_95,…,OWT_18,OWT_19).

TRIP_SET<-c(TRIP_SET_94, TRIP_SET_95, …, TRIP_SET_18, TRIP_SET_19).

These vectors were combined into a data frame, and the **match** function was used to add the catch data to the correct rows in the data frame. "NA" values were converted to zeros using **Bycatch_DF$OWT_Shark<-ifelse(is.na(Bycatch_DF$OWT_Shark,0, Bycatch_DF$OWT_Shark)**.

These procedures were used to obtain the other species-specific catch data. It is important to note that the EXCEL files for 2018 and 2019 had their formats revised and now have their fields in lower-case letters; importing them into R is case-sensitive and requires use of lower case letters.

Loading, initial checks, and deletions from the data frame

The data frame with all sets during 1994−2019 (90,634 sets) had already been loaded. A total of 477 sets were deleted within R, leaving a reduced data frame that included 90,157 longline sets. This file was named "Bycatch_DF_1." The deleted records and associated statements are listed below:

The hooks per float field (Hkpfl) had the largest number of NA values (76). Three trips had NA values for every set (36 in total), although all other operational data fields were present. Another trip exhibited errors (e.g., identical entries for begin and end date/time fields and a questionable hook number). All other sets were corrected using trip data and data from the histories of the vessels, leaving 6576 trips with 90,589 sets.
Deleted (TRIP_ID)= "FSZ265915"; "TVX703934"; "FDL547084"; "AAQ540453."

The latitude and longitude fields were checked for both missing and "out of range" (i.e., eastern or southern hemispheres) values. Ten trips that fished south of the equator were deleted, leaving 6566 trips with 90,463 sets. Five trips deployed sets in the Eastern Hemisphere. NA values for latitude (6) and longitude (9) were corrected using trip data, leaving 6561 trips with 90,405 sets.
Deleted (TRIP_ID)= "SSE167838"; "UAM606939"; "ZQN591533"; "AJB674190"; "FRB975381"; "HDJ346191"; "XWK925179"; "OIX836410"; "YDF372876"; "VYR540817"; "HVM851339"; "ADG287033"; "IPG441874"; "OUR638548"; "VTD946731."

Soak durations were checked for missing, impossible (i.e., negative values caused by errors in the Set or Haul Date/Time fields), and aberrant (i.e., ≤2 hours or ≥48 hours) values. Totals of 86 short and 45 long sets and 17 NA values were deleted, leaving 6559 trips with 90,257 sets.

Hook numbers were checked for very low (<200) and high (>4000) values. Deletion of two trips with multiple sets with low hook numbers, low fish catches, and short soak times (i.e. <5 h), 34 individual sets, and seven NA values, left 6557 trips and 90,185 sets. Checks on high hook numbers began with the maximum (5280), apparently a transposition; 13 other sets on the trip deployed 2024−2737 hooks. This was corrected to 2580. A trip with that included five sets with >4000 hooks and seven NA was deleted, leaving 6556 trips and 90,173 sets.
Deleted (TRIP_ID)= "WVZ774086"; "BQX941669"; "KDH407580."

A double-check on high numbers of hooks per float detected a trip with high numbers of hooks per float (50−53), low hook numbers (741−954), and short soak times (11.8−16.9 h). Deletion left 6555 trips and 90,164 sets.
Deleted (TRIP_ID)= "FDF760033."

Catch data were checked by applying the "table" function to catches of each species. The maximum catch of blue sharks (359) was taken on a trip with a single set that had a long soak duration (45 h) and only two swordfish caught. This was deemed to have been problematic. Deletion left 6554 trips and 90,163 sets.
Deleted (TRIP_ID)= "EIE503148."

Final data preparation steps

The EXCEL files read into R included many character variables. Substrings were obtained using the **substr** function, with their modes then changed from "character" to "numeric." Eleven fields that were no longer required were removed, using the DF$"X" <- NULL function.

Double-checks on fishing dates revealed six sets deployed on December 31, 2019, with the haul completed during 2020. These six sets were deleted, leaving 90,157 sets.

Detailed checks of the final data frame

A series of detailed checks identified an additional 18 questionable observations that included errors. These 18 longline set records were deleted and are listed below. The result was a data frame with 90,139 sets, named **OWT_Data**.

(1) "WVR965765 17": This set from Trip LL0236 exhibited exact agreement between the observer and logbook for swordfish and blue shark, but the logbook listed one shortfin mako whereas the observer listed one oceanic whitetip shark. This was from December 1999; the SST and region typical of shortfin mako habitat.
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to shortfin mako.

(2) "ZMP227973 1": This observer record from Trip LL0280 was in reasonable agreement with the logbook for swordfish (Observer: 17; logbook: 15) and blue shark (Observer:15; logbook: 18), but the observer listed one shortfin mako and one oceanic whitetip shark whereas the logbook listed two mako sharks. This trip was during January-February 2000 when SST was *ca*. 18°C.
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to shortfin mako.

(3) "VCZ151915 2": This set from Trip LL1575 was compared to the logbook, which listed 57 caught blue sharks, all of which were released. The observer record is 56 blue sharks and one oceanic whitetip shark. SST *ca*. 17°C and latitude *ca*. 32°N. This trip was from February 2005.
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to blue shark.

(4) "XXG343661 12": This set from Trip LL1995 was compared to the logbook, which listed three caught blue sharks. The observer record is one blue shark and one oceanic whitetip shark. SST *ca*. 18°C and latitude *ca*. 32°N. This trip was from January 2006. Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to blue shark.

(5) "RQQ190650 16": This set from Trip LL3076 during February 2009 was compared to the logbook. The blue shark, shortfin mako, and swordfish entries agreed. There was no oceanic whitetip shark listed in the logbook, but the observer listed one. The region (*ca.* 31°N, 161°W), and SST (*ca*.18°C) were typical of blue shark or shortfin mako habitat.
Conclusion: Probable observer error.
Action: Oceanic whitetip shark corrected to zero.

(6) "JFB344425 12": This set from Trip LL3466 during February 2010 was in a region (*ca.* 31°N, 150°W), and SST (*ca*.17°C) typical of shortfin mako habitat. The observer listed ≥1 shortfin mako(s) on all other sets. The one oceanic whitetip shark listed was on a set that listed zero shortfin makos.
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to shortfin mako.

(7) "DFA302597 20": This set from Trip LL3522 during April 2010 had observer reports of 15 blue sharks, one oceanic whitetip shark, and one shortfin mako, whereas the logbook listed 16 blue sharks and one shortfin mako. The region (*ca.* 30°N, 160°W), and SST (*ca*.19°C) were typical of shortfin mako habitat.
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to shortfin mako.

(8) "LAQ896049 20": This set from Trip LL3748 during November 2010 was in typical shortfin mako and blue shark habitat (*ca.* 37°N, 140°W; SST *ca*.17°C). Blue sharks were caught on every set, and shortfin makos were caught on 18 of 23 sets. *ca.* 31°N, 150°W), and SST (*ca*.17°C).
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to blue shark

(9) "IZP845113 1": This set during November 2008 was in typical blue shark and shortfin mako habitat (*ca.* 38°N, 136°W; SST *ca*.18°C).
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to blue shark

(10) "QKA915079 3": This set from Trip LL3866 during November 2010 was in typical blue shark and shortfin mako habitat (*ca.* 32°N, 164°W; SST *ca*.18°C). This was the final set of a long (18 sets) trip. On average, 10 blue sharks were caught on

each set, and shortfin makos were also caught on 13 sets.
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to blue shark

(11) "NGH715914 3": This set from Trip LL4236 during March 2012 was in typical blue shark and shortfin mako habitat (*ca.* 30°N, 160°W; SST *ca.*20°C). The observer reported four blue sharks, one oceanic whitetip shark, and one shortfin mako, whereas the logbook listed five blue sharks.
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to blue shark

(12) "OPH316007 13": This set from was from Trip LL4491 during January 2013. This trip was in typical blue shark and shortfin mako habitat (*ca.* 35°N, 135°W; SST *ca.*16°C). The observer reported blue sharks on every set and shortfin makos on 16 of 28 sets. One oceanic whitetip shark was reported on a set with zero shortfin makos, which also had eight blue sharks caught.
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to blue shark

(13) "NLN280450 1": This set from was from Trip LL4550 during March 2013 in typical blue shark and shortfin mako habitat (*ca.* 32°N, 163°W; SST *ca.*18°C). The observer reported blue shark catches on 23 of the 29 sets, shortfin makos on 15 sets, and an oceanic whitetip shark on one set.
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to blue shark

(14) "YBA915780 1": This set from was from Trip LL4566 during March 2013 in typical blue shark and shortfin mako habitat (*ca.* 25°N, 152°W; SST *ca.*21°C). The observer reported blue sharks caught on 10 of 12 sets, shortfin makos on five sets, and an oceanic whitetip shark once. Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to blue shark

(15) "EPJ729658 7": This set from was from Trip LL6219 during January 2018. The observer listed one oceanic whitetip shark on a set with 13 shortfin makos. in typical blue shark and shortfin mako habitat (*ca.* 35°N, 135°W; SST *ca.* 18°C).
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to blue shark

(16) "SQP124811 2": This set from Trip LL6322 was from Trip LL6219 during March 2018. The observer reported blue sharks on all of the 16 sets, shortfin makos on seven sets, and one oceanic whitetip shark on a set with six blue sharks. This was typical blue shark and shortfin mako habitat (*ca.* 25°N, 160°W; SST *ca.* 21°C).
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to blue shark

(17) "SMG249253 9": This set during December 2008 was hampered by bad weather (Beaufort state 5−6) and was deleted.

(18) The observer from Trip 2336 was newly hired and on his first trip.
Conclusion: Misidentification.
Action: Oceanic whitetip shark corrected to blue shark

The result of these checks reduced the number of longline sets in the data frame to 90,139 sets. The R object was named "**OWT_Data**", and copied as **Bycatch_Data** and **Bycatch_Data_OWT** to avoid errors.

<u>Checks of individual fields in the final data frame</u>

The individual data frame fields were checked using the **sum**, **class**, **mod**e, and **unique** functions. By so doing, it ensured that arithmetic operations would be feasible, and the **unique** function returns the "NA" or "not available" along with the other values if any remain. The numerical data fields were also checked with the logical function **is.integer.** The **summary** function was also used to check the variable attributes and to identify unexpected values in numerical fields.

Manipulations of fields

The principal data manipulations entailed preparation of factor variables from several numerical and character variables. Factor variables were denoted by the suffix "_F."

Bycatch_Data_OWT$Haulyr_F<-factor(Bycatch_Data_OWT$Haulyr).

This was checked by attempting to obtain the sum of these numeric and factor fields:

```
sum(Bycatch_Data_OWT$Haulyr)

[1] 181153237

> sum(Bycatch_Data_OWT$Haulyr_F)

Error in Summary.factor(c(1L, 1L, 1L, 1L, 1L, 1L, 1L, 1L, 1L, 1L, 1L,  :

  Noting that sum is not applicable to factor variables.

The fishery sector was a character variable, manipulated as follows:

> Bycatch_Data_OWT$Sector_F<-ifelse(Bycatch_Data_OWT$Sector=="Deep," "1," "2")

> table(Bycatch_Data_OWT$Sector_F)

    1         2

69809 20303

> Bycatch_Data_OWT$Sector_F<-as.factor(as.character(Bycatch_Data_OWT$Sector_F))

> table(Bycatch_Data_OWT$Sector_F)

    1        2

69809 20303

> sum(Bycatch_Data_OWT$Sector_F)

Error in Summary.factor(c(2L, 2L, 2L, 2L, 2L, 2L, 2L, 2L, 2L, 2L, 2L,  :

  Noting that sum is not applicable to factor variables.
```

These procedures were continued until the other necessary factors (e.g., fishing regions) had been entered into the data frame.

Data tabulations and summaries

The **table** function was applied to calculate annual sets, for example:

```
> table(Bycatch_Data_OWT$Haulyr)

1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009

 500   537   629   497    591   441 1424 2800 3429 3161 4016 5006 4179 5102 5490 5276

2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

5194 5028 5036 4775 5129 4740 3880 4234 4449 4596

> table(Bycatch_Data_OWT$Haulyr_F)

1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009
```

```
 500   537   629   497    591   441 1424 2800 3429 3161 4016 5006 4179 5102 5490 5276

2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

5194 5028 5036 4775 5129 4740 3880 4234 4449 4596
```

Numeric and factors have the same numbers per year, as expected.

Two-way tabulations were applied to obtain the sector-specific annual set totals, as follows:

```
> table(Bycatch_Data_OWT$Sector_F,Bycatch_Data_OWT$Haulyr_F)

    1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008

  1  176   266   278   178    274  265   977  2627 3405 3144 3881 3366 3333 3536 3899

  2  323   271   350   319    317  176   447    173    24    17    135  1639  846 1566 1590

    2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

  1 3517 3340 3558 3675 3815 3793 3574 3214 3377 4056 4285

  2 1758 1853  1470 1361  960 1336 1154   665  857   385   311
```

The **tapply** function was also used to calculate various descriptive statistics (e.g., sums, means, standard deviations, variances, medians, etc.) for variables indexed on other(s), as shown:

```
> tapply(OWT_Data$OWT_Shark,OWT_Data$Haulyr_F,mean)

      1994         1995            1996         1997            1998          1999           2000

0.20400000 0.45065177 0.40222576 0.34607646 0.44500846 0.48979592 0.30477528

      2001           2002            2003           2004           2005           2006          2007

0.34178571 0.22513852 0.16355584 0.17504980 0.11506193 0.07106963 0.06997256

      2008          2009             2010           2011           2012           2013            2014

0.03515483 0.05705080 0.05660377 0.06026253 0.03991263 0.04544503 0.07525833

      2015           2016           2017          2018            2019

0.11350211 0.10128866 0.05172414 0.05057316 0.08050479

> tapply(OWT_Data$OWT_Shark,OWT_Data$Haulyr_F,sum)

1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009

 102   242    253  172    263  216   434    957  772   517   703   576   297   357   193   301

2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

 294   303   201   217   386   538   393   219   225   370
```

Total catch of Oceanic Whitetip Shark

```
> sum(OWT_Data$OWT_Shark)
[1] 9501
The catch was 9501 OWT.
```

Appendix B. Summary of fitted model output for the 2013 (Table B.1) and best-fitting ZINB models (Table B.2).

Table B. 1. The R summary function output for the 2013 paper model structure (fitted model object is OWT_2013_ZINB) , based on the results of the forward-entry variable selection shown in Table 2.

```
> f_2013<-formula(OWT_Shark~Haulyr_F+Region_F+Sector_F+SST+offset(log(Hooks)) |
SST +Haulyr_F)
```

```
> OWT_2013_ZINB<-zeroinfl(f_2013,data=OWT_Data,dist=“negbin,” link=“logit”)
```

```
> summary(OWT_2013_ZINB)

Call: zeroinfl(formula = f, data = OWT_Data, dist = “negbin,” link = “logit”)

Pearson residuals:

    Min       1Q       Median      3Q        Max

-0.89168 -0.30300 -0.16413 -0.02618 42.93640

Count model coefficients (negbin with log link):

                 Estimate   Std. Error z value Pr(>|z|)

(Intercept)      -10.45292    0.54605 -19.143  < 2e-16 ***

Haulyr_F1995   0.93849    0.16940   5.540 3.02e-08 ***

Haulyr_F1996   0.55278    0.16242   3.403 0.000665 ***

Haulyr_F1997   0.70427    0.17603   4.001 6.31e-05 ***

Haulyr_F1998   0.40163    0.16906   2.376 0.017519 *

Haulyr_F1999   0.92535    0.18127   5.105 3.31e-07 ***

Haulyr_F2000   0.16269    0.15415   1.055 0.291244

Haulyr_F2001   0.20230    0.14512   1.394 0.163319

Haulyr_F2002  -0.43209    0.14434  -2.994 0.002758 **

Haulyr_F2003  -0.10595    0.15070  -0.703 0.482012

Haulyr_F2004  -0.18227    0.15490  -1.177 0.239317

Haulyr_F2005  -0.51485    0.14375  -3.582 0.000342 ***

Haulyr_F2006  -0.99441    0.15663  -6.349 2.17e-10 ***

Haulyr_F2007  -1.13296    0.14817  -7.647 2.07e-14 ***

Haulyr_F2008  -1.22706    0.17250  -7.113 1.13e-12 ***

Haulyr_F2009  -1.16714    0.15687  -7.440 1.01e-13 ***

Haulyr_F2010  -0.89697    0.15898  -5.642 1.68e-08 ***

Haulyr_F2011  -0.78327    0.16090  -4.868 1.13e-06 ***

Haulyr_F2012  -1.11385    0.17871  -6.233 4.59e-10 ***

Haulyr_F2013  -0.95603    0.18758  -5.097 3.46e-07 ***
```

```
Haulyr_F2014  -0.51803    0.15810  -3.277 0.001051 **
Haulyr_F2015  -0.15711    0.15149  -1.037 0.299700
Haulyr_F2016  -0.30686    0.15673  -1.958 0.050250 .
Haulyr_F2017  -1.01256    0.16296  -6.213 5.18e-10 ***
Haulyr_F2018  -0.92332    0.16532  -5.585 2.34e-08 ***
Haulyr_F2019  -0.85533    0.15424  -5.546 2.93e-08 ***
Region_F2     -0.36281    0.11403  -3.182 0.001464 **
Region_F3     -1.78733    0.11624 -15.376  < 2e-16 ***
Region_F4     -1.63555    0.11309 -14.463  < 2e-16 ***
Region_F5     -2.73967    0.11962 -22.904  < 2e-16 ***
Region_F6     -1.77071    0.11893 -14.888  < 2e-16 ***
Region_F7     -4.40210    0.29301 -15.024  < 2e-16 ***
Region_F8     -2.95524    0.16364 -18.060  < 2e-16 ***
Sector_F2      2.25279    0.04800  46.929  < 2e-16 ***
SST            0.12660    0.01856   6.820 9.13e-12 ***
Log(theta)     0.04338    0.05543   0.783 0.433808

Zero-inflation model coefficients (binomial with logit link):
               Estimate Std. Error z value Pr(>|z|)
(Intercept)    32.08264    1.79451  17.878  < 2e-16 ***
SST            -1.38567    0.07446 -18.611  < 2e-16 ***
Haulyr_F1995  0.64056    0.74204   0.863 0.388006
Haulyr_F1996  0.03533    0.81595   0.043 0.965459
Haulyr_F1997 -0.37150    0.81165  -0.458 0.647158
Haulyr_F1998  0.92887    0.80737   1.150 0.249942
Haulyr_F1999  0.19602    0.75531   0.260 0.795230
Haulyr_F2000  1.40252    0.69167   2.028 0.042588 *
Haulyr_F2001  0.30768    0.66680   0.461 0.644493
Haulyr_F2002 -2.38275    1.45180  -1.641 0.100748
Haulyr_F2003  0.57361    0.78312   0.732 0.463879
Haulyr_F2004  3.07808    0.67275   4.575 4.75e-06 ***
Haulyr_F2005 -0.96951    0.68677  -1.412 0.158037
Haulyr_F2006  1.13595    0.82623   1.375 0.169174
Haulyr_F2007 -0.74638    0.75684  -0.986 0.324040
```

```
Haulyr_F2008  0.68911    0.71550   0.963 0.335492

Haulyr_F2009  0.92001    0.69130   1.331 0.183237

Haulyr_F2010  1.50317    0.67737   2.219 0.026478 *

Haulyr_F2011  1.70301    0.65882   2.585 0.009740 **

Haulyr_F2012  2.12026    0.67511   3.141 0.001686 **

Haulyr_F2013  2.76371    0.73647   3.753 0.000175 ***

Haulyr_F2014  2.78437    0.66456   4.190 2.79e-05 ***

Haulyr_F2015  2.70501    0.64569   4.189 2.80e-05 ***

Haulyr_F2016  2.38434    0.64401   3.702 0.000214 ***

Haulyr_F2017  2.05314    0.68381   3.003 0.002678 **

Haulyr_F2018  2.56696    0.68218   3.763 0.000168 ***

Haulyr_F2019  2.25124    0.68497   3.287 0.001014 **


Theta = 1.0443

Log-likelihood: -2.377e+04 on 63 Df

> AIC(OWT_ZINB_13)

[1] 47674.12
```

Table B. 2. The R summary function output for the base case, or best-fitting ZINB model structure (fitted model object is OWT_Best_ZINB based on the results of the forward-entry variable selection shown in Table 4.

```
> f_Best<-formula(OWT_Shark~Haulyr_F+Region_F+Sector_F+latitude+longitude+SST

+offset(log(Hooks))  | SST +Haulyr_F)
```

```
> OWT_Best_ZINB<-zeroinfl(f_Best,data=OWT_Data,dist="negbin," link="logit")
```

```
> summary(OWT_Best_ZINB),

Call: zeroinfl(formula = f, data = OWT_Data, dist = "negbin," link = "logit")

Pearson residuals:

    Min       1Q      Median      3Q        Max

-0.90941 -0.30049 -0.15569 -0.02246 39.14010

Count model coefficients (negbin with log link):

                    Estimate    Std. Error z value Pr(>|z|)

(Intercept)      -22.804134   0.863317 -26.415  < 2e-16 ***

Haulyr_F1995   1.001911   0.166873   6.004 1.92e-09 ***

Haulyr_F1996   0.603915   0.161472   3.740 0.000184 ***

Haulyr_F1997   0.711352   0.173280   4.105 4.04e-05 ***

Haulyr_F1998   0.404378   0.164859   2.453 0.014172 *

Haulyr_F1999   0.786437   0.179964   4.370 1.24e-05 ***

Haulyr_F2000  -0.025874   0.152324  -0.170 0.865117

Haulyr_F2001   0.052235   0.144529   0.361 0.717789

Haulyr_F2002  -0.450347   0.143893  -3.130 0.001750 **

Haulyr_F2003  -0.117917   0.148630  -0.793 0.427566

Haulyr_F2004  -0.285036   0.154834  -1.841 0.065634 .

Haulyr_F2005  -0.479865   0.143221  -3.351 0.000807 ***

Haulyr_F2006  -1.065257   0.154092  -6.913 4.74e-12 ***

Haulyr_F2007  -1.203005   0.147927  -8.132 4.21e-16 ***

Haulyr_F2008  -1.270597   0.165630  -7.671 1.70e-14 ***

Haulyr_F2009  -1.316790   0.154721  -8.511  < 2e-16 ***

Haulyr_F2010  -1.089455   0.155770  -6.994 2.67e-12 ***

Haulyr_F2011  -0.963988   0.157634  -6.115 9.63e-10 ***

Haulyr_F2012  -1.413079   0.167451  -8.439  < 2e-16 ***

Haulyr_F2013  -1.297550   0.173999  -7.457 8.84e-14 ***

Haulyr_F2014  -0.694037   0.153929  -4.509 6.52e-06 ***
```

```
Haulyr_F2015  -0.210119   0.150376  -1.397 0.162325
Haulyr_F2016  -0.445599   0.154965  -2.875 0.004034 **
Haulyr_F2017  -0.958710   0.159580  -6.008 1.88e-09 ***
Haulyr_F2018  -0.922354   0.163436  -5.644 1.67e-08 ***
Haulyr_F2019  -0.781351   0.153873  -5.078 3.82e-07 ***
Region_F2     -1.255354   0.122659 -10.235  < 2e-16 ***
Region_F3     -1.683700   0.134953 -12.476  < 2e-16 ***
Region_F4     -2.220811   0.138432 -16.043  < 2e-16 ***
Region_F5     -2.101683   0.156567 -13.424  < 2e-16 ***
Region_F6     -2.024358   0.166232 -12.178  < 2e-16 ***
Region_F7     -3.459418   0.326811 -10.585  < 2e-16 ***
Region_F8     -2.987639   0.231960 -12.880  < 2e-16 ***
Sector_F2      2.100802   0.049579  42.373  < 2e-16 ***
Latitude      -0.054870   0.006029  -9.100  < 2e-16 ***
Longitude     -0.090373   0.004350 -20.775  < 2e-16 ***
SST            0.089651   0.019034   4.710 2.48e-06 ***
Log(theta)     0.088479   0.056770   1.559 0.119103

Zero-inflation model coefficients (binomial with logit link):
              Estimate Std. Error  z value Pr(>|z|)
(Intercept)   35.31701    2.42879  14.541  < 2e-16 ***
SST           -1.52196    0.10315 -14.754  < 2e-16 ***
Haulyr_F1995  0.75629    0.74132   1.020 0.307632
Haulyr_F1996  0.15522    0.82461   0.188 0.850693
Haulyr_F1997 -0.74126    0.87240  -0.850 0.395504
Haulyr_F1998  0.74697    0.83920   0.890 0.373412
Haulyr_F1999  0.19398    0.78431   0.247 0.804652
Haulyr_F2000  1.10934    0.72607   1.528 0.126545
Haulyr_F2001  0.04342    0.70834   0.061 0.951121
Haulyr_F2002 -2.54976    1.45128  -1.757 0.078935 .
Haulyr_F2003  0.46149    0.80139   0.576 0.564707
Haulyr_F2004  2.96682    0.71362   4.157 3.22e-05 ***
Haulyr_F2005 -1.31250    0.71183  -1.844 0.065207 .
```

```
Haulyr_F2006  0.72497    0.94684   0.766 0.443869
Haulyr_F2007 -0.97630    0.77833  -1.254 0.209716
Haulyr_F2008  0.18105    0.75507   0.240 0.810497
Haulyr_F2009  0.43637    0.72843   0.599 0.549141
Haulyr_F2010  1.09103    0.70999   1.537 0.124371
Haulyr_F2011  1.39817    0.68433   2.043 0.041040 *
Haulyr_F2012  1.43040    0.71611   1.997 0.045777 *
Haulyr_F2013  1.28306    0.97075   1.322 0.186262
Haulyr_F2014  2.18924    0.70873   3.089 0.002008 **
Haulyr_F2015  2.53290    0.67870   3.732 0.000190 ***
Haulyr_F2016  2.14191    0.67559   3.170 0.001522 **
Haulyr_F2017  1.88389    0.71138   2.648 0.008092 **
Haulyr_F2018  2.50330    0.71708   3.491 0.000481 ***
Haulyr_F2019  2.33607    0.71471   3.269 0.001081 **
---
Theta = 1.0925
Log-likelihood: -2.348e+04 on 65 Df
> AIC(OWT_ZINB_Model)
[1] 47086.78
```

Appendix C. Model diagnostic plots of quantile residuals (Dunn and Smyth 1996) for the best-fitting CPUE standardization model for oceanic whitetip shark caught in the Hawaii longline fishery during 1994-2019 (Figures C.1 to C.9).

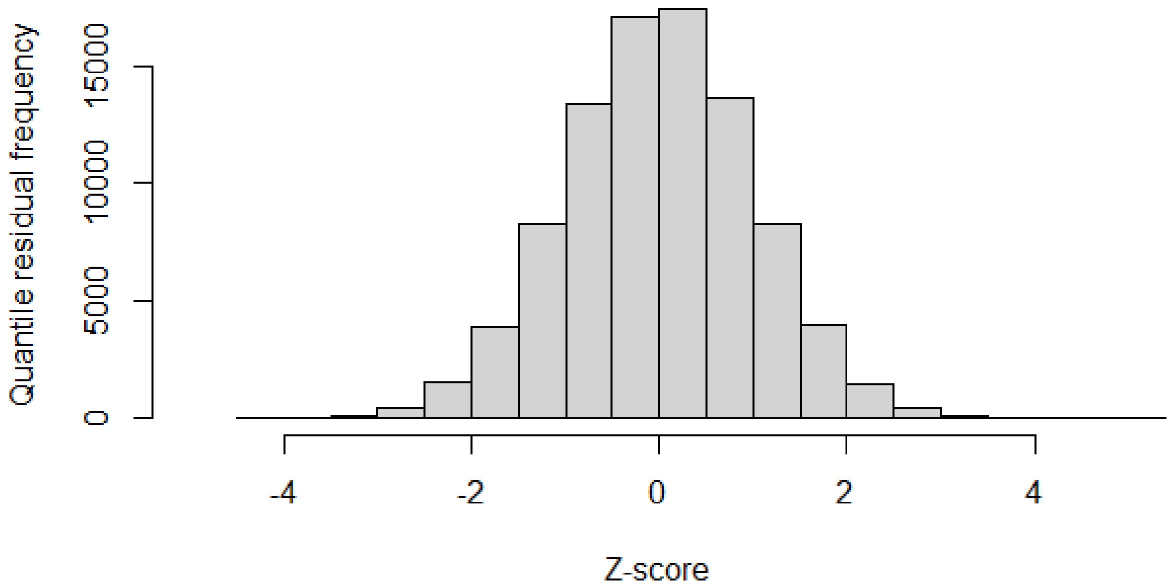


Figure C. 1. Histogram of quantile residuals for the best-fitting CPUE standardization model.

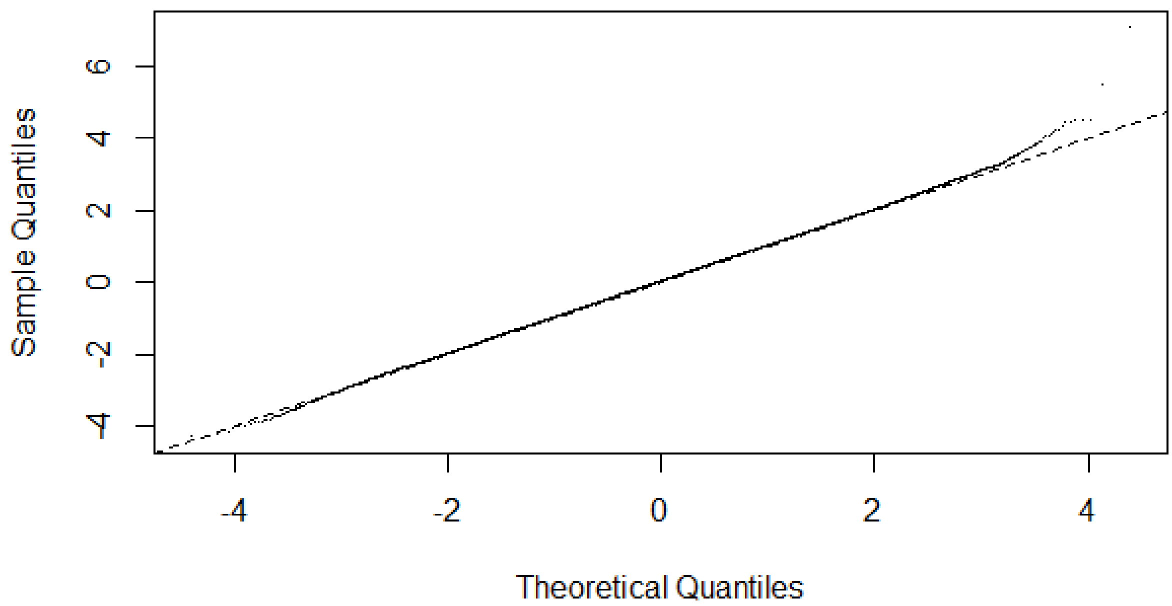


Figure C. 2. Quantile-quantile plot of quantile residuals for the best-fitting CPUE standardization model.

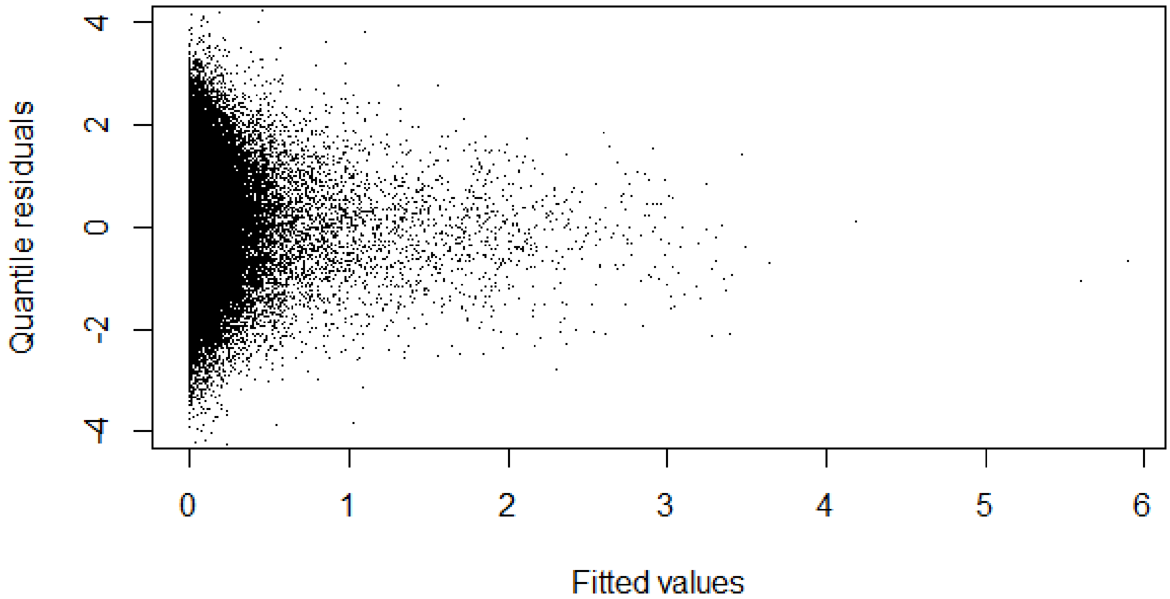


Figure C. 3. Plot of quantile residuals vs. fitted values of oceanic whitetip sharks per set for the best-fitting CPUE standardization model.

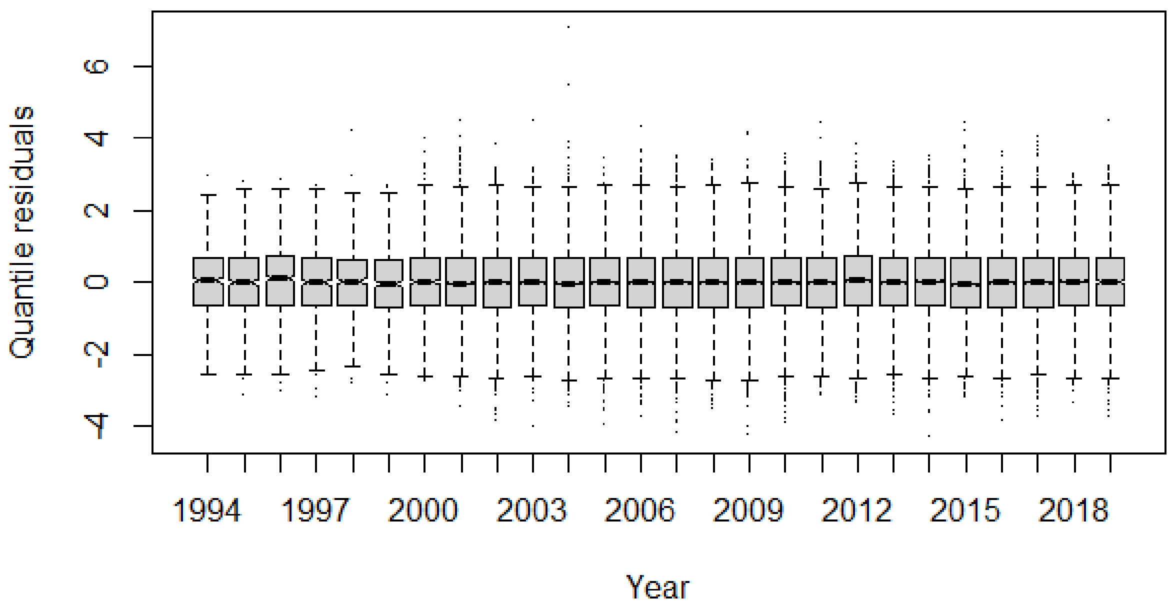


Figure C. 4. Tukey boxplots of quantile residuals vs. year for the best-fitting CPUE standardization model.

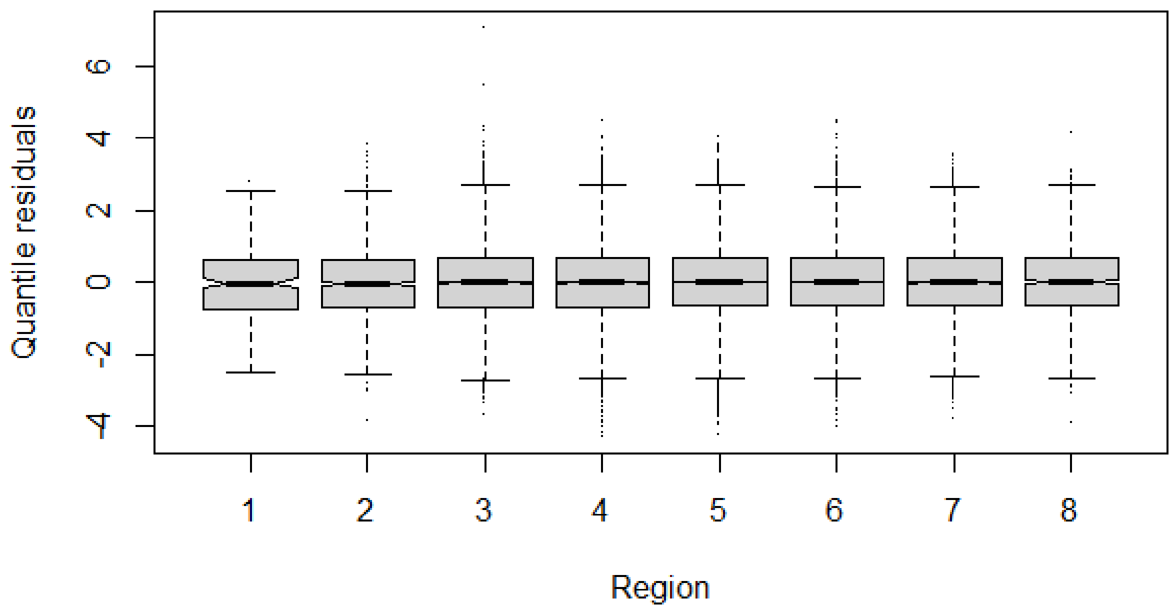


Figure C. 5. Tukey boxplots of quantile residuals vs. fishing region for the best-fitting CPUE standardization model.

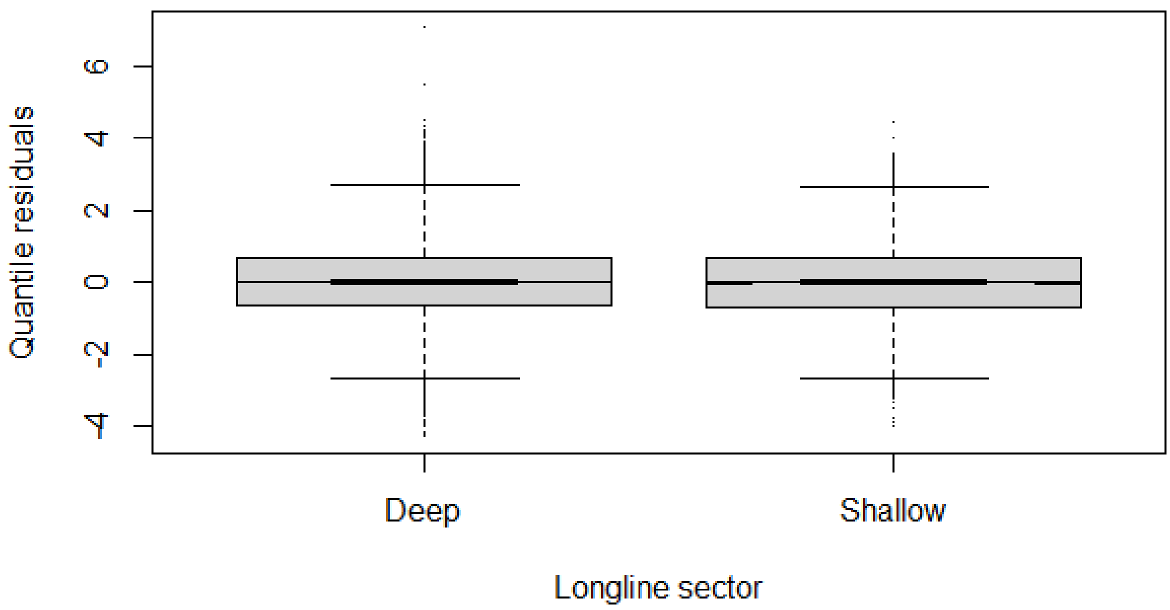


Figure C. 6. Tukey boxplots of quantile residuals vs. fishery sector for the best-fitting CPUE standardization model.

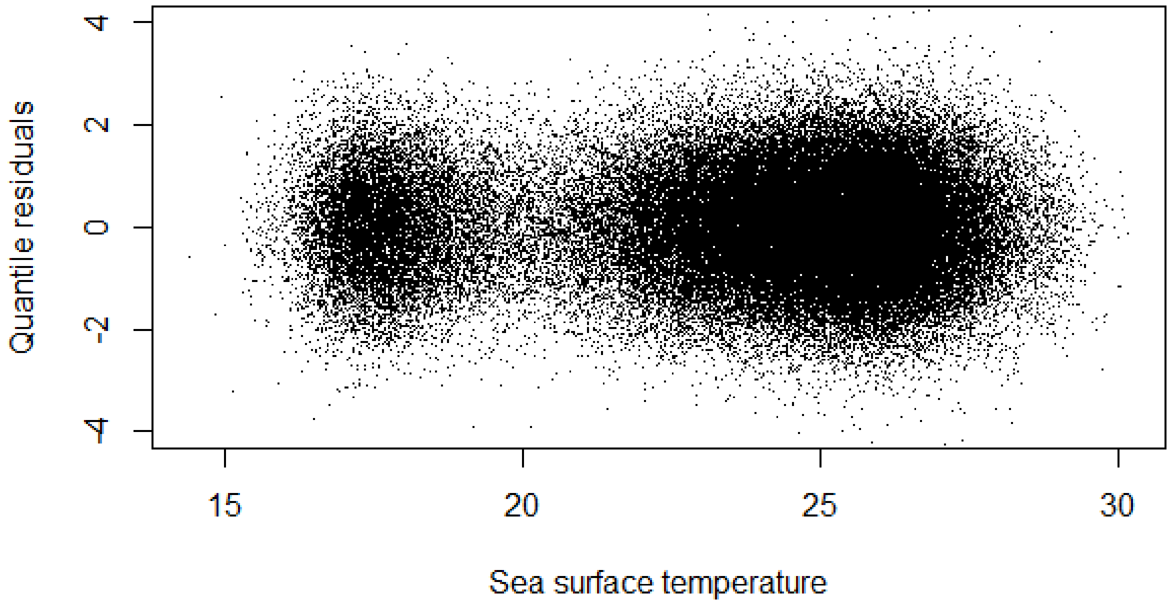


Figure C. 7. Plot of quantile residuals vs. sea surface temperature (°C) for the best-fitting CPUE standardization model.

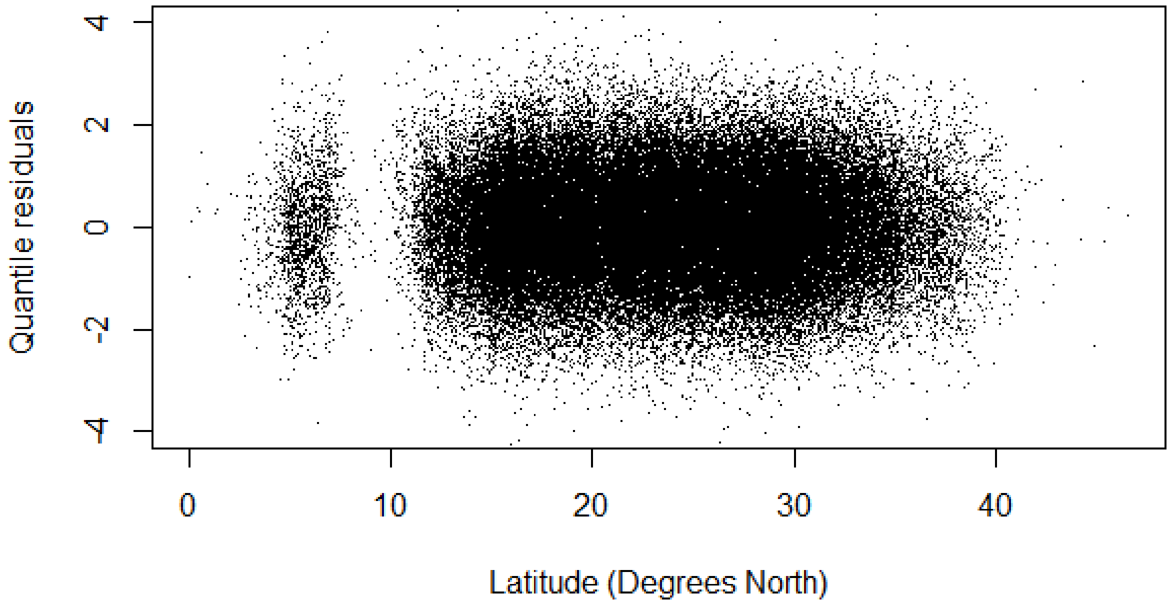


Figure C. 8**. Plot of quantile residuals vs. latitude (°N) for the best-fitting CPUE standardization model.**.

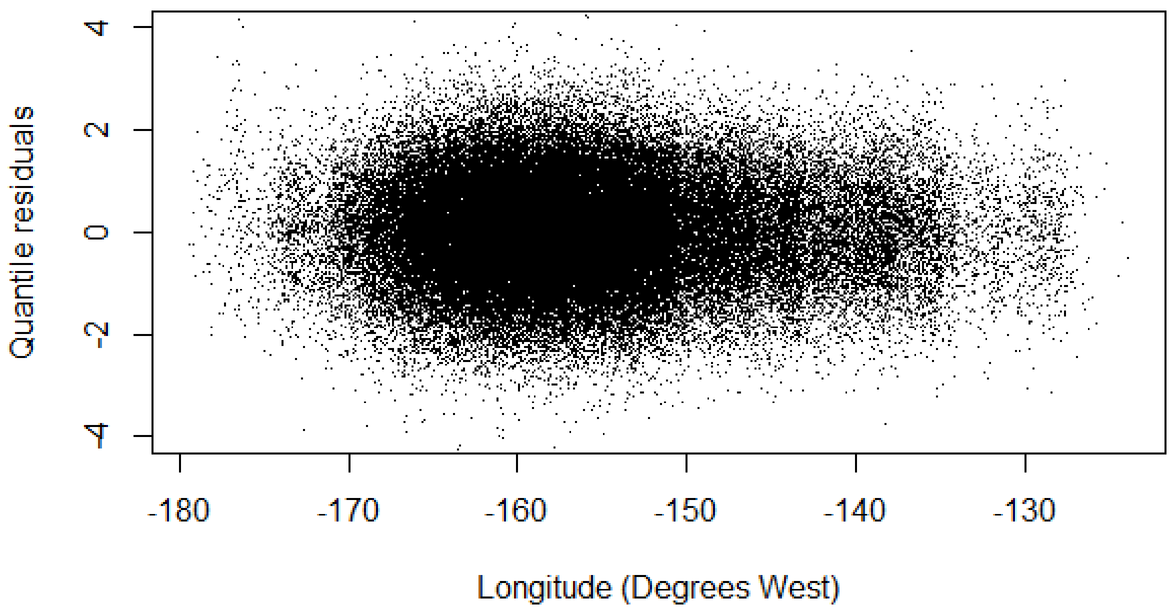


Figure C. 9. Plot of quantile residuals vs. longitude (°W) for the best-fitting CPUE standardization model

Appendix D. Potential impacts of changes in data collection practices on shark bycatch monitoring in the Hawaii longline fishery

We have historically used the PIROP fishery observer data for several types of fishery analyses (Walsh and Brodziak 2016; Walsh and Kleiber 2001; Walsh et al. 2002; Walsh et al. 2009), including the evaluation of self-reporting accuracy of shark catches in commercial logbooks. In this case, we have used 20-year (1995–2014) and 15-year (2000–2014) subsets of the logbook data to compare annual shark catches reported by observers vs. catches reported in logbooks in the set of observed fishing trips. During these time periods, three major changes occurred in the Hawaii longline fishery: (1) the PIROP increased its coverage of the longline fleet by about fourfold during 2000–2001; (2) the two-sector management regime (shallow-set and deep-set) was initiated in 2001; (3) a data entry field for oceanic whitetip shark was added to the logbook form in 2000. These changes impacted the data on shark bycatch collected from the Hawaii longline fishery.

The annual shark catch totals reported by the PIROP observers and in the logbooks throughout 1995–2014 (Figure D.1) show low observed catches that were associated with low observer coverage rates (*ca*. 5%) during 1995–1999. As of 2000–2001, however, the three aforementioned changes in this fishery (Figure D.2) had begun. Blue shark was the predominant shark bycatch species (Figure D.3, 85.7% of observed shark catches), and the observed totals were always greater than the logbook totals (Figures D.1 to D.3). The percent differences between the observer-reported shark catches and the self-reported catches from logbooks were substantial for the monitored shark species in this fishery. The underreporting rates for blue shark, mako sharks, thresher sharks, and oceanic whitetip shark averaged 11.3%, 13.5%, 15.0% and 18.4%, respectively during 2000-2014. It is also important to note that the apparent percent underreporting rates of oceanic whitetip sharks during 2000–2005 were greater and significantly different from those of all other monitored shark species, as indicated by a one-way analysis of covariance and the Tukey HSD test (Table D.2) and shown by the apparent underreporting (Figures D.4 to D.6) trends.

Conclusion

Our previous work (Walsh and Brodziak 2016; Walsh and Kleiber 2001; Walsh et al. 2002; Walsh et al. 2009) has demonstrated that reporting accuracy in commercial logbooks can be adversely affected by changes in data collection procedures. For example, some fishermen were probably confused about their reporting requirements when observer deployments became more frequent beginning in 2000. Thus, the short-term increases in the apparent underreporting of blue sharks, makos, and threshers were not unexpected. However, significantly greater apparent underreporting of oceanic whitetip shark than all other sharks during 2000–2005 was unexpected in two ways. First, because the oceanic whitetip shark was a common bycatch species in this fishery and easily recognized from its (formerly valuable) fins and overall appearance, misidentifications would not be expected. Second, although an entry space for oceanic whitetip shark was added to the logbook form in 2000, the apparent underreporting of this species persisted for six years. Therefore, we conclude that evaluation of the effectiveness of fishery management procedures to restore threatened sharks taken as bycatch may be difficult, particularly if fishery observer coverage rates are low or non-existent or if commercial logbooks with their inherent biases are to be relied upon as the primary monitoring tool.

Table D. 1. Percent differences between observed and self-reported shark bycatch recorded on observed Hawaii longline trips during 2000–2014. Explanatory notes are presented in the footnote[4].

Haul year	Blue shark	Mako shark	Thresher shark	Oceanic whitetip shark
2000	26.5	21.7	10.8	58
2001	23.7	21.5	34.1	28.1
2002	16.6	14.8	20.7	24.3
2003	8.6	3.3	16.1	28.8
2004	8.8	1.9	18.1	25.9
2005	6.8	16	9.4	26.1
2006	11.3	9.4	15.8	**8.1**
2007	5	17.5	14	4.2
2008	6.4	18.6	0.7	5.2
2009	8.7	5.6	12.8	5
2010	6.1	1.5	10.5	18.6
2011	8.5	11.2	14.5	9.9
2012	11.4	20.5	14.4	5
2013	13.9	16.5	24.9	21.4
2014	7.4	22.2	7.6	7.3
Average	11.3	13.5	15.0	18.4

[4] The **boldface** value for oceanic whitetip sharks (2006) was calculated after deleting one trip (LL2103). There were differences between the observer (on his second trip) and the logbooks in total sharks and all individual species, none of which were readily comprehensible.

Table D. 2. Analysis of covariance of the percent underreporting of the four shark species during 2000–2005, spanning the transition period to two-sector management. The observed data consist of the underreported shark catch data from the monitored shark species. The variable “Sp_code” is a factor variable that denotes the four shark species groups tested for significance in underreporting (blue shark, oceanic whitetip shark, mako sharks and thresher sharks), and the “Time” variable denotes the linear term representing temporal trend.

> summary(model)

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Sp_code	3	1276.6	425.5	6.892	0.00249 **
Time	1	794.1	794.1	12.862	0.00197 **
Residuals	19	1173.1	1.7		

> TukeyHSD(model)

Tukey multiple comparisons of means

95% family-wise confidence level

Fit: aov(formula = Species_diffs ~ Sp_code + Time)

Species codes (Sp_code factor levels: 1 = Blue shark; 2 = OWT shark; 3 = Makos; 4 = Threshers)

Sp_code

	diff	lwr	upr	p adj
2-1	16.690600	3.934453	29.4467463	0.0079383
3-1	-1.962648	-14.718795	10.7934988	0.9721145
4-1	3.033578	-9.722569	15.7897244	0.9075687
3-2	-18.653248	-31.409394	-5.8971008	0.0030501
4-2	-13.657022	-26.413169	-0.9008752	0.0333013
4-3	4.996226	-7.759921	17.7523724	0.6930368

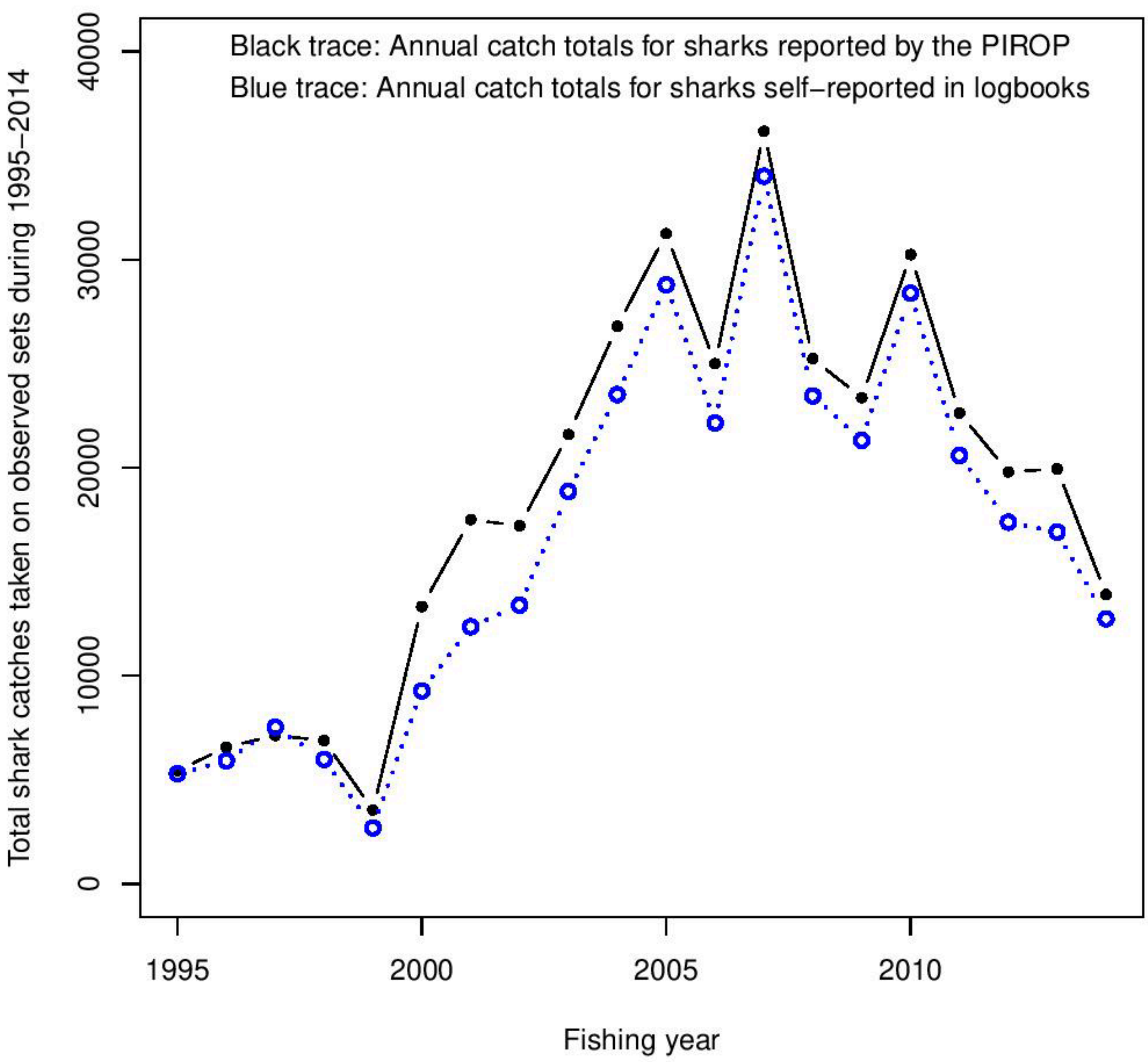


Figure D. 1. Time series plots of total shark catches taken on observed fishing trips during 1995–2014 as reported by PIROP observers (solid circles) and self-reported in commercial logbooks (open circles).

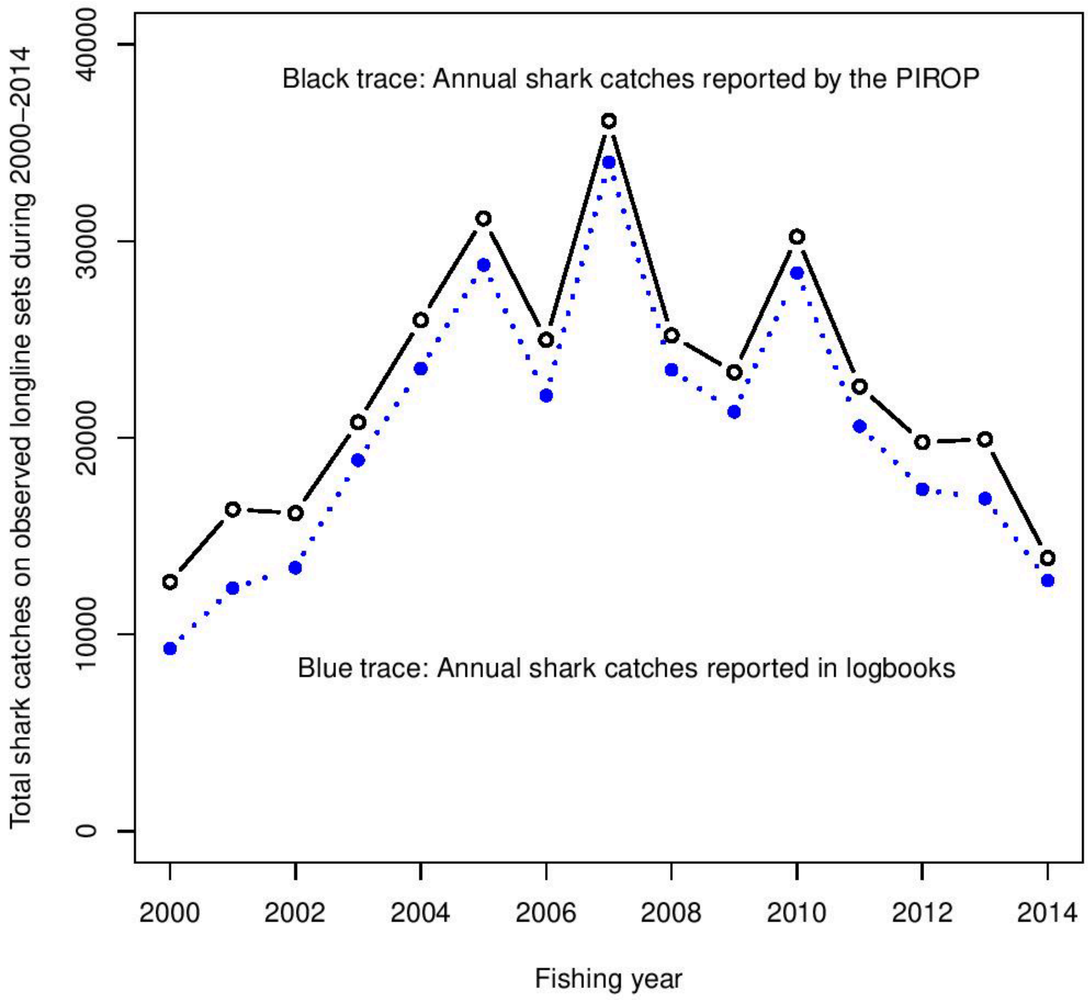


Figure D. 2. Time series plots of total shark catches taken on observed fishing trips during 2000–2014 as reported by PIROP observers (open circles) and self-reported in commercial logbooks (solid circles).

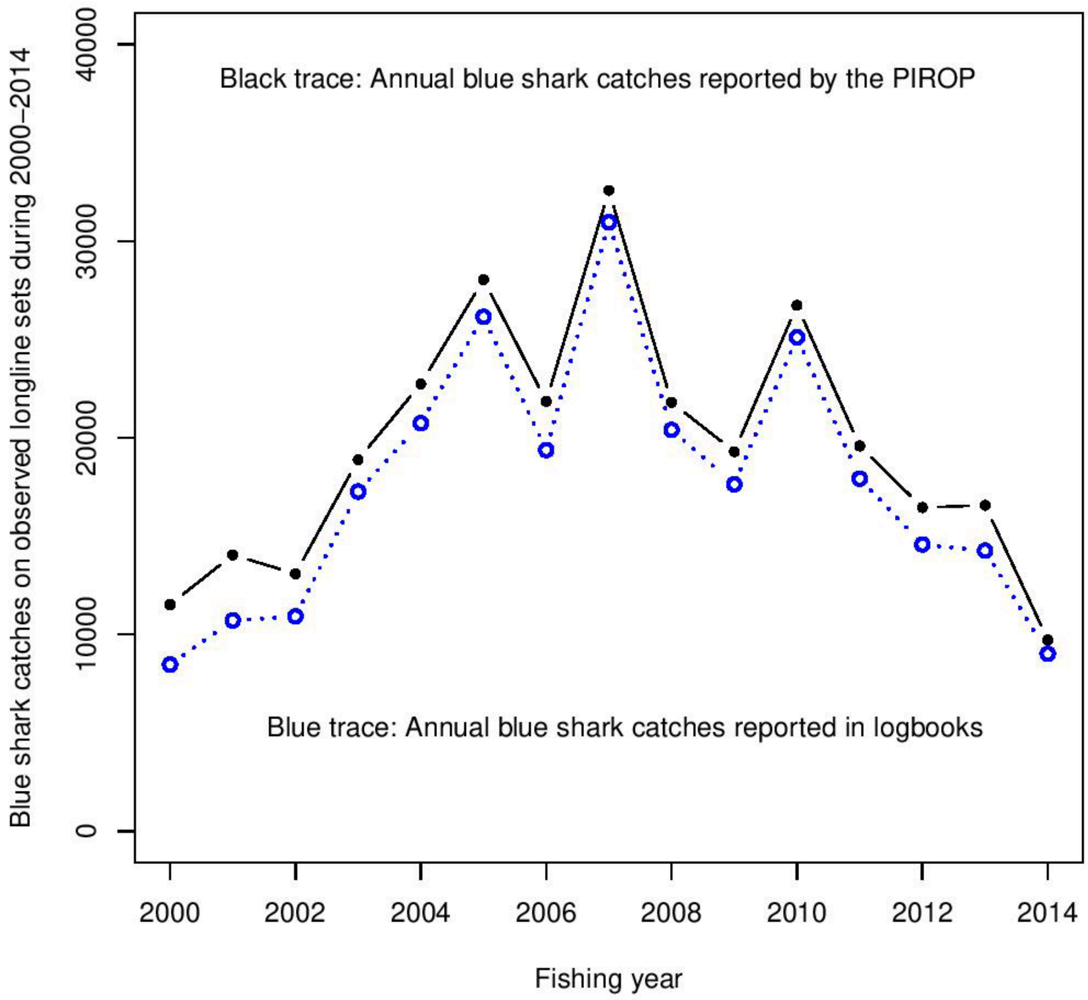


Figure D. 3. Time series plots of blue shark catches taken on observed fishing trips during 2000–2014 as reported by PIROP observers (solid circles) and self-reported in commercial logbooks (open circles).

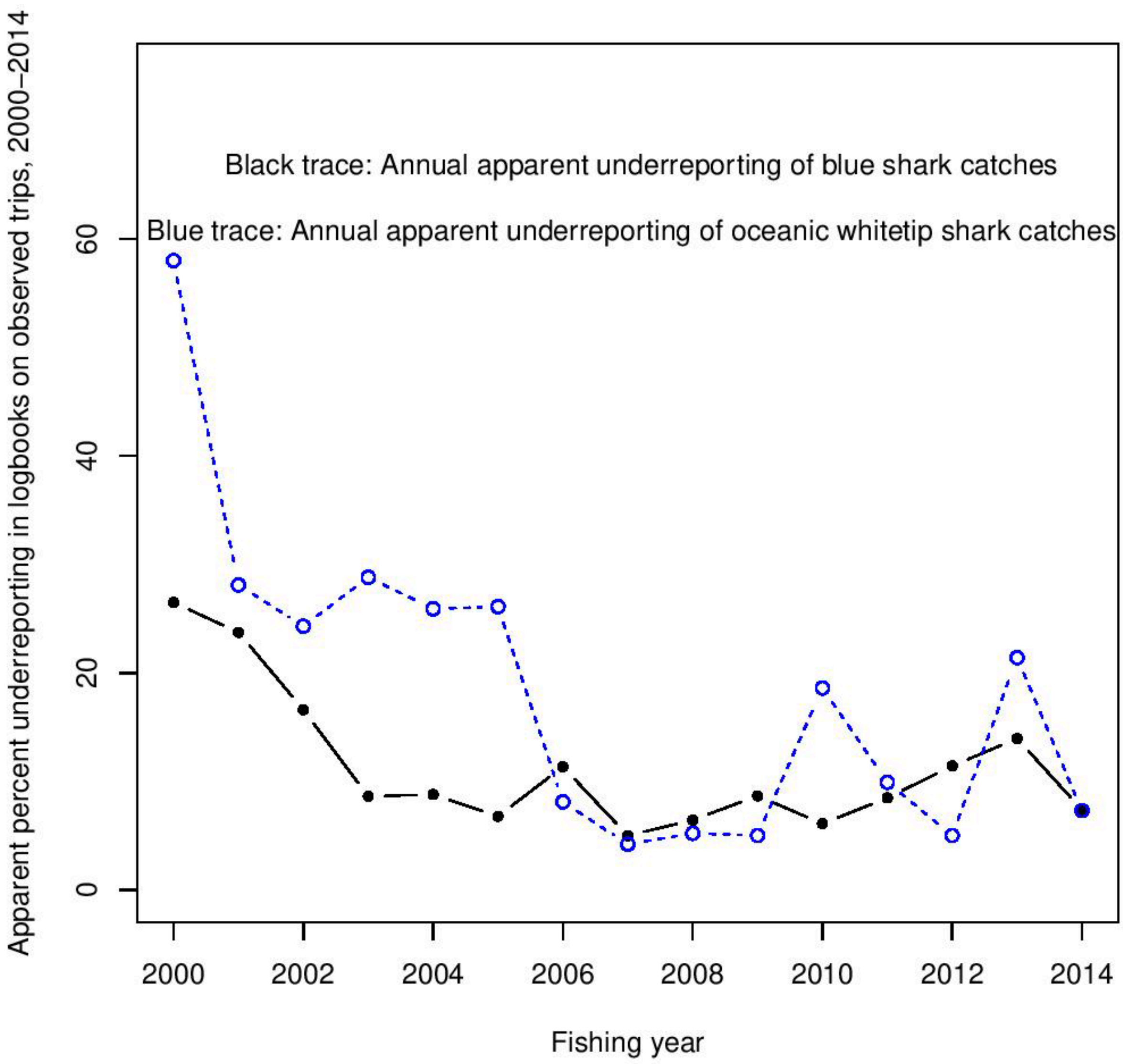


Figure D. 4. Comparison plot showing the oceanic whitetip shark (open circles) apparent underreporting and the blue shark (solid circles) apparent underreporting trends.

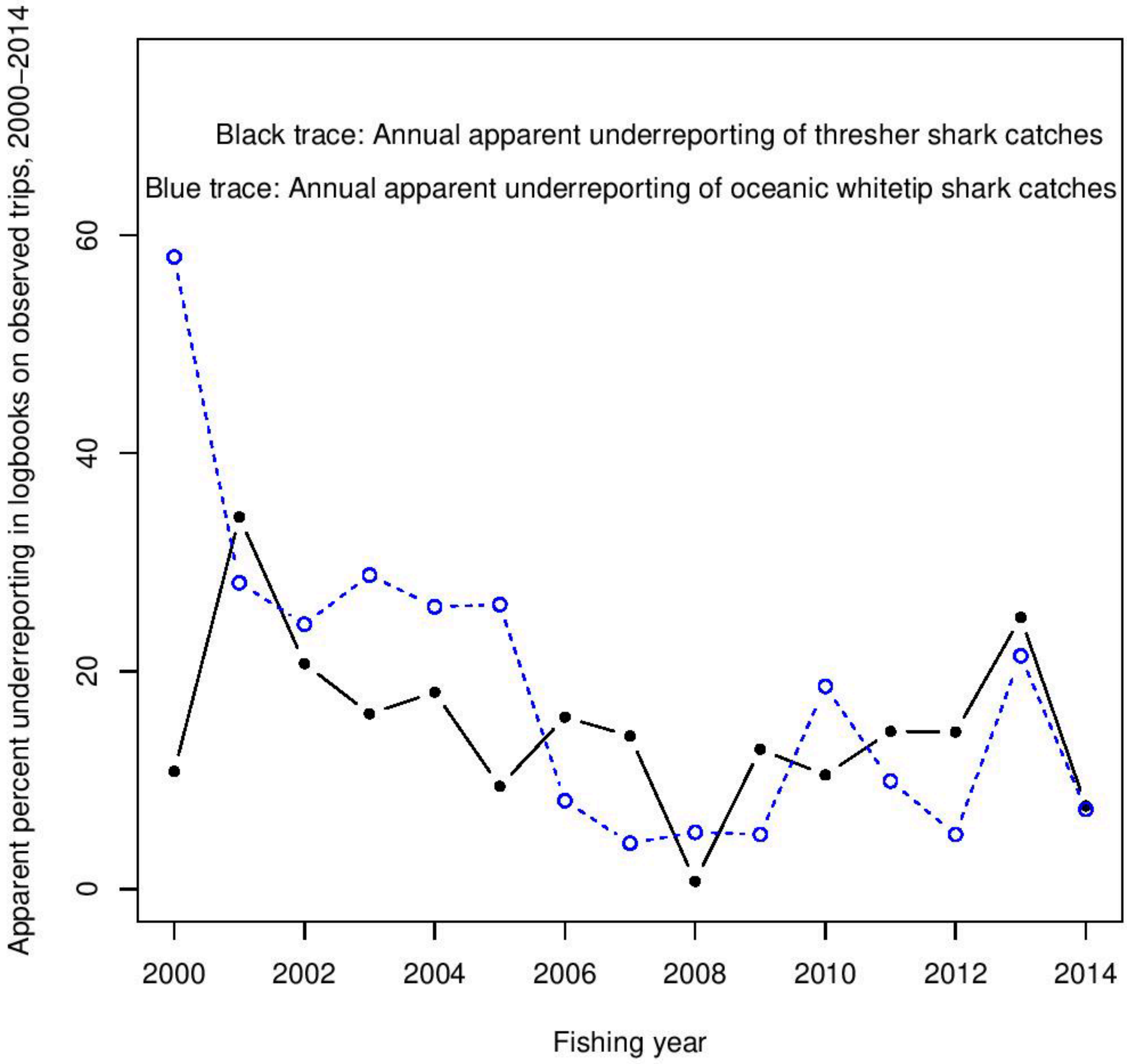


Figure D. 5. Comparison plot showing the oceanic whitetip shark (open circles) apparent underreporting and the thresher shark (solid circles) apparent underreporting trends.

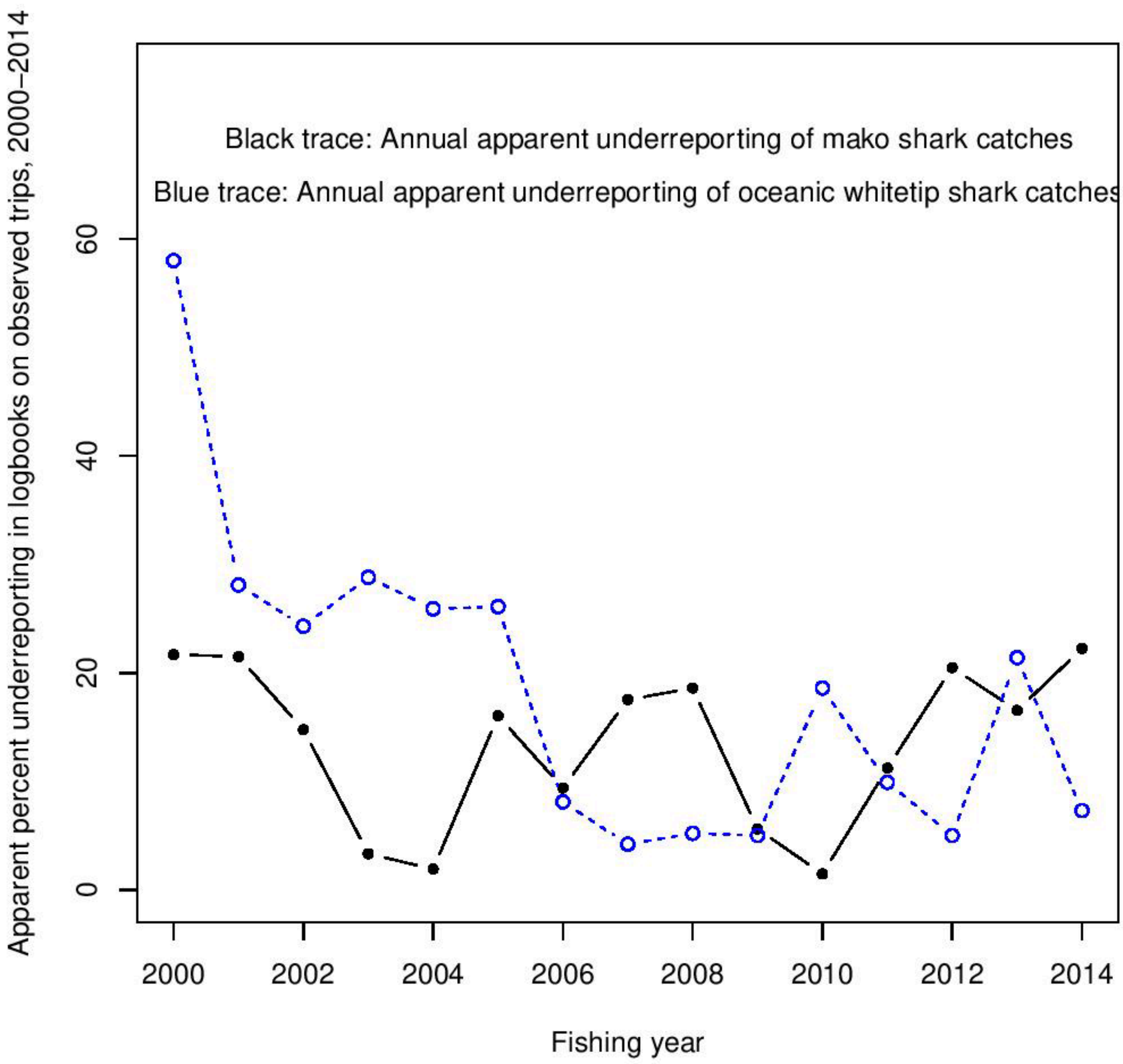


Figure D. 6. Comparison plot showing the oceanic whitetip shark (open circles) apparent underreporting and the thresher shark (solid circles) apparent underreporting trends.