Preliminary standardized catch rate of silky sharks caught by Taiwanese large-scale longline fishery in the Indian Ocean

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SUMMARY

The silky shark catch and effort data from the logbook data of Taiwanese large longline fishing vessels operating in the Indian Ocean from 2005-2018 were analyzed. Based on the effort distribution, four areas, namely, A (north of 10ºS, east to 70ºE), B (north of 10ºS, 70ºE-120ºE), C (south of 10ºS, 20ºE-60ºE), D (south of 10ºS, 60ºE-120ºE) were categorized. Due to the large percentage of zero shark catch, the catch per unit effort (CPUE) of silky shark, as the number of fish caught per 1,000 hooks, was standardized using zero-inflated negative binomial model (ZINB) that allows for “extra” zeros. ZINB model includes the main variables year, quarter, area, hooks per basket (HPB), and CTNO. The standardized CPUE showed a stable trend for silky sharks from 2005 to 2014 and increased steadily thereafter with peaks in 2014. The results obtained in this study can be improved if longer time series logbook data are available.

KEYWORDS

Silky sharks, Taiwanese longline fishery, standardized CPUE, by-catch, zero-inflated negative binomial model

1. Introduction

The silky shark, *Carcharhinus falciformis*, is one of the most abundant and cosmopolitan shark species in tropical and warm temperate seas (Castro et al., 1999). Historically it has been the main shark by-catch of the longline and purse seine fisheries in the open ocean (Matsunaga and Nakano, 1999; Compagno et al., 2005; White and Cavanagh, 2007). Based on recent stock assessments by the Inter-American Tropical Tuna Commission (IATTC) and Western and Central Pacific Fisheries Commission (WCPFC), there is little doubt that silky shark populations have declined substantially in many regions (Aires-da-Silva et al., 2013; Rice and Harley, 2013). The commercial retention of the silky shark is prohibited by several Regional Fisheries Management Organizations (RFMO's), such as ICCAT and WCPFC, but not in the Indian Ocean and IATTC waters. Its stock status (overfishing but not overfished) in the Indian Ocean is still highly uncertain, despite one recent stock assessment study (Ortiz et al., 2018). Moreover, as the assessment is in the preliminary stage and there is considerable uncertainty associated with the estimations, management advice remains unclear.

CPUE is often the main piece of information used in fisheries stock assessments and usually assumed to be proportional to the fish abundance and is used as a relative index of abundance (Maunder, 2001; Campbell, 2004). Therefore, it is necessary to examine the recent trend of silky shark species. The by-catch of Taiwanese tuna longline fleets was never reported until 1981 because of its low economic value compared with tunas and species-specific data which were not available until 2003 because the shark catch was recorded as "sharks" before then. The category "sharks" on the logbook has been further separated into four sub-categories namely the blue shark, *Prionace glauca*, mako shark, Isurus spp., silky shark, and others since 2003, which enable us to get a better estimation of shark by-catch. In addition, the reliable catch estimate for silky shark can be developed because the logbook records of silky sharks were representative of actual catches as all sharks were retained due to its high market value. As the Taiwanese longline fishery has widely covered the Indian Ocean, our fishery statistics must be one of the most valuable information, which describes population status of pelagic sharks. Thus, the objectives of this study are to standardize the CPUE of silky sharks in the Indian based on the logbook data.

A large proportion of zero values is commonly found in by-catch data obtained from fisheries studies involving counts of abundance or CPUE standardization. The zero-inflated negative binomial modeling, which can account for a large proportion of zero values than expected, is an appropriate approach to model "extra" zero data. Such "extra" zero catches could be attributable to reporting error or misidentifications, survey error (in which sharks were present at the site of a longline set but were not observed because the gear deployment did not overlap with the depth distribution of sharks or did not attract sharks), or both (Brodziak and Walsh,2013). As sharks are common by-catch species in the tuna longline fishery, the zero-inflated negative binomial model (ZINB) is commonly used in CPUE standardization to address these excessive zero catch of sharks. In this study, the CPUEs of silky sharks in the Indian Ocean were standardized using zero-inflated negative binomial model based on logbook data and hopefully these CPUE series can be used in the silky shark stock assessment in 2019.

2. Material and methods

2.1. Source of data

The species-specific catch data including tunas, billfishes, and sharks from logbook data in 2005-2018 were used to standardize CPUE of silky shark of Taiwanese large-scale longline fishery in the Indian Ocean. The summary of these data were shown in **Table 1**. The catch rate of silky sharks might be affected by spatial and temporal factors. We used the following stratification in our models. For temporal factors, we separated the data into 4 quarters: the 1st quarter (January to March), the 2nd quarter (April to June), the 3rd quarter (July to September), and the 4th quarter (October to December). For spatial stratification, based on the effort distribution and fishing grounds of the target species (Huang and Liu, 2010) (**Fig. 1**), four areas, namely, A (north of 10ºS, east to 70ºE), B (north of 10ºS, 70ºE-120ºE), C (south of 10ºS, 20ºE-60ºE), D (south of 10ºS, 60ºE-120ºE) were categorized. The areas used in this study are shown in **Figure 2**. For standardization, CPUE was calculated by set of operations based on logbook data during the period of 2005-2018.

2.2. CPUE standardization

Between 2005 and 2018, data from a total of 42,157 longline sets were collected, which amounted to a total effort of 1,446,935,185 hooks and yielded 79,706 silky sharks. A large proportion of sets with zero catch of silky sharks (about 96%) in the Indian Ocean was found in the logbook data. Hence, to address these excessive zero catches, the zero-inflated negative binomial model (ZINB) (Lambert, 1992) was applied to the standardization of silky shark CPUE. This zero-inflated negative binomial model is comprised of a counts model that allows for overdispersion in both the zeros and positive catches and a binomial model that allows for “extra” zeros (Zuur et al., 2009, 2012; Brodziak and Walsh, 2013), with the latter defined as a higher frequency of zeros than expected under the Poisson, negative binomial, or other count distributions (Zuur et al., 2009).

The model was fit using zeroinfl function of statistical computing language R (R Development Core and Team, 2013) to eliminate some biases by change of targeting species, fishing ground and fishing seasons.

Standardized CPUE series for the silky shark was constructed including main effects and interaction terms. The main effects chosen as input into the ZINB analyses were year (Y), quarter (Q), area (A), number of hooks per basket (HPB), and vessel size (CTNO). The following additive model was applied to the data in this study:

Catch= Year + Quarter + Area + HPB + CTNO

(Part 1: Counts model- Negative Binomial; Part 2: Binomial, link = logit)

The probability distribution of a zero-inflated negative binomial random variable Y is given by

$$\Pr(Y = y) = \begin{cases} \omega + (1-\omega)(1+k\lambda)^{1/k} & \text{for } y = 0 \\ (1-\omega)\frac{\Gamma(y+1/k)}{\Gamma(y+1)\Gamma(1/k)}\frac{(k\mu)^y}{(1+k\lambda)^{y+1/k}} & \text{for } y = 1, 2, \ldots \end{cases}$$

where k is the negative binomial dispersion parameter.

3. Results and discussion

The silky shark bycatch data are characterized by many zero values and a long right tail (**Figs. 3 and 4**). Overall, 95.98% of the total sets in the Indian Ocean had zero bycatch of silky sharks (**Table 2**). As a result, the following models with many explanatory variables were finally selected. The best models for ZINB model chosen by BIC values in the Indian Ocean were “SMA~ Year + Quarter + Area + HPB + CTNO”, respectively. The best models were then used in the later analyses.

Standardized CPUE series of the silky shark in the Indian Ocean using the ZINB model were shown in **Figure 5**. The detail values for nominal and standardized CPUE were listed in **Tables 3.** The nominal CPUE of silky shark in the Indian Ocean showed an inter-annual fluctuation, particularly in year 2007 and 2014 (**Fig. 5**). However, this variability was slightly smoothed in the standardized CPUE series. In general, the standardized CPUE series of the silky sharks caught by Taiwanese large-scale longline fishery showed a stable increasing trend (**Fig. 5**). These stable trends suggested that the silky shark stock in the Indian Ocean seems at the level of optimum utilization during the period of 2005-2018.

The diagnostic results from the ZINB model do not indicate severe departure from model assumptions (**Figs. 6-7**). The additional residual plots and ANOVA tables for each model are given in **Appendix Figs. 1-2 and Table 1**. Most main effects and interaction terms tested were significant (mostly $P < 0.01$) and have been included in the final model. However, other factors may affect the standardization of CPUE trend. In addition to the temporal and spatial effects, environmental factors are important which may affect the representation of standardized CPUE of pelagic fish i.e., swordfish and blue shark in the North Pacific Ocean (Bigelow *et al.,* 1999), and big-eye tuna in the Indian Ocean (Okamoto *et al.,* 2001). In this report, environmental effects were not included in the model for standardization. The results obtained in this study can be improved if longer time series of logbook data are available and environmental factors were included in the model.

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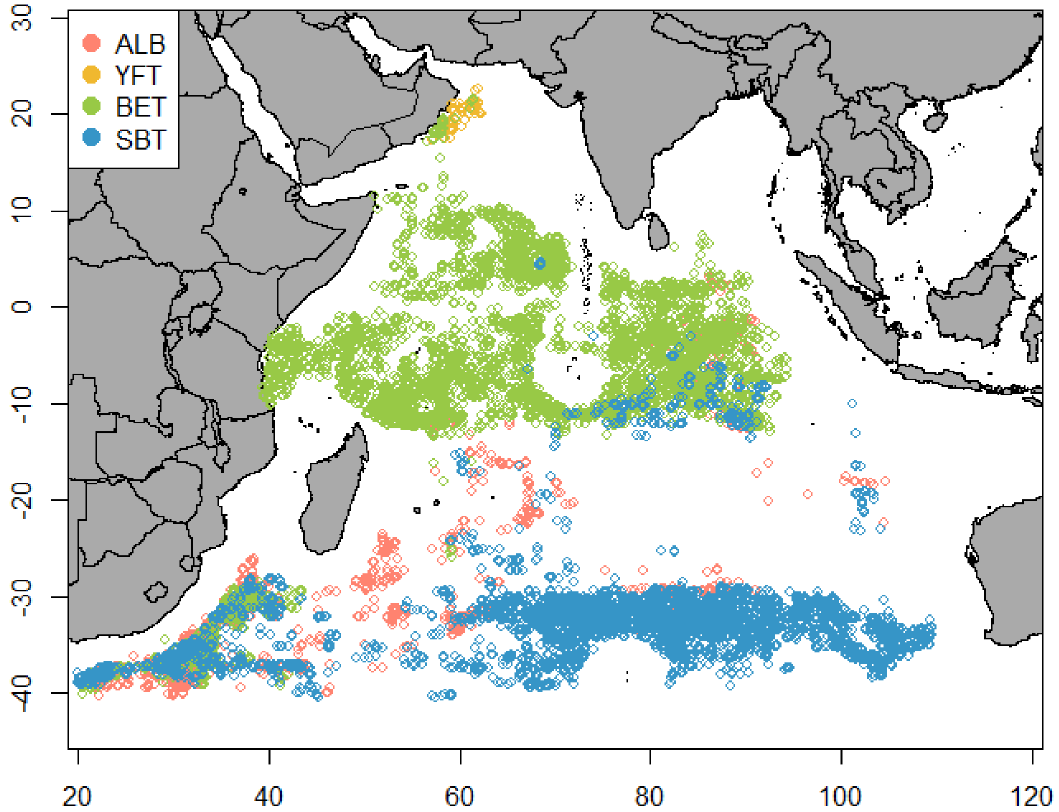


Figure 1. Observed effort distributions in the Indian Ocean from 2005 to 2018.

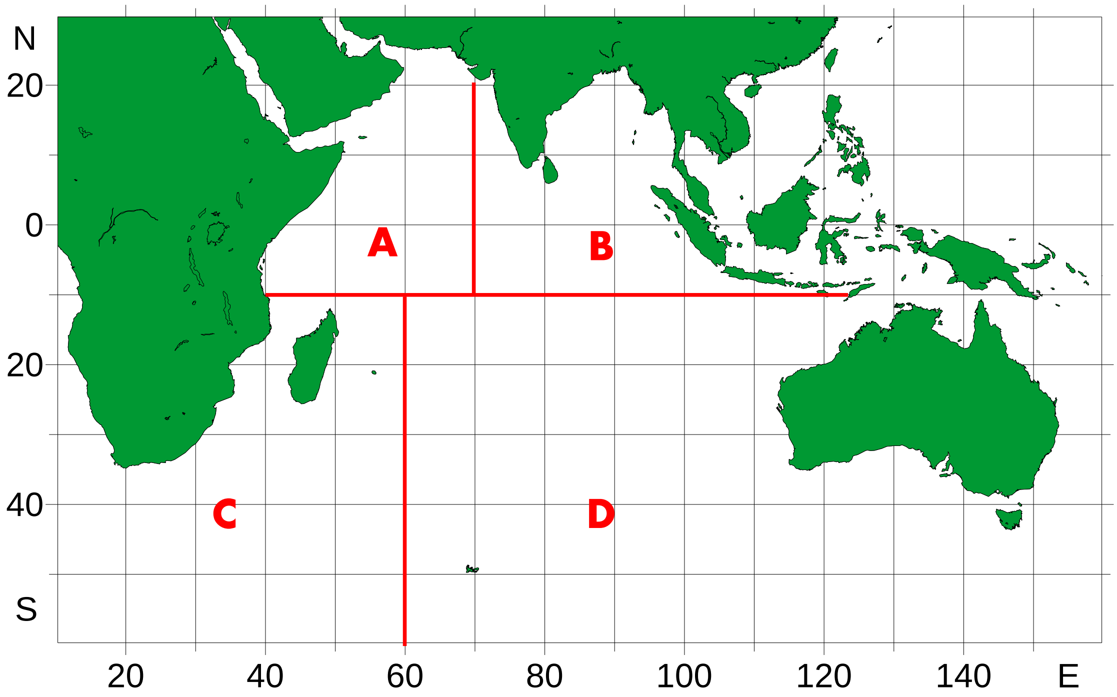


Figure 2. Area stratification based on effort distribution and targeting species in this study.

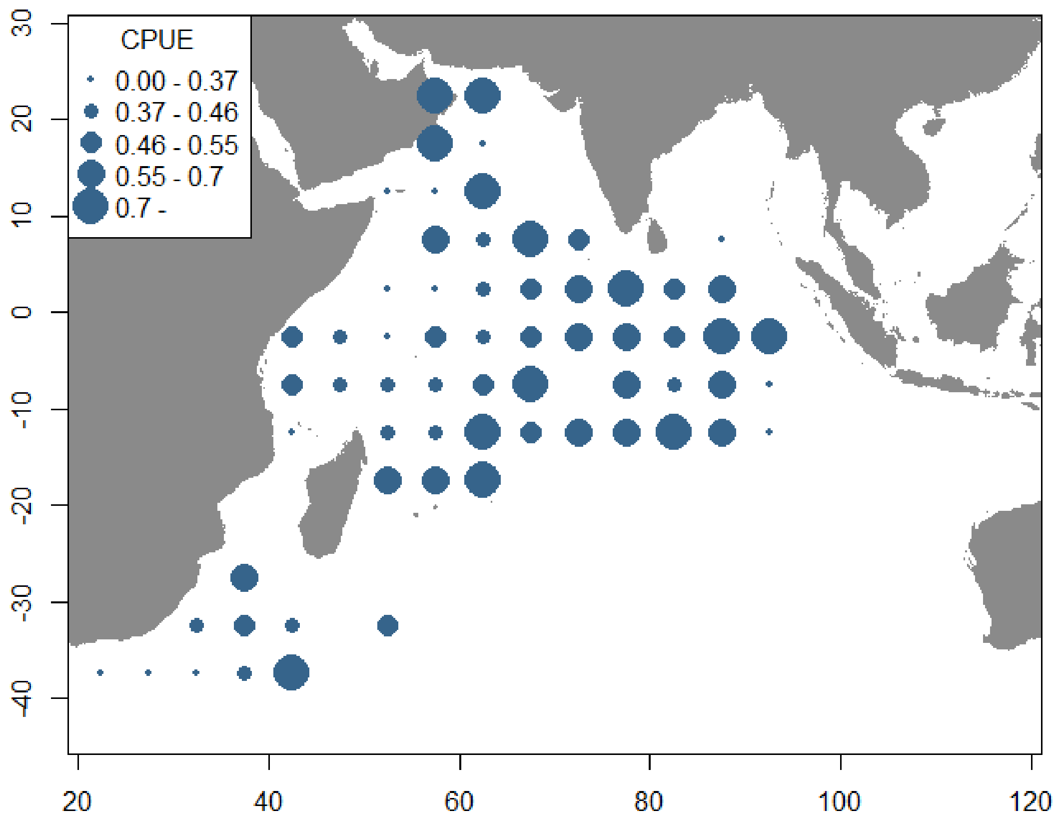


Figure 3. Observed distribution of silky shark CPUE of Taiwanese tuna longline vessels in the Indian Ocean from 2005 to 2018.

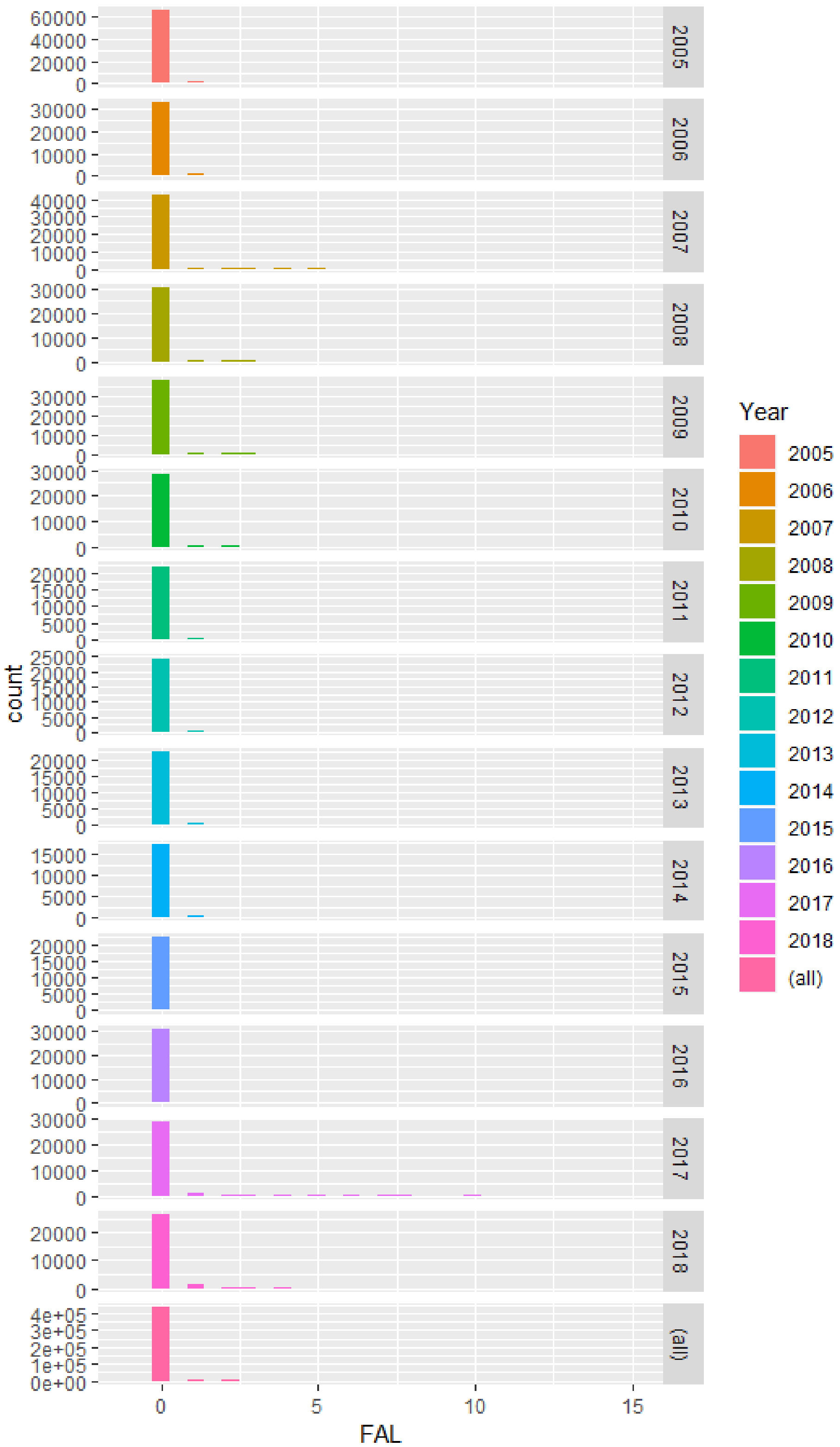


Figure 4. Annual frequency distribution of silky shark bycatch per set in the Indian Ocean, 2005–2018.

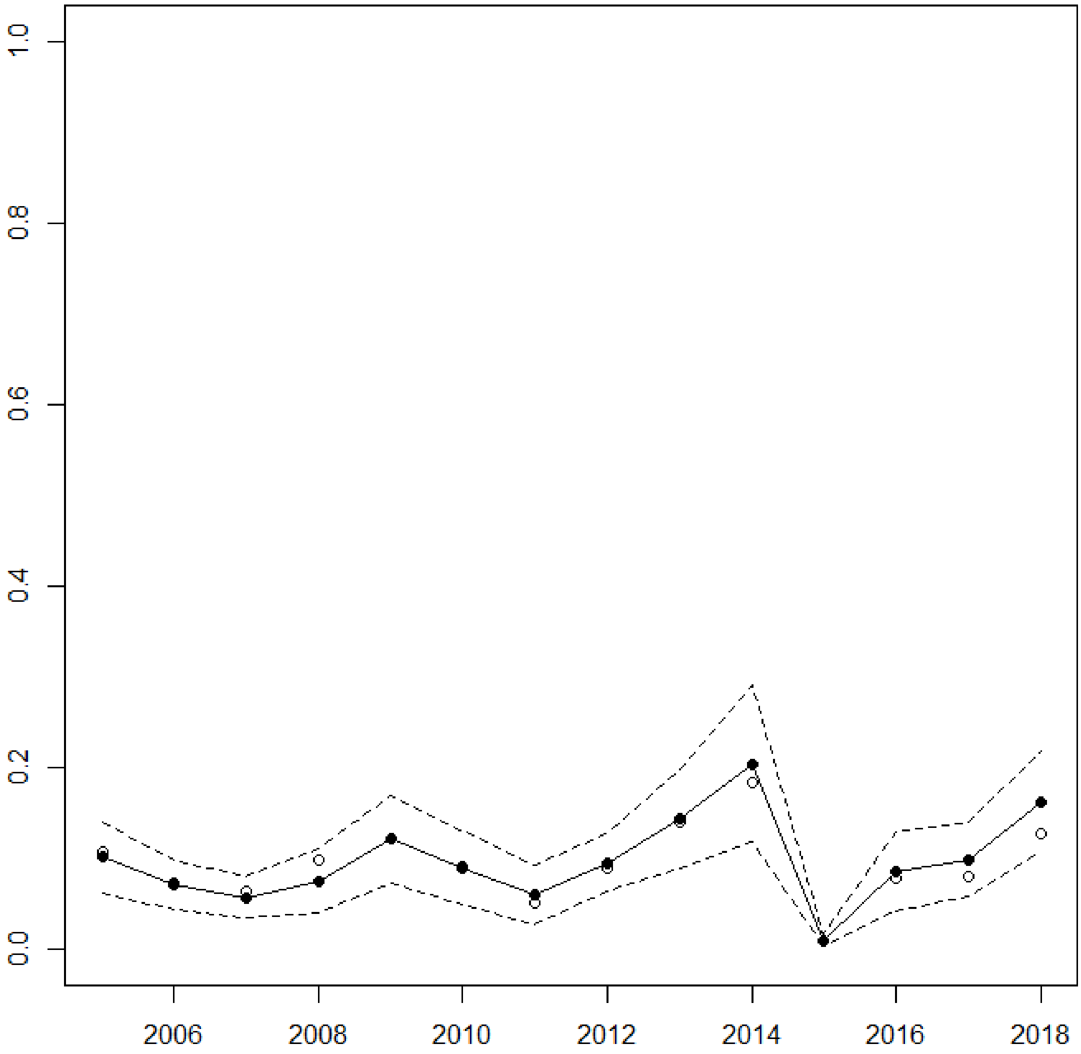


Figure 5. Logbook nominal and standardized CPUE with 95% CI of silky shark by Taiwanese longline vessels in the Indian Ocean from 2005 to 2018.

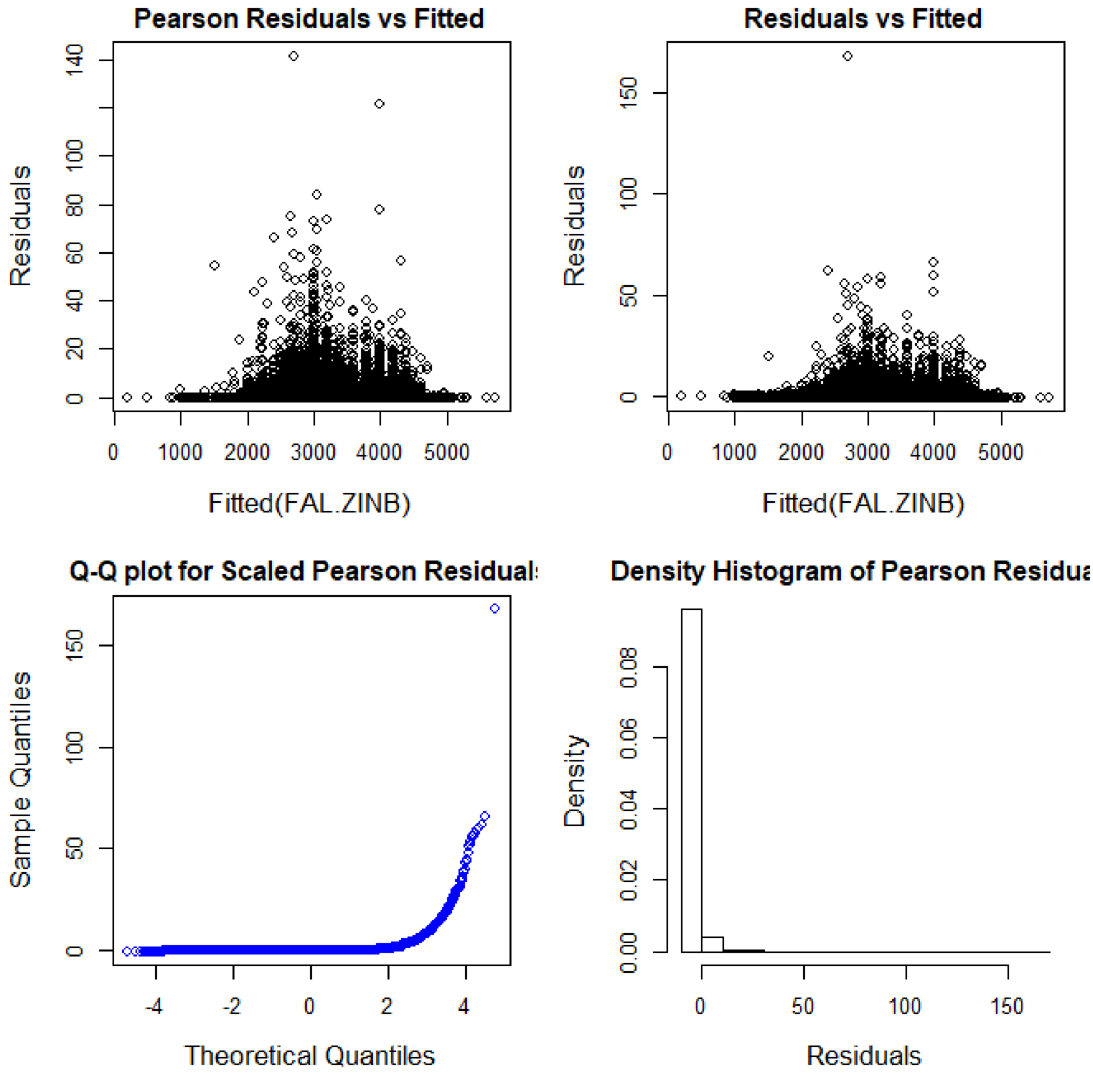


Figure 6. Diagnostic results from the ZINB model fit to the Indian Ocean longline silky shark bycatch data.

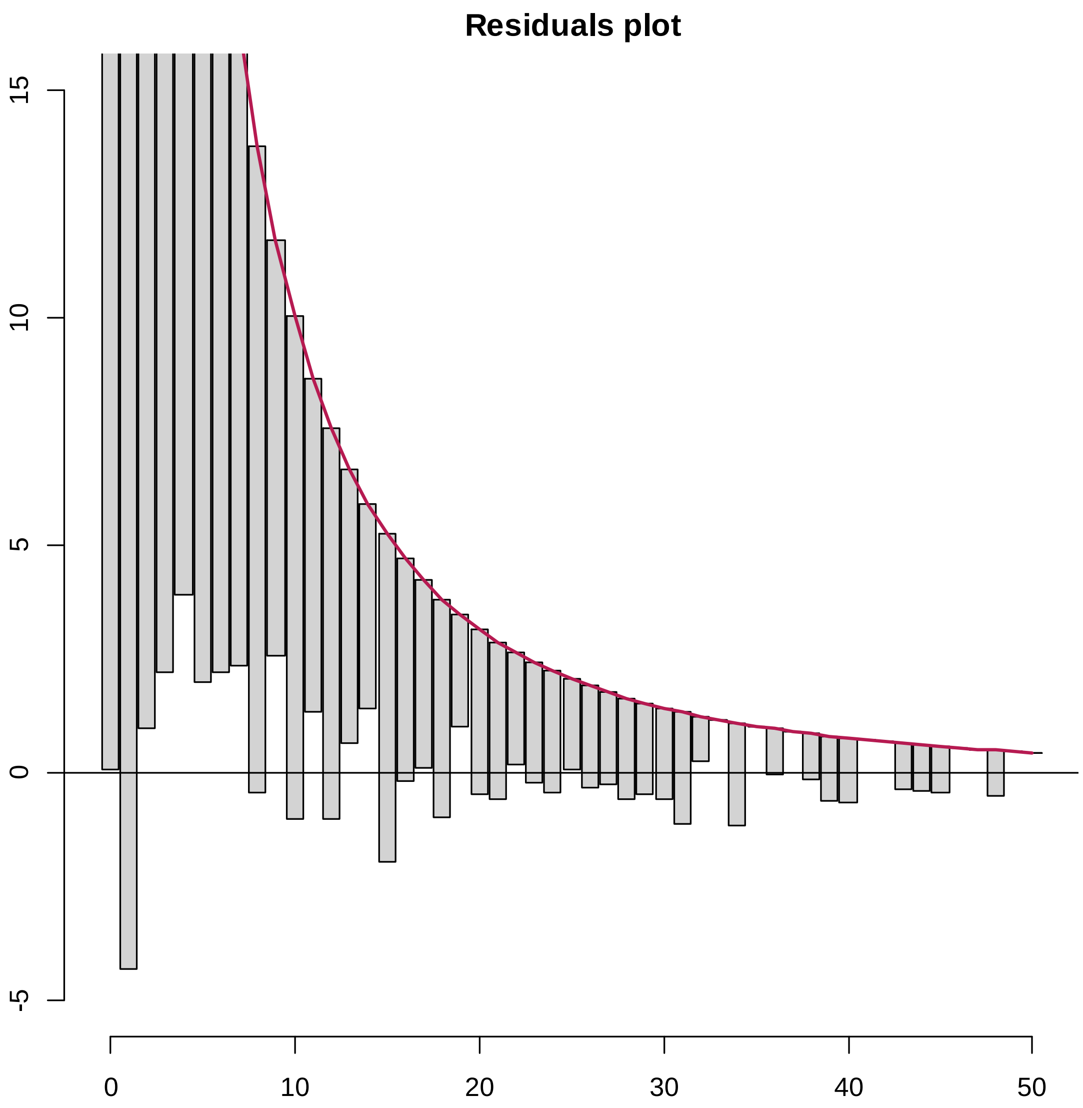


Figure 7. Residual plots for the ZINB model fit to the Indian Ocean longline silky shark bycatch data.

Table 1. Summary of information of the logbook data used in this study.

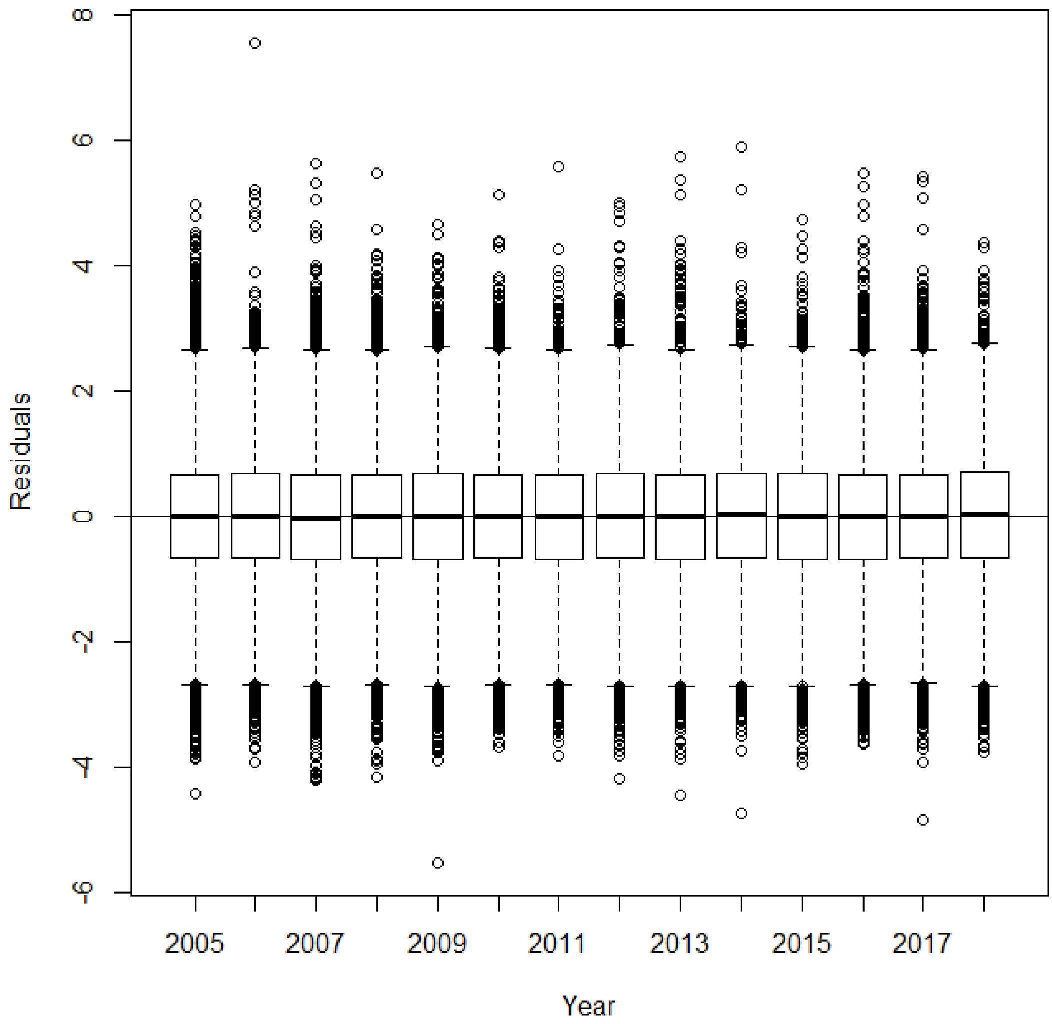
Year	Indian Ocean	
	No. of Hooks	No. of Sets
2005	222,444,476	70,137
2006	109,164,855	34,005
2007	139,730,016	43,506
2008	100,477,617	31,176
2009	126,934,280	39,355
2010	97,311,849	29,756
2011	72,979,298	22,544
2012	76,963,791	25,283
2013	75,816,812	23,723
2014	58,376,963	18,475
2015	70,863,419	22,525
2016	101,592,087	31,567
2017	99,408,067	29,983
2018	94,871,655	28,552
Average	103,352,513	32,185

Table 2. The logbook percentage of zero-catch of silky shark for Taiwanese tuna longline vessels in the Indian Ocean from 2005 to 2018.

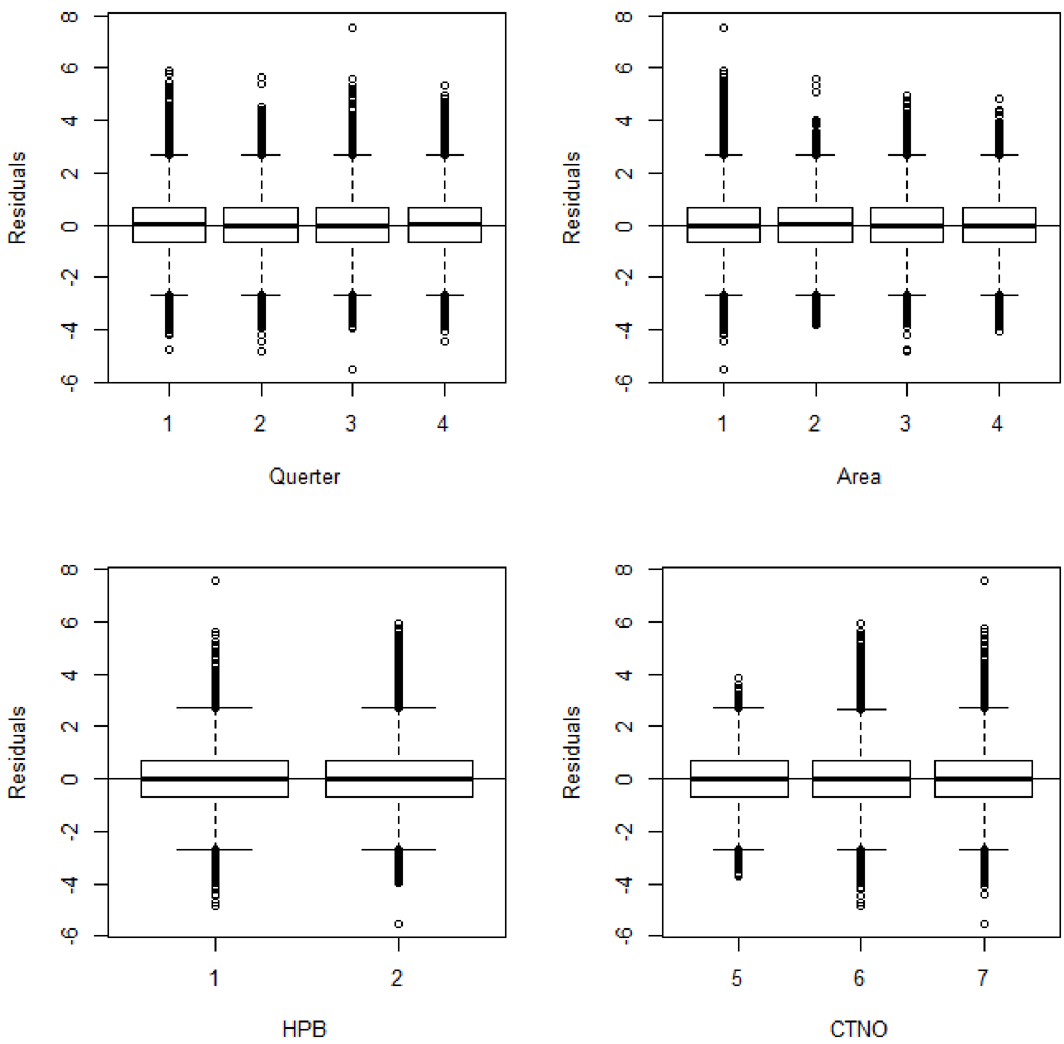
Year	Percentage of zero-catch
2005	94.80%
2006	96.07%
2007	97.30%
2008	97.28%
2009	95.54%
2010	96.44%
2011	97.34%
2012	95.91%
2013	94.74%
2014	93.75%
2015	99.52%
2016	97.51%
2017	95.86%
2018	92.64%
Average	95.98%

Table 3. Estimated nominal and standardized CPUE values for silky shark of the Taiwanese tuna longline fishery in the Indian Ocean.

Year	Nominal	Standardized	Lower CI	Upper CI
2005	0.03359	0.10163	0.06271	0.14054
2006	0.02279	0.07053	0.04338	0.09768
2007	0.01972	0.05736	0.03441	0.08031
2008	0.03056	0.07539	0.04049	0.11029
2009	0.03767	0.12104	0.07197	0.1701
2010	0.0278	0.08989	0.04949	0.13029
2011	0.01579	0.06026	0.02701	0.09352
2012	0.02956	0.09499	0.06336	0.12662
2013	0.04411	0.14371	0.08908	0.19835
2014	0.05799	0.20411	0.11779	0.29042
2015	0.00322	0.01015	0.00357	0.01672
2016	0.02413	0.08552	0.04209	0.12895
2017	0.02402	0.09909	0.05893	0.13924
2018	0.0386	0.16268	0.10721	0.21814



Appendix Fig. 1. Box plots of the Pearson residuals vs. the covariates for the variables Year for ZINB model.



Appendix Fig. 2. Box plots of the Pearson residuals vs. the covariates for the variables Quarter, Area, HPB, and CTNO for ZINB model.

Appendix Table 1. Deviance tables for the ZINB model.

Analysis of Deviance Table (Type II tests)

Response: FAL

Parameter	Df	Chisq	Pr(>Chisq)	
Year	13	1993.0502	< 2e-16	***
Quarter	3	542.4942	< 2e-16	***
Area	3	2432.2672	< 2e-16	***
HPB	1	393.3266	< 2e-16	***
CTNO	2	8.0038	0.01828	*

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1