Standardized CPUE of shortfin mako sharks by the Taiwanese large-scale tuna longline fishery in the Indian Ocean

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SUMMARY

In the present study, the shortfin mako 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. To cope with the large percentage of zero shark catch, the catch per unit effort (CPUE) of shortfin mako 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 and slightly increasing trend for shortfin mako sharks. The results obtained in this study can be improved if longer time logbook data are available and environmental factors are included in the model.

KEYWORDS

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

1. Introduction

Shortfin mako shark, *Isurus oxyrinchus*, is one of the most commonly caught shark species in the Taiwanese commercial offshore longline fishery and the major by-catch of tuna longline fisheries in the far seas. Shortfin mako is a large apex predator that exhibits slow growth, low fecundity and late maturity, and is particularly susceptible to exploitation owing to its life-history characteristics. Clarke et al. (2006) mentioned that about half a million shortfin mako sharks were utilized in the global shark fin trade in 2000. Given the high fishing pressure on this species and declining population trends, the shortfin mako is currently listed as "Vulnerable" on the IUCN Red List of Threatened Species (Dulvy et al., 2008), but very little is known about the stock status of this species in the Indian Ocean. Since the International organizations and regional fisheries management organizations (RFMO's) have concerned on the conservation of elasmobranchs in recent years, it is necessary to examine the recent trend of shark species by examining the logbook of tuna fisheries. Shortfin mako and blue shark (*Prionace glauca*) are the major shark species for Taiwanese large-scale tuna longline (LSTL) fisheries. Reliable catch estimate for shortfin mako shark can be developed because the logbook records of shortfin mako sharks were representative of actual catches as all sharks were retained due to its high market value. Thus, the objectives of this study are to standardize the CPUE of shortfin mako sharks in the Indian Ocean 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 shortfin mako 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 shortfin mako 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 shortfin mako 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 shortfin mako 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 450,588 longline sets were collected, which amounted to a total effort of 1,446,935,185 hooks and yielded 79,706 shortfin mako sharks. A large proportion of sets with zero catch of shortfin mako sharks (about 90%) 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 shortfin mako 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 shortfin mako 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

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

where k is the negative binomial dispersion parameter.

3. Results and discussion

The shortfin mako shark bycatch data are characterized by many zero values and a long right tail (**Figs. 3 and 4**). Overall, 89.96% of the total sets in the Indian Ocean had zero bycatch of shortfin mako 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 shortfin mako 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 shortfin mako shark in the Indian Ocean showed an inter-annual fluctuation, particularly in year 2005 and 2011 (**Fig. 5**). However, this variability was slightly smoothed in the standardized CPUE series. In general, the standardized CPUE series of the shortfin mako sharks caught by Taiwanese large-scale longline fishery showed a stable increasing trend (**Fig. 5**). These stable trends suggested that the shortfin mako 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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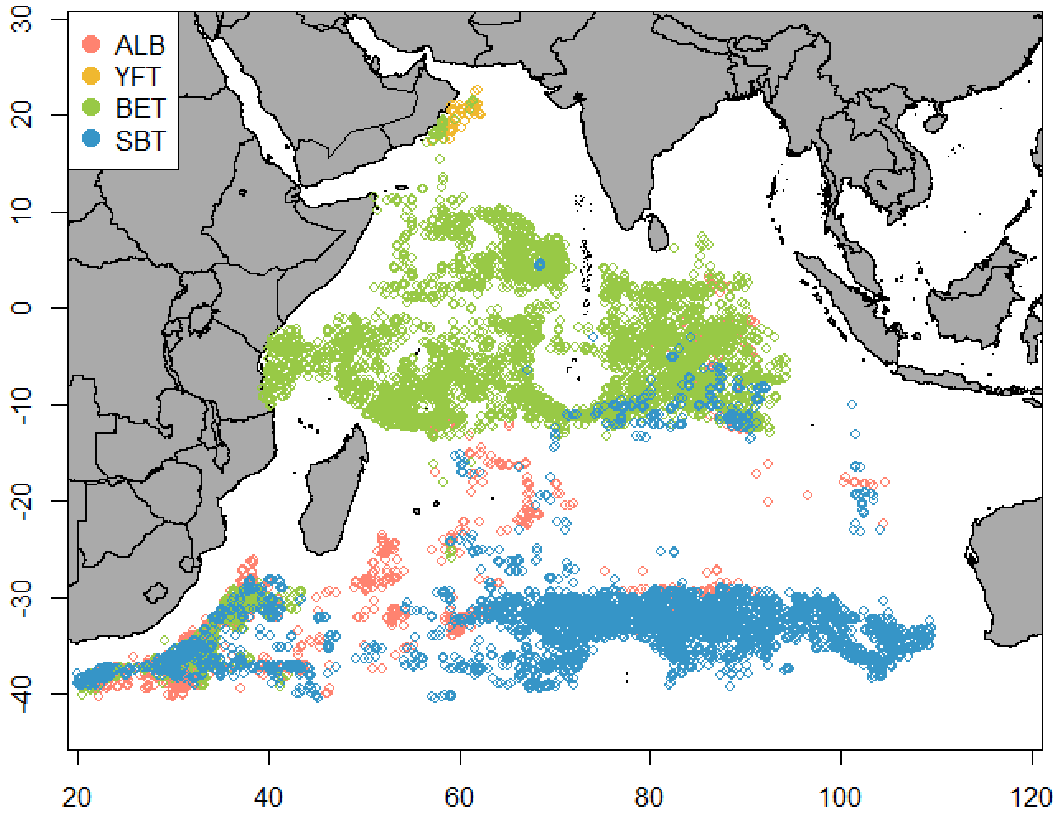


Figure 1. Observed effort distributions in the Indian Ocean from 2005 to 2018.

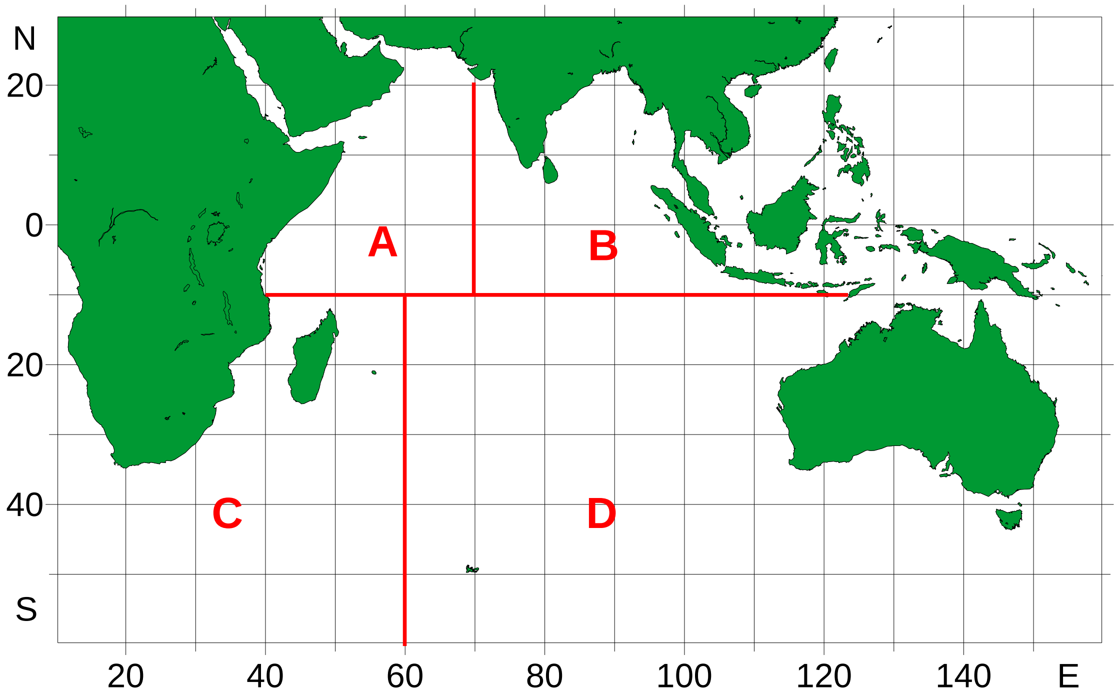


Figure 2. Area stratification based on effort distribution and targeting species in this study.

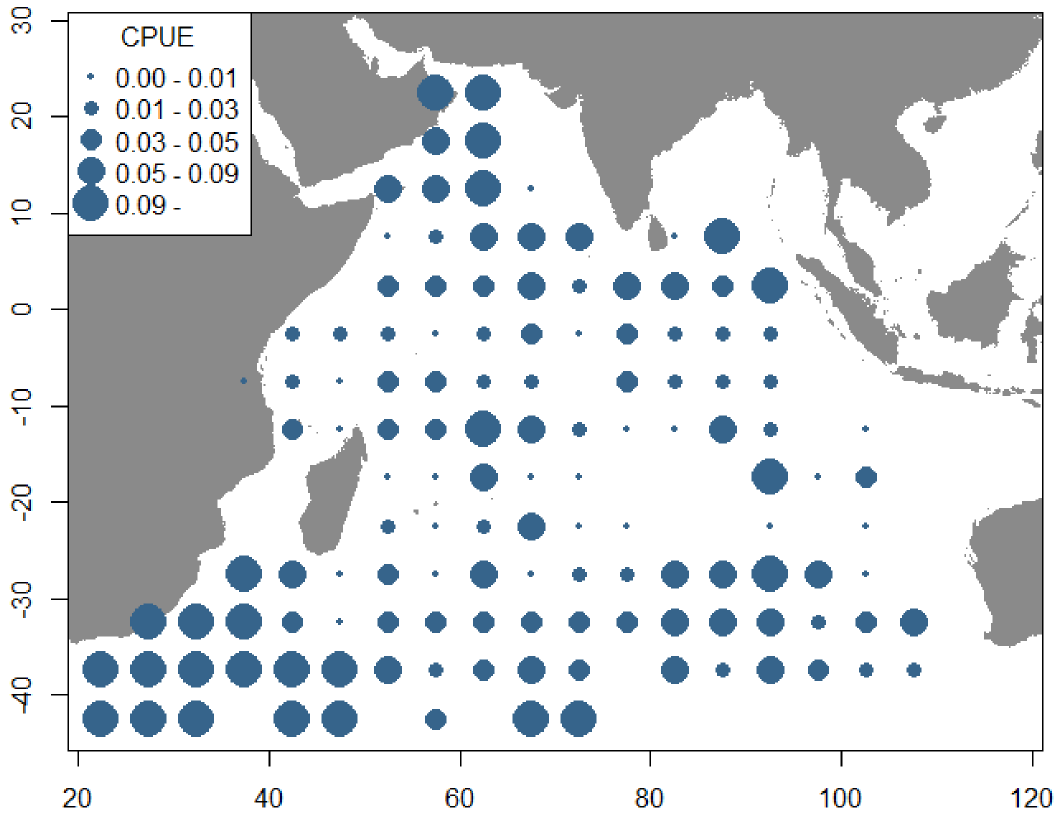


Figure 3. Observed distribution of shortfin mako shark CPUE of Taiwanese tuna longline vessels in the Indian Ocean from 2005 to 2018.

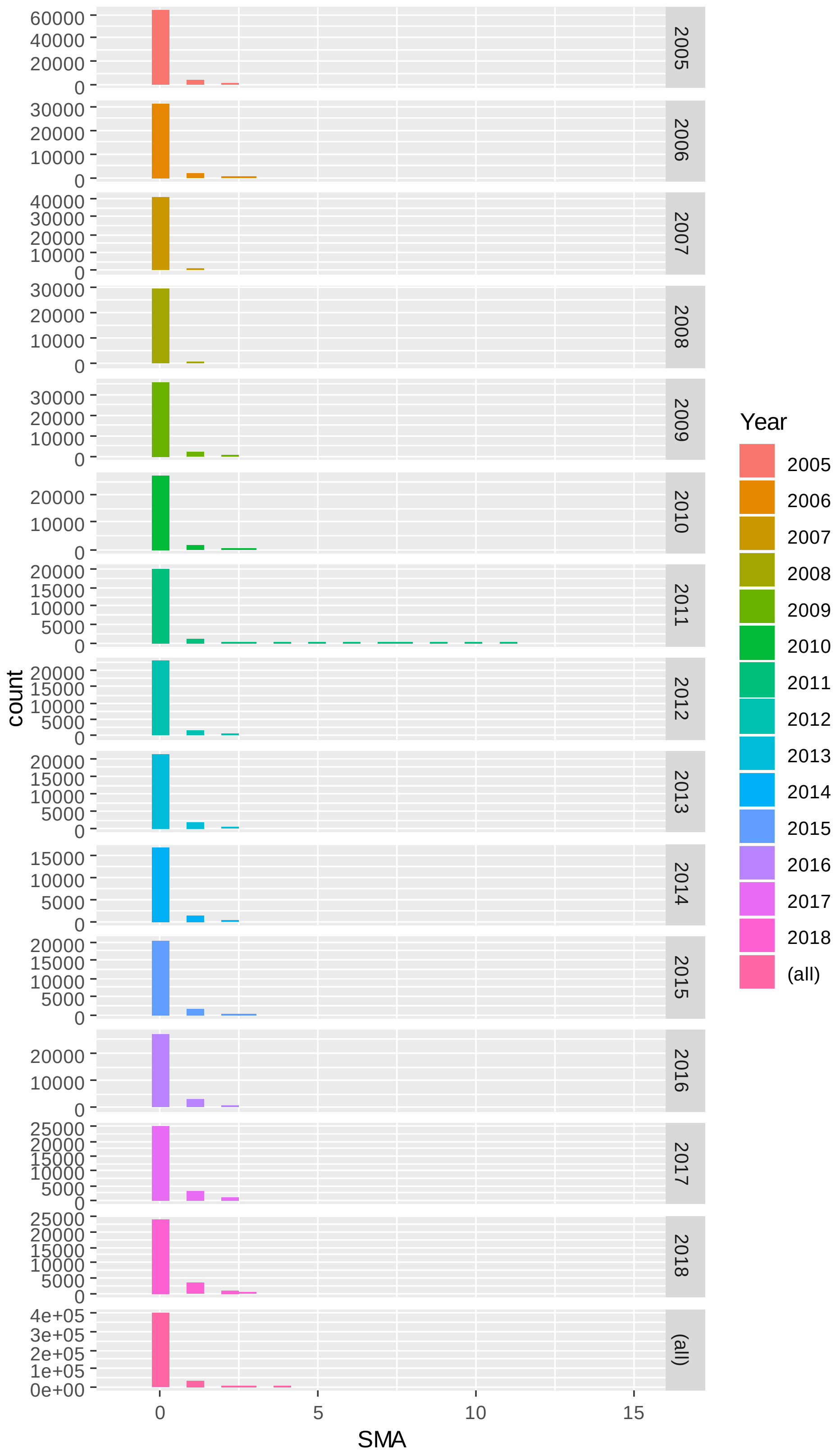


Figure 4. Annual frequency distribution of shortfin mako shark bycatch per set in the Indian Ocean, 2005–2018.

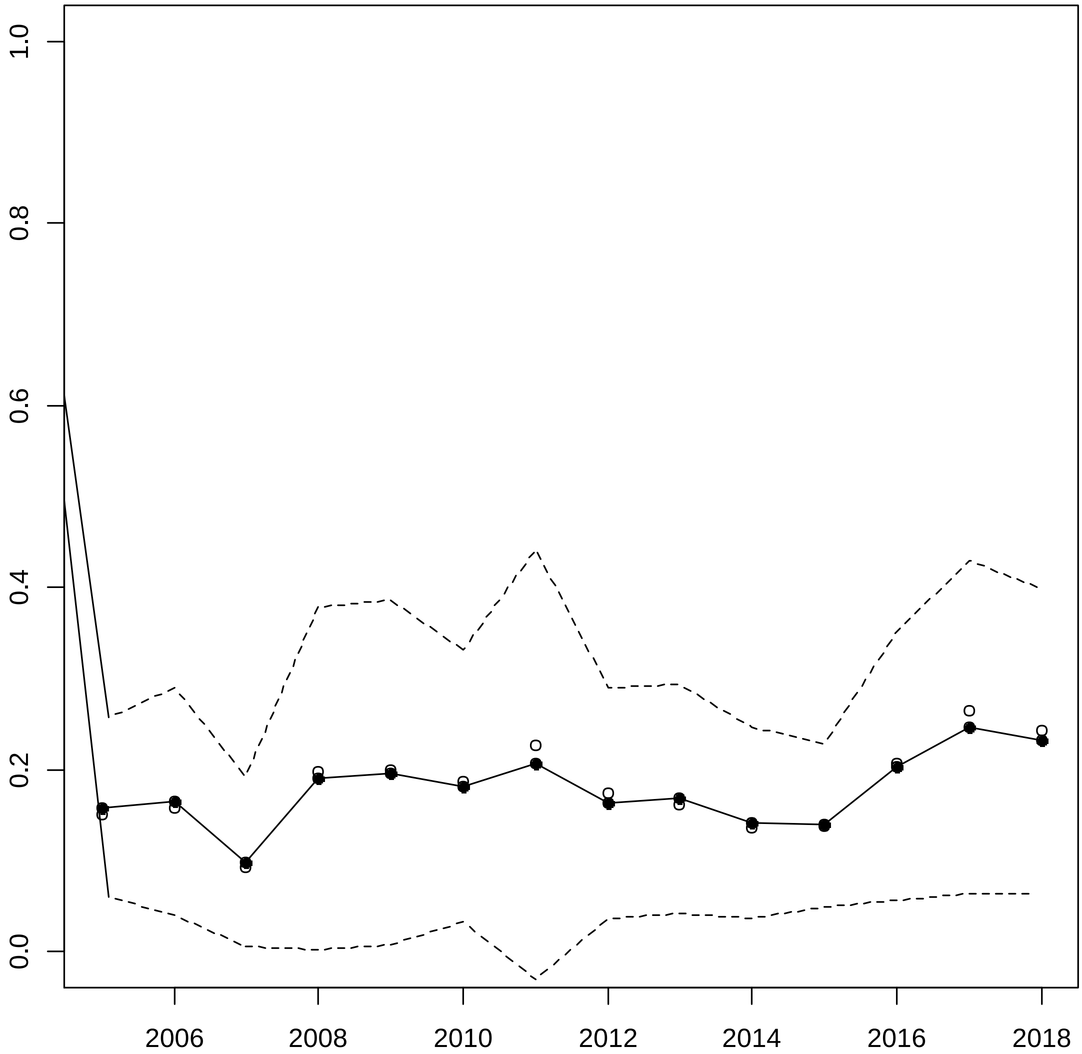


Figure 5. Logbook nominal and standardized CPUE with 95% CI of shortfin shark by Taiwanese longline vessels in the Indian Ocean from 2005 to 2018.

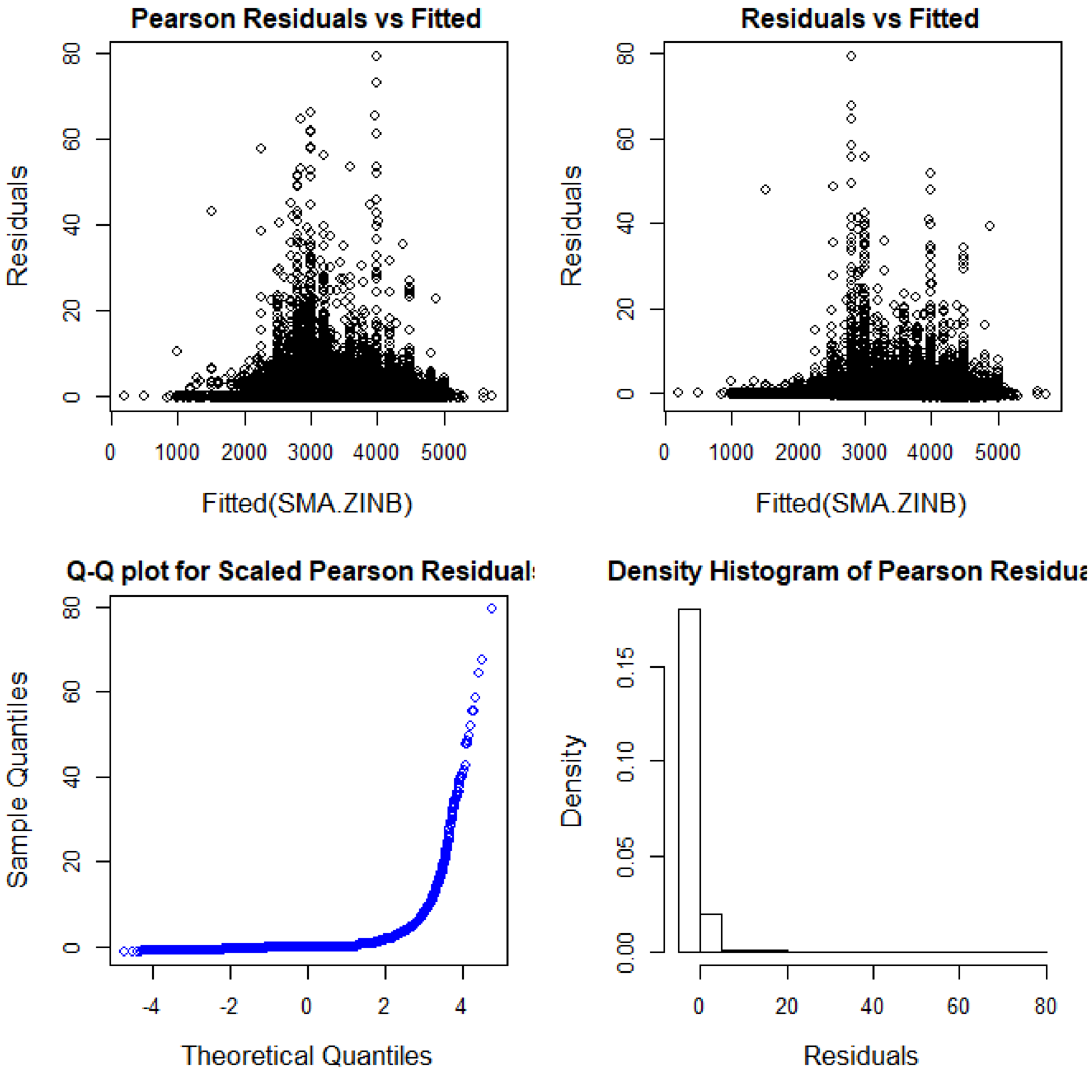


Figure 6. Diagnostic results from the ZINB model fit to the Indian Ocean longline shortfin mako shark bycatch data.

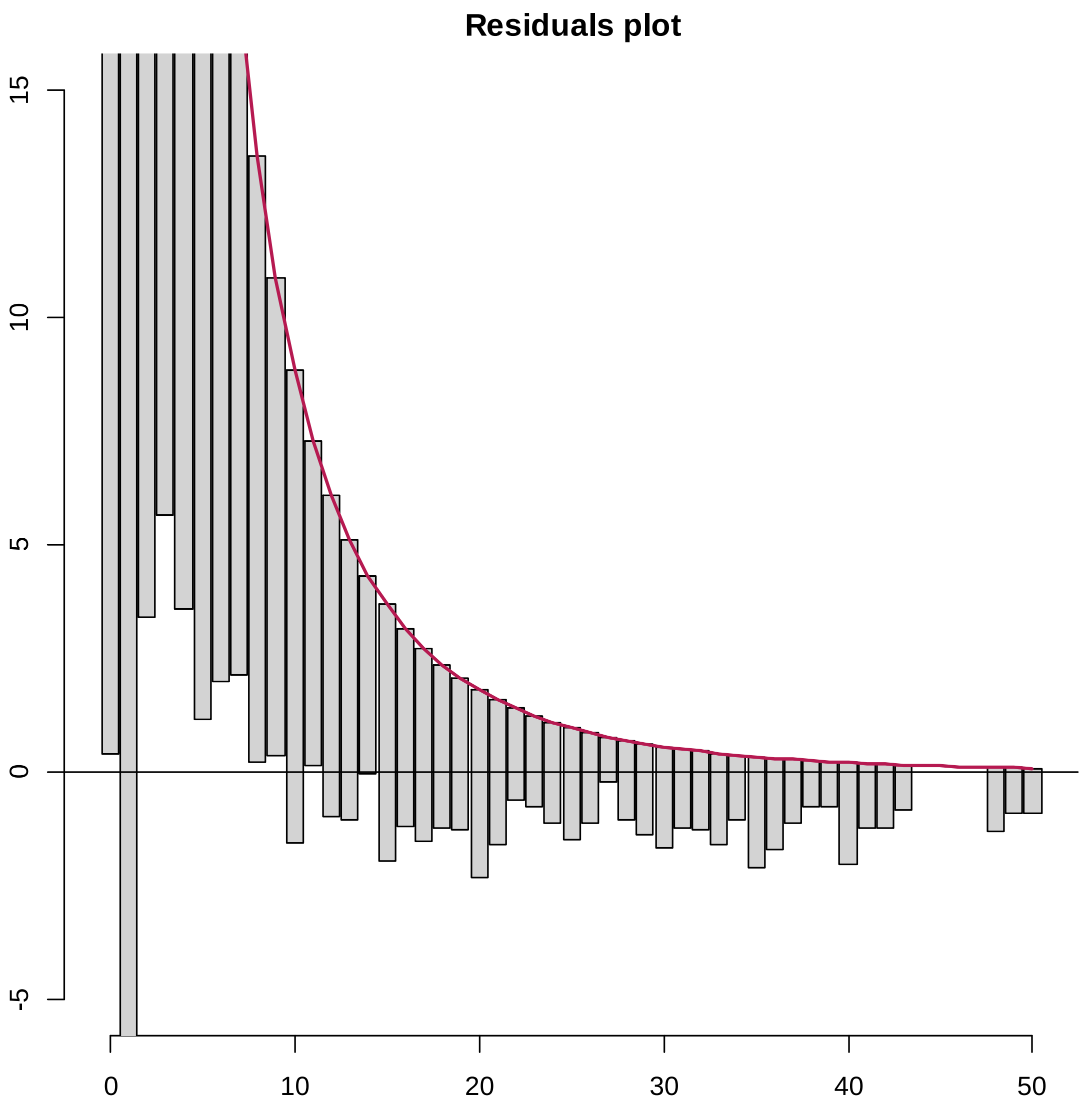


Figure 7. Residual plots for the ZINB model fit to the Indian Ocean longline shortfin mako shark bycatch data.

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

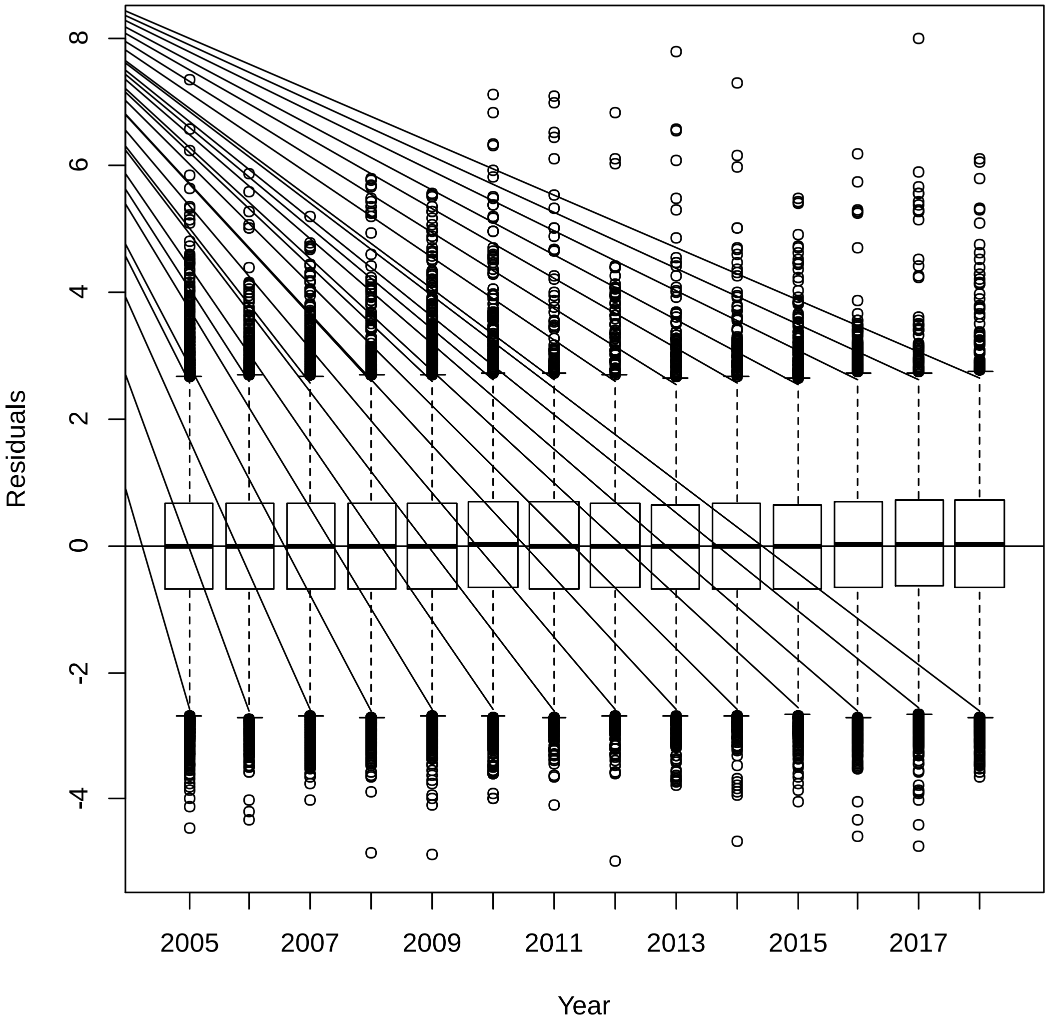
Year	Indian Ocean	
	No. of Hooks	No. of Sets
2005	222,444,476	70,137
2006	109,164,855	34,005
2007	139,730,016	43,506
2008	100,477,617	31,176
2009	126,934,280	39,355
2010	97,311,849	29,756
2011	72,979,298	22,544
2012	76,963,791	25,283
2013	75,816,812	23,723
2014	58,376,963	18,475
2015	70,863,419	22,525
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 shortfin mako shark for Taiwanese tuna longline vessels in the Indian Ocean from 2005 to 2018.

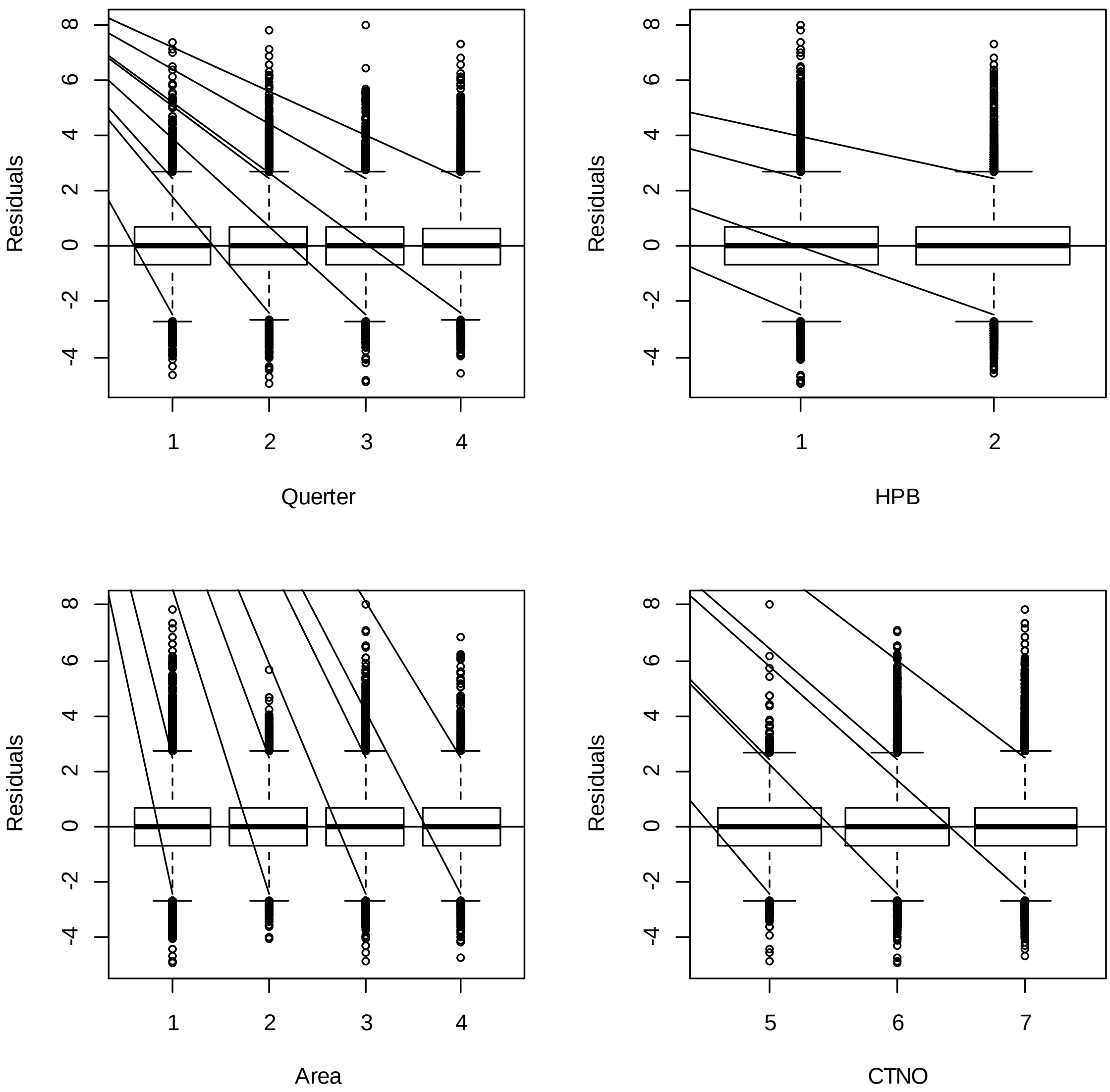
Year	Percentage of zero-catch
2005	90.53%
2006	91.45%
2007	94.72%
2008	93.32%
2009	90.87%
2010	91.12%
2011	89.97%
2012	90.04%
2013	89.52%
2014	90.48%
2015	90.35%
2016	86.11%
2017	83.56%
2018	84.06%
Average	89.96%

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

Year	Nominal	Standardized	Lower CI	Upper CI
2005	0.04718	0.1574	0.06075	0.25405
2006	0.04911	0.1652	0.04038	0.29002
2007	0.02899	0.09857	0.00573	0.19142
2008	0.06137	0.19018	0.00197	0.3784
2009	0.06186	0.19636	0.00665	0.38608
2010	0.05684	0.18141	0.03184	0.33098
2011	0.06973	0.2059	-0.03042	0.44221
2012	0.05712	0.16283	0.03641	0.28925
2013	0.05021	0.168	0.04172	0.29429
2014	0.04306	0.14144	0.03612	0.24675
2015	0.04359	0.13875	0.04895	0.22855
2016	0.06404	0.20355	0.05633	0.35076
2017	0.07968	0.24557	0.06255	0.4286
2018	0.07302	0.23118	0.06372	0.39865



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: SMA

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