Updated and revised standardized catch rate of blue sharks caught by the Taiwanese longline fishery in the Indian Ocean

Wen-Pei Tsai [1,3] and Kwang-Ming Liu [2]

[1] Department of Fisheries Production and Management, National Kaohsiung Marine University, Kaohsiung 808, Taiwan

[2] Institute of Marine Affairs and Resource Management, National Taiwan Ocean University, Keelung 202, Taiwan

[3] Corresponding author. Email: wptsai@webmail.nkmu.edu.tw

SUMMARY

The blue shark catch and effort data from observers’ records of Taiwanese large longline fishing vessels operating in the Indian Ocean from 2004-2016 were analyzed. Based on the effort distribution and fishing grounds of the target species, 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 blue shark, as the number of fish caught per 1,000 hooks, was standardized using a two-step delta-lognormal model that treats the proportion of positive sets and the CPUE of positive catches separately. Each model includes the main variables year, quarter, area, hooks per basket (HPB), and all two-way interactions between quarter, area and HPB. Standardized indices with 95% bootstrapping confidence intervals were reported. The standardized CPUE showed a stable trend for blue sharks from 2004 to 2008 and increased steadily thereafter with peaks in 2014. The results obtained in this study can be improved if longer time series observers' data are available.

KEYWORDS

Blue sharks, Taiwanese longline fishery, standardized CPUE, by-catch, observer programs, delta-lognormal model

1. Introduction

The Taiwanese longline fishery has operated in the Indian Ocean since the late 1970s. However, the shark by-catch of Taiwanese tuna longline fleets was never reported in the logbook until 1981 because of its low economic value compared with tunas. During the period from 1981 to 2002, only one category "sharks" was recorded in the logbook. The category "sharks" in the logbook has been further separated into four sub-categories namely the blue shark, *Prionace glauca*, mako shark, *Isurus spp*., silky shark, *Carcharihnus falciformis*, and others since 2003. As the Taiwanese longline fishery has widely covered the Indian Ocean, our fishery statistics must be one of the most valuable information that can be used to describe the population status of pelagic sharks.

Blue shark is the major shark by-catch species of Taiwanese large longline fishery. Since FAO and international environmental groups has concerned on the conservation of elasmobranchs in recent years, it is necessary to examine the recent trend of sharks by examining the logbook of tuna fisheries. However, standardization of Taiwanese catch rate on sharks is not straightforward because the logbook data have been confounded with many factors, such as under-reporting, no-recording of sharks and target-shifting effects. Consequently, the observer program for the large longline fishery was conducted to obtain detailed and reliable data for more comprehensive stock assessment and management studies. Recently, the increase of coverage rate of observations enabled us to get a better estimation of shark by-catch. Therefore, it is useful to examine recent trends in relative abundance of the blue sharks using the most recent observer data in the Indian Ocean.

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 delta-lognormal modeling, which can account for a large proportion of zero values, is an appropriate approach to model zero-heavy data (Lo *et al*., 1992). As sharks are common by-catch species in the tuna longline fishery, the delta lognormal model (DLN) is commonly used in CPUE standardization to address these excessive zero catch of sharks. In this study, the CPUEs of blue sharks in the Indian Ocean were standardized using delta-lognormal model based on observers' records data and hopefully these CPUE series can be used in the blue shark stock assessment in 2017.

2. Material and methods

2.1. Source of data

The species-specific catch data including tunas, billfishes, and sharks from observers' records in 2004-2016 were used to standardize CPUE of blue shark of Taiwanese longline fishery in the Indian Ocean. The summary of these data were shown in **Table 1**. The catch rate of blue 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 observers' records during the period of 2004-2016.

2.2. CPUE standardization

A large proportion of sets with zero catch of blue sharks (about 55%) in the Indian Ocean was found in observers' records. Hence, to address these excessive zero catches, the delta-lognormal model (DLN) (Lo *et al*., 1992) was applied to the standardization of blue shark CPUE. The DLN is a mixture of two GLM models, one model is used to estimate the proportion of positive catches and a separate model is to estimate the positive catch rate (Delta model, PA). The model was fit using glm 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 blue shark was constructed including main effects and interaction terms. The main effects chosen as input into the DLN analyses were year (Y), quarter (Q), area (A), and number of hooks per basket (HPB). The following additive model was applied to the data in this study:

For the DLN modeling, the catch rates of the positive catch events (sets with positive blue shark catch) were modeled assuming a lognormal error distribution:

$$\ln(CPUE) = \mu+Y+Q+A+HPB+Q*A+Q*HPB+A*HPB+\varepsilon_1 \quad (1)$$

where μ is the mean, Q*A, Q*HPB, A*HPB are interaction terms, ε_1 is a normal random error term. The effect of gear configuration of HPB was categorized into the four classes of 1-9, 10-12, 13-14, and >=15, and quarter was categorized into 4 classes. The area strata used for the analysis were shown in Figure 2. To calculate the proportion of positive records we used a model assuming a binomial error distribution (ε_2):

$$PA= \mu+Y+Q+A+HPB+Q*A+Q*HPB+A*HPB+\varepsilon 2 \quad (2)$$

The best model for both Lognormal and Binominal models were selected using the stepwise AIC method (Venables and Ripley, 2002). For model diagnostics, Cook's distance (Cook and Weisberg, 1982) was used to assess the influence of observations that exert on the model. The final estimate of annual abundance index was obtained by the product of the marginal year means (Lo et al., 1992).

Standardized CPUE= CPUE * PA (3)

Empirical confidence interval of standardized CPUE was estimated by using bootstrap resampling method. The number of bootstrap sub-samples were generated based on the sample size of CPUE in each year. The 95% confidence intervals were then constructed based on bias corrected percentile method with 1,000 replicates (Efron and Tibshirani, 1993).

3. Results and discussion

The blue shark bycatch data are characterized by many zero values and a long right tail (**Figs. 3 and 4**). Overall, 57.96% of the total sets in the Indian Ocean had zero bycatch of blue sharks (**Table 2**). As a result, the following models with many explanatory variables were finally selected. The best models for GLM and Delta models chosen by AIC values in the Indian Ocean were “ln(CPUE) = μ + Y + Q + A + HPB+ Q*A + Q*HPB + A*HPB” and “PA = μ + Y + Q + A + HPB + Q*A + A*HPB”, respectively. The best models were then used in the later analyses.

Standardized CPUE series of the blue shark in the Indian Ocean using the DLN model were shown in **Figure 5**. The detail values for nominal and standardized CPUE were listed in **Tables 3.** Standardized CPUE trend contains the combined effects from two models, one that calculates the probability of a zero observation and another one that estimates the count per year. The nominal CPUE of blue shark in the Indian Ocean showed an inter-annual fluctuation, particularly in year 2009 and 2014 (**Fig. 5**). However, this variability was slightly smoothed in the standardized CPUE series. In general, the standardized CPUE series of the blue sharks caught by Taiwanese large-scale longline fishery showed a stable increasing trend (**Fig. 5**). These stable trends suggested that the blue shark stock in the Indian Ocean seems at the level of optimum utilization during the period of 2004-2016.

The diagnostic results from the DLN 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 observers' data are available and environmental factors were included in the model.

References

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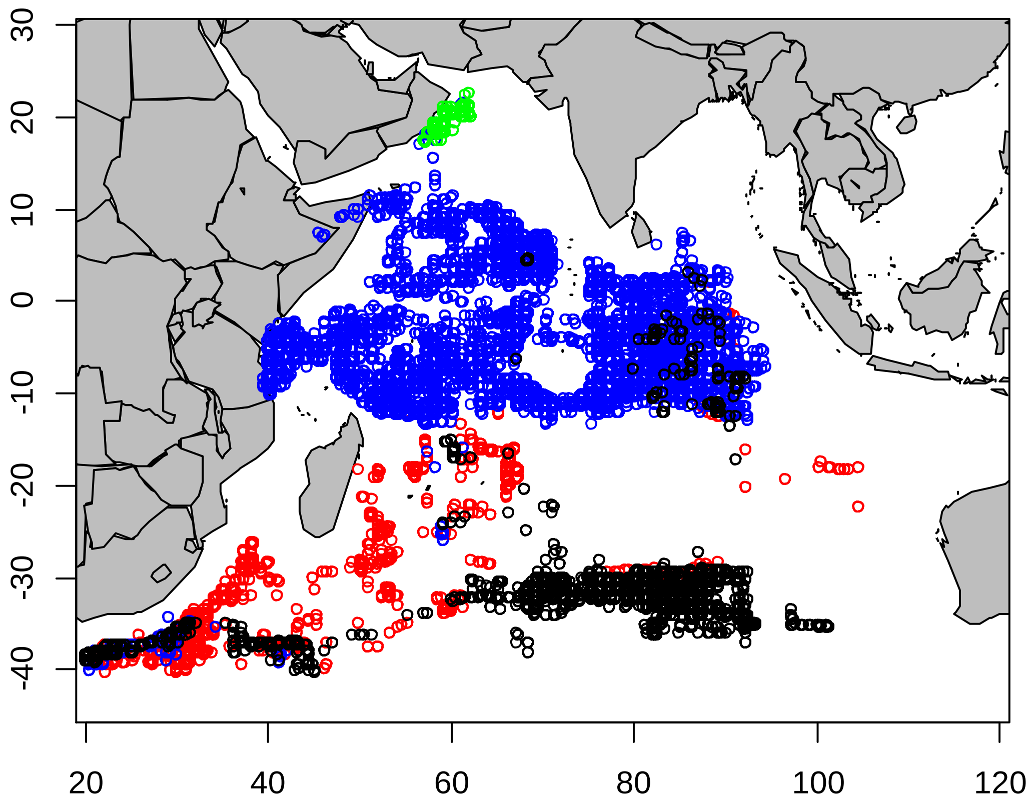


Figure 1. Observed effort distributions in the Indian Ocean from 2004 to 2016. Green circles, yellowfin tuna fleet; blue circles, bigeye fleet; red circles, albacore fleet; black circles, bluefin tuna fleet.

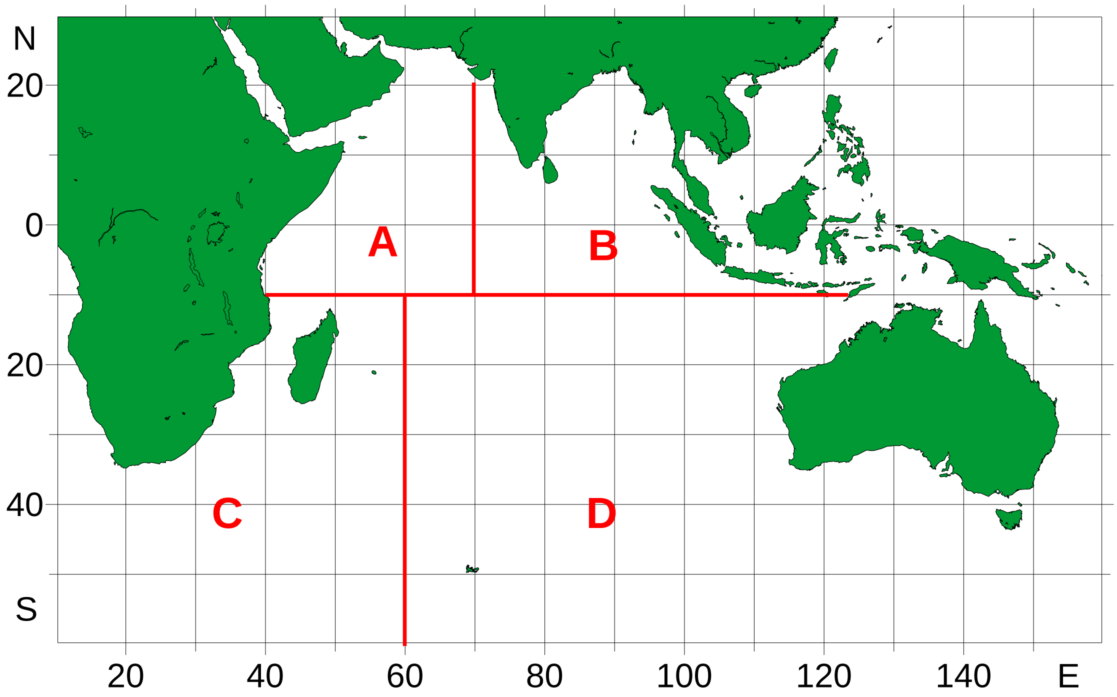


Figure 2. Area stratification based on effort distribution and targeting species in this study.

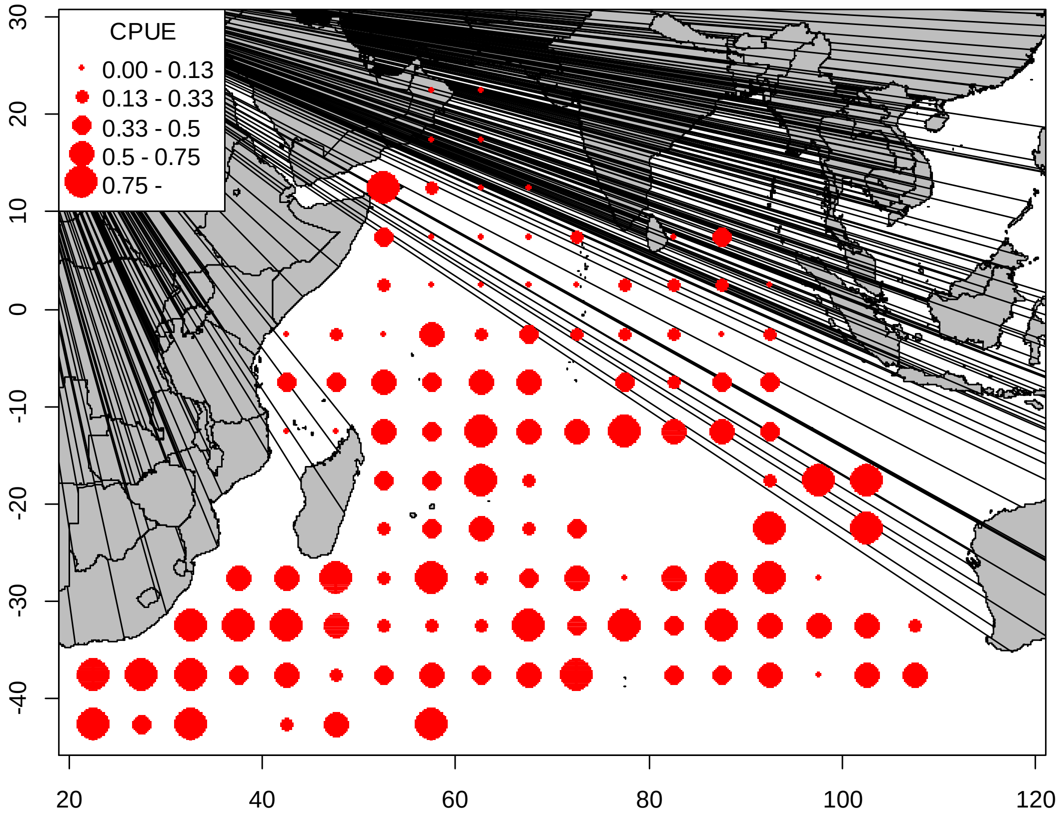


Figure 3. Observed distribution of blue shark CPUE of Taiwanese tuna longline vessels in the Indian Ocean from 2004 to 2016.

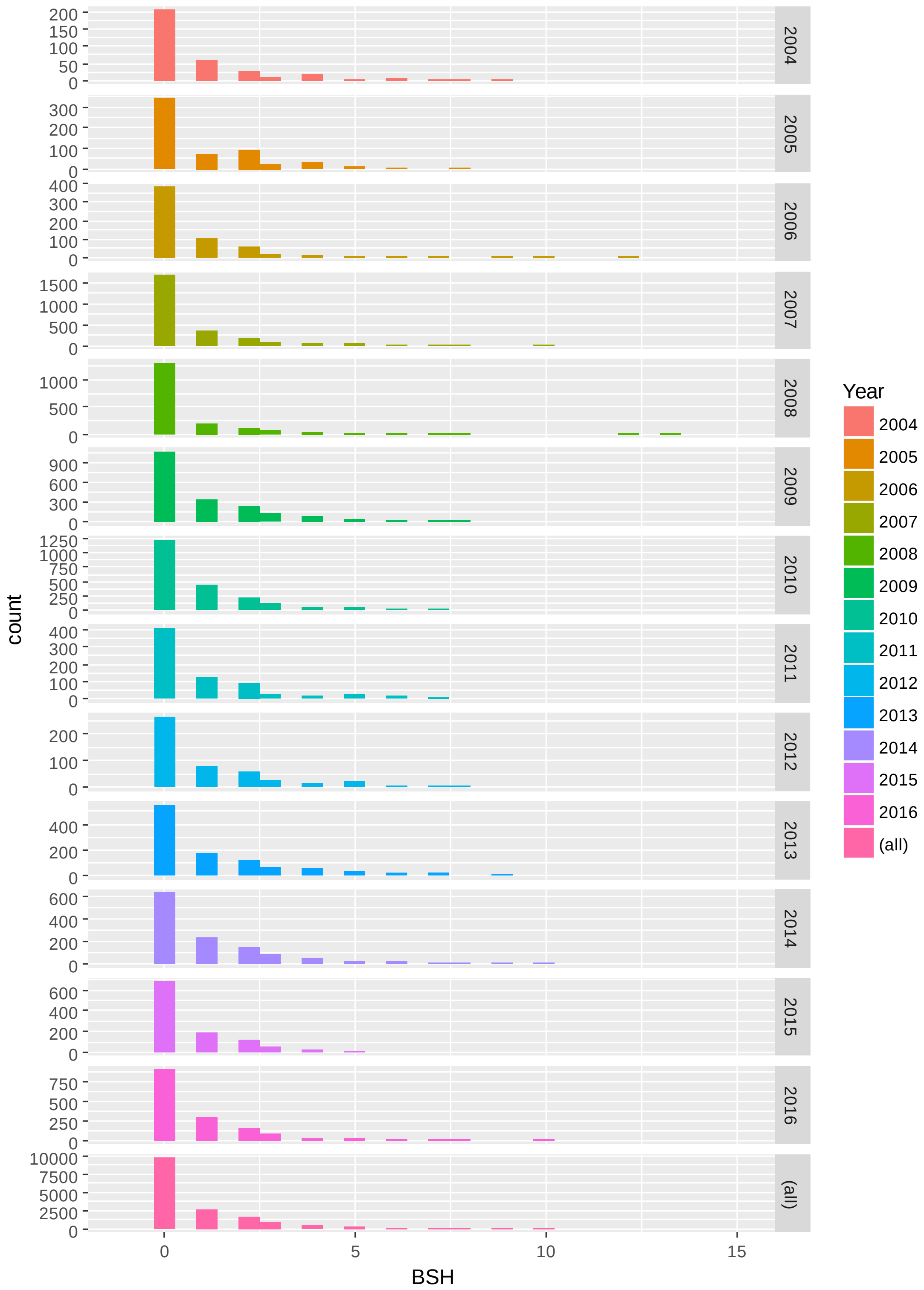


Figure 4. Annual frequency distribution of blue shark bycatch per set in the Indian Ocean, 2004–2016.

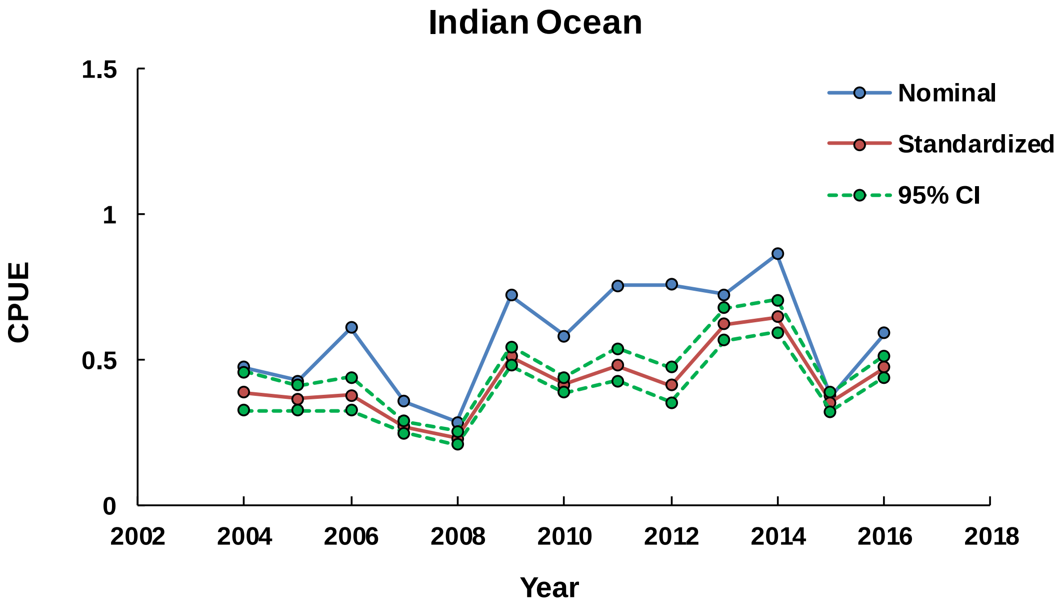


Figure 5. Observed nominal and standardized CPUE with 95% CI of blue shark by Taiwanese longline vessels in the Indian Ocean from 2004 to 2016.

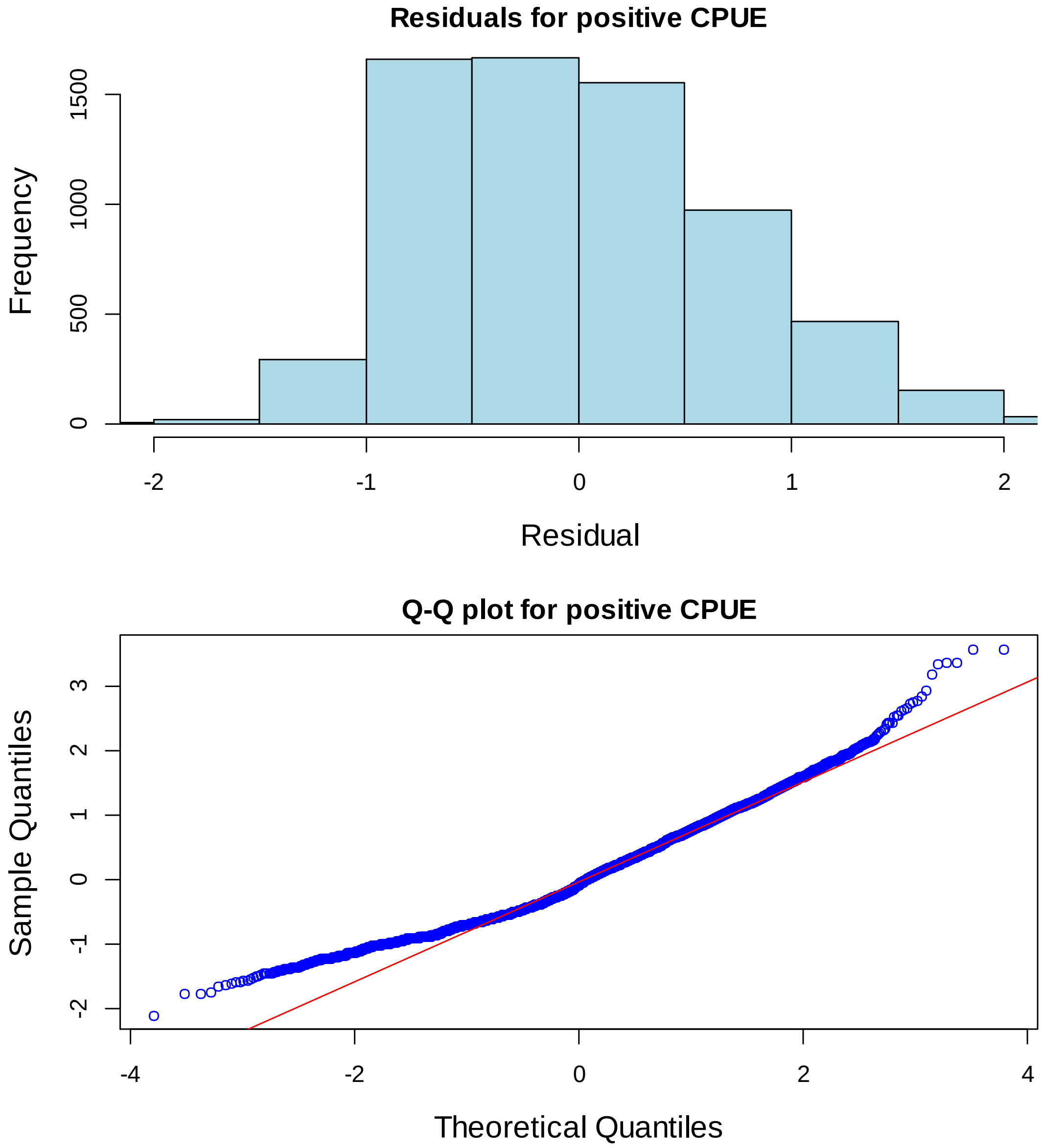


Figure 6. Diagnostic results from the GLM model fit to the Indian Ocean longline blue shark bycatch data.

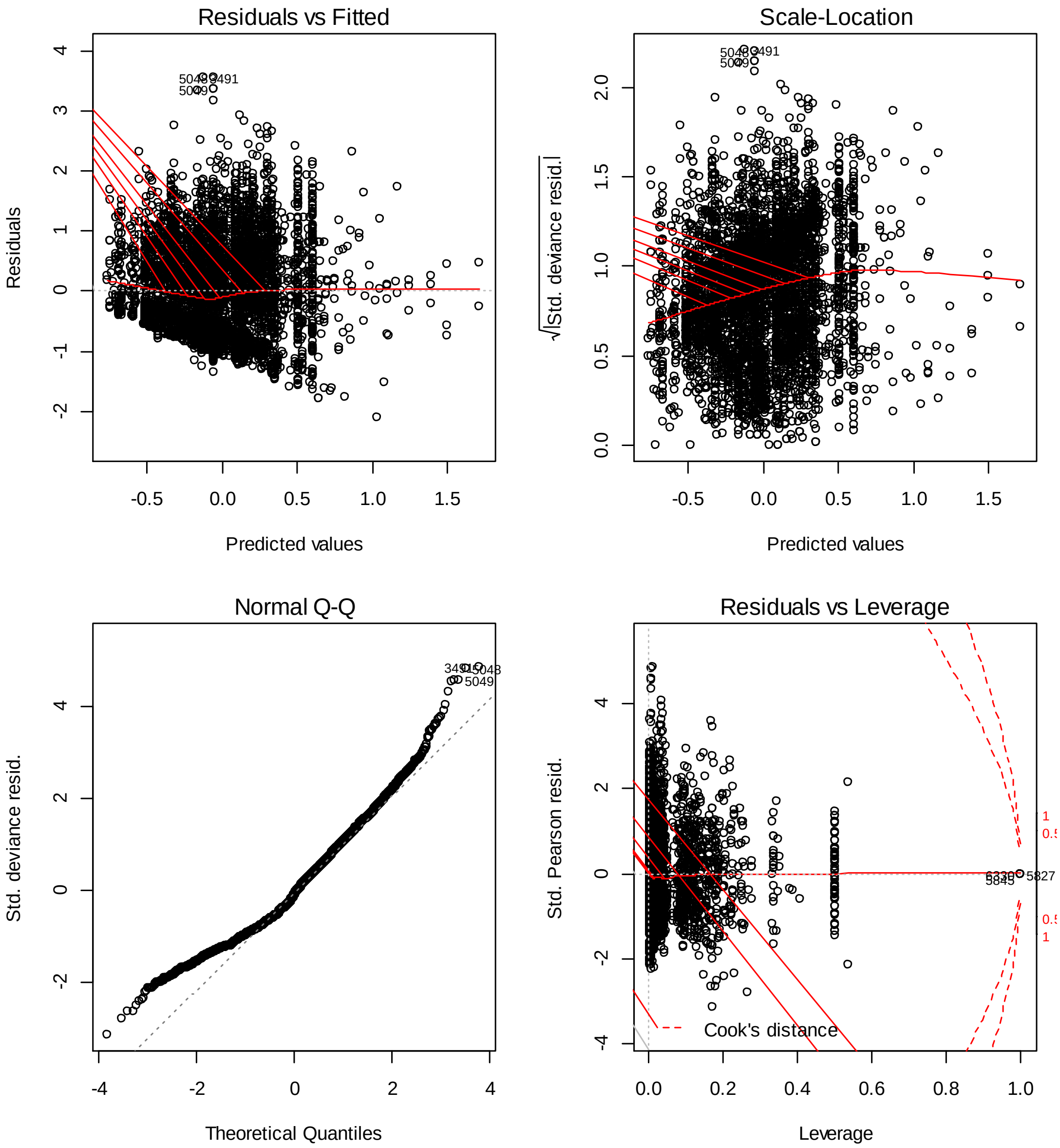


Figure 7. Residual plots for the GLM model fit to the Indian Ocean longline blue shark bycatch data.

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

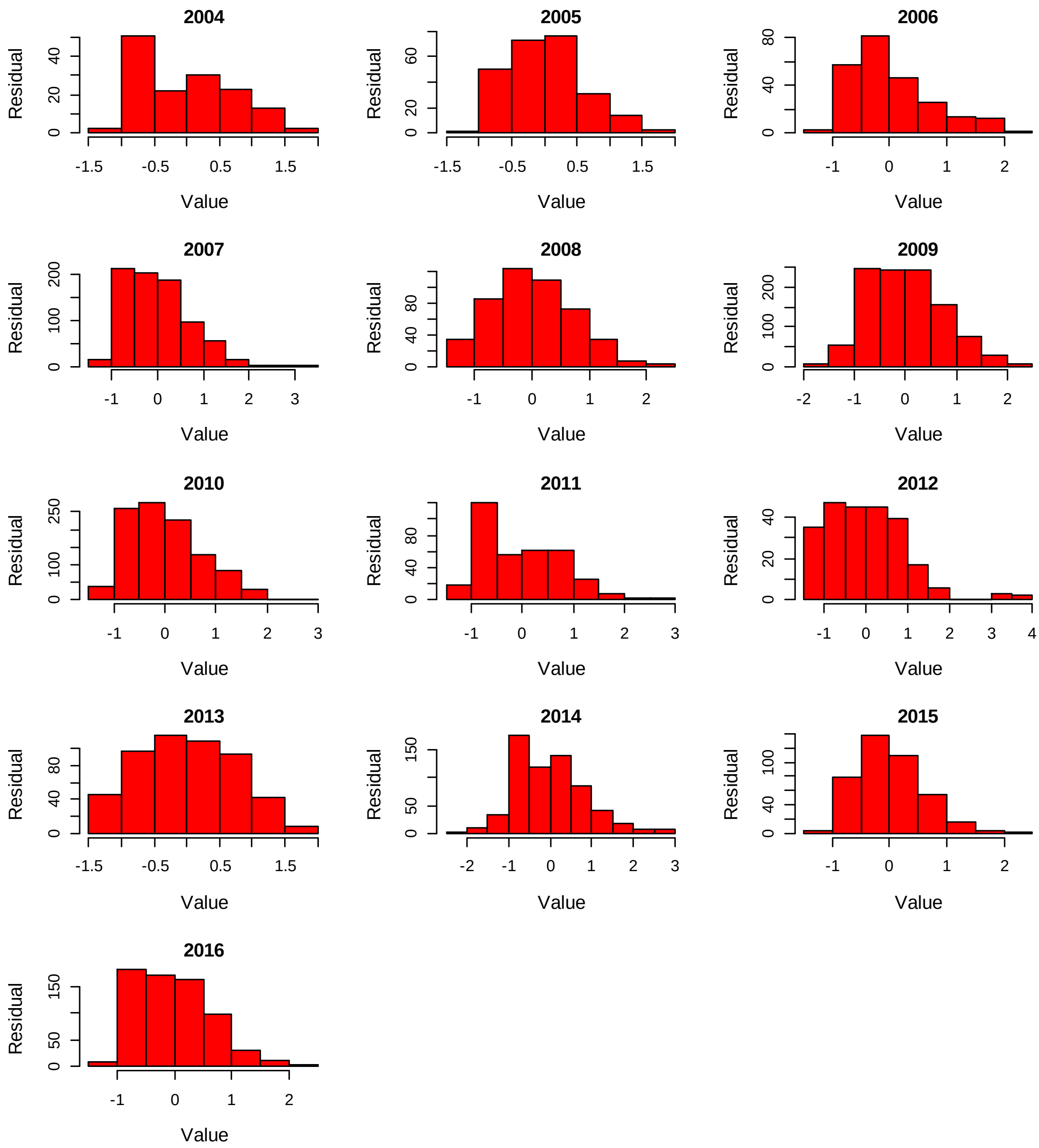
Year	Indian Ocean	
	No. of Hooks	No. of Sets
2004	810,853	349
2005	1,421,228	592
2006	1,419,307	624
2007	5,765,847	2,476
2008	4,248,446	1,781
2009	5,220,475	2,137
2010	5,519,258	2,271
2011	1,876,263	766
2012	1,405,158	507
2013	1,964,276	1,063
2014	2,556,725	1,270
2015	2,151,986	1,089
2016	3,154,781	1,576
Average	2,885,739	1,269

Table 2. The observed percentage of zero-catch of blue shark for Taiwanese tuna longline vessels in the Indian Ocean from 2004 to 2016.

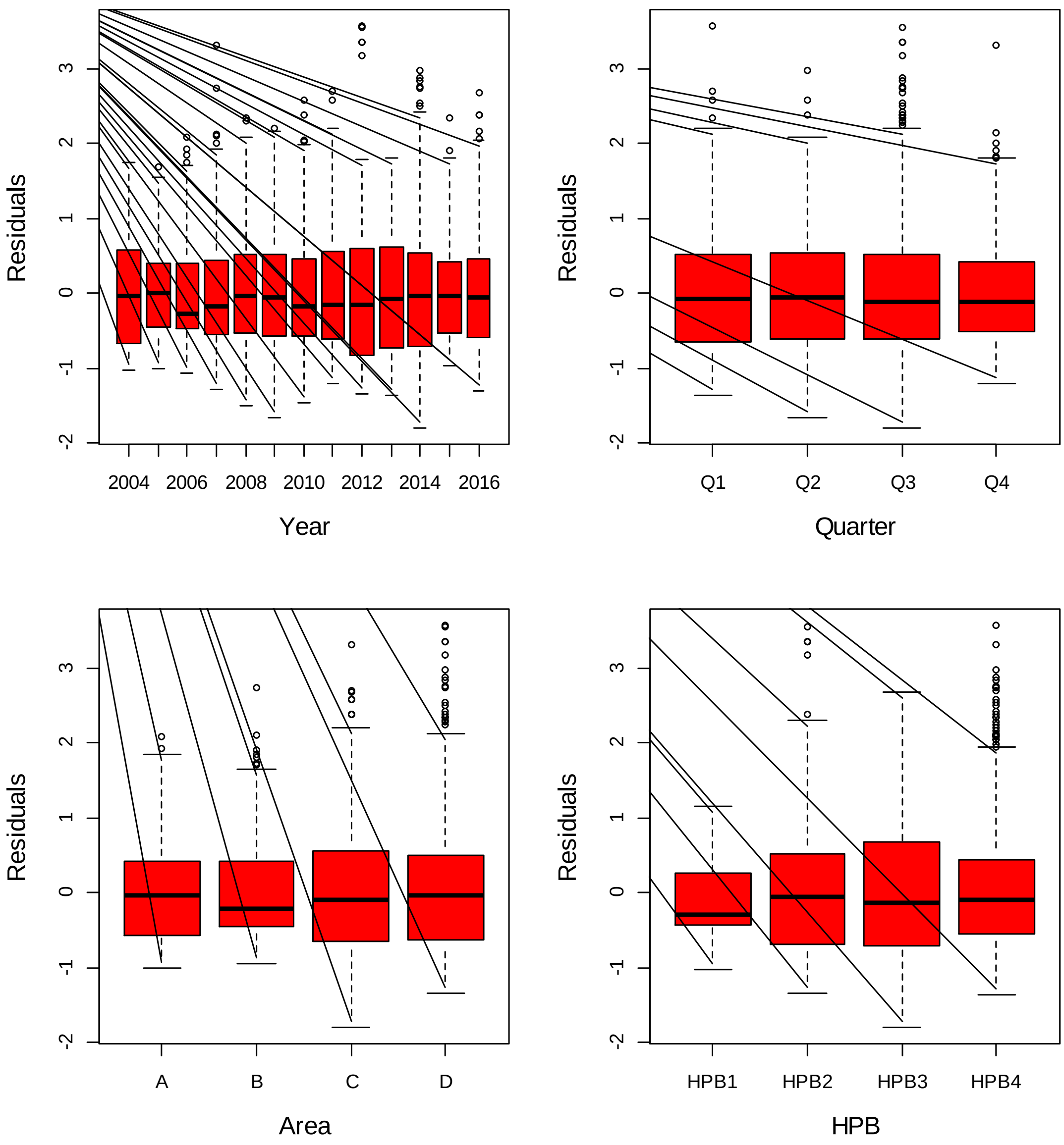
Year	Percentage of zero-catch
2004	59.03%
2005	58.11%
2006	61.86%
2007	68.09%
2008	73.50%
2009	50.44%
2010	53.81%
2011	53.52%
2012	52.86%
2013	52.02%
2014	49.84%
2015	62.90%
2016	57.55%
Average	57.96%

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

Year	Original values		Bias-corrected bootstrap confidence intervals				
	Nominal	Standardized	Lower CI	Upper CI	Mean	STD	CV
2004	0.47111	0.38641	0.32347	0.45853	0.38607	0.03392	8.79%
2005	0.42639	0.36431	0.32353	0.40925	0.36433	0.02193	6.02%
2006	0.61016	0.37731	0.32524	0.43747	0.37835	0.02913	7.70%
2007	0.35363	0.26682	0.24641	0.28747	0.26677	0.01051	3.94%
2008	0.28457	0.22897	0.20748	0.25228	0.22893	0.01142	4.99%
2009	0.71967	0.51056	0.47753	0.54487	0.51071	0.01701	3.33%
2010	0.57997	0.41213	0.38498	0.43866	0.41217	0.01363	3.31%
2011	0.75522	0.47944	0.42506	0.53773	0.47953	0.02847	5.94%
2012	0.75792	0.40910	0.35107	0.47176	0.41010	0.03104	7.57%
2013	0.72393	0.62000	0.56568	0.67637	0.61994	0.02838	4.58%
2014	0.86165	0.64447	0.59324	0.70566	0.64307	0.02799	4.35%
2015	0.37407	0.35023	0.31998	0.38599	0.34858	0.01681	4.82%
2016	0.59117	0.47386	0.43830	0.51393	0.47181	0.01941	4.11%



Appendix Fig. 1. Annual residual plots from the GLM model.



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

Appendix Table 1. Deviance tables for the DLN model.

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Analysis of Deviance Table

Model: gaussian, link: identity

Response: log(DATA$CPUE)

Terms added sequentially (first to last)


      Df Deviance Resid. Df Resid. Dev       F    Pr(>F)    
NULL                   6813     4195.7                      
yy    12  123.955      6801     4071.7 19.1086 < 2.2e-16 ***
Q      3   98.717      6798     3973.0 60.8716 < 2.2e-16 ***
A      3  149.163      6795     3823.9 91.9781 < 2.2e-16 ***
HPB    3   51.946      6792     3771.9 32.0314 < 2.2e-16 ***
Q:A    9   45.475      6783     3726.4  9.3470 3.036e-14 ***
Q:HPB  6   42.868      6777     3683.6 13.2169 6.132e-15 ***
A:HPB  6   23.347      6771     3660.2  7.1981 1.133e-07 ***
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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
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