Updated standardized catch rates for blue shark caught by the Taiwanese large-scale tuna longline fishery in the Indian Ocean

Xing-Han Wu[1] and Wen-Pei Tsai[2,*]

[1] Department of Oceanography, National Sun Yat-sen University, Kaohsiung, Taiwan

[2] Department of Fisheries Production and Management, National Kaohsiung University of Science and Technology, Kaohsiung, Taiwan

[*]Corresponding author. Email: wptsai@nkust.edu.tw

SUMMARY

The catches and efforts of the blue shark in the Indian Ocean were estimated based on the observers' records (2004-2019) of Taiwanese tuna longline fisheries. 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 (DLN) that treats the proportion of positive sets and the CPUE of positive catches separately. The standardized CPUE showed a stable increasing trend for blue sharks from 2008 to 2014 (the peak), although decreased in 2015, it increased again in 2016. Overall, the standardized CPUE series of the blue shark caught by Taiwanese longline fishery showed a stable trend. The stable trend suggested that blue shark stocks in the Indian Ocean seems at the level of optimum utilization.

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 have concerned about 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 the 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 in the coverage rate of observations enabled us to get a better estimation of shark by-catch. Therefore, it is useful to examine recent trends in the 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

Data were collected across the Indian Ocean by scientific fishery observers from the Overseas Fisheries Development Council of the Republic of China onboard Taiwanese large longline vessels. Between 2004 and 2019, data from a total of 22,851 longline sets were collected, which amounted to a total effort of 50,371,334 hooks and yielded 30,462 blue sharks. The summary of these data was shown in **Table 1**. Due to the catch rate of blue sharks might be affected by the changes of targeting species, fishing ground, and fishing seasons, we considered several effects in our models, including fishing strategy and spatial–temporal influence. For standardization, CPUE was calculated by set of operations based on observers' records during the period of 2004-2019.

2.2. CPUE standardization

A large proportion of sets with zero catch of blue sharks (about 56%) 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-quarter (YrQtr), latitude-longtitude (LatLong), hooks per basket (HPB), vessel size (CTNO) and target species (GRP). Additionally, we fit a smoothing spline to the vessel operational hooks data and input it in the both model, as an effort factors. 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:

$$\ln(CPUE) = \mu + YrQr + LatLong + HPBC + ns(Hooks, 10) + CTNO + GRP + HPBC*GRP + \varepsilon_1 \qquad (1)$$

where μ is the mean, HPBC*GRP are interaction terms, ε_1 is a normal random error term. The effect of gear configuration of HPBC was categorized into the four classes of 1-5, 6-9, 10-15, and >15, vessel size was categorized into three classes (CTNO, CT5; CT6; CT7), and target species was categorized into four classes (GRP, ALB; BET; YFT; SBT, Fig.1). To calculate the proportion of positive records we used a model assuming a binomial error distribution (ε_2):

$$PA = \mu + YrQr + LatLong + HPBC + ns(Hooks, 10) + CTNO + GRP + HPBC:GRP + \varepsilon 2 \qquad (2)$$

The best model for both Lognormal and Binominal models were selected using the stepwise AIC method (Venables and Ripley, 2002). The final estimate of annual abundance index was obtained by the product of the marginal year means (Lo et al., 1992).

$$\text{Standardized CPUE} = CPUE * PA \qquad (3)$$

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 spatial distribution of efforts, catch and CPUE of blue sharks for Taiwanese large tuna longline fishery in the Indian Ocean from 2004 to 2019 was showed in **Fig.2**. The blue shark bycatch data from the Taiwanese large longline fishery characterized by many zero values. Overall, 56.44% 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(BPUE) = μ + YrQtr + LatLong + HPBF + ns(Hooks, 10) + CTNO + GRP + HPBF:GRP" and "PA = μ + YrQtr + LatLong + HPBF + ns(Hooks, 10) + GRP + HPBF:GRP", 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 3**. 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 years 2007 and 2009 (**Fig. 3**). 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. 3**). These stable trends suggested that the blue shark stock in the Indian Ocean seems at the level of optimum utilization during the period of 2004-2013.

The diagnostic results from the DLN model do not indicate any severe departure from model assumptions (**Figs. 4-5**). Additionally, the influence plot for the Lognormal model are provided in **Appendix.** The ANOVA tables for each model are given in **Table 4**. Most main effects and interaction terms tested were significant (mostly $P < 0.01$) and have been included in the final model, except vessel size (CTNO) effects in the Binominal model ($P = 0.43$). 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

Bigelow, K.A., Boggs, C.H., and He, X., 1999. Environmental effects on swordfish and blue shark catch rates in the US North Pacific longline fishery. Fish. Oceanogr. 8(3): 178-198.

Efron B., Tibshirani R.J., 1993. An introduction to the bootstrap. London: Chapman and Hall.

Lo, N. C. H., L. D. Jacobson, J. L. Squire. 1992. Indices of relative abundance from fish spotter data based on delta-lognormal models. Can. J. Fish. Aquat. Sci. 49(12): 2515-2526.

Okamoto, H., Miyabe, N., and Matsumoto, T., 2001. GLM analyses for standardization of Japanese longline CPUE for bigeye tuna in the Indian Ocean applying environmental factors. IOTC Proceedings 4: 491-522.

R Development Core Team. 2013. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Venables, W. N. and Ripley, B. D. 2002. Modern Applied Statistics with S. Fourth edition. Springer.

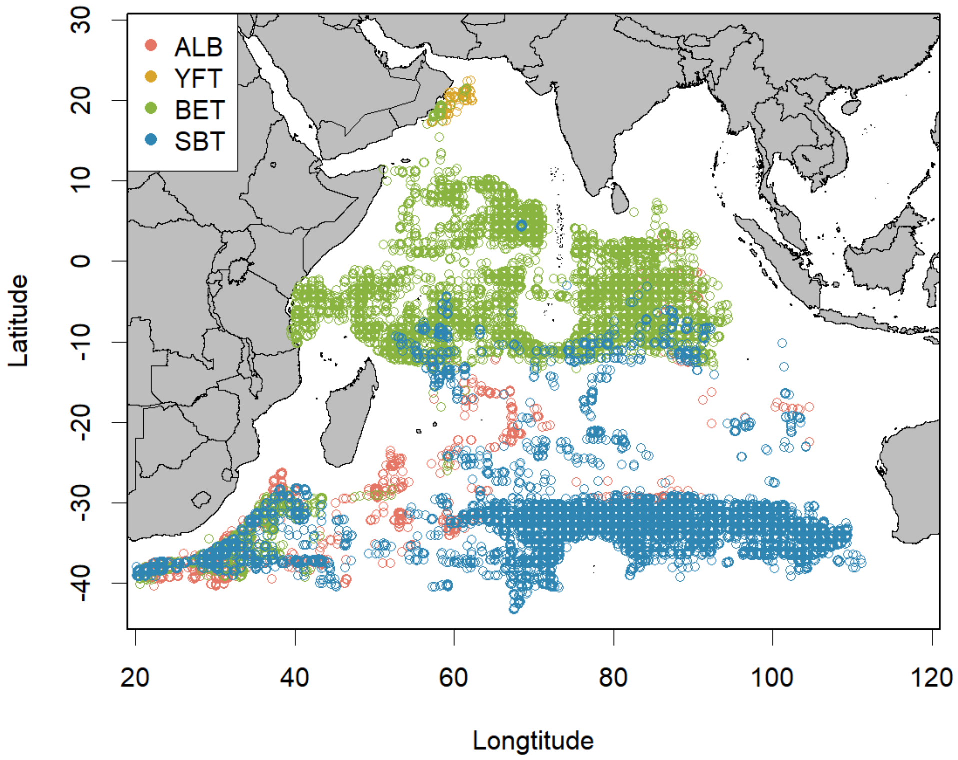


Figure 1. The observed effort distributions of the Taiwanese large-scale tuna longline fishery in the Indian Ocean from 2004 to 2019. Red circles: albacore fleet (ALB); Yellow circles: yellowfin tuna fleet (YFT); Green circles: bigeye tuna fleet (BET); Blue circles: southern bluefin tuna fleet (SBT).

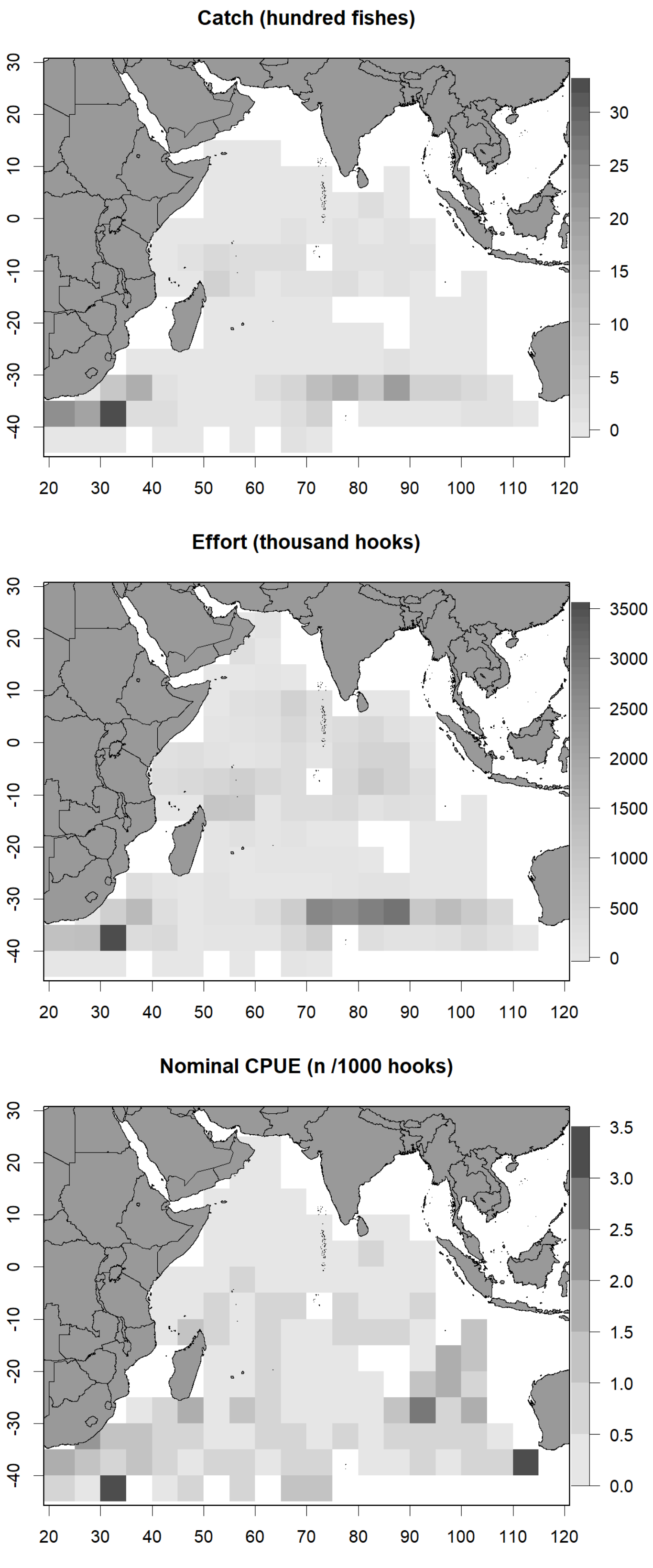


Figure 2. The spatial distribution of efforts, catches and nominal CPUE of blue shark for Taiwanese tuna longline vessels in the Indian Ocean from 2004 to 2019.

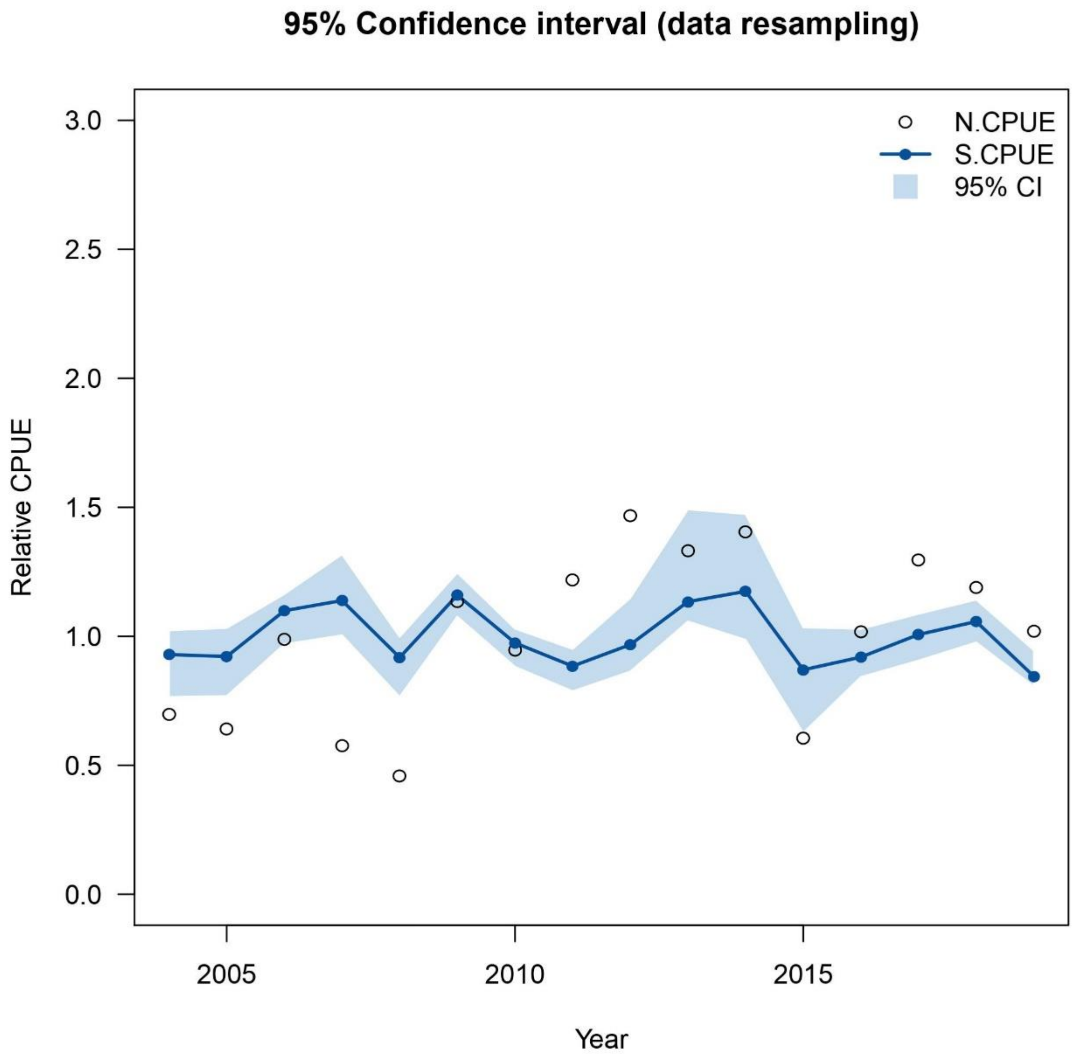


Figure 3. The observed nominal and standardized BPUE with 95% CI of blue shark by Taiwanese longline vessels in the Indian Ocean from 2005 to 2019.

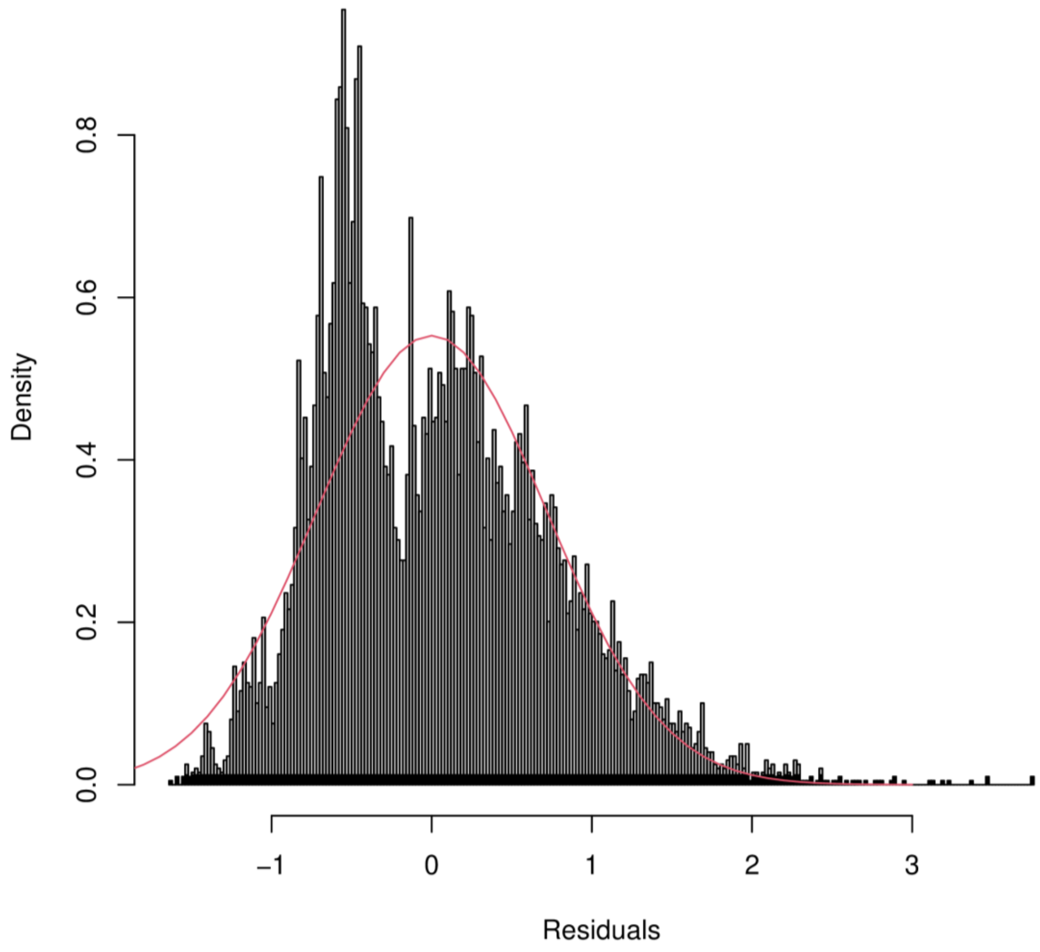


Figure 1. Residual histogram from the GLM model fit to the Indian Ocean longline blue shark bycatch data.

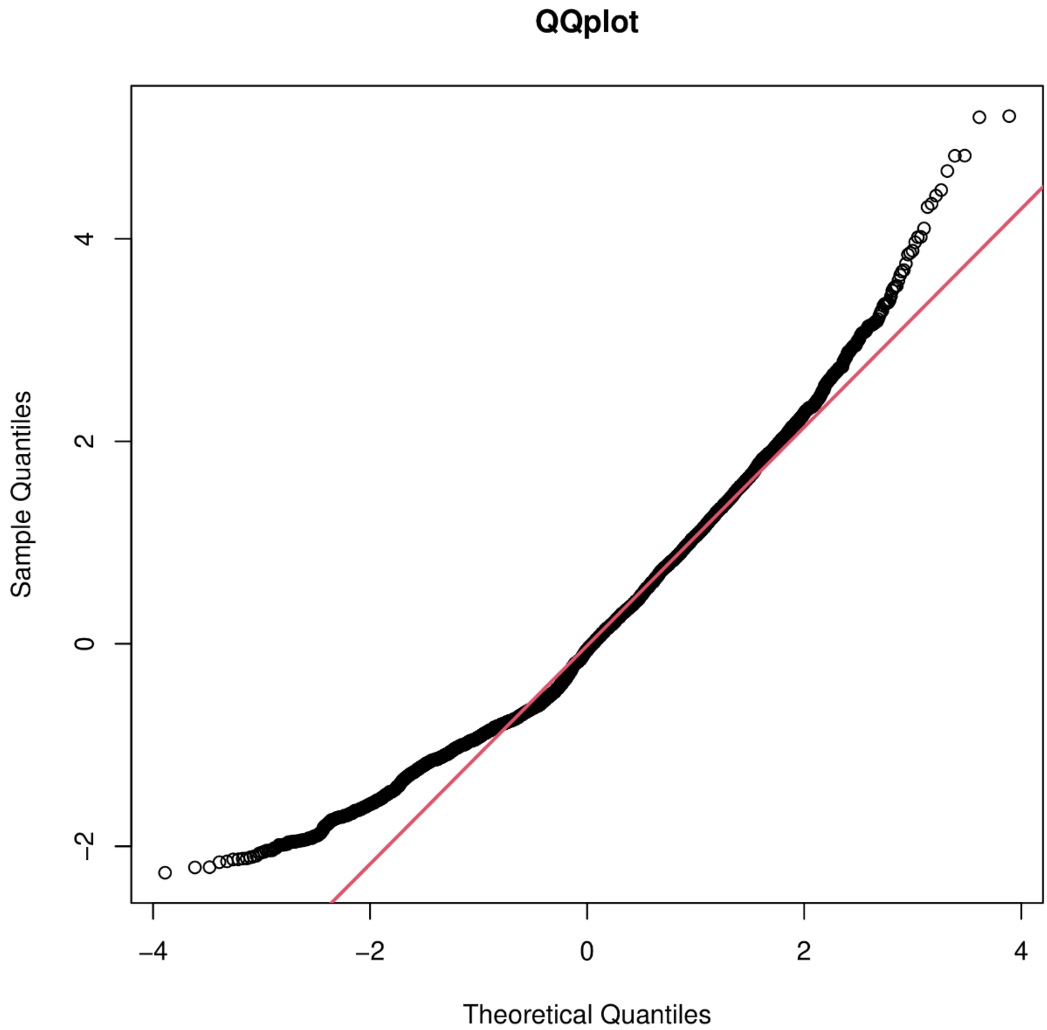


Figure 5. Q-Q plots for the GLM model fit to the Indian Ocean longline blue shark bycatch data.

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

Year	Indian Ocean		
	No. of Sets	No. of Hooks	No. of blue shark catches
2004	349	810,853	349
2005	592	1,418,853	561
2006	624	1,419,307	866
2007	2,441	5,687,204	2,022
2008	1,781	4,244,936	1,201
2009	2,183	5,323,131	3,726
2010	2,274	5,482,599	3,200
2011	764	1,891,751	1,423
2012	506	1,175,039	1,065
2013	1,212	2,458,764	2,022
2014	1,270	2,541,816	2,203
2015	1,089	2,154,457	805
2016	1,684	3,408,190	2,142
2017	1,894	3,870,576	3,096
2018	2,109	4,238,252	3,109
2019	2,079	4,245,608	2,672
Average	1,428	3,148,208	1,904

Table 2. The observed percentage of zero-catch of blue shark for Taiwanese tuna longline vessels in the Indian Ocean from 2004 to 2019.

Year	Percentage of zero-catch
2004	59.03%
2005	58.11%
2006	61.86%
2007	67.96%
2008	73.50%
2009	50.98%
2010	53.91%
2011	53.27%
2012	52.77%
2013	47.94%
2014	49.84%
2015	62.90%
2016	56.95%
2017	47.10%
2018	47.70%
2019	58.87%
Average	56.44%

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

Year	Nominal	Standardized
2004	0.43041	0.99596
2005	0.39539	0.98774
2006	0.61016	1.17797
2007	0.35554	1.22040
2008	0.28293	0.98365
2009	0.69996	1.24289
2010	0.58366	1.04445
2011	0.75221	0.94778
2012	0.90635	1.03692
2013	0.82236	1.21561
2014	0.86670	1.25851
2015	0.37364	0.93245
2016	0.62849	0.98527
2017	0.79988	1.07914
2018	0.73356	1.13299
2019	0.62936	0.90540

Table 1. Deviance tables for the DLN model of blue shark.

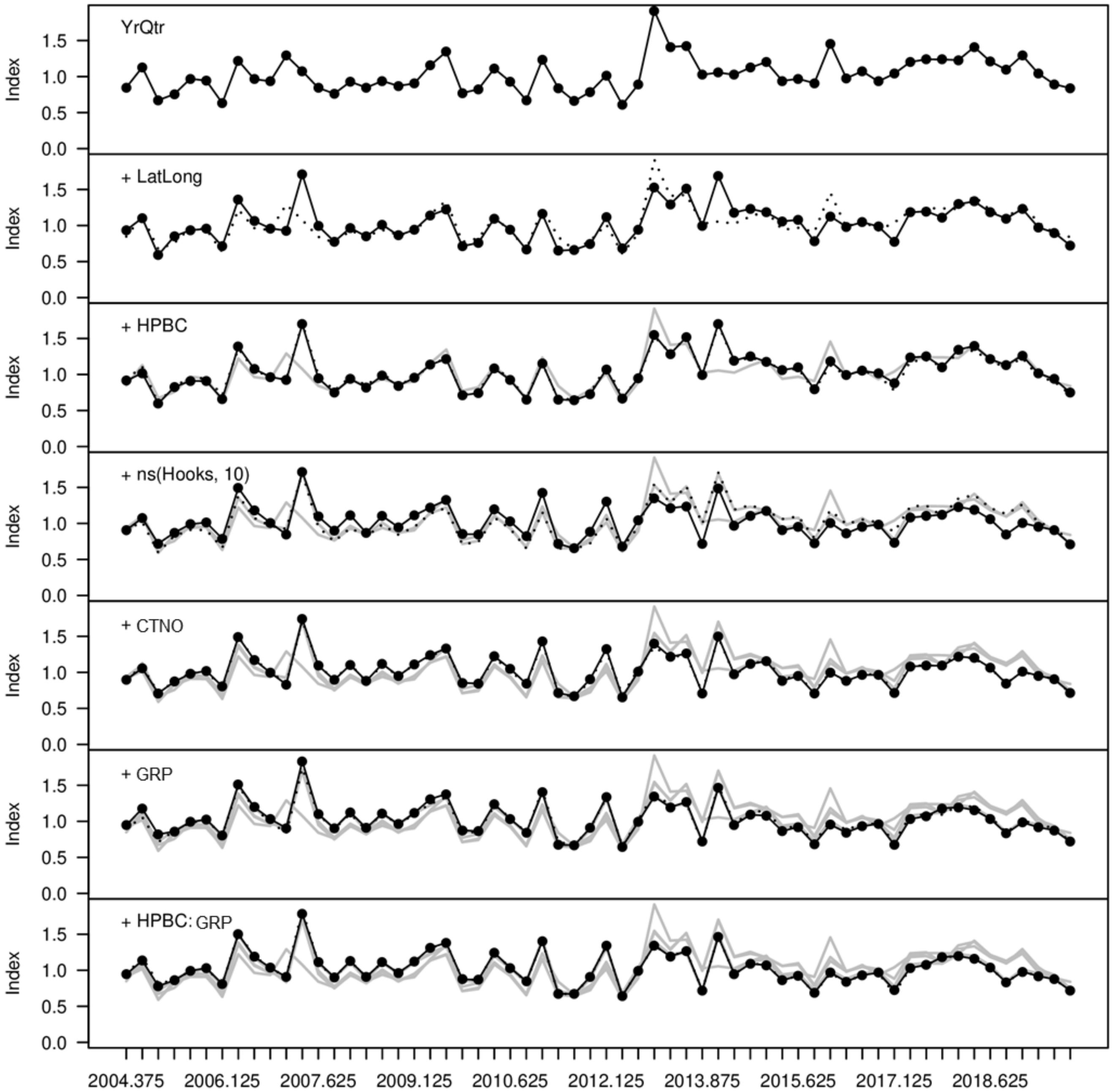
Log-normal Model

	Df	Deviance	Resid. Df	Resid. Dev	F	Pr(>F)	
NULL			9953	500.41			
YrQtr	59	37.561	9894	462.85	16.4482	< 0.001	***
LatLong	124	65.475	9770	397.38	13.6421	< 0.001	***
HPBC	2	1.775	9768	395.6	22.9254	< 0.001	***
ns(Hooks, 10)	10	16.297	9758	379.3	42.1052	< 0.001	***
CTNO	2	0.688	9756	378.62	8.8862	< 0.001	***
GRP	3	0.884	9753	377.73	7.6108	< 0.001	***
HPBC:GRP	3	0.357	9750	377.38	3.0704	< 0.05	*

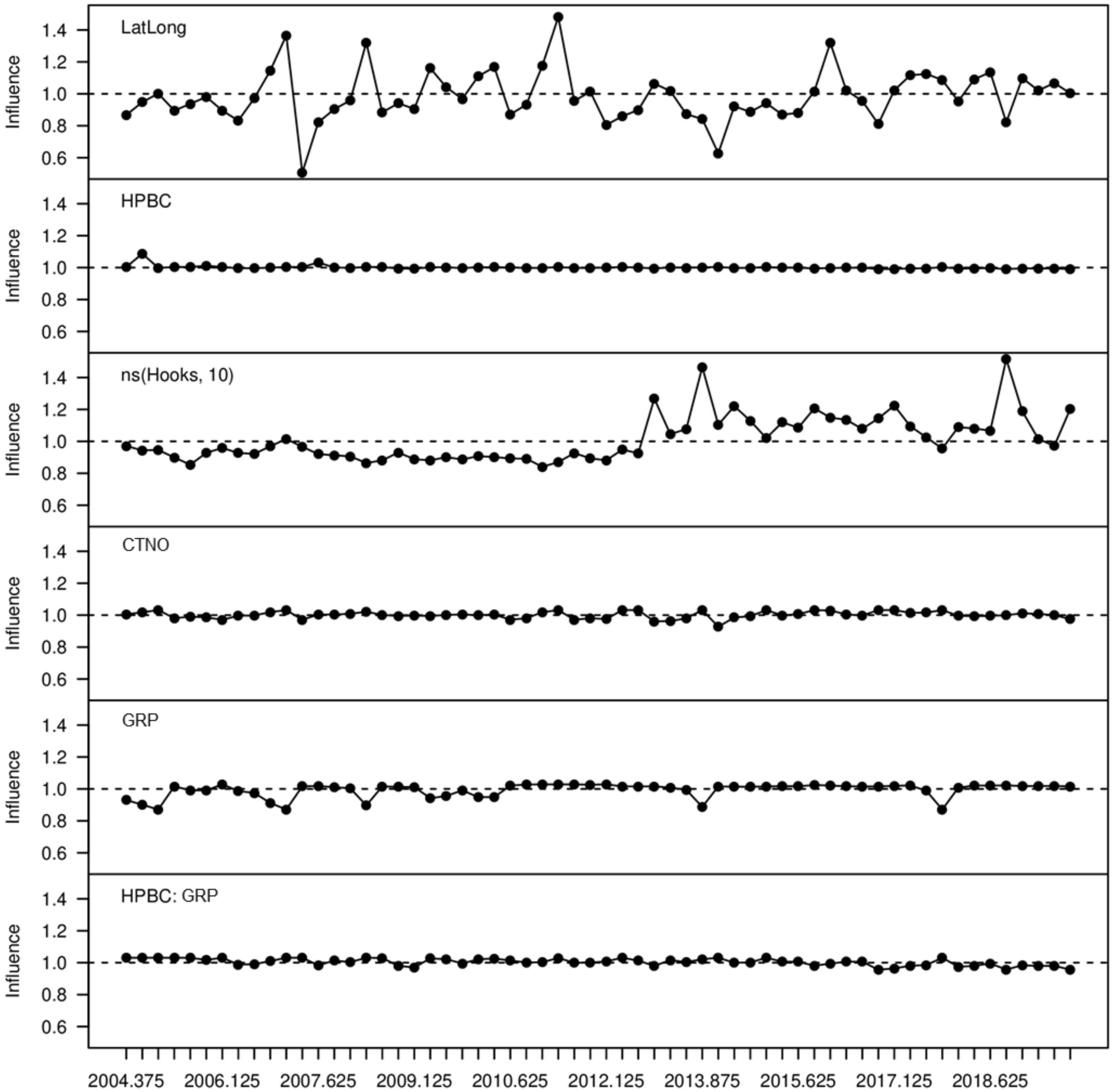
Binomial Model

	Df	Deviance	Resid. Df	Resid. Dev	F	Pr(>F)	
NULL			22850	31298			
YrQtr	59	1310.8	22791	29987	22.2169	< 0.001	***
LatLong	134	1854.17	22657	28133	13.8371	< 0.001	***
HPBC	2	55.77	22655	28077	27.8843	< 0.001	***
ns(Hooks, 10)	10	59.58	22645	28018	5.9585	< 0.001	***
CTNO	2	1.68	22643	28016	0.8417	0.431	
GRP	4	92.11	22639	27924	23.0283	< 0.001	***
HPBC:GRP	3	15.66	22636	27908	5.2186	< 0.01	**

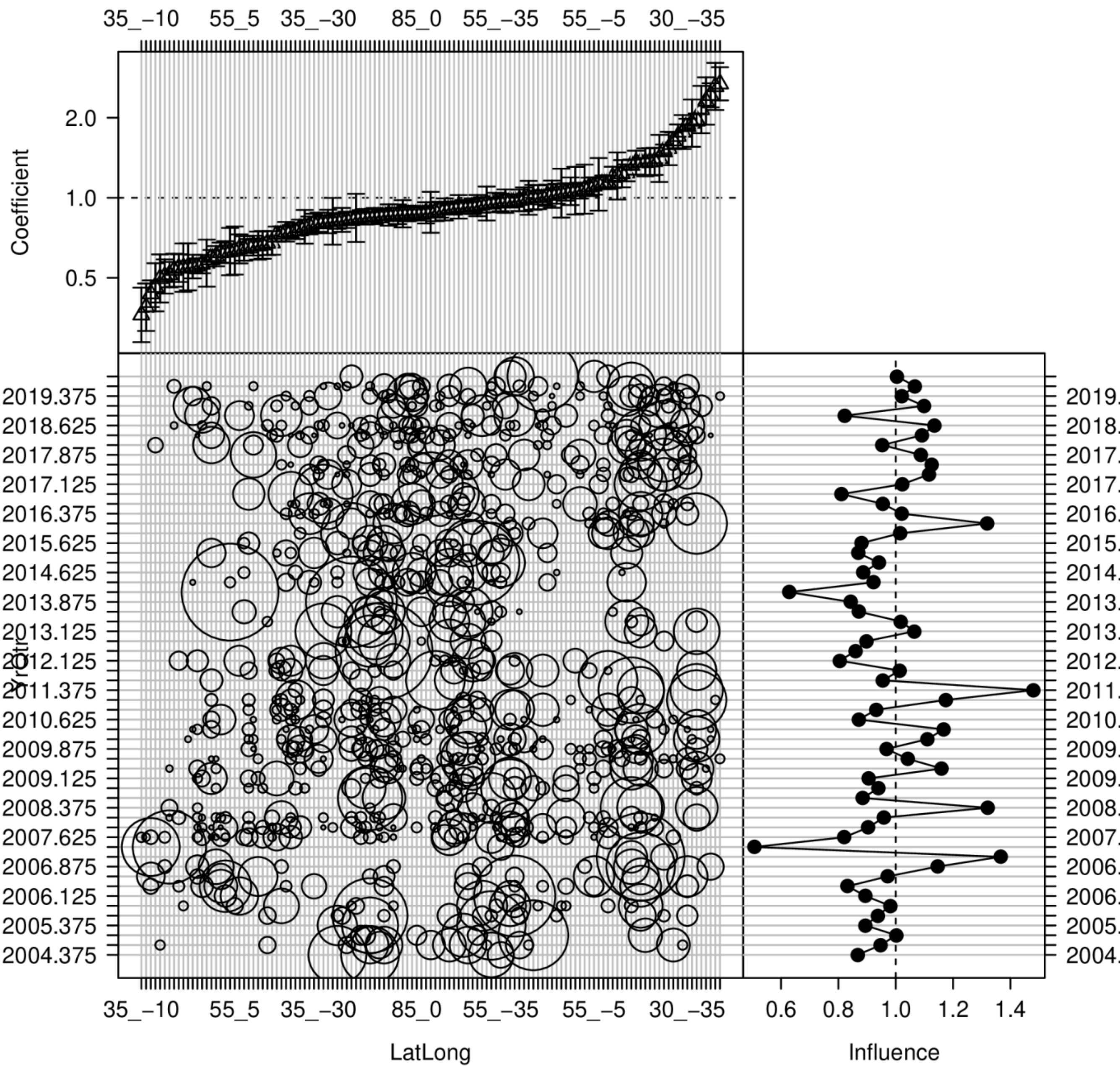
Appendix



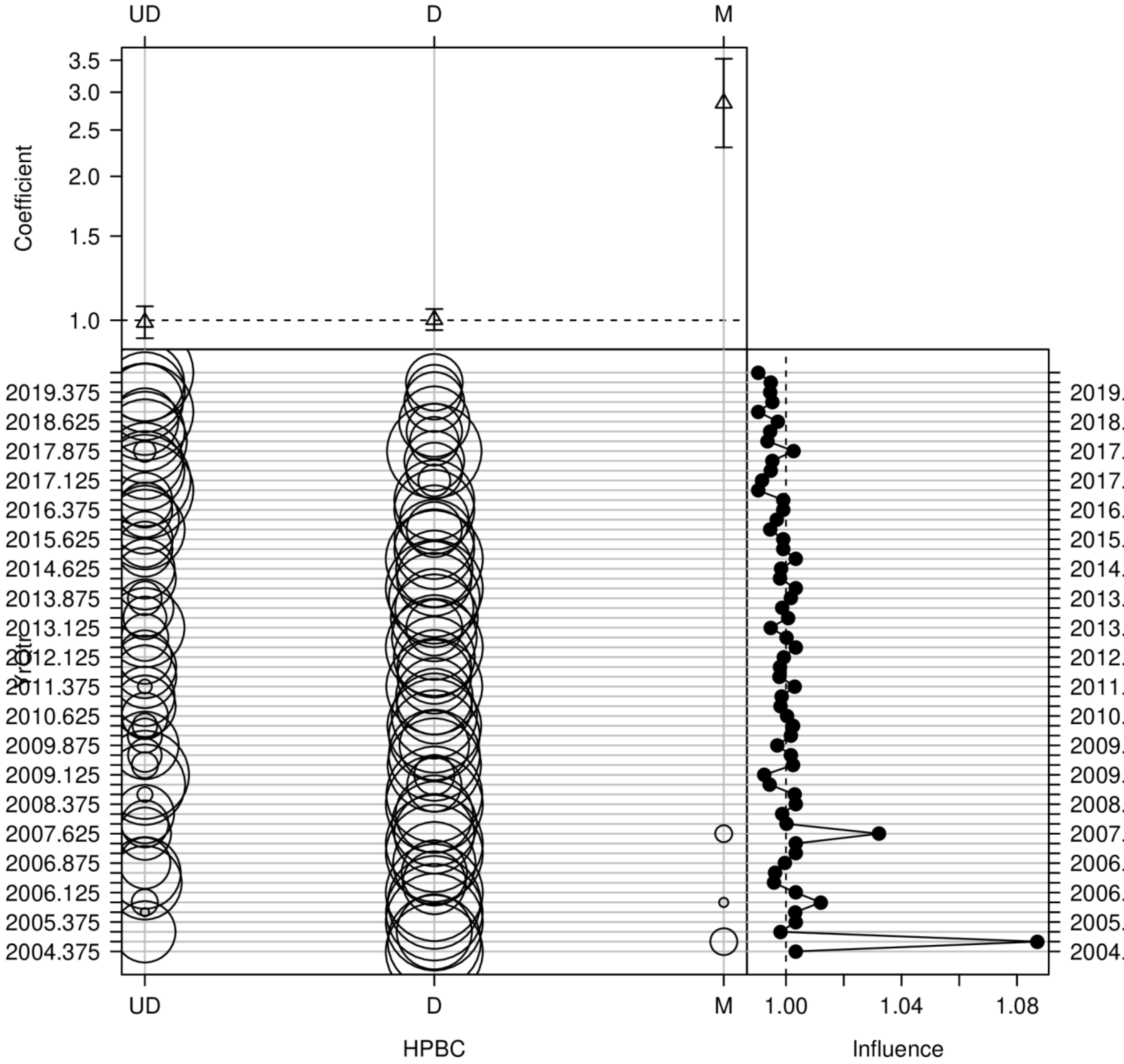
Appendix Fig. 1. Influence plots shows the change in the CPUE time series caused by each covariate for blue shark CPUE in the Indian Ocean by the Taiwanese fleet.



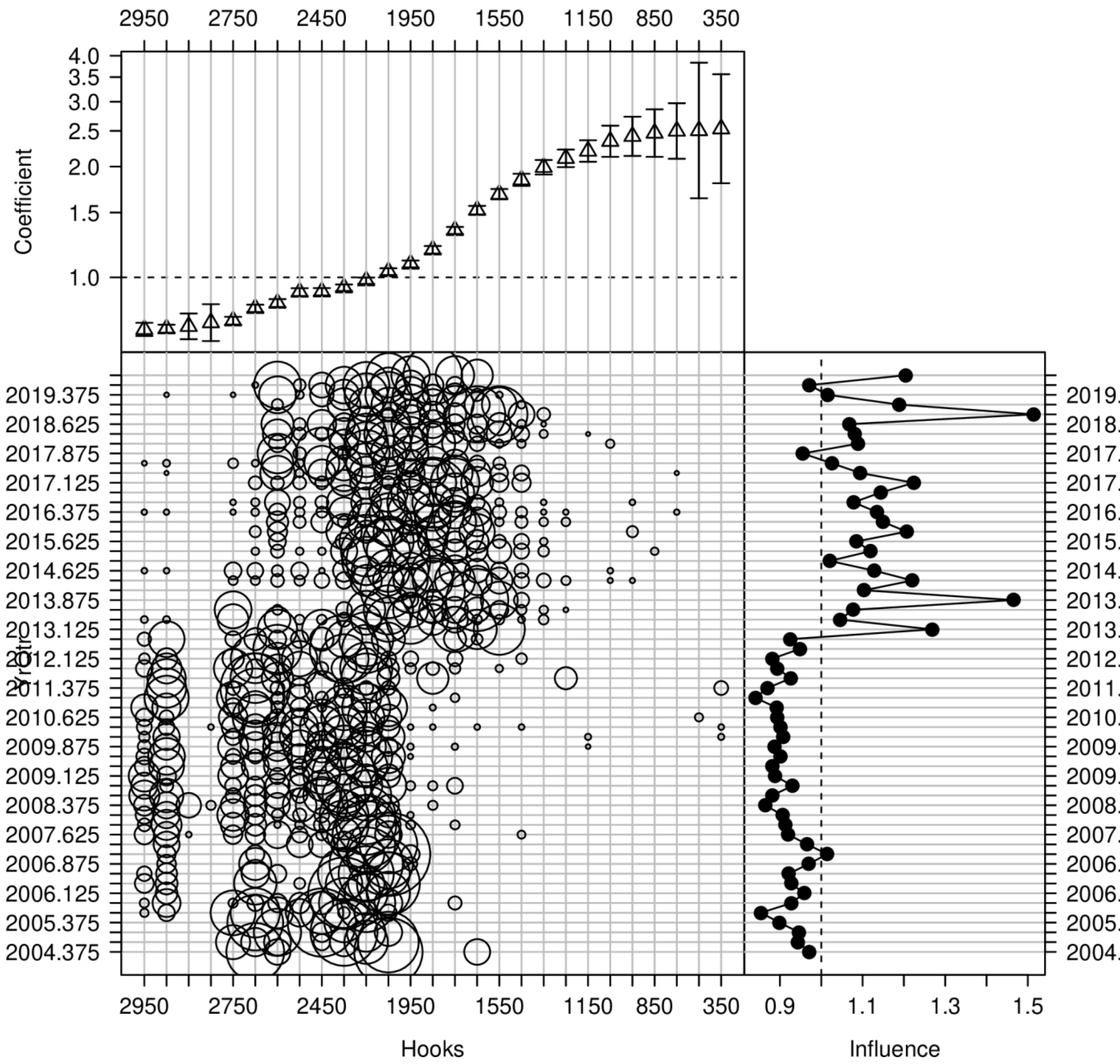
Appendix Fig. 2. The Influence plots shows the change in the CPUE time series caused by each covariate.



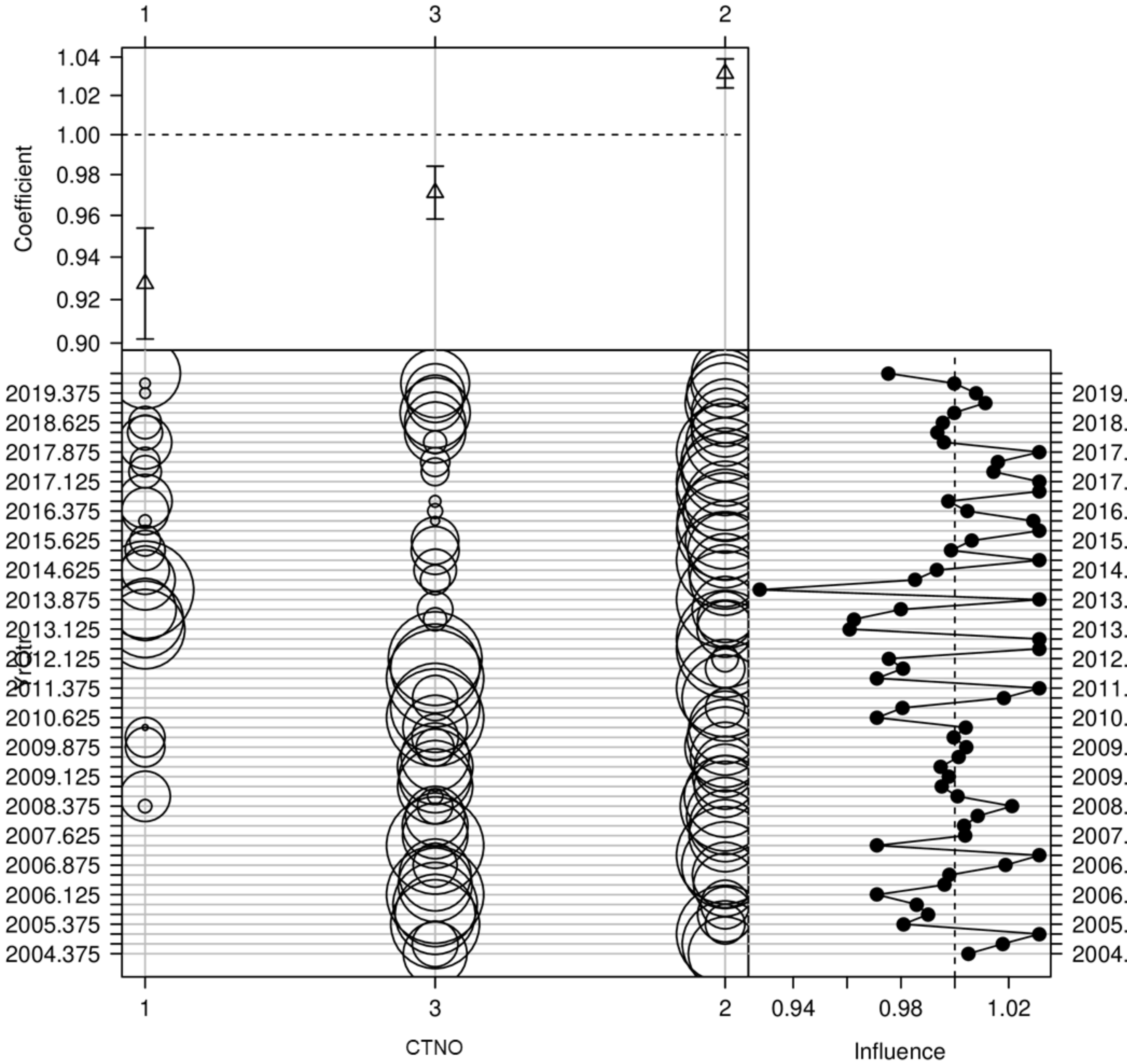
Appendix Fig. 3. The Influence plots shows the influence of the LatLong effect.



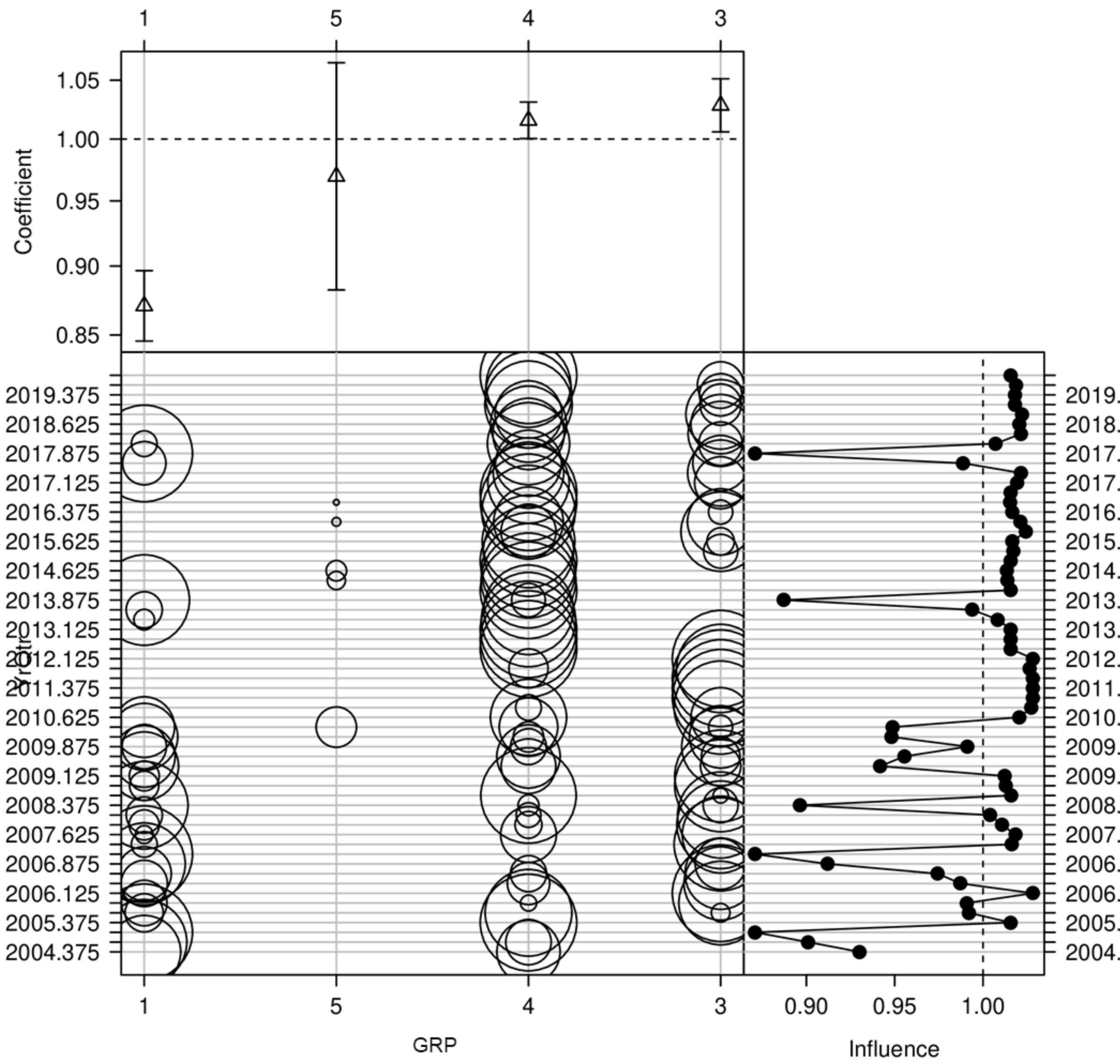
Appendix Fig. 4. The Influence plots shows the influence of the HPBC effect.



Appendix Fig. 5. The Influence plots shows the influence of the Hooks effect.



Appendix Fig. 6. The Influence plots shows the influence of the CTNO effect.



Appendix Fig. 7. The Influence plots shows the influence of the GRP effect.