CPUE standardization of swordfish (*Xiphias gladius*) caught by Taiwanese large scale longline fishery in the Indian Ocean

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ABSTRACT

This paper briefly describes historical patterns of fishing operations and swordfish catches caught by Taiwanese large scale longline in the Indian Ocean. The cluster analysis was adopted to explore the targeting of fishing operations. In addition, the delta-gamma generalized linear models were selected to conduct the CPUE standardizations of swordfish caught by Taiwanese large scale longline fishery because large amounts of zero catches existed in the data sets, which resulted in skewed distributions for nominal CPUE. The results indicate that the effects of targeting (clusters) provided most significant contributions to the explanation of the variance of CPUE for the models with positive catches, while the catch probability might be mainly influenced by the latitude of fishing operations. The standardized CPUE series revealed different trends by areas but they obviously increased in recent years except for the Area SW.

1. INTRODUCTION

Taiwanese longline fishery in the Indian Ocean commenced in the mid-1950s and targeted on yellowfin tuna in the beginning. Following the development of the fishery, two different operation patterns were currently established: the first targets on albacore for canning and the other on tropical tuna species (bigeye tuna and yellowfin tuna) for sashimi market. After 1990, catches of swordfish increased sharply as a result of changes in targeting from tunas to swordfish by part of the Taiwanese longline fleet, along with the development of longline fisheries in Australia, France (La Réunion), Seychelles and Mauritius and arrival of EU longline fleets and other fleets from the Atlantic Ocean. Since the mid-2000s annual catches have fallen steadily, largely due to the decline in the number of Taiwanese longline vessels active in the Indian Ocean in response to the threat of piracy; however since 2012 catches appear to show signs of recovery as a consequence of improvements in security in the area off Somalia. In recent years, swordfish catches were mainly made by Taiwanese longline fleet (21%), Sri Lankan longline-gillnet fleet (18%) and swordfish targeted longline of EU, Spain (12%) (IOTC, 2019).

This paper briefly describes historical patterns of fishing operations and swordfish catches caught by Taiwanese large scale longline in the Indian Ocean. The cluster analysis was adopted to explore the targeting strategies of fishing operations, which were further included in CPUE standardization.

2. MATERIALS AND METHODS

2.1. Catch and Effort data

In this study, daily operational catch and effort data (logbook) with 5x5 degree longitude and latitude grid for Taiwanese longline fishery during 1979-2019 were provided by Oversea Fisheries Development Council of Taiwan (OFDC). It should be noted that the data in 2019 is preliminary.

2.2. Cluster analysis

The characters of fishing operation, such as number of hooks between float (NHBF), material of line, bait and etc., are known to be informative to describe the change in target species. Wang and Nishida (2011) also indicated that the model performance for CPUE standardization was significantly improved when including the effect of NHBF treated as categorical variable. However, NHBF data were available since 1995 and obstructed the incorporation of the effect of NHBF when conducting the CPUE standardization with data before 1995.

Previous studies suggested alternative approaches to account for targeting in multispecies CPUE based on species composition, such as cluster analysis and principle component analysis (e.g. Ortega-García and Gómez-Muňoz, 1992; He et al., 1997; Pech and Laloë, 1997; Hoyle et al., 2004; Winker et al., 2013; Winker et al., 2014). These approaches have been applied to conduct the CPUE standardization for billfishes in the Indian Ocean (Wang, 2015, 2016, 2017, 2018, 2019). IOTC (2015) noted that the use of clustering and PCA was a useful approach in dealing with the absence of HBF, and such techniques help examine sets that are used for targeting certain species groups and use all the data in the database of Taiwan. IOTC (2015) also agreed that the PCA approach should be used instead of the clustering approach as this gave better results on AIC and BIC values, when modelling the positive sets.

However, cluster analysis was commonly adopted to derive targeting strategies and include targeting effects in the standardization for main species in the Indian Ocean since the Second IOTC CPUE Workshop on Longline Fisheries in 2015 (Hoyle et al., 2015, 2018, 2019).

In this study, cluster analysis was performed based on species composition of the catches of albacore (ALB), bigeye tuna (BET), yellowfin tuna (YFT), swordfish (SWO), southern bluefin tuna (SBT), sharks (SKX) and other species (OTH). However, clustering operational set-by-set data might include large amount noise because most of billfishes were caught by Taiwanese vessels as bycatches. Therefore, the cluster analysis was performed based weekly-aggregated data and then merged the clusters with set-by-set operational data to identify the targeting fishing operations.

He et al. (1997) suggested a cluster analysis with two steps to classify the data sets because the large number of data sets precluded direct hierarchical cluster analysis. First, a non-hierarchical cluster analysis (K-means method) was used to group the species composition from all data sets into 64 clusters for taking the mixture of fishing operations into account (P_2^6 which means 2 species can be chosen with priority from 8 species). Second, a hierarchical cluster analysis with Ward minimum variance method was applied to the squared Euclidean distances calculated based on the species composition from 64 non-hierarchical clusters obtained from the first step. Non-hierarchical and hierarchical cluster analyses were conducted using generic functions kmeans() and hclust() of R (R Core Team, 2020).

The number of clusters was commonly selected based on the proportion of data sets or improvement in deviance between/within clusters against different number of clusters in previous studies (e.g. He et al., 1997; Hoyle et al., 2015; Matsumoto et al., 2018; Wang, 2019) and this may be relatively subjective. As Amruthnath and Gupta (2019) recommended, this study selected the number of clusters based the permutation ANOVA (PERMANOVA) for significance test of the centroids of the groups and Beta diversity test for the permutation test for homogeneity of multivariate dispersion, and visualization diagnostics were conducted based on the plot from the principal coordinate analysis (PCoA) for the multivariate dispersions by clusters. In this study, the number of clusters was determined based on the smallest number when both PERMANOVA and Beta diversity test were significant. In addition, cluster analyses were performed by four fishing areas separately (Fig. 1).

2.3. CPUE Standardization

Although Taiwanese longline fishery seasonally targeted swordfish in the southwestern Indian Ocean, a large amount of zero-catches was recorded in the operational catch and effort data sets because swordfish was still mainly the bycatch species of Taiwanese longline fishery in the entire Indian Ocean. Historically, ignoring zero observations or replacing them by a constant was the most common approach. An alternative and popular way to deal with zeros was through the delta approach (Hinton and Maunder, 2004; Maunder and Punt, 2004). IOTC (2016) also noted the use of the delta approach to accommodate the high proportion of zero catches. Therefore, the delta-general linear models with different assumptions of error distribution were applied to conduct the CPUE standardization of swordfish in the Indian Ocean (Pennington, 1983; Lo et. al., 1992; Pennington, 1996; Andrade, 2008; Lauretta et al., 2016; Langley, 2019).

As the approach of Wang (2017), the models were simply conducted with the main effects of year, quarter, longitude, latitude and fishing targeting (clusters), while interactions between main effects were not incorporated into the models. In addition, CPUE standardizations were also performed by areas separately (Fig. 1). The models for positive catches and presence/absence data were conducted as follows:

For CPUE of positive catches:

$$Catch = \mu + Y + Q + CT + Lon + Lat + T + offset(\log(Hooks)) + \varepsilon^{pos}$$

For presence/absence of catches:

$$PA = \mu + Y + Q + CT + Lon + Lat + T + \varepsilon^{del}$$

where	*Catch*	is the catch in number of positive catch of swordfish
	PA	is the presence/absence of catch,
	Hooks	is the effort of 1,000 hooks,
	μ	is the intercept,
	Y	is the effect of year,
	Q	is the effect of quarter,
	CT	is the effect of vessel scale,
	Lon	is the effect of longitude,
	Lat	is the effect of latitude,
	T	is the effect of targeting (cluster),
	ε^{pos}	is the error term assumed based on various distribution,
	ε^{del}	is the error term, ε^{del} ~ Binomial distribution.

To examine the appropriateness to the assumption of error distribution, this study applied normal, poisson, gamma, negative-binomial and tweedie distributions to the error distribution of the model for the positive catches and specified “log” for the model link function. For the model with tweedie distribution, the index of power variance function was tested using values of 1.1-1.9. In addition, the models with negative-binomial and tweedie distributions were also performed by including all of positive and zero catches (catches were added 1 to avoid the problem for the logarithm of zero) to examine the model performance to the data overdispersed with excess of zero catches.

The stepwise searches ("both" direction, i.e. "backward" and "forward") based on the values of Akaike information criterion (AIC) were performed for selecting the explanatory variables for each model. Then, the coefficient of determination (R^2), and Bayesian information criterion (BIC) were calculated for the models with selected explanatory variables. The AIC and BIC, which were calculated based on the likelihoods with full constants obtained glm() and glm.nb(), were used to compare the models with different error distributions (e.g. Setyadji et al., 2019). In addition, dispersion statistics for Pearson residuals were calculated to check whether under- or overdispersions resulted from the models with an assumed error distribution.

The standardized CPUE were calculated based on the estimates of least square means of the interaction between the effects of year and area. The area-specific standardized CPUE trends were estimated based on the exponentiations of the adjust means (least square means) of the year effects (Butterworth, 1996; Maunder and Punt, 2004). The standardized relative abundance index was calculated by the product of the standardized CPUE of positive catches and the standardized probability of positive catches:

$$index = e^{\log(\widehat{CPUE})} \times \left(\frac{e^{\hat{p}}}{1 + e^{\hat{p}}} \right)$$

where $\widehat{CPUE}$ is the adjust means (least square means) of the year effect of the model for positive catches,

$\hat{p}$ is the adjust means (least square means) of the year effect of the model for presence/absence of catches.

3. RESULTS AND DISCUSSION

3.1. Historical fishing trends

Figs. 2 to 4 show the Taiwanese historical nominal catches of swordfish obtained from IOTC database and the area-specific fishing effort (hooks) and catches of swordfish based on the logbook data of Taiwanese large scale longline fishery. The swordfish catches were mainly caught in the Area NE before the 1990s and most of the catches were made in the Area NW thereafter due to the substantial increase of the fishing efforts although substantial catches made in Area SW from the early to mid-1990s. In recent decades, the annual proportions of zero-catch were about 40-70% of total data sets, while the proportions of zero catch decreased in recent years (Fig. 5).

Figs. 6 to 8 show the distributions of catch and CPUE of swordfish and fishing effort (hooks) of Taiwanese large scale longline fishery in the Indian Ocean. The catches of swordfish were mainly made in the tropical area in the central Indian Ocean before the 1990s; expanded to the entire Indian Ocean thereafter due to the expansion of the efforts; mainly concentrated in the tropical area and the southwestern Indian Ocean since the mid-2000s when the efforts substantially decreased in part of the temperate waters. High CPUEs mainly occurred in the tropical area and the southwestern Indian Ocean even for the period from the early 1990s to the mid-2000s when high catches appeared in the entire Indian Ocean.

The fishing operation of the vessels in the Indian Ocean also tended to use deep sets since the early 2000s (Figs. 9 and 10). High CPUEs of swordfish generally occurred with the NHBF less than 9 hooks and the operations were relatively similar to those of targeting albacore tuna (Fig. 11).

3.2. Cluster analysis

Based on the results of PERMANOVA and Beta diversity test (Table 1), 5 clusters were selected for Areas NW, NE and SW, while 4 clusters was selected for Area SE. The improvements in deviances among and between clusters look appropriate, and plots of PCoA for the multivariate dispersions indicated that the centroids of species compositions were obviously distinct by clusters (Figs. 12 and 13).

For each area, the species compositions revealed different patterns by clusters (Fig. 14). Swordfish were not major species for all clusters and areas except for Cluster 4 in Area SW contained relatively high proportions of swordfish in Area SW during the 1990s and 2000s. Distributions of swordfish catches also revealed low proportions for most clusters and areas except for Cluster 4 in Area SW (Fig. 15). Fig. 16 show the swordfish catches and efforts by clusters and areas and swordfish catches were contained in different clusters in different periods when different levels of efforts were deployed. Therefore, the data of all clusters were used to conducted the further CPUE standardizations.

The annual trends of the proportions of zero catches of swordfish roughly decreased by years for all areas (Fig. 17). However, the logarithms of nominal CPUE of swordfish generally revealed skewed distributions obtained from all data and from the data with only positive catches except for Cluster 4 in Area SW (Fig. 18).

3.3. CPUE standardization

For the models with tweedie error distribution, Pearson dispersion statistics would be most appropriate (close to 1) when setting the index of power variance function equal to 1.5 for all areas. Based on the AIC model selections for the models for positive catches and presence/absence catches, all of the effects were statistically significant and remained in the models for all areas. For the models for positive catches, the models with gamma error distribution would be the optimal models for all areas based on the values of AIC, BIC and Pearson dispersion statistics although R^2 may not be higher than other models (Table 2). Diagnostic plots for residuals also indicated that the models with gamma error distribution (Fig. 19) should be most appropriate than other models because there were less increasing or decreasing trends in the range of predicted values when assuming a gamma error distribution (plots for other models by areas were not shown here but the residuals revealed obvious patterns with predicted values). Although AIC and BIC obtained from the models for all of positive and zero catches cannot be comparable with those obtained from the models for only positive catches, Pearson dispersion statistics showed overdispersions resulted from the most of models with negative-binomial and tweedie error distributions except for Area SE (Table 3). In addition, there were also problematic patterns for diagnostic plots for residuals when adopting the models fitted to all of positive and zero catches. Therefore, the results obtained two steps delta approaches, which were based on the models with gamma error distribution for the positive catches and the models for presence/absence catches, were selected to produce the standardized CPUE series.

The ANOVA tables for selected models are shown in Table 4. The results indicate that the effects of *T* (clusters) provided most significant contributions to the explanation of variance of CPUE for the models for positive catches except for Area NE, while the effects of *Lat* were the most significant variable for the models for presence/absence catches except for Area SW. Thus, the catch rates the positive catches of swordfish might be influenced by the targeting of the fishing operation, while the latitude of the fishing operations might influence the opportunity of catching swordfish.

The area-specific standardized CPUE series are shown in Fig. 14. The CPUE series in the Area NW fluctuated with an increasing trend; the CPUE series in the Area NE fluctuated without a trend after the early 1980s; CPUE in the Area SW substantially increased from the early 1990s to mid-1990s, gradually decreased until the mid-2000s, and revealed a stable trend thereafter; the CPUE series in the Area SE gradually increased before the mid-1990s, then substantially decreased until the late 2000s, and revealed an increasing trend in recent years. The standardized CPUE series revealed different trends by areas but they obviously increased in recent years except for the Area SW.

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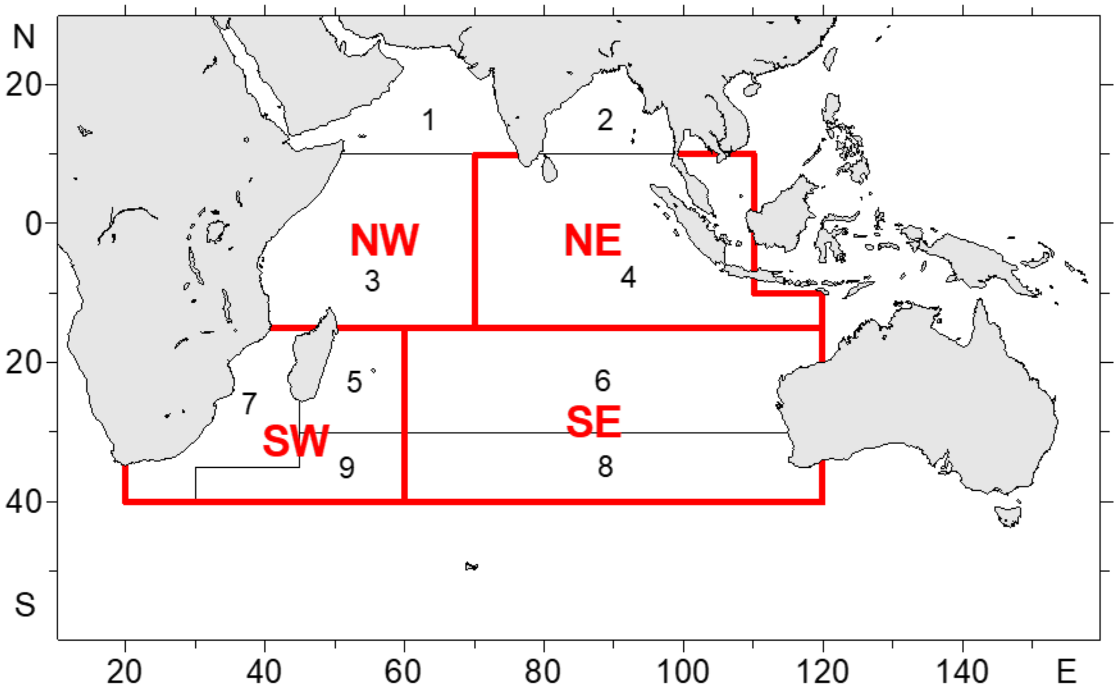


Fig. 1. Area stratification for billfishes in the Indian Ocean.

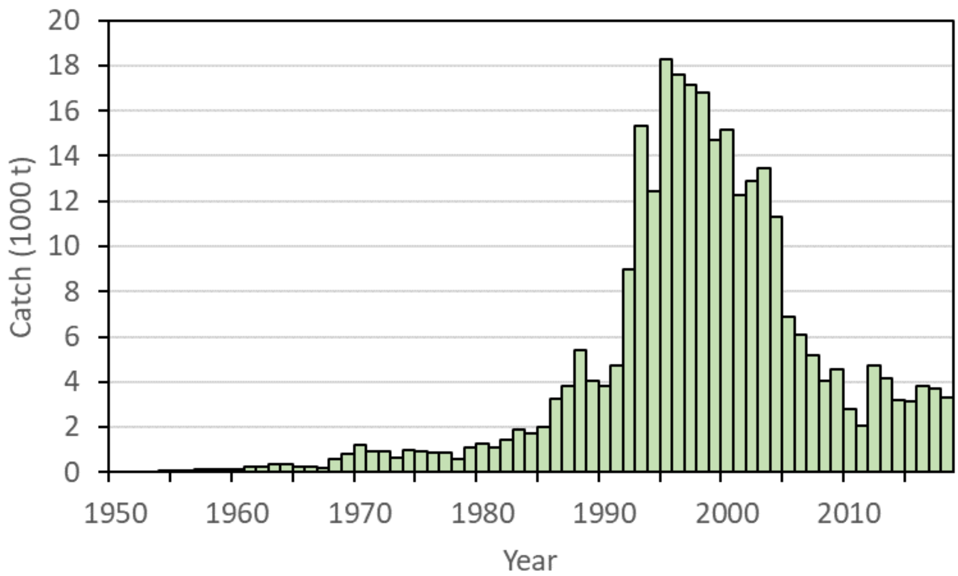


Fig. 2. Annual nominal catches of swordfish caught by Taiwanese large scale longline fishery obtained from IOTC database.

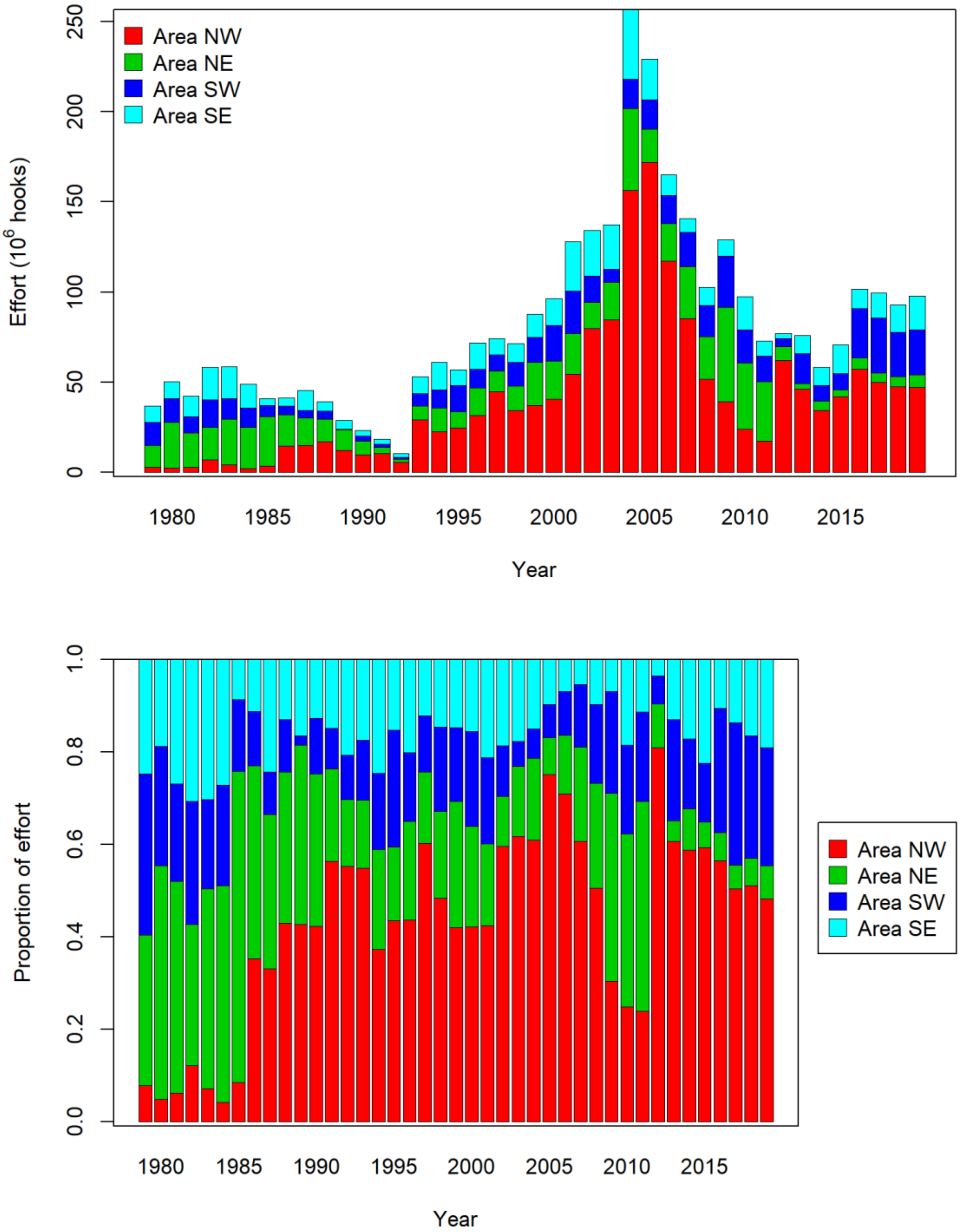
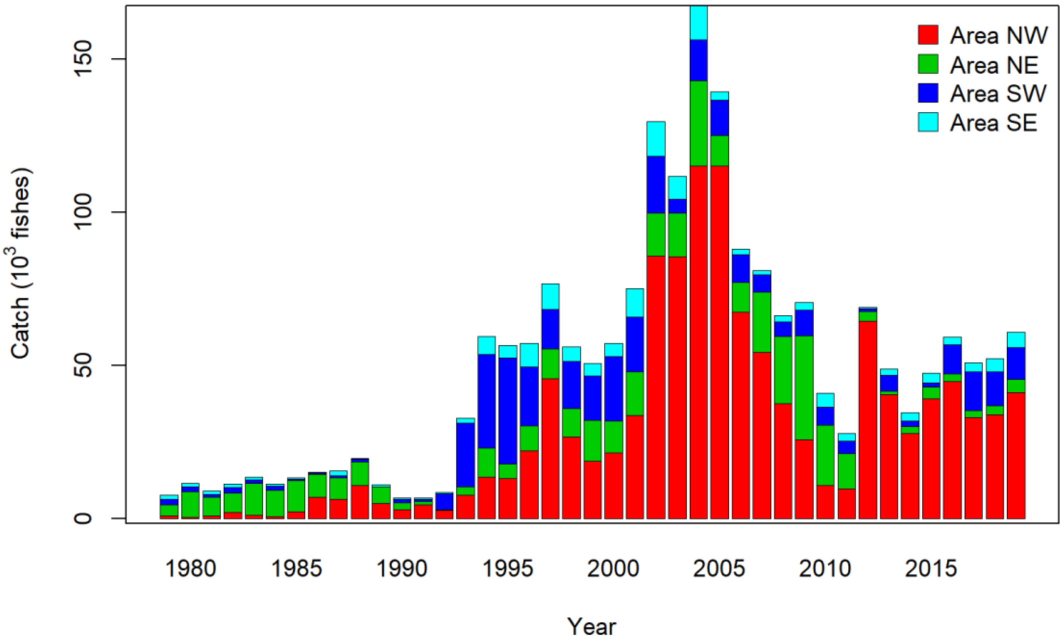


Fig. 3. Annual area-specific fishing effort (hooks) based on the logbook data of Taiwanese large scale longline fishery.



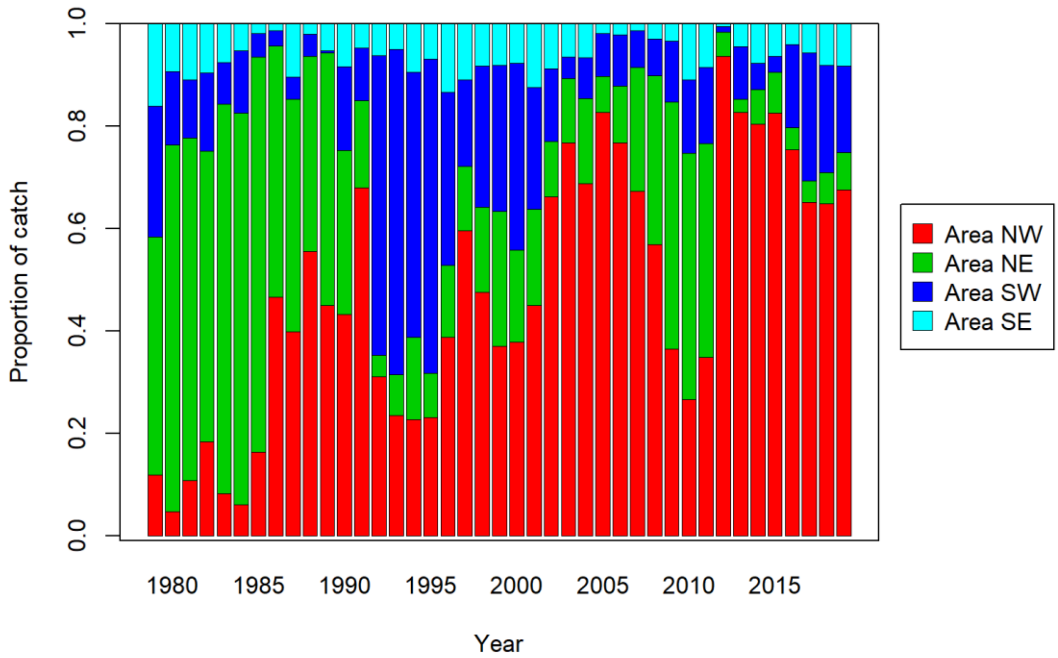


Fig. 4. Annual area-specific catches of swordfish based on the logbook data of Taiwanese large scale longline fishery.

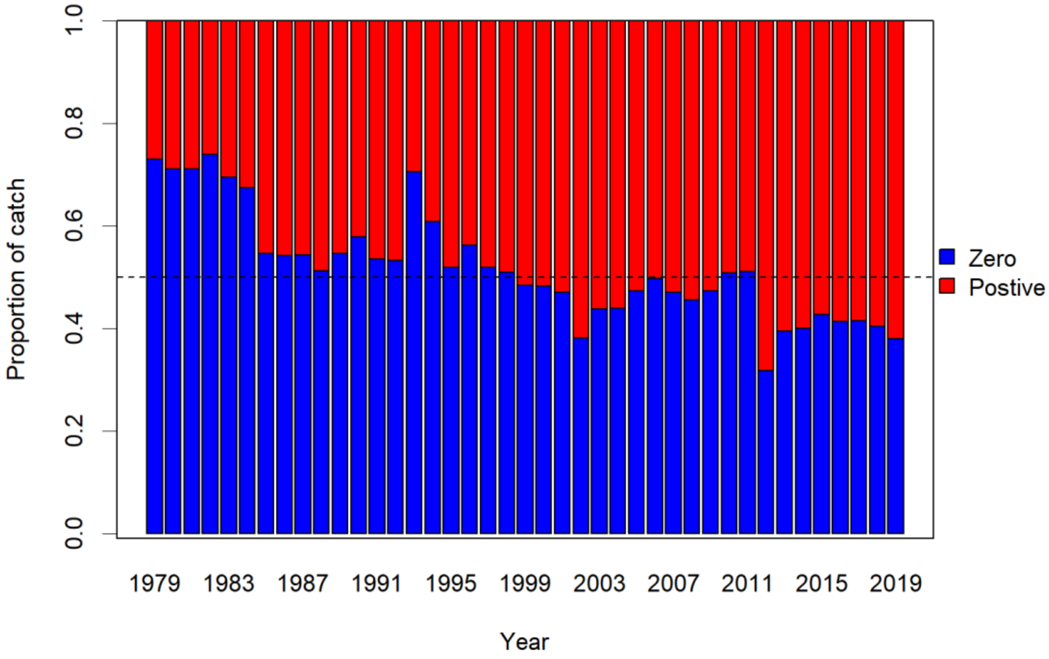


Fig. 5. Annual proportions of positive and zero catches of swordfish caught by Taiwanese large scale longline fishery in the Indian Ocean.

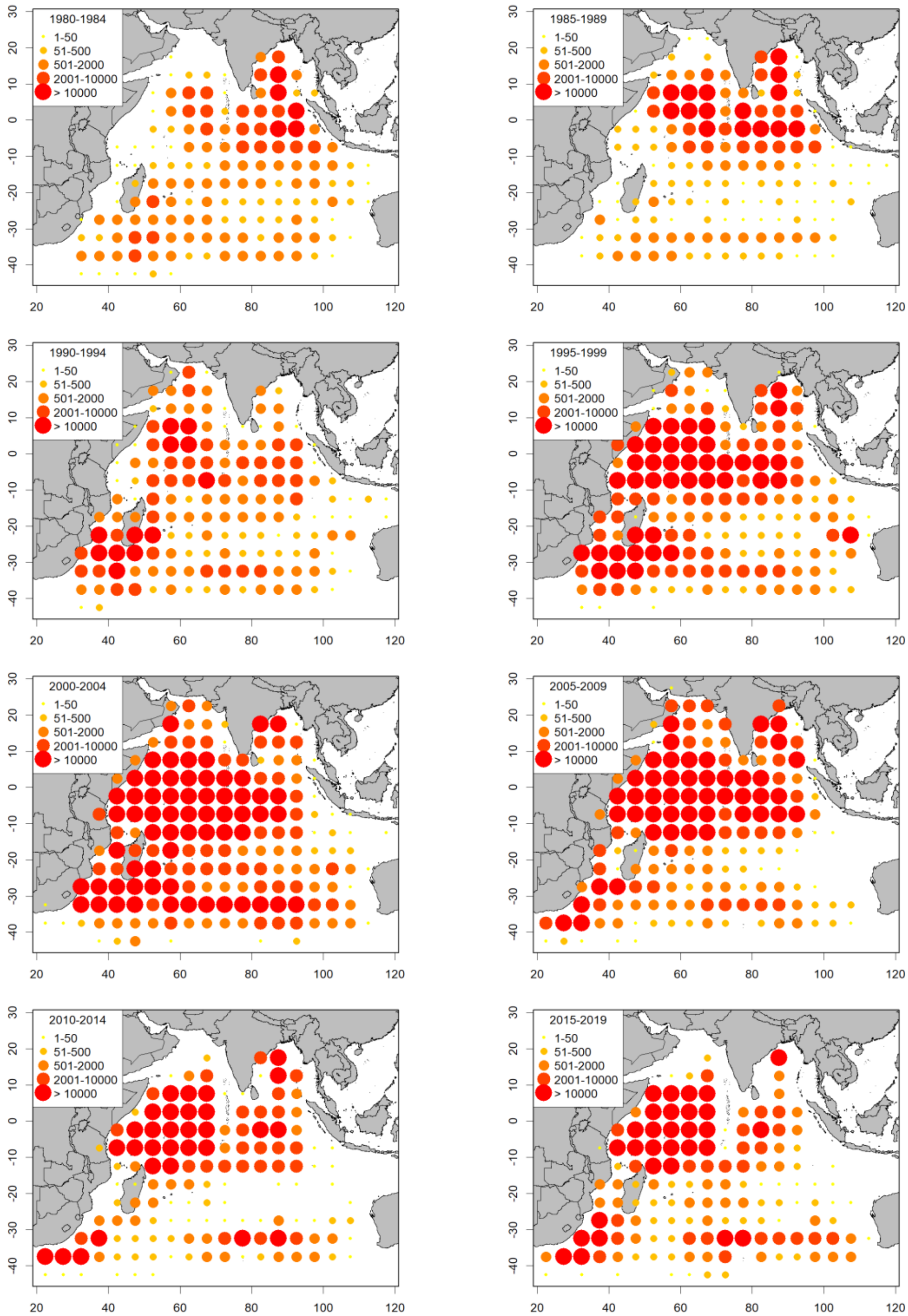


Fig. 6. Catch distributions of swordfish caught by Taiwanese large scale longline fishery in the Indian Ocean.

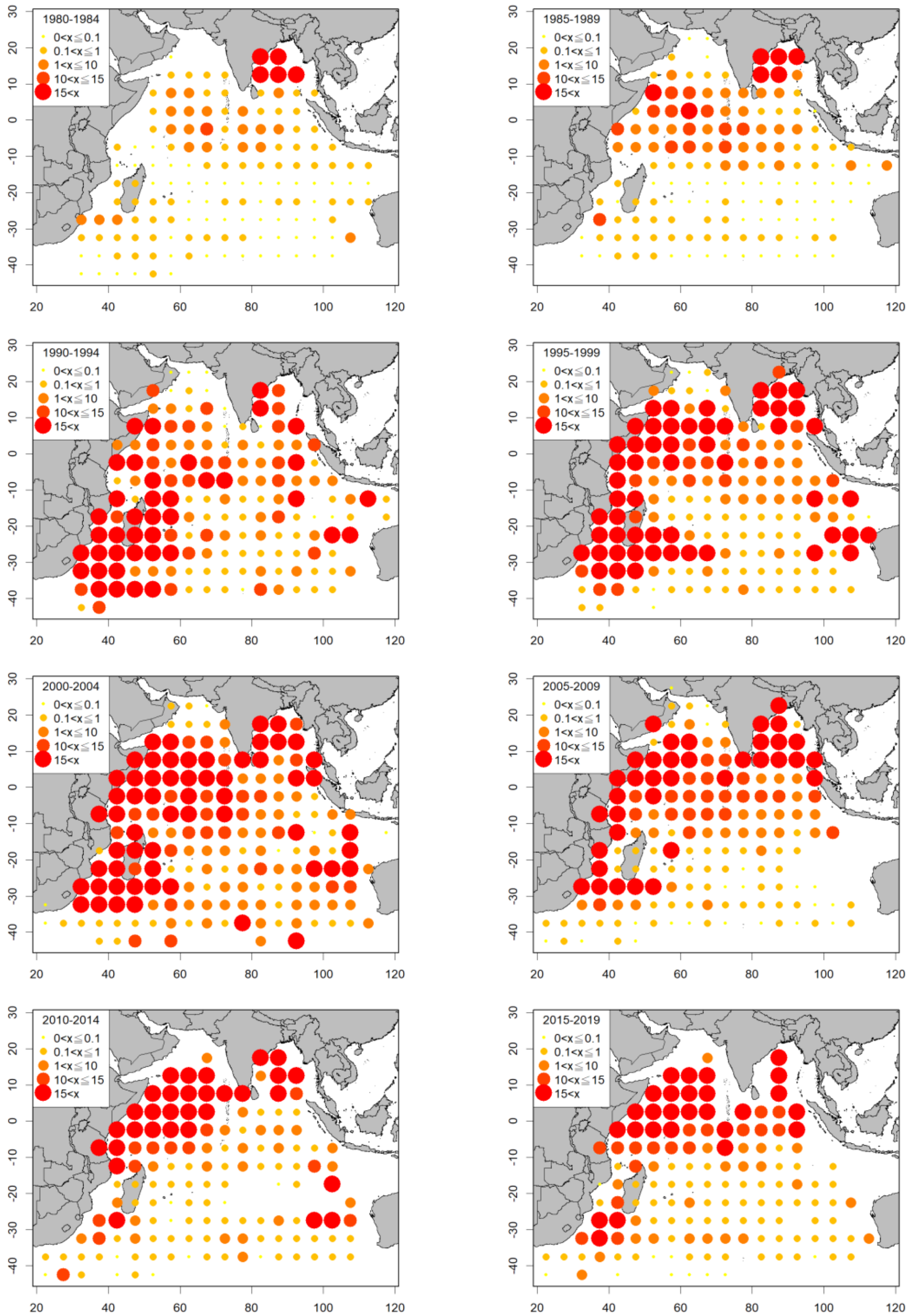


Fig. 7. Nominal CPUE distributions of swordfish caught by Taiwanese large scale longline fishery in the Indian Ocean.

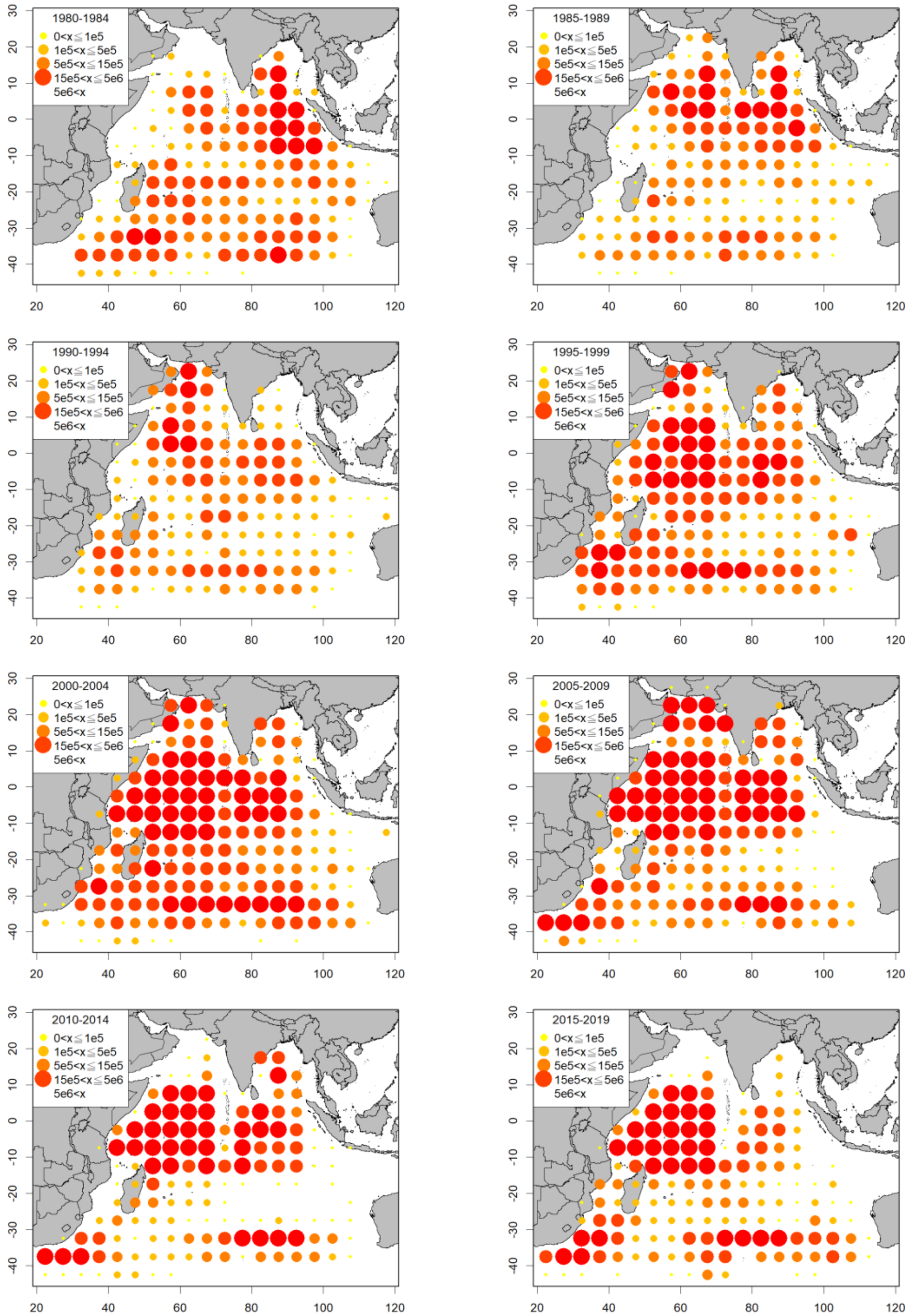
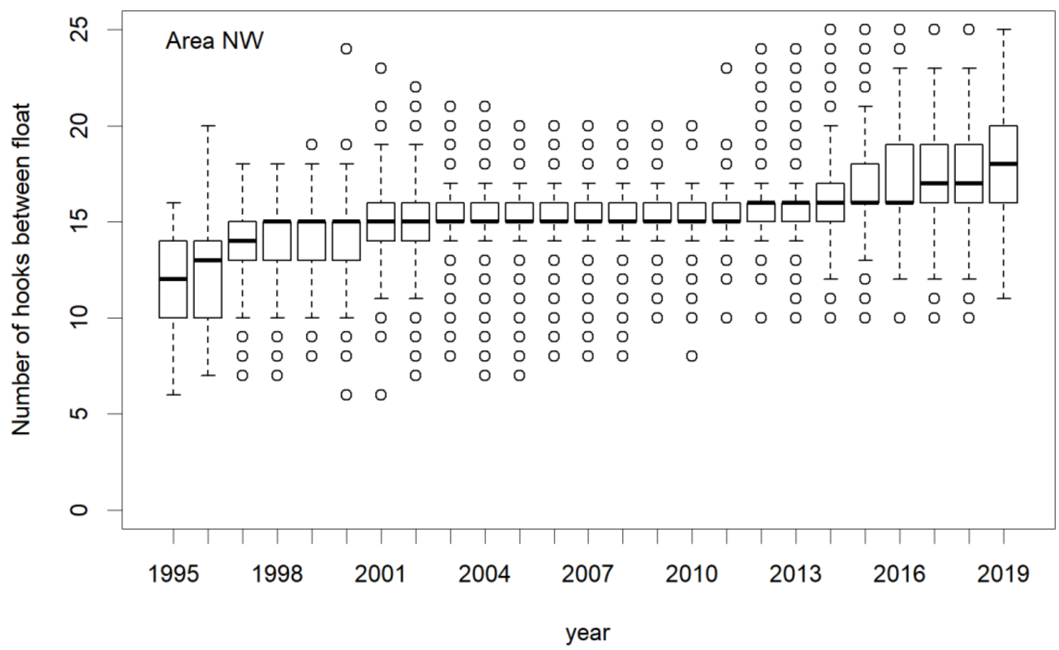


Fig. 8. Effort (hooks) distributions of Taiwanese large scale longline fishery in the Indian Ocean.



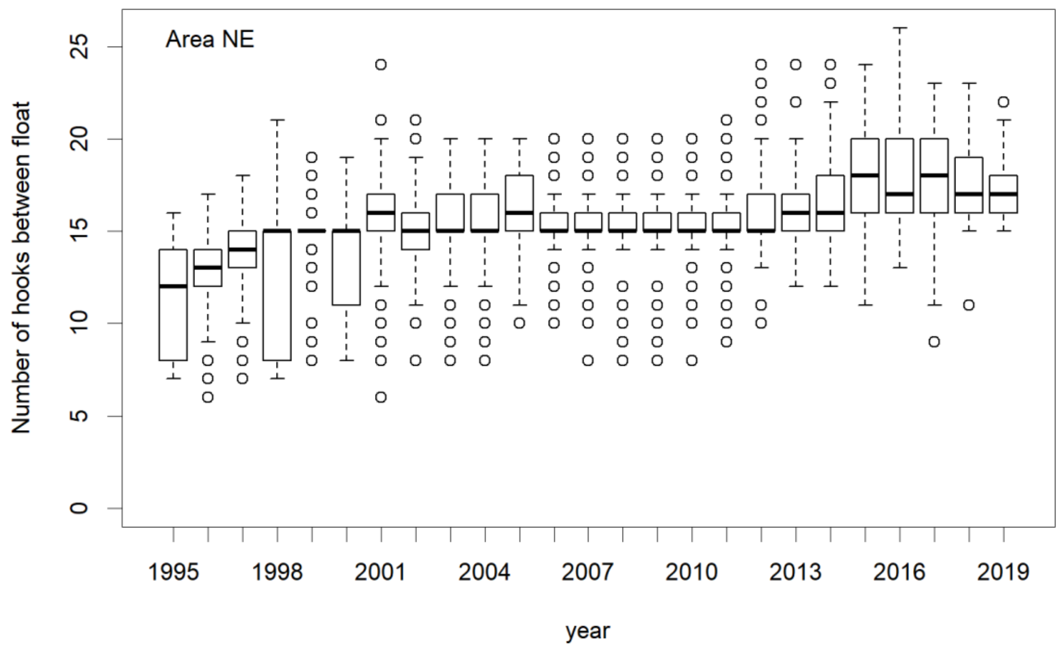
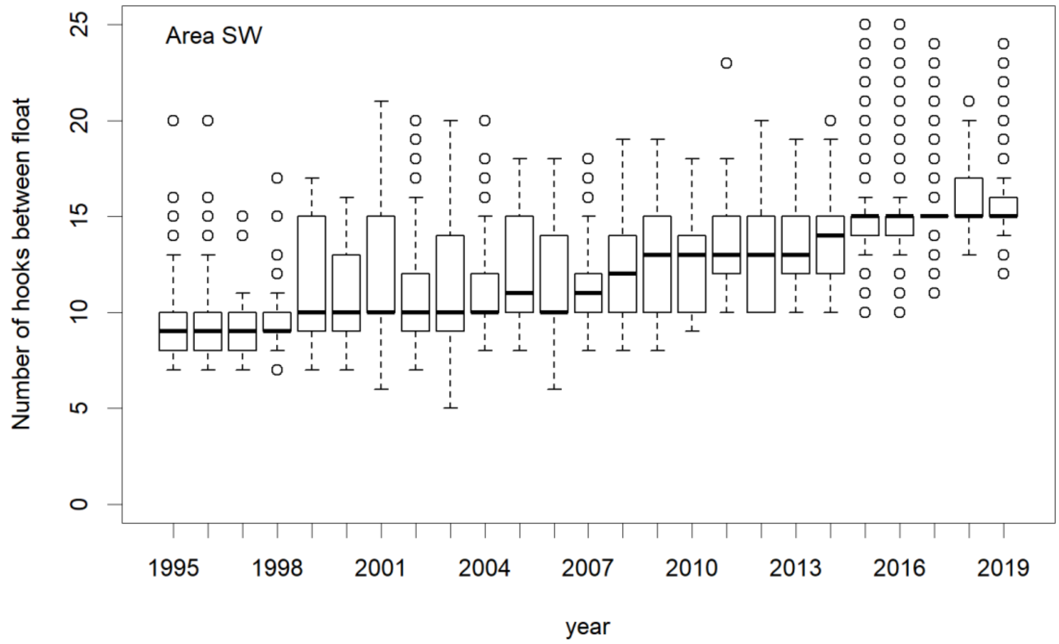


Fig. 9. Annual trend of the boxplot for the number of hooks between float of Taiwanese large scale longline fishery in the Indian Ocean.



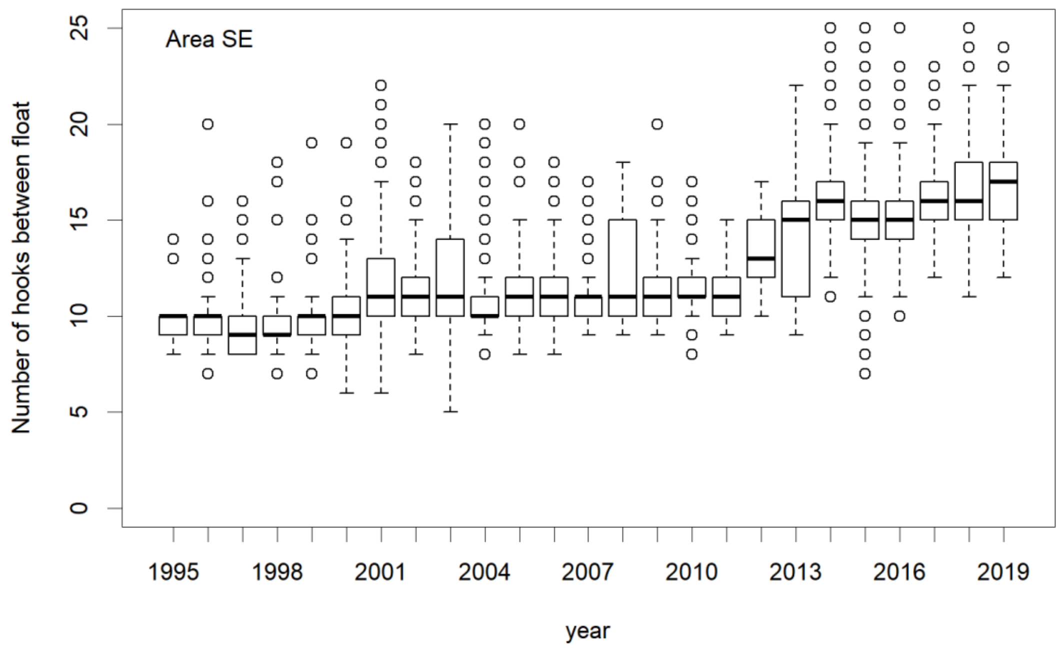


Fig. 9. (continued).

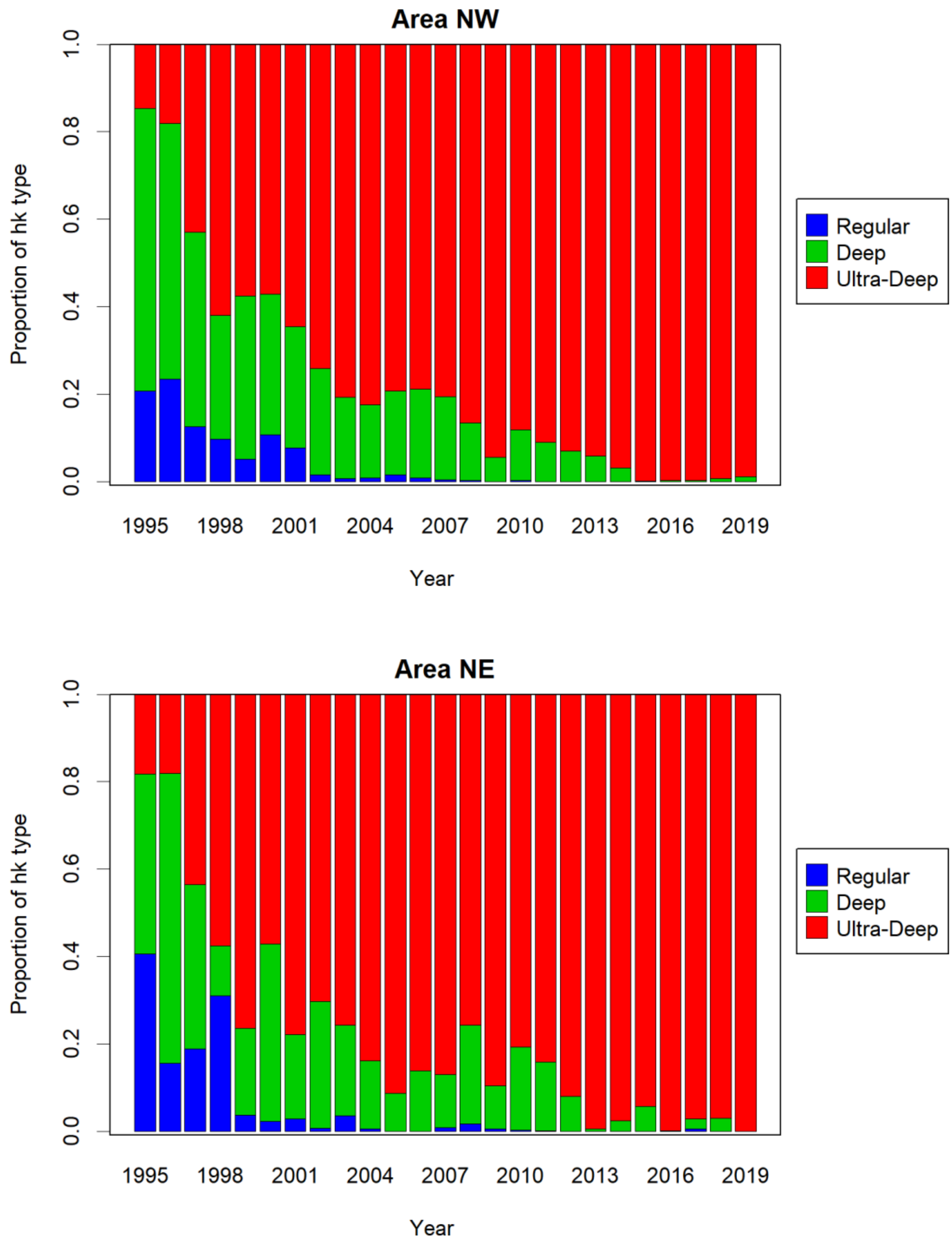
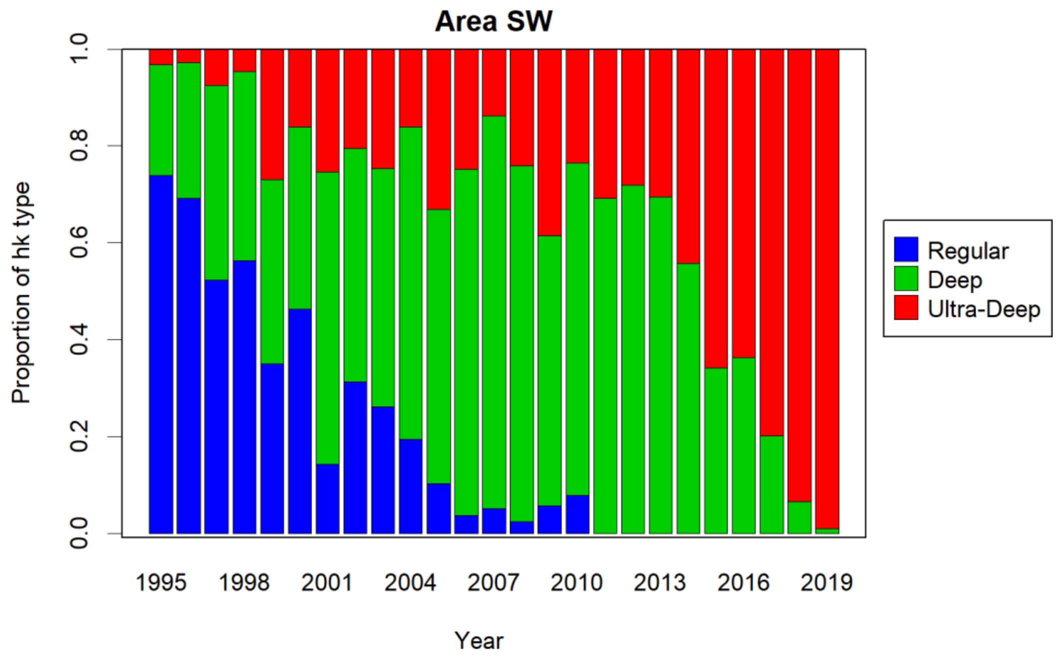


Fig. 10. Annual trend of the proportion of set type of Taiwanese large scale longline fishery in the Indian Ocean. Regular set: number of hooks between float (NHBF) < 10 hooks; Deep set: 10 hooks ≤ NHBF < 15 hooks; Ultra-deep: NHBF ≥ 15 hooks.



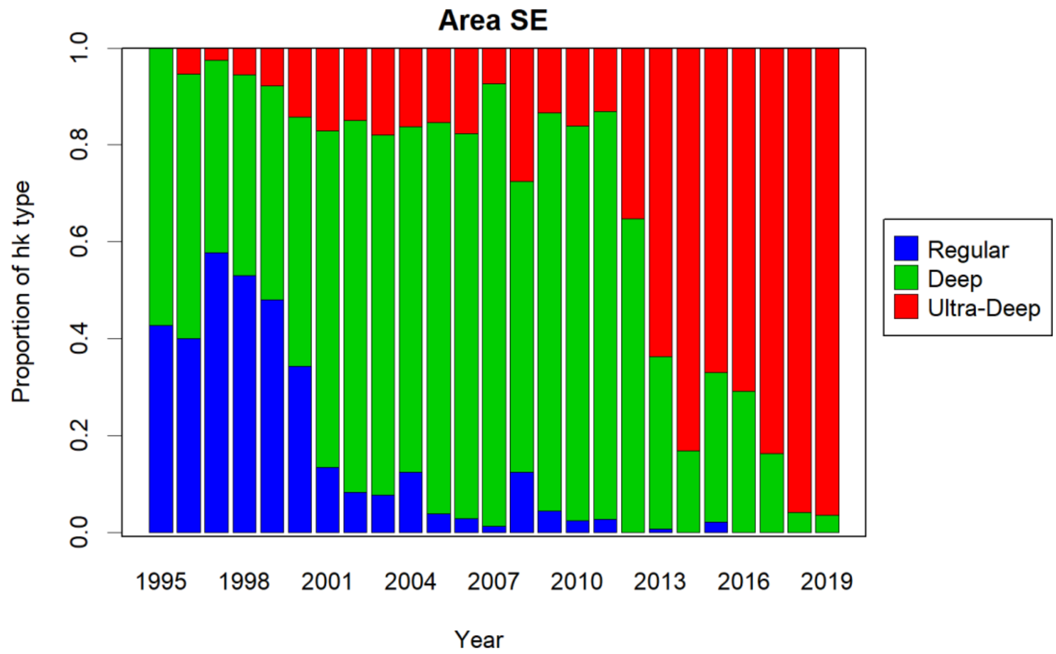


Fig. 10. (continued).

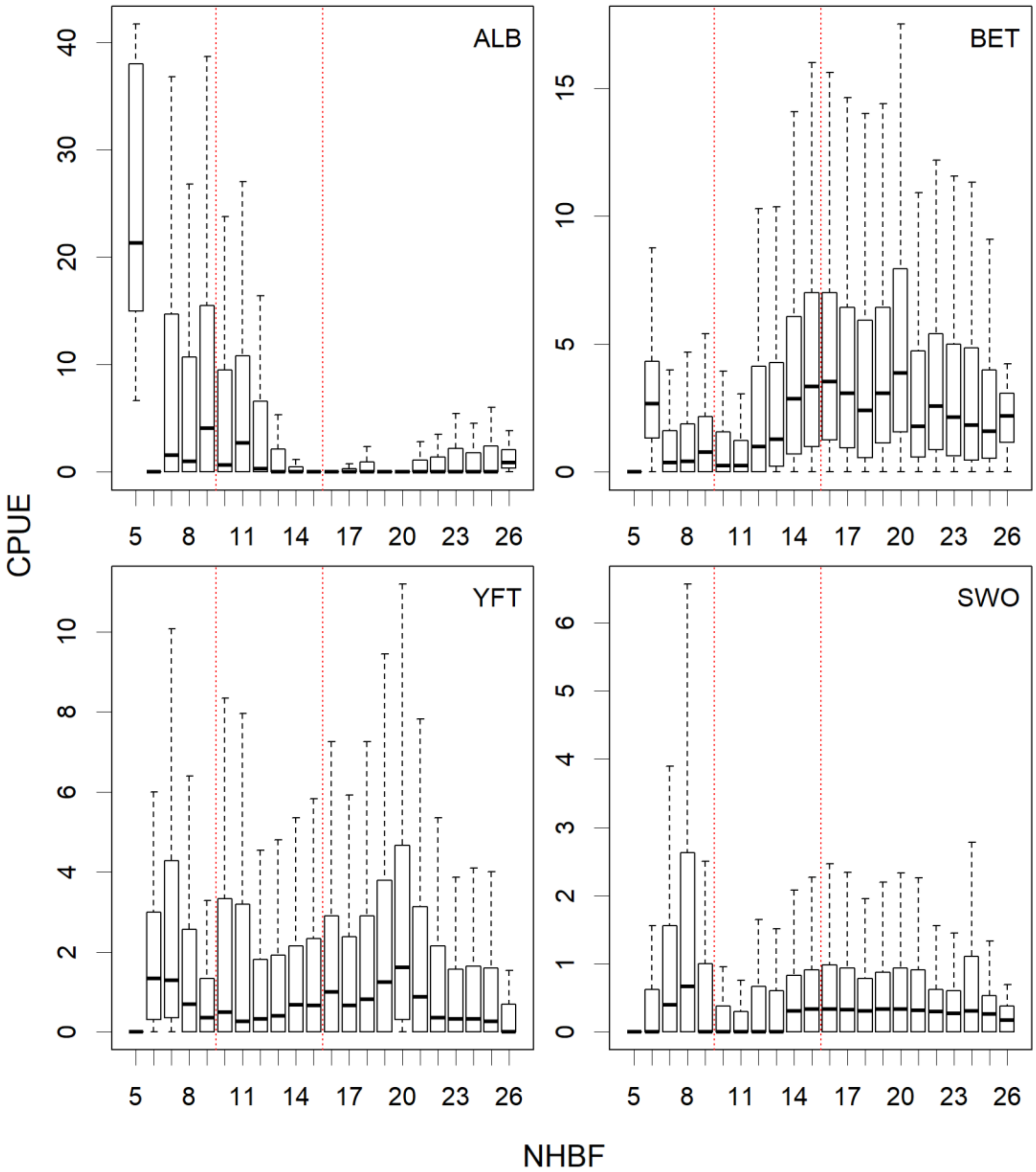


Fig. 11. Nominal CPUEs of main species caught by Taiwanese large scale longline fishery grouped by number of hooks between float (NHBF).

Area NW

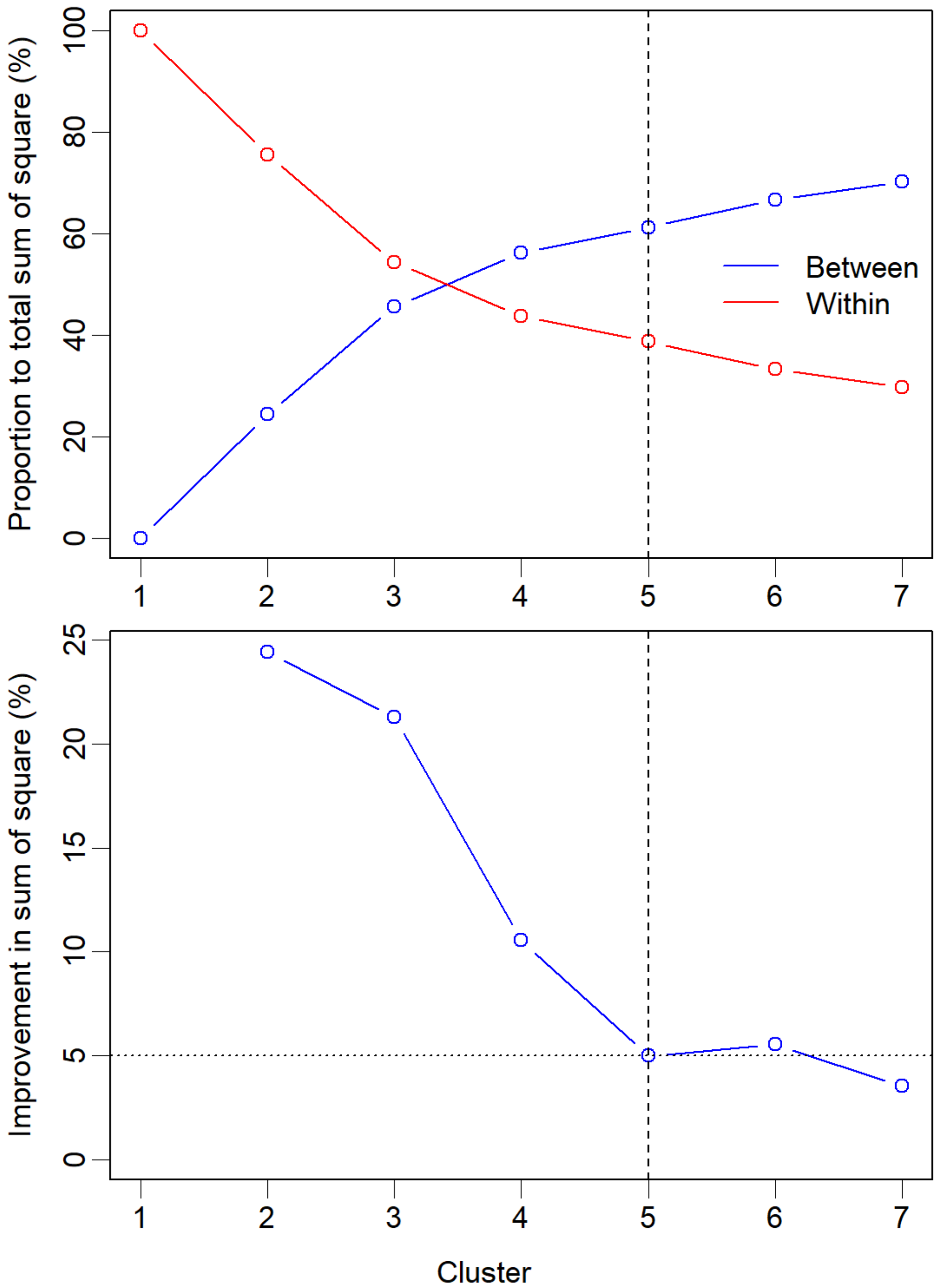


Fig. 12. The improvements in deviances among and between clusters for the data of Taiwanese large scale longline fishery in the Indian Ocean.

Area NE

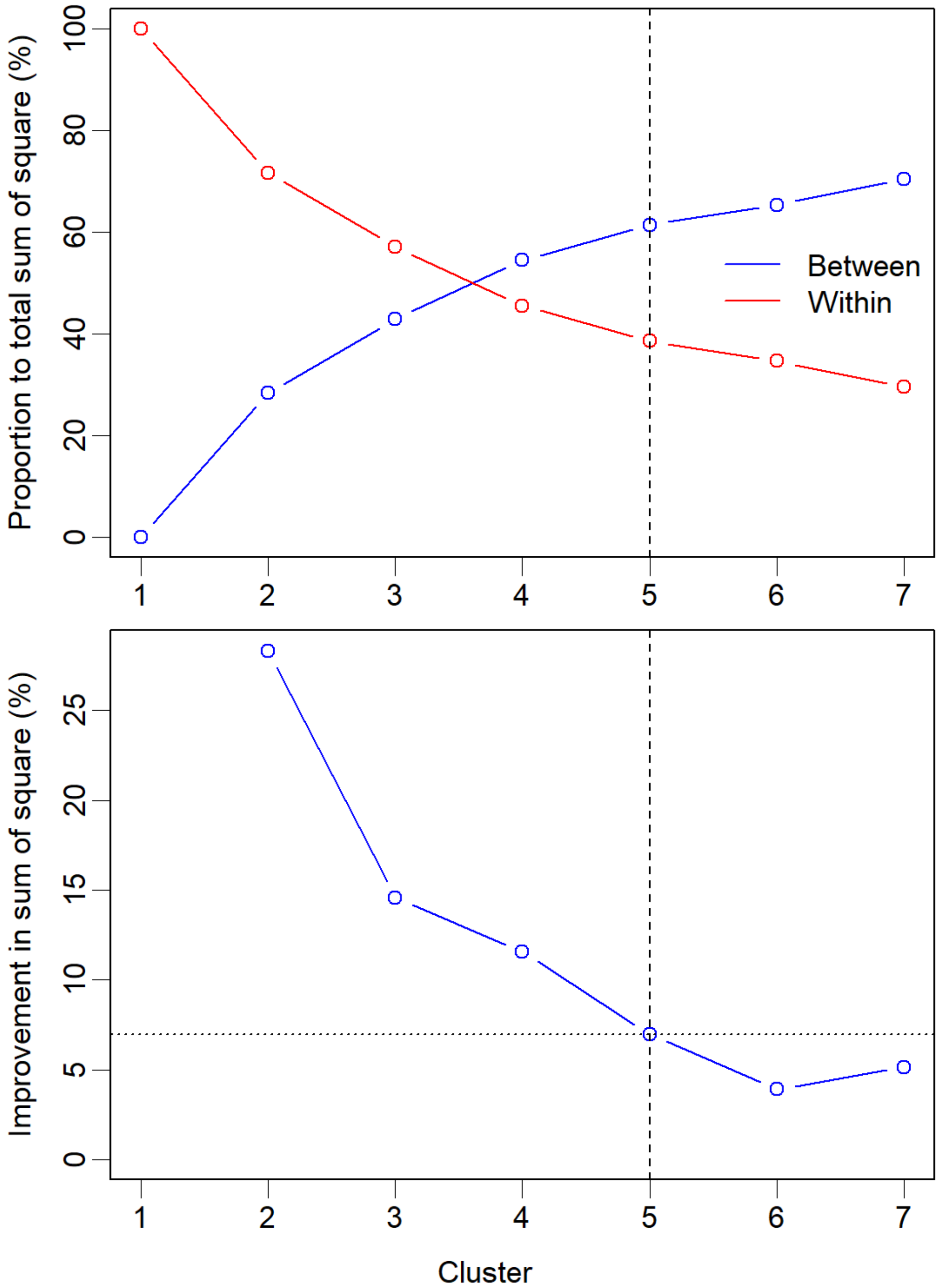


Fig. 12. (continued).

Area SW

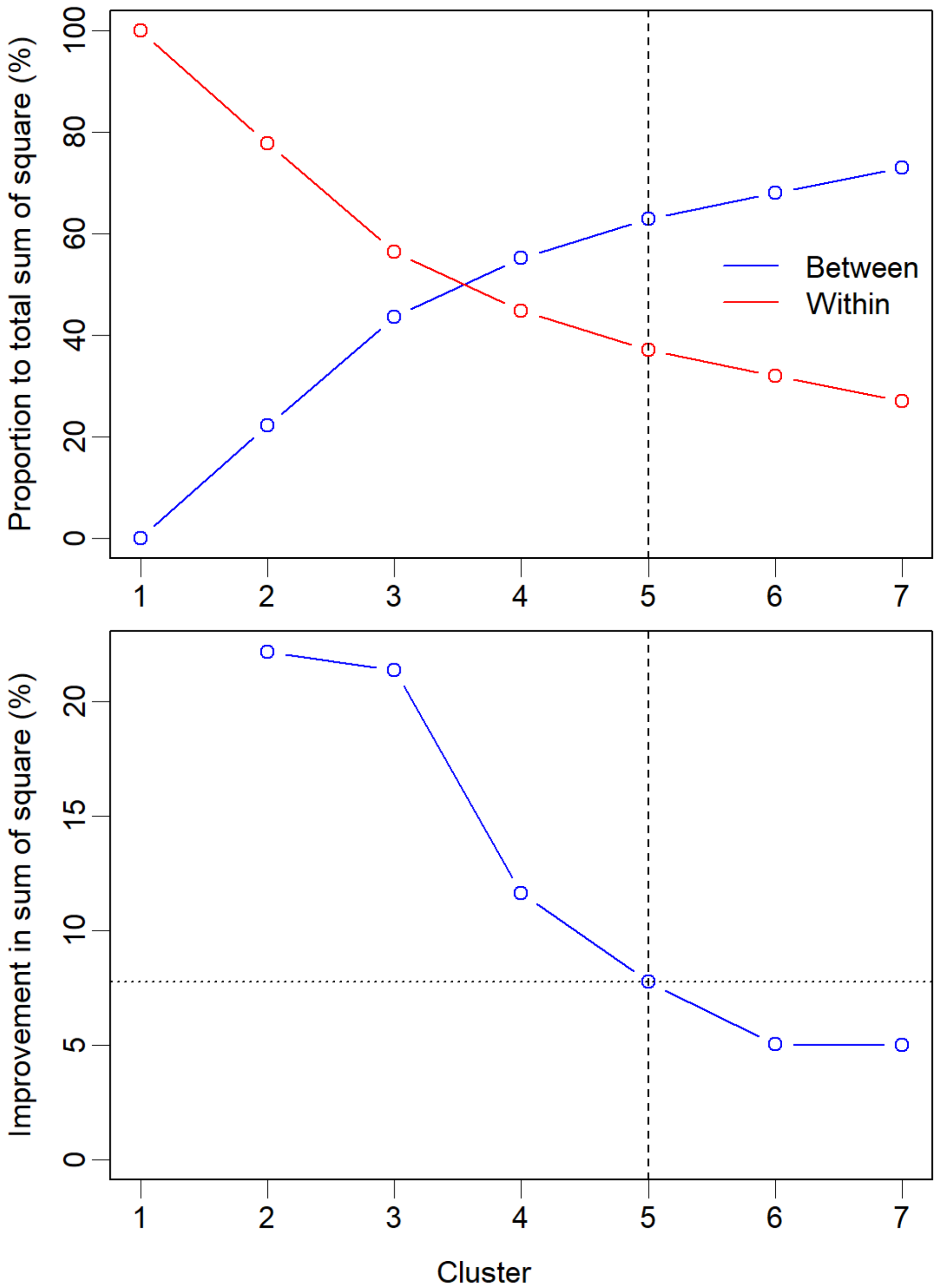


Fig. 12. (continued).

Area SE

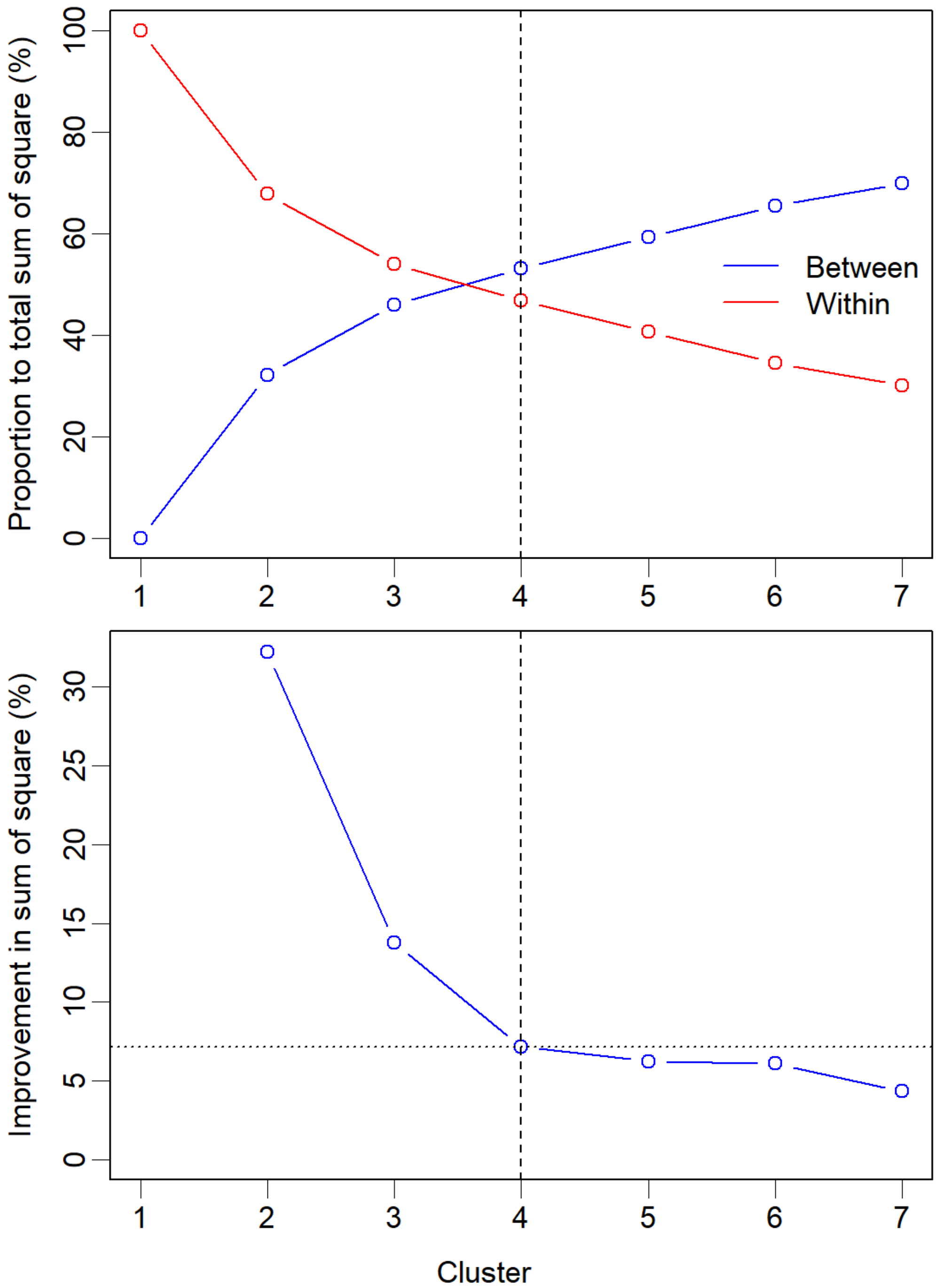


Fig. 12. (continued).

Area NW

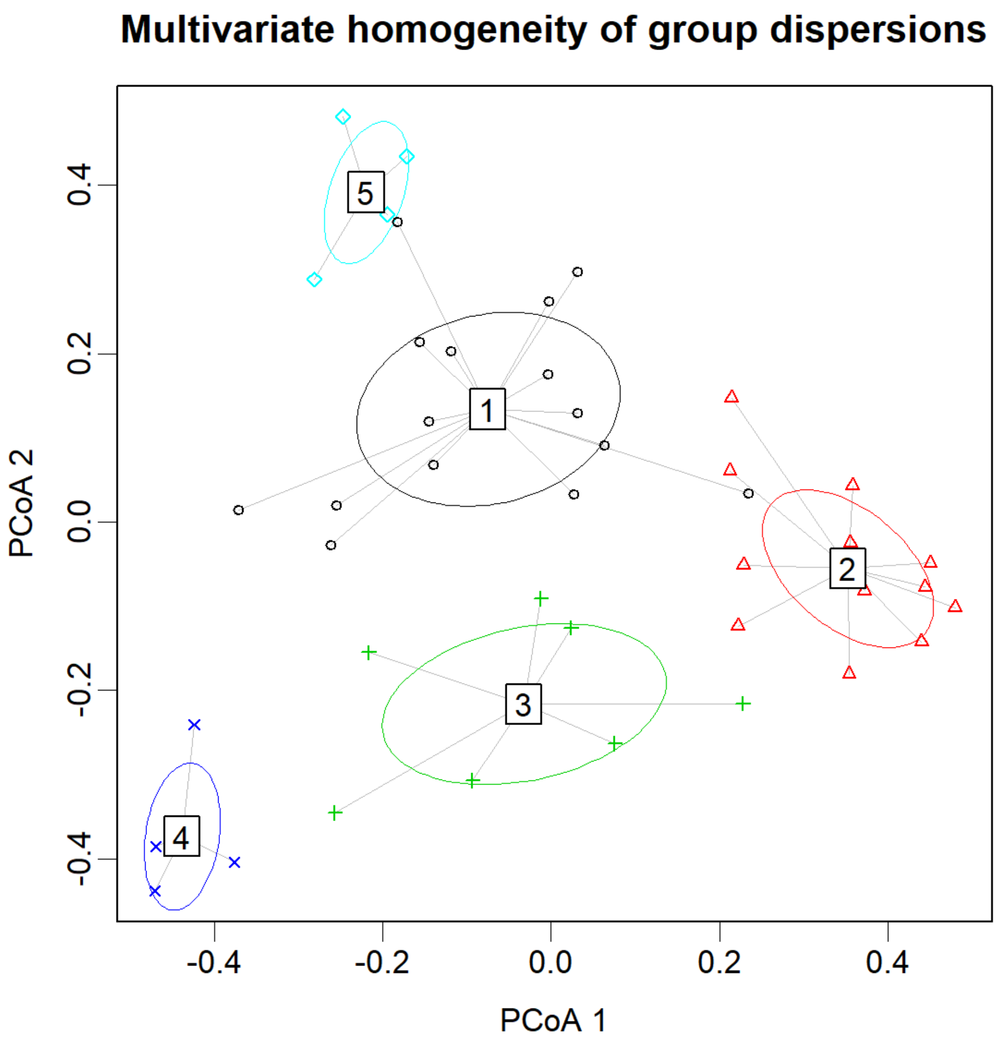


Fig. 13. Plot from the principal coordinate analysis (PCoA) for the multivariate dispersions by clusters for the data of Taiwanese large scale longline fishery in the Indian Ocean.

Area NE

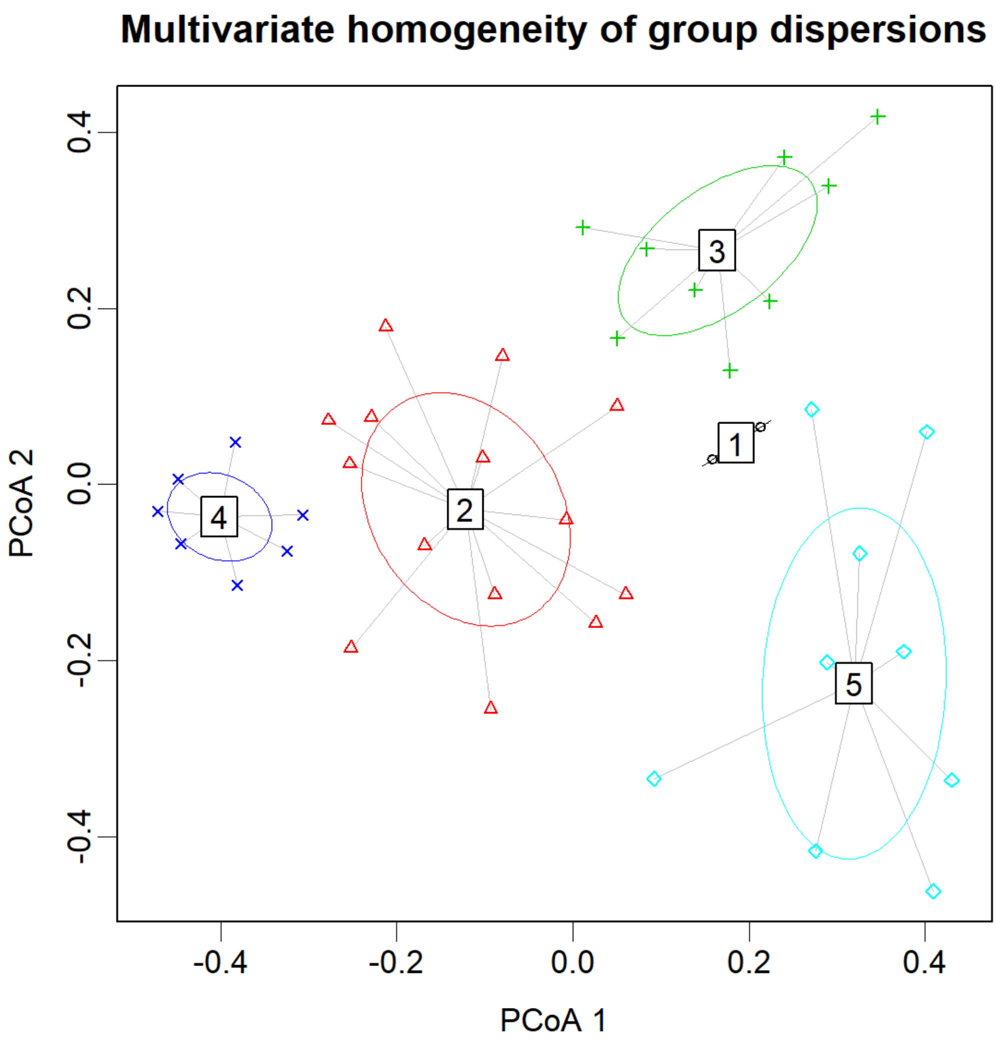


Fig. 13. (continued).

Area SW

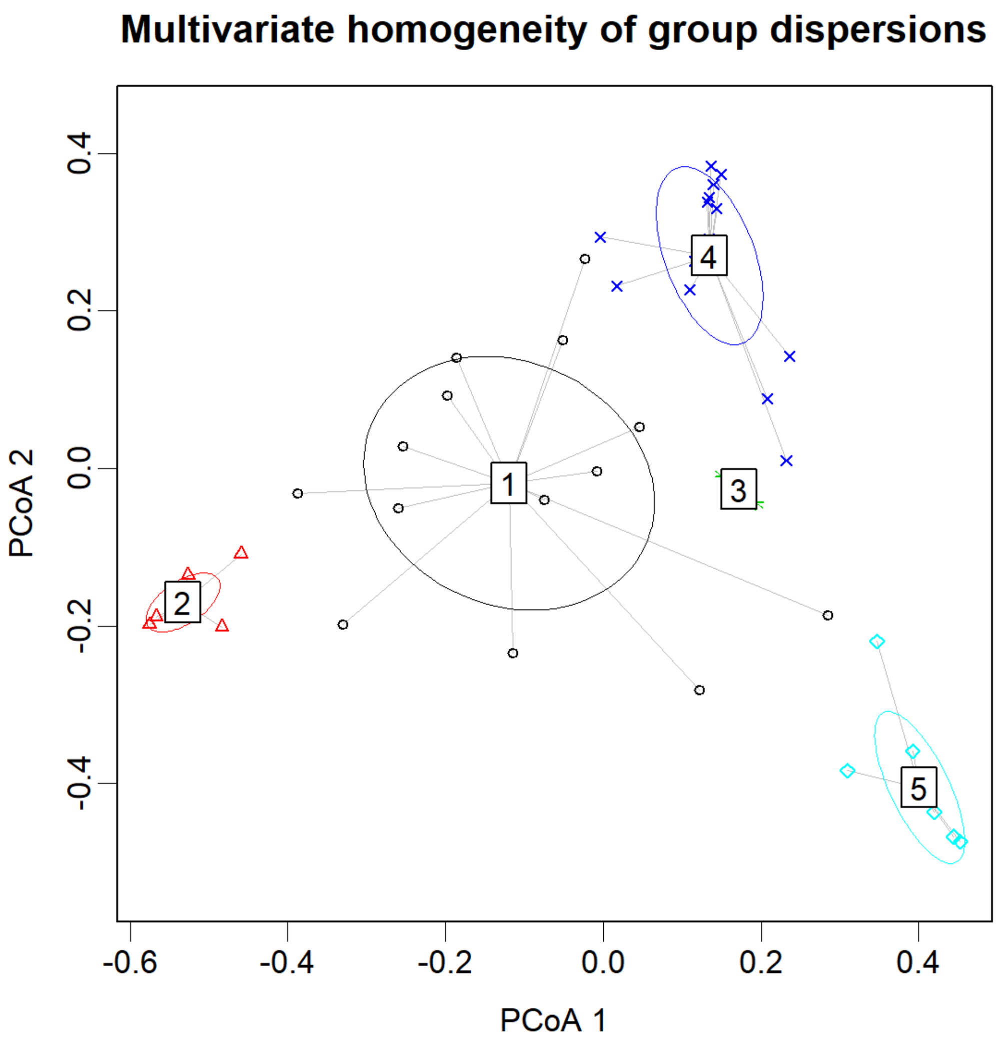


Fig. 13. (continued).

Area SE

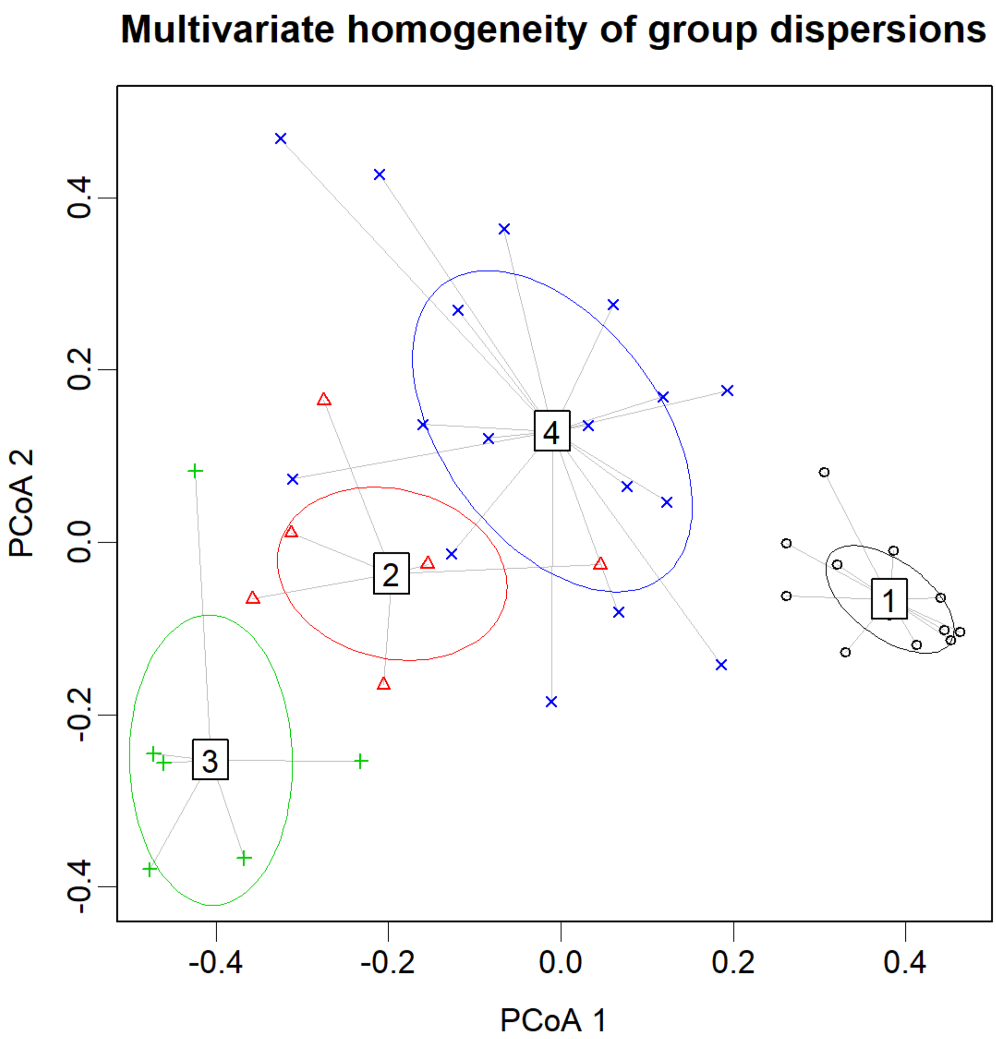


Fig. 13. (continued).

Area NW

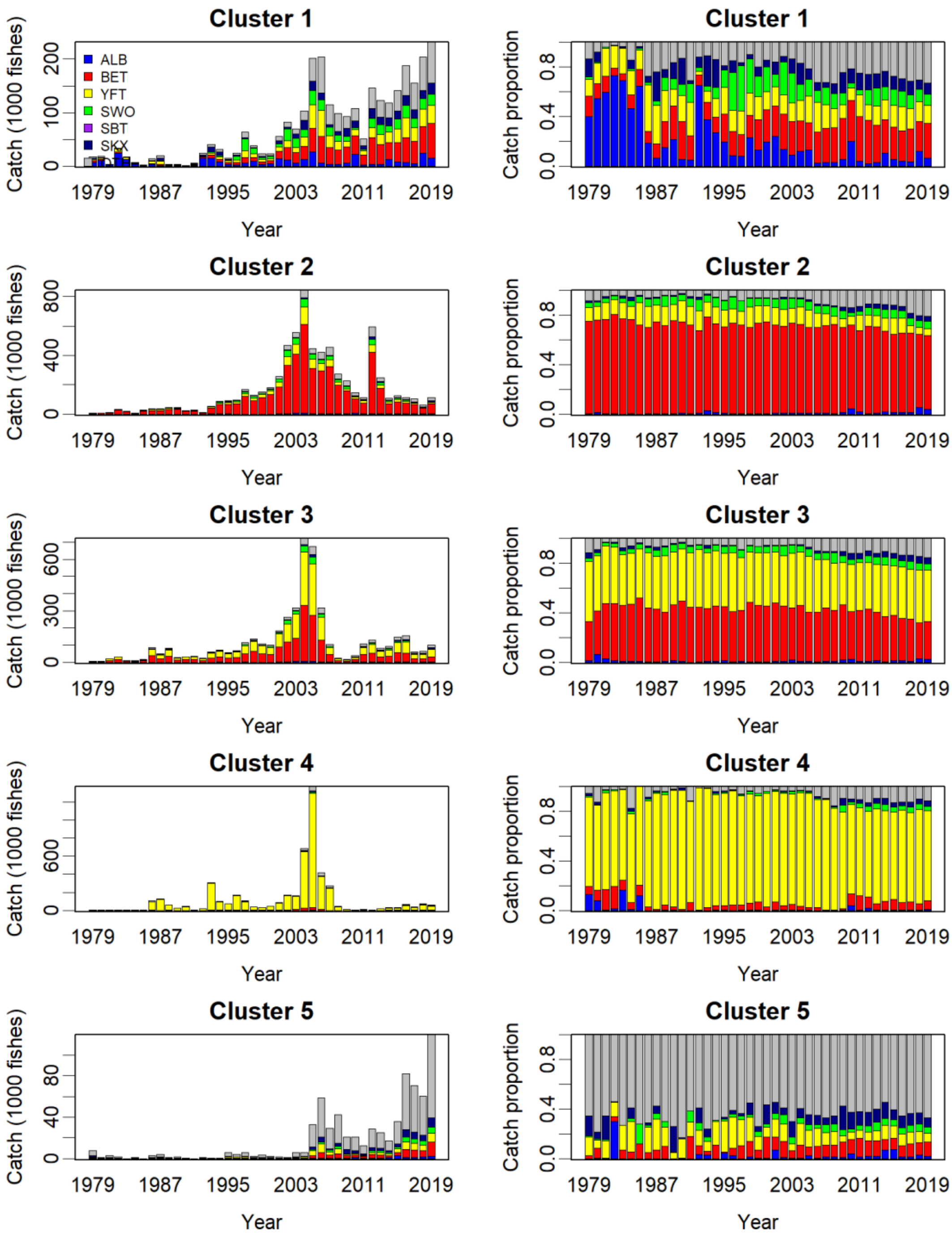


Fig. 14. Annual catches and compositions by species and clusters for Taiwanese large scale longline fishery in the Indian Ocean.

Area NE

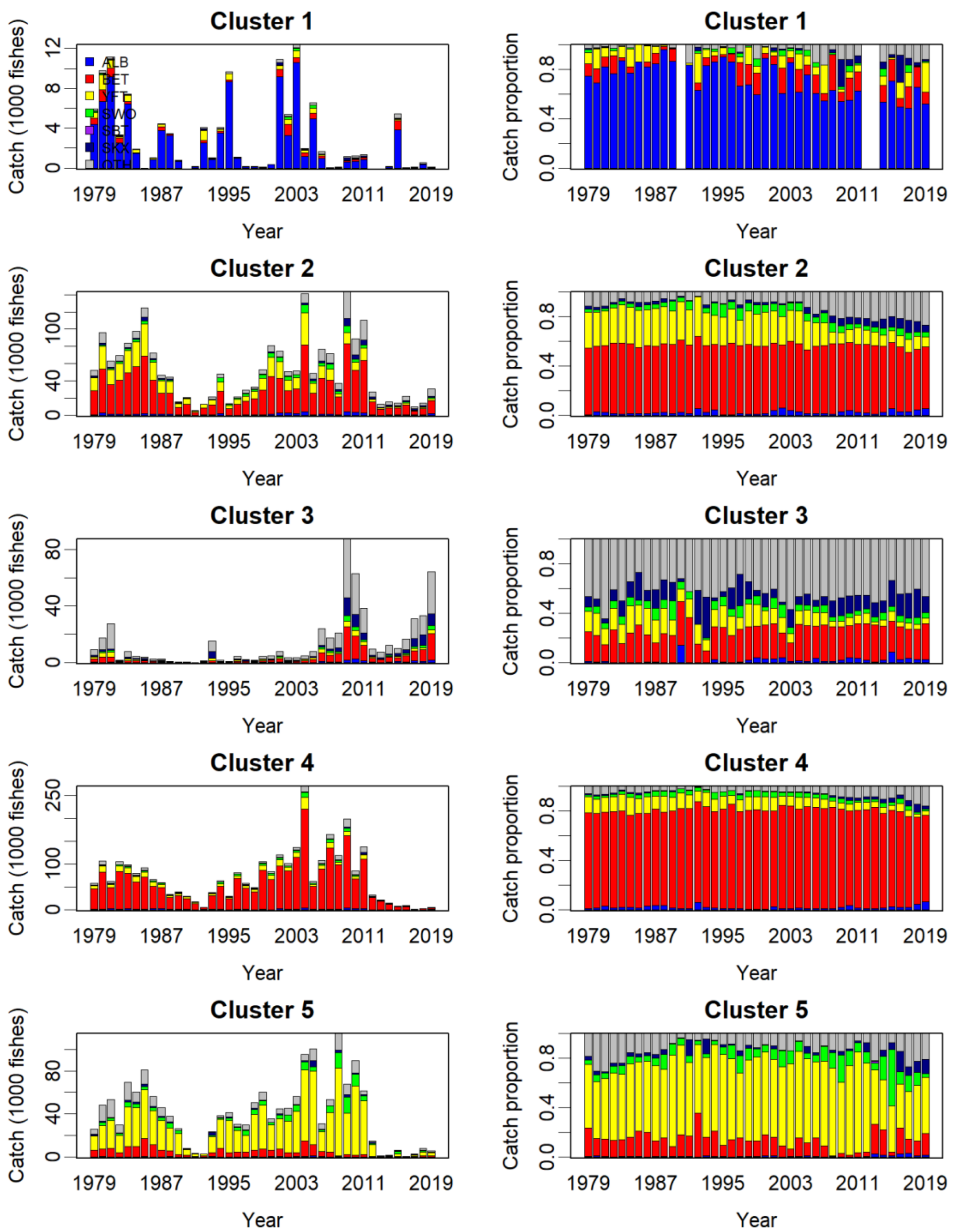


Fig. 14. (continued).

Area SW

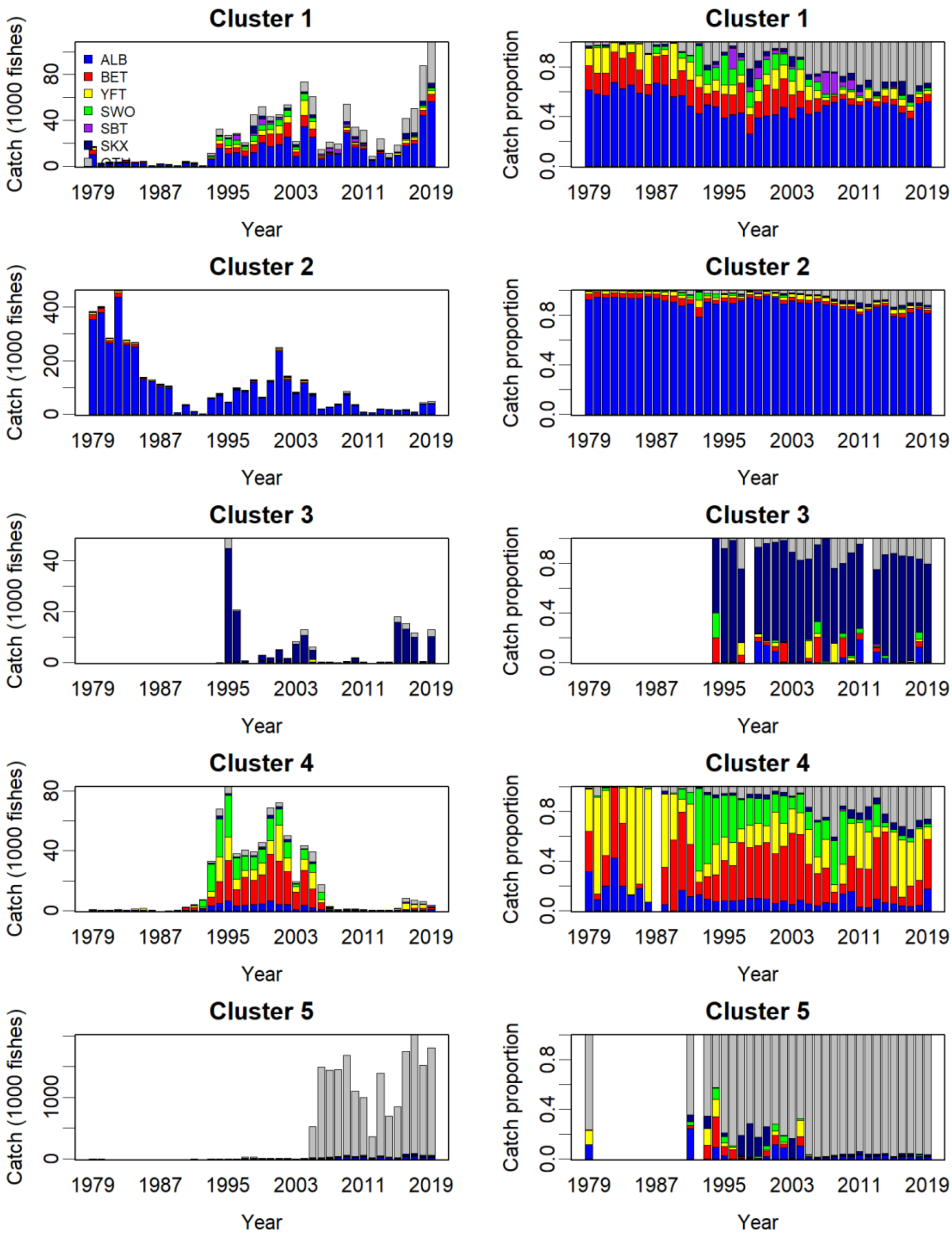


Fig. 14. (continued).

Area SE

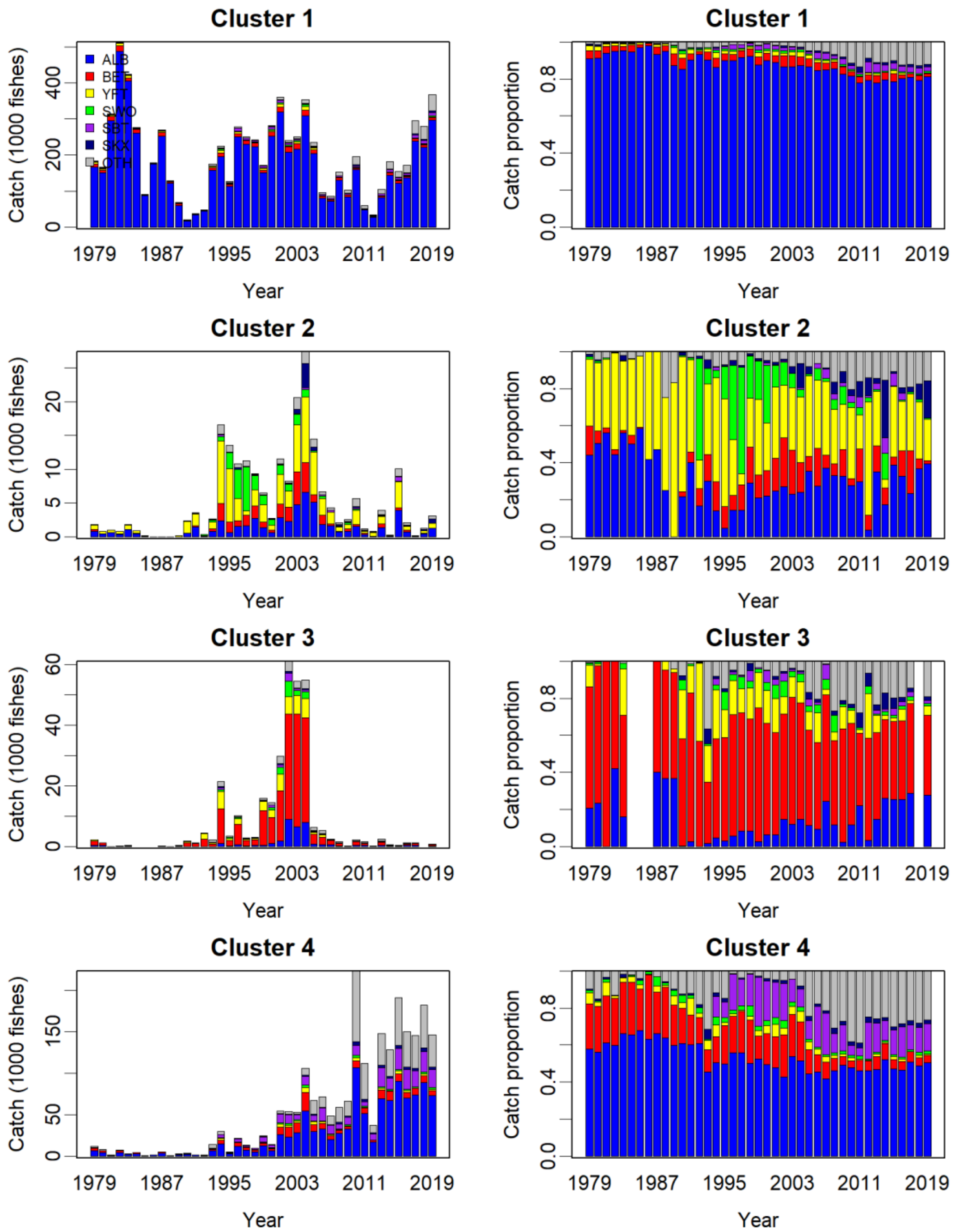


Fig. 14. (continued).

Area NW

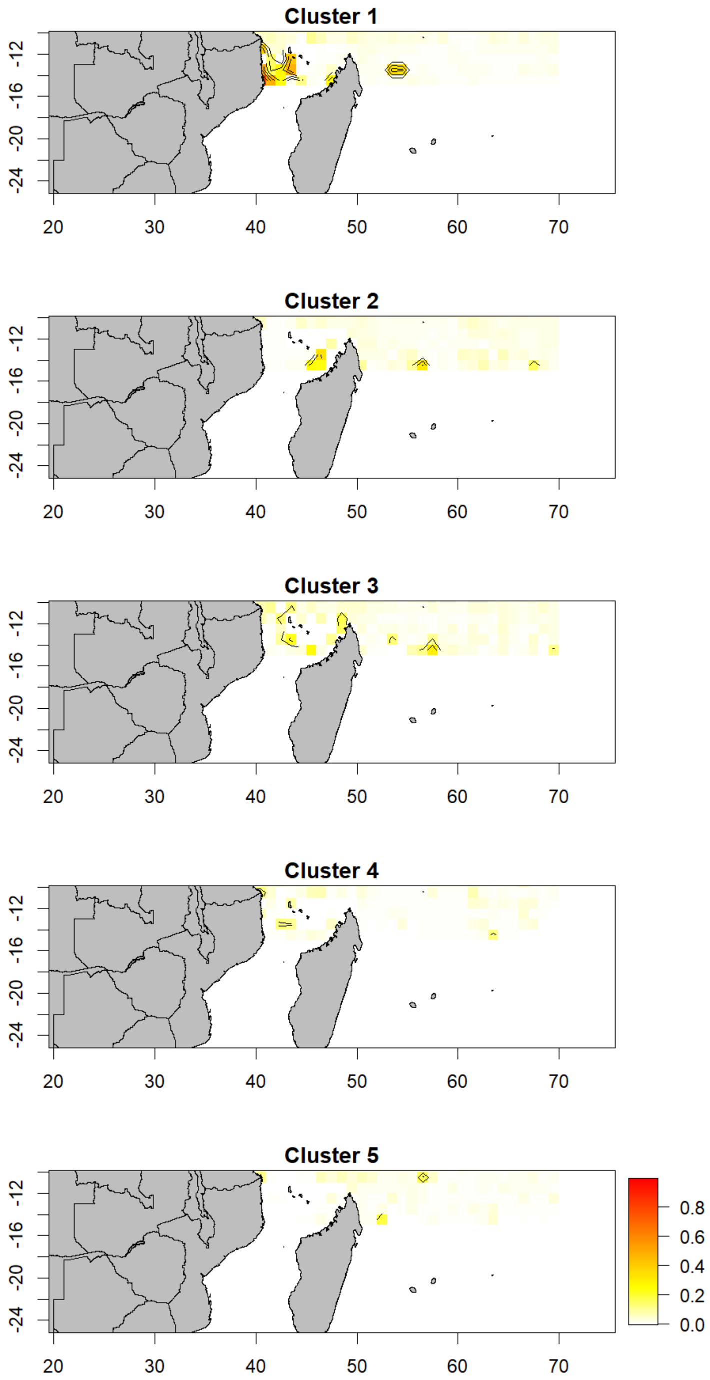


Fig. 15. Distributions of swordfish catches by clusters for Taiwanese large scale longline fishery in the Indian Ocean.

Area NE

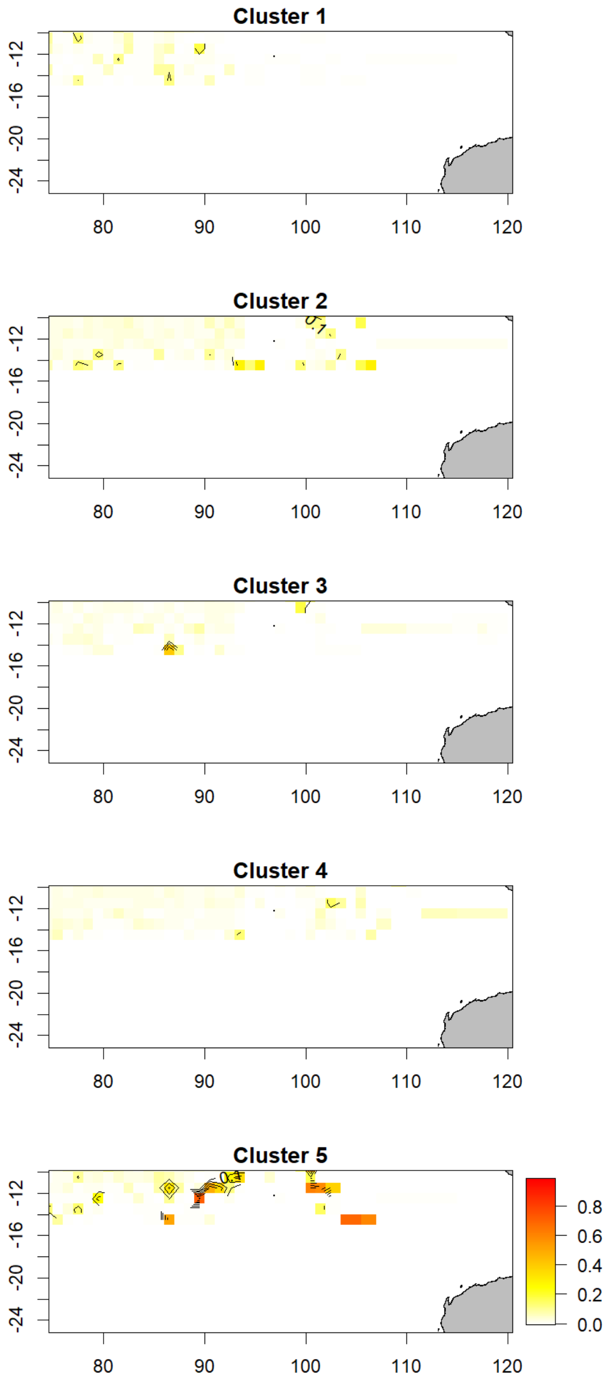


Fig. 15. (continued).

Area SW

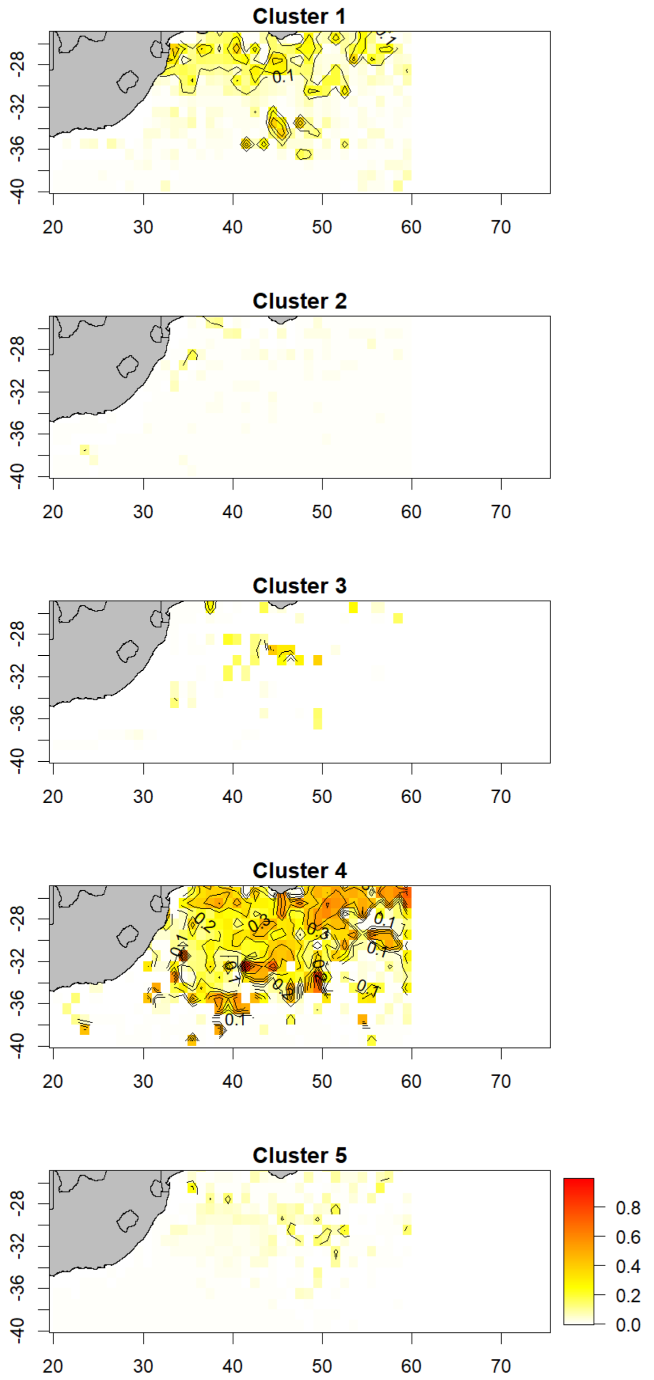


Fig. 15. (continued).

Area SE

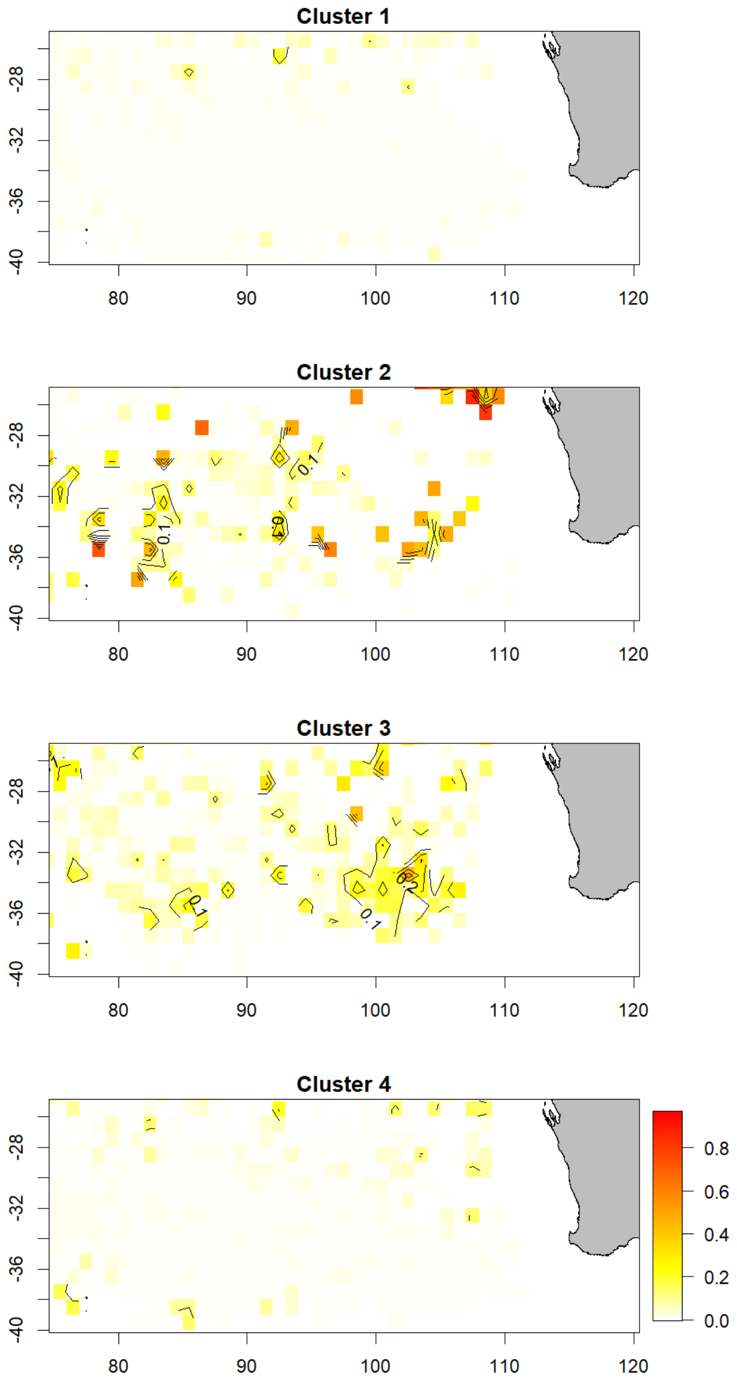
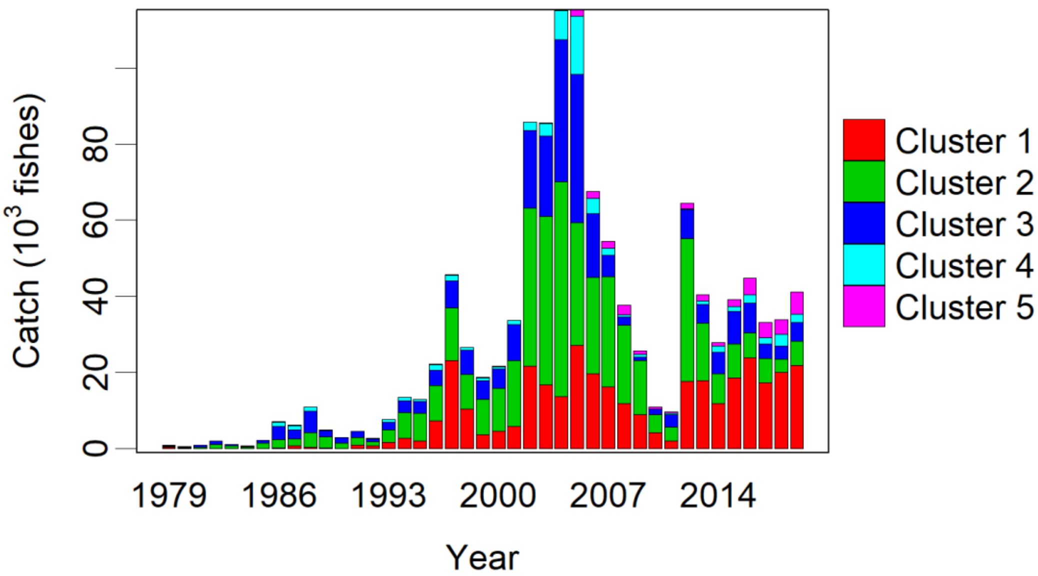


Fig. 15. (continued).

Area NW



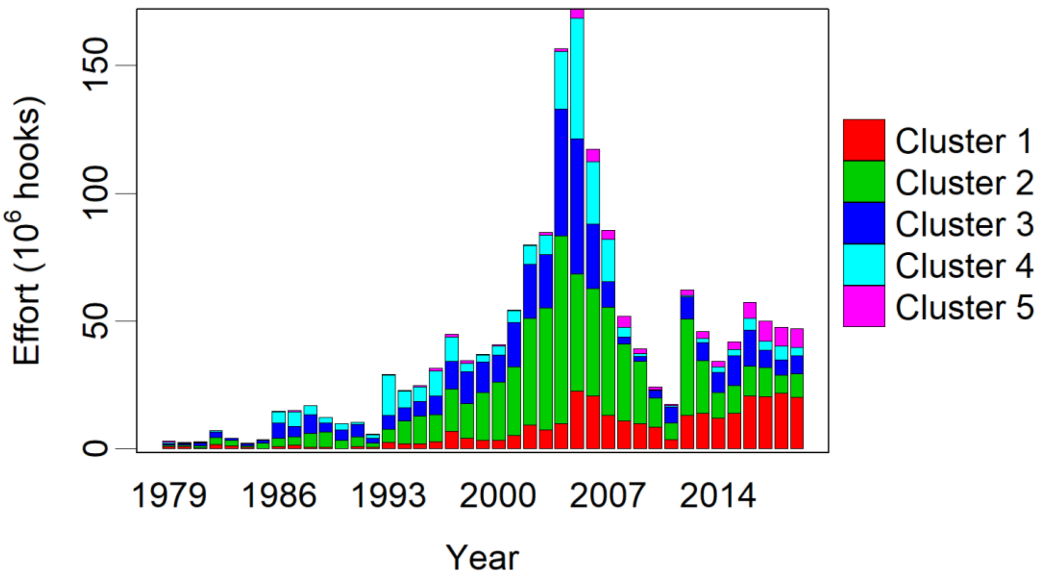
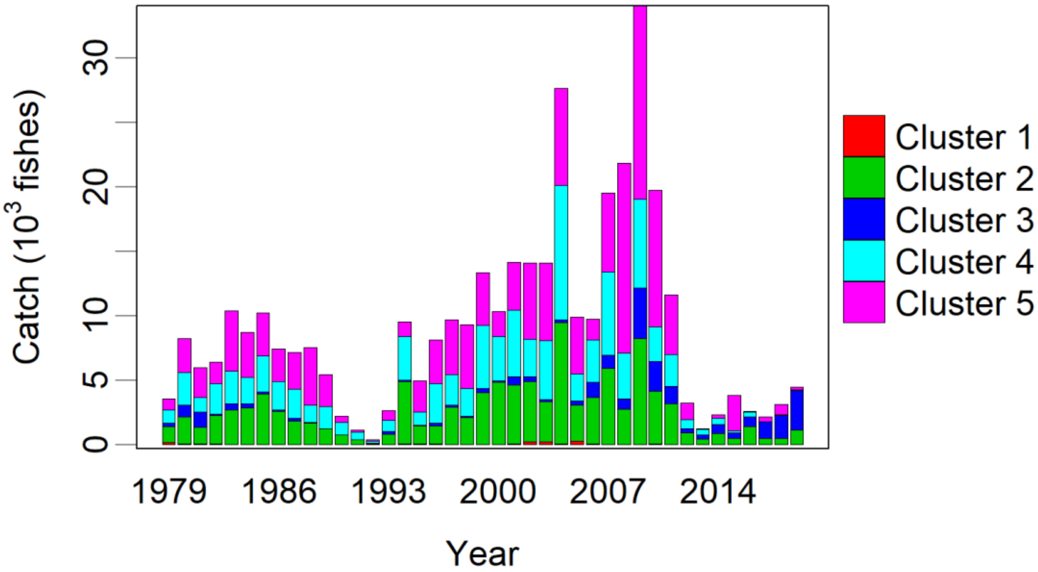


Fig. 16. Annual swordfish catches and efforts by clusters for Taiwanese large scale longline fishery in the Indian Ocean.

Area NE



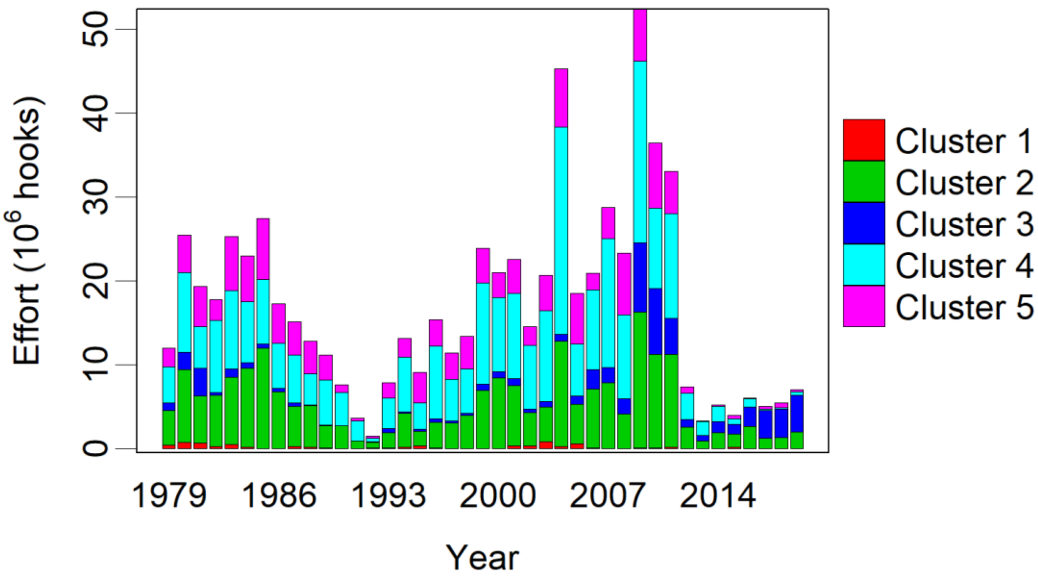
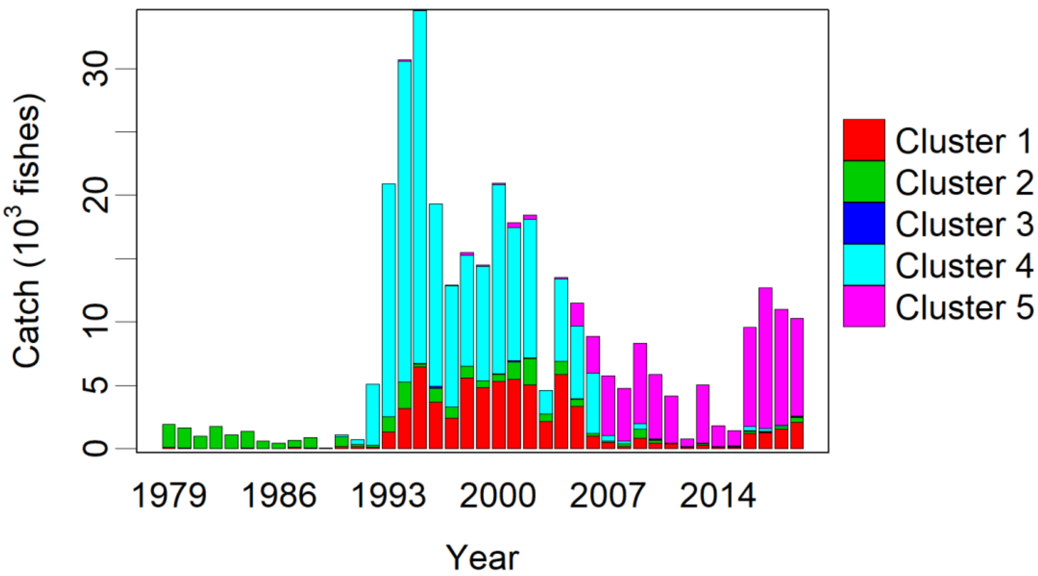


Fig. 16. (continued).

Area SW



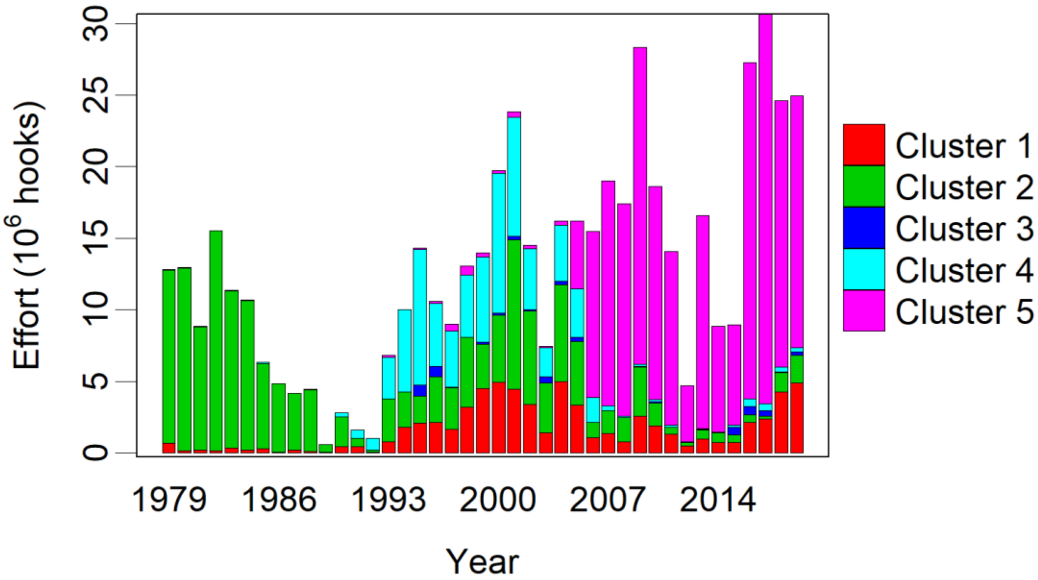
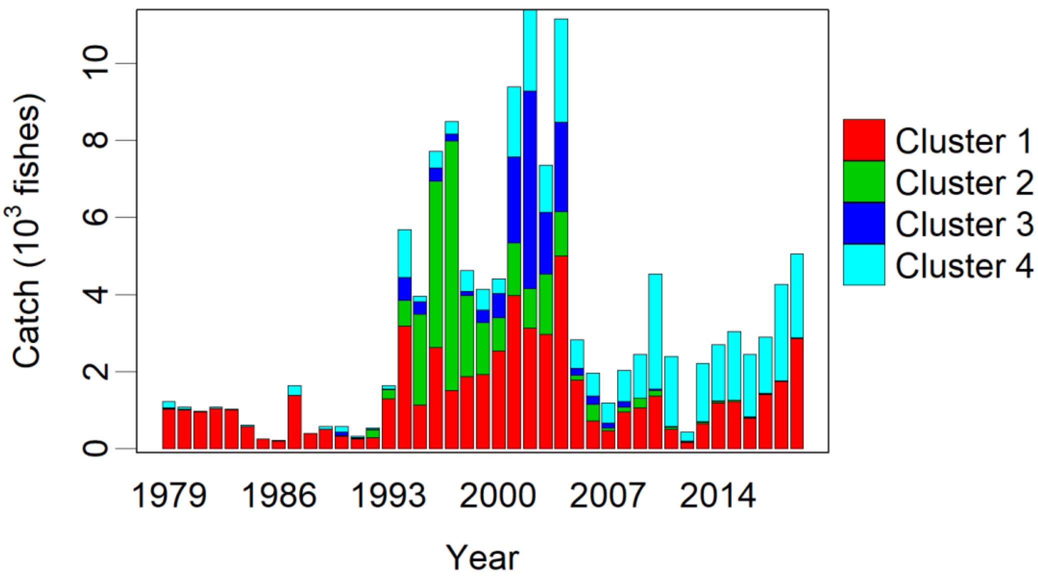


Fig. 16. (continued).

Area SE



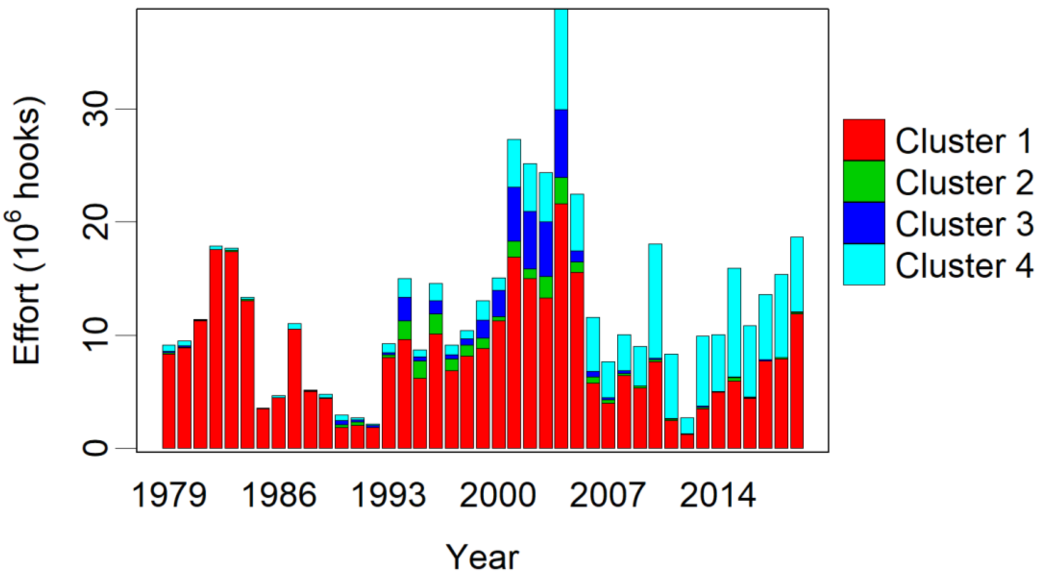
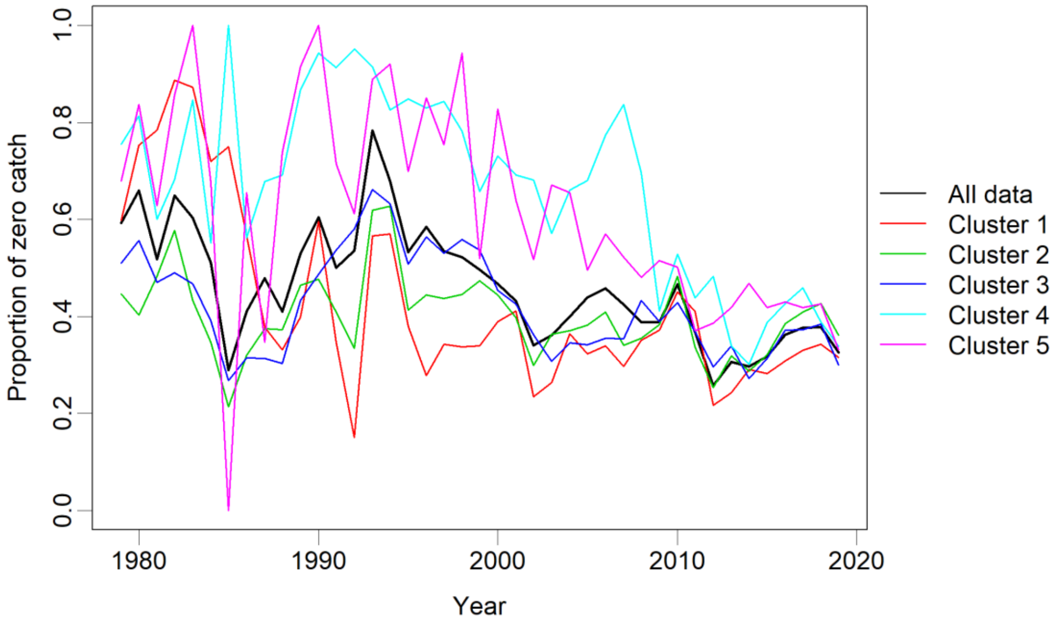


Fig. 16. (continued).

Area NW



Area NE

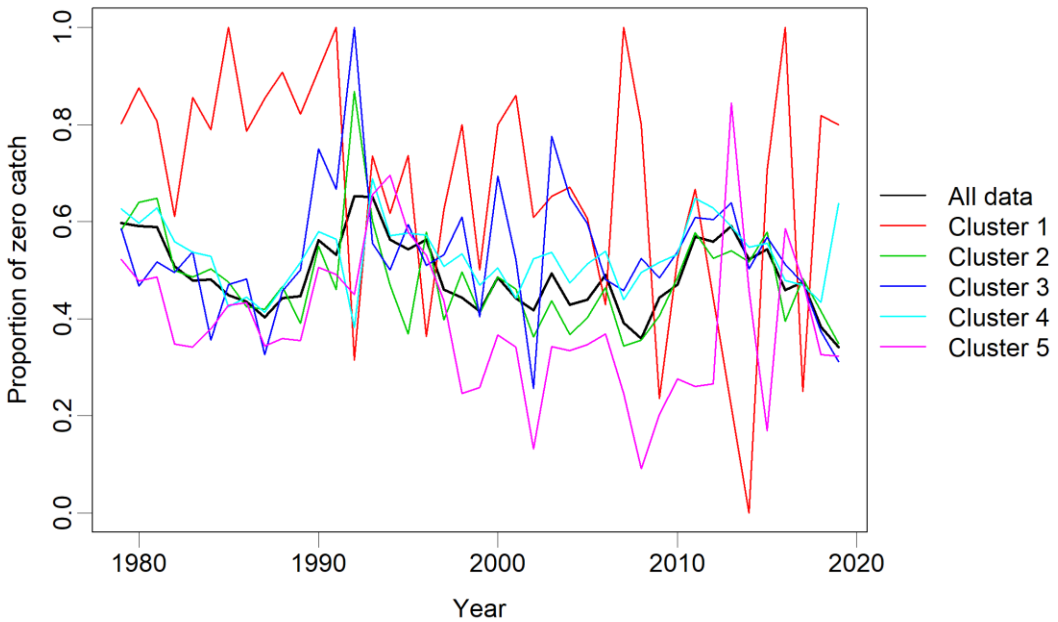
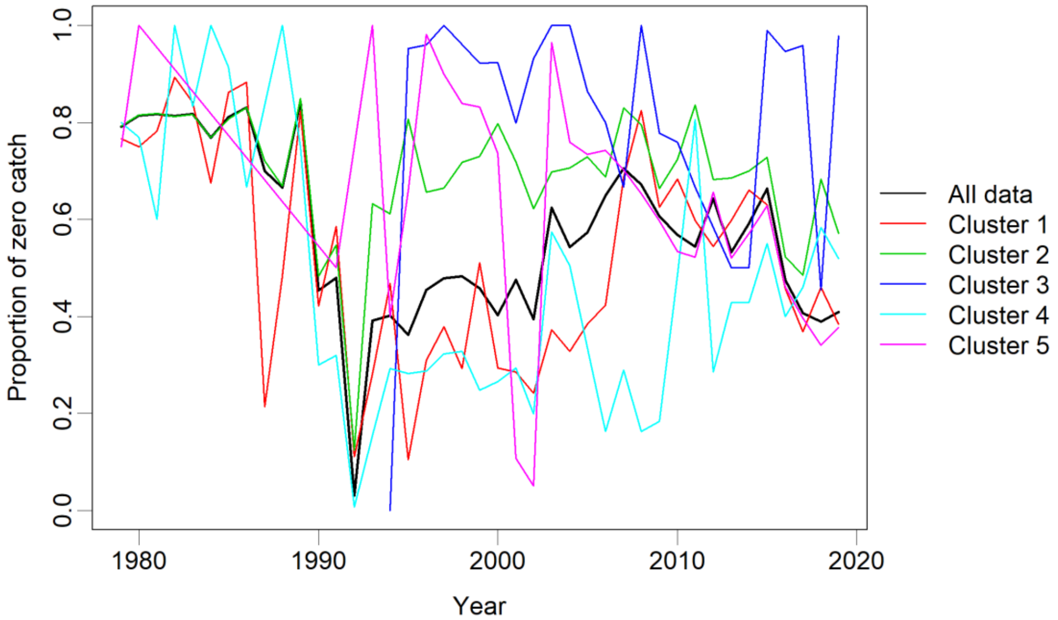


Fig. 17. Annual proportions of zero catches of swordfish caught by Taiwanese large scale longline fishery in the Indian Ocean.

Area SW



Area SE

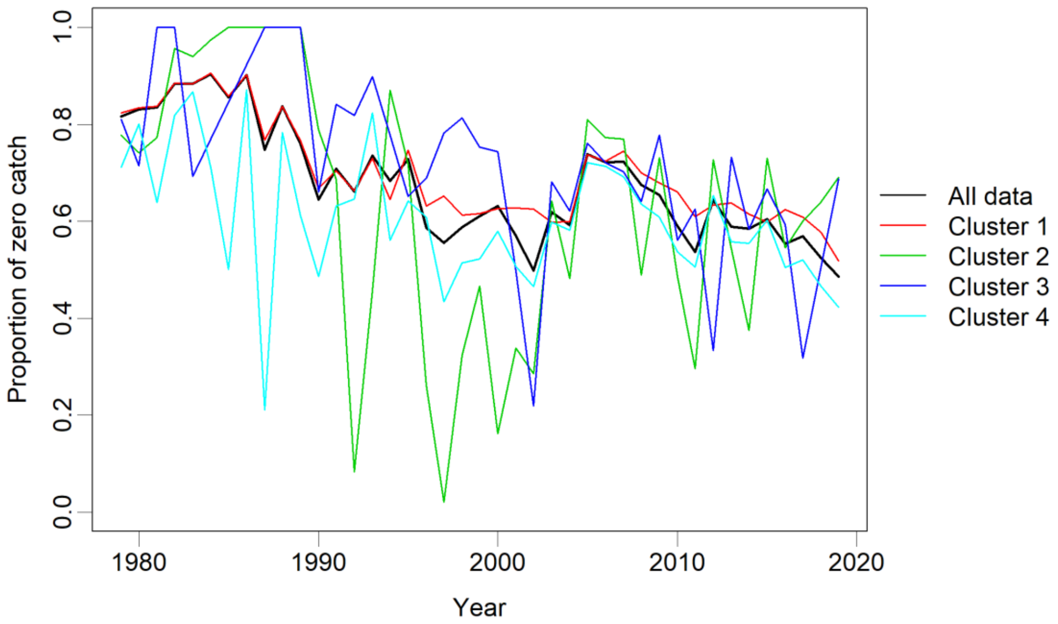
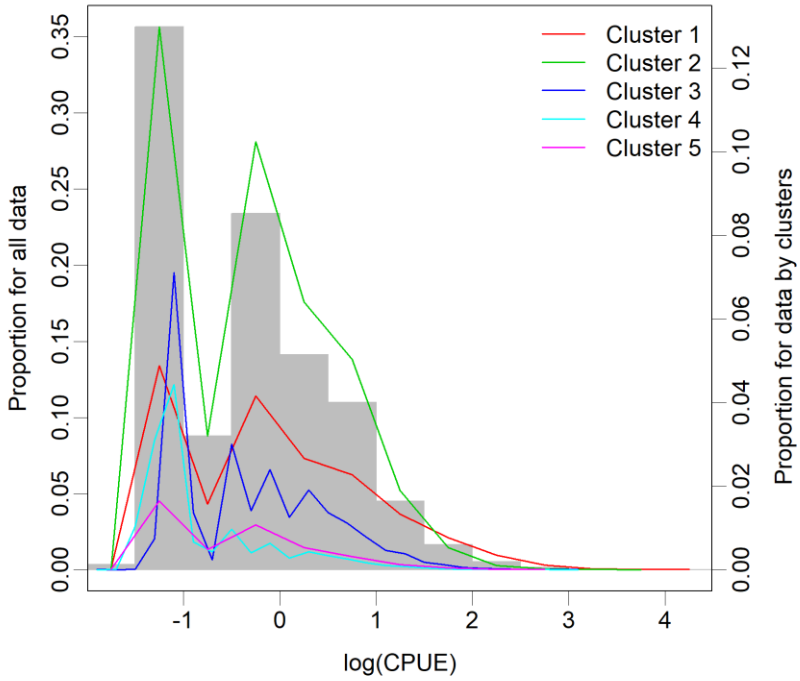


Fig. 17. (continued).

Area NW - all data



Area NW - data with only positive catches

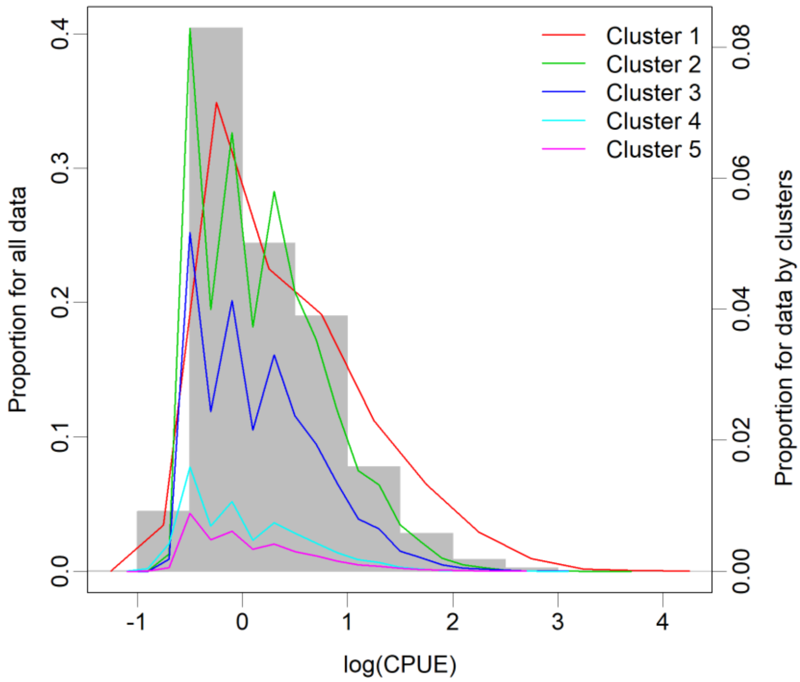
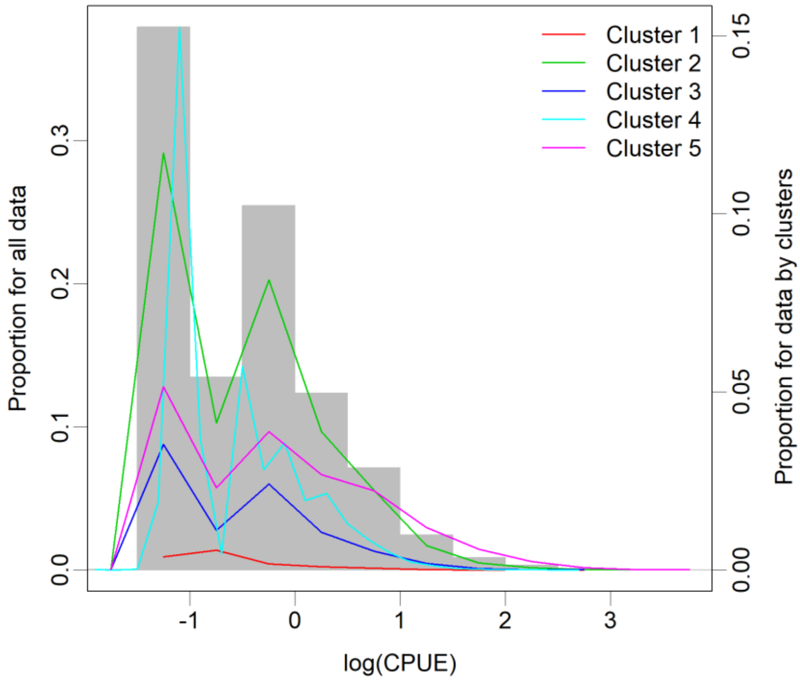


Fig. 18. Distributions of logarithms of nominal CPUE of swordfish aught by Taiwanese large scale longline fishery in the Indian Ocean.

Area NE - all data



Area NE - data with only positive catches

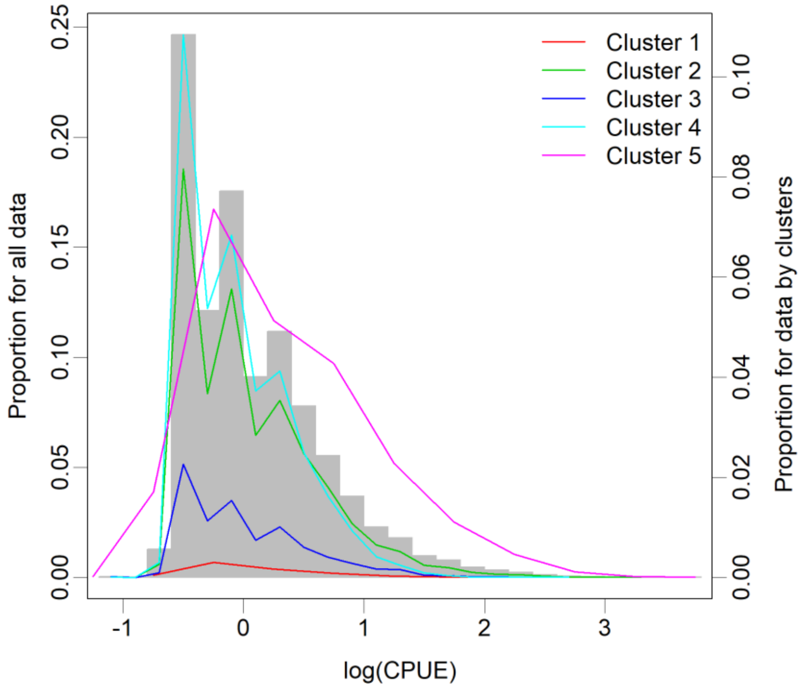
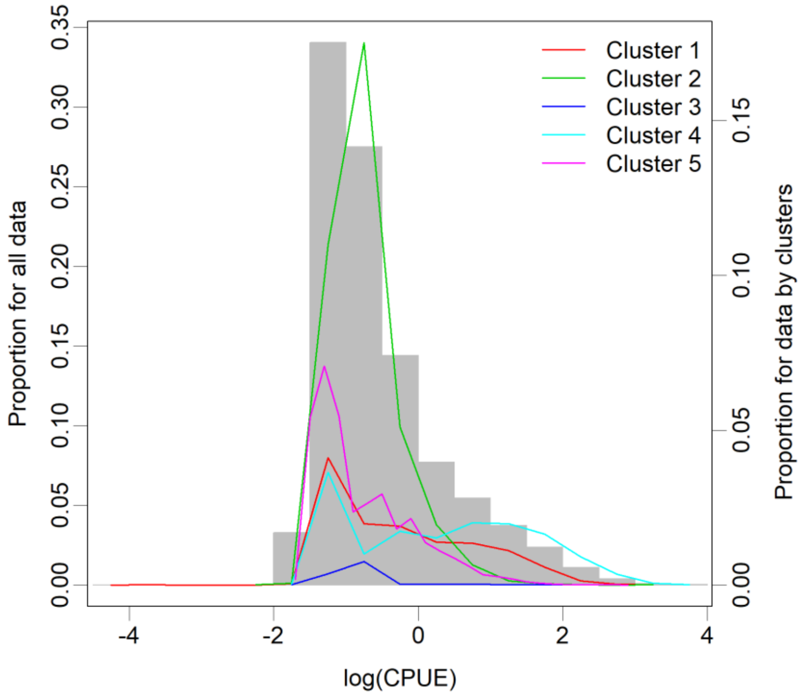


Fig. 18. (continued).

Area SW - all data



Area SW - data with only positive catches

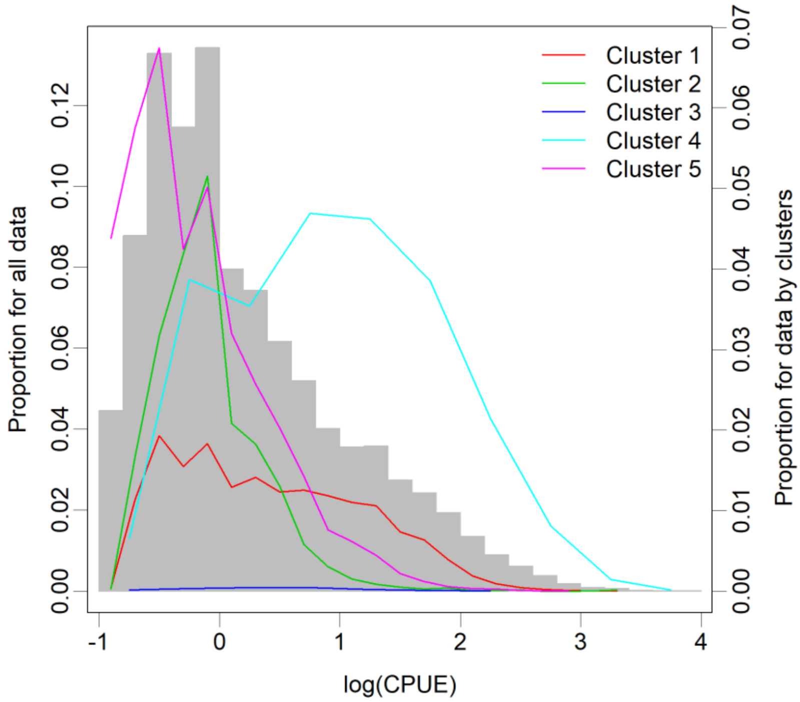
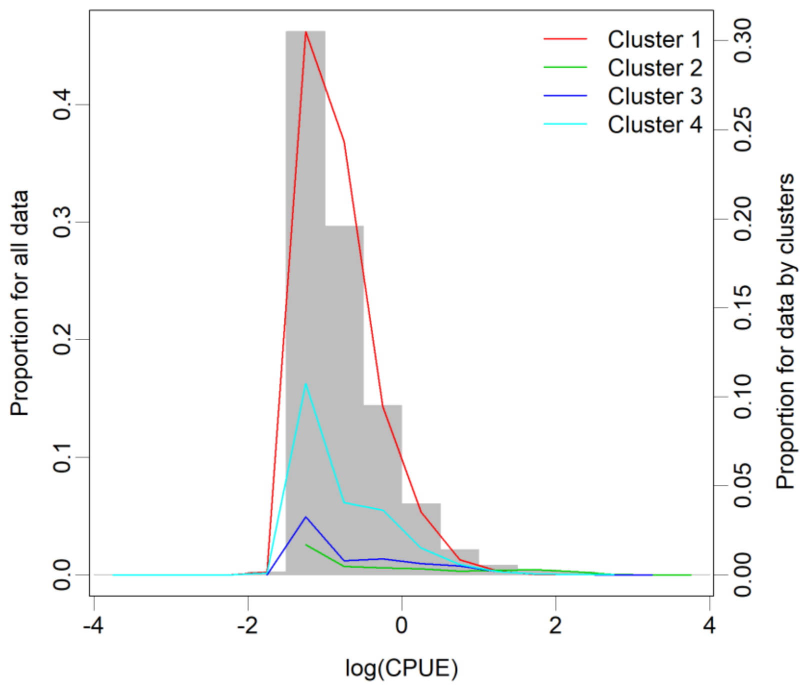


Fig. 18. (continued).

Area SE - all data



Area SE - data with only positive catches

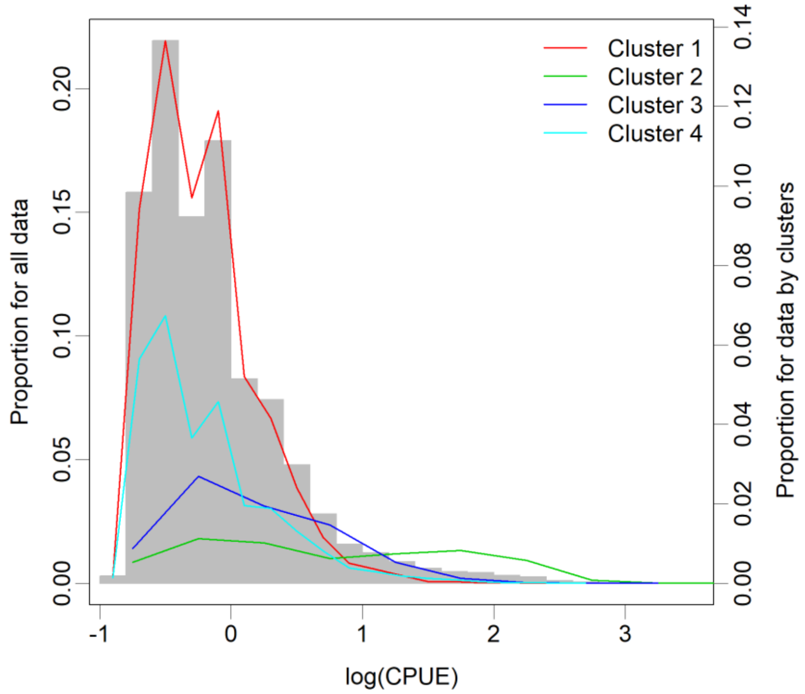


Fig. 18. (continued).

Area NW

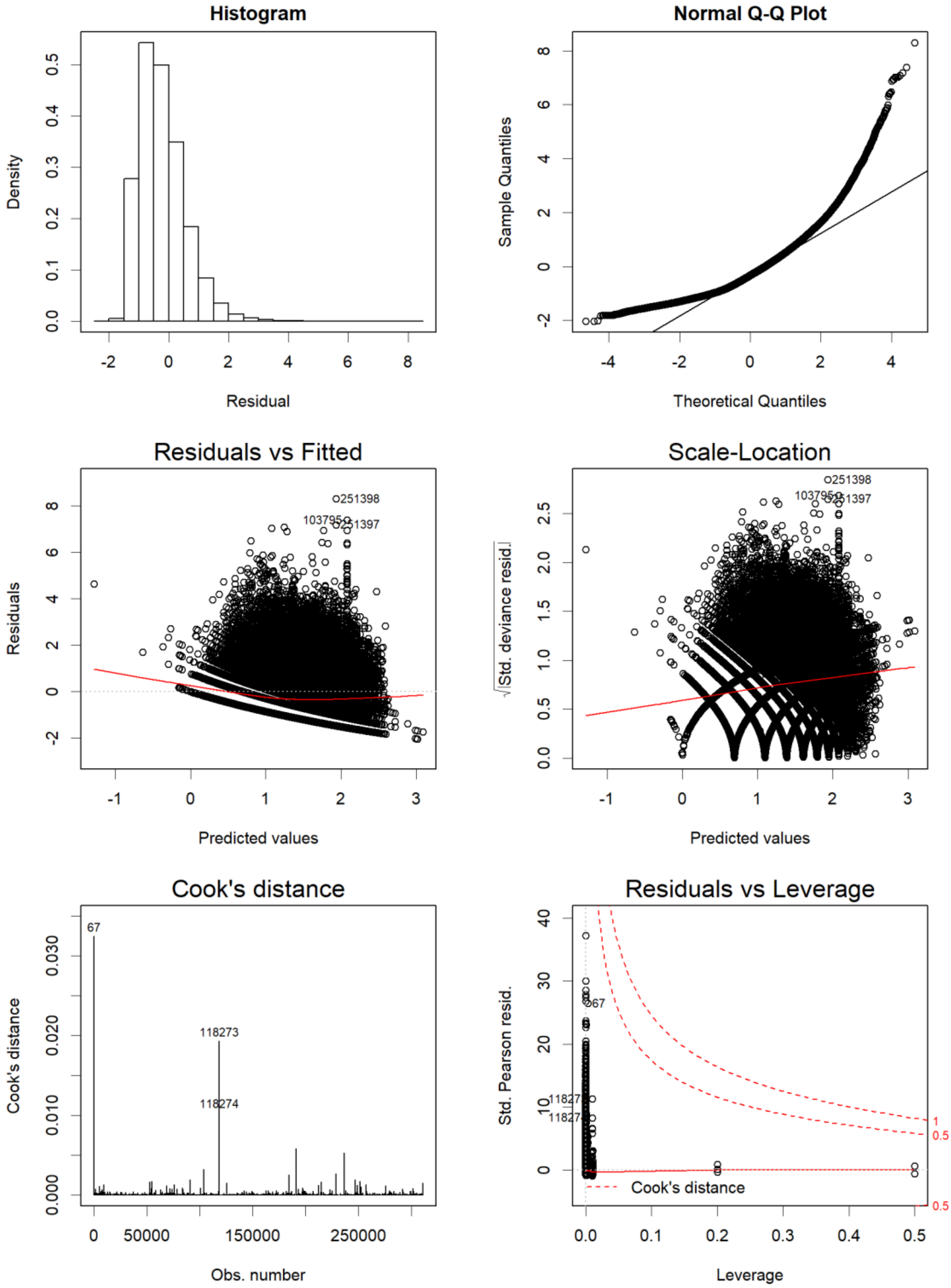


Fig. 19. Diagnostic plots for residuals for the models with gamma error distribution fitted to the data of Taiwanese large scale longline fishery in the Indian Ocean.

Area NE

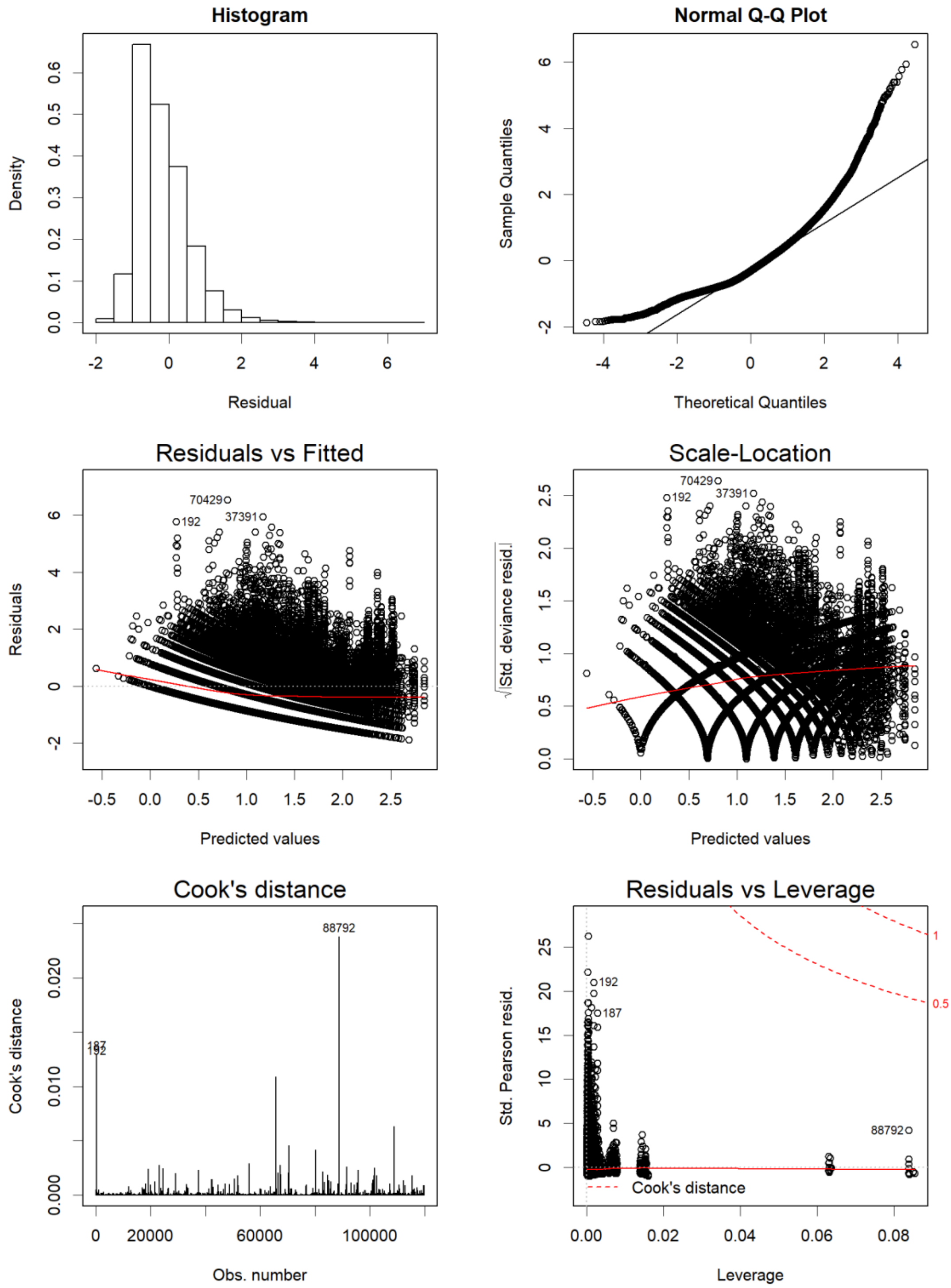


Fig. 19. (continued).

Area SW

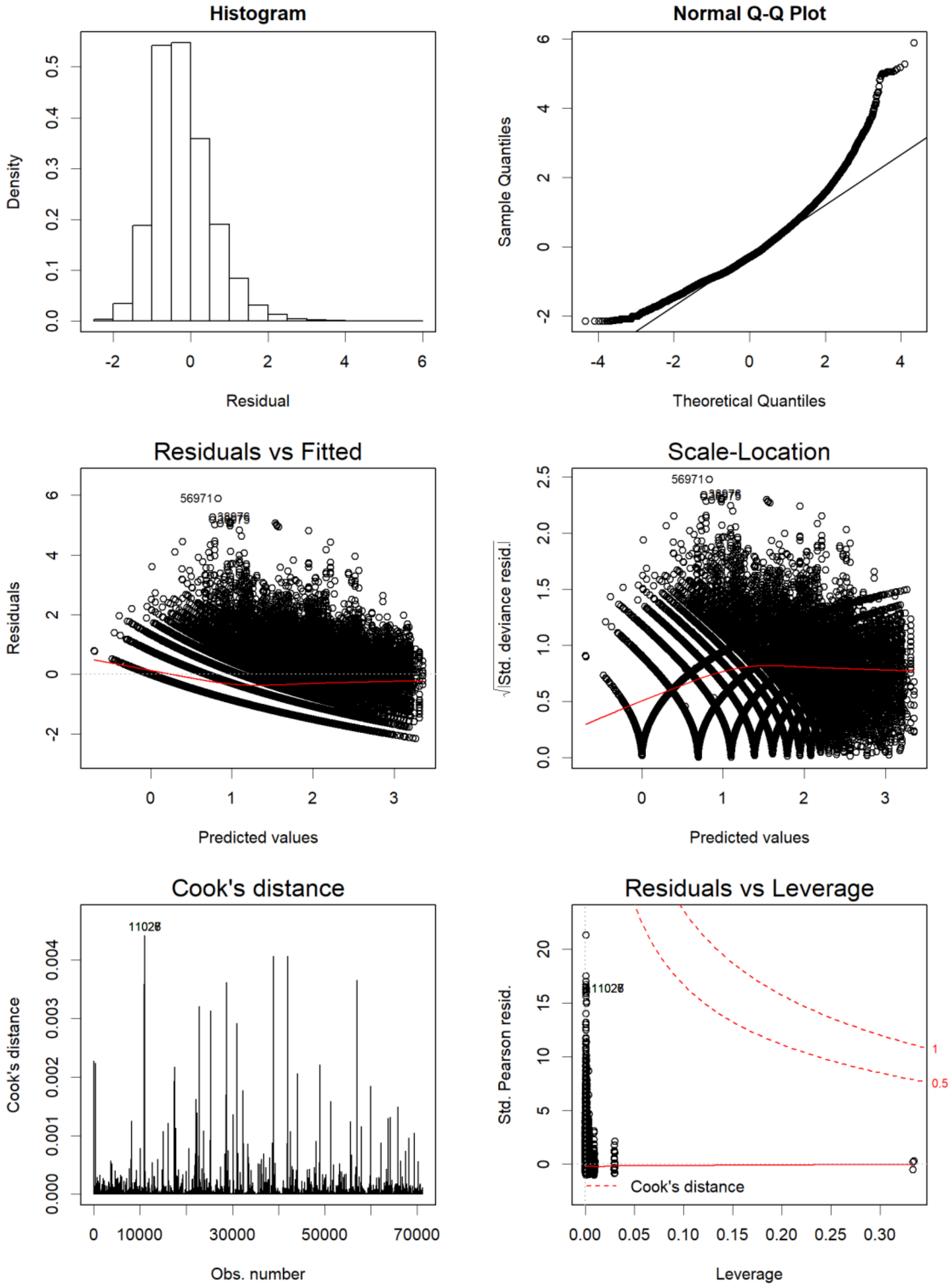


Fig. 19. (continued).

Area SE

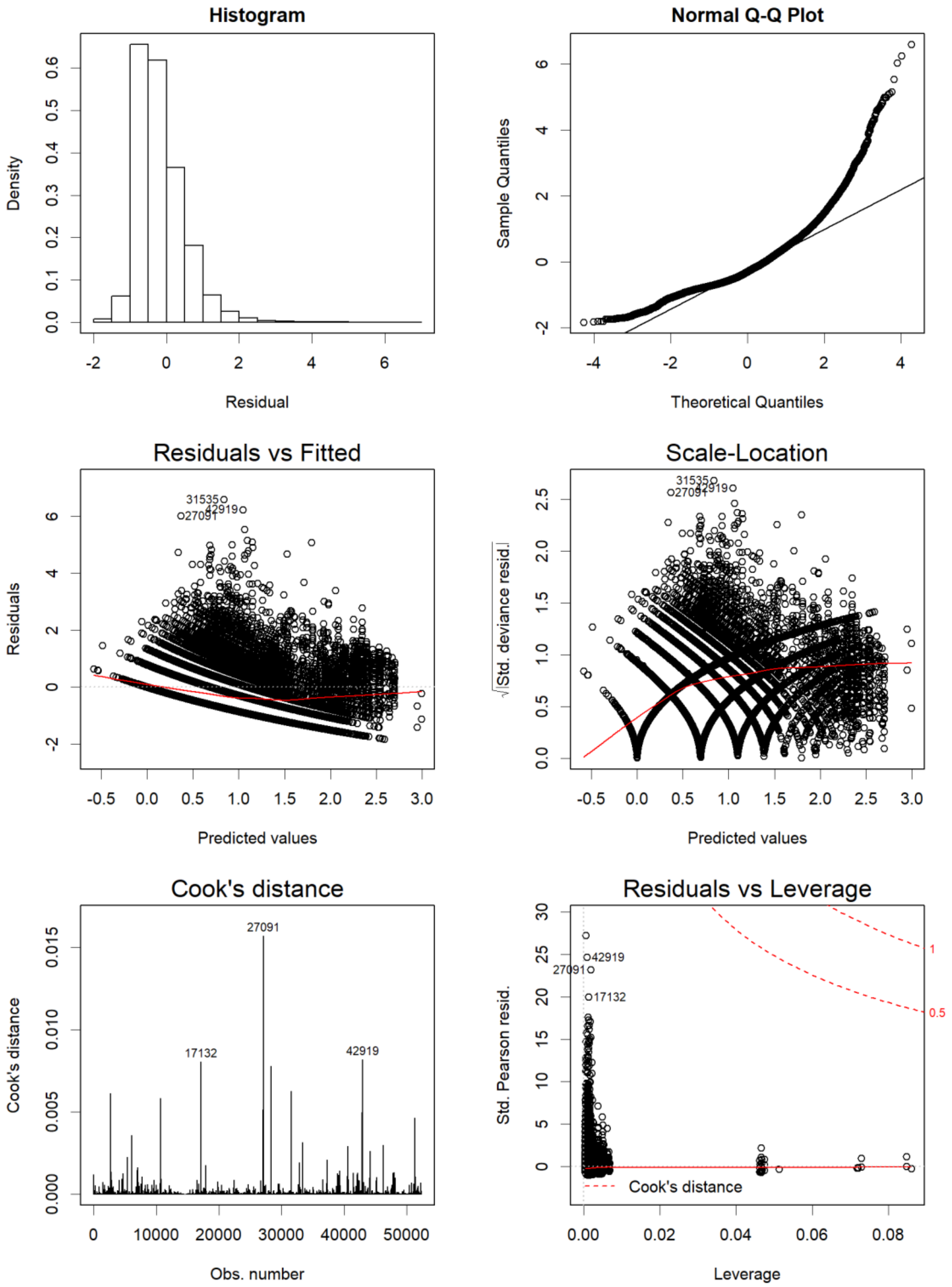
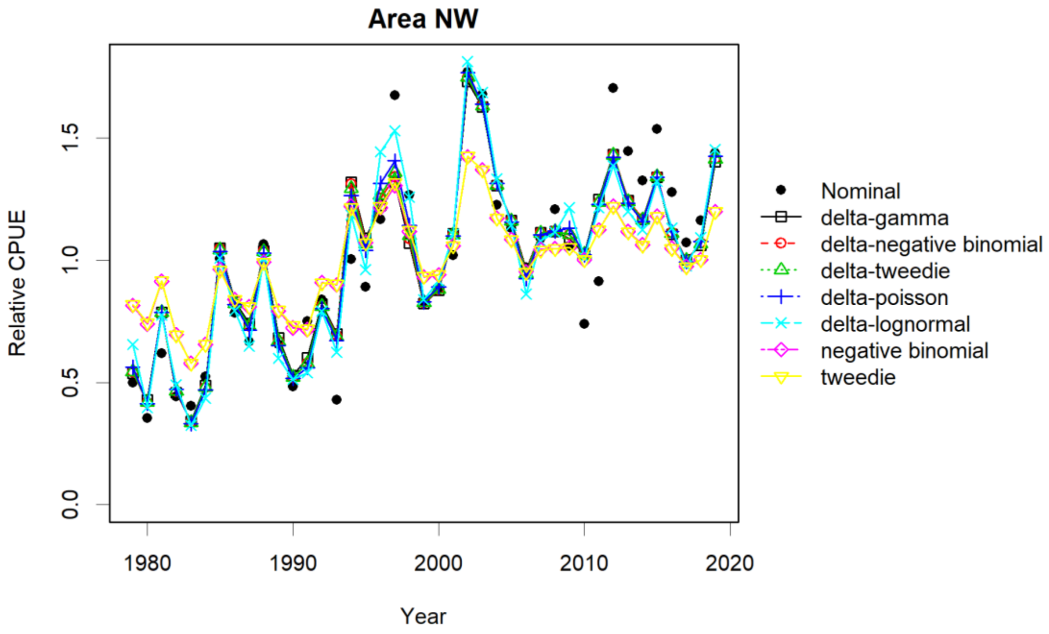


Fig. 19. (continued).



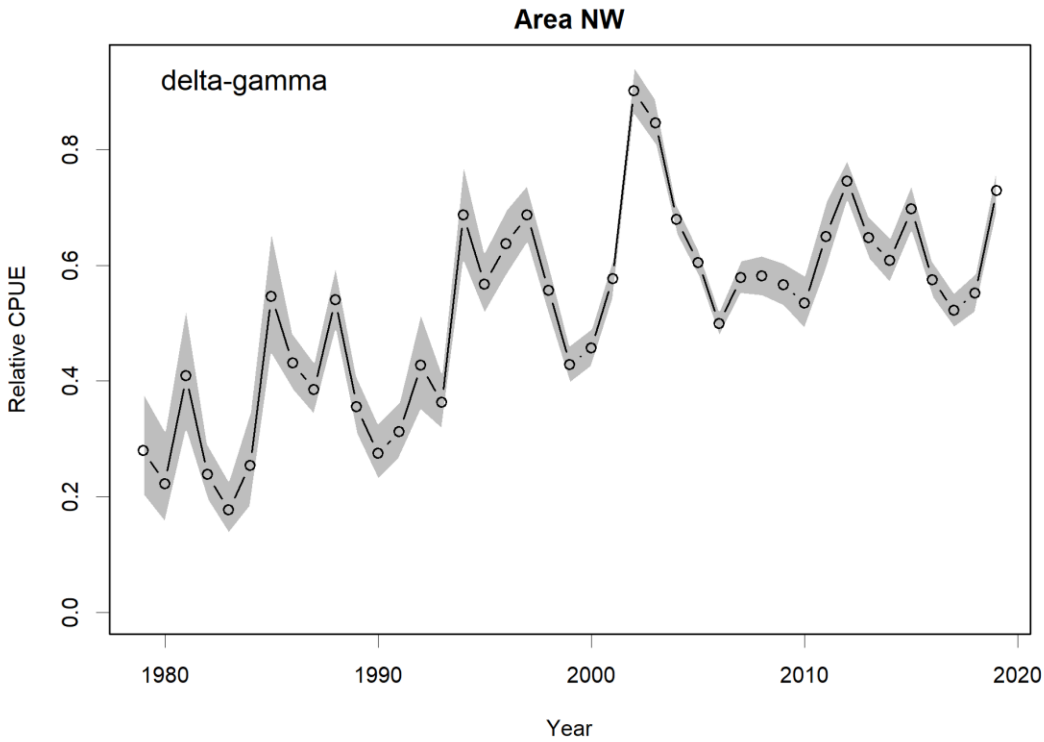
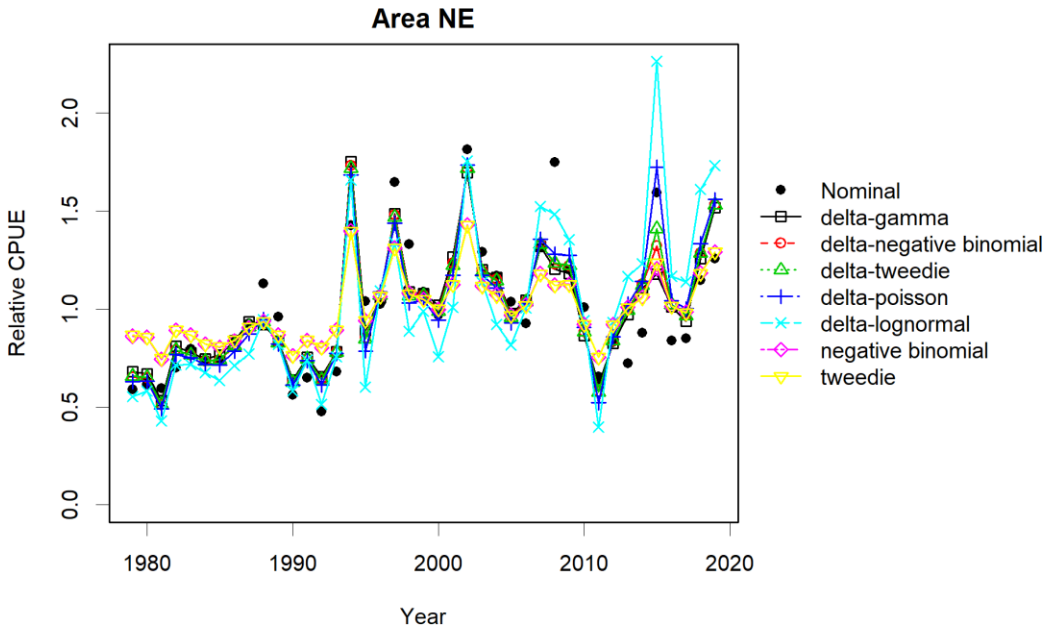


Fig. 20. Area-specific standardized CPUE series of swordfish caught by Taiwanese large scale longline fishery in the Indian Ocean. Gary area shows the 95% confidence interval.



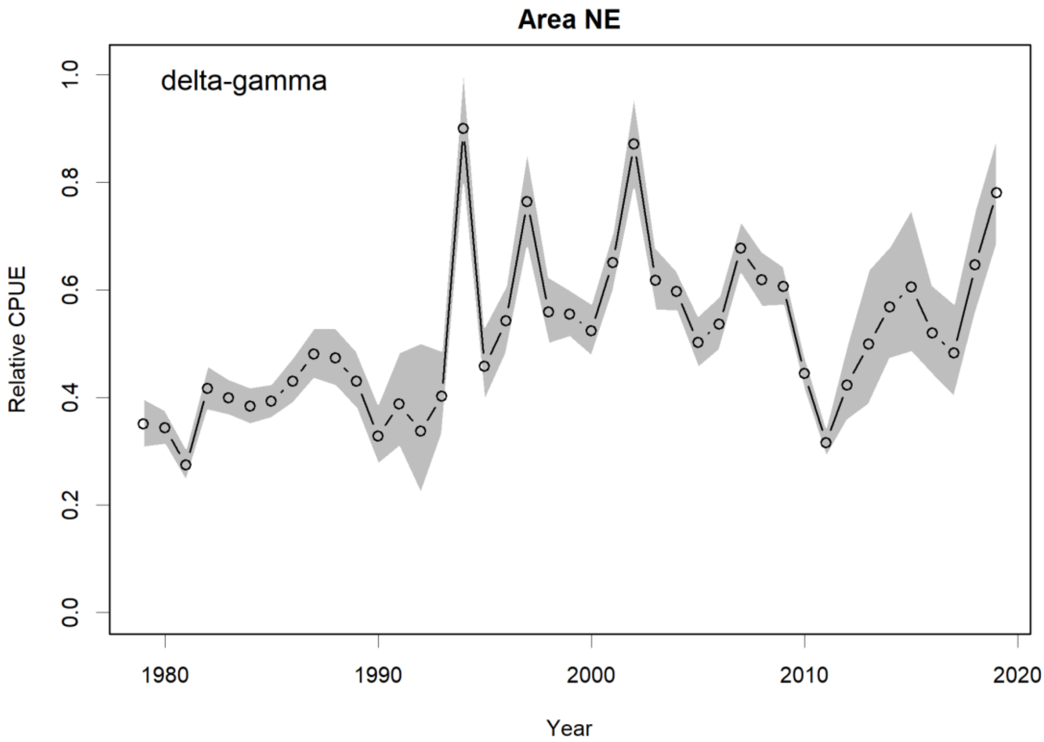
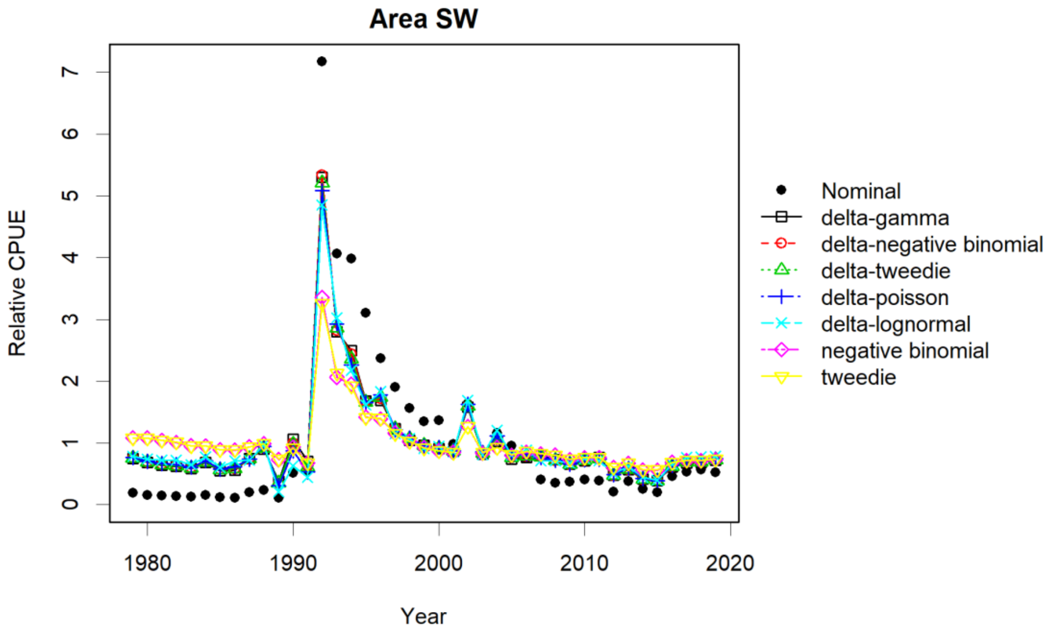


Fig. 20. (continued).



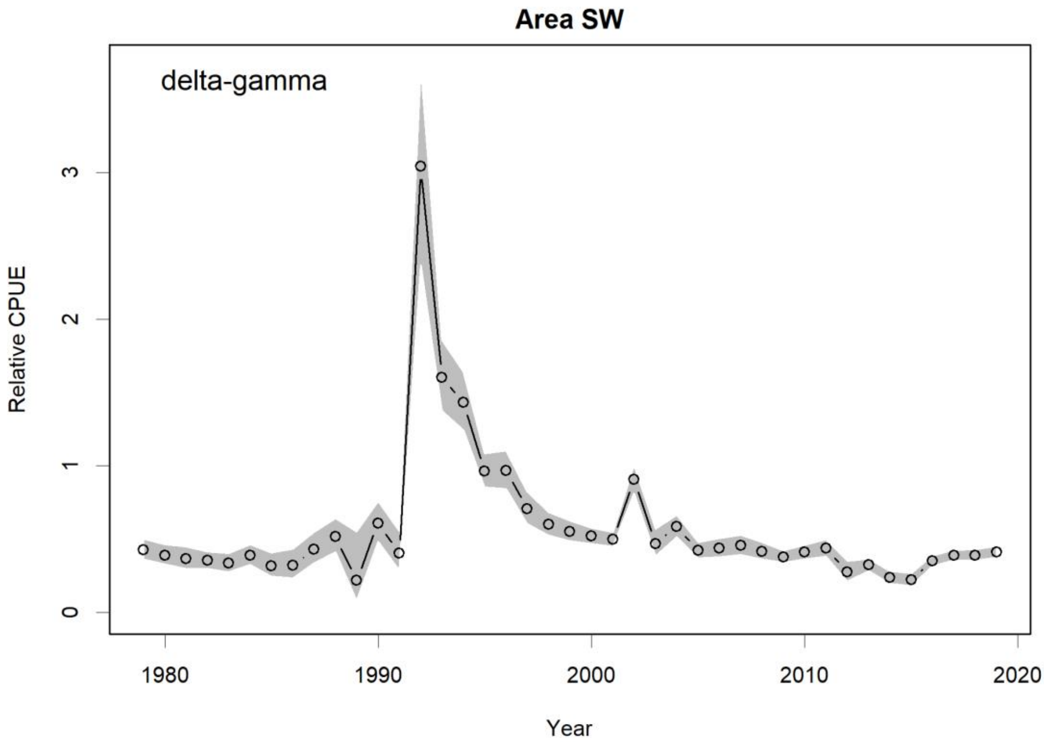
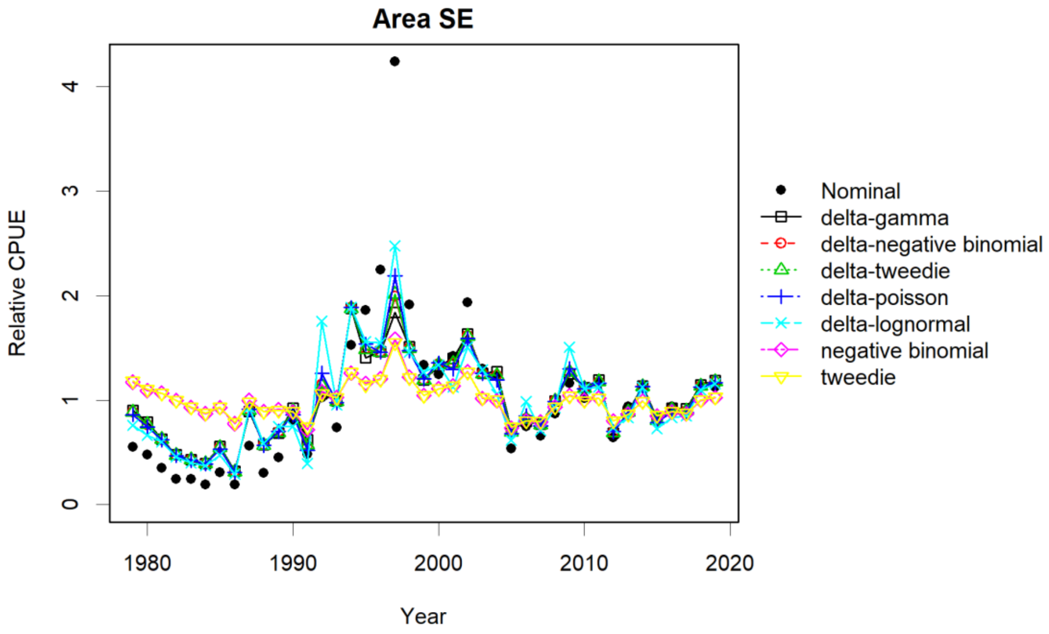


Fig. 20. (continued).



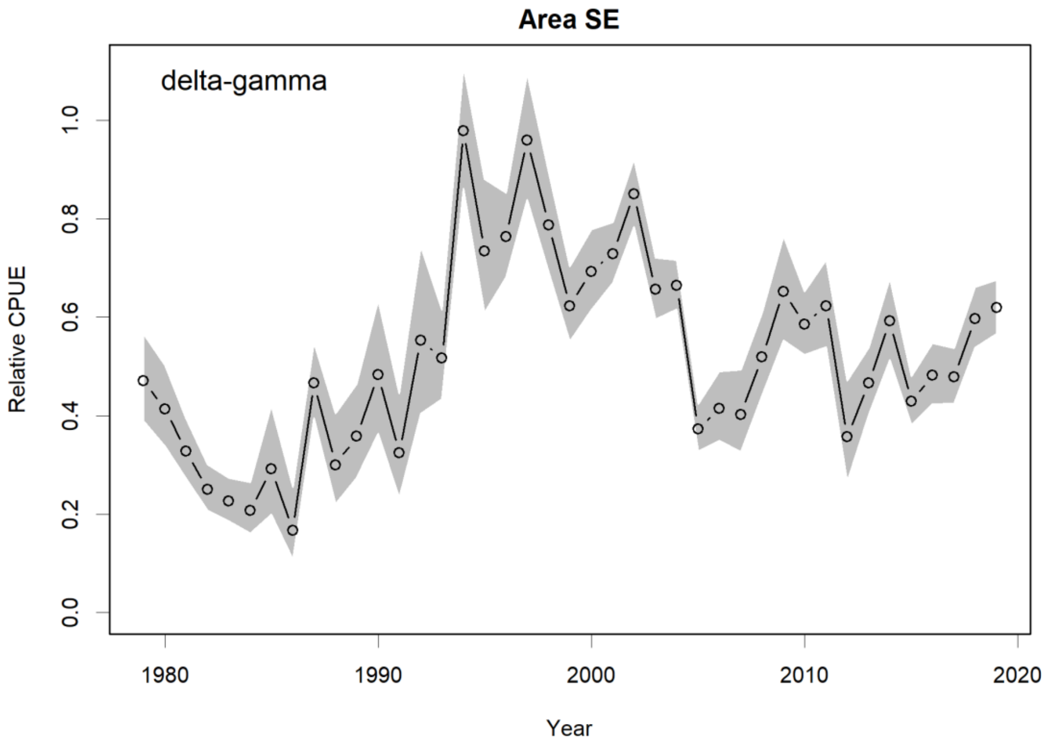


Fig. 20. (continued).

Table 1. The results of PERMANOVA and Beta diversity test for the centroids of the clusters selected for the data of Taiwanese large scale longline fishery in the Indian Ocean.

Area NW

PERMANOVA

	Df	Sum Sq	R2	F	Pr(>F)
Cluster	4	5.2531	0.60744	14.313	0.001 ***
Residual	37	3.3948	0.39256		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Beta diversity test

	Df	Sum Sq	Mean Sq	F	N.Perm	Pr(>F)
Groups	4	0.27297	0.068243	8.8822	999	0.001 ***
Residuals	37	0.28428	0.007683			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Area NE

PERMANOVA

	Df	Sum Sq	R2	F	Pr(>F)
Cluster	4	5.3057	0.64455	16.774	0.001 ***
Residual	37	2.9259	0.35545		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Beta diversity test

	Df	Sum Sq	Mean Sq	F	N.Perm	Pr(>F)
Groups	4	0.16005	0.040013	5.7081	999	0.004 ***
Residuals	37	0.25937	0.00701			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 1. (continued).

Area SW

PERMANOVA

	Df	Sum Sq	R2	F	Pr(>F)
Cluster	4	7.82	0.63094	15.814	0.001 ***
Residual	37	4.5742	0.36906		

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

Beta diversity test

	Df	Sum Sq	Mean Sq	F	N.Perm	Pr(>F)
Groups	4	0.40911	0.10228	11.837	999	0.001 ***
Residuals	37	0.31969	0.00864			

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

Area SE

PERMANOVA

	Df	Sum Sq	R2	F	Pr(>F)
Cluster	3	4.7659	0.53483	14.563	0.001 ***
Residual	38	4.1452	0.46517		

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

Beta diversity test

	Df	Sum Sq	Mean Sq	F	N.Perm	Pr(>F)
Groups	3	0.28666	0.095553	9.0637	999	0.001 ***
Residuals	38	0.40061	0.010542			

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

Table 2. The values of the coefficient of determination (R^2), Akaike information criterion (AIC), Bayesian information criterion (BIC) and dispersion statistics for Pearson residuals obtained from the models for positive catches of swordfish caught by Taiwanese large scale longline fishery in the Indian Ocean.

Area	Model	R^2	AIC	BIC	Dispersion
NE	Gamma	0.245	458,387	459,055	0.876
	Tweedie	0.259	492,345	493,014	1.558
	Negative-binomial	0.266	494,311	494,980	1.368
	Poisson	0.262	563,105	563,764	2.930
	Lognormal	0.231	649,587	650,256	13.202
NW	Gamma	0.170	1,372,788	1,373,512	1.046
	Negative-binomial	0.182	1,438,276	1,439,000	1.534
	Tweedie	0.178	1,457,369	1,458,093	2.052
	Poisson	0.174	1,746,373	1,747,087	4.171
	Lognormal	0.126	1,813,589	1,814,313	19.913
SE	Gamma	0.361	172,148	172,733	0.840
	Tweedie	0.378	187,055	187,640	1.352
	Negative-binomial	0.387	193,155	193,740	1.335
	Poisson	0.382	208,232	208,808	2.272
	Lognormal	0.331	257,396	257,955	7.989
SW	Gamma	0.506	318,173	318,751	0.915
	Negative-binomial	0.530	336,651	337,229	1.326
	Tweedie	0.520	342,450	343,028	1.921
	Poisson	0.504	438,523	439,092	4.441
	Lognormal	0.380	449,017	449,595	32.047

Table 3. The values of the coefficient of determination (R^2), Akaike information criterion (AIC), Bayesian information criterion (BIC) and dispersion statistics for Pearson residuals obtained from the models for all of positive and zero catches of swordfish caught by Taiwanese large scale longline fishery in the Indian Ocean.

Area	Model	R^2	AIC	BIC	Dispersion
NE	Tweedie	0.216	866,799	867,534	1.402
	Negative-binomial	0.223	883,191	883,925	1.327
NW	Negative-binomial	0.228	2,305,762	2,306,535	1.517
	Tweedie	0.221	2,315,936	2,316,709	1.909
SE	Tweedie	0.240	466,588	467,257	1.055
	Negative-binomial	0.246	510,667	511,336	1.179
SW	Tweedie	0.485	659,223	659,864	1.646
	Negative-binomial	0.500	660,036	660,677	1.255

Table 4. ANOVA tables for the models with gamma error distribution for positive catches and the models with binomial error distribution for presence/absence catches of swordfish caught by Taiwanese large scale longline fishery in the Indian Ocean.

Area NW

Models with gamma error distribution for positive catches

	Sum Sq	Df	F values	Pr(>F)
Y	9896	40	236.544	< 2.2e-16 ***
Q	2394	3	762.916	< 2.2e-16 ***
CT	132	4	31.631	< 2.2e-16 ***
Lon	3156	7	431.081	< 2.2e-16 ***
Lat	8210	8	981.246	< 2.2e-16 ***
T	12220	4	2920.942	< 2.2e-16 ***
Residuals	325314	311041		

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

Models with binomial error distribution for presence/absence catches

	LR Chisq	Df	Pr(>Chisq)
Y	10929.3	40	< 2.2e-16 ***
Q	3609.1	3	< 2.2e-16 ***
CT	496.1	4	< 2.2e-16 ***
Lon	1617.2	8	< 2.2e-16 ***
Lat	27000	8	< 2.2e-16 ***
T	3890.6	4	< 2.2e-16 ***

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

Table 4. (continued).

Area NE

Models with gamma error distribution for positive catches

	Sum Sq	Df	F values	Pr(>F)
Y	5052	40	144.188	< 2.2e-16 ***
Q	363	3	137.971	< 2.2e-16 ***
CT	97	4	27.77	< 2.2e-16 ***
Lon	126	9	16.006	< 2.2e-16 ***
Lat	2467	7	402.424	< 2.2e-16 ***
T	1555	4	443.81	< 2.2e-16 ***
Residuals	104941	119808		

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

Models with binomial error distribution for presence/absence catches

	LR Chisq	Df	Pr(>Chisq)
Y	2897.5	40	< 2.2e-16 ***
Q	884.6	3	< 2.2e-16 ***
CT	814.7	6	< 2.2e-16 ***
Lon	654.5	9	< 2.2e-16 ***
Lat	5479.8	7	< 2.2e-16 ***
T	499.8	4	< 2.2e-16 ***

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

Table 4. (continued).

Area SW

Models with gamma error distribution for positive catches

	Sum Sq	Df	F values	Pr(>F)
Y	7179	40	196.204	< 2.2e-16 ***
Q	407	3	148.163	< 2.2e-16 ***
CT	40	3	14.582	1.72E-09 ***
Lon	462	7	72.087	< 2.2e-16 ***
Lat	997	4	272.456	< 2.2e-16 ***
T	3987	4	1089.697	< 2.2e-16 ***
Residuals	65078	71143		

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

Models with binomial error distribution for presence/absence catches

	LR Chisq	Df	Pr(>Chisq)
Y	3617.4	40	< 2.2e-16 ***
Q	1430.3	3	< 2.2e-16 ***
CT	223.6	4	< 2.2e-16 ***
Lon	1040.9	7	< 2.2e-16 ***
Lat	1635.3	4	< 2.2e-16 ***
T	5958.1	4	< 2.2e-16 ***

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

Table 4. (continued).

Area SE

Models with gamma error distribution for positive catches

	Sum Sq	Df	F values	Pr(>F)
Y	1853	40	55.1761	< 2.2e-16 ***
Q	8	3	3.1321	0.02447 ***
CT	141	3	56.128	< 2.2e-16 ***
Lon	264	11	28.5841	< 2.2e-16 ***
Lat	23	4	6.7524	1.99E-05 ***
T	3615	3	1434.9873	< 2.2e-16 ***
Residuals	43905	52282		

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

Models with binomial error distribution for presence/absence catches

	LR Chisq	Df	Pr(>Chisq)
Y	6924.5	40	< 2.2e-16 ***
Q	146.5	3	< 2.2e-16 ***
CT	219.8	4	< 2.2e-16 ***
Lon	491.3	11	< 2.2e-16 ***
Lat	837.9	4	< 2.2e-16 ***
T	482.9	3	< 2.2e-16 ***

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