Update on the CPUE standardization of the bigeye tuna caught by the Taiwanese large-scale tuna longline fishery in the Indian Ocean.

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SUMMARY

In the present study, the bigeye tuna catch and effort data from the logbook records of the Taiwanese large-scale tuna longline fishing vessels operating in the Indian Ocean from 2005-2021 were analyzed. We used cluster analysis to classify longline sets into groups based on the species composition of the catch, to understand whether cluster analysis could identify distinct fishing strategies. Bigeye tuna CPUE were then standardized. CPUE Indices were estimated using two approaches, delta lognormal and lognormal + constant, but the primary approach was the delta lognormal. All analyses were performed using R source code developed in the Collaborative CPUE Workshop applied to Taiwanese longline operational data. Standardized CPUE series of the bigeye tuna caught by Taiwanese longline fishery showed a decreasing trend with smaller scale in tropical region of Indian Ocean.

KEYWORDS

Bigeye tuna, Taiwanese longline fishery, standardized CPUE, delta-lognormal model

1. Introduction

The Working Party on Tropical Tunas (WPTT) and the Scientific Committee of the Indian Ocean Tuna Commission (IOTC) have noted that the CPUE trends from longline fisheries for major tuna species in the Indian Ocean differ considerably between longline countries (Hoyle et al. 2018, Hoyle et al. 2019*a*, 2019*b*). As the fishing technologies, data formats, spatial-temporal coverage were different among the fleets, it is important to discuss and exchange the information among countries using ample time in order to improve the analysis and index. With this end in view, three longline countries, Japan, Korea and Taiwan, have been conducting a collaborative study for developing the abundance index since December 2019. The trilateral cooperation workshop addressed Terms of Reference covering several important and longstanding issues related to the albacore, bigeye and yellowfin tuna CPUE indices in the Indian Ocean. In this paper, a framework analysis suggested by the collaborative study was conducted using updated Taiwanese operational data.

2. Material and methods

2.1. Source of data

In this analysis, operational catch and effort data with 1 degree by 1 degree resolution from the logbooks of Taiwanese longline fishery from 2005-2021 were used, as provided by Overseas Fisheries Development Council (OFDC). From 2013, the Taiwanese Fisheries Agency has supported the Taiwanese pelagic longline fishery industry in submitting logbook data via an E-logbook system. In 2015 the E-logbook coverage rate reached over 80%, and attained 100% after 2016. Therefore, data were compiled from E-logbooks after 2015. Data preparation and cleaning were performed by adopting the suggestions made by the collaborative work. Each set was allocated to a bigeye region and a yellowfin region (**Figure** 1). Basically, the region definitions conformed to the 2019 joint work (Hoyle et al, 2019*a*). **Figure** 2 shows the annual changes in distribution of fishing efforts (number of hooks) for Taiwanese longline fisheries in Indian Ocean.

2.2. Cluster analysis

We adopted the hierarchical two-step clustering method (He et al., 197) to identify effort associated with different fishing strategies. The cluster analysis was performed separately for regions for bigeye tuna. Analyses used species composition to group the data. The data were transformed by centering and scaling, so as to reduce the dominance of species with higher average catches. In the present analyses, the values of “centers” and “nstart” were increased for K-means and the whole process of two-step clustering was repeated through a certain number of iterations with different random seeds for K-means to seek an optimal set with the smallest sum of within-cluster variation obtained from hierarchical clustering. The outputs of the finalized cluster were then used to assign the cluster label fishery target to each catch-effort data. More detailed information can be referred to the collaborative work report (Kitakado et al., 2020, 2021).

2.3. CPUE standardization

Due to the catch rate of bigeye tuna 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 logbook data during the period of 2005-2021. CPUE standardization methods adopted the suggestions made from the collaborative work for Taiwanese fleet to include year-quarter, vessel id, and five by five latitude and longitude grids as main effects. Cluster is also included as a main effect in the model. Analyses were conducted separately for each region for bigeye tuna. CPUE Indices were estimated using two approaches, delta lognormal and lognormal + constant, but the primary approach was the delta lognormal. More detailed information can be obtained from the collaborative work report (IOTC, 2019). All analyses were performed using R source code developed in the Collaborative CPUE Workshop applied to Taiwanese longline operational data.

Delta-lognormal model (DLN)

The DLN is a mixture of two generalized linear models (GLM), 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). For the DLN modeling, the catch rates of the positive catch events (sets with positive bigeye tuna catch) were modeled assuming a lognormal error distribution:

$log\ (CPUE) = Main\ effects + Interactions + Error$ (lognormal error)

To calculate the proportion of positive records we used a model assuming a binomial error distribution:

$PA = Main\ effects + Interactions + Error$ (binomial error)

*Standardized CPUE= CPUE * PA*

Potential covariates used in the analysis were shown below:
- Temporal component (year, month, quarter, year*quarter)
- Spatial component (5° squared longitudinal and latitudinal grid)
- Target (cluster outcomes to express target species of fishery)
- Interactions

Diagnosis and impacts of covariates (Residual plots, Q-Q plots, influence plots)
In addition to the standard residual plots for the diagnosis for fitting of models to the data and Q-Q plots, we used influence plots (Bentley et al. 2012) to interpret the contribution of each covariates to the difference between nominal and standardized temporal effects (year or year*quarter).

Extracts of abundance indices from models with interactions
Once the model fitting and model evaluation were conducted, the final output of the abundance index is extracted through an exercise of the least square means (so-called LS means) to account for heterogeneity of amount of data over covariate categories.

3. Results and discussion

3.1. Cluster analysis

The aims of the cluster analysis were to identify whether cluster analysis could identify distinct fishing strategies in each region; secondly to use the cluster analysis to identify these fishing strategies in the data for each region, and so to better understand the fishing practices.

The optimal group numbers were the lowest value of *k* after which the rate of decline of deviance became slower and smoother. There were 4 groups for each region determined using the cluster analysis (**Figure** 3 and 4). The species compositions estimated by cluster analysis were shown in Figure 5. As expected, the cluster 2 in region R1N and cluster 1 in region R1S and R2 were targeting bigeye tuna. However, using cluster analysis to identify bigeye targeting is challenging, since targeting is probably less an either/or strategy than a mixture of variables that shift the species composition one way or the other. For BET regions, for each cluster in every region, the corresponding fishing strategies were revealed by the various distribution of fishing year, month, number of hooks between floats, location, number of hooks associated with sets in each cluster (**Figure** 6 ~13).

3.2. Conventional regression analysis

For bigeye tuna the western tropical indices in regions R1N and R1S (the top two plots in **Figure** 14) show no strong trend through time. There was a spike in 2012 followed by a moderate decline in the latest 10 years. In the eastern tropical area (R2, the bottom left plot in **Figure** 14), there was also no strong trend through time with relatively lower signal in the last two years. However, CPUE showed a decline pattern with significant variability and reached their lowest observed levels by 2020 in temperate area (R3, the bottom right plot in **Figure** 14). Model fits for each region were presented by using Q-Q plots and plotting the residual densities plots (**Figure** 15 and 16). However, a slightly unfavourable residual pattern is observed for each region (see **Figure** 15 and 16).

The influence plots of the covariate for each region were shown in **Figures** 17~20. For covariate effects, we present an example result for bigeye in region R1N. The spatial distributions of fishing sets (latlong effect) were fairly stable through time with some exceptions (top right, **Figure** 17). The high influence in around 2012 (top right, **Figure** 17) arises because there was a greater than usual proportion of effort occurred in the Somalia area with the highest coefficients. The coefficients for each cluster (bottom left, **Figure** 17) show there was one cluster (R1NC3) with much higher catchability than the other three clusters. There were changes in the distribution of records among clusters, resulting in variable changes in annual influence. Overall, Taiwanese CPUE indices showed a decreasing trend with smaller scale in tropical region of Indian Ocean.

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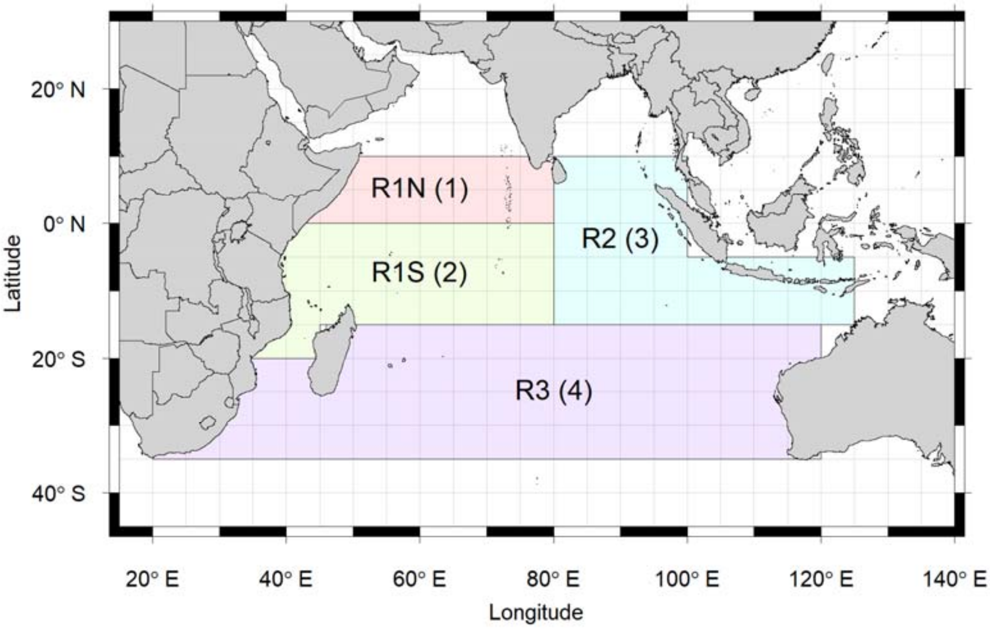

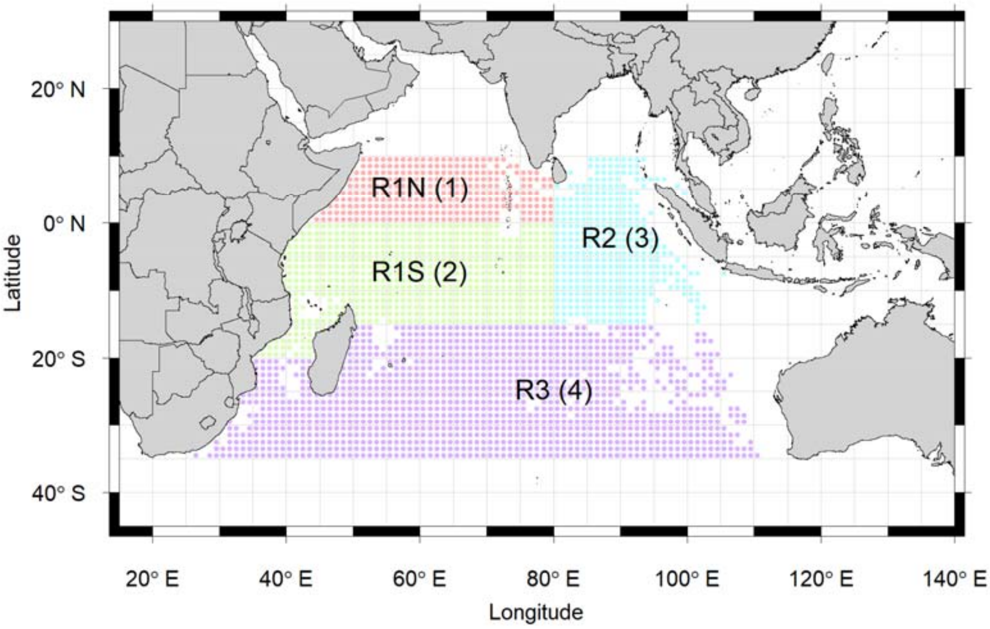

Figure 1. The spatial stratification (upper figure) and observed effort distributions (lower figure) of the Taiwanese large-scale tuna longline fishery in the Indian Ocean from 2005 to 2021.

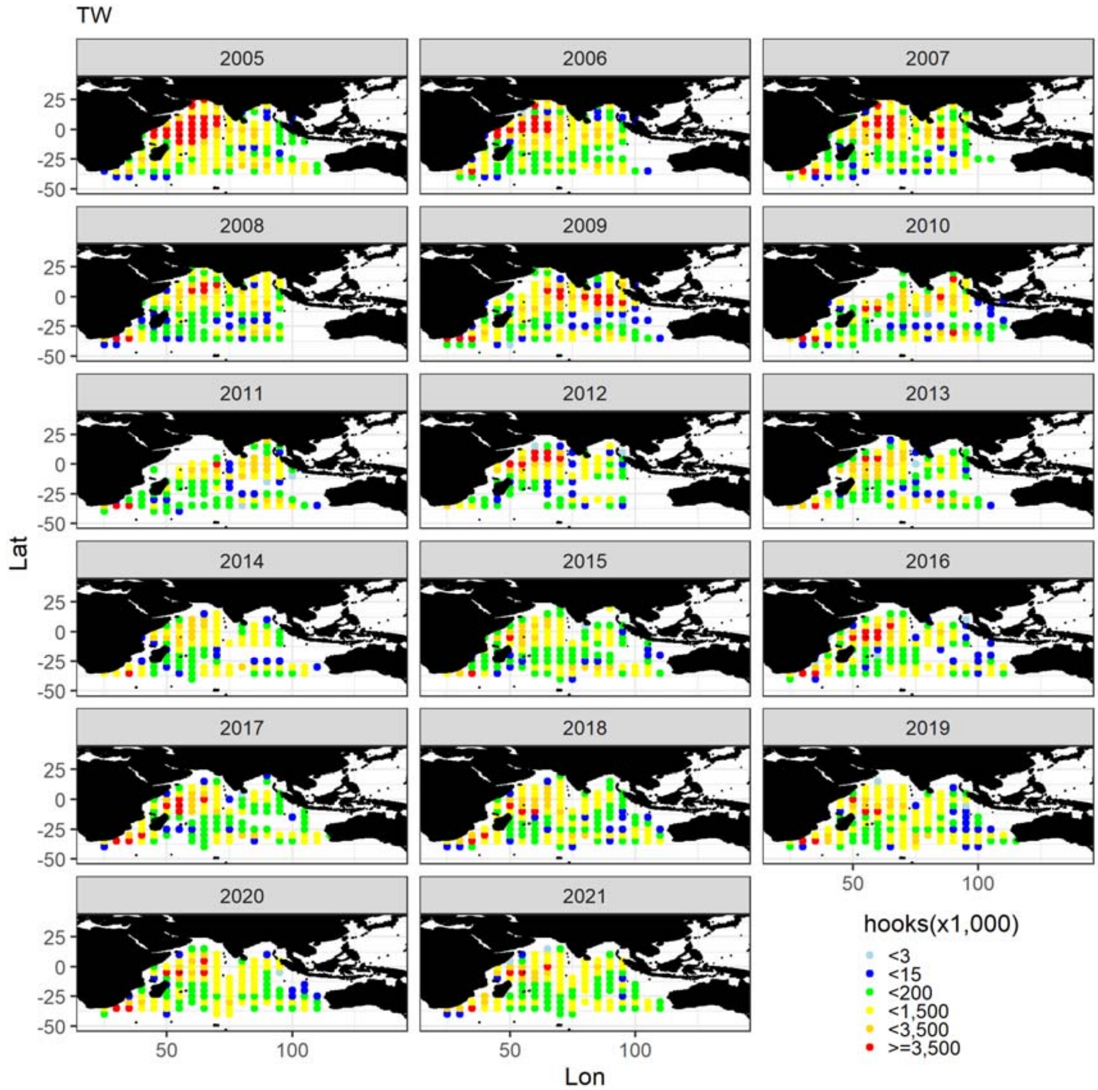

Figure 2. The spatial distribution of observed efforts for Taiwanese tuna longline vessels in the Indian Ocean from 2005 to 2021.

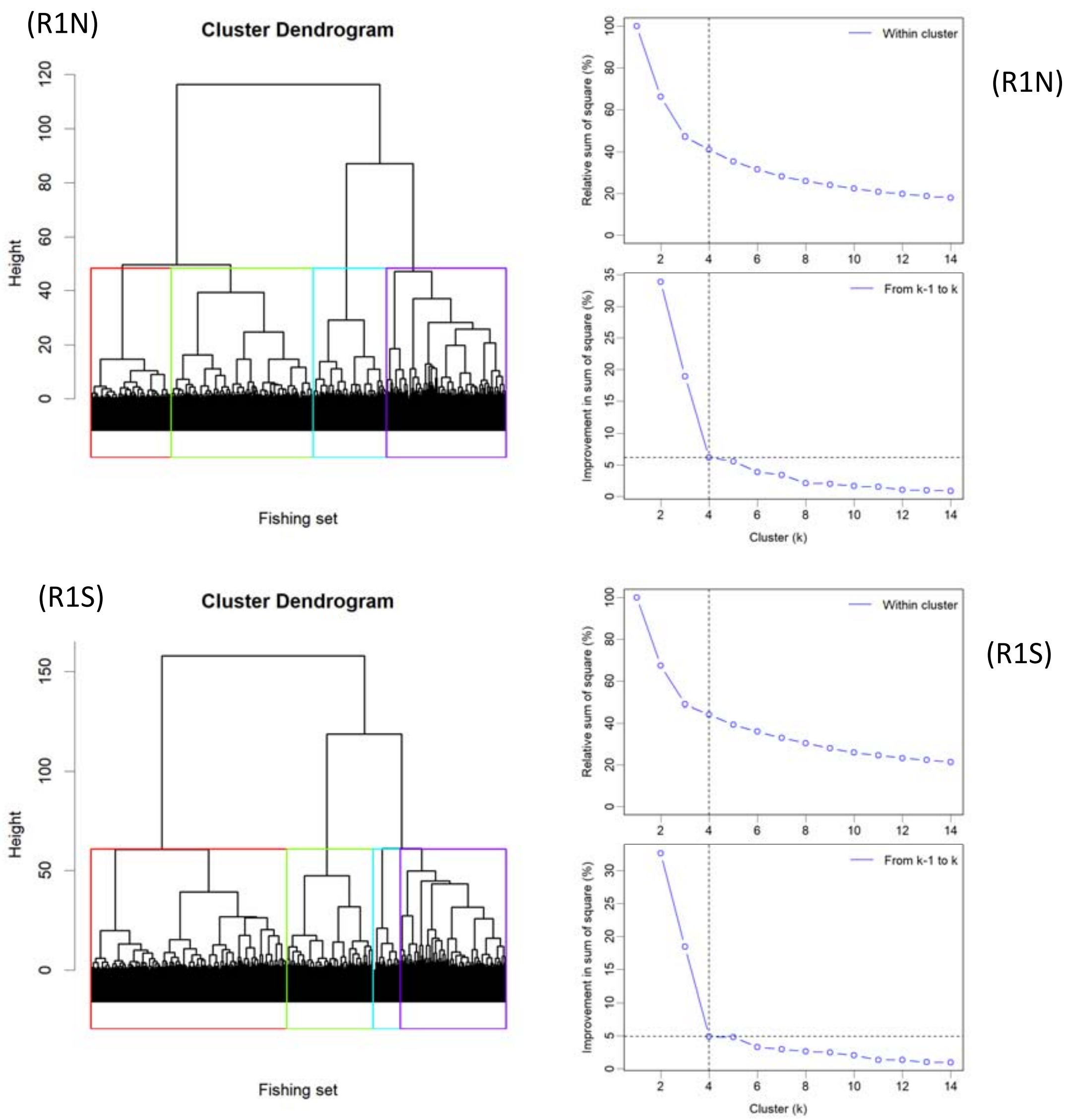

Figure 3. Plots showing analyses to estimate the number of distinct classes of species composition in Taiwanese region R1N, 1S.

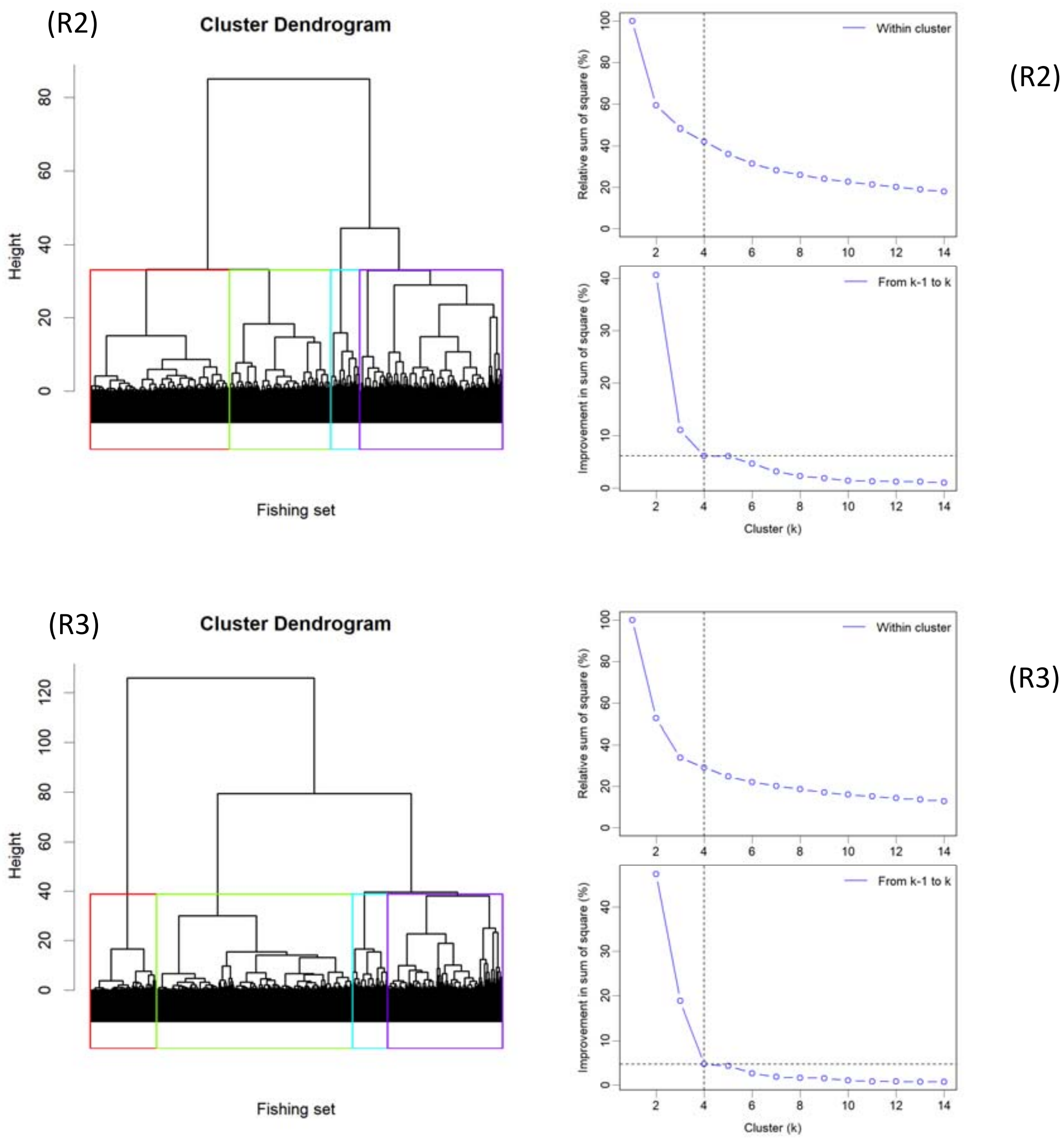

Figure 4. Plots showing analyses to estimate the number of distinct classes of species composition in Taiwanese region R2, R3.

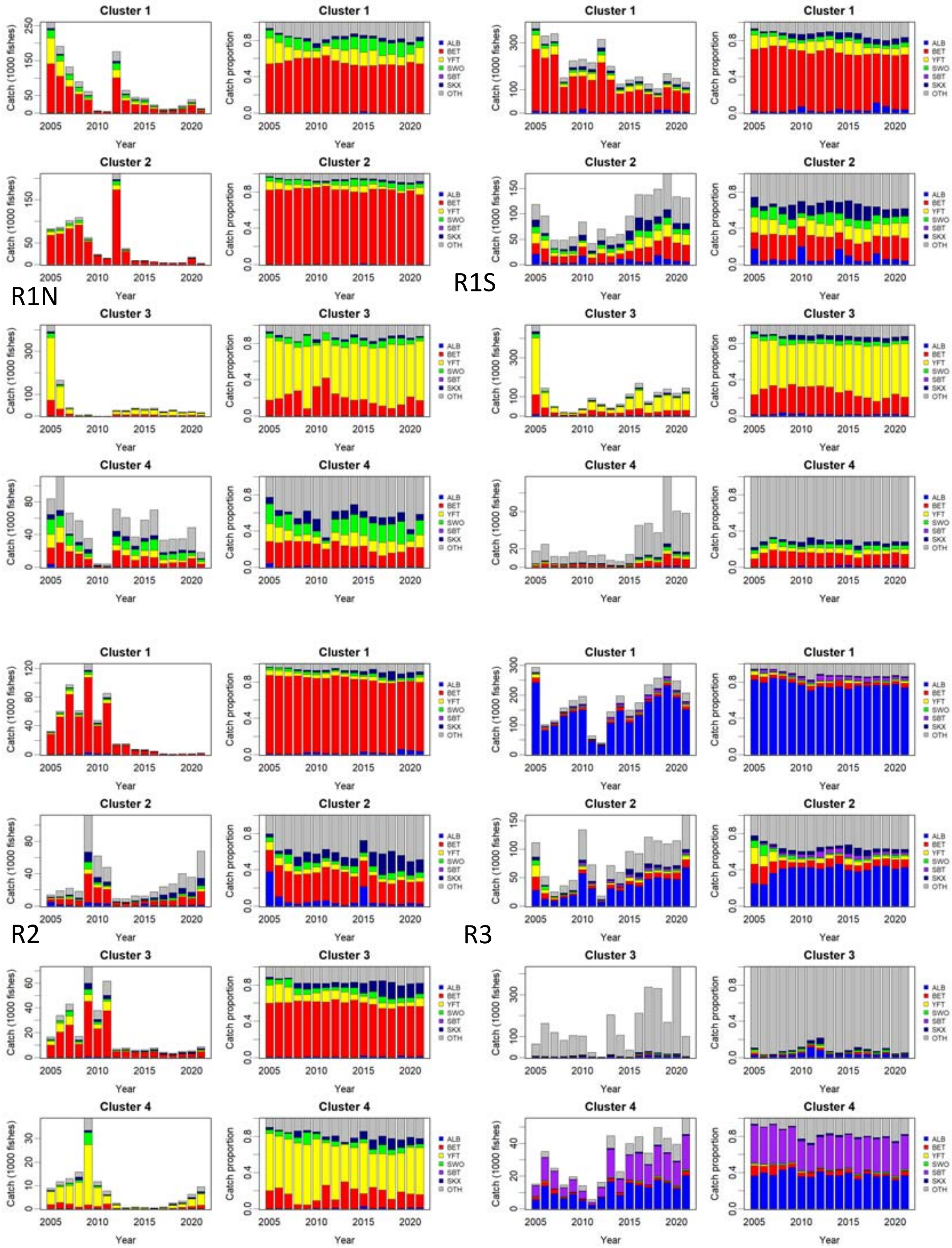

Figure 5. Species composition for each cluster by region.

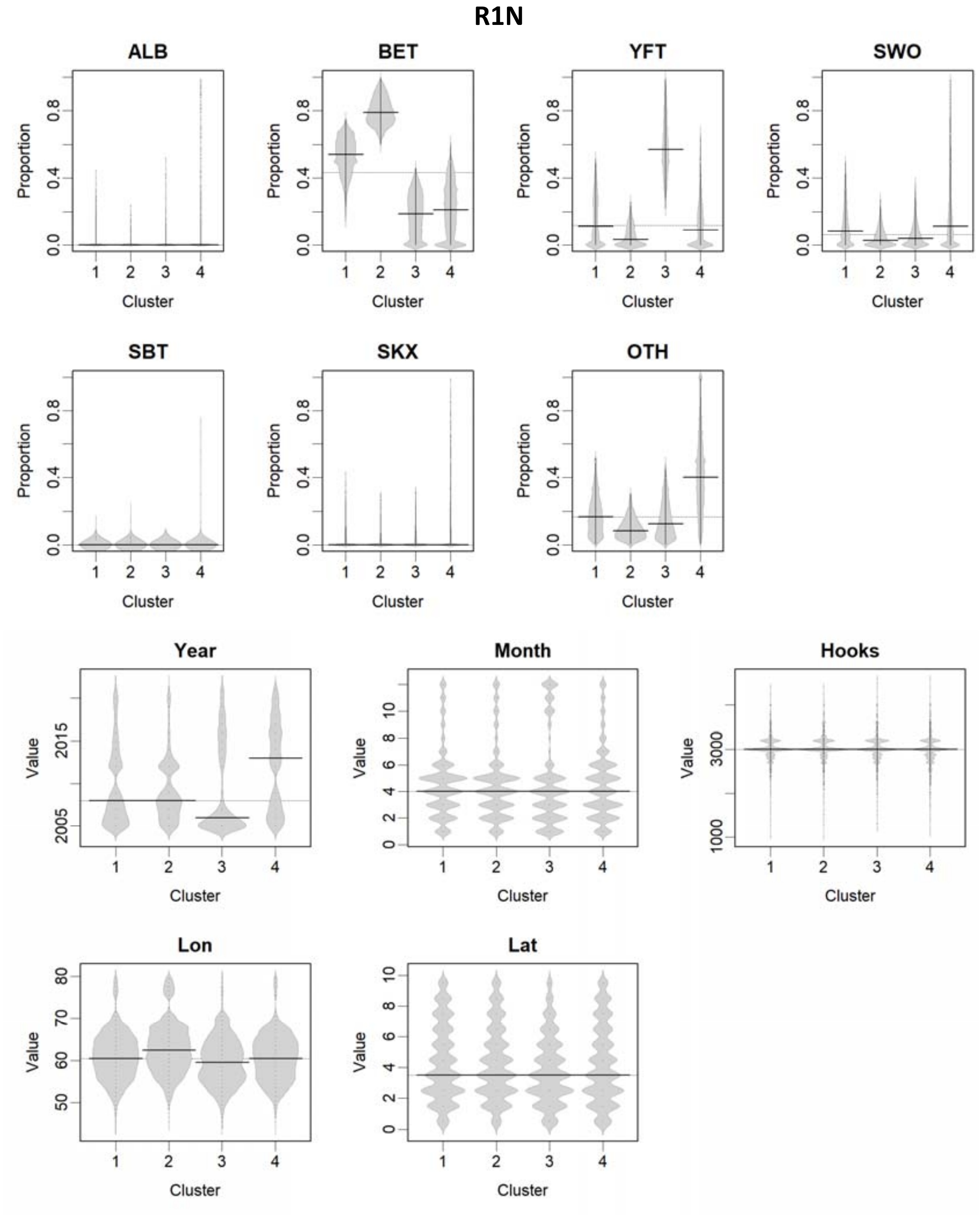

Figure 6. For Taiwanese effort in region R1N for the period 2005-2021, for each species, beanplot of the proportion of the species in the trip versus the cluster. The widths of the boxes are proportional to the numbers of trips in each cluster (above). Beanplot showing the distributions of variables associated with sets in each hcltrp cluster (below).

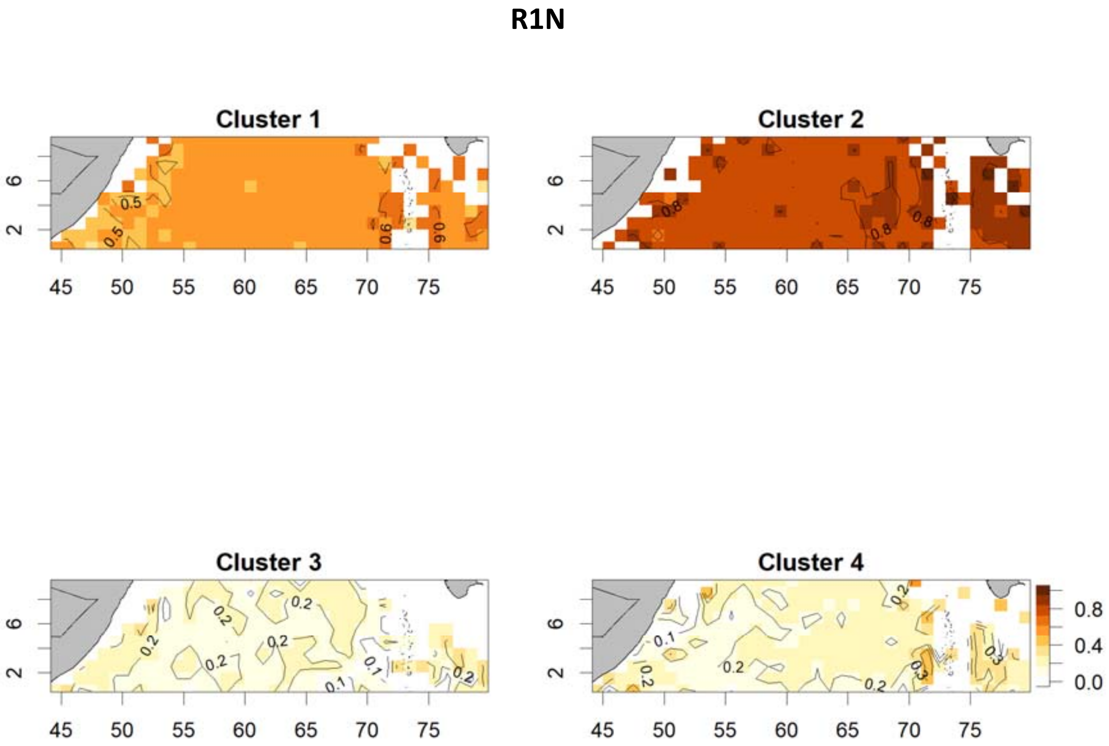

Figure 7. Maps of the spatial distributions of clusters in region R1N of BET for Taiwanese effort.

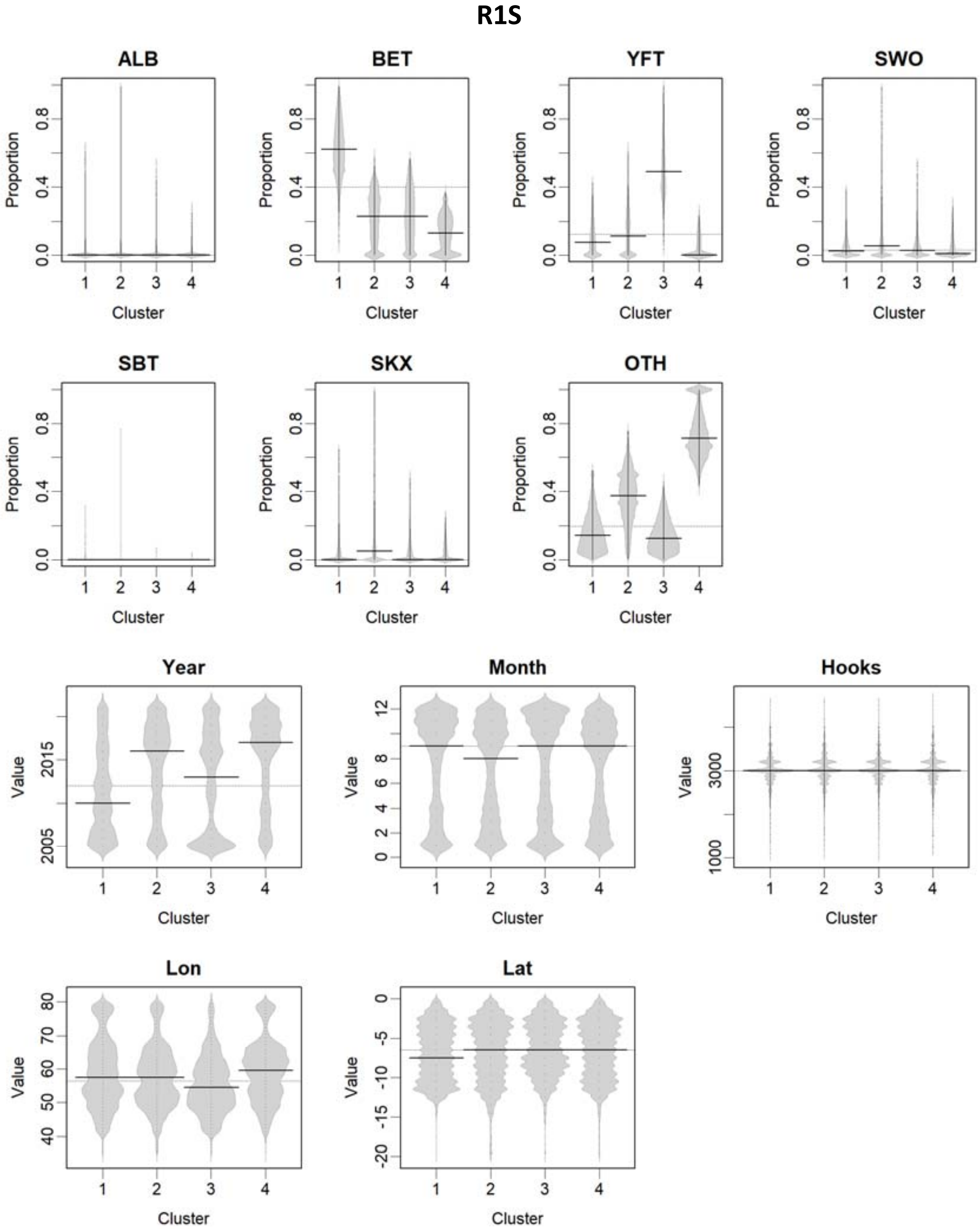

Figure 8. For Taiwanese effort in region R1N of BET for the period 2005-2021, for each species, beanplot of the proportion of the species in the trip versus the cluster. The widths of the boxes are proportional to the numbers of trips in each cluster (above). Beanplot showing the distributions of variables associated with sets in each hcltrp cluster (below).

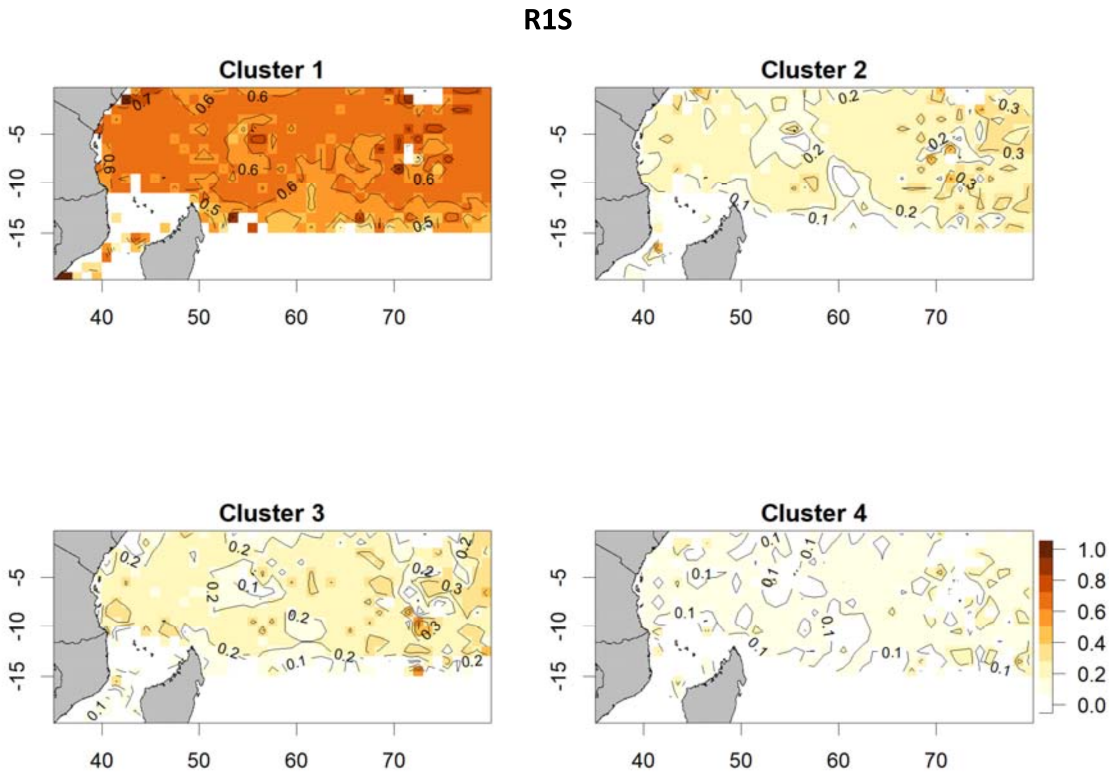

Figure 9. Maps of the spatial distributions of clusters in region R1S of BET for Taiwanese effort.

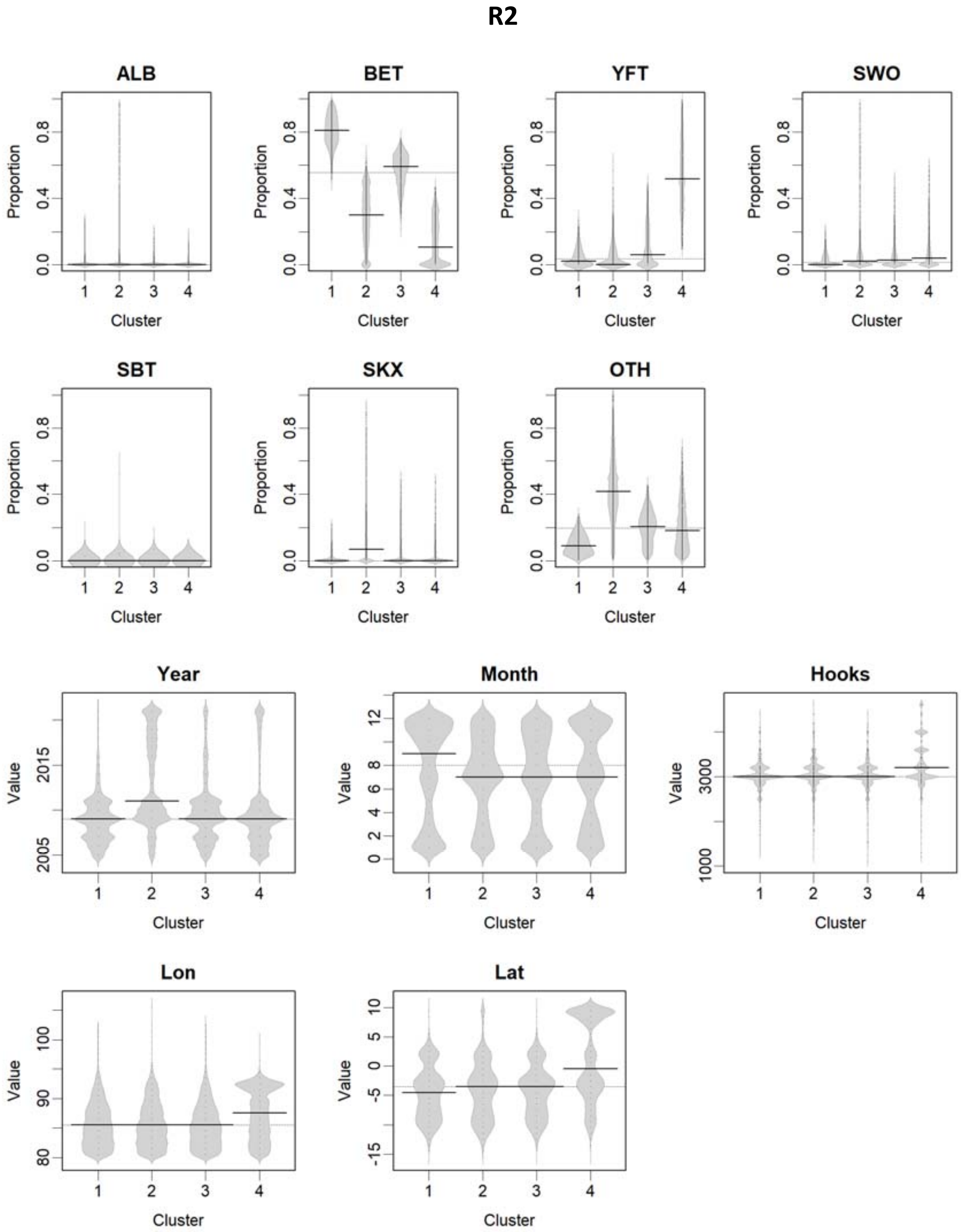

Figure 10. For Taiwanese effort in region R2 of BET for the period 2005-2021, for each species, beanplot of the proportion of the species in the trip versus the cluster. The widths of the boxes are proportional to the numbers of trips in each cluster (above). Beanplot showing the distributions of variables associated with sets in each hcltrp cluster (below).

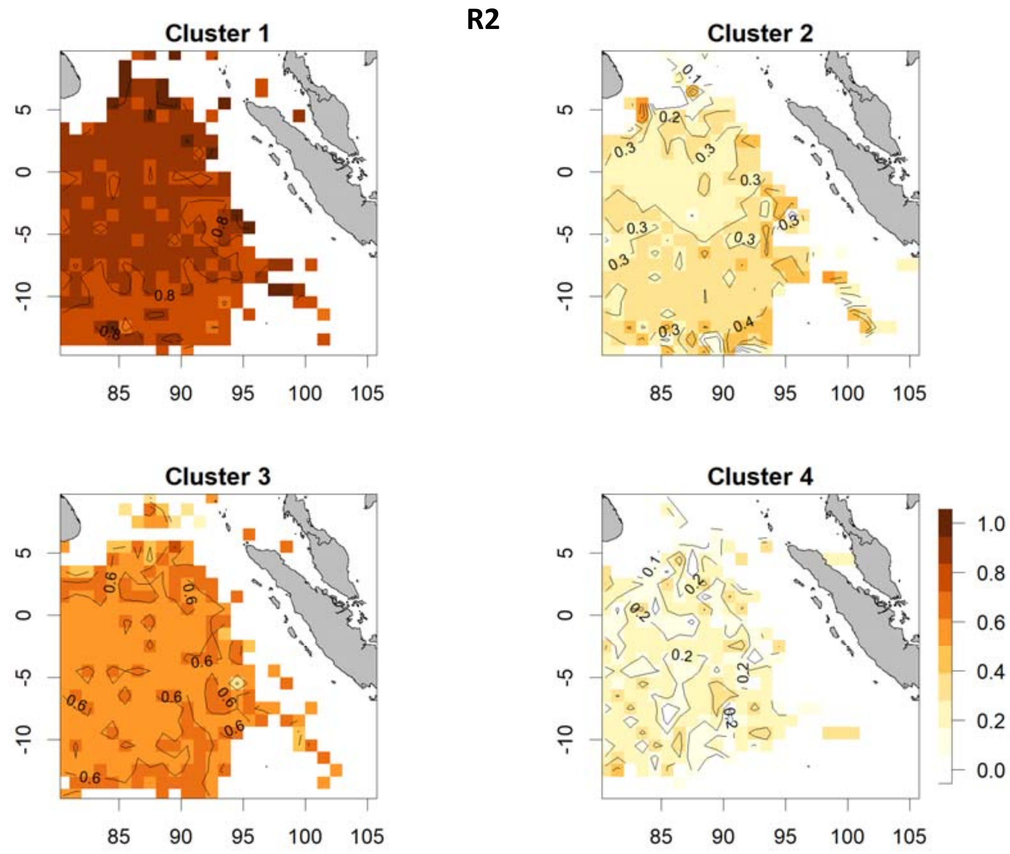

Figure 11. Maps of the spatial distributions of clusters in region R2 of BET for Taiwanese effort.

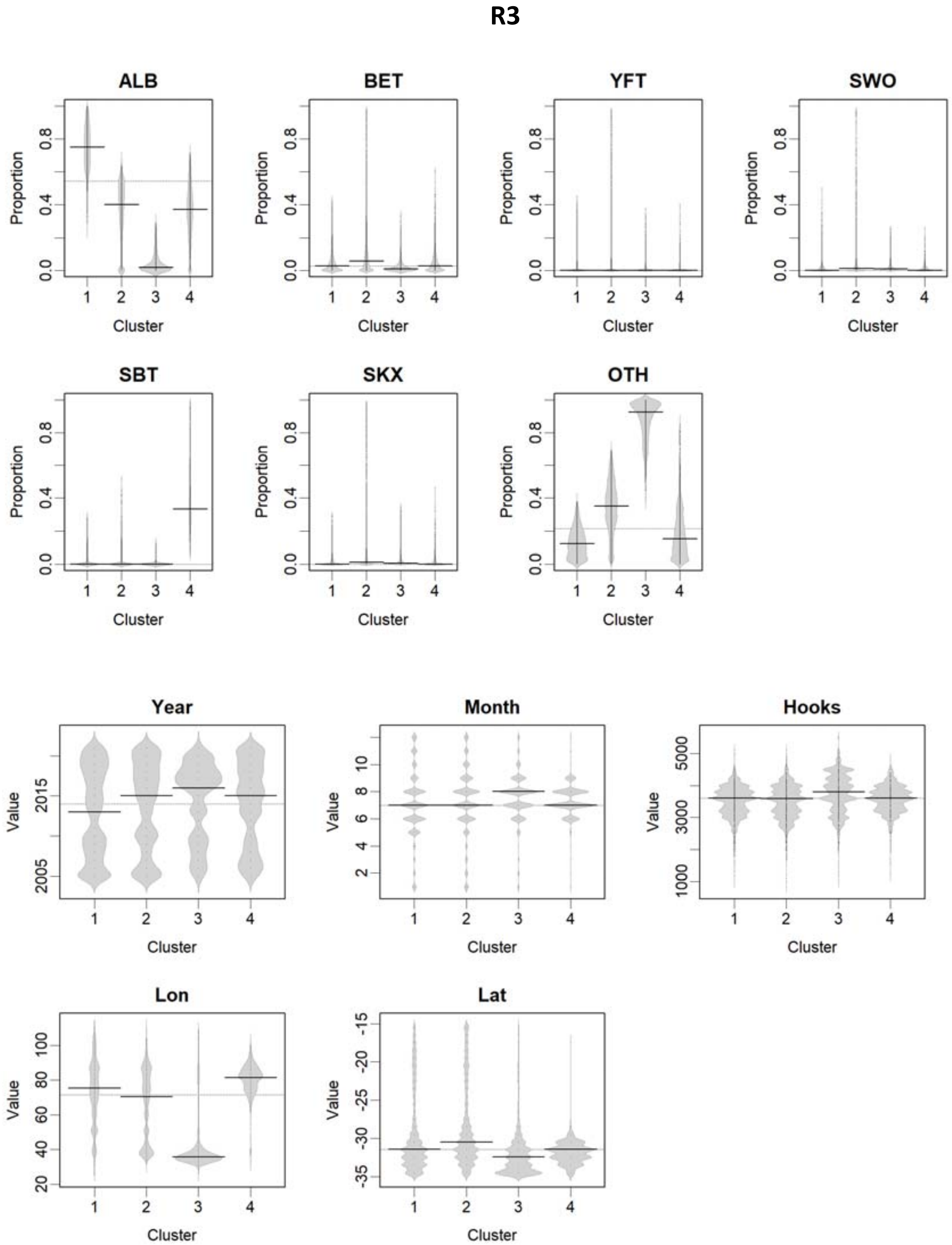

Figure 12. For Taiwanese effort in region R3 of BET for the period 2005-2021, for each species, beanplot of the proportion of the species in the trip versus the cluster. The widths of the boxes are proportional to the numbers of trips in each cluster (above). Beanplot showing the distributions of variables associated with sets in each hcltrp cluster (below).

R3

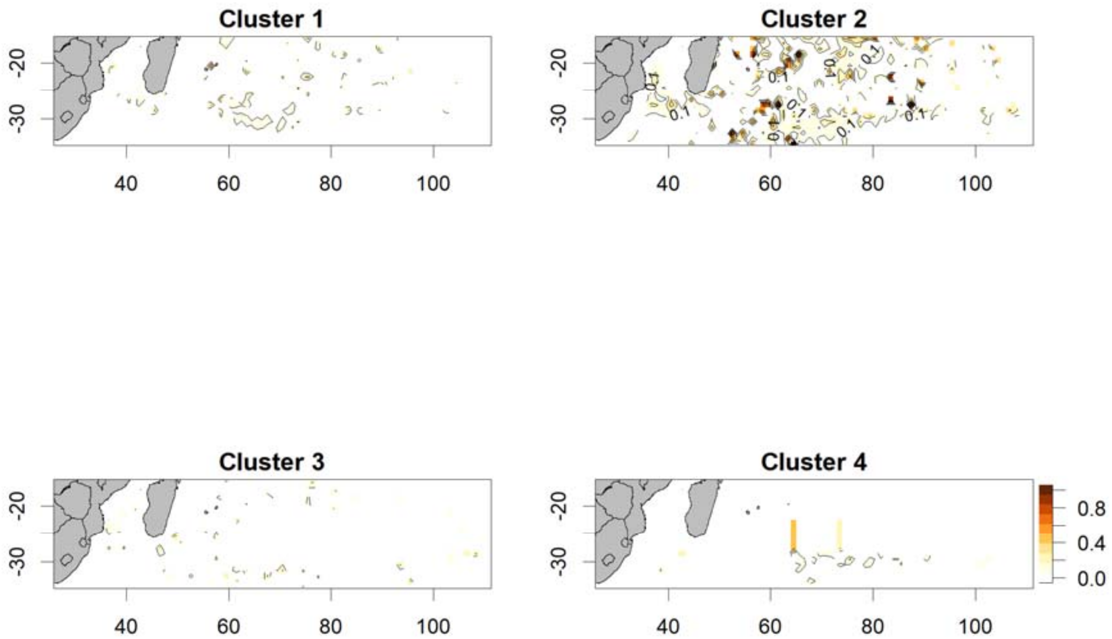

Figure 13. Maps of the spatial distributions of clusters in region R3 of BET for Taiwanese effort.

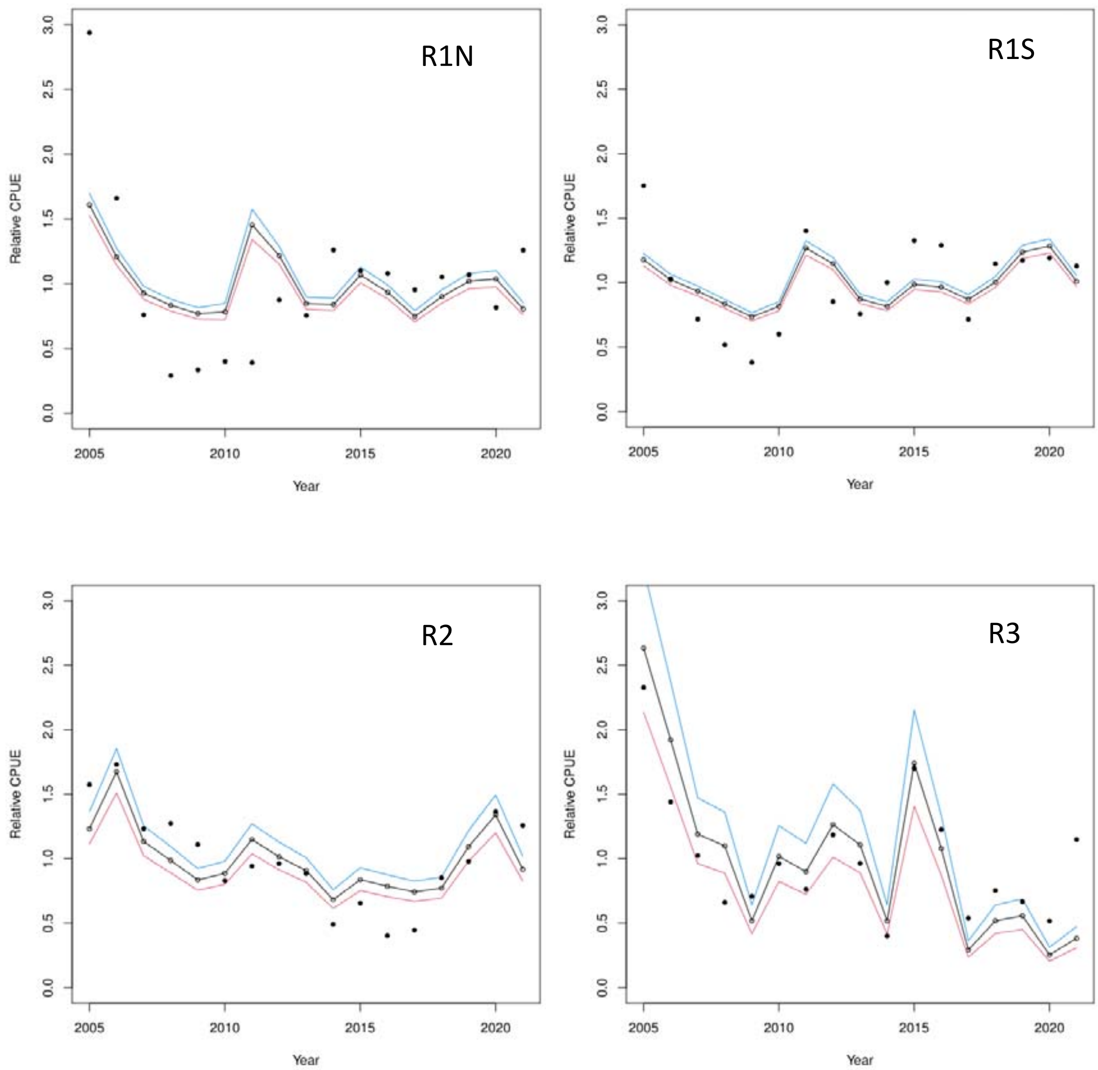

Figure 14. Estimated Bigeye CPUE time series by regions in this analysis.

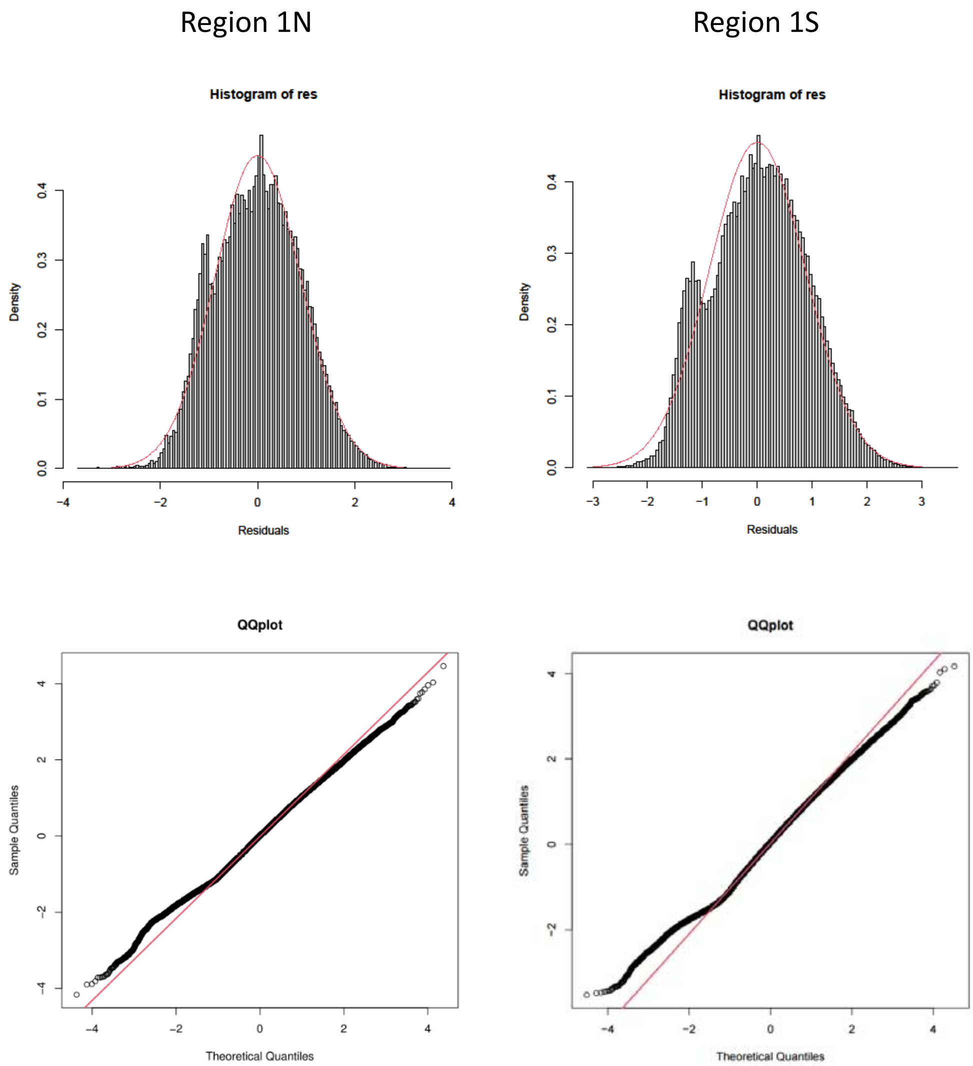

Figure 15. Residual diagnostics (as histogram and QQ plot) for region R1N and R1S on bigeye tuna CPUE indices.

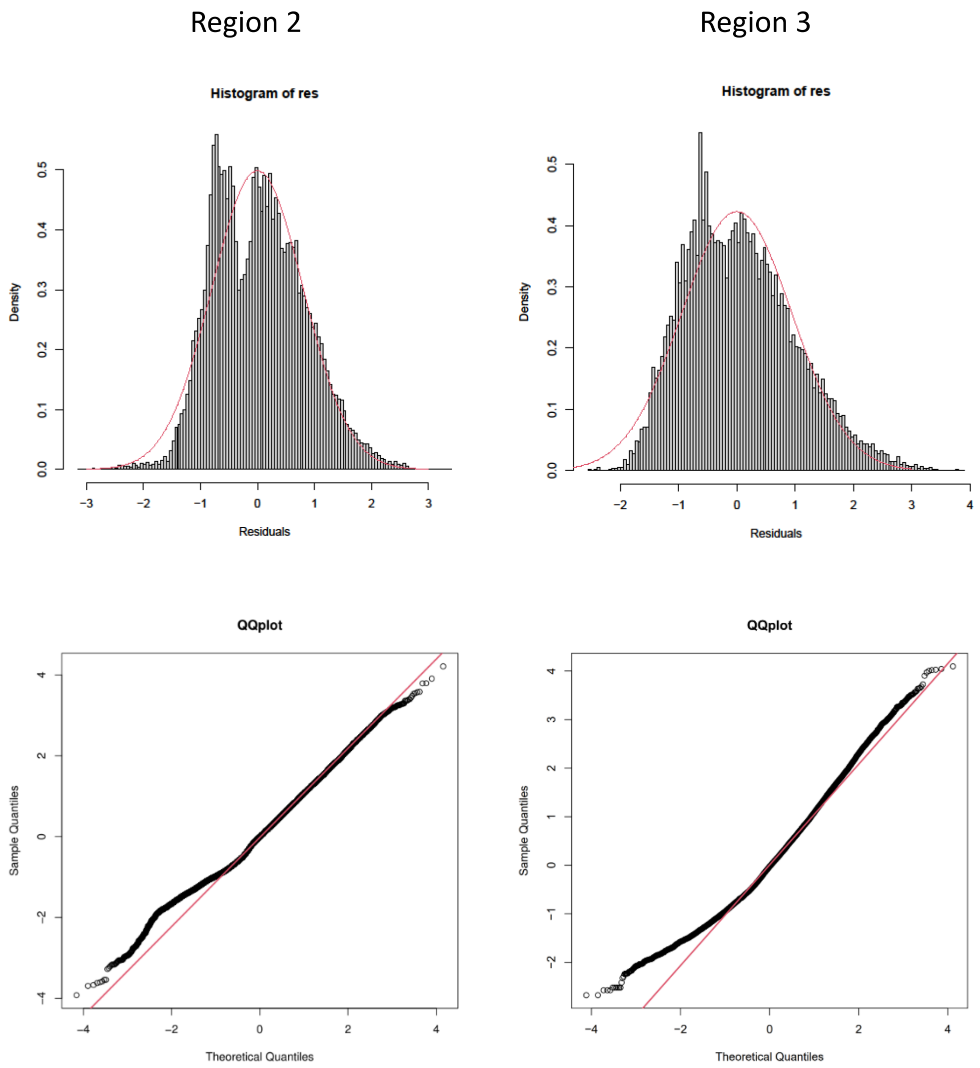

Figure 16. Residual diagnostics (as histogram and QQ plot) for region R2 and R3 on bigeye tuna CPUE indices.

R1N

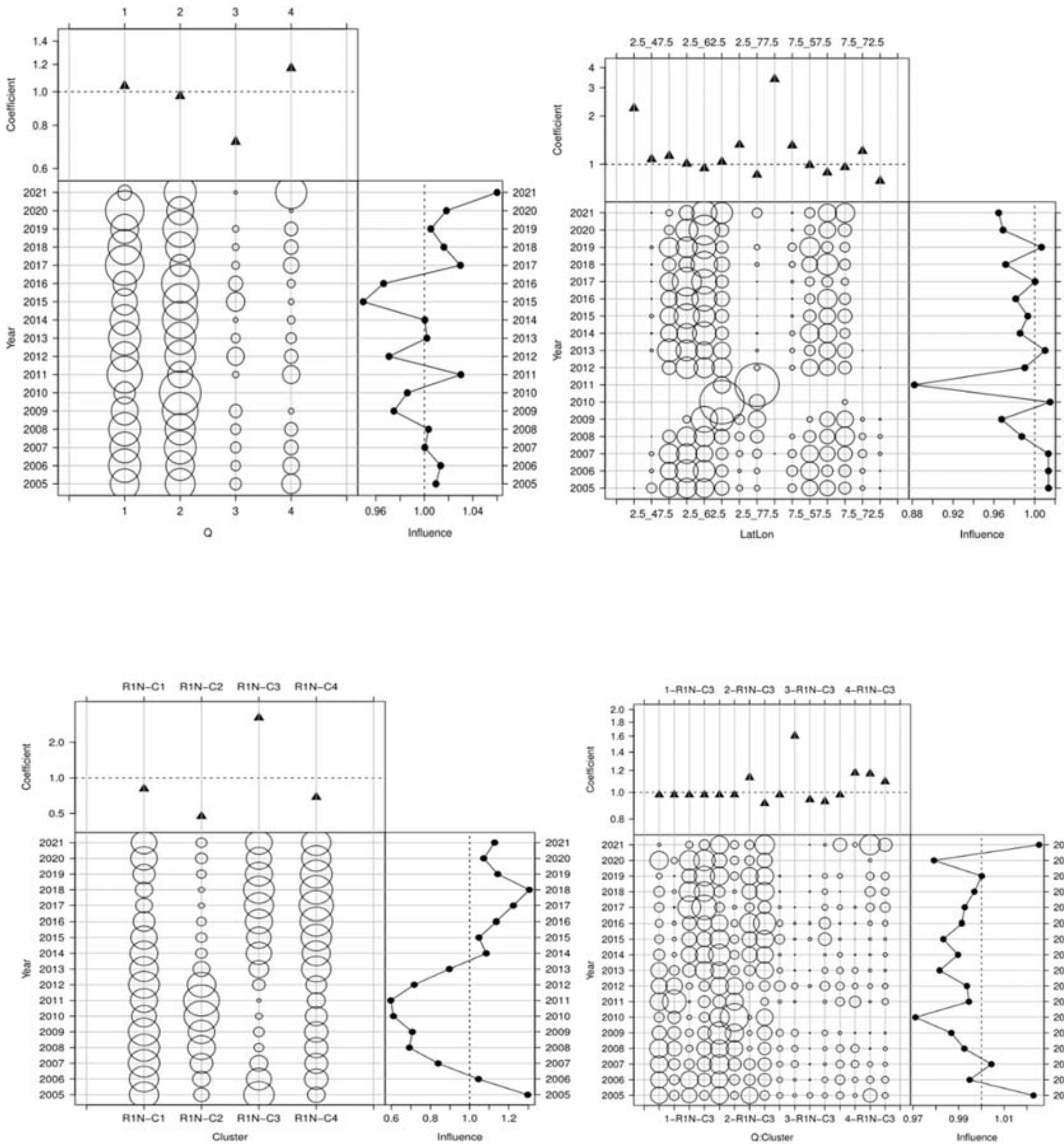

Figure 17. Influence plots for bigeye tuna CPUE in region R1N by the Taiwanese fleet.

R1S

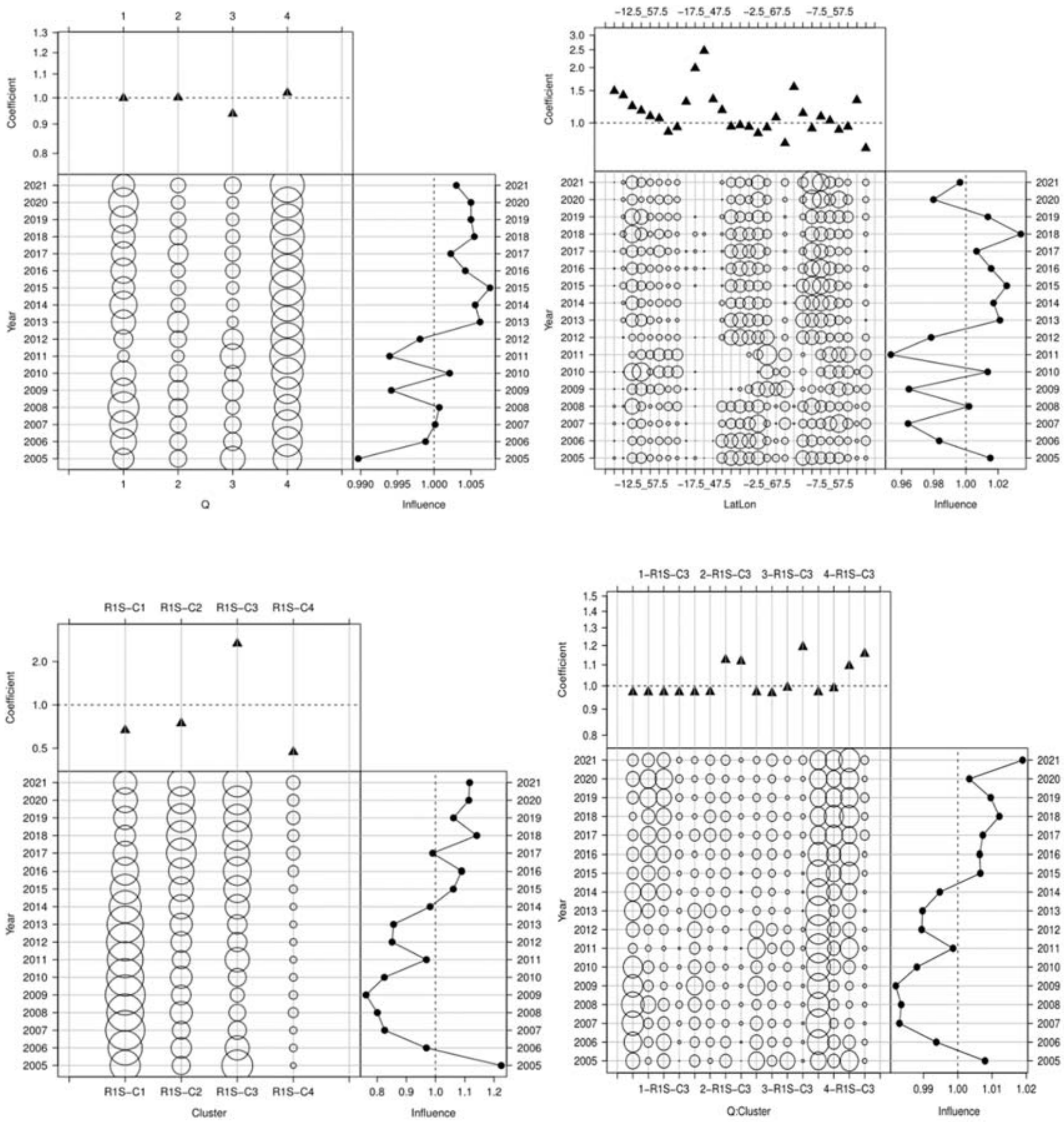

Figure 18. Influence plots for bigeye tuna CPUE in region R1S by the Taiwanese fleet.

R2

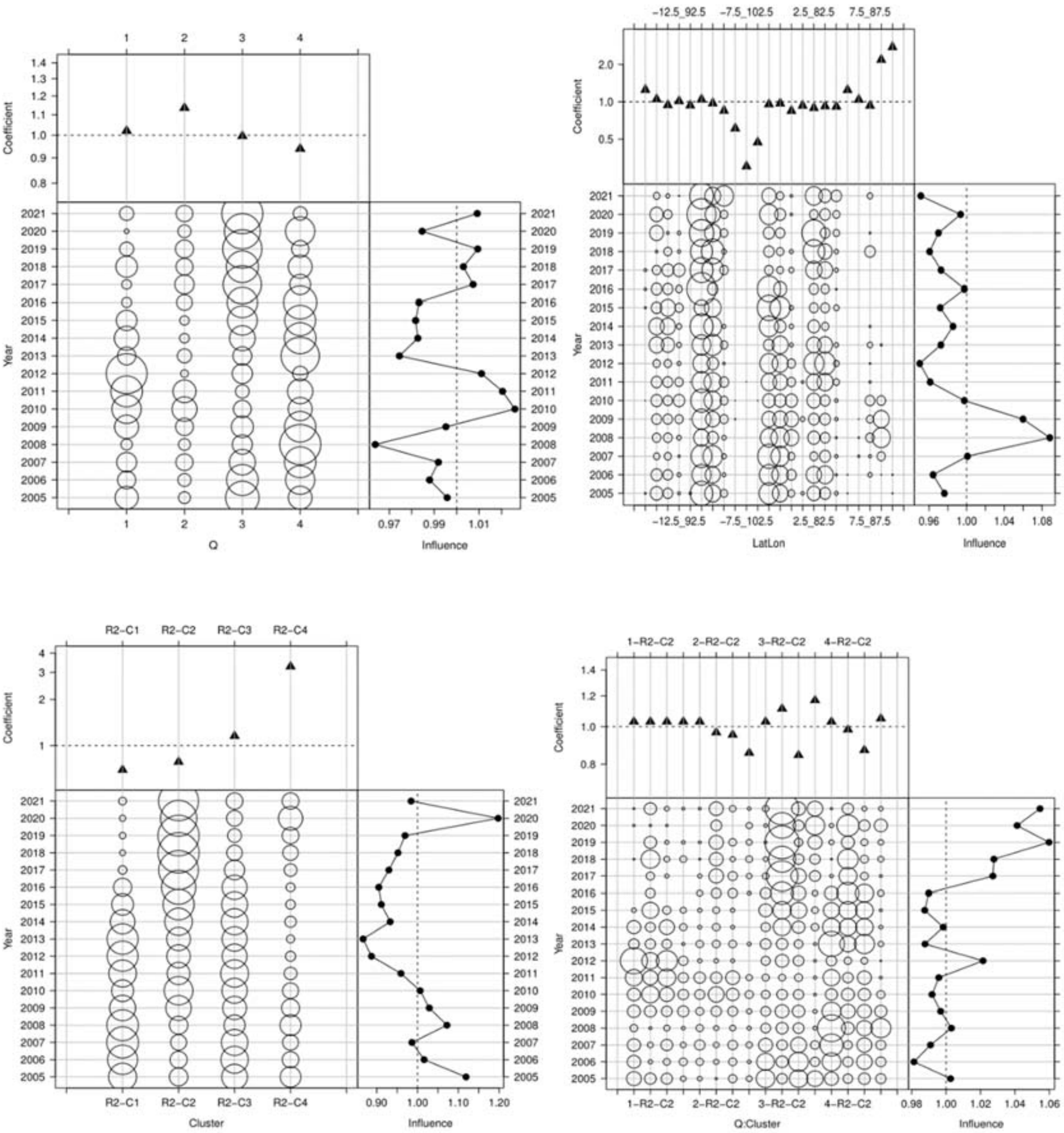

Figure 19. Influence plots for bigeye tuna CPUE in region R2 by the Taiwanese fleet.

R3

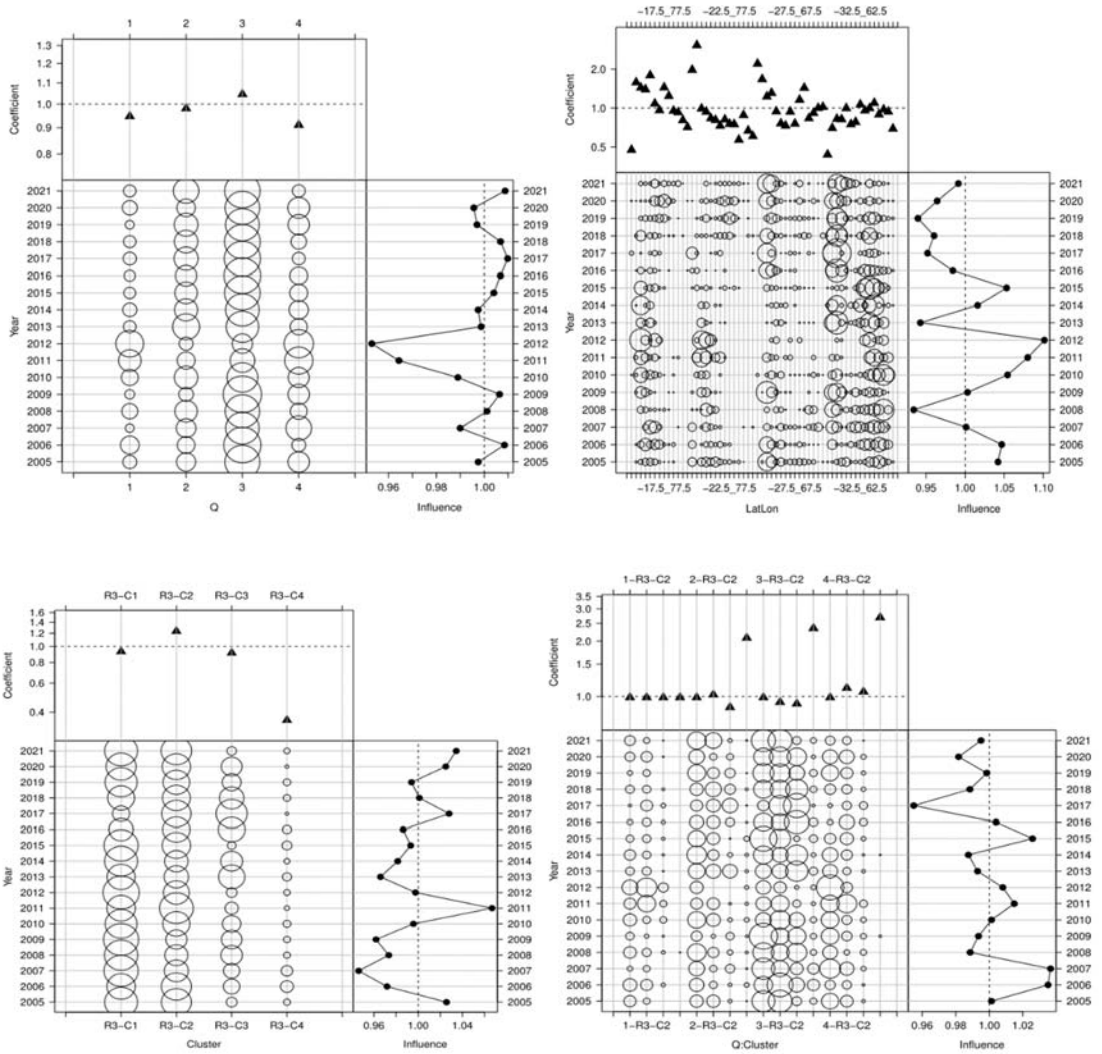

Figure 20. Influence plots for bigeye tuna CPUE in region R3 by the Taiwanese fleet.