Joint CPUE indices for the bigeye tuna in the Indian Ocean based on Japanese, Korean and Taiwanese longline fisheries data up to 2020

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ABSTRACT

Joint CPUE standardization was conducted for the Indian Ocean bigeye tuna based on Japanese, Korean and Taiwanese longline fisheries data up to 2020 to provide the WPTT with information on provisional abundance indices for use in the coming stock assessment for this stock. The intention was to produce combined indices by increasing the spatial and temporal coverage of fishery data. Due to the limitation of remote data access, an approach adopted among the three counties for the previous analyses of tropical tunas for IOTC and ICCAT was used to share only aggregated data. As an underlying analysis, a clustering approach was applied to account for the inter-annual changes of the target in each fishery in each region. For this purpose, a hierarchical clustering method with "fastcluster" was used, and the outputs of the finalized cluster were then used to assign the cluster label on fishery target to each catch-effort data. For standardizing the catch-per-unit-effort data, the conventional linear models and delta-lognormal linear models were employed for the shared aggregated data of monthly and 1° grid resolution in each region. Basically, the trend of CPUE was similar to that for the previous stock assessment. The models were diagnosed by the standard residual plots and influence analyses.

INTRODUCTION

Tuna-RFMOs, including the IOTC, recommended that the joint CPUE of longline fisheries be developed to improve the stock assessments for tropical tunas, and thus the IOTC has conducted collaborative works for several years to produce an abundance index by combining CPUEs data from major longline fleets. An ensemble approach of fishery data from multiple longline fleets has been applied to the tropical and temperate tuna species for their stock assessments (e.g. Hoyle et al. 2018, Hoyle et al. 2019a, 2019b, Kitakado et al. 2021a, 2021b, 2022).

Following these customary practices used in the IOTC and other RFMOs, we conducted a collaborative study for developing provisional abundance indices for the Indian Ocean bigeye tuna based on Japanese, Korean and Taiwanese longline fisheries data up to 2020.

MATERIALS

Data sharing protocol

Under the pandemic circumstance, a data sharing protocol among the three countries adopted for the previous analyses of tropical tunas for IOTC and ICCAT and albacore for IOTC was used with a restriction of data access only by the Chair of the group (Toshihide Kitakado) for reduced resolution of data set (not operational data but some aggregated data over 1° square grid by month by vessel). The data set combined for bigeye tuna CPUE standardization were available from 1975 to 2020, with data fields of year and month of operation, location to 1° of latitude and longitude, vessel id, number of hooks, and catch by species in number. We classified the species into albacore (ALB), bigeye (BET), yellowfin (YFT), southern bluefin tuna (SBT), black marlin (BLM), blue marlin (BUM), swordfish (SWO), other billfishes (BIL), sharks (SKX) and others (OTH).

The data period from the three countries are as follows:

Japan: 1979-2020

Korea: 1979-2020

Taiwan: 2005-2020

Vessel IDs are available from 1975 for Japanese data, but for the consistency with the previous analysis, we used data from 1979.

Figure 1 shows the definition of regions used in the analysis. Figure 2 provides a figure comparing the temporal coverage and similarities/dissimilarities of nominal CPUEs among fisheries data in each region.

Proportion of zero data

Figure 3 provides the time series of positive catch proportions of each fishery data in each region. Except for R3, the proportion of zero catch tends to be small.

METHODS

For clustering analyses to account for the change in target, the data were aggregated by 10-days duration (1st-10th, 11th-20th, and 21st~ for each month) based on the agreement in the data sharing protocol of the trilateral collaborative working group. The number of clusters was determined when the relative improvement of SS within-clusters was less than 10%. See some details shown in Wang et al. (2021).

For standardizing the catch-per-unit-effort data, the conventional linear models and delta-lognormal linear models were employed for data of monthly and 1° grid resolution in each region. Considering relatively small zero-catch proportion, we used the lognormal models except for Region 3. Results based on those models were diagnosed by the standard residual plots and influence analysis. See Table 1 for the list of models with the description below.

Log-normal (LN) regression models with a constant adjustment

We used an adjustment factor (here 10% of mean of CPUE) to the CPUE data to employ conventional log-normal distributions as follows:

$$\log(CPUE + c) = Main\,effects + Interactions + Error$$

Potential covariates used in the analysis were shown below:

- Temporal component (year, quarter, year*quarter)
- Spatial component (5° squared longitudinal and latitudinal grid)
- Vessel ID
- Cluster category
- Interactions between the spatial component and quarter

The error terms are assumed to be independently and identically distributed as the normal distribution with mean 0 and standard deviation σ. The constant adjustment factor, c, is 10% of the overall mean as has been used in previous analyses.

Delta-lognormal (DL) regression model

A delta-lognormal model was also tested to account for "zero data" statistically as has been used in previous analyses (see e.g. Hoyle et al. 2018). For the first component of "zero" or "non-zero" is expressed as a binomial distribution with a probability of "non-zero" catch as a logistic relationship with some explanatory variables, and the second component for positive catch assumed the same regression structures used in the LN regression models with a constant adjustment. The logarithm of the number of hooks was also used in the delta-component of analysis.

Diagnostics and impacts of covariates (Residual plots, Q-Q plots, influence plots)

The standard residual plots were for the diagnosis for fitting of models to the data and Q-Q plots (only for the positive catch component in DL models). In addition, we used influence plots (Bentley et al. 2012) to interpret the contribution of each covariate to the difference between nominal and standardized temporal effects.

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 (as well as the standardized probability of "non-zero" catches in DL models).

RESULTS

Full evaluation of models thought the model selection criterion has not yet reached, but some comparisons of selected results were shown in Figures 4 and 5. Also, the diagnostics and influence plots were shown in Figure 6.

General and specific observations are given below:

- For Regions R1N, R1S, and R2, only the lognormal (LN) model was used. The model "c1v1r0" tended to stabilize, similar to previous estimates used in the 2019 assessment.
- For region R3, in addition to the LN model, a delta lognormal (DL) model was also applied; while the LN model produced a somewhat spiky trajectory, the results based on the DL model appear to be stable.
- While not a perfect match, the std-CPUE series selected for this paper shows a generally similar pattern to the CPUE used previously in the 2019 assessment, as shown in the superimposed figure in Figure 5.
- However, a more careful examination may be needed to understand recent increasing trends in all regions (in regions R1S, R2, and R3, recent data from Japan drives such trends, as does data from Taiwan in R1N).
- There was a reasonable degree of consistency between the cluster information and the estimated coefficients of the target effect.

Caveats:

- The current use of aggregated data means that if there is at least one operation in each data grid (1° grid resolution) for each month of each year in each cluster, all three fisheries' data from three fisheries will be equally weighted in the likelihood. However, the degree of information may vary depending on the actual number of operations. This is one of the disadvantages in analysis with aggregated data.
- The results obtained for R1N show a large spike around 2010, which may be due to piracy effects, but cannot be successfully removed in this analysis. In the stock assessment this year, care must be taken in handling this data this time as in the previous stock assessment.
- As the analysis was preliminary carried out using data up to 2020. The analyses will be finalized once data up to 2021 are shared for use in the 2022 stock assessment.

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Table 1. The list of models used for the quarterly model in this paper.

		Delta-component						Positive-component				
Model	Distribution	YrQtr	LonLat	Target	Vessel	Ln(Effort)	Interaction	YrQtr	LonLat	Target	Vessel	Interaction
c1v1r0	LN							X	X	X	X	
c1v1r1	LN							X	X	X	X	Qtr:LonLat
c1v0e1r0_c1v1r1	DL	X	X	X		X		X	X	X	X	Qtr:LonLat

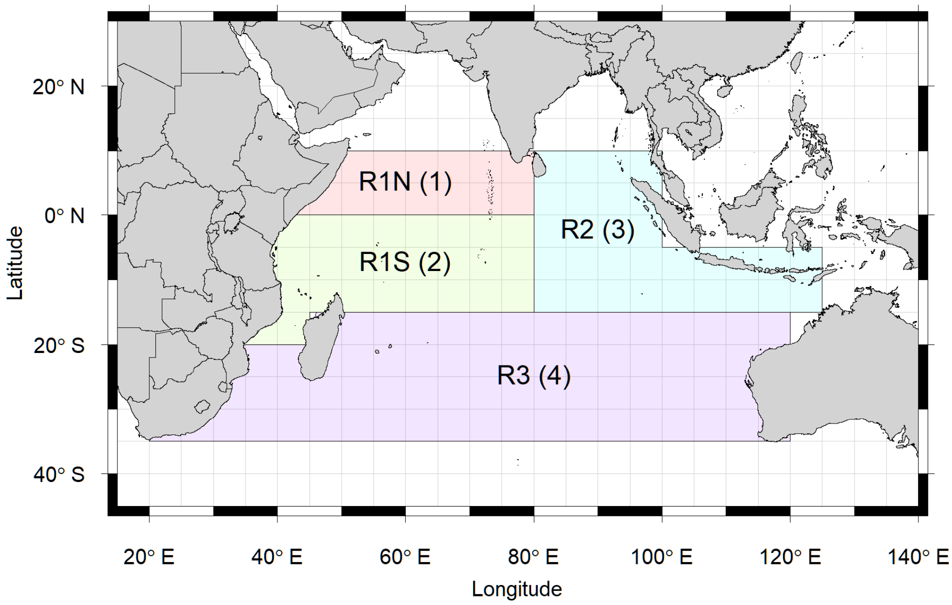
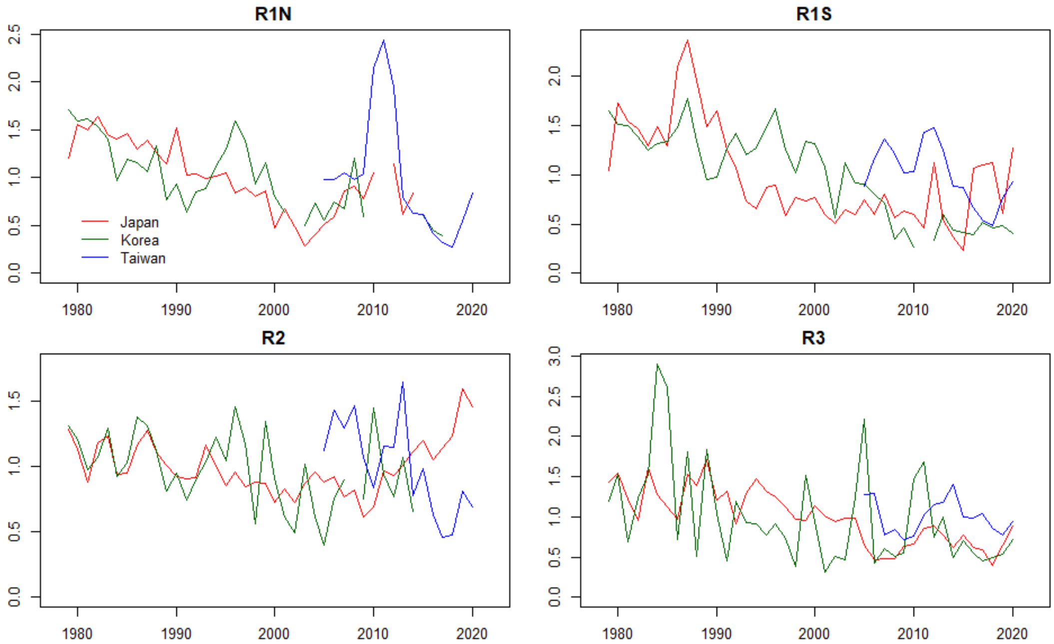


Figure 1. Definition of the regions used in the analysis.

(Annual)



(Quarterly)

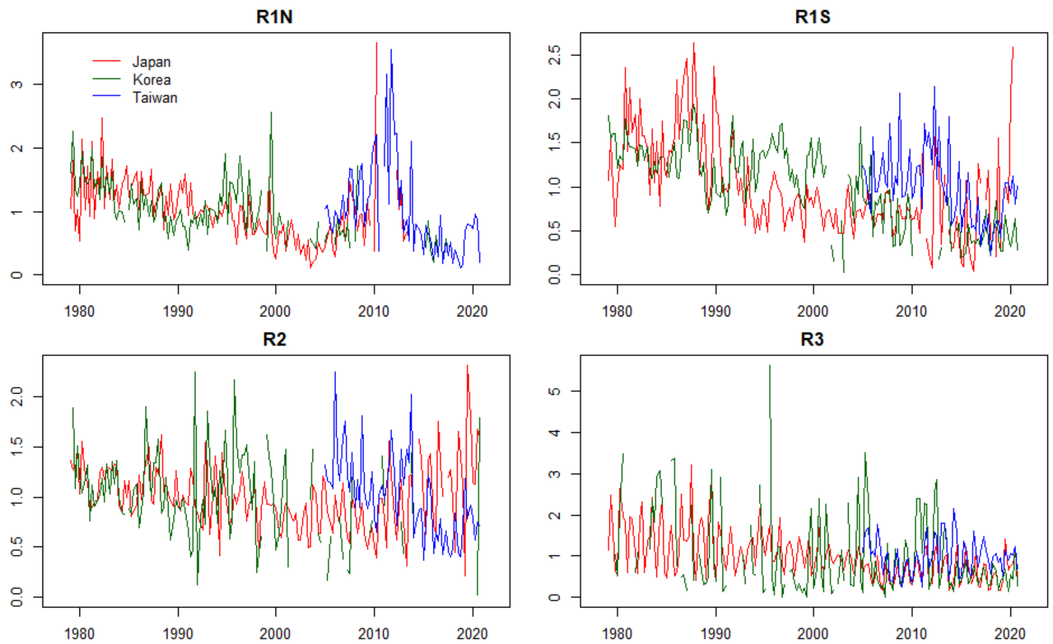


Figure 2. Comparison of time seires among the three fisheries.

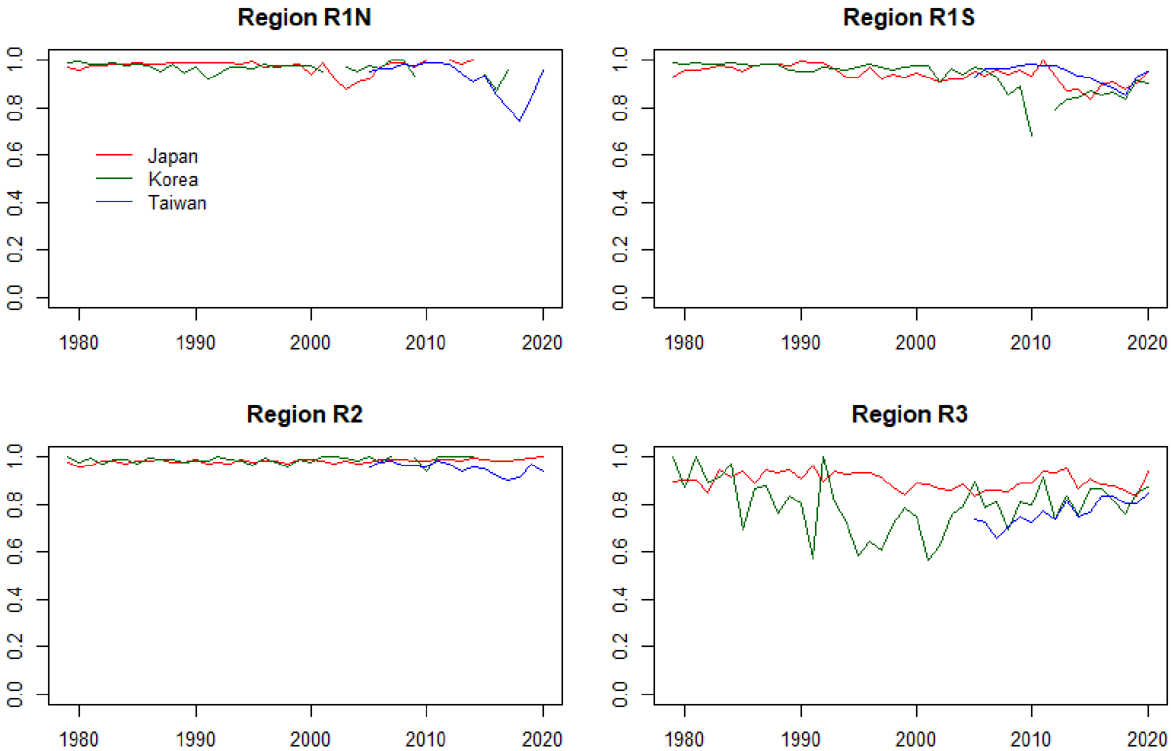
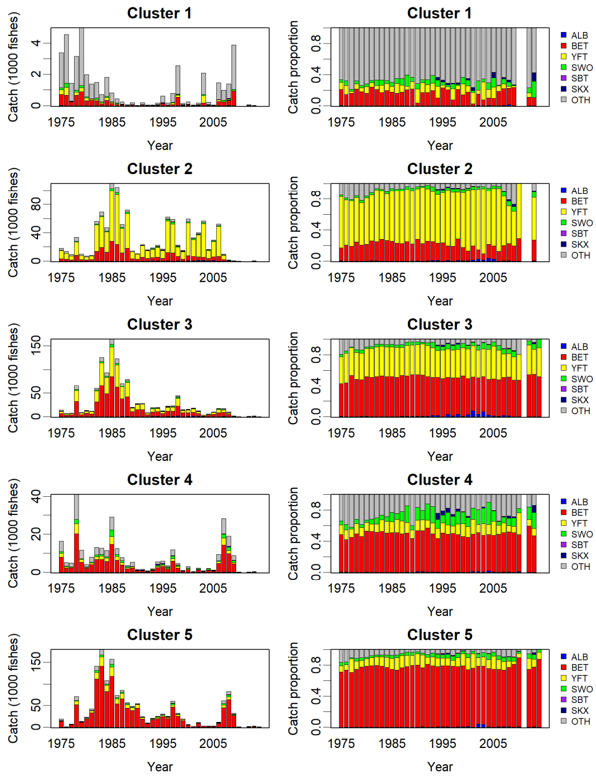


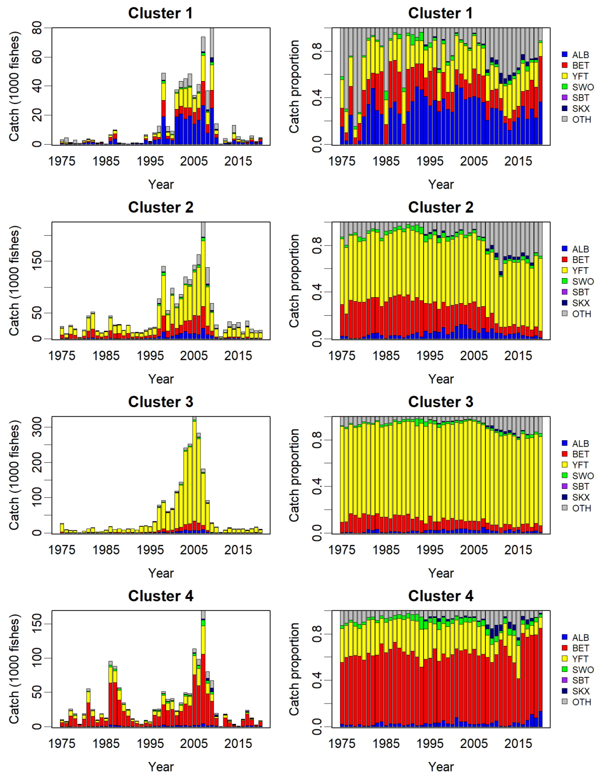
Figure 3 Time series of positive catch proportions of each fishery data in each region.

a) Japan

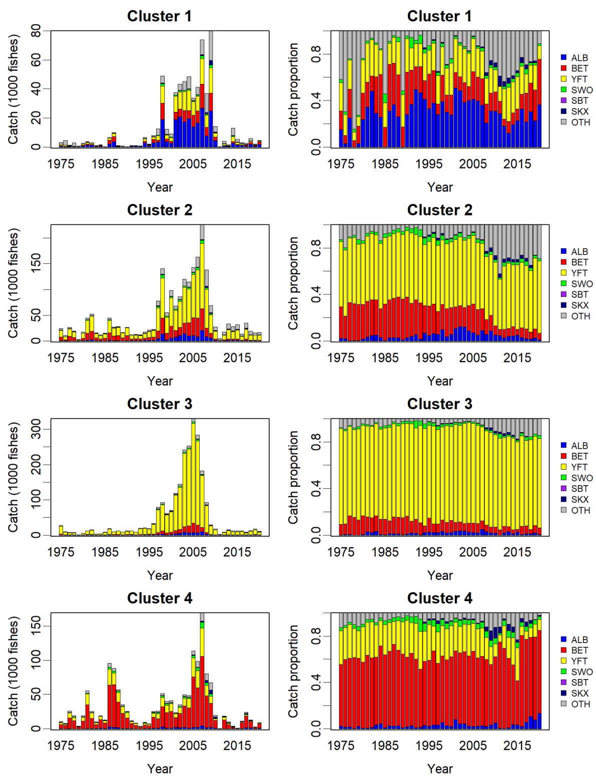
R1N



R1S



R2



R3

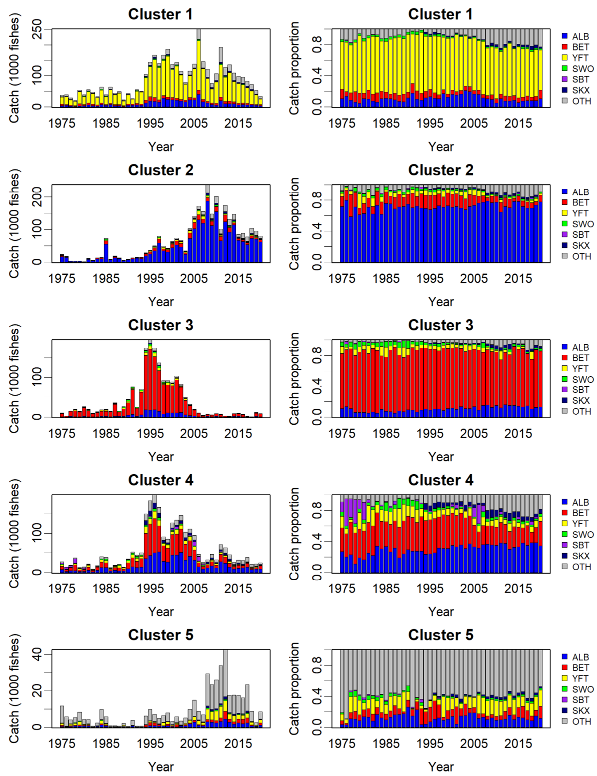


Figure 4(a): Species composition for each cluster in Japanese fisheries.

b) Korea

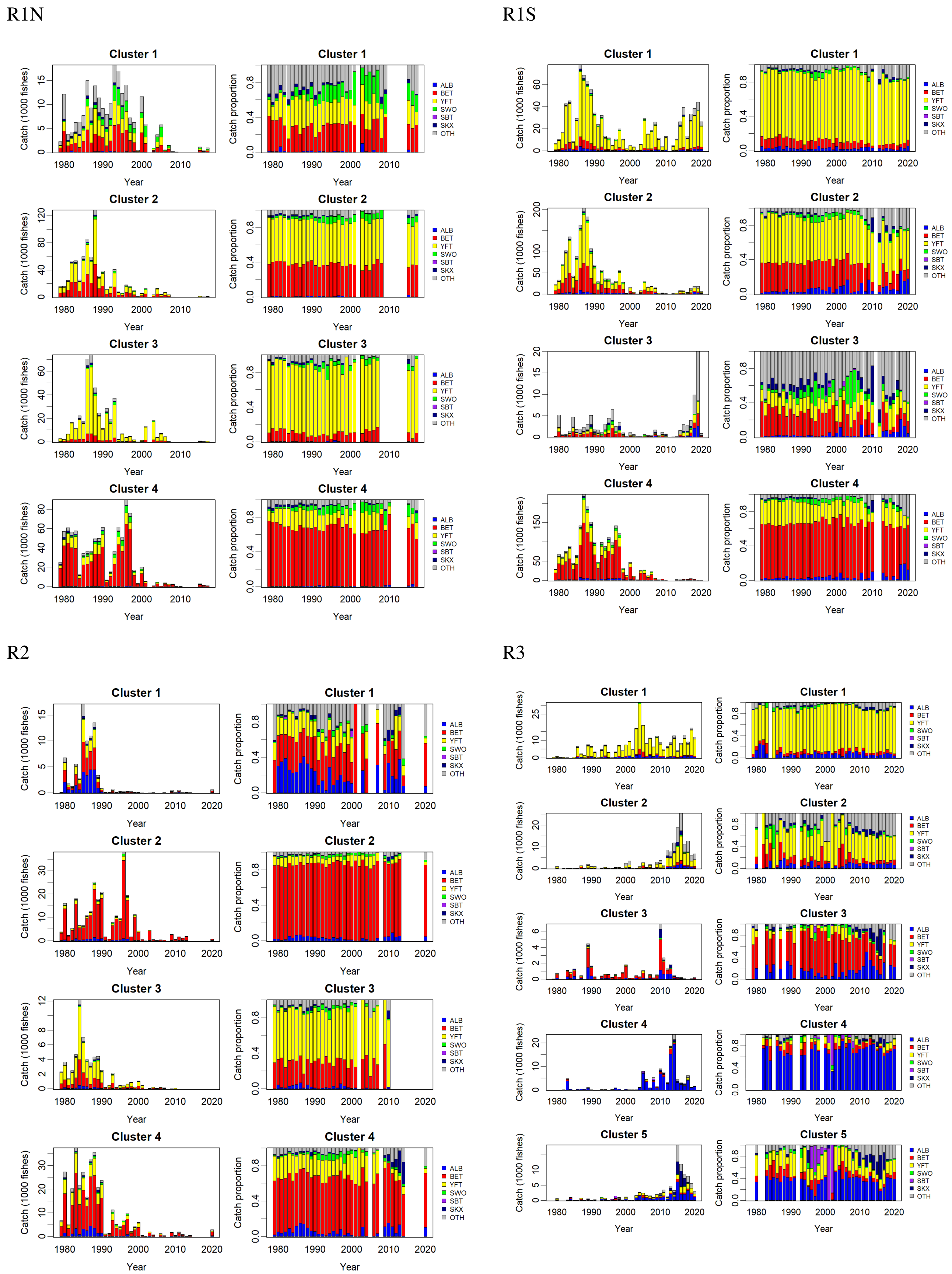
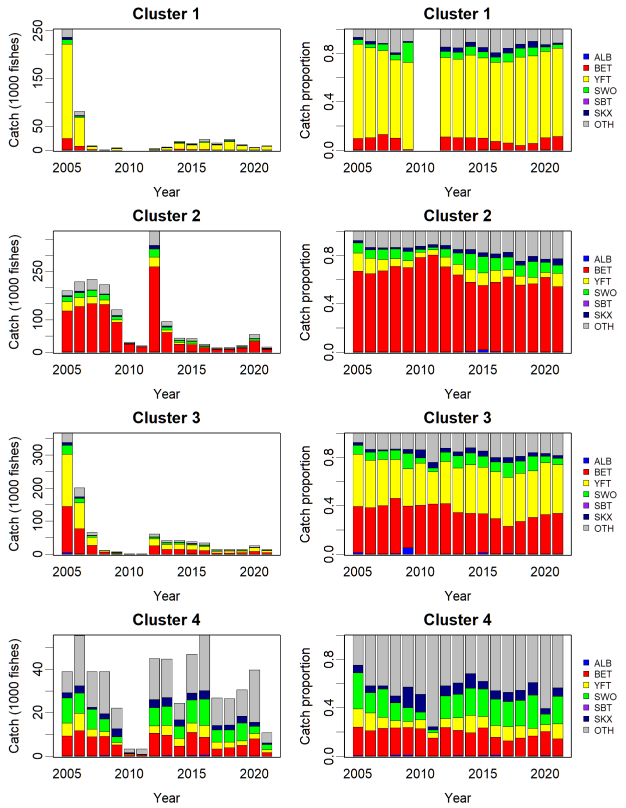


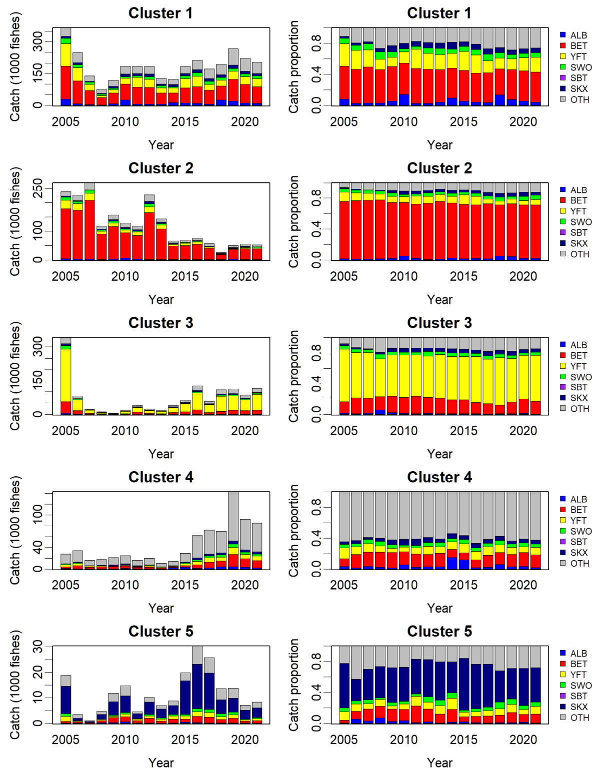
Figure 4(b): Species composition for each cluster in Korean fisheries.

c) Taiwan

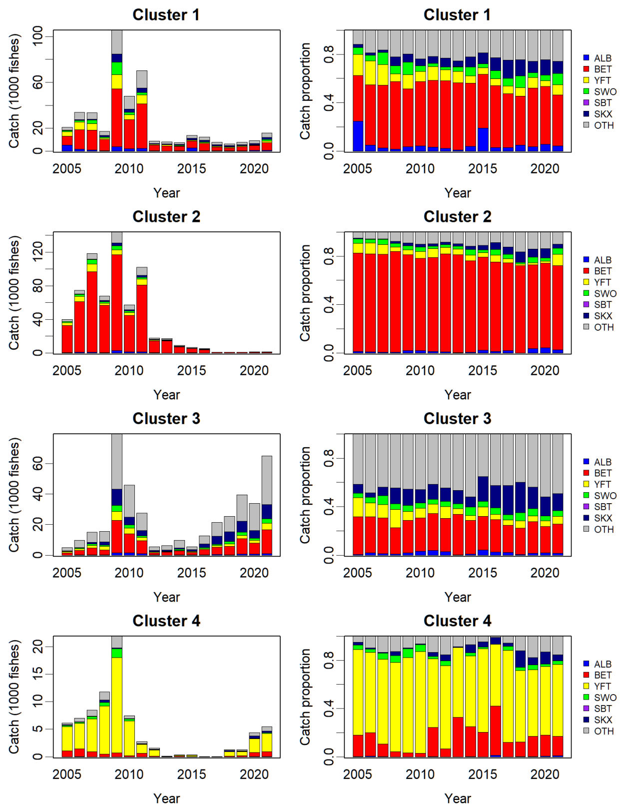
R1N



R1S



R2



R3

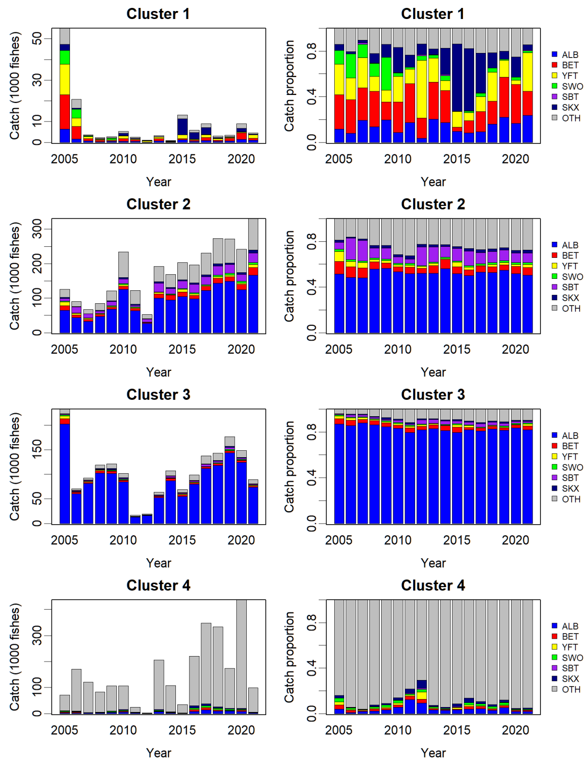
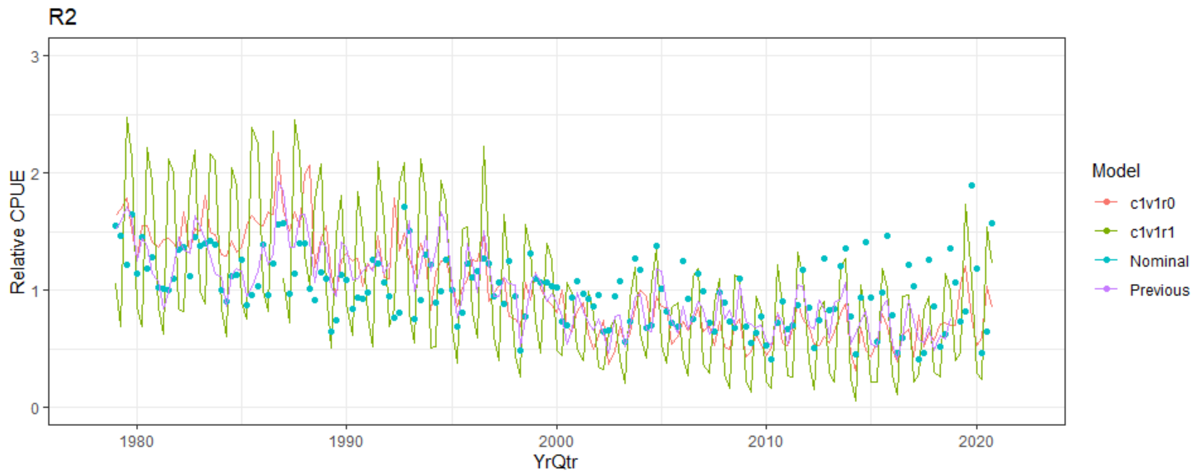


Figure 4(c): Species composition for each cluster in Taiwanese fisheries.

Figure 4(a). Comparison of quarterly (top) and annual (bottom) standardized CPUEs in R1N.

Figure 4(b). Comparison of quarterly (top) and annual (bottom) standardized CPUEs in R1S.



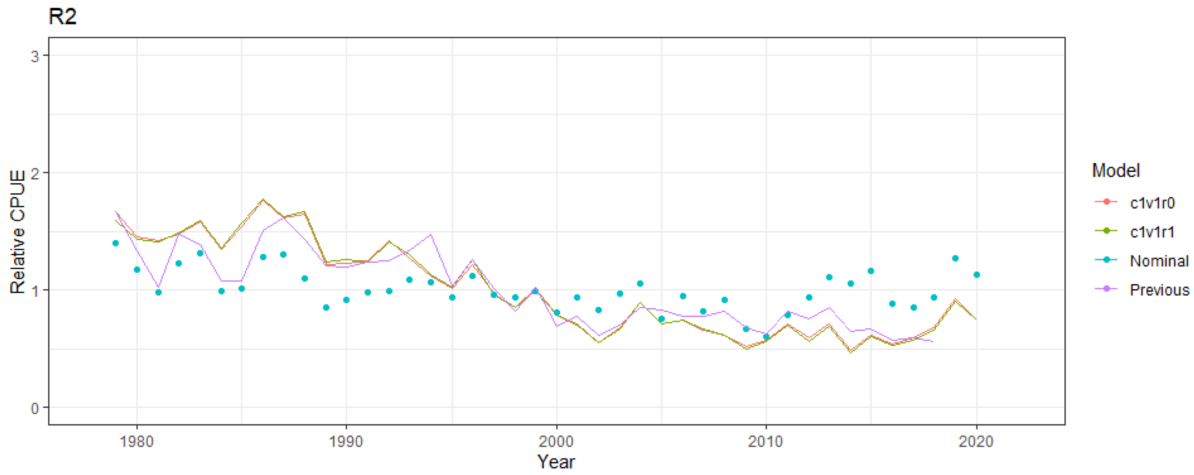
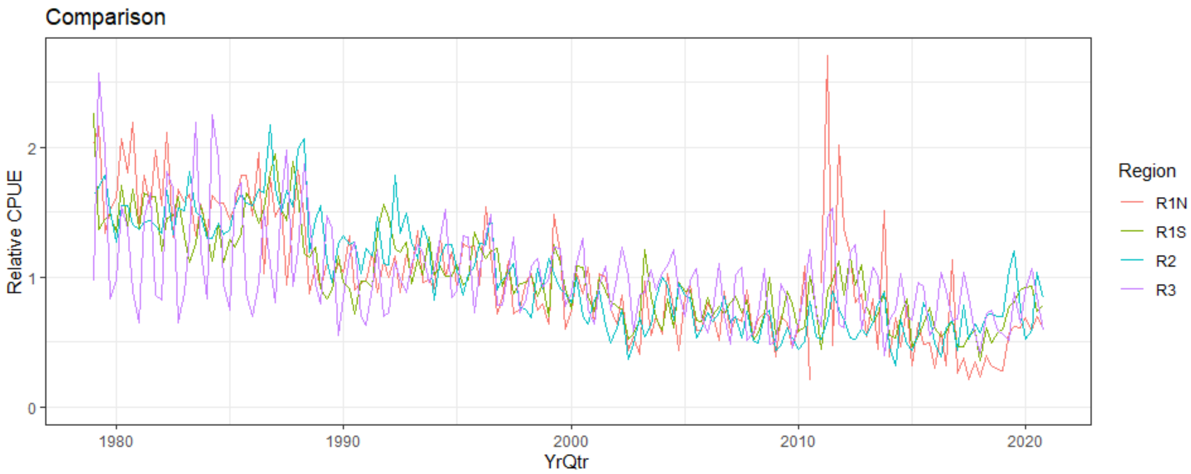


Figure 4(c). Comparison of quarterly (top) and annual (bottom) standardized CPUEs in R2.

Figure 4(d). Comparison of quarterly (top) and annual (bottom) standardized CPUEs in R3.



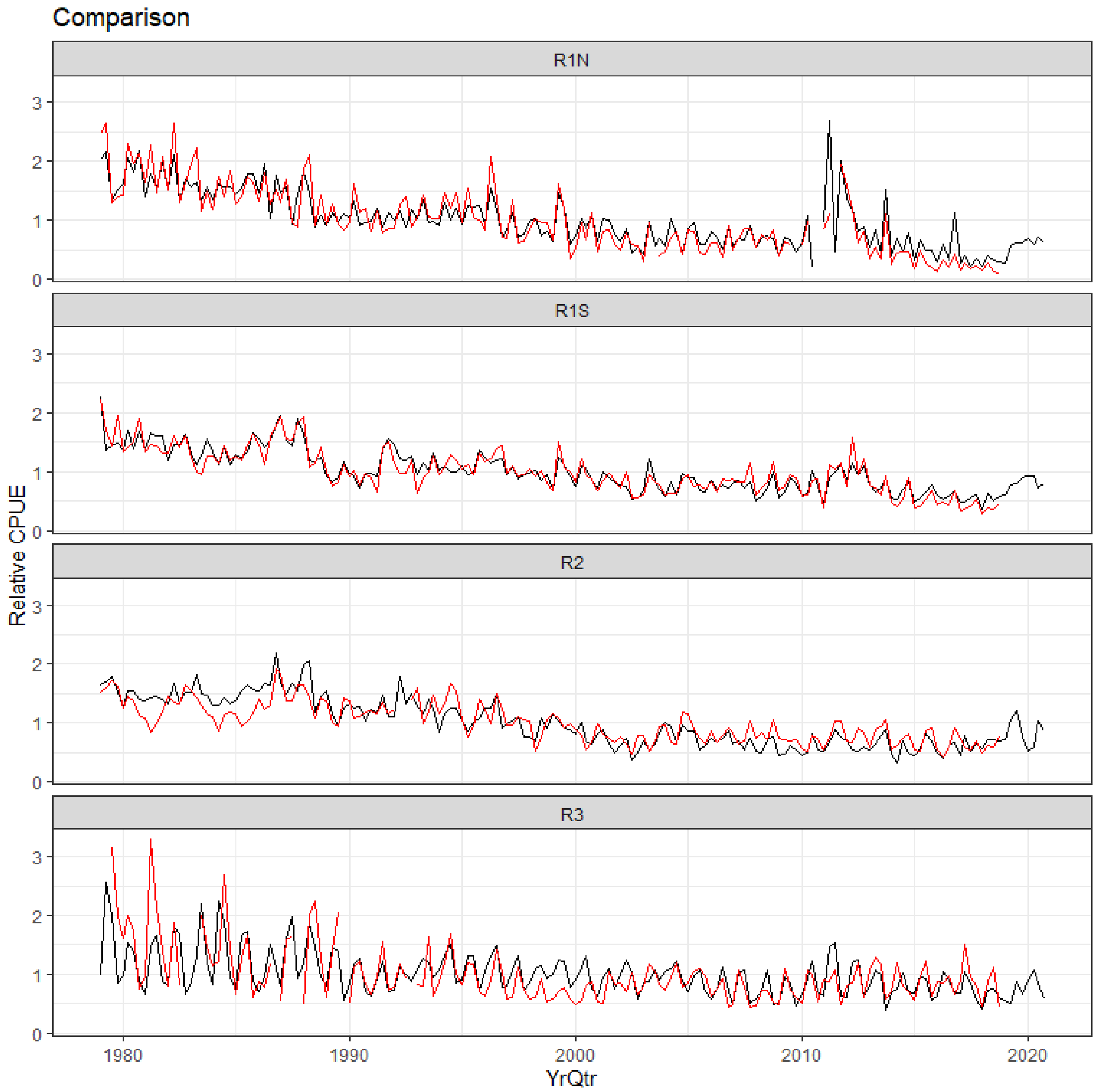


Figure 5(a). Comparison of quarterly region-wise standardized CPUEs (top) and differences between previous (red) and new (black) standardized CPUEs (bottom).

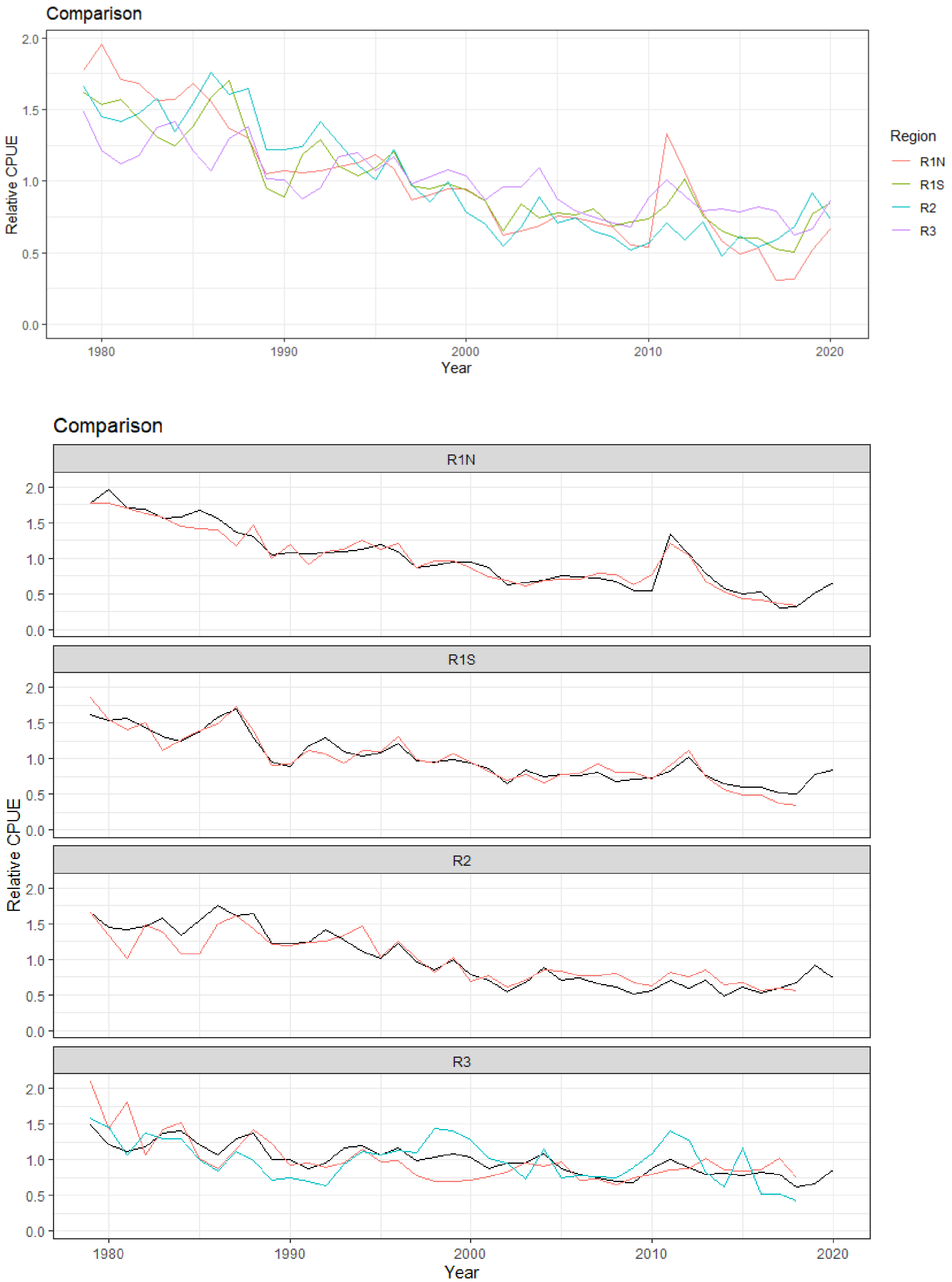


Figure 5(b). Comparison of annual region-wise standardized CPUEs (top) and differences between previous (red or green) and new (black) standardized CPUEs (bottom).

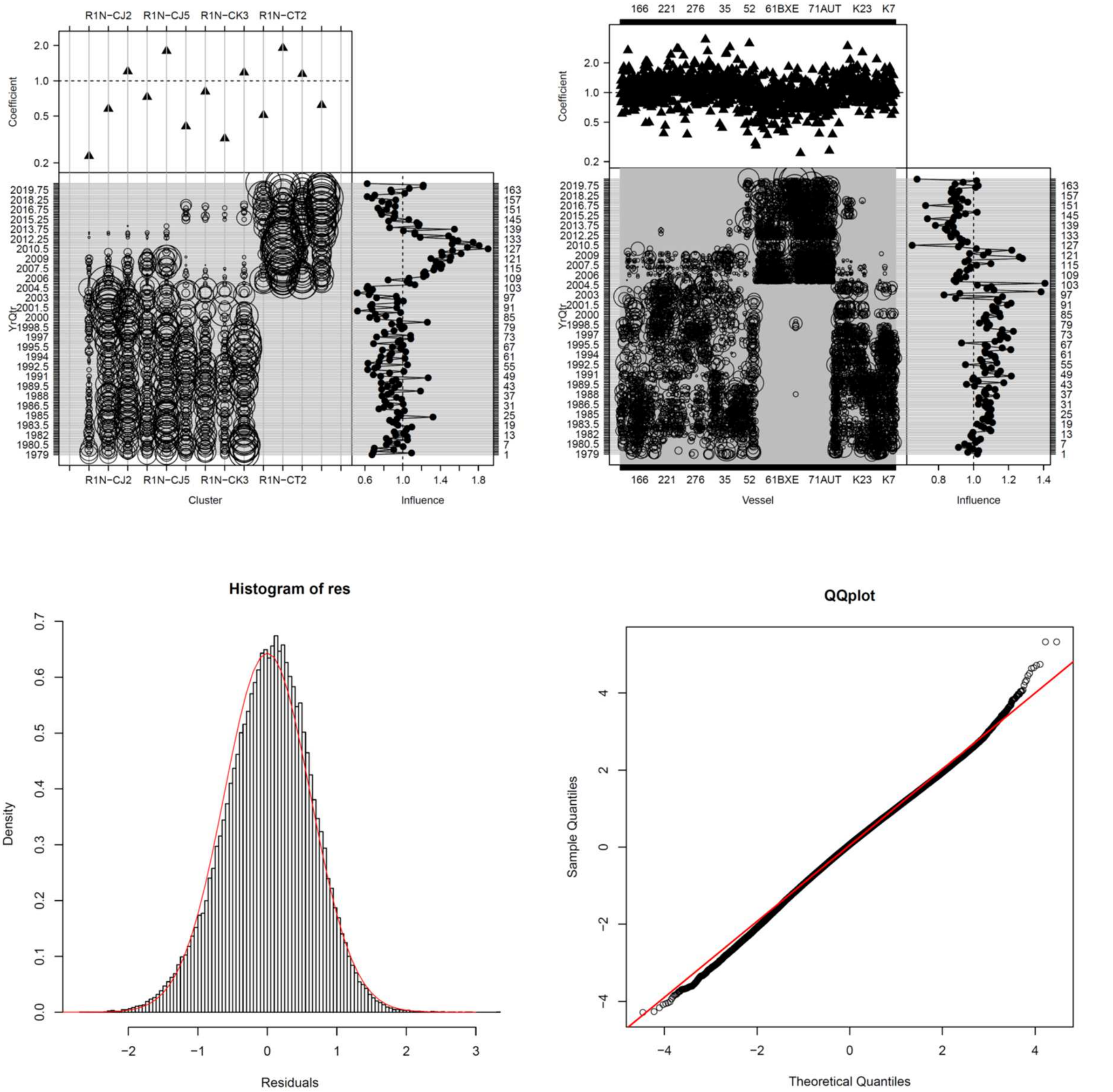


Figure 6(a). Diagnostics and influence plots for the Cluster and Vessel effects for Model c1v1r0 (YrQ + LonLat + Cluster + Vessel) in R1N.

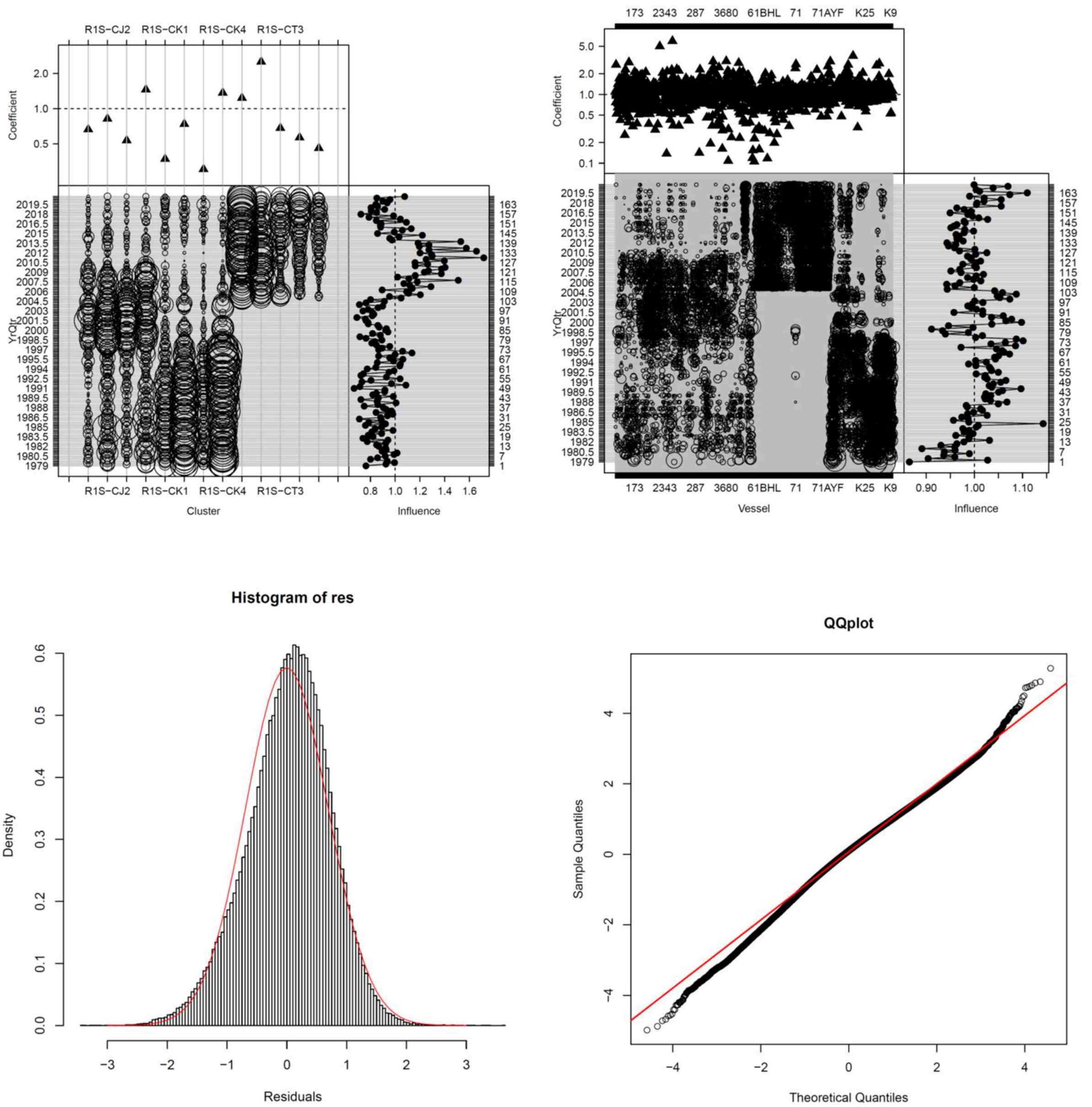


Figure 6(b). Diagnostics and influence plots for the Cluster and Vessel effects for Model c1v1r0 (YrQ + LonLat + Cluster + Vessel) in R1S.

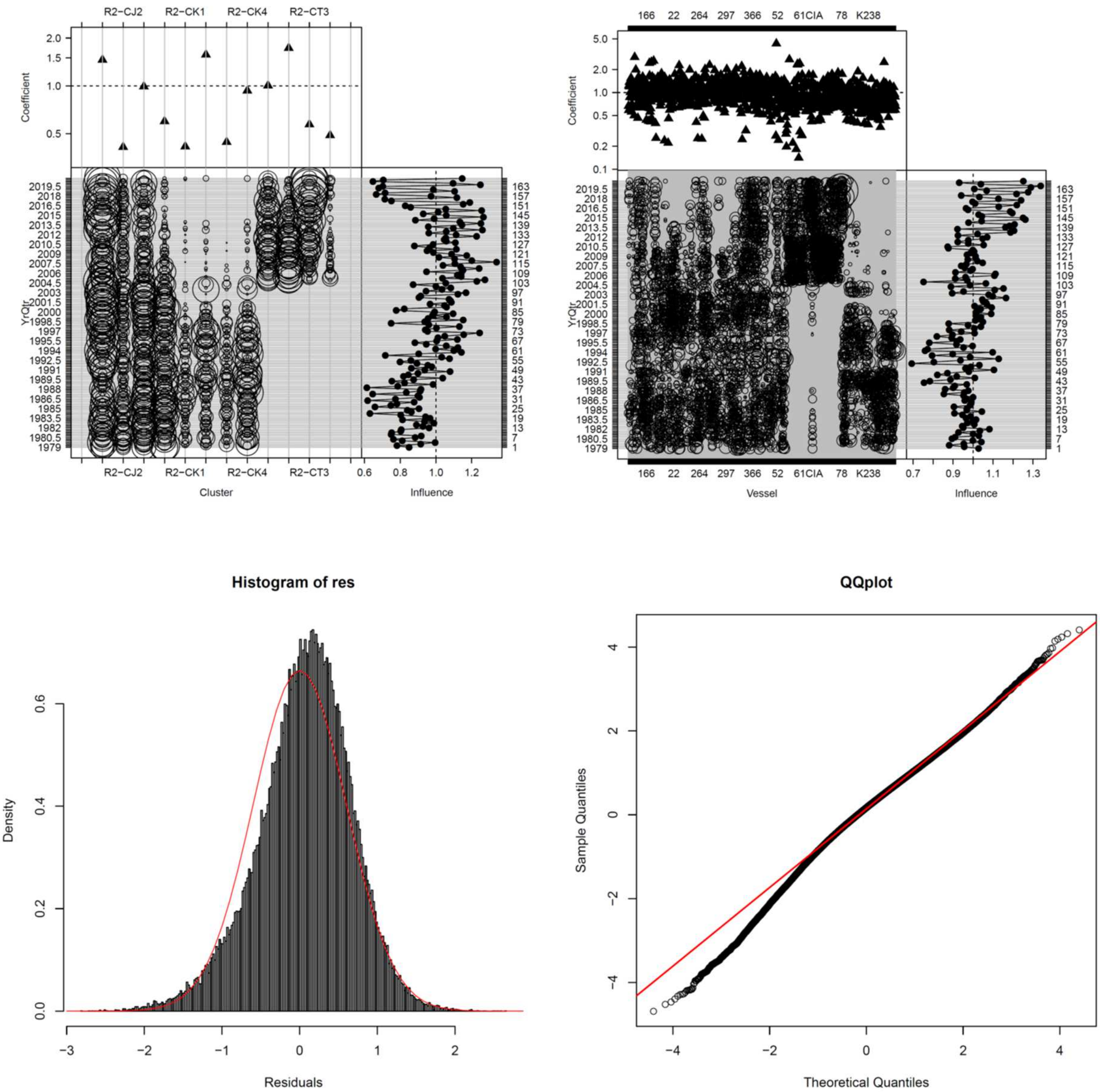
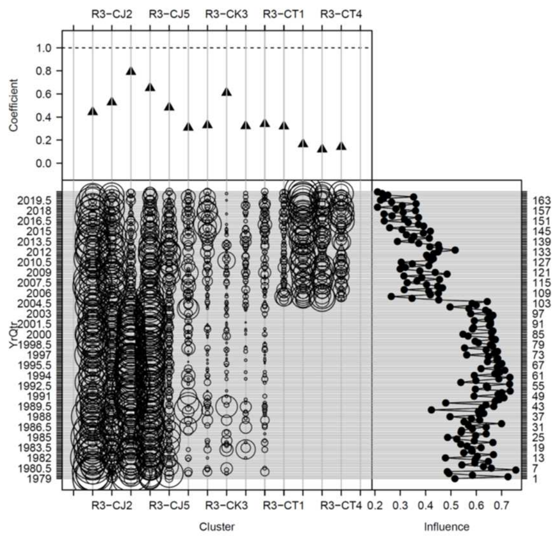
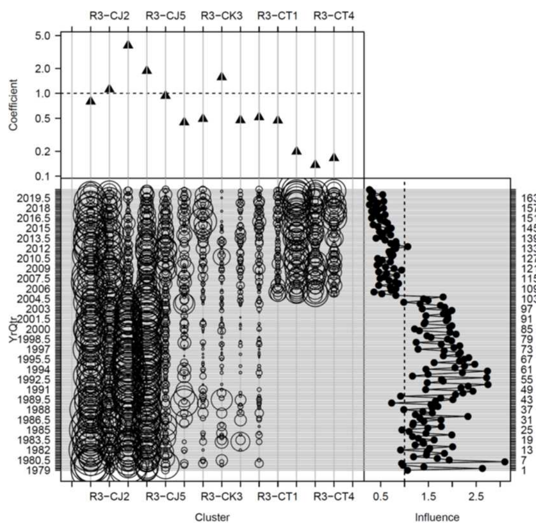


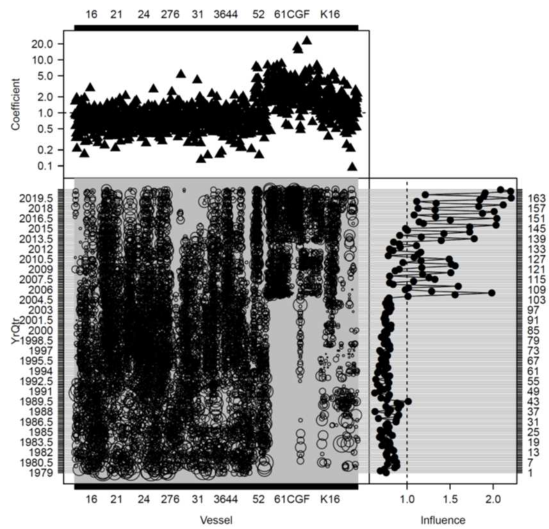
Figure 6(c). Diagnostics and influence plots for the Cluster and Vessel effects for Model c1v1r0 (YrQ + LonLat + Cluster + Vessel) in R2.

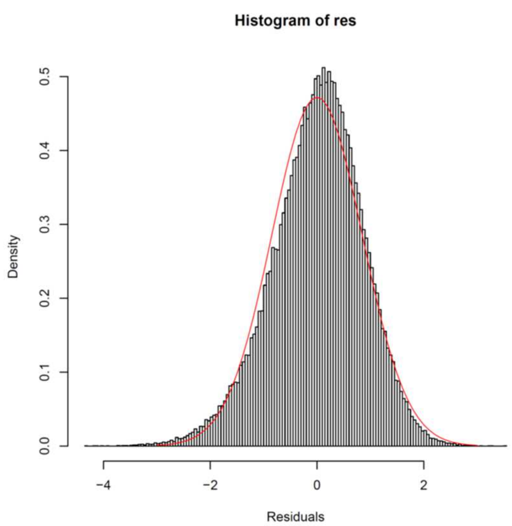
(delta component)



(log-normal component)







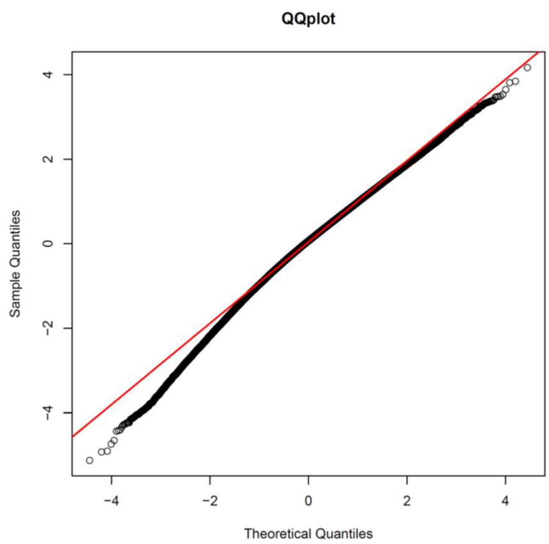


Figure 6(d). Diagnostics and influence plots for delta-lognormal model c1v0e1r0_c1v1r1 (DL~ YrQ + LonLat + Cluster + log(Effort), LN~ YrQ + LonLat + Cluster +Vessel+ LonLat*Q) in R3.