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CPUE analysis for South Pacific albacore

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Executive Summary

Initial work on the development of harvest strategies for South Pacific albacore has focused on developing an empirical management procedure (MP) that uses CPUE as the primary indicator of stock status. This approach relies heavily on the use of CPUE data and is consistent with the focus of recent discussions for the southern longline fishery on catch rates and fleet profitability, as reflected in the economic management objectives that were noted at WCPFC14 (see WCPFC14, attachment K) and in the basis for the TRP that was agreed at WCPFC15 (see WCPFC15, para 207).

Approaches for using CPUE as the primary indicator of stock status are under development and we are still considering the range of options and sources of information available to us. The operational data available for analysis for the 2018 stock assessment cannot be used for MSE modelling given its size and issues of data security. When considering alternative sources of information, it will be necessary to understand how well those data reflect the underlying stock status and their ability to inform the management procedure. This paper therefore examines alternative sources of CPUE data and standardisation approaches to inform this process.

Two approaches are used to standardize CPUE indices based upon aggregate longline catch/effort data: the 'traditional' CPUE analysis and the geostatistical CPUE standardization method. These two approaches are consistent with the 2018 South Pacific albacore stock assessment. The fitness of the model is evaluated based on the diagnostic plot.

The CPUE indices' ability to represent the South Pacific albacore stock adult biomass is also assessed. In addition to the regional longline indices, the CPUE indices from the DWFN and PICT longline fleets are also standardized. The results suggest that the CPUE indices presented here are sufficient to use within the South Pacific albacore MSE framework.

We invite WCPFC-SC to note:

- The ongoing work to develop CPUE inputs that will inform the development of the operating model for South Pacific albacore.
- The potential information available to inform management procedures for South Pacific albacore.

1 Introduction

Initial work on the development of harvest strategies for South Pacific albacore has focused on developing an empirical management procedure (MP) that uses CPUE as the primary indicator of stock biomass. Future work may seek to develop alternative model-based approaches that employ relatively simple assessment models (e.g. surplus production models). Both of these approaches rely heavily on the use of CPUE data and are consistent with the focus of recent discussions for the southern longline fisheries desire for economically viable catch rates, as reflected in the economic management objectives that were noted at WCPFC14 (see WCPFC14, attachment K) and in the basis for the TRP that was agreed at WCPFC15 (see WCPFC15, para 207).

The standardised CPUE series used for the most recent assessment of South Pacific albacore have been calculated from operational catch and effort data (Tremblay-Boyer et al., 2018a). There are, however, a number of potential issues with using these data within the type of simulation framework currently being developed for South Pacific albacore (Scott et al., 2019). Firstly, the dataset is extremely large. Calculations performed on these data can take a long time (in some cases, days) making them unsuitable for use within a simulation framework. In addition, the size of the data files make their transfer across a distributed computing platform less feasible. Secondly, and importantly, the data are subject to a higher level of privacy and security than other datasets held by SPC. These data security agreements do not currently allow for the data to be distributed across a network of machines, either within SPC or remotely. In light of these restrictions on the use of operational catch and effort data we have investigated options for using the raised aggregate (5° x 5°) catch and effort data currently held by OFP-SPC.

In this paper we apply the same (or similar) approaches for the generation of standardised CPUE series for longline fisheries to the raised aggregate data as those conducted for the stock assessment on operational data and we compare the results of the approaches for the two sets of data. The methods considered include the cluster analysis conducted to identify the target species of fishing operations and the calculation of standardised CPUE indices using either a traditional approach or a geostatistical approach.

2 Methods

2.1 Raised aggregate longline catch/effort data

This analysis used raised aggregate longline catch/effort data for the spatial region of the 2018 South Pacific albacore assessment. These data comprise aggregate records of catch/effort, at a year-quarter and five degree resolution for four target species: albacore tuna (ALB), yellowfin tuna (YFT), bigeye tuna (BET) and swordfish (SWO). In contrast the input data for the 2018 South Pacific albacore CPUE standardization (Tremblay-Boyer et al., 2018a) comprised individual records (set-by-set) of fishing activity, at a daily and one degree resolution for ALB, BET, YFT and SWO. A comparison of the two data sets is shown in (Tremblay-Boyer et al., 2018a). In summary, the raised aggregate dataset has a lower temporal and spatial resolution than the data used for the stock assessment analyses and as a consequence vessel identification is at the fleet flag level rather than at the individual vessel identification (ID) level.

Data grooming was applied prior to the standardization to filter out individual records with 0 hooks, more catch (in numbers) than hooks and no catch for any target species. To stay consistent with the 2018 stock assessment, only records within the geographical range from 10°S to 50°S and the temporal span from 1960 to 2016 were included in the analysis.

Dataset	Time	Vessel Identification	Spatial Resolution	Longline Set info
Pacific-wide longline operational dataset	Year-quarter	Vessel ID	One degree	Yes
Raised aggregate catch/effort dataset	Year-quarter	Fleet flag	Five degree	No

Table 1: The comparison between Pacific-wide longline operational dataset and raised aggregate catch/effort dataset.

2.2 Cluster analysis

Previous research has suggested that changes of target species in fishing operations could result in changes in the species specific CPUE (He et al., 1997; Hoyle et al., 2014). Most of the albacore are caught by southern longline along with SWO, YFT and BET. Therefore, the impacts of non-albacore targeting fishing activity should be accounted for when standardizing the CPUE indices. In the 2018 CPUE standardization, a K-mean cluster analysis was used to characterize the target species for a given longline set (Tremblay-Boyer et al., 2018a). For each region we ran the algorithm with 2, 3 and 4 clusters since we only had 4 variables (one for each target species). In 2018, the analysis relied on the aggregated proportion of the four available species (ALB, BET, SWO and YFT) caught by the same flag in a one degree cell in a given month-year in a region (considered to be a 'trip' for the purpose of clustering). For this analysis, the data were aggregated by the same flag in a five degree cell in a given year-quarter in a region. The fitness of each pre-defined number of groups was evaluated using the Elbow method.

2.3 'Traditional' CPUE analysis method

In the 'Traditional' CPUE analysis approach, CPUE indices were standardized by fitting GLM models to each region independently with negative binomial or delta-lognormal errors as described below. Then, the year-quarter effects from these GLMs were extracted to use as standardized indices for a given region. All GLM models were fitted in R via the TMB package (Kristensen et al., 2016). The method used in our analysis is consistent with the previous CPUE standardization (Tremblay-Boyer et al., 2018a).

We use two different classes of model in the traditional method framework. In the negative binomial error distribution, albacore catch-in-numbers was modeled with effort as an explanatory variable with year-quarter and other additional factor variables (including cluster, 5° X 5° cell and fleet flag). In the delta-lognormal error distribution, the GLM was modeled as a two-step process. The probability of having a set with non-zero catch and the CPUE of the catch when positive were modeled separately using a binomial and a log-normal distribution, respectively. The explanatory variables for both steps were identical, including year-quarter, cluster, 5° X 5° cell and fleet flag.

Model fit was assessed by observing the distribution of residuals against model assumptions, and ensuring there were no persistent trends against the covariates used in the model. After evaluations, the configuration of the 'best model' was also used to standardize the DWFN and PICT longline CPUE indices in each region.

2.4 Geostatistical CPUE standardization method

In the geostatistical approach, the spatial correlation was assumed to be a random effect and was fitted by a spatial GLMM with a delta lognormal error distribution. The key difference with the traditional model is that the 5° X 5° cell effect is modeled as a 'geostatistical surface' instead of each cell effect being estimated independently of one another. Also, sets from all regions are included in the same model, instead of running individual GLM models for each region.

The geostatistical surface is fitted assuming a Matern covariance matrix which was used to model the spatial autocorrelation. The surface also requires the definition of knots which are points where the effects are estimated. Each individual record in the data are assigned to the knot which was the closest to them. For more technical details see Thorson (2019) and Tremblay-Boyer et al. (2018a).

The number of knots used in the previous stock assessment was 200 and the explanatory variables include the year-quarter and the targeting cluster (Tremblay-Boyer et al., 2018a). In our analysis, we used the same model framework and tested multiple combinations of the knot size and explanatory variables.

The fitness of the model was examined by diagnosing the distribution of residuals and the reliability of convergence. All analysis was performed in R and the spatial GLMM models were run with the VAST package (Thorson, 2019).

2.5 Stock assessment comparisons

Comparative stock assessments were run across a range of 24 assessment model configurations using the new CPUE indices described in Sections 2.3 and 2.4. The resulting estimates of adult biomass were compared with those obtained from the corresponding 2018 stock assessment model.

3 Results

3.1 Cluster analysis

The results of cluster analyses for two to four pre-defined clusters of each region are shown in Figure 1 to Figure 5. In general, the three-cluster configuration performed best at capturing key spatial and temporal patterns in species targeting. For regions 2 and 5 though, the three-cluster configuration added little extra value so, similar to the approach used for the stock assessment, we retained the two-cluster classification for these regions. These results are consistent with the results from the 2018 albacore stock assessment (Tremblay-Boyer et al., 2018a). The temporal trends in the proportion of trips in each cluster over time from region 1, 2, 3 and 4 display identical patterns to those from the stock assessment. However, temporal trends in the proportion of trips in each cluster over time from region 5 display a slightly different pattern to the stock assessment analyses.

3.2 'Traditional' CPUE analysis method

The results of 'traditional' method for both error distributions (negative binomial and delta-lognormal) suggest an overall declining trend in all regions (Figure 6). Based on the distribution of residuals against model assumptions, (Figure 7, Figure 8), the delta-lognormal model achieves a better overall fit than the model with negative binomial error distribution. This result is different to the CPUE standardization for the albacore stock assessment, where the negative binomial distribution performed better than the delta-lognormal model. However, the overall results using both error distributions are similar to the results from the 2018 analysis.

3.3 Geostatistical CPUE standardization method

We examined multiple combinations of knot size and explanatory variables. Among them, only two models converged with reasonable model configurations. One with the knot size of 200, explanatory variables of year-quarter and spatial autocorrelation, the other one with the knot size of 150, with explanatory variables of year-quarter, spatial autocorrelation and cluster. The results of both CPUE indices indicate declining trends over the time-series (Figure 9). CPUE indices standardized with the 150 knots size display a bigger variances than the CPUE indices standardized with the knot size of 200. In general, the overall results from both models are similar to the results from 2018 analysis.

3.4 Stock assessment result comparison

A comparison of estimates of adult biomass, determined across a range of assessment models and using standardised CPUE indices from either the raised aggregate data or the operational data are displayed in Figure 10 to Figure 15. In total, 24 assessment model configurations were tested although we present only a subset of the results here. In general, the results of stock assessments conducted with standardised CPUE indices calculated from this paper produced comparable estimates of adult biomass to the 2018 stock assessment although for some model configurations estimates of adult biomass were higher, particularly for regions 2 and 5.

For the indices calculated from the traditional approach, those indices standardized with lognormal error distribution and having year-quarter, cluster, flag and 5° X 5° cell as explanatory variables produced the closet estimates of adult biomass to those of the stock assessment (Figure 10 to Fig 12). For the geostatistical CPUE, indices standardized with 200 knots and including year-quarter and spatial effects produced the closest estimates adult biomass compared to the 2018 stock assessment results (Figure 13 to Figure 15).

3.5 CPUE indices comparison

The DWFN, PICT and regional CPUE indices standardized with the traditional and geostatistical method are displayed in Figure 16 and Figure 17. The comparisons among three CPUE indices suggest similar patterns for both methods. The DWFN CPUE indices have longer time-series. Meanwhile, the PICT CPUE indices are only available in the late 1990's and appear to have slightly higher values in the early period of time-series. Overall, both DWFN and PICT indices are highly correlated with their regional indices.

The comparison between the traditional and geostatistical CPUE indices is shown in Figure 18. Both indices display declining trends over the time-series. The traditional CPUE indices display more variance than the geostatistical CPUE indices. The implications of this variability for the performance of any management procedure will need to be evaluated.

4 Discussion

The results of the cluster analysis display almost identical cluster compositions in all regions except region 5. It suggests that data used in our analysis are sufficient to capture the characteristics of the target species even though the spatial resolution is coarse. The difference we observed in region 5 could result from the limited records in the raised aggregate catch/effort dataset in this region. It also suggests that methods that could fill in the time gap (e.g. geostatistical method) should be preferred when standardizing CPUE in this region.

The configuration of the 'best model' selected from both traditional and geostatistical approach in our analysis are different from the previous CPUE standardization (Tremblay-Boyer et al., 2018a), likely due to the difference between two input datasets. However, the CPUE indices standardized with the 'best model' from both methods are able to capture the South Pacific albacore stock status (Tremblay-Boyer et al., 2018b). In addition, the DWFN and PICT CPUE indices show similar patterns to the regional CPUE indices. Therefore, we can conclude that CPUE indices standardized using the raised aggregate data (including DWFN and PICT longline CPUE) are sufficient to be used in the albacore MSE framework.

We note that the development of the albacore MSE framework is ongoing and that options for using CPUE within the management procedure are currently under investigation.

If the standardised CPUE indices used for the assessment are used to inform the management procedure then the standardisation of alternative CPUE indices may not be necessary.

Acknowledgments

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5 Figure

Region 1

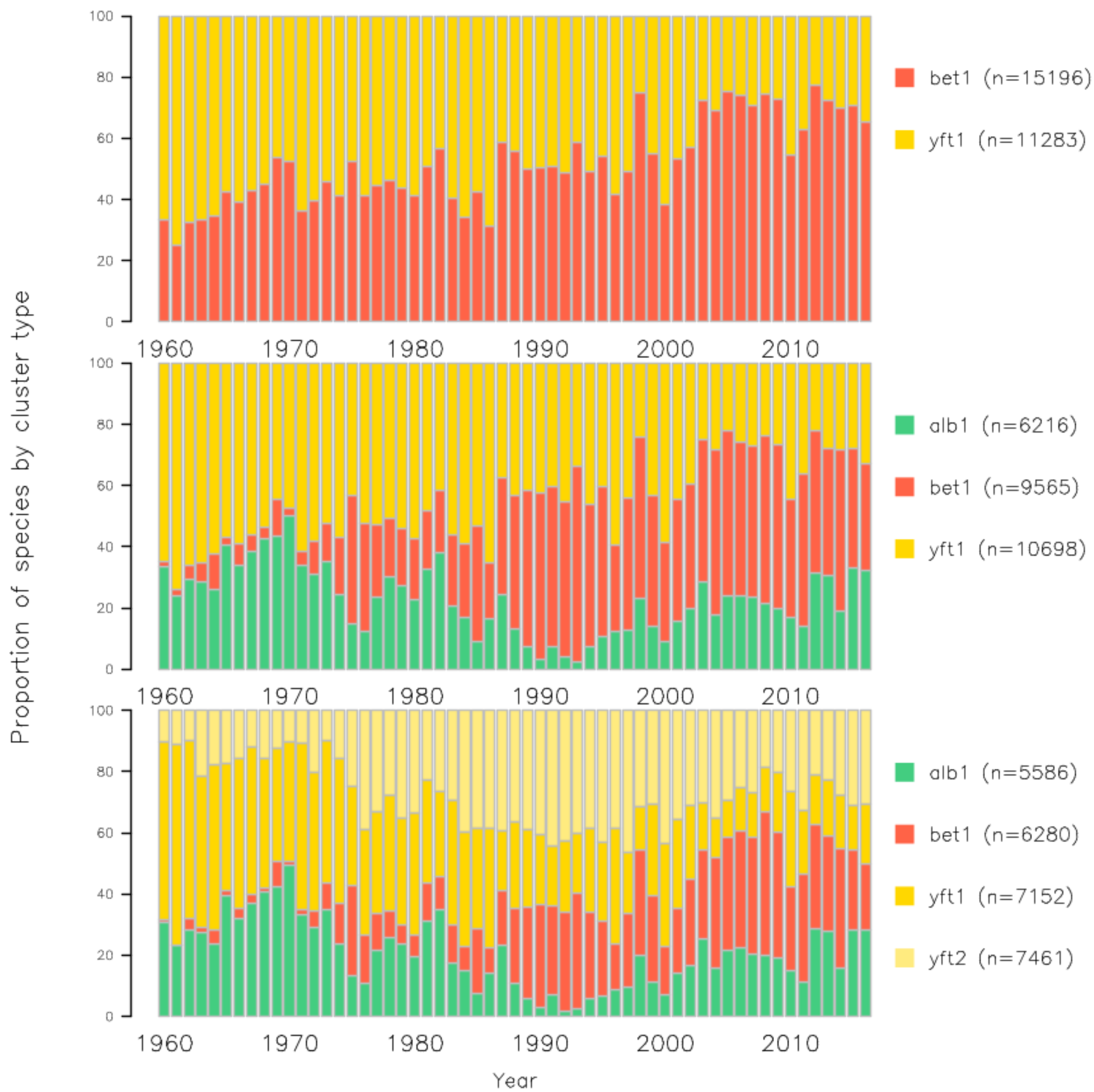

Figure 1: Time-series of cluster membership for the 2, 3 and 4 cluster models in region 1, with the colour matching the most dominant species in the cluster.

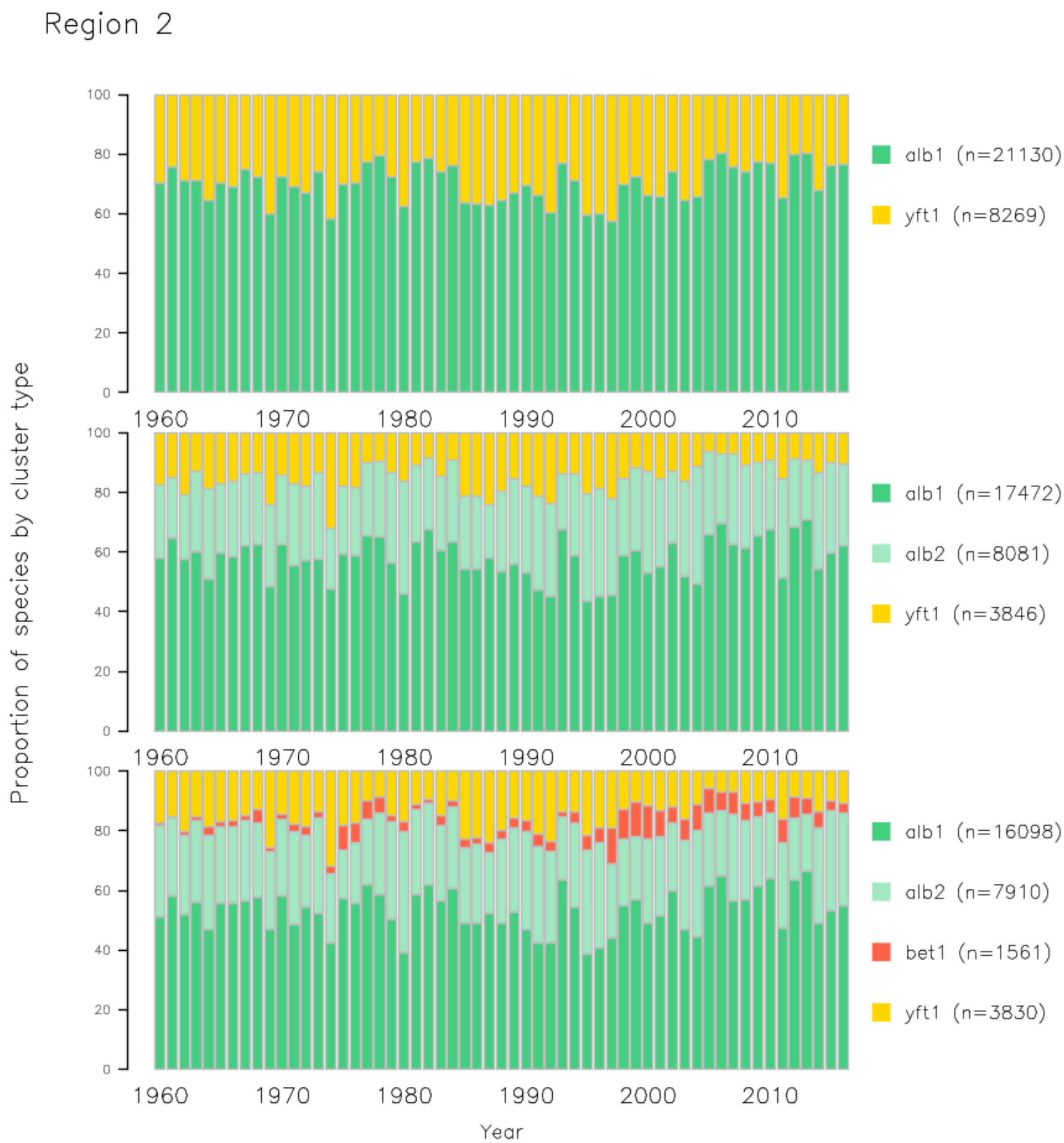

Figure 2: Time-series of cluster membership for the 2, 3 and 4 cluster models in region 2, with the colour matching the most dominant species in the cluster.

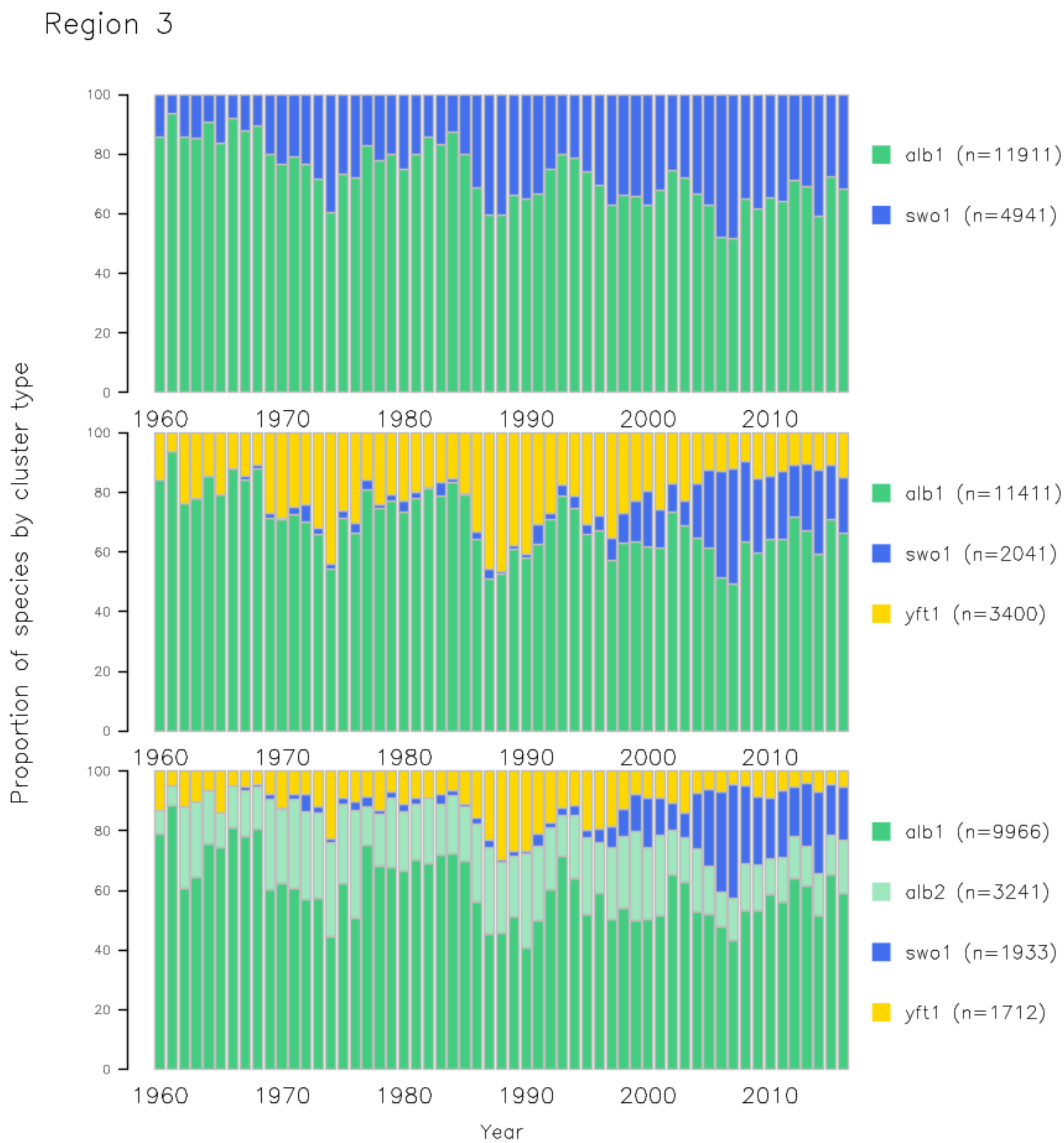

Figure 3: Time-series of cluster membership for the 2, 3 and 4 cluster models in region 3, with the colour matching the most dominant species in the cluster.

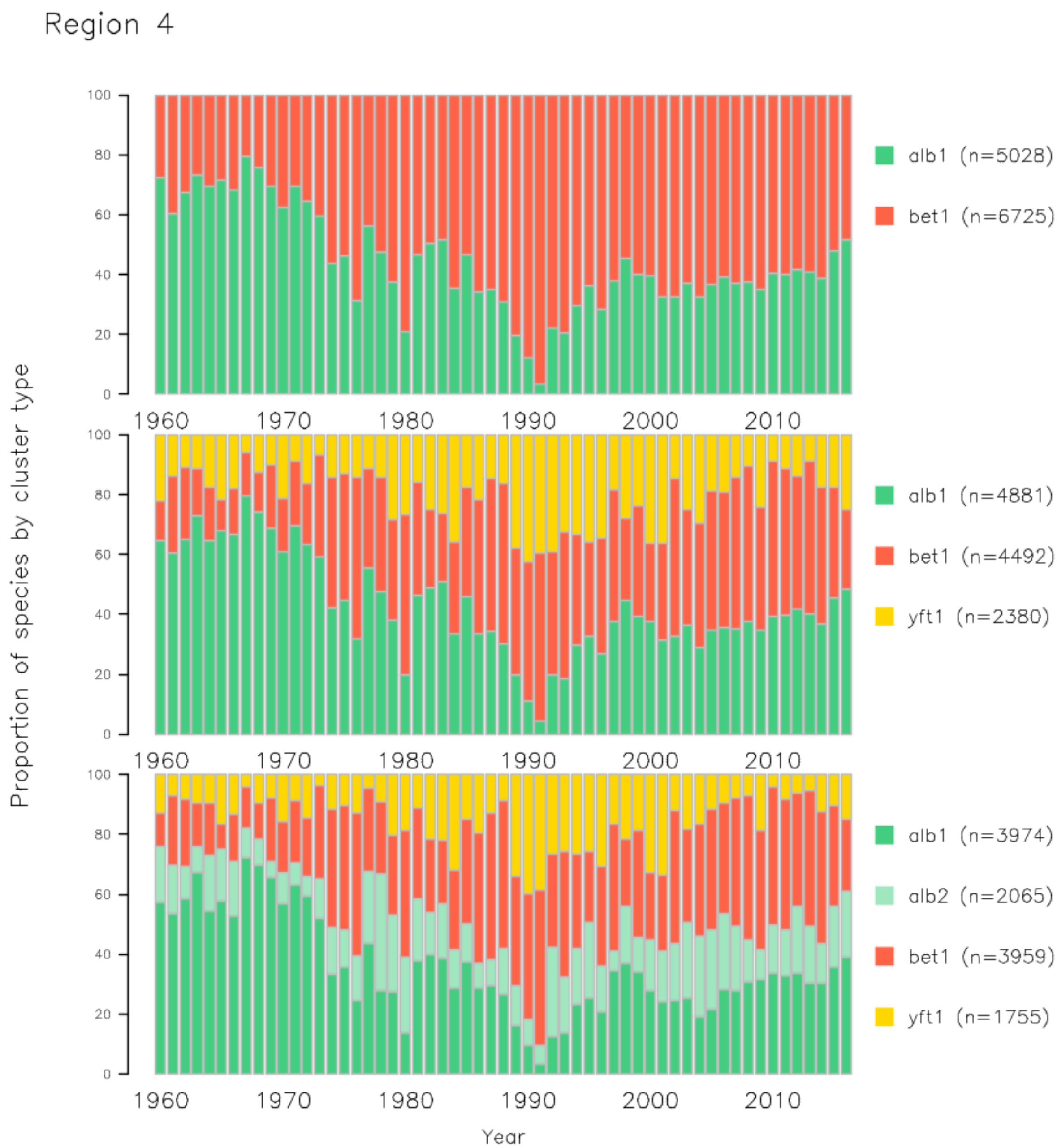

Figure 4: Time-series of cluster membership for the 2, 3 and 4 cluster models in region 4, with the colour matching the most dominant species in the cluster.

Region 5

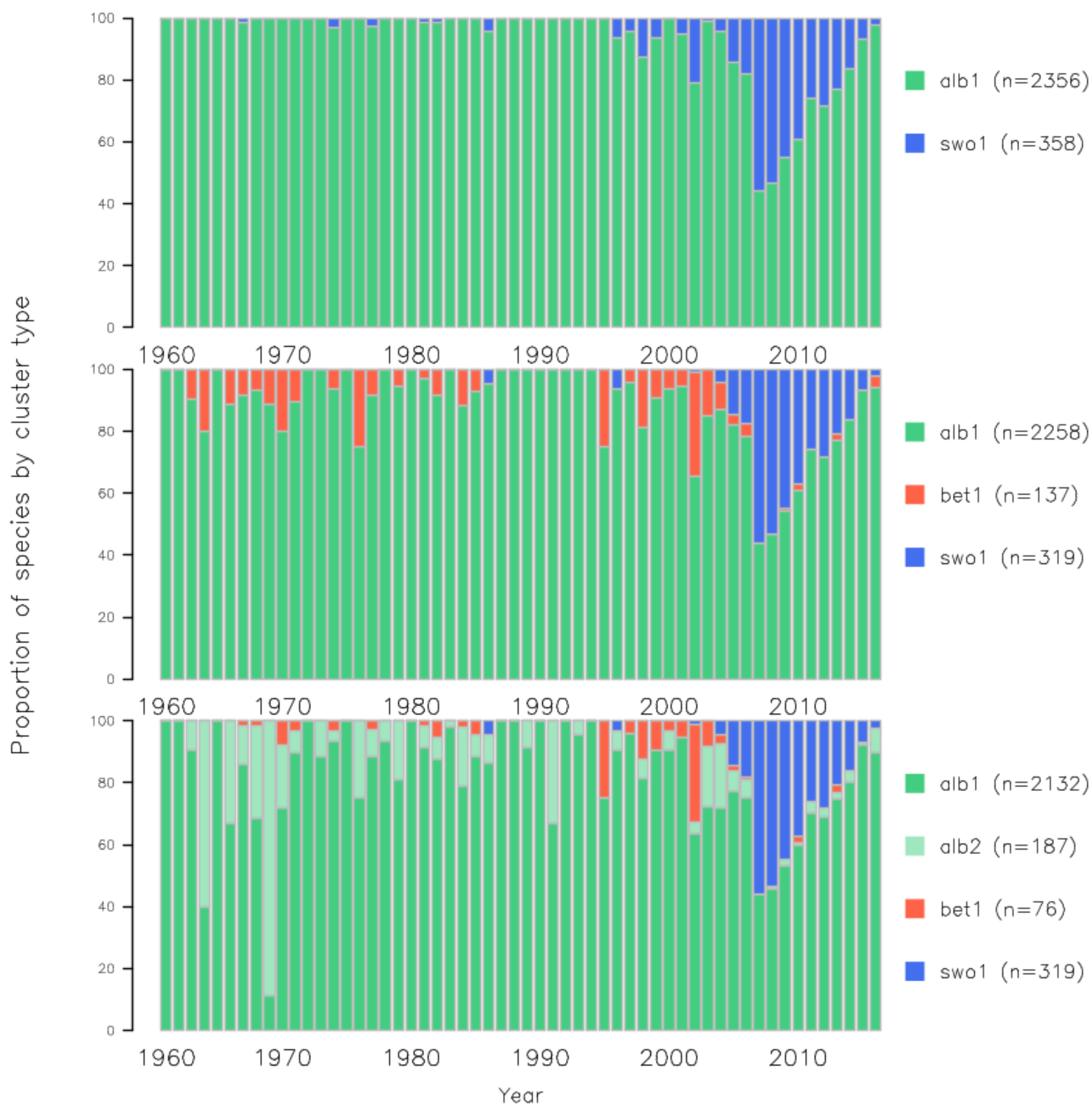

Figure 5: Time-series of cluster membership for the 2, 3 and 4 cluster models in region 5, with the colour matching the most dominant species in the cluster.

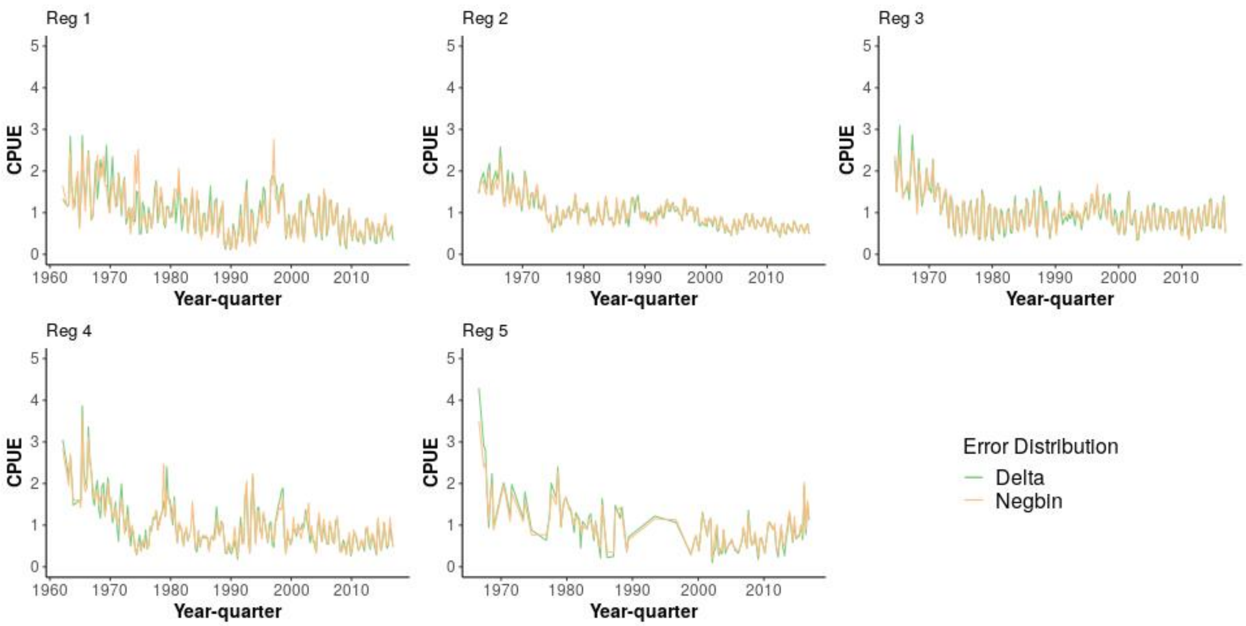

Figure 6: Time-series of two "traditional" CPUE indices standardized with delta-lognormal and negative binominal error distribution.

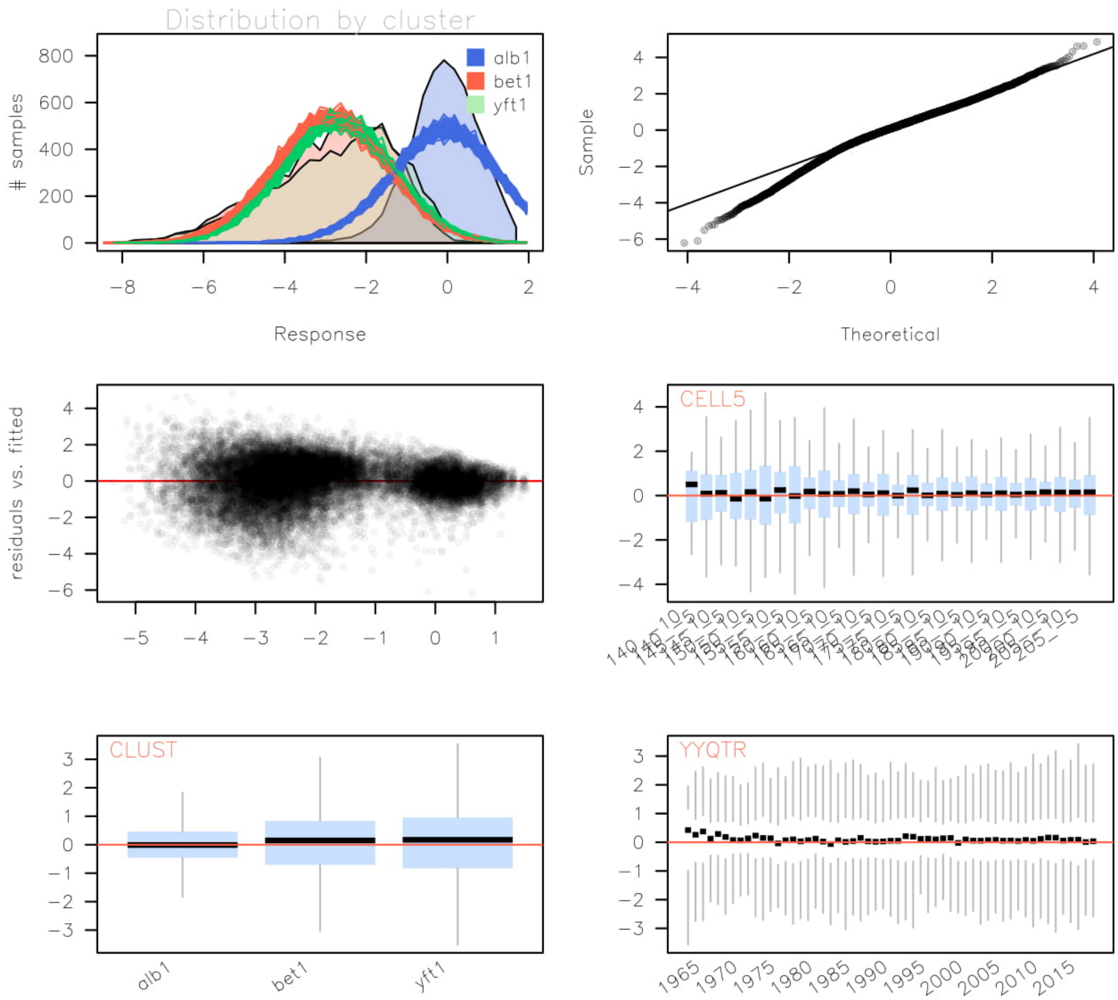

Figure 7: Diagnostic plots of fitted GLM models for region 1 (delta-lognormal distribution) showing characteristics of the model residuals and comparisons between observed and simulated data.

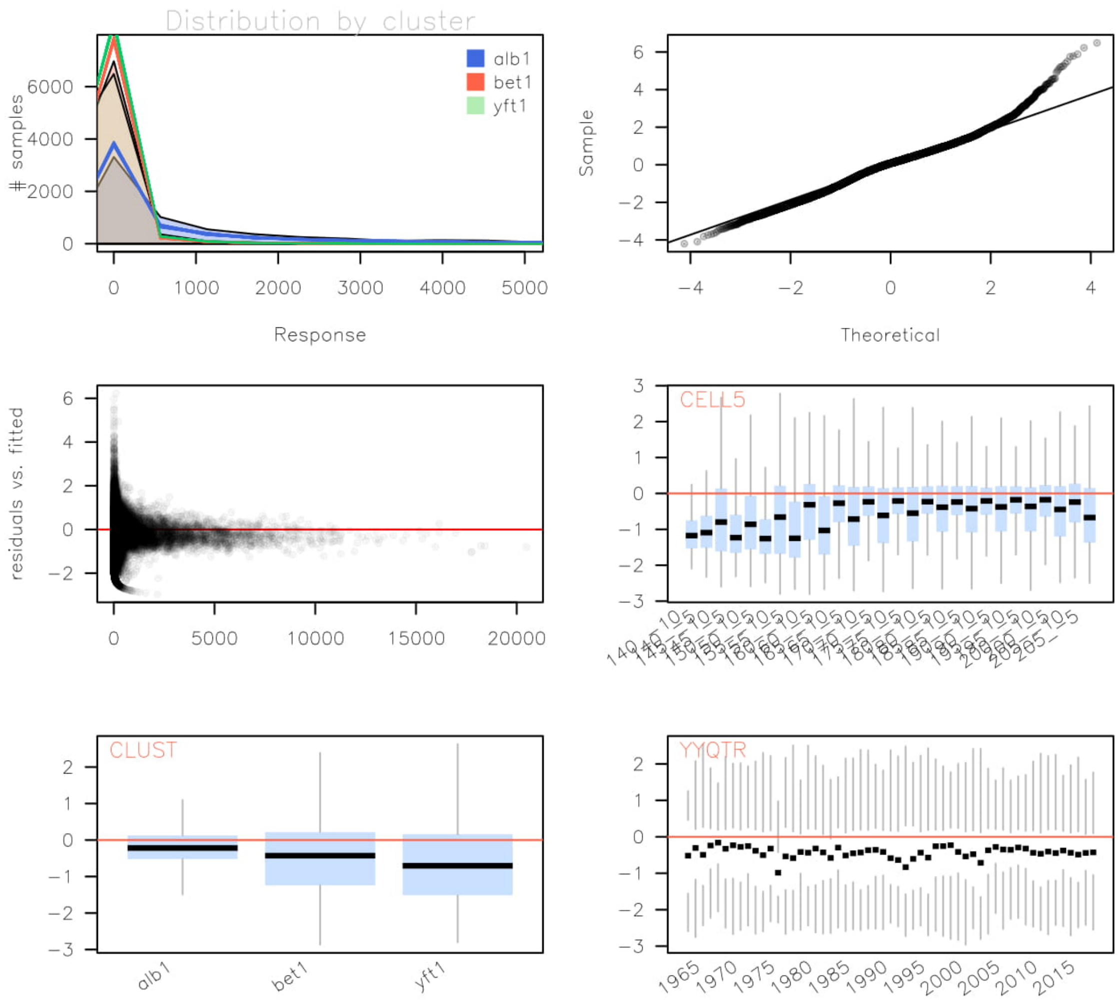

Figure 8: Diagnostic plots of fitted GLM models for region 1 (negative binomial distribution) showing characteristics of the model residuals and comparisons between observed and simulated data.

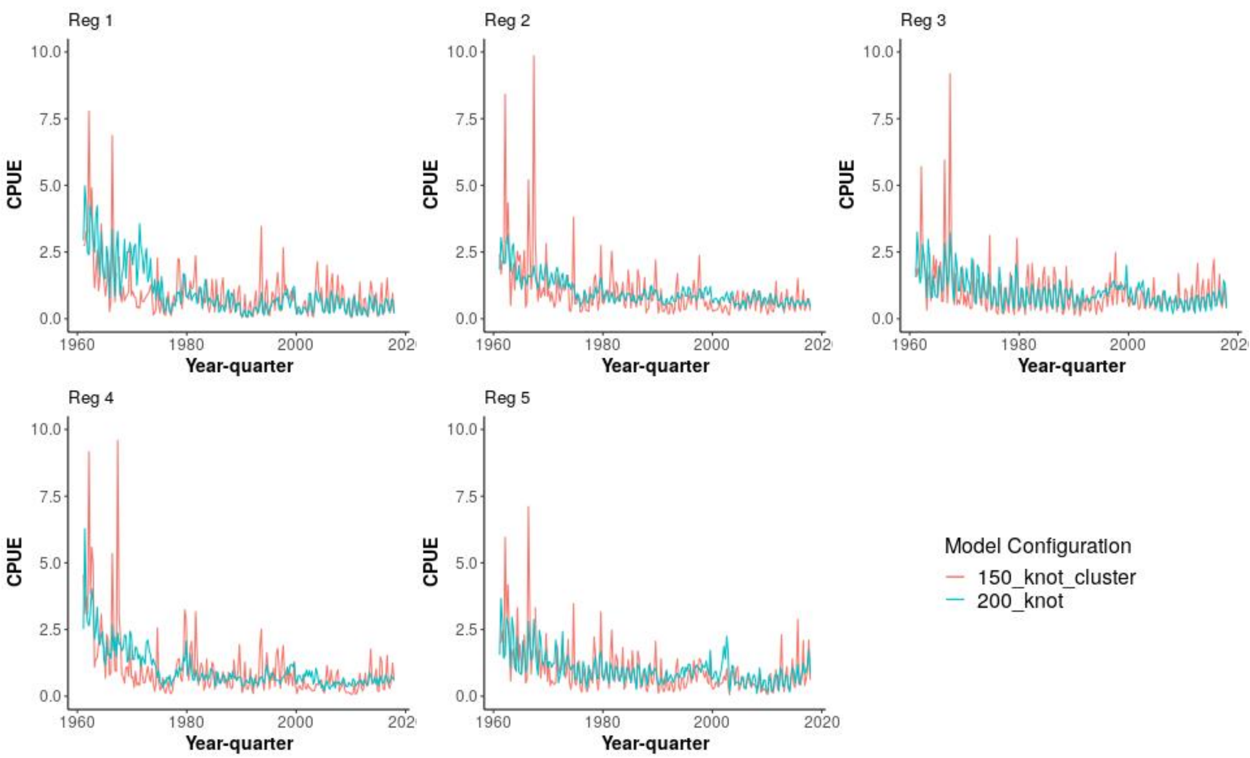

Figure 9: Time-series of two geostatistical CPUE indices standardized from model configuration with 200 knots and 150 knot.

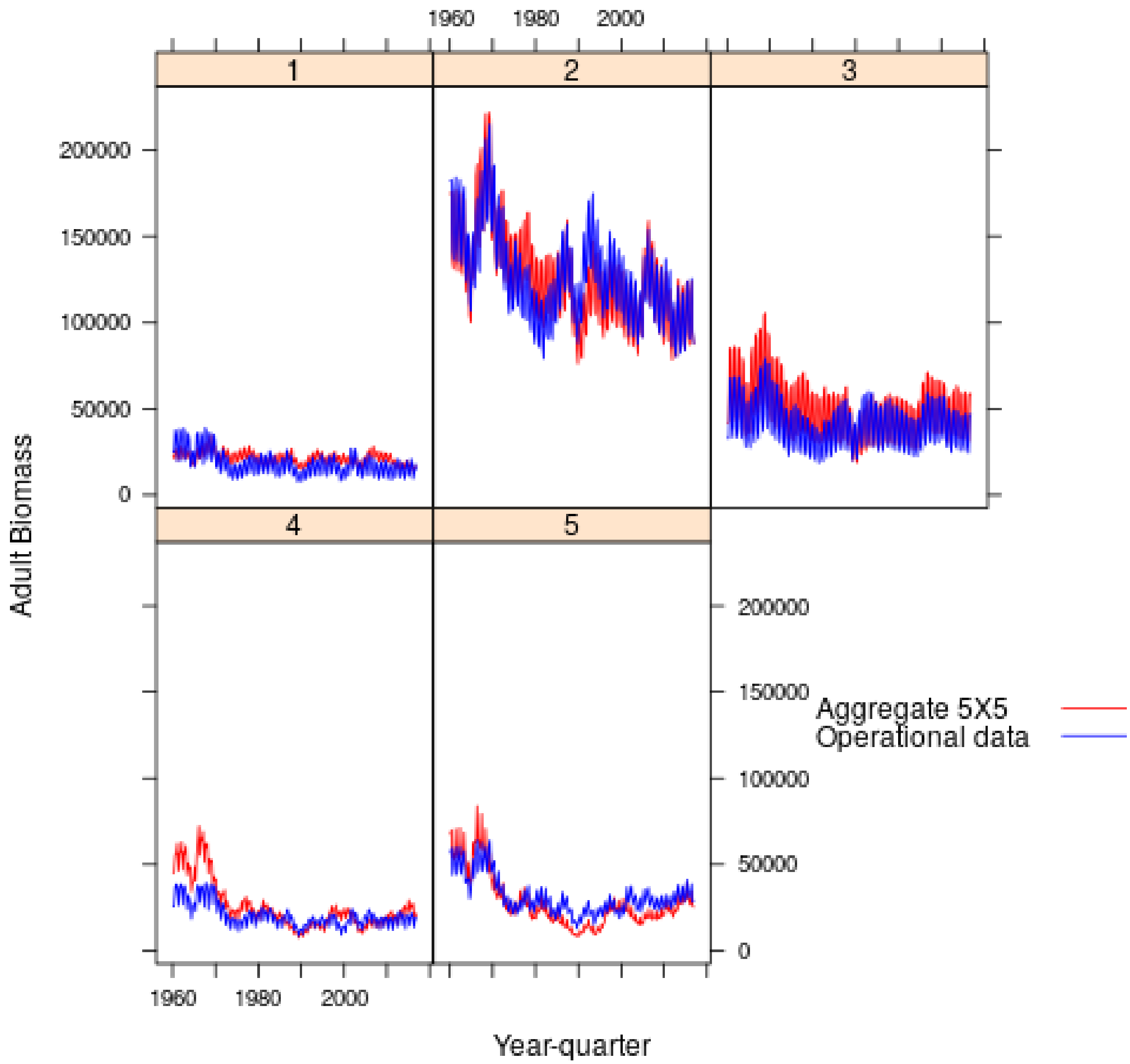

Figure 10: Comparisons of adult biomass between the traditional CPUE (lognormal error distribution and using year-quarter, cluster, flag and 5° X 5° cell as explanatory variables) standardized in our analysis and CPUE used in stock assessment. Model configuration: steepness 0.8, natural mortality 0.3, growth: estimated, size frequency weighting 50 and traditional CPUE.

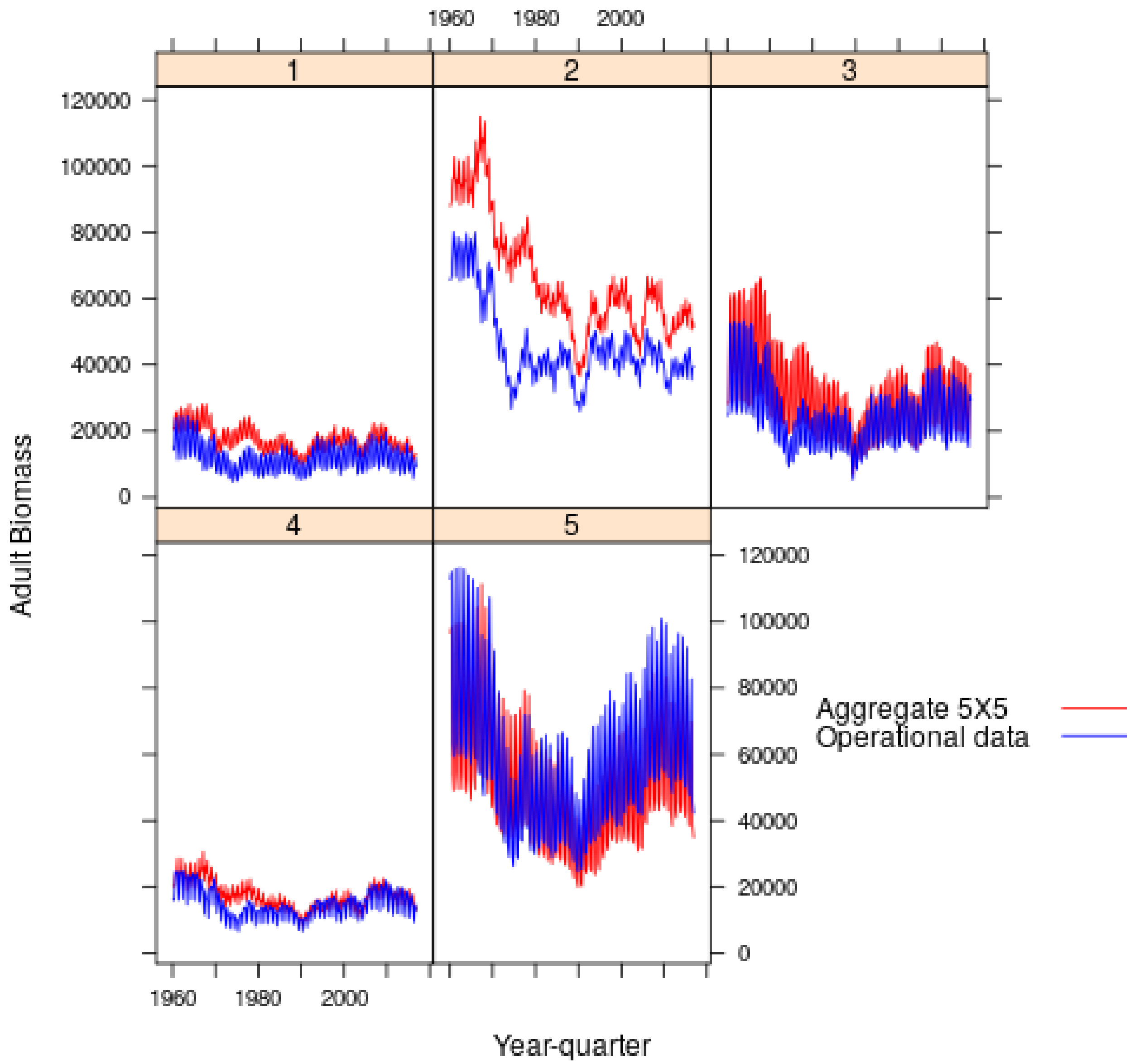

Figure 11: Comparisons of adult biomass between the new traditional CPUE (lognormal error distribution and using year-quarter, cluster, flag and 5° X 5° cell as explanatory variables) standardized in our analysis and CPUE used in stock assessment. Model configuration: steepness 0.65, natural mortality 0.3, growth: Chen-Wells, size frequency weighting 80 and traditional CPUE.

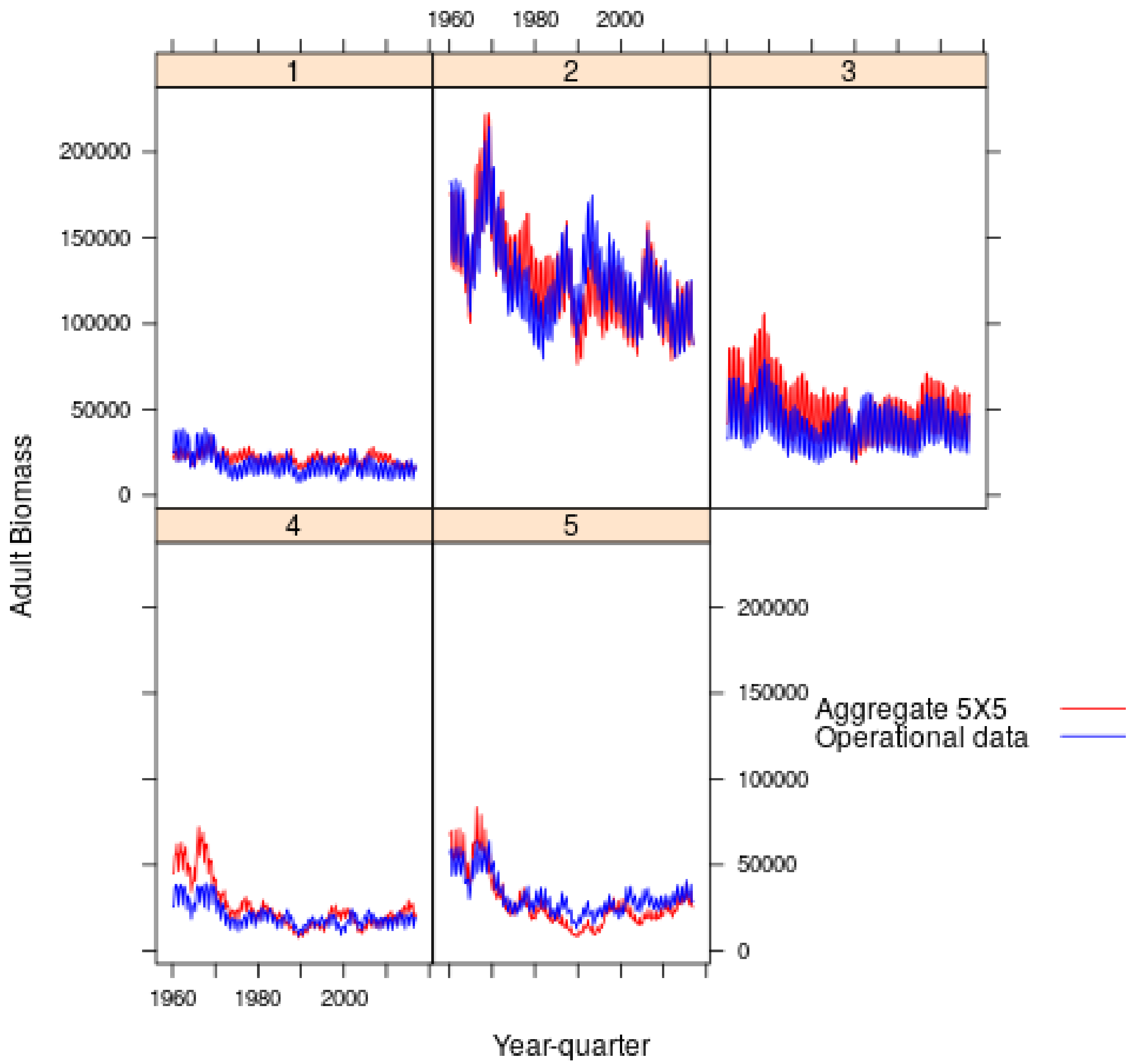

Figure 12: Comparisons of adult biomass between the new traditional CPUE (lognormal error distribution and using year-quarter, cluster, flag and 5° X 5° cell as explanatory variables) standardized in our analysis and CPUE used in stock assessment. Model configuration: steepness 0.95, natural mortality 0.4, growth: estimated, size frequency weighting 50 and traditional CPUE. This model is the diagnostic case.

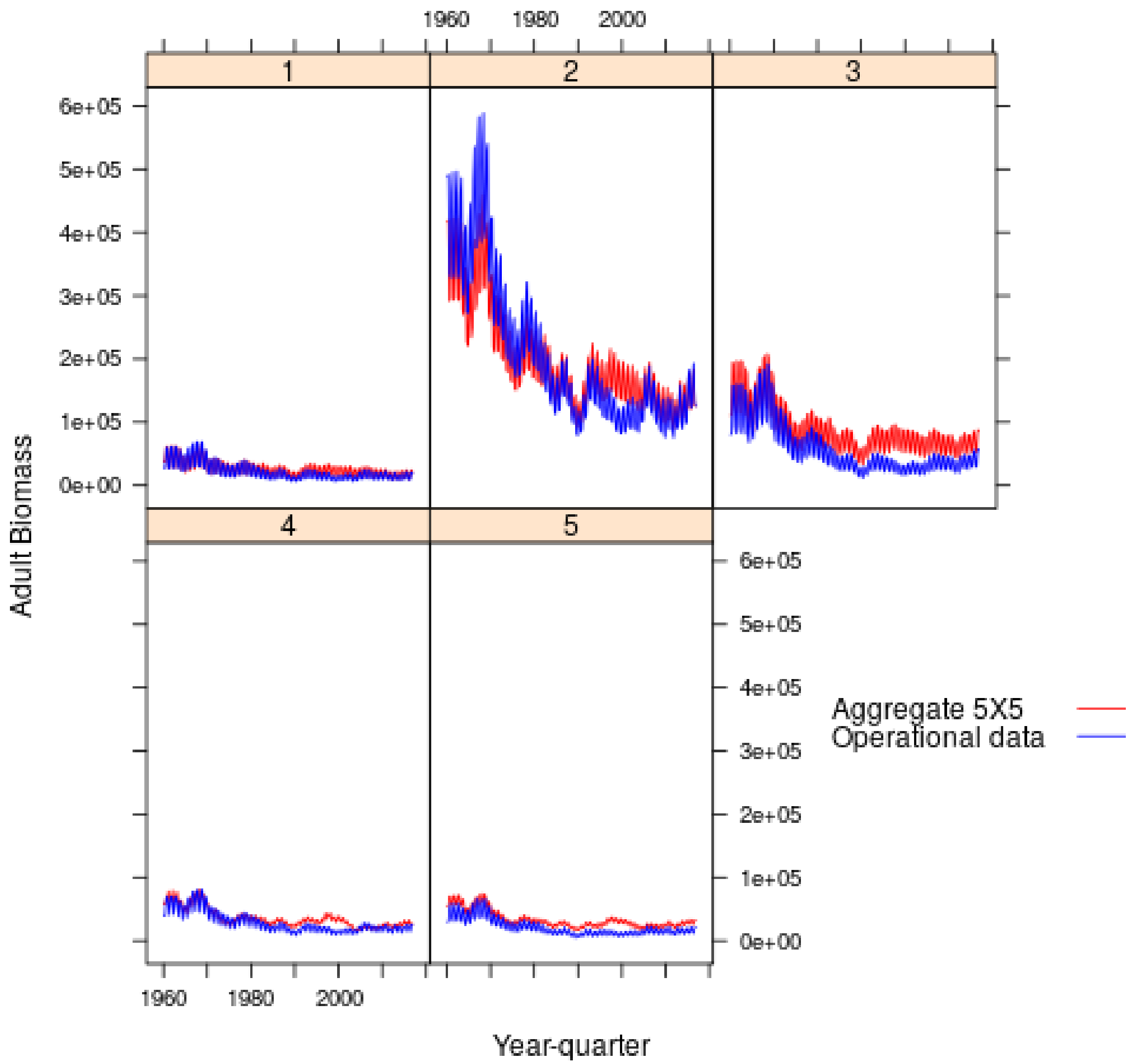

Figure 13: Comparisons of adult biomass between the new geostatistical CPUE (200 knots, delta-lognormal error distribution and using year-quarter, spatial and spatial-temporal effect as explanatory variables) standardized in our analysis and CPUE used in stock assessment. Model configuration: steepness 0.8, natural mortality 0.3, growth: estimated, size frequency weighting 50 and geostatistical CPUE. This model is the diagnostic case.

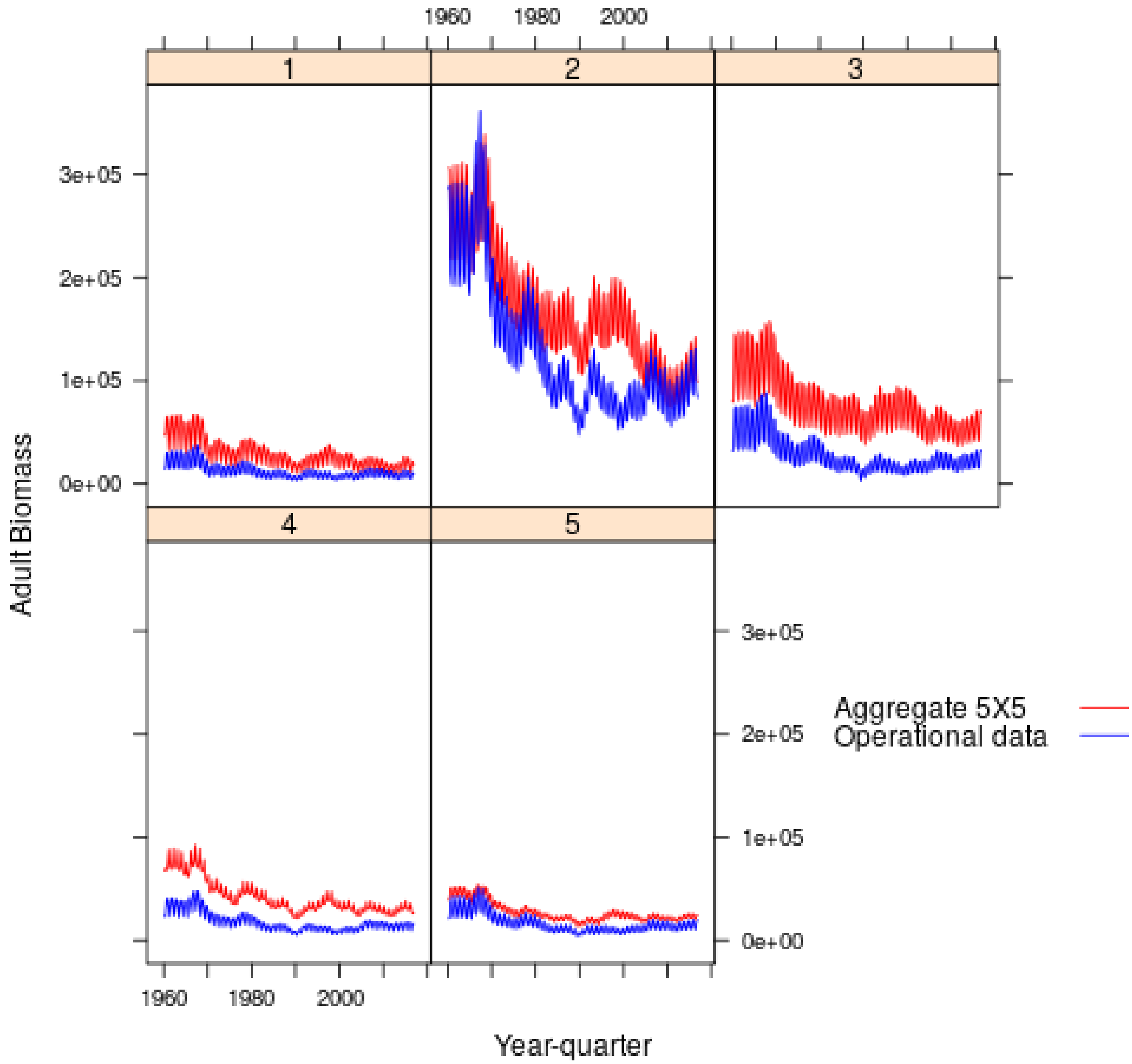

Figure 14: Comparisons of adult biomass between the new geostatistical CPUE (200 knots, delta-lognormal error distribution and using year-quarter, spatial and spatial-temporal effect as explanatory variables) standardized in our analysis and CPUE used in stock assessment. Model configuration: steepness 0.65, natural mortality 0.3, growth: Chen-Wells, size frequency weighting 80 and geostatistical CPUE.

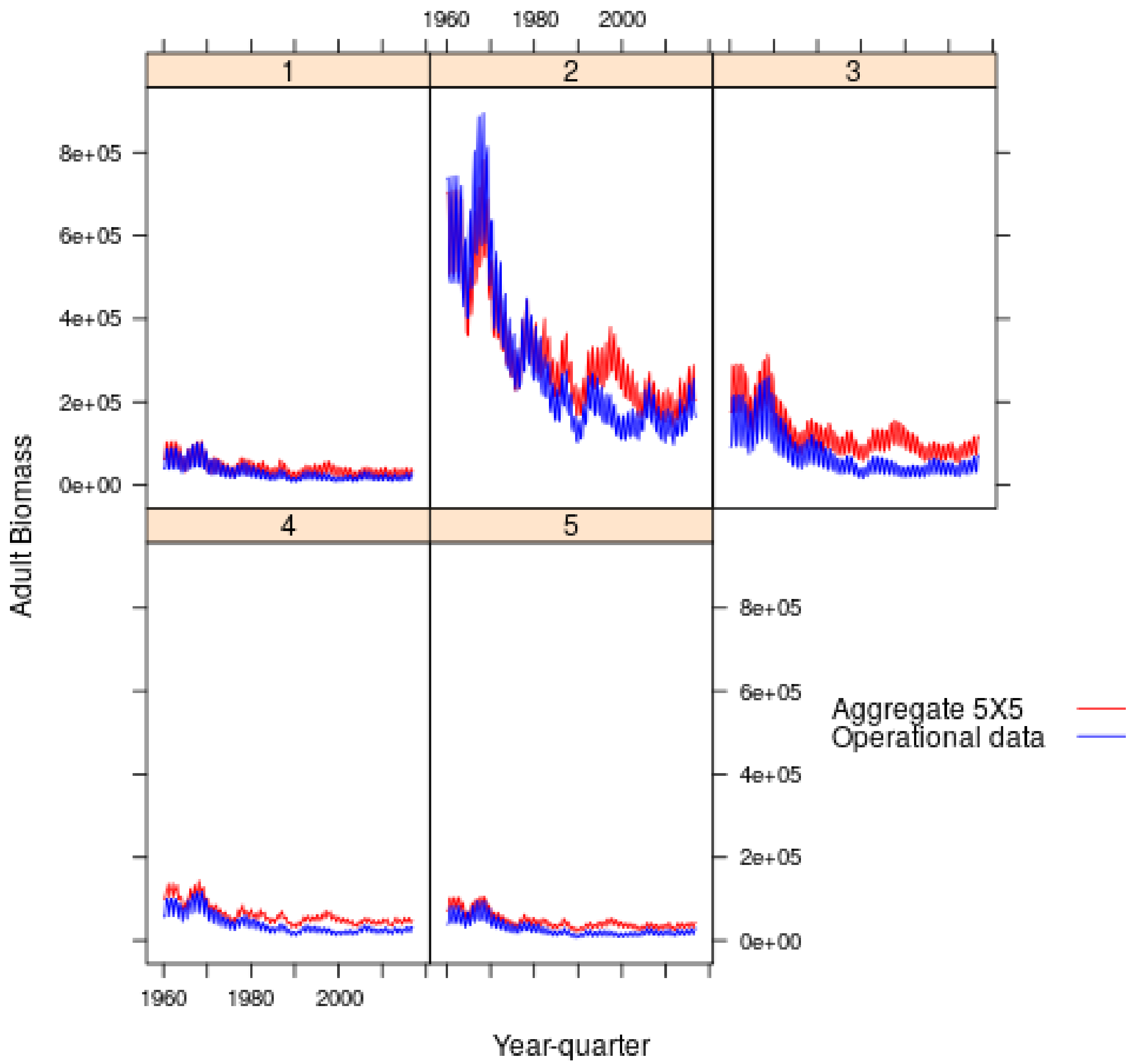

Figure 15: Comparisons of adult biomass between the new geostatistical CPUE (200 knots, delta-lognormal error distribution and using year-quarter, spatial and spatial-temporal effect as explanatory variables) standardized in our analysis and CPUE used in stock assessment. Model configuration: steepness 0.95, natural mortality 0.4, growth: estimated, size frequency weighting 50 and geostatistical CPUE.

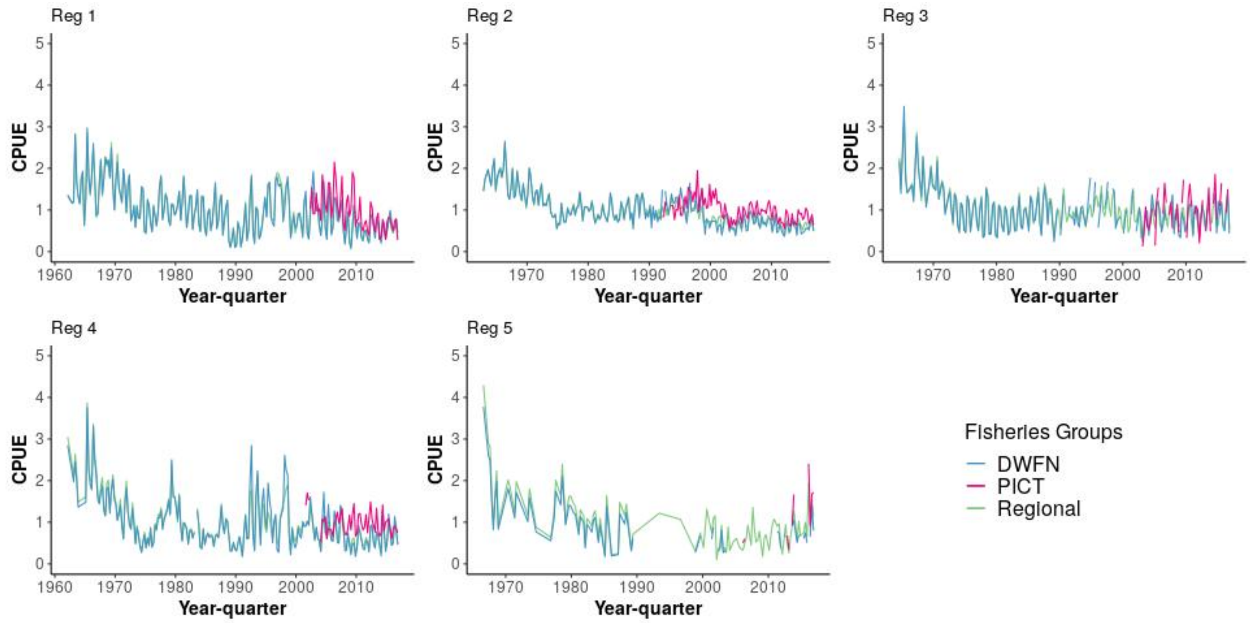

Figure 16: Time-series of regional CPUE, the DWFN CPUE and PICT CPUE indices standardized with 'traditional' CPUE analysis method. The model configuration used here is lognormal error distribution and using year-quarter, cluster, flag and 5° X 5° cell as explanatory variables.

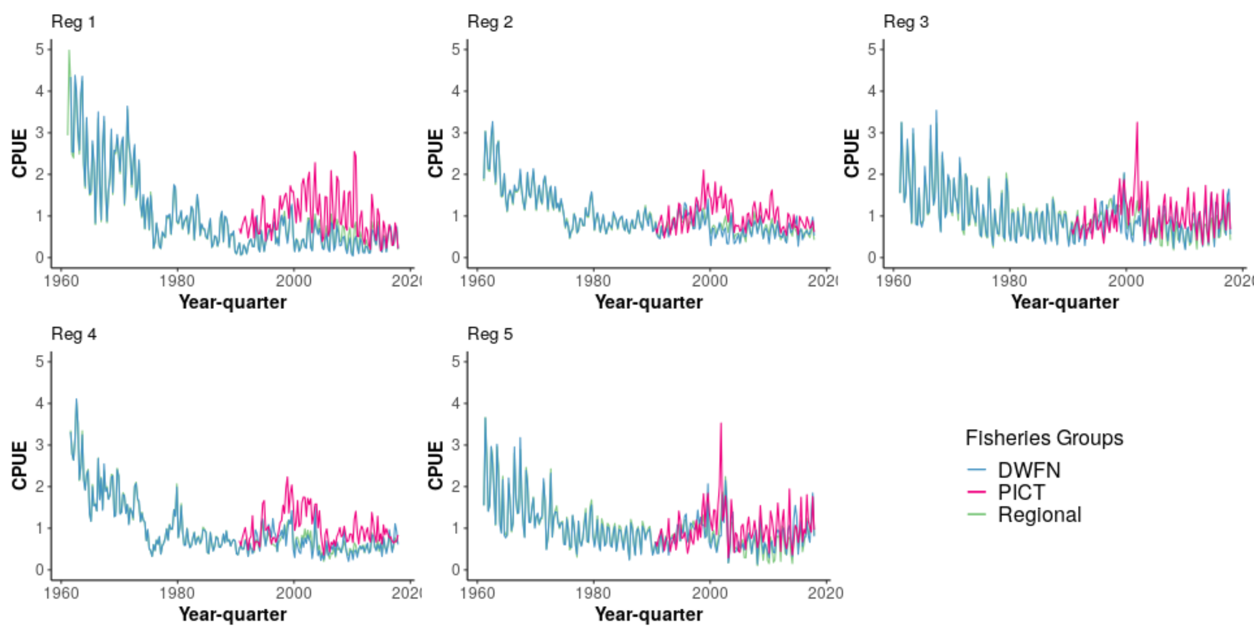

Figure 17: Time-series regional CPUE, the DWFN CPUE and PICT CPUE indices standardized with geostatistical CPUE analysis method. The model configuration used here 200 knots, delta-lognormal error distribution and using year-quarter, spatial and spatial-temporal effects as explanatory variables.

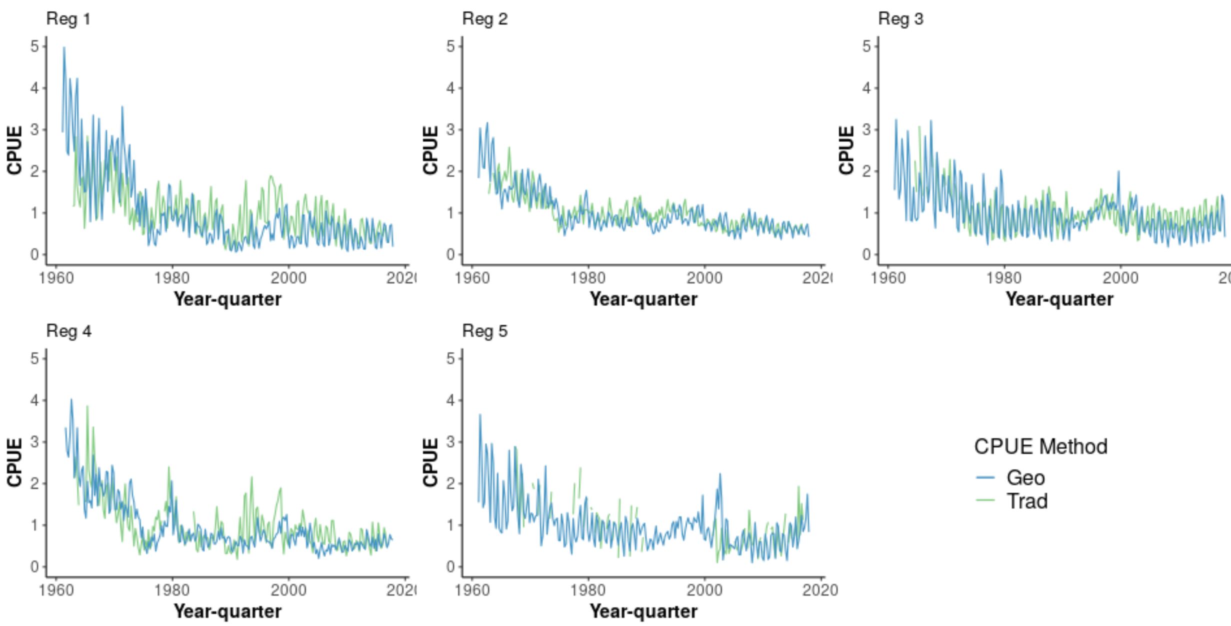

Figure 18: Time-series of the nominal, traditional and geostatistical CPUE in each region.