Regional scaling factors for Indian Ocean albacore tuna

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Abstract

Indian Ocean tuna assessments may be spatially structured, and CPUE indices developed for different regions often indicate different trends through time. In this situation it is useful to determine the relative abundances by region, so that we may either apply regional scaling in a multi-region assessment, or appropriately combine the separate indices into a single index of abundance. Regional scaling, which has been used since 2005 in tuna assessments, estimates the abundance distribution from regional catch rates and areas. We describe the method and explore potential impacts on albacore abundance scaling of changes to the approach previously applied to yellowfin and bigeye tuna. Supported improvements included using cell ocean areas in scaling calculations; adjusting statistical weights in the standardization model based on the density of samples; including fleet effects in the standardization model; and using a region-season interaction term in the standardization model rather than a year-season term.

Introduction

Stock assessments that cover large spatial domains may subdivide the stock into multiple spatially-defined regions, each with its own population structure and trajectory through time. The population trajectories are usually entrained by regional CPUE indices, with migration parameters used to define the transfer rates of individuals between regions. It is also important to constrain the relative abundances among regions, so that they correspond to those in the population. In this paper we describe the methods used to date for estimating these relative abundances and explore some possible improvements.

Regional scaling was developed for use in Western and Central Pacific assessments in 2005 (Hoyle and Langley, 2007; Langley et al., 2005), with some changes in 2007 (Hoyle and Langley, 2007). Relative abundances are estimated from CPUE data, based on the relative catch rates among regions. The model is then constrained to use these relative abundances by adjusting the average values of the CPUE indices to match the estimated relative abundances and sharing the same catchability parameter among the longline fleets associated with these indices.

Indian Ocean albacore tuna assessments have not employed separate regions to date, and therefore regional scaling is not currently used in the assessments themselves. Nevertheless, regional scaling can be used to weight the contribution of indices by region, when combining CPUE indices from separate regions into a single combined index.

This paper closely follows the approach used in the regional scaling paper recently produced for bigeye and yellowfin tunas (Hoyle, 2018). We describe potential

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improvements to the simple approach of weighting by average catch rate, and compare the results.

Changes in catch rates through time or seasonally may affect the relativities among areas, if there are different amounts of data among grid cells. Standardizing the CPUE data before extracting the spatial effects may therefore provide more consistent estimates. The standardization approach is used in the WCPO (Hoyle and Langley, 2007; Langley et al., 2005), and was also applied to the 2016 Indian Ocean bigeye assessment. This approach involves standardizing the aggregated CPUE to obtain relative abundance estimates for each spatial grid cell, which are then summed by region to estimate relative abundance.

In addition, it may be useful to base the spatial effects on a period without substantial target change. The indices of abundance for Indian Ocean albacore tuna are based on operational data and allow for target change by using clustering or HBF, but the scaling factors are based on aggregated data without HBF, so target change cannot be accounted for. The decline in albacore CPUE indices during the late 1960s–early 1970s was inconsistent with the relatively low level of catch taken during this period (Langley and Hoyle, 2016), suggesting that CPUE at this time may be affected by catchability change and may not reliably indicate abundance. Cluster analyses indicate likely target change by the Japanese fleet towards more targeting of bigeye tuna during this period (Hoyle et al., 2017). We therefore explore the use of spatial effects based on several alternative periods, during which targeting approaches have varied.

Different fleets may have different average catch rates, so we included fleet in the standardization model.

A further change was to adjust for the relative sizes of the 5° grid cells. Grid cells in the tropics are larger than temperate cells, and some cells include land, which reduces the ocean area. Calculations to date have simply summed the cell density estimates, but here we calculated cell ocean areas and multiplied them by cell density before summing by region. In addition, we used the cell areas when calculating the statistical weights to apply to each stratum in the model.

Finally, we considered the potential to adjust for seasonal density changes due to tuna movements. Albacore tuna are known to move north and south seasonally (Nikolic et al., 2017). Hitherto the approach had allowed for seasonal changes in catch rate by incorporating year-quarter in the model, but assuming constant proportions in each region. We changed the model to include the quarterly effects in the spatial component of the model rather than in the temporal component.

Methods

Indian Ocean aggregated catch and effort data were downloaded from the data section associated with the Working Party on Tropical Tunas on the IOTC website:

http://www.iotc.org/sites/default/files/documents/2017/09/IOTC-2017-WPTT19-DATA04_-_CELL.zip

Effort was limited to the Japanese, Korean and Taiwanese longline fleets. Korean effort was reported from 1975, so was not included in all analyses. All data from these fleets were reported at a resolution of 1 month and 5° grid cell. We omitted data from grid cells with effort less than 50000 hooks or fishing in fewer than 7 quarters during the period of interest.

Each method was applied across 5 periods: 1960-1975, 1963-1975, 1975-1994, 1979-1994, and 1980-2000. We plotted the number of grid cells fished per year-quarter in each region to examine changes through time in the spatial coverage of the data. We also examined the evidence for target change during these periods based on the results of cluster analysis (Hoyle et al., 2017).

For the means method we calculated the scaling factors by taking the mean CPUE in each 5° grid cell, and then summing the means of all cells in each region.

For the standardization methods we applied generalized linear models with form similar to the following: $\log(CPUE + c) \sim yrqtr + cell + fleet$, where $CPUE$ is the catch divided by the effort in hooks, *c* is an additive constant to allow the inclusion of strata with zero catch, *yrqtr* is the year-quarter effect, *cell* is the 5° grid cell effect, and *fleet* is the fleet, either Japanese or Korean. One analysis method included *year* rather than *yrqtr* and included the variable *reg.qtr*, which indicated the region and quarter of the effort. All effects were modelled as categorical variables. The constant *c* was set to 10% of the mean CPUE in the model dataset.

For each standardization method we used the R function *predict.glm* to predict a standard catch rate in the same year-quarter for each cell, and summed these predicted catch rates for each region, weighting as appropriate for the method. For the method that included *reg.qtr*, catch rates were predicted for all quarters and summed. Each regional sum was then divided by the largest regional sum to produce relative regional scaling factors.

Ocean areas were calculated using the R packages 'maptools' (Bivand et al., 2017a), rgeos (Bivand et al., 2017b), sp (Pebesma and Bivand, 2005), raster (Hijmans et al., 2017a), and geosphere (Hijmans et al., 2017b). We calculated the total area and land area of each cell, and then subtracted the land from the total to leave the ocean area.

The following analyses were carried out using progressive changes.

m1) The method used in the 2008-2013 yellowfin assessments (the "means" method).

m2) Use method based on standardization (the "standardization" method), $\log(CPUE + c) \sim yrqtr + cell$, summing predicted cell densities by region.

m3) Multiply cell densities by areas before summing cells by region.

m4) Include statistical weights by grid cell area in the standardization model.

m5) Add fleet to the standardization model, $\log(CPUE + c) \sim yrqtr + cell + fl$.

m6) Change standardization model to quarterly spatial effects and annual temporal effects, $\log(CPUE + c) \sim year + cell + fl + reg.qtr$.

m7) Use gam instead of glm and replace categorical cell variable with tensor spline surface. The model is $\log(CPUE + c) \sim year + te(lat5, lon5) + fl + reg.qtr$.

m8) Combine m6 and m7, using CPUE predictions from m7 to replace empty cells in m6.

For comparison between scaling factors using data from different periods, each scaling factor was divided by the mean of the respective regional index during the scaling period.

Pooled indices were then prepared via the following steps:

1. Normalize each time series by dividing each index value by the mean of its indices during the scaling period. Each index now has a mean of 1 during the scaling period. Missing values are ignored.
2. Multiply each index by the relevant scaling factor. The mean of each index during the scaling period is now equal to the scaling factor.
3. Sum the indices across regions and by year-quarter or year, to produce a pooled index.

Results

Spatial coverage of data from the five periods varied (Figure 1) but was reasonably good across all regions from 1968 until the present.

The factors in the standardization were all statistically significant (Table 1). The lowest AIC was estimated for model m6, which included the *reg.qtr* term.

Diagnostics for the models showed a small amount of non-normality in the residuals (Figure 2), due to the use of aggregated data in which the variability depends on the number of sets per stratum. This problem is minor and would not substantially affect results. Patterns in the residuals by region and year-quarter (Figure 3) did not appear problematic for any period.

The period covered by the time series influenced the spatial distribution of relative abundance (Figures 4 and 5) for each species, for both the means method and the standardization methods. In the earlier 1960-75 and 1963-75 periods the highest catch rates were relatively higher than they were in the later periods.

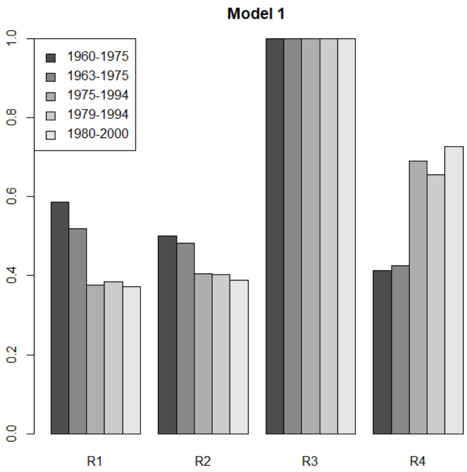
Regional scaling factors were estimated for each region and method, and both species (Tables 2 and **Error! Reference source not found.**).

To compare their potential effects on the assessment, we adjusted the scaling factors relative to the indices of abundance before plotting, by dividing each scaling factor by the mean of the respective index during the scaling period.

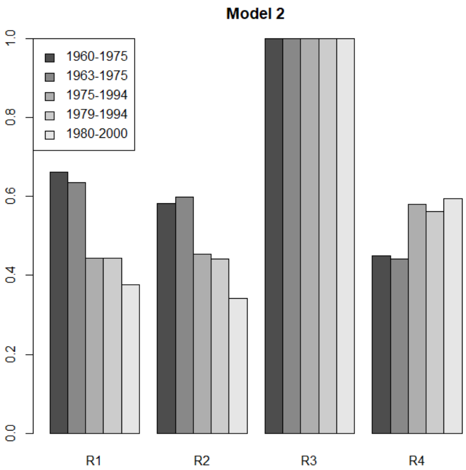
Changing the analysis methods resulted in moderate changes to the scaling factors, as shown in the results for 1979 – 1994 (Figure 6). Changing from using the overall mean (m1 mean) to using the standardization approach (m2 standardized) increased the proportions in northern regions 1 and 2 and reduced the proportion in region 4. Adjusting by area (m3 areas) slightly increased the scaling factor for north western region 2. Introducing statistical weights to the standardization model (m4 statistical weights) had a relatively small effect. Accounting for fleet effects in the model (m5 fleet) had moderately large effect on the 1979-1994 scaling factors, and more impact on the 1980-2000 factors. Including quarterly effects had a limited further impact. Including estimates for missing cells via the spatial smoother had little further effect since in most cases there were no missing cells.

The overall impacts of all the changes were to increase the scale of the eastern relative to the western regions.

The time period had a large impact on the regional scaling factors, with small differences due to a change in start time from 1960 to 1963, but larger and potentially important differences, for the



later periods (



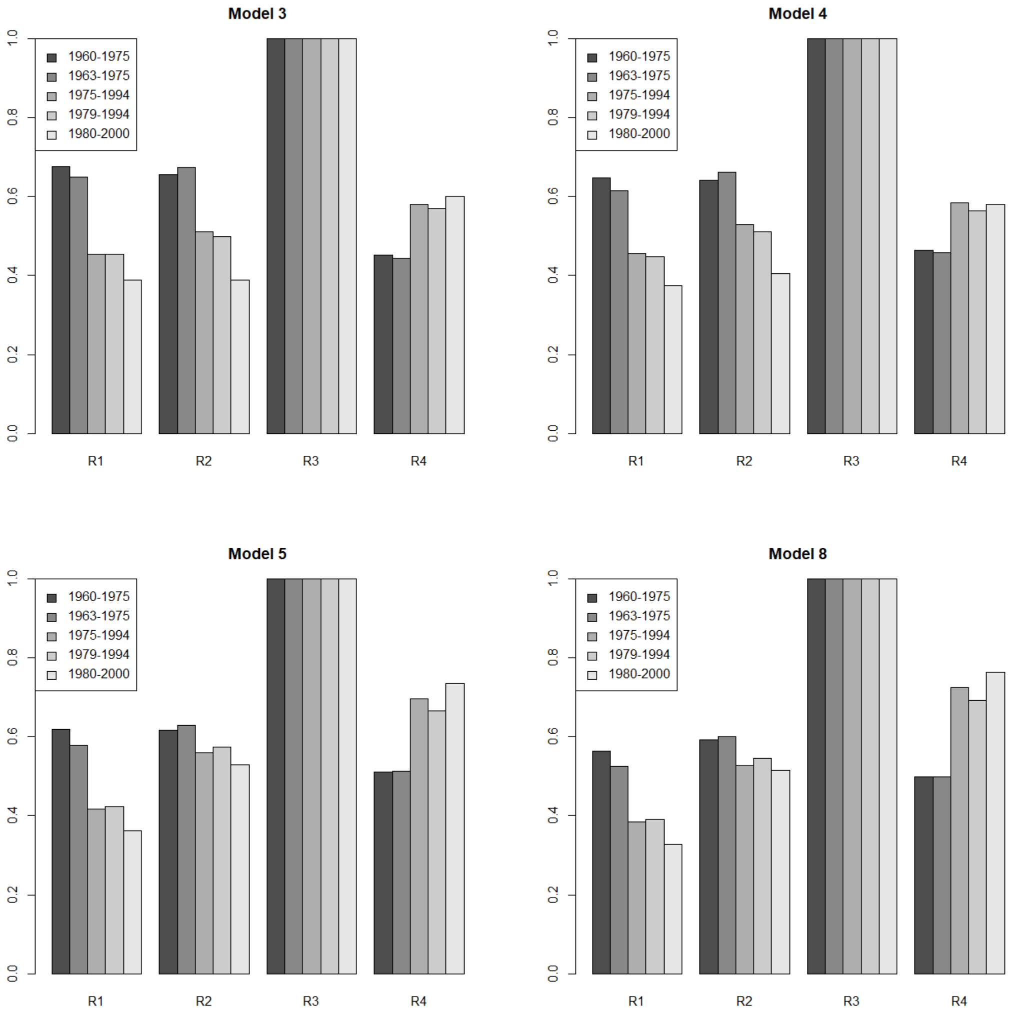


Figure 7). Comparing 1979-1994 to 1963-1975, relatively more biomass occurred in the south-eastern region 4 and less in the north-western region 1. Comparing the 1980-2000 period to 1979-1994, scaling factors increased further in south-eastern region 4 and decreased in north-western region 1.

Discussion

Regional scaling factors are used to generate pooled indices of abundance for Indian Ocean albacore stock assessments that do not use separate regions. Similar approaches may be applied to stock assessments with multiple regions.

Aggregated assessment methods such as surplus production models require a single abundance index. When abundance trends vary in different parts of the stock, as they do here (Hoyle et al., 2019), it is necessary to model this variation and then sum across it later. Approaches that ignore the variation will provide unreliable results.

The analyses presented here indicate that the means and standardization approaches provide different results. Although we lack reliable information about the true relative abundances, the standardization approaches are preferred because they adjust for changes in fishing distribution through time. The means method uses an arithmetic mean, and so may be unduly affected by the large outliers that can occur in a lognormal distribution.

Applying the adjustment for area is easy to justify based on the logic of the approach, the inclusion of statistical weights has been justified by simulations (Campbell, 2004; Punsly, 1987), and the fleet and quarter effects are statistically significant. The approach that fills the gaps due to missing estimates for some cells is also preferred.

These analyses have also shown that the period used for the regional scaling analysis affects the outcome and its implications for the assessment. It seems preferable to use a period when catch rates are thought to be reliable indices of abundance, and when fishing is widely distributed so that estimates area available for most or all spatial cells. It is also preferable to choose a period when trends are similar in all regions, because this is one of the assumptions of the standardization model.

After considering these issues, we recommend the use of the 1979 – 1994 period, and model m8.

There is potential to improve upon the present analysis. Since we are interested in the expected value of a lognormally distributed parameter, it would be appropriate to apply lognormal bias correction before summing the 5° cell values. We have not done so because the appropriate variance estimate is unclear. This should be addressed in future.

The aggregated data used here neither report HBF nor support cluster analysis or vessel-level fishing power. Targeting will tend to reduce the estimated relative abundance for areas where a species is not targeted. Targeting has been a significant factor in both the spatial variation in catch rates and in the changing catch rates through time, so failing to account for it will have biased the scaling factors.

Regional scaling could be estimated better using operational data, where cluster analysis and/or set characteristics such as HBF and hooks per set can be used to account for targeting, and the fishing power of individual vessels can also be taken into account. However, the code for doing these calculations would need to be developed. There are also memory constraints when analysing such large datasets, but they might be resolved by subsampling the datasets.

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Tables

Table 1: AIC, delta AIC, deviance, and degrees of freedom for variables in the full models for 1979-1994 (models 5 and 6).

Method	Variable dropped	DF	Deviance	AIC	δAIC
5	-	-	5944	24425	0
	year-qtr	59	6889	25710	1285
	cell	111	7400	26286	1861
	fleet	2	7642	26810	2385
6	-	-	5853	24214	0
	year	14	6457	25119	905
	cell	108	6973	25661	1447
	fleet	2	7369	26399	2185
	reg.qtr	12	6269	24841	628

Table 2: Regional scaling factors for albacore tuna by period, method, and region.

Period	Method	Region			
		1	2	3	4
6075	1	0.587	0.500	1	0.413
	2	0.662	0.582	1	0.449
	3	0.677	0.656	1	0.452
	4	0.647	0.642	1	0.464
	5	0.619	0.617	1	0.511
	6	0.618	0.650	1	0.547
	7	0.545	0.607	1	0.475
	8	0.564	0.593	1	0.499
6375	1	0.519	0.483	1	0.425
	2	0.635	0.599	1	0.441
	3	0.650	0.675	1	0.445
	4	0.615	0.663	1	0.457
	5	0.579	0.630	1	0.513
	6	0.576	0.659	1	0.546
	7	0.508	0.605	1	0.480
	8	0.526	0.602	1	0.498
7594	1	0.377	0.405	1	0.692
	2	0.445	0.454	1	0.580
	3	0.454	0.512	1	0.580
	4	0.455	0.529	1	0.585
	5	0.416	0.560	1	0.697
	6	0.384	0.527	1	0.726
	7	0.384	0.530	1	0.718
	8	0.384	0.527	1	0.726
7994	1	0.385	0.403	1	0.655
	2	0.444	0.441	1	0.563
	3	0.455	0.498	1	0.570
	4	0.447	0.511	1	0.563
	5	0.424	0.574	1	0.666
	6	0.392	0.546	1	0.693
	7	0.390	0.542	1	0.683
	8	0.392	0.546	1	0.693
8000	1	0.373	0.389	1	0.727
	2	0.376	0.341	1	0.594
	3	0.390	0.389	1	0.601
	4	0.374	0.405	1	0.581
	5	0.363	0.530	1	0.735
	6	0.327	0.516	1	0.764
	7	0.331	0.522	1	0.741
	8	0.327	0.516	1	0.764

Figures

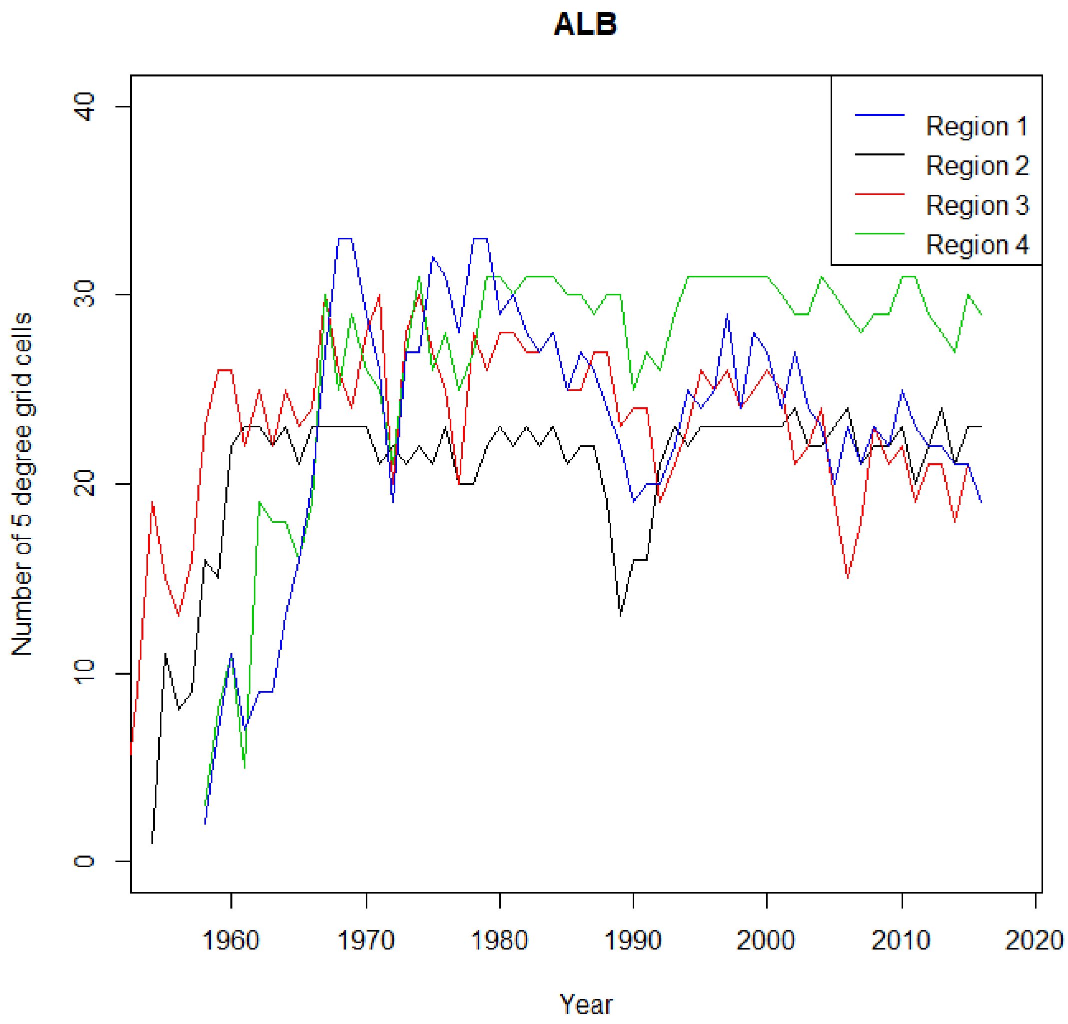

Figure 1: By albacore region and year, the number of 5° grid cells with catch and effort data.

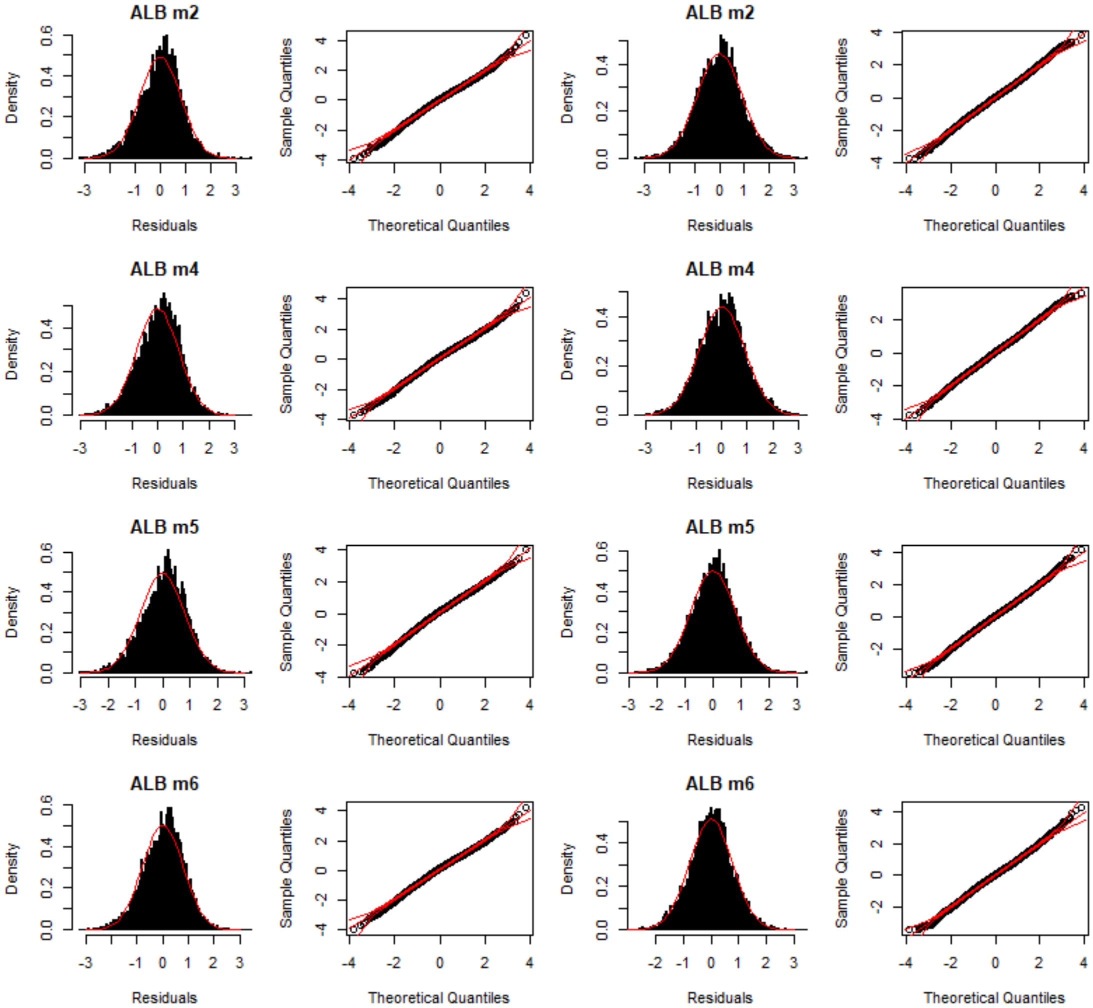

Figure 2: Diagnostic plots for the glm models using data from 1963-1975 (left) and 1979 – 1994 (right).

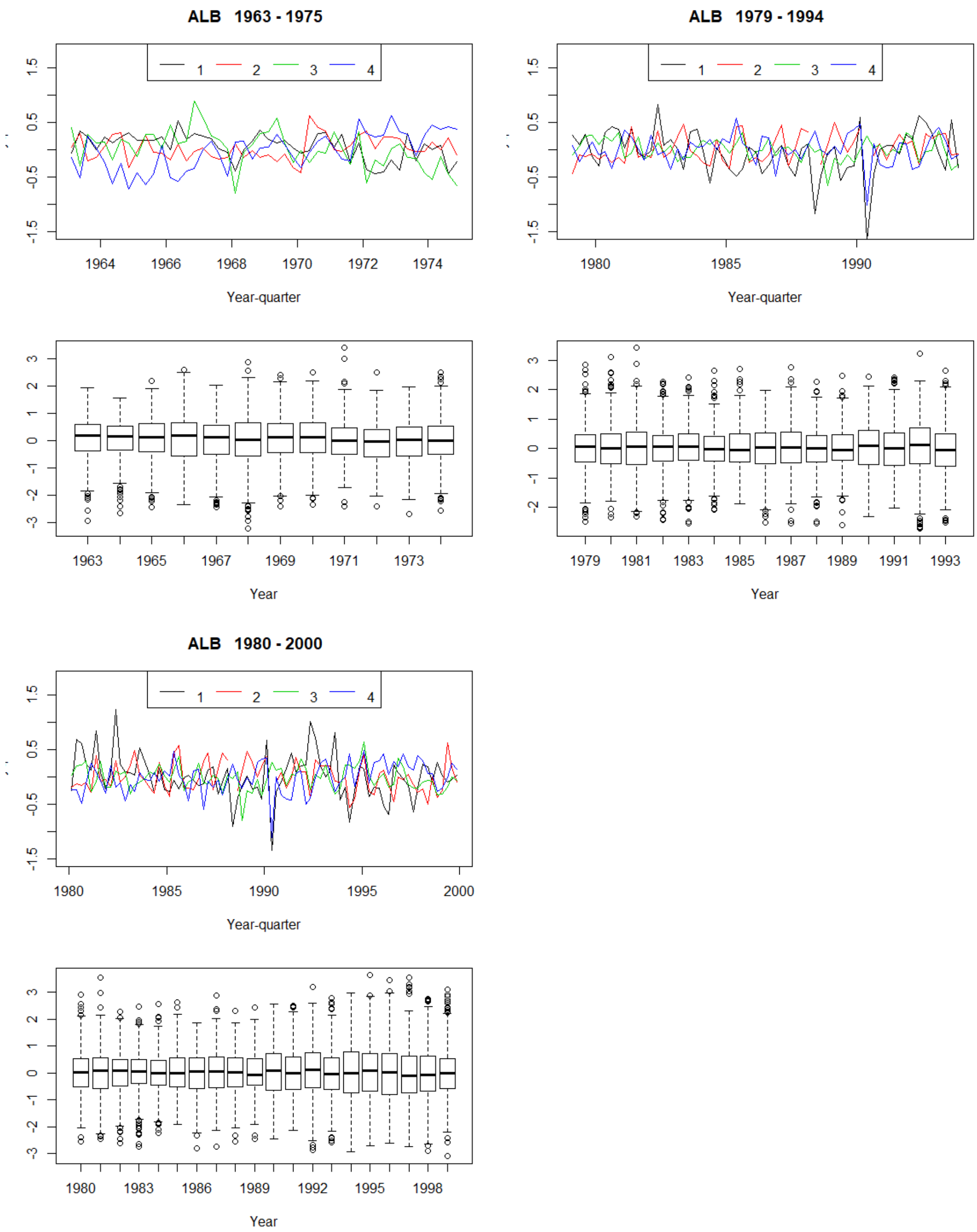

Figure 3: Plots of mean residuals by region, and boxplots of residual distributions, for ALB model 6 for the periods 1963-1975, 1979-1994, and 1980-2000.

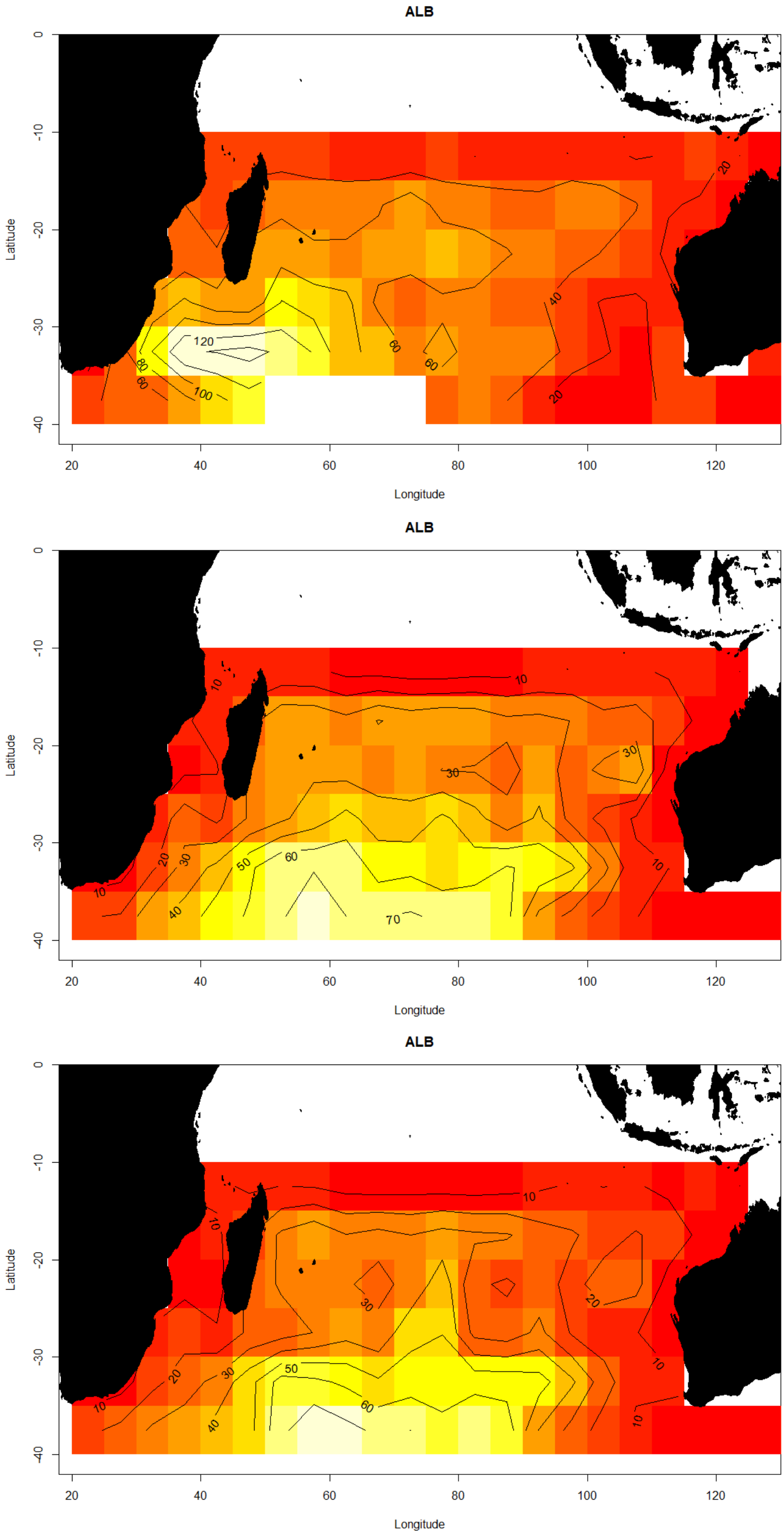

Figure 4: Heat maps of relative biomass by 5° cell estimated using the means method for albacore tuna based on the periods 1963 – 1975 (top), 1979 – 1994 (middle), and 1980 – 2000 (bottom). Yellow indicates higher density, and white indicates no estimate.

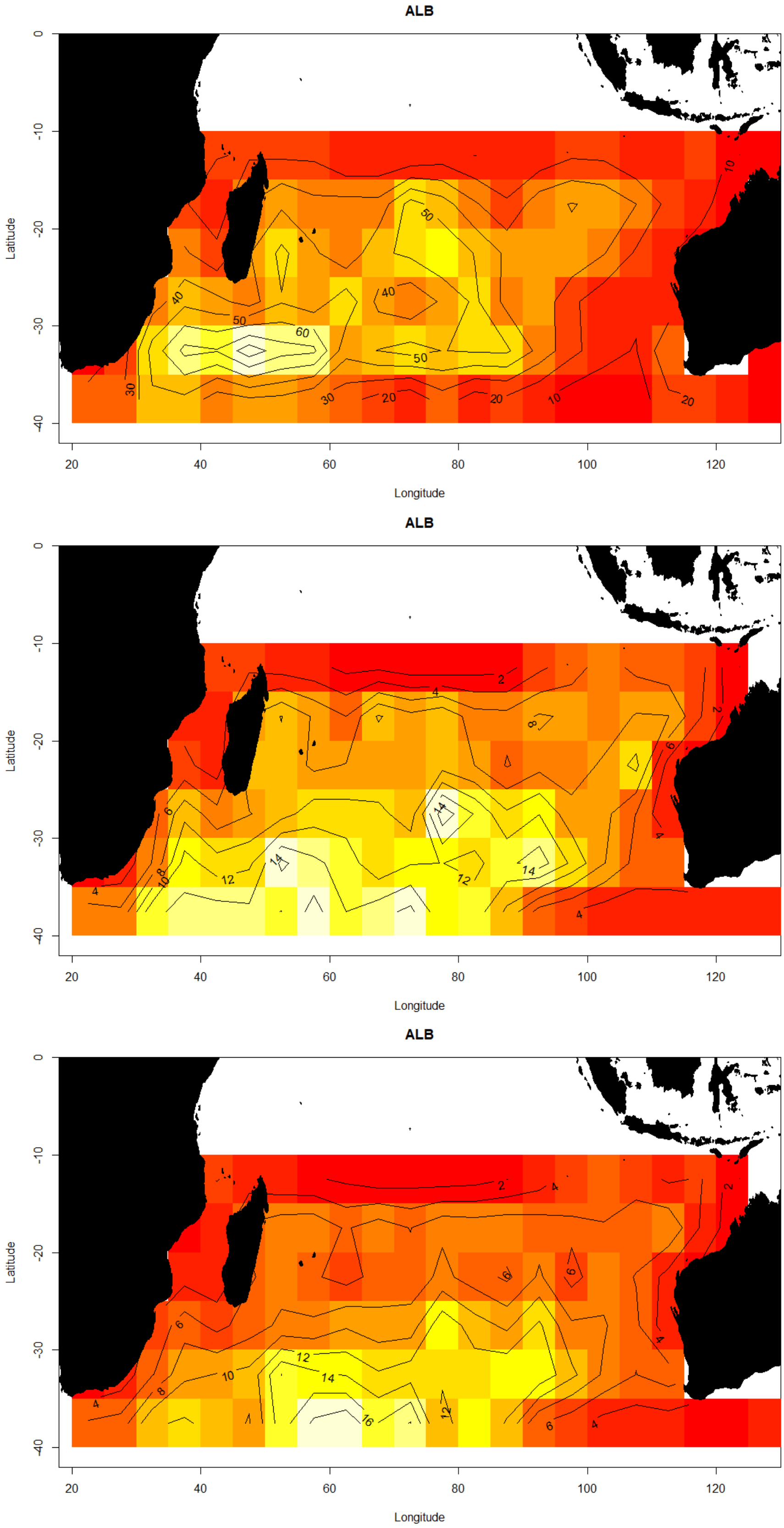

Figure 5: Heat maps of relative biomass by 5° cell estimated using method 8 for albacore tuna based on the periods 1963 – 1975 (top), 1979 - 1994 (middle), and 1980 – 2000 (bottom). Yellow indicates higher density, and white indicates no estimate.

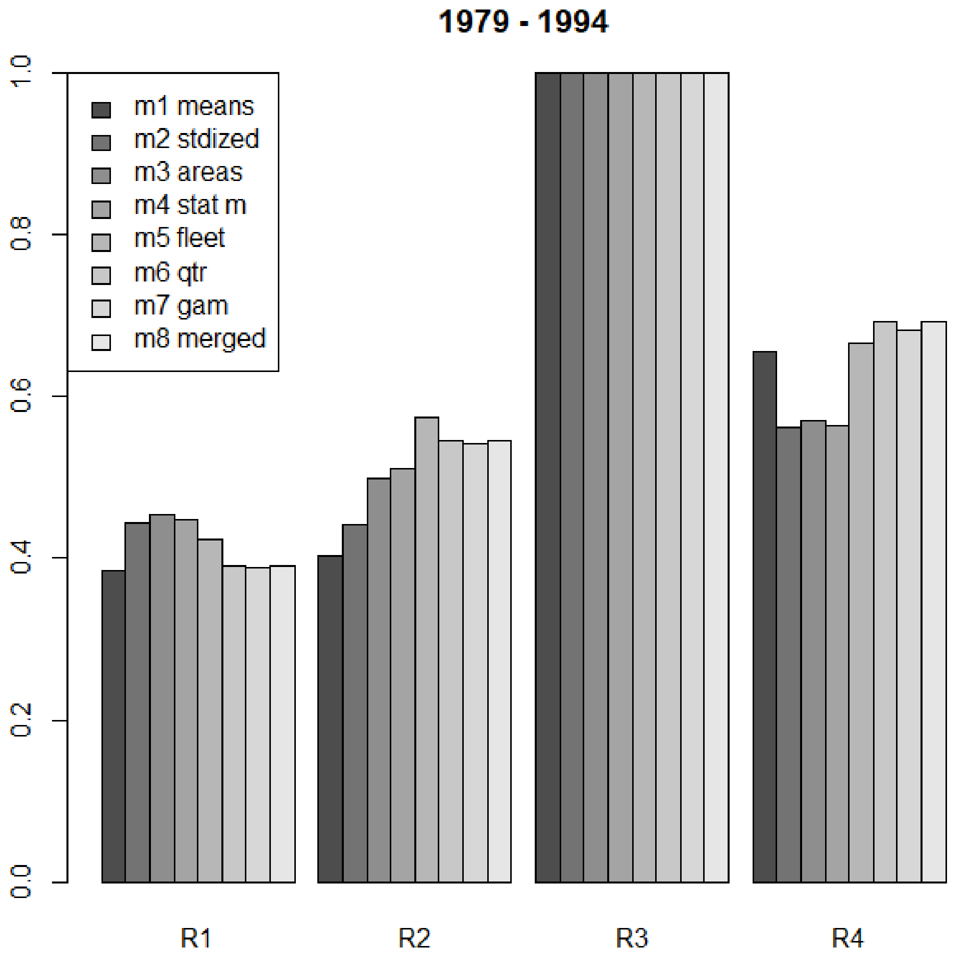

Figure 6: Adjusted scaling factors for albacore tuna by region and method, using data from 1979 - 1994.

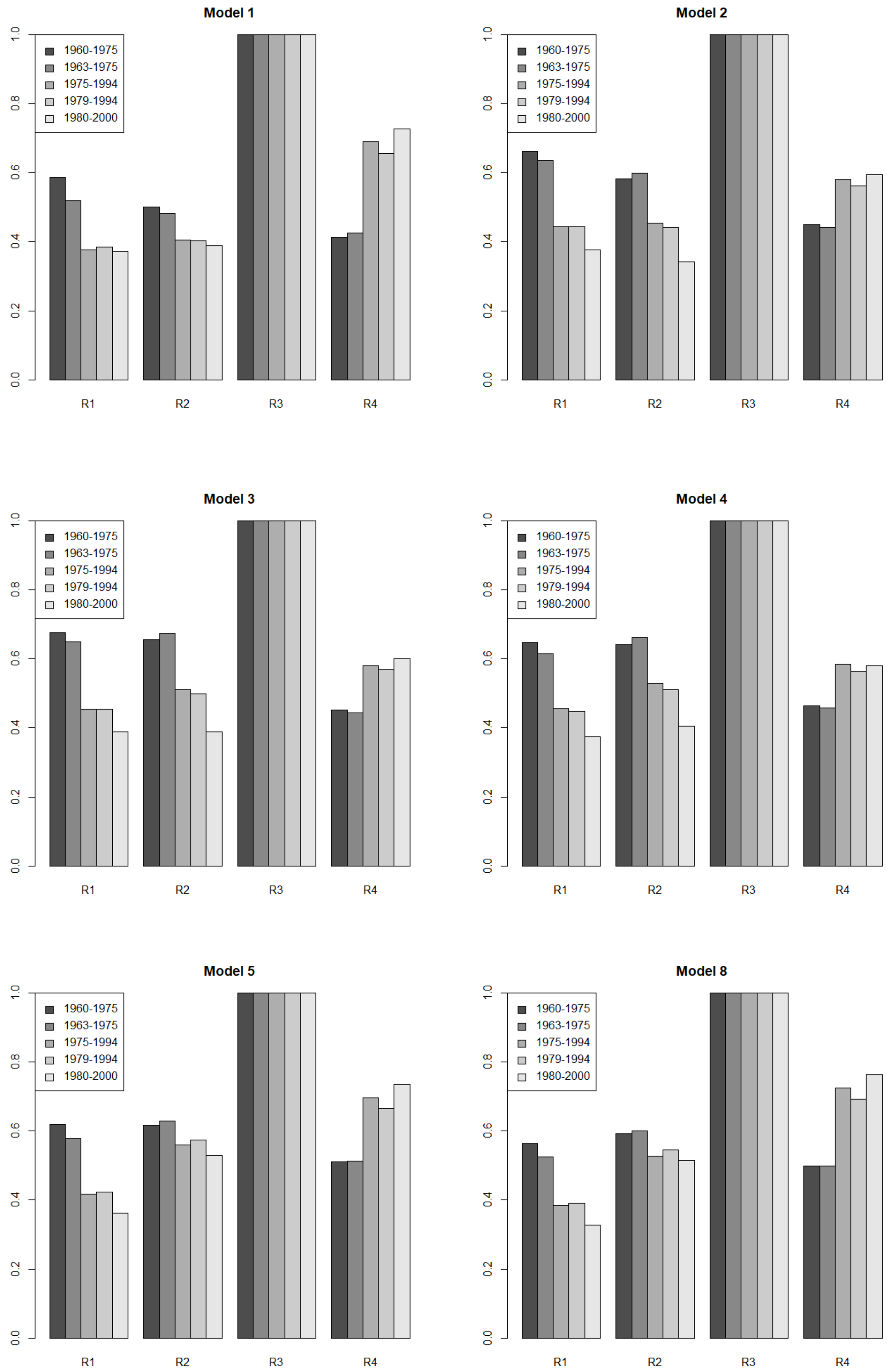

Figure 7: Adjusted scaling factors for albacore tuna by region for methods m1 (means), m2 (standardized), m3 (areas), m4 (statistical weighting), m5 (fleet), and m8 (qtr + merged), using data from 5 alternative periods.