Indian Ocean tropical tuna regional scaling factors that allow for seasonality and cell areas

Simon D. Hoyle[1]

Abstract

Indian Ocean tuna assessments are spatially structured, with regions that contain separate but linked subpopulations. In such multi-region assessments we must determine the relative abundances among regions. 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 improvements to the current practice. 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 (Langley, Bigelow et al. 2005, Hoyle and Langley 2007), 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 yellowfin tuna assessments have employed separate regions and regional scaling since at least 2008 (Langley, Hampton et al. 2008). The first bigeye assessment to use multiple regions was in 2013, with two spatial configurations, with one and three regions (Langley, Herrera et al. 2013). In the three-region version the catchabilities for each region were estimated independently, which led to the southern region being allocated an implausibly large biomass. The three-region model was rejected in favour of the single region model. In 2016 regional scaling was applied to the regions in the bigeye stock assessment (Langley 2016).

[1] IOTC Consultant, Nelson, New Zealand. simon.hoyle@gmail.com.

The method can be implemented in various ways, and the approach used until recently in Indian Ocean yellowfin assessments is described as follows:

"For these longline fisheries, a common catchability coefficient (and selectivity) was estimated in the assessment model, thereby, linking the respective CPUE indices among regions. This significantly increases the power of the model to estimate the relative (and absolute) level of biomass among regions. However, as CPUE indices are essentially density estimates it is necessary to scale the CPUE indices to account for the relative abundance of the stock among regions. For example, a relatively small region with a very high average catch rate may have a lower level of total biomass than a large region with a moderate level of CPUE.

The approach used was to determine regional scaling factors that incorporated both the size of the region and the relative catch rate to estimate the relative level of exploitable longline biomass among regions. This approach is similar to that used in the WCPO regionally disaggregated tuna assessments. The scaling factors were derived from the Japanese longline CPUE data from 1960–75, essentially summing the average CPUE in each of the 5*5 lat/longitude cells within a region. The relative scaling factors thus calculated for regions 1–5 are 0.18, 1.00, 0.28, 0.17, and 0.75, respectively." (Langley, Hampton et al. 2008).

The same approach was used in subsequent assessments, though the time period changed to 1963-1975 in the 2015 assessment (Langley 2015). During the 1963-1975 period the fleet was widely distributed, which is helpful for estimating spatial effects.

However, there are some problems with this approach, and in this paper we describe several potential improvements 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 (Langley, Bigelow et al. 2005, Hoyle and Langley 2007), and was also applied to the 2016 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 yellowfin and bigeye (Hoyle, Assan et al. 2017) 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. Target change is believed to be important in the early period, since the decline in yellowfin CPUE indices during the late 1960s–early 1970s was inconsistent with the relatively low level of catch taken during this period (Langley 2015), which may be partly due to target change. Cluster analyses indicate likely target change by the Japanese fleet towards more targeting of bigeye tuna during this period (Hoyle, Assan et al. 2017). We therefore explore the use of spatial effects based on the 1980 – 2000 period, during which targeting is estimated to have been more consistent.

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. 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 most recent 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 and Korean longline fleets, so as to focus on distant water longliners using similar fishing methods. Korean effort was reported from 1975, so was only included in the 1980 – 2000 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 6 quarters during the period of interest.

Each method was applied across 3 periods: 1960-1975, 1963-1975, 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, Assan 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, Lewin-Koh et al. 2017), rgeos (Bivand, Rundel et al. 2017), sp (Pebesma and Bivand 2005), raster

(Hijmans, van Etten et al. 2017), and geosphere (Hijmans, Williams et al. 2017). 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. The indices calculated in 2017 were used for bigeye, and the 2018 indices were used for yellowfin.

Results

Spatial coverage of data from the five periods varied (Figures 1 and 2). The broadest coverage occurred between 1965 and 1975. However, coverage was also reasonably good between 1985 and about 2009. The proportions of effort in each species composition cluster varied through time. On average across all regions, the targeting changes in the 1960/63 – 1975 periods appeared larger than those in the 1980 – 2000 period.

The factors in the standardization were all statistically significant (Table 1). The lowest AIC for both species 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 3), due to the use of aggregated data in which the variability depends on the number of sets per stratum. Residuals for the 1980-2000 period (not shown) also have a small peak on the left due to clumping of zero catches. These problems are minor and would not substantially affect results. Patterns in the residuals by region and year-quarter (Figure 4) occurred in the 1995-2000 period, due to differing trends by region.

The period covered by the time series influenced the spatial distribution of relative abundance (Figures 5 and 6) for each species, for both the means method and the standardization methods. In the earlier 1960-75 and 1963-75 periods the highest yellowfin catch rates were relatively higher than they were in the 1980-2000 period. The peak bigeye catch rates were more broadly distributed during the 1980-2000 period than in the early period.

Regional scaling factors were estimated for each region and method, and both species (Tables 2 and 3).

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 large and potentially important changes to the scaling factors, as shown in the results for 1979 – 1994 (Figure 7). Changing from using the overall mean (m1 mean) to using the standardization approach (m2 standardized) had a moderate effect for both species, to differing degrees by region. Adjusting by area (m3 areas) had a particularly large effect on yellowfin, reducing the scaling factor for south-western region 3. Introducing statistical weights to the standardization model (m4 statistical weights) had a relatively small effect in the 1979-1994 scaling factors for both yellowfin and bigeye, but slightly more impact on the 1980-2000 factors. Accounting for fleet effects in the model (m5 fleet) was much more impactful on the 1980-2000 factors, with only a small effect on the 1979-1994 scaling factors. Including quarterly effects had a limited further impact. Including estimates for missing cells via the spatial smoother slightly increased the scaling factors for the southern regions and (in the 1979-1994 analysis) the southwestern region, since this was where there were missing cells.

For both bigeye and yellowfin tuna, the overall impacts of all the changes were to reduce the scale of the temperate versus the tropical 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 8). Comparing 1979-1994 to 1963-1975, relatively more biomass occurred in the southwestern tropical region 2S and southwestern temperate region 3. For bigeye, more biomass occurred in both western and eastern tropical regions 1 and 2. Comparing the 1980-2000 period to 1979-1994, yellowfin scaling factors put more weight into south-western region 3 and north-eastern 6, while bigeye scaling factors put less weight into tropical regions 1 and 2, and more into the southern temperate region 3. The differences among time periods for model m8 were smaller than for the simpler standardization model m2.

Discussion

Regional scaling factors are influential components of the stock assessments for yellowfin and bigeye tuna in the Indian Ocean. The same approaches may also be applied to other assessments that have multiple regions.

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 (Punsly 1987, Campbell 2004), 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.

Finally, limiting the dataset to Japanese and Korean data means that the far northern areas are not well covered. Other fisheries have taken significant catches in these areas in some years, and it would be useful to explore the information in these catch rates.

References

Bivand, R., N. Lewin-Koh, E. Pebesma, E. Archer, A. Baddeley, N. Bearman, H.-J. Bibiko, S. Brey, J. Callahan and G. Carrillo (2017). "Package 'maptools'."

Bivand, R., C. Rundel, E. Pebesma, R. Stuetz and K. Hufthammer (2017). rgeos. Interface Geometry Engine–Open Source (GEOS). R package version 0.3–23; 2017.

Campbell, R. A. (2004). "CPUE standardisation and the construction of indices of stock abundance in a spatially varying fishery using general linear models." Fisheries Research **70**(2-3): 209-227.

Hijmans, R. J., J. van Etten, J. Cheng, M. Mattiuzzi, M. Sumner, J. A. Greenberg, O. P. Lamigueiro, A. Bevan, E. B. Racine and A. Shortridge (2017). Package 'raster', R Foundation for Statistical Computing.

Hijmans, R. J., E. Williams, C. Vennes and M. R. J. Hijmans (2017). "Package 'geosphere'."

Hoyle, S. D., C. Assan, S.-T. Chang, D. Fu, R. Govinden, D. N. Kim, S. I. Lee, J. Lucas, T. Matsumoto, K. Satoh, Y.-m. Yeh and T. Kitakado (2017). Collaborative study of tropical tuna CPUE from multiple Indian Ocean longline fleets in 2017. IOTC-2017-WPTT19-32. Indian Ocean Tuna Commission, Working Party on Tropical Tunas.

Hoyle, S. D. and A. Langley (2007). Regional weighting factors for yellowfin tuna in WCP-CA stock assessments. WCPFC Scientific Committee**:** 19.

Langley, A. (2015). Stock assessment of yellowfin tuna in the Indian Ocean using Stock Synthesis, IOTC–2015–WPTT17–30. IOTC Working Party on Tropical Tunas.

Langley, A. (2016). "Stock assessment of bigeye tuna in the Indian Ocean for 2016-model development and evaluation." IOTC Proceedings, volume IOTC-2016-WPTT18-20, page 98p, Victoria, Seychelles: 11-13.

Langley, A., K. Bigelow, M. Maunder and N. Miyabe (2005). Longline CPUE indices for bigeye and yellowfin in the Pacific Ocean using GLM and statistical habitat standardisation methods. WCPFC-SC1, Noumea, New Caledonia**:** 8-19.

Langley, A., J. Hampton, M. Herrera and J. Million (2008). Preliminary stock assessment of yellowfin tuna in the Indian Ocean using MULTIFAN-CL, IOTC-2008-WPTT-10.

Langley, A., M. Herrera and R. Sharma (2013). "Stock assessment of bigeye tuna in the Indian Ocean for 2012." IOTC Working Party Document.

Pebesma, E. and R. S. Bivand (2005). "Classes and Methods for Spatial Data: the sp Package." R news **5**(2): 9-13.

Punsly, R. (1987). Estimation of the relative annual abundance of yellowfin tuna, Thunnus albacares , in the eastern Pacific Ocean during 1970-1985. LA JOLLA, CA ( ), I-ATTC.

Tables

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

Method	Species	Variable dropped	Df	Deviance	AIC	δAIC
5	Bigeye	-	-	5294	26720	0
		year-qtr	59	5533	27096	376
		cell	119	9304	32805	6085
		fleet	1	5365	26867	147
	Yellowfin	-	-	6557	31308	0
		year-qtr	59	6982	31990	681
		cell	146	15782	42190	10882
		fleet	1	6612	31412	103
6	Bigeye	-	-	5241	26547	0
		year	14	5299	26643	95
		cell	115	7265	29979	3432
		fleet	1	5299	26668	120
		reg.qtr	15	5470	26998	450
	Yellowfin	-	-	6450	31051	0
		year	14	6705	31516	464
		cell	140	10024	36380	5329
		fleet	1	6507	31161	110
		reg.qtr	21	6715	31520	469

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

Period	Method	Region						
		1	2	3	4	5	6	7
6075	1	0.362	1.000	0.740	0.397	0.994	0.243	0.732
	2	0.319	0.951	0.677	0.428	1.000	0.267	0.665
	3	0.232	0.917	0.461	0.409	1.000	0.229	0.599
	4	0.225	0.919	0.474	0.434	1.000	0.225	0.595
	5	0.225	0.919	0.474	0.434	1.000	0.225	0.595
	6	0.181	0.920	0.483	0.425	1.000	0.268	0.595
	7	0.131	0.887	0.459	0.413	1.000	0.242	0.574
	8	0.178	0.904	0.474	0.449	1.000	0.263	0.584
6375	1	0.402	1.000	0.762	0.371	0.941	0.261	0.693
	2	0.320	0.957	0.661	0.348	1.000	0.296	0.644
	3	0.230	0.924	0.447	0.332	1.000	0.249	0.584
	4	0.224	0.915	0.462	0.362	1.000	0.246	0.563
	5	0.224	0.915	0.462	0.362	1.000	0.246	0.563
	6	0.177	0.917	0.467	0.354	1.000	0.277	0.561
	7	0.136	0.890	0.445	0.390	1.000	0.261	0.543
	8	0.173	0.899	0.458	0.406	1.000	0.272	0.550
7594	1	0.141	0.989	0.960	0.421	1.000	0.421	0.617
	2	0.121	1.000	0.907	0.428	0.965	0.418	0.599
	3	0.117	1.000	0.602	0.403	0.934	0.349	0.499
	4	0.124	1.000	0.599	0.447	0.974	0.313	0.513
	5	0.121	1.000	0.587	0.426	0.953	0.304	0.507
	6	0.139	1.000	0.595	0.434	0.976	0.226	0.517
	7	0.143	0.991	0.598	0.445	1.000	0.225	0.514
	8	0.139	1.000	0.595	0.455	0.976	0.226	0.517
7994	1	0.152	0.848	0.953	0.400	1.000	0.486	0.595
	2	0.146	0.958	0.927	0.398	1.000	0.498	0.618
	3	0.147	0.993	0.639	0.389	1.000	0.433	0.530
	4	0.165	0.943	0.612	0.412	1.000	0.388	0.519
	5	0.168	0.994	0.610	0.388	1.000	0.389	0.532
	6	0.179	0.967	0.603	0.388	1.000	0.296	0.525
	7	0.148	0.977	0.634	0.417	1.000	0.280	0.514
	8	0.175	0.983	0.623	0.455	1.000	0.290	0.516
8000	1	0.125	0.872	0.992	0.614	1.000	0.598	0.574
	2	0.095	0.762	1.000	0.567	0.880	0.539	0.465
	3	0.109	0.901	0.807	0.634	1.000	0.517	0.470
	4	0.102	0.859	0.763	0.592	1.000	0.501	0.462
	5	0.104	1.000	0.694	0.477	0.996	0.523	0.507
	6	0.103	0.985	0.711	0.474	1.000	0.421	0.507
	7	0.099	0.975	0.730	0.423	1.000	0.429	0.516
	8	0.103	0.985	0.711	0.484	1.000	0.421	0.507

Table 3: Regional scaling factors for bigeye tuna by period, method, and region.

Period	Method	Region				
		1	2	3	4	5
6075	1	0.639	1.000	0.681	0.847	0.665
	2	0.604	1.000	0.508	0.637	0.697
	3	0.602	1.000	0.398	0.582	0.647
	4	0.601	1.000	0.386	0.594	0.652
	5	0.601	1.000	0.386	0.594	0.652
	6	0.610	1.000	0.394	0.615	0.646
	7	0.589	1.000	0.524	0.595	0.634
	8	0.601	1.000	0.548	0.618	0.637
6375	1	0.670	1.000	0.771	0.920	0.703
	2	0.621	1.000	0.562	0.674	0.719
	3	0.617	1.000	0.442	0.614	0.669
	4	0.617	1.000	0.437	0.634	0.672
	5	0.617	1.000	0.437	0.634	0.672
	6	0.627	1.000	0.449	0.656	0.670
	7	0.602	1.000	0.552	0.667	0.653
	8	0.617	1.000	0.587	0.687	0.659
7594	1	0.732	1.000	0.476	0.617	0.648
	2	0.709	1.000	0.398	0.531	0.668
	3	0.722	1.000	0.316	0.502	0.616
	4	0.720	1.000	0.316	0.501	0.625
	5	0.737	1.000	0.314	0.482	0.632
	6	0.732	1.000	0.308	0.505	0.629
	7	0.743	1.000	0.347	0.483	0.603
	8	0.732	1.000	0.376	0.510	0.629
7994	1	0.675	1.000	0.398	0.599	0.617
	2	0.695	1.000	0.333	0.508	0.652
	3	0.707	1.000	0.247	0.482	0.601
	4	0.700	1.000	0.235	0.476	0.608
	5	0.738	1.000	0.226	0.444	0.622
	6	0.736	1.000	0.234	0.473	0.626
	7	0.795	1.000	0.357	0.462	0.604
	8	0.799	1.000	0.373	0.486	0.626
8000	1	0.597	1.000	0.615	0.679	0.541
	2	0.577	1.000	0.727	0.829	0.479
	3	0.585	1.000	0.607	0.799	0.453
	4	0.565	1.000	0.543	0.723	0.462
	5	0.683	1.000	0.447	0.573	0.526
	6	0.687	1.000	0.465	0.598	0.531
	7	0.714	1.000	0.478	0.595	0.531
	8	0.687	1.000	0.489	0.601	0.531

Figures

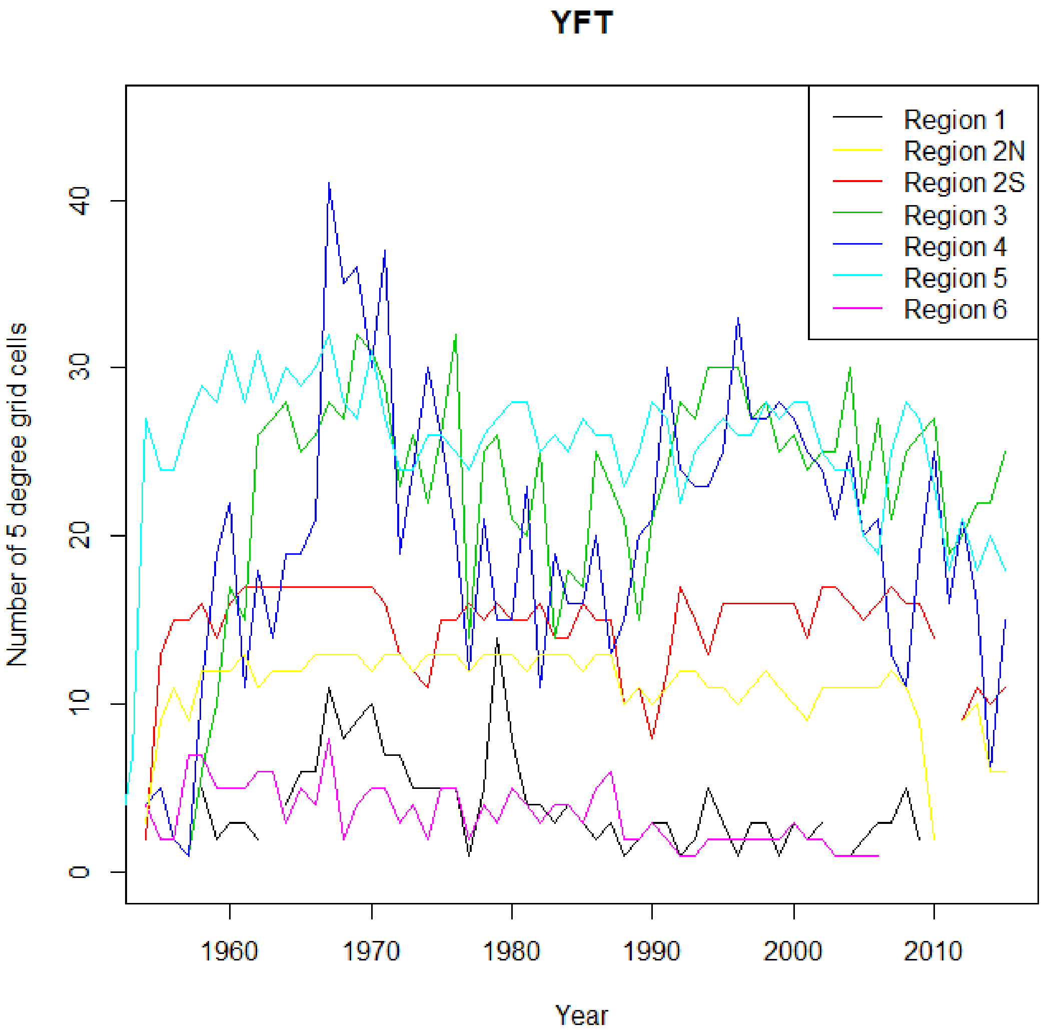


Figure 1: By yellowfin region and year, the number of 5° grid cells with catch and effort data.

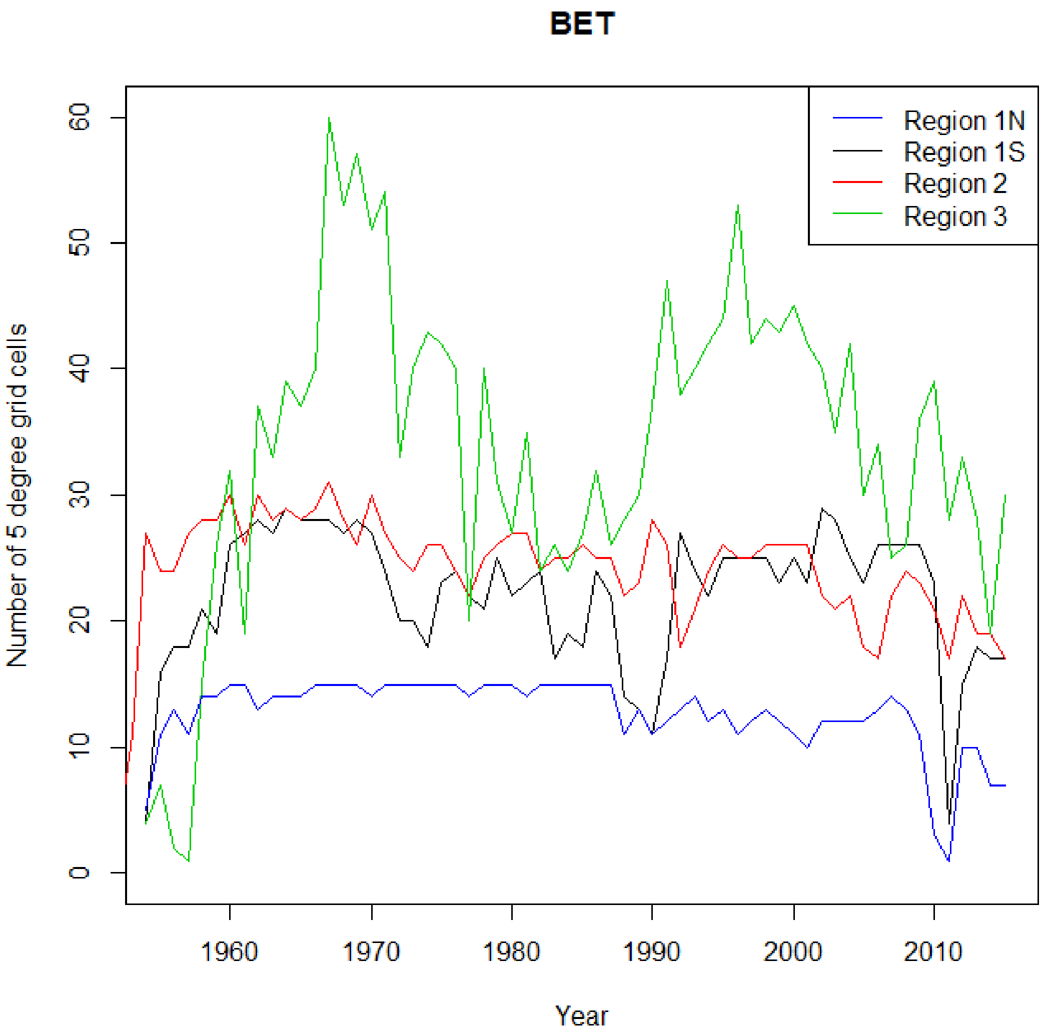


Figure 2: By bigeye region and year, the number of 5° grid cells with catch and effort data.

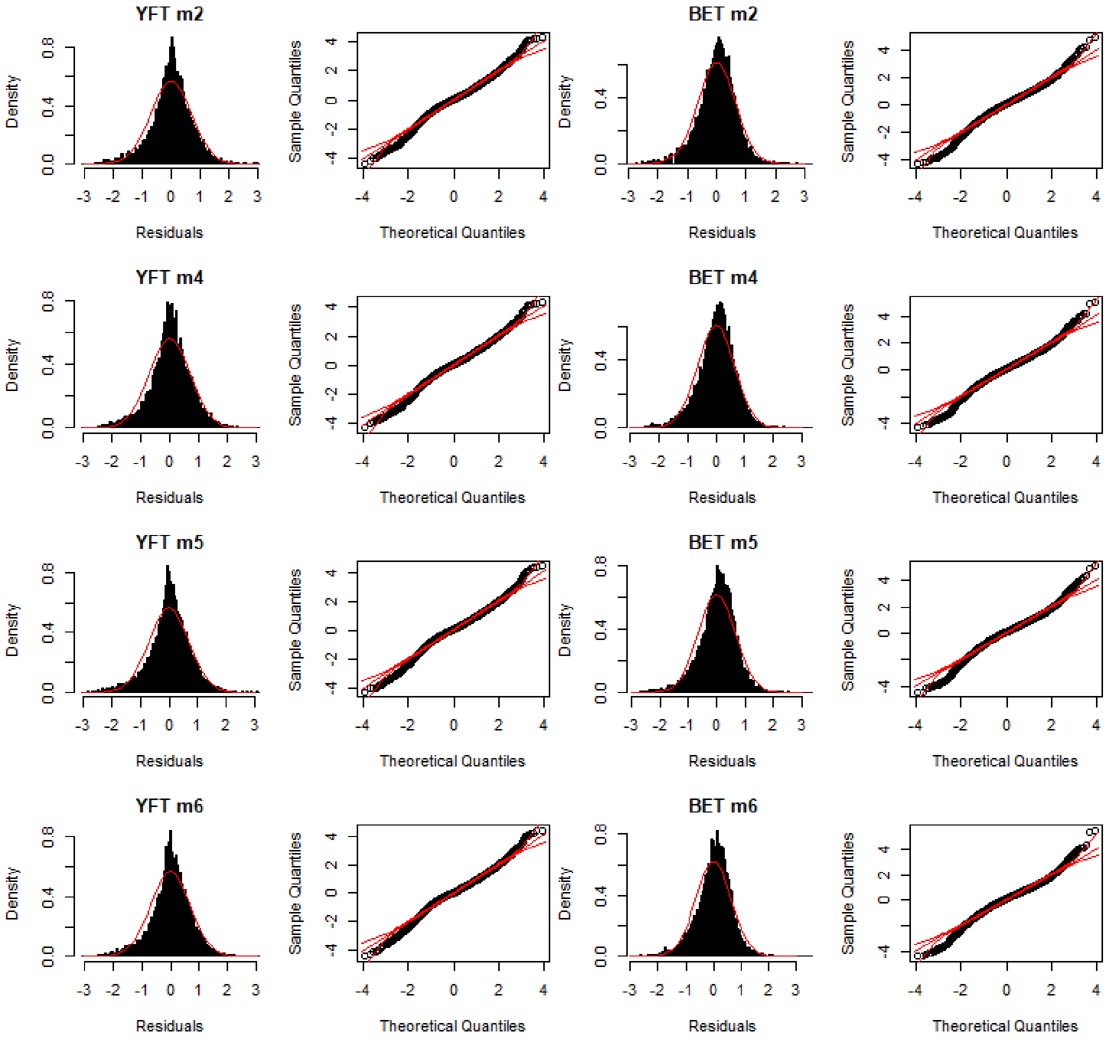


Figure 3: Diagnostic plots for the glm models for the bigeye and yellowfin standardized methods using data from 1979 - 1994.

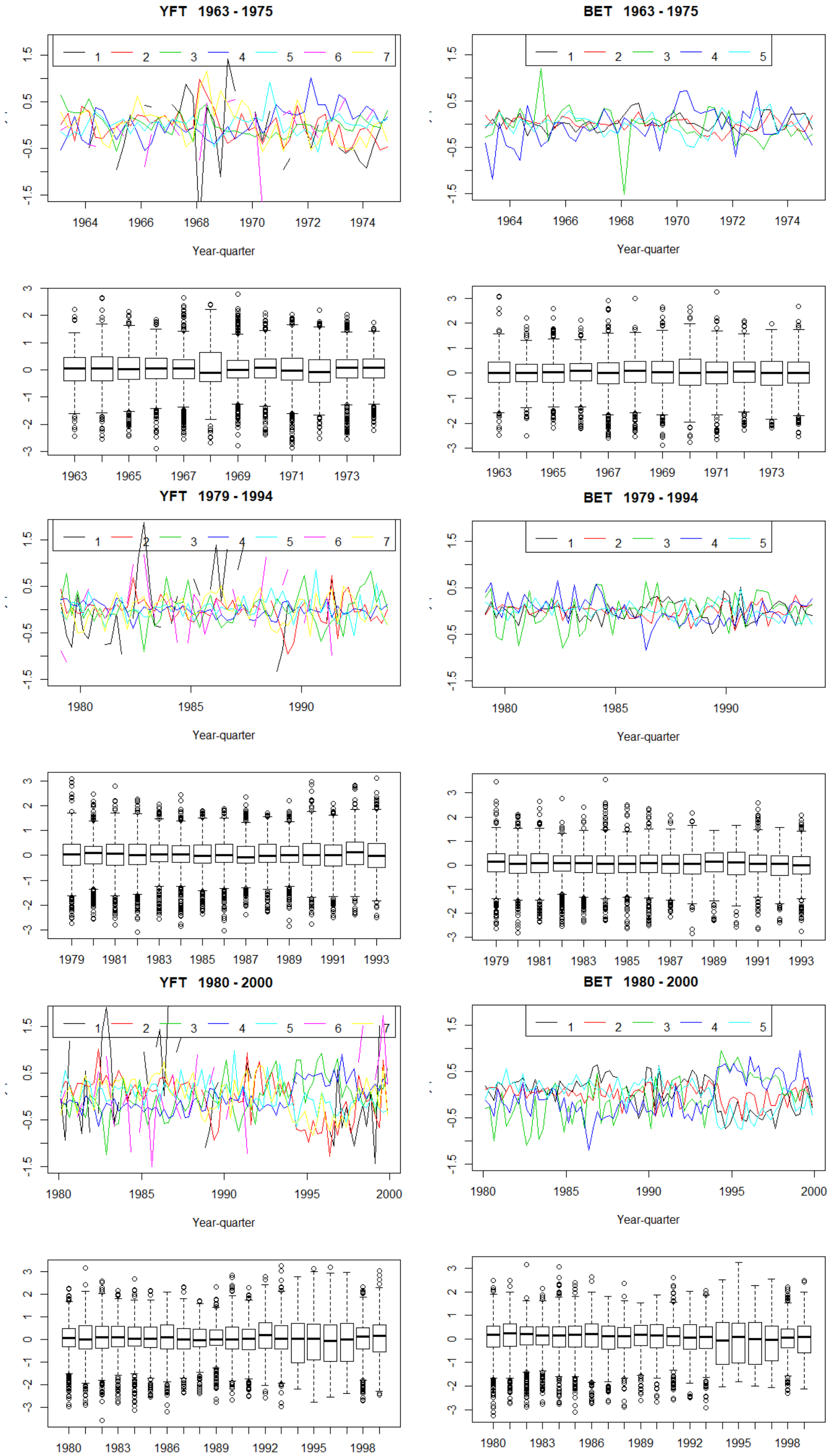


Figure 4: Plots of mean residuals by region, and boxplots of residual distributions, for YFT and BET model 6 for the periods 1963-1975, 1979-1994, and 1980-2000.

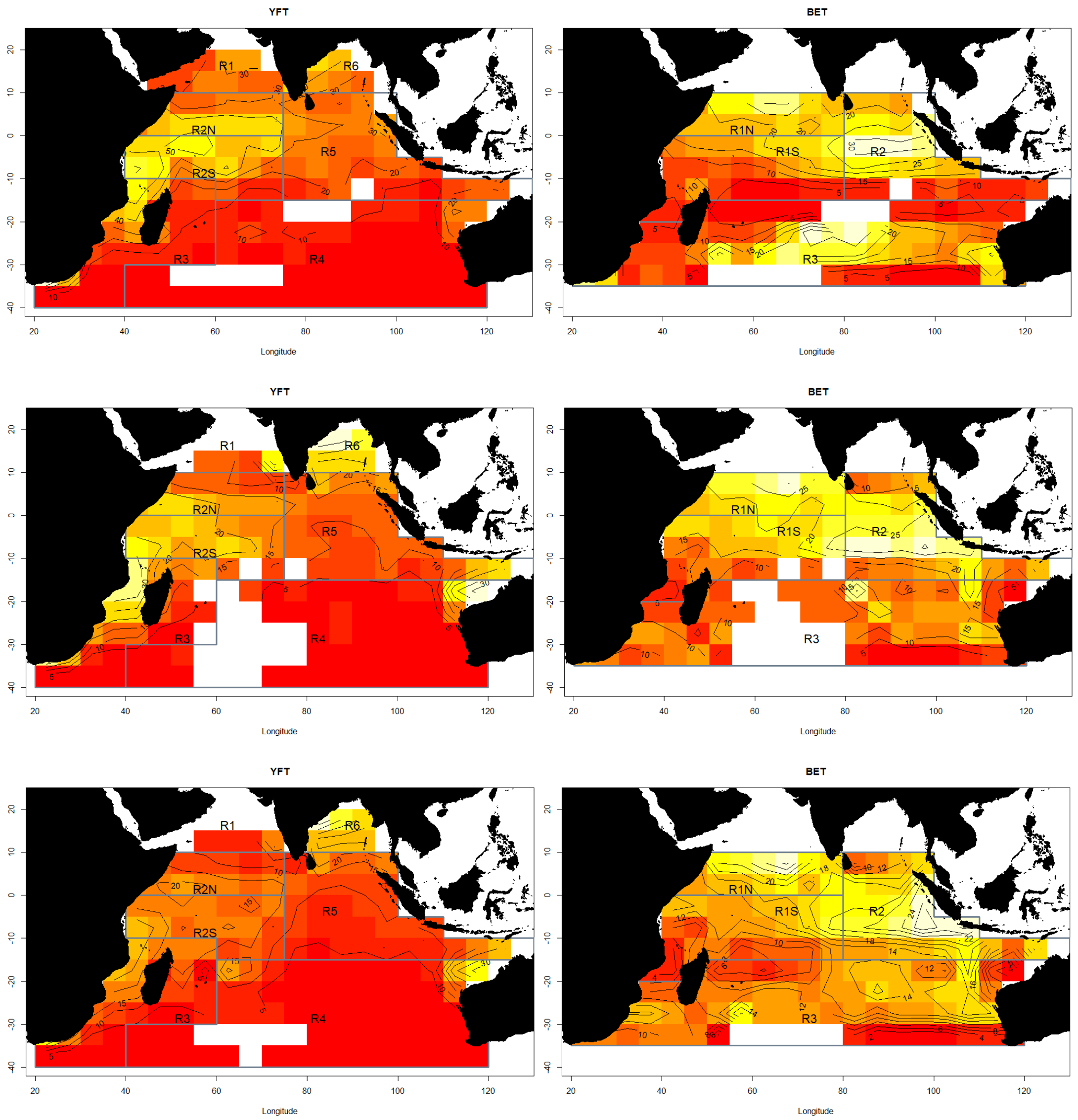


Figure 5: Heat maps of relative biomass by 5° cell estimated using the means method for yellowfin tuna (left) and bigeye tuna (right) based on the periods 1960 – 1975 (top), 1979 – 1994 (middle), and 1980 – 2000 (bottom). Yellow indicates higher density, and white indicates no estimate.

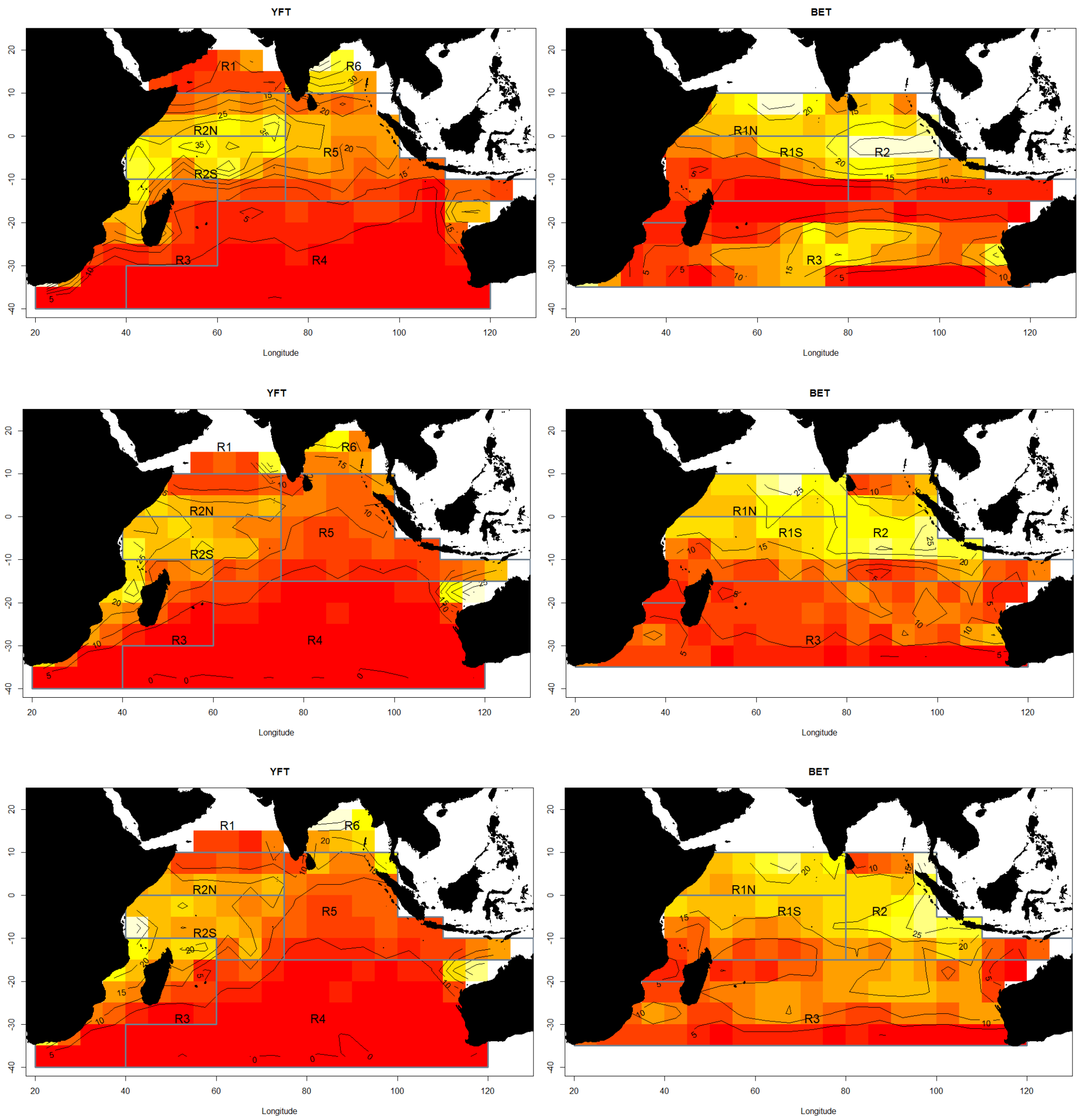
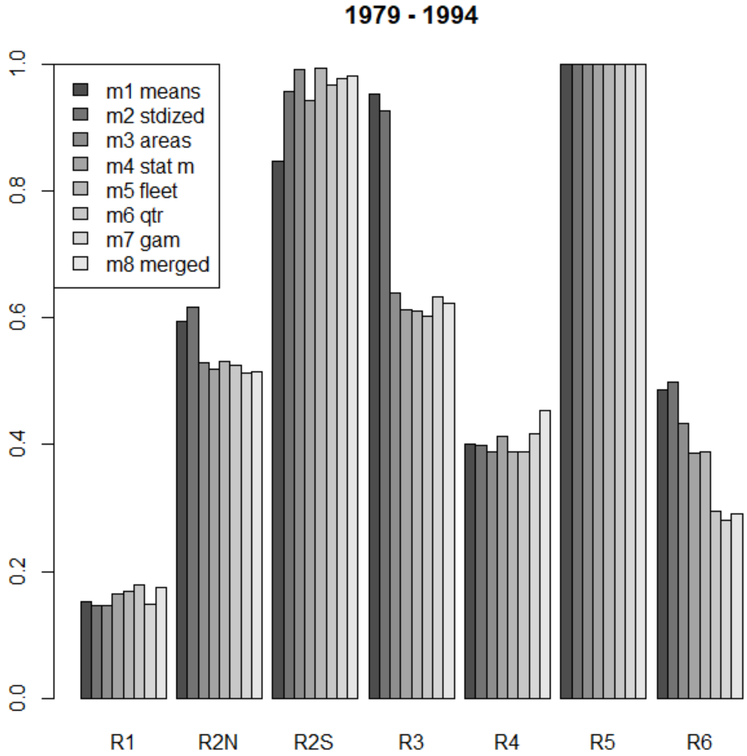


Figure 6: Heat maps of relative biomass by 5° cell estimated using method 8 for yellowfin tuna (left) and bigeye tuna (right) based on the periods 1963 – 1975 (top), 1979 - 1994 (middle), and 1980 – 2000 (bottom). Yellow indicates higher density, and white indicates no estimate.



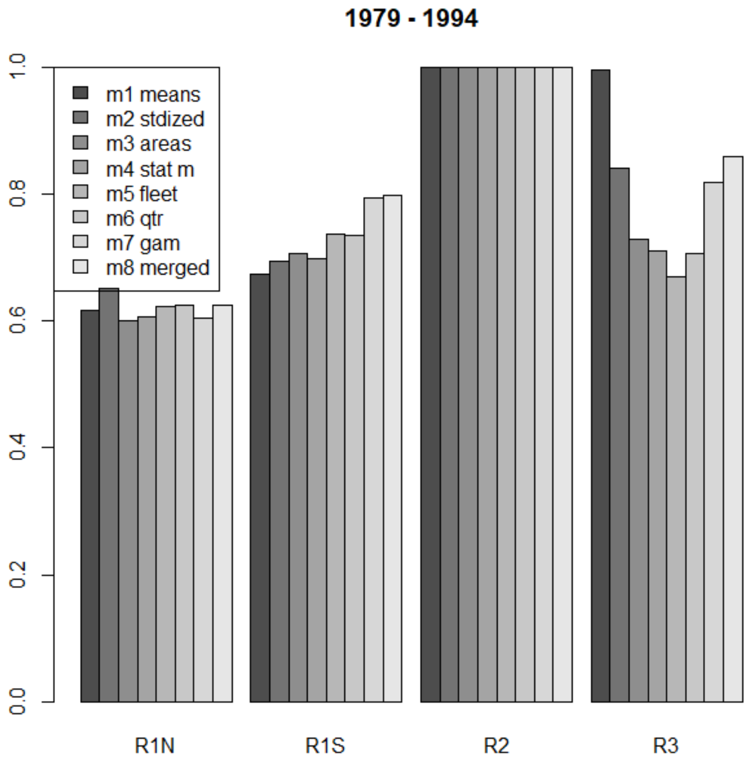


Figure 7: Adjusted scaling factors for yellowfin (above) and bigeye (below) by region and method, using data from 1979 - 1994.

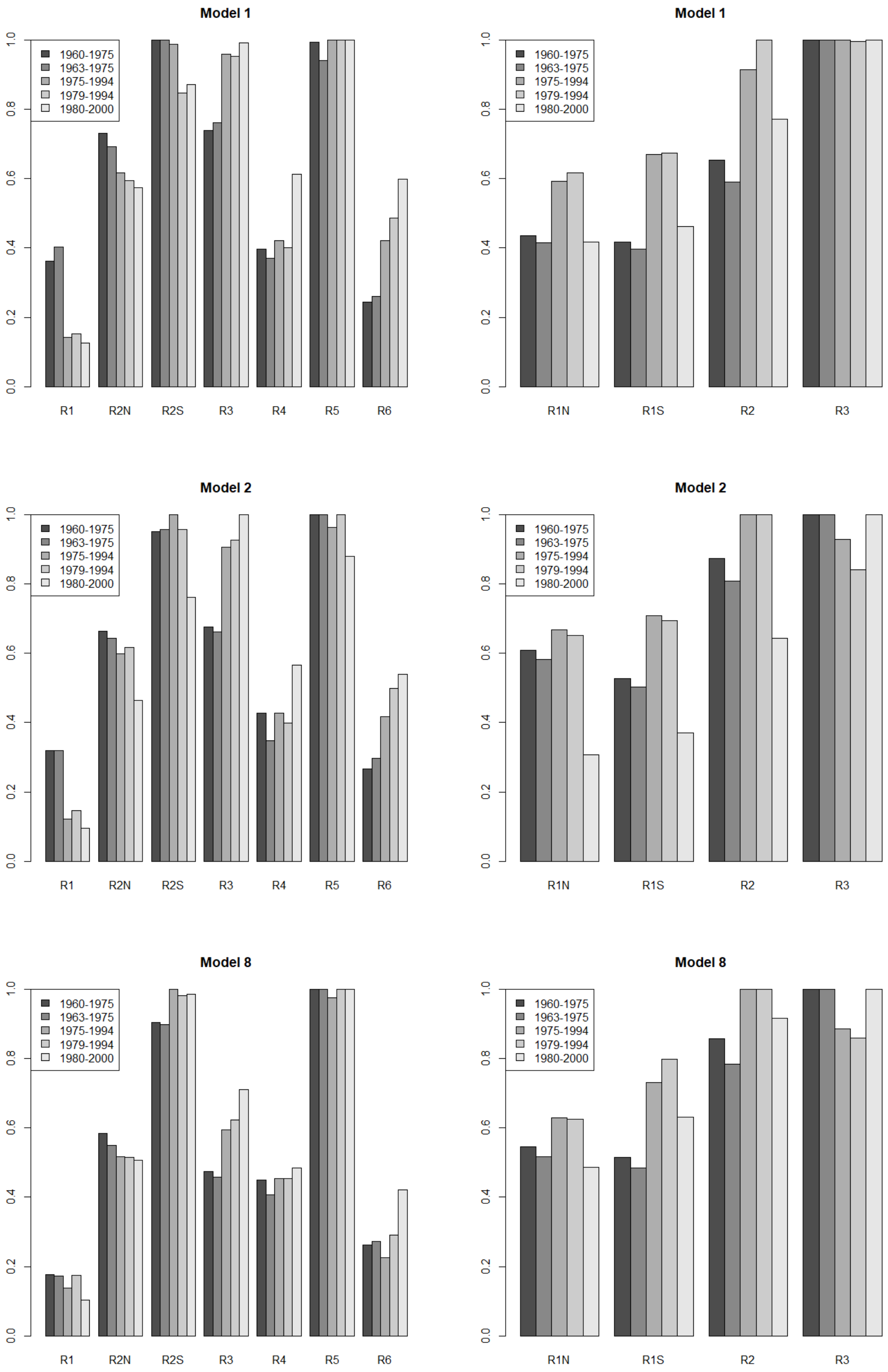


Figure 8: Adjusted scaling factors for yellowfin (left) and bigeye (right) by region for methods m1 (means), m2 (standardized) and m8 (merged), using data from 1979 - 1994.