Received: 2 October 2017
IOTC-2017-WPTT19-36

Regional scaling factors for Indian Ocean stock assessments

Simon D. Hoyle[1]

Introduction

In stock assessments with multiple regions it is important to determine the relative abundances among the regions. Indian Ocean yellowfin assessments have been developed with separate regions since at least 2008 (Langley, Hampton et al. 2008). Relative abundances can be estimated using CPUE data, based on the relative catch rates among regions. Similar approaches have been used in Western and Central Pacific assessments since 2005 (Langley, Bigelow et al. 2005, Hoyle and Langley 2007). 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 this period the fleet was widely distributed, which is helpful for estimating spatial effects.

Alternative approaches are possible, and in this paper I describe several, 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 catch spatial effects may therefore provide more consistent estimates. In addition, the current indices of abundance 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 CPUE indices during the late 1960s–early 1970s is inconsistent with the relatively low level of catch taken during

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

this period (Langley 2015), which may be partly due to target change. It may therefore be useful to base the spatial effects on a period without substantial target change.

Bigeye assessments did not use regional scaling before 2016, with most assessments using a single region. In the 2013 assessment there were 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), using a standardisation approach similar to that used in the WCPO (Langley, Bigelow et al. 2005, Hoyle and Langley 2007).

In this paper I describe the methods used to develop the regional scaling parameters used from 2008 to 2016, test some changes and potential improvements, and apply them to bigeye and yellowfin tuna CPUE data.

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://iotc.org/sites/default/files/documents/2016/09/IOTC-2016-WPTT18-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. All data from these fleets were reported at a resolution of 1 month and 5° grid cell. I omitted data from grid cells with effort less than 50000 hooks during the period of interest, and with fishing in fewer than 6 quarters.

Scaling factors were calculated using two approaches: the method used in the 2008-2013 yellowfin assessments (the "means" method), and a method based on standardization (the "standardization" method).

Each method was applied across 3 periods: 1960-1975, 1963-1975, and 1980-2000.

For the means method I calculated the scaling factors by taking the mean CPUE in each 5° grid cell, and then summing the means for each region.

For the standardization method I applied a generalized linear model with the form $\log(CPUE + c) \sim yrqtr + cell$, 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, and *cell* is the 5° grid cell effect. Both effects were modelled as categorical variables. The constant c was set to 10% of the mean CPUE in the model dataset.

I 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. Each regional sum was then divided by the largest regional sum to produce regional scaling factors.

For comparisons between scaling factors using data from different periods, each scaling factor was divided by the mean of the indices for the region during the period of interest, using the 2017 indices.

Results

Spatial coverage of data from the three 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 period covered by the time series influenced the spatial distribution of relative abundance (Figures 3 to 5) for each species. In the earlier 1960-75 and 1963-75 periods the highest yellowfin catch rates were relatively higher (Figure 3) than they were in the 1980-2000 period (Figure 4). The peak bigeye catch rates were more broadly distributed during the 10980-2000 period than in the early period (Figures 4 and 5).

Similarly, 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 a very large difference for yellowfin when the period changed to 1980-2000 (Figure 6).

We adjusted the scaling factors relative to the indices of abundance, so as to compare their potential effects on the assessment (Figure 7). As expected, this adjustment reduced the impact on scaling of changing the period, but it was still significant and potentially important. For yellowfin, relatively more biomass occurred in the southwestern tropical region 1S and eastern tropical region 2, and less in southwestern temperate region 3. For bigeye, more biomass occurred in eastern tropical region 2.

Changing the analysis method from using the overall mean to using the standardization approach had a moderate effect on both the estimates of the average spatial distribution of abundance (Figures 5 and 6) and the regional scaling factors (Figures 8 and 9).

Diagnostics for the models showed some lack of normality in the residuals, with a small peak to the left due to clumping of zero catches (Figure 10), but the problems appear too small to badly affect results.

Discussion

Regional scaling factors are potentially 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. We cannot prove that one of the approaches is more accurate, since we lack reliable information about the true relative abundances, and have not compared the approaches using simulation. However, the standardization approach has advantages since it adjusts 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.

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. I have not done so because the appropriate variance estimate is unclear. This should be addressed in future.

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.

I compared only the two periods used in previous assessments and a third more recent period, but other options are possible.

The aggregated data used here does not report HBF, and does not 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 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

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.

Figures

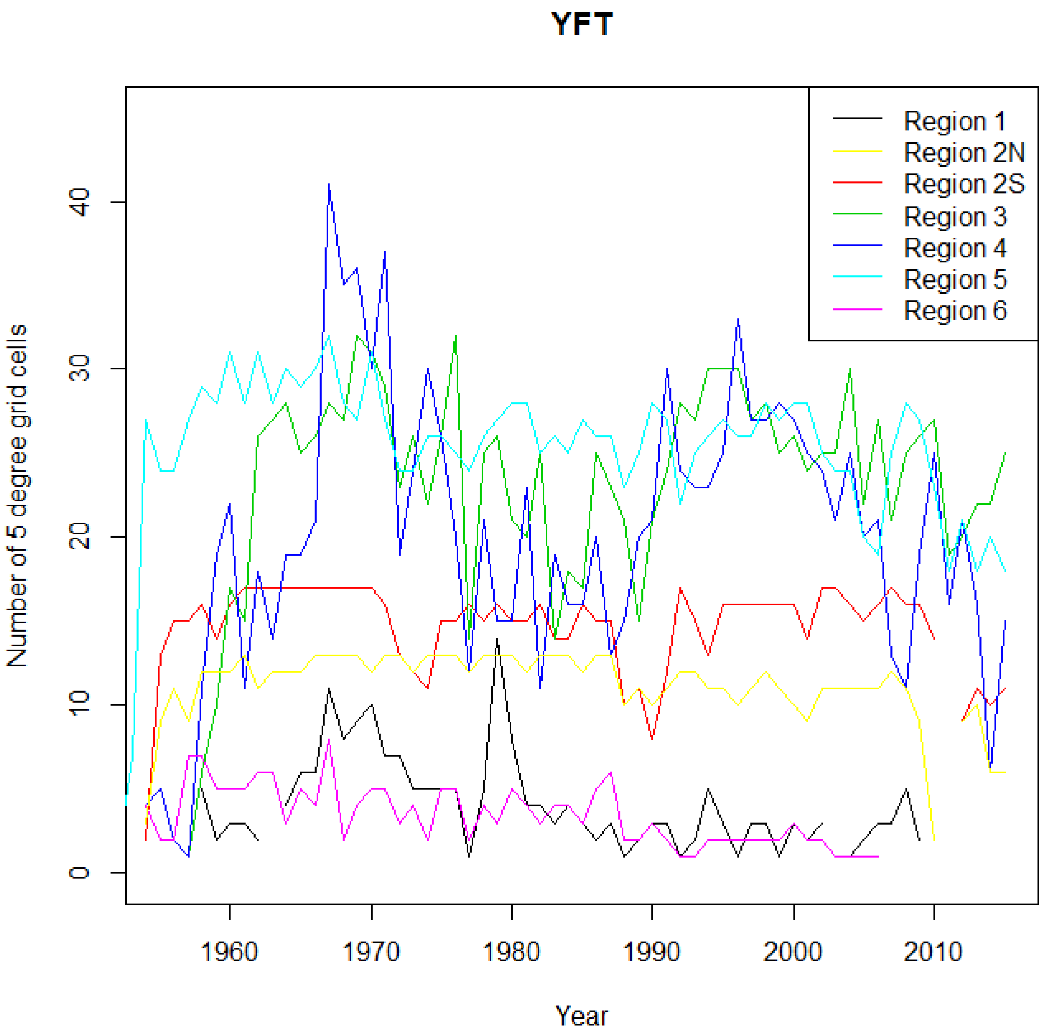


Figure 1: By yellowfin region and year, the number of 5° grid cells with catch and effort data.

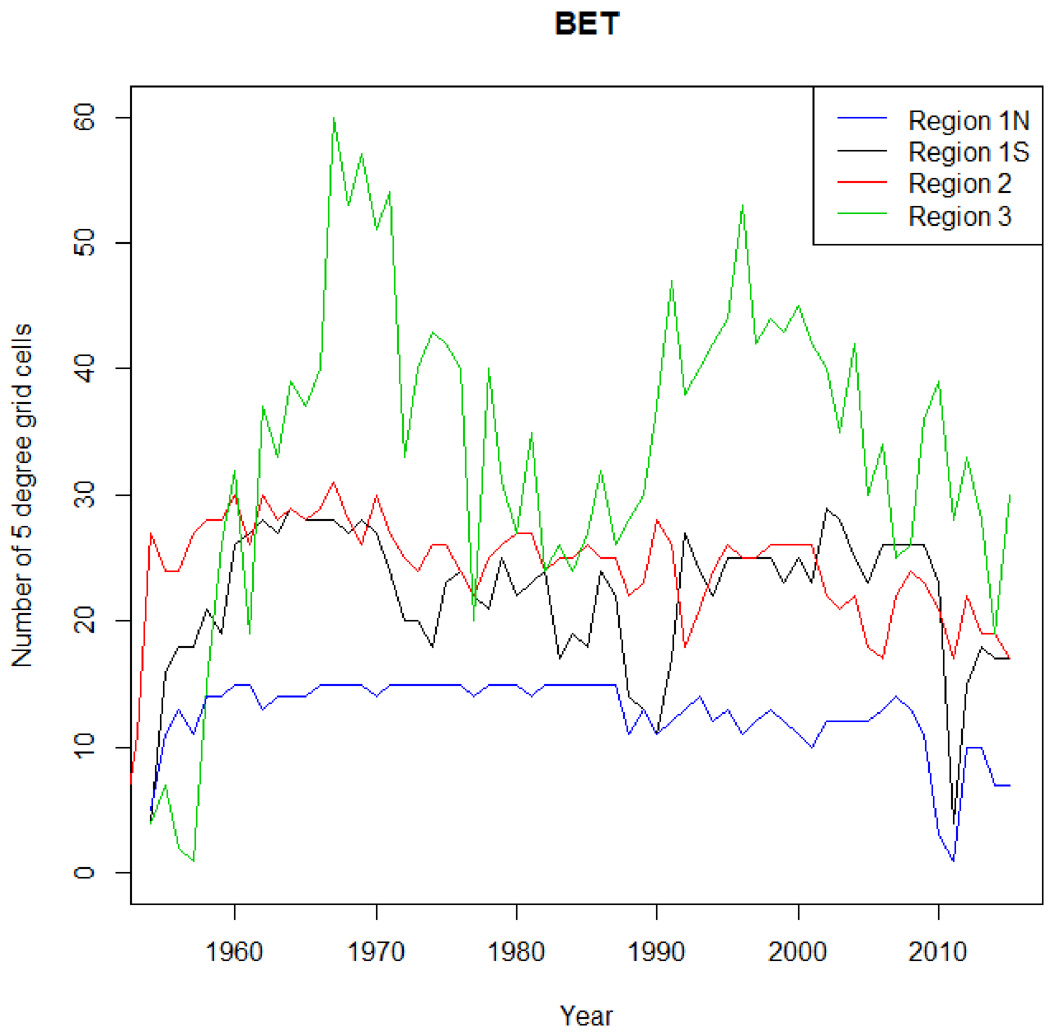


Figure 2: By bigeye region and year, the number of 5° grid cells with catch and effort data.

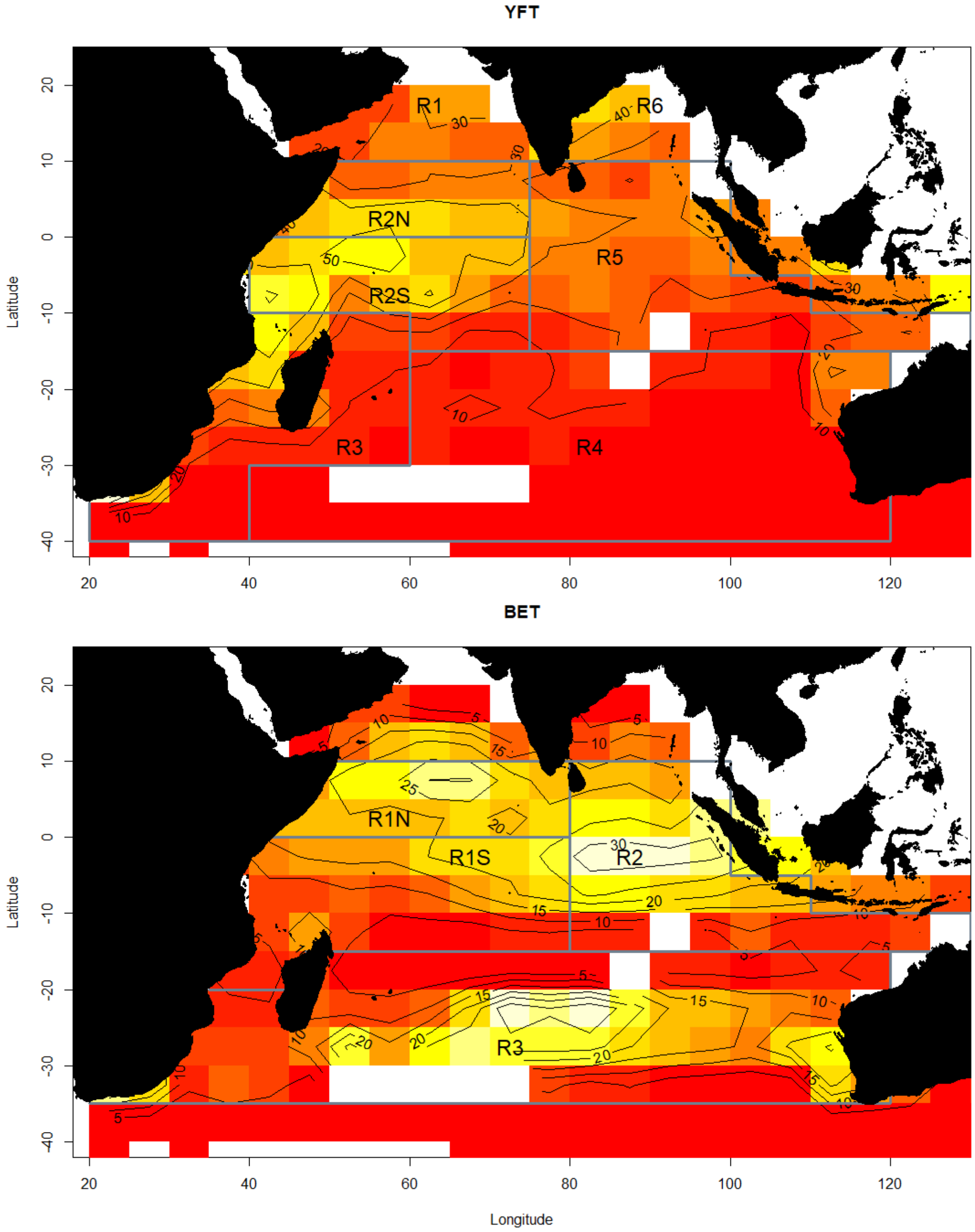


Figure 3: Heat maps of relative yellowfin (above) and bigeye (below) CPUE by 5° grid cell, estimated using the means method. Data are from 1963 to 1975, for cells with cumulative effort of at least 50000 hooks and effort in at least 5 quarters.

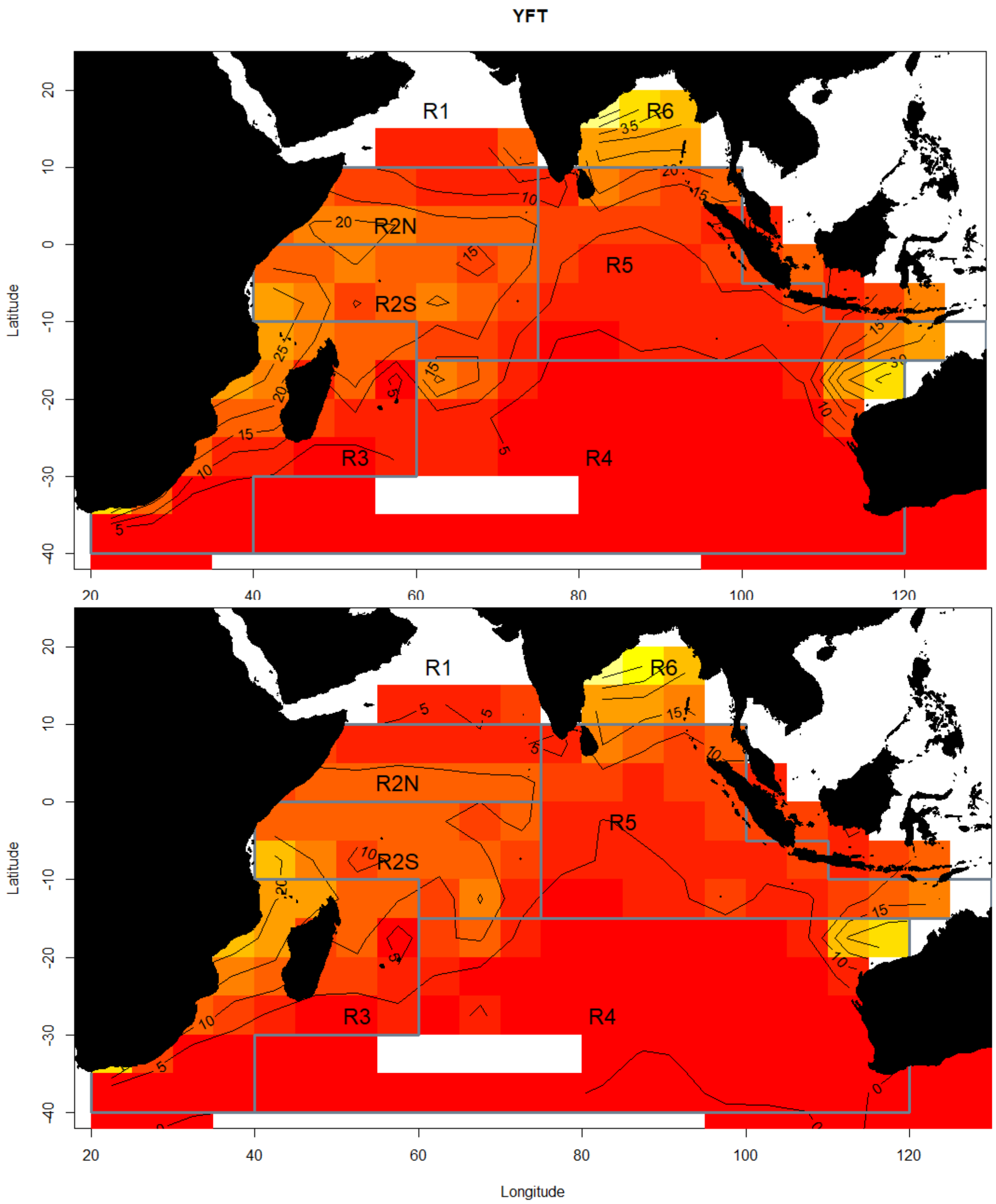


Figure 4: Heat maps of relative yellowfin CPUE by 5° grid cell, estimated using the means method (above) and the standardized method (below). Data are from 1980 to 2000, for cells with cumulative effort of at least 50000 hooks and effort in at least 5 quarters.

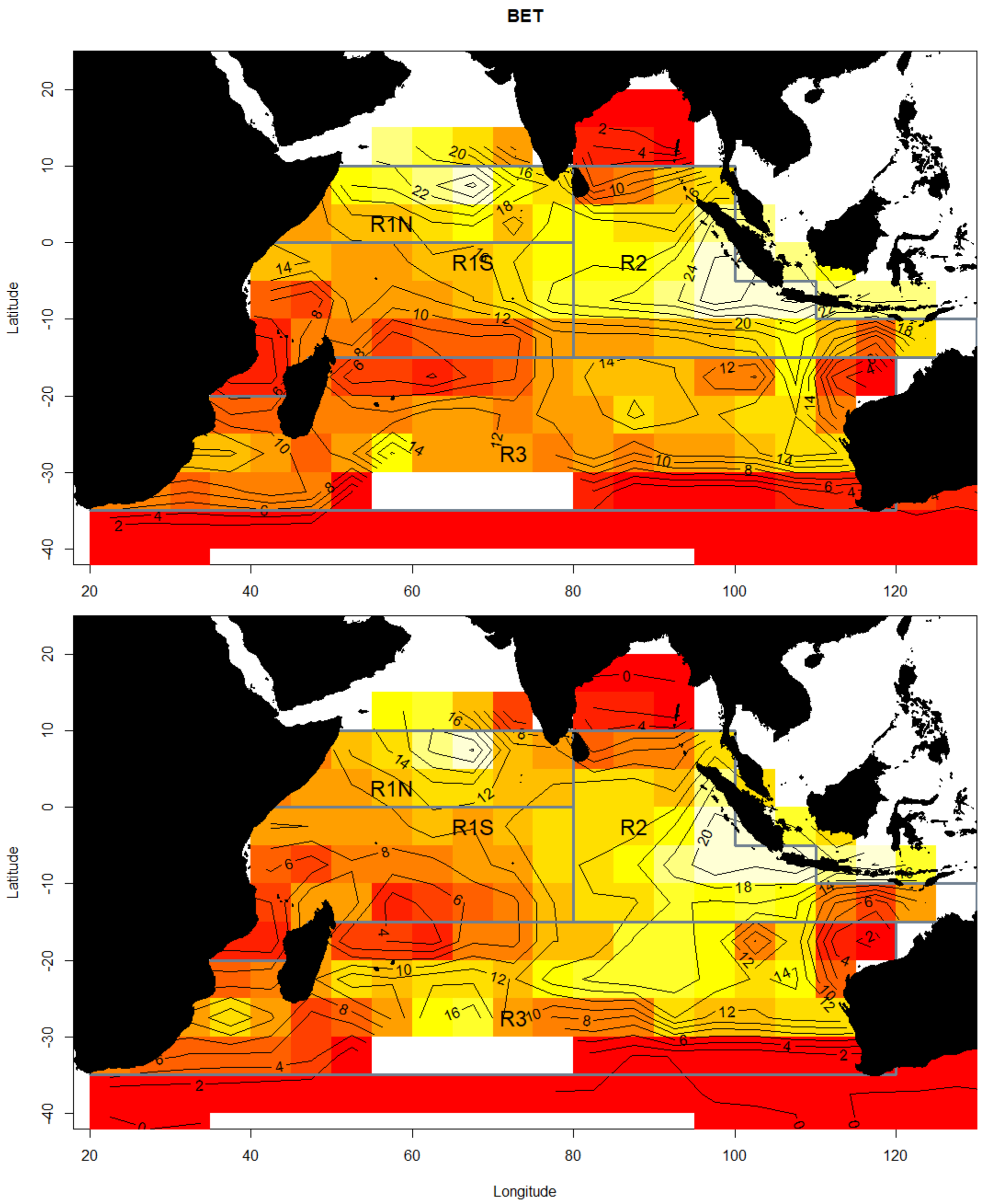
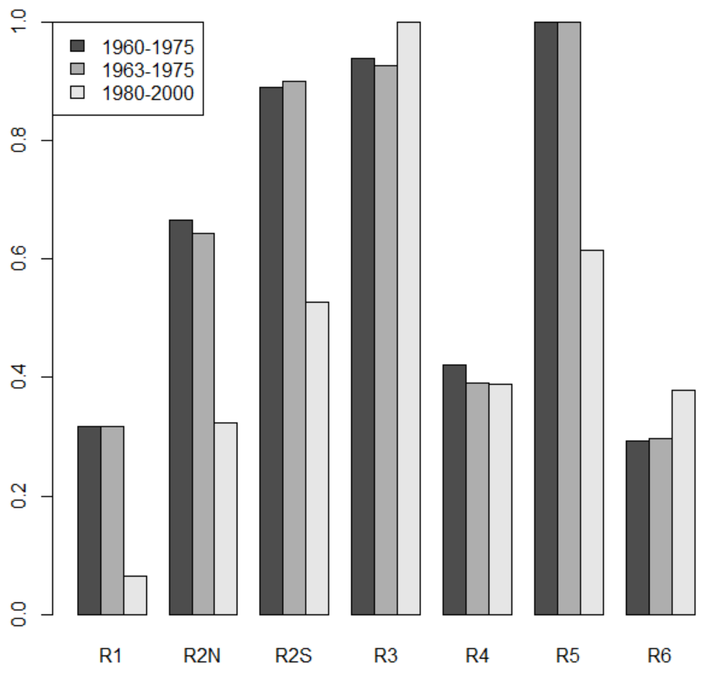


Figure 5: Heat map of relative bigeye CPUE by 5° grid cell, estimated using the means method (above) and the standardized method (below). Data are from 1980 to 2000, for cells with cumulative effort of at least 50000 hooks and effort in at least 5 quarters.



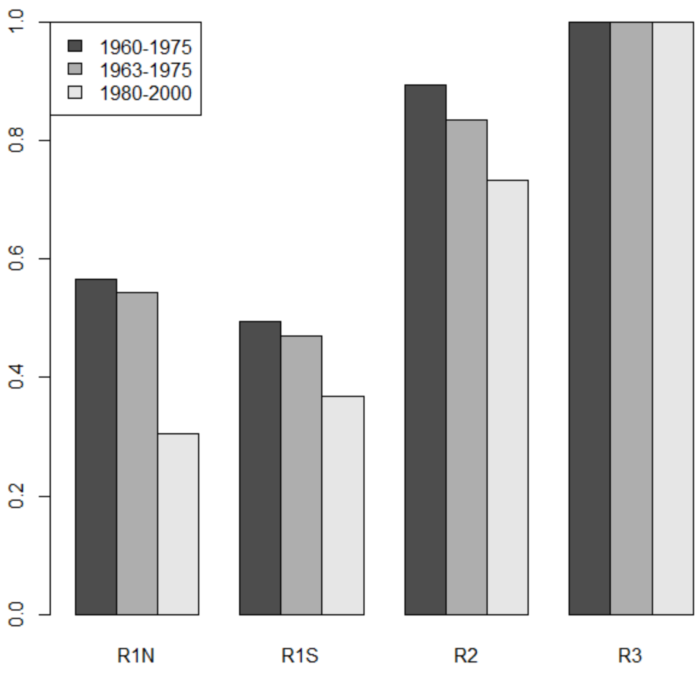


Figure 6: Regional scaling parameters for yellowfin (left) and bigeye (right) based on data for three periods: 1960-1975, 1963-1975, and 1980-2000. Parameters were calculated using the standardized method.

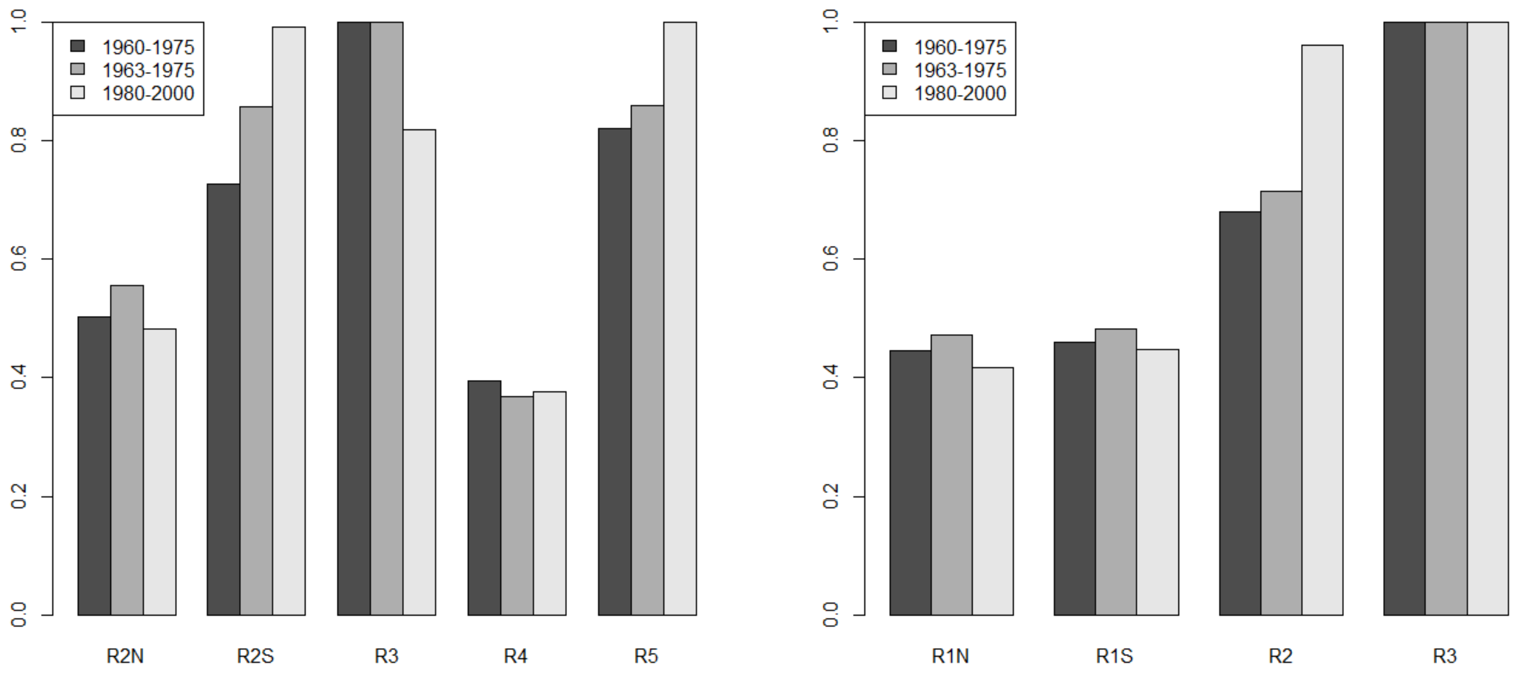


Figure 7: Regional scaling parameters, readjusted to be comparable, for yellowfin (left) and bigeye (right) based on data for three periods: 1960-1975, 1963-1975, and 1980-2000. Parameters were calculated using the standardized method.

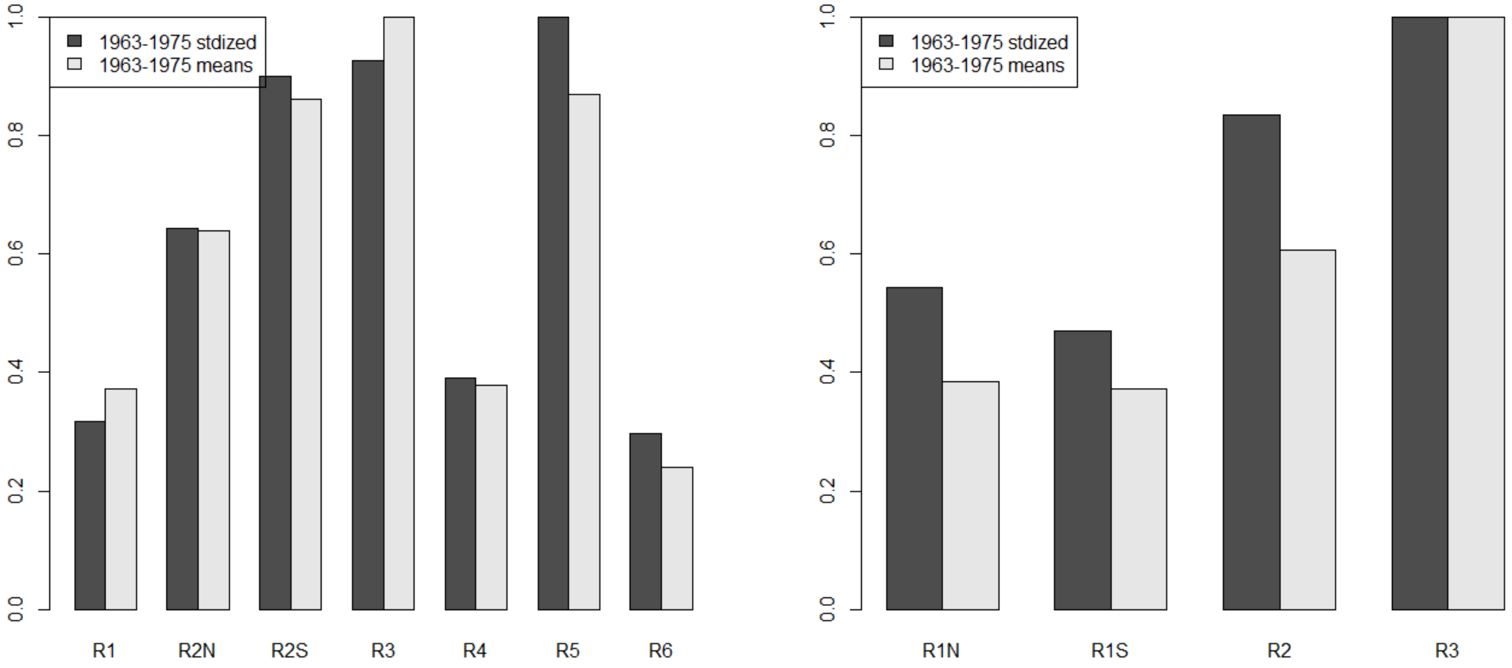


Figure 8: Regional scaling parameters for yellowfin (left) and bigeye (right) based on data from 1963-1975. Parameters were calculated using the two methods: the means method and the standardized method.

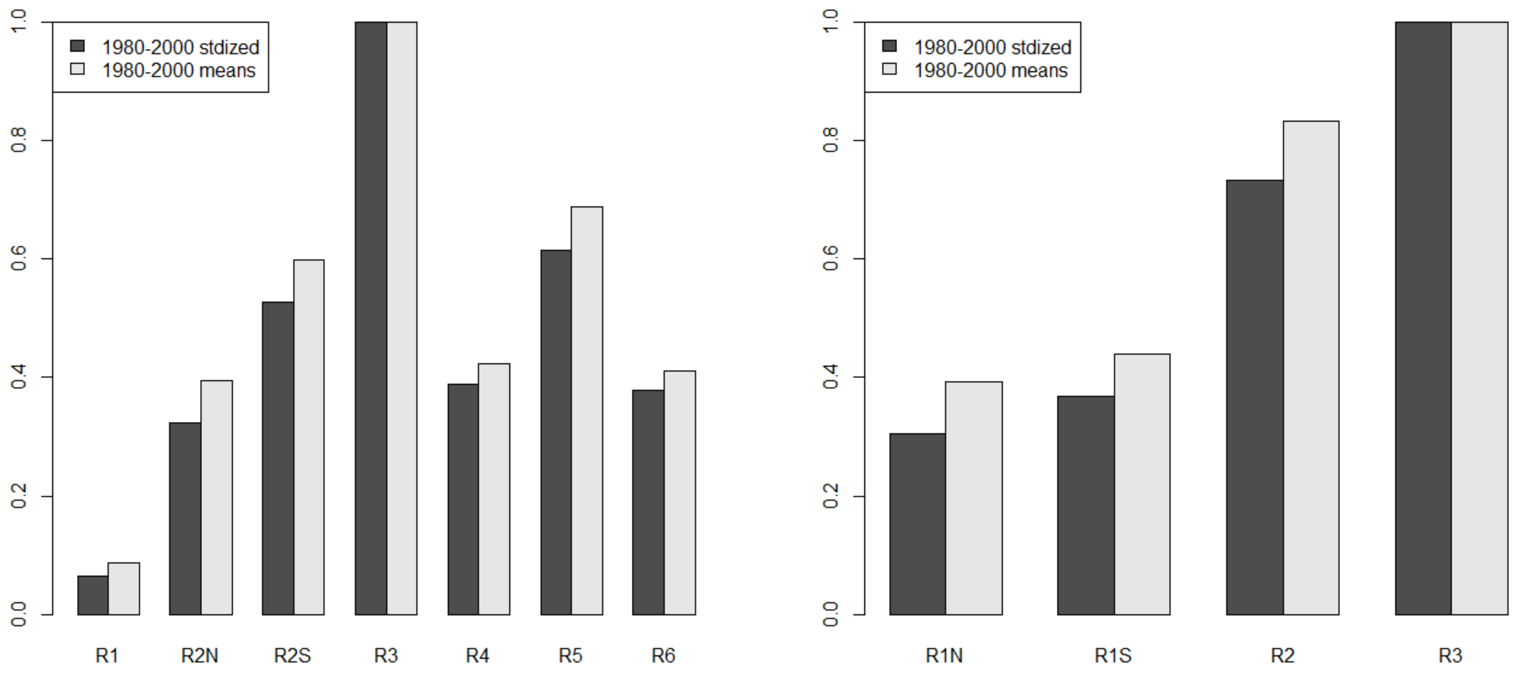


Figure 9: Regional scaling parameters for yellowfin (left) and bigeye (right) based on data from 1980-2000. Parameters were calculated using the two methods: the means method and the standardized method.

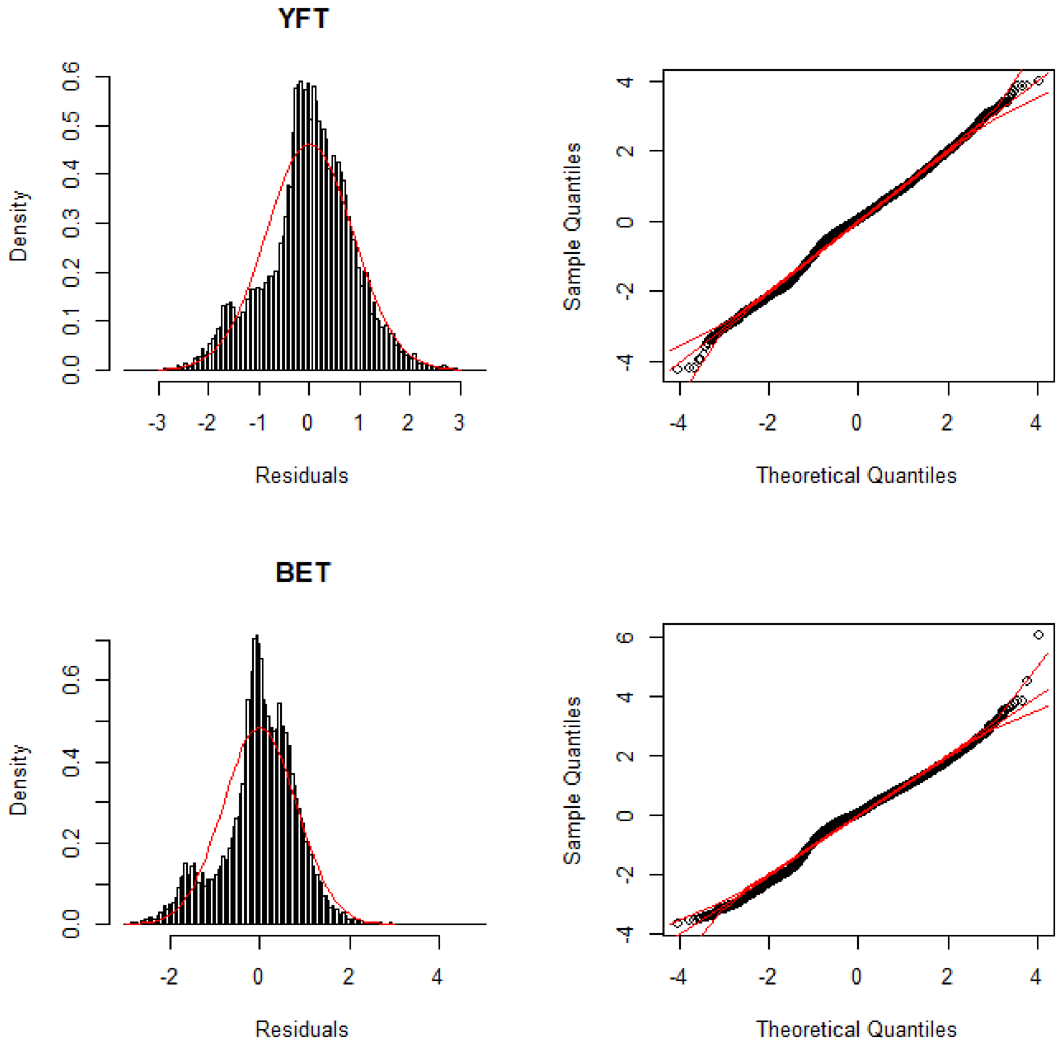


Figure 10: Diagnostic plots for the glm models for the bigeye and yellowfin standardized method using data from 1980-2000.