



Scaling factors for multi-region stock assessments, with an application to Indian Ocean tropical tunas

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ARTICLE INFO

Handled by A.E. Punt

Keywords:

CPUE

Multi-region stock assessments

Spatial modelling

Regional scaling factors

Bigeye tuna

Yellowfin tuna

ABSTRACT

Stock assessments may be spatially structured, with regions that contain separate but linked subpopulations. In such multi-region models we must determine the relative abundances among regions. Regional scaling, which has been used since 2005 in tuna assessments, estimates the relative 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. We also recommend the use of operational data to estimate regional scaling factors.

1. Introduction

Stock assessments that cover large spatial domains may subdivide the stock into multiple regions, which have individual population structures and are linked by movement. One problem in such multi-region stock assessments is determining the relative abundances among regions. In this paper we describe a method, known as regional scaling, which is used for this purpose in tuna stock assessments (e.g. Langley, 2016; McKechnie et al., 2017) but has not previously been reported in the peer-reviewed literature. Regional scaling can be applied in different ways, and in this paper we compare and discuss these approaches. We also describe some improvements to the methods used to date in tuna stock assessments and show that they significantly change the predicted distribution of abundance.

An important reason why stock assessments are partitioned into regions is to deal with spatial variation in population trends (Punt, 2019). Populations of tuna species, such as yellowfin tuna (*Thunnus albacares*), bigeye tuna (*T. obesus*) and albacore tuna (*T. alalunga*), occupy vast areas of the world's oceans. Although these stocks are considered highly migratory, and mixing is believed to occur to some degree, their oceanic scale movements are nevertheless constrained by the distances involved. In addition, fishing pressures vary spatially due to factors such as fleet operational constraints, variation in population density, and variation in value of the fish caught. Trends in environmental factors and in recruitment may also vary spatially. As a result,

abundance trends through time are likely to vary spatially. Spatially disaggregated tuna assessment models typically partition the stock into 3–8 spatial populations linked via movement.

Regional scaling has two components: a method for estimating relative abundance by region, and a method for introducing these relative abundance estimates into the assessment model.

A particularly useful source of information about spatial variation in relative biomass is survey data (Bosley et al., 2019), which has the advantages of being fishery-independent and designed for constant catchability. Biomass estimates from survey data have been used to spatially allocate catch quotas for Alaskan sablefish (Hanselman et al., 2018) and mortality limits for Pacific halibut (Allan Hicks, International Pacific Halibut Commission, pers. comm). To our knowledge they have not been used to scale relative abundances among regions in a stock assessment.

Where survey data are unavailable, standardized catch per unit effort (CPUE) is commonly used in fisheries modelling to provide indices of relative abundance through time (Maunder and Punt, 2013). With tuna populations the spatial scales are generally too large for fishery independent survey techniques. Standardized commercial longline fishery catch per unit effort (CPUE) is the main data type used in the major oceans (e.g. McKechnie et al., 2015; Hoyle et al., 2017; Itoh and Takahashi, 2018; Hoyle et al., 2019; Minte-Vera et al., 2019). Standardised CPUE indices are derived for each spatial region of the assessment model.

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<https://doi.org/10.1016/j.fishres.2020.105586>

Received 20 December 2018; Received in revised form 24 March 2020; Accepted 26 March 2020

Available online 13 April 2020

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Regional scaling is a complement to the use of temporal indices of abundance by region, and assumes that catch per unit effort can be standardized to index relative abundance spatially. A similar principle is applied when modelling CPUE with time-area interactions, with temporal indices estimated by summing across space (Thorson and Ward, 2013; Campbell, 2015; Zhou et al., 2019).

Without this source of information on relative abundance among regions, the model would be informed by sources such as the fits in each region to tagging and composition data, and combinations of catch and CPUE trend data. Information from these sources can be biased and unreliable, particularly in multi-region models that may fail to model spatial variation in parameters such as growth rate. Tag-recapture data can be highly informative about population size but will cause bias unless rather unrealistic assumptions are met about mixing within regions (Hoyle et al., 2013; Kolody and Hoyle, 2013, 2015) and tag reporting rates (Punt, 2019). Similarly, age and size composition data can be informative about depletion and total mortality (Maunder, 2011), and hence population size by region, but these estimates can be biased by unmodelled spatial variation in growth rates (in the case of size data), selectivity, or sampling bias (e.g. Hoyle et al., 2008). Information about biomass is available from the relationship between catch and CPUE trend but this inference depends on numerous other parameters such as selectivity, natural mortality, growth, and movement, and assumptions that parameters are stable in both space and time.

For example, a three-region version of the 2013 Indian Ocean bigeye assessment (Langley et al., 2013) was developed without regional scaling and with independently estimated catchabilities. Biomass estimates for the southern region were implausibly large and the three-region approach was rejected in favour of a one-region model (Langley et al., 2013).

Regional scaling factors can significantly change estimates of abundance distribution and overall biomass. When introduced in the 2005 Western and Central Pacific Ocean (WCPO) assessments for both bigeye and yellowfin tuna, they raised the relative abundance estimates in the tropics compared to the temperate regions (Hampton et al., 2005a,b). Sensitivity analysis during a review of the 2011 WCPO bigeye tuna assessment (Davies et al., 2011) found that changing the regional scaling factors caused the biomass distribution to change among regions, although changes to overall biomass were prevented by constraints on region 5 (Ianelli et al., 2012). In preparatory analyses for the 2008 WCPO skipjack assessment (Langley and Hampton, 2008; Langley and Hoyle, 2008), regional scaling was highly influential in determining both the overall biomass level and the biomass distribution.

Regional scaling was originally developed in 2005 (Langley et al., 2005), and updated in 2007 and 2014 (Hoyle and Langley, 2007; McKechnie et al., 2014) for WCPO assessments that use the software Multifan-CL (Fournier et al., 1998). Indian Ocean yellowfin tuna assessments have employed multiple regions and regional scaling since 2008 (Langley et al., 2008), initially using Multifan-CL and more recently using Stock Synthesis (Methot and Wetzel, 2013). Recent Indian Ocean bigeye assessments (Langley, 2016; Fu, 2019) have also applied regional scaling. The current region definitions for the Indian Ocean tuna assessments are shown in Fig. 1.

The regional scaling method originally used in Indian Ocean yellowfin assessments was applied as follows (Langley et al., 2008):

“For ... longline fisheries, a common catchability coefficient (and selectivity) was estimated in the assessment model, thereby linking the respective CPUE indices among regions. ... 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.”.

Standardizing catch rates, as in WCPO regional scaling analyses (Langley et al., 2005), should provide more reliable indicators of relative abundance. Changes in catch rates through time or seasonally may affect relative catch rates among areas, if there are different

amounts of data among grid cells. Standardizing catch and effort data with a time + area model will provide relative abundance estimates for each spatial grid cell, which are then summed by region to estimate relative abundances among regions.

Scaling factors are estimated using a temporal subset of the available data, and the time period chosen can affect the estimated scaling factors. The fishing effort during the chosen time period should be widely distributed, so that densities can be estimated across as much area as possible. The period 1960–1975 was used in initial Indian Ocean yellowfin tuna assessments. Catch rate data should also be representative of relative abundance, without major changes in catchability or selectivity. Due to concerns about early selectivity change, the scaling period used in the 2015 Indian Ocean yellowfin tuna assessment (Langley, 2015) was changed to 1963–1975.

It is also useful to base the spatial effects on a period without substantial target change, because such changes affect catch rates and therefore density estimates. Scaling factors are generally estimated using aggregated data that may lack targeting indicator variables such as hooks between floats (HBF), so target change cannot be adjusted for. 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 et al., 2017). We therefore explore the use of spatial effects based on the 1980–2000 period, during which targeting is considered to have been more consistent.

It is also helpful to base the estimates on a period when there were similar trends among regions, since the standardization model assumes the same year effects for all grid cells.

We implement several additional changes to improve the performance of the approach. We augment the catch and effort data from the Japanese fleet with data from the Korean fleet, to improve the spatial and temporal coverage of the data. Different fleets may have different average catch rates, so we include fleet (Japan or Korea) as an explanatory variable in the standardization model.

Previous analyses have calculated abundance by adding the density estimates from all cells, but this does not reliably represent abundance if cell areas differ. Grid cells in the tropics are larger than temperate cells, and some cells include land, which reduces the ocean area. Here we calculate cell ocean areas to adjust for the relative sizes of the spatial cells. In addition, when calculating the statistical weights to apply to each stratum in the standardization model (Punsly, 1987; Campbell, 2004), we give each stratum a total statistical weight that is proportional to its area.

We also consider the potential to adjust for seasonal density changes due to tuna movements. Hitherto the approach has allowed for seasonal changes in catch rate by incorporating year-quarter in the model, but assuming constant proportions in each region. We change the model to include the quarterly effects in the spatial component of the model rather than in the temporal component.

Finally, we address the problem of cells with insufficient reliable data to estimate density, by fitting a spatial smoother and using it to fill gaps in the density surface. Spatial smoothers have been used for regional scaling in recent WCPO stock assessments (McKechnie et al., 2014).

Many of these changes can be justified *a priori* as improvements. We present the original and the updated methods to show the impact of each change on the final regional scaling estimates. As well as the value of these developments, this also indicates the potential value of further improving these methods.

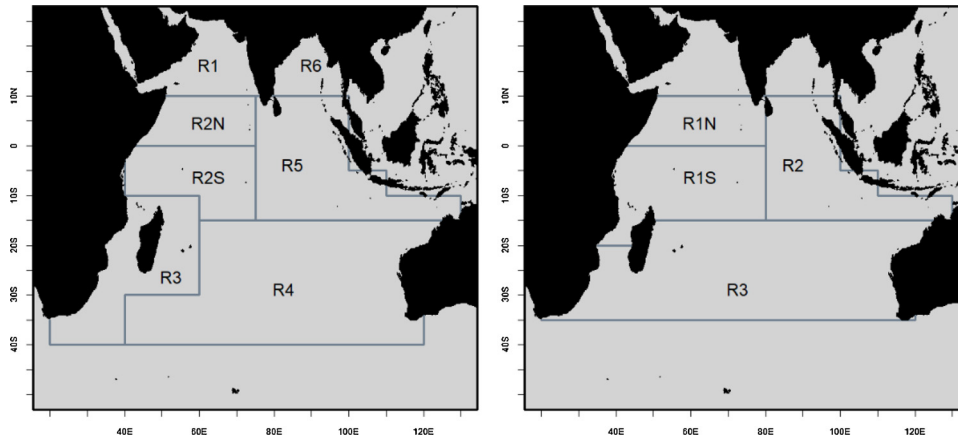


Fig. 1. Regional structures used in stock assessments for Indian Ocean yellowfin tuna (left) and bigeye tuna (right).

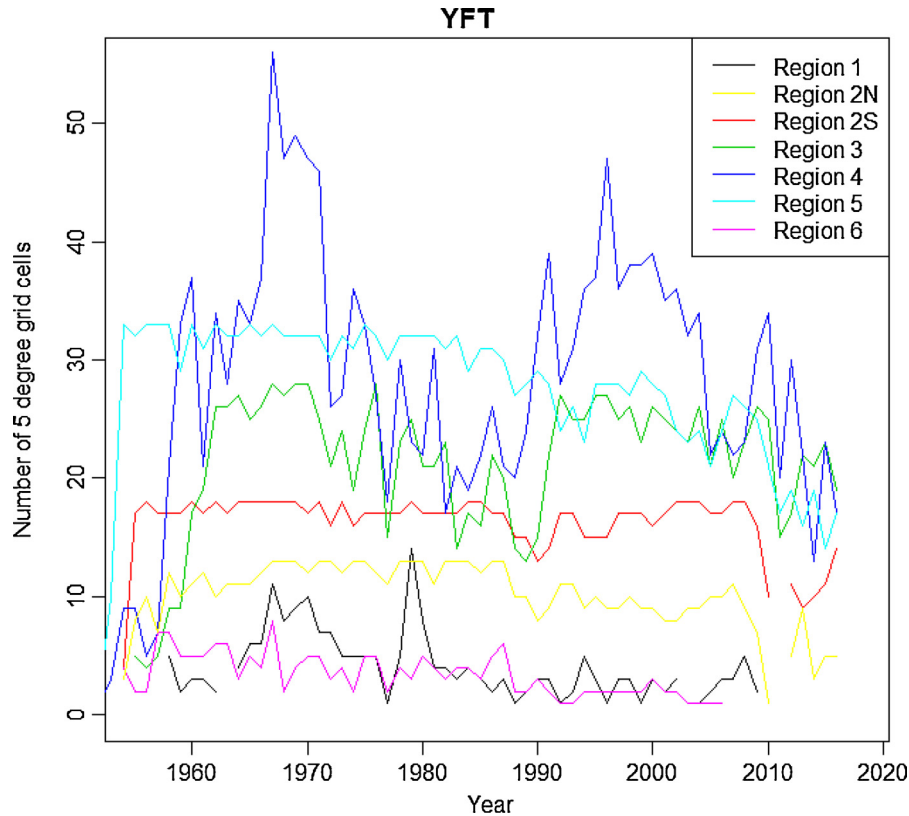


Fig. 2. The number of 5° grid cells with yellowfin tuna catch and effort data by yellowfin model region and year.

2. Methods

2.1. Regional scaling analysis

The general approach for regional scaling analysis is as follows:

Consider a stock assessment divided into R regions, which contain varying numbers C_r of spatial substrata or cells, with catch and effort data available for the period T . An index of abundance through time $I_{r,t}$ is available for each region. Within period T , a temporal subset τ is identified during which fishing effort has broad spatial coverage.

This temporal data subset is used to derive the regional scaling factors, which are estimates of relative abundance by region. Various approaches can be used but for illustration we present a simple method using a generalized linear model (GLM) with no time-area interaction, i.e. all cells are assumed to have the same temporal trend in catch rate.

a) A GLM is fitted in R (R Core Team, 2019), assuming Gaussian errors.

$$\log(CPUE_i + k) \sim \alpha_t + \gamma_c + \beta x_i + \varepsilon$$

where $CPUE_i$ is the expected catch per unit effort in stratum i , which occurs at time t , in spatial cell c , and with covariates x_i . The constant k is set to 10 % of the mean CPUE (Campbell et al., 1996).

b) The expected density in each cell is calculated as $density_c = \exp(\hat{\gamma}_c + \hat{\sigma}_c^2/2)$, where $\hat{\gamma}_c$ is the estimate of the spatial effect for cell c , and $\hat{\sigma}_c$ is the standard error of γ_c . Cell densities are relative to one another, so the base level of the spatial effects does not matter when using a lognormal standardization. However, with other standardization approaches such as delta lognormal the choice of base level does affect the outcome. In these cases, the base should be selected so that predicted catch rates are close to observed catch rates on average.

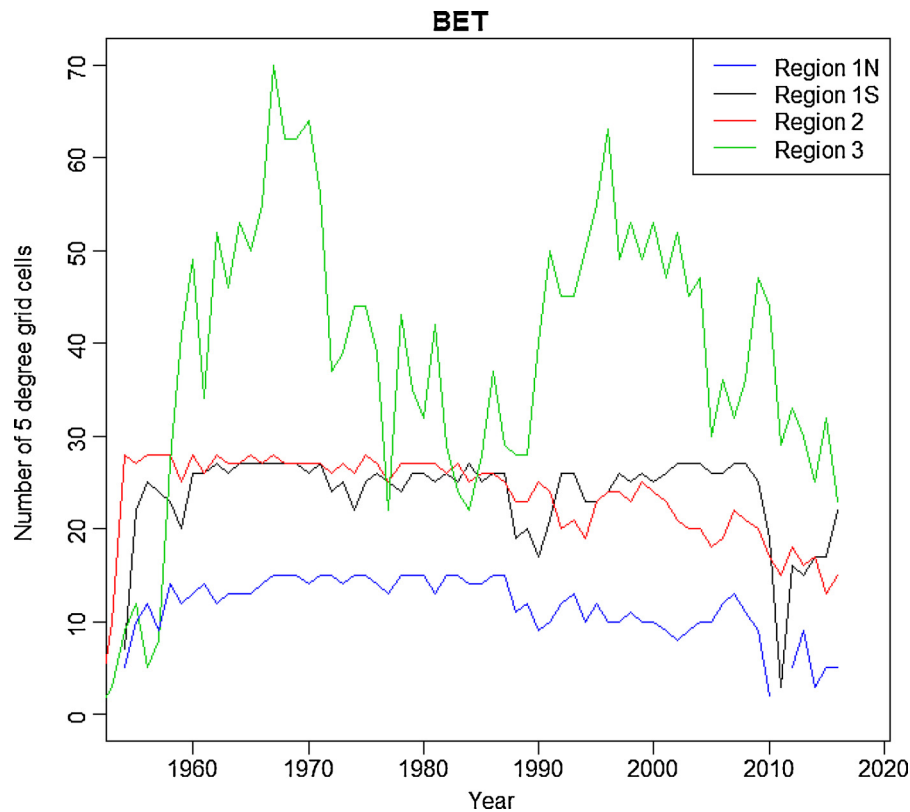


Fig. 3. The number of 5° grid cells with bigeye tuna catch and effort data by bigeye model region and year.

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	–	–	4881	24586	0
		year-qtr	59	5065	24883	297
		cell	125	6874	28172	3586
	Yellowfin	fleet	1	4964	24773	187
		–	NA	6903	30394	0
		year-qtr	59	7416	31171	778
		cell	150	12696	37704	7311
		fleet	1	6972	30517	123
6	Bigeye	–	NA	4684	24065	0
		year	14	4735	24158	92
		cell	121	5318	25244	1178
		fleet	1	4749	24216	151
		reg.qtr	15	5014	24797	732
	Yellowfin	–	NA	6815	30185	0
		year	14	7097	30664	479
		cell	144	9131	33552	3367
		fleet	1	6891	30322	137
		reg.qtr	21	7126	30701	517

c) Cell abundance is the product of density and ocean area:
 $abund_c = density_c \times area_c$.

d) For each region, the abundance is the sum of abundances for all cells in the region:

$$abundance_r = \sum_{c \in C_r} abund_c$$

e) Regional scaling factors for the period τ are obtained by dividing each regional abundance by the most abundant region.

$$RSF_r = abundance_r / \max(abundance_{r \in R})$$

f) The regional scaling factors are used in the stock assessment as follows.

- Each index of abundance I_r is normalised across all time periods so that it has an average of 1 during the scaling period τ .

$$J_{r,t} = I_{r,t} / \text{mean}(I_{r,t \in \tau})$$

- Each normalised index is multiplied (for all time periods) by its respective regional scaling factor.

$$\eta_{r,t} = J_{r,t} \times RSF_r$$

- Finally, each of the normalized and scaled indices $\eta_{r,t}$ is included in the assessment and associated with a fishery in one of the regions. The catchabilities for these fisheries are constrained to be equal, to impose the effect of the normalized and scaled abundance indices on the stock assessment.

2.2. Application

Indian Ocean aggregated catch and effort data for bigeye and yellowfin tuna were downloaded from the data section associated with the most recent IOTC 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 data were not available before 1975, so were not included in analyses where the period ended in 1975. All data were aggregated to a resolution of 1 month and 5° grid (latitude/longitude) cell. Data records included catch by species (number of fish) and number of hooks set. We omitted data from grid cells with total effort less than 50,000

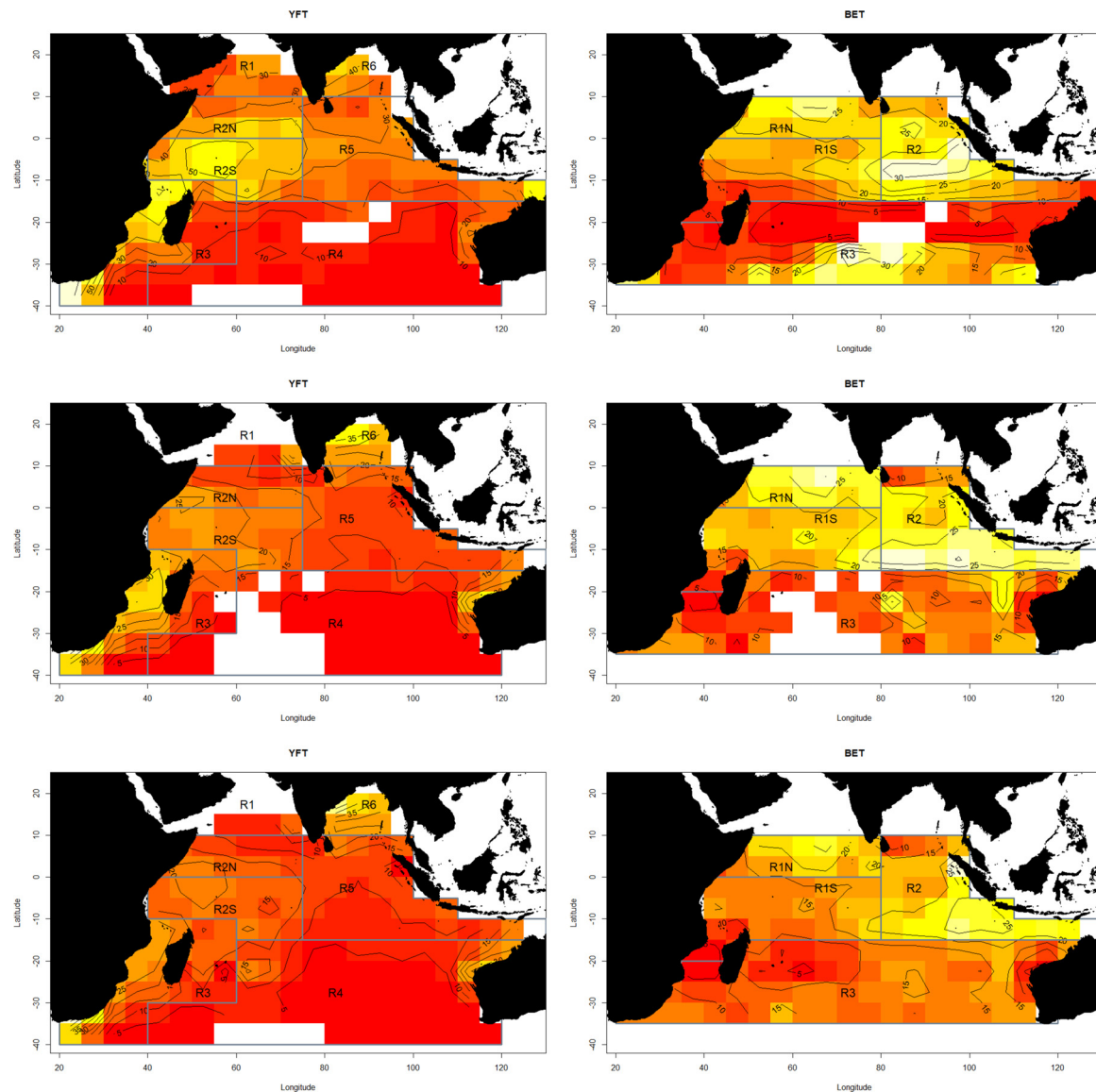


Fig. 4. Heat maps of relative CPUE by 5° cell estimated using the means method for yellowfin tuna (left) and bigeye tuna (right) based on the periods 1963 – 1975 (top), 1979–1994 (middle), and 1980–2000 (bottom). Yellow indicates higher density, and white indicates no estimate. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

hooks or fishing in 6 or fewer quarters during the period of interest.

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.

Eight methods in series were then applied to derive alternative regional scaling factors for the two species, starting with a simple means method, and then introducing standardization methods using different models and an adjustment to the abundance calculation. Each method was applied across 5 alternative periods: 1960–1975, 1963–1975, 1975–1994, 1979–1994, and 1980–2000.

For the means method *m1* we calculated the scaling factors from the mean CPUE during the scaling period in each 5° grid cell, $density_c = mean(CPUE_c)$. For each region, the relative abundance was the sum of densities for all cells in the region. Cells with no data were ignored.

The first standardization method *m2* applied generalised linear models (GLM) using the *glm* function in R base with form similar to the following: $\log(CPUE_i + k) \sim \alpha_{yq} + \gamma_c$, where $CPUE_i$ is the catch in stratum *i* divided by the effort in hooks, *k* is an additive constant to allow the inclusion of strata with zero catch, α_{yq} is the temporal or year-

quarter effect, and γ_c is the spatial or 5° grid cell effect. All effects were modelled as categorical variables. The constant *k* was set to 10 % of the mean CPUE in the model dataset. Errors were assumed normally distributed. The model does not include an interaction between temporal and spatial effects, so assumes that the same temporal trend occurs across all regions during the analysis period.

Analysis method *m3* used the same model as *m2* but multiplied the density of each cell by the respective ocean area before summing cells by region.

Ocean areas were calculated using a script that employed functions from 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.

In analysis method *m4*, instead of giving equal statistical weight to each row of the dataset, weights by row were adjusted so that the sum of statistical weights within a time period for each spatial cell in the model was constant through time. These statistical weights were also adjusted to be proportional to the ocean area of the cell, when

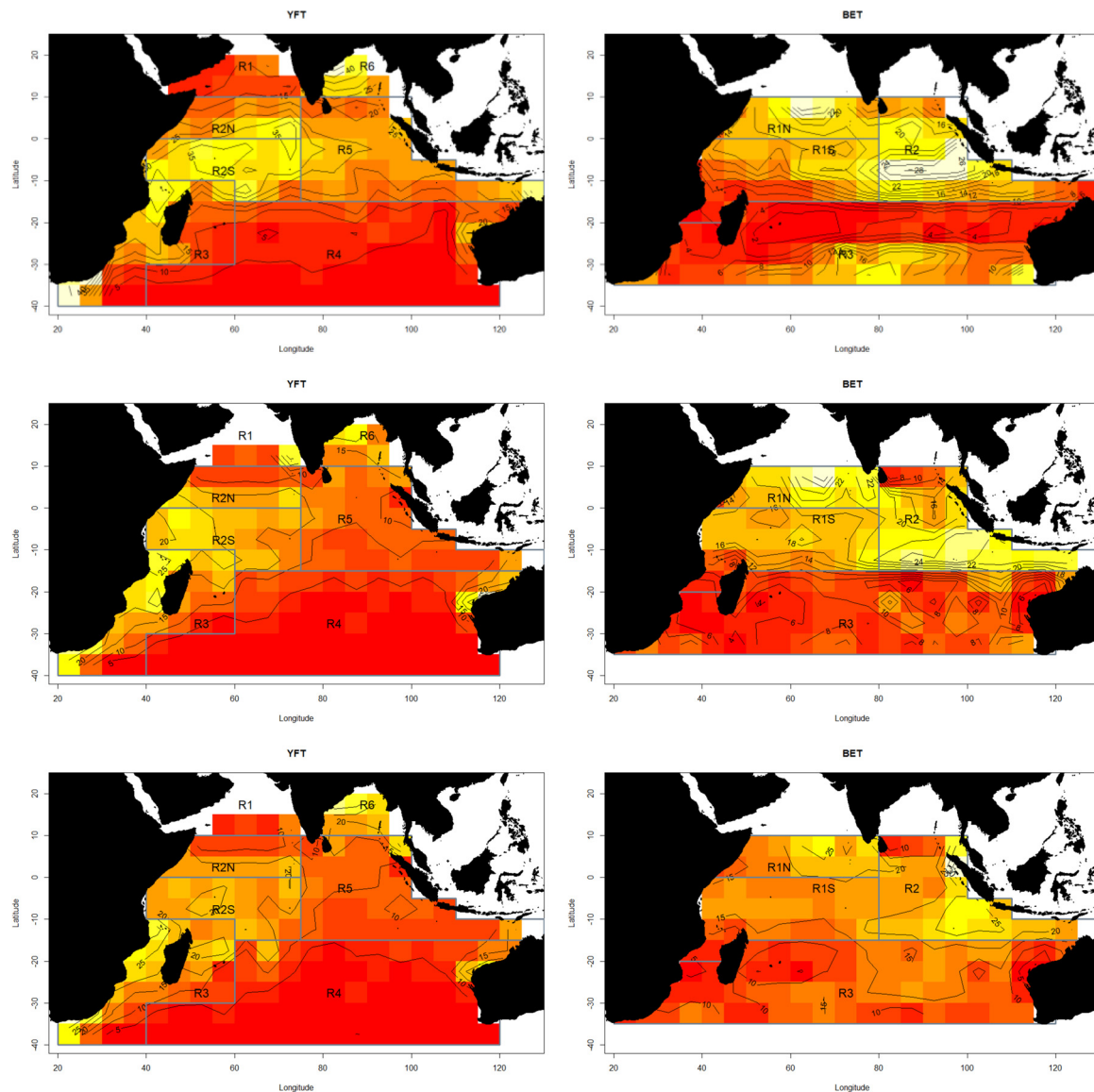


Fig. 5. Heat maps of relative CPUE by 5° cell estimated using method 8 for yellowfin tuna (left) and bigeye tuna (right) based on the periods 1963–1975 (top), 1979–1994 (middle), and 1980–2000 (bottom). Yellow indicates higher density, and white indicates no estimate. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

comparing across cells. [Punsky \(1987\)](#) and [Campbell \(2004\)](#) recommend giving each time-area stratum equal statistical weight to avoid introducing bias when the spatial distribution of fishing effort changes through time (see also [Hoyle et al. \(2016\)](#)). [Campbell \(2004\)](#) also recommends that each stratum should have the same area, but our stratum ocean areas vary, so we adjusted the weights to be proportional to ocean areas.

In analysis method *m5*, fleet was added to the standardization model, as follows: $\log(\text{CPUE}_i + k) \sim \alpha_{yq} + \gamma_c + \beta_{\text{fleet}}$, where β_{fleet} was the fleet effect modelled as a categorical variable.

Analysis method *m6* allowed for seasonal (quarterly) variation in abundance distribution by including the variable $\beta_{\text{reg.qtr}}$, which was a categorical variable linked to the region and quarter of the effort. We also used year rather than year-quarter as the temporal effect. The model was $\log(\text{CPUE}_i + k) \sim \alpha_y + \gamma_c + \beta_{\text{fleet}} + \beta_{\text{reg.qtr}}$.

Analysis method *m7* modelled spatial effects with a tensor spline smoother rather than categorical effects for each cell, as follows: $\log(\text{CPUE}_i + k) \sim \alpha_y + \text{te}_{\text{lat,lon}} + \beta_{\text{fleet}} + \beta_{\text{reg.qtr}}$. For this model the location of each 5° cell was defined as the middle of the cell. To implement this model we replaced the GLM with a generalized additive model

(GAM), using the R package *mgcv* ([Wood, 2011](#)).

In methods *m1* to *m6*, cells with insufficient data were ignored, but the spatial smoother of method *m7* provided CPUE estimates for all cells. Analysis method *m8* replaced the missing values in the results of method *m6* with cell estimates from the *m7* smoother, also resulting in full spatial coverage.

Regional scaling factors differ among time periods, in part because the relative abundances of the regions change through time. When used in the stock assessment, each set of scaling factors is applied to the period of the regional abundance indices from which it was estimated. To validly compare regional scaling factors that use data from different periods, we divided each scaling factor by the mean of the respective normalized abundance index during the scaling period. This adjusted the scaling factors relative to the indices of abundance, to represent the average regional scales for the entire assessment period. The CPUE indices of abundance calculated in 2017 ([Hoyle et al., 2017](#)) were used for bigeye tuna, and the 2018 indices for yellowfin tuna ([Hoyle et al., 2018](#)).

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

Period	Method	Region						
		1	2	3	4	5	6	7
60–75	1	0.273	0.913	0.931	0.507	1	0.183	0.509
	2	0.235	0.846	0.824	0.493	1	0.196	0.453
	3	0.171	0.835	0.609	0.437	1	0.168	0.411
	4	0.168	0.820	0.620	0.465	1	0.167	0.407
	5	0.168	0.820	0.620	0.465	1	0.167	0.407
	6	0.135	0.816	0.625	0.467	1	0.199	0.406
	7	0.106	0.819	0.613	0.474	1	0.186	0.402
	8	0.135	0.816	0.625	0.498	1	0.199	0.406
63–75	1	0.309	0.886	1	0.501	0.962	0.200	0.503
	2	0.237	0.838	0.834	0.453	1	0.218	0.445
	3	0.172	0.827	0.614	0.394	1	0.184	0.406
	4	0.168	0.802	0.621	0.422	1	0.183	0.392
	5	0.168	0.802	0.621	0.422	1	0.183	0.392
	6	0.132	0.797	0.622	0.424	1	0.208	0.390
	7	0.110	0.801	0.606	0.460	1	0.204	0.383
	8	0.132	0.797	0.622	0.466	1	0.208	0.390
75–94	1	0.086	0.619	1	0.536	0.650	0.257	0.370
	2	0.077	0.658	1	0.540	0.679	0.262	0.368
	3	0.106	0.934	1	0.614	0.934	0.311	0.434
	4	0.113	0.950	1	0.657	0.979	0.281	0.452
	5	0.113	0.970	1	0.644	0.983	0.277	0.456
	6	0.130	0.977	1	0.651	0.997	0.209	0.463
	7	0.128	0.973	1	0.671	0.976	0.207	0.452
	8	0.130	0.977	1	0.676	0.997	0.209	0.463
79–94	1	0.097	0.597	1	0.496	0.672	0.309	0.384
	2	0.090	0.644	1	0.466	0.675	0.304	0.379
	3	0.124	0.909	1	0.503	0.927	0.360	0.438
	4	0.148	0.938	1	0.533	0.989	0.340	0.457
	5	0.149	0.974	1	0.508	0.992	0.339	0.466
	6	0.161	0.969	0.988	0.509	1	0.264	0.464
	7	0.127	0.943	1	0.618	0.950	0.253	0.447
	8	0.158	0.950	1	0.632	0.980	0.259	0.455
80–00	1	0.076	0.545	1	0.647	0.641	0.363	0.350
	2	0.059	0.460	1	0.616	0.562	0.323	0.280
	3	0.086	0.685	1	0.753	0.808	0.389	0.354
	4	0.085	0.700	1	0.736	0.846	0.386	0.366
	5	0.092	0.871	1	0.655	0.919	0.423	0.425
	6	0.093	0.872	1	0.651	0.930	0.346	0.429
	7	0.089	0.885	1	0.627	0.895	0.352	0.429
	8	0.093	0.872	1	0.658	0.930	0.346	0.429

3. Results

Spatial coverage of data from the five periods varied (Figs. 2 and 3). The broadest coverage occurred between 1965 and 1975. However, coverage was also reasonably good between 1985 and 2009.

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

Diagnostics for the models showed a small amount of non-normality in the residuals, mostly 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 also have a small peak on the left due to clumping of zero catches. These problems are minor and would not noticeably affect results. Patterns in the residuals by region and year-quarter 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 (Figs. 4 and 5) for each species, for both the means method and the standardization methods. In the earlier 1963–75 period, the highest yellowfin catch rates were considerably higher than they were in the 1980–2000 period. The areas of peak bigeye catch rates were more broadly distributed during the 1980–2000 period than in the early period, with less of a latitudinal break from 10S

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

Period	Method	Region				
		1	2	3	4	5
60–75	1	0.654	1	0.539	0.621	0.511
	2	0.638	1	0.383	0.477	0.524
	3	0.639	1	0.296	0.430	0.488
	4	0.641	1	0.295	0.441	0.482
	5	0.641	1	0.295	0.441	0.482
	6	0.645	1	0.294	0.470	0.473
	7	0.635	1	0.298	0.493	0.471
	8	0.645	1	0.294	0.489	0.473
63–75	1	0.675	1	0.611	0.676	0.546
	2	0.645	1	0.423	0.504	0.546
	3	0.644	1	0.327	0.453	0.508
	4	0.652	1	0.334	0.473	0.502
	5	0.652	1	0.334	0.473	0.502
	6	0.657	1	0.333	0.506	0.496
	7	0.650	1	0.325	0.559	0.496
	8	0.657	1	0.333	0.549	0.496
75–94	1	0.720	1	0.486	0.731	0.568
	2	0.712	1	0.381	0.600	0.563
	3	0.722	1	0.300	0.530	0.525
	4	0.719	1	0.301	0.523	0.521
	5	0.736	1	0.303	0.508	0.526
	6	0.734	1	0.306	0.544	0.524
	7	0.730	1	0.333	0.545	0.524
	8	0.734	1	0.337	0.544	0.524
79–94	1	0.715	1	0.383	0.674	0.541
	2	0.719	1	0.322	0.550	0.545
	3	0.726	1	0.243	0.505	0.509
	4	0.717	1	0.235	0.490	0.498
	5	0.760	1	0.233	0.464	0.510
	6	0.760	1	0.246	0.503	0.513
	7	0.758	1	0.360	0.524	0.516
	8	0.760	1	0.361	0.529	0.513
80–00	1	0.604	1	0.586	0.808	0.482
	2	0.558	0.968	0.710	1	0.433
	3	0.589	1	0.615	0.978	0.432
	4	0.566	1	0.543	0.875	0.420
	5	0.712	1	0.467	0.708	0.471
	6	0.711	1	0.488	0.743	0.472
	7	0.715	1	0.501	0.751	0.479
	8	0.711	1	0.488	0.743	0.472

to 20S.

Regional scaling factors were estimated for each method for both bigeye and yellowfin tuna (Tables 2 and 3).

Changing the analysis methods resulted in some large and potentially important changes to the scaling factors, as shown in the results for 1979–1994 (Fig. 6). 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, increasing the scaling factors for all regions, particularly the tropics, relative to the south-western temperate region 3. Introducing statistical weights to the standardization model (*m4* statistical weights) had a relatively small effect on 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 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 yellowfin tuna the overall impact of all the changes was to

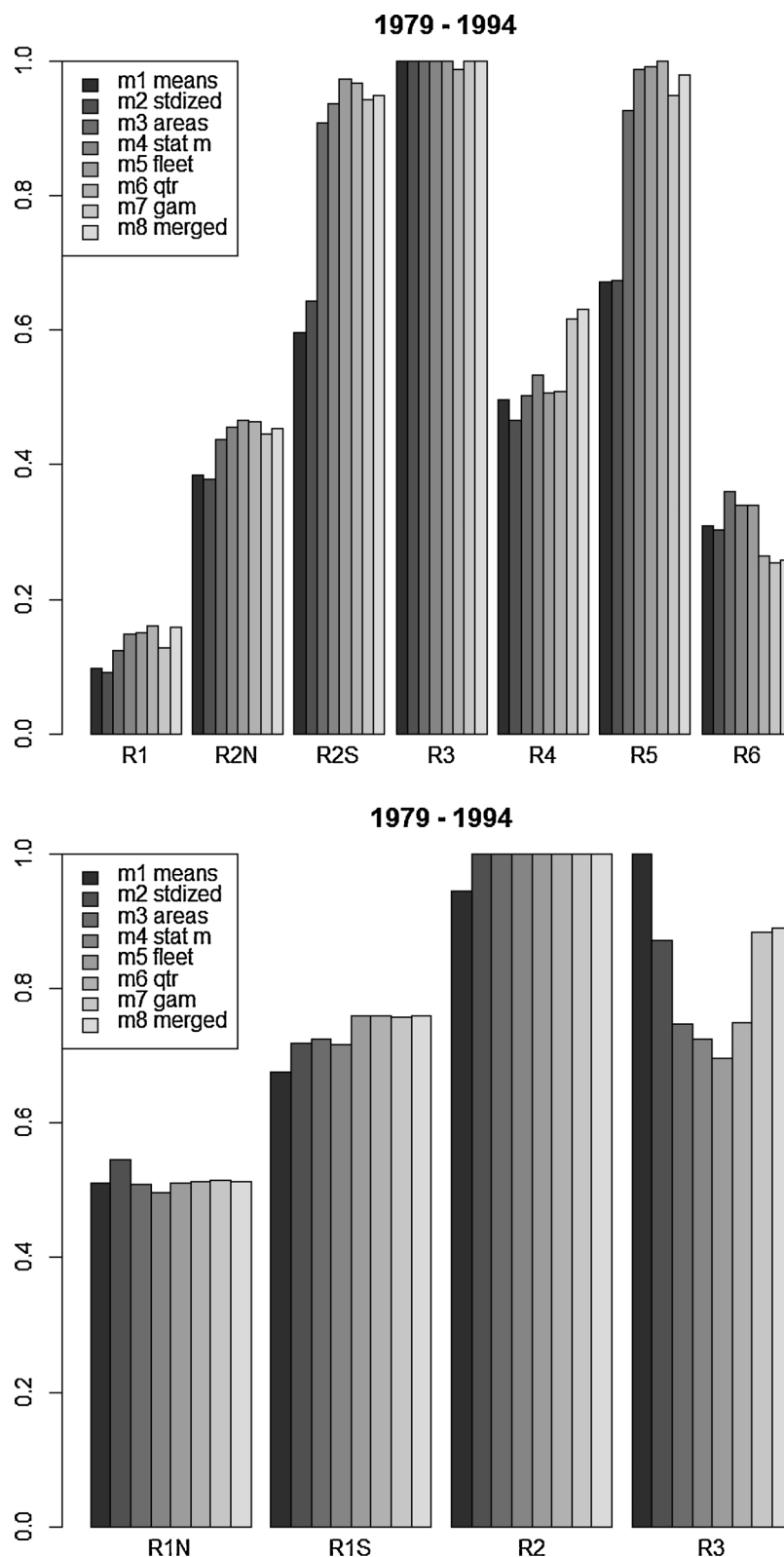


Fig. 6. Adjusted scaling factors for yellowfin (above) and bigeye (below) by region and method, using data from 1979–1994.

increase the scale of the tropical versus the temperate regions. For bigeye tuna the overall effect was smaller but in the same direction.

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 (Fig. 7). 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 southwestern region 3 and north-eastern 6, while bigeye scaling factors put less weight into tropical regions 1 and 2, and more into the southern

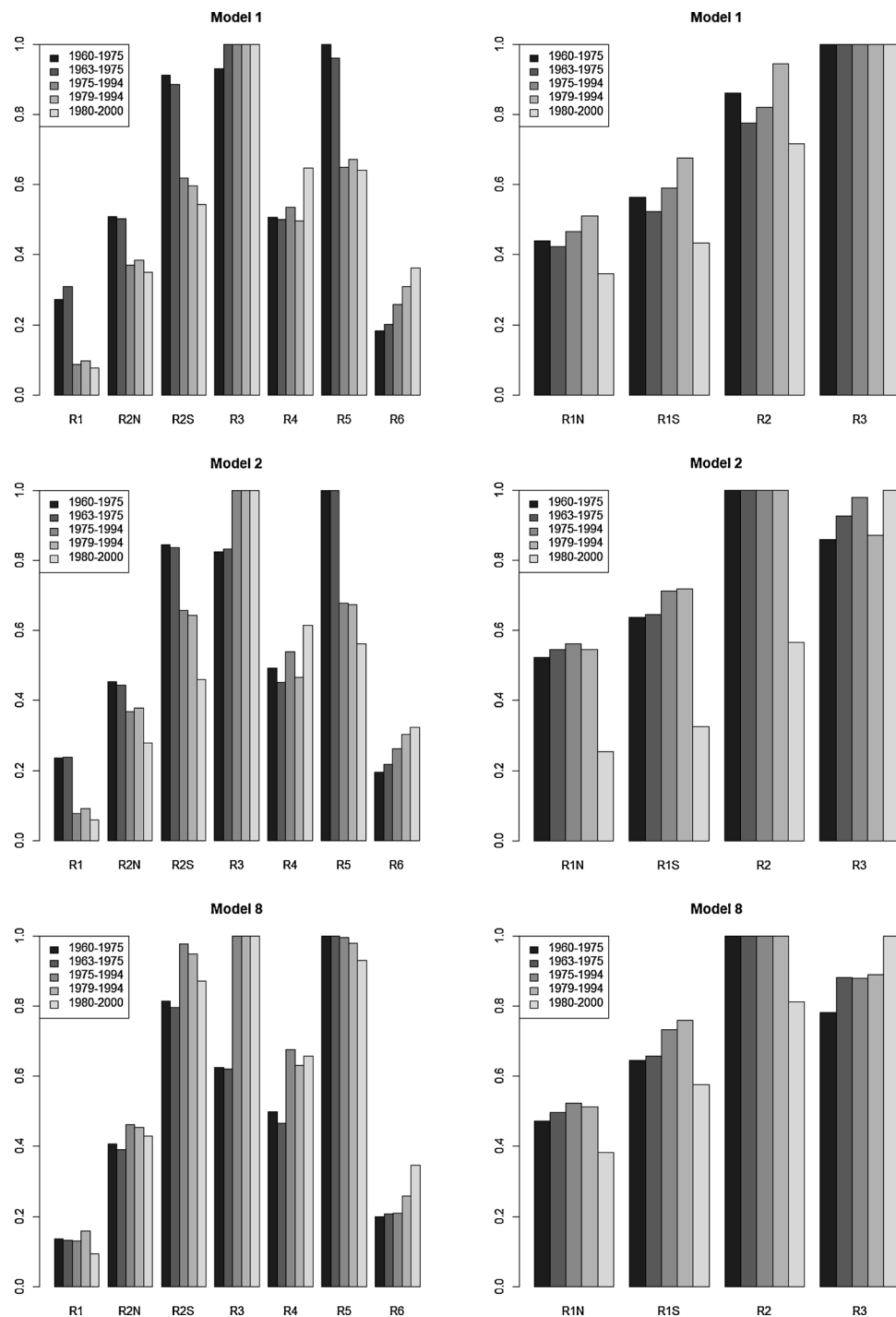


Fig. 7. Adjusted scaling factors for yellowfin (left) and bigeye (right) by region for methods m1 (means), m2 (standardized) and m8 (merged), using data from the periods 1960–1975, 1963–1975, 1975–1994, 1979–1994, and 1980–2000.

temperate region 3. The differences among time periods for model *m8* were smaller than for the simpler standardization model *m2*.

4. Discussion

Regional scaling factors are influential components of the stock assessments for yellowfin and bigeye tuna in the Indian and Pacific Oceans. Regional scaling constrains relative biomasses among regions to levels estimated from standardized CPUE data, based on assumptions consistent with CPUE time series used in the same models. The analyses in this paper employ commercial longline CPUE data, but a similar

approach could be used in fisheries where survey data are available.

The method assumes that catchability, as estimated in the regional scaling analysis, is consistent among regions. This may be broadly true in the case of tuna longline fisheries, although compromised in this analysis because aggregated data precluded adjusting for most covariate effects. Potential improvements to the methods, further discussed below, are mostly aimed at reducing spatial variation in catchability estimates.

Some implementations of regional scaling in stock assessments assume that selectivities are the same among regions (e.g. [Fu et al., 2018](#)), since CPUE is affected by abundance, catchability, and selectivity. If

selectivity is estimated independently among regions, some of the information about relative abundance may be lost. Constraining selectivity to be constant among regions informs the model that differences in fish size among regions are due to population dynamic effects such as movements and differences in recruitment and depletion.

However, there may be real differences in effective selectivity among regions that are not due to movement, recruitment, and depletion. For example, age and size usually vary spatially within tuna assessment regions, and catches tend to be aggregated spatially, causing realized selectivity within a region to differ from gear selectivity. Gear selectivity may also vary spatially, if environmental factors such as the depth of the thermocline or oxygen profiles affect availability at age and size to the fishing gear, or if targeting and setting methods vary spatially. Moreover, growth rates may vary spatially (Williams et al., 2012; Kolody et al., 2016; Lorenzen, 2016) and cause spatial size variation, which requires differences in selectivity in an assessment model that fits to size data and assumes uniform growth. The CPUE data included in the regional scaling estimates are affected by these factors and so should be predicted using the realized selectivities of the regional fisheries, rather than a theoretical uniform selectivity that ignores these effects. An important corollary is that poor fit to composition data can cause assessment scaling problems and conflict with other datasets, which should be avoided (Francis, 2011).

Unfortunately, there is currently little middle ground between allowing the regional selectivities to be estimated independently and fixing them at a uniform level. Further research is required to explore the circumstances that favour each approach. An unsatisfying but potentially useful compromise is to fit the assessment model with uniform selectivities and the resulting poor fit to the composition data, and then run an additional estimation phase with selectivity and movement estimation turned off, and very low or zero weight on the composition data to avoid data conflict due to the poor fit.

We recommend simulation studies to explore the application of regional scaling. Regional scaling involves both a complex CPUE standardization and a complex multi-region stock assessment, so there are many possible approaches, levels of complexity, and issues to explore. A useful approach may be to generate data from a simulator with high spatial resolution such as the spatial assessment model SPM (Dunn et al., 2015), to both address the spatial nature of the problem and allow comparison with a known 'truth' represented by the simulation model. Some questions relate to accuracy of the regional scaling parameter estimates in different circumstances, such as with different targeting strategies spatially; when estimation uses operational versus aggregated data; when trends vary among regions; or when there are spatial gaps in data coverage. Other questions relate to the use of regional scaling in the assessment: such as whether stock assessment results are more stable with or without regional scaling, and whether the fixed estimates reduce uncertainty too much; how estimates are affected by different approaches to selectivity by region; and how regional scaling affects the performance of fishery management strategies.

The analyses presented here provide an example of applying regional scaling to tuna fishery catch and effort data. Although the true relative abundances are unknown, the standardization approaches ($m2$ and others) are preferred to the means method ($m1$) because they adjust for changes in fishing distribution through time, and factors such as fleet effects which are also significant. The means method uses an arithmetic mean, which may be unduly affected by the large outliers that can occur in a lognormal distribution.

Adjusting for ocean area is clearly justified, and significantly changes the regional scaling factors, particularly for yellowfin tuna. This is partly because grid cell areas decline away from the equator, but mostly because many cells with high catch rates are close to the African coast and contain more land than ocean. Including statistical weights has been justified by simulations (Punsly, 1987; Campbell, 2004), and the fleet and quarterly effects were statistically significant and

consistent with our understanding of the fishery. Estimates from the GAM with the spatial smoother were similar to those from the GLM, and substituting GAM-based estimates into the cells that could not be estimated with the GLM clearly improved on the GLM results. It would be reasonable to use either the GAM results or the combined GLM and GAM results. The categorical cell values estimated by the GLM allow more flexible spatial variation in CPUE, but this is a minor advantage which may be offset by greater uncertainty.

These analyses also show that the period used for the regional scaling analysis affects the outcome and has implications for the assessment. It is better to use a period when catch rates are reliable indices of abundance, which suggests avoiding the pre-1975 period when there were large changes in targeting. The 1975–1994 period is problematic because of a break in the operational CPUE indices in 1979, due to the lack of vessel effects in the Japanese data. We also prefer periods when fishing is widely distributed so that estimates are available for most or all spatial cells, although this requirement is reduced by including estimates from the spatial smoother. An important consideration is that trends among regions should be relatively consistent, because the models are relatively simple and ignore issues such as the year-region interactions apparent in the long-term regional CPUE indices. For this reason, we prefer the 1979–1994 period over the 1980–2000 period. It may be possible in future to include year-region interactions in the models. Nevertheless, although trends differ among regions, both the estimation and application of the relative abundance estimates are based on the average abundance distribution during the period.

Further changes to the modelling approach would likely improve the estimates. Since we are interested in the expected value of a log-normally distributed parameter, it would be appropriate to apply log-normal bias correction before summing the 5° cell values. We have not done so because the appropriate variance estimate is unclear.

Targeting can substantially affect catch rates in longline tuna fisheries, with fishing strategies changing both spatially and through time (Hoyle et al., 2016). The current approach does not account for target change and may therefore underestimate the biomass of yellowfin and bigeye in southern areas, where effort is more likely to target other species. Methods are available to account for targeting when operational data are available (e.g. He et al., 1997; Winker et al., 2014; Thorson et al., 2016). However, the aggregated data available for the Indian Ocean do not support such methods, or report covariates associated with targeting methods such as hooks between floats. Without operational data it is difficult to account for target change in regional scaling analyses.

Limiting the dataset to Japanese and Korean data means that northern areas of the Indian Ocean such as the Arabian Sea and the Bay of Bengal are not well covered. The proportions of the stocks in these areas are therefore omitted from the estimates. It would be useful to explore the catch and effort data of fleets that have fished in those areas, such as the Taiwanese and Indian fleets, with a view to including these areas in future.

Given the limitations of aggregated data, we recommend applying regional scaling methods to a multiple-fleet dataset of operational data. This approach could use cluster analysis and/or set characteristics such as HBF or hooks per set to account for targeting, and vessel identities to account for variation in fishing power.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We are grateful to two anonymous reviewers whose advice substantially improved the manuscript. This work was supported by funding from the Food and Agriculture Organization of the United Nations (Indian Ocean Tuna Commission) and the International Seafood Sustainability Foundation. Thanks also to the Secretariat of the Pacific Community for supporting development of the original concept.

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