Long time series CPUE standardization for skipjack tuna (*Katsuwonus pelamis*) of the EU purse-seine fishery on floating objects (FOB) in the Indian Ocean

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Abstract

This report does a simple 1-component GAMM model to standardize SKJ catch per FOB set of the Indian Ocean EU purse-seine fleet for the period 1991-2021.

Introduction

In a companion document, we did a short time series SKJ catch per floating object (FOB) set standardization for the Indian Ocean EU tropical tuna purse-seine fleet for the period 2010-2021. During discussions of that work, it was decided that it would be advantageous to also have a longer time series of standardized CPUEs. This analysis is carried out in this document. Though this time series is longer, all of the variables related to dFAD use and set time must be removed as we do not have the data for these variables before 2010. Therefore, the standardization is principally over vessel and vessel characteristics and to homogenize fishing effort in space over time.

Methods

Catch-effort dataset

The catch-effort data in this study consisted of French and Spanish FOB sets over the period 1991-2021. The initial data consisted of 137,638 FOB sets corresponding to 134,382 fishing activity entries in the data set. The data was filtered to remove the following data entries (numbers of sets indicated are not exclusive):

- Null sets (9,390 sets)
- Fishing activities corresponding to multiple fishing sets (5,970 sets). Such multi-set fishing activities are concentrated in the early part of the time series, but never exceed 15% of all FOB sets in a given year.
- Sets by vessels in the bottom 5% of vessels in terms of number of positive sets or that were active less than 3 years or whose activities spanned less than 5 years (19 vessels corresponding to 2,591 sets)

After applying all of these filters, the final dataset used for building the CPUE standardization model consisted of 121,427 sets.

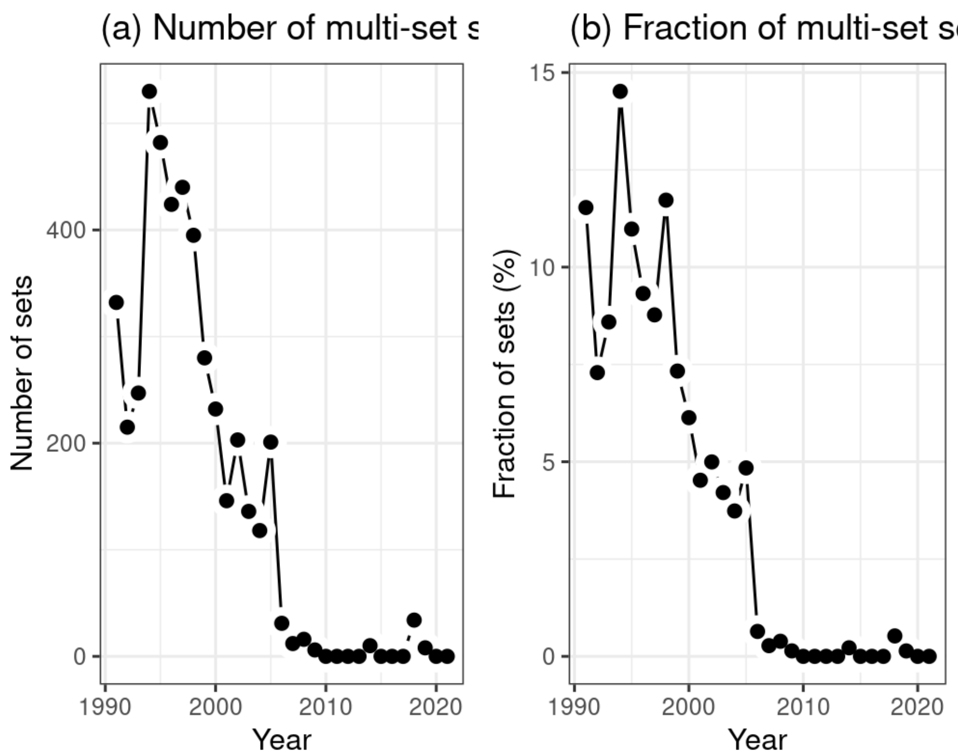

Figure 1: Number and fraction of FOB sets per year that are recorded in multi-set fishing activities.

Predictor variables

The predictor variables consisted of the the standard temporal, spatial, fleet and vessel identifier predictor variables included in previous standardization efforts (Guéry et al. 2021, e.g., Akia et al. 2022):

- lon,lat spatial variables
- year, month temporal variables
- quarter for stratifying spatial smooths and prediction grids
- vessel country, capacity and year of initiation of activity
- vessel unique identifier

Modeling approach

Only a 1-part GAMM model was evaluated for this long time series CPUE.

1-part GAMM model

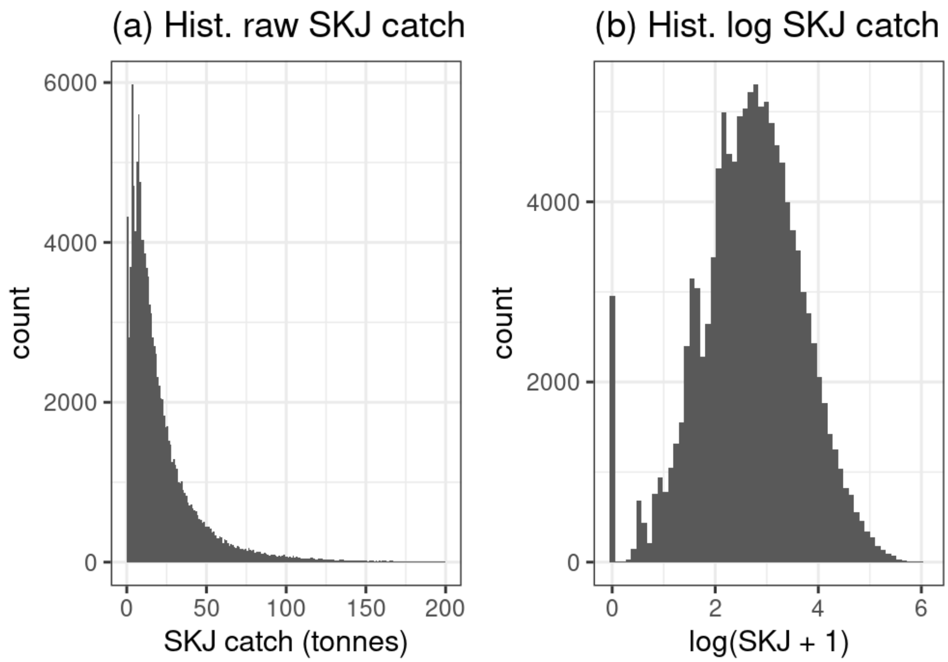

Figure 2: Histograms of SKJ catch data in model training dataset before (a) and afer (b) log transformation.

A single-component general additive mixed-effects model (GAMM) was also run with $\log(SKJ + C)$ as the variable to be predicted, where SKJ is the T3-corrected (Pianet et al. 2000) catch of skipjack per purse seine FOB set. As for a small number of sets (2,960 sets) zero SKJ catch was reported, a small constant, C, was added to SKJ catch before taking the log. This constant C was chosen to be 1 tonne as this amount is generally used as the limit between null and non-null sets and was observed to produce a response variable that was reasonably close to normally distributed before running the model (Figure 2) and the resulting GAMM had reasonably good model diagnostics (see Results below).

Predictor variables for the GAMM model were longitude and latitude as a tensor product smooth by quarter, year and month as a tensor product smooth cyclic in the month dimension, vessel capacity and years of service at the time of fishing as individual smooths and vessel country as a categorical predictor. Vessel identifier was included as a categorical random effect. The precise command used to general the GAMM model was:

```
gm = gamm(logskj~te(lon,lat,by=quarter,k=13) +
te(year,month,k=c(20,11),bs=c("cr","cc")) +
            s(yr_serv,k=10) + s(capacity,k=10) + country,
          data=data,random=list(vessel_id=~1))
saveRDS(gm,"2023-cpue-standardization-iotc-skj.gamm-model-1991-2021.RDS")
```

The model was verified using the `gam.check` function of the `mgcv` package to assure that the numbers of splines used for each smooth (i.e., `k`) were sufficient.

Prediction/standardization approaches

CPUE standardization is based on predicting models on a standard spatio-temporal grid, fixing fishing-efficiency- and catchability-related variables at standardized values, and then averaging over space (and potentially other predictors) to obtain a standardized estimation of abundance. We implemented two different approaches to this spatial averaging process. The first is the approach that has traditionally been used based on predicting catch in each $1^{\circ} \times 1^{\circ}$-month strata occupied by the fishery and then averaging (or summing) over $1^{\circ} \times 1^{\circ}$ grid cells. This spatial averaging is based on the assumption that set size is a true predictor of abundance in each strata. Though spatial thinning is generally used to remove cells with very low fishing effort from the prediction step, this method still has the disadvantage that it combines results from grid cells with potentially highly varying sampling effort (i.e., numbers of fishing sets). Furthermore, catch per set is only partially satisfactory as an estimator of abundance as it implicitly assumes that the number of FOB fish schools is constant over space (so that abundance is entirely reflected in set size), an assumption that is unlikely to be globally valid.

Due to these limitations, we also implement a second approach to developing a spatially-averaged standardized CPUE. In this approach, the predictions in each $1^{\circ} \times 1^{\circ}$-month strata are weighted by the total number of fishing sets carried out in that grid cell and the corresponding quarter (i.e., the weightings are stratified by quarter) over the entire time series of the data. As the number of sets times the average catch per set is the total catch, this approach is akin to using total catch as an indicator of abundance, except that the spatial distribution of fishing effort is standardized over time. This method will place more weight on core fishing areas where most fishing effort occurs relative to the previously described methodology.

Before implementing both standardization approaches, the spatial area to be used for predictions was thinned to remove $1^{\circ} \times 1^{\circ}$ grid cells with little fishing effort. Predictions were only made for grid cells that collectively represent the smallest number of grid cells accounting for at least 95% of the FOB fishing sets in each quarter included in the model training data. The resulting modeling domains for each of the four quarters are shown in Figure 3.

Variables related to fishing efficiency and catchability were fixed at their median values from the training data set. Specifically, when calculating standardized CPUEs, vessel capacity was fixed at 1850 and vessel initial year of activity was fixed at 1992. Predictions were made for all levels of categorical predictor variable vessel country and then averaged across levels, weighting the resulting predictions by the overall prevalence of each level in the model training data (e.g., fraction of Spanish versus French sets).

Predictions from the log-normal GAMM model were converted back to absolute catch using the standard formula for estimating the expected value of a log-normal distribution (Fletcher 2008):

$$\mu_Y = \exp\left(\mu_X + \frac{\sigma_X^2}{2}\right) \qquad (1)$$

where μ_X is the expected value predicted by the GAMM model, σ_X^2 is the residual variance of the GAMM model (i.e., the `scale` parameter of the model outputs) and μ_Y is the final predicted catch.

When averaging GAMM model predictions to obtain annual standardized CPUEs, standard errors were combined via simple addition, equivalent to assuming that all uncertainties in model predictions are correlated. Though undoubtedly inexact, this assumption will lead to conservative estimates of uncertainty (i.e., larger than reality). This issue can be corrected to obtain more exact uncertainty estimates using a bootstrap approach based on the Cholesky trick (Andersen 2022), but there was insufficient time to do so before the WGFAD meeting.

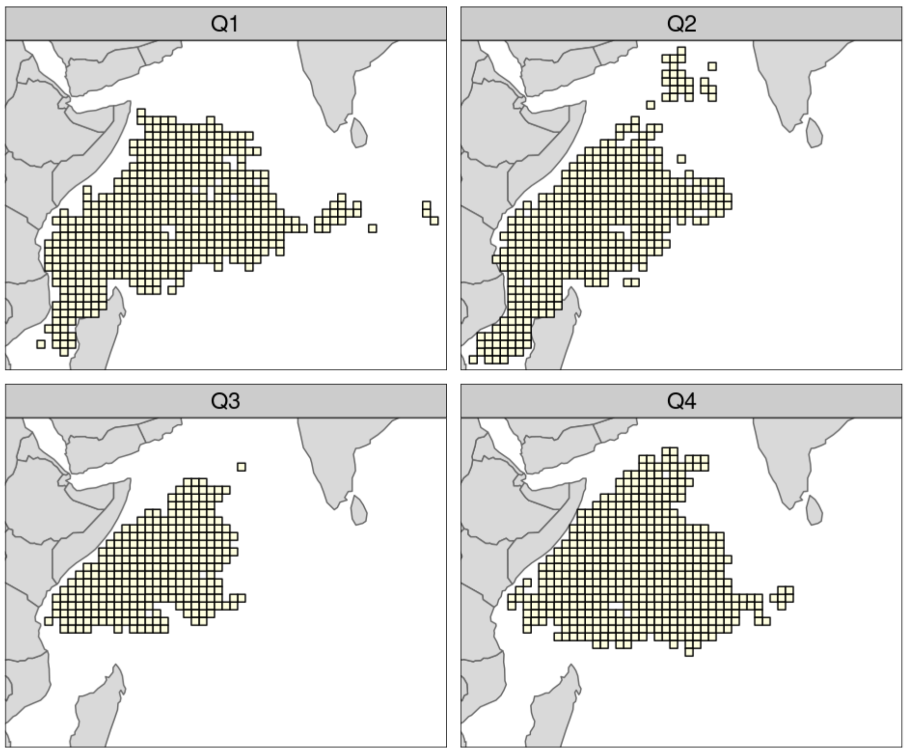

Figure 3: The $1^{\circ} \times 1^{\circ}$ *grid cells used for model prediction for each quarter. The quarter number is indicated at the top of each panel.*

Results

Model diagnostics and significance of predictor variables

GAMM models are actually implemented as the combination of a linear mixed-effects (LME) model for estimating the random effect and a GAM model for estimating the final model with smooths after removing the variance explained by the random effect. Both of these components provide standard diagnostic plots, including a residuals versus fitted plot for the LME model (Figure 4) and a QQ-plot for the GAM (Figure 5). Both of these plots indicate an adequate fit of the data to the model assumptions.

All predictors included in the model, including smoothed, direct and random effects, had a significant impact on SKJ catch per FOB set (see model summaries below and Table 1).

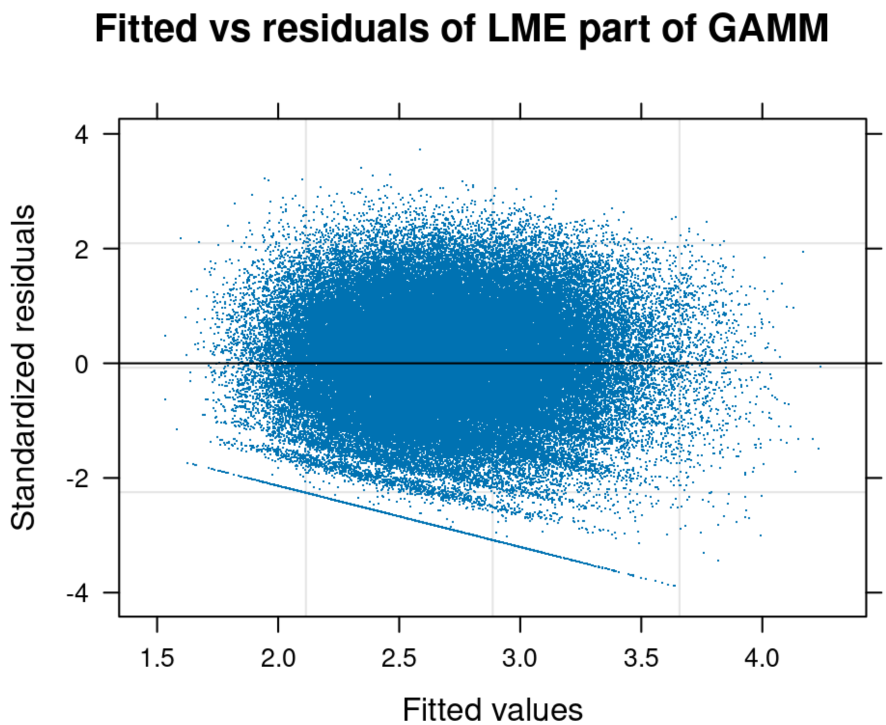

Figure 4: Fitted values versus residuals for LME part (i.e., random part) of GAMM.

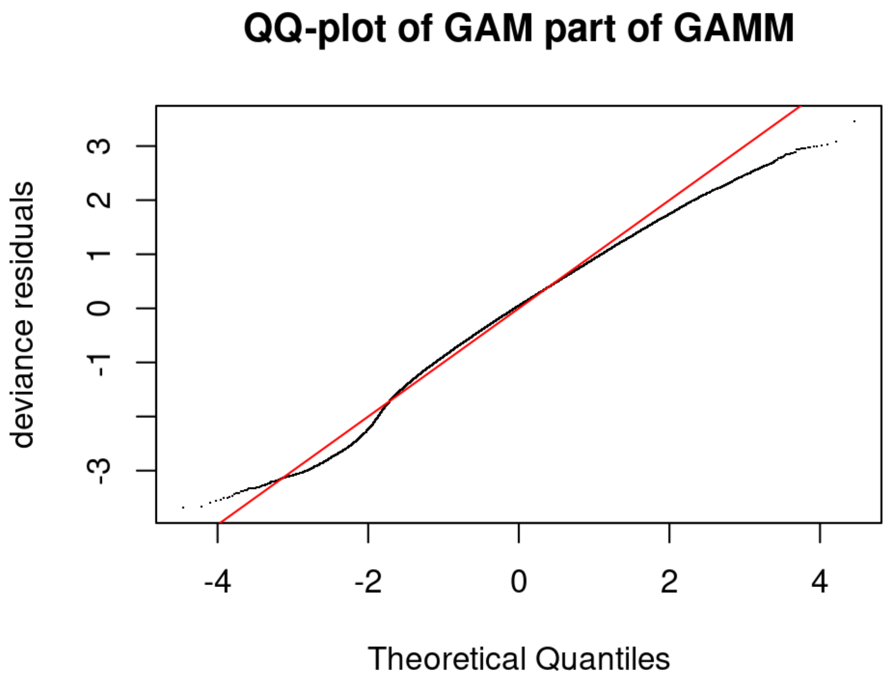

Figure 5: QQ-plot of GAM part (i.e., non-random part) of GAMM.

ANOVA table for LME component of GAMM model (i.e., model for estimating random effect):

```
  numDF  denDF  F-value p-value
X    17 121340 2210.401  <.0001
```

Summary output from GAM part of GAMM model (i.e., non-random part of model):

```
Family: gaussian
Link function: identity

Formula:
logskj ~ te(lon, lat, by = quarter, k = 13) + te(year, month,
    k = c(20, 11), bs = c("cr", "cc")) + s(yr_serv, k = 10) +
    s(capacity, k = 10) + country

Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.71257    0.02284 118.739   <2e-16 ***
countryspain  0.06990    0.03137   2.228   0.0259 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Approximate significance of smooth terms:
                         edf Ref.df     F  p-value    
te(lon,lat):quarter1  46.09  46.09 25.12  < 2e-16 ***
te(lon,lat):quarter2  32.80  32.80 11.64  < 2e-16 ***
te(lon,lat):quarter3  37.01  37.01 36.32  < 2e-16 ***
te(lon,lat):quarter4  44.21  44.21 26.04  < 2e-16 ***
te(year,month)       182.43 182.43 35.49  < 2e-16 ***
s(yr_serv)             1.00   1.00  0.94    0.332    
s(capacity)            1.00   1.00 23.30 1.54e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.121
  Scale est. = 0.87667   n = 121427
```

(a) Parametric terms

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2.713	0.023	118.739	0.000
countryspain	0.070	0.031	2.228	0.026

(b) Smoothed terms

	edf	Ref.df	F	p-value
te(lon,lat):quarter1	46.086	46.086	25.116	0.000
te(lon,lat):quarter2	32.798	32.798	11.645	0.000
te(lon,lat):quarter3	37.009	37.009	36.319	0.000
te(lon,lat):quarter4	44.214	44.214	26.041	0.000
te(year,month)	182.431	182.431	35.494	0.000
s(yr_serv)	1.000	1.000	0.940	0.332
s(capacity)	1.000	1.000	23.295	0.000

Table 1: Summary statistics and p-values for fixed and smooth terms included in the non-random part of the GAMM model.

Marginal effects of predictor variables

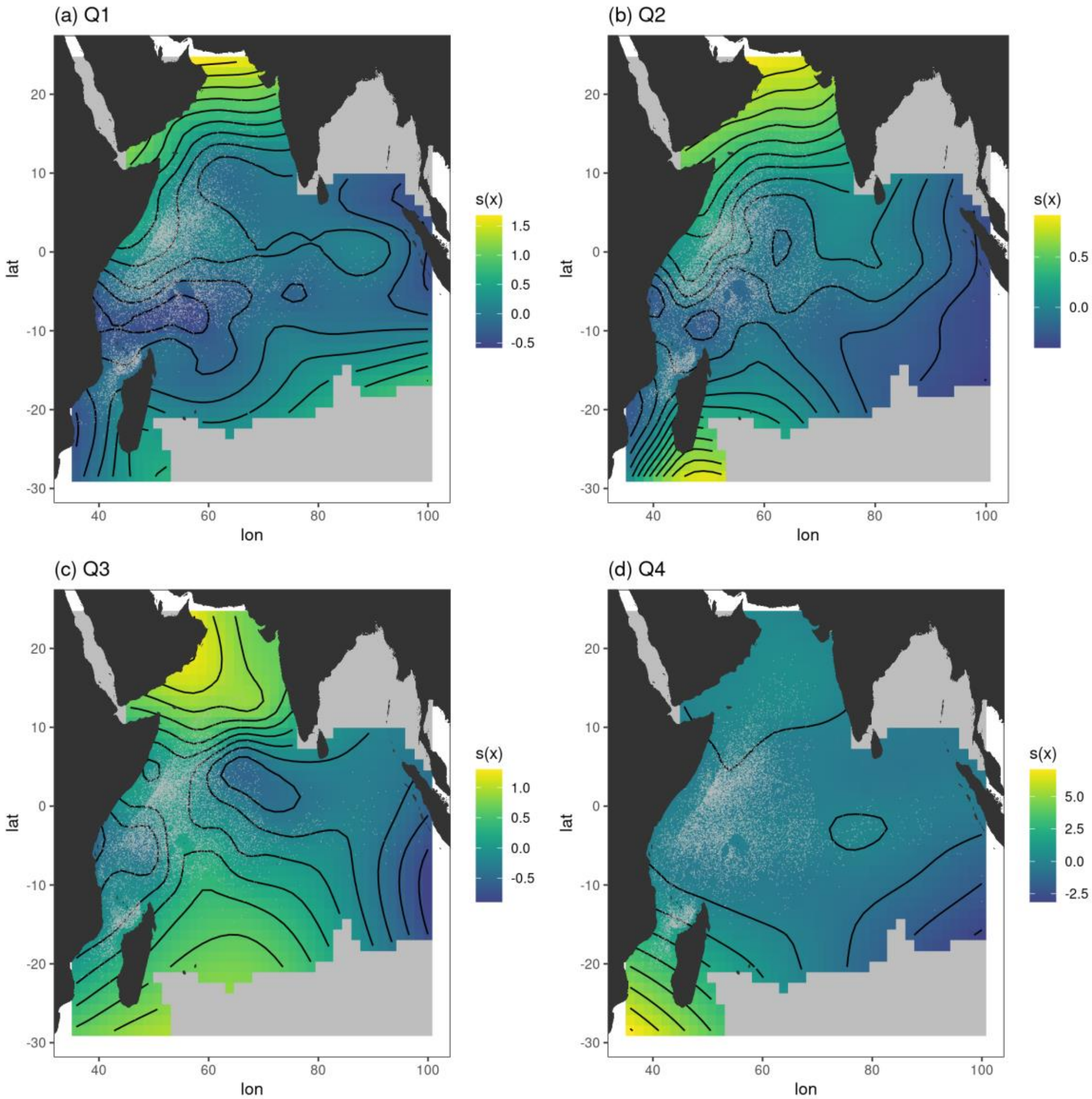

Figure 6: Marginal effect of lon,lat on log SKJ catch per FOB set for each of the four quarters.

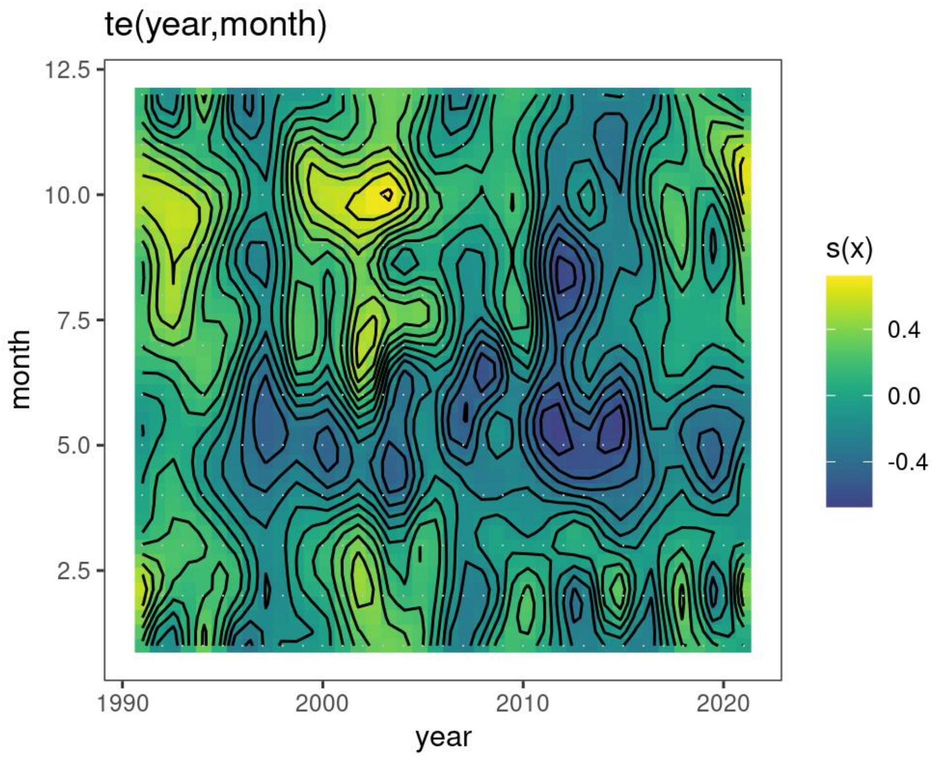

Figure 7: Marginal effect of year,month on log SKJ catch per FOB set.

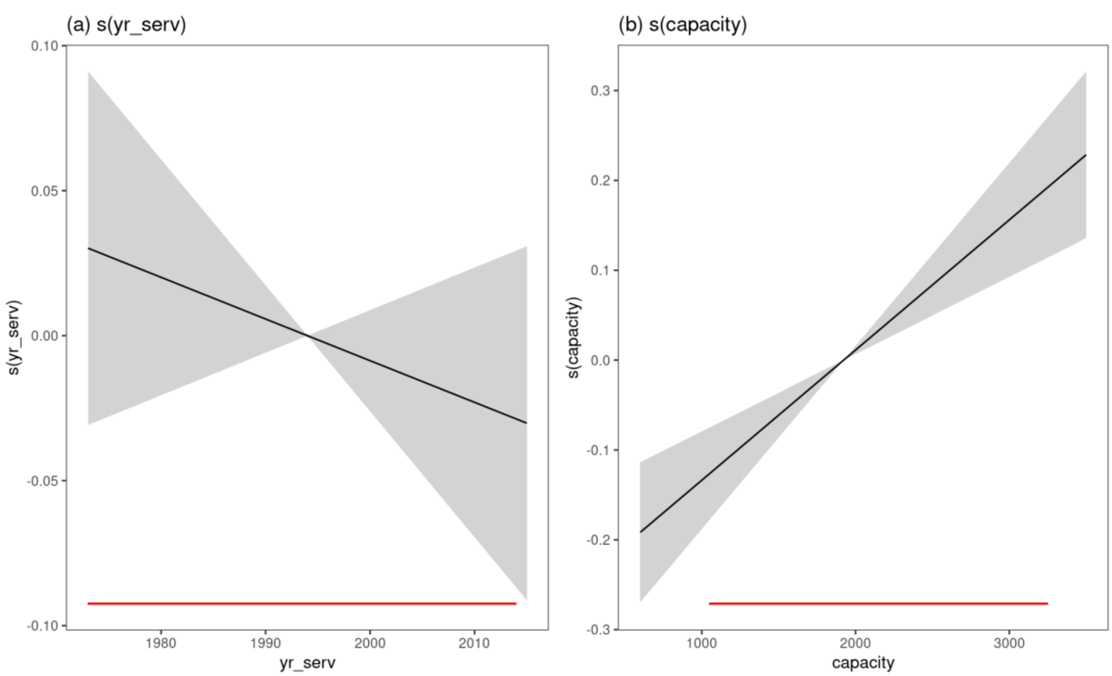

Figure 8: Marginal effects of individual smooths on log SKJ catch per FOB set. The red horizontal bars on the panels indicate the central 95% of the data of the corresponding

predictor variable in the model training data set.

Vessel carrying capacity had a linearly increasing impact on log SKJ catch per set, whereas the effect of year of entry into the fishery was insignificant. The impacts of spatial (Figure 6) and temporal (Figure 7) predictors on log SKJ catch are more difficult to interpret.

Standardized CPUEs

Table 2: Annual spatially weighted and unweighted standardized CPUEs and nominal CPUEs for SKJ catch per FOB set in the Indian Ocean European purse seine fleet. Values are in

Year	Unweighted, Mean	Unweighted, 2.5%	Unweighted, 97.5%	Weighted, Mean	Weighted, 2.5%	Weighted, 97.5%
1991	28.22	23.80	33.51	28.04	24.01	32.80
1992	27.12	23.81	30.88	28.08	24.98	31.58
1993	27.42	24.13	31.17	28.45	25.37	31.90
1994	27.81	24.40	31.68	27.98	24.92	31.42
1995	24.05	21.40	27.02	24.14	21.80	26.72
1996	19.36	17.10	21.92	19.49	17.46	21.75
1997	17.27	15.27	19.52	17.22	15.44	19.20
1998	19.96	17.71	22.50	20.29	18.25	22.55
1999	24.15	21.27	27.40	25.08	22.43	28.04
2000	23.80	21.08	26.88	24.29	21.84	27.02
2001	26.17	23.17	29.57	26.50	23.82	29.48
2002	30.90	27.23	35.05	31.63	28.33	35.32
2003	27.97	24.81	31.54	28.49	25.63	31.66
2004	25.10	22.11	28.49	25.23	22.54	28.24
2005	24.86	21.95	28.16	24.85	22.28	27.72
2006	21.39	19.08	23.98	21.59	19.57	23.82
2007	18.29	16.19	20.65	18.46	16.60	20.53
2008	19.29	17.10	21.75	19.08	17.17	21.21
2009	22.26	19.84	24.97	22.17	20.05	24.51
2010	22.91	20.30	25.84	23.00	20.68	25.58
2011	18.75	16.67	21.08	18.10	16.33	20.06
2012	16.38	14.52	18.47	15.59	14.01	17.34
2013	16.97	15.01	19.18	16.55	14.84	18.44
2014	17.46	15.56	19.58	17.18	15.55	18.97
2015	17.60	15.61	19.84	17.38	15.63	19.30
2016	18.28	16.29	20.50	18.31	16.57	20.23

Year	Unweighted, Mean	Unweighted, 2.5%	Unweighted, 97.5%	Weighted, Mean	Weighted, 2.5%	Weighted, 97.5%
2017	21.82	19.58	24.32	21.90	19.95	24.03
2018	24.39	21.82	27.28	24.37	22.10	26.87
2019	21.93	19.55	24.59	21.94	19.83	24.28
2020	21.88	19.39	24.69	22.04	19.77	24.56
2021	26.30	23.16	29.85	26.66	23.78	29.88

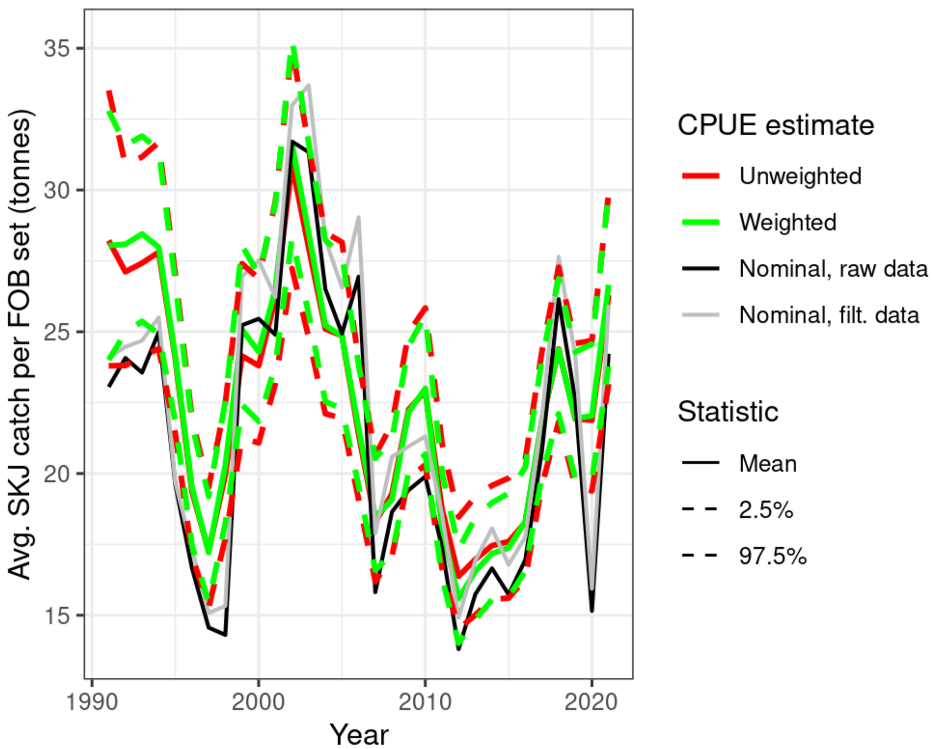

Figure 9: Standardized CPUE predictions from the single-component GAMM model. CPUEs are in units of tonnes of SKJ catch per PS FOB set in the Indian Ocean. Solid curves indicate mean tendencies, whereas dashed curves indicate the upper and lower limits of the 95% confidence interval. Red curves correspond to the spatially unweighted approach to averaging predictions over space, whereas green curves correspond to the spatially weighted approach to spatial averaging. Black and gray curves indicate the nominal CPUE derived from the original, unfiltered data and the filtered data used for training the GAMM model, respectively.

Nominal and standardized CPUE curves are shown in Figure 9 and Table 2. The weighted and unweighted standardized CPUE curves are generally similar to each other and similar to the nominal CPUE curves. The most notable differences between nominal and standardized CPUEs occur in 3 specific periods: (a) 1991-1997: standardized CPUEs are consistently above nominal CPUEs, perhaps due to the balancing of catch between the different fleets; (b) 2007-2012: this period corresponding to the most important impacts of Somali piracy is also characterized by standardized CPUEs exceeding nominal CPUEs; and (c) 2020: fishing in this year was heavily impacted by the onset of COVID. Nominal CPUEs based on the original, unfiltered data and the filtered data used for GAMM model training are generally quite close, but at times the filtered data nominal CPUE exceeds that of the unfiltered data, perhaps due to the elimination of vessels that only briefly participated in the fishery and, therefore, had less experience and lower catch rates.

Discussion

This standardized CPUE appears to reproduce many of the major features seen in the Maldivian pole and line CPUE.

Acknowledgements

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