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CPUE standardization for the offshore fleet fishing for Jack mackerel in the SPRFMO Area, including China

European Union

CPUE standardization for the offshore fleet fishing for Jack mackerel in the SPRFMO area, including China

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Abstract

Prior to 2018 two offshore CPUE series have been used in the assessment of Jack Mackerel: the standardized Chinese CPUE and the nominal offshore fleet CPUE (EU, Vanuatu, Korea, Russia). During the benchmark assessment of 2018, the nominal offshore CPUE has been converted into a standardized CPUE series, following the same methods as used for the Chinese CPUE. This working document presents the results of a fully combined and standardized Offshore CPUE index that is based on the haul-by-haul data of China, EU, Korea, vanuatu and Russia as contained in the SPRFMO database. Permission to utilize that information was granted by the respective Contracting Parties while the analysis was carried out by scientists from the EU delegation. The standardization procedure is identical to the procedure followed during the benchmark in 2018. The working document consists of a description of the data available for the analysis and the methods towards model choice to select the optimal model configuration for CPUE standardization. The final GAM model consists of a number of discrete factors (year, vessel, month and El Nino Effect) and a smoothed interaction between latitude and longitude. The new standardized CPUE series starts in 2008 as this is the first year for which haul by haul information was available to carry out this analysis. CPUE for the offshore fleet has decreased between 2008 and 2012, has slowly increased between 2013 and 2017 and has substantially decreased in 2018, indicating a lower availability of jack mackerel in the offshore waters.

1 Introduction

The assessment of Jack Mackerel in the southern Pacific is based on many different sources of information, including two standardized Catch per Unit Effort time series for China and for other Offshore fleets. Because both fleets are basically operating a similar type of fishery, it was suggested to combine the two fleets into one overarching offshore fleet. With the availability of the Chinese CPUE data, this analysis has now been performed. The standardization approach is identical to the standardization reported in 2018 for the offshore fleet (SC, 2013). Data has been obtained from the SPRFMO secretariat after permission was granted by the different contracting parties that the data could be used for this CPUE analysis.

2 Material and methods

Data from EU, Korea, Russia, Vanuatu and China was made available by Craig Loveridge on 12 August 2019. Data from China has been included for the first time this year, which has promped a new full analysis, similar to the analysis that was carried out during the benchmark meeting in 2018. Two vessels were removed from the dataset because of apparent problems with the units used for catch reporting. Below, summary information by year and contracting party is presented for: * number of vessels participating in the fishery * total catch of jack mackerel * number of fishing hours

Number of vessels participating in the fishery

year	CHN	EU	KOR	RUS	VUT	(all)
2008	0	6	2	0	4	12
2009	13	8	2	0	4	27
2010	9	6	2	0	4	21
2011	6	2	2	0	2	12
2012	3	0	2	0	2	7
2013	2	1	1	0	2	6
2014	3	2	1	0	2	8
2015	6	2	2	1	2	13
2016	2	2	2	0	1	7
2017	2	2	1	1	0	6
2018	2	1	2	1	0	6

Table 1: Number of vessels participating in the Jack mackerel fishery by Contracting Party

Total catch of jack mackerel per year

year	CHN	EU	KOR	RUS	VUT	(all)
2008	0	71,650	12,377	0	101,955	185,982
2009	117,963	90,722	13,759	0	80,166	302,610
2010	63,606	31,258	8,183	0	45,934	148,981
2011	32,862	1,185	9,253	0	7,628	50,928
2012	13,012	0	5,492	0	16,463	34,966
2013	8,329	10,012	5,267	0	15,526	39,133
2014	21,155	20,510	4,078	0	15,473	61,215
2015	29,180	28,007	5,749	2,524	21,224	86,683
2016	20,208	11,470	6,430	0	7,385	45,492
2017	16,586	27,652	1,235	3,188	0	48,662
2018	24,366	9,620	3,717	4,686	0	42,389
(all)	347,267	302,085	75,539	10,398	311,753	1,047,042

Table 2: Total catch of Jack mackerel by contracting party

Length of the fishing season

Fishing season is defined as the number of days between the first haul and the last haul in a year)

year	CHN	EU	KOR	RUS	VUT	(all)
2008	.	172	188	.	245	202
2009	216	190	195	.	198	200
2010	256	173	208	.	171	202
2011	194	31	197	.	149	143
2012	271	.	167	.	263	234
2013	228	233	139	.	202	200
2014	182	165	93	.	201	160
2015	217	148	120	52	159	139
2016	241	136	188	.	167	183
2017	166	277	81	75	.	150
2018	181	182	130	111	.	151
(all)	215	171	155	79	195	176

Table 3: Length of the fishing season (days) by Contracting Party

Number of fishing days

Number of days when at least one haul has been reported.

year	CHN	EU	KOR	RUS	VUT	(all)
2008	0	416	224	0	708	1,348
2009	1,301	537	173	0	584	2,595
2010	869	289	125	0	438	1,721
2011	591	29	205	0	169	994
2012	260	0	116	0	323	699
2013	177	137	89	0	223	626
2014	304	208	77	0	233	822
2015	362	171	104	38	214	889
2016	277	115	195	0	85	672
2017	165	255	31	51	0	502
2018	230	131	92	70	0	523
(all)	4,536	2,288	1,431	159	2,977	11,391

Table 4: Number of fishing days by contracting party

Number of hauls

year	CHN	EU	KOR	RUS	VUT	(all)
2008	0	702	398	0	1,731	2,831
2009	2,331	836	291	0	1,356	4,814
2010	1,518	512	261	0	886	3,177
2011	997	40	432	0	273	1,742
2012	446	0	160	0	562	1,168
2013	269	198	128	0	358	953
2014	485	336	125	0	392	1,338
2015	614	349	198	80	435	1,676
2016	500	202	326	0	180	1,208
2017	294	549	54	87	0	984
2018	377	232	157	132	0	898
(all)	7,831	3,956	2,530	299	6,173	20,789

Table 5: Number of hauls by contracting party

Number of fishing hours

year	CHN	EU	KOR	RUS	VUT	(all)
2008	0	2,829	1,559	0	8,935	13,323
2009	12,622	5,905	1,301	0	7,512	27,340
2010	8,213	3,363	1,381	0	6,357	19,314
2011	6,463	309	2,385	0	2,041	11,198
2012	3,256	0	920	0	4,253	8,429
2013	1,917	1,455	919	0	2,815	7,106
2014	3,655	2,238	649	0	2,809	9,351
2015	3,704	2,033	910	441	2,631	9,719
2016	3,122	1,296	1,775	0	1,097	7,290
2017	1,482	2,944	214	482	0	5,122
2018	2,605	1,641	892	790	0	5,928
(all)	47,039	24,013	12,905	1,713	38,450	124,120

Table 6: Summed fishing hours by contracting party

Average duration of a fishing haul

year	CHN	EU	KOR	RUS	VUT	(all)
2008	.	4.1	3.9	.	5.2	4.4
2009	5.4	7.1	4.5	.	5.5	5.6
2010	5.4	6.6	5.3	.	7.2	6.1
2011	6.5	7.7	5.5	.	7.5	6.8
2012	7.3	.	5.8	.	7.6	6.9
2013	7.1	7.4	7.2	.	7.9	7.4
2014	7.5	6.7	6.1	.	7.2	6.9
2015	6	5.8	5.1	5.5	6	5.7
2016	6.2	6.4	6.2	.	6.1	6.2
2017	5	5.4	4	5.5	.	5
2018	6.9	7.1	5.7	6	.	6.4
(all)	6.3	6.4	5.4	5.7	6.7	6.1

Table 7: Average duration of a fishing haul by contracting party

Mean catch per day of jack mackerel

year	CHN	EU	KOR	RUS	VUT	(all)
2008	.	173	55	.	145	124
2009	91	169	80	.	137	119
2010	73	109	65	.	105	88
2011	56	41	45	.	45	47
2012	50	.	47	.	51	49
2013	47	74	59	.	70	63
2014	70	100	53	.	66	72
2015	81	166	55	68	99	94
2016	73	100	33	.	87	73
2017	101	108	40	63	.	78
2018	106	73	40	67	.	72
(all)	75	111	52	66	89	80

Table 8: Mean catch per day of Jack Mackerel

All hauls of all years on one map

All haul positions for all years where Jack mackerel has been caught.

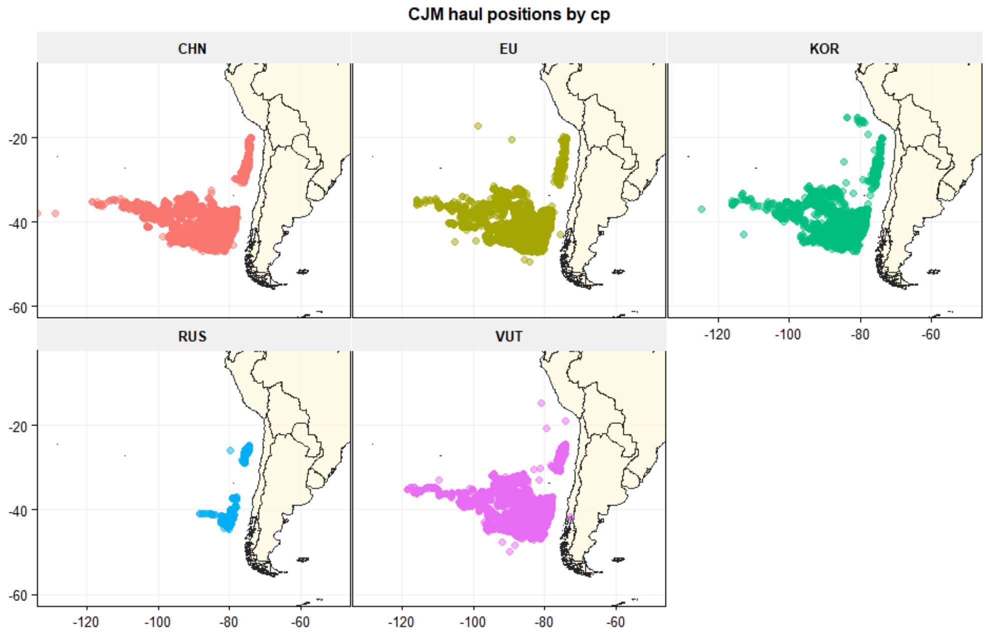


Figure 1: Haul positions where Jack mackerel has been caught (all years combined)

Haul positions by contracting party and year

The yearly postions of Jack mackerel fishery of the offshore fleets.

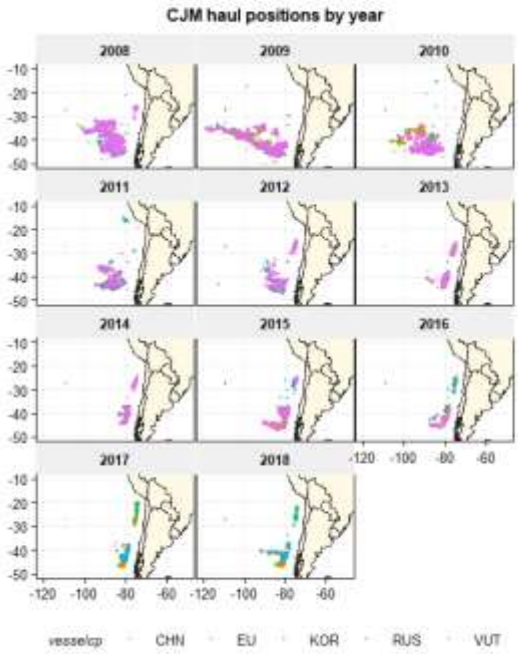


Figure 2: Haul positions where Jack mackerel has been caught (by year). Colours indicate the different contracting parties

Mean catch per day of jack mackerel per one degree longitude and 1/2 degree latitude

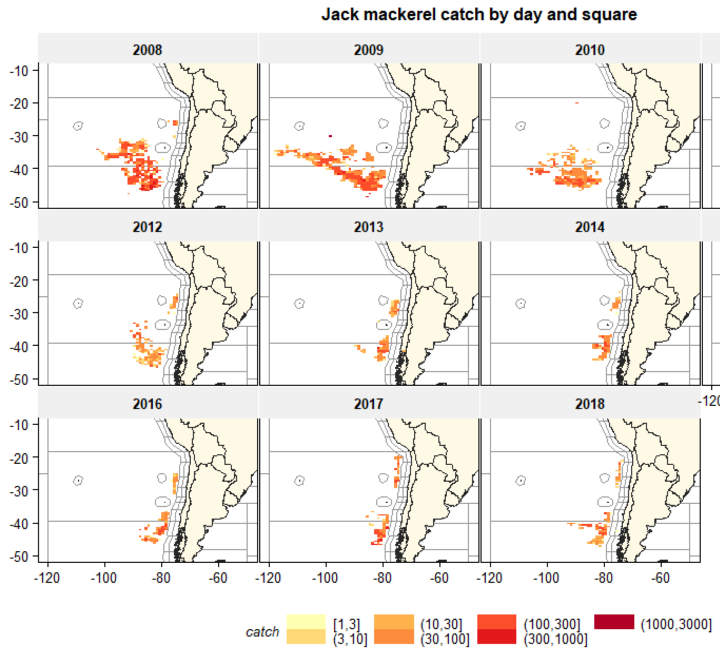


Figure 3: Catch per day (tonnes) of Jack mackerel (summed by 1 degree longitude and 0.5 degree latitude)

Jack mackerel log CPUE by day against latitude and longitude

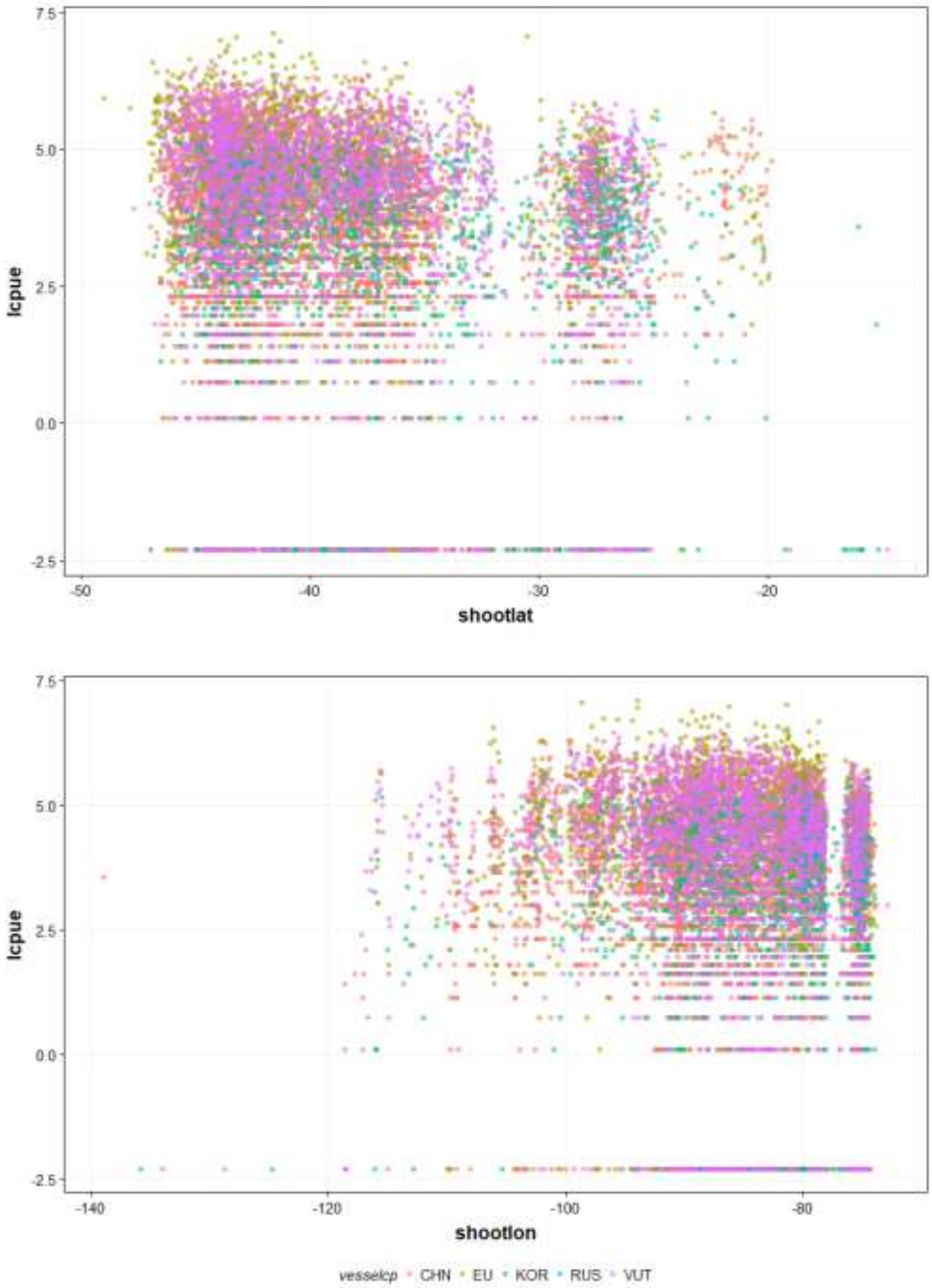


Figure 4: Log catch per day (tonnes) of Jack mackerel against latitude (top) and longitude (bottom).

Comparison of different CPUE metrics: by hour, by day and by week

Average CPUE by year and contracting party has been calculated by hour, by day and by week. Each of the series has been scaled to the maximum of the time series. This indicates that the nominal CPUE by day and by week give the same overall pattern which is differing from the CPUE by hour.

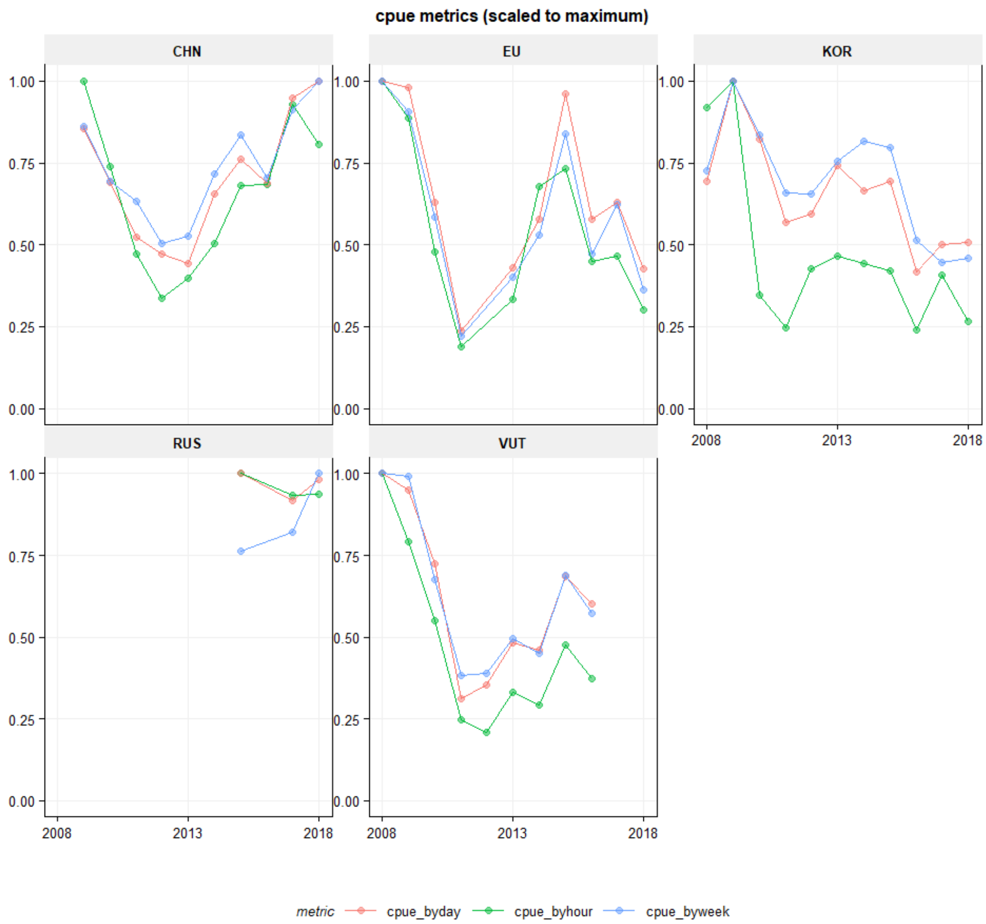


Figure 5: Jack mackerel CPUE metrics by hour, by day and by week, scaled to the maximum of the time series.

Jack mackerel Log CPUE by week and yearly average Log CPUE

The plot below shows the distributions of log CPUE by week and by contracting party. Log CPUE was calculated as the log of catch per week divided by the number of fishing days per week. The average log CPUE is drawn as a dashed black line.

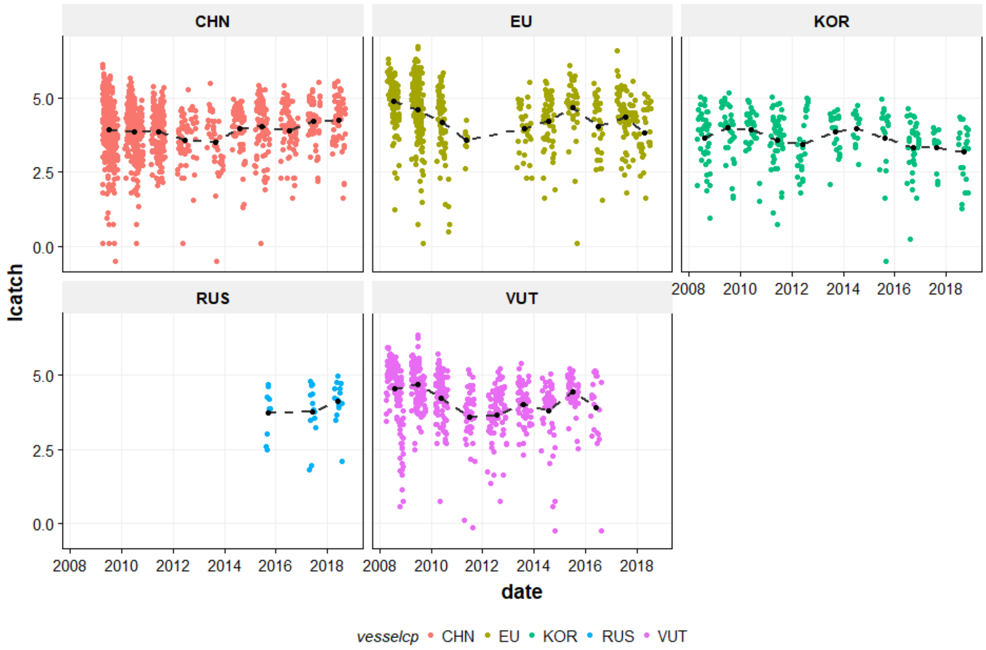


Figure 6: Jack mackerel log CPUE (log(catch / ndays)) by week.

El Nino effect and Humbold_current index

It has been hypothesized that the catch rate of jack mackerel by area and season could be dependent on the climatic situation, characterized by El Nino events (NOAA, https://www.esrl.noaa.gov/psd/data/correlation/oni.data) or the Humboldt Current Index (http://www.bluewater.cl/HCI/)

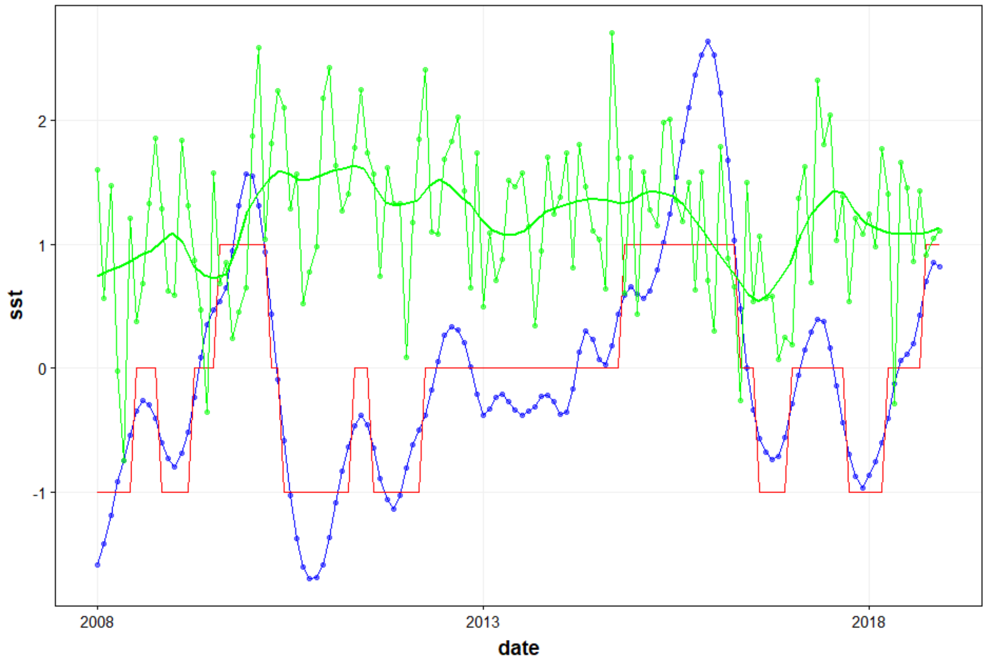


Figure 7: El Nino temperature anomaly (blue line) and ELE indicator (red line). Humboldt Current Index (green line)

Modelling approach

The general modelling approach has been to use GAM models to assess the dependency on the weekly catch of jack mackerel on different variables. In the first instance a test has been carried out to apply a negative binomial distribution to the weekly catch data

The basic model consists of catch (per week) as the main variable, the year effect (as factor) as the main explanatory variable and the log of effort as the offset (the log is taken because of the log-link function). Then the other potential explanatory variables are explored (month, vessel, contracting party, sea surface temperature anomaly, el nino effect and interaction between lat and long). Based on the AIC criteria, the best fitting second, third etc. variable have been selected.

A leave-one-out analysis was carried out to assess the year trends in CPUE if the data from one of the contracting parties was left out. In addition, an analysis was performed using data of one contracting party only.

3 Results

Negative binomial distribution of catch by week

The catch per week data fits closely to a negative binomial distribution.

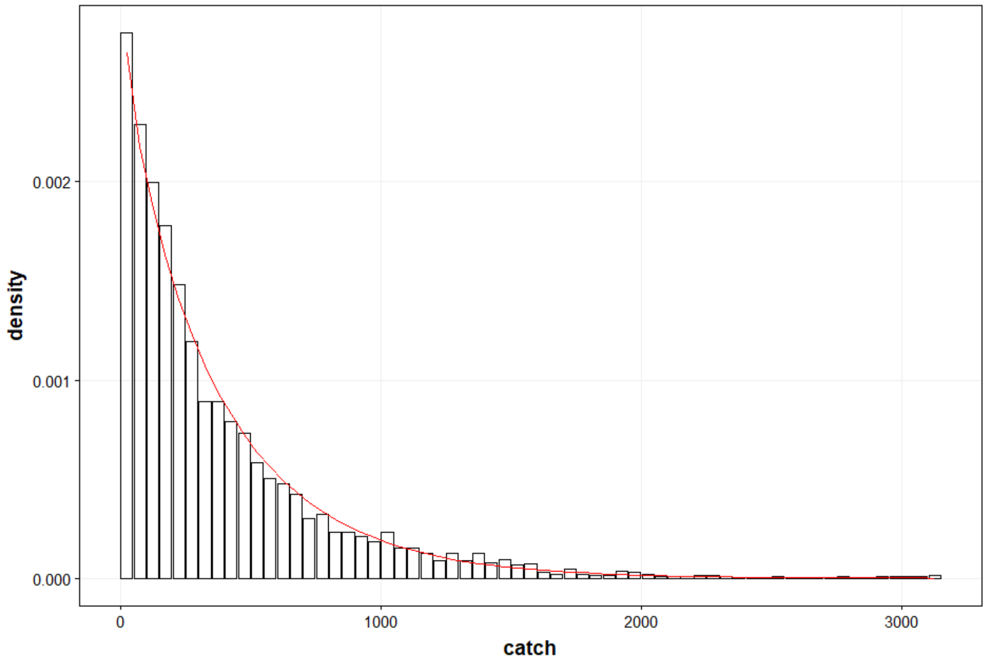


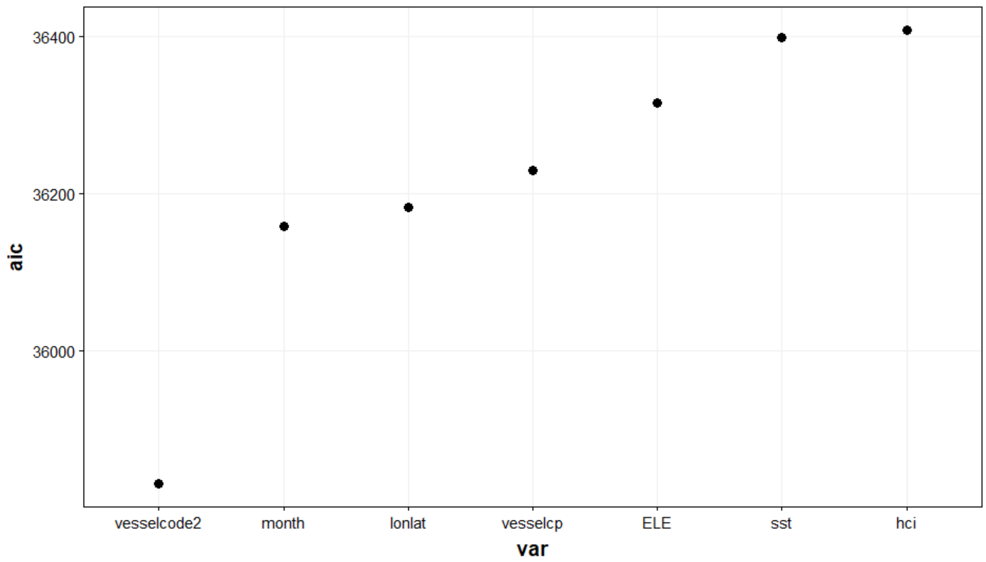
Figure 8: Fitting a negative binomial distribution through the catch data

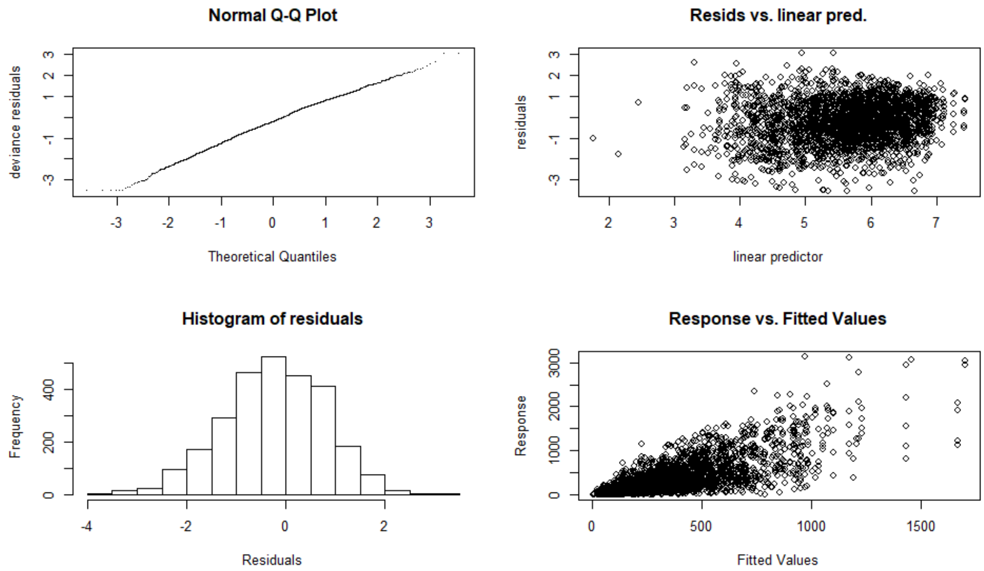
Modelling the first linear effect next to the year trend

The basic model consists of catch (per week) as the main variable, the year effect (as factor) as the main explanatory variable and the log of effort as the offset (the log is taken because of the log-link function). Then the other potential explanatory variables are explored (month, vessel, contracting party, sea surface temperature anomaly, el nino effect and interaction between lat and long).

Based on the AIC criteria, the best fitting first linear effect was the vessel-code.

Catch ~ offset(log(effort)) + year + first linear effect






```
'gamm' based fit - care required with interpretation.
Checks based on working residuals may be misleading.
```

Figure 9: Negative binomial GLM with best fitting first linear effect

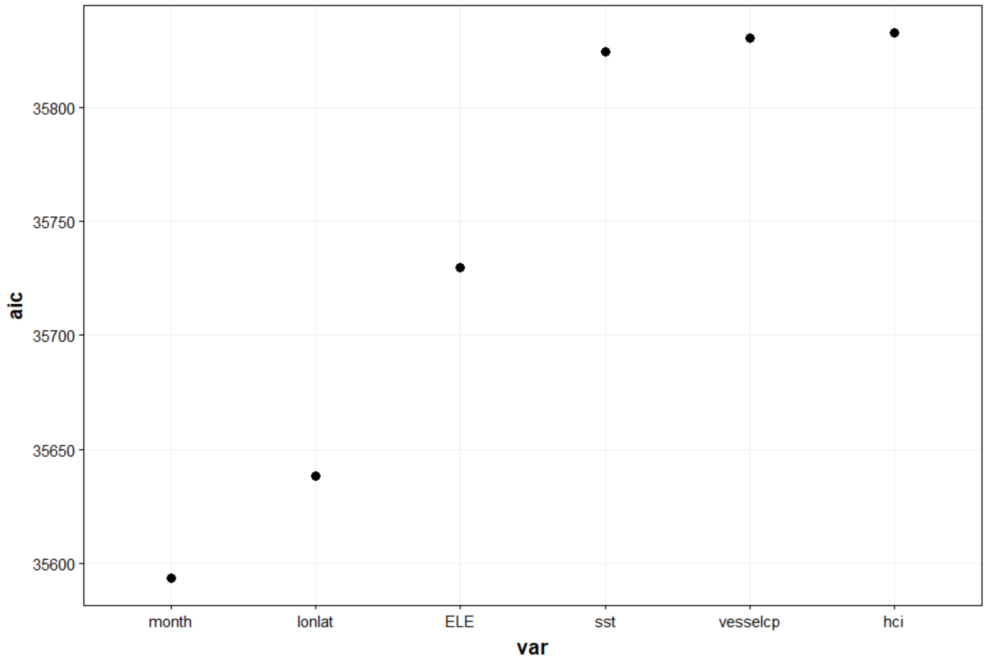
```
Analysis of Deviance Table

Model: Negative Binomial(1.8993), link: log

Response: catch

Terms added sequentially (first to last)

            Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                         2741     4145.7
year        10   445.29      2731     3700.4 < 2.2e-16 ***
vesselcode2 31   707.59      2700     2992.8 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

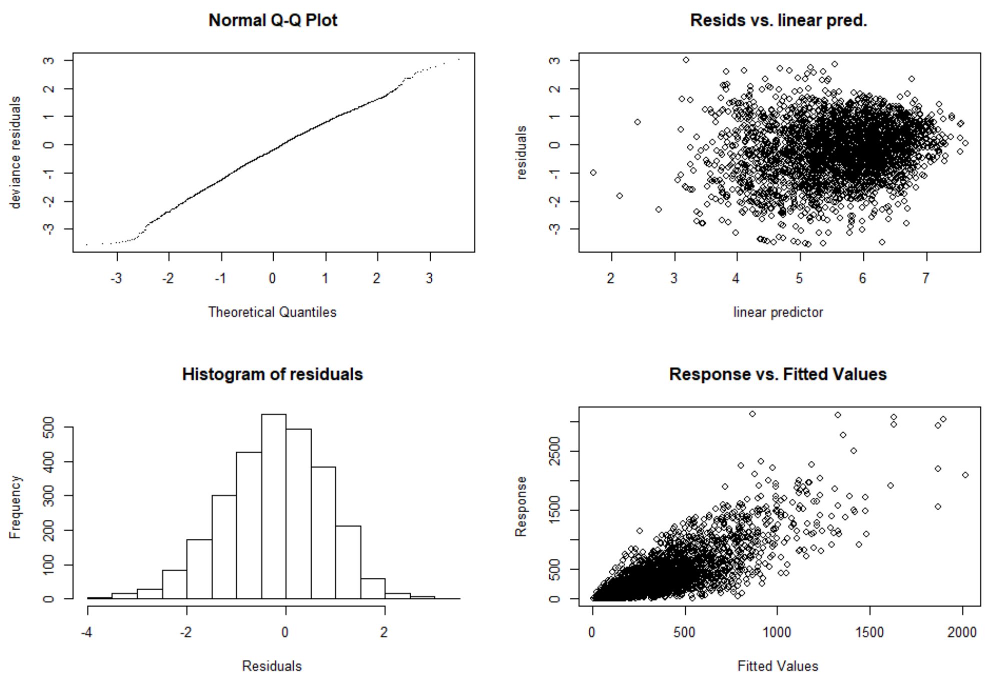
Table 9: ANOVA results for negative binomial GLM with best fitting first linear effect

Modelling the second linear effect next to the year and vessel effect

Catch ~ offset(log(effort)) + year + vessel + second linear effect

Based on the AIC criteria, the best fitting second linear effect was the month.





```
'gamm' based fit - care required with interpretation.
Checks based on working residuals may be misleading.
```

Figure 10: Negative binomial GLM with best fitting second linear effect

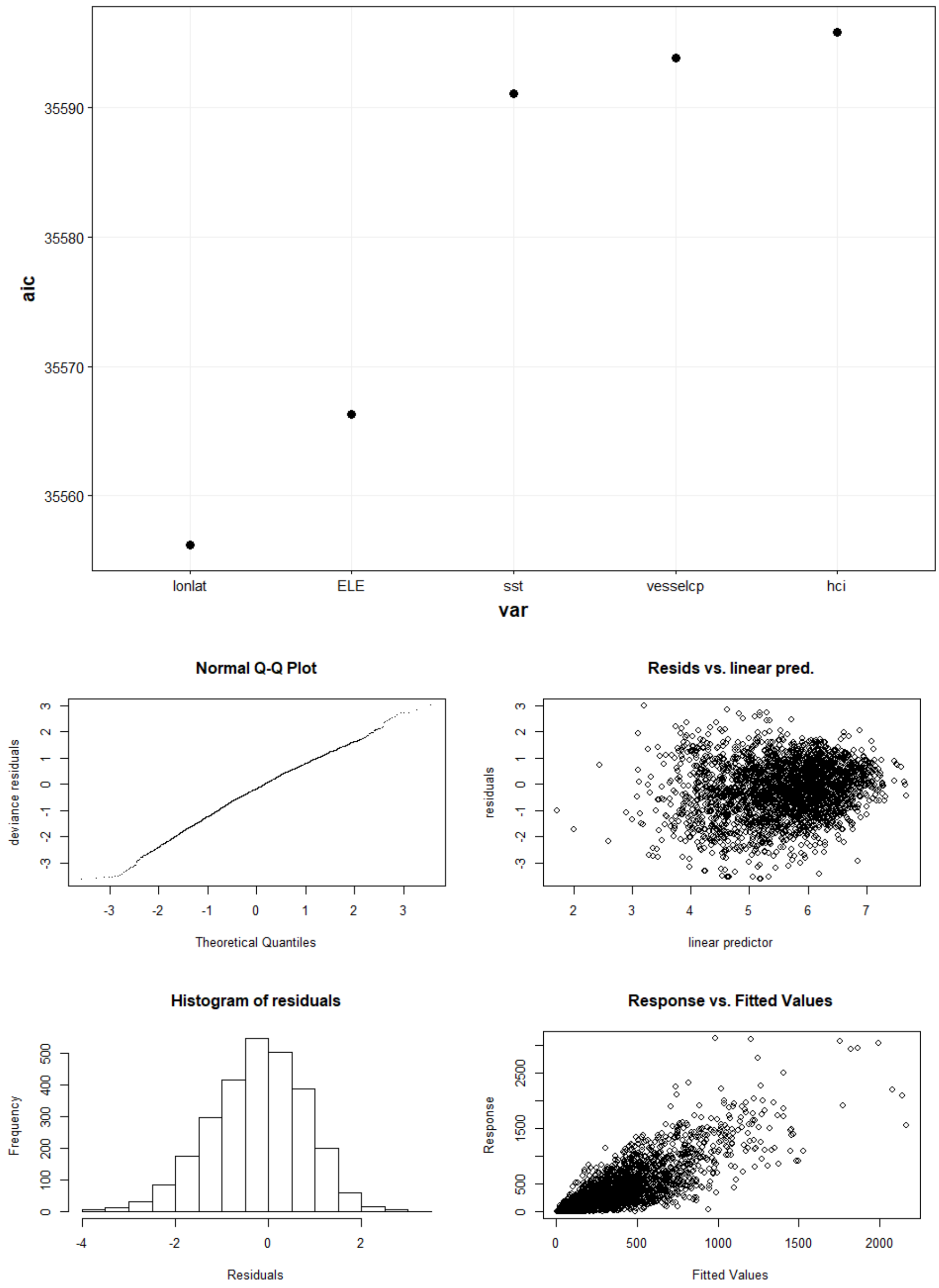
```
Analysis of Deviance Table

Model: Negative Binomial(2.068), link: log

Response: catch

Terms added sequentially (first to last)

            Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                         2741     4504.8
year        10   484.53      2731     4020.3 < 2.2e-16 ***
vesselcode2 31   769.65      2700     3250.6 < 2.2e-16 ***
month       11   269.83      2689     2980.8 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Table 10: ANOVA results for negative binomial GLM with best fitting second linear effect

Modelling the third linear effect next to the year, vessel and month effect

Catch ~ offset(log(effort)) + year + vessel + month + third linear effect

Based on the AIC criteria, the best fitting first linear effect was the combination of latitude and longitude.




```
'gamm' based fit - care required with interpretation.
Checks based on working residuals may be misleading.
```

Figure 11: Negative binomial GLM with best fitting third linear effect

```
Analysis of Deviance Table

Model: Negative Binomial(2.0981), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)    
NULL                               2741     4568.6              
year              10   491.51      2731     4077.1 < 2.2e-16 ***
month             11   350.41      2720     3726.6 < 2.2e-16 ***
vesselcode2       31   703.98      2689     3022.7 < 2.2e-16 ***
shootlon           1     0.44      2688     3022.2   0.50541    
shootlat           1     6.41      2687     3015.8   0.01138 *  
shootlon:shootlat  1    37.10      2686     2978.7  1.12e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Table 11: ANOVA results for negative binomial GLM with best fitting third linear effect

Exploring the El Nino effects

Catch ~ offset(log(effort)) + year + vessel + month + lat-lon + 'El Nino' or Humboldt Current Index

The El Nino effect can be taken in as the sea surface temperature (SST) anomaly or as the El Nino indicator ELE (-1, 0, 1). The Humboldt Current index HCI is taken as the pressure difference between Easter island and Antofagasta.

The only significant effect that resulted from this analysis is the El Nino Index ELE, which will be taken up in the final model formulation.

```
Analysis of Deviance Table

Model: Negative Binomial(2.1139), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                               2741     4602.1
year              10   495.19      2731     4106.9 < 2.2e-16 ***
month             11   353.03      2720     3753.9 < 2.2e-16 ***
vesselcode2       31   709.21      2689     3044.7 < 2.2e-16 ***
shootlon           1     0.45      2688     3044.2   0.50402
shootlat           1     6.45      2687     3037.8   0.01107 *
ELE                2    29.48      2685     3008.3 3.958e-07 ***
shootlon:shootlat  1    30.72      2684     2977.6 2.986e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Table 12: ANOVA results for negative binomial GLM including the El Nino Effect ELE

```
Analysis of Deviance Table

Model: Negative Binomial(2.1009), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                               2741     4574.5
year              10   492.16      2731     4082.3 < 2.2e-16 ***
month             11   350.87      2720     3731.5 < 2.2e-16 ***
vesselcode2       31   704.91      2689     3026.6 < 2.2e-16 ***
shootlon           1     0.44      2688     3026.1   0.50517
shootlat           1     6.41      2687     3019.7   0.01132 *
sst                1     4.01      2686     3015.7   0.04521 *
shootlon:shootlat  1    37.01      2685     2978.7 1.176e-09 ***
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Table 13: ANOVA results for negative binomial GLM including the Sea Surface Temperature (SST) anomaly

```
Analysis of Deviance Table

Model: Negative Binomial(2.0983), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                               2741     4569.1
year              10   491.57      2731     4077.5 < 2.2e-16 ***
month             11   350.45      2720     3727.1 < 2.2e-16 ***
vesselcode2       31   704.07      2689     3023.0 < 2.2e-16 ***
shootlon           1     0.44      2688     3022.6   0.50539
shootlat           1     6.41      2687     3016.2   0.01137 *
hci                1     0.09      2686     3016.1   0.76318
shootlon:shootlat  1    37.39      2685     2978.7 9.678e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Table 14: ANOVA results for negative binomial GLM including the Humboldt Current Index HCI

Modelling the spatial and year smoothers

In this section we explore the added benefits of using the interaction between lat, long and year and whether the smoothers available in GAM provide additional benefits over GLMs. Four different models are compared.

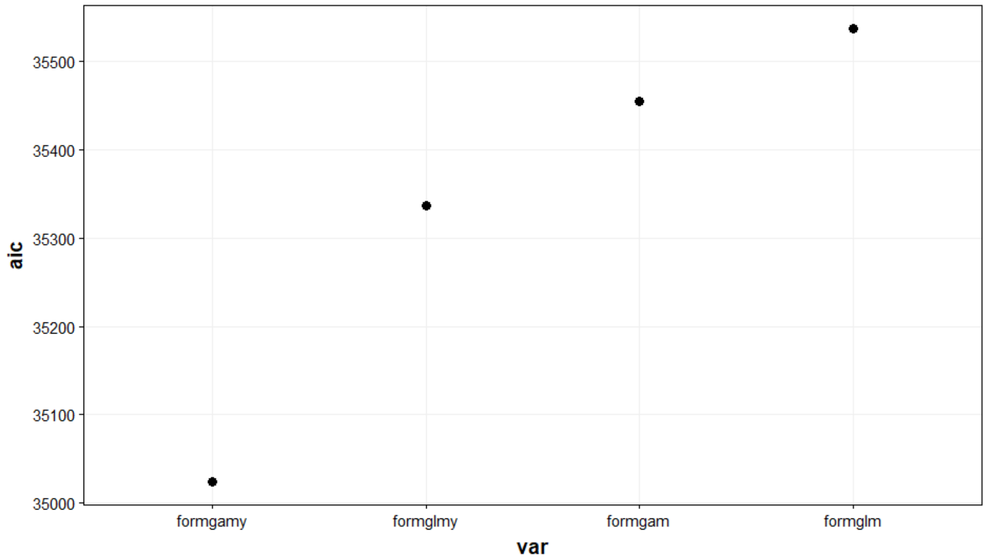


Figure 12: AIC comparison of GLM and GAM models with different spatial and year smoothers

```
Analysis of Deviance Table

Model: Negative Binomial(2.1139), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                               2741     4602.1
year              10   495.19      2731     4106.9 < 2.2e-16 ***
month             11   353.03      2720     3753.9 < 2.2e-16 ***
vesselcode2       31   709.21      2689     3044.7 < 2.2e-16 ***
shootlon           1     0.45      2688     3044.2   0.50402
shootlat           1     6.45      2687     3037.8   0.01107 *
ELE                2    29.48      2685     3008.3 3.958e-07 ***
shootlon:shootlat  1    30.72      2684     2977.6 2.986e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

*Table 15: ANOVA results with negative binomial GLM including interaction lat*lon*

```
Analysis of Deviance Table

Model: Negative Binomial(2.3065), link: log

Response: catch

Terms added sequentially (first to last)

                       Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                                    2741     5010.0
year                   10   539.90      2731     4470.0 < 2.2e-16 ***
month                  11   384.95      2720     4085.1 < 2.2e-16 ***
vesselcode2            31   772.80      2689     3312.3 < 2.2e-16 ***
shootlon                1     0.48      2688     3311.8  0.487714
shootlat                1     7.05      2687     3304.8  0.007914 **
ELE                     2    32.11      2685     3272.7 1.064e-07 ***
shootlon:shootlat       1    33.46      2684     3239.2 7.281e-09 ***
year:shootlon          10    10.08      2674     3229.1  0.433632
year:shootlat          10   153.26      2664     3075.9 < 2.2e-16 ***
year:shootlon:shootlat 10   109.13      2654     2966.7 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

*Table 16: ANOVA results with negative binomial GLM including interaction lat*lon*year*

```
Family: Negative Binomial(2.114)
Link function: log

Formula:
catch ~ year + month + vesselcode2 + s(shootlon, shootlat) +
    ELE + offset(log(effort))

Parametric Terms:
            df Chi.sq  p-value
year        10 274.94  < 2e-16
month       11 108.31  < 2e-16
vesselcode2 31 837.42  < 2e-16
ELE          2  17.73 0.000141

Approximate significance of smooth terms:
                       edf Ref.df Chi.sq p-value
s(shootlon,shootlat) 24.54  27.85  148.5  <2e-16
```

*Table 17: ANOVA results with GAM including smoothing interaction s(lat*lon)*

```
Family: Negative Binomial(2.306)
Link function: log

Formula:
catch ~ year + month + vesselcode2 + s(shootlon, shootlat, by = year) +
    ELE + offset(log(effort))

Parametric Terms:
            df  Chi.sq p-value
year        10  13.086   0.219
month       11 115.582  <2e-16
vesselcode2 31 877.687  <2e-16
ELE          2   0.186   0.911
```

```
Approximate significance of smooth terms:
                                edf Ref.df  Chi.sq  p-value
s(shootlon,shootlat):year2008  5.135  6.896   2.685 0.895569
s(shootlon,shootlat):year2009 16.259 19.317 142.802  < 2e-16
s(shootlon,shootlat):year2010 17.648 19.887  84.865 5.69e-10
s(shootlon,shootlat):year2011 23.586 24.544  94.398 2.77e-10
s(shootlon,shootlat):year2012 10.481 12.876  97.826 5.17e-15
s(shootlon,shootlat):year2013  6.439  7.779  30.969 0.000130
s(shootlon,shootlat):year2014 11.885 12.971  91.594 5.46e-14
s(shootlon,shootlat):year2015  6.284  7.952  13.986 0.074981
s(shootlon,shootlat):year2016 18.178 19.316  47.332 0.000512
s(shootlon,shootlat):year2017 16.032 17.049  80.051 3.89e-10
s(shootlon,shootlat):year2018 15.845 17.269  61.154 9.07e-07
```

*Table 18: ANOVA results with GAM including smoothing interaction s(lat*lon*year)*

Final model

Although the GLM and GAM models that included interaction between lat-long and year performed best (lowest AICs), they have not been selected as the final model as the interpretation of the year effect in the model becomes more problematic while this is the essential output of the model. Therefore, the GAM model without interaction between space and year has been selected. The final model was selected as the following model:

Catch ~ offset(log(effort)) + year + vessel + month + s(lat-lon) + ELE

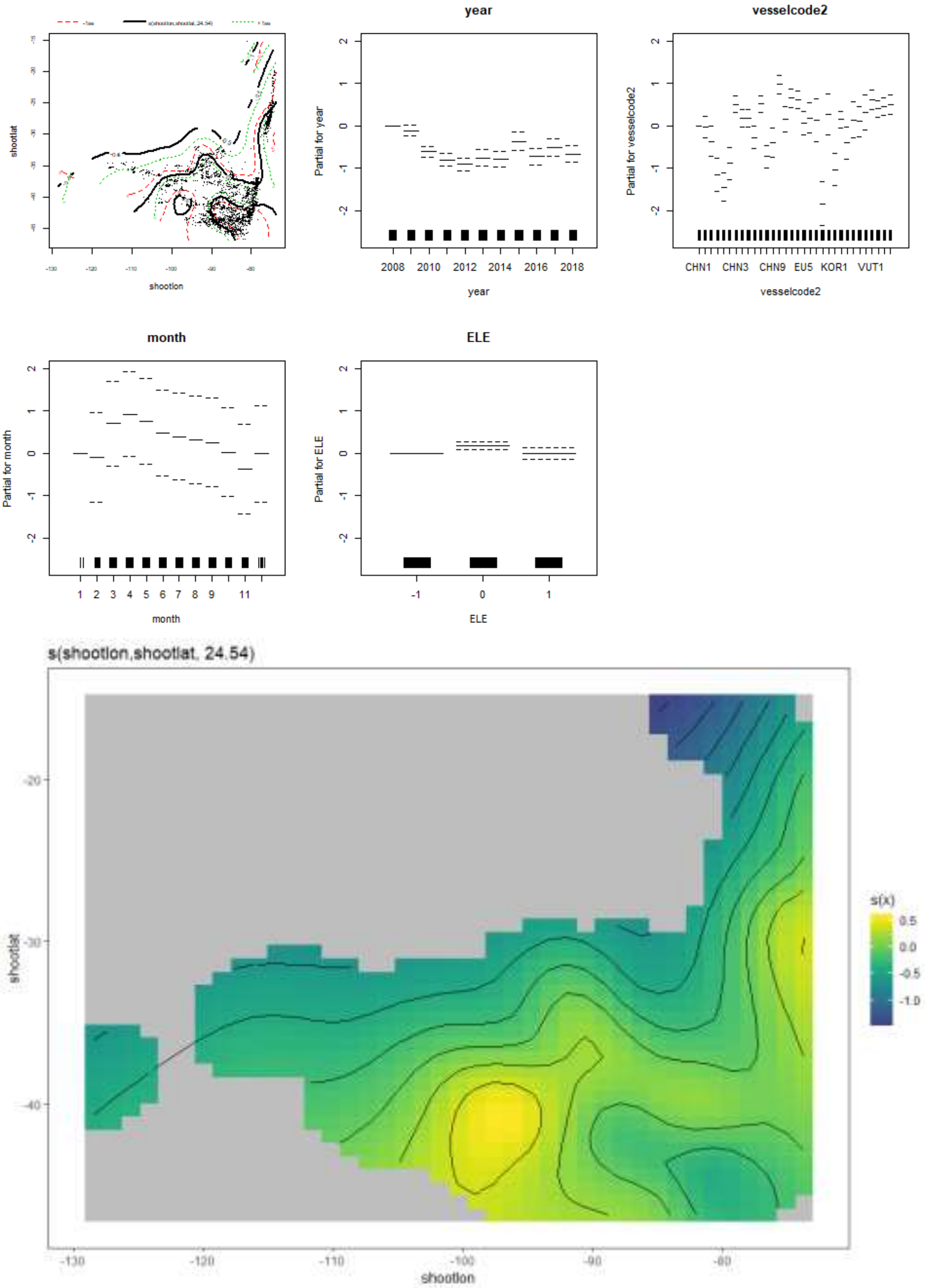


Figure 13: Jack mackerel Final GAM model estimates for selected effects

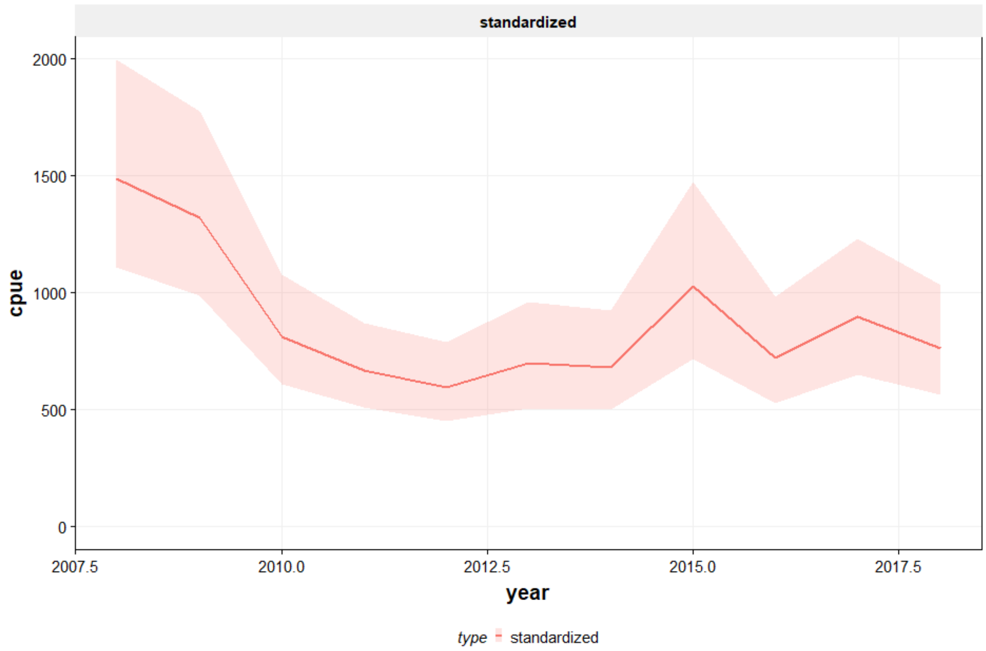


Figure 14: GAM standardized offshore fleet CPUE for jack mackerel

```
Family: Negative Binomial(2.114)
Link function: log

Formula:
catch ~ year + vesselcode2 + month + s(shootlon, shootlat) +
    ELE + offset(log(effort))

Parametric Terms:
            df Chi.sq  p-value
year        10 274.94  < 2e-16
vesselcode2 31 837.42  < 2e-16
month       11 108.31  < 2e-16
ELE          2  17.73 0.000141

Approximate significance of smooth terms:
                       edf Ref.df Chi.sq p-value
s(shootlon,shootlat) 24.54  27.85  148.5  <2e-16
```

Table 19: ANOVA results with final model GAM

year	cpue	lwr	upr
2008	1484	1106	1991
2009	1320	984	1772
2010	809	609	1075
2011	664	507	871
2012	596	450	789
2013	697	507	959
2014	679	499	924
2015	1027	716	1473
2016	719	526	983
2017	894	650	1228
2018	762	563	1031

Table 20: GAM standardized offshore fleet CPUE for jack mackerel

leave one out analysis

The leave-one-out analysis shows that the signal of standardized CPUE is largely similar if data of one of the contracting parties is left out.

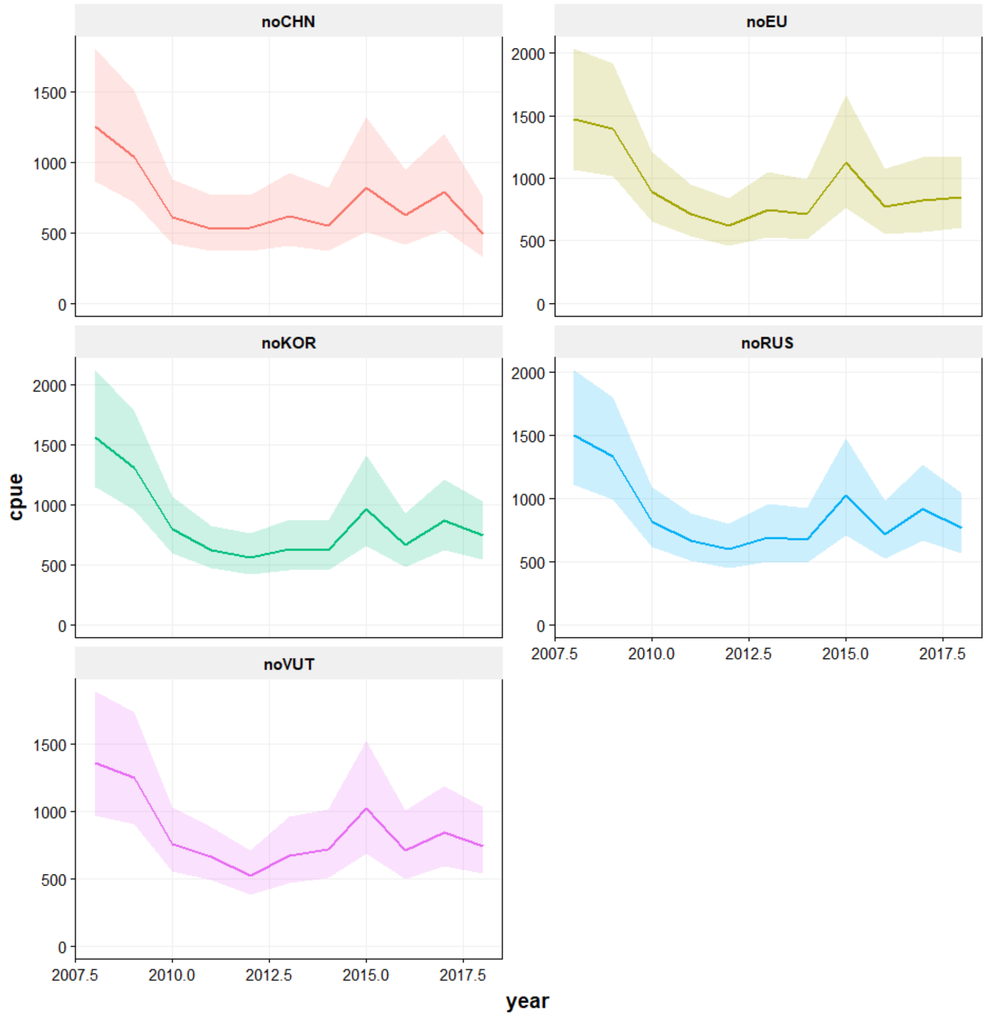
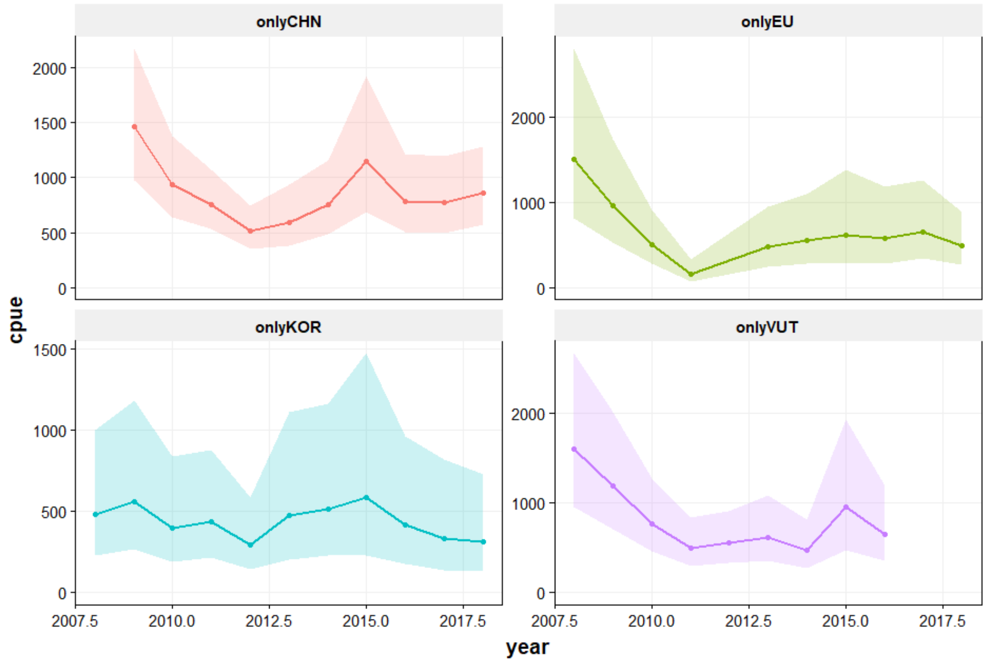


Figure 15: Jack mackerel leave-one-out analysis (leaving out one of the fleets)

Only single fleet analyses

The leave-one-out analysis shows that the signal of standardized CPUE is largely similar if data of one of the contracting parties is left out. Notably when the EU data is left out, the pattern and the variance is somewhat different from the other situations.



4 Discussion and conclusions

This working document describes the work aimed to standardizing all the CPUE data from the offshore fleets (China, EU, Korea, vanuatu and Russia) based on the haul-by-haul data contained in the SPRFMO database. Permission to utilize that information was granted by the delegations of the contracting parties while the analysis was carried out by scientists from the EU delegation.

The final model for standardizing the CPUE of these fleets models the catch by week and takes into account of the vessel, month, and a smooth interaction between latitude and longitude with an offset of log effort (in number of days per week). The new standardized CPUE series starts in 2008 as this is the first year for which haul by haul information was available to carry out this analysis. It is recommended to extend the time-series, where possible, to the years before 2008, in order to get more information on the catch rates during the higher abundances of jack mackerel.

A 'leave-one-out analysis' was carried out by removing the data of one of the contracting parties from the analysis to explore the sensitivity of the results to the data being used. The conclusion from that analysis is that, by and large, the trends are similar. Likewise, the "single-fleet-analysis" indicates that the analysis based on one single fleet at a time, generates comparable trends over time.

5 Acknowledgements

We would like to acknowledge the permission granted by the delegations of China, Russia, Vanuatu and Korea to utilize their haul-by-haul data for the analysis of standardized CPUE of the offshore fleet fishing for Jack mackerel. Sharing access to vessel data has made it possible to improve the indicator that can be used in the assessment.

6 References

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