8th MEETING OF THE SCIENTIFIC COMMITTEE

New Zealand, 3 to 8 October 2020

SC8-JM02

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

European Union

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02/09/2020

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. During SC07, a fully combined and standardized Offshore CPUE index was calculated that is based on the haul-by-haul data of China, EU, Korea, vanuatu and Russia as contained in the SPRFMO database. This analysis has now been updated for SC08. 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 as agreed 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.

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 the SPRFMO secretariat on 3 August 2020. 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	0	2	0	0	4
2019	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	0	3,717	0	0	28,084
2019	22,706	11,789	7,444	9,412	0	51,352
(all)	369,974	304,254	82,983	15,125	311,753	1,084,088

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	.	130	.	.	156
2019	208	143	184	186	.	180
(all)	215	167	158	104	195	177

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	0	92	0	0	322
2019	217	85	111	104	0	517
(all)	4,753	2,242	1,542	193	2,977	11,707

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	0	157	0	0	534
2019	356	154	249	212	0	971
(all)	8,187	3,878	2,779	379	6,173	21,396

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	0	892	0	0	3,497
2019	2,493	985	1,426	1,123	0	6,027
(all)	49,532	23,357	14,331	2,046	38,450	127,716

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	.	5.7	.	.	6.3
2019	7	6.4	5.7	5.3	.	6.1
(all)	6.4	6.4	5.4	5.4	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	.	40	.	.	73
2019	105	142	67	90	.	101
(all)	77	118	53	74	89	82

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.

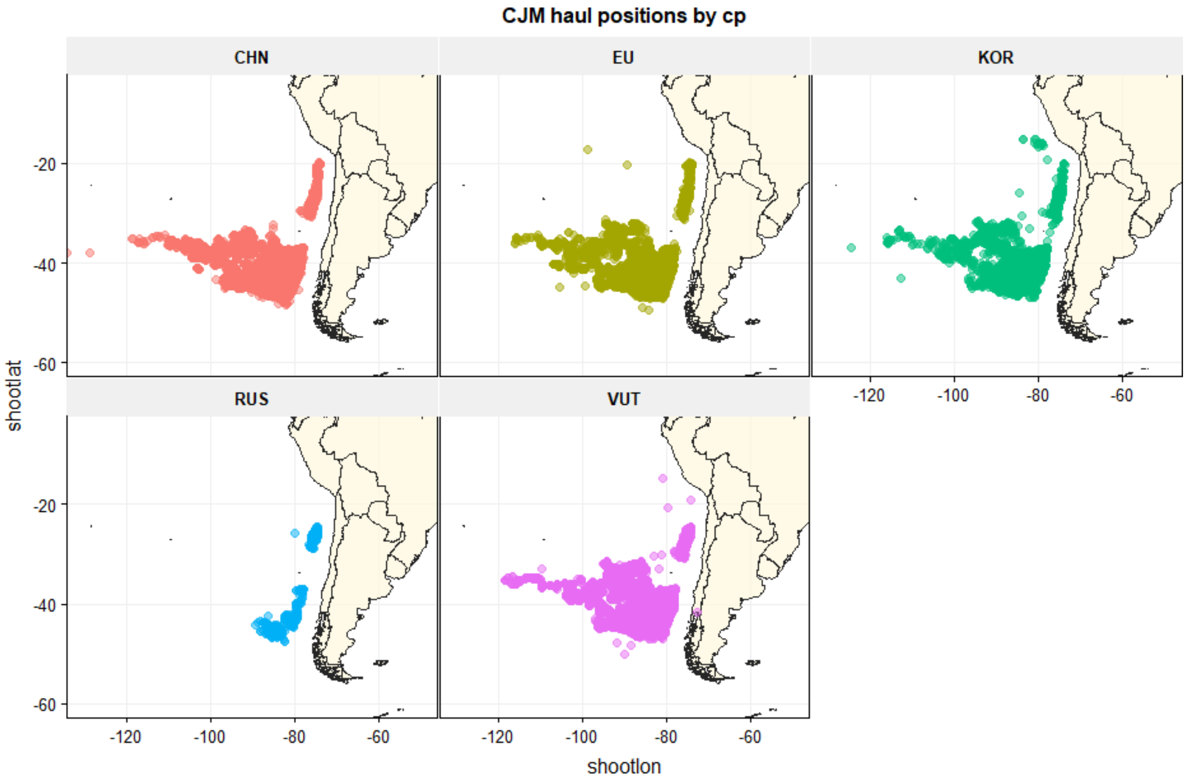


Figure 1: Haul positions where Jack mackerel has been caught (all years combined)

Haul positions by contracting party and year

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

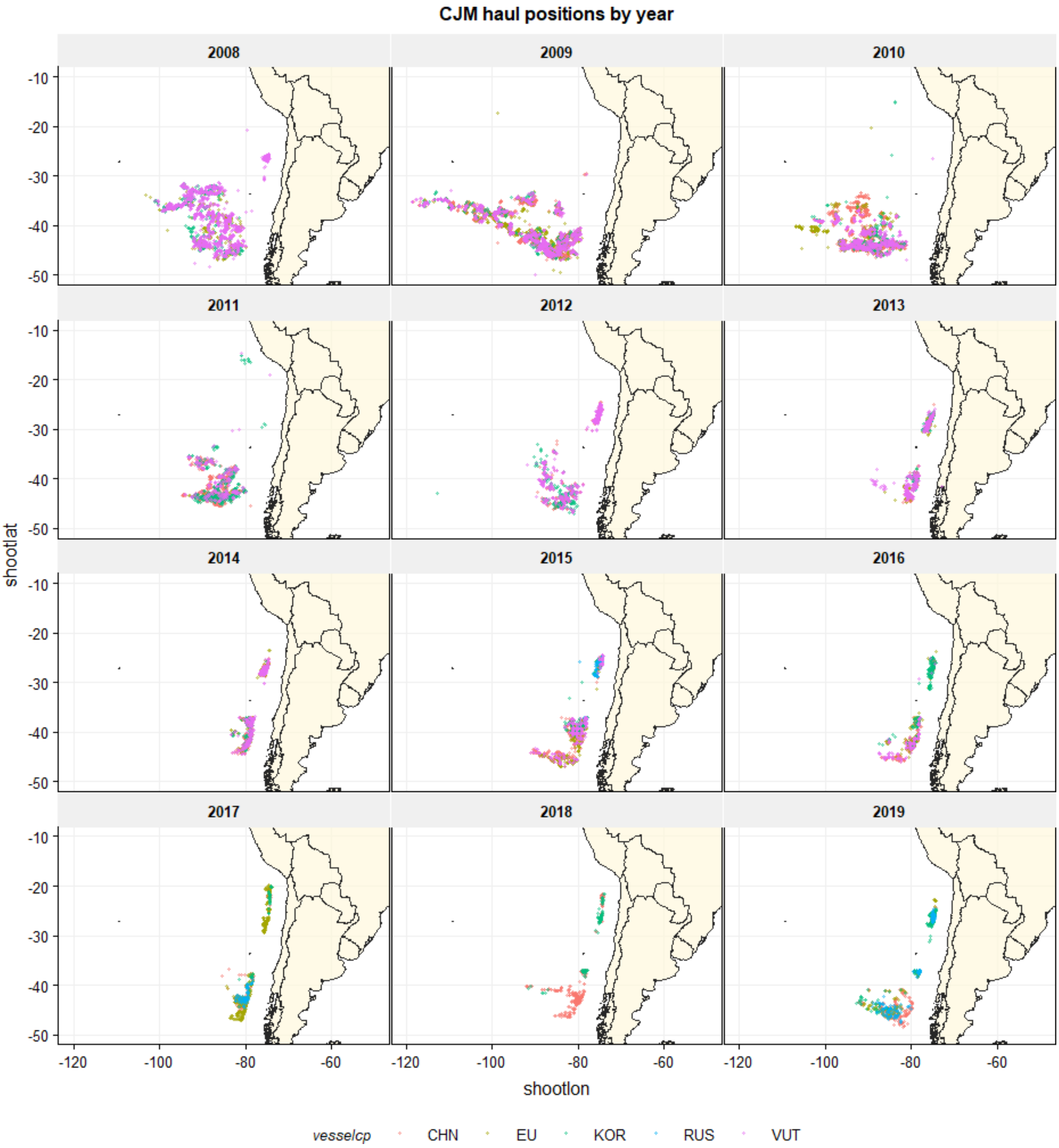


Figure 2: Haul positions where Jack mackerel has been caught (by year). Colours indicate the different contracting parties

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

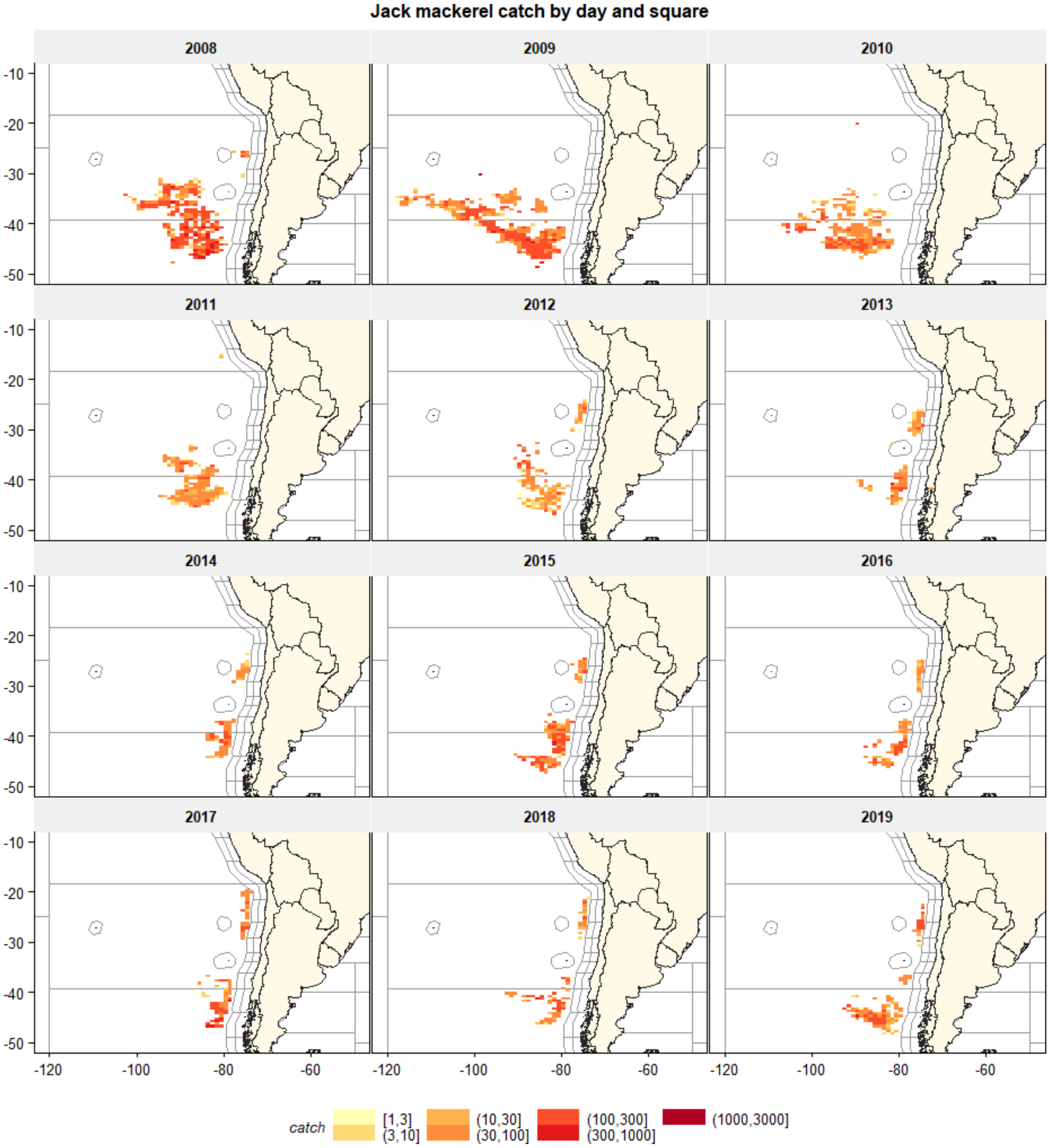


Figure 3: Catch per day (tonnes) of Jack mackerel (summed by 1 degree longitude and 0.5 degree latitude)

Jack mackerel log CPUE by day against latitude and longitude

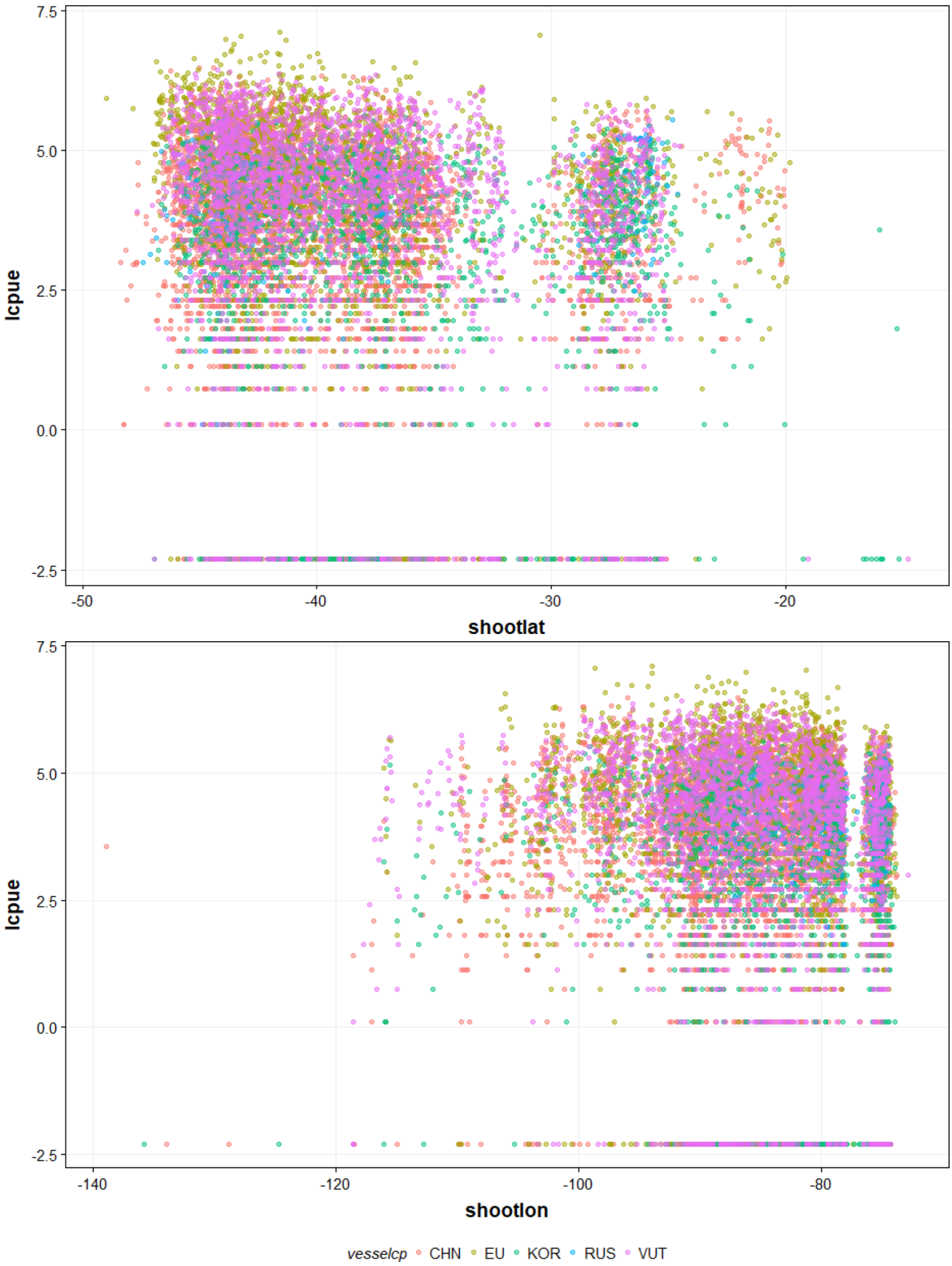


Figure 4: Log catch per day (tonnes) of Jack mackerel against latitude (top) and longitude (bottom).

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.

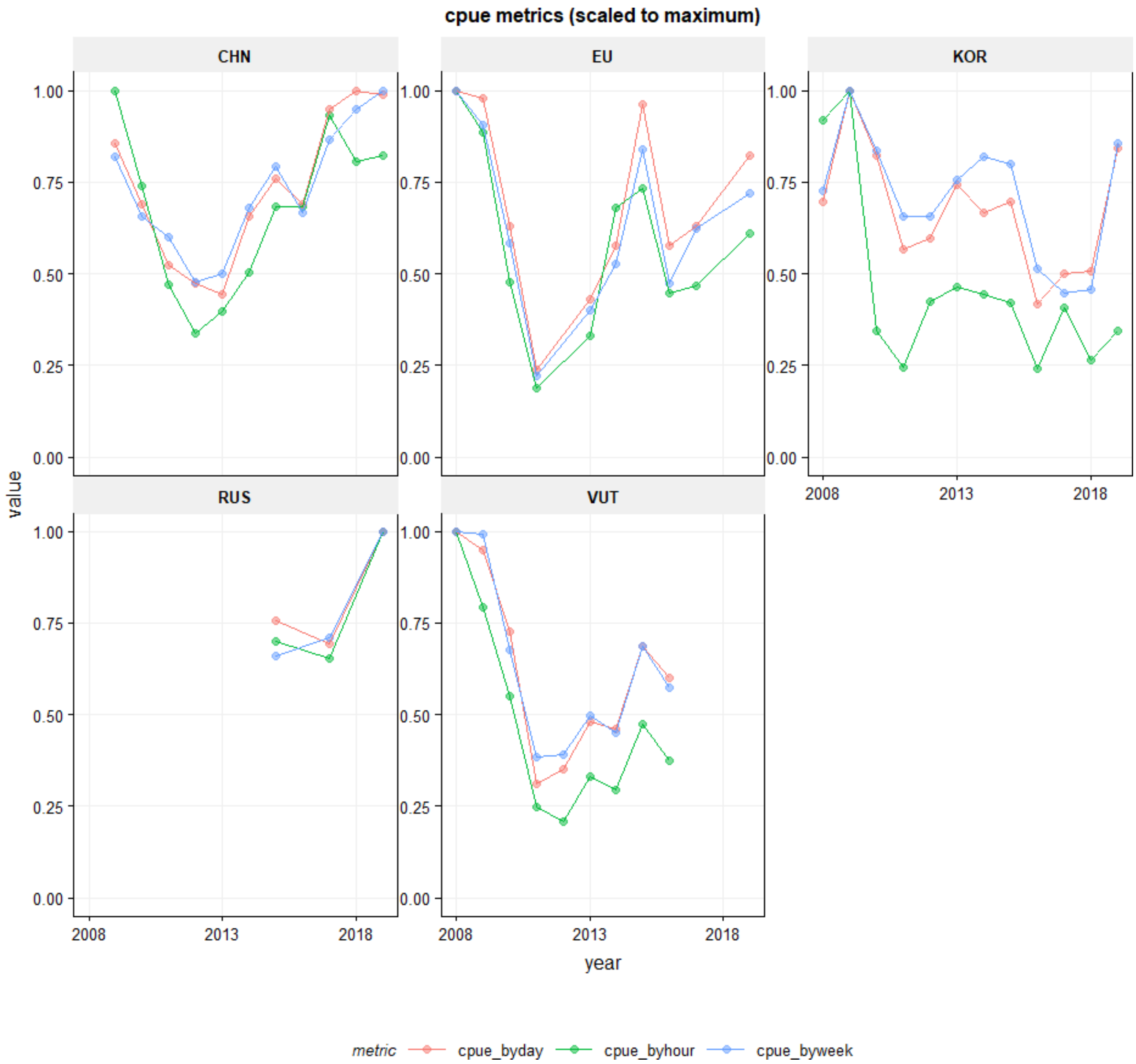


Figure 5: Jack mackerel CPUE metrics by hour, by day and by week, scaled to the maximum of the time series.

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.

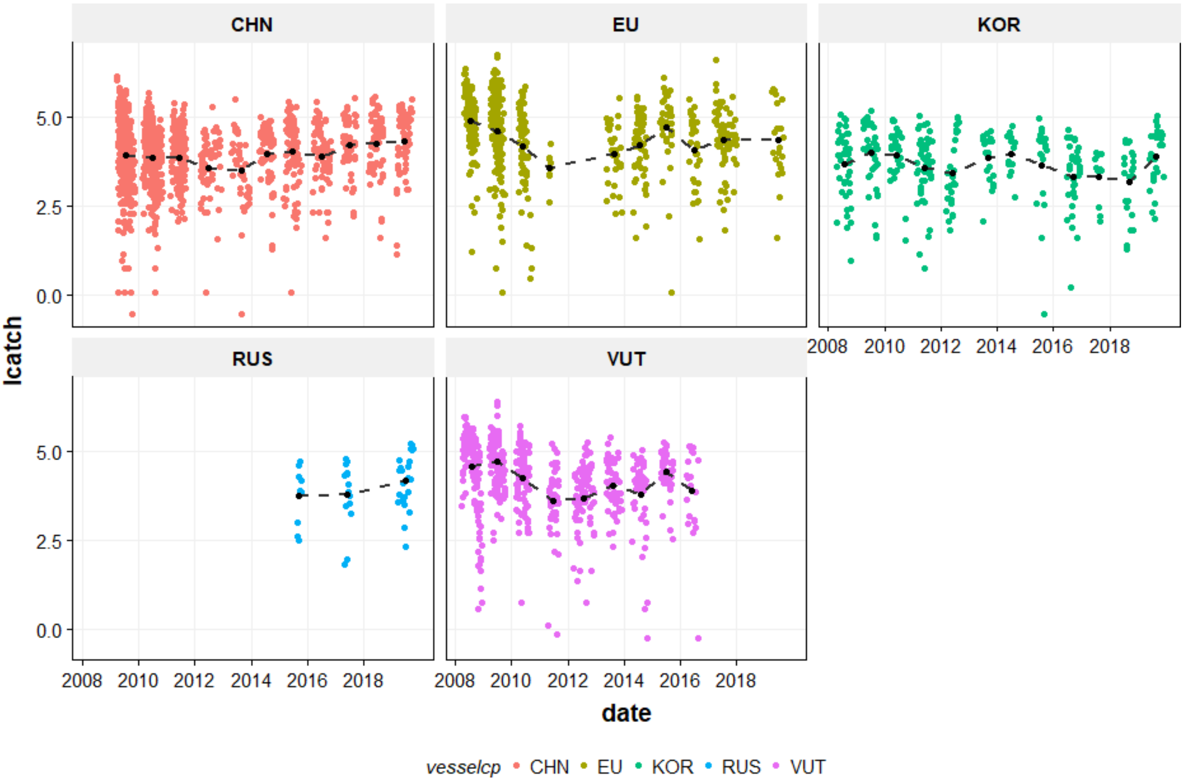


Figure 6: Jack mackerel log CPUE (log(catch / ndays)) by week.

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/)

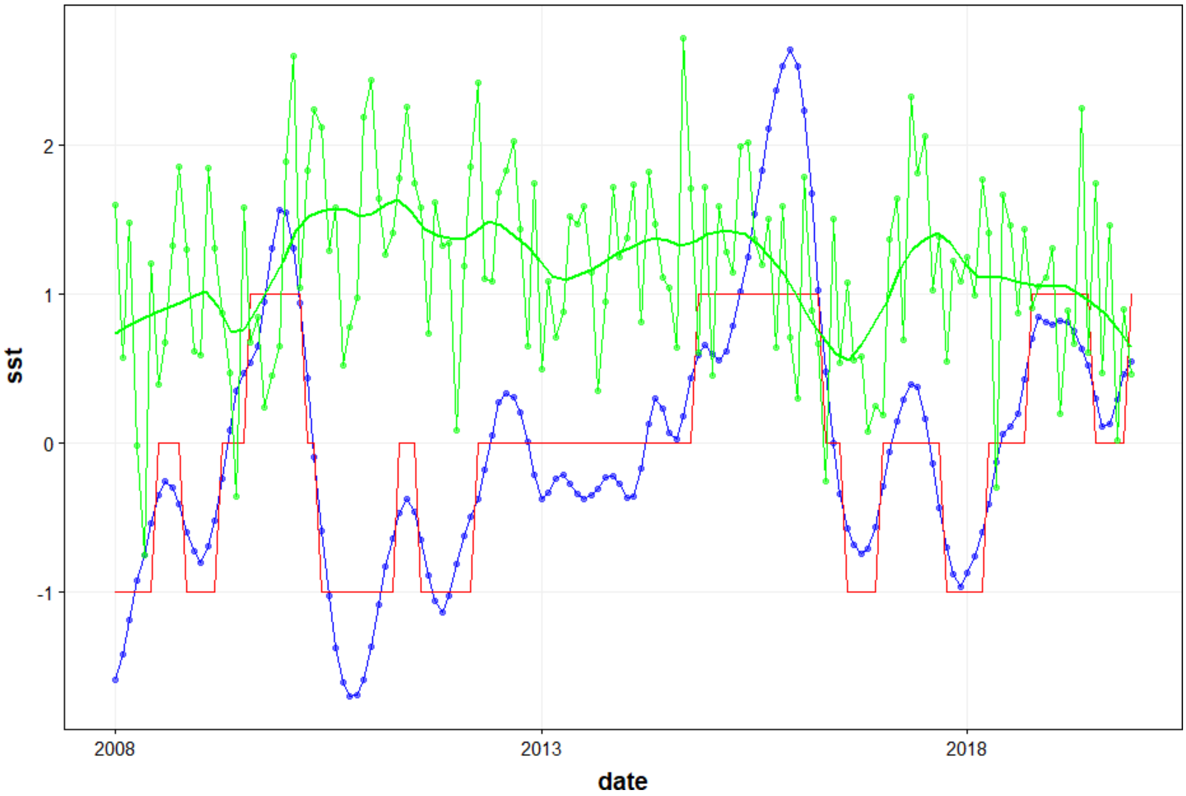


Figure 7: El Nino temperature anomaly (blue line) and ELE indicator (red line). Humboldt Current Index (green line)

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.

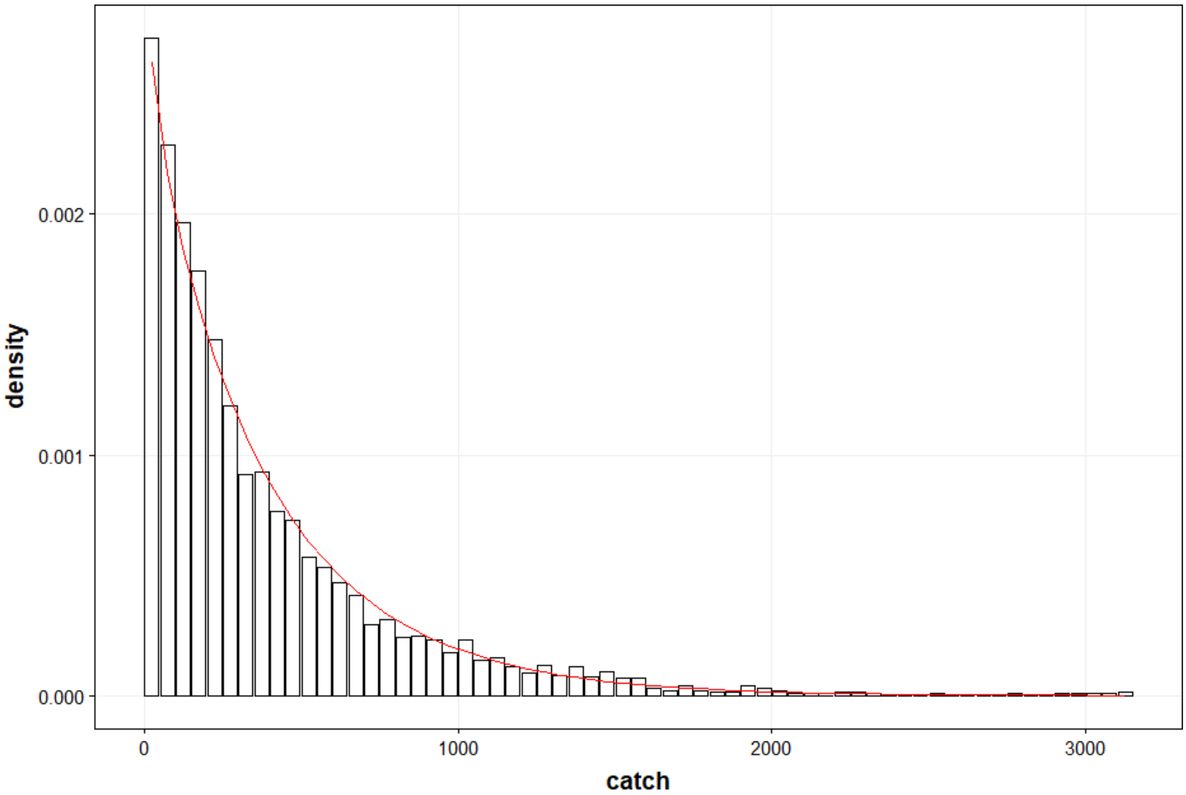


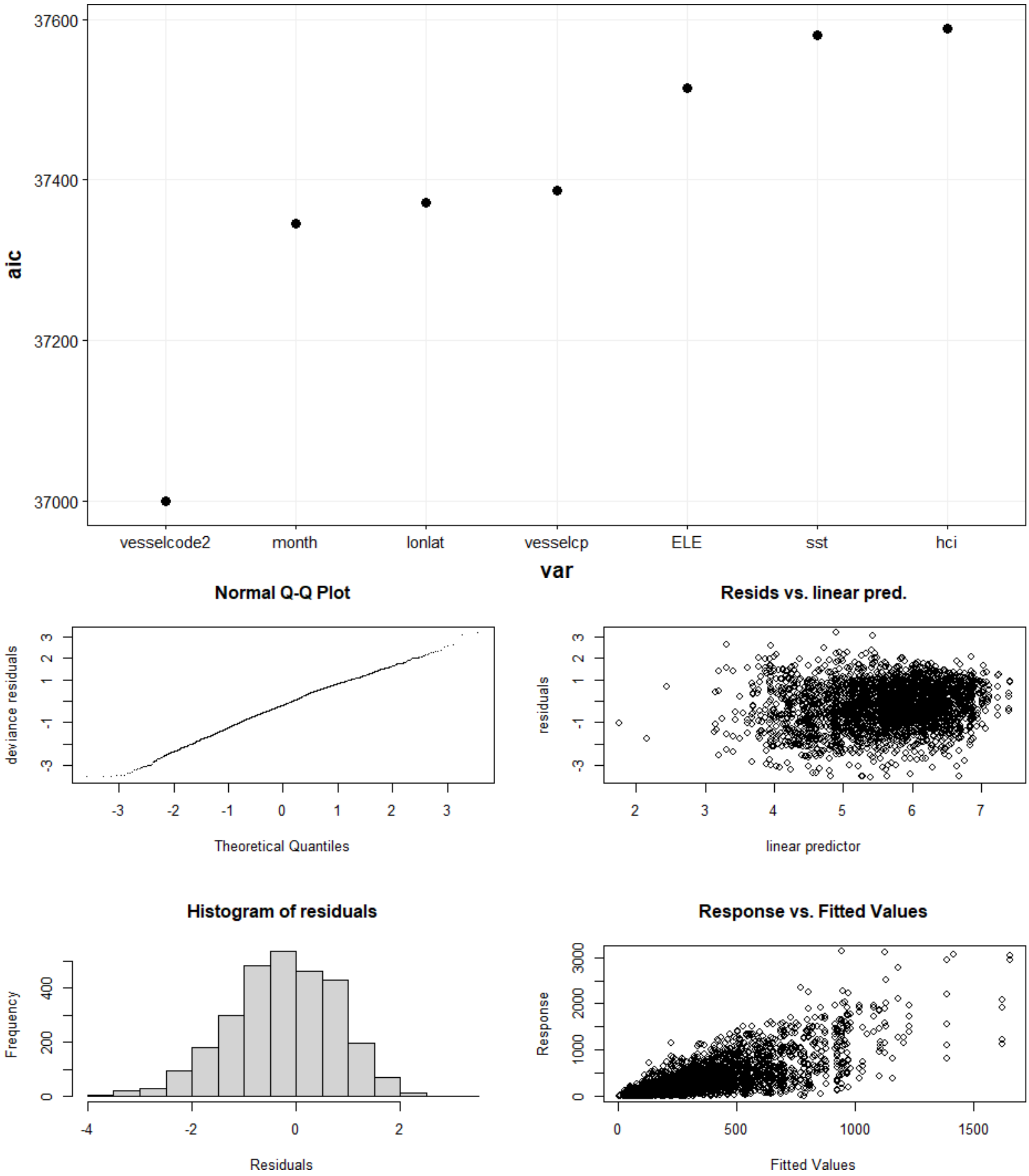
Figure 8: Fitting a negative binomial distribution through the catch data

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 vesselcode.

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

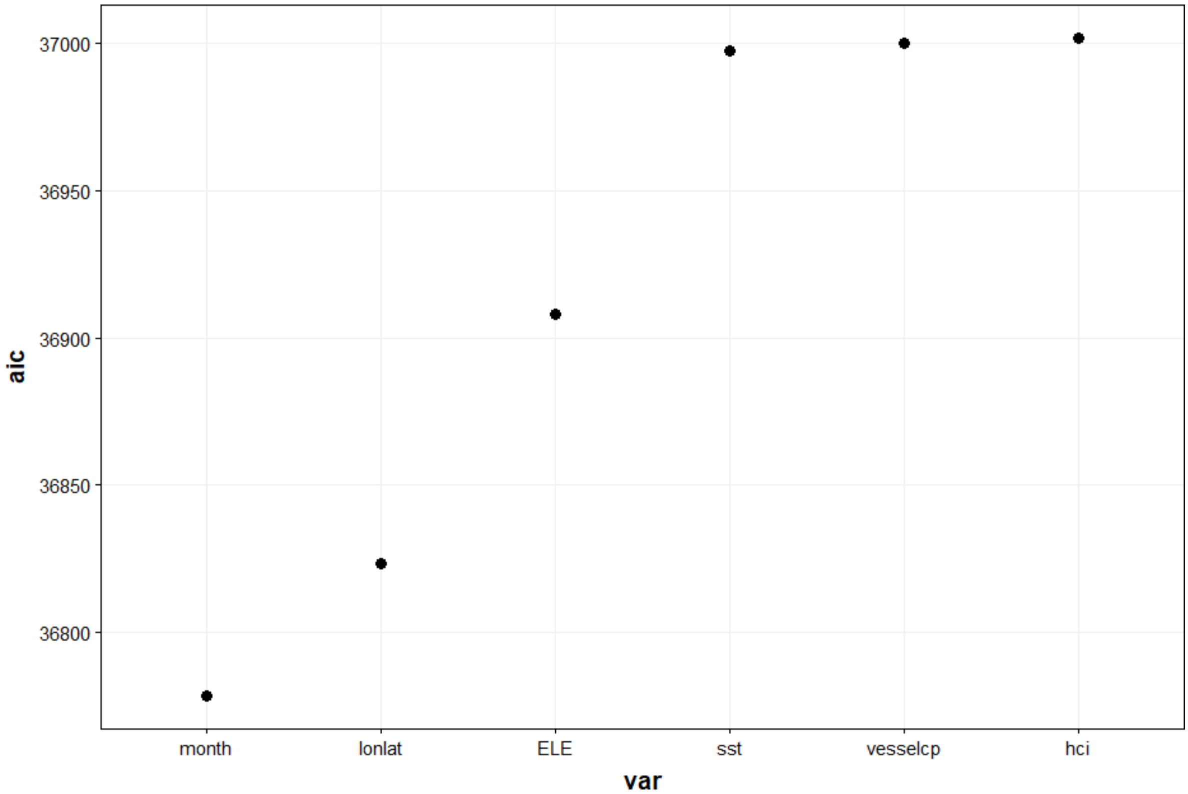
```
Analysis of Deviance Table

Model: Negative Binomial(1.892), link: log

Response: catch

Terms added sequentially (first to last)

            Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                         2827     4242.7
year        11   439.98      2816     3802.7 < 2.2e-16 ***
vesselcode2 30   715.61      2786     3087.1 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

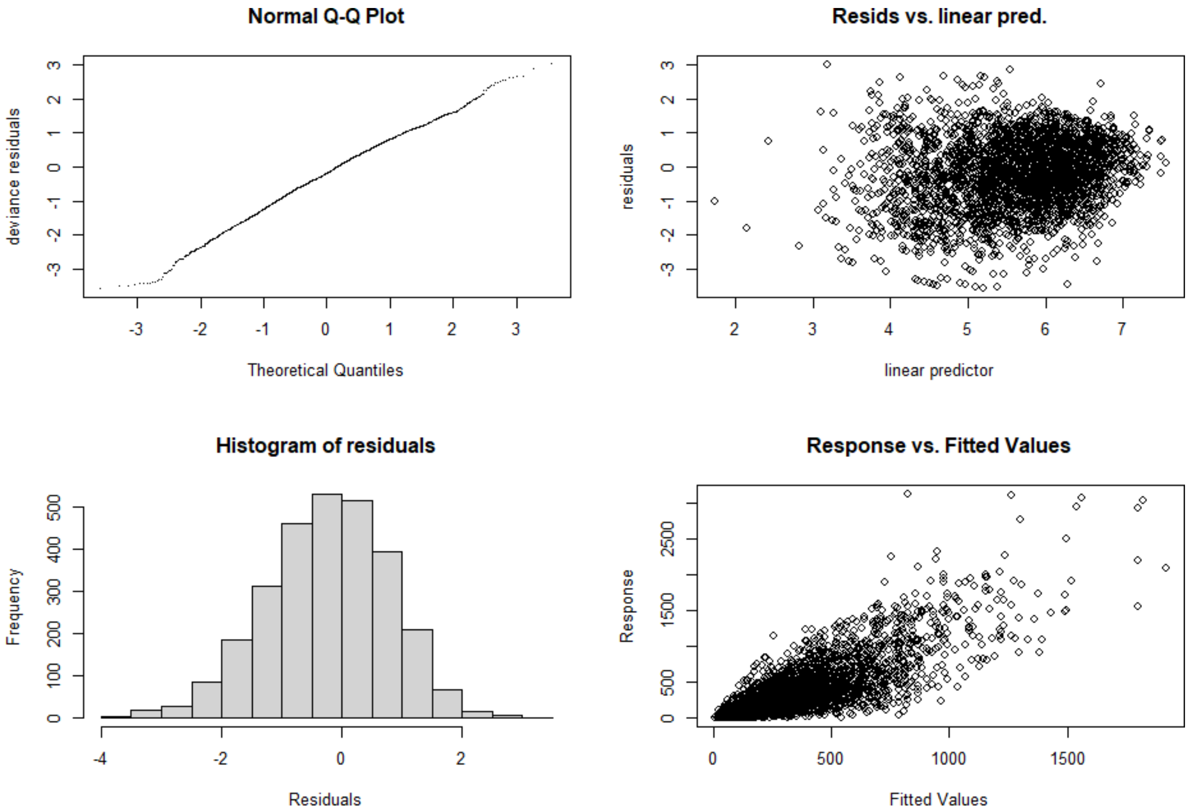
Table 9: ANOVA results for negative binomial GLM with best fitting first linear effect

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

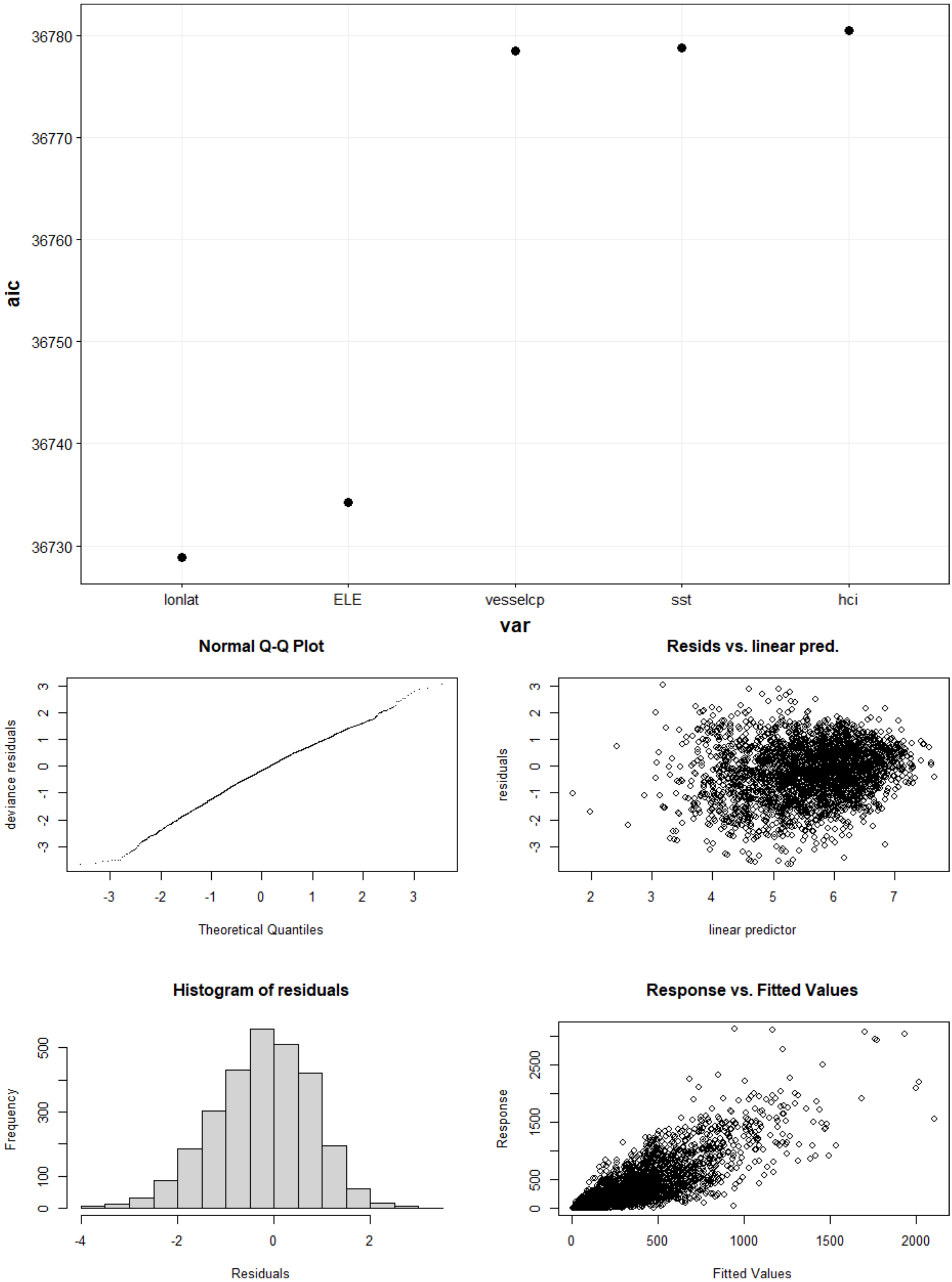
```
Analysis of Deviance Table

Model: Negative Binomial(2.0433), link: log

Response: catch

Terms added sequentially (first to last)

            Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                         2827     4573.6
year        11   474.89      2816     4098.7 < 2.2e-16 ***
vesselcode2 30   772.11      2786     3326.6 < 2.2e-16 ***
month       10   250.90      2776     3075.7 < 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(2.08), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                               2827     4653.7
year              11   483.35      2816     4170.3 < 2.2e-16 ***
month             10   336.71      2806     3833.6 < 2.2e-16 ***
vesselcode2       30   704.46      2776     3129.2 < 2.2e-16 ***
shootlon           1     1.99      2775     3127.2    0.1586
shootlat           1    16.63      2774     3110.6 4.542e-05 ***
shootlon:shootlat  1    37.50      2773     3073.1 9.157e-10 ***
---
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(2.1018), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                               2827     4701.3
year              11   488.38      2816     4212.9 < 2.2e-16 ***
month             10   340.22      2806     3872.7 < 2.2e-16 ***
vesselcode2       30   711.75      2776     3160.9 < 2.2e-16 ***
shootlon           1     2.01      2775     3158.9    0.1566
shootlat           1    16.81      2774     3142.1 4.141e-05 ***
ELE                2    39.15      2772     3103.0 3.159e-09 ***
shootlon:shootlat  1    31.59      2771     3071.4 1.908e-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(2.081), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)    
NULL                               2827     4655.8              
year              11   483.57      2816     4172.2 < 2.2e-16 ***
month             10   336.86      2806     3835.3 < 2.2e-16 ***
vesselcode2       30   704.78      2776     3130.5 < 2.2e-16 ***
shootlon           1     1.99      2775     3128.6    0.1585    
shootlat           1    16.64      2774     3111.9 4.524e-05 ***
sst                1     1.44      2773     3110.5    0.2307    
shootlon:shootlat  1    37.41      2772     3073.1 9.576e-10 ***
---
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(2.0801), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)    
NULL                               2827     4653.8              
year              11   483.36      2816     4170.4 < 2.2e-16 ***
month             10   336.72      2806     3833.7 < 2.2e-16 ***
vesselcode2       30   704.48      2776     3129.2 < 2.2e-16 ***
shootlon           1     1.99      2775     3127.3    0.1586    
shootlat           1    16.63      2774     3110.6 4.541e-05 ***
hci                1     0.01      2773     3110.6    0.9191    
shootlon:shootlat  1    37.57      2772     3073.1 8.831e-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.

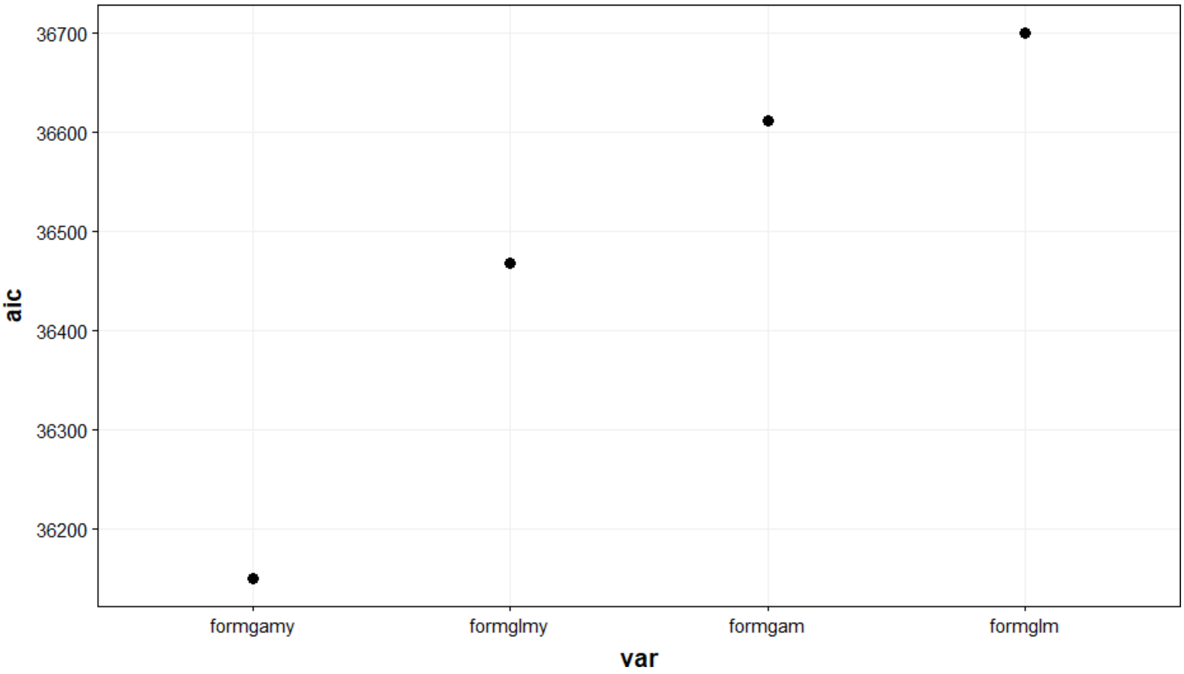


Figure 12: AIC comparison of GLM and GAM models with different spatial and year smoothers

```
Analysis of Deviance Table

Model: Negative Binomial(2.1018), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                              2827     4701.3
year              11   488.38     2816     4212.9 < 2.2e-16 ***
month             10   340.22     2806     3872.7 < 2.2e-16 ***
vesselcode2       30   711.75     2776     3160.9 < 2.2e-16 ***
shootlon           1     2.01     2775     3158.9    0.1566
shootlat           1    16.81     2774     3142.1 4.141e-05 ***
ELE                2    39.15     2772     3103.0 3.159e-09 ***
shootlon:shootlat  1    31.59     2771     3071.4 1.908e-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(2.3148), link: log

Response: catch

Terms added sequentially (first to last)

                       Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                                    2827     5164.5
year                   11   537.41      2816     4627.1 < 2.2e-16 ***
month                  10   374.43      2806     4252.7 < 2.2e-16 ***
vesselcode2            30   782.71      2776     3470.0 < 2.2e-16 ***
shootlon                1     2.20      2775     3467.8   0.13826
shootlat                1    18.52      2774     3449.2 1.685e-05 ***
ELE                     2    43.03      2772     3406.2 4.540e-10 ***
shootlon:shootlat       1    34.72      2771     3371.5 3.810e-09 ***
year:shootlon          11    20.25      2760     3351.2   0.04202 *
year:shootlat          11   173.09      2749     3178.2 < 2.2e-16 ***
year:shootlon:shootlat 11   119.41      2738     3058.7 < 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(2.102)
Link function: log

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

Parametric Terms:
            df Chi.sq  p-value
year        11 290.74  < 2e-16
month       10 116.87  < 2e-16
vesselcode2 30 847.28  < 2e-16
ELE          2  28.43 6.71e-07

Approximate significance of smooth terms:
                       edf Ref.df Chi.sq p-value
s(shootlon,shootlat) 24.71  27.93  160.3  <2e-16
```

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

```
Family: Negative Binomial(2.315)
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        11  15.836   0.147
month       10 127.503  <2e-16
vesselcode2 30 898.714  <2e-16
ELE          2   0.248   0.883

Approximate significance of smooth terms:
                                 edf Ref.df  Chi.sq  p-value
s(shootlon,shootlat):year2008  2.001  2.002   0.004 0.998089
s(shootlon,shootlat):year2009 16.407 19.447 142.250  < 2e-16
s(shootlon,shootlat):year2010 17.685 19.906  86.885 2.89e-10
s(shootlon,shootlat):year2011 23.568 24.576  98.189 1.23e-10
s(shootlon,shootlat):year2012 11.671 14.095 105.677 4.69e-16
s(shootlon,shootlat):year2013  6.537  7.900  30.664 0.000154
s(shootlon,shootlat):year2014 11.635 12.710  94.296 1.38e-14
s(shootlon,shootlat):year2015  5.779  7.347  14.377 0.061923
s(shootlon,shootlat):year2016 13.585 14.803  30.976 0.007983
s(shootlon,shootlat):year2017 15.955 16.984  78.662 6.67e-10
s(shootlon,shootlat):year2018 14.247 15.927  44.857 0.000151
s(shootlon,shootlat):year2019 11.601 13.746  89.919 4.44e-13
```

*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, consistent with the approach selected during the benchmark in 2018 (SCW6), the GAM model without interaction between space and year has been selected. The final model was :

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

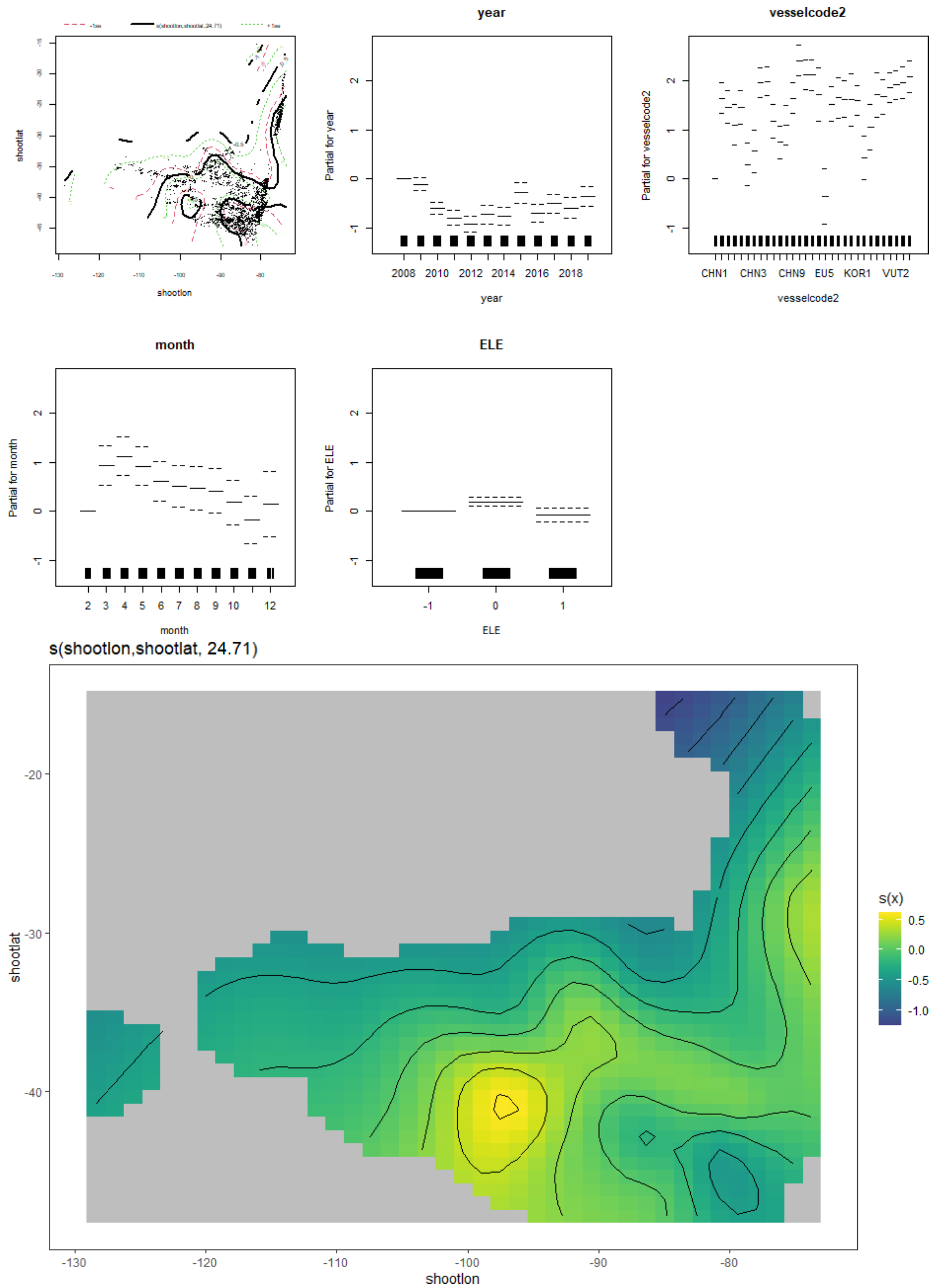


Figure 13: Jack mackerel Final GAM model estimates for selected effects

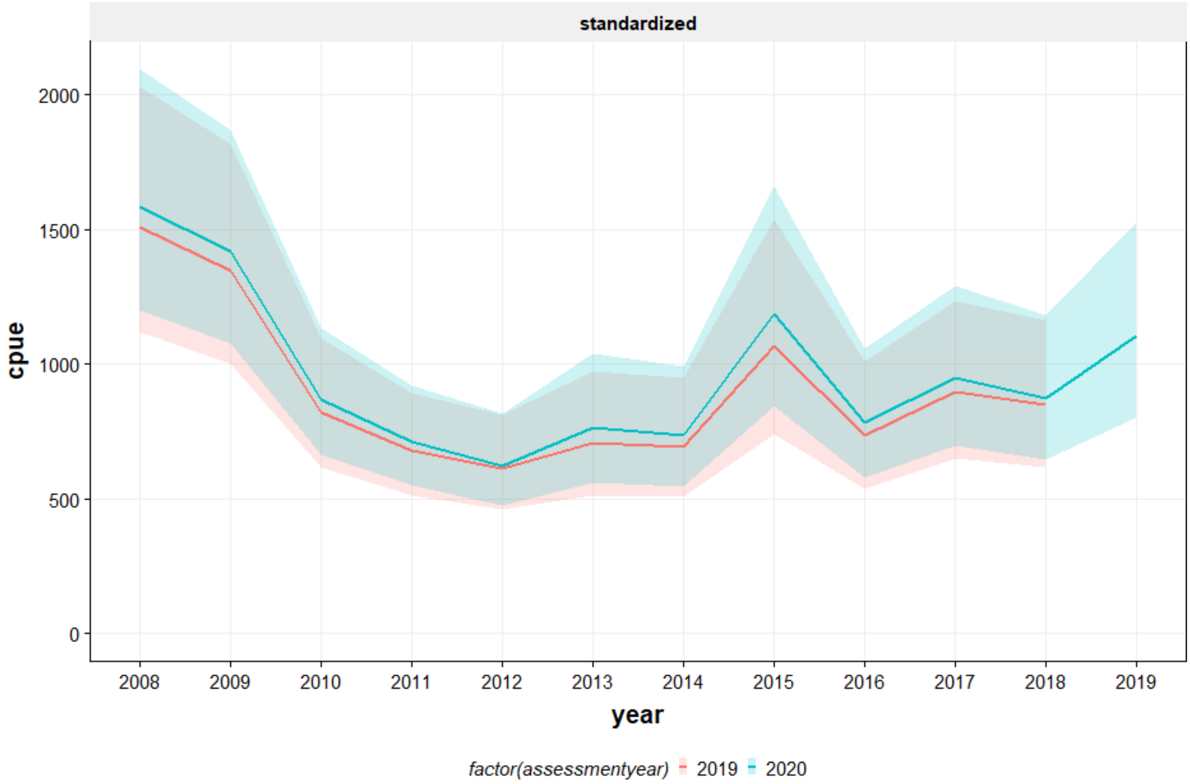


Figure 14: GAM standardized offshore fleet CPUE for jack mackerel

```
Family: Negative Binomial(2.102)
Link function: log

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

Parametric Terms:
            df Chi.sq  p-value
year        11 290.74  < 2e-16
vesselcode2 30 847.28  < 2e-16
month       10 116.87  < 2e-16
ELE          2  28.43 6.71e-07

Approximate significance of smooth terms:
                       edf Ref.df Chi.sq p-value
s(shootlon,shootlat) 24.71  27.93  160.3  <2e-16
```

Table 19: ANOVA results with final model GAM

year	cpue	lwr	upr
2008	1584	1198	2095
2009	1417	1076	1866
2010	867	664	1132
2011	712	551	919
2012	623	476	817
2013	762	558	1040
2014	737	546	994
2015	1184	845	1658
2016	781	578	1057
2017	950	699	1292
2018	873	644	1183
2019	1107	801	1529

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.

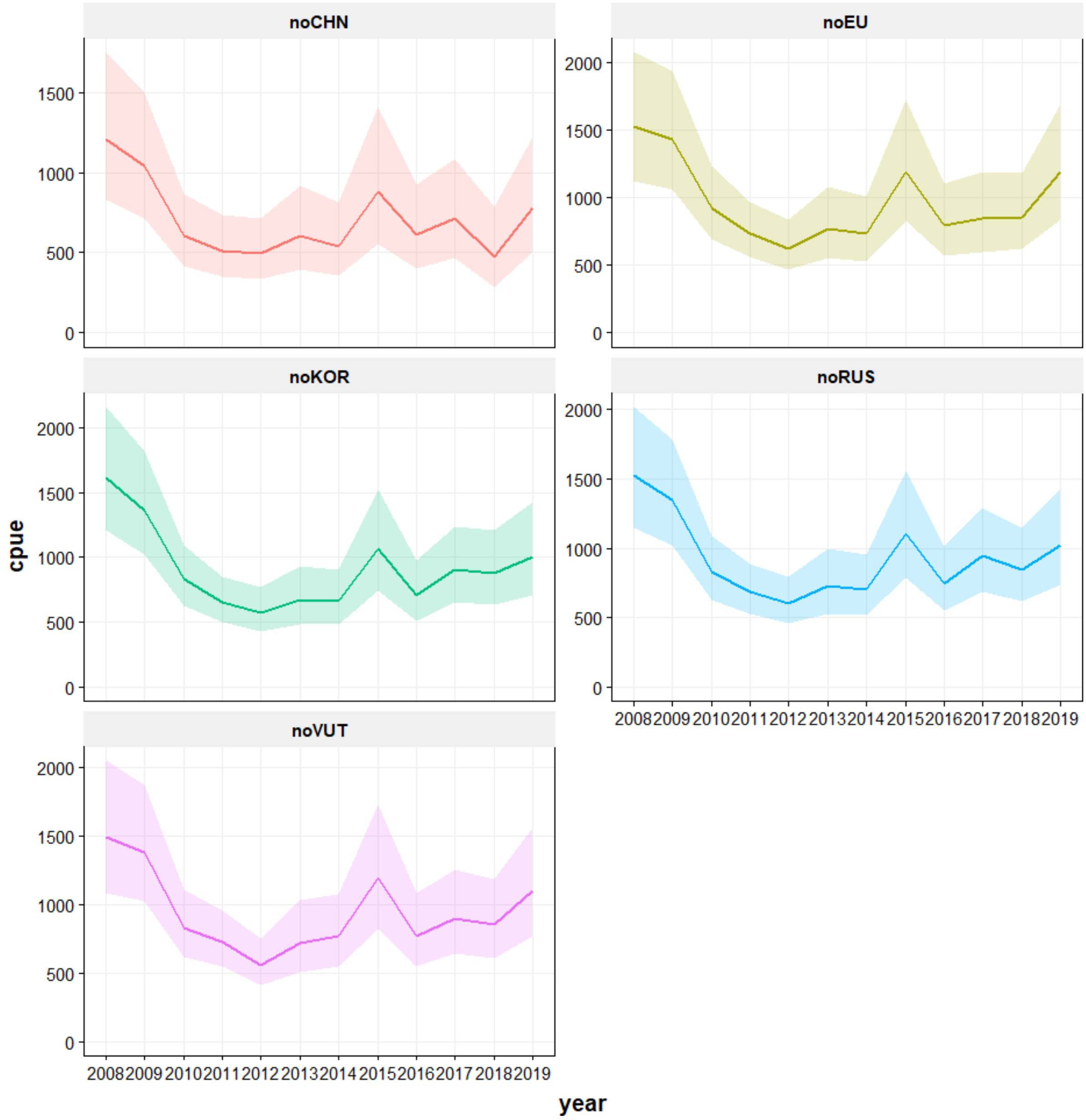
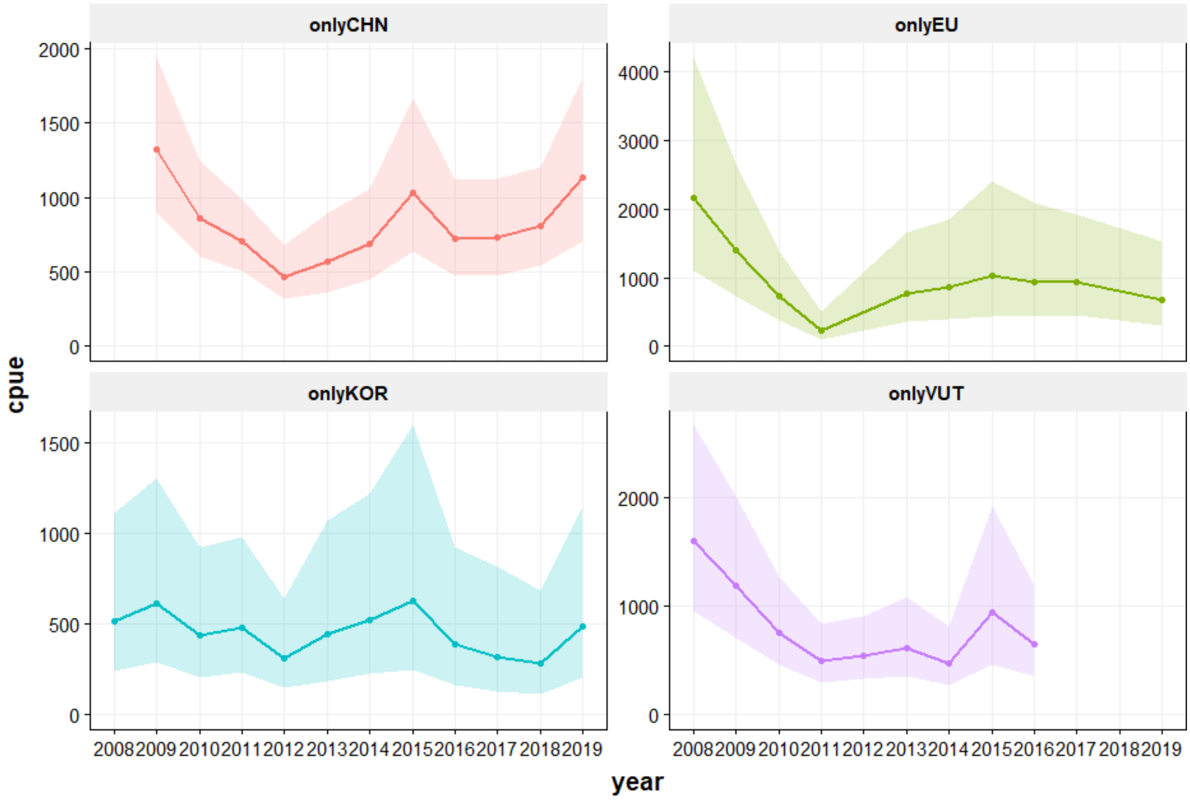


Figure 15: Jack mackerel leave-one-out analysis (leaving out one of the fleets)

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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