South Pacific Regional Fisheries Management Organisation

14th MEETING OF THE SCIENTIFIC COMMITTEE

7 to 12 September 2026, Tórshavn, Faroe Islands

SC14 - JM 21

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

European Union

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European Union

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Abstract

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 SC14. 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, which mostly cover only part of the distribution of the species. To prevent inflation of data sources that contribute little to the overall perception of the stock, at SC07 a standardized CPUE for the entire offshore fleet was developed. This document describes the process and data used to standardize the CPUE.

2 Material and methods

Data from EU, Korea, Russia, Vanuatu and China was made available by the SPRFMO secretariat. Data was checked for quality and cleaned when clear mistakes had been transfered in the data submission from the secretariat to the EU scientist. 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)
2007	0	0	2	0	0	2
2008	0	5	2	0	4	11
2009	13	6	2	0	4	25
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
2019	2	1	2	1	0	6
2020	0	0	0	1	0	1
2021	0	3	0	1	0	4
2022	0	2	0	2	0	4
2023	0	3	0	3	0	6
2024	0	2	1	2	0	5
2025	0	2	1	0	0	3

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)
2007	0	0	10,524	0	0	10,524
2008	0	66,260	12,377	0	101,955	180,592
2009	117,963	80,391	13,759	0	80,166	292,279
2010	63,579	31,258	8,183	0	45,934	148,954
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
2019	22,706	11,789	7,444	9,412	0	51,352
2020	0	0	0	5,245	0	5,245
2021	0	42,990	0	11,839	0	54,830
2022	0	44,425	0	29,443	0	73,869
2023	0	35,927	0	43,938	0	79,865
2024	0	17,749	1,798	12,138	0	31,685
2025	0	33,336	189	0	0	33,525
(all)	369,947	472,581	95,493	122,414	311,753	1,372,187

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)
2007	.	.	162	.	.	162
2008	.	172	188	.	245	202
2009	216	190	195	.	198	200
2010	255	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
2019	208	143	184	186	.	180
2020	.	.	.	71	.	71
2021	.	153	.	112	.	132
2022	.	215	.	255	.	235
2023	.	171	.	295	.	233
2024	.	169	116	159	.	148
2025	.	174	10	.	.	92
(all)	214	171	145	146	195	172

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)
2007	0	0	204	0	0	204
2008	0	361	224	0	708	1,293
2009	1,301	461	173	0	584	2,519
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
2019	217	85	111	104	0	517
2020	0	0	0	55	0	55
2021	0	231	0	66	0	297
2022	0	264	0	215	0	479
2023	0	267	0	293	0	560
2024	0	162	70	153	0	385
2025	0	186	7	0	0	193
(all)	4,753	3,352	1,823	1,045	2,977	13,950

Table 4: Number of fishing days by contracting party

Number of hauls

year	CHN	EU	KOR	RUS	VUT	(all)
2007	0	0	352	0	0	352
2008	0	630	398	0	1,731	2,759
2009	2,331	703	291	0	1,356	4,681
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
2019	356	154	249	212	0	971
2020	0	0	0	116	0	116
2021	0	544	0	188	0	732
2022	0	654	0	558	0	1,212
2023	0	711	0	739	0	1,450
2024	0	349	103	312	0	764
2025	0	573	22	0	0	595
(all)	8,187	6,736	3,256	2,424	6,173	26,776

Table 5: Number of hauls by contracting party

Number of fishing hours

year	CHN	EU	KOR	RUS	VUT	(all)
2007	0	0	1,817	0	0	1,817
2008	0	2,829	1,559	0	8,935	13,323
2009	12,622	5,082	1,301	0	7,512	26,517
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
2019	2,493	985	1,426	1,123	0	6,027
2020	0	0	0	639	0	639
2021	0	2,780	0	1,008	0	3,788
2022	0	3,325	0	2,552	0	5,877
2023	0	3,226	0	3,092	0	6,318
2024	0	2,166	834	1,318	0	4,318
2025	0	2,745	143	0	0	2,888
(all)	49,532	38,417	17,125	11,445	38,450	154,969

Table 6: Summed fishing hours by contracting party

Average duration of a fishing haul

year	CHN	EU	KOR	RUS	VUT	(all)
2007	.	.	5.2	.	.	5.2
2008	.	4.5	3.9	.	5.2	4.5
2009	5.4	7.2	4.5	.	5.5	5.7
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
2019	7	6.4	5.7	5.3	.	6.1
2020	.	.	.	5.5	.	5.5
2021	.	5.1	.	5.4	.	5.2
2022	.	5.1	.	4.6	.	4.8
2023	.	4.5	.	4.2	.	4.3
2024	.	6.3	8.1	4.3	.	6.2
2025	.	4.8	6.5	.	.	5.7
(all)	6.4	6.1	5.7	5.1	6.7	6

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	.	184	55	.	145	128
2009	91	174	80	.	137	120
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
2019	105	142	67	90	.	101
2020	.	.	.	95	.	95
2021	.	209	.	179	.	194
2022	.	169	.	137	.	153
2023	.	139	.	150	.	145
2024	.	125	33	81	.	80
2025	.	179	27	.	.	103
(all)	77	131	50	103	89	91

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.

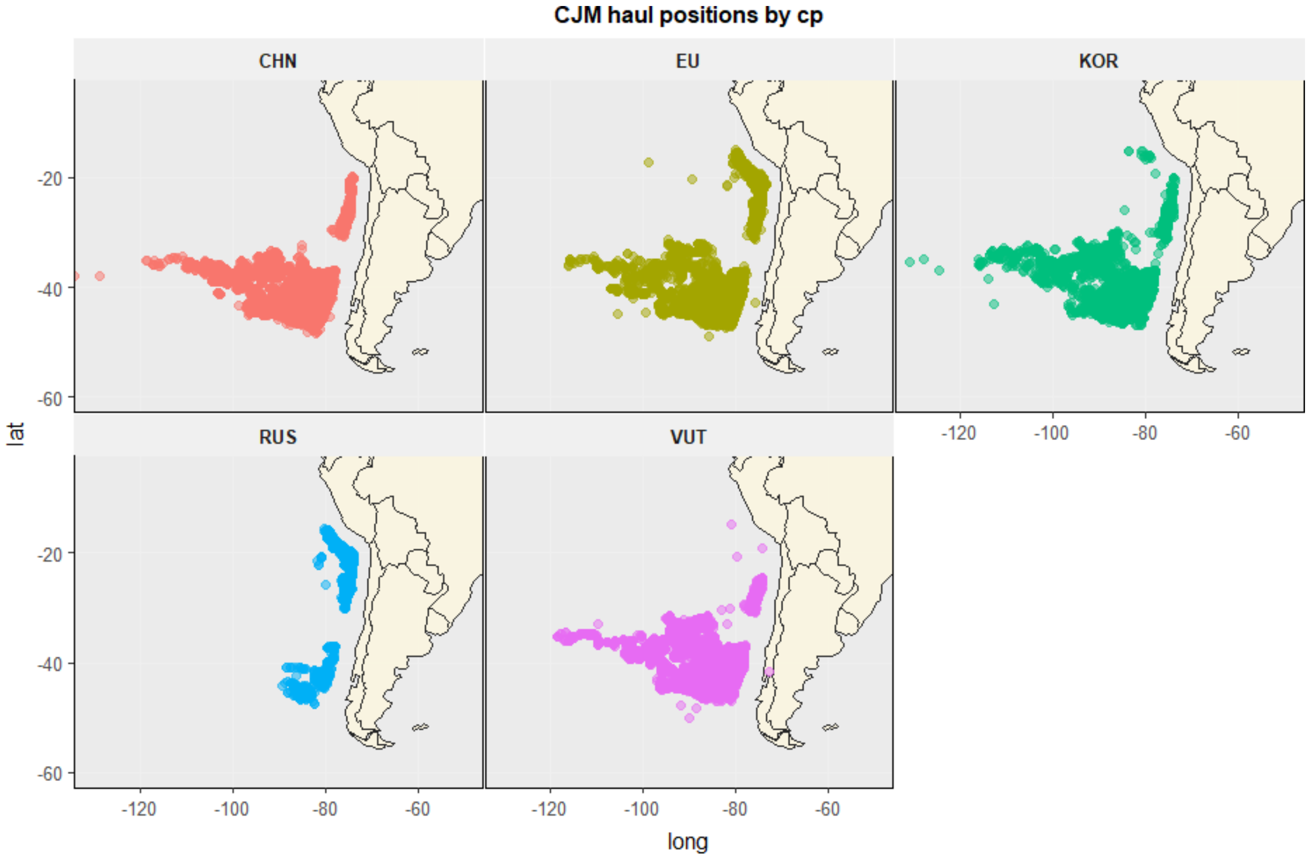


Figure 1: Haul positions where Jack mackerel has been caught (all years combined)

Haul positions by contracting party and year

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

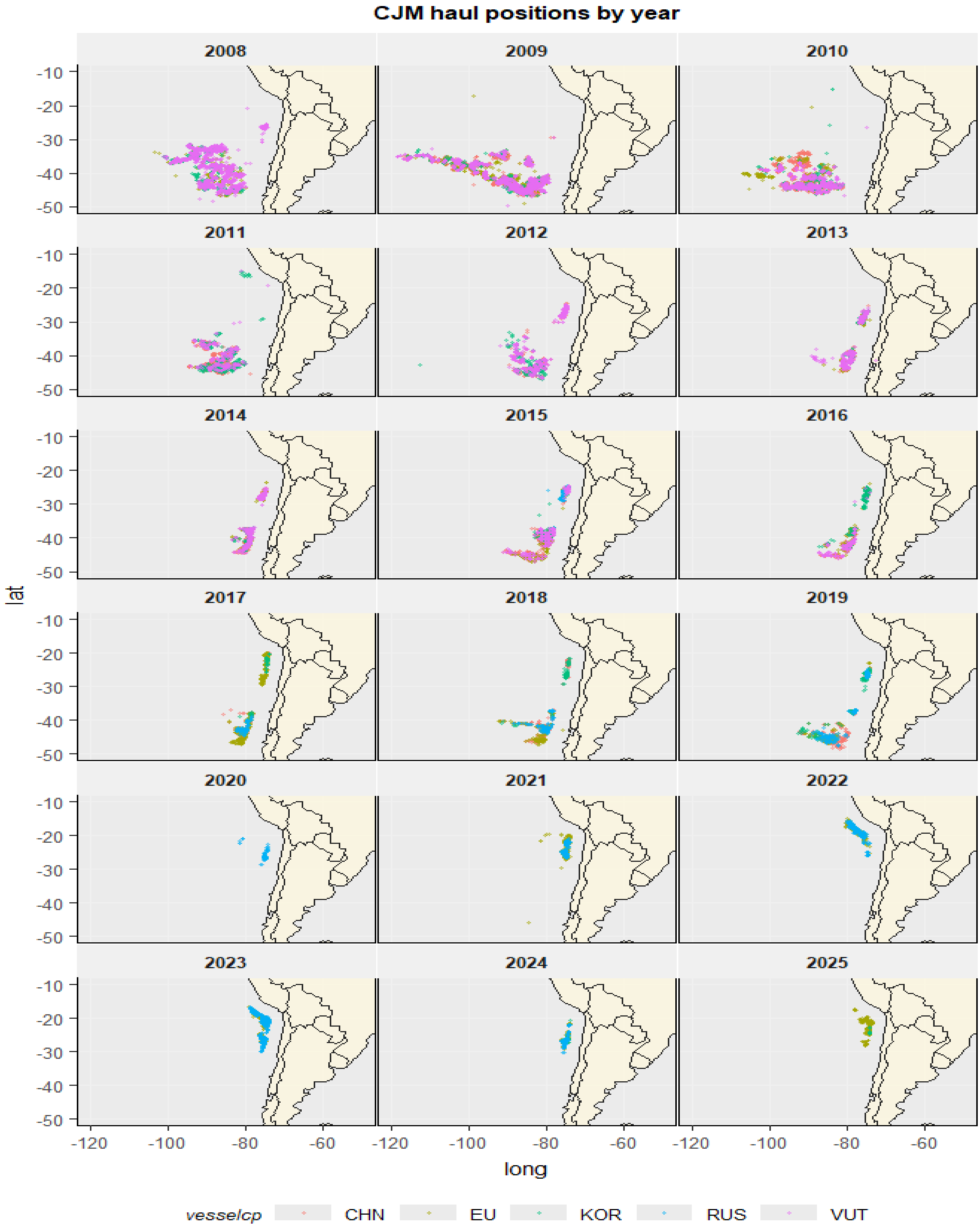


Figure 2: Haul positions where Jack mackerel has been caught (by year). Colours indicate the different contracting parties

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

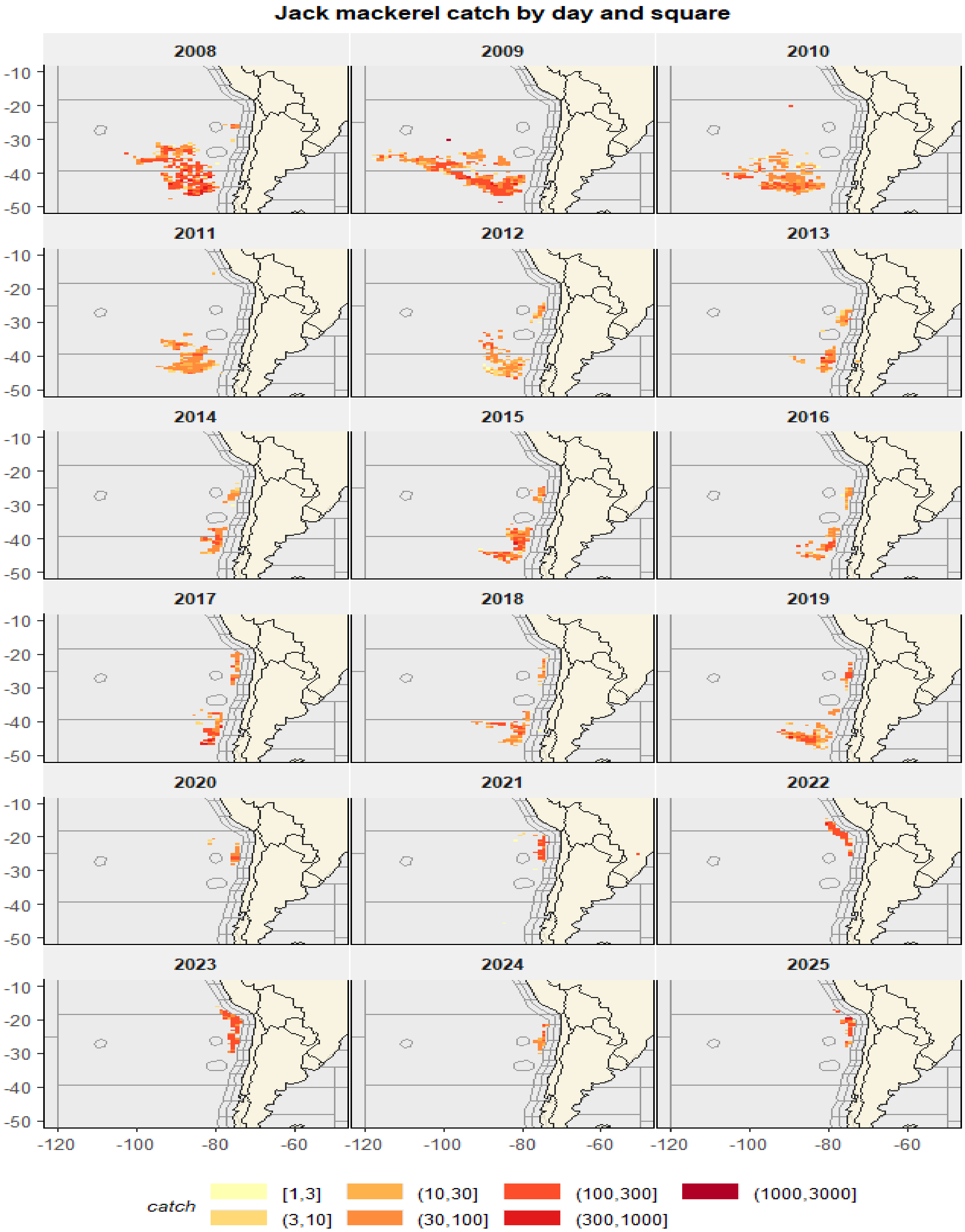


Figure 3: Catch per day (tonnes) of Jack mackerel (summed by 1 degree longitude and 0.5 degree latitude)

Jack mackerel log CPUE by day against latitude and longitude

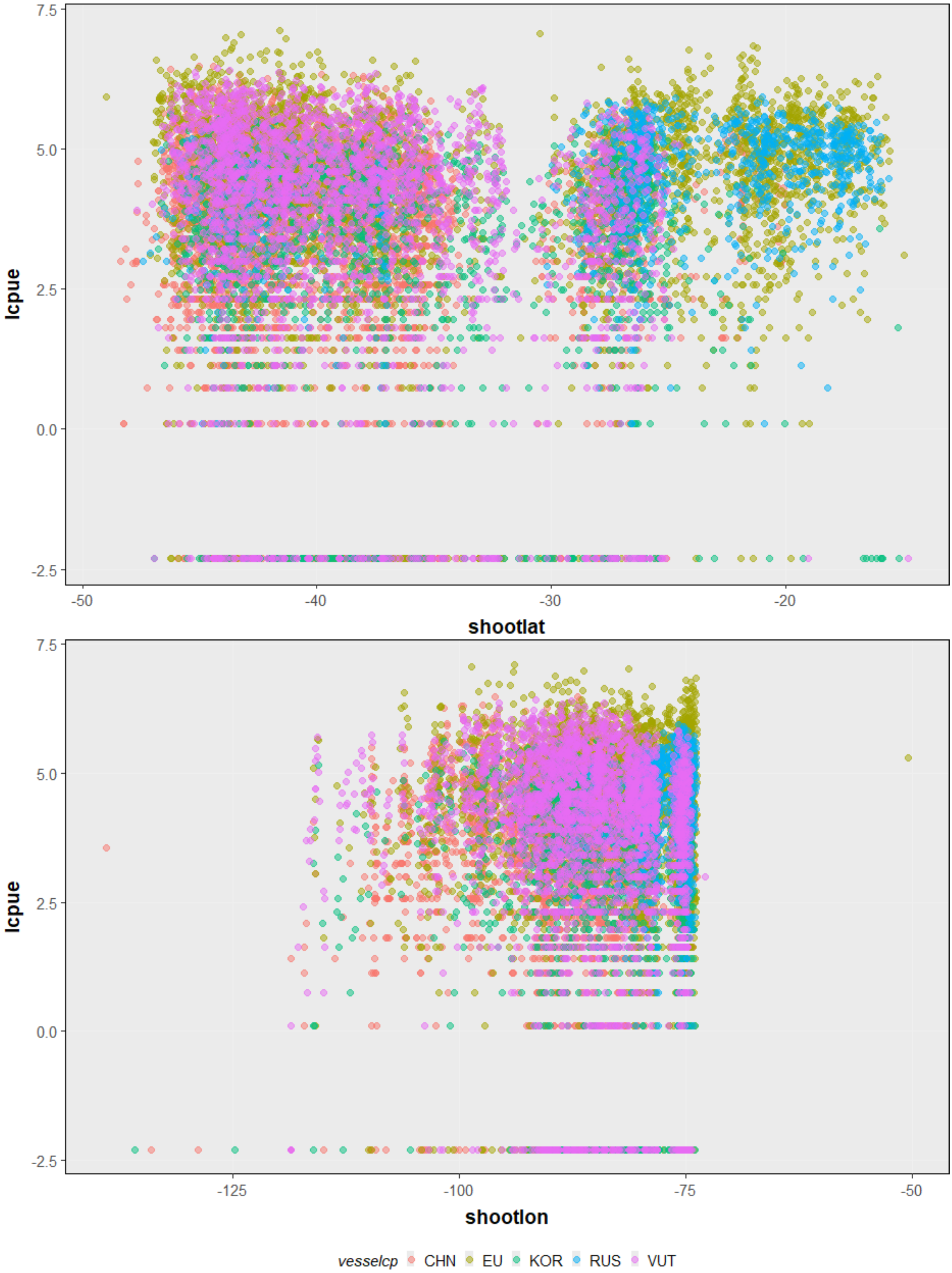


Figure 4: Log catch per day (tonnes) of Jack mackerel against latitude (top) and longitude (bottom).

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.

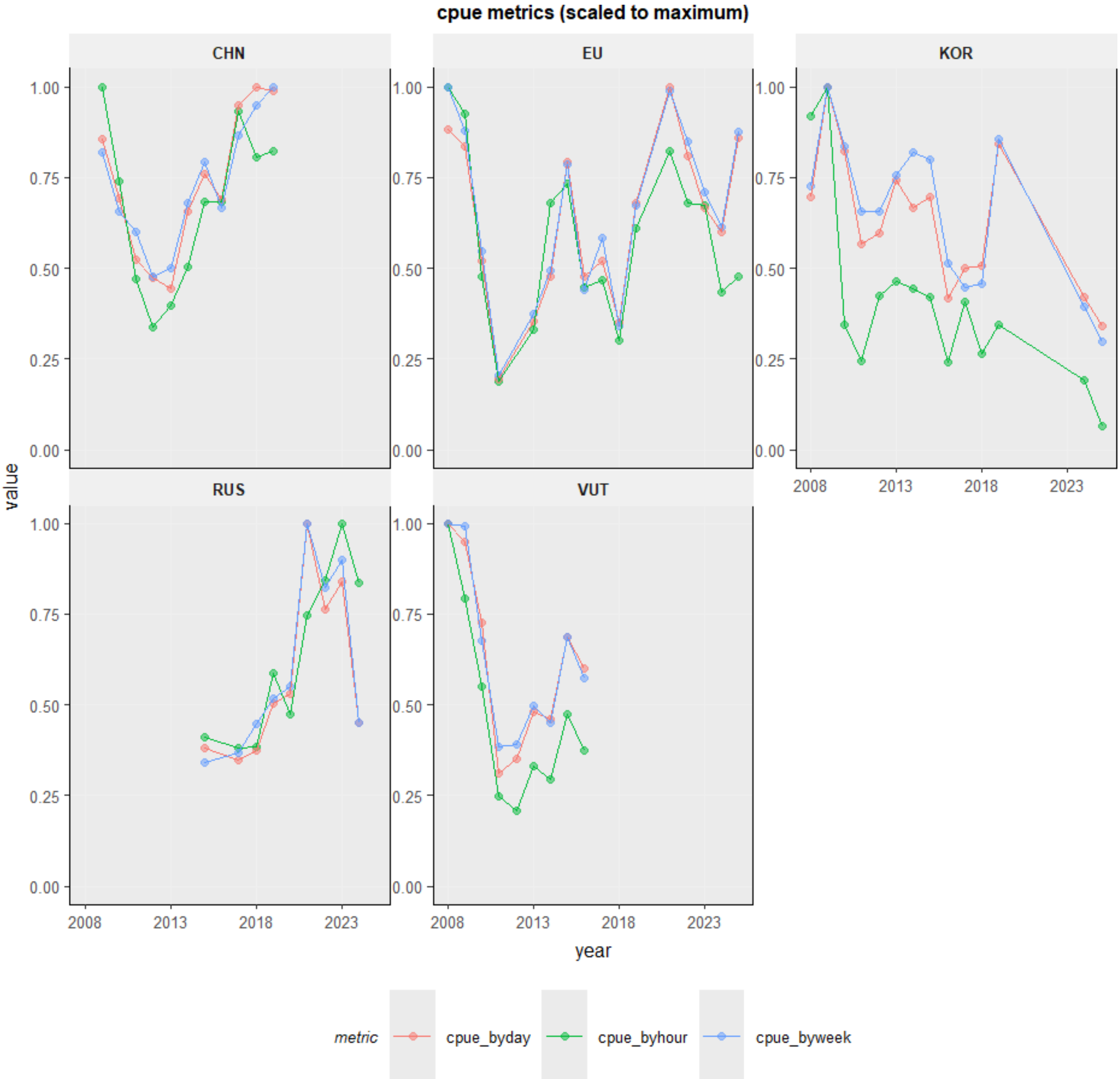


Figure 5: Jack mackerel CPUE metrics by hour, by day and by week, scaled to the maximum of the time series.

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.

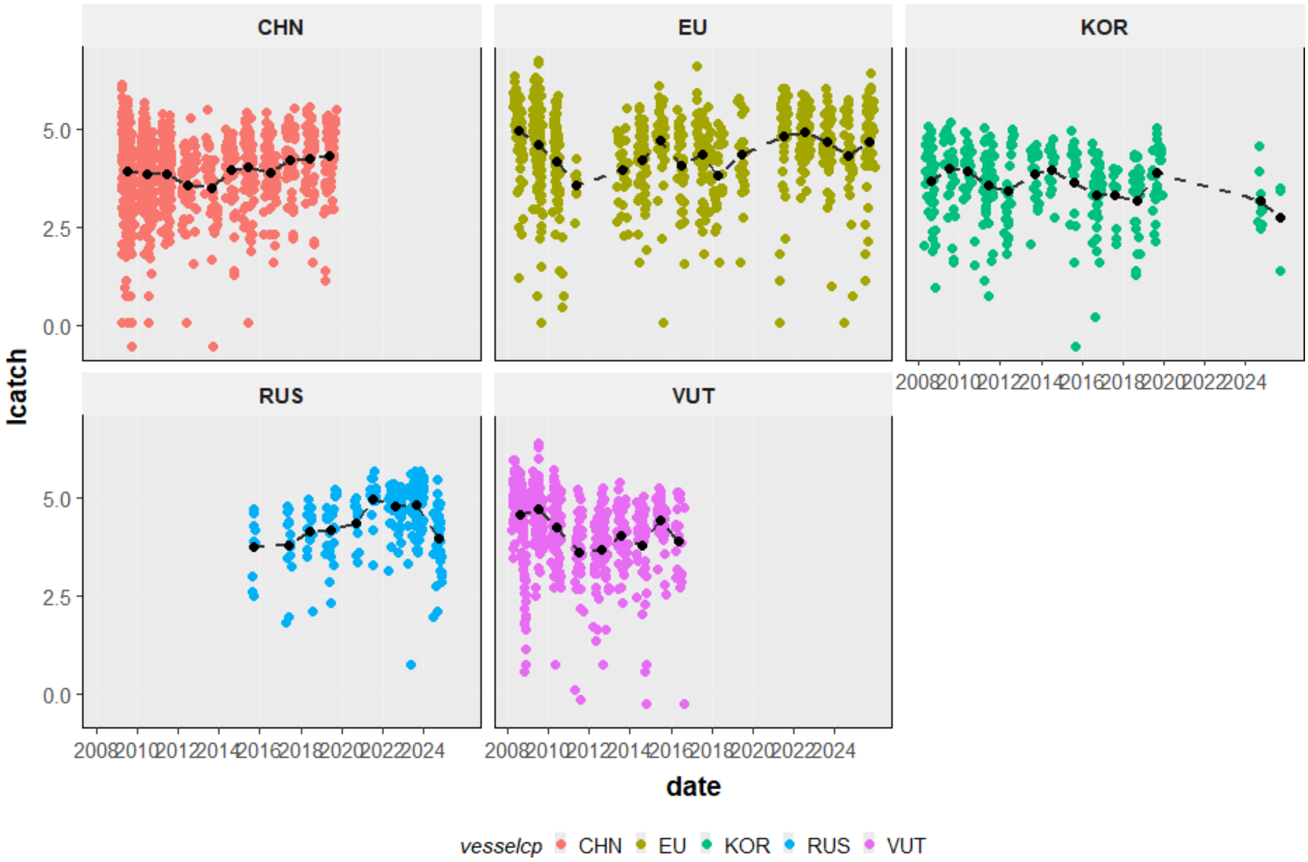


Figure 6: Jack mackerel log CPUE (log(catch / ndays)) by week.

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/)

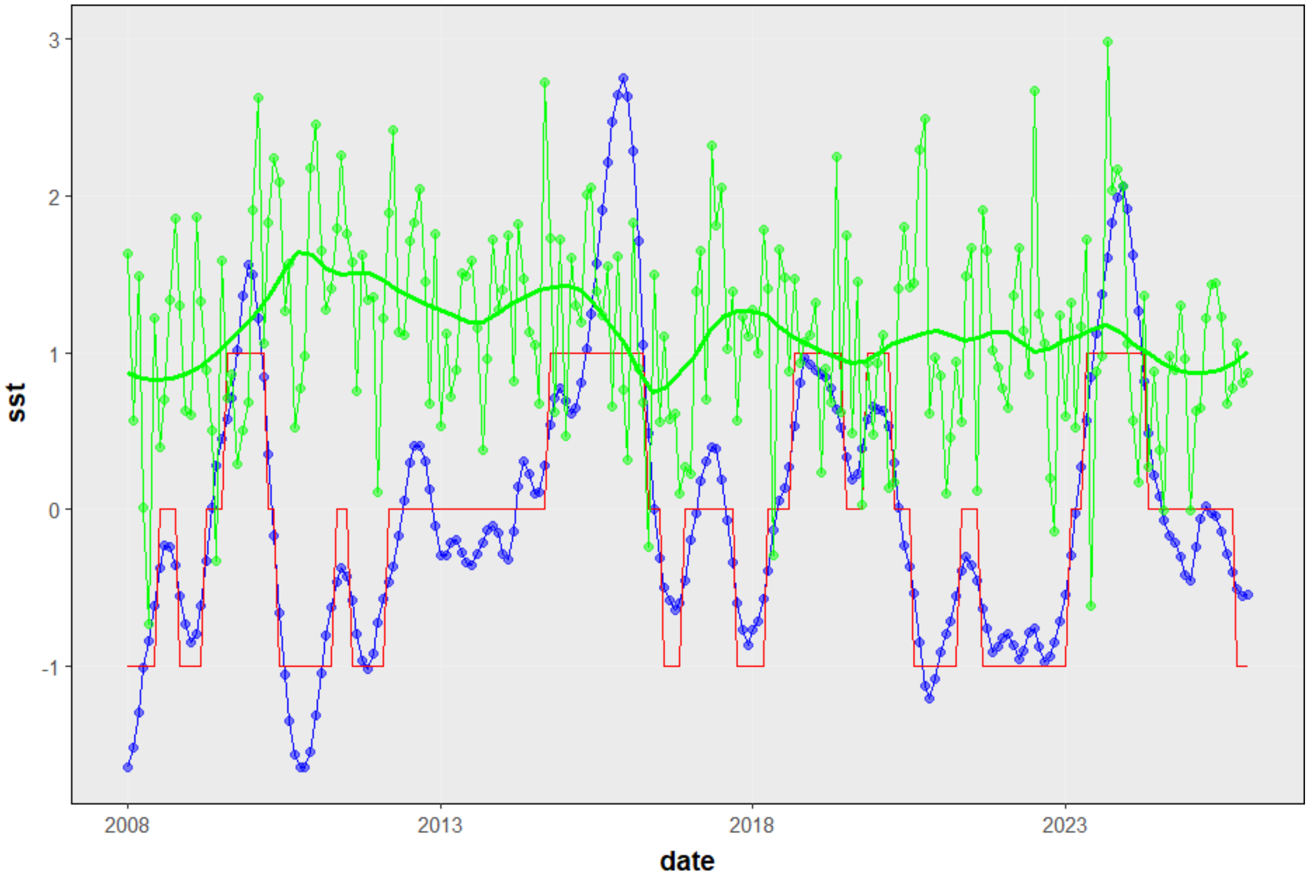


Figure 7: El Nino temperature anomaly (blue line) and ELE indicator (red line). Humboldt Current Index (green line)

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.

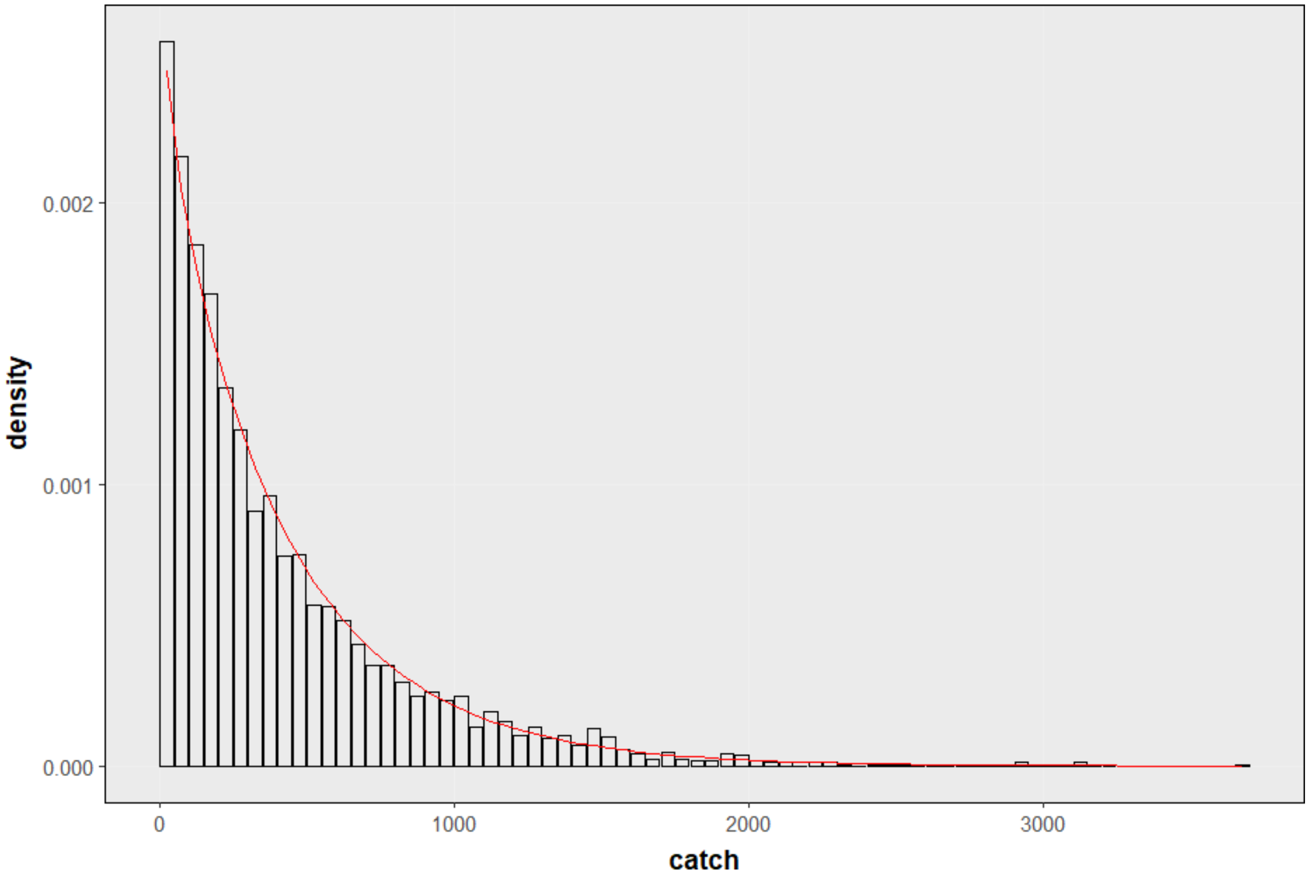


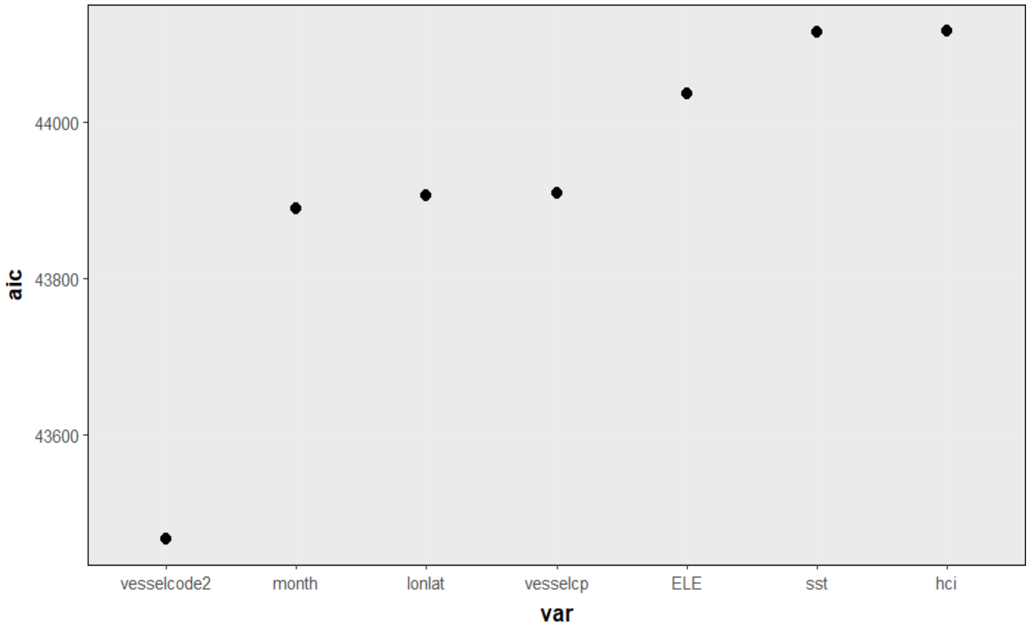
Figure 8: Fitting a negative binomial distribution through the catch data

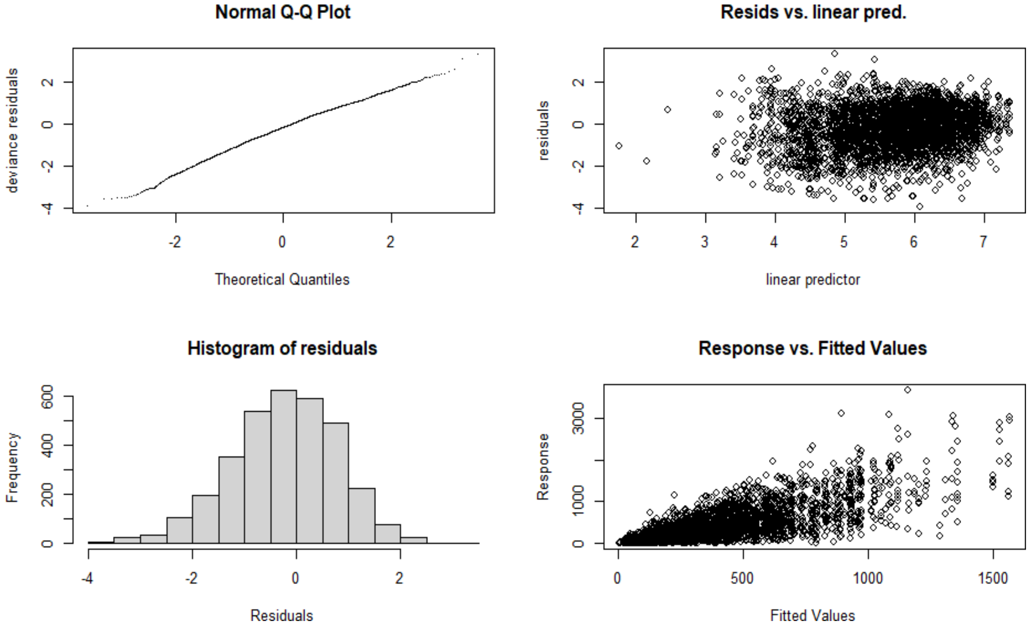
Modelling the first linear effect next to the year trend

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

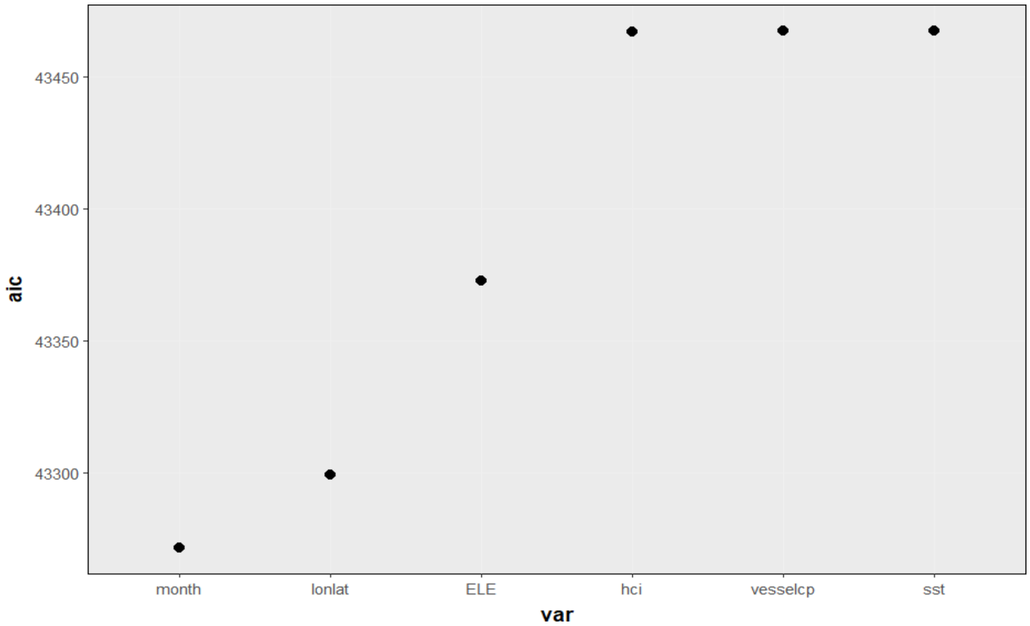
```
Analysis of Deviance Table

Model: Negative Binomial(1.949), link: log

Response: catch

Terms added sequentially (first to last)

            Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                         3293     5048.7
year        17   674.53      3276     4374.2 < 2.2e-16 ***
vesselcode2 31   782.66      3245     3591.5 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

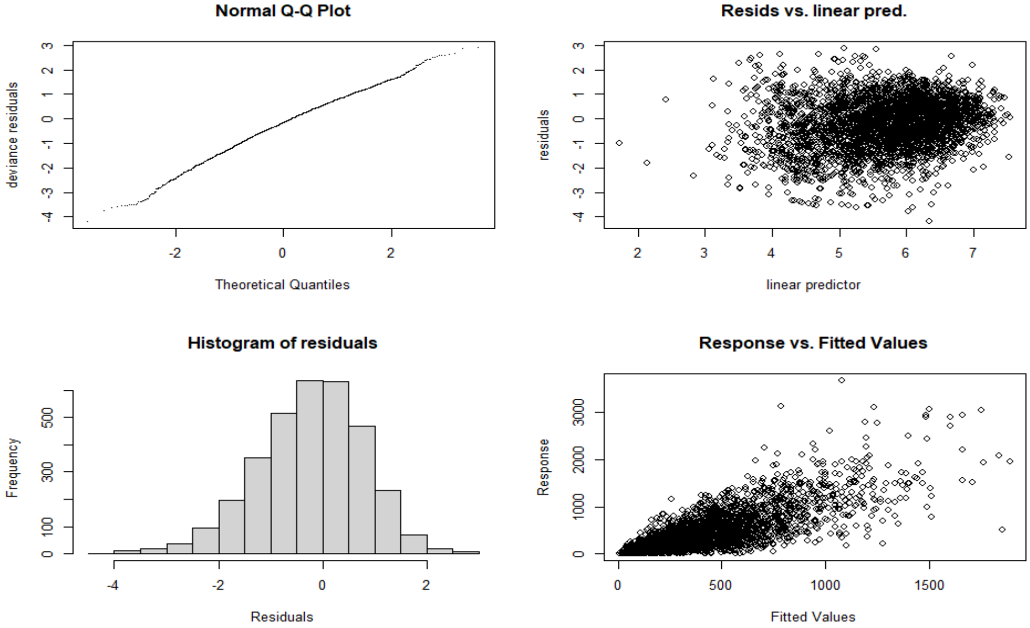
Table 9: ANOVA results for negative binomial GLM with best fitting first linear effect

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

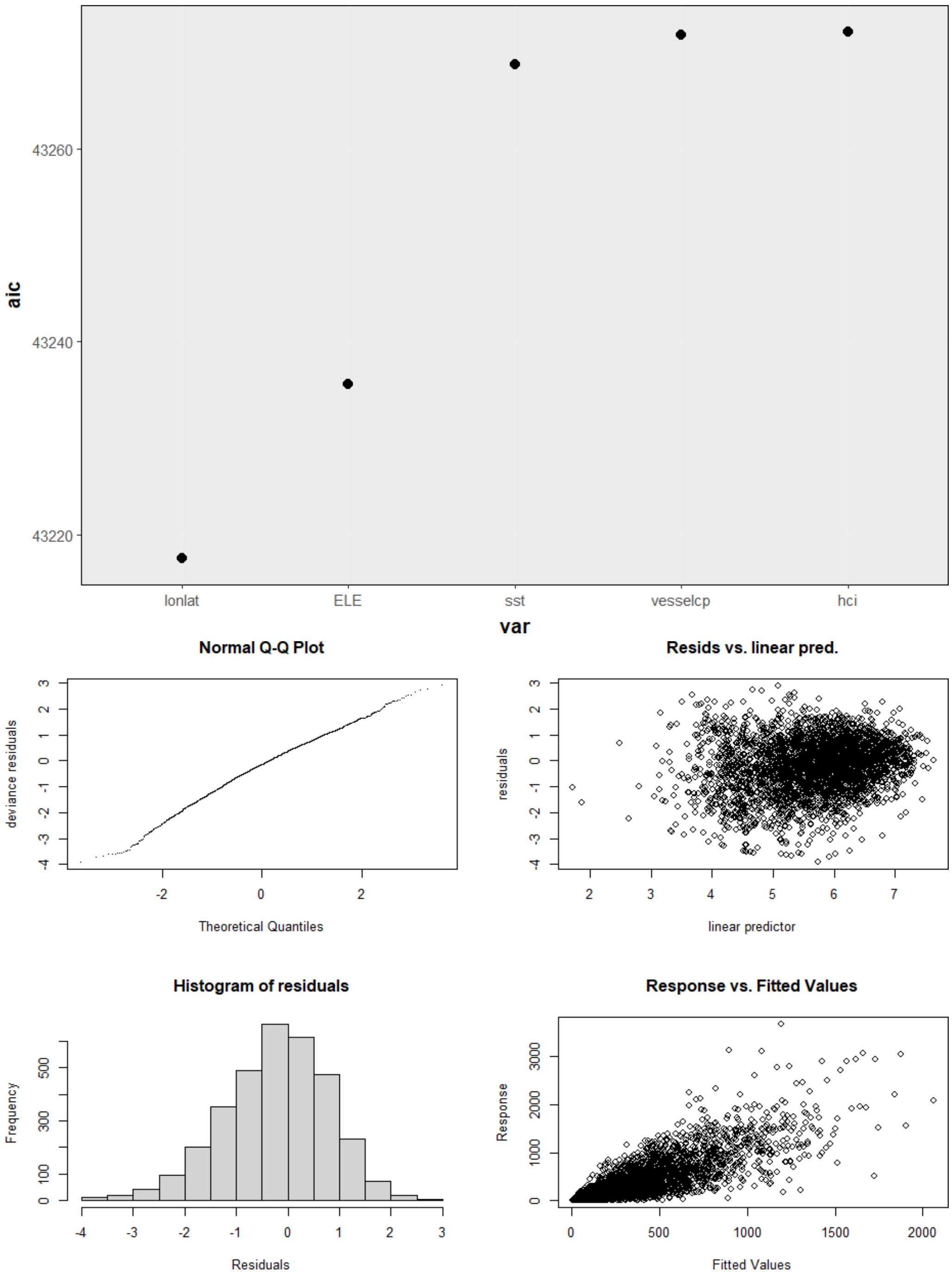
```
Analysis of Deviance Table

Model: Negative Binomial(2.069), link: log

Response: catch

Terms added sequentially (first to last)

            Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                         3293     5351.9
year        17   715.75      3276     4636.1 < 2.2e-16 ***
vesselcode2 31   830.24      3245     3805.9 < 2.2e-16 ***
month       11   224.24      3234     3581.7 < 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(2.1034), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)    
NULL                               3293     5438.8              
year              17   727.57      3276     4711.2 < 2.2e-16 ***
month             11   314.00      3265     4397.2 < 2.2e-16 ***
vesselcode2       31   757.82      3234     3639.4 < 2.2e-16 ***
shootlon           1     2.85      3233     3636.5   0.09149 .  
shootlat           1     0.05      3232     3636.5   0.82458    
shootlon:shootlat  1    57.75      3231     3578.7 2.983e-14 ***
---
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(2.1213), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                               3293     5483.9
year              17   733.72      3276     4750.2 < 2.2e-16 ***
month             11   316.66      3265     4433.5 < 2.2e-16 ***
vesselcode2       31   764.18      3234     3669.3 < 2.2e-16 ***
shootlon           1     2.87      3233     3666.5    0.0902 .
shootlat           1     0.05      3232     3666.4    0.8239
ELE                2    38.54      3230     3627.9 4.287e-09 ***
shootlon:shootlat  1    50.63      3229     3577.2 1.114e-12 ***
---
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(2.1064), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                               3293     5446.4
year              17   728.62      3276     4717.8 < 2.2e-16 ***
month             11   314.46      3265     4403.4 < 2.2e-16 ***
vesselcode2       31   758.90      3234     3644.5 < 2.2e-16 ***
shootlon           1     2.85      3233     3641.6   0.09127 .
shootlat           1     0.05      3232     3641.6   0.82447
sst                1     6.16      3231     3635.4   0.01309 *
shootlon:shootlat  1    56.78      3230     3578.6 4.883e-14 ***
---
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(2.1046), link: log

Response: catch
```

```
Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)    
NULL                               3293     5441.9              
year              17   728.00      3276     4713.9 < 2.2e-16 ***
month             11   314.19      3265     4399.7 < 2.2e-16 ***
vesselcode2       31   758.26      3234     3641.4 < 2.2e-16 ***
shootlon           1     2.85      3233     3638.6    0.0914 .  
shootlat           1     0.05      3232     3638.5    0.8245    
hci                1     1.22      3231     3637.3    0.2696    
shootlon:shootlat  1    58.68      3230     3578.6  1.86e-14 ***
---
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.

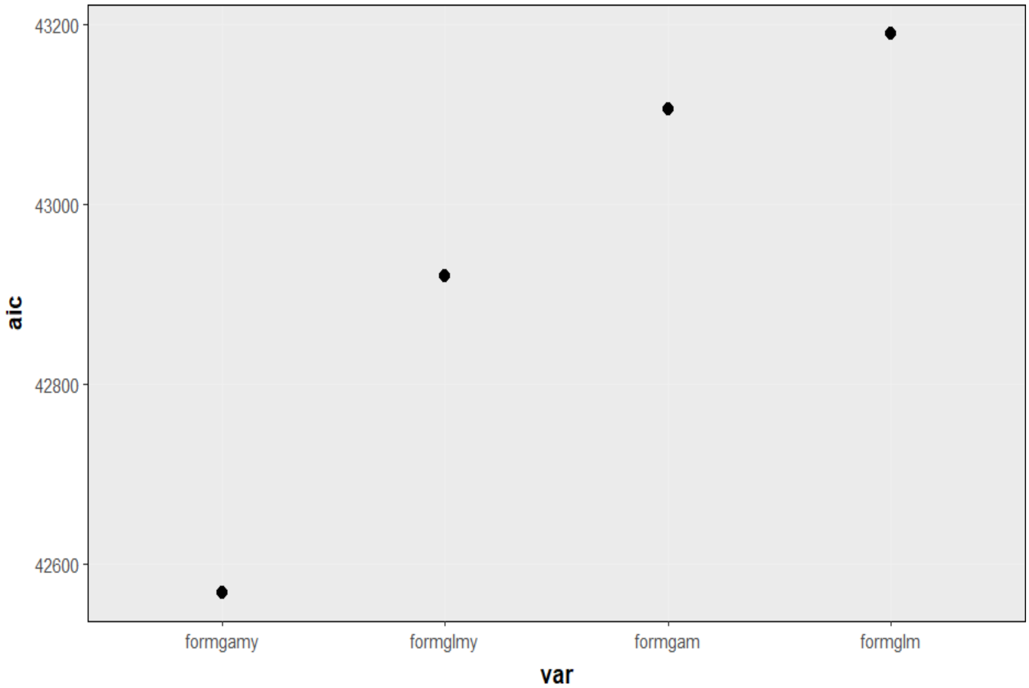


Figure 12: AIC comparison of GLM and GAM models with different spatial and year smoothers

```
Analysis of Deviance Table

Model: Negative Binomial(2.1213), link: log

Response: catch

Terms added sequentially (first to last)

                  Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                               3293     5483.9
year              17   733.72      3276     4750.2 < 2.2e-16 ***
month             11   316.66      3265     4433.5 < 2.2e-16 ***
vesselcode2       31   764.18      3234     3669.3 < 2.2e-16 ***
shootlon           1     2.87      3233     3666.5    0.0902 .
shootlat           1     0.05      3232     3666.4    0.8239
ELE                2    38.54      3230     3627.9 4.287e-09 ***
shootlon:shootlat  1    50.63      3229     3577.2 1.114e-12 ***
---
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(2.3511), link: log

Response: catch

Terms added sequentially (first to last)
```

```
                        Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                                     3293     6062.0
year                    17   812.56      3276     5249.4 < 2.2e-16 ***
month                   11   350.71      3265     4898.7 < 2.2e-16 ***
vesselcode2             31   845.69      3234     4053.0 < 2.2e-16 ***
shootlon                 1     3.16      3233     4049.8   0.07531 .
shootlat                 1     0.05      3232     4049.8   0.81534
ELE                      2    42.64      3230     4007.1 5.504e-10 ***
shootlon:shootlat        1    56.02      3229     3951.1 7.174e-14 ***
year:shootlon           17    63.20      3212     3887.9 3.085e-07 ***
year:shootlat           17   202.31      3195     3685.6 < 2.2e-16 ***
year:shootlon:shootlat  17   125.29      3178     3560.3 < 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(2.121)
Link function: log

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

Parametric Terms:
            df Chi.sq  p-value
year        17 381.11  < 2e-16
month       11 100.17  < 2e-16
vesselcode2 31 912.59  < 2e-16
ELE          2  21.87 1.78e-05

Approximate significance of smooth terms:
                        edf Ref.df Chi.sq p-value
s(shootlon,shootlat) 23.78  27.44  160.7  <2e-16
```

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

```
Family: Negative Binomial(2.351)
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        17  49.965 4.28e-05
month       11  77.250 5.01e-12
vesselcode2 31 983.442  < 2e-16
ELE          2   1.389    0.499

Approximate significance of smooth terms:
                                 edf Ref.df  Chi.sq  p-value
s(shootlon,shootlat):year2008  5.519  7.388  10.229   0.2114
s(shootlon,shootlat):year2009 16.288 19.048 142.169  < 2e-16
s(shootlon,shootlat):year2010 16.792 19.008  89.480  < 2e-16
s(shootlon,shootlat):year2011 16.831 18.715  76.394  < 2e-16
s(shootlon,shootlat):year2012 16.025 17.959 102.782  < 2e-16
s(shootlon,shootlat):year2013  6.391  7.731  16.870   0.0264
s(shootlon,shootlat):year2014 12.125 13.332  92.781  < 2e-16
```

```
s(shootlon,shootlat):year2015  7.799  9.745  15.915   0.0892
s(shootlon,shootlat):year2016  2.000  2.000   6.948   0.0310
s(shootlon,shootlat):year2017 15.231 16.363  58.001 4.95e-06
s(shootlon,shootlat):year2018 16.484 17.820  79.660  < 2e-16
s(shootlon,shootlat):year2019 12.159 14.276  87.227  < 2e-16
s(shootlon,shootlat):year2020  2.000  2.000   1.756   0.4158
s(shootlon,shootlat):year2021  6.137  6.932  96.052  < 2e-16
s(shootlon,shootlat):year2022  2.000  2.000   7.801   0.0202
s(shootlon,shootlat):year2023  2.000  2.000  19.249 6.58e-05
s(shootlon,shootlat):year2024  3.034  3.487  11.761   0.0223
s(shootlon,shootlat):year2025  2.000  2.001   1.427   0.4899
```

Table 18: ANOVA results with GAM including smoothing interaction s(latlonyear)

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

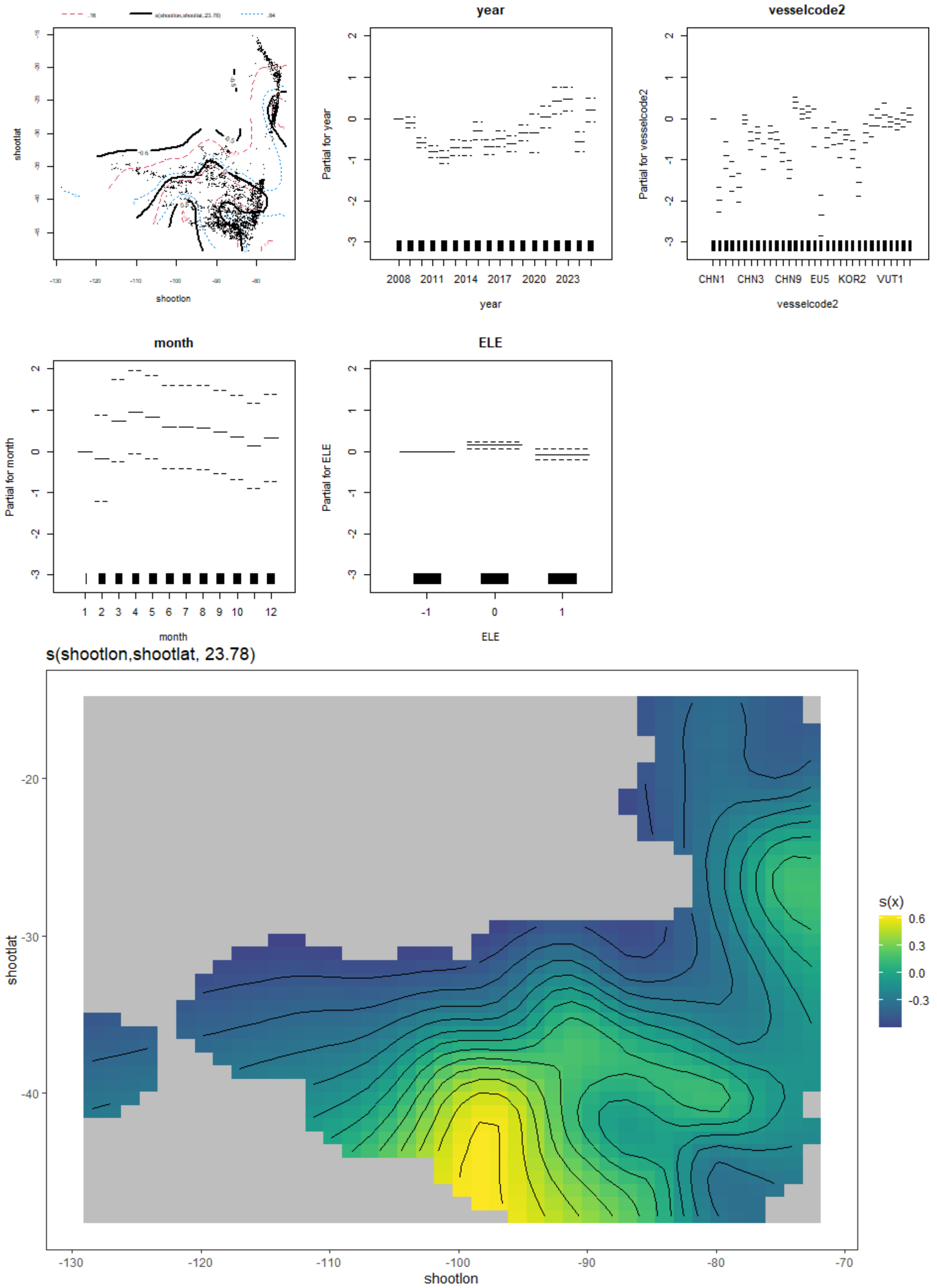


Figure 13: Jack mackerel Final GAM model estimates for selected effects

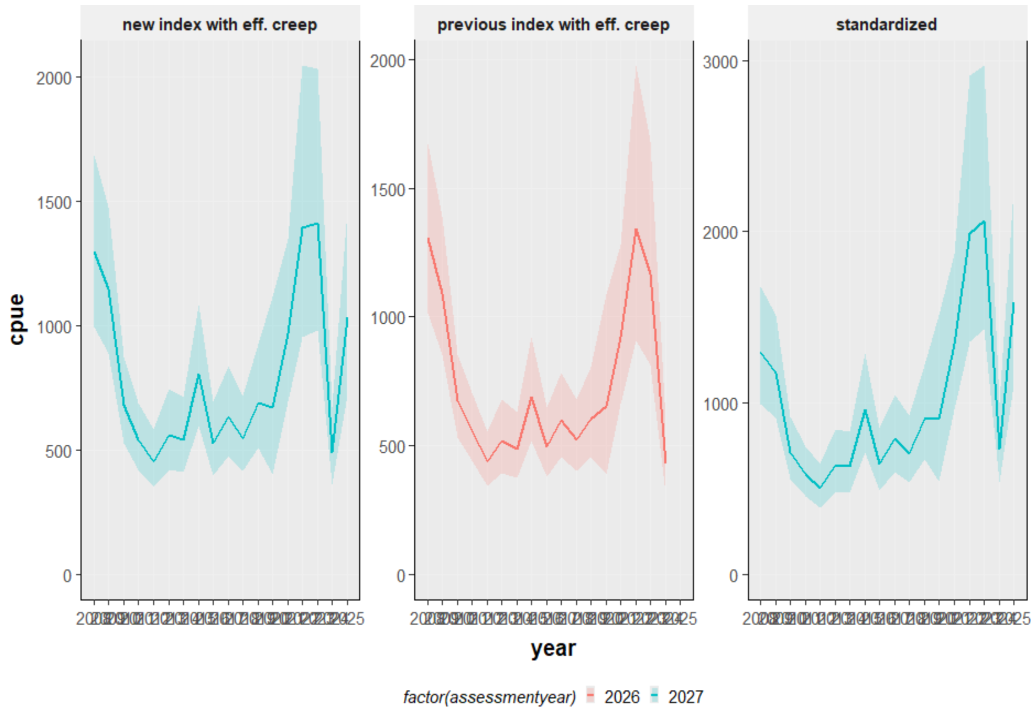


Figure 14: GAM standardized offshore fleet CPUE for jack mackerel

```
Family: Negative Binomial(2.121)
Link function: log

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

Parametric Terms:
            df Chi.sq  p-value
year        17 381.11  < 2e-16
vesselcode2 31 912.59  < 2e-16
month       11 100.17  < 2e-16
ELE          2  21.87 1.78e-05

Approximate significance of smooth terms:
                       edf Ref.df Chi.sq p-value
s(shootlon,shootlat) 23.78  27.44  160.7  <2e-16
```

Table 19: ANOVA results with final model GAM

year	cpue	lwr	upr	type
2008	1295	996	1683	standardized
2009	1175	912	1513	standardized
2010	716	557	921	standardized
2011	583	456	746	standardized
2012	503	391	646	standardized
2013	638	481	847	standardized
2014	632	481	831	standardized
2015	960	715	1290	standardized
2016	645	489	851	standardized
2017	794	600	1052	standardized
2018	706	538	926	standardized
2019	909	675	1223	standardized
2020	907	543	1513	standardized
2021	1342	964	1870	standardized

2022	1987	1356	2911	standardized
2023	2061	1432	2968	standardized
2024	735	539	1003	standardized
2025	1584	1111	2257	standardized
2008	1295	996	1683	new index with eff. creep
2009	1145	889	1476	new index with eff. creep
2010	680	529	875	new index with eff. creep
2011	541	423	691	new index with eff. creep
2012	454	353	584	new index with eff. creep
2013	562	423	746	new index with eff. creep
2014	543	413	714	new index with eff. creep
2015	804	598	1080	new index with eff. creep
2016	527	399	695	new index with eff. creep
2017	632	477	837	new index with eff. creep
2018	548	418	718	new index with eff. creep
2019	688	511	926	new index with eff. creep
2020	669	401	1116	new index with eff. creep
2021	966	693	1345	new index with eff. creep
2022	1394	951	2042	new index with eff. creep
2023	1410	979	2030	new index with eff. creep
2024	490	359	669	new index with eff. creep
2025	1030	722	1468	new index with eff. creep

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.

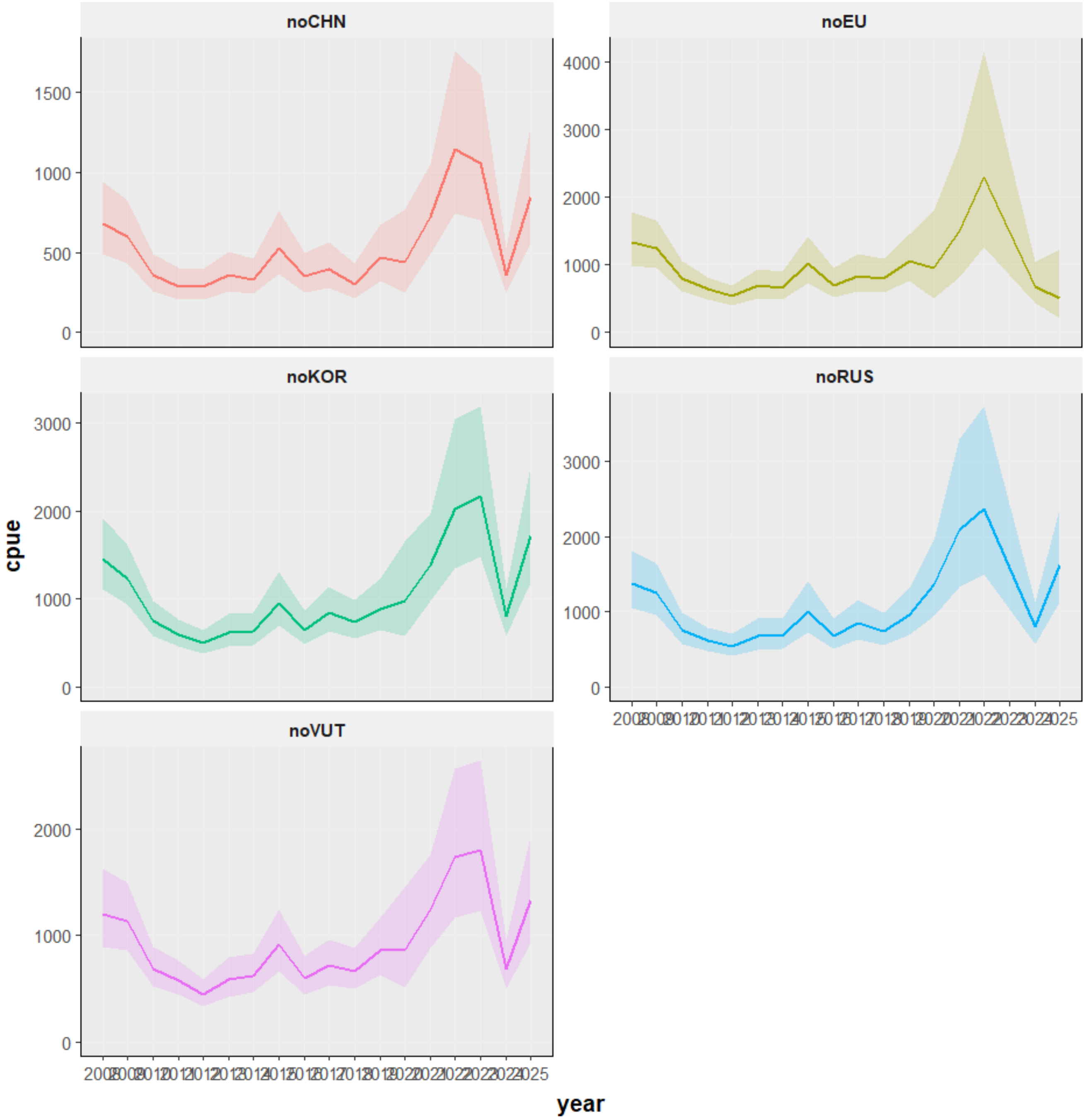
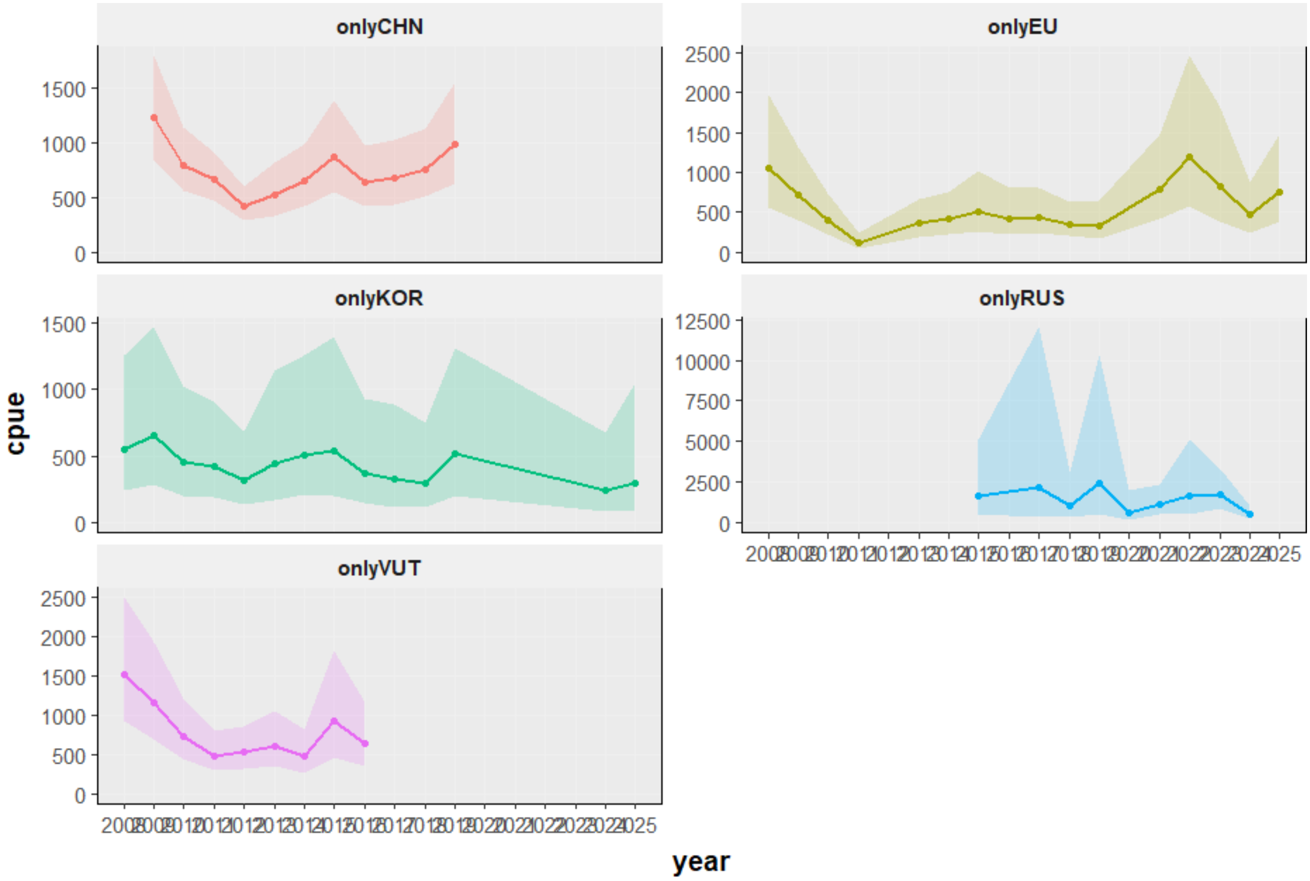


Figure 15: Jack mackerel leave-one-out analysis (leaving out one of the fleets)

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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