BENCHMARK WORKSHOP ON SELECTED STOCKS IN THE WESTERN WATERS IN 2021 (WKWEST)

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International Council for the Exploration of the Sea
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H.C. Andersens Boulevard 44–46
DK-1553 Copenhagen V
Denmark
Telephone (+45) 33 38 67 00
Telefax (+45) 33 93 42 15
www.ices.dk
info@ices.dk

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Editors

Mathieu Lundy • Arved Staby

Authors

Jonathan Ball • Paul Bouch • Neil Campbell • Erwan Duhamel • Angela Larivain • Catarina Maia • Claire Moore • Richard Nash • Rosana Ourens • Lionel Pawlowski • Maria Grazia Pennino • John Gabriel Ramírez • Alberto Rocha • Jeroen Van Der Kooij

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i Executive summary

The Benchmark Workshop for selected Western Stocks (WKWEST), met to progress toward achieving updated assessment methods. Five stocks were proposed for benchmark through WKWEST, plaice (*Pleuronectes platessa*) in in ICES divisions 7 h–k (ple.27.7h–k), sole (*Solea solea*) in divisions 8.c and 9.a (sol.27.8c9a), sardine (*Sardina pilchardus*) in Subarea 7 (pil.27.7), red gurnard (*Chelidonichthys cucculus*) in subareas 3 to 8 (gur.27.3–8) and Pollack (*Pollachius pollachius*) in subareas 6–7 (pol.27.67). Following the data evaluation and progress meeting, it was considered that the issues identified that changes and improvement for the assessment methods of pollack would not be possible. In response to this, the issue list for the stock was updated. It was proposed that this stock would not be taken to the benchmark meeting and that more work was needed. Prior to the benchmark, plaice was considered a data poor, assessed as a category 3 stock. The issues identified prior to the benchmark were focused achieving adoption of a more appropriate assessment model with better data coverage of the assessment area, including discard estimates and to explore development of tuning series. The outcome of the benchmark improved the ability to effectivity assess the status of plaice in 27.7h–k. Although the stock is proposed to remain as category 3, the improvements to the quality of data and assessment method mean that the complete stock area (27.7.h–k) can be assessed. A newly developed survey index for this stock provided some important stability to our perception of this stock. The collated commercial and survey data enabled estimation a number of important life history parameters for this stock. The final assessment method selected for this stock was stochastic surplus production model in continuous time (SPiCT). This method provided stock trends and biological references points, which were then used to provide category 3 advice for this stock. Red gurnard has been considered a Category 6 stock. During WKWEST a newly developed index of abundance made it possible to assess the stock as an ICES category 3 stock. Issue persist with regard to confidence of the landing series due to 'mixed' species reported landings, although it was considered that these data could be used to provide a precautionary understanding of harvest level. WKWEST concluded and agreed way of assessing the stock: Trend-based assessment using the combined biomass index of the delta lognormal GLM model. F_{proxy} (ratio of landings / biomass estimate) as an indicator of harvest level. Prior to the benchmark, the sardine assessment was classified as category 5. The aim of benchmark was to improve and assure the data quality and explore potential tuning series. WKWEST concluded that the landings and the biomass data provided by the PELTIC survey were appropriate to assess the stock and provide advice. The availability of the biomass data to assess the stock implies an upgrade of stock category, being now classified as category 3. Consequently, the ICES guidance on advice rules for stocks of short-lived species in category 3 were explored. The benchmark agreed that a SPiCT model can be used to assess the status of the stock based on the relative biomass and fishing mortality to the reference points (B_{MSY}, F_{MSY}). However, given the high uncertainty associated with absolute values of biomass, fishing mortality and reference points, the model is not appropriate to provide advice. Prior to the benchmark sole was considered a data-limited stock, and it was classified as category 5 stock, as only catch data were available. There was no analytical assessment for sole in this area prior to WKWEST. At WKWEST among all the data-poor methods implemented (i.e., LBI, LBPSR, MLZ and SPiCT) it was agreed that the LBI approach was currently the most adequate for this stock. An index of biomass is was developed agreed as the weighted sum of the Portuguese LPUE and the Spanish Bayesian survey index.

ii Expert group information

Expert group name	Benchmark Workshop on selected stocks in the Western Waters in 2021 (WKWEST)
Expert group cycle	Annual
Year cycle started	2021
Reporting year in cycle	1/1
Chairs	Arved Staby, Norway (External Chair)
	Mathieu Lundy, Northern Ireland (ICES Chair)
Meeting venue and dates	1–4 December 2020, Online meeting (17 participants)
	22–26 February 2021, Online meeting (21 participants)

1 Plaice (ple.27.7h–k)

1.1 Why a benchmark

Plaice in ICES divisions 7 h–k is considered data-poor and is currently a category 3 stock. The issues identified prior to the benchmark are outlined in Table 1 and summarized briefly below:

- **Assessment area:** There is a lack of information on the current state of the stock across the whole area. Although the TAC for this stock is set at the level of 7hjk, the assessment is run on plaice in 7j only, as historically no age-disaggregated data were available for 7.h. Although there was limited improvement to the age data supplied by countries to InterCatch, there was a vast improvement in length and catch data supplied. Which enabled an assessment of the whole stock area.
- **Discard rates:** Historically, no discards included in this assessment as they were not submitted to InterCatch. Increased discard information was made available through the data call for this benchmark. Although this information was highly variable, it provides the first estimates of discarding across the whole stock area. The addition of information on discard rates for is essential for the effective management of this bycatch fishery.
- **Tuning series:** Previously no survey indices had been available for this stock as no specific survey covered the whole stock area and few were designed to effectively capture plaice. VAST was used to combine six fisheries-independent surveys, producing a biomass abundance index for this stock, covering the full stock area. This was used to replace the LPUE that was previously used. This LPUE was not considered fit for purpose due to strong fluctuations in time-series (driven by low sampling levels and individual fisher behaviour), and limited ability to track cohorts.
- **Assessment methods:** Prior to the data call benchmark it was hoped to focus on developing an age-based method for the whole stock area (Table 1). However, the data provided by countries was not sufficient. Therefore, four data-limited methods which focused on length were tested during the benchmark (LBI, MLZ, LBSPR and SPiCT).

Table 1. Summary of benchmark questions outlined prior to the benchmark.

Issue	Problem/Aim	Work needed / possible direction of solution	Data needed to be able to do this: are these available / where should these come from?	Responsible expert from WG	External expertise needed at benchmark type of expertise / proposed names
(New) data to be considered and/or quantified	Problem: Data from 7h is currently not included in the model Aim: Examine inclusion of this information in the assessment.	Data exploration – are the data consistently available across the area, from enough gear types/ quarters, to be able to raise for the remaining métiers where no such data are provided	These data should be available in InterCatch	Stock coordinator	
Discards	Problem: There are currently no discards included in the assessment, as they are not submitted to InterCatch. It may be useful to examine alternative methodologies for estimating these using methods which are capable of operating with missing data points. Aim Investigate the method by which missing data can be estimated, and apply to available data.	Explore possible methods for discard estimation, and use resulting data in assessment to compare the impact on forecasts	They are currently not available, they should come from InterCatch,	Stock coordinator	
Tuning series	Explore possibility a survey index	Run assessment with inclusion of survey index from IAMS, IBTS. And examine their impact on the assessment.	Data are available from DATRAS	Stock coordinator	
Tuning series	Potential new commercial tuning data for 7h	Investigate the possibility of a commercial index from 7h.	Currently not available		
Assessment method	Consider alternative methods	Investigate use of SAM and a4a		Stock Coordinator	A4a expert

Issue	Problem/Aim	Work needed / possible direction of solution	Data needed to be able to do this: are these available / where should these come from?	Responsible expert from WG	External expertise needed at benchmark type of expertise / proposed names
Biological Reference Points	Update as required				
Other	Data compilation	Streamlining of catch-at-age data compilation for Celtic flatfish. Consistency and standardisation of métiers across stocks			
Age	Results of age validation exercise	Calibration of ageing data	To be available by 1st October 2019	Marcin Blaszkowski (Ireland).	

1.2 Summary of decision

This benchmark improved our ability to effectivity assess the status of plaice in 27.7h–k. Although the stock will remain as category 3, the improvements to the quality of data and assessment method mean that the complete stock area (27.7.h–k) can be assessed, as opposed to just 27.7.j. Commercial data, specifically discard rates were vastly improved. This enabled the working group to determine a more realistic average discard rate for this stock. The development of a new survey index for this stock provided some important stability to our perception of this stock, which we now consider to follow similar trends in abundance to those of neighbouring plaice stocks.

The increased availability of commercial and survey data enabled the working group to estimate a number of important life-history parameters for this stock. These estimates were used to apply a number of data-limited assessment methods on this stock. The final assessment method selected for this stock was stochastic surplus production model in continuous time (SPiCT). This method provided stock trends and biological references points, which were then used to provide category 3 advice for this stock.

1.3 Compilation of available data

A full summary of the data made available to the benchmark group can be found in the data compilation report (ICES, 2020). Below is a brief summary of the main data sources used within the assessment model testing. Annex 1.

1.3.1 Commercial catch

Catch data were submitted to InterCatch and accessions by three Member States: France, UK (England) and Ireland. Each country submitted varying length of time-series, covering different ICES divisions, gears and catch categories. These data can be divided into three main categories: length samples, age samples and discard rates. Age data were considered poor, and was therefore not the focus of the models developed. Length and discard rates are described in the proceeding sections.

Length information

France submitted 9265 landings length measurements, for 27.7h, spanning six years (2014–2019) (Figure 2.1). These lengths were majoritively taken from two otter trawl métiers, OTB_DEF_100–119 and OTT_DEF_100–119 (Figure 1.1). No discard lengths were supplied.

Ireland submitted 79 214 landings and 50 320 discard length measurements. Covering ICES divisions 27.7.j and 27.7.k, from 2004–2019 (Figure 1.2). These lengths come from five métiers GNS_DEF_120–219_0_0_all, MIS_MIS_0_0_0_HC, OTB_CRU_100–119, OTB_CRU_70–99, OTB_DEF_100–119_0_0_all, OTB_DEF_70–99_0_0_all, SSC_DEF_100–119_0_0_all.

England submitted 25 439 landings and 5874 discard length measurements, covering 27.7.h, with some minor sampling in 27.7.j (Figure 1.3). The length measurements came mostly from one métier TBB_DEF_70–99_0_0_all, with some minor sampling in set net fisheries (GNS and GTR).

Where discarding lengths and abundances have been submitted, it is clear that each country and métier show very different discarding patterns. Although the minimum conservation reference size for this stock is 27 cm, all métiers are discarding above this size. The maximum length within the dataset is 68 cm.

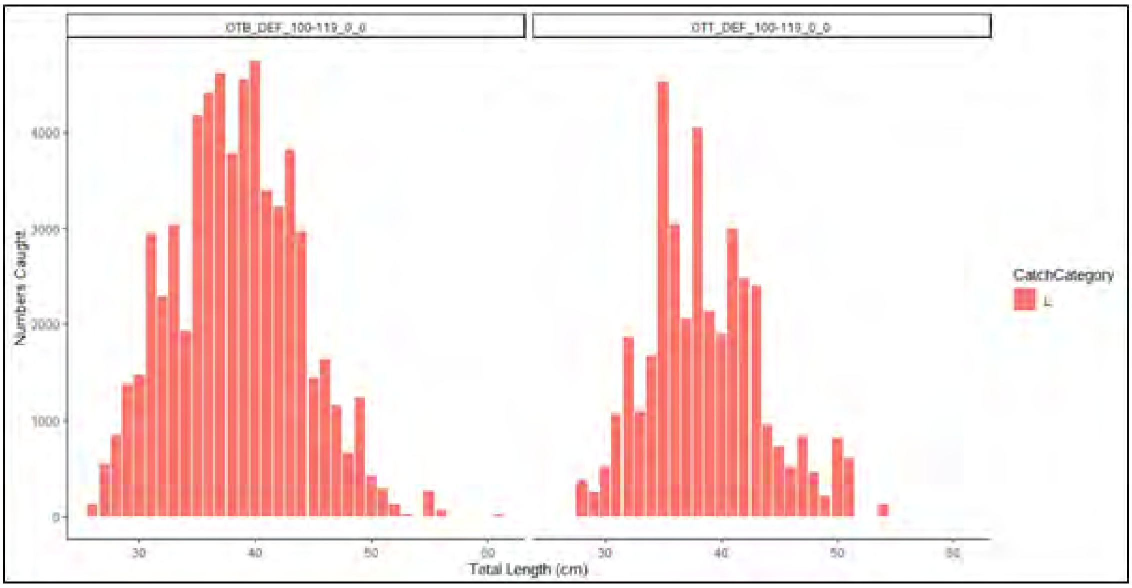

Figure 1.1. Total raised numbers-at-length (cm) submitted by France to InterCatch (2014–2019) for landings (L). No discard information submitted.

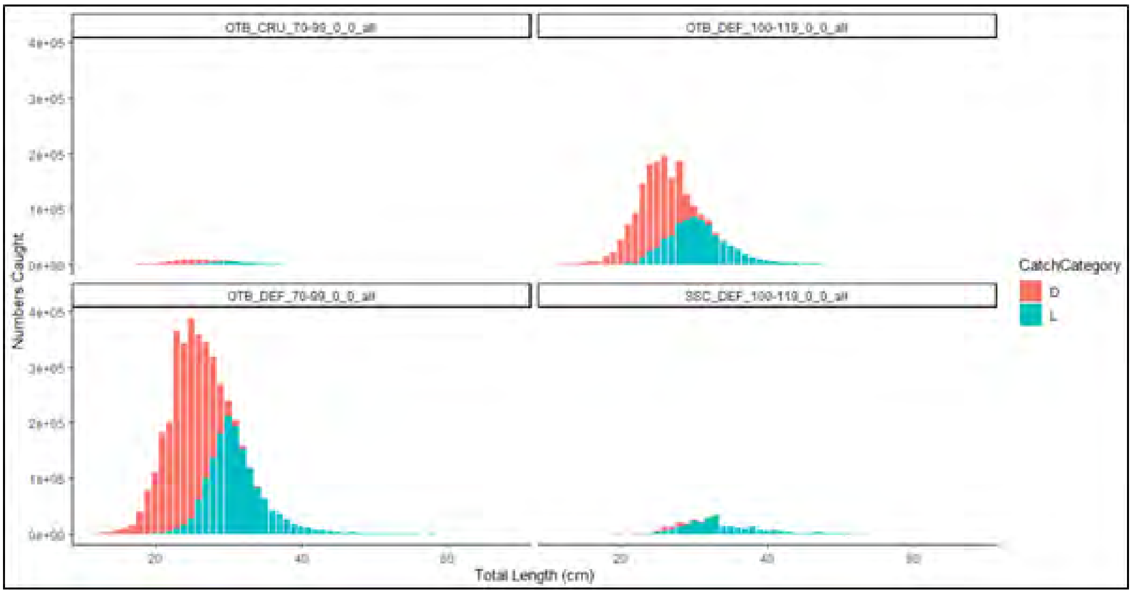

Figure 1.2. Total raised numbers-at-length (cm) submitted by Ireland to InterCatch (2004–2019) for landings (L) and discards (D).

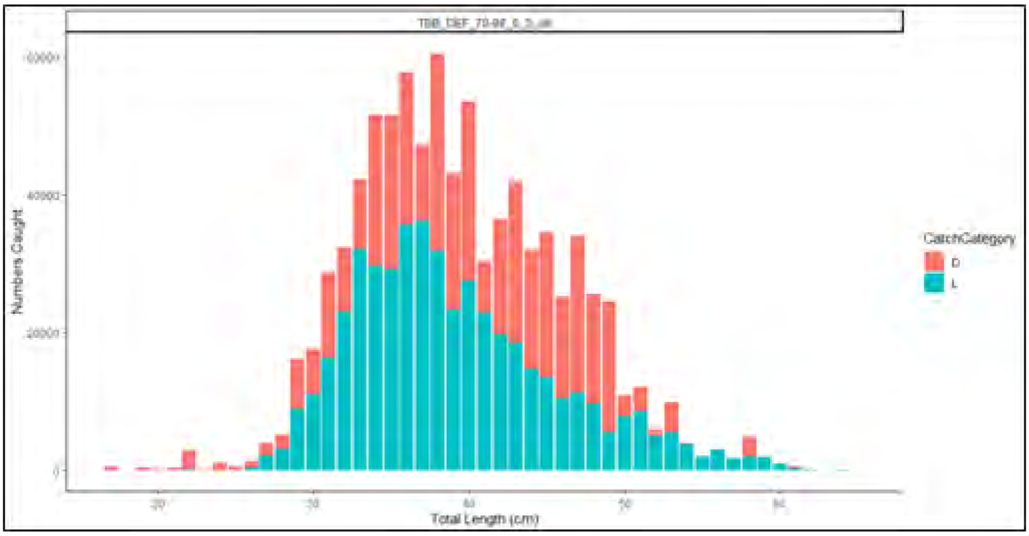

Figure 1.3. Total raised numbers-at-length (cm) submitted by UK (England) to InterCatch (2000–2019) for landings (L) and discards (D).

Catch series

Countries provided data to InterCatch back as far as 2004. In the previous assessment, there were some data made available for ICES divisions 27.7.j back as far as 1996, however these are not available in InterCatch and only feasible for Ireland. Therefore, to extend the time-series and capture the known peak of the fishery, official landings statistics were used (Figure 1.4). This provides important information in our understanding of the fishery as it captures the peak of the fishery, which occurred before 2004. The benchmark group decided to cut the time-series at 1995 to avoid the inclusion of two very high peaks at the beginning of the time-series as we are unable to verify the validity of those early peaks in the time-series. Where the two time-series overlap, three is a good match (Figure 1.4).

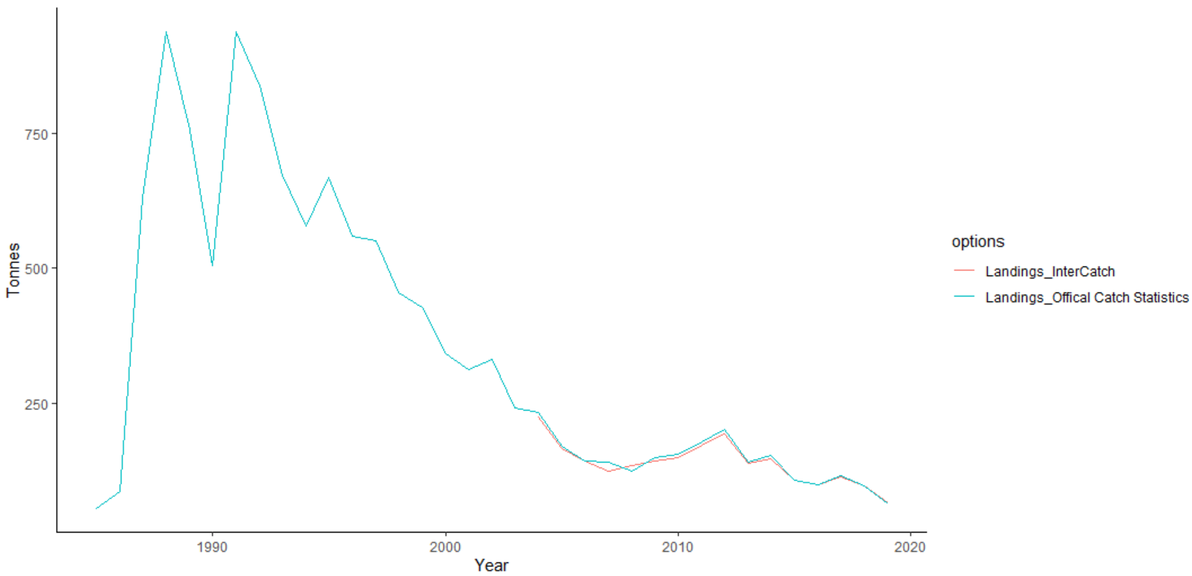

Figure 1.4. Comparison of officially reported landings (1985–2019) and InterCatch landings (2004–2019).

There were sufficient data to calculate discard rates, these were calculated for a number of the Irish and English fleets for a number of years. These rates are highly variable over time (Figure 1.5), this variability may be driven by low and variable sample sampling numbers over time (details van be found in the data compilation report, ICES, 2020). A number of options were considered for the inclusion of these discards into the catch time-series (Figure 1.6):

1. **Raw discard rate applied to sampled years (2004–2019).** This is not recommended as the rate is highly variable, and it does not.
2. **Average discard rate from InterCatch of 34% applied to the sampled years (2004–2019).** Less variable, but doesn't provide any information discarding in the beginning of the time-series.
3. **Average discard rate from InterCatch of 34% applied to the full time-series (1985–2019).** Less variable, this however inflates discards to an unrealistically high value in the beginning of the time-series, when TAC was not restrictive.
4. **Combination** – Average discard rate from InterCatch of 34% applied to the sampled years (2004–2019) and then a tapering discard rate back to 10% in the peak of the fishery in 1990, and fixed at 10% back to 1985. This is the most realistic way of applying discards to the whole time-series.

The benchmark working group concluded that the best option was to apply an average discard rate to the InterCatch time-series (2004–2019). This average of 34% would have to be looked at by the single species working group on an annual basis to account for new sampling and new patterns.

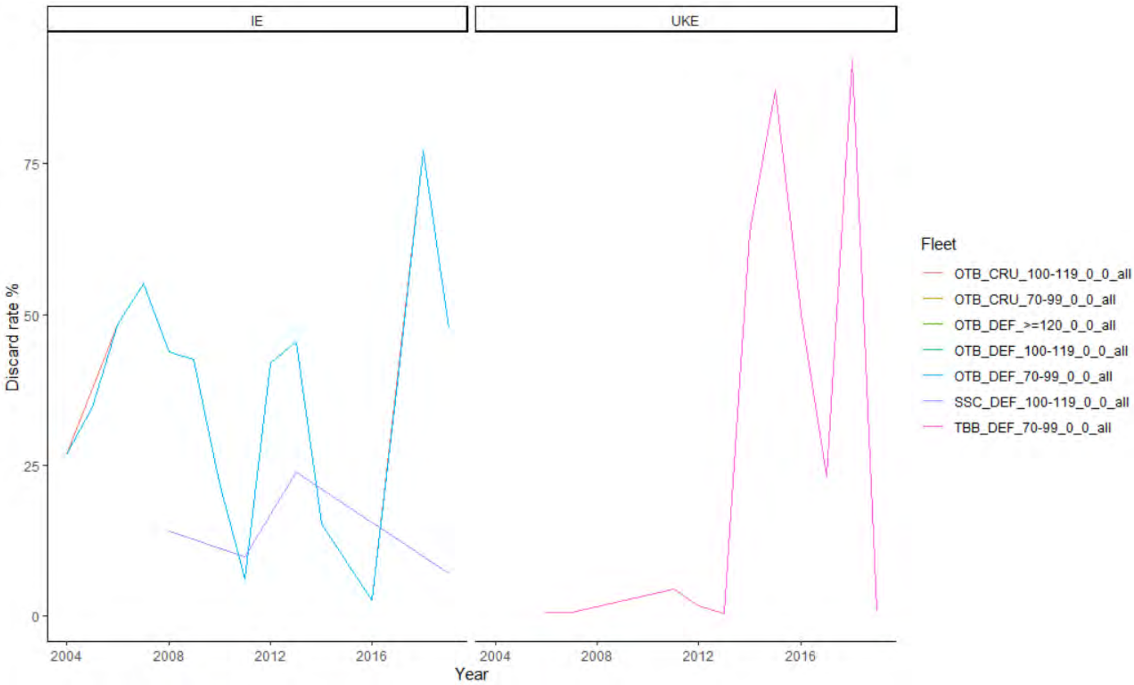

Figure 1.5. Summary of discard rates provided to InterCatch by Ireland (IE) and England (UKE).

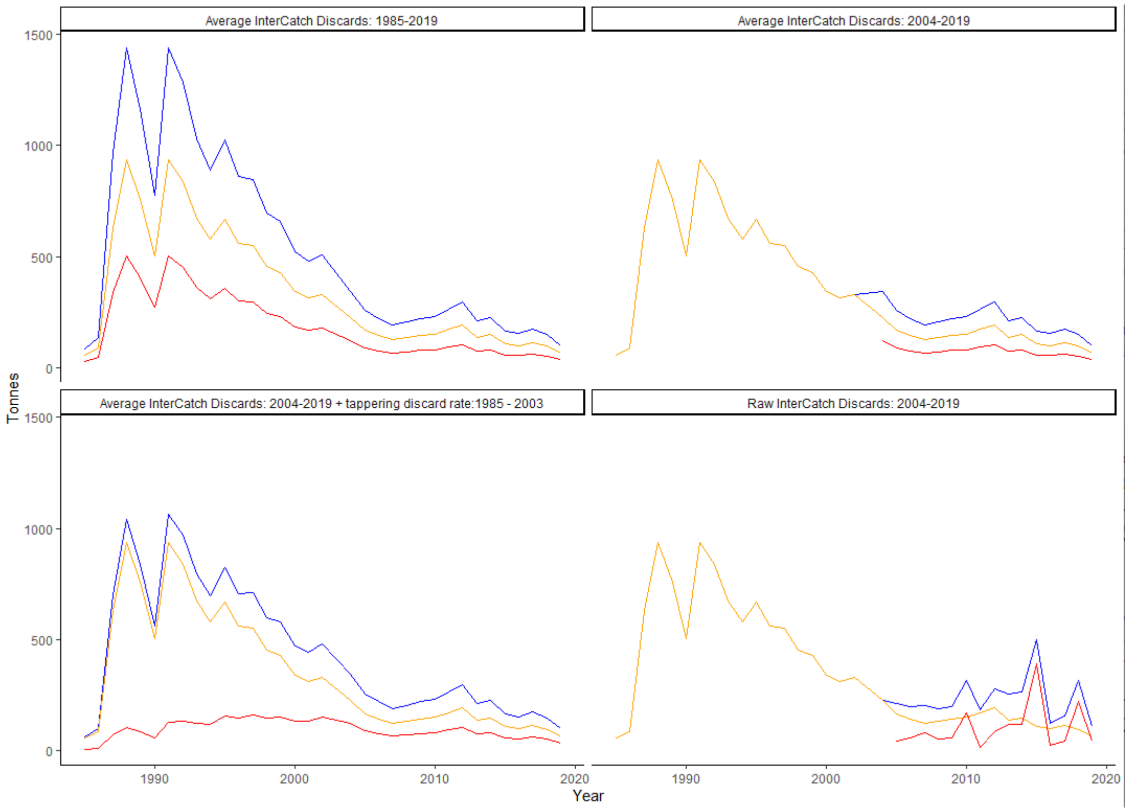

Figure 1.6. Possible option for catch time-series, discards (red), landings (yellow) and catch (blue).

1.3.2 Survey Data – fishery-independent biomass index

Claire Moore, Cóilín Minto, Paul Dolder

The final survey indices included in the model was based on a paper by Dolder *et al.* (2018). This method combined seven fisheries-independent surveys were combined to model the biomass of plaice in this stock area using VAST, which is a Vector Autoregressive Spatio-temporal model in R (Thorson *et al*., 2016). This model implements a spatial delta-generalized linear mixed model (delta-GLMM) which is capable modelling univariate and multivariate spatio-temporal species distributions, and is capable of dealing with zeros and a continuous positive distribution (Thorson, 2019).

The model was parametrised following the guidelines set out by Thorson *et al*. (2019). Haul level data from seven fisheries-independent surveys undertaken in the Celtic Sea (1997–2019) (Table 1.2) was used. The coverage of these surveys varies in space and time, a full description of which can be found in Table 1.2 and Figure 1.4. The raw survey data were checked for quality (specifically, the estimated weights of the catch numbers-at-length were checked against the reported catch weights). For each valid haul, the catch weight, tow duration, tow position (midpoint), survey series and year were used as input values for the VAST model. The model was specified to have spatial autocorrelation but no temporal autocorrelation (i.e. years are independent). VAST can optionally estimate, and correct for, differences in catchability between the two survey series as there is a significant spatial overlap between the two surveys. The model first estimates the likelihood of occurrence and then the biomass using a gamma error distribution or the abundance using a lognormal error distribution. Historically none of these surveys were used to estimate abundances of plaice as individually they do not cover the full stock area, spatially/ temporally, and now of the surveys have been designed with this stock and species in mind. VAST offers a number of advantages over more traditional ways of estimating abundances. It has an ability to deal with gaps in survey coverage, and an ability to account for differences in catchability between surveys or vessels, providing an objective way to combine multiple indices even when the gear is not standardised.

The spatial domain was defined as 1000 knots, and implemented using k-means clustering to give knot positions proportional to sampling intensity (Thorson, 2019) (Figure 1.5). Residual diagnostics on the encounter probability appeared acceptable (Figure 1.6). Visualisation of the Pearson's residuals of positive catches (Figure 1.7 a) and encounter probability (Figure 1.7 b) show no strong patterns. These plots are the default output from the package, however in the future the presence/absence residuals should be revisited. The estimated survey biomass indices are presented in Table 1.3, along with associated uncertainty. Visualisation of spatio-temporal variability in estimated log density of plaice in ICES Division 7h–k (Figure 1.8), show distributional trends in areas of high abundance that mirror that of the known fishery, with high incidence of reported landings occurring in areas similar to the biomass from this VAST index, along the southwest coast of Ireland and the southwest coast of the UK. It is clear that these patches of high abundance spill over into adjoining stock area, plaice 7fg, where landings are substantially higher than the plaice in 27.7h–k.

Table 1.2. Summary of surveys used in the model.

Survey	Years	Quarters	Gear	Sources	Wing spread
IGFS	2003–2019	4	Otter	DATRAS	Available at haul level
IAMS	2016–2019	1	Otter & Beam	DATRAS	Available at haul level
EVOHE	1997–2019	4	Otter	DATRAS	Available at haul level
WGCFS	1997–2004	1,2,4	Otter	CEFAS	Set to 21 m (average of other otter trawl surveys in series)
SWBEAM	2006–2016	1	Beam	CEFAS	Set to 4 m (size of gear)
SWIBTS	2003–2011	4	Otter	CEFAS	Set to 21 m (average of other otter trawl surveys in series)

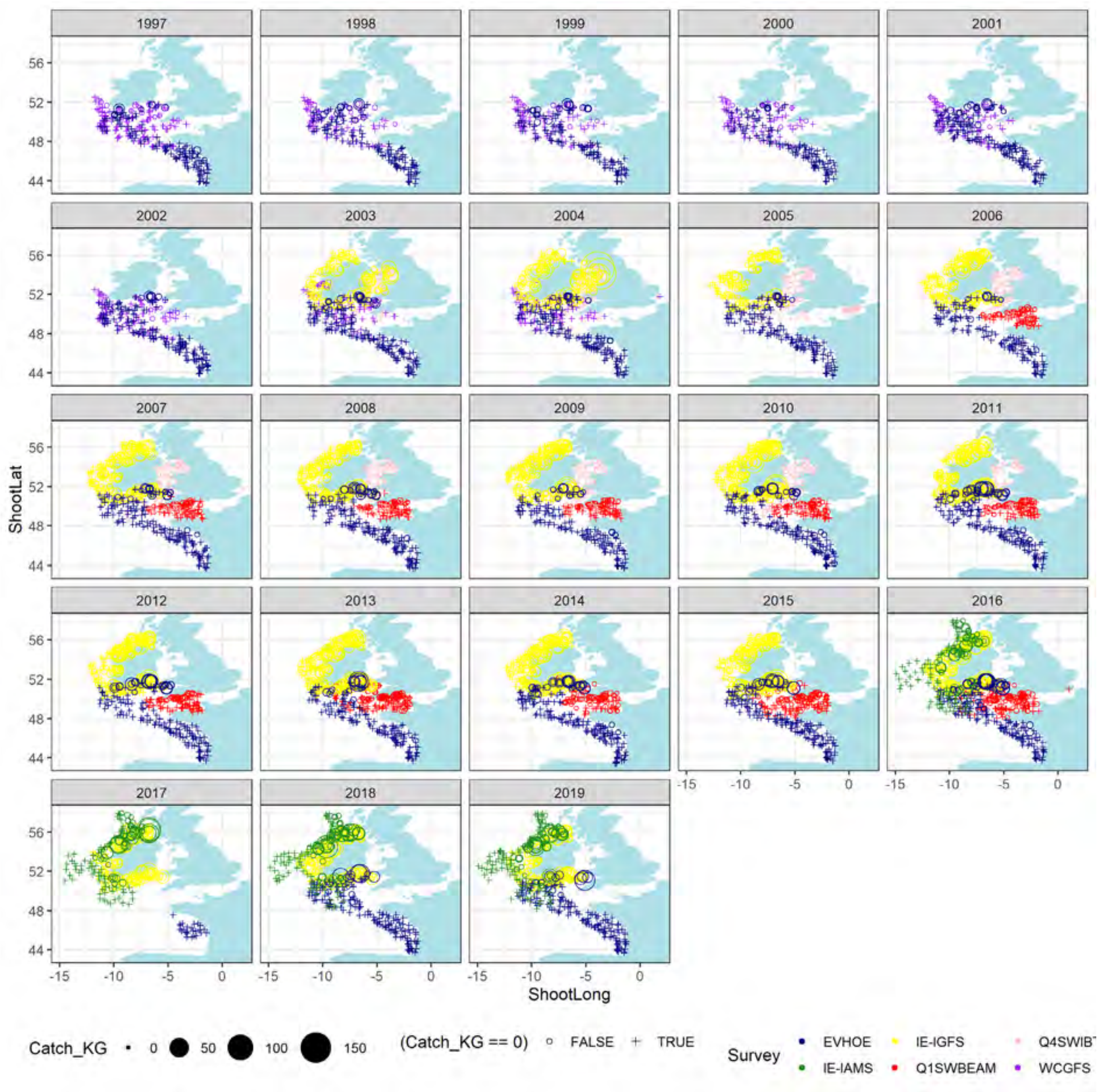

Figure 1.4. Plaice in area 7h–k: survey numbers per haul by year. Each point represents haul with a positive count shown as a circle and a zero as a '+' symbol. Circle diameter is proportional to the count. Colours denote the surveys.

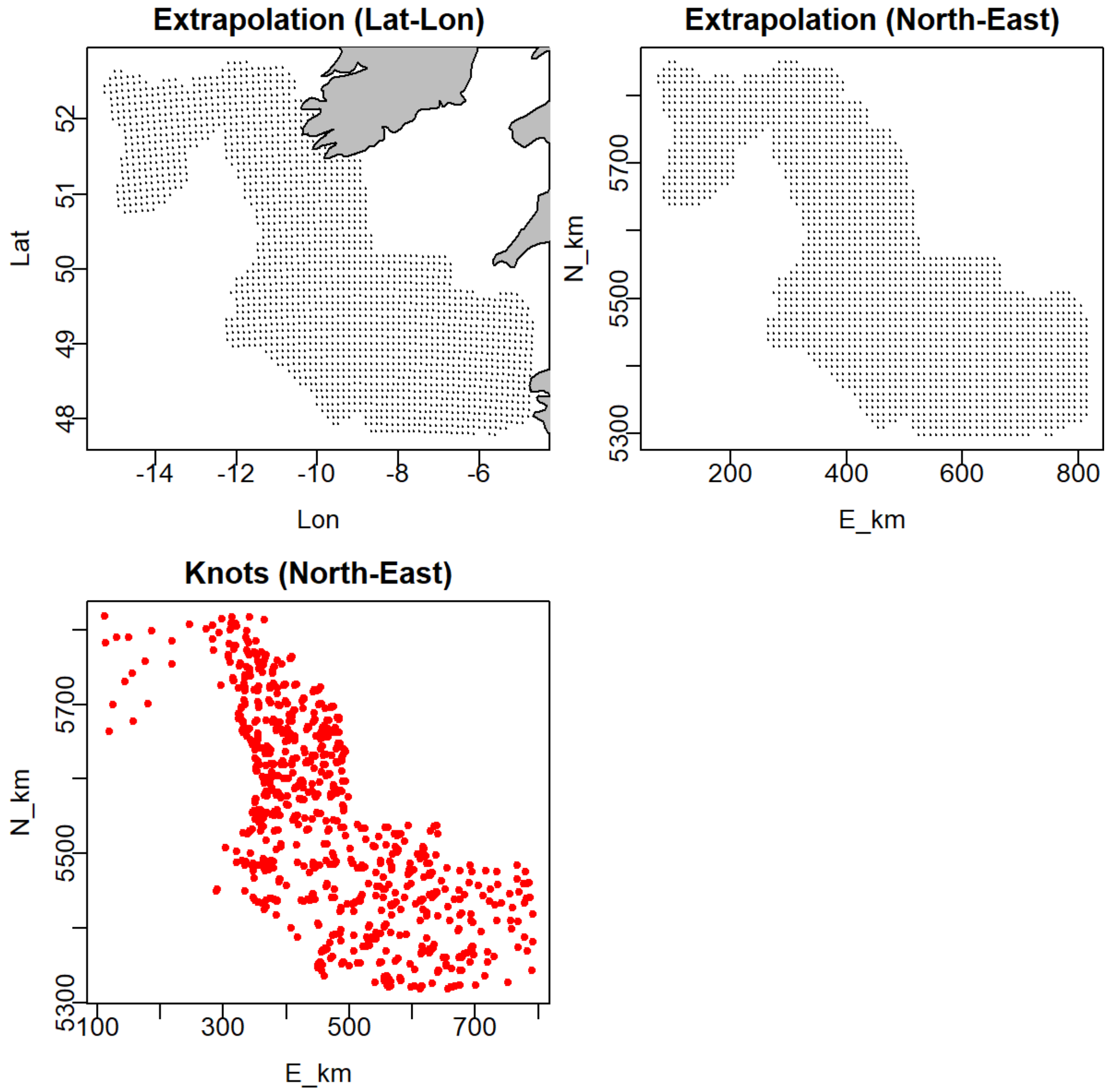

Figure 1.5. The spatial area defined within the model in terms of latitude and longitude (top left), kilometres (top right) and knots (bottom).

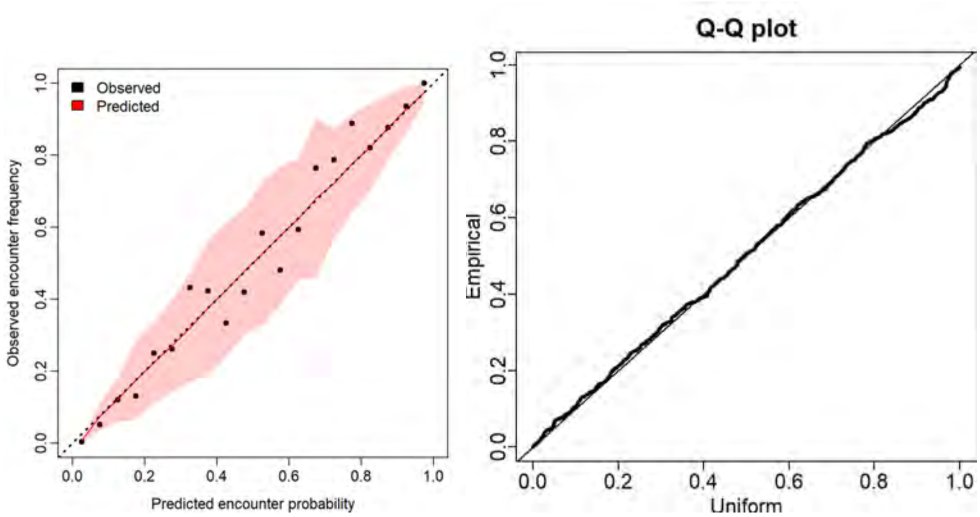

Figure 1.6. Residual diagnostics showing predicted encounter probability against observed encounter probability (left) and QQ plot for positive catches (right).

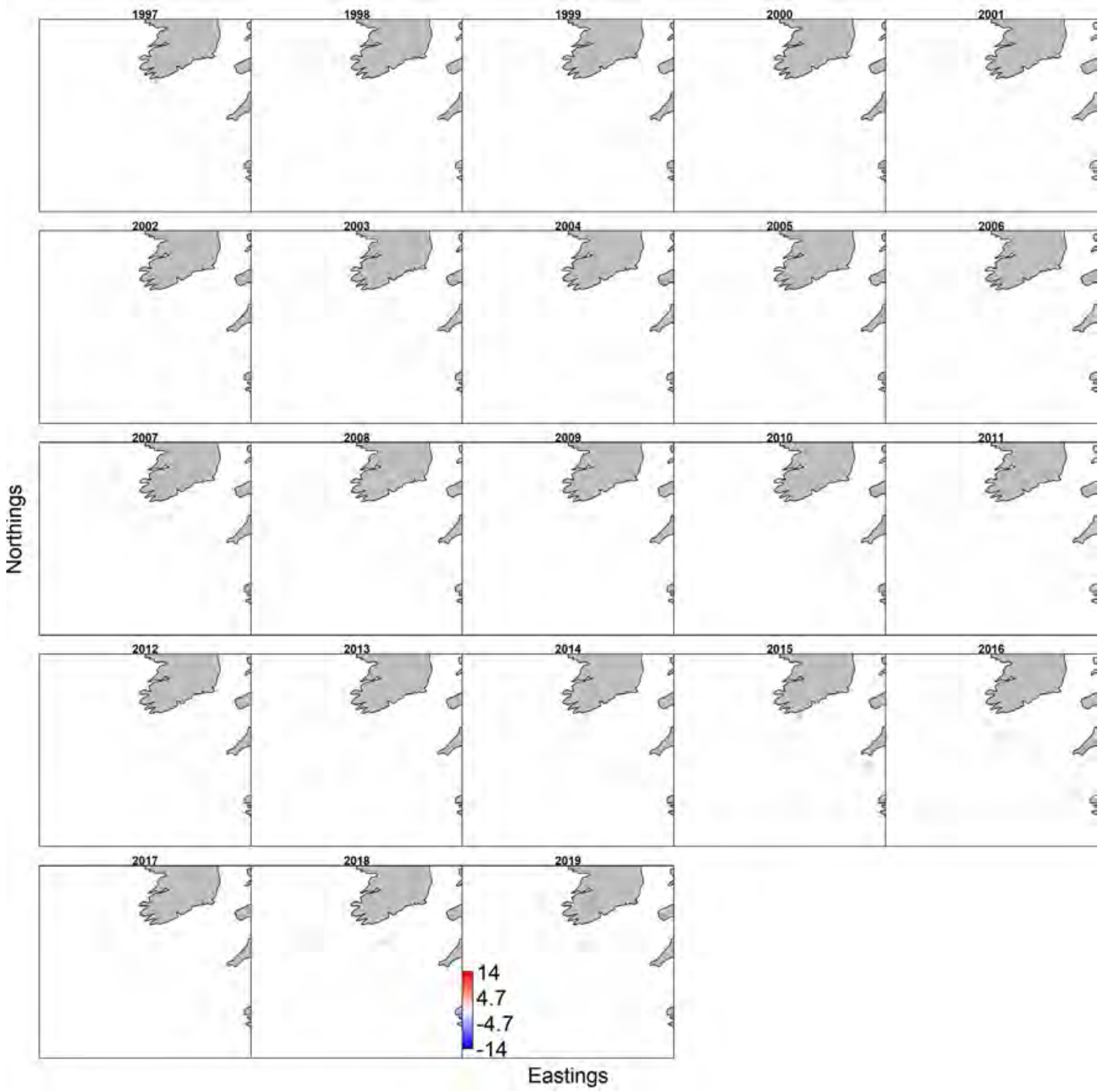

Figure 1.7. (a) Spatio-temporal persons residuals of encounter probability of plaice in ICES division 7h–k.

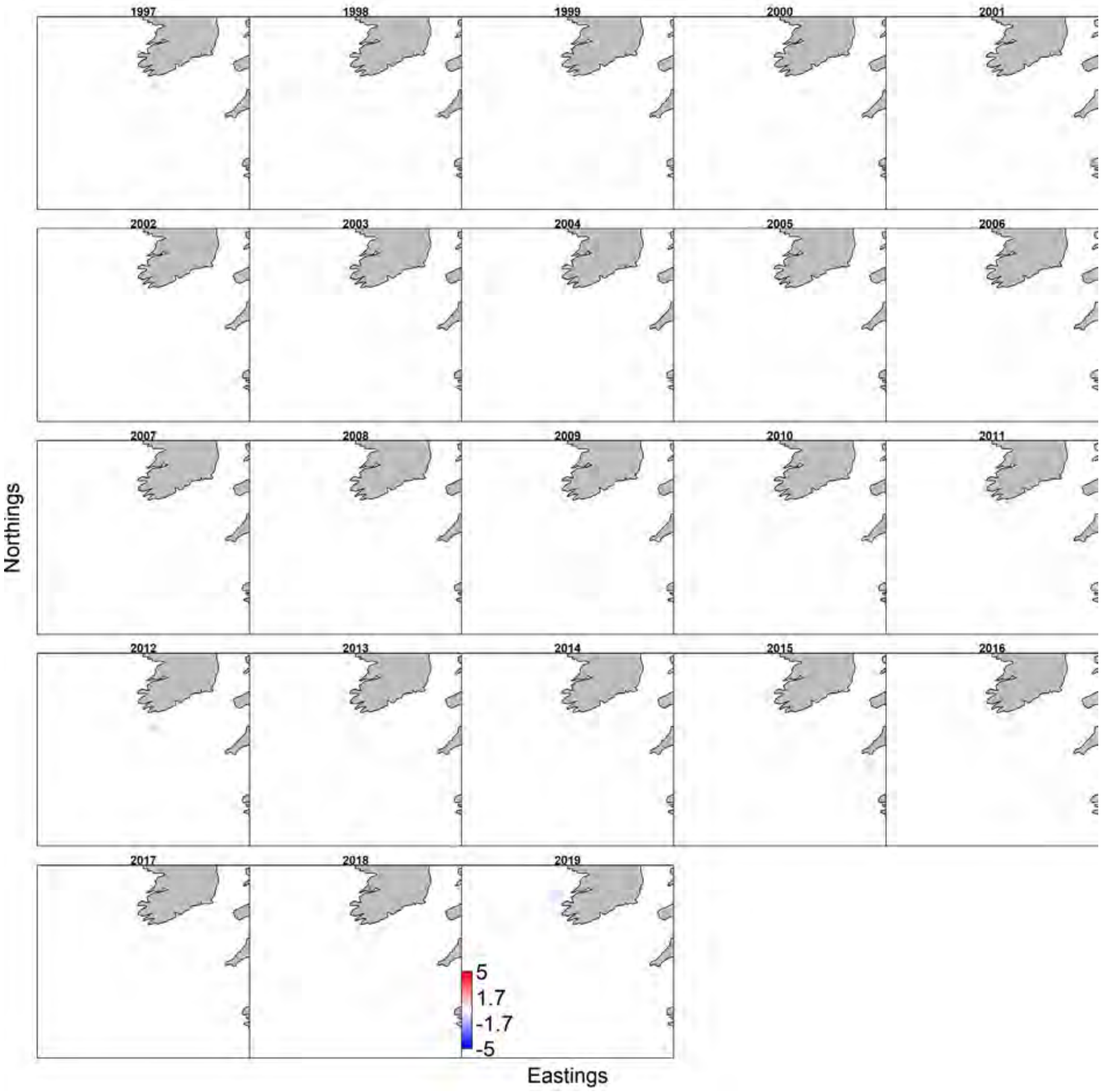

Figure 1.7. (b) Spatio-temporal persons residuals of positive catches of plaice in ICES division 7h–k.

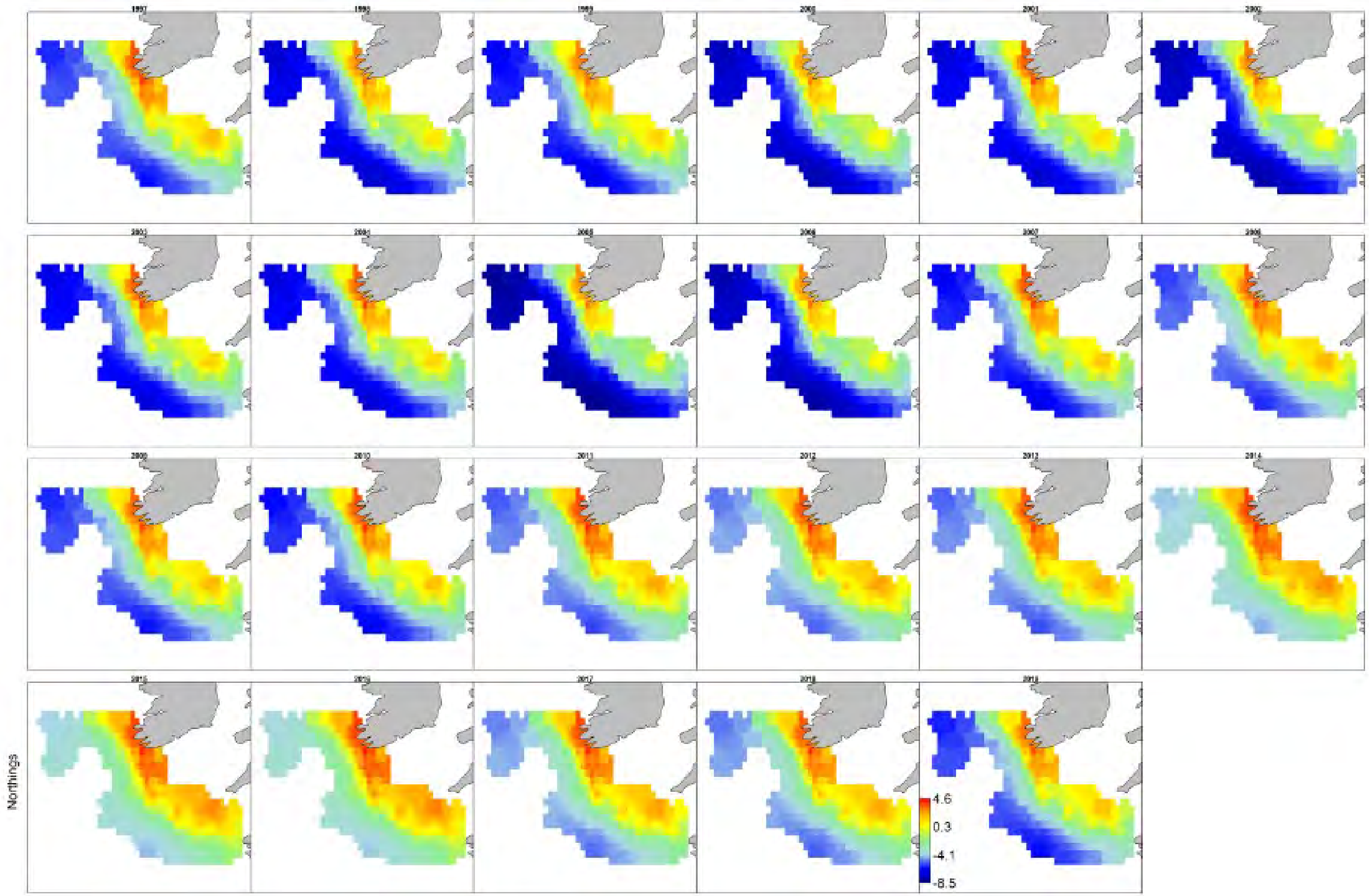

Figure 1.8. Spatio-temporal variability in estimated log density of plaice in ICES division 7h–k.

Table 1.3. Estimated biomass (tonnes) of plaice in ICES divisions 27.7h–k and associated uncertainty; standard deviation (log and tonnes).

Year	Biomass estimate (tonnes)	Standard Deviation (log)	Standard Deviation (tonnes)
1997	431.3054233	0.353321695	152.3895634
1998	198.6819935	0.487470906	96.85169142
1999	227.4019924	0.364315133	82.84598699
2000	131.6434975	0.531800906	70.00813129
2001	287.2999519	0.478975922	137.6097594
2002	154.0788926	0.540795382	83.32515359
2003	285.1272073	0.303835539	86.63177885
2004	267.1851944	0.335534739	89.64991435
2005	118.920992	0.409639594	48.71474692
2006	138.0178105	0.360401443	49.74181802
2007	355.5892449	0.30627808	108.9091913
2008	413.41392	0.27483437	113.6203544
2009	371.2246855	0.30658826	113.8131305
2010	372.2823148	0.279000423	103.8669234
2011	573.9590163	0.245552367	140.9369948
2012	559.3184022	0.249665586	139.6425565
2013	498.207582	0.244583636	121.8534218
2014	808.980367	0.226926851	183.5793673
2015	841.9860469	0.250179801	210.6479016
2016	948.1166424	0.206468744	195.756452
2017	628.8792937	0.274686632	172.7447354
2018	508.810814	0.25189389	128.1663353
2019	327.2707969	0.268482793	87.86657774

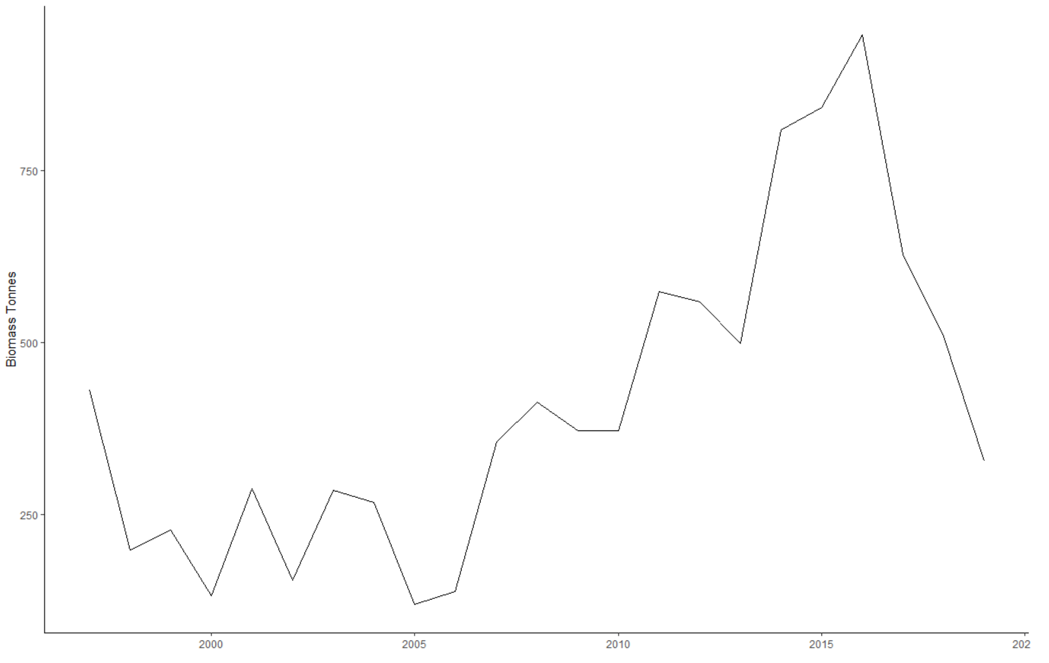

Figure 1.9. Estimated survey abundance (tonnes) of plaice in ICES divisions' 27.7.h–k.

1.3.3 Life-history parameters

Estimates of life-history parameters form an essential input to the data-limited stock assessment methods explored in this benchmark. These parameters were estimated from fisheries-independent surveys available in DATRAS. Samples of hauls provided age, length and maturity data for this plaice in 7 h–k (Figure 1.10). These samples were collected by three surveys, Irish ground fish survey (IGFS, 2003–2019), Irish anglerfish and megrim survey (IAMS, 2016–2019) and the French southern Atlantic bottom trawl survey (EVOHE, 2014–2019). Although none of these surveys are designed to capture the dynamics of this stock, they do provide the samples required to produce estimates of life-history parameters. There is an uneven sample size between the two ICES divisions, 1449 individual fish measurements in 7j and only 13 7j. Due to the low survey coverage in area 7h Cefas also provided samples of age, length and maturity from the landings component of commercial sampling in that area. However, as these data were collected from landings only, it cannot be used to calculate compare with the survey data as they did not contain the smaller length ranges, and would skew the estimated parameters.

A full summary of the parameters estimated can be found in the data compilation workshop report for this benchmark (ICES, 2020a).

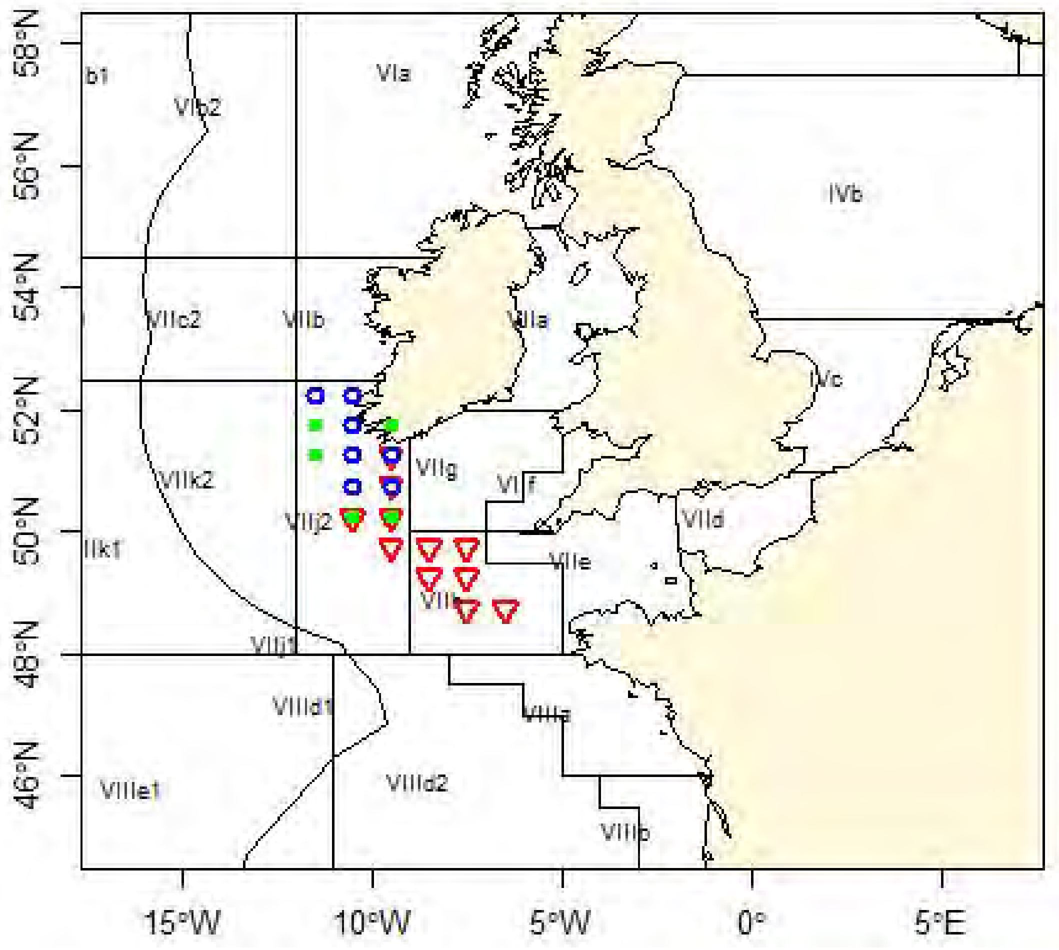

Figure 1.10. Statistical rectangles for which the three surveys available in DATRUS could provide biological sample information. IGFS (green dots), IAMS (blue circles) and EOVHE (red triangles).

1.4 Stock assessment

Four data-poor methods were evaluated to provide trends and reference points for plaice in 27.7.h–k (Table 1.4), each requiring varying inputs. The outcomes of these methods are detailed in the proceeding sections. The final method selected was SPiCT.

Table 1.4. Data-poor methods considered and available data.

Method	Data Requirements	Data availability 7j	7h	Solution
Length-based indicators (LBI)	Length-at-maturity	✓	× no data supplied	Assume 7h same as 7j
	von Bertalanffy growth parameters	✓	× tiny sample size	Assume 7h same as 7j
	Catch-at-length by year	✓	✓	✓
	Length–weight relationship parameters for landings and discards	✓	✓	✓
Mean-length Z (MLZ) – effort	Time-series of length measurements	✓	✓	✓
	von Bertalanffy growth parameters for the stock	✓	× tiny sample size	Assume 7h same as 7j
	Time-series of fishing effort	✓	✓	✓
	Natural mortality	✓	✓	✓
	Weight-at-age	✓	× tiny sample size	Assume 7h same as 7j
	Maturity	✓	× no data supplied	Assume 7h same as 7j
	Fishing effort prior to the first year of the mean length data	×	×	Derive from official landings data
Length-based spawner per recruit (LBSPR)	Length composition data of the catch	✓	✓	✓
	Ratio of natural mortality and the von Bertalanffy growth coefficient	✓	× tiny sample size	Assume 7h same as 7j
	Maximum length	✓	✓	✓
	Maturity-at-length	✓	× no data supplied	Assume 7h same as 7j
	Proportion of animals surviving to maximum age	✓	✓	✓
	Allometric exponent from the length–weight relationship	✓	✓	✓
Surplus Production model in Continuous time (SPiCT)	Landings	✓	✓	✓
	LPUE/effort	✓	✓	✓

1.4.1 LBI – Length-Based Indicators

A set of length-based indicators are used for screening catch/landings–length composition and to classify the stocks according to conservation/sustainability, yield optimization and MSY considerations. Although this method was not used to provide advice, it was used to estimate life-history parameters to input into SPiCT. Ideally this method should applied to catch data; however, discards could not be effectively included as length sampling reported to InterCatch is very variable in quality and quantity, with huge interannual variation. These indicates were produced using the following shiny app: https://scott.shinyapps.io/LBIndicator_shiny/. Assuming length at which 50% are mature (L_{mat}) is 275 cm and von Bertablanfy growth L_{inf} is 471 cm. These values were derived during the data compilation workshop for this benchmark (ICES, 2020a).

The outputs of this analysis are plots of time-series length distributions, indicators, indicators ratios, which are informative of stock status in recent years. The majority of the indicators show a decreasing trend in recent years (Figure 1.11, Table 1.5), which is also corroborated in our final choice if model (SPiCT) (Section 1.5) and our VAST derived survey index (Figure 1.9). Aside from a peak in 2016, the time-series is characterised by a lack of mega-spawners (P_{mega}) in the landings. The mean length is stable across the time-series. The mean length of the landings is close to the theoretical length of optimal yield. However, the core distribution (between 25th and 75th percentile) is below the optimal length.

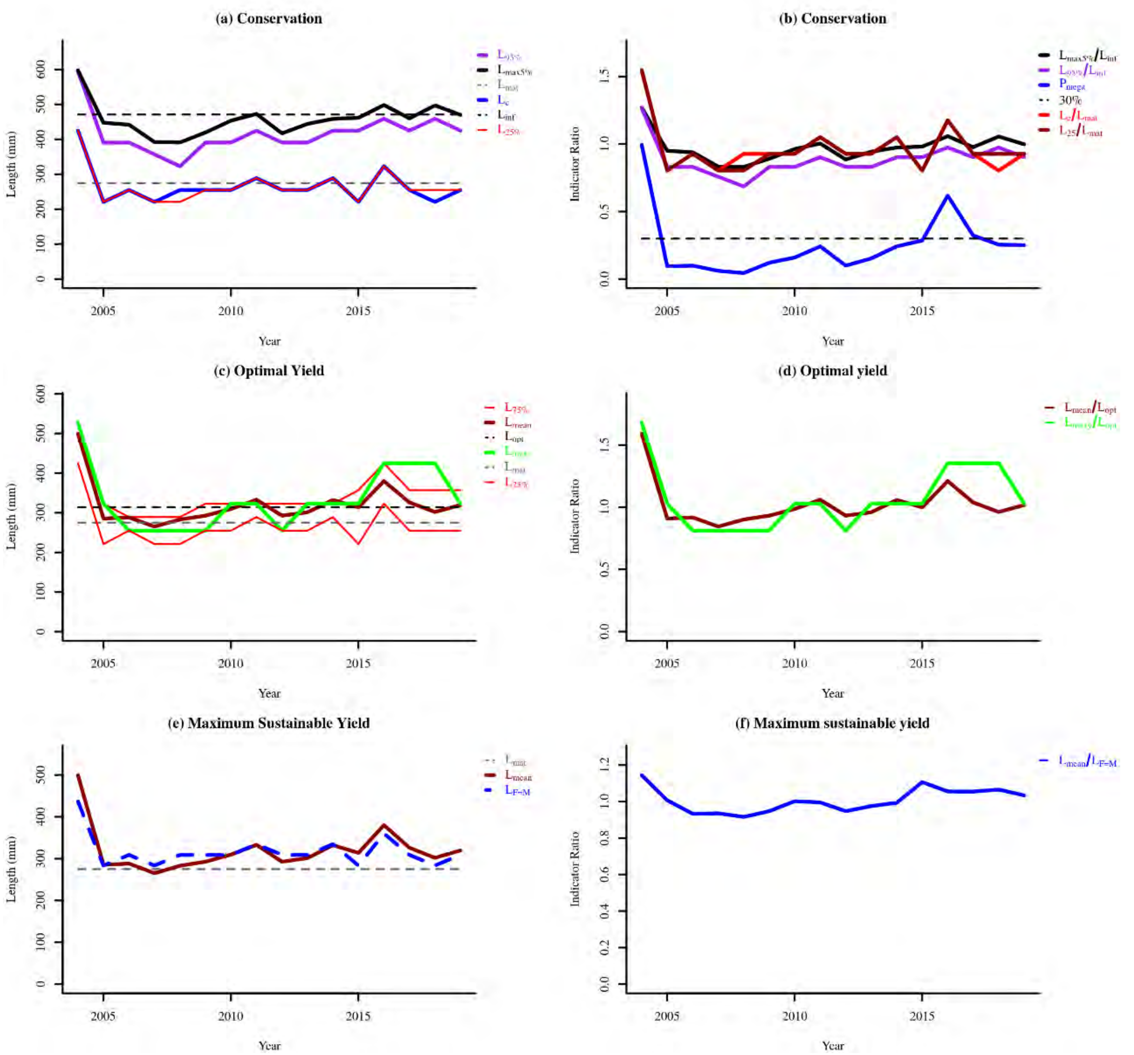

Figure 1.11. Summary of length-based indicators derived from commercial length samples of plaice in 27.7h–k.

Table 1.5. Selected indicators for LBI screening plots for plaice in 27.7h-k

Indicator	Calculation	Reference point	Indicator ratio	Expected value	Property
$L_{max5\%}$	Mean length of largest 5%	L_{inf}	$L_{max5\%}$ / L_{inf}	> 0.8	Conservation (large individuals)
$L_{95\%}$	95th percentile		$L_{95\%}$ / L_{inf}		
P_{mega}	Proportion of individuals above L_{opt} + 10%	0.3–0.4	Pmega	> 0.3	
$L_{25\%}$	25th percentile of length distribution	L_{mat}	$L_{25\%}$ / L_{mat}	> 1	Conservation (immatures)
L_c	Length at first catch (length at 50% of mode)	L_{mat}	L_c/L_{mat}	> 1	
L_{mean}	Mean length of individuals > L_c	$L_{opt} = \frac{3}{3+{}^{M}/_{k}} \times L_{inf}$	L_{mean}/L_{opt}	≈ 1	Optimal yield
L_{max_y}	Length class with maximum biomass in catch	$L_{opt} = \frac{3}{3+{}^{M}/_{k}} \times L_{inf}$	L_{maxy} / L_{opt}	≈1	
L_{mean}	Mean length of individuals > L_c	$L_{F=M}$ = ($0.75L_c+0.25L_{inf}$)	L_{mean} / $L_{F=M}$	≥ 1	MSY

1.4.2 MLZ - Mean length estimates of Z with effort

This method uses the mean length of animals that are fully vulnerable to the sampling gear can be used to estimate total mortality from basic growth parameters and a known length at first capture. The Gedamke–Hoenig length-based estimator of total mortality rate was developed from the Beverton–Holt estimator to allow for non-equilibrium conditions (Gedamke and Hoenig, 2006). The method mean length estimates of Z which incorporates effort (ICES, 2016) however, this method provided no useful indication for the purposes of this stock as the effort supplied by member was provided in three different metrics and could not be aligned.

1.4.3 LB-SPR - Length-based Spawning Potential Ratio

The length-based SPR method was developed for data-limited fisheries where few data are available other than the size structure of the catch (i.e. a representative sample of the size structure of the vulnerable portion of the population) and life history of the species. Knowledge of the natural mortality rate (M) is not required as it uses the ratio of natural mortality and the von Bertalanffy growth coefficient (K) (M/K), which is thought to vary less across stocks and species than M (Prince *et al*., 2015).

Data and parameterisation

Information on the commercial length structure was made available through InterCatch. Low sampling rates for some fleets resulted in little to no available information on length structure of discards in certain years (e.g. 2006, 2015 and 2018) (ICES, 2020a). These gaps in the sampling resulted in distorted length structures for these three years. For this reason, LBSPR could not be used to assess this stock as it was highly sensitive to these gaps in data, which we would have had to represented the length structure represent of the harvested stock, which we do not believe to be the case.

To test this sensitivity of the model to these gaps in data, three different scenarios were implanted to explore the potential effect of bias in annual length structure for plaice in 27.7.h–k:

1. **Raw:** Complete landings and discard length samples of four main métiers (OTB_70–99, OTB_70–100–119, TBB_70–99 and SSC_100–119), (see data compilation report for detailed description of length structure and samples submitted).
2. **Reduced:** Landings and discard length samples of four main métiers (OTB_70–99, OTB_70–100–119, TBB_70–99 and SSC_100–119), with years of reduced sampling removed (2006, 2015 and 2018).
3. **Smoothed:** Landings and discard length samples of four main métiers (OTB_70–99, OTB_70–100–119, TBB_70–99 and SSC_100–119), with the length structure of years of reduced sampling (2006, 2015 and 2018) replaced by an average of previous year, sample year and posterior year.

The life-history parameter estimates input into the model are detailed in Table 1.6. The associated uncertainty in these estimates are visualised in Figure 1.12.

Table 1.6. Summary of life-history parameter inputs.

Type	Estimate (upper, lower)
Asymptotic length(L_{inf}) CV	0.15 (0.3, 0.05)
Asymptotic length (L_{inf})	47.7 (51.7, 43.7)
Natural mortality to constant growth ratio (M/k)	1.78 (1.98, 1.58)
Maturity * A constant L_{50}/ L_{inf} ratio is assumed	L50 <- 29 L95 <- 34

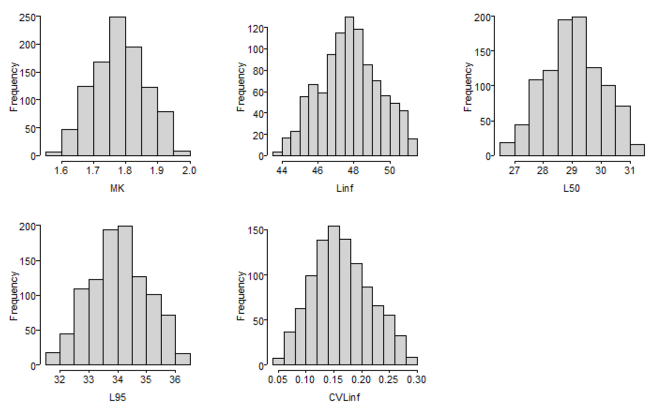

Figure 1.12. Uncertainty of life-history parameters estimates of plaice in 27.7.h–k (1000 draws were considered for each parameter).

Results

As expected the model fit poorly to the dataset containing the raw length structure in the years when discard sampling was low (2004, 2006, 2015 and 2018) (Figure 1.13a), which could create a biased estimates of SPR and F/M. The fit improved with the reduced dataset (Figure 1.13b) however, gaps in the data are not ideal. Finally, when the smoothed length structure is used, the model fitting for 2006 and 2018 improved. However, this is not the case of 2015, where the large spike number of discards (three times the catch number) prevents to the model from fitting well (Figure 1.13c).

The model run with the raw length structure indicates that the SPR is below the reference point until 2014 (Figure 1.14a). During 2016 and 2018 the SPR increased and finally stays near the reference point in 2019 (Figure 1.14a). The model run with the reduced length structure dataset produces a more pessimistic view for SPR before 2010 (Figure 1.14b). However, the largest changes occur in 2015 when SPR drops steadily to a very low value in 2018. This drop may be associated with gaps in the of length structure, mainly for discards, which appear to have an impact on the final estimates of SPR. Finally, the model run with the smoothed length structure improves the model fitting in 2006 and 2018 (Figure 1.14c), and produced comparable estimates to model based on raw length structure. But this procedure does not work to improve the SPR estimates in 2015 and provide an unrealistic distribution of SPR is produced in this year.

Changes to the length structure data demonstrate a larger effect on the estimates of F/M. Although the general reference point and trend are similar trends (Figure 1.15). However, changes to the length structure has a strong impact on inter-annual variation. This between year variation in relative fishing mortality could be interpreted as changes not overfishing for a same year (Figure 1.15, e.g. 2005), or different dispersion on the F/M estimates (Figure 1.15, e.g. 2011). This analysis indicates that the spawning potential ratio of plaice in 27.7.h–k has tended to increase since 2005 and it may be higher than the reference point (0.4) after 2014. However, given the variation/limitations of these length structures due to interannual variation in sampling levels we are unable to draw any concrete conclusions from this method.

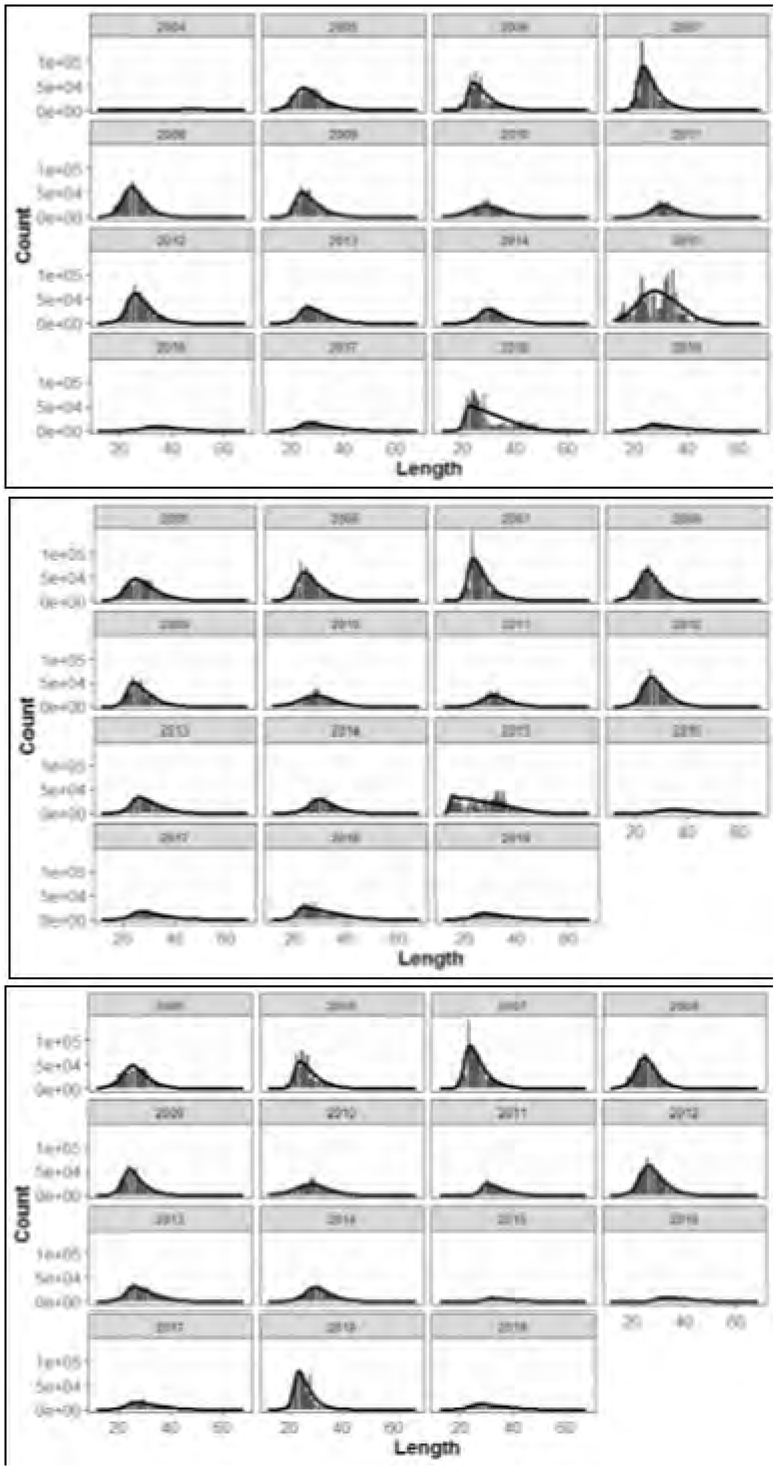

Figure 1.13. LB-SPR model fitting of the catch length structure data for a) raw data (top) b) reduced time-series (middle) and c) smoothed time-series (bottom).

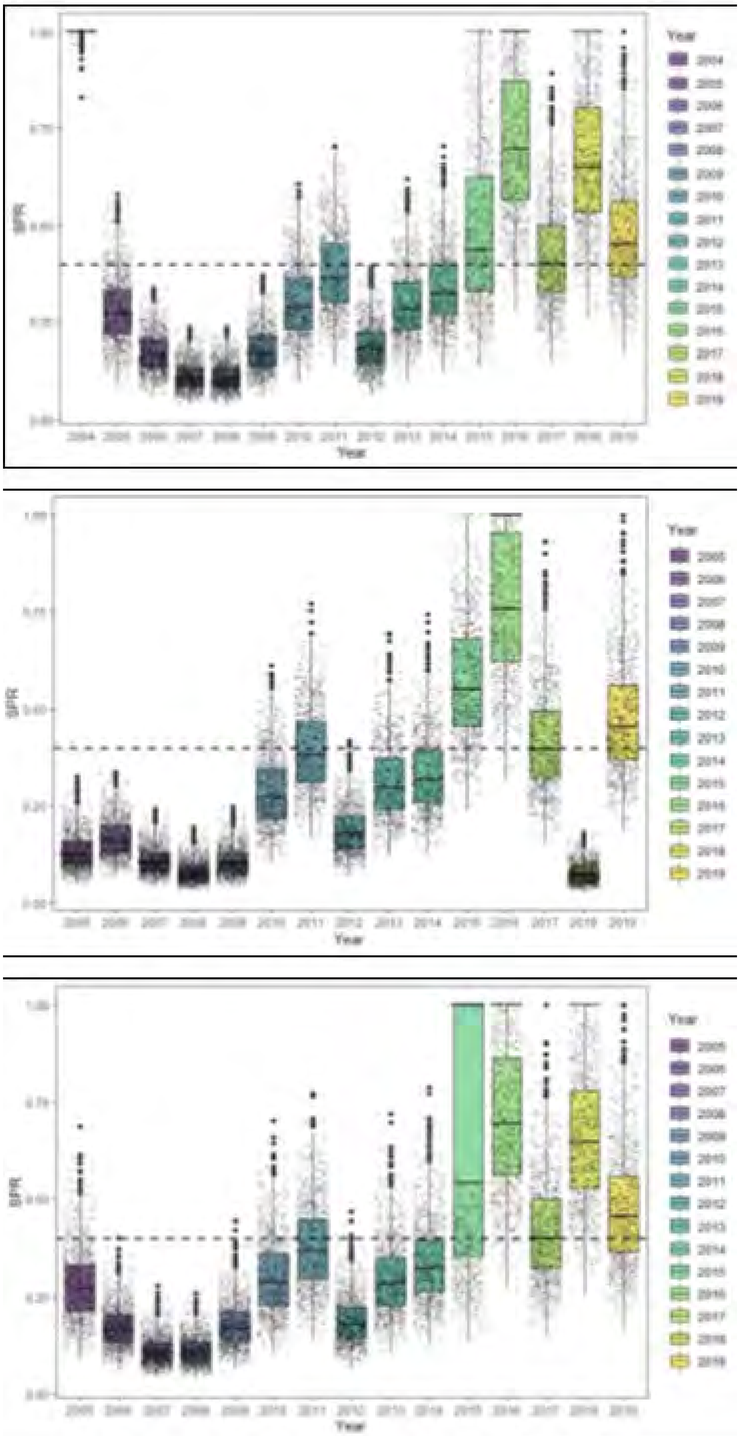

Figure 1.14. Spawning potential ratio (SPR) estimated for a) raw data (top) b) reduced time-series (middle) and c) smoothed time-series (bottom). Reference point for SPR is assumed to be 0.4.

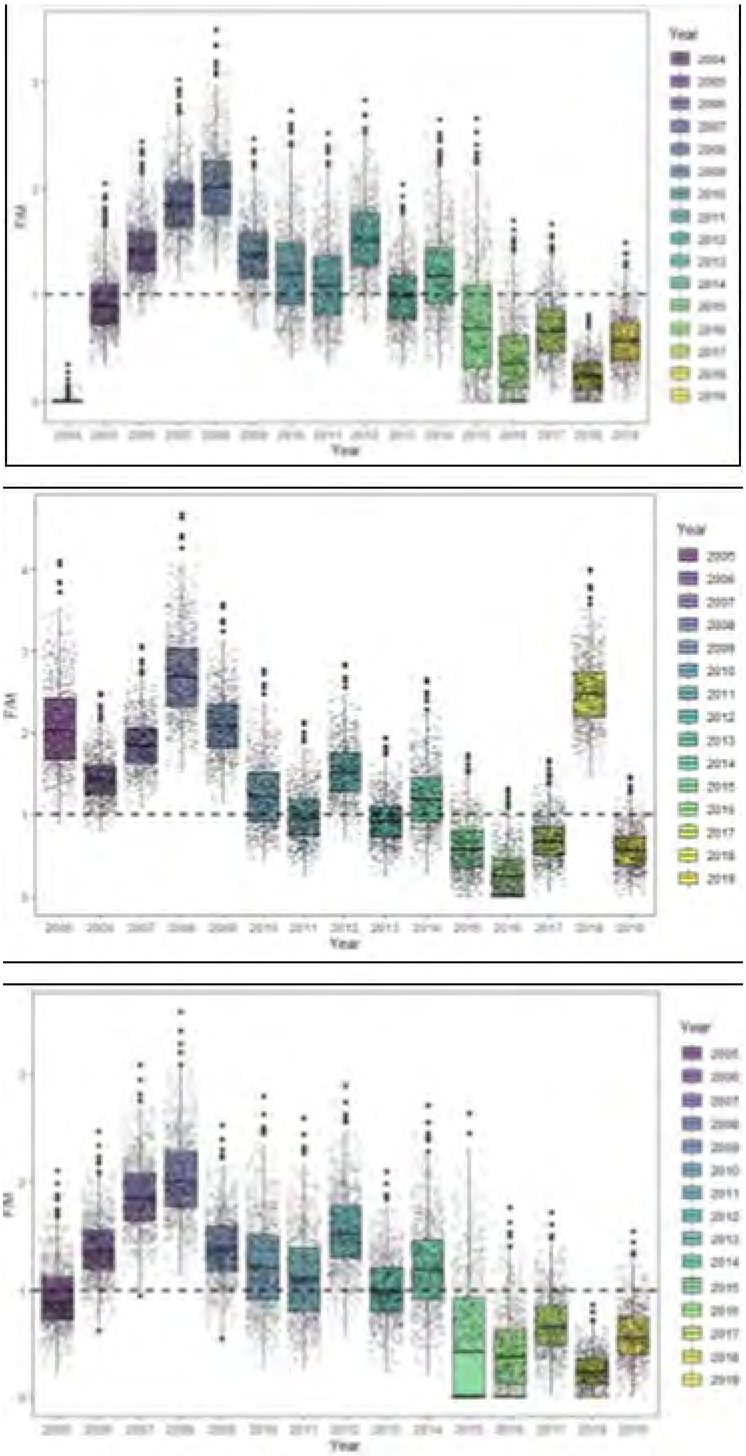

Figure 1.15. Fishing mortality to natural mortality ratio (F/M) estimated a) raw data (top) b) reduced time-series (middle) and c) smoothed time-series (bottom).

1.4.4 SPiCT

Paul Bouch, John Gabriel Ramirez, Claire Moore

Data and parameterisation

As defined in Section 1.3.1, input commercial data combined official landings statistics (1995–2003), InterCatch landings (2004–2019), and average discard rate 34% on InterCatch years (2004–2019) (Section 1.3.1). As the fishery occurred before 1995, the biomass to carrying capacity ratio (*B*/*K*) was set to inform the initial depletion level. Given that there is not quantitative information supporting what prior value should be used, a sensitivity analysis on the depletion level was performed.

As defined in Section 1.3.2, a biomass index was used to provide fishery-independent information of this stock. This index combined information from six survey sources (IGFS, IAMS, EVOHE, Q1SWBEAM, 4SWIBTS, WCGFS). Confidence interval of the annual biomass estimates is higher before 1997. Surveys were performed in first and fourth quarters, mainly taking place in November and March, respectively. SPiCT (method used to perform the stock assessment) demands to properly set the month when the survey takes place (Pedersen *et al*., 2021). Therefore, a sensitivity analysis was carried out setting the survey time.

The exploratory runs for the stock assessment of plaice 7hk on the above-mentioned catch and index data highlighted that the model converged, diagnostics were mostly met and retrospective analysis produced reasonable results. However, there was space enough to do improvements. Main concerns were related to high confidence intervals to *B*/*Bmsy* and *F*/*Fmsy* estimates, some negative *B*/*K* estimates in recent years and deviation of the four retros regarding the full time estimates. Usually, most of the problems here mentioned may improve when an n prior is incorporated. Different n settings were explored using no prior, values derived from meta-analysis for pooled fish and particularly to *Pleuronectiformes* (Thorson *et al*., 2012), and resembling the Schaefer production curve.

Performing sensitivity analysis

In order to properly define what are the prior values to be used in the final model, sensitivity analyses were hierarchically performed as indicated below:

1. Considering that there is fishery-dependent information enough to acknowledge higher catch uncertainty from 1995 to 2004, a prior on standard deviation factor (*stdevfacC)* was used. The values of 3 and 5 were initially applied to all years in this period. The standard deviation factor of 5 promoted increasing of negative values on *B*/*K* curve plot for some runs, while did not show better results in terms of diagnostics and retrospectively analysis than a factor of 3. Therefore, it was decided to fix *stdevfacC* to 3. Once other prior values were defined, new exploration was done. Results finally indicated that 3 met all criteria better than 5.
2. Secondly, a sensitivity analysis was run to define the n prior to be used in the stock assessment. As fixed setting *stdevfacC* = 3, survey time = December and the prior for the initial depletion level, *bkfracC* = 0.5. On the whole, the relative estimates of biomass are more accurately estimated than the absolute levels. The lowest confidence interval for B/B_{MSY} and F/F_{MSY} are achieved when n is fixed to resemble the Schaefer production model. By using this prior the retrospective analysis was also improved. However, by fixing n=2 promoted that the r estimates by SPiCT increases (0.85) compared to other n priors (around 0.6).
3. Knowledge related to landings indicates that exploitation level may be high before 1995. However, the landings reported from 1985 to 1987 were the lowest on the whole time-series. Under this uncertainty level of exploitation, the sensitivity analysis explored high (0.3, 0.4), moderate (0.5) and low (0.6, 0.7) depletion levels. Priors other than *bkfracC* were

set for survey_time= December, *n* prior= 2, and *stdevfacC* (1995–2004) = 3. Confidence interval for both biomass estimates and fishing mortality in the beginning of the time-series are higher, and the estimated *K* is almost 25% larger when 0.3 and 0.4 were used (high depletion level). The lowest Mohn rho values of B/B_{MSY} and F/F_{MSY} from the retrospective analysis were found when *bkfracC* is higher than 0.5 (low depletion level). Considering that the model was consistent regarding *bkfracC* (e.g. F/F_{MSY} no changed on recent years), lower confidence intervals were found from 0.5, diagnostics were always met, no highlighted differences were found in the retrospective analysis and unclear information is available on the depletion level, the model finally sets a *bkfracC= 0.5.*

4. The SPiCT handbook emphasizes the importance of accurately setting the time when the survey occurs (https://github.com/DTUAqua/spict). Given that the biomass index for plaice 7hk comes from surveys carried out on different months, the effect of setting the survey time (October, November, December, February and March) was explored. Both year effect and confidence interval are lower for estimates of biomass if survey time is set to first quarter. Additionally, the long-term biomass ($E(B_\infty)$) is expected to have a lower increase than it is set to fourth quarter survey because it is closer to the estimated *K*. In other words, by setting the survey time in February or March a more optimistic stock status is found. Retrospective analysis showed lower Mohn rho's estimates also when survey was informed to occur in first quarter.

1.5 Final Stock Assessment

The final selected model is parameterized with the following settings:

- Catches from 1995 to 2019;
- Biomass index from 1997 to 2019;
- *stdevfacC= 3* from 1995 to 2004 (to account for unknown discards);
- *bkfracC* = 0.5 (moderatly exploited);
- logn = log(2);
- Survey time = December, by considering the middle time when surveys take place or first quarter, if the best diagnostics are taken into account.

The model meets acceptance of the SPiCT assessment for plaice 7hk (Mildenberger *et al*., 2021). The surplus production curve is well defined and can be seen in Figure 1.16, and the residuals of the catch and index time-series show normality and no autocorrelation (Figure 1.17). The retrospective plots for the assessment also show good agreement and low Mohns Rho values (Figure 1.18).

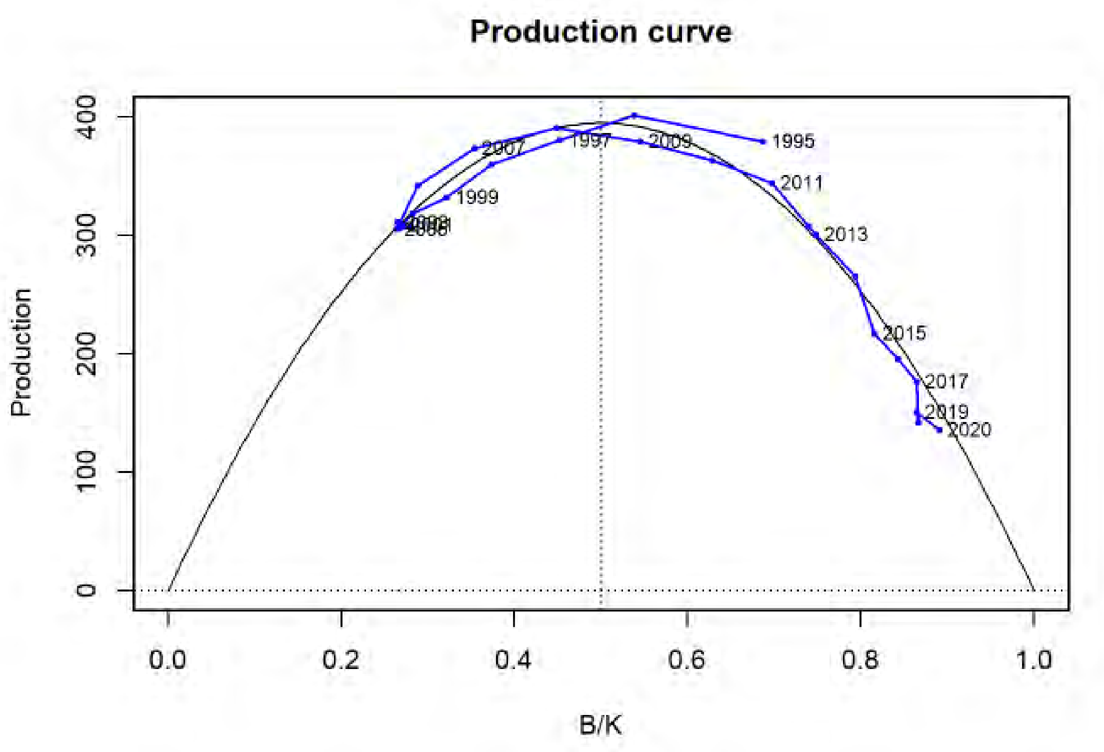

Figure 1.16. The surplus production curve with estimated by the final SPiCT assessment for plaice in 27.7.h–k.

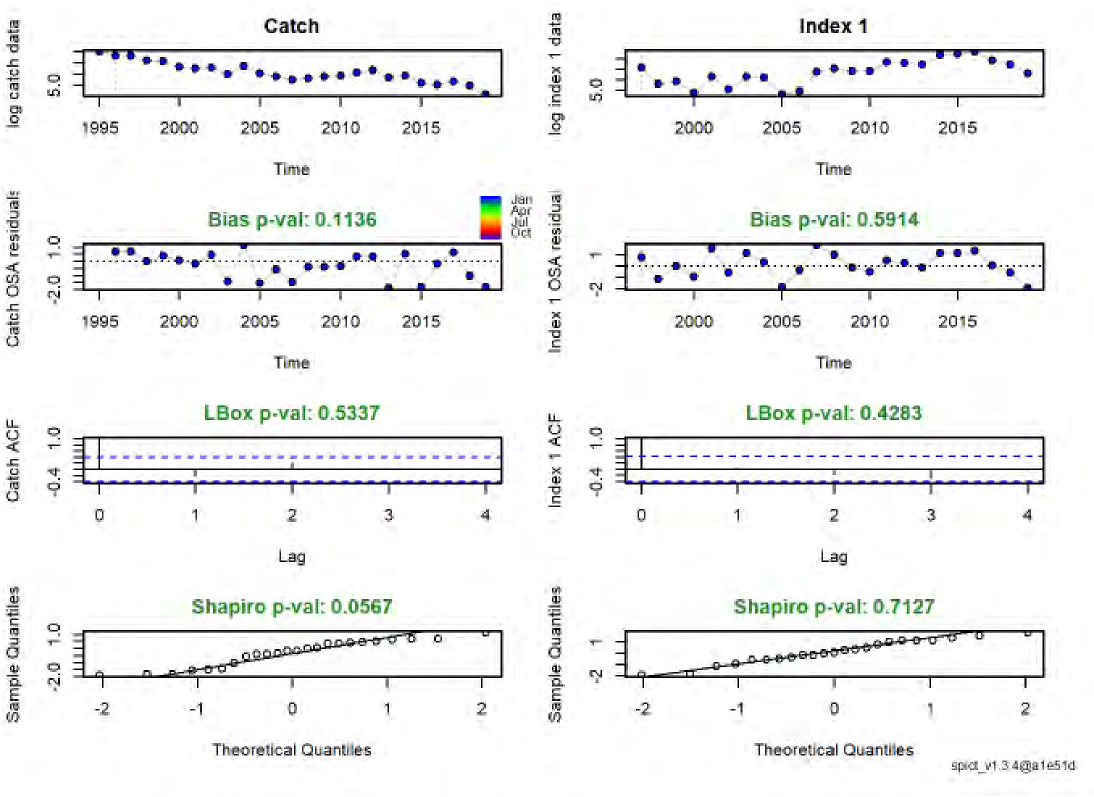

Figure 1.18. Residual plots for the catch and index time-series for the final SPiCT assessment for plaice in 27.7.h–k.

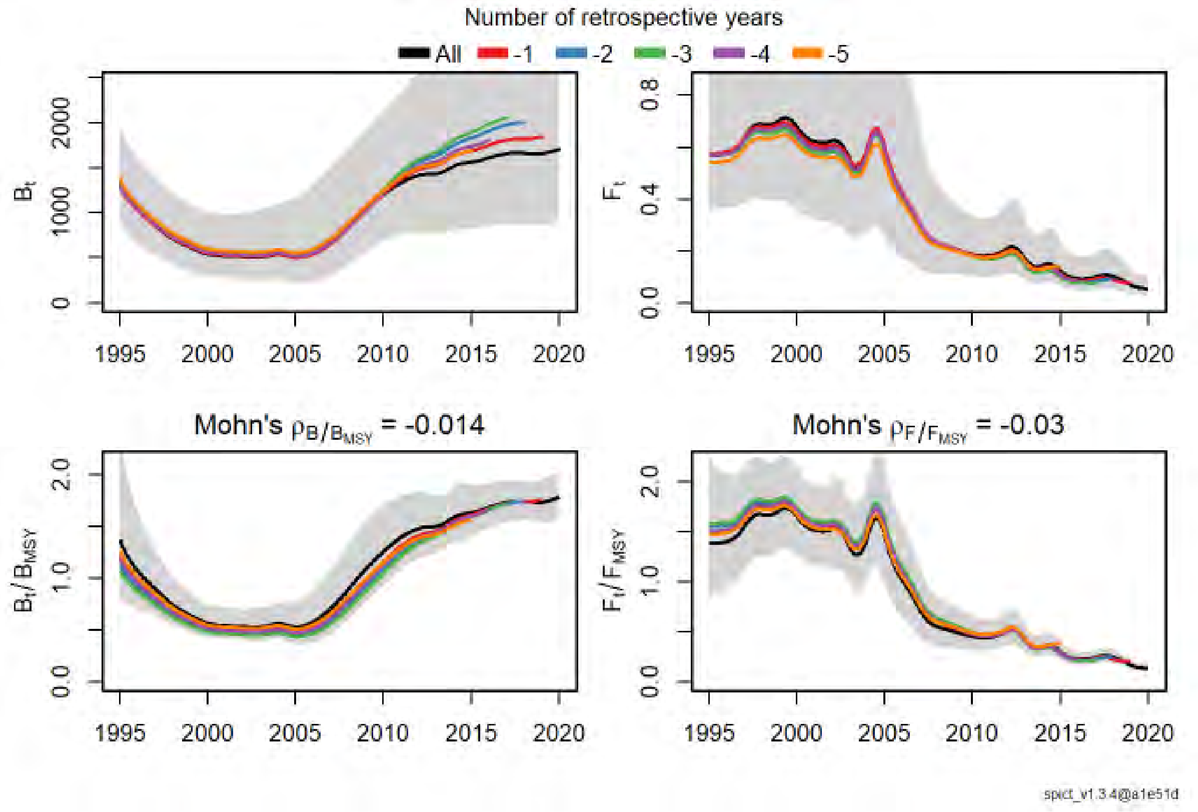

Figure 1.19. Retrospective plots for the final SPiCT assessment for plaice in 27.7.h–k.

There was found a strong correlation between *logK* and *logq* (-0.94) (Figure 4), suggesting that the B/BMSY scale is more poorly estimated (Bouch *et al*., 2021). At the same time, this stock assessment presented smaller confidence interval for relative (B/BMSY) than absolute (BMSY) estimates of the stock size. These results could be of concern for category 1 assessments. Accordingly, this stock assessment was proposed and accepted as category 3. F/FMSY benefits from low correlation n between *logm* and *logq*, suggesting that relative estimates of fishing mortality are reliable.

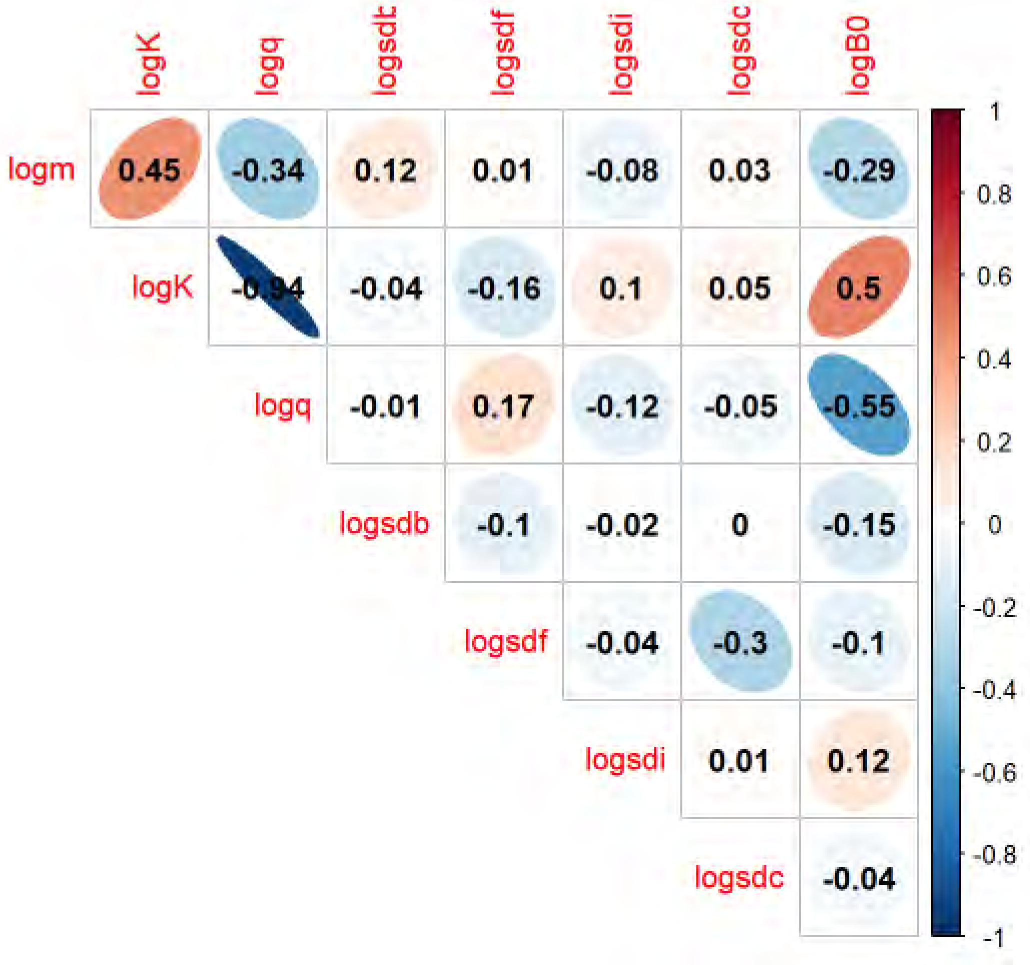

Figure 1.20. Correlation between parameters from the final SPiCT assessment for plaice in 27.7.h–k.

Figure 1.21 shows the input time-series for the final SPiCT assessment, with decreasing catches since the mid-1990s and an increase in the biomass abundance since 2010. The SPiCT catch results correspond well to the reported figures and the greater uncertainty pre-2004 is represented by the wider confidence intervals (Figure 1.22).

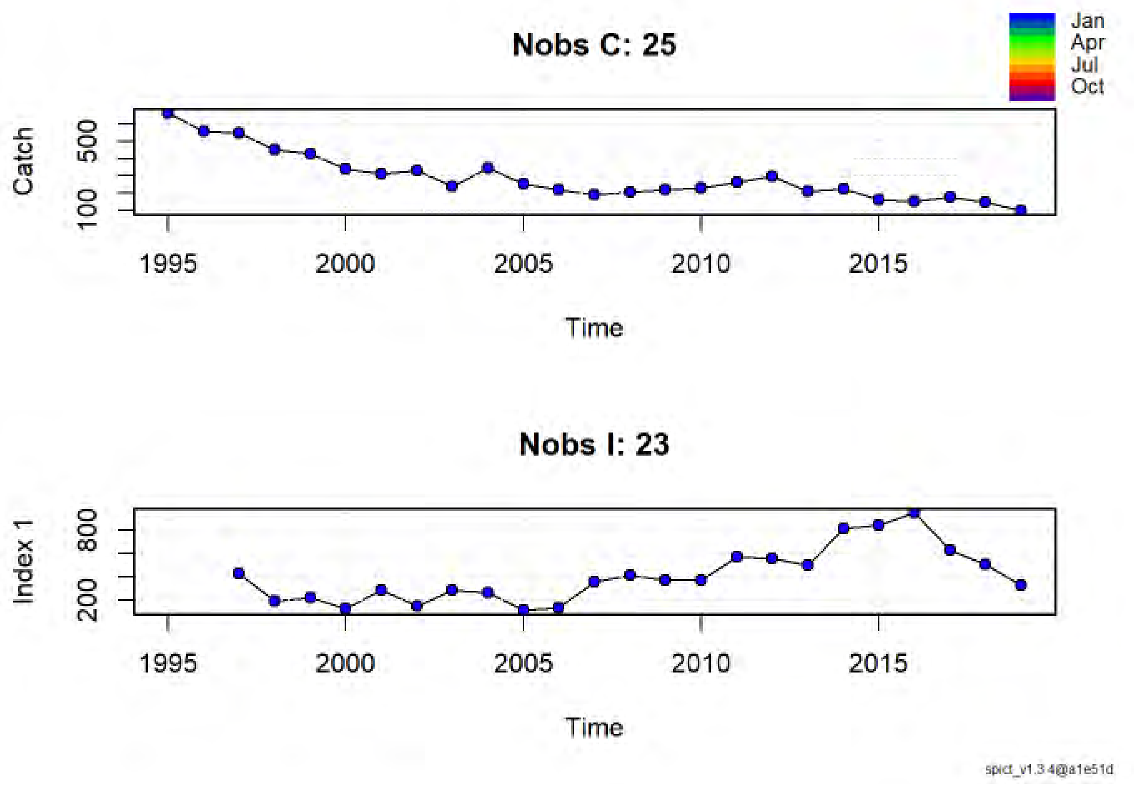

Figure 1.21. Catch and index input time-series for the final SPiCT assessment.

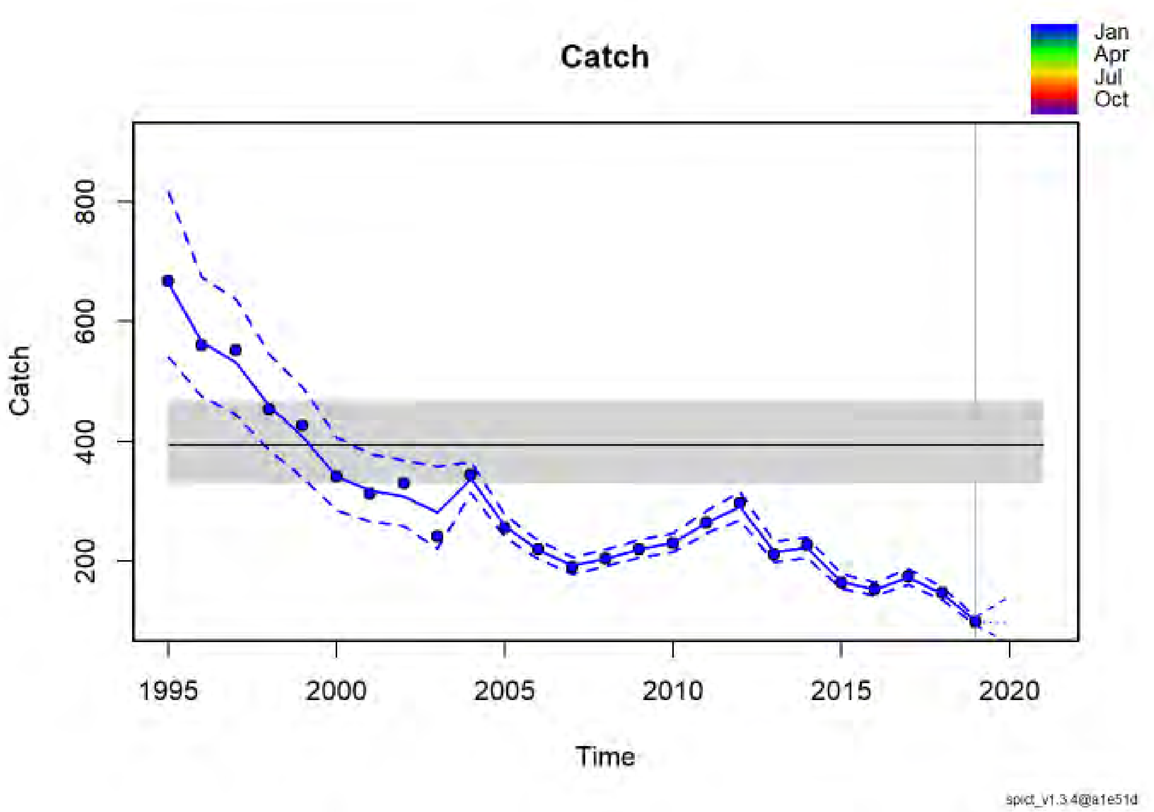

Figure 1.22. Catch time-series generated by the SPiCT assessment with confidence intervals. Points represent reported catches in tonnes. Horizontal lines represent the estimated MSY and confidence interval.

The biomass time-series shows an initial decline pre-2000 dipping below a B/B_{MSY} value of 1 (Figure 1.23). The biomass remained low until 2008 when the biomass began to increase, and go above the B/B_{MSY} >1. The confidence interval of the estimated biomass ranges from a B/B_{MSY} of 1.58 to 2.01 in the final year of the assessment (Table 1.7).

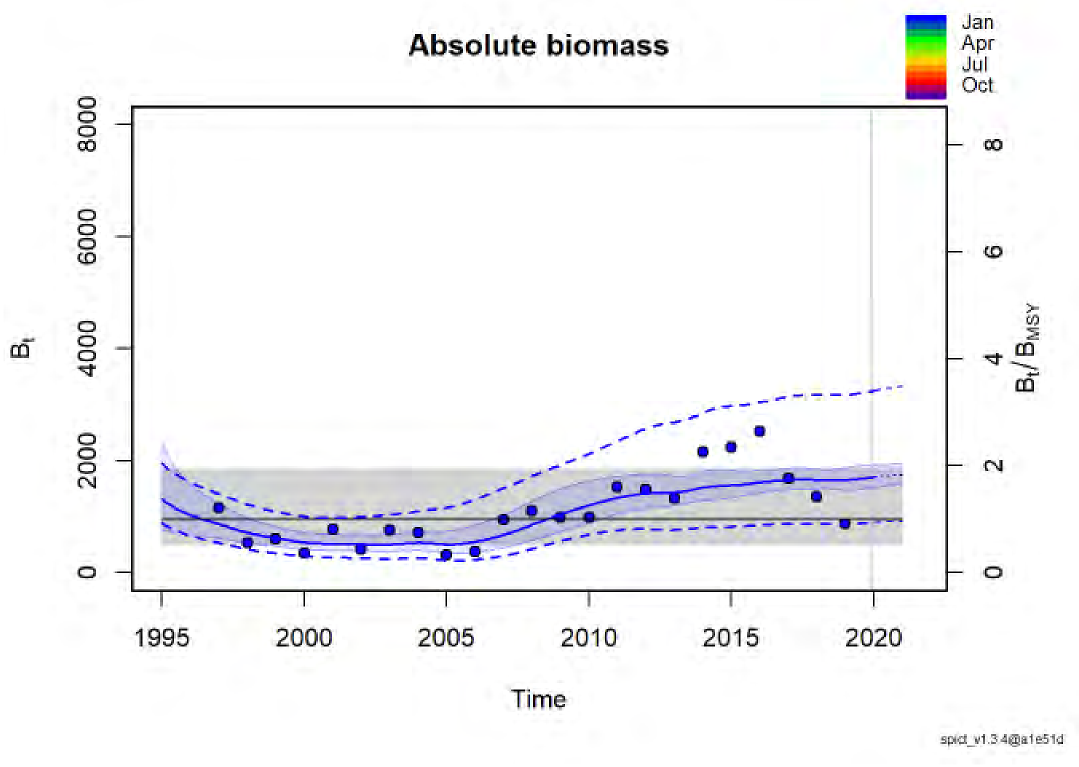

Figure 1.23. Absolute biomass time-series from the SPiCT assessment with confidence intervals. The points represent values from the VAST index and the horizontal line represents a B/B$_{MSY}$ of 1, with the grey shaded area the confidence of that value.

Table 1.7. Final year estimates with upper and lower confidence limits from the SPiCT assessment for plaice 27.7.h–k.

	Estimate	CI Low	CI Upper
Biomass	1703	895	3242
F	0.05	0.03	0.11
F$_{MSY}$	0.41	0.23	0.75
B/B$_{MSY}$	1.78	1.58	2.01
F/F$_{MSY}$	0.13	0.09	0.19

The relative fishing mortality (Figure 1.24) has been decreased significantly from an F/F$_{MSY}$ of 1.5 pre-2005 down to a value of 0.13 in 2020. The confidence limits are greater pre-2004, but in the later years of the assessment, the estimated F/F$_{MSY}$ and the confidence limits are well below the F$_{MSY}$ level (Table 1.7).

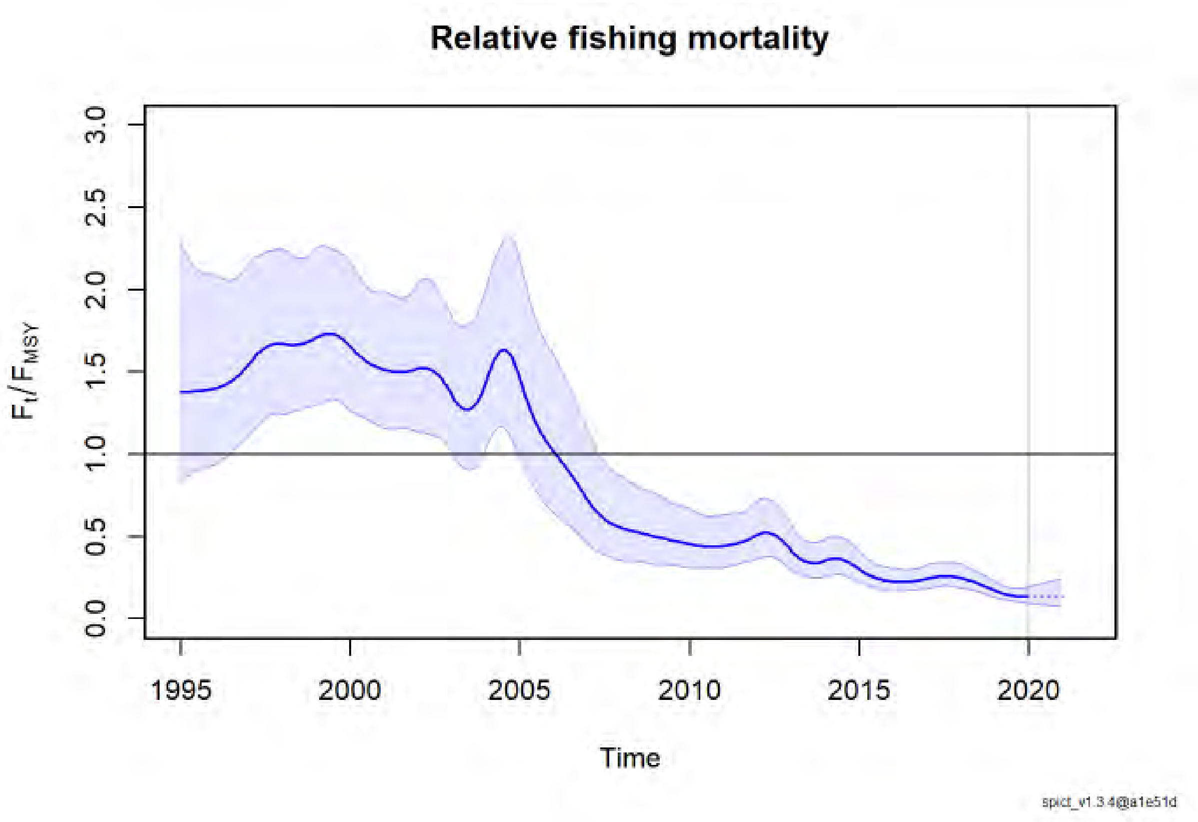

Figure 1.24. Relative fishing mortality and confidence interval from the SPiCT assessment for plaice in 27.7.h–k. The horizontal line represents an F/F_{MSY} value of 1.

Given the estimated values of F_{MSY} of 0.41, and the relative reference points and the relatively tight confidence limits around them gives reasonable confidence in the validity and the robustness of the assessment. This is reinforced by the robust sensitivity analysis and the positive residual and retrospective analyses (Figures 1.16, 1.17, 1.18 and 1.19).

No reference points for category 3 stocks in terms of absolute values. The SPiCT-estimated values of the ratios F/F_{MSY} and B/B_{MSY} are used to estimate stock and exploitation status relative to the proxy MSY reference points.

1.6 Fishing opportunity advice

WKLIFE VIII (ICES, 2020b) developed a harvest control rule to provide MSY advice for category 3 stocks based on the "2 over 3 rule", which compares the trend in a biomass index of the two most recent years to the preceding three years (WKMSYCat34; ICES, 2017a; Fischer *et al.*, 2020). The recommended harvest rule improves on the "2 over 3" rule with the addition of multipliers based on the stock's life-history characteristics, the status of the stock in terms of relative biomass, and the status of the stock relative to a target reference length (ICES, 2018a; ICES, 2019a). The catch rule is defined as:

$$CCyy{+}1 = CCyy \times rr \times ff \times bb \times mm$$

where the advised catch (C) for next year y+1 (set on a biennial basis) is based on the most recent year's advised catch $CCyy$ adjusted by the following components:

Component	Definition	Description and use
r	$\frac{\sum_{i=y-2}^{y-1}(I_i/2)}{\sum_{i=y-5}^{y-3}(I_i/3)}$	The rate of change in the biomass index (I), based on the average of the two most recent years of data (y–2 to y–1) relative to the average of the three years prior to the most recent two (y–3 to y–5), and termed the "2 over 3" rule.
f	$\frac{L_{y-1}}{L_{F=M}}$	The ratio of the mean length (L_{y-1}) in the observed catch that is above the length of first capture relative to the target reference length (mean length/target reference length). The target reference length is $L_{F=M} = 0.75L_c + 0.25L_\infty$, where. L_c is defined as length at 50% of modal abundance (ICES, 2018b).
b	$\min\left\{1, \frac{I_{y-1}}{I_{\text{trigger}}}\right\}$	Biomass safeguard. Adjustment to reduce catch when the most recent index data I_{y-1} is less than $I_{trigger} = 1.4I_{loss}$ such that b is set equal to $I_{y-1}/I_{\text{trigger}}$. When the most recent index data I_{y-1} is greater than I_{trigger}, b is set equal to 1. I_{loss} is generally defined as the lowest observed index value for that stock.
m	[0,1]	Multiplier applied to the harvest control rule to maintain the probability of the biomass declining below B_{lim} to less than 5%. May range from 0 to 1.0.
Stability clause	$min\{max(0.7C_y, C_{y+1}), 1.2C_y\}$	Limits the amount the advised catch can change upwards or downwards between years. The recommended values are +20% and −30%; i.e. the catch would be limited to a 20% increase or a 30% decrease relative to the previous year's advised catch. The stability clause does not apply when b < 1.

Each component of the harvest control rule is combined (multiplied together), in order to determine next year's catch advice by adjusting this year's catch advice upwards or downwards. This is based on the trend in the index (i.e. whether the stock is going up or down, r), the observed mean length in the catch relative to the target mean length (f), and a factor to adjust catch downwards if the current stock falls below a threshold index value (b), defined as IItrigger = 1.4IIloss. IIloss is defined as the lowest observed index value for that stock. The multiplier (m) is then applied as a precautionary measure to ensure that the probability of the stock declining below B_{lim} is less than or equal to 5%.

The performance of the catch rule is driven largely by three factors:

1. The life history of the species;
2. The trend in the index being a good measure of the current status of the stock based on the life history; and
3. The IItrigger value being defined at or near the true threshold level (e.g. $0.5B_{MSY}$).

For the harvest estimate for longer lived stocks with low natural mortality and low growth rates (von Bertalanffy k < 0.2 yr-1, e.g. redfish or ling), a multiplier of 0.95 should be applied to the control rule ($CCyy$+1 = $CCyy$ × rr × ff × bb × 0.95), i.e. by setting the estimated catch for the following year to 95% of the estimated yield, based on the control rule. Medium-lived stocks with 0.2 ≤ k < 0.32 yr-1 (e.g. plaice, red mullet) should apply a multiplier of 0.8 to next year's estimated catch. If there is no reliable information about k, but k is considered to be less than 0.32 yr-1, then a multiplier of 0.8 should be used. The constant harvest rate (chr) rule (Method 2.2) has been developed to deal with some of the cases where k ≥ 0.32 yr-1.

Summary of methodology implemented

Fixed values

```
m=0.95
Lc=27.5
Lmean=32.000
M=0.318
k=0.18
a=1/(2*(M/k)+1)
Linf=47.132
Lfm=(0.75*Lc)+0.25*Linf
```

Catches - InterCatch landings + 34% discard rate

```
catch_series <- read.csv("catch_series_pleh-k.csv")
catch_series <- catch_series[catch_series$Series == "Average InterCat
ch Discards: 2004-2019",]
catch_series <- catch_series[-1]
```

Index - VAST abundance index

```
abundance_index <- read.csv('Table_for_SS3.csv', dec=",")
abundance_index$Estimate_metric_tons <- as.numeric(abundance_index$Es
timate_metric_tons)
```

Computing future catches

Computing *r* parameter:

```
ls=length(abundance_index$Estimate_metric_tons)
a=mean(abundance_index$Estimate_metric_tons[(ls-1):ls])
b=mean(abundance_index$Estimate_metric_tons[(ls-4):(ls-2)])
r=a/b
```

Computing *f* parameter:

```
f=Lmean/Lfm
```

Computing *b* parameter:

```
Itrigger=1.4*min(abundance_index$Estimate_metric_tons);Itrigger

## [1] 166.4894

abundance_index$Estimate_metric_tons

##  [1] 431.3054 198.6820 227.4020 131.6435 287.3000 154.0789 285.127
2 267.1852
##  [9] 118.9210 138.0178 355.5892 413.4139 371.2247 372.2823 573.959
0 559.3184
## [17] 498.2076 808.9804 841.9860 948.1166 628.8793 508.8108 327.270
8
```

The most recent index data I_{y-1} is greater than $I_{trigger}$, hence:

```
b=1
```

Stability clause is implemented as b = 1 We have all the values to compute the catches per the new year: it's the amount the advised catch can change upwards or downwards between years, therefore a 30% decrease relative to the previous year's advised catch

```
(catch_series$Catch[catch_series$Year==2019]*r*f*b*m)*0.7

## [1] 33.66878
```

1.7 Future considerations

Annually the discard rate will need to reviewed by the single species working group, to assess if new information is available.

1.8 Reviewers' comments

Data evaluation

The stock is distributed over the areas 7h to k and is fished mainly as a bycatch species of a flatfish, *Nephrops* or gadoid directed trawling fishery. Fishing patterns and –methods differ largely between the areas and Member States, allowing few to no reasonable data extrapolation and leaving data gaps. Registered landings and estimated discards are available from WGMIXFISH analysis and from InterCatch. Out of the six Member States fishing on the stock, only three reported data to InterCatch.

Census data and estimated discards: historical landings from 1985 to present are available. However, landings before 2004 were not reported in a standardized manner via the InterCatch database but were taken from official catch statistics. Especially the early years of the time-series show large interannual variation that could not be explained during the data compilation and the benchmark. The assessment group therefore decided to cut the landing statistics before 1995 and previous years, were dismissed until those interannual variations can be explained. The benchmark group agreed to this decision. Estimated discards are also only available since 2004 and only for two Member States, England and Ireland. The data are incomplete and show large variation between years and gears. The assessment group presented four different scenarios on how to create a catch time-series (see chapter xxx) that incorporate the discards ratios. The benchmark group discussed each of the scenarios and agreed on averaging the discard rates for the years 2004–2019 and using only landings before 2004.

> Agreed and available catch data for the assessment are therefore: Landings statistics from 1995–2003 (official catch statistics), landings from 2004 to 2019 (InterCatch) and estimated discards from 2004 to 2019 (combined to an averaged "discard-top-up" time-series for 2004–2019).

Sampling data: length measurements for landing and discard fractions were uploaded to InterCatch and cover all three areas with different intensity and displays different patterns both in sampling coverage, but also in fishing pattern between Member States.

Only a few age data were submitted and were already raised according to landings. The respective allocation schemes of InterCatch data were not analysed, leaving some insecurity on the presented data, as it is unclear whether or not an extrapolation has taken place prior to the raising and if the actual numbers of samples are therefore trustworthy. The calculation of life-history parameters from commercial fisheries data showed large variation, and was not considered for the further exploration of LBI assessment models, instead survey data were used.

Survey index: The assessment group presented three different scenarios on how to calculate survey indices. Two of the scenarios, i.e. a VMS LPUE and a standardized LPUE were both disregarded due to bad performance. For the third scenario, the assessment team conducted a thorough analysis regarding the creation of standardized indices of abundance from the six different surveys that are conducted in the distribution area of plaice 7h–k. The surveys were combined in a VAST model after adjusting several fishing parameters, which generates, for the first time, a combined biomass index for the whole stock. The model performed well after several runs, the index showed a similar trend as adjacent plaice stock indices and was considered a reliable measurement and suitable for further assessment purposes (i.e. for ICES DLS category 3, trend-based assessment methods).

The Length–weight data gained from the scientific surveys are showing a good consistency, while the age–length data set does not perform well and display large variations in each age class. Very unequal sampling sizes between subdivisions did not allow statistical comparisons between areas. A linear model compared male and female plaice and performed well. Sex-specific differences in growth are low and were neglected for the assessment. However, the data quality of the survey data did not allow for the calculation of maturity-at-length data, which is needed for some DLS assessment models.

The formerly used Irish commercial tuning fleet will not be used anymore and was not considered in the assessments during the benchmark.

Assessment

The assessment team evaluated several options to calculate DLS reference points for the plaice stock. Generally, DLS methods that rely on age data and age-related life-history parameters, such as LBI, did not perform well given the unsecure data basis from both the commercial sampling data from InterCatch and the different survey data from survey databases. Ultimately, a stochastic production model in continuous time (SPiCT) was applied to the plaice stock and performed well. Input data were official landings from 1995 to 2003, commercial catch (landings and discards) from 2004 to 2019 and the VAST biomass index, consisting of six surveys.

When determining harvest limits using output from SPiCT, the application of the harvest control rule first depends on appropriate model performance. An accepted assessment using SPiCT would ideally fulfil all of the following points:

- Model converged;
- All parameter uncertainties could be estimated and are finite;
- No violation of model assumptions such as bias, auto-correlation of OSA residuals, and normality. This means that p-values are not significant ($p>0.05$);
- Consistent trend in the retrospective analysis. There should not be a tendency to consistently under- or overestimate relative fishing mortality and biomass in successive assessments, in particular if the retrospective estimates are outside the confidence intervals of the base run;
- Non-influential starting values – the results should be the same for all starting values;
- Model parameter estimates and variance parameters should be meaningful. This means that the parameter of the production curve (n) should not be very skewed away from the symmetrical curve (B_{MSY}/K should be between 10% and 90%) and the variance parameters (sdb, sdc, sdi, sdf) should not be unrealistically low. In these cases, a prior on the unrealistic parameter could be considered.

The plaice dataset and results of the SPiCT were tested for all the above criteria. All technical criteria were fulfilled. Several different runs with manually changed priors were conducted to test the variance parameters and determine if the calculated default values are reliable. The benchmark group agreed on the most fitting combination given the quality of the input data and the output of the SPiCT runs.

No reference points are yet defined for this stock in terms of absolute values. The SPiCT-estimated values of the ratios F/F_{MSY} proxy and B/B_{MSY} proxy can be used to estimate stock status relative to the MSY reference points and can therefore be used in the catch advice as an additional indicator of the stock status.

<u>*Concluded and agreed way of assessing the stock:*</u> Trend-based assessment using the combined biomass index of the VAST model (e.g. "2-over-3"). For the estimation of the stock status, proxy reference points of the SPiCT model can be used (Table 1).

Table 1. suggested proxy reference points derived from a SPiCT model to assess stock status in a Cat. 3.2 DLS stock.

Framework	Reference point	Value	Technical basis	Source
MSY approach	MSY $B_{trigger}$ proxy	0.5*	Relative value (B/B_{MSY}) from the SPiCT assessment model. B_{MSY} is estimated directly from the SPiCT model and changes when the assessment is updated.	ICES (2018)
	F_{MSY} proxy	1*	Relative value (F/F_{MSY}) from the SPiCT assessment model. F_{MSY} is estimated directly from the SPiCT model and changes when the assessment is updated.	ICES (2018)

This assessment is a large improvement compared to the former one, where only Irish catches of area 7j and a commercial tuning fleet were used to give advice. Both, the VAST survey index and the commercial catch data performed well in the analysis. The data exploration, methods and assessment runs are documented and well described in the respective working documents of the benchmark and data compilation workshop. Some issues remain and should be solved in a timely manner to further improve the assessment quality and reliability of the results.

Future recommendations

- The stock identity and stock borders should be checked and validated, as migration and interaction with neighbouring stocks is likely happening given the similar stock trends in the survey indices. Life-history parameter comparisons to adjacent stocks might give some indication, but should be supported by further analysis such as tagging, genetic studies and micro-chemical analysis of bony structures (e.g. otoliths).
- The age reading should undergo a validation to improve the quality of age-related life-history parameters that are needed as input to different DLS models. A former age reading exchange in 2019 showed a low agreement of only 73–56% between age readers and no age validation (i.e. the timing of ring formation) has been conducted yet.
- To improve the SPiCT assessment and hence the quality of the advice, more discard estimates are required by national data submitters. The agreed "discard-top-up" should undergo regular validation.
- Landings prior to 2004 should be uploaded to InterCatch.
- The sampling of biological data from commercial catches needs further enhancement, esp. in areas and fisheries where the number of age readings and length measurements is in no relation to the landings. The discarded fraction needs a better sampling coverage.

- Although all landing countries are obliged to submit biological data, not all available information was uploaded by every country. To improve the quality of the assessment, this is however mandatory.
- The SPiCT assessment relies strongly on survey data and catches; adding a tuning fleet using commercial effort of all fishing fleet segments might be beneficial to improve the quality of the output.
- The VAST parameter should be further explored and validated, especially where a spatial overlap of different surveys occurs (e.g. comparison of plaice catchability between beam trawl and bottom trawl gears).
- BMS landings should be sampled additionally to the ongoing discard-sampling to allow reasonable data extrapolation for this part of the catch.

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2 Red Gurnard (gur.27.3–8)

Red gurnard (*Chelidonichthys cucculus*) is species of small benthic fish, widely distributed on the Northeast Atlantic shelf and neighbouring seas. It is most commonly found in waters to 100 m depth, over sandy and coarse substrates. It is of minor commercial interest, with the majority of landings coming from the western English Channel and Celtic Sea. In other areas it is heavily discarded. ICES are not aware of any specific management measures in place for this species, and reference points have not been defined.

2.1 Why a benchmark?

Red gurnard has been considered a category 6 stock according to the ICES system of classification, which is applicable to stocks with "negligible landings […] and stocks caught in minor amounts as bycatch". While there are no known fisheries which target red gurnards, significant and consistent landings come from a number of métiers. Discards in other fleets are however known to be high (approaching 100% of catches). This stock was rated as a high priority for benchmarking by WGWIDE in 2019 (Table 1) mainly on account of the fact that the current approach to assessment relies upon landings data which is known to be unreliable, and excludes survey information, which has been shown to be informative for tracking trends in red gurnard abundances.

An issue list for red gurnards in subareas 3–8 was developed during WGWIDE 2018 (Table 2), highlighting the issues with the assessment and identifying the key impediments to its improvement. Foremost of these is the issue of reliability of landings data, given the significant and variable quantities of "mixed gurnards" reported by some countries, and the general lack of documentation on approaches to catch reporting by species in countries where mixed gurnards are generally not reported. Those countries for who discard information were reported to the working group typically reported high rates of discarding (50–90%, by weight).

Table 2. Benchmark prioritisation table for Red Gurnard (*Chelidonichthys cucculus*) in SAs 3–8, WGWIDE, 2019.

SCORE	Criteria 1 – Need to improve the quality of the previous assessment to provide advice Weight: 0.4	Criteria 2 – Opportunity to improve the assessment Weight: 0.3	Criteria 3 – Management importance* Weight: 0.1	Criteria 4 – Perceived stock status Weight: 0.1	Criteria 5 - Time since previous benchmark Weight: 0.1
Score 4.7	Assessment is inadequate to provide advice (based on landings which are known to be unreliable) Score – 5.	No survey data are used in the assessment, therefore new data and methods will be used. Score – 5.	One attribute (advice is requested). Score – 2.	State of the stock unknown. Score – 5.	Stock has never been benchmarked. Score – 5.

The issue list developed by the working group was addressed at WGCATCH and SIMWG, to which groups recommendations had been directed, and summarised at the data collation workshop for WKWEST in 2020.

2.1.1 Catch data

Problem: Resolution of landings data of all gurnards at the species level is poor. A considerable quantity is landed as "mixed gurnards", while those nations who land them as individual species have not, other than Portugal, documented the process by which this is done.

Work required: Questionnaire circulated to national administrations regarding if and how landings are assigned to species.

Data required: Several years of national landings data.

Action: WGWIDE submitted a recommendation to WGCATCH. (ICES reference 186): It is recommended that differing national approaches to the assignment of mixed gurnard catches to species level be reviewed in order to develop a standardised procedure, which can be used going forwards and investigate the assignment of historical mixed catches.

Response: At the 2019 meeting, WGCATCH only had the time to document how some member countries report and how provided data for red gurnards (gur.27.3–8), which will be provided to WGWIDE. WGCATCH recommends WGWIDE to issue a data call requesting how all countries are assigning individual species landings in a mixed gurnard catches and report back to WGCATCH. WGCATCH can evaluate if the sampling design of the species are according probabilistic sampling design, but due to the diversity of sampling schemes is difficult to standardize procedures to assign mixed catches, as they are dependable on the sampling schemes.

Responses were as follows:

Country	Reported Landings	Biological Sampling
Netherlands	Report landings as what is described in the logbooks.	No biological sampling for these species.
Portugal	No reported landings for GUR. The official landings are not accurate (GUR landings are over reported) and the Portuguese landings were the result of mixed gurnards (1 to 6 species).	For gurnards, the identification and low incidence of the sampling selection for some gurnard species have preclude obstacles to statistical modelling attempts. Currently, there are 6 designations (GUG, GUN, GUR, GUU, GUX and LVD) that are typically associated with the six gurnard species landed on Portuguese auction markets. Most of those designations were found to be applied to mixtures of several of those species. We were able to stablish marked differences on mixture proportions between regions and fishing gear segments. We expect that, from 2017 onwards, improved commercial designation data collection and focus on problematic mixture cases accurate models for realistic gurnard landings can be developed.
Spain	As in logbook.	Despite mixed gurnards landings, sampling showed low contribution of GUR to the total landings of GUX (<1%). Boxes of mixed gurnards are measured by species. The proportion in weight of each species is used after to calculate the proportion of each species in the landings.
UK (England & Wales)	As in logbook.	Box of mixed gurnards are measured by species.

As such, processes around assigning and validating gurnard landings remain for the large part unclear.

2.1.2 Discards

Problem: Several nations have submitted discard rates, by fleet, for red gurnard, via InterCatch. These are not yet used, due to a lack of time to develop an assignment scheme, and a lack of confidence in the figures at a species level.

Work required: Develop raising procedure in InterCatch further, link to work on assignment of catch to species.

Data required: Discard data by fleet.

Response: Data by fleet was requested in the WKWEST data call, and in many cases submitted, although the coverage is somewhat patchy (see table in main working paper). Some time is now required to process this into raised discards. This is likely to improve our understanding in areas where fleets for which discarding it thought to be high operate, however continuing uncertainty over landings and their species composition it may be difficult to raise discards consistently.

2.1.3 Survey data

Problem: Assuming the distribution of landings reported as red gurnard are indicative of the distribution of the stock, whilst it is a widely distributed species, the centre of abundance is focussed on the English Channel and the Celtic Sea. The eastern end of the channel (7d) is covered by the French CFGS, while the Celtic Sea (7h) is covered by the EVHOE surveys (Figure 1). This leaves an area of high abundance in 7e currently not covered by any survey. Data exists in the English Channel Beam Trawl Survey series from 2006 to present, however it has not yet been processed in such a way that it can provide an index.

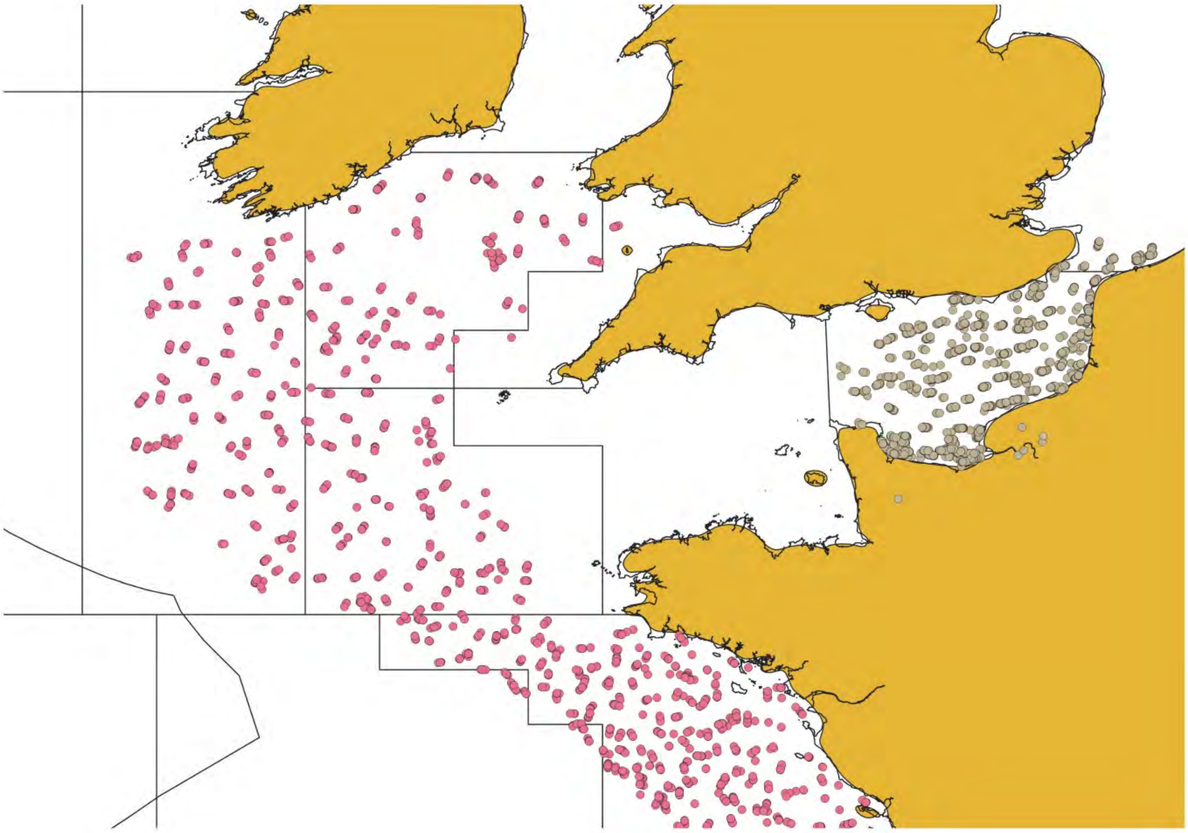


Figure 2. Map showing the coverage of hauls in the French Channel Groundfish and EVHOE surveys, highlighting the gap in coverage in the western Channel.

Work required: Analysis of survey data to enable the production of a time-series of red gurnards in 7e.

Data required: English Channel Beam Trawl Survey data.

Response: English Channel Beam Trawl Survey data is now available through DATRAS, filling the gap between the EVHOE and CGFS survey areas. Catches of red gurnard at length are reported in the survey (Figure 2). A survey index can be derived from these data.

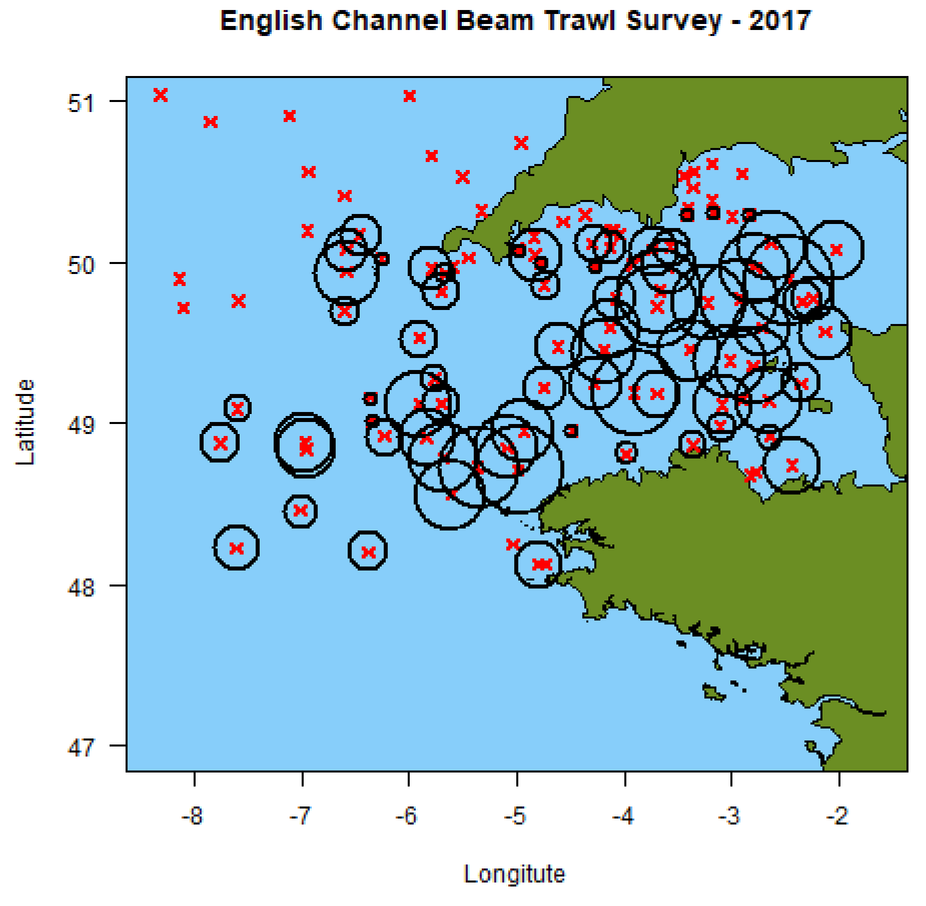


Figure 3. An example of the area covered by the English Channel Beam Trawl Survey (EN-BTS) in 2017.

2.1.4 Stock Assessment Model

Problem: Lack of an assessment method

Issue: Assuming catch data remains unreliable at the species level for some time, a survey-based assessment seems the most likely way to provide more quantitative advice on stock status. A SURBAR model based on the CGFS and EVHOE surveys is in a process of development, and with some refinement, would be a promising candidate for an assessment model.

Work Required: Model tweaking

Data Required: Survey data

Response: Considering the findings of SIMWG regarding conducting a single assessment of the whole area, it becomes difficult to see how this could be done. Age readings are only available routinely from EVHOE, with some readings from CGFS and IGFS in more recent years. Constructing an age–length key and applying it to surveys in very different areas may not be a valid exercise. The two options which seem most defensible are:

> Conduct a survey-based assessment of red gurnard in 7d–h (the area covered by EVHOE, CGFS and southern parts of the IGFS) which is where the majority of landings are reported from, and assume this is indicative of the trends of the wider population.

Develop a survey-based delta-lognormal spatial GLM incorporating catches of SCO-WCGFS, IGFS, EVHOE and CGFS (and explore use of ENG-BTS) and extract the year effect from this model as an indicator of trends in stock status.

2.1.5 Appropriate Assessment Area

Problem: Stock subareas do not correspond to distribution of species

Issue: If the species distribution is heavily focussed on 7d,e,h, what approach should be taken to advice and management outside of this area?

Work Required: Consideration of evidence of presence of red gurnard in significant quantities in each division to determine whether it is justified in changing the stock definition.

Data Required: Spatial distribution of landings and discards over time.

Response: There are three issues here – whether to extend the assessment to cover Division 9a, whether to exclude Subarea 5, and whether to wholly or partially exclude Subarea 3. Landings from Division 9 have been in the order of a hundred tonnes per year, however the Portuguese response to WGCATCH quoted above, cites potential over-reporting of red gurnard from this area. In light of this it may not be as important to extend the assessment to cover this area. Excluding areas where the stock is not present is a less urgent priority.

The current stock used by ICES for assessment and advisory purposes covers subareas 3–8, from the Baltic Sea to the Bay of Biscay and considers red gurnard within this area to be a single stock (Figure 3).

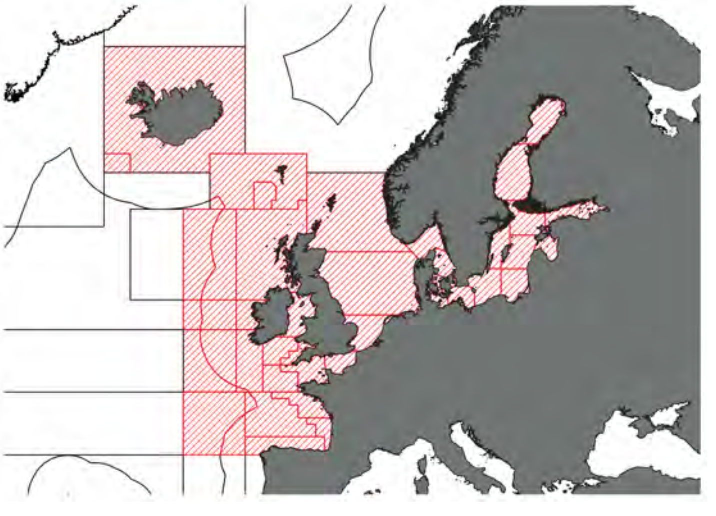


Figure 4. The area used for assessment purposes for Red gurnard (*Chelidonichthys cucculus)* in SA 3–8.

Given the sparse knowledge of the biology and life-history of red gurnards, concerns have been raised about the usefulness and validity of this definition on a number of fronts:

- Red gurnard have not been reported from Subarea 5 in recent times, and while present in a small number of years from Division 3a, are absent from the rest of the Baltic Sea.
- Commercial landings are routinely reported from Division 9a, outside the current stock boundary, causing presentational issues when drawing up advice sheets.
- Two starkly different trajectories are seen in survey data CPUEs for surveys covering northern (subareas 4 and 6) and southern (subareas 7 and 8) of the parts of the range.

A working document was provided to the Stock Identification Methods Working Group (SIMWG) in 2019, with a request to comment on the stock identity of this species in light of the divergent survey trends over its range, and review of the available information that might be relevant to stock structure of red gurnard. SIMWG considered there was insufficient evidence for splitting the stock into two stock areas (North Sea/west of Scotland and Celtic Seas/Biscay) at this time. Although they noted the different trends in abundance between the areas across surveys, this alone was insufficient to support a conclusion regarding stock structure. They recommend that more granularity be required in fishery-dependent data collection (i.e. identification to species), a comparison in gurnard catchability among the various surveys in this region, and starting basic biological data collection for accurate stock identification for the data-poor species before any spatial management changes should be considered or stocks delineated.

2.2 Summary of decision

Having considered the progress made on the issue list and the responses of WGCATCH and SIMWG, a decision was taken to proceed with a single assessment of status for whichever area is felt to be most appropriate. This does, however, leave us with some remaining problems, such as reconciling divergent trends in survey data into a meaningful combined metric.

Given the ongoing concerns around quality and reliability of catch data, an emphasis was placed upon survey-based estimates of status as the basis for advice, rather than attempt a detailed examination of catches and discards which vary in nature and quality across reporting countries.

2.3 Available data

The data call requested countries submit discard information for red, grey and mixed gurnards. The data received in advance of the data evaluation workshop are shown in Table 3. In addition to this, there were a number of other files giving landings by statistical rectangle with no associated country identifier, which need further investigation with the Secretariat to identify which nation has submitted them before the comprehensiveness of the data can be determined.

Table 3. Data received in response to the data call for Red Gurnard (*Chelidonichthys cucculus*) in SA 3–8.

Country	Years	Species	Category	Notes
Belgium	2006–2019	GUG	Landings	Landings by stat rectangle, by métier.
	2006–2019	GUR	Landings	Landings by stat rectangle, by métier.
	2006–2019	GUU	Landings	Landings by stat rectangle, by métier. GUU was not requested in the data call. Need to clarify whether they use the GUX code.
Netherlands	2002–2019	GUG	Landings	Landings and effort by stat rectangle, by métier. Low discarding reported.
	2002–2019	GUR	Landings	Landings and effort by stat rectangle, by métier. Low discarding reported.
	2002–2019	GUX	Landings	Landings and effort by stat rectangle, by métier. No discard data.
France	2004–2019	GUG	Landings & Discards	Landings, discards and effort, by métier, by division, in InterCatch format.
	2004–2019	GUR	Landings & Discards	Landings, discards and effort, by métier, by division, in InterCatch format.
	2004–2019	GUX	Landings & Discards	Landings, discards and effort, by métier, by division, in InterCatch format.
Ireland	2003–2019	GUG	Landings & Discards	Landings, discards and effort, by métier, by division, in InterCatch format.
England & Wales	2004, 2009, 2010, 2012–2019	GUG	Landings	Landings-at-length, and effort, by métier, by division, in InterCatch format.
	2000–2019	GUX	Landings	Landings-at-length, and effort, by métier, by division, in InterCatch format.
	2009–2019	GUR	Landings	Landings by statistical rectangle.
Sweden	2002–2019	GUG	Landings	Effort and landings, by métier, by division, in InterCatch format.
	2002–2019	GUX	Landings	Effort and landings, by métier, by division, in InterCatch format.
Spain	2009–2019	GUG	Landings & Discards	Effort, landings and discards at length, by métier by division, in InterCatch format.
	2009–2019	GUX	Discards	Effort and discards, by métier by division, in InterCatch format.
Poland	2019	GUX	Landings	Landings by stat rectangle.
Scotland	2002–2019	GUG	Landings & Discards	Landings and discards at length and effort, by métier, by division, in InterCatch format.
	2002–2019	GUX	Landings & Discards	Landings and discards at length and effort, by métier, by division, in InterCatch format.
	2002	GUR	Landings & Discards	Landings and discards at length and effort, by métier, by division, in InterCatch format. Only one year available?

Country	Years	Species	Category	Notes
Germany	1995–2001	GUX	Landings	Landings and effort, by métier, by division, in InterCatch format.

While it is possible to make an assessment of trends in the status of red gurnard populations as a whole on the basis of fishery-independent survey data, the fundamental problems with catch data makes translating any observations into management advice flawed. Average catches of red gurnard may represent a floor or minimum estimate of catch, with some proportion of the GUX landings in addition to this representing a truer picture of catch. Following the ICES guidelines for survey-based assessments; there is some implicit understanding of the absolute value of catch in each option. We have a large degree of uncertainty about the first component of the pressure-state-response paradigm which survey-based assessments are predicated upon.

2.3.1 Commercial catch

In addition to red gurnards, two other species of Triglid are caught in commercially significant quantities in Northeast Atlantic waters; the grey gurnard (*Eutrigla gurnardus*) and the tub gurnard (*Chelidonichthys lucerna*) (Figure 4). In some cases, these are landed together, and in combination with red gurnards as “mixed gurnards”, and reported under the species code GUX (Figure 5). The proportion of landings reported as mixed gurnards varies between countries and there is little documentation available on if and how the species composition of gurnard landings is verified. There are no catch limits or minimum conservation reference size set for these species, and anecdotally, little effort goes into validation of species compositions at the quayside. A presentation was made to WGWIDE in 2018 on the work being carried out in Portugal to improve reporting and validation of gurnard landings to species level, however the approaches of other countries remain undocumented.

Figure 5. Red gurnard (*Chelidonichthys cucculus*) (top), grey gurnard (*Eutrigla gurnardus*) (left) and tub gurnard (*Chelidonichthys lucerna*) (right) (D. Feijo, IPMA, Lisbon).

Figure 6. A box of "mixed gurnards", landed under the species code GUX. (D. Feijo, IPMA, Lisbon).

Landings of mixed gurnards from SA 3–8 have ranged between 50% and 100% of the equivalent red gurnard value recorded in the same area (Figure 6). This obviously creates a number of issues with assessing the stock, such as interpreting trends in landings, raising discards and comparing CPUE's across fleets. The impact of this situation on ICES ability to provide meaningful advice is also considerable. Landings of tub gurnards, particularly from the southern North Sea, seem to be at odds with indications from surveys. During 2006–2019, average catches per hour towed in the North Sea IBTS survey were 32.1 kg for grey gurnards, 0.51 kg for red and 0.17 kg for tub.

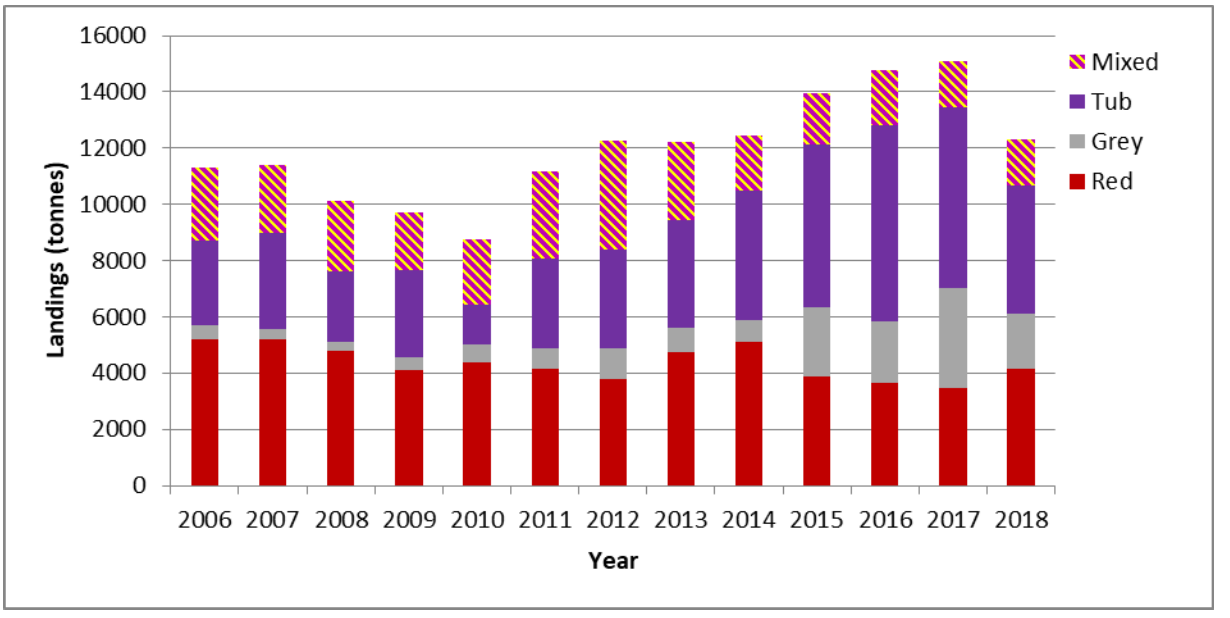


Figure 7. Official landings of red, grey, tub and mixed gurnards, 2006–2018, SA 3–8.

There may be heuristics which could be used to guide us in allocating mixed catches to species, such as apportioning on the basis of reported landings of the three species on a division by division basis, or using the relative proportions observed in surveys considered representative for each area. Given the uncertainty in catch, which is in the same order as the landings themselves, I consider that this is a problem wider than the scope of this benchmark, one which cannot be solved with the data available, and that for our purposes we should restrict our analysis to purely survey-based approaches to determining stock status for red gurnards.

2.3.2 Survey Data – fishery-independent biomass index

As would be expected with a widely distributed species, catches of red gurnard are reported from many bottom trawl surveys which take place in this area. The majority of these are available through DATRAS, making catch-at-length commonly available, and catch-at-age in a small number of cases. Indices and summary data have been made available to the working group for some of those which are not, and these are included below.

2.4 Tuning series

As might be expected for a stock which covers such a wide geographic range, red gurnard are encountered in nearly every bottom trawl survey in the Northeast Atlantic. The spatial distributions and a time-series of catches in each series are presented below. The temporal coverage of the surveys considered in the assessment is shown in Figure 7.

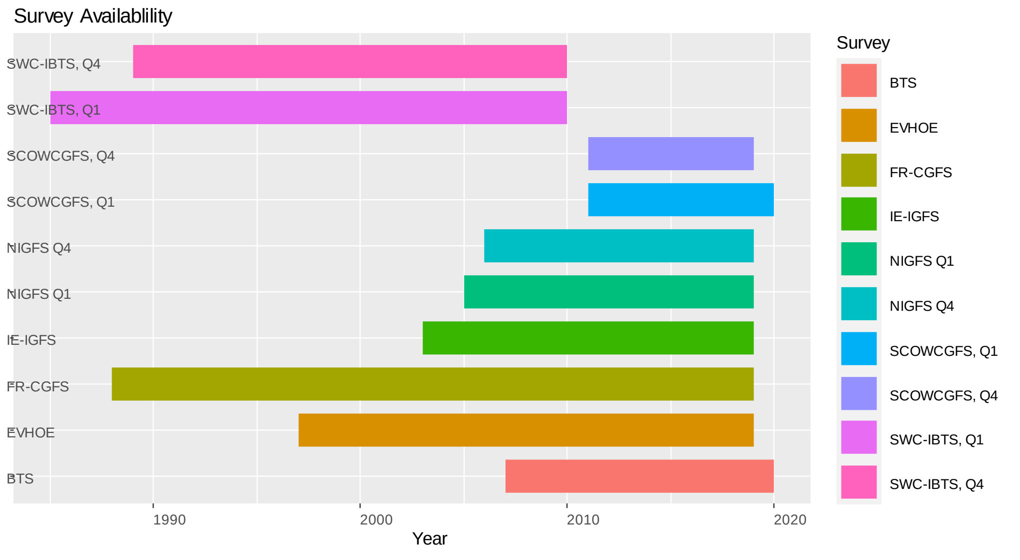


Figure 8. Temporal coverage of survey series used in the assessment of red gurnard (*Cheildonichthys cucullus*) in SA 3–8.

2.4.1 FR-EVHOE

The French survey "Evaluation Halieutique Ouest de l'Europe" (EVHOE) is a bottom trawl survey which has covered the waters so the south of Ireland, southwest of the UK and down the west coast of France, annually, since 1998. Data are not available for 2017 due to disruption to the survey. This survey covers the core area from which landings are reported, and as such is probably the indicator which will correspond most closely to the "fished stock". Otoliths are taken and read for this survey, therefore catch-at-age and catch-at-length data are available for this survey (Figure 10). Although red gurnards are found throughout the area covered by the survey, the area to the west of Ouessant appears to be an area of consistently high abundance (Annex 2. Distribution of Survey Catches, French EVHOE Survey, 1998–2019).

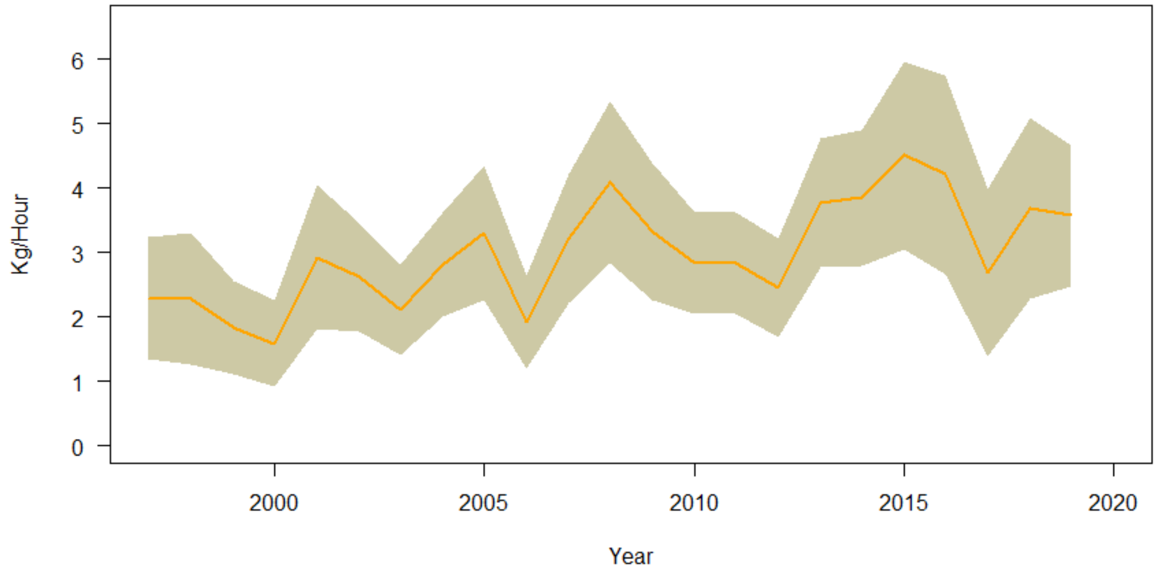


Figure 9. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Quarter 4 ÉValuation des ressources Halieutiques de l'Ouest de l'Europe (EVHOE) survey (error bars are ± two standard error).

2.4.2 FR-CGFS

The French Channel Groundfish Survey (CGFS) covers the eastern half of the Channel (Division 7d). Red gurnard appears routinely in survey catches in the more offshore hauls (Annex 2. Distribution of Survey Catches, French Channel Groundfish Survey (FR-CGFS)). Age data are available for some years in the series (Figure 10). This survey covers the period 1989–2019, although a change in vessel from the *Gwen Drez* to the *Thalassa* and subsequent change in fishing operations, after 2015 has raised questions regarding whether this should be considered as one series or two. Examination of trends in mean abundance over the survey series reveals variation with no particular trend, other than a decline from higher than average in the first years of the series (Figure 9). There is no apparent change in catch rate associated with the switch in vessels.

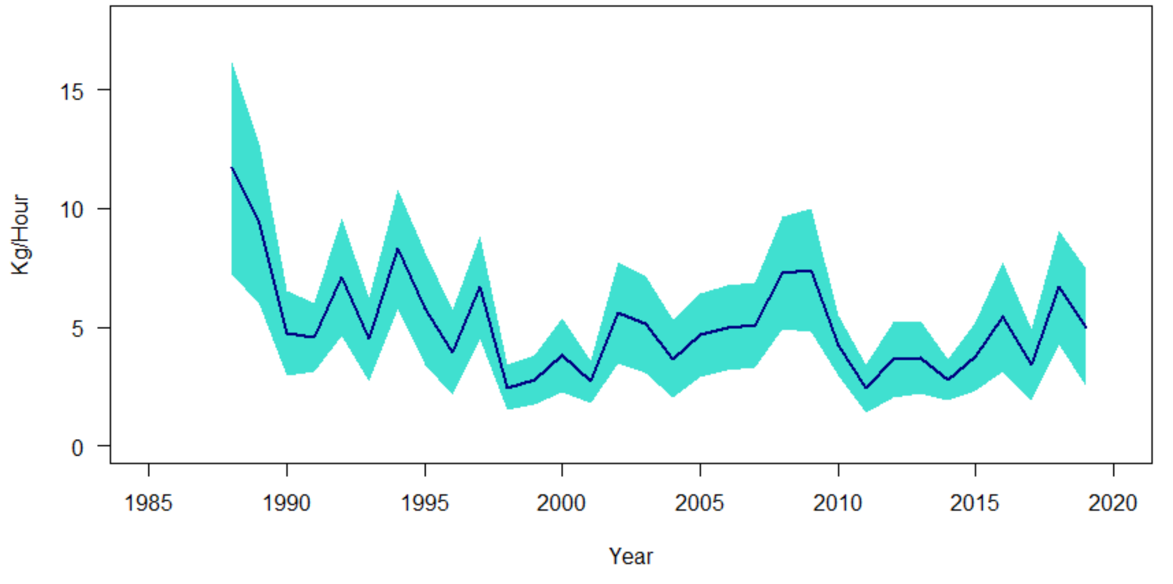


Figure 10. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Quarter 4 French Channel Ground-fish Survey (FR-CGFS) survey (error bars are ± two standard error).

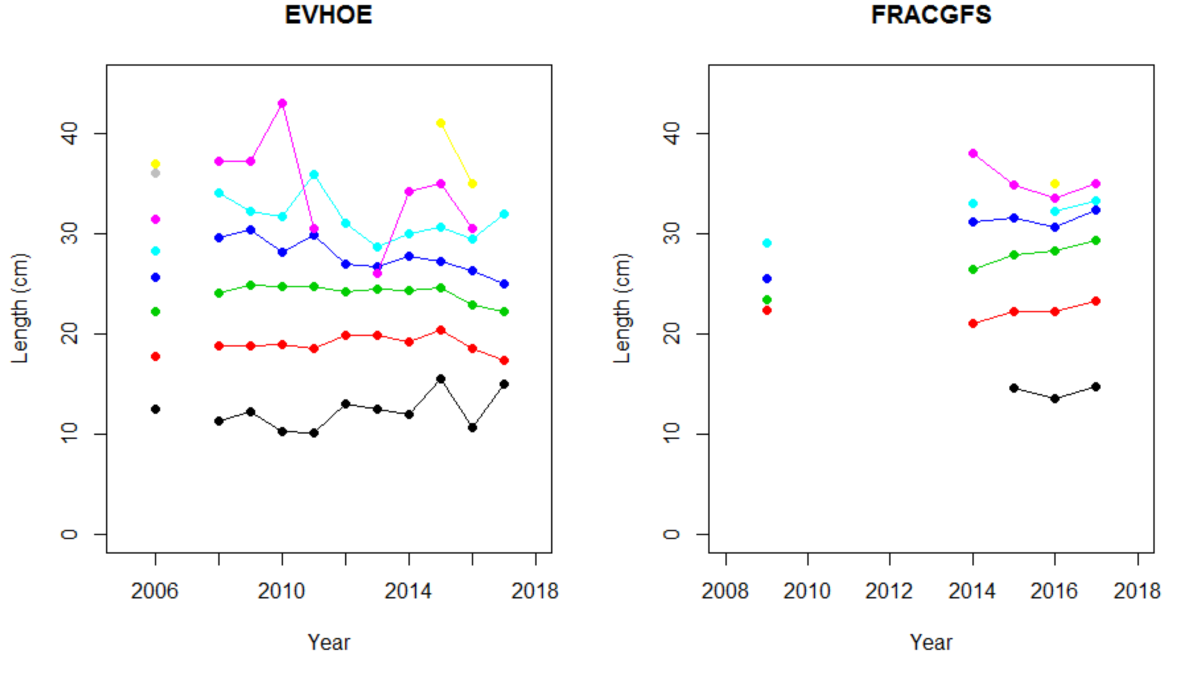


Figure 11. Length-at-age data of red gurnard (*Chelidonichthys cucculus*) from the EVHOE and CGFS surveys.

2.4.3 IE-IGFS

The Irish Groundfish Survey is a more recent series, covering waters around the coast of Ireland over the period 2003–2019. It reveals a consistent yet patchy distribution. Age data are available for some years over the course of the survey.

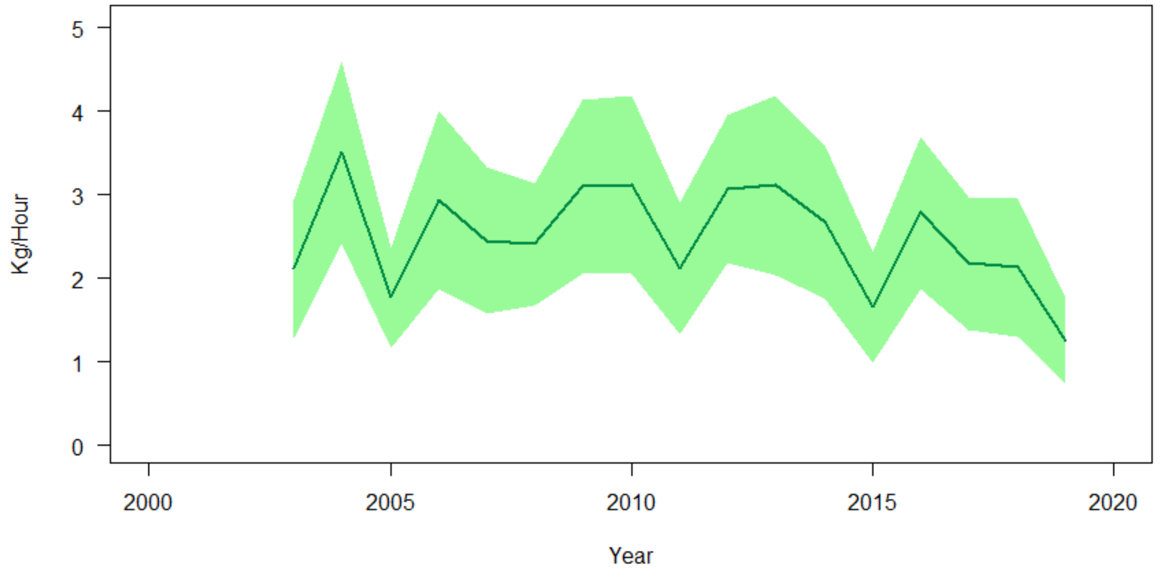


Figure 12. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Quarter 4 Irish Groundfish Survey (FR-CGFS) survey (error bars are ± two standard error).

2.4.4 SCO-WCGFS and SCO-WCIBTS

The Scottish West Coast IBTS survey took place during quarter 1 of 1985–2010, and quarter 4 of 1990–2009. This survey was initially intended to cover the fishing grounds on the continental shelf to the west of Scotland; in 1996 the survey area was extended to include stations in the northern Irish Sea. This survey was replaced in both quarters from 2011 onwards by the Scottish West Coast Groundfish Survey. This involved a change in stratification, from one based on obtaining several tows in each statistical rectangle, to a depth basted random-stratified survey design. Both series use a GOV net, however the earlier series used ground gear “C” (525mm bobbins) while the latter used ground gear “D” – a rockhopper rig with discs up to 16” (406 mm) (Harley and Ellis, 2007).

These surveys cover waters to the west of Scotland, from Shetland to the north of Ireland, differing in the stratification they use. Age data is not available for this survey series. The Scottish west coast IBTS surveys show a slow general upward trend from 1997 to 2010 (Figure 12 and Figure 13). The SWC-GFS series starts at a higher level, not unexpectedly due to the shift to lighter ground gear, but this increasing trend continues until Q4 2012/Q1 2013, before falling to lower levels. This trend is not seen in the Irish, French or Spanish surveys further south.

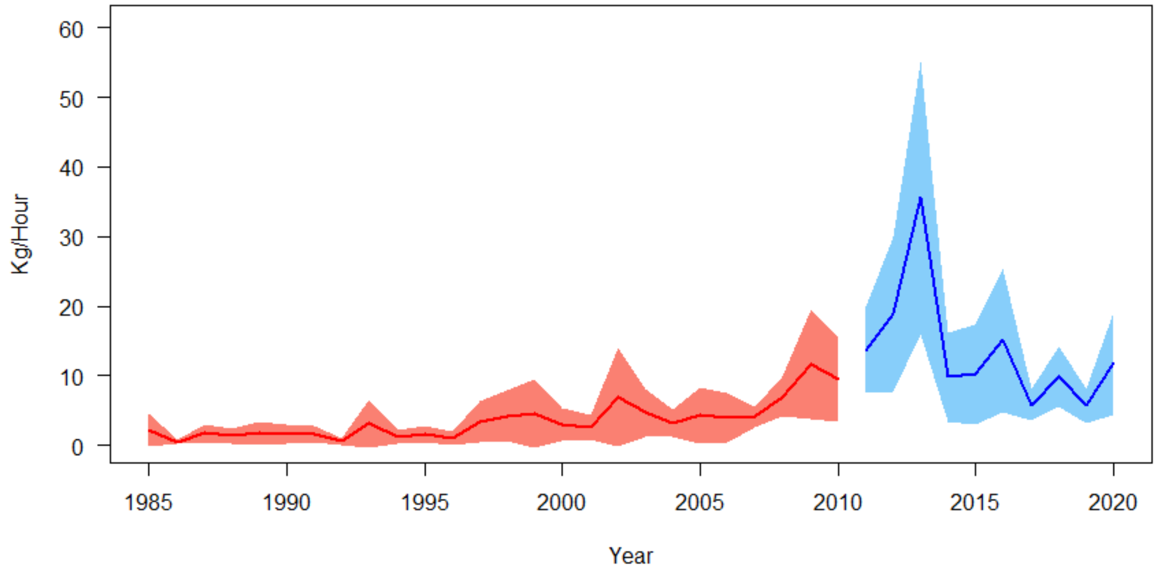


Figure 13. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Quarter 1 Scottish West Coast IBTS (SCO-WCIBTS) (red) and Scottish West Coast Groundfish Survey (SCO-WCGFS) (blue). (error bars are ± two standard error).

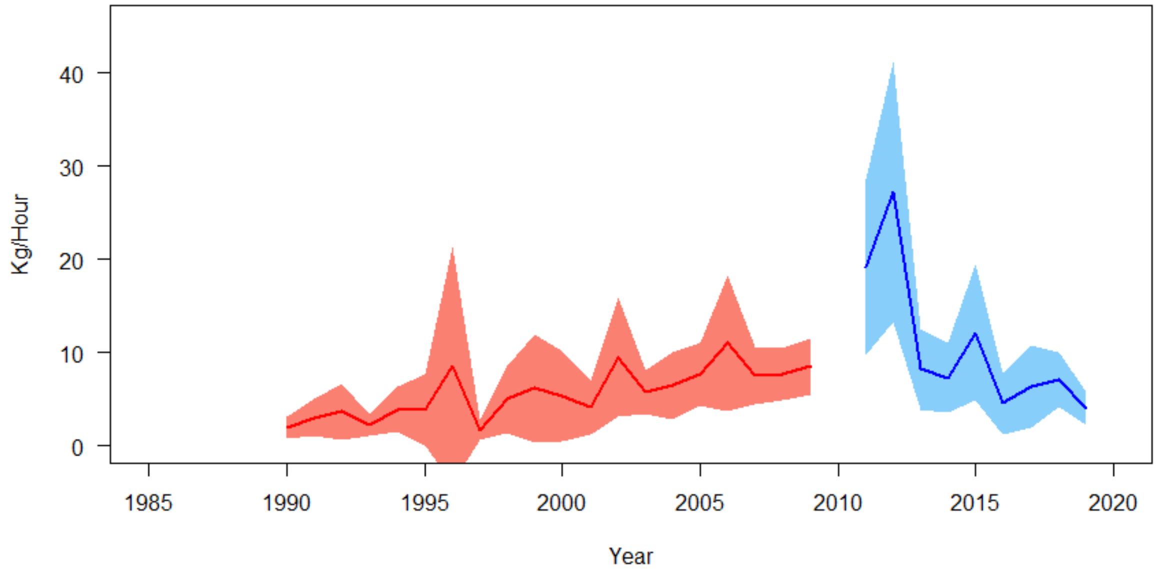
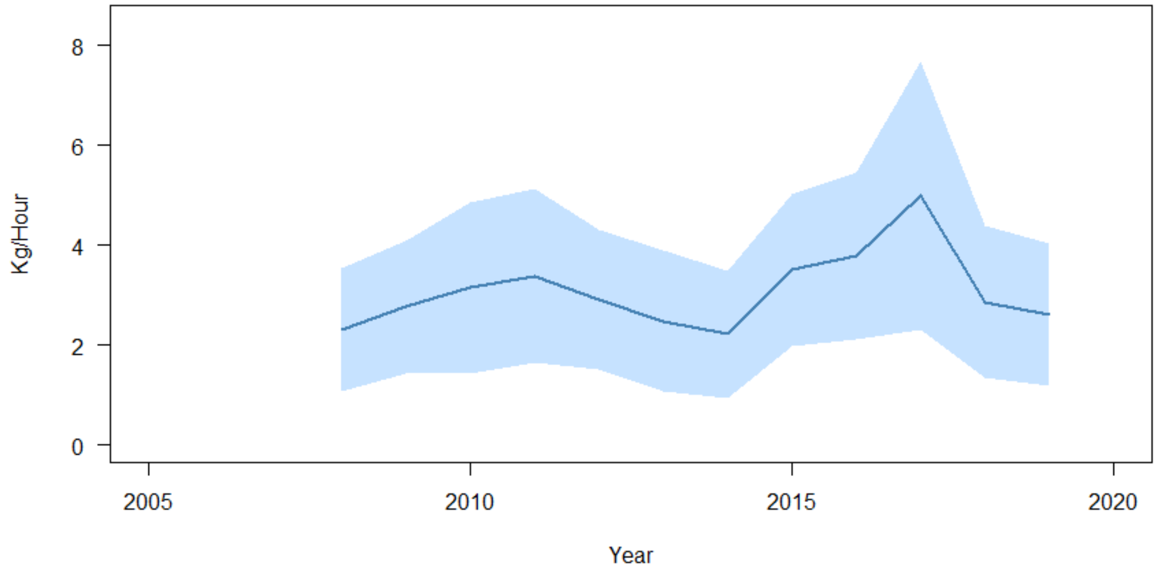


Figure 14. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Quarter 4 Scottish West Coast IBTS (SCO-WCIBTS) (red) and Scottish West Coast Groundfish Survey (SCO-WCGFS) (blue). (error bars are ± two standard error).

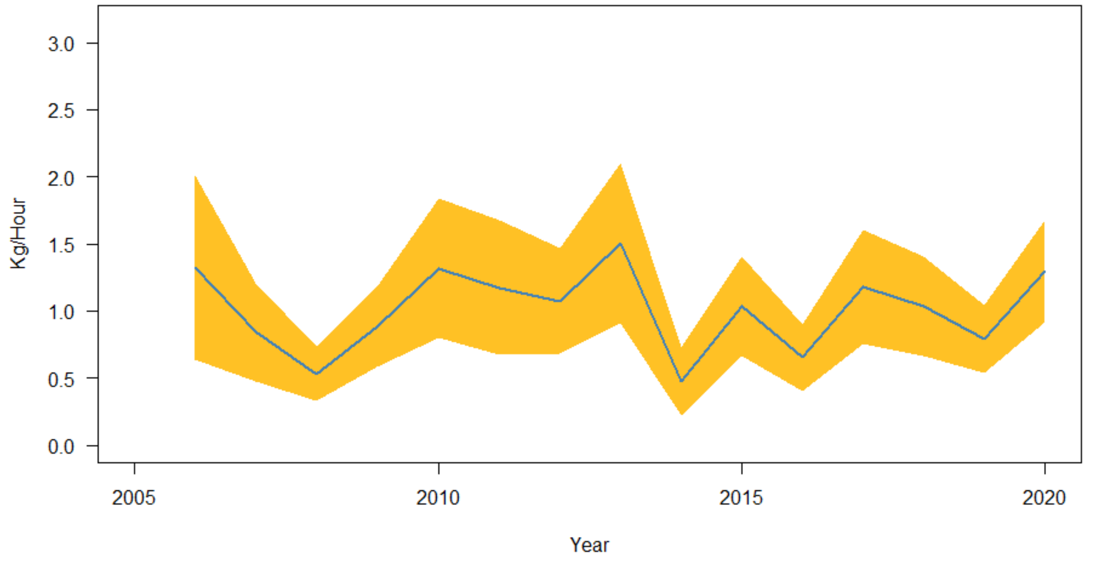
2.4.5 Northern Irish Groundfish Survey

Data are available from this survey, which covers the Irish Sea, since 2008. Catches are relatively flat throughout the period, with some suggestion of a peak in 2017.



2.4.6 English Channel Beam Trawl Survey

Catches in the English Channel beam trawl survey are relatively flat throughout the period, with some suggestion of a peak in 2013.



2.5 Other Surveys

Indices from several other surveys were made available through the accessions process.

2.5.1 Spanish Gulf of Cadiz Groundfish Survey (SP-GCGFS)

Data for this survey were submitted to the benchmark through Accessions for the period 1993–2019. This survey covers Spanish waters of ICES Division 9a. Catches of red gurnard appear to average less than one fish per haul, and less than 300 g, over the entire duration of the available data, with little evidence of variability or strong trends. Without further information such as haul duration, it is difficult to reconcile these data with results of other surveys, however it demonstrates the presence of red gurnard at the southern boundary of Div. 9a, outside the area considered in the current assessment.

2.5.2 Spanish Northern Groundfish Survey (SP-NGFS)

The Spanish northern groundfish survey covers ICES Division 8c and the northern part of 9a corresponding to the Cantabrian Sea and off Galicia waters. This survey covers the period 1990–2019. This survey is conducted during the third and the fourth quarter (September–October) and covers a depth range of 35 to 700 m. Stratification was redefined in 1997, and is based on three depth strata (70–120, 121–200, 201–500 m) and five geographic sectors. Additional hauls both in deeper water (500–700 m) and shallower waters (30–80 m) are conducted yearly depending on the ship time available at sea. The coverage is approximately 5.4 hauls for every 1000 Km^2 (120 hauls per survey).

The survey has been carried out onboard the RV *Cornide de Saavedra* except in 1989 when another research vessel (NV F. *de P. Navarro*) was used to conduct the survey. The gear used is a Baka trawl 44/60 with a 43.6 m footrope and a 60.1 headline. Until 1985, a codend cover of 20 mm mesh was used, and since then, a 20 mm mesh codend liner has been adopted.

Survey catches have varied without particular trend up to 2013, before increasing to a higher level in 2014 and remaining at for the rest of the series (Figure 14).

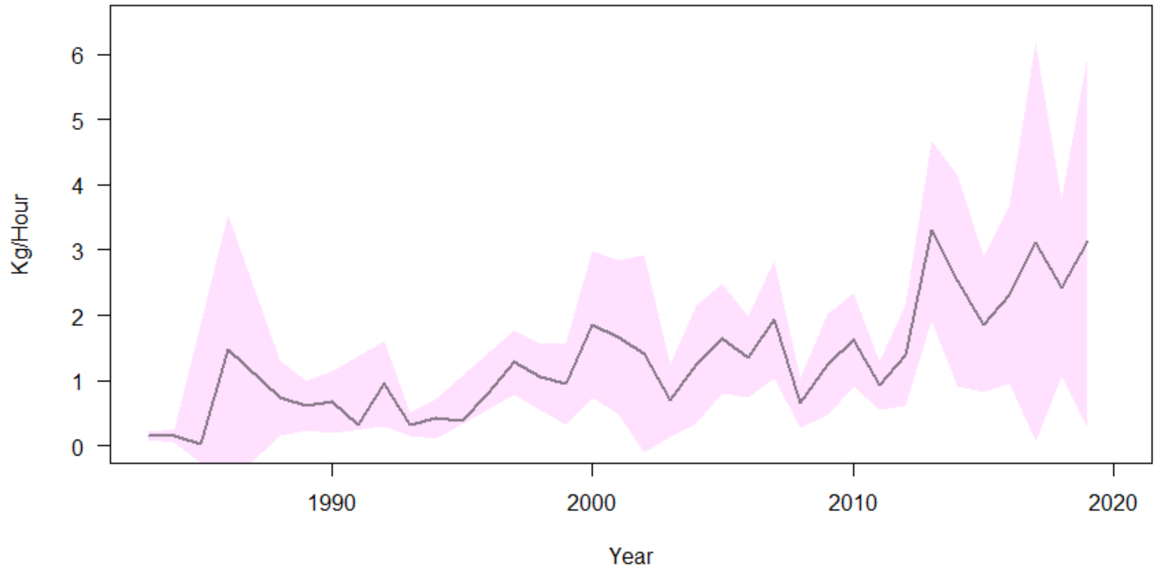


Figure 15. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Spanish Northern Groundfish Survey (SP-NGFS) (error bars are ± two standard error).

2.5.3 Spanish Porcupine Bank Groundfish Survey (SP-PORC)

This survey covers the years 2000–2019, and fishes on Porcupine Bank, to the southwest of Ireland. As with the Spanish Northern Survey mean numbers per tow, per year, and a breakdown of these by length, have been provided for red, grey and mixed gurnards. These species have not been included in the data from these surveys which have been uploaded to the DATRAS database, so it is not possible to include these series in any analytical modelling, however they do show

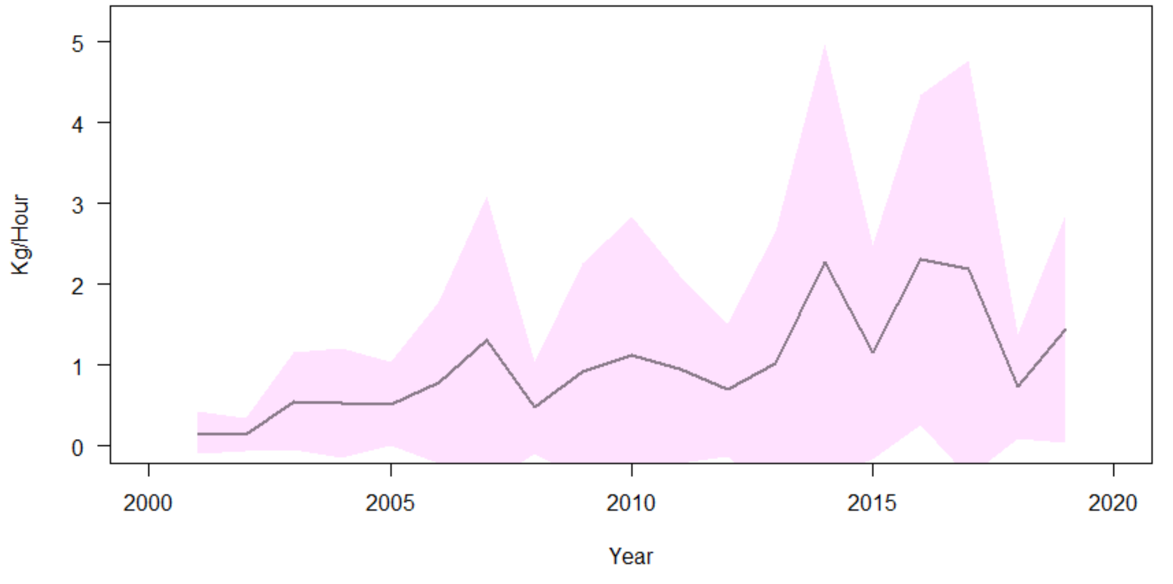


Figure 16. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Spanish Porcupine Bank Survey (SP-PORC) (error bars are ± two standard error).

2.5.4 North Sea IBTS

Red gurnard are relatively frequently reported from Subarea 4 around Shetland, but are otherwise rare in survey data from this region (Annex 2. Distribution of Survey Catches, North Sea International Bottom Trawl Survey (NS-IBTS), 1984–2019.). Indicators produced for the North Sea follow closely with the Scottish West Coast surveys, and it may be a useful exercise to combine hauls from the northern part of the North Sea with those to the west of the 4° line.

2.6 Stock assessment

2.6.1 SURBAR

Age data are available for some years in French and Irish surveys. While an assessment based on such data may not be consistently applicable across the whole stock area, an exploratory assessment using SURBAR was attempted. Given the differences observed in mean length between the different surveys, it was considered unhelpful to apply a single age–length key across all surveys. Likewise, conducting an assessment just for the area covered by the EVHOE and CGFS surveys may be more meaningful, however extrapolating from this to an assessment of status and catch advice which is valid across SA 3–8 would be challenging. This route was therefore discounted.

2.6.2 Delta-lognormal GLM

As an attempt to combine the information from surveys covering the assessment area using a delta-lognormal GLM has been undertaken. Delta-lognormal approach has two distinct components, which can be modelled and fitted separately to obtain first a fitted probability of non-zero tows and then the expected number of fish, given that some were caught.

Haul and catch data were downloaded from the ICES DATRAS database for the surveys listed in Figure 7. Numbers-at-length were converted into a weight-at--length using the length–weight relationship described in Coull *et al.* (1989) and summed to provide a weight per tow.

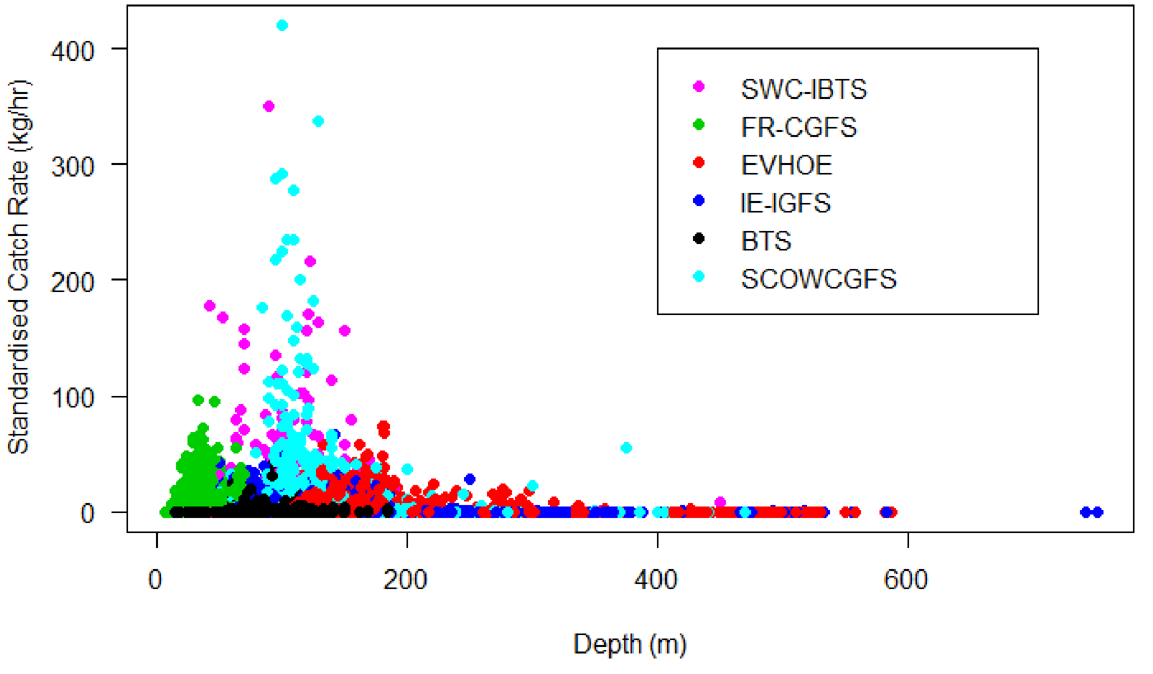


Figure 17. Standardised catch rate (kg/hr) of red gurnard (*Chelidonichthys cucculus*) at depth for each survey in the DATRAS data.

Having explored the distribution of catches in the survey data, a decision was taken to constrain it to hauls shallower than 300 m. This meant retained 99.85% of red gurnard catches, and eliminated a significant number of zero catch hauls at depths beyond the range inhabited by red gurnard, which had undue influence on the significance of parameters within the model (Figure 16).

A process of backwards selection was applied to determine the optimum configuration of the model, using the Akiaike Information Criteria (AIC). It became apparent that the Northern Irish Groundfish Survey was not informative to the results, which is perhaps not surprising given the lack of contrast in the data. The decision was taken to remove this survey from the data. The optimal model configuration for the binomial part of the model was:

```
~ as.factor(Quarter) + HaulLong + Depth * as.factor(Survey)
```

and for the lognormal part:

```
st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
            HaulLat + Depth * as.factor(Survey)
```

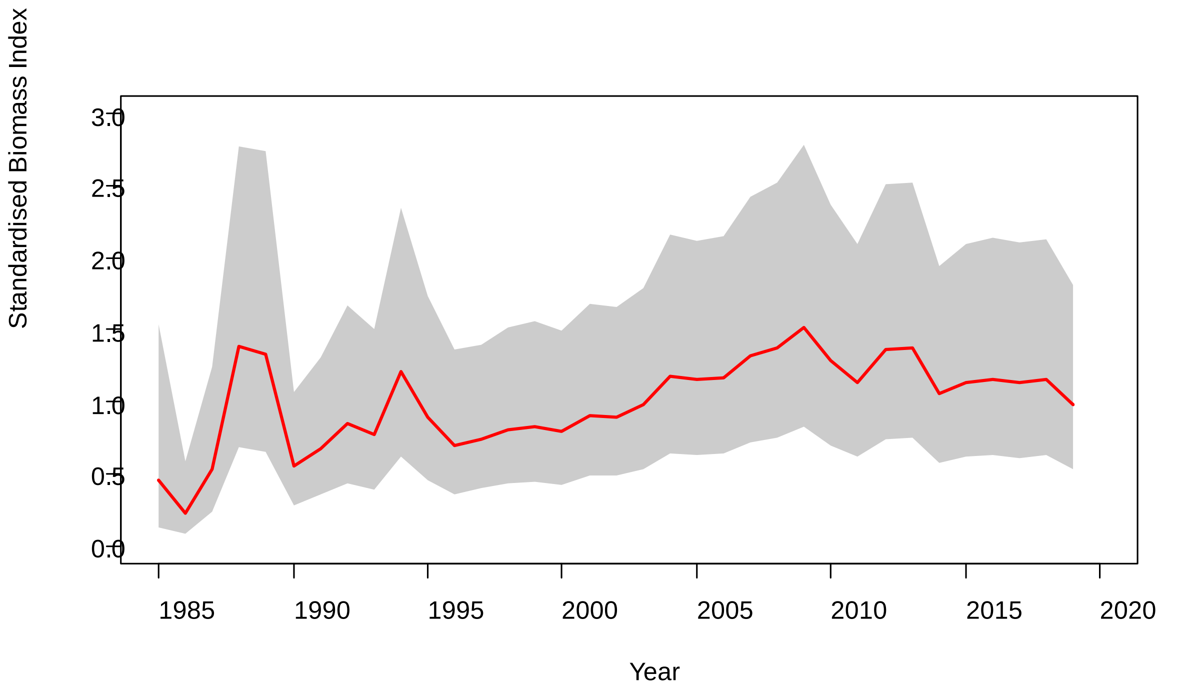


Figure 18. Biomass index extracted from the final model formulation, using the full range of data, 1985–2019 (±2 s.e.).

Extracting the estimates of year effect from the model, together with their associated standard error, and standardising them relative to their average value, provides an index of biomass which is highly variable in the early years of the series (Figure 18). It should be noted that at this time, only the French Channel Groundfish Survey and Scottish West Coast IBTS surveys were active. These areas are widely separated geographically, and there are remaining uncertainties as to the linkages of these in a single stock. The introduction of the EVHOE survey in 1997 provides a wider area of coverage and a more stable index. Using only data from 1997 onwards produces a more consistent index, and this is proposed as the final assessment approach (Figure 19). Residuals and other measures of goodness of fit are shown in Figure 20.

Significance of parameters in the binomial part of the model are shown in Table 4, and for the lognormal part in Table 5.

Table 4. Significance of parameters in the log-normal part of the model.

```
Coefficients:
                                      Estimate Std. Error t value Pr(>|t|)
nz.X(Intercept)                      -4.524276   0.598982  -7.553 4.73e-14 ***
nz.Xas.factor(Year)1998               0.073778   0.165241   0.446 0.655255
nz.Xas.factor(Year)1999               0.118884   0.165925   0.716 0.473708
nz.Xas.factor(Year)2000               0.070436   0.161342   0.437 0.662442
nz.Xas.factor(Year)2001               0.200386   0.154008   1.301 0.193250
nz.Xas.factor(Year)2002               0.181910   0.150794   1.206 0.227720
nz.Xas.factor(Year)2003               0.268395   0.143769   1.867 0.061961 .
nz.Xas.factor(Year)2004               0.454992   0.144048   3.159 0.001591 **
nz.Xas.factor(Year)2005               0.437431   0.142799   3.063 0.002197 **
nz.Xas.factor(Year)2006               0.459025   0.141457   3.245 0.001180 **
nz.Xas.factor(Year)2007               0.575182   0.139725   4.117 3.89e-05 ***
nz.Xas.factor(Year)2008               0.606803   0.137151   4.424 9.81e-06 ***
nz.Xas.factor(Year)2009               0.694359   0.137379   5.054 4.42e-07 ***
nz.Xas.factor(Year)2010               0.584524   0.140059   4.173 3.03e-05 ***
nz.Xas.factor(Year)2011               0.483720   0.139374   3.471 0.000522 ***
nz.Xas.factor(Year)2012               0.602167   0.138287   4.354 1.35e-05 ***
nz.Xas.factor(Year)2013               0.639019   0.138873   4.601 4.26e-06 ***
nz.Xas.factor(Year)2014               0.390433   0.138718   2.815 0.004896 **
nz.Xas.factor(Year)2015               0.551724   0.139603   3.952 7.82e-05 ***
nz.Xas.factor(Year)2016               0.538043   0.139035   3.870 0.000110 ***
nz.Xas.factor(Year)2017               0.518647   0.146564   3.539 0.000404 ***
nz.Xas.factor(Year)2018               0.496219   0.139803   3.549 0.000388 ***
nz.Xas.factor(Year)2019               0.376857   0.141141   2.670 0.007599 **
nz.Xas.factor(Quarter)4               0.122642   0.067004   1.830 0.067232 .
nz.Xas.factor(Survey)EVHOE           -0.388024   0.227833  -1.703 0.088588 .
nz.Xas.factor(Survey)FR-CGFS          2.206010   0.236120   9.343  < 2e-16 ***
nz.Xas.factor(Survey)IE-IGFS          1.207340   0.219072   5.511 3.68e-08 ***
nz.Xas.factor(Survey)NIGFS            0.396534   0.289551   1.369 0.170889
nz.Xas.factor(Survey)SCOWCGFS         2.493015   0.278276   8.959  < 2e-16 ***
nz.Xas.factor(Survey)SWC-IBTS         1.949560   0.252589   7.718 1.33e-14 ***
nz.XHaulLat                           0.066765   0.011201   5.961 2.62e-09 ***
nz.XDepth                             0.009955   0.002090   4.762 1.95e-06 ***
nz.Xas.factor(Survey)EVHOE:Depth      0.002035   0.002266   0.898 0.369316
nz.Xas.factor(Survey)FR-CGFS:Depth   -0.012876   0.004004  -3.216 0.001304 **
nz.Xas.factor(Survey)IE-IGFS:Depth   -0.013827   0.002251  -6.143 8.52e-10 ***
nz.Xas.factor(Survey)NIGFS:Depth      0.004718   0.003960   1.192 0.233482
nz.Xas.factor(Survey)SCOWCGFS:Depth -0.014658   0.002614  -5.607 2.13e-08 ***
nz.Xas.factor(Survey)SWC-IBTS:Depth -0.013672   0.002446  -5.589 2.36e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.534 on 7766 degrees of freedom
Multiple R-squared:  0.3107,	Adjusted R-squared:  0.3073
F-statistic:  92.1 on 38 and 7766 DF,  p-value: < 2.2e-16
```

Table 5. Significance of parameters in the binomial part of the model

```
Coefficients:
                                              Estimate Std. Error z value Pr(>|z|)
bin.X[, -1](Intercept)                      -1.4676938  0.1183773 -12.398  < 2e-16 ***
bin.X[, -1]as.factor(Quarter)4               0.0308263  0.0640507   0.481 0.630318
bin.X[, -1]HaulLong                         -0.1337589  0.0101272 -13.208  < 2e-16 ***
bin.X[, -1]Depth                             0.0016381  0.0014877   1.101 0.270831
bin.X[, -1]as.factor(Survey)EVHOE            1.7508222  0.1549198  11.301  < 2e-16 ***
bin.X[, -1]as.factor(Survey)FR-CGFS         -1.2811173  0.2055218  -6.233 4.56e-10 ***
bin.X[, -1]as.factor(Survey)IE-IGFS          1.3763027  0.1655743   8.312  < 2e-16 ***
bin.X[, -1]as.factor(Survey)NIGFS           -0.7483778  0.2033023  -3.681 0.000232 ***
bin.X[, -1]as.factor(Survey)SCOWCGFS         1.9108973  0.2062592   9.265  < 2e-16 ***
bin.X[, -1]as.factor(Survey)SWC-IBTS         0.6366468  0.1707772   3.728 0.000193 ***
bin.X[, -1]Depth:as.factor(Survey)EVHOE     -0.0050144  0.0015217  -3.295 0.000984 ***
bin.X[, -1]Depth:as.factor(Survey)FR-CGFS    0.0911849  0.0051074  17.854  < 2e-16 ***
bin.X[, -1]Depth:as.factor(Survey)IE-IGFS   -0.0083180  0.0015443  -5.386 7.19e-08 ***
bin.X[, -1]Depth:as.factor(Survey)NIGFS      0.0163954  0.0029240   5.607 2.06e-08 ***
bin.X[, -1]Depth:as.factor(Survey)SCOWCGFS -0.0075287  0.0018379  -4.096 4.20e-05 ***
bin.X[, -1]Depth:as.factor(Survey)SWC-IBTS -0.0007731  0.0016971  -0.456 0.648721
---
```

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

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 20754  on 14971  degrees of freedom
Residual deviance: 18888  on 14955  degrees of freedom
AIC: 18920

Number of Fisher Scoring iterations: 4
```

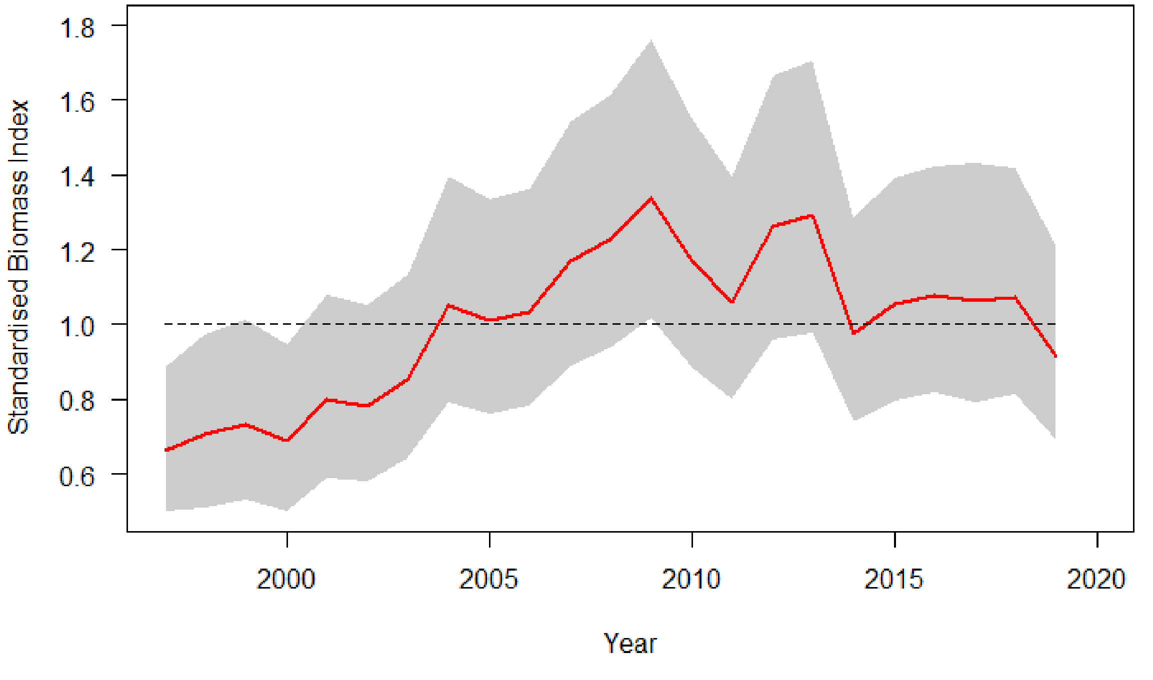


Figure 19. Standardised index of red gurnard (*Chelidonichthys cucullus*) in SA 3–8, 1997–2019. (±2 s.e.)

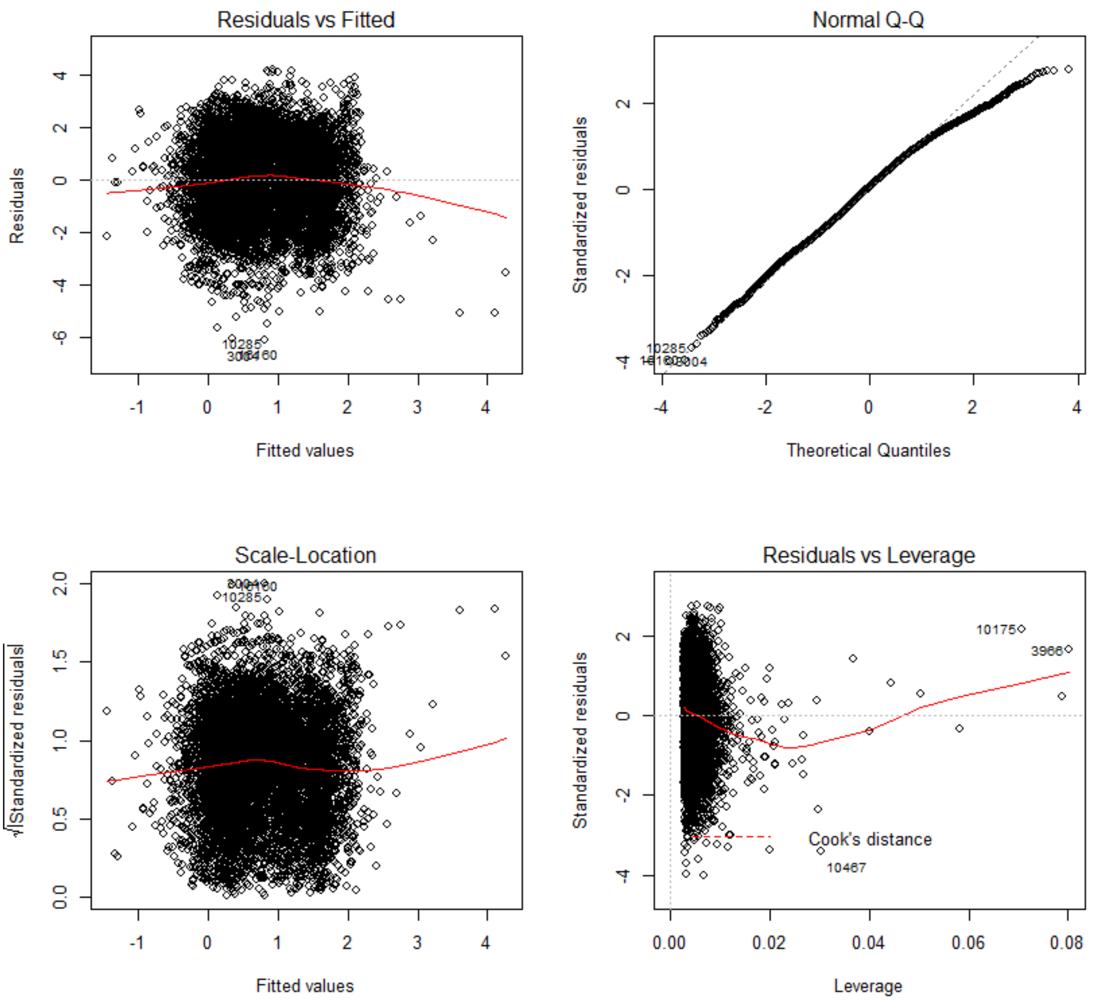


Figure 20. Diagnostic plots of goodness of fit of the final model formulation.

Somewhat unsurprisingly, given the lack of strong trends in any of the input dataseries, there is little evidence of strong trends in the model results either. The picture is of a steady increase in biomass from a low in 1997 to a peak in 2009, followed by a decline to the long-term average by 2014, and stability at this level thereafter.

As there is a significant quantity of data available, the addition of each new year into the model has only a limited effect on the fit of the model as a whole, therefore the retrospective pattern for this assessment is relatively minor.

2.7 TAC advice

Given the uncertainty around catch data and wide range of surveys occurring within the stock area, it was not possible to apply methods to infer MSY-proxies which rely on length-based indications of stock status. A decision was made to explore the application of the DLS 3.2 rule as a means of providing catch advice for this stock.

Biomass reference points as a stock status indicator were considered on the basis of B_{Loss}, however as the lowest point in the time-series is also the first, this was discounted as a reference level. Instead, the 25th percentile of the distribution of biomass indicator values was calculated. This gave an MSY $B_{trigger}$ value of 0.81.

Discussions with ACOM were initiated during the benchmark meeting around an appropriate way to consider fishing mortality when there is such great uncertainty around catch and landings. A proposed way to proceed was to use the ratio of catch of red and mixed gurnards (GUR and GUX) to the biomass indicator value as a precautionary proxy for fishing mortality. This guarantees that any changes in the pattern of reporting of landings do not impact upon perceptions of response of the stock to fishing pressure. The resulting proxy of fishing effort varies without trend over the 2006–2018 period for which consistent landings data are available (Figure 20).

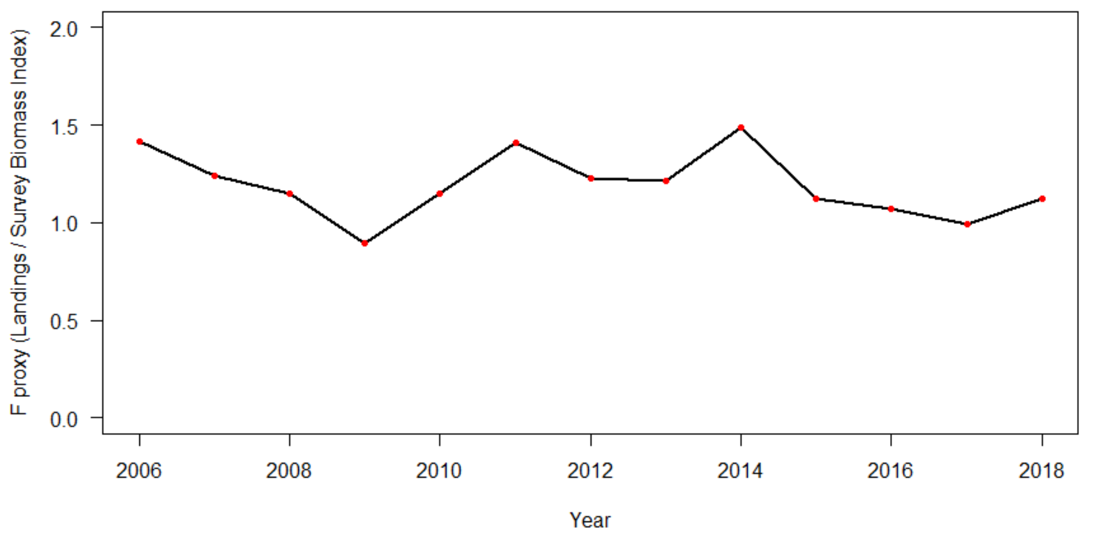


Figure 21. Fishing mortality proxy for red gurnards (*Chelidonichthys cucullus*) in SA 3–8.

Applying the three-over-two rule to recent average catch in this way would have generated advice of 3709 tonnes in 2020.

2.8 Future considerations

Although there are clearly considerable data collected on red gurnards in SA 3–8, it is not clear if it is sufficient to resolve all the issues identified with the assessment.

The consensus view from SIMWG was to continue assessing as a single stock. The question remains as to whether the area used for the assessment is the most appropriate or whether the definition should be revised in the future. Samples have been collected to allow an exploratory investigation of potential stock identity markers through the NS-IBTS, SCO-WCGFS and IE-IBTS surveys, however due to Covid-19 interruptions, these remain unexamined.

Interpretation of landings data is complicated by the reporting of variable quantities of a mixture of several species of gurnard, including red, in addition. It may be the case that the best outcome for now is to proceed with a purely survey-based assessment, consider how this can be used for advice when reported landings may differ significantly from total landings; and where discarding can be high yet unquantifiable, and make recommendations via other ICES bodies aimed at improving data quality and reporting for gurnards in the years ahead.

Given the wide-ranging distribution of the species, it is not surprising that there are multiple surveys which inform on the status of the stock. We have produced an indicator which combines the results of these surveys, but which tells us relatively little about changes in the status of the stock, or where it may be in relation to biologically meaningful reference points. Future work examining length-based indicators may be helpful; however the single greatest contribution that could be made to the assessment and management of red gurnards would be establishing a robust programme of data collection allowing estimation of landings and discards at species level.

2.9 Reviewers' comments

Several gurnard species (red gurnard, grey gurnard, tub gurnard) are landed from a multispecies fishery in ICES areas 3–8. Reporting of landings by species varies by country, with landings of gurnards often not reported by species but labelled as 'mixed'. Only limited information on how the species composition of landings is determined is available. Additionally, discarding of gurnard bycatch, particularly grey gurnard, can be high and is considered problematic in terms of calculating total red gurnard landings. These issues were discussed in detail during the benchmark and are dealt with in the relevant sections below.

The assessment area (3–8) covers a large area, ranging from the Baltic Sea to the Celtic Sea, and from north of Scotland to the Channel. Within this area, the distribution of red gurnard based on both survey and landings data varies visibly. Landings and survey catches of red gurnard in the North Sea, Skagerrak and Baltic Sea are comparatively low. At the benchmark, it was proposed, as also recommended by Stock Identification Methods Working Group (SIMWG) in 2019, and agreed on not to reduce the extent of the assessment area and split the stock into smaller units.

Data evaluation

Discard data for gurnards were submitted to Accessions but was only available for some of the countries which land red gurnard. The data were therefore limited in terms of spatial and temporal coverage, meaning that the allocation of landings from the various gear groups would have to be carefully considered. Due to limited time available, it was not possible to set up an allocation scheme and thus have raised landings for the benchmark meeting.

Commercial data: the resolution of landings data by species varied by country and over time. In some years, equally high catches of mixed gurnard were being reported as red gurnards, creating great uncertainty with regards to total annual red gurnard landings. Concerns regarding the reliability of the landing figures and the subsequent use of the data to determine the status of the stock were raised by the stock assessor. A proposal was therefore put forward to split the 'mixed' gurnard landings based on proportions of the three gurnard species in survey catches by ICES subareas. The proposal was outlined to ACOM members for consideration, who were not in favour of this approach due to i) uncertainty regarding the representativeness of the survey catches, ii) high discard rates of grey gurnard compared to red gurnard, and iii) possible overestimation of the red gurnard catch. However, only using red-gurnard landings could underestimate the harvest level, and consequently, it was agreed at the benchmark that the 'mixed' landings should be considered as 'entirely' red gurnard landings, and therefore be added to the reported red gurnard landings to produce a time-series of 'total' red gurnard landings.

Survey data which are not stored in the ICES DATRAS database (e.g. the English Beamtrawl Survey) were uploaded to Accessions. Station and catch data were assessed with regards to spatial and temporal coverage, i.e. whether survey coverage of the main areas with red gurnard landings was sufficient. It was found that the surveys listed below sufficiently covered the main fishing areas (areas 6–8) and could thus be used in calculating a survey index: SCO-WCGFS Q1 & Q4; SWC-IBTS Q1 & 4; IE-GFS Q4; FR-EVHOE Q4; FR-CGFS Q4; EN-BTS Q1.

The North Sea IBTS surveys (NS-IBTS; Subarea 4) and the Northern Irish Ground Fish Trawl Survey (NIGFS, area 6), as well as Spanish surveys (area 6 -Porcupine bank; area 9) were not included in the survey index calculation, since these surveys either had few stations with limited catches of red gurnard within the survey area, or they covered an area outside the assessment area.

Assessment

Two methods were considered to evaluate the stock status, using survey cpue and biological data: 1) a SURBAR and ii) a delta lognormal GLM model.

SURBAR: Due to limited catch-at-age data (age data were only available for the Irish and French surveys) the SURBAR approach was not developed further during the benchmark. However, despite its patchiness the reviewers recommend further exploration of the available biological data, both age and length data. Though limited to two surveys signals of spatially related changes in length and age composition can be drawn on when making management decisions.

The delta log normal model produced a survey abundance index time-series with acceptable confidence intervals, particularly once data collected prior to 1997, coming from only three surveys, was excluded. Based on data from six surveys, the residuals from the model run showed no concerning pattern and had a good fit between residuals and fitted values. 'Leave one out runs' did not show significant changes in the pattern or trend of the time-series when compared to the baseline run, and only the exclusion of the Channel Groundfish Survey had a limited effect on the estimated biomass index. The retrospective pattern was good and it was agreed that the resulting time-series from this model realistically reflected the stock trend.

The availability of a reliable index of abundance makes it possible to assess the stock as an ICES category 3 stock. Though not considered very reliable a time-series of total red gurnard landings (2006–2019) was available, and a proxy for the harvest level (F_{proxy}) could be calculated for the period 2006–2019.

Concluded and agreed way of assessing the stock: Trend-based assessment using the combined biomass index of the delta lognormal GLM model. F_{proxy} (ratio of landings / biomass estimate) as an indicator of harvest level.

Future recommendations

- It is recommended that a suitable discard allocation scheme be designed in future to take into account the at times high discard rates, covering the different fleets over time and space. This would go hand in hand with having a discard sampling programme in place for the major landings areas and countries landing red gurnard.
- The reviewers recommend further exploration of catch data in areas where surveys overlapped, e.g. FR-EVHOE and EN-BTS, in order to assess similarities /differences in catch trends and catchability and resultantly the suitability of combining catch data from different surveys / fishing gears.
- Despite this, the reviewers recommend further exploration of NS-IBTS and Spanish survey data and their possible inclusion in the overall survey index calculation.
- The reviewers further recommend that the calculation of a survey biomass index time-series using the VAST model could be beneficial. Combined with the applied GLM model the results from the VAST model would provide useful additional information on the status of the stock.
- Given the uncertainty of the total landings time-series the reviewers recommend that possibilities of improving the time-series are explored, i.e. a standardised procedure is developed to capture the composition of 'mixed' landings. This could possibly entail port sampling analysis of landings classified as 'mixed'.

3 Sardine (pil.27.7)

3.1 Why a benchmark

Historically, sardine in Subarea 7 and the Bay of Biscay (divisions 8.a, b, and d) were considered a single stock unit, the Northern stock of sardine in EU Atlantic waters. However, WKPELA benchmark (ICES, 2017) concluded in 2017 that both areas should be assessed independently, claiming different growth rates, the existence of separate spawning grounds, and the presence of all ages in substantial amounts in both areas.

At the time, the data available to assess the stock in Subarea 7 were limited, and the stock was classified as category 5. Since then, the stock has been assessed every two years based on landing trends, although ICES could not provide a quantitative advice so far given the high uncertainty associated with the landings. Following ICES advice (ICES, 2017), new data have been also collected to assess this stock since 2017.

The goals of this benchmark were two: 1) to evaluate the quality of the data available for this stock; and 2) to identify the best approach to assess and provide advice for this stock making use of the available data.

Presentations and working documents

Ouréns, R., Nash, R., Van Der Kooij, J. 2021a. Evaluation of the independent and dependent fisheries data available to assess the sardine (*Sardina pilchardus*) stock in subarea 7 (Southern Celtic Seas and the English Channel). Working document to WKWEST data compilation workshop.

Ouréns, R. Van der Kooij, J., Ball, J., Nash, R. 2021b. Evaluation of stock assessment methods for sardine (*Sardina pilchardus*) in subarea 7 (Southern Celtic Seas and the English Channel). Working document to WKWEST benchmark.

3.2 Summary of decision

The WKWEST data compilation workshop (ICES, 2021) concluded that the landings and the biomass data provided by the PELTIC survey for sardine in Subarea 7 are appropriate to assess the stock and provide advice. The availability of the biomass data to assess the stock implies an upgrade of stock category, being now classified as category 3. Consequently, the ICES guidance on advice rules for stocks of short-lived species in category 3 were explored (ICES, 2020). The benchmark panel agreed that a SPiCT model can be used to assess the status of the stock based on the relative biomass and fishing mortality to the reference points (B_{MSY}, F_{MSY}). However, the model is not appropriate to provide advice given the high uncertainty associated with absolute values of biomass, fishing mortality and reference points.

The 1 over 2 rule, in combination with a 80% symmetrical uncertainty cap and a biomass safeguard, is the most adequate method to assess this stock at the moment. The benchmark agreed that the 1 over 2 rule should be based on the biomass trend derived from the 'total area' because it covers the spatial distribution of the stock better than the index from the 'core area'. The biomass safeguard was also estimated from the historical biomass index in the 'total area' and it was set at 92 858 t. If the biomass index fell below this value, the advised catch should be reduced in proportion to the drop.

The 1 over 2 rule does not necessary lead to MSY exploitation and it is recommended to use it as a provisional harvest control rule until can be replaced by a better approach, such as a constant harvest rate derived from a management strategy evaluation or F_{MSY} obtained from SPiCT. It has been also raised that the landings and biomass used to implement the rule for the first time have a high impact on future advice. The panel concluded the implementation of the rule was out of the scope of this benchmark, and this issue should be addressed by WGHANSA.

Investigations undertaken (summary)

ICES Member Countries were asked to provide a revised time-series of sardine catch, biological sample data, and effort from their commercial fisheries. The time-series should be as far back on time as possible and with a spatial resolution of ICES division. This information was analysed by means of descriptive figures and summary tables. National data submitters were also contacted when needed to better understand the history of their respective fisheries and changes in target species.

The spatial distribution of the sardine stock covered with the PELTIC survey was explored by displaying in a map, the acoustic backscatter of sardine for the concurrently conducted autumn surveys within the ICES Working Group for Acoustic and Egg surveys on small pelagic fish in the Northeast Atlantic. The internal consistency of the PELTIC data was also examined using the acoustically derived raised numbers-at-age for each of the survey years. Age consistency was expressed as a correlation coefficients calculated over years between the $N_{a,y}$, (abundance index for age *a*, and year *y)* and $N_{a+1,y+1}$. This exercise offered an indication of the ability of the survey to track year-class strength effects.

The assessment methods evaluated in this benchmark have been recommended for data-limited stocks of short-lived species by ICES (ICES, 2020a, b). The guidelines published for SPiCT have been also followed to perform the SPiCT model (Mildenberger *et al*., 2020).

3.3 Compilation of available data

The WKWEST data compilation workshop evaluated the quality of the data currently available to assess this stock; specifically, the time-series of catch, fishing effort, size composition of the catch, and the robustness of the biomass data provided by the PELTIC survey (ICES, 2021). Whereas the fishing effort and size frequency data were not appropriate to assess the stock at this stage, the workshop concluded that the landings are now reliable and the PELTIC survey captures the bulk of the sardine stock. Therefore, both time-series can be used to derive the status of the stock and provide catch advice. Annex 3.

3.3.1 Commercial catch

Reported catches by country are very variable over time and across ICES divisions, and it was not clear if this variability was caused by the opportunistic nature of some fleets or by misreporting. The WKWEST data compilation workshop concluded the high variability is primarily explained by shifts in fleets activity and species targeted over the years (Ouréns *et al*., 2021a). Sardine is the main target species for some of the fleets, whereas it is a bycatch species for others. Some fleets are also opportunistic, and they only target sardine when the abundance or the quota of their main target species is low. Variations in the relative abundance of pelagic species, the market, and the fishing opportunities have driven the variability observed in sardine landings over time. In addition, the sardine fishery in Seine Bay (7d) has been closed for human consumption since 2010 due to PCB contamination. This closure has greatly affected the French fleet, whose landings decreased on average by 90% since 2010 (Ouréns *et al*., 2021a).

France submitted a new revised time-series of sardine landings after the WKWEST data compilation workshop. The changes were minor and mainly affected the period 2005–2009, being the landings lower in the new dataset. The updated landings have been used in this benchmark for the stock assessment (Table 1).

Table 4. Revised sardine landings (tons) reported by country for this benchmark.

Year	Belgium	Denmark	France	Germany	Ireland	Lithuania	Netherlands	Poland	UK (England)	UK (Scotland)	Total
2002			7977	130	11417		1905		6636	1222	29287
2003			8186	13	4030		6897		4150		23276
2004			7807	60	2046		2187		2389		14488
2005			10605	140	922		2231		3457		17354
2006			11120	246	2416		2287		1925		17994
2007		4	7315		28		1106		2574	81	11108
2008		53	8562	43	473		2073		3306	164	14675
2009			3918		65		3406		2568		9957
2010		13	706	62	50		6645		2540		10017
2011		3	237	5	1966		513		3614		6337
2012		40	372	587	16		1637		4423		7075
2013		40	1703	214	473		1739		3722		7891
2014	0	953	1100	18			193		3893		6157
2015	0	1011	1208	1551	555		1156		4301		9783
2016	1	2286	925	1941	464	1	4629		9389		19634
2017	0	2460	820	1475	329				7578		12662
2018	1	263	606	758	89		811		8141		10670
2019	0	0	671	53	33	40	90	0	6429	1	7317

3.3.2 Survey Data – fishery-independent biomass index

The PELTIC, Pelagic Ecosystem Survey in the western Channel and Celtic Sea, is an autumn survey conducted annually by Cefas (UK). It includes a typical acoustic survey design with parallel equidistant transects and a pelagic trawl, used opportunistically to validate the species and size composition of the acoustic marks detected on the echogram. Acoustic and trawl data are combined to obtain numbers and biomass-at-age for the most important stocks of small pelagics.

The first surveys (2012–2016) covered only the English waters of ICES areas 7e and all of 7f, but from 2017 survey coverage expanded to include also the French waters as well as one-off coverage of waters further north of the core area (2017), part of the eastern English Channel (2018) and Cardigan Bay in the southern Irish Sea (2020).

Two sardine biomass indices were calculated from PELTIC: one representing the consistently sampled “Core Area” of the whole time-series (2013–2020): English waters of the western Channel (excluding the Isles of Scilly as this area was dropped in 2013 and 2016 due to adverse weather) and the whole of 7f (Bristol Channel in the Celtic Sea). The second, shorter, time-series, “Total Area”, represented full coverage of the western Channel (7e, including the Isles of Scilly) and the eastern Celtic Sea (7f) (Figure 1).

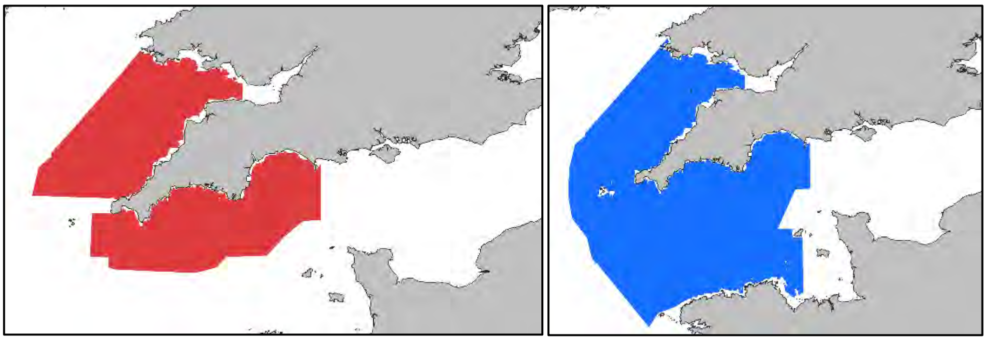


Figure 22. Consistently sampled PELTIC coverage of core area (left) since 2013 and total area, since 2017 (right).

The sardine biomass in the Core Area shows an overall increase over time, with lowest value of 48 kt in 2013 and the highest in 2019 of 274 kt (Figure 2). For the total area, biomass estimates ranged from 146 kt (2018) to 375 kt (2019).

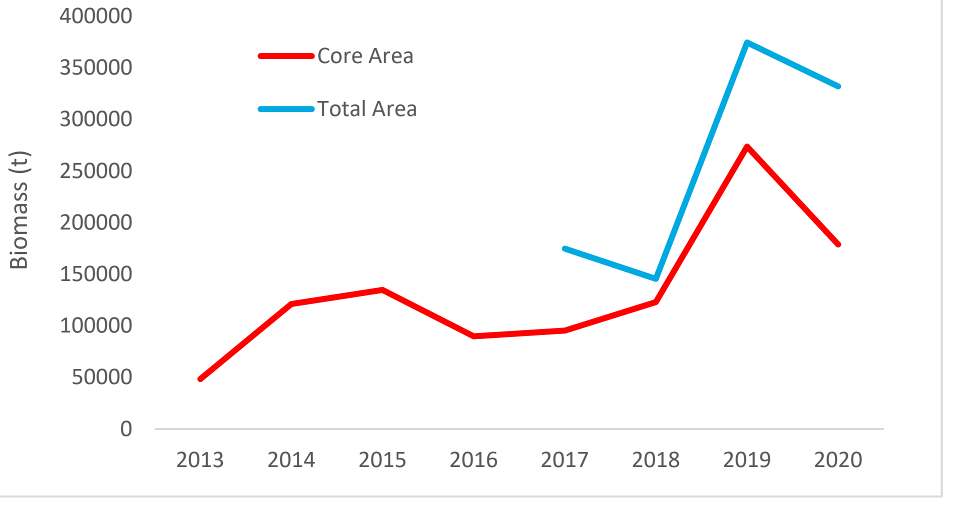


Figure 23. Trends in sardine biomass in area 7. In red, the sardine biomass of the core area (English waters of ICES area 7e (excluding the Isles of Scilly) and 7f); in blue, sardine biomass of the "total" area (ICES area 7e and f).

The spatial coverage of the survey and the internal consistency of the biomass data have been discussed in the WKWEST data validation workshop, and it was agreed the survey data are robust and can be used in the assessment of the sardine stock in Subarea 7.

3.4 Stock assessment

Following the conclusions of the workshop on data-limited stocks of short-lived species (ICES, WKDLSSLS 2020a) and the ICES guidance on advice rules for short-lived stocks in category 3 (ICES, 2020b), this benchmark reviewed a surplus production model in continuous time (SPiCT) tuned to the available data for sardine, and the performance of 1 over 2 ratio-based advice. Although WKDLSSLS found that a constant harvest rate performs better than the 1 over 2 rule, the application of a constant harvest rate for sardine has not been tested due to the absence of a stock-specific management strategy evaluation to identify a sustainable harvest rate.

3.4.1 SPiCT

Different exploratory SPiCT models were run, but the model that produced the most plausible results was based on quarterly data from 2013 to 2020 (Ouréns *et al*., 2021b). The input data were the sardine landings and the biomass estimated in the core area, given the time-series of biomass in the total area was too short to produce meaningful results. A prior for the depletion level of the stock was set at 50% of the carrying capacity in order to provide the model with some information about the fishery before the input data. The exact level of initial exploitation is unknown because there is not information about of the stock size. However, the fishery was already well stablished, and landings were higher than the current ones. There are therefore evidences to believe that the initial exploitation was medium or high. The model was insensitive to medium values of the prior (40–70%), and therefore the 50% value used in the model was considered appropriate. The model also fitted well the data and it did not show residual patterns (Ouréns *et al.*, 2021b).

The outputs show that the stock is in a good state, being the biomass above B_{MSY} and the fishing mortality below F_{MSY} (Figure 3). Although the model can be used to determine the status of the stock, the benchmark concluded that it is not appropriate to provide advice given the high uncertainty associated to the absolute values of biomass, fishing mortality and reference points (Figure 3).

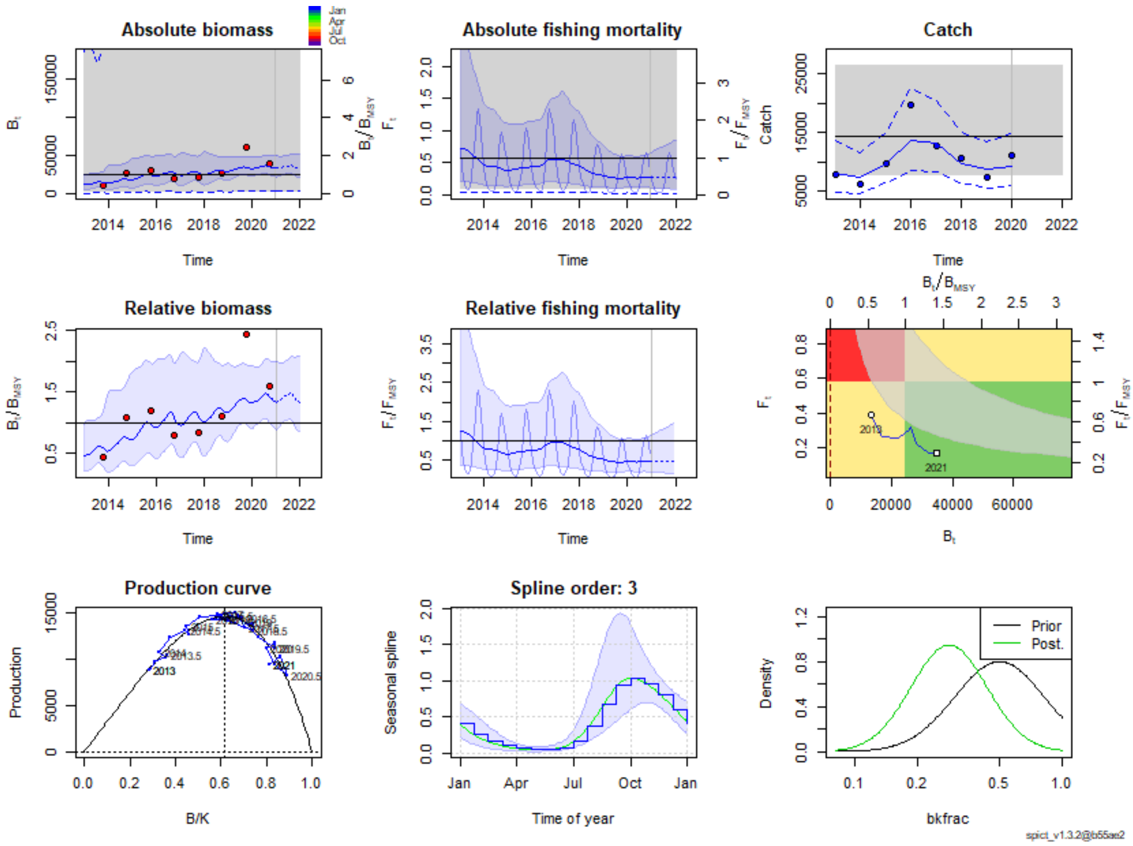


Figure 24. Main outputs of the model with the short time-series (2013–2020) and quarterly data. A prior was included to set the initial depletion of the stock at 50% of the carrying capacity. Legend: Estimates (fishing mortality, biomass, production, catch) are shown using blue lines. 95% CIs of absolute quantities are shown using dashed blue lines. 95% CIs of relative biomass and fishing mortality are shown using shaded blue regions. Estimates of reference points (B_{MSY}, F_{MSY}, MSY) are shown using black lines. 95% CIs of reference points are shown using grey shaded regions. The end of the data range is shown using a vertical grey line. Predictions beyond the data range are shown using dotted blue lines.

The 1 over 2 rule with the 80% symmetrical cap and the biomass safeguard (I_{stat}) was applied to the sardine stock in Subarea 7 using the biomass trend index estimated from both the core area and the total area. This harvest control rule (HCR) was applied with a retrospective character in order to analyse the trend of the advice if the HCR had been implemented when the data became available (i.e. 2016 for the advice derived from the biomass trend in the core area and 2020 for the advice derived from the biomass trend in the total area).

The I_{stat} value for each year was estimated using the biomass index from the total area and core area to set the biomass safeguard. The I_{stat} was estimated using the following equation:

$$I_{stat} = geometric(I_{hist}) \cdot \exp(-1.645 \cdot sd(\log(I_{hist})))$$

Where I_{hist} is the available historical series of the biomass index.

The benchmark panel concluded that the biomass estimated in the total area should be used for the advice as a significant part of the stock (33% on average) has been found outside of the core area. In fact, the advised catch derived from the biomass in the core area was lower than the landings for 3 out of 5 years with data (Figure 4). It was also agreed that the biomass safeguard should be derived from the biomass in the total area because it was also the baseline for the 1 over 2 rule. Using the smallest I_{stat} value of the time-series, the biomass safeguard was set at 92 858 t (Figure 4). Nevertheless, there were some concerns about the limited number of observations available to estimate the biomass safeguard and the risk of reducing unnecessarily the yield of the fishery by setting a high biomass safeguard. This reference point should be revised in the next benchmark when the biomass time-series in the total area becomes longer.

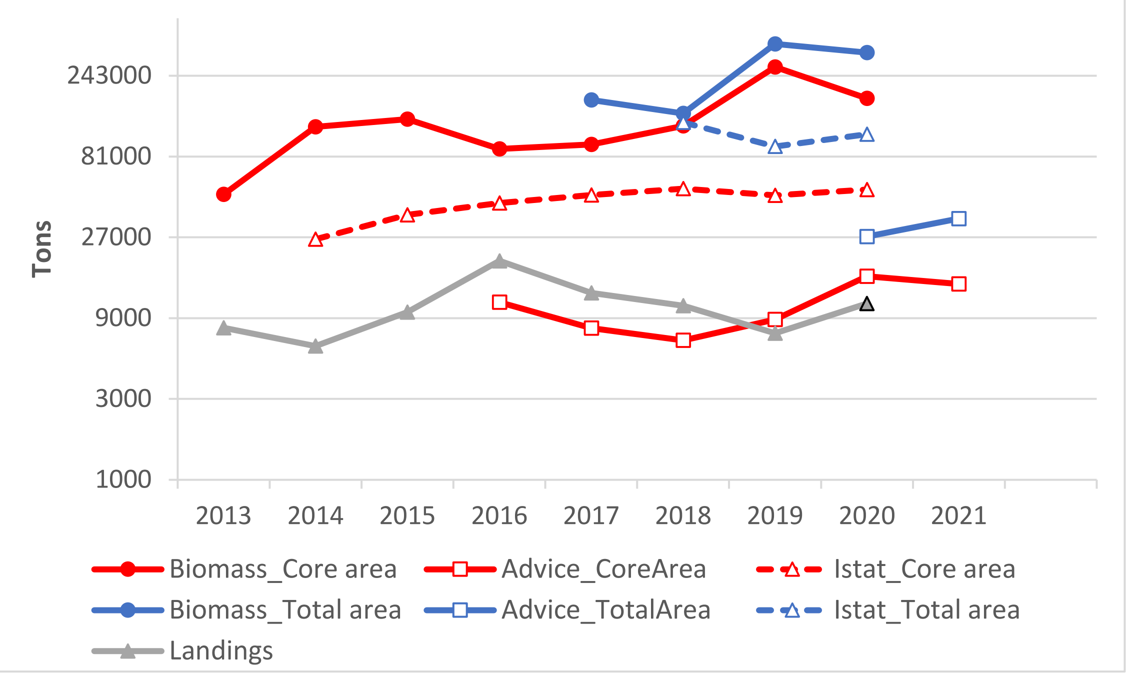


Figure 25. Simulation of advice resulting from applying the 1 over 2 rule with a 80% uncertainty cap with a retrospective character. The rule has been applied using both the biomass trend derived from the total area and the core area. The biomass and I_{stat} values from total area and core area are also represented. Note the y-axis is in a logarithmic scale.

3.4.2 Fishing opportunity advice

The 1 over 2 rule, in combination with a 80% symmetrical uncertainty cap and a biomass safeguard, is considered the most adequate method to assess this stock at the moment. This HCR, however, can result in reductions of catches due to the inability of the rule to take advice back to the previous level after hitting the lower cap. It has been noted that an 80% decrease in advice requires a 500% increase in the following advice to return to the previous level, taking a minimum of three years to achieve when an 80% uncertainty cap is applied (ICES, 2021b). Therefore, the 1 over 2 rule should be considered as a provisional HCR with the aim of achieving a better management approach within ten years (ICES, 2020b). Using the F_{MSY} obtained from a surplus production model or a sustainable constant harvest rate determined by an MSE, are the preferable methods to provide advice for category 3 stocks of short-lived species (ICES, 2020b).

It has been also noted that the initial biomass and landing values used to implement this HCR for the first time have a significant impact on not just next year's advice, but also future advice. Simulating a decrease in biomass for the next year, the advised catches in 2022 for sardine in Subarea 7 could range between 5177 and 19 732 t, depending on the approach used to implement the rule (Ouréns *et al*., 2021b). The benchmark panel concluded the implementation of the rule is out of the scope of this benchmark and this issue should be addressed by WGHANSA.

3.4.3 Future considerations

1. The benchmark recommended to produce an annual advice for this stock instead of biennial. The rationale behind this is that the shorter the lag in time between survey and TAC implementation the better is the performance of all HCRs. For the same reason, it is recommended to continue with the current procedure where the outputs of the PELTIC carried out in October in year *y* are already available for the assessment in November in *y*, and to provide quota advice for the following year (*y*+1).
2. 1o2 is a provisional HCR that does not necessarily lead to MSY exploitation. The benchmark recommended to conduct a management strategy evaluation for this stock in order to identify a robust and sustainable constant harvest rate to base the advice. The SPiCT model should be also revisited when the biomass time-series become longer.
3. England started a self-sampling programme in 2017 to collect the length distribution of the landings throughout the fishing season. These data can provide indications on population trends in the area in the short term, and it could be used in a length structure model in the long term. In either case, some improvements are needed for the data to be informative. Specifically, the discrepancies found between data collected by processors and fishers must be addressed, the methodology unified, and the origin of the samples must be tracked in the system in order to facilitate the raising. Because this initiative is voluntary, there is also a risk of decreasing numbers of samples over time, which would compromise the quality of the assessment. In addition, length-structured models are highly dependent on growth parameters. While the PELTIC survey is able to provide some of these parameters, a dedicated research project would help to increase the knowledge on biological parameters for this area and derive information that may serve as the basis for a future assessment model where a routine biological sampling is not in place.
4. Connectivity between sardine in Subarea 7 and Subarea 8 is still uncertain and a genetic study is currently underway to identify the presence of a boundary between both stocks. This study is expected to reveal some connectivity (gene flow) by larvae dispersal. Additional research might be needed to identify the connectivity among adult populations. This could be addressed by tagging studies examining the adult movements, and currently conducted studies investigating potential differences in life-history parameters

between areas. This research would be expected to also disclose the stock origin of the sardine landed in ICES rectangles 25E4 and 25E5, currently assigned to the stock in the Bay of Biscay.

3.5 Reviewers' comments

Data evaluation

Sardine stock in Subarea 7 has historically been assessed together with the Southern population in the Bay of Biscay (divisions 8.a,b and d). Since 2017, it is considered an independent stock and classified as category 5. Consequently, the stock status has been evaluated based on trends in landings. However, the reliability of the catch data has been questioned and quantitative advice has not been provided.

Commercial data: Since it was unclear whether variability in landings was a consequence of opportunistic fisheries or a lack of reporting for some years, WGHANSA suggested the statistics to be further reviewed. For the WKWEST benchmark, the full time-series of catch data was requested from data submitters and the quality of the data was presented and evaluated. As described in WGHANSA report every year, French catches in statistical rectangles 25E4 and 25E5 have been reallocated to area 8 (Bay of Biscay) because of the continuity with the Biscay purse-seine fishery occurring next to these rectangles. The benchmark agreed that the revision of the reported landings provided confidence in the data. Large fluctuations in annual landings were therefore considered to reflect shifts in fleets activity and species targeted across the years. A characteristic of the available landings data was that in the recent period (from 2010) a drop was observed due to a ban to operate in the Seine Bay (Eastern Channel, 7d) caused by PCB contamination. This was discussed and considered. Effort was not seen as being appropriate in the current metrics as it is reported in different formats among countries and it does not reflect the nature of the fleets. Length distribution data are limited, and therefore not regarded as representative. Data from a self-sampling programme, initiated in 2017, were also presented although considered not yet sufficient. Moreover, some discrepancies were found in the data provided by processors, which requires further scrutiny.

Survey data: Fisheries-independent data were presented and evaluated. The autumn acoustic survey (PELTIC) provides two time-series of biomass index with different spatio-temporal coverage. The first index, "core area", extends from 2013–2020 with a spatial coverage of English waters in 7e (excluding the Isles of Scilly) and the whole of 7f. From 2017, the survey was extended and thus the second index, "total area", represents the whole of 7e and 7f. The PELTIC survey captured the western and northwestern boundary of the population consistently as evidenced by negligible sardine backscatter from the adjacent CSHAS survey. The absence of any (significant) sardine numbers in these waters confirms that the northwestern limit of area 7 sardine is captured within the PELTIC survey coverage. The extension of the PELTIC survey in 2017 suggests a good coverage of the stock distribution, as well as an extensive coverage of the area where the majority of the fishery happens. The methodology and quality of data obtained from the PELTIC survey are ensured by the WGACEGG. In addition, the short time-lag between the survey observations (October) and the assessment (November) further support the use of PELTIC biomass estimates as input data for stock assessment.

Assessment

Appropriateness of ICES advice rules for HCR for short-lived species (stock category 3) were evaluated. The choice of proceeding with the SPiCT modelling was considered appropriate to provide additional information on the status of the stock.

Several configurations of seasonal SPiCT using quarterly catches and survey biomass index of core area were tested. Attempts were made to get rid of the seasonal variation in biomass estimated by the model. Sensitivity analyses with different starting depletion levels for the time-series were carried out. The group found a level of 50% as adequate and supported the use of such modelling configuration for providing proxy MSY reference points to indicate stock status.

Preferred method for providing advice was the 1-over-2 rule using survey trends (Method DLSSL 3, WKLIFE). There was an extensive discussion on which survey time-series was more appropriate to use. Total area appeared to present a reliable indicator of the biomass present in the area and it was well justified and accepted by the reviewers. Therefore, the approach adopted by the benchmark workshop for the assessment was to use the total area biomass index. In particular, estimation of Istat following ICES guidelines was recommended. The Istat biomass safeguard represents a trigger biomass level below which the advice would be corrected downwards. The panel noted that the data basis for estimating Istat was small (short time-series, most recent years) and suggested further care.

Future recommendations

- The performance of the constant harvest rate rule is suggested to be tested through simulation using the framework Management Strategy Evaluation (MSE).
- The self-sampling programme implemented in the English ringnet industry (both fishers and processors) may provide valuable information in future, and therefore its continuation is highly encouraged. Furthermore, implementation of a sampling scheme to routinely collect biological data from commercial catches is recommended as no age data, maturity information or length distribution are routinely available. That information may allow an analytical assessment to be developed in the mid-term.
- SPiCT is considered a potential and promising candidate for future assessment of the stock when the time-series of survey biomass estimates from total area are longer.
- Annual assessment and advice given the highly fluctuating nature of short-lived species as sardine and the results obtained from MSE simulations performed at WKDLSSLS and WKLIFE which indicated that for short-lived species, the shorter the time-lag between observations (survey), advice, and management, the smaller will be the risks usually for higher (or similar) catches.

3.6 References

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4 Sole (sol.27.8c9a)

4.1 Why a benchmark

The common sole (*Solea solea*, Linnaeus, 1758) stock, sol.27.8c9a, is considered as a data-limited stock and it was classified as category 5 stock, as only catch data were available. There was no analytical assessment for sole in this area. Since 2012, ICES provides scientific advice for this stock applying the precautionary approach. A precautionary buffer was applied in 2018 (≥20% reduction in catch relative to 2014–2016 average) and in 2019 (same catch value advised as 2018) with an advises that catches should be no more than 502 tonnes (2020–2021).

The advice and assessment are provided only for common sole species but the management of all Soleidae species is provided under a unique combined Total Allowable Catch (TAC). However, there is no knowledge about the data availability and status of the other Soleidae species, and there was some evidence that the common sole catch could be misclassified in the past, which means that common sole official landings might not have corresponded only to this species but a mix of *Solea solea*, *S. senegalensis*, *Pegusa lascaris* and *Solea* spp.

This stock was rated as a high priority for benchmarking by WGBIE in 2019 (Table 1) mainly on account of the fact that the current approach to assessment relies upon catch data which are known to be unreliable and exclude biomass and length–frequency information.

Table 5. Benchmark prioritisation table for common sole (*Solea solea*) stock, sol8c9a, WGBIE, 2019.

SCORE	Criteria 1 – Need to improve the quality of the previous assessment to provide advice Weight: 0.4	Criteria 2 – Opportunity to improve the assessment Weight: 0.3	Criteria 3 – Management importance* Weight: 0.1	Criteria 4 – Perceived stock status Weight: 0.1	Criteria 5 - Time since previous benchmark Weight: 0.1
Score 4.7	Assessment is inadequate to provide advice Score – 5.	Possibility to provide biomass indices and apply data-poor methods (SPiCT, LBI, LBSPR and MLZ)	One attribute (advice is requested). Score – 2.	State of the stock unknown. Score – 5.	Stock has never been benchmarked. Score – 5.

4.2 Summary of decision

Among all the data-poor methods implemented (i.e. LBI, LBPSR, MLZ and SPiCT) it was agreed that the LBI approach was currently the most adequate for this stock. LBI indicators show that the stock is in a good state (which was supported by results from the LBSPR and MLZ runs) although some attention should be pay on the proportion of mega-spawners that is low, but is increasing in the last years. It was decided that the LBI was the best suited to reflect the status of the stock. Using this method as basis, the catch advise will be provided with the 2-over-3 HCR (Method 2.1, Annex III, WKLIFE VIII, ICES 2018a). As for the 2-over-3 HCR an index of biomass is required, among the all possible options it was agreed to use a weighted sum of the Portuguese LPUE and the Spanish Bayesian survey index with weights varying by year according to the percentage of catches of each country (i.e. Spain and Portugal). In this setting the two indices are standardized before their application:

$$Index_{year} = \frac{1}{2} * [\text{S-BayesianIndex}_{year}/\text{mean(S-BayesianIndex)} + \text{P-LPUE}_{year}/(\text{mean(P-LPUE)})]$$

It was also accepted that the stock should be assessed as a category 3 stock and that the TAC should be only for this species.

4.3 Compilation of available data

4.3.1 Commercial catch

During the WGBIE 2020, Portuguese's colleagues highlighted that catches from Portugal have a problem of misidentification in some ports with the three species (i.e. *Solea solea*, *Solea senegalensis*, *Pegusa lascaris* and *Solea* spp.) (Dinis *et al*., 2020).

For this benchmark, using data from the Data Collection Framework (DCF) sampling, Portuguese catches were proportionally divided by sole species applying the species weight proportion to the total weight of Soleidae in each year, landing port, and semester and using a simple random sampling estimator, following Figueiredo *et al*. (2020). Details on data available and catch estimation procedures can be found in Annex 4 (Pennino *et al.*, 2021). At the moment the new Portuguese catches are considered reliable.

In addition, from the WKWEST 2021 data call, catches for *S. solea* were also reported by France and now are available in InterCatch from 2009 to 2019 (Figure 1). Information on discards indicates that discarding can be considered negligible (< 1%).

For the years 2009–2010, only catches from Spain and France are available, while for the other years (2011–2019) catches are available for the three countries (i.e. Portugal, Spain and France) (Figure 2).

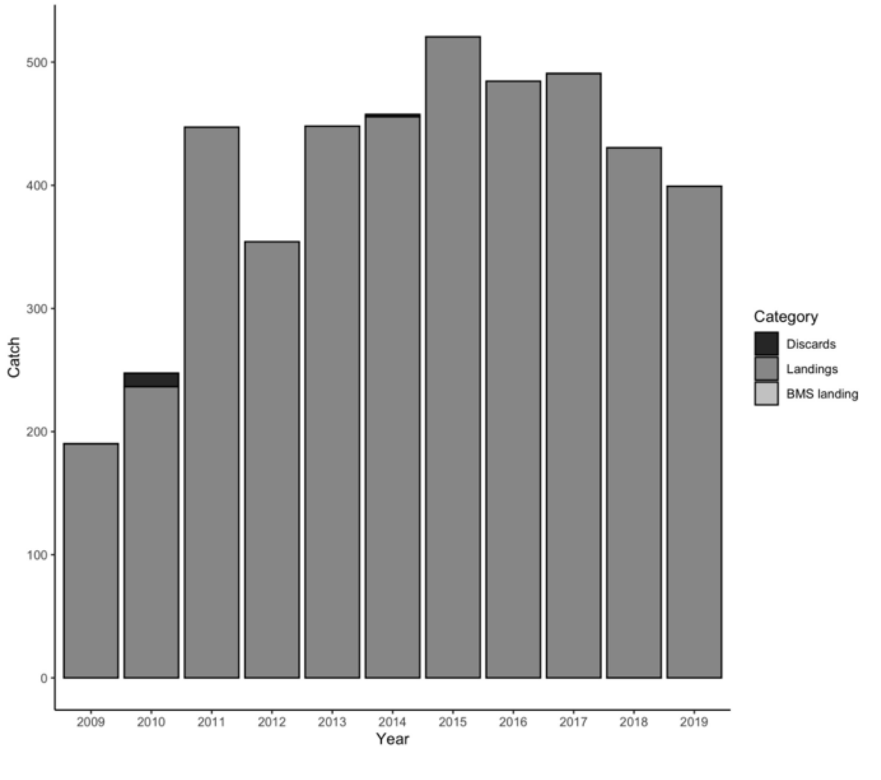

Figure 1. Catches for *Solea solea* by category (landings, discards and BMS landing) in the ICES divisions 8c9a for Portugal, Spain and France from 2009 to 2019. Source data: InterCatch.

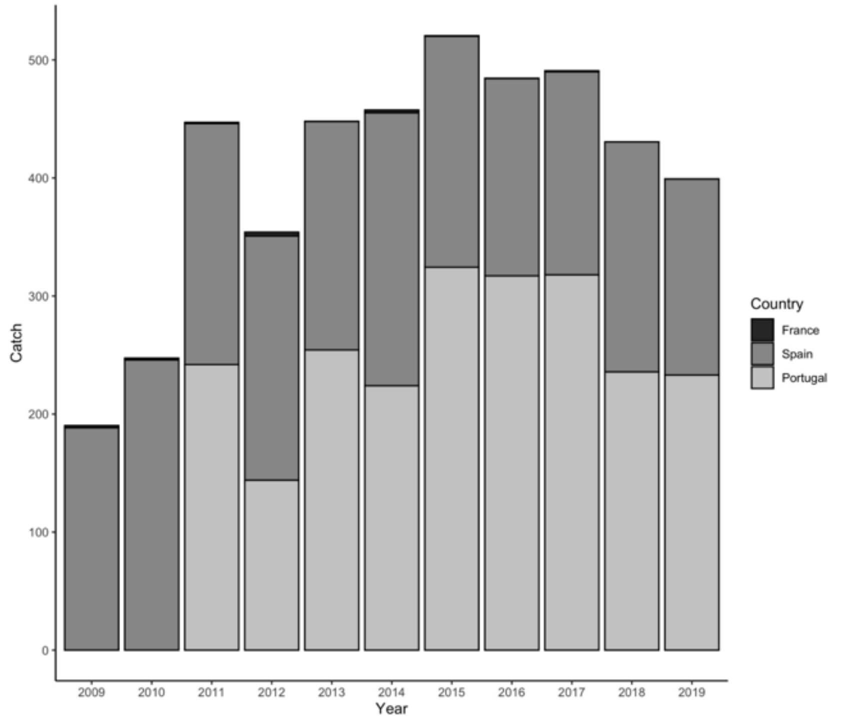

Figure 2. Catches for *Solea solea* in the ICES divisions 8c9a by country from 2009 to 2019. Source data: InterCatch.

From the "Historical Nominal Catches from 2000–2010, Source: Eurostat/ICES database on catch statistics – ICES, 2011, Copenhagen. Version 26-06-2019" dataset, catches are available for *S. solea* for 2000–2010, but some years data were reported only by Portugal, others by Spain and for this reason are considered possible underestimated (Figure 3).

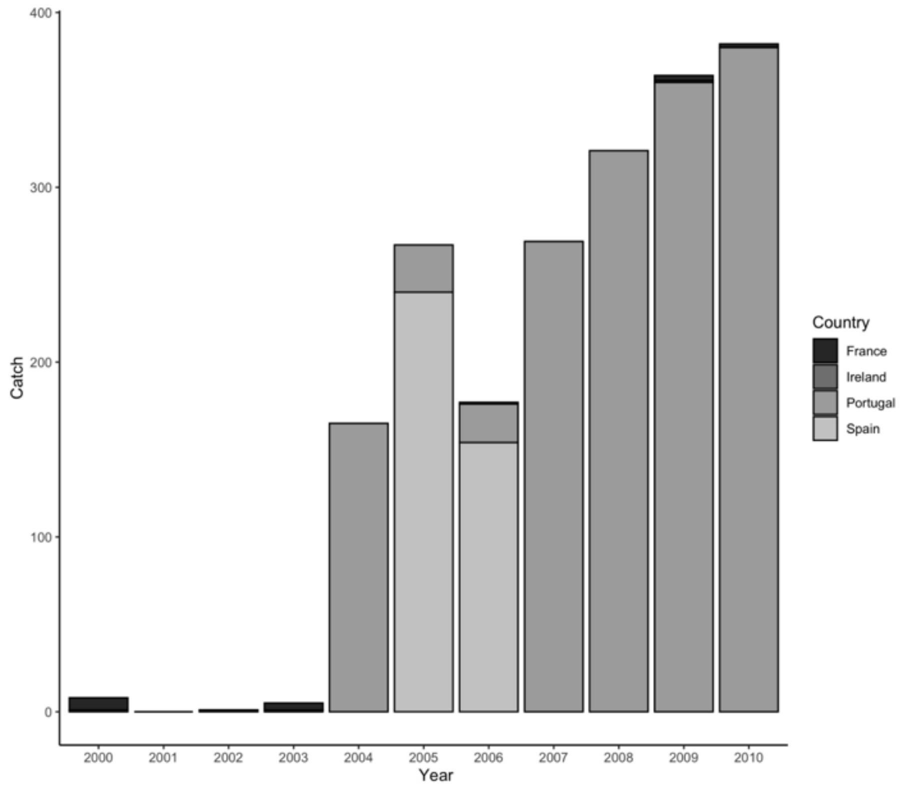

Figure 3. Catches for *Solea solea* in the ICES divisions 8c9a by country from 2000 to 2010. Source data: Eurostat/ICES database on catch statistics.

When catches are analysed by division it is possible to see that the majority of them are in the ICES Division 9a and that, although different fleets fish this stock, the two main ones are the polyvalent fleet from Portugal (i.e. "MIS_MIS_0_0_0") and the trammel net fleet from Spain (i.e. "GRT_DEF_60-79_0_0"). The distribution of the catches is almost homogenous along the year for the two main countries (i.e. Portugal and Spain), as well as for the main fleets.

4.3.2 Length–frequency distribution

In InterCatch, data on length–frequency distribution are available for the years 2011–2019 (Figure 4). The majority of the data are of the polyvalent fleet (i.e. métier "MIS_MIS_0_0_0") from Portugal.

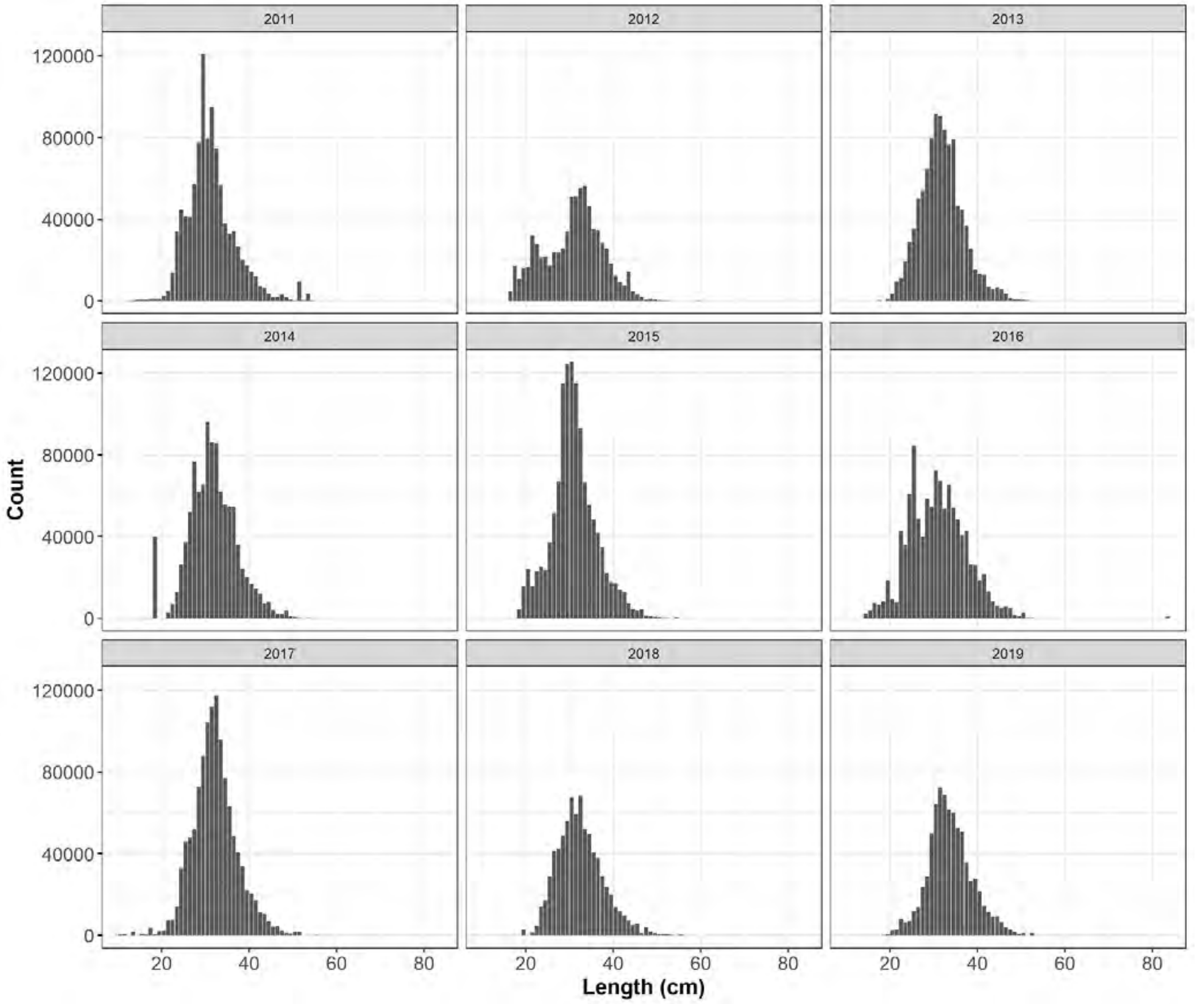

Figure 4. Length–frequency distribution of catches for *Solea solea* in the ICES divisions 8c9a by year (from 2011 to 2019) for Portugal, Spain and France. Source data: InterCatch.

4.3.3 Other sole species

For the WKWEST 2021, an official data call was requested for this stock to get all the possible data, not only for the common sole (*S. Solea*) but also for the other sole species *Solea senegalensis*, *Pegusa lascaris* and Sole spp. (Figure 5).

For Portugal, *S. Senegalensis* and *P. lascaris* landings and length–frequency distribution are available for the period 2011–2019. For *Solea* spp. landings are also available for the period 2011–2019. For Spain, *S. Senegalensis, P. lascaris* and *Solea* spp. landings are available for the period 2009–2019. No French data on these species were available.

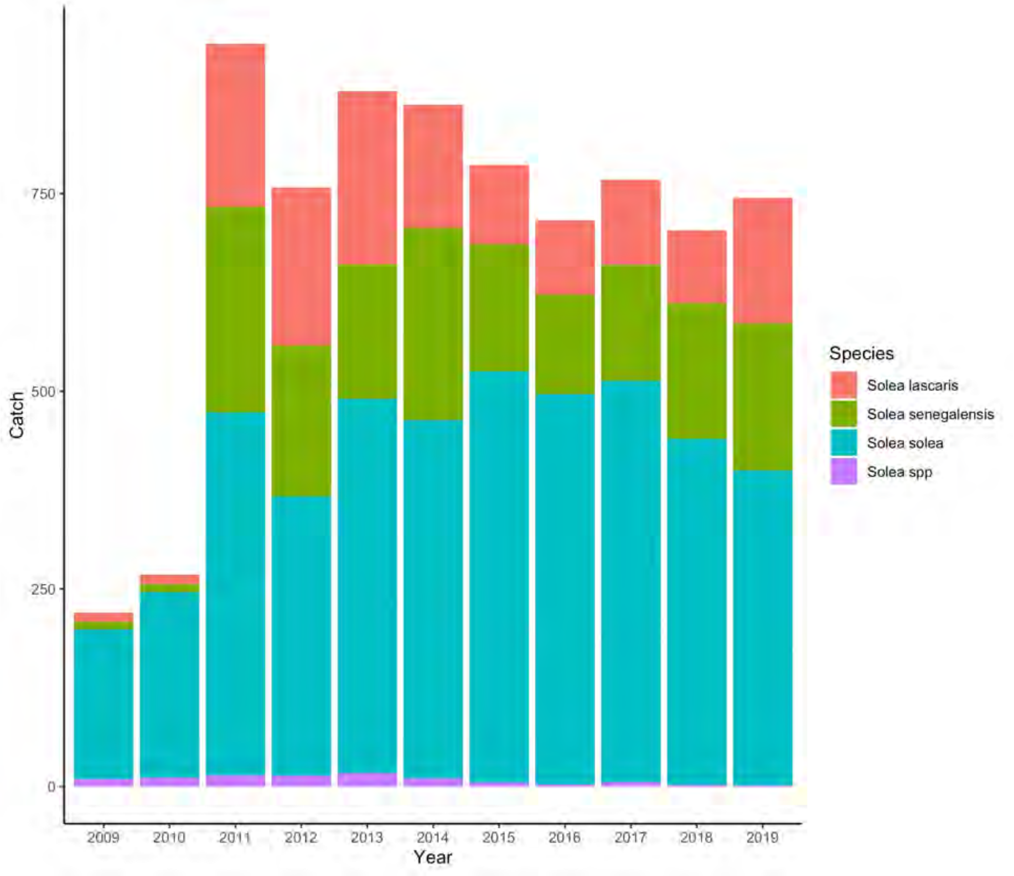

Figure 5. All sole species landings for the division 8c9a. Data are from Spain and Portugal together.

4.3.4 Survey Data - fishery-independent biomass index

Spanish abundance index from scientific survey

Common sole data were collected during the scientific survey series SP-NSGFS Q4 performed by the Instituto Español de Oceanografía (IEO) in autumn (September and October) between 2000 and 2019. Surveys were conducted on the northern continental shelf of the Iberian Peninsula (ICES divisions 8c and the northern part of 9a) which has a total surface area of almost 18 000 km^2 (Figure 6).

Surveys were performed using a stratified sampling design based on depth with three bathymetric strata: 70–120 m, 121–200 m and 201–500 m. Sampling stations consisted of 30 min trawling hauls located randomly within each stratum at the beginning of the design. The gear used is the baka 44/60 and the survey follow the protocol of the International Bottom Trawl Survey Working Group (IBTSWG) of ICES (ICES, 2017).

Figure 6. Map of the study area. Black dots represent annual sampling locations.

However, the common sole is a species with a biological bathymetric range between 0 and 200 meters in the Iberian Atlantic waters. The SP-NSGFS Q4 only covers partially the common sole bathymetric range and the resultant abundance index is probably underestimated. For this reason, and with the aim to correct this sampling bias, a hurdle Bayesian spatio-temporal was applied to this dataset.

Two response variables were analysed in order to characterize the spatio-temporal behaviour of common sole individuals. Firstly, a presence/absence variable was considered to measure the occurrence probability of the species. Secondly, the weight by haul (kg) was used as an indicator of the conditional-to-presence abundance of the species.

As environmental variable we used the bathymetry. Bathymetry values were retrieved from the European Marine Observation and Data Network (EMODnet, http://www.emodnet.eu/) with a spatial resolution of 0.02 x 0.02 decimal degrees (20 m).

Models were fitted using the integrated nested Laplace approximation approach INLA (Rue *et al.*, 2009) in the R software (R Core Team, 2021). The spatial component was modelled using the spatial partial differential equations (SPDE) module (Lindgren *et al.*, 2011) of INLA and implementing a multivariate Gaussian distribution with zero mean and a Matérn covariance matrix (Muñoz *et al.*, 2013).

As spatio-temporal structure we used the progressive one (Paradinas *et al.*, 2017, 2020), which contains an autoregressive ϱ parameter that controls the degree of autocorrelation between consecutive years. This ϱ parameter is bounded to [0, 1], where parameter values close to 0 represent more opportunistic behaviours and parameter values close to 1 represent more persistent distributions over time. In addition, an extra temporal effect g(t) was added using a second order random walk (RW2) prior to allow non-linear effects. In the presence of bathymetric and spatial autocorrelation terms, g(t) can be regarded as a spatially standardized stock size temporal trend.

Occurrence (Y_{st}) was modelled using a Bernoulli distribution and conditional-to-presence abundance (Z_{st}) using a gamma distribution, which is a probability distribution that captures the over-dispersion of continuous data. The means of both variables were modelled through the logit and log link functions respectively to the bathymetric and spatio-temporal effects as:

$$
\begin{gathered}
Y_{st} \sim \mathrm{Ber}(\pi_{st}) \qquad (1)\\
Z_{st} \sim \mathrm{Gamma}(\mu_{st}, \phi)\\
\mathrm{logit}(\pi_{st}) = \alpha(Y) + f(ds) + g(t) + U_{st}(Y)\\
\log(\mu_{st}) = \alpha(Z) + \theta\, f(ds) + \eta\, g(t) + U_{st}(Z)
\end{gathered}
$$

where π_{st} represents the probability of occurrence at location *s* at time *t* and μ_{st} and ϕ are the mean and dispersion of common sole conditional-to-presence abundance. The linear predictors, which contain the effects that link the parameters π_{st} and μ_{st}, include: $\alpha(Y)$ and $\alpha(Z)$, terms that represent the intercepts of each variable respectively; ds corresponds to the depth at location *s*, being f(ds) the bathymetric effect modelled as a second order random walk (RW2) smooth function parametrised as unknown values $f = (f_0, \ldots\ f_{i-1})_t$ at $i = 14$ equidistant values of ds, with hyperparameter σ representing the variance of the f(ds) model. In the same way, g(t) corresponds to the temporal trend fitted through a RW2 effect over the years. The terms f(ds) and g(t) are shared between both predictors and multiplied by θ and η in the conditional-to-presence abundance model to allow for differences in scales between both predictors (i.e. the logit transformed probability and the logarithm of the conditional-to-presence abundance); $U_{st}(Y)$ and $U_{st}(Z)$ refer to the progressive spatio-temporal structures of common sole occurrence and conditional-to-presence abundance respectively.

Following the Bayesian approach, penalised complexity priors (i.e., PC priors, weak informative priors; Simpson *et al*., 2017) were assigned so that the probability of the spatial effect range being smaller than 0.5 degrees was 0.05, and the probability of the spatial effect variance being larger than 0.5 was 0.5. PC priors were also used for the variance of the bathymetric and the temporal trend RW2 effects. Specifically, the size of these effects was constrained by setting a 0.05 probability that sigma was greater than 0.5 and 1 respectively. Sensitivity analysis for the selection of priors was performed by testing different priors and verifying that the posterior distributions were consistent and concentrated comfortably within the support of the priors.

From this analysis, the most important results that we obtained were the predicted distribution of the species (Figure 7), and a new spatio-temporal abundance index (Figure 8).

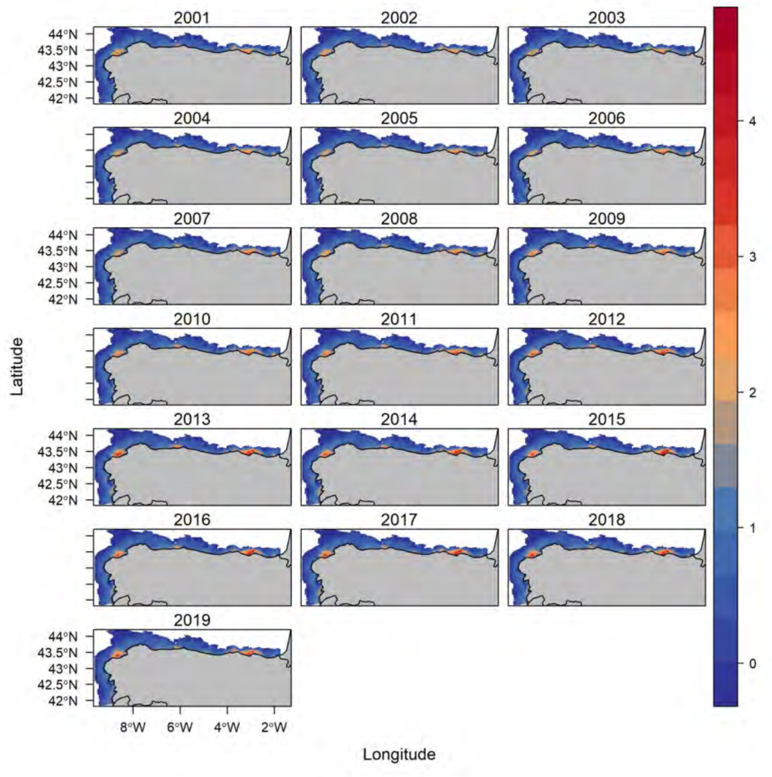

Figure 7. Prediction maps (2001–2019) of the common sole conditional-to-presence median abundance estimated by the hurdle Bayesian spatio-temporal model.

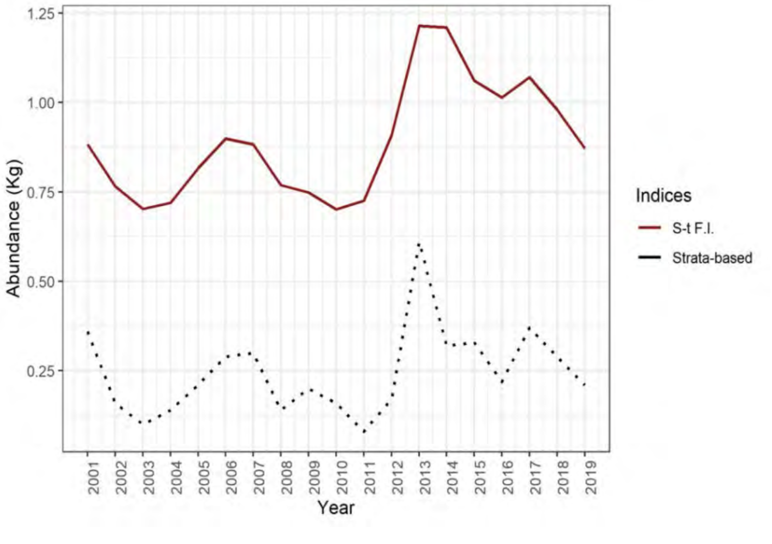

Figure 8. Temporal trend of the spatio-temporal abundance index (red) and the designed-based index for the SP-NSGFS Q4.

Spanish Catch Per Unit of Effort (CPUE) from Galician waters

Fishery-dependent data were collected by the Galician government Technical Unit of Artisanal Fisheries (Unidade Técnica de Pesca de Baixura, UTPB, in Galician). Usually an on-board observer is assigned to fishing vessels randomly selected from this sector and covers the full set of multiple gears used in Galician waters and all along the geographical range (Figure 9). In a single trip each vessel usually performs several hauls. At each haul, observers record all basic operational data (i.e. date, geographical position, gear, etc.) and the number and weight of all retained and discarded taxa. The analysed database in this study counts 4350 hauls in which common sole was caught from January 2000 until December 2018.

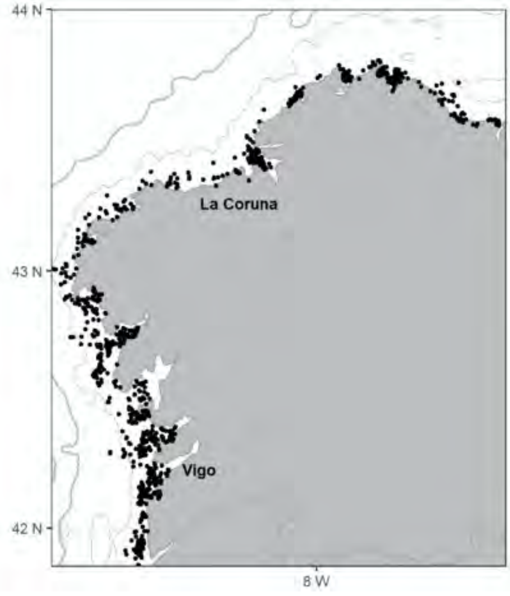

Figure 9. Data collected by observer on board trammel net fleet in Galicia (Spain) from 2000–2018 for common sole (*S. Solea*).

Before fitting any model, we selected the data for trammel nets, which is the most representative gear for the common sole, in order to reduce sources of variation. This selection was based on three criteria: i) proportion of hauls with zero catch, ii) total number of individuals sampled and iii) the spatio-temporal coverage. The first and second criterion were used as proxies of gear catchability and thus constant catchability was assumed along the time-series.

An exploratory analysis highlighted that common sole data have two main features, namely strong spatial and temporal dependence and a large proportion of observed zeros (i.e. zero inflated data). For this reason, we applied the same hurdle Bayesian spatio-temporal models that we performed for the SP-NSGFS Q4 data. As environmental variables we included bathymetry and type of substratum, both present in the dataset. Bathymetry was fitted using a non-linear RW2 effect. Gear saturation can exert a significant nonlinear effect on catchability, thus preliminary models included it but was left out of the final model due to its negligible contribution to the model. In addition to the spatio-temporal correlation structure (i.e. same of applied to the Spanish survey) we fitted a cyclic non-linear month effect to capture the intra-annual variability of the abundance. The remaining potential source of abundance variability could be driven by the differences between vessels, caused by a skipper effect or unobserved gear characteristics. To remove bias caused by vessel-specific differences in fishing operation, we included a vessel random effect. The final CPUE index is showed in Figure 10.

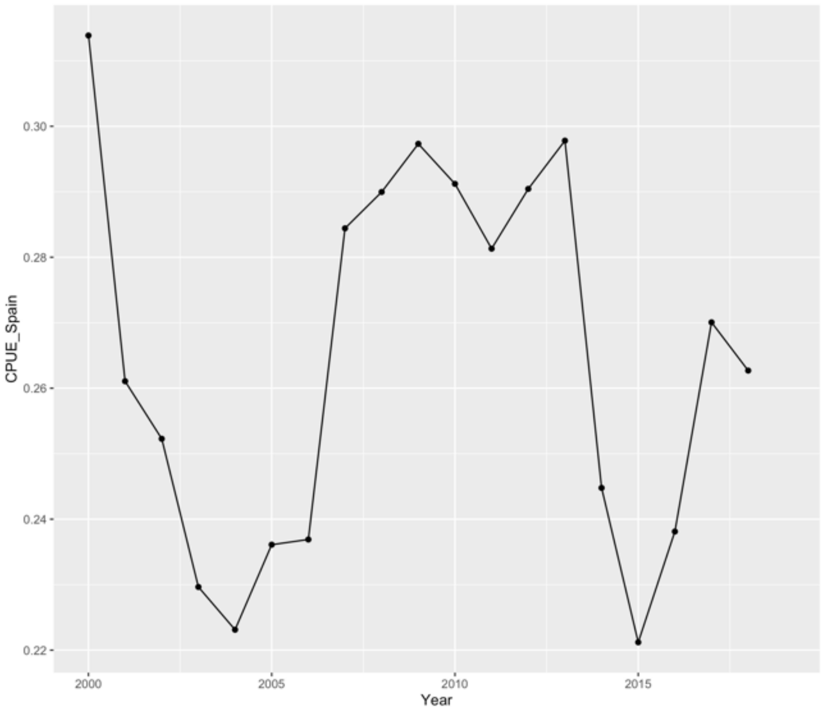

Figure 10. CPUE index derived from the hurdle Bayesian spatio-temporal model for 2000–2018 for common sole (*S. Solea*).

Portuguese LPUE

Portuguese LPUE estimates relied on fishery-dependent data derived from the polyvalent fleet and are based on the estimated *S. solea* landed weight by fishing trip. The analysis was restricted to the most important landing ports in terms of *S. solea* landed weight: Viana do Castelo, Matosinhos, Aveiro, Peniche and Setúbal. The Portuguese polyvalent fleet segment comprises multigear/multispecies fisheries, usually licensed to operate with more than one fishing gear (most commonly gill and trammel nets, longlines and traps), that can be deployed in the same trip, targeting different species. The time period considered in the present study extends from 2011 to 2019.

The dataset was subset to trips with positive landings of the species. The LPUE standardization procedure was done via the adjustment of a General Linear Model (GLM) to the matrix data, where the response variable was the *S. solea* landed weight by trip (unit effort) and was fitted with a Gamma distribution. Several variables were evaluated as candidate to be included in the model: region, landing port, year, semester, quarter, month and vessel size group (<9 m and >9 m).

All the explanatory variables were considered as categorical variables. The function "bestglm" implemented in R software was used to select the best subset of explanatory variables (McLeod and Xu, 2010). The selection of the set explanatory variables to enter into the model is done following McLeod and Xu (2010) procedure, which is based on a variety of information criteria and their comparison following a simple exhaustive search algorithm (Morgan and Tatar, 1972). The diagnostic plots, distribution of residuals and the quantile-quantile (Q-Q) plots, were used to assess model fitting. Changes in deviance explained by the selected model and the proportions of deviance explained to the total explained deviance was determined and used as indicative of r2. Finally, annual estimates of LPUE and the corresponding standard error were determined using estimated marginal means (R package: emmeans).

The final model explained 87% of the variability and included as explanatory variables the year, the month, the landing port and the vessel size. Estimated effects of each explanatory variable, as well as, the residual graphical analysis for the best model selected are presented in Figures 11 and 12. The final LPUE index is presented in Figure 13. Finally, it worth to be mentioned that sensitivity tests were carried out to this dataset to assess the sensibility of the model to a possible increase or reduction of the weight per trip by 25% for data from 2019. Results highlighted that the model performed well and consequently obtained consistent outputs with the original dataset.

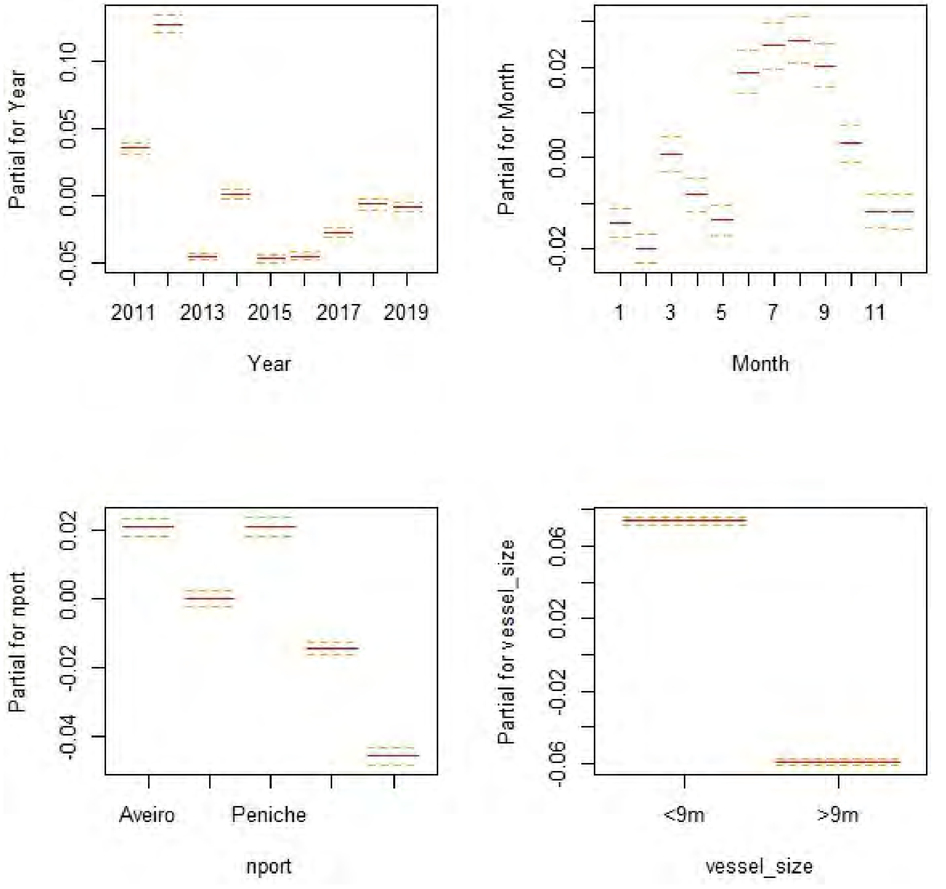

Figure 11. ***Solea solea*** **in Portuguese waters (Division 9a). Effect of each explanatory variable included in the standardization of the LPUE for** ***S. solea*** **caught by the polyvalent segment in mainland Portugal (Division 9a): year, month, landing port (nport) and vessel size (vessel_size).**

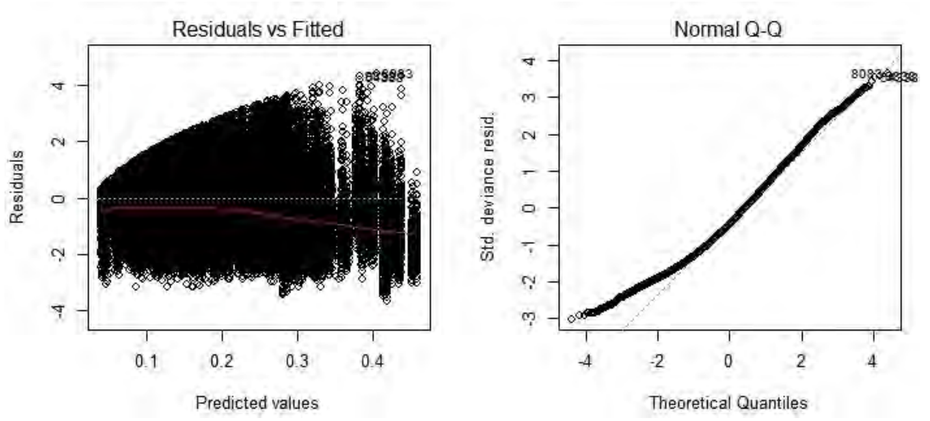

Figure 12. ***Solea solea*** **in Portuguese waters (Division 9a). Residuals of the best GLM model fitted to the LPUE data for the Portuguese polyvalent fleet: (left) fitted vs. residuals (right) quantile-quantile (Q-Q) plot.**

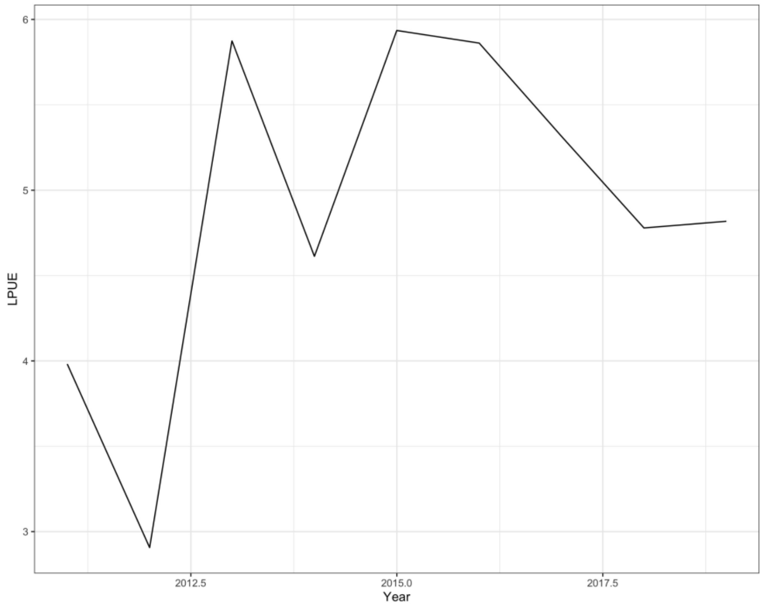

Figure 13. LPUE index by year of *Solea solea* in the in Portuguese waters (Division 9a).

4.4 Stock assessment

As recommend by the ICES guidelines for data-poor stocks, four different methods were tested to evaluate the status of the common sole stock, such as (1) stochastic surplus production model in continuous time (SPiCT), (2) Length-based indicators (LBI) method, (3) Length-based spawning potential ratio (LBSPR) method and (4) Mean length-based mortality estimators (MLZ).

4.4.1 SPiCT, stochastic surplus production model in continuous time

The SPiCT explicitly models both abundance and fishing dynamics as stochastic processes in a state–space framework. It is formulated as a continuous time model to allow a representation of seasonal fishing patterns and incorporation of subannual catch and index data (Pedersen and Berg, 2017).

The most important input for fitting SPiCT is catch data (by weight). Pedersen and Berg (2017) define the catch as the product of instantaneous fishing mortality and stock biomass. Fishing mortality is not decomposed into the product of effort and catchability. Therefore, it is not necessary to standardize the catch data based on changes in fishing efficiency: all such changes will be encompassed in the instantaneous fishing mortality.

Here we used as catch data the common sole official landings provided by Spain in ICES divisions 8.c and 9.a (2009–2019) and from the historical ICES database (2000–2008).

For this time-series the observation noise was not constant in time. Indeed, there is some evidence that the common sole catch could be misclassified in the past, which means that common sole official landings might not have corresponded only to this species but a mix of sole species. As in the SPiCT, it is possible to add knowledge that certain datapoints are more uncertain than others, the first eight years of the catch were considered uncertain relative to the remaining time-series and therefore are scaled by a factor 5. In particular using the *stdevfacC* vector that contains the factor that is multiplied onto the standard deviation of the datapoints of the corresponding observation vector.

Catch data must be supplemented in the SPiCT model by at least one independent abundance index. An important advantage of SPiCT over other surplus production models is that it allows the use of multiple abundance indices with different time-series in addition to the catch time-series. Here we performed different runs using: 1) the Spanish survey abundance index; 2) the spatio-temporal abundance index produced with the Bayesian model; 3) the Spanish CPUE and; 4) the Portuguese LPUE.

The continuous-time SPiCT formulation, time-stepping is achieved through a Euler scheme with a default time increment equal to $^1/_{16}$ (where time is measured in years).

As common sole catch data were collected annually, the discrete-time realization of SPiCT, obtained by setting the time-step dt_{Euler} equal to one, was considered sufficient.

Twelve different runs (see runs in Annex 5) were tested for this stock using:

- default priors;
- fixing *n* to resemble the Schaefer production model;
- setting the priors for the ratio between biomass in the initial year relative to K, mean of log(0.5) and sd of 0.2;
- setting priors for the ratio between biomass in the initial year relative to K, mean of log(0.3) and sd of 1.

All the models presented high uncertainty intervals as well as, in some cases, didn't comply with all the theorical diagnostic plots. In addition, retrospective patterns were divergent in many cases. These models were also presented during the WKMSYSPiCT, and reviewers suggested that SPICT should be dismissed for this stock for the moment.

4.4.2 Length-based indicators (LBI) method

Length-based indicators are calculated from length frequency distributions obtained from catch or landings and compared to appropriate indicators derived from life-history parameters. These indicators are related to conservation, optimal yield and length distribution relative to expectations under maximum sustainable yield (MSY) and thus can provide a description of the stock status.

LBI method requires the following data:

- Length-at-maturity (L_{mat}, also known as L_{50}, length at which the probability of having reached the maturity is 50%);
- von Bertalanffy asymptotic average maximum body size (L_{inf});
- ratio of natural mortality to von Bertalanffy growth rate (M/k);
- catch/landings-at-length per year;
- length–weight relationship parameters (a and b parameters in $W=aL^b$ being W and L the corresponding weight and length, respectively). Instead of *a* and *b* parameters, the mean weights-at-length per year can be also introduced as input data.

Indicators

The length-based indicator $L_{max5\%}$ (Table 2) analyses the conservation of large individuals through the comparison of such indicators, which characterize the upper portion of the length frequency distribution, to the reference point L_{inf}. The corresponding ratio provides information about the degree of truncation of the population length structure that may be caused by fishing, and is expected to be above 0.8, based on a simulation study carried out by Miethe and Dobby (2015).

The indicator P_{mega} (Table 2) is the proportion of mega-spawners in the stock (fish larger than the optimum length $L_{opt}=3L_{inf}/(3+(M/k))$ plus 10%) and follows the idea summarized by Froese (2004) as "Let the mega-spawners live". Froese (2004) and ICES (2015) suggested that values above 0.3 correspond to healthy stocks. Length indicators $L_{25\%}$ and L_c relate to the conservation of immatures and follow the principle "Let them spawn" (Froese, 2004). The ratio of both indicators to L_{mat} is expected to be greater than 1 (Table 2). Finally, the ratio L_{mean}/L_{opt} relates to the optimal yield and follows the principle "Let them grow" (Froese, 2004), whereas the ratio $L_{mean}/L_{F=M}$ focuses on MSY considerations since $L_{F=M}$ is a length-based proxy for MSY. These ratios are expected to be greater than 1 (Table 2).

In order to interpret and discuss correctly the results provided by the LBI method is crucial to take into account that it assumes equilibrium conditions (total mortality and recruitment have been constant for a period as long as the lifetime of the time-series) and logistic selectivity curve (i.e. the curve is flat-topped not dome-shaped).

Table 2. Set of length-based indicators, their references, the corresponding indicator ratios and their expected values grouped in terms of conservation/sustainability, optimal yield and MSY considerations.

Indicator	Calculation	Reference point	Indicator ratio	Expected value	Property
$L_{max5\%}$	Mean length of largest 5%	L_{inf}	$L_{max5\%}/L_{inf}$	>0.8	Conservation (large individuals); CL
P_{mega}	Proportion of individuals above Lopt + 10%	0.3-0.4	P_{mega}	>0.3	Conservation (large individuals); CL
$L_{25\%}$	25th percentile of length distribution	L_{mat}	$L_{25\%}/L_{mat}$	>1	Conservation (immatures); CI
L_c	Length at first catch (length at 50% of mode)	L_{mat}	L_c/L_{mat}	>1	Conservation (immatures); CI
L_{mean}	Mean length of individuals > L_c	$L_{opt}=3L_{inf}/(3+(M/k))$	L_{mean}/L_{opt}	≈1	Optimal yield; OY
L_{mean}	Mean length of individuals > L_c	$L_{F=M}=(1-a)L_c+aL_{inf}$ $a=1/(2(M/k)+1)$	$L_{mean}/L_{F=M}$	≥1	MSY

4.4.3 Implementation and sensitivity analysis

The values of the life-history parameters derived from literature review are the following ones:

- M/K=1.41, derived from the M=0.31 (from Cerim *et al*., 2020), the K=0.22 (from Teixeira and Cabral (2010) we have that K=0.23 for females and K=0.21 for males then we consider the mean of both sexes).
- L_{inf} =48.9 cm (from Teixeira and Cabral (2010) we have that L_{inf} = 52.1 cm for females and L_{inf} = 45.7 cm for males, and hence we compute the mean of both sexes).
- L_{mat} =26 cm (from Jardim *et al*., 2011, we have that L_{mat} =25 cm for males and L_{mat} =27 cm for females, and then the mean of both sexes is computed).
- Length–weight relationship parameters a=0.00759 and b=3.06 (Bayesian length–weight model based on LWR estimates for this species Frose *et al*., 2014).

The LBI method adjusted using the above values was defined as the reference model. The LBI method was also applied using a different set of life-history parameter values. More precisely, we used the mean of each one of the distributions of the life-history parameters derived from FishBase. Finally, the reference model was also adjusted using different length–weight relationship parameters derived from fishery-dependent data collected by observers on board the artisanal Galician fisheries (Spain). In particular the parameters were a=0.009476898 and b=3.018329.

A sensitivity analysis of the parameters L_{inf}, M/K and L_{mat} (around our literature/reference values) was also carried out overestimating and underestimating them by 5 and 10%.

Results

From the reference model we can conclude that the stock is exploited at MSY level and the optimal yield is attained (Table 3 and Figure 14). The immatures are good preserved whereas the proportion of mega-spawners is low, although it has been increased in the last years. If we use the FishBase life-history parameters our perception of the stock status is better since the proportion of mega-spawners in the last years is above 0.3. On the other hand, LBI results for the second dataset of mean weights-at-length per year match the results provided by the reference model.

Table 3. Traffic light indicator table for the LBI analysis.

	Conservation				Optimizing Yield	MSY
Year	L_c/L_{mat}	$L_{25\%}/L_{mat}$	$L_{max5\%}/L_{inf}$	P_{mega}	L_{mean}/L_{opt}	$L_{mean}/L_{F=M}$
2011	1.10	1.10	0.94	0.13	1.00	0.99
2012	0.83	1.02	0.90	0.17	0.96	1.12
2013	1.02	1.10	0.89	0.14	0.99	1.01
2014	1.02	1.10	0.91	0.15	0.99	1.02
2015	1.06	1.10	0.88	0.12	0.98	0.98
2016	0.87	0.98	0.93	0.17	0.95	1.08
2017	1.10	1.13	0.91	0.15	1.02	1.00
2018	1.02	1.10	0.93	0.18	1.00	1.03
2019	1.13	1.17	0.94	0.23	1.05	1.01

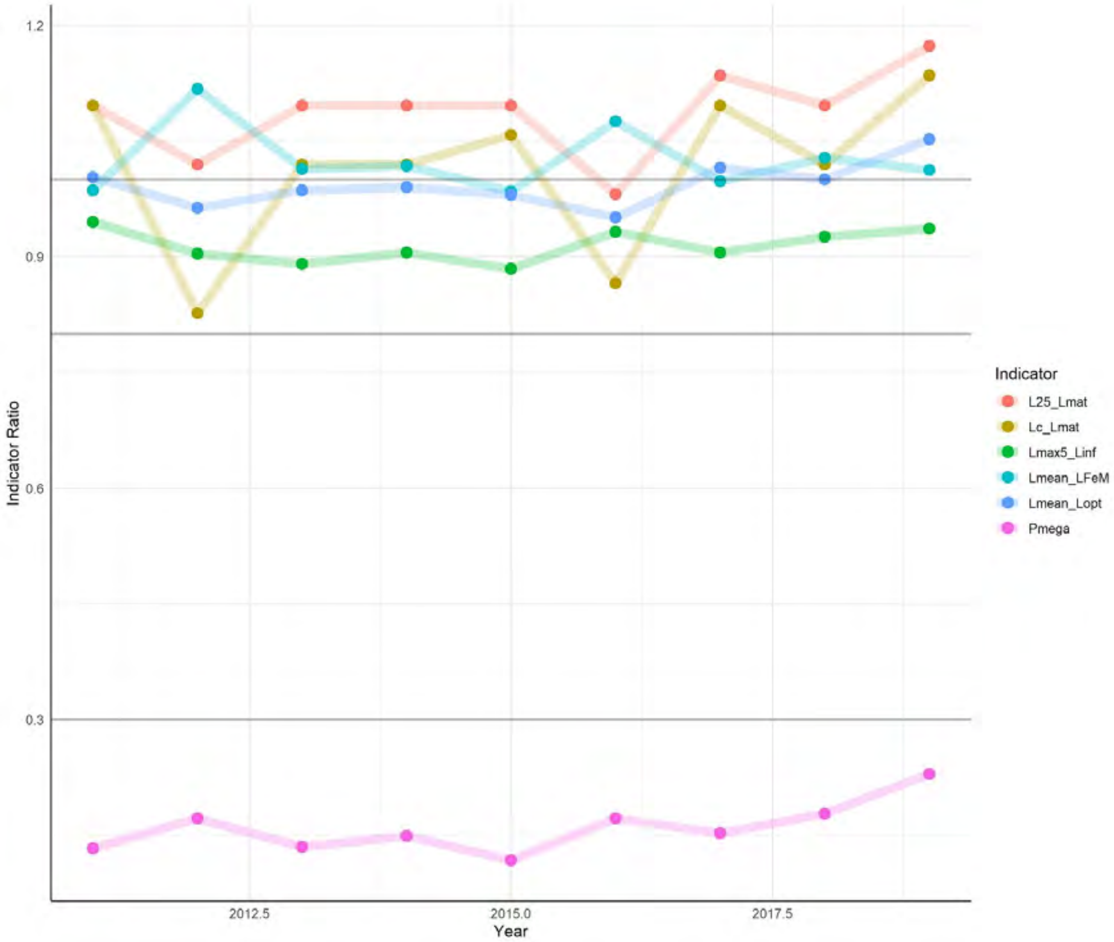

Figure 14. Temporal trends of the indicator ratios estimates.

Finally, the sensitivity analysis (Figure 15) shows that:

- L_{inf}: overestimation of this parameter leads to a decreasing in the proportion of mega-spawners and also affects the MSY indicator; although this indicator is in red for some years, it is not worrisome since its values are close to 1. Underestimation leads to the opposite situation, the proportion of mega-spawners increased attaining values above the threshold of 0.3.
- M/K: the conclusions are similar to the ones derived from the reference model (although of course under overestimation the proportion of mega-spawners increased and was larger or close to the threshold of 0.3).
- L_{mat}: overestimation leads to a decreasing in the values of the indicators related to the conservation of immatures, in spite of this the conclusion derived from the last year still maintain that conservation is correct.

From the above explanations we conclude that the stock status is good but attention to the conservation of mega-spawners is required.

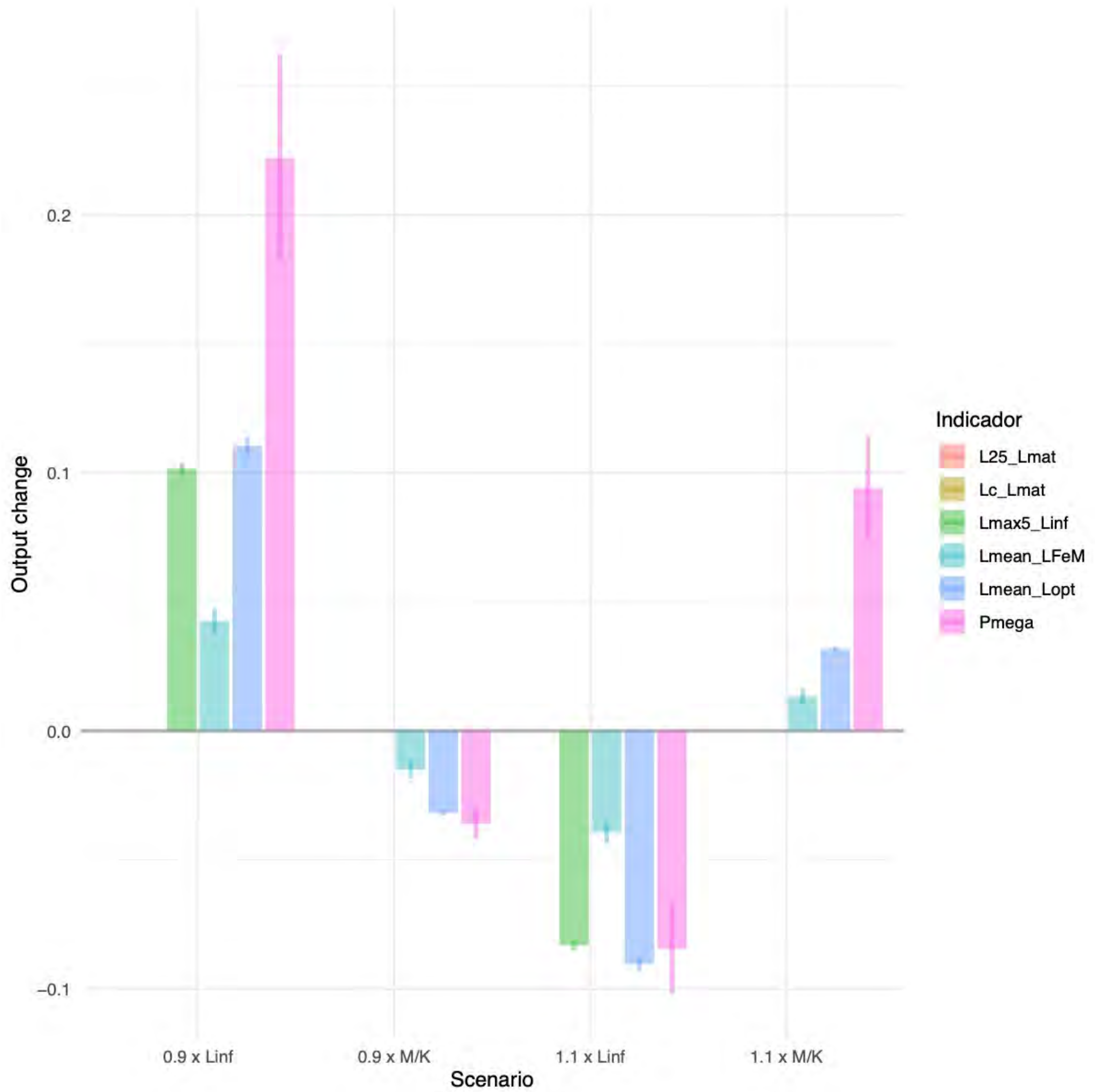

Figure 15. Sensitive analysis of the parameters L_{inf} and M/K (around our reference model), overestimating and underestimating them by 5 and 10%.

4.4.4 Length-based spawning potential ratio (LBSPR) method

The LBSPR method uses length frequency composition data to estimate the spawning potential ratio (SPR) by developing a computationally efficient length-structured per recruit model that splits the population into a number of sub-cohorts, or growth-type-groups, to account for length-dependent fishing mortality rates.

This method requires the following parameters:

- the ratio M/k and L_{inf} (parameters described previously in the LBI method).
- knowledge of maturity-at-size (L_{50} and L_{95}, length at 50% and 95% of maturity, respectively).
- data on the length frequency composition of the catch to estimate the SPR.

It is worth mentioning that SPR estimates in the range of 0.35–0.4 are usually associated to a stock at MSY level; whereas SPR estimates below 0.1–0.15 indicate that the stock is collapsed. The LBSPR method assumes that the length frequency composition data are representative of the exploited population at a steady state, the selectivity curve is logistic and that the method is equilibrium based (as the LBI method).

Implementation and sensitivity analysis

The values of the life-history parameters derived from literature review are the following ones:

- M/K=1.41, derived from the M=0.31 (from Cerim *et al*., 2020), the K=0.22 (from Teixeira and Cabral (2010) we have that K=0.23 for females and K=0.21 for males, then we consider the mean of both sexes).
- L_{inf} =48.9 cm (from Teixeira and Cabral (2010) we have that L_{inf} = 52.1 cm for females and L_{inf} = 45.7 cm for males, and hence we compute the mean of both sexes).
- L_{mat} =26 cm (from Jardim *et al*. (2011) we have that L_{mat} =25 cm for males and L_{mat} =27 cm for females, and then the mean of both sexes is computed).
- L_{95}=27.5 cm (derived from stock annex sol-bisc Division 8a,b).

The LBSPR model was adjusted using the above values and it is termed as reference model. Furthermore, LBSPR method was also applied using a different set of life-history parameters values. More precisely, we used the mean of each one of the distributions of the life-history parameters derived from FishBase.

Additionally, a sensitivity analysis of the parameters L_{inf}, M/K and L_{50},L_{95} (around our literature/reference values) was carried out overestimating and underestimating them by 5 and 10%.

Results

From the reference model we can conclude that the common sole stock is in a healthy status (stock at MSY level) as the SPR ratio is within the expected range values (Figure 16) and shows an increasing pattern. These results agree with the LBI results.

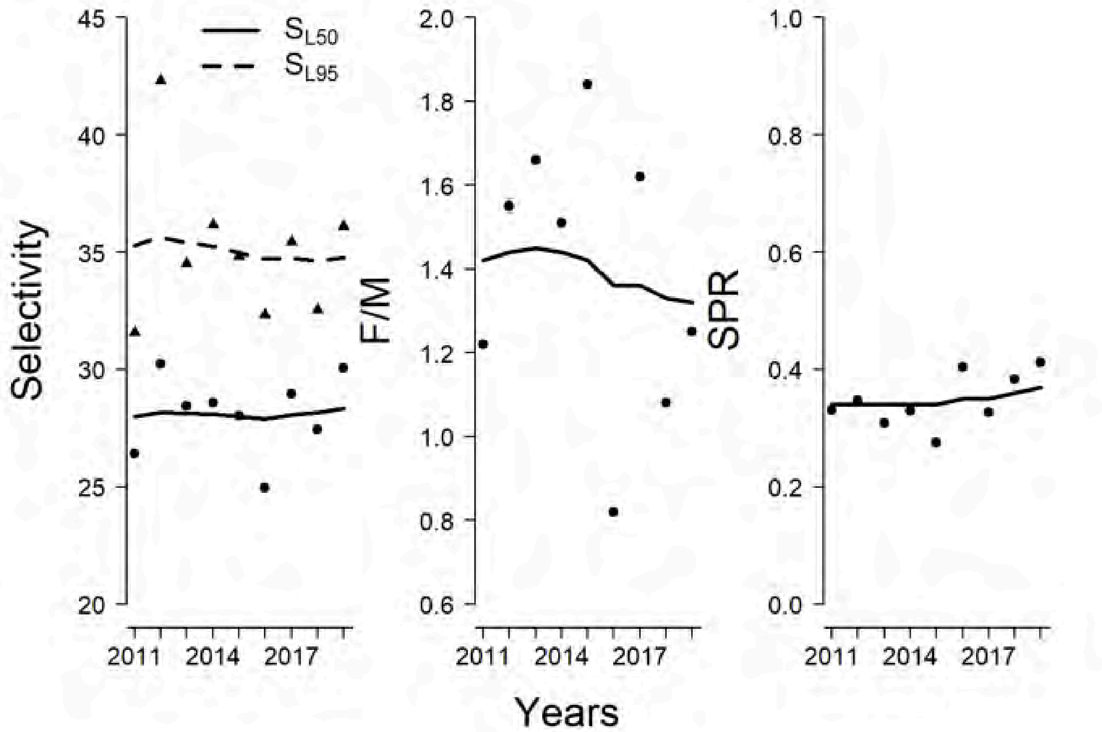

Figure 16. Results of LBSPR application for the *S. solea* species.

When the FishBase life-history parameters were used our perception of the stock status is even better. Finally, the sensivitity analysis showed that Linf is a crucial parameter and hence is value must come from a reliable resource, as in our case (Figure 17). On the other hand, the parameters M/K, L50 and L95 have also an effect on the results but softer. Furthermore, all models agree that stock is far from collapse.

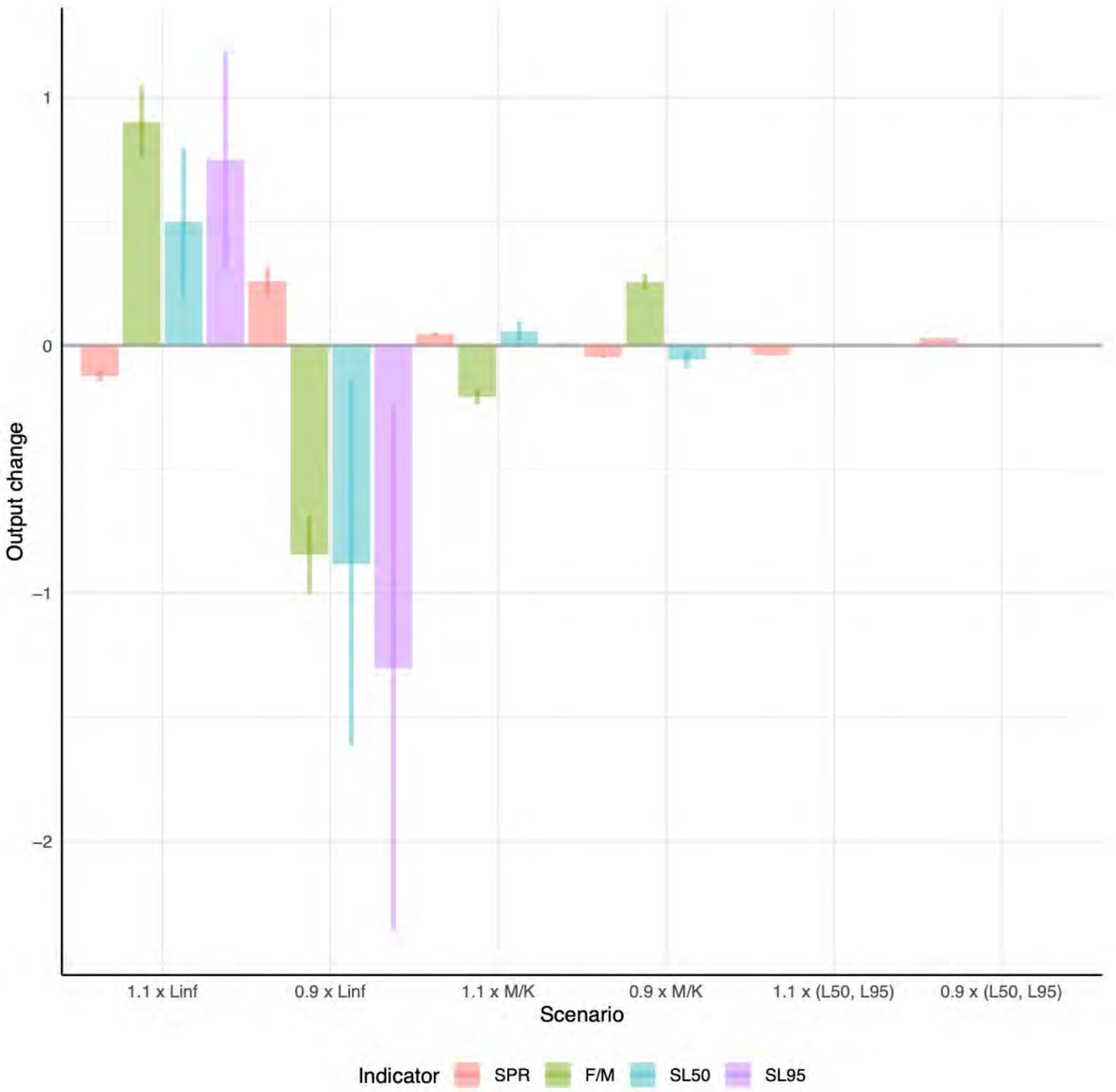

Figure 17. Sensitivity analysis of the parameters L_{inf}, M/K and L_{50},L_{95} (around our reference model) overestimating and underestimating them by 5 and 10%.

4.4.5 Mean length-based mortality estimators (MLZ)

The mean length of animals that are fully vulnerable to the sampling gear can be used to estimate total mortality from basic growth parameters and a known length at first capture. This approach may in some cases represent the best opportunity to reconstruct the mortality history of a stock.

Description

Beverton–Holt length-based mortality estimator is widely used in data-limited fish stock assessment, however, the method requires equilibrium conditions. It assumes equilibrium length frequency composition such that the mean length reflects the current Z rate experienced by the stock.

Gedamke and Hoenig (2006) modified the Beverton and Holt estimator by relaxing the strict assumption of equilibrium population. This was done by modelling the transition of mean length from one equilibrium period to the next, following step-wise changes in Z. Using a time-series of mean length observations, the Gedamke-Hoenig estimator yields period-specific estimates of Z and the corresponding years of change in mortality.

Then *et al*. (2018) developed a new formulation of the Gedamke-Hoenig estimator that utilizes additional information from a time-series of fishing effort to estimate the catchability coefficient q and the natural mortality rate M and thus year-specific total and fishing mortality rates.

Assumptions

Then *et al*. (2018) method assumes constant fishery recruitment and knife-edge selection of lengths (flat-topped selectivity curve) by the fishery gear. Other model assumptions include: mean length-at-age known and constant over time; no individual variability in growth; natural mortality M independent of stock size and constant with age and over time, and constant catchability q over time and over age for all ages ≥tc (being the age at which animals are fully vulnerable to the fishery and to the sampling gear).

Data required

Time-series of length measurements, von Bertalanffy growth parameters Linf and K for the stock, time-series of fishing effort and the so-called length of first capture (Lc, i.e. the smallest size at which animals are fully vulnerable to the fishery and to the sampling gear). The effort time-series can be derived as the ratio of the catch and a CPUE/LPUE series.

Fitting MLZ model

The values of the life-history parameters derived from literature review are the following ones:

- K=0.22 (from Teixeira and Cabral (2010) we have that K=0.23 for females and K=0.21 for males, then we consider the mean of both sexes).
- L_{inf} =48.9 cm (from Teixeira and Cabral (2010) we have that L_{inf} = 52.1 cm for females and L_{inf} = 45.7 cm for males, and hence we compute the mean of both sexes).

For the reference model the effort time-series was derived from the ratio of the catch and a LPUE series of Portugal.

Both Gedamke-Hoenig and Then methods were applied. The adjustment using the above values is termed as reference model. The MLZ method was also applied using a different set of life-history parameters values. More precisely, we used the mean of each one of the distributions of the life-history parameters derived from FishBase.

A sensitivity analysis of the parameters L_{inf} and K (around the reference model) was carried out overestimating and underestimating them by 10%. In Then model such analysis was carried out also for the initial value of parameter q. Finally, the Spanish CPUE was also considered as an alternative of the reference model effort (i.e. catch/LPUE series of Portugal).

Results

Gedamke and Hoenig

As the time-series is too short (i.e. 2011–2019), it was not possible to define different periods of different mortalities. Hence, we only estimate the total mortality for the all time period 2011–2019 (Figure 18).

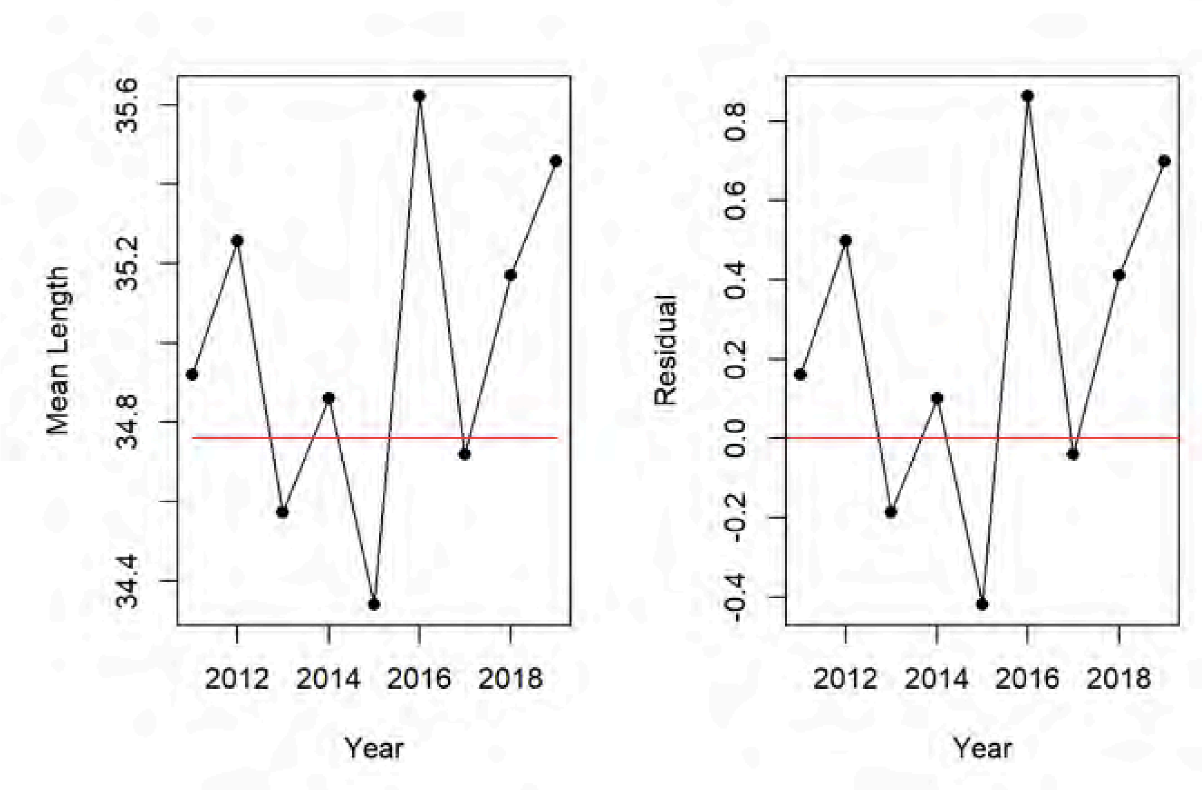

Figure 18. Results of Mean Z application (Gedamke and Hoenig model) for the *S. solea*.

The Gedamke and Hoenig model estimate of the total mortality is close to 0.5. The sensitive analysis showed that the results did not change so much varying K whereas the effect of L_{inf} is larger. In any case, the larger value of total mortality obtained was close to 0.60.

For the Then model the initial value of *q* have been fixed as: 0.2/mean(effort), where 0.2 is a guess for the fishing mortality and mean(effort) is the mean of the time-series of effort.

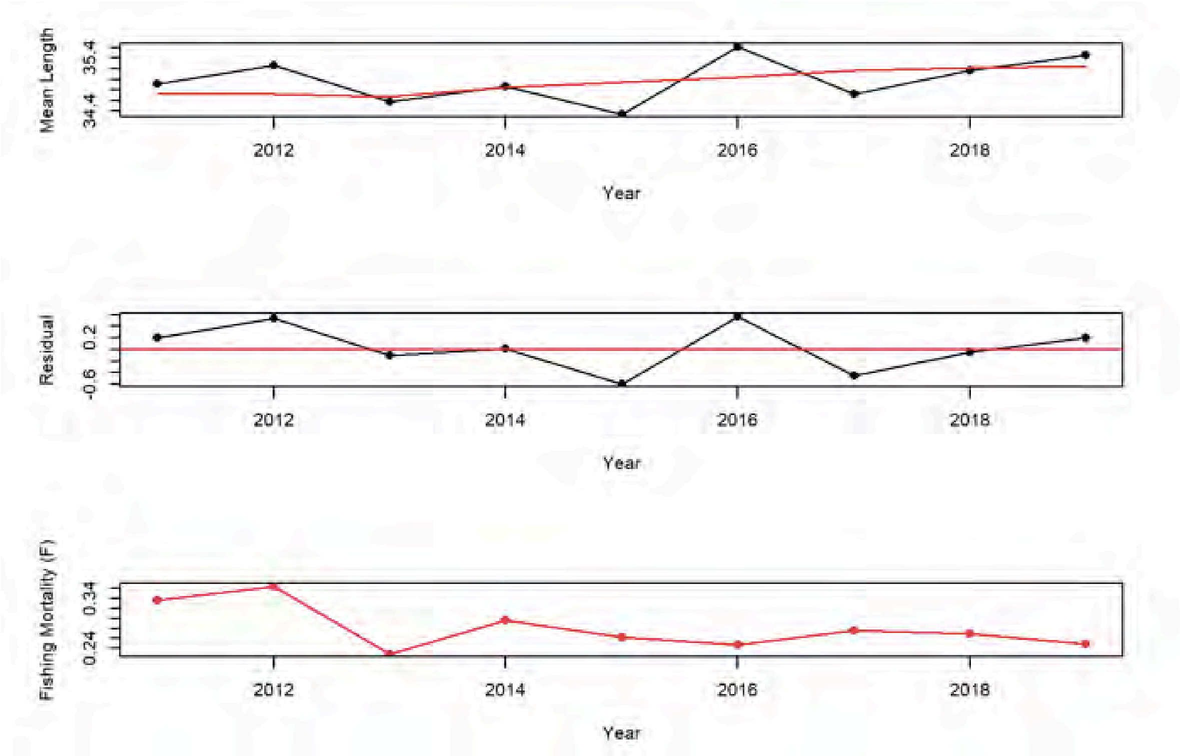

Figure 19. Results of Mean Z application (Then model) for the *S. solea.*

The above model estimates the natural mortality, while another option in the Then model was to fix such parameter. For this reason, we also tested this option, using a natural mortality of 0.31 derived from Cerim *et al.* (2020).

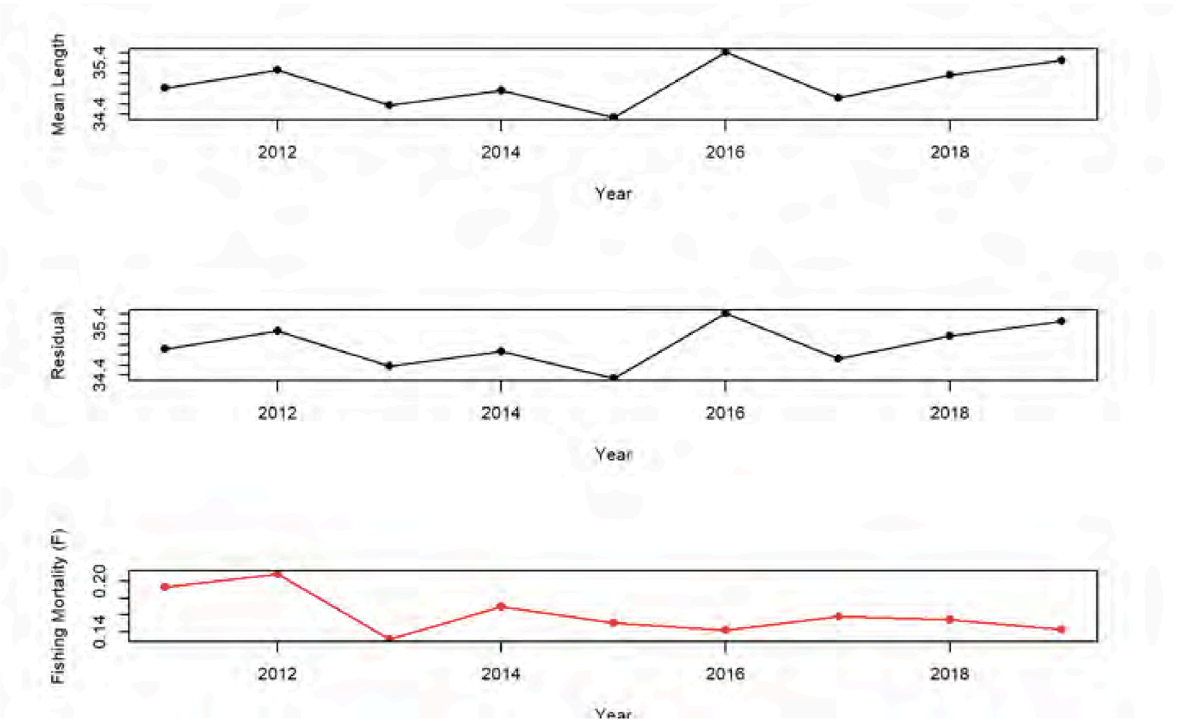

Figure 20. Results of Mean Z application (Then model fixing natural mortality) for the *S. solea.*

In both cases results were very similar showing a decreasing F temporal trend for the studied time-series (Figures 19 and 20) and the fishing mortality estimates ranged from 0.33 to 0.24.

The natural mortality was estimated around 0.18 in the reference model, which is smaller than the value suggested by Cerim *et al*. (2020). However, it is important to mention that overestimation and underestimation of the initial value of q leads to a natural mortality estimate very close to the suggested by Cerim *et al*. (2020). The same happens if, instead the initial effort defined as catch/LPUE we used the weighted efforts (using the CPUE from Spain). Indeed, for such effort the natural mortality was close to 0.3. Finally, although in the sensitive analysis there was an effect when the overestimation and underestimation of L_{inf} and K were tested, the important point is that the larger fishing mortality estimate was close to 0.25 and the temporal trend of F was consistent in time (always decreasing).

4.5 Fishing opportunity advice

Advice rules for harvest control rules for length-based approaches

WKLIFE VIII developed a harvest control rule to provide MSY advice for category 3 and 4 stocks based on the "2-over-3 rule", which compares the trend in stock index of the two most recent years to the preceding three years (WKMSYcat34; ICES, 2017a). The recommended harvest rule improves on 2-over-3 with the addition of multipliers based on the stock's life-history characteristics, the status of the stock in terms of relative biomass, and the status of the stock relative to a target reference length (Section 3, WKLIFE VIII; ICES, 2018a). The catch rule is defined as:

$$C_{y+1} = m \times C_y \times r \times f \times b$$

where the advised catch (C) for next year y+1 (set on a biennial basis) is based on the most recent year's advised catch C_y adjusted by the following components:

Component	Definition and use
r	The rate of change in the index, based on the average of the two most recent years of data (y−2 to y−1) relative to the average of the three years prior to the most recent two (y−3 to y−5), and termed the "2-over-3" rule.
f	The ratio of the mean length in the observed catch that is above the length of first capture relative to the target reference length (mean length/target reference length). The target reference length is $L_{F=M} = 0.75L_c + 0.25L_{inf}$, where. $L_c$is defined as length at 50% of modal abundance (ICES, 2018b).
b	Adjustment to reduce catch when the most recent index data I_{y-1} is less than $I_{trigger} = 1.4I_{loss}$ such that *b* is set equal to $I_{y-1}/I_{trigger}$. When the most recent index data I_{y-1} is greater than $I_{trigger}$, *b* is set equal to 1. I_{loss} is generally defined as the lowest observed index value for that stock.
m	Multiplier applied to the harvest control rule to maintain the probability of the biomass declining below B_{lim} to less than 5%. May range from 0 to 1.0.
Stability clause	Limits the amount the advised catch can change upwards or downwards between years. The recommended values are +20% and −30%; i.e. the catch would be limited to a 20% increase or a 30% decrease relative to the previous year's advised catch.

Each component of the harvest control rule is combined (multiplied together), in order to determine next year's catch advice by adjusting this year's catch advice upwards or downwards. This is based on the trend in the index (i.e. whether the stock is going up or down, *r*) the observed mean length in the catch relative to the target mean length (*f*), and a factor to adjust catch downwards if the current stock falls below a threshold index value (*b*), defined as $I_{trigger}$= 1.4 × I_{loss}. I_{loss} is defined as the lowest observed index value for that stock. The multiplier (*m*) is then applied as a precautionary measure to ensure that the probability of the stock declining below B_{lim} is less than or equal to 5%.

The performance of the catch rule is driven largely by three factors:

1. The life history of the species;
2. The trend in the index being a good measure of the current status of the stock based on the life history; and
3. The $I_{trigger}$ value being defined at or near the true threshold level (e.g. 0.5 B_{MSY}).

4.5.1 Application of the length-based harvest control rule

Incorporating a multiplier (*m*) less than 1 will decrease risk in harvest control rule performance (i.e. a reduced probability of the stock declining below B_{lim}) by buffering against the uncertainty of each component of the harvest control rule sufficiently to reflect the true state of the stock and lead to the correct management action. The risk of the stock declining below B_{lim} is related to the life-history dynamics of the stock. It is recommended that the application of the harvest control rule include a life history-based multiplier to reduce risk.

For the harvest estimate for longer-lived stocks with low natural mortality and low growth rates (von Bertalanffy*k* < 0.19, e.g. redfish or ling), a multiplier should be applied to the harvest control rule of 0.85 by setting the estimated catch for the following year to 85% of the estimated yield, based on the harvest control rule ($C_{y+1} = 0.85 \times C_y \times r \times f \times b$). Medium-lived stocks with *k* between 0.20 and 0.32 (e.g. plaice, red mullet) should apply a multiplier of 0.90 to next year's estimated catch. If there is no reliable information about *k*, but *k* is considered to be no more than 0.32, then a multiplier of 0.80 should be used.

The harvest control rule is not recommended for use for stocks with fast life-history dynamics ($k > 0.32$, e.g. brill or sardine). The 2-over-3 (*r*) component of the harvest control rule does not adequately capture the trend in biomass for life-history dynamics with high interannual variability, because the trend in biomass over the last two years relative to the preceding three years may not be indicative of current stock conditions. The current PA approach for data-limited stocks in ICES is the application of the "2 over 3" rule in conjunction with a PA buffer and an uncertainty cap (ICES, 2012). It is recommended that this approach should be continued for stocks with k>0.32 but not characterised as short-lived stocks.

It is recommended to apply a stability clause of +20% and -30%, where the advised catch would be limited to increase by 20% or decrease by 30% relative to the previous year's advised catch, in all applications of the harvest control rule.

Application

As we have different biomass indices, we applied this rule to different setting:

1. LPUE from Portugal as biomass index. Catch advice= 305 t;
2. Weighted biomass index between CPUE from Spain and LPUE from Portugal. Weight for both index as 0.5 and without variation in time. Catch advice= 402.5008 t;
3. Spanish demersal survey as biomass index. Catch advice= 296.4939 t;

4. Bayesian spatio-temporal biomass index derived from the Spanish survey data. Catch advice= 285.1123 t;
5. Weighted biomass indices between LPUE from Portugal and CPUE from Spain with weight varying by year on the percentage proportion of the catches. Catch advice= 366.67 t;
6. Weighted biomass indices between Portuguese LPUE and the Spanish survey index with weights varying by year according to the percentage of catches of each of the countries (i.e. Spain and Portugal). In this setting the two indices are standardized before their application as:

   $$Index_{year} = ½ * [S\text{-}Index_{year}/mean(S\text{-}Index) + P\text{-}LPUE_{year}/(mean(P\text{-}LPUE)]$$

   In this scenario the catch advice was of 300.5197 t.

7. Weighted sum of the Portuguese LPUE and the Spanish Bayesian survey index with weights varying by year according to the percentage of catches of each of the countries (i.e. Spain and Portugal). In this setting the two indices are standardized before their application:

   $$Index_{year} = ½ * [S\text{-}BayesianIndex_{year}/mean(S\text{-}BayesianIndex) + P\text{-}LPUE_{year}/(mean(P\text{-}LPUE)]$$

   In this scenario the catch advise was of 309.9102 t.

This last configuration was the accepted by the group because it was considered that it is better to have two biomass indices (one for each country). Among Spanish indices, the CPUE from the Galician artisanal fishery was dismissed because is not representative of the all area, while the Spanish survey cover the entire Spanish area. Among the Spanish survey index and the Bayesian one it was selected the last one as improves the bias of the Spanish survey (Figure 21) smoothing the variability of the sampling.

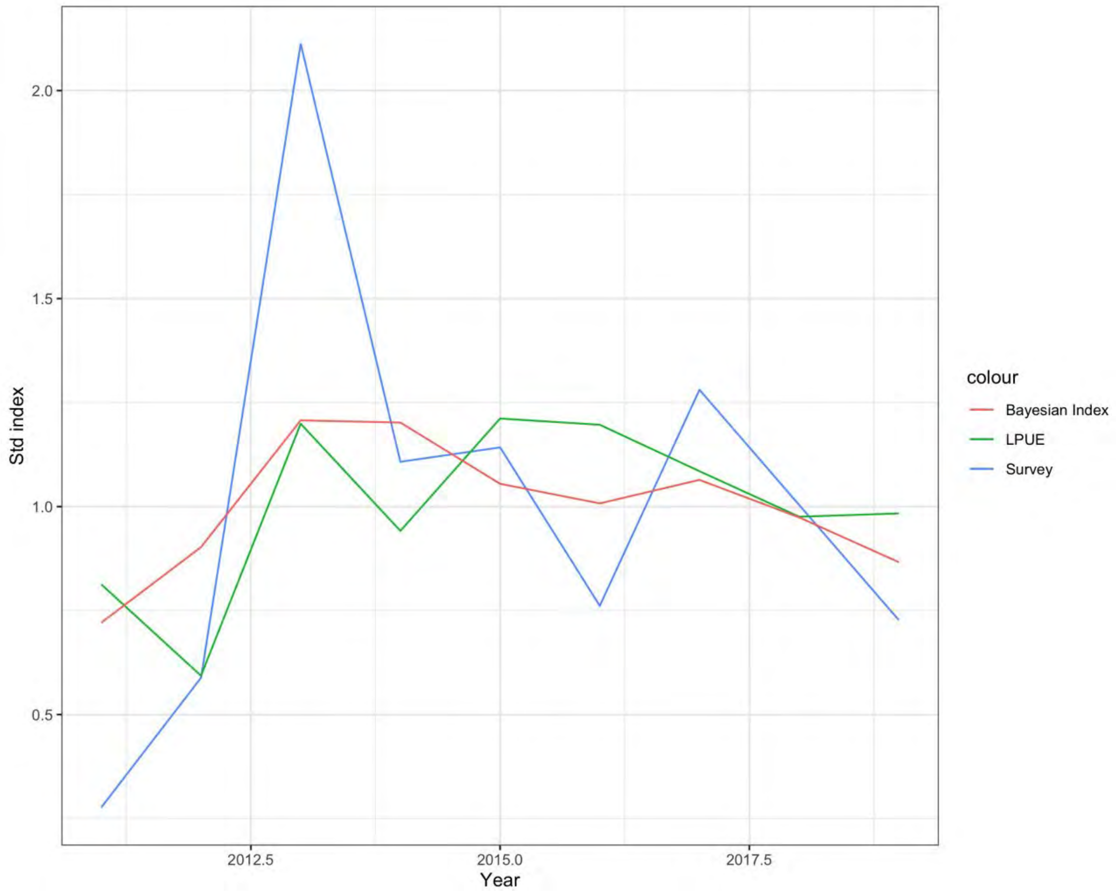

Figure 21. Different standardized biomass indices.

4.6 Future considerations

From this benchmark all the available information for this stock was retrieved. This information is key to improving the advice for this stock, which can be now evaluated using the methods suggested by ICES for category 3 stocks. However, despite the recent improvement of the data available for this stock, some issues still need to be addressed. Catches of this stock must be checked regularly as all the Soleidae species are often mixed at landing ports. The biomass indices can be further improved and, as the Portuguese survey will change the gear, it could be used in the future. It would be necessary to obtain a better quantity and quality of the data from the artisanal fleet both in Spain and in Portugal, given that it is the one that fishes this species most. Initial runs of the SPiCT model for this stock were promising. When the time-series are longer, the use of this model for the assessment of this stock should be explored. Information on the biology of this stock in this area is still scarce and specific studies should be made to better define the life-history parameters. The information available for the other Soleidae species is scares and should be improved but should be treated separately from the common sole stock. No study has ever been done on the definition of the stock identity, and this is an important issue to be addressed in the future. The TAC derived from the common sole stock assessment should be applied only to the *Solea solea*. Catch data of the other Soleidae species should also annually reported to monitoring their status.

4.7 Reviewer's comments

Data evaluation

The sole in 8c9a used to be a category 5 stock as only catch data were available. Since 2012, ICES provided scientific advice for this stock applying the precautionary approach.

Commercial data: Commercial landings and length distributions of sole (*Solea solea*) in 8c9a are available for Portugal (2011–2019), Spain (2009–2019) and France (2009–2019). Great efforts were made to improve the fisheries-dependent data. Three species (*Solea solea*, *Solea senegalensis* and *Pegusa lascaris*) with a common TAC are usually caught in the fishery, and a problem of misidentification in some Portuguese ports with the three species was identified. This was solved by the Portuguese colleagues and landings by species were provided by the two main countries involved in the fishery, Portugal and Spain. A new data call was made in order to get more length samples, especially from the commercial Portuguese fleet. A standardized LPUE was estimated using a Generalized Linear Model with a gamma link with the commercial landings of the polyvalent fleet at one Portuguese port, considered the most representative for the sole fishery in Portugal. Another index, a CPUE for a fleet operating in Galician waters in Spain, was estimated, although it is not considered representative of the catches from Spain as it only covers a small portion of the fishery of that country.

Survey data: Two scientific surveys have been carried out in the area of the sole. The Portuguese bottom trawl survey is not considered representative for sole as the gear used does not touch the bottom. The Spanish survey (2000–2019) only covers depths deeper than 70 meters and therefore only covers a limited part of the bathymetric distribution of sole. The swept area indices were corrected for the area not covered by applying a Bayesian spatio-temporal model to estimate index based on the whole depth distribution of the stock. Although some concerns about this model were raised, it was considered to be better than only using the raw data of the survey, as the index derived from them is underestimated.

Assessment

The four methods approved by ICES for the calculation of MSY reference points for category 3 and 4 stocks -SPiCT, LBI, LBSPR and MLZ- were applied using the four available indices (Spanish raw survey index, Spanish Bayesian survey index, Portuguese LPUE and Galician CPUE). Several runs of each of the models, with different combinations of the available data and always performing sensitivity analyses, were carried out. Although the SPiCT produced promising results, most runs had issues, and it was decided by the benchmark, in agreement with the recommendation by the WKMSYSPiCT 2021 that at this moment the time-series is too short to apply this method and use it as the basis of the assessment of this stock.

Of the length-based methods it was agreed that the LBI approach was currently the most adequate for this stock. The LBI indicators produced all showed that the stock was in a good state, which was supported by results from the LBSPR and MLZ runs. It was decided that the LBI was best suited to reflect the status of the stock, and with this method as basis, the 2-over-3 HCR (Method 2.1, WKLIFE X) was applied to get the advice for this stock. Some discussions were raised about the most suitable data to be used in the HCR. The conclusion was to use a weighted sum of the Portuguese LPUE and the Spanish Bayesian survey index, with weights varying by year according to the percentage of catches of each of the countries. It was accepted that the stock should be assessed as a category 3 stock.

The reviewers agreed that the assessment of *Solea solea* performed during the benchmark was appropriate with the data available in this moment.

Future recommendations

- Improving data sampling: more length samples are needed, especially from the Spanish commercial fleet. Biological samples to refine the biological parameters used in the models would be very beneficial.
- It is planned to change the gear deployed by the Portuguese survey to one that might be more representative for the sole. If this happens, studies of the data provided by this survey would be necessary and very useful for the assessment.
- Initial runs of the SPiCT model for this stock were promising. When the time-series are longer, the use of this model for the assessment of this stock should be explored.
- More sensitivity analyses for the Portuguese LPUE are needed. The addition of more data, for example from several Portuguese ports, would be helpful to produce a more accurate LPUE from this fleet.
- The Bayesian spatio-temporal model has to be further studied in order to know if the assumed hypothesis in the model is precise. As the area shallower than 70 meters has never been surveyed, to assume that the distribution of the catches in that depth range is the same as in the deeper strata (>70 m) could be risky. Improving the hypothesis of this model, or trying another model(s) to provide an estimated index of abundance for sole, would be beneficial.

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5 Reviewers' general comments across all assessments

The reviewers have been through the working documents and acknowledge the comprehensive effort made in the preparation and presentation, as well as the timely delivery of some of these working documents in advance of the inter-benchmark working group meeting. The data exploration, methods and assessments runs are documented and well described in the respective working documents of the benchmark and data compilation workshop. The prepared material provided a good basis for further discussions and evaluations of the assessments brought forward during the benchmark working group meeting.

The reviewers note that this was a benchmark assessment of four stocks with a five-day meeting duration. Comprehensive ToRs were formulated for each of the stocks to be assessed. The reviewers also note that the ToRs included the development of recommendations for future work to improve the assessments, which are included at the end of each species review report. The reviewers believe that the benchmark improved the basis for assessing all four stocks.

There have been some issues with the data call prior to the data compilation workshop in December, where some formulation where perceived differently by data submitter, e.g. units of effort for the commercial fleets, gear codes and métiers to be used and units of sampling data. This caused additional work for the stock assessors as they had to contact several data submitters and request different data formats between the data compilation and the benchmark. The reviewers therefore recommend the introduction of a feedback loop, where data submitters and stock coordinators get the chance to check the data call before it is published and feedback whether the formulations are clear and if the requested data can be delivered or not.

6 Working Documents

The following working documents were presented to the WKWEST and are included in full in Section 6.

Subsection 6.1: WKWEST_ple.27.7h–k. Plaice (ple.27.7h–k)

Subsection 6.2: WKWEST_gur.27.3–8. Red Gurnard in Subareas 3–8, Neil Campbell, Marine Scotland Science.

Subsection 6.3: WKWEST_pil27.7. Evaluation of stock assessment methods for sardine (*Sardina pilchardus*) in Subarea 7 (Southern Celtic Seas and the English Channel), Rosana Ouréns, Jeroen Van Der Kooij, Johnathan Ball, Richard Nash, Centre for Environment, Fisheries and Aquaculture Science (Cefas).

Subsection 6.4: WKWEST_sol.27.8c9a. Common sole (*Solea solea*) stock in ICES divisions 8c9a. Data compilation and preliminary assessment. Maria Grazia Pennino, Catarina Maia, Alberto Rocha, Cristina Silva, Ivone Figueiredo, Marta Cousido, Francisco Izquierdo, Santiago Cerviño, Francisco Velasco, Josefina Teruel Gomez, José Rodríguez.

Subsection 6.5: WKWEST_sol.27.8c9a_Spict. Stochastic surplus production model in continuous time (SPiCT).

Subsection 6.6: Data compilation for the French databases of sardine (*Sardina pilchardus*) in the English Channel (27.7.de stock including or not the 25E4/25E5 of the Douarnenez Bay). Angela Larivain, Erwan Duhamel, Lionel Pawlowski.

1 Plaice (ple.27.7h-k)

1.1 Fishery and management

Landings of plaice are similar in ICES divisions 7h and 7j, but are considered negligible in 7k (Fig 1). The plaice fisheries7h and 7j are targeted by two very distinct gear types (Fig 2). Plaice in 7j is typically targeted by the Irish otter trawl fleet, which operate on sandy grounds off the southwest of Ireland, close to shore and this species is a small, but valuable component of the landings in a mixed fishery. Whereas, plaice in 7h is mostly targeted by the beam trawl fleet, and some otter trawl. Which operate close to the boundaries of other plaice stocks (ple.27.7.fg & ple.27.7.e) (Fig 2).

An analysis of WGMIXFISH data was conducted to demonstrate that plaice 7h-k is taken as a minor bycatch in a mixed fishery. The WGMIXFISH dataset (ICES 2020) summarises retained catch of the main commercially important species over a 9-year period (2009 – 2019), for six countries (Belgium, Ireland, France, Scotland, England (inc. Wales) and Northern Ireland), aggregated to DCF métier level 4 (2010/93/EU Appendix IV). From this analysis it can be concluded that plaice is not a target species of any fishery operating within ICES Divisions 7. h-k, representing a very minor proportion of all retained catch (1-4% of total retained catch) (Figure 7.a, Table 1). Plaice is caught as incidental catch, alongside an economically important species such haddock and hake (figure 7.b). The characteristics of this mixed fishery for plaice is effected by both location of the fishery and the nationality of the fleet fishing it. Figure 6 illustrates the variation in the characteristics of the plaice mixed fishery, with Belgian fleet landings plaice as part of a majoritively flatfish, whereas the French and Irish fleet is dominated by gadoids and *Nephrops*.

Despite a decreasing trend in the total landings, and subsequent total value at first sale of plaice, there is an increasing trend in the price per kg of the species (Fig 5). The Probyfish project to be considered valuable bycatch of collateral bycatch of other fisheries (Fig 4). Restricting the landings by TAC for this stock is unlikely to reduce the catches.

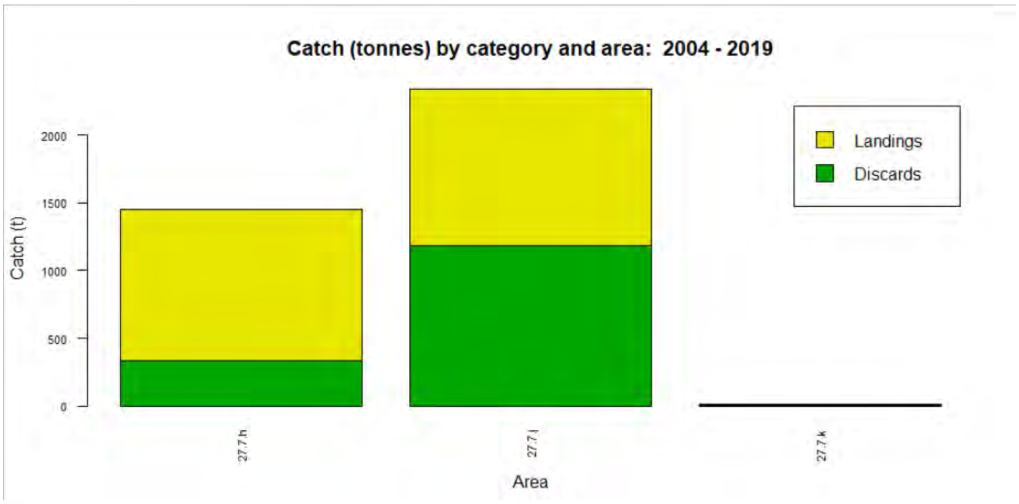


Figure 1 Total Landings of Plaice across the three ICES areas (27.7.h-k) from 2004 - 2019

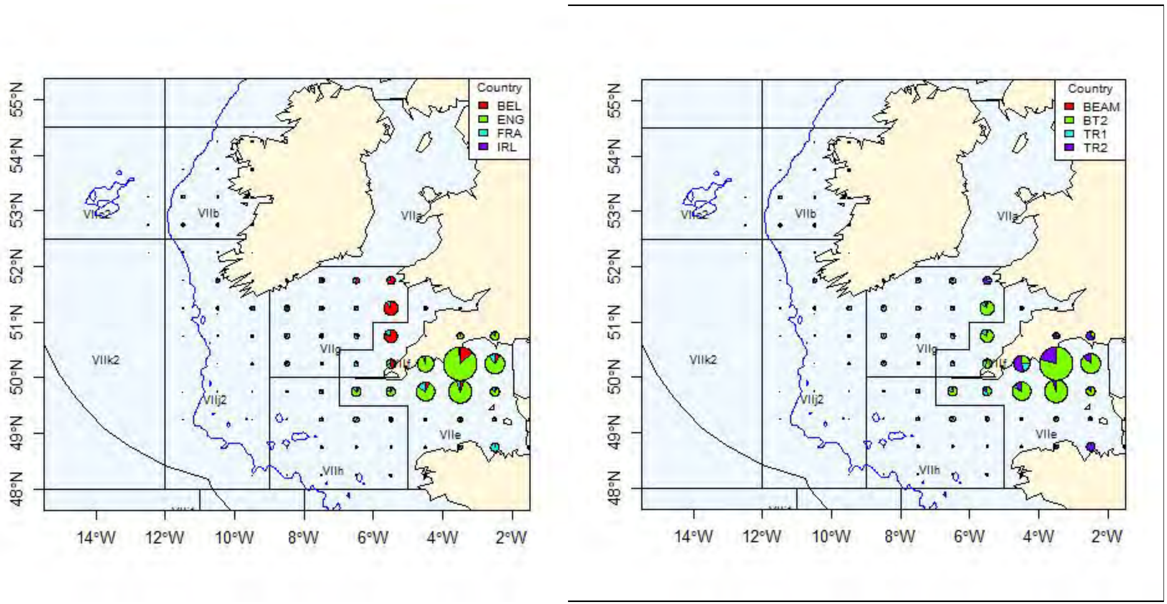


Figure 2 The spatial distribution of plaice landings reported to the STECF fisheries dependant information data call in 2016 (the last data year available), disaggregated by Member State (left) and gear (right). Note beam trawlers are described as beam and BT2, and otter trawlers are described as TR1 and TR2.

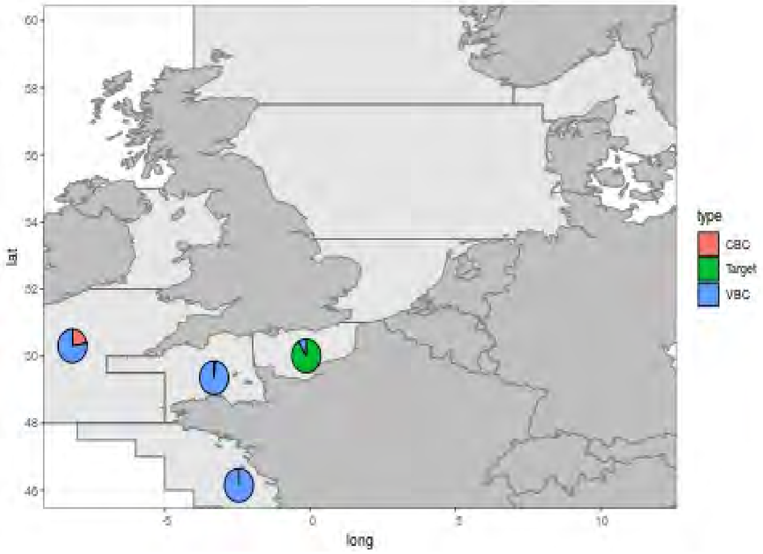


Figure 3 Result of the Probyfish project, where plaice in this area was determined to be valuable bycatch and collateral bycatch https://probyfish.shinyapps.io/GlobalAnalysis/

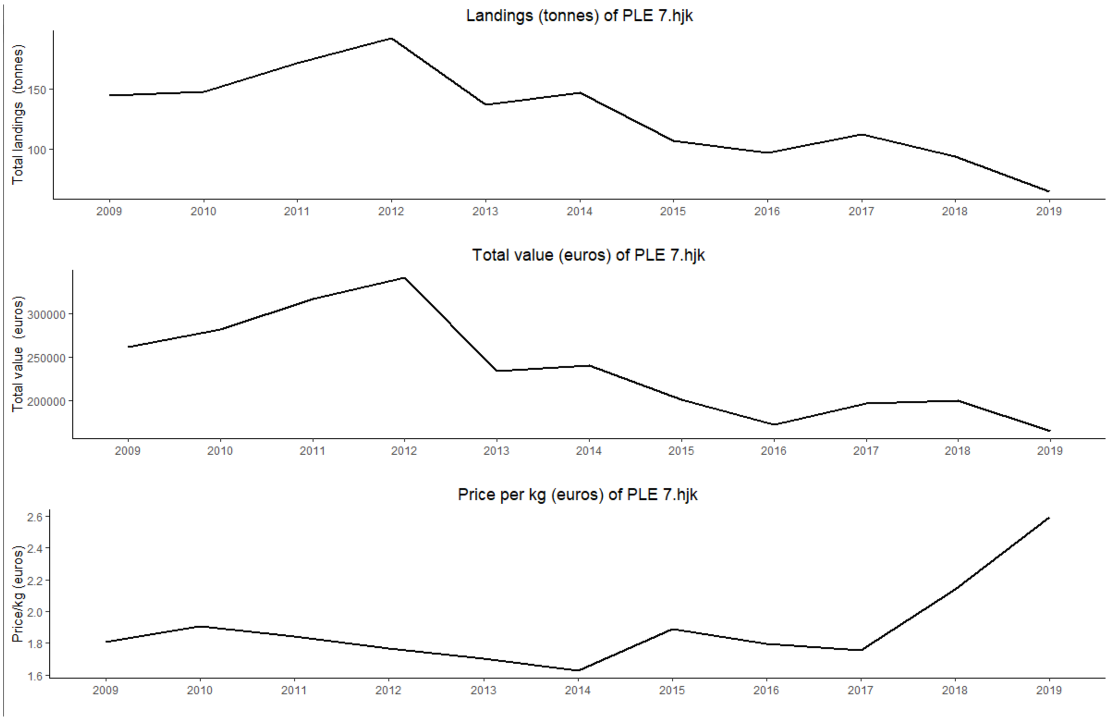


Figure 4 Summary of retained catch of plaice in ICES divisions 7.h-k from 2009 – 2019. (ICES 2020)

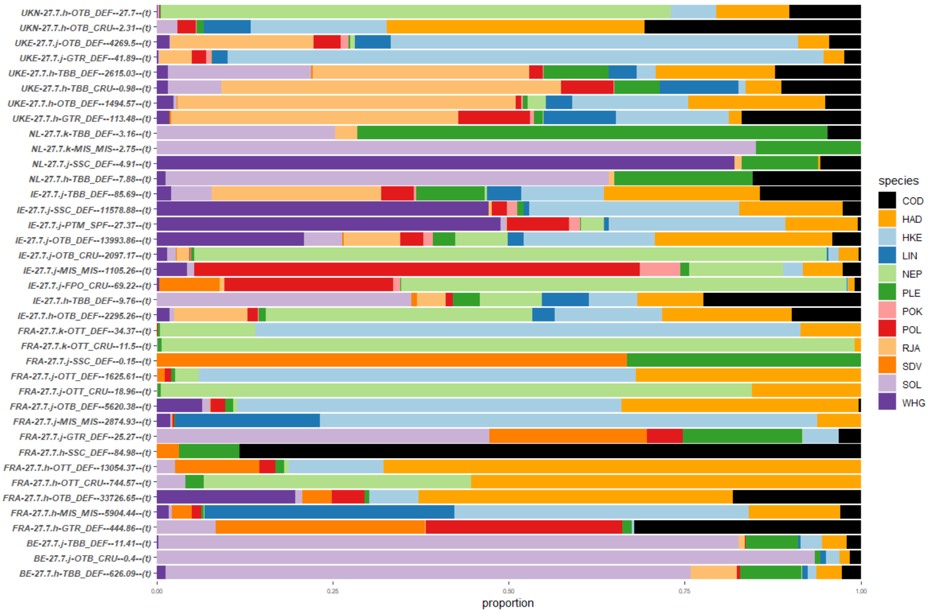


Figure 5 Retained catch profiles of métiers fishing plaice in ICES Division 7.h-k, from 2009-2019. The profiles describe the proportion of species per métier. Both country and ICES Division are included in the aggregation as this is the level at which the stock are managed by TAC. The y axis indicates the métier and its total retained catch in tonnes. (ICES 2020)

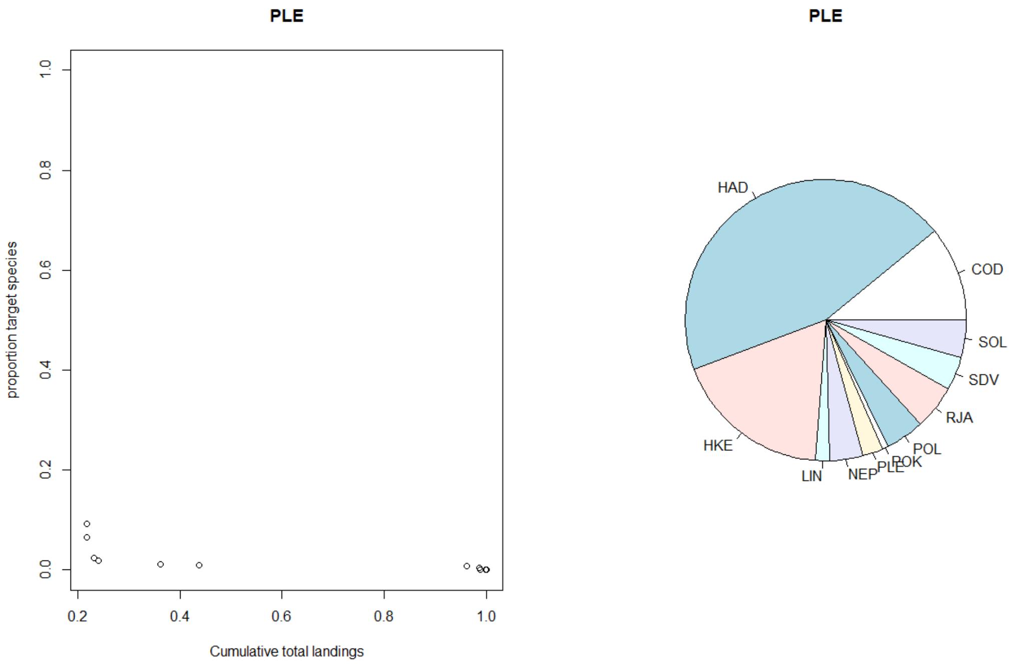


Figure 6 Summary of the mixed fisheries interactions of plaice and the other species with which it is caught. Combined, these two plots allow us to make some inferences about the extent of mixed in relation to each of these valuable TAC specie: The plot on the left-hand side (7a) shows the cumulative landings, ordered by the proportion of the species landed by each unique level 4 métier. This plot indicates to what extent a species is being targeted and whether or not they are part of a mixed fishery. A clean fishery will have all the points along the top of the plot, while a by-catch species, such as plaice, will quickly drop down to a low proportion. The pie-plot on the right (7b) shows overall species composition of the métiers which landed plaice in ICES division 7.h-k. (ICES 2020)

Table 1 Summary of the portion of retained plaice in relation to the total retained catch of each métier. The low proportion of plaice in the landings indicate that plaice is not currently targeted in ICES Division 7. h-k. (ICES 2020)

Metier (lvl 5)	PLE Landings (tonnes)	Total Landings (tonnes)	Proportion of PLE per metier (%)
TBB_DEF	309.53	3359.28	9
TBB_CRU	0.06	0.98	7
OTT_CRU	19.29	775.02	2
GTR_DEF	11.91	625.53	2
OTT_DEF	173.35	14714.34	1
SSC_DEF	106.69	11725.09	1
OTB_DEF	741.53	91019.11	1
MIS_MIS	35.96	10352.39	0
FPO_CRU	0.10	69.32	0
PTM_SPF	0.04	29.87	0
OTB_CRU	14.96	19271.64	0
GNS_DEF	4.56	105898.63	0

1.2 Stock definition and structure

To date no stock identification studies have been conducted on plaice in 7h-k, which is on the south-western margins of the species distribution, which is reflected in the reported landings that show high landings in adjoining stock areas, 27.7.e and 27.7.fg (Fig 2). There are no relevant tagging studies completed in this area. Some samples were collected in the 1950’s by CEFAS (Brut et al. 2006) but this author could not find any analysis of this data, suggesting connectivity other adjoin stock areas. However, there is evidence in other areas to suggest that plaice is a highly mobile species (Hunter & Darnaude 2004), and therefore it is possible that ple.27.7.h-k is an extension of larger adjoining populations, but tagging and genetic would need to be completed to determine this.

2 Catch data - InterCatch

Catch data was submitted to InterCatch and accessions by three member states: France, UK (England) and Ireland. Each country submitted varying length of time series, covering different ICES divisions, gears and catch categories. This data can be divided into three main categories: length samples, age samples and discard rates. These submissions have been described in the proceeding sections.

2.1 Length samples

France submitted 9,265 landings length measurements (Table 2.1), for 27.7h, spanning 6 years (2014 – 2019)(Figure 2.1). These lengths were majoritively taken from two otter trawl métiers, OTB_DEF_100-119 and OTT_DEF_100-119 (Table 2.2c). No discard lengths were supplied. This information was raised from 142 number of samples (Table 2.2a). Note that sample numbers are estimated from the data supplied in InterCatch (NumSampleslngth), therefore there is likely to be double counting of sample numbers as it is unclear which groups of trips have been grouped and allocated to provided distributions to raise the data.

Ireland submitted 79,214 landings and 50,320 discard length measurements (Table 2.1). Covering ICES divisions 27.7.j and 27.7.k, from 2004 – 2019 (Figure 2.2). These lengths come from 5 metiers came from GNS_DEF_120-219_0_0_all, MIS_MIS_0_0_0_HC, OTB_CRU_100-119, OTB_CRU_70-99, OTB_DEF_100-119_0_0_all, OTB_DEF_70-99_0_0_all, SSC_DEF_100-119_0_0_all. This information was raised from 1,627 number of samples (Table 2.2c).

England submitted 25,439 landings and 5,874 discard length measurements (Table 2.1), covering 27.7.h, with some minor sampling in 27.7.j (Figure 2.2b). The length measurements came mostly from one métier TBB_DEF_70-99_0_0_all, with some minor sampling in set net fisheries (GNS and GTR). This information was raised from 150 samples (Table 2.2c)

Where discarding lengths and abundances have been submitted it is clear that each country and métier show very different discarding patterns. Although the minimum conservation reference size for this stock is 27cm, all metiers are discarding above this size. The maximum length within the dataset is 68cm.

Table 2.1 – Summary of the total raised length samples submitted to InterCatch by country. Note, there were not samples submitted for 2002. These are aggregated numbers form InterCatch and not raw sample numbers.

	2000	2001	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
FR	-	-	-	-		-	-	-	14	-	-	-	-	14220	30066	4991	31130	14258	5099
IE	-	-	-	481770	577090	524397	769993	653987	531438	321396	226154	641783	365332	277525	51464	66843	198864	602774	161994
UKE	21931	50	30228	19533	30472	19229	18972	7939	20730	43516	66378	55790	64039	72657	170263	38427	12092	164179	10143

Table 2.2.a – Sample numbers from which these lengths were raised. No sample numbers provided for 2003 data. These are aggregated numbers form InterCatch and not raw sample numbers.

	2000	2001	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
FR	-	-	-	-	-	-	-	13	-		-	-	25	30	19	19	16	21	143
IE	-	-	99	161	87	68	82	112	192	86	124	80	56	53	91	153	108	75	1627
UKE	1	4	-	-	4	5	-	-	-	5	24	18	12	8	21	20	16	12	150
Grand Total	1	4	99	161	91	73	82	125	192	91	148	98	93	91	131	192	140	108	1920

Table 2.2.b - Sample numbers by metier. No sample numbers provided for 2003 data. These are aggregated numbers form InterCatch and not raw sample numbers.

	2000	2001	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Grand Total
FPO_CRU_0_0_all	-	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	1
GNS_DEF_120-219_0_0_all	-	-	-	-	-	-	1	-	1	-	-	-	-	-	-	-	2	-	4
GNS_DEF_all_0_0_all	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	1	-	-	2
GTR_DEF_all_0_0_all	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-	1
MIS_MIS_0_0_0_HC	-	4	-	-	-	6	5	4	3	5	3	1	1	-	-	-	-	-	32
OTB_CRU_100-119_0_0_all	-	-	17	-	3	10	18	17	36	22	32	25	4	16	24	-	29	-	253
OTB_CRU_70-99_0_0_all	-	-	32	49	27	28	12	24	38	16	11	8	4	8	18	37	15	16	343
OTB_DEF_>=120_0_0_all	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-	1
OTB_DEF_100-119_0_0	-	-	-	-	-	-	-	-	-	-	-	-	22	6	19	12	11	21	91
OTB_DEF_100-119_0_0_all	-	-	17	14	3	10	18	17	36	22	64	25	25	15	24	66	29	21	406
OTB_DEF_70-99_0_0_all	-	-	32	98	54	14	24	48	76	16	11	8	13	8	18	37	15	16	488
OTT_DEF_100-119_0_0	-	-	-	-	-	-	-	-	-	-	-	-	-	20	-	7	5	-	32
OTT_DEF_70-99_0_0	-	-	-	-	-	-	-	-	-	-	-	-	3	-	-	-	-	-	3
OTT-DEF	-	-	-	-	-	-	-	13	-	-	-	-	-	-	-	-	-	-	13
SSC_DEF_100-119_0_0_all	-	-	1	-	-	-	4	1	2	5	3	13	9	10	7	13	18	22	108
TBB_DEF_70-99_0_0_all	1	-	-	-	4	5	-	-	-	5	24	17	12	8	20	18	16	12	142
Grand Total	1	4	99	161	91	73	82	125	192	91	148	98	93	91	131	192	140	108	1920

Table 2.2.c - Sample numbers by ICES division. No sample numbers provided for 2003 data. These are aggregated numbers form InterCatch and not raw sample numbers.

	2000	2001	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Grand Total
27.7.h	1	4	-	-	4	5	-	13	-	5	24	18	37	39	40	38	32	33	293
27.7.j	-	-	99	112	60	54	70	88	154	86	92	80	52	52	91	121	108	75	1394
27.7.k	-	-	-	49	27	14	12	24	38	-	32	-	4	-	-	33	-	-	233
Grand Total	1	4	99	161	91	73	82	125	192	91	148	98	93	91	131	192	140	108	1920

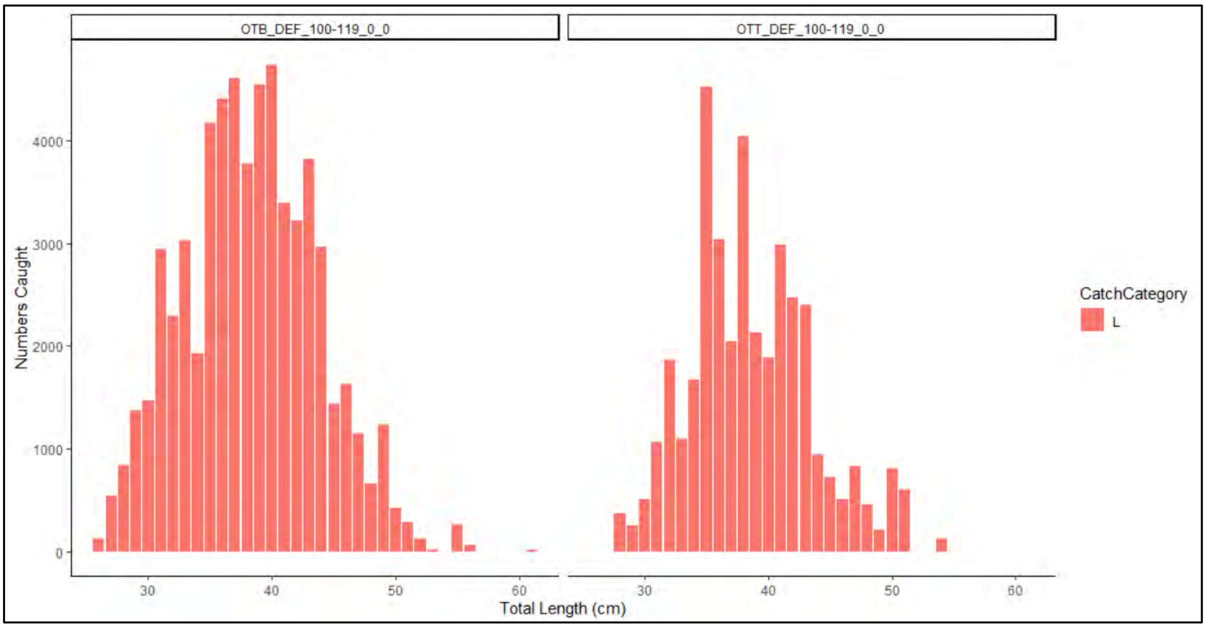


Figure 2.1 Total raised numbers at length (cm) submitted by France to InterCatch (2014 – 2019) for landings (L). No discard information submitted.

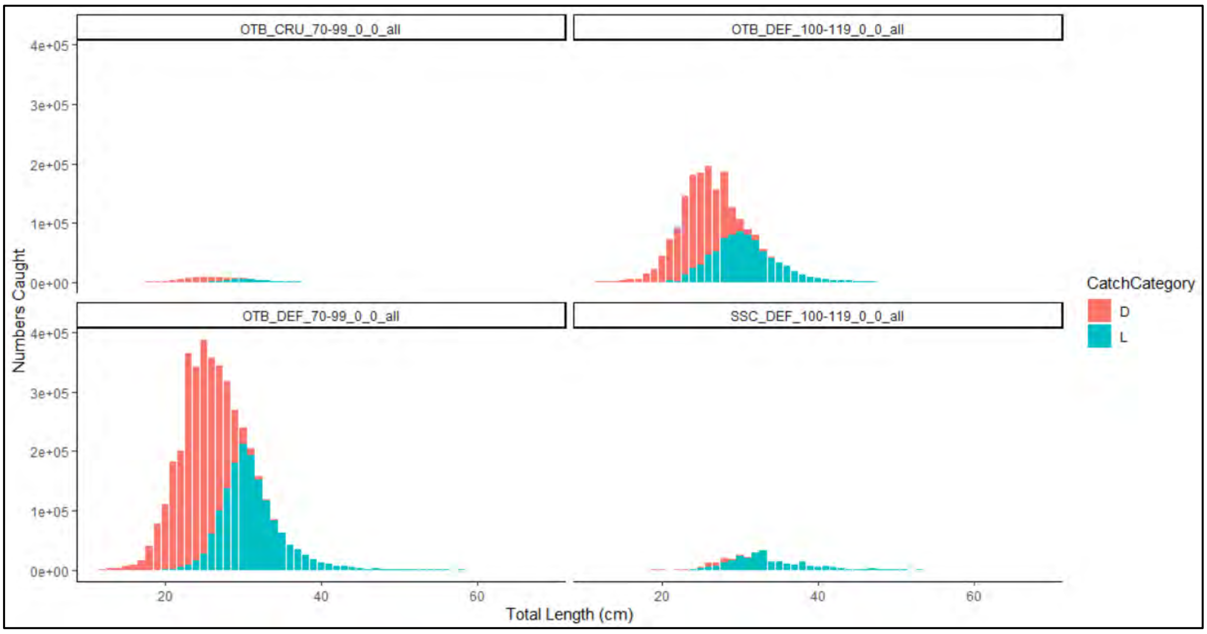


Figure 2.2 Total raised numbers at length (cm) submitted by Ireland to InterCatch (2004 – 2019) for landings (L) and discards (D).

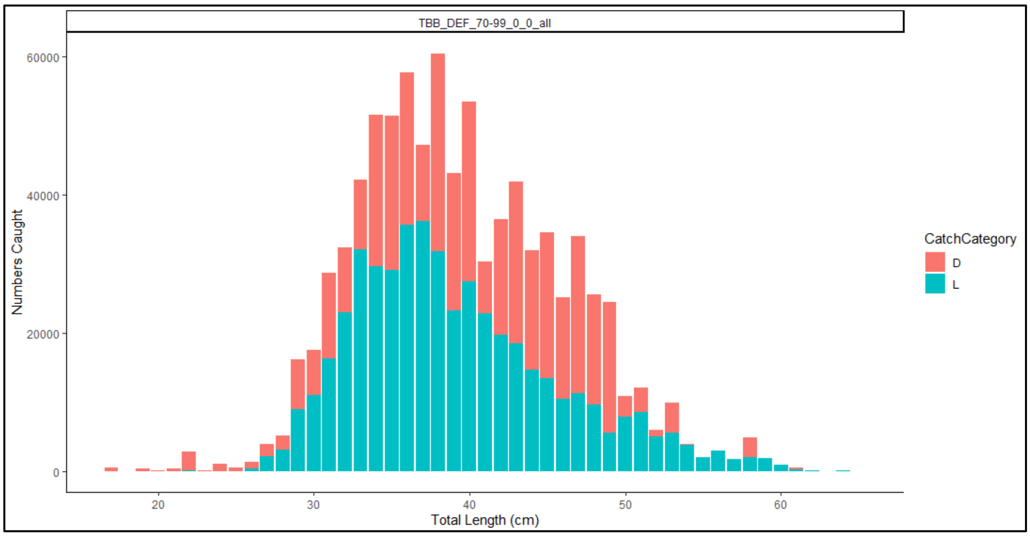


Figure 2.3 Total raised numbers at length (cm) submitted by UK (England) to InterCatch (2000 – 2019) for landings (L) and discards (D).

2.2 Age samples

Notably fewer age samples were submitted then length, however this was still an improvement on the previously available data. Note that sample numbers are estimated from the data supplied in InterCatch (NumSamplesAges), therefore there is likely to be double counting of sample numbers as it is unclear which groups of trips have been grouped and allocated to provided distributions to raise the data. France submitted 2 landings age measurements (Table 2.3), therefore this data could not be incorporated.

Ireland submitted 2,639,433 landings and 3,694,355 discard age measurements (Table 2.3). Covering ICES divisions 27.7.j and 27.7.k, from 2004 – 2019 (Figure 2.7). These ages come from the following metiers GNS_DEF_120-219_0_0_all, MIS_MIS_0_0_0_HC, OTB_CRU_100-119, OTB_CRU_70-99, OTB_DEF_100-119_0_0_all, OTB_DEF_70-99_0_0_all, SSC_DEF_100-119_0_0_all (Figure 2.4c). This information was raised from 14,435 number of samples (Table 2.4a).

England submitted 242,876 landings and 181,288 discard age measurements (Table 2.3), covering 27.7.h, with some minor sampling in 27.7.j (Figure 2.8). The age measurements came mostly from one métier TBB_DEF_70-99_0_0_all, with some minor sampling in the OTB_DEF_>=120_0_0_all métier (Table 2.4c). This information was raised from 1146 samples (Table 2.4a). Where discarding lengths and abundances have been submitted it is clear that each country and métier show very different discarding patterns at age (Figure 2.7 and 2.8).

Table 2.3 – Summary of the total raised age samples submitted to InterCatch by country. Only two single measurements submitted by France, therefore not included. No age data was submitted for 2002 or 2003. These are aggregated numbers form InterCatch and not raw sample numbers.

	2000	2001	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
FR	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
IE	-	-	-	481770	577090	524397	769993	653987	531438	321396	226154	641783	365036	277525	50809	66843	80799	602774	6333788
UKE	21930	50	30224	12263	11865	13261	7661	-	-	-	-	29701	64030	13473	17399	30995	8403	159732	424165
Grand Total	21930	50	30224	494033	588956	537657	777654	653987	531438	321396	226154	671484	429066	290998	68208	97838	89202	762506	6757954

Table 2.4.a – Sample numbers from which age submission was raised. No sample numbers were provided for 2002. These are aggregated numbers form InterCatch and not raw sample numbers.

	2000	2001	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
FR	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
IE	-	-	-	99	161	87	68	82	112	192	86	124	80	56	52	91	105	108	75	1578
UKE	4	4	11	3	1	2	1	-	-	-	-	3	14	1	1	3	3	3	2	56
Total	4	4	11	102	162	89	69	82	112	192	86	127	94	57	53	94	108	111	77	1634

Table 2.4.b - Sample numbers by metier. No sample numbers were provided prior to 2004. These are aggregated numbers form InterCatch and not raw sample numbers.

	2000	2001	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
FPO_CRU_0_0_0_all	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	1
GNS_DEF_120-219_0_0_all	-	-	-	-	-	-	-	1		1	-	-	-	-	-	-	-	2	-	4
MIS_MIS_0_0_0_HC	-	4	-	-	-	-	6	5	4	3	5	3	1	1	-	-	-	-	-	32
OTB_CRU_100-119_0_0_all	-	-	-	17	-	3	10	18	17	36	22	32	25	4	15	24	-	29	-	252
OTB_CRU_70-99_0_0_all	-	-	-	32	49	27	28	12	24	38	16	11	8	4	8	18	25	15	16	331
OTB_DEF_>=120_0_0_all	-	-	-	-	-	-	-	-	-	-	-	-	3	-	-	-	-	-	-	3
OTB_DEF_100-119_0_0_all	-	-	-	17	14	3	10	18	17	36	22	64	25	25	15	24	42	29	21	382
OTB_DEF_70-99_0_0_all	-	-	-	32	98	54	14	24	48	76	16	11	8	13	8	18	25	15	16	476
SSC_DEF_100-119_0_0_all	-	-	-	1	-	-	-	4	1	2	5	3	13	9	6	7	13	18	22	104
TBB_DEF_70-99_0_0_all	4	-	11	3	1	2	1	-	-	-	-	3	11	1	1	3	3	3	2	49
Total	4	4	11	102	162	89	69	82	112	192	86	127	94	57	53	94	108	111	77	1634

Table 2.4.c - Sample numbers by ICES division. No sample numbers were provided prior to 2004. These are aggregated numbers form InterCatch and not raw sample numbers.

	2000	2001	2002	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
27.7.h	4	4	11	3	1	2	1	-	-	-	-	3	14	1	1	3	3	3	2	56
27.7.j	-	-	-	99	112	60	54	70	88	154	86	92	80	52	52	91	84	108	75	1357
27.7.k	-	-	-	-	49	27	14	12	24	38	-	32	-	4	-	-	21	-	-	221
Total	4	4	11	102	162	89	69	82	112	192	86	127	94	57	53	94	108	111	77	1634

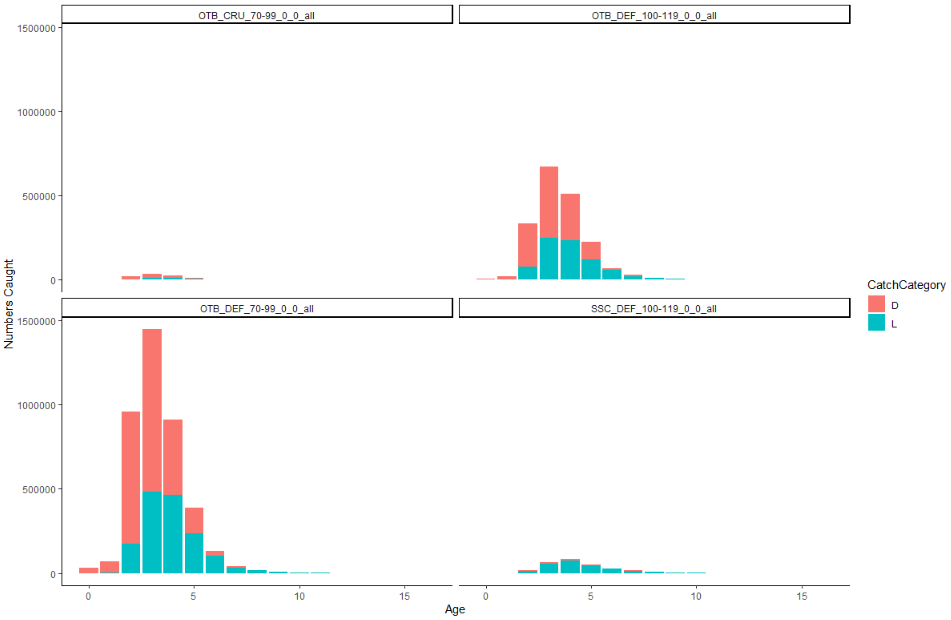


Figure 2.7 Total raised numbers at age (cm) submitted by Ireland to InterCatch (2004 – 2019) for landings (L) and discards (D).

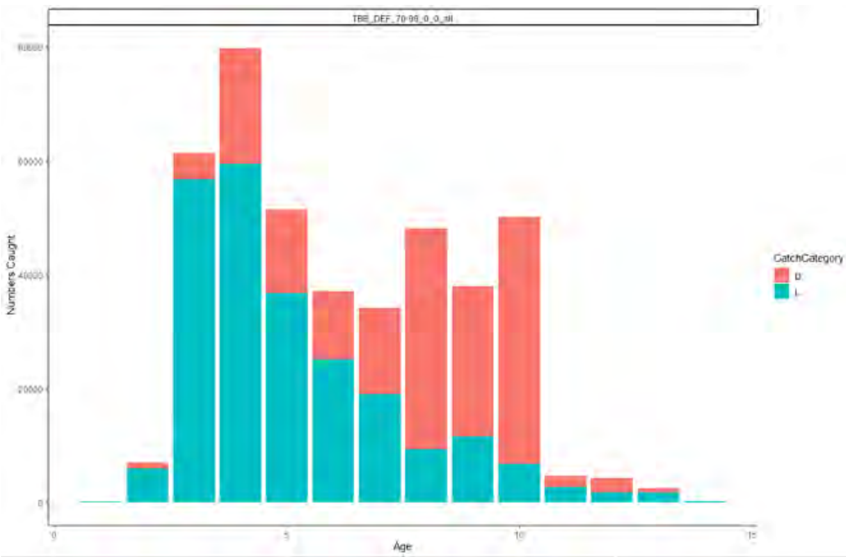


Figure 2.8 Total raised numbers at age (cm) submitted by UK (England) to InterCatch (2004 – 2019) for landings (L) and discards (D).

2.3 Commercial mean weight at length

Using the InterCatch submission by Country Although the raw data would suggest a slight variation in density of mean weight per ICES division (Fig2.9), modelling shows that there is no significant difference in this. A linear model was fit to log transformed length and weight data to test if there was significant variation in mean length at weight within the data set. No significant variation was found in relation to ICES division (Figure 2.10, $F(2) = 6.2700\text{e-}02$, $MSE = 0$, p 0.9392), or métiers (Figure 2.11, $F(15) = 3.4880\text{e-}01$, $MSE = 0$, p 0.9899).

Therefore the length weight relationship of the stock can be described with the parameters: *Beta* = 0.322334, log(*alpha*) = 1.657866. With only a slight (and insignificant difference for landings (*beta* = 0.3299154, log(*Alpha*) = 1.6532021) and discards (*Beta* = 0.3435492, log(*Alpha*) = 1.6828777).

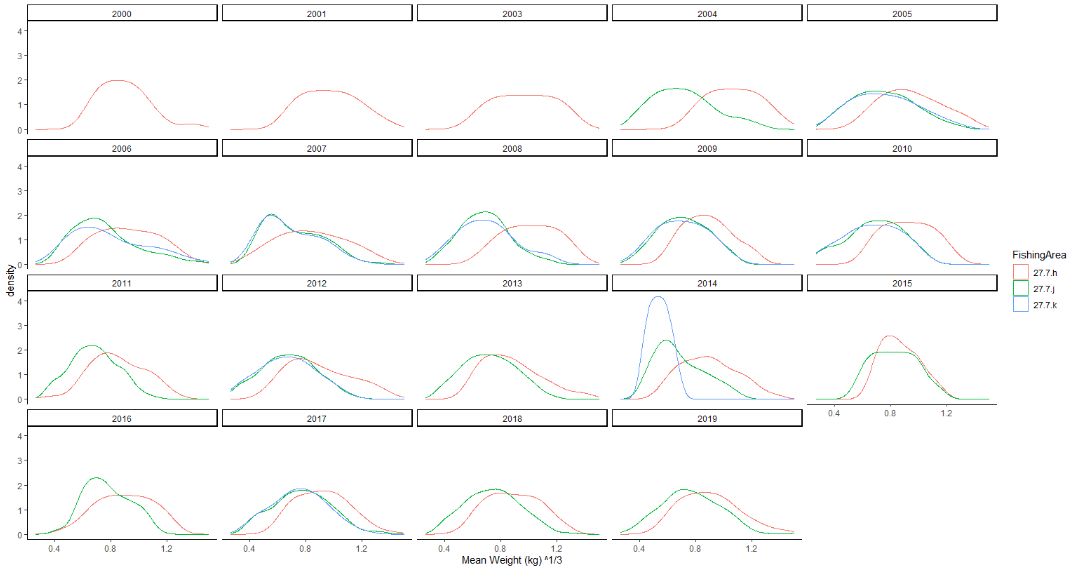


Figure 2.9 Density plot of raised mean weight per year (2000 – 2019) by ICES division (27.7.h-k).

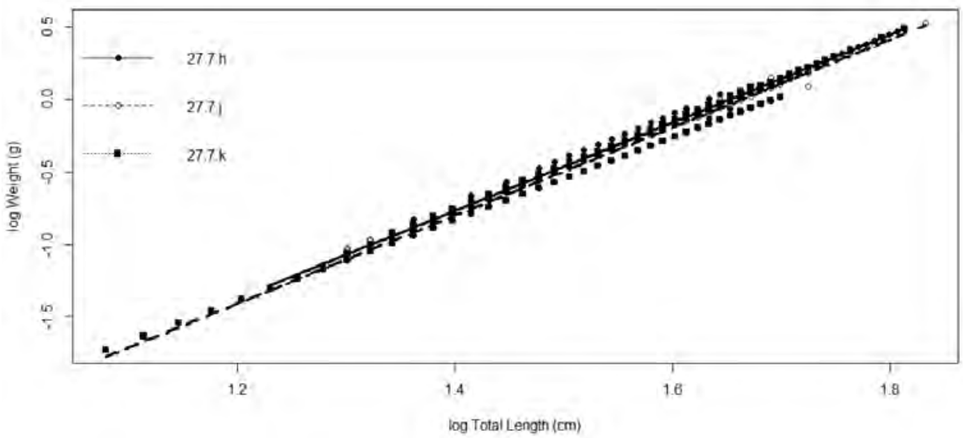


Figure 2.10 Natural log transformed total length (cm) and weight (g) of raised plaice in ICES division 27.7h-k

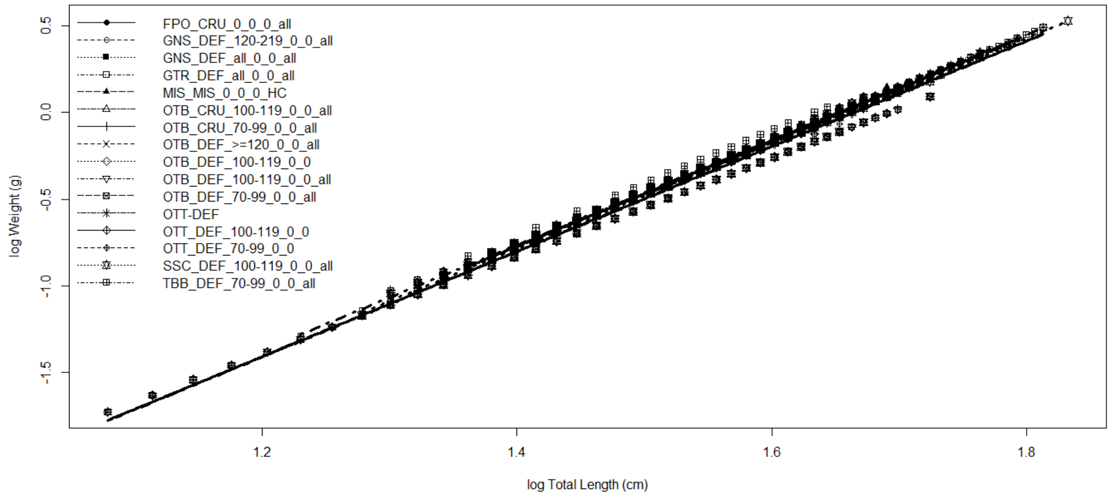


Figure 2.11 Natural log transformed total length (cm) and weight (g) of raised plaice in ICES division 27.7h-k per métier.

2.4 Discard rates

There was sufficient data to calculate discard rates were calculated for a number of the Irish and English fleets for a number of years. These rates are highly variable over time (Figure 2.7), this variability may be driven by low and variable sample sampling numbers over time (Table 2.2a).

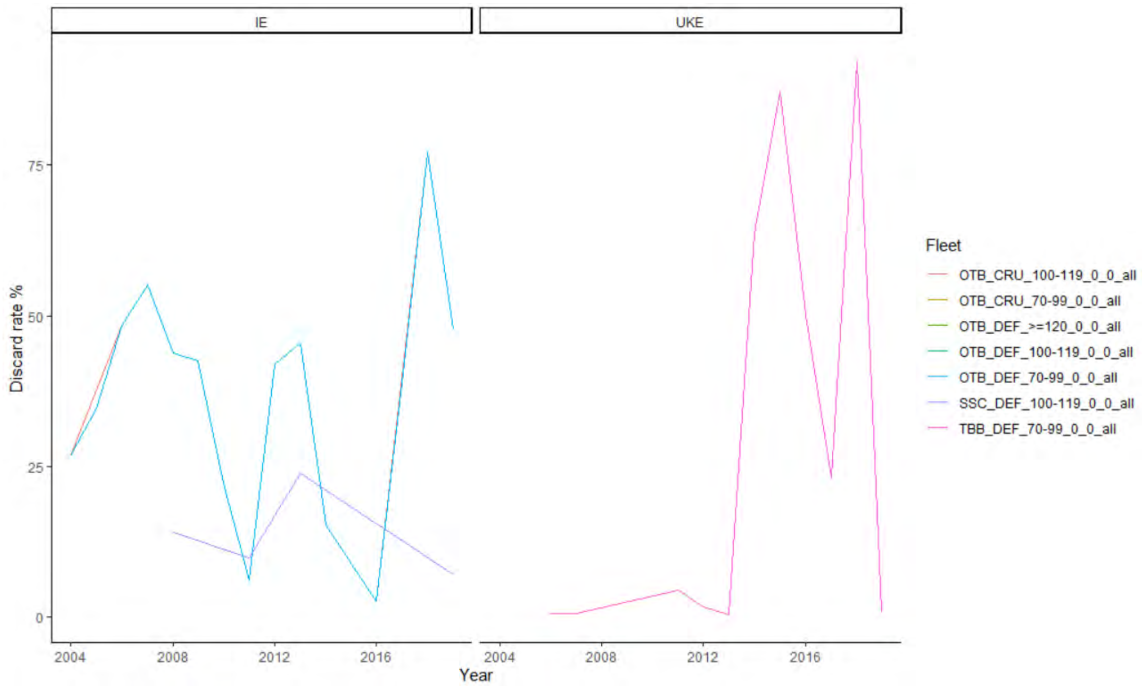


Figure 2.12 Summary of discard rates provided to InterCatch by Ireland (IE) and England (UKE).

These discard rates are highly variable over time. Therefore, a number of options should be considered when developing a catch time series. There are four possible options:

1- **Raw discard rate applied to sampled years (2004 – 2019).** This is not recommended as the rate is highly variable, and it does not
2- **Average discard rate from InterCatch of 34% applied to the sampled years (2004-2019).** Less variable, but doesn't provide any information discarding in the beginning of the time series.
3- **Average discard rate from InterCatch of 34% applied to the full time series (1985-2019).** Less variable, this however inflates discards to an unrealistically high value in the beginning of the time series, when TAC was not restrictive.
4- **Combination** – Average discard rate from InterCatch of 34% applied to the sampled years (2004-2019) and then a tapering discard rate back to 10% in the peak of the fishery in 1990, and fixed at 10% back to 1985. This is the most realistic way of applying discards to the whole time series.

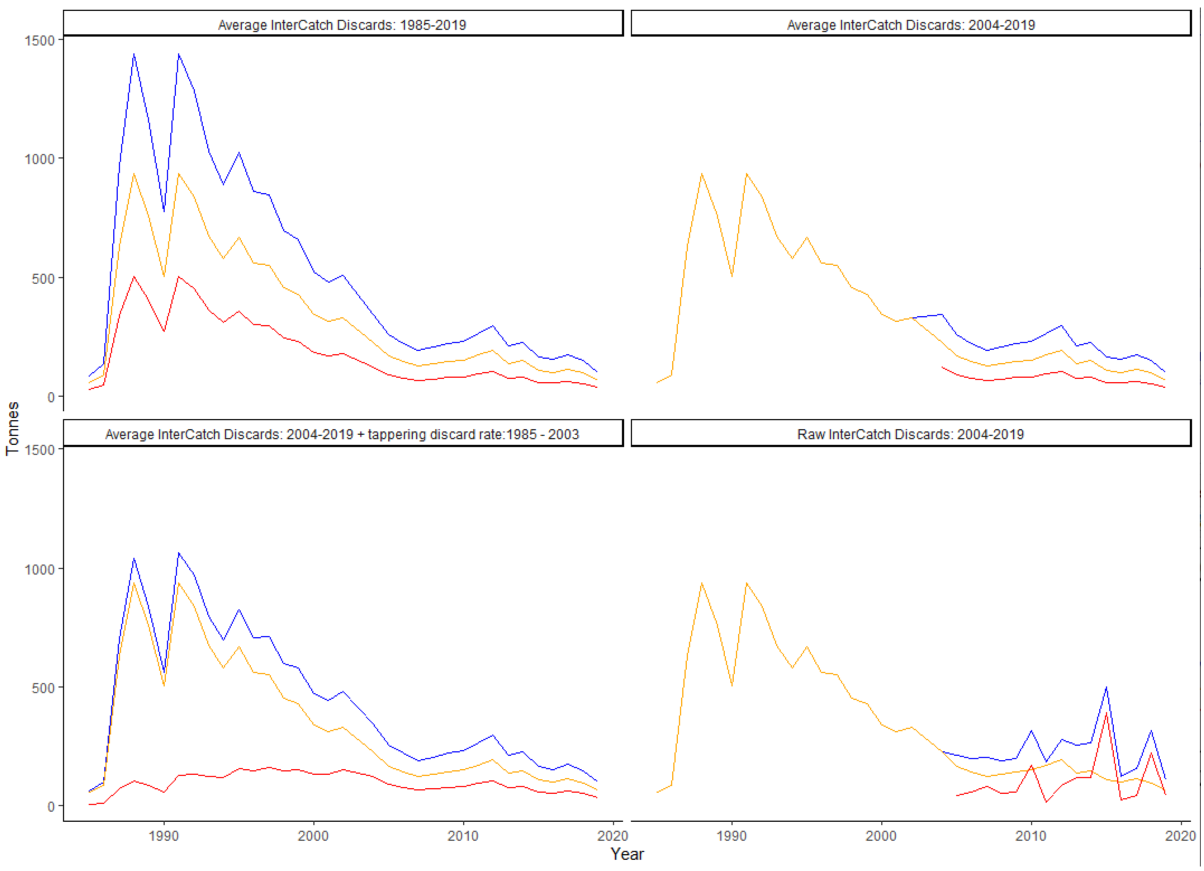


Figure 2.13 Possible option for catch time series, discards (red), landings (yellow) and catch (blue).

2.5 Discard survivability estimates

There is currently no available information on discard survivability in this area. However in other areas there is evidence of high discard survivability, such as the English Channel where the discard mortality of adult plaice captured by beam trawl was found to vary by season, fish size and other factors like vessel type (Revill et al., 2013; Depestele et al., 2014; Uhlmann et al., 2016 a,b). These studies suggest variable but potentially high survival rates, between 4 and 93%, (Depestele et al., 2014; Uhlmann et al., 2016 a). Additional studies in ICES division 27.7.e such as Catchpole et al. (2015) estimated the survival rate of plaice in the UK otter trawl fishery to be between 47–63%, the trammel net fishery between 71–72%.

2.6 Review historic data

In the last assessment used to produce, advice estimates of catch weights and numbers at age from 1993 – 2018 were used. This data was for 7j only and only accounted for the Irish fleet. This data has never been entered into InterCatch or inspected by a benchmark. Other member states do not or have not made sample data prior to 2000 available in InterCatch, since the beginning of this assessment. To create a longer time series of landings the official reported landings values were used for the period between 1985 – 2003 (Fig 2.14). This provides important information in our understanding of the fishery as it captures the peak of the fishery, which occurred before 2004.

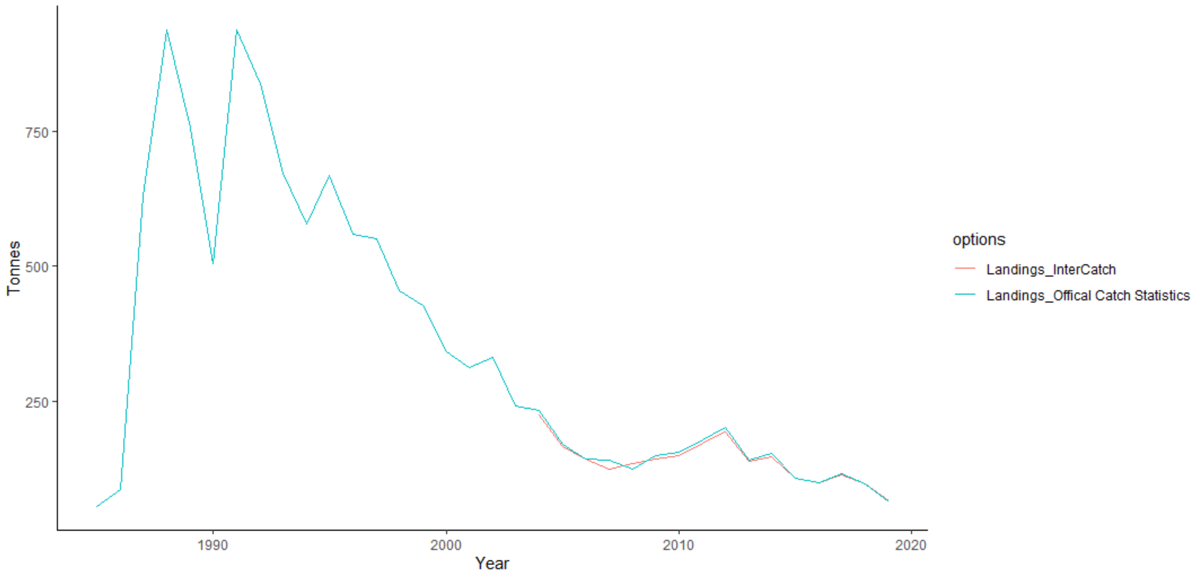


Figure 2.14 Comparison of officially reported landings (1985 – 2019) and InterCatch landings (2004 – 2019)

3 Life history parameters

3.1 Sample size and distribution

Samples available in DATRAS, provided age, length and maturity data for this plaice in 7 h-k (Figure 3.1). These samples were collected by three surveys, Irish ground fish survey (IGFS, 2003 - 2019), Irish anglerfish and megrim survey (IAMS, 2016 - 2019) and the French southern Atlantic bottom trawl survey (EVOHE, 2014 - 2019). Although none of these surveys are designed to capture the dynamics of this stock, they do provide the samples required to produce estimates of life history parameters. There is an uneven sample size between the two ICES divisions, 1449 individual fish measurements in 7j and only 13 7j. Due to the low survey coverage in area 7h CEFAS also provided samples of age, length and maturity from the landings component of commercial sampling in that area. However, as this data was collected from landings only, it cannot be used to calculate compare with the survey data as it did not contain the smaller length ranges, and would skew the estimated parameters.

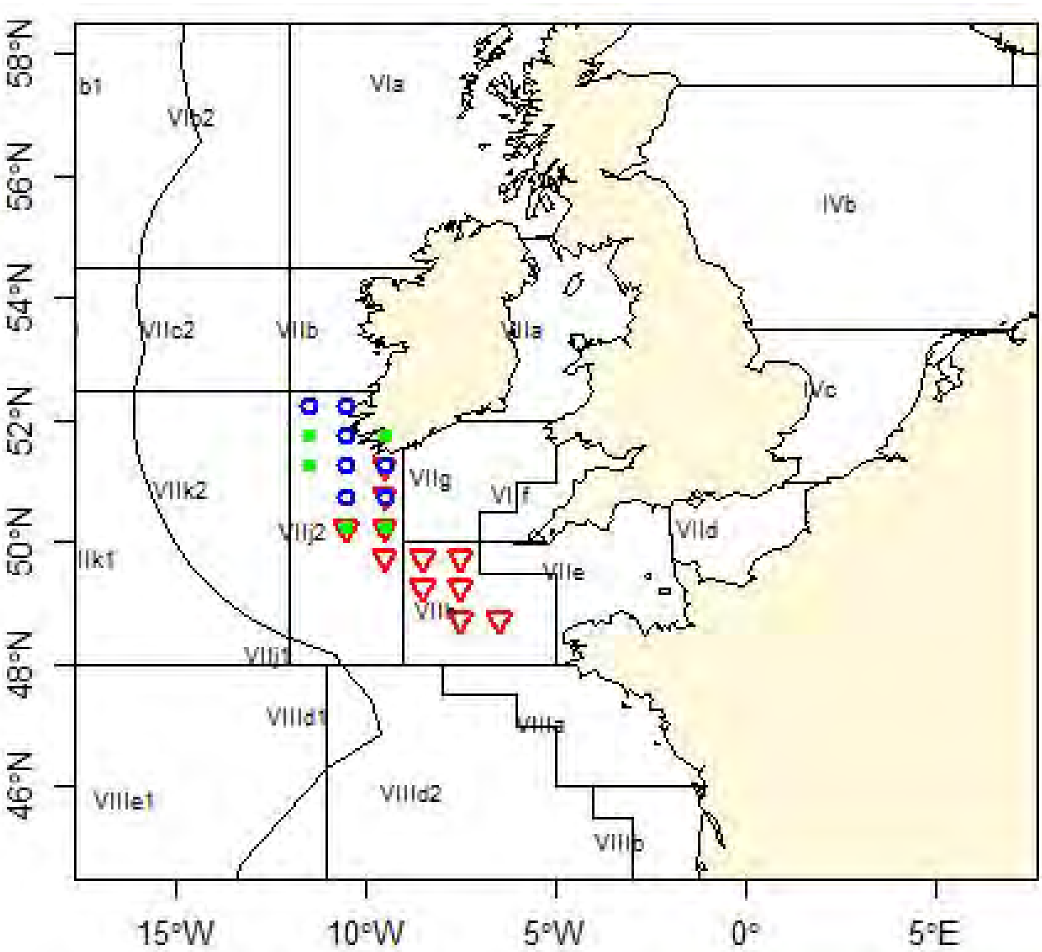


Figure 3.1 Statistical rectangles for which the three surveys available in DATRUS could provide biological sample information. IGFS (green dots), IAMS (blue circles) and EOVHE (red triangles).

3.2 Length weight relationship

With such as uneven sample size between 27.7h and 27.7j, 11 and 1426 respectively, it was not possible to statistically compare the length weight relationship between the two ICES divisions (Figure 3.2).

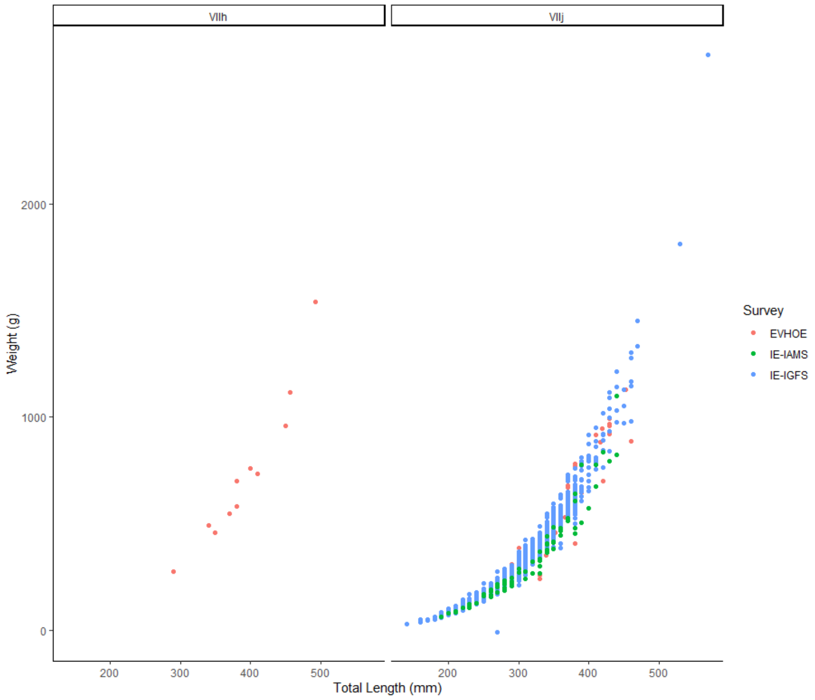


Figure 3.2 Length (mm) and weight (g) samples available in Datras for plaice in ICES divisions 27.7h and 27.7j.

A simple linear model of the natural log of length and natural log of weight was used to describe the length weight relationship for the stock area. From this estimates of the parameters log(*alpha)*(1.72) and *beta*(0.306) were obtained. As would be expected the length weight relationship was found to vary significantly by sex (Figure 3.3, $F(1) = 34.380$, $MSE = 0.059$, $p < 0.001$). Resulting in male length weight parameter estimates of log(*alpha)*(1.686) and *beta*(0.323) and female estimates of log(*alpha)*(1.725) and *beta*(0.304).

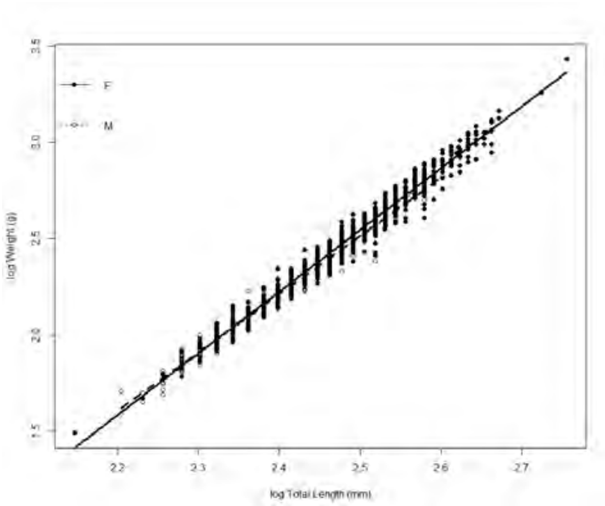


Figure 3.3 Linear model of the Length (mm) and weight (g) relationship of male and female plaice in ICES divisions 27.7h and 27.7j, in Datras.

3.3 Age at length

With such as uneven sample size between 27.7h and 27.7j, 11 and 1426 respectively, it was not possible to statistically compare the length weight relationship between the two ICES divisions (Figure 3.4).

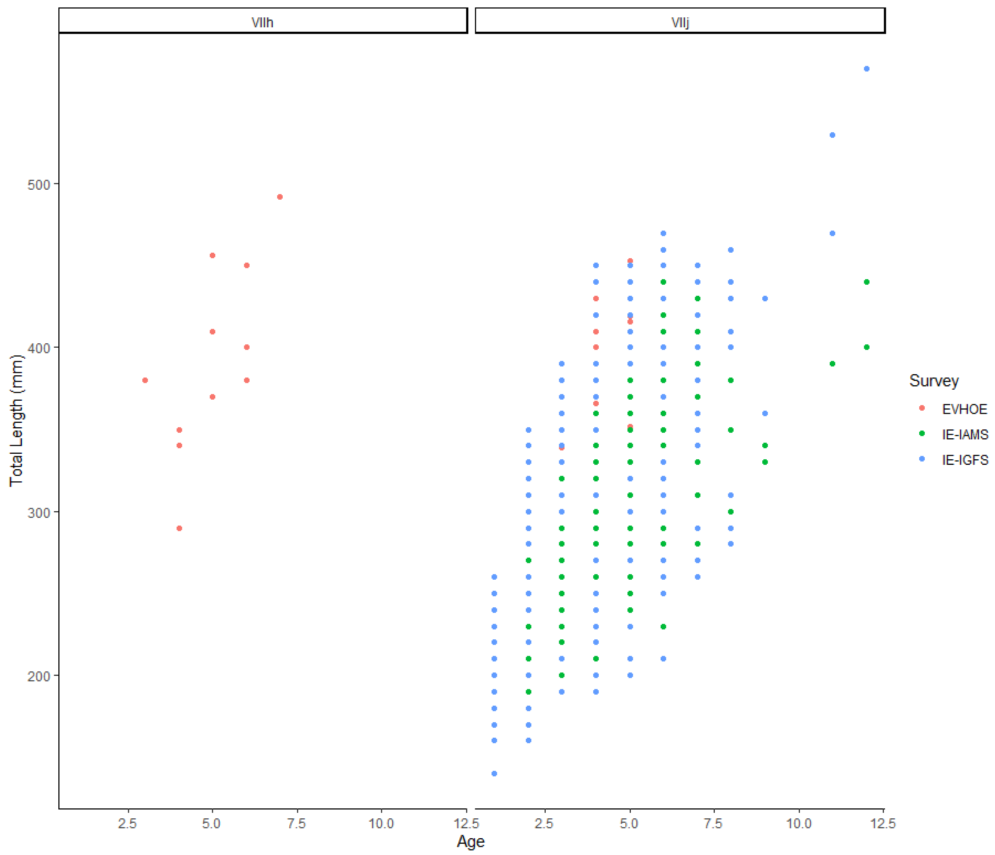


Figure 3.4 Length (mm) and age (yr) samples available in Datras for plaice in ICES divisions 27.7h and 27.7j.

The FSA package in R (Ogle et al. 2020) was used to determine the starting values Ford-Walford (vbStarts{FSA}) and to fit a Von Bertalanfy growth curve was fit to the survey data for all areas combined, by bootstrapping a nonlinear regression (nls{stats}(R Core 2020)). Due to the uneven sample size it was not possible to determine if these growth parameters vary between ICES division 7j and 7h. However we could estimate the growth parameters for the whole stock as linf = 471.32 (SD ± 24.55), K = 0.18 (SD± 0.03), t0 = -2.13 (SD± 0.34) (Figure 3.5). Residuals of model fitted considered acceptable (Figure 3.6)

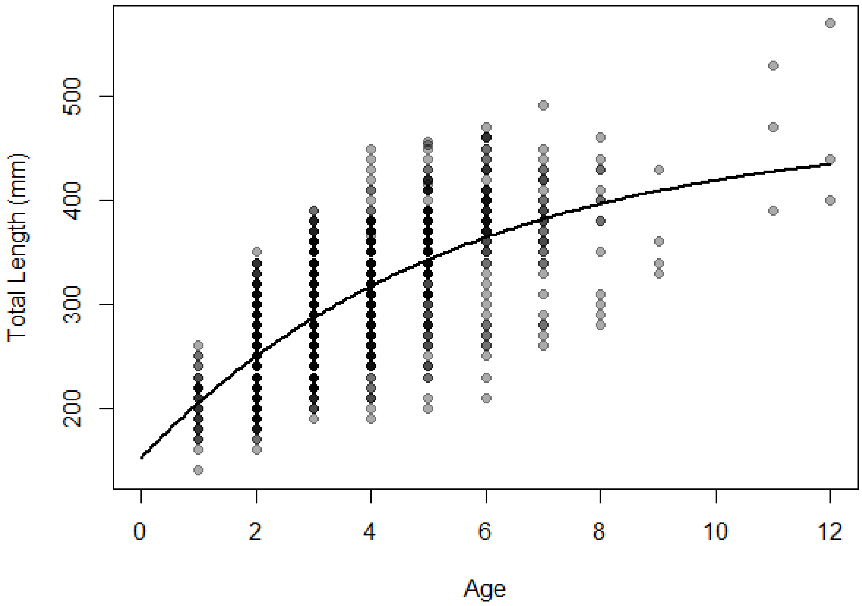


Figure 3.5 Length (mm) versus age (dots) with superimposed best-fit von Bertalanffy growth function (black line) of all plaice in ICES divisions 27.7h and 27.7j available in Datras.

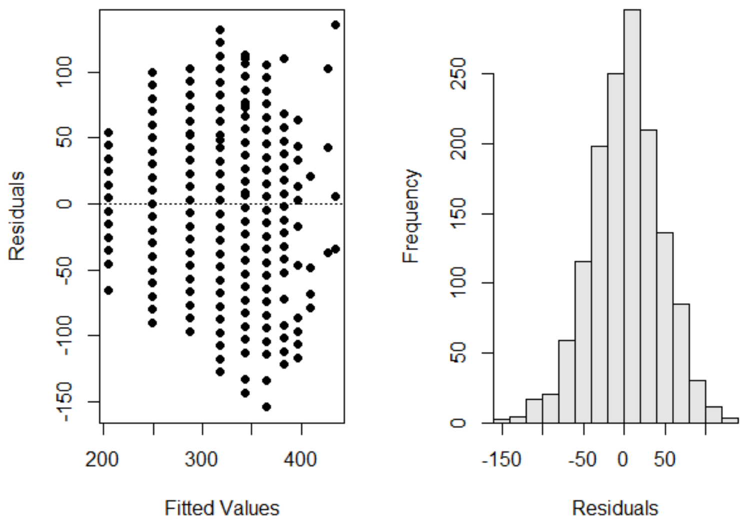


Figure 3.6 Residual plot (left) and histogram of residuals (right) of von Bertalanffy growth function (black line) on plaice in ICES divisions 27.7h and 27.7j available in Datras.

It was possible to show that this growth varied significantly by sex (Figure 3.3, $F(1) = 34.380$, $MSE = 0.059$, $p < 0.001$). Resulting in male growth parameter estimates growth parameters of linf = 324.10 (SD ± 21.90), K = 0.35 (SD± 0.09), t0 = -2.00 (SD± 0.81) (Figure 3.7, 2.15). And female estimates of growth parameters for the whole stock as linf = 477.47 (SD ± 21.85), K = 0.20 (SD± 0.03), t0 = -1.95 (SD± 0.34) (Figure 3.8, Figure 2.17).

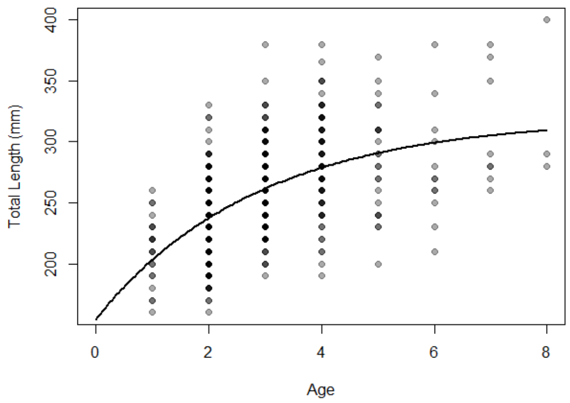


Figure 3.7 Length (mm) versus age (dots) with superimposed best-fit von Bertalanffy growth function (black line) of male plaice in ICES divisions 27.7h and 27.7j available in Datras.

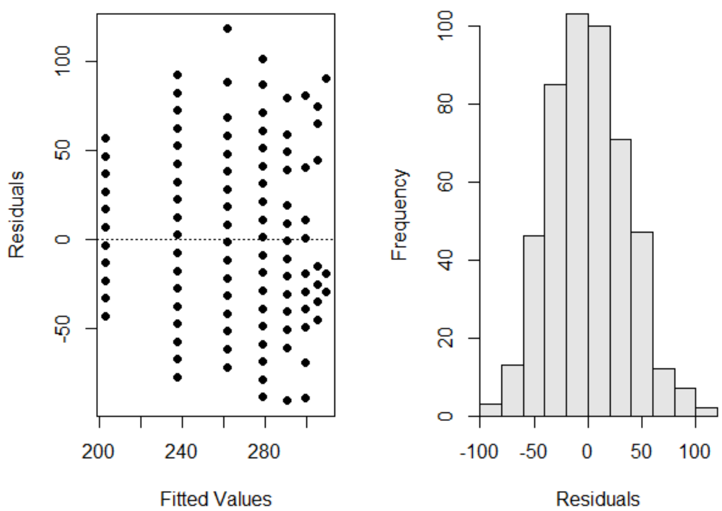


Figure 3.8 Residual plot (left) and histogram of residuals (right) of von Bertalanffy growth function (black line) on male plaice in ICES divisions 27.7h and 27.7j available in Datras.

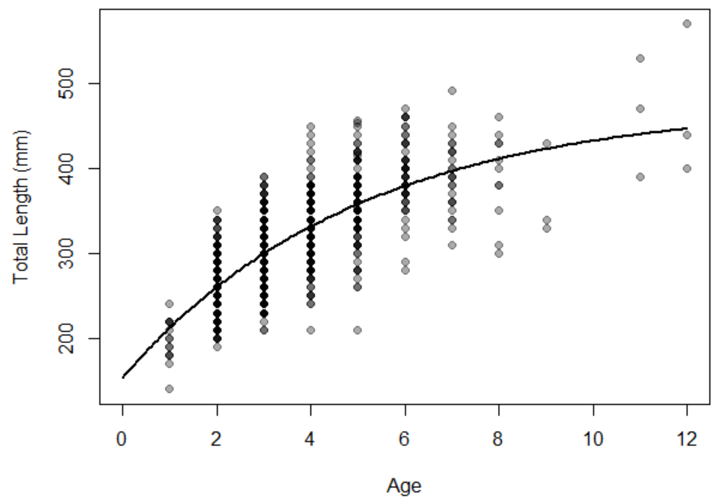


Figure 3.9 Length (mm) versus age (dots) with superimposed best-fit von Bertalanffy growth function (black line) of female plaice in ICES divisions 27.7h and 27.7j available in Datras.

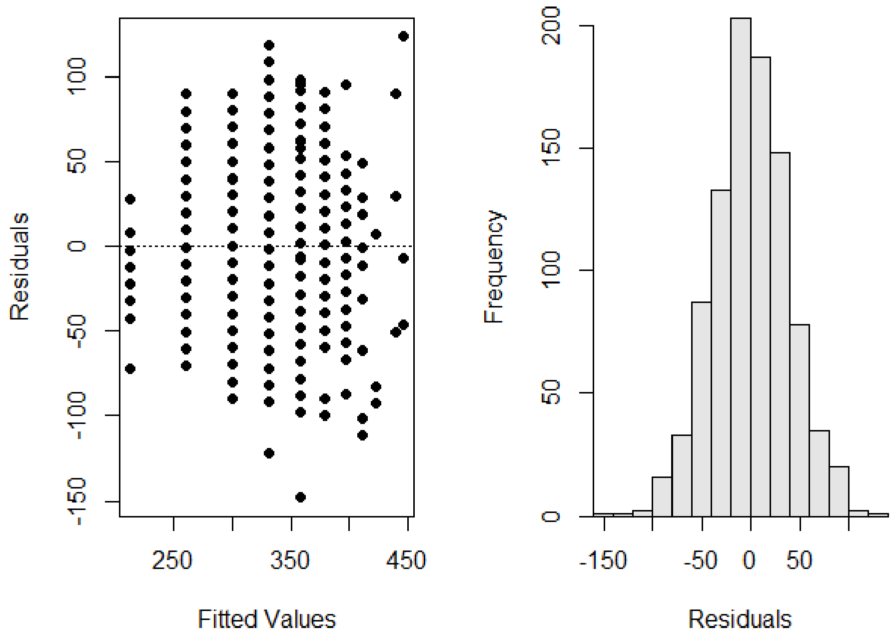


Figure 3.10 Residual plot (left) and histogram of residuals (right) of von Bertalanffy growth function (black line) on female plaice in ICES divisions 27.7h and 27.7j available in Datras.

3.4 Proportion of animals surviving to maximum age

The maximum age within the commercial data is 16 (Table 3.1). The proportion of animals surviving to this 0.002 (Table 3.1).

Table 3.1 – The proportion of animals surviving to maximum age of ple.27.h-k in DATRAS.

Age	Frequency	Proportion
1	60	0.032
2	181	0.097
3	223	0.120
4	245	0.132
5	223	0.120
6	200	0.108
7	176	0.095
8	143	0.077
9	124	0.067
10	108	0.058
11	62	0.033
12	56	0.030
13	27	0.015
14	13	0.007
15	15	0.008
16	2	0.001

3.5 Age Reading Report

In 2019 an age reading exchange was conducted for plaice in this ICES division 27.7h-k (https://smartdots.ices.dk/ViewEvent?key=159). Before this, there had been no age calibration data available for plaice stock in divisions 7.h-k (Celtic Sea South, southwest of Ireland). Therefore, the Working Group on Biological Parameters called for full scale otoliths exchange in order to identify and resolve age interpretation differences between readers and laboratories (WGBIOP 2018). A total of 11 participants, from four countries were involved in the otoliths exchange. Major differences in the age estimation processes were identified, with 3 of the countries producing estimates of age using whole otolith readings. Whereas the UK-CEFAS employed techniques that required sectioned, broken or burnt otoliths. The differences in these techniques have been attributed to low readability and inter/intra reader agreement. With whole otolith readings resulting in an average percentage agreement of 76% and variance CV=13%, and sectioned readings only 56% percentage agreement and variance CV=18%.

There were also a number if issues obtaining samples from 7h. The exchange was run on a sample set of 191 whole plaice otoliths and 64 of sectioned were selected and uploaded for analysing using the SmartDots application. Despite the fact that landings are evenly distributed between areas 7h and 7jk, acquiring the samples of whole otoliths from 7h proved difficult, and thus only 20 samples supplied by IFRAMER, France have been included in the exchange. The remaining 171 whole otoliths from division 7j were provided by Marine Institute, Ireland and all 64 sectioned otoliths by CEAFAS, UK. No sampling by any of the participating institutes had taken place in division 7k, therefore no otoliths were available to include in the exchange from this area.

The workshop concluded that using two different preparation methods for ageing the same stock may cause confusion and bias in interpretation of ages. That a review the methods used to age plaice for stock assessment purposes in 7h-k and identify how to ensure consistency between institutes. That it was necessary to define a framework/roadmap for improved reader agreement, i.e. regular mini exchanges utilising the SmartDots platform, revised protocol, unbalanced sample size for 7h and 7jk divisions. It is recommended that readers involved in age determination of plaice in 7.h-k should familiarize themselves with current reference sets/ interpretation protocols and consistently follow them while ageing. Regular exchanges, both internally and externally in order to learn and to improve the agreements between readers should be organised using SmartDots application.

3.6 Length at maturity

Length at maturity could not be calculate using DATRAS data as only two stages were made available (NA = no information, 62/63 = mature), and it was unclear which fish were immature. France, and insufficient maturity data supplied no maturity data was supplied for commercial landings data. Therefore, length at maturity could only be determined for the 7j component of the stock, which was supplied by Ireland.

Length at maturity in 7j was calculated using data from the Marine Institute Q1 Biological sampling programme (2010-2019), At-Sea Observer programme (2010-2019), Irish Anglerfish and megrim survey (2016-2019), the Irish beam trawl Ecosystem survey (2016-2019 and the MI Biological sampling survey (2004-2009). Proportions mature-at-age were estimated by constructing a matrix containing the sample numbers by age, sex and maturity state (mature/immature) at each length class. Unsexed individuals (usually small fish with undeveloped gonads) were assigned in equal numbers to both sexes. This Age-Sex-Maturity-Length Key (ASMLK) was applied to the length-frequency data to estimate the proportions mature-at-age for either sex and both sexes combined. Any gaps in the ASMLK were filled in using a multinomial model (Gerritsen et al., 2006).

Figure 2.18 shows the L50 over time for ple7hk. Data for ple in 7j is variable so the results should be interpreted with caution based as the information is based on limited sample numbers (Table 3.2 (b)). Table 3.10 shows the estimated proportions mature-at-age. “All” sexes is a weighted maturity ogive and included unsexed individuals most likely to be immature. The estimate of maturity for age 2 and age 3 is higher than that used in WGCSE. Because Irish sampling generally does not cover the full extent of the stocks, it is difficult to determine whether the Irish estimates are unbiased. It is possible that the lack of full spatial coverage can explain some of the differences.

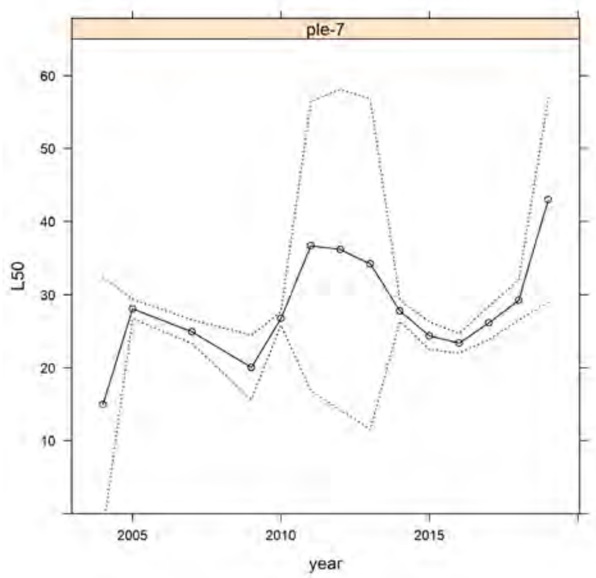


Figure 3.10 Length at 50% maturity (L50; cm) for females by stock and year.

Table 3.2 (a) Estimated proportions mature (sample numbers in table below) by stock, sex and age.

	1	2	3	4	5	6	7	8	9	10	11	12
M	0	0.36	0.68	0.72	0.77	0.76	0.92	0.81	0.35	1	NA	NA
F	0	0.25	0.48	0.59	0.67	0.81	0.72	0.62	0.68	0.5	0.45	0.72
Both	0	0.48	0.64	0.74	0.76	0.86	0.81	0.57	0.78	0.59	0.34	0.8

Table 3.2 (b) Sample numbers by stock, sex and age for associated maturity in Table 3.1(a) above.

	1	2	3	4	5	6	7	8	9	10	11	12
M	5	63	184	124	62	24	8	10	3	2	NA	NA
F	2	73	352	263	195	55	29	15	12	2	4	3
Both	8	138	546	390	259	79	37	26	15	4	4	3

3.7 Natural mortality

Previous stock assessments of plaice in 27.7 h-k assumed a constant rate of natural mortality (*M*) at 0.12, which was applied for all ranges of ages and years. As only length based data poor methods are being considered for this benchmark only one M value for all ages combined was estimated using available data in DATRUS. A number of methods were applied using the convenience function metaM{FSA} (Ogle *et al*. 2020) (metaM(tmp, Linf =

47.132, K = 0.18 , T=10 , tmax=12). These estimates are summarised in table 2.7. All estimates are much higher than the current one used in the assessment.

Table 3.3: Estimates of M from available DATRAS data (IAMS, IBTS, BTS) for ple.27.7h-k

Method	*M*	*Reference*
PaulyL	0.318	The "Pauly (1980) equation using fish lengths" from his equation 11. This is the most commonly used method in the literature. Note that Pauly used common logarithms as used here but the model is often presented in other sources with natural logarithms. Requires K, Linf, and T.
HoenigOF	0.350	The original "Hoenig (1983) composite", "fish", "mollusc", and "cetacean" (fit with OLS) equations from the second column on page 899 of Hoenig (1983). Requires only tmax.
tmax	0.426	The "one-parameter tmax equation" from the first line of Table 3 in Then et al. (2015). Requires only tmax.
PaulyLNoT	0.330	The "modified Pauly length equation" as described on the sixth line of Table 3 in Then et al. (2015). Then et al. (2015) suggested that this is the preferred model if maximum age (tmax) information was not available. Requires K and Linf.

4 Survey and commercial indices

4.1 Current index

Currently there is no survey available to estimation of the abundance in ICES area 7h-k that effectively catches and captures the dynamics of this stock. Therefore, a commercial tuning index has been used in the assessment to date. This index comes from the Irish VMS data, which are linked to logbook landings (see Gerritsen *et al*., 2011 for details on linking VMS and logbook data). These data were used to identify plaice fishing grounds, which are targeted by OTB vessels (Fig 4.1), and to estimate the effort and landings of the OTB vessels within these fishing grounds (Fig 4.1). The lpue trends identified by Gerritsen *et al.* (2011) in VMS-based, mirrored the lpue of Irish OTB vessels in the whole of 7.j. However, it should be noted that this index is not sensitive to changes in the spatial distribution of the fleet as it assumes that all vessels operating in 7.j are capable of catching plaice. This is not the case, as only vessels close to the shore catch plaice and not those which operate further offshore. In the last assessment in 2019 (Fig 4.2) shows the log standardised numbers-at-age in the tuning index by year and cohort. No year effects are obvious, but cohort tracking is not particularly good either. This is probably results from the lack of contrast in recruitment (Fig 4.3).

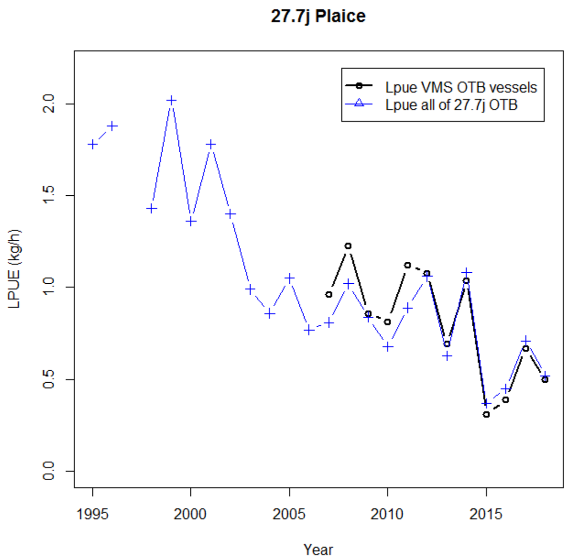


Figure 4.1. Top: the proportion of plaice in landings of Irish vessels with VMS over the years 2006–2016. The black line indicates the polygon inside which plaice are caught. Effort and landings from the VMS/logbooks data inside the polygon were used as a tuning index. Bottom: the VMS lpue index (black line) and the lpue of plaice in the whole of 7.j.

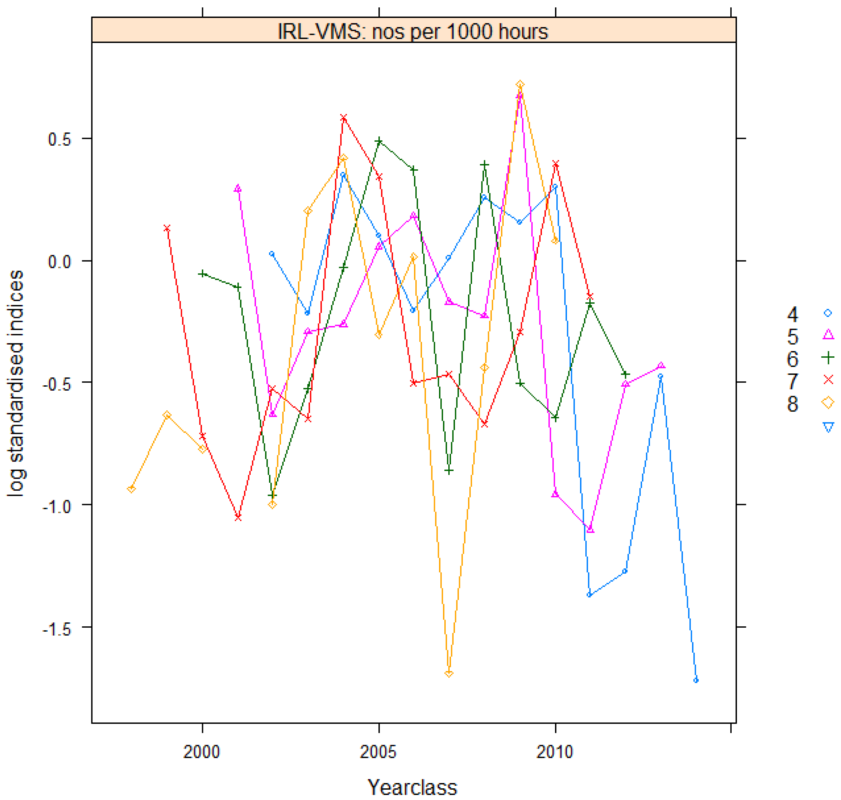


Figure 4.2. The log-standardised tuning index by year (top) and cohort (bottom). Due to the lack of contrast in the numbers-at-age cohorts are not tracked particularly well.

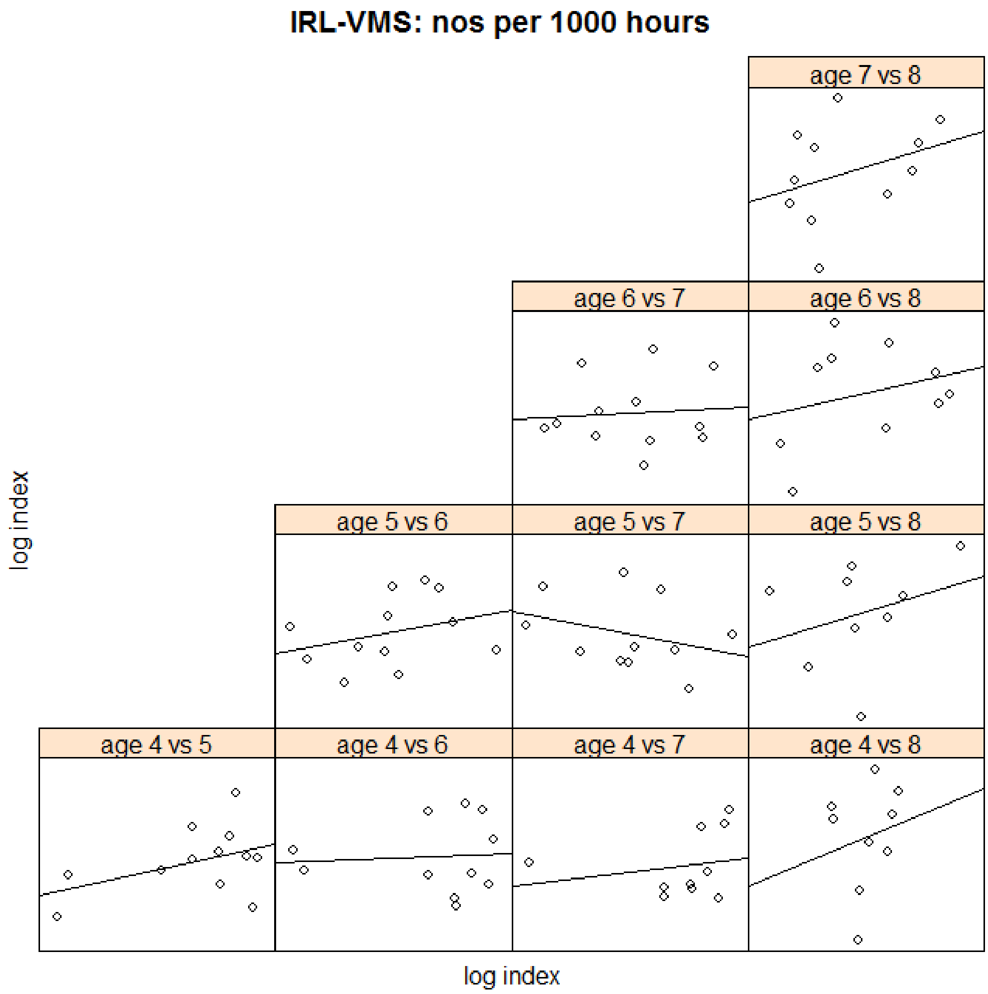


Figure 4.3. Internal consistency of the tuning fleet.

4.2 LPUE index for whole stock area

An effort was made to improve the historical LPUE index used in the assessment by modelling the LPUE , using a glm, to take account the statistical rectangles, and specifically those with zero recorded landings. It is based on trip information so plenty zeros and you need to model those separately. The use of a commercial tuning fleet has the potential to introduce bias if the behaviour or efficiency of the fleet changes. e.g. changes to the gear, vessel power, towing speed, etc. can influence the catch rates. By limiting the index to an area where plaice is known to be caught, some of the potential bias due to changes in spatial effort distribution will be avoided.

Using this method it was possible to produce an LPUE for the main English, French and Irish fleets catching plaice (Fig 4.4 – 4.9). However, these LPUE series cannot be combined as they are made with three different effort metrics. Only the Irish LPUE has been quality controlled and contains a complete set of zeros, which is essential if the LPUE is to be effectively modelled and standardised. Additionally, this form of abundance index is likely to be highly impacted by the large scale changes to sampling and the fishery, such as COVID.

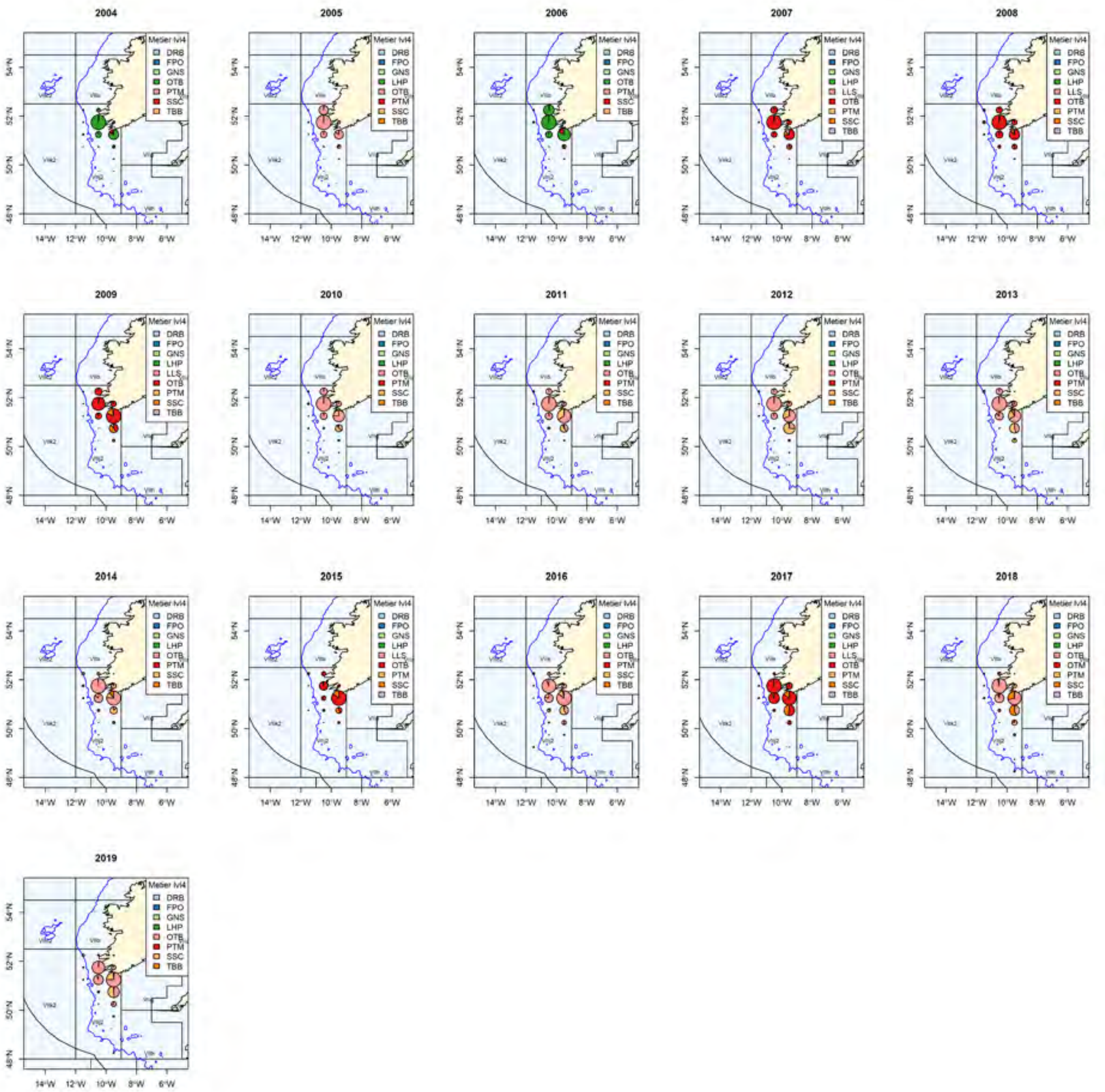


Figure 4.4 Observed landings of plaice taken by Irish vessels by gear type and year.

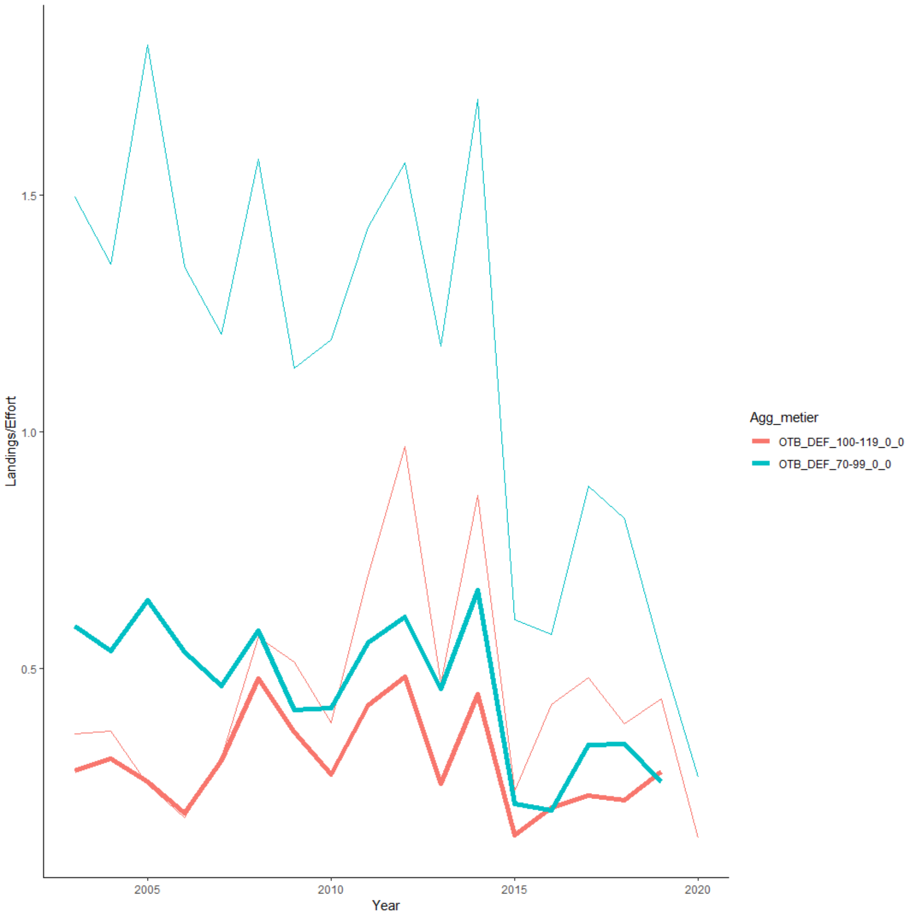


Figure 4.5 Observed LPUE of Irish OTB_DEF fleet (thin line) and standardised LPUE

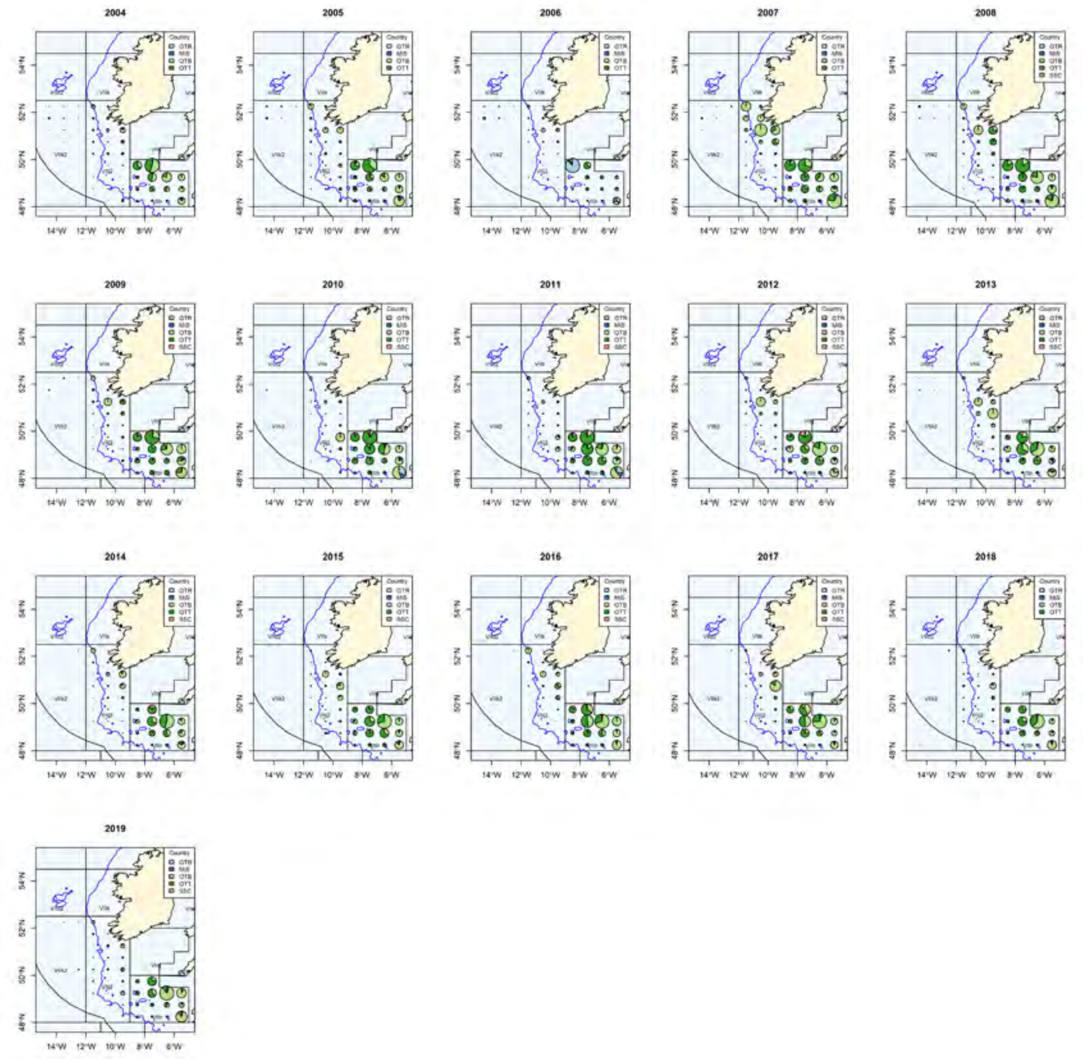


Figure 4.6 Observed landings of plaice taken by French vessels by gear type and year.

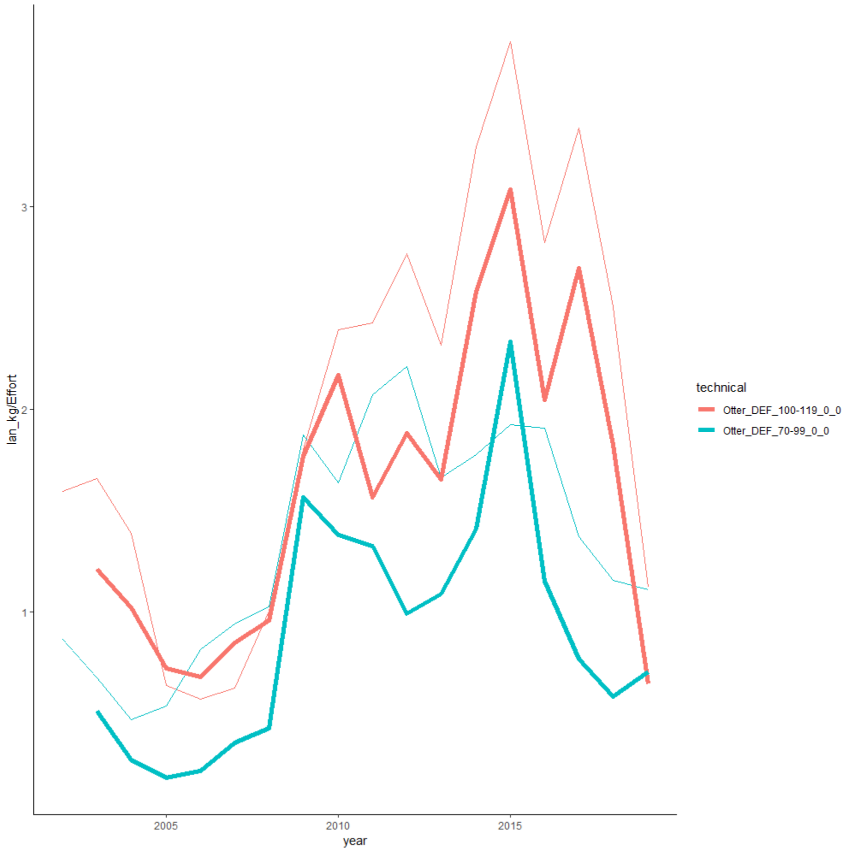


Figure 4.7 Observed LPUE of French Otter_DEF fleet (thin line) and standardised LPUE (thick line)

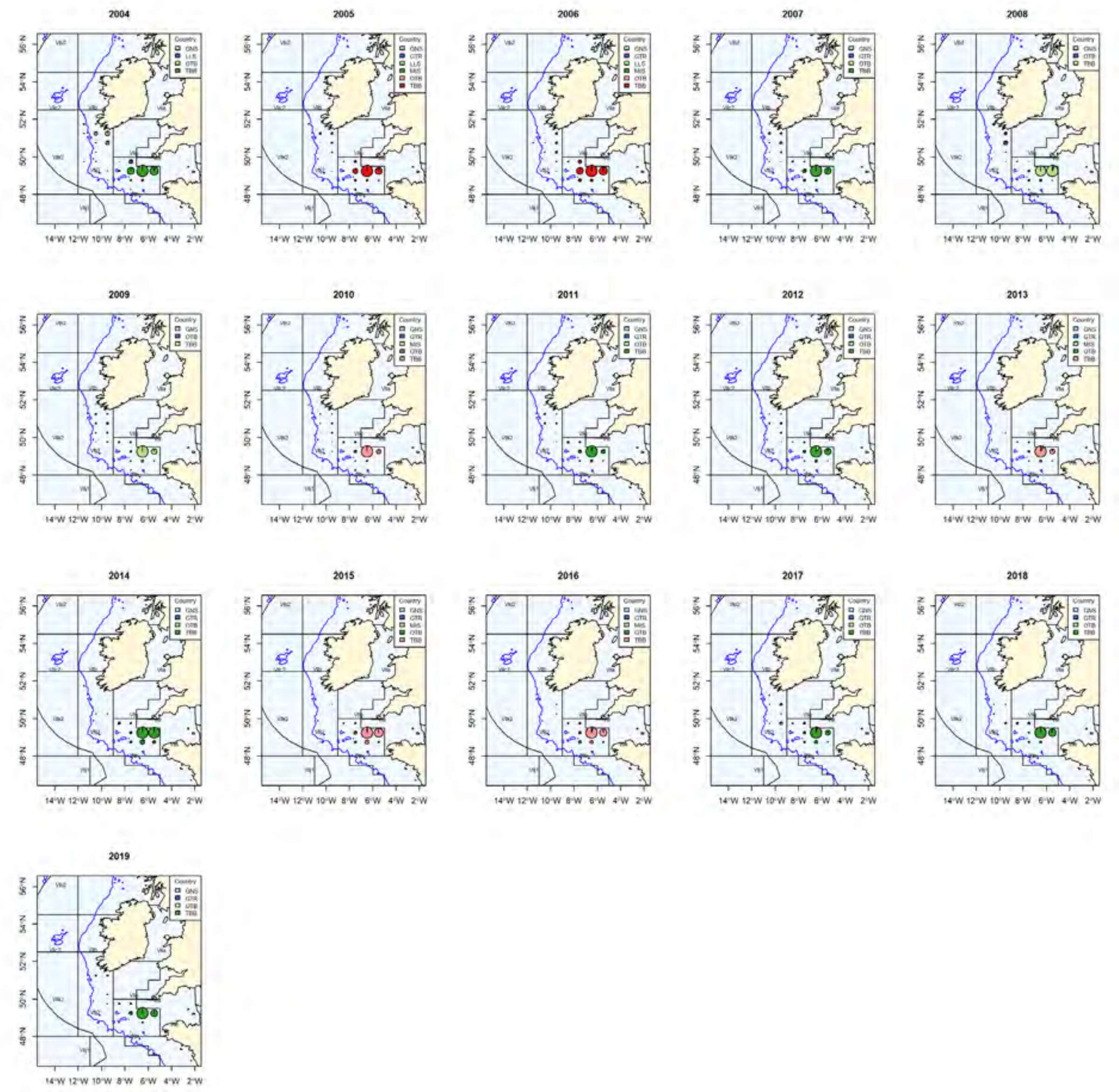


Figure 4.8 Observed landings of plaice taken by English vessels by gear type and year.

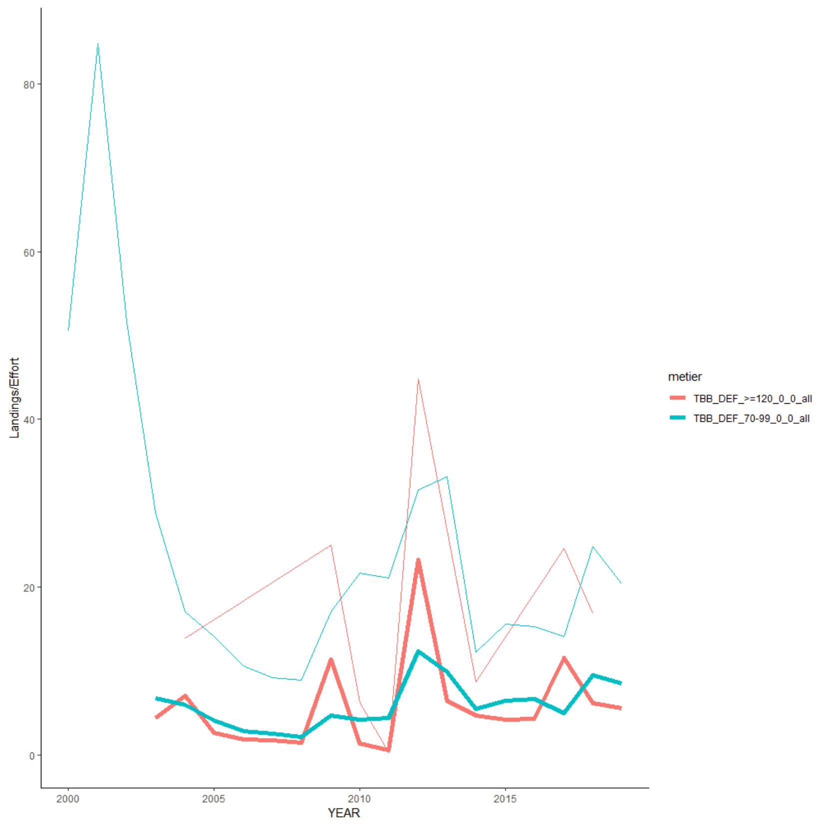


Figure 4.9 Observed LPUE of English TBB_DEF fleet (thin line) and standardised LPUE (thick line)

4.3 Survey abundance index

Cóilín Minto, Claire Moore, Paul Dolder

Based on a paper by Dolder *et al.* (2020) seven fisheries-independent surveys were combined to model the biomass of plaice in this stock area using VAST, which is a Vector Autoregressive Spatiotemporal model in R (Thorson *et al.*, 2016). This model implements a spatial delta-generalized linear mixed model (delta-GLMM) to standardizing survey. VAST is spatially explicit model that predicts population density for all locations within a spatial domain, and then predicts derived quantities (i.e. biomass abundance) by aggregating population density across spatial domain while weighting density estimates by the area associated with each estimate.

The model was parametrised using haul level data from seven fisheries-independent surveys undertaken in the Celtic Sea (1997 – 2019)(Table 4.1). The coverage of these surveys varies in space and time, a full description of which can be found in Table 4.1 and Figure 4.10. The raw survey data as checked for quality (specifically, the estimated weights of the catch numbers-at-length were checked against the reported catch weights). For each valid haul, the catch weight, tow duration, tow position (midpoint), survey series and year were used as input values for the VAST model. The model was specified to have spatial autocorrelation but no temporal autocorrelation (i.e. years are independent). VAST can optionally estimate, and correct for, differences in catchability between the two survey series as there is a significant spatial overlap between the two surveys. The model first estimates the likelihood of occurrence and then the biomass using a gamma error distribution or the abundance using a lognormal error distribution.

We investigate distributional assumptions via Pearson residual diagnostics (qq plots, spatialdistribution of residuals) by age. Marginal standard deviations of the random components ofthe model are tabled to detail where most of the variability arises. Estimated survey indices byage (i.e., summed density across the stock area) are output along with associated uncertainty.

Historically none of these surveys were used to estimate abundances of plaice as individually they do not cover the stock area, spatially/ temporally, and now of the surveys have been designed with this stock and species in mind. Vast offers a number of advantages over more traditional ways of estimating abundances. It has an ability to deal with gaps in survey coverage, and an ability to account for differences in catchability between surveys ir vessels, providing an objective way to combine multiple indices even when the gear is not standardised. In this case VAST has successfully modelled the catches of the survey. Insert observed and predicted catches.

Table 4.1 Summary of surveys used in the model

Survey	Years	Quarters	Gear	Sources	Wing spread
IGFS	2003 - 2019	4	Otter	DATRAS	Available at haul level
IAMS	2016 - 2019	1	Otter & Beam	DATRAS	Available at haul level
EVOHE	1997 - 2019	4	Otter	DATRAS	Available at haul level
WGCFS	1997 - 2004	1,2,4	Otter	CEFAS	Set to 21 m (average of other otter trawl surveys in series)
SWBEAM	2006 - 2016	1	Beam	CEFAS	Set to 4 m (size of gear)
SWIBTS	2003 - 2011	4	Otter	CEFAS	Set to 21 m (average of other otter trawl surveys in series)

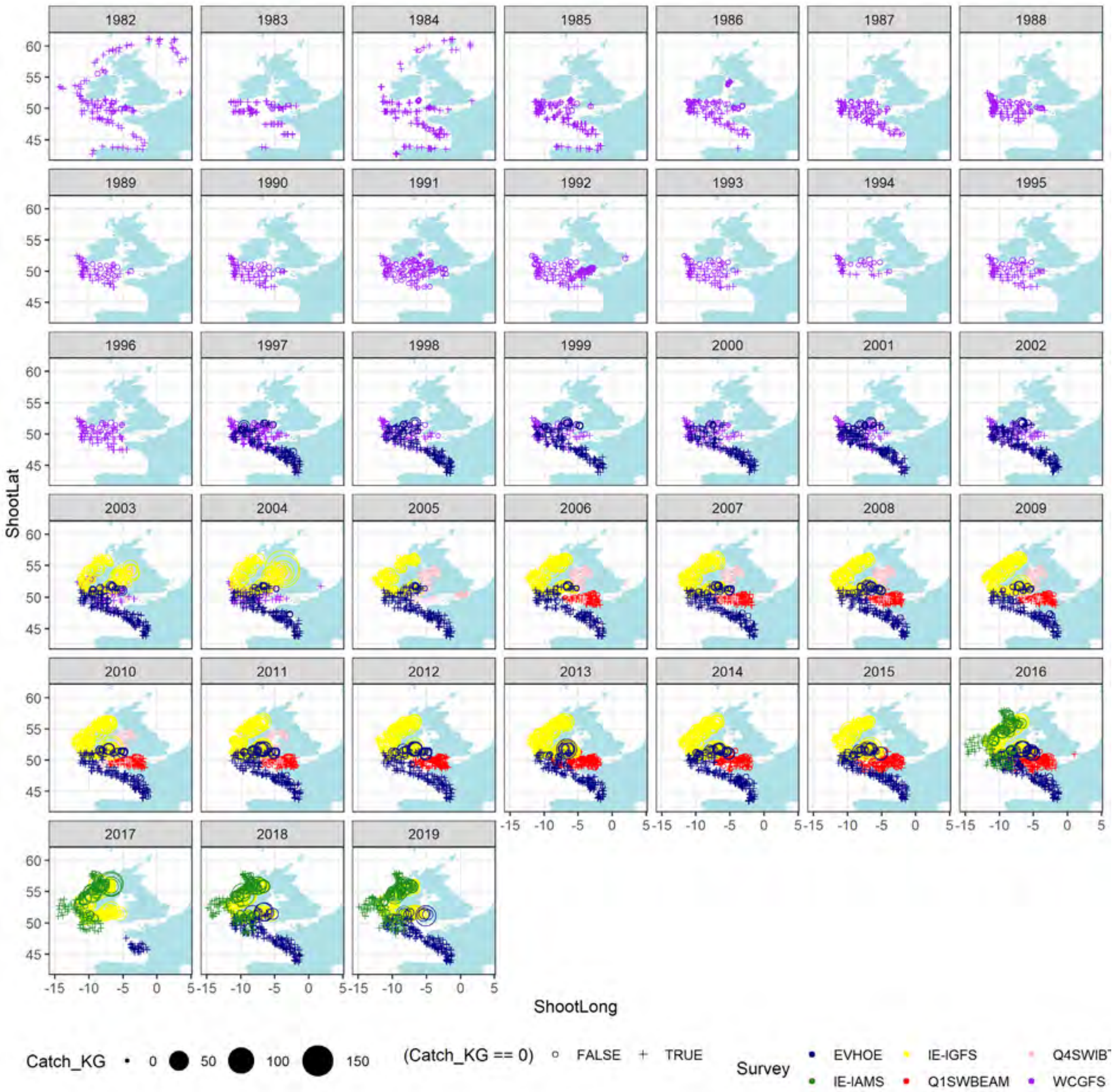
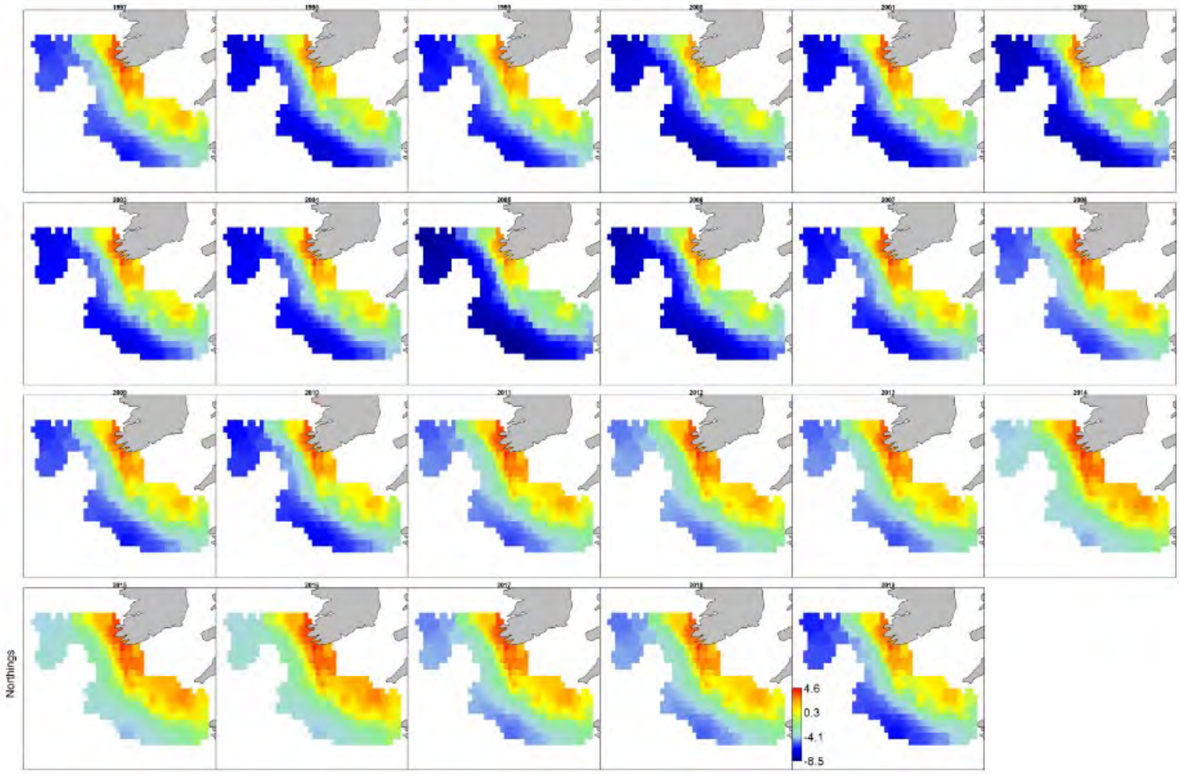
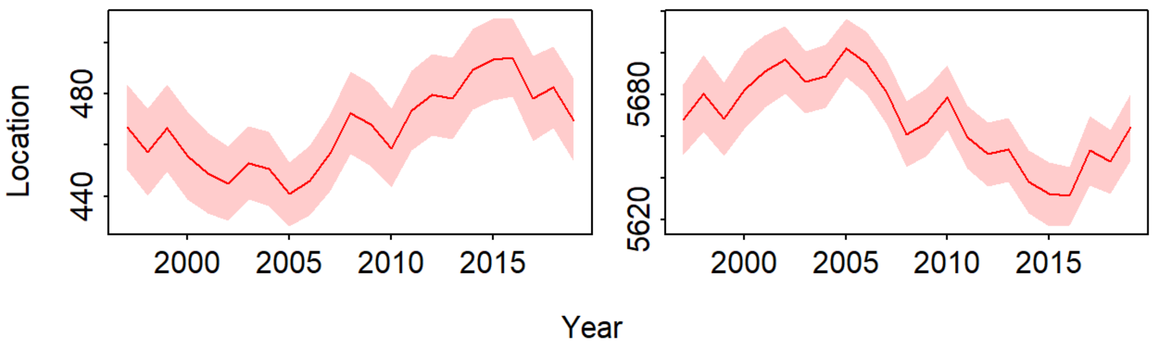


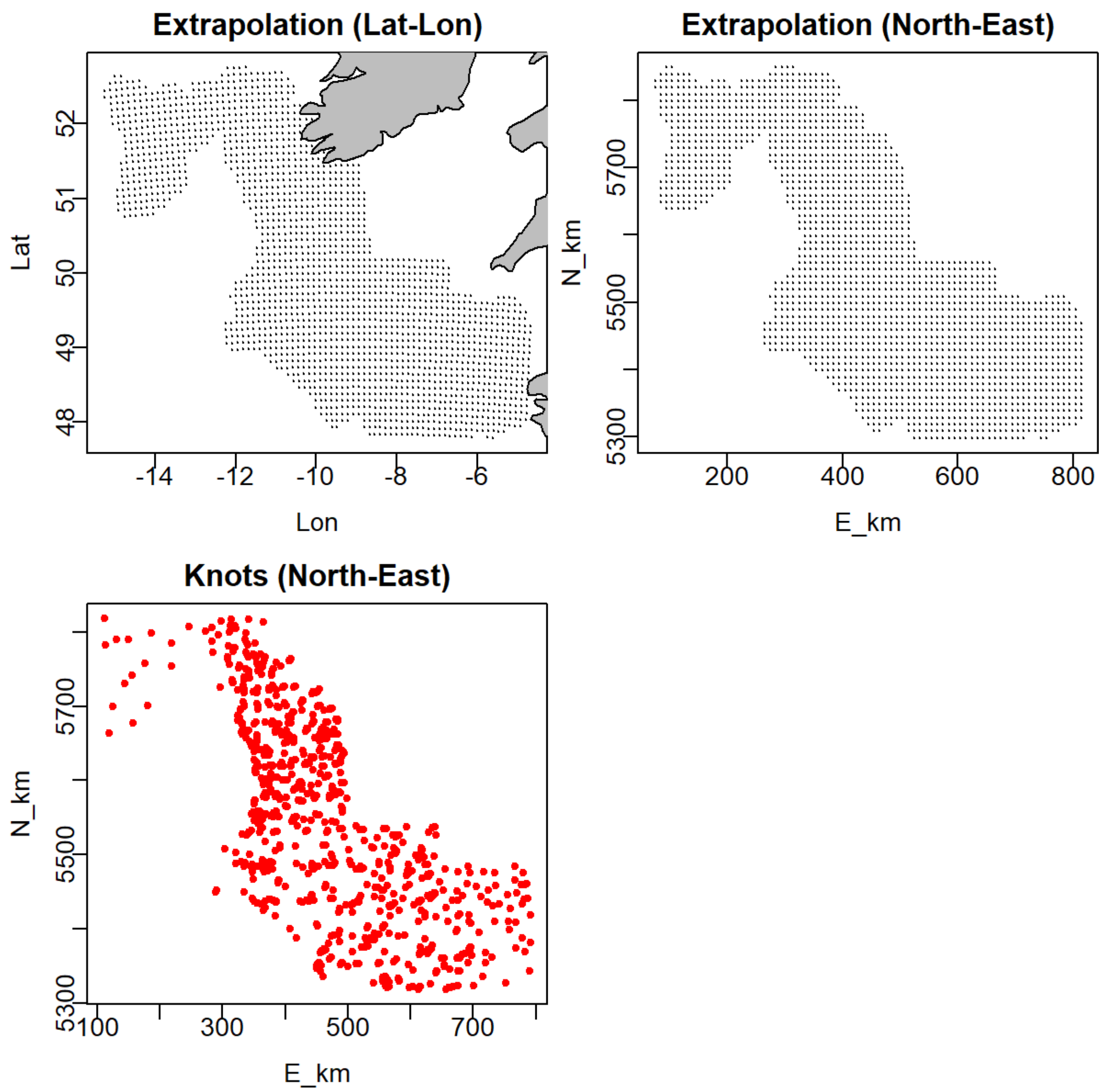
Figure 4.10 Plaice in area 7h-k: survey numbers per haul by year. Each point represents haul with a positive count shown as a circle and a zero as a '+' symbol. Circle diameter is proportional to the count. Colours denote the surveys.

Figure 7 Observed catches of plaice from 6 surveys (Table 4.1) in ICES division 7h-k



The centre of gravity





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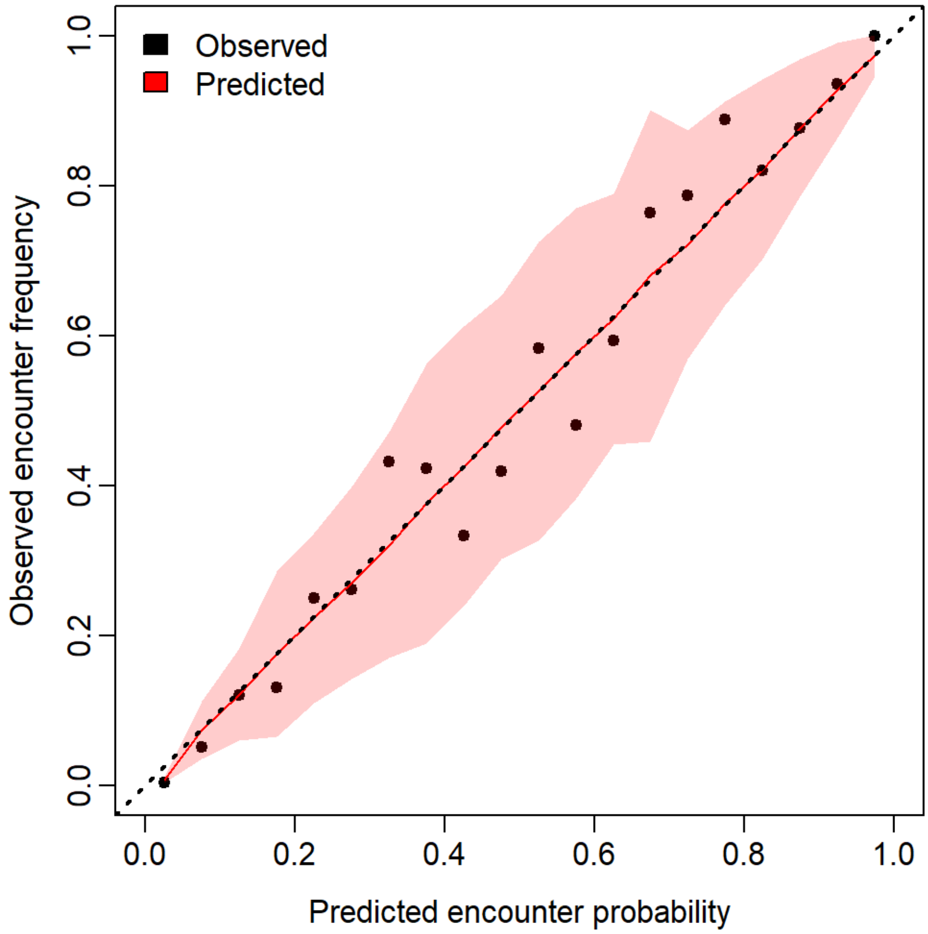

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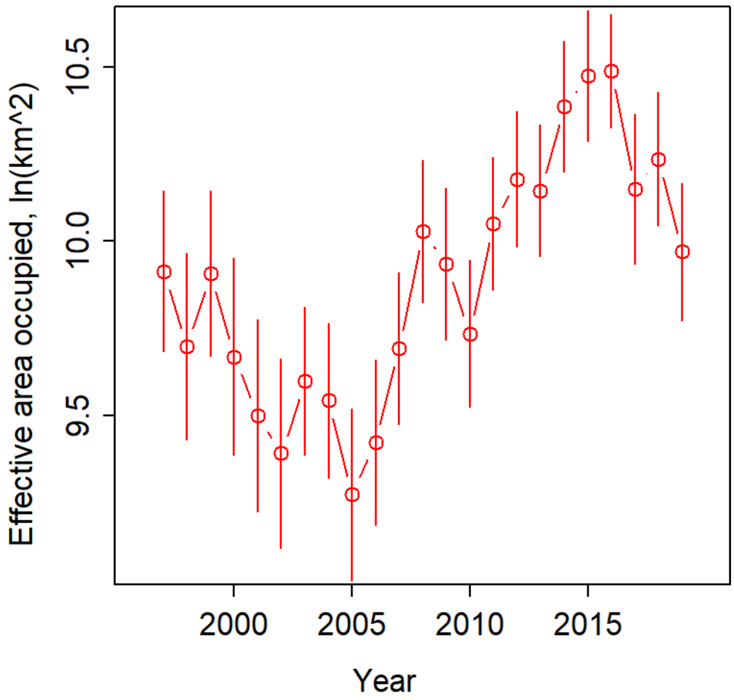

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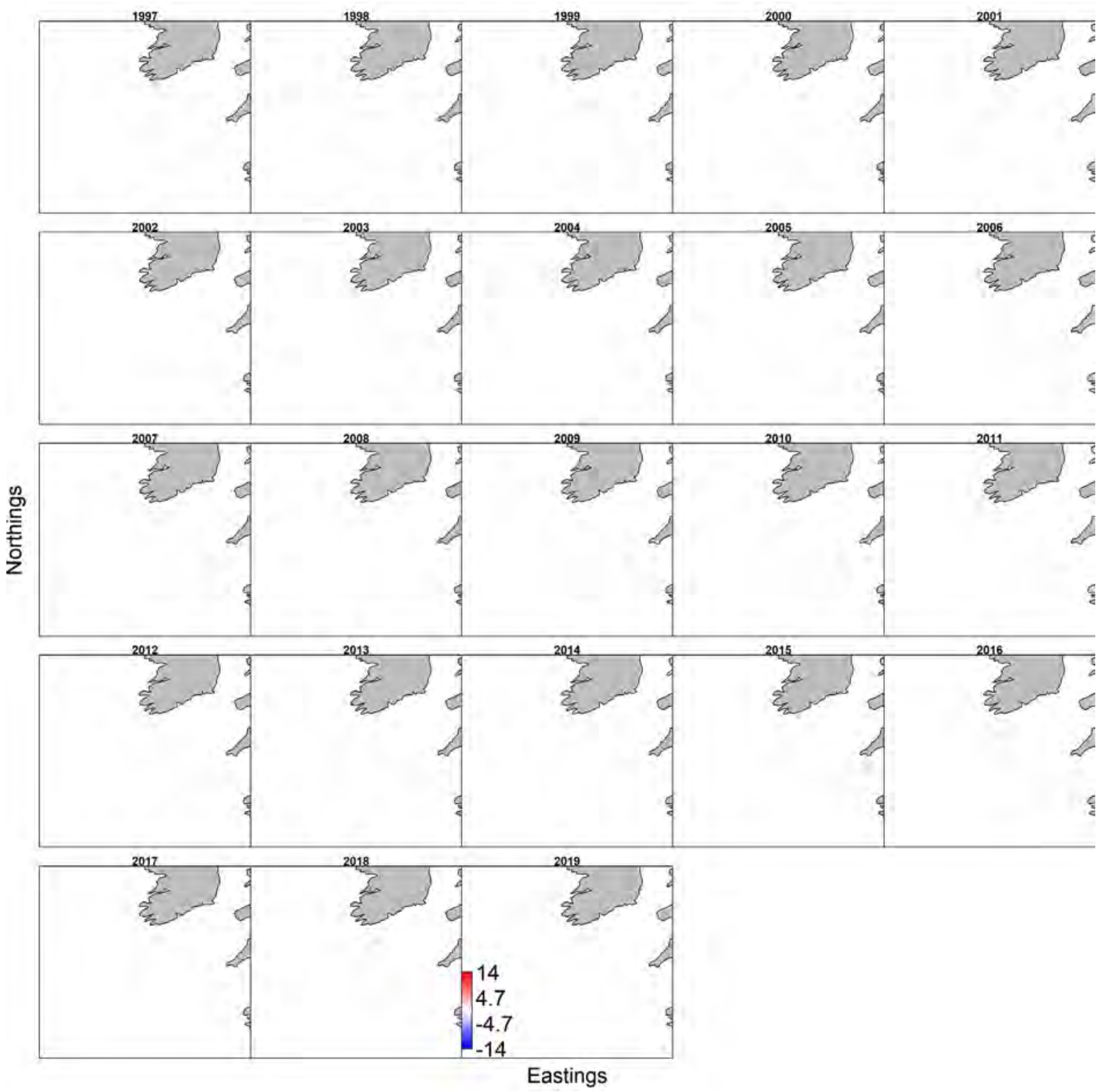

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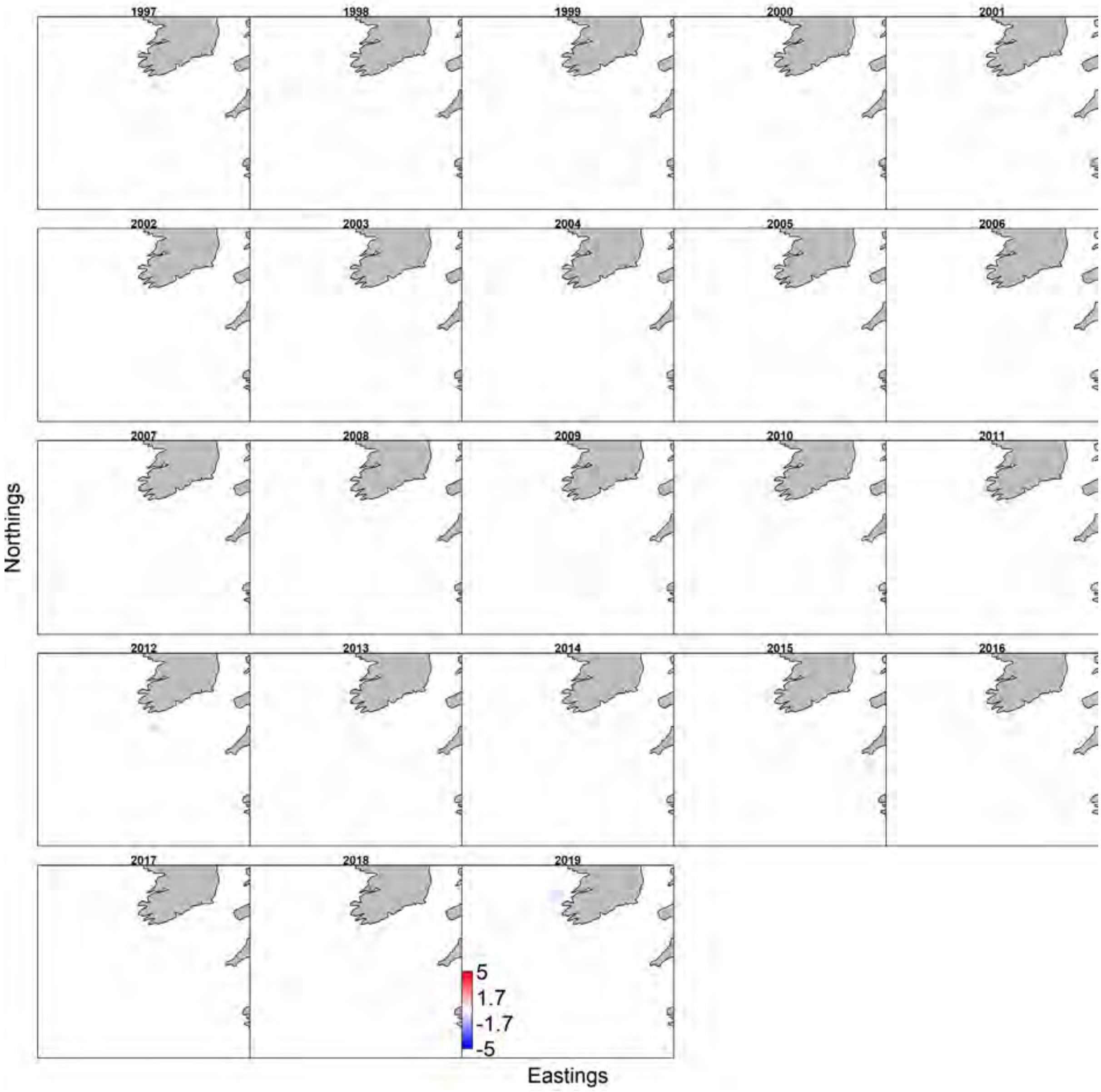
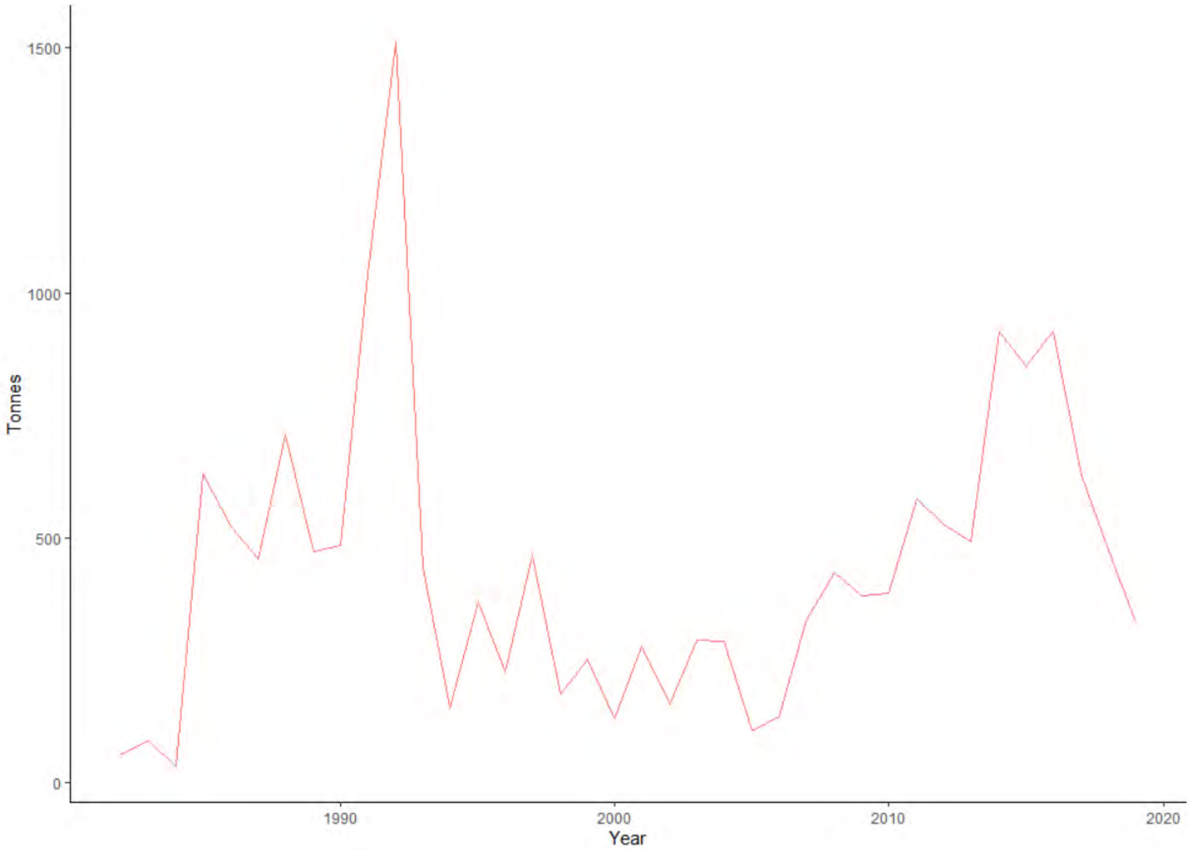


Above is persons residuals 2

Table abundance index – what is the SD log and SD mt

Year	Biomas estimate (tonnes)	SD_log	SD_mt
1982	57.53153	0.735294	42.30259
1983	85.25246	0.739569	63.05009
1984	33.16115	0.84626	28.06296
1985	628.994	0.483334	304.014
1986	522.6108	0.463016	241.9773
1987	456.9217	0.442597	202.2323
1988	710.1276	0.401309	284.9802
1989	472.1151	0.459227	216.8081
1990	483.0495	0.605814	292.6382

1991	1035.888	0.390585	404.6026
1992	1512.998	0.388188	587.3281
1993	438.5426	0.565933	248.1856
1994	151.9097	0.607252	92.24747
1995	368.2032	0.523145	192.6238
1996	224.1065	0.602118	134.9385
1997	464.3265	0.372952	173.1717
1998	180.4588	0.518806	93.62315
1999	249.5006	0.378151	94.34887
2000	130.8905	0.561661	73.51606
2001	277.844	0.509487	141.5579
2002	160.4721	0.575329	92.32435
2003	289.3585	0.324611	93.92888
2004	286.9944	0.345005	99.01456
2005	105.113	0.44037	46.28864
2006	135.247	0.376087	50.86458
2007	330.0501	0.312893	103.2705
2008	427.8539	0.285887	122.3177
2009	381.9936	0.315558	120.5411
2010	386.4903	0.292538	113.0631
2011	578.1579	0.26459	152.9748
2012	526.4118	0.266429	140.2514
2013	490.851	0.255196	125.2633
2014	921.8106	0.244293	225.192
2015	850.0936	0.2681	227.9099
2016	921.6753	0.214563	197.7572
2017	627.4054	0.298872	187.5138
2018	474.9554	0.270244	128.3538
2019	327.9639	0.284881	93.43085


1500
1000
500
0
Tonnes
1990
2000
2010
2020
Year

5 Assessment options

A number of data poor methods for the evaluation of reference points and trends (Table 5.1) were tested during this benchmark, each requiring varying inputs. The outcomes of these methods are detailed in the proceeding sections. The final method selected was SPiCT.

Table 5.1: Data poor methods considered and available data

Method	Data Requirements	Data availability		Solution
		7j	7h	
Length-based indicators (LBI)	Length at maturity	✓	× no data supplied	Assume 7h same as 7j / MYDAS estimate
	Von Bertalanffy growth parameters	✓	× tiny sample size	Assume 7h same as 7j / MYDAS estimate
	Catch at length by year	✓	✓	✓
	Length-weight relationship parameters for landings and discards	✓	✓	✓
Mean-length Z (MLZ) – effort	Time-series of length measurements	✓	✓	✓
	von Bertalanffy growth parameters for the stock	✓	× tiny sample size	Assume 7h same as 7j/ MYDAS estimate
	Time-series of fishing effort	✓	✓	✓
	Natural mortality	✓	✓	✓
	Weight at age	✓	× tiny sample size	Assume 7h same as 7j/ MYDAS estimate
	Maturity	✓	× no data supplied	Assume 7h same as 7j / MYDAS estimate
	Fishing effort prior to the first year of the mean length data	×	×	Make assumptions from official landings data
Length-based spawner per recruit (LBSPR)	Length composition data of the catch	✓	✓	✓
	Ratio of natural mortality and the von Bertalanffy growth coefficient	✓	× tiny sample size	Assume 7h same as 7j/ MYDAS estimate
	Maximum length	✓	✓	✓
	Maturity-at-length	✓	× no data supplied	Assume 7h same as 7j/ MYDAS estimate
	Proportion of animals surviving to maximum age	✓	✓	✓
	Allometric exponent from the length–weight relationship	✓	✓	✓
Surplus Production model in Continuous tome (SPiCT)	Landings	✓	✓	✓
	LPUE/effort	✓	✓	✓

5.1 LBI

Length Based Indicators - The technical guidelines suggest that Length Based Indicators (LBI) should be used for screening; even if the assumption of equilibrium conditions are not met. In the case of black anglerfish there are strong pulses of recruitment which clearly violate those assumptions. The LBI indicators are presented therefore only for screening purposes (Figure 1). Discard data are only available since 2003, which affects most of the indicators; therefore the indicators before 2003 should be considered separately. Some of the indicators show a moderate increasing trend in recent years (e.g. the mean length of the largest 5%; the 95%ile; the mean length above Lc)

https://scott.shinyapps.io/LBIndicator_shiny/

we have no discard data! This has only been run on Catch

5.2 MLz

This method could not be used as

5.3 LBSPR

John Gabriel Ramirez

To be supplied by John Gabrial early next week

5.4 SPiCT

Paul Bouch, John Gabriel Ramirez, Claire Moore

This stock is bycatch of the anglerfish fishery. Landings are reported since 1985, shortening it to start in 1995 because before this year they are not fully reliable. Discards are reported since 2004, acknowledging highly variable annual estimates promoted by sampling size. Accordingly, the average estimate of 35% for discards for the period 2004-2019 was applied to whole time series. It was informed on large uncertainty in catch from 1995 to 2004 through setting a standard deviation factor. Fishery occurred before 1995, requiring to set a biomass to carrying capacity ratio (*B/K*) to inform the initial depletion level. Given that there is not quantitative information supporting what prior value should be used, a sensitivity analysis on the depletion level was performed.

Index time series

There is not a survey targeted in plaice 7hk. The biomass index used to provide fishery-independent information of this stock has been built by VAST (Thorson, 2019) from six survey sources (IGFS, IAMS, EVOHE, Q1SWBEAM, 4SWIBTS, WCGFS). Confidence interval of the annual biomass estimates is higher before 1997. This is promoted by lower data availability in the beginning of the time series. In order to do the catch and index length times comparable, biomass index was also shortening to start in 1997. Therefore, it was not required to inform about different uncertainty estimates after that year. Surveys were performed in first and fourth quarters, mainly taking place in November and March, respectively. SPiCT (method used to perform the stock assessment) demands to properly set the month when the survey takes place (Perdersen et al., 2021). Therefore, a sensitivity analysis was carried out setting the survey time.

Additional model settings

The exploratory runs for the stock assessment of plaice 7hk on the above-mentioned catch and index data highlighted that the model converged, diagnostics were mostly met and retrospective analysis produced reasonable results. However, there was space enough to do improvements. Main concerns were related to high confidence intervals to *B/Bmsy* and *F/Fmsy* estimates, some negative *B/K* estimates in recent years and deviation of the four retros regarding the full time estimates. Usually, most of the problems here mentioned may improve when an n prior is incorporated. Different n settings were explored using no prior, values derived from meta-analysis for pooled fish and particularly to Pleuronectiformes (Thorson et al., 2012), and resembling the Schaefer production curve.

Performing sensitivity analysis

In order to properly define what are the prior values to be used in the final model, sensitivity analyses were hierarchically performed as indicated below:

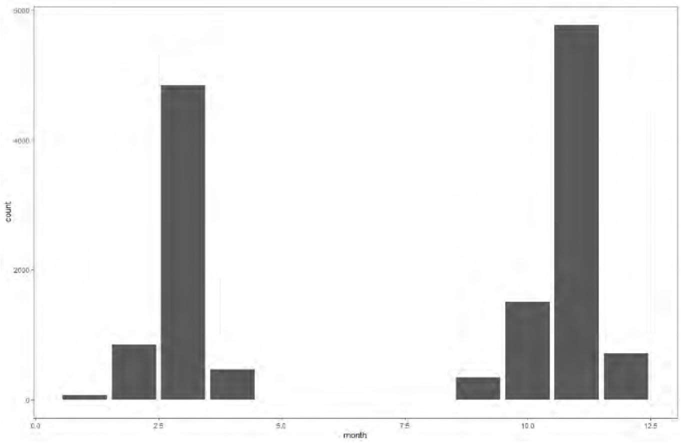
1. Considering that there is fishery-dependent information enough to acknowledge higher catch uncertainty from 1995 to 2004, a prior on standard deviation factor (*stdevfacC)* was used. The values of 3 and 5 were initially applied to all years in this period. The standard deviation factor of 5 promoted increasing of negative values on *B/K* curve plot for some runs, while did not show better results in terms of diagnostics and retrospectively analysis than a factor of 3. Therefore, it was decided to fix *stdevfacC* to 3. Once other prior values were defined, new exploration was done. Results finally indicated that 3 met all criteria better than 5.

2. Secondly, a sensitivity analysis was run to define the n prior to be used in the stock assessment. As fixed setting *stdevfacC* = 3, survey time = December and the prior for the initial depletion level, *bkfracC* = 0.5. On the whole, the relative estimates of biomass are more accurately estimated than the absolute levels. The lowest confidence interval for *B/Bmsy* and *F/Fmsy* are achieved when n is fixed to resemble the Schaefer production model. By using this prior the retrospective analysis was also improved. However, by fixing n=2 promoted that the r estimates by SPiCT increases (0.85) compared to other n priors (around 0.6).

3. Knowledge related to landings indicates that exploitation level may be high before 1995. However, the landings reported from 1985 to 1987 were the lowest on the whole time series. Under this uncertainty level of exploitation, the sensitivity analysis explored high (0.3, 0.4), moderate (0.5) and low (0.6, 0.7) depletion levels. Priors other than *bkfracC* were set for survey_time= December, *n* prior= 2, and *stdevfacC* (1995-2004) = 3. Confidence interval for both biomass estimates and fishing mortality in the beginning of the time series are higher, and the estimated *K* is almost 25% larger when 0.3 and 0.4 were used (high depletion level). The lowest Mohn rho values of *B/Bmsy* and F/Fmsy from the retrospective analysis were found when *bkfracC* is higher than 0.5 (low depletion level). Considering that the model was consistent regarding *bkfracC* (e.g. *F/Fmsy* no changed on recent years), lower confidence intervals were found from 0.5, diagnostics were always met, no highlighted differences were found in the retrospective analysis and unclear information is available on the depletion level, the model finally sets a *bkfracC= 0.5.*

4. The SPiCT handbook emphasizes the importance of accurately setting the time when the survey occurs (https://github.com/DTUAqua/spict). Given that the biomass index for plaice 7hk comes from surveys carried out on different months, the effect of setting the

survey time (October, November, December, February and March) was explored. Both year effect and confidence interval are lower for estimates of biomass if survey time is set to first quarter. Additionally, the long term biomass (E(B∞)) is expected to have a lower increase than it is set to fourth quarter survey because it is closer to the estimated *K*. In other words, by setting the survey time in February or March a more optimistic stock status is found. Retrospective analysis showed lower Mohn rho's estimates also when survey was informed to occur in first quarter.



Final stock assessment settings

The model that properly reflects both fishery and stock knowledge and meet all criteria has the next settings:

- Catches from 1995 to 2019
- Biomass index from 1997 to 2019
- *stdevfacC= 3* from 1995 to 2004
- *bkfracC* = 0.5 (moderate exploited)
- logn = log(2)
- Survey time = December, by considering the middle time when surveys take place or first quarter, if the best diagnostics are taken into account.

The above-mentioned model meets all criteria for the acceptance of the SPiCT assessment for plaice 7hk (Mildenberger et al., 2021). The surplus production curve is well defined and can be seen in Figure 1, and the residuals of the catch and index time series show normality and no autocorrelation (Figure 2). The restrospective plots for the assessment also show good agreement and low Mohns Rho values (Figure 3).

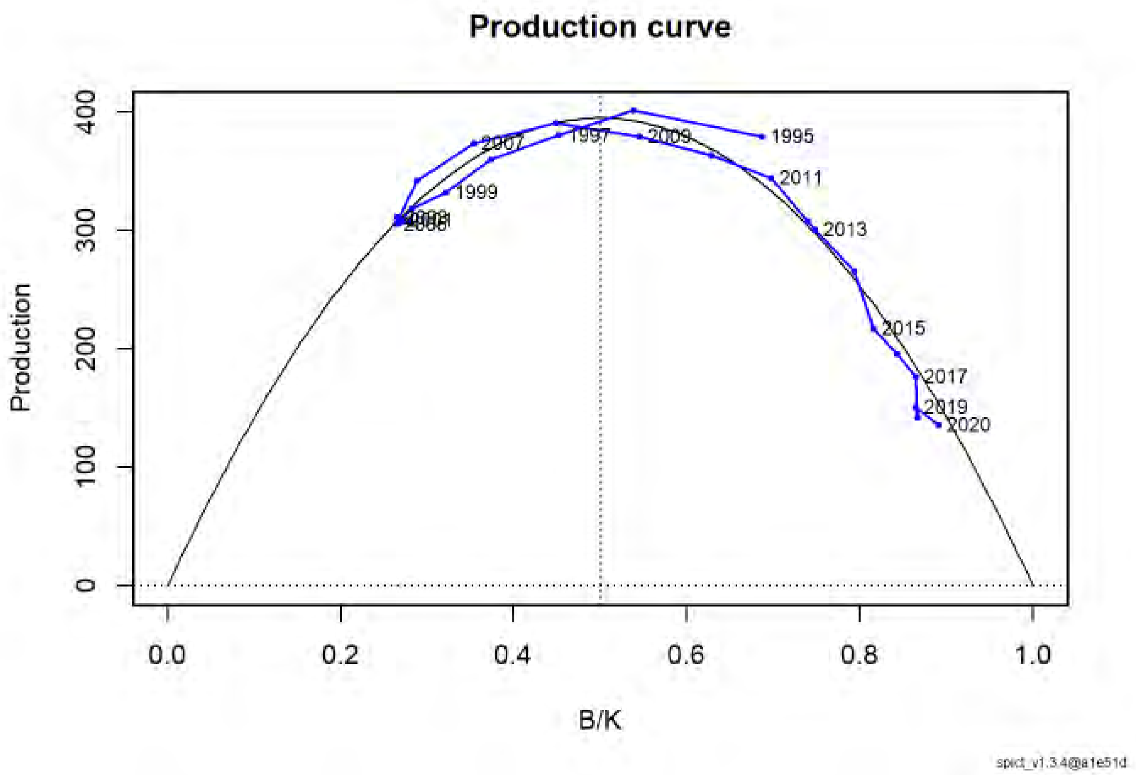


Figure 1 The surplus production curve with estimated by the final SPiCT assessment for PLE7HK

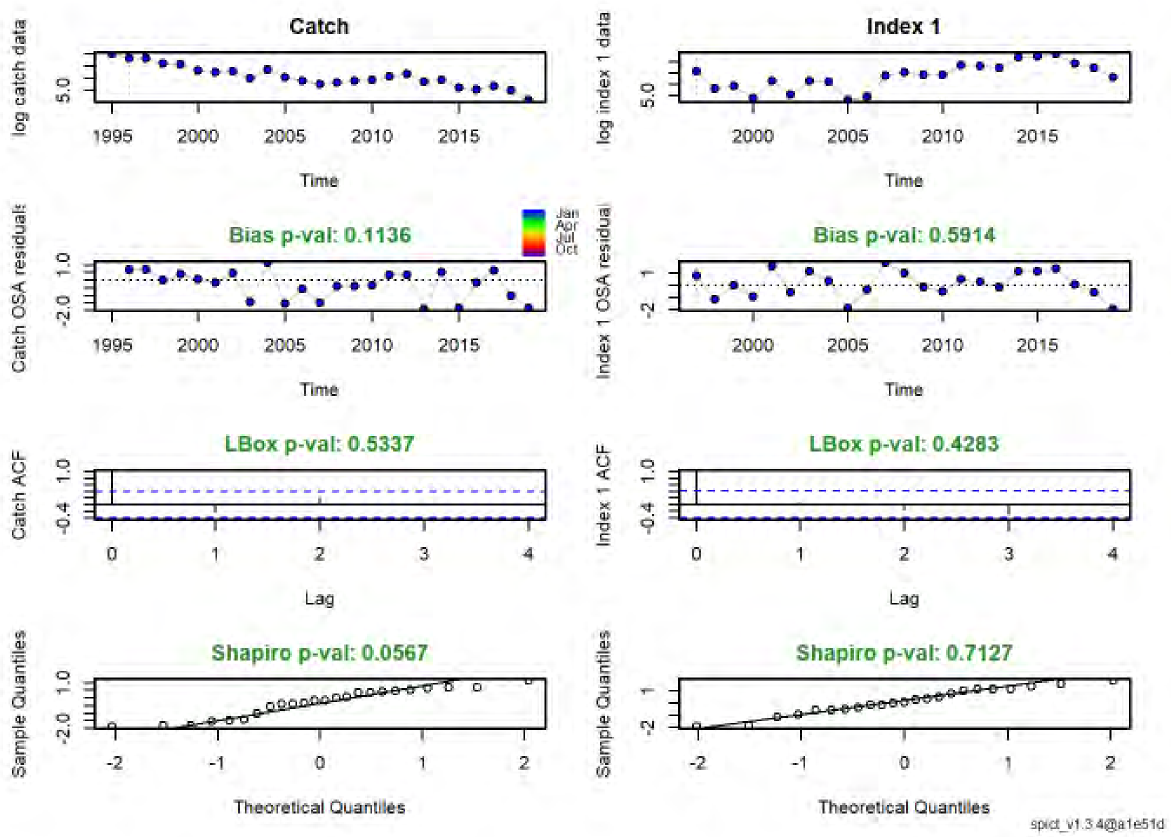


Figure 2 Residual plots for the catch and index time series for the final SPiCT assessment for PLE7HK.

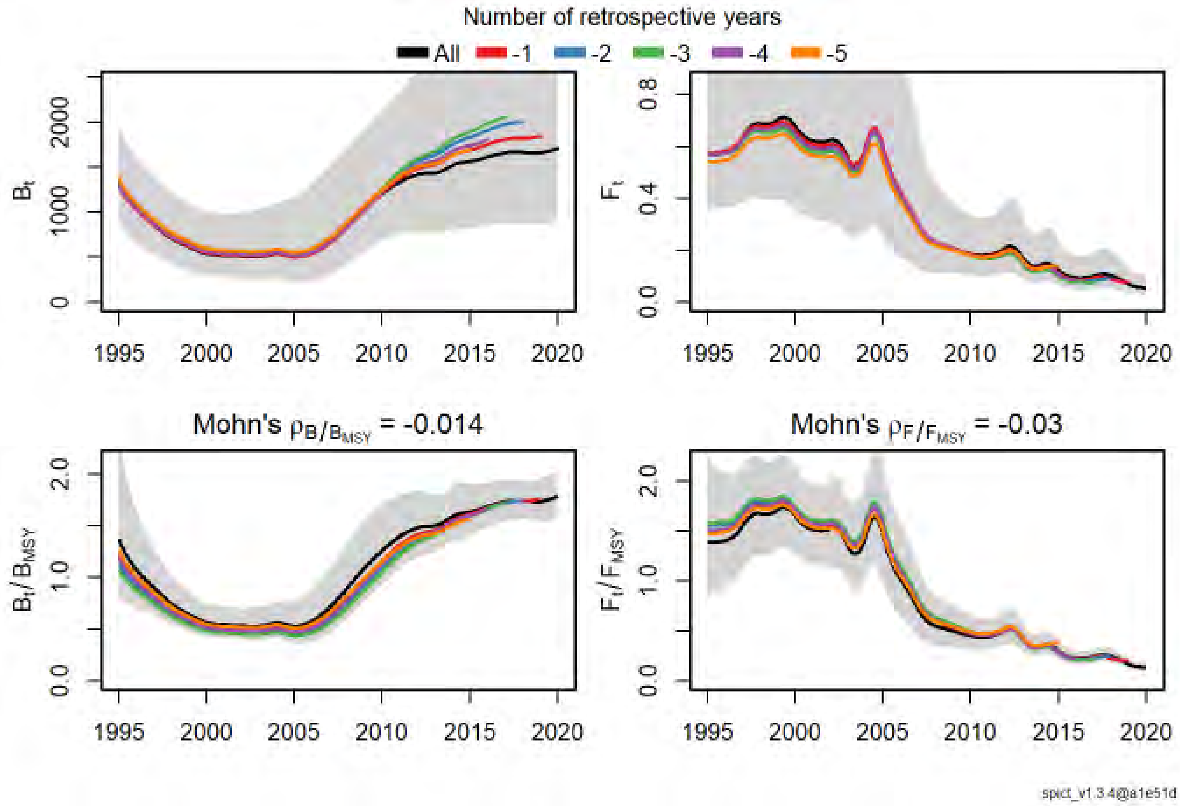


Figure 3 Retrospective plots for the final SPiCT assessment for PLE7HK

There was found a strong correlation between *logK* and *logq* (-0.94) (Figure 4), suggesting that the *B/Bmsy* scale is more poorly estimated (Bouch et al. 2021). At the same time, this stock assessment presented smaller confidence interval for relative (*B/Bmsy*) than absolute (*Bmsy*) estimates of the stock size. These results could be of concern for category 1 assessments. Accordingly, this stock assessment was proposed and accepted as category 3. *F/Fmsy* benefits from low correlation n between *logm* and *logq*, suggesting that relative estimates of fishing mortality are reliable.

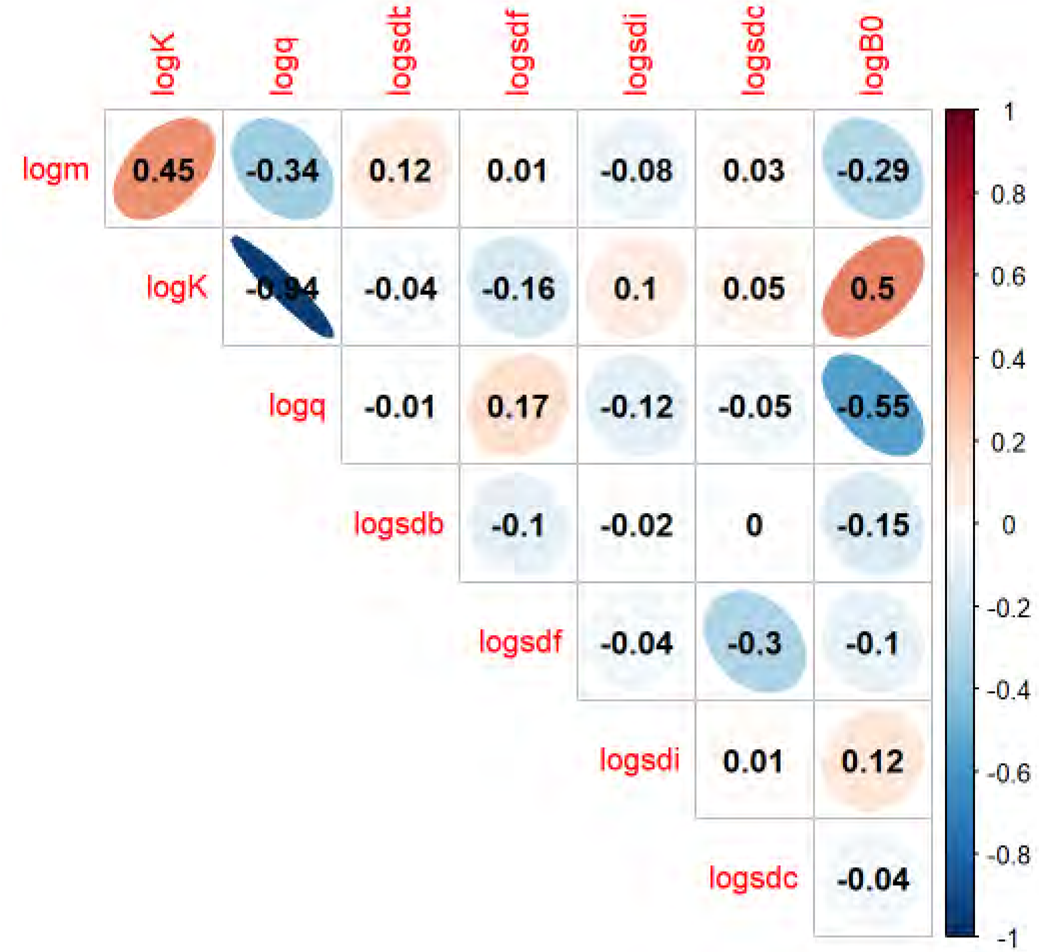


Figure 4 Correlation between parameters from the final SPiCT assessment for PLE7HK

Final SPiCT Stock Assessment

Figure 5 shows the input time series for the final SPiCT assessment, with decreasing catches since the mid 1990's and an increase in the biomass abundance since 2010. The SPiCT catch results correspond well to the reported figures and the greater uncertainty pre 2004 is represented by the wider confidence intervals (Figure 6).

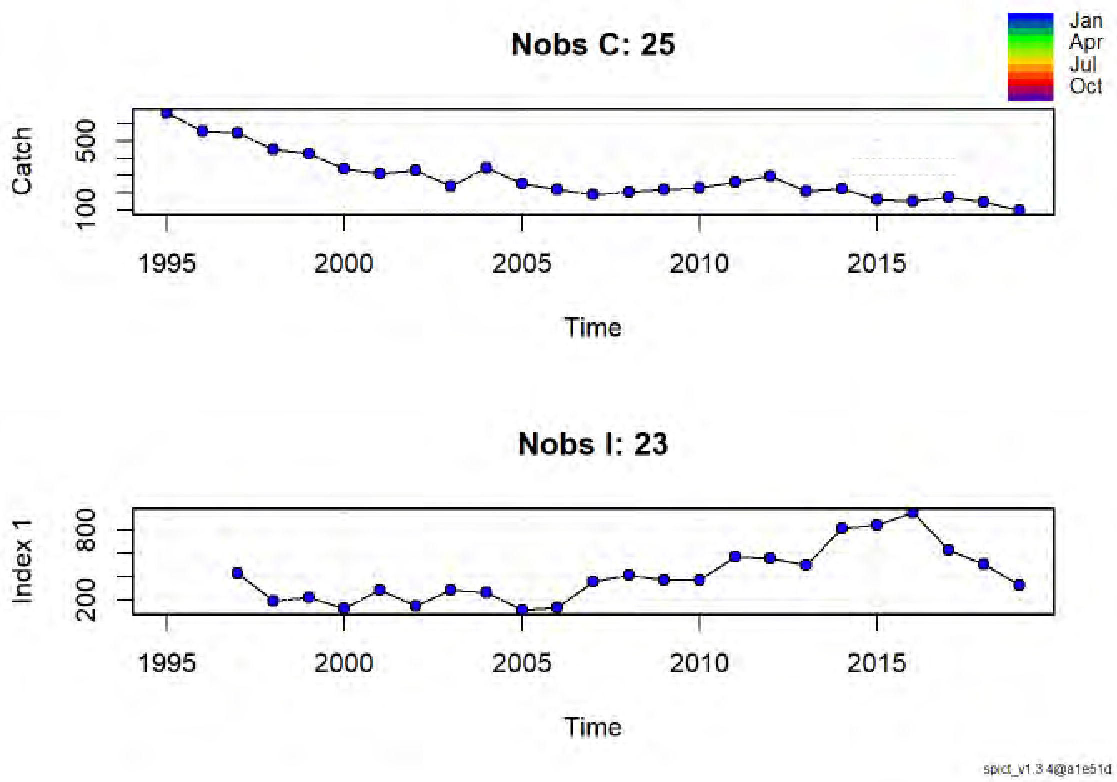


Figure 5 Catch and index input time series for the final SPiCT assessment

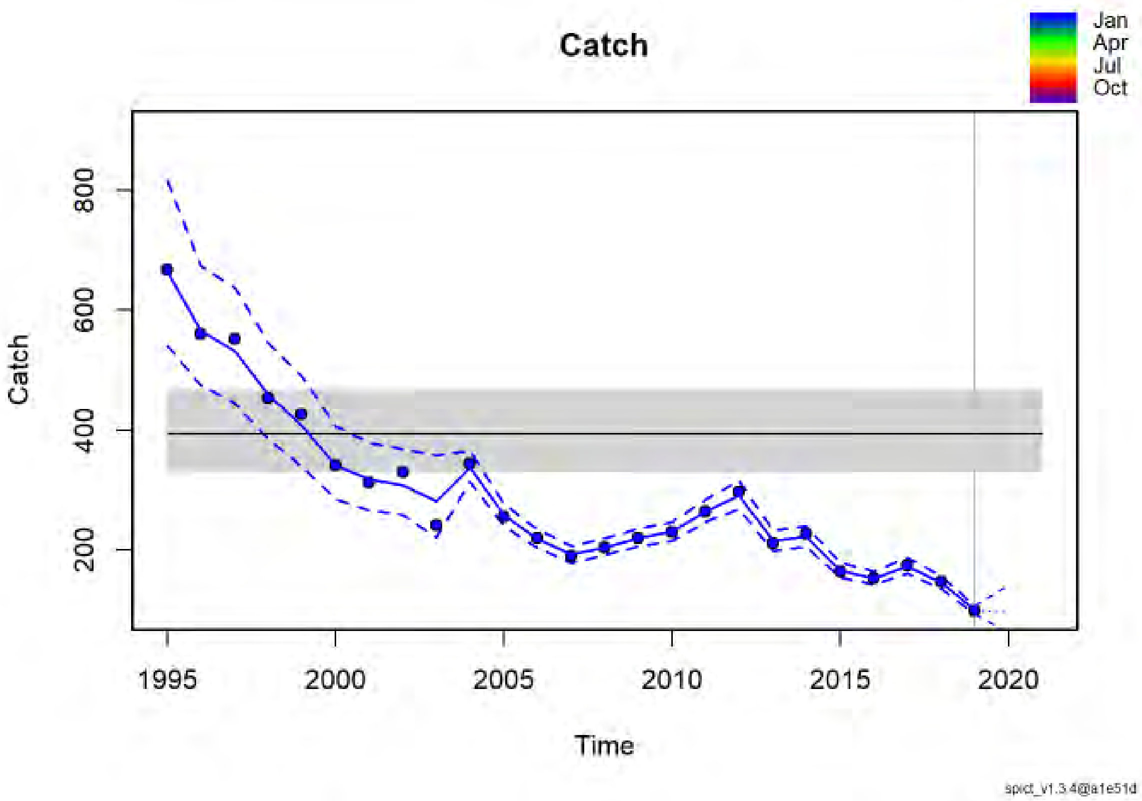


Figure 6 Catch time series generated by the SPiCT assessment with confidence intervals. Points represent reported catches in tonnes. Horizontal lines represent the estimated MSY and confidence interval.

The biomass time series shows an initial decline pre 2000 dipping below a B/B_{MSY} value of 1 (Figure 7). The biomass remained low until 2008 when the biomasss began to increase, and go above the $B/B_{MSY} >1$. The confidence interval of the estimated biomass ranges from a B/B_{MSY} of 1.58 to 2.01 in the final year of the assessment (Table 1).

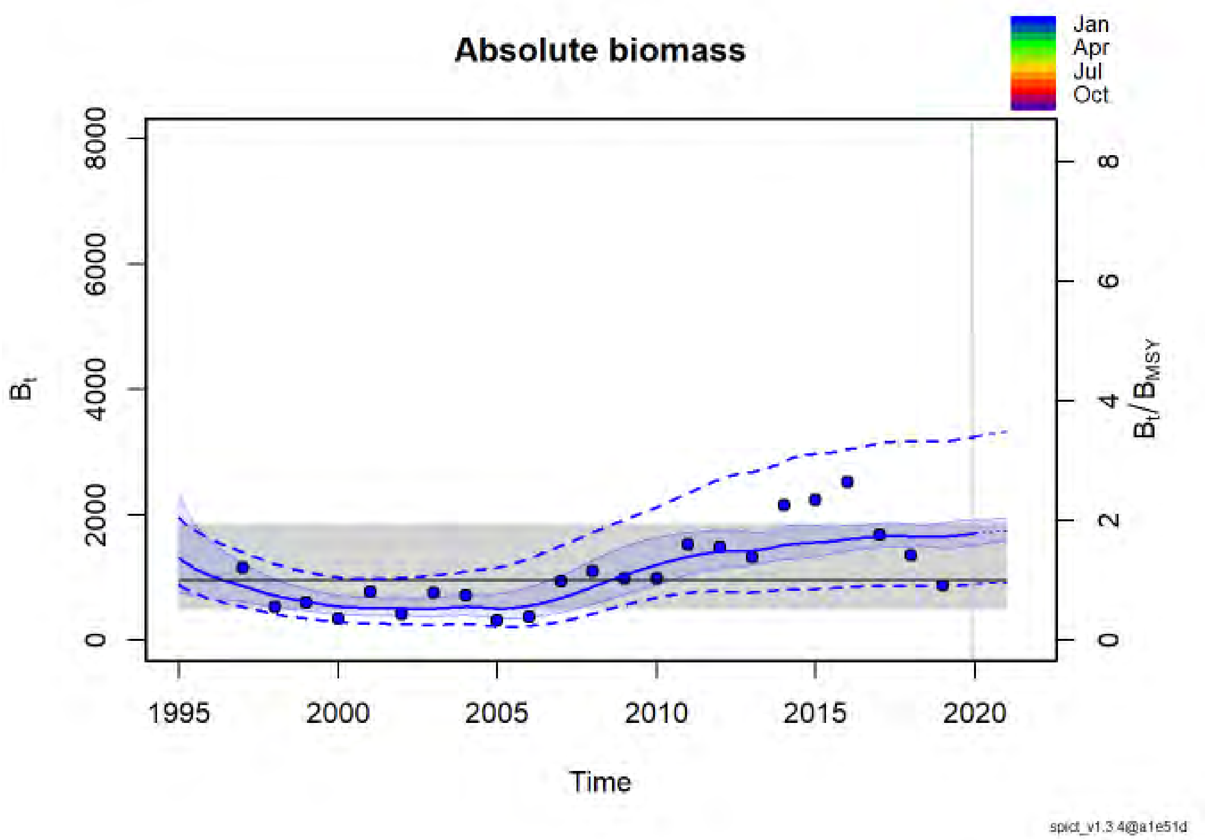


Figure 7 Absolute biomass time series from the SPiCT assessment with confidence intervals. The points represent values from the VAST index and the horizontal line represents a B/B_{MSY} of 1, with the grey shaded area the confidence of that value.

Table 1 Final year estimates with upper and lower confidence limits from the SPiCT assessment for PLE7HK

	Estimate	CI Low	CI Upper
Biomass	1703	895	3242
F	0.05	0.03	0.11
FMSY	0.41	0.23	0.75
B/BMSY	1.78	1.58	2.01
F/FMSY	0.13	0.09	0.19

The relative fishing mortality (Figure 8) has been decreased significantly from an F/F_{MSY} of 1.5 pre 2005 down to a value of 0.13 in 2020. The confidence limits are greater pre 2004, but in the later years of the assessment, the estimated F/F_{MSY} and the confidence limits are well below the F_{MSY} level (Table 1).

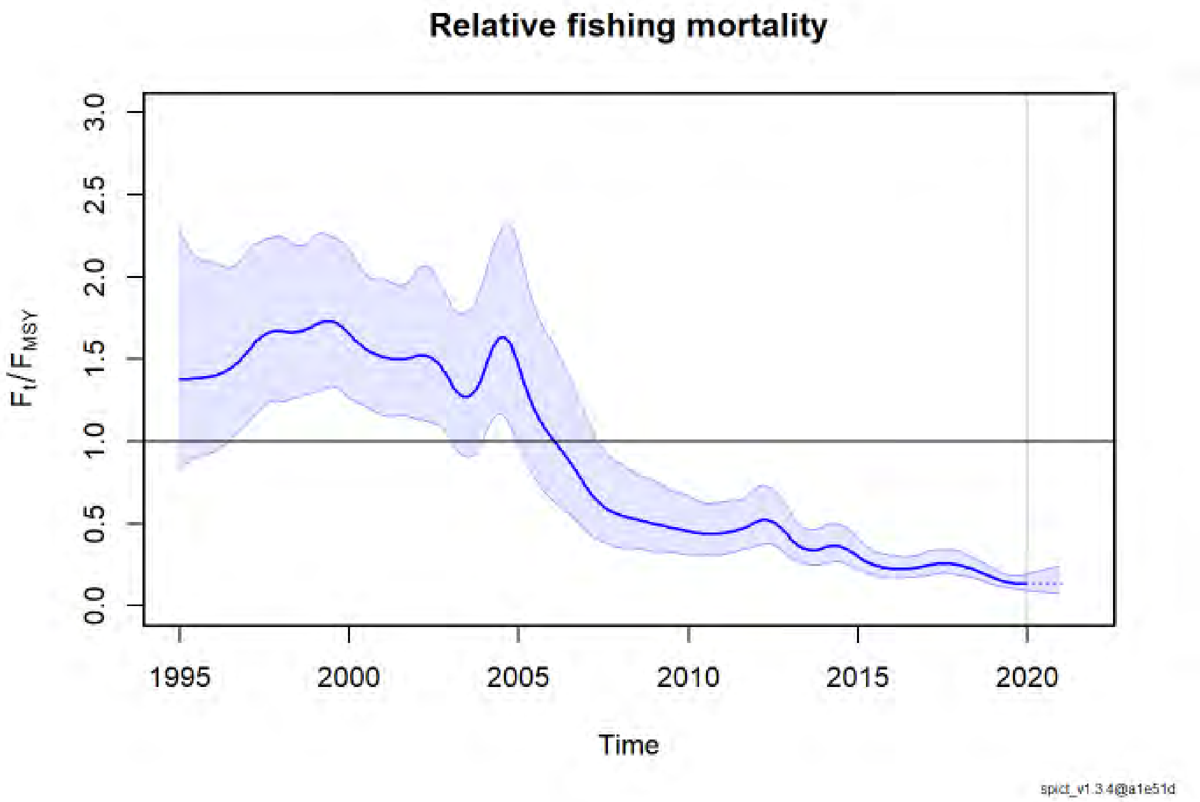


Figure 8 Relative fishing mortality and confidence interval from the SPiCT assessment for PLE7HK. The horizontal line represents an F/F_{MSY} value of 1.

Given the estimated values of FMSY of 0.41, and the relative reference points and the relatively tight confidence limits around them gives reasonable confidence in the validity and the robustness of the assessment. This is reinforced by the robust sensitivity analysis and the positive residual and retrospective analyses (Figures 1, 2, 3 and 4)

No reference points are defined for this stock in terms of absolute values. The SPiCT-estimated values of the ratios F/FMSY and B/BMSY are used to estimate stock and exploitation status relative to the proxy MSY reference points.

6 Recommendations

No recommendations

7 References

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Issue	**Problem/Aim**	**Work needed / possible direction of solution**	**Data needed to be able to do this: are these available / where should these come from?**	**Responsible expert from WG**	**External expertise needed at benchmark type of expertise / proposed names**
(New) data to be Considered and/or quantified	**Problem:** Data from 7h is currently not included in the model **Aim:** Examine inclusion of this information in the assessment.	Data exploration – are the data consistently available across the area, from enough gear types/ quarters, to be able to raise for the remaining metiers where no such data are provided	This data should be available in InterCatch	Stock Coordinator	
Discards	**Problem:** There are currently no discards included in the assessment as they are not submitted to InterCatch. It may be useful to examine alternative methodologies for estimating these using methods which are capable of operating with missing data points. **Aim** Investigate the method by which missing data can be estimated, and apply to available data.	Explore possible methods for discard estimation, and use resulting data in assessment to compare the impact on forecasts	They are currently not available, they should come from InterCatch,	Stock Coordinator	
Tuning series	Explore possibility a survey index	Run assessment with inclusion of survey index from IAMS, IBTS. And examine their impact on the assessment.	Data are available from DATRAS	Stock co-ordinator	
Tuning series	Potential new commercial tuning data for 7h	Investigate the possibility of a commercial index from 7h.	Currently not available		

Issue	**Problem/Aim**	**Work needed / possible direction of solution**	**Data needed to be able to do this: are these available / where should these come from?**	**Responsible expert from WG**	**External expertise needed at benchmark type of expertise / proposed names**
Assessment method	Consider alternative methods	Investigate use of SAM and a4a		**Stock Coordinator**	**A4a expert**
Biological Reference Points	Update as required				
Other	Data compilation	Streamlining of catch-at-age data compilation for Celtic flatfish. Consistency and standardisation of metiers across stocks			
Age	Results of age validation exercise	Calibration of ageing data	To be available by 1st October 2019	*Marcin Blaszkowski (Ireland).*	

Red Gurnard in Subareas 3 – 8

WKWEST Benchmark Workshop, 2021

Neil Campbell

Marine Scotland Science

neil.campbell@gov.scot

Contents

Introduction

Red gurnard (*Chelidonichthys cucculus*) (Figure 1) is species of small benthic fish, widely distributed on the northeast Atlantic shelf and neighbouring seas (Figure 2). It is most commonly found in waters to 100m depth, over sandy and coarse substrates. It is of minor commercial interest, with the majority of landings coming from the western English Channel and Celtic Sea. In other areas it is heavily discarded. ICES are not aware of any specific management measures in place for this species, and reference points have not been defined.

Figure 1. A red gurnard (*Chelidonichthys cucculus* L.) (D. Feijo, IPMA, Lisbon)

Figure 2. Distributional range of red gurnard (*Chelidonichthys cucculus*) as reported by Fishbase.

Benchmark Scoring

Red gurnard is currently considered a Category 6 stock according to the ICES system of classification, which is applicable to stocks with “negligible landings […] and stocks caught in minor amounts as bycatch”. While there are no known fisheries which target red gurnards, significant and consistent landings come from a number of metiers. Discards in other fleets are however known to be high (approaching 100% of catches). This stock was rated as a high priority for benchmarking by WGWIDE in 2019 (

Table 1) mainly on account of the fact that the current approach to assessment relies upon landings data which is known to be unreliable, and excludes survey information, which has been shown to be informative for tracking trends in red gurnard abundances.

An issue list for red gurnards in Subareas 3-8 was developed during WGWIDE 2018 (Table 2), highlighting the issues with the assessment and identifying the key impediments to its improvement. Foremost of these is the issue of reliability of landings data, given the significant and variable quantities of "mixed gurnards" reported by some countries, and the general lack of documentation of approaches to catch reporting by species in countries where mixed gurnards are generally not reported. Those countries for who discard information were reported to the working group typically reported high rates of discarding (50-90%, by weight).

Table 1. Benchmark prioritisation table for Red Gurnard (*Chelidonichthys cucculus*) in SAs 3-8, WGWIDE, 2019.

SCORE	**Criteria 1 – Need to improve the quality of the previous assessment to provide advice** Weight: 0.4	**Criteria 2 – Opportunity to improve the assessment** Weight: 0.3	**Criteria 3 – Management importance*** Weight: 0.1	**Criteria 4 – Perceived stock status** Weight: 0.1	**Criteria 5 - Time since previous benchmark** Weight: 0.1
Score 4.7	Assessment is inadequate to provide advice (based on landings which are known to be unreliable) Score – 5.	No survey data is used in the assessment, therefore new data and methods will be used. Score – 5.	One attribute (advice is requested). Score – 2.	State of the stock unknown. Score – 5.	Stock has never been benchmarked. Score – 5.

<u>* Attributes:</u>

a) Advice on fishing opportunities is requested for the stock.
b) Stock is the object of an agreed management plan.
c) Stock is the object of a directed fishery.
d) Stock is included in a mixed fishery analysis, is a likely choke stock, or the object of a pelagic fishery

Table 2. Issue list for red gurnard (*Chelidonichthys cucculus*) in Divs. 3-8, developed during WGWIDE, 2018.

Type	Problem/Aim	Work Required	Data Required	Expertise Required
Data to be considered	Resolution of landings data of all gurnards at the species level is poor. A considerable quantity are landed as "mixed gurnards", while those nations who land them as individual species have not, other than Portugal, documented the process by which this is done.	Questionnaire circulated to national administrations regarding if and how landings are assigned to species.	Several years of national landings data	
Discards	Several nations have submitted discard rates, by fleet, for red gurnard, via intercatch. These are not yet used, due to a lack of time to develop an assignment scheme, and a lack of confidence in the figures at a species level.	Develop raising procedure in intercatch further, link to work on assignment of catch to species.	Discard data by fleet	
Data to be considered	Assuming the distribution of landings reported as red gurnard are indicative of the distribution of the stock, whilst it is a widely distributed species, the centre of abundance is focussed on the English Channel and the Celtic Sea. The eastern end of the channel (7d) is covered by the French CFGS, while the Celtic Sea (7h) is covered by the EVHOE surveys. This leaves an area of high abundance in 7e currently not covered by any survey. Data exists in the English Channel Beam Trawl Survey series from 2006 to present, however it has not yet been processed in such a way that it can provide an index.	Analysis of survey data to enable the production of a time series of red gurnards in 7e.	English Channel Beam Trawl Survey data	People with experience of processing survey data and calculating CPUE indices
Assessment method	Assuming catch data remains unreliable at the species level for some time, a survey based assessment seems the most likely way to provide more quantitative advice on stock status. A SURBAR model based on the CGFS and EVHOE surveys is in a process of development, and with some refinement, would be a promising candidate for an assessment model.	Model tweaking	Survey data	Survey-based assessment.
Management area divisions	If the species distribution is heavily focussed on 7d,e,h, what approach should be taken to advice and management outside of this area?	Scratching of chins. Deep thought.	Spatial distribution of landings and discards over time.	

Stock Definition

The current stock used by ICES for assessment and advisory purposes covers Subareas 3 – 8, from the Baltic Sea to the Bay of Biscay and considers red gurnard within this area to be a single stock (Figure 3).

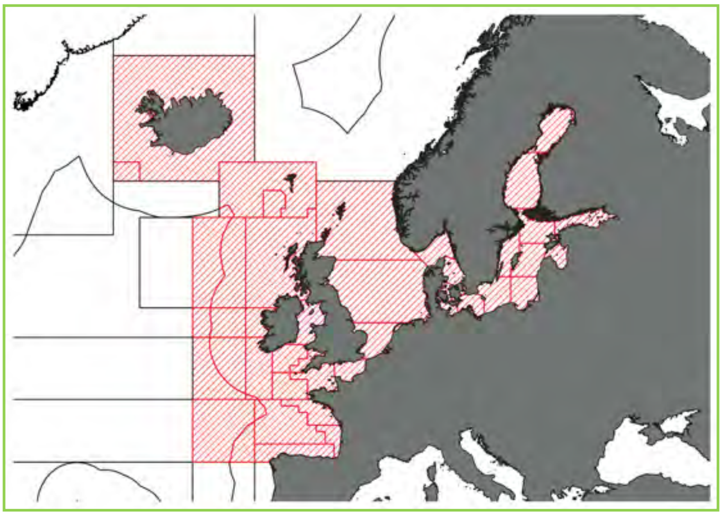


Figure 3. The area used for assessment purposes for Red gurnard (Chelidonichthys cucculus in SA 3-8).

Given the sparse knowledge of the biology and life-history of red gurnards, concerns have been raised about the usefulness and validity of this definition on a number of fronts:

- Red gurnard have not been reported from Subarea 5 in recent times, and while present in a small number of years from Division 3a, are absent from the rest of the Baltic Sea.
- Commercial landings are routinely reported from Division 9a, outside the current stock boundary, causing presentational issues when drawing up advice sheets
- Two starkly different trajectories are seen in survey data CPUEs for surveys covering northern (Subareas 4 and 6) and southern (Subareas 7 and 8) of the parts of the range.

A working document was provided to the Stock Identification Methods Working Group (SIMWG) in 2019, with a request to comment on the stock identity of this species in light of the divergent survey trends over its range, and review of the available information that might be relevant to stock structure of red gurnard. SIMWG considered the working paper and concluded there was sufficient evidence for splitting the stock into two stock areas (North Sea/west of Scotland and Celtic Seas/Biscay) at this time. Although they noted that there is evidence of different trends in abundance between the areas across surveys, this alone was insufficient to support a conclusion regarding stock structure. They recommend that more granularity be required in fishery dependent data collection (i.e., identification to species), a comparison in gurnard catchability among the various surveys in this region, and starting basic biological data collection for accurate stock identification for this data poor species before any spatial management changes should be considered or stocks delineated.

On this basis of this conclusion, the current assessment has proceed with a single assessment of status for red gurnards in SA 3-8.

Biological Data

Red gurnard do not appear to have been subject to tagging, genetic, parasitological or morphometric stock identification studies, and migration patterns are therefore inferred by seasonal changes in the abundance of red gurnard in the areas from where landings are reported. Seasonal patterns in areas fished by fleets and countries more likely to discard gurnards are unknown. The fish appear in the central and western Channel during September and remain in an area between Ouessant and the Isle of Wight, and particularly around the Hurd Deep, from November to January. Spawning commences in February, and spent fish appear to move west. Spawning continues through the summer and, by July and August, the majority of fish are caught in the western Channel (Pawson, 1995).

The changes in sex ratio of red gurnard in the fishery suggest that females migrate back to the central Channel before the males, which arrive there in December, and that males leave more rapidly after spawning. It has also been suggested that males favour rocky grounds which cannot be trawled effectively. Female red gurnard caught in the Channel appear to grow faster than males. Their mean lengths at ages 5 and 10 respectively are 35.5 cm and 40.5 cm compared with 32 cm and 34.5 cm for males. Growth data are not available for red gurnard from regions outside the Channel. Red gurnard first attain maturity in the Channel at approximately 25 cm and 50% are mature when 26-29 cm in total length at age 3 (Pawson, 1995).

Fishery Dependent Data

Official Landings

In addition to red gurnards, two other species of Triglid are caught in commercially significant quantities in northeast Atlantic waters – the grey gurnard (*Eutrigla gurnardus*) and the tub gurnard (*Chelidonichthys lucerna*) (Figure 4). In some cases these are landed together, and in combination with red gurnards as “mixed gurnards”, and reported under the species code GUX (Figure 5). The proportion of landings reported as mixed gurnards varies between countries (see Annex 1), and there is little documentation available on if and how the species composition of gurnard landings is verified. There are no catch limits or minimum conservation reference size set for these species, and anecdotally, little effort goes into validation of species compositions at the quayside. A presentation was made to WGWIDE in 2018 on the work being carried out in Portugal to improve reporting and validation of gurnard landings to species level, however the approaches of other countries remain undocumented.

Figure 4. Grey gurnard (*Eutrigla gurnardus*) (left) and tub gurnard (*Chelidonichthys lucerna*) (right) (D. Feijo, IPMA, Lisbon).

Figure 5. A box of "mixed gurnards", landed under the species code GUX. (D. Feijo, IPMA, Lisbon).

Landings of mixed gurnards from SA 3-8 have ranged between 50% and 100% of the equivalent red gurnard value recorded in the same area (Figure 6). This obviously creates a number of issues with assessing the stock, such as interpreting trends in landings, raising discards and comparing CPUE's across fleets. The impact of this situation on ICES ability to provide meaningful advice is also considerable. Landings of tub gurnards, particularly from the southern North Sea, seem to be at odds with indications from surveys (Annex 1, Landings of gurnards, by species, for each division, 2006 – 2018.). During 2006 – 2019, average catches per hour towed in the North Sea IBTS survey were 32.1kg for grey gurnards, 0.51kg for red and 0.17kg for tub.

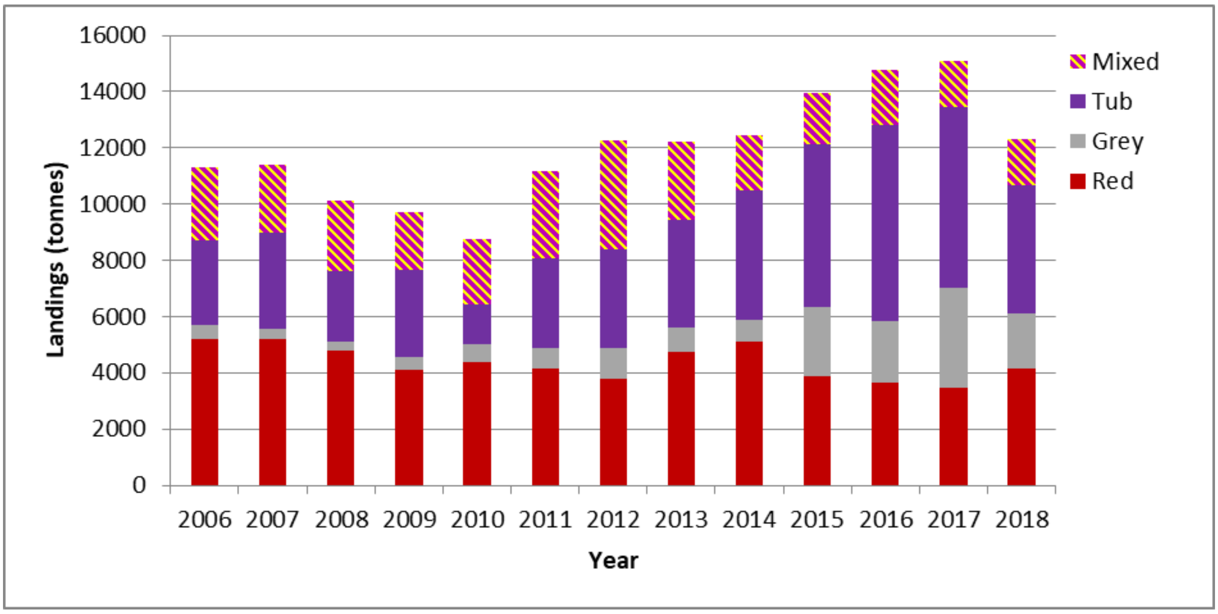


Figure 6. Official landings of red, grey, tub and mixed gurnards, 2006 - 2018, SA 3-8.

There may be heuristics which could be used to guide us in allocating mixed catches to species, such as apportioning on the basis of reported landings of the three species on a division by division basis, or using the relative proportions observed in surveys considered representative for each area. Given the uncertainty in catch, which is in the same order as the landings themselves, I consider that this is a problem wider than the scope of this benchmark, one which cannot be solved with the data available, and that for our purposes we should restrict our analysis to purely survey-based approaches to determining stock status for red gurnards.

Data Call – Landings & Discards

The data call requested countries submit discard information for red, grey and mixed gurnards. The data received in advance of the data evaluation workshop is shown in Table 3. In addition to this, there were a number of other files giving landings by statistical rectangle with no associated country identifier, which need further investigation with the Secretariat to identify which nation has submitted them before the comprehensiveness of the data can be determined.

Table 3. Data received in response to the data call for Red Gurnard (*Chelidonichthys cucculus*) in SA 3-8.

Country	Years	Species	Category	Notes
Belgium	2006 – 2019	GUG	Landings	Landings by stat rectangle, by metier.
	2006 – 2019	GUR	Landings	Landings by stat rectangle, by metier.
	2006 – 2019	GUU	Landings	Landings by stat rectangle, by metier. GUU was not requested in the data call. Need to clarify whether they use the GUX code.
Netherlands	2002 – 2019	GUG	Landings	Landings and effort by stat rectangle, by metier. Low discarding reported.
	2002 – 2019	GUR	Landings	Landings and effort by stat rectangle, by metier. Low discarding reported.
	2002 – 2019	GUX	Landings	Landings and effort by stat rectangle, by metier. No discard data.
France	2004 – 2019	GUG	Landings & Discards	Landings, discards and effort, by metier, by division, in Intercatch format.
	2004 – 2019	GUR	Landings & Discards	Landings, discards and effort, by metier, by division, in Intercatch format.
	2004 – 2019	GUX	Landings & Discards	Landings, discards and effort, by metier, by division, in Intercatch format.
Ireland	2003 - 2019	GUG	Landings & Discards	Landings, discards and effort, by metier, by division, in intercatch format.
England & Wales	2004, ’09, ’10, ’12-‘19	GUG	Landings	Landings at length, and effort, by metier, by division, in intercatch format.
	2000 – 2019	GUX	Landings	Landings at length, and effort, by metier, by division, in intercatch format.
	2009 - 2019	GUR	Landings	Landings by statistical rectangle.
Sweden	2002 – 2019	GUG	Landings	Effort and landings, by metier, by division, in intercatch format.
	2002 – 2019	GUX	Landings	Effort and landings, by metier, by division, in intercatch format.
Spain	2009 - 2019	GUG	Landings & Discards	Effort, landings and discards at length, by metier by division, in intercatch format.
	2009 - 2019	GUX	Discards	Effort and discards, by metier by division, in intercatch format.

Country	Years	Species	Category	Notes
Poland	2019	GUX	Landings	Landings by stat rectangle.
Scotland	2002 – 2019	GUG	Landings & Discards	Landings and discards at length and effort, by metier, by division, in Intercatch format.
	2002 - 2019	GUX	Landings & Discards	Landings and discards at length and effort, by metier, by division, in Intercatch format.
	2002	GUR	Landings & Discards	Landings and discards at length and effort, by metier, by division, in Intercatch format. Only one year available?
Germany	1995 - 2001	GUX	Landings	Landings and effort, by metier, by division, in intercatch format.

While it is possible to make an assessment of trends in the status of red gurnard populations as a whole on the basis of fishery independent survey data, the fundamental problems with catch data makes translating any observations into management advice flawed. Average catches of red gurnard may represent a floor or minimum estimate of catch, with some proportion of the GUX landings in addition to this representing a truer picture of catch. Following the ICES guidelines for survey based assessments; there is some implicit understanding of the absolute value of catch in each option. We have a large degree of uncertainty about the first component of the pressure-state-response paradigm which survey-based assessments are predicated upon.

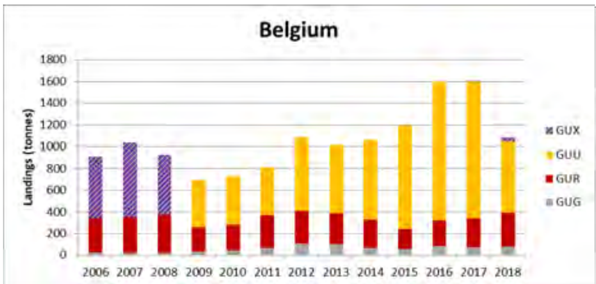
Fishery Independent Data

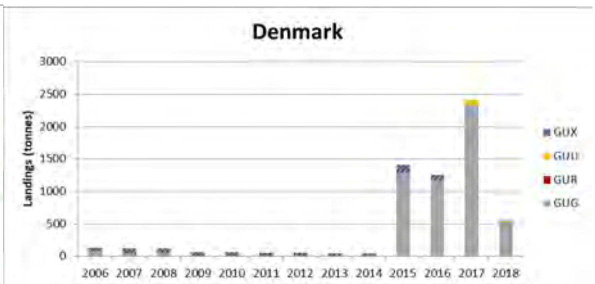
As would be expected with a widely distributed species, catches of red gurnard are reported from many bottom trawl surveys which take place in this area. The majority of these are available through Datras, making catch at length commonly available, and catch at age in a small number of cases. Indices and summary data have been made available to the working group for some of those which are not, and these are included below.

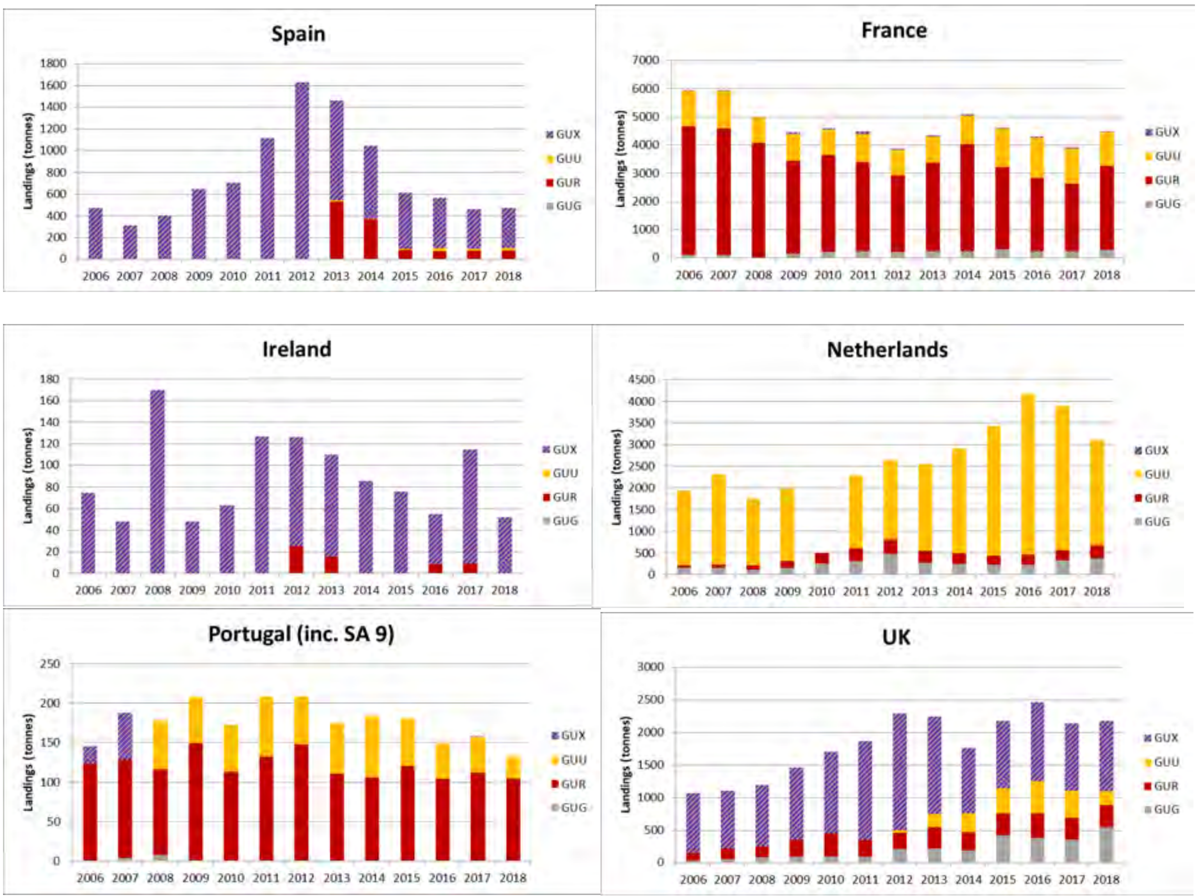
Surveys in Datras

As might be expected for a stock which covers such a wide geographic range, red gurnard are encountered in nearly every bottom trawl survey in the northeast Atlantic. The spatial distributions of catches in each series are presented in Annex 1

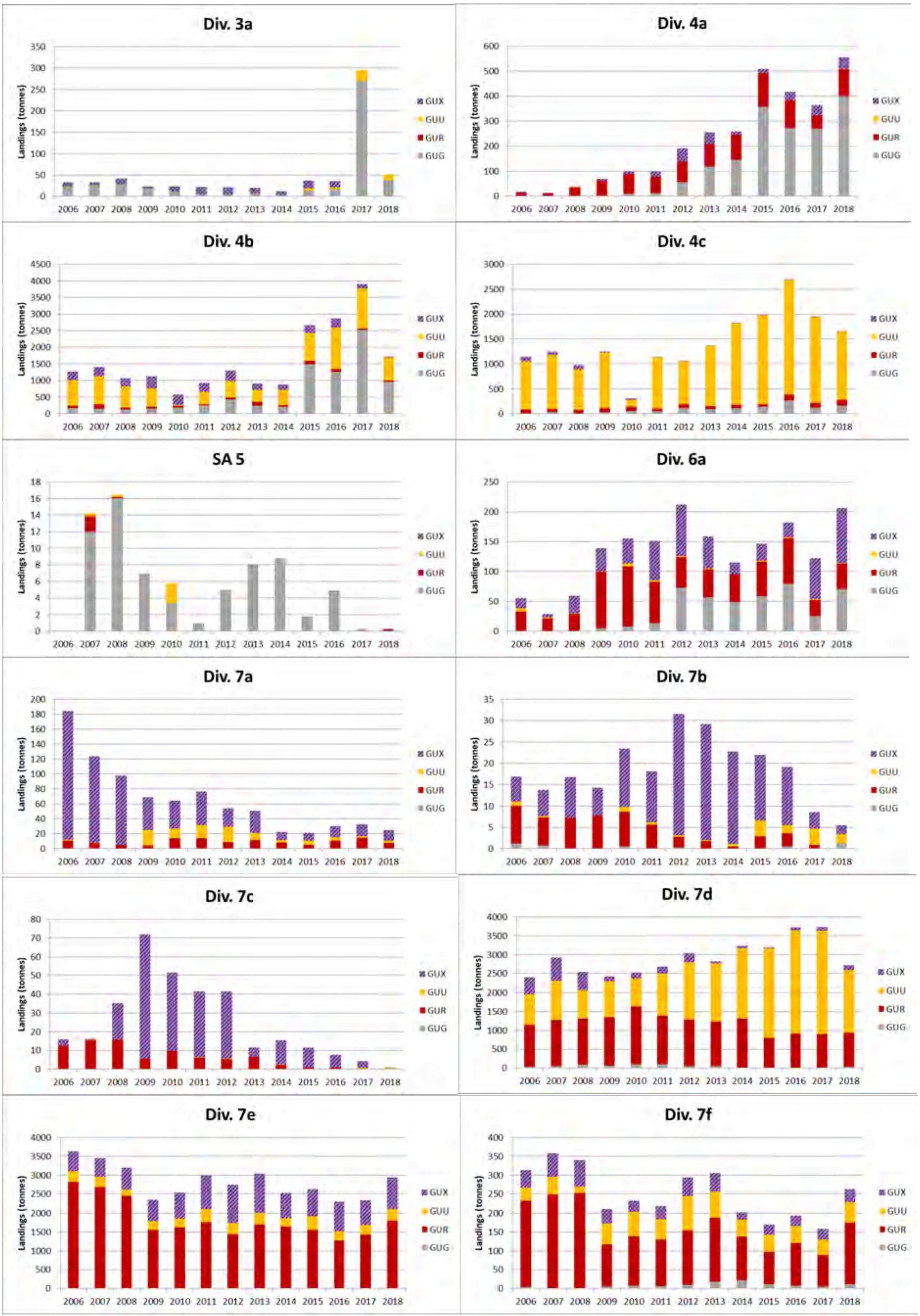
Landings of gurnards, by species, for each country, 2006 – 2018.



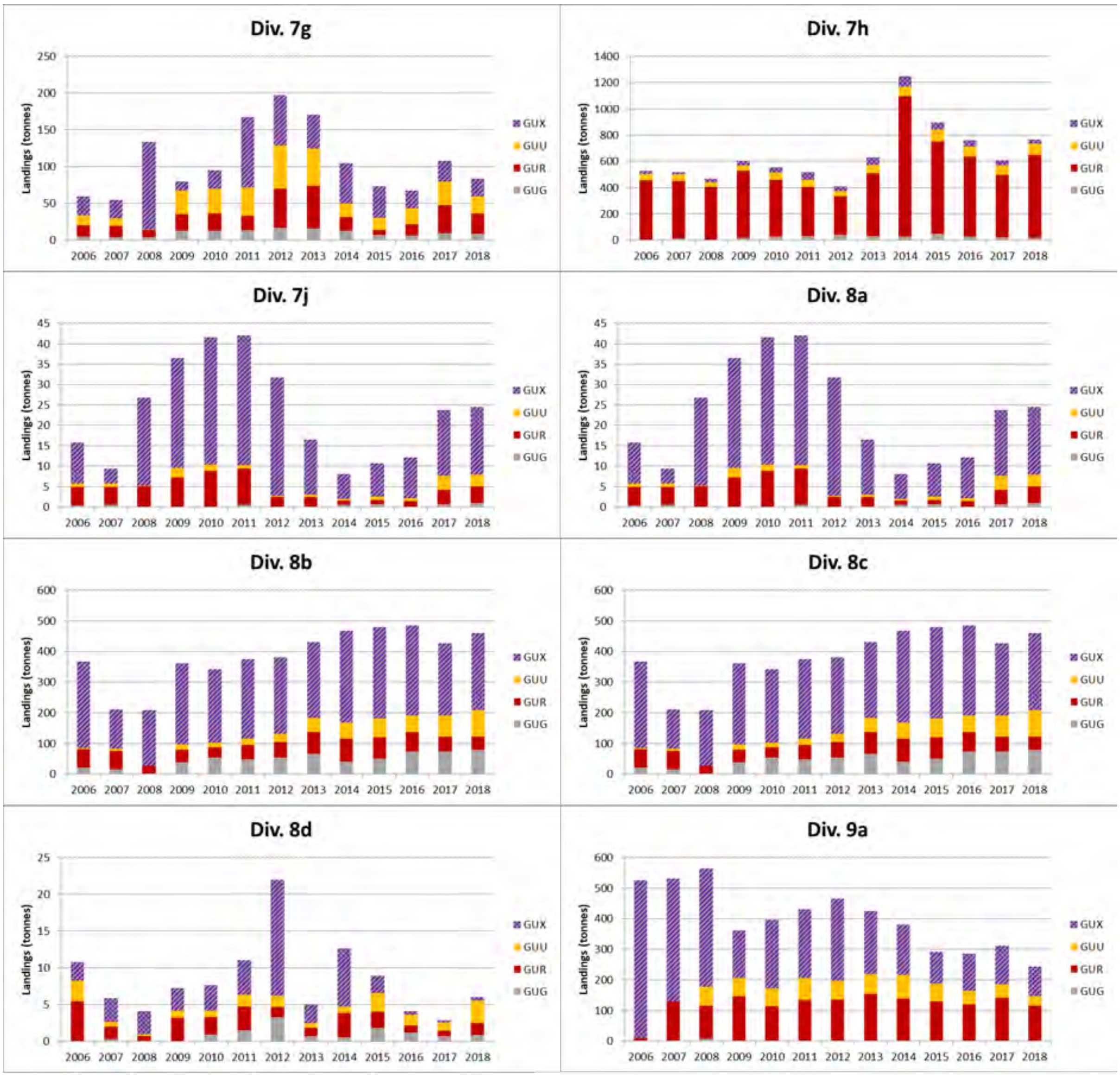



Spain
Landings (tonnes)
0
200
400
600
800
1000
1200
1400
1600
1800
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018
GUX
GUU
GUR
GUG
France
Landings (tonnes)
0
1000
2000
3000
4000
5000
6000
7000
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018
GUX
GUU
GUR
GUG
Ireland
Landings (tonnes)
0
20
40
60
80
100
120
140
160
180
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018
GUX
GUU
GUR
GUG
Netherlands
Landings (tonnes)
0
500
1000
1500
2000
2500
3000
3500
4000
4500
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018
GUX
GUU
GUR
GUG
Portugal (inc. SA 9)
Landings (tonnes)
0
50
100
150
200
250
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018
GUX
GUU
GUR
GUG
UK
Landings (tonnes)
0
500
1000
1500
2000
2500
3000
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018
GUX
GUU
GUR
GUG

Landings of gurnards, by species, for each division, 2006 – 2018.



Landings of gurnards, by species, for each division, 2006 – 2018 (cont.).



Landings of gurnards, by subarea, for the major fishing countries.

Annex 2. Catch at length data is available for each haul contained in Datras. Associated age data is available for a subset of these, allowing the calculation of catch at age in certain cases.

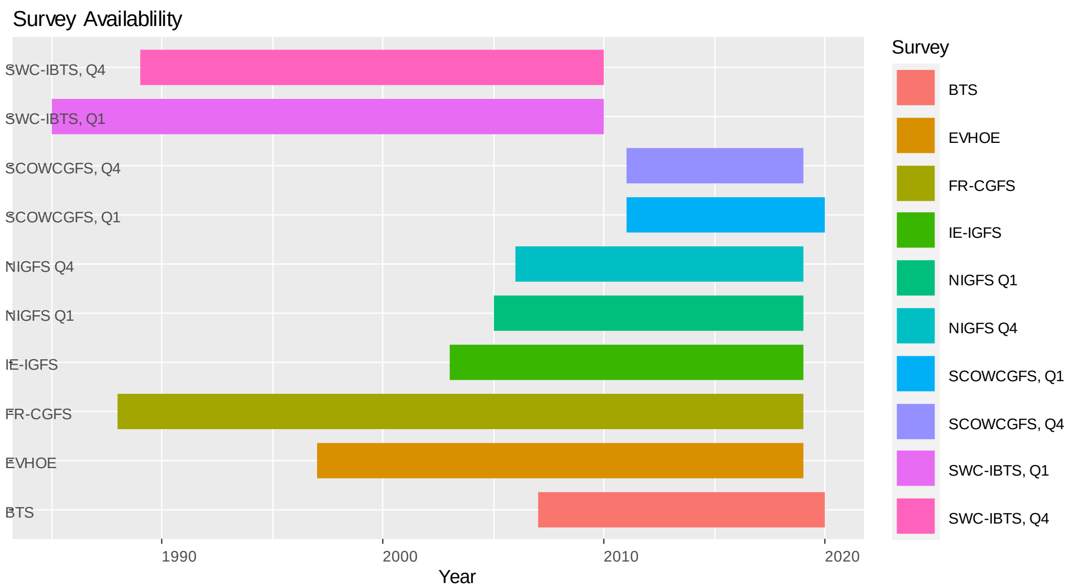


Figure 7. Periods of availability of survey catches of red gurnard (*Chelidonichthys cucculus*) for each survey in the DATRAS database.

These surveys cover variable periods in time, summarised in Figure 7, and space, detailed in the text below and in Annex 2. Distribution of Survey Catches.

FR-EVHOE

The French survey "Evaluation Halieutique Ouest de l'Europe" (EVHOE) is a bottom trawl survey which has covered the waters so the south of Ireland, southwest of the UK and down the west coast of France, annually, since 1998. Data is not available for 2017 due to disruption to the survey. This survey covers the core area from which landings are reported, and as such is probably the indicator which will correspond most closely to the "fished stock". Otoliths are taken and read for this survey, therefore catch-at-age and catch-at-length data are available for this survey (Figure 10). Although red gurnards are found throughout the area covered by the survey, the area to the west of Ouessant appears to be an area of consistently high abundance (Annex 2. Distribution of Survey Catches, French EVHOE Survey, 1998 – 2019).

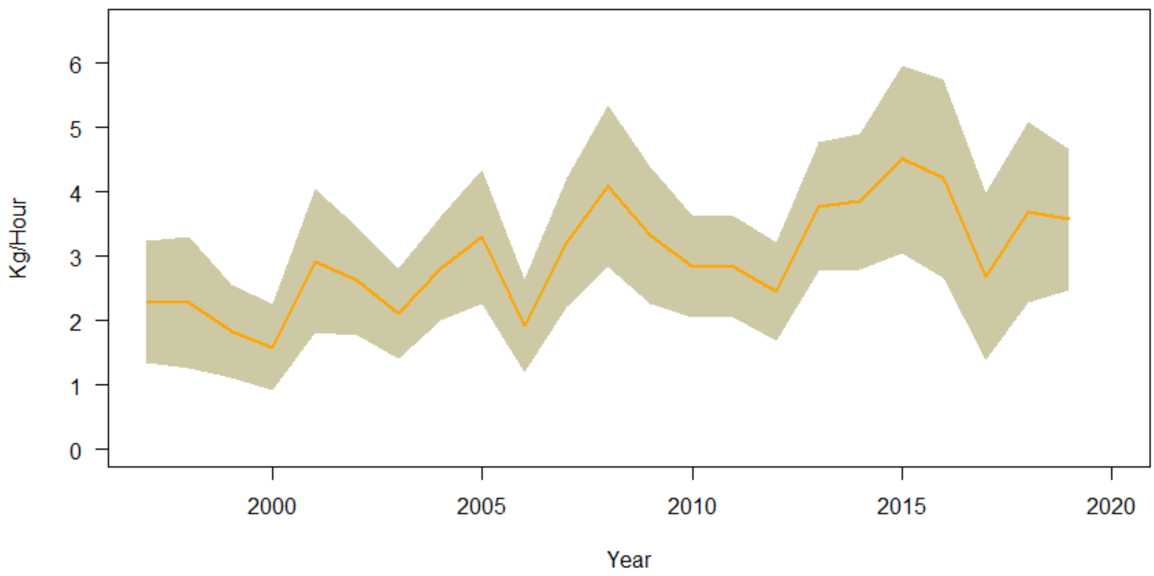


Figure 8. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Quarter 4 ÉValuation des ressources Halieutiques de l'Ouest de l'Europe (EVHOE) survey (error bars are ± two standard error).

FR-CGFS

The French Channel Groundfish Survey (CGFS) covers the eastern half of the Channel (Div. 7d). Red gurnard appears routinely in survey catches in the more offshore hauls (Annex 2. Distribution of Survey Catches, French Channel Groundfish Survey (FR-CGFS)). Age data is available for some years in the series (Figure 10). This survey covers the period 1989 – 2019, although a change in vessel from the *Gwen Drez* to the *Thalassa* and subsequent change in fishing operations, after 2015 has raised questions regarding whether this should be considered as one series or two. Examination of trends in mean abundance over the survey series reveals variation with no particular trend, other than a decline from higher than average in the first years of the series (Figure 9). There is no apparent change in catch rate associated with the switch in vessels.

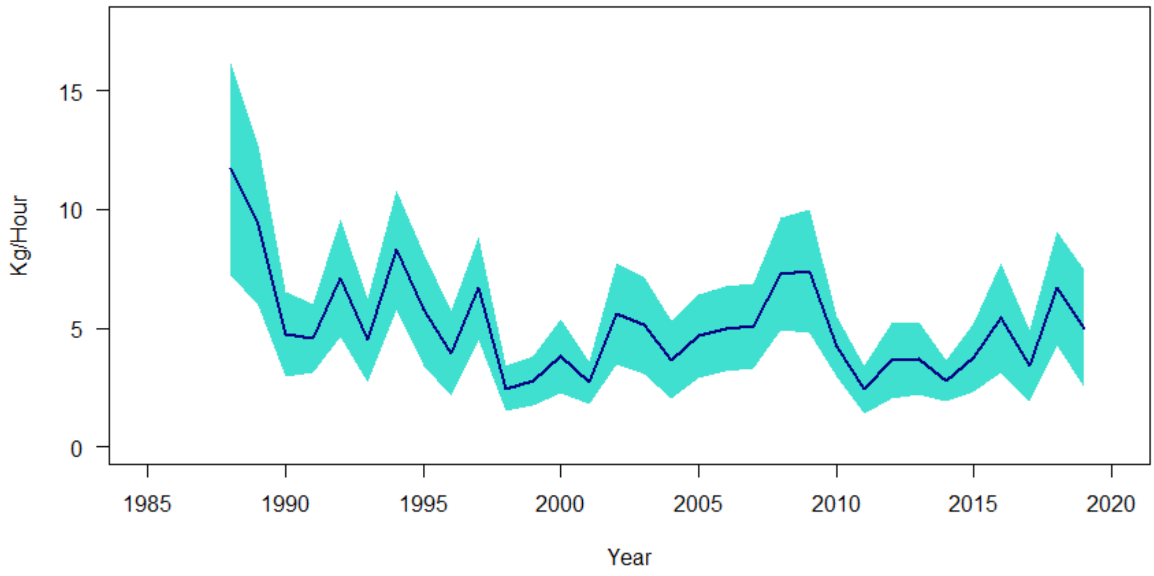


Figure 9. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Quarter 4 French Channel Groundfish Survey (FR-CGFS) survey (error bars are ± two standard error).

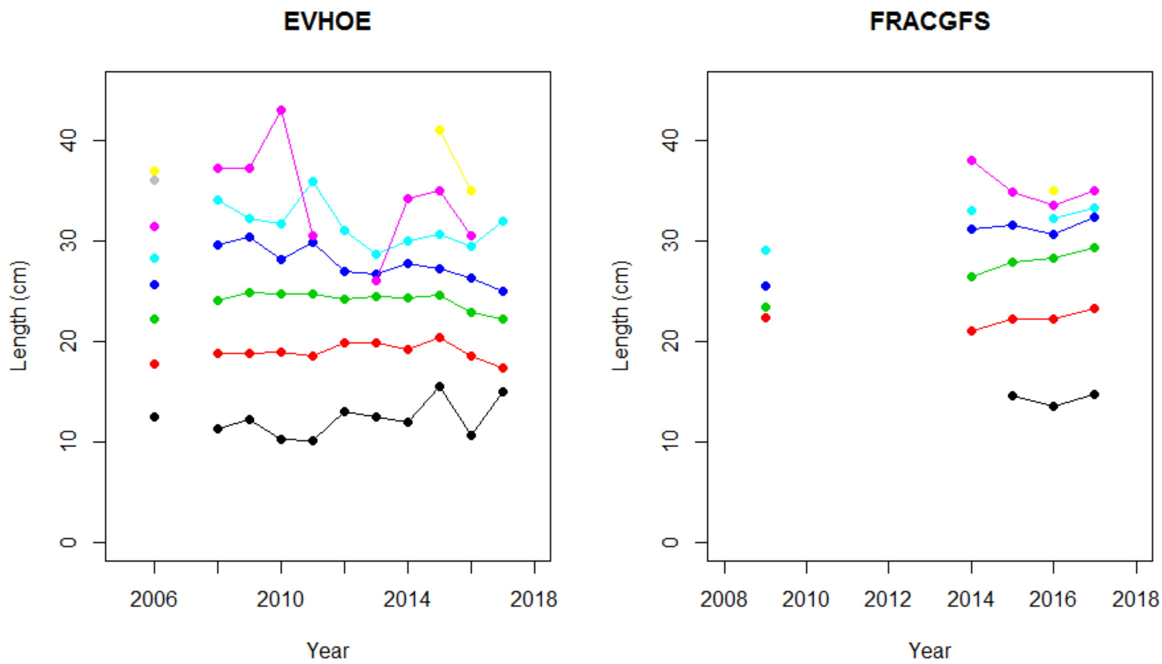


Figure 10. Length at age data of red gurnard (*Chelidonichthys cucculus*) from the EVHOE and CGFS surveys.

IE-IGFS

The Irish Groundfish Survey is a more recent series, covering waters around the coast of Ireland over the period 2003 – 2019. It reveals a consistent yet patchy distribution. Age data is available for some years over the course of the survey.

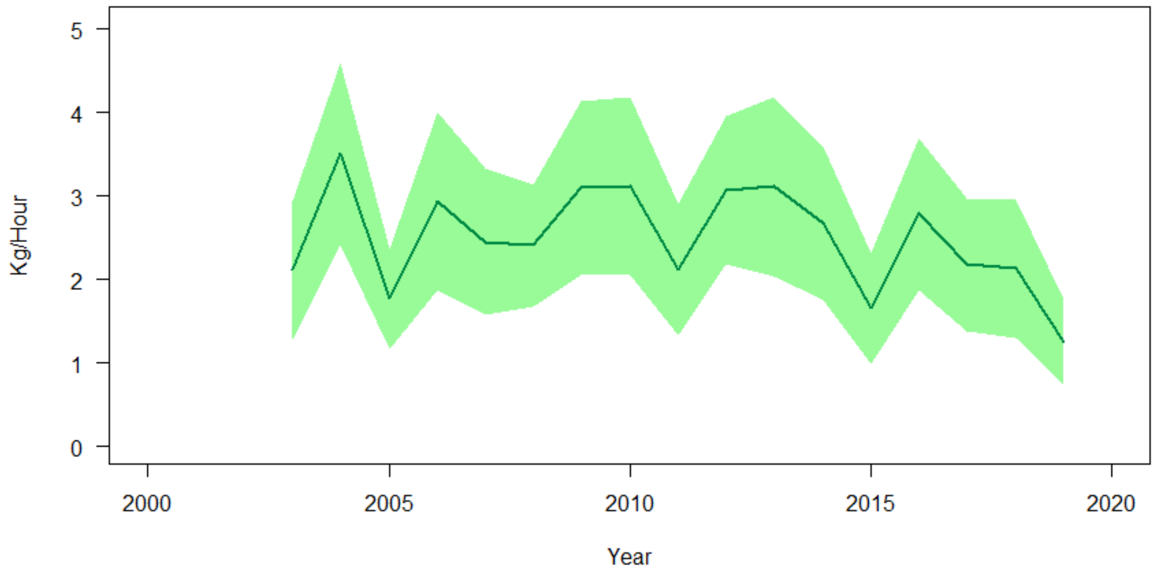


Figure 11. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Quarter 4 Irish Groundfish Survey (FR-CGFS) survey (error bars are ± two standard error).

SCO-WCGFS and SCO-WCIBTS

The Scottish West Coast IBTS survey took place during quarter 1 of 1985 – 2010, and quarter 4 of 1990 – 2009. This survey was initially intended to cover the fishing grounds on the continental shelf to the west of Scotland; in 1996 the survey area was extended to include stations in the northern Irish Sea. This survey was replaced in both quarters from 2011 onwards by the Scottish West Coast Groundfish Survey. This involved a change in stratification, from one based on obtaining several tows in each statistical rectangle, to a depth basted random-stratified survey design. Both series use a GOV net, however the earlier series used groundgear "C" (525mm bobbins) while the latter used groundgear "D" – a rockhopper rig with discs up to 16" (406mm) (Harley & Ellis, 2007).

These surveys cover waters to the west of Scotland, from Shetland to the north of Ireland, differing in the stratification they use. Age data is not available for this survey series. The Scottish west coast IBTS surveys show a slow general upward trend from 1997 to 2010 (Figure 12 & Figure 13). The SWC-GFS series starts at a higher level, not unexpectedly due to the shift to lighter ground gear, but this increasing trend continues until Q4 2012/Q1 2013, before falling to lower levels. This trend is not seen in the Irish, French or Spanish surveys further south.

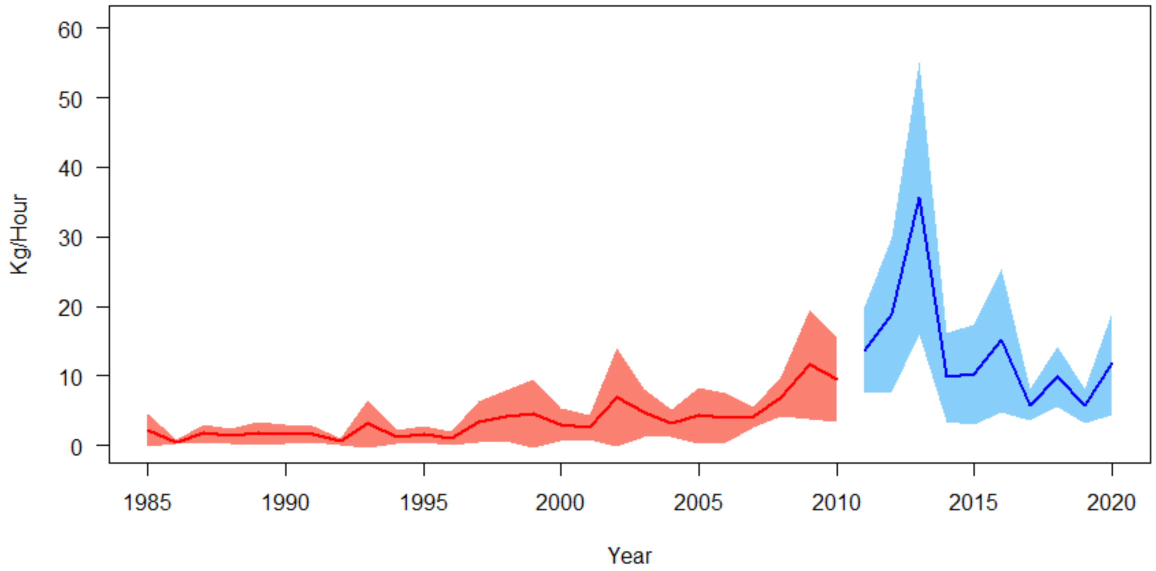


Figure 12. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Quarter 1 Scottish West Coast IBTS (SCO-WCIBTS) (red) and Scottish West Coast Groundfish Survey (SCO-WCGFS) (blue). (error bars are ± two standard error).

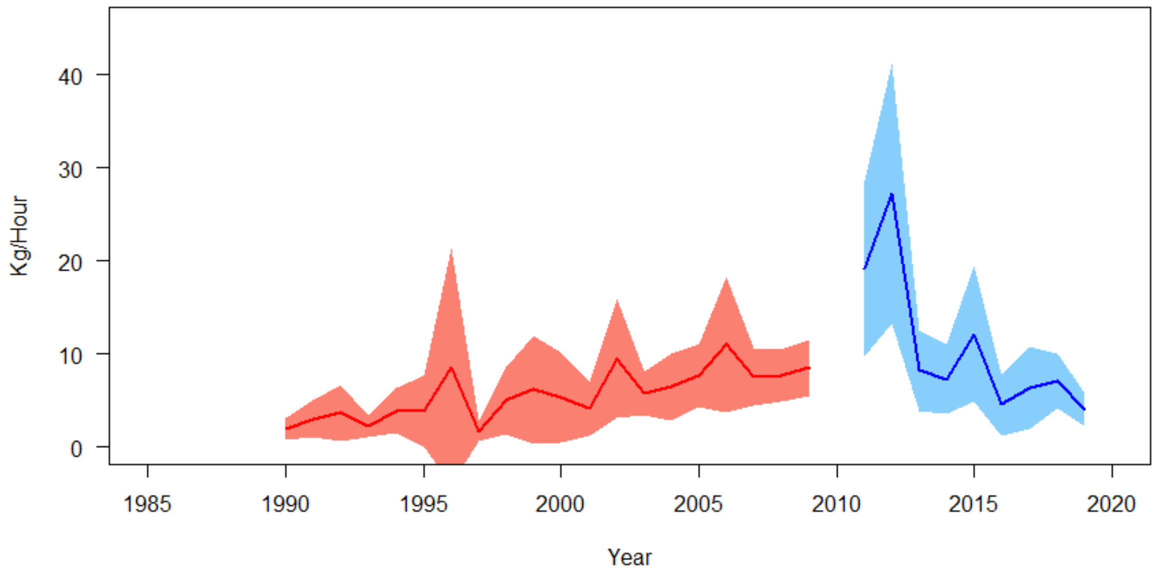
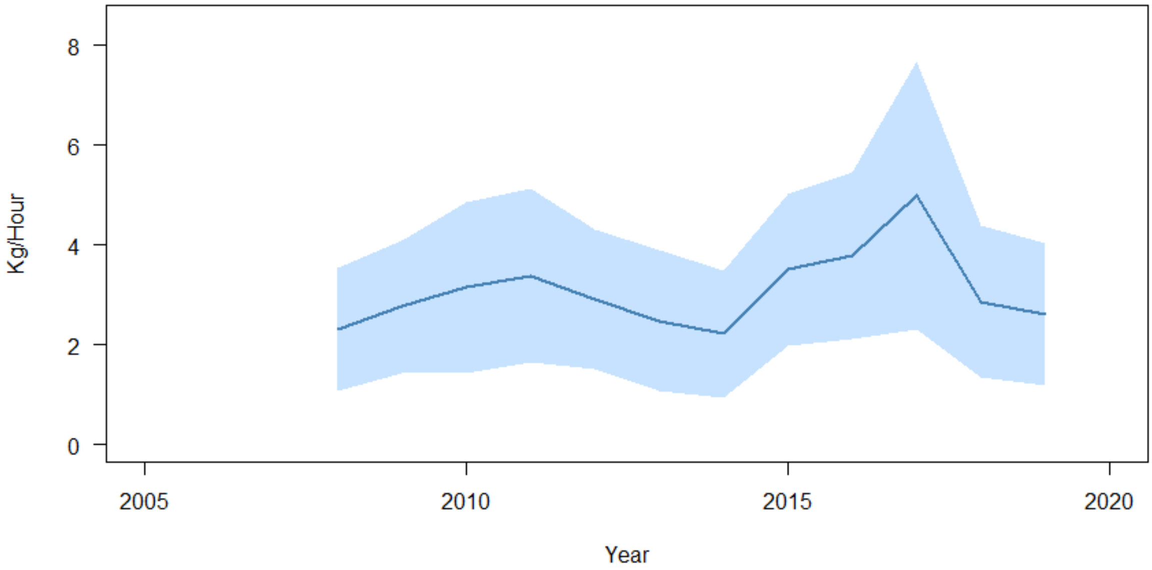


Figure 13. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Quarter 4 Scottish West Coast IBTS (SCO-WCIBTS) (red) and Scottish West Coast Groundfish Survey (SCO-WCGFS) (blue). (error bars are ± two standard error).

Northern Irish Groundfish Survey

Data is available from this survey, which covers the Irish Sea, since 2008. Catches are relatively flat throughout the period, with some suggestion of a peak in 2017.



Other Surveys

Indices from several other surveys were made available through the accessions process.

Spanish Gulf of Cadiz Groundfish Survey (SP-GCGFS)

Data for this survey was submitted to the benchmark through Accessions for the period 1993 - 2019. This survey covers Spanish waters of ICES Division 9a. Catches of red gurnard appear to average less than one fish per haul, and less than 300g, over the entire duration of the available data, with little evidence of variability or strong trends. Without further information such as haul duration it is difficult to reconcile this data with results of other surveys, however it demonstrates the presence of red gurnard at the southern boundary of Div. 9a, outside the area considered in the current assessment.

Spanish Northern Groundfish Survey (SP-NGFS)

The Spanish northern groundfish survey covers ICES Division 8c and the northern part of 9a corresponding to the Cantabrian Sea and off Galicia waters. This survey covers the period 1990 – 2019. This survey is conducted during the third and the fourth quarter (September-October) and covers a depth range of 35 to 700 m. Stratification was redefined in 1997, and is based on three depth strata (70-120, 121-200, 201-500 m) and 5 geographic sectors. Additional hauls both in deeper water (500-700 m) and shallower waters (30-80 m) are conducted yearly depending on the ship time available at sea. The coverage is approximately 5.4 hauls for every 1000 Km^2 (120 hauls per survey).

The survey has been carried out onboard the R/V *Cornide de Saavedra* except in 1989 when another research vessel (N/V F. *de P. Navarro*) was used to conduct the survey. The gear used is a Baka trawl 44/60 with a

43.6m footrope and a 60.1 headline. Until 1985, a codend cover of 20 mm mesh was used, and since then, a 20 mm mesh codend liner has been adopted.

Survey catches have varied without particular trend up to 2013, before increasing to a higher level in 2014 and remaining at for the rest of the series (Figure 14).

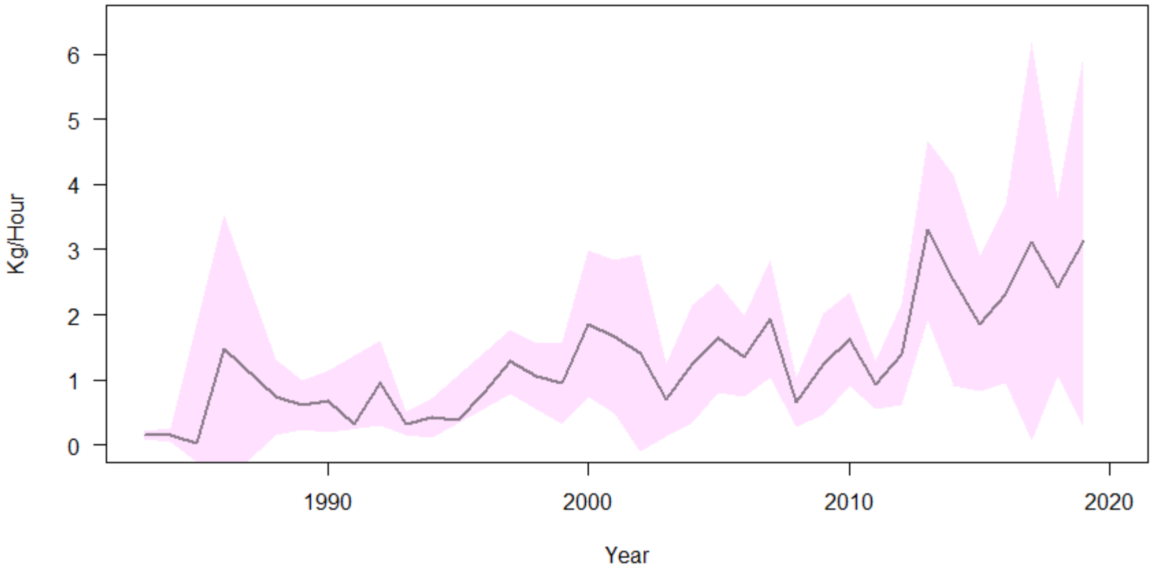


Figure 14. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Spanish Northern Groundfish Survey (SP-NGFS) (error bars are ± two standard error).

Spanish Porcupine Bank Groundfish Survey (SP-PORC)

This survey covers the years 2000 – 2019, and fishes on Porcupine Bank, to the southwest of Ireland. As with the Spanish Northern Survey mean numbers per tow, per year, and a breakdown of these by length, have been provided for red, grey and mixed gurnards. These species have not been included in the data from these surveys which have been uploaded to the Datras database, so it is not possible to include these series in any analytical modelling, however they do show

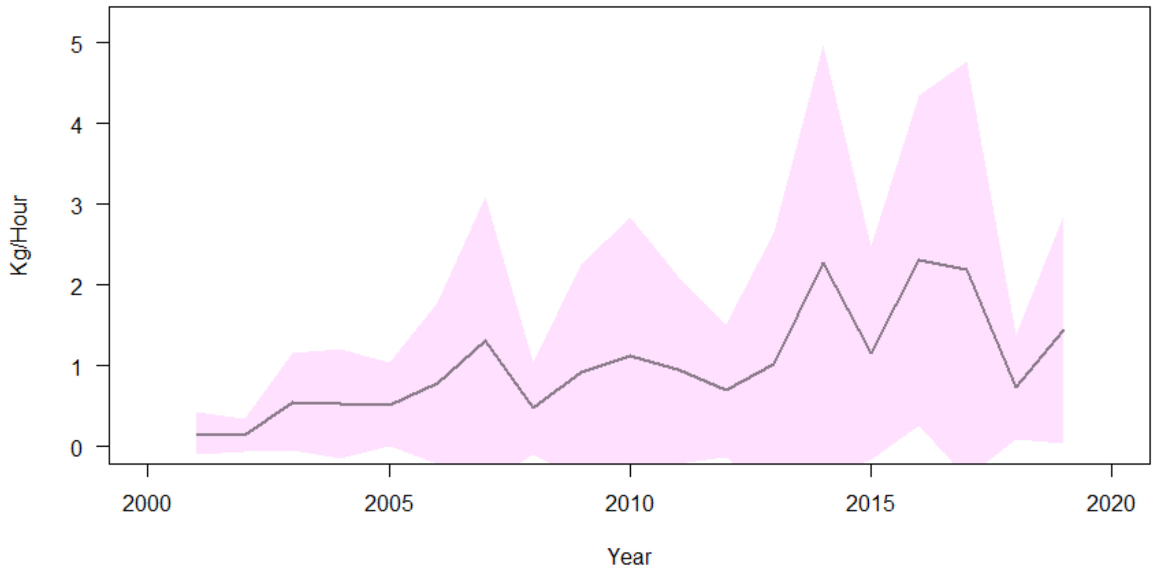


Figure 15. Mean catch of red gurnard (*Chelidonichthys cucculus*) per hour fished in the Spanish Porcupine Bank Survey (SP-PORC) (error bars are ± two standard error).

North Sea IBTS

Red gurnard are relatively frequently reported from Subarea 4 around Shetland, but are otherwise rare in survey data from this region (Annex 2. Distribution of Survey Catches, North Sea International Bottom Trawl Survey (NS-IBTS), 1984 – 2019.). Indicators produced for the North Sea follow closely with the Scottish West Coast surveys, and it may be a useful exercise to combine hauls from the northern part of the North Sea with those to the west of the 4˚ line

Assessment Model

Given the uncertainty around catch data, it was felt that a survey based approach was the most appropriate way to assess the status of red gurnards in SA 3-8.

SURBAR

Age data is available for some years in French and Irish surveys. Such data is not consistently applicable. An exploratory assessment using Surbar was attempted. Given the differences observed in mean length between the different surveys it was considered unhelpful to apply a single age-length key across all surveys. Likewise, conducting an assessment just for the area covered by the EVHOE and CGFS surveys may be more meaningful, however extrapolating from this to an assessment of status and catch advice which is valid across SA 3-8 would be challenging. This route was therefore discounted.

Delta-lognormal GLM

As an attempt to combine the information from surveys covering the assessment area using a delta-lognormal GLM has been undertaken. Delta-lognormal approach has two distinct components, which can be modelled and fitted separately to obtain first a fitted probability of non-zero tows and then the expected number of fish, given that some were caught.

Haul and catch data were downloaded from the ICES DATRAS database for the surveys listed in Figure 7. Numbers at length were converted into a weight at length using the length-weight relationship described in Coull *et al.* (1989) and summed to provide a weight per tow.

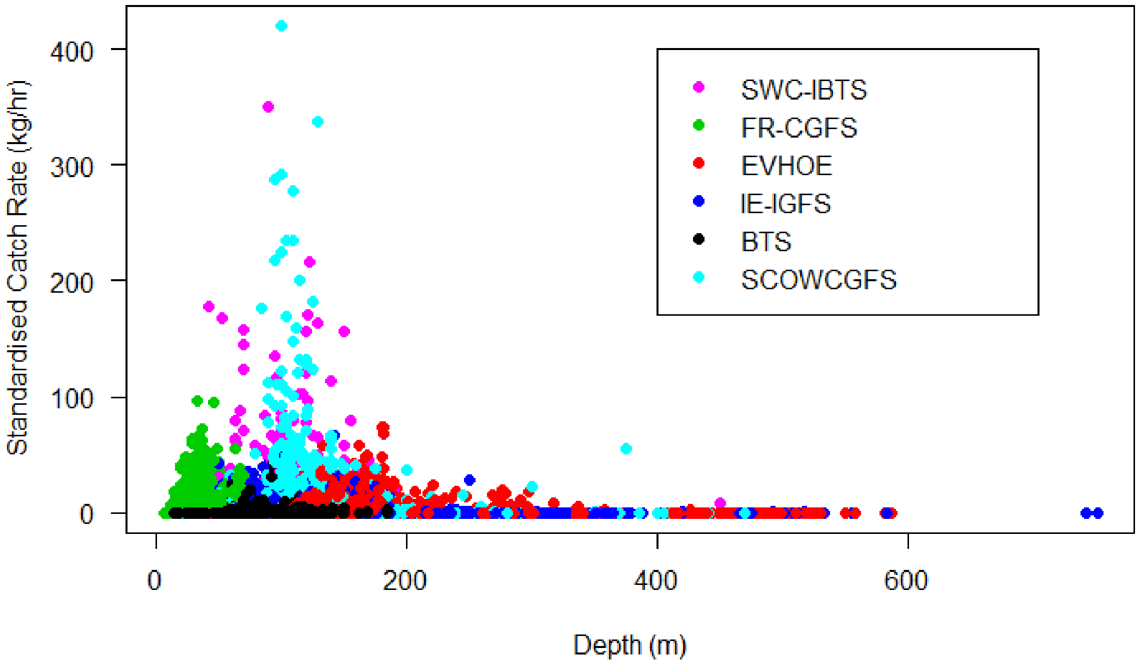


Figure 16. Standardised catch rate (kg/hr) of red gurnard (*Chelidonichthys cucculus*) at depth for each survey in the Datras data.

Having explored the distribution of catches in the survey data, a decision was taken to constrain it to hauls shallower than 300m. This meant retained 99.85% of red gurnard catches, and eliminated a significant number of zero catch hauls at depths beyond the range inhabited by red gurnard, which had undue influence on the significance of parameters within the model (Figure 16).

A process of backwards selection was applied to determine the optimum configuration of the model, using the Akiaike Information Criteria. It became apparent that the Northern Irish Groundfish Survey was not informative to the results, which is perhaps not surprising given the lack of contrast in the data. The decision was taken to remove this survey from the data. The final model configuration for the binomial part of the model was:

```
~ as.factor(Quarter) + HaulLong + Depth * as.factor(Survey)
```

and for the lognormal part:

```
st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
            HaulLat + Depth * as.factor(Survey)
```

Significance of parameters in the binomial part of the model are shown in Table 4, and for the lognormal part in Table 5. Residuals and other measures of goodness of fit are shown in Figure 17.

	Estimate	Std. Error	z value	Pr(>|z|)	
bin.X[, -1](Intercept)	-1.4850615	0.1183509	-12.548	< 2e-16	***
bin.X[, -1]as.factor(Quarter)4	0.3993168	0.0687027	5.812	6.16e-09	***
bin.X[, -1]HaulLong	-0.1480214	0.0098320	-15.055	< 2e-16	***
bin.X[, -1]Depth	0.0010120	0.0014837	0.682	0.495189	
bin.X[, -1]as.factor(Survey)EVHOE	1.3399956	0.1561780	8.580	< 2e-16	***
bin.X[, -1]as.factor(Survey)FR-CGFS	-1.6143181	0.1945342	-8.298	< 2e-16	***
bin.X[, -1]as.factor(Survey)IE-IGFS	0.9257651	0.1658455	5.582	2.38e-08	***
bin.X[, -1]as.factor(Survey)SCOWCGFS	1.6821794	0.2065904	8.143	3.87e-16	***
bin.X[, -1]as.factor(Survey)SWC-IBTS	0.2846889	0.1634053	1.742	0.081469	.
bin.X[, -1]Depth:as.factor(Survey)EVHOE	-0.0045159	0.0015195	-2.972	0.002959	**
bin.X[, -1]Depth:as.factor(Survey)FR-CGFS	0.0899175	0.0044930	20.013	< 2e-16	***
bin.X[, -1]Depth:as.factor(Survey)IE-IGFS	-0.0079151	0.0015432	-5.129	2.91e-07	***
bin.X[, -1]Depth:as.factor(Survey)SCOWCGFS	-0.0070669	0.0018437	-3.833	0.000127	***
bin.X[, -1]Depth:as.factor(Survey)SWC-IBTS	0.0003019	0.0016584	0.182	0.855544	

Table 4. Results of the binomial part of the delta-lognormal GLM.

	Estimate	Std. Error	t value	Pr(>|t|)	
nz.X(Intercept)	-4.964511	0.614600	-8.078	7.56e-16	***
nz.Xas.factor(Year)1986	-0.683194	0.476798	-1.433	0.151932	
nz.Xas.factor(Year)1987	0.175006	0.418639	0.418	0.675932	
nz.Xas.factor(Year)1988	1.120429	0.348043	3.219	0.001290	**
nz.Xas.factor(Year)1989	1.083736	0.360939	3.003	0.002686	**
nz.Xas.factor(Year)1990	0.200161	0.329877	0.607	0.544018	
nz.Xas.factor(Year)1991	0.410389	0.326077	1.259	0.208223	
nz.Xas.factor(Year)1992	0.638752	0.337030	1.895	0.058096	.
nz.Xas.factor(Year)1993	0.534820	0.335199	1.596	0.110633	
nz.Xas.factor(Year)1994	0.985903	0.331594	2.973	0.002956	**
nz.Xas.factor(Year)1995	0.686056	0.332572	2.063	0.039156	*
nz.Xas.factor(Year)1996	0.436754	0.335531	1.302	0.193063	
nz.Xas.factor(Year)1997	0.501881	0.313215	1.602	0.109117	
nz.Xas.factor(Year)1998	0.584525	0.315500	1.853	0.063962	.
nz.Xas.factor(Year)1999	0.613430	0.315625	1.944	0.051985	.
nz.Xas.factor(Year)2000	0.569134	0.313370	1.816	0.069382	.
nz.Xas.factor(Year)2001	0.698331	0.310099	2.252	0.024352	*
nz.Xas.factor(Year)2002	0.686320	0.308563	2.224	0.026159	*
nz.Xas.factor(Year)2003	0.772443	0.305067	2.532	0.011359	*
nz.Xas.factor(Year)2004	0.960070	0.305166	3.146	0.001661	**
nz.Xas.factor(Year)2005	0.940577	0.304569	3.088	0.002020	**
nz.Xas.factor(Year)2006	0.953640	0.303890	3.138	0.001707	**
nz.Xas.factor(Year)2007	1.075352	0.303033	3.549	0.000389	***
nz.Xas.factor(Year)2008	1.117513	0.302651	3.692	0.000224	***
nz.Xas.factor(Year)2009	1.216356	0.303223	4.011	6.09e-05	***
nz.Xas.factor(Year)2010	1.050216	0.304398	3.450	0.000563	***
nz.Xas.factor(Year)2011	0.925536	0.305438	3.030	0.002452	**
nz.Xas.factor(Year)2012	1.107489	0.304857	3.633	0.000282	***
nz.Xas.factor(Year)2013	1.113187	0.304728	3.653	0.000261	***
nz.Xas.factor(Year)2014	0.849234	0.304993	2.784	0.005375	**
nz.Xas.factor(Year)2015	0.924688	0.305443	3.027	0.002475	**
nz.Xas.factor(Year)2016	0.946534	0.305015	3.103	0.001921	**
nz.Xas.factor(Year)2017	0.923790	0.309261	2.987	0.002825	**
nz.Xas.factor(Year)2018	0.941680	0.305476	3.083	0.002059	**
nz.Xas.factor(Year)2019	0.781174	0.306181	2.551	0.010749	*
nz.Xas.factor(Quarter)4	0.167678	0.068301	2.455	0.014110	*
nz.Xas.factor(Survey)EVHOE	-0.422323	0.225670	-1.871	0.061324	.
nz.Xas.factor(Survey)FR-CGFS	2.208761	0.225970	9.775	< 2e-16	***
nz.Xas.factor(Survey)IE-IGFS	1.185062	0.218207	5.431	5.77e-08	***
nz.Xas.factor(Survey)SCOWCGFS	2.521000	0.275465	9.152	< 2e-16	***
nz.Xas.factor(Survey)SWC-IBTS	1.872557	0.239891	7.806	6.65e-15	***

```
nz.XHaulLat                             0.065862   0.010164   6.480 9.73e-11 ***
nz.XDepth                               0.010381   0.002074   5.007 5.66e-07 ***
nz.Xas.factor(Survey)EVHOE:Depth        0.001587   0.002248   0.706 0.480389
nz.Xas.factor(Survey)FR-CGFS:Depth    -0.010326   0.003661  -2.821 0.004806 **
nz.Xas.factor(Survey)IE-IGFS:Depth    -0.014280   0.002233  -6.394 1.71e-10 ***
nz.Xas.factor(Survey)SCOWCGFS:Depth -0.015028   0.002592  -5.798 6.96e-09 ***
nz.Xas.factor(Survey)SWC-IBTS:Depth -0.015258   0.002346  -6.503 8.36e-11 ***
```

Table 5. Results of the lognormal part of the model.

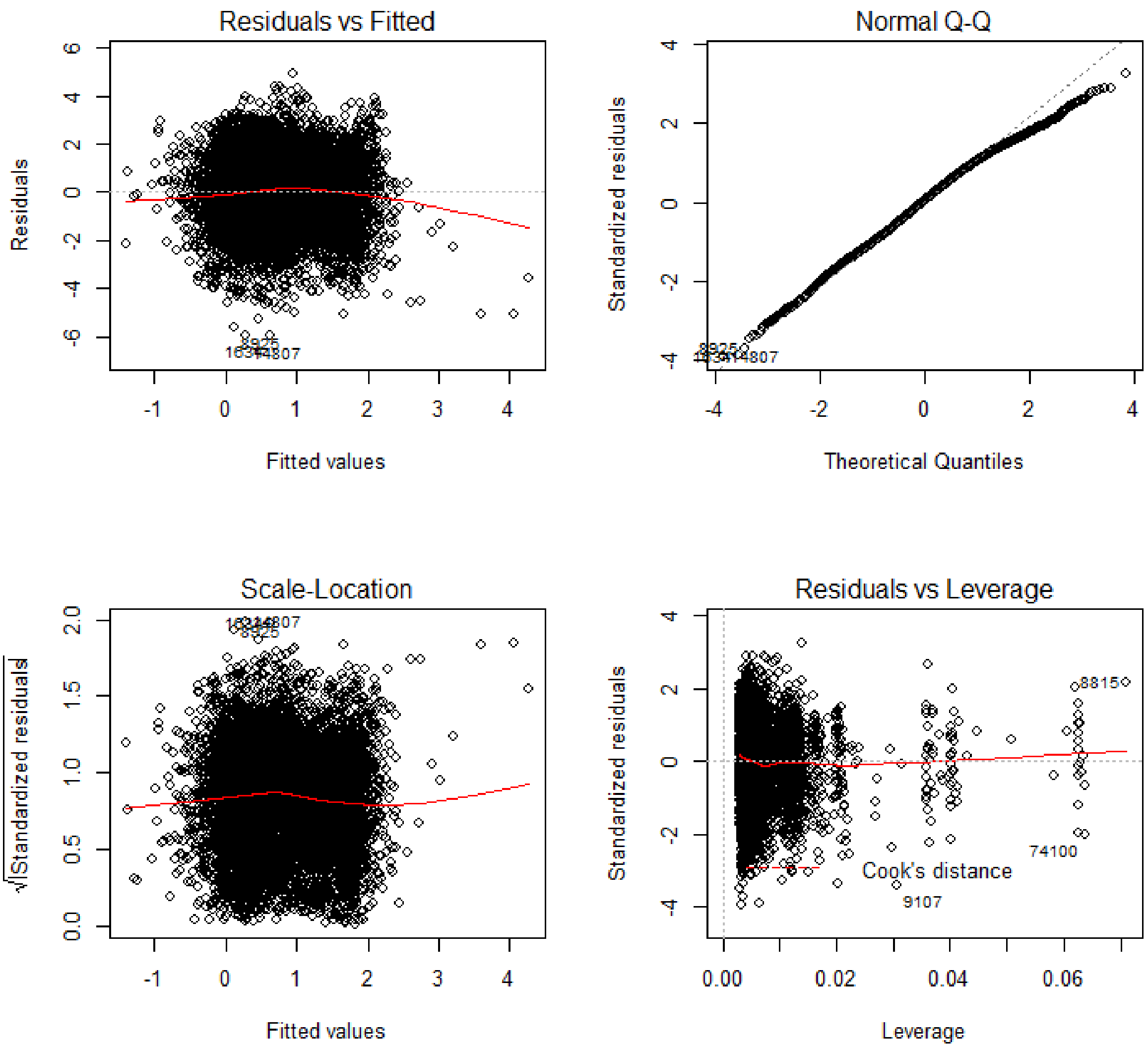


Figure 17. Goodness of fit measures for the final model.

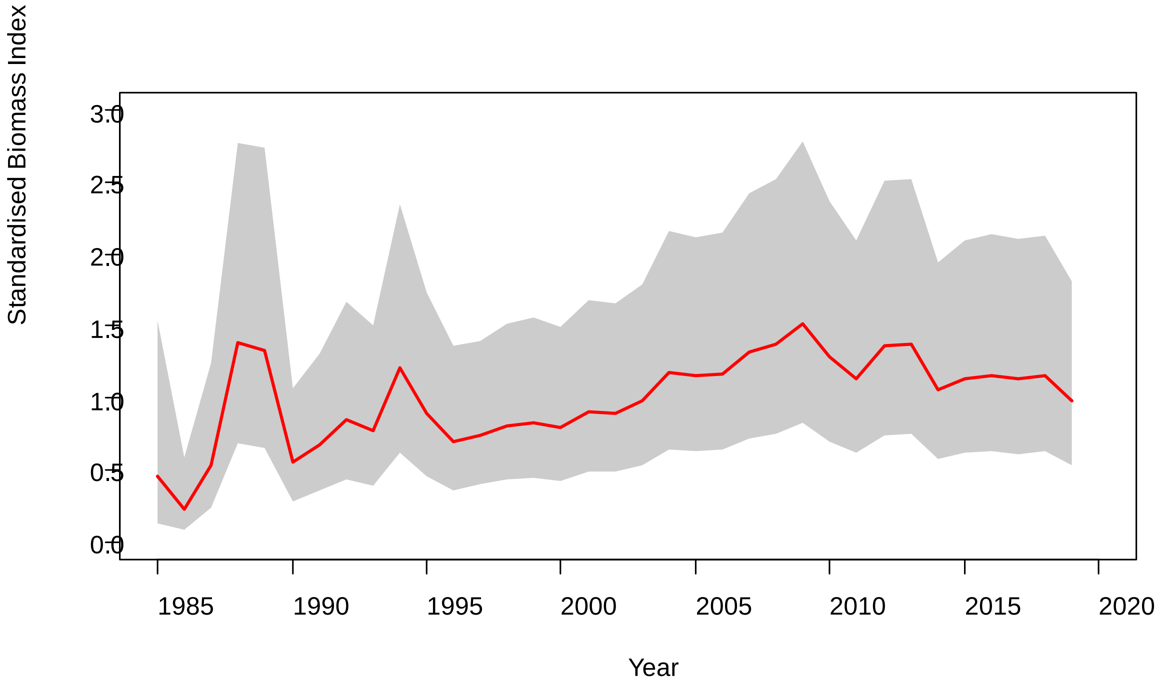


Figure 18. Biomass index extracted from the final model formulation, 1985 - 2019 (±2 s.e.).

Extracting the estimates of year effect from the model, together with their associated standard error, and standardising them relative to their average value, provides an index of biomass which is highly variable in the early years of the series (Figure 18). It should be noted that at this time, only the French Channel Groundfish Survey and Scottish West Coast IBTS surveys were active. These areas are widely separated geographically, and there are remaining uncertainties as to the linkages of these in a single stock. The introduction of the EVHOE survey in 1997provides a wider area of coverage and a more stable index. Using only data from 1997 onwards produces a more consistent index, and this is proposed as the final assessment approach.

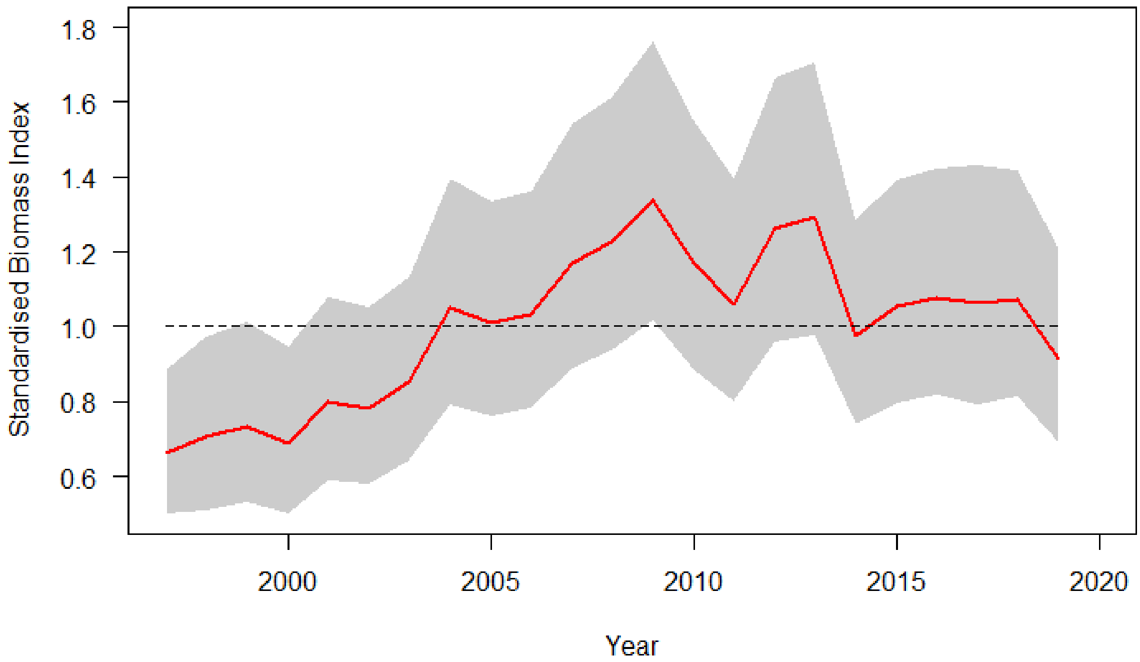


Figure 19. Biomass index calculated from the final model run, scaled relative to the 1997 - 2019 mean. (±2 s.e.)

Somewhat unsurprisingly, given the lack of strong trends in any of the input data series, there is little evidence of strong trends in the model results either. The picture is of a steady increase in biomass from a low in 1997 to a peak in 2009, followed by a decline to the long term average by 2014, and stability at this level thereafter.

As there is a significant quantity of data available, the addition of each new year into the model has only a limited effect on the fit of the model as a whole, therefore the retrospective pattern for this assessment is relatively minor (Figure 20).

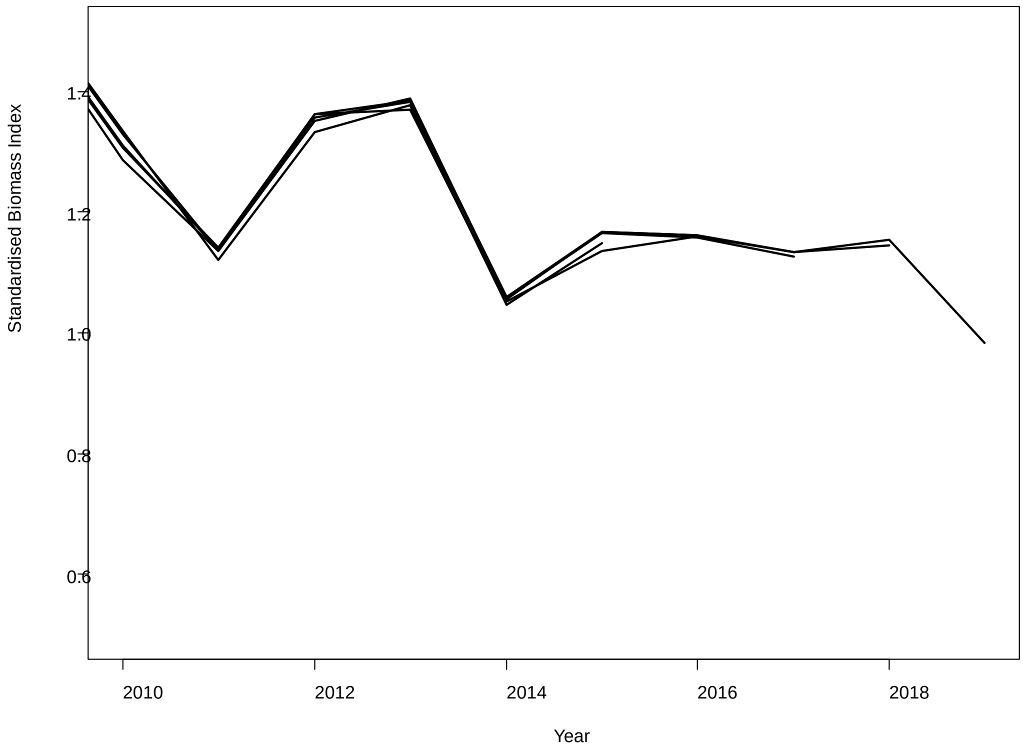


Figure 20. Five retrospective peels in the red gurnard (*Chelidonichthys cucculus*) assessment model, 2015 - 2019.

A “leave-one-out” analysis of the influence of the different survey series on overall perceptions shows that the index is relatively robust to the removal of single series from the analysis (Figure 21). The exception to this is the French Channel Groundfish Survey, the exclusion of which results in a more negative perception of state in the early years of the series, and a more positive one later. This survey, and the Scottish west coast IBTS, are the only two series present before 1997. This goes some way to justify our exclusion of this period in the final analysis.

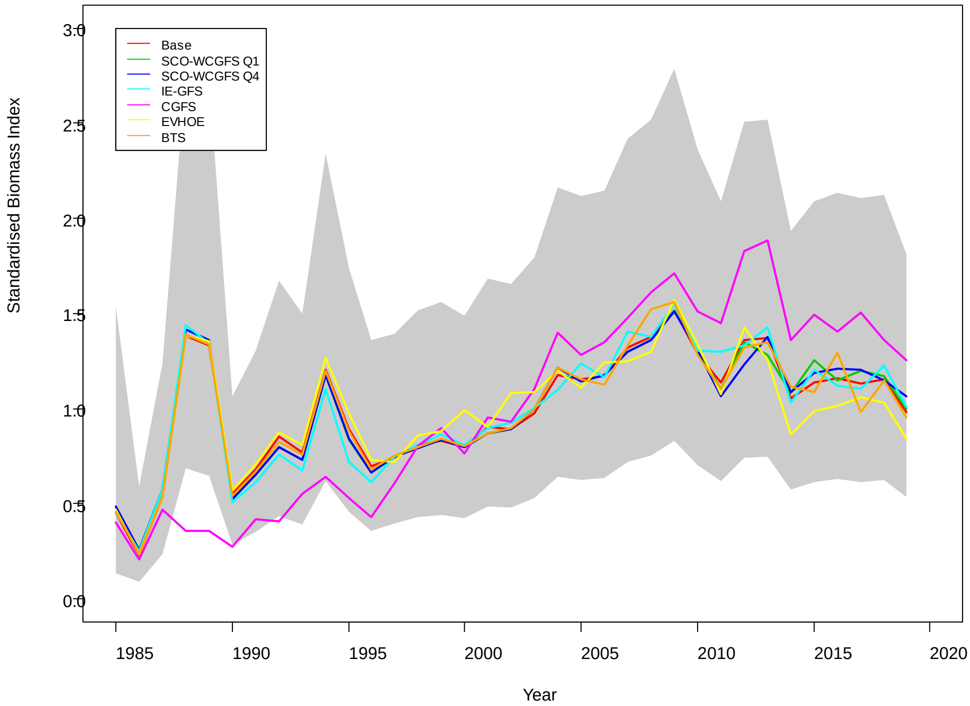


Figure 21. Leave one out analysis of the influence of the different survey series on perception of trends.

Conclusions

Although there is clearly considerable data collected on red gurnards in SA 3-8, it is not clear if it is sufficient to resolve all the issues identified with the assessment.

The consensus view from SIMWG was to continue assessing as a single stock. The question remains as to whether the area used for the assessment is the most appropriate or whether the definition should be revised in the future.

Interpretation of landings data is complicated by the reporting of variable quantities of a mixture of several species of gurnard, including red, in addition. It may be the case that the best outcome for now is to proceed with a purely survey based assessment, consider how this can be used for advice when reported landings may differ significantly from total landings; and where discarding can be high yet unquantifiable, and make recommendations via other ICES bodies aimed at improving data quality and reporting for gurnards in the years ahead.

Given the wide ranging distribution of the species, it is not surprising that there are multiple surveys which inform on the status of the stock. We have produced an indicator which combines the results of these surveys, but which tells us relatively little about changes in the status of the stock, or where it may be in relation to biologically meaningful reference points. Future work examining length based indicators may be helpful, however the single greatest contribution that could be made to the assessment and management of red gurnards would be establishing a robust programme of data collection allowing estimation of landings and discards at species level.

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Harley, B. and Ellis, J. (2007). The modified GOV and ground gear "D". ICES CM/Q:02, 32pp.

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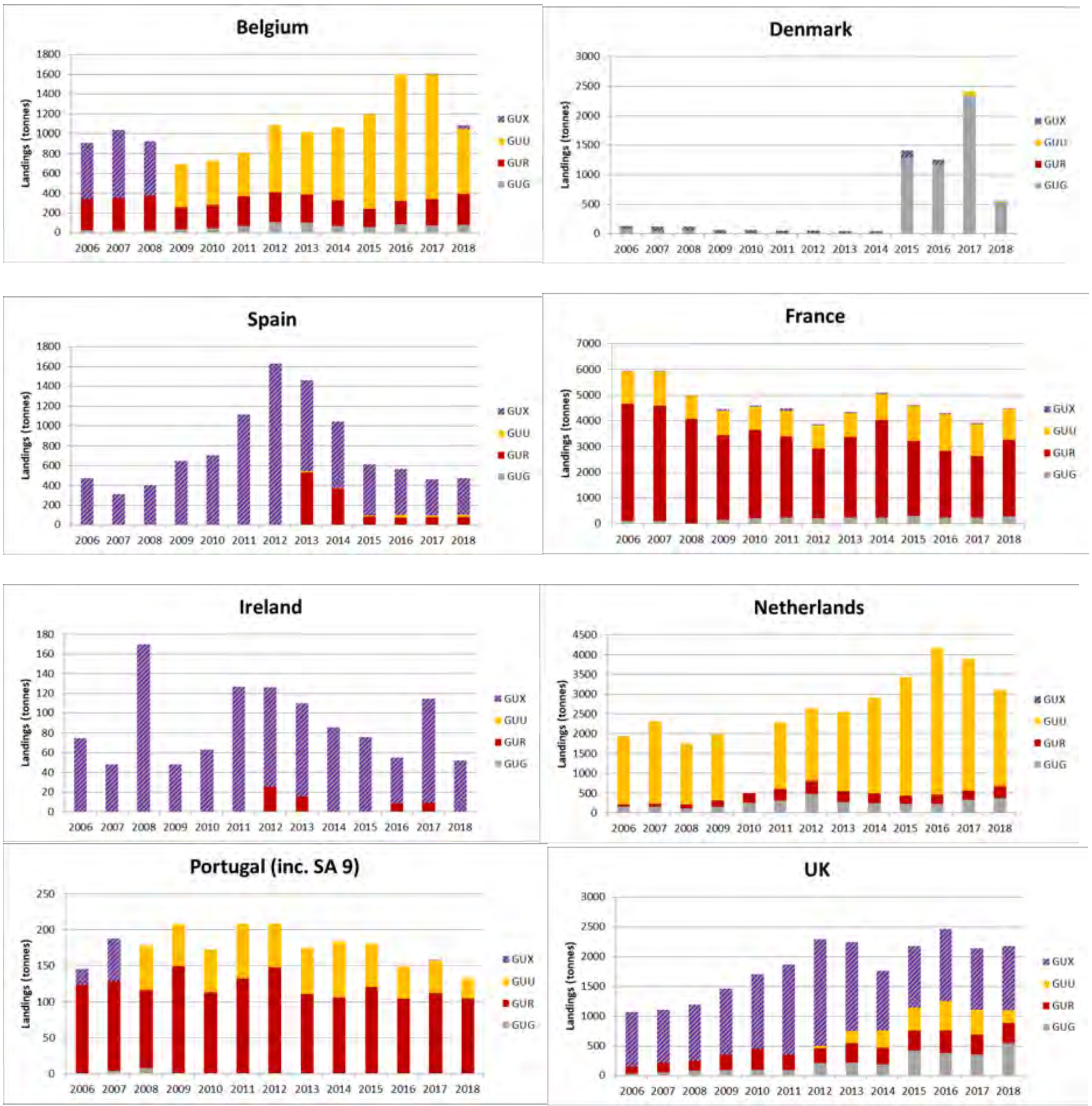
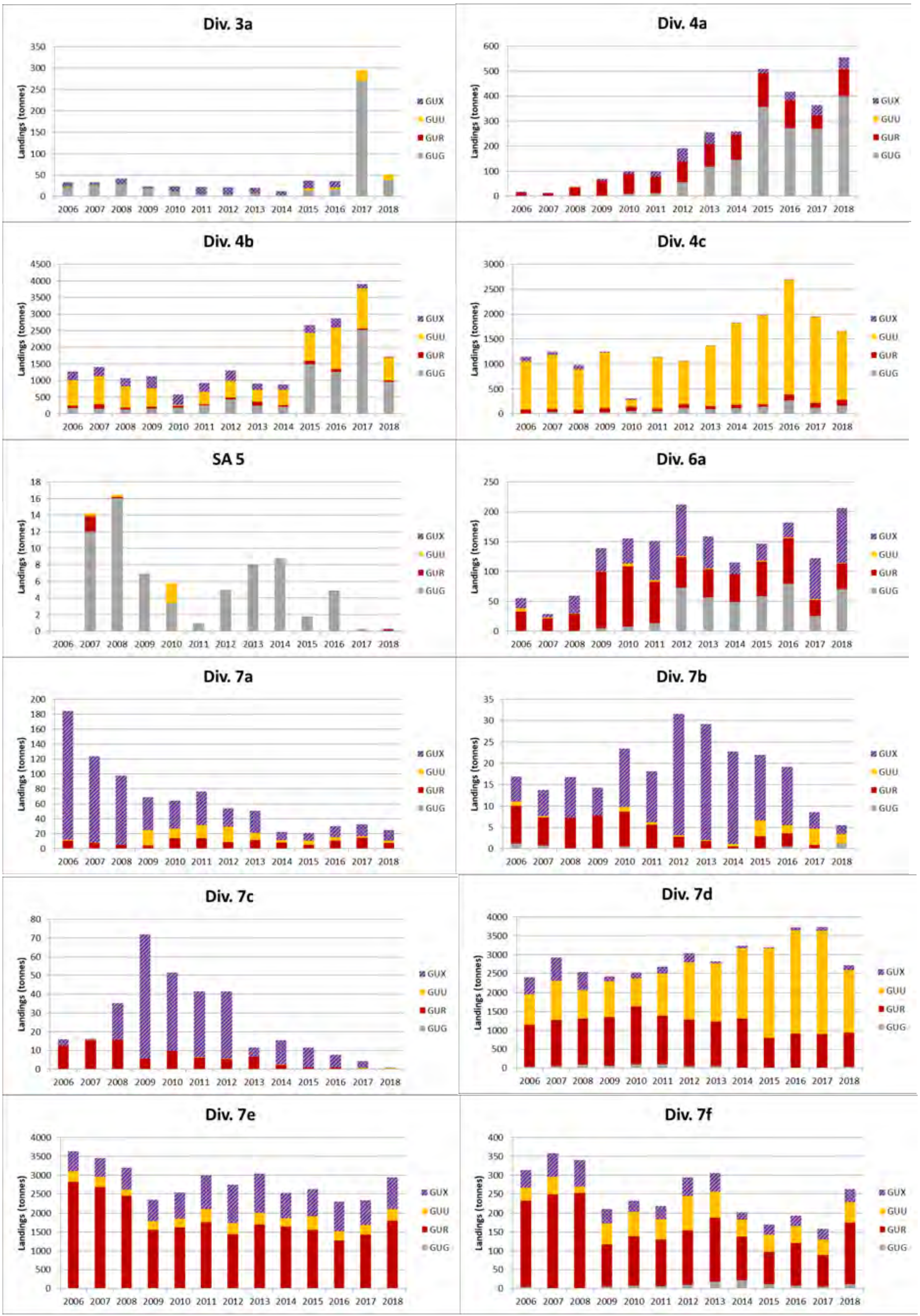
Annex 1

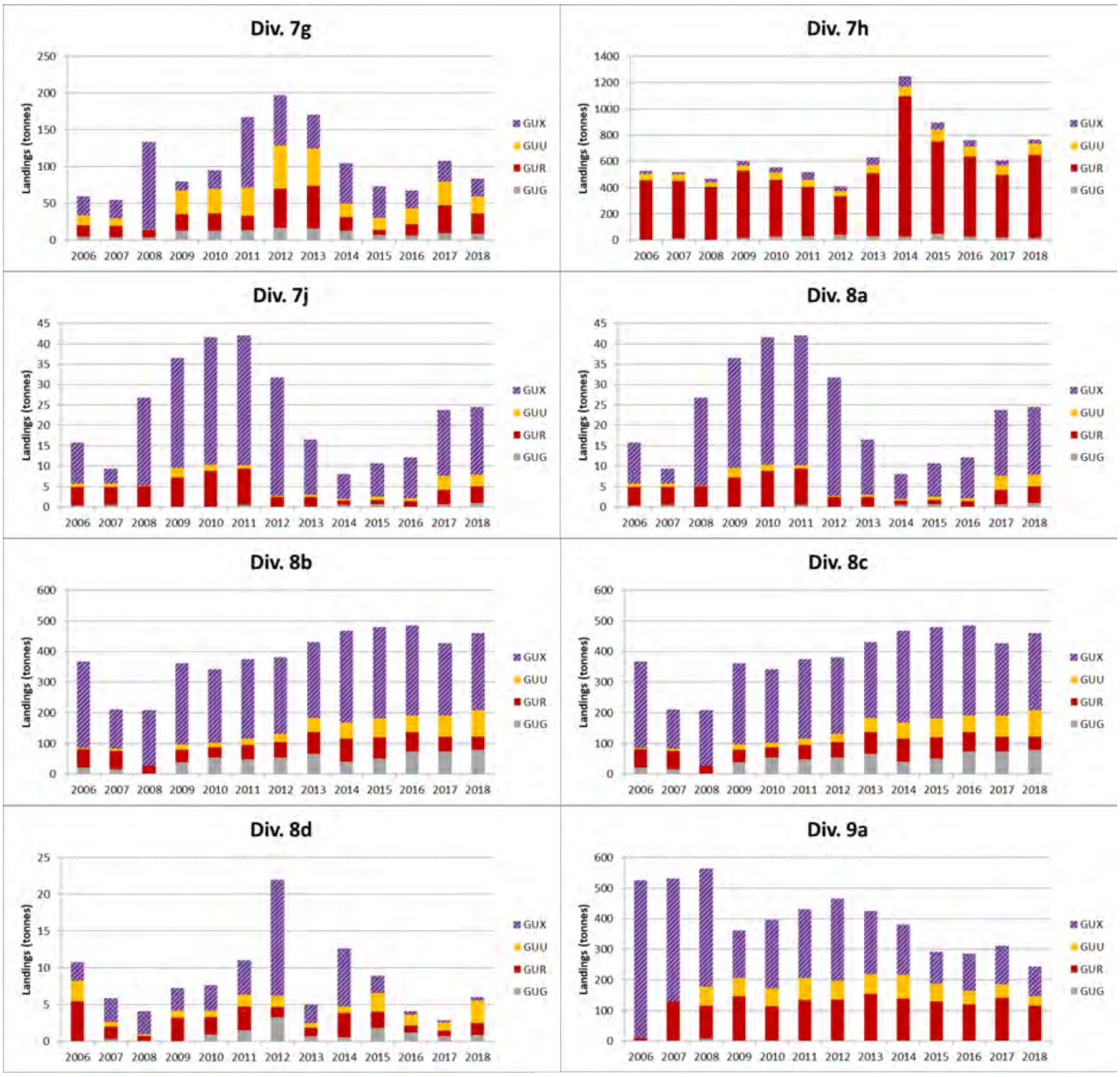
Landings of gurnards, by species, for each country, 2006 – 2018.



Landings of gurnards, by species, for each division, 2006 – 2018.



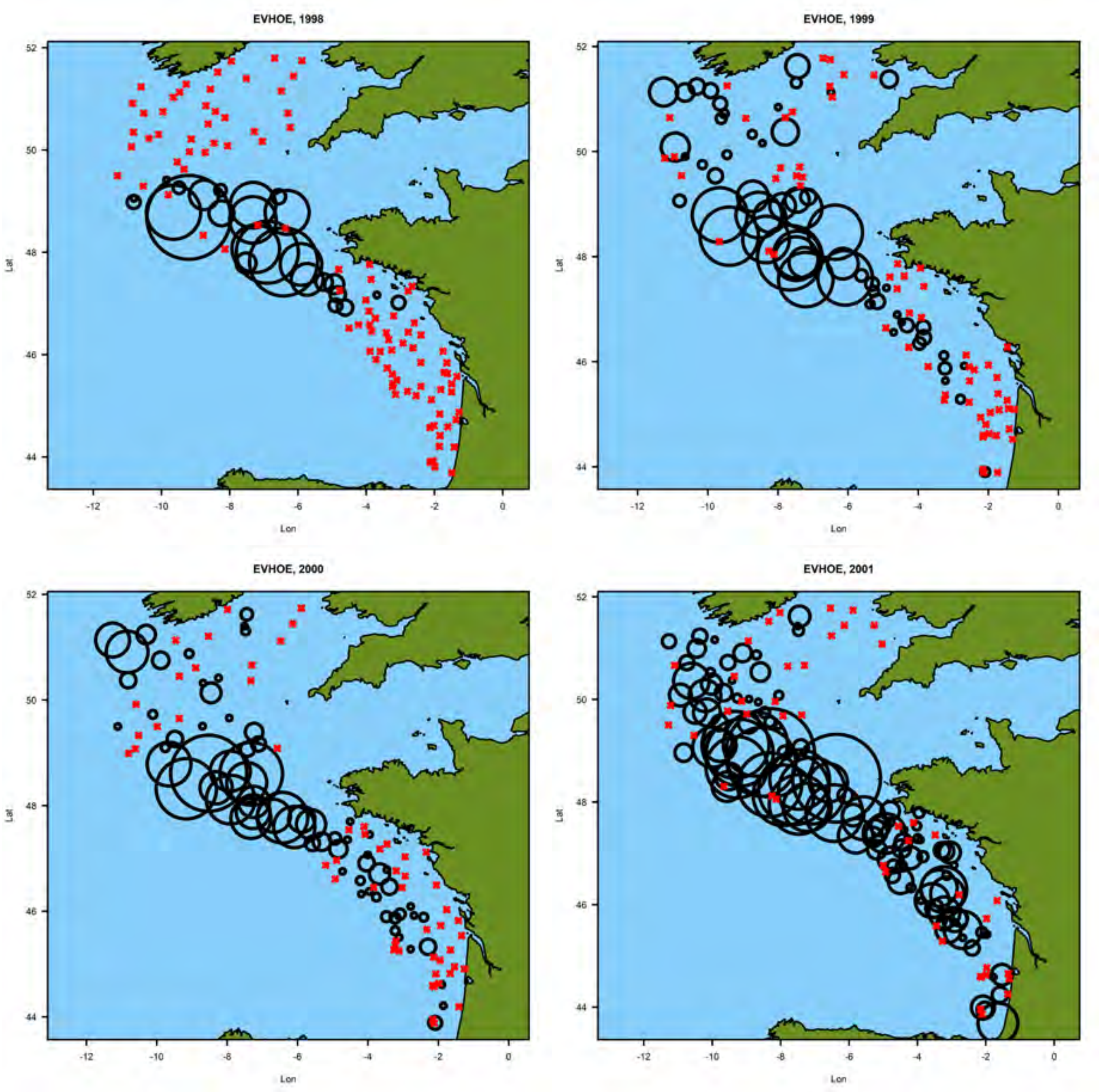
Landings of gurnards, by species, for each division, 2006 – 2018 (cont.).

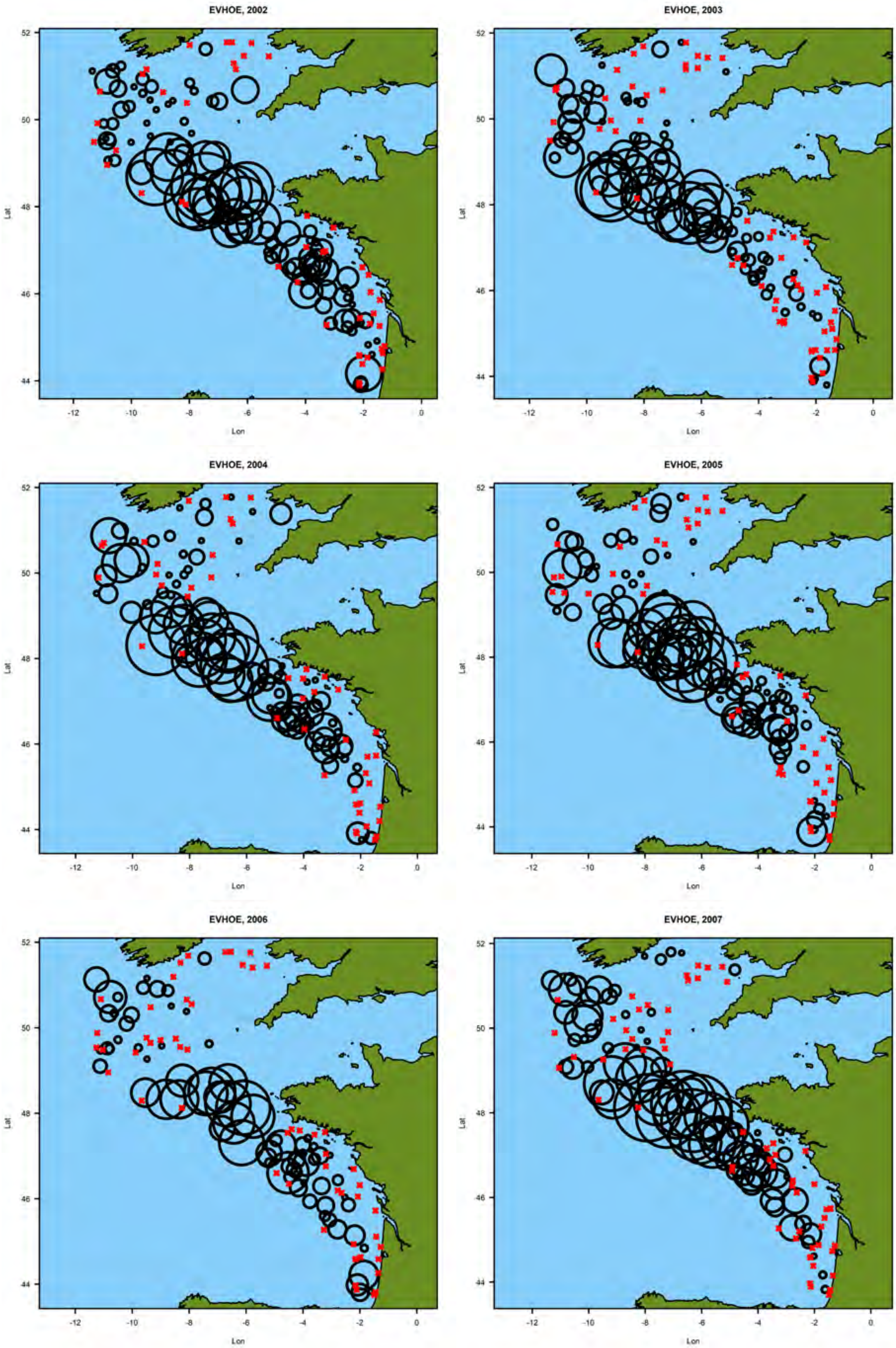


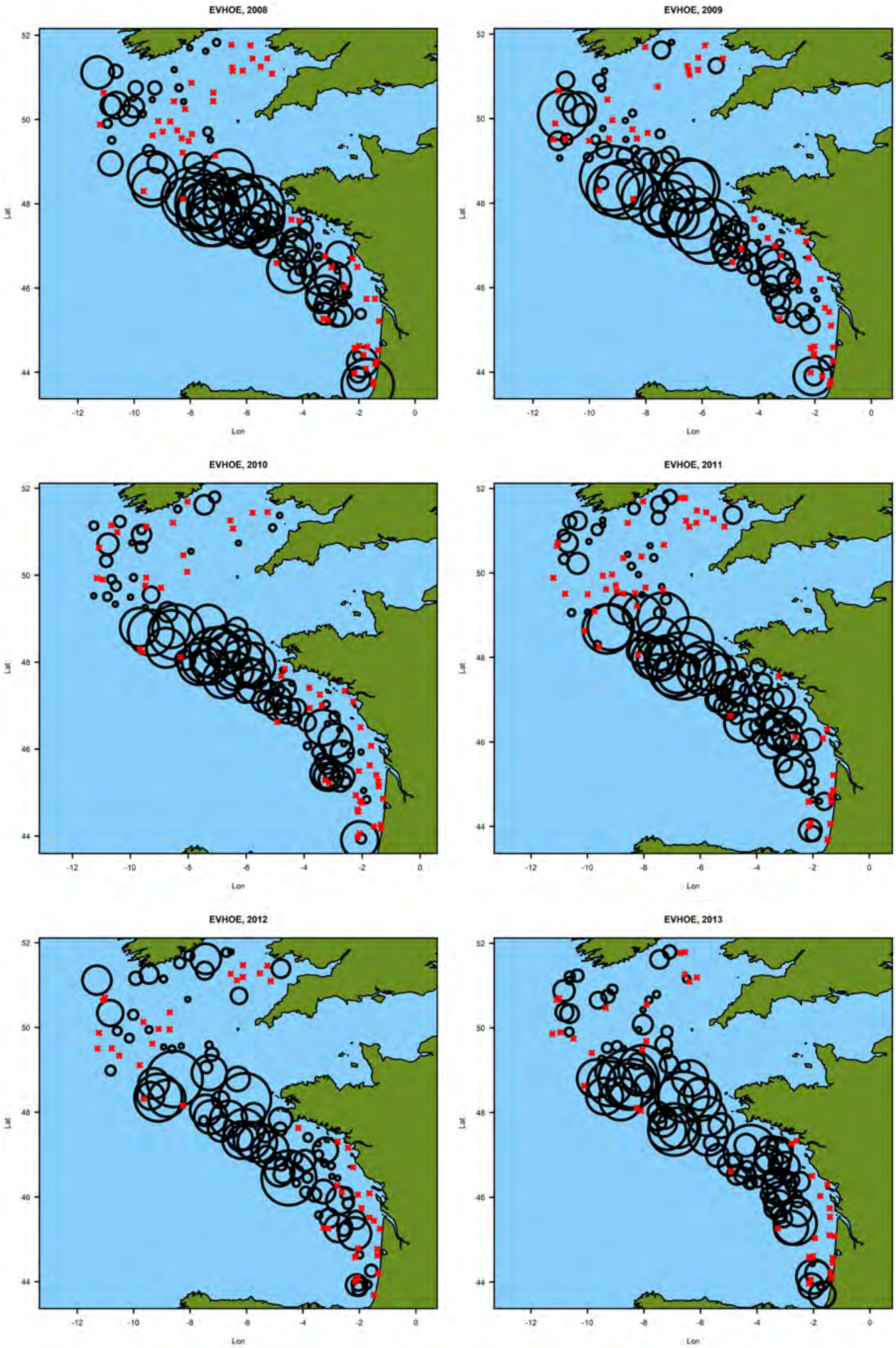
Landings of gurnards, by subarea, for the major fishing countries.

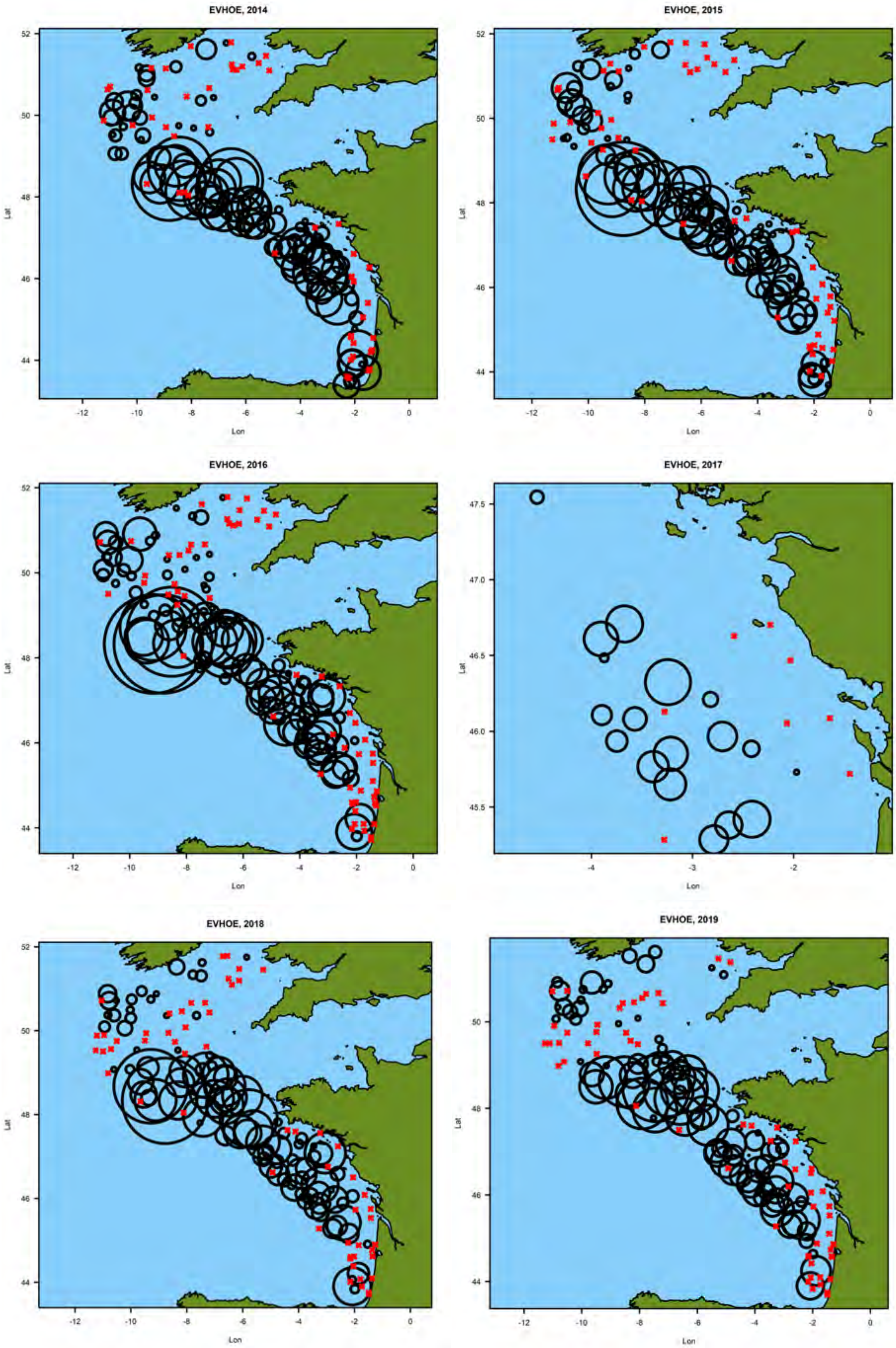
Annex 2. Distribution of Survey Catches

French EVHOE Survey, 1998 – 2019

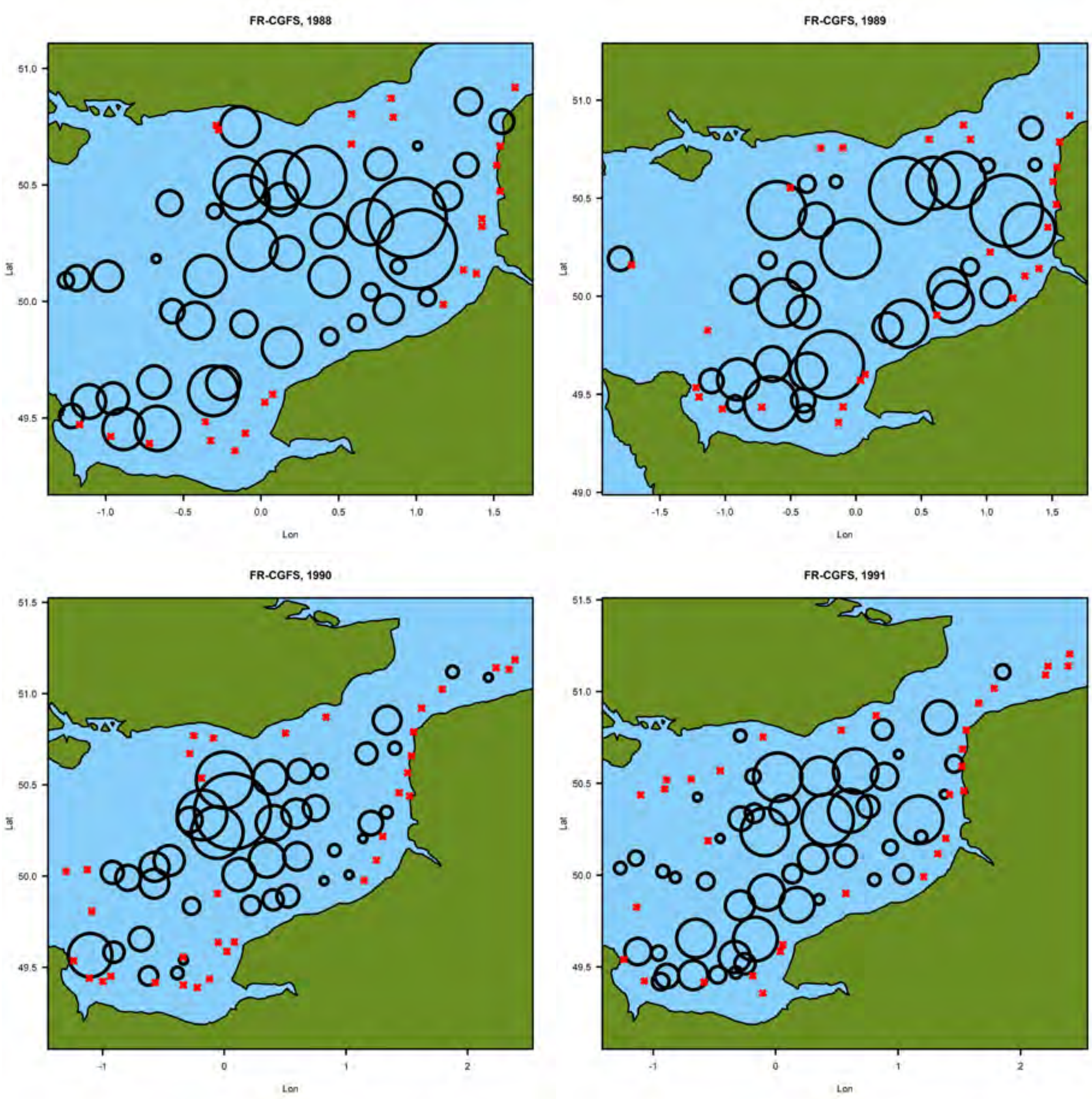



EVHOE, 2002
EVHOE, 2003
EVHOE, 2004
EVHOE, 2005
EVHOE, 2006
EVHOE, 2007
Lat
Lon

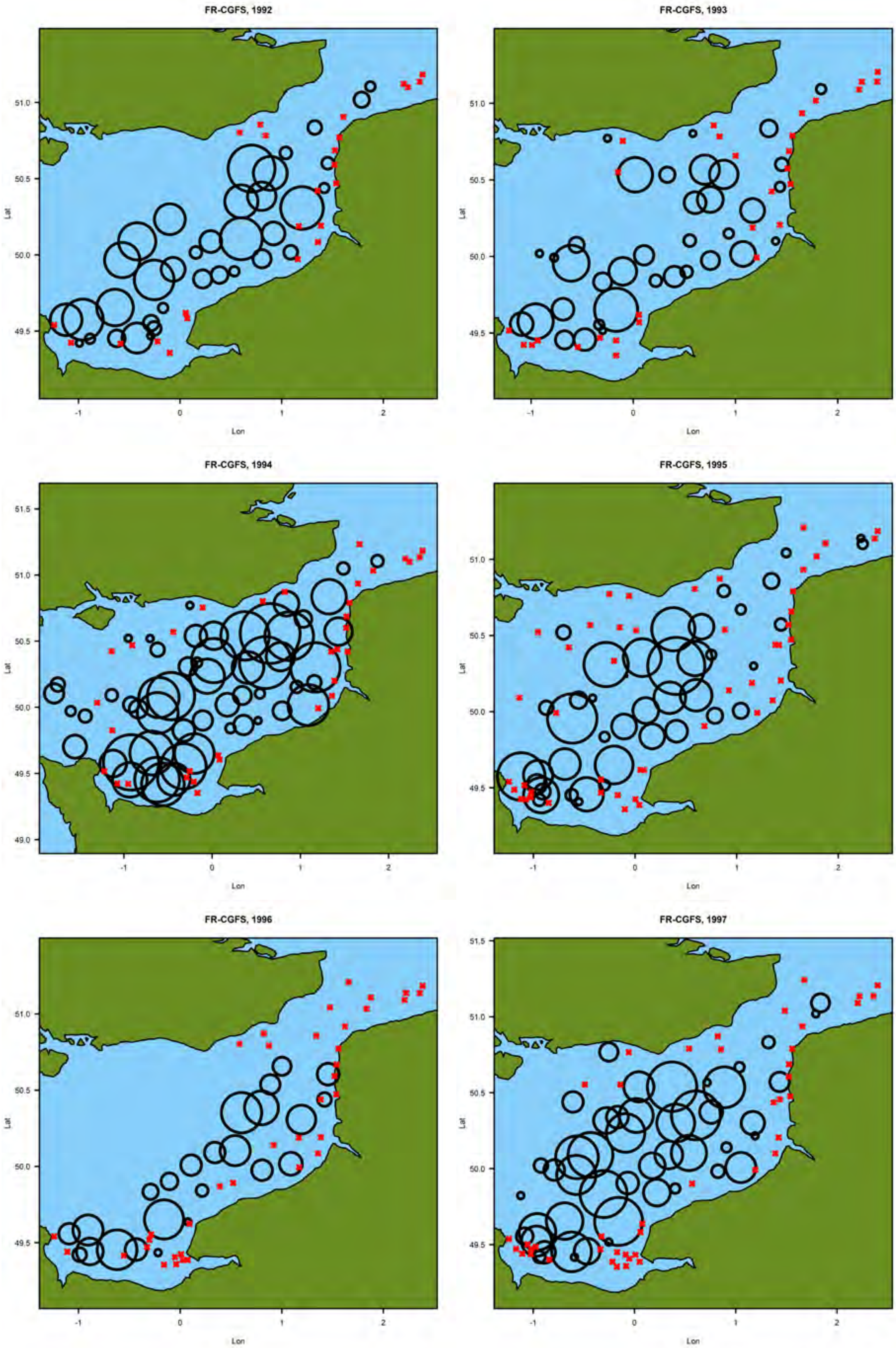

EVHOE, 2008
EVHOE, 2009
EVHOE, 2010
EVHOE, 2011
EVHOE, 2012
EVHOE, 2013
Lat
Lon

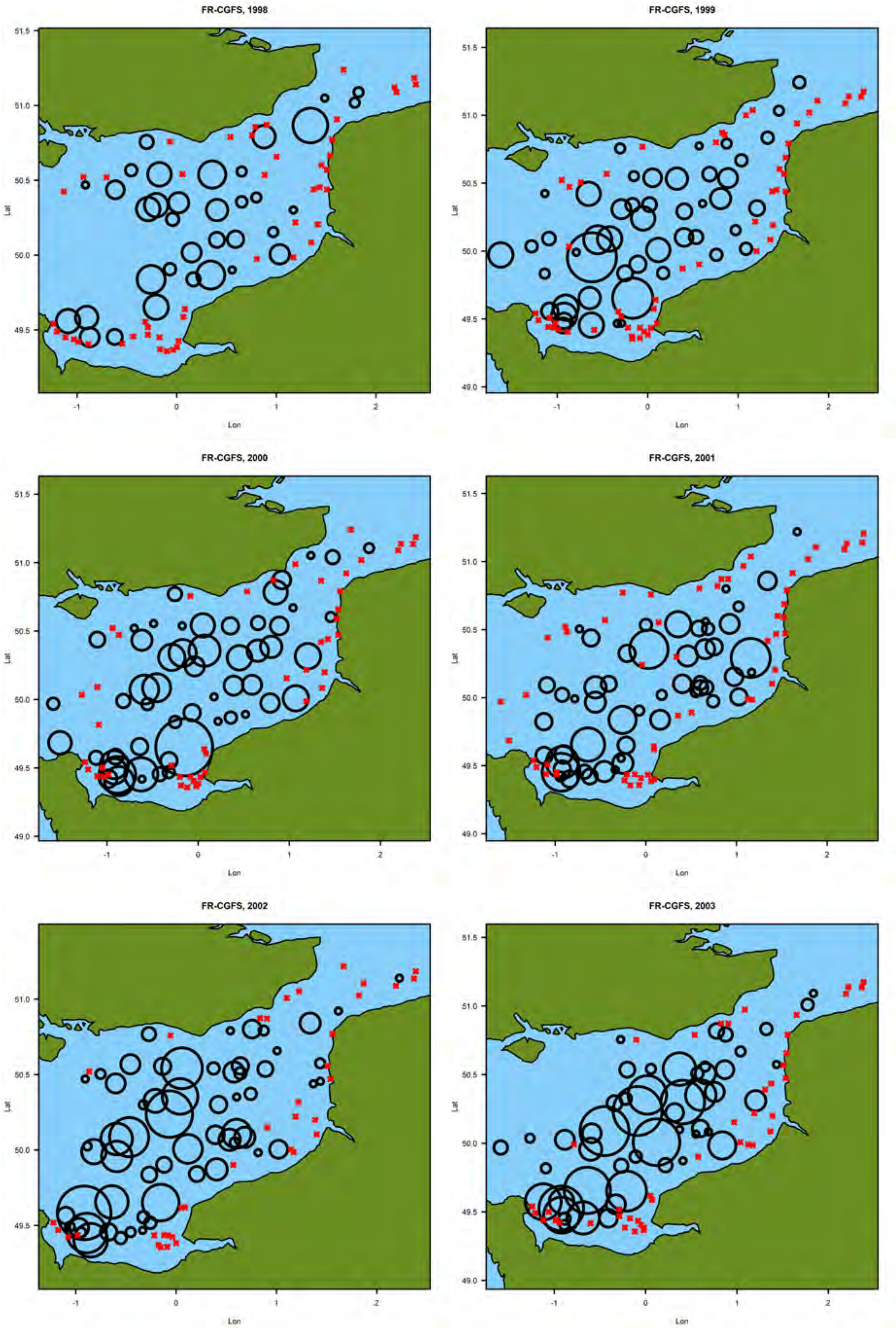

EVHOE, 2014
EVHOE, 2015
EVHOE, 2016
EVHOE, 2017
EVHOE, 2018
EVHOE, 2019
Lat
Lon
52
50
48
46
44
47.5
47.0
46.5
46.0
45.5
-12
-10
-8
-6
-4
-3
-2
0

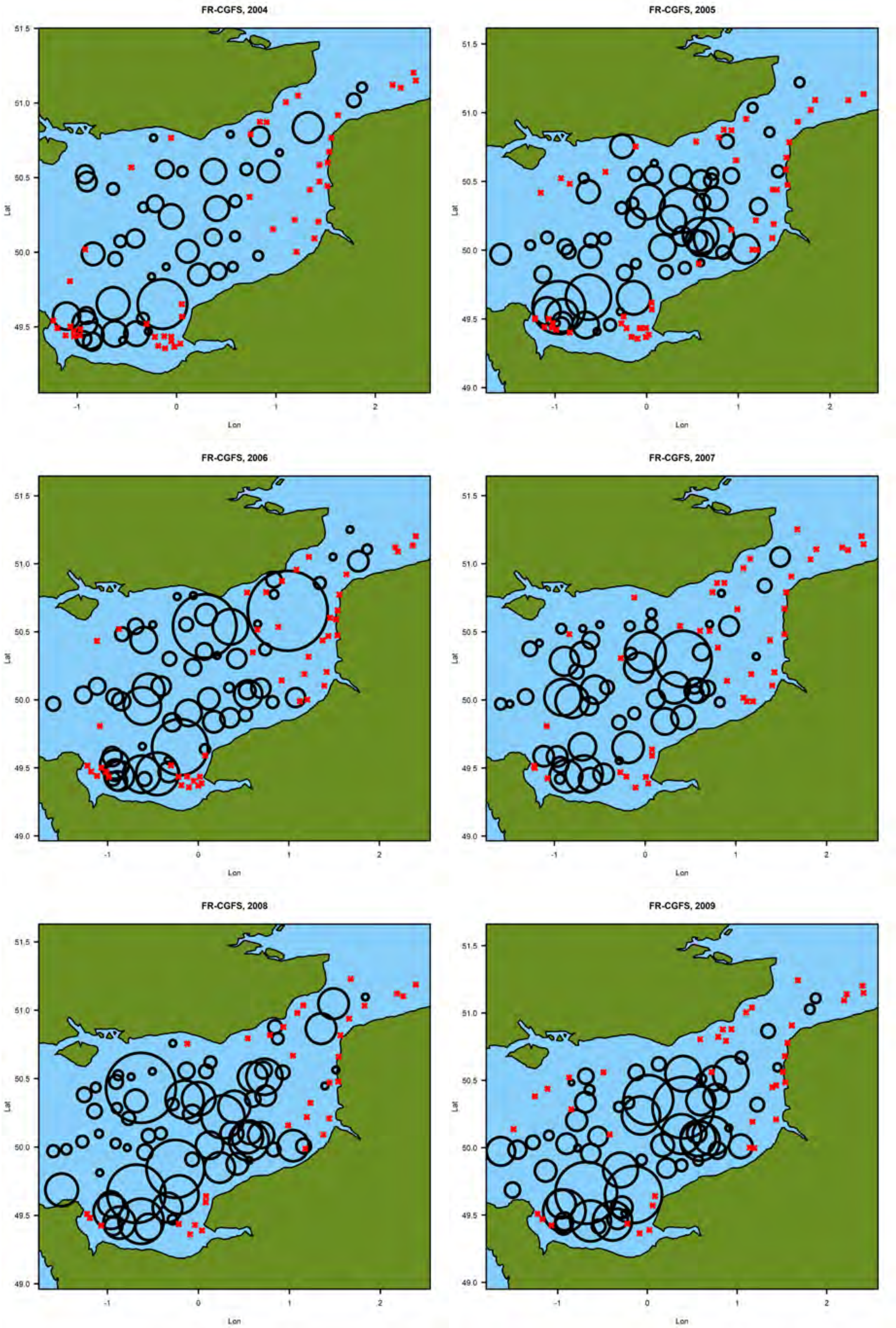
French Channel Groundfish Survey (FR-CGFS)

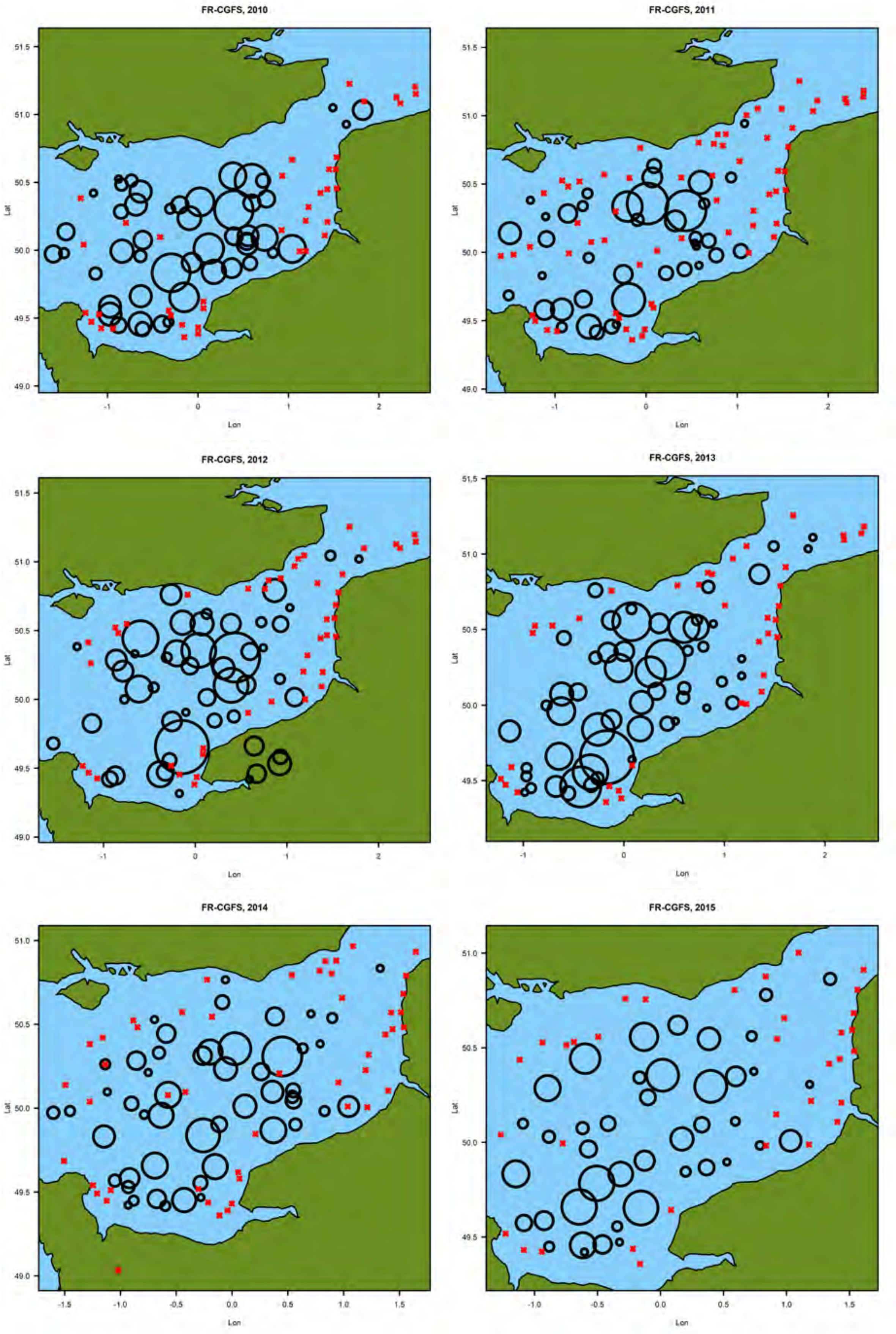


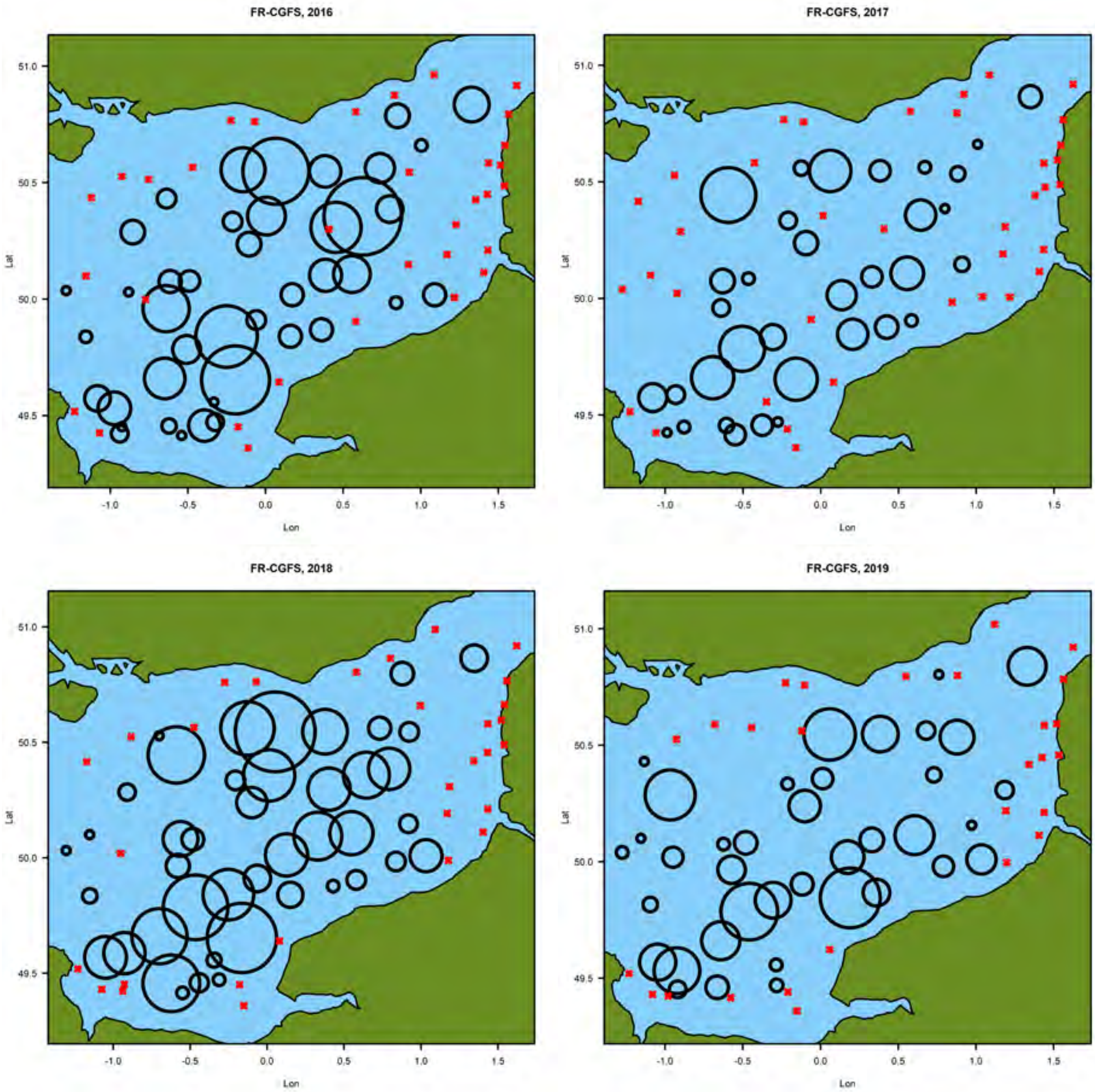
8


FR-CGFS, 1992
FR-CGFS, 1993
FR-CGFS, 1994
FR-CGFS, 1995
FR-CGFS, 1996
FR-CGFS, 1997
Lat
Lon

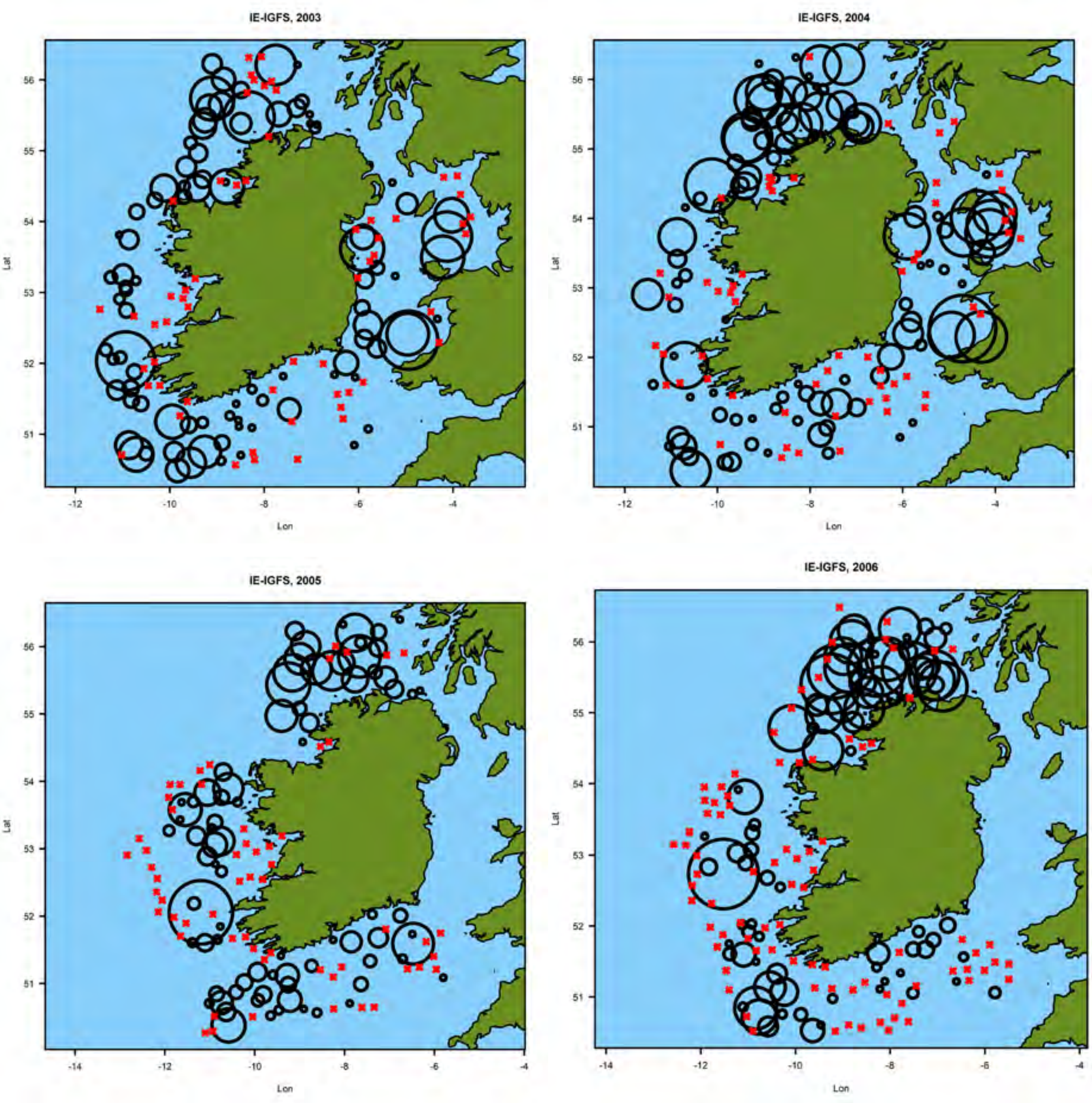

FR-CGFS, 1998
FR-CGFS, 1999
FR-CGFS, 2000
FR-CGFS, 2001
FR-CGFS, 2002
FR-CGFS, 2003
Lat
Lon

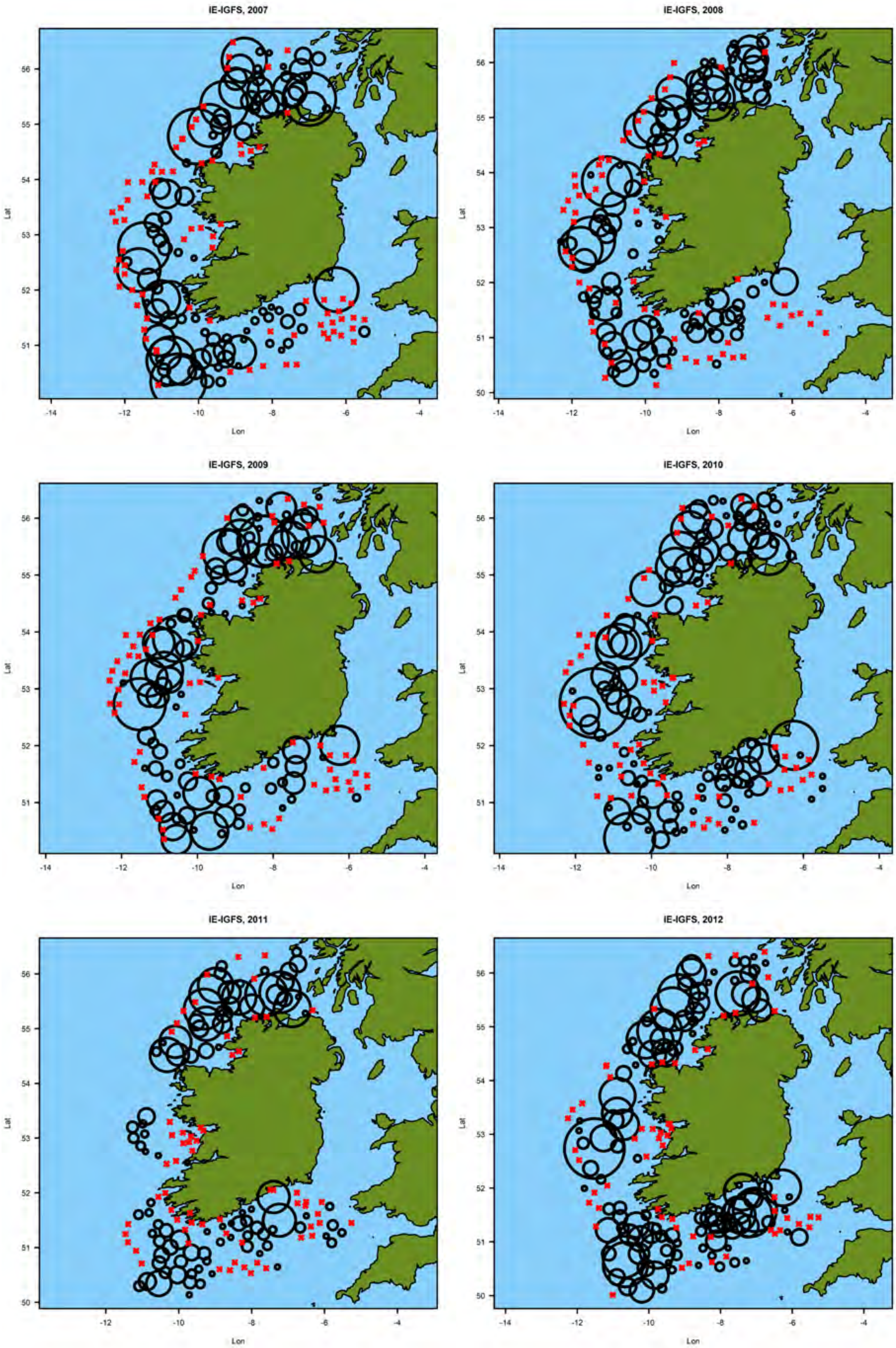

FR-CGFS, 2004
FR-CGFS, 2005
FR-CGFS, 2006
FR-CGFS, 2007
FR-CGFS, 2008
FR-CGFS, 2009
Lat
Lon
49.0
49.5
50.0
50.5
51.0
51.5
-1
0
1
2

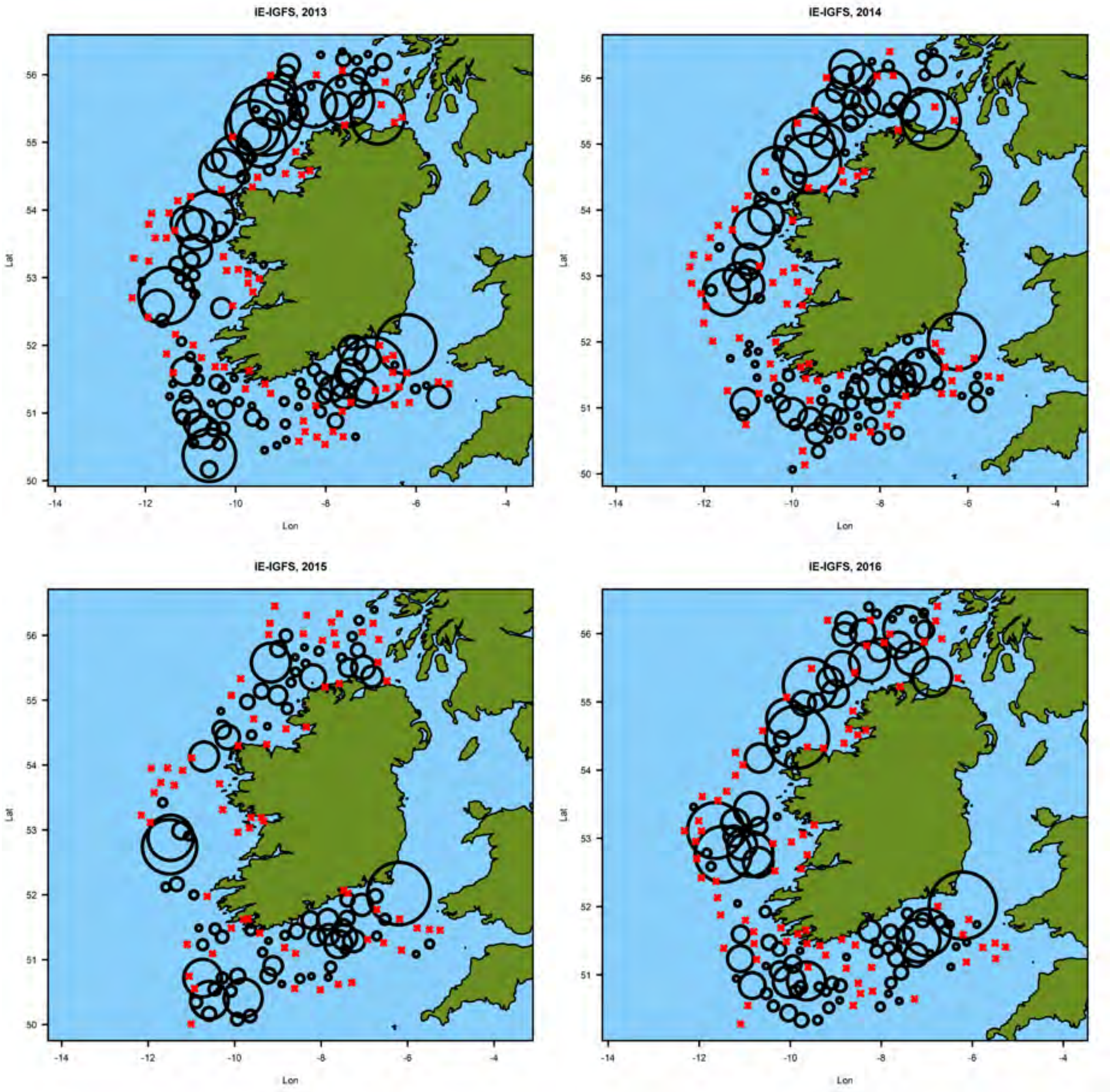

FR-CGFS, 2010
FR-CGFS, 2011
FR-CGFS, 2012
FR-CGFS, 2013
FR-CGFS, 2014
FR-CGFS, 2015
Lat
Lon

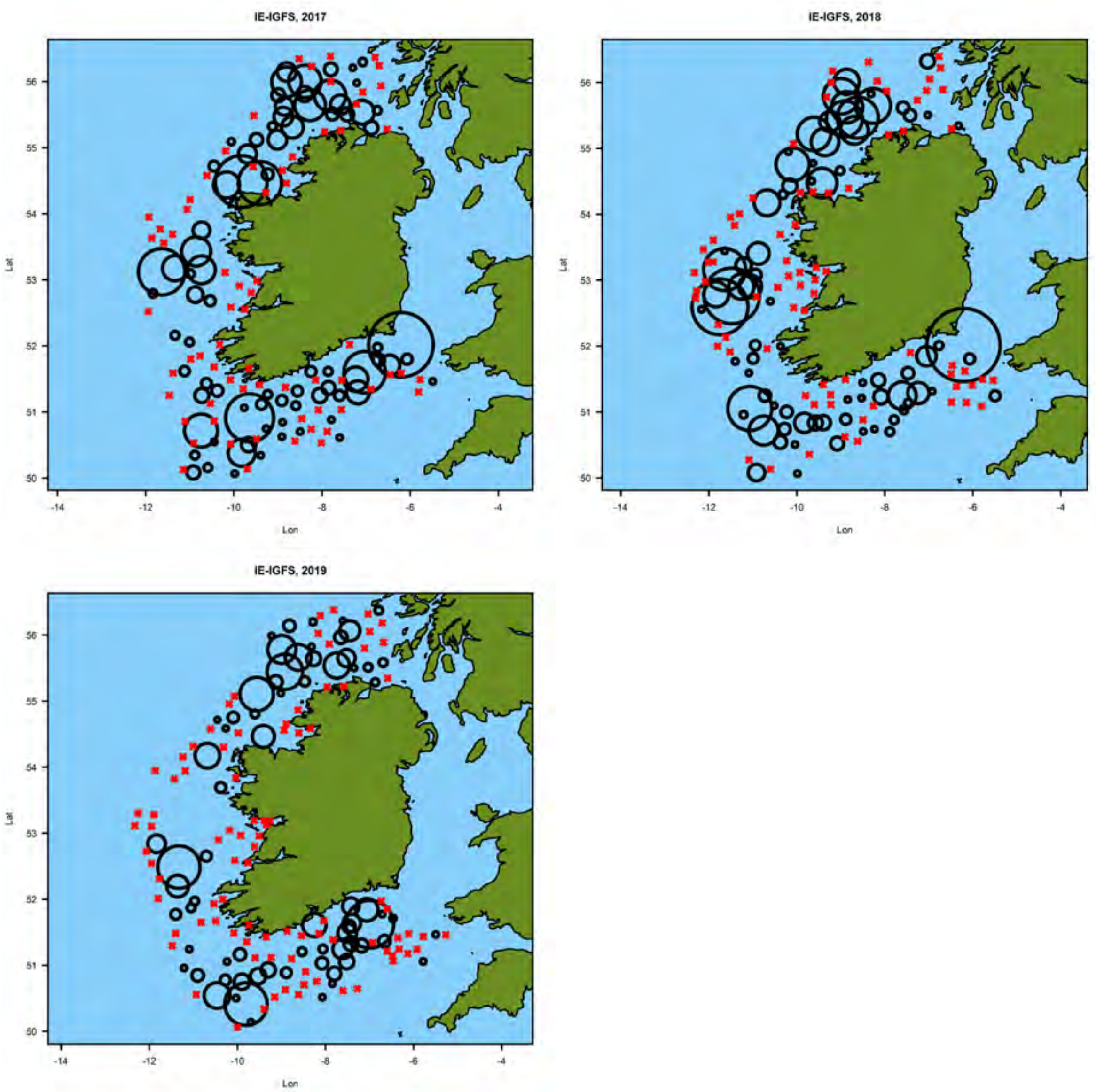

FR-CGFS, 2016
FR-CGFS, 2017
FR-CGFS, 2018
FR-CGFS, 2019
Lat
Lon
51.0
50.5
50.0
49.5
-1.0
-0.5
0.0
0.5
1.0
1.5

Irish Groundfish Survey – IEGFS

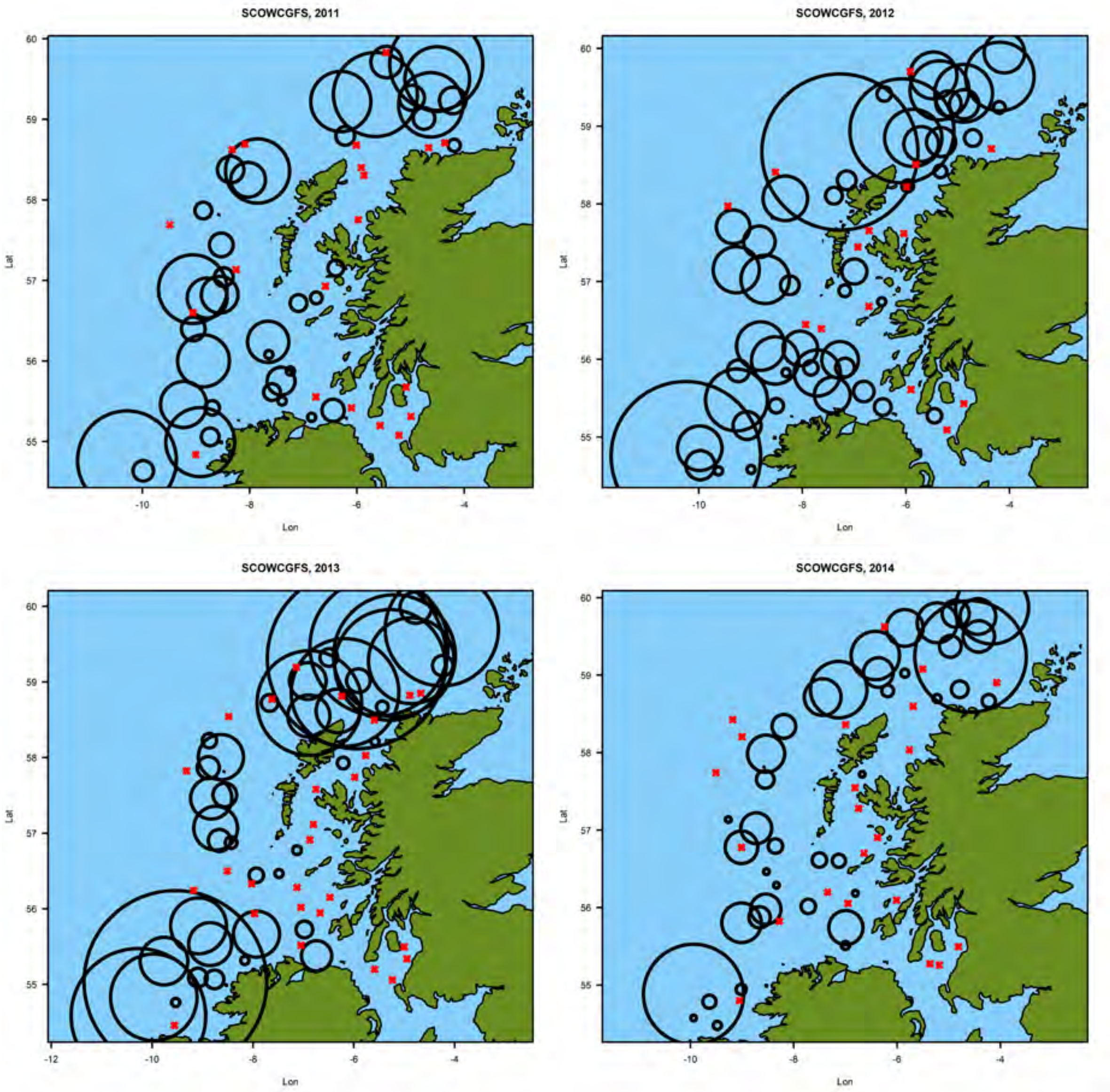


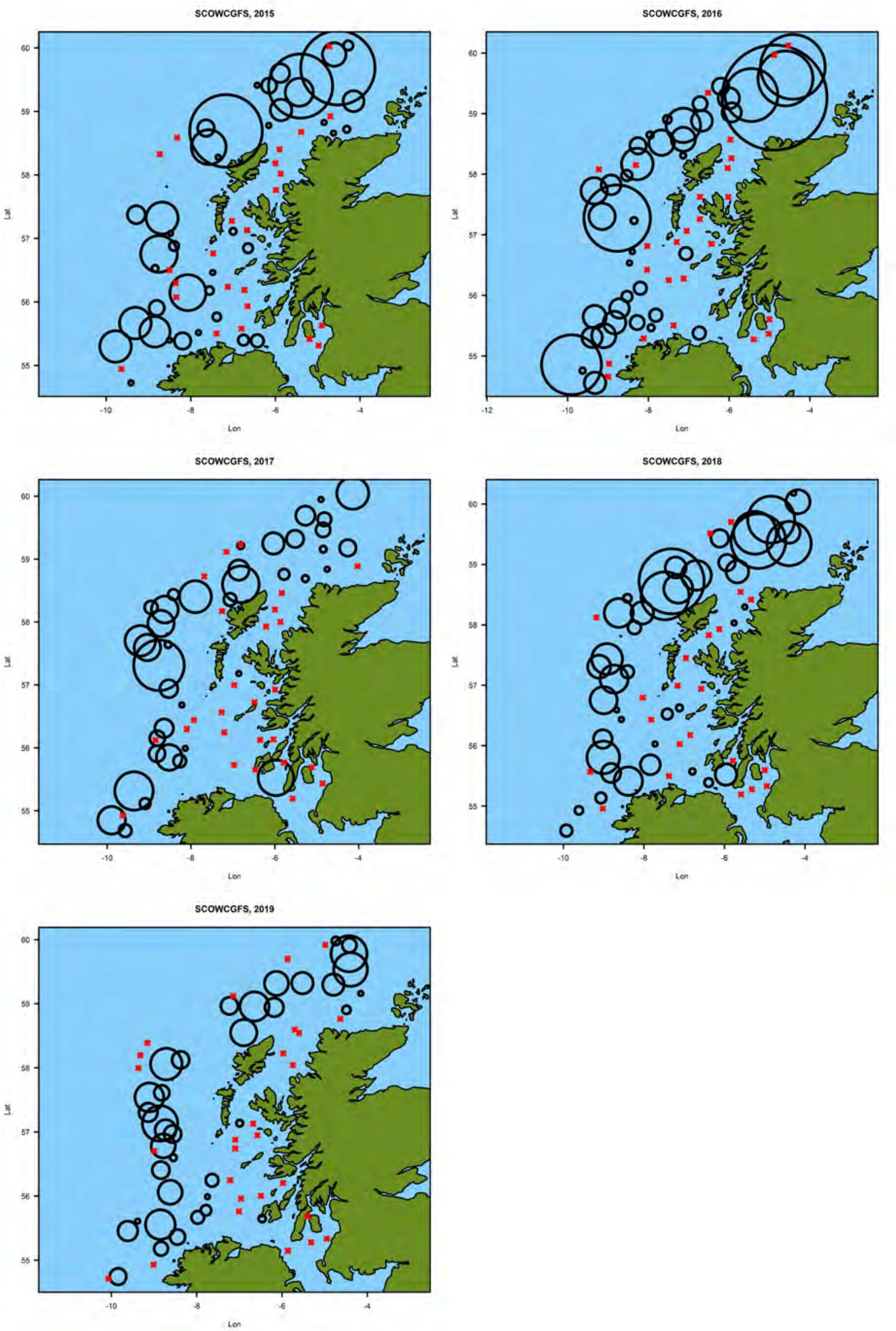

IE-IGFS, 2007
IE-IGFS, 2008
IE-IGFS, 2009
IE-IGFS, 2010
IE-IGFS, 2011
IE-IGFS, 2012
Lat
Lon


IE-IGFS, 2013
IE-IGFS, 2014
IE-IGFS, 2015
IE-IGFS, 2016
Lat
Lon


IE-IGFS, 2017
IE-IGFS, 2018
IE-IGFS, 2019
Lat
Lon
56
55
54
53
52
51
50
-14
-12
-10
-8
-6
-4

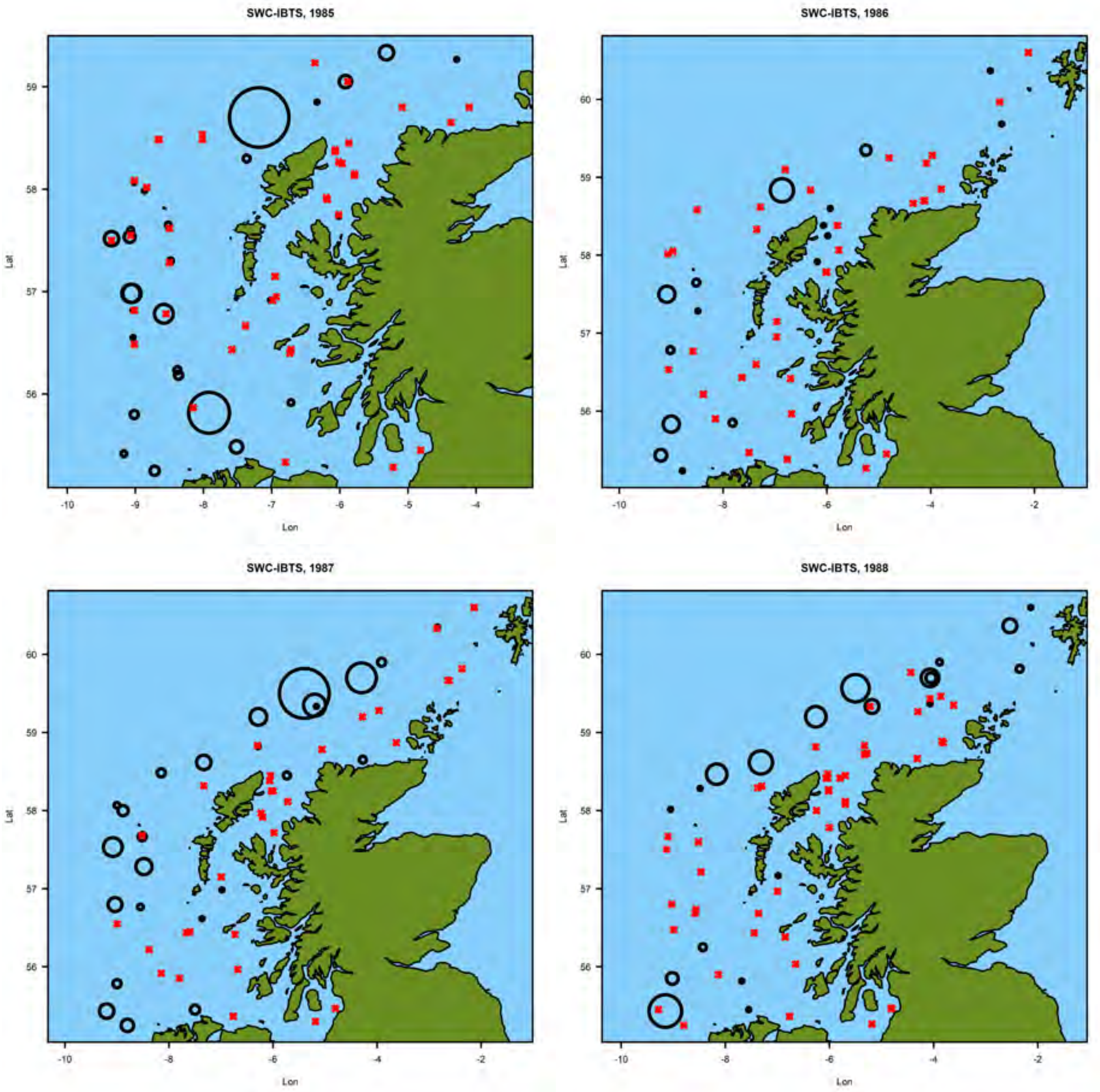
Scottish West Coast Groundfish Survey – SWC-GFS

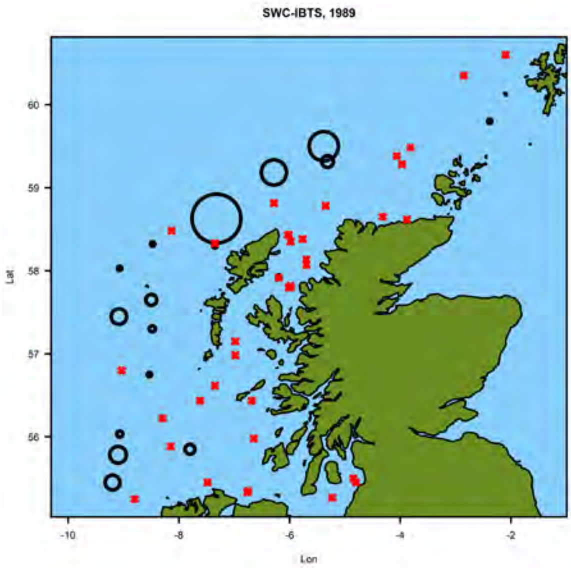


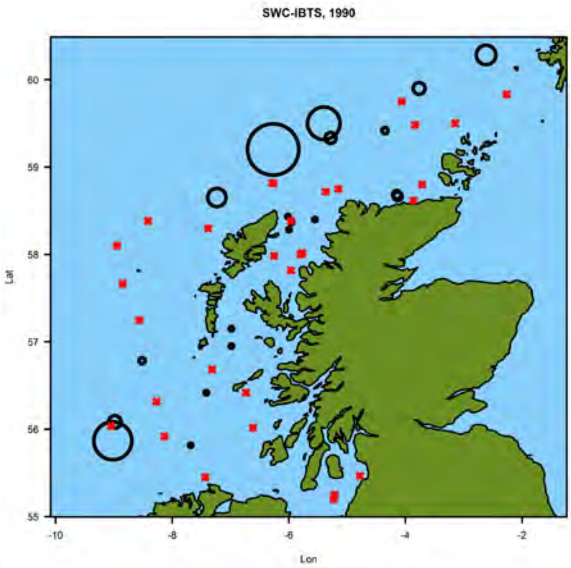


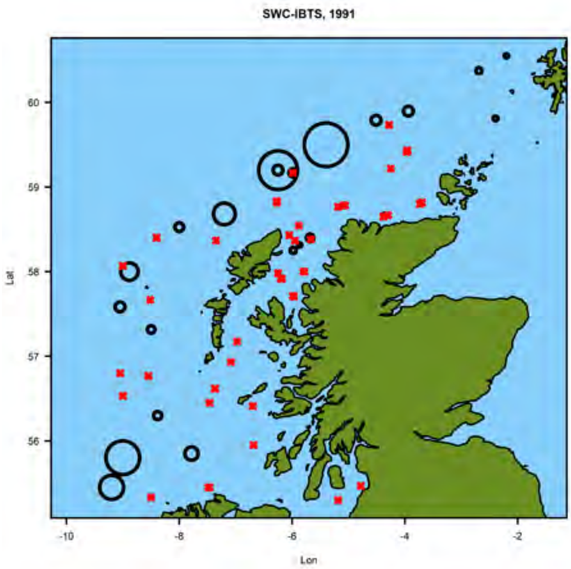
SCOWCGFS, 2015
SCOWCGFS, 2016
SCOWCGFS, 2017
SCOWCGFS, 2018
SCOWCGFS, 2019
Lat
Lon

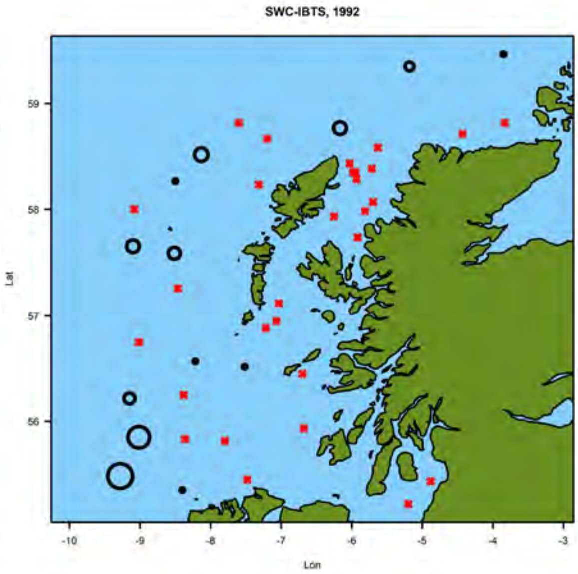
Scottish West Coast International Bottom Trawl Survey – SWC-IBTS

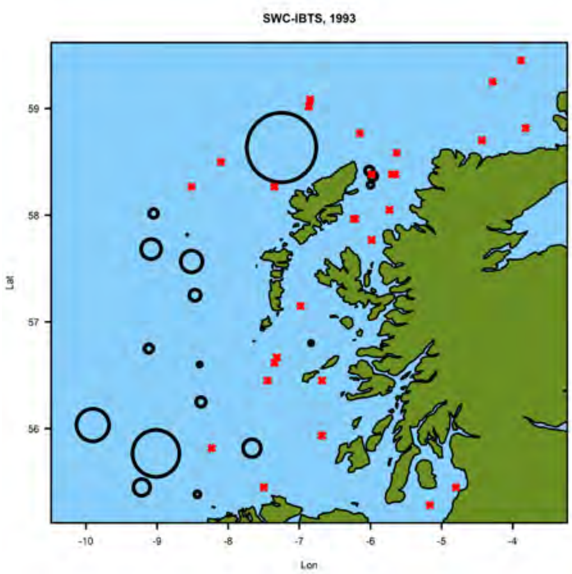


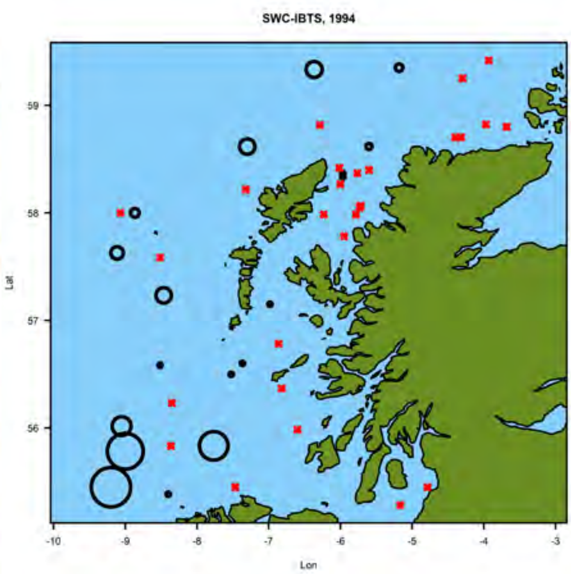

SWC-IBTS, 1989
Lat
Lon

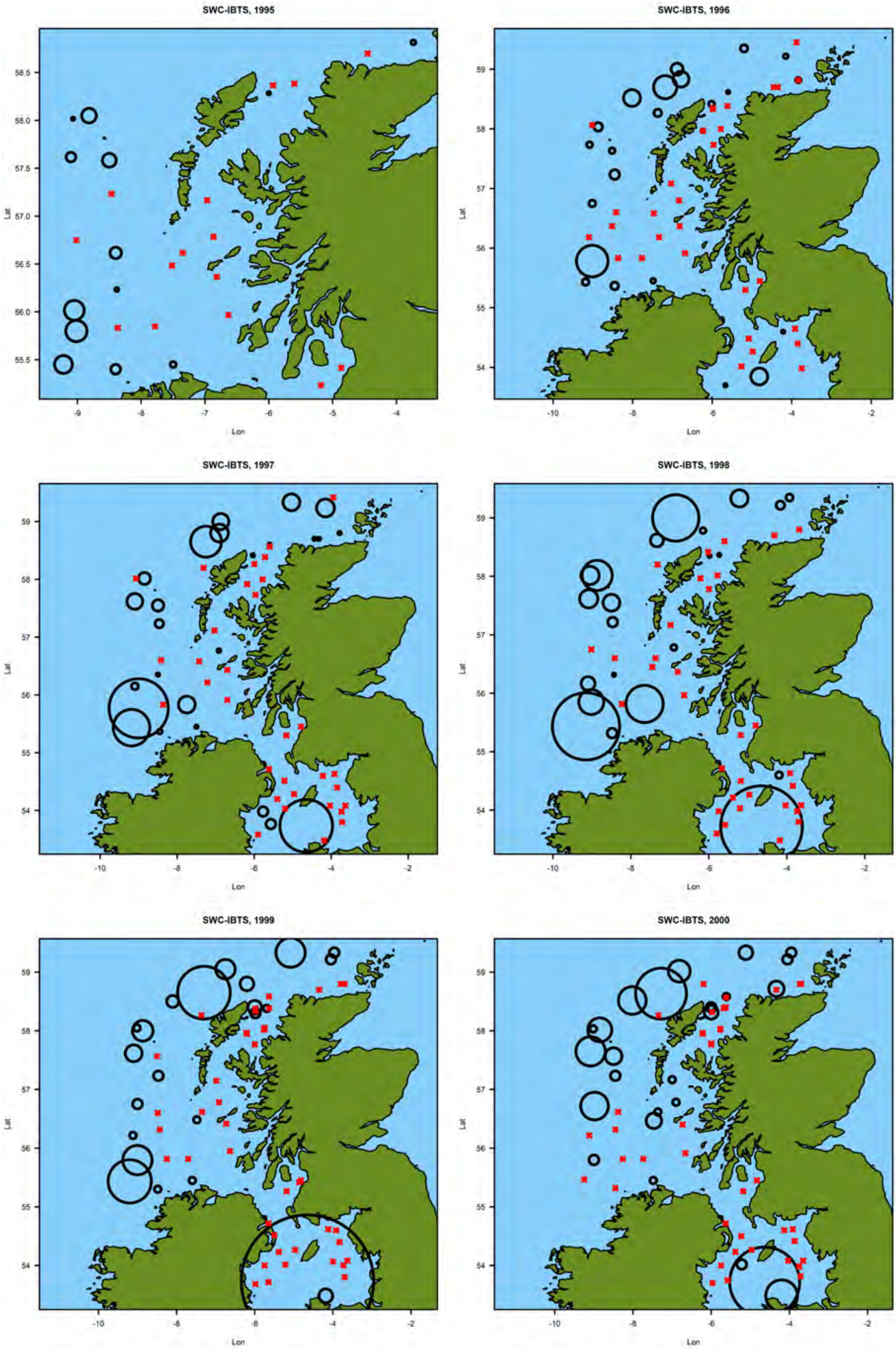

SWC-IBTS, 1990
Lat
Lon

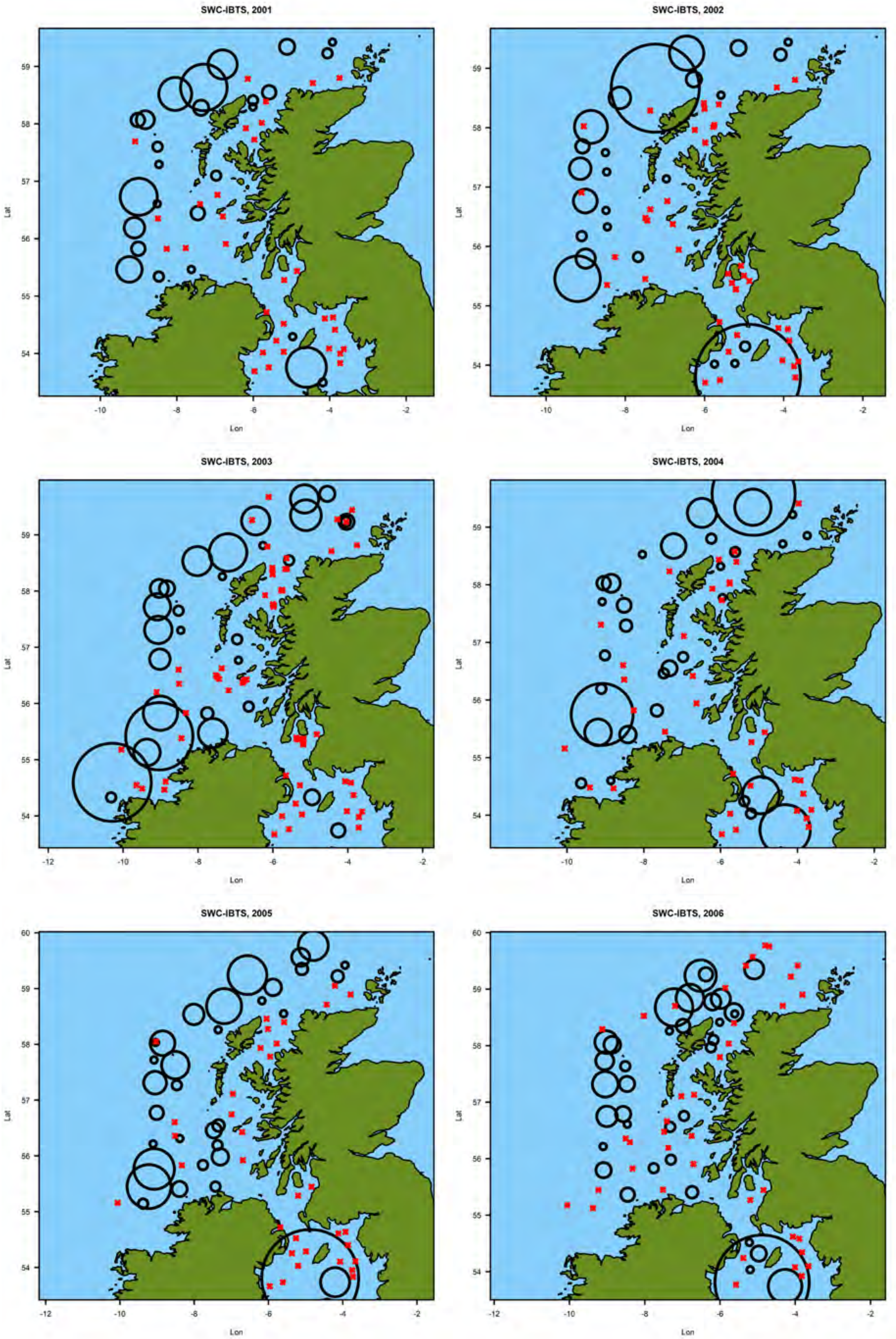

SWC-IBTS, 1991
Lat
Lon

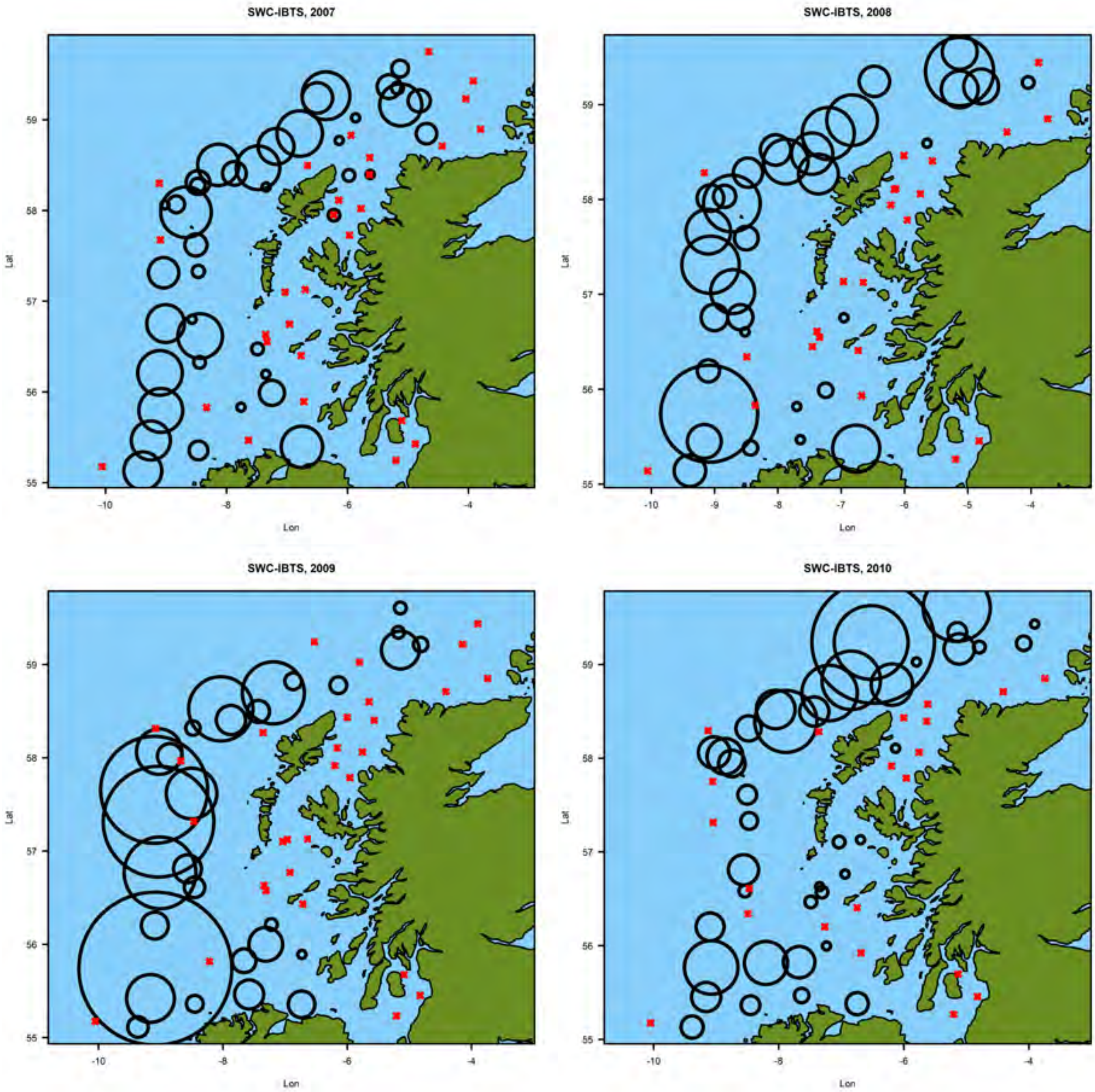

SWC-IBTS, 1992
Lat
Lon


SWC-IBTS, 1993
Lat
Lon

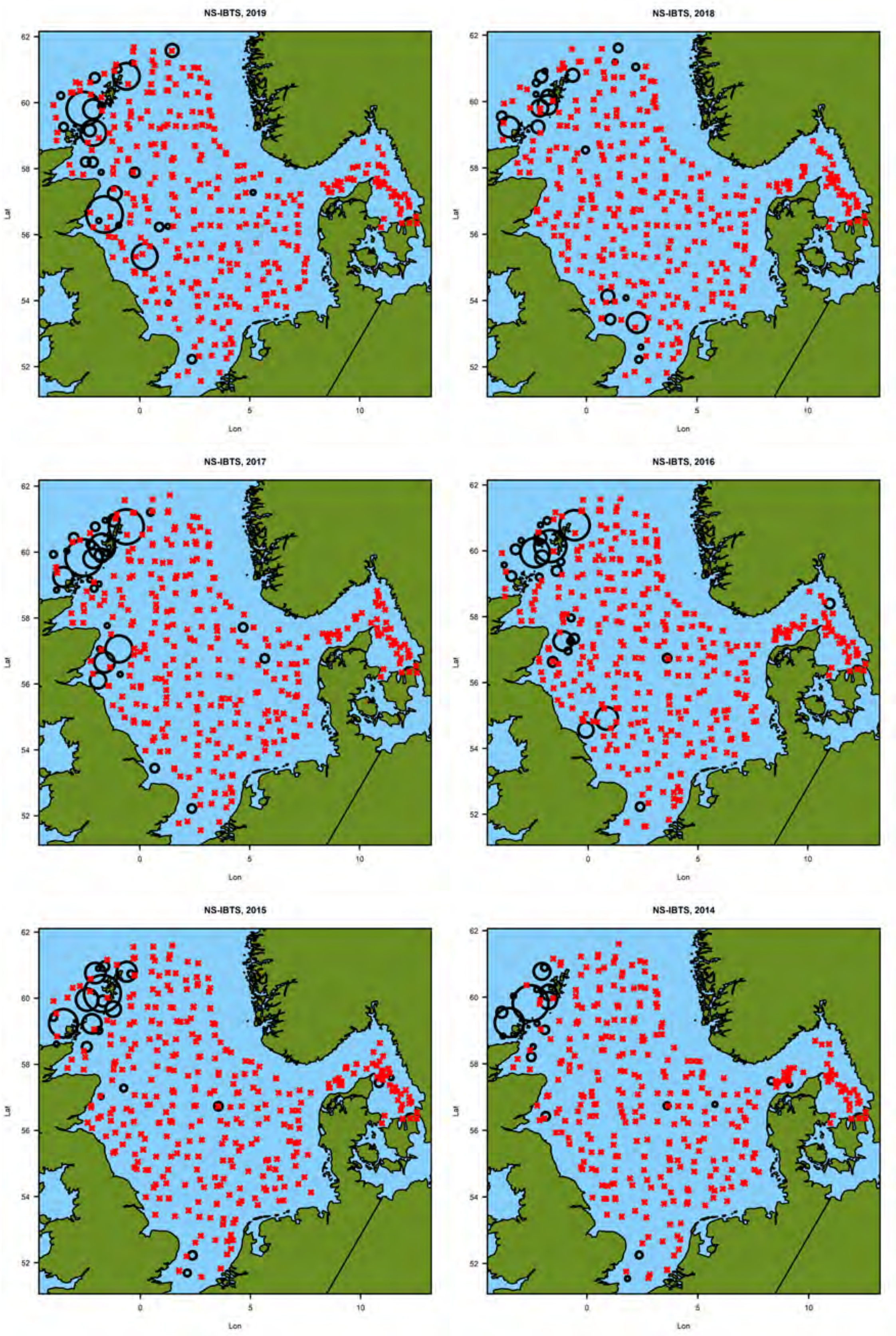

SWC-IBTS, 1994
Lat
Lon

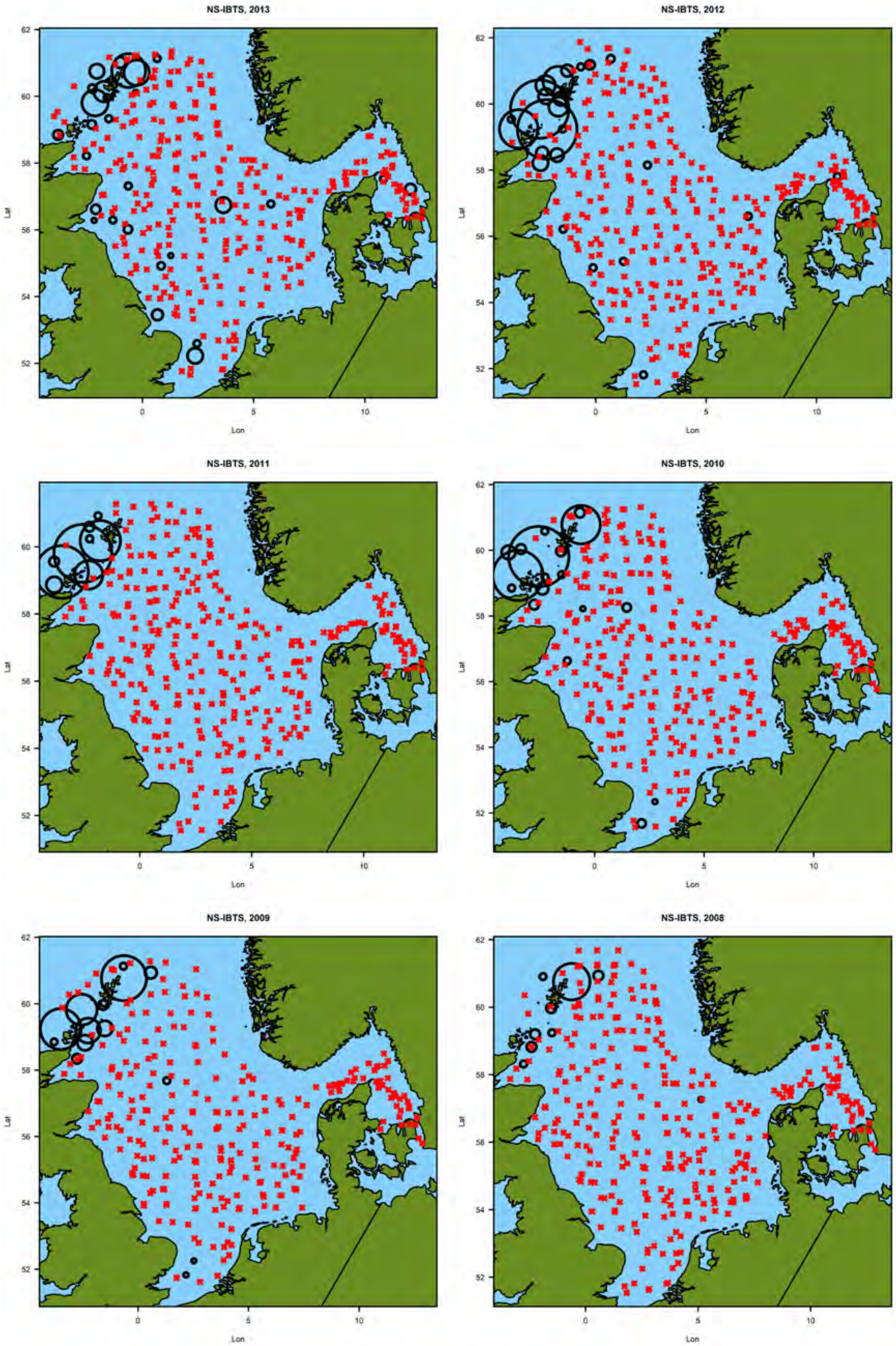

SWC-IBTS, 1995
SWC-IBTS, 1996
SWC-IBTS, 1997
SWC-IBTS, 1998
SWC-IBTS, 1999
SWC-IBTS, 2000
Lat
Lon

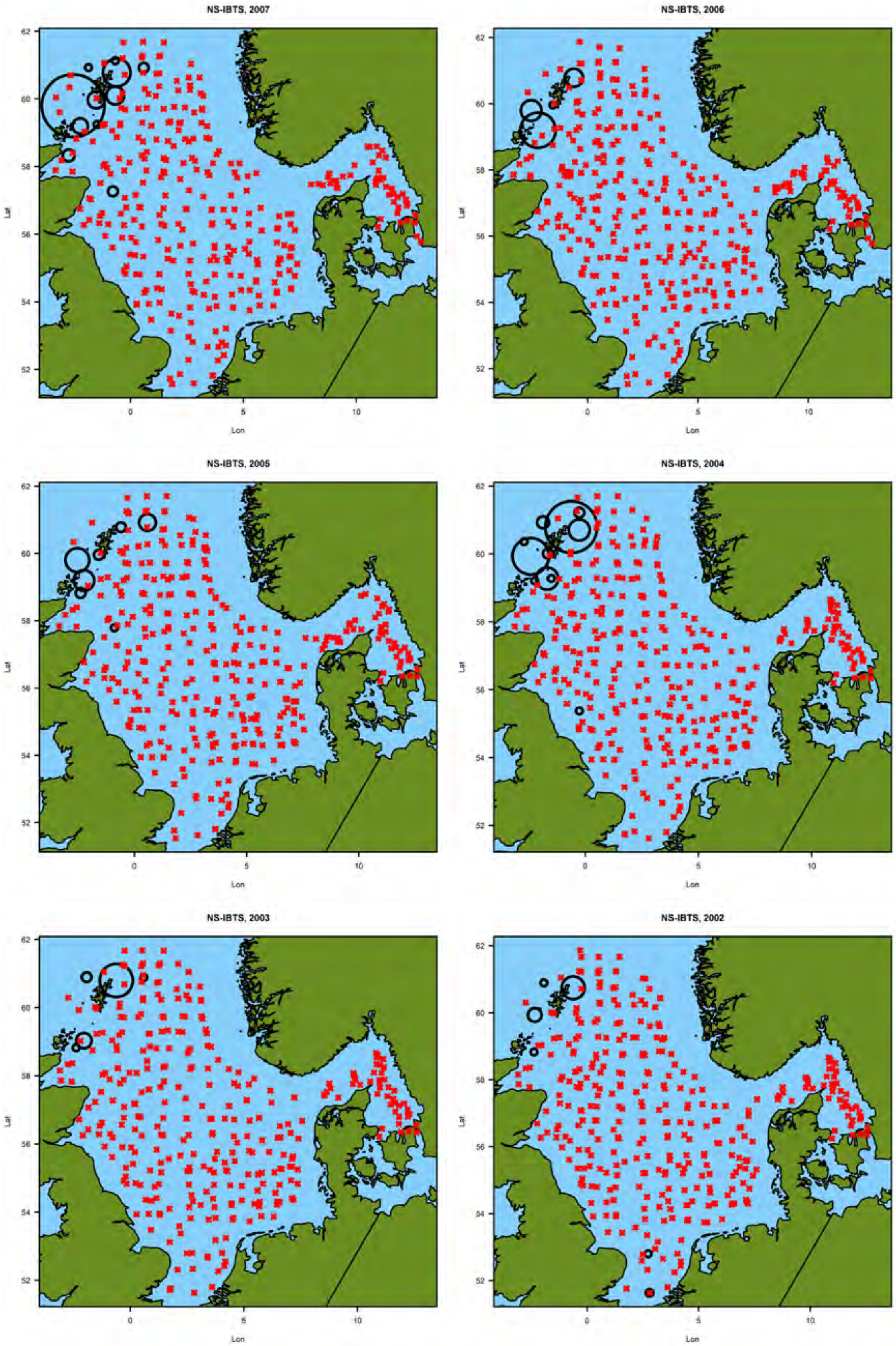

SWC-IBTS, 2001
SWC-IBTS, 2002
SWC-IBTS, 2003
SWC-IBTS, 2004
SWC-IBTS, 2005
SWC-IBTS, 2006
Lat
Lon

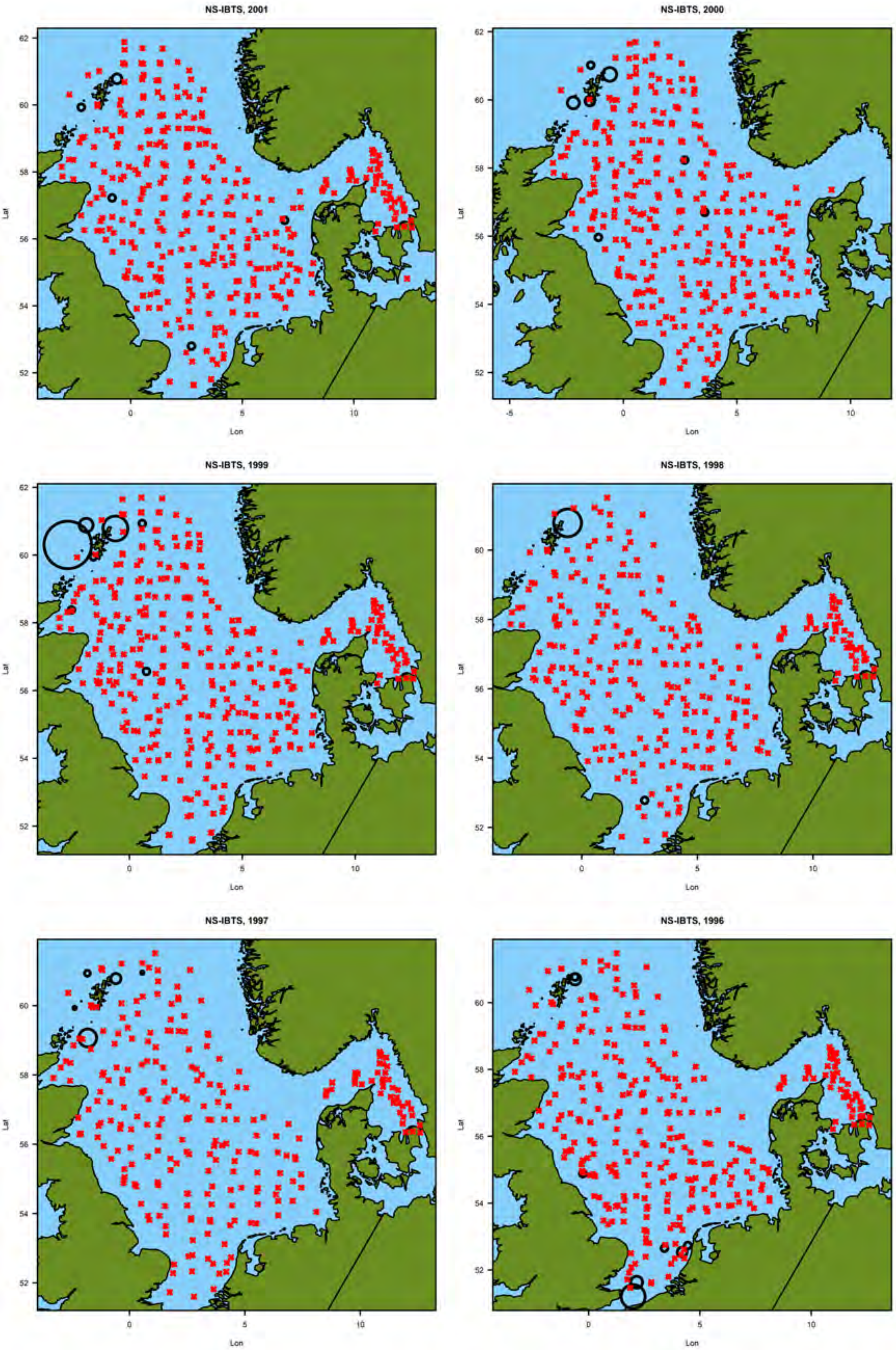

SWC-IBTS, 2007
SWC-IBTS, 2008
SWC-IBTS, 2009
SWC-IBTS, 2010
Lat
Lon

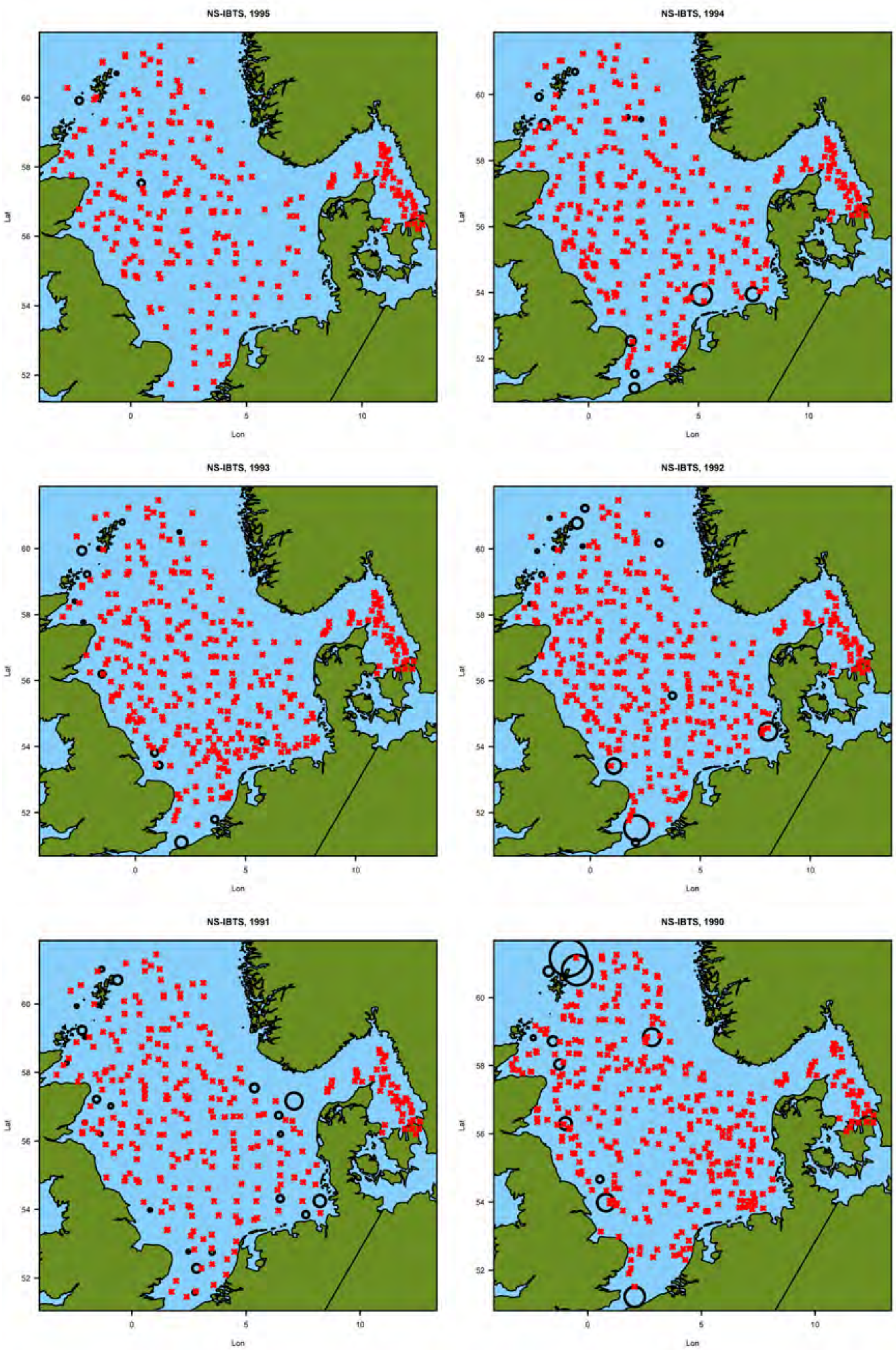
North Sea International Bottom Trawl Survey (NS-IBTS), 1984 – 2019.

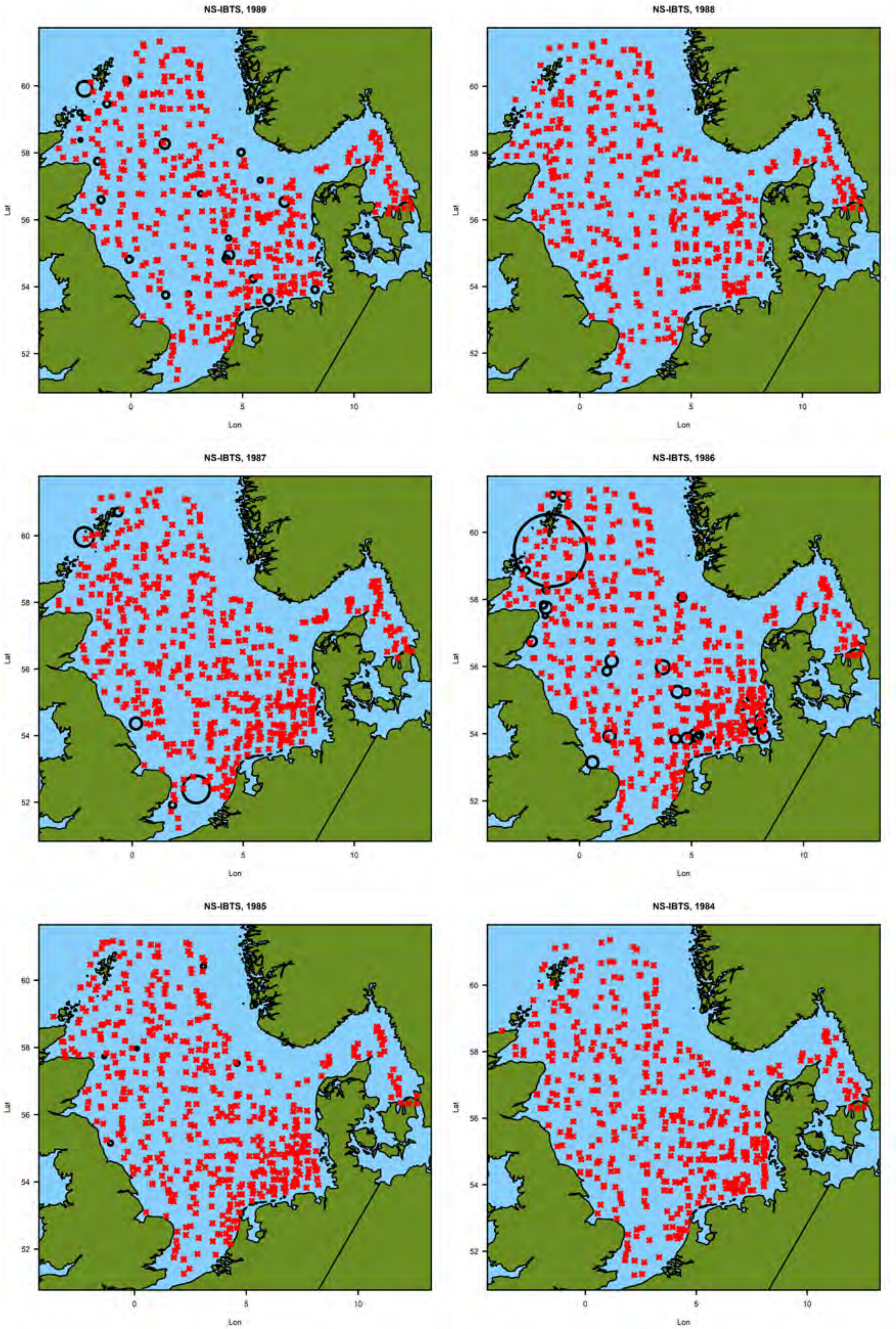



NS-IBTS, 2013
NS-IBTS, 2012
NS-IBTS, 2011
NS-IBTS, 2010
NS-IBTS, 2009
NS-IBTS, 2008
Lat
Lon


NS-IBTS, 2007
NS-IBTS, 2006
NS-IBTS, 2005
NS-IBTS, 2004
NS-IBTS, 2003
NS-IBTS, 2002
Lat
Lon


NS-IBTS, 2001
NS-IBTS, 2000
NS-IBTS, 1999
NS-IBTS, 1998
NS-IBTS, 1997
NS-IBTS, 1996
Lat
Lon


NS-IBTS, 1995
NS-IBTS, 1994
NS-IBTS, 1993
NS-IBTS, 1992
NS-IBTS, 1991
NS-IBTS, 1990
Lat
Lon
52
54
56
58
60
0
5
10


NS-IBTS, 1989
NS-IBTS, 1988
NS-IBTS, 1987
NS-IBTS, 1986
NS-IBTS, 1985
NS-IBTS, 1984
Lat
Lon

Annex 3. Data Processing and Model Code

```
rm(list=ls())

library(icesDatras)
library(fishMod)
library(mgcv)

year.range <- 1985:2020

gur <- 127259

## WoRMS recognises Aspitrigla cucculus - a deprecated synonym - as 150662.

## Surveys we want are;
#   SWC-IBTS 1985 - 2010. Q1 & Q4
#   SCOWCGFS 2011 - 2020, Q1 & Q4
#    IE-IGFS 2003 - 2019, Q4
#    FR-CGFS 1988 - 2019, Q4
#      EVHOE 1997 - 2019, Q4
#        BTS 2007 - 2020, Q1
#      NIGFS 2006 - 2019, Q1 & Q4

## Other surveys we can explore are;
#   NS-IBTS (4a)
#   SP-PORC
#   SP-NORTH
#   PT-IBTS



     survey.list <- c("SWC-IBTS", "SWC-IBTS", "SCOWCGFS", "SCOWCGFS", "IE-IGFS", "FR-CGFS",
"EVHOE", "BTS", "NIGFS", "NIGFS")
 survey.quarters <- c(1, 4, 1, 4, 4, 4, 4, 1, 1, 4)
      start.year <- c(1985, 1989, 2011, 2011, 2003, 1988, 1997, 2007, 2005, 2006)
      end.year   <- c(2010, 2010, 2020, 2019, 2019, 2019, 2019, 2020, 2019, 2019)

survey.availability <- data.frame(survey.name = survey.list, quarter = survey.quarters, start
= start.year, end = end.year)


### Length-weight relationship
#   From Coull et al., Length-weight Relationships for 88 Species of Fish Encountered in the
North East Atlantic
#   Scottish Fisheries Research Report, Number, 43 1989
#   480 obs, min = 12cm, max = 46cm, collected in Div 6a, 1977 - 1982
#   https://www2.gov.scot/Uploads/Documents/No%2043.pdf
#   Figure 73
#   0.0045 x L ^ 3.2228

# length.a <- 0.0045
# length.b <- 3.2228

# haul.data <- length.data <- NULL

# for (i in (1:length(year.range))){

#   temp.year <- year.range[i]

#  for(j in (1:dim(survey.availability))){

#  if(survey.availability$quarter[j] %in%
getSurveyYearQuarterList(survey.availability$survey.name[j], temp.year) == FALSE){next}


#    temp.hl <- getHLdata(survey.availability$survey.name[j], year = temp.year, quarter =
survey.availability$quarter[j])
#    temp.hh <- getHHdata(survey.availability$survey.name[j], year = temp.year, quarter =
survey.availability$quarter[j])

#   if(150662 %in% temp.hl$Valid_Aphia == TRUE){print("uh-oh! synonym used in data")}

#    temp.hl <- temp.hl[temp.hl$Valid_Aphia == gur,]

#    haul.data <- rbind(haul.data, temp.hh)
```

```
#    length.data <- rbind(length.data, temp.hl)

#   }

#  }

# length.data <- length.data[!is.na(length.data$LngtClass),]
## there are some invalid rows

# length.data$LngtClass[length.data$LngtClass>50] <-
length.data$LngtClass[length.data$LngtClass>50]/10
## and some surveys measure in mm


# length.data$wtClass <- round(length.a * (length.data$LngtClass ^ length.b), 0)/1000
## calculate weights

#length.data$TotalWt <- length.data$wtClass * length.data$HLNoAtLngt
## multinply by no at length

#haul.data <- haul.data[haul.data$HaulVal == "V",]
## lose the invalid hauls


# head(haul.data)

# haul.data$unique.id <- paste(haul.data$Survey, haul.data$Year, haul.data$Quarter,
haul.data$HaulNo, sep = "-")
# length.data$unique.id <- paste(length.data$Survey, length.data$Year, length.data$Quarter,
length.data$HaulNo, sep ="-")

# haul.weights <- tapply(length.data$TotalWt, length.data$unique.id, sum)

# haul.data$kg.gur <- NA

# for(i in (1:length(haul.weights))){
#    haul.data$kg.gur[match(names(haul.weights)[i], haul.data$unique.id)] <- haul.weights[i]
# }

#haul.data$kg.gur[is.na(haul.data$kg.gur)] <- 0

#haul.data$st.kg.gur <- haul.data$kg.gur * (60/haul.data$HaulDur)


#haul.data   <- haul.data[!is.na(haul.data$Depth),] ## 17 data points have no depth
associated. Chosen to remove these


haul.data   <- read.csv("C:/Work/WKWEST/Data/haul_data.csv")
length.data <- read.csv("C:/Work/WKWEST/Data/length_data.csv")



########################
##  Exploratory Maps  ##
########################

coast <- read.csv("C:/Work/europe_coast.csv")
sea <- list(x=c(-90,90,90,-90), y=c(0,0,90,90))

years.available <- c(2011:2020)

for(i in (1:length(years.available))){

  png(filename=paste("C:/Work/WKWEST/Surveys_", years.available[i], ".png", sep=""))

  plot(sea, xlim=c(-14, 4), ylim=c(44, 60), asp=1.5, xlab="Longitute", ylab="Latitude", las
=1)
  polygon(sea, col="grey80")
  polygon(coast, col="olivedrab")
  box()
  title(main = paste("Survey Data Coverage - ", years.available[i], sep=""))
  points(x=haul.data$ShootLong[haul.data$Year == years.available[i]],
         y=haul.data$ShootLat[haul.data$Year == years.available[i]],
```

```
         pch=16, cex = 0.4, col= as.factor(haul.data$Survey[haul.data$Year ==
years.available[i]]))

  dev.off()
}



#######################
##  Look at Lengths  ##
#######################

survey.list <- c("SCOWCGFS", "SCOWCGFS", "IE-IGFS", "FR-CGFS", "EVHOE", "BTS", "NIGFS",
"NIGFS")
survey.quarters <- c(1, 4, 4, 4, 4, 1, 1, 4)
avail.years <- c(2011:2019)

sur.name <- q.no <- sur.year <- mean.l <- NULL

for(i in (1:length(survey.list))){

  for(j in (1:length(avail.years))){

    temp <- length.data[length.data$Survey == survey.list[i] & length.data$Quarter ==
survey.quarters[i] & length.data$Year == avail.years[j],]

    temp.lf <- tapply(as.numeric(temp$HLNoAtLngt), as.factor(temp$LngtClass), sum)

    png(filename = paste("C:/Work/WKWEST/LF/", survey.list[i], "-Q", survey.quarters[i], "-",
avail.years[j], ".png", sep=""))

    plot(x=as.numeric(names(temp.lf)), y=temp.lf/max(temp.lf), xlab="Length (cm)", ylab =
"Proportion of Catch", type = "l",
     lwd=3, col=2, las=1, xlim=c(0,40), ylim=c(0,1))
    title(main = paste(survey.list[i], "-Q", survey.quarters[i], "-", avail.years[j], sep=""))
    dev.off()

    sur.name <- c(sur.name, survey.list[i])
    q.no <- c(q.no, survey.quarters[i])
    sur.year <- c(sur.year, avail.years[j])
    mean.l <- c(mean.l, mean(rep(temp$LngtClass, temp$HLNoAtLngt)))


  }

}

mean.l.data <- data.frame(survey = sur.name, quarter = q.no, year = sur.year, mean.length =
mean.l)


##################
##  Start GLMs  ##
##################

m1 <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) + HaulLat +
Depth, ~ as.factor(Year) + as.factor(Quarter) + HaulLat + Depth, data = haul.data)

m1a <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) + HaulLat
+ HaulLong + Depth, ~ as.factor(Year) + as.factor(Quarter) + HaulLat + HaulLong + Depth, data
= haul.data)

m1b <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) + HaulLat
+ Depth, ~ as.factor(Survey) + as.factor(Quarter) + HaulLat + HaulLong + Depth, data =
haul.data)

m1c <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) + HaulLat
+ Depth, ~ as.factor(Survey) + as.factor(Quarter) + HaulLong + Depth, data = haul.data)

m1d <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) + HaulLat
+ HaulLong + Depth, ~ as.factor(Survey) + as.factor(Quarter) + HaulLong + Depth, data =
haul.data)
```

```
m1e <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) + HaulLat
+ Depth, ~ as.factor(Quarter) + HaulLong + Depth * as.factor(Survey), data = haul.data)

m1f <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) + HaulLat
+ Depth * as.factor(Survey), ~ as.factor(Quarter) + HaulLong + Depth * as.factor(Survey), data
= haul.data)

haul.data.2 <- haul.data[haul.data$Survey != "NIGFS" & haul.data$Year != 2020,]

m1f.2 <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth * as.factor(Survey), ~ as.factor(Quarter) + HaulLong + Depth *
as.factor(Survey), data = haul.data.2)


m1g <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) + HaulLat
+ Depth * as.factor(Survey), ~ as.factor(Survey) + as.factor(Quarter) + HaulLong + Depth *
as.factor(Survey), data = haul.data)


m2 <- deltaLN(st.kg.gur ~ Year + as.factor(Quarter) + as.factor(Survey) + HaulLat + Depth, ~
Year + as.factor(Quarter) + HaulLat + Depth, data = haul.data)

m3 <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) + HaulLat,
~ as.factor(Year) + as.factor(Quarter) + HaulLat, data = haul.data)

m4 <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) + HaulLat +
HaulLong, ~ as.factor(Year) + as.factor(Quarter) + HaulLat + HaulLong, data = haul.data)

m5 <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Survey) + HaulLat + HaulLong, ~
as.factor(Year) + HaulLat + HaulLong, data = haul.data)



gur.mod <- m1f.2 # this is the best one

mod.sum <- summary(gur.mod$lnMod)

year.effect <- mod.sum$coefficients[1]

year.effect <- c(year.effect, mod.sum$coefficients[1]+ mod.sum$coefficients[2:35])
lower.bound <- year.effect - (2*mod.sum$coefficients[1:35,2])
upper.bound <- year.effect + (2*mod.sum$coefficients[1:35,2])


exp.year.effect <- exp(year.effect)
exp.lower.bound <- exp(lower.bound)
exp.upper.bound <- exp(upper.bound)

plot(x=c(1985:2019), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2, las=1,
xlab = "Year", ylab = "Standardised Biomass Index", ylim=c(0,3), xlim=c(1985, 2020))

poly.1 <- c(exp.lower.bound, rev(exp.upper.bound))/mean(exp.year.effect)
polygon(x=c(1985:2019, 2019:1985), y=poly.1, c="grey80", border = 0)

lines(x=c(1985:2019), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2)


### Truncate Results to 1997 - 2019

year.effect <- c(mod.sum$coefficients[1]+ mod.sum$coefficients[13:35])
lower.bound <- year.effect - (2*mod.sum$coefficients[13:35,2])
upper.bound <- year.effect + (2*mod.sum$coefficients[13:35,2])


exp.year.effect <- exp(year.effect)
exp.lower.bound <- exp(lower.bound)
exp.upper.bound <- exp(upper.bound)

plot(x=c(1997:2019), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2, las=1,
xlab = "Year", ylab = "Standardised Biomass Index", ylim=c(0,3), xlim=c(1997, 2019))

poly.1 <- c(exp.lower.bound, rev(exp.upper.bound))/mean(exp.year.effect)
polygon(x=c(1997:2019, 2019:1997), y=poly.1, c="grey80", border = 0)
```

```
lines(x=c(1997:2019), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2)

lines(x=c(1997, 2019), y=c(1,1), lty = 2)


### Restrospective runs

dev.off()
windows(width=10, height=8)
plot(x=c(1985:2019), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=1, las=1,
xlab = "Year", ylab = "Standardised Biomass Index", ylim=c(0.5,1.5), xlim=c(2010,2019))

temp.data <- haul.data[haul.data$Year < 2019,]

temp.gur.mod <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth, ~ as.factor(Year) + as.factor(Quarter) + HaulLat + Depth, data = temp.data)

temp.mod.sum <- summary(temp.gur.mod$lnMod)

temp.year.effect <- temp.mod.sum$coefficients[1]

temp.year.effect <- c(temp.year.effect, temp.mod.sum$coefficients[1]+
temp.mod.sum$coefficients[2:34])

temp.exp.year.effect <- exp(temp.year.effect)

lines(x=c(1985:2018), y = temp.exp.year.effect/mean(temp.exp.year.effect), type="l", lwd=2,
col=1)

temp.data <- haul.data[haul.data$Year < 2018,]

temp.gur.mod <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth, ~ as.factor(Year) + as.factor(Quarter) + HaulLat + Depth, data = temp.data)

temp.mod.sum <- summary(temp.gur.mod$lnMod)

temp.year.effect <- temp.mod.sum$coefficients[1]

temp.year.effect <- c(temp.year.effect, temp.mod.sum$coefficients[1]+
temp.mod.sum$coefficients[2:33])

temp.exp.year.effect <- exp(temp.year.effect)

lines(x=c(1985:2017), y = temp.exp.year.effect/mean(temp.exp.year.effect), type="l", lwd=2,
col=1)


temp.data <- haul.data[haul.data$Year < 2017,]

temp.gur.mod <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth, ~ as.factor(Year) + as.factor(Quarter) + HaulLat + Depth, data = temp.data)

temp.mod.sum <- summary(temp.gur.mod$lnMod)

temp.year.effect <- temp.mod.sum$coefficients[1]

temp.year.effect <- c(temp.year.effect, temp.mod.sum$coefficients[1]+
temp.mod.sum$coefficients[2:32])

temp.exp.year.effect <- exp(temp.year.effect)

lines(x=c(1985:2016), y = temp.exp.year.effect/mean(temp.exp.year.effect), type="l", lwd=2,
col=1)



temp.data <- haul.data[haul.data$Year < 2016,]

temp.gur.mod <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth, ~ as.factor(Year) + as.factor(Quarter) + HaulLat + Depth, data = temp.data)

temp.mod.sum <- summary(temp.gur.mod$lnMod)
```

```
temp.year.effect <- temp.mod.sum$coefficients[1]

temp.year.effect <- c(temp.year.effect, temp.mod.sum$coefficients[1]+
temp.mod.sum$coefficients[2:31])

temp.exp.year.effect <- exp(temp.year.effect)

lines(x=c(1985:2015), y = temp.exp.year.effect/mean(temp.exp.year.effect), type="l", lwd=2,
col=1)



###  Leave One Out Analysis

#   SWC-IBTS 1985 - 2010. Q1 & Q4
#   SCOWCGFS 2011 - 2019, Q1 & Q4
#    IE-IGFS 2003 - 2019, Q4
#    FR-CGFS 1988 - 2019, Q4
#      EVHOE 1997 - 2019, Q4
#        BTS 2007 - 2019, Q1

year.effect <- mod.sum$coefficients[1]

year.effect <- c(year.effect, mod.sum$coefficients[1]+ mod.sum$coefficients[2:35])
lower.bound <- year.effect - (2*mod.sum$coefficients[1:35,2])
upper.bound <- year.effect + (2*mod.sum$coefficients[1:35,2])


exp.year.effect <- exp(year.effect)
exp.lower.bound <- exp(lower.bound)
exp.upper.bound <- exp(upper.bound)

### DROP SCOTTISH Q1

no.swcgfsq1.haul.data <- haul.data[(haul.data$Survey == "SCOWCGFS" & haul.data$Quarter == 1)
== FALSE,]


loo.gur.mod <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth, ~ as.factor(Year) + as.factor(Quarter) + HaulLat + Depth, data =
no.swcgfsq1.haul.data)


loo.mod.sum <- summary(loo.gur.mod$lnMod)

loo.year.effect <- loo.mod.sum$coefficients[1]

loo.year.effect <- c(loo.year.effect, loo.mod.sum$coefficients[1]+
loo.mod.sum$coefficients[2:35])


loo.exp.year.effect <- exp(loo.year.effect)

windows(width=10, height=8)
plot(x=c(1985:2019), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2, las=1,
xlab = "Year", ylab = "Standardised Biomass Index", ylim=c(0,3), xlim=c(1985, 2020))

poly.1 <- c(exp.lower.bound, rev(exp.upper.bound))/mean(exp.year.effect)
polygon(x=c(1985:2019, 2019:1985), y=poly.1, c="grey80", border = 0)

lines(x=c(1985:2019), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2)

lines(x=c(1985:2019), y = loo.exp.year.effect/mean(loo.exp.year.effect), type="l", lwd=2,
col=3)

### DROP Scottish Q4

no.swcgfsq4.haul.data <- haul.data[(haul.data$Survey == "SCOWCGFS" & haul.data$Quarter == 4)
== FALSE,]


loo.gur.mod <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth, ~ as.factor(Year) + as.factor(Quarter) + HaulLat + Depth, data =
no.swcgfsq4.haul.data)
```

```
loo.mod.sum <- summary(loo.gur.mod$lnMod)

loo.year.effect <- loo.mod.sum$coefficients[1]

loo.year.effect <- c(loo.year.effect, loo.mod.sum$coefficients[1]+
loo.mod.sum$coefficients[2:35])


loo.exp.year.effect <- exp(loo.year.effect)

lines(x=c(1985:2019), y = loo.exp.year.effect/mean(loo.exp.year.effect), type="l", lwd=2,
col=4)


### DROP IRISH GFS
no.iegfs.haul.data <- haul.data[haul.data$Survey != "IE-IGFS",]


loo.gur.mod <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth, ~ as.factor(Year) + as.factor(Quarter) + HaulLat + Depth, data =
no.iegfs.haul.data)


loo.mod.sum <- summary(loo.gur.mod$lnMod)

loo.year.effect <- loo.mod.sum$coefficients[1]

loo.year.effect <- c(loo.year.effect, loo.mod.sum$coefficients[1]+
loo.mod.sum$coefficients[2:35])


loo.exp.year.effect <- exp(loo.year.effect)

lines(x=c(1985:2019), y = loo.exp.year.effect/mean(loo.exp.year.effect), type="l", lwd=2,
col=5)


### DROP CHANNEL GFS
no.cgfs.haul.data <- haul.data[haul.data$Survey != "FR-CGFS",]


loo.gur.mod <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth, ~ as.factor(Year) + as.factor(Quarter) + HaulLat + Depth, data =
no.cgfs.haul.data)


loo.mod.sum <- summary(loo.gur.mod$lnMod)

loo.year.effect <- loo.mod.sum$coefficients[1]

loo.year.effect <- c(loo.year.effect, loo.mod.sum$coefficients[1]+
loo.mod.sum$coefficients[2:35])


loo.exp.year.effect <- exp(loo.year.effect)

lines(x=c(1985:2019), y = loo.exp.year.effect/mean(loo.exp.year.effect), type="l", lwd=2,
col=6)



### DROP CHANNEL EVHOE
no.evhoe.haul.data <- haul.data[haul.data$Survey != "EVHOE",]


loo.gur.mod <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth, ~ as.factor(Year) + as.factor(Quarter) + HaulLat + Depth, data =
no.evhoe.haul.data)


loo.mod.sum <- summary(loo.gur.mod$lnMod)

loo.year.effect <- loo.mod.sum$coefficients[1]
```

```
loo.year.effect <- c(loo.year.effect, loo.mod.sum$coefficients[1]+
loo.mod.sum$coefficients[2:35])


loo.exp.year.effect <- exp(loo.year.effect)

lines(x=c(1985:2019), y = loo.exp.year.effect/mean(loo.exp.year.effect), type="l", lwd=2,
col=7)



### DROP CHANNEL BTS
no.bts.haul.data <- haul.data[haul.data$Survey != "BTS",]


loo.gur.mod <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth, ~ as.factor(Year) + as.factor(Quarter) + HaulLat + Depth, data =
no.bts.haul.data)


loo.mod.sum <- summary(loo.gur.mod$lnMod)

loo.year.effect <- loo.mod.sum$coefficients[1]

loo.year.effect <- c(loo.year.effect, loo.mod.sum$coefficients[1]+
loo.mod.sum$coefficients[2:35])


loo.exp.year.effect <- exp(loo.year.effect)

lines(x=c(1985:2019), y = loo.exp.year.effect/mean(loo.exp.year.effect), type="l", lwd=2,
col="orange")
legend(x=1985, y=3, legend = c("Base", "SCO-WCGFS Q1", "SCO-WCGFS Q4", "IE-GFS", "CGFS",
"EVHOE", "BTS"), lwd=1, col = c(2,3,4,5,6,7,"orange"), cex=0.75, bg="white")



###  Effect of Starting Year
# base model starts in 1985, with Scottish WC survey series.
# investigate changing to 1988 (CGFS), 1997 (EVHOE) and 2003 (IE-GFS)

s.yr <- 1996

lim.haul.data <- haul.data[haul.data$Year>= s.yr,]

lim.mod <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth * as.factor(Survey), ~ as.factor(Survey) + as.factor(Quarter) + HaulLong +
Depth * as.factor(Survey), data = lim.haul.data)

mod.sum <- summary(lim.mod$lnMod)

year.effect <- mod.sum$coefficients[1]

year.effect <- c(year.effect, mod.sum$coefficients[1]+ mod.sum$coefficients[2:25])
lower.bound <- year.effect - (2*mod.sum$coefficients[1:25,2])
upper.bound <- year.effect + (2*mod.sum$coefficients[1:25,2])


exp.year.effect <- exp(year.effect)
exp.lower.bound <- exp(lower.bound)
exp.upper.bound <- exp(upper.bound)


plot(x=c(1996:2018), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2, las=1,
xlab = "Year", ylab = "Standardised Biomass Index", ylim=c(0, 2), xlim=c(1998, 2018))

              poly.1 <- c(exp.lower.bound, rev(exp.upper.bound))/mean(exp.year.effect)
polygon(x=c(1996:2018, 2018:1996), y=poly.1, c="grey80", border = 0)

lines(x=c(1996:2018), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2)


dev.off()
```

```
### What if Scottish Series considered as one?

temp.haul.data <- haul.data

temp.haul.data$Survey <- paste(temp.haul.data$Survey)

temp.haul.data$Survey[temp.haul.data$Survey %in% c("SWC-IBTS", "SCOWCGFS")]  <-
as.factor("SCO_SURV")

temp.haul.data$Survey <- as.factor(temp.haul.data$Survey)

m1f <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) + HaulLat
+ Depth * as.factor(Survey), ~ as.factor(Quarter) + HaulLong + Depth * as.factor(Survey), data
= temp.haul.data)


gur.mod <- m1f

mod.sum <- summary(gur.mod$lnMod)

year.effect <- mod.sum$coefficients[1]

year.effect <- c(year.effect, mod.sum$coefficients[1]+ mod.sum$coefficients[2:36])
lower.bound <- year.effect - (2*mod.sum$coefficients[1:36,2])
upper.bound <- year.effect + (2*mod.sum$coefficients[1:36,2])


exp.year.effect <- exp(year.effect)
exp.lower.bound <- exp(lower.bound)
exp.upper.bound <- exp(upper.bound)

plot(x=c(1985:2020), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2, las=1,
xlab = "Year", ylab = "Standardised Biomass Index", ylim=c(0,3))

poly.1 <- c(exp.lower.bound, rev(exp.upper.bound))/mean(exp.year.effect)
polygon(x=c(1985:2020, 2020:1985), y=poly.1, c="grey80", border = 0)

lines(x=c(1985:2020), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2)

### AIC 63003.05 vs 62880.69 using spilt series



temp.haul.data <- haul.data[haul.data$Year %in% c(1997:2019),]

m1f <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) + HaulLat
+ Depth * as.factor(Survey), ~ as.factor(Quarter) + HaulLong + Depth * as.factor(Survey), data
= temp.haul.data, se.fit = T)

gur.mod <- m1f

mod.sum <- summary(gur.mod$lnMod)

year.effect <- mod.sum$coefficients[1]

year.effect <- c(year.effect, mod.sum$coefficients[1]+ mod.sum$coefficients[2:23])
lower.bound <- year.effect - (2*mod.sum$coefficients[1:23,2])
upper.bound <- year.effect + (2*mod.sum$coefficients[1:23,2])


exp.year.effect <- exp(year.effect)
exp.lower.bound <- exp(lower.bound)
exp.upper.bound <- exp(upper.bound)

plot(x=c(1997:2019), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2, las=1,
xlab = "Year", ylab = "Standardised Biomass Index", ylim=c(0,2))

poly.1 <- c(exp.lower.bound, rev(exp.upper.bound))/mean(exp.year.effect)
polygon(x=c(1997:2019, 2019:1997), y=poly.1, c="grey80", border = 0)

lines(x=c(1997:2019), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2)

conf.df <- predict.confidence(m1f$lnMod, temp.haul.data$Survey)
```

```
head(conf.df, 2)



#### Single or Split Series for CGFS?

haul.data.2 <- haul.data
haul.data.2$Survey <- paste(haul.data.2$Survey)
haul.data.2$Survey[haul.data$Survey == "FR-CGFS" & haul.data$Year >= 2015] <- "FR-
CGFS_Thalassa"
haul.data.2$Survey[haul.data$Survey == "FR-CGFS" & haul.data$Year < 2015] <- "FR-
CGFS_GwenDrez"
haul.data.2$Survey <- as.factor(haul.data.2$Survey)

m1f.2 <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth * as.factor(Survey), ~ as.factor(Quarter) + HaulLong + Depth *
as.factor(Survey), data = haul.data.2)

## adding a second series for more recent years has a slight negative impact on the AIC
(62884.1)



###  What if we only include data from 1997 onwards? (ie. post-EVHOE)

haul.data.2 <- haul.data[haul.data$Year >=1997,]

m1f.2 <- deltaLN(st.kg.gur ~ as.factor(Year) + as.factor(Quarter) + as.factor(Survey) +
HaulLat + Depth * as.factor(Survey), ~ as.factor(Quarter) + HaulLong + Depth *
as.factor(Survey), data = haul.data.2)

gur.mod <- m1f.2

mod.sum <- summary(gur.mod$lnMod)

year.effect <- mod.sum$coefficients[1]

year.effect <- c(year.effect, mod.sum$coefficients[1]+ mod.sum$coefficients[2:23])
lower.bound <- year.effect - (2*mod.sum$coefficients[1:23,2])
upper.bound <- year.effect + (2*mod.sum$coefficients[1:23,2])


exp.year.effect <- exp(year.effect)
exp.lower.bound <- exp(lower.bound)
exp.upper.bound <- exp(upper.bound)

plot(x=c(1997:2019), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2, las=1,
xlab = "Year", ylab = "Standardised Biomass Index", ylim=c(0,3), xlim=c(1997, 2020))

poly.1 <- c(exp.lower.bound, rev(exp.upper.bound))/mean(exp.year.effect)
polygon(x=c(1997:2019, 2019:1997), y=poly.1, c="grey80", border = 0)

lines(x=c(1997:2019), y = exp.year.effect/mean(exp.year.effect), type="l", lwd=2, col=2)
lines(x=c(1997,2019), y=c(1,1), lty=2)
```

Evaluation of stock assessment methods for sardine (*Sardina pilchardus*) in subarea 7 (Southern Celtic Seas and the English Channel)

Rosana Ouréns, Jeroen Van Der Kooij, Johnathan Ball, Richard Nash

Centre for Environment, Fisheries and Aquaculture Science (CEFAS)
Pakefield Rd, Lowestoft, NR33 0HT, UK

Summary

This working document evaluates the performance of two methods recommended by ICES to assess data-limited stocks of short-lived species when applied to sardine in subarea 7: a surplus production model in continuous time (SPiCT) and the 1 over 2 rule, which consists in multiplying the most recent catch advice by the ratio of the most recent biomass value and the average of the two preceding values. Different exploratory SPiCT models were run, but the model that produced the most plausible results was based on quarterly data (landings and biomass) from 2013 to 2020. The output of the model shows that the stock is in a good state, being the biomass above B_{MSY} and the fishing mortality below F_{MSY}. Although the outputs of the model can be used to determine the status of the stock, they are not appropriate to provide advice given the high uncertainty associated to the absolute values of biomass, fishing mortality and reference points.

The 1 over 2 rule, in combination with a 80% symmetrical uncertainty cap and a biomass safeguard, seems to be the most adequate method to assess this stock at the moment. The starting point of the method was demonstrated to have a high impact on the future advice and it should be taken into account in its implementation. In addition, this method does not necessary lead to MSY exploitation and it is recommended to use it as a provisional harvest control rule until can be replaced by a better approach, such as a constant harvest rate derived from a management strategy evaluation or FMSY obtained from SPiCT.

1. Background

Historically, sardine in subarea 7 and the Bay of Biscay (divisions 8.a, b, and d) were considered a single stock unit, the Northern stock of sardine in EU Atlantic waters. However, WKPELA benchmark (ICES, 2017) concluded in 2017 that both areas should be assessed independently, claiming different growth rates, the existence of separate spawning grounds, and the presence of all ages in substantial amounts in both areas.

At the time, the data available to assess the stock in subarea 7 was limited and the stock was classified as category 5. Since then, the stock has been assessed every two years based on landing trends, although ICES could not provide a quantitative advice so far given the high uncertainty associated with the landings.

The WKWEST data compilation workshop evaluated the quality of the data currently available to assess this stock; specifically, the time series of catch, fishing effort, size composition of the catch, and the robustness of the biomass data provided by the PELTIC survey (ICES, 2021a). Whereas the fishing effort and size frequency data were not appropriate to assess the stock at this stage, the workshop concluded that the landings are now reliable and the PELTIC survey captures the bulk of the sardine stock. Therefore, both time series can be used to derive the status of the stock and provide catch advice.

The availability of the biomass data to assess the stock implies an upgrade of stock category, being now classified as category 3: stocks for which survey-based assessments indicate trends. Consequently, the assessment methods used for category 3 stocks have been explored in this benchmark.

1.1. Assessment methods for short-lived species, category 3 stocks

Short-lived species, such as sardine, undergo extreme fluctuations in annual recruitment and abundance, mainly driving by climatic forcing. The common management approaches applied to data-limited stocks in the NE Atlantic might be not appropriate for short-lived species as they are too slow responding to this high interannual variability. With the aim of finding new approaches to manage these resources, the workshop on data-limited stocks of short-lived species (WKDLSSLS) has recently tested different harvest control rules based on trends on biomass indices for short-lived species (ICES 2019, 2020a), and ICES has published the main conclusions of this workshop as a specific technical guidance on advice rules for short-lived stocks in category 3 (ICES, 2020b). The main conclusions from WKDLSSLS relevant for this benchmark are the following:

- The shorter the lag between observations, advice, and management, the bigger the catches and the smaller the risks. This means that in-year (or seasonal) advice should always be preferred over the normal calendar (with an interim) year advice, and the assessments should be annual if the survey data is provided every year.
- For short-lived stocks with sufficiently long input data series (and with enough contrast of biomasses and production in the series) surplus production models will be applicable, and the advice can be formulated on the basis of F_{MSY} (rather than on constant catch at MSY), or preferably less than F_{MSY} (accounting for the strong fluctuations of these short-lived species).
- If a surplus production model cannot be fitted and the stock has an accepted survey, the best way to adjust catches to the highly fluctuating nature of these stocks may be achieved by removing a constant fraction of the stock every year, corresponding with a sustainable harvest rate. This constant harvest rate is dependent on the actual life history of the stock and it is conditioned on the survey catchability and observation error. A stock-specific management strategy evaluation (MSE) process should be conducted when implementing this method in order to determine the constant harvest rate that is most robust to the operational model and observation system uncertainties.
- When knowledge of survey catchability or associate uncertainties are so poor to preclude the definition of a constant harvest rate, then a harvest control rule (HCR) based on biomass trends can be used. The recommendation is to apply the 1 over 2 rule (i.e., ratio between the biomass of the most recent year and the average of the two previous years),

coupled preferably with a symmetric Uncertainty Cap of 80% and an a biomass safeguard (I_{stat}). This trend-based rule does not necessarily lead to MSY exploitation and it should be revised within 10 years.

Following these guidelines, this benchmark reviewed a SPiCT (surplus production model in continuous time) assessment tuned to the available data for sardine, and the performance of 1 over 2 ratio-based advice. Although WKDLSSLS found that a constant harvest rate performs better than the 1 over 2 rule, the application of a constant harvest rate for sardine has not been tested due to the absence of a stock-specific MSE to identify a sustainable harvest rate.

2. Data available for the assessment

2.1. Landings

Reported catches by country are very variable over time and across ICES divisions and it was not clear if this variability was caused by the opportunistic nature of some fleets or by misreporting. To address this issue, the WKWEST data compilation workshop analysed the revised catches from 2002 to 2019 submitted by the countries participating in the sardine fishery, and it was agreed that they are now reliable and can be used in the stock assessment (ICES, 2021a). The high variability is primarily explained by shifts in fleets activity and species targeted over the years. Sardine is the main target species for some of the fleets, whereas it is a by-catch species for others. Some fleets are also opportunistic, and they only target sardine when the abundance or the quota of their main target species is low. Variations in the relative abundance of pelagic species, the market, and the fishing opportunities have driven the variability observed in sardine landings over time. In addition, the sardine fishery in Seine Bay (7d) has been closed for human consumption since 2010 due to PCB contamination. This closure has greatly affected the French fleet, whose landings decreased on average by 90% since 2010.

France submitted a new revised time series of sardine landings after the WKWEST data compilation workshop. The changes were minor and mainly affected the period 2005-2009, where the landings are lower in the new dataset. The updated landings have been used in this benchmark for the stock assessment (Table 1).

Table 1. Revised sardine landings (tons) reported by country for this benchmark

Year	Belgium	Denmark	France	Germany	Ireland	Lithuania	Netherlands	Poland	UK (England)	UK (Scotland)	Total
2002			7977	130	11417		1905		6636	1222	29287
2003			8186	13	4030		6897		4150		23276
2004			7807	60	2046		2187		2389		14488
2005			10605	140	922		2231		3457		17354
2006			11120	246	2416		2287		1925		17994
2007		4	7315		28		1106		2574	81	11108
2008		53	8562	43	473		2073		3306	164	14675
2009			3918		65		3406		2568		9957
2010		13	706	62	50		6645		2540		10017
2011		3	237	5	1966		513		3614		6337
2012		40	372	587	16		1637		4423		7075
2013		40	1703	214	473		1739		3722		7891
2014	0	953	1100	18			193		3893		6157
2015	0	1011	1208	1551	555		1156		4301		9783
2016	1	2286	925	1941	464	1	4629		9389		19634
2017	0	2460	820	1475	329				7578		12662
2018	1	263	606	758	89		811		8141		10670
2019	0	0	671	53	33	40	90	0	6429	1	7317

2.2. Biomass indices

The PELTIC, Pelagic Ecosystem Survey in the western Channel and Celtic Sea, is an autumn survey conducted annually by CEFAS (UK). It includes a typical acoustic survey design with parallel equidistant transects and a pelagic trawl used opportunistically to validate the species and size composition of the acoustic marks detected on the echogram. Acoustic and trawl data are combined in the post-processing step in ICES-endorsed software StoX and EchoR to obtain numbers and biomass at age for the most important stocks of small pelagics.

The first surveys (2012-2016) covered only the English waters of ICES areas 7e and all of 7f, but from 2017 survey coverage expanded to include also the French waters as well as one-off coverage of waters further north of the core area (2017), part of the eastern English Channel (2018) and Cardigan Bay in the southern Irish Sea (2020).

Two sardine biomass indices were calculated from PELTIC: one representing the consistently sampled “Core” Area of the whole time series (2013-2020): English waters of the western Channel (excluding the Isles of Scilly as this area was dropped in 2013 and 2016 due to adverse weather) and the whole of 7f (Bristol Channel in the Celtic Sea). The second, shorter, time series, “Total Area”, represented full coverage of the western Channel (7e, including the Isles of Scilly) and the eastern Celtic Sea (7f) (Figure 1).

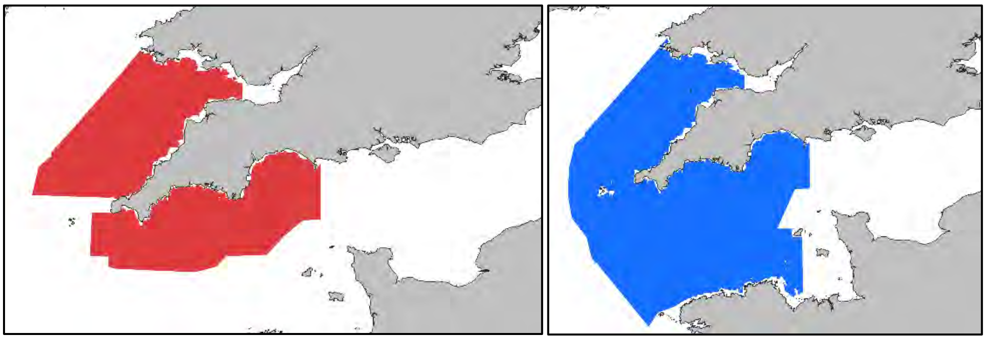


Figure 1. Consistently sampled PELTIC coverage of core area (left) since 2013 and total area, since 2017 (right)

The sardine biomass in the Core Area shows an overall increase over time, with lowest value of 48 kt in 2013 and the highest in 2019 of 274kt (Figure 2). For the total area, biomass estimates ranged from 146 kt (2018) to 375kt (2019).

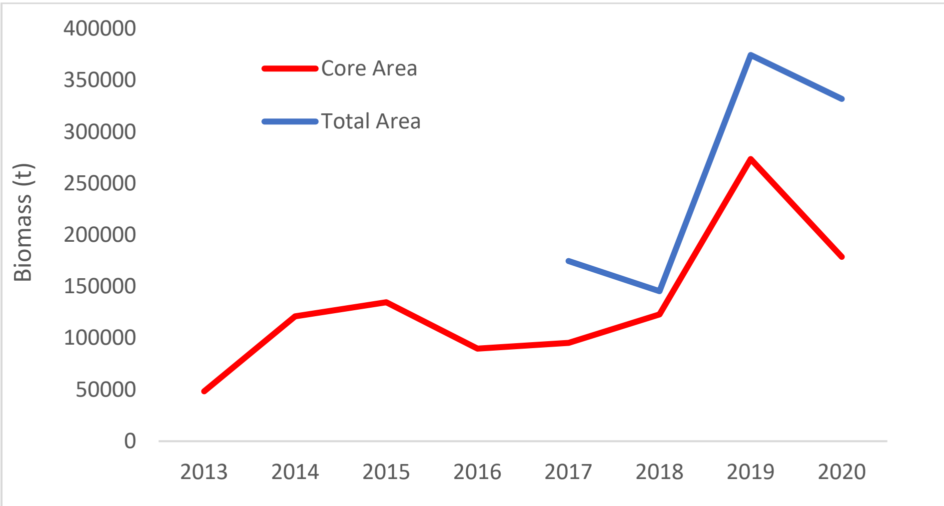


Figure 2. Trends in sardine biomass in area 7. In red, the sardine biomass of the core area (English waters of ICES area 7e (excluding the Isles of Scilly) and 7f); in blue, sardine biomass of the "total" area (ICES area 7e and f)

The spatial coverage of the survey and the internal consistency of the biomass data have been discussed in the WKWEST data validation workshop and it was agreed the survey data is robust and can be used in the assessment of the sardine stock in subarea 7.

3. Assessment methods for short-lived species, category 3 stocks

3.1. SPiCT

A Surplus Production Model in Continuous Time (SPiCT, Pedersen and Berg, 2017) was applied to estimate MSY proxy reference points and the stock status of sardine in subarea 7. The input data were the biomass index provided by the PELTIC survey for the core area (2013-2020) and the revised landing time series reported to ICES for this benchmark (2002-2019). Because the preliminary landings from France and England in 2020 were available, total landings in 2020 were estimated as 10977 t, based upon the assumption that England and France contributed with 90% of the total landings, similar to 2018 and 2019. The biomass index for the total area was not used in the model because the time series was too short (2017-2020) to produce meaningful results.

Using a LPUE time series as an indicator of biomass was suggested during the benchmark, but this option was finally rejected given the nature of the fishery. The fleet catching sardine targets diverse pelagic stocks, and their preferent species change over time depending on the relative abundance of the stocks and the markets. In addition, the most consistent contributor to the landings in recent years is the Cornish Sardine fleet in England, who self-regulate the landings based on demand and previous catches. Consequently, variations in the LPUE are mainly caused by changes in the fleet behaviour rather than by changes in sardine biomass.

Two exploratory SPiCT assessments were performed: 1) using all available data since 2002; and 2) restricting the model to the years with biomass information (2013-2020). The reason for shortening the time series of the model was to avoid the high decrease observed in landings since 2010. This decline was primarily caused by the closure of the fishery for human consumption in Seine Bay due to PCB contamination and the consequent decrease of French landings. In addition, landings from opportunistic fleets whose main target species is not sardine have been also low in recent years (Ouréns et al. 2021). Because there is not biomass information before 2013, the model could misinterpret this decrease in landings and associate it with a drop in stock size.

Both models with the long and short time series were run twice, using annual and quarterly data. In order to provide the model with some information about the level of exploitation before the input data, the initial depletion level was assumed to be 50% of the carrying capacity. The exact level of initial exploitation is unknown because there is not information about of the stock size. However, the fishery was already well stablished, and landings (although not revised) were higher than the current ones (ICES, 2020c). There are therefore evidences to believe that the initial exploitation was medium or high. The sensitivity of the models to this prior was tested by running them with different initial depletion levels, ranging from 30 to 80 in increments of 10.

The models with annual data did not converge given the limited number of observations and/or a lack of contrast in biomass and production. The model with the long time series (2002-2020) and quarterly data did not converge when applying the prior of initial depletion. The model fitted well the data without the prior, but it misinterpreted the drop in landings in 2010, associating it with a high increase in fishing mortality and a decrease in biomass (Figure 3). In addition, the model was very unstable and did not converge when trying to slightly tune it. Consequently, the benchmark agreed it was inappropriate to assess the stock.

The model with the short time series (2013-2020) and quarterly data (Figure 4) was stable and produced more realistic outputs:

```
Convergence: 0  MSG: relative convergence (4)
Objective function at optimum: 37.1813156
Euler time step (years):  1/16 or 0.0625
Nobs C: 32,  Nobs I1: 8

Priors
 logbkfrac  ~  dnorm[log(0.5), 0.5^2]
      logn  ~  dnorm[log(2), 2^2]
```

```
  logalpha  ~  dnorm[log(1), 2^2]
   logbeta  ~  dnorm[log(1), 2^2]

Model parameter estimates w 95% CI
            estimate        cilow        ciupp    log.est
 alpha  3.622680e+00    0.3735136 3.513609e+01  1.2872141
 beta   1.097009e+00    0.3462243 3.475867e+00  0.0925877
 r      2.157659e+00    0.1196200 3.891900e+01  0.7690236
 rc     1.171897e+00    0.1904448 7.211233e+00  0.1586236
 rold   8.043955e-01    0.1207334 5.359347e+00 -0.2176642
 m      1.462823e+04 7808.8193661 2.740302e+04  9.5907087
 K      4.058716e+04 3977.4408377 4.141651e+05 10.6112069
 q      4.543162e+00    0.4413643 4.676481e+01  1.5136232
 n      3.682335e+00    0.4667739 2.904960e+01  1.3035472
 sdb    9.322690e-02    0.0097271 8.935082e-01 -2.3727185
 sdf    3.604641e-01    0.1317467 9.862434e-01 -1.0203630
 sdi    3.377314e-01    0.1902136 5.996547e-01 -1.0855045
 sdc    3.954324e-01    0.2894425 5.402345e-01 -0.9277753
 phi1   1.637200e-01    0.0559713 4.788927e-01 -1.8095973
 phi2   2.708380e-02    0.0144327 5.082450e-02 -3.6088198
 phi3   1.075133e+00    0.3847712 3.004149e+00  0.0724440

Deterministic reference points (Drp)
           estimate        cilow        ciupp    log.est
 Bmsyd 2.496505e+04 2634.2249659 2.365986e+05 10.1252322
 Fmsyd 5.859484e-01    0.0952224 3.605617e+00 -0.5345235
 MSYd  1.462823e+04 7808.8193661 2.740302e+04  9.5907087
Stochastic reference points (Srp)
           estimate       cilow        ciupp    log.est rel.diff.Drp
 Bmsys 2.468858e+04 2570.342721 237138.03698 10.1140961 -0.011198362
 Fmsys 5.811209e-01    0.093167      3.62469 -0.5427964 -0.008307236
 MSYs  1.434572e+04 7776.353230  26464.79365  9.5712067 -0.019693423

States w 95% CI (inp$msytype: s)
                    estimate        cilow        ciupp    log.est
 B_2020.94      3.305866e+04 2832.1058447 3.858878e+05 10.4060388
 F_2020.94      2.703956e-01    0.0251878 2.902752e+00 -1.3078690
 B_2020.94/Bmsy 1.339026e+00    0.8968200 1.999277e+00  0.2919427
 F_2020.94/Fmsy 4.653001e-01    0.1921561 1.126710e+00 -0.7650726

Predictions w 95% CI (inp$msytype: s)
                  prediction        cilow        ciupp    log.est
 B_2022.00      3.296067e+04 2728.5166834 3.981671e+05 10.4030702
 F_2022.00      2.703958e-01    0.0225819 3.237719e+00 -1.3078686
 B_2022.00/Bmsy 1.335057e+00    0.8583444 2.076529e+00  0.2889741
 F_2022.00/Fmsy 4.653003e-01    0.1479763 1.463102e+00 -0.7650722
 Catch_2021.00  9.377101e+03 4705.7227015 1.868576e+04  9.1460260
 E(B_inf)       3.680186e+04           NA           NA 10.5133037
```

The model shows the stock is in a good state, being the biomass above the biomass at MSY (B_{MSY}) and the fishing mortality below the fishing mortality at MSY (F_{MSY}). However, the confidence intervals of both reference points (B_{MSY} and F_{MSY}) and the absolute values of biomass and fishing mortality were very wide and therefore these values are not reliable (Figure 5).

The robustness of the model was analysed by means of the residual patterns, retrospective analysis, and the sensitivity of the model to the prior of initial depletion. The diagnosis of the residuals shows the assumptions of the model are met: the catch and biomass data have normal distributions, and there are not auto-correlation or bias in the data (Figure 6). The retrospective patterns of the model could not be properly analysed given the short time series of data. The model only converged eliminating information from one year, and although the retrospective trajectories for the relative biomass and fishing mortality were inside of the confidence intervals, a longer time series is needed to analyse temporal patterns in successive assessments (Figure 7).

The temporal trends of relative biomass and fishing mortality to the reference points were very similar when the initial depletion level of the population was assumed to be between 40 and 80% of the carrying capacity (Figure 8, Figure 9). In these cases, the posterior value of the depletion level after running the models was around 75%. Both relative fishing mortality and biomass showed very strong seasonality when the prior for the initial depletion level was 80% and high confident intervals when the prior was 30%. Because the model was only sensitive to extreme values of the prior, the 50% value used in the final model was considered appropriate.

The benchmark concluded that the relative fishing mortality and biomass obtained from the model are robust and can be used to identify the status of the stock. However, the outputs of the model cannot be used to provide advice given the high uncertainty associated with the absolute values of biomass, fishing mortality and the reference points.

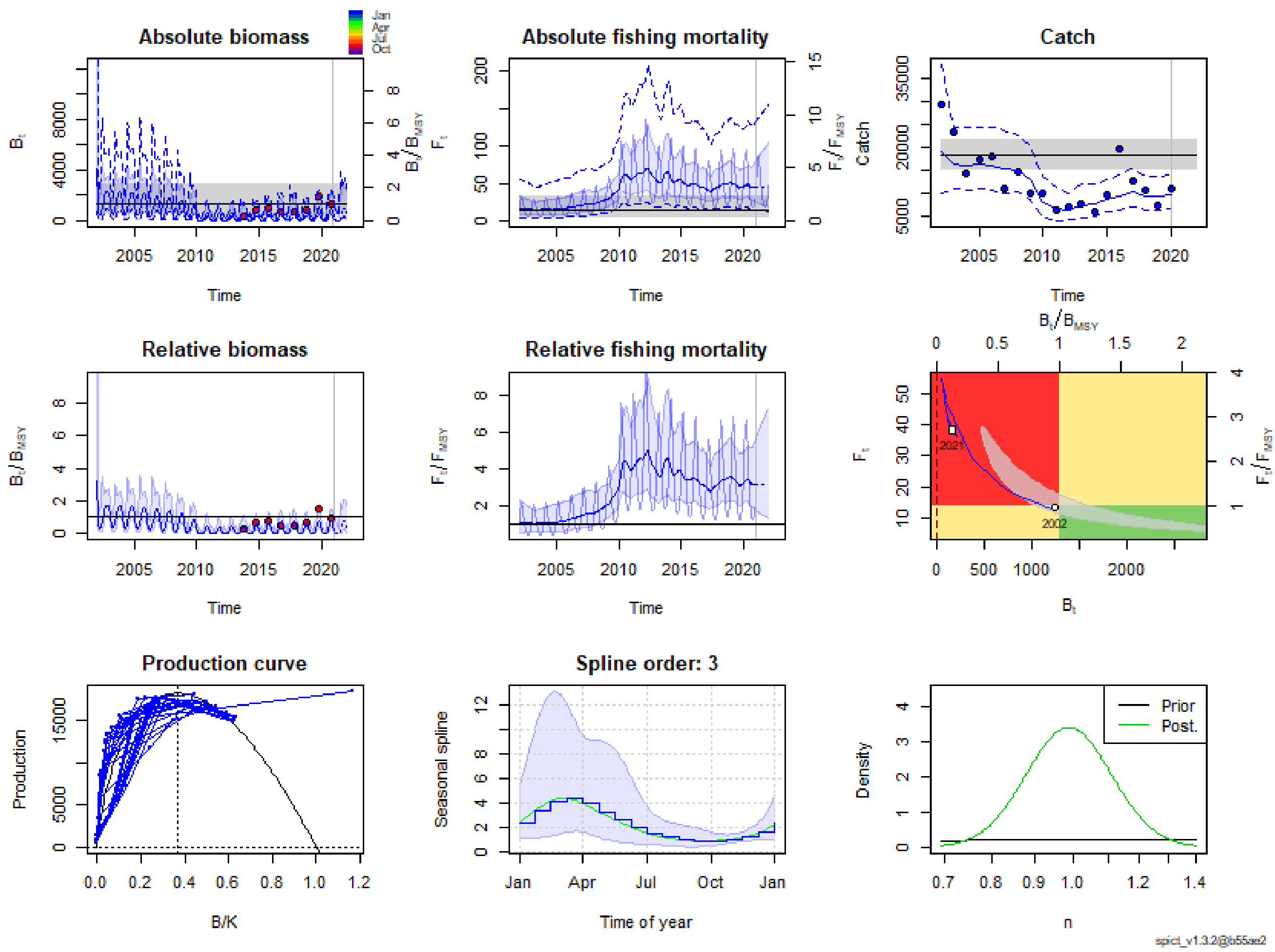


Figure 3. Main outputs of the model with the long time series (2002-2020) and quarterly data. Legend: Estimates (fishing mortality, biomass, production, catch) are shown using blue lines. 95% CIs of absolute quantities are shown using dashed blue lines. 95% CIs of relative biomass and fishing mortality are shown using shaded blue regions. Estimates of reference points (B_{MSY}, F_{MSY}, MSY) are shown using black lines. 95% CIs of reference points are shown

using grey shaded regions. The end of the data range is shown using a vertical grey line. Predictions beyond the data range are shown using dotted blue lines.

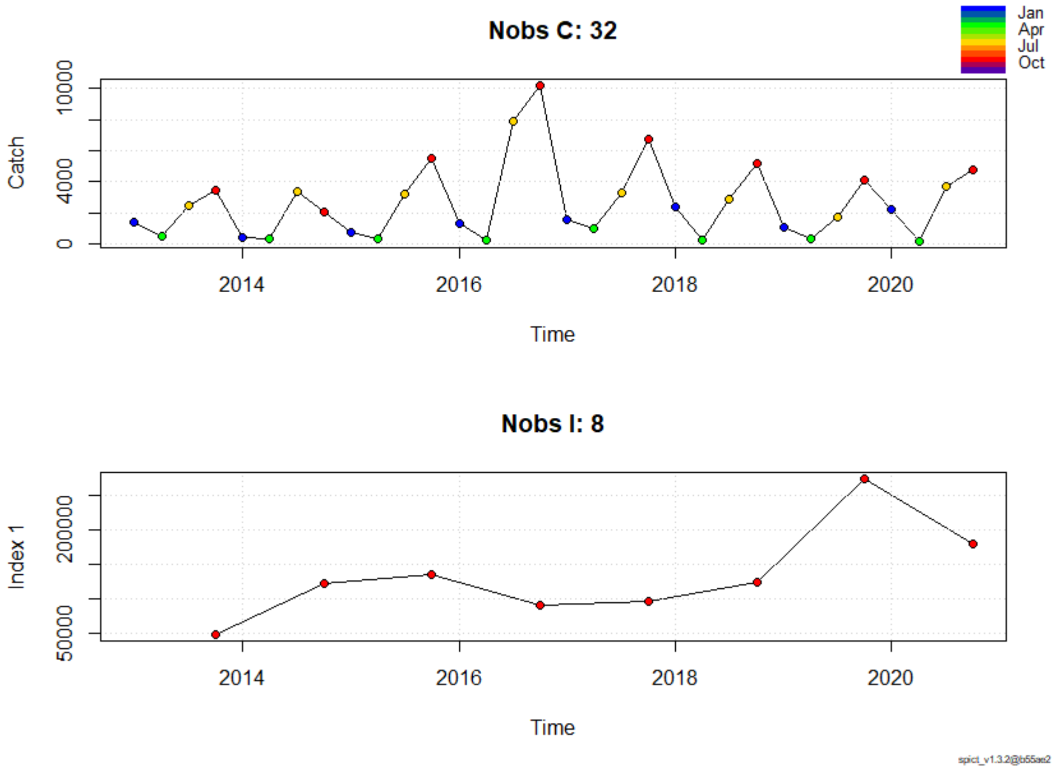


Figure 4. Input data of the SPiCT model with the short time series (2013-2020) and quarterly data. Each season is represented by a colour: blue is quarter 1, green is quarter 2, yellow is quarter 3, and red is quarter 4.

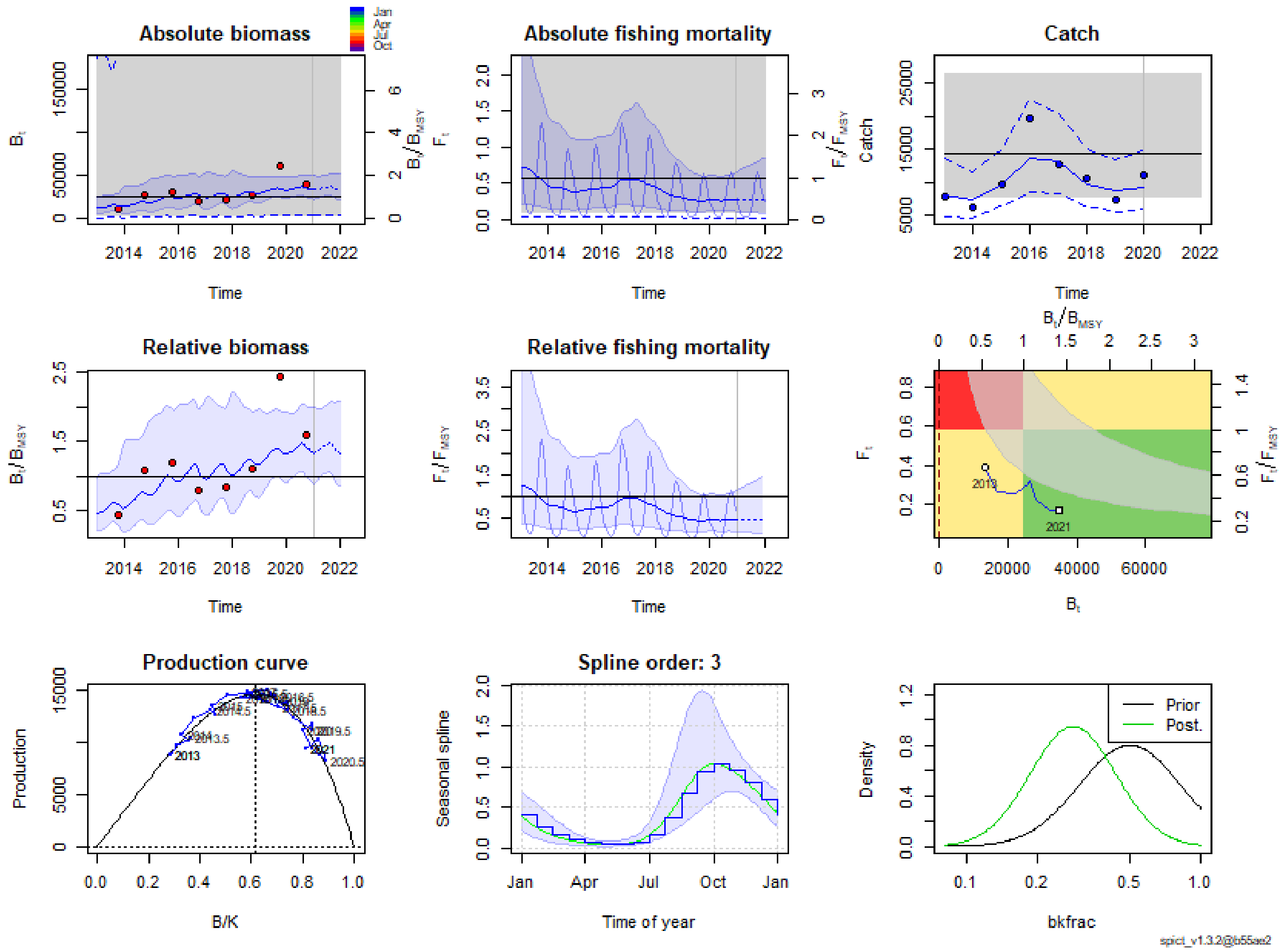


Figure 5. Main outputs of the model with the short time series (2013-2020) and quarterly data. A prior was included to set the initial depletion of the stock at 50% of the carrying capacity. Legend: Estimates (fishing mortality, biomass, production, catch) are shown using blue lines. 95% CIs of absolute quantities are shown using dashed blue lines. 95% CIs of relative biomass and fishing mortality are shown using shaded blue regions. Estimates of reference points (B_{MSY}, F_{MSY}, MSY) are shown using black lines. 95% CIs of reference points are shown using grey shaded regions. The end of the data range is shown using a vertical grey line. Predictions beyond the data range are shown using dotted blue lines.

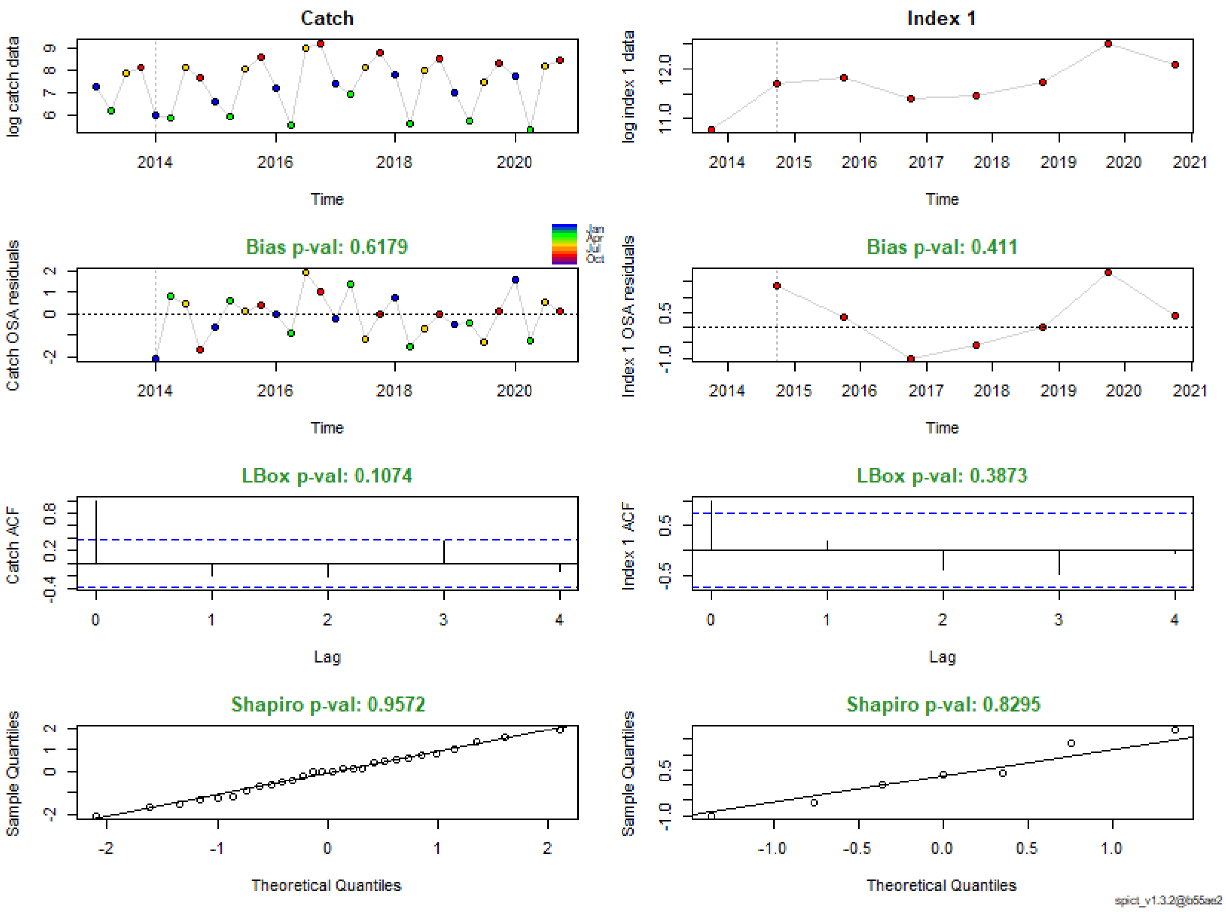


Figure 6. Residual diagnostics of the SPiCT model with the short time series and quarterly data

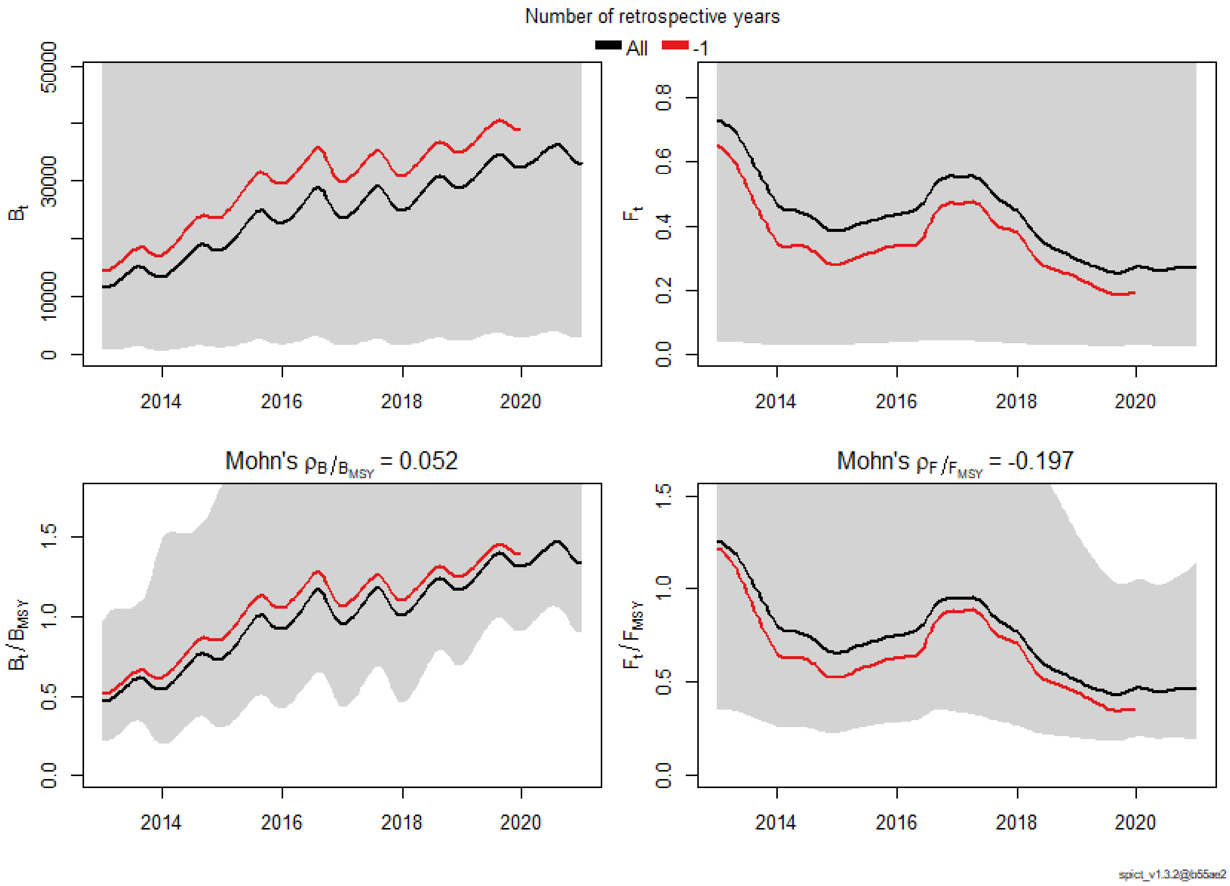


Figure 7. Retrospective analysis of the SPiCT model with the short time series and quarterly data

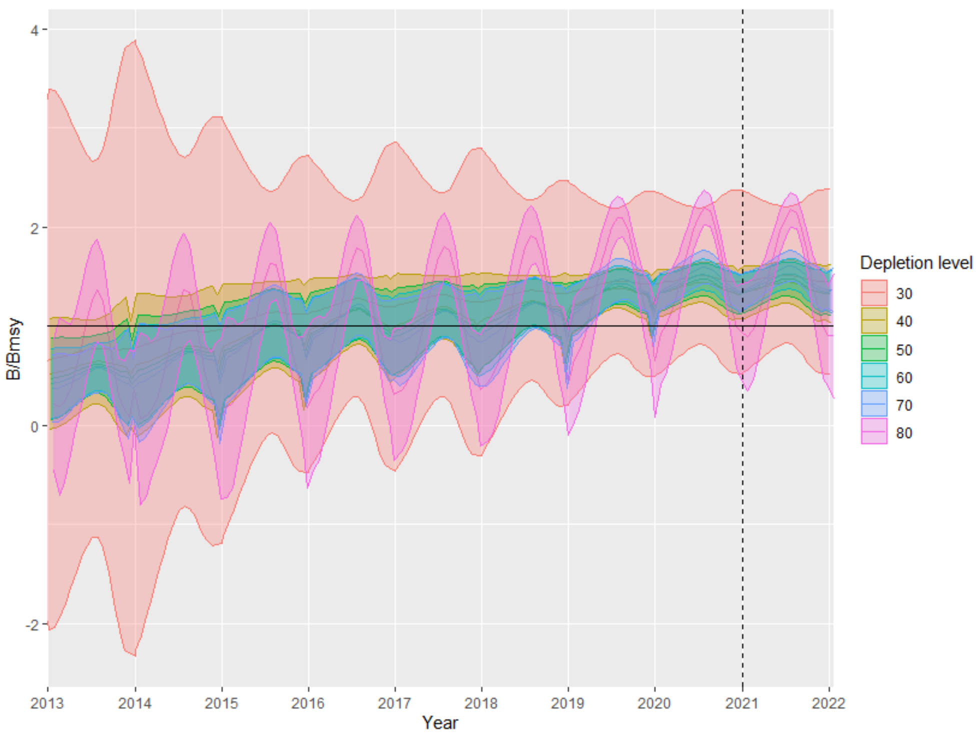
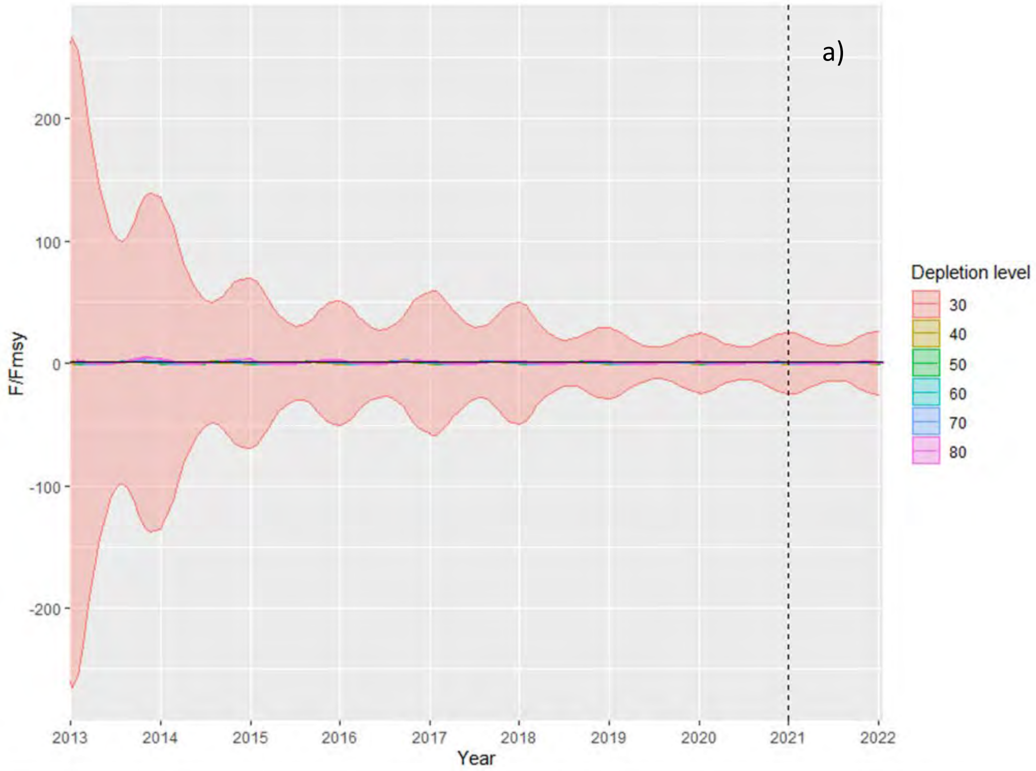


Figure 8. Temporal trend of the relative biomass produced by the SPiCT model with the short time series and quarterly data. The initial depletion of the stock was set at different depletion levels, ranging from 30 to 80% of the

carrying capacity. The end of the data range is shown using a vertical dashed line. The value $B/B_{MSY} = 1$ is shown with a horizontal solid line.



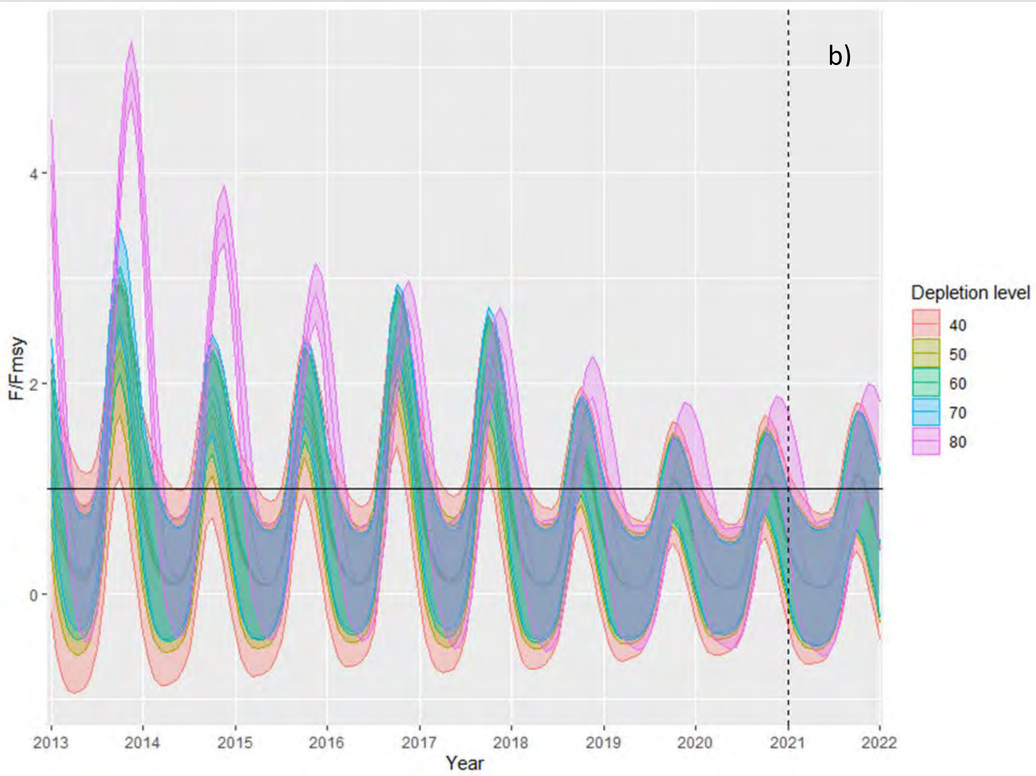


Figure 9 Temporal trend of the relative fishing mortality produced by the SPiCT model with the short time series and quarterly data. The initial depletion of the stock was set at different levels, ranging from 30 to 80% of the carrying capacity (a). The output for the model without the depletion at 30% was removed in b) given the high uncertainty of the output. The end of the data range is shown using a vertical dashed line. The value $B/B_{MSY} = 1$ is shown with a horizontal solid line.

3.2. 1 over 2 rule

Indices based on biomass trends are commonly used to provide advice for stocks in category 3. The 1 over 2 approach consists in multiplying the most recent catch advice by the ratio of the most recent biomass value and the average of the two preceding values. It was proposed for short lived Category 3 stocks by WKDLSSLS to replace the previous generic index-based 2 over 3 rule (ratio of the average of the two most recent biomass values and the three preceding values). This replacement was suggested because the 2 over 3 rule was demonstrated to be slow in responding to rapid changes in the size of stocks with a short life span and expressing rapid changes in biomass (*r* selection species). In a situation of rapidly decreasing or increasing biomass, this index is unable to respond in an appropriate timeframe or to an appropriate extent (ICES, 2019).

WKDLSSLS (ICES 2019, 2020a) examined and tested *via* MSE the application of 1 over 2 ratio-based advice with a range of different uncertainty caps and safeguards applied to data limited, short lived species. The emergent recommendation was to apply the 1 over 2 rule in combination with a 80% symmetrical uncertainty cap, which restricts the degree of inter-annual change in advice to 80%, and a biomass safeguard defined as I_{stat}, which is derived from the historical biomass index. If the biomass index falls below I_{stat}, the advised catch will be reduced in proportion to the drop of the biomass index in relation to I_{stat} (ICES 2020a, 2020b).

The 1 over 2 rule with the 80% symmetrical cap and the biomass safeguard was applied to the sardine stock in subarea 7 using the biomass trend index estimated from both the core area and the total area. This HCR was applied with a retrospective character in order to analyse the trend of the advice if the HCR had been implemented when the data became available (i.e., 2016 for the advice derived from the biomass trend in the core area and 2020 for the advice derived from the biomass trend in the total area). Following the ICES guidelines, the HCR was implemented the first year by applying the biomass ratio to the mean of landings of the two previous years. After that, the ratio was applied to the previous catch advice. Like in the SPiCT model, total landings in 2020 were assumed to be 10977 t, based upon the assumption that England and France contributed with 90% of the total landings.

Figure 10 shows that the HCR responds smoothly to abrupt changes in biomass because of the historical data included in the denominator of the biomass ratio. It seems that there is also 1 year lag in the response due to the time between the survey and the implementation of the advice, but this lag is actually smaller given the survey takes place in October of year *y* and the advice with the new information is implemented in January of *y+1*. Nevertheless, it is worth to note that this stock is currently assessed every two years. It is highly recommended to perform an annual assessment in order to use the most updated biomass values in the advice and obtain a better performance of the HCR.

The benchmark panel concluded that the biomass estimated in the total area should be used for the advice as a significant part of the stock (33% on average) has been found outside of the core area. In fact, the advised catch derived from the biomass in the core area was lower than the landings for 3 out of 5 years with data (Figure 10).

The I_{stat} value for each year was estimated using the biomass index from the total area and core area to set the biomass safeguard. The I_{stat} was estimated using the following equation:

$$I_{stat} = geometric(I_{hist}) \cdot \exp(-1.645 \cdot sd(\log(I_{hist})))$$

Where I_{hist} is the available historical series of the biomass index.

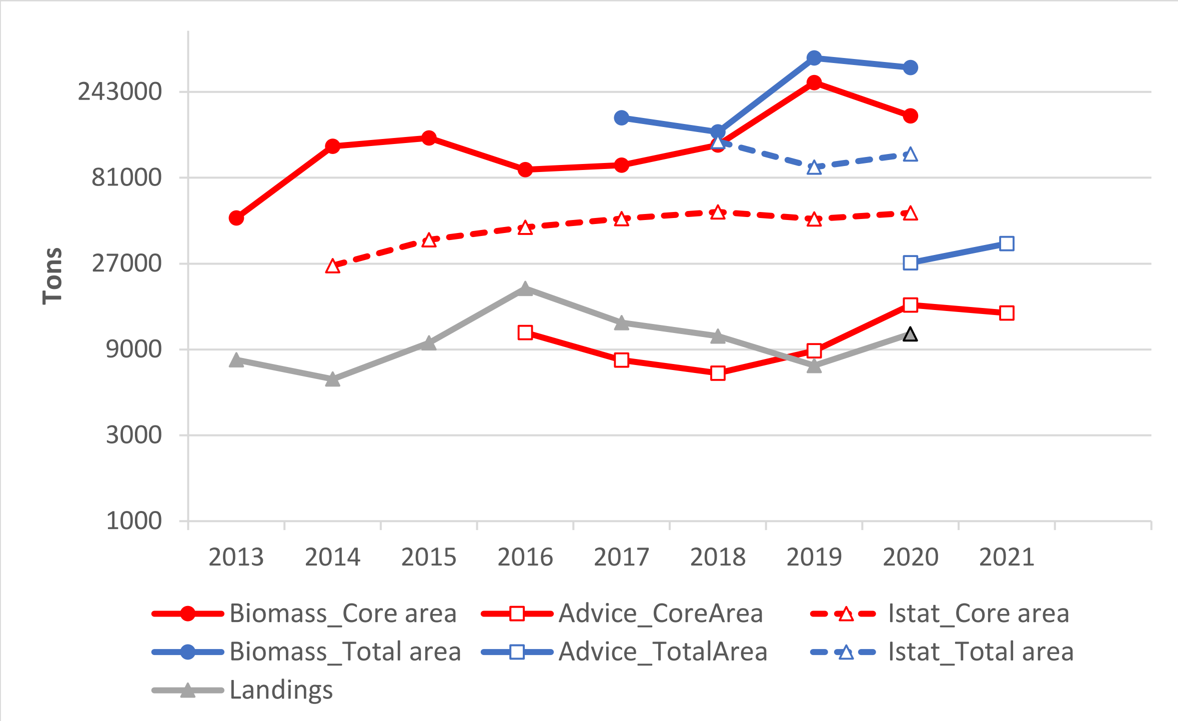


Figure 10. Simulation of advice resulting from applying the 1 over 2 rule with a 80% uncertainty cap with a retrospective character. The rule has been applied using both the biomass trend derived from the total area and the core area. The biomass and I_{stat} values from total area and core area are also represented. Note the y-axis is in a logarithmic scale.

The benchmark panel also agreed that the biomass safeguard should be derived from the biomass in the total area because it was also the baseline for the 1 over 2 rule. Using the smallest I_{stat} value of the time series, the biomass safeguard was set at 92858 t (Table 2). Nevertheless, there were some concerns about the limited number of observations available to estimate the biomass safeguard and the risk of reducing unnecessarily the yield of the fishery by setting a high biomass safeguard. This reference point should be revised in the next benchmark when the biomass time series in the total area becomes longer.

Table 2. I_{stat} values derived from the biomass in the total area and in the core area.

	Core Area	Total Area
2014	26327	
2015	36601	
2016	43068	
2017	47994	
2018	52324	128932
2019	47778	92858

2020	51599	109965

WKDLSSLS demonstrated that the 1 over 2 rule applied with a 80% symmetric uncertainty cap and a biomass safeguard is a precautionary harvest control rule that keeps the probability of the stock falling below 20% B_{lim} lower than 0.2 in a ten-year time frame (ICES, 2020a). This HCR, however, can result in reductions of catches due to the inability of the rule to take advice back to the previous level after hitting the lower cap. It has been noted that an 80% decrease in advice requires a 500% increase in the following advice to return to the previous level, taking a minimum of 3 years to achieve when an 80% uncertainty cap is applied (ICES, 2021b). This would lead to depressed catch advice, which may run contrary to an observed high biomass index value. The 1 over 2 rule should be therefore considered as a provisional HCR with the aim of achieving a better management approach within 10 years (ICES, 2020b).

It has been also noted that the initial biomass and landing values used to implement this HCR for first time have a significant impact on not just next year's advice, but also future advice. To demonstrate this, the HCR was applied to the sardine stock in subarea 7 using 3 different approaches: 1) The HCR is implemented in 2022 for first time by applying the biomass ratio to the average landings of 2019 and 2020; 2) The HCR is implemented in 2022 for first time by applying the biomass ratio to the average landings of the last 5 years available (2016-2020); and 3) The HCR is implemented in 2022 for first time by using a retrospective approach, i.e., the biomass ratio was applied to the catch that had been advised in 2021 if the HCR was implemented in 2020, when the biomass data in the total area became available. A drop in biomass and a following increase was simulated to estimate the catch advice with the three approaches.

The advice changes considerably between the three approaches considered here (Figure 11). The current recommendation is to apply the biomass trend index to the mean landings of the two previous years (approach 1), as this was the approach used in WKDLSSLS. While this may be appropriate for stocks which are fully exploited, the sardine fishery has not been at its maximum capacity in recent years and the landings were low. The main reasons for these low landings were previously discussed: the main contributor to the landings in recent years are the Cornish sardine fleet in the UK, who self-regulate the landings (usually at below 10000 t) based on several factors such as demand and previous catches. In addition, the landings from opportunistic fleets that target sardine sporadically but with a high intensity were low in recent years. If the advice is based on recent landings the yield of the fishery will be unnecessarily low, and it will not take into account the potentially large contributions from opportunistic fleets. The catch advice for 2022 would be 5177 t using the approach 1 under the simulated scenario (2.6% harvest rate). This advice is below the minimum landings recorded in the last two decades, despite the fact that there is strong evidence that the stock is in good condition.

The advised catches would be slightly higher if the approach 2 is used, given the average landings of the 5 last years were higher than in the last two years. The advice in 2022 would be 6935 t (3.5% harvest rate). The catch advice increases considerably with the approach 3, and the advised catches for 2022 would be 19732 t under the simulated scenario, 9.87% harvest rate.

This harvest rate is of the order of the constant harvest rate suggested for sprat in 7de (8.57%) at its recent inter-benchmark (ICES, 2021b).

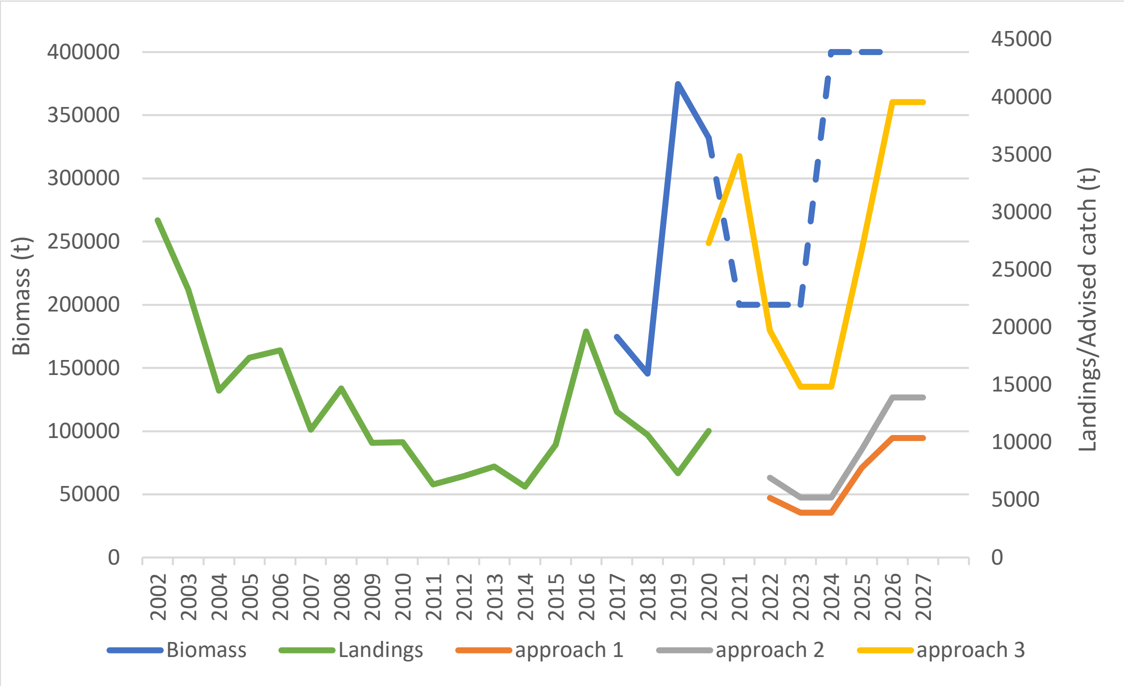


Figure 11. Simulation of advice resulting from applying the 1 over 2 rule with 80% uncertainty cap with three different approaches: 1) using the mean landings in the last two years, 2) using the mean landings in the last 5 years, and 3) implementing the rule with a retrospective character. The dashed blue line indicates simulated survey biomass

The impact of the initial landings and biomass on the future advice should be further explored in order to provide an updated guidance to implement the 1 over 2 rule. It might be not possible to provide a specific guidance, and the implementation of the HCR might have to be individually analysed in order to adapt it to the current condition of the stock and characteristics of the fishery. Similar open approach has been taken by ICES regarding the application of the precautionary buffer in combination with the 1 over 2 rule. This HCR has been tested without any precautionary buffer and it is probably unnecessary for lightly exploited stocks. The ICES guidelines states that the convenience of applying such a precautionary buffer would depend on an early assessment of the exploitation levels and depletion of the resource (ICES, 2020b).

4. Conclusions

Sardine in subarea 7 has moved from category 5 stock to category 3 as the biomass data provided by the PELTIC have been considered robust and representative of the stock. A SPiCT model based on quarterly data since 2013 will be used to assess the stock based on the relative biomass and fishing mortality to the reference points (B_{MSY}, F_{MSY}). However, the SPiCT model was considered inappropriate to provide catch advice given the high uncertainty associated to the absolute values of biomass, fishing mortality and reference points. The 1 over 2 rule based on the biomass trend index derived from the total area, in combination with a 80% symmetrical uncertainty cap and a biomass safeguard, seems to be the most adequate method to assess this stock at the moment. It has been demonstrated that the initial landings and biomass when applying the HCR for first time have a high impact on the future advice and therefore the implementation of the rule must be carefully designed. In addition, the 1 over 2 rule is a provisional HCR that not necessary leads to MSY exploitation and it should be replaced by a better approach in the near future. Using the F_{MSY} obtained from a surplus production model or a sustainable constant harvest rate determined by a MSE, are the preferable methods to provide advice for category 3 stocks of short-lived species (ICES, 2020b).

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Working Document to the ICES WKWEST,
Data Compilation Meeting, January 2021

Common sole (*Solea solea*) stock in ICES divisions 8c9a. Data compilation and preliminary assessment.

Maria Grazia Pennino[1], Catarina Maia[2], Alberto Rocha[2], Cristina Silva[2], Ivone Figueiredo[2], Marta Cousido[1], Francisco Izquierdo[1], Santiago Cerviño[1], Francisco Velasco[3], Josefina Teruel Gomez[1], José Rodríguez[1]

[1]Instituto Español de Oceanografía (IEO), Centro Oceanográfico de Vigo, Spain.
[2] Instituto Português do Mar e da Atmosfera (IPMA), Portugal.
[3]Instituto Español de Oceanografía (IEO), Centro Oceanográfico de Santander, Spain.

Background

The common sole (*Solea solea*, Linnaeus, 1758) is a species of flatfish which is widely distributed in Northeast Atlantic shelf waters, from the northwest of Africa to southern Norway, including the North Sea, the western Baltic and the Mediterranean Sea. Inhabiting sandy and muddy bottoms (Quero et al., 1986), this species is generally targeted by multi-species fleets (gillnetters and trawlers) and has traditionally been considered of great relevance due to its high commercial value (Teixeira and Cabral, 2010).
The life cycle of common sole is complex and presents different ontogenetic migrations (Tanner et al., 2017). Common sole spawn in coastal waters at depths ranging from 30 to 100 m (van der Land, 1991). The spawning period is commonly between February and May, although it can occur in early winter in warmer areas. The development of the larvae is temperature-dependent and takes place in shallow waters (Tanner et al., 2017). It is during transport from spawning areas to coastal nurseries that the larvae metamorphose into benthic life (Marchand, 1993). Nursery areas are generally located within estuaries where juveniles of common sole spend up to 2 years in a residence phase before returning to the adult feeding and spawning areas on the continental shelf (e.g., Vasconcelos et al., 2010).

The unit management of the common sole stock in the Iberian Atlantic waters includes the ICES Subdivision 8.c and 9.a. where both the Portuguese and Spanish fleets operate. In this area common sole is target mainly by multi-species fleets using as main fishing gears trammel and gill nets.

The minimum landing size of sole is 24 cm. There are other regulations regarding the mesh size for trammel and trawl nets, fishing grounds and vessel's size. Sole is under the Landing Obligation in Divisions 8.abde (all bottom trawls, mesh sizes between 70 mm and 100 mm, all beam trawls, mesh sizes between 70 mm and 100 mm and all trammel and gill nets, mesh size larger or equal to 100 mm) and in Division 9.a (all trammel nets and gill nets, mesh size larger or equal to 100 mm). In Portugal all catches of sole from all gears and mesh sizes are under the Landing Obligation (more restrictively than required by European regulations).

The common sole stock, sol8c9a, is considered as a data-limited stock and it is classified as category 5 stock, as only catches data were available. There is no analytical assessment for sole in this area. Since 2012, ICES provides scientific advice for this stock applying the precautionary approach. A precautionary buffer was applied in 2018 (≥20% reduction in catch relative to 2014-2016 average) and in 2019 (same catch value advised as 2018) with an advises that catches should be no more than 502 tones (2020-2021).
The advice and assessment are provided only for common sole species. The management of all sole species is provided under a unique combined Total Allowable Catch (TAC).

The EU multiannual plan (MAP; EU, 2019) for stocks in the Western Waters and adjacent waters applies to this stock. The MAP stipulates that when the F_{MSY} ranges are not available, fishing opportunities should be based on the best available scientific advice.
At the moment this stock is going to be benchmarked in the WKWEST21 (Data meeting: 1-4 December 2020; Assessment meeting: in February 2021) as well as the WKMSYSPiCT21. For the WKWEST21 an official data call was requested for this stock to get all the possible data, not only for the common sole (*S. Solea*) but also for the other sole species *Solea senegalensis*, *Pegusa lascaris* and sole spp.

Data

Catches

From the recent data call, catches for *S. solea* are available in InterCatch from 2009 to 2019 (Figure 1). Information on discards indicates that discarding can be considered negligible (< 1%).
For the years 2009-2010, only catches from Spain and France were available (Figure 2), while for the other years (2011-2019) catches are available for the three countries (i.e., Portugal, Spain and France).
During the WGBIE2020, Portuguese's colleagues highlight that catches from Portugal have a problem of misidentification in some ports with the three species (Dinis et al., 2020).
For this benchmark, using data from the Data Collection Framework (DCF) sampling, Portuguese catches were proportionally divided by sole species applying the species weight proportion to the total weight of Soleidae in each year, landing port, and semester and using a simple random sampling estimator, following Figueiredo et al. (2020) (see details in annex 1).
At the moment the new data are considered reliable.

From the "*Historical Nominal Catches from 2000-2010, Source: Eurostat/ICES database on catch statistics - ICES 2011, Copenhagen. Version 26-06-2019*" dataset, catches are available for *S. sole* for 2000-2010 but some years data were reported only by Portugal, others by Spain and for this reason are considered possible underestimated (Figure 3).

When catches are analyzed by division it is possible to see that the majority of them are in the Area 9a (Figure 4).
Different métiers fish this stock (Figure 5). However, when the proportion of the catches by fleet on the total catches is computed (Table 1) it is possible to see that there are two main métiers that catch this stock, the "MIS_MIS_0_0_0" from Portugal and "GRT_DEF_60-79_0_0" from Spain (Figure 6).

When catches are analyzed by quarter it is possible to see that the distribution is almost homogenous along the year (Figure 7), also for the two main countries (i.e. Portugal and Spain) (Figure 8), as well as for the main métiers (Figure 9).

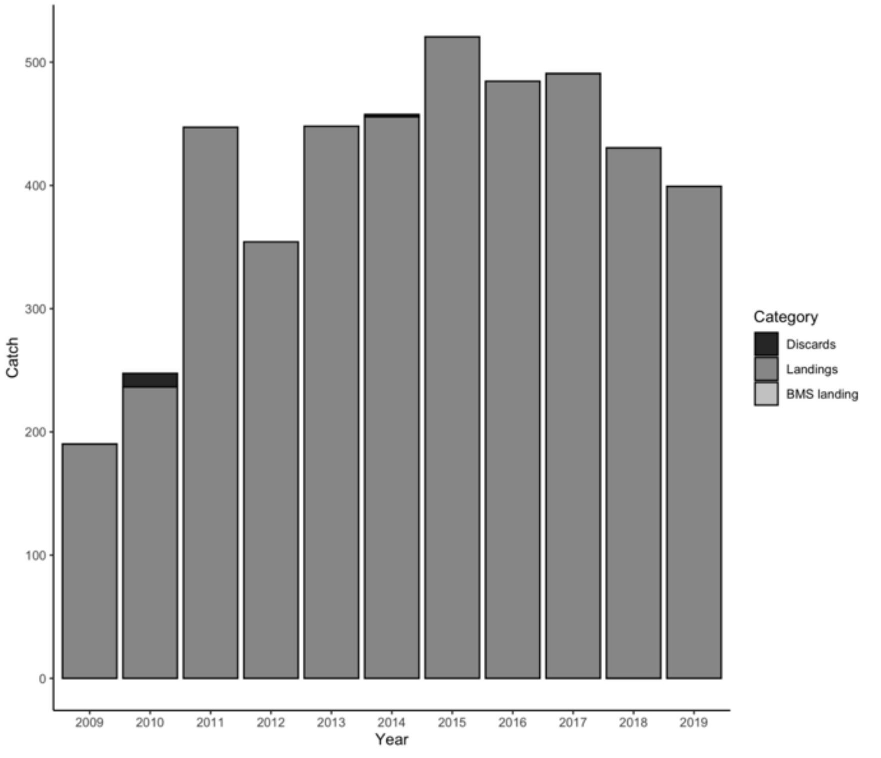


Figure 1: Catches for *Solea solea* by category in the ICES divisions 8c9a for Portugal, Spain and France from 2009 to 2019. Source data: InterCatch.

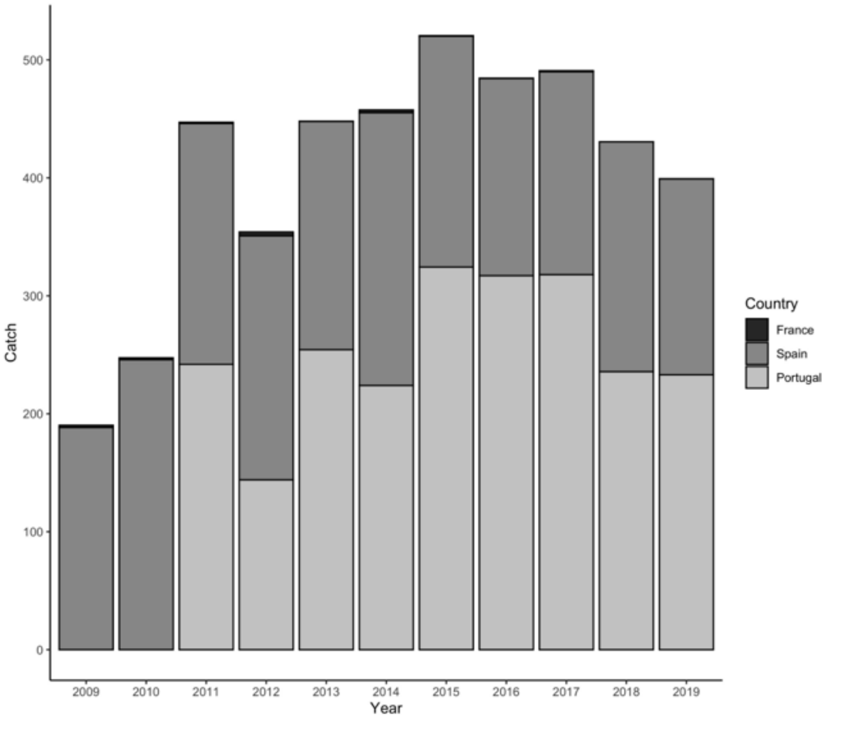


Figure 2: Catches for *Solea solea* by country in the ICES divisions 8c9a for Portugal, Spain and France from 2009 to 2019. Source data: InterCatch.

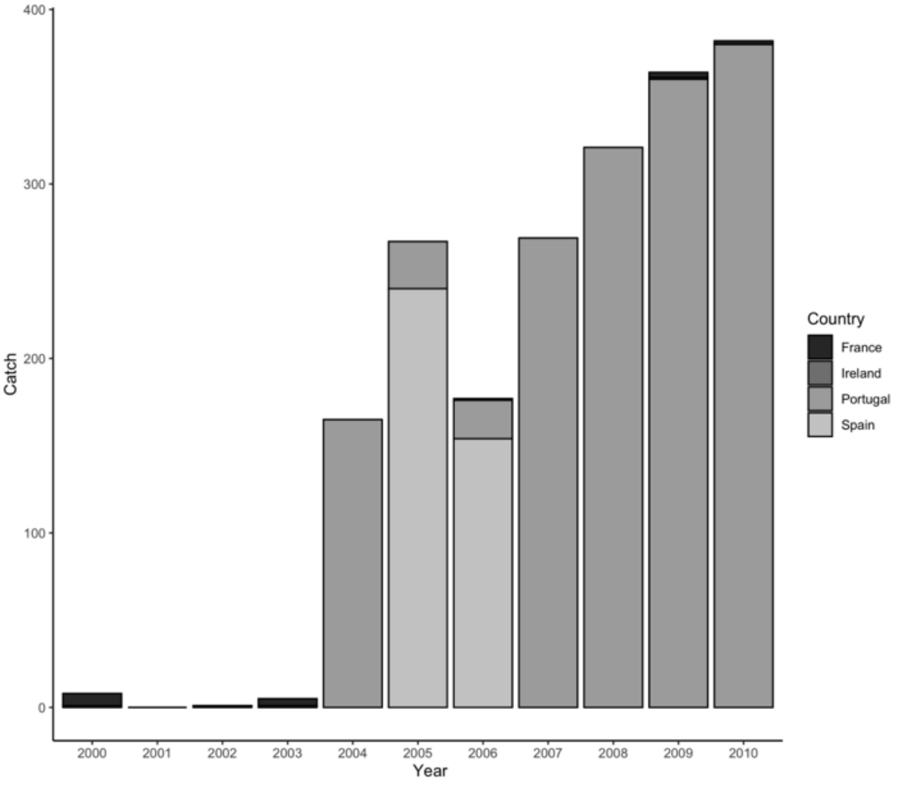


Figure 3: Catches for *Solea solea* by country in the ICES divisions 8c9a for Portugal, Spain, Ireland and France from 2000 to 2010. Source data: Eurostat/ICES database on catch statistics.

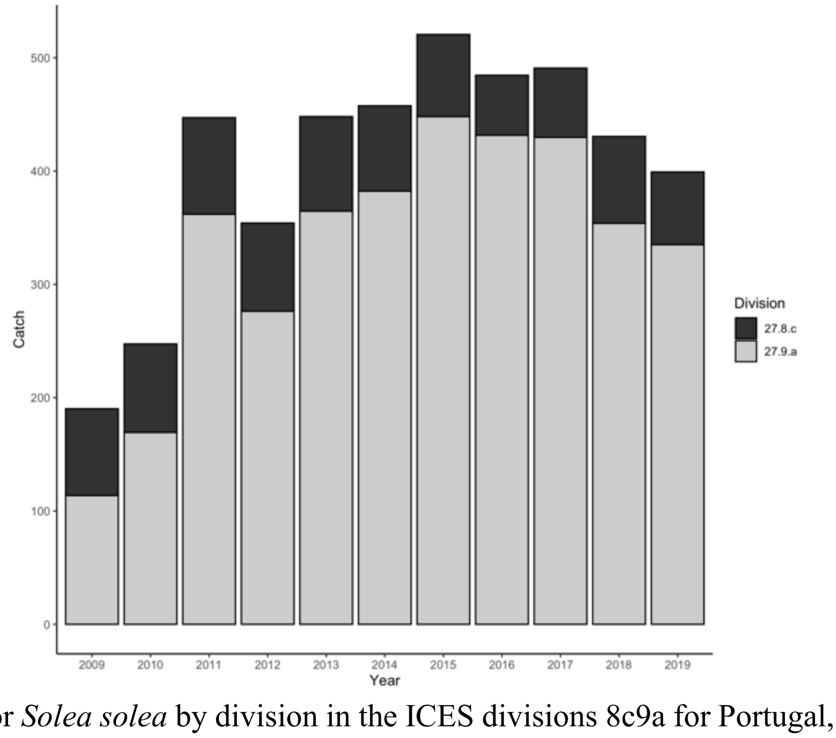


Figure 4: Catches for *Solea solea* by division in the ICES divisions 8c9a for Portugal, Spain, Ireland and France from 2000 to 2010. Source data: Eurostat/ICES database on catch statistics.

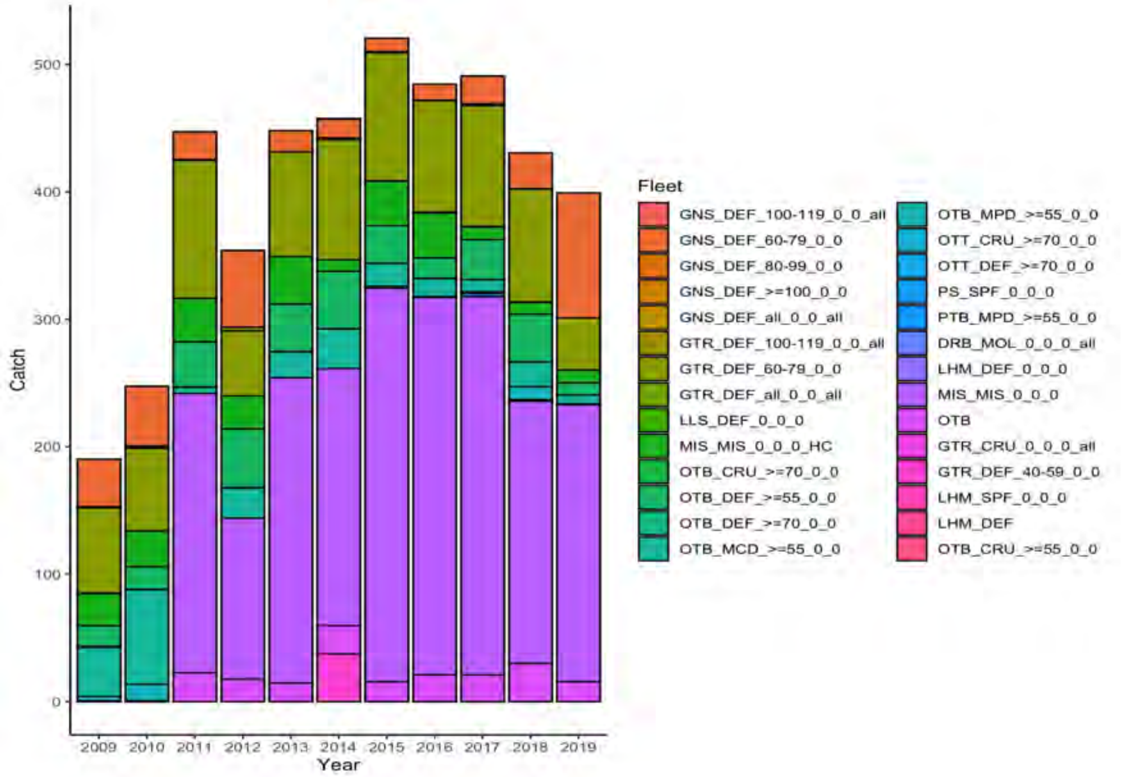


Figure 5: Catches for *Solea solea* by fleet in the ICES divisions 8c9a for Portugal, Spain and France from 2009 to 2019. Source data: InterCatch.

Table 1: Proportion of the catches by metier with respect the total catches by year.

Metier	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
GNS_DEF100_119_0_0_all	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
GNS_DEF_all_0_0_all	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
GNS_DEF_60-79_0_0	**0.05**	**0.17**	**0.04**	**0.03**	**0.02**	**0.03**	**0.04**	**0.07**	**0.25**
GTR_DEF100-119_0_0_all	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
GTR_DEF_60-79_0_0	**0.24**	**0.14**	**0.18**	**0.21**	**0.19**	**0.18**	**0.19**	**0.21**	**0.10**
GTR_DEF_40-59_0_0	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00
GTR_CRU_0_0_0_all	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OTB_CRU_>=70_0_0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OTB_DEF_>=55_0_0	0.08	0.13	0.08	0.10	0.06	0.03	0.06	0.09	0.02
OTB_DEF_>=70_0_0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OTB_MCD_>=55_0_0	0.01	0.07	0.05	0.07	0.03	0.03	0.02	0.04	0.02
OTB_MPD_>=55_0_0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00
OTB	0.05	0.05	0.03	0.05	0.03	0.04	0.04	0.07	0.04
OTT_DEF_>=70_0_0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OTT_CRU_>=70_0_0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MIS_MIS_0_0_0_HC	0.08	0.07	0.08	0.02	0.07	0.07	0.02	0.02	0.02
MIS_MIS_0_0_0	**0.49**	**0.36**	**0.53**	**0.44**	**0.59**	**0.61**	**0.60**	**0.48**	**0.54**

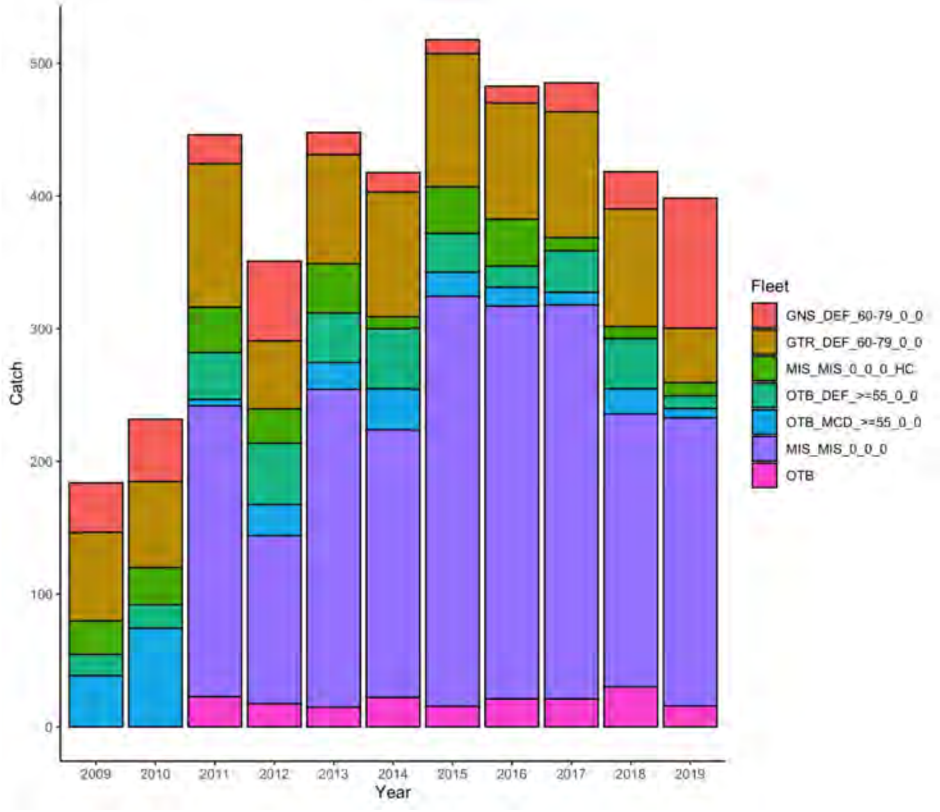


Figure 6: Catches for *Solea solea* by the main fleet in the ICES divisions 8c9a for Portugal, Spain and France from 2009 to 2019. Source data: InterCatch.

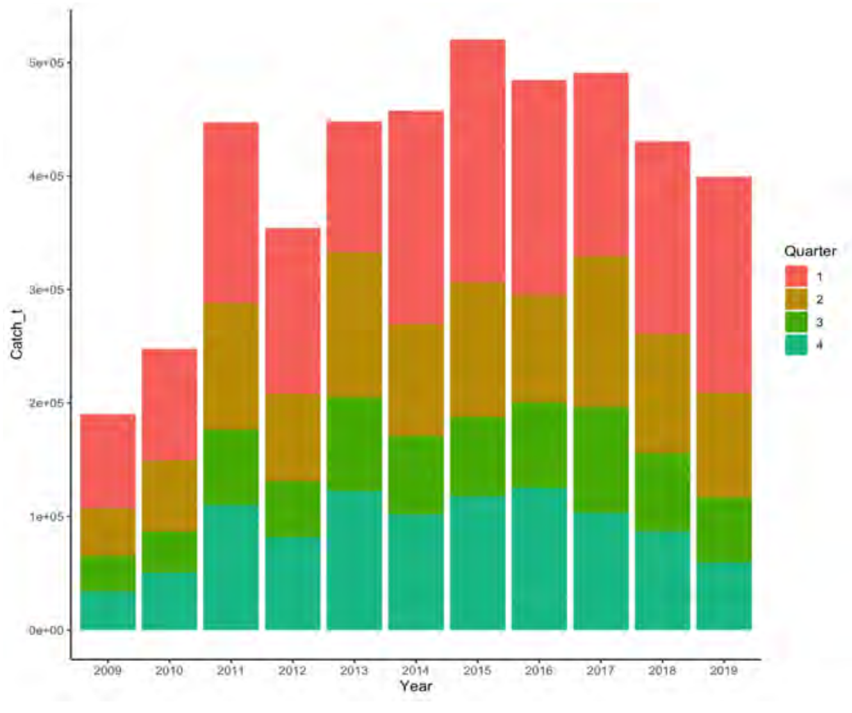


Figure 7: Catches for *Solea solea* by quarter in the ICES divisions 8c9a for Portugal, Spain and France from 2009 to 2019. Source data: InterCatch.

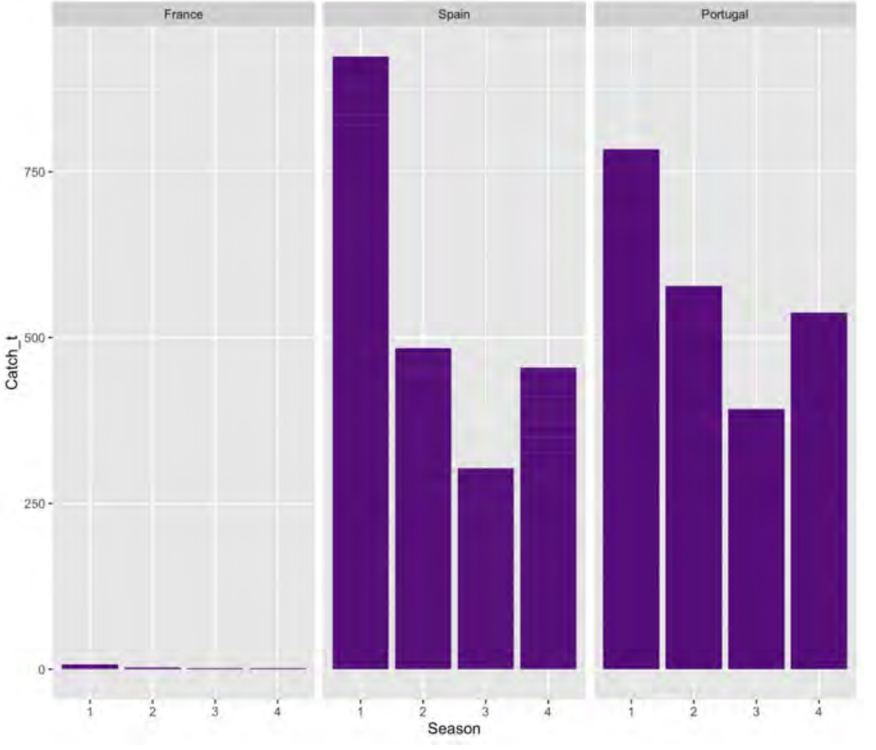


Figure 8: Catches for *Solea solea* by quarter and country in the ICES divisions 8c9a for Portugal, Spain and France from 2009 to 2019. Source data: InterCatch.

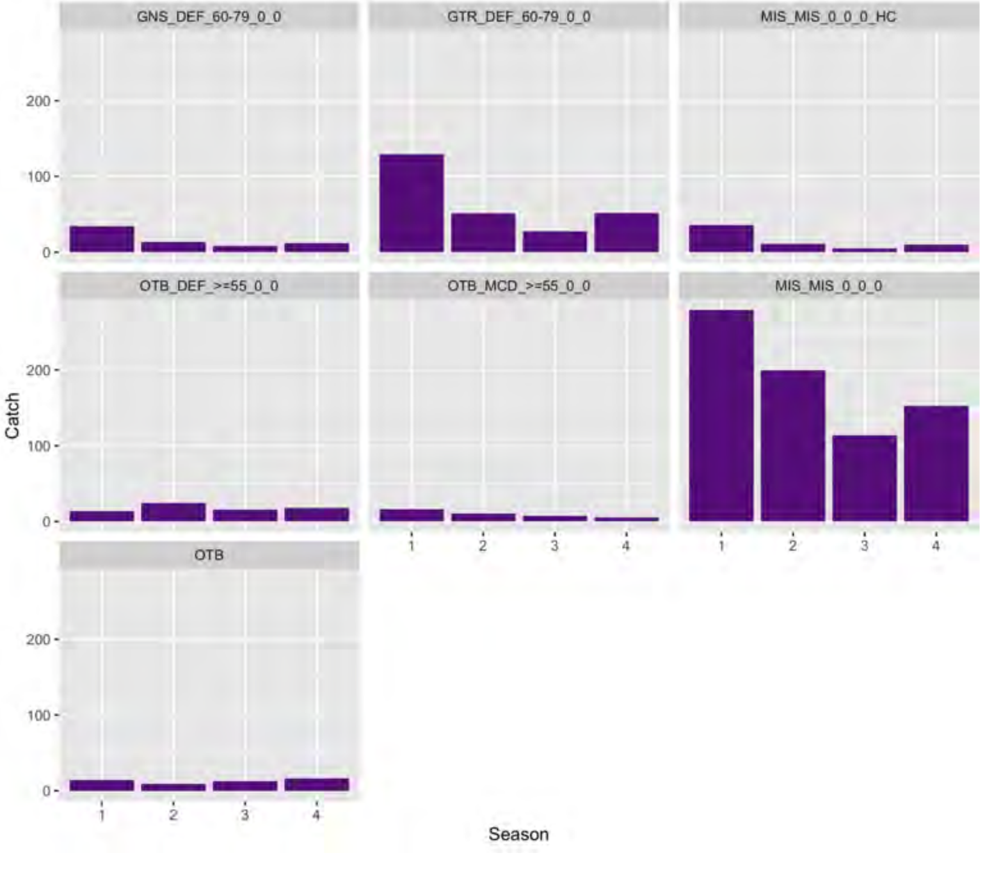


Figure 9: Catches for *Solea solea* by quarter and the main fleet in the ICES divisions 8c9a for Portugal, Spain and France from 2009 to 2019. Source data: InterCatch.

Length distribution

In InterCatch data of length distribution are available for the years 2011-2019 (Figure 10). The majority of the data are of the polyvalent fleet (i.e. metier “MIS_MIS_0_0_0”) from Portugal (Table 2). The sampling level of this fleet is showed in Table 3.

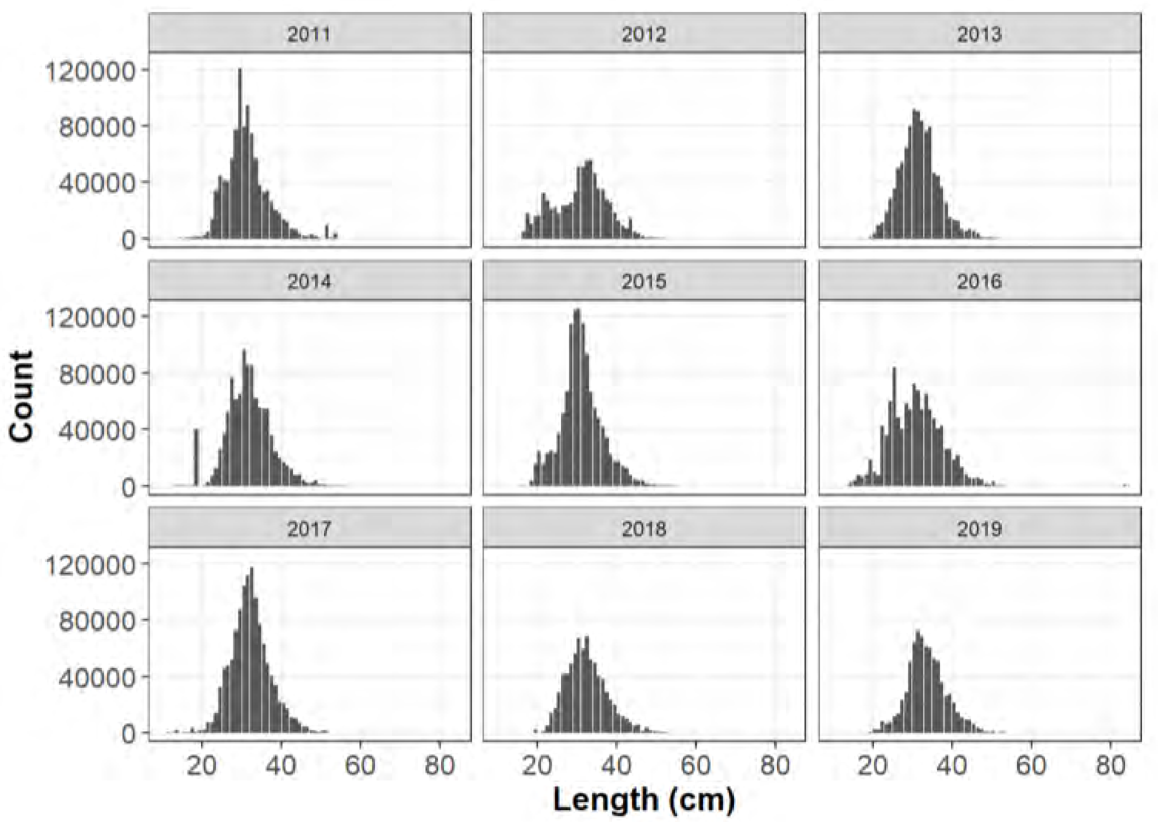


Figure 10: Length distribution of catches for *Solea solea* by year in the ICES divisions 8c9a for Portugal, Spain and France from 2011 to 2019. Source data: InterCatch.

Table 2: Proportion of catches of which length distribution data are available by fleets and year.

Year	OTB_MCD_>=55_0_0	GNS_DEF_60_79_0_0	OTB	OTB_DEF_>=55_0_0	GTR_DEF_60_79_0_0	MIS_MIS_0_0_0
2011	0.02	0.03	0.08	0.12		0.75
2012	0.11		0.08	0.22		0.59
2013	0.06		0.05	0.12		0.77
2014			0.07	0.13	0.20	0.60
2015	0.04		0.04	0.08		0.84
2016	0.03		0.06	0.05		0.86
2017	0.01	0.02	0.05	0.08	0.10	0.74
2018			0.11	0.14		0.75
2019		0.13	0.05	0.03	0.07	0.72

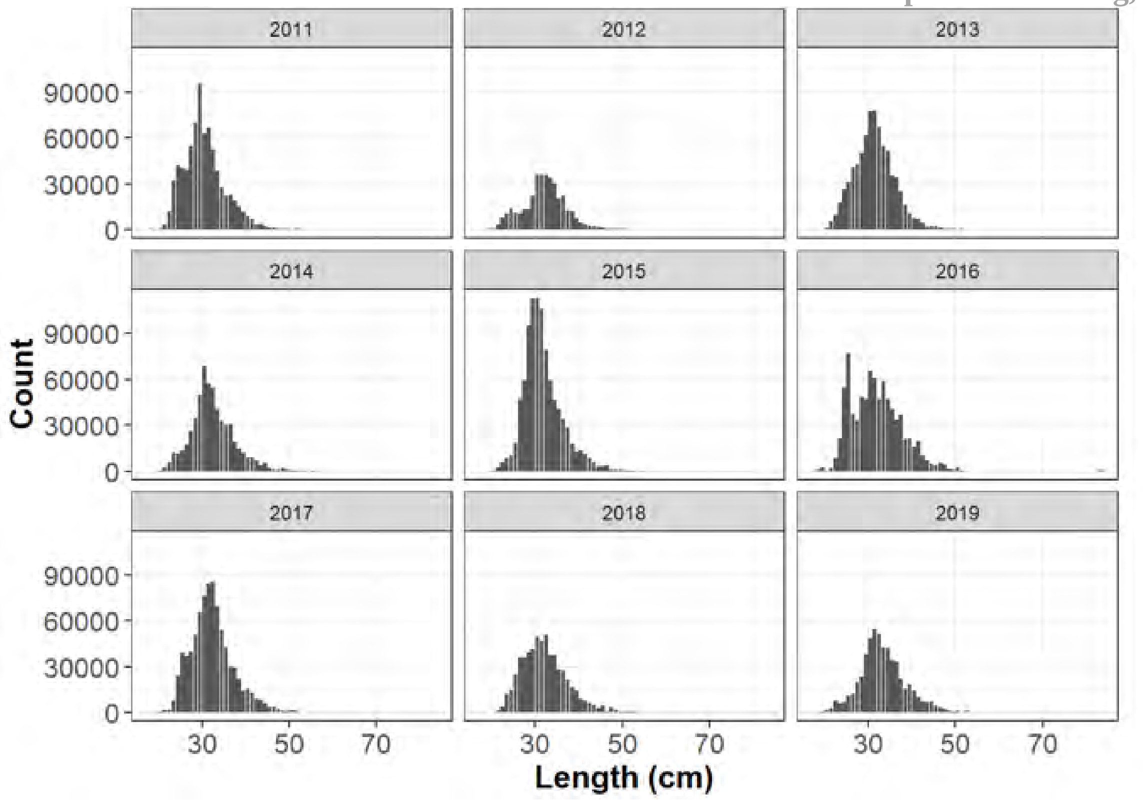


Figure 11: Length distribution of catches for *Solea solea* for the polyvalent fleet (i.e. metier "MIS_MIS_0_0_0") from Portugal from 2011 to 2019. Source data: InterCatch.

Table 3: Sampling level of the polyvalent fleet (i.e. metier "MIS_MIS_0_0_0") from Portugal from 2011 to 2019 for *Solea solea* catches.

Year	quarter	Weight sampled	N_trips_sampled	N_ind_sampled	N_ind_sampled_rounded
2011	1	434.15	32	1255.792957	1256
2011	2	264.21	53	1129.736434	1130
2011	3	197.18	46	898	898
2011	4	328.76	53	1099.621128	1100
2012	1	426.75	38	1262.444966	1262
2012	2	158.25	39	579.3333333	579
2012	3	253.58	45	1020.217914	1020
2012	4	319.89	52	969.914165	970
2013	1	1054.18	59	2661.538692	2662
2013	2	445.74	71	1738.379368	1738
2013	3	204.1	39	798.9576068	799
2013	4	468.68	40	1525.620143	1526
2014	1	1050.01	69	2584.5385	2585
2014	2	148.51	54	523.7630662	524
2014	3	114.98	35	407	407
2014	4	207.22	37	619.8571429	620
2015	1	1251.66	60	3557.671448	3558
2015	2	186.22	48	609.9268551	610
2015	3	310.02	39	836.1594119	836
2015	4	409.2	40	1227.930597	1228
2016	1	832.74	47	1622.107357	1622
2016	2	370.32	42	1478.164061	1478
2016	3	236.3	34	909.194498	909
2016	4	686.54	44	1488.60686	1489
2017	1	573.8566861	55	1144	1144
2017	2	202.1950331	43	664.5412844	665
2017	3	120.2943545	33	398	398
2017	4	275.4673121	28	803.1052632	803
2018	1	411.6433341	38	854.9257642	855
2018	2	373.8434497	55	961.720556	962
2018	3	109.3227089	31	361	361
2018	4	212.3981377	33	436	436
2019	1	672.067038	55	1156	1156
2019	2	136.2011109	37	369	369
2019	3	100.4059854	27	381	381
2019	4	141.3537688	29	321	321

Spanish abundance index from scientific survey

Common sole data was collected during the scientific survey series SP-NSGFS Q4 performed by the Instituto Español de Oceanografía (IEO) in autumn (September and October) between 2000 and 2019. Surveys were conducted on the northern continental shelf of the Iberian Peninsula (ICES divisions 8c and the northern part of 9a) which has a total surface area of almost 18,000 km^2 (Figure 12). The sea bottom composition of this area is mainly rock or sand sediments until 100 m of depth. Below 100 m depth, muddy bottoms characterize the Galician waters (ICES division 9a) whereas rocky ground and deep canyons are typical in the Cantabrian Sea (ICES division 8c) (Abad et al., 2019).
Surveys were performed using a stratified sampling design based on depth with three bathymetric strata: 70–120 m, 121–200 m and 201–500 m. Sampling stations consisted of 30 min trawling hauls located randomly within each stratum at the beginning of the design. The gear used is the baka 44/60 and the survey follow the protocol of the International Bottom Trawl Survey Working Group (IBTSWG) of ICES (ICES, 2017).

Figure 12: Map of the study area. Black dots represent annual sampling locations.

In Figure 13 are showed the hauls where common sole was found by year.

The common sole (*Solea solea*) is a species with a biological bathymetric range between 0 and 200 meters in the Iberian Atlantic waters. The SP-NSGFS Q4 only covers partially the common sole bathymetric range and the resultant abundance index is probably underestimated.

For this reason, and with the aim to correct this sampling bias, we applied to this dataset a hurdle Bayesian spatiotemporal.
Two variables were analysed in order to characterize the spatiotemporal behaviour of common sole individuals. Firstly, a presence/absence variable was considered to measure the occurrence probability of the species. Secondly, the weight by haul (kg) was used as an indicator of the conditional-to-presence abundance of the species.
Bathymetry values were retrieved from the European Marine Observation and Data Network (EMODnet, http://www.emodnet.eu/) with a spatial resolution of 0.02 x 0.02 decimal degrees (20 m).

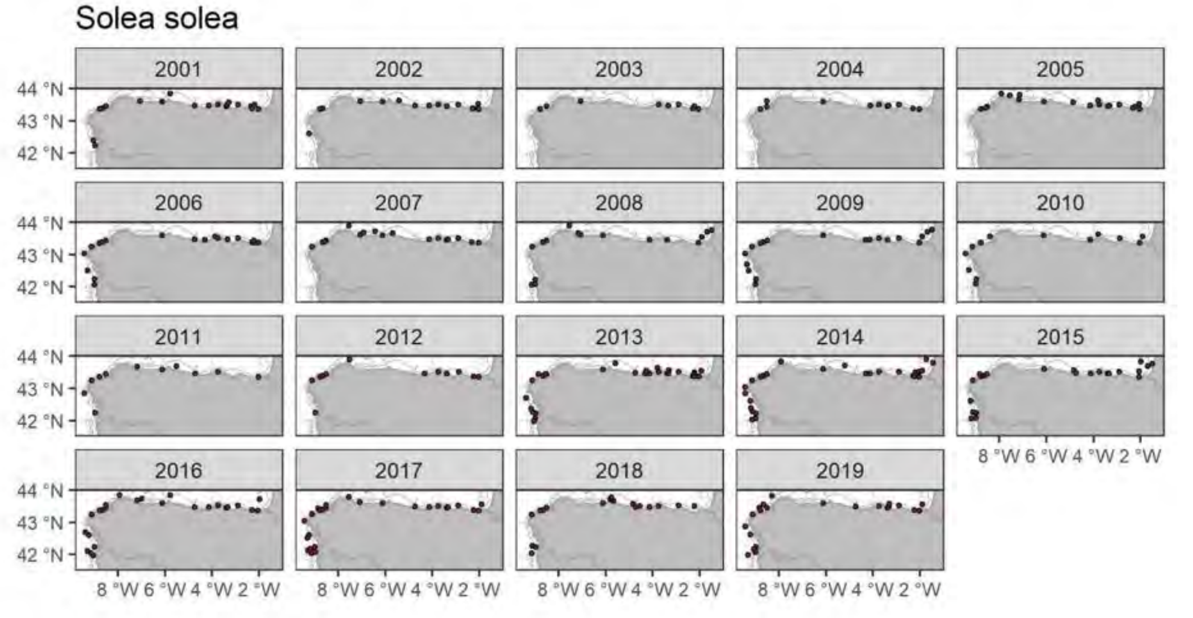


Figure 13: Dots indicates hauls where the species *S.Solea* was present by year.

Spatiotemporal modelling

An exploratory analysis highlighted that common sole abundance data have two main features, namely strong spatial and temporal dependence and a large proportion of observed zeros (i.e., zero inflated data). These data are commonly analysed using two-part models, also known as delta models (Quiroz et al., 2015) and in general, occurrence and abundance are modelled independently. However, the abundance and occurrence processes are often related, which consequently violates the independence assumption of common delta models (Pennino et al., 2019).

In this study we applied hurdle Bayesian spatiotemporal models that simultaneously fitted common sole occurrence and conditional-to-presence abundance processes while sharing bathymetry effects. These effects were incorporated as described in Paradinas et al., (2017, 2020) in order to integrate information on both the occurrence and the conditional-to-presence abundance to better fit informed environmental effects and avoid the violation of the aforementioned independence assumption.

Models were fitted using the integrated nested Laplace approximation approach INLA (Rue et al., 2009) in the R software (R Core Team, 2019). The spatial component was modelled using the spatial partial differential equations (SPDE) module (Lindgren et al., 2011) of INLA and implementing a multivariate Gaussian distribution with zero mean and a Matérn covariance matrix. This matrix depends on the distance between locations and two hyperparameters, r_w and σ_w representing the range and the variance of the spatial effect respectively (Muñoz et al., 2013).

As spatiotemporal structure we used the progressive one (Paradinas et al., 2017, 2020), which contains an autoregressive ρ parameter that controls the degree of autocorrelation between consecutive years. This ρ parameter is bounded to [0, 1], where parameter values close to 0 represent more opportunistic behaviours and parameter values close to 1 represent more persistent distributions over time. In addition, an extra temporal effect g(t) was added using a second order random walk (RW2) prior to allow non-linear effects. In the presence of bathymetric and spatial autocorrelation terms, g(t) can be regarded as a spatially standardized stock size temporal trend.

Y_{st} and Z_{st} were considered the spatiotemporally distributed occurrence and conditional-to-presence abundance, respectively, s = 1, ..., n_t refers to the spatial location and t = 1, ..., m to the temporal index. Occurrence (Y_{st}) was modelled using a Bernoulli distribution and conditional-to-presence abundance (Z_{st}) using a gamma distribution, which is a probability distribution that captures the overdispersion of continuous data. The means of both variables were modelled through the logit and log link functions respectively to the bathymetric and spatiotemporal effects as:

$$Y_{st} \sim Ber(\pi_{st}) \quad (1)$$
$$Z_{st} \sim Gamma(\mu_{st}, \phi)$$
$$logit(\pi_{st}) = \alpha(Y) + f(ds) + g(t) + U_{st}(Y)$$
$$log(\mu_{st}) = \alpha(Z) + \theta\, f(ds) + \eta\, g(t) + U_{st}(Z)$$

where π_{st} represents the probability of occurrence at location *s* at time *t* and μ_{st} and ϕ are the mean and dispersion of common sole conditional-to-presence abundance. The linear predictors, which contain the effects that link the parameters π_{st} and μ_{st}, include: $\alpha(Y)$ and $\alpha(Z)$, terms that represent the intercepts of each variable respectively; ds corresponds to the depth at location *s*, being f(ds) the bathymetric effect modelled as a second order random walk (RW2) smooth function parametrised as unknown values f = $(f_0, \ldots f_{i-1})_t$ at $i = 14$ equidistant values of ds, with hyperparameter σ representing the variance of the f(ds) model. In the same way, g(t) corresponds to the temporal trend fitted through a RW2 effect over the years. The terms f(ds) and g(t) are shared between both predictors and multiplied by θ and η in the conditional-to-presence abundance model to allow for differences in scales between both predictors (i.e. the logit transformed probability and the logarithm of the conditional-to-presence abundance); $U_{st}(Y)$ and $U_{st}(Z)$ refer to the progressive spatiotemporal structures of common sole occurrence and conditional-to-presence abundance respectively.

Moreover, a median length model was fitted to assess whether different common sole life stages occupy different areas. Median length was modelled using a Gaussian distribution with the usual identity link. The distributed median length V_{st} was modelled as:

$$V_{st} \sim Gaussian(\mu_{st}, \sigma) \quad (2)$$
$$\mu_{st} = \alpha(V) + f(ds) + U_{st}(V)$$

where μ_{st} represents the mean while σ the variance of the distribution and the remaining model parameters follow the same structures as in Eq. (1). In addition, bathymetry f(ds) and the year effect g(t) were included in the model as explicative variables and fitted with RW2 functions.

The Bayesian approach requires prior distributions for all the parameters of the model and vague prior distributions for the dispersion and precision of the conditional-to-presence-abundance and median size models respectively. Following this approach, the fixed effects and the scaling parameter of the shared effects were assigned. Penalised complexity priors (i.e., PC priors, weak informative priors; Simpson et al., 2017) were assigned so that the probability of the spatial effect range being smaller than 0.5 degrees was 0.05, and the probability of the spatial effect variance being larger than 0.5 was 0.5. PC priors were also used for the variance of the bathymetric and the temporal trend RW2 effects. Specifically, the size of these effects was constrained by setting a 0.05 probability that sigma was greater than 0.5 and 1 respectively. Sensitivity analysis for the selection of priors was performed by testing different priors and verifying that the posterior distributions were consistent and concentrated comfortably within the support of the priors.

From this analysis, the most important results that we obtained are the predicted distribution of the species (Figure 14), the median length distribution (Figure 15) and a new spatiotemporal abundance index (Figure 16).

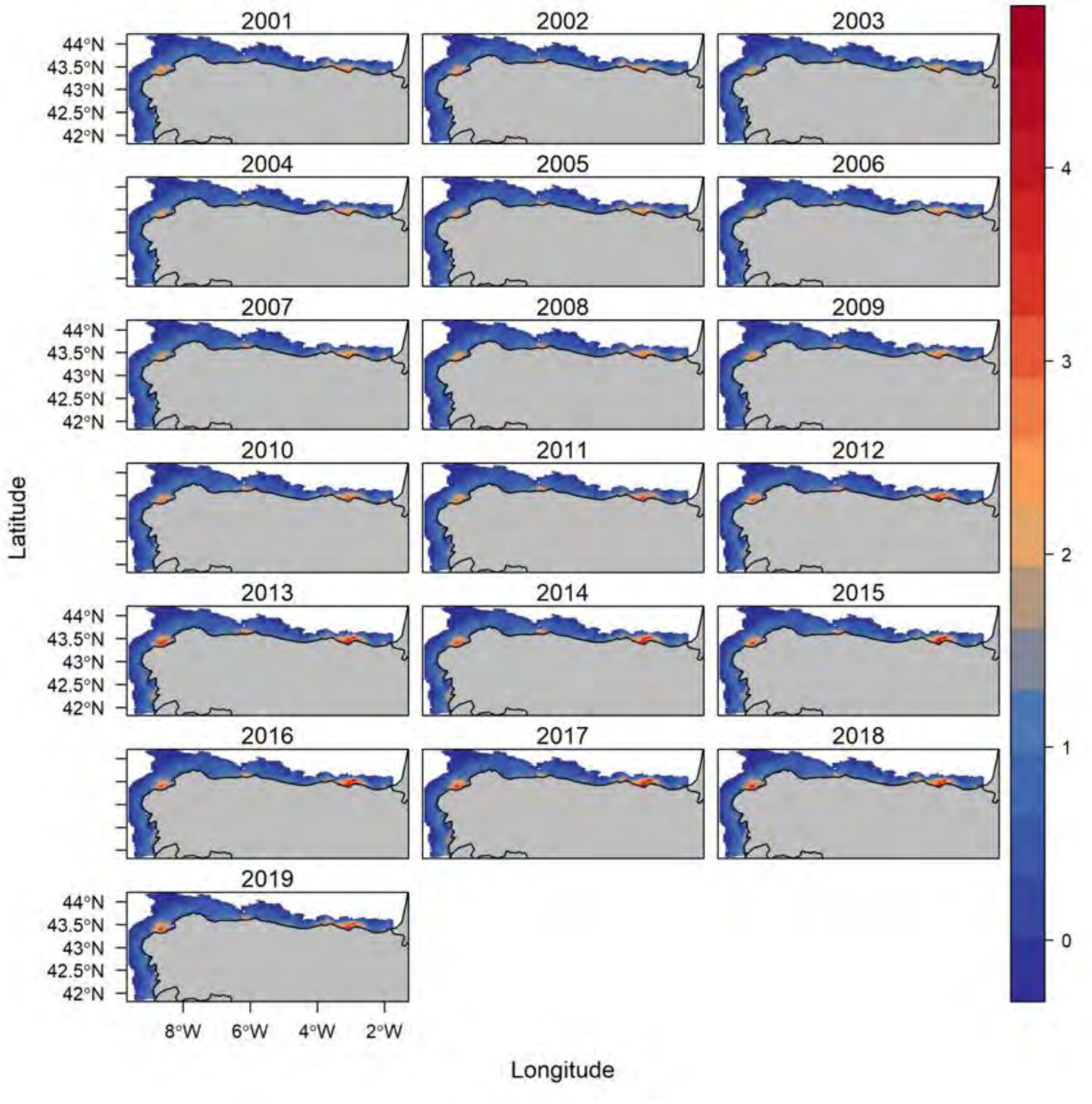


Figure 14: Prediction maps (2001-2019) of the common sole conditional-to presence median abundance estimated by the hurdle Bayesian spatiotemporal model.

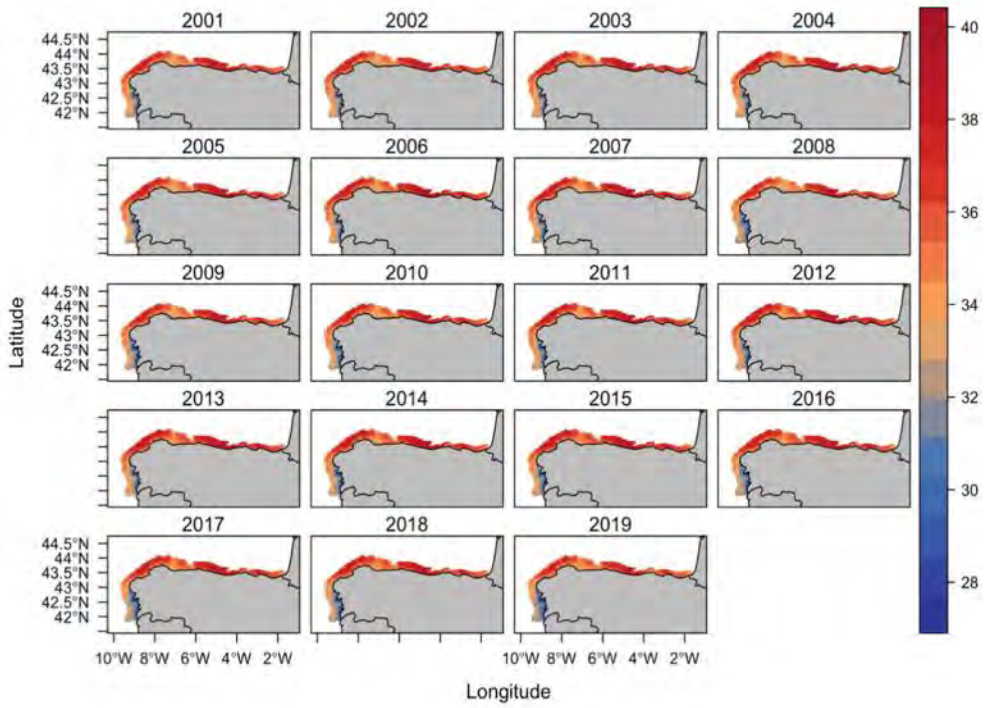


Figure 15: Prediction maps (2001-2019) of the common sole median length distribution estimated by the Bayesian spatiotemporal model.

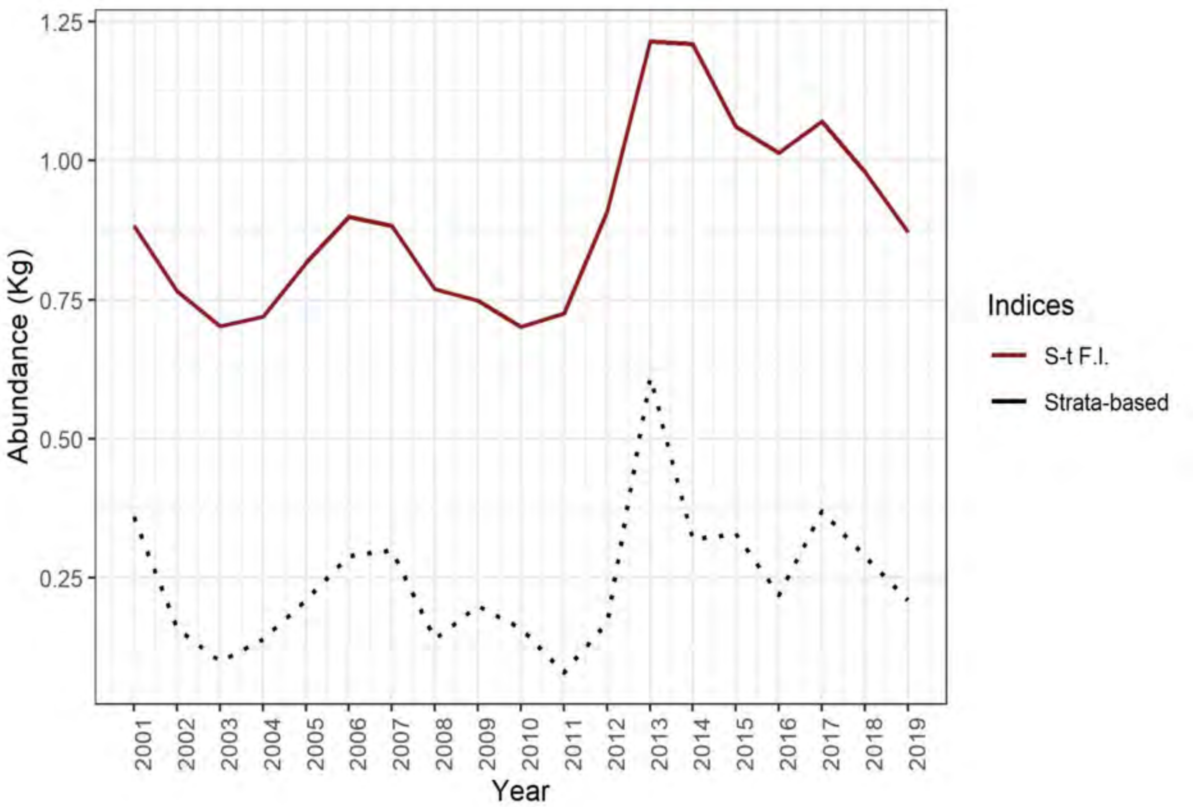


Figure 16: Temporal trend of the spatiotemporal abundance index (red) and the designed-based index for the SP-NSGFS Q4.

A sensitive analysis was performed to check if the area used to standardize the survey index and the area used by the Bayesian model for the prediction are similar (see Annex 1).

Catch Per Unit Effort (CPUE) from Spain

Fishery-dependent data were collected by the Galician government Technical Unit of Artisanal Fisheries (Unidade Técnica de Pesca de Baixura, UTPB, in Galician). Usually an on-board observer is assigned to fishing vessels randomly selected from this sector and covers the full set of multiple gears used in Galician waters and all along the geographical range (Figures 17 and 18). In a single trip each vessel usually performs several hauls. At each haul, observers record all basic operational data (i.e., date, geographical position, gear, etc.) and the number and weight of all retained and discarded taxa. The analysed database in this study counts 4350 hauls for which common sole was caught from January 2000 until December 2018.

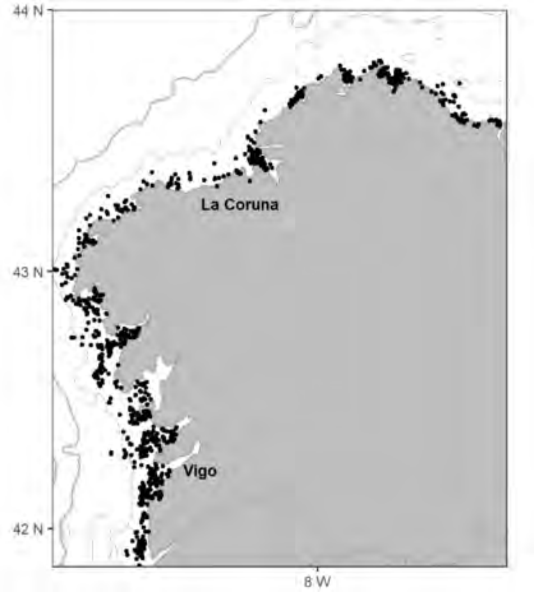


Figure 17: Data collected by observer on board on trammel net fleet in Galicia (Spain) from 2000-2018 for common sole (*S. Solea*).

Before fitting any model, we selected the data for the trammel net which is the most representative gear for the common sole in order to reduce sources of variation. This selection was based on three criteria: i) proportion of hauls with zero catch, ii) total number of individuals sampled and iii) the spatiotemporal coverage. The first and second criterion were used as proxies of gear catchability and thus constant catchability was assumed along the time series.

An exploratory analysis highlighted that common sole data have two main features, namely strong spatial and temporal dependence and a large proportion of observed zeros (i.e., zero inflated data). For this reason, we applied the same hurdle Bayesian spatiotemporal models that we performed for the SP-NSGFS Q4 data. As environmental variables we included bathymetry and type of substratum, both present in the dataset. Bathymetry was fitted using a non-linear RW2 effect. Gear saturation can exert a significant nonlinear effect on catchability, thus preliminary models included it but was left out of the final model due to its negligible contribution to the model. In addition to the spatiotemporal correlation structure (ie. Same of model above) we fitted a cyclic non-linear month effect to capture the intra-annual variability of the abundance. The remaining potential source of abundance variability could be driven by the differences between vessels, caused by a skipper effect or unobserved gear characteristics. To remove bias caused by vessel-specific differences in fishing operation, we included a vessel random effect.
The final CPUE index is showed in Figure 19.

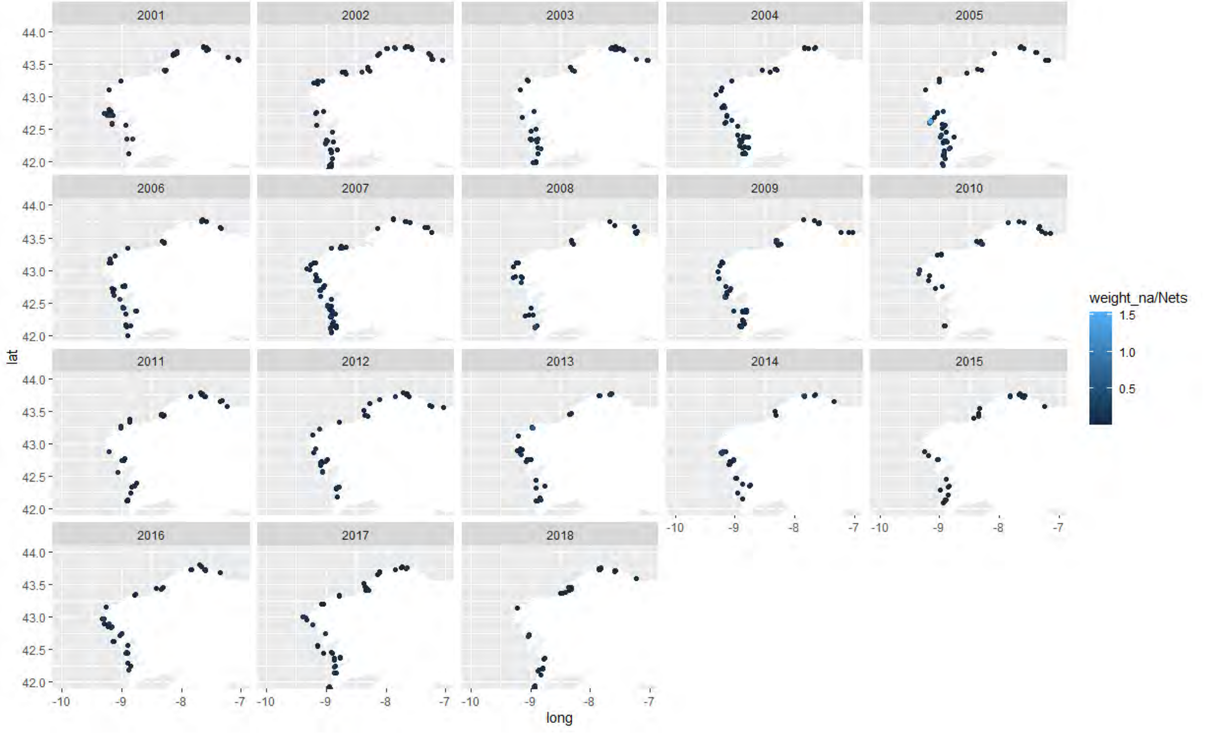


Figure 18: Data collected by observer on board on trammel net fleet in Galicia (Spain) from 2000-2018 for common sole (*S. Solea*) by year.

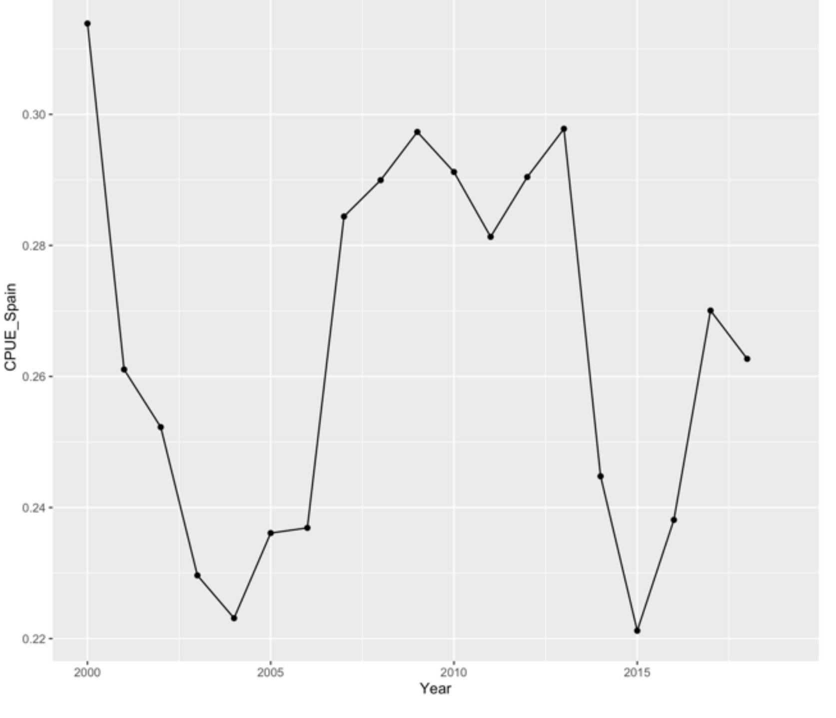


Figure 19: CPUE index derived from the hurdle Bayesian spatiotemporal model for 2000-2018 for common sole (*S. Solea*).

Portuguese survey data

The Portuguese Groundfish Survey (PtGFS-WIBTS-Q4) has been conducted by the Portuguese Institute for the Sea and Atmosphere (IPMA) and covers Division 9a in Portuguese continental waters (from latitude 41°20’N to 36°30’N). The survey is mainly conducted at the beginning of the 4th quarter, in October, and aims to monitor the abundance and distribution of *Merluccius merluccius* (hake) and *Trachurus trachurus* (horse mackerel) recruitment (Cardador et al., 1997). Data on all Soleidae species caught is collected in this survey, including species identification, number of specimens caught and weight. The surveys have been carried with the Portuguese RV “Noruega”, which is a stern trawler of 47.5 m LOA, 1500 HP and 495 GRT and using a Norwegian Campelen Trawl (1800/96 NCT) gear with a 20 mm codend mesh size and groundrope with bobbins. PT-GFS fishing operations are performed during daylight and the duration of each tow changed in 2002, from 60 to 30 min. The sampling scheme (Figure 20) is based on a systematic and stratified random sampling covering depths from 20 to 500 m, following the standard IBTS methodology for the western and southern areas (ICES, 2017). The mixed systematic and stratified sampling scheme comprises 66 fixed and 30 random trawl positions. The surveyed area is stratified into 12 sectors (from north to south: CAM: Caminha, MAT: Matosinhos, AVE: Aveiro, FIG: Figueira, BER: Berlenga, LIS: Lisboa, SIN: Sines, MIL: Vila Nova de Mil Fontes, SAG: Sagres, POR: Portimão, VSA: Vila Real de Santo António), each further divided into four depth strata: 1) 20-100 m, 2) 101-200 m, 3) 201-500 m, and 4) 501-750 m. The deeper stratum (4) was only sampled in the period before the yearly 2000’s. In 1996, 1999, 2003 and 2004 the surveys were conducted using a different vessel, the RV “Capricórnio” and a different bottom trawl net, CAR type FGAV019, without rollers in the groundrope (ICES, 2007). In 2018, due to technical problems in the RV “Noruega” part of the survey was conducted on the commercial trawler “Calypso” (24.8 m LOA, 7215 GRT), using a CAR bottom trawl net type FGAV019, without rollers in the groundrope, and covering the centre and southwest coasts (sectors: LIS, SIN, MIL and ARR). In 2012 and 2019 no survey was conducted. In December 2020, the survey is planned to be conducted in a new vessel, RV “Mário Ruivo” (72.6 m LOA, and 2290 GRT) using a similar NCT net but with differences in the groundrope and bobbins.

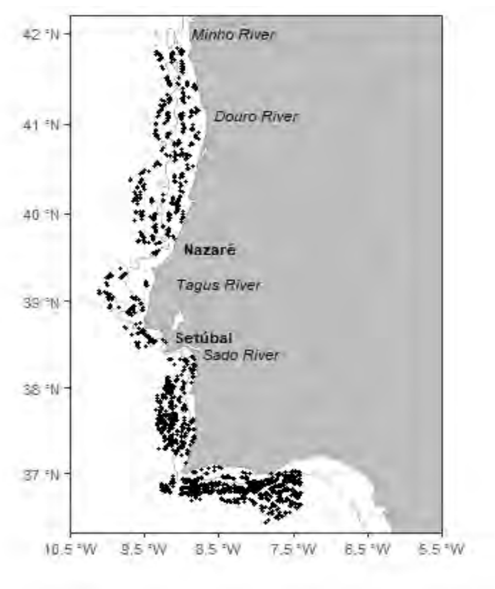


Figure 20: Map of the sampling scheme of the Portuguese survey.

Data from the annual Portuguese Groundfish Survey were provided by the Instituto Português do Mar e da Atmosfera (IPMA) from 2000 to 2018. Despite of the partially overlay between the survey and *Solea solea* distribution in Portuguese waters (Cabral et al. (2012) references preferential empirical bathymetrical range, as assumed by fishermen, to be between 50 and 150 m), the species is rarely caught and numbers per hour are very low (Figure 21 and 22). Both the number of hauls and the proportion of hauls with catches of the species are very low (Figure 23). The fishing gear used in this survey has low catchability for the species and it is considered inadequate for monitoring its populations. The catchability of this survey for the common sole species is worst with respect the Spanish in both spatial and temporal coverage (Figure 24).

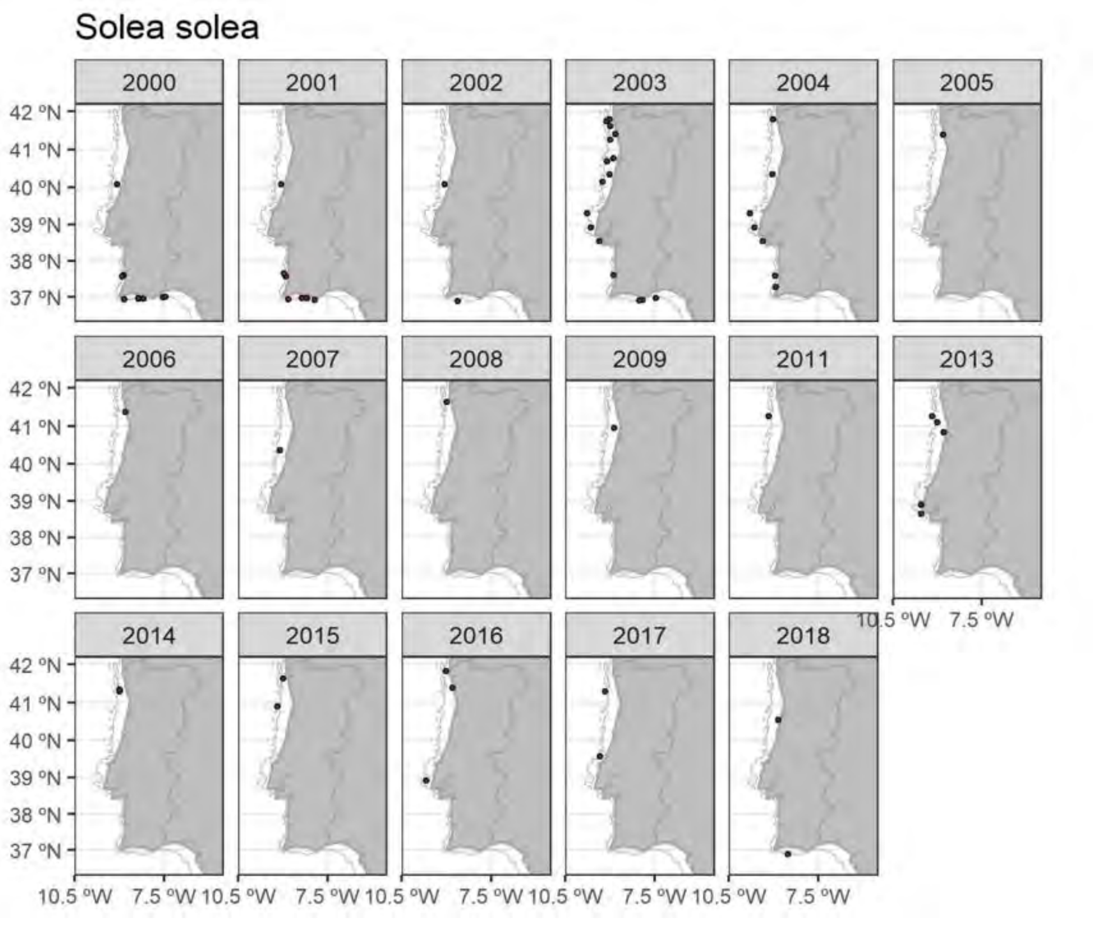


Figure 21: Dots indicates hauls where the species *S.Solea* was present by year.

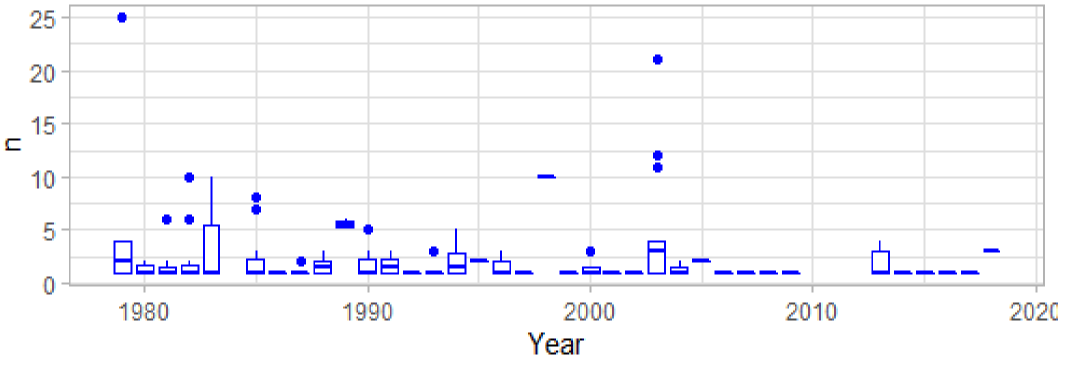


Figure 22: Boxplots of the number of *Solea solea* individuals caught per hour in the Portuguese Groundfish Survey.

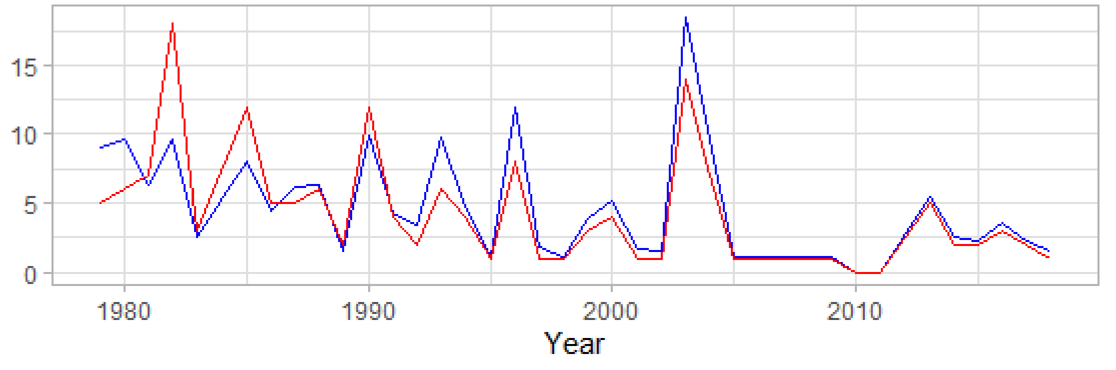


Figure 23: Number of hauls (red) and percentage of total hauls (blue) with *Solea solea* in the Portuguese Groundfish Survey.

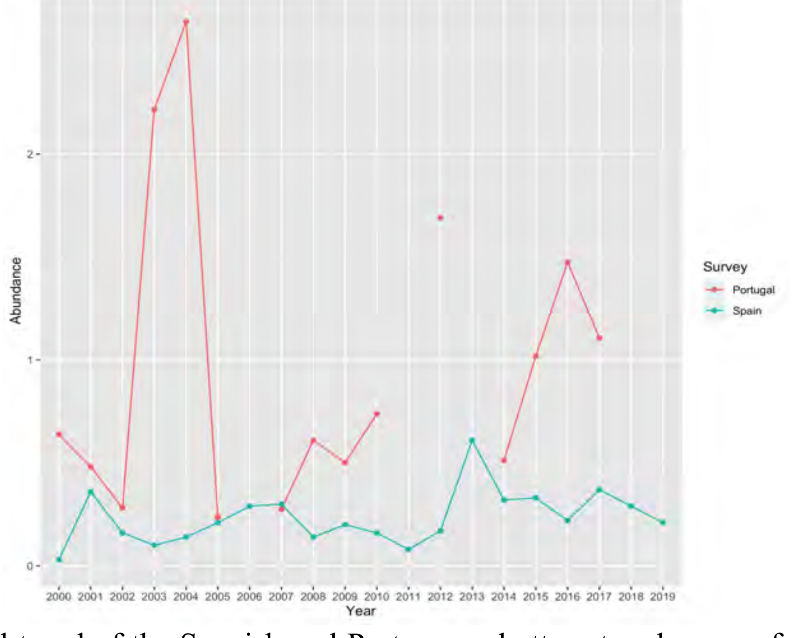


Figure 24: Temporal trend of the Spanish and Portuguese bottom trawl survey from 2000 to 2019 for common sole.

LPUE standardization of common sole *Solea solea* caught in the polyvalent fleet in Portuguese waters (Division 9a)

Input data

The LPUE estimates relied on fishery dependent data derived from the Portuguese polyvalent fleet and are based on the estimated *S. solea* landed weight by fishing trip (see Annex 2 to more information on data). The analysis was restricted to the most important landing ports in term of *S. solea* landed weight: Viana do Castelo, Matosinhos, Aveiro, Peniche and Setúbal.

The Portuguese polyvalent fleet segment comprises multi-gear/multi-species fisheries, usually licensed to operate with more than one fishing gear (most commonly gill and trammel nets, longlines and traps), that can be deployed in the same trip, targeting different species. The time period considered in the present study extends from 2011 to 2019.

Methods

The dataset was subset to trips with positive landings of the species. The LPUE standardization procedure was done via the adjustment of a GLM model to the matrix data, where the response variable was the *S. solea* landed weight by trip (unit effort). Several variables were evaluated as candidate to be included in the model: region, port, year, semester, quarter, month and vessel size group (<9m and >9m).

All the explanatory variables were considered as categorical variables. The function "bestglm" implemented in R software was used to select the best subset of explanatory variables (McLeod and Xu, 2010). The selection of the set explanatory variables to enter into the model is done following McLeod and Xu (2010) procedure, which is based on a variety of information criteria and their comparison following a simple exhaustive search algorithm (Morgan and Tatar, 1972).

The diagnostic plots, distribution of residuals and the quantile-quantile (Q-Q) plots, are used to assess model fitting. Changes in deviance explained by the selected model and the proportions of deviance explained to the total explained deviance was determined and used as indicative of r2. Annual estimates of LPUE and the corresponding standard error are determined for a reference condition where one level of each explanatory variable other the Year is fixed.

All the statistical analysis was performed using R programming language, version 3.6.2 (R Development Core Team, 2019).

Data overview

Most *S. solea* landings were derived from the polyvalent fleet (between 87 and 95% for the period 2011-2019, Table 4). The data set used to estimate LPUE was constrained to landing ports of Viana do Castelo, Matosinhos, Aveiro, Peniche and Setúbal. For the period 2011-2019, these five landings ports were the ones more frequently included in the top 5 ports with the highest *S. solea* annual total landed weight.

Table 4. *Solea solea* in Portuguese waters (Division 9a). *Solea solea* estimated landed weight per fleet, polyvalent and trawl, for the period 2011-2019. Percentages of the total national landed weight are present in brackets.

Year	Polyvalent (in Ton)	Trawl (in Ton)
2011	219.2 (90.6%)	22.7 (9.4%)
2012	126.5 (87.8%)	17.5 (12.2%)
2013	239.6 (94.2%)	14.7 (5.8%)
2014	201.8 (90.1%)	22.1 (9.9%)
2015	308.9 (95.2%)	15.5 (4.8%)
2016	296 (93.4%)	21 (6.6%)
2017	296.9 (93.4%)	21 (6.6%)
2018	205.6 (87.3%)	30 (12.7%)
2019	217.2 (93.3%)	15.7 (6.7%)

For each year, landing port and vessel size (<9m or >9m), the 1st, 2nd, 3rd and 4th quantiles of the number of trips, of the annual landed weight and of the average landed weight per trip were estimated. For each landing port, year and vessel size group, the vessels with occasional landings and reduced activity on the species capture were excluded if the annual number of trips, total annual landed weight and average landed weight per fishing trip were smaller than the correspondent 1st quantile. For the selected landing port, the total landed weigh of the excluded vessels represented between 3-7% of the total.

The density distribution and the boxplot of the nominal LPUE (kg/trip) of *S. solea* per year are presented in Figure 24. There is a high density of fishing trips with landed weight close to zero, as well as, the presence of some fishing trips with very high values. The LPUE analysis proceed with the exclusion of very high values of landed weight per fishing trip, i.e., fishing trips with landed weight above 95% quantile corresponding to 35 $kg.trip_{-1}$).

For vessels >9m the landed weight per fishing trip was highly variable. This group was also the one for which landed weight per trip attained the higher values (Figure 25).

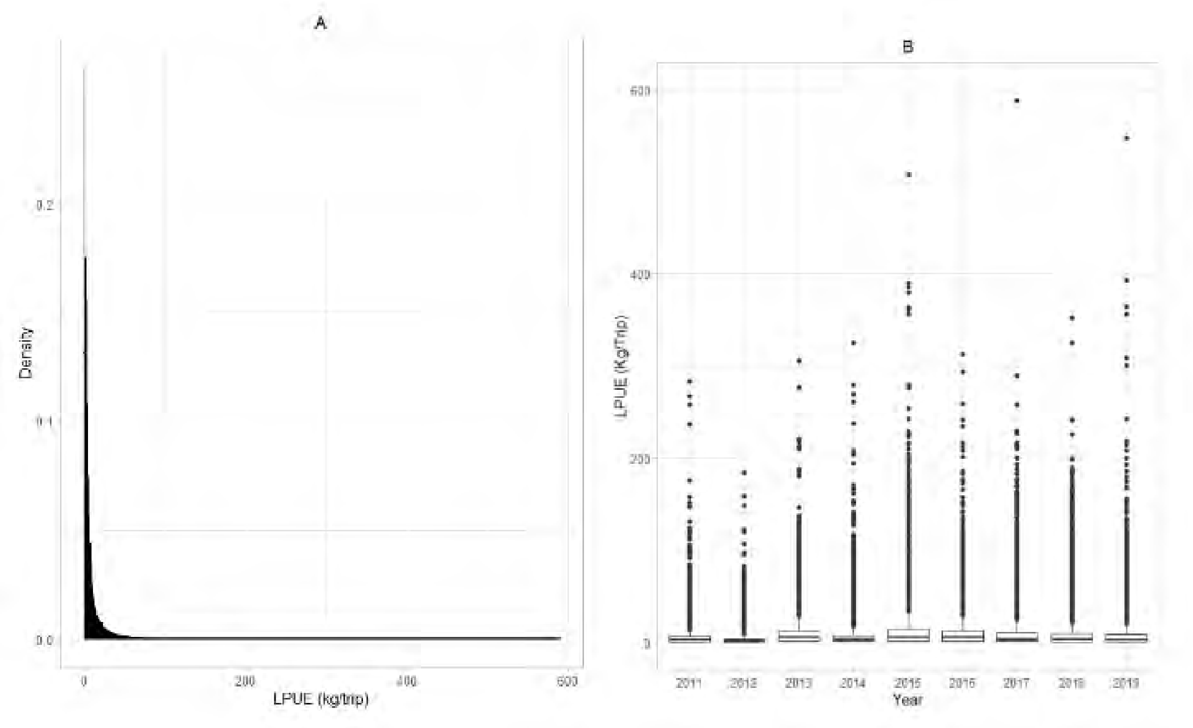


Figure 24. *Solea solea* in Portuguese waters (Division 9a). Nominal LPUE of *Solea solea* in the reference ports (all data excluding occasional vessels). A) density distribution and B) distribution by year.

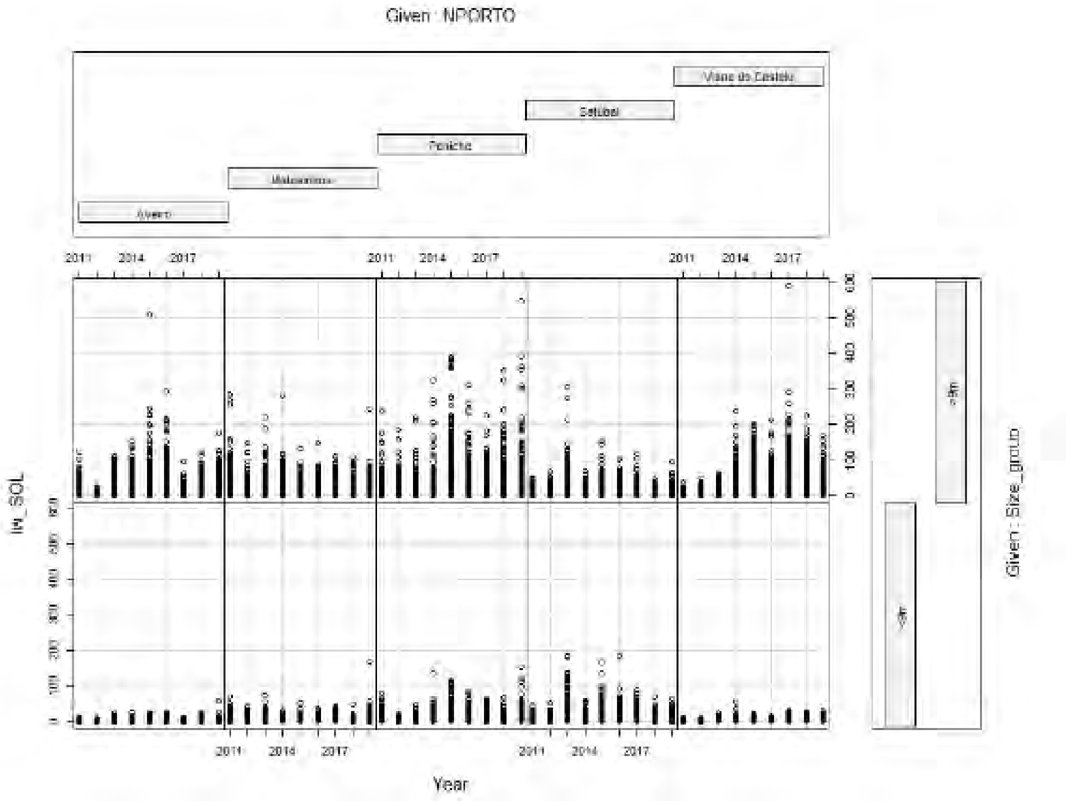


Figure 25. *Solea solea* in Portuguese waters (Division 9a). Coplot between estimated landed weight (lw_SOL, all data excluding occasional vessels) and year by trip of the polyvalent fleet given the vessel size (Size_group, <9m or >9m) and and the landing port (nport).

For the period 2011-2019, the mean nominal CPUE by year varied between 3.6-12.9 kg/trip, with a minimum registered in 2012 and a peak in 2015, slightly decreasing afterwards (Figure 26).

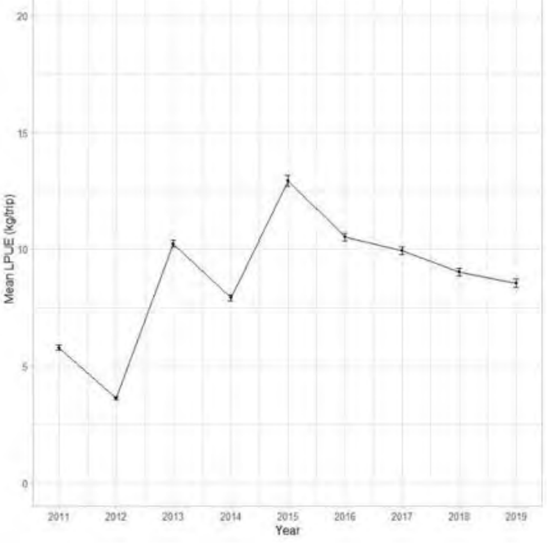


Figure 26: *Solea solea* in Portuguese waters (Division 9a). Mean nominal CPUE and associated standard error by year of *Solea solea* in the selected ports (all data excluding occasional vessels).

CPUE standardization model

To build the dataset, the following settings were considered: landing ports of Viana do Castelo, Matosinhos, Aveiro, Peniche and Setúbal; occasional vessels were removed; trips with landed weight of *S. solea* below the quantile 95% (<35 kg.trip-1).

The GLM model with the best adjustment included the explanatory variables year, month, landing port and vessel size and can be expressed as:

glm(LPUE ~ Year + Month + Port+ Vessel size, family=Gamma)

Estimated effects of each explanatory variable, as well as, the residual graphical analysis for the best model selected are presented in Figures 27 and 28.

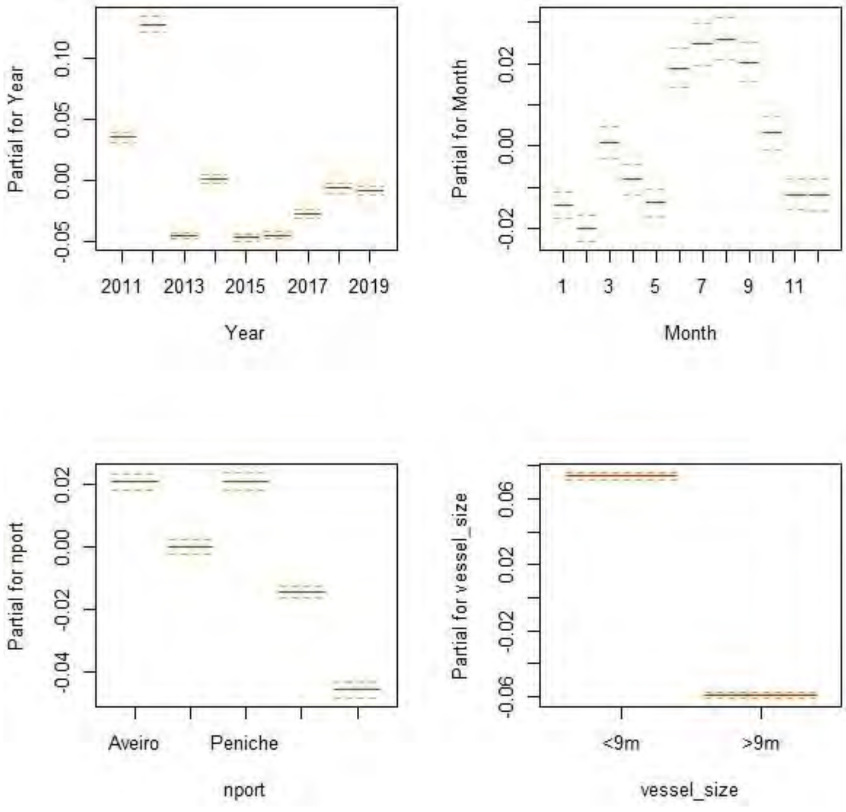


Figure 27. *Solea solea* in Portuguese waters (Division 9a). Effect of each explanatory variable included in the standardization of the LPUE for *S. solea* caught by the polyvalent segment in mainland Portugal (Division 9a): year, month, landing port (nport) and vessel size (vessel_size).

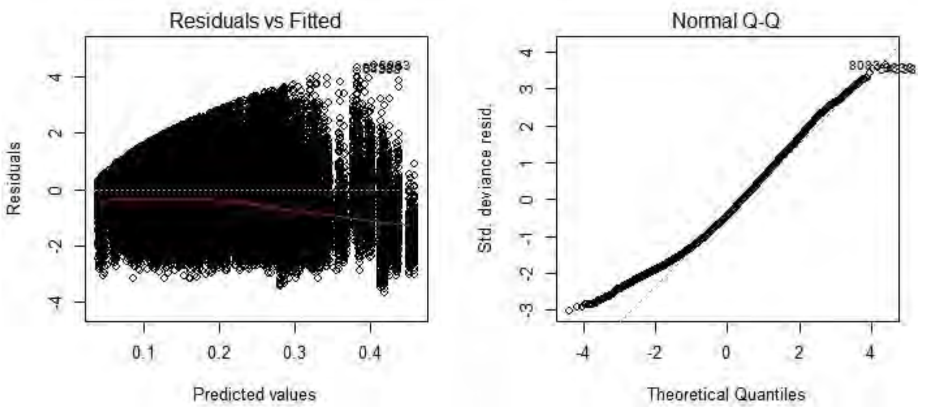


Figure 28. *Solea solea* in Portuguese waters (Division 9a). Residuals of the best GLM model fitted to the LPUE data for the Portuguese polyvalent fleet: (left) fitted vs. residuals (right) quantile-quantile (Q-Q) plot.

The value of r^2 was about 87% and the annual standardized mean LPUE (by fixing the landing port at Peniche, the month at February and for ≤9m vessel size group) is presented in Figure 4 and Table 5.

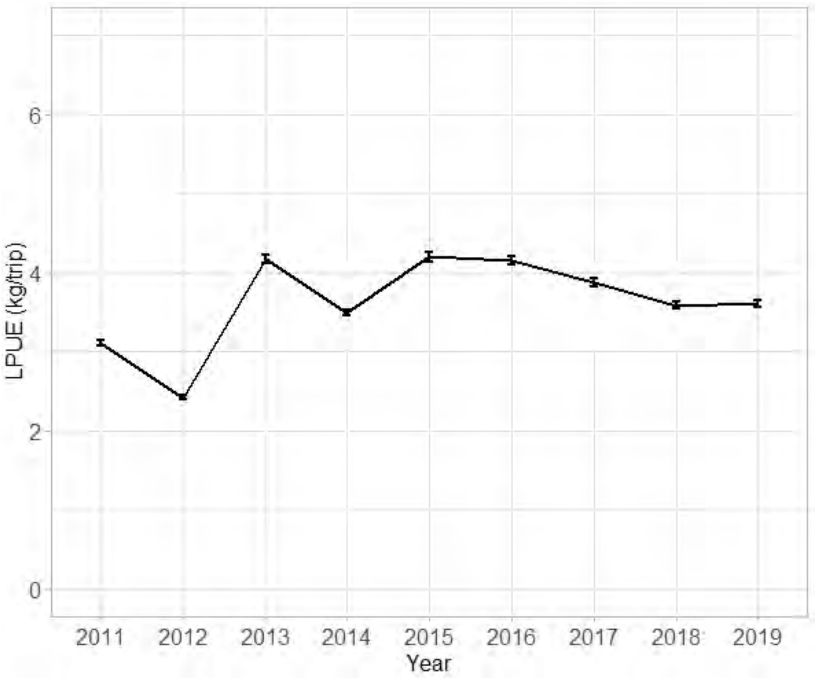


Figure 29. *Solea solea* in Portuguese waters (Division 9a). Standardized LPUE index (kg.trip-1) and respective standard error for the Portuguese polyvalent fishery from 2011 to 2019 (Explained variance = 0.87).

Table 5. *Solea solea* in Portuguese waters (Division 9a). Standardized LPUE index (kg.trip-1) and respective standard error for the Portuguese polyvalent fishery from 2011 to 2019.

Year	LPUE	Lower s.e.	Upper s.e.
2011	3.11	3.08	3.15
2012	2.42	2.39	2.44
2013	4.16	4.11	4.21
2014	3.49	3.45	3.53
2015	4.19	4.14	4.25
2016	4.16	4.10	4.21
2017	3.87	3.83	3.92
2018	3.58	3.54	3.62
2019	3.60	3.56	3.64

Test of model sensitivity

Test 1 - reduce weight per trip by 25% for data from 2019

Data from 2019 was reduced by 25% in order to test the sensitivity of the model to an decrease.

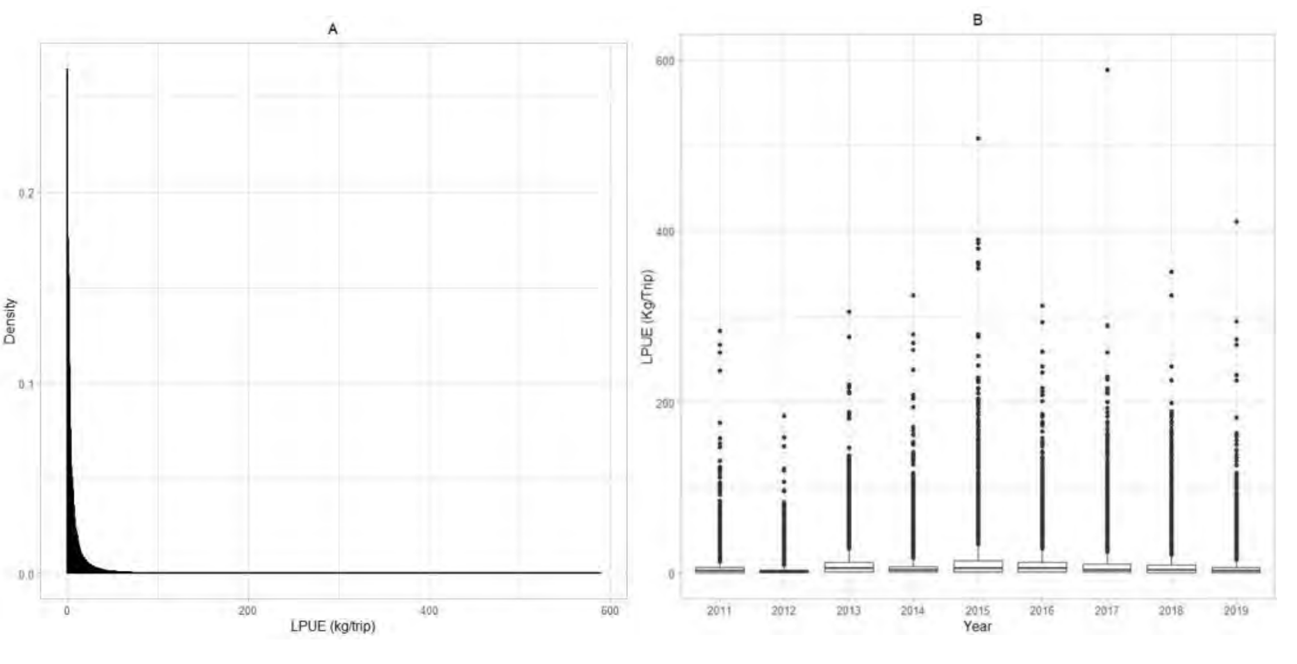


Figure 30. Test 1 - *Solea solea* in Portuguese waters (Division 9a). Nominal LPUE of *Solea solea* in the reference ports (all data excluding occasional vessels). A) density distribution and B) distribution by year.

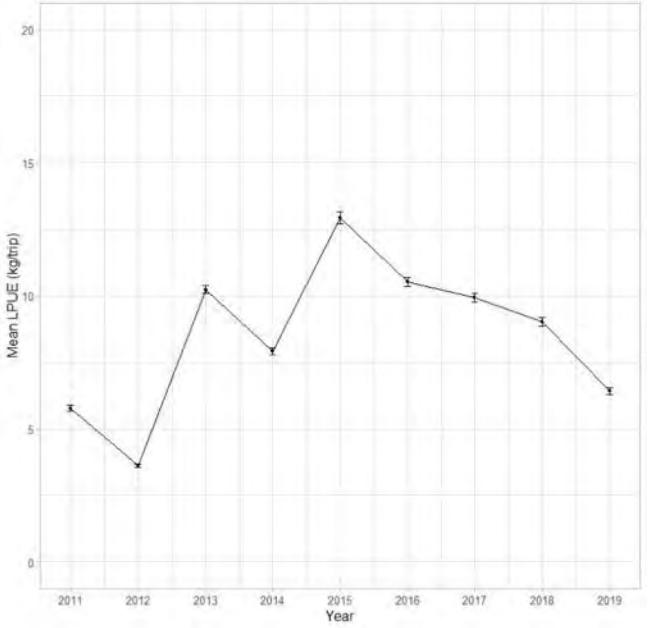


Figure 31. Test 1 - *Solea solea* in Portuguese waters (Division 9a). Mean nominal CPUE and associated standard error by year of *Solea solea* in the selected ports (all data excluding occasional vessels).

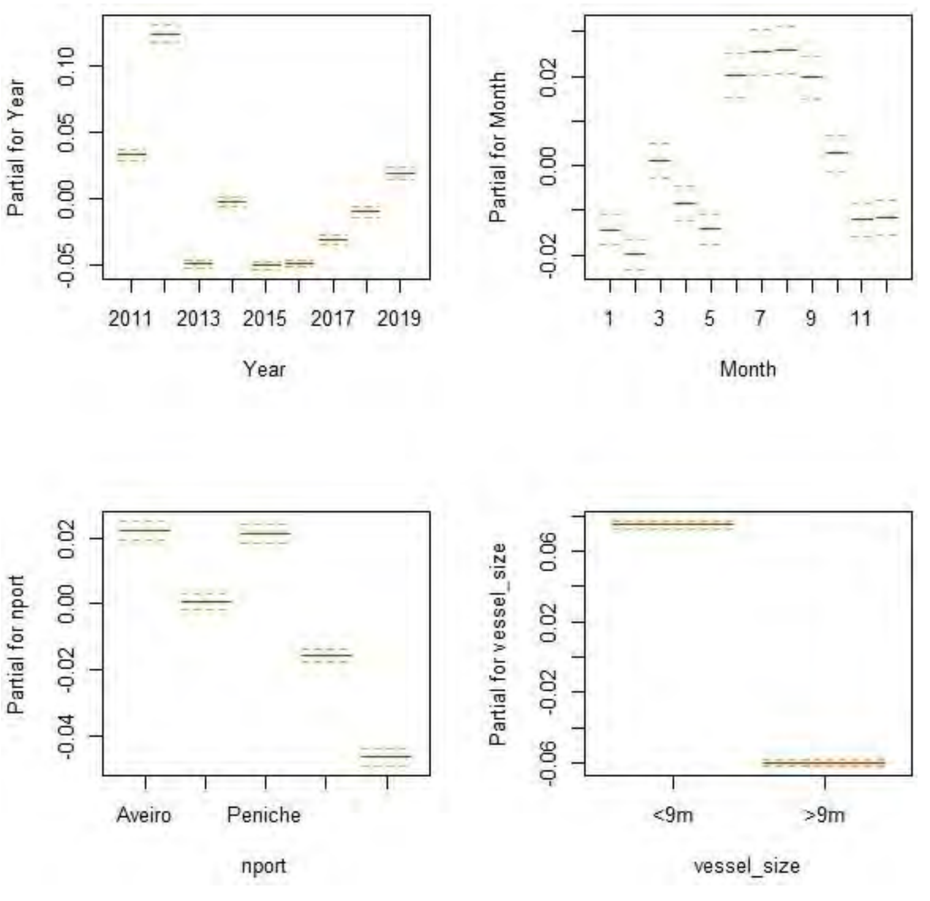


Figure 32. Test 1 - *Solea solea* in Portuguese waters (Division 9a). Effect of each explanatory variable included in the standardization of the LPUE for *S. solea* caught by the polyvalent segment in mainland Portugal (Division 9a): year, month, landing port (nport) and vessel size (vessel_size).

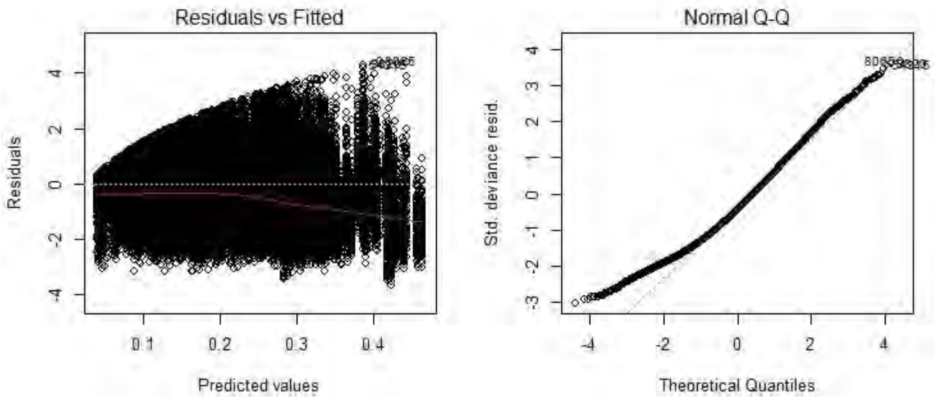


Figure 33. Test 1 - *Solea solea* in Portuguese waters (Division 9a). Residuals of the best GLM model fitted to the LPUE data for the Portuguese polyvalent fleet: (left) fitted vs. residuals (right) quantile-quantile (Q-Q) plot.

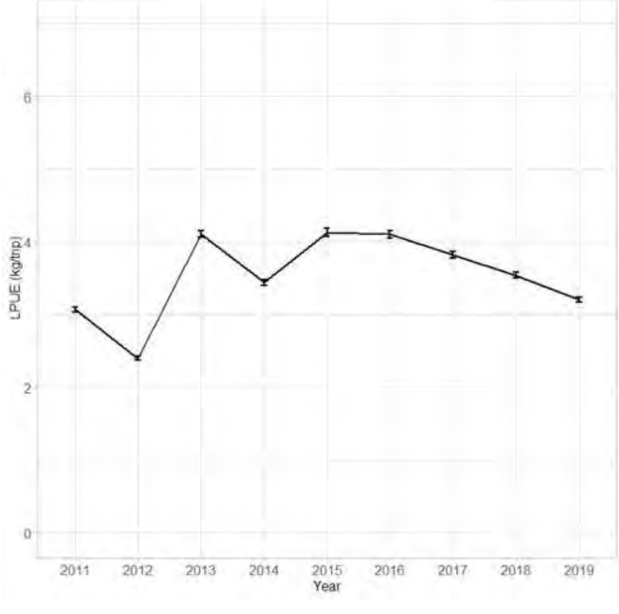


Figure 34. Test 1 - *Solea solea* in Portuguese waters (Division 9a). Standardized LPUE index (kg.trip-1) and respective standard error for the Portuguese polyvalent fishery from 2011 to 2019 (Explained variance = 0.87).

Table 6. Test 1 - *Solea solea* in Portuguese waters (Division 9a). Standardized LPUE index (kg.trip-1) and respective standard error for the Portuguese polyvalent fishery from 2011 to 2019.

Year	LPUE	Lower_SE	Upper_SE
2011	3,07	3,04	3,10
2012	1,40	2,37	2,42
2013	4,10	4,05	4,15
2014	3,44	3,40	3,48
2015	4,13	4,08	4,18
2016	4,10	4,05	4,15
2017	3,82	3,77	3,86
2018	3,54	3,49	3,58
2019	3,20	3,17	3,24

Test 2 - increase by weight per trip by 25% for data from 2019

Data from 2019 was increased by 25% in order to test the sensitivity of the model to an increase.

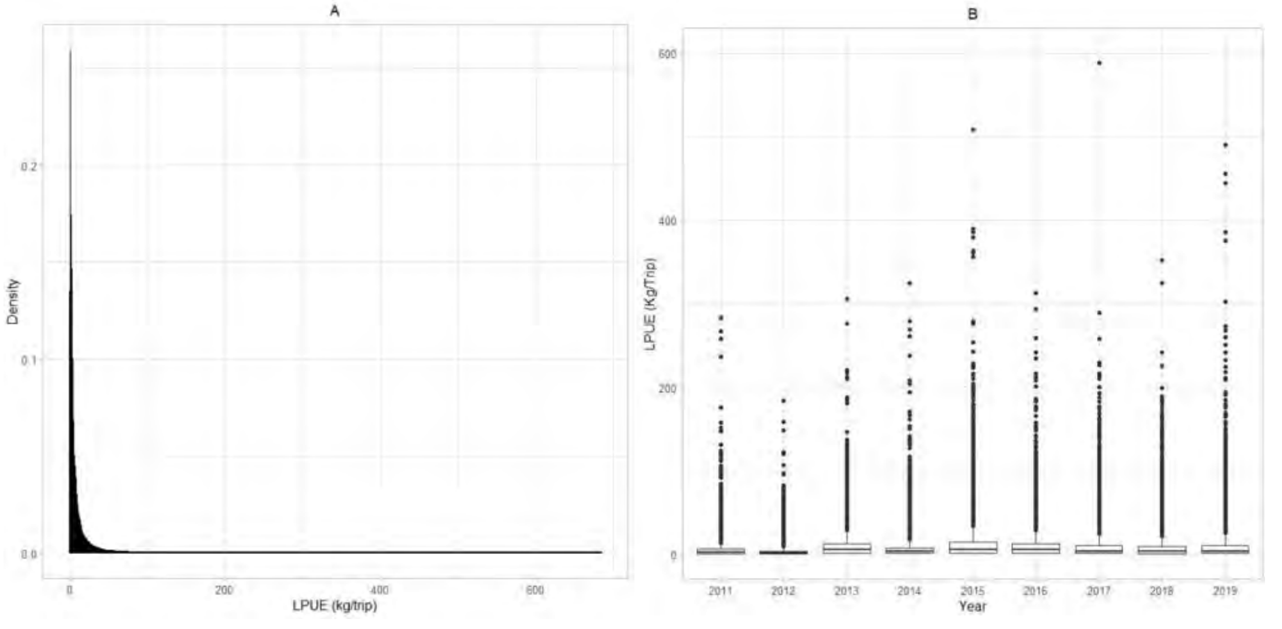


Figure 35. Test 2 - *Solea solea* in Portuguese waters (Division 9a). Nominal LPUE of *Solea solea* in the reference ports (all data excluding occasional vessels). A) density distribution and B) distribution by year.

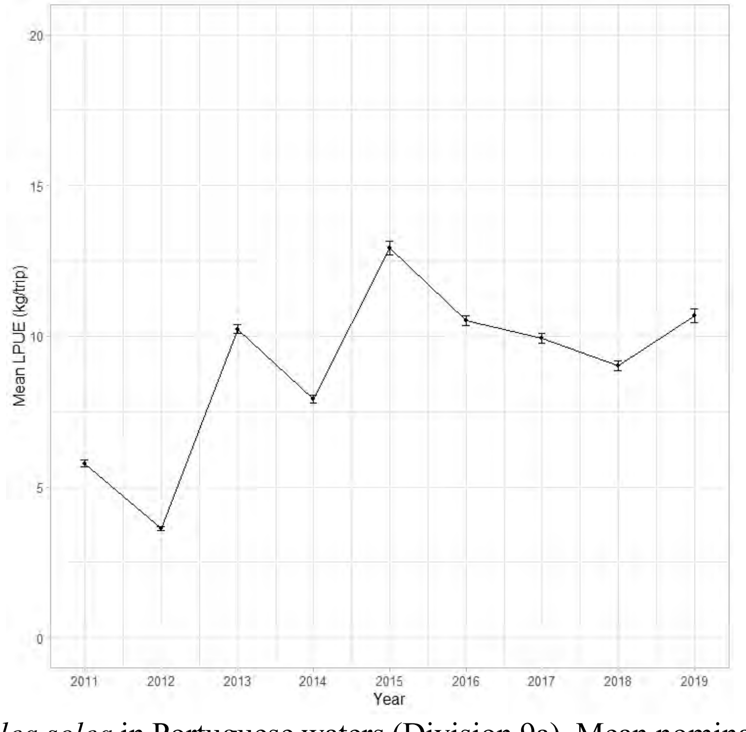


Figure 36. Test 2 - *Solea solea* in Portuguese waters (Division 9a). Mean nominal CPUE and associated standard error by year of *Solea solea* in the selected ports (all data excluding occasional vessels).

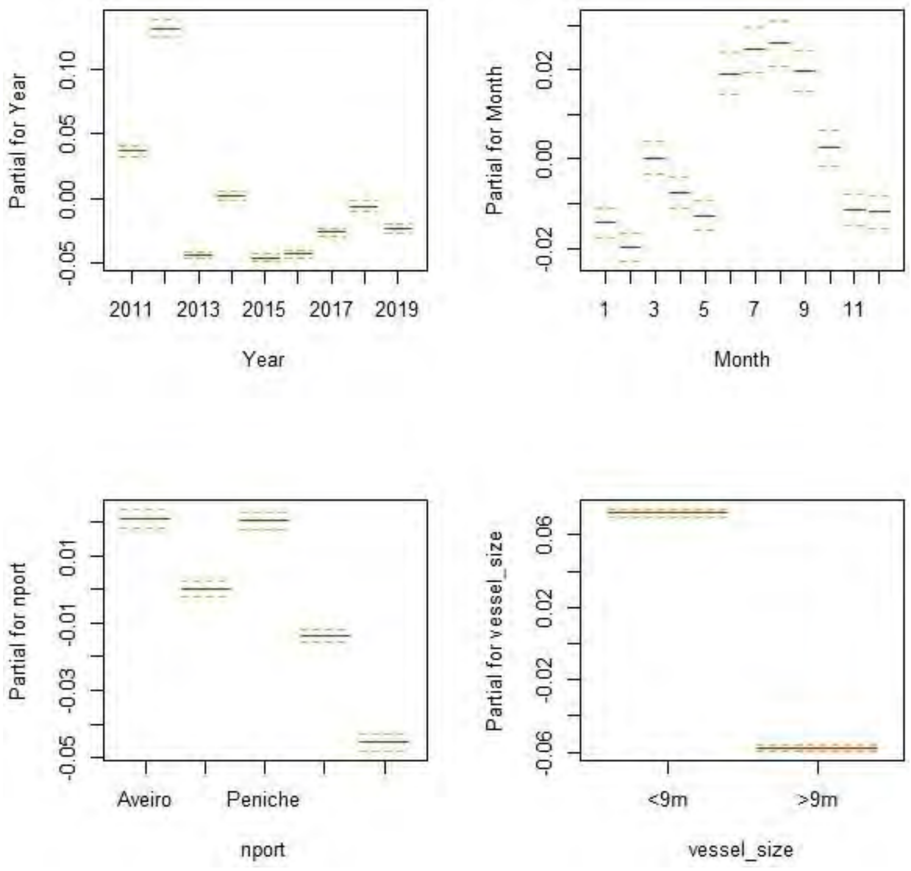


Figure 37. Test 2 - *Solea solea* in Portuguese waters (Division 9a). Effect of each explanatory variable included in the standardization of the LPUE for *S. solea* caught by the polyvalent segment in mainland Portugal (Division 9a): year, month, landing port (nport) and vessel size (vessel_size).

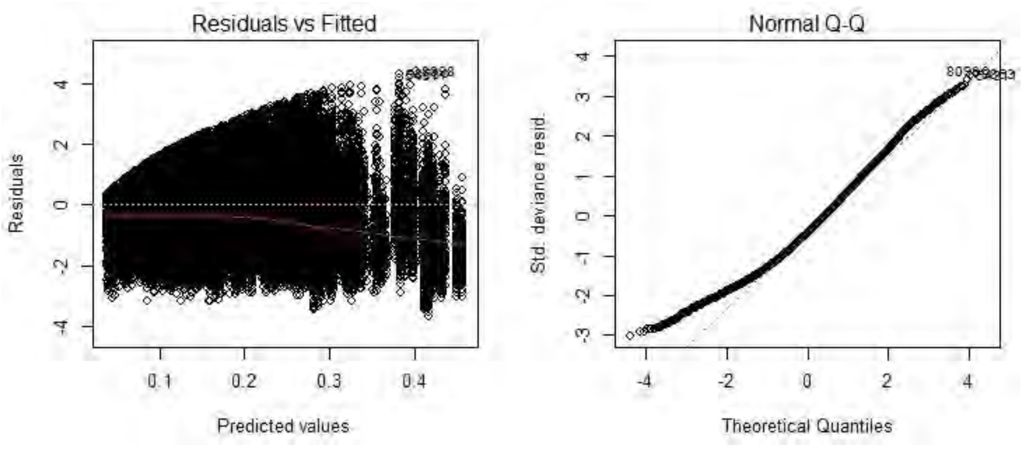


Figure 38. Test 2 - *Solea solea* in Portuguese waters (Division 9a). Residuals of the best GLM model fitted to the LPUE data for the Portuguese polyvalent fleet: (left) fitted vs. residuals (right) quantile-quantile (Q-Q) plot.

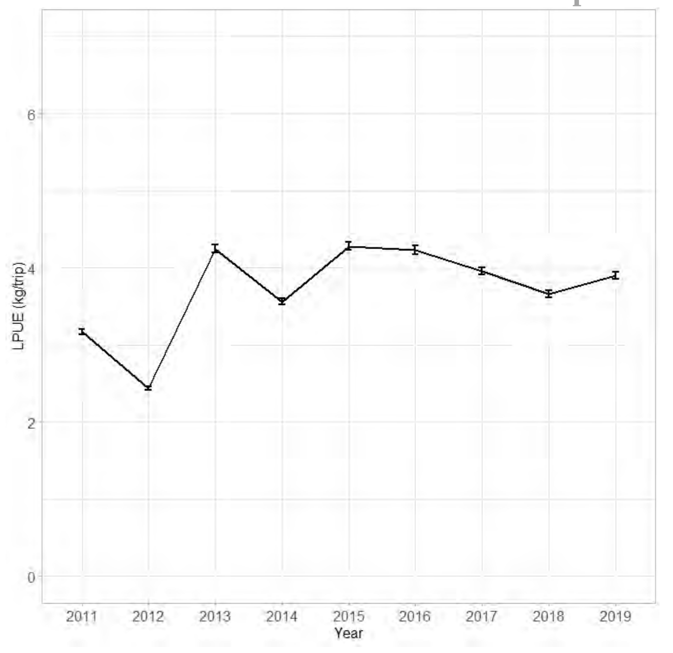


Figure 39. Test 2 - Standardized LPUE index (kg.trip-1) and respective standard error for the Portuguese polyvalent fishery from 2011 to 2019 (Explained variance = 0.86).

Table 7. Test 2 - *Solea solea* in Portuguese waters (Division 9a). Standardized LPUE index (kg.trip-1) and respective standard error for the Portuguese polyvalent fishery from 2011 to 2019.

Year	LPUE	Lower_SE	Upper_SE
2011	3,17	3,13	3,20
2012	2,44	2,41	2,46
2013	4,24	4,19	4,30
2014	3,56	3,52	3,60
2015	4,28	4,23	4,33
2016	4,23	4,18	4,28
2017	3,95	3,91	4,00
2018	3,66	3,62	3,70
2019	3,90	3,86	3,95

Plot Model, test 1 and test 3 outputs together

The model seems to be sensitive to small increases or decreases.

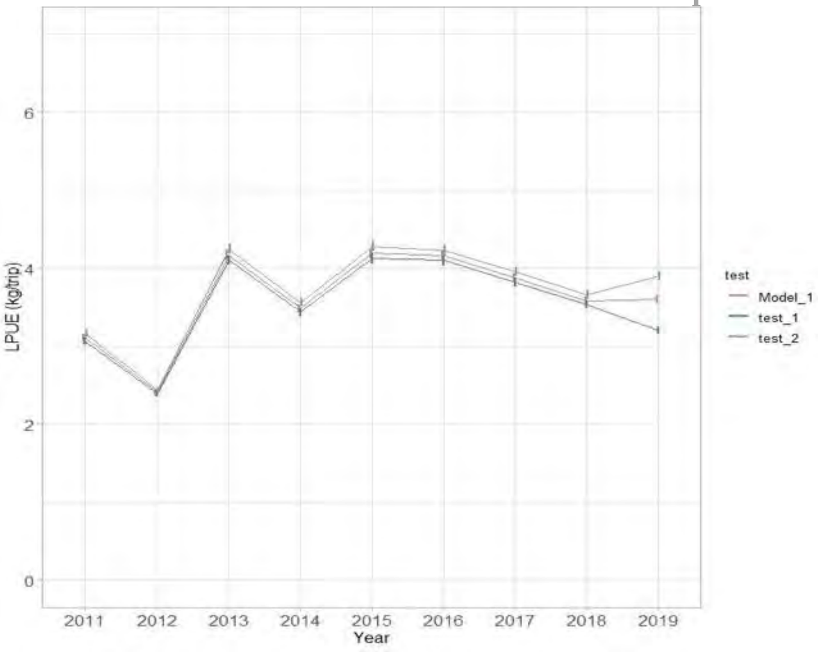


Figure 40. Standardized LPUE index (kg.trip-1) and respective standard error for the Portuguese polyvalent fishery from 2011 to 2019 for: red - model; green - test 1 (2019 data reduced by 25%) and; blue - Test 2 (2019 data increased by 25%).

Comparison with reference situation

The reference situation selected for prediction was the landing port of Peniche, month 2 and vessels <9m. Are the prediction trends different if we select a different reference situation? Following is the comparison between LPUE for the different levels of the variable "Port" and for the different levels of the variable "Vessel size". Apart from the absolute values, trends are similar.

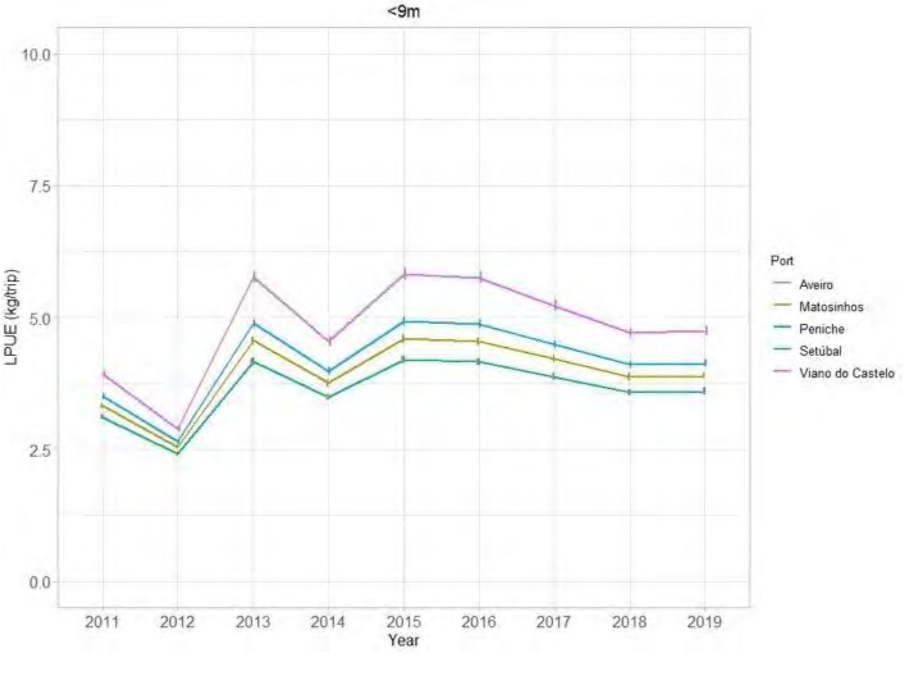


Figure 41. Standardized LPUE index (kg.trip-1) and respective standard error for the Portuguese polyvalent fishery with LOA <9m from 2011 to 2019 considering different reference situations (i.e. the different levels of the explanatory variable "Port").

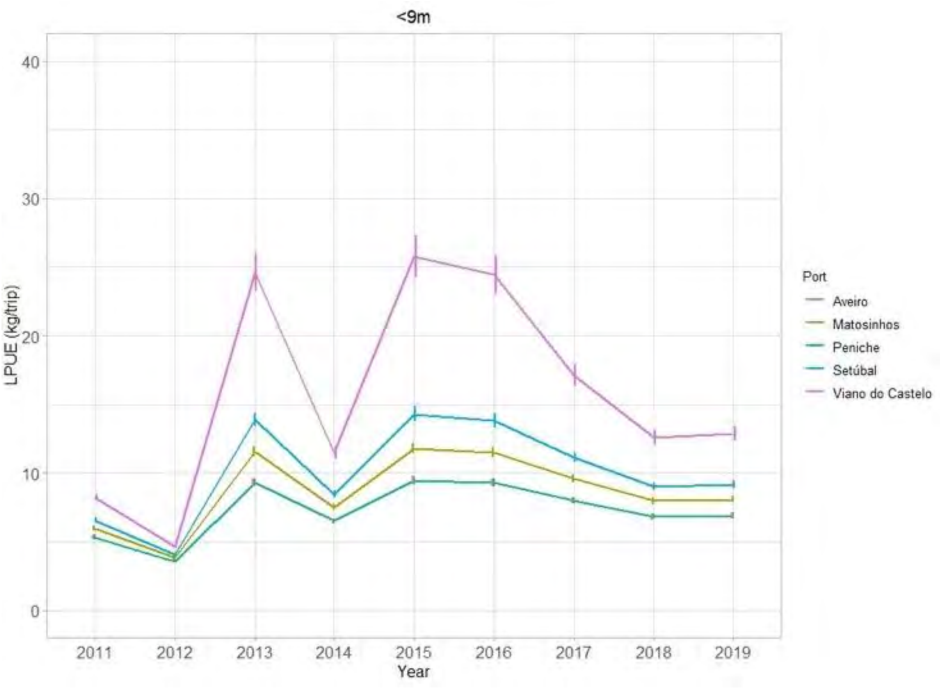


Figure 42. Standardized LPUE index (kg.trip-1) and respective standard error for the Portuguese polyvalent fishery with LOA >9m from 2011 to 2019 considering different reference situations (i.e. the different levels of the explanatory variable "Port").

Least-square means (lsmeans)

Instead of set a reference situation, the standardized LPUE can be fitted using estimated marginal means (R package: emmeans). The least-squares mean (lsmeans() method) catch per unit effort with 95% confidence intervals and respective standard error for the Portuguese polyvalent fishery from 2011 to 2019 is presented in Table 8.

Table 8. *Solea solea* in Portuguese waters (Division 9a). lsmeans method - Standardized LPUE index (kg.trip-1) and respective standard error for the Portuguese polyvalent fishery from 2011 to 2019.

Year	LS mean (kg/trip)	Standard error	Lower bound (95%)	Upper bound (95%)
2011	3,98	0,04	4,06	3,91
2012	2,91	0,03	2,97	2,85
2013	5,87	0,05	5,98	5,77
2014	4,61	0,04	4,70	4,53
2015	5,94	0,06	6,05	5,83
2016	5,86	0,05	5,97	5,76
2017	5,31	0,05	5,41	5,22
2018	4,78	0,05	4,88	4,68
2019	4,82	0,05	4,91	4,72

The comparison between the previous method (the reference situation Peniche, month 2 and vessels with LOA <9m) and the results obtained with the estimated marginal means are present in Figure 21. Trends in the LPUE are similar.

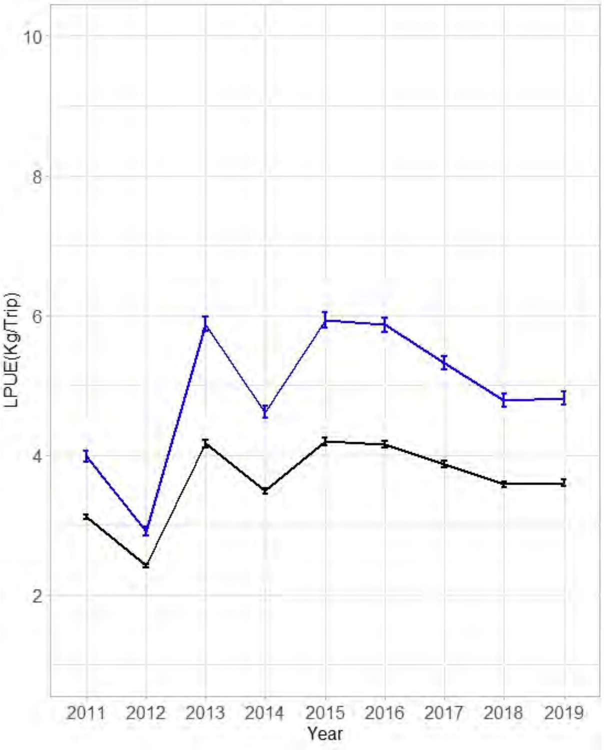


Figure 43. *Solea solea* in Portuguese waters (Division 9a). Standardized LPUE index (kg.trip-1) and respective standard error for the Portuguese polyvalent fishery from 2011 to 2019; black line - reference situation Peniche, month 2 and >9m and; blue line - least-squares mean catch per unit effort with 95% confidence intervals.

General biology

In Portuguese waters, sole length of first maturity was estimated as 25 cm for males and 27 cm for females (Jardim, et al., 2011).

Growth studies based on *S. solea* otolith readings in the Portuguese coast indicate Linf of 52.1cm for females and 45.7 cm for males. The growth coefficient estimate of females (K=0.23) was slightly higher than for males (K=0.21) and t_0 estimate, -0.11 and 1.57 for females and males, respectively (Teixeira and Cabral, 2010).

The natural mortality parameter M is not known for this stock but for the stock of common sole ICES division 8a, b is used a M of 0.2. A recent study of Cerim et al. (2020) defined the M of the common sole M= 0.31 yr-1.

L_{95} is not known for this stock but for the common sole ICES division 8a, b is 27.5 (see stock annex sol-bisc division 8a,b).

Bayesian length-weight: a=0.00759 (0.00629 - 0.00915), b=3.06 (3.00 - 3.12), in cm Total Length, based on LWR estimates for this species (Frose et al., 2014).

Stock identity and possible assessment areas

There is no clear information to support the definition of the common sole stock for ICES Subdivision 8.c and 9.a.

Others sole species

For the WKWEST21 an official data call was requested for this stock to get all the possible data, not only for the common sole (*S. Solea*) but also for the other sole species *Solea senegalensis*, *Pegusa lascaris* and sole spp.

For Portugal, the *S. Senegalensis* and *P. lascaris* landings and length distribution are available for 2011-2019. For Solea spp. landings are also available for 2011-2019.
For Spain, the *S. Senegalensis, P. lascaris* and Solea spp. landings are available for 2009-2019.
For France no data were available for these other species.

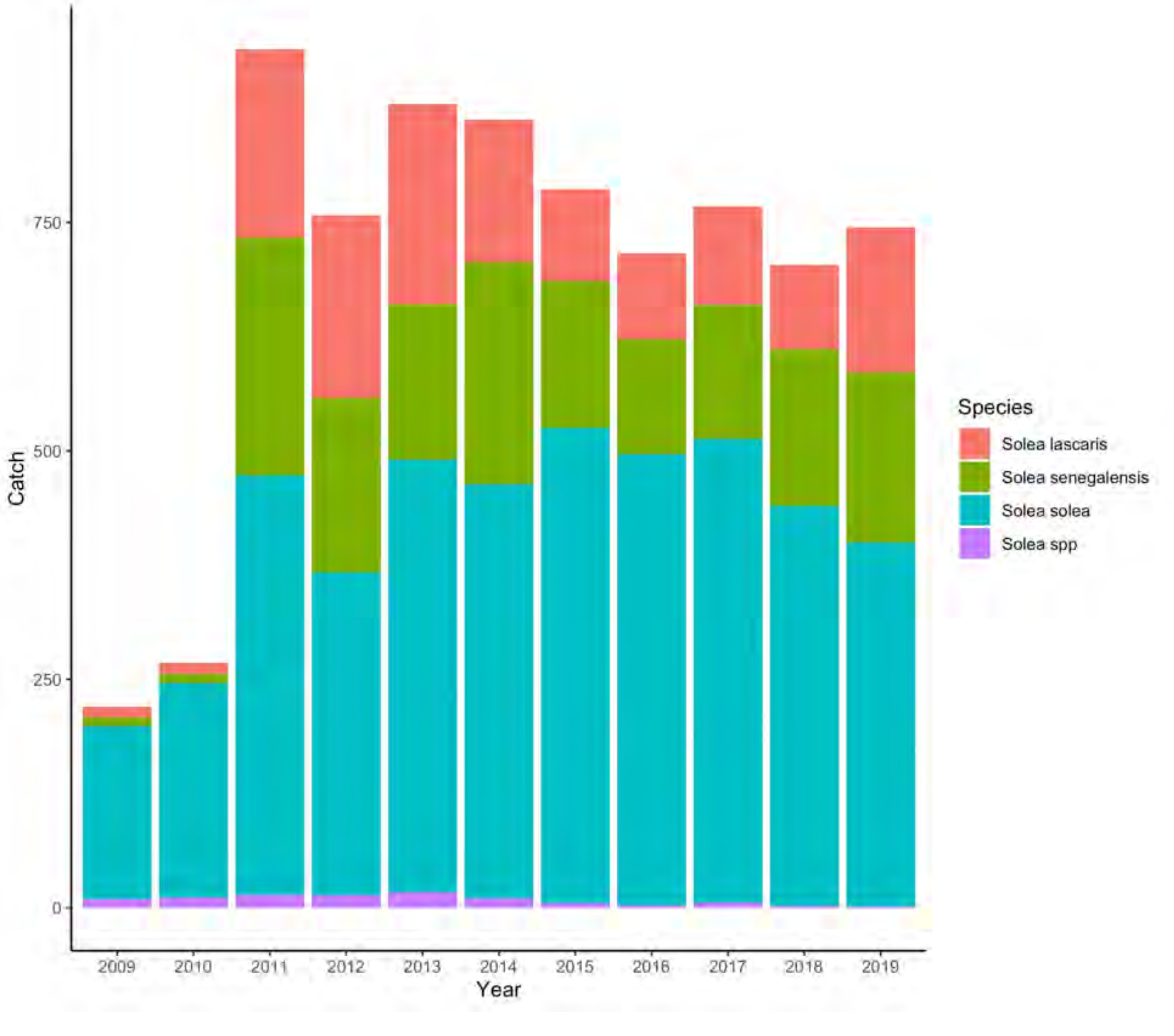


Figure 44: All sole species landings for the Division 8c9a. Data are from Spain and Portugal together.

S. senegalensis

The majority of this species is caught my Portugal (Figure 45), by the polyvalent fleet (Figure 46), homogenously along all the year (Figure 47) and in the ICES division 9a.

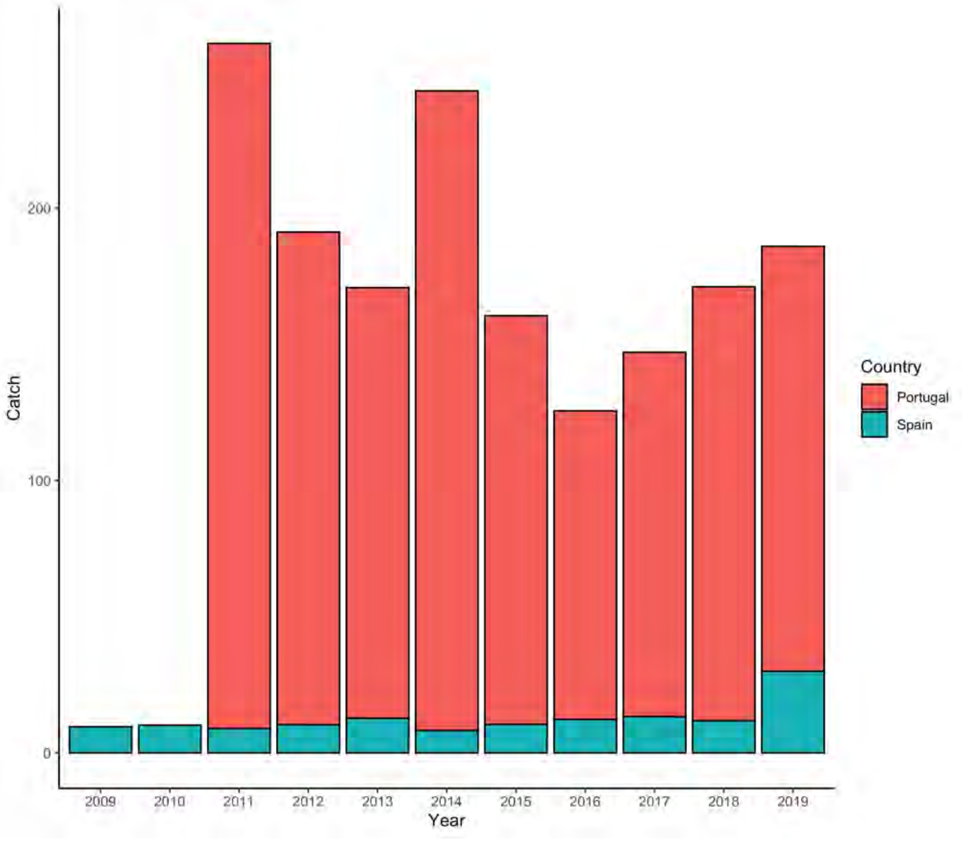


Figure 45: *S. Senegalensis* catches by country from 2009 to 2019.

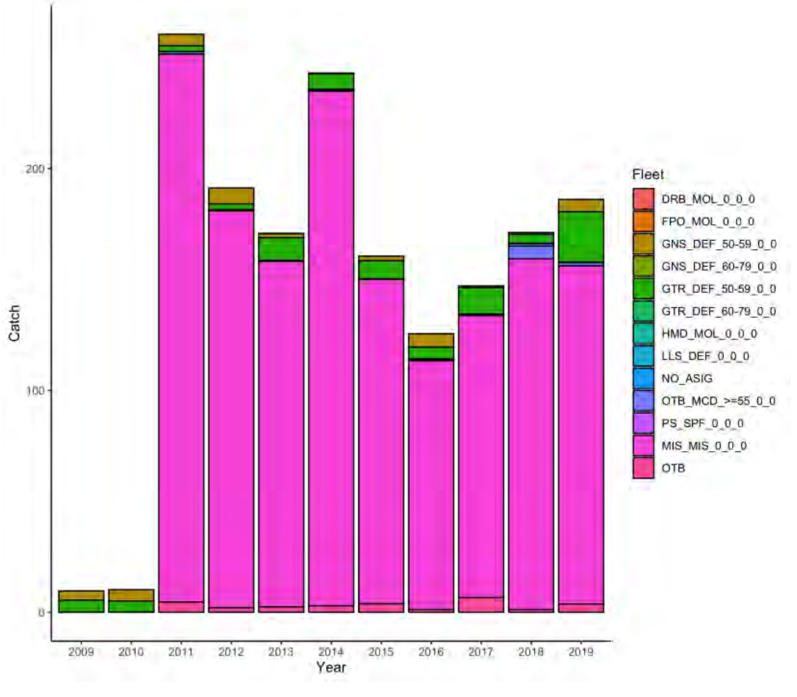


Figure 46: *S. Senegalensis* catches by fleet from 2009 to 2019.

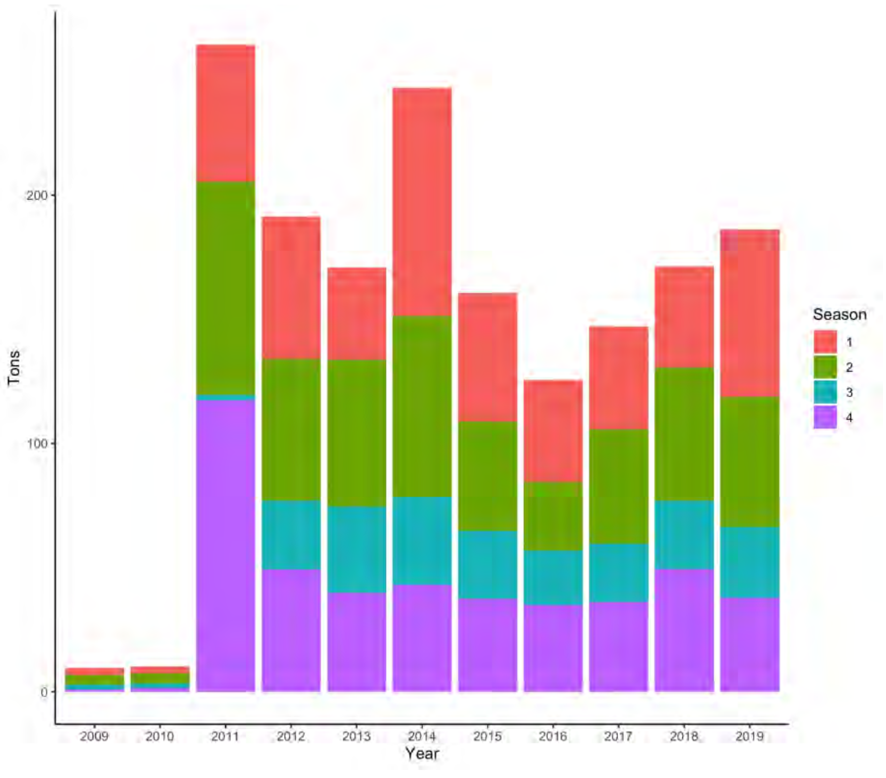


Figure 47: *S. Senegalensis* catches by quarter from 2009 to 2019.

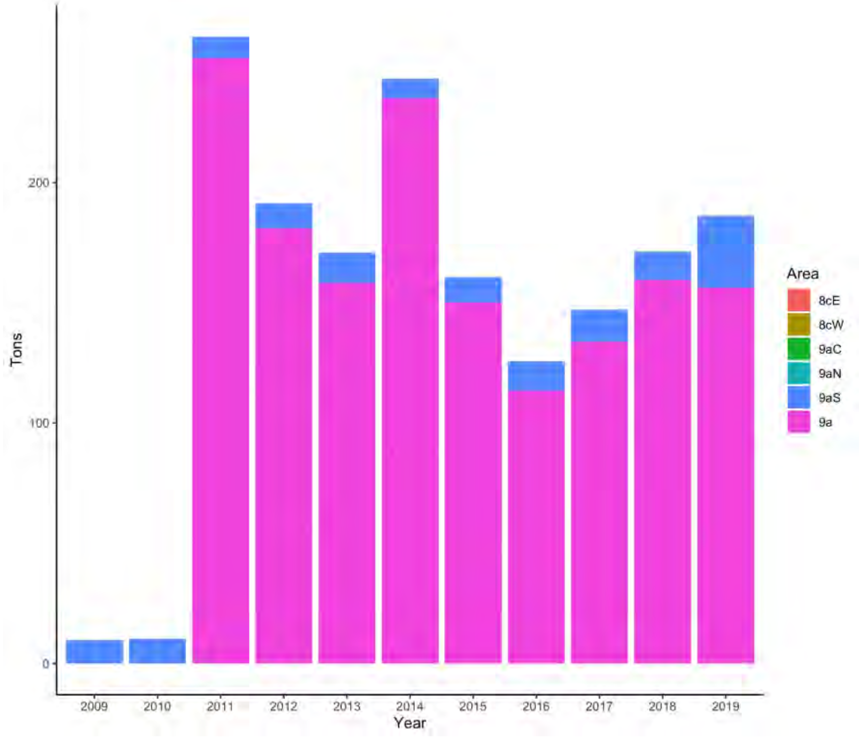


Figure 48: *S. Senegalensis* catches by area from 2009 to 2019.

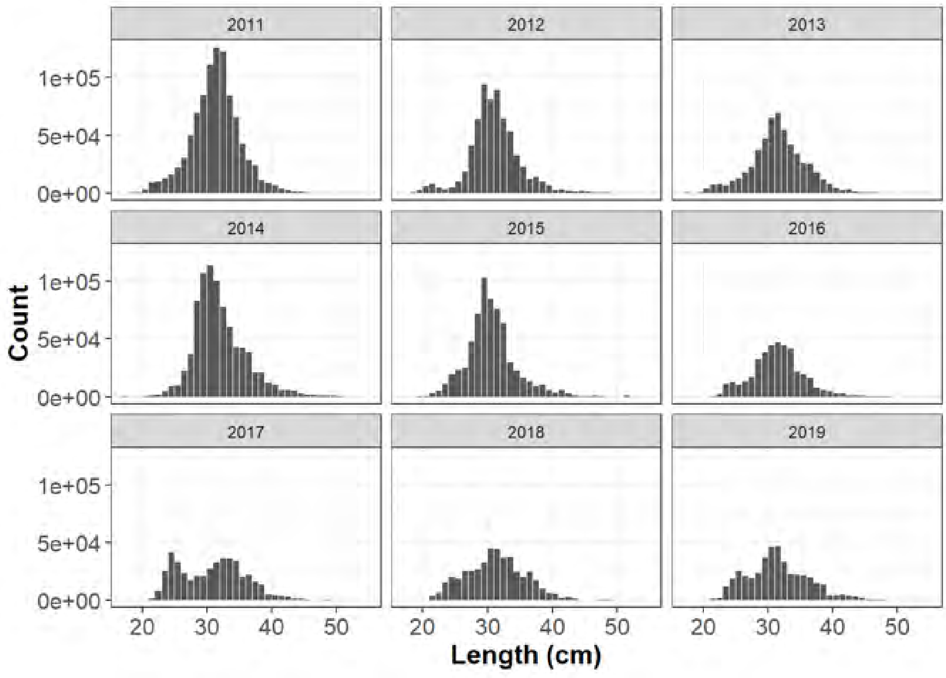


Figure 49. *S. Senegalensis* length distribution from 2011 to 2019 for Portugal.

There is no abundance information for this species for Spain. The bottom trawl demersal surveys performed by Spain don’t catch this species and in the Portuguese survey (PtGFS-WIBTS-Q4) the catch of this species is very sporadic (Figure 50).

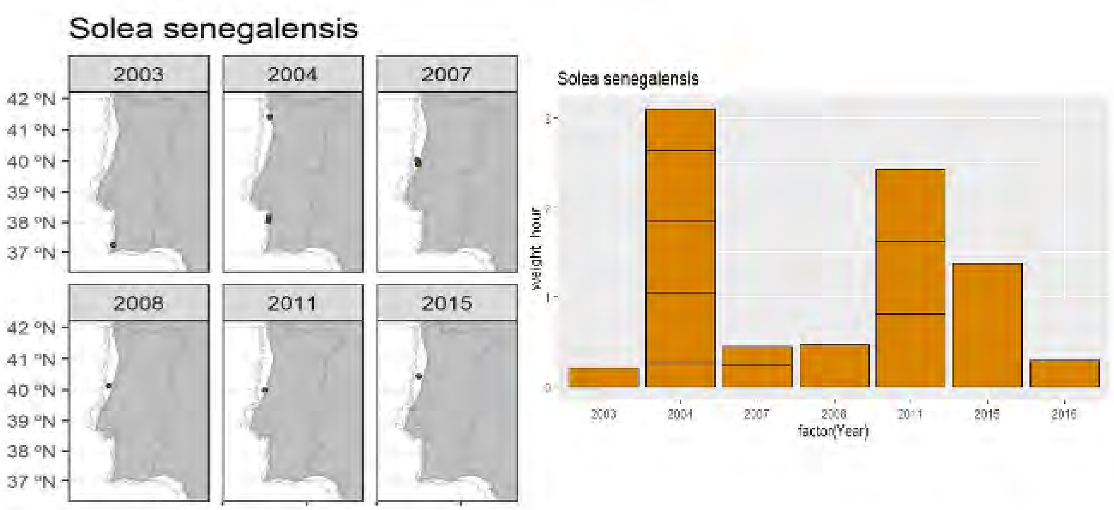


Figure 50. Hauls where the *S. Senegalensis* was present in the in Portuguese bottom trawl survey **(**PtGFS-WIBTS-Q4) (left) and temporal trend of the abundance caught (right).

P. lascaris

Similar to the *S. senegalensis* this species is for the majority caught my Portugal (Figure 51), by the polyvalent fleet (Figure 52), homogenously along all the year (Figure 52) and in the ICES division 9a (Figure 54).

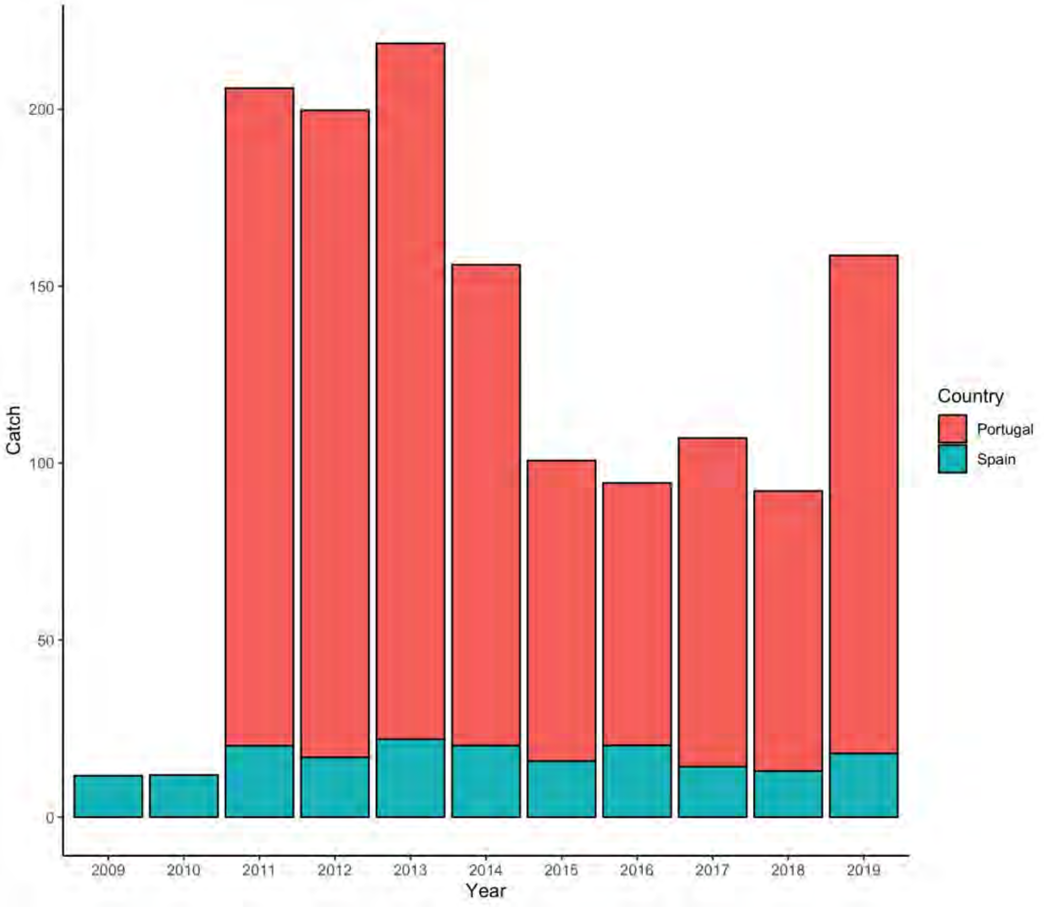


Figure 51: *P.lascaris* catches by country from 2009 to 2019.

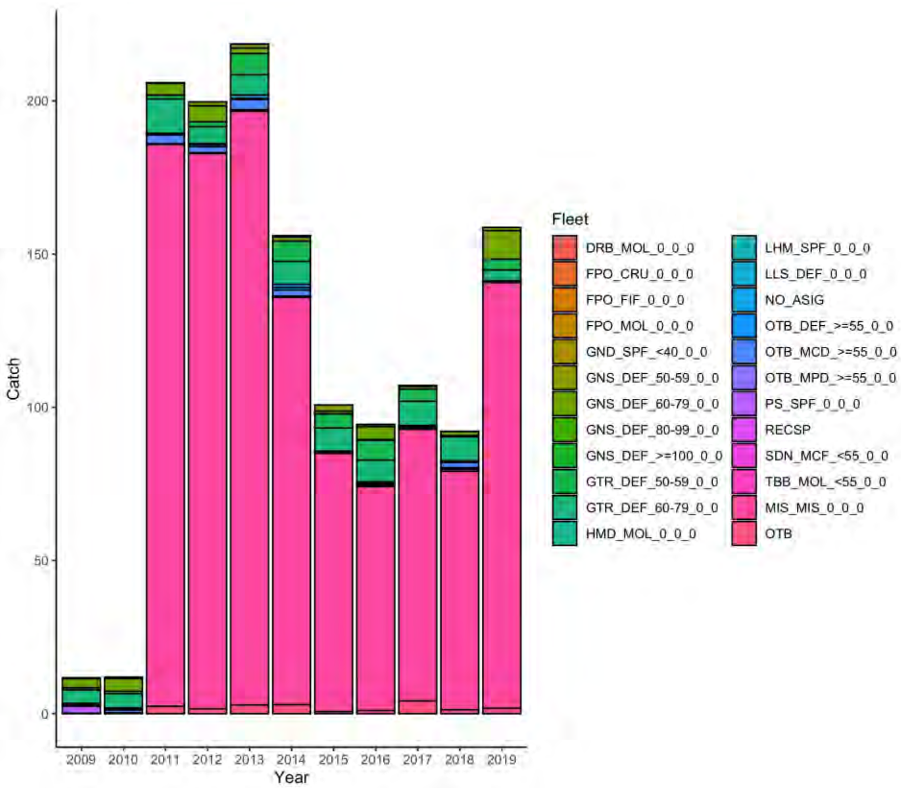


Figure 52: *P.lascaris* catches by fleet from 2009 to 2019.

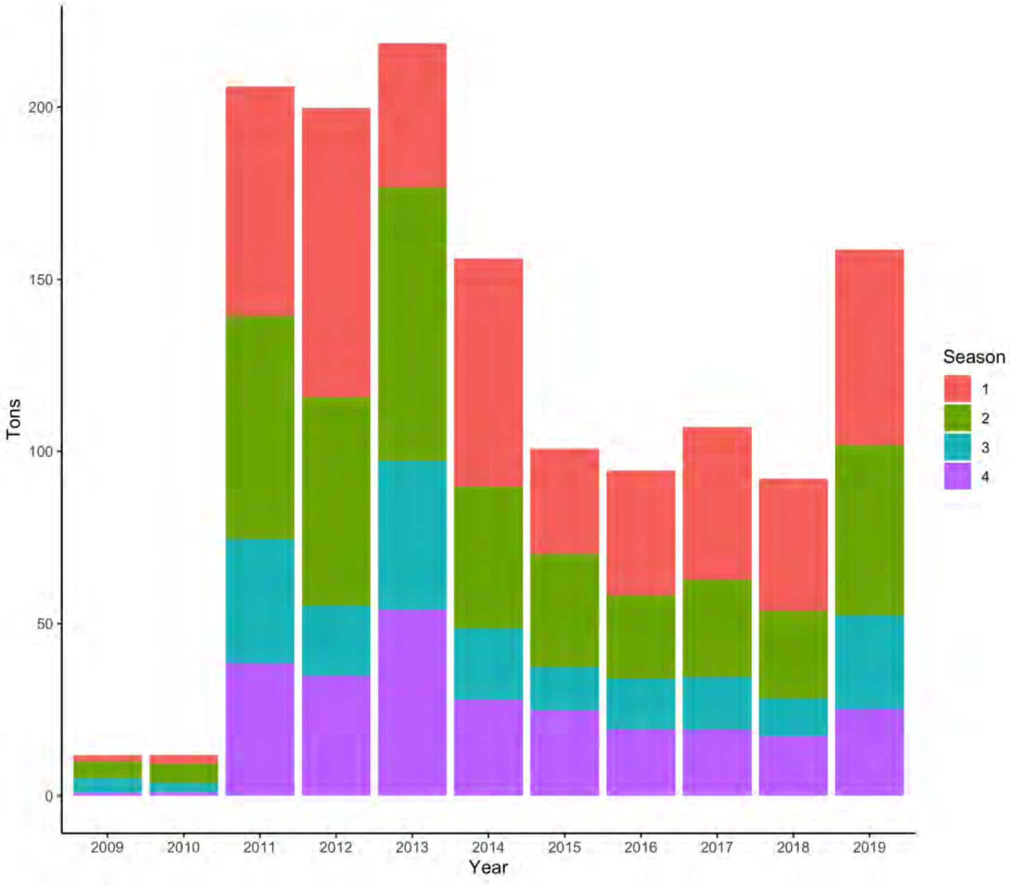


Figure 53: *P.lascaris* catches by quarter from 2009 to 2019.

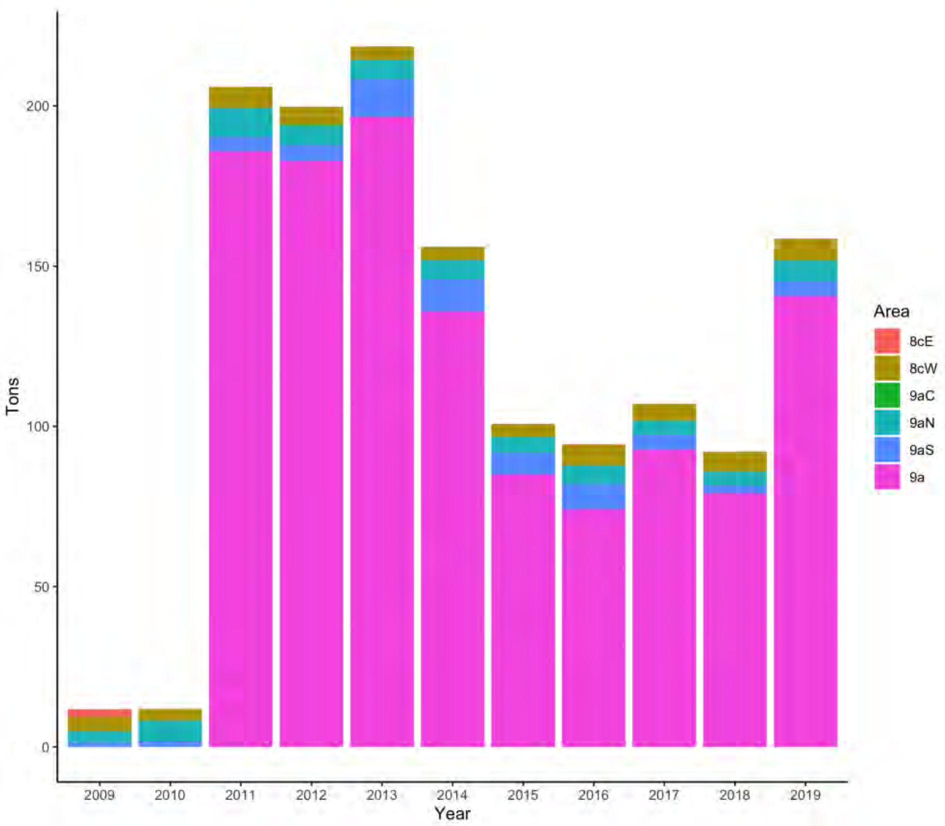


Figure 54: *P.lascaris* catches by area from 2009 to 2019.

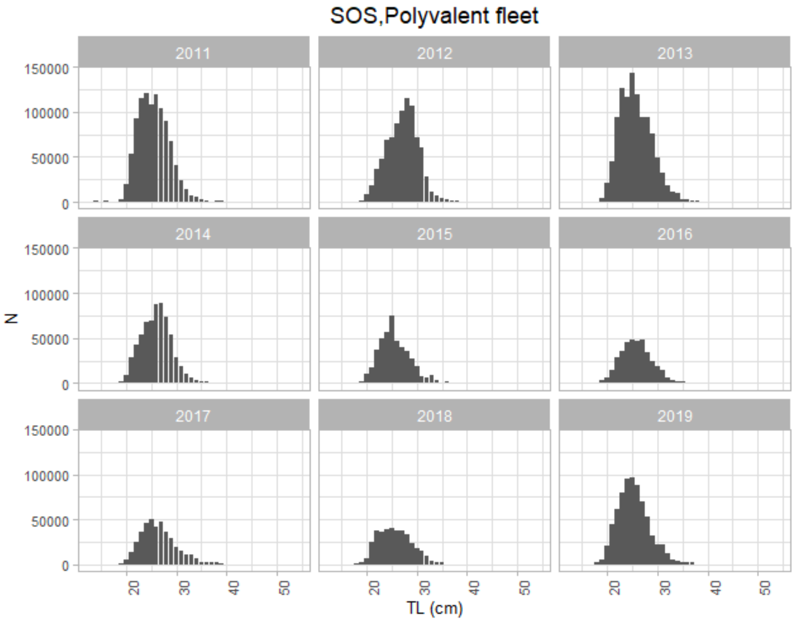


Figure 55. *P.lascaris* length distribution in Portuguese waters (Division 9a) for the main fleet.

This species is very sporadically caught by the Spanish (SP-NSGFS Q4) and Portuguese (PtGFS-WIBTS-Q4) bottom trawl demersal surveys (Figures 38 and 39).

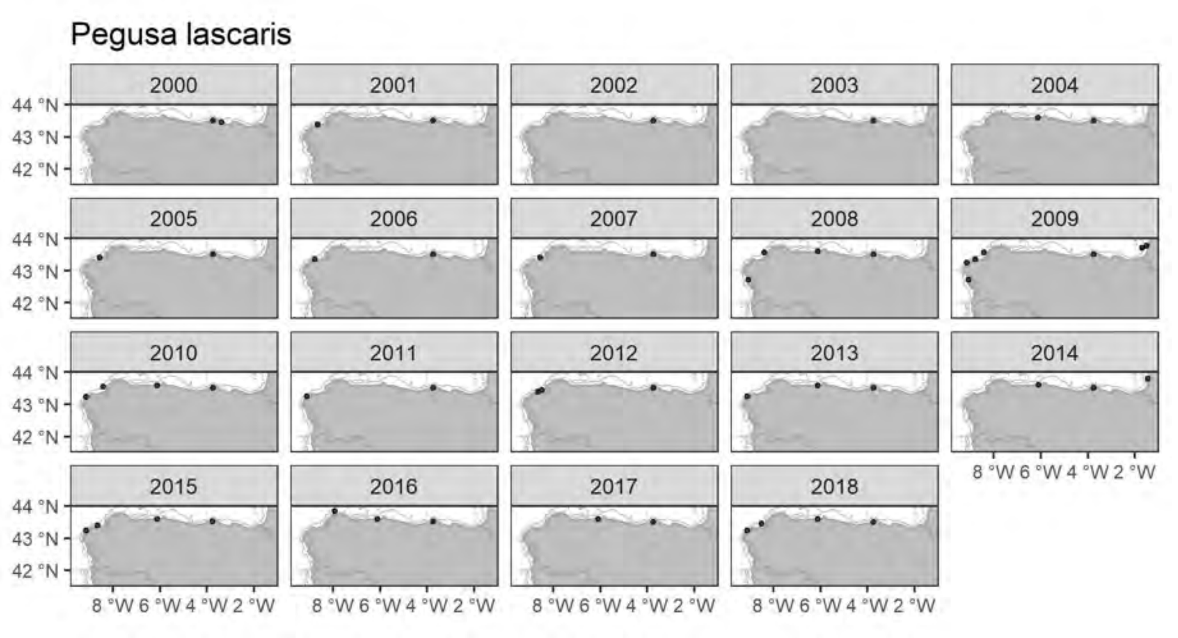
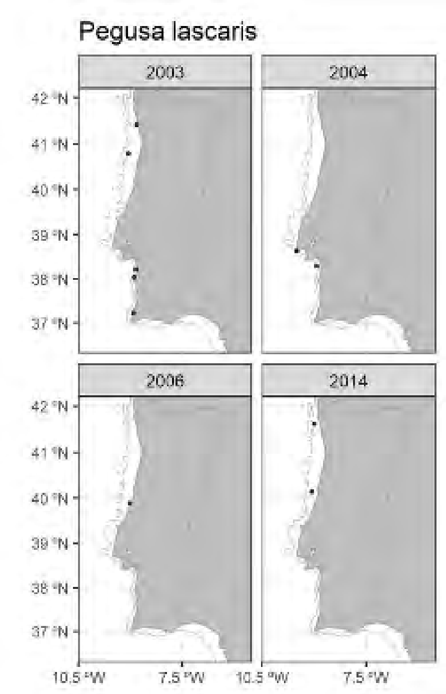


Figure 56: Hauls where the *P.lascaris* was caught during the Spanish survey (SP-NSGFS Q4).



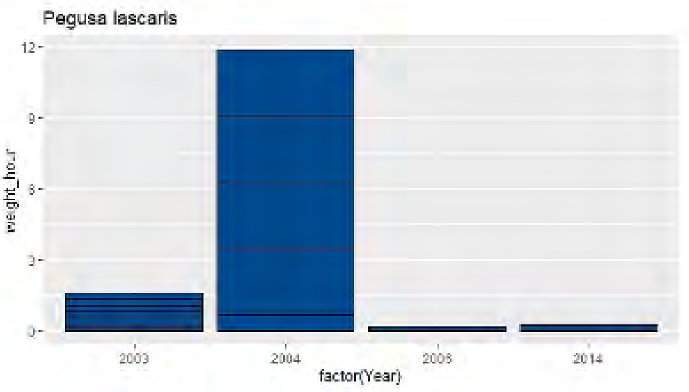


Figure 57: Hauls where the *P.lascaris* was caught during the Portuguese survey (PtGFS-WIBTS-Q4) (left) and temporal trend of the abundance caught (right).

Solea spp

The majority of the catches Solea spp. are in Spain (Figure 58), by the bottom trawlers (Figure 59), Along all the year (Figure 60) in the area 9aS (gulf of Cadiz, Spain) (Figure 61).

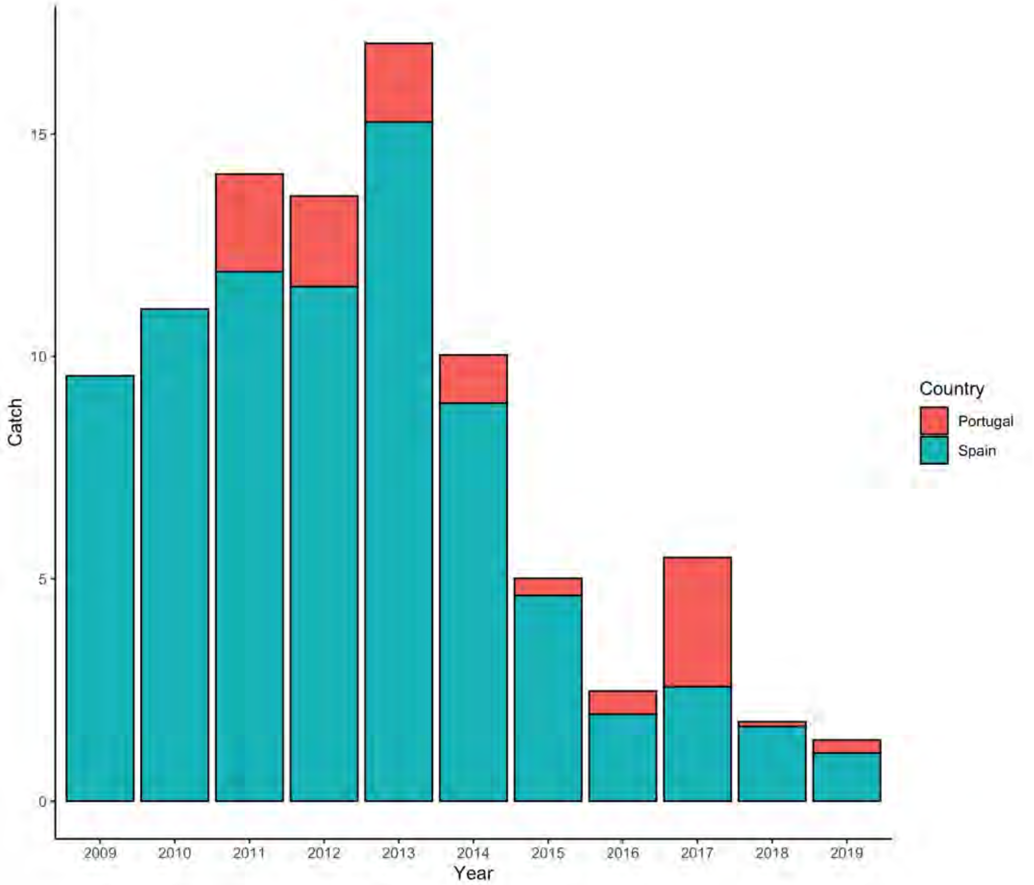


Figure 58: Solea spp. catches by country from 2009 to 2019.

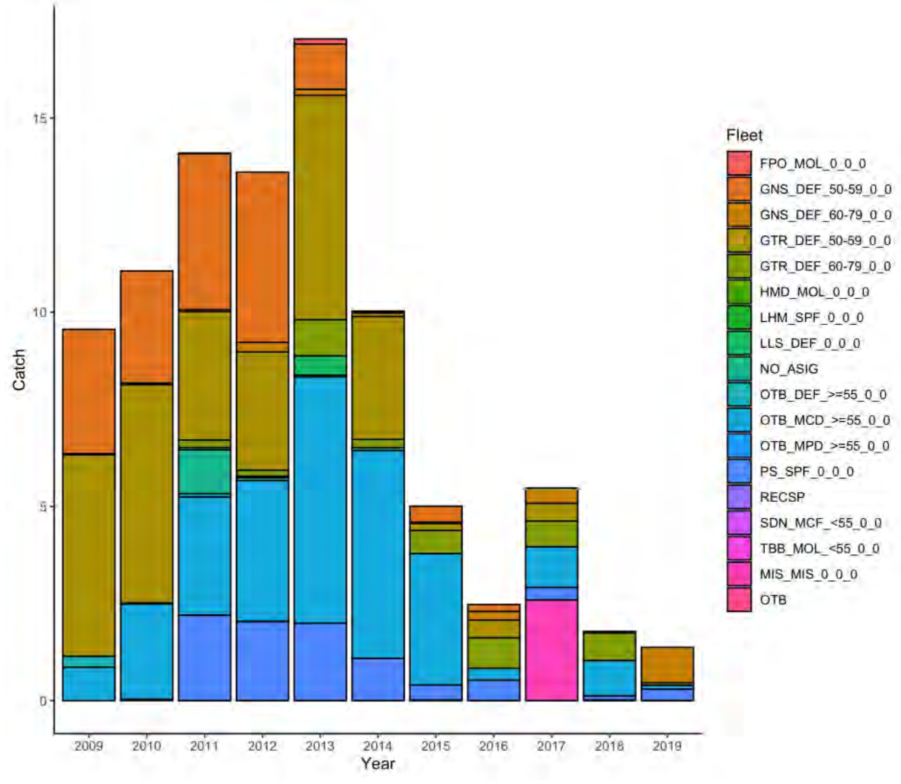


Figure 59: Solea spp. catches by fleet from 2009 to 2019.

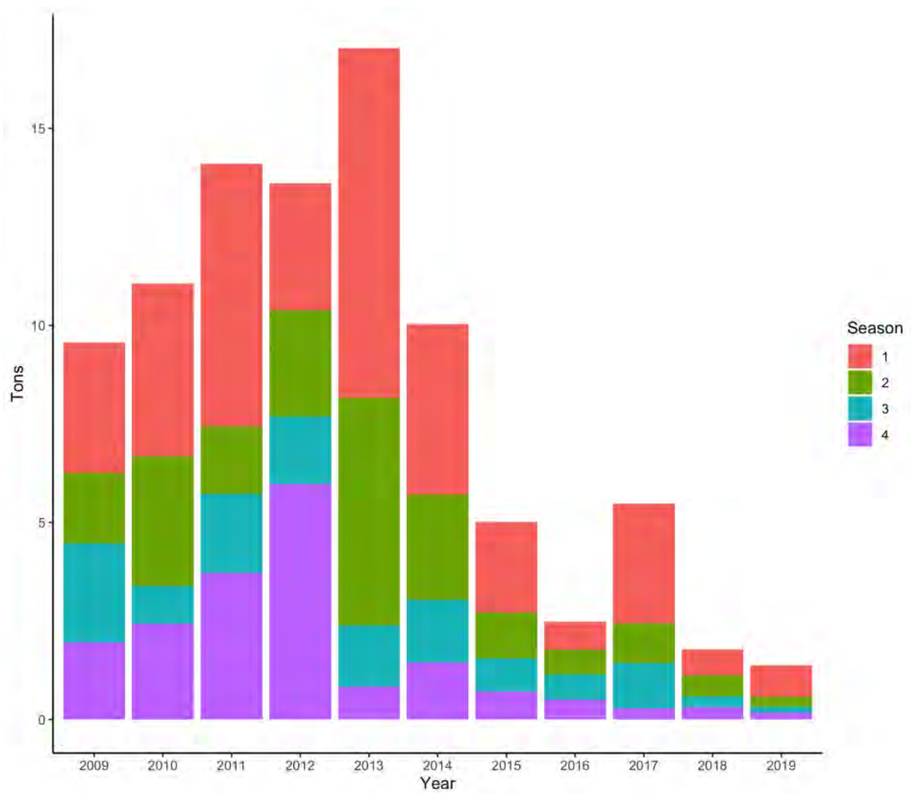


Figure 60: Solea spp. catches by quarter from 2009 to 2019.

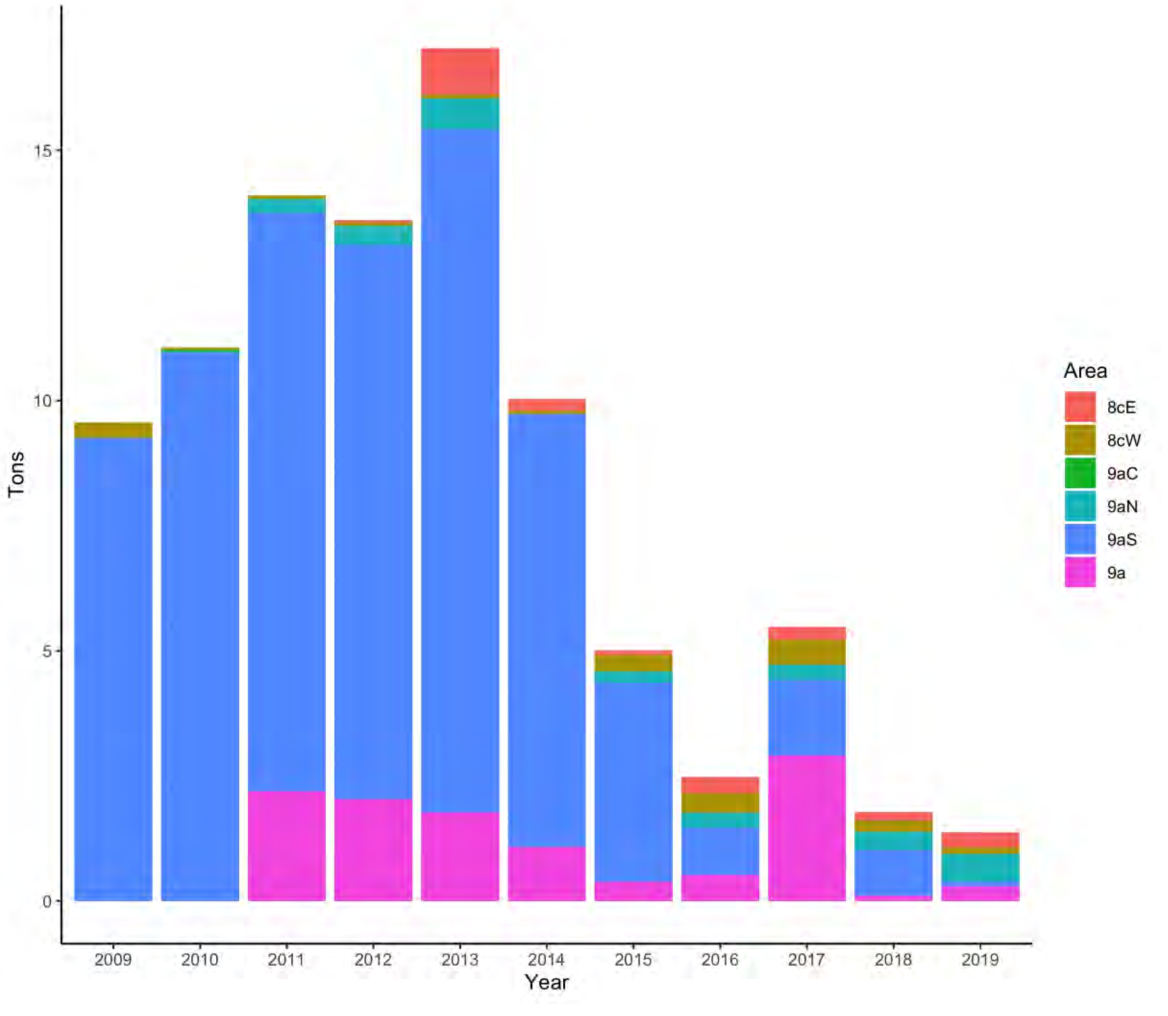


Figure 61: Solea spp. catches by area from 2009 to 2019.

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ANNEX 2
S. solea spatiotemporal model prediction and strata areas issue

In order to check if there was any issue with the spatial prediction of the abundance index generated with the Bayesian model, we compared the areas used for prediction for both the Bayesian model and the usual survey index.

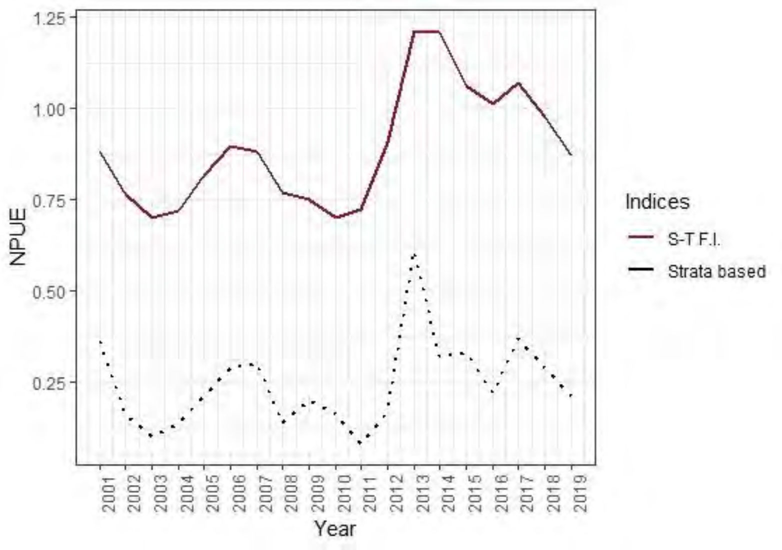


Figure 1. In red the spatio-temporal abundance index obtained for fishery-independent data (2001-2019) versus the survey abundance index standardized for the three bathymetric strata (i.e.,70–120 m and 121–200 m).

We mapped firstly the bathymetry map used for the model and we cropped for the bathymetric strata 70-200 as was the one used for the predictions.

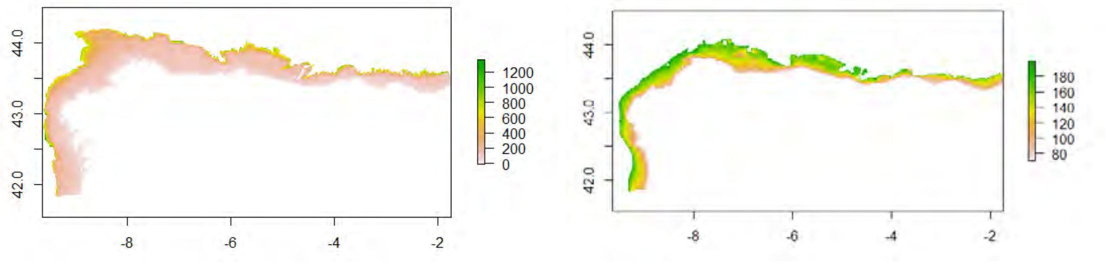


Figure 2. Bathymetry map for the entire study area (left panel), and the cropped one between 70 and 200 m (right panel).

We then computed the superficies of each bathymetric strata used for standardize the survey index.

Figure 3. Spatio-temporal averaged (2001-2019) predicted abundance performed between 70 and 200 m.

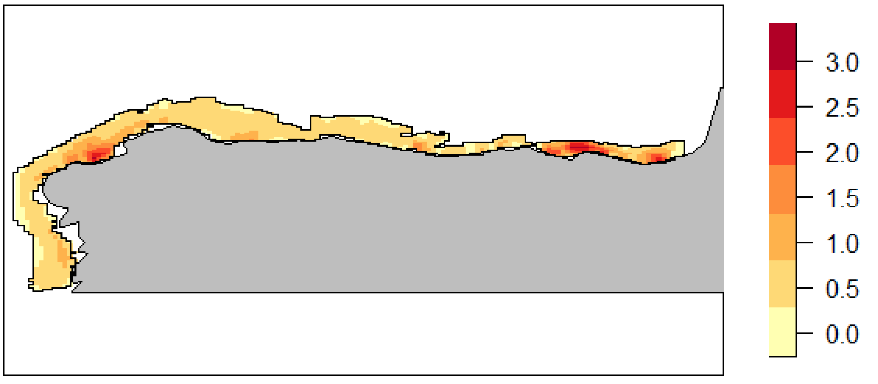


Figure 4. Spatio-temporal averaged (2001-2019) predicted abundance area performed between 70 and 200 m. This area is 21566 km^2.

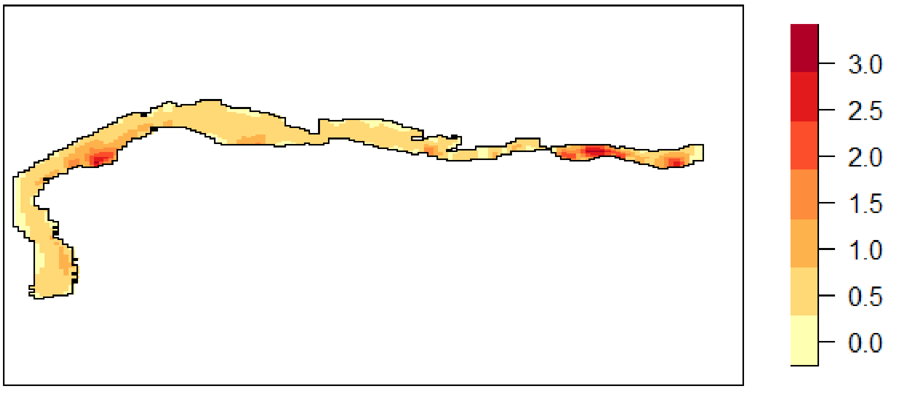


Figure 5. Spatio-temporal averaged (2001-2019) predicted abundance area performed between 70 and 200 m. This area is 21566 km^2.

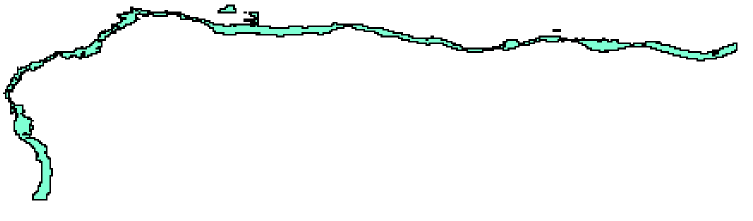


Figure 6. Bathymetric strata corresponding to the 70-120 m isobaths. This area is 5740 km^2.

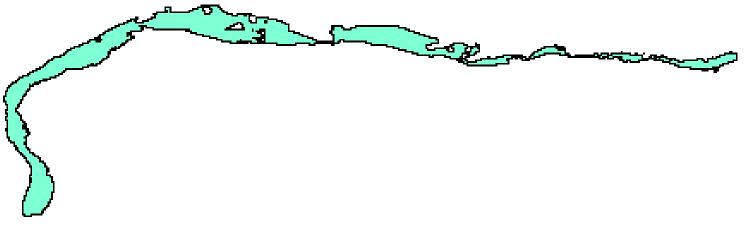


Figure 7. Bathymetric strata corresponding to the 121-200 m isobaths. This area is 11951 km^2.

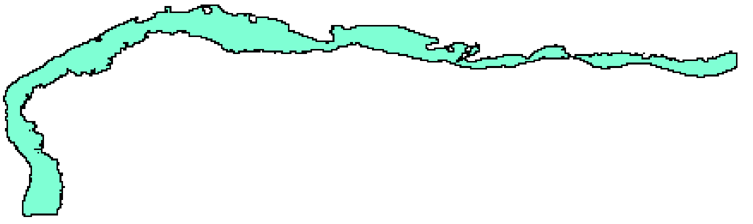


Figure 8. Bathymetric strata corresponding to the 70-200 m isobaths. This is the total bathymetric strata where sampling point and prediction take place. This area is 17591 km^2.

Finally, we computed the intersection area between the prediction area and the strata used for standardize the survey index.

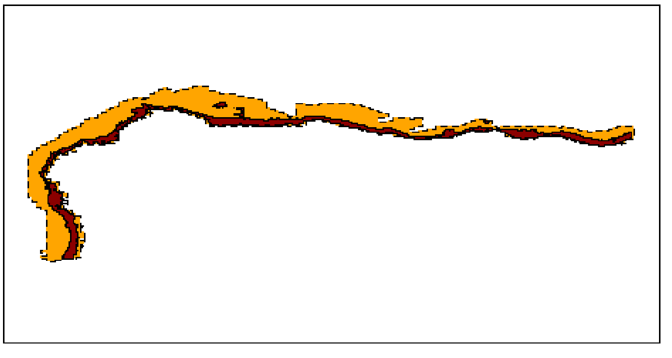


Figure 9. Intersection between predicted abundance area (orange) and 70-121 m strata. This area is 5740 km^2, what means the total strata area.

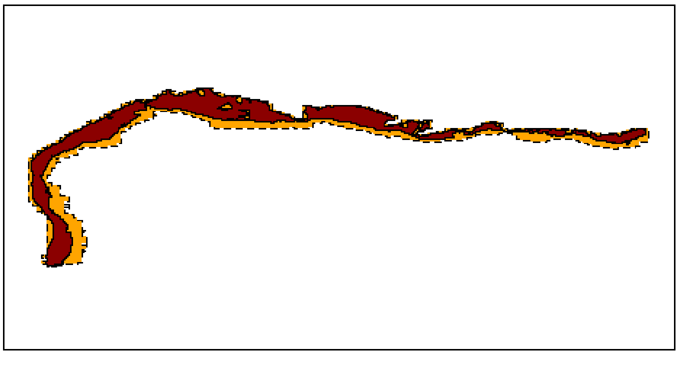


Figure 10. Intersection between predicted abundance area (orange) and 121-200 m strata. This area is 11944 km^2, what means almost the total strata area.

Figure 11. Intersection between predicted abundance area (orange) and 70-121 m strata. This area is 17573 km^2, what means the total strata area.

Figure 13. Sp-GNF survey strata areas.

Table 1. SP GNF strata areas.

	Id	AREA	Primary	Secondary	ID3	ID4	ZLEVEL	Area_KM2
0	0	1181159977	MF	a	<NA>	<NA>	0	1181.1600
1	0	2190284192	MF	b	<NA>	<NA>	0	2190.2842
2	0	956077943	MF	c	<NA>	<NA>	0	956.0779
3	0	908414198	AB	a	<NA>	<NA>	0	908.4142
4	0	921466432	AB	b	<NA>	<NA>	0	921.4664
5	0	538619575	AB	c	<NA>	<NA>	0	538.6196
6	0	1024129435	PA	a	<NA>	<NA>	0	1024.1294
7	0	2623404925	PA	b	<NA>	<NA>	0	2623.4049
8	0	1273646608	EP	a	<NA>	<NA>	0	1273.6466
9	0	1137910064	FE	a	<NA>	<NA>	0	1137.9101
10	0	955632958	PA	c	<NA>	<NA>	0	955.6330
11	0	3253610715	FE	b	<NA>	<NA>	0	3253.6107
12	0	3010442407	EP	b	<NA>	<NA>	0	3010.4424
13	0	665875091	EP	c	<NA>	<NA>	0	665.8751
14	0	3400494018	FE	c	<NA>	<NA>	0	3400.4940

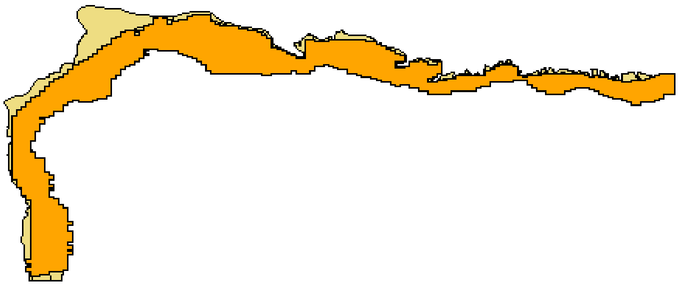


Figure 14. Prediction abundance area over SP-GNF strata areas.

Figure 15. Part of SP-GNF strata areas (green) that are overlapped by the abundance predicted area.

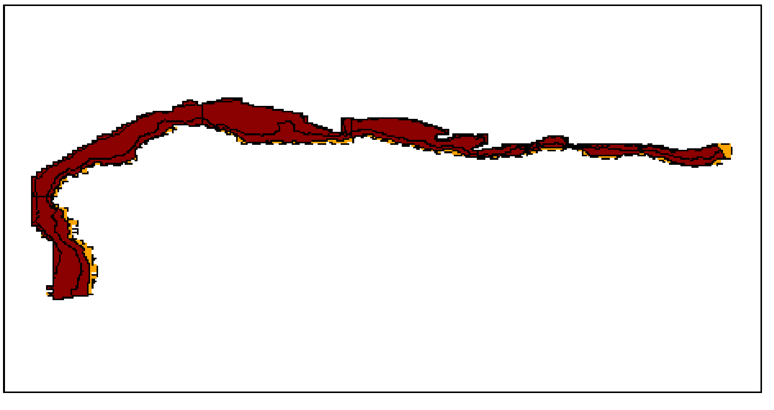


Figure 16. Intersection (dark red) between SP-GNF strata areas and the abundance predicted area.

Table 2. Intersected area between prediction abundance area (21566 km^2) and each SP-GNF strata area.

```
> inti#intersected area with prediction
 [1] 1085.8616 2073.4222  474.8008  909.0725  915.4009  134.6158
 [7] 1024.2816 2597.0128 1270.5984 1124.9613  350.3088 3183.4571
[13] 2965.8259  212.7180  584.5996
```

Table 3. Overlapping proportion (SP-GNF areas/intersection areas).

```
> por# proportion between total and inti
 [1] 0.9243313 0.9520981 0.4996263 0.9999888 0.9926920 0.2497405
 [7] 1.0000000 0.9898615 0.9991208 0.9927144 0.3665065 0.9826559
[13] 0.9869415 0.3199327 0.1726801
```

ANNEX 2

Soleidae Portuguese landings estimation

1. Data available

Table 1. Summary of the data sources used in Soleidae landings estimation.

Type	Period	Description	Source
Official daily landings	2011-2019	Weight (Kg) and value (€) of all landed species (or commercial name) by trip	Portuguese Directorate General for Natural Resources (DGRM)
Landings sampling by species	2011-2019	Commercial common name and total weight (Kg) of each auction box landing soleidae species by trip. Species, weight (kg), total length (cm) by each soleidae specimen in each auction box landed by trip.	DCF-PNAB sampling programme. Data was extracted by Cristina Silva in August 2020

1.1. Polyvalent Fleet

Table 2. Number of trips landing Soleidae species sampled under the DCF sampling program for the Polyvalent fleet per region, landing port, year and semester. * for analysis purposes, data will be pooled together.

Region	Landing Port	Semester	2011	2012	2013	2014	2015	2016	2017	2018	2019
North	**Aveiro**	**1**	14	2	15	16	15	16	21	2	9
		2	18	17	11	14	22	24	28	23	2
	Figueira da Foz	**1**		5	11	15	9	5	8	4	13
		2	1	8	5	8	9	7	6	7	12
	Matosinhos*	**1**	26	18	29	3	22	16	13	15	18
		2	19	2	27	17	18	11	15	16	18
	Póvoa de Varzim*	**1**	12	13	11	14	19	7	7	12	14
		2	6	5	15	1	2	5	4	4	6
	Viana do Castelo	**1**				3	4	4	8	7	4
		2				4	5	2	4	3	1
Southwest	**Costa da Caparica**	**1**				6	8	11	17	7	9
		2				6	4	8	9	6	
	Nazaré	**1**					3	1	4	1	
		2				1	2	1	2	1	1
	Peniche	**1**	3	41	4	57	35	39	43	34	33
		2	28	28	38	33	31	32	2	14	13
	Sesimbra*	**1**	5	5	7	5	7	11	1	12	13

		2	1	4	4	3	7	5	3	12	12
	Setúbal*	**1**	3	4	2	5	11	3	4	6	1
		2	5	2	2	6	7	5	4	9	1
	Sines	**1**	22	17	19	19	3	3	1		3
		2	19	17	15	1	4	1	2	3	4
South	**Lagos**	**1**	1			2	1			1	
		2				1	1				
	Olhão	**1**	21	27	72	34	6	8	3	5	3
		2	49	55	57	12	2	5	2	7	3
	Portimão	**1**	1				1			1	1
		2					1	1	1		1
	Quarteira	**1**					3	2	2	2	3
		2				7		4	3	2	1
	Sagres	**1**				2	3	2	1	2	3
		2				3	3	1			1
	Vila Real de Santo António	**1**				1	1			2	3

1.2. Trawl Fleet

Table 3. Number of trips landing Soleidae species sampled under the DCF sampling program for the Trawl fleet per Region and year.

Region	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
North	44	30	35	51	49	54	43	36	22
Southwest	24	26	24	31	26	33	22	47	41
South	1	1	3	1	3	4	3		

2. Estimation method

2.1. Polyvalent Fleet

Due to the proximity of the landing ports of Póvoa de Varzim to Matosinhos and Setúbal to Sesimbra (far apart around 11 nautical miles, i.e. around 21 km), data available for each pair was pooled together. Vessels landing in these areas often select one of the landing ports either because of the distance between it and the fishing ground or because commercial reasons.

The species weight proportion to the total weight of Soleidae in each year, landing port, and semester ($p\hat{a}_{(s,y,p,g)}$) was calculated using a simple random sampling estimator, following equation (Figueiredo et al. 2020):

$$P\hat{a}_{(s,y,p,g)} = \sum_{i=1} w_{(s,y,p,g)i} \, / \, wt_{(y,p,g)}$$

where $\boldsymbol{w}_{(s,p,y,g)i}$ is the landed weight of of s^{th} Soleidae species in the i^{th} fishing trip and $\boldsymbol{wt}_{(y,p,g)}$ is the total landed weight of Soleidae in the sampled trips at the y^{th} year, p^{th} port and g^{th} semester.
The estimate of the total landed weight of one species $\hat{W}_{(s,y,p,g)}$ in year y port p and semester g is given by:

$$\hat{W}_{(s,y,p,g)} = \sum_{g} p\hat{a}_{(s,y,p)g} \; x \; Wt_{(y,p)g}$$

Where $\boldsymbol{Wt}_{(y,p)g}$ is the total landed weight of Soleidae species at the y^{th} year, p^{th} port and g^{th} semester.

When a group (port and semester) was not sampled in one of the semesters (considered less than 3 sampled trips), the proportion applied was the one obtained for the all region (North, southwest or South),($p\hat{a}_{(s,y,r)}$), following equation:

$$P\hat{a}_{(s,y,r)} = \sum_{i=1} w_{(s,y,r,g)i} \,/\, wt_{(y,r,g)}$$

where $\boldsymbol{w}_{(s,y,r,g)i}$ is the landed weight of of s^{th} Soleidae species in the i^{th} fishing trip and $\boldsymbol{wt}_{(y,r,g)}$ is the total landed weight of Soleidae in the sampled trips at the y^{th} year, region r^{th} and g^{th} semester.
The estimate of the total landed weight of one species $\hat{W}_{(s,y,r,g)}$ in year y region r and semester g is given by:

$$\hat{W}_{(s,y,r,g)} = \sum_{g} p\hat{a}_{(s,y,r)g} \; x \; Wt_{(y,r)g}$$

Where $\boldsymbol{Wt}_{(y,r)g}$ is the total landed weight of Soleidae species at the y^{th} year, r^{th} region and g^{th} semester.

2.2. Trawl Fleet

Due to due to the general low number of samples, soleidae species weight proportions will be estimated considering only the year and region ($p\hat{a}_{(s,y,r)}$), using a simple random sampling estimator, following equation:

$$P\hat{a}_{(s,y,r)} = \sum_{i=1} w_{(s,y,r)i} \,/\, wt_{(y,r)}$$

where $\boldsymbol{w}_{(s,y)i}$ is the landed weight of of s^{th} Soleidae species in the i^{th} fishing trip and $\boldsymbol{wt}_{(y)}$ is the total landed weight of Soleidae in the sampled trips at the region r^{th} and year y^{th} .

The estimate of the total landed weight of one species $\hat{W}_{(s,y,r)}$ in year y and region r is given by:

$$\hat{W}_{(s,y,r)} = \sum_{g} p\hat{a}_{(s,y)r} \; x \; Wt_{(y)r}$$

Where $\boldsymbol{Wt}_{(y)r}$ is the total landed weight of Soleidae species at the y^{th} year and r^{th} region.

Data is lacking for the South region in years 2011, 2012, 2014, 2018 and 2019. Assuming a certain stability in the trawl fleet:

- 2011-2012 apply proportions estimated for 2013
- 2014 apply proportions estimated for 2015
- 2018-2019 apply proportions estimated for 2017

2.3. Purseine Fleet

Given the lack of data from the purseine fleet, Soleidae landings from this fleet segment were considered to be *Solea* spp.

Stochastic surplus production model in continuous time (SPiCT)

Solea Solea February 2021

2021-02-08

First charge libraries in the workspace:

```
# Download libraries
library(spict)
```

```
## Loading required package: TMB
```

```
## Welcome to spict_v1.3.0@9635ec
```

```
library(knitr)
library(formatR)
library(ellipse)
```

```
##
## Attaching package: 'ellipse'
```

```
## The following object is masked from 'package:graph
ics':
##
##     pairs
```

```
library(icesAdvice)
```

1 Loading data

Firstly, we create the **inp** object for the model. Note data are structured as:

- obsC (catch observations),
- timeC (time of catch observations),
- obsI (index of abundance),
- timeI (time of obs abundance).

2 Run 1: Using three

abundance indices: Portugues LPUE, Spanish survey (spat-index) and CPUE from Spain. Default priors.

```
## Load data
setwd("~/Downloads/WKWEST/SPiCT")
load("data.RData")

#Catch data
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)

## Indices Spanish_survey
I_sol8c9a <- data.frame(obsI = data$Spat_index,timeI
= 2000:2019)

## LPUE Portugual
I2_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)

## Indices CPUE Spain
I3_sol8c9a <- data.frame(obsI =data$CPUE,timeI = 2000
:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp <- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_sol
8c9a$obsC,
                timeI = list(I_sol8c9a$timeI+0.833333
3,I2_sol8c9a$timeI+0.5, I3_sol8c9a$timeI+0.5),
                obsI = list(I_sol8c9a$obsI,I2_sol8c9a
$obsI,I3_sol8c9a$obsI))


inp=check.inp(inp)
```

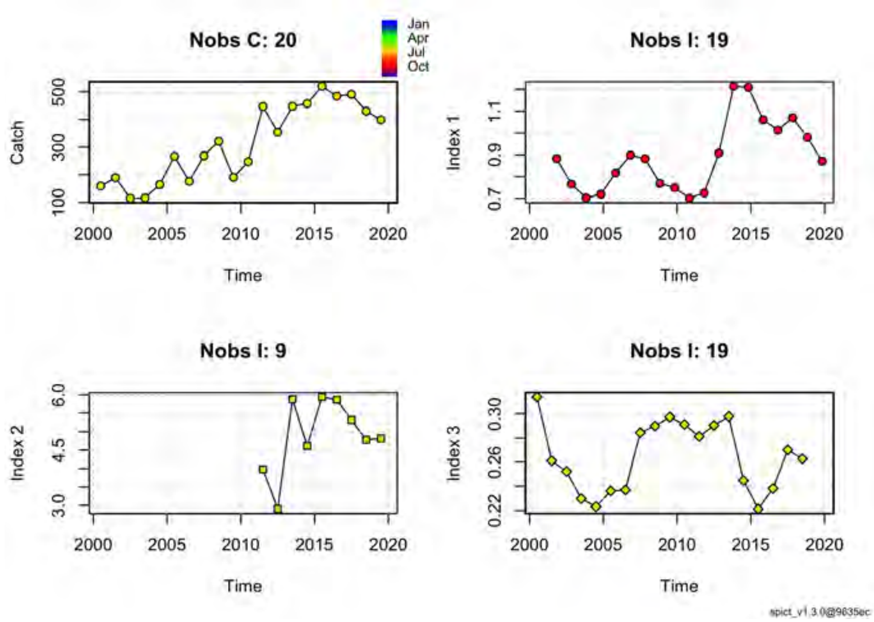
```
## Removing zero, negative, and NAs in  I  series  1

## Removing zero, negative, and NAs in  I  series  2

## Removing zero, negative, and NAs in  I  series  3
```

```
inp$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

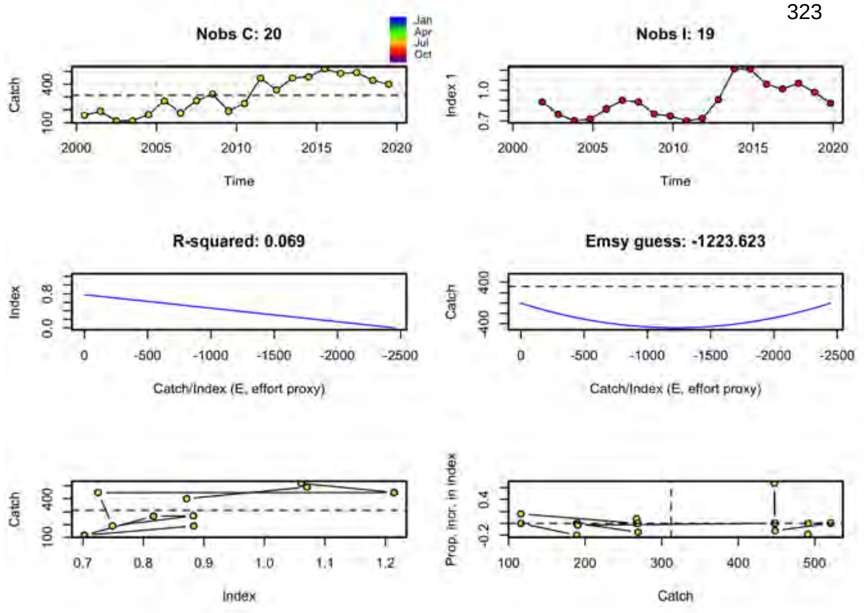
```
plotspict.data(inp)
```



Note that the number of catch and index observations are given in the respective plot headers. Furthermore, the color of individual points shows the month when the observation was made and the corresponding colors are shown in the color legend in the top right corner.

There is also a more advanced function for plotting data, which at the same time does some basic model fitting (linear regression) and shows the results

```
plotspict.ci(inp)
```



In the plot the dashed horizontal line representes a MSY guessed from a linear regression between the biomass index and the catch divided by the index (middle left plot). The regression is expected to have a negative slop. The plot in the middle row, on the right is obtained from catch versus catch/index to approximately find the optimal effort (or effort proxy). Proportional increase in the index as a function of catch (bottom row, right). Positive increases in index at large catches could indicate model violations.

Scaling the uncertainty of individual data points. We do this for catch from 2000:2008. Historical Nominal Catches from 2000-2008, Source: Eurostat/ICES database on catch statistics - ICES 2011, Copenhagen. Version 26-06-2019

```
inp$stdevfacC <- rep(1, length(inp$obsC))
inp$stdevfacC[1:8] <- 5
```

Numerical solver time step (probably don't need to change)

```
inp$dteuler <- 1/16
```

The model is fitted to data by running

```
res1 <- fit.spict(inp)
```

The results are summarised using

```
capture.output(summary(res1))
```

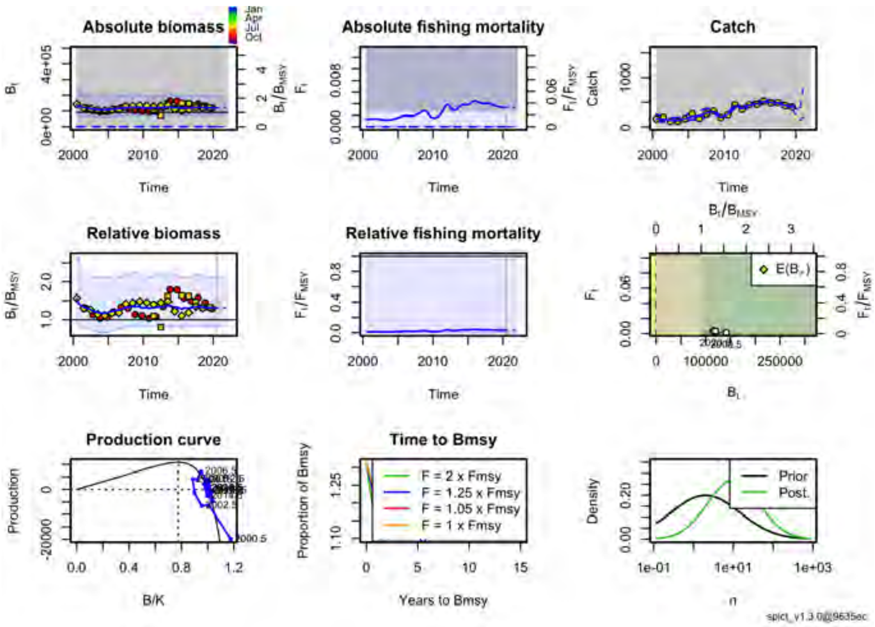
```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: 0.7114126"
```

```
##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 19,  Nobs I2: 9,  Nobs
 I3: 19"
##  [5] ""

##  [6] "Priors"

##  [7] "     logn  ~  dnorm[log(2), 2^2]"

##  [8] " logalpha  ~  dnorm[log(1), 2^2]"

##  [9] "  logbeta  ~  dnorm[log(1), 2^2]"

## [10] ""

## [11] "Model parameter estimates w 95% CI "

## [12] "            estimate      cilow        ciupp
     log.est  "
## [13] " alpha1 1.963198e+00  0.7493127 5.143574e+00
   0.6745747  "
## [14] " alpha2 2.737335e+00  1.0483649 7.147326e+00
   1.0069850  "
## [15] " alpha3 1.037543e+00  0.3486371 3.087722e+00
   0.0368550  "
## [16] " beta   1.548295e-01  0.0433183 5.533965e-01
  -1.8654305  "
## [17] " r      1.165051e+00  0.2423984 5.599641e+00
   0.1527650  "
## [18] " rc     2.338816e-01  0.0124704 4.386447e+00
  -1.4529401  "
## [19] " rold   1.299883e-01  0.0052275 3.232341e+00
  -2.0403111  "
## [20] " m      1.087297e+04  7.3012443 1.619198e+07
   9.2940356  "
## [21] " K      1.201640e+05 93.9749612 1.536514e+08
  11.6966127  "
## [22] " q1     7.400000e-06  0.0000000 9.679700e-03
 -11.8080001  "
## [23] " q2     3.990000e-05  0.0000000 5.208400e-02
 -10.1292065  "
## [24] " q3     2.200000e-06  0.0000000 2.866500e-03
 -13.0242141  "
## [25] " n      9.962741e+00  0.5433214 1.826842e+02
   2.2988523  "
## [26] " sdb    8.091910e-02  0.0336510 1.945826e-01
  -2.5143052  "
## [27] " sdf    3.156643e-01  0.1992478 5.001007e-01
  -1.1530759  "
## [28] " sdi1   1.588602e-01  0.1105312 2.283208e-01
  -1.8397306  "
## [29] " sdi2   2.215028e-01  0.1368784 3.584456e-01
  -1.5073203  "
```

```
## [30] " sdi3   8.395700e-02  0.0486564 1.448685e-01
  -2.4774503  "
## [31] " sdc    4.887420e-02  0.0178770 1.336178e-01
  -3.0185064  "
## [32] " "

## [33] "Deterministic reference points (Drp)"

## [34] "           estimate      cilow        ciupp
  log.est  "
## [35] " Bmsyd 9.297844e+04 70.3541964 1.228781e+08
11.440123  "
## [36] " Fmsyd 1.169408e-01  0.0062352 2.193224e+00
-2.146087  "
## [37] " MSYd  1.087297e+04  7.3012443 1.619198e+07
 9.294036  "
## [38] "Stochastic reference points (Srp)"

## [39] "           estimate      cilow        ciupp
  log.est rel.diff.Drp  "
## [40] " Bmsys 9.082664e+04 68.9509404 1.196427e+08
11.416708  -0.02369126  "
## [41] " Fmsys 1.023256e-01  0.0026953 3.884729e+00
-2.279595  -0.14283055  "
## [42] " MSYs  9.262443e+03  4.7885863 1.791611e+07
 9.133723  -0.17387767  "
## [43] ""

## [44] "States w 95% CI (inp$msytype: s)"

## [45] "                    estimate      cilow
   ciupp    log.est  "
## [46] " B_2020.44      1.193838e+05 91.3299775 1.56
0548e+08 11.6900984  "
## [47] " F_2020.44      3.313400e-03  0.0000025 4.36
5365e+00 -5.7097872  "
## [48] " B_2020.44/Bmsy 1.314413e+00  0.8219167 2.10
2017e+00  0.2733906  "
## [49] " F_2020.44/Fmsy 3.238070e-02  0.0000139 7.53
6619e+01 -3.4301920  "
## [50] ""

## [51] "Predictions w 95% CI (inp$msytype: s)"

## [52] "                  prediction       cilow
    ciupp    log.est  "
## [53] " B_2022.00      1.194545e+05  91.4152099 1.5
60942e+08 11.6906911  "
## [54] " F_2022.00      3.313600e-03   0.0000024 4.5
48353e+00 -5.7097145  "
## [55] " B_2022.00/Bmsy 1.315193e+00   0.8253076 2.0
95863e+00  0.2739832  "
## [56] " F_2022.00/Fmsy 3.238310e-02   0.0000134 7.8
29241e+01 -3.4301192  "
```

```
## [57] " Catch_2021.00  3.957723e+02 201.3312437326.7
80001e+02  5.9808391  "
## [58] " E(B_inf)       1.158212e+05           NA
       NA 11.6598032  "
```

```
plot(res1)
```



Some general comments can be made regarding the style and colours of these plots:

- Estimates (biomass, fishing mortality, catch, production) are shown using blue lines.
- 95 CIs of absolute quantities are shown using dashed blue lines.
- 95 CIs of relative biomass and fishing mortality are shown using shaded blue regions.
- Estimates of reference points (BMSY , FMSY , MSY) are shown using black lines.
- 95 CIs of reference points are shown using grey shaded regions.
- The end of the data range is shown using a vertical grey line.
- Predictions beyond the data range are shown using dotted blue lines.
- Data are shown using points colored by season. Different index series use different point characters.

3 Checklist for the acceptance of a SPiCT assessment

- 1: Convergence of the model fit, which has code 0 if the fit was succesful. If this is not the case convergence was not obtained and reported results should not be used.

```
res1$opt$convergence
```

```
## [1] 0
```

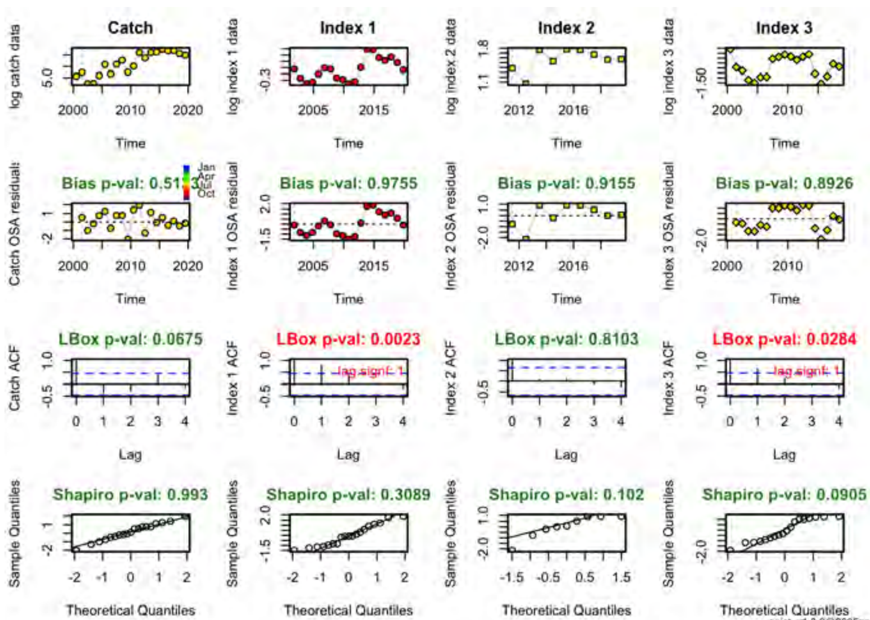
- 2: All variance parameters of the model parameters are finite should be TRUE

```
all(is.finite(res1$sd))
```

```
## [1] TRUE
```

- 3: No violation of model assumptions based on one-step-ahead residuals (bias, auto-correlation, normality).This means, that p-values are insignificant (0.05), indicated by green titles in the graphs of spictplot.diagnostics(fit). Slight violations of these assumptions do not necessarily invalidate model results.

```
r1 <- calc.osa.resid(res1)
plotspict.diagnostic(r1)
```



The first column of the plot contains information related to catch data and the second column contains information related to the biomass index data. The rows contain:

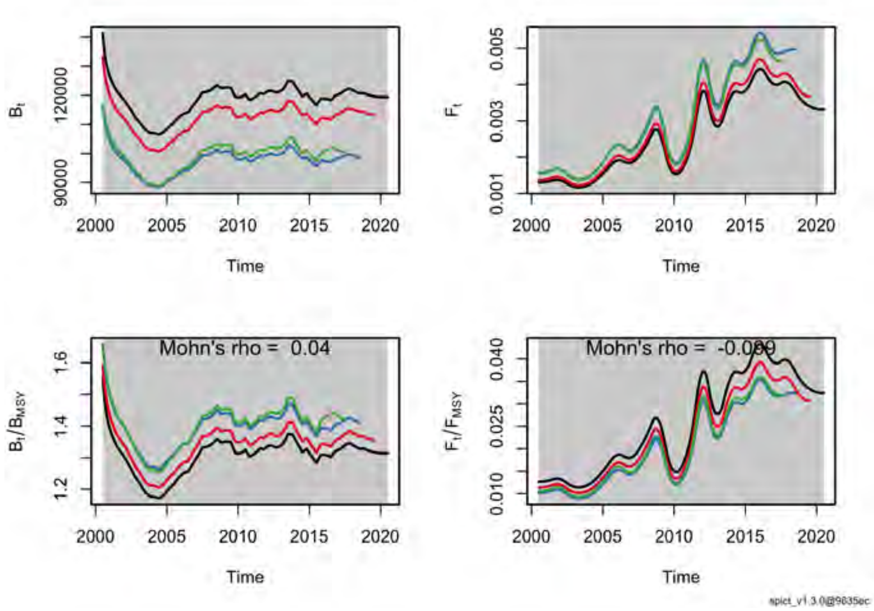
- Log of the input data series.
- OSA residuals with the p-value of a test for bias (i.e. that the mean of the residuals is different from zero) in the plot header. If the header is green the test was not significant, otherwise the header wouldbe red.

Empirical autocorrelation of the residuals. Two tests for significant autocorrelation is performed. Ljung-Box simultaneous test of multiple lags (here 4) with p-value shown in the header, and tests for individual lags shown by dashed horizontal lines in the plot. Here no violation is identified.

- Tests for normality of the residuals both as a QQ-plot and with a Shapiro test with p-value shown invthe plot header.

- 4: Consistent patterns in the retrospective analysis. This means that there is no tendency of consistent under- or overestimation of the relative fishing mortality F and relative biomass B in successive assessment. The retrospective trajectories of those two quantities should be inside the confidence intervals of the base run. (fit <- fit.retro(fit))

```
r1<- fit.spict(inp)
rep1=retro(r1, nretroyear=3)
plotspict.retro(rep1)
```




```
m1=mohns_rho(rep1, what = c("FFmsy", "BBmsy"));m1
```

```
##       FFmsy       BBmsy
## -0.13232642  0.05363205
```

- 5. Realistic production curve. The shape of the production curve should not be too skewed. BMSY/K should be between 0.1 and 0.9 Low values of BMSY/K allow for an infinite population growth rate K. calc.bmsyk(res)
- 6. It is prudent to check that the same parameter estimates are obtained if using different initial values. If the optimum of the objective function is poorly defined, i.e. possibly containing multiple optima, it is possible that

different parameter estimates will be returned depending on the initial values. To check whether this is the case run:

```
set.seed(123)
check.ini(inp, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ... model fitted!
##  Trial 2 ... model fitted!
##  Trial 3 ... model fitted!
##  Trial 4 ... model fitted!
##  Trial 5 ... model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 8 ... model fitted!
##  Trial 9 ... model fitted!
##  Trial 10 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 11 ... model fitted!
##  Trial 12 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 13 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
## Error in nlminb(obj$par, obj$fn, obj$gr, control =
 inp$optimiser.control) :
##   gradient function must return a numeric vector o
f length 12
## obj$par:
##         logm         logK         logq         log
q         logq         logn
##  4.542568110  6.403138210 -9.396442194 -8.61801870
6 -6.378010842  2.271474022
##       logsdb       logsdf       logsdi       logsd
i       logsdi       logsdc
## -0.009356955 -1.620825268 -2.125635906 -2.77708344
```

```
5 -3.400404894 -2.116032260                          331
## obj$fn:
## [1] NaN
## obj$gr:
## [1] NaN
## Error in fit.spict(inpsens) :
##   Could not fit model. Error msg:Error in nlminb(o
bj$par, obj$fn, obj$gr, control = inp$optimiser.contr
ol) :
##   gradient function must return a numeric vector o
f length 12
##
##  fit failed!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 17 ... model fitted!
##  Trial 18 ... model fitted!
##  Trial 19 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
```

```
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 20 ... model fitted!
## $propchng
##            logm  logK  logq  logq  logq  logn logsd
b logsdf logsdi logsdi logsdi
## Trial 1  -1.41  0.17 -0.07 -0.24 -0.27  0.28  -0.0
8  -1.12  -0.15   0.12  -1.31
## Trial 2   1.18  0.04 -0.32 -0.25  0.16  0.28   0.4
9  -1.30  -1.11  -0.55  -0.40
## Trial 3   1.03  0.13  0.04 -0.06  0.13  0.22  -1.3
2  -1.15  -0.55  -0.85   1.36
## Trial 4   1.72 -0.17 -0.15  0.17  0.22  0.05   0.2
5   0.38   0.99   1.03   0.76
## Trial 5  -1.55  0.22 -0.36  0.04 -0.18  0.23  -0.1
7   0.84   1.07  -0.72  -1.13
## Trial 6   1.10 -0.24 -0.09  0.14 -0.19  0.03  -0.8
9  -0.89  -0.84   0.17  -0.73
## Trial 7   1.40 -0.30 -0.02  0.17  0.07 -0.07   0.4
2   1.11   0.73  -0.48   0.24
## Trial 8  -2.64 -0.04  0.39 -0.24 -0.24  0.20   1.0
6  -0.44   0.45  -0.45   0.51
## Trial 9   1.88 -0.24 -0.03 -0.01 -0.06  0.10   0.0
3  -1.30   0.05  -1.12  -1.19
## Trial 10 -0.59 -0.21  0.35  0.12  0.27 -0.28  -0.6
3   1.02  -0.14  -1.30  -0.24
## Trial 11  0.98 -0.11 -0.15  0.17  0.08 -0.30   0.9
9   1.17   1.02  -0.54  -0.34
## Trial 12  1.15  0.14  0.02 -0.10 -0.20 -0.18  -1.3
7   0.17   0.54   0.26   1.40
## Trial 13  2.28 -0.16 -0.21  0.26  0.16 -0.14  -0.9
9   0.01   0.32   0.73   1.11
## Trial 14  0.48 -0.17 -0.04  0.17  0.00  0.09  -0.4
3   0.36   0.41  -0.10  -0.69
## Trial 15 -0.58 -0.14  0.10  0.20 -0.22 -0.15  -0.4
8  -0.34   0.37  -0.09  -1.07
```

```
## Trial 16  2.26 -0.11  0.17  0.15 -0.06  0.01   0.6
7  -0.18  -1.18  -1.15   0.65
## Trial 17  3.23  0.07  0.35  0.02  0.06 -0.10   0.9
9  -0.21   0.75  -1.32  -0.29
## Trial 18 -0.65  0.23 -0.11  0.13  0.20  0.20   0.0
5   0.71   0.81  -0.50   1.29
## Trial 19 -0.98 -0.05  0.26 -0.26  0.13 -0.29  -0.6
5  -0.53   1.28   0.30   0.06
## Trial 20  1.32  0.25  0.09  0.04 -0.03  0.27   0.6
8   0.29   0.86  -0.95   0.99
##          logsdc
## Trial 1    0.13
## Trial 2   -1.41
## Trial 3    0.06
## Trial 4    0.10
## Trial 5    0.36
## Trial 6   -0.37
## Trial 7   -0.82
## Trial 8    0.89
## Trial 9   -0.31
## Trial 10   0.27
## Trial 11  -1.12
## Trial 12   0.90
## Trial 13   0.31
## Trial 14   0.80
## Trial 15  -0.23
## Trial 16   0.51
## Trial 17  -0.04
## Trial 18  -0.57
## Trial 19  -0.17
## Trial 20  -0.87
##
## $inimat
##          Distance  logn logK logm logq1 logq2 logq
3 logsdb logsdf logsdi1
## Basevec      0.00  0.69 7.64 5.74 -7.45 -7.45 -7.4
5  -1.61  -1.61   -1.61
## Trial 1      4.73 -0.29 8.97 5.32 -5.68 -5.42 -9.5
4  -1.48   0.20   -1.37
## Trial 2      5.29  1.51 7.98 3.92 -5.61 -8.62 -9.5
6  -2.40   0.48    0.18
## Trial 3      4.54  1.41 8.60 5.95 -7.01 -8.42 -9.0
7   0.52   0.24   -0.73
## Trial 4      3.95  1.88 6.34 4.91 -8.68 -9.09 -7.8
4  -2.01  -2.21   -3.21
## Trial 5      4.81 -0.38 9.29 3.65 -7.71 -6.07 -9.1
9  -1.33  -2.96   -3.32
## Trial 6      3.92  1.45 5.78 5.21 -8.49 -6.00 -7.6
8  -0.18  -0.17   -0.25
## Trial 7      4.01  1.66 5.34 5.63 -8.74 -8.00 -6.9
3  -2.29  -3.40   -2.79
## Trial 8      4.93 -1.14 7.34 7.98 -5.64 -5.67 -8.9
4  -3.31  -0.90   -2.33
## Trial 9      4.19  1.99 5.77 5.59 -7.39 -6.99 -8.2
```

```
2  -1.66   0.48   -1.69
## Trial 10     4.95  0.28 6.02 7.75 -8.36 -9.47 -5.3
9  -0.59  -3.26   -1.38
## Trial 11     4.70  1.37 6.81 4.86 -8.74 -8.05 -5.2
2  -3.20  -3.49   -3.26
## Trial 12     4.40  1.49 8.73 5.84 -6.71 -5.97 -6.1
3   0.60  -1.89   -2.48
## Trial 13     4.41  2.27 6.40 4.54 -9.40 -8.62 -6.3
8  -0.01  -1.62   -2.13
## Trial 14     2.86  1.02 6.34 5.49 -8.75 -7.44 -8.1
2  -0.92  -2.19   -2.28
## Trial 15     3.50  0.29 6.56 6.34 -8.90 -5.77 -6.3
1  -0.83  -1.07   -2.20
## Trial 16     3.94  2.26 6.78 6.70 -8.53 -7.01 -7.5
3  -2.69  -1.31    0.29
## Trial 17     4.36  2.93 8.19 7.76 -7.60 -7.88 -6.7
1  -3.21  -1.27   -2.81
## Trial 18     4.25  0.24 9.39 5.12 -8.42 -8.96 -8.9
6  -1.69  -2.75   -2.92
## Trial 19     4.30  0.01 7.22 7.22 -5.52 -8.45 -5.3
2  -0.56  -0.75   -3.67
## Trial 20     4.39  1.61 9.56 6.29 -7.78 -7.25 -9.4
8  -2.71  -2.08   -3.00
##          logsdi2 logsdi3 logsdc
## Basevec    -1.61   -1.61  -1.61
## Trial 1    -1.81    0.49  -1.82
## Trial 2    -0.72   -0.96   0.67
## Trial 3    -0.25   -3.80  -1.71
## Trial 4    -3.27   -2.84  -1.77
## Trial 5    -0.44    0.21  -2.19
## Trial 6    -1.89   -0.44  -1.01
## Trial 7    -0.84   -1.99  -0.28
## Trial 8    -0.89   -2.44  -3.05
## Trial 9     0.19    0.30  -1.11
## Trial 10    0.48   -1.22  -2.05
## Trial 11   -0.73   -1.06   0.19
## Trial 12   -2.03   -3.86  -3.07
## Trial 13   -2.78   -3.40  -2.12
## Trial 14   -1.45   -0.50  -2.89
## Trial 15   -1.47    0.12  -1.23
## Trial 16    0.24   -2.65  -2.43
## Trial 17    0.52   -1.14  -1.54
## Trial 18   -0.81   -3.69  -0.68
## Trial 19   -2.09   -1.71  -1.33
## Trial 20   -0.08   -3.21  -0.21
##
## $resmat
##           Distance        m         K  q  q  q
n  sdb  sdf  sdi  sdi  sdi
## Basevec       0.00 10872.97 120164.00  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 1       1.24 10873.11 120165.23  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 2       1.39 10873.10 120165.38  0  0  0 9.9
```

```
6 0.08 0.32 0.16 0.22 0.08
## Trial 3       1.37 10873.09 120165.36  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 4       1.29 10873.09 120165.28  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 5       1.14 10873.08 120165.13  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 6       1.19 10873.08 120165.18  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 7       0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 8  121051.34 72426.10  15930.41  0  0  0 2.0
4 0.11 0.33 0.17 0.22 0.10
## Trial 9  121051.34 72426.09  15930.41  0  0  0 2.0
4 0.11 0.33 0.17 0.22 0.10
## Trial 10      0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 11      1.24 10873.09 120165.23  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 12      0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 13      0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 14      1.15 10873.06 120165.14  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 15      1.41 10873.10 120165.40  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 16      0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 17      1.37 10873.10 120165.36  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 18      0.88 10873.05 120164.87  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 19      0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 20 121051.34 72426.08  15930.41  0  0  0 2.0
4 0.11 0.33 0.17 0.22 0.10
##            sdc
## Basevec  0.05
## Trial 1  0.05
## Trial 2  0.05
## Trial 3  0.05
## Trial 4  0.05
## Trial 5  0.05
## Trial 6  0.05
## Trial 7    NA
## Trial 8  0.05
## Trial 9  0.05
## Trial 10   NA
## Trial 11 0.05
## Trial 12   NA
## Trial 13   NA
## Trial 14 0.05
## Trial 15 0.05
```

```
## Trial 16   NA
## Trial 17 0.05
## Trial 18 0.05
## Trial 19   NA
## Trial 20 0.05
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
##  [1] 2001.833 2002.833 2003.833 2004.833 2005.833
2006.833 2007.833 2008.833
##  [9] 2009.833 2010.833 2011.833 2012.833 2013.833
2014.833 2015.833 2016.833
## [17] 2017.833 2018.833 2019.833
##
## [[2]]
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[3]]
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5
##
## [[1]]
##  [1] 0.8830629 0.7655780 0.7023948 0.7199932 0.816
7087 0.8987942 0.8824258
##  [8] 0.7693151 0.7487957 0.7009754 0.7251867 0.907
7803 1.2142796 1.2089463
## [15] 1.0609294 1.0135286 1.0703598 0.9796291 0.871
3699
##
## [[2]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
##
## [[3]]
##  [1] 0.3138639 0.2610667 0.2522755 0.2296472 0.223
1178 0.2361038 0.2368988
##  [8] 0.2844170 0.2899648 0.2973215 0.2912091 0.281
3124 0.2904401 0.2978007
## [15] 0.2447735 0.2211997 0.2381125 0.2700604 0.262
```

```
6929                                                   337
```

The argument **ntrials** set the number of different initial values to test for. For real data cases 30 trials shoudl be usee at minimum. The **propchng** contains the proportional change of the new randomly generated initial value relative to the base initial value, **inimat** contains the new randomly generated initial values, and **resmat** contains the resulting parameter estimates and a distance from the estimated parameter vector to the base parameter vector. The distance should preferably be close to zero. If that is not the case further investigation is required, i.e. inspection of objective function values, differences in results and residual diagnostics etc. should be performed. The example shown here looks fine in that all converged runs return the same parameter estimates.

- 7. High assessment uncertainty can indicate a lack of contrast in the input data or violation of the ecological model assumptions. The main variance parameters (logsdb, logsdc, logsdi, logsdf) should not be unrealistically high. Confidence intervals for B and F should not span more than 1 order of magnitude:

```
(calc.om(res1))
```

```
##          lower  est upper CI range order magnitude
## B/Bmsy  0.82 1.31  2.10     1.28               1
## F/Fmsy  0.00 0.03 75.37    75.37               6
```

4 Run 1b: Using three abundance indices: Portugues LPUE, Spanish survey and CPUE from Spain. Default priors.

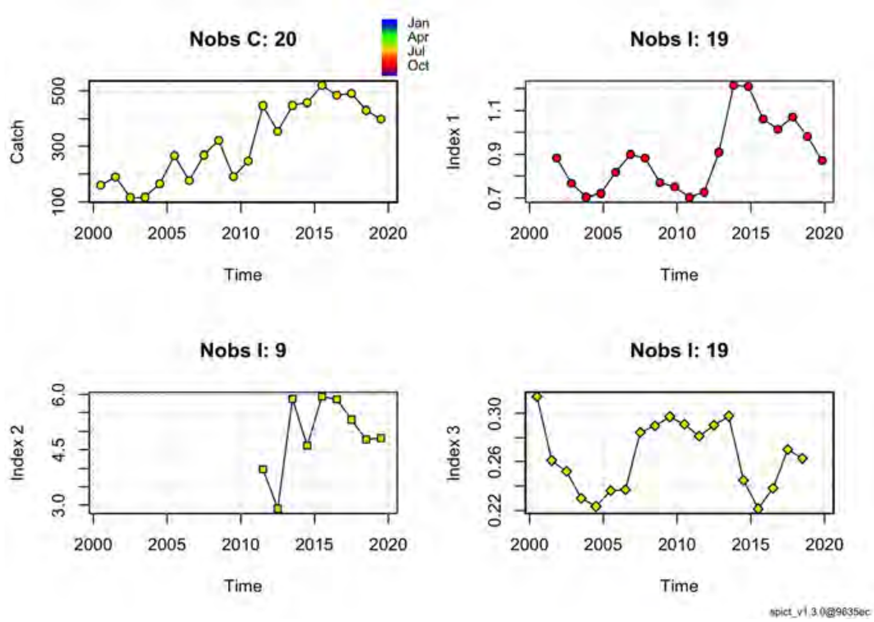
```
#Catch data
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2000:2019)

## Indices Spanish_survey
I_sol8c9a <- data.frame(obsI = data$Survey,timeI = 2000:2019)

## LPUE Portugual
I2_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000:2019)
```

```
## Indices CPUE Spain
I3_sol8c9a <- data.frame(obsI =data$CPUE,timeI = 2000
:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp1b <- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_s
ol8c9a$obsC,
                timeI = list(I_sol8c9a$timeI+0.833333
3,I2_sol8c9a$timeI+0.5, I3_sol8c9a$timeI+0.5),
                obsI = list(I_sol8c9a$obsI,I2_sol8c9a
$obsI,I3_sol8c9a$obsI))


inp1b=check.inp(inp)
inp1b$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

```
plotspict.data(inp1b)
```




```
inp1b$stdevfacC <- rep(1, length(inp1b$obsC))
inp1b$stdevfacC[1:8] <- 5
```

Numerical solver time step (probably don't need to change)

```
inp1b$dteuler <- 1/16
```

The model is fitted to data by running

```
res1b <- fit.spict(inp1b)
```

The results are summarised using

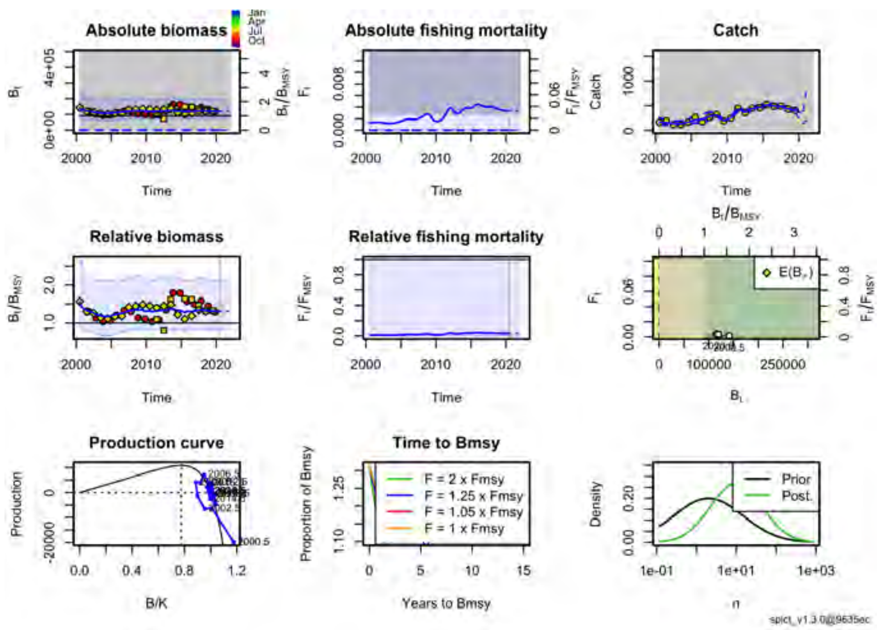
```
capture.output(summary(res1b))
```

```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: 0.7114126"

##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 19,  Nobs I2: 9,  Nobs
 I3: 19"
##  [5] ""

##  [6] "Priors"

##  [7] "     logn  ~  dnorm[log(2), 2^2]"

##  [8] " logalpha  ~  dnorm[log(1), 2^2]"

##  [9] "  logbeta  ~  dnorm[log(1), 2^2]"

## [10] ""

## [11] "Model parameter estimates w 95% CI "

## [12] "            estimate      cilow        ciupp
     log.est  "
## [13] " alpha1 1.963198e+00  0.7493127 5.143574e+00
   0.6745747  "
## [14] " alpha2 2.737335e+00  1.0483649 7.147326e+00
   1.0069850  "
## [15] " alpha3 1.037543e+00  0.3486371 3.087722e+00
   0.0368550  "
## [16] " beta   1.548295e-01  0.0433183 5.533965e-01
  -1.8654305  "
## [17] " r      1.165051e+00  0.2423984 5.599641e+00
   0.1527650  "
## [18] " rc     2.338816e-01  0.0124704 4.386447e+00
  -1.4529401  "
## [19] " rold   1.299883e-01  0.0052275 3.232341e+00
  -2.0403111  "
## [20] " m      1.087297e+04  7.3012443 1.619198e+07
   9.2940356  "
## [21] " K      1.201640e+05 93.9749612 1.536514e+08
  11.6966127  "
## [22] " q1     7.400000e-06  0.0000000 9.679700e-03
 -11.8080001  "
## [23] " q2     3.990000e-05  0.0000000 5.208400e-02
 -10.1292065  "
```

```
## [24] " q3     2.200000e-06  0.0000000 2.866500e+03
 -13.0242141  "
## [25] " n      9.962741e+00  0.5433214 1.826842e+02
   2.2988523  "
## [26] " sdb    8.091910e-02  0.0336510 1.945826e-01
  -2.5143052  "
## [27] " sdf    3.156643e-01  0.1992478 5.001007e-01
  -1.1530759  "
## [28] " sdi1   1.588602e-01  0.1105312 2.283208e-01
  -1.8397306  "
## [29] " sdi2   2.215028e-01  0.1368784 3.584456e-01
  -1.5073203  "
## [30] " sdi3   8.395700e-02  0.0486564 1.448685e-01
  -2.4774503  "
## [31] " sdc    4.887420e-02  0.0178770 1.336178e-01
  -3.0185064  "
## [32] " "

## [33] "Deterministic reference points (Drp)"

## [34] "           estimate      cilow        ciupp
  log.est  "
## [35] " Bmsyd 9.297844e+04 70.3541964 1.228781e+08
11.440123  "
## [36] " Fmsyd 1.169408e-01  0.0062352 2.193224e+00
-2.146087  "
## [37] " MSYd  1.087297e+04  7.3012443 1.619198e+07
 9.294036  "
## [38] "Stochastic reference points (Srp)"

## [39] "           estimate      cilow        ciupp
  log.est rel.diff.Drp  "
## [40] " Bmsys 9.082664e+04 68.9509404 1.196427e+08
11.416708  -0.02369126  "
## [41] " Fmsys 1.023256e-01  0.0026953 3.884729e+00
-2.279595  -0.14283055  "
## [42] " MSYs  9.262443e+03  4.7885863 1.791611e+07
 9.133723  -0.17387767  "
## [43] ""

## [44] "States w 95% CI (inp$msytype: s)"

## [45] "                     estimate      cilow
   ciupp    log.est  "
## [46] " B_2020.44      1.193838e+05 91.3299775 1.56
0548e+08 11.6900984  "
## [47] " F_2020.44      3.313400e-03  0.0000025 4.36
5365e+00 -5.7097872  "
## [48] " B_2020.44/Bmsy 1.314413e+00  0.8219167 2.10
2017e+00  0.2733906  "
## [49] " F_2020.44/Fmsy 3.238070e-02  0.0000139 7.53
6619e+01 -3.4301920  "
## [50] ""
```

```
## [51] "Predictions w 95% CI (inp$msytype: s)"  341

## [52] "                    prediction       cilow
    ciupp    log.est  "
## [53] " B_2022.00      1.194545e+05  91.4152099 1.5
60942e+08 11.6906911  "
## [54] " F_2022.00      3.313600e-03   0.0000024 4.5
48353e+00 -5.7097145  "
## [55] " B_2022.00/Bmsy 1.315193e+00   0.8253076 2.0
95863e+00  0.2739832  "
## [56] " F_2022.00/Fmsy 3.238310e-02   0.0000134 7.8
29241e+01 -3.4301192  "
## [57] " Catch_2021.00  3.957723e+02 201.3312437 7.7
80001e+02  5.9808391  "
## [58] " E(B_inf)       1.158212e+05          NA
       NA 11.6598032  "
```

```
plot(res1b)
```



5 Checklist for the acceptance of a SPiCT assessment

- 1: Convergence of the model fit

```
res1b$opt$convergence
```

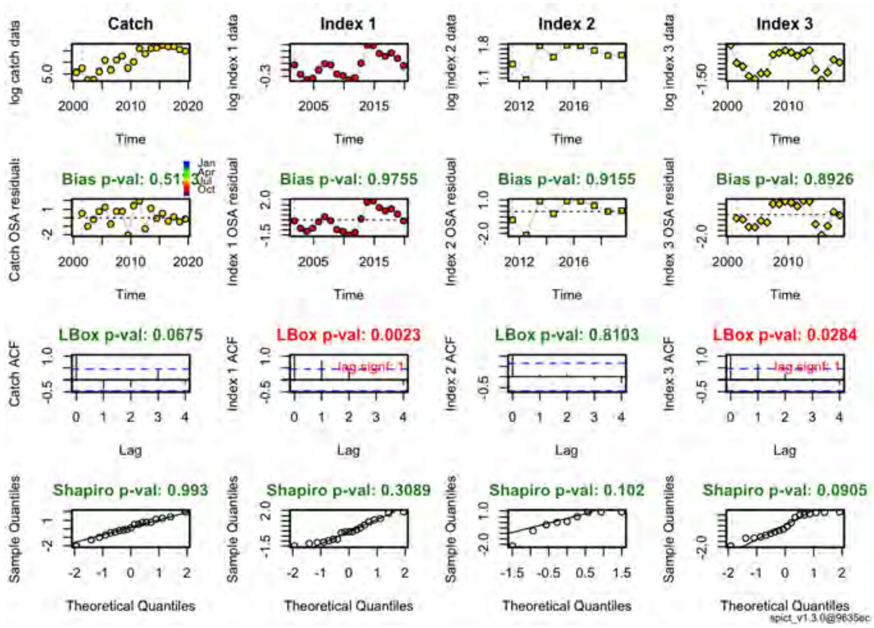
```
## [1] 0
```

- 2: All variance parameters of the model parameters are finite should be TRUE

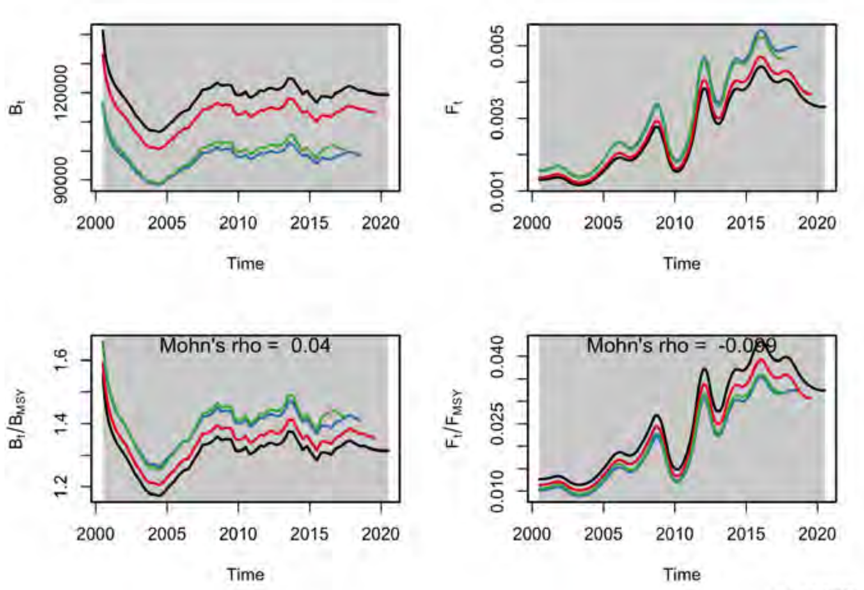
```
all(is.finite(res1b$sd))
```

```
## [1] TRUE
```

```
r1b <- calc.osa.resid(res1b)
plotspict.diagnostic(r1b)
```




```
r1b<- fit.spict(inp1b)
rep1b=retro(r1b, nretroyear=3)
plotspict.retro(rep1b)
```




```
m1b=mohns_rho(rep1b, what = c("FFmsy", "BBmsy"));m1b
```

```
##        FFmsy        BBmsy
```

```
## -0.13232642  0.05363205
```

```
set.seed(123)
check.ini(inp1b, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ... model fitted!
##  Trial 2 ... model fitted!
##  Trial 3 ... model fitted!
##  Trial 4 ... model fitted!
##  Trial 5 ... model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 8 ... model fitted!
##  Trial 9 ... model fitted!
##  Trial 10 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 11 ... model fitted!
##  Trial 12 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
```

```
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 13 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
## Error in nlminb(obj$par, obj$fn, obj$gr, control =
 inp$optimiser.control) :
##   gradient function must return a numeric vector o
f length 12
## obj$par:
##         logm         logK         logq         log
q         logq         logn
##  4.542568110  6.403138210 -9.396442194 -8.61801870
6 -6.378010842  2.271474022
##       logsdb       logsdf       logsdi       logsd
i       logsdi       logsdc
## -0.009356955 -1.620825268 -2.125635906 -2.77708344
5 -3.400404894 -2.116032260
## obj$fn:
```

```
## [1] NaN
## obj$gr:
## [1] NaN
## Error in fit.spict(inpsens) :
##   Could not fit model. Error msg:Error in nlminb(o
bj$par, obj$fn, obj$gr, control = inp$optimiser.contr
ol) :
##   gradient function must return a numeric vector o
f length 12
##
##  fit failed!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 17 ... model fitted!
##  Trial 18 ... model fitted!
##  Trial 19 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 20 ... model fitted!
## $propchng
##            logm  logK  logq  logq  logq  logn logsd
b logsdf logsdi logsdi logsdi
## Trial 1  -1.41  0.17 -0.07 -0.24 -0.27  0.28  -0.0
8  -1.12  -0.15   0.12  -1.31
## Trial 2   1.18  0.04 -0.32 -0.25  0.16  0.28   0.4
9  -1.30  -1.11  -0.55  -0.40
## Trial 3   1.03  0.13  0.04 -0.06  0.13  0.22  -1.3
2  -1.15  -0.55  -0.85   1.36
## Trial 4   1.72 -0.17 -0.15  0.17  0.22  0.05   0.2
5   0.38   0.99   1.03   0.76
## Trial 5  -1.55  0.22 -0.36  0.04 -0.18  0.23  -0.1
7   0.84   1.07  -0.72  -1.13
## Trial 6   1.10 -0.24 -0.09  0.14 -0.19  0.03  -0.8
9  -0.89  -0.84   0.17  -0.73
## Trial 7   1.40 -0.30 -0.02  0.17  0.07 -0.07   0.4
2   1.11   0.73  -0.48   0.24
## Trial 8  -2.64 -0.04  0.39 -0.24 -0.24  0.20   1.0
6  -0.44   0.45  -0.45   0.51
## Trial 9   1.88 -0.24 -0.03 -0.01 -0.06  0.10   0.0
3  -1.30   0.05  -1.12  -1.19
## Trial 10 -0.59 -0.21  0.35  0.12  0.27 -0.28  -0.6
3   1.02  -0.14  -1.30  -0.24
## Trial 11  0.98 -0.11 -0.15  0.17  0.08 -0.30   0.9
9   1.17   1.02  -0.54  -0.34
## Trial 12  1.15  0.14  0.02 -0.10 -0.20 -0.18  -1.3
7   0.17   0.54   0.26   1.40
## Trial 13  2.28 -0.16 -0.21  0.26  0.16 -0.14  -0.9
9   0.01   0.32   0.73   1.11
## Trial 14  0.48 -0.17 -0.04  0.17  0.00  0.09  -0.4
3   0.36   0.41  -0.10  -0.69
## Trial 15 -0.58 -0.14  0.10  0.20 -0.22 -0.15  -0.4
8  -0.34   0.37  -0.09  -1.07
## Trial 16  2.26 -0.11  0.17  0.15 -0.06  0.01   0.6
7  -0.18  -1.18  -1.15   0.65
```

```
## Trial 17  3.23  0.07  0.35  0.02  0.06 -0.10   0.9
9  -0.21   0.75  -1.32  -0.29
## Trial 18 -0.65  0.23 -0.11  0.13  0.20  0.20   0.0
5   0.71   0.81  -0.50   1.29
## Trial 19 -0.98 -0.05  0.26 -0.26  0.13 -0.29  -0.6
5  -0.53   1.28   0.30   0.06
## Trial 20  1.32  0.25  0.09  0.04 -0.03  0.27   0.6
8   0.29   0.86  -0.95   0.99
##           logsdc
## Trial 1    0.13
## Trial 2   -1.41
## Trial 3    0.06
## Trial 4    0.10
## Trial 5    0.36
## Trial 6   -0.37
## Trial 7   -0.82
## Trial 8    0.89
## Trial 9   -0.31
## Trial 10   0.27
## Trial 11  -1.12
## Trial 12   0.90
## Trial 13   0.31
## Trial 14   0.80
## Trial 15  -0.23
## Trial 16   0.51
## Trial 17  -0.04
## Trial 18  -0.57
## Trial 19  -0.17
## Trial 20  -0.87
##
## $inimat
##           Distance  logn logK logm logq1 logq2 logq
3 logsdb logsdf logsdi1
## Basevec      0.00  0.69 7.64 5.74 -7.45 -7.45 -7.4
5  -1.61  -1.61   -1.61
## Trial 1      4.73 -0.29 8.97 5.32 -5.68 -5.42 -9.5
4  -1.48   0.20   -1.37
## Trial 2      5.29  1.51 7.98 3.92 -5.61 -8.62 -9.5
6  -2.40   0.48    0.18
## Trial 3      4.54  1.41 8.60 5.95 -7.01 -8.42 -9.0
7   0.52   0.24   -0.73
## Trial 4      3.95  1.88 6.34 4.91 -8.68 -9.09 -7.8
4  -2.01  -2.21   -3.21
## Trial 5      4.81 -0.38 9.29 3.65 -7.71 -6.07 -9.1
9  -1.33  -2.96   -3.32
## Trial 6      3.92  1.45 5.78 5.21 -8.49 -6.00 -7.6
8  -0.18  -0.17   -0.25
## Trial 7      4.01  1.66 5.34 5.63 -8.74 -8.00 -6.9
3  -2.29  -3.40   -2.79
## Trial 8      4.93 -1.14 7.34 7.98 -5.64 -5.67 -8.9
4  -3.31  -0.90   -2.33
## Trial 9      4.19  1.99 5.77 5.59 -7.39 -6.99 -8.2
2  -1.66   0.48   -1.69
## Trial 10     4.95  0.28 6.02 7.75 -8.36 -9.47 -5.3
```

```
9  -0.59  -3.26   -1.38
## Trial 11     4.70  1.37 6.81 4.86 -8.74 -8.05 -5.2
2  -3.20  -3.49   -3.26
## Trial 12     4.40  1.49 8.73 5.84 -6.71 -5.97 -6.1
3   0.60  -1.89   -2.48
## Trial 13     4.41  2.27 6.40 4.54 -9.40 -8.62 -6.3
8  -0.01  -1.62   -2.13
## Trial 14     2.86  1.02 6.34 5.49 -8.75 -7.44 -8.1
2  -0.92  -2.19   -2.28
## Trial 15     3.50  0.29 6.56 6.34 -8.90 -5.77 -6.3
1  -0.83  -1.07   -2.20
## Trial 16     3.94  2.26 6.78 6.70 -8.53 -7.01 -7.5
3  -2.69  -1.31    0.29
## Trial 17     4.36  2.93 8.19 7.76 -7.60 -7.88 -6.7
1  -3.21  -1.27   -2.81
## Trial 18     4.25  0.24 9.39 5.12 -8.42 -8.96 -8.9
6  -1.69  -2.75   -2.92
## Trial 19     4.30  0.01 7.22 7.22 -5.52 -8.45 -5.3
2  -0.56  -0.75   -3.67
## Trial 20     4.39  1.61 9.56 6.29 -7.78 -7.25 -9.4
8  -2.71  -2.08   -3.00
##          logsdi2 logsdi3 logsdc
## Basevec    -1.61   -1.61  -1.61
## Trial 1    -1.81    0.49  -1.82
## Trial 2    -0.72   -0.96   0.67
## Trial 3    -0.25   -3.80  -1.71
## Trial 4    -3.27   -2.84  -1.77
## Trial 5    -0.44    0.21  -2.19
## Trial 6    -1.89   -0.44  -1.01
## Trial 7    -0.84   -1.99  -0.28
## Trial 8    -0.89   -2.44  -3.05
## Trial 9     0.19    0.30  -1.11
## Trial 10    0.48   -1.22  -2.05
## Trial 11   -0.73   -1.06   0.19
## Trial 12   -2.03   -3.86  -3.07
## Trial 13   -2.78   -3.40  -2.12
## Trial 14   -1.45   -0.50  -2.89
## Trial 15   -1.47    0.12  -1.23
## Trial 16    0.24   -2.65  -2.43
## Trial 17    0.52   -1.14  -1.54
## Trial 18   -0.81   -3.69  -0.68
## Trial 19   -2.09   -1.71  -1.33
## Trial 20   -0.08   -3.21  -0.21
##
## $resmat
##           Distance        m         K  q  q  q
n  sdb  sdf  sdi  sdi  sdi
## Basevec       0.00 10872.97 120164.00  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 1       1.24 10873.11 120165.23  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 2       1.39 10873.10 120165.38  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 3       1.37 10873.09 120165.36  0  0  0 9.9
```

```
6 0.08 0.32 0.16 0.22 0.08
## Trial 4       1.29 10873.09 120165.28  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 5       1.14 10873.08 120165.13  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 6       1.19 10873.08 120165.18  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 7       0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 8  121051.34 72426.10  15930.41  0  0  0 2.0
4 0.11 0.33 0.17 0.22 0.10
## Trial 9  121051.34 72426.09  15930.41  0  0  0 2.0
4 0.11 0.33 0.17 0.22 0.10
## Trial 10      0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 11      1.24 10873.09 120165.23  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 12      0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 13      0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 14      1.15 10873.06 120165.14  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 15      1.41 10873.10 120165.40  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 16      0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 17      1.37 10873.10 120165.36  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 18      0.88 10873.05 120164.87  0  0  0 9.9
6 0.08 0.32 0.16 0.22 0.08
## Trial 19      0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 20 121051.34 72426.08  15930.41  0  0  0 2.0
4 0.11 0.33 0.17 0.22 0.10
##            sdc
## Basevec  0.05
## Trial 1  0.05
## Trial 2  0.05
## Trial 3  0.05
## Trial 4  0.05
## Trial 5  0.05
## Trial 6  0.05
## Trial 7    NA
## Trial 8  0.05
## Trial 9  0.05
## Trial 10   NA
## Trial 11 0.05
## Trial 12   NA
## Trial 13   NA
## Trial 14 0.05
## Trial 15 0.05
## Trial 16   NA
## Trial 17 0.05
```

```
## Trial 18 0.05
## Trial 19   NA
## Trial 20 0.05
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
##  [1] 2001.833 2002.833 2003.833 2004.833 2005.833
2006.833 2007.833 2008.833
##  [9] 2009.833 2010.833 2011.833 2012.833 2013.833
2014.833 2015.833 2016.833
## [17] 2017.833 2018.833 2019.833
##
## [[2]]
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[3]]
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5
##
## [[1]]
##  [1] 0.8830629 0.7655780 0.7023948 0.7199932 0.816
7087 0.8987942 0.8824258
##  [8] 0.7693151 0.7487957 0.7009754 0.7251867 0.907
7803 1.2142796 1.2089463
## [15] 1.0609294 1.0135286 1.0703598 0.9796291 0.871
3699
##
## [[2]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
##
## [[3]]
##  [1] 0.3138639 0.2610667 0.2522755 0.2296472 0.223
1178 0.2361038 0.2368988
##  [8] 0.2844170 0.2899648 0.2973215 0.2912091 0.281
3124 0.2904401 0.2978007
## [15] 0.2447735 0.2211997 0.2381125 0.2700604 0.262
6929
```

```
(calc.om(res1b))
```

```
##         lower  est upper CI range order magnitude
## B/Bmsy   0.82 1.31  2.10     1.28               1
## F/Fmsy   0.00 0.03 75.37    75.37               6
```

6 Run 2: Using two abundance indices: Spanish survey (spat-index) and LPUE from Portugal. Default priors

```
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)

## Indices Portugues_survey
I2_sol8c9a <- data.frame(obsI =data$Spat_index,timeI
= 2000:2019)

## Indices CPUE Spain
I3_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp2 <- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_so
l8c9a$obsC,
             timeI = list(I2_sol8c9a$timeI+0.8333333,
 I3_sol8c9a$timeI+0.5),
             obsI = list(I2_sol8c9a$obsI,I3_sol8c9a$o
bsI))


inp2=check.inp(inp2)
```

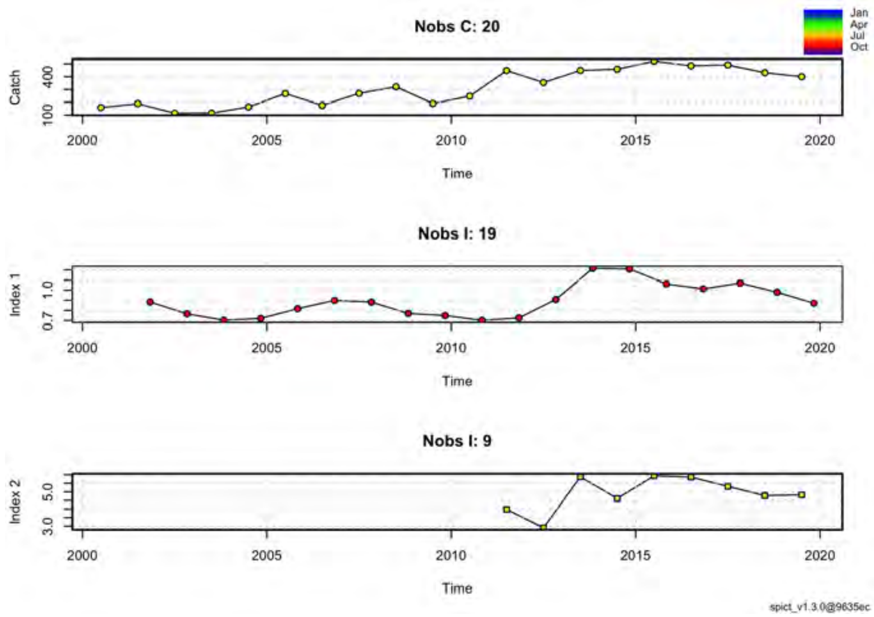
```
## Removing zero, negative, and NAs in  I  series  1

## Removing zero, negative, and NAs in  I  series  2
```

```
inp2$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command


```
plotspict.data(inp2)
```




```
inp2$stdevfacC <- rep(1, length(inp2$obsC))
inp2$stdevfacC[1:10] <- 5
```

Numerical solver time step (probably don't need to change)

```
inp2$dteuler <- 1/16
```

The model is fitted to data by running

```
res2 <- fit.spict(inp2)
```

The results are summarised using

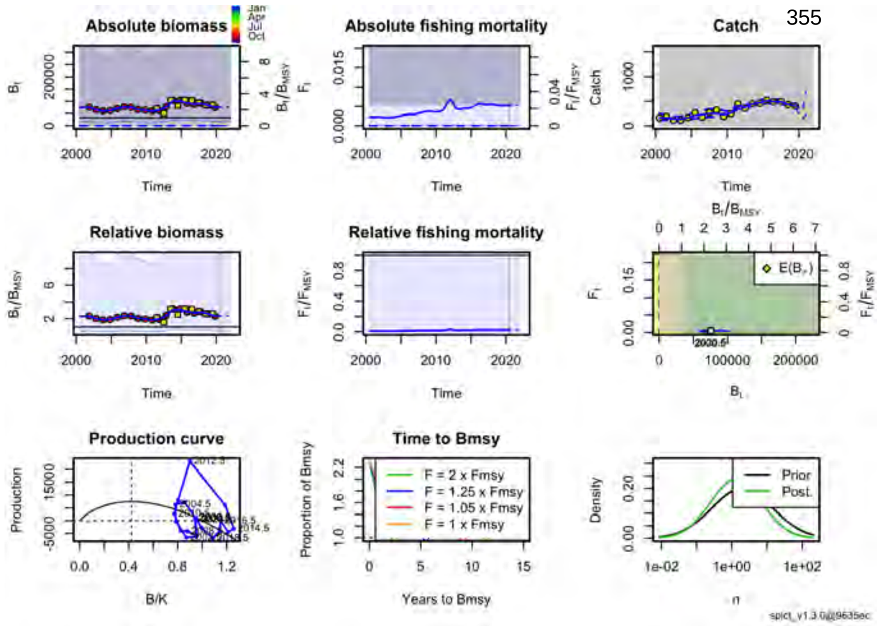
```
capture.output(summary(res2))
```

```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: 3.9041561"

##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 19,  Nobs I2: 9"

##  [5] ""

##  [6] "Priors"

##  [7] "     logn  ~  dnorm[log(2), 2^2]"
```

```
## [8] " logalpha ~ dnorm[log(1), 2^2]"

## [9] "  logbeta ~ dnorm[log(1), 2^2]"

## [10] ""

## [11] "Model parameter estimates w 95% CI "

## [12] "            estimate      cilow        ciupp
     log.est  "
## [13] " alpha1 2.308364e-01  0.0315623 1.688263e+00
  -1.4660458  "
## [14] " alpha2 1.265735e+00  0.6512625 2.459969e+00
   0.2356531  "
## [15] " beta   2.264892e-01  0.0577309 8.885601e-01
  -1.4850581  "
## [16] " r      2.979315e-01  0.0778278 1.140507e+00
  -1.2108917  "
## [17] " rc     4.445194e-01  0.0119265 1.656793e+01
  -0.8107616  "
## [18] " rold   8.750705e-01  0.0000018 4.239042e+05
  -0.1334509  "
## [19] " m      7.428078e+03  3.4866998 1.582480e+07
   8.9130224  "
## [20] " K      7.902878e+04 53.4135276 1.169282e+08
  11.2775673  "
## [21] " q1     1.160000e-05  0.0000000 1.905830e-02
 -11.3608773  "
## [22] " q2     5.660000e-05  0.0000000 9.268190e-02
  -9.7797393  "
## [23] " n      1.340466e+00  0.0499732 3.595624e+01
   0.2930171  "
## [24] " sdb    1.253291e-01  0.0845470 1.857829e-01
  -2.0768118  "
## [25] " sdf    2.412369e-01  0.1250822 4.652557e-01
  -1.4219760  "
## [26] " sdi1   2.893050e-02  0.0042719 1.959254e-01
  -3.5428577  "
## [27] " sdi2   1.586335e-01  0.0939069 2.679738e-01
  -1.8411588  "
## [28] " sdc    5.463750e-02  0.0228230 1.308005e-01
  -2.9070341  "
## [29] " "

## [30] "Deterministic reference points (Drp)"

## [31] "           estimate      cilow        ciupp
  log.est  "
## [32] " Bmsyd 3.342071e+04 19.2592861 5.799510e+07
10.416931  "
## [33] " Fmsyd 2.222597e-01  0.0059633 8.283963e+00
-1.503909  "
## [34] " MSYd  7.428078e+03  3.4866998 1.582480e+07
 8.913022  "
```

```
## [35] "Stochastic reference points (Srp)"

## [36] "           estimate      cilow        ciupp
  log.est rel.diff.Drp  "
## [37] " Bmsys 3.272814e+04 19.1029123 5.607163e+07
10.395991  -0.02116134  "
## [38] " Fmsys 2.209436e-01  0.0054016 9.037267e+00
-1.509848  -0.00595668  "
## [39] " MSYs  7.230163e+03  3.2371809 1.614839e+07
 8.886017  -0.02737343  "
## [40] ""

## [41] "States w 95% CI (inp$msytype: s)"

## [42] "                    estimate      cilow
   ciupp    log.est  "
## [43] " B_2020.44      7.550415e+04 45.7427895 1.24
6290e+08 11.2319429  "
## [44] " F_2020.44      5.261100e-03  0.0000032 8.68
3339e+00 -5.2474167  "
## [45] " B_2020.44/Bmsy 2.307010e+00  0.5163197 1.03
0814e+01  0.8359523  "
## [46] " F_2020.44/Fmsy 2.381190e-02  0.0000058 9.75
5318e+01 -3.7375690  "
## [47] ""

## [48] "Predictions w 95% CI (inp$msytype: s)"

## [49] "                  prediction       cilow
    ciupp    log.est  "
## [50] " B_2022.00      7.553972e+04  45.1883623 1.2
62770e+08 11.2324138  "
## [51] " F_2022.00      5.261300e-03   0.0000031 8.8
87546e+00 -5.2473708  "
## [52] " B_2022.00/Bmsy 2.308097e+00   0.5210532 1.0
22412e+01  0.8364232  "
## [53] " F_2022.00/Fmsy 2.381300e-02   0.0000057 9.9
59501e+01 -3.7375231  "
## [54] " Catch_2021.00  3.973776e+02 226.5828882 6.9
69149e+02  5.9848871  "
## [55] " E(B_inf)       7.485671e+04          NA
       NA 11.2233310  "
```

```
plot(res2)
```



7 Checklist for the acceptance of a SPiCT assessment

- 1: Convergence of the model fit, which has code 0 if the fit was succesful. If this is not the case convergence was not obtained and reported results should not be used.

```
res2$opt$convergence
```

```
## [1] 0
```

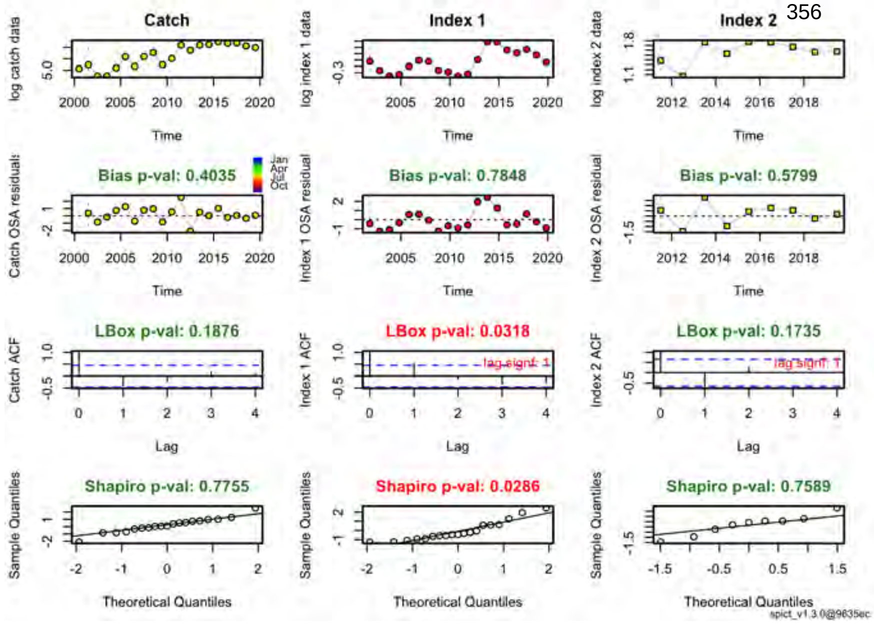
- 2: All variance parameters of the model parameters are finite should be TRUE

```
all(is.finite(res2$sd))
```

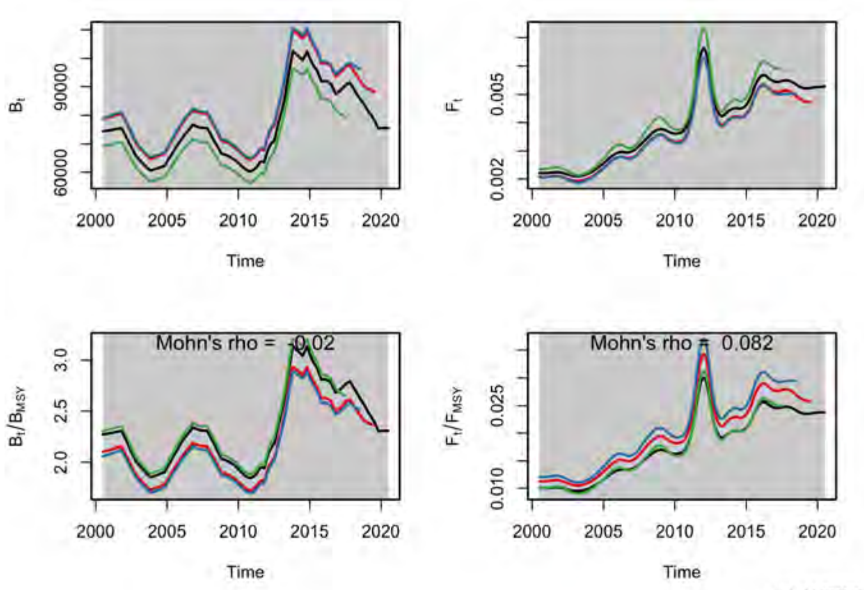
```
## [1] TRUE
```

- 3: No violation of model assumptions.

```
r2 <- calc.osa.resid(res2)
plotspict.diagnostic(r2)
```




```
r2<- fit.spict(inp2)
rep2=retro(r2, nretroyear=3)
plotspict.retro(rep2)
```




```
m2=mohns_rho(rep2, what = c("FFmsy", "BBmsy"));m2
```

```
##       FFmsy       BBmsy
##  0.10921893 -0.02694258
```

```
set.seed(123)
check.ini(inp2, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ... model fitted!
```

```
##  Trial 2 ... model fitted!
##  Trial 3 ... model fitted!
##  Trial 4 ... model fitted!
##  Trial 5 ... model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ... convergence not obtained!
##  Trial 8 ... model fitted!
##  Trial 9 ... model fitted!
##  Trial 10 ... model fitted!
##  Trial 11 ... model fitted!
##  Trial 12 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  model fitted!
##  Trial 13 ... model fitted!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ... model fitted!
##  Trial 17 ... model fitted!
##  Trial 18 ... convergence not obtained!
##  Trial 19 ... model fitted!
##  Trial 20 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
## $propchng
##           logm  logK  logq  logq  logn logsdb logs
df logsdi logsdi logsdc
## Trial 1  -1.41  0.17 -0.07 -0.24 -0.27   1.30  -0.
08  -1.12  -0.15   0.12
## Trial 2   3.04 -0.03  0.14 -0.04  0.25  -1.14   0.
73   1.31   0.49  -1.30
## Trial 3   2.59  0.12  0.11 -0.31 -0.10  -0.60  -0.
13  -0.27   0.60   1.01
## Trial 4   3.08  0.24  0.15 -0.18  0.29   0.06  -0.
74   0.81   0.52   0.77
## Trial 5  -2.37 -0.05 -0.07  0.08  0.21   1.03   0.
76   0.10   0.67  -1.02
## Trial 6  -3.02 -0.03  0.24  0.23 -0.04   0.84   1.
07  -0.72  -1.13   0.36
## Trial 7   1.10 -0.24 -0.09  0.14 -0.19   0.15  -0.
```

```
89  -0.89  -0.84   0.17
## Trial 8   1.69  0.08  0.17  0.31  0.02   0.80   0.
34  -0.32   0.42   1.11
## Trial 9  -1.70  0.10 -0.07 -0.18  0.25   0.19  -1.
39  -1.12  -1.11   0.93
## Trial 10 -2.45  0.09 -0.13 -0.10  0.11   0.89  -0.
81   1.16   0.10  -0.03
## Trial 11  0.66 -0.10 -0.01 -0.28  0.01  -1.12  -1.
19  -0.31   0.26   1.01
## Trial 12  2.89 -0.12 -0.35 -0.28 -0.14   1.02  -0.
14  -1.30  -0.24   0.27
## Trial 13  0.98 -0.11 -0.15  0.17  0.08  -1.39   0.
99   1.17   1.02  -0.54
## Trial 14  0.79  0.24  0.14 -0.15 -0.01  -0.46  -0.
92  -0.82  -1.37   0.17
## Trial 15 -1.25 -0.05 -0.39  0.20 -0.21   0.77   0.
75   1.21   0.73  -0.66
## Trial 16  2.31  0.00 -0.09  0.16  0.24   0.31  -0.
21   0.81   0.16   0.81
## Trial 17  0.02 -0.09  0.12  0.08  0.09  -0.10  -0.
69   0.80   0.25   0.67
## Trial 18  0.86 -0.19  0.29 -0.15 -0.10  -0.34   0.
37  -0.09  -1.07  -0.23
## Trial 19  2.26 -0.11  0.17  0.15 -0.06   0.05   0.
67  -0.18  -1.18  -1.15
## Trial 20 -1.50 -0.11  0.39 -0.07 -0.27   0.10   0.
27  -0.46   0.99  -0.21
##
## $inimat
##          Distance  logn logK logm logq1 logq2 logs
db logsdf logsdi1 logsdi2
## Basevec      0.00  0.69 7.64 5.74 -7.45 -7.45  -1.
61  -1.61   -1.61   -1.61
## Trial 1      4.23 -0.29 8.97 5.32 -5.68 -5.42  -3.
70  -1.48    0.20   -1.37
## Trial 2      4.78  2.80 7.43 6.56 -7.11 -9.28   0.
23  -2.78   -3.72   -2.40
## Trial 3      3.85  2.49 8.53 6.39 -5.17 -6.73  -0.
65  -1.41   -1.18   -2.58
## Trial 4      4.56  2.83 9.49 6.62 -6.09 -9.64  -1.
71  -0.42   -2.92   -2.45
## Trial 5      3.76 -0.95 7.25 5.35 -8.05 -9.05  -3.
27  -2.84   -1.77   -2.69
## Trial 6      4.38 -1.40 7.38 7.12 -9.19 -7.17  -2.
96  -3.32   -0.44    0.21
## Trial 7      3.69  1.45 5.78 5.21 -8.49 -6.00  -1.
85  -0.18   -0.17   -0.25
## Trial 8      3.73  1.87 8.24 6.71 -9.75 -7.56  -2.
90  -2.16   -1.09   -2.29
## Trial 9      4.58 -0.49 8.42 5.36 -6.12 -9.28  -1.
91   0.62    0.20    0.17
## Trial 10     3.52 -1.01 8.35 5.02 -6.73 -8.27  -3.
05  -0.31   -3.48   -1.76
## Trial 11     3.89  1.15 6.87 5.69 -5.35 -7.53   0.
```

```
19   0.30   -1.11   -2.02
## Trial 12     4.66  2.70 6.73 3.72 -5.39 -6.43  -3.
26  -1.38    0.48   -1.22
## Trial 13     4.30  1.37 6.81 4.86 -8.74 -8.05   0.
62  -3.20   -3.49   -3.26
## Trial 14     3.85  1.24 9.44 6.54 -6.36 -7.35  -0.
87  -0.13   -0.29    0.60
## Trial 15     4.46 -0.17 7.22 3.49 -8.90 -5.87  -2.
85  -2.81   -3.56   -2.78
## Trial 16     3.35  2.29 7.63 5.23 -8.61 -9.24  -2.
12  -1.28   -2.91   -1.86
## Trial 17     2.44  0.70 6.97 6.43 -8.02 -8.11  -1.
45  -0.50   -2.89   -2.01
## Trial 18     3.31  1.29 6.19 7.42 -6.31 -6.67  -1.
07  -2.20   -1.47    0.12
## Trial 19     3.71  2.26 6.78 6.70 -8.53 -7.01  -1.
70  -2.69   -1.31    0.29
## Trial 20     3.81 -0.35 6.82 7.98 -6.89 -5.43  -1.
76  -2.04   -0.88   -3.21
##            logsdc
## Basevec   -1.61
## Trial 1   -1.81
## Trial 2    0.48
## Trial 3   -3.23
## Trial 4   -2.85
## Trial 5    0.04
## Trial 6   -2.19
## Trial 7   -1.89
## Trial 8   -3.40
## Trial 9   -3.11
## Trial 10  -1.56
## Trial 11  -3.23
## Trial 12  -2.05
## Trial 13  -0.73
## Trial 14  -1.89
## Trial 15  -0.54
## Trial 16  -2.91
## Trial 17  -2.69
## Trial 18  -1.23
## Trial 19   0.24
## Trial 20  -1.27
##
## $resmat
##           Distance       m        K  q  q    n  sdb
  sdf  sdi  sdi  sdc
## Basevec      0.00 7428.08 79028.78  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 1      0.04 7428.07 79028.73  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 2      0.06 7428.07 79028.72  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 3      0.16 7428.10 79028.93  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 4      0.13 7428.06 79028.64  0  0 1.34 0.13
```

```
 0.24 0.03 0.16 0.05
## Trial 5      0.16 7428.06 79028.62  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 6      0.22 7428.09 79028.99  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 7      0.00      NA       NA NA NA   NA   NA
   NA   NA   NA   NA
## Trial 8      0.21 7428.10 79028.99  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 9      0.29 7428.11 79029.06  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 10     0.06 7428.07 79028.71  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 11     7.08 7427.34 79021.73  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 12     0.22 7428.06 79028.56  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 13     0.03 7428.08 79028.81  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 14     0.35 7428.13 79029.12  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 15     0.18 7428.06 79028.60  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 16     0.37 7428.10 79029.14  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 17     0.02 7428.08 79028.75  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 18     0.00      NA       NA NA NA   NA   NA
   NA   NA   NA   NA
## Trial 19     0.11 7428.07 79028.67  0  0 1.34 0.13
 0.24 0.03 0.16 0.05
## Trial 20     0.00      NA       NA NA NA   NA   NA
   NA   NA   NA   NA
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
##  [1] 2001.833 2002.833 2003.833 2004.833 2005.833
2006.833 2007.833 2008.833
##  [9] 2009.833 2010.833 2011.833 2012.833 2013.833
2014.833 2015.833 2016.833
## [17] 2017.833 2018.833 2019.833
##
## [[2]]
```

```
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[1]]
##  [1] 0.8830629 0.7655780 0.7023948 0.7199932 0.816
7087 0.8987942 0.8824258
##  [8] 0.7693151 0.7487957 0.7009754 0.7251867 0.907
7803 1.2142796 1.2089463
## [15] 1.0609294 1.0135286 1.0703598 0.9796291 0.871
3699
##
## [[2]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
```

- 7. High assessment uncertainty

```
(calc.om(res2))
```

```
##        lower  est upper CI range order magnitude
## B/Bmsy  0.52 2.31 10.31     9.79               2
## F/Fmsy  0.00 0.02 97.55    97.55               7
```

8 RUN 3: Using two abundance indices: Spanish survey and the LPUE. Default priors

```
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)

## Indices Spanish_survey
I_sol8c9a <- data.frame(obsI = data$Survey,timeI = 20
00:2019)

## Indices Portugues_survey
I2_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp3 <- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_so
l8c9a$obsC,
             timeI = list(I_sol8c9a$timeI+0.8333333,I
2_sol8c9a$timeI+0.5),
```

```
              obsI = list(I_sol8c9a$obsI,I2_sol8c9a$ob
sI))


inp3=check.inp(inp3)
```

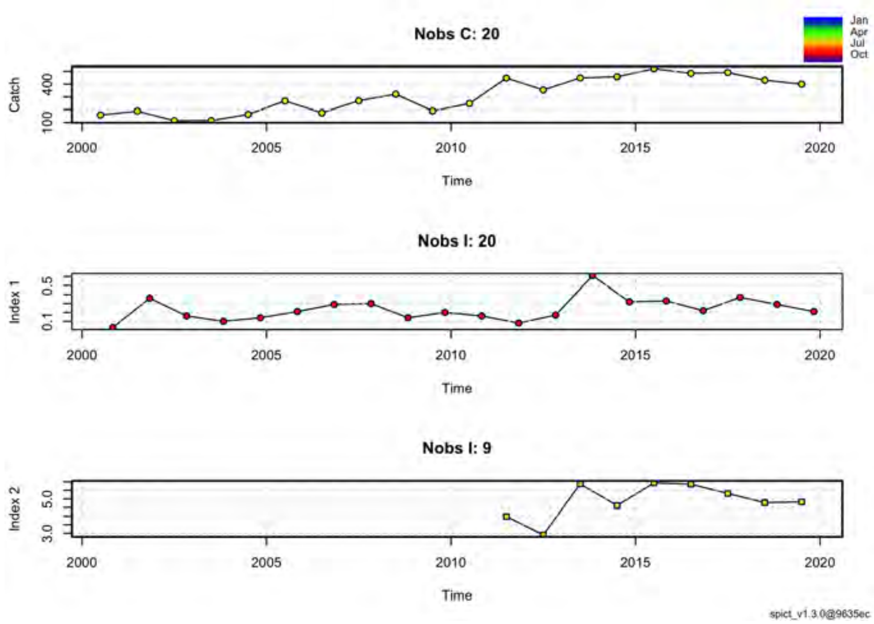
```
## Removing zero, negative, and NAs in  I  series  2
```

```
inp3$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

```
plotspict.data(inp3)
```




```
inp3$stdevfacC <- rep(1, length(inp3$obsC))
inp3$stdevfacC[1:10] <- 5
```

Numerical solver time step (probably don't need to change)

```
inp3$dteuler <- 1/16
```

The model is fitted to data by running

```
res3 <- fit.spict(inp3)
```

The results are summarised using

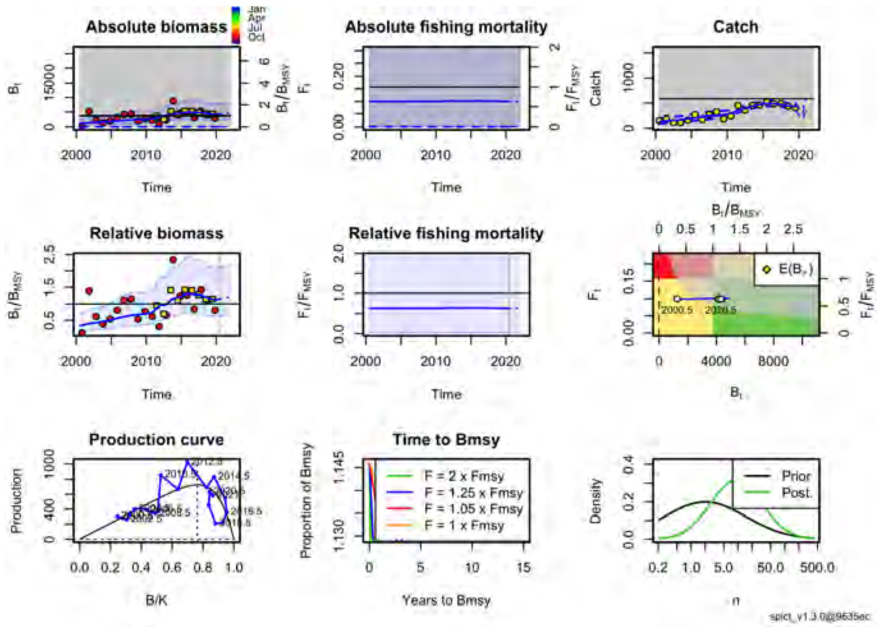
```
capture.output(summary(res3))
```

```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: 34.6936507"

##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 20,  Nobs I2: 9"

##  [5] ""

##  [6] "Priors"

##  [7] "     logn  ~  dnorm[log(2), 2^2]"

##  [8] " logalpha  ~  dnorm[log(1), 2^2]"

##  [9] "  logbeta  ~  dnorm[log(1), 2^2]"

## [10] ""

## [11] "Model parameter estimates w 95% CI "

## [12] "            estimate      cilow        ciupp
    log.est  "
## [13] " alpha1    4.6770097  1.1573572 1.890032e+01
  1.5426590  "
## [14] " alpha2    1.3450319  0.2971396 6.088421e+00
  0.2964177  "
## [15] " beta      3.1181516  0.2476406 3.926201e+01
  1.1372404  "
## [16] " r         1.7134117  0.0185428 1.583241e+02
  0.5384865  "
## [17] " rc        0.3721511  0.0080633 1.717617e+01
 -0.9884554  "
## [18] " rold      0.2087451  0.0044475 9.797565e+00
 -1.5666412  "
## [19] " m       726.8397763 17.9516763 2.942879e+04
  6.5887061  "
## [20] " K      5119.3477543  3.0378886 8.626953e+06
  8.5407823  "
## [21] " q1        0.0000694  0.0000000 1.892880e-01
 -9.5757208  "
## [22] " q2        0.0011132  0.0000004 2.959251e+00
 -6.8005263  "
## [23] " n         9.2081510  0.7765119 1.091935e+02
  2.2200891  "
## [24] " sdb       0.1193201  0.0310937 4.578823e-01
 -2.1259458  "
## [25] " sdf       0.0289185  0.0023584 3.546000e-01
 -3.5432731  "
## [26] " sdi1      0.5580611  0.4043790 7.701491e-01
 -0.5832869  "
## [27] " sdi2      0.1604893  0.0926675 2.779487e-01
 -1.8295281  "
```

```
## [28] " sdc       0.0901723  0.0535469 1.5184913e-01
 -2.4060327  "
## [29] " "

## [30] "Deterministic reference points (Drp)"

## [31] "           estimate      cilow        ciupp
  log.est  "
## [32] " Bmsyd 3906.1542689  2.2484085 6.786152e+06
 8.270309  "
## [33] " Fmsyd    0.1860755  0.0040316 8.588085e+00
-1.681602  "
## [34] " MSYd   726.8397763 17.9516763 2.942879e+04
 6.588706  "
## [35] "Stochastic reference points (Srp)"

## [36] "           estimate      cilow        ciupp
  log.est rel.diff.Drp  "
## [37] " Bmsys 3754.4041781  2.2771272 6.190059e+06
 8.230685  -0.04041922  "
## [38] " Fmsys    0.1571675  0.0016944 1.457843e+01
-1.850443  -0.18393143  "
## [39] " MSYs   585.6837148 31.7646641 1.079896e+04
 6.372780  -0.24101073  "
## [40] ""

## [41] "States w 95% CI (inp$msytype: s)"

## [42] "                     estimate     cilow
  ciupp    log.est  "
## [43] " B_2020.44      4303.3712053 1.5213428 1.217
280e+07  8.3671540  "
## [44] " F_2020.44         0.0992871 0.0000350 2.815
988e+02 -2.3097395  "
## [45] " B_2020.44/Bmsy    1.1462195 0.6270275 2.095
313e+00  0.1364691  "
## [46] " F_2020.44/Fmsy    0.6317278 0.0191880 2.079
847e+01 -0.4592966  "
## [47] ""

## [48] "Predictions w 95% CI (inp$msytype: s)"

## [49] "                   prediction       cilow
    ciupp    log.est  "
## [50] " B_2022.00      4557.3893839   1.6469616 1.2
61098e+07  8.4245052  "
## [51] " F_2022.00         0.0992874   0.0000350 2.8
16830e+02 -2.3097368  "
## [52] " B_2022.00/Bmsy    1.2138782   0.6776505 2.1
74425e+00  0.1938204  "
## [53] " F_2022.00/Fmsy    0.6317295   0.0191746 2.0
81307e+01 -0.4592940  "
## [54] " Catch_2021.00   445.7805104 340.7421940 5.8
31983e+02  6.0998267  "
```

```
## [55] " E(B_inf)       4148.2480564          NA
       NA  8.3304414  "
```

```
plot(res3)
```



9 Checklist for the acceptance of a SPiCT assessment

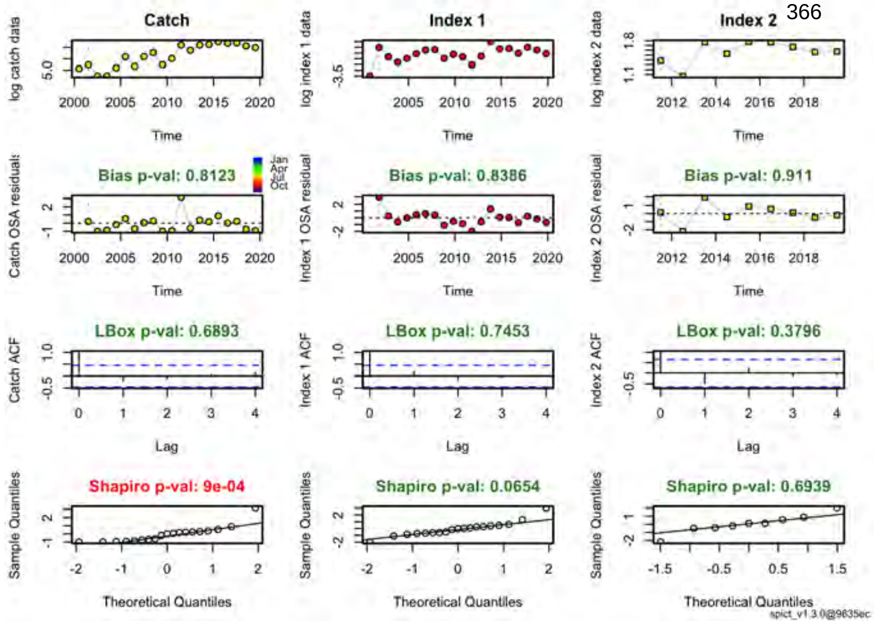
```
res3$opt$convergence
```

```
## [1] 0
```

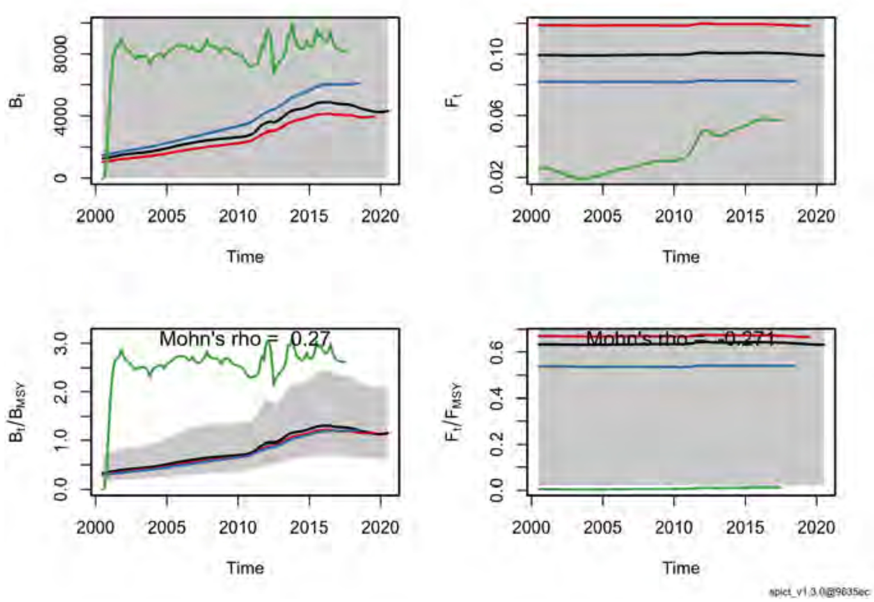
```
all(is.finite(res3$sd))
```

```
## [1] TRUE
```

```
r3 <- calc.osa.resid(res3)
plotspict.diagnostic(r3)
```




```
r3<- fit.spict(inp3)
rep3=retro(r3, nretroyear=3)
plotspict.retro(rep3)
```




```
m3=mohns_rho(rep3, what = c("FFmsy", "BBmsy"));m3
```

```
##      FFmsy      BBmsy
## -0.3611538  0.3594639
```

```
set.seed(123)
check.ini(inp3, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ... model fitted!
```

```
##  Trial 2 ...
```



```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 3 ... model fitted!
##  Trial 4 ... model fitted!
##  Trial 5 ... model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 8 ... model fitted!
##  Trial 9 ... model fitted!
##  Trial 10 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
```

```
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 11 ... model fitted!
##  Trial 12 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  model fitted!
##  Trial 13 ... model fitted!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ... model fitted!
##  Trial 17 ... model fitted!
##  Trial 18 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 19 ... convergence not obtained!
##  Trial 20 ... model fitted!
## $propchng
##           logm  logK  logq  logq  logn logsdb logs
df logsdi logsdi logsdc
## Trial 1  -1.41  0.17 -0.07 -0.22 -0.25   1.30  -0.
08  -1.12  -0.15   0.12
## Trial 2   3.04 -0.03  0.14 -0.04  0.22  -1.14   0.
73   1.31   0.49  -1.30
## Trial 3   2.59  0.12  0.11 -0.28 -0.09  -0.60  -0.
13  -0.27   0.60   1.01
## Trial 4   3.08  0.24  0.15 -0.17  0.27   0.06  -0.
74   0.81   0.52   0.77
## Trial 5  -2.37 -0.05 -0.07  0.07  0.20   1.03   0.
76   0.10   0.67  -1.02
## Trial 6  -3.02 -0.03  0.24  0.21 -0.03   0.84   1.
07  -0.72  -1.13   0.36
## Trial 7   1.10 -0.24 -0.09  0.13 -0.18   0.15  -0.
89  -0.89  -0.84   0.17
## Trial 8   1.69  0.08  0.17  0.28  0.01   0.80   0.
34  -0.32   0.42   1.11
## Trial 9  -1.70  0.10 -0.07 -0.16  0.22   0.19  -1.
```

```
39  -1.12  -1.11   0.93
## Trial 10 -2.45  0.09 -0.13 -0.09  0.10   0.89  -0.
81   1.16   0.10  -0.03
## Trial 11  0.66 -0.10 -0.01 -0.26  0.01  -1.12  -1.
19  -0.31   0.26   1.01
## Trial 12  2.89 -0.12 -0.35 -0.25 -0.12   1.02  -0.
14  -1.30  -0.24   0.27
## Trial 13  0.98 -0.11 -0.15  0.16  0.07  -1.39   0.
99   1.17   1.02  -0.54
## Trial 14  0.79  0.24  0.14 -0.13 -0.01  -0.46  -0.
92  -0.82  -1.37   0.17
## Trial 15 -1.25 -0.05 -0.39  0.18 -0.19   0.77   0.
75   1.21   0.73  -0.66
## Trial 16  2.31  0.00 -0.09  0.14  0.22   0.31  -0.
21   0.81   0.16   0.81
## Trial 17  0.02 -0.09  0.12  0.07  0.08  -0.10  -0.
69   0.80   0.25   0.67
## Trial 18  0.86 -0.19  0.29 -0.14 -0.10  -0.34   0.
37  -0.09  -1.07  -0.23
## Trial 19  2.26 -0.11  0.17  0.13 -0.05   0.05   0.
67  -0.18  -1.18  -1.15
## Trial 20 -1.50 -0.11  0.39 -0.07 -0.25   0.10   0.
27  -0.46   0.99  -0.21
##
## $inimat
##          Distance  logn logK logm  logq1  logq2 lo
gsdb logsdf logsdi1 logsdi2
## Basevec      0.00  0.69 7.64 5.74  -8.14  -8.14  -
1.61  -1.61   -1.61   -1.61
## Trial 1      4.23 -0.29 8.97 5.32  -6.37  -6.11  -
3.70  -1.48    0.20   -1.37
## Trial 2      4.78  2.80 7.43 6.56  -7.80  -9.96
0.23  -2.78   -3.72   -2.40
## Trial 3      3.85  2.49 8.53 6.39  -5.86  -7.42  -
0.65  -1.41   -1.18   -2.58
## Trial 4      4.56  2.83 9.49 6.62  -6.77 -10.32  -
1.71  -0.42   -2.92   -2.45
## Trial 5      3.76 -0.95 7.25 5.35  -8.74  -9.74  -
3.27  -2.84   -1.77   -2.69
## Trial 6      4.38 -1.40 7.38 7.12  -9.88  -7.85  -
2.96  -3.32   -0.44    0.21
## Trial 7      3.69  1.45 5.78 5.21  -9.17  -6.69  -
1.85  -0.18   -0.17   -0.25
## Trial 8      3.73  1.87 8.24 6.71 -10.44  -8.25  -
2.90  -2.16   -1.09   -2.29
## Trial 9      4.58 -0.49 8.42 5.36  -6.81  -9.96  -
1.91   0.62    0.20    0.17
## Trial 10     3.52 -1.01 8.35 5.02  -7.41  -8.96  -
3.05  -0.31   -3.48   -1.76
## Trial 11     3.89  1.15 6.87 5.69  -6.04  -8.21
0.19   0.30   -1.11   -2.02
## Trial 12     4.66  2.70 6.73 3.72  -6.07  -7.12  -
3.26  -1.38    0.48   -1.22
## Trial 13     4.30  1.37 6.81 4.86  -9.43  -8.74
```

```
0.62  -3.20   -3.49   -3.26
## Trial 14     3.85  1.24 9.44 6.54  -7.04  -8.04  -
0.87  -0.13   -0.29    0.60
## Trial 15     4.46 -0.17 7.22 3.49  -9.59  -6.56  -
2.85  -2.81   -3.56   -2.78
## Trial 16     3.35  2.29 7.63 5.23  -9.30  -9.93  -
2.12  -1.28   -2.91   -1.86
## Trial 17     2.44  0.70 6.97 6.43  -8.71  -8.80  -
1.45  -0.50   -2.89   -2.01
## Trial 18     3.31  1.29 6.19 7.42  -7.00  -7.36  -
1.07  -2.20   -1.47    0.12
## Trial 19     3.71  2.26 6.78 6.70  -9.22  -7.70  -
1.70  -2.69   -1.31    0.29
## Trial 20     3.81 -0.35 6.82 7.98  -7.58  -6.12  -
1.76  -2.04   -0.88   -3.21
##          logsdc
## Basevec   -1.61
## Trial 1   -1.81
## Trial 2    0.48
## Trial 3   -3.23
## Trial 4   -2.85
## Trial 5    0.04
## Trial 6   -2.19
## Trial 7   -1.89
## Trial 8   -3.40
## Trial 9   -3.11
## Trial 10  -1.56
## Trial 11  -3.23
## Trial 12  -2.05
## Trial 13  -0.73
## Trial 14  -1.89
## Trial 15  -0.54
## Trial 16  -2.91
## Trial 17  -2.69
## Trial 18  -1.23
## Trial 19   0.24
## Trial 20  -1.27
##
## $resmat
##          Distance        m        K  q  q    n  sd
b  sdf  sdi  sdi  sdc
## Basevec      0.00   726.84  5119.35  0  0 9.21 0.1
2 0.03 0.56 0.16 0.09
## Trial 1      0.02   726.84  5119.33  0  0 9.21 0.1
2 0.03 0.56 0.16 0.09
## Trial 2      0.00       NA       NA NA NA   NA   N
A   NA   NA   NA   NA
## Trial 3      0.18   726.83  5119.17  0  0 9.21 0.1
2 0.03 0.56 0.16 0.09
## Trial 4  23944.62 23098.53 13654.71  0  0 0.95 0.4
5 0.18 0.46 0.16 0.07
## Trial 5      0.03   726.84  5119.32  0  0 9.21 0.1
2 0.03 0.56 0.16 0.09
## Trial 6  23944.59 23098.51 13654.69  0  0 0.95 0.4
```

```
5 0.18 0.46 0.16 0.07
## Trial 7      0.00       NA       NA NA NA   NA   N
A   NA   NA   NA   NA
## Trial 8      0.02   726.84  5119.33  0  0 9.21 0.1
2 0.03 0.56 0.16 0.09
## Trial 9      0.04   726.84  5119.30  0  0 9.21 0.1
2 0.03 0.56 0.16 0.09
## Trial 10     0.00       NA       NA NA NA   NA   N
A   NA   NA   NA   NA
## Trial 11 23944.65 23098.55 13654.73  0  0 0.95 0.4
5 0.18 0.46 0.16 0.07
## Trial 12  1578.69   874.14  3547.55  0  0 8.79 0.3
2 0.02 0.57 0.12 0.05
## Trial 13     0.01   726.84  5119.34  0  0 9.21 0.1
2 0.03 0.56 0.16 0.09
## Trial 14     0.01   726.84  5119.34  0  0 9.21 0.1
2 0.03 0.56 0.16 0.09
## Trial 15     0.01   726.84  5119.34  0  0 9.21 0.1
2 0.03 0.56 0.16 0.09
## Trial 16     0.03   726.84  5119.32  0  0 9.21 0.1
2 0.03 0.56 0.16 0.09
## Trial 17 23944.59 23098.50 13654.70  0  0 0.95 0.4
5 0.18 0.46 0.16 0.07
## Trial 18     0.00       NA       NA NA NA   NA   N
A   NA   NA   NA   NA
## Trial 19     0.00       NA       NA NA NA   NA   N
A   NA   NA   NA   NA
## Trial 20 23944.37 23098.31 13654.59  0  0 0.95 0.4
5 0.18 0.46 0.16 0.07
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
##  [1] 2000.833 2001.833 2002.833 2003.833 2004.833
2005.833 2006.833 2007.833
##  [9] 2008.833 2009.833 2010.833 2011.833 2012.833
2013.833 2014.833 2015.833
## [17] 2016.833 2017.833 2018.833 2019.833
##
## [[2]]
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[1]]
```

```
##  [1] 0.03 0.36 0.16 0.10 0.14 0.21 0.29 0.30 0.24
0.20 0.16 0.08 0.17 0.61 0.32
## [16] 0.33 0.22 0.37 0.29 0.21
##
## [[2]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
```

```
(calc.om(res3))
```

```
##         lower  est upper CI range order magnitude
## B/Bmsy  0.63 1.15   2.1     1.47               1
## F/Fmsy  0.02 0.63  20.8    20.78               3
```

10 RUN 3b: Using two abundance indices: Spanish CPUE and the LPUE. Default priors

```
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)

## Indices Spanish_survey
I_sol8c9a <- data.frame(obsI = data$CPUE,timeI = 2000
:2019)

## Indices Portugues_survey
I2_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp3b <- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_s
ol8c9a$obsC,
             timeI = list(I_sol8c9a$timeI+0.5,I2_sol8
c9a$timeI+0.5),
             obsI = list(I_sol8c9a$obsI,I2_sol8c9a$ob
sI))


inp3b=check.inp(inp3b)
```

```
## Removing zero, negative, and NAs in  I  series  1
```

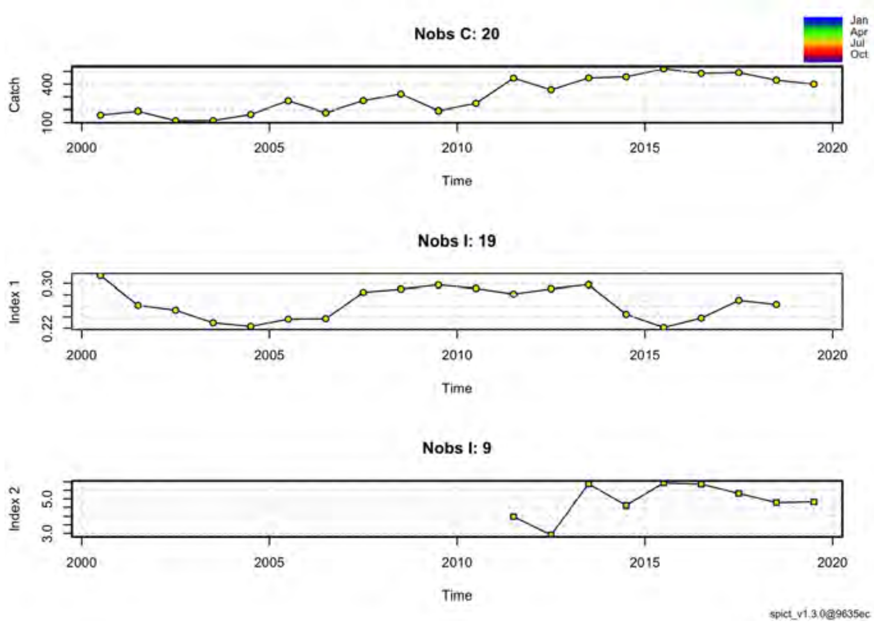
```
## Removing zero, negative, and NAs in  I  series3732
```

```
inp3b$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

```
plotspict.data(inp3b)
```




```
inp3b$stdevfacC <- rep(1, length(inp3b$obsC))
inp3b$stdevfacC[1:10] <- 5
```

Numerical solver time step (probably don't need to change)

```
inp3b$dteuler <- 1/16
```

The model is fitted to data by running

```
res3b <- fit.spict(inp3b)
```

The results are summarised using

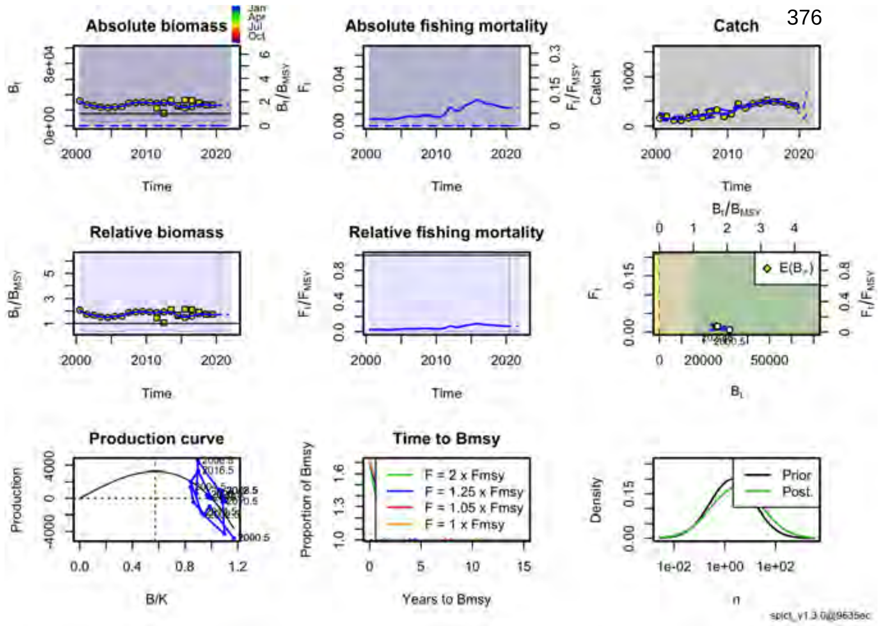
```
capture.output(summary(res3b))
```

```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: 2.8101532"

##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 19,  Nobs I2: 9"
```

```
##  [5] ""

##  [6] "Priors"

##  [7] "     logn  ~  dnorm[log(2), 2^2]"

##  [8] " logalpha  ~  dnorm[log(1), 2^2]"

##  [9] "  logbeta  ~  dnorm[log(1), 2^2]"

## [10] ""

## [11] "Model parameter estimates w 95% CI "

## [12] "            estimate      cilow        ciupp
     log.est  "
## [13] " alpha1 2.561229e-01  0.0307695 2.131949e+00
  -1.3620980  "
## [14] " alpha2 2.695684e+00  1.4285521 5.086767e+00
   0.9916519  "
## [15] " beta   2.146874e-01  0.0624500 7.380406e-01
  -1.5385724  "
## [16] " r      6.183696e-01  0.1944205 1.966773e+00
  -0.4806689  "
## [17] " rc     4.202654e-01  0.0052850 3.341986e+01
  -0.8668689  "
## [18] " rold   3.182947e-01  0.0004021 2.519539e+02
  -1.1447775  "
## [19] " m      3.277575e+03  5.2155503 2.059706e+06
   8.0948592  "
## [20] " K      2.718580e+04 65.4716707 1.128836e+07
  10.2104500  "
## [21] " q1     9.800000e-06  0.0000000 4.561200e-03
 -11.5321806  "
## [22] " q2     1.797000e-04  0.0000004 8.403750e-02
  -8.6244588  "
## [23] " n      2.942758e+00  0.0307315 2.817896e+02
   1.0793472  "
## [24] " sdb    9.950560e-02  0.0628098 1.576403e-01
  -2.3075416  "
## [25] " sdf    2.528067e-01  0.1404914 4.549118e-01
  -1.3751303  "
## [26] " sdi1   2.548570e-02  0.0035425 1.833516e-01
  -3.6696397  "
## [27] " sdi2   2.682356e-01  0.1693982 4.247407e-01
  -1.3158897  "
## [28] " sdc    5.427440e-02  0.0238323 1.236017e-01
  -2.9137027  "
## [29] " "

## [30] "Deterministic reference points (Drp)"

## [31] "           estimate      cilow        ciupp
```

```
 log.est  "
## [32] " Bmsyd 1.559765e+04 32.6738385 7.445913e+06
 9.654875  "
## [33] " Fmsyd 2.101327e-01  0.0026425 1.670993e+01
-1.560016  "
## [34] " MSYd  3.277575e+03  5.2155503 2.059706e+06
 8.094859  "
## [35] "Stochastic reference points (Srp)"

## [36] "          estimate      cilow        ciupp
 log.est rel.diff.Drp  "
## [37] " Bmsys 15345.50880 32.6617575 7.209797e+06
9.638578  -0.01643068  "
## [38] " Fmsys     0.20539  0.0020012 2.108013e+01 -
1.582845  -0.02309115  "
## [39] " MSYs   3150.61805  4.2999282 2.308502e+06
8.055354  -0.04029599  "
## [40] ""

## [41] "States w 95% CI (inp$msytype: s)"

## [42] "                    estimate      cilow
  ciupp    log.est  "
## [43] " B_2020.44      2.62554e+04 54.7695853 1.258
629e+07 10.1756270  "
## [44] " F_2020.44      1.50681e-02  0.0000313 7.262
410e+00 -4.1951752  "
## [45] " B_2020.44/Bmsy 1.71095e+00  0.3954052 7.403
419e+00  0.5370489  "
## [46] " F_2020.44/Fmsy 7.33634e-02  0.0000393 1.371
235e+02 -2.6123304  "
## [47] ""

## [48] "Predictions w 95% CI (inp$msytype: s)"

## [49] "                   prediction       cilow
    ciupp    log.est  "
## [50] " B_2022.00      2.627733e+04  54.5628310 1.2
65510e+07 10.1764617  "
## [51] " F_2022.00      1.506830e-02   0.0000303 7.4
90236e+00 -4.1951589  "
## [52] " B_2022.00/Bmsy 1.712379e+00   0.4004438 7.3
22481e+00  0.5378836  "
## [53] " F_2022.00/Fmsy 7.336460e-02   0.0000383 1.4
06451e+02 -2.6123142  "
## [54] " Catch_2021.00  3.958689e+02 225.7841962 6.9
40795e+02  5.9810831  "
## [55] " E(B_inf)       2.582862e+04          NA
       NA 10.1592385  "
```

```
plot(res3b)
```



11 Checklist for the acceptance of a SPiCT assessment

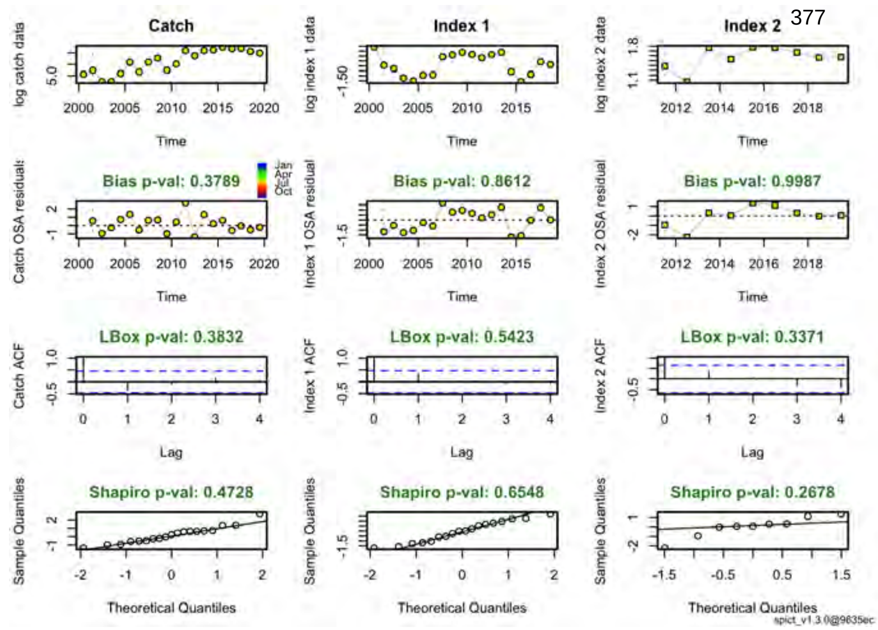
```
res3b$opt$convergence
```

```
## [1] 0
```

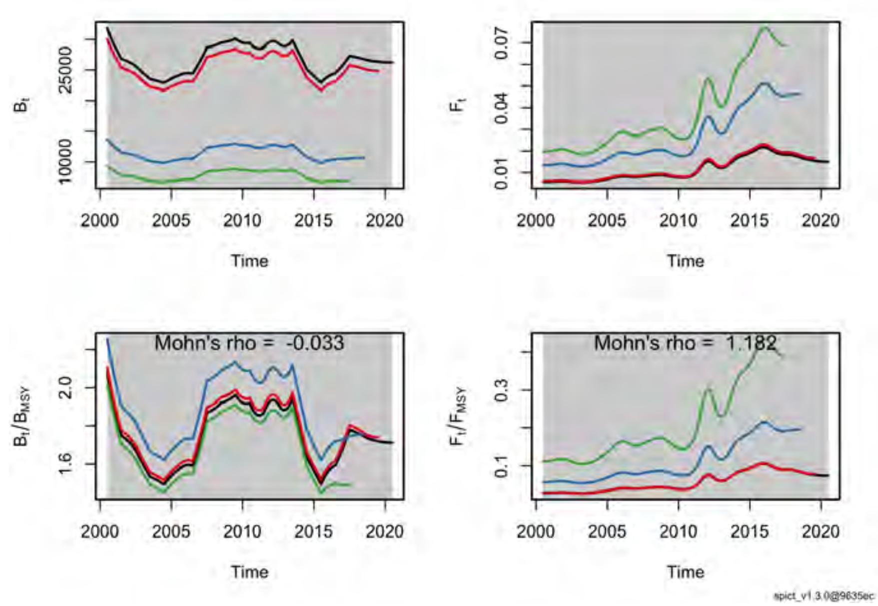
```
all(is.finite(res3b$sd))
```

```
## [1] TRUE
```

```
r3b <- calc.osa.resid(res3b)
plotspict.diagnostic(r3b)
```




```
r3b<- fit.spict(inp3b)
rep3b=retro(r3b, nretroyear=3)
plotspict.retro(rep3b)
```




```
m3b=mohns_rho(rep3b, what = c("FFmsy", "BBmsy"));m3b
```

```
##       FFmsy       BBmsy
##  1.57542063 -0.04350281
```

```
set.seed(123)
check.ini(inp3b, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 2 ... model fitted!
##  Trial 3 ... model fitted!
##  Trial 4 ... model fitted!
##  Trial 5 ... convergence not obtained!
##  Trial 6 ... model fitted!
##  Trial 7 ... model fitted!
##  Trial 8 ... model fitted!
##  Trial 9 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 10 ... model fitted!
##  Trial 11 ... model fitted!
##  Trial 12 ... model fitted!
##  Trial 13 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
## Error in nlminb(obj$par, obj$fn, obj$gr, control =
 inp$optimiser.control) :
##   gradient function must return a numeric vector o
f length 10
## obj$par:
##        logm        logK        logq        logq
     logn      logsdb
##   4.8585751   6.8114272 -10.0904974  -9.4010057
1.3742218   0.6204739
##      logsdf      logsdi      logsdi      logsdc
##  -3.2018952  -3.4927499  -3.2585175  -0.7344229
## obj$fn:
## [1] NaN
```

```
## obj$gr:
## [1] NaN
## Error in fit.spict(inpsens) :
##   Could not fit model. Error msg:Error in nlminb(o
bj$par, obj$fn, obj$gr, control = inp$optimiser.contr
ol) :
##   gradient function must return a numeric vector o
f length 10
##
##  fit failed!
##  Trial 14 ... model fitted!
##  Trial 15 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 16 ... model fitted!
##  Trial 17 ... model fitted!
##  Trial 18 ... model fitted!
##  Trial 19 ... model fitted!
##  Trial 20 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
## $propchng
##           logm  logK  logq  logq  logn logsdb logs
df logsdi logsdi logsdc
## Trial 1  -1.41  0.17 -0.07 -0.20 -0.23   1.30  -0.
08  -1.12  -0.15   0.12
## Trial 2   3.04 -0.03  0.14 -0.04  0.21  -1.14   0.
```

```
73   1.31   0.49  -1.30
## Trial 3   2.59  0.12  0.11 -0.26 -0.08  -0.60  -0.
13  -0.27   0.60   1.01
## Trial 4   3.08  0.24  0.15 -0.15  0.25   0.06  -0.
74   0.81   0.52   0.77
## Trial 5  -2.37 -0.05 -0.07  0.07  0.18   1.03   0.
76   0.10   0.67  -1.02
## Trial 6  -3.02 -0.03  0.24  0.20 -0.03   0.84   1.
07  -0.72  -1.13   0.36
## Trial 7   1.10 -0.24 -0.09  0.12 -0.16   0.15  -0.
89  -0.89  -0.84   0.17
## Trial 8   1.69  0.08  0.17  0.26  0.01   0.80   0.
34  -0.32   0.42   1.11
## Trial 9  -1.70  0.10 -0.07 -0.15  0.21   0.19  -1.
39  -1.12  -1.11   0.93
## Trial 10 -2.45  0.09 -0.13 -0.08  0.09   0.89  -0.
81   1.16   0.10  -0.03
## Trial 11  0.66 -0.10 -0.01 -0.24  0.01  -1.12  -1.
19  -0.31   0.26   1.01
## Trial 12  2.89 -0.12 -0.35 -0.23 -0.12   1.02  -0.
14  -1.30  -0.24   0.27
## Trial 13  0.98 -0.11 -0.15  0.15  0.07  -1.39   0.
99   1.17   1.02  -0.54
## Trial 14  0.79  0.24  0.14 -0.12 -0.01  -0.46  -0.
92  -0.82  -1.37   0.17
## Trial 15 -1.25 -0.05 -0.39  0.17 -0.18   0.77   0.
75   1.21   0.73  -0.66
## Trial 16  2.31  0.00 -0.09  0.13  0.20   0.31  -0.
21   0.81   0.16   0.81
## Trial 17  0.02 -0.09  0.12  0.07  0.08  -0.10  -0.
69   0.80   0.25   0.67
## Trial 18  0.86 -0.19  0.29 -0.13 -0.09  -0.34   0.
37  -0.09  -1.07  -0.23
## Trial 19  2.26 -0.11  0.17  0.12 -0.05   0.05   0.
67  -0.18  -1.18  -1.15
## Trial 20 -1.50 -0.11  0.39 -0.06 -0.23   0.10   0.
27  -0.46   0.99  -0.21
##
## $inimat
##          Distance  logn logK logm  logq1  logq2 lo
gsdb logsdf logsdi1 logsdi2
## Basevec      0.00  0.69 7.64 5.74  -8.80  -8.80  -
1.61  -1.61   -1.61   -1.61
## Trial 1      4.23 -0.29 8.97 5.32  -7.04  -6.77  -
3.70  -1.48    0.20   -1.37
## Trial 2      4.78  2.80 7.43 6.56  -8.47 -10.63
0.23  -2.78   -3.72   -2.40
## Trial 3      3.85  2.49 8.53 6.39  -6.52  -8.08  -
0.65  -1.41   -1.18   -2.58
## Trial 4      4.56  2.83 9.49 6.62  -7.44 -10.99  -
1.71  -0.42   -2.92   -2.45
## Trial 5      3.76 -0.95 7.25 5.35  -9.40 -10.40  -
3.27  -2.84   -1.77   -2.69
## Trial 6      4.38 -1.40 7.38 7.12 -10.54  -8.52  -
```

```
2.96  -3.32   -0.44    0.21
## Trial 7      3.69  1.45 5.78 5.21  -9.84  -7.35  -
1.85  -0.18   -0.17   -0.25
## Trial 8      3.73  1.87 8.24 6.71 -11.10  -8.91  -
2.90  -2.16   -1.09   -2.29
## Trial 9      4.58 -0.49 8.42 5.36  -7.47 -10.63  -
1.91   0.62    0.20    0.17
## Trial 10     3.52 -1.01 8.35 5.02  -8.08  -9.63  -
3.05  -0.31   -3.48   -1.76
## Trial 11     3.89  1.15 6.87 5.69  -6.71  -8.88
0.19   0.30   -1.11   -2.02
## Trial 12     4.66  2.70 6.73 3.72  -6.74  -7.78  -
3.26  -1.38    0.48   -1.22
## Trial 13     4.30  1.37 6.81 4.86 -10.09  -9.40
0.62  -3.20   -3.49   -3.26
## Trial 14     3.85  1.24 9.44 6.54  -7.71  -8.70  -
0.87  -0.13   -0.29    0.60
## Trial 15     4.46 -0.17 7.22 3.49 -10.26  -7.22  -
2.85  -2.81   -3.56   -2.78
## Trial 16     3.35  2.29 7.63 5.23  -9.97 -10.59  -
2.12  -1.28   -2.91   -1.86
## Trial 17     2.44  0.70 6.97 6.43  -9.38  -9.47  -
1.45  -0.50   -2.89   -2.01
## Trial 18     3.31  1.29 6.19 7.42  -7.66  -8.03  -
1.07  -2.20   -1.47    0.12
## Trial 19     3.71  2.26 6.78 6.70  -9.88  -8.37  -
1.70  -2.69   -1.31    0.29
## Trial 20     3.81 -0.35 6.82 7.98  -8.25  -6.79  -
1.76  -2.04   -0.88   -3.21
##           logsdc
## Basevec   -1.61
## Trial 1   -1.81
## Trial 2    0.48
## Trial 3   -3.23
## Trial 4   -2.85
## Trial 5    0.04
## Trial 6   -2.19
## Trial 7   -1.89
## Trial 8   -3.40
## Trial 9   -3.11
## Trial 10  -1.56
## Trial 11  -3.23
## Trial 12  -2.05
## Trial 13  -0.73
## Trial 14  -1.89
## Trial 15  -0.54
## Trial 16  -2.91
## Trial 17  -2.69
## Trial 18  -1.23
## Trial 19   0.24
## Trial 20  -1.27
##
## $resmat
##           Distance        m        K  q  q     n  s
```

```
db  sdf  sdi  sdi  sdc                                    382
## Basevec      0.00  3277.58 27185.80  0  0  2.94 0.
10 0.25 0.03 0.27 0.05
## Trial 1      0.00       NA       NA NA NA    NA
NA   NA   NA   NA   NA
## Trial 2  25635.41   707.54  1679.55  0  0 16.39 1.
26 0.06 0.02 0.09 1.62
## Trial 3      0.02  3277.57 27185.82  0  0  2.94 0.
10 0.25 0.03 0.27 0.05
## Trial 4      0.33  3277.53 27185.47  0  0  2.94 0.
10 0.25 0.03 0.27 0.05
## Trial 5      0.00       NA       NA NA NA    NA
NA   NA   NA   NA   NA
## Trial 6      0.11  3277.56 27185.69  0  0  2.94 0.
10 0.25 0.03 0.27 0.05
## Trial 7      0.01  3277.57 27185.79  0  0  2.94 0.
10 0.25 0.03 0.27 0.05
## Trial 8      0.29  3277.55 27185.51  0  0  2.94 0.
10 0.25 0.03 0.27 0.05
## Trial 9      0.00       NA       NA NA NA    NA
NA   NA   NA   NA   NA
## Trial 10     0.01  3277.57 27185.79  0  0  2.94 0.
10 0.25 0.03 0.27 0.05
## Trial 11     0.28  3277.62 27186.07  0  0  2.94 0.
10 0.25 0.03 0.27 0.05
## Trial 12     0.02  3277.57 27185.78  0  0  2.94 0.
10 0.25 0.03 0.27 0.05
## Trial 13     0.00       NA       NA NA NA    NA
NA   NA   NA   NA   NA
## Trial 14     0.01  3277.57 27185.79  0  0  2.94 0.
10 0.25 0.03 0.27 0.05
## Trial 15     0.00       NA       NA NA NA    NA
NA   NA   NA   NA   NA
## Trial 16     0.02  3277.57 27185.78  0  0  2.94 0.
10 0.25 0.03 0.27 0.05
## Trial 17     0.03  3277.58 27185.83  0  0  2.94 0.
10 0.25 0.03 0.27 0.05
## Trial 18 27379.37 18036.93  4125.20  0  0  2.02 0.
10 0.23 0.10 0.22 0.06
## Trial 19     0.01  3277.58 27185.81  0  0  2.94 0.
10 0.25 0.03 0.27 0.05
## Trial 20     0.00       NA       NA NA NA    NA
NA   NA   NA   NA   NA
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
```

```
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5
##
## [[2]]
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[1]]
##  [1] 0.3138639 0.2610667 0.2522755 0.2296472 0.223
1178 0.2361038 0.2368988
##  [8] 0.2844170 0.2899648 0.2973215 0.2912091 0.281
3124 0.2904401 0.2978007
## [15] 0.2447735 0.2211997 0.2381125 0.2700604 0.262
6929
##
## [[2]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
```

```
(calc.om(res3b))
```

```
##        lower  est  upper CI range order magnitude
## B/Bmsy   0.4 1.71   7.40     7.01               1
## F/Fmsy   0.0 0.07 137.12   137.12               7
```

12 RUN 4: Using two abundance indices: Spanish survey (spat-index) and the LPUE. Fixing n to resemble the Schaefer production model.

```
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)

## Indices Spanish_survey
I_sol8c9a <- data.frame(obsI = data$Spat_index,timeI
= 2000:2019)
```

```
## Indices Portugues_LPUE
I2_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp4<- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_sol
8c9a$obsC,
             timeI = list(I_sol8c9a$timeI+0.8333333,I
2_sol8c9a$timeI+0.5),
             obsI = list(I_sol8c9a$obsI,I2_sol8c9a$ob
sI))


inp4=check.inp(inp4)
```

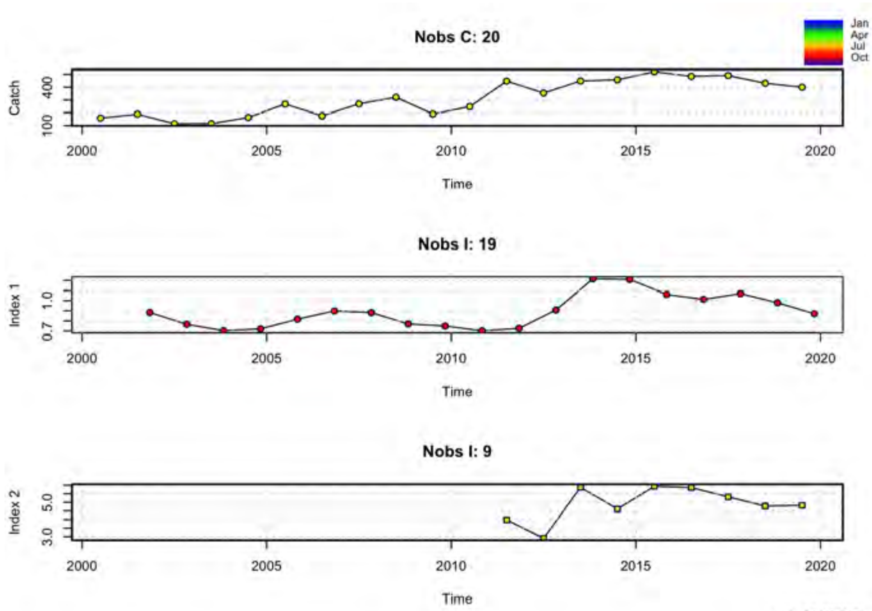
```
## Removing zero, negative, and NAs in  I  series  1

## Removing zero, negative, and NAs in  I  series  2
```

```
inp4$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

```
plotspict.data(inp4)
```




```
inp4$stdevfacC <- rep(1, length(inp4$obsC))
inp4$stdevfacC[1:10] <- 5
```

Fixing n to resemble the Schaefer production model (or the meta study, alternatively):

```
inp4$ini$logn <- log(2); inp4$phases$logn <- -1
```

Numerical solver time step (probably don't need to change)

```
inp4$dteuler <- 1/16
```

The model is fitted to data by running

```
res4 <- fit.spict(inp4)
```

The results are summarised using

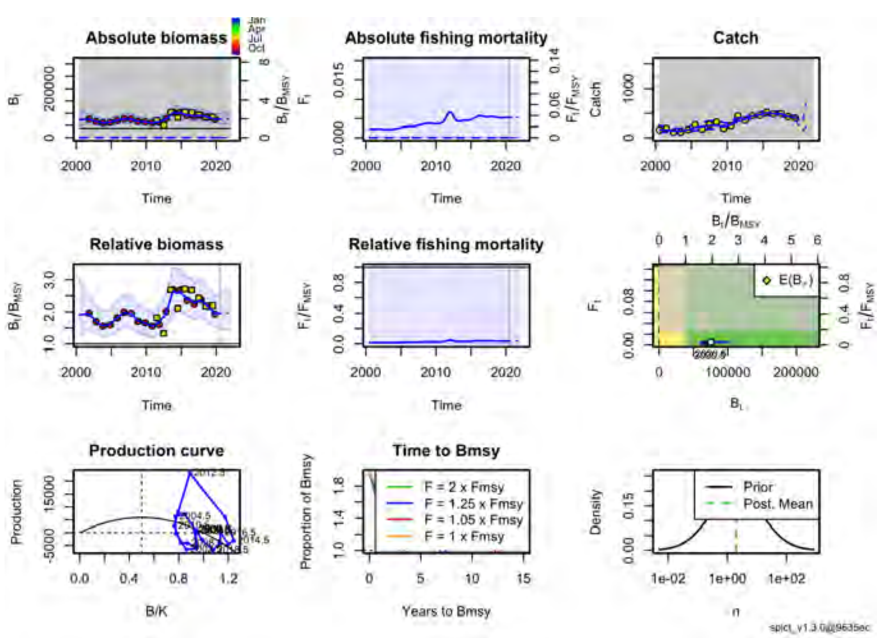
```
capture.output(summary(res4))
```

```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: 3.9337253"

##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 19,  Nobs I2: 9"

##  [5] ""

##  [6] "Priors"

##  [7] "     logn  ~  dnorm[log(2), 2^2]"

##  [8] " logalpha  ~  dnorm[log(1), 2^2]"

##  [9] "  logbeta  ~  dnorm[log(1), 2^2]"

## [10] ""

## [11] "Fixed parameters"

## [12] "   fixed.value  "

## [13] " n           2  "

## [14] ""

## [15] "Model parameter estimates w 95% CI "

## [16] "            estimate      cilow        ciupp
    log.est  "
## [17] " alpha1 2.324433e-01  0.0317899 1.699590e+00
  -1.459109  "
## [18] " alpha2 1.269839e+00  0.6546427 2.463162e+00
```

```
  0.238890  "
## [19] " beta   2.266370e-01  0.0577299 8.897352e-01
  -1.484406  "
## [20] " r      2.948839e-01  0.0771373 1.127295e+00
  -1.221174  "
## [21] " rc     2.948839e-01  0.0771373 1.127295e+00
  -1.221174  "
## [22] " rold   2.948839e-01  0.0771373 1.127295e+00
  -1.221174  "
## [23] " m      5.861974e+03  3.6510457 9.411752e+06
   8.676242  "
## [24] " K      7.951569e+04 53.7720442 1.175842e+08
  11.283710  "
## [25] " q1     1.170000e-05  0.0000000 1.916430e-02
 -11.356618  "
## [26] " q2     5.680000e-05  0.0000000 9.319560e-02
  -9.775467  "
## [27] " sdb    1.248934e-01  0.0844724 1.846562e-01
  -2.080295  "
## [28] " sdf    2.411142e-01  0.1249525 4.652653e-01
  -1.422485  "
## [29] " sdi1   2.903060e-02  0.0042911 1.964010e-01
  -3.539404  "
## [30] " sdi2   1.585944e-01  0.0939234 2.677948e-01
  -1.841405  "
## [31] " sdc    5.464540e-02  0.0228244 1.308300e-01
  -2.906890  "
## [32] " "

## [33] "Deterministic reference points (Drp)"

## [34] "           estimate      cilow        ciupp
  log.est  "
## [35] " Bmsyd 3.975784e+04 26.8860221 5.879212e+07
10.590562  "
## [36] " Fmsyd 1.474419e-01  0.0385686 5.636476e-01
-1.914321  "
## [37] " MSYd  5.861974e+03  3.6510457 9.411752e+06
 8.676242  "
## [38] "Stochastic reference points (Srp)"

## [39] "           estimate      cilow        ciupp
  log.est rel.diff.Drp  "
## [40] " Bmsys 3.853228e+04 26.0547222 5.698531e+07
10.559252  -0.03180623  "
## [41] " Fmsys 1.435671e-01  0.0365861 5.633703e-01
-1.940953  -0.02698978  "
## [42] " MSYs  5.527217e+03  3.4104357 8.957836e+06
 8.617440  -0.06056521  "
## [43] ""

## [44] "States w 95% CI (inp$msytype: s)"

## [45] "                    estimate      cilow
```

```
   ciupp   log.est  "
## [46] " B_2020.44      7.530799e+04 45.5566977 1.24
4887e+08 11.229342  "
## [47] " F_2020.44      5.279300e-03  0.0000032 8.72
5346e+00 -5.243968  "
## [48] " B_2020.44/Bmsy 1.954413e+00  1.4873592 2.56
8129e+00  0.670090  "
## [49] " F_2020.44/Fmsy 3.677210e-02  0.0000204 6.64
2820e+01 -3.303015  "
## [50] ""

## [51] "Predictions w 95% CI (inp$msytype: s)"

## [52] "                  prediction       cilow
    ciupp    log.est  "
## [53] " B_2022.00      7.555085e+04  45.1118006 1.2
65286e+08 11.2325613  "
## [54] " F_2022.00      5.279500e-03   0.0000031 8.9
30297e+00 -5.2439223  "
## [55] " B_2022.00/Bmsy 1.960716e+00   1.4200650 2.7
07205e+00  0.6733097  "
## [56] " F_2022.00/Fmsy 3.677380e-02   0.0000199 6.7
97003e+01 -3.3029692  "
## [57] " Catch_2021.00  3.984815e+02 227.2206215 6.9
88251e+02  5.9876609  "
## [58] " E(B_inf)       7.373401e+04          NA
       NA 11.2082194  "
```

```
plot(res4)
```



13 Checklist for the acceptance of a SPiCT

assessment

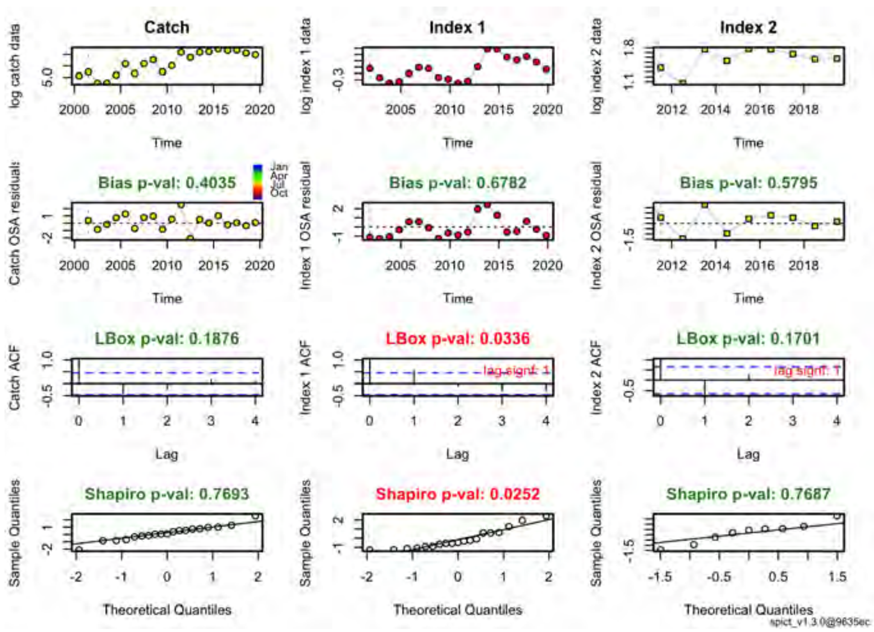
```
res4$opt$convergence
```

```
## [1] 0
```

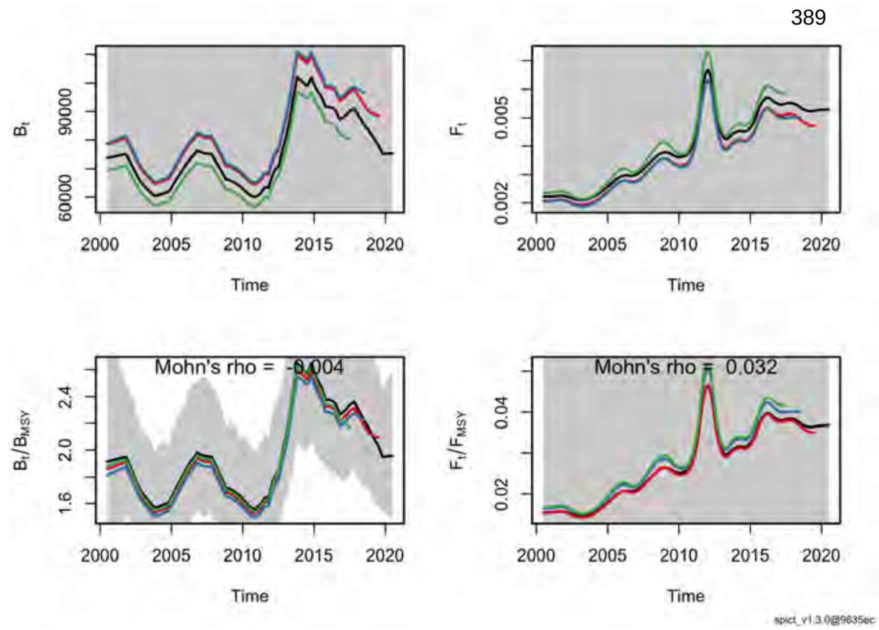
```
all(is.finite(res4$sd))
```

```
## [1] TRUE
```

```
r4<- calc.osa.resid(res4)
plotspict.diagnostic(r4)
```




```
r4<- fit.spict(inp4)
rep4=retro(r4, nretroyear=3)
plotspict.retro(rep4)
```




```
m4=mohns_rho(rep4, what = c("FFmsy", "BBmsy"));m4
```

```
##        FFmsy        BBmsy
##  0.042885155 -0.005722555
```

```
set.seed(123)
check.ini(inp4, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ... convergence not obtained!
##  Trial 2 ... model fitted!
##  Trial 3 ... convergence not obtained!
##  Trial 4 ... model fitted!
##  Trial 5 ... model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ... model fitted!
##  Trial 8 ... model fitted!
##  Trial 9 ... model fitted!
##  Trial 10 ... model fitted!
##  Trial 11 ... model fitted!
##  Trial 12 ... model fitted!
##  Trial 13 ... model fitted!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ... model fitted!
##  Trial 17 ... model fitted!
##  Trial 18 ... model fitted!
##  Trial 19 ... model fitted!
##  Trial 20 ... convergence not obtained!
## $propchng
##           logm  logK  logq  logq logsdb logsdf log
sdi logsdi logsdc
```

```
## Trial 1  -0.13  0.23  0.06 -0.24  -1.26   1.30  -0
.08  -1.12  -0.15
## Trial 2  -0.03  0.37  0.03 -0.11  -0.21   1.14  -1
.14   0.73   1.31
## Trial 3  -0.10  0.36 -0.24 -0.12  -0.40  -1.41  -0
.45  -0.60  -0.13
## Trial 4   0.06 -0.17  0.22 -0.29  -1.15  -0.55  -0
.85   1.36   0.06
## Trial 5   0.16 -0.23  0.11  0.17   1.02   0.24   0
.25   0.38   0.99
## Trial 6  -0.22 -0.21  0.02  0.14  -1.02   1.30   0
.17  -0.86   1.08
## Trial 7   0.04 -0.24  0.23 -0.16  -1.13   0.36  -0
.47   1.16   0.33
## Trial 8  -0.14  0.25  0.03 -0.19  -0.89  -0.84   0
.17  -0.73  -0.37
## Trial 9   0.13 -0.40  0.02  0.17   0.34  -0.32   0
.42   1.11   0.73
## Trial 10  0.10 -0.07 -0.18  0.25   0.19  -1.39  -1
.12  -1.11   0.93
## Trial 11 -0.22  0.12  0.10 -0.10   0.51   0.89  -0
.81   1.16   0.10
## Trial 12  0.01  0.08  0.10  0.01  -1.30   0.05  -1
.12  -1.19  -0.31
## Trial 13 -0.05 -0.28 -0.27  0.12   1.26  -1.28  -0
.63   1.02  -0.14
## Trial 14  0.27  0.07  0.06 -0.09   0.52   0.55   0
.80   0.37  -1.39
## Trial 15 -0.21 -0.33  0.22 -0.12  -0.34  -1.12  -0
.50  -0.68  -0.06
## Trial 16  0.10  0.26 -0.18 -0.30   0.17   0.54   0
.26   1.40   0.90
## Trial 17  0.21 -0.22  0.16  0.26   0.73  -0.66  -0
.99   0.01   0.32
## Trial 18 -0.15 -0.31  0.07 -0.04   0.81   0.16   0
.81  -0.01   0.42
## Trial 19  0.09 -0.10  0.09 -0.02  -0.69   0.80   0
.25   0.67  -0.37
## Trial 20 -0.19  0.29 -0.15 -0.10  -0.34   0.37  -0
.09  -1.07  -0.23
##
## $inimat
##          Distance logK logm logq1 logq2 logsdb log
sdf logsdi1 logsdi2 logsdc
## Basevec      0.00 7.64 5.74 -7.45 -7.45  -1.61  -1
.61   -1.61   -1.61  -1.61
## Trial 1      4.22 6.66 7.07 -7.87 -5.68   0.42  -3
.70   -1.48    0.20  -1.37
## Trial 2      4.22 7.44 7.85 -7.66 -6.63  -1.27  -3
.44    0.23   -2.78  -3.72
## Trial 3      4.01 6.85 7.84 -5.65 -6.56  -0.96   0
.67   -0.89   -0.65  -1.41
## Trial 4      4.38 8.07 4.77 -9.07 -5.31   0.24  -0
.73   -0.25   -3.80  -1.71
```

```
## Trial 5      3.36 8.83 4.44 -8.28 -8.68  -3.25  -2
.00   -2.01   -2.21  -3.21
## Trial 6      4.19 5.98 4.51 -7.60 -8.52   0.04  -3
.70   -1.88   -0.23  -3.35
## Trial 7      3.77 7.92 4.39 -9.16 -6.28   0.21  -2
.19   -0.85   -3.48  -2.14
## Trial 8      3.31 6.60 7.19 -7.68 -6.02  -0.17  -0
.25   -1.89   -0.44  -1.01
## Trial 9      3.68 8.61 3.44 -7.56 -8.74  -2.16  -1
.09   -2.29   -3.40  -2.79
## Trial 10     4.43 8.42 5.36 -6.12 -9.28  -1.91   0
.62    0.20    0.17  -3.11
## Trial 11     3.52 5.94 6.45 -8.17 -6.73  -2.44  -3
.05   -0.31   -3.48  -1.76
## Trial 12     3.51 7.69 6.20 -8.22 -7.50   0.48  -1
.69    0.19    0.30  -1.11
## Trial 13     4.45 7.23 4.12 -5.44 -8.36  -3.63   0
.45   -0.59   -3.26  -1.38
## Trial 14     3.70 9.73 6.14 -7.89 -6.77  -2.44  -2
.49   -2.90   -2.21   0.62
## Trial 15     3.87 6.05 3.86 -9.10 -6.57  -1.06   0
.19   -0.81   -0.52  -1.51
## Trial 16     4.19 8.38 7.23 -6.13 -5.24  -1.89  -2
.48   -2.03   -3.86  -3.07
## Trial 17     3.82 9.22 4.51 -8.65 -9.40  -2.78  -0
.54   -0.01   -1.62  -2.13
## Trial 18     2.97 6.47 3.95 -7.95 -7.12  -2.91  -1
.86   -2.91   -1.60  -2.28
## Trial 19     2.42 8.33 5.17 -8.11 -7.29  -0.50  -2
.89   -2.01   -2.69  -1.01
## Trial 20     3.25 6.19 7.42 -6.31 -6.67  -1.07  -2
.20   -1.47    0.12  -1.23
##
## $resmat
##          Distance        m        K  q  q  sdb  sd
f  sdi  sdi  sdc
## Basevec      0.00  5861.97 79515.69  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 1      0.00       NA       NA NA NA   NA   N
A   NA   NA   NA
## Trial 2      0.05  5861.98 79515.64  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 3      0.00       NA       NA NA NA   NA   N
A   NA   NA   NA
## Trial 4      0.12  5861.97 79515.57  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 5      0.23  5861.96 79515.46  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 6      0.41  5861.95 79515.27  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 7      0.18  5861.97 79515.50  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 8  93174.90 68846.06 10852.98  0  0 0.21 0.2
3 0.16 0.21 0.06
```

```
## Trial 9      0.27  5861.96 79515.42  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 10     0.20  5861.96 79515.49  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 11     0.11  5861.97 79515.58  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 12     0.16  5861.97 79515.52  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 13     0.37  5861.95 79515.32  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 14     0.24  5861.96 79515.45  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 15     0.25  5861.96 79515.43  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 16     0.03  5861.98 79515.66  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 17     0.27  5861.96 79515.42  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 18     0.14  5861.97 79515.55  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 19     0.32  5861.95 79515.36  0  0 0.12 0.2
4 0.03 0.16 0.05
## Trial 20     0.00       NA       NA NA NA   NA   N
A   NA   NA   NA
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
##  [1] 2001.833 2002.833 2003.833 2004.833 2005.833
2006.833 2007.833 2008.833
##  [9] 2009.833 2010.833 2011.833 2012.833 2013.833
2014.833 2015.833 2016.833
## [17] 2017.833 2018.833 2019.833
##
## [[2]]
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[1]]
##  [1] 0.8830629 0.7655780 0.7023948 0.7199932 0.816
7087 0.8987942 0.8824258
##  [8] 0.7693151 0.7487957 0.7009754 0.7251867 0.907
7803 1.2142796 1.2089463
## [15] 1.0609294 1.0135286 1.0703598 0.9796291 0.871
```

```
3699                                                          393
##
## [[2]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
```

```
(calc.om(res4))
```

```
##         lower  est upper CI range order magnitude
## B/Bmsy  1.49 1.95  2.57     1.08                0
## F/Fmsy  0.00 0.04 66.43    66.43                6
```

14 RUN 4b: Using two abundance indices: CPUE and the LPUE. Fixing n to resemble the Schaefer production model.

```
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)

## Indices Spanish_CPUE
I_sol8c9a <- data.frame(obsI = data$CPUE,timeI = 2000
:2019)

## Indices Portugues_LPUE
I2_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp4b<- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_so
l8c9a$obsC,
             timeI = list(I_sol8c9a$timeI+0.5,I2_sol8
c9a$timeI+0.5),
             obsI = list(I_sol8c9a$obsI,I2_sol8c9a$ob
sI))


inp4b=check.inp(inp4b)
```

```
## Removing zero, negative, and NAs in  I  series  1
```

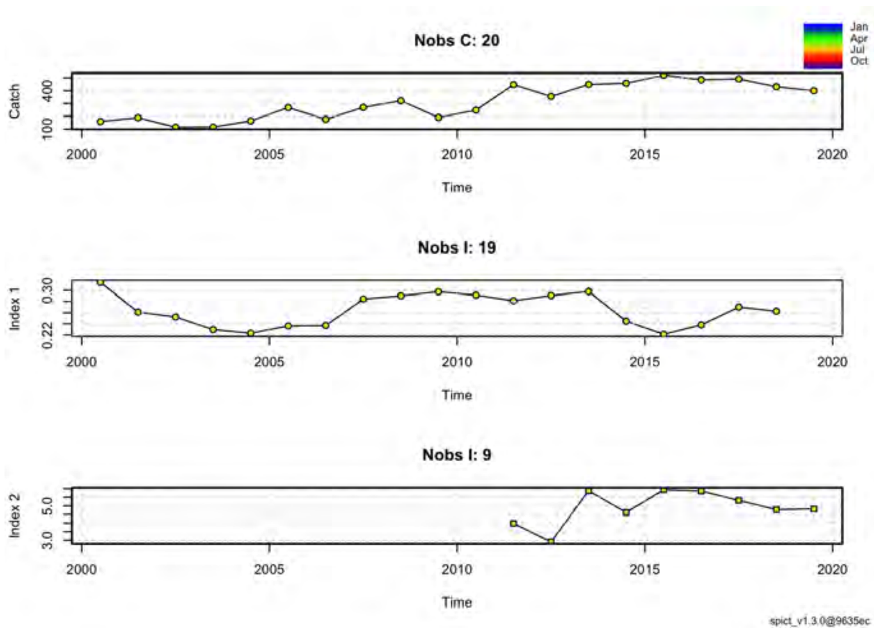
```
## Removing zero, negative, and NAs in  I  series3942
```

```
inp4b$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

```
plotspict.data(inp4b)
```




```
inp4b$stdevfacC <- rep(1, length(inp4b$obsC))
inp4b$stdevfacC[1:10] <- 5
```

Fixing n to resemble the Schaefer production model (or the meta study, alternatively):

```
inp4b$ini$logn <- log(2); inp4b$phases$logn <- -1
```

Numerical solver time step (probably don't need to change)

```
inp4b$dteuler <- 1/16
```

The model is fitted to data by running

```
res4b <- fit.spict(inp4b)
```

The results are summarised using

```
capture.output(summary(res4b))
```

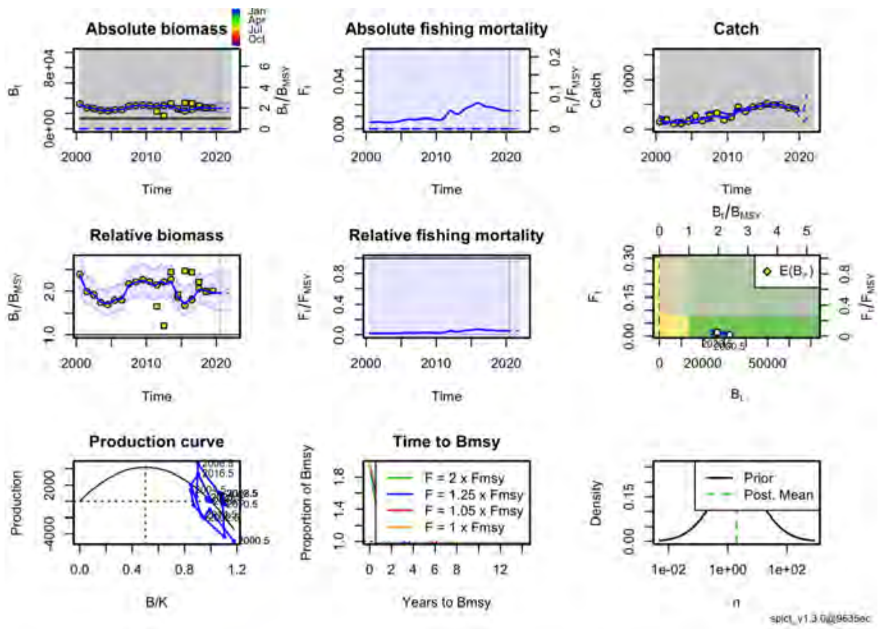
```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
```

```
##  [2] "Objective function at optimum: 2.8240887"

##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 19,  Nobs I2: 9"

##  [5] ""

##  [6] "Priors"

##  [7] "     logn  ~  dnorm[log(2), 2^2]"

##  [8] " logalpha  ~  dnorm[log(1), 2^2]"

##  [9] "  logbeta  ~  dnorm[log(1), 2^2]"

## [10] ""

## [11] "Fixed parameters"

## [12] "   fixed.value  "

## [13] " n           2  "

## [14] ""

## [15] "Model parameter estimates w 95% CI "

## [16] "            estimate      cilow        ciupp
     log.est  "
## [17] " alpha1 2.584646e-01  0.0313302 2.132251e+00
  -1.3529967  "
## [18] " alpha2 2.694396e+00  1.4249746 5.094666e+00
   0.9911741  "
## [19] " beta   2.150054e-01  0.0624982 7.396592e-01
  -1.5370919  "
## [20] " r      6.042695e-01  0.2039230 1.790587e+00
  -0.5037349  "
## [21] " rc     6.042695e-01  0.2039230 1.790587e+00
  -0.5037349  "
## [22] " rold   6.042695e-01  0.2039230 1.790587e+00
  -0.5037349  "
## [23] " m      4.164456e+03 11.4757215 1.511251e+06
   8.3343409  "
## [24] " K      2.756688e+04 63.4386480 1.197902e+07
  10.2243702  "
## [25] " q1     9.600000e-06  0.0000000 4.680500e-03
 -11.5509055  "
## [26] " q2     1.764000e-04  0.0000004 8.625870e-02
  -8.6430007  "
## [27] " sdb    9.955050e-02  0.0626437 1.582011e-01
  -2.3070904  "
## [28] " sdf    2.525600e-01  0.1402437 4.548266e-01
  -1.3761065  "
```

```
## [29] " sdi1   2.573030e-02  0.0036228 1.827421e-01
  -3.6600870  "
## [30] " sdi2   2.682284e-01  0.1693796 4.247649e-01
  -1.3159163  "
## [31] " sdc    5.430180e-02  0.0238457 1.236567e-01
  -2.9131985  "
## [32] " "

## [33] "Deterministic reference points (Drp)"

## [34] "           estimate      cilow        ciupp
  log.est  "
## [35] " Bmsyd 1.378344e+04 31.7193240 5.989509e+06
 9.531223  "
## [36] " Fmsyd 3.021348e-01  0.1019615 8.952932e-01
-1.196882  "
## [37] " MSYd  4.164456e+03 11.4757215 1.511251e+06
 8.334341  "
## [38] "Stochastic reference points (Srp)"

## [39] "           estimate      cilow        ciupp
  log.est rel.diff.Drp  "
## [40] " Bmsys 1.362661e+04 31.3716476 5.918859e+06
 9.519779 -0.011509316  "
## [41] " Fmsys 2.997356e-01  0.1006434 8.926711e-01
-1.204854 -0.008004286  "
## [42] " MSYs  4.084003e+03 11.2591202 1.481384e+06
 8.314833 -0.019699494  "
## [43] ""

## [44] "States w 95% CI (inp$msytype: s)"

## [45] "                    estimate      cilow
   ciupp    log.est  "
## [46] " B_2020.44      2.667045e+04 53.1296706 1.33
8825e+07 10.1913117  "
## [47] " F_2020.44      1.482920e-02  0.0000294 7.48
2864e+00 -4.2111537  "
## [48] " B_2020.44/Bmsy 1.957234e+00  1.5644558 2.44
8625e+00  0.6715322  "
## [49] " F_2020.44/Fmsy 4.947440e-02  0.0001174 2.08
4406e+01 -3.0062994  "
## [50] ""

## [51] "Predictions w 95% CI (inp$msytype: s)"

## [52] "                  prediction       cilow
    ciupp    log.est  "
## [53] " B_2022.00      2.666673e+04  52.8588822 1.3
45307e+07 10.1911720  "
## [54] " F_2022.00      1.482950e-02   0.0000285 7.7
15375e+00 -4.2111373  "
## [55] " B_2022.00/Bmsy 1.956961e+00   1.5474681 2.4
74813e+00  0.6713925  "
```

```
## [56] " F_2022.00/Fmsy 4.947520e-02   0.0001138 2.1
51136e+01 -3.0062829  "
## [57] " Catch_2021.00  3.954659e+02 225.6955829 6.9
29391e+02  5.9800646  "
## [58] " E(B_inf)       2.642921e+04          NA
       NA 10.1822251  "
```

```
plot(res4b)
```



15 Checklist for the acceptance of a SPiCT assessment

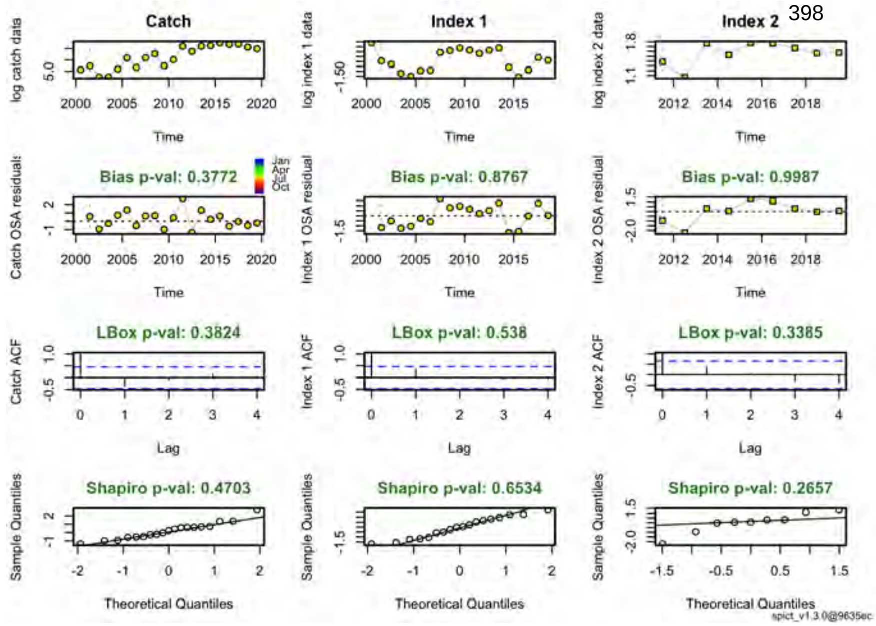
```
res4b$opt$convergence
```

```
## [1] 0
```

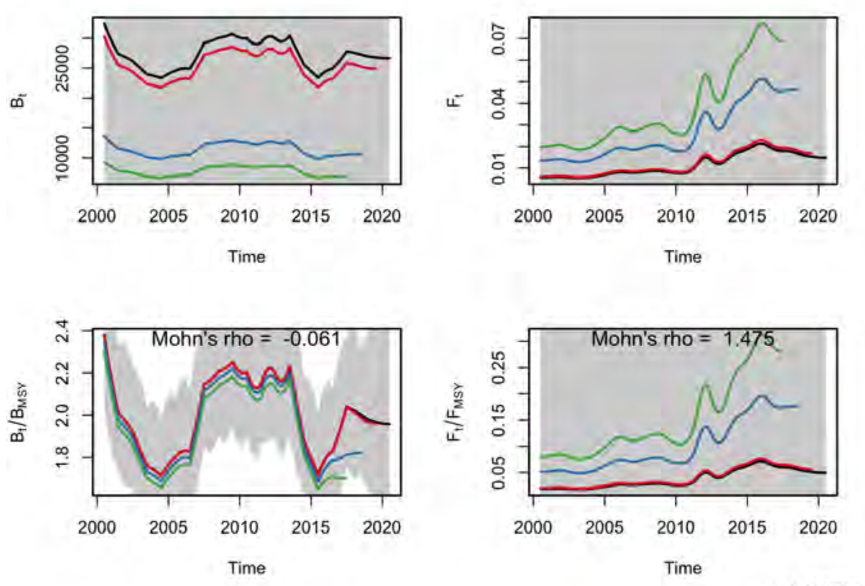
```
all(is.finite(res4b$sd))
```

```
## [1] TRUE
```

```
r4b<- calc.osa.resid(res4b)
plotspict.diagnostic(r4b)
```




```
r4b<- fit.spict(inp4b)
rep4b=retro(r4b, nretroyear=3)
plotspict.retro(rep4b)
```




```
m4b=mohns_rho(rep4b, what = c("FFmsy", "BBmsy"));m4b
```

```
##       FFmsy       BBmsy
##  1.96730767 -0.08196615
```

```
set.seed(123)
check.ini(inp4b, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ... model fitted!
```

```
##  Trial 2 ... model fitted!
##  Trial 3 ... model fitted!
##  Trial 4 ... model fitted!
##  Trial 5 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ... model fitted!
##  Trial 8 ... model fitted!
##  Trial 9 ... model fitted!
##  Trial 10 ... model fitted!
##  Trial 11 ... model fitted!
##  Trial 12 ... model fitted!
##  Trial 13 ... model fitted!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ... model fitted!
##  Trial 17 ... model fitted!
##  Trial 18 ... model fitted!
##  Trial 19 ... model fitted!
##  Trial 20 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  model fitted!
## $propchng
##             logm  logK  logq  logq logsdb logsdf log
sdi logsdi logsdc
## Trial 1  -0.13  0.23  0.05 -0.20  -1.26   1.30  -0
.08  -1.12  -0.15
## Trial 2  -0.03  0.37  0.02 -0.09  -0.21   1.14  -1
.14   0.73   1.31
## Trial 3  -0.10  0.36 -0.20 -0.10  -0.40  -1.41  -0
.45  -0.60  -0.13
## Trial 4   0.06 -0.17  0.18 -0.24  -1.15  -0.55  -0
.85   1.36   0.06
## Trial 5   0.16 -0.23  0.10  0.14   1.02   0.24   0
.25   0.38   0.99
## Trial 6  -0.22 -0.21  0.02  0.12  -1.02   1.30   0
.17  -0.86   1.08
## Trial 7   0.04 -0.24  0.19 -0.13  -1.13   0.36  -0
.47   1.16   0.33
## Trial 8  -0.14  0.25  0.03 -0.16  -0.89  -0.84   0
.17  -0.73  -0.37
## Trial 9   0.13 -0.40  0.01  0.15   0.34  -0.32   0
```

```
.42   1.11   0.73
## Trial 10  0.10 -0.07 -0.15  0.21   0.19  -1.39  -1
.12  -1.11   0.93
## Trial 11 -0.22  0.12  0.08 -0.08   0.51   0.89  -0
.81   1.16   0.10
## Trial 12  0.01  0.08  0.09  0.01  -1.30   0.05  -1
.12  -1.19  -0.31
## Trial 13 -0.05 -0.28 -0.23  0.10   1.26  -1.28  -0
.63   1.02  -0.14
## Trial 14  0.27  0.07  0.05 -0.08   0.52   0.55   0
.80   0.37  -1.39
## Trial 15 -0.21 -0.33  0.19 -0.10  -0.34  -1.12  -0
.50  -0.68  -0.06
## Trial 16  0.10  0.26 -0.15 -0.25   0.17   0.54   0
.26   1.40   0.90
## Trial 17  0.21 -0.22  0.14  0.22   0.73  -0.66  -0
.99   0.01   0.32
## Trial 18 -0.15 -0.31  0.06 -0.04   0.81   0.16   0
.81  -0.01   0.42
## Trial 19  0.09 -0.10  0.08 -0.02  -0.69   0.80   0
.25   0.67  -0.37
## Trial 20 -0.19  0.29 -0.13 -0.09  -0.34   0.37  -0
.09  -1.07  -0.23
##
## $inimat
##          Distance logK logm  logq1  logq2 logsdb l
ogsdf logsdi1 logsdi2 logsdc
## Basevec      0.00 7.64 5.74  -8.80  -8.80  -1.61
-1.61   -1.61   -1.61  -1.61
## Trial 1      4.22 6.66 7.07  -9.22  -7.04   0.42
-3.70   -1.48    0.20  -1.37
## Trial 2      4.22 7.44 7.85  -9.01  -7.98  -1.27
-3.44    0.23   -2.78  -3.72
## Trial 3      4.01 6.85 7.84  -7.01  -7.91  -0.96
 0.67   -0.89   -0.65  -1.41
## Trial 4      4.38 8.07 4.77 -10.43  -6.67   0.24
-0.73   -0.25   -3.80  -1.71
## Trial 5      3.36 8.83 4.44  -9.64 -10.04  -3.25
-2.00   -2.01   -2.21  -3.21
## Trial 6      4.19 5.98 4.51  -8.96  -9.88   0.04
-3.70   -1.88   -0.23  -3.35
## Trial 7      3.77 7.92 4.39 -10.52  -7.63   0.21
-2.19   -0.85   -3.48  -2.14
## Trial 8      3.31 6.60 7.19  -9.04  -7.37  -0.17
-0.25   -1.89   -0.44  -1.01
## Trial 9      3.68 8.61 3.44  -8.91 -10.09  -2.16
-1.09   -2.29   -3.40  -2.79
## Trial 10     4.43 8.42 5.36  -7.47 -10.63  -1.91
 0.62    0.20    0.17  -3.11
## Trial 11     3.52 5.94 6.45  -9.52  -8.08  -2.44
-3.05   -0.31   -3.48  -1.76
## Trial 12     3.51 7.69 6.20  -9.57  -8.85   0.48
-1.69    0.19    0.30  -1.11
## Trial 13     4.45 7.23 4.12  -6.80  -9.72  -3.63
```

```
 0.45   -0.59   -3.26  -1.38
## Trial 14     3.70 9.73 6.14  -9.24  -8.12  -2.44
-2.49   -2.90   -2.21   0.62
## Trial 15     3.87 6.05 3.86 -10.45  -7.92  -1.06
 0.19   -0.81   -0.52  -1.51
## Trial 16     4.19 8.38 7.23  -7.48  -6.59  -1.89
-2.48   -2.03   -3.86  -3.07
## Trial 17     3.82 9.22 4.51 -10.00 -10.75  -2.78
-0.54   -0.01   -1.62  -2.13
## Trial 18     2.97 6.47 3.95  -9.31  -8.47  -2.91
-1.86   -2.91   -1.60  -2.28
## Trial 19     2.42 8.33 5.17  -9.47  -8.64  -0.50
-2.89   -2.01   -2.69  -1.01
## Trial 20     3.25 6.19 7.42  -7.66  -8.03  -1.07
-2.20   -1.47    0.12  -1.23
##
## $resmat
##           Distance        m        K q q sdb  sdf
sdi  sdi  sdc
## Basevec      0.00  4164.46 27566.88 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 1  27281.08 18120.67  4125.85 0 0 0.1 0.23 0
.10 0.22 0.06
## Trial 2  27281.10 18120.71  4125.86 0 0 0.1 0.23 0
.10 0.22 0.06
## Trial 3  27281.08 18120.65  4125.85 0 0 0.1 0.23 0
.10 0.22 0.06
## Trial 4      0.10  4164.44 27566.78 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 5      0.04  4164.45 27566.84 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 6      0.02  4164.45 27566.85 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 7      0.06  4164.45 27566.82 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 8  27281.10 18120.71  4125.86 0 0 0.1 0.23 0
.10 0.22 0.06
## Trial 9      0.02  4164.45 27566.86 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 10     0.05  4164.45 27566.83 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 11     0.10  4164.47 27566.98 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 12     0.04  4164.46 27566.91 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 13     0.02  4164.45 27566.85 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 14     0.01  4164.45 27566.87 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 15     0.01  4164.45 27566.86 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 16     0.01  4164.46 27566.88 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 17     0.27  4164.50 27567.15 0 0 0.1 0.25 0
```

```
.03 0.27 0.05
## Trial 18     0.02  4164.45 27566.86 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 19     0.51  4164.38 27566.37 0 0 0.1 0.25 0
.03 0.27 0.05
## Trial 20 27566.52 13774.16  1729.57 0 0 0.1 0.24 0
.02 0.27 0.06
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5
##
## [[2]]
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[1]]
##  [1] 0.3138639 0.2610667 0.2522755 0.2296472 0.223
1178 0.2361038 0.2368988
##  [8] 0.2844170 0.2899648 0.2973215 0.2912091 0.281
3124 0.2904401 0.2978007
## [15] 0.2447735 0.2211997 0.2381125 0.2700604 0.262
6929
##
## [[2]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
```

```
(calc.om(res4b))
```

```
##         lower  est upper CI range order magnitude
## B/Bmsy  1.56 1.96  2.45     0.88               0
## F/Fmsy  0.00 0.05 20.84    20.84               5
```

16 Run 5: Using three

abundance indices. Fixing n to resemble the Schaefer production model:

```
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)

## Indices Portugues_survey
I1_sol8c9a <- data.frame(obsI =data$Spat_index,timeI
= 2000:2019)

## Indices CPUE Spain
I2_sol8c9a <- data.frame(obsI =data$CPUE,timeI = 2000
:2019)

## Indices LPUE Portugal
I3_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp5 <- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_so
l8c9a$obsC,
             timeI = list(I1_sol8c9a$timeI+0.8333333,
I2_sol8c9a$timeI+0.5, I3_sol8c9a$timeI+0.5),
             obsI = list(I1_sol8c9a$obsI,I2_sol8c9a$o
bsI,I3_sol8c9a$obsI))


inp5=check.inp(inp5)
```

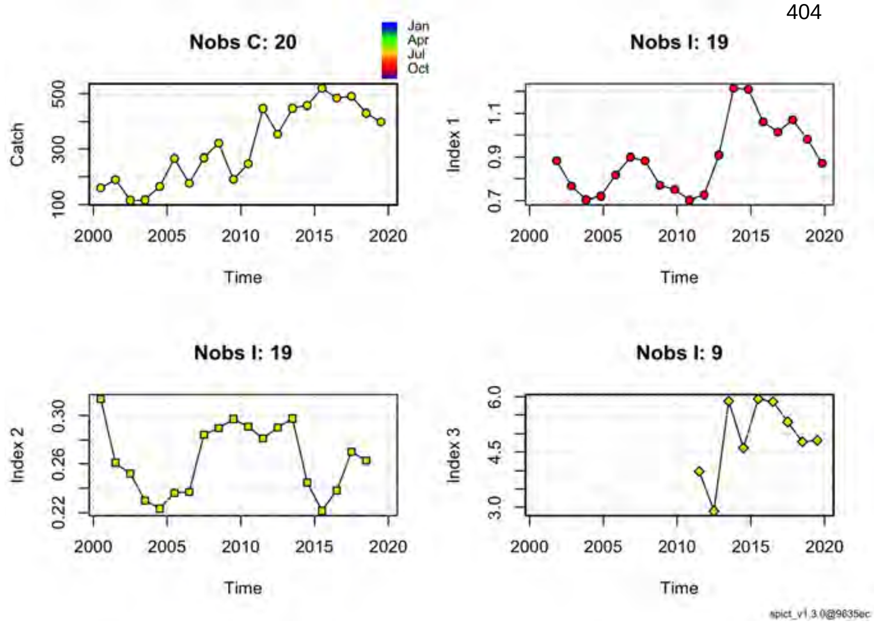
```
## Removing zero, negative, and NAs in  I  series  1

## Removing zero, negative, and NAs in  I  series  2

## Removing zero, negative, and NAs in  I  series  3
```

```
inp5$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

```
plotspict.data(inp5)
```




```
inp5$stdevfacC <- rep(1, length(inp5$obsC))
inp5$stdevfacC[1:10] <- 5
```

Numerical solver time step (probably don't need to change)

```
inp5$dteuler <- 1/16
```

```
inp5$ini$logn <- log(2); inp5$phases$logn <- -1
```

The model is fitted to data by running

```
res5<- fit.spict(inp5)
```

The results are summarised using

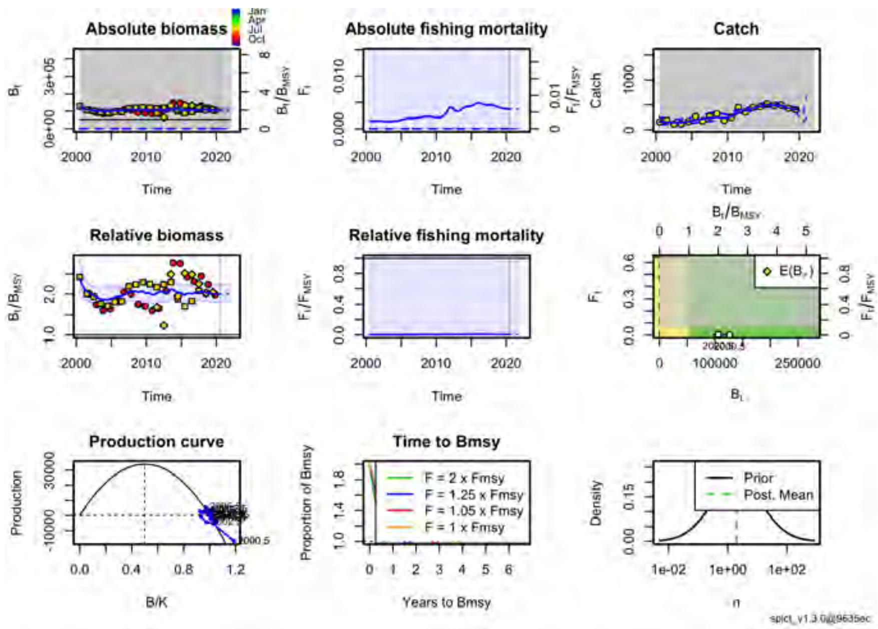
```
capture.output(summary(res5))
```

```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: -0.7503231"

##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 19,  Nobs I2: 19,  Nob
s I3: 9"
##  [5] ""

##  [6] "Priors"

##  [7] "     logn  ~  dnorm[log(2), 2^2]"

##  [8] " logalpha  ~  dnorm[log(1), 2^2]"
```

```
## [9] "  logbeta  ~  dnorm[log(1), 2^2]"

## [10] ""

## [11] "Fixed parameters"

## [12] "   fixed.value  "

## [13] " n           2  "

## [14] ""

## [15] "Model parameter estimates w 95% CI "

## [16] "            estimate      cilow        ciupp
     log.est  "
## [17] " alpha1 1.853010e+00  0.6342971 5.413308e+00
   0.6168113  "
## [18] " alpha2 1.011818e+00  0.3004661 3.407294e+00
   0.0117491  "
## [19] " alpha3 2.560705e+00  0.9061270 7.236525e+00
   0.9402826  "
## [20] " beta   2.544805e-01  0.0604884 1.070624e+00
  -1.3685312  "
## [21] " r      1.273146e+00  0.1999724 8.105626e+00
   0.2414913  "
## [22] " rc     1.273146e+00  0.1999724 8.105626e+00
   0.2414913  "
## [23] " rold   1.273146e+00  0.1999724 8.105626e+00
   0.2414913  "
## [24] " m      3.393918e+04 23.5207321 4.897246e+07
  10.4323255  "
## [25] " K      1.066309e+05 77.2492220 1.471878e+08
  11.5771285  "
## [26] " q1     8.300000e-06  0.0000000 1.162030e-02
 -11.7024638  "
## [27] " q2     2.500000e-06  0.0000000 3.439500e-03
 -12.9190161  "
## [28] " q3     4.450000e-05  0.0000000 6.290320e-02
 -10.0190624  "
## [29] " sdb    8.644020e-02  0.0326337 2.289627e-01
  -2.4483030  "
## [30] " sdf    2.289559e-01  0.1128430 4.645464e-01
  -1.4742259  "
## [31] " sdi1   1.601745e-01  0.1107565 2.316420e-01
  -1.8314917  "
## [32] " sdi2   8.746170e-02  0.0498999 1.532981e-01
  -2.4365539  "
## [33] " sdi3   2.213477e-01  0.1361927 3.597462e-01
  -1.5080203  "
## [34] " sdc    5.826480e-02  0.0241872 1.403548e-01
  -2.8427572  "
## [35] " "
```

```
## [36] "Deterministic reference points (Drp)"

## [37] "           estimate      cilow        ciupp
   log.est  "
## [38] " Bmsyd 5.331545e+04 38.6246110 7.359392e+07
10.8839813  "
## [39] " Fmsyd 6.365732e-01  0.0999862 4.052813e+00
-0.4516559  "
## [40] " MSYd  3.393918e+04 23.5207321 4.897246e+07
10.4323255  "
## [41] "Stochastic reference points (Srp)"

## [42] "           estimate      cilow        ciupp
   log.est rel.diff.Drp  "
## [43] " Bmsys 5.297880e+04 38.3241038 7.323728e+07
10.8776471 -0.006354333  "
## [44] " Fmsys 6.351124e-01  0.0991762 4.067183e+00
-0.4539532 -0.002300075  "
## [45] " MSYs  3.364700e+04 23.2814110 4.862767e+07
10.4236793 -0.008683722  "
## [46] ""

## [47] "States w 95% CI (inp$msytype: s)"

## [48] "                    estimate      cilow
   ciupp    log.est  "
## [49] " B_2020.44      1.059302e+05 75.0153287 1.49
5855e+08 11.5705355  "
## [50] " F_2020.44      3.740400e-03  0.0000026 5.30
9567e+00 -5.5885710  "
## [51] " B_2020.44/Bmsy 1.999482e+00  1.7928942 2.22
9875e+00  0.6928883  "
## [52] " F_2020.44/Fmsy 5.889300e-03  0.0000040 8.73
7869e+00 -5.1346177  "
## [53] ""

## [54] "Predictions w 95% CI (inp$msytype: s)"

## [55] "                  prediction       cilow
    ciupp   log.est  "
## [56] " B_2022.00      1.059952e+05  75.1235593 1.4
95534e+08 11.571149  "
## [57] " F_2022.00      3.740600e-03   0.0000026 5.4
23563e+00 -5.588507  "
## [58] " B_2022.00/Bmsy 2.000710e+00   1.7900406 2.2
36173e+00  0.693502  "
## [59] " F_2022.00/Fmsy 5.889700e-03   0.0000039 8.9
24439e+00 -5.134553  "
## [60] " Catch_2021.00  3.964364e+02 238.6310985 6.5
85973e+02  5.982515  "
## [61] " E(B_inf)       1.056896e+05          NA
       NA 11.568262  "
```

```
plot(res5)
```

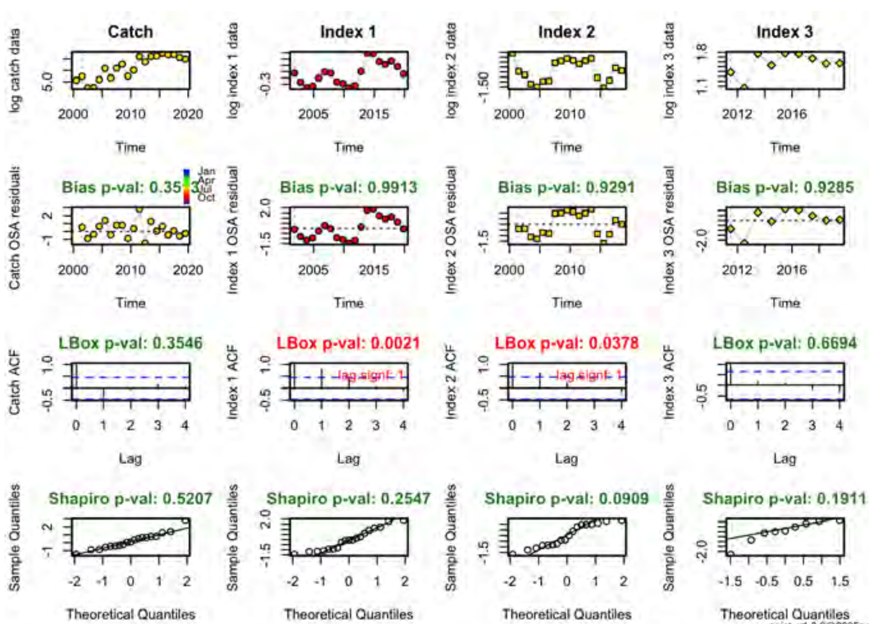

```
res5$opt$convergence
```

```
## [1] 0
```

```
all(is.finite(res5$sd))
```

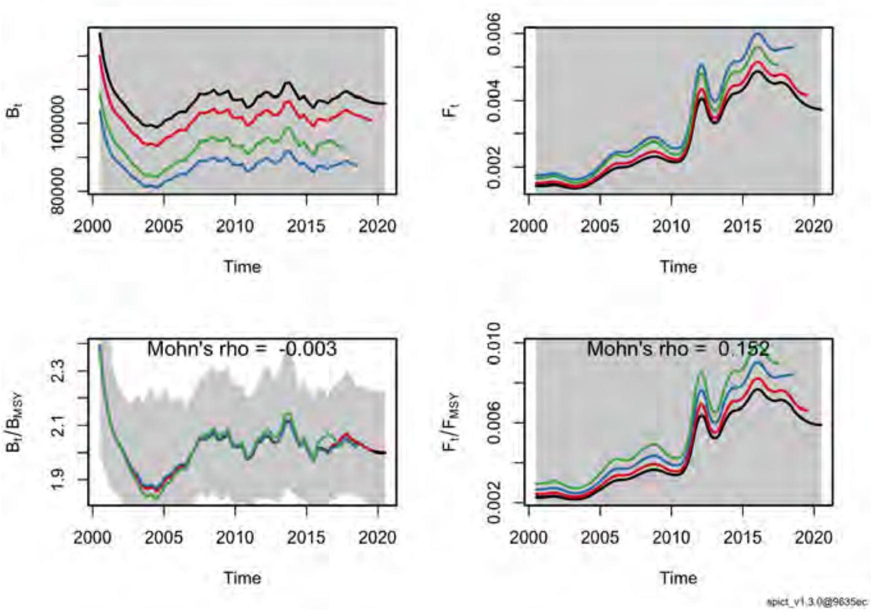
```
## [1] TRUE
```

```
r5<- calc.osa.resid(res5)
plotspict.diagnostic(r5)
```




```
r5<- fit.spict(inp5)
```

```
rep5=retro(r5, nretroyear=3)
plotspict.retro(rep5)
```


```
m5=mohns_rho(rep5, what = c("FFmsy", "BBmsy"));m5
```

```
##        FFmsy        BBmsy
##  0.203132943 -0.003441474
```

```
set.seed(123)
check.ini(inp5, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ... model fitted!
##  Trial 2 ... model fitted!
##  Trial 3 ... model fitted!
##  Trial 4 ... model fitted!
##  Trial 5 ... model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ... model fitted!
##  Trial 8 ... model fitted!
##  Trial 9 ... model fitted!
##  Trial 10 ... model fitted!
##  Trial 11 ... model fitted!
##  Trial 12 ... model fitted!
##  Trial 13 ... model fitted!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ... model fitted!
##  Trial 17 ... model fitted!
##  Trial 18 ... model fitted!
##  Trial 19 ... model fitted!
##  Trial 20 ... model fitted!
```

```
## $propchng
##            logm  logK  logq  logq  logq logsdb logs
df logsdi logsdi logsdi
## Trial 1  -0.13  0.23  0.06 -0.24 -0.27   1.30  -0.
08  -1.12  -0.15   0.12
## Trial 2  -0.03  0.14 -0.04  0.25 -0.25   0.73   1.
31   0.49  -1.30  -1.11
## Trial 3   0.08  0.40 -0.10 -0.13 -0.03  -0.27   0.
60   1.01  -1.32  -1.15
## Trial 4   0.18 -0.38  0.01 -0.16  0.18   0.52   0.
77   1.02   0.24   0.25
## Trial 5  -0.21 -0.29  0.17  0.02  0.14  -1.02   1.
30   0.17  -0.86   1.08
## Trial 6  -0.18 -0.30 -0.16 -0.24  0.08  -0.47   1.
16   0.33   0.65  -0.90
## Trial 7   0.19  0.25 -0.18  0.04 -0.16  -0.37  -0.
60   1.43   0.07   0.80
## Trial 8   0.07 -0.12  0.24  0.16 -0.10   0.24  -0.
82   1.14   0.19  -1.39
## Trial 9   0.23 -0.26  0.23 -0.09  0.10  -0.45   0.
51   0.89  -0.81   1.16
## Trial 10  0.01  0.08  0.10  0.01 -0.28   0.05  -1.
12  -1.19  -0.31   0.26
## Trial 11  0.26 -0.16  0.27 -0.28 -0.14   1.02  -0.
14  -1.30  -0.24   0.27
## Trial 12 -0.11 -0.15  0.17  0.08 -0.30   0.99   1.
17   1.02  -0.54  -0.34
## Trial 13  0.10  0.19 -0.01 -0.10 -0.20  -0.82  -1.
37   0.17   0.54   0.26
## Trial 14 -0.19  0.27  0.17  0.16  0.26   0.73  -0.
66  -0.99   0.01   0.32
## Trial 15 -0.23 -0.09 -0.04  0.18  0.03   0.81  -0.
01   0.42  -0.43   0.36
## Trial 16  0.02  0.19  0.17  0.05  0.14  -0.37   0.
90  -1.04  -0.71  -0.48
## Trial 17 -0.08  0.02 -0.23 -0.05 -0.21   0.54  -0.
60   0.67  -0.27   0.05
## Trial 18  0.04  0.33 -0.25  0.14  0.11  -1.39  -0.
34  -1.25   0.10   0.27
## Trial 19 -0.21  0.06  0.16 -0.29 -0.06  -0.04   0.
28  -1.09   0.39   0.61
## Trial 20 -0.20 -0.01  0.15  0.18 -0.11   1.29  -0.
57   0.42   0.26  -0.92
##           logsdc
## Trial 1    -1.31
## Trial 2    -0.55
## Trial 3    -0.55
## Trial 4     0.38
## Trial 5    -0.17
## Trial 6     0.15
## Trial 7     0.34
## Trial 8    -1.12
## Trial 9     0.10
## Trial 10    1.01
```

```
## Trial 11  -0.42
## Trial 12  -1.12
## Trial 13   1.40
## Trial 14   0.73
## Trial 15   0.41
## Trial 16  -0.34
## Trial 17   0.67
## Trial 18  -0.46
## Trial 19   0.94
## Trial 20  -1.20
##
## $inimat
##          Distance logK logm logq1 logq2 logq3 logs
db logsdf logsdi1 logsdi2
## Basevec      0.00 7.64 5.74 -7.45 -7.45 -7.45  -1.
61  -1.61   -1.61   -1.61
## Trial 1      4.72 6.66 7.07 -7.87 -5.68 -5.42  -3.
70  -1.48    0.20   -1.37
## Trial 2      4.73 7.43 6.56 -7.11 -9.28 -5.61  -2.
78  -3.72   -2.40    0.48
## Trial 3      4.43 8.29 8.02 -6.73 -6.49 -7.24  -1.
18  -2.58   -3.23    0.52
## Trial 4      3.92 9.00 3.55 -7.55 -6.26 -8.75  -2.
45  -2.85   -3.25   -2.00
## Trial 5      4.49 6.04 4.08 -8.68 -7.60 -8.52   0.
04  -3.70   -1.88   -0.23
## Trial 6      4.17 6.29 4.03 -6.28 -5.63 -8.03  -0.
85  -3.48   -2.14   -2.65
## Trial 7      3.99 9.07 7.18 -6.09 -7.72 -6.28  -1.
01  -0.64   -3.91   -1.72
## Trial 8      4.42 8.16 5.06 -9.24 -8.63 -6.67  -1.
99  -0.28   -3.44   -1.91
## Trial 9      4.22 9.42 4.25 -9.15 -6.74 -8.17  -0.
89  -2.44   -3.05   -0.31
## Trial 10     3.89 7.69 6.20 -8.22 -7.50 -5.35  -1.
69   0.19    0.30   -1.11
## Trial 11     4.71 9.65 4.83 -9.47 -5.39 -6.43  -3.
26  -1.38    0.48   -1.22
## Trial 12     4.65 6.81 4.86 -8.74 -8.05 -5.22  -3.
20  -3.49   -3.26   -0.73
## Trial 13     4.16 8.44 6.84 -7.35 -6.71 -5.97  -0.
29   0.60   -1.89   -2.48
## Trial 14     4.25 6.19 7.32 -8.69 -8.65 -9.40  -2.
78  -0.54   -0.01   -1.62
## Trial 15     2.95 5.85 5.24 -7.12 -8.75 -7.70  -2.
91  -1.60   -2.28   -0.92
## Trial 16     3.42 7.80 6.85 -8.73 -7.85 -8.53  -1.
01  -3.07    0.07   -0.47
## Trial 17     3.18 7.05 5.88 -5.72 -7.07 -5.88  -2.
47  -0.65   -2.69   -1.17
## Trial 18     4.36 7.94 7.65 -5.60 -8.49 -8.27   0.
63  -1.06    0.40   -1.76
## Trial 19     3.97 6.04 6.08 -8.65 -5.32 -6.98  -1.
54  -2.06    0.14   -2.24
```

```
## Trial 20     4.20 6.13 5.66 -8.58 -8.75 -6.64 -13.
69  -0.68   -2.29   -2.03
##          logsdi3 logsdc
## Basevec    -1.61  -1.61
## Trial 1    -1.81   0.49
## Trial 2     0.18  -0.72
## Trial 3     0.24  -0.73
## Trial 4    -2.01  -2.21
## Trial 5    -3.35  -1.33
## Trial 6    -0.16  -1.85
## Trial 7    -2.90  -2.16
## Trial 8     0.62   0.20
## Trial 9    -3.48  -1.76
## Trial 10   -2.02  -3.23
## Trial 11   -2.05  -0.93
## Trial 12   -1.06   0.19
## Trial 13   -2.03  -3.86
## Trial 14   -2.13  -2.78
## Trial 15   -2.19  -2.28
## Trial 16   -0.83  -1.07
## Trial 17   -1.70  -2.69
## Trial 18   -2.04  -0.88
## Trial 19   -2.58  -3.13
## Trial 20   -0.13   0.32
##
## $resmat
##             Distance         m         K    q q    q
  sdb  sdf  sdi  sdi  sdi
## Basevec       0.00  33939.18 106630.89 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 1   97938.31  71194.57  16055.24 0.00 0 0.00
 0.11 0.23 0.17 0.10 0.22
## Trial 2       0.19  33939.17 106630.71 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 3       0.81  33939.00 106630.11 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 4       0.35  33939.12 106630.55 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 5       0.33  33939.11 106630.56 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 6       0.19  33939.16 106630.71 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 7       0.34  33939.11 106630.56 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 8       0.31  33939.14 106630.58 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 9       2.46  33938.47 106628.54 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 10      0.01  33939.19 106630.88 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 11      0.20  33939.25 106631.08 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 12      0.67  33939.40 106631.52 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
```

```
## Trial 13      0.31  33939.12 106630.59 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 14 116517.86 103381.45  13067.10 0.00 0 0.00
 0.09 0.24 0.17 0.03 0.27
## Trial 15      0.51  33939.06 106630.40 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 16      0.75  33939.11 106630.15 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
## Trial 17 111150.84    641.26    584.87 0.01 0 0.04
 0.04 0.05 0.01 0.21 0.16
## Trial 18  97938.33  71194.64  16055.25 0.00 0 0.00
 0.11 0.23 0.17 0.10 0.22
## Trial 19  97938.33  71194.62  16055.24 0.00 0 0.00
 0.11 0.23 0.17 0.10 0.22
## Trial 20      0.48  33939.08 106630.43 0.00 0 0.00
 0.09 0.23 0.16 0.09 0.22
##           sdc
## Basevec  0.06
## Trial 1  0.06
## Trial 2  0.06
## Trial 3  0.06
## Trial 4  0.06
## Trial 5  0.06
## Trial 6  0.06
## Trial 7  0.06
## Trial 8  0.06
## Trial 9  0.06
## Trial 10 0.06
## Trial 11 0.06
## Trial 12 0.06
## Trial 13 0.06
## Trial 14 0.06
## Trial 15 0.06
## Trial 16 0.06
## Trial 17 0.15
## Trial 18 0.06
## Trial 19 0.06
## Trial 20 0.06
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
##  [1] 2001.833 2002.833 2003.833 2004.833 2005.833
2006.833 2007.833 2008.833
```

```
##  [9] 2009.833 2010.833 2011.833 2012.833 2013.833
2014.833 2015.833 2016.833
## [17] 2017.833 2018.833 2019.833
##
## [[2]]
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5
##
## [[3]]
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[1]]
##  [1] 0.8830629 0.7655780 0.7023948 0.7199932 0.816
7087 0.8987942 0.8824258
##  [8] 0.7693151 0.7487957 0.7009754 0.7251867 0.907
7803 1.2142796 1.2089463
## [15] 1.0609294 1.0135286 1.0703598 0.9796291 0.871
3699
##
## [[2]]
##  [1] 0.3138639 0.2610667 0.2522755 0.2296472 0.223
1178 0.2361038 0.2368988
##  [8] 0.2844170 0.2899648 0.2973215 0.2912091 0.281
3124 0.2904401 0.2978007
## [15] 0.2447735 0.2211997 0.2381125 0.2700604 0.262
6929
##
## [[3]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
```

```
(calc.om(res5))
```

```
##        lower  est upper CI range order magnitude
## B/Bmsy  1.79 2.00  2.23     0.44               0
## F/Fmsy  0.00 0.01  8.74     8.74               6
```

17 RUN 5b: Using three abundance indices: CPUE, Spanish survey and the LPUE. Fixing n to resemble the Schaefer production

model.

```
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)

## Indices Spanish_CPUE
I_sol8c9a <- data.frame(obsI = data$CPUE,timeI = 2000
:2019)

## Indices Portugues_LPUE
I2_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)

## Indices Spanish_survey
I3_sol8c9a <- data.frame(obsI =data$Survey,timeI = 20
00:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp5b<- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_so
l8c9a$obsC,
             timeI = list(I_sol8c9a$timeI+0.5,I2_sol8
c9a$timeI+0.5,I3_sol8c9a$timeI+0.8333333),
             obsI = list(I_sol8c9a$obsI,I2_sol8c9a$ob
sI,I3_sol8c9a$obsI))


inp5b=check.inp(inp5b)
```

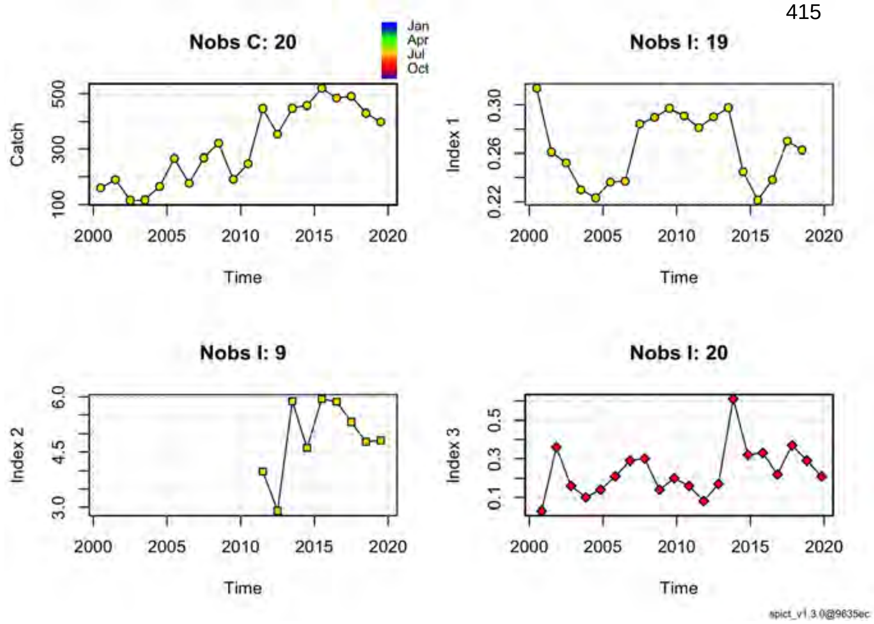
```
## Removing zero, negative, and NAs in  I  series  1

## Removing zero, negative, and NAs in  I  series  2
```

```
inp5b$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

```
plotspict.data(inp5b)
```




```
inp5b$stdevfacC <- rep(1, length(inp5b$obsC))
inp5b$stdevfacC[1:10] <- 5
```

Fixing n to resemble the Schaefer production model (or the meta study, alternatively):

```
inp5b$ini$logn <- log(2); inp5b$phases$logn <- -1
```

Numerical solver time step (probably don't need to change)

```
inp5b$dteuler <- 1/16
```

The model is fitted to data by running

```
res5b <- fit.spict(inp5b)
```

The results are summarised using

```
capture.output(summary(res5b))
```

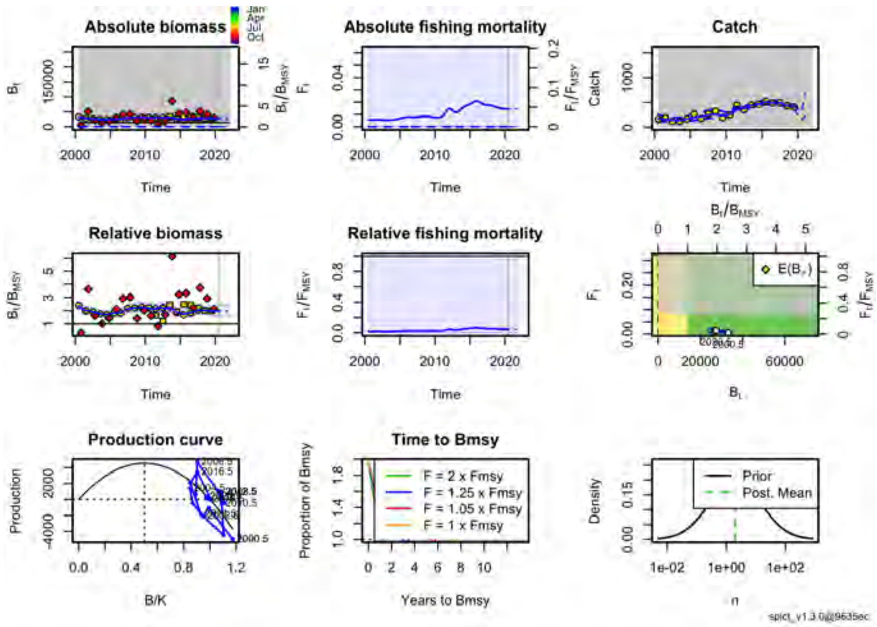
```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: 25.0773627"

##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 19,  Nobs I2: 9,  Nobs
 I3: 20"
##  [5] ""

##  [6] "Priors"

##  [7] "     logn  ~  dnorm[log(2), 2^2]"
```

```
## [8] " logalpha  ~  dnorm[log(1), 2^2]"

## [9] "  logbeta  ~  dnorm[log(1), 2^2]"

## [10] ""

## [11] "Fixed parameters"

## [12] "   fixed.value  "

## [13] " n           2  "

## [14] ""

## [15] "Model parameter estimates w 95% CI "

## [16] "            estimate      cilow        ciupp
     log.est  "
## [17] " alpha1 2.607784e-01  0.0308710 2.202892e+00
  -1.3440842  "
## [18] " alpha2 2.612503e+00  1.3630446 5.007298e+00
   0.9603086  "
## [19] " alpha3 6.392900e+00  3.6117754 1.131553e+01
   1.8551879  "
## [20] " beta   2.145758e-01  0.0623576 7.383673e-01
  -1.5390920  "
## [21] " r      6.415621e-01  0.2117392 1.943910e+00
  -0.4438492  "
## [22] " rc     6.415621e-01  0.2117392 1.943910e+00
  -0.4438492  "
## [23] " rold   6.415621e-01  0.2117392 1.943910e+00
  -0.4438492  "
## [24] " m      4.530761e+03 10.6420284 1.928936e+06
   8.4186452  "
## [25] " K      2.824831e+04 56.6172985 1.409405e+07
  10.2487888  "
## [26] " q1     9.400000e-06  0.0000000 5.208400e-03
 -11.5754198  "
## [27] " q2     1.720000e-04  0.0000003 9.591230e-02
  -8.6682364  "
## [28] " q3     7.100000e-06  0.0000000 3.973200e-03
 -11.8540795  "
## [29] " sdb    1.024036e-01  0.0632886 1.656932e-01
  -2.2788336  "
## [30] " sdf    2.522840e-01  0.1399547 4.547703e-01
  -1.3771997  "
## [31] " sdi1   2.670460e-02  0.0036415 1.958348e-01
  -3.6229179  "
## [32] " sdi2   2.675296e-01  0.1685996 4.245092e-01
  -1.3185250  "
## [33] " sdi3   6.546558e-01  0.4813812 8.903009e-01
  -0.4236457  "
## [34] " sdc    5.413410e-02  0.0237646 1.233137e-01
```

```
  -2.9162917  "
## [35] " "

## [36] "Deterministic reference points (Drp)"

## [37] "           estimate      cilow        ciupp
  log.est  "
## [38] " Bmsyd 1.412415e+04 28.3086493 7.047023e+06
 9.555642  "
## [39] " Fmsyd 3.207811e-01  0.1058696 9.719552e-01
-1.136996  "
## [40] " MSYd  4.530761e+03 10.6420284 1.928936e+06
 8.418645  "
## [41] "Stochastic reference points (Srp)"

## [42] "           estimate      cilow        ciupp
  log.est rel.diff.Drp  "
## [43] " Bmsys 1.396041e+04 27.9865376 6.963812e+06
 9.543981 -0.011729275  "
## [44] " Fmsys 3.182551e-01  0.1045224 9.690398e-01
-1.144902 -0.007936949  "
## [45] " MSYs  4.442558e+03 10.4375360 1.890898e+06
 8.398986 -0.019854194  "
## [46] ""

## [47] "States w 95% CI (inp$msytype: s)"

## [48] "                    estimate      cilow
   ciupp    log.est  "
## [49] " B_2020.44      2.740778e+04 47.9501418 1.56
6599e+07 10.2185821  "
## [50] " F_2020.44      1.442570e-02  0.0000251 8.28
7459e+00 -4.2387444  "
## [51] " B_2020.44/Bmsy 1.963251e+00  1.5777248 2.44
2982e+00  0.6746015  "
## [52] " F_2020.44/Fmsy 4.532740e-02  0.0000925 2.22
1665e+01 -3.0938425  "
## [53] ""

## [54] "Predictions w 95% CI (inp$msytype: s)"

## [55] "                  prediction       cilow
    ciupp    log.est  "
## [56] " B_2022.00      2.739173e+04  47.7059444 1.5
72774e+07 10.2179964  "
## [57] " F_2022.00      1.442590e-02   0.0000244 8.5
39046e+00 -4.2387275  "
## [58] " B_2022.00/Bmsy 1.962101e+00   1.5605735 2.4
66940e+00  0.6740158  "
## [59] " F_2022.00/Fmsy 4.532820e-02   0.0000897 2.2
90865e+01 -3.0938256  "
## [60] " Catch_2021.00  3.952070e+02 225.4978307 6.9
26388e+02  5.9794096  "
## [61] " E(B_inf)       2.714269e+04          NA
```

```
      NA 10.2088631  "                              418
```

```
plot(res5b)
```



18 Checklist for the acceptance of a SPiCT assessment

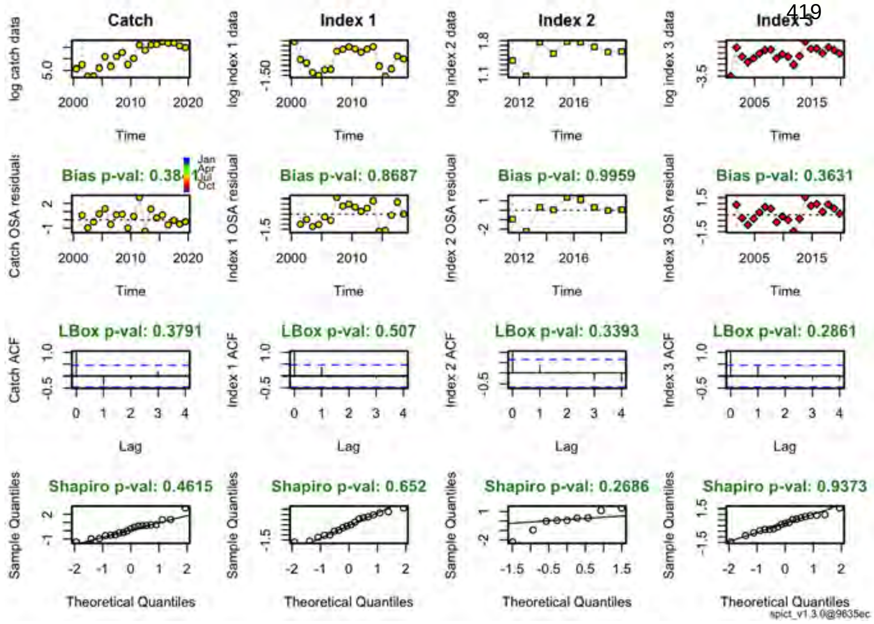
```
res5b$opt$convergence
```

```
## [1] 0
```

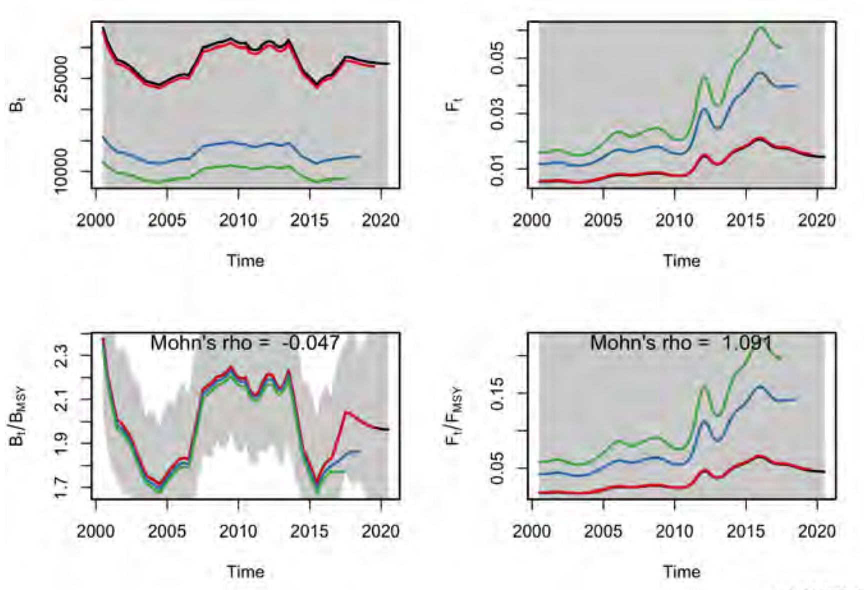
```
all(is.finite(res5b$sd))
```

```
## [1] TRUE
```

```
r5b<- calc.osa.resid(res5b)
plotspict.diagnostic(r5b)
```




```
r5b<- fit.spict(inp5b)
rep5b=retro(r5b, nretroyear=3)
plotspict.retro(rep5b)
```




```
m5b=mohns_rho(rep5b, what = c("FFmsy", "BBmsy"));m5b
```

```
##       FFmsy       BBmsy
##  1.45488326 -0.06271142
```

```
set.seed(123)
check.ini(inp5b, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  model fitted!
##  Trial 2 ... model fitted!
##  Trial 3 ... model fitted!
##  Trial 4 ... model fitted!
##  Trial 5 ... model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ... model fitted!
##  Trial 8 ... model fitted!
##  Trial 9 ... model fitted!
##  Trial 10 ... model fitted!
##  Trial 11 ... model fitted!
##  Trial 12 ... model fitted!
##  Trial 13 ... model fitted!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ... model fitted!
##  Trial 17 ... model fitted!
##  Trial 18 ... model fitted!
##  Trial 19 ... model fitted!
##  Trial 20 ... model fitted!
## $propchng
##           logm  logK  logq  logq  logq logsdb logs
df logsdi logsdi logsdi
## Trial 1  -0.13  0.23  0.05 -0.20 -0.23   1.30  -0.
08  -1.12  -0.15   0.12
## Trial 2  -0.03  0.14 -0.04  0.21 -0.21   0.73   1.
31   0.49  -1.30  -1.11
## Trial 3   0.08  0.40 -0.08 -0.11 -0.02  -0.27   0.
60   1.01  -1.32  -1.15
## Trial 4   0.18 -0.38  0.01 -0.14  0.15   0.52   0.
77   1.02   0.24   0.25
## Trial 5  -0.21 -0.29  0.14  0.02  0.12  -1.02   1.
30   0.17  -0.86   1.08
## Trial 6  -0.18 -0.30 -0.13 -0.21  0.07  -0.47   1.
16   0.33   0.65  -0.90
## Trial 7   0.19  0.25 -0.15  0.03 -0.13  -0.37  -0.
60   1.43   0.07   0.80
## Trial 8   0.07 -0.12  0.20  0.13 -0.09   0.24  -0.
82   1.14   0.19  -1.39
## Trial 9   0.23 -0.26  0.19 -0.08  0.08  -0.45   0.
51   0.89  -0.81   1.16
## Trial 10  0.01  0.08  0.09  0.01 -0.24   0.05  -1.
12  -1.19  -0.31   0.26
## Trial 11  0.26 -0.16  0.23 -0.23 -0.12   1.02  -0.
14  -1.30  -0.24   0.27
## Trial 12 -0.11 -0.15  0.15  0.07 -0.25   0.99   1.
17   1.02  -0.54  -0.34
## Trial 13  0.10  0.19 -0.01 -0.08 -0.17  -0.82  -1.
```

```
37   0.17   0.54   0.26
## Trial 14 -0.19  0.27  0.14  0.14  0.22   0.73  -0.
66  -0.99   0.01   0.32
## Trial 15 -0.23 -0.09 -0.04  0.15  0.03   0.81  -0.
01   0.42  -0.43   0.36
## Trial 16  0.02  0.19  0.15  0.05  0.12  -0.37   0.
90  -1.04  -0.71  -0.48
## Trial 17 -0.08  0.02 -0.20 -0.04 -0.18   0.54  -0.
60   0.67  -0.27   0.05
## Trial 18  0.04  0.33 -0.21  0.12  0.09  -1.39  -0.
34  -1.25   0.10   0.27
## Trial 19 -0.21  0.06  0.14 -0.24 -0.05  -0.04   0.
28  -1.09   0.39   0.61
## Trial 20 -0.20 -0.01  0.13  0.15 -0.09   1.29  -0.
57   0.42   0.26  -0.92
##          logsdc
## Trial 1   -1.31
## Trial 2   -0.55
## Trial 3   -0.55
## Trial 4    0.38
## Trial 5   -0.17
## Trial 6    0.15
## Trial 7    0.34
## Trial 8   -1.12
## Trial 9    0.10
## Trial 10   1.01
## Trial 11  -0.42
## Trial 12  -1.12
## Trial 13   1.40
## Trial 14   0.73
## Trial 15   0.41
## Trial 16  -0.34
## Trial 17   0.67
## Trial 18  -0.46
## Trial 19   0.94
## Trial 20  -1.20
##
## $inimat
##          Distance logK logm  logq1  logq2  logq3 l
ogsdb logsdf logsdi1 logsdi2
## Basevec      0.00 7.64 5.74  -8.80  -8.80  -8.80
-1.61  -1.61   -1.61   -1.61
## Trial 1      4.72 6.66 7.07  -9.22  -7.04  -6.77
-3.70  -1.48    0.20   -1.37
## Trial 2      4.73 7.43 6.56  -8.47 -10.63  -6.96
-2.78  -3.72   -2.40    0.48
## Trial 3      4.43 8.29 8.02  -8.08  -7.84  -8.60
-1.18  -2.58   -3.23    0.52
## Trial 4      3.92 9.00 3.55  -8.90  -7.61 -10.11
-2.45  -2.85   -3.25   -2.00
## Trial 5      4.49 6.04 4.08 -10.03  -8.96  -9.88
 0.04  -3.70   -1.88   -0.23
## Trial 6      4.17 6.29 4.03  -7.63  -6.98  -9.38
-0.85  -3.48   -2.14   -2.65
```

```
## Trial 7      3.99 9.07 7.18  -7.44  -9.08  -7.63
-1.01  -0.64   -3.91   -1.72
## Trial 8      4.42 8.16 5.06 -10.59  -9.98  -8.03
-1.99  -0.28   -3.44   -1.91
## Trial 9      4.22 9.42 4.25 -10.50  -8.09  -9.52
-0.89  -2.44   -3.05   -0.31
## Trial 10     3.89 7.69 6.20  -9.57  -8.85  -6.71
-1.69   0.19    0.30   -1.11
## Trial 11     4.71 9.65 4.83 -10.82  -6.74  -7.78
-3.26  -1.38    0.48   -1.22
## Trial 12     4.65 6.81 4.86 -10.09  -9.40  -6.57
-3.20  -3.49   -3.26   -0.73
## Trial 13     4.16 8.44 6.84  -8.70  -8.06  -7.32
-0.29   0.60   -1.89   -2.48
## Trial 14     4.25 6.19 7.32 -10.04 -10.00 -10.75
-2.78  -0.54   -0.01   -1.62
## Trial 15     2.95 5.85 5.24  -8.47 -10.10  -9.05
-2.91  -1.60   -2.28   -0.92
## Trial 16     3.42 7.80 6.85 -10.08  -9.20  -9.88
-1.01  -3.07    0.07   -0.47
## Trial 17     3.18 7.05 5.88  -7.07  -8.42  -7.24
-2.47  -0.65   -2.69   -1.17
## Trial 18     4.36 7.94 7.65  -6.95  -9.84  -9.62
 0.63  -1.06    0.40   -1.76
## Trial 19     3.97 6.04 6.08 -10.00  -6.67  -8.33
-1.54  -2.06    0.14   -2.24
## Trial 20     4.20 6.13 5.66  -9.94 -10.11  -8.00
-3.69  -0.68   -2.29   -2.03
##          logsdi3 logsdc
## Basevec    -1.61  -1.61
## Trial 1    -1.81   0.49
## Trial 2     0.18  -0.72
## Trial 3     0.24  -0.73
## Trial 4    -2.01  -2.21
## Trial 5    -3.35  -1.33
## Trial 6    -0.16  -1.85
## Trial 7    -2.90  -2.16
## Trial 8     0.62   0.20
## Trial 9    -3.48  -1.76
## Trial 10   -2.02  -3.23
## Trial 11   -2.05  -0.93
## Trial 12   -1.06   0.19
## Trial 13   -2.03  -3.86
## Trial 14   -2.13  -2.78
## Trial 15   -2.19  -2.28
## Trial 16   -0.83  -1.07
## Trial 17   -1.70  -2.69
## Trial 18   -2.04  -0.88
## Trial 19   -2.58  -3.13
## Trial 20   -0.13   0.32
##
## $resmat
##          Distance        m        K q q q  sdb  sd
f  sdi  sdi  sdi  sdc
```

```
## Basevec      0.00  4530.76 28248.31 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 1  33701.71 27345.10  3442.83 0 0 0 0.10 0.2
4 0.02 0.27 0.62 0.06
## Trial 2      0.73  4530.88 28249.03 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 3      0.20  4530.75 28248.11 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 4      0.04  4530.76 28248.27 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 5      0.06  4530.76 28248.37 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 6      0.22  4530.73 28248.08 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 7  31547.14 27458.23  6579.13 0 0 0 0.14 0.2
3 0.10 0.22 0.63 0.06
## Trial 8      0.29  4530.80 28248.60 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 9      0.07  4530.74 28248.24 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 10     0.00  4530.76 28248.31 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 11     0.25  4530.80 28248.55 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 12     0.10  4530.76 28248.20 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 13 31547.46 27458.68  6579.14 0 0 0 0.14 0.2
3 0.10 0.22 0.63 0.06
## Trial 14     0.18  4530.73 28248.13 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 15     0.09  4530.75 28248.21 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 16     0.79  4530.87 28249.09 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 17     1.37  4530.55 28246.95 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
## Trial 18 31547.49 27458.76  6579.18 0 0 0 0.14 0.2
3 0.10 0.22 0.63 0.06
## Trial 19 31547.36 27458.54  6579.13 0 0 0 0.14 0.2
3 0.10 0.22 0.63 0.06
## Trial 20     0.05  4530.77 28248.36 0 0 0 0.10 0.2
5 0.03 0.27 0.65 0.05
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
```

```
## Index observations:
## [[1]]
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5
##
## [[2]]
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[3]]
##  [1] 2000.833 2001.833 2002.833 2003.833 2004.833
2005.833 2006.833 2007.833
##  [9] 2008.833 2009.833 2010.833 2011.833 2012.833
2013.833 2014.833 2015.833
## [17] 2016.833 2017.833 2018.833 2019.833
##
## [[1]]
##  [1] 0.3138639 0.2610667 0.2522755 0.2296472 0.223
1178 0.2361038 0.2368988
##  [8] 0.2844170 0.2899648 0.2973215 0.2912091 0.281
3124 0.2904401 0.2978007
## [15] 0.2447735 0.2211997 0.2381125 0.2700604 0.262
6929
##
## [[2]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
##
## [[3]]
##  [1] 0.03 0.36 0.16 0.10 0.14 0.21 0.29 0.30 0.14
0.20 0.16 0.08 0.17 0.61 0.32
## [16] 0.33 0.22 0.37 0.29 0.21
```

```
(calc.om(res5b))
```

```
##         lower  est upper CI range order magnitude
## B/Bmsy  1.58 1.96  2.44     0.87               0
## F/Fmsy  0.00 0.05 22.22    22.22               6
```

19 Run 6: Using three abundance indices: Portugues LPUE, the Spanish survey (spat index)

and CPUE from Spain. Fixing n to resemble the Schaefer production model and set priors for the ratio between biomass in the initial year relative to K, mean of log(0.5) and sd of 0.2.

```
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)

## Indices Spanish_survey
I_sol8c9a <- data.frame(obsI = data$Spat_index,timeI
= 2000:2019)

## Indices Portugues_LPUE
I2_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)

## Indices CPUE Spain
I3_sol8c9a <- data.frame(obsI =data$CPUE,timeI = 2000
:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp6<- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_sol
8c9a$obsC,
             timeI = list(I_sol8c9a$timeI+0.8333333,I
2_sol8c9a$timeI+0.5, I3_sol8c9a$timeI+0.5),
             obsI = list(I_sol8c9a$obsI,I2_sol8c9a$ob
sI,I3_sol8c9a$obsI))


inp6=check.inp(inp6)
```

```
## Removing zero, negative, and NAs in  I  series  1

## Removing zero, negative, and NAs in  I  series  2

## Removing zero, negative, and NAs in  I  series  3
```

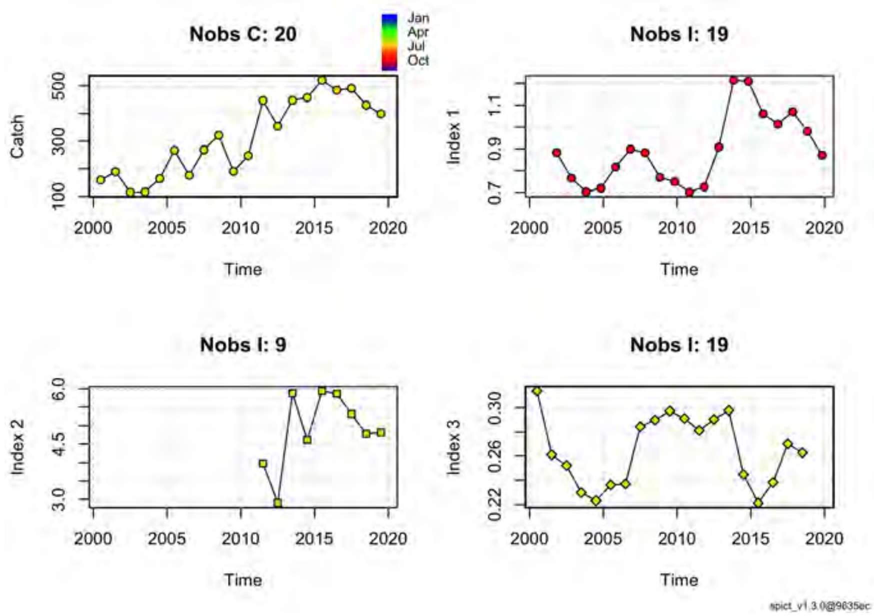
```
inp6$dtc
```



```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

```
plotspict.data(inp6)
```




```
inp6$stdevfacC <- rep(1, length(inp6$obsC))
inp6$stdevfacC[1:10] <- 5
```

```
inp6$priors$logbkfrac <- c(log(0.5), 0.2, 1)
#inp$priors$logsdf<- c(log(0.3), 0.2, 1)
```

```
inp6$ini$logn <- log(2); inp6$phases$logn <- -1
```

Numerical solver time step (probably don't need to change)

```
inp6$dteuler <- 1/16
```

The model is fitted to data by running

```
res6 <- fit.spict(inp6)
```

The results are summarised using

```
capture.output(summary(res6))
```

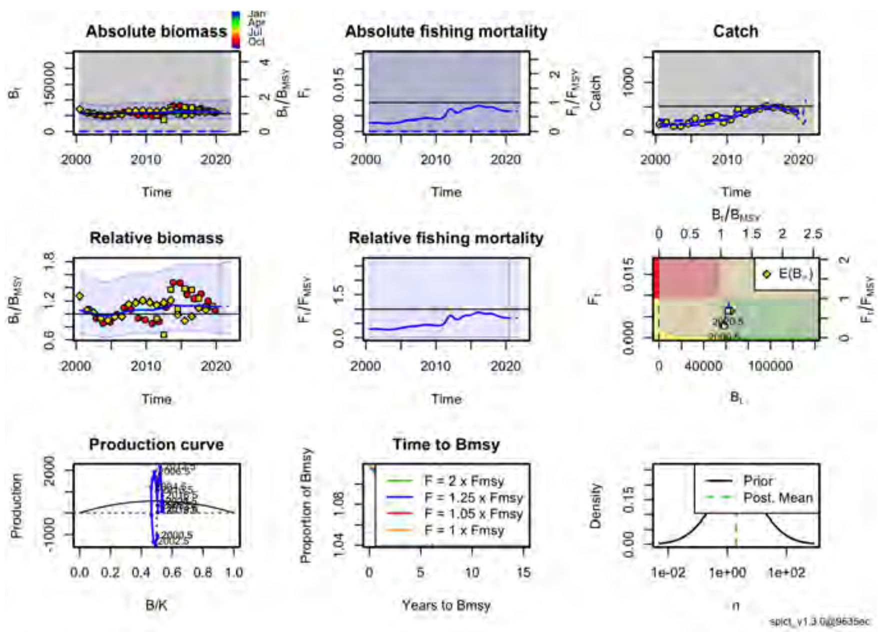
```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: -1.6798814"
```

```
##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 19,  Nobs I2: 9,  Nobs
 I3: 19"
##  [5] ""

##  [6] "Priors"

##  [7] "      logn  ~  dnorm[log(2), 2^2]"

##  [8] "  logalpha  ~  dnorm[log(1), 2^2]"

##  [9] "   logbeta  ~  dnorm[log(1), 2^2]"

## [10] " logbkfrac  ~  dnorm[log(0.5), 0.2^2]"

## [11] ""

## [12] "Fixed parameters"

## [13] "   fixed.value  "

## [14] " n           2  "

## [15] ""

## [16] "Model parameter estimates w 95% CI "

## [17] "            estimate       cilow        ciup
p     log.est  "
## [18] " alpha1 3.333001e+00   0.7527496 1.475776e+0
1   1.2038731  "
## [19] " alpha2 4.807982e+00   1.1827748 1.954446e+0
1   1.5702775  "
## [20] " alpha3 2.591255e+00   0.5755145 1.166713e+0
1   0.9521422  "
## [21] " beta   2.786592e-01   0.0489851 1.585194e+0
0  -1.2777658  "
## [22] " r      1.945240e-02   0.0003256 1.162060e+0
0  -3.9397864  "
## [23] " rc     1.945240e-02   0.0003256 1.162060e+0
0  -3.9397864  "
## [24] " rold   1.945240e-02   0.0003256 1.162060e+0
0  -3.9397864  "
## [25] " m      5.660947e+02  10.6089951 3.020675e+0
4   6.3387614  "
## [26] " K      1.164063e+05 190.4083007 7.116513e+0
7  11.6648421  "
## [27] " q1     1.480000e-05   0.0000000 8.820600e-0
3 -11.1181422  "
## [28] " q2     7.750000e-05   0.0000001 4.625740e-0
2  -9.4653621  "
## [29] " q3     4.500000e-06   0.0000000 2.643000e-0
```

```
3 -12.3203771  "
## [30] " sdb    4.294200e-02   0.0113639 1.622696e-0
1  -3.1479040  "
## [31] " sdf    2.212564e-01   0.0939952 5.208183e-0
1  -1.5084329  "
## [32] " sdi1   1.431259e-01   0.0920284 2.225944e-0
1  -1.9440310  "
## [33] " sdi2   2.064646e-01   0.1269041 3.359041e-0
1  -1.5776265  "
## [34] " sdi3   1.112738e-01   0.0651523 1.900447e-0
1  -2.1957618  "
## [35] " sdc    6.165510e-02   0.0226667 1.677069e-0
1  -2.7861987  "
## [36] " "

## [37] "Deterministic reference points (Drp)"

## [38] "           estimate      cilow        ciupp
  log.est  "
## [39] " Bmsyd 5.820316e+04 95.2041503 3.558257e+07
10.971695  "
## [40] " Fmsyd 9.726200e-03  0.0001628 5.810303e-01
-4.632934  "
## [41] " MSYd  5.660947e+02 10.6089951 3.020675e+04
 6.338761  "
## [42] "Stochastic reference points (Srp)"

## [43] "           estimate       cilow        ciupp
   log.est rel.diff.Drp  "
## [44] " Bmsys 5.541740e+04 104.1366706 2.949094e+07
 10.922649  -0.05026869  "
## [45] " Fmsys 9.265200e-03   0.0001265 6.787626e-01
 -4.681491  -0.04975446  "
## [46] " MSYs  5.121686e+02   9.7131139 2.700645e+04
  6.238654  -0.10528975  "
## [47] ""

## [48] "States w 95% CI (inp$msytype: s)"

## [49] "                     estimate      cilow
   ciupp    log.est  "
## [50] " B_2020.44      6.186107e+04 98.9106355 3.86
8939e+07 11.0326463  "
## [51] " F_2020.44      6.414500e-03  0.0000102 4.01
7219e+00 -5.0491909  "
## [52] " B_2020.44/Bmsy 1.116275e+00  0.7042819 1.76
9278e+00  0.1099974  "
## [53] " F_2020.44/Fmsy 6.923247e-01  0.0110400 4.34
1603e+01 -0.3677001  "
## [54] ""

## [55] "Predictions w 95% CI (inp$msytype: s)"

## [56] "                   prediction       cilow
```

```
    ciupp    log.est  "
## [57] " B_2022.00      6.203186e+04  97.2211916 3.9
57935e+07 11.0354034  "
## [58] " F_2022.00      6.414800e-03   0.0000100 4.1
08924e+00 -5.0491532  "
## [59] " B_2022.00/Bmsy 1.119357e+00   0.6914074 1.8
12188e+00  0.1127545  "
## [60] " F_2022.00/Fmsy 6.923509e-01   0.0106589 4.4
97180e+01 -0.3676624  "
## [61] " Catch_2021.00  3.975433e+02 243.5778391 6.4
88303e+02  5.9853039  "
## [62] " E(B_inf)       6.452534e+04          NA
       NA 11.0748133  "
```

```
plot(res6)
```



20 Checklist for the acceptance of a SPiCT assessment

```
res6$opt$convergence
```

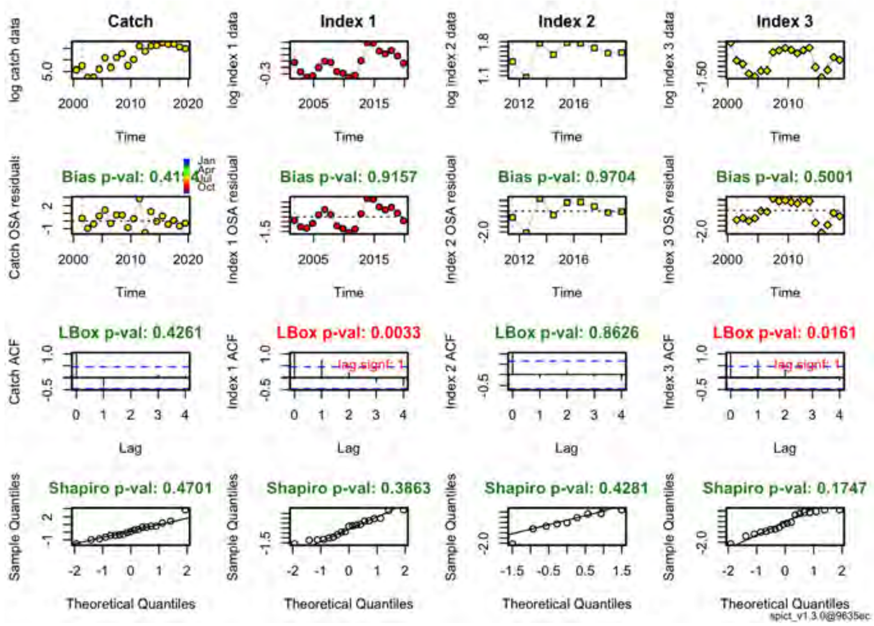
```
## [1] 0
```

```
all(is.finite(res6$sd))
```

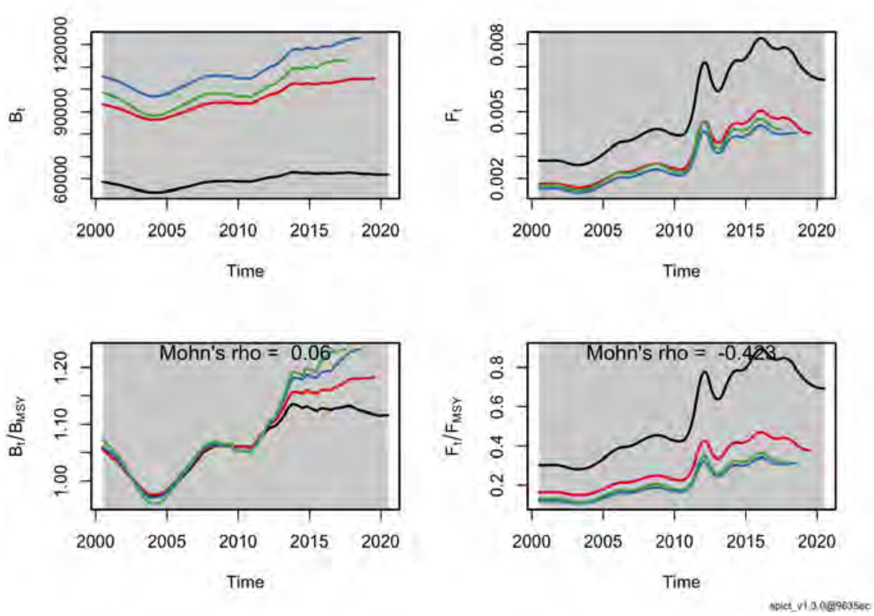
```
## [1] TRUE
```

```
r6 <- calc.osa.resid(res6)
```

```
plotspict.diagnostic(r6)
```




```
r6<- fit.spict(inp6)
rep6=retro(r6, nretroyear=3)
plotspict.retro(rep6)
```




```
m6=mohns_rho(rep6, what = c("FFmsy", "BBmsy"));m6
```

```
##      FFmsy      BBmsy
## -0.5641415  0.0796907
```

```
set.seed(123)
check.ini(inp6, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
```

```
alues...
##  Trial 1 ... model fitted!
##  Trial 2 ... model fitted!
##  Trial 3 ... model fitted!
##  Trial 4 ... model fitted!
##  Trial 5 ... model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ... model fitted!
##  Trial 8 ... model fitted!
##  Trial 9 ... model fitted!
##  Trial 10 ... model fitted!
##  Trial 11 ... model fitted!
##  Trial 12 ... model fitted!
##  Trial 13 ... model fitted!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ... model fitted!
##  Trial 17 ... model fitted!
##  Trial 18 ... model fitted!
##  Trial 19 ... model fitted!
##  Trial 20 ... model fitted!
## $propchng
##           logm  logK  logq  logq  logq logsdb logs
df logsdi logsdi logsdi
## Trial 1  -0.13  0.23  0.06 -0.24 -0.27   1.30  -0.
08  -1.12  -0.15   0.12
## Trial 2  -0.03  0.14 -0.04  0.25 -0.25   0.73   1.
31   0.49  -1.30  -1.11
## Trial 3   0.08  0.40 -0.10 -0.13 -0.03  -0.27   0.
60   1.01  -1.32  -1.15
## Trial 4   0.18 -0.38  0.01 -0.16  0.18   0.52   0.
77   1.02   0.24   0.25
## Trial 5  -0.21 -0.29  0.17  0.02  0.14  -1.02   1.
30   0.17  -0.86   1.08
## Trial 6  -0.18 -0.30 -0.16 -0.24  0.08  -0.47   1.
16   0.33   0.65  -0.90
## Trial 7   0.19  0.25 -0.18  0.04 -0.16  -0.37  -0.
60   1.43   0.07   0.80
## Trial 8   0.07 -0.12  0.24  0.16 -0.10   0.24  -0.
82   1.14   0.19  -1.39
## Trial 9   0.23 -0.26  0.23 -0.09  0.10  -0.45   0.
51   0.89  -0.81   1.16
## Trial 10  0.01  0.08  0.10  0.01 -0.28   0.05  -1.
12  -1.19  -0.31   0.26
## Trial 11  0.26 -0.16  0.27 -0.28 -0.14   1.02  -0.
14  -1.30  -0.24   0.27
## Trial 12 -0.11 -0.15  0.17  0.08 -0.30   0.99   1.
17   1.02  -0.54  -0.34
## Trial 13  0.10  0.19 -0.01 -0.10 -0.20  -0.82  -1.
37   0.17   0.54   0.26
## Trial 14 -0.19  0.27  0.17  0.16  0.26   0.73  -0.
66  -0.99   0.01   0.32
## Trial 15 -0.23 -0.09 -0.04  0.18  0.03   0.81  -0.
01   0.42  -0.43   0.36
```

```
## Trial 16  0.02  0.19  0.17  0.05  0.14  -0.37  -0.
90  -1.04  -0.71  -0.48
## Trial 17 -0.08  0.02 -0.23 -0.05 -0.21   0.54  -0.
60   0.67  -0.27   0.05
## Trial 18  0.04  0.33 -0.25  0.14  0.11  -1.39  -0.
34  -1.25   0.10   0.27
## Trial 19 -0.21  0.06  0.16 -0.29 -0.06  -0.04   0.
28  -1.09   0.39   0.61
## Trial 20 -0.20 -0.01  0.15  0.18 -0.11   1.29  -0.
57   0.42   0.26  -0.92
##          logsdc
## Trial 1   -1.31
## Trial 2   -0.55
## Trial 3   -0.55
## Trial 4    0.38
## Trial 5   -0.17
## Trial 6    0.15
## Trial 7    0.34
## Trial 8   -1.12
## Trial 9    0.10
## Trial 10   1.01
## Trial 11  -0.42
## Trial 12  -1.12
## Trial 13   1.40
## Trial 14   0.73
## Trial 15   0.41
## Trial 16  -0.34
## Trial 17   0.67
## Trial 18  -0.46
## Trial 19   0.94
## Trial 20  -1.20
##
## $inimat
##          Distance logK logm logq1 logq2 logq3 logs
db logsdf logsdi1 logsdi2
## Basevec      0.00 7.64 5.74 -7.45 -7.45 -7.45  -1.
61  -1.61   -1.61   -1.61
## Trial 1      4.72 6.66 7.07 -7.87 -5.68 -5.42  -3.
70  -1.48    0.20   -1.37
## Trial 2      4.73 7.43 6.56 -7.11 -9.28 -5.61  -2.
78  -3.72   -2.40    0.48
## Trial 3      4.43 8.29 8.02 -6.73 -6.49 -7.24  -1.
18  -2.58   -3.23    0.52
## Trial 4      3.92 9.00 3.55 -7.55 -6.26 -8.75  -2.
45  -2.85   -3.25   -2.00
## Trial 5      4.49 6.04 4.08 -8.68 -7.60 -8.52   0.
04  -3.70   -1.88   -0.23
## Trial 6      4.17 6.29 4.03 -6.28 -5.63 -8.03  -0.
85  -3.48   -2.14   -2.65
## Trial 7      3.99 9.07 7.18 -6.09 -7.72 -6.28  -1.
01  -0.64   -3.91   -1.72
## Trial 8      4.42 8.16 5.06 -9.24 -8.63 -6.67  -1.
99  -0.28   -3.44   -1.91
## Trial 9      4.22 9.42 4.25 -9.15 -6.74 -8.17  -0.
```

```
89  -2.44   -3.05   -0.31                            433
## Trial 10     3.89 7.69 6.20 -8.22 -7.50 -5.35  -1.
69   0.19    0.30   -1.11
## Trial 11     4.71 9.65 4.83 -9.47 -5.39 -6.43  -3.
26  -1.38    0.48   -1.22
## Trial 12     4.65 6.81 4.86 -8.74 -8.05 -5.22  -3.
20  -3.49   -3.26   -0.73
## Trial 13     4.16 8.44 6.84 -7.35 -6.71 -5.97  -0.
29   0.60   -1.89   -2.48
## Trial 14     4.25 6.19 7.32 -8.69 -8.65 -9.40  -2.
78  -0.54   -0.01   -1.62
## Trial 15     2.95 5.85 5.24 -7.12 -8.75 -7.70  -2.
91  -1.60   -2.28   -0.92
## Trial 16     3.42 7.80 6.85 -8.73 -7.85 -8.53  -1.
01  -3.07    0.07   -0.47
## Trial 17     3.18 7.05 5.88 -5.72 -7.07 -5.88  -2.
47  -0.65   -2.69   -1.17
## Trial 18     4.36 7.94 7.65 -5.60 -8.49 -8.27   0.
63  -1.06    0.40   -1.76
## Trial 19     3.97 6.04 6.08 -8.65 -5.32 -6.98  -1.
54  -2.06    0.14   -2.24
## Trial 20     4.20 6.13 5.66 -8.58 -8.75 -6.64  -3.
69  -0.68   -2.29   -2.03
##            logsdi3 logsdc
## Basevec    -1.61  -1.61
## Trial 1    -1.81   0.49
## Trial 2     0.18  -0.72
## Trial 3     0.24  -0.73
## Trial 4    -2.01  -2.21
## Trial 5    -3.35  -1.33
## Trial 6    -0.16  -1.85
## Trial 7    -2.90  -2.16
## Trial 8     0.62   0.20
## Trial 9    -3.48  -1.76
## Trial 10   -2.02  -3.23
## Trial 11   -2.05  -0.93
## Trial 12   -1.06   0.19
## Trial 13   -2.03  -3.86
## Trial 14   -2.13  -2.78
## Trial 15   -2.19  -2.28
## Trial 16   -0.83  -1.07
## Trial 17   -1.70  -2.69
## Trial 18   -2.04  -0.88
## Trial 19   -2.58  -3.13
## Trial 20   -0.13   0.32
##
## $resmat
##            Distance        m         K q q q  sdb
sdf  sdi  sdi  sdi  sdc
## Basevec       0.00   566.09 116406.32 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 1  114830.28 45579.78  10766.55 0 0 0 0.10 0
.23 0.17 0.22 0.11 0.06
## Trial 2       0.14   566.10 116406.46 0 0 0 0.04 0
```

```
.22 0.14 0.21 0.11 0.06
## Trial 3       0.06   566.09 116406.26 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 4       1.16   566.10 116407.48 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 5       0.06   566.09 116406.26 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 6       0.76   566.10 116407.08 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 7       0.08   566.10 116406.40 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 8       0.01   566.09 116406.34 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 9       0.04   566.09 116406.28 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 10 114830.31 45579.73  10766.49 0 0 0 0.10 0
.23 0.17 0.22 0.11 0.06
## Trial 11      0.00   566.09 116406.33 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 12      0.11   566.10 116406.21 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 13      0.07   566.09 116406.25 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 14      0.03   566.09 116406.35 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 15      0.08   566.09 116406.24 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 16      0.25   566.09 116406.57 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 17      0.41   566.09 116405.91 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
## Trial 18 114830.29 45579.80  10766.55 0 0 0 0.10 0
.23 0.17 0.22 0.11 0.06
## Trial 19 114830.30 45579.82  10766.55 0 0 0 0.10 0
.23 0.17 0.22 0.11 0.06
## Trial 20      0.21   566.10 116406.53 0 0 0 0.04 0
.22 0.14 0.21 0.11 0.06
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
##  [1] 2001.833 2002.833 2003.833 2004.833 2005.833
2006.833 2007.833 2008.833
##  [9] 2009.833 2010.833 2011.833 2012.833 2013.833
```

```
2014.833 2015.833 2016.833
## [17] 2017.833 2018.833 2019.833
##
## [[2]]
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[3]]
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5
##
## [[1]]
##  [1] 0.8830629 0.7655780 0.7023948 0.7199932 0.816
7087 0.8987942 0.8824258
##  [8] 0.7693151 0.7487957 0.7009754 0.7251867 0.907
7803 1.2142796 1.2089463
## [15] 1.0609294 1.0135286 1.0703598 0.9796291 0.871
3699
##
## [[2]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
##
## [[3]]
##  [1] 0.3138639 0.2610667 0.2522755 0.2296472 0.223
1178 0.2361038 0.2368988
##  [8] 0.2844170 0.2899648 0.2973215 0.2912091 0.281
3124 0.2904401 0.2978007
## [15] 0.2447735 0.2211997 0.2381125 0.2700604 0.262
6929
```

```
(calc.om(res6))
```

```
##         lower  est upper CI range order magnitude
## B/Bmsy  0.70 1.12  1.77     1.06               1
## F/Fmsy  0.01 0.69 43.42    43.40               3
```

21 Run 7: Using three abundance indices: Portugues LPUE and the Spanish survey and CPUE. Fixing n to resemble the

Schaefer production model and set priors for the ratio between biomass in the initial year relative to K, mean of log(0.5) and sd of 0.2.

```
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)

## Indices Spanish_survey
I_sol8c9a <- data.frame(obsI = data$Survey,timeI = 20
00:2019)

## Indices Portugues_LPUE
I2_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)


## Indices Spanish CPUE
I3_sol8c9a <- data.frame(obsI =data$CPUE,timeI = 2000
:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp7 <- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_so
l8c9a$obsC,
             timeI = list(I_sol8c9a$timeI+0.8333333,I
2_sol8c9a$timeI+0.5,I3_sol8c9a$timeI+0.5),
             obsI = list(I_sol8c9a$obsI,I2_sol8c9a$ob
sI, I3_sol8c9a$obsI))


inp7=check.inp(inp7)
```

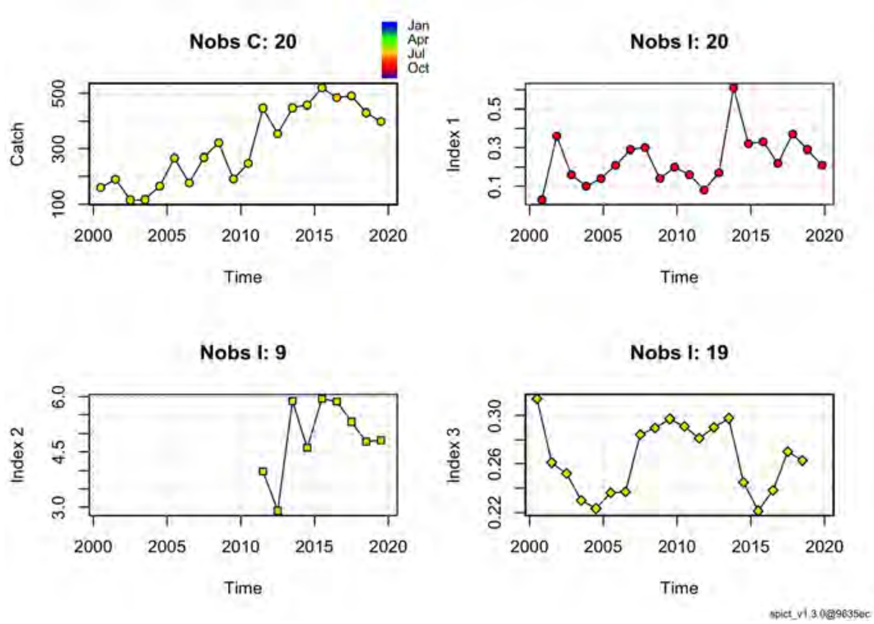
```
## Removing zero, negative, and NAs in  I  series  2

## Removing zero, negative, and NAs in  I  series  3
```

```
inp7$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

```
plotspict.data(inp7)
```




```
inp7$stdevfacC <- rep(1, length(inp7$obsC))
inp7$stdevfacC[1:10] <- 5
```

```
inp7$priors$logbkfrac <- c(log(0.5), 0.2, 1)
#inp$priors$logsdf<- c(log(0.3), 0.2, 1)
```

```
inp7$ini$logn <- log(2); inp7$phases$logn <- -1
```

Numerical solver time step (probably don't need to change)

```
inp7$dteuler <- 1/16
```

The model is fitted to data by running

```
res7<- fit.spict(inp7)
```

The results are summarised using

```
capture.output(summary(res7))
```

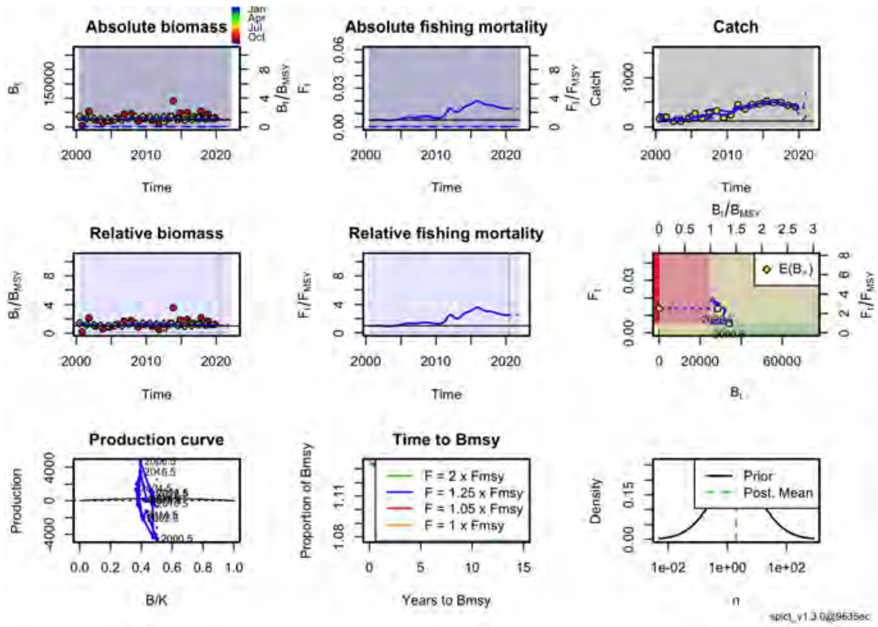
```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: 24.0624551"

##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 20,  Nobs I2: 9,  Nobs
 I3: 19"
```

```
##  [5] ""

##  [6] "Priors"

##  [7] "      logn  ~  dnorm[log(2), 2^2]"

##  [8] "  logalpha  ~  dnorm[log(1), 2^2]"

##  [9] "   logbeta  ~  dnorm[log(1), 2^2]"

## [10] " logbkfrac  ~  dnorm[log(0.5), 0.2^2]"

## [11] ""

## [12] "Fixed parameters"

## [13] "   fixed.value  "

## [14] " n           2  "

## [15] ""

## [16] "Model parameter estimates w 95% CI "

## [17] "            estimate       cilow        ciup
p    log.est  "
## [18] " alpha1 7.392680e+00   4.3273558 1.262936e+0
1   2.000490  "
## [19] " alpha2 3.017673e+00   1.6372146 5.562100e+0
0   1.104486  "
## [20] " alpha3 3.432670e-01   0.0396995 2.968103e+0
0  -1.069247  "
## [21] " beta   2.118004e-01   0.0609156 7.364194e-0
1  -1.552111  "
## [22] " r      1.500960e-02   0.0000023 9.956698e+0
1  -4.199065  "
## [23] " rc     1.500960e-02   0.0000023 9.956698e+0
1  -4.199065  "
## [24] " rold   1.500960e-02   0.0000023 9.956698e+0
1  -4.199065  "
## [25] " m      2.550116e+02   1.7666774 3.680973e+0
4   5.541309  "
## [26] " K      6.795959e+04 160.5783738 2.876169e+0
7  11.126668  "
## [27] " q1     6.800000e-06   0.0000000 2.756400e-0
3 -11.897760  "
## [28] " q2     1.646000e-04   0.0000004 6.644650e-0
2  -8.711984  "
## [29] " q3     9.000000e-06   0.0000000 3.613900e-0
3 -11.618277  "
## [30] " sdb    8.857360e-02   0.0565802 1.386578e-0
1  -2.423921  "
## [31] " sdf    2.551866e-01   0.1421124 4.582302e-0
1  -1.365760  "
```

```
## [32] " sdi1   6.547963e-01   0.4816526 8.901815e-0
1  -0.423431  "
## [33] " sdi2   2.672862e-01   0.1683886 4.242680e-0
1  -1.319435  "
## [34] " sdi3   3.040440e-02   0.0045721 2.021879e-0
1  -3.493168  "
## [35] " sdc    5.404860e-02   0.0234846 1.243904e-0
1  -2.917871  "
## [36] " "

## [37] "Deterministic reference points (Drp)"

## [38] "           estimate      cilow        ciupp
  log.est  "
## [39] " Bmsyd 3.397979e+04 80.2891869 1.438085e+07
10.433521  "
## [40] " Fmsyd 7.504800e-03  0.0000011 4.978349e+01
-4.892212  "
## [41] " MSYd  2.550116e+02  1.7666774 3.680973e+04
 5.541309  "
## [42] "Stochastic reference points (Srp)"

## [43] "           estimate       cilow        ciupp
   log.est rel.diff.Drp  "
## [44] " Bmsys 2.503242e+04 528.6658846 1.185289e+06
 10.127927   -0.3574315  "
## [45] " Fmsys 5.543500e-03   0.0000000 7.974848e+02
 -5.195128   -0.3538020  "
## [46] " MSYs  1.212190e+02   0.0001349 1.089290e+08
  4.797599   -1.1037262  "
## [47] ""

## [48] "States w 95% CI (inp$msytype: s)"

## [49] "                     estimate      cilow
   ciupp    log.est  "
## [50] " B_2020.44      2.841176e+04 67.3089005 1.19
9289e+07 10.2545585  "
## [51] " F_2020.44      1.387920e-02  0.0000329 5.85
6885e+00 -4.2773647  "
## [52] " B_2020.44/Bmsy 1.134999e+00  0.0530509 2.42
8275e+01  0.1266314  "
## [53] " F_2020.44/Fmsy 2.503684e+00  0.0011851 5.28
9576e+03  0.9177630  "
## [54] ""

## [55] "Predictions w 95% CI (inp$msytype: s)"

## [56] "                   prediction       cilow
    ciupp    log.est  "
## [57] " B_2022.00      2.801392e+04  64.0561752 1.2
25143e+07 10.2404569  "
## [58] " F_2022.00      1.387940e-02   0.0000319 6.0
48293e+00 -4.2773471  "
```

```
## [59] " B_2022.00/Bmsy 1.119106e+00   0.0523185440.3
93793e+01  0.1125298  "
## [60] " F_2022.00/Fmsy 2.503728e+00   0.0011552 5.4
26494e+03  0.9177806  "
## [61] " Catch_2021.00  3.906799e+02 219.8699513 6.9
41865e+02  5.9678885  "
## [62] " E(B_inf)       0.000000e+00          NA
       NA          NA  "
```

```
plot(res7)
```



22 Checklist for the acceptance of a SPiCT assessment

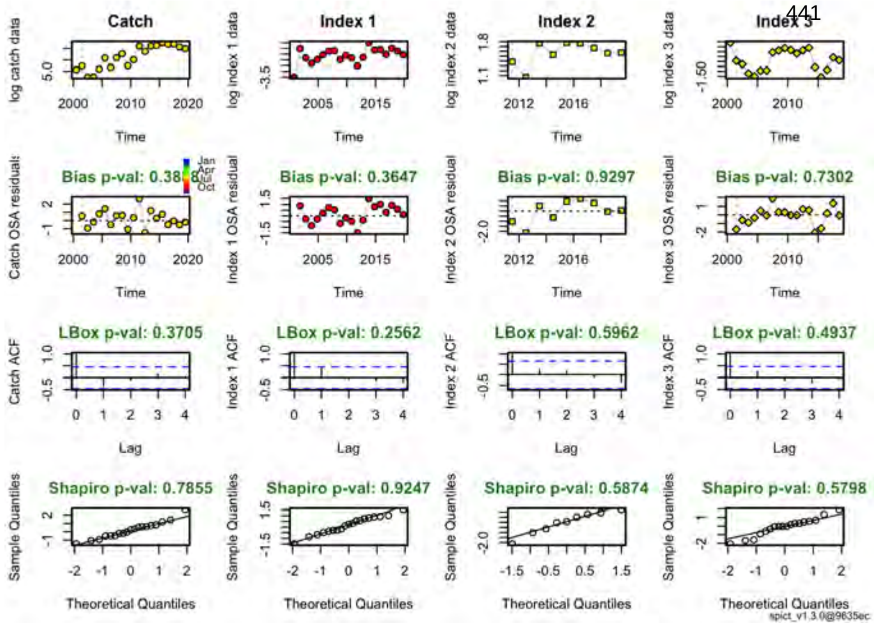
```
res7$opt$convergence
```

```
## [1] 0
```

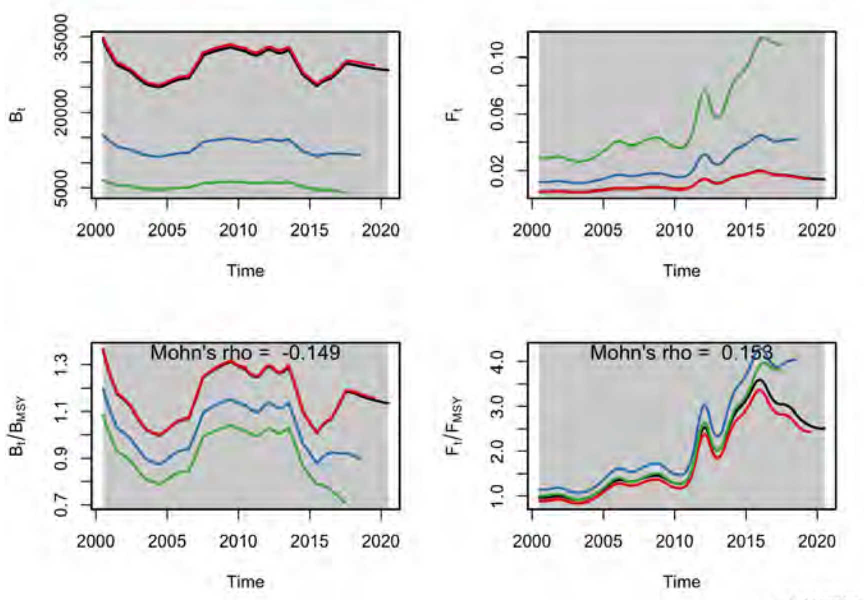
```
all(is.finite(res7$sd))
```

```
## [1] TRUE
```

```
r7<- calc.osa.resid(res7)
plotspict.diagnostic(r7)
```



```
r7<- fit.spict(inp7)
rep7=retro(r7, nretroyear=3)
plotspict.retro(rep7)
```



```
m7=mohns_rho(rep7, what = c("FFmsy", "BBmsy"));m7
```

```
##      FFmsy      BBmsy
##  0.2041707 -0.1991812
```

```
set.seed(123)
check.ini(inp7, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ... model fitted!
```

```
##  Trial 2 ... model fitted!
##  Trial 3 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 4 ... model fitted!
##  Trial 5 ... model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ... convergence not obtained!
##  Trial 8 ... model fitted!
##  Trial 9 ... model fitted!
##  Trial 10 ... model fitted!
##  Trial 11 ... model fitted!
##  Trial 12 ... model fitted!
##  Trial 13 ... model fitted!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ... model fitted!
##  Trial 17 ... model fitted!
##  Trial 18 ... model fitted!
##  Trial 19 ... model fitted!
##  Trial 20 ... model fitted!
## $propchng
##           logm  logK  logq  logq  logq logsdb logs
df logsdi logsdi logsdi
## Trial 1  -0.13  0.23  0.05 -0.22 -0.25   1.30  -0.
08  -1.12  -0.15   0.12
## Trial 2  -0.03  0.14 -0.04  0.22 -0.23   0.73   1.
31   0.49  -1.30  -1.11
## Trial 3   0.08  0.40 -0.09 -0.12 -0.02  -0.27   0.
60   1.01  -1.32  -1.15
## Trial 4   0.18 -0.38  0.01 -0.15  0.16   0.52   0.
77   1.02   0.24   0.25
## Trial 5  -0.21 -0.29  0.15  0.02  0.13  -1.02   1.
30   0.17  -0.86   1.08
## Trial 6  -0.18 -0.30 -0.14 -0.22  0.07  -0.47   1.
16   0.33   0.65  -0.90
## Trial 7   0.19  0.25 -0.17  0.03 -0.14  -0.37  -0.
```

```
60   1.43   0.07   0.80
## Trial 8   0.07 -0.12  0.22  0.15 -0.10   0.24  -0.
82   1.14   0.19  -1.39
## Trial 9   0.23 -0.26  0.21 -0.09  0.09  -0.45   0.
51   0.89  -0.81   1.16
## Trial 10  0.01  0.08  0.09  0.01 -0.26   0.05  -1.
12  -1.19  -0.31   0.26
## Trial 11  0.26 -0.16  0.25 -0.25 -0.12   1.02  -0.
14  -1.30  -0.24   0.27
## Trial 12 -0.11 -0.15  0.16  0.07 -0.27   0.99   1.
17   1.02  -0.54  -0.34
## Trial 13  0.10  0.19 -0.01 -0.09 -0.18  -0.82  -1.
37   0.17   0.54   0.26
## Trial 14 -0.19  0.27  0.15  0.15  0.24   0.73  -0.
66  -0.99   0.01   0.32
## Trial 15 -0.23 -0.09 -0.04  0.16  0.03   0.81  -0.
01   0.42  -0.43   0.36
## Trial 16  0.02  0.19  0.16  0.05  0.13  -0.37   0.
90  -1.04  -0.71  -0.48
## Trial 17 -0.08  0.02 -0.21 -0.05 -0.19   0.54  -0.
60   0.67  -0.27   0.05
## Trial 18  0.04  0.33 -0.23  0.13  0.10  -1.39  -0.
34  -1.25   0.10   0.27
## Trial 19 -0.21  0.06  0.15 -0.26 -0.06  -0.04   0.
28  -1.09   0.39   0.61
## Trial 20 -0.20 -0.01  0.14  0.16 -0.10   1.29  -0.
57   0.42   0.26  -0.92
##          logsdc
## Trial 1   -1.31
## Trial 2   -0.55
## Trial 3   -0.55
## Trial 4    0.38
## Trial 5   -0.17
## Trial 6    0.15
## Trial 7    0.34
## Trial 8   -1.12
## Trial 9    0.10
## Trial 10   1.01
## Trial 11  -0.42
## Trial 12  -1.12
## Trial 13   1.40
## Trial 14   0.73
## Trial 15   0.41
## Trial 16  -0.34
## Trial 17   0.67
## Trial 18  -0.46
## Trial 19   0.94
## Trial 20  -1.20
##
## $inimat
##          Distance logK logm  logq1 logq2  logq3 lo
gsdb logsdf logsdi1 logsdi2
## Basevec      0.00 7.64 5.74  -8.14 -8.14  -8.14  -
1.61  -1.61   -1.61   -1.61
```

```
## Trial 1      4.72 6.66 7.07  -8.55 -6.37  -6.11  -
3.70  -1.48    0.20   -1.37
## Trial 2      4.73 7.43 6.56  -7.80 -9.96  -6.29  -
2.78  -3.72   -2.40    0.48
## Trial 3      4.43 8.29 8.02  -7.42 -7.18  -7.93  -
1.18  -2.58   -3.23    0.52
## Trial 4      3.92 9.00 3.55  -8.24 -6.95  -9.44  -
2.45  -2.85   -3.25   -2.00
## Trial 5      4.49 6.04 4.08  -9.36 -8.29  -9.21
0.04  -3.70   -1.88   -0.23
## Trial 6      4.17 6.29 4.03  -6.97 -6.32  -8.71  -
0.85  -3.48   -2.14   -2.65
## Trial 7      3.99 9.07 7.18  -6.78 -8.41  -6.96  -
1.01  -0.64   -3.91   -1.72
## Trial 8      4.42 8.16 5.06  -9.93 -9.32  -7.36  -
1.99  -0.28   -3.44   -1.91
## Trial 9      4.22 9.42 4.25  -9.84 -7.43  -8.86  -
0.89  -2.44   -3.05   -0.31
## Trial 10     3.89 7.69 6.20  -8.91 -8.19  -6.04  -
1.69   0.19    0.30   -1.11
## Trial 11     4.71 9.65 4.83 -10.16 -6.07  -7.12  -
3.26  -1.38    0.48   -1.22
## Trial 12     4.65 6.81 4.86  -9.43 -8.74  -5.91  -
3.20  -3.49   -3.26   -0.73
## Trial 13     4.16 8.44 6.84  -8.04 -7.40  -6.65  -
0.29   0.60   -1.89   -2.48
## Trial 14     4.25 6.19 7.32  -9.37 -9.34 -10.08  -
2.78  -0.54   -0.01   -1.62
## Trial 15     2.95 5.85 5.24  -7.80 -9.44  -8.39  -
2.91  -1.60   -2.28   -0.92
## Trial 16     3.42 7.80 6.85  -9.42 -8.54  -9.21  -
1.01  -3.07    0.07   -0.47
## Trial 17     3.18 7.05 5.88  -6.41 -7.76  -6.57  -
2.47  -0.65   -2.69   -1.17
## Trial 18     4.36 7.94 7.65  -6.28 -9.18  -8.96
0.63  -1.06    0.40   -1.76
## Trial 19     3.97 6.04 6.08  -9.34 -6.01  -7.67  -
1.54  -2.06    0.14   -2.24
## Trial 20     4.20 6.13 5.66  -9.27 -9.44  -7.33  -
3.69  -0.68   -2.29   -2.03
##           logsdi3 logsdc
## Basevec    -1.61  -1.61
## Trial 1    -1.81   0.49
## Trial 2     0.18  -0.72
## Trial 3     0.24  -0.73
## Trial 4    -2.01  -2.21
## Trial 5    -3.35  -1.33
## Trial 6    -0.16  -1.85
## Trial 7    -2.90  -2.16
## Trial 8     0.62   0.20
## Trial 9    -3.48  -1.76
## Trial 10   -2.02  -3.23
## Trial 11   -2.05  -0.93
## Trial 12   -1.06   0.19
```

```
## Trial 13   -2.03  -3.86
## Trial 14   -2.13  -2.78
## Trial 15   -2.19  -2.28
## Trial 16   -0.83  -1.07
## Trial 17   -1.70  -2.69
## Trial 18   -2.04  -0.88
## Trial 19   -2.58  -3.13
## Trial 20   -0.13   0.32
##
## $resmat
##           Distance       m         K  q    q  q  sdb
  sdf  sdi  sdi  sdi  sdc
## Basevec      0.00  255.01 67959.59  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 1  67873.37  436.63    86.47  0 0.09  0 0.08
 0.12 0.64 0.27 0.02 0.18
## Trial 2      0.04  255.01 67959.63  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 3      0.00      NA       NA NA   NA NA   NA
   NA   NA   NA   NA   NA
## Trial 4      0.05  255.01 67959.54  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 5      0.68  255.01 67958.91  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 6      0.08  255.01 67959.51  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 7      0.00      NA       NA NA   NA NA   NA
   NA   NA   NA   NA   NA
## Trial 8      0.13  255.01 67959.46  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 9      0.20  255.01 67959.39  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 10     0.04  255.01 67959.63  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 11     0.02  255.01 67959.57  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 12     0.34  255.01 67959.25  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 13 67104.34 3714.05   944.46  0 0.01  0 0.13
 0.24 0.64 0.22 0.11 0.06
## Trial 14     0.03  255.01 67959.62  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 15     0.07  255.01 67959.66  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 16     2.54  255.00 67962.13  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 17 67104.35 3714.02   944.45  0 0.01  0 0.13
 0.24 0.64 0.22 0.11 0.06
## Trial 18 67104.35 3714.05   944.45  0 0.01  0 0.13
 0.24 0.64 0.22 0.11 0.06
## Trial 19     0.44  255.01 67959.14  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
## Trial 20     0.19  255.01 67959.78  0 0.00  0 0.09
 0.26 0.65 0.27 0.03 0.05
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
##  [1] 2000.833 2001.833 2002.833 2003.833 2004.833
2005.833 2006.833 2007.833
##  [9] 2008.833 2009.833 2010.833 2011.833 2012.833
2013.833 2014.833 2015.833
## [17] 2016.833 2017.833 2018.833 2019.833
##
## [[2]]
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[3]]
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5
##
## [[1]]
##  [1] 0.03 0.36 0.16 0.10 0.14 0.21 0.29 0.30 0.14
0.20 0.16 0.08 0.17 0.61 0.32
## [16] 0.33 0.22 0.37 0.29 0.21
##
## [[2]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
##
## [[3]]
##  [1] 0.3138639 0.2610667 0.2522755 0.2296472 0.223
1178 0.2361038 0.2368988
##  [8] 0.2844170 0.2899648 0.2973215 0.2912091 0.281
3124 0.2904401 0.2978007
## [15] 0.2447735 0.2211997 0.2381125 0.2700604 0.262
6929
```

```
(calc.om(res7))
```

```
##        lower  est   upper CI range order magnitude
## B/Bmsy  0.05 1.13   24.28    24.23               3
## F/Fmsy  0.00 2.50 5289.58  5289.57               6
```

23 Run 8: Using two abundance indices: Portugues LPUE and CPUE. Fixing n to resemble the Schaefer production model and set priors for the ratio between biomass in the initial year relative to K, mean of log(0.5) and sd of 0.2. Adding uncertunity to Portugal index

```
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)


## Indices Portugues LPUE
I2_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)

## Indices CPUE Spain
I3_sol8c9a <- data.frame(obsI =data$CPUE,timeI = 2000
:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp8<- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_sol
8c9a$obsC,
             timeI = list(I2_sol8c9a$timeI+0.5, I3_so
l8c9a$timeI+0.5),
             obsI = list(I2_sol8c9a$obsI,I3_sol8c9a$o
bsI))



inp8<-check.inp(inp8)
```

```
## Removing zero, negative, and NAs in  I  series  1
```

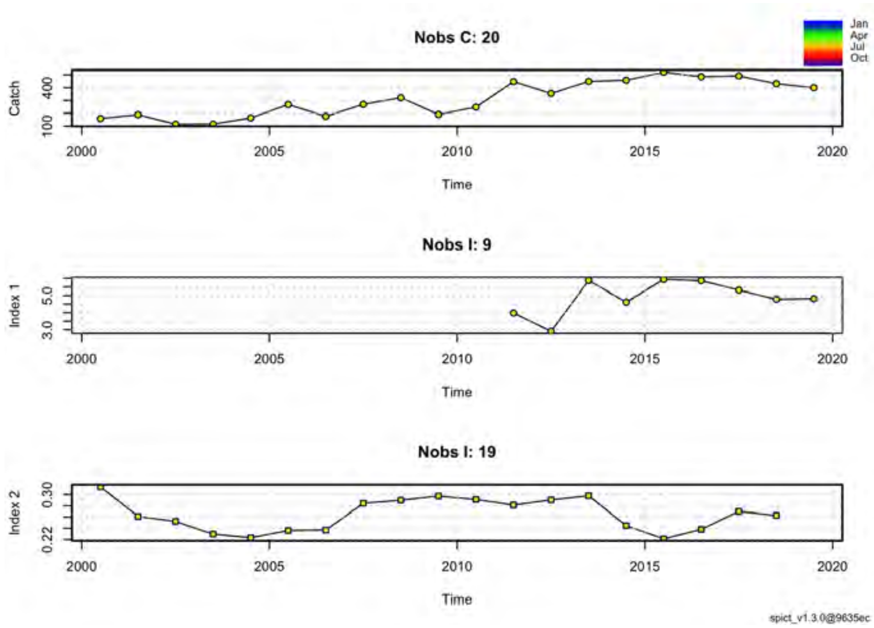
```
## Removing zero, negative, and NAs in  I  series  2
```

```
inp8$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

```
plotspict.data(inp8)
```




```
inp8$stdevfacC <- rep(1, length(inp8$obsC))
inp8$stdevfacC[1:10] <- 5
```

```
inp8$stdevfacI[[2]] <- rep(5,length(inp8$stdevfacI[[2
]]))
```

```
inp8$priors$logbkfrac <- c(log(0.5), 0.2, 1)
#inp$priors$logsdf<- c(log(0.3), 0.2, 1)
```

```
inp8$ini$logn <- log(2); inp8$phases$logn <- -1
```

Numerical solver time step (probably don't need to change)

```
inp8$dteuler <- 1/16
```

The model is fitted to data by running

```
res8 <- fit.spict(inp8)
```

The results are summarised using

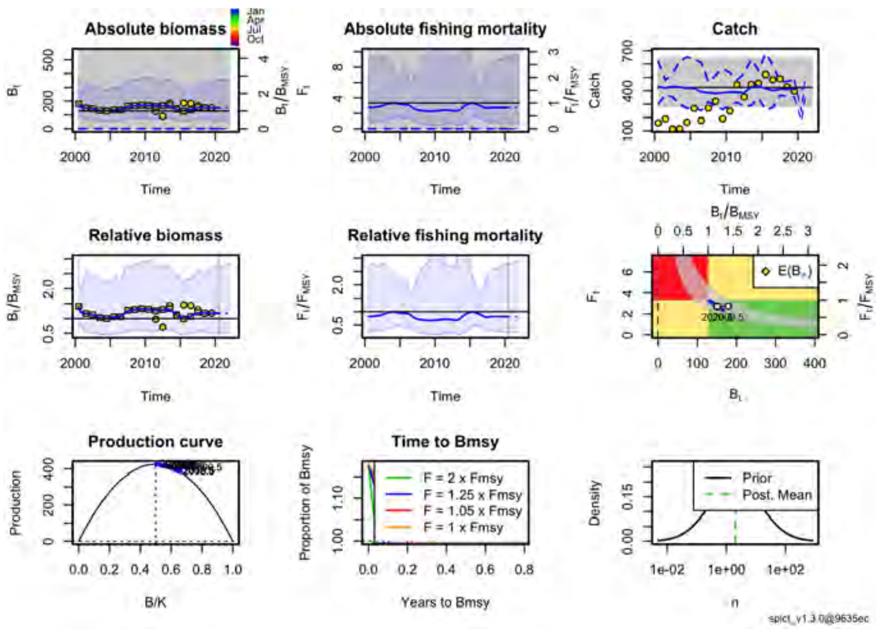
```
capture.output(summary(res8))
```

```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: 7.8656409"

##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 9,  Nobs I2: 19"

##  [5] ""

##  [6] "Priors"

##  [7] "      logn  ~  dnorm[log(2), 2^2]"

##  [8] "  logalpha  ~  dnorm[log(1), 2^2]"

##  [9] "   logbeta  ~  dnorm[log(1), 2^2]"

## [10] " logbkfrac  ~  dnorm[log(0.5), 0.2^2]"

## [11] ""

## [12] "Fixed parameters"

## [13] "   fixed.value  "

## [14] " n           2  "

## [15] ""

## [16] "Model parameter estimates w 95% CI "

## [17] "           estimate       cilow        ciupp
    log.est  "
## [18] " alpha1   8.6482763   0.7948788 9.409319e+01
  2.1573600  "
## [19] " alpha2   0.1692564   0.0103891 2.757477e+00
 -1.7763404  "
## [20] " beta     1.5254801   0.2918163 7.974501e+00
  0.4223092  "
## [21] " r        6.6596708   0.0022514 1.969953e+04
  1.8960701  "
## [22] " rc       6.6596708   0.0022514 1.969953e+04
  1.8960701  "
## [23] " rold     6.6596708   0.0022514 1.969953e+04
  1.8960701  "
## [24] " m      425.3089000 278.4801256 6.495532e+02
  6.0528157  "
## [25] " K      255.4534064   0.1202703 5.425817e+05
  5.5430400  "
```

```
## [26] " q1       0.0319032   0.0000268 3.793245e-01
 -3.4450485  "
## [27] " q2       0.0017439   0.0000015 2.065008e+00
 -6.3516227  "
## [28] " sdb      0.0307644   0.0028784 3.288043e-01
 -3.4813986  "
## [29] " sdf      0.1191076   0.0323619 4.383744e-01
 -2.1277280  "
## [30] " sdi1     0.2660586   0.1695013 4.176204e-01
 -1.3240385  "
## [31] " sdi2     0.0052071   0.0008812 3.076790e-02
 -5.2577390  "
## [32] " sdc      0.1816963   0.1102685 2.993922e-01
 -1.7054188  "
## [33] " "

## [34] "Deterministic reference points (Drp)"

## [35] "         estimate       cilow       ciupp  l
og.est  "
## [36] " Bmsyd 127.726703   0.0601351 271290.8738 4.
849893  "
## [37] " Fmsyd   3.329835   0.0011257   9849.7658 1.
202923  "
## [38] " MSYd  425.308900 278.4801256    649.5532 6.
052816  "
## [39] "Stochastic reference points (Srp)"

## [40] "         estimate       cilow       ciupp  l
og.est  rel.diff.Drp  "
## [41] " Bmsys 127.706175   0.0605873 269179.5143 4.
849732 -0.0001607487  "
## [42] " Fmsys   3.331082   0.0011415   9720.8637 1.
203297  0.0003743177  "
## [43] " MSYs  425.399803 279.8227955    646.7128 6.
053029  0.0002136891  "
## [44] ""

## [45] "States w 95% CI (inp$msytype: s)"

## [46] "                     estimate     cilow
 ciupp    log.est  "
## [47] " B_2020.44      150.5896765 0.1341393 1.6905
75e+05  5.0145588  "
## [48] " F_2020.44        2.7316399 0.0023141 3.2244
89e+03  1.0049021  "
## [49] " B_2020.44/Bmsy   1.1791887 0.5021802 2.7688
98e+00  0.1648266  "
## [50] " F_2020.44/Fmsy   0.8200458 0.2406561 2.7943
41e+00 -0.1983951  "
## [51] ""

## [52] "Predictions w 95% CI (inp$msytype: s)"
```

```
## [53] "                 prediction       cilow
  ciupp    log.est  "
## [54] " B_2022.00      150.654208   0.1330902 1.705
361e+05  5.0149872  "
## [55] " F_2022.00        2.731641   0.0023002 3.243
946e+03  1.0049024  "
## [56] " B_2022.00/Bmsy   1.179694   0.4926025 2.825
154e+00  0.1652551  "
## [57] " F_2022.00/Fmsy   0.820046   0.2325529 2.891
709e+00 -0.1983948  "
## [58] " Catch_2021.00  411.529792 344.6439972 4.913
963e+02  6.0198814  "
## [59] " E(B_inf)       150.675342          NA
     NA  5.0151275  "
```

```
plot(res8)
```



24 Checklist for the acceptance of a SPiCT assessment

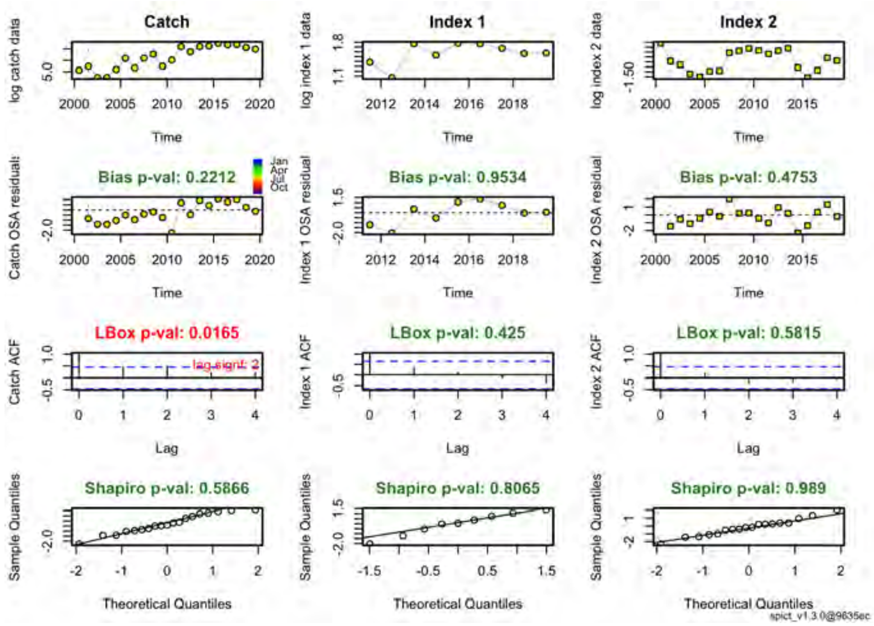
```
res8$opt$convergence
```

```
## [1] 0
```

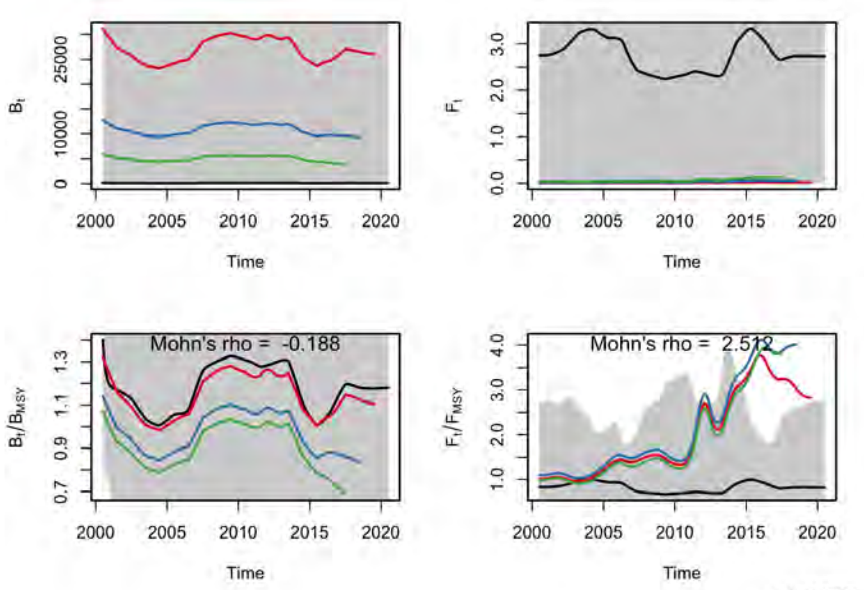
```
all(is.finite(res8$sd))
```

```
## [1] TRUE
```

```
r8<- calc.osa.resid(res8)
plotspict.diagnostic(r8)
```




```
r8<- fit.spict(inp8)
rep8=retro(r8, nretroyear=3)
plotspict.retro(rep8)
```




```
m8=mohns_rho(rep8, what = c("FFmsy", "BBmsy"));m8
```

```
##      FFmsy      BBmsy
##  3.3495374 -0.2504127
```

```
set.seed(123)
check.ini(inp8, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  model fitted!
##  Trial 2 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  model fitted!
##  Trial 3 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 4 ... model fitted!
##  Trial 5 ... model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ... model fitted!
##  Trial 8 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  model fitted!
##  Trial 9 ... model fitted!
##  Trial 10 ... model fitted!
##  Trial 11 ... model fitted!
##  Trial 12 ... model fitted!
##  Trial 13 ... model fitted!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ... model fitted!
##  Trial 17 ... model fitted!
##  Trial 18 ... model fitted!
##  Trial 19 ... model fitted!
##  Trial 20 ... model fitted!
## $propchng
##            logm  logK  logq  logq logsdb logsdf log
sdi logsdi logsdc
## Trial 1  -0.13  0.22  0.07 -0.30  -1.26   1.30  -0
.08  -1.12  -0.15
## Trial 2  -0.03  0.34  0.04 -0.14  -0.21   1.14  -1
.14   0.73   1.31
## Trial 3  -0.10  0.34 -0.31 -0.15  -0.40  -1.41  -0
.45  -0.60  -0.13
## Trial 4   0.06 -0.16  0.28 -0.36  -1.15  -0.55  -0
.85   1.36   0.06
## Trial 5   0.16 -0.21  0.14  0.21   1.02   0.24   0
.25   0.38   0.99
## Trial 6  -0.22 -0.20  0.03  0.18  -1.02   1.30   0
.17  -0.86   1.08
## Trial 7   0.04 -0.22  0.29 -0.20  -1.13   0.36  -0
.47   1.16   0.33
## Trial 8  -0.14  0.23  0.04 -0.24  -0.89  -0.84   0
.17  -0.73  -0.37
## Trial 9   0.13 -0.37  0.02  0.22   0.34  -0.32   0
.42   1.11   0.73
## Trial 10  0.10 -0.06 -0.23  0.31   0.19  -1.39  -1
.12  -1.11   0.93
## Trial 11 -0.22  0.11  0.12 -0.12   0.51   0.89  -0
.81   1.16   0.10
## Trial 12  0.01  0.07  0.13  0.01  -1.30   0.05  -1
.12  -1.19  -0.31
## Trial 13 -0.05 -0.26 -0.34  0.16   1.26  -1.28  -0
.63   1.02  -0.14
## Trial 14  0.27  0.06  0.08 -0.12   0.52   0.55   0
.80   0.37  -1.39
## Trial 15 -0.21 -0.31  0.28 -0.15  -0.34  -1.12  -0
.50  -0.68  -0.06
## Trial 16  0.10  0.24 -0.22 -0.38   0.17   0.54   0
.26   1.40   0.90
## Trial 17  0.21 -0.20  0.21  0.33   0.73  -0.66  -0
.99   0.01   0.32
## Trial 18 -0.15 -0.29  0.09 -0.06   0.81   0.16   0
.81  -0.01   0.42
## Trial 19  0.09 -0.09  0.11 -0.03  -0.69   0.80   0
.25   0.67  -0.37
```

```
## Trial 20 -0.19  0.27 -0.19 -0.13  -0.34   0.37 -0
.09  -1.07  -0.23
##
## $inimat
##           Distance logK logm logq1 logq2 logsdb log
sdf logsdi1 logsdi2 logsdc
## Basevec       0.00 7.64 6.17 -5.86 -5.86  -1.61  -1
.61   -1.61   -1.61  -1.61
## Trial 1       4.22 6.66 7.50 -6.28 -4.10   0.42  -3
.70   -1.48    0.20  -1.37
## Trial 2       4.22 7.44 8.27 -6.08 -5.04  -1.27  -3
.44    0.23   -2.78  -3.72
## Trial 3       4.01 6.85 8.26 -4.07 -4.97  -0.96   0
.67   -0.89   -0.65  -1.41
## Trial 4       4.38 8.07 5.20 -7.49 -3.73   0.24  -0
.73   -0.25   -3.80  -1.71
## Trial 5       3.36 8.83 4.86 -6.70 -7.10  -3.25  -2
.00   -2.01   -2.21  -3.21
## Trial 6       4.19 5.98 4.94 -6.02 -6.94   0.04  -3
.70   -1.88   -0.23  -3.35
## Trial 7       3.77 7.92 4.82 -7.58 -4.69   0.21  -2
.19   -0.85   -3.48  -2.14
## Trial 8       3.31 6.60 7.62 -6.10 -4.43  -0.17  -0
.25   -1.89   -0.44  -1.01
## Trial 9       3.68 8.61 3.87 -5.97 -7.15  -2.16  -1
.09   -2.29   -3.40  -2.79
## Trial 10      4.43 8.42 5.79 -4.53 -7.69  -1.91   0
.62    0.20    0.17  -3.11
## Trial 11      3.52 5.94 6.87 -6.58 -5.14  -2.44  -3
.05   -0.31   -3.48  -1.76
## Trial 12      3.51 7.69 6.63 -6.63 -5.91   0.48  -1
.69    0.19    0.30  -1.11
## Trial 13      4.45 7.23 4.54 -3.86 -6.78  -3.63   0
.45   -0.59   -3.26  -1.38
## Trial 14      3.70 9.73 6.56 -6.30 -5.18  -2.44  -2
.49   -2.90   -2.21   0.62
## Trial 15      3.87 6.05 4.29 -7.51 -4.99  -1.06   0
.19   -0.81   -0.52  -1.51
## Trial 16      4.19 8.38 7.65 -4.54 -3.65  -1.89  -2
.48   -2.03   -3.86  -3.07
## Trial 17      3.82 9.22 4.93 -7.06 -7.81  -2.78  -0
.54   -0.01   -1.62  -2.13
## Trial 18      2.97 6.47 4.38 -6.37 -5.53  -2.91  -1
.86   -2.91   -1.60  -2.28
## Trial 19      2.42 8.33 5.59 -6.53 -5.71  -0.50  -2
.89   -2.01   -2.69  -1.01
## Trial 20      3.25 6.19 7.84 -4.72 -5.09  -1.07  -2
.20   -1.47    0.12  -1.23
##
## $resmat
##           Distance       m        K    q   q  sdb  s
df  sdi  sdi  sdc
## Basevec       0.00  425.31   255.45 0.03  0 0.03 0.
12 0.27 0.01 0.18
```

```
## Trial 1   1715.89 2069.72   745.53 0.01  0 0.06 0.
24 0.22 0.02 0.06
## Trial 2   1715.90 2069.73   745.55 0.01  0 0.06 0.
24 0.22 0.02 0.06
## Trial 3      0.00      NA       NA   NA NA   NA
NA   NA   NA   NA
## Trial 4   1715.88 2069.72   745.53 0.01  0 0.06 0.
24 0.22 0.02 0.06
## Trial 5  69151.28  231.89 69406.46 0.00  0 0.08 0.
25 0.27 0.01 0.05
## Trial 6  69151.02  231.89 69406.20 0.00  0 0.08 0.
25 0.27 0.01 0.05
## Trial 7  69150.92  231.89 69406.10 0.00  0 0.08 0.
25 0.27 0.01 0.05
## Trial 8   1715.90 2069.74   745.52 0.01  0 0.06 0.
24 0.22 0.02 0.06
## Trial 9  69151.75  231.89 69406.93 0.00  0 0.08 0.
25 0.27 0.01 0.05
## Trial 10 69151.31  231.89 69406.49 0.00  0 0.08 0.
25 0.27 0.01 0.05
## Trial 11     0.01  425.31   255.45 0.03  0 0.03 0.
12 0.27 0.01 0.18
## Trial 12  1715.89 2069.72   745.53 0.01  0 0.06 0.
24 0.22 0.02 0.06
## Trial 13     0.01  425.31   255.44 0.03  0 0.03 0.
12 0.27 0.01 0.18
## Trial 14 69151.23  231.89 69406.42 0.00  0 0.08 0.
25 0.27 0.01 0.05
## Trial 15 69151.18  231.89 69406.36 0.00  0 0.08 0.
25 0.27 0.01 0.05
## Trial 16     0.00  425.31   255.45 0.03  0 0.03 0.
12 0.27 0.01 0.18
## Trial 17 69150.98  231.89 69406.16 0.00  0 0.08 0.
25 0.27 0.01 0.05
## Trial 18  1715.90 2069.73   745.53 0.01  0 0.06 0.
24 0.22 0.02 0.06
## Trial 19  1715.89 2069.73   745.53 0.01  0 0.06 0.
24 0.22 0.02 0.06
## Trial 20  1715.89 2069.73   745.53 0.01  0 0.06 0.
24 0.22 0.02 0.06
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
```

```
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[2]]
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5
##
## [[1]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
##
## [[2]]
##  [1] 0.3138639 0.2610667 0.2522755 0.2296472 0.223
1178 0.2361038 0.2368988
##  [8] 0.2844170 0.2899648 0.2973215 0.2912091 0.281
3124 0.2904401 0.2978007
## [15] 0.2447735 0.2211997 0.2381125 0.2700604 0.262
6929
```

```
(calc.om(res8))
```

```
##         lower  est upper CI range order magnitude
## B/Bmsy  0.50 1.18  2.77     2.27               1
## F/Fmsy  0.24 0.82  2.79     2.55               1
```

25 Run 9: Using two abundance indices: Portugues LPUE and Spanish survey. Fixing n to resemble the Schaefer production model and set priors for the ratio between biomass in the initial year relative to K, mean of log(0.5) and sd of 0.2.

```
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)
```

```
## Indices Spanish_survey
I_sol8c9a <- data.frame(obsI = data$Survey,timeI = 20
00:2019)

## Indices Portugues_LPUE
I2_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)


## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp9<- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_sol
8c9a$obsC,
             timeI = list(I_sol8c9a$timeI+0.8333333,I
2_sol8c9a$timeI+0.5),
             obsI = list(I_sol8c9a$obsI,I2_sol8c9a$ob
sI))


inp9=check.inp(inp9)
```

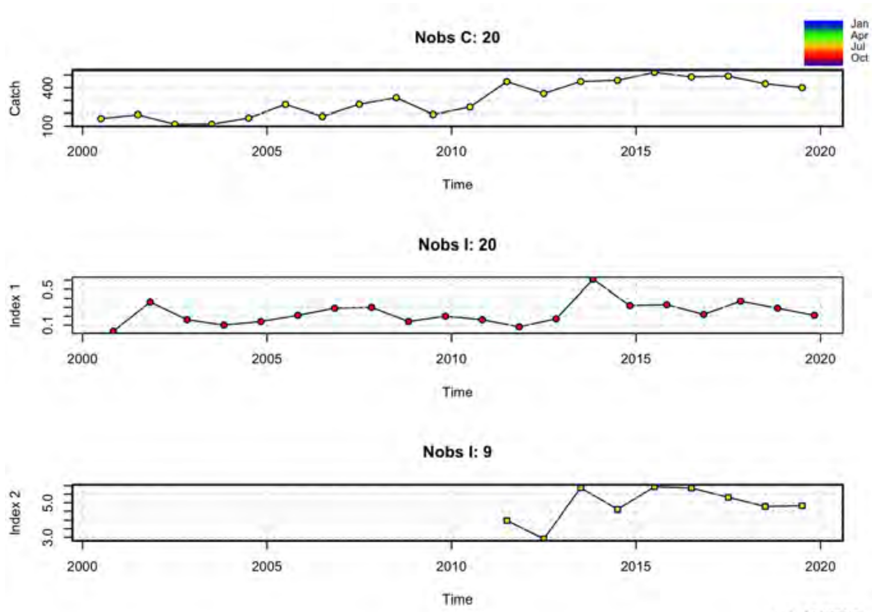
```
## Removing zero, negative, and NAs in  I  series  2
```

```
inp9$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

```
plotspict.data(inp9)
```



```
inp9$stdevfacC <- rep(1, length(inp9$obsC))
inp9$stdevfacC[1:10] <- 5
```

```
inp9$priors$logbkfrac <- c(log(0.5), 0.2, 1)
#inp$priors$logsdf<- c(log(0.3), 0.2, 1)
```

```
inp9$ini$logn <- log(2); inp9$phases$logn <- -1
```

Numerical solver time step (probably don't need to change)

```
inp9$dteuler <- 1/16
```

The model is fitted to data by running

```
res9 <- fit.spict(inp9)
```

The results are summarised using

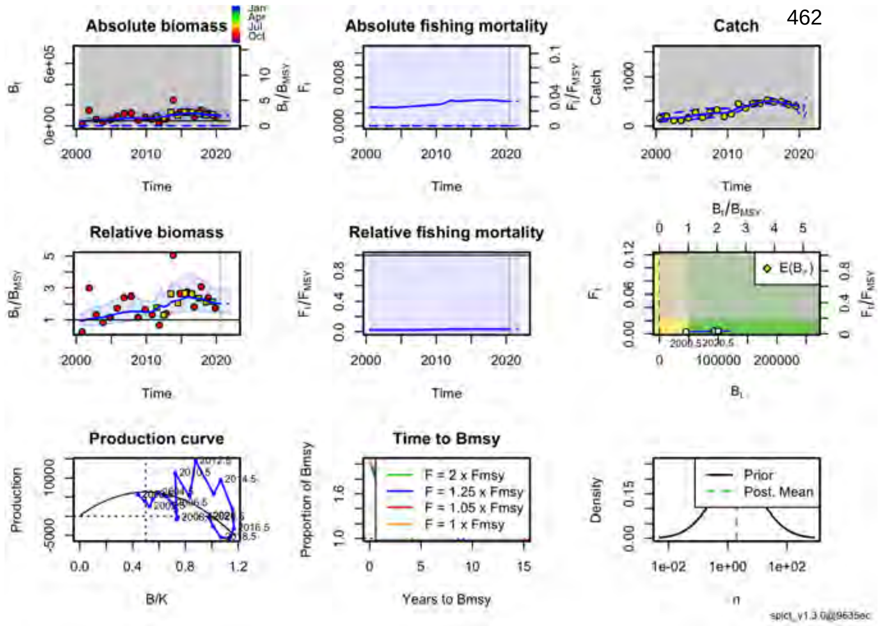
```
capture.output(summary(res9))
```

```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: 32.705348"

##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 20,  Nobs I2: 9"

##  [5] ""

##  [6] "Priors"

##  [7] "      logn  ~  dnorm[log(2), 2^2]"

##  [8] "  logalpha  ~  dnorm[log(1), 2^2]"

##  [9] "   logbeta  ~  dnorm[log(1), 2^2]"

## [10] " logbkfrac  ~  dnorm[log(0.5), 0.2^2]"

## [11] ""

## [12] "Fixed parameters"

## [13] "   fixed.value  "

## [14] " n           2  "

## [15] ""
```

```
## [16] "Model parameter estimates w 95% CI "    460

## [17] "            estimate      cilow        ciupp
     log.est  "
## [18] " alpha1 4.224767e+00  1.0952877 1.629586e+01
   1.4409641  "
## [19] " alpha2 1.324251e+00  0.2931007 5.983062e+00
   0.2808468  "
## [20] " beta   9.144507e-01  0.0783568 1.067195e+01
  -0.0894317  "
## [21] " r      2.469621e-01  0.0625276 9.754147e-01
  -1.3985203  "
## [22] " rc     2.469621e-01  0.0625276 9.754147e-01
  -1.3985203  "
## [23] " rold   2.469621e-01  0.0625276 9.754147e-01
  -1.3985203  "
## [24] " m      6.284860e+03  3.7731840 1.046847e+07
   8.7458989  "
## [25] " K      1.017947e+05 50.7788934 2.040644e+08
  11.5307135  "
## [26] " q1     2.500000e-06  0.0000000 5.219500e-03
 -12.9143982  "
## [27] " q2     4.560000e-05  0.0000000 9.887320e-02
  -9.9948021  "
## [28] " sdb    1.281942e-01  0.0350219 4.692427e-01
  -2.0542088  "
## [29] " sdf    9.219310e-02  0.0116609 7.288951e-01
  -2.3838696  "
## [30] " sdi1   5.415907e-01  0.3931630 7.460531e-01
  -0.6132447  "
## [31] " sdi2   1.697613e-01  0.0944673 3.050674e-01
  -1.7733621  "
## [32] " sdc    8.430610e-02  0.0431649 1.646595e-01
  -2.4733013  "
## [33] " "

## [34] "Deterministic reference points (Drp)"

## [35] "           estimate      cilow        ciupp
  log.est  "
## [36] " Bmsyd 5.089736e+04 25.3894467 1.020322e+08
10.837566  "
## [37] " Fmsyd 1.234811e-01  0.0312638 4.877073e-01
-2.091667  "
## [38] " MSYd  6.284860e+03  3.7731840 1.046847e+07
 8.745899  "
## [39] "Stochastic reference points (Srp)"

## [40] "           estimate      cilow        ciupp
  log.est rel.diff.Drp  "
## [41] " Bmsys 4.897371e+04 24.3410906 9.853397e+07
10.799039  -0.03927922  "
## [42] " Fmsys 1.193904e-01  0.0301682 4.724873e-01
-2.125356  -0.03426293  "
```

```
## [43] " MSYs  5.839123e+03  3.4877563 9.775727e+06
 8.672336  -0.07633638  "
## [44] ""

## [45] "States w 95% CI (inp$msytype: s)"

## [46] "                    estimate      cilow
   ciupp    log.est  "
## [47] " B_2020.44      9.976195e+04 45.0118736 2.21
1071e+08 11.5105421  "
## [48] " F_2020.44      4.013900e-03  0.0000018 8.78
4504e+00 -5.5179808  "
## [49] " B_2020.44/Bmsy 2.037051e+00  1.4584405 2.84
5215e+00  0.7115032  "
## [50] " F_2020.44/Fmsy 3.362030e-02  0.0000182 6.19
8025e+01 -3.3926244  "
## [51] ""

## [52] "Predictions w 95% CI (inp$msytype: s)"

## [53] "                  prediction       cilow
    ciupp    log.est  "
## [54] " B_2022.00      9.881261e+04  43.9959575 2.2
19279e+08 11.5009805  "
## [55] " F_2022.00      4.014200e-03   0.0000018 8.8
10159e+00 -5.5179207  "
## [56] " B_2022.00/Bmsy 2.017666e+00   1.4064061 2.8
94596e+00  0.7019416  "
## [57] " F_2022.00/Fmsy 3.362230e-02   0.0000182 6.2
16642e+01 -3.3925643  "
## [58] " Catch_2021.00  3.978007e+02 280.0692641 5.6
50224e+02  5.9859511  "
## [59] " E(B_inf)       9.307755e+04          NA
       NA 11.4411883  "
```

```
plot(res9)
```



26 Checklist for the acceptance of a SPiCT assessment

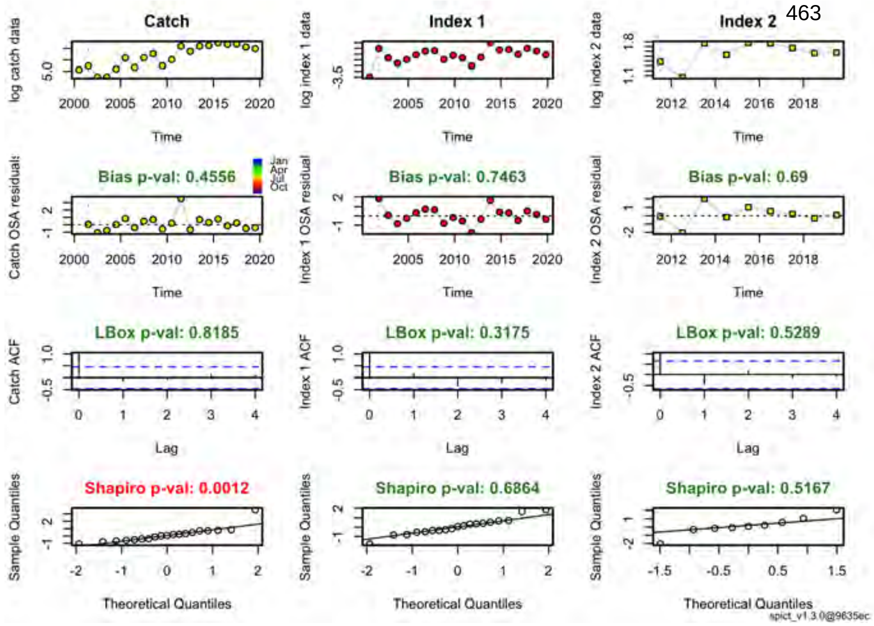
```
res9$opt$convergence
```

```
## [1] 0
```

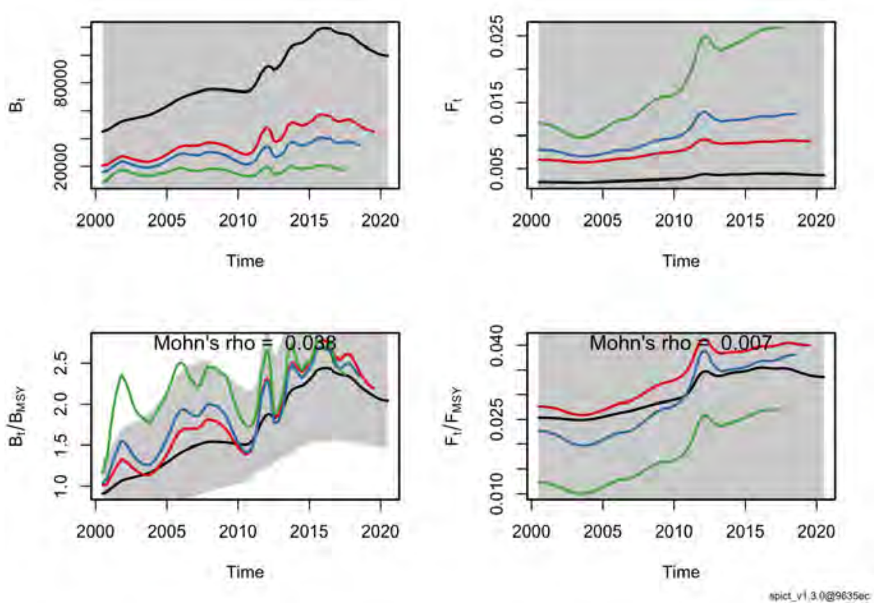
```
all(is.finite(res9$sd))
```

```
## [1] TRUE
```

```
r9 <- calc.osa.resid(res9)
plotspict.diagnostic(r9)
```




```
r9<- fit.spict(inp9)
rep9=retro(r9, nretroyear=3)
plotspict.retro(rep9)
```




```
m9=mohns_rho(rep9, what = c("FFmsy", "BBmsy"));m9
```

```
##       FFmsy       BBmsy
## 0.009956741 0.051207767
```

```
set.seed(123)
check.ini(inp9, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ... model fitted!
```

```
##  Trial 2 ... model fitted!
##  Trial 3 ... model fitted!
##  Trial 4 ... model fitted!
##  Trial 5 ... model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ... model fitted!
##  Trial 8 ... model fitted!
##  Trial 9 ... model fitted!
##  Trial 10 ... model fitted!
##  Trial 11 ... model fitted!
##  Trial 12 ... model fitted!
##  Trial 13 ... model fitted!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ... model fitted!
##  Trial 17 ... model fitted!
##  Trial 18 ... model fitted!
##  Trial 19 ... model fitted!
##  Trial 20 ... model fitted!
## $propchng
##            logm  logK  logq  logq logsdb logsdf log
sdi logsdi logsdc
## Trial 1  -0.13  0.23  0.05 -0.22  -1.26   1.30  -0
.08  -1.12  -0.15
## Trial 2  -0.03  0.37  0.03 -0.10  -0.21   1.14  -1
.14   0.73   1.31
## Trial 3  -0.10  0.36 -0.22 -0.11  -0.40  -1.41  -0
.45  -0.60  -0.13
## Trial 4   0.06 -0.17  0.20 -0.26  -1.15  -0.55  -0
.85   1.36   0.06
## Trial 5   0.16 -0.23  0.10  0.15   1.02   0.24   0
.25   0.38   0.99
## Trial 6  -0.22 -0.21  0.02  0.13  -1.02   1.30   0
.17  -0.86   1.08
## Trial 7   0.04 -0.24  0.21 -0.14  -1.13   0.36  -0
.47   1.16   0.33
## Trial 8  -0.14  0.25  0.03 -0.18  -0.89  -0.84   0
.17  -0.73  -0.37
## Trial 9   0.13 -0.40  0.01  0.16   0.34  -0.32   0
.42   1.11   0.73
## Trial 10  0.10 -0.07 -0.16  0.22   0.19  -1.39  -1
.12  -1.11   0.93
## Trial 11 -0.22  0.12  0.09 -0.09   0.51   0.89  -0
.81   1.16   0.10
## Trial 12  0.01  0.08  0.09  0.01  -1.30   0.05  -1
.12  -1.19  -0.31
## Trial 13 -0.05 -0.28 -0.25  0.11   1.26  -1.28  -0
.63   1.02  -0.14
## Trial 14  0.27  0.07  0.05 -0.08   0.52   0.55   0
.80   0.37  -1.39
## Trial 15 -0.21 -0.33  0.20 -0.11  -0.34  -1.12  -0
.50  -0.68  -0.06
## Trial 16  0.10  0.26 -0.16 -0.27   0.17   0.54   0
.26   1.40   0.90
```

```
## Trial 17  0.21 -0.22  0.15  0.24   0.73  -0.66-0
.99   0.01   0.32
## Trial 18 -0.15 -0.31  0.06 -0.04   0.81   0.16   0
.81  -0.01   0.42
## Trial 19  0.09 -0.10  0.08 -0.02  -0.69   0.80   0
.25   0.67  -0.37
## Trial 20 -0.19  0.29 -0.14 -0.10  -0.34   0.37  -0
.09  -1.07  -0.23
##
## $inimat
##          Distance logK logm logq1  logq2 logsdb lo
gsdf logsdi1 logsdi2 logsdc
## Basevec      0.00 7.64 5.74 -8.14  -8.14  -1.61  -
1.61   -1.61   -1.61  -1.61
## Trial 1      4.22 6.66 7.07 -8.55  -6.37   0.42  -
3.70   -1.48    0.20  -1.37
## Trial 2      4.22 7.44 7.85 -8.35  -7.32  -1.27  -
3.44    0.23   -2.78  -3.72
## Trial 3      4.01 6.85 7.84 -6.34  -7.25  -0.96
0.67   -0.89   -0.65  -1.41
## Trial 4      4.38 8.07 4.77 -9.76  -6.00   0.24  -
0.73   -0.25   -3.80  -1.71
## Trial 5      3.36 8.83 4.44 -8.97  -9.37  -3.25  -
2.00   -2.01   -2.21  -3.21
## Trial 6      4.19 5.98 4.51 -8.29  -9.21   0.04  -
3.70   -1.88   -0.23  -3.35
## Trial 7      3.77 7.92 4.39 -9.85  -6.97   0.21  -
2.19   -0.85   -3.48  -2.14
## Trial 8      3.31 6.60 7.19 -8.37  -6.71  -0.17  -
0.25   -1.89   -0.44  -1.01
## Trial 9      3.68 8.61 3.44 -8.25  -9.42  -2.16  -
1.09   -2.29   -3.40  -2.79
## Trial 10     4.43 8.42 5.36 -6.81  -9.96  -1.91
0.62    0.20    0.17  -3.11
## Trial 11     3.52 5.94 6.45 -8.86  -7.41  -2.44  -
3.05   -0.31   -3.48  -1.76
## Trial 12     3.51 7.69 6.20 -8.91  -8.19   0.48  -
1.69    0.19    0.30  -1.11
## Trial 13     4.45 7.23 4.12 -6.13  -9.05  -3.63
0.45   -0.59   -3.26  -1.38
## Trial 14     3.70 9.73 6.14 -8.58  -7.45  -2.44  -
2.49   -2.90   -2.21   0.62
## Trial 15     3.87 6.05 3.86 -9.78  -7.26  -1.06
0.19   -0.81   -0.52  -1.51
## Trial 16     4.19 8.38 7.23 -6.82  -5.93  -1.89  -
2.48   -2.03   -3.86  -3.07
## Trial 17     3.82 9.22 4.51 -9.34 -10.08  -2.78  -
0.54   -0.01   -1.62  -2.13
## Trial 18     2.97 6.47 3.95 -8.64  -7.80  -2.91  -
1.86   -2.91   -1.60  -2.28
## Trial 19     2.42 8.33 5.17 -8.80  -7.98  -0.50  -
2.89   -2.01   -2.69  -1.01
## Trial 20     3.25 6.19 7.42 -7.00  -7.36  -1.07  -
2.20   -1.47    0.12  -1.23
```

```
##                                                                     466
## $resmat
##          Distance       m        K q q  sdb  sdf  
sdi  sdi  sdc
## Basevec      0.00 6284.86 101794.7 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 1      1.77 6284.74 101792.9 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 2      2.00 6284.99 101796.7 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 3      0.08 6284.85 101794.6 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 4      2.08 6284.72 101792.6 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 5      7.15 6285.30 101801.9 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 6      2.16 6284.73 101792.6 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 7      0.46 6284.89 101795.2 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 8      0.11 6284.86 101794.6 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 9      2.62 6285.02 101797.3 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 10     0.44 6284.83 101794.3 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 11     1.24 6284.80 101793.5 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 12     0.72 6284.90 101795.4 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 13     1.15 6284.96 101795.9 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 14     1.33 6284.94 101796.0 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 15     1.35 6284.94 101796.1 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 16     3.64 6285.09 101798.4 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 17     1.52 6284.95 101796.2 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 18     0.90 6284.91 101795.6 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 19     0.21 6284.87 101794.9 0 0 0.13 0.09 0
.54 0.17 0.08
## Trial 20     1.43 6284.95 101796.1 0 0 0.13 0.09 0
.54 0.17 0.08
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
```

```
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
##  [1] 2000.833 2001.833 2002.833 2003.833 2004.833
2005.833 2006.833 2007.833
##  [9] 2008.833 2009.833 2010.833 2011.833 2012.833
2013.833 2014.833 2015.833
## [17] 2016.833 2017.833 2018.833 2019.833
##
## [[2]]
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[1]]
##  [1] 0.03 0.36 0.16 0.10 0.14 0.21 0.29 0.30 0.14
0.20 0.16 0.08 0.17 0.61 0.32
## [16] 0.33 0.22 0.37 0.29 0.21
##
## [[2]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
```



```
(calc.om(res9))
```

```
##        lower  est upper CI range order magnitude
## B/Bmsy  1.46 2.04  2.85     1.39               0
## F/Fmsy  0.00 0.03 61.98    61.98               6
```

27 Run 10: Using three abundance indices: Portugues LPUE, the Spanish survey (spat index) and CPUE from Spain. Fixing n to resemble the Schaefer production model and set priors for the ratio between biomass in the

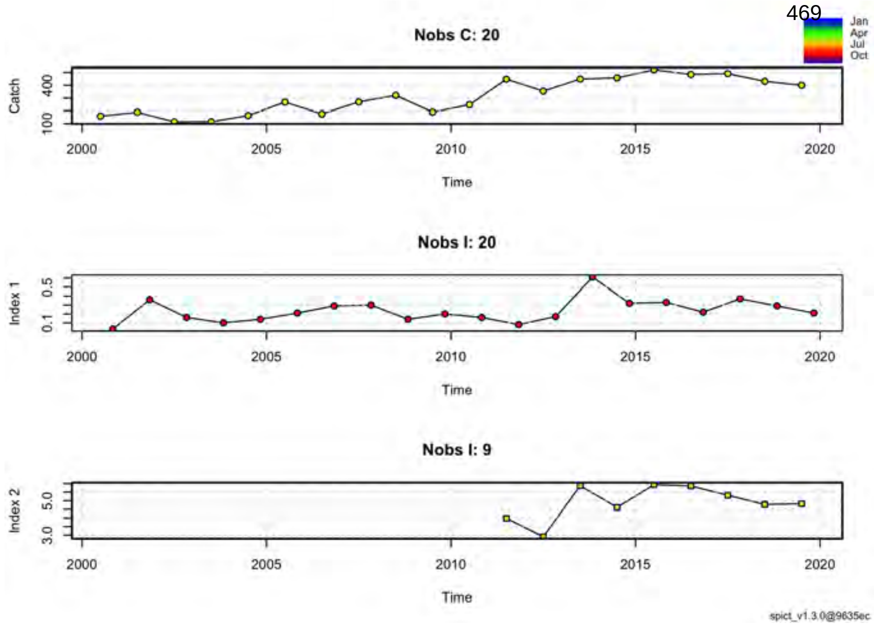
initial year relative to K, mean of log(0.3) and sd of 1. Intensive exploitation before starting time series.

```
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)

## Indices Spanish_survey
I_sol8c9a <- data.frame(obsI = data$Spat_index,timeI
= 2000:2019)

## Indices Portugues_LPUE
I2_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)

## Indices CPUE Spain
I3_sol8c9a <- data.frame(obsI =data$CPUE,timeI = 2000
:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp10<- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_so
l8c9a$obsC,
             timeI = list(I_sol8c9a$timeI+0.8333333,I
2_sol8c9a$timeI+0.5, I3_sol8c9a$timeI+0.5),
             obsI = list(I_sol8c9a$obsI,I2_sol8c9a$ob
sI,I3_sol8c9a$obsI))


inp10=check.inp(inp9)
inp10$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

```
plotspict.data(inp10)
```




```
inp10$stdevfacC <- rep(1, length(inp10$obsC))
inp10$stdevfacC[1:10] <- 5
```

Intensive exploitation before starting time series

```
inp10$priors$logbkfrac <- c(log(0.3),0.5,1)
inp10$priors$logn <- c(log(1.5), 0.5, 1)
```

Numerical solver time step (probably don't need to change)

```
inp10$dteuler <- 1/16
```

The model is fitted to data by running

```
res10<- fit.spict(inp10)
```

The results are summarised using

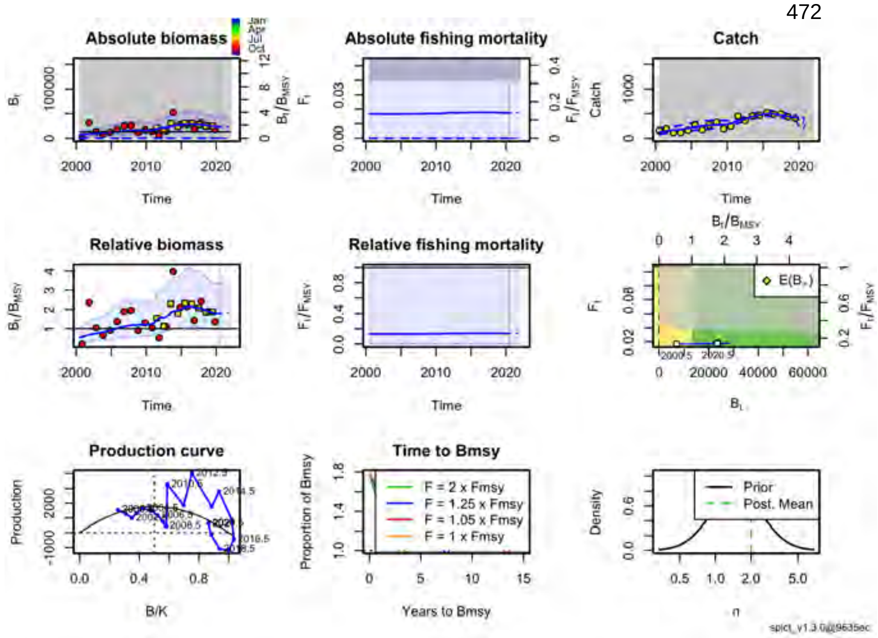
```
capture.output(summary(res10))
```

```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: 30.8628387"

##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 20,  Nobs I2: 9"

##  [5] ""

##  [6] "Priors"

##  [7] "      logn  ~  dnorm[log(1.5), 0.5^2]"
```

```
## [8] "  logalpha  ~  dnorm[log(1), 2^2]"

## [9] "   logbeta  ~  dnorm[log(1), 2^2]"

## [10] " logbkfrac  ~  dnorm[log(0.3), 0.5^2]"

## [11] ""

## [12] "Fixed parameters"

## [13] "   fixed.value  "

## [14] " n           2  "

## [15] ""

## [16] "Model parameter estimates w 95% CI "

## [17] "            estimate      cilow        ciupp
     log.est  "
## [18] " alpha1 4.279796e+00  1.3335059 1.373571e+01
   1.4539054  "
## [19] " alpha2 1.283822e+00  0.3497736 4.712188e+00
   0.2498416  "
## [20] " beta   2.391336e+00  0.1617343 3.535730e+01
   0.8718522  "
## [21] " r      2.603500e-01  0.0819284 8.273339e-01
  -1.3457284  "
## [22] " rc     2.603500e-01  0.0819284 8.273339e-01
  -1.3457284  "
## [23] " rold   2.603500e-01  0.0819284 8.273339e-01
  -1.3457284  "
## [24] " m      1.770836e+03  1.6624349 1.886305e+06
   7.4792070  "
## [25] " K      2.720701e+04 14.3838860 5.146183e+07
  10.2112298  "
## [26] " q1     1.170000e-05  0.0000000 3.401990e-02
 -11.3560895  "
## [27] " q2     1.958000e-04  0.0000001 5.782091e-01
  -8.5386520  "
## [28] " sdb    1.267679e-01  0.0420869 3.818318e-01
  -2.0653971  "
## [29] " sdf    3.825680e-02  0.0027241 5.372695e-01
  -3.2634327  "
## [30] " sdi1   5.425409e-01  0.3919956 7.509030e-01
  -0.6114917  "
## [31] " sdi2   1.627475e-01  0.0920528 2.877342e-01
  -1.8155555  "
## [32] " sdc    9.148500e-02  0.0557428 1.501451e-01
  -2.3915804  "
## [33] " "

## [34] "Deterministic reference points (Drp)"
```

```
                                                                  471
## [35] "           estimate     cilow        ciupp
 log.est  "
## [36] " Bmsyd 13603.502848 7.1919430 2.573092e+07
9.518083  "
## [37] " Fmsyd     0.130175 0.0409642 4.136670e-01 -
2.038876  "
## [38] " MSYd   1770.835977 1.6624349 1.886305e+06
7.479207  "
## [39] "Stochastic reference points (Srp)"

## [40] "           estimate    cilow        ciupp
log.est rel.diff.Drp  "
## [41] " Bmsys 1.312317e+04 7.012982 2.455698e+07  9
.482135  -0.03660170  "
## [42] " Fmsys 1.261769e-01 0.039621 4.018225e-01 -2
.070070  -0.03168646  "
## [43] " MSYs  1.653921e+03 1.593844 1.716263e+06  7
.410904  -0.07068932  "
## [44] ""

## [45] "States w 95% CI (inp$msytype: s)"

## [46] "                     estimate     cilow
  ciupp    log.est  "
## [47] " B_2020.44      2.343866e+04 7.7209268 7.115
347e+07 10.0621420  "
## [48] " F_2020.44      1.747960e-02 0.0000059 5.217
843e+01 -4.0467197  "
## [49] " B_2020.44/Bmsy 1.786051e+00 0.9557653 3.337
618e+00  0.5800072  "
## [50] " F_2020.44/Fmsy 1.385326e-01 0.0000810 2.368
348e+02 -1.9766496  "
## [51] ""

## [52] "Predictions w 95% CI (inp$msytype: s)"

## [53] "                   prediction       cilow
    ciupp    log.est  "
## [54] " B_2022.00      2.376841e+04   7.6734360 7.3
62249e+07 10.0761128  "
## [55] " F_2022.00      1.747990e-02   0.0000059 5.2
20207e+01 -4.0467056  "
## [56] " B_2022.00/Bmsy 1.811179e+00   0.9522480 3.4
44868e+00  0.5939779  "
## [57] " F_2022.00/Fmsy 1.385345e-01   0.0000810 2.3
69521e+02 -1.9766356  "
## [58] " Catch_2021.00  4.136918e+02 304.7510591 5.6
15761e+02  6.0251213  "
## [59] " E(B_inf)       2.358989e+04          NA
       NA 10.0685733  "
```

```
plot(res10)
```



28 Checklist for the acceptance of a SPiCT assessment

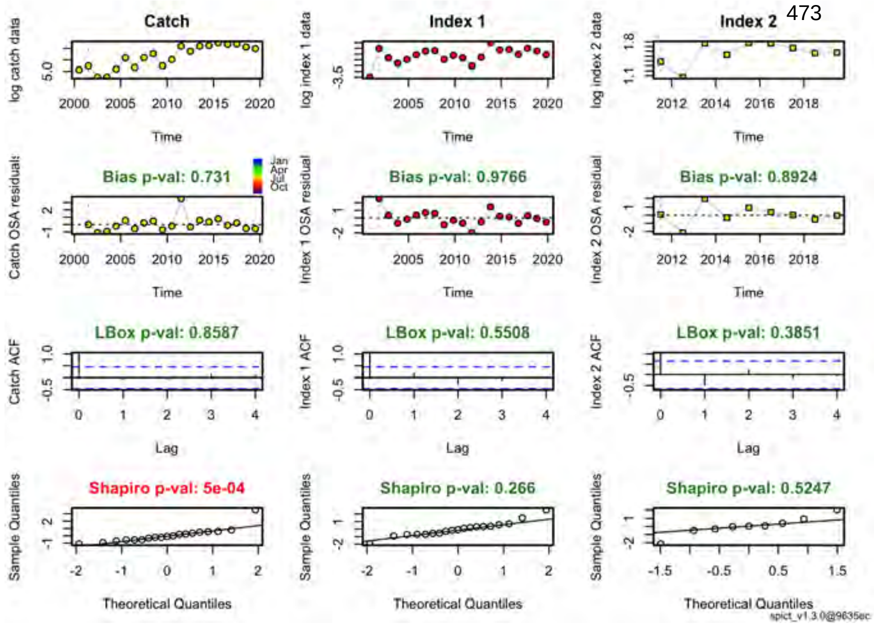
```
res10$opt$convergence
```

```
## [1] 0
```

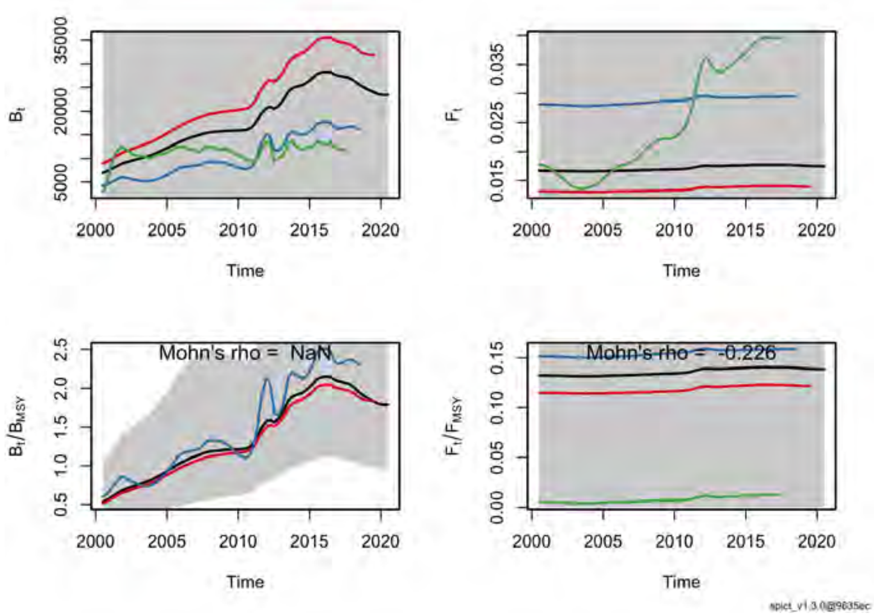
```
all(is.finite(res10$sd))
```

```
## [1] TRUE
```

```
r10 <- calc.osa.resid(res10)
plotspict.diagnostic(r10)
```




```
r10<- fit.spict(inp10)
rep10=retro(r10, nretroyear=3)
plotspict.retro(rep10)
```




```
m10=mohns_rho(rep10, what = c("FFmsy", "BBmsy"));m10
```

```
##       FFmsy      BBmsy
## -0.3010964        NaN
```

```
set.seed(123)
check.ini(inp10, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ... model fitted!
```

```
##  Trial 2 ... model fitted!
##  Trial 3 ... model fitted!
##  Trial 4 ... model fitted!
##  Trial 5 ... model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ... model fitted!
##  Trial 8 ... model fitted!
##  Trial 9 ... model fitted!
##  Trial 10 ... model fitted!
##  Trial 11 ... model fitted!
##  Trial 12 ... model fitted!
##  Trial 13 ... model fitted!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ... model fitted!
##  Trial 17 ... model fitted!
##  Trial 18 ... model fitted!
##  Trial 19 ... model fitted!
##  Trial 20 ... model fitted!
## $propchng
##            logm  logK  logq  logq logsdb logsdf log
sdi logsdi logsdc
## Trial 1  -0.13  0.23  0.05 -0.22  -1.26   1.30  -0
.08  -1.12  -0.15
## Trial 2  -0.03  0.37  0.03 -0.10  -0.21   1.14  -1
.14   0.73   1.31
## Trial 3  -0.10  0.36 -0.22 -0.11  -0.40  -1.41  -0
.45  -0.60  -0.13
## Trial 4   0.06 -0.17  0.20 -0.26  -1.15  -0.55  -0
.85   1.36   0.06
## Trial 5   0.16 -0.23  0.10  0.15   1.02   0.24   0
.25   0.38   0.99
## Trial 6  -0.22 -0.21  0.02  0.13  -1.02   1.30   0
.17  -0.86   1.08
## Trial 7   0.04 -0.24  0.21 -0.14  -1.13   0.36  -0
.47   1.16   0.33
## Trial 8  -0.14  0.25  0.03 -0.18  -0.89  -0.84   0
.17  -0.73  -0.37
## Trial 9   0.13 -0.40  0.01  0.16   0.34  -0.32   0
.42   1.11   0.73
## Trial 10  0.10 -0.07 -0.16  0.22   0.19  -1.39  -1
.12  -1.11   0.93
## Trial 11 -0.22  0.12  0.09 -0.09   0.51   0.89  -0
.81   1.16   0.10
## Trial 12  0.01  0.08  0.09  0.01  -1.30   0.05  -1
.12  -1.19  -0.31
## Trial 13 -0.05 -0.28 -0.25  0.11   1.26  -1.28  -0
.63   1.02  -0.14
## Trial 14  0.27  0.07  0.05 -0.08   0.52   0.55   0
.80   0.37  -1.39
## Trial 15 -0.21 -0.33  0.20 -0.11  -0.34  -1.12  -0
.50  -0.68  -0.06
## Trial 16  0.10  0.26 -0.16 -0.27   0.17   0.54   0
.26   1.40   0.90
```

```
## Trial 17  0.21 -0.22  0.15  0.24   0.73  -0.66  -0
.99   0.01   0.32
## Trial 18 -0.15 -0.31  0.06 -0.04   0.81   0.16   0
.81  -0.01   0.42
## Trial 19  0.09 -0.10  0.08 -0.02  -0.69   0.80   0
.25   0.67  -0.37
## Trial 20 -0.19  0.29 -0.14 -0.10  -0.34   0.37  -0
.09  -1.07  -0.23
##
## $inimat
##          Distance logK logm logq1  logq2 logsdb lo
gsdf logsdi1 logsdi2 logsdc
## Basevec      0.00 7.64 5.74 -8.14  -8.14  -1.61  -
1.61   -1.61   -1.61  -1.61
## Trial 1      4.22 6.66 7.07 -8.55  -6.37   0.42  -
3.70   -1.48    0.20  -1.37
## Trial 2      4.22 7.44 7.85 -8.35  -7.32  -1.27  -
3.44    0.23   -2.78  -3.72
## Trial 3      4.01 6.85 7.84 -6.34  -7.25  -0.96
0.67   -0.89   -0.65  -1.41
## Trial 4      4.38 8.07 4.77 -9.76  -6.00   0.24  -
0.73   -0.25   -3.80  -1.71
## Trial 5      3.36 8.83 4.44 -8.97  -9.37  -3.25  -
2.00   -2.01   -2.21  -3.21
## Trial 6      4.19 5.98 4.51 -8.29  -9.21   0.04  -
3.70   -1.88   -0.23  -3.35
## Trial 7      3.77 7.92 4.39 -9.85  -6.97   0.21  -
2.19   -0.85   -3.48  -2.14
## Trial 8      3.31 6.60 7.19 -8.37  -6.71  -0.17  -
0.25   -1.89   -0.44  -1.01
## Trial 9      3.68 8.61 3.44 -8.25  -9.42  -2.16  -
1.09   -2.29   -3.40  -2.79
## Trial 10     4.43 8.42 5.36 -6.81  -9.96  -1.91
0.62    0.20    0.17  -3.11
## Trial 11     3.52 5.94 6.45 -8.86  -7.41  -2.44  -
3.05   -0.31   -3.48  -1.76
## Trial 12     3.51 7.69 6.20 -8.91  -8.19   0.48  -
1.69    0.19    0.30  -1.11
## Trial 13     4.45 7.23 4.12 -6.13  -9.05  -3.63
0.45   -0.59   -3.26  -1.38
## Trial 14     3.70 9.73 6.14 -8.58  -7.45  -2.44  -
2.49   -2.90   -2.21   0.62
## Trial 15     3.87 6.05 3.86 -9.78  -7.26  -1.06
0.19   -0.81   -0.52  -1.51
## Trial 16     4.19 8.38 7.23 -6.82  -5.93  -1.89  -
2.48   -2.03   -3.86  -3.07
## Trial 17     3.82 9.22 4.51 -9.34 -10.08  -2.78  -
0.54   -0.01   -1.62  -2.13
## Trial 18     2.97 6.47 3.95 -8.64  -7.80  -2.91  -
1.86   -2.91   -1.60  -2.28
## Trial 19     2.42 8.33 5.17 -8.80  -7.98  -0.50  -
2.89   -2.01   -2.69  -1.01
## Trial 20     3.25 6.19 7.42 -7.00  -7.36  -1.07  -
2.20   -1.47    0.12  -1.23
```

```
##                                                                476
## $resmat
##           Distance        m        K q q  sdb  sdf
 sdi  sdi  sdc
## Basevec      0.00  1770.84 27207.01 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 1      0.50  1770.81 27206.51 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 2      0.18  1770.82 27206.82 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 3      0.25  1770.82 27206.76 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 4      0.17  1770.82 27206.84 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 5      0.21  1770.85 27207.22 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 6      0.04  1770.83 27206.97 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 7      0.34  1770.82 27206.66 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 8  15518.94 15208.96 19444.62 0 0 0.44 0.17
0.51 0.14 0.06
## Trial 9      0.05  1770.84 27207.06 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 10     0.26  1770.82 27206.74 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 11 15518.97 15209.13 19444.87 0 0 0.44 0.17
0.51 0.14 0.06
## Trial 12     0.16  1770.83 27206.85 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 13     0.20  1770.82 27206.81 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 14     0.32  1770.81 27206.69 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 15     0.05  1770.84 27207.05 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 16     0.12  1770.83 27206.88 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 17     0.09  1770.83 27206.92 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 18     0.26  1770.82 27206.74 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 19     0.19  1770.82 27206.82 0 0 0.13 0.04
0.54 0.16 0.09
## Trial 20 15519.04 15209.21 19444.87 0 0 0.44 0.17
0.51 0.14 0.06
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
```

```
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
##  [1] 2000.833 2001.833 2002.833 2003.833 2004.833
2005.833 2006.833 2007.833
##  [9] 2008.833 2009.833 2010.833 2011.833 2012.833
2013.833 2014.833 2015.833
## [17] 2016.833 2017.833 2018.833 2019.833
##
## [[2]]
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[1]]
##  [1] 0.03 0.36 0.16 0.10 0.14 0.21 0.29 0.30 0.14
0.20 0.16 0.08 0.17 0.61 0.32
## [16] 0.33 0.22 0.37 0.29 0.21
##
## [[2]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5
.861519 5.314860 4.778739
## [9] 4.817878
```

```
(calc.om(res10))
```

```
##        lower  est  upper CI range order magnitude
## B/Bmsy  0.96 1.79   3.34     2.38               1
## F/Fmsy  0.00 0.14 236.83   236.83               7
```

29 Run 11: Using three abundance indices: Portugues survey, the Spanish survey and CPUE from Spain. Setting priors for the ratio between biomass in the initial year relative to K, mean of log(0.3) and sd of 1. Intensive exploitation before

starting time series.

```
C_sol8c9a <- data.frame(obsC = data$Catches,timeC = 2
000:2019)

## Indices Spanish_survey
I_sol8c9a <- data.frame(obsI = data$Spat_index,timeI
= 2000:2019)

## Indices Portugues_LPUE
I2_sol8c9a <- data.frame(obsI =data$LPUE,timeI = 2000
:2019)

## Indices CPUE Spain
I3_sol8c9a <- data.frame(obsI =data$CPUE,timeI = 2000
:2019)

## create a list with these objects and plot series,,
,
#times index demersale 10/12=0.8333333
#times index cpue 6/12=0.5
inp11<- list(timeC = C_sol8c9a$timeC+0.5, obsC = C_so
l8c9a$obsC,
             timeI = list(I_sol8c9a$timeI+0.8333333,I
2_sol8c9a$timeI+0.5, I3_sol8c9a$timeI+0.5),
             obsI = list(I_sol8c9a$obsI,I2_sol8c9a$ob
sI,I3_sol8c9a$obsI))


inp11=check.inp(inp11)
```

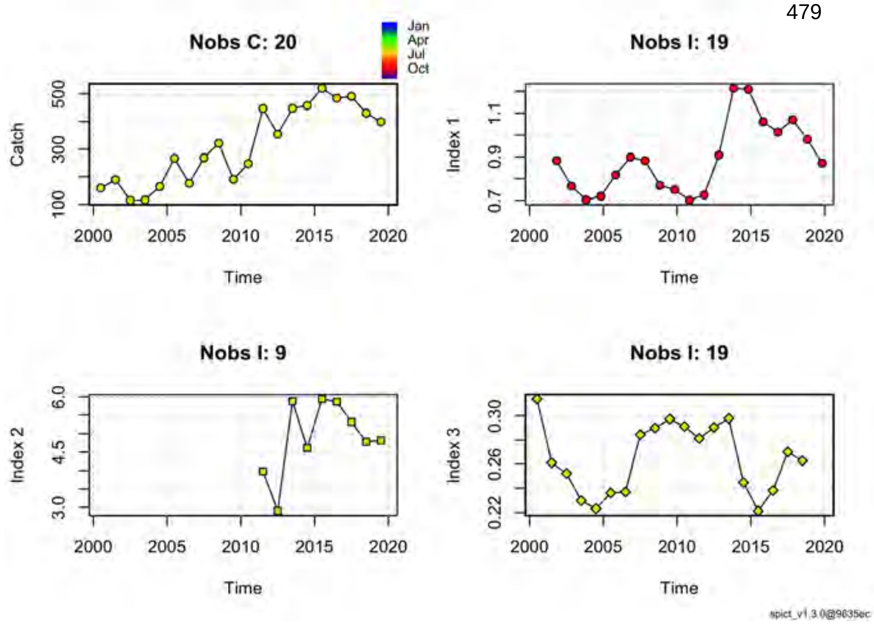
```
## Removing zero, negative, and NAs in  I  series  1

## Removing zero, negative, and NAs in  I  series  2

## Removing zero, negative, and NAs in  I  series  3
```

```
inp11$dtc
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

The data can be plotted using the command

```
plotspict.data(inp11)
```




```
inp11$stdevfacC <- rep(1, length(inp11$obsC))
inp11$stdevfacC[1:10] <- 5
```

Intensive exploitation before starting time series

```
inp11$priors$logbkfrac <- c(log(0.3),0.5,1)
```

Numerical solver time step (probably don't need to change)

```
inp11$dteuler <- 1/16
```

The model is fitted to data by running

```
res11<- fit.spict(inp11)
```

The results are summarised using

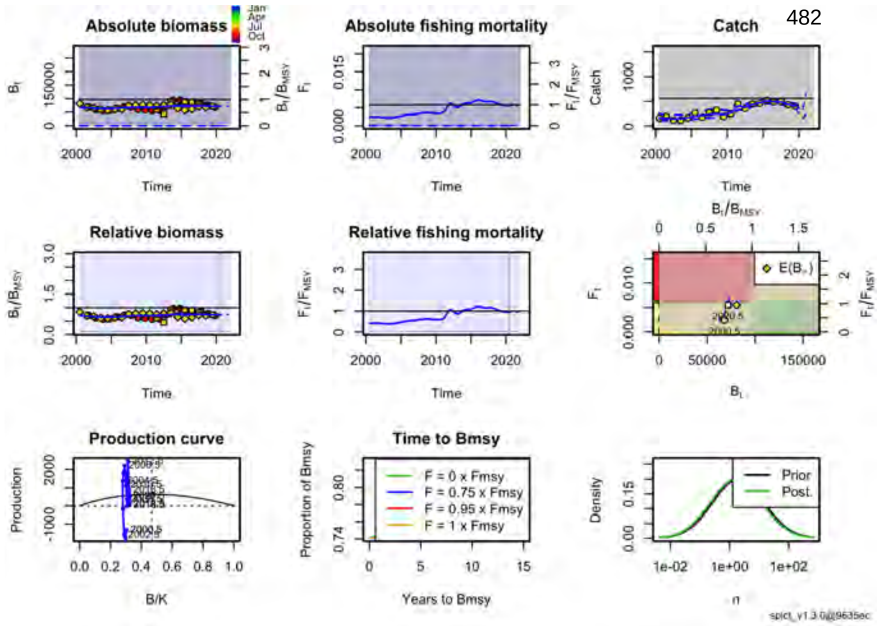
```
capture.output(summary(res11))
```

```
##  [1] "Convergence: 0  MSG: relative convergence (4
)"
##  [2] "Objective function at optimum: -0.7615155"

##  [3] "Euler time step (years):  1/16 or 0.0625"

##  [4] "Nobs C: 20,  Nobs I1: 19,  Nobs I2: 9,  Nobs
 I3: 19"
##  [5] ""

##  [6] "Priors"

##  [7] "      logn  ~  dnorm[log(2), 2^2]"
```

```
## [8] "  logalpha  ~  dnorm[log(1), 2^2]"

## [9] "   logbeta  ~  dnorm[log(1), 2^2]"

## [10] " logbkfrac  ~  dnorm[log(0.3), 0.5^2]"

## [11] ""

## [12] "Model parameter estimates w 95% CI "

## [13] "            estimate       cilow        ciup
p     log.est  "
## [14] " alpha1 3.293495e+00   0.7568159 1.433256e+0
1   1.1919494  "
## [15] " alpha2 4.753569e+00   1.1894726 1.899700e+0
1   1.5588957  "
## [16] " alpha3 2.558610e+00   0.5787089 1.131223e+0
1   0.9394642  "
## [17] " beta   2.776326e-01   0.0491646 1.567792e+0
0  -1.2814566  "
## [18] " r      1.036320e-02   0.0000583 1.843326e+0
0  -4.5694980  "
## [19] " rc     1.226640e-02   0.0001241 1.212130e+0
0  -4.4008886  "
## [20] " rold   1.502610e-02   0.0000041 5.442741e+0
1  -4.1979671  "
## [21] " m      6.428391e+02   7.0813826 5.835613e+0
4   6.4658944  "
## [22] " K      2.242429e+05 241.0844507 2.085779e+0
8  12.3204851  "
## [23] " q1     1.280000e-05   0.0000000 1.064190e-0
2 -11.2651656  "
## [24] " q2     6.690000e-05   0.0000001 5.575690e-0
2  -9.6123447  "
## [25] " q3     3.800000e-06   0.0000000 3.190800e-0
3 -12.4676014  "
## [26] " n      1.689678e+00   0.0337652 8.455493e+0
1   0.5245378  "
## [27] " sdb    4.343230e-02   0.0117121 1.610609e-0
1  -3.1365512  "
## [28] " sdf    2.215850e-01   0.0945467 5.193191e-0
1  -1.5069492  "
## [29] " sdi1   1.430442e-01   0.0917816 2.229383e-0
1  -1.9446018  "
## [30] " sdi2   2.064586e-01   0.1268067 3.361426e-0
1  -1.5776556  "
## [31] " sdi3   1.111264e-01   0.0648129 1.905343e-0
1  -2.1970870  "
## [32] " sdc    6.151920e-02   0.0226713 1.669344e-0
1  -2.7884058  "
## [33] " "

## [34] "Deterministic reference points (Drp)"
```

```
## [35] "           estimate      cilow        ciupp
  log.est  "
## [36] " Bmsyd 1.048127e+05 77.2238294 1.422579e+08
11.559930  "
## [37] " Fmsyd 6.133200e-03  0.0000621 6.060652e-01
-5.094036  "
## [38] " MSYd  6.428391e+02  7.0813826 5.835613e+04
 6.465894  "
## [39] "Stochastic reference points (Srp)"

## [40] "           estimate     cilow        ciupp
 log.est rel.diff.Drp  "
## [41] " Bmsys 96711.558436 93.590371 9.993684e+07 1
1.479488  -0.08376597  "
## [42] " Fmsys     0.005808  0.000038 8.866877e-01 -
5.148523  -0.05599475  "
## [43] " MSYs    559.063401  6.925093 4.513324e+04
6.326263  -0.14985001  "
## [44] ""

## [45] "States w 95% CI (inp$msytype: s)"

## [46] "                    estimate      cilow
   ciupp    log.est  "
## [47] " B_2020.44      7.164879e+04 82.6914623 6.20
8076e+07 11.1795315  "
## [48] " F_2020.44      5.537900e-03  0.0000064 4.80
7162e+00 -5.1961421  "
## [49] " B_2020.44/Bmsy 7.408503e-01  0.1174958 4.67
1310e+00 -0.2999567  "
## [50] " F_2020.44/Fmsy 9.534973e-01  0.0094966 9.57
3492e+01 -0.0476187  "
## [51] ""

## [52] "Predictions w 95% CI (inp$msytype: s)"

## [53] "                  prediction       cilow
    ciupp    log.est  "
## [54] " B_2022.00      7.183915e+04  81.5294369 6.3
30061e+07 11.1821849  "
## [55] " F_2022.00      5.538100e-03   0.0000062 4.9
11607e+00 -5.1960985  "
## [56] " B_2022.00/Bmsy 7.428187e-01   0.1173514 4.7
01941e+00 -0.2973033  "
## [57] " F_2022.00/Fmsy 9.535389e-01   0.0092010 9.8
81914e+01 -0.0475750  "
## [58] " Catch_2021.00  3.974904e+02 243.2564354 6.4
95147e+02  5.9851708  "
## [59] " E(B_inf)       8.054622e+04          NA
       NA 11.2965864  "
```

```
plot(res11)
```



30 Checklist for the acceptance of a SPiCT assessment

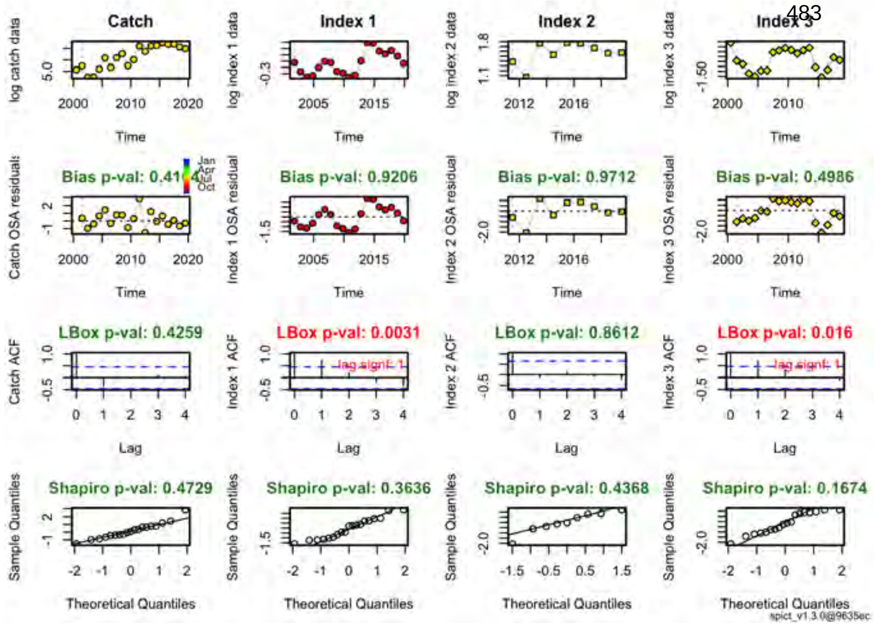
```
res11$opt$convergence
```

```
## [1] 0
```

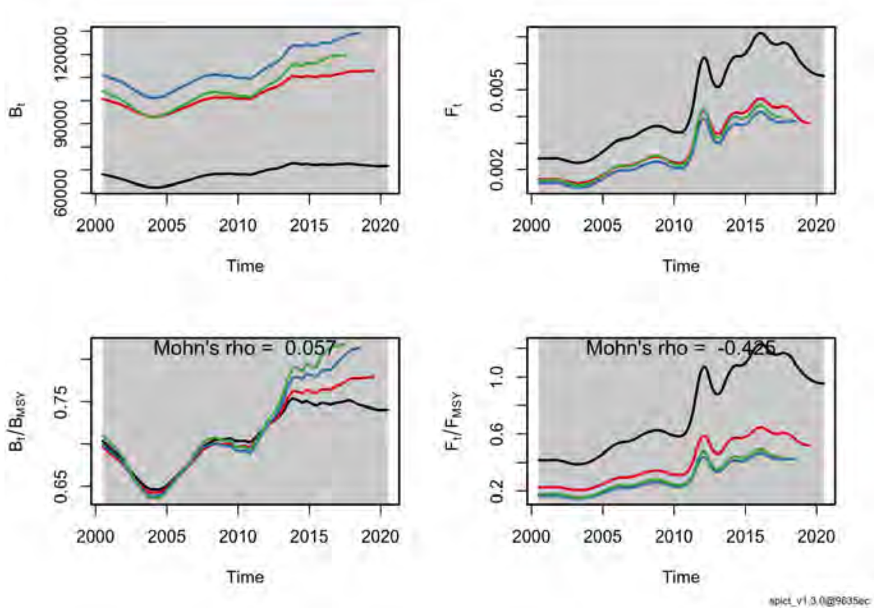
```
all(is.finite(res11$sd))
```

```
## [1] TRUE
```

```
r11<- calc.osa.resid(res11)
plotspict.diagnostic(r11)
```




```
r11<- fit.spict(inp11)
rep11=retro(r11, nretroyear=3)
plotspict.retro(rep11)
```




```
m11=mohns_rho(rep11, what = c("FFmsy", "BBmsy"));m11
```

```
##       FFmsy       BBmsy
## -0.56728956  0.07548768
```

```
set.seed(123)
check.ini(inp11, ntrials=20)
```

```
## Checking sensitivity of fit to initial parameter v
alues...
##  Trial 1 ... model fitted!
```

```
##  Trial 2 ... model fitted!
##  Trial 3 ... model fitted!
##  Trial 4 ... model fitted!
##  Trial 5 ... model fitted!
##  Trial 6 ... model fitted!
##  Trial 7 ... model fitted!
##  Trial 8 ... model fitted!
##  Trial 9 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 10 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation

## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
##  convergence not obtained!
##  Trial 11 ... model fitted!
##  Trial 12 ... model fitted!
##  Trial 13 ...
```

```
## Warning in nlminb(obj$par, obj$fn, obj$gr, control
 = inp$optimiser.control): NA/
## NaN function evaluation
```

```
## Error in nlminb(obj$par, obj$fn, obj$gr, control =
 inp$optimiser.control) :
##   gradient function must return a numeric vector o
f length 12
## obj$par:
##         logm         logK         logq         log
q         logq         logn
##  4.542568110  6.403138210 -9.396442194 -8.61801870
6 -6.378010842  2.271474022
##       logsdb       logsdf       logsdi       logsd
i       logsdi       logsdc
## -0.009356955 -1.620825268 -2.125635906 -2.77708344
5 -3.400404894 -2.116032260
## obj$fn:
## [1] NaN
## obj$gr:
## [1] NaN
## Error in fit.spict(inpsens) :
##   Could not fit model. Error msg:Error in nlminb(o
bj$par, obj$fn, obj$gr, control = inp$optimiser.contr
ol) :
##   gradient function must return a numeric vector o
f length 12
##
##  fit failed!
##  Trial 14 ... model fitted!
##  Trial 15 ... model fitted!
##  Trial 16 ... model fitted!
##  Trial 17 ... model fitted!
##  Trial 18 ... model fitted!
##  Trial 19 ... model fitted!
##  Trial 20 ... model fitted!
## $propchng
##           logm  logK  logq  logq  logq  logn logsd
b logsdf logsdi logsdi logsdi
## Trial 1  -1.41  0.17 -0.07 -0.24 -0.27  0.28  -0.0
8  -1.12  -0.15   0.12  -1.31
## Trial 2   1.18  0.04 -0.32 -0.25  0.16  0.28   0.4
9  -1.30  -1.11  -0.55  -0.40
## Trial 3   1.03  0.13  0.04 -0.06  0.13  0.22  -1.3
2  -1.15  -0.55  -0.85   1.36
## Trial 4   1.72 -0.17 -0.15  0.17  0.22  0.05   0.2
5   0.38   0.99   1.03   0.76
```

```
## Trial 5  -1.55  0.22 -0.36  0.04 -0.18  0.23  -0.1
7   0.84   1.07  -0.72  -1.13
## Trial 6   1.10 -0.24 -0.09  0.14 -0.19  0.03  -0.8
9  -0.89  -0.84   0.17  -0.73
## Trial 7   1.40 -0.30 -0.02  0.17  0.07 -0.07   0.4
2   1.11   0.73  -0.48   0.24
## Trial 8  -2.64 -0.04  0.39 -0.24 -0.24  0.20   1.0
6  -0.44   0.45  -0.45   0.51
## Trial 9   1.88 -0.24 -0.03 -0.01 -0.06  0.10   0.0
3  -1.30   0.05  -1.12  -1.19
## Trial 10 -0.59 -0.21  0.35  0.12  0.27 -0.28  -0.6
3   1.02  -0.14  -1.30  -0.24
## Trial 11  0.98 -0.11 -0.15  0.17  0.08 -0.30   0.9
9   1.17   1.02  -0.54  -0.34
## Trial 12  1.15  0.14  0.02 -0.10 -0.20 -0.18  -1.3
7   0.17   0.54   0.26   1.40
## Trial 13  2.28 -0.16 -0.21  0.26  0.16 -0.14  -0.9
9   0.01   0.32   0.73   1.11
## Trial 14  0.48 -0.17 -0.04  0.17  0.00  0.09  -0.4
3   0.36   0.41  -0.10  -0.69
## Trial 15 -0.58 -0.14  0.10  0.20 -0.22 -0.15  -0.4
8  -0.34   0.37  -0.09  -1.07
## Trial 16  2.26 -0.11  0.17  0.15 -0.06  0.01   0.6
7  -0.18  -1.18  -1.15   0.65
## Trial 17  3.23  0.07  0.35  0.02  0.06 -0.10   0.9
9  -0.21   0.75  -1.32  -0.29
## Trial 18 -0.65  0.23 -0.11  0.13  0.20  0.20   0.0
5   0.71   0.81  -0.50   1.29
## Trial 19 -0.98 -0.05  0.26 -0.26  0.13 -0.29  -0.6
5  -0.53   1.28   0.30   0.06
## Trial 20  1.32  0.25  0.09  0.04 -0.03  0.27   0.6
8   0.29   0.86  -0.95   0.99
##          logsdc
## Trial 1    0.13
## Trial 2   -1.41
## Trial 3    0.06
## Trial 4    0.10
## Trial 5    0.36
## Trial 6   -0.37
## Trial 7   -0.82
## Trial 8    0.89
## Trial 9   -0.31
## Trial 10   0.27
## Trial 11  -1.12
## Trial 12   0.90
## Trial 13   0.31
## Trial 14   0.80
## Trial 15  -0.23
## Trial 16   0.51
## Trial 17  -0.04
## Trial 18  -0.57
## Trial 19  -0.17
## Trial 20  -0.87
##
```

```
## $inimat
##           Distance  logn logK logm logq1 logq2 logq
3 logsdb logsdf logsdi1
## Basevec      0.00  0.69 7.64 5.74 -7.45 -7.45 -7.4
5  -1.61  -1.61   -1.61
## Trial 1      4.73 -0.29 8.97 5.32 -5.68 -5.42 -9.5
4  -1.48   0.20   -1.37
## Trial 2      5.29  1.51 7.98 3.92 -5.61 -8.62 -9.5
6  -2.40   0.48    0.18
## Trial 3      4.54  1.41 8.60 5.95 -7.01 -8.42 -9.0
7   0.52   0.24   -0.73
## Trial 4      3.95  1.88 6.34 4.91 -8.68 -9.09 -7.8
4  -2.01  -2.21   -3.21
## Trial 5      4.81 -0.38 9.29 3.65 -7.71 -6.07 -9.1
9  -1.33  -2.96   -3.32
## Trial 6      3.92  1.45 5.78 5.21 -8.49 -6.00 -7.6
8  -0.18  -0.17   -0.25
## Trial 7      4.01  1.66 5.34 5.63 -8.74 -8.00 -6.9
3  -2.29  -3.40   -2.79
## Trial 8      4.93 -1.14 7.34 7.98 -5.64 -5.67 -8.9
4  -3.31  -0.90   -2.33
## Trial 9      4.19  1.99 5.77 5.59 -7.39 -6.99 -8.2
2  -1.66   0.48   -1.69
## Trial 10     4.95  0.28 6.02 7.75 -8.36 -9.47 -5.3
9  -0.59  -3.26   -1.38
## Trial 11     4.70  1.37 6.81 4.86 -8.74 -8.05 -5.2
2  -3.20  -3.49   -3.26
## Trial 12     4.40  1.49 8.73 5.84 -6.71 -5.97 -6.1
3   0.60  -1.89   -2.48
## Trial 13     4.41  2.27 6.40 4.54 -9.40 -8.62 -6.3
8  -0.01  -1.62   -2.13
## Trial 14     2.86  1.02 6.34 5.49 -8.75 -7.44 -8.1
2  -0.92  -2.19   -2.28
## Trial 15     3.50  0.29 6.56 6.34 -8.90 -5.77 -6.3
1  -0.83  -1.07   -2.20
## Trial 16     3.94  2.26 6.78 6.70 -8.53 -7.01 -7.5
3  -2.69  -1.31    0.29
## Trial 17     4.36  2.93 8.19 7.76 -7.60 -7.88 -6.7
1  -3.21  -1.27   -2.81
## Trial 18     4.25  0.24 9.39 5.12 -8.42 -8.96 -8.9
6  -1.69  -2.75   -2.92
## Trial 19     4.30  0.01 7.22 7.22 -5.52 -8.45 -5.3
2  -0.56  -0.75   -3.67
## Trial 20     4.39  1.61 9.56 6.29 -7.78 -7.25 -9.4
8  -2.71  -2.08   -3.00
##           logsdi2 logsdi3 logsdc
## Basevec    -1.61   -1.61  -1.61
## Trial 1    -1.81    0.49  -1.82
## Trial 2    -0.72   -0.96   0.67
## Trial 3    -0.25   -3.80  -1.71
## Trial 4    -3.27   -2.84  -1.77
## Trial 5    -0.44    0.21  -2.19
## Trial 6    -1.89   -0.44  -1.01
## Trial 7    -0.84   -1.99  -0.28
```

```
## Trial 8    -0.89   -2.44  -3.05
## Trial 9     0.19    0.30  -1.11
## Trial 10    0.48   -1.22  -2.05
## Trial 11   -0.73   -1.06   0.19
## Trial 12   -2.03   -3.86  -3.07
## Trial 13   -2.78   -3.40  -2.12
## Trial 14   -1.45   -0.50  -2.89
## Trial 15   -1.47    0.12  -1.23
## Trial 16    0.24   -2.65  -2.43
## Trial 17    0.52   -1.14  -1.54
## Trial 18   -0.81   -3.69  -0.68
## Trial 19   -2.09   -1.71  -1.33
## Trial 20   -0.08   -3.21  -0.21
##
## $resmat
##           Distance        m         K  q  q  q
n  sdb  sdf  sdi  sdi  sdi
## Basevec       0.00   642.84 224242.91  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 1       1.36   642.84 224244.26  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 2       1.16   642.84 224244.07  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 3       0.31   642.84 224243.22  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 4       0.90   642.84 224243.81  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 5       0.03   642.84 224242.88  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 6       0.86   642.84 224243.77  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 7       1.01   642.84 224243.92  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 8  218668.03 62390.13  14474.03  0  0  0 2.0
5 0.11 0.23 0.17 0.22 0.10
## Trial 9       0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 10      0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 11      0.80   642.84 224243.71  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 12      0.70   642.84 224243.61  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 13      0.00       NA        NA NA NA NA   N
A   NA   NA   NA   NA   NA
## Trial 14      1.34   642.84 224244.25  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 15      0.03   642.84 224242.88  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 16      0.74   642.84 224243.65  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 17      2.09   642.84 224245.00  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 18      0.31   642.84 224242.60  0  0  0 1.6
```

```
9 0.04 0.22 0.14 0.21 0.11
## Trial 19      0.93   642.84 224243.84  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
## Trial 20      1.01   642.84 224243.92  0  0  0 1.6
9 0.04 0.22 0.14 0.21 0.11
##           sdc
## Basevec  0.06
## Trial 1  0.06
## Trial 2  0.06
## Trial 3  0.06
## Trial 4  0.06
## Trial 5  0.06
## Trial 6  0.06
## Trial 7  0.06
## Trial 8  0.06
## Trial 9    NA
## Trial 10   NA
## Trial 11 0.06
## Trial 12 0.06
## Trial 13   NA
## Trial 14 0.06
## Trial 15 0.06
## Trial 16 0.06
## Trial 17 0.06
## Trial 18 0.06
## Trial 19 0.06
## Trial 20 0.06
```

```
## Catch observations:
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 201
6.5 2017.5 2018.5 2019.5
##  [1] 159.0000 189.0000 115.0000 116.0000 164.0000
267.0000 176.0000 269.0000
##  [9] 321.0000 190.2614 247.4675 447.1744 354.1656
448.0787 457.6295 520.5519
## [17] 484.5457 490.9033 430.5631 399.2396
## Index observations:
## [[1]]
##  [1] 2001.833 2002.833 2003.833 2004.833 2005.833
2006.833 2007.833 2008.833
##  [9] 2009.833 2010.833 2011.833 2012.833 2013.833
2014.833 2015.833 2016.833
## [17] 2017.833 2018.833 2019.833
##
## [[2]]
## [1] 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017
.5 2018.5 2019.5
##
## [[3]]
##  [1] 2000.5 2001.5 2002.5 2003.5 2004.5 2005.5 200
6.5 2007.5 2008.5 2009.5
```

```
## [11] 2010.5 2011.5 2012.5 2013.5 2014.5 2015.5 2016.5 2017.5 2018.5
##
## [[1]]
##  [1] 0.8830629 0.7655780 0.7023948 0.7199932 0.8167087 0.8987942 0.8824258
##  [8] 0.7693151 0.7487957 0.7009754 0.7251867 0.9077803 1.2142796 1.2089463
## [15] 1.0609294 1.0135286 1.0703598 0.9796291 0.8713699
##
## [[2]]
## [1] 3.981842 2.906621 5.873748 4.612534 5.935406 5.861519 5.314860 4.778739
## [9] 4.817878
##
## [[3]]
##  [1] 0.3138639 0.2610667 0.2522755 0.2296472 0.2231178 0.2361038 0.2368988
##  [8] 0.2844170 0.2899648 0.2973215 0.2912091 0.2813124 0.2904401 0.2978007
## [15] 0.2447735 0.2211997 0.2381125 0.2700604 0.2626929
```

```
(calc.om(res11))
```

```
##        lower  est upper CI range order magnitude
## B/Bmsy  0.12 0.74  4.67     4.55               1
## F/Fmsy  0.01 0.95 95.73    95.73               4
```

31 Comparison of AIC s. and Mhon rho

```
kable(data.frame(AIC=c(unlist(lapply(list(res1, res1b, res2,res3,res4,res4b, res5, res5b, res6,res7,res8,res9,res10,res11), get.AIC)))))
```

AIC
25.42283
25.42283
27.80831
89.38730
25.86745
23.64818
20.49935
72.15473
18.64024
70.12491

33.73128
83.41070
79.72568
22.47697

```
m1; m1b; m2;m3;m4;m4b; m5;m5b; m6;m7;m8;m9;m10;m11
```

```
##       FFmsy       BBmsy
## -0.13232642  0.05363205
```

```
##       FFmsy       BBmsy
## -0.13232642  0.05363205
```

```
##       FFmsy       BBmsy
##  0.10921893 -0.02694258
```

```
##      FFmsy      BBmsy
## -0.3611538  0.3594639
```

```
##        FFmsy        BBmsy
##  0.042885155 -0.005722555
```

```
##       FFmsy       BBmsy
##  1.96730767 -0.08196615
```

```
##        FFmsy        BBmsy
##  0.203132943 -0.003441474
```

```
##       FFmsy       BBmsy
##  1.45488326 -0.06271142
```

```
##      FFmsy      BBmsy
## -0.5641415  0.0796907
```

```
##      FFmsy      BBmsy
##  0.2041707 -0.1991812
```

```
##      FFmsy      BBmsy
##  3.3495374 -0.2504127
```

```
##       FFmsy       BBmsy
## 0.009956741 0.051207767
```

```
##      FFmsy      BBmsy
## -0.3010964        NaN
```

```
##       FFmsy       BBmsy
## -0.56728956  0.07548768
```

32 Sensitivity Analysis for prior values (from Paz Sampedro), define alternative priors for Bkfrac

```
BKPrior <- list ("Baseline" = c(log(0.3),0.5, 1), "Hi
ghMean" = c(log(0.8),1,1), "LowMean" = c(log(0.1),1,1
),"HighSD" = c(log(0.3),1,1))

nPrior <- list ("Baseline" = c(log(1.5),0.5, 1), "Low
Mean" = c(log(0.9),1,1),"HighMean" = c(log(2.5),1,1))



warn<-options(warn=-1)
options(warn)

out2 <- data.frame()
for (i in 1:length (BKPrior))
  {
  for (j in 1:length (nPrior))
      {
      sol8c9aSens <- inp
      sol8c9aSens$priors$logbkfrac <- BKPrior[[i]]
      sol8c9aSens$priors$logn <- nPrior [[j]]
      res <- tryCatch(fit.spict(sol8c9aSens),
             error = function()  next)
      out <- cbind(names(BKPrior[i]),names(nPrior[j])
, as.numeric(as.character(res$opt$convergence)), res$
opt$message,as.numeric(as.character(round(res$opt$obj
ective,3))),as.numeric(as.character(round(res$report$
MSY,0))),as.numeric(as.character(round(res$value["Fms
y"],2))),as.numeric(as.character(round(res$value["Bms
y"],0))),calc.bmsyk(res), as.numeric(as.character(res
$value["K"])), round(sumspict.parest(res)["n",1],2),
sumspict.states(res)[3,1], sumspict.states(res) [3,2]
,sumspict.states(res) [3,3],sumspict.states(res) [4,1
], sumspict.states(res) [4,2], sumspict.states(res) [
4,3])

    out2 <- rbind(out2, out)
    }
  }
```

```
names(out2) <- c("BKPrior", "NPrior", "Convergence",
"TypeConve", "ObjectiveFunction", "MSY", "Fmsy", "Bms
y", "BKfrac", "K", "n", "BBmsy", "BBmsycilow","BBmsyc
iupp","FBmsy", "FBmsycilow","FBmsyciupp")

rownames(out2) <- NULL
out2
```

```
##      BKPrior   NPrior Convergence
## 1  Baseline Baseline           0
## 2  Baseline  LowMean           0
## 3  Baseline HighMean           0
## 4  HighMean Baseline           0
## 5  HighMean  LowMean           0
## 6  HighMean HighMean           0
## 7   LowMean Baseline           0
## 8   LowMean  LowMean           0
## 9   LowMean HighMean           0
## 10   HighSD Baseline           0
## 11   HighSD  LowMean           0
## 12   HighSD HighMean           0
##                                                 TypeConve
 ObjectiveFunction   MSY Fmsy
## 1                              relative convergence (4)
            -0.458   574 0.01
## 2                              relative convergence (4)
             0.216   599 0.01
## 3                              relative convergence (4)
             0.254   600    0
## 4                              relative convergence (4)
            -2.661 39822 0.79
## 5                              relative convergence (4)
            -1.924 53326 1.34
## 6                              relative convergence (4)
            -2.071 23214 0.35
## 7  both X-convergence and relative convergence (5)
             0.253  1021    0
## 8                              relative convergence (4)
              0.93   882    0
## 9                              relative convergence (4)
             0.881 21102 0.33
## 10                             relative convergence (4)
            -1.802 37971 0.77
## 11                             relative convergence (4)
            -1.064 50716 1.29
## 12                             relative convergence (4)
            -1.213 22200 0.34
##       Bmsy            BKfrac                K     n
     BBmsy BBmsycilow
## 1  101872 0.442570416065267 250908.827348388 1.49
0.78401095 0.26629142
## 2   73375 0.343028118818267 228522.762355247 0.87
0.99308522 0.25648533
```

```
## 3  134683 0.536093052860848 277179.605188877 2.41
0.65246531 0.18403596
## 4   50291 0.450097641969933  112302.03512211 1.54
2.22142842 1.43441123
## 5   39773 0.360990915487468 110587.538953493 0.96
2.76636404 0.98724053
## 6   67124 0.592260991293227 114375.794178074 3.25
1.69442131 0.84125241
## 7  324048 0.443081167206477 852805.928327853 1.49
0.27834345 0.03418937
## 8  228278 0.343228966770627 780961.109289623 0.87
0.36292608 0.04046015
## 9   63469 0.592741957076947 108056.465857704 3.26
1.69247786 0.84061881
## 10  49270 0.450180348267455  109992.62215338 1.55
  2.220639 1.43387597
## 11  39138 0.361320268317534 108710.776245752 0.96
2.76325126 0.98564856
## 12  65416 0.592561797560396 111408.003199231 3.26
1.69331457 0.84096226
##    BBmsyciupp      FBmsy FBmsycilow   FBmsyciupp
## 1  2.30827256  0.8755077 0.00731448 104.79404083
## 2  3.84512534 0.70491622  0.0064192  77.40951903
## 3  2.31319458 0.99564526 0.00588955 168.31680095
## 4  3.44025764 0.00446899   2.82e-06   7.08817212
## 5   7.7516773 0.00269044   1.31e-06    5.5303391
## 6   3.4128444  0.0100498   4.83e-06  20.92258104
## 7  2.26605708  1.3743789 0.00831591 227.14509417
## 8  3.25543374 1.42492452 0.01064092 190.81142105
## 9  3.40758648 0.01106796     5.2e-06  23.57679377
## 10 3.43909633 0.00468835   2.91e-06   7.55250253
## 11 7.74673431 0.00283153   1.36e-06    5.9022212
## 12 3.40956348  0.0105156       5e-06  22.12240304
```

Data compilation for the French databases of sardine (*Sardina pilchardus*) in the English Channel (27.7.de stock including or not the 25E4/25E5 of the Douarnenez Bay)

Angela Larivain, Erwan Duhamel, Lionel Pawlowski
IFREMER - Institut Français de Recherche pour l'Exploitation de la Mer; Unité STH - Sciences et Technologies Halieutiques, Lorient, FRANCE

Background

Historically, the Northern sardine stock in EU Atlantic waters was considered as a single area regrouping subarea 7 and 8.abd ICES divisions. Since different growth rates and spawning grounds were pointed (ICES, 2017) as well as strong contrast in terms of data availability between the data rich and well surveyed Bay of Biscay and subarea 7 (English Channel and Celtic sea) for which almost only catches were available, it was decided to assess separately both regions.

The sardine stock in the Bay of Biscay (8.abd) is well monitored by surveys and collection of biological parameters on fish coming from the commercial fleet, providing ongoing times series for 19 years. In contrast, in the English Channel (7.de), the sardine is not monitored under the DCF (Data Collection Framework) resulting in a lack of coverage of this data-poor fishery. Only one survey provides a short-time series Biomass Index in the area: the PELTIC – Pelagic Ecosystem – acoustic Survey, conducted by CEFAS during the autumn in the western Channel and Celtic Sea [2012-2020] with a variable spatial coverage (see WD).

Sardine landings have been highly variable between years due to some opportunistic nature of the pelagic fishing fleets operating in that area with changes in targeted species over the time in the English Channel. It is also important to note the Seine Bay closure to fishing in 2010. Due to PCB contaminants, there has been a fishing ban in this area, leading to a drop in the sardine landings (maximum production reached 11,210 T before the closure while nowadays it is not exceeding 2,000 T in 7.de itself). Before the ban *i.e.* 2010, most of the catch were made in the 7.d division, which were mostly divided by France and England, and also Netherland still well represented (especially 2 vessels of 25 m length, mainly operating in the Fécamp region). Other countries like Ireland, Denmark, Germany contributing sporadically, catching sardine as by-catch.

Sardine fishery is considered as seasonal, with most of the landings reported in quarter 3 and quarter 4. Since at least 2000, the sardine landings of the 25E4 (7.h division) 25E5 (7.e) French statistical squares (for Douarnenez Bay) were allocate to the Bay of Biscay assessment, despite the strong bordering with the English Channel (WGHANSA, 2020).

Even if different growth rates were pointed between the two population of either subarea 7 or 8.abd divisions, no genetic evidences could distinguish them at this stage, so the Douarnenez Bay still belongs to the 8.abd stock. Current ongoing projects will investigate the genetic components to provide a better understanding of the stock connectivity between both areas. Because different stories have been observed and the allocation of the two statistical squares may affect future management decision, results will be separately considered and shown.

1.1 Stock definition and structure

Historically, sardine in subarea 7 and the Bay of Biscay (divisions 8.a, b, and d) were considered a single stock unit. This stock ID was supported by studies that did not find genetic differentiation among areas (Shaw et al., 2012; ICES, 2013). SIMWG (stock id working group) later informed that there were no biological reasons to separate those areas given the current knowledge on the dynamic of the stock. However, WKPELA benchmark (ICES, 2017) concluded in 2017 that both areas should be assessed independently, claiming different growth rates, the existence of separate spawning grounds, and the presence of all ages in substantial amounts in both areas. Sardine in subarea 7 was classified as category 5 stock and since then it has been assessed every two years using the precautionary approach. Nevertheless, given the uncertainty associated with landings, ICES could not provide a quantitative advice on fishing opportunities for this stock so far.

The connectivity between sardine in subarea 7 and 8 as well as the exact location of the boundary between stocks is still unknown, although a genetic study is ongoing to shed light on these uncertainties. It must be also noted that French catches from rectangles 25E4 (Division 7h) and 25E5 (Division 7e) have been traditionally reallocated to Division 8a due to localised fishing effort straddling the borders between divisions, but the identity of these catches should be further explored.

1.2 Catch data

Catch data have been reported by 9 countries for different time periods, ranging the beginning of the time series from 1987 to 2002. Total catch is therefore only available for the period 2002-2019. In addition, effort data was provided as *Kilowatt days* by 7 countries, and the size frequency of landings and discards was submitted to Intercatch by 4 and 3 countries, respectively. The size composition of the English landings obtained from an ongoing self-sampling programme in England was also available for this workshop.

A detailed description of the fisheries dependent data can be found in the working document Ouréns et al. (2021).

1.2.1 Excluding rectangles linked to other stock

French catches from rectangles 25E4 (Division 7h) and 25E5 (Division 7e) – *i.e.* the Douarnenez Bay - although in subarea 7, is historically linked to the Bay of Biscay sardine assessment (8.abd). Those FR catches occur at the boundary and are considered more closely associated North of the Bay of Biscay. Therefore, the Douarnenez catches, largely supported in 25E5, represent 25% of the total catches in the 8.abd stock (WGHANSA, 2019). There is still some debates, while waiting for the outcome of the ongoing genetic studies, about that partitionning considering this would affect the current management considerations. Douarnenez Bay is also particularly distinguishable from the rest of the English Channel by the fact, catches are largely carried out by Brittany purse seiners (99.9% of the sardine catches), belonging to this area. Considering the need to manage the expansion of this gear in Brittany waters, and to ensure the transparency of landings, a fishing license is given to fish only South the 48° 30’ (deliberation given by the “Comité Régional des Pêches Maritimes et des Elevages Marins” (CRPMEM) in 2014 - http://www.cdpmem56.fr/wp-content/uploads/2019/01/176-2018-Bolinche-2019.pdf).

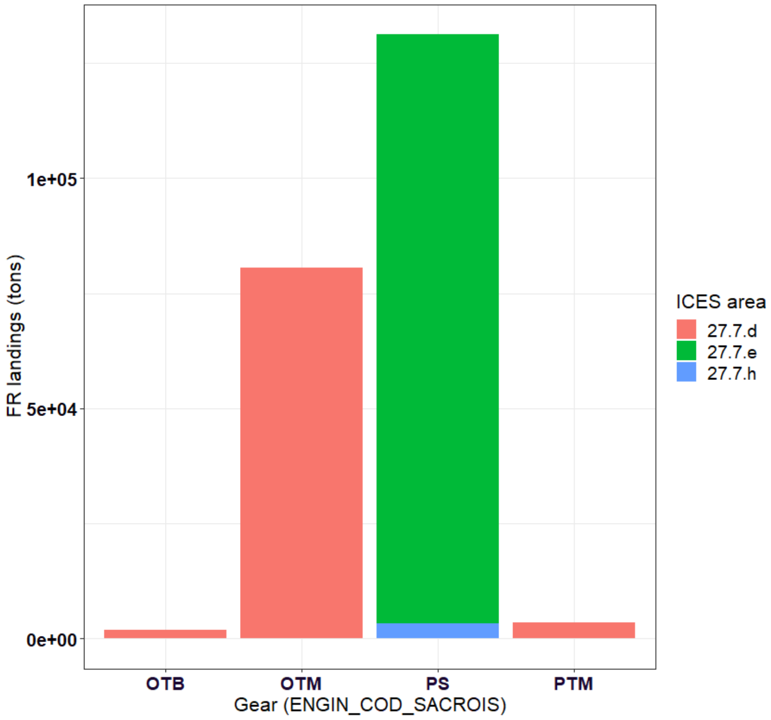


Figure 1. French landings (in tons) by the main gear types (PS: Purse Seine; OTM: Midwater Otter Trawl; PTM: Pelagic Pair Trawl; OTB: Bottom Otter Trawl) represented by ICES area in the English Channel (27.7.d; 27.7.e and the 27.7.h) along the time series (2000-2020). The 27.7h small proportion represents the 25E4 squares of the Douarnenez Bay.

1.2.2 Revision in the French catch data

Time series, compilation of selected variables and applied correction are summarized in this section.This year benchmark aimed at compiling available data for the English Channel stock (7.de divisions, excluding both 25E4/25E5 statistical squares), in order to identify the most appropriate method to assess this unit, currently considered as a category 5.

Because of high uncertainties in the landings, French data have been revised. Different available data sources were cross-validated using the IFREMER SACROIS algorithm which compiles the reported sales and VMS on-board collected data in the logbooks), and both raw sales and logbooks.

An informal exchange with the FROM Nord (producers' organization) was also scheduled in order to validate, as a direct process, the recent pelagic species productions. Around 170 vessels are members to the structure, mainly fishing in the zone of interest, where the highest catch are observed *i.e.* Fécamp area before the 2010 closure of the Seine’s Bay and the Boulogne/Dieppe area since. Some members have been landing sardines more or less regularly since the closure, revealing a rather opportunistic fishery. The market, landing and seasonality of the fishery was discussed in order to get a better understanding of the fishery. The available production in the IFREMER databases, compare to the production directly followed by the FROM Nord before a banking phase fitted well for the three last years extracted by the organization.

The whole process implied the three different IFREMER databases to be compiled for the period 2000 to 2020 in order to compare variable outputs. Both SACROIS and logbooks have statistical squares which allowed the selection of 7.de divisions data and dissociation of the two 25E4 25E5 statistical squares for the Douarnenez Bay to be treated apart.
During the validation process and exploration of databases, some correction were applied:

- **SACROIS and Logbooks**
    - Landing ports have been reallocated to the appropriate statistical squares, following the added knowledge about the fishery and legislation for the Brittany purse seiners
    - Gear codes were crossed with vessels and métiers, and both were renamed when needed
    - Métiers were aggregated to represent the landings, matching the ICES coding fleet. The cumulative sum of landings by code métiers allowed the aggregation of the catch < 0.1% in 'OTHERS' gears.

- Sales
    - No statistical squares were available, but landing ports were used and selected to match the previous filters in the two other databases.
    - Vessels matching SACROIS database are also selected.

The final estimates of landings of sardine for the English Channel (7.de divisions) stock unit, excluding the two 25E4/25E5 statistical squares for Douarnenez Bay, are shown in Fig.8. Selected landings come from the SACROIS database of IFREMER, which after regular corrections showed many similarities with the two others (raw logbook and sales declarations). Landings match particularly well between databases for the post 2010 period.

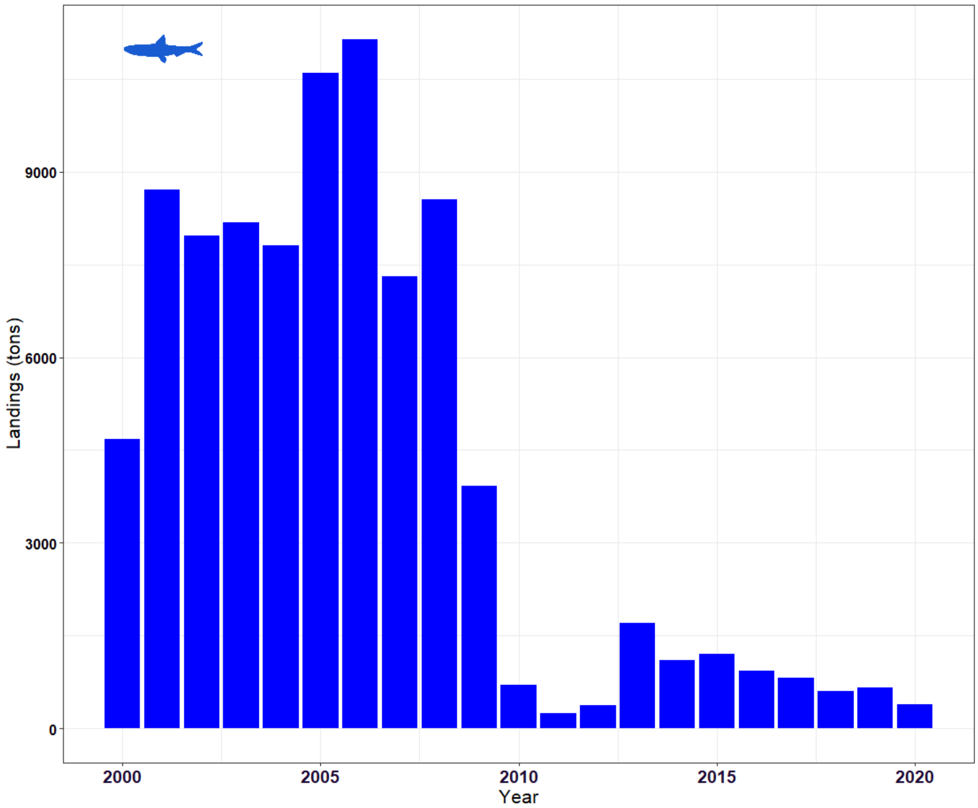


Figure 2. Sardine FR landings in the English Channel (7.de divisions **excluding** 25E4/25E5).

The closure of the Seine Bay, due to the high levels of PCB contaminants in 2010, resulted in a drop down of the landings (maximum of 11,150 t in 2006, minimum of 237 t in 2011). In addition, the sardines were mostly caught in Q1 and Q2 before 2010 whereas Q3 and Q4 are now highly represented (Fig. 9).

Although the Douarnenez Bay is currently part of the 8.abd stock unit assessment, it is bordering both 8 and 7 area, with fishing that occur in both side of the border. 99.9% of the catch are carried out by Britain Purse Seiners in this Bay with only a fishing license to lead the fishery. Vessels are allowed to fish only South the 48° 30’ limit.

In the Fig. 9, landings for both 7.de including or excluding the 25E4/25E5 rectangles are presented by quarter for the 2000-2020 period. This figure shows the importance of these two statistical squares in the sardine landings. Adding or removing them tells two different stories. It is worth mentioning that the fishery did not suffer the COVID-19 crisis with around 13,000 T landed in 2020 for Douarnenez.

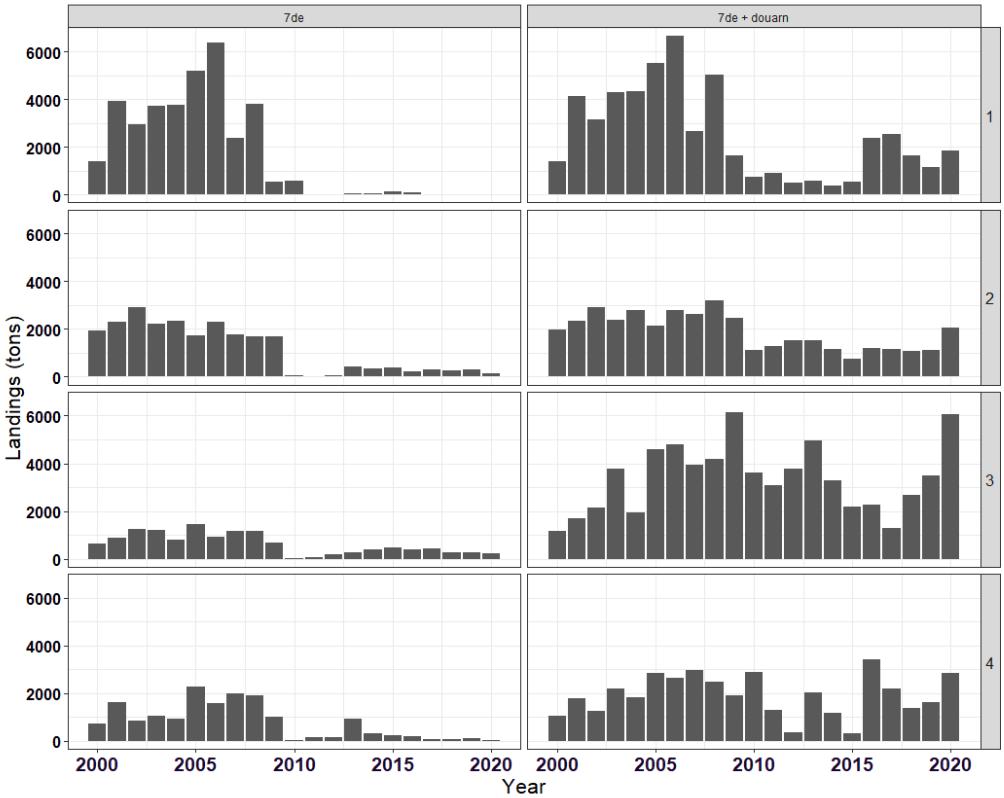


Figure 3. Sardines FR landings by quarter (1: Jan-Mar; 2: Apr-Jun; 3: Jul-Sep; 4: Oct-Dec) in 7.de, excluding both 25E4/25E5 statistical squares (Douarnenez Bay) on the left, and including them on the right (7.de + douarn).

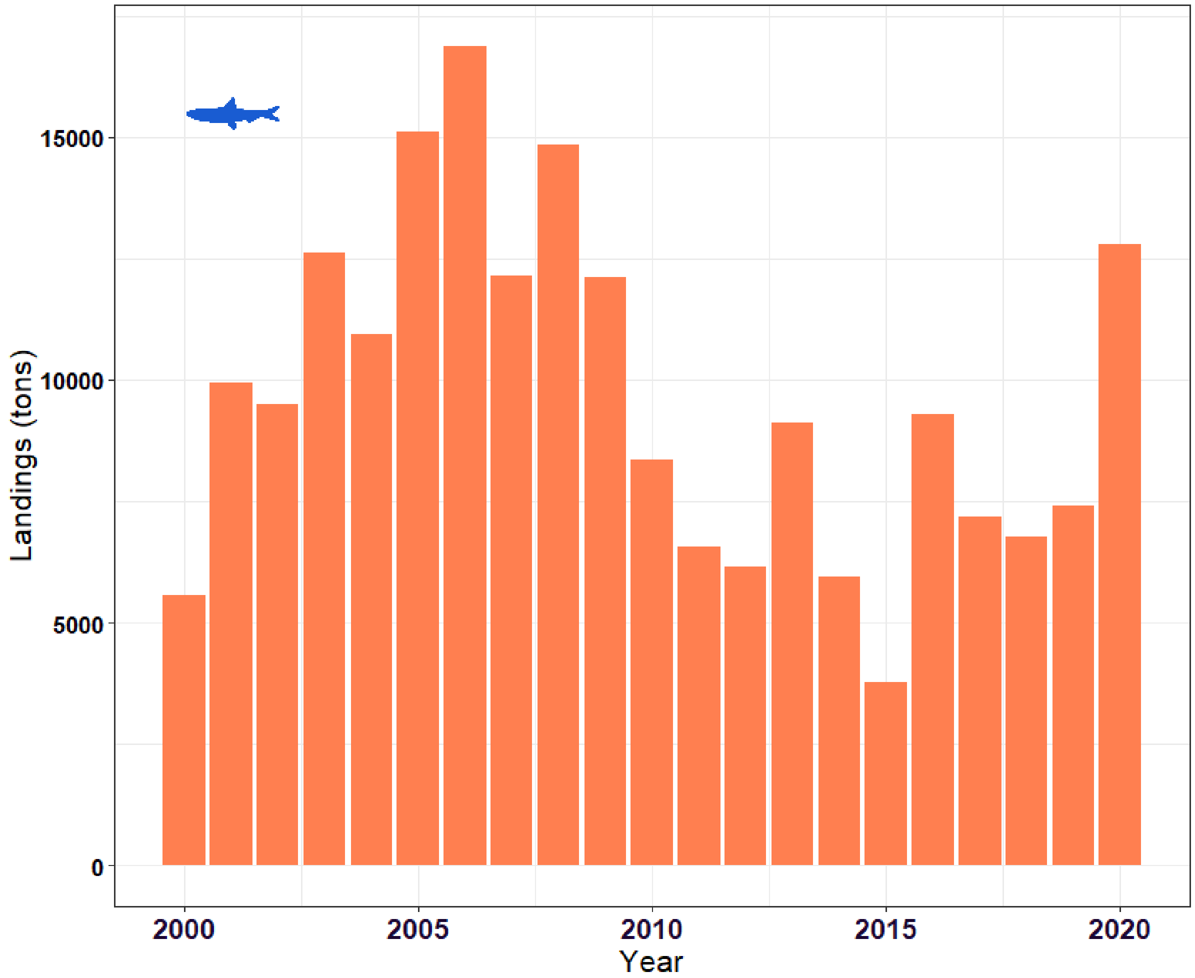


Figure 4. Sardines FR year landings in the English Channel 7.de divisions including the two statistical squares 25E4/25E5 of the Douarnenez Bay.

Annex 1: Participants list

Name	Institute	Institute Country	Email
Jonathan Ball	Cefas Lowestoft Laboratory	UK	johnathan.ball@cefas.co.uk
Paul Bouch	Marine Institute	Ireland	paul.bouch@marine.ie
Neil Campbell	Marine Scotland Science	UK	Neil.campbell@gov.scot
Rui Catarino	ICES	Denmark	Rui.catarino@ices.dk
Erwan Duhamel	Ifremer	France	Erwan.Duhamel@ifremer.fr
Diana Gonzalez-Troncoso Invited Expert	IEO	Spain	diana.gonzalez@ieo.es
Ursula Krampe	DGMare	Belgium	Ursula.Krampe@ec.europa.eu
Angela Larivain	Ifremer	France	alarivai@ifremer.fr
Mathieu Lundy ICES Chair	AFBINI	Northern Ireland	mathieu.lundy@afbini.gov.uk
Catarina Maia	IPMA	Portugal	cmaia@ipma.pt
Claire Moore	Marine Institute	Ireland	Claire.moore@marine.ie
Richard Nash	Cefas Lowestoft Laboratory	UK	Richard.nash@cefas.co.uk
Rosana Ourens	Cefas Lowestoft Laboratory	UK	Rosana.ourens@cefas.co.uk
Lionel Pawlowski	Ifremer	France	lionel.pawlowski@ifremer.fr
Maria Grazia Pennino	IEO	Spain	Grazia.pennino@ieo.es
Marta Quinzan Invited Expert	IEO	Spain	marta.quinzan@ieo.es
John Gabriel Ramírez	Galway-Mayo Institute of Technology	Ireland	John.ramirez@gmit.ie
Alberto Rocha	IPMA	Portugal	arocha@ipma.pt
Arved Staby External Chair	Institute of Marine Research	Norway	arved.staby@hi.no
Sven Stötera Invited Expert	Thunen Institute	Germany	sven.stoetera@thuenen.de

Name	Institute	Institute Country	Email
Jeroen Van Der Kooij	Cefas Lowestoft Laboratory	UK	jeroen.vanderkooij@cefas.co.uk

Annex 2: Stock annexes

The table below provides an overview of the Stock Annexes WKWEST updated in the benchmark process. Stock Annexes for other stocks are available on the ICES website Library under the Publication Type "Stock Annexes". Use the search facility to find a particular Stock Annex, refining your search in the left-hand column to include the *year*, *ecoregion*, *species*, and *acronym* of the relevant ICES expert group.

Stock ID	Stock name	Last updated	Link
gur.27.3–8	Red gurnard (*Chelidonichthys cuculus*) in subareas 3–8 (Northeast Atlantic)	March 2012 To be updated at WGWIDE 2021	Red gurnard in NEA
pil.27.7	Sardine (*Sardina pilchardus*) in Subarea 7 (southern Celtic Seas and the English Channel)	February 2017 To be updated at WGHANSA 2021	Sardine in 7.a
ple.27.7h–k	Plaice (*Pleuronectes platessa*) in divisions 7h–k (Celtic Sea South, southwest of Ireland)	May 2014 To be updated at WGCSE 2021	Plaice in 7.h–k
sol.27.8c9a	Sole (*Solea* spp.) in divisions 8.c and 9.a (Cantabrian Sea and Atlantic Iberian waters)	March 2021	Sole in 8.c and 9.a