# ICES WKIrish3 REPORT 2017

ICES Benchmark Steering Group Committee

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# Report of the Benchmark Workshop on the Irish Sea Ecosystem (WKIrish3)

30 January–3 February 2017

Galway, Ireland

International Council for the Exploration of the Sea

Conseil International pour l'Exploration de la Mer

**International Council for the Exploration of the Sea**
**Conseil International pour l'Exploration de la Mer**

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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## Contents

## Executive summary

The Stock Assessment Workshop for Irish Sea stocks (WKIrish3), chaired by External Chair Daniel Howell, Norway and ICES Chair Hans Gerritsen, Ireland, and attended by invited external experts Jim Ianelli, US, and Rebecca Lauerburg, Germany met in Galway, Ireland, 30 January–3 February 2017. As part of the WKIrish regional benchmark process, WKIrish3 built on the conclusions and recommendations of the Scoping Workshop (WKIrish1) and the Data Evaluation Workshop (WKIrish2).

The objectives of the workshop were to develop methods to determine stock status and short-term outlook and to propose biological reference points for the Irish Sea stocks of cod, haddock, herring, plaice and whiting.

The meeting was mainly conducted through plenary sessions with some time scheduled to address feedback given by the group. The report sections are structured along the ToRs of the workshop as well as the headings in the stock annex.

The main outcomes of the workshop are as follows:

- Cod: ASAP model accepted, new reference points proposed. This will form the basis of the advice for 2018.
- Haddock: ASAP model accepted, new reference points proposed. Shortly after the workshop ended, the advice for 2017 was re-issued, based on the new method and reference points.
- Whiting: ASAP model accepted, new reference points proposed. This will form the basis of the advice for 2018.
- Plaice: SAM model accepted by correspondence, shortly after the meeting, new reference points proposed. This will form the basis of the advice for 2018.
- Herring: SAM model rejected. No new reference points proposed. WKIrish3 recommends that the remaining issues are addressed before the assessment working group (HAWG) through an inter-benchmark.

## 1 Opening of the meeting

The Stock Assessment Workshop for Irish Sea stocks (WKIrish3), chaired by External Chair Daniel Howell, Norway and ICES Chair Hans Gerritsen, Ireland, and attended by invited external experts Jim Ianelli, US, and Rebecca Lauerburg, Germany met in Galway, Ireland, 30 January–3 February 2017.

As part of the WKIrish regional benchmark process, WKIrish3 will work building on the conclusions and recommendations of the Scoping Workshop (WKIrish1) and the Data Evaluation Workshop (WKIrish2), to:

a ) Evaluate the appropriateness of data and methods to determine stock status and investigate methods for short-term outlook for the stocks listed in the table below. The evaluation shall include consideration of (while paying particular attention to the conclusions and recommendations of WKIrish 1 and 2):

  i ) Stock identity and migration issues;

  ii ) Life-history data;

  iii ) Fishery-dependent and fishery-independent data, also including recreational fisheries;

  iv ) Further inclusion of environmental drivers, multispecies information, and ecosystem impacts for stock dynamics in the assessments and outlook.

b ) Agree and document the preferred method for evaluating stock status and (where applicable) short-term forecast and update the stock annex as appropriate. Knowledge of environmental drivers, including multispecies interactions, and ecosystem impacts should be integrated in the methodology.

  If no analytical assessment method can be agreed, then an alternative method (the former method, or following the ICES approach for stocks without analytical assessments) should be put forward;

c ) Evaluate the possible implications for biological reference points, when new standard analyses methods are proposed. Re-examine and update, if necessary, MSY and PA reference points according to ICES guidelines (see reports of WKMSYREF3, WKMSYREF4 and ACOMs Technical document on reference points);

d ) Develop recommendations for future improving of the assessment methodology and data collection;

e ) Identify aspects that require special attention by the ongoing Irish Sea regional benchmark process, in particular pertaining to the development of integrated multispecies and ecosystem advice (to culminate in the synthesis workshop WKIrish4).

f ) Ensure that relevant work is prepared in advance of the meeting, as the meeting should mainly focus on evaluating and reviewing the work. The main aspects of the work should be presented as working documents and be ready at least seven days prior to the start of the meeting.

| Stocks | Stock leader |
|---|---|
| cod-27.7 | Pia Schuchert |
| had.27.7a | Mathieu Lundy |
| her.27.nirs | Pieter-Jan Schön |
| ple.27.7a | Timothy Earl |
| whg.27.7a | Sara-Jane Moore / Colm Lordan |

The meeting was mainly conducted through plenary sessions with some time scheduled to address feedback given by the group. The external chair coordinated the input of the external experts and took responsibility of the technical chairing during the meeting. The ICES chair focused on the preparation before the meeting as well as the finalisation of the report.

The report sections are structured along the ToRs of the workshop as well as the headings in the stock annex.

## 2 Derivation of natural mortality (M)

*Drivers for focus on M estimates*

Natural mortality is, along with the shape of the stock–recruit relationship, a key variable and source of uncertainty in estimation of MSY reference points and associated $F_{MSY}$ catch forecasts. Estimates of recruitment and biomass from catch-based assessments inflate substantially as input M values are increased, and fishing mortality estimates are consequently reduced for a given catch. Incorrect M values are a problem if the assessment model estimates of abundance are being treated as absolute, for example to compute total food consumption by the stock. As the next phase (WKIrish4) in the Irish Sea benchmark process will run ecosystem models which require information on fishery selectivity and biomass from single-species assessments, WKIrish participants felt it was desirable to carry out these assessments using values or ranges of values of M, and age dependence of M, that are likely to encompass the true values and for which there is evidence to help bound the plausible ranges. Previous ICES assessments of Irish Sea cod, haddock, whiting and plaice have used age and year invariant values of M (0.2 for gadoids; 0.12 for plaice).

*M in herring*

There are no direct estimates of M for Irish Sea herring. Age-dependent estimates of M for North Sea herring from the stochastic multispecies assessment model (SMS) runs for the North Sea have been used in the Irish Sea herring stock assessment for many years (Table 2.1). There are no data to indicate if M is likely to be similar in the two areas, although differences in life history (growth, maturity, maximum observed age, etc.) could be examined.

**Table 2.1. Mean M-at-age for cod, haddock and whiting since 2000 given by North Sea SMS key runs (ICES, WGSAM) and reported by the ICES North Sea assessment working group (WGNSSK) in 2016. Herring figures are for the North Sea stock from the same model, but as reported by the ICES Herring Assessment WG as being used for Irish Sea herring.**

| AGE | COD | HADDOCK | WHITING | HERRING |
|---|---|---|---|---|
| 0 | 1.172 | | | |
| 1 | 1.180 | 1.272 | 1.313 | 0.787 |
| 2 | 0.888 | 0.495 | 0.729 | 0.380 |
| 3 | 0.234 | 0.321 | 0.610 | 0.353 |
| 4 | 0.200 | 0.294 | 0.604 | 0.335 |
| 5 | 0.200 | 0.276 | 0.568 | 0.315 |
| 6 | 0.200 | 0.236 | 0.568 | 0.311 |
| 7 | 0.200 | 0.216 | 0.568 | 0.304 |

*M in plaice*

The M value used for many years by ICES for Irish Sea plaice was apparently based on statistical modelling of data from tagging studies that were carried out in the Irish Sea between the 1960s and 1980s (Siddeek, 1989). The annual *M* values derived by Siddeek were 0.17 (SE 0.06) for males and 0.11 (SE 0.08) for females. Estimates using data only for mature male plaice were lower, indicating an age or size dependence. The 1989 Siddeek paper states that the less precise estimate of *M* for females, and higher *M* values obtained by applying traditional methods to the same dataset, indicated that a value of 0.2 is more appropriate to both sexes, which is almost double the currently used value. WKIrish could not evaluate the potential for bias in these estimates for plaice.

#### *M in cod, haddock and whiting*

For Irish Sea cod, haddock, whiting and herring, there are no direct estimates of M from tagging, multispecies assessments or other methods. All three of the gadoid species show very steep age profiles in fishery and survey catches, and apparent short lifespans. Evidence on age dependence and magnitude of M for other stocks of these species can be obtained from the SMS model key runs for the North Sea. The stocks of cod, haddock and whiting in the North Sea show M ~1.2 at age 1, with steep decline up to age 3 (Table 2.1). From age 3, the M for cod and haddock is 0.2–0.3, close to or just above the "traditional" value of 0.2 previously used as a year- and age-invariant value for assessments of the three gadoid species in the Irish Sea. The SMS estimate of M for whiting remains relatively high at 0.6 from age 3 onwards. There are differences in predator populations in the North and Irish Seas, and sea temperatures in the Irish Sea (and more southerly Celtic Sea) are seasonally at or near the upper range for North Atlantic cod. Fast initial growth and early maturity are features of Irish Sea cod, haddock and whiting. M-at-age for these stocks could potentially be higher than in the North Sea. North Sea plaice are not included in the SMS model.

#### *Life-history based inferences on M*

In the absence of multispecies model estimates of M for Irish Sea gadoid and plaice stocks, and poor understanding of biases in the plaice tagging estimates of M, WKIrish2 explored possible M values given by a wide range of life-history based methods, including those such as from Lorenzen (1996) giving age-dependent values. These methods use one or more stock-specific datasets on size-at-age, growth parameters, maturity and maximum observed ages. The methods and results are described in detail in the WKIrish2 data evaluation workshop report, and values considered by WKIrish3 are described in the separate stock sections of the present report.

Brodziak *et al*. (2009) reviewed the use of maximum observed age and life-history parameters for deriving plausible size/age-dependent or age-invariant natural mortality rate for fish and invertebrate fishery resources. Empirical evidence and ecological theory indicated that M scales with body mass or size, and that for a given species, early life-history stages experience higher M than juvenile stages which, in turn, experience higher M than mature adults. Brodziak *et al*. note that the traditional assumption of a constant M may be appropriate when only mature fish are of explicit interest in the assessment, but when juvenile fish need to be modelled explicitly (e.g. because these juveniles are targeted in a fishery or caught as bycatch), then size dependence in M should be incorporated into the assessment application, for example, by means of a Lorenzen (1996) curve.

Also, the size-dependent mortality model for juveniles may be extended into the adult age groups, or combined with either a constant adult M or a more complex model for adults that allows for increasing M at age due to reproduction or senescence. Brodziak et al. suggest that, where multiple estimates of M are available, averaging the set of candidate estimates is considered good practice, unless a single best value can be identified based on relative credibility or goodness-of-fit to observed data; however it is important to characterize the variability of estimates of M for stock assessment applications.

A more recent evaluation of the predictive performance of empirical estimators of natural mortality rate, using information on over 200 fish species, is presented by Then *et al*. (2015). They evaluated estimators based on various combinations of maximum age ($t_{max}$), growth parameters, and water temperature by seeing how well these estimators matched 200 independent, direct estimates of M. They concluded that a $t_{max}$ based estimator performs the best among all estimators evaluated. The $t_{max}$-based estimators in turn performed better than the Alverson–Carney (1975) method based on $t_{max}$ and the von Bertalanffy K coefficient, Pauly's (1980) method based on growth parameters and water temperature and methods based just on K. Based on cross-validation prediction error, model residual patterns, model parsimony, and biological considerations, they recommend the use of a $t_{max}$ based estimator (M = 4.899$t_{max}$ −0.916, prediction error = 0.32) when possible and a growth-based method (M = 4.118K0.73 Linf−0.33,prediction error = 0.6) otherwise.

#### *Evidence to help bound plausible ranges of M*

A wide range of values are given by life-history methods for each stock, and there is very little information to bound the range of plausible values. North Sea SMS estimates of M may not reflect the values in the Irish Sea due to differences in the ecosystems. Overestimation of M carries high risk because M values are positively correlated with both the assessment model estimates of biomass and the derived values of $F_{MSY}$. Since changes in the input M values translate into changes in biomass across the age ranges affected, this offers a possibility to use fishery-independent survey estimates of biomass to identify M vectors that lead to assessment model estimates of SSB in the same biomass range. This is not feasible from trawl surveys without knowledge of the true catchability at-age, but could potentially be done using the acoustic surveys for herring and the annual egg production method (AEPM) estimates of SSB for cod, haddock and plaice (Armstrong *et al*., 2012).

The AEPM estimates of SSB for Irish Sea cod and plaice are for 1995, 2000, 2006, 2008 and 2010. Haddock SSB was estimated in the final three of these years. The AEPM estimates are based on well-understood aspects of reproductive biology, and were designed to give SSB estimates as close to absolute as possible in order to address opinions from the fishing industry that stocks such as cod were far more abundant than indicated by ICES assessments. The AEPM surveys were therefore designed to reduce biases as far as possible. There are some differences in estimates when applying stratified mean vs. GAM estimates of egg abundance in each survey, but the estimates are relatively close. Underestimation of SSB is possible, as annual egg production was for stage-1 eggs without consideration of early stage egg mortality which is difficult to estimate with sufficient accuracy. The use of the AEPM estimates to constrain assumptions about M assumes that catch estimates are unbiased, and that fleet selectivity patterns have been accurately described and parameterised given that estimates of M and selectivity can be confounded.

For Irish Sea herring, an assumption that the industry-led acoustic surveys can give an absolute estimate of SSB could potentially be used for evaluating assessment model SSB estimates at different M, but this would require an evaluation of the range of uncertainty around the survey catchability and how accurately the reported landings data represent the true fishery removals each year.

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# 3 Irish Sea herring

Irish Sea herring is a commercially important stock in the Irish Sea, and is currently managed as an ICES category one (data-rich) stock under the MSY approach. The current assessment of Irish Sea herring uses catch-at-age, acoustic survey-at-age and a larval survey (biomass) as input data to estimate fisheries exploitation and stock size. For the WKIrish3 benchmark no new model is proposed; instead the inclusion of a new survey index and the model settings are investigated.

Figure 1.1 shows that trends in SSB closely follow the trends in recruitment, which seems to be very smooth over time. This pattern may be overly smoothed by the model fitted configuration to reflect the biological processes within the stock, as recruitment seems to spike from time to time. The current assessment model uses a random walk to predict recruitment. In those cases where the information of recruitment in the catch and survey data are not good, the random walk prediction dominates the results, resulting in overly smooth recruitment patterns.


**Figure 1.1. Original ICES 2016 assessment of Irish Sea herring, showing spawning–stock biomass, fishing mortality and recruitment.**

The observation variances from the current assessment model (Figure 1.2) indicate that the larval survey (NINEL) and the age-1 data in both the catch and the survey have a very high observation variance, in part implying that the data are ignored by the assessment model, and that the model fits to the catch data much better. In general, the stock trends are informed to a larger extent by the catch than the survey data, something that is common across many stock assessments but not necessarily the ideal situation. In this case, if we compare the assessment with a VPA run (without any tuning), we note that results are markedly the same in terms of SSB, but not for fishing mortality and recruitment (Figure 1.3) supporting the view that SAM model smooths out recruitment and fishing mortality.

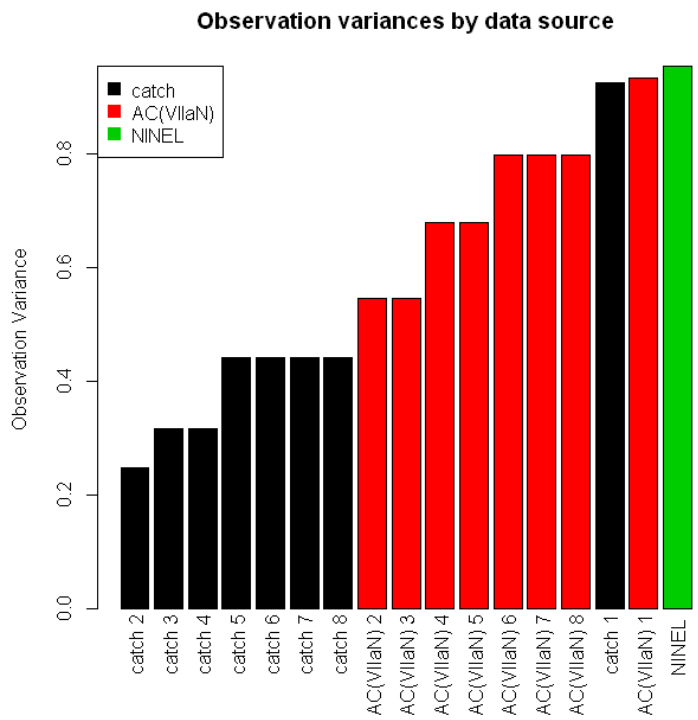



**Figure 1.2. Original ICES 2016 assessment of Irish Sea herring, showing spawning–stock biomass, fishing mortality and recruitment.**

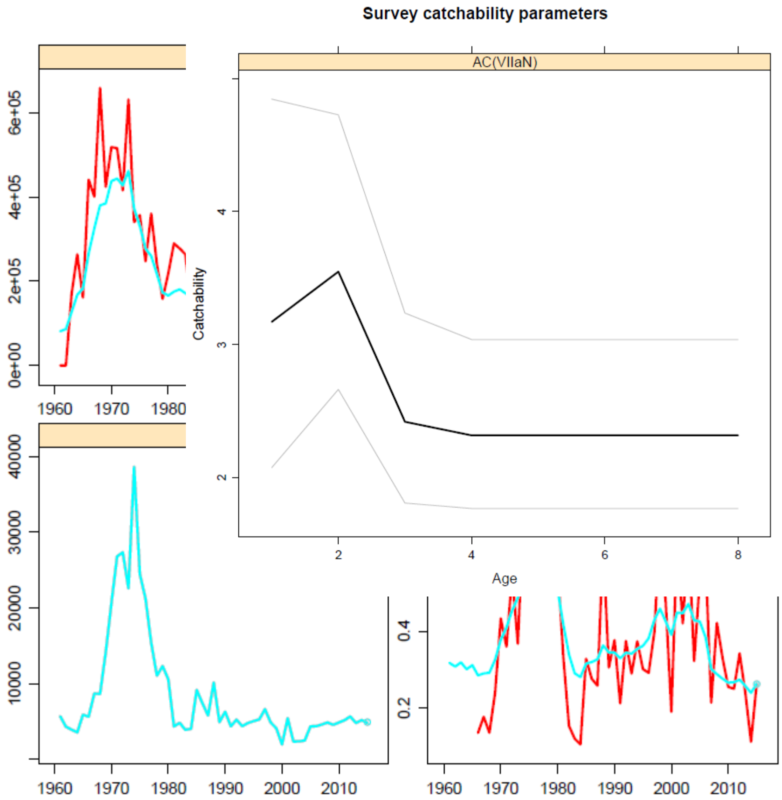



**Figure 1.3. VPA (in red) compared to the SAM assessment (in blue).**

It also considered that the current assessment model may not accurately estimate the catchability of the acoustic survey. By design, acoustic surveys are designed to get an as absolute estimate of stock biomass as possible, which would result in a catchability of ~1 in the assessment. This assessment estimates catchability to be around ~2.5 (see Figure 1.5). Also, there appears to be a year-effect in the survey in 2001. Dropping this year of data results in improved correlation within the survey with on average a 16% improvement between each age-pairs.

**Figure 1.5. Estimated survey catchability of the acoustic survey including confidence bounds.**

The SAM model has the ability to estimate process error, which represents the mismatch between cohort patterns estimated in year y and in the following year. This is not accounted for in the VPA. The process error does not show specific blocks of under–over estimation of numbers-at-age (Figure 1.6) and it is likely that the modelled process error can be explained by variation in natural mortality processes.

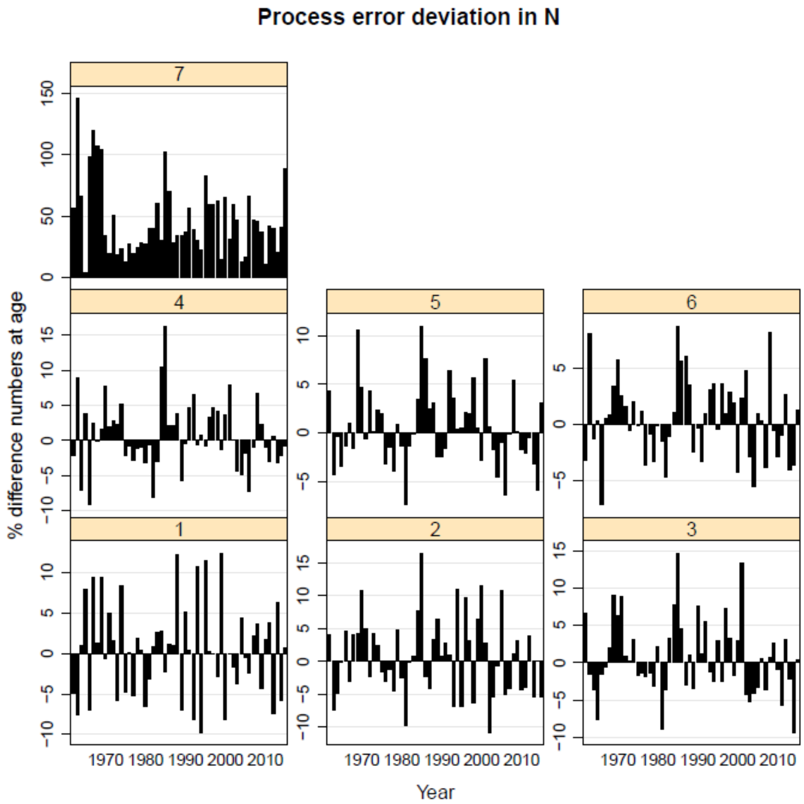



**Figure 1.6. Process error as estimated by the SAM model for each age and year combination. Process error expressed as difference in relative numbers-at-age.**

## 3.1 Issue list

There are some concerns over the quality of the current stock assessment that is used as the basis of the advice, specifically in relation to the acoustic survey time-series. An inter-benchmark was initially proposed to review overall assessment quality, and to consider possible solutions to address the issues with survey coverage in relation to the adult stock as well as catchability in the fishery and survey.

A new survey index is available for formal inclusion in the assessment model that only focuses on the Irish Sea spawning population: 7aN spawning–stock biomass index (2007–present). The primary aims were to 1) find an optimal set of parameters to include a new survey index in the stock assessment, 2) investigate inflated catchability estimates for the current acoustic survey and 3) review if the current assessment methodology can be improved or propose other assessment tools that merits investigation.

## 3.2 Data

Additional tuning series data were presented at WKIrish2 (2016) and WGIPS (2017).

### Stock identity and migration

Stock identity and migration issues were considered at the previous benchmark of the stock (WKPELA 2012).

WKIrish considered the evidence of mixing between the Irish Sea and Celtic Sea stocks, but found there were insufficient data to quantify to which extent this takes place.

No new information is available that will change this evaluation and no changes in existing stock areas have thus been proposed.

### Life-history data

No changes in existing biological data are proposed for the stock.

### Fishery-dependent data

Fishery-dependent data are available as a time-series of landings. Catch-at-age data are maintained annual by national labs and coordinated through the Herring Assessment Working Group (HAWG). The stock is well sampled and in most years, 90–100% of all landings are sampled.

### Fishery-independent data

A number of tuning series are available. The suitability of these as input data were explored at WKIrish2 (ICES, 2016). An acoustic survey of 7.aN herring 2007–present is proposed as an additional source of useful information of the spawning–stock biomass. The existing acoustic survey (AC_7.a(N)) and NINEL larval survey are also available.

### Environmental drivers and ecosystem impacts

Explicit environmental drivers are not included in the current assessment investigation.

**Summary of Input data types and characteristics**

| Type | Name | Year range | Age range | Variable from year to year Yes/No |
|---|---|---|---|---|
| Caton | Catch in tonnes | 1961–last data year | NA | Yes |
| Canum | Catch-at-age in numbers | 1961–last data year | 1–8+ | Yes |
| Weca | Weight-at-age in the commercial catch | 1961–1971 | 1–8+ | Yes |
| | | 1972–1983 | 1–8+ | No |
| | | 1984–last data year | 1–8+ | Yes |
| West | Weight-at-age of the spawning stock at spawning time. | 1961–1971 | 1–8+ | Yes |
| | | 1972–1983 | 1–8+ | No |
| | | 1984–last data year | 1–8+ | Yes |
| Mprop | Proportion of natural mortality before spawning | 1961–last data year | NA | No |
| Fprop | Proportion of fishing mortality before spawning | 1961–last data year | NA | No |
| Matprop | Proportion mature at age | 1961–last data year | 1–8+ | Yes |
| Natmor | Natural mortality | 1961–last data year | 1–8+ | No |

**Tuning data:**

| Type | Name | Year range | Age range |
|---|---|---|---|
| Tuning fleet 1 | AC_VIIa(N) | 1994–last data year | 1–8+ |
| Tuning fleet 2 | NINEL | 1993–last data year | SSB |

**New tuning data:**

| Type | Name | Year range | Age range |
|---|---|---|---|
| Tuning fleet 3 | VIIaNSpawn | 2007–last data year | 1–8+ |

### Overview of 7.aNSpawn

The 7.aNSpawn acoustic survey is conducted annually within the territorial waters around the Isle of Man and north along the Mull of Galloway, during the spawning area closure (late September). The survey is conducted on board a commercial fishing vessel using commercial fishing gear. The survey design consists of systematic; parallel transects covering approximately 620 nm and randomized within +/-4 nm of a baseline starting position each year. Transect spacing is set between 2 and 4 nm in strata around the Isle of Man (where highest densities of adult herring are expected based on previous surveys and fishery data) to improve precision of estimates of adult herring biomass.

A sphere-calibrated Simrad EK60 acoustic system with a 38 kHz split-beam sounder is employed, and resultant data archived and analysed using Echoview software (Echoview Software Ltd, Tasmania) Targets are identified where possible by aimed midwater trawling. Acoustic records are manually partitioned to species by scrutinising the echograms and using trawl compositions where appropriate. ICES-recommended target strengths are used for herring, sprat, mackerel, horse mackerel and gadoids. The survey design and implementation follows, where possible, the guidelines for ICES herring acoustic surveys in the North Sea and West of Scotland. The survey data are analysed in 15-minute elementary distance sampling units (approximately 2.5 nm). An estimate of density by age class, and spawning–stock biomass, is obtained for each EDSU and a distance-weighted average calculated for each stratum. These are raised by stratum area to give population numbers and SSB by stratum.

## 3.3 Model exploration

### Biomass dynamic model

As an exploratory assessment, a biomass dynamic assessment model was fitted to the input data of the 2016 ISH assessment. The data were fitted to the landings data and a survey time-series (Figure 1.7). This survey time-series (AC_7.a(N)) was calculated as the sum of the product of survey-at-age and stock weights-at-age, per year. The model has five parameters: The first is $B_1$ the biomass in the first year of the assessment. This is the year for the first survey information (1994). The parameters $r$ and $K$ stand for the intrinsic population growth rate and the carrying capacity, respectively. The catchability of the survey is estimated in a $q$ parameter. Finally, the observation error in the survey is estimated in a $\sigma$ parameter.

The model is implemented in TMB. More specifically, a grid of plausible starting values was created from which the nlminb routine was used for optimization. Unfortunately, there was no solution found for which the Hessian was positive definite. The results should thus be interpreted with care, and no uncertainty estimates can be given from the final model (Figure 1.8).

## Results

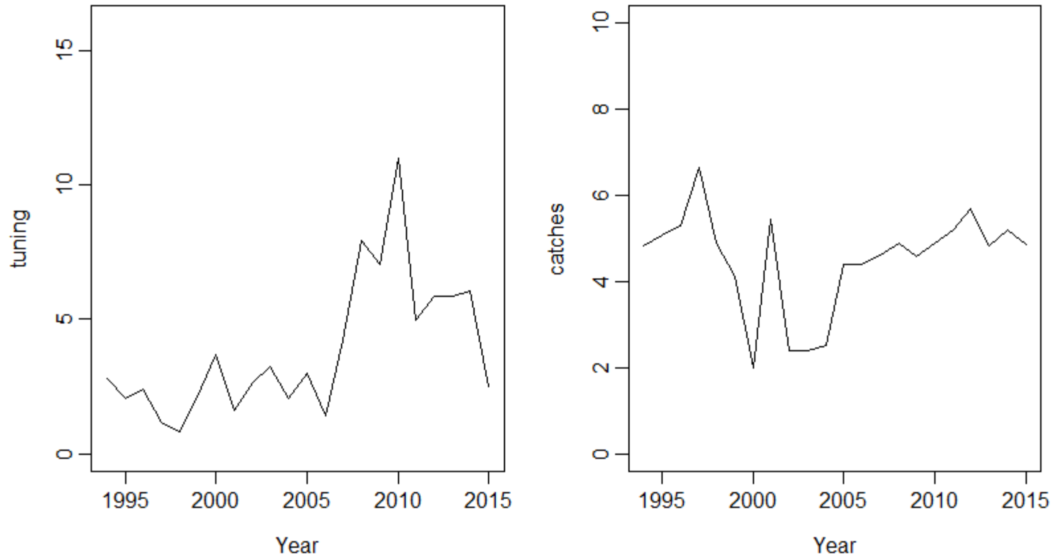



**Figure 1.7. Input data to unstructured biomass dynamics model. Left, the acoustic survey converted into biomass and right, the catch data (in tonnes).**

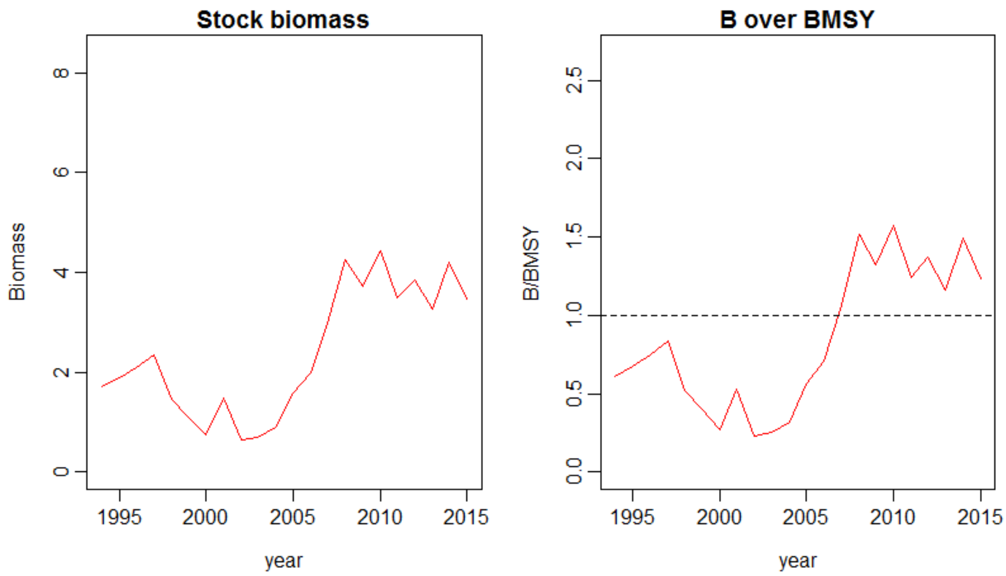



**Figure 1.8. Outputs from unstructured biomass dynamics model. Left, the estimated stock biomass and right, the estimated Biomass versus $B_{MSY}$.**

## Alternative catch-at-age model

This AAP model (Aarts and Poos, 2009) uses a tensor spline (Wood, 2007) to describe the F-at-age matrix underlying the data were fitted to catch only, as discards are regarded as negligible.

Not all data were used in this assessment: the NINEL SSB survey was removed from the model, and the model was started in 1985. The SSB survey was removed, because the interannual variability in that survey is very large, and this variability is not seen in the other data sources. This suggests that the observation error in the survey will be estimated to be large, and the survey to have only a small effect on the final outcomes of the assessment. Indeed the SAM model that is currently used for this stock, estimates the SSB survey to have the largest observation error among all of the data in the model. The model was started in 1985 because AC_7.a(N) only started in 1994, and estimates prior to this year will be almost completely "VPA like" and depending on the assumed relationship between the F values of the oldest ages.

The AAP assessment requires a number of settings: First, a vector $k_f$ with two elements, describing the dimensions of the component (marginal) bases of the tensor product for age and year. Second, a $k_u$ vector giving the number of knots for the basis spline describing the catchability at-age for the surveys. Third, a $p_u$ plateau for the age above which the survey selectivity is constant. Finally, a $p_f$ plateau for the age above which the F-at-age selectivity is constant. The plateaus' ages above which the survey and F-at-age selectivities are constant ($p_u$ and $p_f$), were chosen to mimic the current SAM assessment.

The $k_f$ (of length 2) and $k_u$ (of length 1) vectors are currently chosen arbitrarily: $k_f$ is set to 5,10, and $k_u$ is set to 4 (equal to the number of ages up to the plateau).

The observation errors for each age of the catch-at-age matrix and the age-structured survey are estimated using a quadratic polynomial function of age assuming lognormal distributions. The coefficients for these polynomials are independently (but simultaneously) estimated for the catch-at-age model and the age-structured survey. Parameter estimation for the model is done in ADMB (Fournier *et al*., 2012). Uncertainties in resulting $SSB$, $\bar{F}$, and $R$ are calculated using the delta method.

## Results

The model has 98 parameters, and a negative log-likelihood of 304.7 (see also Appendix C). An overview of the assessment results is given in Figure 1.8. The AAP assessment results are given in blue, with the light blue areas giving the 95% CI. The current SAM results are given by the dashed black lines. Clearly, the results from the AAP model in terms of $SSB$ and $\bar{F}$ are fairly similar to the SAM results, with the exception of $\bar{F}$ in the recent years being consistently lower in the AAP assessment. The recruitment, however, is substantially less smooth than the SAM estimates of recruitment. The survey catchabilities are estimated to be >1 for all ages. The observation errors ("Sigma") are consistently lower for the landings than for the survey for all ages. Both landings-at-age and survey-at-age observation errors are lower for ages 4–6. Estimated landings and observed landings follow similar trends, and since 2005, their correspondence is high.

Figure 1.9 shows some of the background information on the assessment fit. The selectivities in the F-at-age matrix are generally increasing with age, with the exception of the most recent decade, where the selectivity in the F-at-age matrix is rather flat after age 3.

The residuals show some marked year effects in the data, the negative residuals for the survey in 2015 being a case in point. In that year, all residuals apart for age 1 are negative. Something similar is seen in 1997, 1998, and 2006. The F-at-age residuals also show some year effects, for instance, in 2001, all residuals are positive. This result (of large catch observations compared to model results) can also be seen in landings panel of Figure 1.8, where the observed landings (in red) spike, while the model estimated landings follow a smoother trend.

The standard deviation of the standardised residuals (also Figure 1.9, bottom panels) suggest that there is some underestimation of the observation error of age 1 in both data sources, with some overestimation of age 2 and 3 observation error. The reason for this is that the variance in age 1 is large, and the quadratic polynomial smooths out the observation error estimated in the model. This could be improved by extending the quadratic polynomial to e.g. a cubic polynomial.

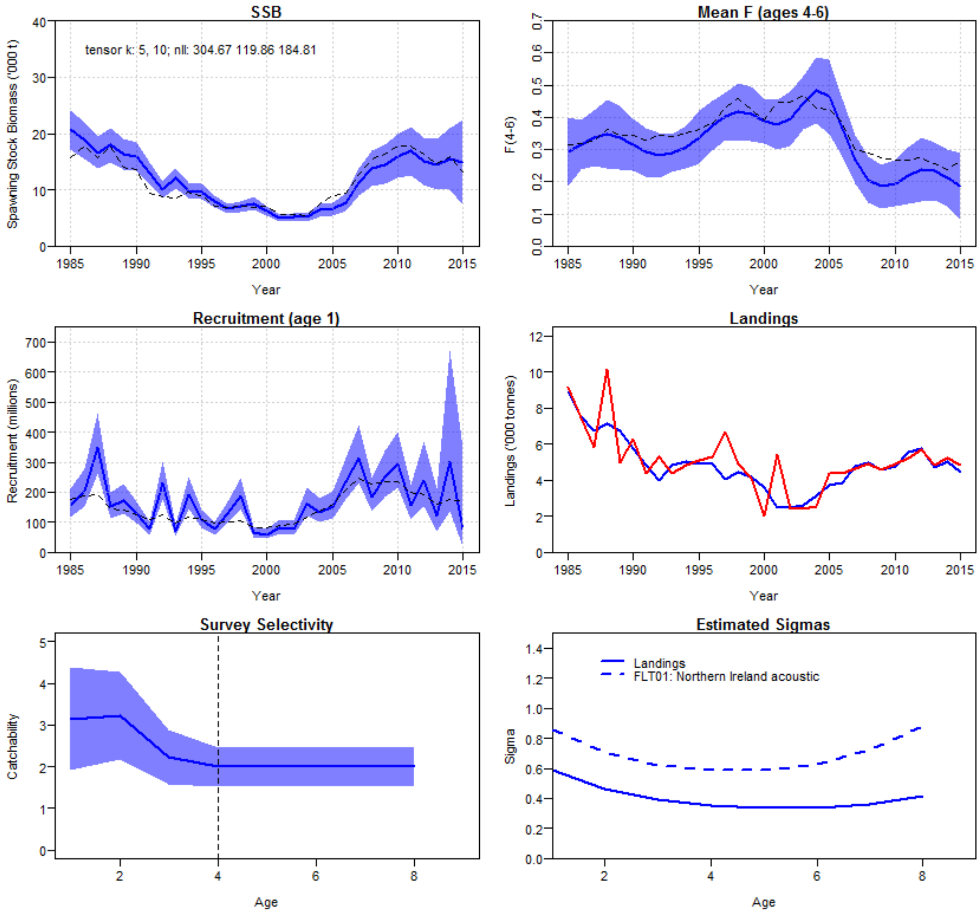



**Figure 1.8. Summary plot for the AAP assessment. The black dashed lines in the SSB, mean F and recruitment plot show the SAM 2016 assessment results.**

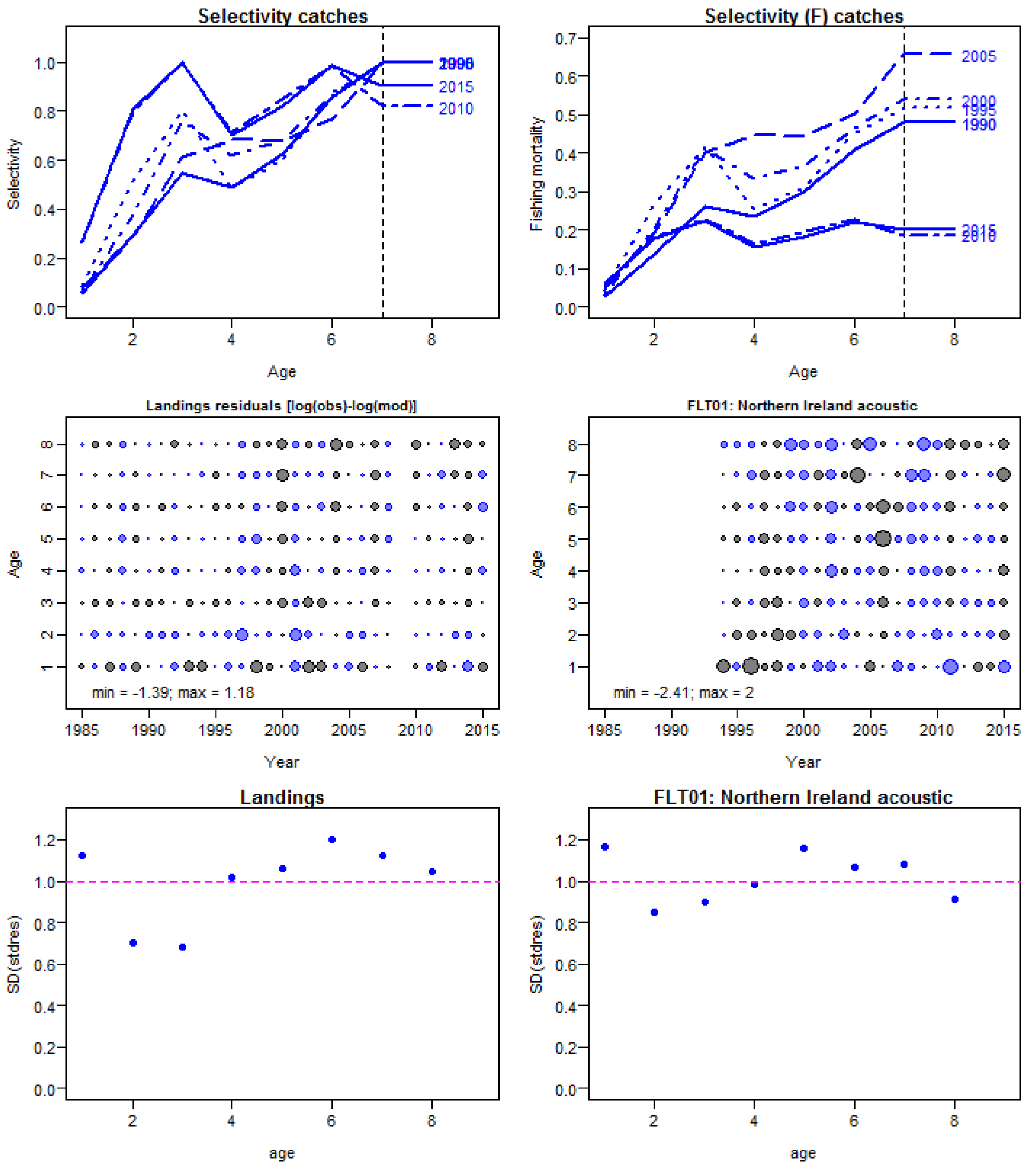



**Figure 1.9. Background plot of assessment run. In case of residual plots, grey indicates negative.**

## Investigate the catchability estimates of the acoustic survey

### Imposing a survey catchability equal to 1

The catchability of AC_7.a(N) for the age 4+ was set manually to 1 (while the Q for younger ages is still estimated by the model). The resulting assessment (named noQ) is compared to the original Irish Sea Herring assessment (ISH) to investigate reasons why Q is estimated to be around ~2.5 in the ISH, a value which is regarded as relatively large. The AC_7.a(N) values were plotted against the modelled abundances-at-age on a log scale. The model assumes a slope of 1 and the value of Q corresponds to the intercept (log(Obs) = log(Q) + log (N)).

For ages four and five, the points are indeed closer to the expected to the 1:1 line (expected with a Q=1), showing that the model has effectively used a Q=1 (Figure 2.0). In comparison, the points for ISH are on average log(2.2)= 0.8 above the 1:1 line. The slope of the linear regression seems to be different from 1, suggesting that a power model may be more appropriate.

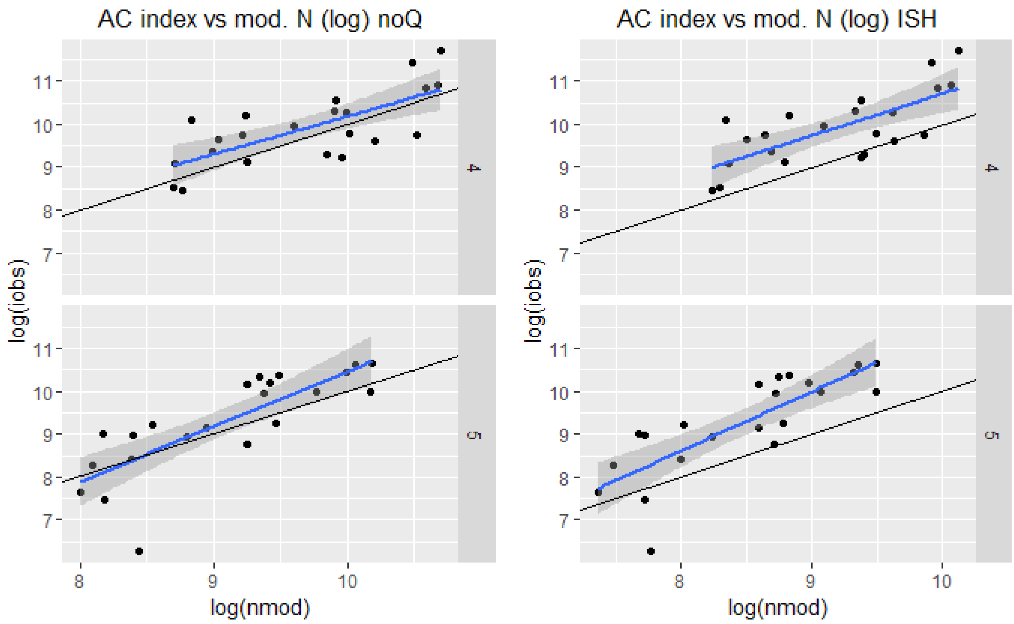



**Figure 2.0. Observed AC_7.a(N) for age four and five vs. estimated numbers-at-age (log–log relationship) for the ISH and noQ assessments. Black line is the 1:1 line, blue line is the linear regression of the datapoints.**

### Assessment output

As expected, forcing the model to have a Q=1 for AC_7.a(N) for ages 4+ mechanically increases the stock number-at-age estimated for the period covered by the survey, which reflects in the difference in the SSB time-series (Figure 2.1), up to 80% higher in the recent year. The difference of at least 10% is also visible is the six years preceding the start of the AC survey, which can be explained by the random walks in the model prevent abrupt changes from happening. The recruitment is also estimated higher in the noQ assessment than in the ISH assessment, but by no more than 40%. The fishing mortality is estimated to be much (50%) lower.

The age profile of the fishing mortality is also different between the ISH and noQ assessments (Figure 2.2). Shortly after the start of the AC_7.a(N), the selection pattern of the noQ assessment starts to change toward a more flat shape, with quite similar F values for ages 2 and older, while for most of the years (except the recent years) the F values in the ISH kept increasing with age). Assuming a Q=1 would therefore imply that marked changed in the fishing practices occurred at around the time of the start of the survey, going from targeting older fish to targeting equally all ages (except recruits).

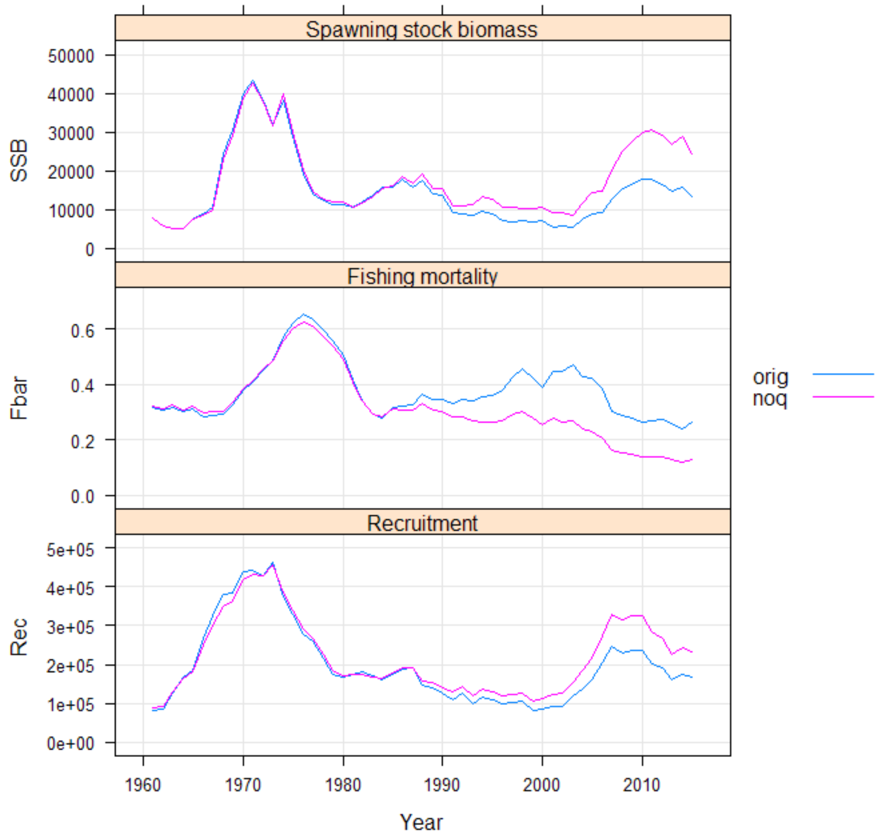



**Figure 2.1. Comparison of the historical stock development for the ISH and noQ assessments.**

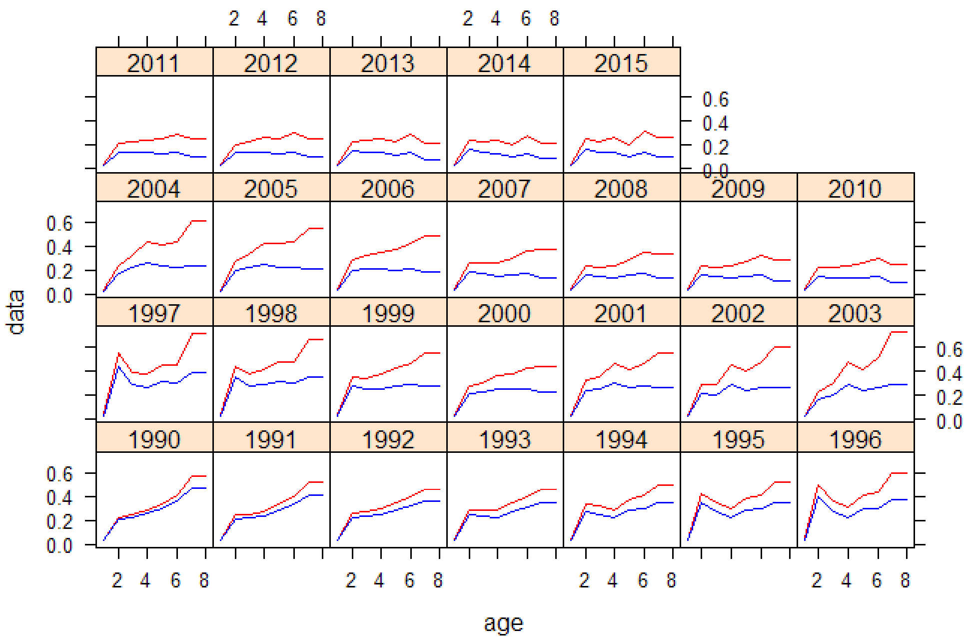



**Figure 2.2. Age profiles for the fishing mortality from the ISH assessment (red) and the noQ (blue).**

Fixing the Q value at 1 affects the other model parameters (Figure 2.3). The other "scale parameters" (Qs) are all lower. The Q for the young ages of the AC (logFpar1-3 on Figure 4) remains higher than 1, which is interpreted by the fact that some juvenile herring from the Celtic Sea stock are also probably sampled by the survey. The noQ assessment has a less variable F random walk variance and a smaller recruitment variability, but a larger process error, which is not a good sign. Observation variances are not very different and remain very large (>0.5) for catches at-age 1, and all survey indices, indicating that the assessment mostly relies on the catches. The parameter standard deviations are not markedly different (Figure 2.4) expect the process error, which is better defined in noQ and some of the observation variances, which are less well defined.

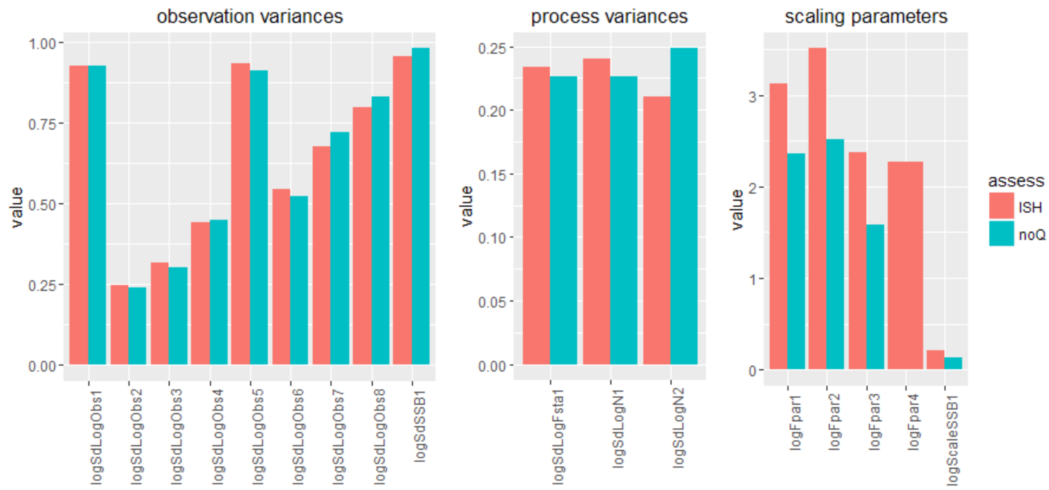



**Figure 2.3. Parameter value from the ISH and noQ assessments.**

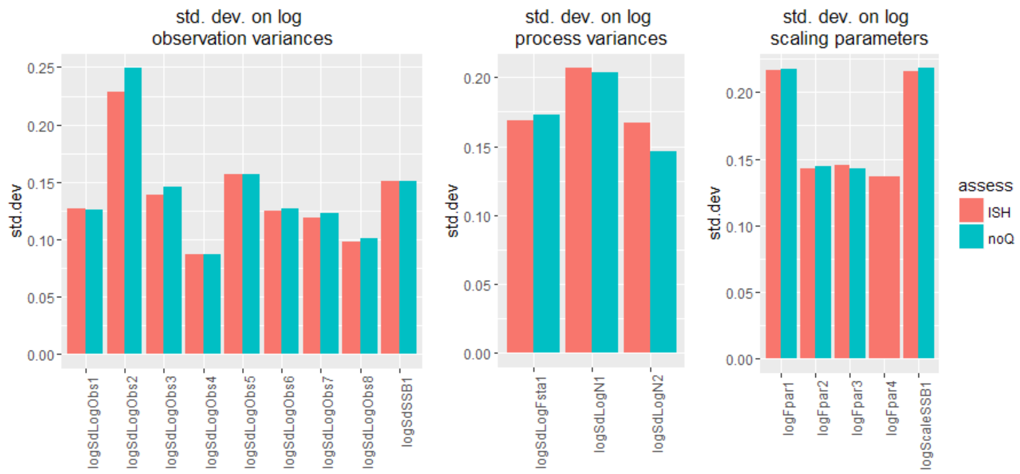



**Figure 2.4. Standard deviation to the parameter estimates from the ISH and noQ assessments.**

The model uncertainty (standard deviation on logSSB and $\log F_{bar}$) are quite similar with a slightly larger uncertainty for the noQ assessment, except for the years after 2010, when noQ is slightly less uncertain than ISH (Figure 2.5).

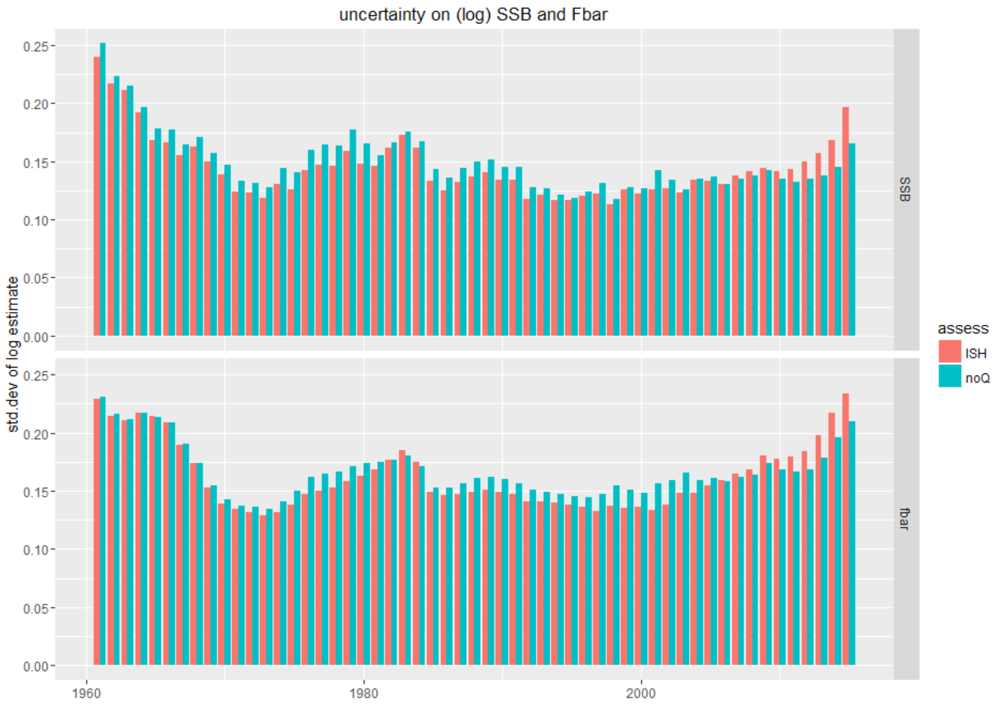



**Figure 2.5. Standard deviation of the log SSB and log $F_{bar}$ from the ISH and noQ assessments.**

### Log catch curve estimate of F

The log catch curve method was used to get an estimate of the total mortality (and using the natural mortality used in the assessment, of the fishing mortality). The method uses the assumption of a constant F applied on a cohort over its lifetime. A rapid inspection of the log catches plotted against the age of the cohort (figure 2.6), shows that age 1 are not fully recruited an should not be incorporated, as well as the plus group.

Total mortality was therefore estimated as the slope of the regression of log catches from age 2 to 7 against the age. The average natural mortality over these ages (0.3388) was subtracted to get a proxy for F (Figure 2.7). Since the log catch curve method assumes a flat selection pattern over ages 2 and older, which is not the case for SAM, the order of magnitude of F are not directly comparable. The log catch curve estimate has in general a similar trend as the F estimate from the ISH with a rise of F in the late 1960s high F in the 1970s, a decrease in the 1980s and a slow increase from the 1980s to the 2000s. The F estimate from the noQ assessment differs for this latter period in that it is stable or even decreasing and not increasing as the log Catch ratio F suggests.

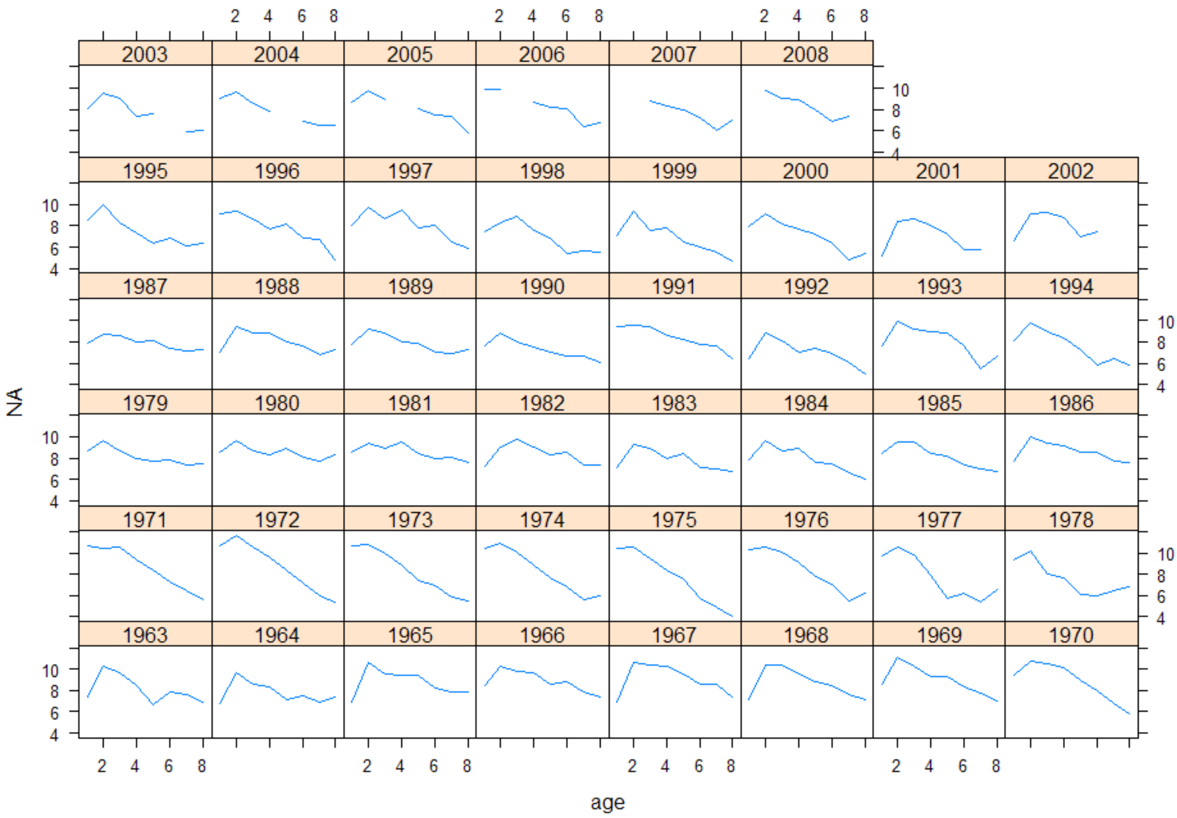



Figure 2.6. Log catches-at-age plotted by cohort.

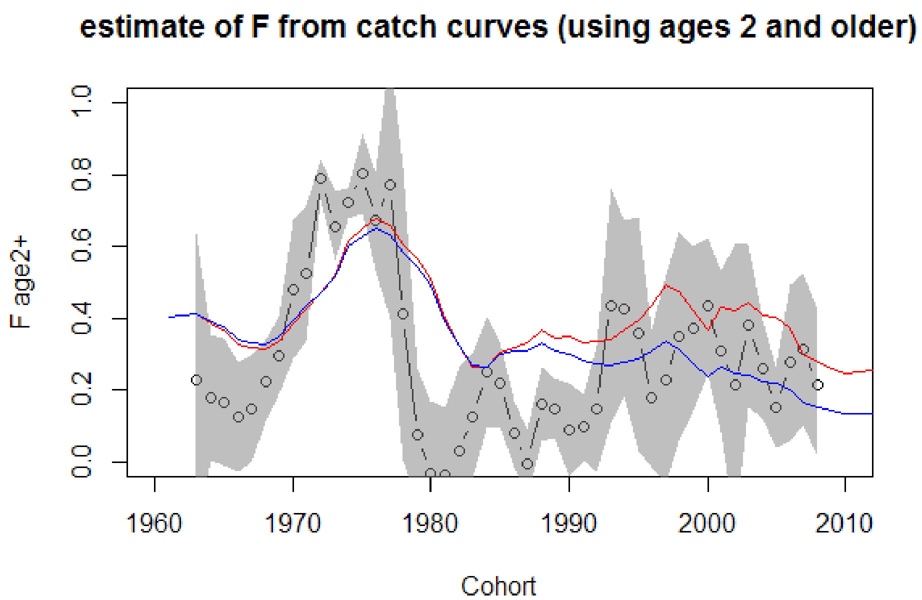



Figure 2.7. Log catch curve estimate of F (black line with dots), with the average fishing mortality for ages 2 and older, from the ISH assessment and the noQ assessment (in red and blue respectively).

The correlations between parameter estimates are shown on Figure 2.8. The catchability of the AC survey for ages 4+ (logFpar4) is positively correlated to the other catchabilities, but no correlation with any other parameters. This indicates that the catchability are well defined, and that there is no confounding with any other parameters.

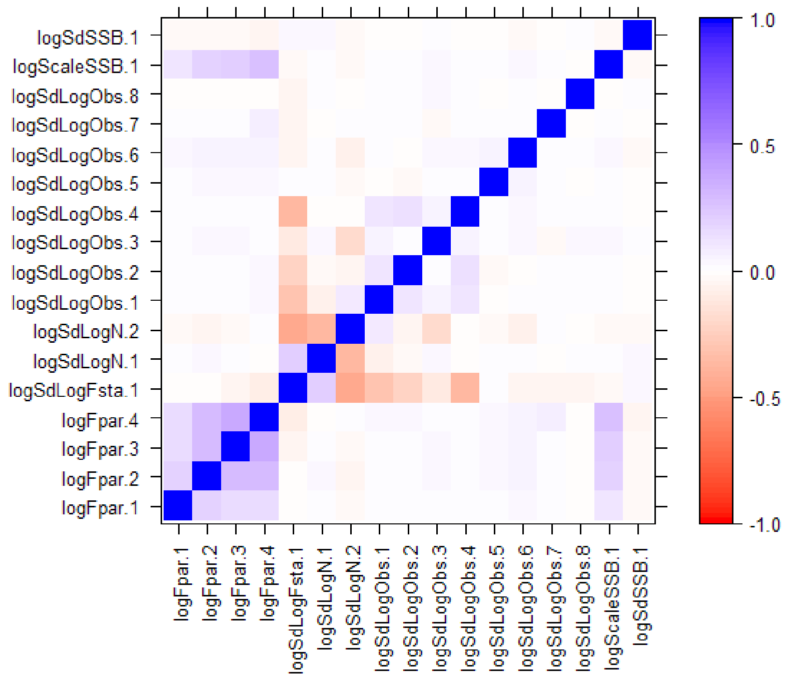



**Figure 2.8. Parameter correlation for the current assessment.**

### Sensitivity to Linear vs. power catchability model

The scatterplots of observed vs fitted for the AC_7.a(N) (Figure 2.0) show some sign of a slope higher than 1 for some ages. A slope different from 1 would suggest that a power model would be more appropriate to represent the relationship between the modelled stock-numbers-at-age and the abundance index : log (Index) = log(Q) + sl * log(modelled N). The SAM model was fitted estimating a slope with the same age groupings as for the catchability estimates. Among the four slopes estimated, only the slope for age 3 was different (larger) from 1. The slope estimates for the ages 4 to 8 was very close to 1 (Table 2.1). The stock trajectories from the assessment with and without a power model for the catchability of the AC survey are very close (Figure 2.9).

**Table 2.1. Estimated slopes by SAM using a power low model.**

| Age | Value | CV | Lower bound | Upper Bound |
|---|---|---|---|---|
| 1 | 1.83 | 0.38 | 0.86 | 3.87 |
| 2 | 1.42 | 0.22 | 0.91 | 2.20 |
| 3 | 1.59 | 0.18 | 1.13 | 2.24 |
| 4 | 0.97 | 0.09 | 0.81 | 1.17 |
| 5 | 0.97 | 0.09 | 0.81 | 1.17 |
| 6 | 0.97 | 0.09 | 0.81 | 1.17 |
| 7 | 0.97 | 0.09 | 0.81 | 1.17 |
| 8 | 0.97 | 0.09 | 0.81 | 1.17 |

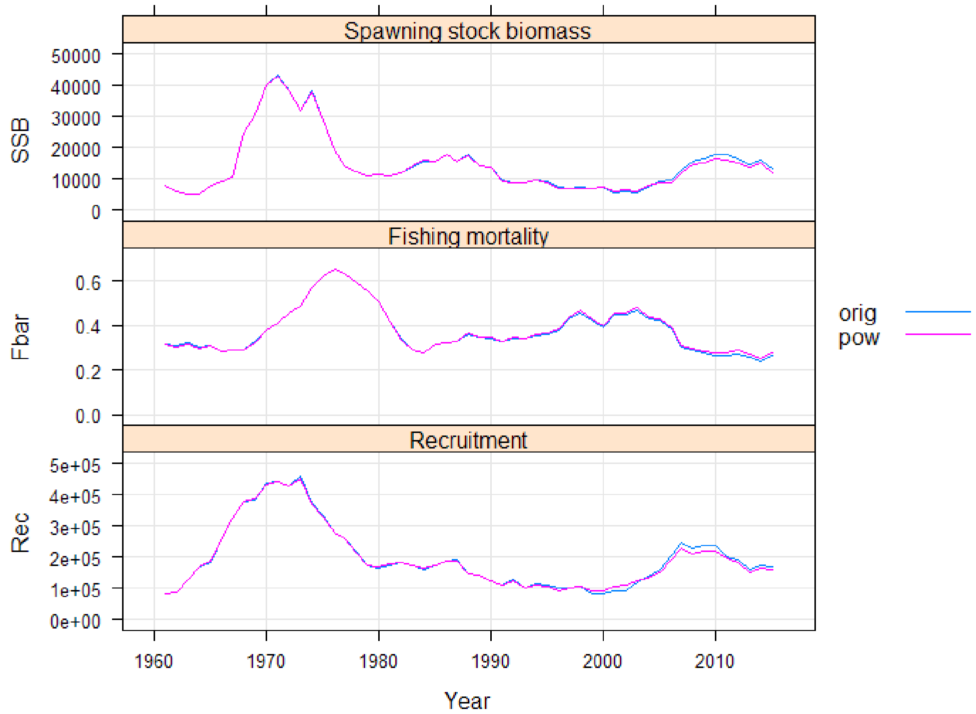



**Figure 2.9. Stock trajectories from the assessment with and without a power model for the catchability of the AC_7.a(N) survey.**

### Sensitivity of the assessment to the scale of the catches and of AC_VIIa(N)

The assessment was run with a catch-at-age matrix doubled; wherein the estimated numbers are age are all multiplied by 2 and the estimated catchability is then close to one. Other model parameters (observation and process variances) are unchanged. Performing a similar exercise with the AC_7.a(N) index does not modify the assessment output compare to ISH. Only the value of Q is different.

### Sensitivity to one particular year in the AC_7.a(N)

To visualise how much influence the AC_7.a(N) has on the assessment output, the index for the terminal assessment year was divided by two. This affects the stock trajectory over the last decade (Figure 3.2). Even if the observation variance is large, a single year of data has quite an effect on the resulting stock trajectories.

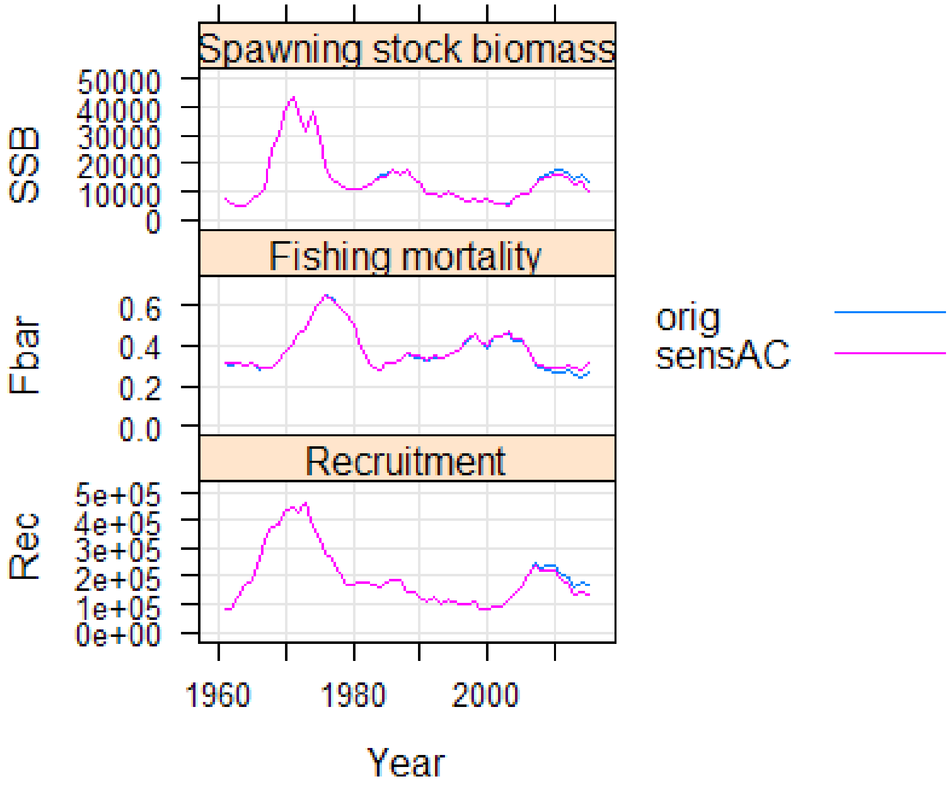



**Figure 3.2. Sensitivity of the assessment to a single year of AC_7.a(N).**

#### Sensitivity to replace the random walk recruitment by Beverton and Holt model

The estimate recruitment variability is very low. The high observation variances for the catches and survey at-age 1 mean that the estimates of recruitment are not following any of these two sources of information, and by default, recruitment is estimated as a very correlated random walk. In order to relax the random walk constraint, the model was fitted using a Beverton and Holt model for recruitment. The resulting recruitment is a little more variable, but no major different is seen in the other model parameters or in the trajectories of $F_{bar}$ and SSB.

#### Sensitivity to changing the Selectivity plateau

Figure 2.2 shows that a flat selectivity pattern is observed when a value of Q = 1 is imposed. The model was run imposing a catchability plateau at a young age (4+). The estimated Q for the AC_7.a(N) survey ages 4+ decreases from 2.2 to 1.9 and consequently the SSB estimated slightly larger.

### Incorporating a new survey time-series in the assessment model

Since 2007, another acoustic survey is in place (7.aNSpawn) with repeated survey activity during the spawning season. This survey is available as a numbers-at-age index, but also as an SSB survey. The inclusion of this information within a SAM framework was proposed as a potential model solution. We investigated how this survey could be used in the current SAM assessment.

The internal consistency of the numbers-at-age survey is low (Figure 3.3) and suggests there are issues with sampling, with low numbers of targeted trawls occurring during the acoustic survey. The tuning index was converted to an SSB index. The current SAM framework does not allow using two SSB indices at the same time.

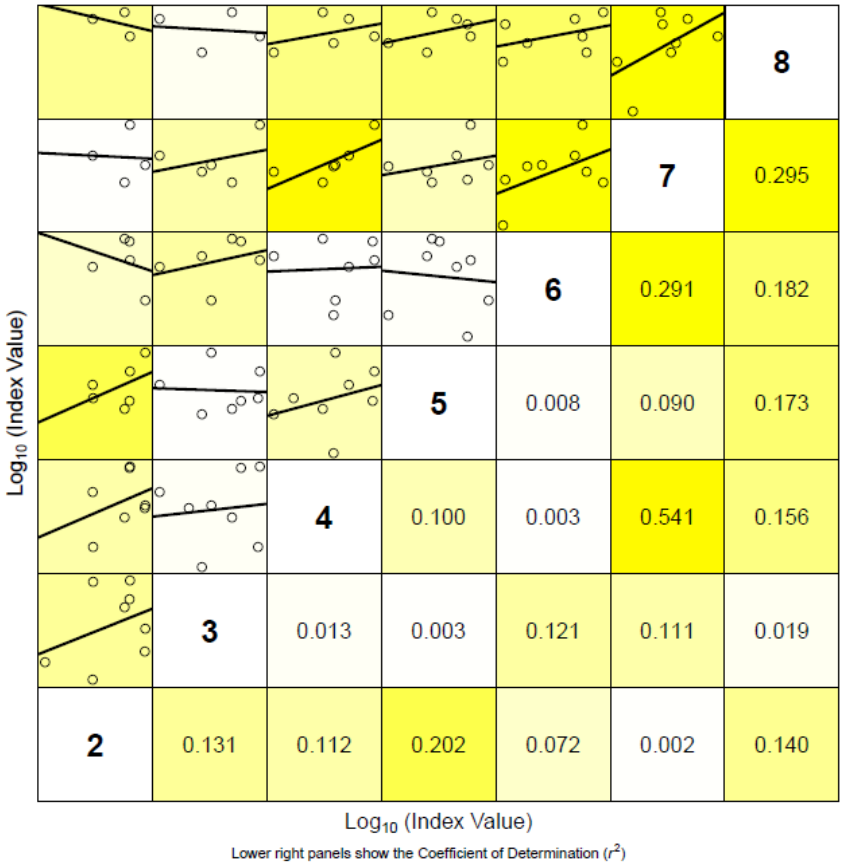



**Figure 3.3. Internal consistency of new acoustic survey showing the correlation in age-pairs. Darker yellow colours indicate higher correlation.**

Four different types of parameter settings;

- one parameter for all ages,
- free parameters for all ages,
- the same type of binding as the other acoustic survey,
- interpreting the maximum freedom version and binding those parameters that result in similar observation variances.

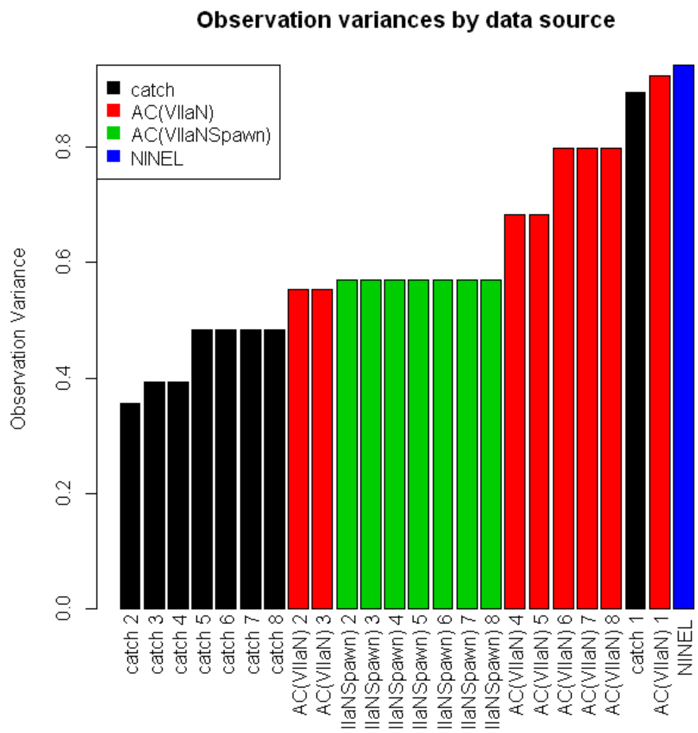



**Figure 3.4. Estimated observation variances for the new acoustic survey (in green) under the best parameter configuration.**

Using AIC criteria identified that using only one parameter for all ages is statistically most sound. The resulting observation variances are shown in Figure 3.4. The current SAM framework does not allow use of two SSB indices at the same time. Given that the NINEL survey has a very small contribution to the assessment given its large observation variance (which downscales its weight in the assessment fitting), this survey was removed and replaced with the new acoustic survey converted SSB time-series.

At first, the new SSB survey was fitted in a similar manner as the NINEL survey, estimating freely a catchability parameter and an observation variance parameter. The results in terms of observation variance are given in Figure 3.5. The results show that the index is fitted well, and shows low observation variance. The catchability of the survey is estimated at ~3.8, well above the expected value of one. In an attempt to use the new acoustic SSB survey as an absolute survey, the catchability of the survey was fixed to one. Given that observation variance is estimated by the model too, the model has the possibility to increase observation variance if catchability is fixed to thereby ignore the survey. To circumvent this problem, a range of fixed observation variances for the SSB survey was evaluated with the attempt to keep observation variance as high as possible, (but not exceeding 0.4, i.e. the estimate from the free assessment). An observation variance of 0.1 was found to result in a residual pattern with both positive and negative residuals. Although there still are more positive than negative residuals. Lowering the observation variance even further to e.g. 0.05 did not result in any improvement in the residual pattern. In addition, the random walk assumption for recruitment was turned off leaving a free estimation of recruitment (Dickey-Collas *et al*., 2015).

Based on the assessment, the observation variances of all other data sources were evaluated as well as their residual patterns, which showed to be very similar between the original assessment (using 1980 as a starting year) and the assessment with fixed observation variance and catchability. The biggest change in model fit, was observed in the fishery selection patterns over time (see Figure 3.6), which has become almost flat at ages 2+. The catchability of the age-disaggregated 7.aNSpawn index is shown in Figure 3.7 and shows a substantial reduction to values ~0.72.

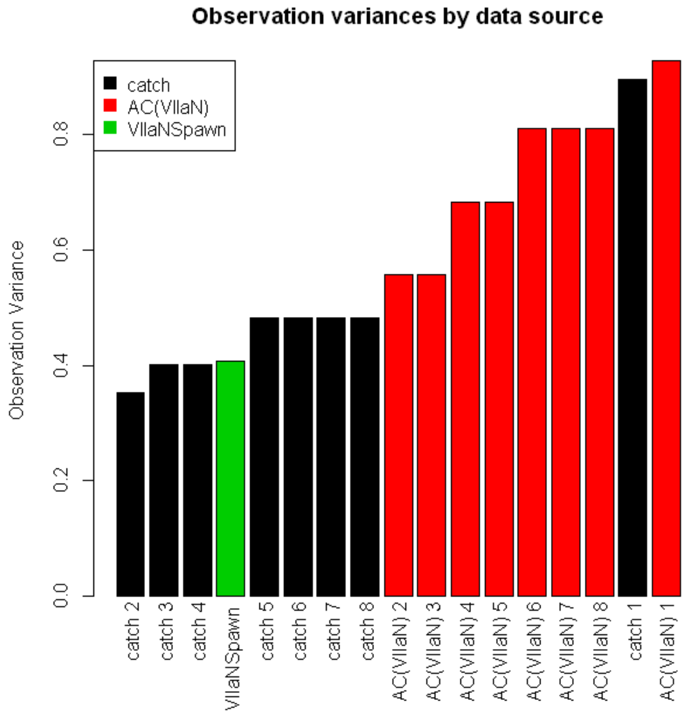



**Figure 3.5. Estimated observation variances for the new acoustic survey as SSB index (in green).**

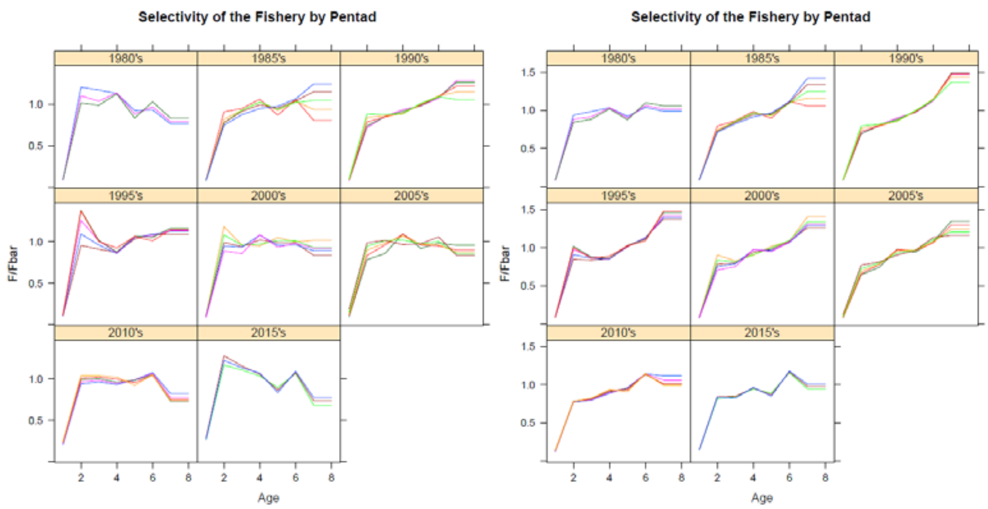



**Figure 3.6. Selection pattern of the fishery under the assessment model with fixed variance and catchability for the SSB survey (left) and the original 2016 assessment (time-series truncated to start from 1980 onwards) (right).**

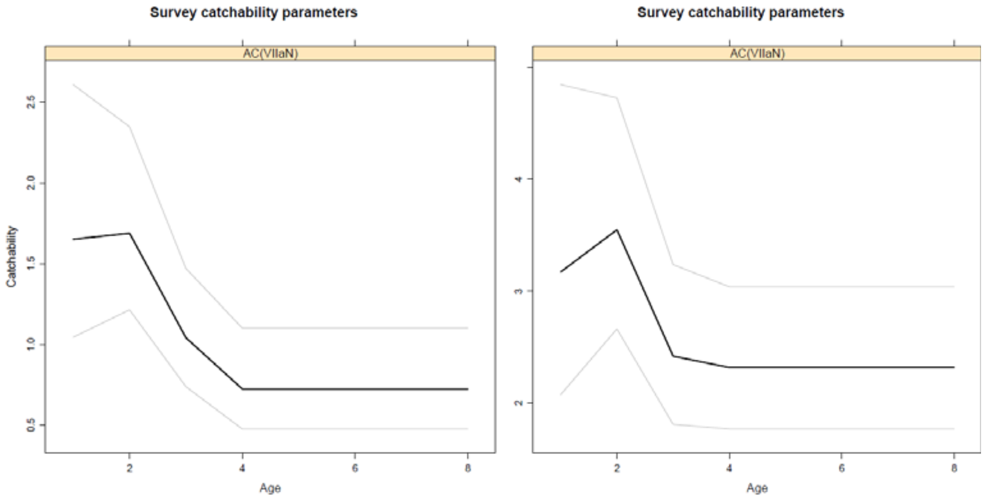



**Figure 3.7. Catchability of the acoustic survey (age-disaggregated) under the assessment model with fixed variance and catchability for the SSB survey (left) and the original 2016 assessment (time-series truncated to start from 1980 onwards) (right).**

To test whether the model is suitable for advice purposes, a retrospective assessment was run, and the results are given in Figure 3.8. This shows that the assessment is sensitive to the fixed catchability, and does not converge back in time. For the fishing mortality, this effect is most profound with considerable changes over retrospective runs. Although mohns rho is only 13% for this assessment, the retrospective pattern in F needs to be investigated prior to continuing with this assessment for advice purposes.

Furthermore, under the this alternative assessment, it is advised to re-consider all other parameter settings, to ensure the best model configuration is found, as there appear correlations between parameters that may result from too rigid or too much freedom parameter in binding assumptions which may cause the observed retrospective pattern as well.

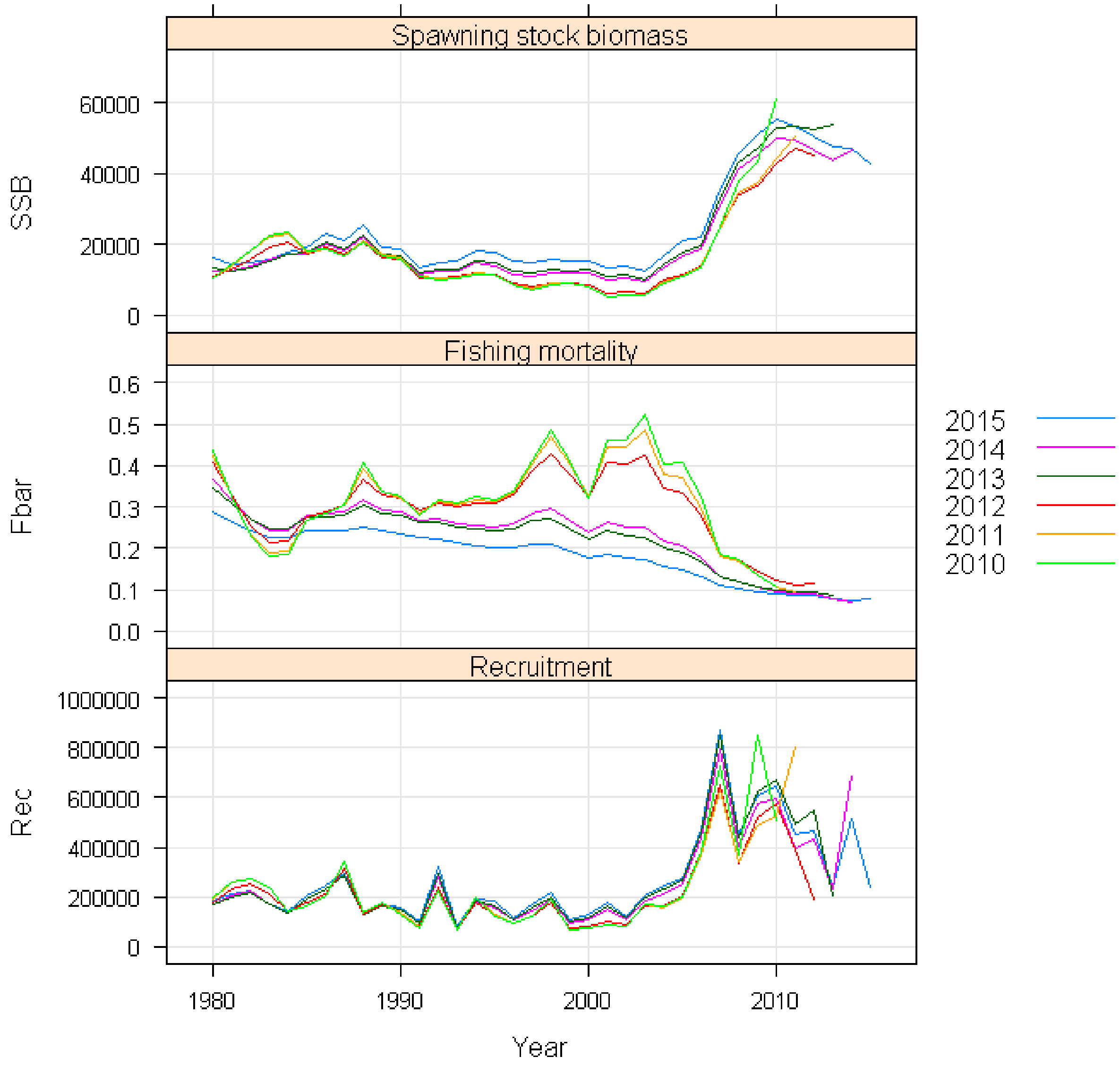



**Figure 3.8. Retrospective analyses of the assessment including the acoustic SSB index with fixed variance and catchability.**

The lack of recruitment pattern in the original 2016 assessment was compared to the new configuration with the new SSB survey, while the random walk assumption on recruitment was turned on again. The results in recruitment are shown in Figure 3.9. The lack in any variability in recruitment is apparent from this figure and may cause problems in reliably estimating reference points.

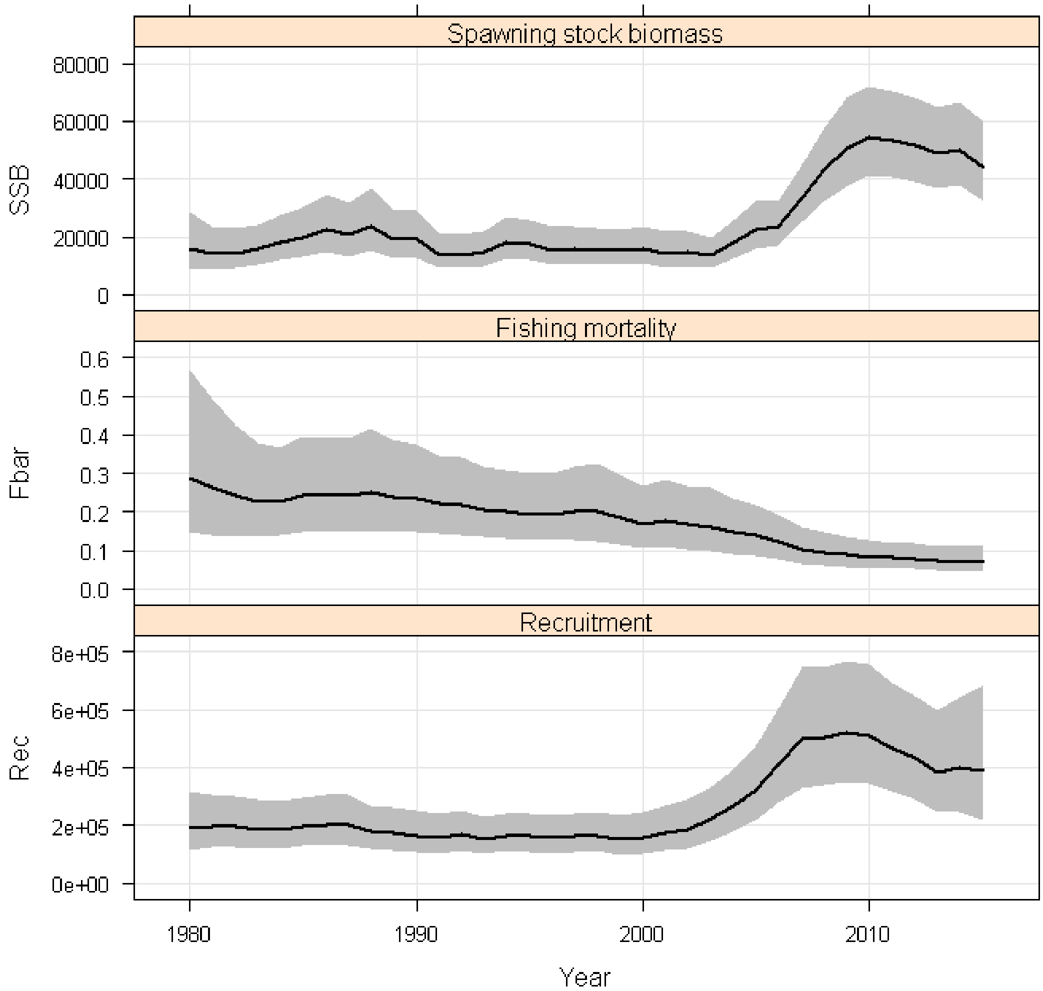



**Figure 3.9. Assessment results including the acoustic SSB index with fixed variance and catchability and random walk assumption on recruitment.**

## 3.4 Follow-up exploratory model runs for IBP

During the WKIrish3 meeting, the group could not agree on an accepted model for Irish Sea herring. The group recommended an Inter-Benchmark Protocol (IBP) to deal with the remaining issues. The report of this IBP is included below:

### Issues to be addressed

- Examine the difference of the model with q = 1 and freely estimated q for the 7.aNSpawn SSB index;
- Compare the ratio of the model-estimated mean SSB from 2007–2015 to the period 1994–2006 with the ratio of SSB from AC_7.a(N) survey for these two periods.

#### Comparing Irish Sea herring (ISH) without the spawning SSB survey (Original) and with the spawning SSB survey (with a q set to 1, Q=1)

Concern was raised at WKIrish3 that the trends seem to show different perceptions of stock status in the recent years compared to the period before ~2002 where either with or without the 7.NSpawn the dynamics are, in absolute terms, very similar (Figure 4.0). The concern related to catchability estimated for the AC_7.a(N), which were lower under the two survey model configuration (noQ). As catchability is an estimated parameter applicable to the entire time-series, it was unclear why stock trends would not be markedly different in the period before 2002, as the same lower catchability would apply (suggesting that biomass would be estimated lower under the 'original' model configuration for the period before 2002).

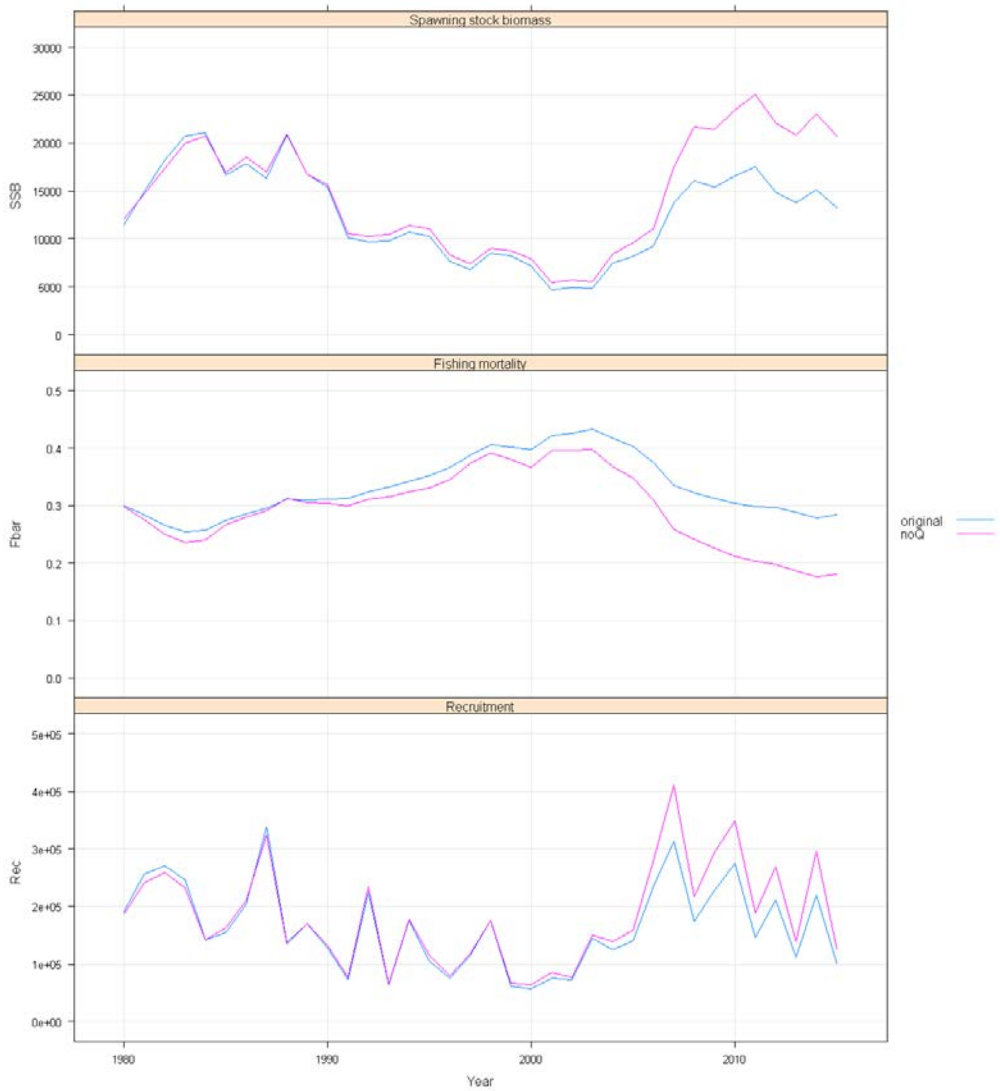



**Figure 4.0. Spawning–stock biomass (top panel), fishing mortality (middle panel) and recruitment (bottom panel) for the two different model configurations.**

The differences in parameter estimates between the two models are presented in Figure 4.1. Under the noQ model, the catchabilities for the acoustic survey are lower, which is to be explained by the increase in biomass estimated for the stock, being more in line with absolute acoustic survey estimates. The variance in the random walk for fishing mortalities increases with age and are generally larger than under the original model configuration. As the step changes from year to year are higher in SSB and R, this implies higher step changes in F as well, resulting in larger RW-F variances. The RW-N is not well estimated under the original model (hitting the predefined parameter boundary of a variance of 0.05) while the RW-N is estimated appropriately under the noQ model. Under the original model, RW-N is bound to 0.05, while it is estimated to be 0.1 under the noQ model configuration. It is therefore that this difference shows a 100% change. The observation variances under the noQ model are generally smaller (less noisy) than under the original model configuration.

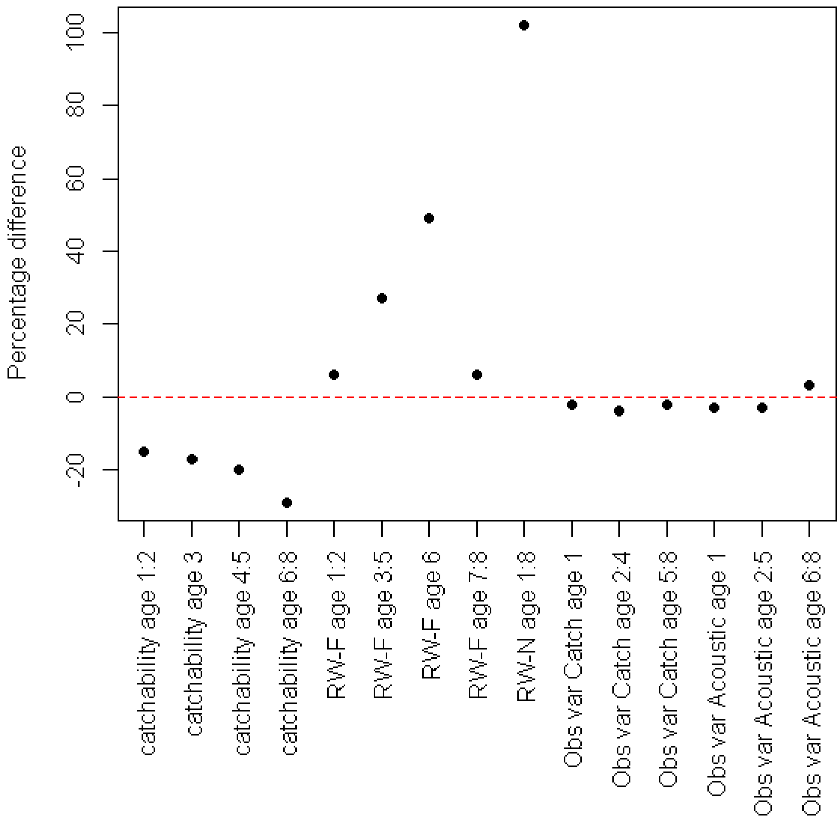



**Figure 4.1. Comparison of parameters estimated for the two model configurations, expressed as percentage difference.**

These results do however, not explain the biomass in the period before 2002 being similar under both model configurations, while catchability dropped under the noQ model. Therefore, the entire model fit was investigated through a comparison of the residuals by age and model configuration over time (Figure 4.2.A and 4.2.B).

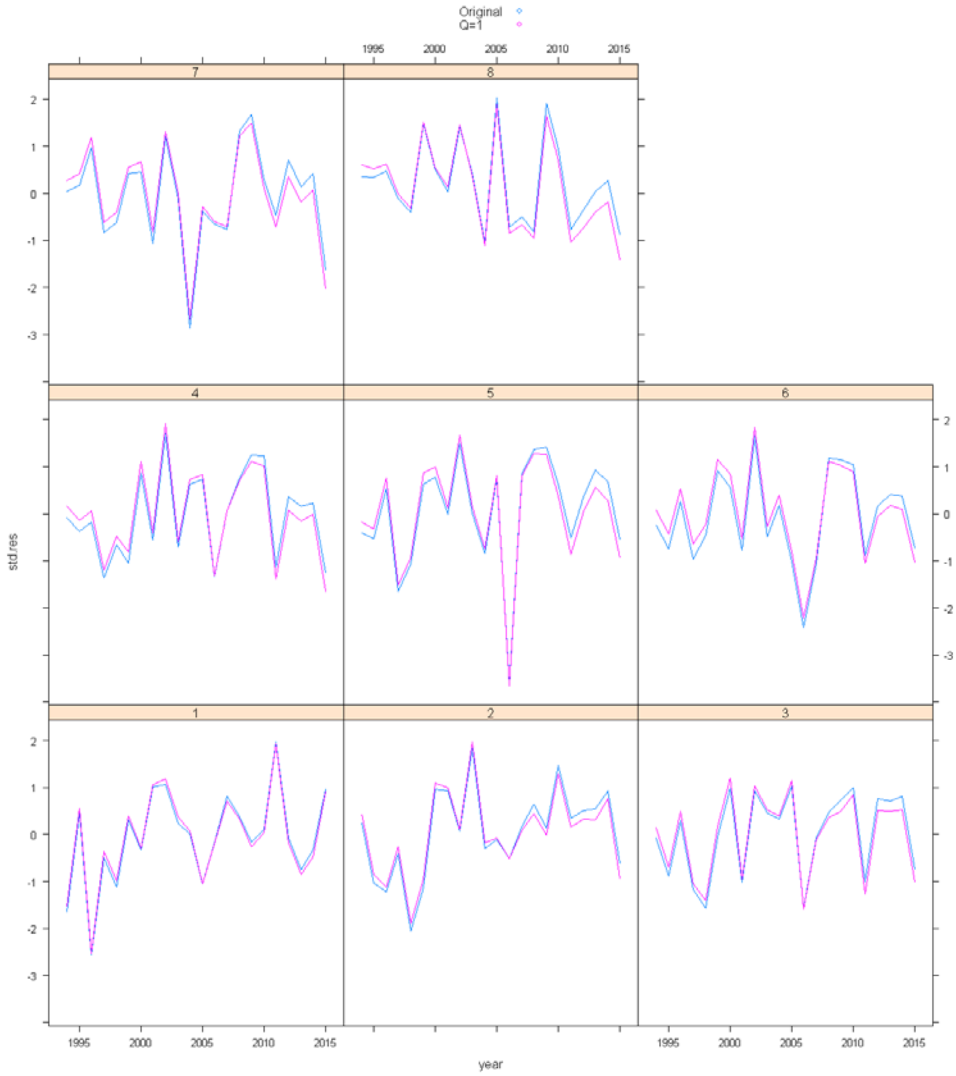



**Figure 4.2.A. Comparison of standardized residuals, by age, for the two model configurations.**

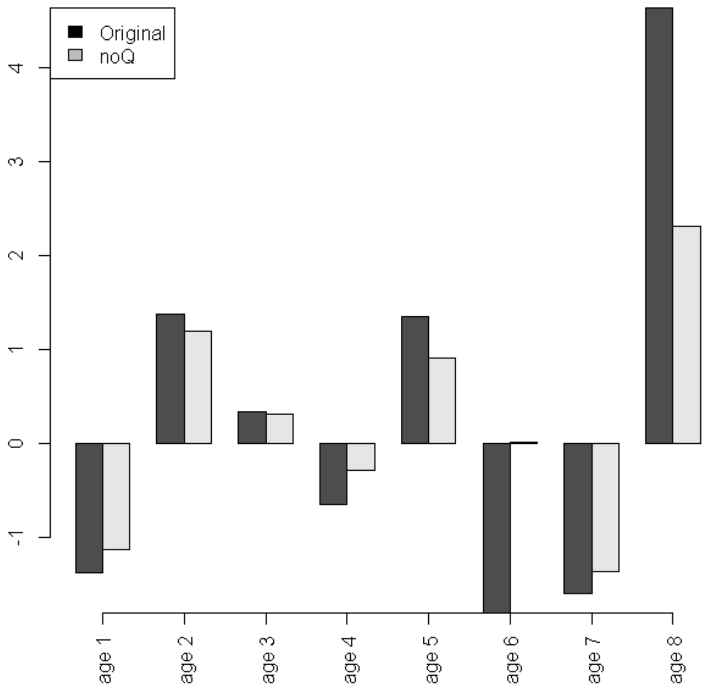



**Figure 4.2.B. Summed standardised residuals for the entire time-series by age for the two model configurations.**

The differences in the standardized residuals (Figure 4.2) show residuals under the original model configuration tend to be more negative for the period before 2002 and more positive for the period after 2002 in comparison with the noQ model configuration. This implies that the acoustic survey fit is not a matter of catchability scaling, but a matter of data interpretation as a whole over the period, with the fit to the data by the acoustic survey is tilted with a turning point around 2002. The summed standardized residuals for the noQ model is lower (Figure 4.2.B).

### SSB ratio comparison

To explore the validity of the perceived stepwise shift in SSB in the noQ model it was compared with the SSB trend from the AC_7.a(N) survey (1994–2015). The acoustic index has been converted to an SSB estimate by multiplying index-at-age with stock-weight-at-age and maturity-at-age. The ratio of SSB between the 1994–2006 and 2007–2015 period for the model with a fixed catchability of 1 for the SSB survey is 2.579. The ratio in the model without the 7.aNSpawn survey (original model) is 2.0 compared to the SSB trend form and the data ratio in the AC_7.a(N) survey was 2.858. This suggests that the SSB trend in the noQ model is not the product of the Q assumptions, but allows the model estimated SSB to be a more appropriate reflection of SSB trend for the stock.

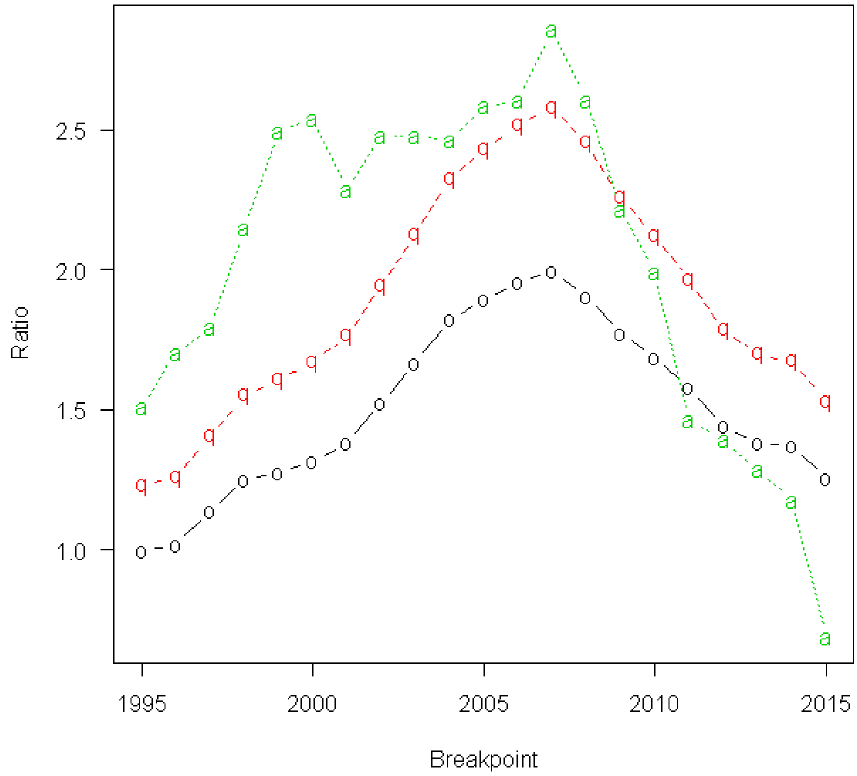



**Figure 4.3. Ratio of most recent period vs historic period in assessment without SSB survey ('o'), in the acoustic survey ('a') and the model with the SSB survey catchability set to 1 ('q').**

Figure 4.3 indicates that the trend in ratio is very similar between the two model configurations and that data-wise, the acoustic survey shows a clear breakpoint in 2007. This breakpoint is related to the interpretation of the influence of the 7.aNSpawn survey (which starts in 2007). From 2007 onwards, there is a larger absolute difference visible in the two assessment model configurations, which seems to coincide with the breakpoint in acoustic survey data as well.

## 3.5 Conclusion

Whilst the benchmark accepted the SAM model configuration for Irish Sea herring, further exploration of the sensitivity to catchability assumption for the SSB survey was requested. Following the WKIrish3 meeting, further exploration and analysis was carried out and reviewed. This was completed after the benchmark meeting; it was proposed that HAWG (ICES, 2017) was the best place to review the final assessment model. The report of this work is provided here in Annex 12. Reference points were estimated during WKIrish3; however, it was agreed that these should be re-examined following the work carried out after the WKIrish3 meeting Annex 13.

# 4 Irish Sea cod

## 4.1 Issue list

- Natural mortality – Lorenzen M is proposed to replace 0.2 for all ages
- Tuning series – Available surveys were reviewed by WKIrish2
- Discard data reconstruction – Documented by WKIrish2
- Changes in growth and maturity – Documented by WKIrish2
- Assessment method – ASAP is proposed as the new assessment method
- Biological reference points – estimated according to ICES procedures

Not addressed:

- Prey relations – Investigate the role of whiting in Irish Sea multispecies foodweb dynamics.
- Ecosystem drivers – some discussing by WKIrish2, no firm conclusions.

## 4.2 Data

Data exploration was done by WKIrish2, below is a description of the sensitivity of the proposed model to the input data.

### 4.2.1 Stock identity and migration

See WKIrish2.

### 4.2.2 Life-history data

See Section 2 for a discussion on natural mortality, the choice of the Lorenzen method for estimating M is documented in the WKIrish2 report. Assessment runs were performed with M=0.2 and Lorenzen M.

Sensitivity to maturity was not investigated. Other biological information is in WKIrish2 report.

### 4.2.3 Fishery-dependent data

No sensitivity analysis was performed to the fisheries-dependent data. Data quality and quantity has been described in WKIrish2 report.

### 4.2.4 Fishery-independent data

The available fishery-independent data are described in the WKIrish2 report.

### 4.2.5 Environmental drivers and ecosystem impacts

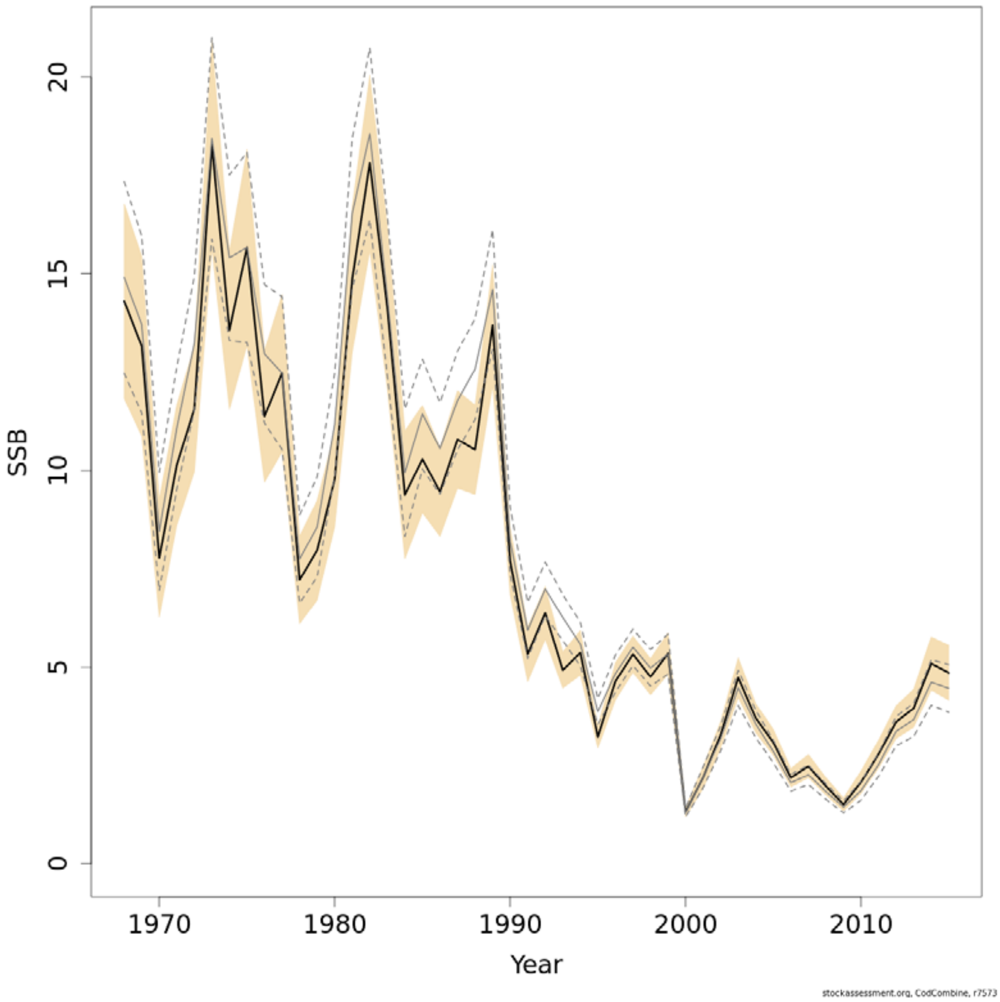
The WKIrish2 report includes a discussion on environmental drives and ecosystem impacts.

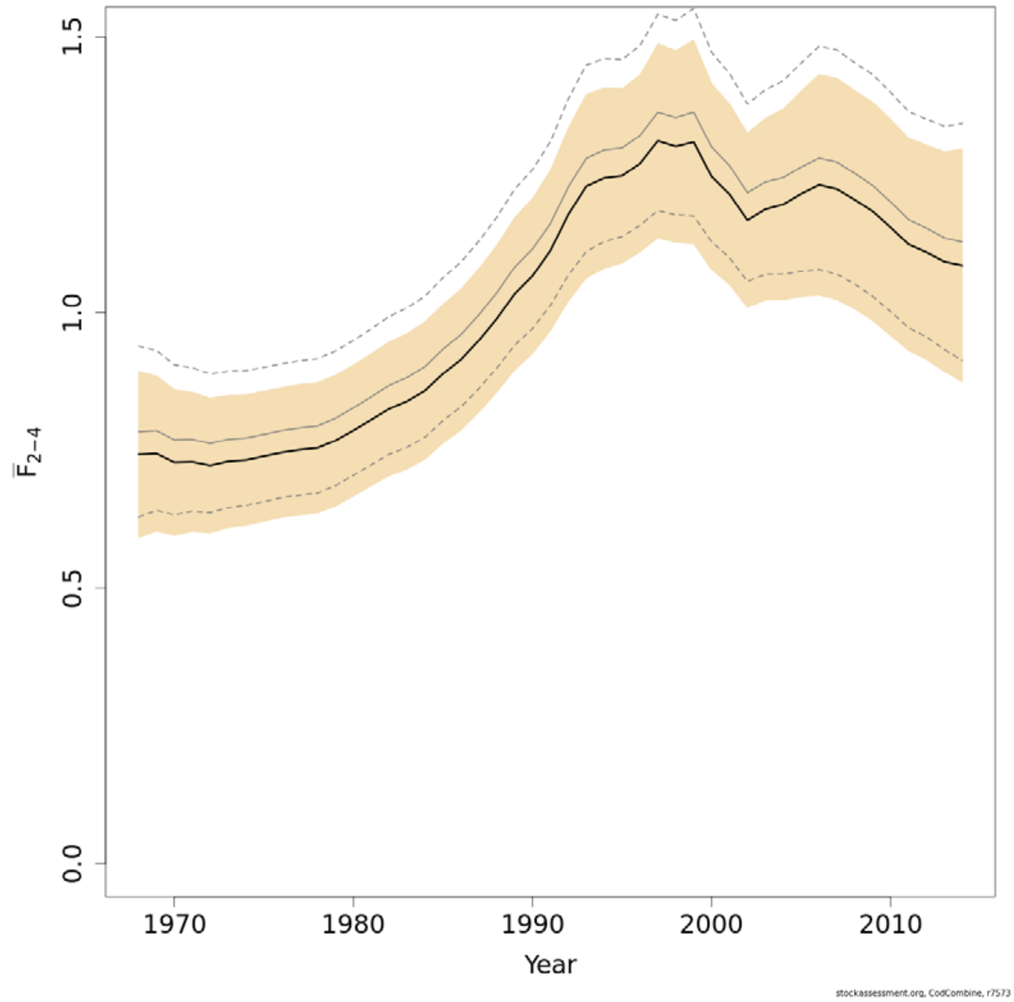
## 4.3 Assessment and forecast

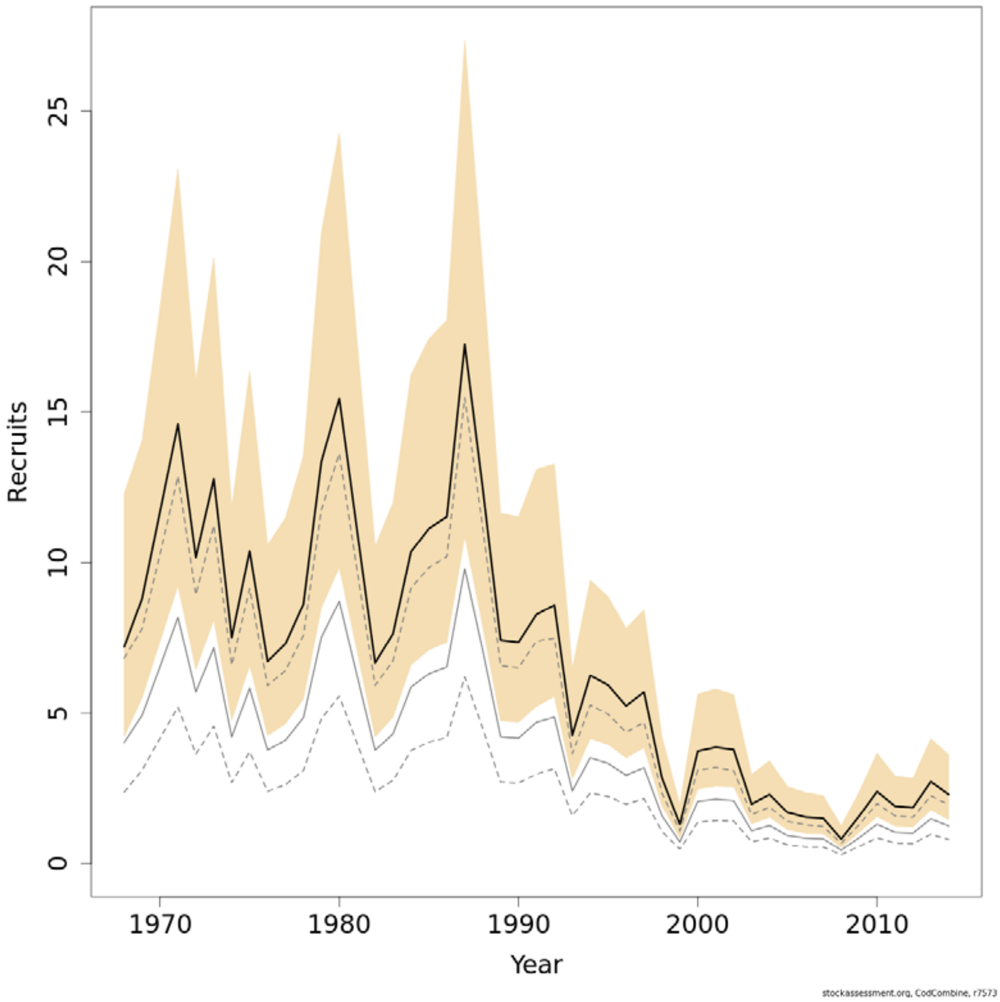
### 4.3.1 Assessment models and runs

Initial assessment runs were performed using SAM and ASAP. Initial considerations included the updating of the previous SAM model with data agreed at the WKIrish2 workshop, such as inclusion of some discards, maturity ogive and a range of M values, such as Lorenzen and Gislason M.

Exploration in SAM did however not look at the inclusion of age 0 cod or the different combination of indices.


SSB
0
5
10
15
20
1970
1980
1990
2000
2010
Year
stockassessment.org, CodCombine, r7573


1.5
1.0
0.5
0.0
$\overline{F}_{2-4}$
1970
1980
1990
2000
2010
Year
stockassessment.org, CodCombine, r7573


Recruits
0
5
10
15
20
25
1970
1980
1990
2000
2010
Year
stockassessment.org, CodCombine, r7573

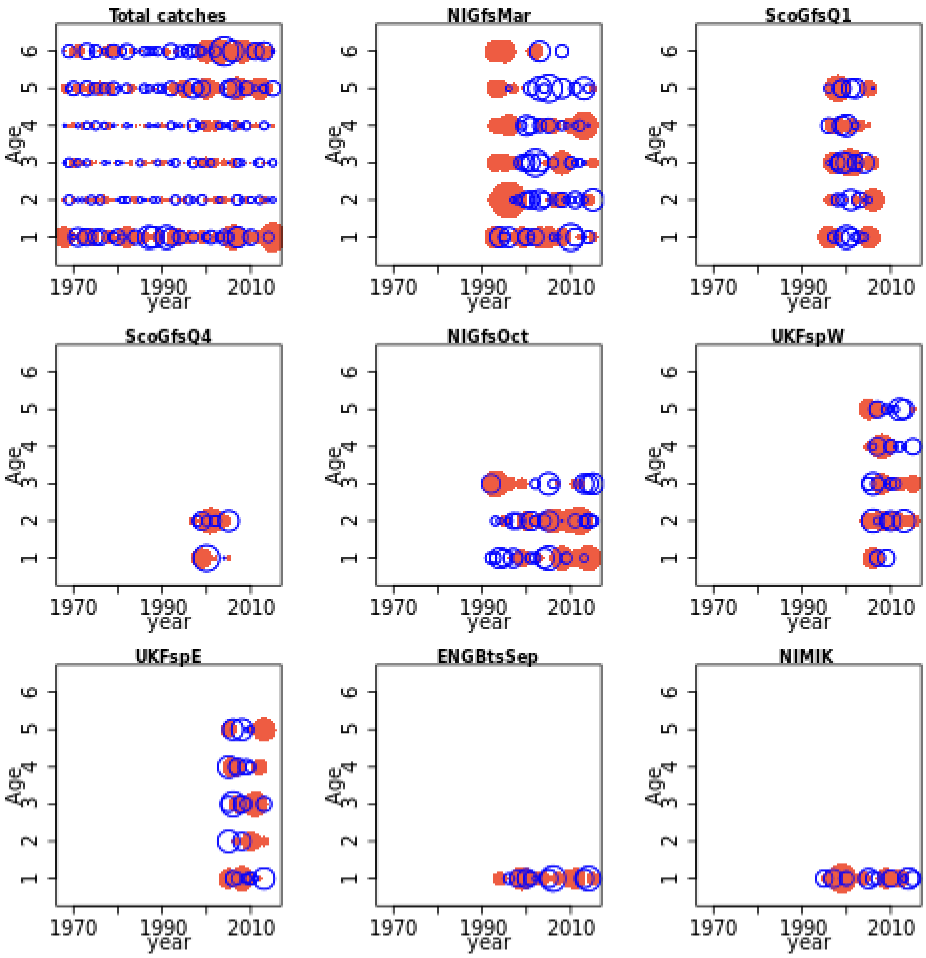



**Figure 4.1. SAM outputs. Estimates from the updated run and point wise 95% confidence intervals are shown by black line and shaded area. The previous version is the overlying grey lines. This version, as well as the previous one, do not believe the catches in the last seven years.**

Further exploration was in ASAP, as WKIrish3 preferred the use of ASAP as an assessment method for the following reasons:

- It allows uncertainty in the catch data;
- It allows the fixing of parameters to values, which enables rigorous testing and integration of parameters;
- ASAP was also proposed for the other gadoids in the Irish Sea.

It focused on the inclusion/exclusion of various survey indices and the sensitivity of the model to settings in CVs, lambdas and the number/shape of selectivities. ASAP was set to believe the catches in the recent years. Due to the change in fisheries in 2000, the introduction of two fleets was explored but resulted in the model failing to converge. Currently this is still investigated in a slightly different manner. Failing the two fleet model, a two fishery selectivity model was explored with success. To give more influence to the surveys and prevent the model from latching on to the strong catch series, a range of options were explored: truncating the catch series in 1993, strengthening survey data by putting more confidence into them relative to catches (survey CVs considerably lower than catch CVs, survey ESS larger than catch ESS).

The following runs were performed. The model diagnostics are available on the SharePoint under the section working documents (cod_asap_diagnostics - runXX.pdf).

#### Run 1-Exploratory run

The first run was presented at the workshop after a range of settings and tests prior to the workshop. This was a run including two catch selectivities, catch CVs of 0.2 (1968–2002, 2007–present) /0.8 (2003–2006) and survey CVs as in Run 4. A number of settings were changed during the workshop to provide a more realistic starting point (see run 2).

#### Run 2-Base run

The settings of the base run were similar for the cod, haddock and whiting ASAP models. They are described below.

| Input | Justification |
|---|---|
| Fleets | A single fleet (see final run for justification). |
| Selectivity | Three selectivity blocks were used to allow a smooth transition to reflect changes in fishery from 2000 onwards. Additionally the second block was to ensure that older fish would be represented in-between the first selectivity block and the start of the UKFSPW survey.<br>1st Block (1968–1999): Single logistic<br>2nd Block (2000–2006): Fixed to 1 for ages 2,3 and 4<br>3rd Block: Double logistic |
| Index specification | The two Northern Irish groundfish surveys (Q1 and Q4) were included (Q1: ages 1–4, Q4: ages 0–2), the UKFSPW (ages 2–5) survey as well as the NI MIK net survey (see final run for justification). |
| Index selectivity | The MIK net only catches one age class (age 0).<br>Q1 Groundfish: set to 1 ages 2–4 and estimated at-age 1<br>Q4 Groundfish: Estimated for ages 0–2<br>UKFSPW: Single logistic function |
| Index CV and ESS | The CVs of the two NI groundfish indices were set to CVs calculated from survey data. The CV for the MIK net was set to 0.7; The CV for the UKFSP was set to 0.4. The effective sample size for the proportions-at-age was set at 50 for all surveys including catch-at-age information which was slightly lower than the number of stations in the survey. |
| Fleet CV and ESS | The CV for the catches (catch volume) was initially set at 0.05 for all years except 2003–2005. Years 2003–3005 had experienced problems in fisheries data collection which is reflected in CVs of 0.075. The actual precision is lower but the starting point was to assume accurate and precise catch data.<br>The effective samples size for the proportions-at-age was set at 100 prior 1990, 50 from 1990 onwards. Years 2003–2005 were assigned values of 1 to reflect the poor data quality. |
| Recruitment Deviations | The CV for recruitment deviations was set at 0.5 to allow considerable variability between years, the lambda was set to 0.1 to allow unconstrained variation in recruitment. |

#### Run 3–M =0.2

M was set to 0.2 for all ages/years as in recent cod assessment. All other parameters were equal to base run.

This change had more impact on the stock trend than any of the other changes. Changes had effect on the stock–recruitment which was considerably lower than in the base run. SSB was lowest of all runs and F highest. Lorenzen M is considered to be a better reflection of mortality and has been applied to other gadoid stocks in Europe.

#### Run 4–survey CVs

The survey CVs of Q1 were reduced to 0.2 and those of Q4 to 0.4 as in the exploratory runs. This was to investigate the impact of rather high CV settings in the base run which uses real CV values. All other settings like base run. This change had little impact on the output, it was hence decided to use real survey CVs.

#### Run 5–Two selectivities (option 1)

Catch selectivity blocks were reduced to two, removing the third selectivity block. All other settings were as in the base run. Fit-at-age in catch declined slightly, otherwise there was little impact on the model output.

#### Run 6–Truncate time–series in 1993

Because the model has been observed to latch onto the strong catch curve at an early point in time, it was considered to truncate the catch series prior to 1993.

Though likelihood results are not comparable to those of the other runs, the cut of the catch curve had no impact on the dynamics in the later years.

#### Run 7–Two selectivities (option 2)

Catch selectivities were reduced to two blocks. In contrast to Run 5 the third block was removed and the second block was allowed to be estimated by a double logistic function. All other settings were like base run. The outcome was a strong dome-shaped selection curve for the second selectivity block.

This run produced the best likelihoods and best fit of catch-at-age and survey at-age data.

This option is the best at the current time, but will have to be revisited should the fishery one day return to a fleet targeting large cod.

#### Run 8–Less precise catch data

The catch CV was increased to 0.1 (0.15 for year 2003–2005) which was believed to be more realistic. All other settings like base run.

These changes had very little impact on the stock trend but poor fit to catches and surveys.

### Comparison of stock trends

Figure 4.2 provides an overview of the runs described above.

**Table 4.1. Likelihoods/objective functions for the various runs and parameters. Highlighted are generally the two best fitting runs for each parameter. Run 6 was not comparable due to the nature of the run (time-series 1993–2015).**

| Run | Total | Catch | Total Index | Catch Age comp | Catch-at-age Index | N Year 1 | Recruitment Deviation |
|---|---|---|---|---|---|---|---|
| 1 | 2589.65 | 405.748 | 631.974 | 514.234 | 428.858 | 52.79 | 537.212 |
| 2 | 1758.36 | 303.199 | 440.806 | 563.433 | 392.825 | 54.72 | 5.417 |
| 3 | 1705.55 | 302.866 | 443.041 | 517.698 | 380.019 | 51.01 | 4.423 |
| 4 | 1794.68 | 305.412 | 468.221 | 562.56 | 399.37 | 55.01 | 5.463 |
| 5 | 1808.66 | 303.445 | 445.694 | 603.438 | 398.13 | 55.16 | 5.463 |
| 6 | This run is not comparable in Likelihoods due to a considerably shorter time-series | | | | | | |
| 7 | 1721.06 | 303.251 | 440.851 | 529.301 | 381.354 | 54.69 | 5.415 |
| 8 | 1785.99 | 336.971 | 439.989 | 561.308 | 390.927 | 53.09 | 5.422 |

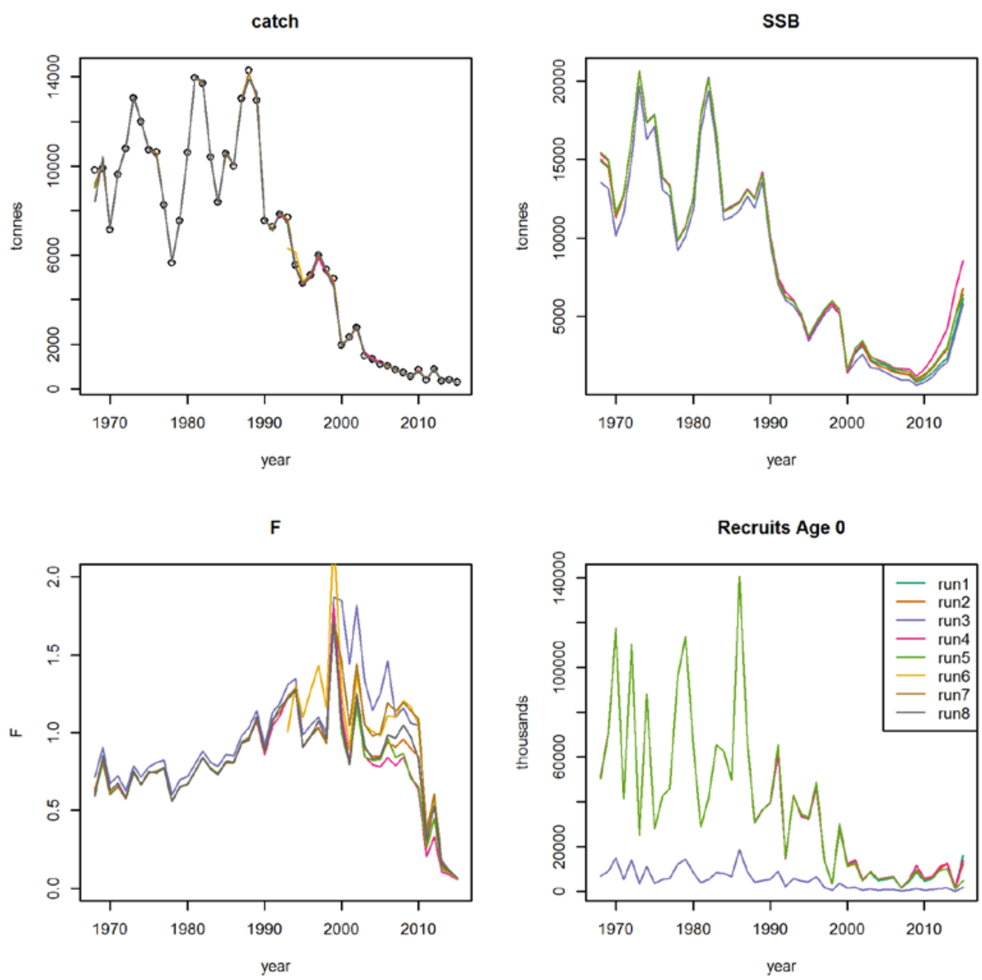



**Figure 4.2. Comparing the 8 runs as listed above.**

### 4.3.2 Final assessment model run

*Describe the model configuration and justify the choice of settings*

| Type | Name | Year range | Age range | Variable from year to year? |
|---|---|---|---|---|
| Caton | Catch in tonnes | 1968–current | | Yes (except years 2003–2005) |
| Canum | Catch-at-age in numbers | 1968–current | 0–6+ | Yes (except years 2003–2005) |
| Weca | Weight-at-age in the commercial catch | 1968–current | 0–6+ | Yes (except years 2003–2005) |
| West | Weight-at-age of the spawning stock at spawning time. | 1968–current | 0–6+ | Yes (except years 2003–2005) |
| Mprop | Proportion of natural mortality before spawning | 1968–current | 0–6+ | No |
| Fprop | Proportion of fishing mortality before spawning | Not relevant | | |
| Matprop | Proportion mature at-age | 1968–current | 0–6+ | Yes |
| Natmor | Natural mortality | 1968–current | 0–6+ | No |

The final run was Run 7, based on the best likelihood fit and most appropriate settings. The two-selectivity approach with the dome-shaped 2nd selectivity block is prioritized over the three selectivity base run as a simpler model. The effect on the stock trend was very small. This can probably be explained by the lack of older fish in the population. If the age structure recovers, it might be important to consider the three selectivity option again.

The final settings are justified below.

| Input | Justification |
|---|---|
| Fleets | A single fleet was used because models with separate landings and discard fleets were unlikely to converge. |
| Selectivity | Two selectivity blocks were used in the final run, with the first selectivity block (1968–1999) an asymptotic shape and the second one a sharply dome-shaped. For cod and haddock, fisheries selectivity is believed to have changed with the decline of the midwater gadoid fleet and introduction of restrictions in 2000.<br>The choice of selectivity blocks was based on patterns in the logratios of the catch numbers-at-age (cnaa) as well as estimated F patterns in runs with a single selectivity block.<br>The final choice for two selectivity blocks rather than three was for a simpler model. It was also based on a better likelihood fit. Allowing the second selectivity block to dome-shape rather than to force it to higher selectivity values for ages 2–4 resulted in a better fit and is likely to represent the current fishery better.<br>If the age structure recovers, it might be important to consider this option again. |
| Catch | All available age classes (age 0–6) were included. Note that ASAP treats the first age class (in this case age 0) as age 1. Therefore the outputs need to be offset by one age class. |
| Index specification | The two Northern Irish groundfish surveys (Q1, ages 1–4, and Q4, ages 0–2) were included (all available ages) as well as the NI MIK net survey and UK FSPW (ages 2–5) survey. |
| Index selectivity | The MIK net only catches one age class (age 0).<br>Q1 Groundfish: set to 1 ages 2–4 and estimated at-age 1<br>Q4 Groundfish: Estimated for ages 0–2<br>UKFSPW: Single logistic function |
| Index CV and ESS | The CVs for all years of the two NI groundfish indices were set to real Q1 and Q4 survey CVs. CVs of all years for MIKNET were set to 0.7 and to 0.4 for UKFSPW. The effective sample size for the proportions-at-age was set at 50 which was slightly lower than the number of stations in the survey. |
| Fleet CV and ESS | The CV for the catches (catch volume) was initially set at 0.05 for all years, except 2003–2005 it was 0.075 to represent difficulties in sampling and high uncertainties in those years.<br>The effective samples size for the proportions-at-age was set at 100 for years 1968–1990 and to 50 for 1991–present to reflect the small number of fish sampled for age from large portions of the catch. Years 2003–2005 were assigned an effective sample size of 1 to account for the absence of sampling effort. |
| Recruitment deviations | Lambda for recruitment deviations was set at 0.1 to allow unconstrained variation in recruitment. If future runs fail to converge Lambda can be set to 1 with a high CV to reduce the number of parameters. This appears to have very little impact on the stock trend or fit to catches. |

**Diagnostic plots**

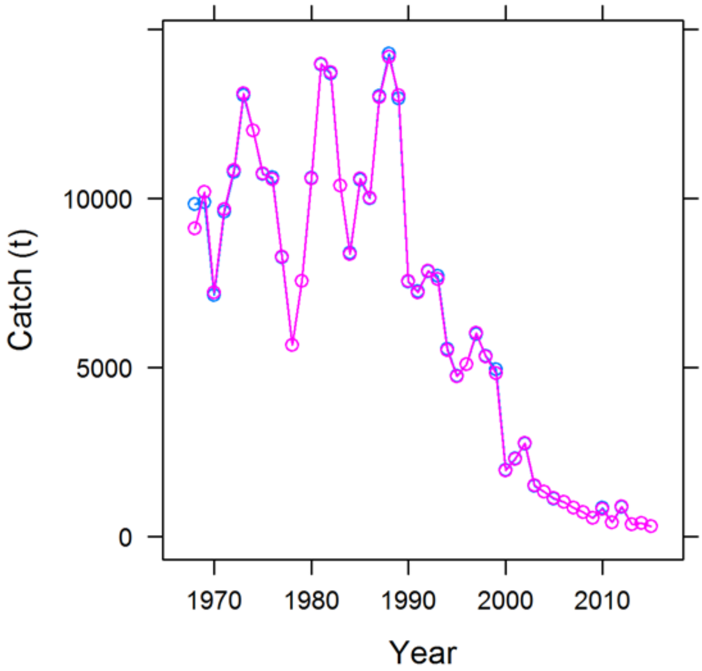
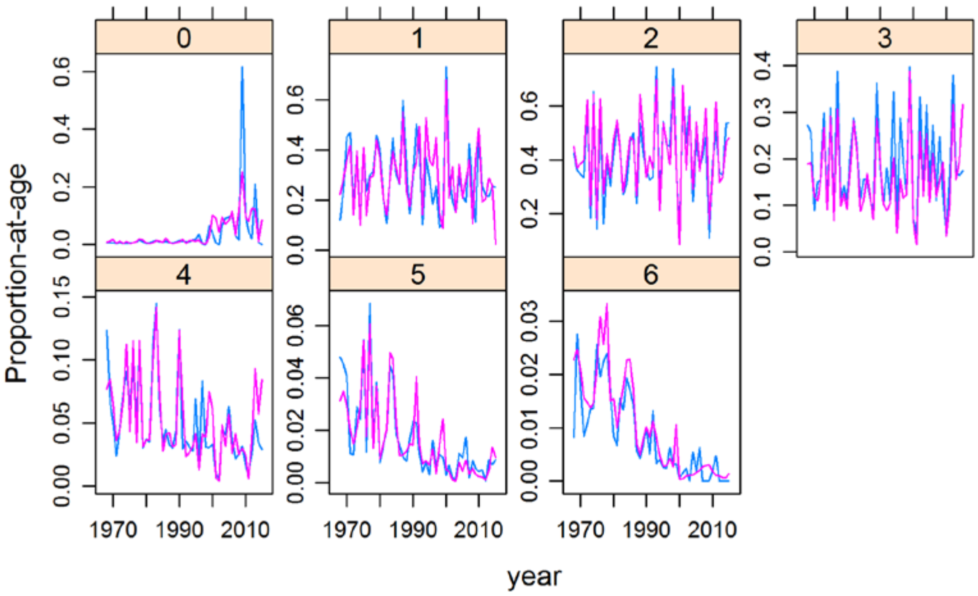
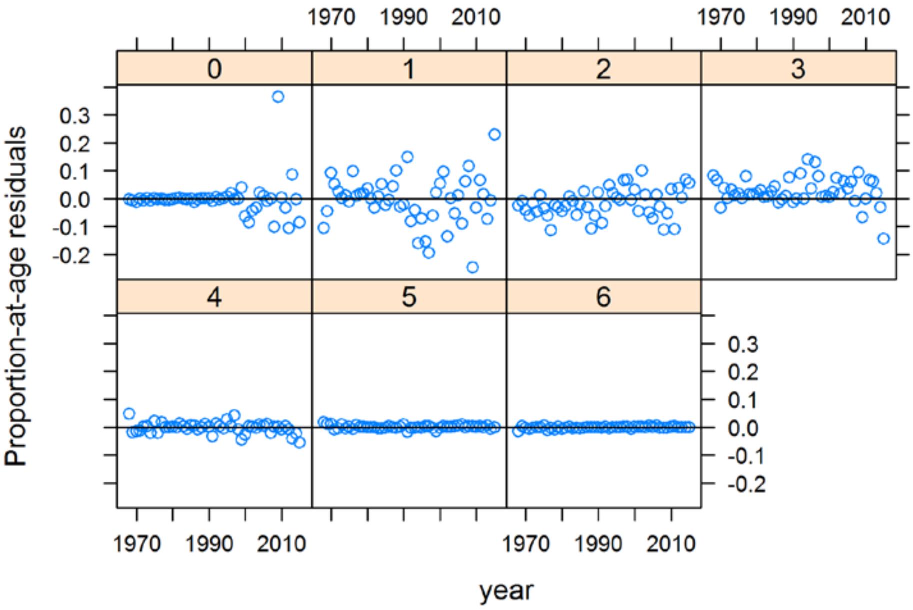



**Figure 4.3. Catch Fit.**


Proportion-at-age
year
0
1
2
3
4
5
6


Proportion-at-age residuals
year
0
1
2
3
4
5
6

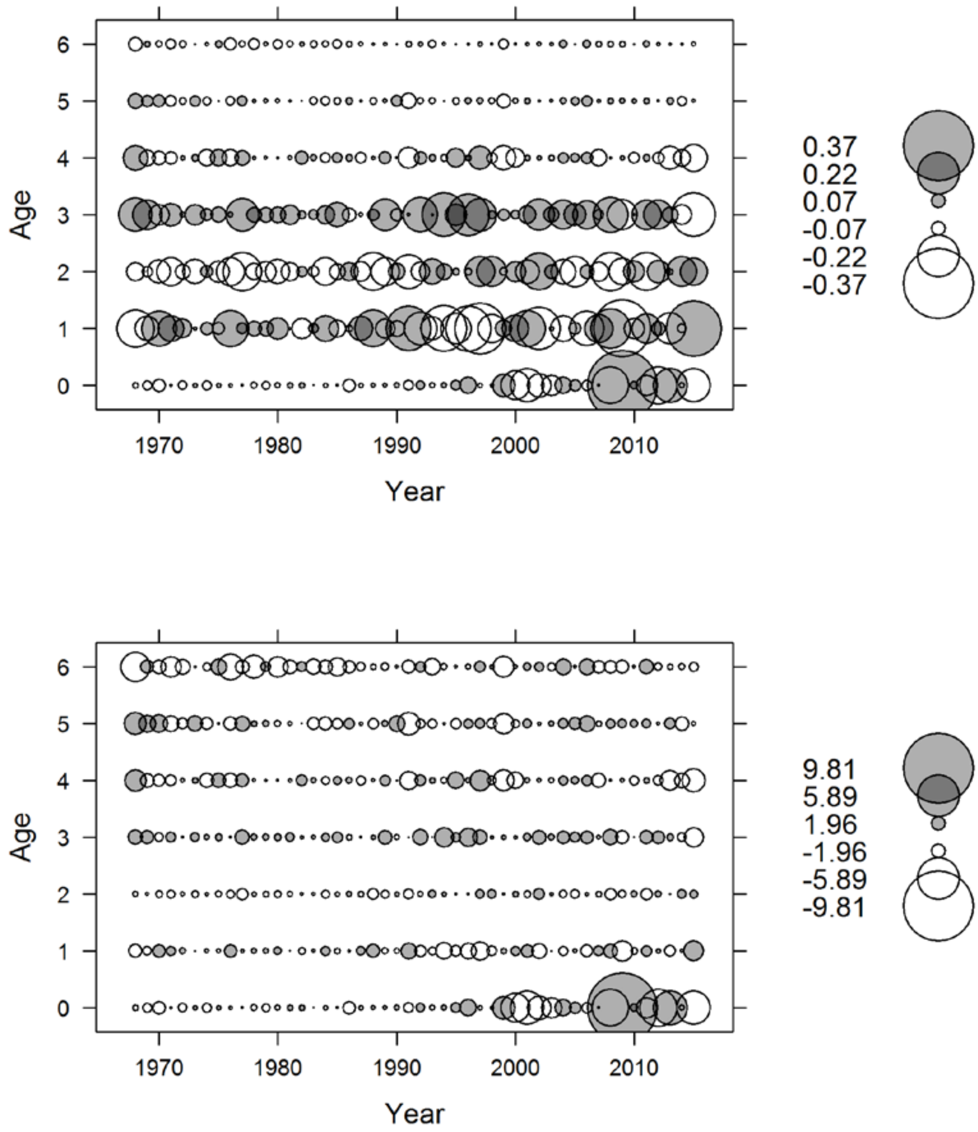



**Figure 4.4. Catch proportion-at-age residuals, bottom figure Standardized residuals.**

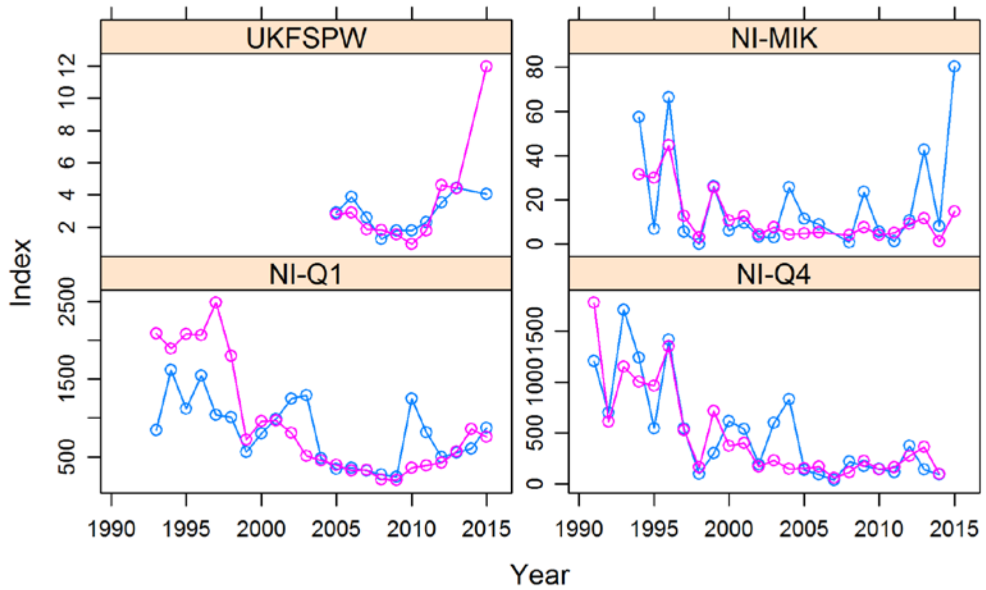



**Figure 4.5. Index fit.**

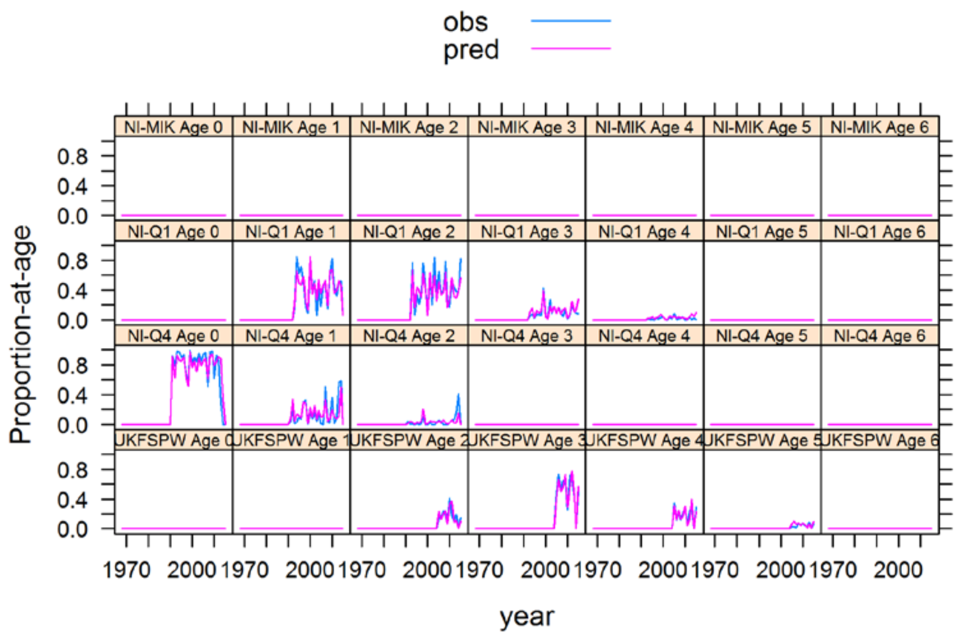
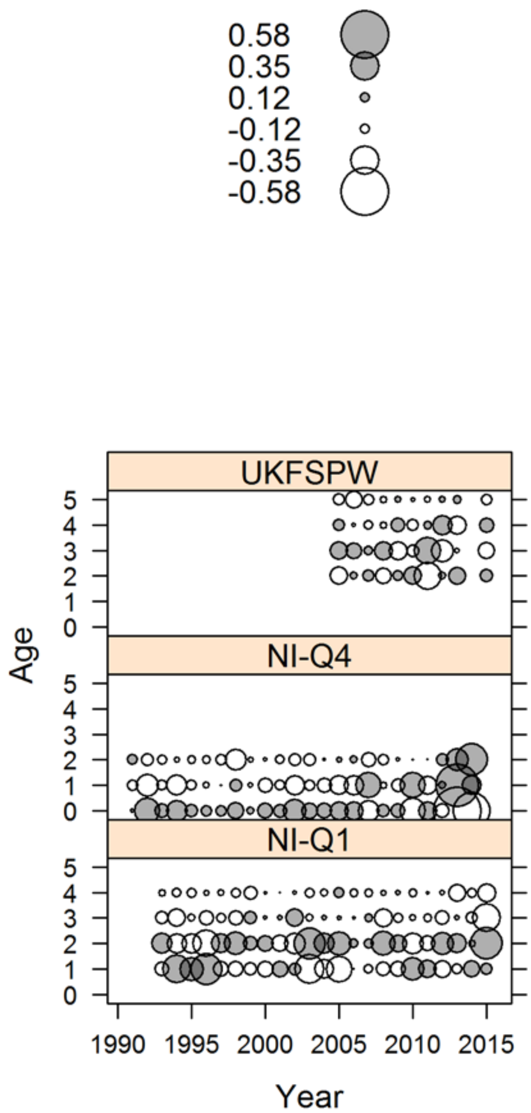



**Figure 4.6. Catch-at-age proportion index fit.**


0.58
0.35
0.12
-0.12
-0.35
-0.58
UKFSPW
NI-Q4
NI-Q1
Age
5
4
3
2
1
0
1990
1995
2000
2005
2010
2015
Year

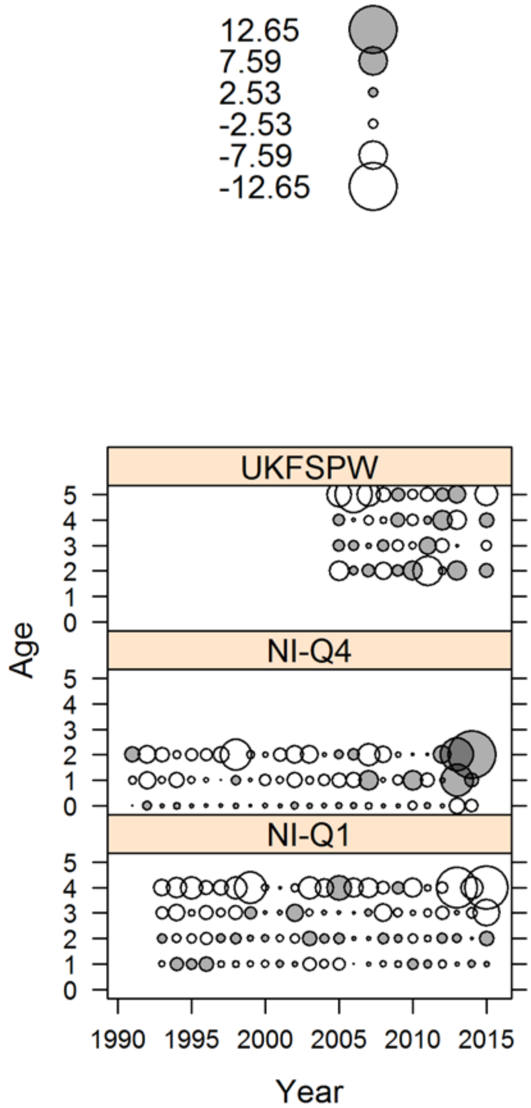



**Figure 4.7. Index proportion-at-age residuals.**

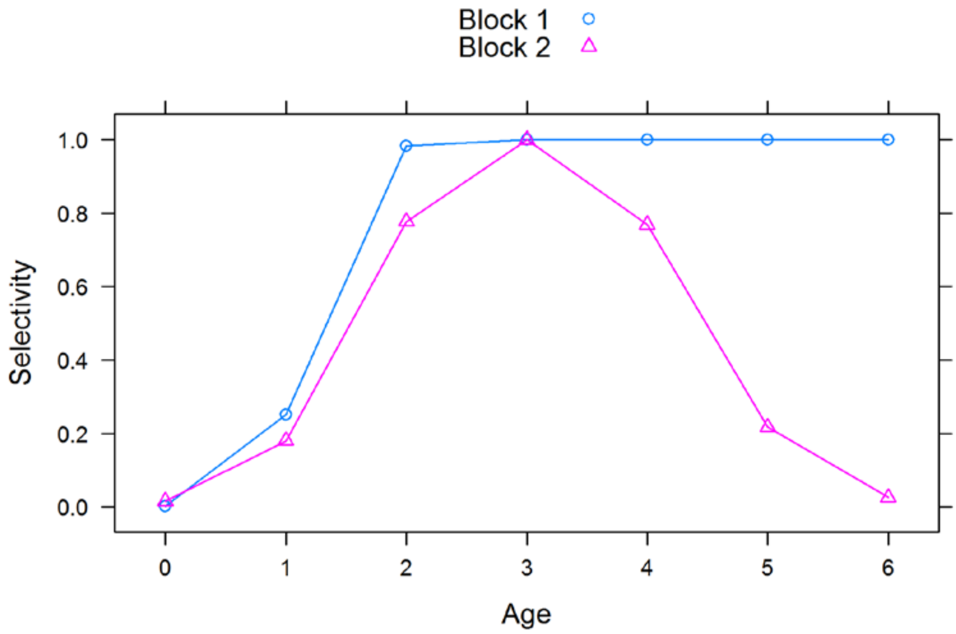



**Figure 4.8. Catch selectivities, block 1: 1968–1999, Block 2: 2000–current.**

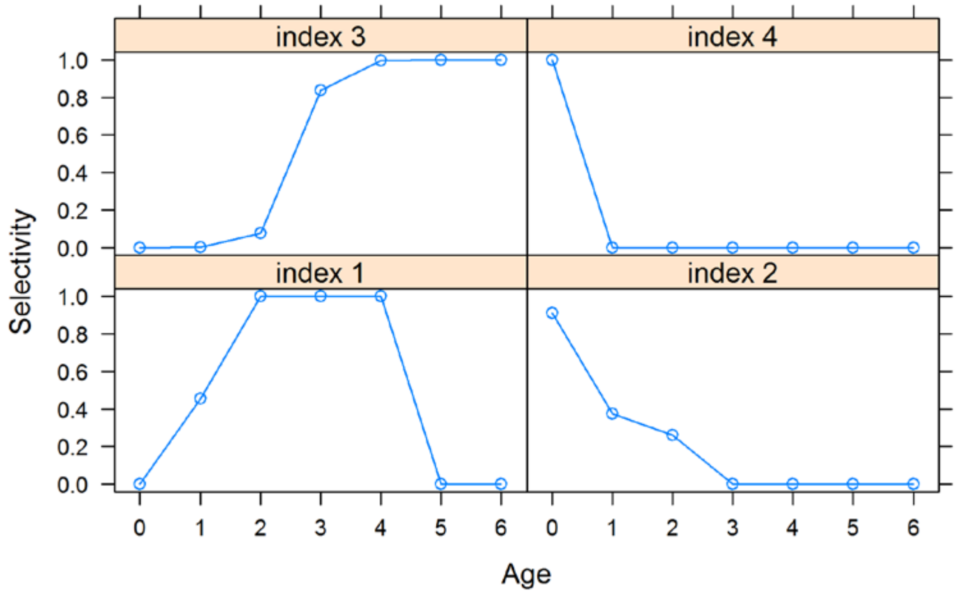



**Figure 4.9. Index selectivities: Index1-Q1, index2-Q4, Index3-UKFSPW, Index4-MIKNET.**

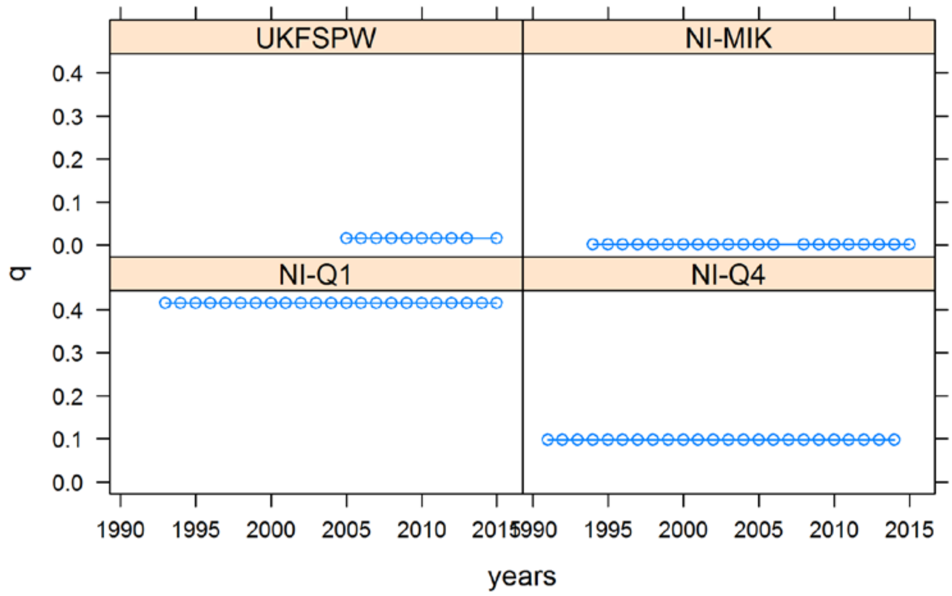



Figure 4.10. Index catchability.

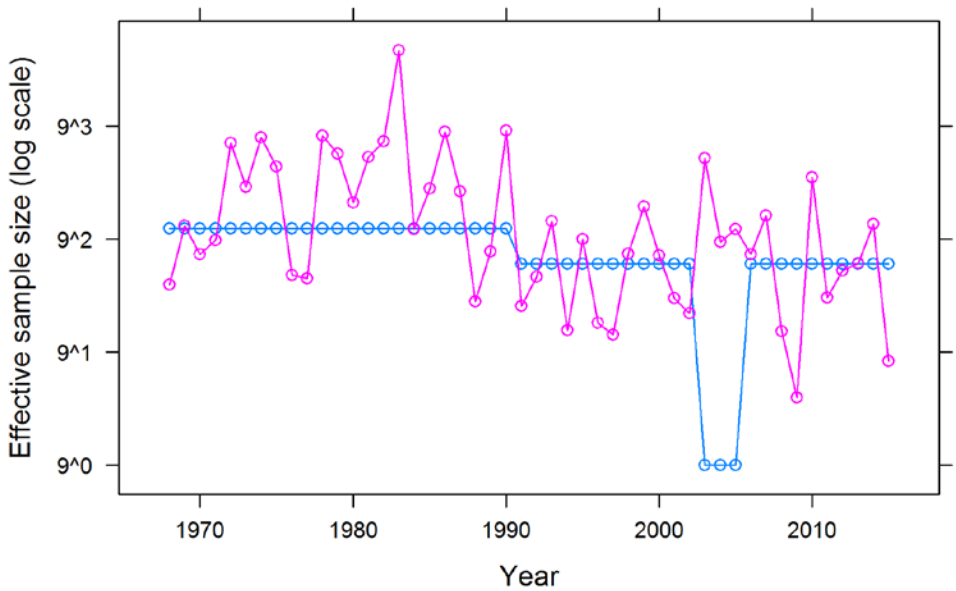



Figure 4.11. Catch effective sample size.

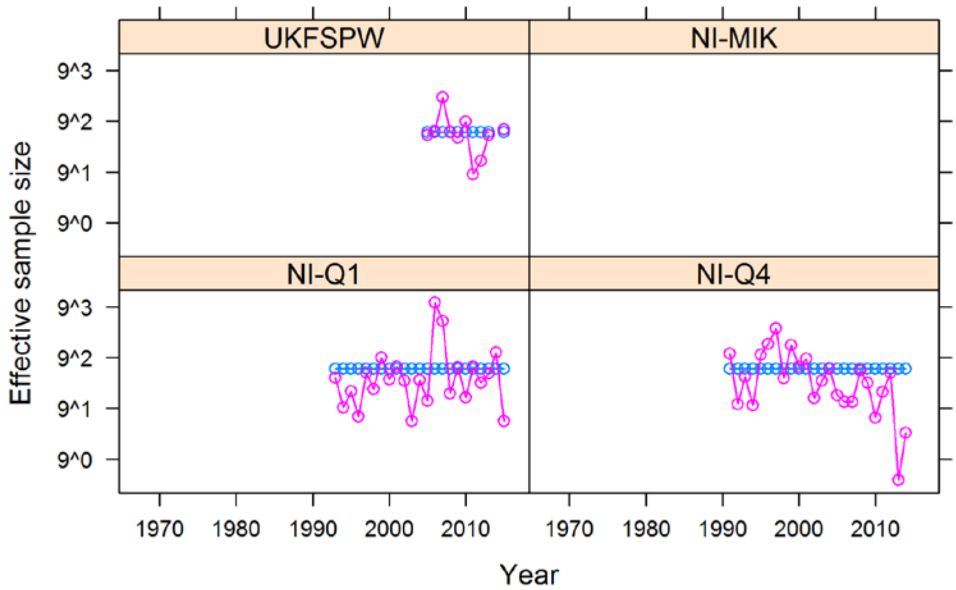



**Figure 4.12. Index effective sample size.**

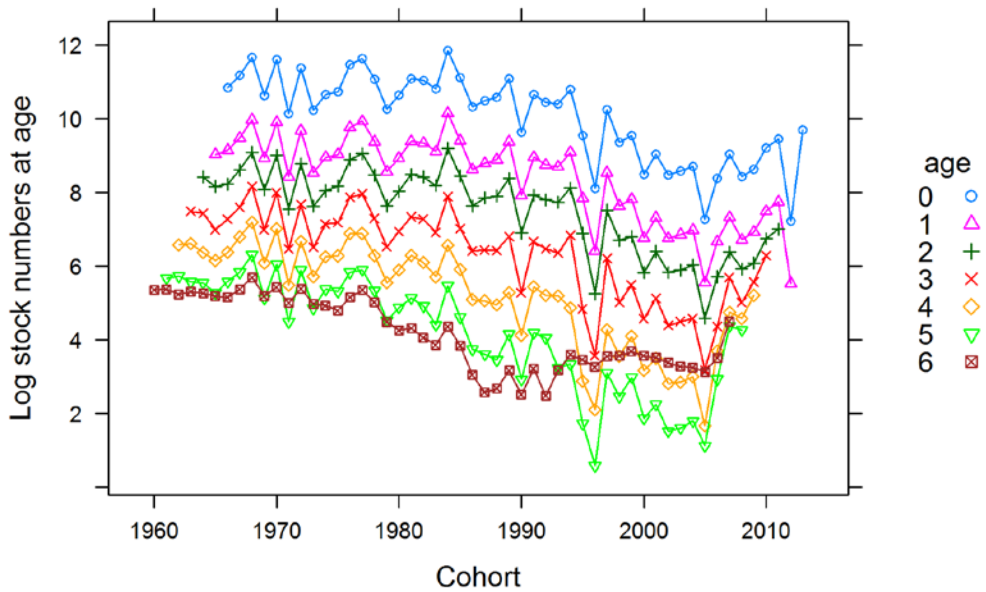



**Figure 4.13. Log stock numbers-at-age.**

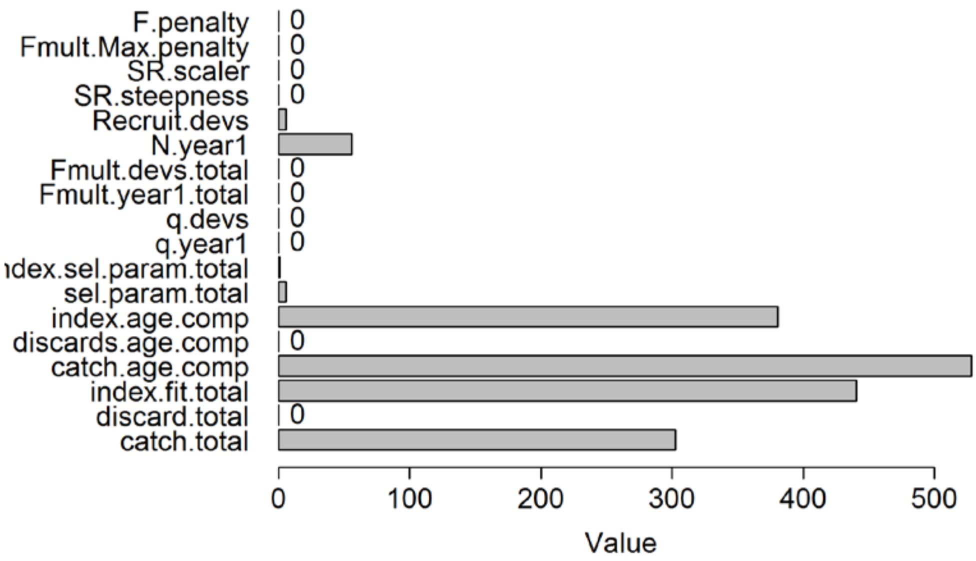



**Figure 4.14. Objective function.**

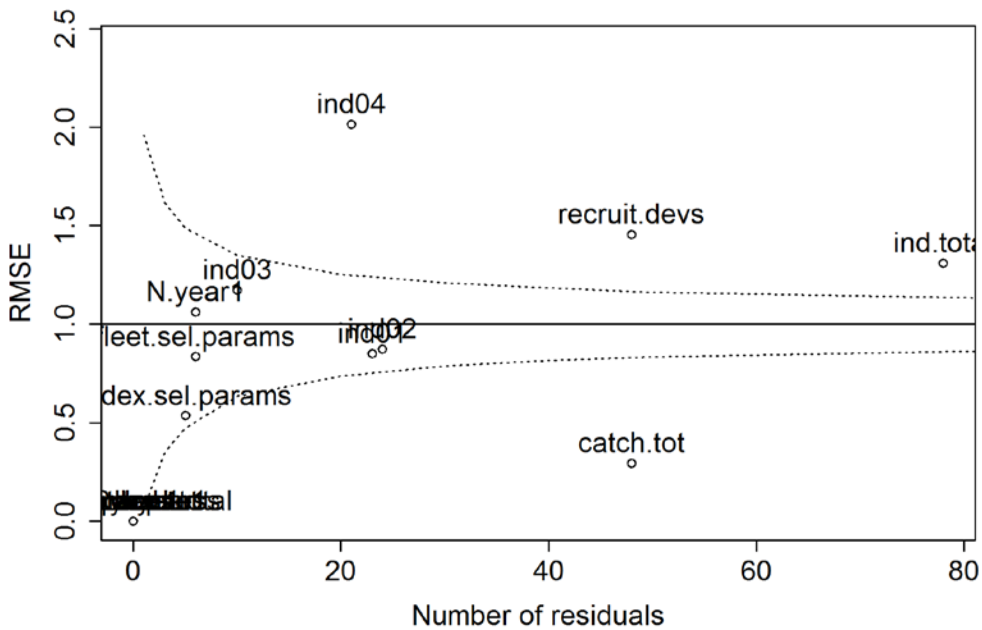



**Figure 4.15. RMSE fit.**

**Stock trends**

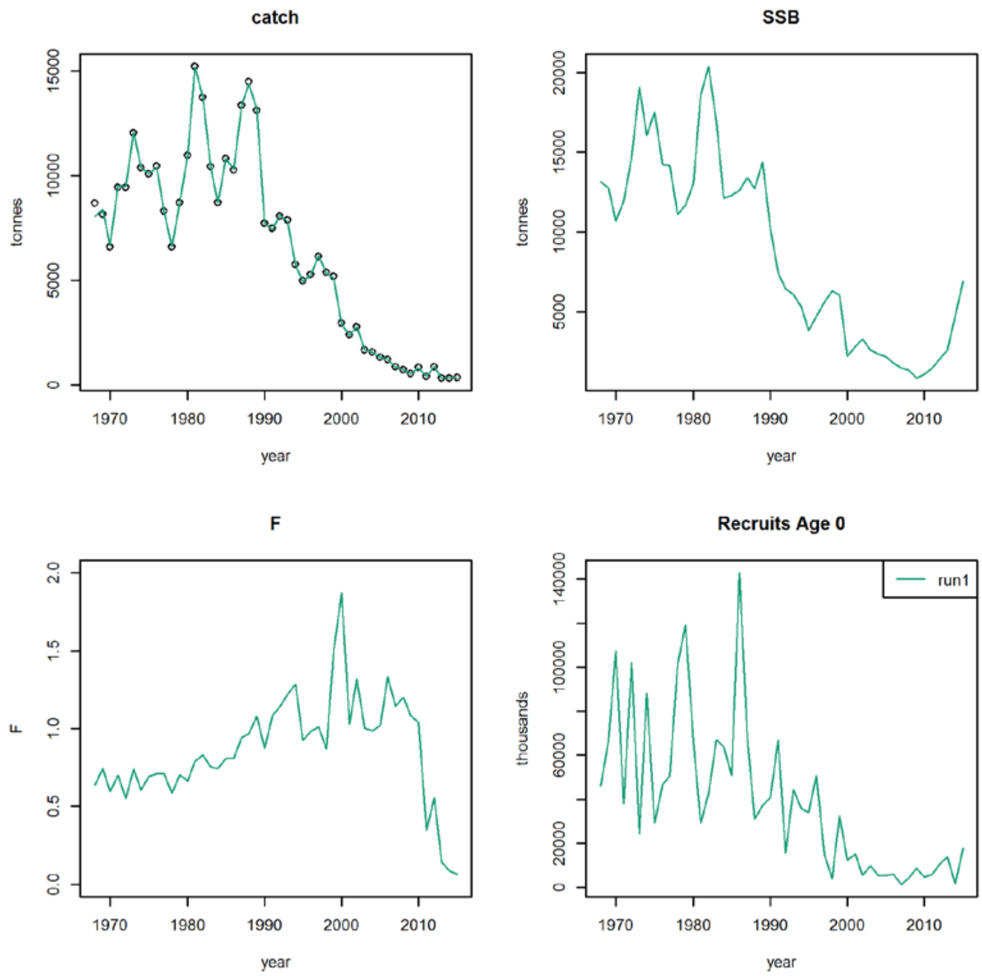



**Figure 4.16. Stock trends from the final model run.**

### 4.3.3 Short-term forecast

Model used:

Software used:

Initial stock size:

Maturity:

F and M before spawning:

Weight-at-age in the stock:

Weight-at-age in the catch:

Exploitation pattern:

Intermediate year assumptions:

Stock–recruitment model used:

Procedures used for splitting projected catches:

## 4.4 Reference points

The derivation of the MSY reference points is described in Annex 8.

| | TYPE | VALUE | TECHNICAL BASIS |
|---|---|---|---|
| MSY | MSY $B_{trigger}$ | 17 521 t | $B_{pa}$ |
| Approach | $F_{MSY}$ | 0.61 | Median point estimates of 'EqSim' simulations |
| | $B_{lim}$ | 6000 t | Suggested breakpoint in SSB where recruitment changes |
| Precautionary | $B_{pa}$ | 17 521 t | $B_{lim}$ combined with the assessment error; $B_{lim}$ x exp(1.645 x σ); σ = 0.15 |
| Approach | $F_{lim}$ | 1.27 | F with 50% probability of SSB < $B_{lim}$ |
| | $F_{pa}$ | 0.914 | $F_{lim}$ combined with the assessment error; $F_{lim}$ x exp(-1.645 x σ); σ = 0.2 |

## 4.5 Future research and data requirements

### Introduction of multiple fleets

The stock has been harvested by a range of different fleets and vessels/gears. A step forward will be to explore the introduction of multiple fleets to the model which would represent these trends.

## 4.6 Multispecies information: WKIrish4

None identified.

# 5 Irish Sea haddock

Stock assessment models for Irish Sea haddock were explored during WKIrish3. Exploratory assessment models were formulated for the stock on the basis of the issue list below and data decisions made at WKIrish 2. Initial model solutions were compared with existing trends based assessment model (SurbaR) and model solutions previously used for the stock (XSA). Potential assessment solutions explored included SAM, A4A and ASAP and update of SPiCT model. Initial exploratory model configurations are presented in working documents provided to WKIrish3.

## 5.1 Issue list

- Maturity – update to time-series of proportion mature at-age from NIGFS-Q1 by WKIrish2;
- Tuning series – available surveys were reviews updated by WKIrish2;
- Discard data incorporated into catch estimates as previously created by WKRound 2013;
- Assessment method – ASAP is proposed as the new assessment method;
- Biological reference points – estimated according to ICES procedures.

Not addressed:

- Prey relations – Investigate the role of whiting in Irish Sea multispecies foodweb dynamics;
- Ecosystem drivers – some discussing by WKIrish2, no firm conclusions.

## 5.2 Data

Data exploration was done by WKIrish2, below is a description of the sensitivity of the proposed model to the input data.

### 5.2.1 Stock identity and migration

### 5.2.2 Life-history data

Estimates of natural mortality were calculated at WKIrish2 (ICES, 2016) for a discussion on natural mortality, the choice of the Lorenzen method for estimating M is documented in the WKIrish2 report. Assessment runs were performed with M=0.2, Lorenzen M, Lorenzen M rescaled to M=2 at-age 5 and Gislason M. The proportion of fish 'mature at-age' was estimated from the NIFGS-Q1 survey for female haddock, with LOWESS smoother fitted for temporal smoothing.

### 5.2.3 Other biological information

Stock weights-at-age are estimated as the Q1 weights-at-age from survey and commercial catches. Stock weights are calculated by fitting a von Bertalanffy growth curve to all available survey estimates of mean length-at-age in March and first-quarter landings, with an additional vector of parameters estimated to allow for year-class effects in asymptotic length.

### 5.2.4 Fishery-dependent data

An underling requirement of the current assessment exploration is to address changes in the quality of the commercial catch series data and assumptions of selectivity change in the fishery due to technical measures and management prescriptions which may have resulted in data quality and fishery selectivity changes over time.

Sensitivity analysis in ASAP model assumptions to the confidence in the catch series was applied by introducing a time-series of variable coefficient of variation (CV) estimates for the catch estimates. These were formulated to reflect the discussion of the catch estimates presented in WKIrish2 (ICES, 2016).

Sensitivity analysis to fishery selectivity patterns, due to management prescriptions, was explored by means of defining selectivity blocks within the commercial fleet. Blocks were selected to reflect change points in management. The initial model formulation consisted of a two block model based on specific time points of management measures. Sensitivity to introduction of a transitional block to reflect gradual changes in fishery behaviour was explored.

### 5.2.5 Fishery-independent data

A number of tuning series are available. The suitability of these as input data were explored at WKIrish2 (ICES, 2016). Initial exploration of tuning series identified NIGFS-Q1, NIGFS-Q4, NI-MIK and UKFSPW as robust dataset for inclusion in the assessment models of haddock. Sensitivity testing was applied for scenarios of survey series CV. At WKIRISH2 CV's for NIGFS-Q1 and NIGFS-Q4 and NIMIK surveys were derived from as observed CVs.

### 5.2.6 Environmental drivers and ecosystem impacts

Explicit environmental drivers are not included in the current assessment investigation.

## 5.3 Assessment and forecast

Initial assessment runs were performed using, SurbaR, VPA, XSA, SAM, A4A and ASAP. At present, ASAP is presented as the preferred assessment method for the following reasons:

- It allows uncertainty in catch data to be accounted for;
- Allows appropriate incorporation of selectivity change;
- ASAP was also proposed for the other gadoids in the Irish Sea.

### 5.3.1 Assessment models and runs

**Run 1: Exploratory model**

A preferred model ASAP model configuration was presented at the workshop. Review of initial model explorations and normalisation with other Irish Sea gadoid species being explored at WKIrish3 suggested provided a base model configuration as detailed in Table 5.1.

The initial model included three tuning indices, NIGFS-Q1, NIGFS-Q4 & NI-MIK. A highly divergent retrospective pattern when the UKFSPW index was included was reported. The model included two selectivity blocks in fishery-dependent data, reflecting bycatch and targeted fishery until the year 2000 (asymptotic). This was replaced by a fleet selectivity pattern without targeted fishing of older fish (dome-shaped) after 2000, reflecting management measures.

**Table 5.1. Initial model configuration and justification (Base Model).**

| INPUT | JUSTIFICATION |
|---|---|
| Fleets | A single fleet was (see final run for justification). |
| Selectivity | Two selectivity blocks were used. Block 1; 1993 to 2000 asymptotic selection reflecting bycatch and targeted nature of catches. Block 2; 2001 to present domed-shaped selection reflecting limited targeted fishery activity. |
| Index specification | NIGFS-Q1 [ages 1 : 4]; NIGFS-Q4 [age 0:3]; NIMIK [age 0]. |
| Index selectivity | Selectivity-at-age for NIGFS-Q1 and NIGFS-Q4 surveys were asymptotic. |
| Index CV and ESS | The CVs for NIGFS-Q1 and NIGFS-Q4 indices were as observed for numbers of fish measured between stations; the effective sample size for the proportions-at-age was set at 50 which is slightly lower than the number of stations in the survey (63). |
| Fleet CV and ESS | The CV for the catches (catch volume) was initially set at 0.3 <2003, 0.7 for 2003–2006 and 0.3 2007 to present. The effective samples size for the proportions-at-age was set at 50 for all years apart from 2003–2006 when it is set to 1. |
| Recruitment Deviations | The CV for recruitment deviations was set at 1 to allow considerable variability between years. |

#### Run 2: Normalisation to Irish Sea gadoids

Review of initial model explorations and in discussion with other gadoid stocks being examined at WKIrish3 initial settings were normalised between stocks to reflect the shared fishery history, survey sources and sampling of commercial fisheries. This refined the catch CV to a 0.35 before 2003, 0.4 during 2003–2006 and 0.30 after 2006. Examination of this initial in Run 1 model suggested that it was disproportionally tuned to the survey series compared to the catch series (Figure 5.1). In the Run 2 the CV for survey series was set to 0.3 for NIGFS-Q1 & NIGFS-Q4 and 0.6 for NI-MIK.

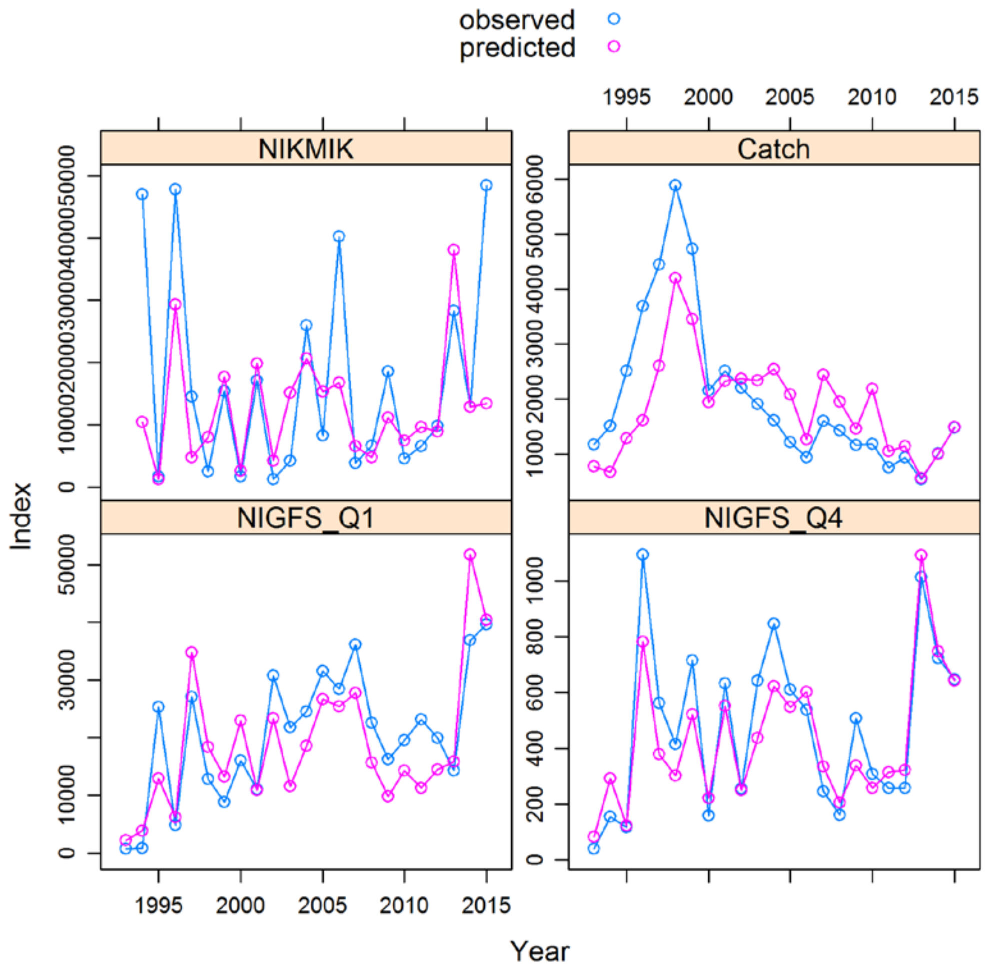



**Figure 5.1. Fitted and observed index and catch series from model Run 2.**

### Run 3: Sensitivity to catch coefficient of variation

It was proposed that a sensitivity analysis to catch CV scenarios was required with fixed CVs of survey series. The catch information from 2007 to present is regarded as the most confident, during 2003–2006 it is regarded that catch and sampling information is of relatively lower quality due to lack of sampling opportunity. Before 2003 the catch series is regarded as of intermediate confidence. The highest confidence period was initially set at 0.05, 0.1 and 0.075, for the high, low and intermediate confidence periods. These CVs were increased by increments of 0.025 for 5 iterations and settings as in Run 1. The model fit and log-likelihood compared (Figures 5.2 and 5.3 and Table 5.2).

Examination of the model fit log-likelihoods shows that selecting highest confidence in catch resulted in the smallest overall log-likelihood, but demonstrated that this was a trade-off between fit to the indices vs. fit the catch. There was clear incremental improved of fit to catch by increasing the confidence scenario (Figure 5.2). However, the highest catch confidence resulted in a fit to the survey indices which were substantially different from that achieved by other scenarios. The survey indices are regarded to reflect the stock status and track clear classes well (WKIrish2), furthermore data issues have been noted with catch data, including back population of a discard series and low confidence associated with applying mist report estimates before 2007.

It was therefore decided that given only the marginal improved model fit to both catch and indices that the lowest confidence scenario could should be used.

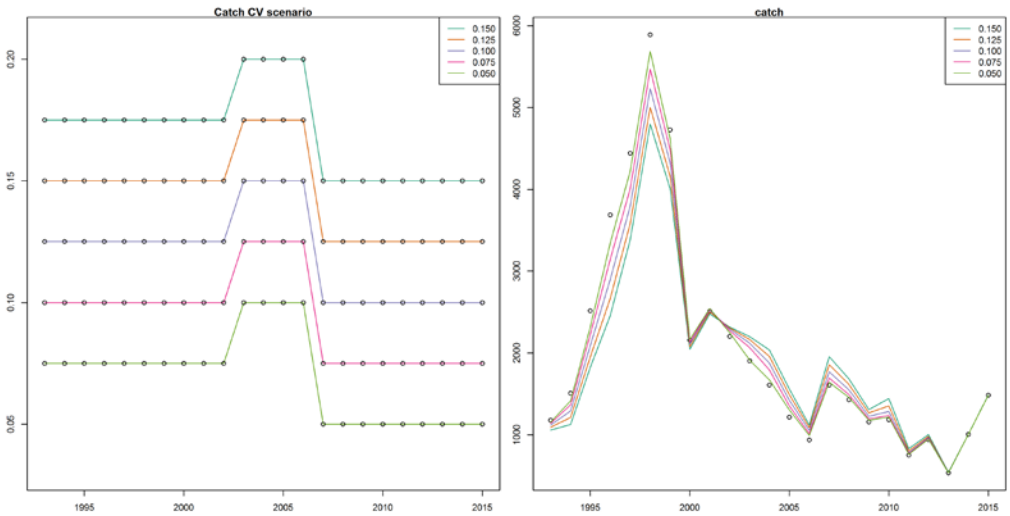



**Figure 5.2. Catch coefficients of variation (CV) scenarios used for sensitivity testing.**

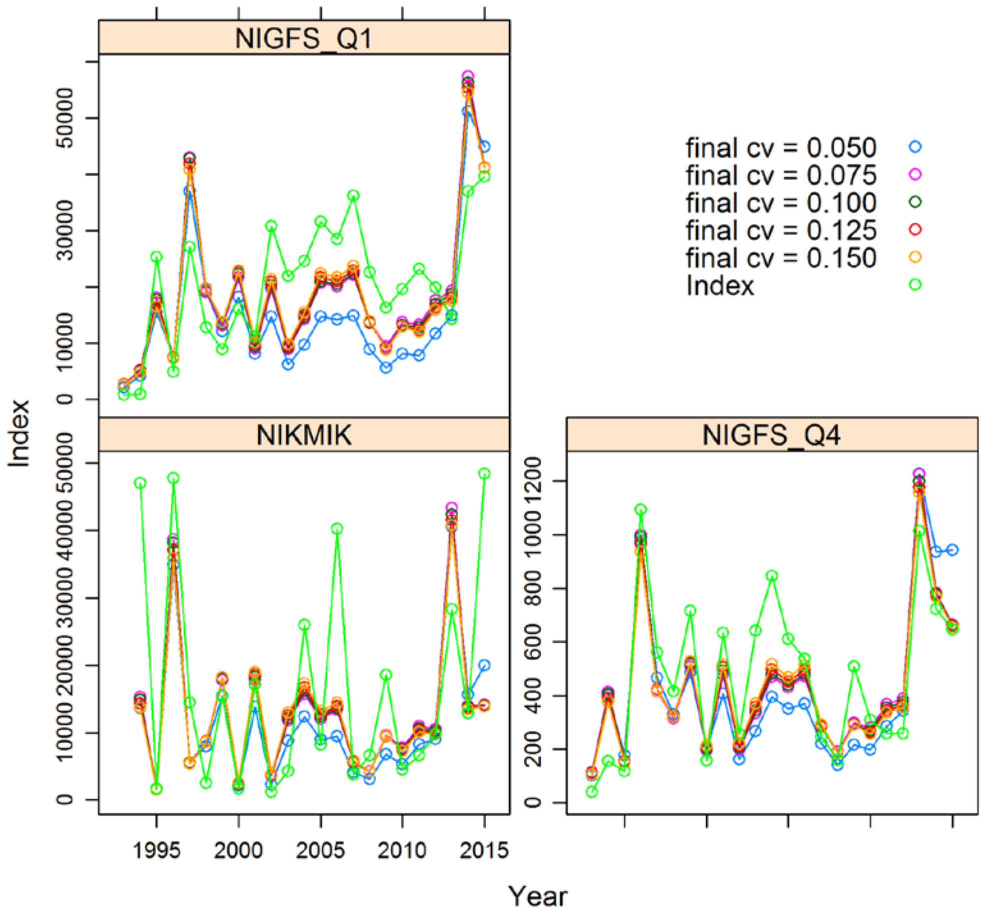



**Figure 5.3. Index fit Index fit and model predicted fit under catch CV scenarios.**

**Table 5.2. Model fit log likelihood values for catch coefficient of variation (CV) sensitivity testing.**

| Catch CV | Total | Catch | Index | Catch age | Index age | Selectivity parameters | Index selectivity |
|---|---|---|---|---|---|---|---|
| 0.15* | 1370.96 | 164.53 | 639.21 | 204.44 | 347.42 | 14.87 | 0.49 |
| 0.125 | 1371.15 | 158.46 | 642.35 | 205.43 | 350.39 | 14.10 | 0.43 |
| 0.1 | 1370.33 | 151.20 | 644.93 | 206.47 | 354.23 | 13.15 | 0.35 |
| 0.075 | 1367.89 | 142.74 | 646.33 | 207.54 | 358.93 | 12.08 | 0.27 |
| 0.05 | 1336.14 | 133.07 | 663.16 | 192.03 | 337.70 | 9.48 | 0.71 |

***Selected model for further sensitivity testing and model configuration runs.**

### Run 4: Sensitivity to natural mortality assumptions

At WKIrish2, Lorenzen estimates of M and Gislason estimates of M were calculated for Irish Sea haddock. Sensitivity to these estimates was carried out using the model selected from Run 3. In addition to Lorenzen and Gislason estimates, a rescaled Lorenzen M was used, with M = 0.2 at oldest age (5) and M=0.2, for all ages (Figure 5.4).

Examination of the model fit log-likelihoods supported selection of the Lorenzen estimates of natural mortality, with the lowest total log-likelihood of all sensitivity, and lowest log-likelihood to catch age survey age (Table 5.3). The Lorenzen M estimates were selected for further sensitivity testing and model configuration runs.

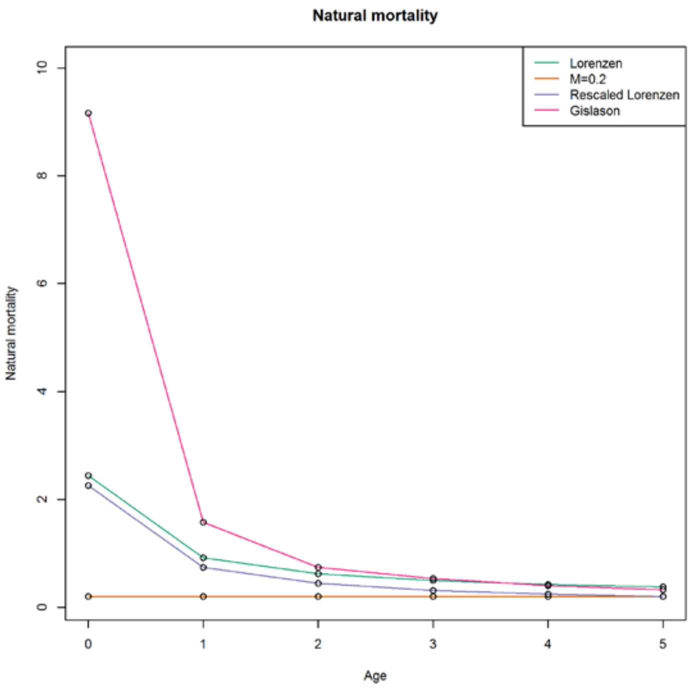



**Figure 5.4. Estimates of natural mortality used for sensitivity testing.**

**Table 5.3. Model fit log-likelihood values for natural mortality sensitivity testing.**

| Natural Mortality | Total | Catch | Index | Catch age | Index age | Selectivity parameters | Index selectivity |
|---|---|---|---|---|---|---|---|
| Lorenzen* | 1370.96 | 164.53 | 639.21 | 204.44 | 347.42 | 14.87 | 0.49 |
| M=0.2 | 1560.86 | 158.05 | 634.45 | 299.42 | 462.36 | 1.83 | 4.74 |
| Re-scaled Lorenzen | 1398.63 | 163.05 | 636.78 | 215.83 | 369.65 | 7.80 | 5.53 |
| Gislason | 2382.95 | 151.31 | 637.43 | 734.76 | 452.45 | 404.57 | 2.43 |

***Selected model for further sensitivity testing and model configuration runs.**

### Run 5: Sensitivity to survey CV assumptions

At WKIrish2 coefficients of variation were calculated for survey indices, as CV of the number of fish measured between survey strata. These observed CVs were used and comparison made with a fixed CV, as used in Run1 and a rescaled observed CV, re-scaled to have a mean of the fixed CV. A lower limit of 0.1 was applied to all observed CVs.

The CV series for indices and the resultant fit of the model to observer catch is shown in Figure 5.5. Examination of the log-likelihood values of the model fit (Table 5.4). Using observed CVs resulted in the best model fit in terms, of total fit, fit to catch series, fit to survey series, fit to catch age and fit to index age. Using an observed CV series was selected for further model configuration runs and sensitivity testing.

**Table 5.4. Model fit log likelihood values for natural mortality sensitivity testing.**

| Survey CV | Total | Catch | Index | Catch age | Index age | Selectivity parameters | Index selectivity |
|---|---|---|---|---|---|---|---|
| Fixed | 1370.96 | 164.53 | 639.21 | 204.44 | 347.42 | 14.87 | 0.49 |
| Scaled | 1374.12 | 167.62 | 643.73 | 202.49 | 343.74 | 16.03 | 0.52 |
| Observed* | 1359.44 | 160.57 | 640.27 | 200.85 | 340.79 | 16.40 | 0.56 |

***Selected model for further sensitivity testing and model configuration runs.**

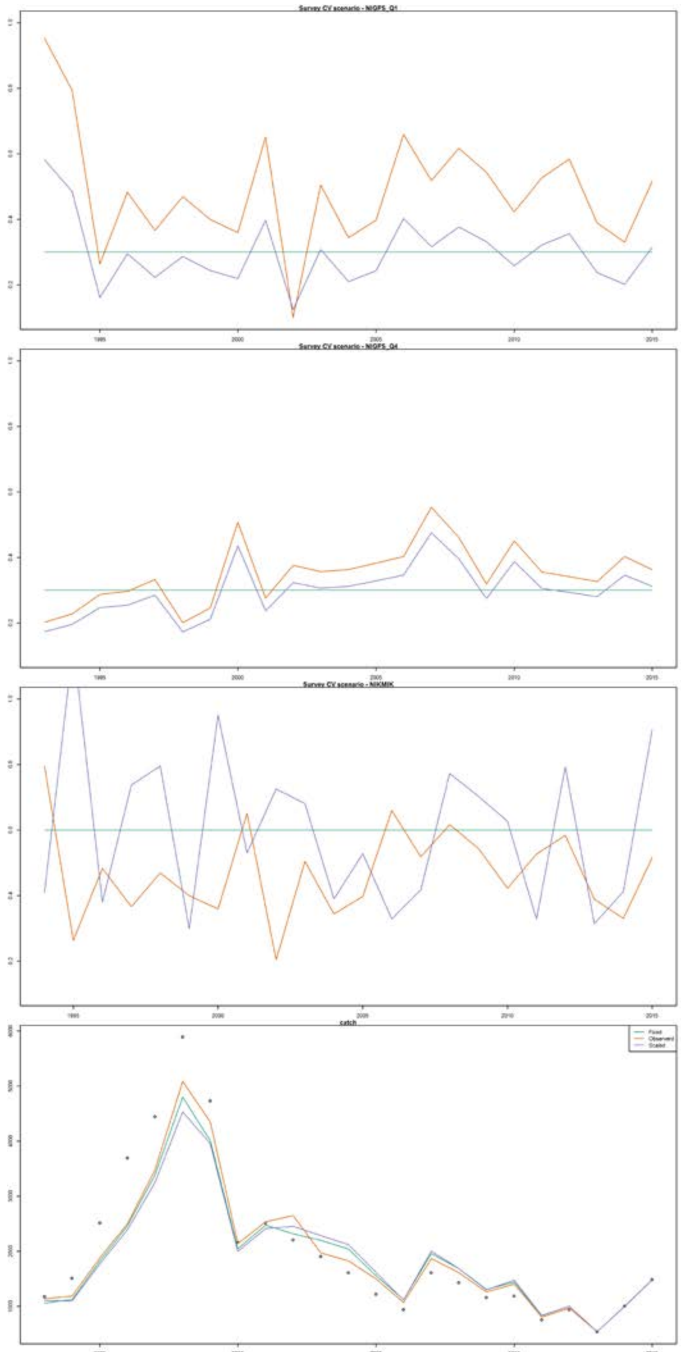


**Figure 5.5. Time-series of indices coefficient of variation (CV) used in sensitivity testing and model fit to catch series.**

#### Run 6: Sensitivity to Survey selectivity

Initial model configuration and testing was applied with asymptotic selection by age for survey series. It was discussed during the benchmark meeting that it is likely that the survey gear used in the NIGFS-Q1 and Q4 surveys is likely to have a domed-shaped selectivity. Domed shape selectivity was parameterised using the double logistic function for the NIGFS-Q1 survey. Given the age range used in the NIGSF-Q4 survey the selectivity pattern was retained as asymptotic.

Although considered a more appropriate selection pattern for the NIGFS-Q1 survey dome shaped selection did not provide an overall improved (Table 5.5). It was considered necessary to examine this assumption in the context of the imposed breakpoint in catch selectivity and the inclusion of a tuning series which targeted old fish, namely the UKFSPW series.

**Table 5.5. Model fit log likelihood values for assumptions of selectivity of NIGFS-Q1 survey.**

| Survey selectivity | Total | Catch | Index | Catch age | Index age | Selectivity parameters | Index selectivity |
|---|---|---|---|---|---|---|---|
| Domed* | 1373.63 | 159.59 | 649.46 | 200.87 | 349.07 | 11.27 | 3.39 |
| Asymptotic | 1359.44 | 160.57 | 640.27 | 200.85 | 340.79 | 16.40 | 0.56 |

***Selected model for further sensitivity testing and model configuration runs.**

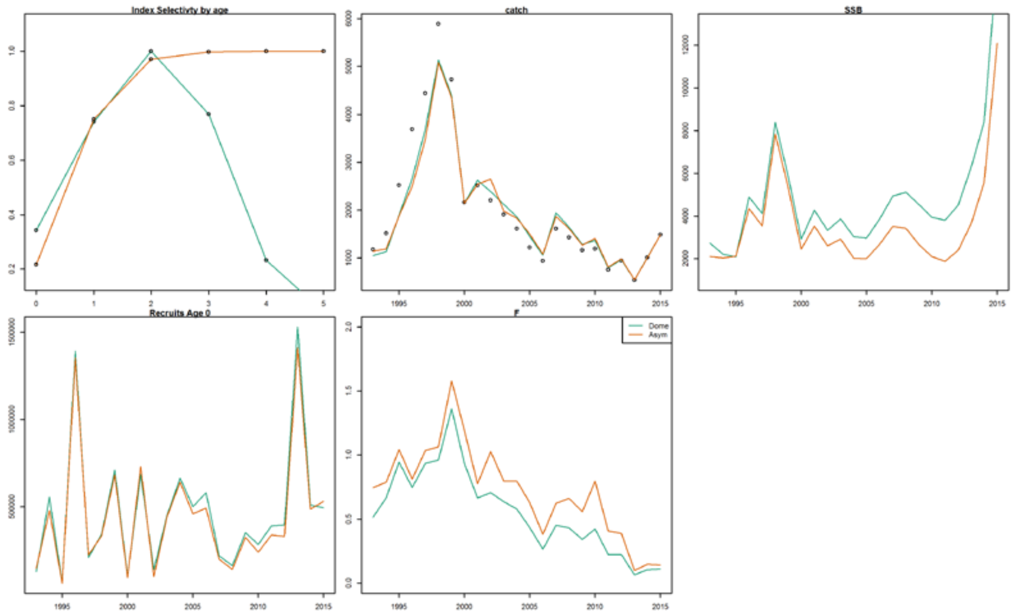



**Figure 5.6. NIGFS index selectivity scenarios tested and stock trend plots of model fit to catch, predicted SSB, recruitment and fishing pressure – F.**

### Run 7: Sensitivity to catch selectivity

In the previously model configurations a breakpoint in selectivity was applied in 2000, associated with management measures to reduce fishing mortality on cod. A third selectivity block was suggested to allow a transition between a fully selected stock to a regime without targeted fishing of older fish. A third selectivity was introduced form 2000–2007. The initial block prior to 2000 was maintained as a asymptotic, with the later blocks fitted as age-based selection using defined coefficients of selectivity for each age; allowing the model to select final parameterisation, but giving initial values which reflected an increasingly dome shape selection in the later two blocks. The log-likelihood model fit parameters in Table 5.6 support the use of a three selectivity blocks. This configuration was selected for trial with the inclusion of the UKFSPW index.

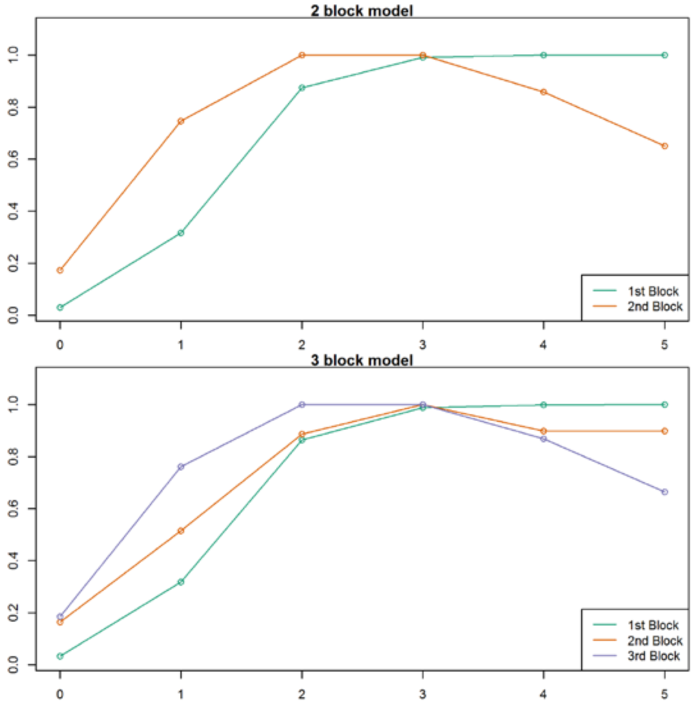



**Figure 5.7. Selectivity patterns applied for a two block and three block selectivity pattern for the fishery.**

**Table 5.6. Model fit log-likelihood values comparison for a two block and three block fishery selectivity model.**

| Fishery selectivity | Total | Catch | Index | Catch age | Index age | Selectivity parameters | Index selectivity |
|---|---|---|---|---|---|---|---|
| Two Blocks | 1373.634 | 159.5875 | 649.4597 | 200.8671 | 349.0659 | 11.26902 | 3.385016 |
| Three Blocks* | 1344.325 | 159.2254 | 641.9206 | 201.5052 | 338.3684 | -0.68547 | 3.991138 |

***Selected model for further comparison with model including UKFSPW survey.**

#### Run 8: Sensitivity to inclusion of UKFSPW survey

Having both a dome-shape selection in the fishery, NIGFS-Q1 survey prompted a requirement to include a source of information for older aged fish, with higher selectivity coefficients. The UKFSPW survey a continuing survey series, targeting older fish was included, although the series is short; 2007–present (excluding 2014). While the log-likelihood fit of the model including a fourth index was not reduced, the additional information provided by the index was deemed an important addition. The UKFSPW index includes the only fully selected source of information for the oldest age fish. It is assumed to asymptotic selection of fish, in contrast to the NIGFS-Q1 and NIGFS-Q4 surveys which target juvenile fish and commercial fishery data which, due to recent management measures has resulted in limited targeted fishing form haddock.

The use of current specified selectivity blocks may require review at annual at regular intervals. With advice and management for haddock or other species it is possible that the character of the fishery may change. A model including the UKFSPW survey with four selectivity blocks was applied (Table 5.7). In recent years 2013–present it has been observed that targeted fishing of haddock has increased, due to the strength of the 2013 year class. As this year class has matured and the cohort progressed full selection of the older fish may need to be taken into consideration in model configuration; at present this selectivity period is too short to be parameterised robustly.

**Table 5.7. Model fit log-likelihood values comparison of models including the FSP index and a model with this index.**

| Fourth Index | Total | Catch | Index | Catch age | Index age | Selectivity parameters | Index selectivity |
|---|---|---|---|---|---|---|---|
| UKFSPW excluded | 1344.325 | 159.2254 | 641.9206 | 201.5052 | 338.3684 | -0.68547 | 3.991138 |
| UKFSPW* included | 1426.381 | 158.809 | 677.7911 | 200.102 | 382.1372 | 0.311632 | 7.229801 |
| 4 Block model | 1458.015 | 163.691 | 681.8343 | 196.782 | 409.185 | -1.098711 | 7.621659 |

***Final model configuration.**

A retrospective analysis demonstrated a consistent historic downward revision of the perceived SSB trend and upward revision of the F trend. The initial two years of the retrospective plot show significant deviations. This was considered due to the model having a selectivity block, beginning in 2007, with reduced selection for older fish and the introduction of the UKFSPW, with an asymptotic selectivity pattern, starting in 2007. The short period to estimate the selectivity parameters for both the fishery and survey index are considered to contribute to the instability of the model during this time.

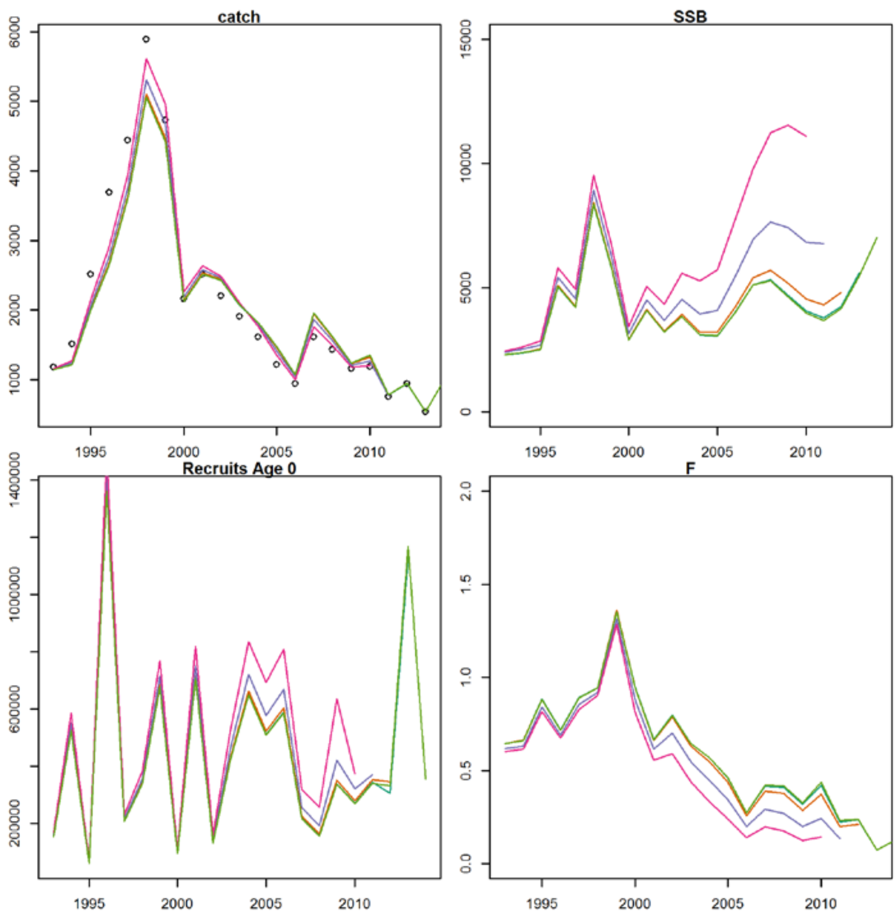



**Figure 5.8. A retrospective plot the final assessment model.**

### 5.3.2 Final assessment model run

Describe the model configuration and justify the choice of settings.

| | | | |
|---|---|---|---|
| Catch (tonnes) | 1993–current | 0–5+ | Yes |
| Catch-at-age in numbers (thousands) | 1993–current | 0–5+ | Yes |
| Weight-at-age in the commercial catch (kg) | 1993–current | 0–5+ | Yes |
| Weight-at-age of the stock at spawning time (kg). | 1993–current | 0–5+ | Yes |
| Weight-at-age of the stock at Jan. 1 (same as stock weights) | 1993–current | 0–5+ | Yes |
| Proportion of natural mortality before spawning (Lorenzen M) | 1993–current | 0–5+ | No |
| Proportion of fishing mortality before spawning | 1993–current | 0–5+ | No |
| Proportion mature-at-age | 1993–current | 0–5+ | No |

Model configuration

| INPUT | JUSTIFICATION |
|---|---|
| Fleets | A single fleet. Recommendation to consider splitting fleets in future. Age disaggregation not possible without review of all ageing data |
| Selectivity | Three selectivity blocks were used. Block 1; 1993 to 2000 asymptotic selection reflecting bycatch and targeted nature of catches. Block 2; 2001 to 2007; 2007–present - increasing dome-shaped selection reflecting limited targeted fishery activity. A fourth block should be considered if the recent / current fishery behaviour is considered to have change |
| Index specification | NIGFS-Q1 [ages 1 : 4]; NIGFS-Q4 [age 0:3]; NI MIK [age 0]; UKFSPW [2–5]. |
| Index selectivity | Dome-shape selectivity for NIGFS-Q1; Asymptotic selection for NIGFS-Q4 & UKFSPW. |
| Index CV and ESS | The CVs for NIGFS-Q1 and NIGFS-Q4 indices were as observed for numbers of fish measured between strata; the effective sample size for the proportions-at-age was set at 50 which is slightly lower than the number of stations in the survey (63). The effective sample size for the UKFSPW was 10 with a CV of 0.7. |
| Fleet CV and ESS | The CV for the catches (catch volume) was initially set at 0.175 <2003, 0.2 for 2003–2006 and 0.15 2007 to present. The effective samples size for the proportions-at-age was set at 50 for all years apart from 2003–2006 when it is set to 1. |
| Recruitment Deviations | The CV for recruitment deviations was set at 1 to allow considerable variability between years. |
| Natural Mortality | Lorenzen M |

ASAP model settings

| Option | Setting |
|---|---|
| Use likelihood constant | Yes |
| Mean F (Fbar) age range | 2–4 |
| Fleet selectivity block 1 | Assymtotpic |
| Fleet selectivity block 2 | Age coefficineits (age 0–5) (0.2;0.5;0.8;1;0.7;0.5) |
| Fleet selectivity block 3 | Age coefficients (age 0–5) (0.3;0.6;0.7;8;0.6;0.4) |
| Discards | Included in catch (not specified separately from landings) |
| Index units | 4 (numbers) |
| Index month | NIGFS-Q1 (3); NIGFS-Q4 (10); NIMIK (7); UKFSPW(3) |
| Index selectivity linked to fleet | -1 (not linked) |
| Index age range | NIGFS-Q1 (1–4); NIGFS-Q4 (0–3); NIMIK (0); UKFSPW(2–5) |
| Index Selectivity (NIGFS-Q1) | Double logistic |
| Index Selectivity (NIGFS-Q4) | Asytotpic |
| Index Selectivity (NIMIK) | NA (age 0 only) |
| Index Selectivity (UK-FSPW) | Aysmytotic |
| Index CV & ESS (NIGFS-Q1) | Observed strata CV (lower limit 0.1); ESS = 50 |
| Index CV & ESS (NIGFS-Q4) | Observed strata CV (lower limit 0.1); ESS = 50 |
| Index CV & ESS (NIMIK) | Observed station CV (lower limit 0.1); ESS = 50 |
| Index CV & ESS (UK-FSPW) | CV = 0.7; ESS = 10 |
| Phase for F-Mult in 1st year | 1 |
| Phase for F-Mult deviations | 2 |
| Phase for recruitment deviations | 3 |
| Phase for N in 1st Year | 1 |
| Phase for catchability in 1st Year | 3 |
| Phase for catchability deviations | -5 (Assume constant catchability in indices) |
| Phase for unexploited stock size | 1 |
| Phase for steepness | -5 (Do not fit stock–recruitment curve) |
| Catch total CV | 1993-2000 (0.175); 2003-2006 (0.2); 2007-2015 (0.15) |
| Catch effective sample size | 1993-2000 (50); 2003-2006 (1); 2007-2015 (50) |
| Lambda for recruit deviations | 0 (freely estimated) |
| Lambda for total catch | 1 |
| Lambda for total discards | NA (discards included in catch) |
| Lambda for F-Mult in 1st year | 0 (freely estimated) |
| Lambda for F-Mult deviations | 0 (freely estimated) |
| Lambda for index | 1 for both indices in the model |
| Lambda for index catchability | 0 for all indices (freely estimated) |
| Lambda for catchability devs | NA (phase is negative) |
| Lambda N in 1st year deviations | 0 (freely estimated) |
| Lambda devs initial steepness | 0 (freely estimated) |
| Lambda devs unexpl stock size | 0 (freely estimated) |

### 5.3.3 Short-term forecast

Software used*:* FLAssess – Short-Term Forecast (stf)

| | |
|---|---|
| Initial stock size | Long-term GM (omitting last two years)<br>Stock numbers-at-age 1 and older from model |
| Natural mortality | Lorenzen M, as in model |
| Maturity | Most rectent estimate |
| F and M before spawning | 0 for all ages in all years |
| Stock / catch weights-at-age | Average last 3 years |
| Exploitation pattern | Average last 3 years |
| Intermediate year assumptions | F in the last year – check retrospective pattern for evidence of bias |
| Stock–recruit model | None, long-term GM recruitment (omitting last two years) |
| Fbar range | 2–4 |
| Rescale to last year | No |

## 5.4 Reference points

The derivation of reference points is documented in Annex 9.

$B_{lim}$ was set to the SSB in 1993, from which the fishery developed, an SSB of 2300 t in 1993. The S–R plot for Irish Sea haddock shows no obvious S–R relationship (Figure 5.9), mainly because the recruitment is highly variable. The S–R pairs from 1993:2012 were not used initially as the 2013 recruitment event and 2015 SSB were considered to be highly influential. The fitted relationship, compared to the selecting $B_{lim}$ at 2300 t provides a $B_{lim}$ of 4035 t, a value which has only been exceeded on eight occasions. However, the fitted segmented regression in a much better fitted given an Akaike Information Criterion weight of 94%. Whereas the selected $B_{lim}$ of 2300 t is used proposed as a more realistic value for the stock, the modelled relationship is used for further MSY simulations.

The entire time-series is used for MSY simulations (1993–2105). $F_{cv}$ is 0.22 (F error in last year) and SSBcv as 0.15 (SSB error in last year). $B_{pa}$ was calculated as $B_{lim}$ combined with the assessment error; $B_{lim}$ x exp(1.645 x σ); σ = 0.15 as 3093 t. MSY$B_{trigger}$ is set to $B_{pa}$ as the stock has not been fished at or below $F_{MSY}$ for more than five years. $F_{MSY}$ median point estimates is 0.27 (0.273). The upper bound of the $F_{MSY}$ range giving at least 95% of the maximum yield was estimated to 0.35(0.351) and the lower bound at 0.19 (0.192) (Figure 5.4.2). $F_{p.05}$, without assessment error of $B_{trigger}$ as estimated 0.40 (0.0445) and therefore the upper bound does not need to be restricted because of precautionary limits. $F_{lim}$ is estimated to be 0.47 (0.445) as F with 50% probability of SSB <$B_{lim}$ with $F_{pa}$ as 0.34 calculated as $F_{lim}$ combined with the assessment error; $F_{lim}$ x exp(-1.645 x σ); σ = 0.22.

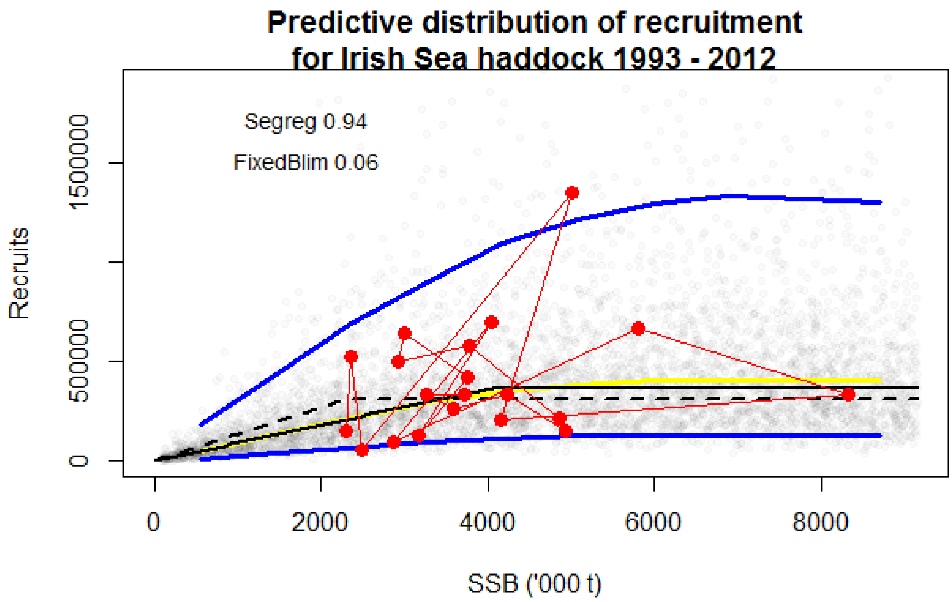
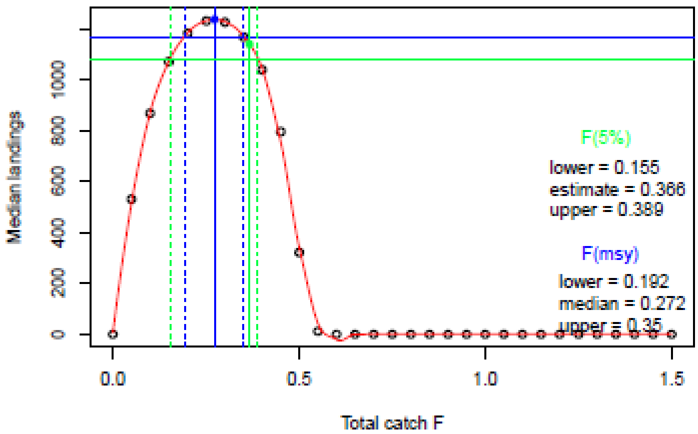
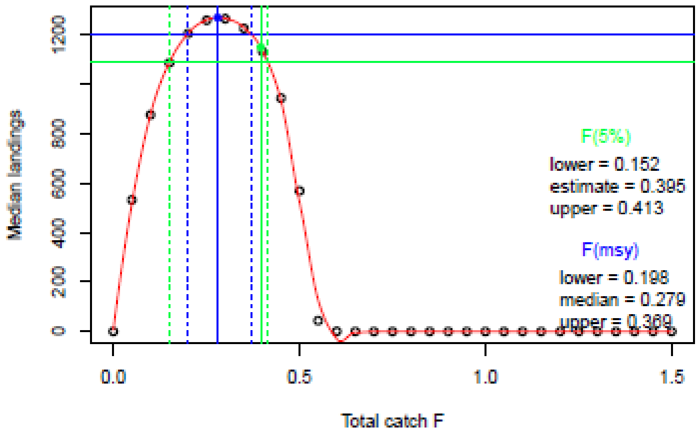



**Figure 5.9. Stock–recruitment relationship for Irish Sea haddock with fitted segmented regression.**



No MYSB$_{trigger}$, No error – to estimate F$_{lim}$.

| | Type | Value | Technical basis |
|---|---|---|---|
| MSY | MSY B$_{trigger}$ | 3093 t | B$_{pa}$ |
| Approach | F$_{MSY}$ | 0.27 | Median point estimates of 'EqSim' simulations |
| | B$_{lim}$ | 2300t | SSB in 1993 – SSB at start of current period of stock development |
| Precautionary | B$_{pa}$ | 3093t | B$_{lim}$ combined with the assessment error; B$_{lim}$ x exp(1.645 x σ); σ = 0.15 |
| Approach | F$_{lim}$ | 0.47 | F with 50% probability of SSB <B$_{lim}$ |
| | F$_{pa}$ | 0.34 | F$_{lim}$ combined with the assessment error; F$_{lim}$ x exp(-1.645 x σ); σ = 0.22 |

## 5.5 Future research and data requirements

This section addresses Tor d)

Consider selection blocks = additional blocks as fishery develops / changes

Consider splitting model

## 5.6 Multispecies information: WKIrish4

This section addresses Tor e).

Identify aspects that require special attention by the ongoing Irish Sea regional benchmark process, in particular pertaining to the development of integrated multi-species and ecosystem advice (to culminate in the synthesis workshop WKIrish4).

# 6 Irish Sea whiting

## 6.1 Issue list

- Natural mortality – Lorenzen M is proposed to replace 0.2 for all ages
- Tuning series – Available surveys were reviewed by WKIrish2
- Discard data reconstruction – Documented by WKIrish2
- Changes in growth and maturity – Documented by WKIrish2
- Assessment method – ASAP is proposed as the new assessment method
- Biological reference points – estimated according to ICES procedures

Not addressed:

- Prey relations – Investigate the role of whiting in Irish Sea multispecies foodweb dynamics.
- Ecosystem drivers – some discussing by WKIrish2, no firm conclusions.

## 6.2 Data

Data exploration was done by WKIrish2, below is a description of the sensitivity of the proposed model to the input data.

### 6.2.1 Stock identity and migration

See WKIrish2.

### 6.2.2 Life-history data

See Section 2 for a discussion on natural mortality; the choice of the Lorenzen method for estimating M is documented in the WKIrish2 report. Assessment runs were performed with M=0.2 and time-varying M. However there is too much uncertainty about M to justify estimating it for each year as this can potentially just add noise.

Sensitivity to maturity was not investigated; this appears to be consistently knife-edged at-age 2.

### 6.2.3 Other biological information

### 6.2.4 Fishery-dependent data

No sensitivity analysis was performed to the fisheries-dependent data.

### 6.2.5 Fishery-independent data

The inclusion of different available surveys was tested in a series of preliminary model runs. (Described in working document: "WD Whg7a ASAP runs.docx" on the WKIrish3 SharePoint site.)

#### 6.2.6 Environmental drivers and ecosystem impacts

## 6.3 Assessment and forecast

### 6.3.1 Assessment models and runs

Exploratory assessment runs were performed using XSA and ASAP (see working documents). WKIrish3 preferred the use of ASAP as an assessment method for the following reasons:

- It allows uncertainty in the catch data;
- ASAP is more transparent than XSA;
- ASAP was also proposed for the other gadoids in the Irish Sea;
- The XSA shows strong trends in catchability residuals and a substantial retrospective bias.

XSA did inform the periods chosen for selection blocks for the ASAP.

The following runs were performed. The model diagnostics are available on the SharePoint under the section working documents (5_asap_diagnostics - runXX.pdf)

**Run 1–Exploratory run**

The first run was presented at the workshop. A number of settings were changed during the workshop to provide a more realistic starting point (see run 2).

**Run 2–Base run**

The settings of the base run were similar for the cod, haddock and whiting ASAP models. They are described below.

| Input | Justification |
|---|---|
| Fleets | A single fleet was (see final run for justification). |
| Selectivity | Two selectivity blocks were used (see final run for justification). |
| Index specification | The two Northern Irish groundfish surveys (Q1 and Q4) were included (all available ages) as well as the NI MIK net survey (see final run for justification). |
| Index selectivity | Selectivity-at-age for the two NI groundfish surveys was set at 1 for all ages (see final run for justification). The MIK net only catches one age class (age 0). |
| Index CV and ESS | The CVs for all years of the two NI groundfish indices were set to 0.2 (which is similar to the between-station variability of the survey). The CV for the MIK net was set to 0.5; the effective sample size for the proportions-at-age was set at 50 which was slightly lower than the number of stations in the survey. |
| Fleet CV and ESS | The CV for the catches (catch volume) was initially set at 0.05 for all years. The actual precision is lower but the starting point was to assume accurate and precise catch data.<br>The effective samples size for the proportions-at-age was set at 50. |
| Recruitment Deviations | The CV for recruitment deviations was set at 1 to allow considerable variability between years. However, the lambda was set to 1, which constrains the recruitment somewhat and helps with convergence. |

#### Run 3–Less precise catch data

The catch CV was increased to 0.2 which was believed to be more realistic, the effective sample size was reduced to 10 to reflect the small number of age samples taken for significant portions of the catches throughout the time-series. All other settings like run 2.

These changes had very little impact on the stock trend or fit to catches.

#### Run 4–survey selectivity

The selectivity of the surveys was initially set to 1 for all ages. To investigate if this was a realistic assumption, a single logistic curve was estimated for both groundfish surveys (the MIK net survey only has a single age class). All other settings like run 3.

The logistic curves suggested partial selection for age 1 (and age 0 for the Q4 survey) and full selection for the other ages.

These changes resulted in a slight decrease in SSB in recent years and increase in F but very similar trends. The residual patterns improved somewhat and therefore this change was considered sensible.

#### Run 5–survey CV

The survey CV was increased to 0.5 to account for additional variability like year-effects. This increase was later considered too high but subsequent runs used this value. All other settings like run 4.

#### Run 6–time-varying M

Because there have been significant changes in the mean size-at-age, this is likely to affect the natural mortality. A time-varying M was calculated based in the Lorenzen method applied to the catch weights smoothed over five years. All other settings like run 5.

This change had more impact on the stock trend than any of the other changes. In principle this is a sensible approach. However, there is a lack of knowledge of M to justify this approach as it potentially introduces additional noise to the assessment.

#### Run 7–double logistic survey selectivity

Survey selectivity was estimated by a double logistic curve for both groundfish surveys. All other settings like run 5.

The outcome was a strong dome-shaped selection curve for both surveys. However the effect on the stock trend was very small. This can probably be explained by the lack of older fish in the population. If the age structure recovers, it might be important to consider this option again. However because there is very little information to inform the shape of the curve, therefore the workshop decided to use the simpler single logistic model.

In order to further investigate the possible shape of the selectivity of the surveys, relative to the catches, the mean catch curves over the period of the surveys were plotted (Figure 6.3.1.1). These catch curves were close to parallel, therefore there is no strong evidence of dome-shaped selectivity in the surveys (relative to the commercial catches).

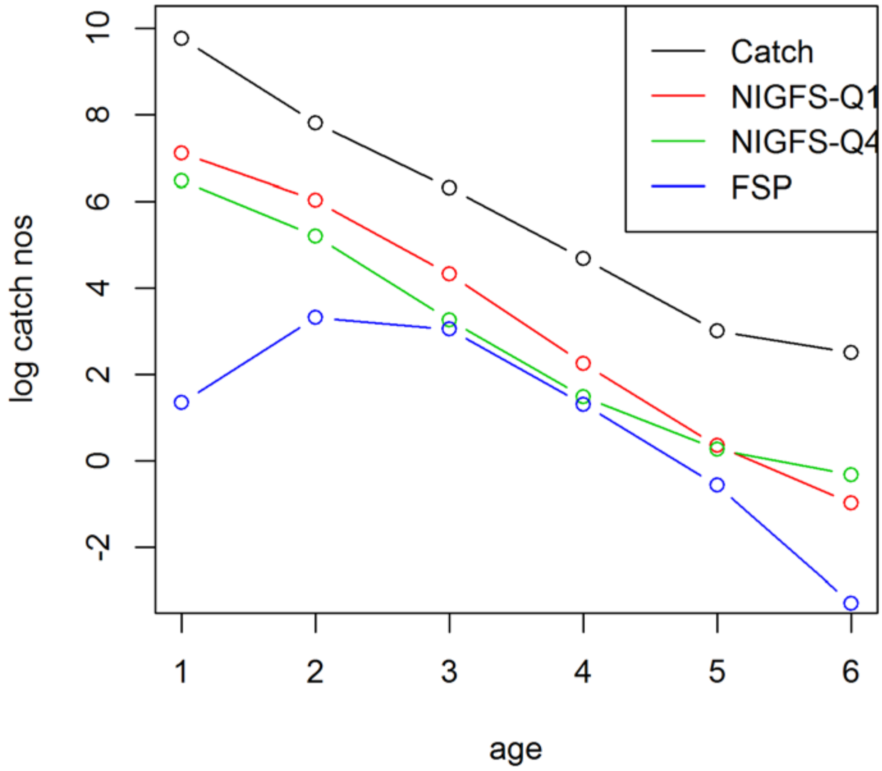



**Figure 6.3.1.1. Mean catch curves for the period 1992–2015 for the commercial catch and the two NI groundfish surveys as well as the UK Fisheries-Science Partnership survey.**

### Run 8–FSP survey

The UK Fisheries Science Partnership survey is the only potential tuning fleet that catches older fish. However, it is discontinued and the time-series is relatively short and only covers a small spatial area (the only area where most large whiting are found). This run includes the FSP survey. All other settings like run 5.

The model converged when all age classes were included. However there single logistic selectivity curve did not fit well. This appeared to be caused by the youngest fish (age 1) which were more abundant than the model expected, causing strong negative residuals at-age 2 and positive residuals at-age 3. The next step was to omit age 1 from the survey as these are poorly selected anyway. However the model failed to converge. There was insufficient time available to investigate this further and it was agreed to omit the FSP survey.

### Comparison of stock trends

Figure 6.3.1.2 provides an overview of the runs described above.

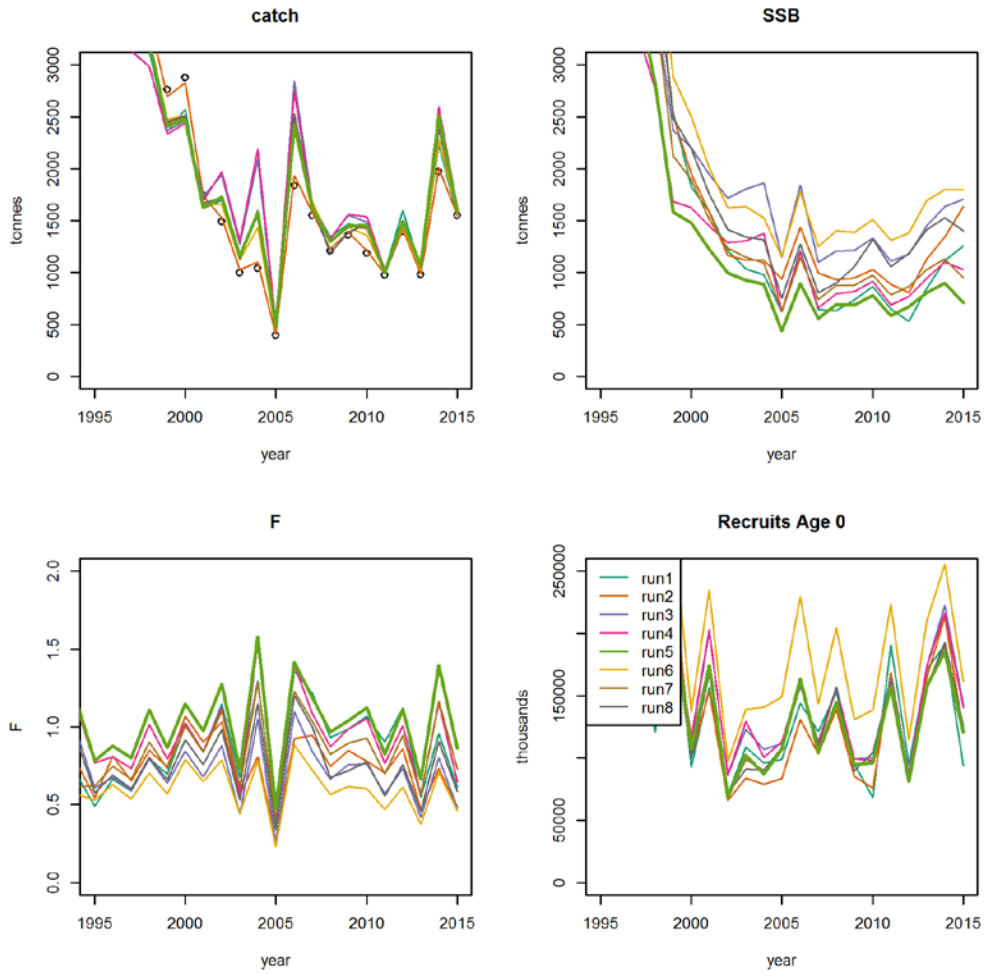



**Figure 6.3.1.2. Comparison of the stock trends in the exploratory runs. The plots were 'cropped' to the last 20 years as the differences between the runs were nearly imperceptible if the full time-series was shown. 1) Exploratory run; 2) Base run; 3) Less precise catch data; 4) survey selectivity; 5) survey CV; 6) time-varying M; 7) double logistic survey selectivity. 8) FSP survey.**

| Type | Name | Year range | Age range | Variable from year to year? |
|---|---|---|---|---|
| Caton | Catch in tonnes | 1980–current | | Yes |
| Canum | Catch-at-age in numbers | 1980–current | 0–6+ | Yes |
| Weca | Weight-at-age in the commercial catch | 1980–current | 0–6+ | Yes |
| West | Weight-at-age of the spawning stock at spawning time. | 1980–current | 0–6+ | Yes |
| Mprop | Proportion of natural mortality before spawning | 1980–current | 0–6+ | No |
| Fprop | Proportion of fishing mortality before spawning | Not relevant | | |
| Matprop | Proportion mature at-age | 1980–current | 0–6+ | No |
| Natmor | Natural mortality | 1980–current | 0–6+ | No |

### 6.3.2 Final assessment model run

The final run was based on run 5 with the following changes:

- The CV for the groundfish surveys was changed to 0.3 as this was considered the most realistic value.
- Lambda for recruitment deviations was set at 0.1 to allow unconstrained variation in recruitment.

These changes had very little impact on the stock trend or fit to catches. However these settings were considered to be more appropriate.

The final settings are justified below.

| Input | Justification |
|---|---|
| Fleets | A single fleet was used because models with separate landings and discard fleets were unlikely to converge. |
| Selectivity | Two selectivity blocks were used. For cod and haddock, fisheries selectivity is believed to have changed with the decline of the midwater gadoid fleet. This fleet did not catch much whiting and the reason for using more than one selectivity block is an apparent step-change in total mortality.<br>The choice of selectivity blocks was based on patterns in the logratios of the catch numbers-at-age (cnaa) as well as estimated F patterns in XSA runs. The logratio patterns suggest a step change since the 1995 cohort, the F-patterns from the XSA suggested a change from 2000 onwards. The F-bar estimate was quite sensitive to the year range of the two selectivity blocks.<br>The final choice was for the first selectivity block to run from 1980–1994 and the second block from 1995–2015. This choice was mainly based on residual patterns in the cnaa in early runs.<br>The model tended to not converge if selectivity was estimated for more than two age classes. Therefore a single logistic models were used for both catch selectivity blocks. |
| Catch | All available age classes (age 0–6) were included. Note that ASAP treats the first age class (in this case age 0) as age 1. Therefore the outputs need to be offset by one age class. |
| Index specification | The two Northern Irish groundfish surveys (Q1 and Q4) were included (all available ages) as well as the NI MIK net survey. The UK beam trawl survey was not included because it is unlikely that this survey catches whiting in a quantitative way, considering their vertical distribution. The UK FSP survey was not included because it prevented the model to converge. |
| Index selectivity | Single logistic. The MIK net only catches one age class (age 0). |
| Index CV and ESS | The CVs for all years of the two NI groundfish indices were set to 0.3 (which is somewhat higher than the between-station variability of the survey in order to account for other variability like year effects.). The effective sample size for the proportions-at-age was set at 50 which was slightly lower than the number of stations in the survey.<br>The CV for the MIK net was set to 0.5 |
| Fleet CV and ESS | The CV for the catches (catch volume) was initially set at 0.2 for all years.<br>The effective samples size for the proportions-at-age was set at 10 to reflect the small number of fish sampled for age from large portions of the catch. |
| Recruitment deviations | Lambda for recruitment deviations was set at 0.1 to allow unconstrained variation in recruitment. Note that this prevents some of the retrospective runs to converge. If future runs fail to converge Lambda can be set to 1 with a high CV to reduce the number of parameters. This appears to have very little impact on the stock trend or fit to catches. |

#### Diagnostic plots and Stock trends

See Annex 6.

### 6.3.3 Short-term forecast

Model used: FLAssess::stf FLAssess::project

Software used*:* R

wts.nyears: 3 (Number of years over which to calculate mean for *.wt, *.spwn, mat and m slots)

fbar.nyrs: 3 (Number of years over which to calculate mean for harvest slot)

Intermediate year assumptions: recruitment = GM from 2000 onwards, excluding last year

Stock–recruitment model used: none

Procedures used for splitting projected catches: average proportions landings.n and discards.n last three years

## 6.4 Reference points

A full re-evaluation of reference points was carried out following the ICES Guidelines (ICES, 2016). This analysis is detailed in Annex 7 and the resulting reference points are provided below.

**Whiting in Division 7.a. Reference points, values, and their technical basis.**

| Reference point | Value | Technical basis |
|---|---|---|
| MSY $B_{trigger}$ | 16 300 t | $B_{pa}$ |
| $F_{MSY}$ | 0.22 | Median point estimates of EqSim with a combined S–R relationship |
| $B_{lim}$ | 10 000 t | Below 10 000 recruitment is impaired. |
| $B_{pa}$ | 16 300 t | $B_{lim}$ combined with the assessment error; $B_{lim}$ x exp(1.645 x σ); σ = 0.297 |
| $F_{lim}$ | 0.37 | F with 50% probability of SSB < $B_{lim}$ |
| $F_{pa}$ | 0.22 | $F_{lim}$ combined with the assessment error; $F_{lim}$ x exp(-1.645 x σ); σ = 0.423 |
| SSBMGT | Not applicable | |
| FMGT | Not applicable | |

## 6.5 Future research and data requirements

#### Time-varying M

The stock shows very strong changes in weights-at-age over time (they can change by a factor of up to 2). This is likely to affect the natural mortality. Further information to support this would be very useful for future benchmarks.

#### Dome-shaped selectivity surveys

There are very few data to inform the question whether survey catchability is flat-topped or dome-shaped. At the moment the highly truncated age structure means that this makes little difference in the model outputs. However if the stock recovers and a greater number of older fish appear, then this will need to be revisited.

#### FSP survey

The FSP survey potentially has useful information on the older fish (although the survey is discontinued). Including the survey in the final assessment run resulted in many of the retrospective runs to fail to converge. It appears therefore that it causes the model to be unstable and was omitted from the final run. For future benchmarks it may be useful to investigate why this survey makes the model unstable.

## 6.6 Multispecies information: WKIrish4

No specific issues identified.

# 7 Irish Sea plaice

## 7.1 Issue list

The following issues were identified prior to WKIrish:

**Discards**

- Raised estimates of discards are only available for the period from 2004 onwards, but make up a substantial proportion of the catch (around 60–70% by weight from Figure 5 in Fischer, 2017).

**Biological parameters**

- Review the estimates of M and maturity currently used in the assessment to ensure that they remain the best available.

**Assessment method**

- The current assessment method (AP; Aarts and Poos) estimates discard ogive at-age based on a spline. The model is currently configured with zero discards above age 5, but discard fractions above this age are substantial (Figure 1 in Fischer, 2017). The convergence of the AP model has been sensitive to the optimiser used, which affects the scaling of the stock trajectory, and so the assessment has been accepted as a category 3 assessment (trends only).

**Recalculation of reference points**

- Currently there are proxy reference points. The adoption of a new assessment method requires the estimation of reference points consistent with the model of the stock.

## 7.2 Data

### 7.2.1 Stock identity and migration

No evidence was presented to WKIrish2 (2016) to revise the stock hypothesis, or provide information about migration.

### 7.2.2 Life-history data

WKIrish2 (2016) identified uncertainty about the rate of natural mortality, and provided guidance about possible sensitivity runs; investigating M in the range 0.12–0.2, and the effect of a Lorenzen age profile compared to constant across all ages.

### 7.2.3 Other biological information

There is considerable uncertainty about the survival rate of discarded fish. The conclusion of WKIrish2 was that a survival rate of around 40% may be suitable, but that sensitivities over the whole range 0–100% should be investigated.

### 7.2.4 Fishery-dependent data

The availability of landings and discards estimates, and the quality of these estimates was evaluated by WKIrish2 (2016). Methods for reconstructing discards prior to 2003 are documented in Annex 4 of this report.

### 7.2.5 Fishery-independent data

WKIrish2 (2016) noted that the maturity ogive assumed by the NI surveys differed from that used in the assessment, and recommended to investigate the impact of updating the maturity ogives on the indices, and assessment.

### 7.2.6 Environmental drivers and ecosystem impacts

No relevant environmental drivers or ecosystem impacts were identified by WKIrish1 or WKIrish2 (2016).

## 7.3 Assessment and forecast

### 7.3.1 Assessment models and runs

The model runs were performed using the R package 'stockassessment' (Nielsen *et al.*, 2016) using the software and package specified in Table 7.1. In all the outputs from the model, $F_{bar}$ and catch refer to that portion of the catch assumed to suffer mortality, i.e. all of the landings, and the proportion of the discards that does not survive.

A baseline run of the model was performed using discards since 1981 reconstructed according to the medium discard scenario (Annex 4). Discard survival was set at 40%, and natural mortality followed a Lorenzen curve, scaled to 0.12. The updated SSB indices were used for the NI Q1 and Q4 survey. The model followed the default parameterisation provided in the package. The output from this model, and the diagnostics are shown in Figures 1–5. The UKBTS catchability (Figure 1) shows the expected decreasing selectivity by age. The catch and survey residuals (Figure 2) show an acceptable fit to the data, but there is evidence that the method of discard reconstruction at-age 1 reduces the residual variability compared to the data since 2004. There is a trend in residuals in the catch plusgroup showing that in the second half of the assessment period, catches have been below the model expectations, suggesting that there may be some model misspecification in this area. Figure 4 shows the retrospective pattern, when the same assessment is fitted to successively fewer years. In general the retrospective pattern is acceptable, as the future assessments remain within the confidence intervals of previous assessments, and there is little evidence of bias. The 2005 assessment was the assessment that seems most inaccurate in hindsight, this is likely to be due to a combination of the stock trajectory changing, and the limited amount of (unreconstructed) catch data included at that time. Figure 5 shows the effect on the model output of including different combinations of survey data. The largest impact is the inclusion or exclusion of the UKBTS, which is consistent with being the only age-based fisheries-independent data. The inclusion of the SSBQ1 survey has a slightly larger effect than the SSBQ4, but these changes are relatively minor rescaling of the assessment.

Sensitivities of the model to key assumptions were tested by running alternative models. These sensitivity runs are summarised in the table below.

| MODEL NO | NAME IN R SCRIPT | PURPOSE | DIFFERENCES FROM MODEL 1 |
|---|---|---|---|
| 1 | fit_b9 | Baseline run | |
| 2 | fit_b9_app1 | Sensitivity to discards reconstruction | Discards numbers-at-age from the high discards scenario (discards review working document) |
| 3 | fit_b9_app2 | | Discards numbers-at-age from the low discards scenario (discards review working document) |
| 4 | fit_list[[1]] | Sensitivity to discards survival (model 1 assumes 40% survival) | Discard survival 0% at all ages |
| 5 | fit_list[[2]] | | Discard survival 20% at all ages |
| 6 | fit_list[[4]] | | Discard survival 60% at all ages |
| 7 | fit_list[[5]] | | Discard survival 80% at all ages |
| 8 | fit_list[[6]] | | Discard survival 100% at all ages |
| 9 | fit_m1 | Sensitivity to natural mortality | M=0.12 for all ages |
| 10 | fit_m2 | | M=0.2 for all ages |
| 11 | fit_m3 | | Lorenzen M scaled to 0.2 across ages 3–6 |
| 12 | fit_surv_old | Sensitivity to change in NI survey maturity | NI SSB survey indices calculated as in WGCSE (2016) |
| 13 | fit_b9 | Sensitivity to assumptions about F random walks in model | SAM configured so that random walks in F at-age were uncorrelated. |
| 14 | fit_b9_1964 | Sensitivity of assessement to length of catch data | Catch-at-age data (reconstructed) was extended back to 1964 |
| 15 | fit_b9_1997 | | Catch-at-age data (reconstructed) was truncated to 1997.<br>Convergence failed |

The largest effect on model outputs was related to methods of discard estimation, shown in Figure 5. The low and medium discards reconstruction methods show a broadly similar trend, albeit rescaled to reflect that a larger catch would have required a larger stock to sustain it while following the same trajectory. The high discard scenario implies high recruitment in the 1980s, and a strong growth in SSB in the most recent years. There is no evidence available to the working group to support (or refute) the high early recruitment, and the recent recruitment is growing more rapidly that the survey indices, so this scenario may imply greater productivity of the stock than is supported by evidence.

The effect of different assumptions about discard survival is shown in Figure 7.6. This is implemented by modifying the catch data before they are supplied to the SAM model, by reducing the discards-at-age by the discard survival rate. As a consequence, the model outputs relate only to the portion of the catch that does not survive, hence the scaling evident on the catch data, catch fit and $F_{bar}$ estimates. WKIrish2 (2016) acknowledged significant uncertainty about the survival rate, and suggested a most likely value of 40%, but to test sensitivity to all values (0–100%). The model output in Figure 7.6 shows that the recruitment trends and SSB estimates have a very low sensitivity to survival rate, except in the case that survival is 100%. This seems to be caused by the reduction in cohort signals, and hence increase in process error, at ages 1–3 which are mostly discarded. The consequence is that recruitment year-class strengths are poorly estimated.

WKIrish2 (2016) noted that there is considerable uncertainty about the rate of natural mortality, and that the only data specific to this stock (Siddeek, 1981) may not reflect current rates within the stock. Four scenarios are shown in Figure 7, based on M values of 0.12 and 0.2 either flat across all ages, or used to scale a Lorenzen relationship scaled to these values across the $F_{bar}$ ages (3–6). The choice of a Lorenzen relationship over a flat relationship makes little difference to the model outputs, and the higher M leads to a higher recruitment and SSB, but following very similar trends.

The data compilation workshop noted that the maturity ogive used for assessment was not the same as the maturity ogive used to estimate SSB from the length-based data collected during the NI surveys. The ogive used in the surveys was modified to be consistent with the assessment assumption. The resulting effect on the model is shown in Figure 8, and is very minor.

Figure 9 shows the impact of alternative assumptions about the correlation in the random walk deviations used to model fishing mortality (F) at-age. The effect of removing the correlation is that estimates of the stock trajectory become smoother, and a slightly larger stock is estimated.

As well as the baseline run starting in 1981, assessments were tried starting in 1964, and 1997, all using the same method of discard reconstruction. The shorter time-series failed to converge, and the model predictions (Figure 7.10) were insensitive to the inclusion of a longer time-series.

### 7.3.2 Final assessment model run

#### Describe the model configuration and justify the choice of settings

The largest sensitivity of the model output was to assumptions about discards. The medium discards scenario, and a survival rate of 60% incorporate the best available data, notwithstanding that the stock size is estimated to be considerably below the AEPM method of estimating stock size (Figure 7.11). The model run was insensitive to inclusion of catch data prior to 1981, but the quality of these data is lower because of a lack of data on discarding practices, and so the stock trajectory in the early period is speculative, and should not be included.

Decisions about the maturity used by the SSB surveys and the natural mortality had a smaller impact on the assessment than the catch data. Consideration of the impact of these values on multispecies models led to using the Lorenzen M scaled to 0.12, and the most recent maturity ogive for the survey. The choice of M reflected that the value had been estimated specifically for this stock, and that biological principles supported the higher rates of mortality in young fish.

The benchmark discussed the configuration of the model to include correlation in the random walks between F at-age, and accepted that in the absence of any convincing difference in the diagnostics, correlation seemed more plausible than independence.

These considerations lead to model 1, the baseline run, being preferred by the benchmark, using the configuration outlined in Table 7.2.

| Type | Name | Year range | Age range | Variable from year to year? |
|---|---|---|---|---|
| Caton | Catch in tonnes | 1981–present | All | Yes |
| Canum | Catch-at-age in numbers | 1981–present | 1–8+ | Yes |
| Weca | Weight-at-age in the commercial catch | 1981–present | 1–8+ | Yes |
| West | Weight-at-age of the spawning stock at spawning time. | 1981–present | 1–8+ | Yes |
| Mprop | Proportion of natural mortality before spawning | All | All | No |
| Fprop | Proportion of fishing mortality before spawning | 1981–present | 1–8+ | No |
| Matprop | Proportion mature at-age | 1981–present | 1–8+ | No |
| Natmor | Natural mortality | 1981–present | 1–8+ | No |

### 7.3.3 Short-term forecast

Model used: FLR projection

Software used*:* FLR projection

Initial stock size: Taken from last year of assessment

Maturity: The constant maturity ogive used in the assessment

F and M before spawning: 0

Weight-at-age in the stock: Average of the last three years' catch weights-at-age

Weight-at-age in the catch: Average of the last three years' catch weights-at-age

Exploitation pattern: Average of the last three years' selectivity

Intermediate year assumptions: average F from last three years

Stock–recruitment model used: Geometric mean recruitment

Procedures used for splitting projected catches: Split according to average landings fractions at-age from last ten years. Discard numbers multiplied by 5/3 to account for discard survival. Total catch is sum of three components: landings, discards assumed to die, and discards assumed to survive.

## 7.4 Reference points

Precautionary and MSY reference points were updated according to the technical guidance provided by ACOM. Detailed application to this stock is shown in Annex 5.

| | TYPE | VALUE | TECHNICAL BASIS |
|---|---|---|---|
| MSY | MSY $B_{trigger}$ | 10 400 t | Lower 5%ile of current biomass |
| Approach | $F_{MSY}$ | 0.154 | Stochastic simulations with segmented regression from entire time-series (1981–2015). |
| | $B_{lim}$ | 4200 t | Median breakpoint of stochastic fitting of segmented regression stock–recruit function |
| Precautionary | $B_{pa}$ | 7900 t | SSB cv taken from model outputs (0.38) |
| Approach | $F_{lim}$ | 0.48 | F that gives average SSB of $B_{lim}$ with no assessment error. |
| | $F_{pa}$ | 0.25 | F cv taken from model outputs (0.40) |

## 7.5 Future research and data requirements

The issues that remain outstanding from the stock issue list are:

- Incorporating data on changes in maturity and natural mortality over time, linked to the decreasing in weights-at-age observed in survey data.
- Incorporate information about the differences in growth and maturity between the east and west sides of the Irish Sea, and by sex.
- Creating age-based indices for the NI groundfish surveys.

## 7.6 Multispecies information: WKIrish4

None identified.

### References

Armstrong, M., Aldridge, J., Beggs, S., Goodsir, F., Greenwood, L., Maxwell, D., Milligan, S., Praël, A., Roslyn, S., Taylor, N., Walton, A., Warren, E. and Witthames, P. 2012. Egg production survey estimates of spawning–stock biomass of cod, haddock and plaice in the Irish Sea: 1995, 2000, 2006, 2008 and 2010. Working Document to ICES WKROUND, February 2012. (Copy on WKIrish3 SharePoint).

Fischer, S. 2017. Stock assessment input data including discards for Irish Sea plaice (ple-iris, plaice 7a). Working document for ICES WKIrish (2017).

Anders Nielsen, Casper Berg, Kasper Kristensen, Mollie Brooks and Christoffer Moesgaard Albertsen. 2016. Stock assessment: State–Space Assessment Model. R package version 0.0.5. https://github.com/fishfollower/SAM .

ICES. 2015. Report of the Benchmark Workshop on sharing information on the Irish Sea ecosystem, stock assessments and fisheries issues, and scoping needs for assessment and management advice (WKIrish1), 14–15 September 2015, Dublin, Ireland. ICES CM 2015/BSG:01. 37 pp.

ICES. 2016. Report of the Second workshop on the impact of ecosystem and environmental drivers on Irish Sea fisheries management (WKIrish2), AFBI in Belfast, UK, 26–29 September 2016. ICES CM 2016/2/BSG02.

**Table 7.1. Plaice in 7.a. Details of the software used.**

```
R version 3.3.0 (2016-05-03)
Platform: i386-w64-mingw32/i386 (32-bit)
Running under: Windows 7 x64 (build 7601) Service Pack 1

Package: stockassessment
Title: State-Space Assessment Model
Version: 0.0.5
Date: 2016-11-23
Authors@R: c(person("Anders","Nielsen",role=c("aut","cre"),
email="an@aqua.dtu.dk"),
             person("Casper","Berg",role="aut"),
person("Kasper","Kristensen",role="aut"), person("Mollie",
             "Brooks", role="aut"), person(c("Christoffer","Moesgaard"),
"Albertsen", role="aut"))
Description: Fitting SAM...
License: GPL-2
Imports: TMB
LinkingTo: TMB, RcppEigen
Suggests: knitr, testthat
VignetteBuilder: knitr
URL: https://github.com/fishfollower/SAM
LazyData: TRUE
BugReports: https://github.com/fishfollower/SAM/issues
Author: Anders Nielsen [aut, cre], Casper Berg [aut], Kasper Kristensen [aut],
Mollie Brooks [aut], Christoffer
             Moesgaard Albertsen [aut]
Maintainer: Anders Nielsen <an@aqua.dtu.dk>
Built: R 3.3.2; x86_64-w64-mingw32; 2017-01-04 11:02:33 UTC; windows
RemoteType: github
RemoteHost: https://api.github.com
RemoteRepo: SAM
RemoteUsername: fishfollower
RemoteRef: mack
RemoteSha: 3115cd5eee77e316a48d308b269c22b0a47077d2
RemoteSubdir: stockassessment
GithubRepo: SAM
GithubUsername: fishfollower
GithubRef: mack
GithubSHA1: 3115cd5eee77e316a48d308b269c22b0a47077d2
GithubSubdir: stockassessment
```

**Table 7.2. Plaice in 7.a. Parameters for the model 1 run used as baseline and preferred model.**

| PARAMETER | VALUE |
|---|---|
| minAge, maxAge, maxAgePlusGroup | 1 8 1 |
| keyLogFsta | 0 1 2 3 4 5 6 6<br>-1 -1 -1 -1 -1 -1 -1 -1<br>-1 -1 -1 -1 -1 -1 -1 -1<br>-1 -1 -1 -1 -1 -1 -1 -1 |
| CorFlag | 2 |
| keyLogFpar | -1 -1 -1 -1 -1 -1 -1 -1<br>0 1 2 3 4 5 6 -1<br>7 -1 -1 -1 -1 -1 -1 -1<br>8 -1 -1 -1 -1 -1 -1 -1 |
| KeyQpow | -1 -1 -1 -1 -1 -1 -1 -1<br>-1 -1 -1 -1 -1 -1 -1 -1<br>-1 -1 -1 -1 -1 -1 -1 -1<br>-1 -1 -1 -1 -1 -1 -1 -1 |
| KeyVarF | 0 0 0 0 0 0 0 0<br>-1 -1 -1 -1 -1 -1 -1 -1<br>-1 -1 -1 -1 -1 -1 -1 -1<br>-1 -1 -1 -1 -1 -1 -1 -1 |
| keyVarLogN | 0 1 1 1 1 1 1 1 |
| KeyVarObs | 0 0 0 0 0 0 0 0<br>1 1 1 1 1 1 1 -1<br>2 -1 -1 -1 -1 -1 -1 -1<br>3 -1 -1 -1 -1 -1 -1 -1 |
| obsCorStruct | ID ID ID ID |
| KeyVarObs | NA NA NA NA NA NA NA<br>NA NA NA NA NA NA -1<br>NA -1 -1 -1 -1 -1 -1<br>NA -1 -1 -1 -1 -1 -1 |
| stockRecruitmentModelCode | 0 |
| noScaledYears | 0 |
| keyScaledYears | numeric(0) |
| keyParScaledYA | <0 x 0 matrix> |
| FbarRange | 3 6 |
| obsLikelihoodFlag | LN LN LN LN |

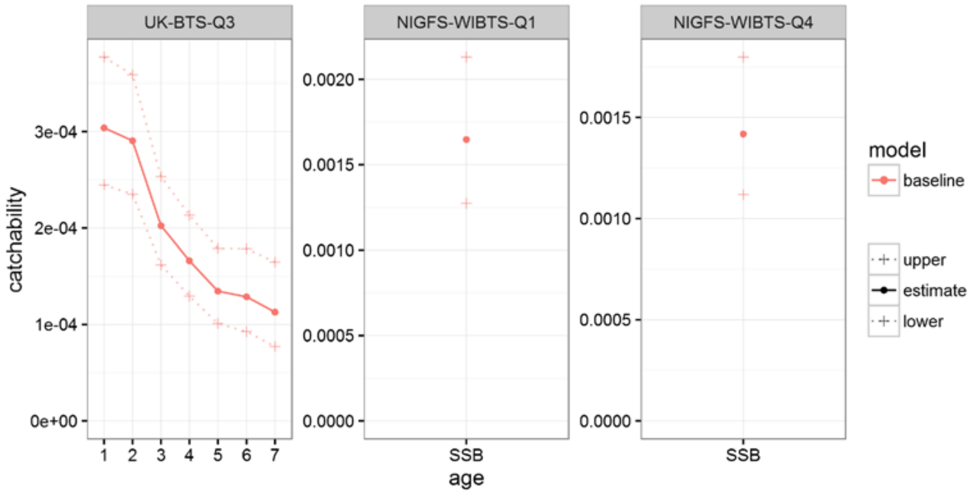



**Figure 7.1. Plaice in 7.a. Baseline model estimates of survey selectivity for the UK Quarter 3 beam trawl survey and the NI Quarter 1 and Quarter 4 surveys.**

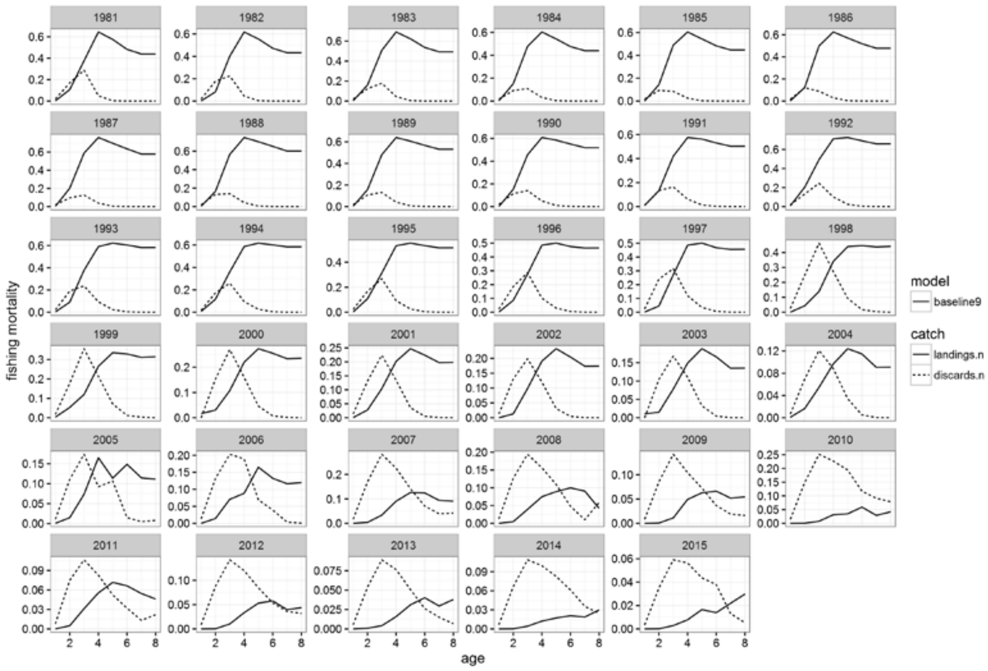



**Figure 7.2. Plaice in 7.a. Landings and discards partial fishing mortality estimated by the baseline model.**

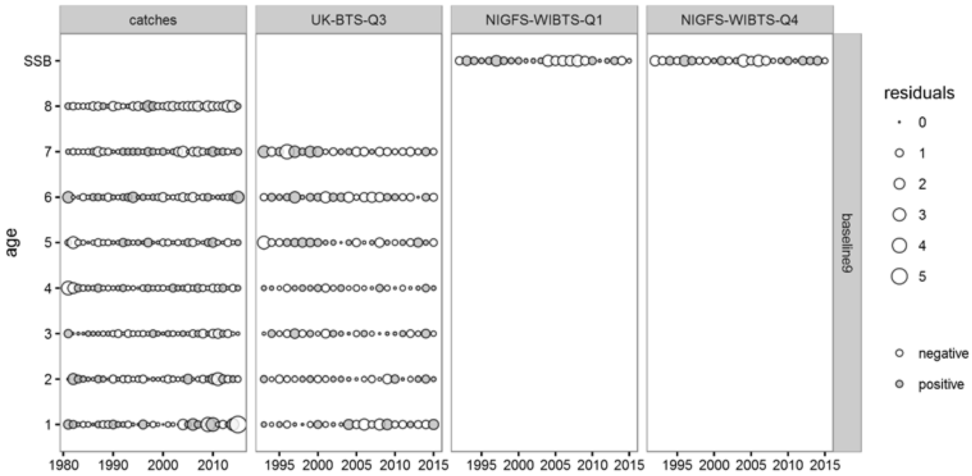



**Figure 7.3. Plaice in 7.a. Residuals in fits to catch and survey data from the baseline model.**

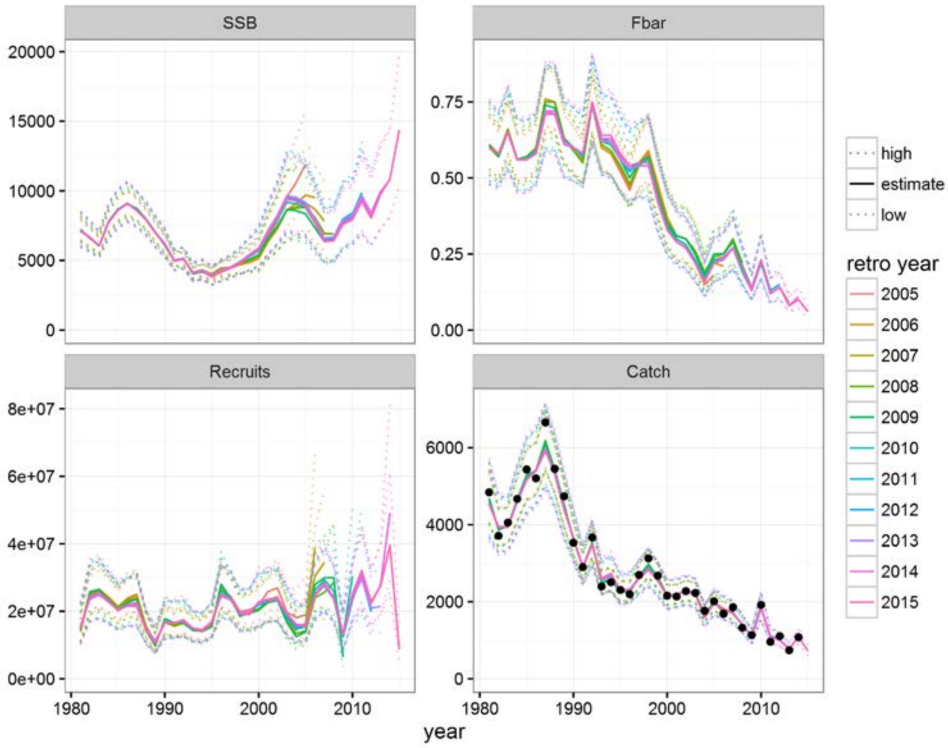



**Figure 7.4. Plaice in 7.a. Retrospective assessments for years 2005–2015 from the baseline model.**

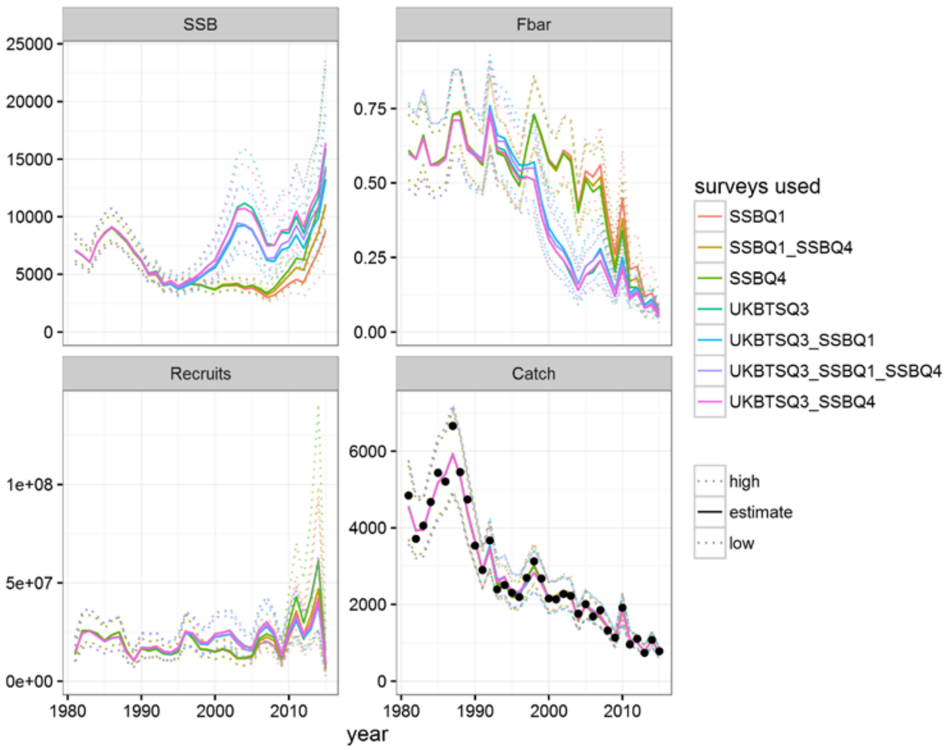



**Figure 7.5. Plaice in 7.a. Effect of using different combinations of surveys.**

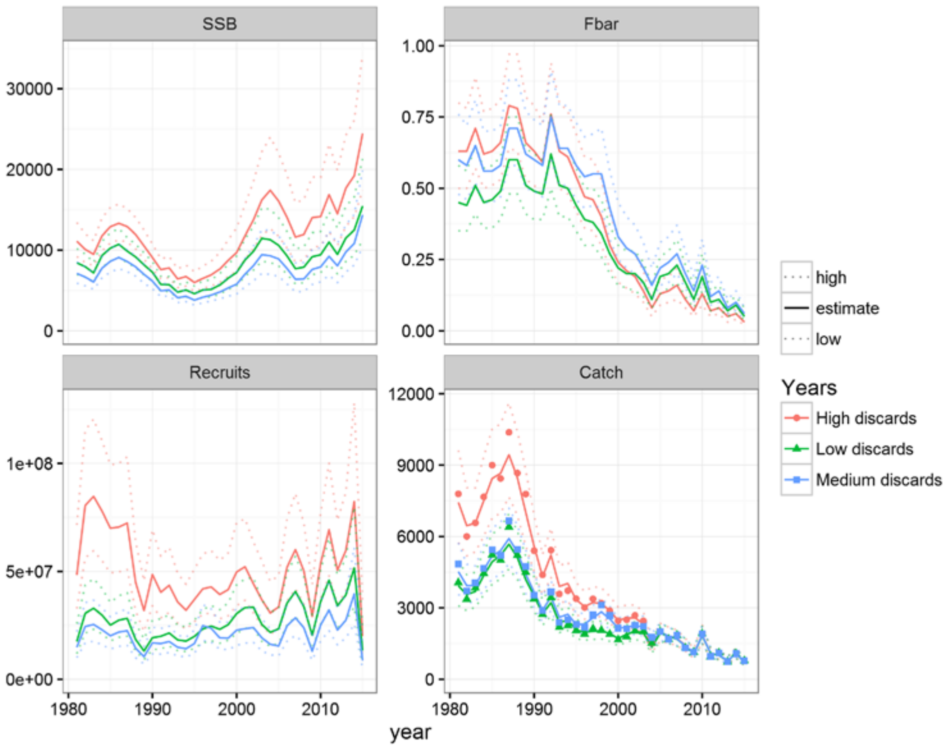



**Figure 7.6. Plaice in 7.a. Impact of alternative methods of discard reconstruction on key model outputs.**

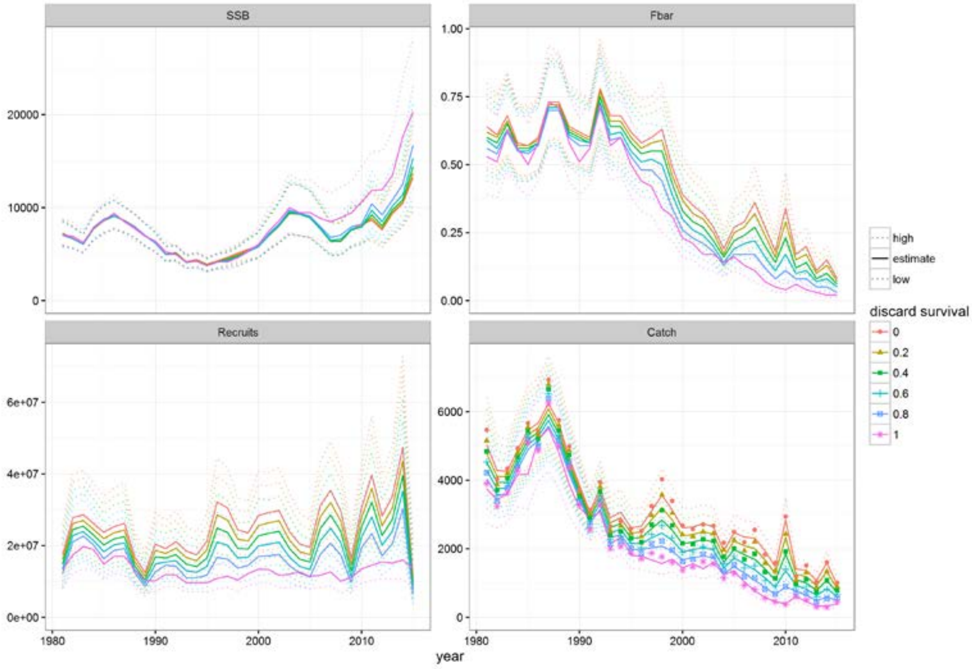



**Figure 7.7. Plaice in 7.a. Impact of alternative discard survival rates on key model outputs. Note that Catch and $F_{bar}$ refer to the portion of the catch which does not survive.**

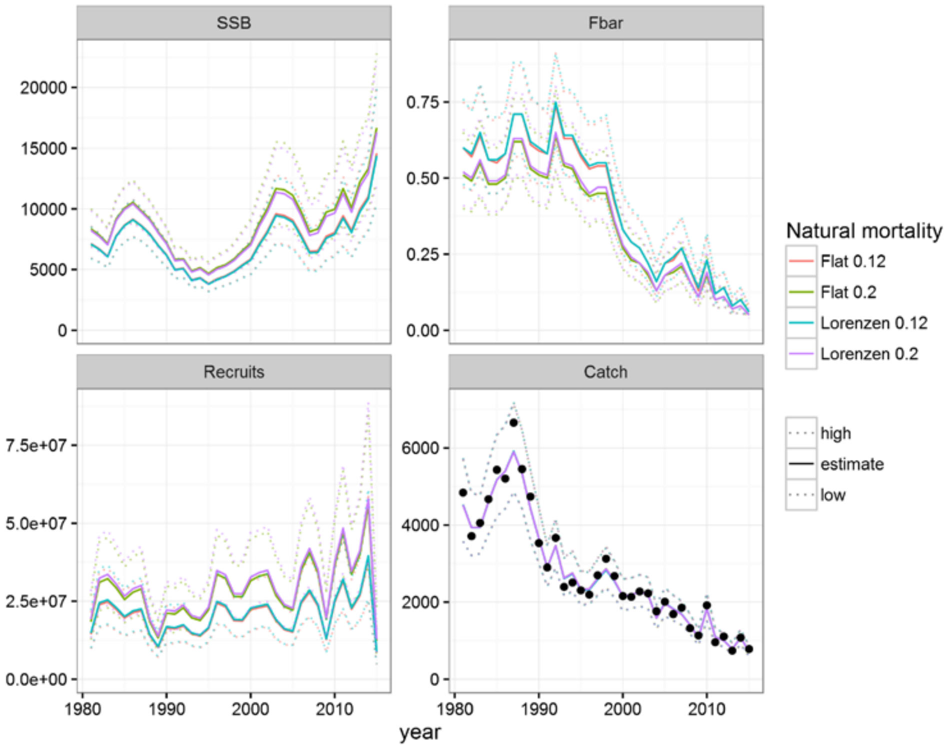



**Figure 7.8. Plaice in 7.a. Impact of alternative natural mortality assumptions on key model outputs.**

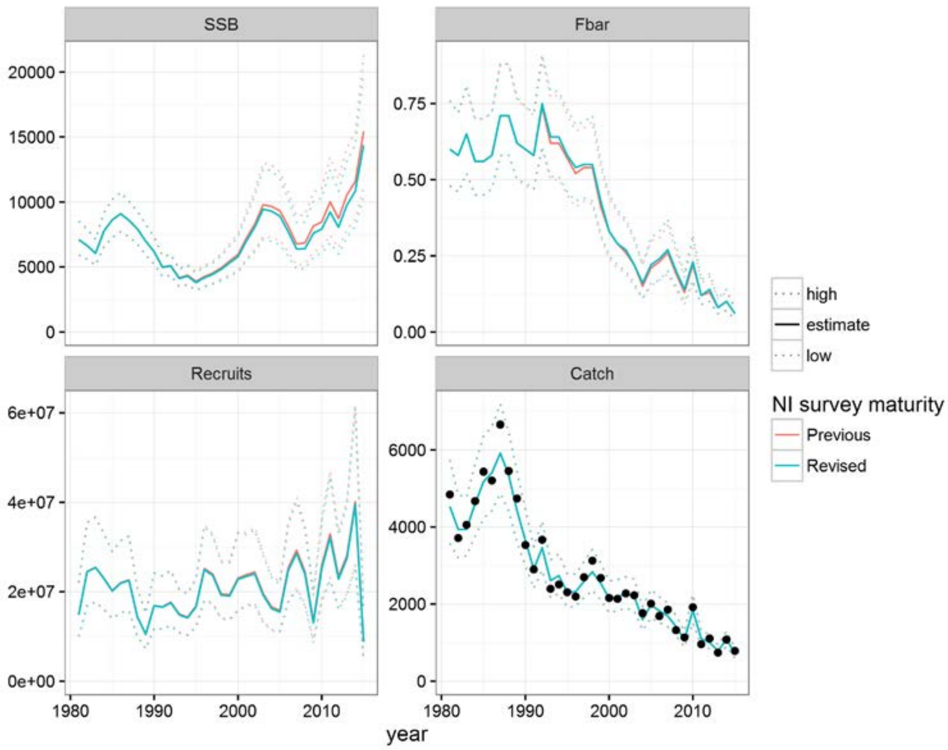



**Figure 7.9. Plaice in 7.a. Impact of alternative survey maturity ogives assumptions on key model outputs.**

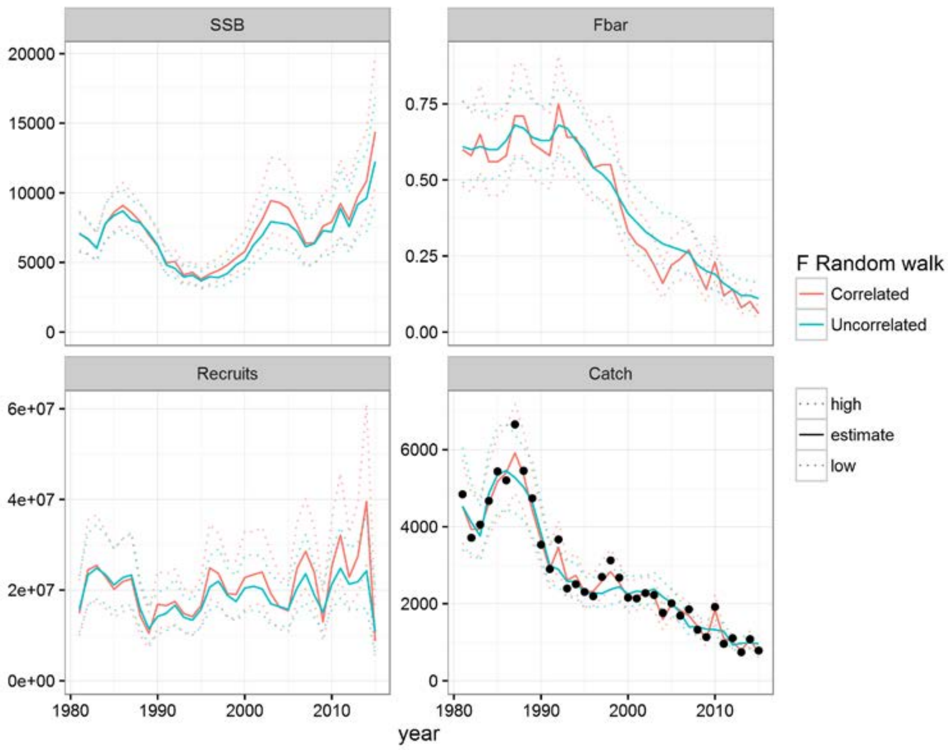



**Figure 7.10. Plaice in 7.a. Impact of alternative F random walk assumptions on key model outputs.**

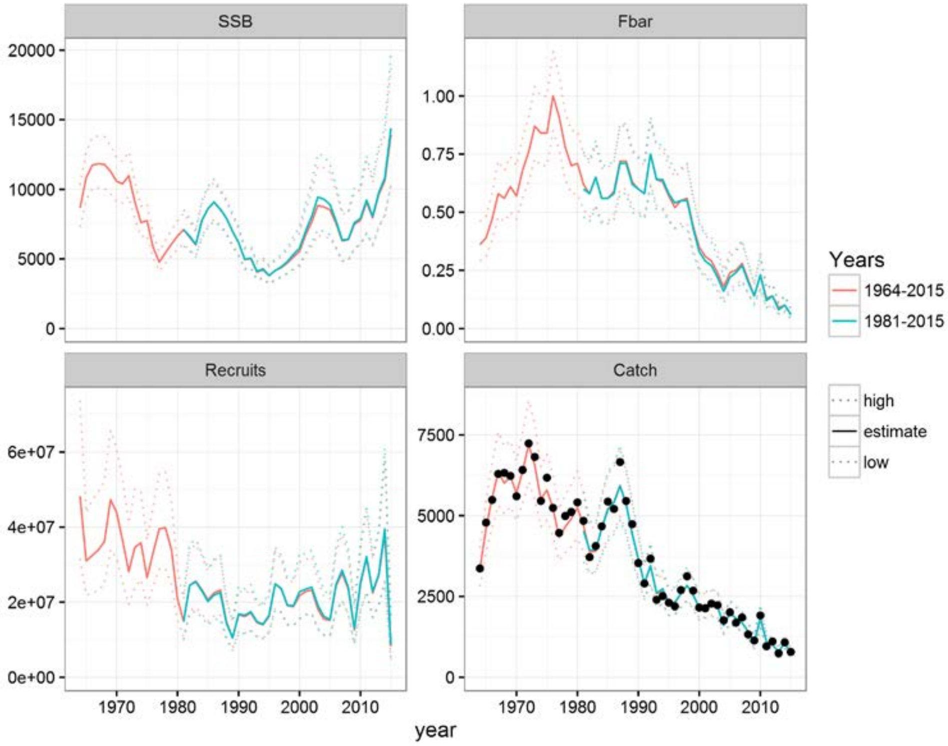



**Figure 7.11. Plaice in 7.a. Impact of assessment length on key model outputs.**

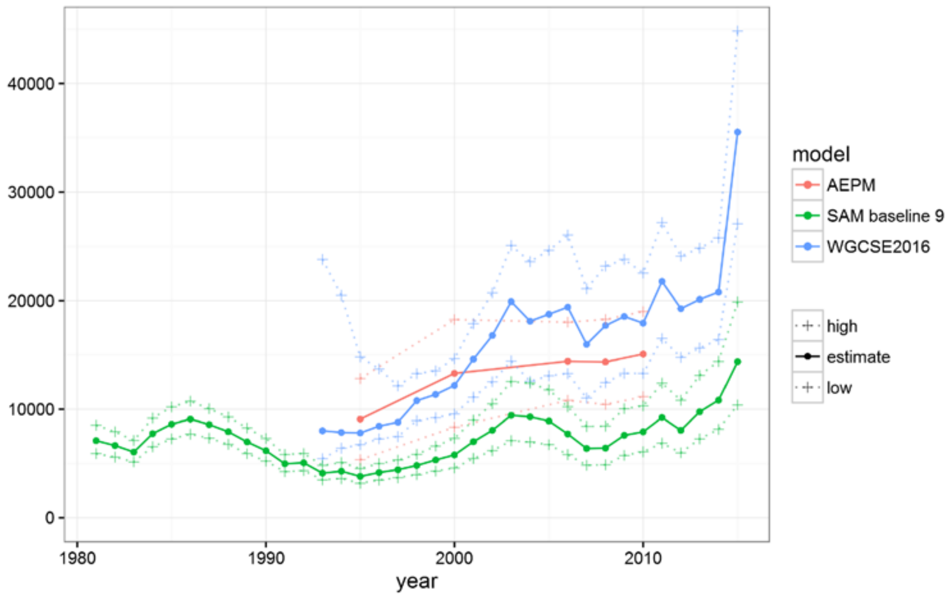



**Figure 7.12. Plaice in 7.a. Comparison of the baseline model with the previous model used by WGCSE and the annual egg production method estimates (Armstrong *et al.*, 2012).**

# Annex 1: Participants list

| NAME | ADDRESS | PHONE/FAX | E-MAIL |
|---|---|---|---|
| Mike Armstrong | Cefas<br>Lowestoft Laboratory<br>Pakefield Road<br>Lowestoft<br>Suffolk NR33 0HT<br>UK | +44 1502 524362<br>Fax +44 1502 524511 | mike.armstrong@cefas.co.uk |
| Jacob Bentley | Scottish Ass for Marine Science<br>Oban<br>Argyll<br>Scotland PA37 1QA<br>UK | | jb283@st-andrews.ac.uk |
| Timothy Earl | Cefas<br>Lowestoft Laboratory<br>Pakefield Road<br>Lowestoft<br>Suffolk NR33 0HT<br>UK | +44 1502 521303 | timothy.earl@cefas.co.uk |
| Hans Gerritsen<br>Chair | Marine Institute<br>Rinville<br>Oranmore<br>Co Galway<br>Ireland | +353 91 387297/353 85 1463240<br>Fax +353 91 387201 | hans.gerritsen@marine.ie |
| Sheila Heymans | Scottish Ass for Marine Science<br>Oban<br>Argyll<br>Scotland PA37 1QA<br>UK | | Sheila.heymans@sams.ac.uk |
| Daniel Howell<br>External Chair | IMR<br>PO Box 1870<br>Nordnes<br>5817 Bergen<br>Norway | +47 55 23 86 79<br>Fax +47 55 23 8531 | daniel.howell@imr.no |
| Jim Ianelli<br>Invited Expert | NOAA Fisheries<br>Alaska Fisheries Science Center, Bldg. 4<br>Sand Point Way<br>Seattle, WA 98115<br>US | +1 206 526 6510 | jim.ianelli@noaa.gov |
| Scott Large | ICES<br>H.C. Andersens Blvd.<br>1553 Copenhagen V<br>Denmark | | scott.large@ices.dk |

| Name | Address | Phone/Fax | E-mail |
|---|---|---|---|
| Rebecca Lauerburg<br>Invited Expert | University of Hamburg<br>Institute of Hydrobiology and Fishery<br>Olbersweg 24<br>Department of Biology<br>22767 Hamburg<br>Germany | +49 40 42838-6609 | rebecca.lauerburg@uni-hamburg.de |
| Colm Lordan | Marine Institute<br>Rinville<br>Oranmore<br>Co Galway<br>Ireland | +353 91 387 387 (or *200)<br>Cell +35 876 995 708<br>Fax +353 91 387201 | colm.lordan@marine.ie |
| Matt Lundy | Agri-Food and Biosciences Institute NI<br>18a Newforge Lane<br>Belfast<br>NI BT9 5PX<br>UK | +44 2890255521 | mathieu.lundy@afbini.gov.uk |
| Alan McCulla | Anglo North Irish Fish Producers' Organisation<br>The Harbour<br>Kilkeel<br>Co Down<br>NI BT34 4AX<br>UK | | alan@anifpo.com |
| Claire Moore | Marine Institute<br>Rinville<br>Oranmore<br>Co Galway<br>Ireland | | Claire.moore@marine.ie |
| Sara Jane Moore | Marine Institute<br>Rinville<br>Oranmore<br>Co Galway<br>Ireland | +353 91 387298<br>Fax +353 91 387201 | sara-jane.moore@marine.ie |
| Pieter-Jan Schön | Agri-Food and Biosciences Institute NI<br>18a Newforge Lane<br>Belfast<br>NI BT9 5PX<br>UK | +44 28 90255015<br>Fax +44 28 90255004 | pieter-jan.schon@afbini.gov.uk |
| Jonathan Shrives | European Commission<br>Directorate-General for Maritime Affairs and Fisheries<br>Unit C.2 - Atlantic and outermost regions<br>J79 02/03<br>1049 Brussels<br>Belgium | +32 229-62681 | Jonathan.SHRIVES@ec.europa.eu |

| Name | Address | Phone/Fax | E-mail |
|---|---|---|---|
| Pia Schuchert | Agri-Food and Biosciences Institute NI<br>18a Newforge Lane<br>Belfast<br>NI BT9 5PX<br>UK | | Pia.Schuchert@afbini.gov.uk |
| Robert Thorpe | Cefas<br>Pakefield Road<br>Lowestoft<br>Suffolk NR33 0HT<br>UK | | Robert.thorpe@cefas.co.uk |
| Jonathan White | Marine Institute<br>Rinville, Oranmore<br>Co Galway<br>Ireland | | Jonathan.white@marine.ie |

# Annex 2: Agenda

| Agenda WKIrish3 30 January – 3 February 2017, Marine Institute, Galway, Ireland | | | | | |
|---|---|---|---|---|---|
| | | | | | |
| | **Monday** | **Tuesday** | **Wednesday** | **Thursday** | **Friday** |
| **0900-1100** | start 10:00 Introductions etc. | WHG: present WD, agree on work required during WS | Update on all stocks | Present work done and final conclusions | Reference points |
| **coffee** | | | | | |
| **1115-1300** | HAD: present WD, agree on work required during WS | HER: present WD, agree on work required during WS | Subgroups all stocks | Present work done and final conclusions | Reference points |
| **lunch** | | | | | |
| **1400-1600** | COD: present WD, agree on work required during WS | Subgroups all stocks | Present work done and final conclusions | Reference points | Recommendations, stock annex and report |
| **coffee** | | | | | |
| **1615-1800** | PLE: present WD, agree on work required during WS | Subgroups all stocks | Present work done and final conclusions | Reference points | Recommendations, stock annex and report |
| | | | | | |
| **plenary** | | | | | |
| **subgroups** | | | | | |

## Annex 3: Radiocarbon ($^{14}C$) activities in gadoid Otoliths

Stella Heymans (SAMS) presented work on $^{14}C$ activities in gadoid otoliths that could be used to help inform on migration and stock boundaries.

WKIrish3 would support a proposal for the use the Sellafield $^{14}C$ signal to investigate the possibility of southward migration of gadoids, such as cod and whiting from the Irish Sea to the Celtic Sea. Initial studies performed by SAMS/SUERC have shown that the signal in $^{14}C$ between the Irish Sea and the Celtic Sea are substantially different, and if it was possible to use this signal either for stock movement or individual movement (via age rings in the otoliths), it would improve our understanding of specifically the whiting stocks in the Irish Sea and their possible movement to the Celtic Sea.

In the UK, the Sellafield nuclear fuel reprocessing facility is authorised to discharge waste $^{14}C$ to the marine environment. Low-level radioactive effluent containing $^{14}C$ is discharged via pipelines that extend 2.1 km offshore into the Irish Sea. $^{14}C$ is released primarily as inorganic carbon and is incorporated into the dissolved inorganic carbon (DIC) component of seawater (Begg *et al.*, 1991; 1992; Begg, 1992; Cook *et al.*, 1995). >99% of Sellafield $^{14}C$ dispersed through the North Channel (Gulliver *et al.*, 2001).

Sellafield $^{14}C$ discharges are made in addition to existing "background" inputs of $^{14}C$ from natural production and fallout from atmospheric testing of nuclear weapons in the 1950s and early 1960s. The background activities range from 248 ± 1.0 Bq kg$^{-1}$ C in 1995 (Cook *et al.*, 1998) to 249 ± 0.8 Bq kg$^{-1}$ C for 2014 (Tierney *et al.*, 2016a). Any $^{14}C$ activities which are higher than these background activities in UK waters can be defined as enriched and the only significant source of additional $^{14}C$ to waters on the UK west coast is Sellafield.

$^{14}C$ enters the marine foodweb via the efficient uptake of soluble $^{14}C$ in DIC during photosynthesis by primary producing organisms, mainly phytoplankton (Muir *et al.*, 2017; Tierney *et al.*, 2017). Enriched $^{14}C$ activities have been found in a range of marine species occupying the lowest (phytoplankton) to middle-upper (e.g. piscivorous fish) trophic levels in the Irish Sea (Muir *et al.*, 2017) and West of Scotland (Tierney *et al.*, 2017) marine environments. The uptake of Sellafield-derived $^{14}C$ in carbonate producing organisms, specifically molluscs, has also been investigated (Cook *et al.*, 2004; Muir *et al.*, 2015; Tierney *et al.*, 2016). Similarly to $^{14}C$ uptake by molluscs, fish will produce otoliths with a $^{14}C$ signature representative of the environment it inhabits. In UK waters, the Irish Sea has the highest $^{14}C$ activity. Net northerly dispersion has resulted in enriched activities being found in the West of Scotland and lower, closer to background, activities are expected in the Celtic Sea.

In the first instance, a small number of cod otoliths (twelve) were analysed for $^{14}C$ activity to investigate differences in $^{14}C$ activity in these different UK coastal areas and to consider the possible migration of immature Irish Sea cod to other areas. The results are shown in Table 1. Irish Sea otolith $^{14}C$ activity was highest. The east basin was more variable with proximity to the pipelines affecting activity. The sample with the highest activity (802 ± 3 Bq kg$^{-1}$ C) comes from an individual caught due west of Sellafield, the other two samples (413 ± 2 and 349 ± 2 Bq kg$^{-1}$ C) come from fish caught further south. The large difference in $^{14}C$ activity suggests that these immature fish had not moved any real distance by this stage of their lives. The west basin appears to be more consistent (415–422 Bq kg$^{-1}$ C), which is expected due to dilution and subsequent dispersion of discharged $^{14}C$. These activities are comparable to published $^{14}C$ activities for Irish Sea shells and organisms (Cook *et al*., 1998; 2004; Muir *et al*., 2015; 2017; Tierney *et al*., 2016).

Two of the West of Scotland otolith samples come from fish caught relatively far north and therefore have enriched activities which are only slightly above background (252 ± 1 and 256 ± 1 Bq kg$^{-1}$ C). The third West of Scotland otolith has a higher activity (265 ± 1 Bq kg$^{-1}$ C) and is comparable to activities measured in West of Scotland shells and organisms (Tierney *et al*., 2016; Tierney *et al*., 2017).

The Celtic Sea activities are higher than would be expected and warrant further investigation. The activities measured indicate that either $^{14}C$ is being transported southwards through the St Georges Channel, which is unlikely based on previous studies (Cook *et al*., 1998; Gulliver *et al*., 2001). The alternative is that these cod have spent a period of time in the Irish Sea. Thus we can use the $^{14}C$ signal to investigate the possibility of southward migration of gadoids, such as cod and whiting from the Irish Sea. To undertake this study we would need to measure $^{14}C$ from otoliths obtained in both the Irish and Celtic seas and ambient seawater for DIC $^{14}C$ activity. Larger otoliths could also be used to address an individual's movement through time; i.e. higher activities in the Irish Sea vs. lower activities in the Celtic Sea.

**Table 1. $^{14}C$ activities in cod otoliths.**

| Year | Area | Latitude | Longitude | Otolith weight (mg) | Otolith $^{14}C$ activity (Bq kg$^{-1}$ C) |
|---|---|---|---|---|---|
| 2005 | Irish Sea E | 54.330 | -3.924 | 71.5 | 802 ± 3 |
| 2005 | Irish Sea E | 53.515 | -4.235 | 44.7 | 413 ± 2 |
| 2005 | Irish Sea E | 52.558 | -6.040 | 156.0 | 349 ± 2 |
| 2005 | Irish Sea W | 54.117 | -5.532 | 41.3 | 415 ± 2 |
| 2005 | Irish Sea W | 53.958 | -5.692 | 41.6 | 426 ± 2 |
| 2005 | Irish Sea W | 53.583 | -5.899 | 31.9 | 422 ± 2 |
| 2010 | W Scotland | 55.767 | -9.081 | 1210.0 | 265 ± 1 |
| 2010 | W Scotland | 58.795 | -6.215 | 7340.0 | 252 ± 1 |
| 2010 | W Scotland | 58.134 | -6.127 | 3338.0 | 256 ± 1 |
| 2010 | N Celtic Sea | 51.460 | -8.505 | 117.0 | 273 ± 1 |
| 2010 | N Celtic Sea | 51.590 | -7.464 | 166.0 | 292 ± 2 |
| 2010 | N Celtic Sea | 51.348 | -8.108 | 148.0 | 273 ± 1 |

# Annex 4: Reconstructing Irish Sea plaice discard numbers

Tim Earl, Simon Fischer and Mike Armstrong

9 February 2017

## Introduction

WKIrish2 (ICES, 2016a) and WKFLAT (ICES, 2011) identified the importance of modelling discards within this stock because of the large proportion of the catch that is currently discarded; in the period 2011–2015 66% of catch by weight was discarded (ICES, 2016b). Discards have been routinely sampled since 2004 by UK, Ireland and Belgium to provide raised estimates of discard numbers-at-age, but there is limited data on discard levels before 2004. WKIrish2 identified the following sources of data:

- Discard numbers-at-age since 2004 (shown as proportions in Figure A1);
- Discard numbers-at-length since 2004 (Figures A2–A4);
- UK beam trawl survey data showing changing length-at-age since 1993 (Figure A5);
- Legislation setting a minimum landing size (MLS) of 250 mm in 1981 (Council Regulation (EEC) No 2527/80) and 270 mm in 1998 (Council Regulation (EEC) No 850/98);
- A report showing numbers discarded and retained by length and age for a set of UK (England) vessels sampled in 1993 during a selectivity investigation in the eastern Irish Sea during the period when the MLS was 250 mm (Emberton *et al.*, 1995);
- A report giving observer data from 1998/1999 (Commission 2002) showing overall discard rates of 69–83% by number in 1999 and 2000 for UK (Northern Ireland) single and multiple rig *Nephrops* trawlers, and 91–100% for UK(NI) midwater trawlers.

Observer data from 2004–2006 are based on relatively few trips with data on plaice (Figure A6).

From these data sources the following conclusions can be drawn:

- A large proportion of the discards occur below the minimum landing size, and this was still true when the minimum landing size was 250 mm based on a single study.
- The growth rate of plaice in the Irish Sea has been declining over time, so constant selectivity and discarding ogive by length will have led to an increasing trend in discard rates at-age.
- Discards have made up a substantial proportion of the catch during the time period back to the early 1990s for which reports exist, although the rates decline going back in time due to the changes in growth and MLS. No direct evidence of discard rates prior to the early 1990s was available to WKIrish.

## Scenarios

Three possible scenarios are investigated as potential discard reconstructions to be used in stock assessment models:

- **Low discards:** The decline in discard fractions at-age between 2008 and 2004 is extrapolated backwards to a point where the fraction is zero. No discarding occurred before that.
- **Medium discards:** The method is described in more detail below. It creates a discard time-series that is consistent with the key conclusions drawn from the historical data.
- **High discards:** The discard fractions at-age between 2008 and 2004 are assumed to be typical of the entire period. WKIrish3 noted that it was sensitive to the reference period (i.e. changing 2008–2004 to 2009–2005 increased catches in some years by around 70%)

The high and low discards scenarios do not fit well with the key conclusions drawn from the review of discards, and are treated as upper and lower bounds that can be used in sensitivity testing the assessment model. The low discards option requires an extrapolation of a trend that is heavily driven by 2004–2006 data which are based on relatively few observer trips (Figure A6) and is likely to be extremely inaccurate, as well as invoking an implausible assumption of zero discarding in earlier years. The medium discards scenario will be taken forward as a potential input to the assessment used for management.

### Medium discards reconstruction method

The intention of this method was to derive historical discards numbers using a method that is data-driven as far as possible, although some important assumptions are required. The data sources available suggest a strong relationship across age groups between mean size-at-age and the fraction of the catch that is discarded. Data on length-at-age distributions of landings were not available for the entire time-series, and so landings weights-at-age are used as a proxy. These landings data have high variability between years, and so a lowess smoother (with smoothing span 0.15 chosen by eye) was fitted to remove the intra-annual variability, while retaining information about the longer term trends. The fit of the smoother is shown in Figure 1 and a comparison of the trends across all year is shown in Figure 2.

A plot of the relationship between the smoothed landings weights and discard fractions at-age based on the observer data from 2004 onwards is shown in Figure 3. Each point represents a combination of age and year, colour indicates ages 1:8+. Existing data show little or no retention of fish below the MLS (Commission 2002; Appendix Figures A2–A4), but some discarding above the MLS. The line plotted in Figure 3 therefore indicates a lower bound on discards (fitted by eye rather than a best fit) to capture the discarding due only to the MLS and not influenced by other factors (e.g. economic) that may have been responsible for higher rates of discarding in each age class in recent years. This means that the discard fractions estimated from this relationship are likely to be an underestimate of the discard fractions.

Prior to 1998, the MLS was 250 mm, rather than 270 mm. Using the length–weight relationship used by the NI survey (a=8E-6, b=3.0572) the change in length would equate to a change in weight of 40 g, and so prior to 1998 the logistic fit was shifted to the left by this amount.

The relationships between smoothed landings weights and discard fraction was used to estimate the discard fraction prior to 2004, and the estimated proportions are shown in Figure 4. For ages 3–8+, discard numbers prior to 2004 are estimated by raising the landings numbers by the discard fraction. The discard fractions at-ages 1 and 2 exceed 90% at some points prior to the start of discards data, implying a raising factor of at least ten times would be applied to landings to estimate discards. In years with zero landings at these ages, no figure for discards can be obtained. These factors would substantially amplify the errors in landings estimation, and create very noisy estimate of discard numbers (and hence catch numbers) at these youngest ages, and so an alternative approach is needed to estimate discard numbers at these ages.

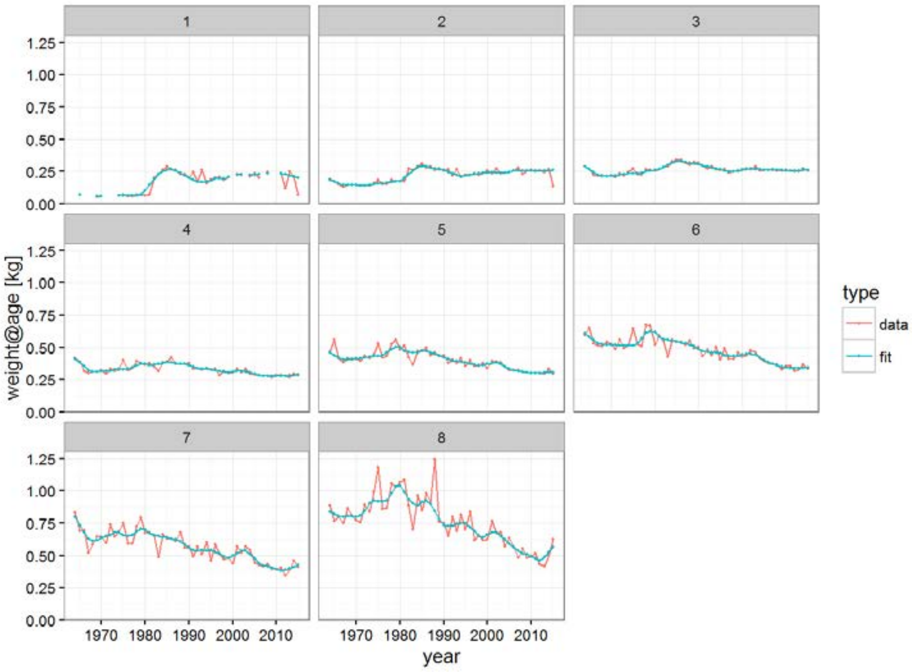



**Figure 1. Plaice 7.a. Landings weight-at-age (red) and a lowess smoother (blue) fitted to the data.**

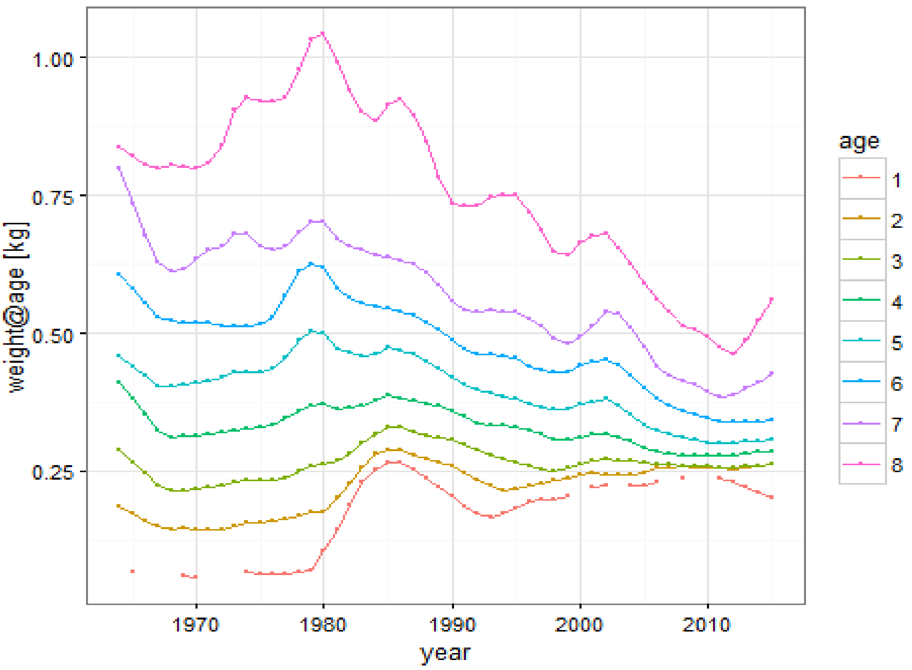



**Figure 2. Plaice 7.a. Smoothed landings weight-at-age. Note that in some years there were no samples of age 1 fish in the landings, which is indicated by the breaks in this line.**

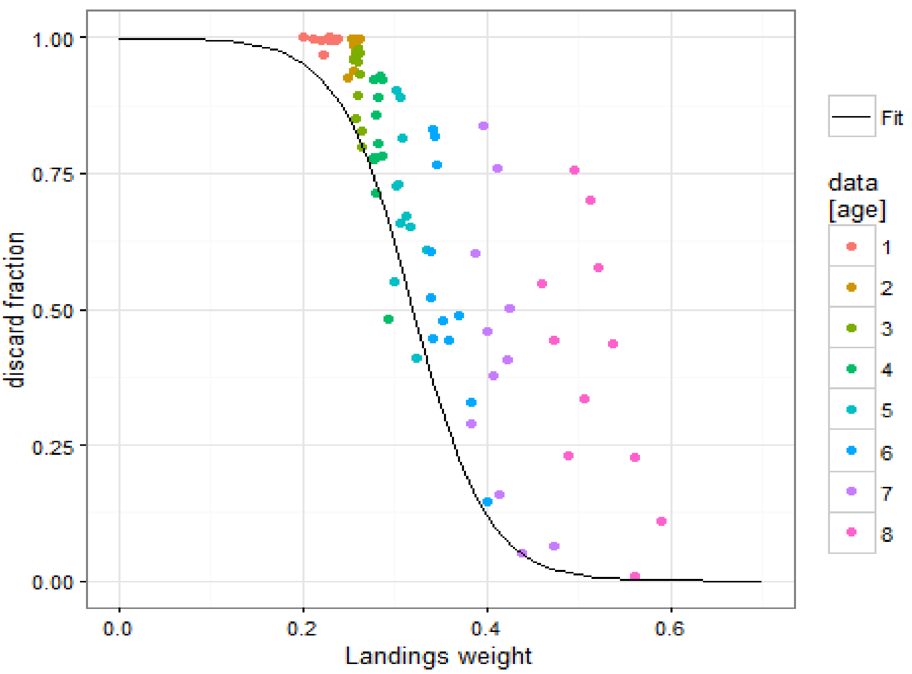



**Figure 3. Plaice 7.a. Relationship between smoothed landings weights and proportion discarded, showing a logistic function fitted as a lower bound (black line).**

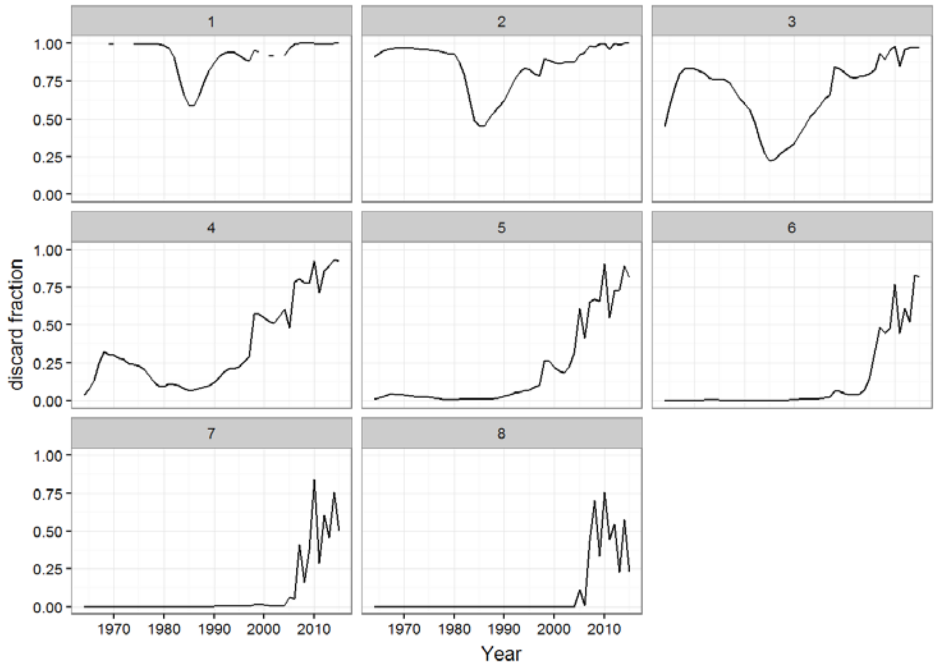



**Figure 4. Plaice 7.a. Discard fraction in numbers by age. 2004–2015 based on data from WGCSE. Fractions prior to 2004 based on relationship with smoothed landings weights as described in the text.**

## An alternative approach to estimating discards for ages 1 and 2

An alternative approach to estimating discards at-ages 1 and 2 is to assume that there will be a cohort effect that is a large number of discards at-age 1 in one year, would be associated with a large number of discards at-age 2 in the subsequent year. Therefore, we fit the following linear models to the period for which discards data exist:

$$discards_{(age=i-1,year=1994:2014)} = a_i \frac{df_{(age=i-1,year=1994:2014)}}{df_{(age=i,year=1995:2015)}} discards_{(age=i,year=1995:2015)}$$

for $i = 2, 3$

where $discards_{(age,year)}$ is the number of discards at-age in a given year

$df_{(age,year)}$ is the fraction (n) of the catch that is discarded at-age in a given year.

These models are used to predict age 2 and age 1 catch numbers from age 3 catch numbers (raised from landings using the weight-varying landings factors). The discard fractions estimated by this method for the medium discard scenario are shown in Figure 5. This method was also applied to the high and low discard scenarios.

The calculated proportions discarded at-age in Figure 5 are compared below with values derived from a crude visual inspection of the proportions discarded in the Emberton *et al*. (1995) report, as presented in the Commission (2002) report. Given that the Emberton study covered only part of the fleet, the estimates from Figure 5 at-ages 1–3 are not completely out of line with Emberton, though are much lower at-ages 4 and 5.

| Source | % discarded at age | | | | |
|---|---|---|---|---|---|
| | Age 1 | Age 2 | Age 3 | Age 4 | Age 5 |
| Present study (Figure 5) estimates for 1993 | 94% | 78% | 51% | 21% | 6% |
| Emberton *et al.*, 1995/ Commission 2012 | ~100% | 60–80% | 50–65% | 40–50% | 20–40% |

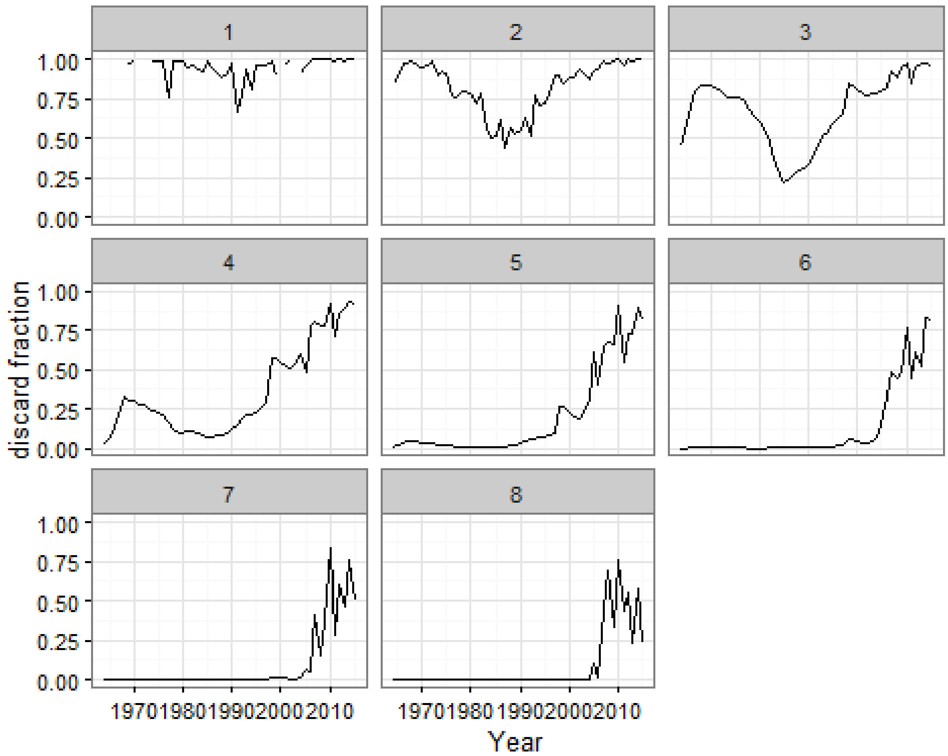



**Figure 5. Plaice 7.a. Discard fraction in numbers by age. 2004–2015 based on data from WGCSE. Fractions prior to 2004 based on relationship with smoothed landings weights as described in the text, with alternative approach for ages 1 and 2.**

## Reconstructed time-series

Figures 6–8 show the total weight of discards implied by each of the three discard scenarios, low, medium and high respectively.

Given the lack of information about the MLS prior to 1981, or any survey data to indicate if changes in mean weight-at-age in landings are related to changes in discarding ogives rather than growth, it is recommended to use data from 1981–present for the baseline stock assessment run, and consider the inclusion of the earlier period as a sensitivity run.

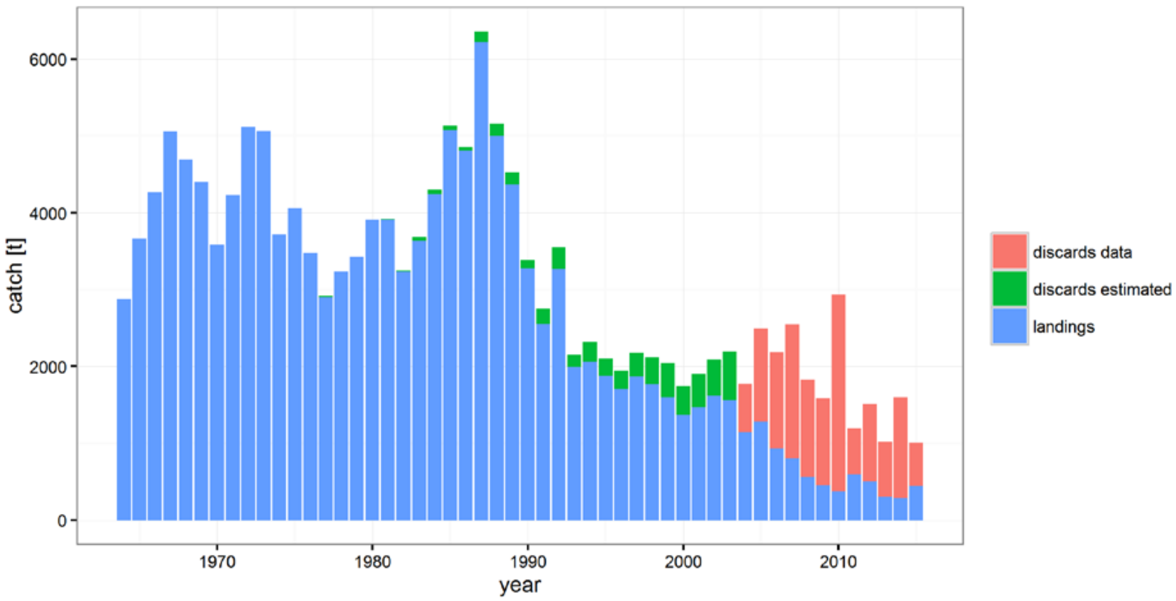



**Figure 6. Plaice 7.a. Discards reconstruction from the low discards scenario (green), compared to discards data (red) and landings data (blue).**

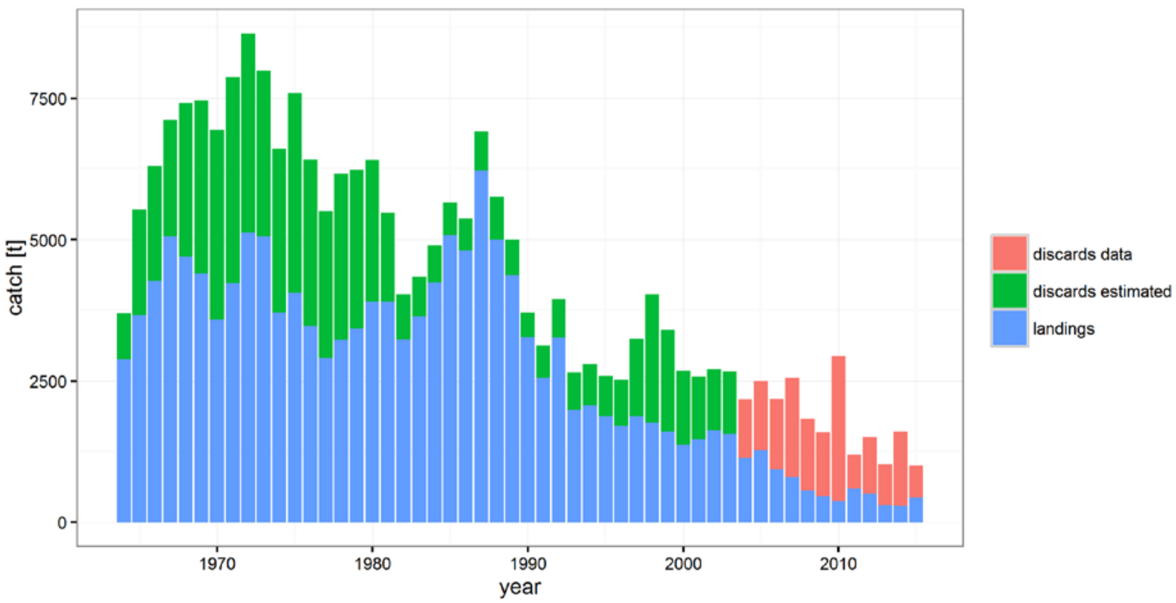



**Figure 7. Plaice 7.a. Discards reconstruction from the medium discards scenario (green), compared to discards data (red) and landings data (blue).**

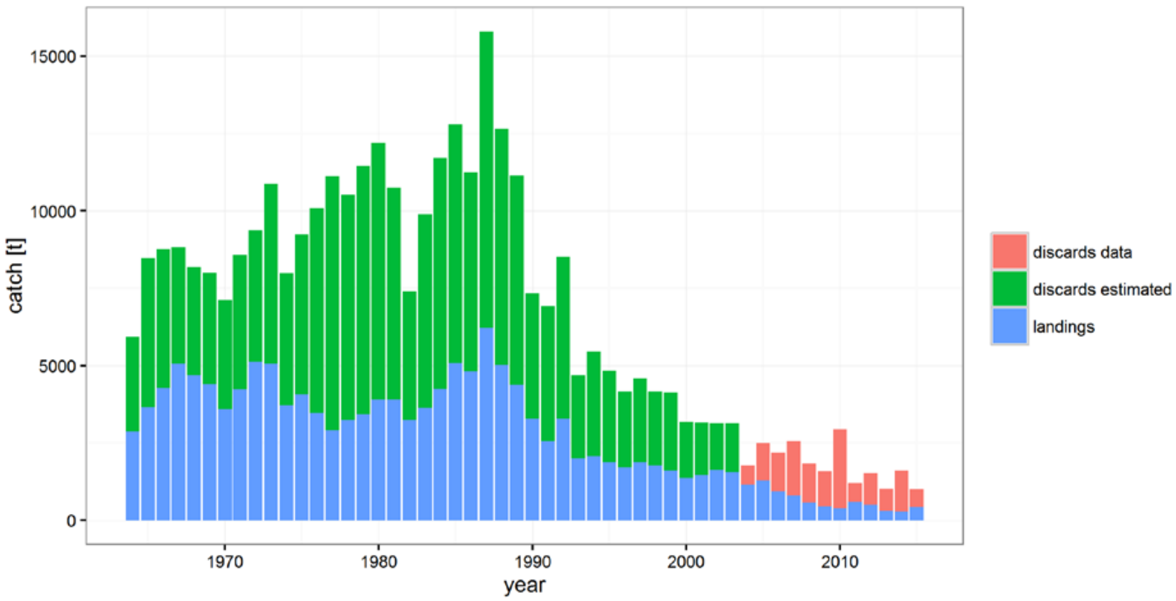



**Figure 8. Plaice 7.a. Discards reconstruction from the high discards scenario (green), compared to discards data (red) and landings data (blue).**

## Conclusion

The medium discards scenario for the period 1980–2015 provides a discards dataset that can be used in a stock assessment for catch advice. Additional sensitivity runs should look at the effect of including a longer time-series (back to 1964) or the high/low discards scenario.

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## Appendix

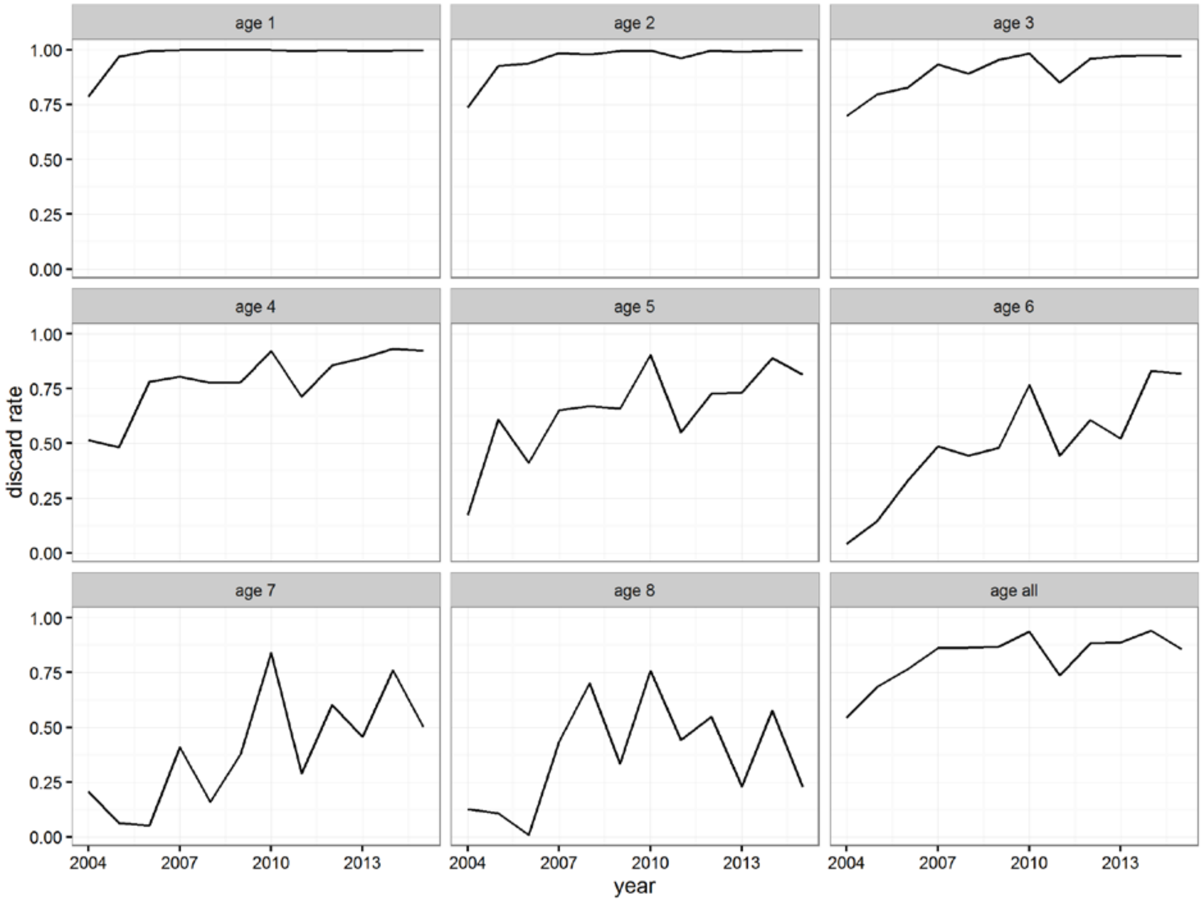



**Figure A1. Plaice 7.a. Discard fractions by age from the period 2004–present based on WGCSE (ICES, 2016) data.**

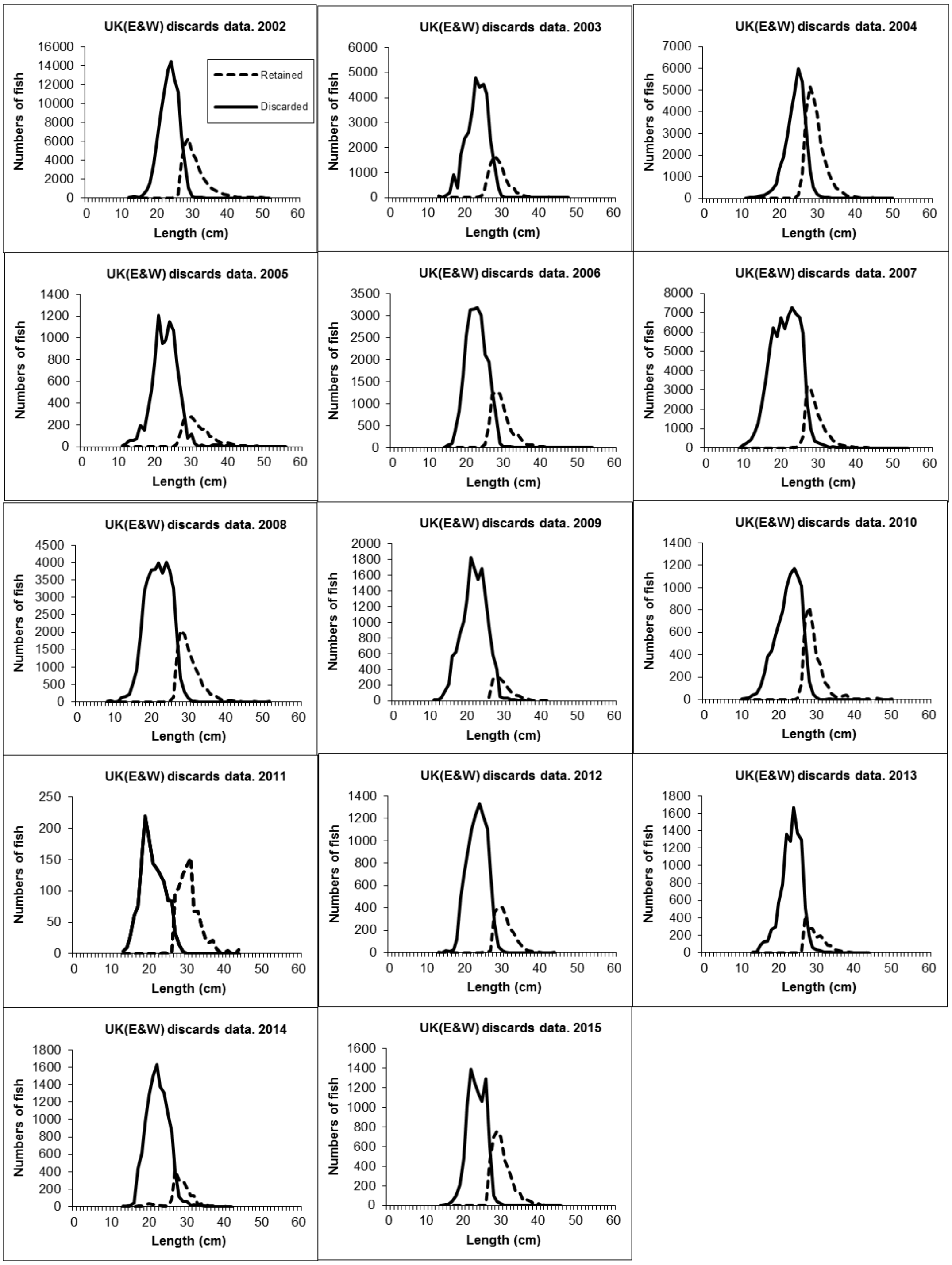



**Figure A2. Plaice 7.a. Length distributions of discarded and retained catches from UK(E&W). Source: ICES (2016).**

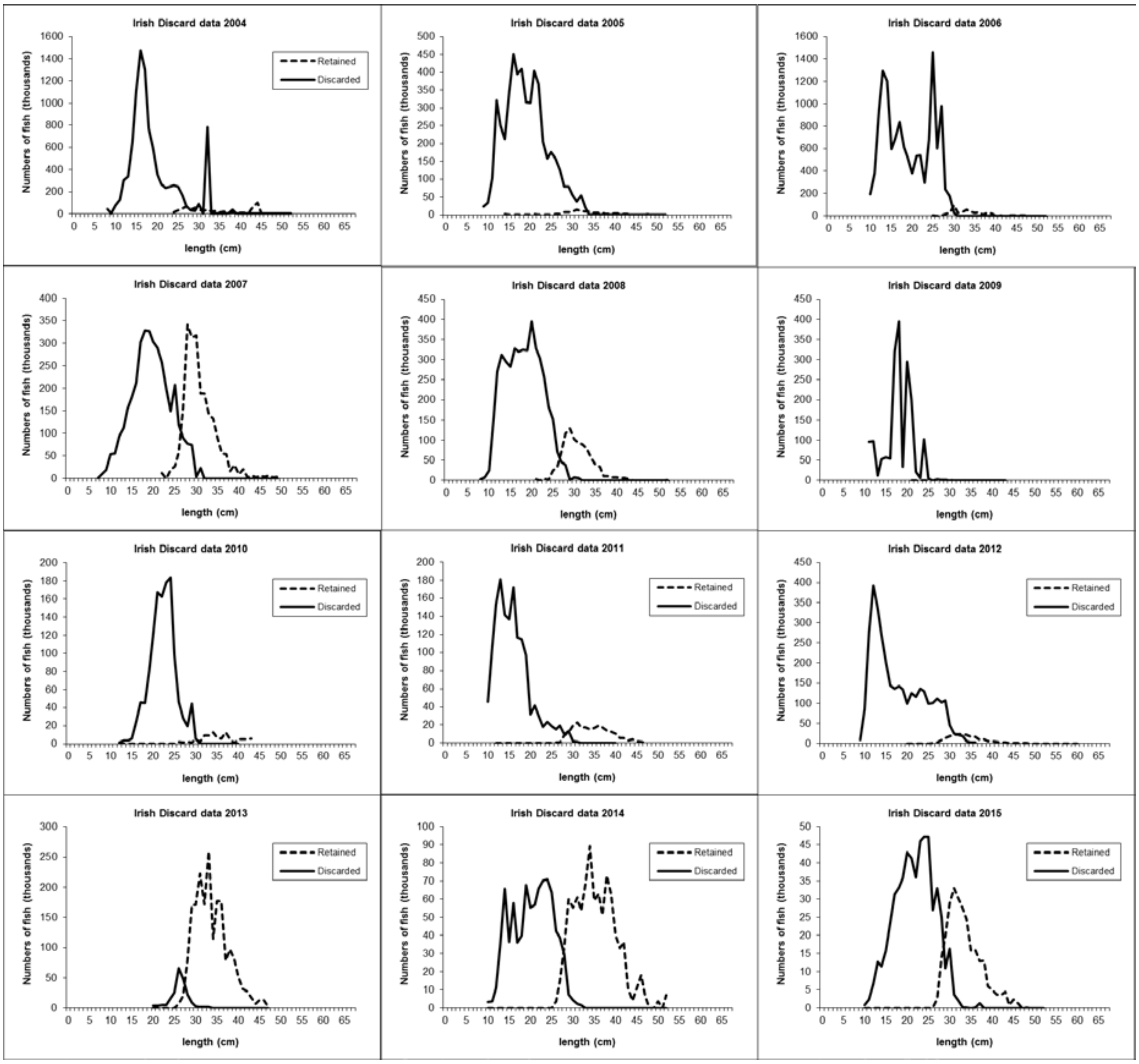



**Figure A3. Plaice 7.a. Length distributions of discarded and retained catches from Ireland. Source: ICES (2016).**

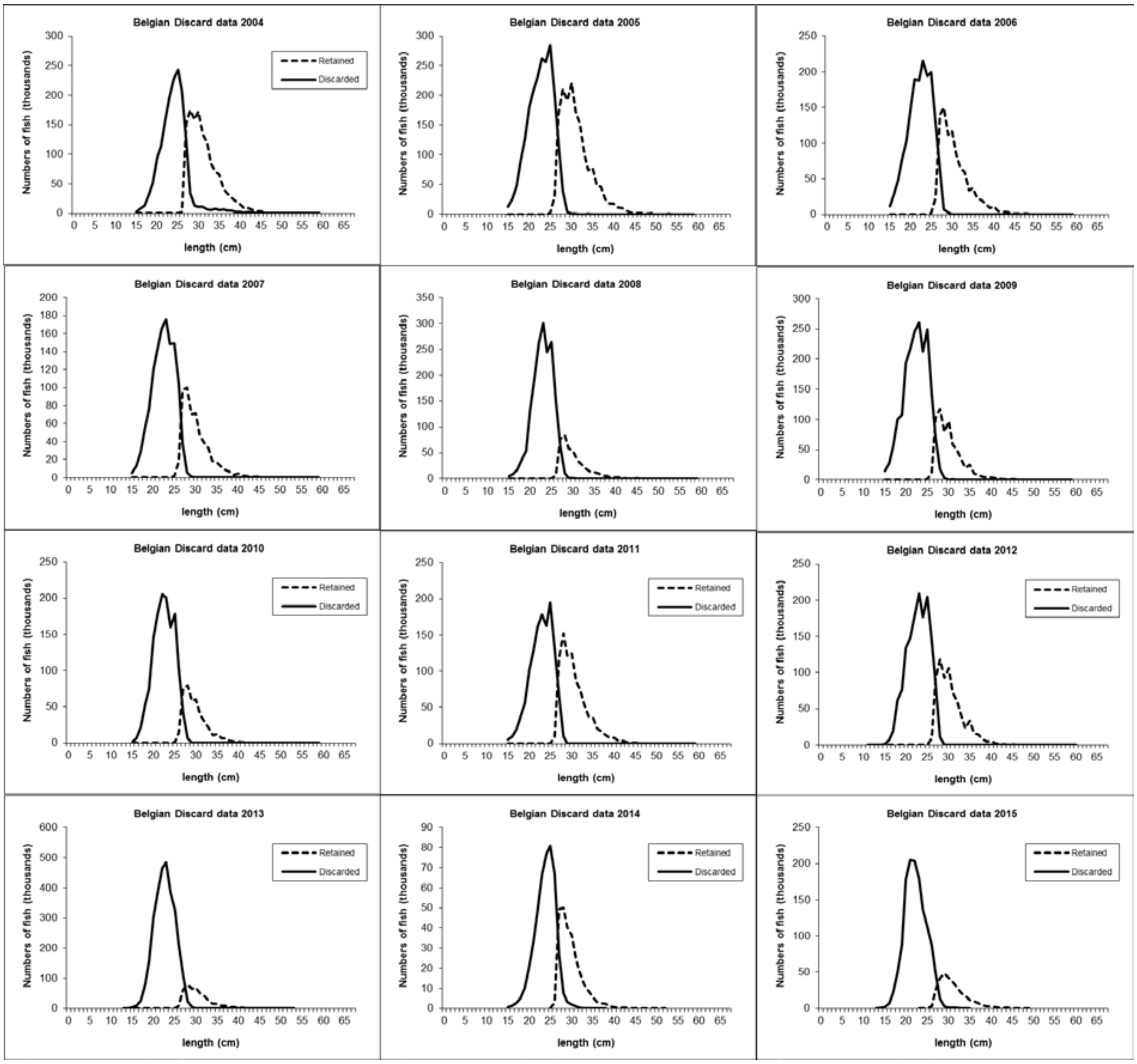



**Figure A4. Plaice 7.a. Length distributions of discarded and retained catches from Belgium. Source: ICES (2016).**


**Figure A5. Plaice 7.a. Length-at-age over time from the UKBTS, broken down by sex and area within the Irish Sea. Source: ICES (2016).**

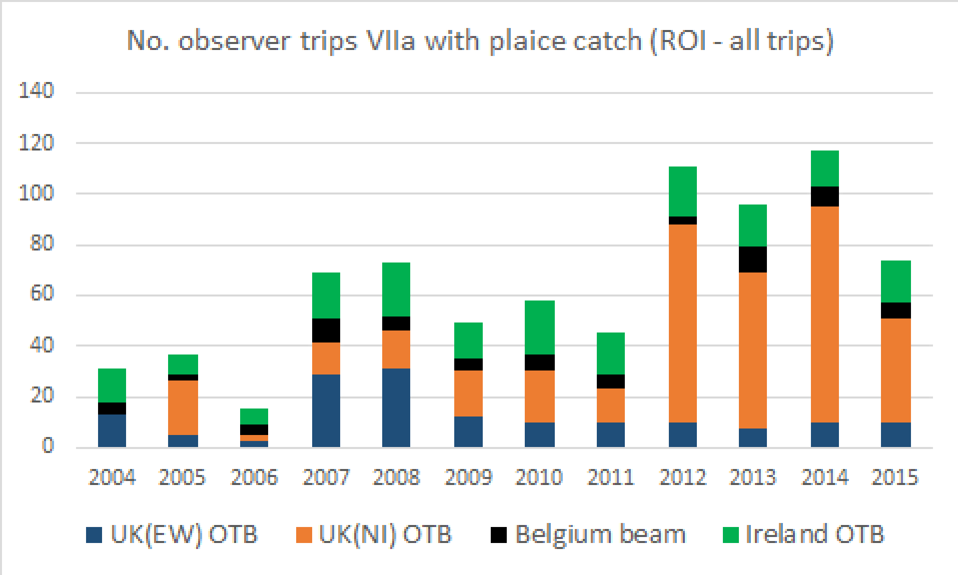



**Figure A6. Plaice 7.a. Numbers of observer trips in the Irish Sea, by country and gear since 2004, where plaice were recorded (Ireland is all trips; OTB: bottom otter trawl).**

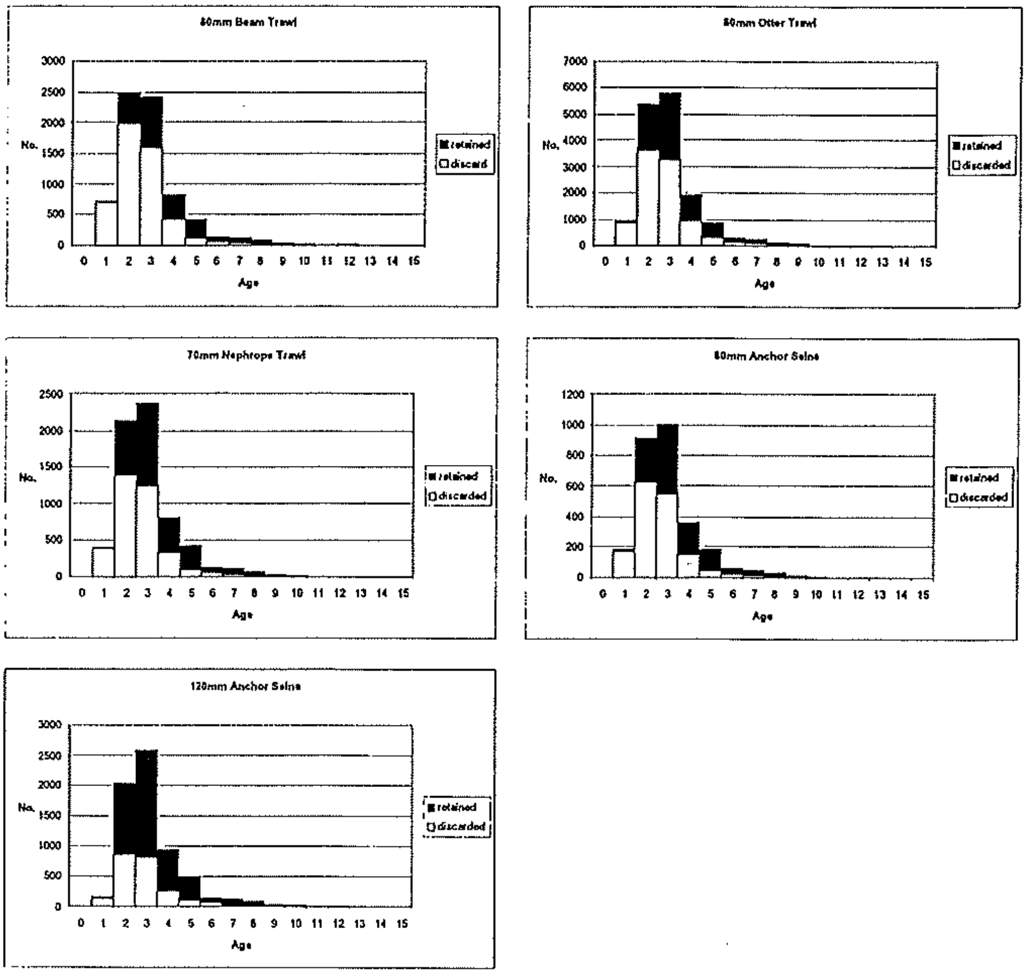



**Figure A6. Plaice in 7.a. Catch-at-age distributions for beam trawl, otter trawl, Nephrops trawl and anchor seine gear types for plaice in the Irish Sea between October 1993 and August 1994, sampled as part of the Emberton *et al.* (1995) study but as given in the Commission (2002) report (presumably through reworking of the data by SeaFish).**

# Annex 5: Plaice in 7.a reference points

Read in assessment outputs

```
library(msy)
library(icesAdvice)
library(FLCore)
withr::with_libpaths(new = paste0(.libPaths(), "/../library2"),
                     library("stockassessment"))
path <- "C:/Ple7a Benchmark/Models/SAM/"


load(paste0(path, "SAM/fit_b9.rdata"))          ## Model fit
load(paste0(path, "data/new_stocks/ple7a_dis_app5_1981.RData"))   ## Input Ple7a


SAM_to_FLStock <- function(stock_object, ### FLStock object
                           SAM_object ### SAM object
){
  ### enter stock numbers estimations
  stock.n(stock_object)[] <- exp(SAM_object$pl$logN)

  ### get ages available in F@age estimations
  ### (neccessary because of possible linked F patterns at age)
  ages <- SAM_object$conf$keyLogFsta[1, ] + 1
  ### enter F estimations
  harvest(stock_object)[] <- exp(SAM_object$pl$logF)[ages, ]

  return(stock_object)

}
ple7a_proj <- SAM_to_FLStock(stock,fit_b9)
plot(rec(ple7a_proj),type='l')
```

**Figure 13. Plaice in 7.a. Recruitment time-series.**

Finding $B_{lim}$

Plot stock–recruit data to determine the stock–recruit relationship type.

```
##Find Blim by using eqsr_fit to estimate breakpoint
FIT <- eqsr_fit(ple7a_proj,
                nsamp = 1000,
                models = c("Segreg"))



eqsr_plot(FIT,n=2e4)
```

**Figure 14. Plaice in 7.a. Stock–recruit relationship, showing stochastic fits of segmented regression form.**

It doesn't seem clear at this point whether the form best fits in ICES Type 2 (Stocks with a wide dynamic range of SSB, and evidence that recruitment is or has been impaired.) or Type 5 (Stocks showing no evidence of impaired recruitment…). Type 2 implies $B_{lim}$ would be the breakpoint, Type 5 implies lowest SSB. Choosing the breakpoint, as slightly more precautionary, but it doesn't make a difference in the end.

```
bp <- median(FIT$sr.sto[,2]) ##median breakpoint
bp
## [1] 4209.485
Blim <- bp
```

Calculating $F_{lim}$ from $B_{lim}$

ICES advice suggests a Beverton–Holt relationship as a preferred form for Type 2, and segmented regression for Type 5, so plot these and see what the relative weighting shows.

```
FIT2 <- eqsr_fit(ple7a_proj,
                 nsamp = 1000,
                 models = c("Segreg", "Bevholt"))
#Combination of approaches for Types 2 and 5
eqsr_plot(FIT2,n=2e4)
```

**Figure 15. Plaice in 7.a. Stock–recruit fits using segmented regression and Beverton–Holt stock–recruit forms.**

This plot highlights a problem, although the forms are equally likely from the data, the Beverton–Holt has the undesirable property of assuming that recruits remain high at very low stock sizes. In practice, forward projections are unlikely to use this part of the curve much, but to avoid overestimating recruitment, only the segmented regression will be used going forward.

Find $F_{lim}$ by looking for the F that gives a median SSB of $B_{lim}$ assuming no assessment error, see Page 10 of guidance, approach a).

```
#Find Flim by looking for the F that gives a median SSB of
Blim
```

```
#Page 10 of guidance, approach a)

SIM0 <- eqsim_run(FIT, #for finding Flim
                  bio.years = c(2006:2015),
                  sel.years = c(2006:2015),
                  Fcv=0, ##
                  Fphi=0, ##Default from WKMSYREF4
                  Blim=Blim,
                  Bpa=Bpa,
                  Fscan = seq(0,1.2,len=40),
                  verbose=FALSE,
                  extreme.trim=c(0.05,0.95),
                  Btrigger=0)

eqsim_plot_range(SIM0, type="ssb")
```

**Figure 16. Plaice in 7.a. Relationship between Median SSB and F assuming no assessment error.**

Reading across from our $B_{lim}$ gives:

```
Flim <- approx(SIM0$rbp[SIM0$rbp$variable=="Spawning-stock bio-
mass","p50"],
               SIM0$rbp[SIM0$rbp$variable=="Spawning-stock bio-
mass","Ftarget"],
               Blim)$y
Flim
```

## [1] 0.4821977

$F_{pa}$ and $B_{pa}$

Using the CVs from the assessment outputs, we can calculate the PA reference points.

```
SSBcv                                                          <-
mean(ssbtable(fit_b9)["2015",3]/ssbtable(fit_b9)["2015",1]-1)
SSBcv
## [1] 0.383187
Bpa <- Bpa(Blim, SSBcv)
Bpa
## [1] 7906.481
Fcv                                                            <-
mean(fbartable(fit_b9)["2015",3]/fbartable(fit_b9)["2015",1]-
1)
Fcv
## [1] 0.3950325
```

Calculating $F_{MSY}$, step 1

Step 1, from page 13 of guidance, $F_{MSY}$ without $B_{trigger}$

```
SIM1 <- eqsim_run(FIT,
                  bio.years = c(2006:2015),
                  sel.years = c(2006:2015),
                  Fcv=Fcv,
                  Fphi=0.423, ##Default from WKMSYREF4
                  Blim=Blim,
                  Bpa=Bpa,
                  Fscan = seq(0,1.2,len=40),
                  verbose=FALSE,
                  Btrigger=0,
                  extreme.trim=c(0.05,0.95))



Fmsy.notrig <- SIM1$Refs2["lanF","meanMSY"]
Fmsy.notrig
## [1] 0.1538462
Fmsy.notrig < Fpa  #True, so MSY consistent with PA
## [1] TRUE
eqsim_plot(SIM1,catch=TRUE)

eqsim_plot_range(SIM1, type="median")

eqsim_plot_range(SIM1, type="ssb")
```

So $F_{MSY}$ with no trigger is 0.154, and this is consistent with the precautionary approach.

Calculating $F_{MSY}$, step 2

Step 2, from page 13 of guidance, select MSY $B_{trigger}$.

```
fbar(ple7a_proj) < Fmsy.notrig
## An object of class "FLQuant"
## , , unit = unique, season = all, area = unique
##
##      year
## age   1981  1982  1983  1984  1985  1986  1987  1988  1989
1990  1991
##   all FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE FALSE
##      year
```

```
## age   1992  1993  1994  1995  1996  1997  1998  1999  2000
2001  2002
##   all FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE FALSE
##      year
## age   2003  2004  2005  2006  2007  2008  2009  2010  2011
2012  2013
##   all FALSE  TRUE FALSE FALSE FALSE FALSE  TRUE FALSE  TRUE
TRUE  TRUE
##      year
## age   2014  2015
##   all  TRUE  TRUE
##
## units:  f
```

F below candidate $F_{MSY}$ for last five years, so go down in flowchart (page 16)

```
eqsim_plot_range(SIM1,   type="ssb")       ##Lower=11232   >>
Bpa,        down in flowchart
```

Lower 5%ile of Biomass much bigger than $B_{pa}$, so go down in flowchart. There's no current $B_{trigger}$ to compare to, so have a look at which options make more sense; seems sensible to go to bottom left box, in which case go right, to choose MSY $B_{trigger}$ as the lower 5%ile of current biomass.

```
Btrigger <-ssbtable(fit_b9)["2015","Low"]
Btrigger <- 10392.13 #lower 5% of current SSB
```

Calculating $F_{MSY}$, step 3

Step 3, from page 13 of guidance, evaluate whole advice rule including $B_{trigger}$.

```
SIM.trig <- eqsim_run(FIT,
                 bio.years = c(2006:2015),
                 sel.years = c(2006:2015),
                 Fcv=Fcv, ##
                 Fphi=0.423, ##Default from WKMSYREF4
                 Blim=Blim,
                 Bpa=Bpa,
                 Fscan = seq(0,1.2,len=40),
                 verbose=FALSE,
                 Btrigger=Btrigger,
                 extreme.trim=c(0.05,0.95))


eqsim_plot(SIM.trig,catch=TRUE)
```

```
eqsim_plot_range(SIM.trig, type="median")
```

```
eqsim_plot_range(SIM.trig, type="ssb") ##lower percentile=11274
>> Blim
```

# Annex 6: Diagnostics and stock summary plots

# ASAP assessment

*Hans Gerritsen*

*February 02, 2017*

### R and FLR versions

```
library(FLCore)
```

```
## Warning: package 'FLCore' was built under R version 3.1.2
```

```
library(lattice)
sessionInfo()
```

```
## R version 3.1.1 (2014-07-10)
## Platform: i386-w64-mingw32/i386 (32-bit)
##
## locale:
## [1] LC_COLLATE=English_Ireland.1252  LC_CTYPE=English_Ireland.1252
## [3] LC_MONETARY=English_Ireland.1252 LC_NUMERIC=C
## [5] LC_TIME=English_Ireland.1252
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
## [1] FLCore_2.5.20150309 MASS_7.3-33         lattice_0.20-29
##
## loaded via a namespace (and not attached):
##  [1] digest_0.6.8    evaluate_0.8.3  formatR_1.3     grid_3.1.1
##  [5] htmltools_0.2.6 knitr_1.12.3    rmarkdown_0.9.5 stats4_3.1.1
##  [9] stringr_0.6.2   tools_3.1.1     yaml_2.1.13
```

### Read the stock object

First set the main directory and data and output directories

```
maindir <- '.'
#datadir <- paste0(maindir,'/1_Data/LowestoftFiles')
asapdir <- paste0(maindir,'/asap')
outdir <- paste0(maindir,'/4_Outputs')
```

The ASAP assessment is not done in R, however it produces an rdat file with outputs

Note that in this asap assessment the first age is age 0, so be careful!

```
asap <- dget(file.path(asapdir,'run-final.rdat'))
retrofiles <- paste0('run-final_',sprintf('%03d',0:8),'.rdat')
retro <- lapply(retrofiles,FUN=function(x) dget(file.path(asapdir,x)))
```

```
pal <- c("#1B9E77", "#D95F02", "#7570B3", "#E7298A", "#66A61E", "#E6AB02",
"#A6761D", "#666666")
for(i in 1:8) retro[[i]]$col <- pal[i]
# years 2010 and 2014 converged but hessian was not positive
# maybe leave out

#xsa results
load('./4_Outputs/whg7a_xsa.Rdata')
load('./4_Outputs/whg7a_stock.Rdata')
```

### Some housekeeping

Some handy parameters to keep for later

```
years <- asap$parms$styr:asap$parms$endyr
nyears <- length(years)
ages <- 1:asap$parms$nages -1 # note the age offset
nages <- length(ages)
nindices <- asap$parms$nindices
indices <- c('NI-Q1','NI-Q4','NI-MIK')
fbarage <- asap$options$Freport.agemin:asap$options$Freport.agemax - 1 # note the age offset
```

A Function to save the plots

```
SavePlot0<-function(plotname,width=6,height=4){
  file <- file.path(outdir,paste0('whg7a_asap_',plotname,'.png'))
  dev.print(png,file,width=width,height=height,units='in',res=300,pointsize=8)
}
```

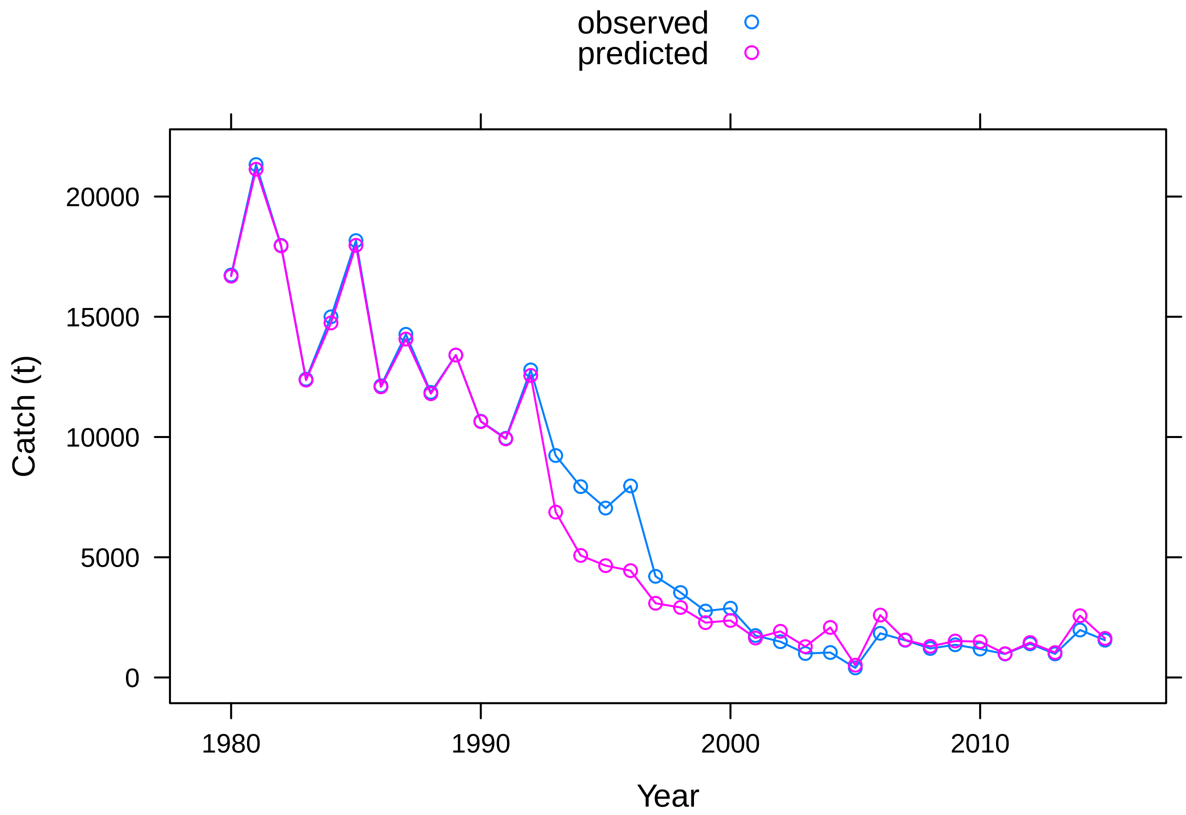
A bubble plot function

```
bubbles <- function(x,z,cex,  key.space = 'right',...){
  maxz <- max(abs(z),na.rm=T)
  panel.fun <- function(x,z,subscripts,cex,...){
    pt.cex <- sqrt(abs(z)/maxz)*cex
    pt.bg <- ifelse(z<0, '#FF000050','#00000050')
    lpoints(x,cex=pt.cex[subscripts],pch=21,fill=pt.bg[subscripts],col=1,...)
  }
  text <- as.character(round(seq(maxz,-maxz,length=6),2))
  key = list(space = key.space, text = list(text),
               points = list(pch = c(21), cex=sqrt(abs(seq(cex,-cex,length=6)))^2,
                 fill = rep(c('#00000050','#FF000050'),each=3)),
                 rep = FALSE)
  xyplot(x,z=z,cex=cex,panel=panel.fun,key=key,...)
}
```

### Diagnostic plots

Observed and predicted catch

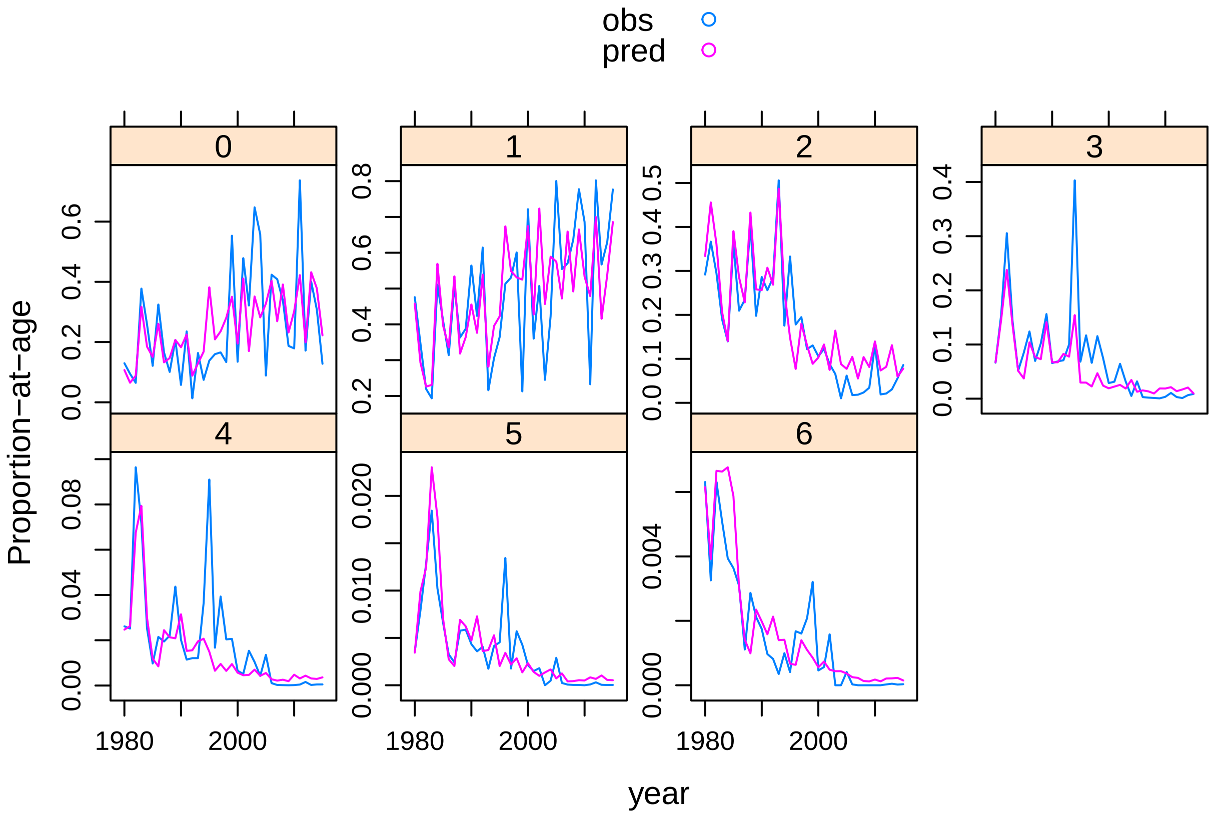
```r
catch <- data.frame(years,observed=c(asap$catch.obs),predicted=c(asap$catch.pred))
xyplot(observed+predicted~years,data=catch,type='b',auto.key=T,xlab='Year',ylab='Catch (t)')
```



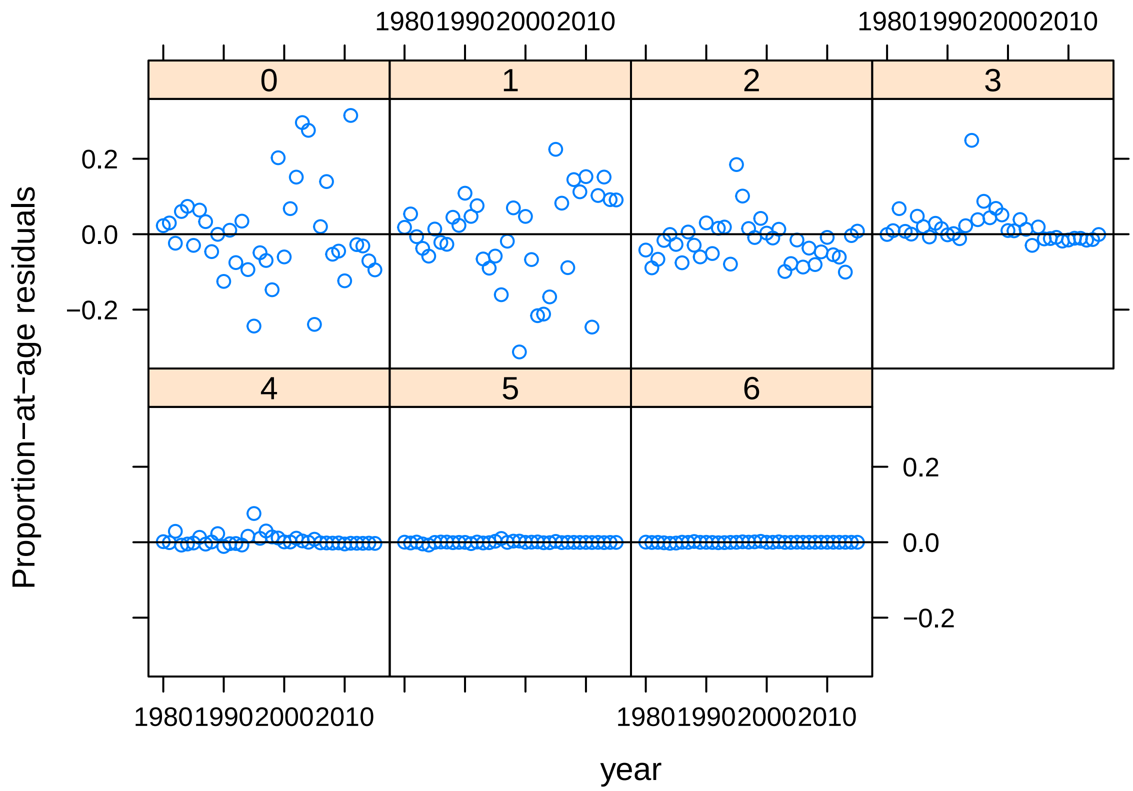

```r
a <- SavePlot0('Fleet_Catch',4,4)
```

Catch-at-age proportions-at-age (only for first fleet)

```r
res1 <- data.frame(year=years,age=rep(ages,each=nyears),obs=c(asap$catch.comp.mats$catch.fleet1.ob),pred
res1$res <- res1$obs-res1$pred
res2 <- merge(res1,with(res1,aggregate(list(obsbar=obs),list(age=age),mean)))
res2$sres <- res2$res/res2$obsbar
res2$sres <- ifelse(is.finite(res2$sres),res2$sres,NA)

xyplot(obs+pred~year|factor(age),data=res1,type='l',auto.key=T,as.table=T,scales=list(y='free',alternati
```

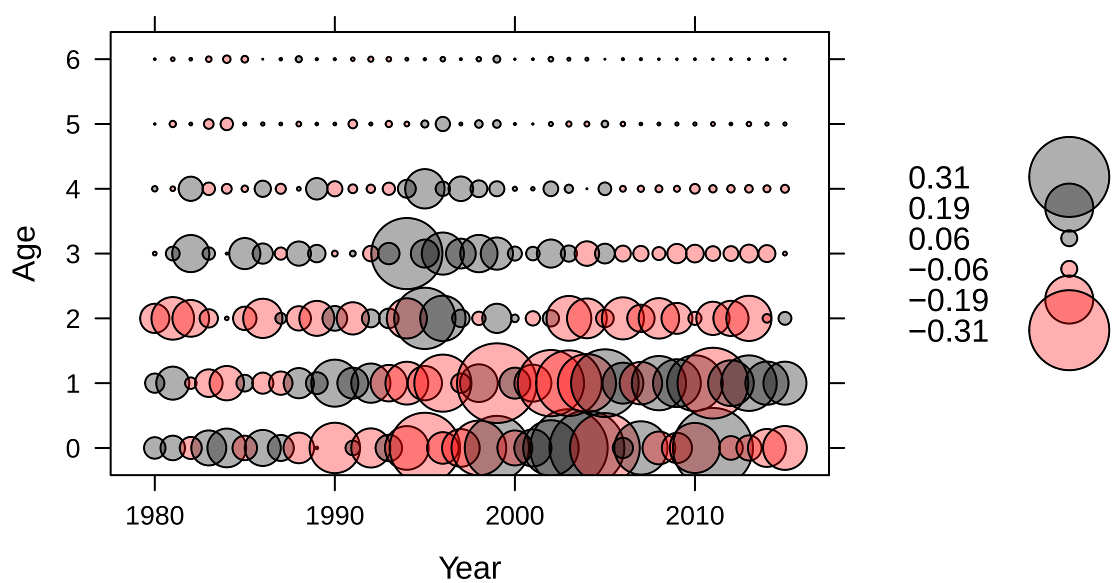



```
a <- SavePlot0('FleetCaaRes1')

panfun <- function(x, y) {
          panel.xyplot(x, y)
          panel.abline(h=0)
        }
xyplot(res~year|factor(age),data=res1,type='l',auto.key=T,as.table=T,ylab='Proportion-at-age residuals'
```

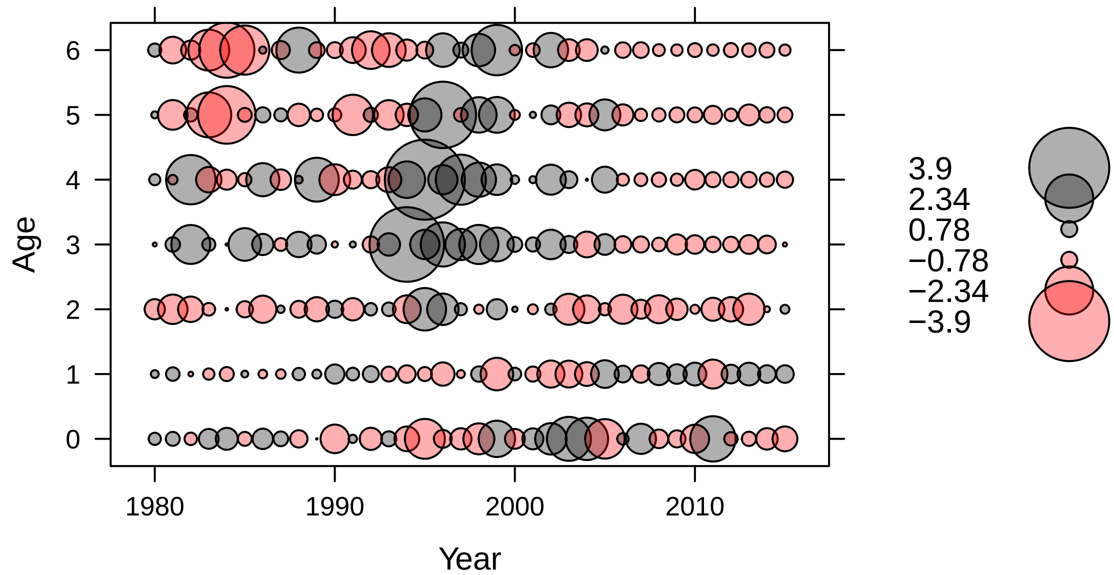



```
a <- SavePlot0('FleetCaaRes2')
```

```
bubbles(age~year,data=res1,z=res1$res,cex=5,xlab='Year',ylab='Age')
```



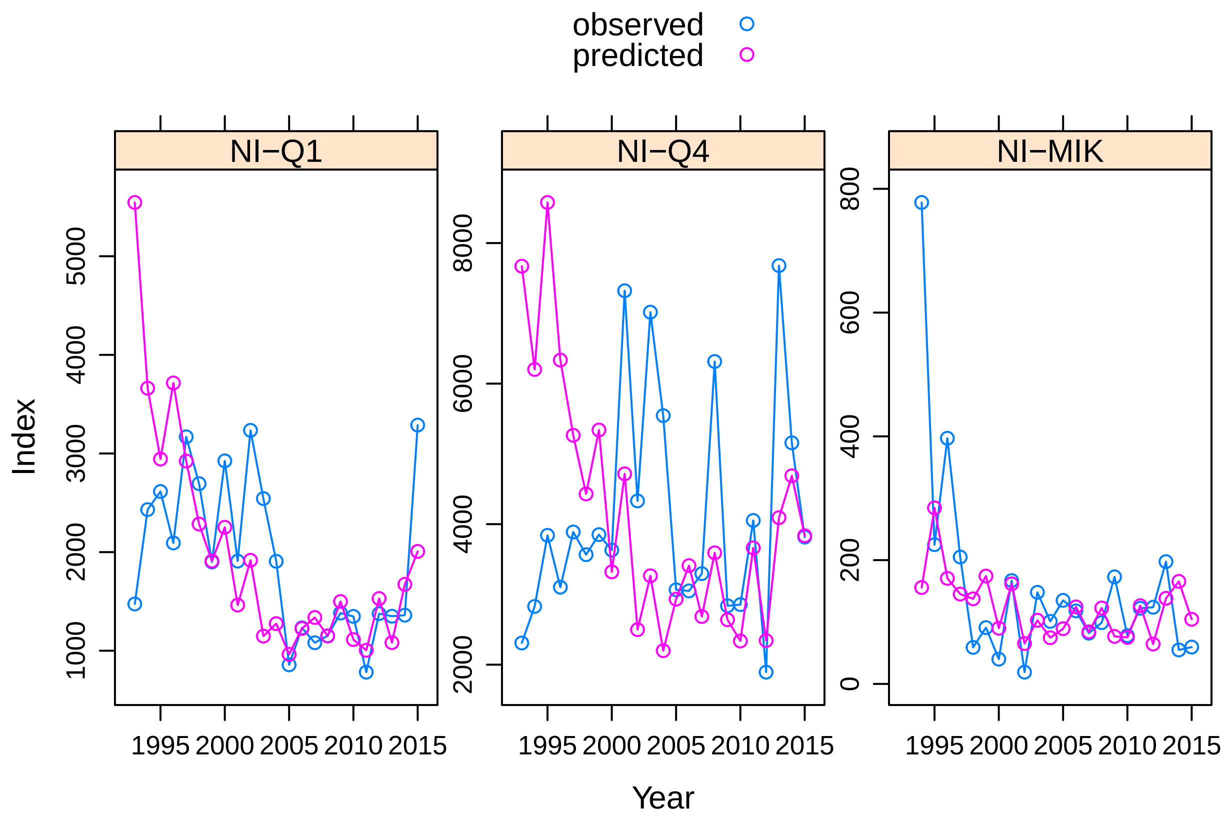
```
a <- SavePlot0('FleetResidualsAge',6,3.5)

bubbles(age~year,data=res2,z=res2$sres,cex=5,xlab='Year',ylab='Age')
```




```
a <- SavePlot0('FleetStResidualsAge',6,3.5)
```

Index fit

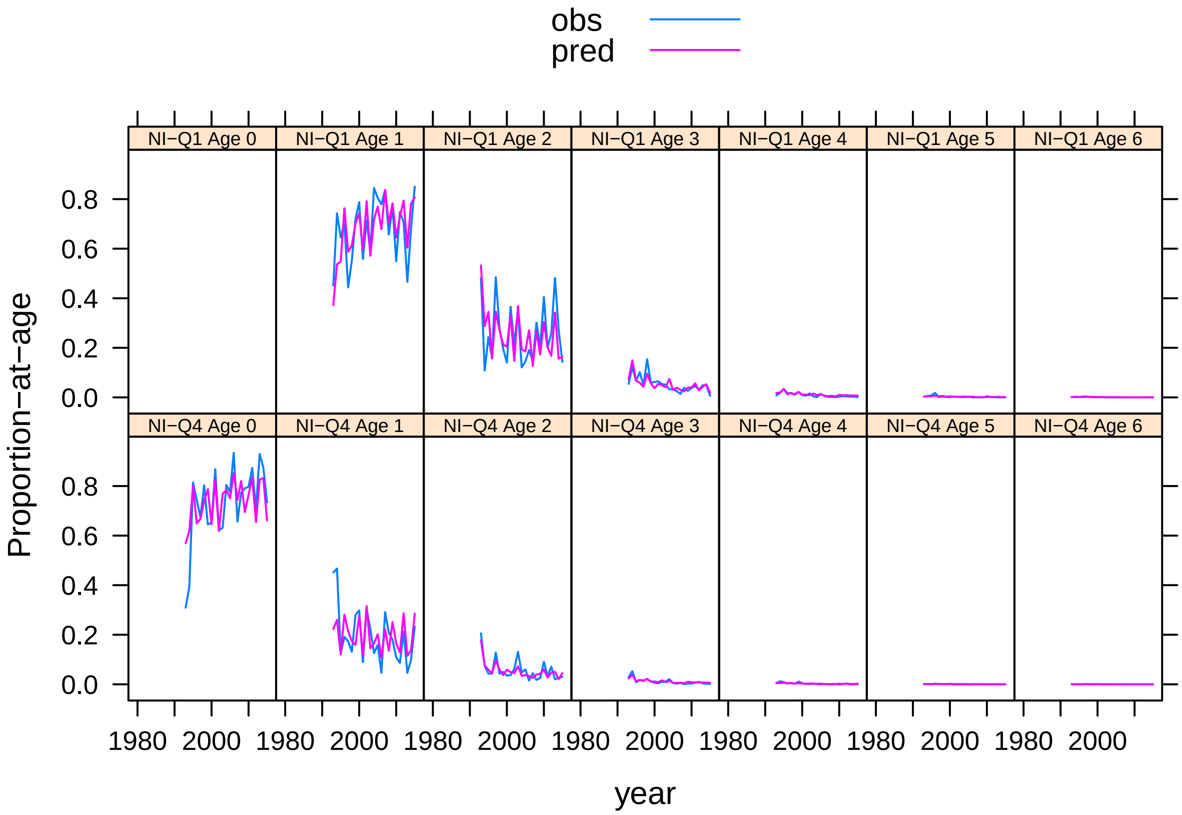
```
ind1 <- NULL
for(i in 1:nindices){
  ind1 <- rbind(ind1, data.frame(years=years[asap$index.year.counter[[i]]],name=indices[i],observed=asap
}
xyplot(observed+predicted~years|name,data=ind1,type='b',xlab='Year',ylab='Index',scales=list(alternatin
```



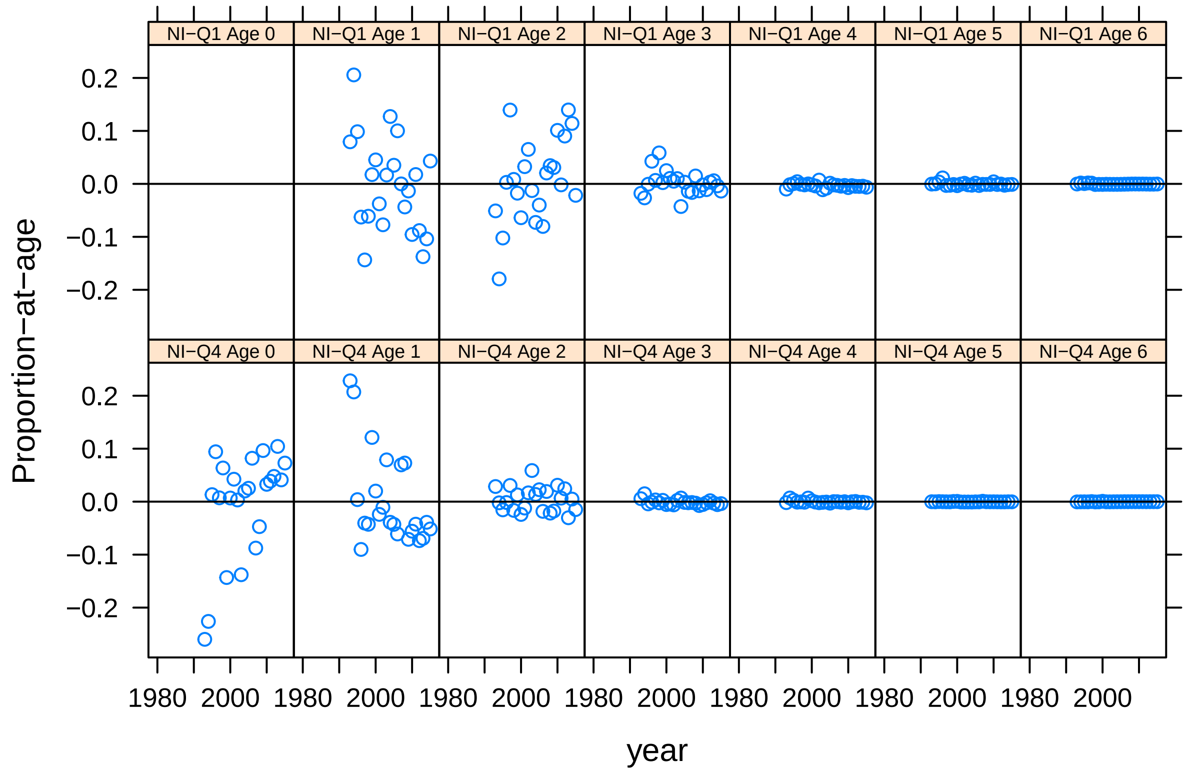

```r
a <- SavePlot0('IndexFit')
```

Index proportions-at-age fit

```r
#note: hard-coded for 2 indices with naa
res1 <- NULL
for(i in 1:2){
  iob <- grep('ob',names(asap$index.comp.mats))[i]
  ipr <- grep('pr',names(asap$index.comp.mats))[i]
  res1 <- rbind(res1,data.frame(year=years,age=rep(ages,each=nyears),name=indices[i],obs=unlist(asap$in
}
res1$obs <- ifelse(res1$obs==0 & res1$pred==0, NA,res1$obs)
res1$pred <- ifelse(res1$obs==0 & res1$pred==0, NA,res1$pred)
res1$res <- res1$obs-res1$pred
res2 <- merge(res1,with(res1,aggregate(list(obsbar=obs),list(age=age,name=name),mean,na.rm=T)))
res2$sres <- res2$res/res2$obsbar
#key <- simpleKey(text=c('obs','pred'),points=F,lines=T,space='right')
key <- simpleKey(text=c('obs','pred'),points=F,lines=T,space='top')
xyplot(obs+pred~year|paste(name,'Age',age),data=res1,type='l',key=key,scales=list(alternating=1),par.st
```

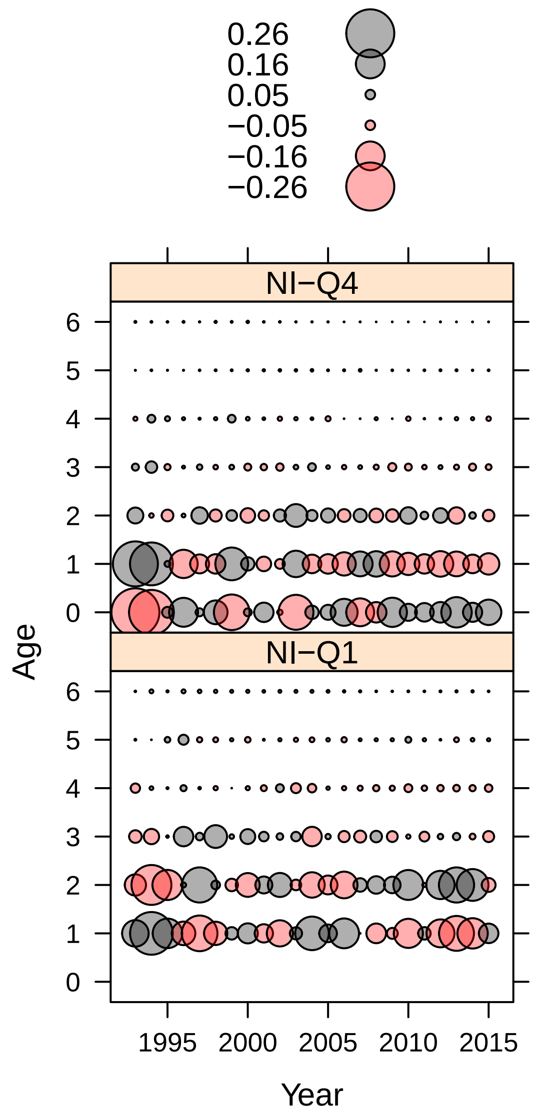



```
a <- SavePlot0('IndexCaa',6,6)

panfun <- function(x, y) {
          panel.xyplot(x, y)
          panel.abline(h=0)
        }
xyplot(res~year|paste(name,'Age',age),data=res1,type='l',scales=list(alternating=1),par.strip.text=list
```

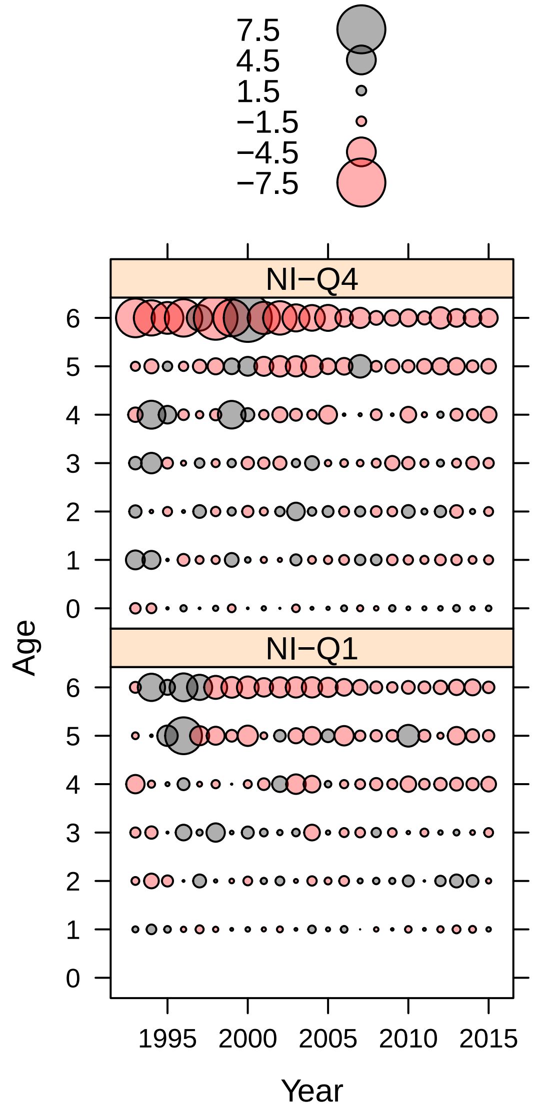



```
a <- SavePlot0('IndexResAge',6,6)
```

```
res1 <- subset(res1,res!=0 & name!='NI-MIK')
bubbles(age~year|name,data=res1,z=res1$res,cex=3,xlab='Year',ylab='Age',layout=c(1,2),scales=list(alter
```



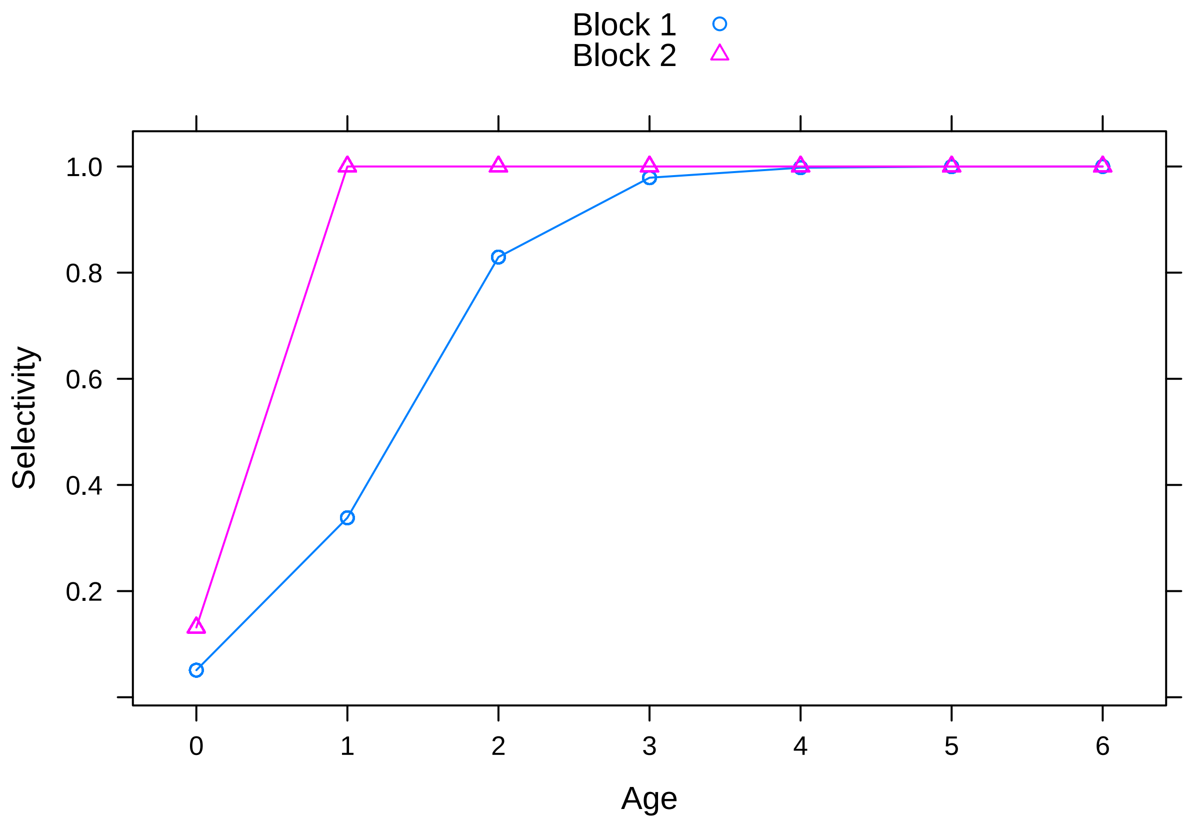

```
a <- SavePlot0('IndexResidualsAge',3.1,6)

res2 <- subset(res2,sres!=0 & is.finite(sres))
bubbles(age~year|name,data=res2,z=res2$sres,cex=3,xlab='Year',ylab='Age',layout=c(1,2),scales=list(alte
```




```
a <- SavePlot0('IndexStResidualsAge',3.1,6)
```

Selectivity at age in catches. Age 0 is fixed at 0% and ages 3+ are fixed at 100%.

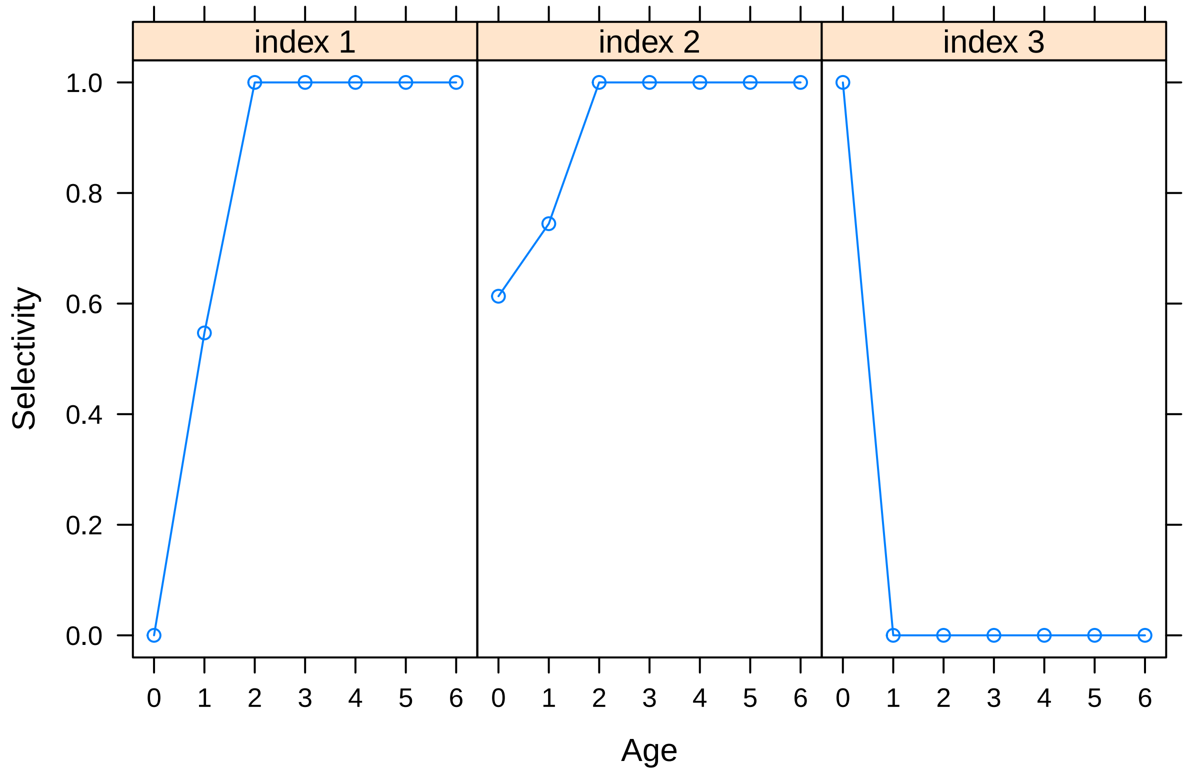
```
sel <- stack(as.data.frame(asap$fleet.sel.mats$sel.m.fleet1))
sel <- data.frame(years,sel)
sel$block <- c(asap$fleet.sel.blocks)
sel$age <- as.numeric(as.character(sel$ind))-1
  key <- simpleKey(text=paste('Block',unique(sel$block)),points=T,space='right')
  key$points$pch <- unique(sel$block)
  key$space<-'top'
  xyplot(values~age,groups=block,data=sel,xlab='Age',ylab='Selectivity',type='b',key=key,pch=key$points
```




```
a <- SavePlot0('Fleet_S')
```

Index selectivity-at-age. For index 1 (EVHOE/IGFS) ages 1+ are fixed at 100%, for index 2 (IRL-GAD) ages 4+ are fixed at 100%.

```
sel1 <- data.frame(name=paste('index',1:nindices),age=rep(ages,each=nindices),sel=c(asap$index.sel))
sel1$sel <- ifelse(sel1$sel<0,NA,sel1$sel)
xyplot(sel~age|name,data=sel1,type='b',xlab='Age',ylab='Selectivity',scales=list(alternating=1),ylim=c(
```



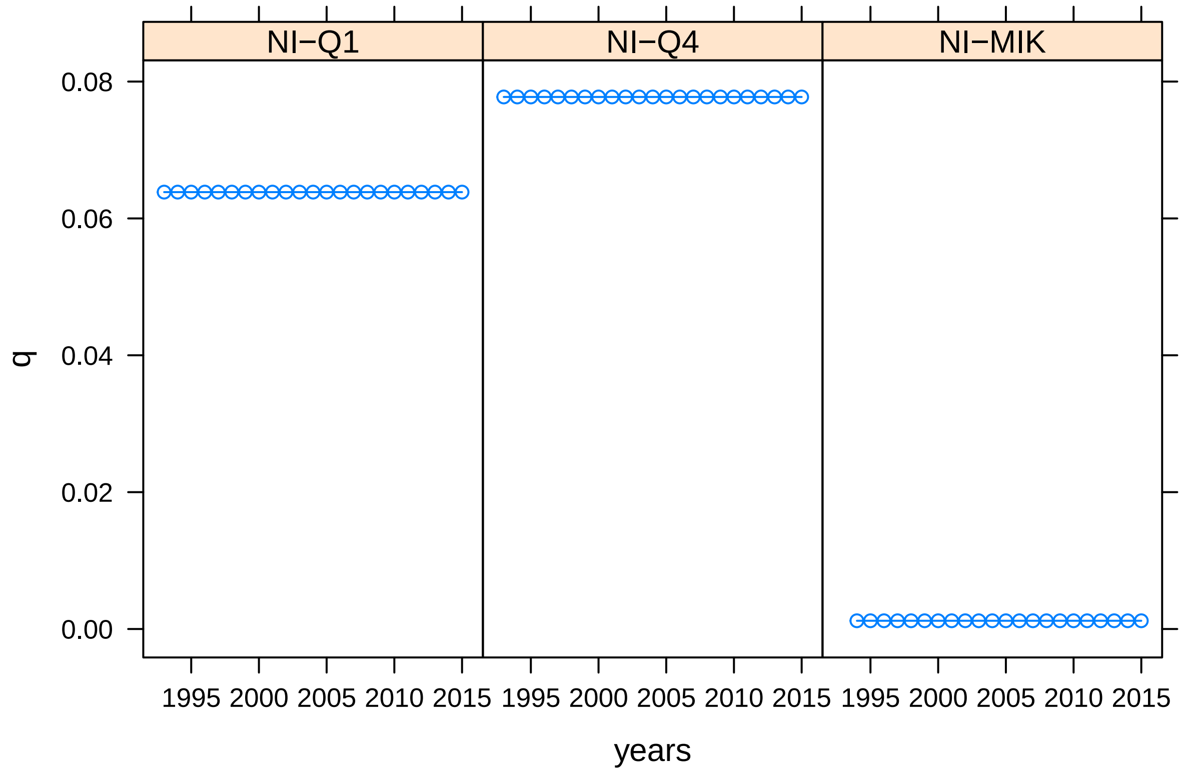

```
a <- SavePlot0('IndexSelectivity')
```

Save selectivity at age table for report

```
sel2 <- data.frame(ages,subset(sel,years==max(years))$values,t(asap$index.sel))
names(sel2) <- c('Age','Catch',indices[1:nindices])
for(i in 2:ncol(sel2)) sel2[,i] <- ifelse(sel2[,i]<0,NA,sel2[,i])
write.csv(sel2,file.path(outdir,'whg7a_asap_sel.csv'),row.names=F)
```

Index q

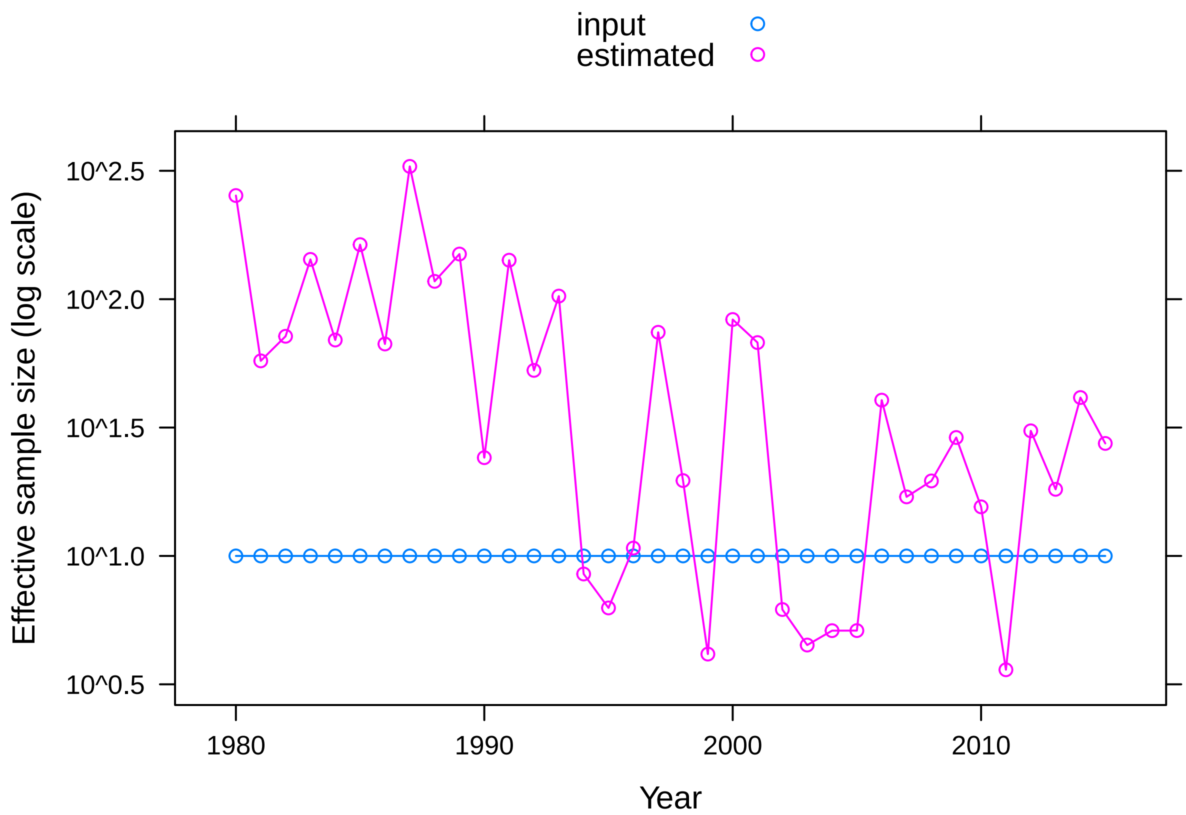
```
ind3 <- NULL
for(i in 1:nindices){
  ind3 <- rbind(ind3, data.frame(years=years[asap$index.year.counter[[i]]],name=indices[i],q=asap$q.ind
}
xyplot(q~years|name,data=ind3,type='b',scales=list(alternating=1))
```




```
a <- SavePlot0('IndexQ')
```

Catch and discards effective sample size

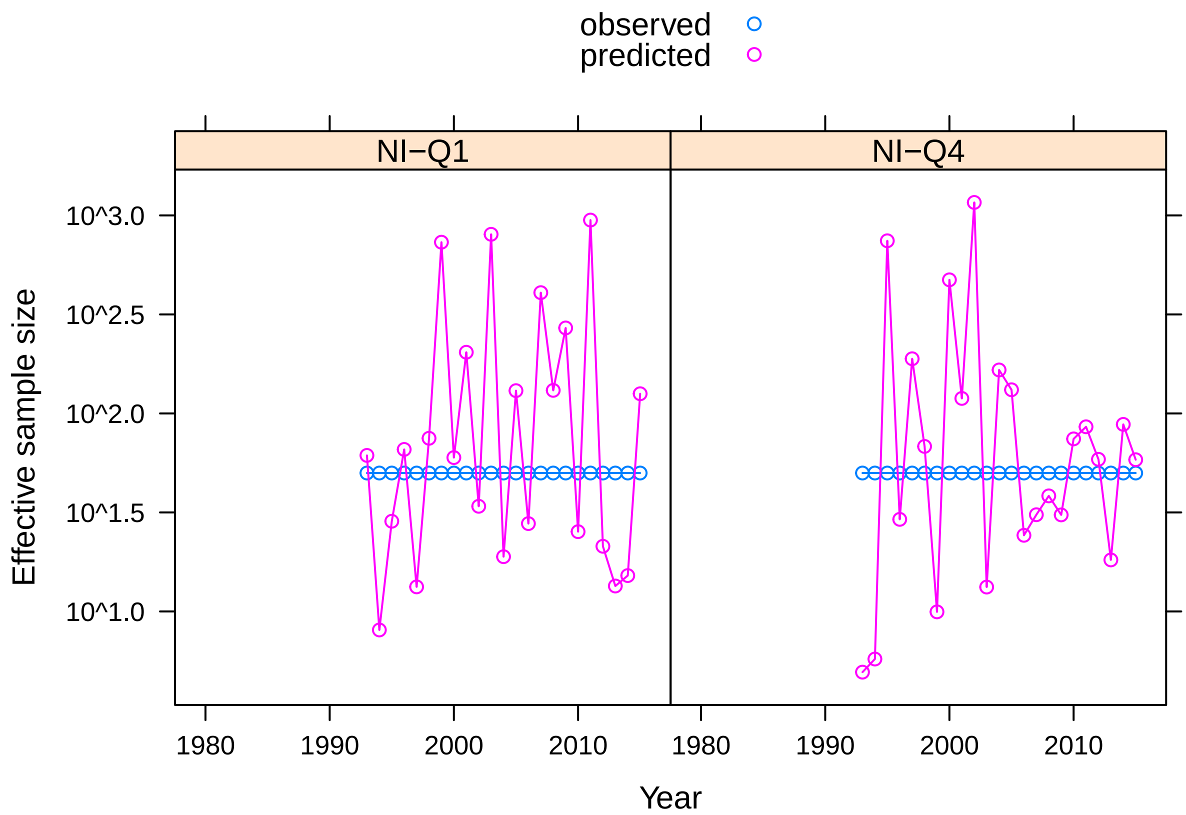
```
ees <- rbind(data.frame(years,type='input',value=c(asap$fleet.catch.Neff.init))
  ,data.frame(years,type='estimated',value=c(asap$fleet.catch.Neff.est)))
xyplot(value~years,groups=type,data=ees,type='b',auto.key=T,xlab='Year',ylab='Effective sample size (lo
```




```
a <- SavePlot0('Fleet_EES')
```

Index effective sample size

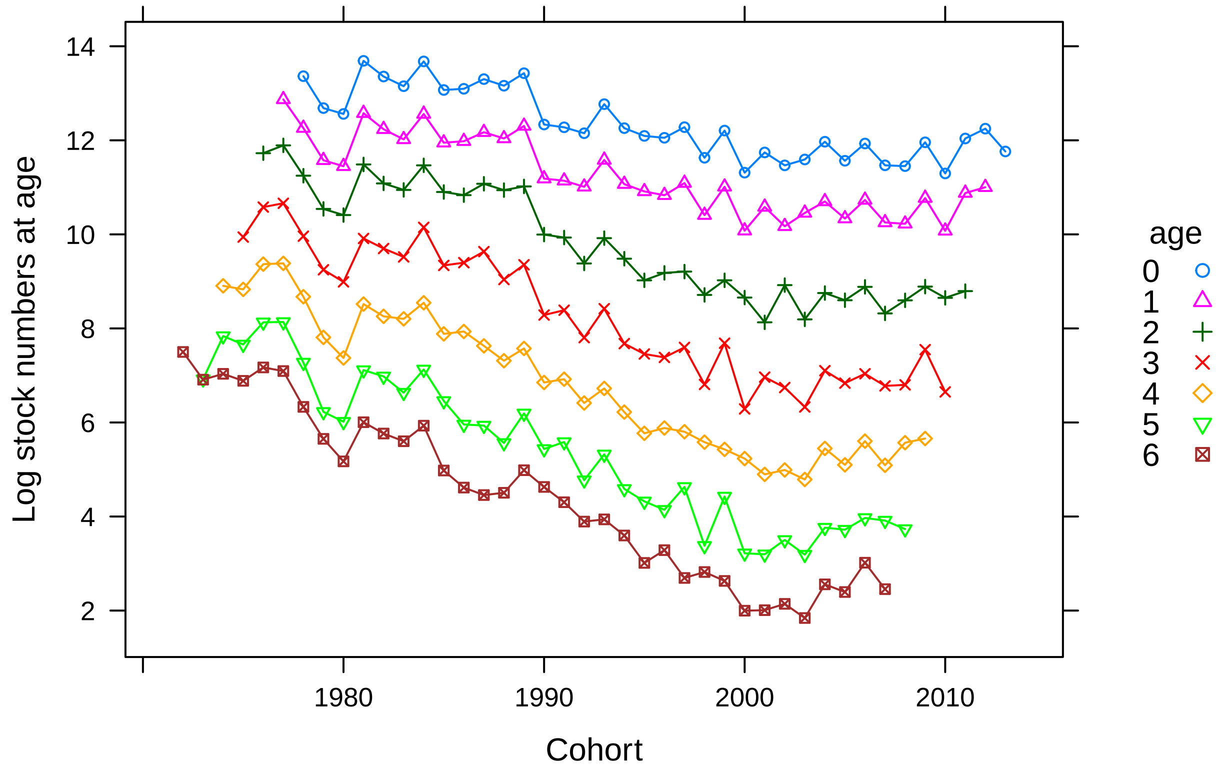
```
ind2 <- NULL
for(i in 1:2){
  ind2 <- rbind(ind2, data.frame(years,name=indices[i],observed=asap$index.Neff.init[i,],predicted=asap$
}
xyplot(observed+predicted~years|name,data=ind2,type='b',auto.key=T,xlab='Year',ylab='Effective sample si
```




```
a <- SavePlot0('IndexEffSampSize')
```

Population numbers.

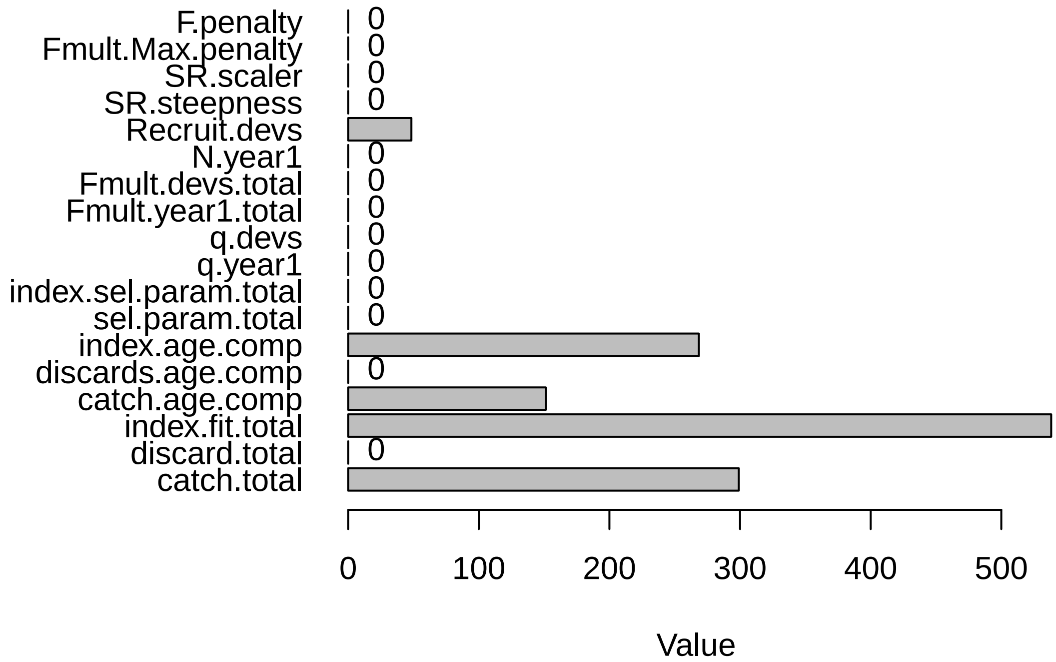
```
snaa <- asap$N.age
snaa.df <- stack(as.data.frame(snaa))
snaa.df$year <- years
# something wrong with cohorts i think
snaa.df$cohort <- snaa.df$year - as.numeric(as.character(snaa.df$ind))-1
key <- simpleKey(as.character(ages),space='right',title='age',cex.title=1)
key$points$pch <- 1:nages
xyplot(log(values)~cohort,groups=factor(ind),data=snaa.df,type='b',key=key,pch=1:nages,scales=list(alte
```




```
a <- SavePlot0('StockNos')
```

The objective function. I think you want the value to be approximately evenly spread between the parameters

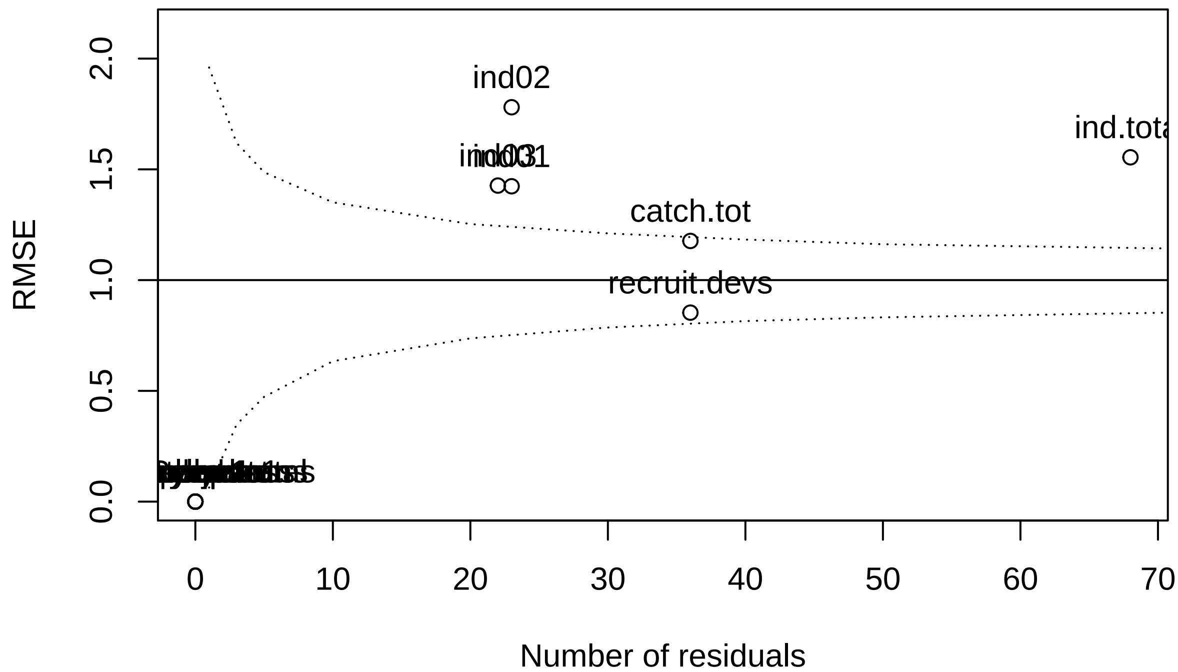
```
obj <- unlist(asap$like)[-1]
par(las=1,mar=c(5,12,4,2))
b <- barplot(obj,names=gsub('lk.','',names(obj)),horiz=T,xlab='Value')
text(obj,b,ifelse(obj==0,0,''),pos=4)
```




```r
a <- SavePlot0('ObjectiveFunction')
```

RMSE

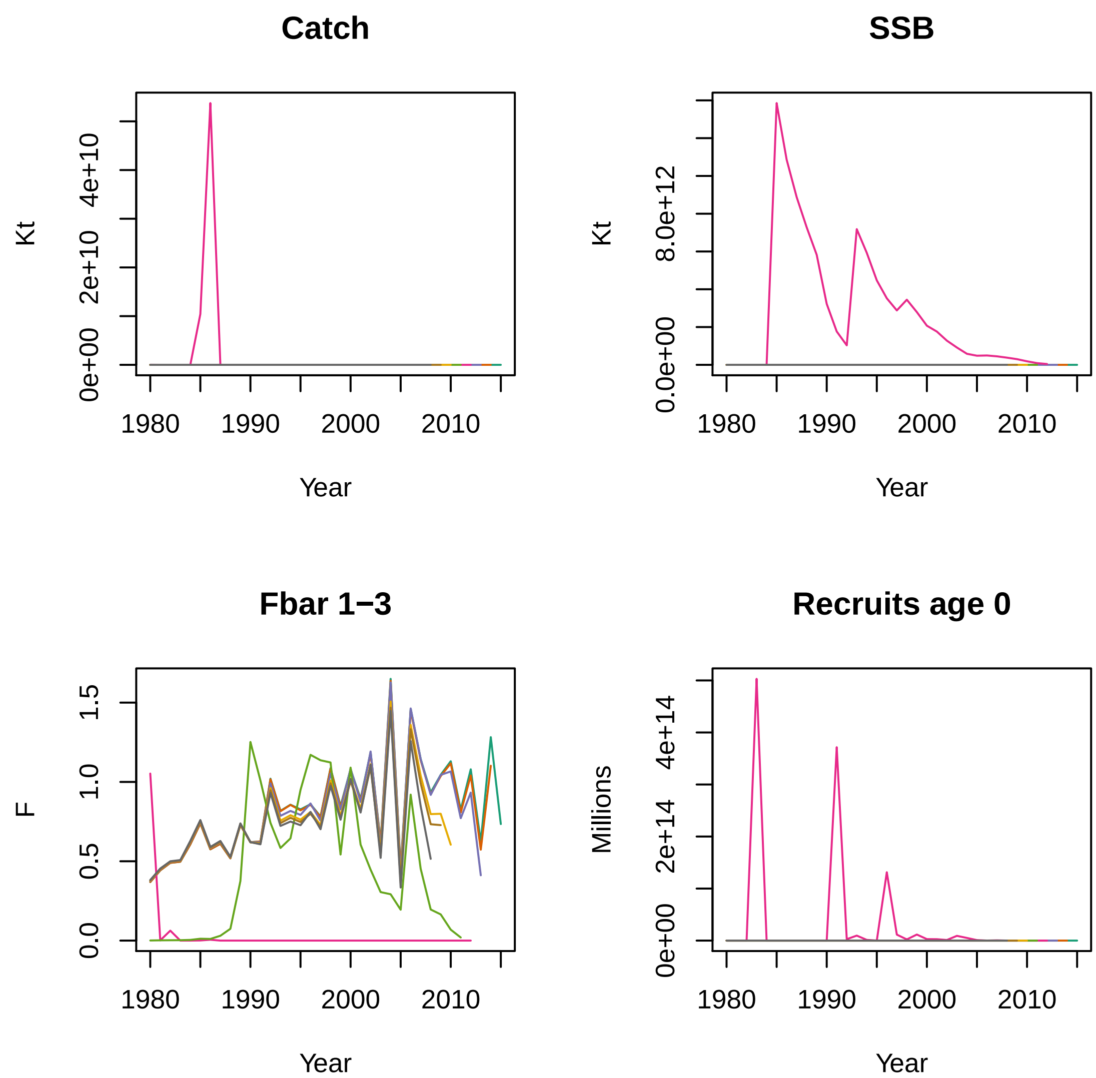
```r
rmse <- unlist(asap$RMSE)
rmse.n <- unlist(asap$RMSE.n)
ylim <- c(0,max(rmse)*1.2)
plot(rmse~rmse.n,ylim=ylim,xlab='Number of residuals',ylab='RMSE')
text(rmse~rmse.n,labels=gsub('rmse.','',names(rmse)),pos=3)
abline(h=1)
lines(c(1,3,5,10,20,30,40,50,100),c(.063,.348,.473,.634,.737,.786,.815,.832,.883),lty=3)
lines(c(1,3,5,10,20,30,40,50,100),c(1.960,1.619,1.487,1.351,1.253,1.211,1.183,1.162,1.116),lty=3)
```




```
a <- SavePlot0('RMSE')
```

Retrospective

```
par(mfrow=c(2,2))
xlim <- range(years)
ylim <- c(0,max(unlist(lapply(retro,function(x) x$catch.pred/1000))))
plot(NA,xlim=xlim,ylim=ylim,xlab='Year',ylab='Kt',main='Catch')
a <- lapply(retro,function(x) lines(as.numeric(colnames(x$catch.pred)),x$catch.pred/1000,col=x$col))
ylim <- c(0,max(unlist(lapply(retro,function(x) x$SSB/1000))))
plot(NA,xlim=xlim,ylim=ylim,xlab='Year',ylab='Kt',main='SSB')
a <- lapply(retro,function(x) lines(as.numeric(colnames(x$catch.pred)),x$SSB/1000,col=x$col))
ylim <- c(0,max(unlist(lapply(retro,function(x) x$F.report))))
plot(NA,xlim=xlim,ylim=ylim,xlab='Year',ylab='F',main=paste0('Fbar ',paste(range(fbarage),collapse='-'))
a <- lapply(retro,function(x) lines(as.numeric(colnames(x$catch.pred)),x$F.report,col=x$col))
ylim <- c(0,max(unlist(lapply(retro,function(x) x$N.age[,1]/1000))))
plot(NA,xlim=xlim,ylim=ylim,xlab='Year',ylab='Millions',main='Recruits age 0')
a <- lapply(retro,function(x) lines(as.numeric(colnames(x$catch.pred)),x$N.age[,1]/1000,col=x$col))
```

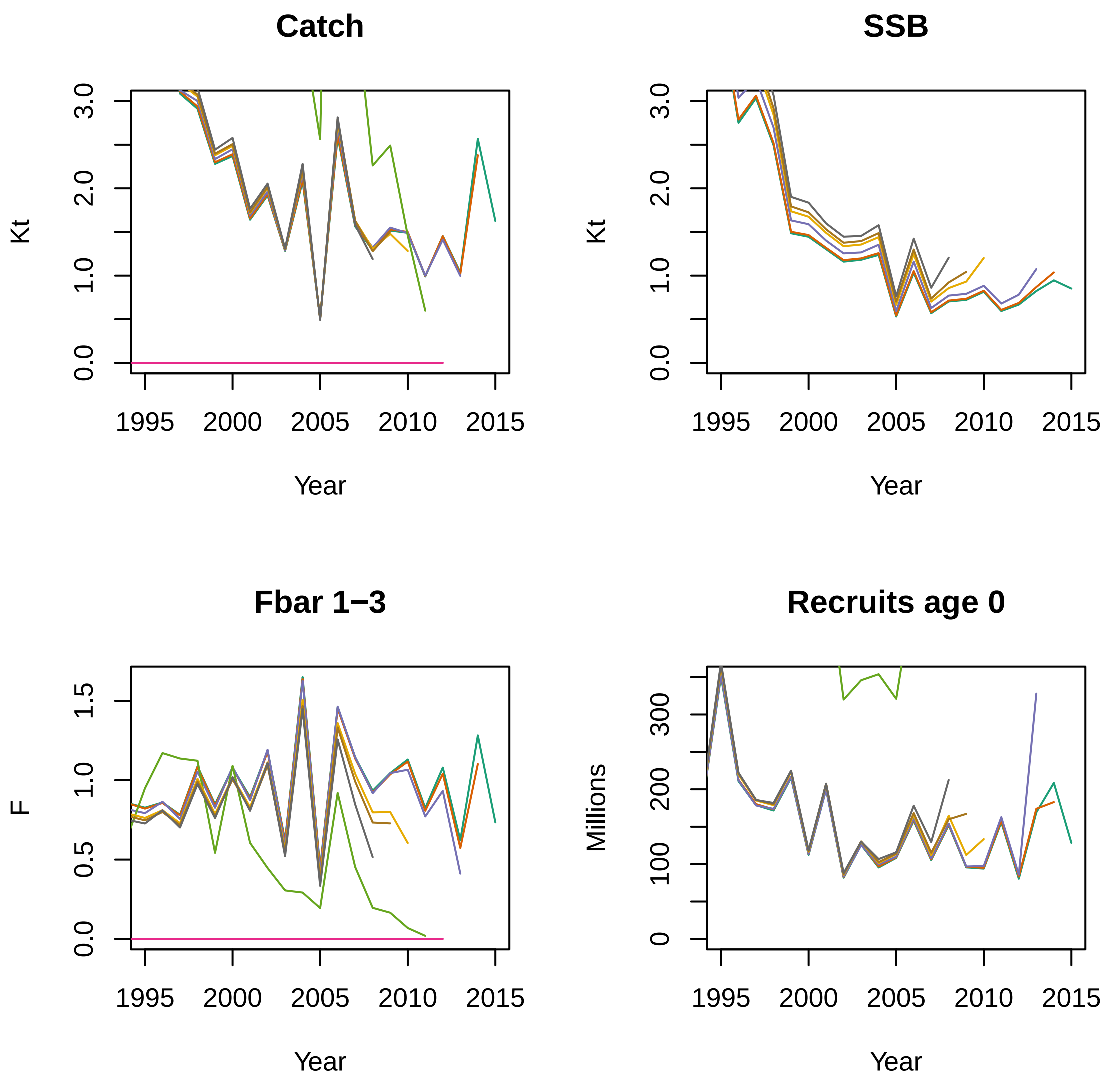



```
a <- SavePlot0('Retrospective',6,6)
```

Retrospective, zoomed in

```
par(mfrow=c(2,2))
xlim <- c(1995,2015)
ylim <- c(0,3)
plot(NA,xlim=xlim,ylim=ylim,xlab='Year',ylab='Kt',main='Catch')
a <- lapply(retro,function(x) lines(as.numeric(colnames(x$catch.pred)),x$catch.pred/1000,col=x$col))
ylim <- c(0,3)
plot(NA,xlim=xlim,ylim=ylim,xlab='Year',ylab='Kt',main='SSB')
a <- lapply(retro,function(x) lines(as.numeric(colnames(x$catch.pred)),x$SSB/1000,col=x$col))
ylim <- c(0,max(unlist(lapply(retro,function(x) x$F.report))))
plot(NA,xlim=xlim,ylim=ylim,xlab='Year',ylab='F',main=paste0('Fbar ',paste(range(fbarage),collapse='-'))
a <- lapply(retro,function(x) lines(as.numeric(colnames(x$catch.pred)),x$F.report,col=x$col))
ylim <- c(0,350)
```

```
plot(NA,xlim=xlim,ylim=ylim,xlab='Year',ylab='Millions',main='Recruits age 0')
a <- lapply(retro,function(x) lines(as.numeric(colnames(x$catch.pred)),x$N.age[,1]/1000,col=x$col))
```




```
a <- SavePlot0('Retrospective1',6,6)
```

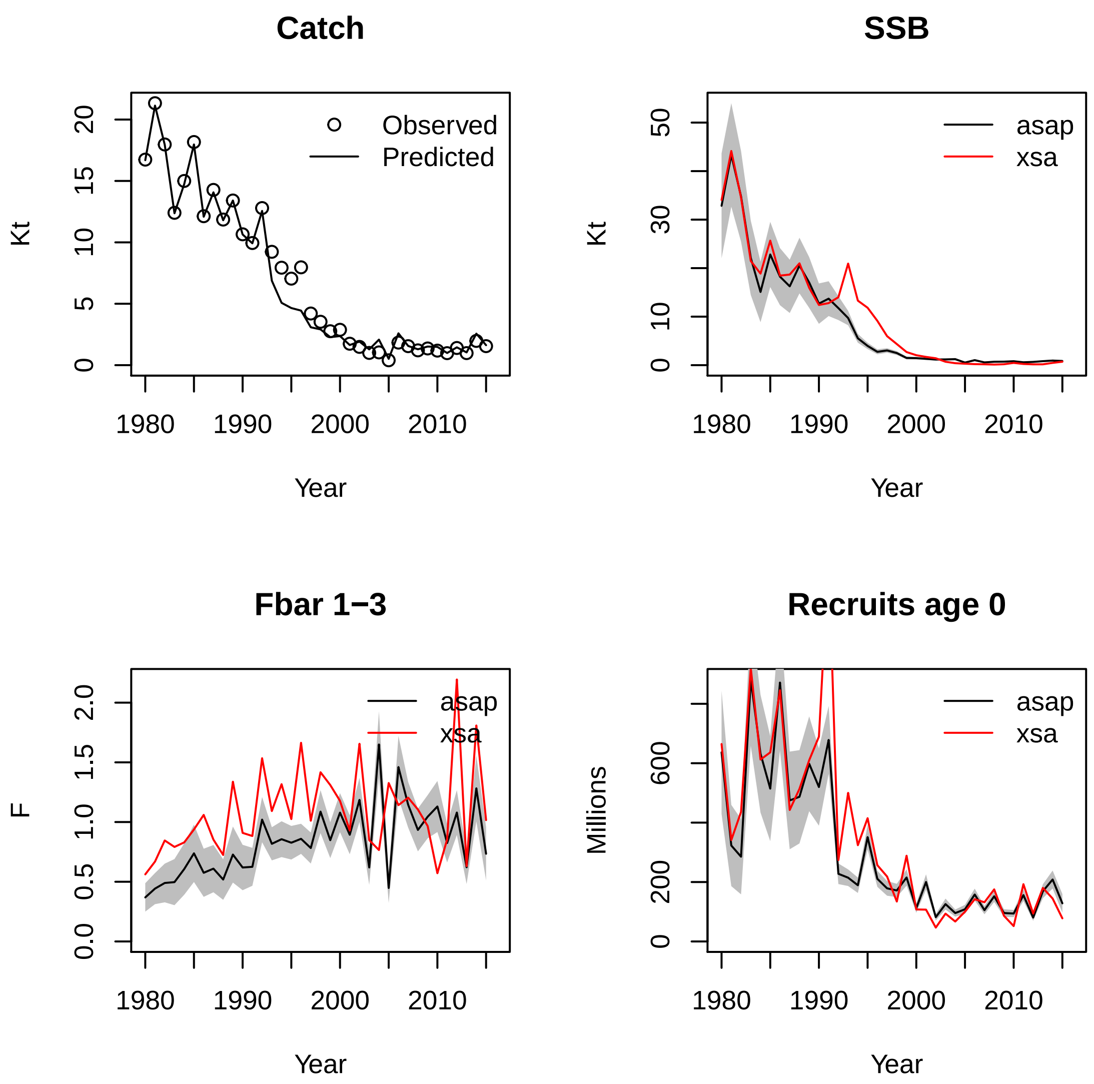
Organise the data for the tables

```
asap.std <- read.table(file.path(asapdir,'run-final.std'),header=T,fill=T)

#lan <- c(stock0@landings)
#dis <- c(stock0@discards)
catch <- c(asap$catch.obs)
catch.pred <- c(asap$catch.pred) # asap predicted catch
#catchInt <- c(landings(stf1)[,nyears+1]+discards(stf1)[,nyears+1]) # catch in intermediate year, assum
#landInt <- c(landings(stf1)[,nyears+1])
```

```
ssb <- c(asap$SSB)
#ssbInt <- c(ssb(stf1)[,nyears+1]) # ssb in intermediate year (1 jan)
tsb <- c(apply(asap$N.age * asap$WAA.mats$WAA.ssb,1,sum))
recr <- c(asap$N.age[,1])
fbar <- c(asap$F.report)
ssbSTD <- subset(asap.std,name=='SSB')$std # standard deviation
recrSTD <- subset(asap.std,name=='recruits')$std # standard deviation
fbarSTD <- subset(asap.std,name=='Freport')$std # standard deviation
```

### Summary plot

```
par(mfrow=c(2,2))


xlim <- range(years)+0:1
ylim <- c(0,max(catch)/1000)
plot(NA,xlim=xlim,ylim=ylim,xlab='Year',ylab='Kt',main='Catch')
points(years,catch/1000)
lines(years,catch.pred/1000)
legend('topright',c('Observed','Predicted'),lty=c(NA,1),pch=c(1,NA),bty='n')
#lines(years,lan/1000,lty=2)
#points(max(years)+1,catchInt/1000)
#points(max(years)+1,landInt/1000,pch=2)
#legend('topright',c('Catch','Landings','Catch Fsq','Land Fsq'),lty=c(1,2,NA,NA),pch=c(NA,NA,1,2),bty='

ylim <- c(0,max(ssb+ssbSTD)/1000)
plot(NA,xlim=xlim,ylim=ylim,xlab='Year',ylab='Kt',main='SSB')
polygon(c(years,rev(years)),c((ssb-ssbSTD),rev((ssb+ssbSTD)))/1000,border=0,col='grey')
lines(years,ssb/1000)
lines(years,c(ssb(xsa+stock))/1000,col=2)
legend('topright',c('asap','xsa'),lty=1,col=1:2,bty='n')
#points(max(years)+1,ssbInt/1000)
#legend('topleft',c('StDev',paste('1 jan',max(years)+1)),fill=c('grey',NA),border=NA,,pch=c(NA,1),bty='

ylim <- c(0,max(fbar+fbarSTD,fbar(xsa+stock)))
plot(NA,xlim=xlim,ylim=ylim,xlab='Year',ylab='F',main=paste0('Fbar ',paste(range(fbarage),collapse='-'))
polygon(c(years,rev(years)),c((fbar-fbarSTD),rev((fbar+fbarSTD))),border=0,col='grey')
lines(years,fbar)
lines(years,c(fbar(xsa+stock)),col=2)
legend('topright',c('asap','xsa'),lty=1,col=1:2,bty='n')

#points(max(years)+1,fsq)
#legend('bottomleft',c('StDev','Fsq'),pch=c(NA,1),fill=c('grey',NA),border=NA,bty='n')

ylim <- c(0,max(recr/1000))
plot(NA,xlim=xlim,ylim=ylim,xlab='Year',ylab='Millions',main='Recruits age 0')
polygon(c(years,rev(years)),c((recr-recrSTD),rev((recr+recrSTD)))/1000,border=0,col='grey')
lines(years,recr/1000)
lines(years,c(xsa@stock.n[1,])/1000,col=2)
legend('topright',c('asap','xsa'),lty=1,col=1:2,bty='n')
```




```
#points(max(years)+1,GM/1000)
#legend('topleft',c('StDev','GM'),pch=c(NA,1),fill=c('grey',NA),border=NA,bty='n')

a <- SavePlot0('Summary',6,6)
```

# Annex 7: Whiting reference points

# Whiting 7a MSY evaluations

*Colm Lordan*

*17 February 2017*

### The ICES approach to setting Reference Points

This Markdown document outlines the steps involved in estimating PA and MSY reference points for Irish Sea whiting as part of the WKIRISH3 benchmark. The objective is to have a reproducible document that transparently outlines the process, settings and decisions.

The ICES **technical guidelines document** establishes the procedures to be followed.

These have been developed based on the experiences and approach applied at **WKMSYREF4** which estimated PA reference points and Fmsy and MSY ranges for category 1 stocks in western waters and **WKMSYREF3** which estimated Fmsy and MSY ranges for North Sea stocks.

For typical age-based assessments the preferred ICES approach used the EqSim methodology. This is available from the developmental repository for the 'msy package' which is located on github, more specifically on github.com/ices-tools-prod/msy

To download the required packages for the very first time run the following code chunk by switching 'eval = TRUE'.

```
install.packages("devtools")
install.packages("icesAdvice")
install.packages("ggplot2")
library(devtools)
install.packages("FLCore", repo = "http://flr-project.org/R")
install.packages("ggplotFL", repo = "http://flr-project.org/R")
install_github("ices-tools-prod/msy")
```

```
knitr::opts_chunk$set(eval = TRUE, echo = TRUE, message = FALSE, warning = FALSE)
```

### Load Packages

First we load the various packages needed to preform the analysis.

```
library(ggplot2)
library(ggplotFL)
library(FLCore)
library(msy)
library(icesAdvice)
library(knitr)
```

### Load the data

Next we load the data. The current version of eqsim only takes FLStock objects as inputs. Note 'eqsim' will internally use the landings and catch numbers at age provided in the FLStock object used as input to eqsim to calculate a discard ratio at age, which it then uses to split the long-term catch into landings and discards (at age).

### Fix for zero weights

If there are a few zeros in the catch and stock weights and numbers that produces NaNs so this is a fix to fill them in with a low value.

```
load("L:/Data for ICESWG/2016/Benchmarks/WKIRISH/whgVIIa/Assessment/4_Outputs/whg7a_asap.Rdata")

stock@stock.n <- ifelse(stock@stock.n==0,0.000001,stock@stock.n)
stock@stock.wt <- ifelse(stock@stock.wt==0,0.000001,stock@stock.wt)
stock@catch.n <- ifelse(stock@catch.n==0,0.000001,stock@catch.n)
stock@catch.wt <- ifelse(stock@catch.wt==0,0.000001,stock@catch.wt)
stock@discards.n <- ifelse(stock@discards.n==0,0.000001,stock@discards.n)
stock@discards.wt <- ifelse(stock@discards.wt==0,0.000001,stock@discards.wt)
stock@landings.n <- ifelse(stock@landings.n==0,0.000001,stock@landings.n)
stock@landings.wt <- ifelse(stock@landings.wt==0,0.000001,stock@landings.wt)
```

### Stock Recruit summary

The first step in the process is to examine the stock and recruit pairs and decide on a Blim value. The default is approach is to choose the SSB value below which recruitment reduces with SSB, e.g. the change point of a segmented regression. However you should use the **technical guidelines document** to guide your expert decision.

In the case of Irish Sea Whiting there is clear evidence of impaired recruitment at stock sizes below 10,000t based on the S/R pairs from the assessment and that looks like and appropriate Blim. Various summary statistics on the SSB estimates are provided in Table 1.

```
# plotting SR relationship
ssb <-as.data.frame(ssb(stock))
ssb$var <- "SSB"
rec <-as.data.frame(rec(stock))
rec$var <- "Recruitment"
sr <- data.frame(year=ssb$year, SSB=ssb$data, Recruitment=rec$data)
ggplot(sr, aes(SSB, Recruitment)) + geom_point() +
        geom_text(aes(label=year), hjust=-0.1) + theme_bw() +
        xlim(0, max(sr$SSB)*1.05)
```

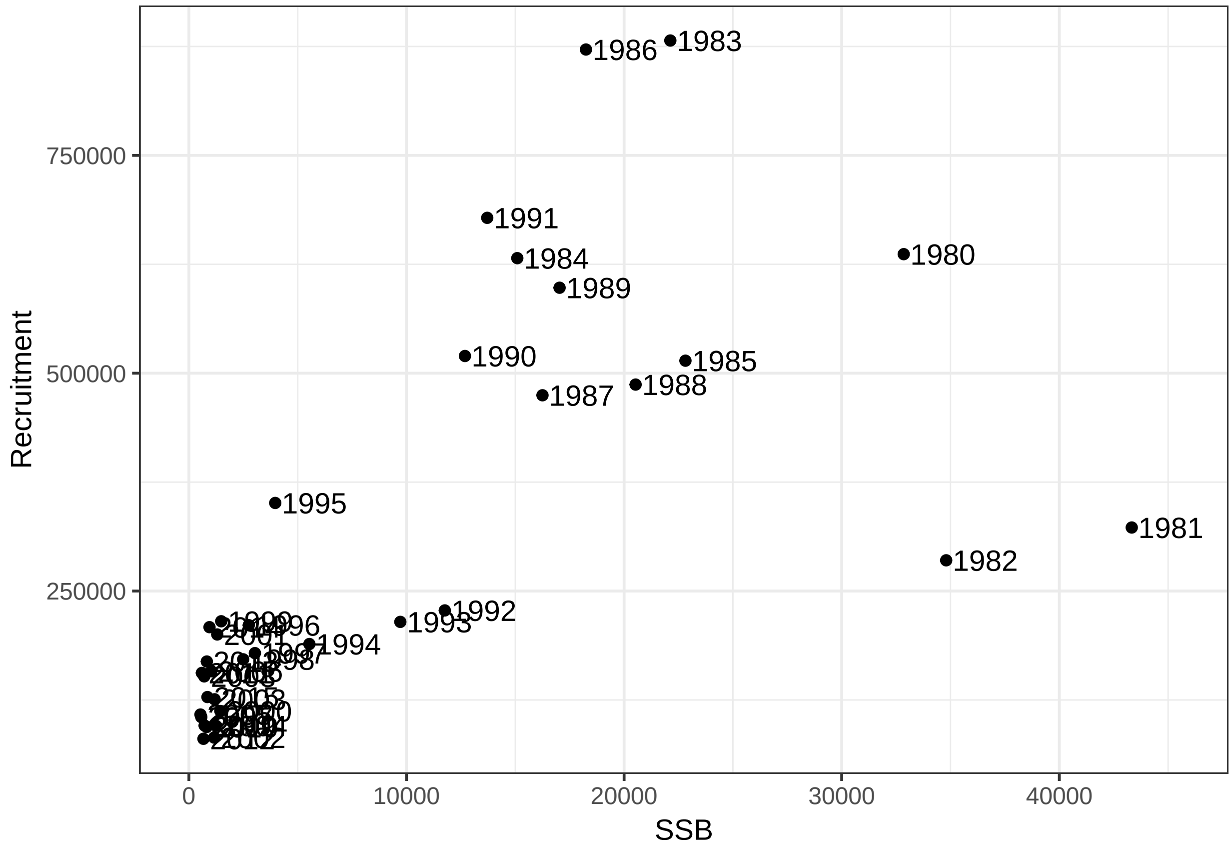



Figure 1: Stock and recruitment pairs for Irish Sea whiting by year.

```
stock.cur <- ssb$data[ssb$year==stock@range[5]]
stock.loss <- min(ssb$data)
stock.50 <- as.numeric(quantile(ssb$data,0.5))
stock.75 <- as.numeric(quantile(ssb$data,0.75))
stock.max <- max(ssb$data)
```

An example fit of a Beverton and Holt stock and recruitment model is shown in Figure 2 below. The functional form of the relationship is quite different to the fitted model but despite that the residuals by year show a reasonable fit. There is no indication of autocorrelation in residuals as the slope in panel 3 is pretty much horizontal. The clumped nature of the stock-recruit pairs with lots of recruitments observed at low stock size is particularly obvious in the residuals by SSB plot (panel 4). The Q-Q plot and the residuals by recruits look relatively good.

```
srbh <- fmle(as.FLSR(stock, model="bevholt"), method="L-BFGS-B", lower=c(1e-6, 1e-6), upper=c(max(rec(s
```

```
## iter   10 value -24.250382
## final  value -24.487859
## converged
```

```
plot(srbh)
```

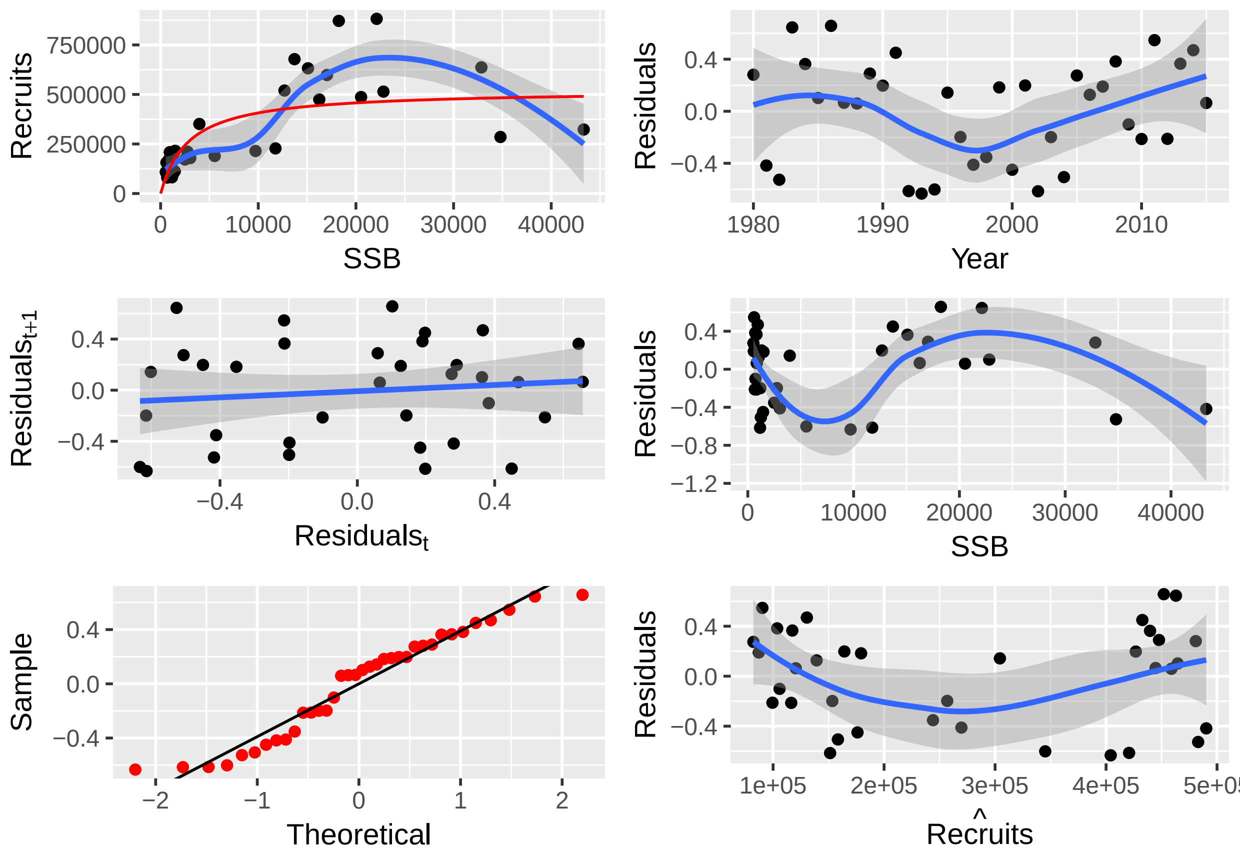



Figure 2: Example of fit with Beverton and Holt Stock and recruitment model. Panels: (1) stock-recruit data, fitted model in this case a Beverton and Holt and lowess smoother, (2) residuals by year, (3) lag 1-correlated residuals, (4) residuals by SSB, (5) residuals qqplot and (6) residuals by fitted values. Blue lines are loewess smoothers, to better visualize trends in the data shown.

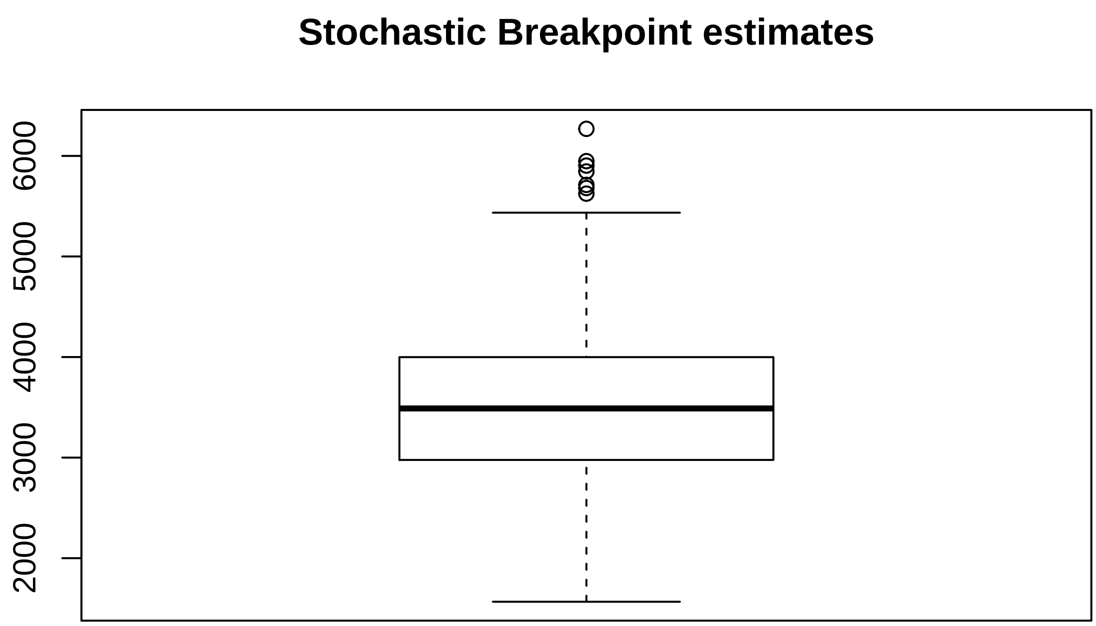
**Table 1. Summary of SSB values**

| SSB ref value | SSB Estimate |
|---|---|
| Terminal SSB | 852t |
| Min observed | 531t |
| 50th Percentile | 2622t |
| 75th Percentile | 15380t |
| Max observed | 43330t |

### Estimating the breakpoint stochastically

The msy package can be use to estimate the break-point stochastically. In the case of Irish Sea whiting the break-point is very low because there are many observations of low recruitment at low stock size and the estimated break-point is not considered a good candidate for Blim. Figure 3 below gives the estimates of the stochastic breakpoints.

```
fit <- eqsr_fit(stock, nsamp = 1000, models = "Segreg")
boxplot(fit$sr.sto$b.b, main="Stochastic Breakpoint estimates")
```




```
med.bp <- median(fit$sr.sto$b.b)
```

Figure 3: Box plot of break-point estimates for Irish Sea whiting.

The median estimate of the break-point is 3489t.

### Uncertainty parameters

In the ICES approach Bpa is the estimated SSB which ensures that the true SSB has less than 5% probability of being below Blim. In practice this requires an estimate of sigma, the standard deviation of ln(SSB) at the start of the year following the terminal year of the assessment.

In the absence of an estimate the default is 0.2.

In the case of the ASAP assessments you can take the Fcv and SSBcv from the final year of the assessment model.

```
Fcv <- 0.303757
SSBcv <- 0.297147
Blim <- 10000
Bpa <- round(Bpa(Blim, SSBcv)/100, 0)*100
Fphi <- 0.423
```

For Irish Sea whiting Blim is set at 10000 t and Bpa is estimated at 16300 t.

### Estimating Fmsy using multiple Stock and Recruit models

The base Eqsim analysis largely uses default settings for the input parameters: Selection pattern is the default 10 year range. Biological parameters is the default of 10 years (although this is something the WG should monitor as trends maybe developing) The scan sequence is fairly granular to have more consistent interpolations. The uncertainties are as specified above.

In the case of the Irish Sea whiting we have a priori ruled out the segmented regression alone as a S/R relationship. The software allows for uncertainty in the stock-recruitment model is taken into account by applying model averaging using smooth AIC weights (Buckland et al. 1997). Here we use the three standard model and also specify a segmented regression with a fixed break-point at Blim.

The fit of the mixed model to the observations looks good. The Beverton and Holt gets most of the weight. The two segmented regression options get no weight.

The issue here is that the F0.5 - the 5% probability of dropping below Blim is pretty much the same and Fmsy. This is potentially not a problem and F0.5 becomes the upper bound of the Fmsy range.

```
setup <- list(data = stock,
bio.years = c(2006, 2015),
bio.const = FALSE,
sel.years = c(2006, 2015),
sel.const = FALSE,
Fscan = seq(0, 1.5, by=0.025),
Fcv = Fcv, Fphi = Fphi,
Blim = Blim,
Btrigger = 0,
Bpa = Bpa(Blim, SSBcv),
extreme.trim=c(0.05,0.95)
)

FixedBlim<-function (ab, ssb)
{log(ifelse(ssb >= Blim, ab$a * Blim, ab$a * ssb))}

res <- within(setup,
{
fit <- eqsr_fit(data, nsamp = 1000, models =  c("Ricker", "Bevholt", "FixedBlim",
                                                "Segreg"))
sim <- eqsim_run(fit, bio.years = bio.years, bio.const = bio.const,
sel.years = sel.years, sel.const = sel.const, Fscan = Fscan,
Fcv = Fcv, Fphi = Fphi, Blim = Blim, Bpa = Bpa, Btrigger = Btrigger,
extreme.trim = extreme.trim, verbose = FALSE)
})
```

Fmsy is initially calculated as the F that maximizes median long-term yield in stochastic simulation under constant F exploitation (i.e. without MSY Btrigger). EqSim internally uses the landings and catch numbers at age provided in the FLStock object used as input to calculate a discard ratio at age, which it then uses to split the long-term catch into landings and discards (at age). The choice of yield is a choice for policy and, following discussions with clients, ICES defines yield to be catch above the minimum catch/conservation size. When the selection pattern corresponding to this cannot be estimated, ICES uses the recent landings selection to define yield. In the case of Irish Sea whithing where discarding accounts for more than 95% of the catch the logic of defining Fmsy based on the sparse landings at age data in recent years is open to question. Nevertheless we estimate Fmsy here according to the guidelines although there is a strong caveat that it is based on current retention practices and selection patterns which are not well estimated.

In figure 4 below we see that the median estimate if Fmsy is 0.22 which is expected to generate median landings of around 1600t. The Fmsy value is also very close to F(5%). Following the ICES procedure we need to calculate the Fpa because if Fmsy is greater than Fpa then we reduce Fmsy to Fpa.

```
eqsim_plot_range(res$sim, type="median")
```

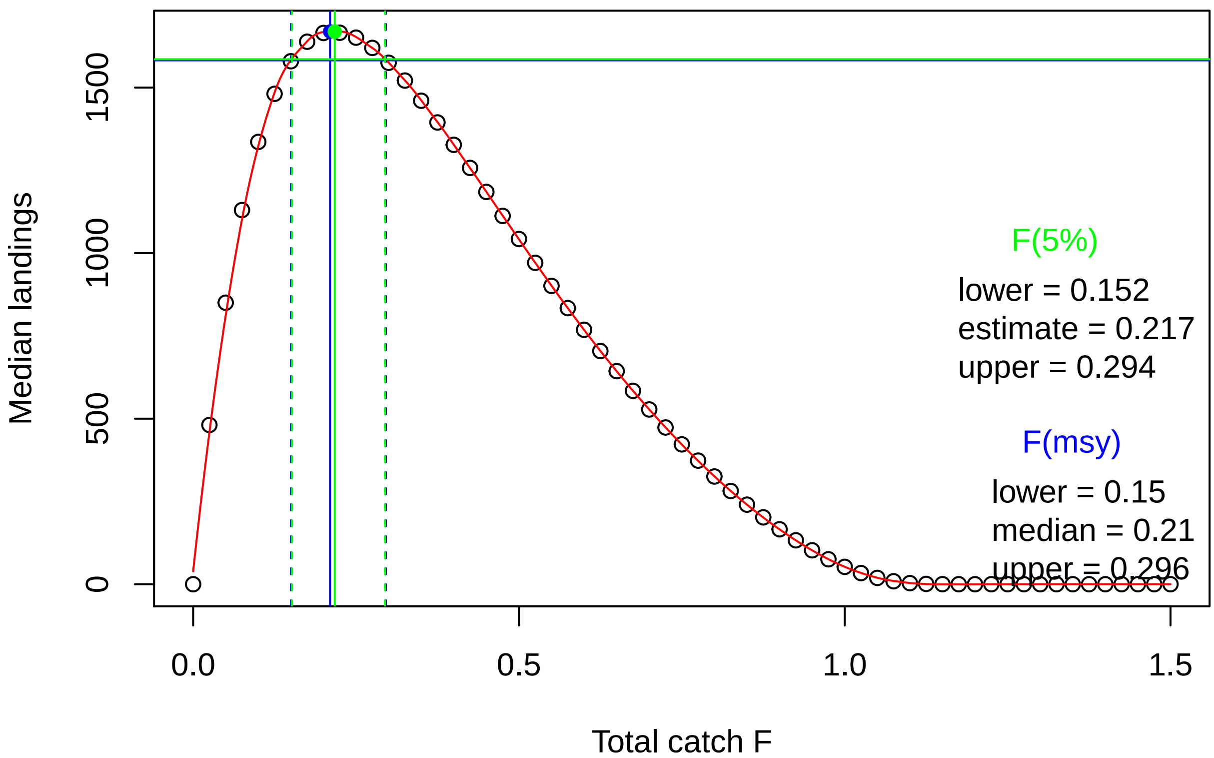



Figure 4: Yield curve and FMSY upper and lower ranges (vertical blue lines) and Flim upper and lower ranges (vertical green lines) for the mixed stock recruit model. Fmsy median point estimates and upper and lower bound are given (bottom right).

The Median SSB for the Fmsy range is shown in Figure 5 below. The value for median SSB corresponding to the lower and upper Fmsy bounds are also shown on the plot. For some reason the code returns an NA for the median SSB corresponding to the median Fmsy.

```
eqsim_plot_range(res$sim, type="ssb")
```

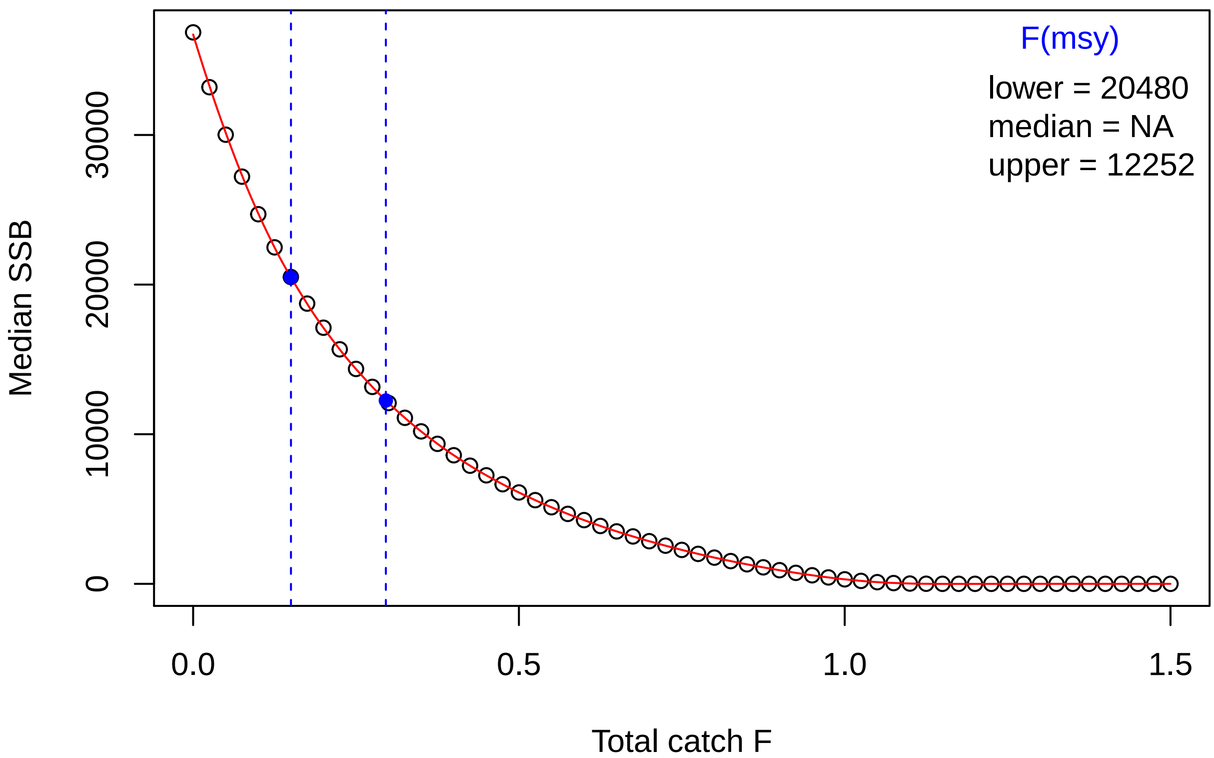



Figure 5: Median SSB curve over a range of target F values. Blue line correspond to the FMSY range.

Figure 6 shows the Eqsim summary of various recruitment models using the default "Buckland" method (Ricker, Beverton and Holt, segmented regression and fixed break-point). This plot indicates that the final SR model is driven by the Beverton and Holt and the two segmented regression options don't fit well to the data.

```
eqsr_plot(res$fit,ggPlot=FALSE)
```

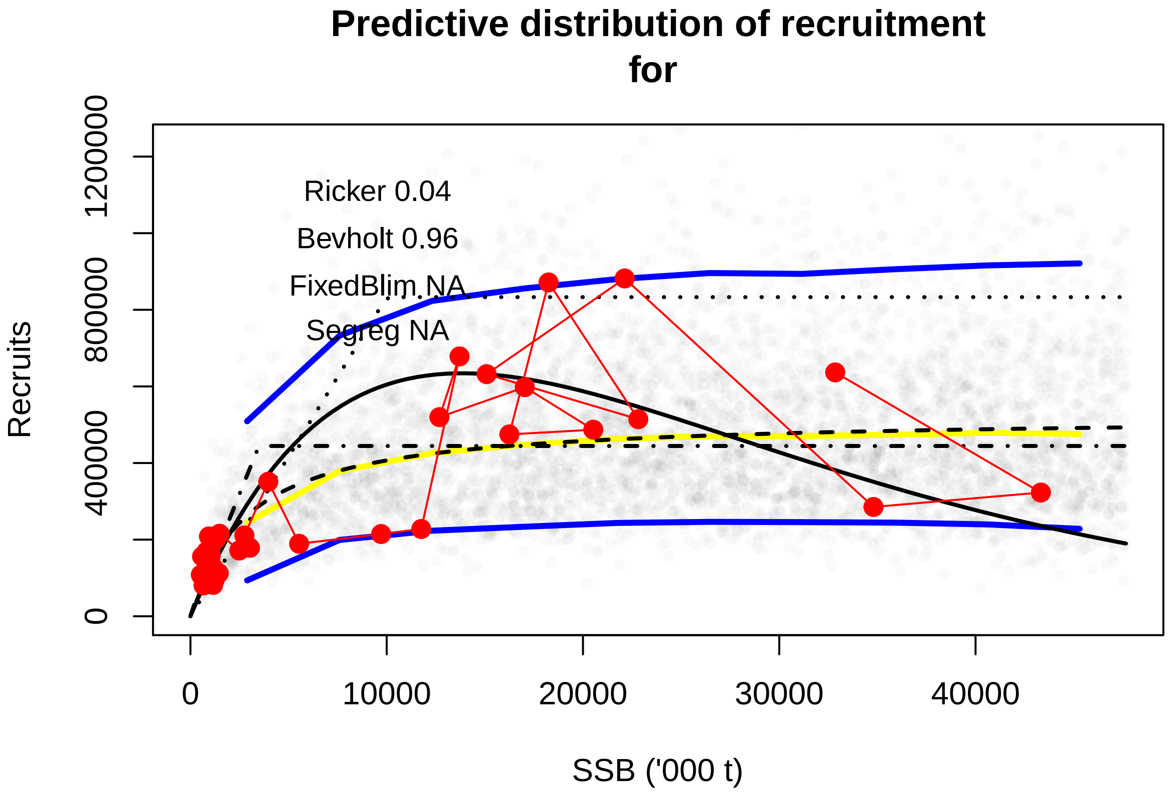



Figure 6: Eqsim summary of recruitment models using the default "Buckland" method (Ricker, Beverton and Holt and segmented regression). The final model is shown in yellow, the Ricker is shown as black, the Beverton an Holt is the black dashed line, estimated segmented regression is the black dash and dot line and the fixed break-point at 10,000t is the black dotted line. The various weights are also indicated on the plot.

The Eqsim summary plots in Figure 7b and c highlight the fact that F and catch in the past has been well above the sustainable ranges estimated. Figure 5d indicates that the risk to Blim overlaps with the Fmsy probability at a fairly low F values.

```
eqsim_plot(res$sim,  catch = TRUE)
```

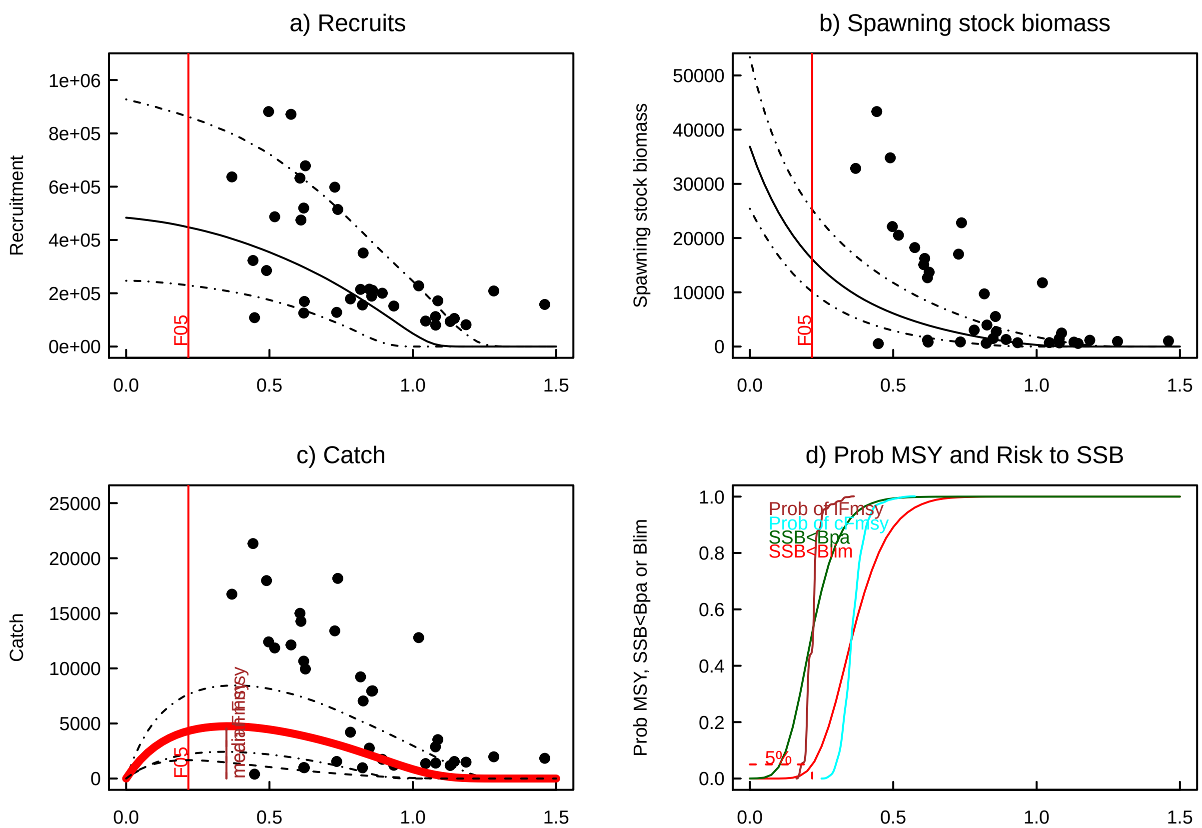



Figure 7: Eqsim summary plot. Panels a-c: historic values (dots) median (solid black) and 90% intervals (dotted black) recruitment, SSB and landings for exploitation at fixed values of F. Panel c also shows mean landings (red solid line). Panel d shows the probability of SSB less than Blim (red), SSB less than BPA (green) and the cumulative distribution of FMSY based on yield as landings (brown) and catch (cyan).

Carmen said The same output can be obtained from the slot refs_interval. In this case, the value to use is the one labelled FmsyMedianL, which should coincide with the one obtained in Refs2 (minor differences between both values could occur because the interpolation has been done differently for the 2 slots. but the differences should, if they exist at all, be very minor… otherwise it d be a signal that something is wrong in the EqSim code).

**Table 2. Output values from the Eqsim analysis.**

```
kable(t(res$sim$Refs2), digits=c(3,3,0,0,0,0))
```

| | catF | lanF | catch | landings | catB | lanB |
|---|---|---|---|---|---|---|
| F05 | 0.217 | NA | 4144 | NA | 16114 | NA |
| F10 | 0.243 | NA | 4300 | NA | 14706 | NA |
| F50 | 0.356 | NA | 4548 | NA | 9990 | NA |
| medianMSY | NA | 0.210 | NA | 1669 | NA | 16511 |
| meanMSY | 0.350 | 0.225 | 4550 | 1666 | 10189 | 15673 |
| Medlower | NA | 0.150 | NA | 1584 | NA | 20480 |
| Meanlower | NA | 0.152 | NA | 1709 | NA | NA |
| Medupper | NA | 0.296 | NA | 1584 | NA | 12252 |
| Meanupper | NA | 0.297 | NA | 1705 | NA | NA |

```r
refs <- round(t(res$sim$refs_interval), 3)
refs[c(5,4,6),]
```

```
## FmsylowerMedianL      FmsyMedianL FmsyupperMedianL
##            0.158            0.219            0.294
```

```r
fmsy <- refs[4,]
```

### No error run to estimate Flim and MSY Btrigger

Next Eqsim is run with no error to estimate Flim and the MSY Btrigger you would get from the analysis. There a a few different approaches to estimating the Flim point. Here we use a loess smoother to predict the F that has a 50% probability of bringing the stock to Blim. A similar approach is used to estimate the MSY Btrigger you would get from the analysis to test if this is higher than Bpa.

```r
setup <- list(data = stock,
bio.years = c(2006, 2015),
bio.const = FALSE,
sel.years = c(2006, 2015),
sel.const = FALSE,
Fscan = seq(0, 1.5, by=0.025),
Fcv = 0, Fphi = 0,
Blim = 10000,
Btrigger = 0,
Bpa = 16300,
extreme.trim=c(0.05,0.95)
)

res <- within(setup,
{
fit <- eqsr_fit(data, nsamp = 1000, models =  c("Ricker", "Bevholt", "FixedBlim",
                                                "Segreg"))
sim <- eqsim_run(fit, bio.years = bio.years, bio.const = bio.const,
sel.years = sel.years, sel.const = sel.const, Fscan = Fscan,
Fcv = Fcv, Fphi = Fphi, Blim = Blim, Bpa = Bpa, Btrigger = Btrigger,
extreme.trim = extreme.trim, verbose = FALSE)
})


data.95 <- res$sim$rbp
x.95 <- data.95[data.95$variable == "Spawning stock biomass", ]$Ftarget
b.95 <- data.95[data.95$variable == "Spawning stock biomass", ]$p50
#plot(b.95~x.95, ylab="SSB", xlab="F")
b.lm <- loess(x.95 ~ b.95, span = 0.3)
flim<- round(predict(b.lm, Blim), 3)
fpa<- round(Fpa(flim, Fcv),3)

###BTrigger
data.05 <- res$sim$rbp
x.05 <- data.05[data.05$variable == "Spawning stock biomass", ]$Ftarget
b.05 <- data.05[data.05$variable == "Spawning stock biomass", ]$p05
#plot(b.05~x.05, ylab="SSB", xlab="F")
b.lm <- loess(b.05 ~ x.05, span = 0.2)
msybtrig <- predict(b.lm, 0.5)
```

Running the code with no error gives an estimate of Flim = 0.371, and estimate of Fpa = 0.225, and MSY Btrigger of 4281t.

In this case the Fmsy estimate 0.219 very close to Fpa 0.225 so the lower of the two values should be used as fmsy.

```
fmsy <- ifelse(fmsy>fpa, fpa, fmsy)
```

### Evaluate the ICES MSY Advice Rule

The next step is to evaluate the ICES advice rune via the stochastic simulation with these values of FMSY and MSY Btrigger. If the Fmsy is less than the F5% in this run the the Fmsy stays the same if it is greater than Fmsy is reduced to F5%.

So EqSim is run again this time including the selected MSY Btrigger value and error.

```
setup <- list(data = stock,
bio.years = c(2006, 2015),
bio.const = FALSE,
sel.years = c(2006, 2015),
sel.const = FALSE,
Fscan = seq(0, 1.5, by=0.025),
Fcv = 0.303757, Fphi = 0.423, #in the absence of this use WKMSYREF4 defaults
                              #Fcv=0.212, Fphi=0.423
Blim = 10000,
Btrigger = 16300,
Bpa = 16300,
extreme.trim=c(0.05,0.95)
)


res <- within(setup,
{
fit <- eqsr_fit(data, nsamp = 1000, models = c("Ricker", "Bevholt", "FixedBlim",
                                                "Segreg"))
sim <- eqsim_run(fit, bio.years = bio.years, bio.const = bio.const,
sel.years = sel.years, sel.const = sel.const, Fscan = Fscan,
Fcv = Fcv, Fphi = Fphi, Blim = Blim, Bpa = Bpa,
extreme.trim = extreme.trim, verbose = FALSE)
})

knitr::kable(t(res$sim$Refs2), digits=c(2,2,0,0,0,0))
```

| | catF | lanF | catch | landings | catB | lanB |
|---|---|---|---|---|---|---|
| F05 | 0.22 | NA | 4114 | NA | 16246 | NA |
| F10 | 0.24 | NA | 4274 | NA | 14803 | NA |
| F50 | 0.36 | NA | 4537 | NA | 10010 | NA |
| medianMSY | NA | 0.23 | NA | 1672 | NA | 15628 |
| meanMSY | 0.35 | 0.22 | 4538 | 1670 | 10272 | 15733 |
| Medlower | NA | 0.15 | NA | 1590 | NA | 20181 |
| Meanlower | NA | 0.15 | NA | 1708 | NA | NA |
| Medupper | NA | 0.30 | NA | 1590 | NA | 12328 |
| Meanupper | NA | 0.30 | NA | 1704 | NA | NA |

```
refs <- round(t(res$sim$refs_interval), 3)
refs[c(5,4,6),]
```

```
## FmsylowerMedianL      FmsyMedianL FmsyupperMedianL
##            0.158            0.226            0.294
```

If the FMSY calculated above is less than the EqSim output Fp.05 (F that gives 5% probability of SSB less than Blim), then FMSY stays unchanged. In this case Fmsy = 0.219 is very close to the Fp.05 =0.226 but the lower of the two becomes the final choice of FMSY.

```
fmsy <- ifelse(fmsy>refs[4,], refs[4,], fmsy)
```

## Retrospective analysis

This code does a retrospective analysis. It takes a long time to run so only run it when you need to.

The objective of the retrospective analysis is to investigate how stable the Fmsy estimate has been over time using the same input data but with a moving window for biological data and selection. Because the approach is to optimise the Fmsy on landings and the F is partioned between landings and discards based on numbers in the catch it is useful to see that the Fmsy is relatively stable over time.

The Fmsy for Irish Sea whiting shows a slightly declining trend over time (Figure 8). The distribution Fmsy estimate look to be very skewed with median estimates close to or at the lower bound in some years. The range also seems to be narrower towards the end of the time serise.

```
out <- NULL
setup$Fscan <- seq(0, 1.5, by=0.05)
for(y in 2006:2015){
  setup$bio.years <- c(y-10,y)
  setup$sel.years <- c(y-10,y)
  fit <- eqsr_fit(trim(setup$data, year=stock@range[4]:y), nsamp=1000,
                  models=c("Ricker", "Segreg", "Bevholt", "FixedBlim"))
  sim <- with(setup, eqsim_run(fit, bio.years = bio.years, bio.const = bio.const,
  sel.years = sel.years, sel.const = sel.const, Fscan = Fscan,
  Fcv = Fcv, Fphi = Fphi, Blim = Blim, Bpa = Bpa,
  extreme.trim = extreme.trim, verbose = FALSE))

  out0 <- data.frame(y,
          Fmsy05 = with(subset(sim$p,variable=='pFmsyLandings'),
                        Ftarget[which.min(abs(value-0.05))]),
          Fmsy95 = with(subset(sim$p,variable=='pFmsyLandings'),
                        Ftarget[which.min(abs(value-0.95))]),
          FmsyMed = sim$Refs2[2,4],
          FmsyMean = sim$Refs2[2,5]
  )
  out <- rbind(out,out0)
}

write.csv(out,
    "L:/Data for ICESWG/2016/Benchmarks/WKIRISH/whgVIIa/Assessment/4_Outputs/out.csv",
    row.names = FALSE)
```

```
out <- read.csv("L:/Data for ICESWG/2016/Benchmarks/WKIRISH/whgVIIa/Assessment/4_Outputs/out.csv")

  par(mar=c(4.5,4,.5,.5))
```

```
plot(out$y,out$FmsyMed,type='b',ylim=c(0,0.7),xlab='Year', ylab='Fmsy')
lines(out$y,out$Fmsy05-out$FmsyMed+out$FmsyMean,lty=3)
lines(out$y,out$Fmsy95-out$FmsyMed+out$FmsyMean,lty=3)
legend('bottomright',c('FmsyMedian','5% and 95%'),lty=c(1,3),pch=c(1,NA),bty='n',inset=0.02)
```

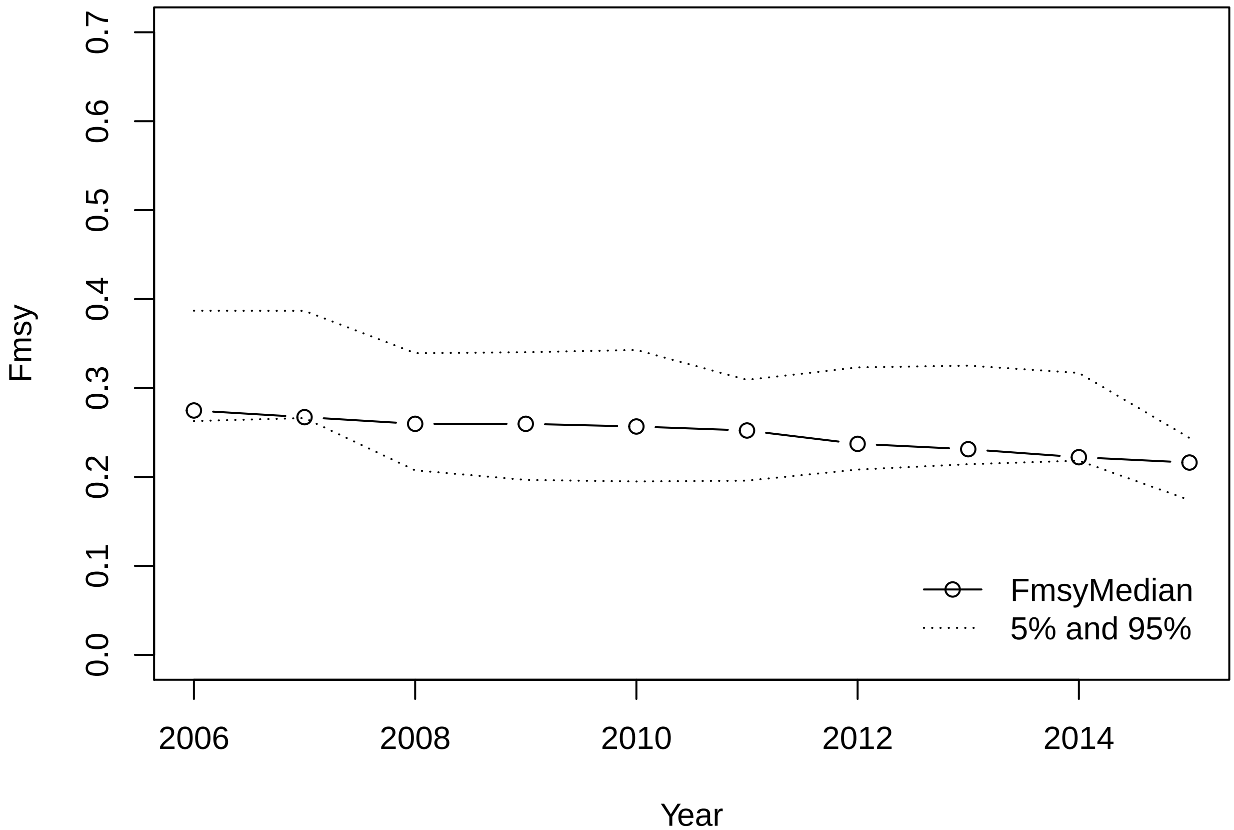



Figure 8: Retrospective analysis using a 10 year moving window of biological parameters and selection to estimate Fmsy and the 95% confidence intervals (broken lines).

**Table 2. Summary of reference ploints**

| Reference point | Value | Technical basis |
|---|---|---|
| MSY Btrigger | 16300 t | Bpa |
| FMSY | 0.22 | Median point estimates of EqSim with combined SR |
| Blim | 10000 t | Below 10,000 t recruitment is impaired |
| Bpa | 16300 t | Blim combined with the assessment error |
| Flim | 0.37 | F with 50% probability of SSB less than Blim |
| Fpa | 0.22 | Flim combined with the assessment error |

```
rps <- FLPar(Catch=NA, Rec=NA, SSB=Blim, Harvest=fmsy)
rps2 <- FLPar(Catch=NA, Rec=NA, SSB=16000, Harvest=0.4)
plot(stock, rps) + theme_bw()
```

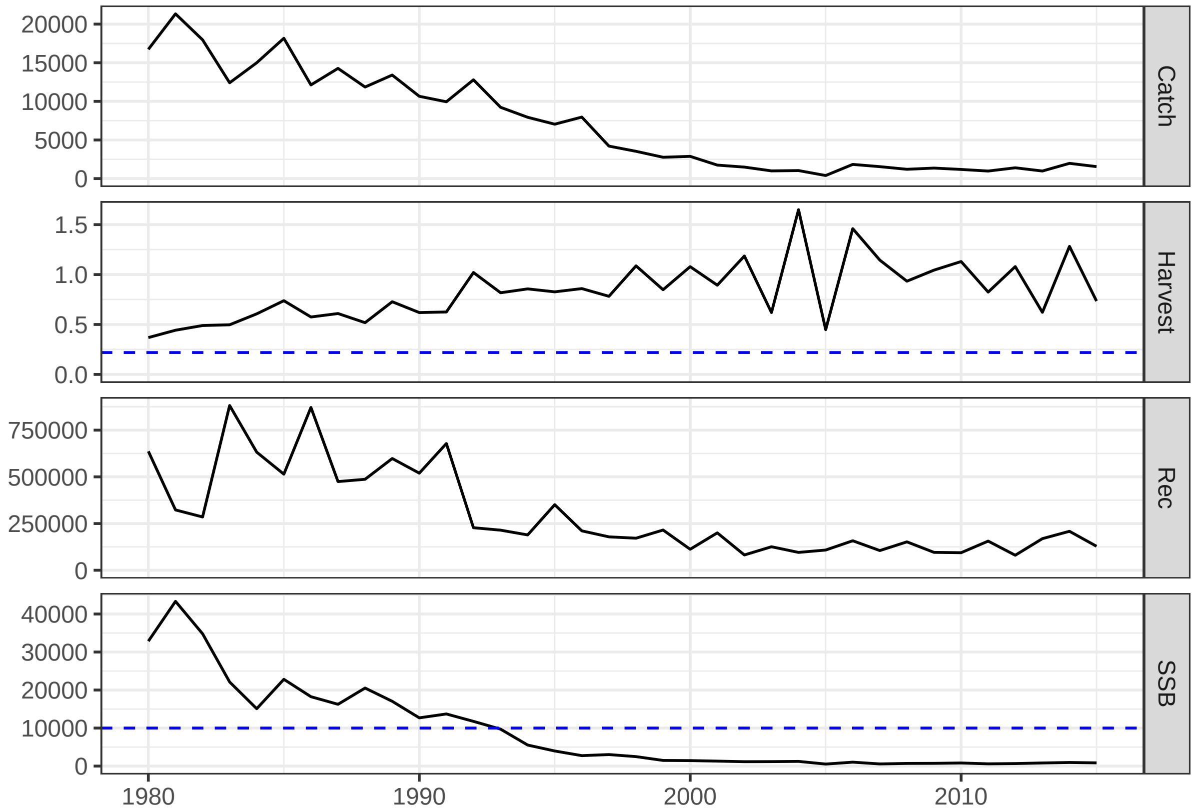



Figure 9: Stock summary plot with Blim and Fmsy shown as blue lines.

### Session information

```r
sessionInfo()
```

```
## R version 3.3.2 (2016-10-31)
## Platform: i386-w64-mingw32/i386 (32-bit)
## Running under: Windows Server 2008 R2 x64 (build 7601) Service Pack 1
##
## locale:
## [1] LC_COLLATE=English_Ireland.1252  LC_CTYPE=English_Ireland.1252
## [3] LC_MONETARY=English_Ireland.1252 LC_NUMERIC=C
## [5] LC_TIME=English_Ireland.1252
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
## [1] knitr_1.15.1          icesAdvice_1.2-0      msy_0.1.18
## [4] ggplotFL_2.5.9.9000   FLCore_2.6.0.20170214 lattice_0.20-34
## [7] MASS_7.3-45           ggplot2_2.2.1
##
## loaded via a namespace (and not attached):
##  [1] Rcpp_0.12.9      magrittr_1.5     munsell_0.4.3    colorspace_1.3-2
##  [5] highr_0.6        stringr_1.1.0    plyr_1.8.4       tools_3.3.2
```

```
##  [9] grid_3.3.2       gtable_0.2.0     htmltools_0.3.5  yaml_2.1.14
## [13] lazyeval_0.2.0   rprojroot_1.2    digest_0.6.12    assertthat_0.1
## [17] tibble_1.2       Matrix_1.2-7.1   gridExtra_2.2.1  reshape2_1.4.2
## [21] evaluate_0.10    rmarkdown_1.3    labeling_0.3     stringi_1.1.2
## [25] scales_0.4.1     backports_1.0.5  stats4_3.3.2
```

# Annex 8: Cod reference points

# Cod 7a MSY evaluations

*WKIrish3*

*Sys.date()*

### R Markdown To Look at various eqsim runs

First load librarys and data.

```
library(FLCore)
```

```
## Warning: package 'FLCore' was built under R version 3.3.2
```

```
library(msy)
library(dplyr)
```

```
## Warning: package 'dplyr' was built under R version 3.3.2
```

```
library(icesAdvice)
```

```
## Warning: package 'icesAdvice' was built under R version 3.3.2
```

```
#setwd("C:/Users/User1/Documents/")
load("~/Cod7a_asap.Rdata")
```

## SR summary

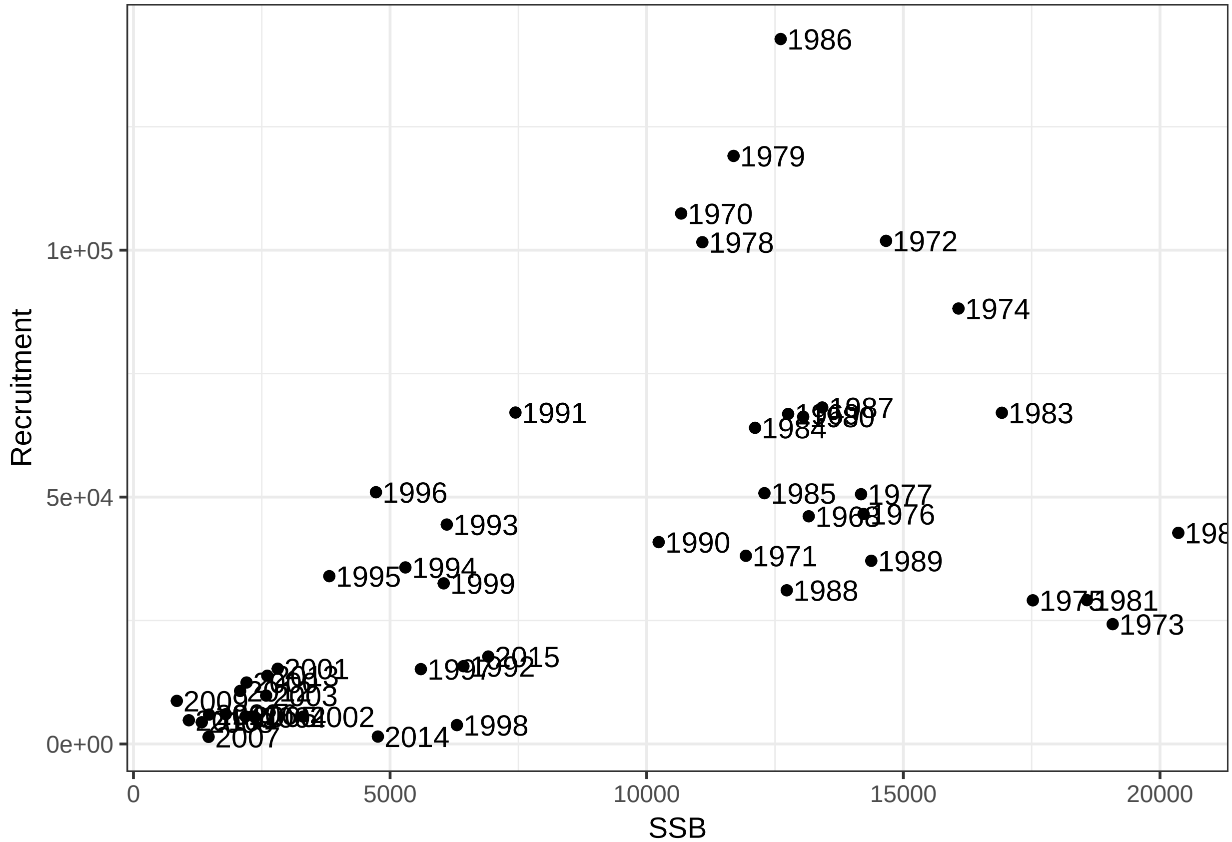



Table 1. Summary of values for SSB

| SSB ref value | SSB Estimate |
|---|---|
| Terminal SSB | 6913t |
| Min observed | 845t |
| 50th Percentile | 7178t |
| 75th Percentile | 13076t |
| Max observed | 20357t |

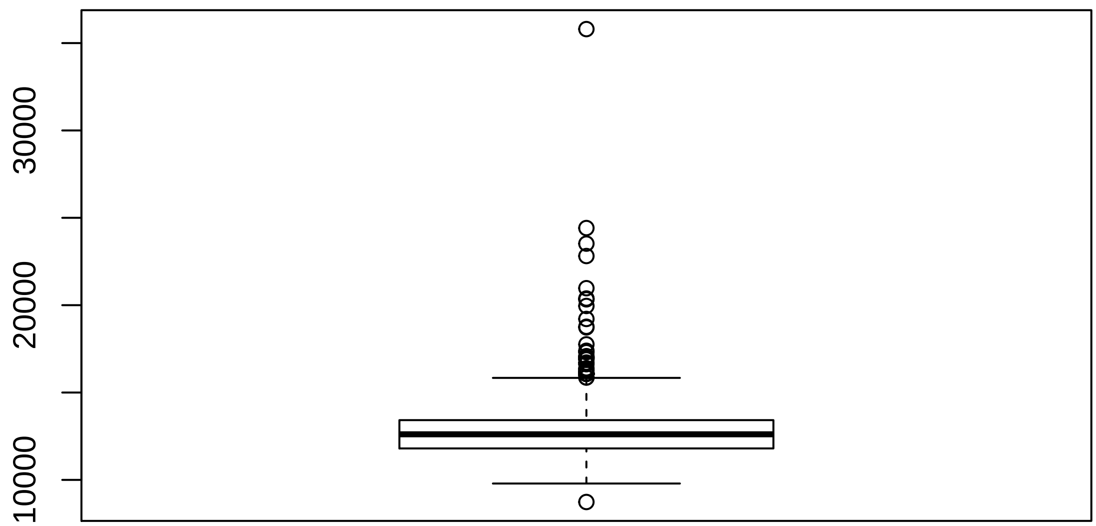
There have been several TCMs introduced and changes in mesh size for some fleets over time.

## fix for zero weights

```
stock@catch.n <- ifelse(stock@catch.n==0,0.001,stock@catch.n)
stock@catch.wt <- ifelse(stock@catch.wt==0,0.001,stock@catch.wt)
stock@discards.n <- ifelse(stock@discards.n==0,0.001,stock@discards.n)
stock@landings.n <- ifelse(stock@landings.n==0,0.001,stock@landings.n)
stock@landings.wt <- ifelse(stock@landings.wt==0,0.001,stock@landings.wt)
stock@discards.wt <- ifelse(stock@discards.wt==0,0.001,stock@discards.wt)
stock@discards<-stock@catch-stock@landings
```

Stock recruitment fitted by 'segmented regression'

```r
fit <- eqsr_fit(stock, nsamp = 1000, models = "Segreg")
boxplot(fit$sr.sto$b.b)
```




```r
median(fit$sr.sto$b.b)
```

```
## [1] 12609.55
```

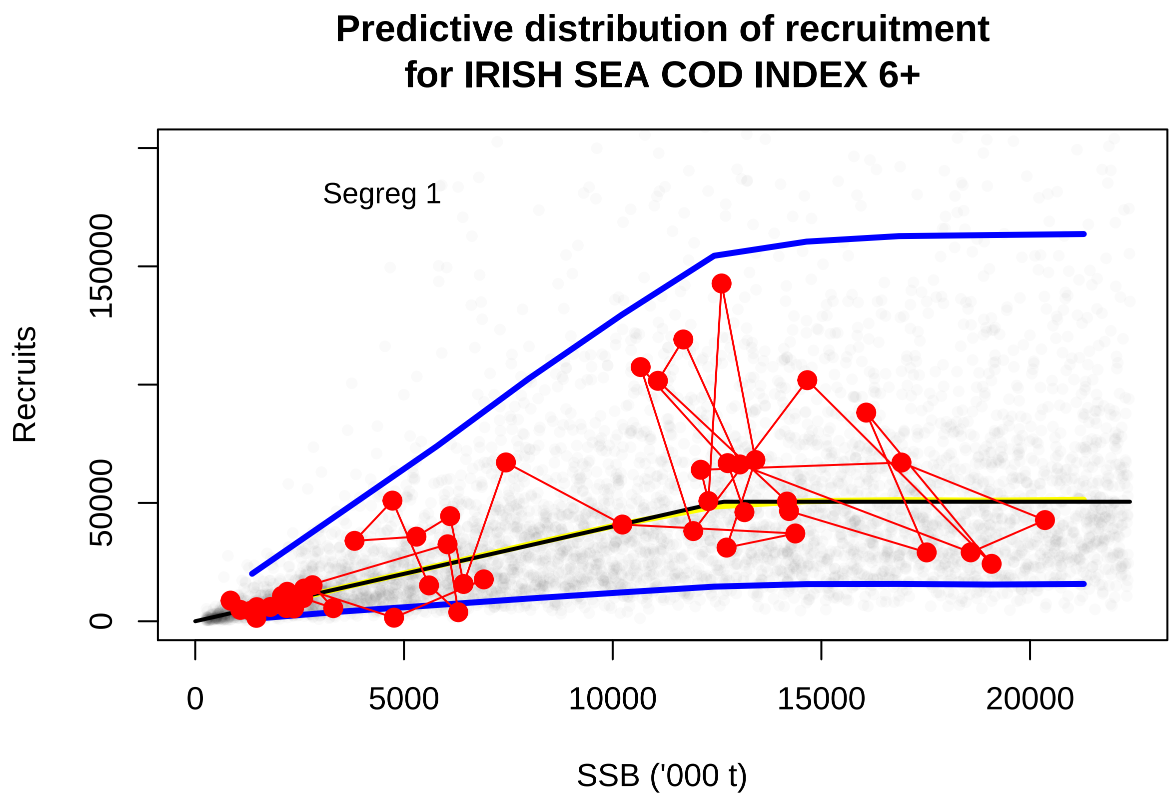
```r
Blim <- median(fit$sr.sto$b.b)
median(ssb(stock))
```

```
## [1] 7178.078
```

```r
Bpa(Blim, SSBcv)
```

```
## [1] 17521.95
```

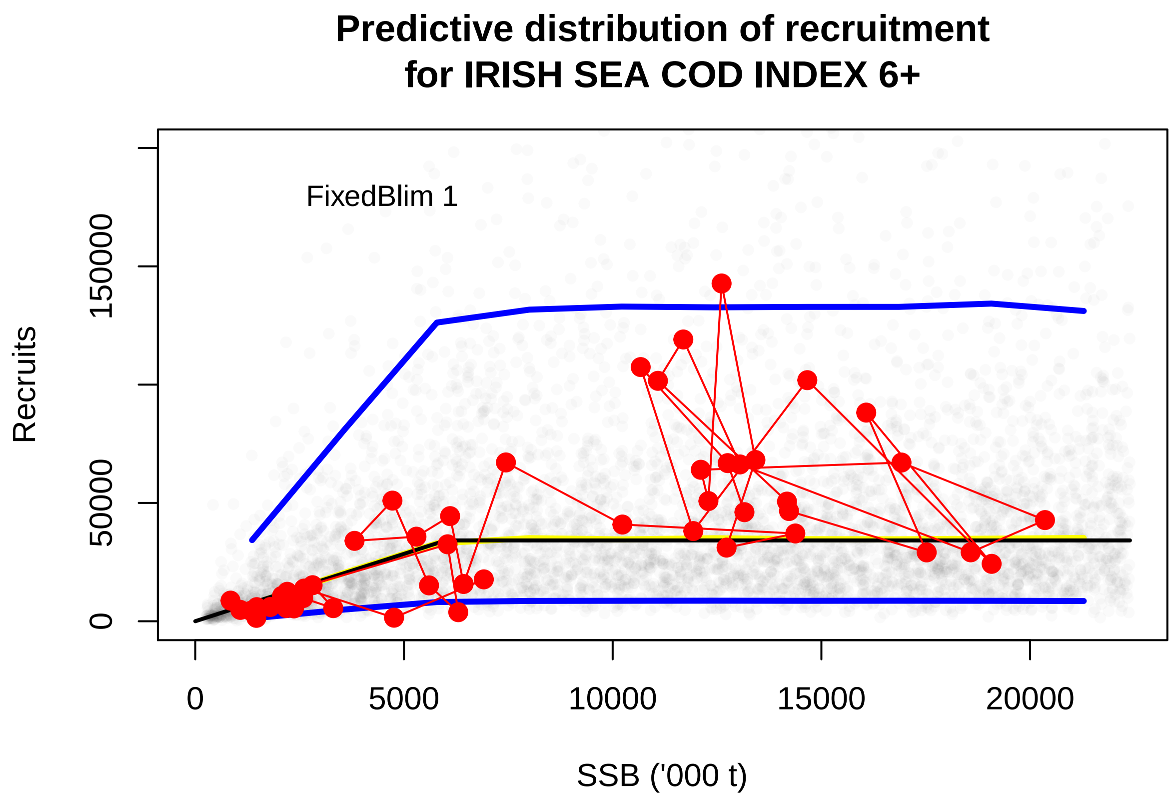
```r
eqsr_plot(fit,ggPlot=FALSE)
```




Stock-recruitment comparrison of segmented regression, Ricker and Beverton-Holt

Stock-recruitment comparison of 'fixed' segmented regression

```
SetBlim<- 6000
FixedBlim<-function (ab, ssb)
{log(ifelse(ssb >= SetBlim, ab$a * SetBlim, ab$a * ssb))}
fit <- eqsr_fit(stock, nsamp = 1000, models = "FixedBlim")
eqsr_plot(fit, ggPlot = FALSE)
```



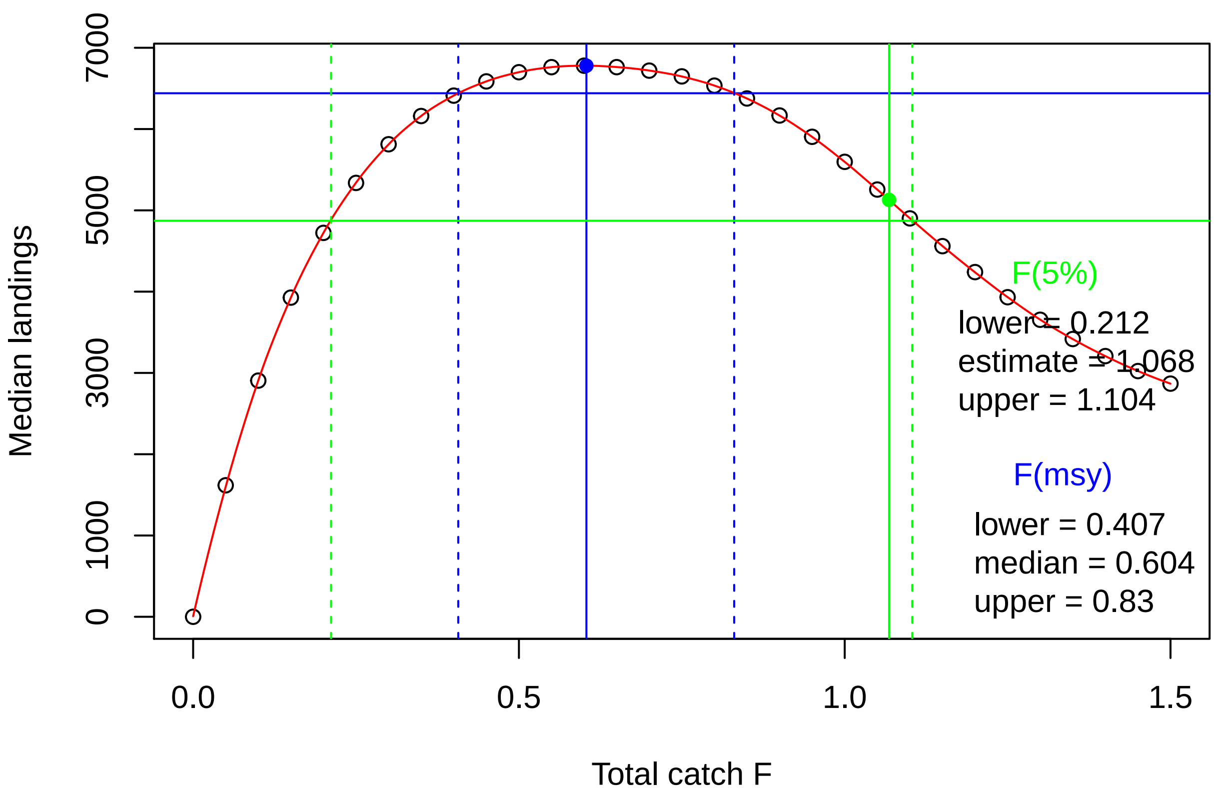

MSY reference points with Blim set at 6000 using SR estimated by segreg

```
Blim<-6000

Fcv <- 0.15
SSBcv <- 0.2
setup <- list(data = stock,
bio.years = c(2006, 2015),
bio.const = FALSE,
sel.years = c(2006, 2015),
sel.const = FALSE,
Fscan = seq(0,1.5,by=0.05),
Fcv = Fcv, Fphi = 0.423,
Blim = Blim,
Btrigger = Bpa(Blim, SSBcv),
Bpa = Bpa(Blim, SSBcv),
extreme.trim=c(0.05,0.95)
)

res <- within(setup,
{
fit <- eqsr_fit(stock, nsamp = 1000, models = "Segreg")
sim <- eqsim_run(fit, bio.years = bio.years, bio.const = bio.const,
sel.years = sel.years, sel.const = sel.const, Fscan = Fscan,
Fcv = Fcv, Fphi = Fphi, Blim = Blim, Bpa = Bpa, Btrigger = Btrigger,
extreme.trim = extreme.trim, verbose = FALSE)
})
```

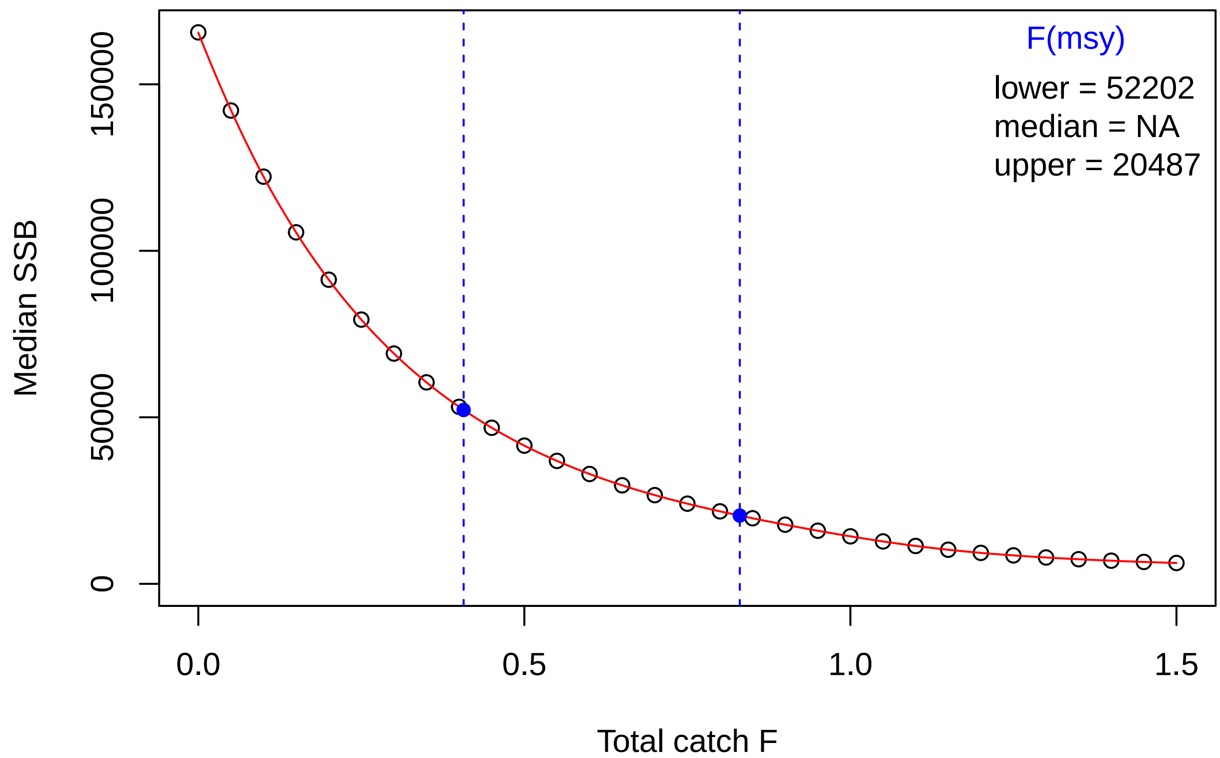
```
knitr::kable(t(res$sim$Refs2), digits=c(2,2,0,0,0,0))
```

| | catF | lanF | catch | landings | catB | lanB |
|---|---|---|---|---|---|---|
| F05 | 1.07 | NA | 8105 | NA | 12239 | NA |
| F10 | 1.14 | NA | 7425 | NA | 10382 | NA |
| F50 | NA | NA | NA | NA | NA | NA |
| medianMSY | NA | 0.60 | NA | 6780 | NA | 32717 |
| meanMSY | 0.75 | 0.60 | 9686 | 6780 | 24071 | 32983 |
| Medlower | NA | 0.41 | NA | 6441 | NA | 52202 |
| Meanlower | NA | 0.42 | NA | 6910 | NA | NA |
| Medupper | NA | 0.83 | NA | 6444 | NA | 20487 |
| Meanupper | NA | 0.85 | NA | 6909 | NA | NA |

```
eqsim_plot_range(res$sim, type="median")
```




```
eqsim_plot_range(res$sim, type="ssb")
```




```
#eqsr_plot(res$fit,ggPlot=FALSE)

#eqsim_plot2(res$sim, ymax.multiplier = 1.1, catch = FALSE) # note I modify the eqsim_plot function
```

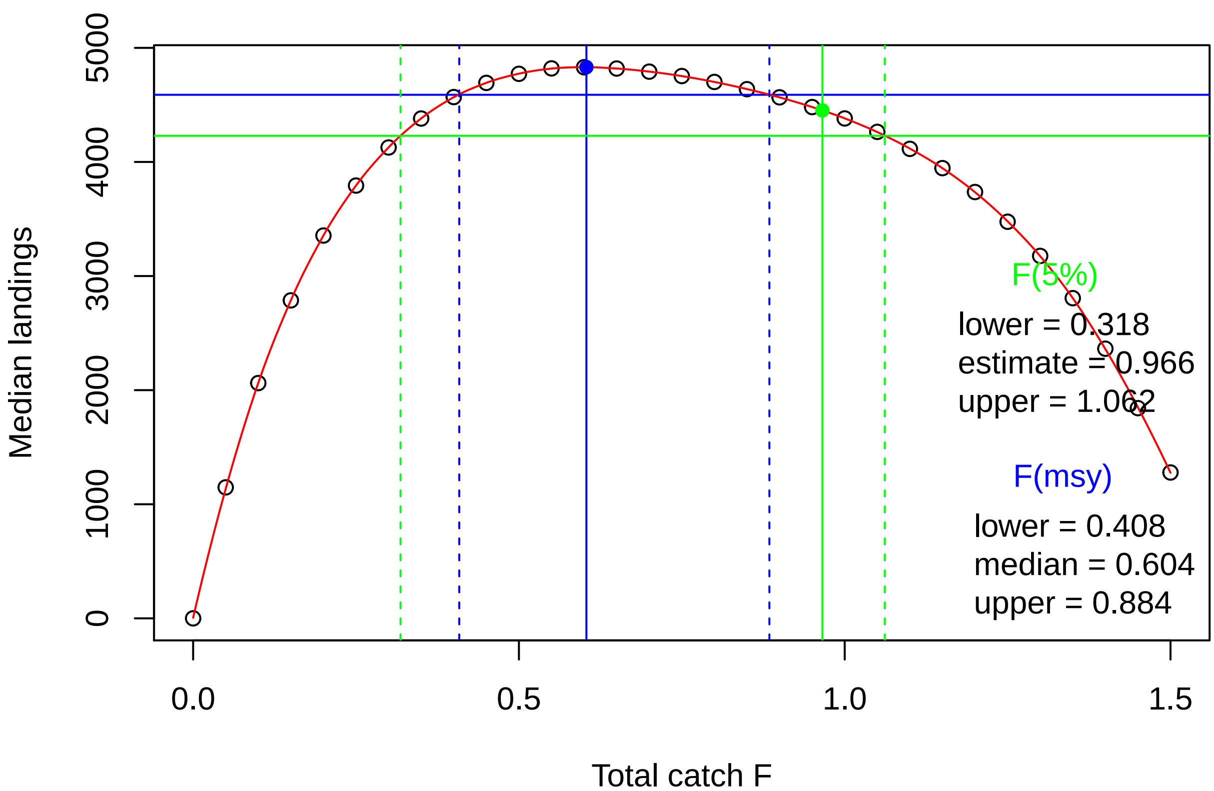
No error run to estimate Flim and MSY Btrigger with fixed Blim from SegReg For the record we run Eqsim with no error to estimate Flim and the MSY Btrigger you would get from the analysis to test if this is higher than Bpa.

```
setup <- list(data = stock,
bio.years = c(2006, 2015),
bio.const = FALSE,
sel.years = c(2006, 2015),
sel.const = FALSE,
Fscan = seq(0,1.5,by=0.05),
Fcv = 0.0, Fphi = 0.0,
Blim = Blim,
Btrigger = Bpa(Blim, SSBcv),
Bpa = Bpa(Blim, SSBcv),
extreme.trim=c(0.05,0.95)
)


res <- within(setup,
{
fit <- eqsr_fit(data, nsamp = 1000, models = "FixedBlim")
sim <- eqsim_run(fit, bio.years = bio.years, bio.const = bio.const,
sel.years = sel.years, sel.const = sel.const, Fscan = Fscan,
```

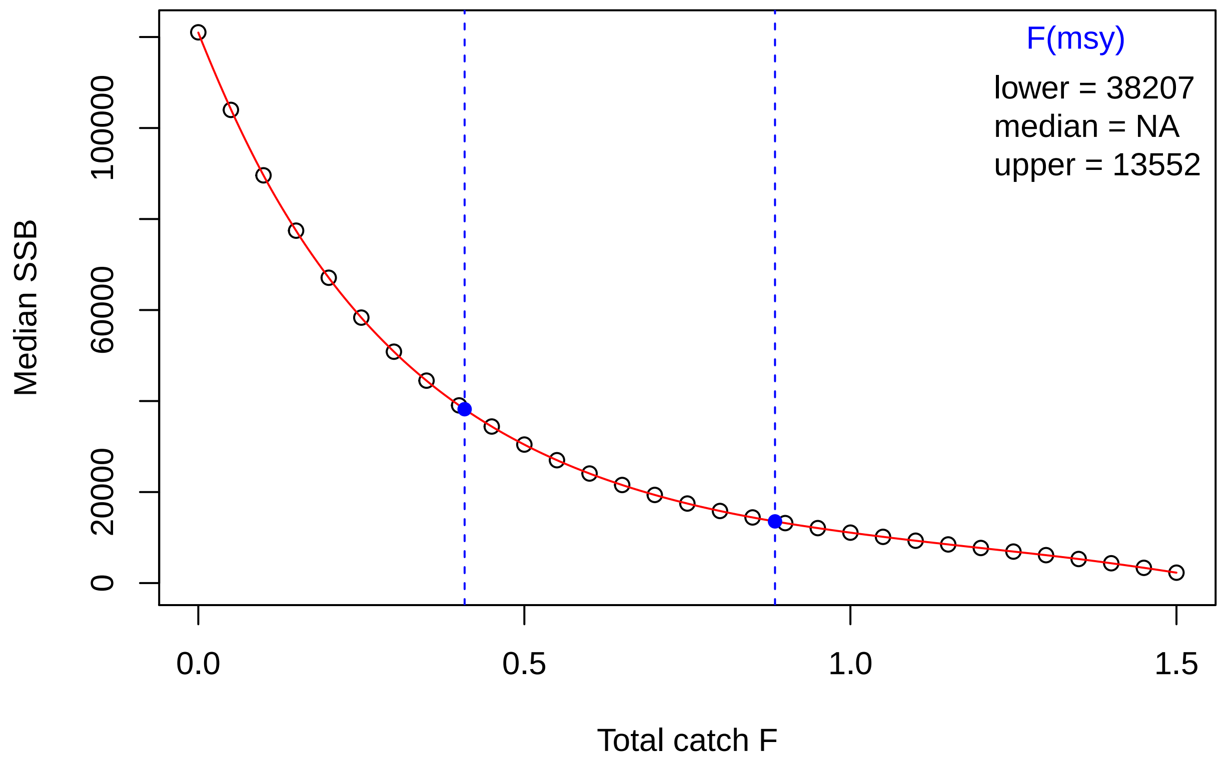
```
Fcv = Fcv, Fphi = Fphi, Blim = Blim, Bpa = Bpa,
extreme.trim = extreme.trim, verbose = FALSE)
})

knitr::kable(t(res$sim$Refs2), digits=c(2,2,0,0,0,0))
```

| | catF | lanF | catch | landings | catB | lanB |
|---|---|---|---|---|---|---|
| F05 | 0.97 | NA | 6892 | NA | 11765 | NA |
| F10 | 1.03 | NA | 6775 | NA | 10482 | NA |
| F50 | 1.31 | NA | 5376 | NA | 5997 | NA |
| medianMSY | NA | 0.60 | NA | 4831 | NA | 23876 |
| meanMSY | 0.80 | 0.60 | 7025 | 4830 | 15842 | 24074 |
| Medlower | NA | 0.41 | NA | 4593 | NA | 38207 |
| Meanlower | NA | 0.42 | NA | 5032 | NA | NA |
| Medupper | NA | 0.88 | NA | 4590 | NA | 13552 |
| Meanupper | NA | 0.92 | NA | 5031 | NA | NA |

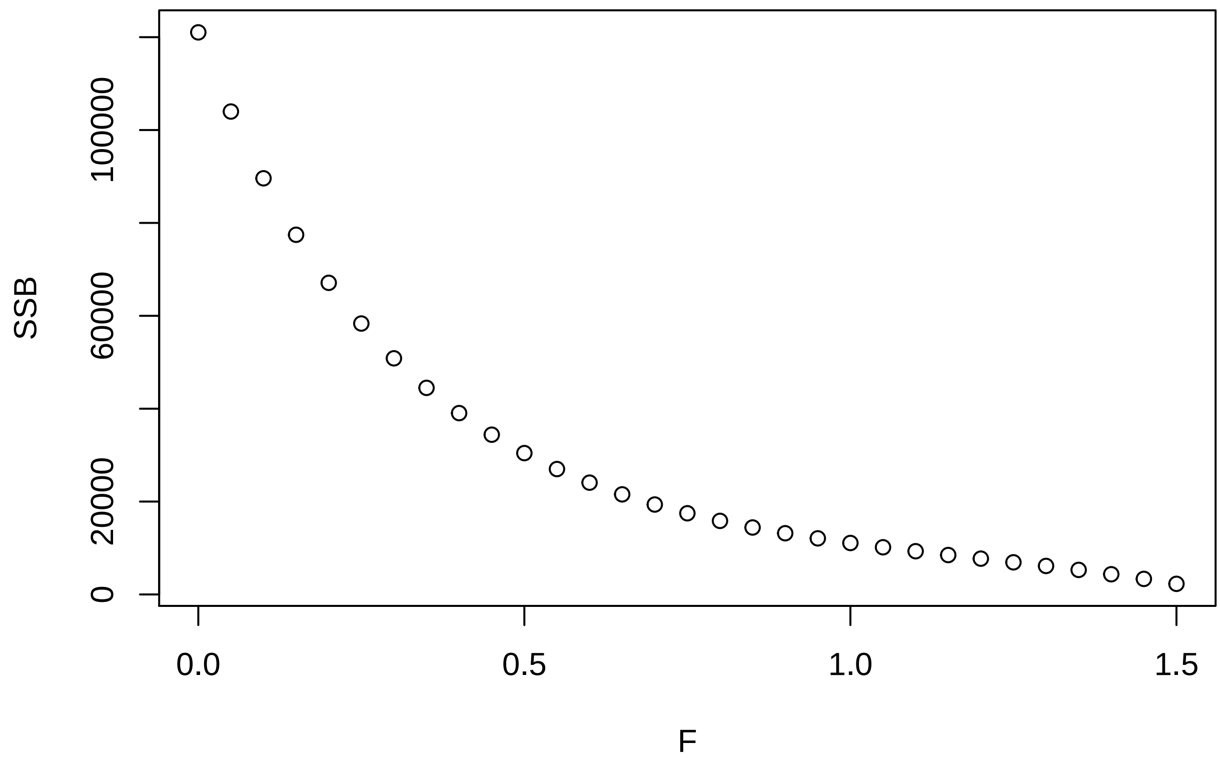
```
eqsim_plot_range(res$sim, type="median")
```




```
eqsim_plot_range(res$sim, type="ssb")
```



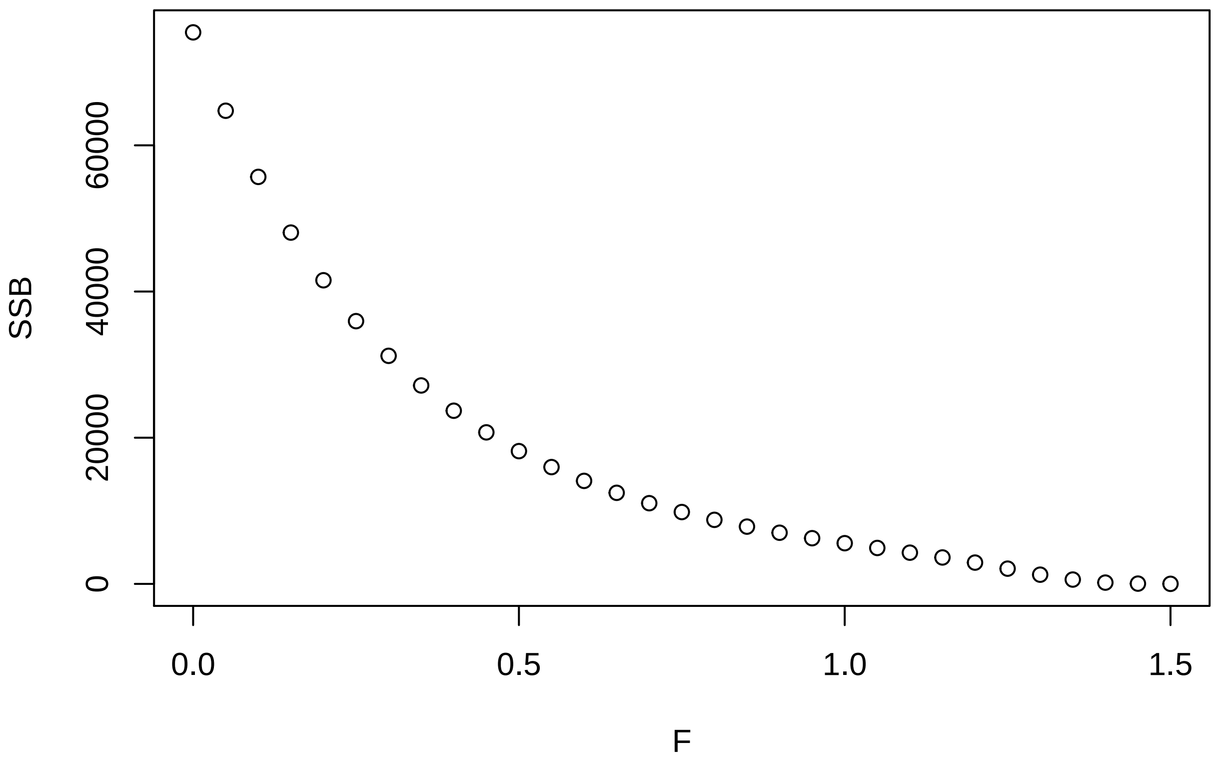

```
# eqsr_plot(res$fit,ggPlot=FALSE)
# eqsim_plot(res$sim, catch = FALSE)

data.95 <- res$sim$rbp
x.95 <- data.95[data.95$variable == "Spawning stock biomass", ]$Ftarget
b.95 <- data.95[data.95$variable == "Spawning stock biomass", ]$p50
plot(b.95~x.95, ylab="SSB", xlab="F")
```




```
b.lm <- loess(x.95 ~ b.95, span = 0.3)
(flim<- predict(b.lm, Blim))
```

```
## [1] 1.307203
```

```
###BTrigger
data.05 <- res$sim$rbp
x.05 <- data.05[data.05$variable == "Spawning stock biomass", ]$Ftarget
b.05 <- data.05[data.05$variable == "Spawning stock biomass", ]$p05
plot(b.05~x.05, ylab="SSB", xlab="F")
```




```
b.lm <- loess(b.05 ~ x.05, span = 0.2)
msybtrig <- predict(b.lm, 0.5)
```

Running the code with no error gives an estimate of Flim = 1.31 and MSY Btrigger of 18167t.

# Annex 9: Haddock reference points

# Haddock 7a MSY evaluations

*WKIrish3*

*16 February 2017*

## R Markdown To Look at various eqsim runs

First load librarys and data.

```
library(FLCore)
library(msy)
library(dplyr)
library(icesAdvice)
load("C:\\Users\\Matt Lundy\\Desktop\\HaddockBenchmark\\Outputs\\had7aso.Rdata")
```

## SR summary

Next set some parameters

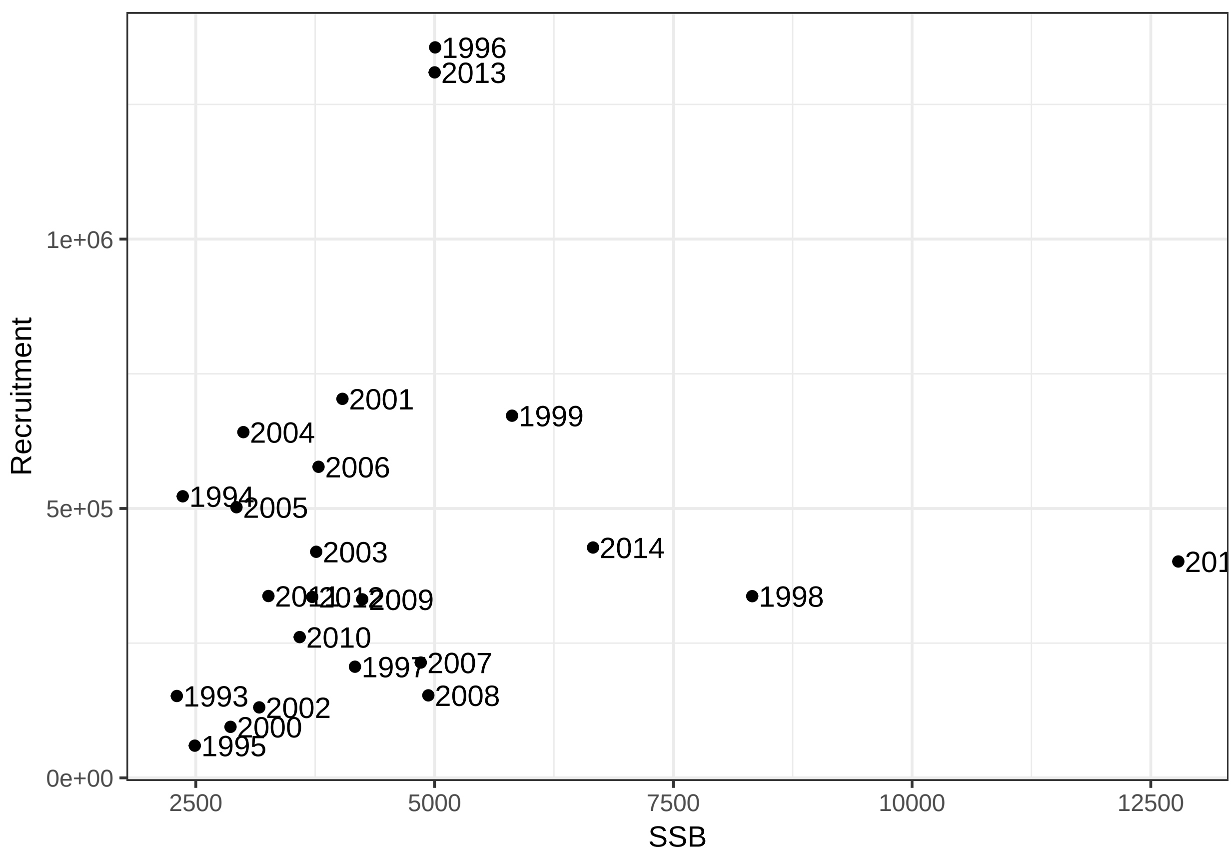



Table 1. Summary of values for SSB

| SSB ref value | SSB Estimate |
|---|---|
| Terminal SSB | 12788t |

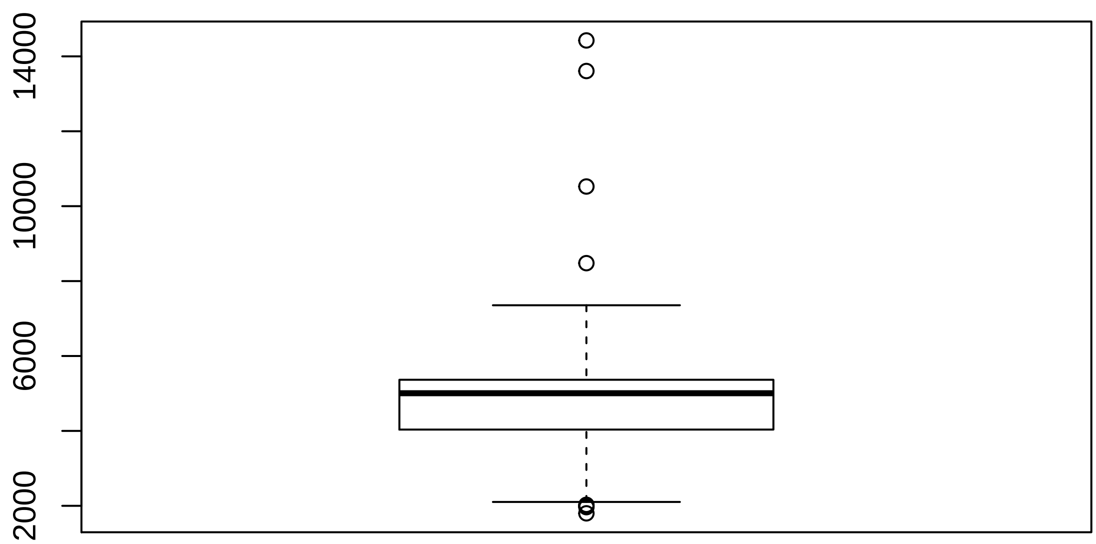
| SSB ref value | SSB Estimate |
|---|---|
| Min observed | 2301t |
| 50th Percentile | 3785t |
| 75th Percentile | 4968t |
| Max observed | 12788t |

There have been several TCMs introduced and changes in mesh size for some fleets over time.

## fix for zero weights

```
stock@catch.n <- ifelse(stock@catch.n==0,0.001,stock@catch.n)
stock@catch.wt <- ifelse(stock@catch.wt==0,0.001,stock@catch.wt)
stock@discards.n <- ifelse(stock@discards.n==0,0.001,stock@discards.n)
stock@landings.n <- ifelse(stock@landings.n==0,0.001,stock@landings.n)
stock@landings.wt <- ifelse(stock@landings.wt==0,0.001,stock@landings.wt)
stock@discards.wt <- ifelse(stock@discards.wt==0,0.001,stock@discards.wt)
```

```
fit <- eqsr_fit(stock, nsamp = 1000, models = "Segreg")
boxplot(fit$sr.sto$b.b)
```




```
median(fit$sr.sto$b.b)
```

```
## [1] 5006.099
```

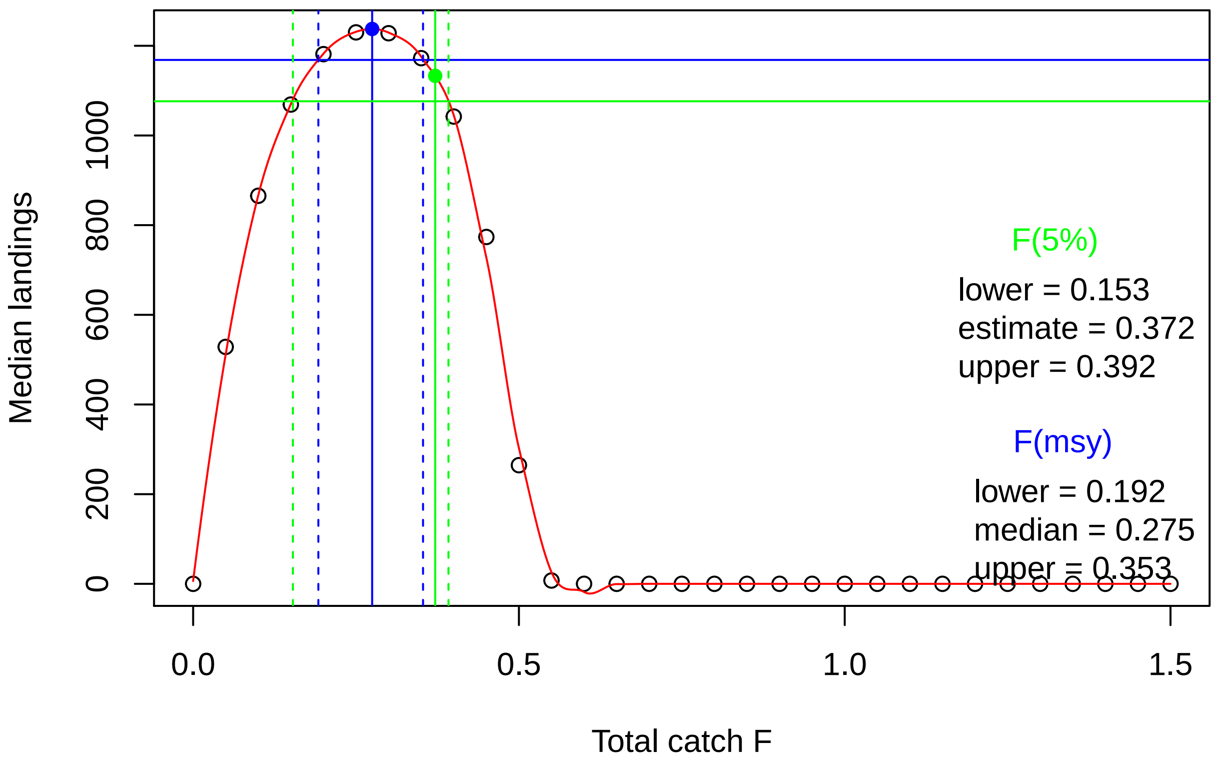
```r
Blim <- median(fit$sr.sto$b.b)
Blim<-median(ssb(stock))
Blim<-2300#SSB in 1993
Bpa(Blim, SSBcv)
```

```
## [1] 3092.591
```

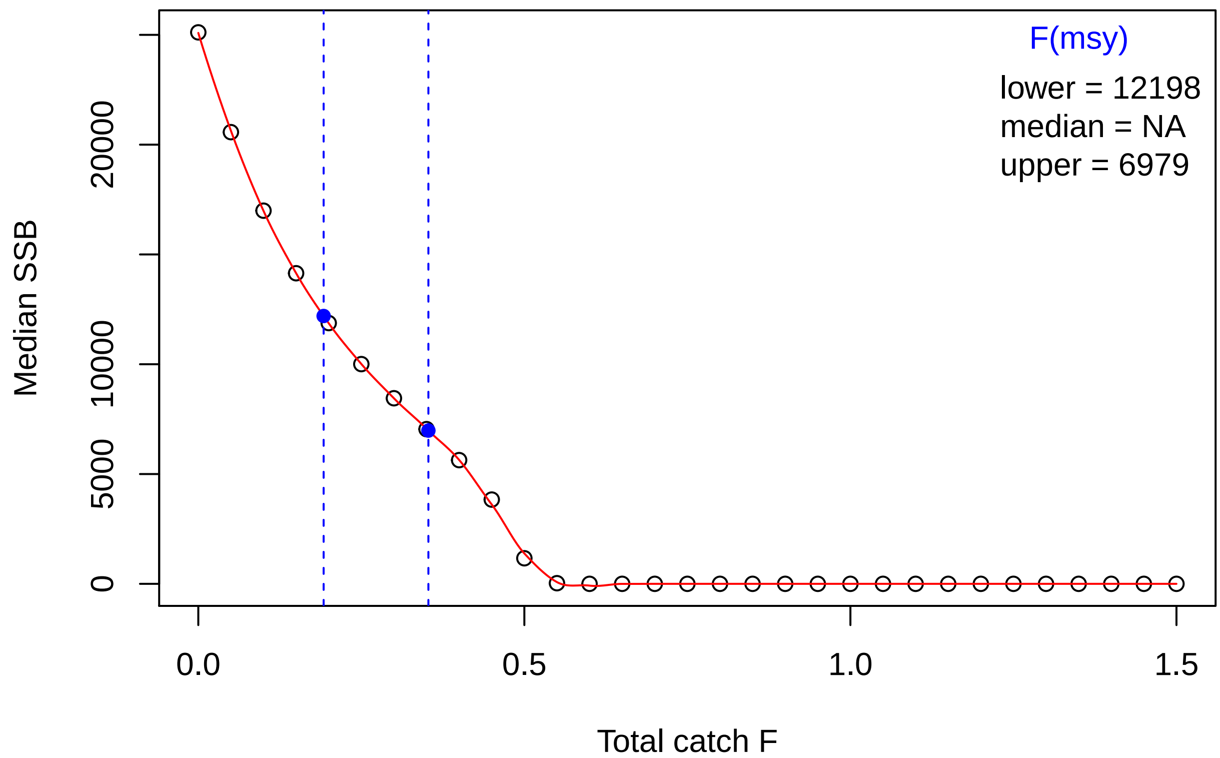
```r
Fcv <- 0.22
SSBcv <- 0.15
setup <- list(data = stock,
bio.years = c(2003,2012),
bio.const = FALSE,
sel.years = c(2003,2012),
sel.const = FALSE,
Fscan = seq(0,1.5,by=0.05),
Fcv = 0.22, Fphi = 0.423,
Blim = Blim,
Btrigger = NA,
Bpa = Bpa(Blim, SSBcv),
extreme.trim=c(0.05,0.95)
)


res <- within(setup,
{
fit <- eqsr_fit(data, nsamp = 1000, models = "Segreg")
sim <- eqsim_run(fit, bio.years = bio.years, bio.const = bio.const,
sel.years = sel.years, sel.const = sel.const, Fscan = Fscan,
Fcv = Fcv, Fphi = Fphi, Blim = Blim, Bpa = Bpa,
extreme.trim = extreme.trim, verbose = FALSE)
})

knitr::kable(t(res$sim$Refs2), digits=c(2,2,0,0,0,0))
```

| | catF | lanF | catch | landings | catB | lanB |
|---|---|---|---|---|---|---|
| F05 | 0.37 | NA | 1980 | NA | 6438 | NA |
| F10 | 0.40 | NA | 1910 | NA | 5601 | NA |
| F50 | 0.48 | NA | 908 | NA | 2158 | NA |
| medianMSY | NA | 0.27 | NA | 1238 | NA | 9210 |
| meanMSY | 0.35 | 0.30 | 2028 | 1228 | 7045 | 8452 |
| Medlower | NA | 0.19 | NA | 1169 | NA | 12198 |
| Meanlower | NA | 0.19 | NA | 1252 | NA | NA |
| Medupper | NA | 0.35 | NA | 1170 | NA | 6979 |
| Meanupper | NA | 0.35 | NA | 1253 | NA | NA |

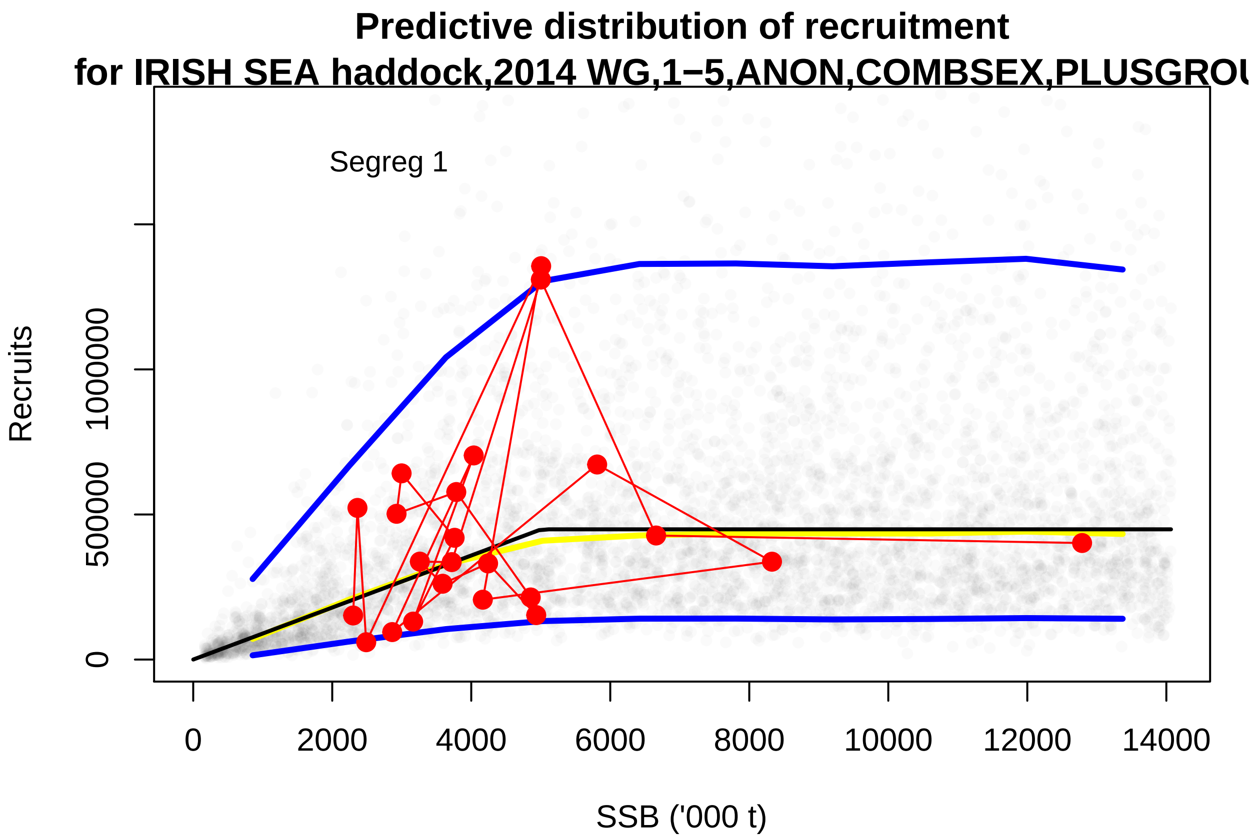
```r
eqsim_plot_range(res$sim, type="median")
```




```
eqsim_plot_range(res$sim, type="ssb")
```




```
eqsr_plot(res$fit,ggPlot=FALSE)
```




```
#eqsim_plot2(res$sim, ymax.multiplier = 1.1, catch = FALSE) # note I modify the eqsim_plot function
```

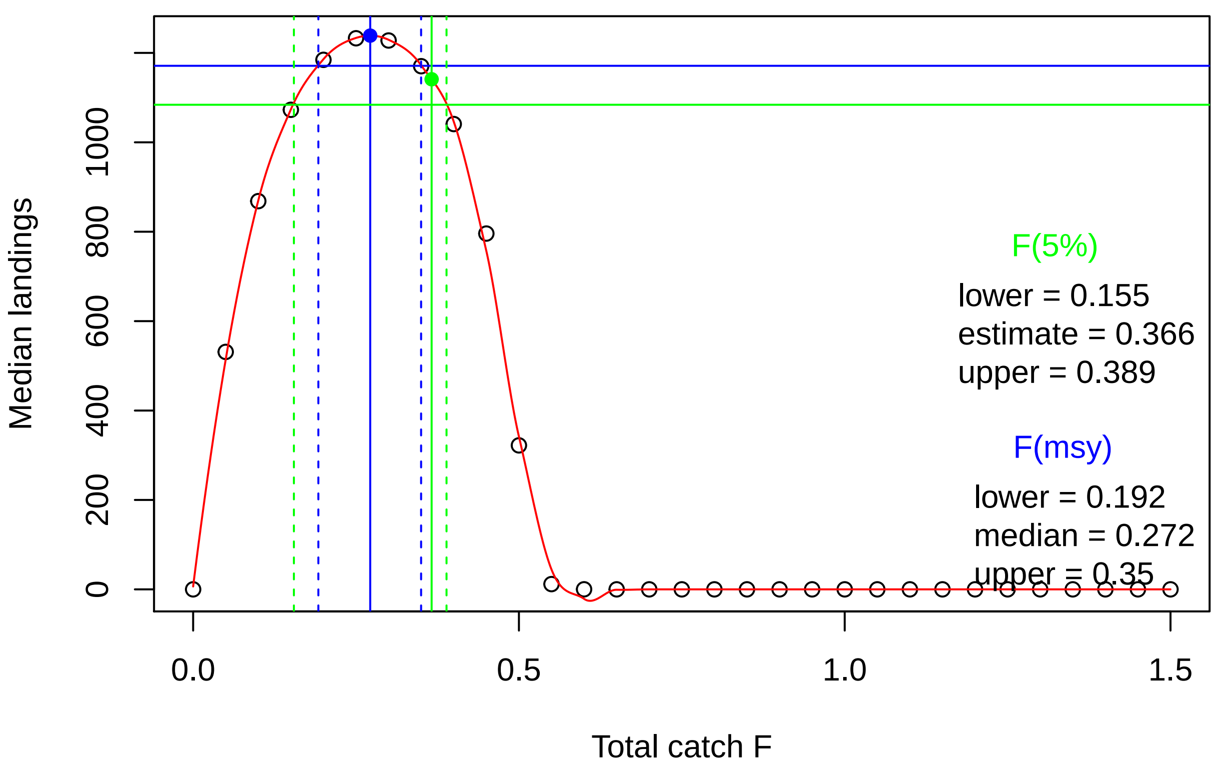
Another run with with Btrigger as BPa

```
setup <- list(data = stock,
bio.years = c(2003,2012),
bio.const = FALSE,
sel.years = c(2003,2012),
sel.const = FALSE,
Fscan = seq(0,1.5,by=0.05),
Fcv = Fcv, Fphi = 0.423,
Blim = Blim,
Btrigger = Bpa(Blim, SSBcv),
Bpa = Bpa(Blim, SSBcv),
extreme.trim=c(0.05,0.95)
)


res <- within(setup,
{
fit <- eqsr_fit(data, nsamp = 1000, models = "Segreg")
sim <- eqsim_run(fit, bio.years = bio.years, bio.const = bio.const,
sel.years = sel.years, sel.const = sel.const, Fscan = Fscan,
Fcv = Fcv, Fphi = Fphi, Blim = Blim, Bpa = Bpa,
extreme.trim = extreme.trim, verbose = FALSE)
})
```

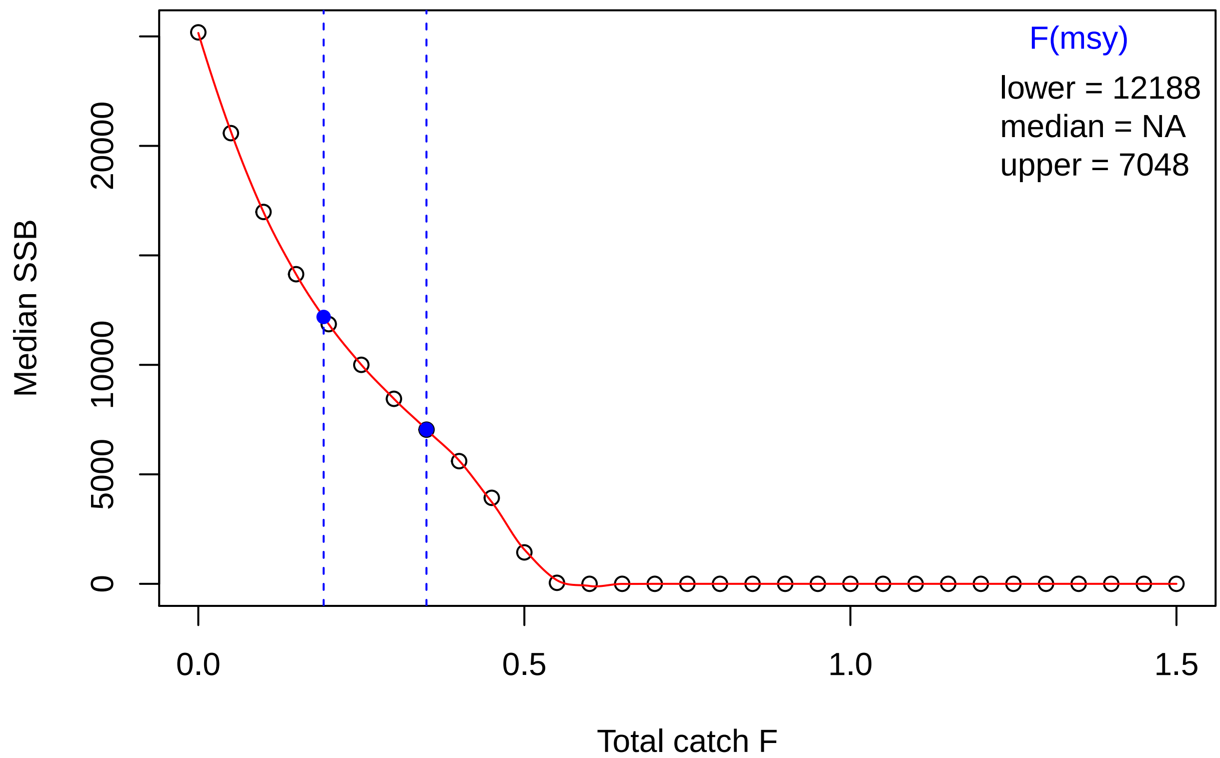
```
knitr::kable(t(res$sim$Refs2), digits=c(2,2,0,0,0,0))
```

| | catF | lanF | catch | landings | catB | lanB |
|---|---|---|---|---|---|---|
| F05 | 0.37 | NA | 1985 | NA | 6580 | NA |
| F10 | 0.40 | NA | 1916 | NA | 5708 | NA |
| F50 | 0.49 | NA | 924 | NA | 2163 | NA |
| medianMSY | NA | 0.27 | NA | 1239 | NA | 9299 |
| meanMSY | 0.35 | 0.25 | 2022 | 1233 | 7041 | 10001 |
| Medlower | NA | 0.19 | NA | 1172 | NA | 12188 |
| Meanlower | NA | 0.19 | NA | 1256 | NA | NA |
| Medupper | NA | 0.35 | NA | 1172 | NA | 7048 |
| Meanupper | NA | 0.35 | NA | 1256 | NA | NA |

```
eqsim_plot_range(res$sim, type="median")
```




```
eqsim_plot_range(res$sim, type="ssb")
```



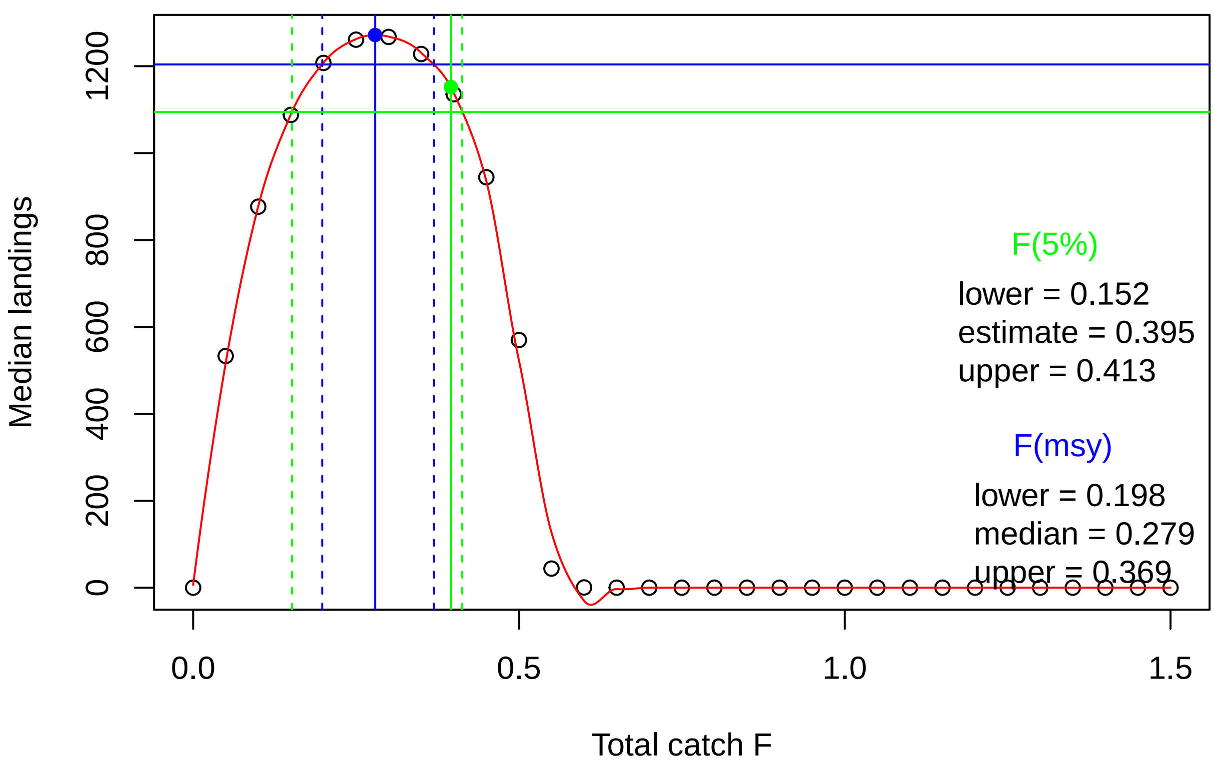

```
#eqsim_plot2(res$sim, ymax.multiplier = 1.1, catch = FALSE) # note I modify the eqsim_plot function
```

Another run with with no Btrigger and no error

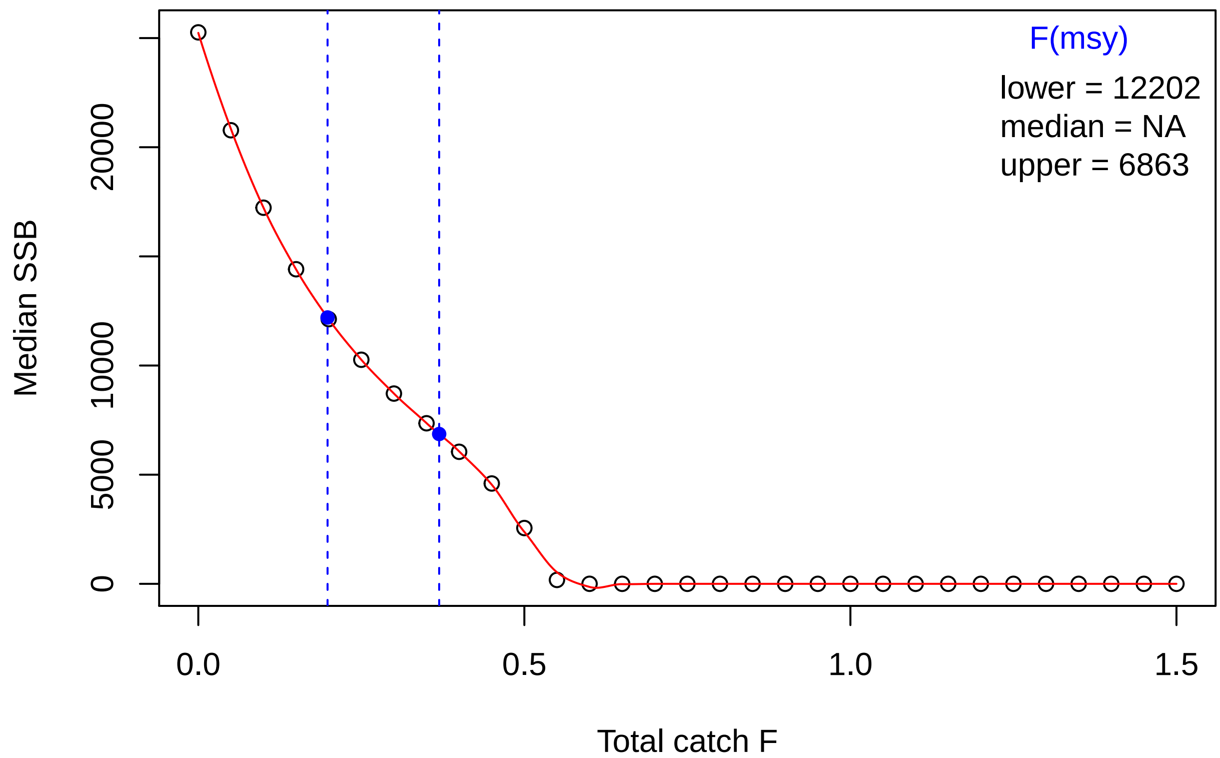
```
setup <- list(data = stock,
bio.years = c(2003,2012),
bio.const = FALSE,
sel.years = c(2003,2012),
sel.const = FALSE,
Fscan = seq(0,1.5,by=0.05),
Fcv = Fcv, Fphi = 0.423,
Blim = Blim,
Btrigger = Bpa(Blim, SSBcv),
Bpa = Bpa(Blim, SSBcv),
extreme.trim=c(0.05,0.95)
)


res <- within(setup,
{
fit <- eqsr_fit(data, nsamp = 1000, models = "Segreg")
sim <- eqsim_run(fit, bio.years = bio.years, bio.const = bio.const,
sel.years = sel.years, sel.const = sel.const, Fscan = Fscan, Blim = Blim, Bpa = Bpa,
extreme.trim = extreme.trim, verbose = FALSE)
})

knitr::kable(t(res$sim$Refs2), digits=c(2,2,0,0,0,0))
```

| | catF | lanF | catch | landings | catB | lanB |
|---|---|---|---|---|---|---|
| F05 | 0.40 | NA | 2061 | NA | 6167 | NA |
| F10 | 0.41 | NA | 1989 | NA | 5617 | NA |
| F50 | 0.50 | NA | 1083 | NA | 2349 | NA |
| medianMSY | NA | 0.28 | NA | 1272 | NA | 9332 |
| meanMSY | 0.35 | 0.30 | 2106 | 1267 | 7355 | 8716 |
| Medlower | NA | 0.20 | NA | 1205 | NA | 12202 |
| Meanlower | NA | 0.20 | NA | 1275 | NA | NA |
| Medupper | NA | 0.37 | NA | 1204 | NA | 6863 |
| Meanupper | NA | 0.37 | NA | 1275 | NA | NA |

```
eqsim_plot_range(res$sim, type="median")
```




```
eqsim_plot_range(res$sim, type="ssb")
```




```
#eqsim_plot2(res$sim, ymax.multiplier = 1.1, catch = FALSE) # note I modify the eqsim_plot function
```

```
data.95<-res$sim$rbp
x.95<-data.95[data.95$variable == "Spawning stock biomass",]$Ftarget
b.95<-data.95[data.95$variable == "Spawning stock biomass",]$p50
b.lm<-loess(x.95~b.95)
(flim<-predict(b.lm, 2300))
```

```
## [1] 0.4457289
```

```
Fpa(flim, .2)
```

```
## [1] 0.3207657
```

# Annex 10: Stock Annexes

The table below provides an overview of the stock annexes updated at WKIrish3. 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 |
|---|---|---|---|
| cod.27.7a | Cod (*Gadus morhua*) in Division 7.a (Irish Sea) | March 2017 | cod.27.7a |
| had.27.7a | Haddock (*Melanogrammus aeglefinus*) in Division 7.a (Irish Sea) | March 2017 | had.27.7a |
| whg.27.7a | Whiting (*Merlangius marlangus*) in Division 7.a (Irish Sea) | May 2017 | whg.27.7a |
| ple.27.7a | Plaice (*Pleuronectes platessa*) in Division 7.a (Irish Sea) | May 2017 | ple.27.7a |

# Annex 11: Summary report from external panel

Daniel Howell, Jim Ianelli and Rebecca Lauerburg acted as external experts for the WKIrish3 benchmark of the Irish Sea Whiting, Cod, Haddock, Plaice and Herring stocks. The panel reviewed modelling approaches used for assessment concerning suitability for advice at the workshop held at the Marine Institute in Oranmore, Ireland 29 January–4 February 2017.

The reviewers highlight the efforts of all working group participants during the benchmark process. All requests from the panel were addressed extensively from the researchers during the workshop which enhanced the panel's understanding of the individual stock assessments. In summary, the work conducted by the working group during the benchmark process greatly improved the consistency in assessment applications and was successful in implementing valuable information in the management process.

In the following section the panel outlines the central topics of each stock assessment that were addressed during the workshop along with conclusions on the eligibility of the current assessment for providing advice and additional recommendations for future work.

## Recommendations for future work

### Discard estimation approaches

Specifically for plaice the issue arose in which the method which used the recent period for which data were available to expand and estimate historical discards was problematic because of known changes in the fisheries. Historically more plaice were landed and in recent years, a much larger fraction is estimated to be discarded.

### Disaggregating fishery data

For the cod and haddock assessments (and perhaps whiting?) the models would be improved by splitting the fisheries such that the *Nephrops* and bycatch fisheries were treated separately from the directed fishery. This would be preferred for a number of reasons. Namely, the advice could be tailored to account for the expected effort in the bycatch fishery (and concomitant impacts) relative to future potential allowances in directed fisheries.

### Natural mortality specifications / estimation

The group noted that in general the following treatment / specification of natural mortality advanced for these stocks was considered extensively (see section of main report titled "Derivation of natural mortality (M) values for cod, haddock, whiting, plaice and herring"). This should be considered further, specifically as relates to the potential for evaluating time-varying values (similar to what's being done in the North Sea from multispecies model estimates).

### Consideration of environmental factors

In general, fish distributions in the Irish Sea seem likely to be affected by environmental drivers and this seems to be a benefit of having a regional benchmark. However, common environmental effects on how fish distributions may change due to interannual variability and longer term factors could have been provided and discussed at least in general terms. Application of the ICES FISHDISH working group document might have been helpful in setting the stage for potential trends/changes in distributional characteristics of stocks within this region.

## Cod

### Issues addressed at the benchmark

The current assessment is based on survey trends and the analysts provided results from SAM (a work in progress), and ASAP were presented. The group agreed that the analyst's choice of proceeding with the ASAP modelling framework was appropriate. Alternative model configurations (some 20 or so) were evaluated and a candidate configuration was selected based on evaluations of residuals, the likelihood values of data fitting and model assumptions, and interpretation of known fishery patterns (e.g., uncertain catch totals and shifts to being primarily a bycatch fishery).

### Use of final stock annex as basis for providing stock advice

The review panel felt able accept the final model as suitable for use in assessments, and felt that a reasonable job had been done in exploring and evaluating the model settings. The group noted that the model selected had fishery selectivity in the most recent period that declined significantly in the oldest ages and that should the stock increase and a fishery redevelop, that a change in selectivity where older ages are more fully selected might be considered.

## Haddock

### Issues addressed at the benchmark

The group evaluated a large number of model configurations (within the ASAP model framework) The final model included FSP survey, 3 selectivity blocks, a consideration of uncertainty in catches during the period 2004–2007, and downweighting the influence of the internal penalty on the stock–recruitment relationship.

### Use of final stock annex as basis for providing stock advice

The review panel felt able accept the final model as suitable for use in assessments, and felt that a reasonable job had been done in exploring and evaluating the model settings. They noted that, as with cod, future changes in fishery selectivity are likely should the directed fishery redevelop and that this should be a consideration in updating advice to ICES.

## Herring

### Issues addressed at the benchmark

The key issue for herring addressed at the benchmark was that the model results have been considerably lower than that suggested by the acoustic surveys. A new SSB acoustic series was therefore presented, with the aim of using this as an absolute estimate (i.e. q=1) in the model tuning. An evaluation of the impact of introducing this new acoustic SSB tuning series, both with and without fixed catchability (q=1), was conducted using the SAM modelling framework. When the catchability was not fixed the model estimated a very high catchability (q=3.8), indicating almost a fourfold difference between the survey and model biomass estimates.

The analysis was complicated by a number of factors. Within the SAM model, the ability to ascertain what aspects of the model process errors and/or data components are tending to underestimate the spawning biomass estimated using acoustic methods was problematic. Furthermore the version of SAM used was not well suited to exploring sensitivity issues around survey q or CV, with hardcoded changes required at each stage. Partly as a result of these difficulties, analysing the effect of the different proposed model variants was difficult.

There was extensive, and somewhat inconclusive, discussion around the quality of the survey, it's suitability as an absolute estimate, and the degree to which the survey had been evaluated by other working groups. The methodology used is consistent with other approaches to develop acoustic-trawl survey biomass estimates, and the survey appeared to present a reasonable, if somewhat noisy, SSB estimate. The issue of discussion centred only on the issue of whether to use the survey as a relative or absolute estimate.

### Use of final stock annex as basis for providing stock advice

The new SSB tuning series only covers the latter part of the time-series of the model (2007 onwards). With q set to one for this survey, the model gives a strong increase in modelled SSB around the year the acoustic SSB survey begins. This implies that the model is forcing an increase to occur at the start of the survey series, which is likely resulting in an artificially high stock post 2007 relative to the earlier period (which has no fixed q survey data). The result of only having a forced catchability for part of the time-series is thus to produce an over rapid rise in the stock and distort the historical stock dynamics. The review panel therefore does not believe that this forms an acceptable basis for an assessment.

Some reviewers are not, in principle against fixing q=1 for an acoustic survey for this stock. One reviewer (JI) was comfortable treating the survey as an absolute index of biomass provided an appropriate CV was used. One reviewer (RL) did not agree to use the new acoustics survey in terms of absolute estimates without justification of the underlying model assumptions that are used to calculate the SSB from the hydroacoustics data and thoroughly presentation of uncertainties and error estimates. However, all reviewers agreed that diagnostics to evaluate models with this option were insufficient and hence the panel was unwilling to accept as the basis for an assessment.

Subsequent to the review, a number of email exchanges on this topic occurred along with updated diagnostics and some further evaluation. Our discussions were provided to the HAWG for further consideration.

### Recommendations for further work

The review panel strongly recommends further work on this topic to try to resolve the discrepancy between the survey and model levels of biomass, and supports the WG recommendation for the forthcoming HAWG assessment group to decide on ToRs for an inter-benchmark focussed specifically on this issue. We consider that it would be preferable for future work on this stock to include a reviewer with greater knowledge of the stock.

As part of the analysis we recommend that, if the q was to be fixed in future assessment model, then a sensitivity of the resulting population estimate to the choice of q should be conducted. A situation where SSB (and hence catch) is sensitive to a (somewhat uncertain) choice of survey CV would be rather unfortunate. It would also seem likely from the analysis at this WG that any absolute estimates would need to apply to the whole model time-series to avoid distorting stock dynamics.

The review panel notes that the standard ICES benchmark workflow (issues list, data evaluation meeting prior to the benchmark) has not been well followed for the herring (although it was for the other stocks). This contributed to the situation where magnitude of the proposed change, and major problems in the proposed assessment model, were not identified until late in the physical meeting. We would recommend that future work on this stock be more structured to avoid a repetition of this issue.

## Plaice

### Issues addressed at the benchmark

A variety of methods (AP, XSA, SAM, and SPICT) were presented with the most extensive being the application of the SAM modelling framework for the assessment. Sensitivities ranged over natural mortality, discard approaches, retrospectives, time-series lengths, data omissions (sensitivities to inputs), linkages to plus group, and a number of other aspects related to random walk specifications. The biggest effect was discard approach selected followed by M specifications. The updated runs made during the week with the Lorenzen "shape" but scaled to have the mean M (for the older ages) were most defensible because the original M estimate was based on an earlier tagging study.

The Panel considered these sensitivities as useful and going forward, thought that the SAM model configuration with the higher discard estimates, using 9+ instead of 8+, correlation flag set to 2 for F-over ages, Lorenzen M vector scaled to 0.12 for older ages, updated SSB index (to be consistent with maturity at age / size assumption).

### Use of final stock annex as basis for providing stock advice

Discard estimation was evaluated against size-selection expansions by ages and the updated results of this during the week caused unacceptable patterns in the retrospective analyses (lack of convergence, etc.), and in some cases complete lack of convergence. The working group will revisit the discard estimation and at such time the SAM assessment model framework will be reviewed by the externals and potentially accepted for the annex and upcoming advice.

As a follow-up a well-documented revision of the discard estimation method was presented to the reviewers. Three different approaches to provide discard reconstructions were evaluated. The low and high discards scenarios were rejected since both were more inaccurate compared to the third scenario. The medium discards scenario was chosen for input to the assessment used for management since it was the most data-driven approach and was consistent with the key conclusions drawn from the historical data. Discard estimates for the period 1980–2015 were used for the baseline stock assessment run, since there is no information on the minimum landing size prior to 1981. The panel felt comfortable with the final discard estimates that were used in the assessment model.

Apart from the discard issue, the review panel was happy to accept the proposed model configuration and appreciated the detailed examinations that were carried out prior to and during the benchmark review.

The group reviewed the selection choices for near-term projections for this stock and agreed with the analysts view that a 3-year mean for partial Fs and landing fractions was appropriate, as was the median recruitment estimates from 1992–2015.

## Whiting

### Issues addressed at the benchmark

A characteristic of the available data was that the recent period (2004–2015) suggest greater negative slopes for the older whiting in both the surveys and in the fishery data. The fishery data was partially explainable because the catch has shifted to primarily bycatch in the *Nephrops* fishery but the survey data suggest a higher mortality even though the catch has remained relatively low over this period. This was discussed at length and may reflect a change in natural mortality.

The current assessment is based on survey trends and the analysts provided results from XSA and ASAP were presented. The group agreed that proceeding with the ASAP model framework for this assessment was appropriate. A broad array of configurations were evaluated and the group stepped through decision points for final specifications. This included evaluating sensitivities for time-varying natural mortality (based on estimated changes in mean weight-at-age via the Lorenzen formula), the number of periods selectivity was allowed to change, specified CV on catch biomass estimates, effective sample sizes for composition data, CV assumed for index data, including FSP survey explicitly, and some minor output changes such as age range over which F was averaged.

### Use of final stock annex as basis for providing stock advice

The review panel felt able accept the final model as suitable for use in assessments, and felt that a reasonable job had been done in exploring and evaluating the model settings.

## Regional Benchmark General comments

In general having a Regional Benchmark covering similar fish was helpful in that it identified common trends, and allowed consistency in approaches between stocks. The fact that the same model was chosen for many of the stocks evaluated here facilitated this partial harmonization of approaches between stocks. It also allowed for the different stock assessors to borrow strength from each other, which facilitated the work. This is a region where many of the stocks experienced strong declines in biomass, and consequent changes in selectivity, at around the same time.

Having herring in the list of stocks was problematic due to the lack of herring external experts and the fact that a long running intractable problem was included in the benchmark at a rather late stage (the proposed survey had not been evaluated at the data workshop). It may be sensible if regional benchmarks become the norm to have a separate place to address particularly difficult issues (where these can be identified in advance), and avoid them dominating over much of the regional benchmark.

The panel was presented with a wide range of model approaches to assess the different Irish Sea fish stocks subject to WKIrish3. A lot of work has been carried out on model choice and model improvement by sensitivity analyses of model settings. The model settings for the Irish Sea herring stock could not be agreed on during the meeting and the panel suggested a revision of the model settings during an inter-benchmark workshop.

The panel felt able to accept the final model settings for whiting, haddock and cod stocks and considered those model to be useful to provide the basis for stock assessment and advice. After a successful resolution to the plaice discard estimation issue, the same can be said for the plaice assessment. A reasonable job had been done in exploring and evaluating the model settings.

# Annex 12: Irish Sea herring-WKIrish3 follow-up document 2017

Following the WKIrish3 benchmark, there were a few outstanding issues with the Irish Sea herring assessment model that were not agreed upon. Specifically the points to address were:

- Examine the difference of the model with and without q=1. Until the point where the survey series started, apparently, the difference was minimal, but something happens once the survey time-series is added. Potentially it is not feasible to set q=1 for only part of the model time-series, however, if this is chosen, then it needs to be evaluated to ensure that it isn't distorting the stock dynamics.
- Thorough examination of the diagnostics is needed (effects on SSB, etc.); the benchmark did not have time enough to do these.

The reviewers were also request to highlight any specific model runs. The following were requested:

- For the two cases, i.e., excluding the SSB survey (case A) and with the SSB survey q set to 1 and CV of 0.4 (case B), provide the following:
    - output on variance terms estimated for the two cases;
    - ratio of the model-estimated mean SSB from 2007–2015 (the period of the "new" SSB series) relative to the period prior (and post decline, say from 1994–2006);
    - ratio of the average acoustic survey data index over the same periods (2007–2015 divided by the mean index values from 1994–2006).

## 12.1 Comparing Irish Sea herring (ISH) without the spawning SSB survey (Original-Case A) and with the spawner survey (with a q set to 1, Q=1-Case B); including a thorough examination of the diagnostics

Concern was raised at WKIrish3 that the trends seem to show different perceptions of stock status in the recent years compared to the period before ~2002, with or without the inclusion of the 7.aNSpawn survey. The dynamics are, in absolute terms, very similar (Figure 1.1). The concern, however, relates to catchability estimated for the main acoustic survey (AC_7.a(N)) used in the current assessment, which were lower under the two survey model configuration (noQ; for clarification the noQ refers to the fact that Q is not estimated the model with the default model assumption being Q=1 and thus in effect setting it to 1). As catchability is an estimated parameter applicable to the entire time-series, it is unclear why stock trends are not be markedly different in the period before 2002. The same lower catchability would apply, suggesting that biomass would be estimated lower under the 'original' model configuration for the period before 2002 and this is clearly not the case.

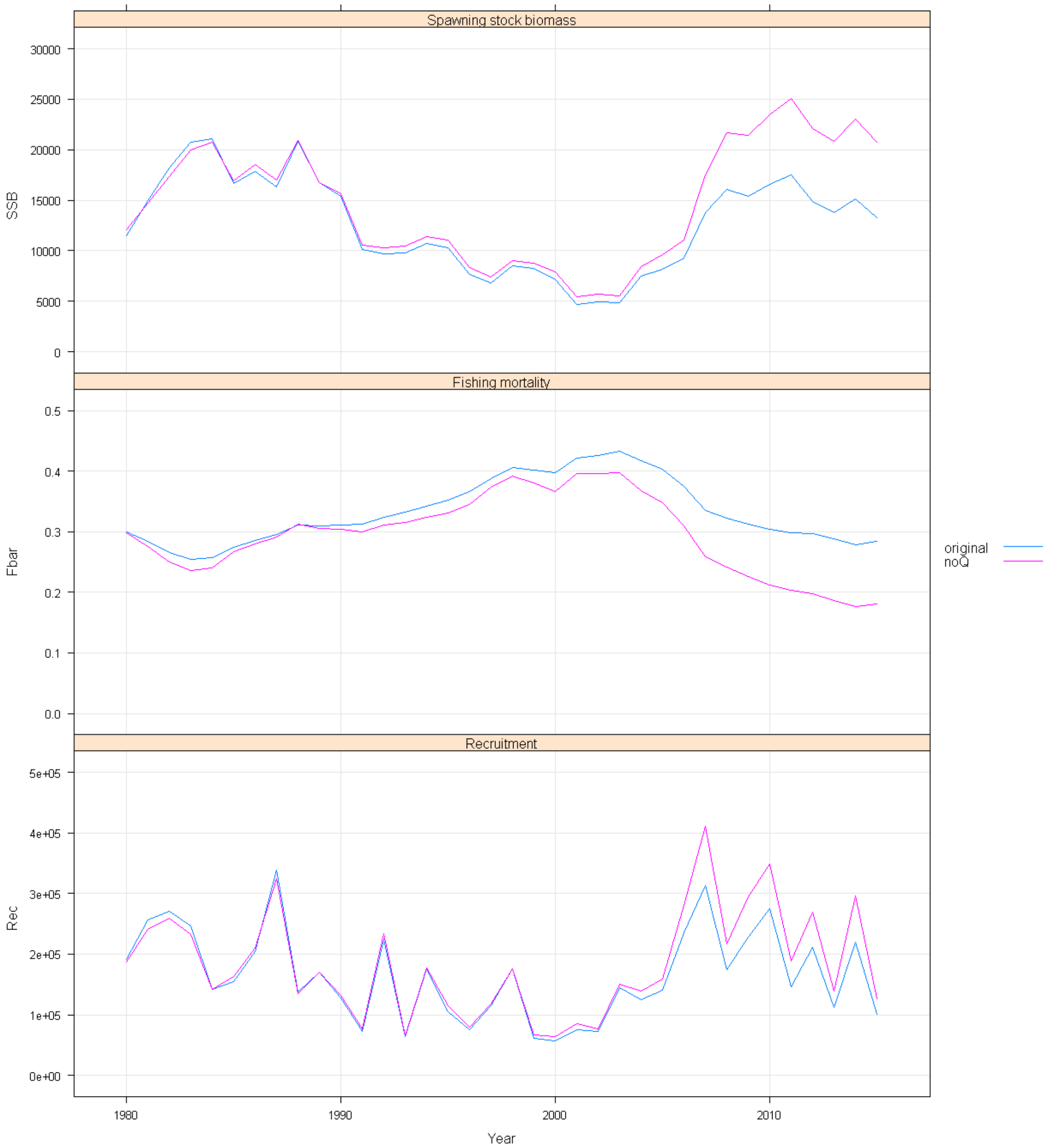



**Figure 1.1. Spawning–stock biomass (top panel), fishing mortality (middle panel) and recruitment (bottom panel) for the two different model configurations.**

For completeness, the detailed model residuals for the different runs are appended to this document:

- The default assessment currently used to provide advice with the data starting in 1980 (*Appendix 1 - defaultTS1980.pdf*).
- Same as the default above, but with no random walk on R. This is similar to the assessment labeled "original" in the figures (*Appendix 2 - samISH-NoRW.pdf*).
- Assessment with new SSB survey included, q=1 and var = 0.4. Assumption on random walk on R the same as in Appendix 2, i.e., no random walk. This is the same as the assessment labeled "noQ" in the figures (*Appendix 3 - samISHNoQSSBVar04NoRW.pdf*).

An examination of the residual plots illustrates an equally good fit to all the models. The observed differences are generally small, but more significant differences are further examined here.

Notably, the differences in the random walk on R assumption improves the fit tremendously for the youngest ages in the benchmark configured models, compared to the currently used assessment model. The two models with the no RW assumption have been taken forward, similar to what was presented at WKIrish3.

The differences in parameter estimates between the two models are presented in Figure 1.2. Under the noQ model, the catchabilities for the acoustic survey are lower. This is explained by the increase in biomass estimated for the stock, being more in line with absolute acoustic survey estimates. The variance in the random walk for fishing mortalities increases with age and are generally larger than under the original model configuration. As the step-changes from year to year are higher in SSB and R, it implies higher step-changes in F as well and result in larger RW-F variances. The RW-N is not well estimated under the original model (hitting the pre-defined parameter boundary of a variance of 0.05), but is estimated appropriately under the noQ model. RW-N is bound to 0.05 in the original model, while it is estimated to be 0.1 under the noQ model configuration (thus illustrated by a 100% change). The observation variances under the noQ model are generally smaller (less noisy) than under the original model configuration.

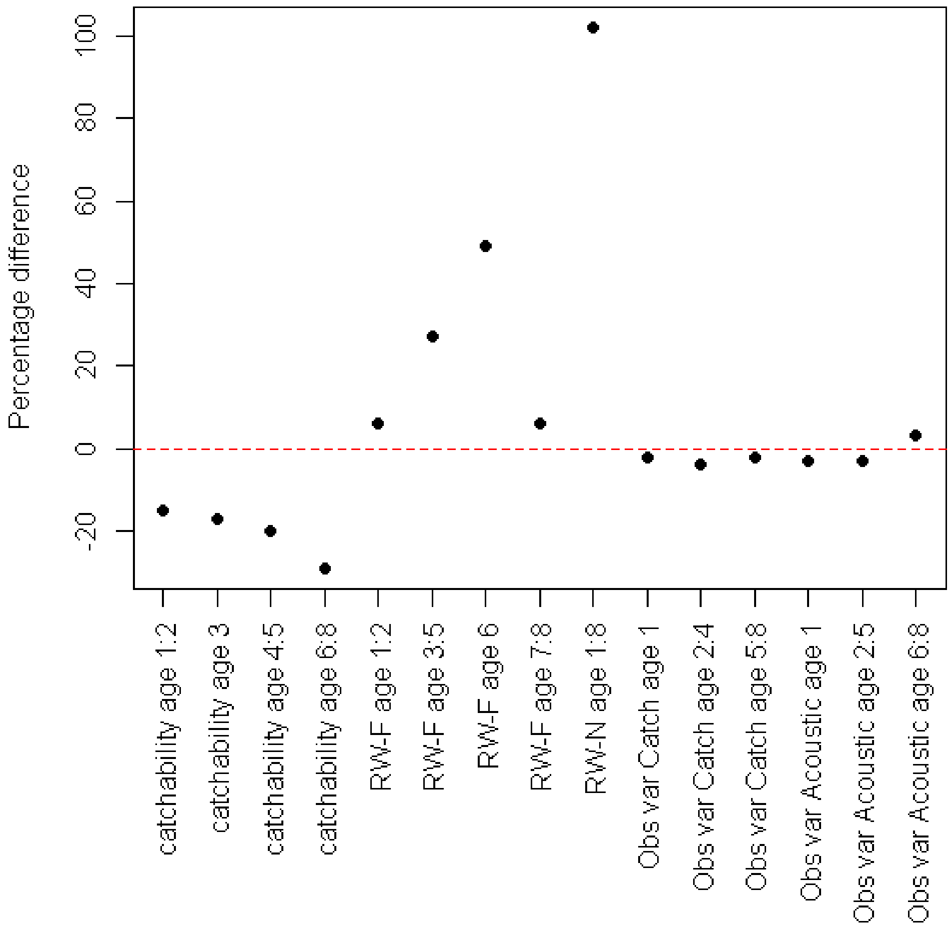



**Figure 1.2. Comparison of parameters estimated for the two model configurations, expressed as percentage difference.**

An evaluation of the differences in parameter estimates does however, not provide explanation why the biomass pre-2002 are similar under both model configurations (while catchability decreases under the noQ model for the main acoustic survey). Therefore, the entire model fit was investigated through a comparison of the residuals by age and model configuration over time (Figure 1.3).

The differences in the standardized residuals (Figure 1.3) show residuals under the original model configuration tend to be more negative for the period before 2002 and more positive for the period after 2002, in comparison with the noQ model configuration. This implies that the acoustic survey fit is not just linked to catchability scaling, but a matter of data interpretation as a whole over the period. The fit to the data by the acoustic survey is tilted with a turning point around 2002.

The summed standardized residuals for the two model configurations (Figure 1.4), as an illustration of the contribution to the log-likelihood for the acoustic survey, shows that the contribution for the noQ model is lower for all ages.

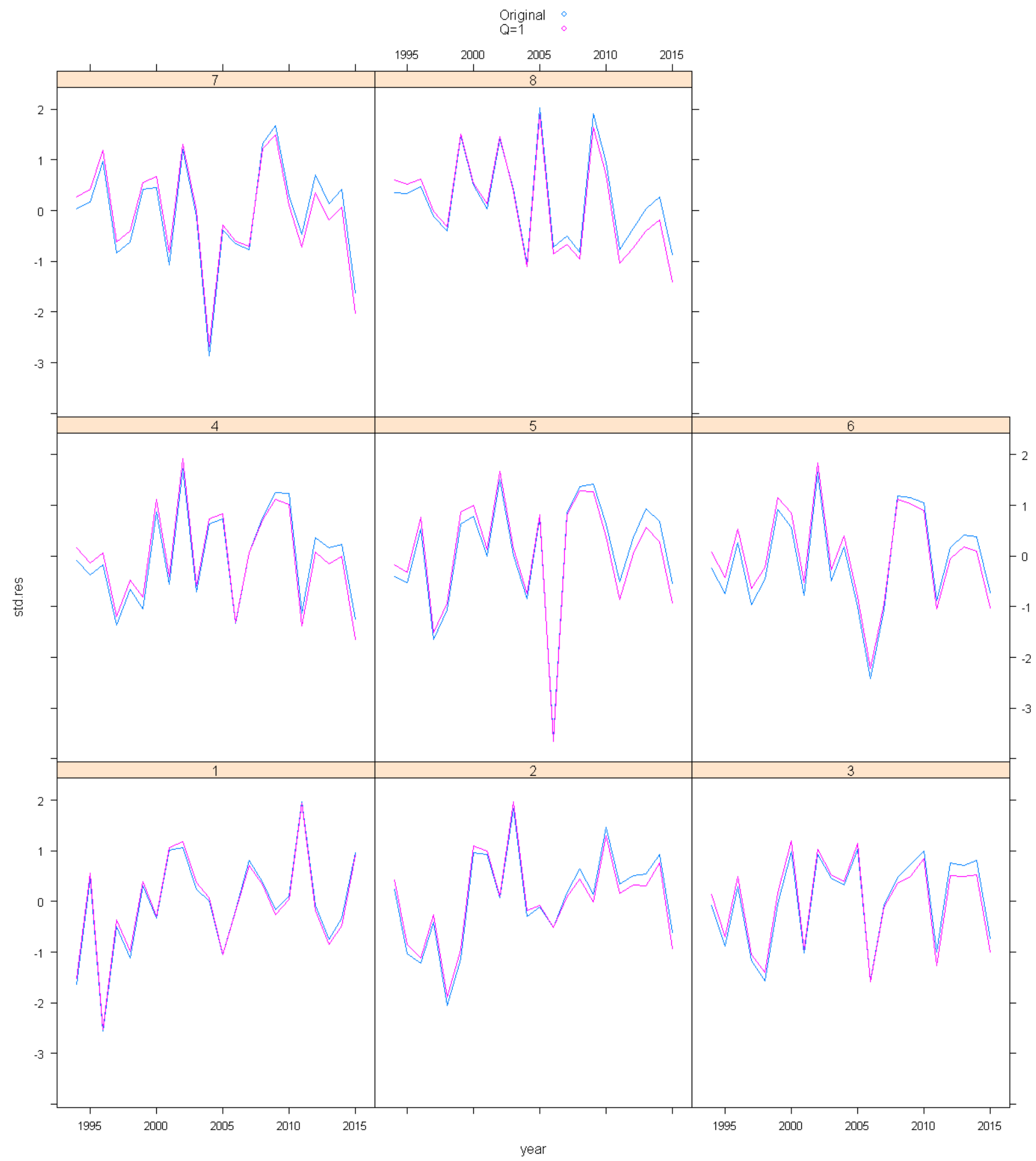



**Figure 1.3. Comparison of standardized residuals for the two model configurations.**

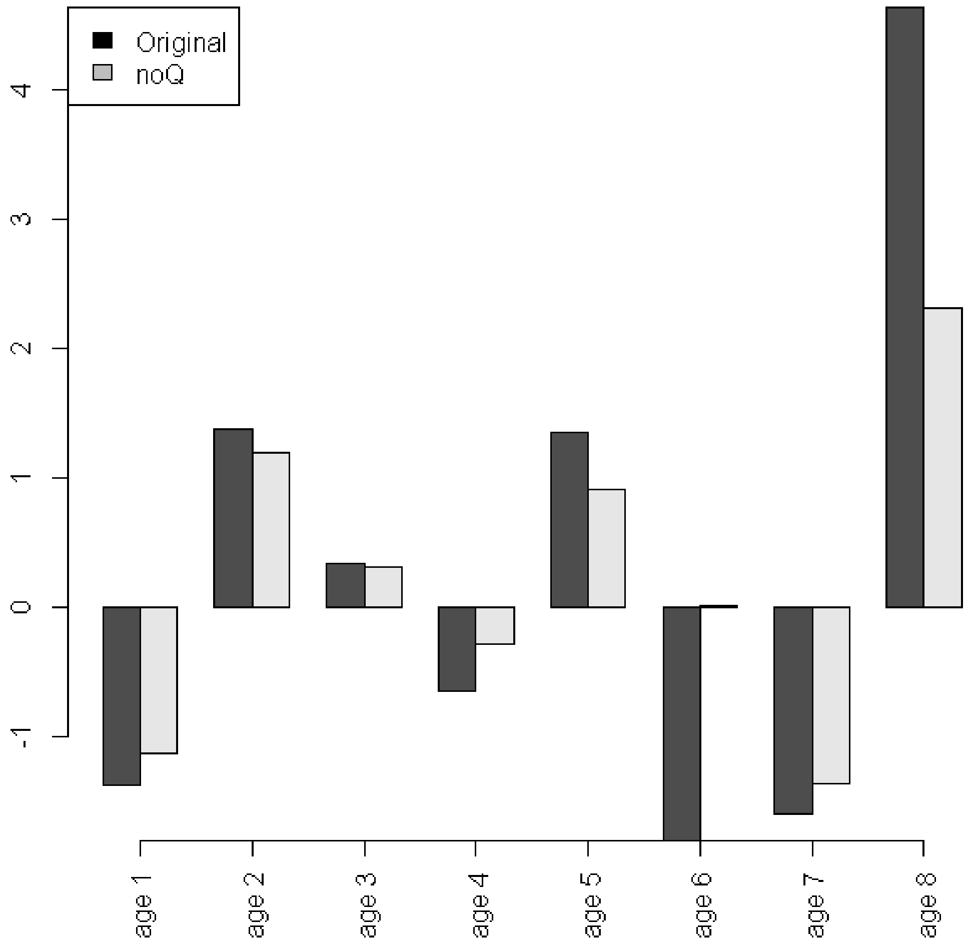



**Figure 1.4. Summed standardised residuals for the entire time-series by age for the two model configurations.**

## 12.2 SSB ratio comparison with the acoustic survey index between periods

| | Ratio 2007–2015 vs 1994–2006 |
|---|---|
| NoQ | 2.579 |
| Original | 2.000 |
| Acoustic | 2.858 |

For this statistic, the acoustic index has been converted to an SSB estimate by multiplying index-at-age with stock-weight-at-age and maturity-at-age (which are sampled from that same acoustic survey). It shows the ratio between the 1994–2006 and 2007–2015 periods for the model with a fixed catchability of 1 for the SSB survey, the ratio in the model without the SSB survey (original) and the data ratio in the acoustic survey.

The comparison of ratio of the model estimated SSB to that derived from the acoustic survey index was further examined. Figure 2.1 compares the ratio of survey index and model estimated SSB for the survey and the two different assessments for "current" and "historic" periods. The breakpoint is the point of split between the two periods (e.g. a breakpoint to 2000 means that the periods compared were 2000–2015 vs. 1994–1999; the statistics provided in the text table above has a breakpoint of 2007).

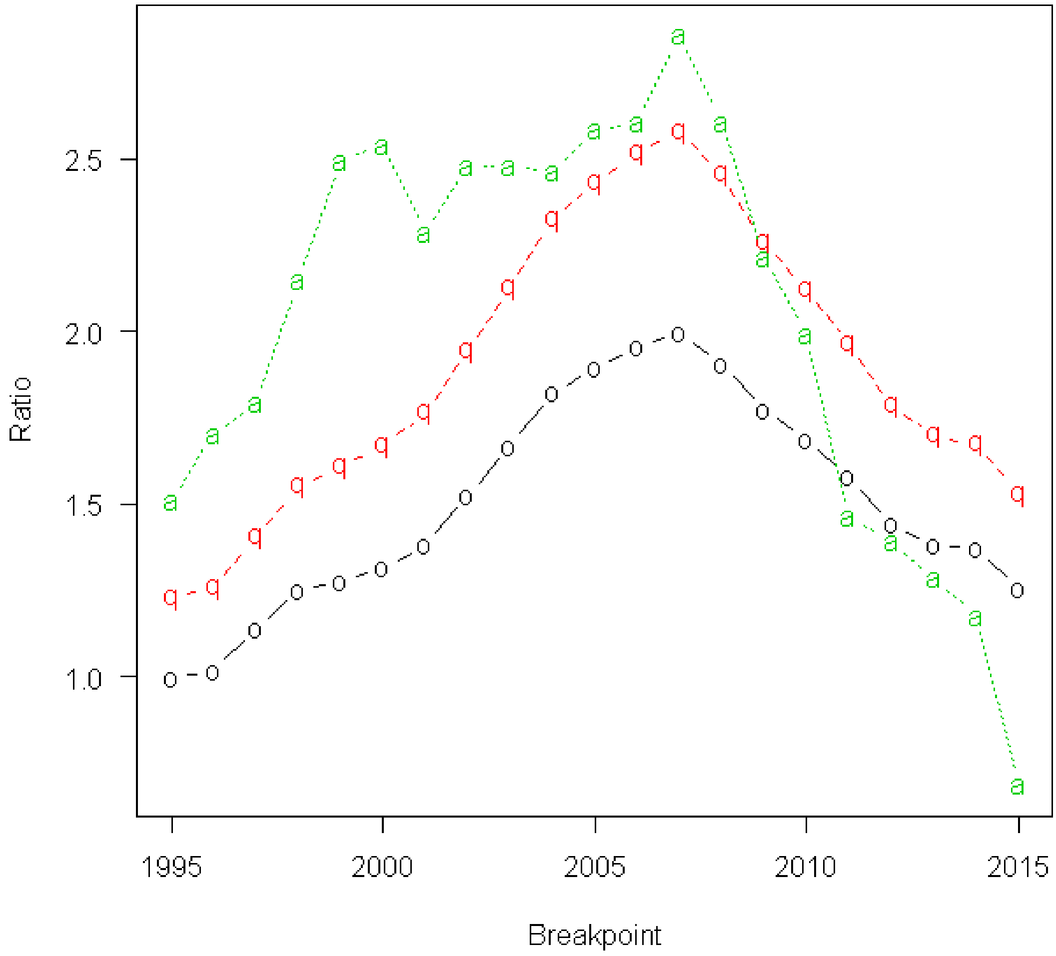



**Figure 2.1. Ratio of most recent period vs historic period in assessment without SSB survey ('o'), in the acoustic survey ('a') and the model with the SSB survey catchability set to 1 ('q').**

The figure indicates that the trend in ratio is very similar between the two model configurations, and that data-wise, the acoustic survey shows a clear breakpoint in 2007. This breakpoint is related to the interpretation of the influence of the SSB survey (which starts in 2007). From 2007 onwards, there is a larger absolute difference visible in the two assessment model configurations, which seems to coincide with the breakpoint in acoustic survey data as well.

## 12.3 Influence of catch data: investigating immigration-emigration model configurations

As reported at WKIrish3, for the current assessment model, the stock trends are informed to a larger extent by the catch than the survey data. In fact, a comparison between a VPA (without any tuning) and the assessment model estimated (with survey data), shows a very similar trend in SSB (Figure 3.1). The information from the catch dominating an assessment is something that is common across many stock assessments, but not necessarily the ideal situation, especially if at sea observation gives a different perspective of stock size.

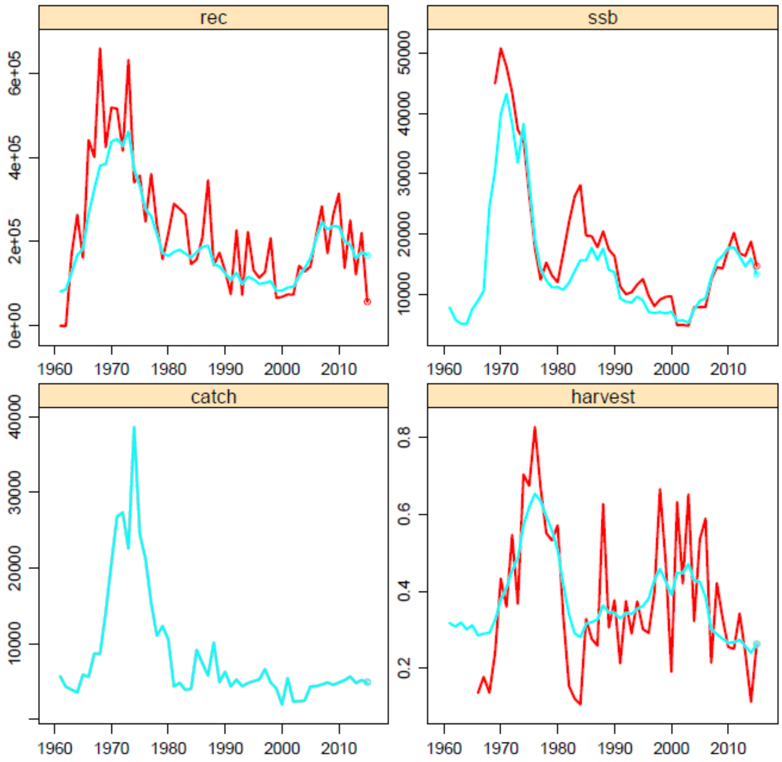



**Figure 3.1. Stock summary trends for VPA (in red) compared to the SAM assessment (in blue).**

The model estimated SSB form the current assessment model (dominated by catch information is significantly lower than the SSB estimates generated from repeated acoustic surveys since 2007. This raises questions on the quality of the information coming from the data catch (nearly all landings are sampled, so there is not much scope to increase the quality of the data itself or the representativeness thereof). The migration patterns and mixing of stocks form different spawning origins are well documented. The catch data collected from a fishery operating on this "mixture" might be the cause of this mismatch. This was further investigated here, though a very preliminary analysis ultimately aimed to evaluate the quality of the signal coming from the catch.

Substantial immigration and emigration of herring in and out of the Irish Sea takes place. To account for the immigration and emigration of herring in the Irish Sea, two options were considered: 1) a data wise approach by which herring from different origin are separated in the catch and surveys, or 2) an assessment approach in which these processes are accounted for. The first approach has been attempted in the past, but proved expensive and also extremely difficult, due to evidence of mixing of herring from different spawning origin seasons (winter and autumn) within the autumn spawning aggregations. The second approach was attempted here.

In the SAM a catch-multiplier feature is embedded which allows, based on the fit to all the data, to multiply the catch-at-age numbers. This feature is recently evaluated in the ICES WKBALT meeting as a useful proxy for migration dynamics.

From 1994 onwards, there are sufficient data available (more than only the catch data) to estimate catch multipliers. An overview of the estimated multipliers by age is given in Figure 3.2. An increasing (but uncertain) trend in catch multipliers have been observed, which is in agreement with the biological understanding of immigration and emigration.

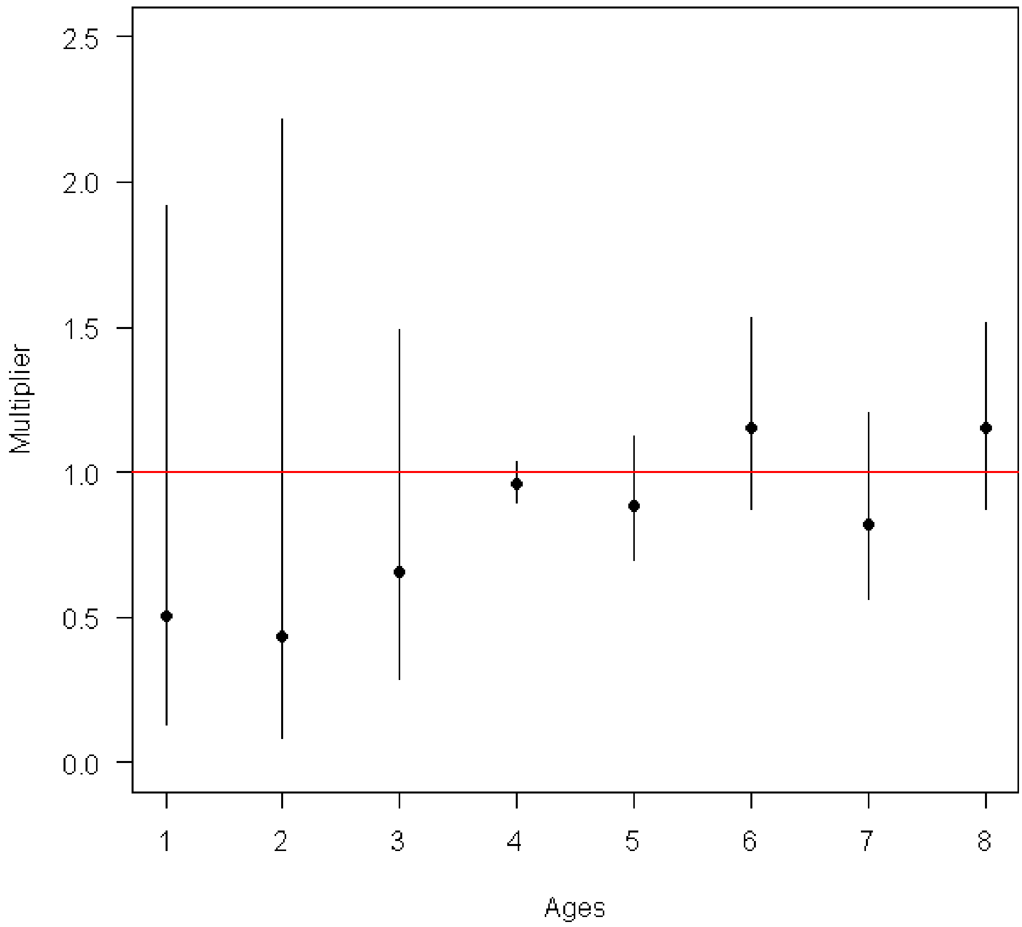



**Figure 3.2. Estimated catch multipliers by age for the period 1994–2015.**

The baseline situation is where no trend over time is assumed, (same catch multiplier by age for the period 1994–2015). To assess whether there is a trend over time, ages 1–2, 3–6 and 7–8 are bound together to reduce the amount of parameters to estimate in the model. Three time period blocks were considered, i.e. 1994–2001, 2002–2008 and 2009–2015 (each ~7 years). Under the baseline "no-year-trend" analysis, the AIC of the model fit equals 954 and for the three block-trend analyses, the AIC amounts to 936, indicated a substantially better fit. The catch multipliers increase substantially in the 2000s compared to the 1990s (Figure 3.3). There could be several reasons for this, e.g. 1) Irish Sea herring migration rates have increased, 2) the catch information is no longer informative on year-class strength (owing to temporal window being very short (1–2 week fishing season)), 3) changes in migration rates of other stocks have changed (e.g. Celtic Sea herring). Note that in this analysis the catchability for the SSB survey is estimated freely, and the parameter estimates of the catch multipliers is based especially on age data coming from the catch and the acoustic survey.

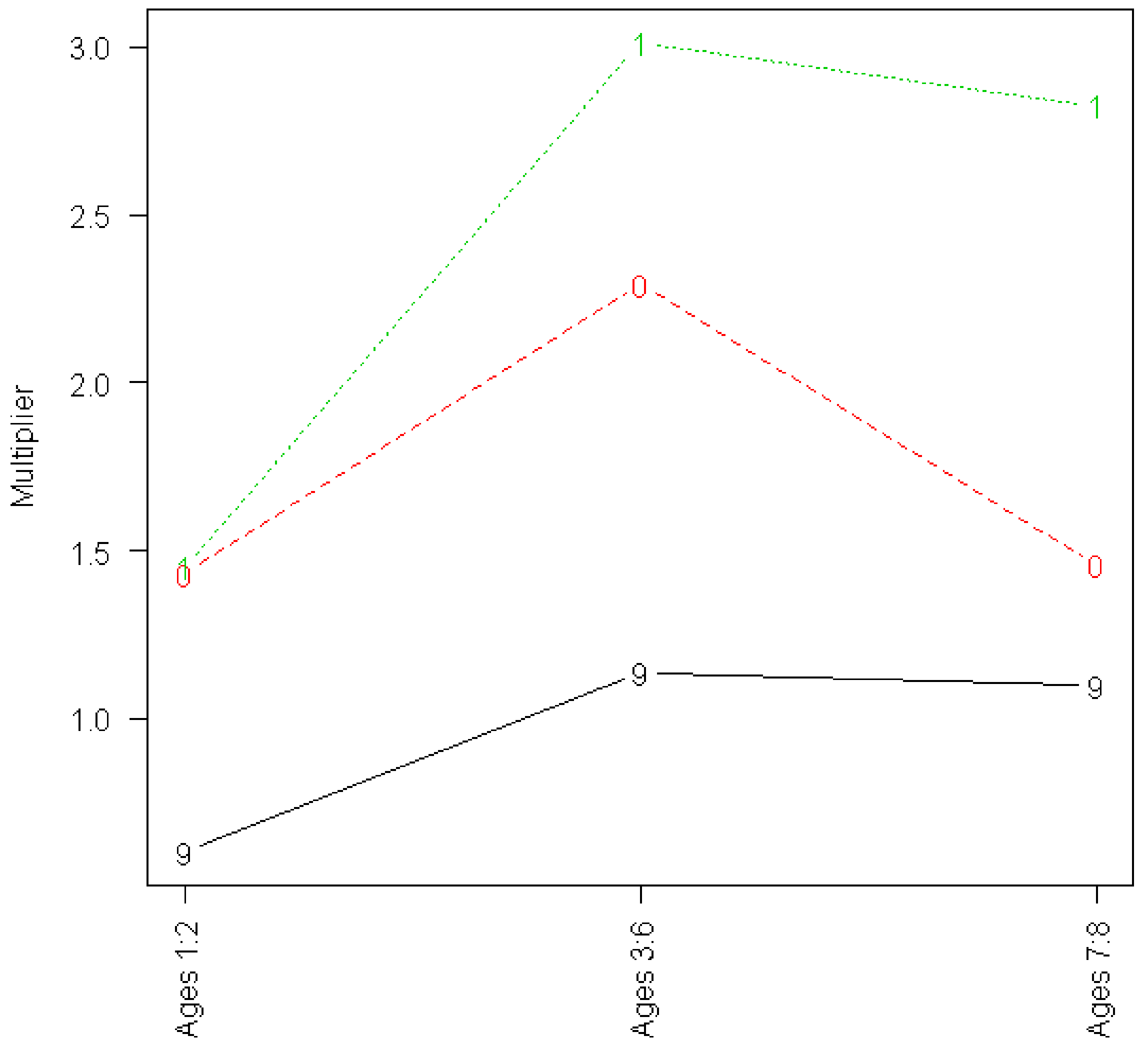



**Figure 3.3. Estimated catch multipliers by age and ~7 year period ('9' being 1994–2001, '0' being 2002–2008 and '1' being 2009–2015).**

## 12.4 Discussion and conclusion

The primary issue with the current perception of stock status of Irish Sea herring is trying to reconcile the SAM model estimates of stock size (primarily driven by catch data), and the much higher estimate of stock size estimates from nine years of repeat surveys that specifically focussed on the spawning population within the Irish Sea. This is clearly not an ideal situation to form the basis of advice.

By design, acoustic surveys are designed to get an as absolute estimate of stock biomass as possible, which would result in a catchability of ~1. The current assessment estimates catchability to be around ~2.5 for the acoustic survey. During the WKIrish3 benchmark, an attempt was made to improve the assessment of stock by including an acoustically derived spawning–stock biomass survey in the assessment model. This had little influence on the model estimates. To try to reconcile the model output with at-sea observation, an assessment was proposed with the catchability of the spawning–stock biomass survey set to 1. In effect, this constrains the model to give more weight to the absolute SSB observed at sea. There are, of course, a number of acoustic survey assumptions made to derive at this point, and this was discussed thoroughly at the benchmark. In an attempt to accommodate this, the variance of the catchability was set at 0.4 (which is the same as what it is when catchability is allowed to be estimated by the model), rather than fixing the variance at a very low value as was initially proposed.

A few issues with the model fit remained unresolved, and what has been addressed in this document. A thorough examination of the diagnostics was done, comparing an assessment without the SSB survey (Original - Case A) and with the SSB survey (with a q set to 1, Q=1 - Case B). The observation variances for the assessment with the spawning survey included (with catchability at 1) were found to be generally smaller (less noisy) and the summed standardized residuals lower than for the assessment without this survey. Thus, indicating an improved assessment model.

An investigation of the fit of the assessment model over the entire time-series and the apparent change to the model only during the recent period that overlapped with the spawning survey data period was explained. The analysis shows that the acoustic survey fit was not just linked to catchability scaling, but rather a matter of data interpretation as a whole over the period. The fit to the data by the acoustic survey is tilted with a turning point around 2002.

A preliminary investigate on the quality of the catch data also indicated that there are very significant issues with the catch data, on which the current assessment and advice is based on. This provides further rational for finding an assessment solution that deviates from the catch data and provides more weight to robust survey observations.

All the concerns from the benchmark have been satisfactorily addressed, and did not highlight any major issues that could not be explained. In general, the assessment model fit has been improved in the proposed model where the SSB survey is included at the catchability set to 1. Given that the primary aim is to provide credible scientific advice, the best proposal on this trade-off scenario (neither of which are ideal), is to base the assessment and advice on a more balanced assessment model.

# Annex 13: Herring NIRS MSY evaluations

See below.

# Herring NIRS msy evaluations

*HAWG / WKIRISH - post review*

*1st June 2017*

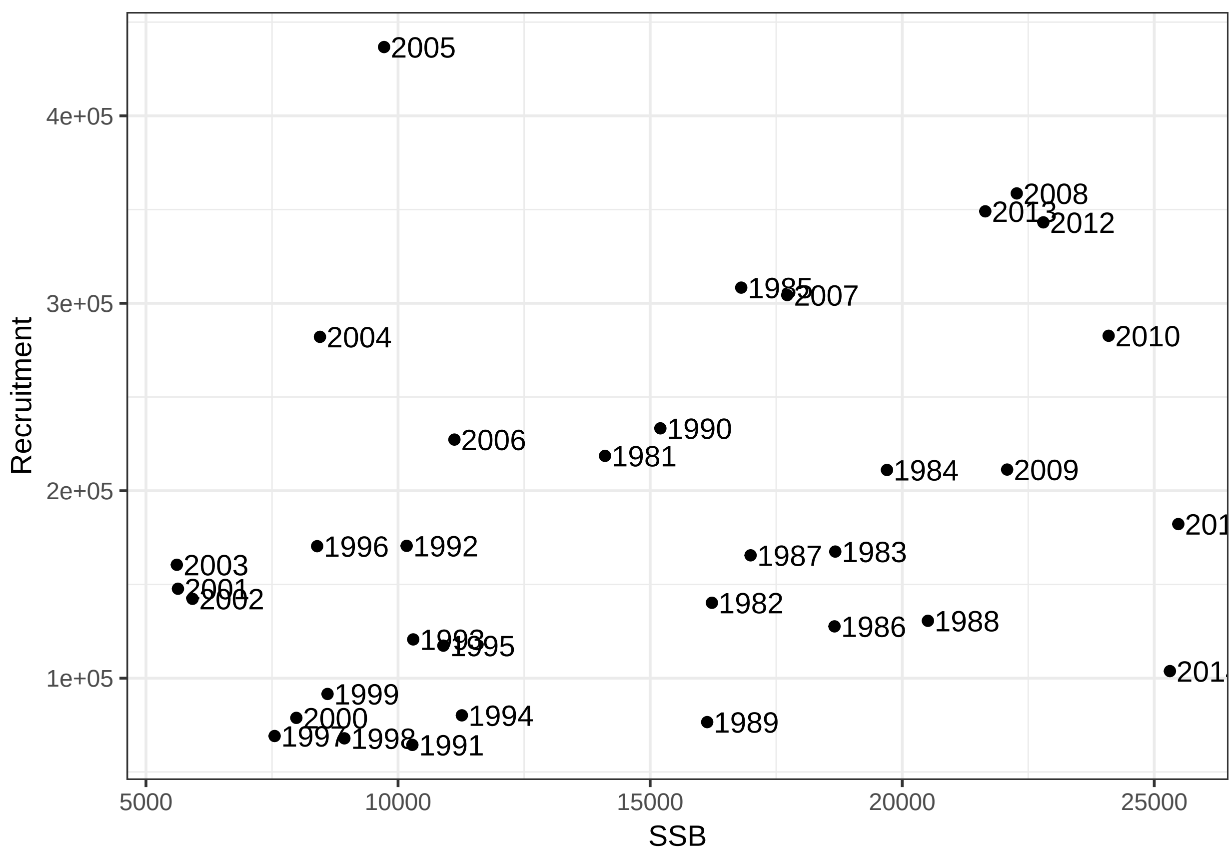
## The ICES approach to setting Reference Points

This Markdown document outlines the steps involved in estimating PA and MSY reference points for Northern Irish Sea herring as part of the WKIRISH3 benchmark. The outputs of individual Eqsim runs can have small varaiations at the 3rd decimal place. The recruimnet age is shifted by 2 years.

```
## Warning: replacing previous import 'FLCore::tail' by 'utils::tail' when
## loading 'FLSAM'
```

## SSB summary and recruitment summary

Next set some parameters - for autumn spawning herring S/R pairs recruiment is offset by two years.




The first step in the process is to examine the stock and recruit pairs and decide on a Blim value. The default is approach is to choose the SSB value below which recruitment reduces with SSB, e.g. the change point of a segmented regression. However you should use the technical guidelines document to guide your expert decision.

In the case of Northern Irish Sea herring it is identified as a 'TYPE 1' stock - Spasmodic stocks - stockswith occasional large year classes.The lowest SBB at which above average recruitment has been observed.

Blim of 8500t is based on the lowest SSB with above average recruitment (8451t)

Table 1. Summary of values for SSB and recruitment

| SSB ref value | SSB Estimate |
|---|---|
| Terminal SSB | 25868t |
| Min observed | 5611t |
| 50th Percentile | 15203t |
| 75th Percentile | 20510t |
| Max observed | 25868t |
| Average Recruitment | 186541t |
| Lowest SSB | 8451t |

Fix for zero weights If there are a few zeros in the catch and stock weights and numbers that produces NaNs so this is a fix to fill them in with a low value.

## Estimating the breakpoint stochastically

The msy package can be use to estimate the break-point stochastically, as a candidate of Blim, using segemented regression. In the case of Northern Irish Sea herring the break-point is much higher that that derived by the technical guidance. Figure 2 below gives the estimates of the stochastic breakpoints as estimated by the segmented regression and that using a fixed breakpoint at 8500t.

While the fit to the Stock - Recruit pairs may be better (86% vs. 14%) the use of this method to select Blim as "A deterministic biomass limit below which a stock is considered to have reduced reproductive capacity." is not appropiate especially given highest observed recruitment occurred below this point.

```
SetBlim<- 8500
FixedBlim<-function (ab, ssb)
{log(ifelse(ssb >= SetBlim, ab$a * SetBlim, ab$a * ssb))}

fit <- eqsr_fit_shift(stock, nsamp = 1000, models = c("Segreg","FixedBlim"), rshift = 2)
eqsr_plot(fit,ggPlot=FALSE)
```

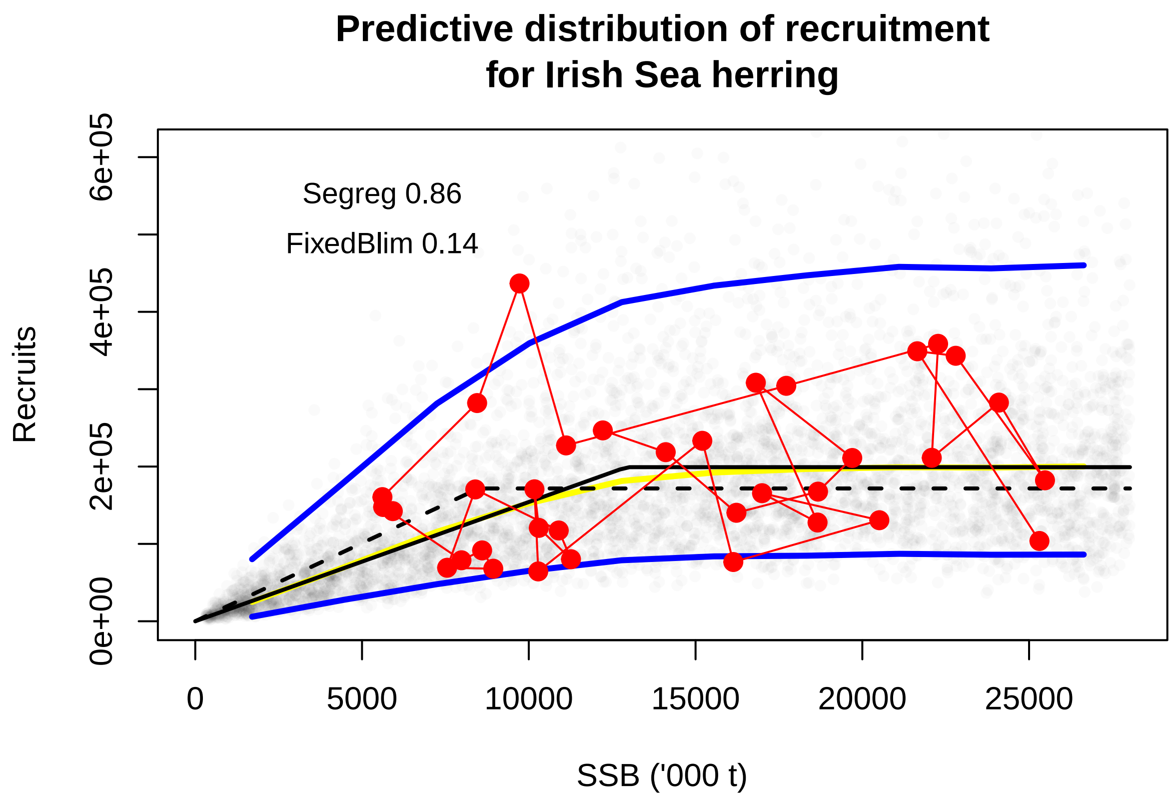



Figure 2. Fitted and Fixed segmented regression breakpoints of stock - recruit relationships. The fixed breakpoint and fitted segmented regession breakpoints of the Northern Irish Sea herring stock - recruit relationships. The yellow line in is the model averaged fit based on AIC.

## Uncertainty parameters

In the ICES approach Bpa is the estimated SSB which ensures that the true SSB has less than 5% probability of being below Blim. In practice this requires an estimate of sigma, the standard deviation of ln(SSB) at the start of the year following the terminal year of the assessment.

The SSBcv from the final year of the Northern Irish Sea herring assessment is 0.201 and Fcv is 0.231.

| Refernce Point | Estimate |
|---|---|
| Blim | 8500t |
| Bpa | 11831t |

## Estimating Fmsy using model averaged stock recruit relationship

The base Eqsim analysis largely uses default settings for the input parameters: Selection pattern is the default 10 year range. Biological parameters is the default of 10 years. The scan sequence is fairly granular to have more consistent interpolations. The uncertainties are as specified above.

In the case of the Northern Irish Sea herring we use a model averaged stock recruit relationship of segmented regression, Berton-Holt and Ricker models. This is considered appropriate guven the equal weighting of the separate models. Blim and Bpa are set from the analysis above with Blim from the stock recruit pairs as

8500t as having a priori ruled out the segmented regression alone as a S/R relationship.

```
fit <- eqsr_fit_shift(stock, nsamp = 1000, models = c("Segreg","Ricker", "Bevholt"), rshift = 2)
eqsr_plot(fit,ggPlot=FALSE)
```

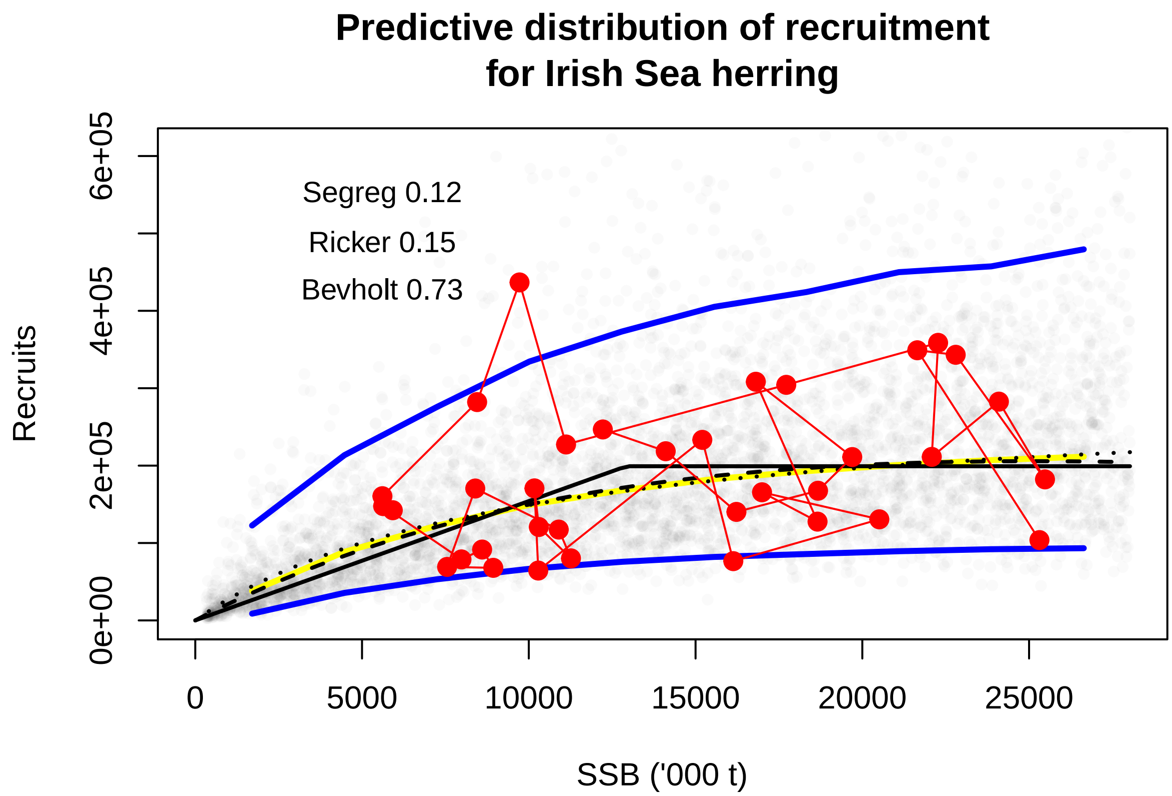



Figure 3. Model averaged stock recruit relationship

## Run with with Blim = 8500t, error and model averaged stock recruit relationships

## Step 1

```
setup <- list(data = stock,
              bio.years = c(2007,2016),
              bio.const = FALSE,
              sel.years = c(2007,2016),
              sel.const = FALSE,
              Fscan = seq(0,1.5,by=0.05),
              Fcv = Fcv, Fphi = 0.423,
              Blim = blim,
              Btrigger = NA,
              Bpa = Bpa(blim, SSBcv),
              extreme.trim=c(0.05,0.95)
)
```

```
res <- within(setup,
              {
                fit <- eqsr_fit_shift(stock, nsamp = 1000, models = c("Segreg", "Ricker", "Bevholt"), r
                sim <- eqsim_run(fit, bio.years = bio.years, bio.const = bio.const,
                                 sel.years = sel.years, sel.const = sel.const, Fscan = Fscan,
                                 Fcv = Fcv, Fphi = Fphi, Blim = Blim, Bpa = Bpa,
                                 extreme.trim = extreme.trim, verbose = FALSE)
              })

knitr::kable(t(res$sim$Refs2), digits=c(3,3,0,0,0,0))
```

| | catF | lanF | catch | landings | catB | lanB |
|---|---|---|---|---|---|---|
| F05 | 0.257 | NA | 4717 | NA | 16343 | NA |
| F10 | 0.282 | NA | 4701 | NA | 14782 | NA |
| F50 | 0.401 | NA | 4108 | NA | 8503 | NA |
| medianMSY | NA | 0.266 | NA | 4707 | NA | 15740 |
| meanMSY | 0.250 | 0.250 | 4722 | 4693 | 16795 | 16795 |
| Medlower | NA | 0.198 | NA | 4465 | NA | 20602 |
| Meanlower | NA | 0.195 | NA | 4653 | NA | NA |
| Medupper | NA | 0.345 | NA | 4466 | NA | 11106 |
| Meanupper | NA | 0.332 | NA | 4653 | NA | NA |

Fmsy is initially calculated as the F that maximizes median long-term yield in stochastic simulation under constant F exploitation (i.e. without MSY Btrigger). In figure 3 below we see that the median estimate of Fmsy is 0.266 which is expected to generate median landings of 4706.745 t.

```
fmsy<-round((res$sim$Refs2["lanF", "medianMSY"]),3)
eqsim_plot_range(res$sim, type="median")
```

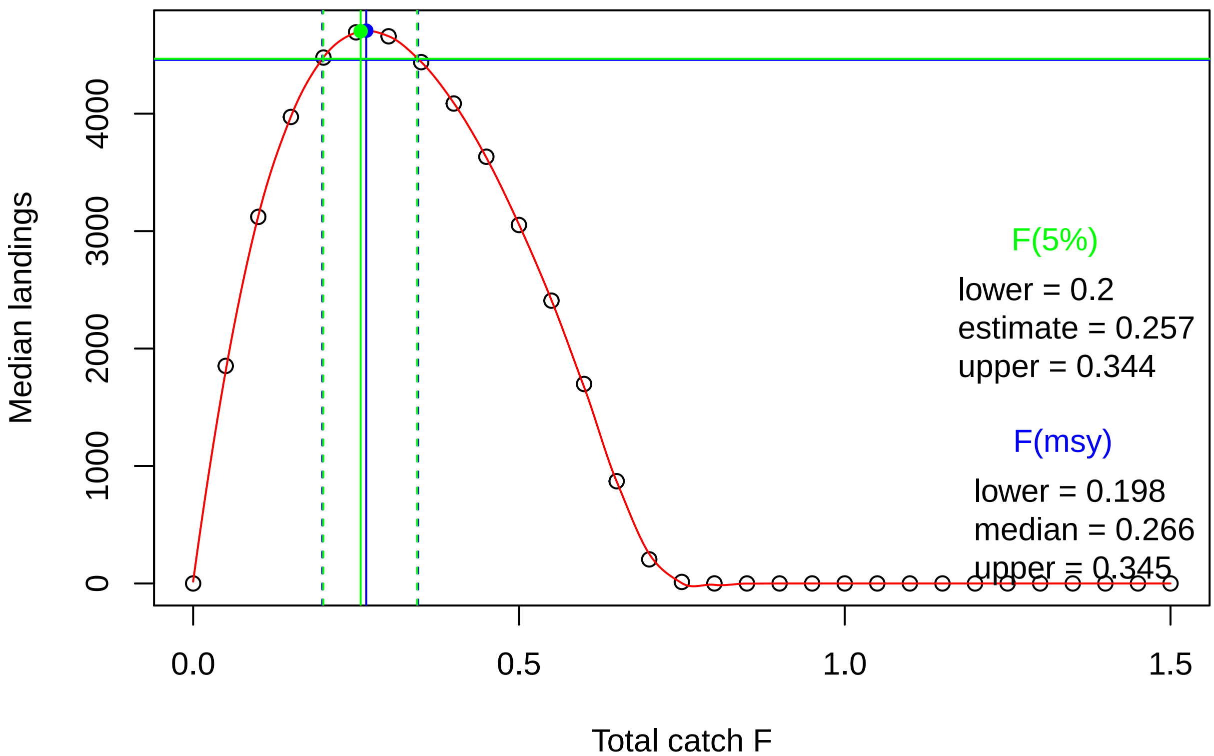



Figure 4: Yield curve and FMSY upper and lower ranges (vertical blue lines) and Flim upper and lower ranges (vertical green lines) for the segmented regression recruit model. Fmsy median point estimates and upper and lower bound are given. The value for median SSB corresponding to the lower and upper Fmsy bounds are also shown on the plot.

## Fpa (Segmented regression stock recruit relationship)

Following the ICES procedure we need to calculate the Fpa because if Fmsy is greater than Fpa then we reduce Fmsy to Fpa

Eqsim is run with no error to estimate Flim with segmented regression with breakpoint at BLim.

To calulate Flim we use a loess smoother to predict the F that has a 50% probability of bringing the stock to Blim.

```
setup <- list(data = stock,
              bio.years = c(2007,2016),
              bio.const = FALSE,
              sel.years = c(2007,2016),
              sel.const = FALSE,
              Fscan = seq(0,1.5,by=0.05),
              Fcv = 0, Fphi = 0,
              Blim = blim,
              Btrigger = NA,
              Bpa = Bpa(blim, SSBcv),
              extreme.trim=c(0.05,0.95)
)
```

```
res <- within(setup,
              {
                fit <- eqsr_fit_shift(stock, nsamp = 1000, models = c("FixedBlim"), rshift = 2)
                sim <- eqsim_run(fit, bio.years = bio.years, bio.const = bio.const,
                                 sel.years = sel.years, sel.const = sel.const, Fscan = Fscan,
                                 Fcv = Fcv, Fphi = Fphi, Blim = Blim, Bpa = Bpa,
                                 extreme.trim = extreme.trim, verbose = FALSE)
              })


data.95<-res$sim$rbp
x.95<-data.95[data.95$variable == "Spawning stock biomass",]$Ftarget
b.95<-data.95[data.95$variable == "Spawning stock biomass",]$p50
b.lm<-loess(x.95~b.95)
(flim<-predict(b.lm, blim))
```

```
## [1] 0.3973859
```

```
(fpa<-Fpa(flim, .2))
```

```
## [1] 0.285976
```

```
fmsy<-ifelse(fmsy>fpa,fpa,fmsy)
```

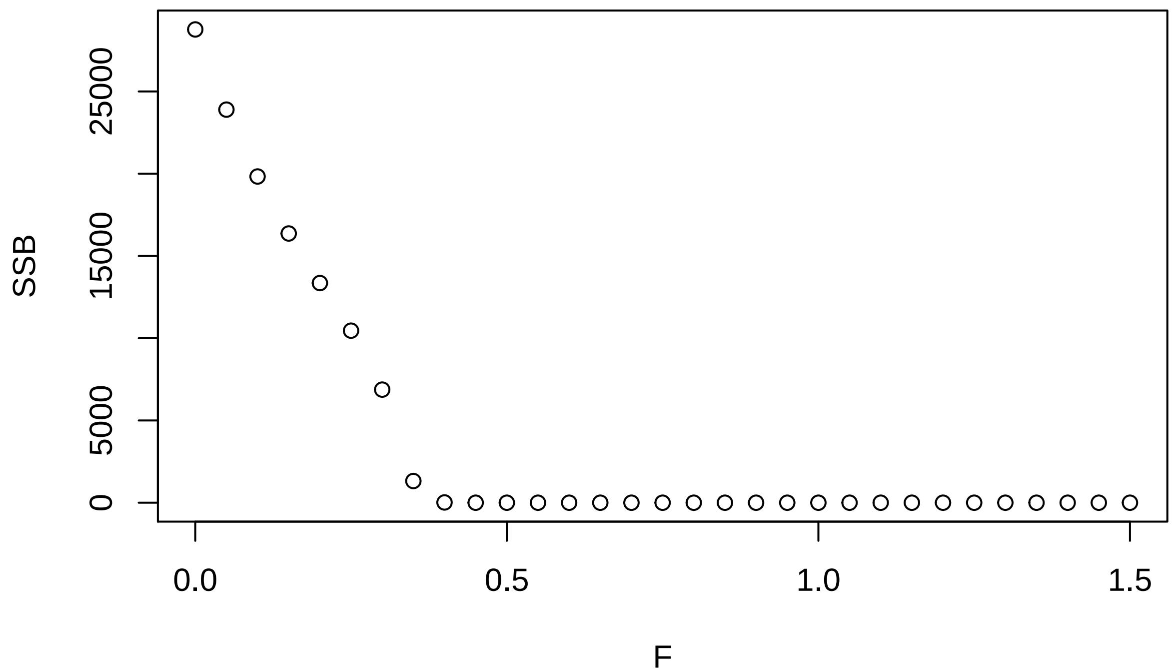
Running the code with no error gives an estimate of Flim = 0.397, and estimate of Fpa = 0.286.

## MSY Btrigger without error and model averaged stock recruit relationships

Following the ICES procedure we calculate, with no assessment/advice errorand Btrigger = 0 A similar approach is used to estimate the MSYBtrigger you would get from the analysis to test if this is higher than Bpa.

```
setup <- list(data = stock,
              bio.years = c(2007,2016),
              bio.const = FALSE,
              sel.years = c(2007,2016),
              sel.const = FALSE,
              Fscan = seq(0,1.5,by=0.05),
              Fcv = 0, Fphi = 0,
              Blim = blim,
              Btrigger = 0,
              Bpa = Bpa(blim, SSBcv),
              extreme.trim=c(0.05,0.95)
)

res <- within(setup,
              {
                fit <- eqsr_fit_shift(stock, nsamp = 1000, models = c("Segreg", "Ricker", "Bevholt"), r
                sim <- eqsim_run(fit, bio.years = bio.years, bio.const = bio.const,
                                 sel.years = sel.years, sel.const = sel.const, Fscan = Fscan,
                                 Fcv = Fcv, Fphi = Fphi, Blim = Blim, Bpa = Bpa, Btrigger = 0,
                                 extreme.trim = extreme.trim, verbose = FALSE)
              })
```

```
data.05<-res$sim$rbp
x.05 <- data.05[data.05$variable == "Spawning stock biomass", ]$Ftarget
b.05 <- data.05[data.05$variable == "Spawning stock biomass", ]$p05
plot(b.05~x.05, ylab="SSB", xlab="F")
```




```
b.lm <- loess(b.05 ~ x.05)
(msybtrig <- predict(b.lm, fmsy))
```

```
## [1] 8632.065
```

```
msybtrig<-ifelse(msybtrig<bpa,bpa,msybtrig)
```

This gives MSYBtrigger of 11831t (Bfmsy). Northern Irish Sea herring has been fished at, or below Fmsy for > 5years. The 5th percentile of Bfmsy 11831t is smaller than Bpa 11831t MSYBtrigger is Bpa 11831t

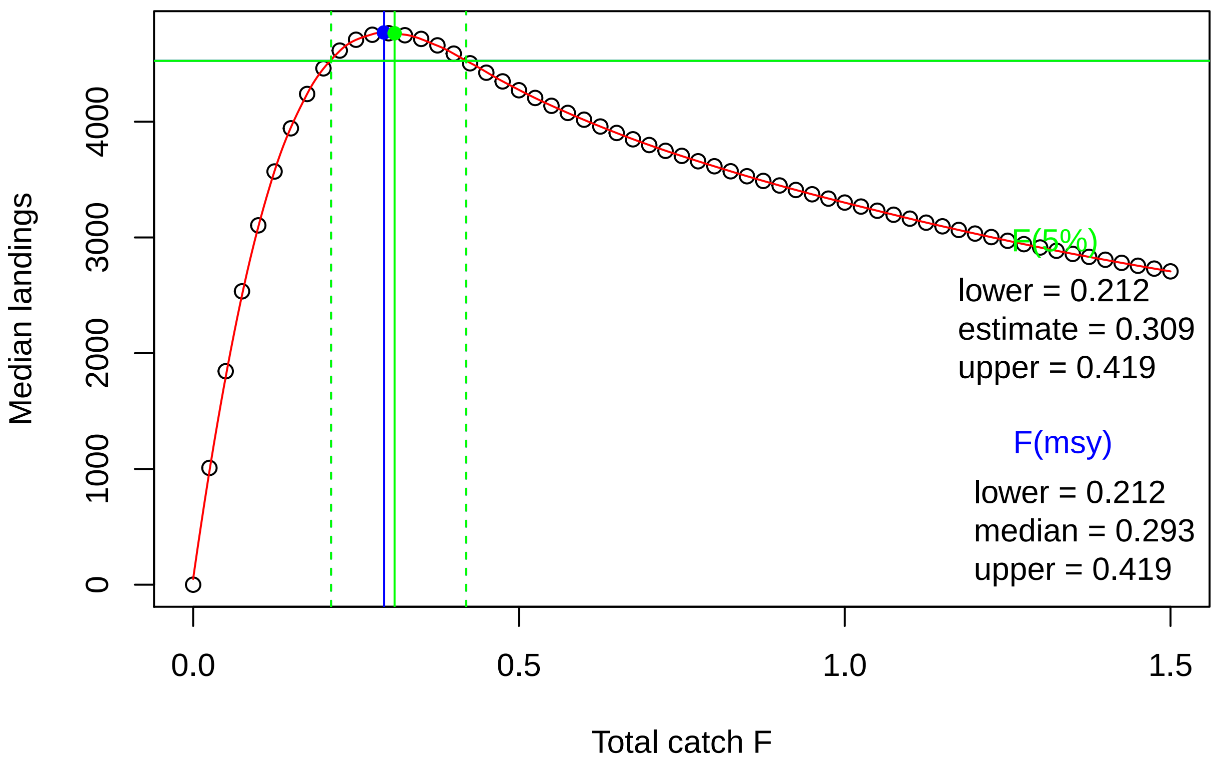
### ICES Advice rule - assessment error and Btrigger and model averaged stock recruit relationships

The next step is to evaluate the ICES advice run via the stochastic simulation with these values of FMSY and MSY Btrigger. If the F5% in this run is larger than the candidate Fmsy the the initial Fmsy is reduced to F5%.

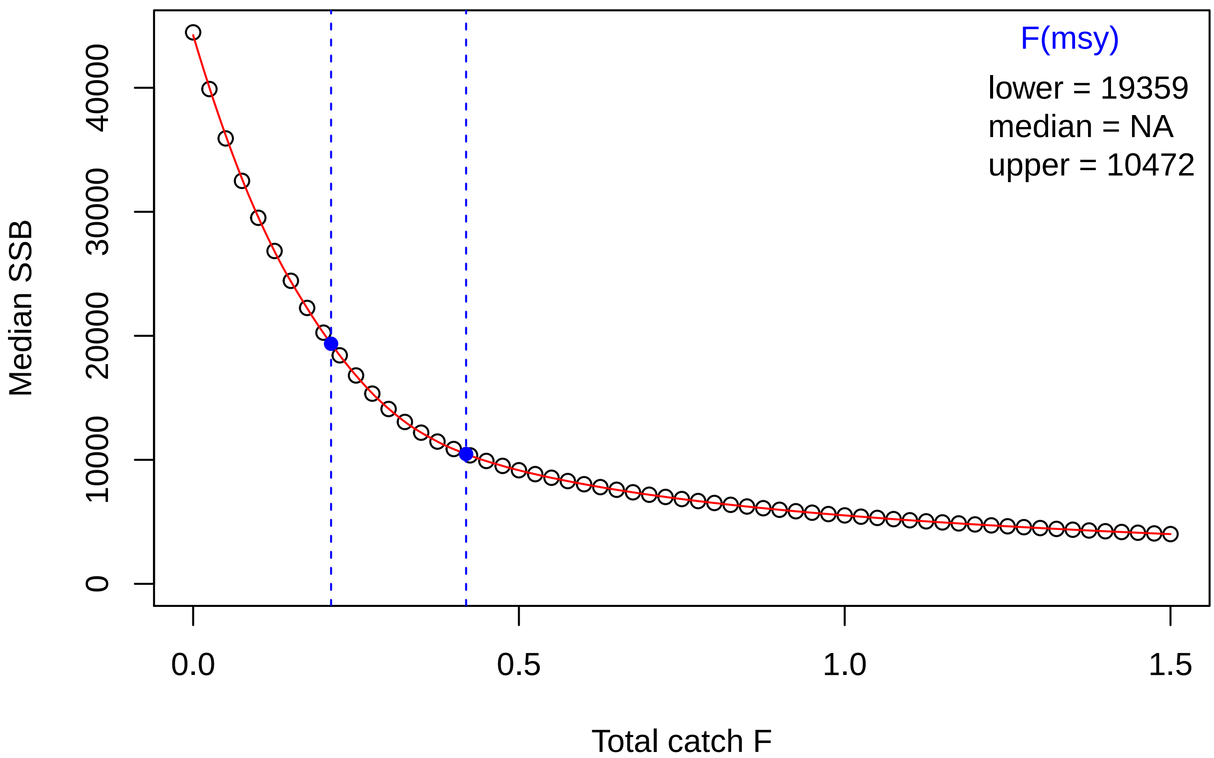
So EqSim is run again this time including the selected MSY Btrigger value and error.

```
setup <- list(data = stock,
              bio.years = c(2007, 2016),
              bio.const = FALSE,
```

```
                sel.years = c(2007, 2016),
                sel.const = FALSE,
                Fscan = seq(0, 1.5, by=0.025),
                Fcv = Fcv, Fphi = 0.423,
                Blim = blim,
                Btrigger = msybtrig,
                Bpa = bpa,
                extreme.trim=c(0.05,0.95)
)
res <- within(setup,
              {
                fit <- eqsr_fit_shift(stock, nsamp = 1000, models = c("Segreg", "Ricker", "Bevholt"), r
                sim <- eqsim_run(fit, bio.years = bio.years, bio.const = bio.const,
                                   sel.years = sel.years, sel.const = sel.const, Fscan = Fscan,
                                   Fcv = Fcv, Fphi = Fphi, Blim = Blim, Bpa = Bpa,Btrigger = Btrigger,
                                   extreme.trim = extreme.trim, verbose = FALSE)
              })

eqsim_plot_range(res$sim, type="median")
```




```
eqsim_plot_range(res$sim, type="ssb")
```




```
ffmsy<-round((res$sim$Refs2[2,4]),3)
ff5<-round<- round((res$sim$Refs["catF", "F05"]),3)
fmsy<-ifelse(ff5>fmsy,fmsy, ff5)
```

Fmsy estimated as to 0.266

| Reference Point | Value | Rationale |
|---|---|---|
| MSY Btrigger | 11831t | 5th percentile of SSB when fishing at Fmsy |
| Fmsy | 0.266 | Median point estimates of (F05) EqSim with combined SR |
| Blim | 8500t | Lowest SBB with above ave recruitment |
| Bpa | 11831t | Blim combined with the assessment error |
| Flim | 0.397 | F with 50% probability of SSB less than Blim |
| Fpa | 0.286 | Flim combined with the assessment error |