ICES WGMG REPORT 2013

Report of the Working Group on Methods of Fish Stock Assessments (WGMG)

30 September – 4 October 2013

Reykjavik, Iceland

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Executive summary

The ICES Working Group on Methods of Fish Stock Assessment (WGMG) met in Reykjavik, Iceland from 30 September–4 October 2013. Work conducted prior to the meeting focused on aspects of the ICES data-limited stocks (DLS) framework; in particular, how robust it is (in terms of delivering more conservative catch advice when less data are available) and whether the performance of some of its age-aggregated methods (e.g. for Category 3) can be improved by including in the Harvest Control Rule (HCR) either a confidence interval for the age-aggregated index used or the average length in the catch relative to some reference level. Indications are that the DLS framework does not always deliver more conservative catch advice when less data are available, and that the performance of HCRs can potentially be improved with additional auxiliary information. The development of generic HCRs, and the use of F_{proxy} values and targets in HCRs were also considered, and suggestions made for the preparation of survey indices for use in HCRs. Work conducted during the meeting itself included a comparison of a range of methods for estimating reference points when applied to two ICES datasets (North Sea cod and herring); for neither of these datasets was F_{MSY} estimated consistently across models and SR forms, highlighting the challenges for estimating reference points from stock–recruit data. A brief review of current mixed fishery and multispecies approaches was conducted, and a recommendation provided for evaluating a mixed fishery approach under a minimum realistic multispecies operating model. A summary of the workshop held as part of the World Conference on Stock Assessment Methods is provided, with a look forward to the possible future development of the simulation exercises conducted as part of the workshop.

1   Introduction

1.1   Terms of Reference (ToRs)

The Working Group on Methods of Fish Stock Assessments (WGMG) chaired by José De Oliveira, UK will meet in Reykjavik, Iceland, 30 September – 4 October 2013 to:

a) Develop and suggest ways to evaluate management approaches for all species in mixed fisheries, including data limited stocks that have a high probability of being consistent with the precautionary and MSY approaches.

b) With regard to the ICES Data Limited Stock (DLS) approach:

   i) Investigate the robustness of the DLS approach as a framework for providing advice.

   ii) Consider ways of extending management approaches using only age-aggregated abundance indices, tested on data rich species with age data, to data-limited situations without age data.

c) Evaluate the outcomes from the Assessment Methods Evaluation Scheme, applied during the SISAM World Conference on Stock Assessment methods for Sustainable Fisheries (WCSAM, Boston, July 2013), and based on this, develop recommendations for stock assessment approaches within ICES.

d) Based on work from WKFRAME2, WKGMSE and WKMSYREF, review and evaluate recent software developments in terms of methodology for computation of the reference points within the ICES MSY and PA approaches.

1.2   Background

The 2013 meeting was held immediately after the ICES Annual Science Conference (ASC) in the same city (Reykjavik); this appeared to work well for the group, and allowed WGMG to have a presence at the ASC, including contributing to the SCICOM Open Sessions, and planning additional work under the ICES Strategic Initiative on Stock Assessment Methods (SISAM) with others attending the ASC, but not available for the WGMG meeting. There is a proposal to again have the WGMG meeting follow the ASC in 2014, although it would have to transfer to nearby Vigo since there are no suitable venues in A Coruña.

Three ToRs were developed during the 2012 meeting, and a fourth was added following the WKMSYREF meeting in January 2013. WGMG received additional recommendations from WGNSSK and WGCSE during 2013, and these have been incorporated into future ToRs under the new ICES multi-annual ToR approach.

The meeting was structured around the four ToRs, and the same approach was used for the report. Work under ToR 1 took the form of a brief review and discussion of mixed fishery and multispecies approaches currently in use, with a recommendation for evaluating a mixed fishery approach under a minimum realistic multispecies operating model. Under ToR 2, simulation work developed specifically for this ToR was presented on (a) the robustness of the ICES DLS framework (in terms of its ability to produce more conservative catch advice when less data are available), and (b) whether performance of age-aggregated methods under Category 3 of the DLS framework could be improved by incorporating into the Harvest Control Rule (HCR) either a

confidence interval for the age-aggregated index used or the average length in the catch relative to some reference level. Other areas of work presented under ToR 2 related to the development of generic HCRs for data-poor fisheries, a comparison of HCRs that use F_{proxy} values and targets with the current ICES Category 3, method 3.2 rule, and suggestions for the preparation of survey indices for use in HCRs.

WGMG continues to support SISAM, and was instrumental in the collation and provision of datasets, as well as the development of the assessment methods evaluation scheme, presented to the World Conference on Stock Assessment Methods (WCSAM) held in Boston, July 2013. Work under ToR 3 provides both a summary of the workshop held as part of WCSAM, and a look forward to where the simulation testing exercises go next. Work under ToR 4 was conducted during the meeting, and compared three methods (although a fourth was also presented) applied to two ICES datasets (North Sea cod and herring). The three methods, all candidates for estimating reference points (along with the fourth method), were an equilibrium approach with variance, a stochastic projection approach, and a nonparametric approach. The fourth method considered reference point estimation in the context of evaluating a HCR using Management Strategy Evaluation (MSE).

A number of recommendations were developed from the work presented and discussions held, and these are presented in Annex 3. Multi-annual ToRs were developed under a number of broad themes, and these are reported in Annex 4. Details of methods presented and issues that arose during the meeting that required clarification are presented in Annexes 5-11.

2   ToR 1 – Mixed Fishery and Multispecies approaches

Mixed fishery approaches

A summary of the work carried out by the Working Group on Mixed Fisheries Advice for the North Sea (WGMIXFISH) and the Working Group on Multispecies Assessment Methods (WGSAM) was presented with a focus on the existing tools and models used within these groups. Although the approaches carried out by these groups are different, both groups provide multispecies and mixed fisheries considerations to ACOM for North Sea stocks.

WGMIXFISH aims to apply mixed fisheries forecasts to the draft North Sea single species advice provided by the Working Group on the Assessment of Demersal Stocks in the North Sea and Skagerrak (WGNSSK), and in 2013 included outcomes from management scenarios for consideration by the ACOM advice drafting group for the North Sea. The Fcube tool (Fleet and Fishery Forecast) is the only tool used by this group. The species considered as part of the demersal mixed fisheries of the North Sea are cod, haddock, whiting, saithe, plaice, sole and *Nephrops norvegicus*. All species except Nephrops are subject to monospecific multi-annual management plans. These plans are based on harvest control rules to derive annual TACs according to the state of each individual stock relative to their biomass reference points and their target fishing mortalities. Input data for Fcube consist mainly of catch and effort by fleet and métier, and fishing mortality estimates from the single-species stock assessments. Catch, effort and fishing pressure are recombined by fleets and métiers. Projections are carried out based on five effort scenarios: *status quo* effort, *min* where fishing stops when one quota is reached, *max* where fishing stops when all quotas are taken, *cod* where all fleets set their effort according to their cod quota share, and *Ef_mgt* where effort is adjusted according to the EU effort management regime.

The absence of species interactions in Fcube was discussed, but since this tool is only used for short-term forecasts, these interactions are not considered important at such a short time-scale. In the long term, however, they might impact the fishery. Generally, it is assumed that for short-term forecast, the fishery does not change much. Key parameters such as catchability are assumed to change little and can be set as the average of previous years for purposes of a short-term forecast.

If Fcube was to be implemented as a tool for management evaluation, the forecasts would have to be repeated over several years. In that case, some assumptions would probably have to be revised to include changes in the fleets, and species interactions may have to be included over a long period of time.

An option for further development of Fcube could be to provide a global indicator of the mixed fishery as a whole with respect to harvesting. Such an indicator does not currently exist because Fcube is based on outputs from single-species stock assessments, and the forecasts it produces for each species are compared with the corresponding forecasts derived from single-species assessments. As a consequence, there are no mixed-fishery Fmsy and other reference points which could be used to assess the status of the fishery as a whole.

Fcube has not been tested on data-limited stocks (DLS). Given that the main inputs are effort, catch and fishing mortalities for fleets and métiers, it is necessary to obtain this information directly (although it may also be possible to use proxies for fishing mortality) in order to run Fcube. However, obtaining estimates (or even proxies) of fishing mortality is potentially problematic for DLS.

Discussions focused on the various management scenarios that were included in the WGMIXFISH report. Those scenarios are quite generic because they do not necessarily reflect fishermen's fishing strategy. Fishermen's knowledge of microstructures (e.g. spawning area, local zone of interest) within their fishing zone allow them to adjust their effort or target species, or to avoid certain areas to modulate the composition of their catches. This information is not generally taken into account in any management scheme, which tends to be based on aggregated information at the global scale of the fishery, such as aggregated catch and effort. The scenarios presented were considered to be simple, exploratory scenarios. The *max* scenario (fishing only stops when all species quotas are taken) goes too high and is detrimental to most stocks, while the *min* scenario (fishing stops when the smallest quota is reached) is too restrictive and would not maintain the economic viability of the fishery.

A "middle road" probably exists between the *min* and *max* scenarios, and alternative scenarios to those presented were discussed. One included setting a range of TAC intervals. This would allow more flexibility, because several species could, with such a system, be within an acceptable range of catches without exceeding TACs as is currently the case in scenarios other than the *min* one. Such a scenario would, however, be difficult to implement as it would imply setting effort to meet a range of TACs. TAC-based management makes the whole exercise difficult. Furthermore, forecasts may still be driven by the most valuable species, so that one of the consequences of such a scenario may be to simply shift baselines towards some other level, resulting in TAC-overshoots still occurring to some extent.

It is recommended that the extent to which stocks within a mixed fishery might "safely" (from a precautionary point of view) be landed over their TACs, be evaluated. The idea is not to promote overshooting of TACs *per se*, but to evaluate for each stock the consequences of being overlanded (likely to happen in any case, except for the *min* scenario) or discarded because of the multispecies nature of the fishery.

An alternate solution might consider a system with financial penalty. New Zealand allows landings over TAC but with penalties set to a "deemed value" in order for the vessels not to make profit from the additional catch in that situation (Marchal *et al.*, 2009; Mace *et al.*, in press). It is possible to include fish prices in Fcube. A target for a management scenario could be to find the proper balance between economically reasonable profit and biologically sustainable landings.

An alternative to the *max* scenario, perhaps called *capped max*, could also include a cap on maximum effort so that fishing stops when this cap is reached. However this cap has to be set and the group did not discuss on which basis it would be set, although something like the maximum observed effort over some recent period (e.g. 3 or 5 years) could be considered.

Multispecies approaches

A summary of the modelling approaches followed by WGSAM was also presented. This working group focuses mainly on ecosystem modelling (although multispecies assessments are also carried out) and associated parameterization, and covers a diverse range of models, mostly developed within a regional context. Those models include, in most cases, some fishery components which range from basic representation of vessels as a part of the foodweb to mixed fishery fleets. Additional work carried out at WGSAM also includes building a stomach content sampling programme within ICES, building virtual multispecies datasets for model testing, and developing foodweb indicators.

WGSAM also carries out exploratory analyses around the concept of MSY within a multispecies context and how it affects other biological reference points. These analyses include considering "balanced" fishing, where vessels would target evenly every component of the ecosystem, from plankton to whales, and how indicators such as cannibalism among cod could be used for the HCR in the Barents Sea. In all cases, ecosystem models are hard to calibrate and there are uncertainties regarding parameters and outcomes related to external pressure such as fishing mortalities. Therefore, the results of all these approaches lack robustness and are not currently suitable as part of any advisory process, particularly as they are still under development. However, WGMG recognizes the huge amount of work and effort in the development of those models.

Given the diverse and complex nature of multispecies approaches, which are currently under varying levels of development, it was not possible to investigate them in any depth for the current WGMG meeting; it seems unlikely that any of them are currently usable, from an operational point of view, for testing mixed fishery management scenarios. However, it is worth noting that WGSAM did provide some multispecies considerations through simulations for the North Sea stocks. In future WGMG meetings, it would be worth considering these multispecies approaches again, as they are developed further, particularly with regard to their potential for evaluating management scenarios (e.g. MSC and Lenfest reports advocating lower F on forage fish species; Smith *et al*., 2011, Pikitch *et al*., 2012).

In summary

Given the complex nature multispecies and ecosystem approaches and associated difficulties with estimation/calibration, a possible way forward to tackling ToR 1 would be consider developing a minimum realistic model (e.g. MICE; Plagányi *et al*., 2012) to serve as an operating model in order to evaluate the performance of mixed-fishery models (such as Fcube) within a management strategy evaluation framework.

3 ToR 2 – ICES Data-limited approach

3.1 Evaluating robustness

Introduction

The ICES Data-Limited Stocks (DLS) framework has been set up with the intention of achieving greater precaution in catch advice when less information is available. This implies that as one moves down the DLS categories, from data rich in Category 1 to increasingly data-limited stocks in lower categories, one would expect that the DLS framework would provide concomitantly more conservative catch advice.

The ICES DLS framework is described in ICES DLS Guidance Report (ICES, 2012), which includes descriptions of the methods to apply in each of the DLS categories. The approach used here was to start with a data-rich stock in Category 1, then to systematically strip away data from this stock to demote it to lower categories, each time applying one of the methods appropriate to that category, and focusing on the methods most commonly used by ICES working groups. At this point, it should be noted that some of the lower categories do not necessarily use "less" data to provide catch advice, but rather focus on different data. The most obvious example is method 3.2 of Category 3 which uses a time-series of an aggregated index of abundance, but not catch-at-age data, whereas method 4.1.3 of Category 4 uses only catch-at-age data (ICES, 2012). However, the simulations presented here focus only on DLS Categories 1-3, with an extension to include Category 4 being presented at the WKLIFE-3 meeting towards the end of October 2013.

A Management Strategy Evaluation (MSE) framework was used for the analysis (based on FLR; Kell *et al.*, 2007), requiring operating models and a management model that incorporates the method to be evaluated (see below). The simulations in this section have been designed to investigate a particular question: based on the same conditions (stock, fishery, etc.), does more conservative catch advice follow if less data are available? Therefore, full feedback has not been implemented between the operating and management models (see below). The simulations presented in this section can therefore not be used to evaluate the potential effects of a given DLS method on the underlying stock (full feedback would need to be taken into account for this).

Operating models

The operating models are based on those developed at the June 2008 STECF meeting (STECF, 2008; De Oliveira *et al.*, 2010), and are given in Table 3.1.1. The simulated populations were generated based upon a cod-like stock (loosely conditioned on North Sea cod). The operating model represents the true stock and fishery dynamics, from which data are generated (with observation error) to be supplied to the management model (here catch-at-age and survey index-at-age). Having been supplied the data; the management model applies the method for the relevant DLS category to provide catch advice. If full feedback were considered, the catch advice would be returned to the operating model and would have an impact on the true population. However, the objective of the simulations presented in this section was to provide a direct comparison of the catch advice that each of the DLS categories would deliver given the same underlying stock conditions (the only difference being the amount of information to which the given DLS category had access from the stock), so no feedback was included. Instead, a comparison of the DLS categories was made based on

four exploitation history scenarios: well-managed, well-managed to overexploited, overexploited, and overexploited to well-managed (Table 3.1.1).

Table 3.1.1. Operating Model scenarios. F_{MSY}, the harvest rate that should give rise to the MSY when the stock is at B_{MSY}, the spawning-stock biomass (SSB) that produces the MSY. The cod-like Operating Model assumes a Ricker stock–recruit relationship with steepness of 0.9 and variance of the log recruit residuals about the stock–recruit curve of 0.5^2. Each scenario is constituted by the productivity (steepness of the stock–recruitment relationship), the initial status and the error model. A 30-year projection is used, and 100 simulations conducted.

Scenario	Factor	Level
cod	Stock	Cod like
cod.instat1	Initial status (up to yr 0)	Well managed, i.e. $F \sim F_{MSY}$ and $SSB \sim B_{MSY}$
cod.instat2		Overfished, i.e. $F \sim 2F_{MSY}$ and $SSB \ll B_{MSY}$
cod.#.fustat1	Future status (yr 1 to 30)	Initial status continues
cod.#.fustat2		Linear change from initial status to alternative status (e.g. from instat1 to instat2 or vice versa) over years 10 to 20.
cod.#.#.err1	Error models (including 10% on catch-at-age)	assuming I_y is log-normally distributed with median B_y/q and 30% CV, where B_y is the true stock size (note: q=1 and is held constant, while I_y could either be the total biomass or SSB index, in which case B_y would represent the corresponding quantity)
cod.#.#.err2		As above, but q increases from 0.7 in year 0 to 1 in year 30 (note: this increase is not directly accounted for by the HCR, which assumes it remains constant over time)

Management Models, incorporating methods for each DLS category

A selection of methods, one for each DLS category, with a focus on the most common methods within the lower categories (e.g. method 3.2 in DLS Category 3; ICES, 2012) was considered. Neither change limits nor a precautionary buffer (ICES, 2012) is applied to Category 1. A change limit of ±20% is applied to Categories 2-3, and a precautionary buffer of -20%, when appropriate (see below) to Categories 3 (but not to Category 2). The catch advice for year $y+1$ is indicated as C_{y+1}, and both the change limit and precautionary buffer are relative to C_{y-1}, where the latter is interpreted as the average catch for years $y-3$, $y-2$ and $y-1$ for the purposes of these simulations. Although the methods call for a transition to F_{MSY}, or an appropriate proxy, by 2015, this transition has not been applied in the simulations presented because such a transition would be applied for a single year only.

Category 1:

The method receives a complete set of data (catch-at-age, including discards, and a survey index-at-age) and relies on a full analytical assessment, short-term forecast and application of the ICES MSY rule, as follows (assuming $y-1$ as the final year of data, y as the year when the assessment is conducted and $y+1$ the year for which catch advice is needed):

1. Conduct a full assessment (FLXSA is used); extract an estimate of F_{MSY} and $B_{MSY\text{-trigger}}$ the first time the assessment is applied (i.e. in year 0)

2. Perform a short-term forecast, assuming three-year means (for weights-at-age, natural mortality, maturity and fishery selection), geometric mean recruitment and status quo F for year y ($F_y=F_{y-1}$).

3. Use the ICES MSY rule to calculate F_{y+1}:

$$F_{y+1} = F_{MSY} \times \min\{SSB_{y+1} / B_{MSY-trigger}; 1\}$$

4. Apply the Baranov catch equation to calculate C_{y+1}, the catch advice.

Category 2:

The method receives incomplete catch-at-age data (discards are omitted) but complete survey index-at-age. It follows the same procedure as Category 1, but F_{MSY} is replaced by $F_{0.1}$, and a change limit of ±20% is applied such that:

$$0.8C_{y-1} \leq C_{y+1} \leq 1.2C_{y-1}$$

3.1.1

Category 3:

A time-series of an aggregated index of abundance (here total biomass) is available, but no catch data. The method was originally proposed by the European Commission (De Oliveira *et al.*, 2010), and involves adjusting catch advice based on a recent trend in the aggregated index.

$$C_{y+1} = C_{y-1} \left(\frac{\sum_{i=y-x}^{y-1} I_i / x}{\sum_{i=y-z}^{y-x-1} I_i / (z-x)} \right)$$

3.1.2

which is then subject to a ±20% change limit, as for Category 2. Here the version originally proposed by the European Commission (with $x=2$ and $z=5$) is used. In addition to the change limit, a precautionary buffer of -20% is applied unless the following condition is met (in which case the precautionary buffer is omitted):

$$\frac{\sum_{i=y-x}^{y-1} I_i / x}{\sum_{i=y-z}^{y-x-1} I_i / (z-x)} > 1.5$$

3.1.3

Results

Results are shown in Figures 3.1.1-3.1.4 for the various exploitation history scenarios (well-managed, well-managed to overexploited, overexploited and overexploited to well-managed). Results always show the catch advice from a higher category (one that uses more data) divided by that from a lower category, so the expectation is that the distribution of this ratio (derived from 100 simulations) should be above 1 in each case – for the purposes of the results shown, the performance of the DLS framework is interpreted in this context (i.e. good performance is when the DLS framework provides more conservative catch advice when there is less data available).

Well-managed

For the well-managed scenario (Figure 3.1.1) under no trend in survey catchability (b), both the medians and inter-quartile ranges (25-75%) are generally above 1 with the lower extreme of the distributions around or below 1. Performance improves in the presence of a positive trend in survey catchability (c), a feature that is repeated for all stock scenarios. This implies that the lower categories introduce greater precaution when there is a trend in survey catchability that is not taken into account by the HCR, likely due to the additional constraints that the lower categories impose (change limit and precautionary buffer).
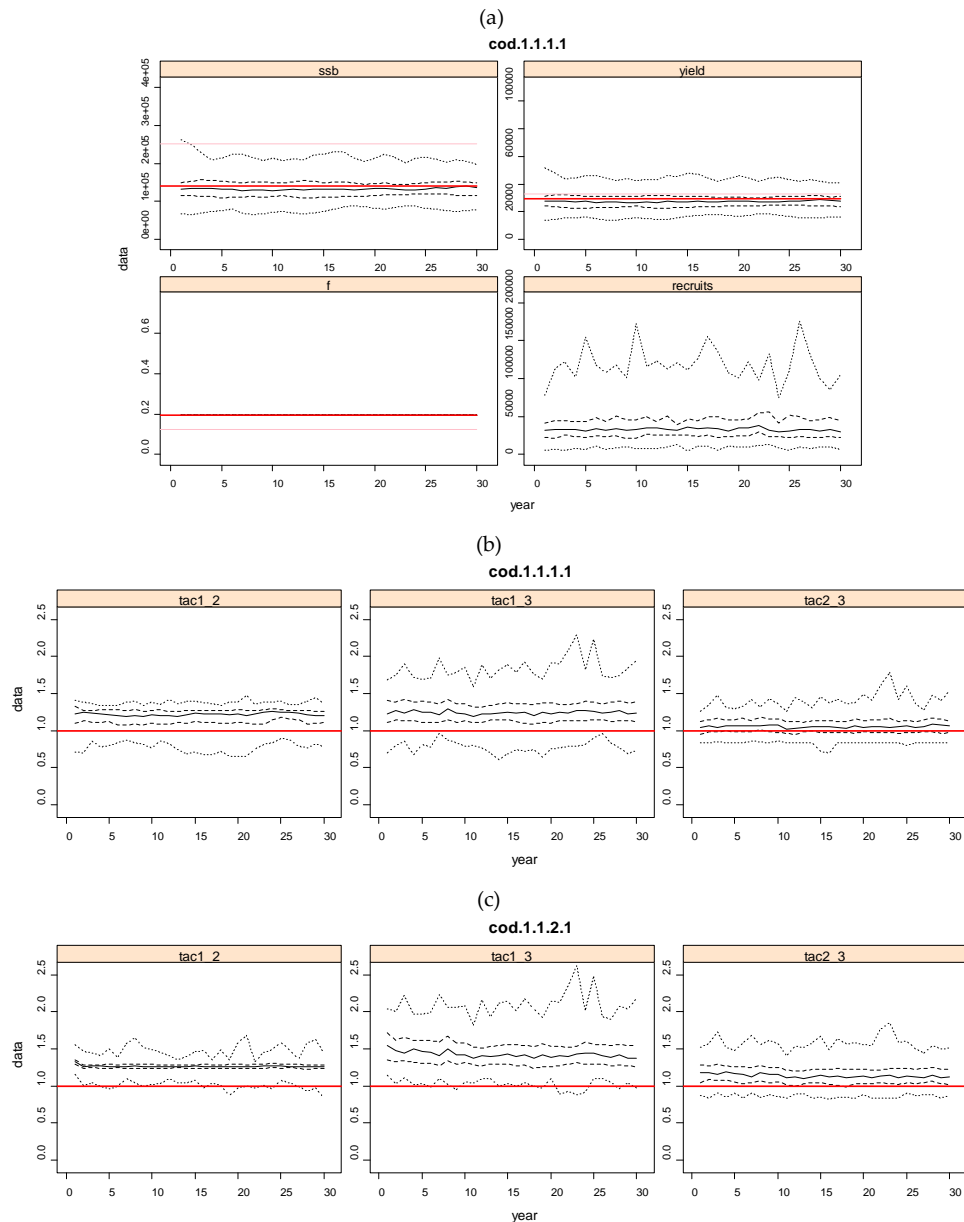
Figure 3.1.1. The well-managed scenario, with future projections of SSB, F, yield (landings) and recruits shown in (a) (dark red line corresponds to F_{MSY}, light red lines to $F_{0.1}$). Catch advice across DLS categories (e.g. TACx_y is catch advice for Category x divided by that for Category y) are compared in (b) for a constant survey catchability and (c) for a trend in survey catchability, with red lines indicating a TACx_y ratio of 1. In all cases the solid black line is the median, the hashed lines the 25th and 75th quantile, and the dotted lines the minimum and maximum.

Well-managed to overexploited

Performance of the DLS framework deteriorates somewhat when an initially well-managed stock becomes overexploited (Figure 3.1.2), particularly when comparing Category 1 with the other categories. This feature is likely due to the impact of the change-limit (implemented for all Categories apart from Category 1), which does not allow a greater than 20% change of C_{y+1} relative to C_{y-1}, and is in effect a 10% year-to-year change – this is somewhat restrictive, particularly when a greater change is needed under a declining stock scenario. When compared to Category 2, Category 3 does seem to provide more conservative catch advice (although the lower end of the distribution does stray below 1, but not more so than for the well-managed scenario).

(a)

cod.1.2.1.1

(b)

cod.1.2.1.1

(c)

cod.1.2.2.1
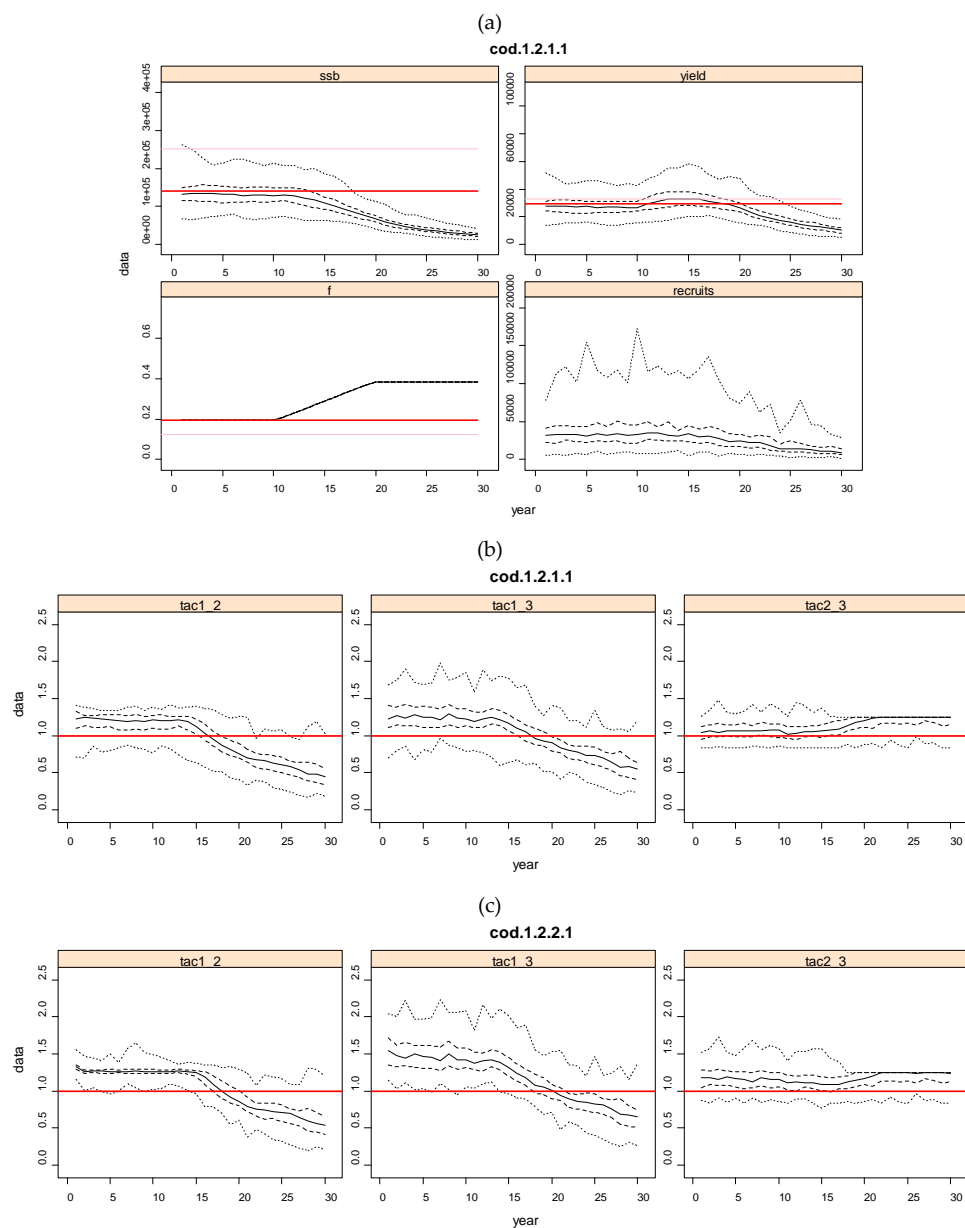
Figure 3.1.2. The well-managed to overexploited scenario (see Figure 3.1.1 for details).

Overexploited

In an overexploited stock scenario (Figure 3.1.3), the performance of the DLS framework is poor, particularly when comparing Category 1 to the other categories as before, with both the median and inter-quartile range (25-75%) falling below 1 in most cases for Category 1 relative to Category 2, and the median falling below 1 in most cases for Category 1 relative to Category 3 for the case where there is no trend in survey catchability (b). This is concerning as it implies that for an overexploited stock scenario, Categories 2 and 3 provide less conservative catch advice than Category 1 in most cases.
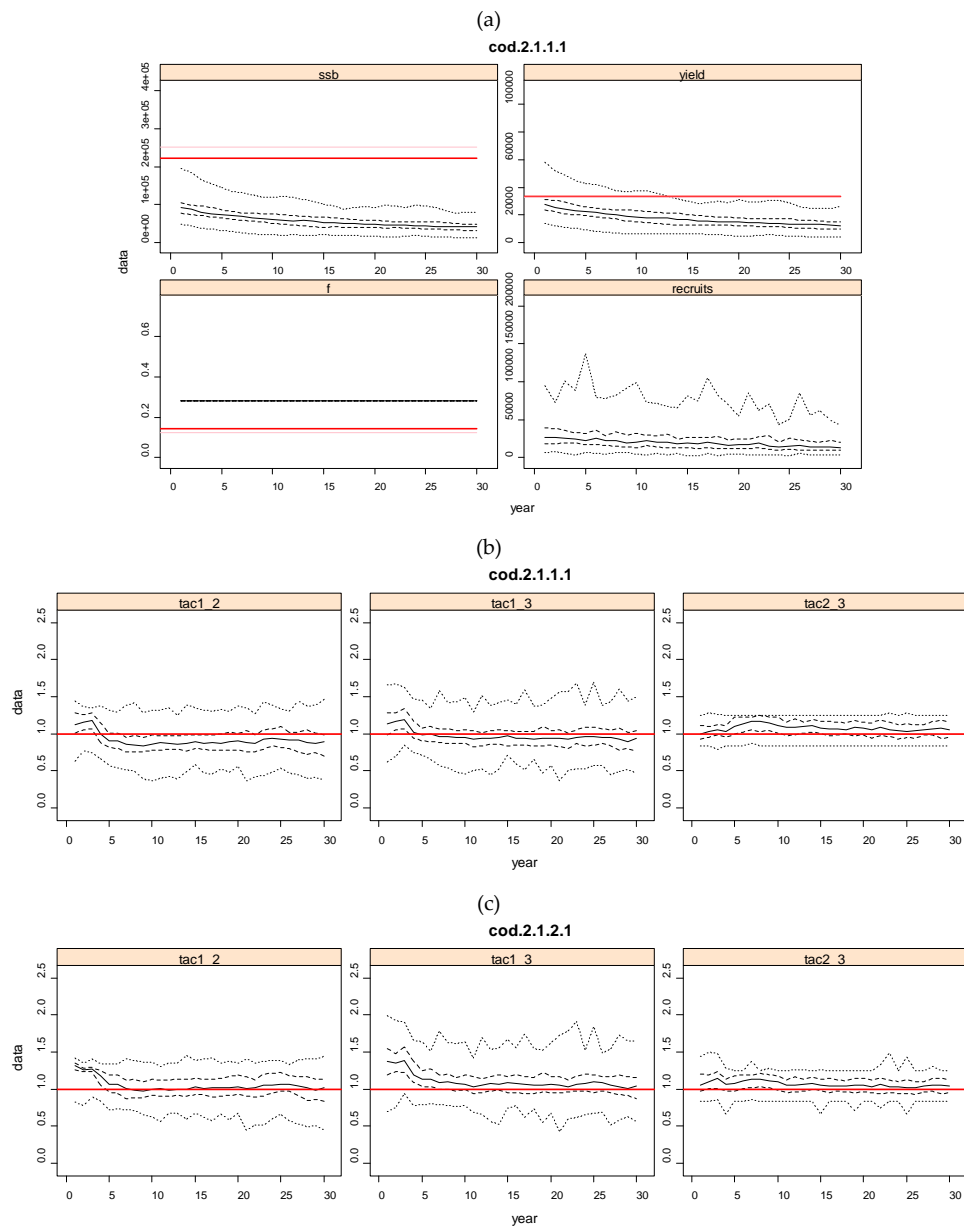
Figure 3.1.3. The overexploited scenario (see Figure 3.1.1 for details).

Over-exploited to well-managed

This stock scenario provides similar results to the over-exploited scenario initially and the opposite of the well-managed to overexploited scenario later, with the 20% change limit restricting the amount by which the catch advice is able to increase for the lower categories compared to Category 1.
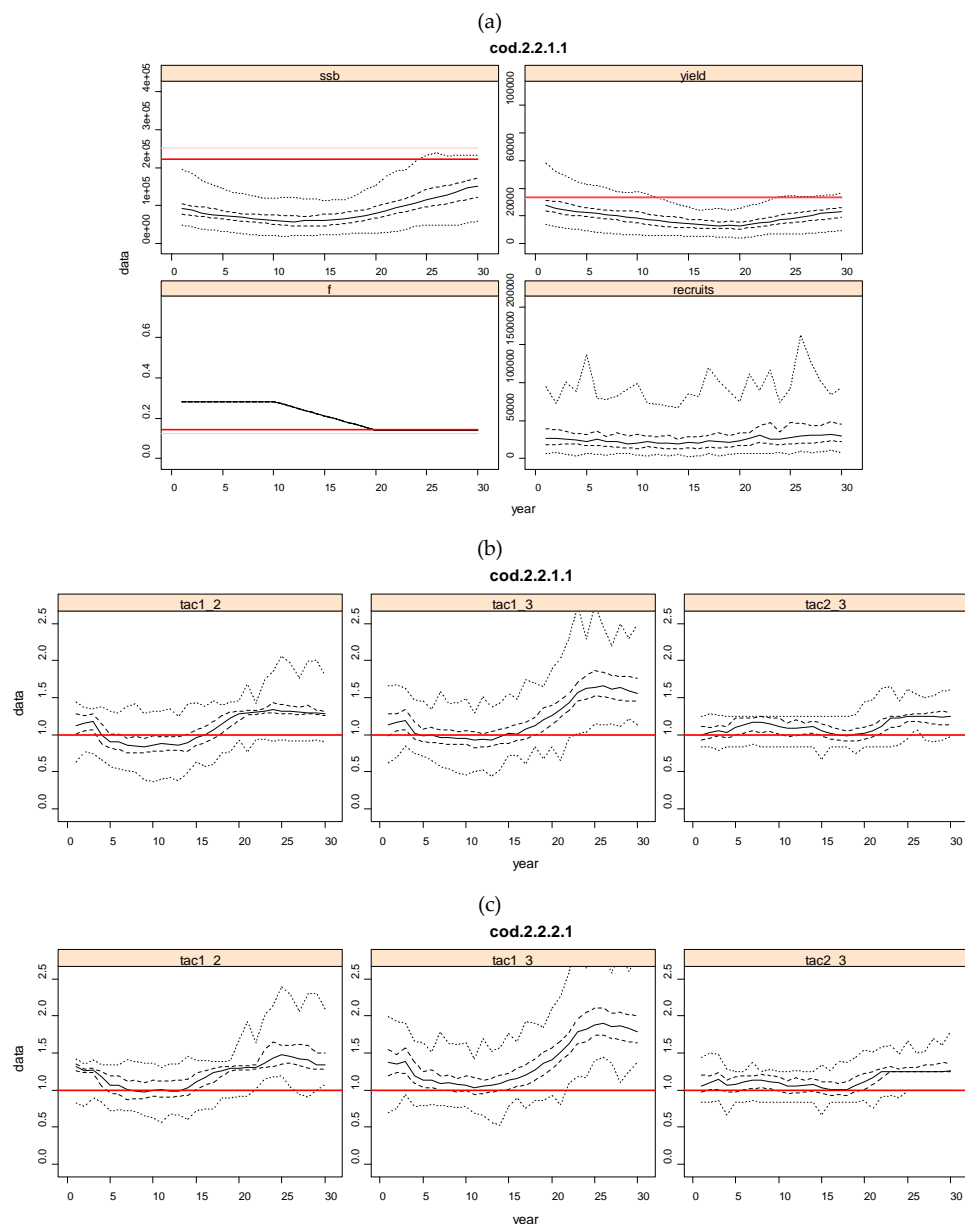
Figure 3.1.3. The overexploited to well-managed scenario (see Figure 3.1.1 for details).

Conclusions

These conclusions should be seen in the context of the assumptions that underlie the simulations; furthermore, the simulations are not comprehensive and only consider the DLS methods most commonly used by ICES WGs. Nevertheless, it is possible to draw some general conclusions as follows (note that performance of the DLS frame-

work refers to its ability to deliver more conservative catch advice when less data are available, i.e. when one moves down the DLS categories):

- Under a well-managed stock scenario, the DLS framework delivers, in most cases (but not all), more conservative catch advice when there are less data available (i.e. as one moves down the DLS categories)

- The performance of the DLS framework deteriorates when a well-managed stock becomes overexploited, with a large part of this deterioration being caused by the 20% change limit imposed in the lower categories for catch advice in a particular year relative to some catch level two years earlier (effectively resulting in a constraint on changes in catch of 10% per year).

- The performance of the DLS framework is poor when a stock is overexploited. A particular concern is that in most cases under an overexploited stock, Categories 2 and 3 provide less conservative catch advice than Category 1.

It should be noted that the simulations presented do not include feedback (i.e. the catch advice does not affect the underlying population) because the intention was to make a direct comparison of catch advice that each DLS category would provide under a variety of identical stock situations.

Summary of discussion

Category 2 – trends-based assessment

The approach recommended under Category 2 of the DLS approach differs from that of Category 1 only in that it uses a more precautionary reference point and includes a catch change limit.

Regarding more precautionary reference points, $F_{0.1}$ is recommended as a precautionary proxy for F_{MSY} in current ICES DLS guidelines (ICES, 2012). The group expressed some concern that it may not generally be the case (given that $F_{0.1}$ is based on YPR) that this holds true. YPR analyses exclude a stock recruit relationship and therefore take no account of the potential for recruitment overfishing. $F_{0.1}$ calculated in a production model context is inherently more precautionary than F_{MSY}. Caution should be exercised to ensure that the chosen proxy is indeed more precautionary. Regarding the catch change limit, it was noted that the recommended 20% change limit may be too restrictive. Since this change limit applies to the catch in the previous year (C_{y-1}) and is applied to the recommended catch for the next year (C_{y+1}), this implies a 20% change over two years. This effectively results in a change limit of 10% per year, and may result in HCRs which apply this limit not being able to react quickly enough in the case of a declining, overexploited stock. Approaches exist where application of a change limit may be overridden if resource abundance declines below some threshold. This should be implemented on a sliding scale to prevent step changes in catch advice.

The simulation results where survey catchability (q) increases over time showed that under scenarios of increasing exploitation or overexploitation, the Category 2 HCR still produced more conservative TACs compared to the Category 1 HCR than under an assumption of constant q. This result was somewhat surprising, but could be explained by the inclusion of the catch change limit in Category 2, preventing larger, ill-informed increases in TAC as survey catchability changed.

Category 3 – Method 3.2 (age-aggregated index)

The simulations of the Category 3 HCR focused on the '2 vs. 3' rule most commonly applied to stocks in this category.

To simplify the application of this rule, C_{y-1} was taken as the average of the last three years' catch (C_{y-3} to C_{y-1}). In practice, if a trend in catch was observed, C_{y-1} would be used on its own. In an overexploited scenario including feedback, this simplification could potentially result in higher TACs than would be advised in practice as the stock (and associated catches) could show a declining trend over time resulting in a lower C_{y-1} value being used in the HCR than the average of the last three years. However, the results presented to the group did not include feedback so are unaffected by this issue.

Another simplification required was when a precautionary buffer (additional 20% reduction in catch) was applied. There are various guidelines in the DLS approach to consider here regarding estimates of the sustainability of the current level of exploitation of the stock. The simplest of these to apply in simulations, and most commonly applied in practice, is that a 50% increase in survey biomass (according to the 2 vs. 3 ratio) is required to prevent the application of a precautionary buffer. It is not clear in the guidelines over what period this increase should be measured, and certain stocks applied different periods for the ratio (e.g. 3 vs. 5 years).

It was noted that the 2 vs. 3 rule essentially examines the change in stock size (as indicated by the survey) between 4 years ago (average from 5 to 3 years ago) and 1.5 years ago (average of 1 and 2 years ago), a period of 2.5 years. This change over 2.5 years is then applied to recommend a change in catch over 2 years without correcting for this difference in time periods. This problem increases if longer time periods are used.

A general criticism of trend-based HCRs (such as the 2 vs. 3 rule) is that while they may arrest an increase in exploitation on the stock, they may be likely to maintain stocks near to their current condition (which may be suboptimal). It was argued that target-based strategies (in terms of F_{MSY} proxies or index targets) could be preferable. While there is still uncertainty over exactly what the targets should be, they do at least allow for moving the stock in a more favourable direction than the current status for overexploited stocks (see Sections 3.2 and 3.3).

Under Category 3 the same limitations of using a 20% catch change limit apply. However, some of the concerns regarding the delayed response for a declining overexploited stock could be addressed by the application of a precautionary buffer (potentially allowing a 36% change, or 18% per year). While this buffer is not intended to be applied on an annual basis, it would allow for a larger initial reduction in catch for overexploited stocks.

General comments

The results indicated that the DLS approach does not always provide increasing precaution with increasing uncertainty. This is evident for scenarios of overexploitation or increasing exploitation (SSB declining).

The DLS approach should ideally be more precautionary as one steps down the levels of data/method availability. Hence the simulation results were considered to support this idea of increasing level of precaution if the TACs resulting from lower categories were lower than those arising out of higher categories (i.e. TACcat1> TACcat2>TACcat3). However, 'precautionary' could be considered as an 'on-off' concept

(i.e. beyond a certain point one is no longer being more precautionary, but perhaps more wasteful). This could be evaluated more efficiently in a feedback simulation.

The approaches below Category 1 in the DLS framework could (if they pass certain tests) be considered 'precautionary' but care should be taken in the ICES introduction to advice when stating that they represent MSY-equivalent management.

3.2 Age–aggregated approaches

Method

This proposal presents alternative harvest control rules (HCRs) in addition to those described in ICES (2012). The general HCR can take the form

$$C_{y+1} = C_{y-1}\alpha(.)$$

3.2.1

Different forms for $\alpha(.)$ leads to alternative HCRs. The base model considered here (hereinafter referred to as HCR1) takes

$$\alpha(.) = \frac{\sum_{i=y-2}^{y-1} I_i / 2}{\sum_{i=y-5}^{y-3} I_i / 3}$$

3.2.2

i.e. it includes a comparison of the two most recent index values with the three preceding values. Thus,

$$C_{y+1} = C_{y-1} \frac{\sum_{i=y-2}^{y-1} I_i / 2}{\sum_{i=y-5}^{y-3} I_i / 3}$$

3.2.3

Other HCRs were considered based on survey confidence interval and length-based reference points:

- HCR2: $\alpha(.) = \frac{\sum_{i=y-2}^{y-1} I_i / 2}{\sum_{i=y-5}^{y-3} I_i / 3} \cdot \frac{L_{SQ}}{L_{F=M}}$

- HCR3: $\alpha(.) = \delta$

- HCR4: $\alpha(.) = \delta \cdot \frac{L_{SQ}}{L_{F=M}}$

where

$$IC_{99\%}(\mu_I) = [\mu_I + z_{0.01}\frac{\sigma_I}{\sqrt{n_I}}, \mu_I + z_{0.99}\frac{\sigma_I}{\sqrt{n_I}}] = [low, up] \qquad 3.2.4$$

$$\delta = \begin{cases} 0.85, & I_{y-1} < low \\ 1, & low \le I_{y-1} \le up \\ 1.15, & I_{y-1} > up \end{cases} \qquad 3.2.5$$

with μ_I the index mean, σ_I the index standard deviation, n_I the length of the index time-series, and z_x the z-statistic from the standard normal distribution for which $\text{Prob}(Z \le z_x) = x$. Furthermore:

$$L_{SQ} = \frac{\sum_{a=1}^{A} C_{a,Y} L_a}{\sum_{a=1}^{A} C_{a,Y}} = \text{mean length in the catch,} \qquad 3.2.6$$

$$L_{F=M} = 0.75L_c + 0.25L_\infty \qquad 3.2.7$$

$$L_c = L_{a_c} = L_\infty(1 - \exp(-K(a_c - a_0))) = \text{mean length at first capture.} \qquad 3.2.8$$

The length-based reference points L_{SQ} and $L_{F=M}$ are used, respectively, as proxies of current fishing mortality, F_{SQ}, and the fishing mortality at MSY, F_{MSY} (ICES-WKLIFE-2, 2012). Thus,

$$L_{F=M} \sim L_{F=F_{MSY}} \qquad 3.2.9$$

and

$$\frac{L_{SQ}}{L_{F=M}} \propto \frac{F_{SQ}}{F_{MSY}}, \qquad 3.2.10$$

From Beverton and Holt (1957) can be show that

$$L_{F=M} = \frac{2ML_c + KL_\infty}{2M + K}, \qquad 3.2.11$$

and assuming $K = 2M/3$ equation 3.2.7 holds.

Simulation

The simulation study used information on life-history traits from the first WKLIFE meeting (ICES-WKLIFE, 2012) and was performed in FLR (code in Annex 5). To run the simulation the following 3-steps algorithm was applied:

1. Use information about life-history traits of several fish stocks to build coherent

population dynamics under no-exploitation scenario.

2. Simulate for each stock two exploitation history:

(i) "development" - 15 years with linear increasing fishing mortality from no

fishing up to $2F_{MSY}$ $2F_{MSY}$;

(ii) "overexploitation" - 25 years of stable fishing mortality at a $2F_{MSY}$ after the development phase;

3. Add observation error (only) in abundance indices modelled as independent lognormal errors in catchability, with a fixed coefficient of variation of 20%. Abundance indices were simulated with constant catchability over time and an asymptotically flat curve by age.

The approach taken regarding the population dynamics aims to simulate stocks and exploitation histories that are consistent with population dynamics theory and loosely based on the biology of the species, so that a large range of life histories traits and commercial exploitation patterns are considered.

Parameters used for the simulations were those indicated at ICES-WKLIFE-2 (2012) and the following settings:

- Stock–recruit relationship: Beverton–Holt with h=0.9 and virgin biomass of 1000t;

- Fleet with an asymptotically flat selection pattern, where the age of 50% retention is the same as the age of 50% maturity;

- Growth model: parameters of the von Bertalanffy growth model (or proxies) from ICES-WKLIFE-2 (2012);

- Natural mortality computed following Gislason *et al.* (2010).

The confidence interval for the index used in HCR3 and HCR4, is updated every year considering the full time-series of the abundance index.

Applications and results

Irish Sea Plaice example

One run was conducted applying the HCRs to Irish Sea Plaice (ple-iris).

A set of outcomes are shown below for the two scenarios considered. Figures 3.2.1-3.2.4 presents the development scenario (dev) and Figures 3.2.5-3.2.8 the overexploited scenario (hi). The variables presented are the multiplier of catch (idxRatio), recruitment (rec), spawning-stock biomass (ssb), catch, catch advice (catch-adv) and fishing mortality (f).
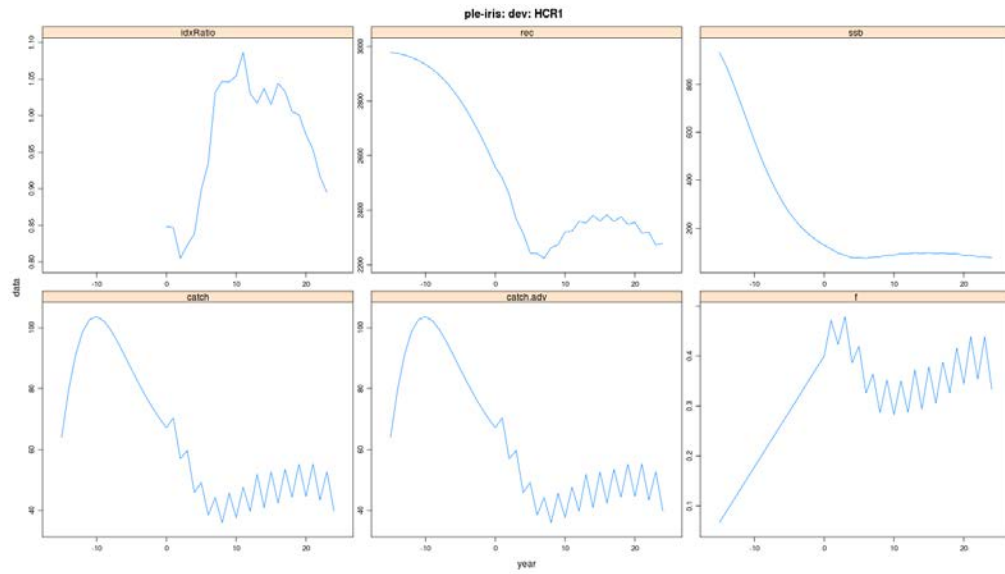
Figure 3.2.1. Irish Sea plaice. HCR 1 under the development scenario for six variables.
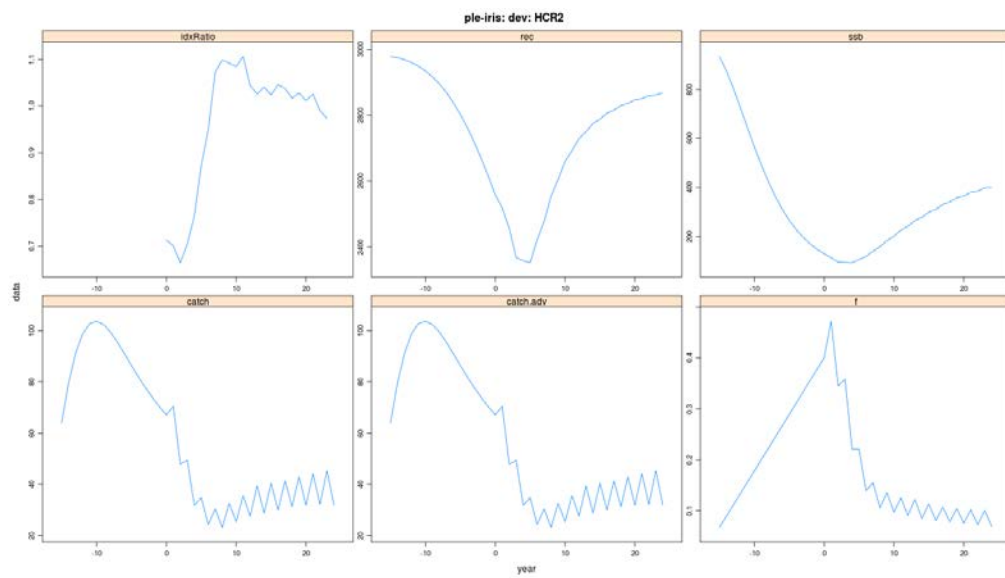
Figure 3.2.2. Irish Sea plaice. HCR 2 under the development scenario for six variables.
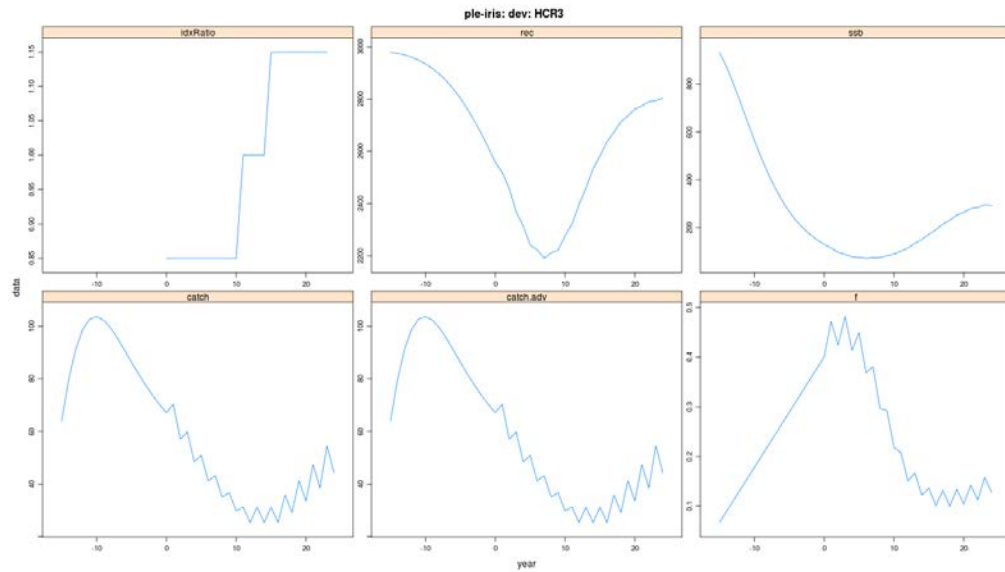
Figure 3.2.3. Irish Sea plaice. HCR 3 under the development scenario for six variables.
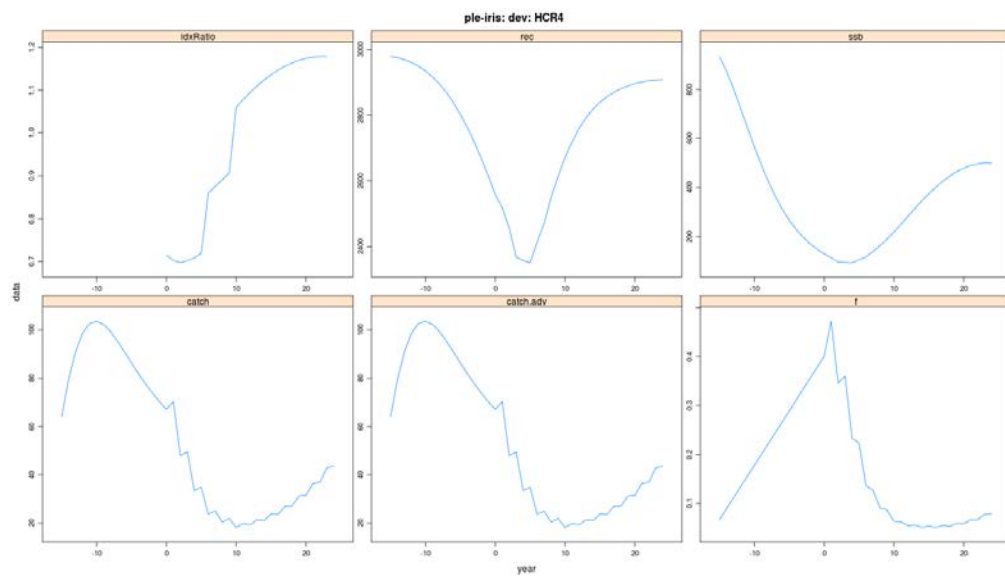
Figure 3.2.4. Irish Sea plaice. HCR 4 under the development scenario for six variables.
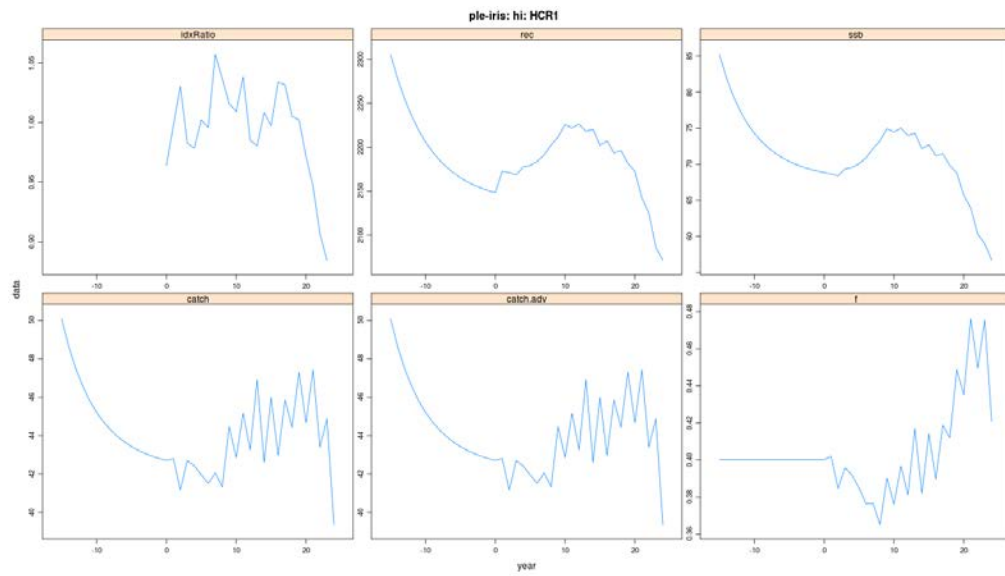
Figure 3.2.5. Irish Sea plaice. HCR 1 under the overexploited scenario for six variables.
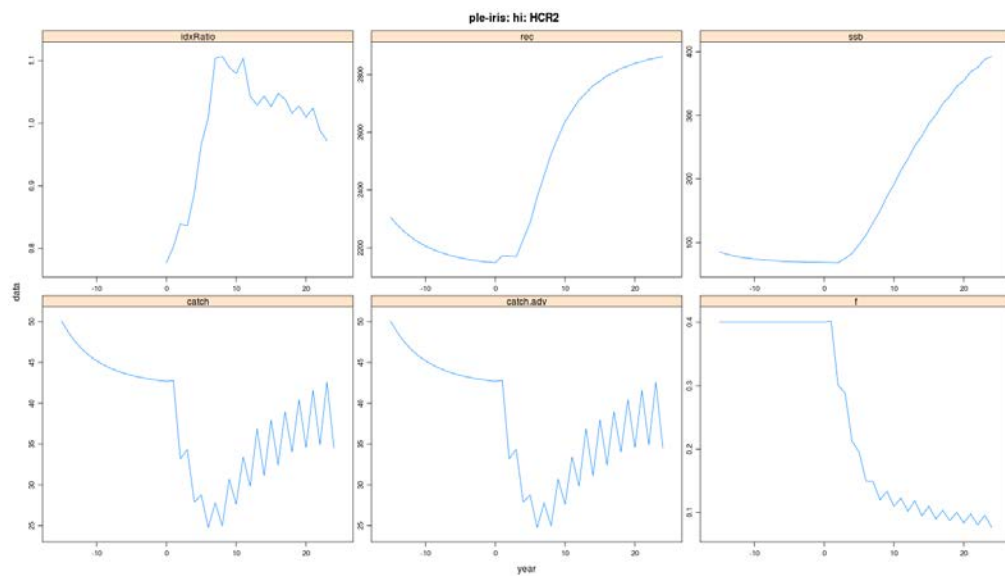
Figure 3.2.6. Irish Sea plaice. HCR 2 under the overexploited scenario for six variables.
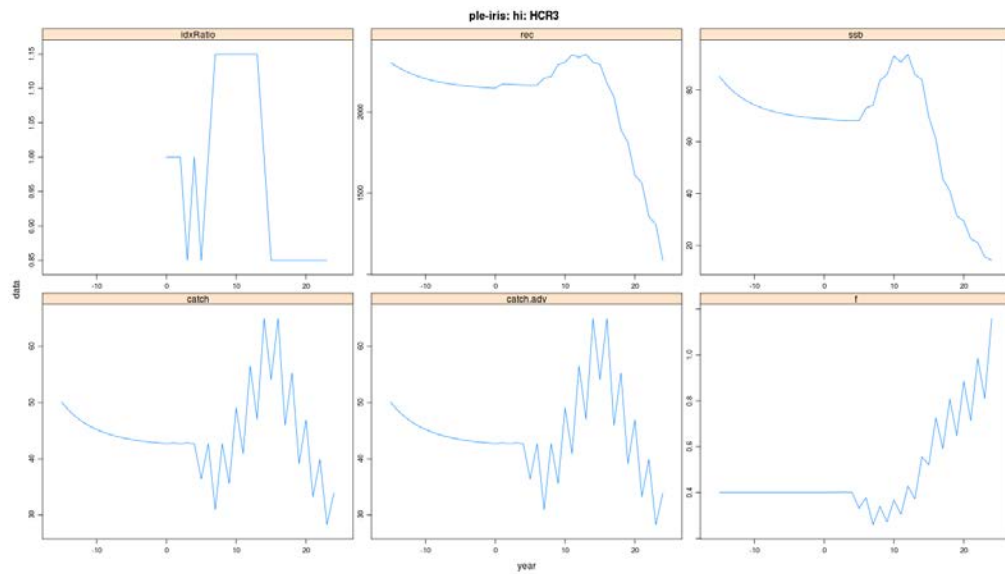
Figure 3.2.7. Irish Sea plaice. HCR 3 under the overexploited scenario for six variables.
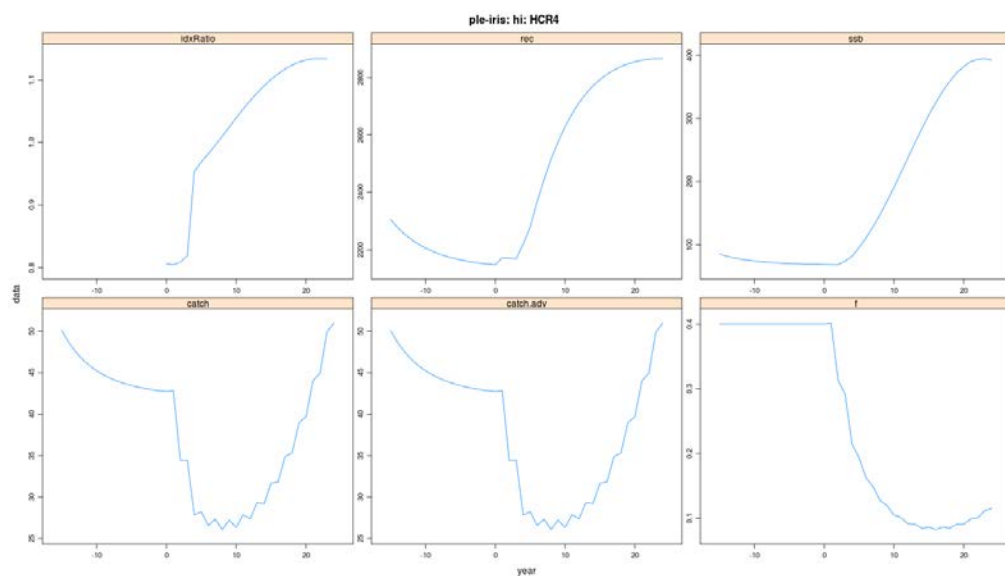
Figure 3.2.8. Irish Sea plaice. HCR 4 under the overexploited scenario for six variables.

In terms of SSB recovery and catch stability, the results from the run performed for the Irish Sea Plaice are summarized in Table 3.2.1).

Table 3.2.1. Irish Sea Plaice. Performance of the HCRs with respect to SSB recovery and catch stability.

	Development scenario		Overexploitation scenario	
	SSB recovery	Catch stability	SSB recovery	Catch stability

HCR1	No	No	No	No
HCR2	Yes+	No	Yes	No
HCR3	Yes	Yes	No	No
HCR4	Yes++	Yes+	Yes	Yes

The outcomes of this run show that the poorest performance regarding SSB and catch is obtained with HCR1: SSB does not recover from low/very low levels and the catch is not stable, for both scenarios. The best performing HCR in both scenarios is HCR4 since SSB can recover from low levels and the catch is stable.

Results for all WKLIFE stocks

The approach applied to Irish Sea Plaice was also applied to all the WKLIFE stocks. In some cases, due to inconsistent life-history parameters, the scenario was excluded. Figures 3.2.9-3.2.12 summarizes the outcome of one simulation per stock for the main indicators: Catch multiplier (previously, idxRatio), SSB (previously, ssb), Catch (previously, catch) and F (previously, f).

In terms of SSB recovery (Figure 3.2.10), the results indicate that HCR1 (currently applied for advice) is not able to recover SSB, keeping the biomass at the levels of the recent period. HCR3 is able to recover SSB in the case of the development scenario; however, if the biomass is stable at low levels, this HCR does not recover SSB with the present parameterization (IC of 99% in equation 3.2.4 and symmetric catch multipliers of 15% in equation 3.2.5). HCR2 and HCR4 showed the best performance in terms of recovering SSB due to the additional term with length-based reference points.
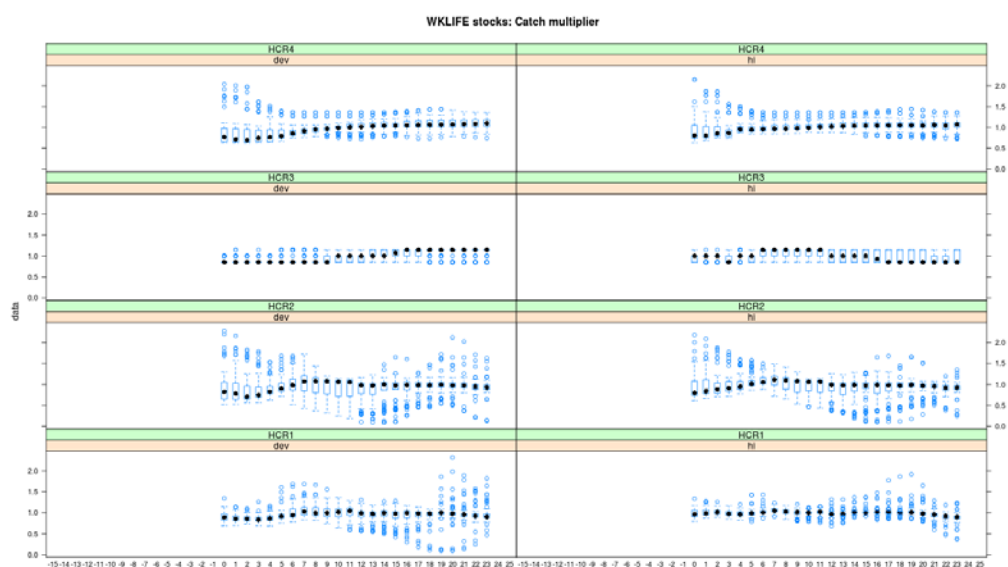
Figure 3.2.9. WKLIFE stocks. Performance in terms of Catch multiplier for the four HCRs (ordered in rows from HCR4 at the top to HCR1 at the bottom) under the development (left) and overexploited (right) scenarios.
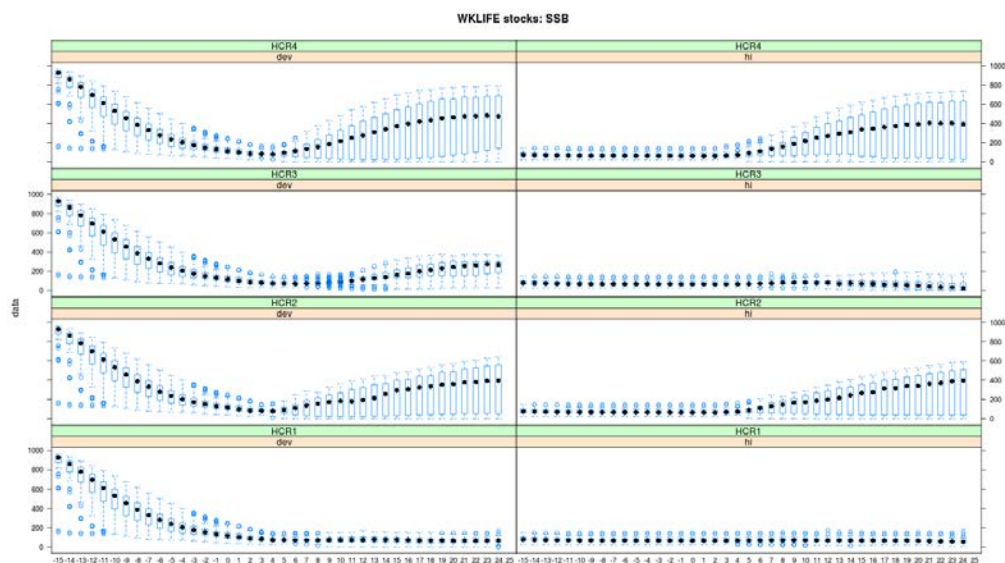
Figure 3.2.10. WKLIFE stocks. Performance in terms of SSB for the four HCRs (ordered in rows from HCR4 at the top to HCR1 at the bottom) under the development (left) and overexploited (right) scenarios.
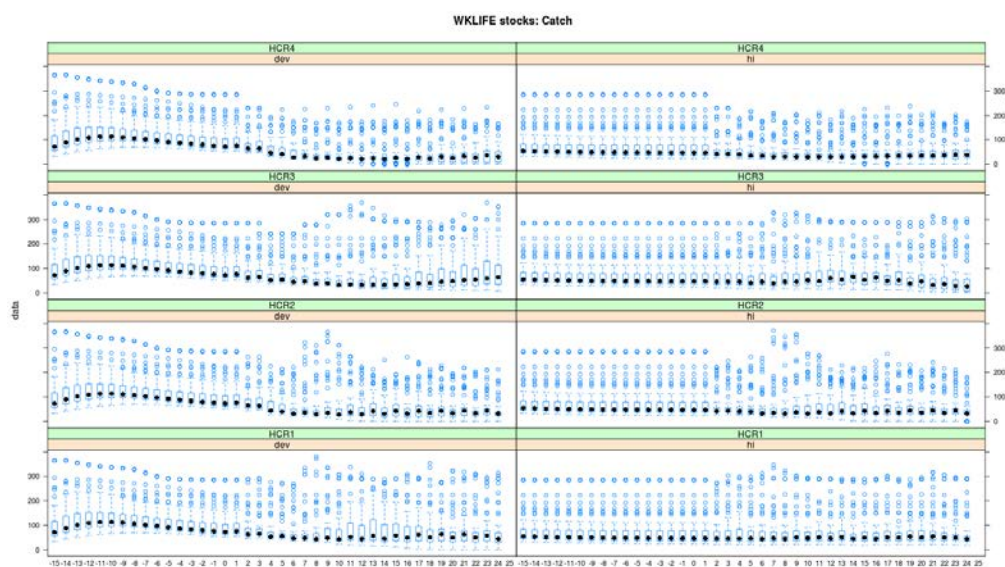
Figure 3.2.11. WKLIFE stocks. Performance in terms of Catch for the four HCRs (ordered in rows from HCR4 at the top to HCR1 at the bottom) under the development (left) and overexploited (right) scenarios.
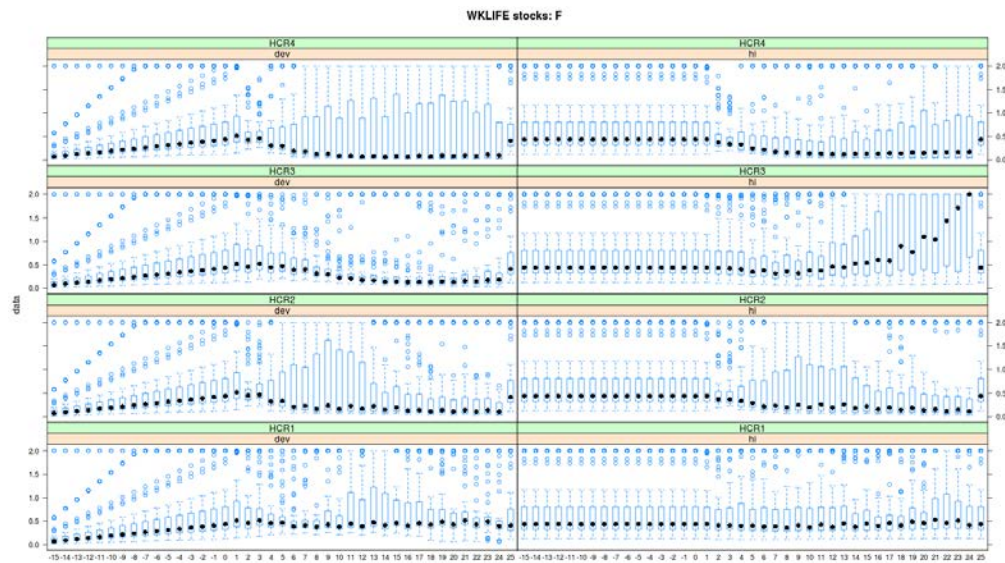
Figure 3.2.12. WKLIFE stocks. Performance in terms of F for the four HCRs (ordered in rows from HCR4 at the top to HCR1 at the bottom) under the development (left) and overexploited (right) scenarios.

Summary of discussion

The primary conclusion of these analyses was that in simple index-based HCRs, accounting for average length in the catch could result in better performance in terms of stock recovery and catch stability. Another conclusion is that the HCR focused on the '2vs.3' rule (referred to as HCR 1 in the simulations) keeps the stock at the current biomass which is a concern particularly for overexploited stocks.

The only source of stochasticity in the simulations was measurement error in the index. Given that this method applies some length-based components in the HCRs applied, it may be necessary to include error in length observations before firm recommendations could be made on the value of including such components in HCRs.

Another aspect that deserves consideration when using mean length in the catch as an indicator of current fishing mortality is that under different circumstances, low mean length could reflect either a healthy (good recruitment) or a threatened (few older fish) stock. Hence analyses on the performance of HCRs including length-based reference points should consider variability and patterns in recruitment.

For HCR3 and HCR4 where δ is used (equations 3.2.4-5), some thought is needed when calculating the index mean and its confidence interval, and selecting a suitable starting point for the period used for these calculations that captures the recent level and variability of the index. It was recommended that, when used as part of a HCR, the time period over which the index mean and its confidence interval are calculated remains constant (i.e. the window considered should remain of the same length but be moved forward in time). The current simulations considered the whole index period (i.e. extending it as new data became available) and thus the 99% confidence limits would result in a change only when the survey index moved almost completely out of the range of observed values, perhaps resulting in an overly inert rule.

3.3 Other approaches

3.3.1 Generic HCRs for data-poor fisheries

The majority of fish stocks worldwide are not managed quantitatively as there are not sufficient data, such as a direct index of abundance, on which to base a resource assessment. Often these stocks are relatively "low-value", which renders dedicated scientific management too costly, and a generic approach is therefore desirable. The aim of work presented (Geromont and Butterworth, in press) was to design and test some very simple "off-the-shelf" management procedures (MPs) that could be applied to groups of data-poor stocks which share similar key characteristics in terms of demographic parameters. For this initial investigation, a selection of empirical MPs was simulation tested over a wide range of Bayes-like operating models (OMs) representing the underlying dynamics of resources classified as severely depleted, in order to ascertain how well these different MPs perform. While the moderately data-poor MPs (based on an index of abundance such as a survey or reliable cpue) performed somewhat better than the very data-poor ones (based on mean length of catch data) as would be expected, the very data-poor MPs nevertheless performed surprisingly well across the wide range of uncertainty considered for key parameters. These simple MPs could well provide the basis to develop candidate MPs to manage the data-poor stocks, ensuring if not optimal, at least relatively stable sustainable future catches.

The Working Group considered this initial work to be a valuable exercise with potential for use once taken further and finalized. ICES does not have the resources to evaluate HCRs on a stock by stock basis. Having a set of generic HCRs that have been tested for robustness according to the likely dynamics of the stock in question would be preferable to non-specific and untested HCRs.

Robustness testing against further uncertainties would be important for the next stage of these evaluations. An important factor to consider would be alternative models (to the log-normal) for recruitment variability. In particular, herring-like recruitment with occasional strong year-classes among others which are generally weak, would lead to changing bias over time in mean length of the catch as an index of abundance. Robustness tests should also consider the factors in the analyses reported in Section 3.1.

3.3.2 Rules using F_{proxy} values and targets

F_{proxy} rules (in this context, F_{proxy} is used to mean a value proportional to F, or more generally an index of F) have the potential to reduce the delay between data availability and advice (albeit requiring some assumptions in certain cases). Such delays (or lags) can cause unnecessary variability in advice.

F_{proxy} rules with associated F_{proxy} targets are similar to specified F based on the results of analytical assessment, albeit with more uncertainty in location of the corresponding target relative to MSY. The standard ICES slope rule (e.g. method 3.2 of ICES DLS Category 3; ICES, 2012) can be viewed in the context of an F_{proxy} approach, albeit with a moving F_{proxy} target. The following demonstrates this.

We define $F_{proxy,y} = \dfrac{C_y}{U_y}$, where C_y is the catch in year y and U_y the index of abundance. The F_{proxy} rule is then:

$$C_{y+1} = F_{proxy,target} U_{pred,y+1} \qquad\qquad 3.3.2.1$$

where $U_{pred,y+1}$ is the predicted value of the index based on index values in preceding years (e.g. the intermediate year, if available, and earlier years). The ICES Category 3 DLS rule (ICES, 2012) is:

$$C_{y+1} = C_{y-1} \frac{\dfrac{1}{2}\sum_{y-2}^{y-1} U_i}{\dfrac{1}{3}\sum_{y-5}^{y-3} U_i} \qquad\qquad 3.3.2.2$$

If we replace C_{y-1} by $F_{proxy,y-1} U_{y-1}$ we get:

$$C_{y+1} = F_{proxy,y-1} U_{y-1} \frac{\dfrac{1}{2}\sum_{y-2}^{y-1} U_i}{\dfrac{1}{3}\sum_{y-5}^{y-3} U_i} \qquad\qquad 3.3.2.3$$

This fits with the equation 3.3.2.1 if we model the following:

$$U_{y-1} \frac{\dfrac{1}{2}\sum_{y-2}^{y-1} U_i}{\dfrac{1}{3}\sum_{y-5}^{y-3} U_i} \qquad\qquad 3.3.2.4$$

as a predictor for U_{y+1} and assume that $F_{proxy,y-1}$ is a candidate for $F_{proxy,target}$, i.e. a moving $F_{proxy,target}$. In practice the F_{proxy} rule would be augmented by a trigger point $U_{trigger}$ so the final rule would be:

$$C_{y+1} = \min\left(\frac{U_{pred,y+1}}{U_{trigger}}, 1\right) F_{proxy,target} U_{pred,y+1} \qquad\qquad 3.3.2.5$$

One of the main problems with the F_{proxy} rule (and all rules based on surveys) is the prediction of U_{y+1}. In many cases U_y is available, and if U_{y+1} becomes available relatively early in the advisory year then management might include updating advice when U_{y+1} becomes available. Smoothing of the advice is another factor that needs to be included; 20% (10%) change limit is one approach but smoothing of indices before computing the TAC provides an alternative.

It is recommended that further work be conducted to examine some F_{proxy}-based rules as potential candidates for target-based rules in the ICES DLS framework. Work to be presented at WKLIFE 3 in November 2013 indicates that the Category 3 rule has some major problems compared to the F_{proxy} rule, related to the lack of a target, the constraint between C_{y+1} and C_{y-1} and the use of a recent trend in prediction.

3.3.3   Preparation of survey indices for use in HCRs

Typical indices used for assessments are based on a weighted average of abundance at each station, where the weighting factor for each station is a measure of the density of stations in the stratum where the station is located. Associated with the estimate of survey index is an estimate of the standard error, which essentially is a measure of patchiness or the part of the uncertainty that can be reduced by increasing the number of stations by some factor.

Noisy survey indices are often accompanied by high estimated standard error, or more specifically, abnormally high values compared to adjacent years do usually have much higher variance.

Some methods are not sensitive to occasional outliers; for example a F_{proxy} rule with x% maximum interannual catch change. All estimations of trend are sensitive to noise, so rules that dampen out the high values might be useful; an example would be weighted (or unweighted) average of $C^b_{station}$ where the power b might could lie in the range 0.5-0.75. This kind of index will in all cases have lower variability than a direct mean but, if it is biased, it needs to be tested based on examples where an analytical assessment is available. Examples of this kind of index for four Icelandic species is shown in Figure 3.3.3.1, demonstrating that the index calculated as an average of the square root of biomass at each station performs best for saithe, for which the data are really noisy.

An alternative to dealing with high values would be to smooth indices by, for example, a LOESS smoother or smoothing spline, weighting each observation by the inverse of the estimated variance or inverse of CV squared. Options to take account of very low values of CV might have to be included.

Results for Icelandic lemon sole showed that this kind of smoothing increased stability in TACs. The smoothed index seemed to follow the data well, but to evaluate performance of the index, retrospective analyses are required (Figure 3.3.3.2).

Questions were raised about how to take the relationship between level of index and associated variance into account when simulation testing this method. These questions will also apply to cases where indices are used directly, as it is a common feature of survey indices compiled as a weighted mean over stations that a sudden increase in the index is often associated with a few large hauls, reflected by an associated higher estimated CV; in contrast, a low survey index might occur in years with no large haul (low CV), although the "typical" haul could be similar.

The usefulness of an index for providing advice may increase if sizes/ages that are a little below the age at first capture in the fishery are included in the index, since these fish will be of marketable size in the advice year.
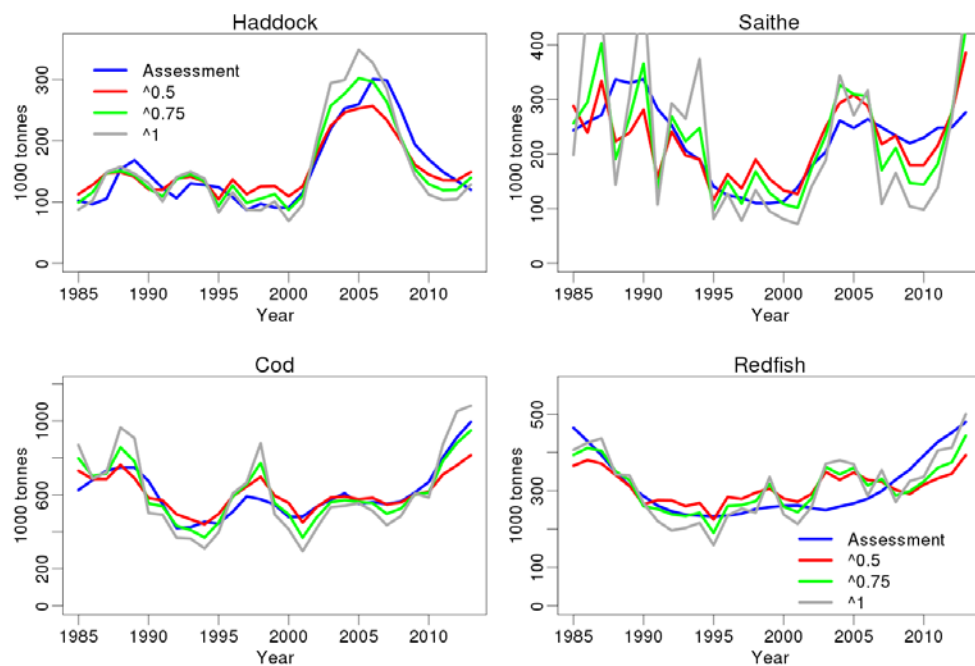
Figure 3.3.3.1. Comparison of survey indices calculated as the average of biomass at each station to a given power (1, 0.75 and 0.5) with biomass estimates from assessment of four Icelandic species.
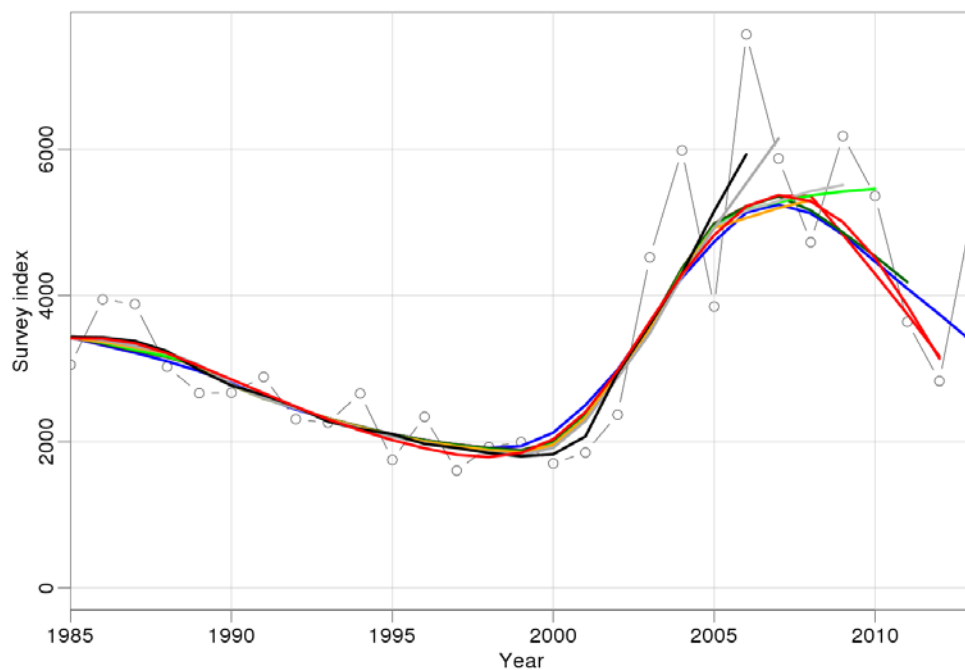
Figure 3.3.3.2. Lemon sole in Icelandic waters. Retrospective patterns of a smoothing spline. The points show the index each year, and the coloured lines a smoothing spline fitted to the data points until the year where each line ends. Degrees of freedom in the smoothing spline is the number of data points divided by 3.

4   ToR 3 – World Conference on Stock Assessment Methods

4.1   Summary of the WCSAM workshop

Fisheries Datasets from Around the World

Before the workshop, the Icelandic modelling teams (and presumably others) had mixed success analysing the datasets that had been selected for the exercise. Datasets were in many cases too complex for simple age-based models. Problems included unclear landings data for North Sea cod and M varying between ages and years. In other cases, data were found to be overly aggregated for length-based models. Some modelling teams gave up after attempting to work on several datasets, without finding out that Georges Bank yellowtail flounder was the most practical dataset for simple age-based models.

At the workshop, it became clear that the modelling efforts were spread across many datasets, but a fairly broad model comparison was available with the Georges Bank yellowtail flounder, although the comparison did not include SAM, for example (Deroba *et al.*, in press).

Simulation Analysis

Data were simulated with multinomial observation noise, using the Popsim software. The basis for the simulated data was not the original data, but fitted assessment models. When the operating model is the same as the estimation model it is called "self test", but using different operating and estimation models is called a "cross test". From a statistical viewpoint, a self test is one variation of a parametric model-conditioned bootstrap which can, among other things, detect estimator bias.

Conclusions

On the whole, it was difficult to draw general conclusions from the collaborative effort. For example the meeting did not quantitatively rank the models in terms of estimation performance.

Analysis of the original datasets indicated a large degree of model uncertainty, perhaps more than expected.

In the simulation analysis (see Section 4.2), the estimation models performed best when the operating model was the same (or closely related) model, as expected. Across the comparison cases, SAM tended to perform better than SCA.

When models gave very different results, it was often a matter of scale, while the models might agree about the relative changes in stock size. The opposite could be seen in some cases; however, where models were comparable in scale but disagreed on the relative changes.

Other Discussion Points

Existing models, description and availability

The meeting did not focus on providing a technical overview of assessment models used around the world. The NOAA Toolbox was often mentioned, but no direct effort was made towards an analogous ICES Toolbox.

Predicting next year's survey

One point made during (and before) the meeting was that perhaps a practical way to evaluate the estimation performance of different models was to predict next year's survey results (the survey following the last survey year in the data). The simplest approach would be to work with the original datasets and perform retrospective analysis, focusing on predicting next year's survey.

The advantages of this approach include (1) performance evaluation does not depend on a specific operating model, and (2) unrelated models can be evaluated on a common ground. For example, it is unclear whether biomass models relate to spawning biomass, vulnerable biomass or something else, but the survey numbers are a common basis for all models.

Compare TAC advice, not B or F

Another point raised is that what matters in the end is the advice. It is possible that models can give different estimation results, but still lead to similar advice, e.g. in the form of the recommended TAC. This adds a layer of complexity, but may be considered in a future collaborative exercise. This might also add a layer of subjectivity, where the advice might not only depend on the statistical results, but on personal preference regarding precaution.

In some cases, the advised TAC and the most recent survey are the same thing. For example, the advice for Icelandic lumpfish is a function of the most recent survey (and the previous year's survey). Management procedures often base the TAC advice on the most recent survey in a similar way.

One model or many?

In the discussion, it was mentioned that it might be beneficial to adopt one generalized model for most assessments. By changing one or a few settings, one can conduct a scientific comparison to quantify the effect of specific assumptions, etc. The Stock Synthesis development team is working towards this goal, currently striving for greater variety of options as well as code modularization.

The other viewpoint was also mentioned, that it can be beneficial to have a wide variety of unrelated models to evaluate model uncertainty in the broadest terms. Applying unrelated models that are inherently different, in terms of statistical approaches, number of areas, number of species, or overall structure, one may find a wider range of possible scenarios than within one generalized model.

Both viewpoints are probably correct: the one's goal is to understand the effect of different assumptions, whereas the other's is to explore model uncertainty in the broadest terms.

Missing textbook

It was noted that fisheries biology textbooks do not cover recent methods used in stock assessment today: HCR evaluation, uncertainty methods, state-space, age- or length-based multispecies models, or area-specific models. A new textbook with basic examples would be beneficial.

4.2 What next for the WCSAM simulation–testing exercise?

The Working Group discussed the outcomes from the methods simulation testing exercise conducted in conjunction with the World Conference on Stock Assessment Methods (WCSAM; ICES, 2013). The Working Group agreed that this had been a

valuable exercise. It had been substantial and wide-ranging, with considerable effort contributed by Jon Deroba from the NEFSC in Woods Hole who had standardized and collated the datasets for the selected stocks. A number of studies were conducted using these datasets, with results recorded in Deroba *et al.* (in press). Furthermore some additional studies are planned using these and other datasets to investigate the advantages and disadvantages of assessments using aggregated vs. disaggregated data e.g. combining fleets, combining length distribution and age–length keys into age distributions.

The Working Group focused in particular on the results reported at WCSAM for North Sea Cod and North Sea herring in terms of the Scheme developed at the Group's previous meeting in Lisbon in 2012 [ICES-WGMG, 2012 – this report provides full details of this Scheme]. It is important to recall the underlying objectives of this particular exercise, which are to enhance understanding of the different assessment methods, and in particular to examine the robustness of different methods when estimating the underlying stock dynamics even when these were not in accord with the assumptions made by the assessment method applied. This is with a view ultimately to be able to advise which method is the best to apply (at least in certain circumstances). Towards this end the stocks selected for consideration and their associated assessment-related information were relatively straightforward, and the three assessment methods (Extended Survivors Analysis [XSA; Shepherd, 1999], State-space Assessment Model [SAM; Nielsen and Berg, submitted; ICES-WGMG, 2008, 2009, 2011] and Statistical Catch-at-age [SCA; see e.g. Rademeyer *et al.*, 2008; Butterworth and Rademeyer, 2008]) were chosen to contrast the most important differences among the general category of assessment methods making use of catch-at-age information. Thus, for example, XSA treats catch-at-age information as exactly correct, whereas in contrast SCA is able to allow for error in this information by instead assuming some continuity in the pattern of age-specific selectivities that applies over time.
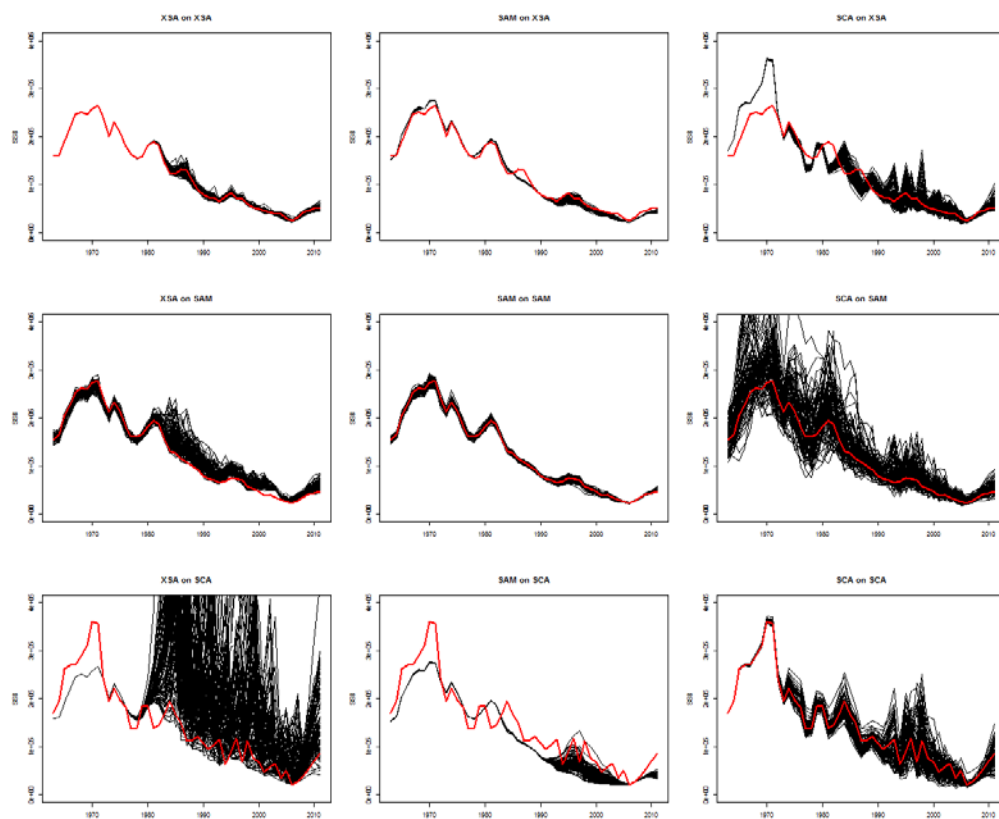
Figure 4.2.1. SSB for North Sea Cod. Rows indicate the "truth" (red line) as provided by the given model fit to the original data (top: XSA, middle: SAM, bottom: SCA) and from which 100 sets of pseudo-data are generated (with observation error only); columns indicate estimates (black lines) of each given model applied to the 100 sets of pseudo-data (left: XSA, middle: SAM, right: SCA). Plots in the diagonal reflect how well each model estimates itself (self-test), while those in off-diagonals reflect how well each model estimates other models (cross-test).
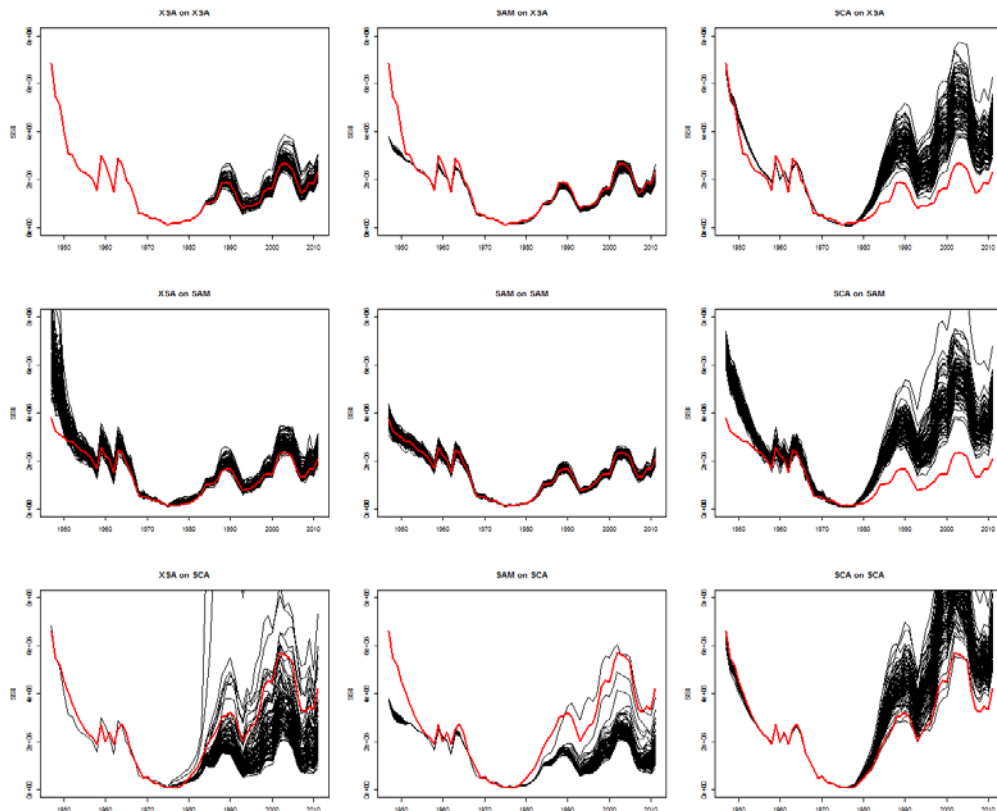
Figure 4.2.2. SSB for North Sea Herring. Details in the caption for Figure 4.2.1.

The Working Group stressed that the results of the exercise as reported at WCSAM should not be seen as complete, and accordingly advises that it would be premature to make final recommendations for stock assessment processes based on these results to ICES at this stage. For example, the poor results for the self-test of SCA for North Sea herring (see the bottom right panel of Figure 4.2.2) might suggest such simulation self-tests should become standard practice for methods used by ICES, and applied routinely during, say, benchmark assessments. However thus far this problem had arisen in only one application and the reasons for the occurrence first needed to be better understood. Similarly though the comparisons in Figures 4.2.1 and 4.2.2 pro-vided a potential case to select among the different assessment methods considered on the basis of robustness of estimation, the Working Group agreed that the existing calculations needed to be pursued further before that might be appropriate.

The Working Group considered that the first priority was to take the existing compu-tations for North Sea cod and herring to conclusion, and developed the following ordered set of work for the following 12 month period.

I) Investigate further, and if necessary adjust for, the following aspects of the

existing comparisons and their results

- For North Sea cod, why in the SCA applications to the SAM-generated pseudo-datasets, and especially the XSA applications to the SCA-generated pseudo-datasets was there such variability in the resultant SSB trajectories.

- For North Sea herring, what were the reasons for the biases evident in SSB estimates for SCA applied to all three sets of pseudo-datasets, including those from the SCA assessment model fit itself (i.e. the self-test).

- Why estimates for the SAM assessment method are considerably more stable than those from the XSA and SCA approaches.

- For North Sea cod, a comparability difference arises because of the catch multipliers estimated for some years (ICES-WGNSSK, 2013), which is not possible using the XSA software. These multipliers should be set at the values currently estimated by SAM, and the different assessments then proceed on the comparable basis that these revised catches were fixed with known input values.

- A number of approaches for understanding and perhaps resolving the self-test bias in SCA for North Sea herring should be pursued. In this context it is important to note that completion of results in time for presentation at WCSAM had been a rushed process, so that lesser levels of skill had been able to be applied in refining the XSA and SCA assessments for these two stocks compared to SAM which is the approach in current use for them. Accordingly some further refinement of these other approaches is desirable to ensure that the comparative testing of all the approaches is taking place on a level playing field. For example, it appears that for North Sea herring the SCA model does not fit the original dataset in the same way as XSA and SAM, judging from the red "true" baseline shown in the simulation plots (Figure 4.2.2). This potential lack of fit may reverberate into strange SCA simulated datasets that all estimation models find problematic. It is therefore worth examining whether the SCA fit can be improved without really changing the model, by setting different initial parameter values.

    i) Taking account of clear autocorrelation in the residuals of the fit to the IBTS0 0-ringer index in both the SCA model fit and generation of pseudo-data from this fit. (Note that this autocorrelation could also have implications for the way the other assessments models are fit.)

    ii) Perhaps omitting the IBTS0 series from the fits by all the assessment models if it becomes evident that the problems arising are a reflection of data conflicts between this series and other data.

    iii) Noting the clear pattern in proportions-at-age residuals in the SCA model fit, first examine the (implicit) selectivity patterns for the XSA and SAM models, and then move towards creating further selectivity blocks for the SCA assessment to diminish this patterning.

II) Simulations including process error (Section 3.3 and Annex 6 of ICES-WGMG, 2012)

- At present these simulations have been conducted only for the SAM method applied to North Sea cod and herring. These should be extended to the SCA method for both stocks (this is not possible for XSA given its structure).

III) Further simulations of this type

- The reason to consider extension to further stocks is to be able to strengthen the case for the generic nature of certain results.
- Extension of the approach to include North Sea haddock should be considered. This stock had been included in provisional results reported to the previous Working Group meeting in Lisbon (ICES-WGMG, 2012), but with an unrefined B-ADAPT approach applied together with SAM and XSA. The B-ADAPT approach should be replaced by the SCA version currently applied to the North Sea cod and herring.
- Extension to include other catch-at-age methods should be considered:

  i)   ASAP (hopefully with the assistance of Jon Deroba, though it was considered that for consistency with the other approaches, it was important that the pseudo-data should be generated from the best fit of this model and using the same error distribution functions).

  ii) Different selectivity blocking of the SCA. An extreme approach of no blocking was NOT supported, as this would NOT reflect model-misspecification in fits to the proportions-at-age data. Instead two options should be considered, one "under-splitting" and the other "over-splitting" while still both reasonably reflecting the data, to give some sense of the implications of the bias-variance trade-off involved in this part of the selection process.

IV) Output statistics

- For the initial reports, the only output statistics considered had been estimates of trajectories of SSB, recruitment and F. However, the most important recommendations that follow from assessments are for catch limits. It is therefore important to use these simulations to check how well the various methods estimate such catches. Accordingly, the importance of also reporting on an output catch measure related to sound harvest strategy was emphasized (for example, if a method that produces positively biased estimates of abundance and negatively biased estimates of fishing mortality, this may not be that great a concern if the two biases near cancel when developing catch advice).
- The measure recommended was the $F_{40\%SPR}$ catch limit for the forthcoming year, calculated based on the average of the estimated recruitments for the last 10 years, as this would be relatively easy to calculate (see Annex 6, Section A6.1). To enhance this ease without compromising the intent of the exercise, data would be assumed to be available in time to allow catch advice to be given for the "following" year, i.e. without the need to make assumptions for an intervening year between that for the most recent data considered and the year for which catch limit advice is being provided.
- Subsidiary measures suggested (see Annex 6, Section A6.2) were:

  i)   The ten year Replacement Yield.

  ii) A prediction of a survey result for the next year.

V) Reporting schedule and the longer term

- It would be desirable to report back during the next ICES ASC to ensure a wider audience

- With a hopefully complete analysis of perhaps three stocks using three-to-five approaches at that stage, that would be the time to seek to encourage still wider application to both more stocks and using further methods, if the outcomes from the next year's work were considered sufficiently valuable.

- SCICOM Chair Manuel Barange had suggested use of one of the Monday morning business slots for such discussions. The Working Group endorsed this idea, considering that this together with presentation of papers in some hopefully appropriate theme sessions would be an effective way of moving the SISAM process forward.

- More detailed discussion should take place during the 2014 WGMG meeting

- More broadly, and to enhance promoting exchanges on a wider world scale, a four-yearly stock assessment review meeting should be organized to precede or follow each four-yearly World Fisheries Congress.

5 ToR 4 – Estimating reference points

Estimation of MSY reference points has been discussed by previous ICES groups, for example, most recently by the WKFRAME series of meetings (ICES-WKFRAME, 2010; ICES-WKFRAME-2, 2011; ICES-WKFRAME-3, 2012); furthermore, ICES-WKMSYREF held in January 2013 (ICES-WKMSYREF, 2013) focused on practical tools for implementation, and this work was continued during this WGMG meeting, and will be carried forward in the follow-up WKMSYREF 2 meeting in January 2014.

It should be noted that many methods calculate MSY and related quantities deterministically. MSY estimates are not unique because they depend, for example, on selectivity. In practical implementation, stochasticity needs to be taken into account, and the associated results will differ from deterministic ones and depend on the HCRs applied because of stochasticity. For instance, the trigger biomass level below which F is reduced in an otherwise constant F approach to calculating MSY can have an appreciable effect on the results.

5.1 Existing methods and possible improvements

Four methods for estimating MSY reference points were presented.

Method 1 – PlotMSY (J.A.A. De Oliveira and T.J. Earl)
Method 2 – EqSim (E.J. Simmonds and C.P. Millar)
Method 3 – StochSim (H. Björnsson)
Method 4 – NSR (N.G. Cadigan)

PlotMSY (Method 1: equilibrium approach with variance) is intended to provide robust estimation of deterministic (i.e. no future process error) MSY estimates that could be applied easily and widely. It fits three stock–recruit functions, namely the Ricker, Beverton–Holt, and a smooth Hockey-stick (Mesnil and Rochet, 2010), to estimate MSY quantities. Uncertainty in MSY estimates is characterized by MCMC sampling of the joint pdf of the stock–recruit parameters and sampling from the distributions of other productivity parameters (i.e. natural mortality, weights-at-age, maturities, and selectivity). Stock–recruit model error is taken into account by model averaging of the three functions. Annex 7 provides a more detailed description of the method, including examples and guidelines for use.

EqSim (Method 2: stochastic equilibrium reference point software) provides MSY reference points based on the equilibrium distribution of stochastic projections. Productivity parameters (i.e. year vectors for natural mortality, weights-at-age, maturities, and selectivity) are resampled at random from the last 3-5 years of the assessment (although there may be no variability in these values). Recruitments are resampled from their predictive distribution. Uncertainty in the stock–recruitment model is taken into account by applying model averaging using smooth AIC weights (Buckland *et al*. 1997). The method is described in more detail in Annex 8.

StochSim (Method 3: stochastic simulations) has been used to estimate reference points for a number of Icelandic stocks, where uncertainty is included in parameters, recruitment, weights at age and the assessment (Björnsson 2013, Hjörleifsson and Björnsson 2013). A Hockey-stick stock–recruit relationship has most commonly been used. The standard deviation and autocorrelation of stochastic noise in recruitment are estimated from available data, and sensitivity to different values investigated. Predictions are carried out under a specified HCR where the TAC is a proportion of the reference biomass, but specified fishing mortality could also be used. Simulations

are conducted with and without a trigger point, but the HCR selected always includes a trigger point. Harvest rate MSY (H_{MSY}) is defined as the harvest ratio giving maximum mean yield when not including a trigger point, and H_{pa} is the harvest rate giving 5% probability of the spawning stock being above B_{lim} (see Figure A9.1, Annex 9). Contrary to many of the methods described in this report, characteristics of the residuals from the stock–recruitment function are a more important consideration than the exact form of the function. For both Icelandic saithe and haddock, H_{MSY} is higher than H_{pa}, a feature expected to be seen in stocks where variability and autocorrelation of recruitment is high. H_{MSY} from stochastic simulations can be used as the advisory H_{MSY} if appropriate uncertainty is included and $H_{MSY} > H_{pa}$. If $H_{MSY} < H_{pa}$, H_{pa} could be treated as an upper bound for the target harvest ratio.

NSR (Method 4: nonparametric stock–recruit functions) provides deterministic MSY estimates based on a nonparametric stock–recruit model smoother. Bootstrap methods are used to characterize uncertainty in the stock–recruit model. Uncertainties in the values of biological parameters are not taken into account. Annex 10 describes the approach in more detail.

Discussion

Discussions on the four methods pointed out the need to account for covariance among biological variables (mean weights, maturity, etc.). PlotMSY and NSR ignore this effect but EqSim uses re-sampling of year vectors to account for this (although temporal autocorrelation is not considered). StochSim accounts for variability and autocorrelation in weights at age; implementations of StochSim are species-specific. M and maturities are treated as constant over time.

Estimation of MSY reference points often requires extrapolating recruitment outside the range of stock–recruit observations. This is especially a problem when there is no evidence of departures from a linear relation through the origin in the stock–recruit data. Solutions to this problem will usually be quite subjective. In addition, Beverton–Holt fits are problematic when there is a decline in recruitment with increasing SSB, because these can result in a very high steepness estimate implying little possibility of recruitment overfishing when in fact the relationship is more likely to be Ricker-like.

The Hockey-stick model leads to a sudden and unrealistic drop-off in the yield vs. F curves (this happens when $F > F_{crash}$). However, in stochastic simulations this behaviour usually does not occur because when the spawning stock approaches the SSB-break, more and more stochastic replicates end below the SSB-break, gradually (and not abruptly) leading to impaired recruitment.

Another approach to account for stock–recruit model uncertainty is to include a third parameter as aliasing different stock–recruit shapes, for example $R = \alpha S / (\beta + S^{\gamma})$, instead of applying model averaging techniques to existing models (e.g. Ricker, Beverton–Holt, Hockey-stick). The range of γ needs to be constrained (i.e. $\gamma > 0$) so that the recruitment rate (R/S) declines monotonically as S increases.

One should plot residuals to check for bias and the behaviour of variance, and thereby whether distributional assumptions (e.g. lognormality) are appropriate (i.e. plot against time and against SSB). If not, alternative estimation approaches should be pursued.

When fitting stock–recruit models, there is sometimes insufficient information to estimate maximum recruitment, with the result that stock–recruit models sometimes

produce unrealistic large recruitments that are well beyond the range of observed data. This is particularly problematic for the Beverton–Holt model, but sometimes also for the Ricker model and the nonparametric smoother. Introducing a limit on this maximum is one way of stabilizing estimation. Appropriate approaches will be case specific, and there are different ways to achieve this. One possibility is to define a prior for the expected maximum recruitment. Another is to use the Hockey-stick model, which effectively serves as a surrogate for a prior on maximum recruitment.

The sensitivity of MSY estimates should be checked to explore the reliability of the estimates. In cases where estimates are highly sensitive to assumptions that are uncertain, then management approaches should not be based on MSY reference points estimated from stock–recruit curves.

In PlotMSY, the influence of implicit priors on MCMC-based estimates should be checked. This could be done by downweighting data to check to what extent prior information is updated. Annex 11 investigates this issue by using alternative parameterization of the implicit priors for the smooth Hockey-stick model in plotMSY, as applied to North Sea cod data; the influence of implicit priors appears to be negligible for this example.

The model averaging procedure used in plotMSY (i.e. trimmed harmonic mean weighting) has been criticized in the literature for being a poor estimator (see e.g. Raftery *et al*., 2007). There is a need to consider alternatives such as smoothed AIC.

In EqSim and StochSim one can use a constant F harvest rule (traditionally used to define MSY) or some other type of harvest rule (e.g. ICES MSY rule). This can have an effect on MSY values in stochastic projections. For example, it is possible that maximum equilibrium yield may be higher with a ramp-type harvest control rule (e.g. Lande *et al*., 1997). Hence, there is a need to clarify whether MSY estimation has been carried out assuming constant F or a different HCR.

5.2 Comparison of three methods

Three of the four methods presented in Section 5.1 (Methods 1, 2 and 4) were used during the meeting in a comparative exercise by applying each method to two example datasets. North Sea cod stock–recruit and biological data were taken from the 2013 assessment (ICES-WGNSSK, 2013). The stock recruit data (1963-present) are shown in Figure 5.2.1 (left), the main features are a strong increasing trend in recruitment vs. SSB, but limited evidence of a plateau in recruits at large SSB. North Sea Herring was taken from an example assessment at www.stockassessment.org, using data from 1989-2010 (note: ICES HAWG estimates recruitment and SSB from 1947 onwards; ICES-HAWG, 2013). The stock recruit relationship shown in Figure 5.2.1 (right) indicates a scattering of points with no clear relationship between stock and recruitment.
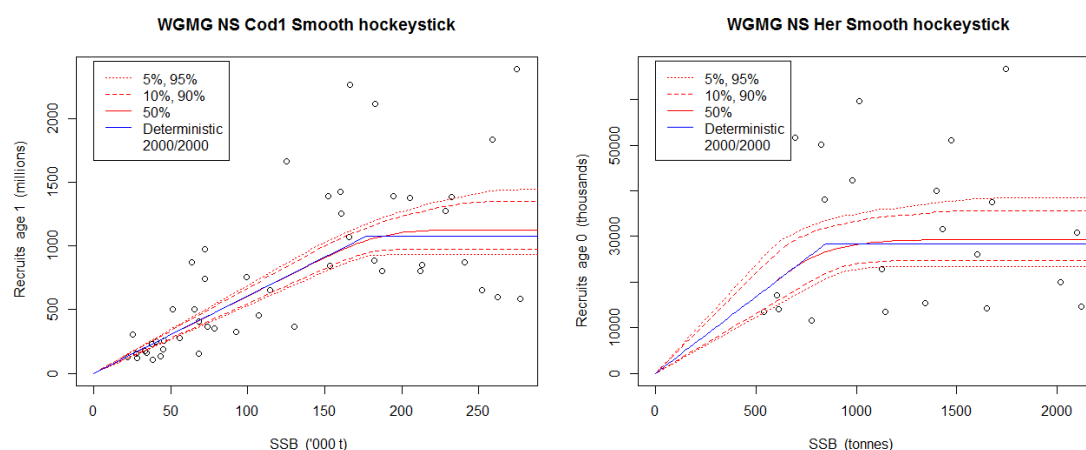
Figure 5.2.1. Fits of the smooth Hockey-stick model from Method 1 to North Sea cod (left) and North Sea herring (right).

The three methods described in Section 5.1 (and Annexes 7, 8 and 10) were applied to both stocks using settings described in Table 5.2.1. The outputs are shown in Figures 5.2.2 and 5.2.3, where the row names correspond to the settings used, and each method shows a median estimate as a character, and 95% range as a line (see figure captions for more details).

Table 5.2.1. Details of the stock recruit fits applied to the example datasets.

NAME	MODEL	DESCRIPTION OF STOCK–RECRUIT RELATIONSHIP
M1 BH	PlotMSY	Beverton–Holt
M1 HS	PlotMSY	Hockey-stick
M1 RI	PlotMSY	Ricker
M1 WA	PlotMSY	Weighted average of other M1 methods
M2 1B	EqSim	Beverton–Holt –recruitment process error
M2 2B	EqSim	Beverton–Holt – no recruitment process error
M2 1S	EqSim	Hockey-stick – recruitment process error
M2 2S	EqSim	Hockey-stick – no recruitment process error
M2 1R	EqSim	Ricker – recruitment process error
M2 2R	EqSim	Ricker – no recruitment process error
M2 1all	EqSim	Combined methods with smooth AIC weights – recruitment process error
M2 2all	EqSim	Combined methods with smooth AIC weights – no recruitment process error
M4 NSR	NSR	NSR and simple regression bootstrapping.
M4 TS Boot	NSR	NSr and regression bootstrapping with autocorrelated errors.
M4 HS	NSR	Hockey-stick
M4 BH	NSR	Beverton–Holt
M4 RK	NSR	Ricker

Output for NS cod (Figure 5.2.2) shows that broadly the three methods provide similar medians/point estimates of F_{MSY} within each SR form, but there are large differences between SR forms. Method 1 indicates a wide uncertainty about MSY and B_{MSY} compared to Method 4; this may be attributed to Method 4 having more restrictive limits on the maximum recruitment, which is poorly estimated by Method 1. The nonparametric method indicates very wide uncertainty in F_{MSY} compared to the boot-

strapped parametric models. In Method 2, allowing for uncertainty in recruitment about the expected values in each simulation increases the F_{MSY} estimate, but makes only a small difference to the yield estimate.

Output for NS Herring (Figure 5.2.3) shows a very wide ranges of F_{MSY} for Method 1, and only slightly smaller ranges for Method 4. These models are consistent in their ordering of the F_{MSY} estimate between SR forms, but not scale. Method 2 shows a different pattern, although the low F_{MSY} estimated for the Hockey-stick may reflect a numerical optimization issue. An assessment covering a longer period is available (ICES-HAWG, 2013) and would be more informative about which SR forms are consistent with the data. In contrast to the cod data, estimates of B_{MSY} are relatively consistent between models with the exceptions of model M2 1S and M2 2S. This reflects that the maximum recruitment is well estimated, even if the form of the SR relation is not.

In neither stock is F_{MSY} consistently estimated across models and SR forms. Nevertheless, it is possible that these data could inform reference point choice if further information in the form of expert judgement or data from earlier periods was taken into account, or a SR form that is precautionary for the particular stock was chosen. If this is not possible, then alternatives to management based upon direct estimates of F_{MSY} should be considered.
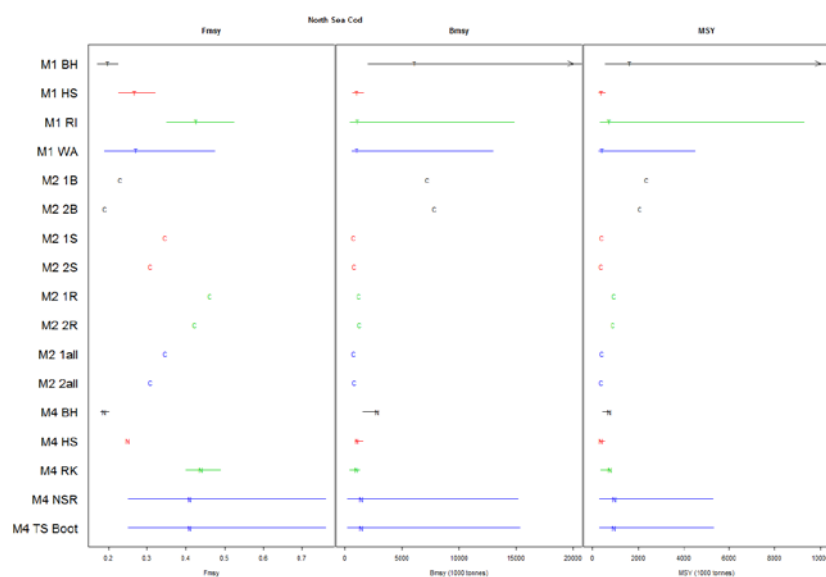
Figure 5.2.2. North Sea cod. Comparison of Methods 1, 2 and 4, with row names corresponding to setting described in Table 5.2.1. Each method shows a median estimate as a character, and 95% range as a line (note: although possible to do so, the 95% range was not calculated for Method 2). The character indicates who ran the model (Timothy Earl, Colin Millar, Noel Cadigan), and the colours indicate the stock recruit form fitted (Beverton–Holt=black; Hockey-stick=red; Ricker=green; other=blue).
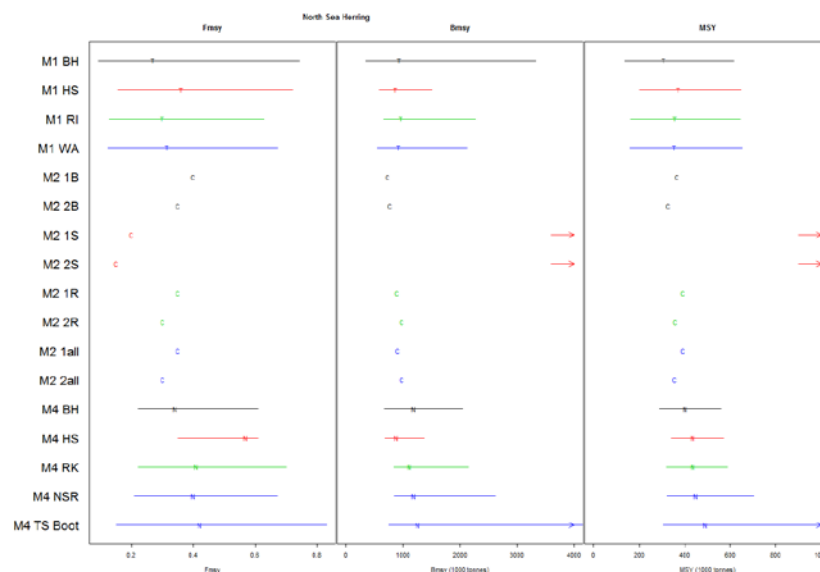
Figure 5.2.3. North Sea cod. Comparison of Methods 1, 2 and 4, with row names corresponding to setting described in Table 5.2.1. Details are provided in Figure 5.2.2. Arrows indicate the median or upper confidence intervals are beyond the range shown.

5.3 Wider issues

Reliable estimation of MSY reference points requires reliable estimation of stock–recruit functions. Questions that need to be addressed are:

- Has the production and survival rates of recruits changed in the time-series of data available?
- If so, is it anticipated that such changes will occur in the future for MSY calculations?
- Are there sudden regime shifts or gradual changes?

There is a need to compare internal (i.e. within assessment model) vs. external estimation of stock–recruit parameters. Where possible estimation should be carried out internally to take proper account of covariance structures, provided there is no evidence of model misspecification in such a process. Model diagnostics should always be carefully explored in such circumstances.

Often there is temporal autocorrelation in stock–recruit residuals. It may be important to try to account for this in simple ways when estimating stock–recruit model parameters. It may also be important to include this correlation in stochastic MSY analyses. Model diagnostics should always be carefully explored in such circumstances.

6 Recommendations, selection of chair and proposed multi-annual ToRs

6.1 Response to recommendations received from other groups

The following recommendations were received from WGNSSK and WGCSE respectively:

WGNSSK:

There is an increasing focus on using SAM assessment model in WGNSSK; WGNSSK expressed however some concerns that total catch data are treated as a usual observation with two-sided uncertainty around. Since it doesn't make much sense that true catches can be assumed to be lower than observed catches, WGNSSK recommends that further investigation is given to analysis and parameterization of one-sided uncertainty for catch information in statistical catch-at-age models

WGCSE:

It was recommended that ICES reconsiders the settings of the A&P model for all stocks using this model, after another year and another stock failing to deliver an agreed assessment.

WGMG response

These requests were received during 2013, after the ToR for the current meeting had already been published. While WGMG endeavours to be flexible in its approach to handling such requests, it did not have access to the relevant experts (on the SAM and A&P models) during the 2013 meeting to be able to respond to these requests. Nevertheless, these requests have been accommodated in the future ToRs for the group (see ToR c(i) in Annex 4), and it is hoped that the necessary expertise will be available in future to deal with them.

6.2 Recommendations to other groups

Recommendations aimed at WGSAM and WGMIXFISH jointly, and at WKLIFE, SISAM and WKMSYREF, based on discussions and work conducted during the meeting, are given in Annex 3 (with a reference to which section in this report they correspond, for context).

6.3 Selection of chair

WGMG proposes that David Miller (The Netherlands) take over as the new Chair from 2014 onwards.

6.4 Proposed multi-annual ToRs

WGMG tackled the issue of defining multi-annual ToRs by agreeing on a number of themes under which it will operate for the next three years (2014-2016). These themes are meant to capture broad areas of work relevant to WGMG and topics that are currently a priority for ICES and its assessment working groups. These cover the continued development of stock assessment methods, for both data-rich and data-limited stocks, and the development of methods to deal with inaccuracies in catch data (including the impact of the new landings regulations) and the estimation of

reference points. A number of ToRs that are associated with each of these themes have also been developed. The themes and associated ToRs are given in Annex 4.

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Annex 1: List of participants

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Annex 2: Work plan

Day 1:

Welcome, round-table, logistics and adoption of Agenda

Presentations by ToR leaders on status of ToR work and plans [ToR 1-Lionel, ToR 2-David, ToR 3-Doug/Arni, ToR 4-Tim]

ToR 4 – decision on datasets

ToR 1 presentations (Colin verbally on a4a, José on size-based community model)

Commence subgroup work

Day 2:

ToR 4 presentations (Tim on plotMSY, Colin on EqSim, Höski on StochSim, Noel on NSR)

Subgroup work

ToR 2 presentations (José on ToR 2a, Nuno on ToR 2b)

Day 3:

Subgroup work

ToR 2 presentations continued (Doug on ToR 2b)

Wrap-up ToRs 1, 2 and 3

Initiate discussion on Multi-annual ToRs

Day 4:

Wrap-up ToR 4, multi-annual ToRs

Recommendations, new chair, next meeting

ToR 2 additional presentation on F-proxy rules and smoothing (Höski: comparison to DLS Category 3 rule)

Continue work on report

Day 5:

Finalize work on report

Annex 3: Recommendations

Recommendation	Addressed to
Consider developing a minimum realistic model (e.g. MICE) to serve as an operating model in order to evaluate the performance of mixed-fishery models within a management strategy evaluation framework. [Section 2]	WGSAM, WGMIXFISH
In a YPR-context F0.1 is not necessarily a precautionary proxy for FMSY (which also incorporates stock–recruit effects), and it is recommended that this issue be further investigated as YPR-based calculations fail to account for the possibility of recruitment overfishing. [Section 3.1]	WKLIFE
The 20% change limit implemented in the DLS approach may be too restrictive (effectively 10% per year) and in some cases prevents HCRs from reacting quickly enough in the face of declining stocks; it is recommended that approaches that override the change limit when the resource is below some threshold be investigated (this should be a smooth rather than a step change). [Section 3.1]	WKLIFE
Target-based HCRs may be preferable to trends-based ones because the latter may tend to maintain stocks near current conditions, which may be suboptimal, whereas the former introduce greater stability in catches; it is recommended that target-based HCRs be considered. [Section 3]	WKLIFE
It is recommended that candidate HCRs should always be simulation tested to the extent possible, because behaviour in a stochastic environment can differ substantially from the deterministic behaviour used to motivate the rule. Furthermore, if rules make use of variance estimates for indices of abundance, the simulation testing must take care to have plausible statistical models to generate simulated variance estimates. [Section 3]	WKLIFE
When including length-based metrics as part of a HCR, it is recommended that the effect of recruitment patterns and error in length observations on the calculation of those metrics be included as part of the evaluation of such HCRs. [Section 3.2]	WKLIFE
When the confidence interval for the mean of recent index values is used as part of a HCR, it is recommended that the time-period over which this mean and its confidence interval are calculated remain constant (i.e. the window considered should remain of the same length but be moved forward with time). [Section 3.2]	WKLIFE
It is recommended that the SISAM assessment methods evaluation scheme, as developed during the WGMG 2012 meeting in Lisbon, continue to be developed. This should deal first with the validity of results and consistency of approaches to date, and then be extended to haddock, to further process error considerations, and to further methods, using the ICES ASC in 2014 as a platform for the communication of results. [Section 4.2]	SISAM
The sensitivity of MSY estimates should be checked to explore the reliability of the estimates. In cases where estimates are highly sensitive to assumptions that are uncertain, then management approaches should not be based on MSY reference points estimated from stock–recruit curves. [Section 5.1]	WKMSYREF
Reference points should be based on as long a time-series of data as possible, keeping in mind the implications of regime shifts and data reliability. [Section 5.2]	WKMSYREF
The calculations shown in Section 5.2 should be repeated using assessments based on a longer period of data which may resolve some of the uncertainties.	WKMSYREF

Annex 4: WGMG draft resolution for multi-annual ToRs (Category 2)

The **Working Group on Methods of Fish Stock Assessment** (WGMG), chaired by David Miller, the Netherlands, will meet in Vigo, Spain, 22-26 September 2014, to work on ToRs and generate deliverables as listed in the Table below.

WGMG will report on the activities of 2014 (the first year) by Date Month Year to SSGXX.

The following are the general themes under which WGMG will operate for the next three years (2014-2016):

1) Review selected methods proposed for implementation in ICES assessment WGs, including those requested by these WGs

2) Review and advise methods for the evaluation of selected harvest control rules using management strategy evaluation

3) Develop and test refinements of methods to deal with inaccuracies in catch, specifically:

   a) underreported catch (e.g. discards or IUU fishing),

   b) the impact of new landings regulations (with their implications for discarding) on continuity of dataseries and on assessments

4) Improve methods to estimate reference points

5) Evaluate the performance of data-limited stock assessment methods

6) Support the SISAM initiative to improve the assessment methods used by ICES Working Groups

   - Conclude the evaluation of alternative catch-at-age based assessment methods for identified stocks based on the SISAM methods evaluation scheme, as developed during the WGMG 2012 Lisbon meeting

7) Address additional requests that fall under the above themes

ToR descriptors

ToR	Description	Background	Science Plan Topics Addressed	Duration	Expected Deliverables
a	Review selected assessment methods proposed by ICES assessment WGs [theme 1]	WGMG is the only forum for the review and development of stock assessment methods within ICES on behalf of its assessment WGs, which can sometimes lack sufficient expertise to undertake this. This ToR is intended to accommodate such exercises.	112, 211	Continuing	Peer-reviews of assessment methods suggested for assessment WGs to use.
b	Review selected methods for evaluating HCRs proposed by ICES assessment WGs [theme 2]	WGMG is an appropriate forum for evaluating proposals for testing HCRs, given the reliance of these testing methods on the MSE approach with which WGMG members have the considerable experience necessary to suggest consistency and quality checks	312	Continuing	Peer-reviews of proposals for the evaluation of HCRs often used as part of management plans.

c (i)	Investigate applications of the state-space assessment model (SAM), the Aarts and Poos model (A&P) and the time-series analysis model (TSA) that deal with estimation of underreported catch [theme 3a]	A number of important stocks assessed by ICES have poor-quality catch data due to a lack of estimates of discards, and illegal, unreported or unregulated (IUU) catches (e.g. North Sea cod, Northeast Atlantic mackerel). The SAM (Nielsen and Berg, submitted), A&P (Aarts and Poos, 2009) and TSA (Fryer, 2001) assessment models can include methods to internally account for this problem. The group will evaluate these approaches, suggest improvements (where applicable) and make recommendations on best practice when applying such methods. This investigation is motivated by requests from WGNSSK and WGCSE.	112, 211	One or two years	Guidelines for best practice when accounting for un-estimated discards and IUU catches in the SAM, A&P and TSA stock assessment models used by ICES WGs.
c (ii)	For two selected stocks, investigate implications for assessment methods for what was previously discarded and not estimated, but will now be landed [theme 3b]	The implementation of the "landings obligation" in EU waters will, for some stocks, result in a change in the congruity between reported landings and actual catch. This is particularly a problem for stocks where discarding is known to have occurred but no reliable discard estimates exist. The group will evaluate the likely impacts of this on the fitting of stock assessment models to such data and attempt to determine how best to account for this for two (yet to be decided) case studies.	112, 211	One or two years? This should be completed before the implementation of the "landings obligation".	A report illustrating the most likely issues to arise given this change in the quality of catch data. Guidelines for best practice to account for these issues to assist ICES WGs following the implementation of the "landings obligation".
d (i)	Review and consolidate the current suite of reference points [theme 4]	Currently ICES uses a large number of limit and target points, F_{MSY}, F_{pa}, F_{lim}, B_{lim}, B_{pa}, $B_{trigger}$, B_{MSY} and F_{target} (or perhaps B_{target}). This is confusing for most people. For many stock only three values are needed: B_{lim}, F_{target} and $B_{trigger}$. Most management plans have some F_{target} (H_{target}) which will not be implemented perfectly due to stabilizers in the management plans, assessment errors and implementation errors.	211, 312	Two to three years	Recommendations for a consolidated list of reference points.
d (ii)	Review approaches for specifying B_{lim} [theme 4]	B_{lim} is an influential biomass limit reference point that affects the interpretation of results from HCR evaluations. This is because the precautionary nature of the HCR is determined by the probability of the stock being below this level. For stocks that have not been overexploited historically, estimating an appropriate level for B_{lim} is problematic, often resulting in the use of B_{loss} (the lowest observed biomass) as a proxy for B_{lim}. This may result in overly precautious management. The group will work on (new) methods that could be used to determine B_{lim}.	211, 312	Three years	Guidelines for best practice when determining B_{lim} to assist ICES benchmark assessments.

d (iii)	Review developments of the non-parametric stock–recruit models for reference point estimation [theme 4]	Estimates of MSY-based reference points which take account of stock–recruitment effects are heavily dependent on the approach used to estimate a stock–recruitment relationship from the available information. The non-parametric method developed by Cadigan [Method 4 in Section 5; Annex 10] shows promise as an approach that might be generally applicable by WGs. Further investigation will aim at the provision, if found to be appropriate, of a set of guidelines for practical implementation of this or a related approach.	211, 312	Two years	A set of guidelines on the estimation of stock–recruitment relationships and hence calculation of MSY-based reference points, together with advice on interpretation and application of the results, to serve as the default for use by ICES WGs.
e (i)	Investigate specific data-limited methods that are advised as a priority based on high current usage for some of the stocks to which they have been applied [theme 5]	There is a strong need to test proposed methods that support the provision of advice for data-limited stocks in a way that ensures that the methods used are consistent with the objectives of the ICES DLS framework.	112, 211	Three years	The confirmation that certain methods are consistent with the objectives of the ICES DLS framework for application by assessment WGs.
e (ii)	Investigate different ways of compiling survey indices that are suitable for the application of data-limited methods [theme 5]	Methods that rely on trends in survey indices are sensitive to noise in these indices. The noise is often caused by a few tows accounting for a large proportion of the catch. A possible solution is to take the average of nonlinear functions of abundance at each station (square root or similar). This reduces variability but might lead to biases. Simulation testing could be tricky as it might involve modelling the distribution of fish in surveys.	112, 211	Three years	Advice on the general applicability or otherwise of such methods.
f	Conclude the evaluation of alternative catch-at-age based assessment methods for identified stocks based on the SISAM methods evaluation scheme, as developed during the WGMG 2012 Lisbon meeting[theme 6]	Initial results of simulation studies using the Scheme for North Sea cod and herring and presented at WCSAM have potentially important implications for assessment methods used by ICES Working Groups. However these need first to be checked, refined and possibly extended.	112, 211	Two years	Recommendations on appropriate selection among catch-at-age based methods for application in ICES WGs, and on general diagnostics to be applied to methods considered in benchmark assessments
g	Consider additional requests that fall under the six WGMG themes	This ToR allows flexibility for WGMG to handle additional requests	112, 211, 312	Continuing	As appropriate

Supporting information

Priority	The current activities of this Group will lead ICES into methods related to provision of catch advice on a sound scientific basis, including for data-limited stocks. Consequently, these activities are considered to have a very high priority.
Resource requirements	The research programmes which provide the main input to this group are already underway, and resources are already committed. The additional resource required to undertake additional activities in the framework of this group is negligible.
Participants	The Group is normally attended by some 10–15 members and guests.
Secretariat facilities	None.
Financial	No financial implications.
Linkages to ACOM and groups under ACOM	ACOM has strongly supported the work of this group. The work conducted by WGMG is highly relevant to ICES Expert Groups that conduct stock assessment.
Linkages to other committees or groups	WGMG will report to SCICOM in 2014. WGMG is involved with the ICES Strategic Initiative on Stock Assessment Methods (SISAM).
Linkages to other organizations	Possible future links with other organizations that have similar Methods Working Groups (e.g. ICCAT)

Annex 5: R Code for the simulation study in Section 3.2

```
FILE #1 (FUNCTIONS)
##############################################################################
# EJ(20120413)
# Auxiliary functions for LH generation of datasets
# Parameters:
#  a1, sr, sl = 50% selectivity age, right variance, left variance
#  s, v = steepness and virgin biomass for S/R
#  M1, M2 = two components of M
#  a50, asym = age of 50% maturity, age of asymptotic maturity
#  linf, k, t0 = vonBertalanffy growth pars
#  a, b = length~weight pars
##############################################################################

iterMedians <- function(x, ...){
    return(apply(x, c(1:5), median, na.rm = FALSE))
}

iterSums <- function(x, ...){
    return(apply(x, c(1:5), sum, na.rm = FALSE))
}

iterCv <- function(object, ...){
    sqrt(iterVars(object))/iterMeans(object)
}

#============================================================================
# gislasim - cleaned version
#============================================================================

setGeneric("gislasim", function(linf, ...) standardGeneric("gislasim"))

setMethod("gislasim", signature(linf="numeric"), function (linf, t0 = -0.1, a =
1e-05, b = 3, ato95 = 1, sl = 2, sr = 5000, s = 0.9, v = 1000, asym=1, bg=b,
iter=1, k="missing", M1="missing", M2="missing", a50="missing", a1="missing"){
    if(missing(k))  k <- 3.15 * linf^(-0.64)
    if(missing(M1)) M1 <- 0.55 + 1.44 * log(linf) + log(k)
    if(missing(M2)) M2 <- -1.61
    if(missing(a50)) a50 <- FLBRP:::invVonB(FLPar(linf=linf, t0=t0, k=k), 0.72
* linf^0.93)
    if(missing(a1)) a1 <- a50
    par <- FLPar(linf=linf, k=k, t0 = t0, a = a, b = b, asym=asym, bg=bg,
sl=sl, sr=sr, s=s, v=v, M1=M1, M2=M2, ato95 = ato95, a50=a50, a1=a1, iter=iter)
    attributes(par)$units = c("cm", "kg", "1000s")
    return(par)
})

setMethod("gislasim", signature(linf="FLPar"), function (linf){
    # Renaming to avoid confusing the argument with the object.
    # linf here is an FLPar object that can contain several parameters
    object <- linf
    rm(linf)
    # now the real thing
    v0 <- dimnames(object)$params
    if(!("linf" %in% v0)) stop("The function requires linf.")
    par <- FLPar(c(linf=NA, t0 = -0.1, a = 1e-05, b = 3, ato95 = 1, sl = 2, sr
= 5000, s = 0.9, v = 1000, asym=1, bg=3, k=NA, M1=NA, M2=NA, a50=NA, a1=NA),
iter=ncol(object))
    dimnames(par)$iter <- dimnames(object)$iter
    par[dimnames(object)$params] <- object
    if(!("bg" %in% v0)) par["bg"] = par["b"]
    if(!("k" %in% v0)) par["k"] = 3.15 * par["linf"]^(-0.64)
    if(!("M1" %in% v0)) par["M1"] = 0.55 + 1.44 * log(par["linf"]) +
log(par["k"])
    if(!("M2" %in% v0)) par["M2"] = -1.61
    if(!("a50" %in% v0)) par["a50"] = FLBRP:::invVonB(FLPar(linf=par["linf"],
t0=par["t0"], k=par["k"]), c(0.72 * par["linf"]^0.93))
    if(!("a1" %in% v0)) par["a1"] = par["a50"]
    attributes(par)$units = c("cm", "kg", "1000s")
    return(par)
})
```

```
#===============================================================================
# genFunctions
#===============================================================================

genObs <- function(stock, qcv=0.1, ccv=0.1) {
   ages <- 1:range(stock)["maxfbar"]
   n <- stock.n(stock)[ac(ages)]
   z <- harvest(stock)[ac(ages)] + m(stock)[ac(ages)]
   logq <- -exp(-exp(0.2 * ages)) - 3 # trawl like catchability
   # observe index in 1st quarter with qcv
   index <- FLIndex(index = n[ac(ages)] * exp(-0.25 * z[ac(ages)]) * exp(logq +
rnorm(prod(dim(n[ac(ages)])), 0, qcv)))  # 10% cv
   range(index)[c("startf","endf")] <- 0.25
   # observe catch with ccv
   catch.n(stock) <- catch.n(stock) * exp(rnorm(prod(dim(catch.n(stock))), 0,
ccv))
   catch(stock) <- computeCatch(stock)
   list(stock = stock, index = list(index))
}

genIdx <- function(stock, qcv=0.1, ccv=0.1) {
   ages <- 1:range(stock)["maxfbar"]
   n <- stock.n(stock)[ac(ages)]
   z <- harvest(stock)[ac(ages)] + m(stock)[ac(ages)]
   logq <- -exp(-exp(0.2 * ages)) - 3 # trawl like catchability
   # observe index in 1st quarter with qcv
   index <- FLIndex(index = n[ac(ages)] * exp(-0.25 * z[ac(ages)]) * exp(logq +
rnorm(prod(dim(n[ac(ages)])), 0, qcv)))  # 10% cv
   range(index)[c("startf","endf")] <- 0.25
   list(stock = stock, index = list(index))
}
#===============================================================================
# cat3 hcr projection
#===============================================================================

cat3hcr <- function(data, HCR, iyr = 1, fyr = 25, srviyr= -9, qcv = 0.1,
rndseed=12345){

   # hcr: cat3 , ic, cat3len, iclen

   # lh
   stk <- data$stock
   lhPars <- attr(stk, "lhPars")
   refpts <- attr(stk, "refpts")
   k <- lhPars["k"]
   linf <- lhPars["linf"]
   t0 <- lhPars["t0"]
   srModel <- "bevholt" # sr hard coded ...
   v <- lhPars["v"]
   s <- lhPars["s"]

   # stock object
   stk <- qapply(stk, function(x){dimnames(x)[[2]] <- -15:0; x})
   range(stk)[4:5] <- c(-15,0)
   stk <- window(stk, stf=list(nyears=fyr-iyr+1))

   # index
   idx <- qapply(data$index[[1]], function(x){dimnames(x)[[2]] <- -15:0; x})
   idx <- window(idx, start=srviyr, end=fyr)
   idx.wt <- stock.wt(stk)[dimnames(index(idx))[[1]],1]

   # S/R
   sr <- FLSR(model=srModel)
   params(sr) <- FLPar(abPars(srModel,
c(refpts["virgin","ssb"]/refpts["virgin","rec"]), v=c(v), s=c(s)))

   # objects for results
   Cadv <- catch(stk)
   Cadv[,ac(iyr)] <- mean(Cadv[,ac(iyr-c(1:3))])

   idxRatio <- catch(stk)
   idxRatio[] <- NA

   # loop
   set.seed(rndseed)
   for(i in iyr:(fyr-1)){
```

```
        # biomass index for advice
        idxadv <- window(index(idx), end=i-1)
        nobs <- length(dimnames(idxadv)[[2]])
        idxadv <- quantSums(idxadv*idx.wt[,rep(1,nobs)])

        if(HCR=="cat3"){
            # mean index last 2 years
            i1 <- mean(idxadv[,ac(i-c(1,2))])
            # mean index previous 3 years
            i2 <- mean(idxadv[,ac(i-c(3:5))])
            idxRatio[,ac(i-1)] <- i1/i2
        }

        if(HCR=="cat3len"){
            # mean index last 2 years
            i1 <- mean(idxadv[,ac(i-c(1,2))])
            # mean index previous 3 years
            i2 <- mean(idxadv[,ac(i-c(3:5))])
            # Lc
            ages <- as.numeric(dimnames(catch.n(stk))[[1]])
            lenbar <- vonB(FLPar(k=k, linf=linf, t0=t0), ages+0.5)
            Lc <- lenbar[1]
            Lmf <- (3*Lc+linf)/4
            #Lsq
            Lsq <- weighted.mean(lenbar, c(catch.n(stk)[,ac(i-1)]))
            idxRatio[,ac(i-1)] <- i1/i2*Lsq/Lmf
        }

        # idx <> IC
        if(HCR=="ic"){
            idxRatio[,ac(i-1)] <- 1
            if(idxadv[,ac(i-1)] > yearMeans(idxadv) +
qnorm(0.99)*sqrt(yearVars(idxadv)/nobs)) idxRatio[,ac(i-1)] <- 1.15
            if(idxadv[,ac(i-1)] < yearMeans(idxadv) +
qnorm(0.01)*sqrt(yearVars(idxadv)/nobs)) idxRatio[,ac(i-1)] <- 0.85
        }

        # idx <> IC * len
        if(HCR=="iclen"){
            idxRatio[,ac(i-1)] <- 1
            if(idxadv[,ac(i-1)] > yearMeans(idxadv) +
qnorm(0.99)*sqrt(yearVars(idxadv)/nobs)) idxRatio[,ac(i-1)] <- 1.15
            if(idxadv[,ac(i-1)] < yearMeans(idxadv) +
qnorm(0.01)*sqrt(yearVars(idxadv)/nobs)) idxRatio[,ac(i-1)] <- 0.85
            # Lc
            ages <- as.numeric(dimnames(catch.n(stk))[[1]])
            lenbar <- vonB(FLPar(k=k, linf=linf, t0=t0), ages+0.5)
            Lc <- lenbar[1]
            Lmf <- (3*Lc+linf)/4
            #Lsq
            Lsq <- weighted.mean(lenbar, c(catch.n(stk)[,ac(i-1)]))
            idxRatio[,ac(i-1)] <- idxRatio[,ac(i-1)]*Lsq/Lmf

        }

        # cacth for next year
        Cadv[,ac(i+1)] <- Cadv[,ac(i-1)]*idxRatio[,ac(i-1)]
        # note: will need rewrite to account for iters
        #browser()
        trg <- fwdControl(data.frame(year=i, quantity='catch',
val=c(Cadv[,ac(i)])))
        stk[,ac(i)] <- fwd(stk, ctrl=trg, sr=sr)[,ac(i)]
        #stk <- fwd(stk, ctrl=trg, sr=sr)
        idx[,ac(i)] <- genIdx(stk, qcv = qcv)$index[[1]][, ac(i)]
    }

    # output
    flqs <- FLQuants(ssb=ssb(stk), catch=catch(stk), rec=rec(stk), f=fbar(stk),
catch.adv=Cadv, idxRatio=idxRatio)
    attr(flqs, "lhPars") <- lhPars
    attr(flqs, "refpts") <- refpts
    flqs
}

#=============================================================================
# extract
```

```
#===============================================================================

getStkInfo <- function(object, scn, hcr){
   res <- lapply(object, function(x){
       lh <- as.data.frame(attr(x, "lhPars"))
       rp <- as.data.frame(attr(x, "refpts"))[c("msy", "f0.1", "fmax"),
"harvest")]
       data.frame(params=c(ac(lh[,1]), ac(rp[,1])), value=c(lh[,3], rp[,4]),
scn=scn, hcr=hcr)
   })

   res <- do.call("rbind", res)
   res$stk <- unlist(lapply(strsplit(rownames(res), "[.]"), "[[", 1))
   rownames(res) <- NULL
   res

}

getRes <- function(object, scn, hcr){
   res <- lapply(object, as.data.frame)
   res <- do.call("rbind", res)
   res$stk <- unlist(lapply(strsplit(rownames(res), "[.]"), "[[", 1))
   rownames(res) <- NULL
   res$scn <- scn
   res$hcr <- hcr
   res
}


FILE #2 (SIMULATING STOCKS)
library(FLBRP)
library(plyr)
library(Hmisc)
library(parallel)
library(reshape)
source("funs.R")

# read data
wklifeLst <- read.table("allStockslifeHistoryParam.txt", sep="\t", head=TRUE)
wklifeLst <-transform(wklifeLst, value=as.numeric(as.character(value)))
wklifeLst <- wklifeLst[!is.na(wklifeLst$value),]
# remove "fle-2232" the parameters are duplicated and seem inconsistent
wklifeLst <- subset(wklifeLst, stock != "fle-2232")

set.seed(123)
wklife.brp <- mclapply(split(wklifeLst, wklifeLst$stock), function(x){
    cat(as.character(x$stock)[1], "\n")
    # get parameters
    par <- FLPar(x$value, tolower(x$param))
    if(!("linf" %in% dimnames(par)$params) & "lmax" %in% dimnames(par)$params){
       dimnames(par)$params[dimnames(par)$params == "lmax"] <- "linf"
    }
    if("linf" %in% dimnames(par)$params){
      # complete with gislasim
      dnms <- dimnames(par)$params
      par <- par[dnms %in% dimnames(gislasim(0))$params]
      par <- gislasim(par)
         # set max age if not available compute from linf
         if(!("tmax" %in% x$param)){
             tmax <- floor(invVonB(FLPar(c(linf=par["linf"], k=par["k"],
t0=par["t0"])), par["linf"]-1))
         } else {
             tmax <- x[x$param=="tmax", "value"]
         }
         # run lh
         res <- lh(par, range=c(min=1, max=tmax, minfbar=ceiling(tmax/10),
maxfbar=floor(tmax/2), plusgroup=tmax))
         res@desc <- as.character(x$stock[1])
         attr(res, "lhPars") <- par
         attr(res, "refpts") <- refpts(res)
         res
    } else {
      NULL
    }
}, mc.cores=4)
wklife.brp <- wklife.brp[!unlist(mclapply(wklife.brp, is.null))]
```

```
       wklife.stk <- mclapply(wklife.brp, function(x){
         cat(x@desc, "\n")
          #Fc <- c(refpts(x)["crash","harvest"]*0.7)
          Fc <- c(refpts(x)["msy","harvest"])*2
         if(!is.na(Fc)){
          Fmsy <- c(refpts(x)["msy","harvest"])
          Ftrg <- c(seq(0, Fc, len=19), rep(Fc, 20), seq(Fc, Fmsy, len=10))
          trg <- fwdControl(data.frame(year=c(2:50), quantity=rep('f', 49), val=Ftrg))
          ex.stk <- as(x, "FLStock")[,1:50]
          #ex.sr <- as.FLSR(ex.stk, model=x@model, params=x@params)
          ex.sr <- fmle(as.FLSR(ex.stk, model="bevholt"), control=list(trace=0))
          stk <- fwd(ex.stk, ctrl=trg, sr=ex.sr)
          stk@name <- x@desc
          stk@desc <- paste("simulated data loosely based on", x@desc)
          attr(stk, "lhPars") <- x@lhPars
          attr(stk, "refpts") <- x@refpts
          stk
         } else {
           NULL
         }
       }, mc.cores=4)
       wklife.stk <- wklife.stk[!unlist(mclapply(wklife.stk, is.null))]
       wklife.stk <- FLStocks(wklife.stk)

       # subset full time-series to get just developing period
       stks01 <- window(wklife.stk, start=5, end=20)
       # generating survey index and adding observation error to catches
       set.seed(239246)
       stks01 <- mclapply(stks01, genIdx, qcv=0.2, mc.cores=4)

       # subset full time-series to get just stable at high exploitation period
       stks03 <- window(wklife.stk, 25,40)
       # generating survey index and adding observation error to catches
       set.seed(239246)
       stks03 <- mclapply(stks03, genIdx, qcv=0.2, mc.cores=4)

       save(list=ls(), file="RData.data")

       FILE #3 (TESTING HCR)
       library(FLBRP)
       library(parallel)
       source("funs.R")
       load("RData.data")

       #====================================================================
       # Run simulations
       #====================================================================

       # scenario development
       cat3.scn1 <- mclapply(stks01, cat3hcr, HCR="cat3", mc.cores=1)
       cat3len.scn1 <- mclapply(stks01, cat3hcr, HCR="cat3len", mc.cores=4)
       cat3ic.scn1 <- mclapply(stks01, cat3hcr, HCR="ic", mc.cores=4)
       cat3iclen.scn1 <- mclapply(stks01, cat3hcr, HCR="iclen", mc.cores=4)

       # scenario over-exploitation
       cat3.scn2 <- mclapply(stks03, cat3hcr, HCR="cat3", mc.cores=4)
       cat3len.scn2 <- mclapply(stks03, cat3hcr, HCR="cat3len", mc.cores=4)
       cat3ic.scn2 <- mclapply(stks03, cat3hcr, HCR="ic", mc.cores=4)
       cat3iclen.scn2 <- mclapply(stks03, cat3hcr, HCR="iclen", mc.cores=4)

       #====================================================================
       # process results
       #====================================================================

       o1 <- getStkInfo(cat3.scn1, scn="dev", hcr="HCR1")
       o2 <- getStkInfo(cat3len.scn1, scn="dev", hcr="HCR2")
       o3 <- getStkInfo(cat3ic.scn1, scn="dev", hcr="HCR3")
       o4 <- getStkInfo(cat3iclen.scn1, scn="dev", hcr="HCR4")
       o5 <- getStkInfo(cat3.scn2, scn="hi", hcr="HCR1")
       o6 <- getStkInfo(cat3len.scn2, scn="hi", hcr="HCR2")
       o7 <- getStkInfo(cat3ic.scn2, scn="hi", hcr="HCR3")
       o8 <- getStkInfo(cat3iclen.scn2, scn="hi", hcr="HCR4")

       stkInfo <- rbind(o1, o2, o3, o4, o5, o6, o7, o8)
```

```
o1 <- getRes(cat3.scn1, scn="dev", hcr="HCR1")
o2 <- getRes(cat3len.scn1, scn="dev", hcr="HCR2")
o3 <- getRes(cat3ic.scn1, scn="dev", hcr="HCR3")
o4 <- getRes(cat3iclen.scn1, scn="dev", hcr="HCR4")
o5 <- getRes(cat3.scn2, scn="hi", hcr="HCR1")
o6 <- getRes(cat3len.scn2, scn="hi", hcr="HCR2")
o7 <- getRes(cat3ic.scn2, scn="hi", hcr="HCR3")
o8 <- getRes(cat3iclen.scn2, scn="hi", hcr="HCR4")

res <- rbind(o1, o2, o3, o4, o5, o6, o7, o8)

rm(o1, o2, o3, o4, o5, o6, o7, o8)

#=====================================================================
# plots
#=====================================================================

bwplot(data~factor(year)|scn*hcr, groups=stk, data=subset(res,
qname=="idxRatio" & stk!="rng-comb"), main="WKLIFE stocks: Catch multiplier")
bwplot(data~factor(year)|scn*hcr, groups=stk, data=subset(res, qname=="ssb" &
stk!="rng-comb"), main="WKLIFE stocks: SSB")
bwplot(data~factor(year)|scn*hcr, groups=stk, data=subset(res, qname=="catch" &
stk!="rng-comb"), main="WKLIFE stocks: Catch")
bwplot(data~factor(year)|scn*hcr, groups=stk, data=subset(res, qname=="f" &
stk!="rng-comb"), main="WKLIFE stocks: F")

# ple-iris
xyplot(data~year|qname, data=window(cat3.scn1[["ple-iris"]], end=24), type="l",
scales=list(relation="free"), main="ple-iris: dev: HCR1")
xyplot(data~year|qname, data=window(cat3len.scn1[["ple-iris"]], end=24),
type="l", scales=list(relation="free"), main="ple-iris: dev: HCR2")
xyplot(data~year|qname, data=window(cat3ic.scn1[["ple-iris"]], end=24),
type="l", scales=list(relation="free"), main="ple-iris: dev: HCR3")
xyplot(data~year|qname, data=window(cat3iclen.scn1[["ple-iris"]], end=24),
type="l", scales=list(relation="free"), main="ple-iris: dev: HCR4")

xyplot(data~year|qname, data=window(cat3.scn2[["ple-iris"]], end=24), type="l",
scales=list(relation="free"), main="ple-iris: hi: HCR1")
xyplot(data~year|qname, data=window(cat3len.scn2[["ple-iris"]], end=24),
type="l", scales=list(relation="free"), main="ple-iris: hi: HCR2")
xyplot(data~year|qname, data=window(cat3ic.scn2[["ple-iris"]], end=24),
type="l", scales=list(relation="free"), main="ple-iris: hi: HCR3")
xyplot(data~year|qname, data=window(cat3iclen.scn2[["ple-iris"]], end=24),
type="l", scales=list(relation="free"), main="ple-iris: hi: HCR4")
```

Annex 6: ToR 3 additional output statistics

A6.1. Catch associated with $F_{40\%SPR}$

The derivation of $F_{x\%SPR}$ is described in detail in Annex 7, Section A7.2 (here we are interested in x=40). Essentially, $F_{40\%SPR}$ is the F value that gives 40% of the B_{ssb}/R value corresponding to F=0 (Annex 7, Equation A7.2.10, with associated definitions in Table A7.2.1). Once this is calculated, it is possible to calculate the Y/R associated with $F_{40\%SPR}$, $Y/R_{40\%SPR}$, by inserting $F_{40\%SPR}$ into Equation A7.2.9 in Annex 7. The yield associated with $F_{40\%SPR}$ is then derived by simply multiplying $Y/R_{40\%SPR}$ by an appropriate level of recruitment, R. A possible candidate for this level of recruitment, and also other population vectors required for the calculations (e.g. mean weights, maturity, natural mortality and fishery selection at age), could be the corresponding averages over the last ten years for the most recent assessment of the stock.

A6.2. Replacement Yield and prediction of a survey result for next year

Replacement Yield is the catch that can be taken from a stock in one year which will result in an unchanged biomass at the start of the following year. In a deterministic age-aggregated model, Replacement Yield is identical to the sustainable yield at the present biomass, and provides a useful measure of the current productivity of the resource. However the equivalence is less straightforward in age structured models because of non-stationary age structure, and transient effects can then distort impressions of resource productivity if the single-year prescription is applied blindly. To damp out such effects, it is more customary for such models to compute ten year Replacement Yield as that constant catch which, if taken each year for the next ten years, will result in the same spawning biomass at the end of that period as at the start. As for $F_{40\%SPR}$ above, the population vectors required for this calculation could be the corresponding averages over the last ten years for the most recent assessment of the stock. An iterative process is needed to determine this catch through repeated ten year population projections with different constant catches until the criterion of an unchanged spawning biomass is satisfied.

When a population model is fit to data including survey data, the model will include some relationship linking population quantities (e.g. numbers-at-age, survey selectivity-at-age, and some survey catchability coefficient) to the expected value for a survey abundance index. The model fitting process then tries to match these expected values for each past year as closely as possible to the values obtained from the actual surveys for those years. To produce an expected survey result for the next year, this process is effectively reversed. The assessment provides a population model, stock–recruitment relationship of some form and associated parameter values; these enable projection of the population forward in time. The projection to the next year then provides the values for numbers-at-age that year which are needed for input to the relationship providing the value of the expected survey abundance.

Annex 7: Method 1: PlotMSY

A7.1. Description and examples

The PlotMSY software was developed in 2010 in order to support the estimation of yield-per-recruit and MSY-based fishing mortality reference points, and was applied in ICES WGs for a number of stocks that year. Because .sen and .sum files was a common output from ICES WGs at the time, the software was developed to rely on the availability of these files in order to facilitate its rapid application, given carefully derived inputs to these files. It was developed within ADMB and in such a way as to provide robust estimation of stock–recruit parameters using the .sum file (by normalizing inputs, re-parameterizing SR functions and automating the process of selecting sensible initial values); it uses the MCMC functionality in ADMB to characterize uncertainty of this estimation, and combines these with biological and fishery-based variables for deriving the F reference points. The option of including additional uncertainty due to these biological and fishery-based variables, and based on the estimates of precision supplied in the .sen file, is also provided.

The software fits three stock–recruit functions, namely Ricker, Beverton–Holt and a smooth version of the Hockey-stick (to ensure differentiability in ADMB). Although reference points are estimated for each of these stock–recruit functions individually, an option is provided to combine appropriate outputs from any number of these stock–recruit functions (all three or two out of the three) in order to derive integrated estimates for the given combination, where the default weighting is based on harmonic means of the likelihood of individual samples from the MCMC chains. Integrated estimates can also be derived by using manually inputted weights as an alternative to the default weighting option.

A mathematical description of the approach is supplied in Section A7.2-A7.4 and a user-manual with instruction on how to use the software in Section A7.5. Example applications for North Sea herring and cod stocks are given below. [Note: a more detailed description of the .sen and .sum files than given in the tables in this section is provided in Section A7.5.]

Some example implementations

North Sea Herring

The information used by PlotMSY, extracted from the .sen and .sum files, is given in Table A7.1.1. Despite the low variability in the fits within each SR (Figure A7.1.1) for NS Herring, estimates of F_{MSY} and F_{crash} are highly variable, and overlap for two of the three models (Figures A7.1.2-A7.1.4). If this were to be taken at face value, it would imply that F_{MSY} was not a suitable target for this stock, as it would be above F_{pa} and so inconsistent with the precautionary approach. Further simulations (not shown) indicated that the high variability in F_{MSY} and F_{crash} was driven mainly by variability in the selection pattern, which may have been overestimated in the assessment method used to obtain these estimates (Table A7.1.1). The aggregated estimates of F_{MSY} and F_{crash} assuming no *a priori* information about the most suitable SR form are shown in Figures A7.1.5 and A7.1.6 both with and without variability in selectivity (note differing horizontal axis scales). Both of these plots indicate that the most weight is given to the Hockey-stick SR form, which estimates different reference points to the other two forms, emphasizing the importance of expert judgement of which SR forms are appropriate to this stock.

Table A7.1.1. Herring input files. Extracts of the relevant information from the sen and sum files used by PlotMSY.

(a) Sen file

```
…
sH0 0.04 0.66
sH1 0.02 0.64
sH2 0.07 0.38
sH3 0.09 0.38
sH4 0.09 0.36
sH5 0.12 0.36
sH6 0.10 0.59
sH7 0.09 0.56
sH8 0.09 0.56
WH0 0.01 0.26
WH1 0.05 0.18
WH2 0.12 0.08
WH3 0.16 0.08
WH4 0.19 0.09
WH5 0.22 0.09
WH6 0.23 0.07
WH7 0.25 0.07
WH8 0.26 0.05
WS0 0.01 0.42
WS1 0.05 0.14
WS2 0.14 0.12
WS3 0.18 0.08
WS4 0.22 0.07
WS5 0.24 0.07
WS6 0.26 0.09
WS7 0.28 0.09
WS8 0.30 0.10
 M0 0.90 0.15
 M1 0.79 0.10
 M2 0.38 0.10
 M3 0.36 0.12
 M4 0.34 0.13
 M5 0.32 0.14
 M6 0.31 0.14
 M7 0.31 0.14
 M8 0.31 0.14
MT0 0.00 0.00
MT1 0.00 0.00
MT2 0.81 0.19
MT3 0.96 0.08
MT4 1.00 0.01
MT5 1.00 0.00
MT6 1.00 0.00
MT7 1.00 0.00
MT8 1.00 0.00
…
[Column 1: sH=human consumption selection, WH=human consumption mean weights,
WS=stock mean weights, M=natural mortality, MT=maturity; Column 2: point
estimates; Column 3: estimates of precision (CV)]
```

(b) Sum file

```
"Stock summary, North Sea herring"
…
1948  67254871 3745254 6280750   689002   689002 0 0 0.172 0.172 0 0
1949  59233629 3153426 6022422   712831   712831 0 0 0.186 0.186 0 0
1950  81899218 3063290 6095126   657368   657368 0 0 0.196 0.196 0 0
1951  74850249 3002633 6205832   762990   762990 0 0 0.234 0.234 0 0
1952  74700698 2833434 6064726   829020   829020 0 0 0.246 0.246 0 0
1953  80117110 2788460 5950584   843234   843234 0 0 0.261 0.261 0 0
1954  75150250 2615589 5821101   915293   915293 0 0 0.292 0.292 0 0
1955  66386216 2438759 5471153   866312   866312 0 0 0.289 0.289 0 0
1956  49130963 2409669 4911058   850007   850007 0 0 0.292 0.292 0 0
1957 129994149 2226630 5576099   784655   784655 0 0 0.306 0.306 0 0
1958  49674387 2043143 5267150   790958   790958 0 0 0.315 0.315 0 0
1959  56911045 1696368 5460222  1131438  1131438 0 0 0.329 0.329 0 0
1960  23068993 2605148 4439268   839029   839029 0 0 0.287 0.287 0 0
1961 108146787 2231088 5050511   756910   756910 0 0 0.322 0.322 0 0
1962  52904555 2124400 4699657   666636   666636 0 0 0.346 0.346 0 0
1963  79319932 1522707 5362817   658026   658026 0 0 0.244 0.244 0 0
1964  82145285 2443642 5677378   931918   931918 0 0 0.324 0.324 0 0
1965  38186782 2373794 5020299  1217122  1217122 0 0 0.501 0.501 0 0
1966  34935009 1945442 3886424   976764   976764 0 0 0.510 0.510 0 0
1967  42926504 1575369 3169232   835679   835679 0 0 0.654 0.654 0 0
1968  40873807 1021722 2755198   806936   806936 0 0 0.948 0.948 0 0
1969  19560054  567502 2137185   556821   556821 0 0 0.864 0.864 0 0
1970  36506468  510936 2063677   532853   532853 0 0 0.905 0.905 0 0
1971  26990621  489432 1947389   540906   540906 0 0 1.212 1.212 0 0
1972  17716377  348363 1684535   472598   472598 0 0 0.645 0.645 0 0
1973   8966446  350109 1292385   443743   443743 0 0 0.827 0.827 0 0
1974  16387018  304370  949794   274581   274581 0 0 0.845 0.845 0 0
1975   3870909  204434  783871   265136   265136 0 0 0.968 0.968 0 0
1976   4901246  119491  543617   147709   147709 0 0 0.723 0.723 0 0
1977   5520616  166708  408399    61023    61023 0 0 0.337 0.337 0 0
1978   5826925  124492  462777    52680    52680 0 0 0.250 0.250 0 0
1979  11172880  154817  590662    65578    65578 0 0 0.207 0.207 0 0
1980  17072849  190042  811792    81064    81064 0 0 0.183 0.183 0 0
1981  37468083  210660 1405635   159213   159213 0 0 0.201 0.201 0 0
1982  59709399  309589 2128653   271848   271848 0 0 0.185 0.185 0 0
1983  56232194  431922 2861911   403124   403124 0 0 0.231 0.231 0 0
1984  53650428  647582 3602001   453613   453613 0 0 0.304 0.304 0 0
1985  67456938 1034057 4093865   606221   606221 0 0 0.388 0.388 0 0
1986  79717524 1097999 4685579   766048   766048 0 0 0.379 0.379 0 0
1987  81409294 1123546 4615820   785441   785441 0 0 0.374 0.374 0 0
1988  42926504 1294972 4538014  1033023  1033023 0 0 0.365 0.365 0 0
1989  35640743 1646233 3801856   794923   794923 0 0 0.350 0.350 0 0
1990  29978769 1696368 3704282   695231   695231 0 0 0.300 0.300 0 0
1991  31642129 1741052 3433189   672663   672663 0 0 0.329 0.329 0 0
1992  59174425 1501537 3460764   698716   698716 0 0 0.369 0.369 0 0
1993  51392356 1151988 3191495   680784   680784 0 0 0.422 0.422 0 0
1994  36397112  818313 2827773   598391   598391 0 0 0.437 0.437 0 0
1995  46828381  874144 2746945   544705   544705 0 0 0.379 0.379 0 0
1996  44233811  921723 2934360   297747   297747 0 0 0.229 0.229 0 0
1997  31108760 1058115 3131429   284077   284077 0 0 0.201 0.201 0 0
1998  22098052 1217122 3325066   384231   384231 0 0 0.222 0.222 0 0
1999  71128595 1467396 3412651   361494   361494 0 0 0.212 0.212 0 0
2000  48496394 1536473 4329662   373249   373249 0 0 0.212 0.212 0 0
2001  84901303 1531870 4852478   385001   385001 0 0 0.187 0.187 0 0
2002  44278067 2084418 5626510   407176   407176 0 0 0.176 0.176 0 0
2003  21274080 2397651 5962498   495836   495836 0 0 0.201 0.201 0 0
2004  24865702 2455891 5040420   584201   584201 0 0 0.244 0.244 0 0
2005  23277552 2419327 4231216   635394   635394 0 0 0.260 0.260 0 0
2006  27480851 2294441 3513067   507372   507372 0 0 0.231 0.231 0 0
2007  26245366 1797667 2996633   363669   363669 0 0 0.197 0.197 0 0
2008  26192928 1444105 3051061   252458   252458 0 0 0.128 0.128 0 0
2009  35039971 1525755 3509556   183506   183506 0 0 0.076 0.076 0 0
2010  37095269 1899308 4085685   192336   192336 0 0 0.078 0.078 0 0
2011  31139884 2004690 4231216   217075   217075 0 0 0.093 0.093 0 0
```

[Col2=Recruitment, Col3=SSB, Col4=TSB, Col5=total catch, Col6=human consumption landings, Col7=discards, Col8=industrial bycatch, Col9=total F, Col10=human consumption F, Col11=discards F, Col12=industrial bycatch F]
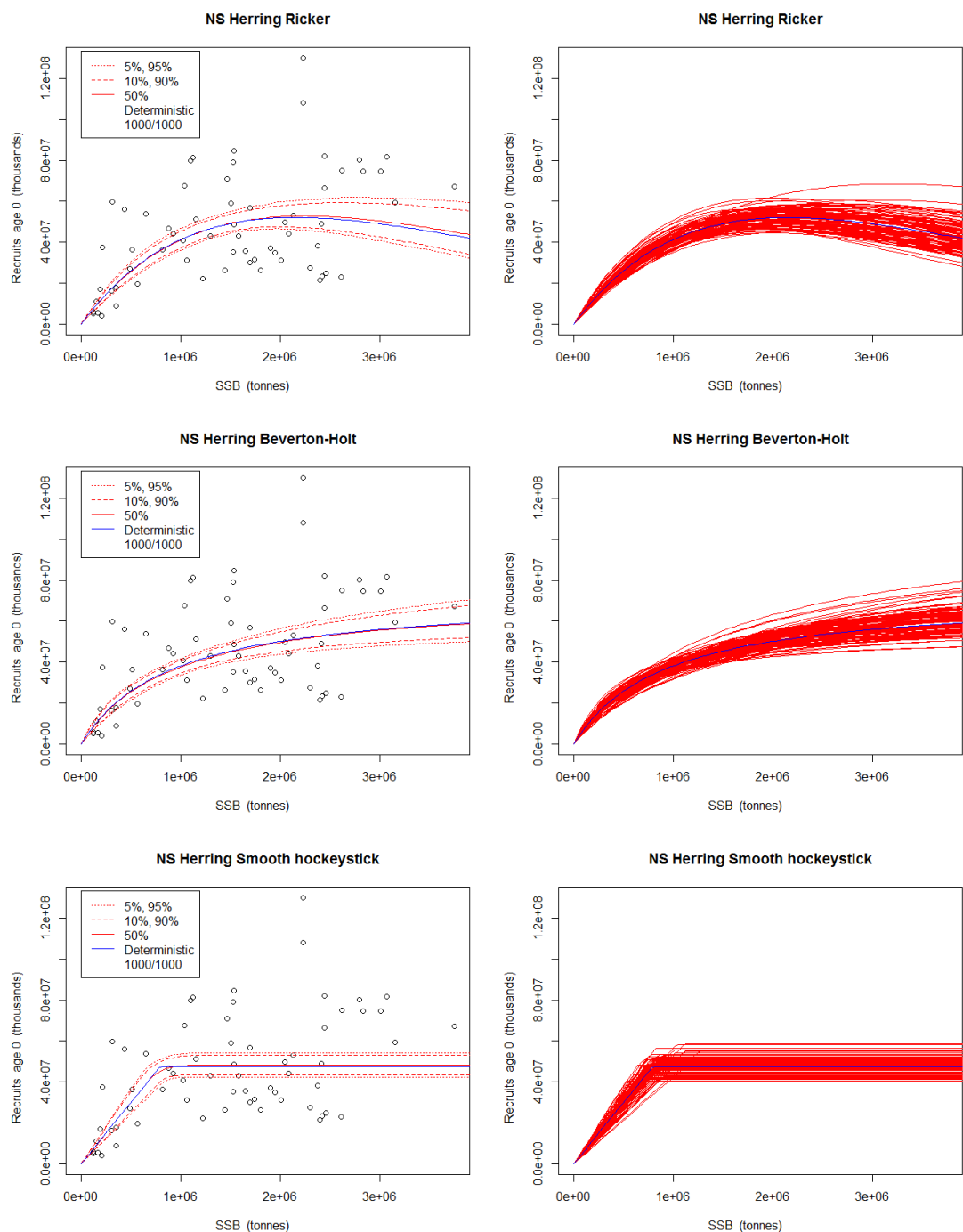
Figure A7.1.1. North Sea herring stock–recruit fits for Ricker (top), Beverton–Holt (middle) and smooth Hockey-stick (bottom). The left hand figures illustrate the 95th, 90th, median, 10th, and 5th percentiles from the successful MCMC samples, plotted with the assessment data points; the right hand figures provide 100 illustrative resamples. The estimates derived from MCMC sampling are illustrated in red; the deterministic estimates in blue. The bottom row in the legends indicates the number of successful resamples (i.e. with feasible stock–recruit parameters).

NS Herring Ricker
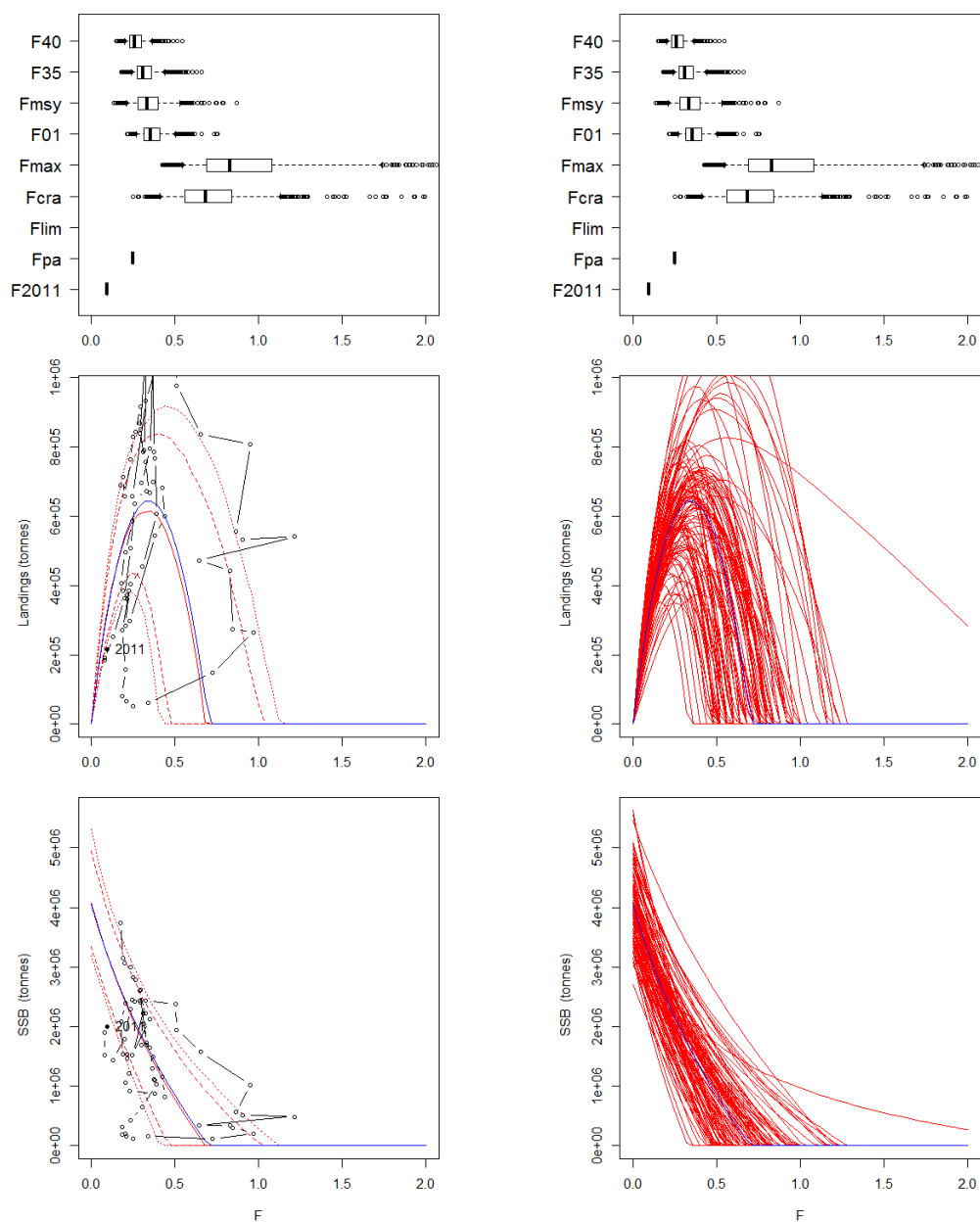
Figure A7.1.2. North Sea herring yield and SSB based on the Ricker stock and recruitment model estimates. Top: box plots of Fmsy and Fcrash with proxies for Fmsy based on the yield-per-recruit: Fmax, F0.1, F35% and F40% SPR also Flim, Fpa and F in the final year; middle: equilibrium landings vs. fishing mortality; bottom: equilibrium SSB vs. fishing mortality. The left hand figures illustrate the 95th, 90th, median, 10th, and 5th percentiles from the successful MCMC samples, plotted with the assessment data points; the right hand figures provide 100 illustrative resamples. The estimates derived from MCMC sampling are illustrated in red; the deterministic estimates in blue.
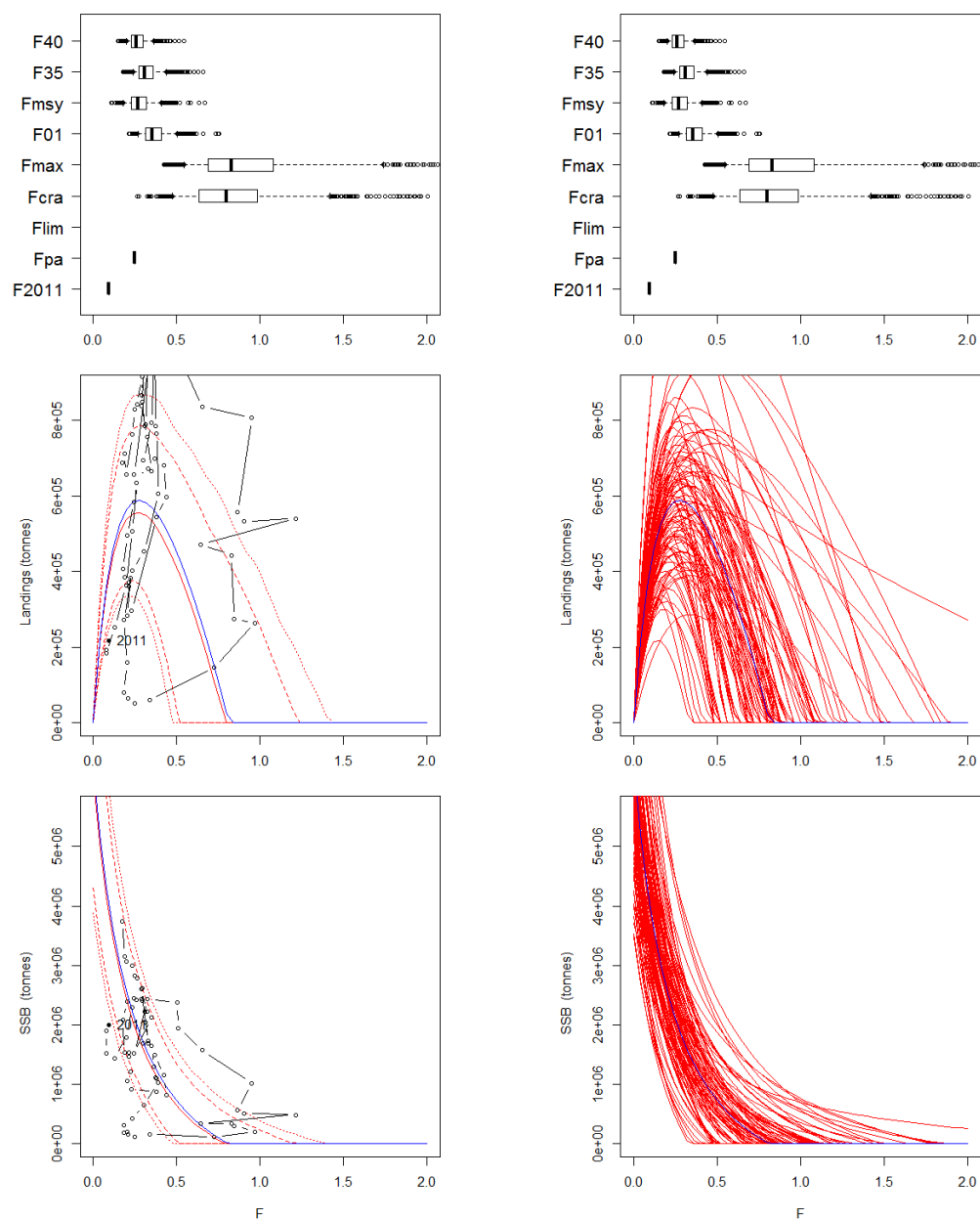
Figure A7.1.3. North Sea herring yield and SSB based on the Beverton–Holt stock and recruitment model estimates. See Figure A7.1.2 for further details.

NS Herring Smooth hockeystick
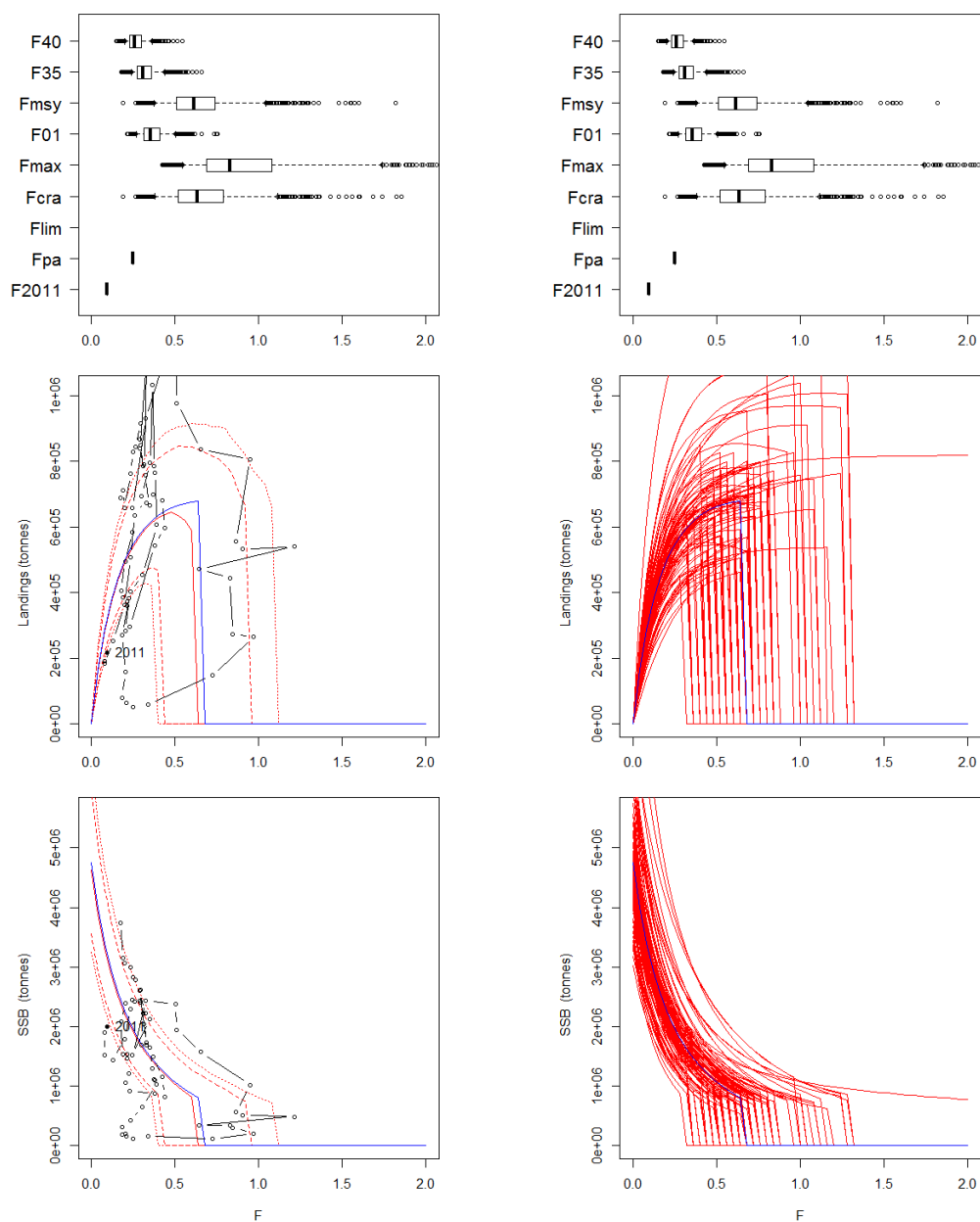
Figure A7.1.4. North Sea herring yield and SSB based on the Hockey-stick stock and recruitment model estimates. See Figure A7.1.2 for further details.

NS Herring - combined Fmsy distribution: automatically weighted

NS Herring - combined Fcrash distribution: automatically weighted
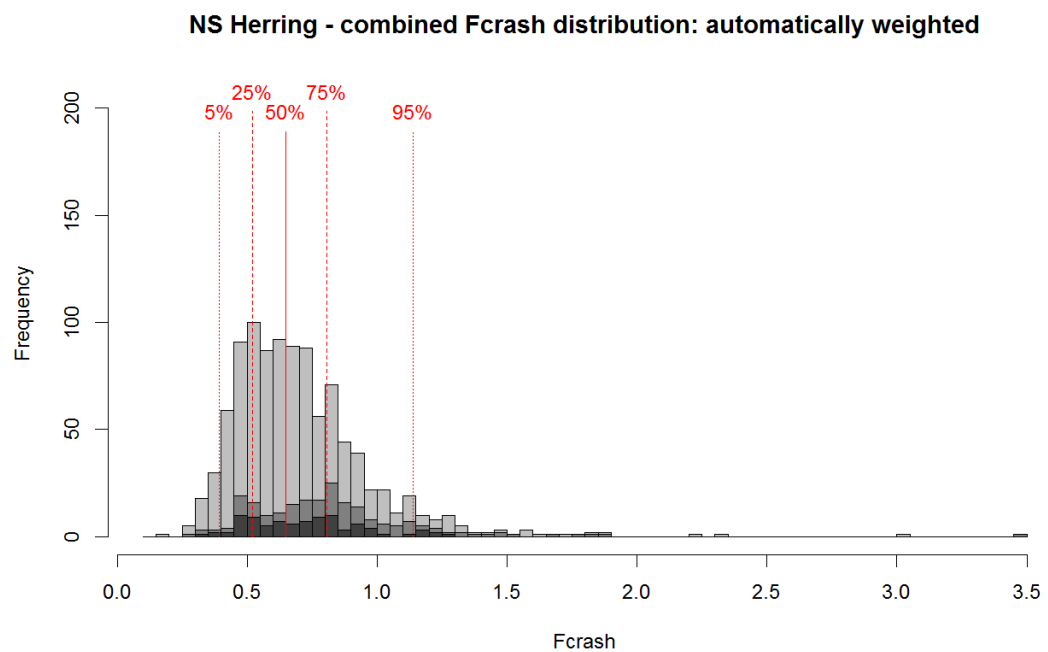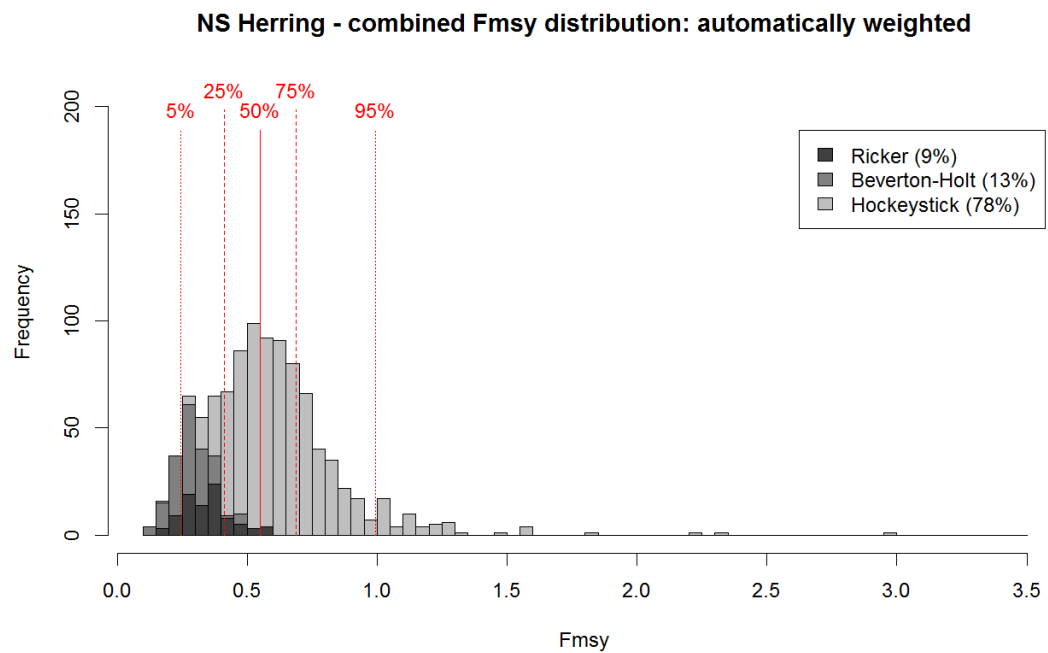
Figure A7.1.5. North Sea herring combined distribution of F_{MSY} and F_{crash} weighted by model likelihood. The weights derived likelihood are given in the legend.

NS Herring noselvar - combined Fmsy distribution: automatically weighted
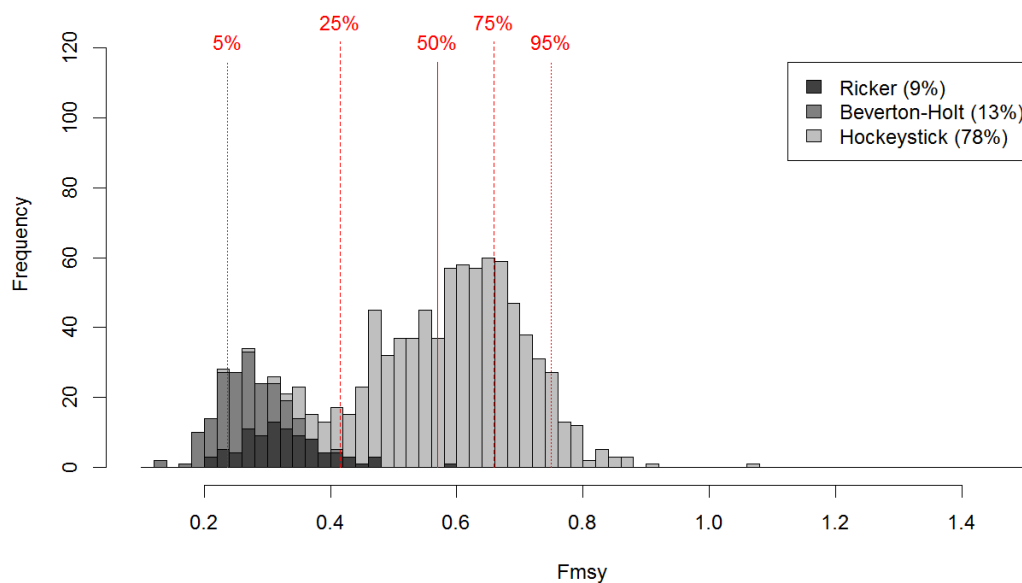
NS Herring noselvar - combined Fcrash distribution: automatically weighted
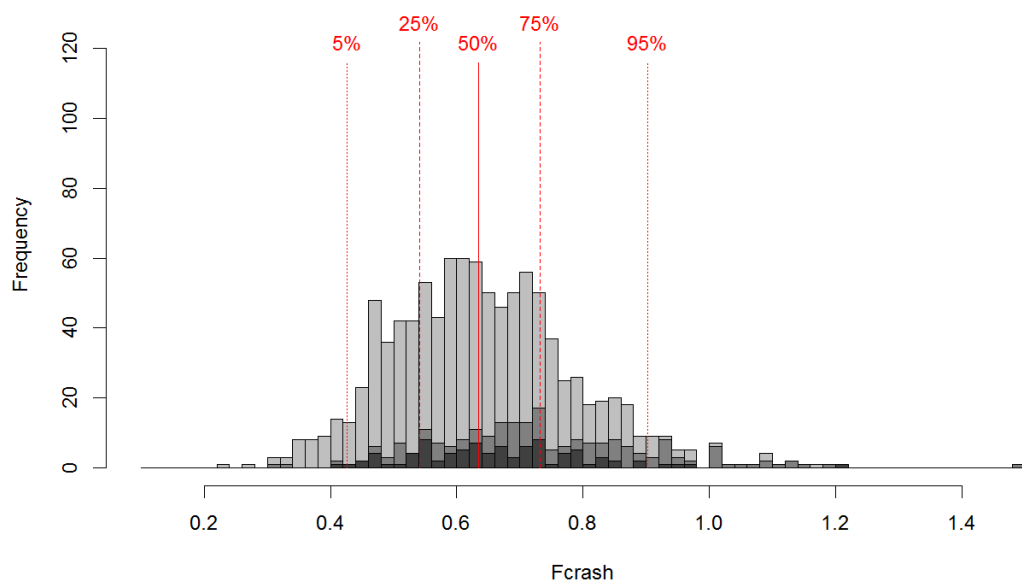
Figure A7.1.6. North Sea herring combined distribution of F_{MSY} and F_{crash} weighted by model likelihood with no selectivity variability. [Note the scale on the horizontal axis differs from Figure A7.1.5.]

North Sea Cod

Information from the .sen and .sum files, is given in Table A7.1.2. For North Sea Cod, the SR fits show that the SR relationship is estimated to be mostly linear within the historically observed range (Figure A7.1.7). Consequently any movement in the direction of FMSY should be cautious as the maxima of the Beverton–Holt and Ricker SR curves are poorly estimated. For all three SR forms (Figures A7.1.8-A7.1.10), FMSY is estimated with reasonably tight bounds and well below Fcrash. Weighting the estimates by likelihood (Figure A7.1.11) gives an estimate of FMSY around 0.24, but for all Ricker and Beverton–Holt SR forms the actual yield and SSB that can be achieved at FMSY is uncertain, as these F levels have not been observed during the period for which data exists. Figure A7.1.12 plots the probability of SSB < Blim for when results are weighted by the likelihood values, where the F associated with a 5% probability is given as 0.69. This value is slightly higher than the value currently used value for Fpa (0.65). The rather narrow confidence intervals on the F-based reference points (Figures A7.1.8-A7.1.10) raises the possibility that the CVs used in the sen file may be too small for this stock, and highlights the care with which this file needs to be constructed.

Table A7.1.2. Cod input files: Extracts of the relevant information from the sen and sum files used by PlotMSY.

(a) Sen file

```
…
sH1 0.016 0.175
sH2 0.176 0.097
sH3 0.483 0.076
sH4 0.598 0.079
sH5 0.648 0.085
sH6 0.698 0.109
sH7 0.690 0.109
sD1 0.128 0.175
sD2 0.280 0.097
sD3 0.159 0.076
sD4 0.060 0.079
sD5 0.021 0.085
sD6 0.018 0.109
sD7 0.026 0.109
WH1 0.747 0.112
WH2 1.306 0.143
WH3 2.634 0.137
WH4 4.236 0.097
WH5 6.104 0.062
WH6 7.642 0.050
WH7 9.701 0.040
WD1 0.286 0.255
WD2 0.755 0.282
WD3 1.726 0.419
WD4 3.542 0.542
WD5 5.964 0.480
WD6 6.674 0.345
WD7 8.823 0.792
WS1 0.339 0.196
WS2 0.964 0.138
WS3 2.404 0.136
WS4 4.173 0.093
WS5 6.112 0.061
WS6 7.647 0.059
WS7 9.770 0.036
 M1 1.039 0.100
 M2 0.698 0.100
 M3 0.490 0.100
 M4 0.233 0.100
 M5 0.200 0.100
 M6 0.200 0.100
 M7 0.200 0.100
MT1 0.010 0.000
MT2 0.050 0.100
MT3 0.230 0.100
MT4 0.620 0.100
MT5 0.860 0.000
MT6 1.000 0.000
MT7 1.000 0.000
…
[Column 1: sH=human consumption selection, sD=discard selection, WH=human
consumption mean weights, WD=discard mean weights, WS=stock mean weights,
M=natural mortality, MT=maturity; Column 2: point estimates; Column 3:
estimates of precision (CV)]
```

(b) Sum file

…
```
1963   466 152   514 125 111 14 0 0.49 0.43 0.05 0
1964   853 164   687 153 140 13 0 0.51 0.47 0.04 0
1965  1070 204   863 203 182 21 0 0.54 0.49 0.06 0
1966  1379 227  1051 249 217 32 0 0.56 0.49 0.07 0
1967  1272 251  1136 298 265 34 0 0.61 0.54 0.07 0
1968   657 262   944 300 279 21 0 0.64 0.59 0.04 0
1969   606 259   805 240 228 12 0 0.62 0.59 0.03 0
1970  1839 274  1333 268 244 24 0 0.64 0.58 0.06 0
1971  2369 276  1460 352 291 61 0 0.71 0.58 0.12 0
1972   584 241   977 362 328 34 0 0.77 0.70 0.07 0
1973   875 213   801 260 235 25 0 0.75 0.68 0.07 0
1974   808 232   755 241 216 25 0 0.74 0.66 0.08 0
1975  1378 213   859 238 206 32 0 0.77 0.67 0.10 0
1976   849 183   659 238 200 37 0 0.80 0.68 0.13 0
1977  2097 161  1008 244 181 63 0 0.80 0.59 0.21 0
1978  1272 160  1122 324 284 40 0 0.86 0.75 0.11 0
1979  1435 167  1007 314 272 42 0 0.80 0.70 0.11 0
1980  2274 182  1173 339 273 66 0 0.86 0.69 0.17 0
1981   886 195   990 363 325 38 0 0.89 0.80 0.09 0
1982  1407 188  1019 335 294 40 0 0.98 0.87 0.12 0
1983   819 155   818 282 257 26 0 0.97 0.88 0.09 0
1984  1427 132   828 246 200 47 0 0.92 0.74 0.17 0
1985   379 127   570 226 203 23 0 0.89 0.80 0.09 0
1986  1693 116   777 206 162 45 0 0.94 0.73 0.20 0
1987   671 109   740 248 218 30 0 0.94 0.83 0.11 0
1988   462 101   551 200 187 13 0 0.95 0.89 0.06 0
1989   768  94   538 169 136 33 0 0.97 0.78 0.19 0
1990   334  80   379 136 114 22 0 0.91 0.76 0.15 0
1991   370  74   350 120 105 15 0 0.91 0.80 0.11 0
1992   793  71   518 135 108 27 0 0.88 0.70 0.18 0
1993   447  69   431 149 124 26 0 0.89 0.74 0.15 0
1994   944  72   527 153 115 38 0 0.91 0.68 0.23 0
1995   558  81   563 186 152 34 0 0.93 0.76 0.17 0
1996   404  79   459 166 143 23 0 0.96 0.82 0.13 0
1997  1059  75   632 166 126 40 0 0.96 0.73 0.23 0
1998   171  61   343 141 109 32 0 0.98 0.76 0.22 0
1999   303  56   257 101  86 15 0 1.00 0.86 0.14 0
2000   549  50   345 102  81 21 0 1.00 0.79 0.20 0
2001   209  42   248  91  72 19 0 0.96 0.75 0.20 0
2002   256  43   266  89  79  9 0 0.93 0.83 0.10 0
2003   119  37   151  61  51 10 0 0.90 0.76 0.14 0
2004   200  32   150  48  38  9 0 0.86 0.69 0.17 0
2005   137  30   145  47  39  8 0 0.80 0.67 0.14 0
2006   345  26   157  42  32 10 0 0.72 0.56 0.17 0
2007   147  33   186  56  29 27 0 0.67 0.35 0.32 0
2008   179  38   186  54  30 24 0 0.63 0.35 0.29 0
2009   191  47   212  57  38 19 0 0.60 0.40 0.20 0
2010   326  52   246  62  46 16 0 0.58 0.43 0.15 0
2011   166  56   237  67  50 17 0 0.57 0.43 0.14 0
```

[Col2=Recruitment, Col3=SSB, Col4=TSB, Col5=total catch, Col6=human consumption landings, Col7=discards, Col8=industrial bycatch, Col9=total F, Col10=human consumption F, Col11=discards F, Col12=industrial bycatch F]
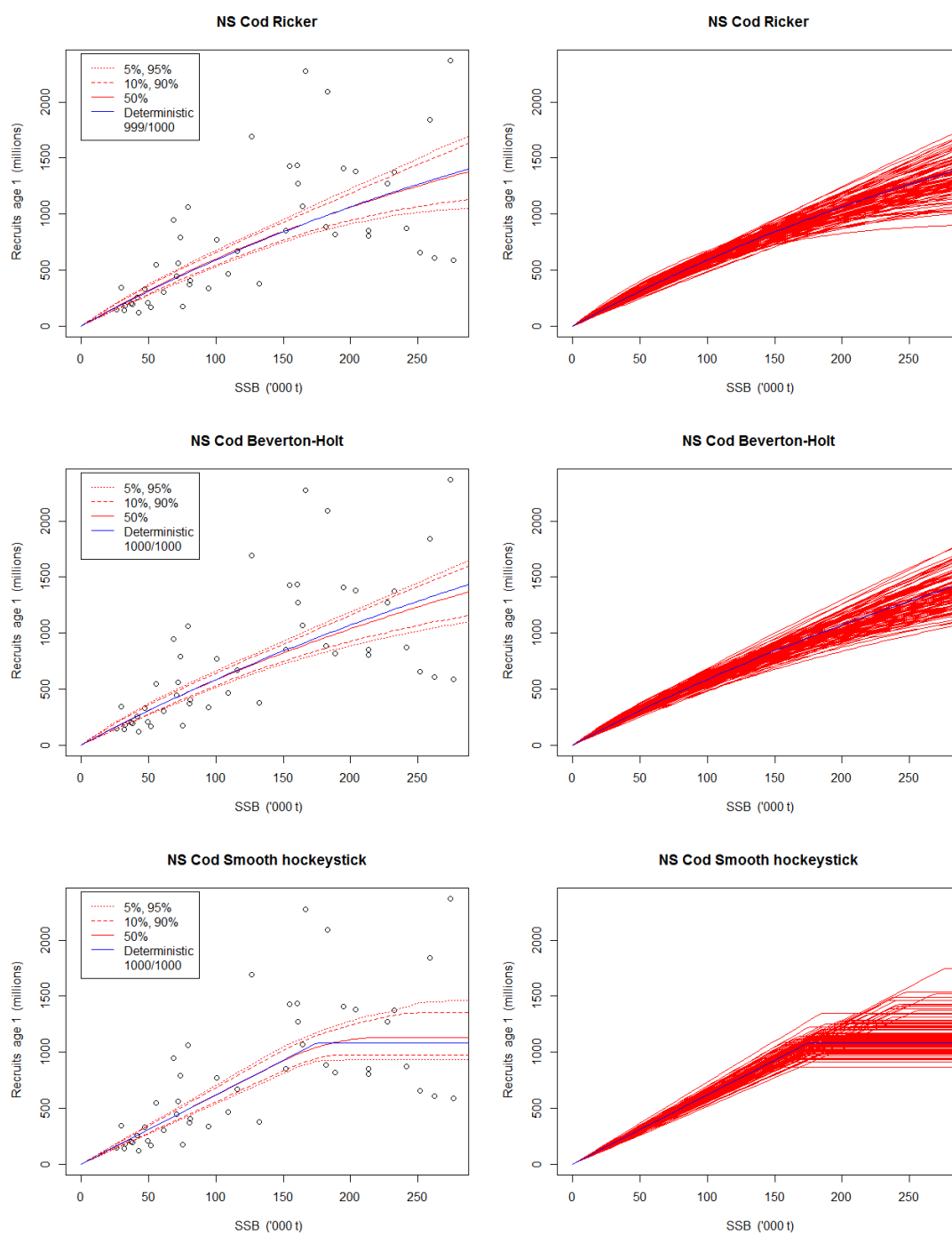
Figure A7.1.7. North Sea cod stock–recruit fits for Ricker (top), Beverton–Holt (middle) and smooth Hockey-stick (bottom). See Figure A7.1.1 for more details.

NS Cod Ricker
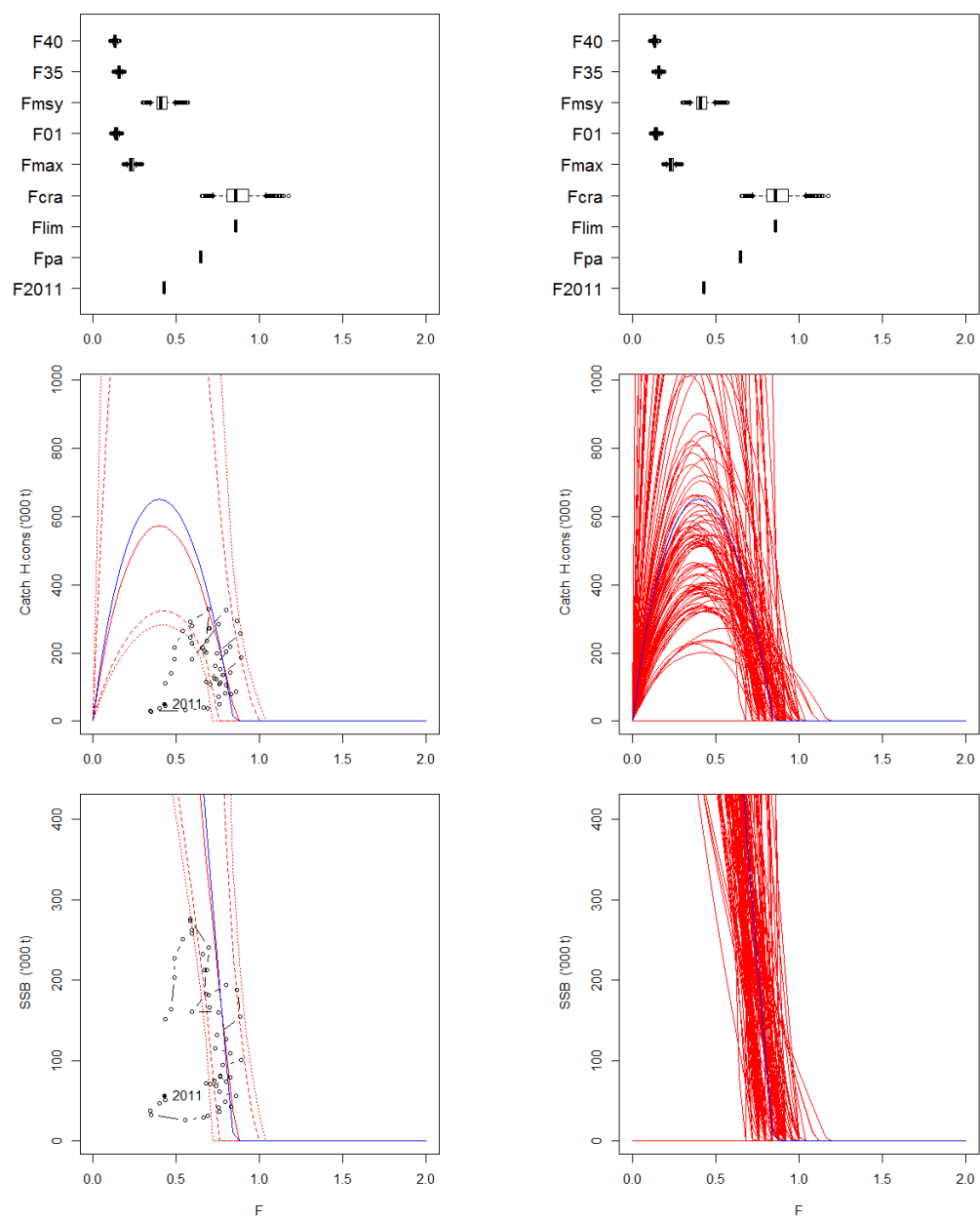
Figure A7.1.8. North Sea cod yield and SSB based on the Ricker stock and recruitment model estimates. See Figure A7.1.2 for further details.

NS Cod Beverton-Holt
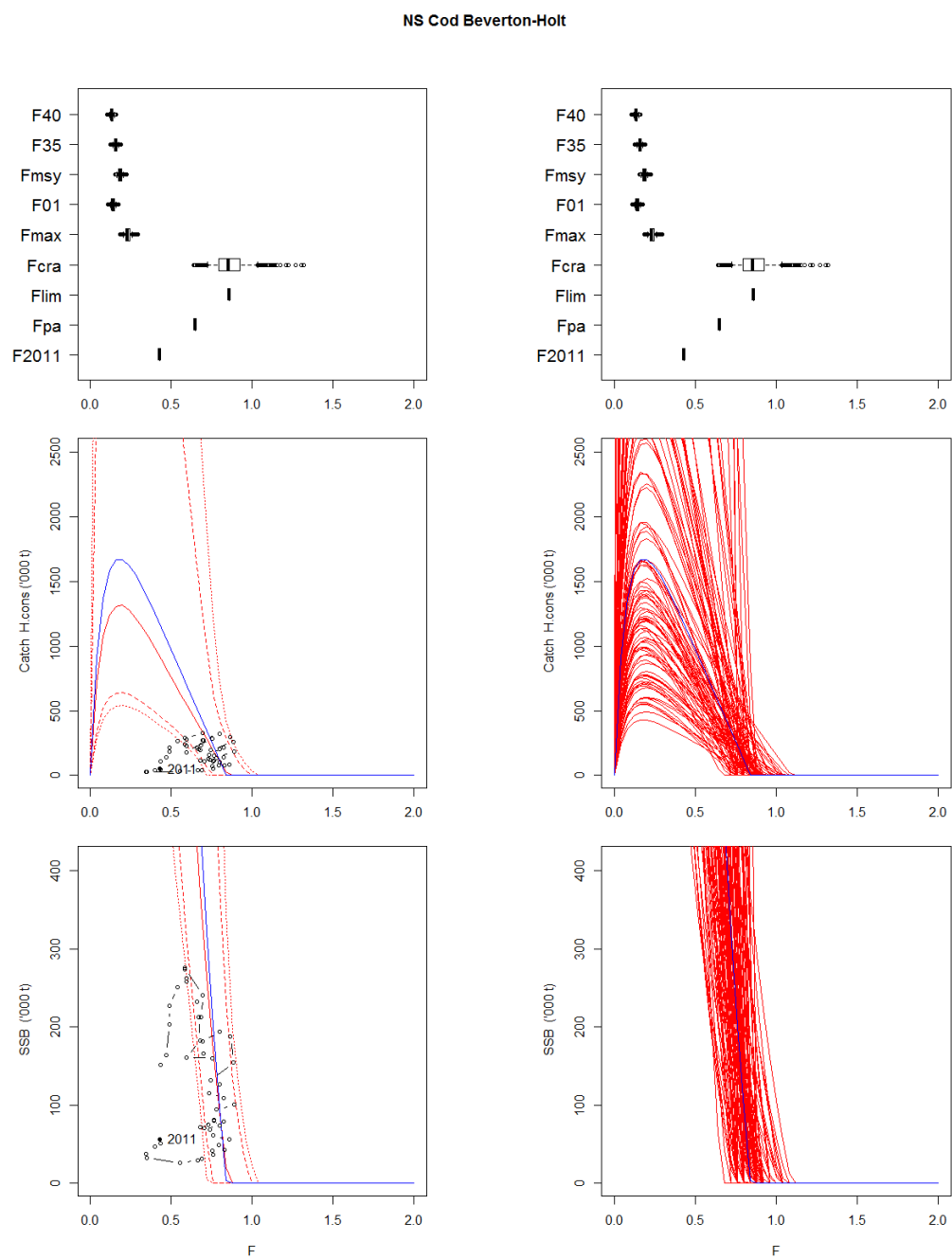
Figure A7.1.9. North Sea cod yield and SSB based on the Beverton–Holt stock and recruitment model estimates. See Figure A7.1.2 for further details.

NS Cod Smooth hockeystick
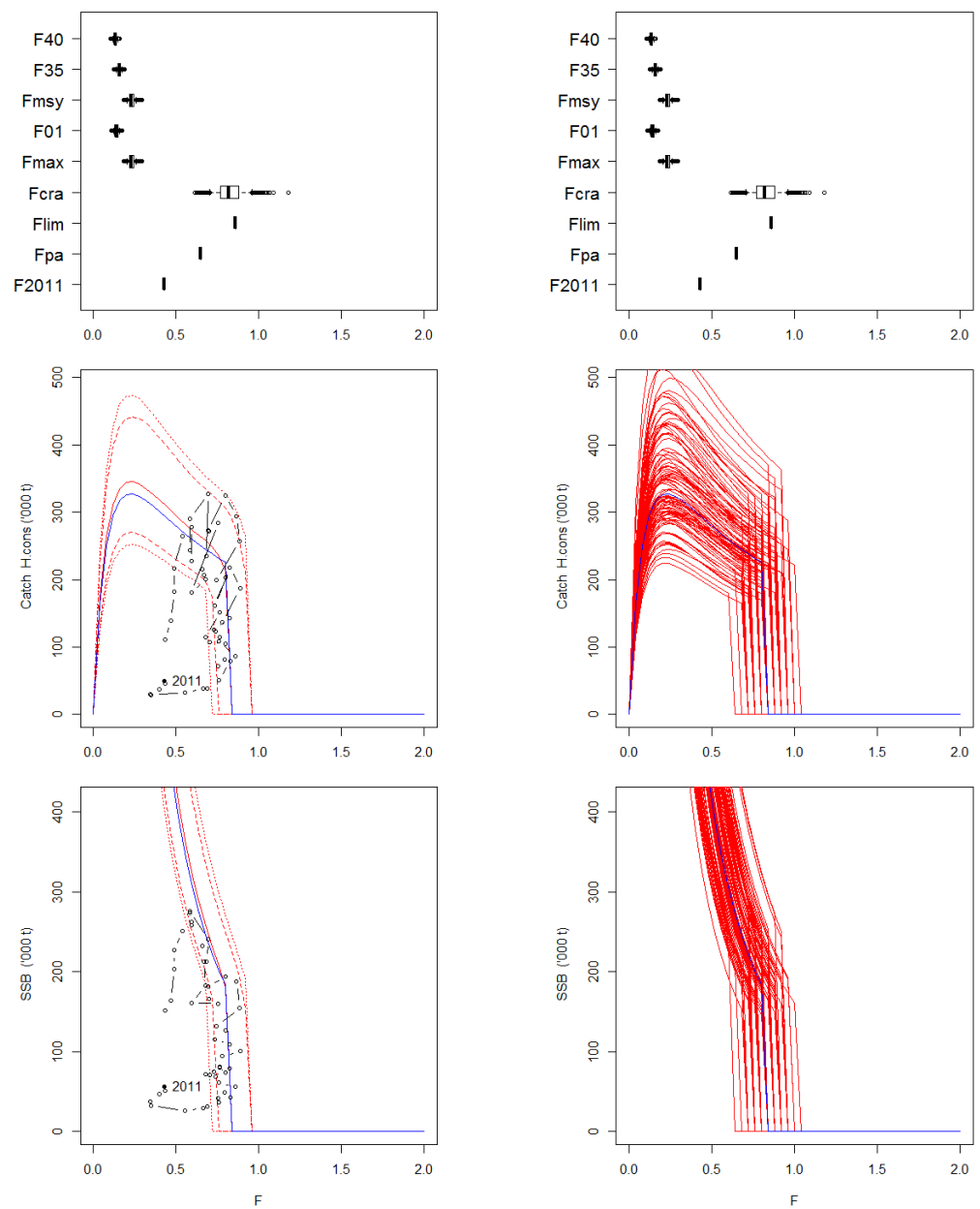
Figure A7.1.10. North Sea cod yield and SSB based on the Hockey-stick stock and recruitment model estimates. See Figure A7.1.2 for further details.

NS Cod - combined Fmsy distribution: automatically weighted

NS Cod - combined Fcrash distribution: automatically weighted
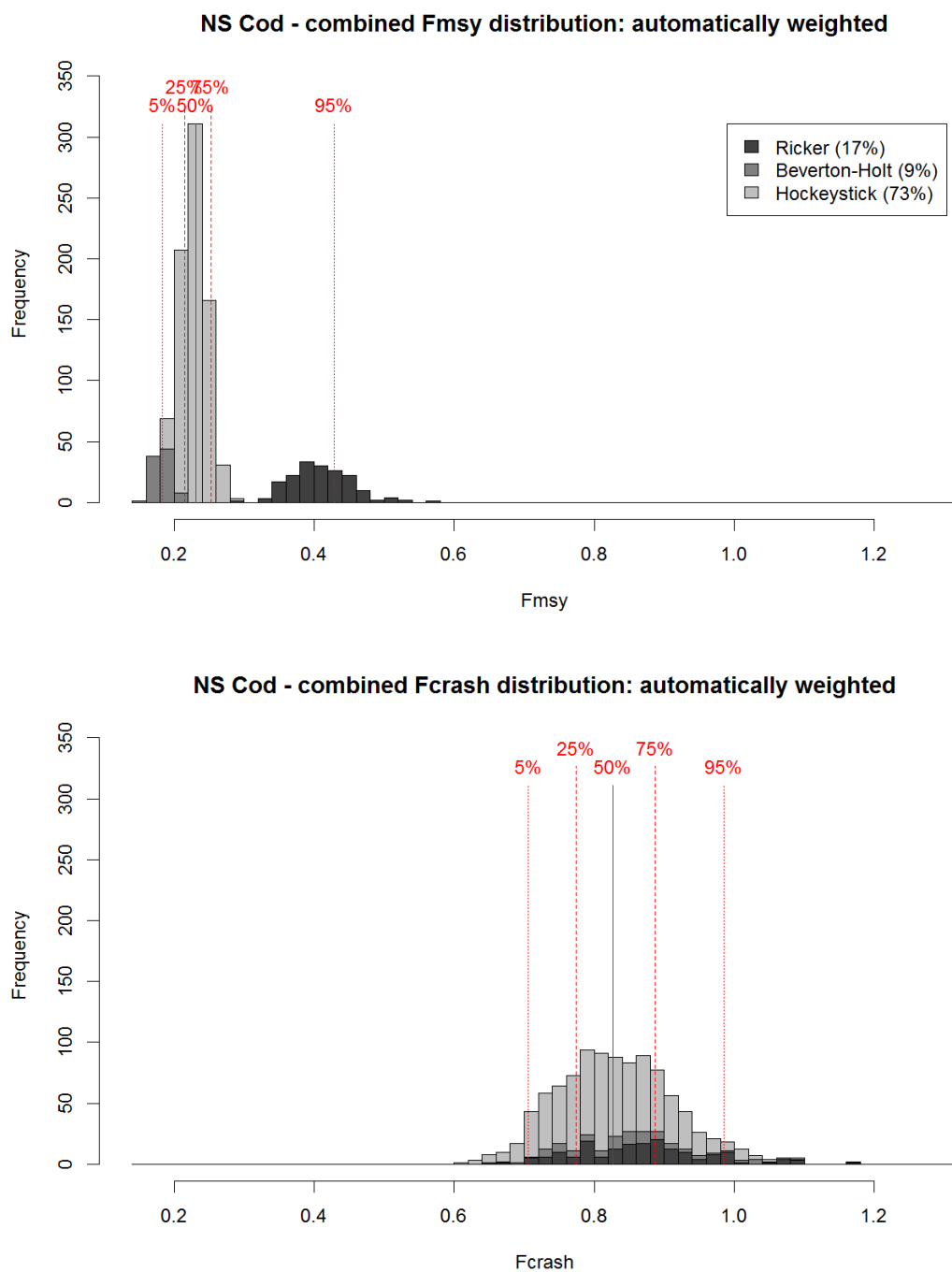
Figure A7.1.11. North Sea cod combined distribution of F_{MSY} and F_{crash} weighted by model likelihood.
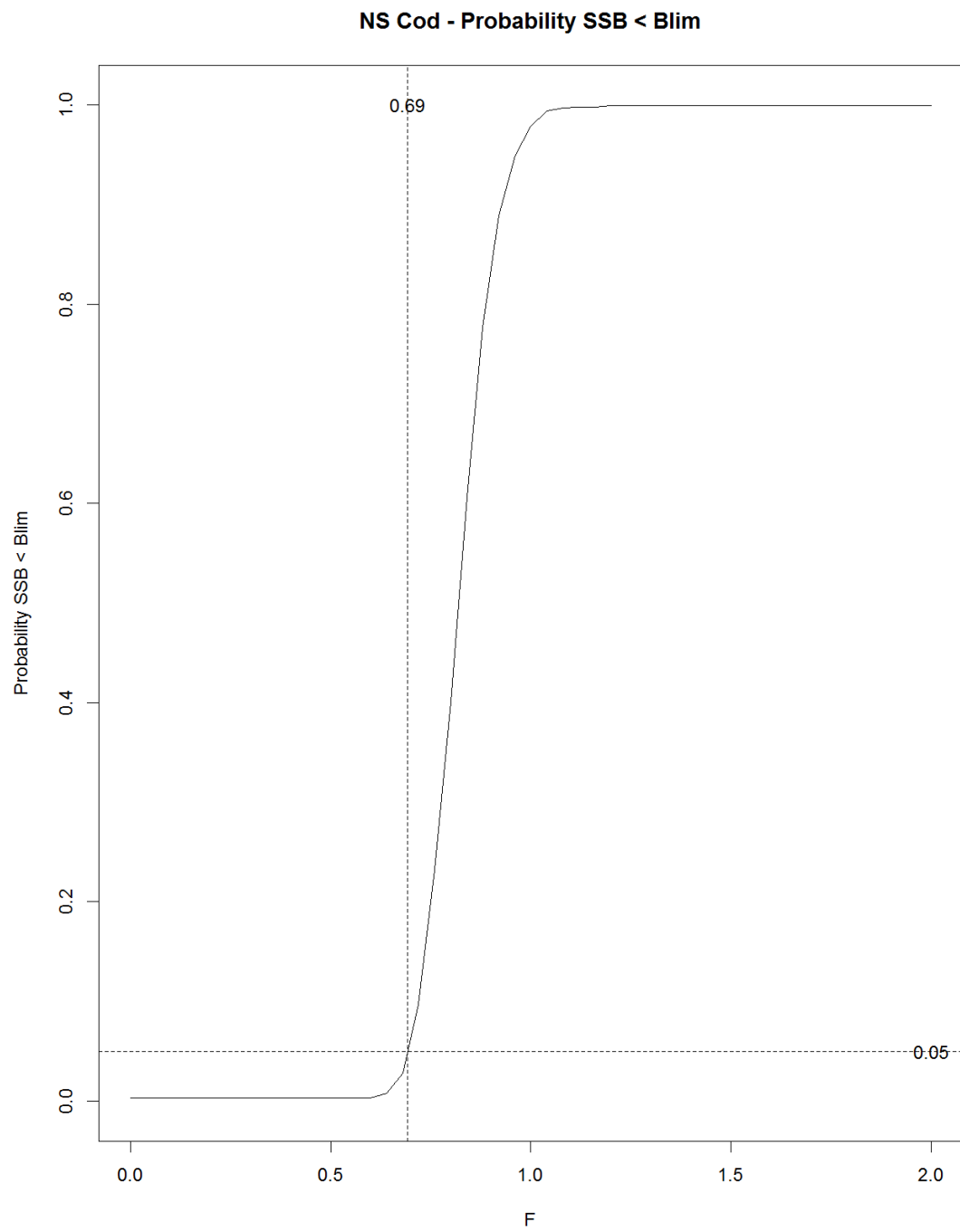
Figure 7.1.12. North Sea cod probability of SSB < Blim for the combined analysis weighted by model likelihood, indicating the F value coinciding with a 5% probability.

A7.2. Derivation of basic equations

Population Dynamics

Definitions for all symbols used are provided in Table A7.2.1.

Stock–recruit function:

$$N_{y,r} = R_y = g(B_{ssb,y-r}) \tag{A7.2.1}$$

Population numbers-at-age:

$$N_{y+1,a+1} = N_{y,a}\, e^{-s_{c,a} F_y - M_{y,a}} \qquad , \quad a = r, r+1, \ldots, A-2 \tag{A7.2.2}$$

$$N_{y+1,A} = N_{y,A-1}\, e^{-s_{c,A-1} F_y - M_{y,A-1}} + N_{y,A}\, e^{-s_{c,A} F_y - M_{y,A}} \tag{A7.2.3}$$

Catch numbers-at-age:

$$C_{y,a} = \frac{s_{c,a} F_y}{s_{c,a} F_y + M_{y,a}} N_{y,a}(1 - e^{-s_{c,a} F_y - M_{y,a}}) \qquad , \quad a = r, r+1, \ldots, A \tag{A7.2.4}$$

Spawning-stock biomass:

$$B_{ssb,y} = \sum_{a=r}^{A} w_{s,y,a}\, Q_a\, N_{y,a}\, e^{-f s_{c,a} F_y - m M_{y,a}} \tag{A7.2.5}$$

Stock–recruit functions g:

Ricker:

$$R_y = \alpha\, B_{ssb,y-r}\, e^{-\beta B_{ssb,y-r}} \tag{A7.2.6}$$

Beverton–Holt:

$$R_y = \frac{\alpha\, B_{ssb,y-r}}{\beta + B_{ssb,y-r}} \tag{A7.2.7}$$

Smooth Hockey-stick:

$$R_y = \alpha \left[B_{ssb,y-r} + \sqrt{\beta^2 + \gamma^2/4} - \sqrt{(B_{ssb,y-r} - \beta)^2 + \gamma^2/4} \right] \tag{A7.2.8}$$

where $\gamma = 0.01 \overline{B}_{ssb}$. This formulation reduces to the following when γ=0:

$$R_y = \begin{cases} 2\alpha\beta & , B_{ssb,y-r} \geq \beta \\ 2\alpha B_{ssb,y-r} & , B_{ssb,y-r} < \beta \end{cases} \tag{A7.2.8a}$$

Yield-per-recruit and SSB-per-recruit

Derivations of yield- and SSB-per-recruit are given in Section A7.3, and are as follows (given that these follow from equilibrium considerations, the year subscript is dropped):

$$Y/R = w_r \frac{s_r F}{s_{c,r} F + M_r}[1 - e^{-s_{c,r} F - M_r}] + \sum_{a=r+1}^{A-1}\left[e^{-\sum_{i=r}^{a-1}(s_{c,i} F + M_i)} w_a \frac{s_a F}{s_{c,a} F + M_a}[1 - e^{-s_{c,a} F - M_a}] \right] + e^{-\sum_{i=r}^{A-1}(s_{c,i} F + M_i)} w_A \frac{s_A F}{s_{c,A} F + M_A}$$

A7.2.9

and

$$B_{ssb}/R = w_{s,r} Q_r e^{-f s_{c,r} F - m M_r} + \sum_{a=r+1}^{A-1}\left[e^{-\sum_{i=r}^{a-1}(s_{c,i} F + M_i)} w_{s,a} Q_a e^{-f s_{c,a} F - m M_a} \right] + \frac{e^{-\sum_{i=r}^{A-1}(s_{c,i} F + M_i)} w_{s,A} Q_A e^{-f s_{c,A} F - m M_A}}{1 - e^{-s_{c,A} F - M_A}}$$

A7.2.10

A specification of whether total, landings or discard yield-per-recruit (ypr) is being considered is needed in order to complete the formulation of equation A7.2.9, where Y/R, w_a and s_a are formulated generically; for example, these need to be replaced by Y_C/R, $w_{c,a}$ and $s_{c,a}$ for total ypr, and by Y_L/R, $w_{l,a}$ and $s_{l,a}$ for landings ypr ($a=r$, $r+1$, …, A; Section A7.3).

Calculation of $F_{0.1}$, F_{max} and $F_{x\%SPR}$

$F_{0.1}$ and F_{max} are estimated calculating the derivative with respect to F of ypr equation A7.2.9, as shown in Section A7.4. $F_{x\%SPR}$ (typically $x=35$ or 40) is derived by solving equation A7.2.10 for the F that gives $x\%$ of $B_{ssb}/R_{F=0}$ (the B_{ssb}/R value for $F=0$ in equation A7.2.10).

Calculation of MSY quantities

MSY quantities are also derived from ypr equation A7.2.9, but they need to incorporate the stock–recruit relationship. In order to do this, the stock–recruit functions, g, need to be re-formulated as $R = g(B_{ssb}/R)$:

Ricker:

$$R = \frac{\ln[\alpha(B_{ssb}/R)]}{\beta(B_{ssb}/R)}$$

A7.2.11

Beverton–Holt:

$$R = \frac{\alpha(B_{ssb}/R) - \beta}{(B_{ssb}/R)}$$

A7.2.12

Smooth Hockey-stick:

$$R = \frac{2\alpha\left[\sqrt{\beta^2 + \gamma^2/4}\,(1 - \frac{1}{\alpha(B_{ssb}/R)}) + \beta\right]}{(2 - \frac{1}{\alpha(B_{ssb}/R)})}$$

A7.2.13

Doing this makes it straight-forward to multiply equation A7.2.9 with the stock–recruit function and then to substitute equation A7.2.10 into the resultant equation in order to have an expression of yield in terms of F.

Yield is calculated by substituting the relevant equations A7.2.9-13 into the following, so that it is expressed in terms of F (and not R or B_{ssb}):

$$Y = (Y/R) \times g(B_{ssb}/R)$$
A7.2.14

[Note, however, that this procedure (of expressing g in terms of B_{ssb}/R) is not, strictly speaking, needed for the Hockey-stick model, as only the horizontal part of the curve would be used in calculations of MSY quantities, which amounts to multiplying equation A7.2.9 by a constant ($2\alpha\beta$ in equation A7.2.8a).]

F_{MSY} is then the value of F for which $\partial Y/\partial F = 0$. Other MSY quantities follow by making relevant substitutions in equations A7.2.9-13.

Including uncertainty in biological and fishery-related variables

Assuming that estimates of precision (CVs) are available for the variables M'_a, Q'_a, $w'_{s,a}$, w'_a and s'_a (given here as point estimates, with the latter two being treated generically, but could be specific to one of several catch components), say v_{M_a}, v_{Q_a}, $v_{w_{s,a}}$, v_{w_a} and v_{s_a} (note these are all CVs) then given a random variable ε drawn from a $N(0;1)$ distribution (one for each biological or fishery-related variable at age), uncertainty in these variables are included as follows:

Natural mortality:

$$M_a = \max\{M'_a(1+v_{M_a}\varepsilon_{M_a}); 0.001\}$$

Proportion mature:

For $Q'_a > 0$:

Set $Q''_a = \min\{Q'_a; 0.9999999\}$

and transform $P_a = \ln\left(\dfrac{Q''_a}{1-Q''_a}\right) + \dfrac{v_{Q_a}\varepsilon_{Q_a}}{(1-Q''_a)}$

so that $Q_a = \dfrac{e^{P_a}}{1+e^{P_a}}$

For $Q'_a = 0$: Set $Q_a = 0$

Mean weights (for stock $w=w_{s,a}$, and for the relevant catch component, e.g. landings, $w=w_{l,a}$):

$$w = w' e^{v'_w \varepsilon_w - 0.5 v'^2_w}$$

where $v'_w = \sqrt{\ln(v_w^2 + 1)}$

Selectivity of the relevant catch component (e.g. for landings $s_a=s_{l,a}$):

$$s_a = \max\{s'_a(1+v_{s_a}\varepsilon_{s_a}); 0\}$$

Table A7.2.1. Definition of terms

y	Year
a	Age
r; A	age at recruitment (r) and of the plus-group (A)
$N_{y,a}$	Number of fish in year y and age a
R_y	Recruitment in year y
$B_{ssb,y}$	Spawning-stock biomass in year y. For the purposes of fitting the smooth Hockey-stick given in equation A7.2.8, the average over the whole time-series, $\overline{B}_{ssb}$, is used.
g	The stock–recruit function
α, β, γ	Parameters of the stock–recruit functions (note, γ is fixed to $0.01\overline{B}_{ssb}$)
$M_{y,a}$	Natural mortality in year y and age a
F_y	Fishing mortality in year y
s_a; $s_{c,a}$; $s_{l,a}$; $s_{d,a}$	Fishery selection at age a, given in generic form (s_a) for the purposes of equation A7.2.9, and relevant to the total catch (c), landings (l) and discards (d), respectively
$C_{y,a}$	Total catch numbers in year y and age a
Q_a	Proportion mature at age a
f, m	Proportion of fishing (f) and natural mortality (m) prior to spawning
$w_{s,y,a}$	Mean weights in the stock in year y and age a. For equilibrium equations, the year subscript is dropped to give $w_{s,a}$.
w_a; $w_{c,a}$; $w_{l,a}$; $w_{d,a}$	Mean weights at age a, given in generic form (w_a) for the purposes of equation A7.2.9, and relevant to the total catch (c), landings (l) and discards (d), respectively
Y/R; Y_C/R; Y_L/R; Y_D/R	Yield-per-recruit, given in generic form (Y/R) for the purposes of equation A7.2.9, and relevant to the total catch (C), landings (L) and discards (D), respectively
B_{ssb}/R	Spawning-stock biomass per recruit
$F_{0.1}$; F_{max}; $F_{x\%SPR}$	Fishing mortality reference points based on yield-per-recruit. Typically, x=35 or 40 in $F_{x\%SPR}$.
F_{MSY}	Fishing mortality at maximum sustainable yield

A7.3. Equilibrium calculations

Assuming $N_{y,r} = R$ and $F_y = F$ for all y, we have:

Age	Population numbers	Total Yield	SSB
r	R	$R\, w_{c,r}\, \dfrac{s_{c,r}\, F}{s_{c,r}\, F + M_r}[1 - e^{-s_{c,r}F - M_r}]$	$R\, w_{s,r}\, Q_r\, e^{-f\, s_{c,r}F - m M_r}$
$r+1$	$R\, e^{-s_{c,r}F - M_r}$	$R\, e^{-s_{c,r}F - M_r}\, w_{c,r+1}\, \dfrac{s_{c,r+1}\, F}{s_{c,r+1}\, F + M_{r+1}}[1 - e^{-s_{c,r+1}F - M_{r+1}}]$	$R\, e^{-s_{c,r}F - M_r}\, w_{s,r+1}\, Q_{r+1}\, e^{-f\, s_{c,r+1}F - m M_{r+1}}$
…	…	…	…
a	$R\, e^{-\sum\limits_{i=r}^{a-1}(s_{c,i}F + M_i)}$	$R\, e^{-\sum\limits_{i=r}^{a-1}(s_{c,i}F + M_i)}\, w_{c,a}\, \dfrac{s_{c,a}\, F}{s_{c,a}\, F + M_a}[1 - e^{-s_{c,a}F - M_a}]$	$R\, e^{-\sum\limits_{i=r}^{a-1}(s_{c,i}F + M_i)}\, w_{s,a}\, Q_a\, e^{-f\, s_{c,a}F - m M_a}$
…	…	…	…
A	$R\, e^{-\sum\limits_{i=r}^{A-1}(s_{c,i}F + M_i)} + R\, e^{-\sum\limits_{i=r}^{A-1}(s_{c,i}F + M_i)}\, e^{-s_{c,A}F - M_A}$ $+ R\, e^{-\sum\limits_{i=r}^{A-1}(s_{c,i}F + M_i)}\{e^{-s_{c,A}F - M_A}\}^2 + \ldots$ $= R\, e^{-\sum\limits_{i=r}^{A-1}(s_{c,i}F + M_i)}\left[1 + \{e^{-s_{c,A}F - M_A}\} + \{e^{-s_{c,A}F - M_A}\}^2 + \ldots\right]$ $= \dfrac{R\, e^{-\sum\limits_{i=r}^{A-1}(s_{c,i}F + M_i)}}{1 - e^{-s_{c,A}F - M_A}}$ $\quad$, because: $\;-1 < e^{-s_{c,A}F - M_A} < 1$	$R\, e^{-\sum\limits_{i=r}^{A-1}(s_{c,i}F + M_i)}\, w_{c,A}\, \dfrac{s_{c,A}\, F}{s_{c,A}\, F + M_A}$	$\dfrac{R\, e^{-\sum\limits_{i=r}^{A-1}(s_{c,i}F + M_i)}\, w_{s,A}\, Q_A\, e^{-f\, s_{c,A}F - m M_A}}{1 - e^{-s_{c,A}F - M_A}}$

Summing across all ages, Total Yield and SSB can therefore be calculated as follows:

Total Yield:

$$Y_C = R \left\{ w_{c,r} \frac{s_{c,r} F}{s_{c,r} F + M_r}[1 - e^{-s_{c,r}F - M_r}] + \sum_{a=r+1}^{A-1} \left[e^{-\sum_{i=r}^{a-1}(s_{c,i}F + M_i)} w_{c,a} \frac{s_{c,a} F}{s_{c,a} F + M_a}[1 - e^{-s_{c,a}F - M_a}] \right] + e^{-\sum_{i=r}^{A-1}(s_{c,i}F + M_i)} w_{c,A} \frac{s_{c,A} F}{s_{c,A} F + M_A} \right\}$$

A7.3.1

SSB:

$$B_{ssb} = R \left\{ w_{s,r} Q_r e^{-f s_{c,r} F - mM_r} + \sum_{a=r+1}^{A-1} \left[e^{-\sum_{i=r}^{a-1}(s_{c,i}F + M_i)} w_{s,a} Q_a e^{-f s_{c,a} F - mM_a} \right] + \frac{e^{-\sum_{i=r}^{A-1}(s_{c,i}F + M_i)} w_{s,A} Q_A e^{-f s_{c,A} F - mM_A}}{1 - e^{-s_{c,A}F - M_A}} \right\}$$

A7.3.2

Total Yield-per-recruit and SSB-per-recruit follow by simply dividing equations A7.3.1 and A7.3.2 by R.

Where the catch is made up of different components (e.g. landings and discards), then the weight-at-age of the catch is calculated as follows:

$$w_{c,a} = \frac{L_a w_{l,a} + D_a w_{d,a}}{L_a + D_a} \qquad , a = r, r+1, \ldots, A$$

A7.3.3

Substituting equation A7.3.3 into A7.3.1 means that Y_C can be expressed as $Y_C = Y_L + Y_D$, where for example Landings Yield Y_L is as follows:

$$Y_L = R \left\{ w_{l,r} \frac{s_{l,r} F}{s_{c,r} F + M_r}[1 - e^{-s_{c,r}F - M_r}] + \sum_{a=r+1}^{A-1} \left[e^{-\sum_{i=r}^{a-1}(s_{c,i}F + M_i)} w_{l,a} \frac{s_{l,a} F}{s_{c,a} F + M_a}[1 - e^{-s_{c,a}F - M_a}] \right] + e^{-\sum_{i=r}^{A-1}(s_{c,i}F + M_i)} w_{l,A} \frac{s_{l,A} F}{s_{c,A} F + M_A} \right\}$$

A7.3.4

where

$$s_{l,a} = \frac{L_a \, s_{c,a}}{L_a + D_a}$$

A7.3.5

Similar expressions can be obtained for Y_D and $s_{d,a}$.

A7.4. Derivation of $F_{0.1}$ and F_{max}

Differentiating equation A7.2.9 with respect to F, we have:

$$\frac{\partial Y/R}{\partial F} = w_r \frac{s_r}{s_{c,r} F + M_r}[1 - e^{-s_{c,r} F - M_r}] - w_r \frac{s_r s_{c,r} F}{(s_{c,r} F + M_r)^2}[1 - e^{-s_{c,r} F - M_r}] + w_r \frac{s_r F}{s_{c,r} F + M_r}[e^{-s_{c,r} F - M_r} s_{c,r}]$$

$$+ \sum_{a=r+1}^{A-1} \left\{ -e^{-\sum_{i=r}^{a-1}(s_{c,i} F + M_i)} (\sum_{i=r}^{a-1} s_{c,i}) w_a \frac{s_a F}{s_{c,a} F + M_a}[1 - e^{-s_{c,a} F - M_a}] + e^{-\sum_{i=r}^{a-1}(s_{c,i} F + M_i)} w_a \frac{s_a}{s_{c,a} F + M_a}[1 - e^{-s_{c,a} F - M_a}] \right.$$

$$\left. -e^{-\sum_{i=r}^{a-1}(s_{c,i} F + M_i)} w_a \frac{s_a s_{c,a} F}{(s_{c,a} F + M_a)^2}[1 - e^{-s_{c,a} F - M_a}] + e^{-\sum_{i=r}^{a-1}(s_{c,i} F + M_i)} w_a \frac{s_a F}{s_{c,a} F + M_a}[e^{-s_{c,a} F - M_a} s_{c,a}] \right\}$$

$$-e^{-\sum_{i=r}^{A-1}(s_{c,i} F + M_i)} (\sum_{i=r}^{A-1} s_{c,i}) w_A \frac{s_A F}{s_{c,A} F + M_A} + e^{-\sum_{i=r}^{A-1}(s_{c,i} F + M_i)} w_A \frac{s_A}{s_{c,A} F + M_A} - e^{-\sum_{i=r}^{A-1}(s_{c,i} F + M_i)} w_A \frac{s_A s_{c,A} F}{(s_{c,A} F + M_A)^2}$$

and therefore:

$$\frac{\partial Y/R}{\partial F} = \frac{w_r s_r}{s_{c,r} F + M_r} \left\{ [1 - e^{-s_{c,r} F - M_r}](1 - \frac{s_{c,r} F}{s_{c,r} F + M_r}) + s_{c,r} F e^{-s_{c,r} F - M_r} \right\}$$

$$+ \sum_{a=r+1}^{A-1} \left\{ \frac{w_a s_a e^{-\sum_{i=r}^{a-1}(s_{c,i} F + M_i)}}{s_{c,a} F + M_a} \left[[1 - e^{-s_{c,a} F - M_a}](1 - \frac{s_{c,a} F}{s_{c,a} F + M_a} - \sum_{i=r}^{a-1} s_{c,i} F) + s_{c,a} F e^{-s_{c,a} F - M_a} \right] \right\}$$

$$+ \frac{w_A s_A e^{-\sum_{i=r}^{A-1}(s_{c,i} F + M_i)}}{s_{c,A} F + M_A} \left\{ 1 - \frac{s_{c,A} F}{s_{c,A} F + M_A} - \sum_{i=r}^{A-1} s_{c,i} F \right\}$$

A7.4.1

$F_{0.1}$ is calculated by finding the value of F which results in:

$$\frac{\partial Y/R}{\partial F} = 0.1 \frac{\partial Y/R}{\partial F}\bigg|_{F=0}$$

A7.4.2

where the right-hand-side is derived by setting $F=0$ in equation A7.4.1:

$$\frac{\partial Y/R}{\partial F}\bigg|_{F=0} = \frac{w_r s_r}{M_r}[1-e^{-M_r}] + \sum_{a=r+1}^{A-1}\left\{\frac{w_a s_a}{M_a} e^{-\sum_{i=r}^{a-1}M_i}[1-e^{-M_a}]\right\} + \frac{w_A s_A}{M_A} e^{-\sum_{i=r}^{A-1}M_i}$$

A7.4.3

F_{max} is calculated by finding the value of F which results in:

$$\frac{\partial Y/R}{\partial F} = 0$$

A7.4.4

A7.5. Installation and user instructions

The R function plotMSY() provides an interface to ADMB code to calculate F_{MSY} and potential proxies for fish stocks. F_{MSY} is calculated based on the three common stock recruit relationships; Ricker, Beverton–Holt and Hockey-stick (approximated by a continuous function as formulated by Mesnil and Rochet, 2010). Data are input as sen and sum files in the Aberdeen file format, and output as a tab delimited text file (suitable for importing into Excel) and plots in Portable Network Graphics (PNG) format.

Full details of the method used in this program to calculate MSY and related quantities are given in Sections A7.2-4. Please report any bugs to timothy.earl@cefas.co.uk to see whether these can be removed in future versions.

Installation

While running, the function creates and deletes a number of files in the working directory. It is therefore recommended that no user files are stored in the same directory as the executable files. Input and output files may be stored in subdirectories of the working directory.

The minimum requirement for the program to run in R is that there must be a directory containing the following files:

- **srmsymc.exe** and **srmsymc2.exe** – compiled ADMB code. Where the executables are provided as source code, they should be compiled with ADMB 4.4.0 or later.
- **readLow.r** – for reading Lowestoft format files to find pf and pm
- **plotMSY.r** as an interface to the ADMB code
- **run_plotMSY.r** – a simplified interface for running plotMSY.r
- **convertSumSen.r** for file type conversions
- A subdirectory called "**output**" used by default for text and PDF output files.

The functions have been tested with R versions 2.8, 2.9, 2.10 and 2.14. It may work under other versions, and has no dependencies except base packages.

Running the program

The program requires a sen and sum file in the Aberdeen file formats (see Tables A7.5.1 and A7.5.2). These should be in the same directory (as each other) and have the same name except for the extension. Optionally an index file in the Lowestoft file format can be provided, which is used to find the files containing pm and pf, the proportion of fishing mortality and natural mortality occurring before spawning.

If sen and sum files of the required format are not available, dat files can be provided in the format required by ADMB – examples are provided in Table A7.5.3.

An example of the input files, is the files cod.sum and cod.sen (Tables A7.5.1 and A7.5.2 respectively). These should be saved in a directory called "cod data" within the working directory to run the examples below.

<u>Method 1</u>

Edit the working directory and "settings" section in `run_plotMSY.r` and save it. This script can then be run in R. After executing the script, the variable `stock` contains the data from this run.

<u>Method 2</u>

Set the R working directory to the folder containing the directory with the executable files and R scripts. This can be done from the "file" menu in R, by choosing "Change dir..." (this only needs to be done once in each R session), or using the command `setwd()`.

Run the command

```
> source("plotMSY.r")
```

This should indicate that plotMSY has been loaded successfully. If not, ensure that the files listed in the "Installation" section are in the same folder, and that this is the working directory.

Run the `plotMSY()` function with appropriate parameters, for example to use the example cod data (instructions for saving this data are above) use a command such as:

```
cod = plotMSY (".\\cod data\\cod.sen", pfpm=c(0,0), nits=10)
```

which will produce output in folder . \\output\\cod\\. The R object called "cod" may also be useful for diagnostics

Table A7.5.1. cod.sum (information used by PlotMSY given in bold).

```
Stock summary      Cod in Division 347
12
1         0         0
Year
1963     2011
 Recruits          age 1    (millions)
1        1000000
 SSB      ('000 t)
1000
 TSB      ('000 t)
1000
 Catch    Total  ('000 t)
1000
 Catch    H.cons ('000 t)
1000
 Not used          used
1000
 Not used          used
1000
 Mean F   Total
2        4
 Mean F   H.cons.
2        4
 Not used          used
0         0
 Not used          used
0         0
```

Year	Col2	Col3	Col4	Col5	Col6	Col7	Col8	Col9	Col10	Col11	Col12
1963	465.56	151.90	514.01	124.99	111.46	13.54	0	0.485	0.432	0.053	0
1964	852.56	164.23	686.94	152.82	139.57	13.25	0	0.513	0.469	0.044	0
1965	1069.82	203.82	862.85	203.21	182.00	21.21	0	0.543	0.486	0.057	0
1966	1379.18	227.29	1050.73	249.20	217.11	32.09	0	0.560	0.488	0.072	0
1967	1271.87	251.45	1135.97	298.05	264.53	33.51	0	0.605	0.537	0.068	0
1968	656.71	262.24	944.11	299.54	278.63	20.91	0	0.635	0.591	0.044	0
1969	606.22	258.59	804.52	239.67	227.53	12.14	0	0.623	0.591	0.032	0
1970	1839.49	273.76	1333.08	268.07	244.04	24.03	0	0.639	0.582	0.057	0
1971	2369.05	276.23	1460.08	351.86	290.81	61.05	0	0.705	0.583	0.122	0
1972	584.20	241.35	976.76	361.86	327.54	34.32	0	0.768	0.695	0.073	0
1973	875.02	213.20	800.51	259.63	235.05	24.58	0	0.752	0.681	0.071	0
1974	807.74	232.35	755.40	240.87	215.94	24.93	0	0.736	0.660	0.076	0
1975	1377.80	212.99	859.41	238.47	206.32	32.15	0	0.772	0.668	0.104	0
1976	849.16	182.96	659.34	237.52	200.21	37.31	0	0.803	0.677	0.126	0
1977	2096.96	161.14	1007.52	244.02	181.09	62.93	0	0.798	0.592	0.206	0
1978	1271.87	160.33	1122.42	323.51	283.95	39.56	0	0.858	0.753	0.105	0
1979	1435.47	166.71	1006.51	314.27	272.41	41.86	0	0.804	0.697	0.107	0
1980	2273.88	181.50	1172.91	339.42	272.98	66.45	0	0.860	0.692	0.168	0
1981	885.58	194.66	989.54	362.94	324.70	38.24	0	0.890	0.796	0.094	0
1982	1407.04	188.34	1018.66	334.70	294.49	40.21	0	0.983	0.865	0.118	0
1983	819.13	154.97	817.50	282.38	256.81	25.57	0	0.972	0.884	0.088	0
1984	1426.88	132.46	828.19	246.22	199.59	46.63	0	0.916	0.743	0.173	0
1985	378.51	126.63	569.78	225.71	202.93	22.78	0	0.887	0.797	0.090	0
1986	1692.98	115.73	776.85	206.49	161.64	44.85	0	0.936	0.733	0.203	0
1987	671.32	108.99	739.70	248.20	218.27	29.93	0	0.938	0.825	0.113	0
1988	462.31	100.61	550.73	199.59	186.64	12.94	0	0.948	0.887	0.061	0
1989	767.58	94.28	538.21	169.06	136.47	32.59	0	0.966	0.780	0.186	0
1990	333.70	80.18	378.89	136.22	114.42	21.79	0	0.906	0.761	0.145	0
1991	370.28	73.64	350.46	120.21	105.48	14.74	0	0.910	0.798	0.112	0
1992	792.54	71.11	517.62	134.86	107.77	27.09	0	0.877	0.701	0.176	0
1993	446.86	68.60	431.06	149.34	123.69	25.66	0	0.891	0.738	0.153	0
1994	944.11	72.11	527.02	153.43	115.05	38.38	0	0.906	0.679	0.227	0
1995	557.94	81.06	562.98	185.91	152.10	33.80	0	0.934	0.764	0.170	0
1996	403.53	79.22	459.09	165.55	142.84	22.71	0	0.955	0.824	0.131	0
1997	1059.17	75.21	632.23	166.38	126.33	40.04	0	0.961	0.730	0.231	0
1998	170.59	61.27	342.83	140.79	108.72	32.07	0	0.980	0.757	0.223	0
1999	303.46	55.94	256.53	100.91	86.42	14.50	0	0.999	0.856	0.144	0
2000	548.53	49.66	344.90	101.93	81.09	20.83	0	0.995	0.792	0.203	0
2001	208.98	41.73	247.95	90.85	71.59	19.26	0	0.956	0.753	0.203	0
2002	255.76	42.57	266.47	88.52	79.03	9.49	0	0.926	0.827	0.099	0
2003	119.13	36.90	151.00	60.72	51.03	9.69	0	0.901	0.757	0.144	0
2004	200.19	31.98	149.64	47.62	38.27	9.35	0	0.857	0.689	0.168	0
2005	137.45	29.76	144.93	47.05	39.11	7.94	0	0.800	0.665	0.135	0
2006	344.90	26.24	156.53	41.61	31.93	9.68	0	0.723	0.555	0.168	0
2007	147.12	32.83	185.54	56.11	29.20	26.90	0	0.669	0.348	0.321	0
2008	178.80	38.25	186.09	54.12	29.66	24.46	0	0.630	0.345	0.285	0
2009	191.19	47.19	211.72	56.90	37.67	19.23	0	0.602	0.399	0.203	0
2010	326.44	51.79	246.23	61.82	45.83	15.99	0	0.583	0.432	0.151	0
2011	165.71	56.33	236.81	66.90	50.16	16.75	0	0.572	0.429	0.143	0

[Col2=Recruitment, Col3=SSB, Col4=TSB, Col5=total catch, Col6=human consumption landings, Col7=discards, Col8=industrial bycatch, Col9=total mean F, Col10=human consumption mean F, Col11=discards mean F, Col12=industrial bycatch mean F]

Table A7.5.2. cod.sen (information used by PlotMSY given in bold).

```
cod347
1       7       2011    3       First  age,  last  age,  starting  year,  number  of  catch
components
                                (H=human consumption, D=discards, I=industrial bycatch)
1       1       0       Catch components used (1=used, 0=not used)
'N1'    327748  0.458   Population estimates in 2011 (survivors) with CV
'N2'    49021   0.214
'N3'    32860   0.165
'N4'    6374    0.147
'N5'    2101    0.148
'N6'    821     0.176
'N7'    829     0.198
'sH1'   0.016   0.175   Human consumption F at age in 2011 with CV
'sH2'   0.176   0.097
'sH3'   0.483   0.076
'sH4'   0.598   0.079
'sH5'   0.648   0.085
'sH6'   0.698   0.109
'sH7'   0.690   0.109
'sD1'   0.128   0.175   Discard F at age in 2011 with CV
'sD2'   0.280   0.097
'sD3'   0.159   0.076
'sD4'   0.060   0.079
'sD5'   0.021   0.085
'sD6'   0.018   0.109
'sD7'   0.026   0.109
'WH1'   0.747   0.112   Human consumption weights at age in 2011 with CV
'WH2'   1.306   0.143
'WH3'   2.634   0.137
'WH4'   4.236   0.097
'WH5'   6.104   0.062
'WH6'   7.642   0.05
'WH7'   9.701   0.04
'WD1'   0.286   0.255   Discard weights at age in 2011 with CV
'WD2'   0.755   0.282
'WD3'   1.726   0.419
'WD4'   3.542   0.542
'WD5'   5.964   0.48
'WD6'   6.674   0.345
'WD7'   8.823   0.792
'WS1'   0.339   0.196   Stock weights at age in 2011 with CV
'WS2'   0.964   0.138
'WS3'   2.404   0.136
'WS4'   4.173   0.093
'WS5'   6.112   0.061
'WS6'   7.647   0.059
'WS7'   9.770   0.036
'M1'    1.0385  0.1     Natural mortality-at-age in 2011 with CV
'M2'    0.6975  0.1
'M3'    0.4895  0.1
'M4'    0.2325  0.1
'M5'    0.2     0.1
'M6'    0.2     0.1
'M7'    0.2     0.1
'MT1'   0.01    0       Proportion mature at age in 2011 with CV
'MT2'   0.05    0.1
'MT3'   0.23    0.1
'MT4'   0.62    0.1
'MT5'   0.86    0
'MT6'   1       0
'MT7'   1       0
'R06'   117233  0.458   Estimated recruitment for 2012 with CV
'R07'   117233  0.458   Estimated recruitment for 2013 with CV
'HF06'  1       0.05    Year-effect multipliers on human consumption & discard F
with CV
'HF07'  1       0.05    (Industrial multiplier would appear separately if used)
'HF08'  1       0.05
'K06'   1       0.1     Year-effect multipliers on natural mortality with CV
'K07'   1       0.1
'K08'   1       0.1
Cod                     Information from Aberdeen suite files (can be ignored)
347
1
1       7       1
2
H.cons.
2       4
Discards
2       4
1963    2011
Stock numbers in 2011 are SAM estimates
-1
```

Table A7.5.3. Example dat files when sum and sen files are not used.

(a) srmsymc.dat

```
#stkname, filname // stkname=stock dealing with; filname=name of 2nd file
out out.dat
#ybeg, yend, r, A, Ropt, simopt, senopt,penopt // ybeg=1st yr; yend=last yr;
# r=recr age; A=plusgroup; Ropt=S-R function type, simopt (0=no sim, 1=do sim);
# senopt (0=error only in recr, 1=error in recr & steady-state vectors);
# penopt(0=no SR constraints, 1=apply SR constraints)
1963 2011 1 7 1 1 1 1
#R, Bssb // R=recr; Bssb=SSB
 465.56 151.90
 852.56 164.23
1069.82 203.82
1379.18 227.29
1271.87 251.45
 656.71 262.24
 606.22 258.59
1839.49 273.76
2369.05 276.23
 584.20 241.35
 875.02 213.20
 807.74 232.35
1377.80 212.99
 849.16 182.96
2096.96 161.14
1271.87 160.33
1435.47 166.71
2273.88 181.50
 885.58 194.66
1407.04 188.34
 819.13 154.97
1426.88 132.46
 378.51 126.63
1692.98 115.73
 671.32 108.99
 462.31 100.61
 767.58  94.28
 333.70  80.18
 370.28  73.64
 792.54  71.11
 446.86  68.60
 944.11  72.11
 557.94  81.06
 403.53  79.22
1059.17  75.21
 170.59  61.27
 303.46  55.94
 548.53  49.66
 208.98  41.73
 255.76  42.57
 119.13  36.90
 200.19  31.98
 137.45  29.76
 344.90  26.24
 147.12  32.83
 178.80  38.25
 191.19  47.19
 326.44  51.79
 165.71  56.33
```

(b) out.dat

```
#fno, sno, f, m // fno=nr fleets; sno=fleet for ypr stats; f=F before spwn;
# m=M before spwn
2 1 0 0
#sdat // col1=sel fleet 1 (landings); col2=sel fleet 2
0.0273348519362187 0.2186788154897490
0.3006833712984050 0.4783599088838270
0.8251708428246010 0.2716400911161730
1.0216400911161700 0.1025056947608200
1.1070615034168600 0.0358769931662870
1.1924829157175400 0.0307517084282460
1.1788154897494300 0.0444191343963554
#sdat cv // col1=sel fleet 1 (landings); col2=sel fleet 2
0.175 0.175
0.097 0.097
0.076 0.076
0.079 0.079
0.085 0.085
0.109 0.109
0.109 0.109
#wdat // col1=wght fleet 1 (landings); col2=wght fleet 2
0.747 0.286
1.306 0.755
2.634 1.726
4.236 3.542
6.104 5.964
7.642 6.674
9.701 8.823
#wdat cv // col1=wght fleet 1 (landings); col2=wght fleet 2
0.112 0.255
0.143 0.282
0.137 0.419
0.097 0.542
0.062 0.480
0.050 0.345
0.040 0.792
#biodat // col1=natural mortality; col2=maturity; col3=wght in stock
1.0385 0.01 0.339
0.6975 0.05 0.964
0.4895 0.23 2.404
0.2325 0.62 4.173
0.2000 0.86 6.112
0.2000 1.00 7.647
0.2000 1.00 9.770
#biodat cv // col1=natural mortality; col2=maturity; col3=wght in stock
0.1 0.0 0.112
0.1 0.1 0.143
0.1 0.1 0.137
0.1 0.1 0.097
0.1 0.0 0.062
0.1 0.0 0.050
0.1 0.0 0.040
```

Notes on dat files shown in Table A7.5.3:

- Positioning of comment lines is important. Additional comment lines should not be added.
- Filename in "srmsymc.dat" indicates the name of the file called "out.dat" in this example.
- multiple entries on a line should be separated by space(s) or tab(s)
- line breaks separate data for each year (srmsymc.dat) or age (out.dat). The number of lines should correspond to the year range and age range given in line 4 of srmsymc.dat.
- The remaining parameters on line 4 are:

    Ropt – stock recruit option (ignored by plotMSY)

    simopt – use Monte Carlo Markov Chain, always 1 (TRUE)

    senopt – add noise to biological parameters 1 (TRUE) or 0 (FALSE)

    penopt – penalise unfeasible SR relationships, i.e. where alpha or beta are less than zero, or the Hockey-stick breakpoint is outside the range of the data.

Function arguments

In general, the program is run with the following command (Table A7.5.4 describes the arguments used):

```
plotMSY(senfilename, indexfilename, pfpm, srweights, trimming,
nits, nhair, varybiodata, stockname, fpa, flim, bpa, blim,
outputfolder, datfilename, silent, onlyYPR)
```

Table A7.5.4. Description of arguments to the plotMSY() function.

senfilename	Name of the sen file, including absolute or relative path, e.g. ".\\data\\cod.sen".
	Default is NA, which provides interactive file selection in Windows.
indexfilename	Name and path of the Lowestoft index file used to find pf and pm.
	Default is NA which provides interactive file selection occurs in Windows. indexfilename is ignored if pfpm is provided and pfpm is not NA.
pfpm	A vector of two numbers, pf and pm, e.g. c(0,0). pf is the proportion of fishing mortality that occurs before spawning, pm is the proportion of natural mortality that occurs before spawning.
	Default is NA which looks up pf and pm from the Lowestoft format file indicated by indexfilename.
srweights	The relative weights to be given to each of the stock–recruit functions, a vector of 3 non-negative numbers, in the order Ricker, Beverton–Holt, smooth Hockey-stick. NA is used to indicate automatic weighting by likelihood. If any value is NA, all values must by NA or 0 – i.e. manual and automatic weighting cannot be combined.
	Default is c(NA,NA,NA). See below for details of automatic weights and trimming.
trimming	Proportion of least likely iterations to trim from the harmonic mean when calculating automatic weights for SR models. NA is used to create a diagnostic for choosing a suitable value of trimming. See below for details of automatic weights and trimming.
nits	Number of iterations of the MCMC to output. The MCMC will perform 100,000 iterations as a burn in, and then output every 10,000th iteration until nits iterations have been output.
	Default is 100.
nhair	Maximum number of lines to output on "hair plots".
	Default is 100.
varybiodata	If TRUE, (default) bootstraps the biological data (weight, maturity, mortality)
	If FALSE, varies SR relationship only.
stockname	Display title for stock used in titles and output path.
	Defaults to senfilename without the ".sen" extension.
fpa	Value of F_{pa} to be plotted on output.
	Default NA indicates no value plotted.
flim	Value of F_{lim} to be plotted on output.
	Default NA indicates no value plotted.
bpa	Value of B_{pa} – currently not used.
	Default NA indicates no value plotted.
blim	Value of B_{lim} to be plotted on output.
	Default NA indicates no value plotted.
outputfolder	Location for output files.
	Defaults to ".\\output\\[stockname]\\"
	(Note: the '.' is interpreted by R as the current working directory.)

Datfilename	Name and path of a pre-calculated dat file. If `datfilename` is provided, `senfilename`, `indexfilename`, `varybiodata` and `pfpm` are ignored*. Default is `NA`.
Silent	Suppresses the majority of the output to screen. Default is `TRUE`.
onlyYPR	Calculates only the yield-per-recruit statistics. Used when the SRRs are not believed to be reliable, or are hard to estimate.

*if `datfilename` and `senfilename` are both provided, data from the dat file will be passed to the ADMB executable. If a sum file with the same name as `senfilename` exists, this will be used to add historic data points to the yield and SSB plots, and provide text for the plot axis labels. The sen file need not exist.

During execution, the R window may appear to stop responding, as it has passed control to an external executable. It will resume when the executable is complete. The only way to halt execution is to close R (Since R version 2.14, pressing 'escape' may cancel execution part way through). The largest influence on the execution time is the value of `nits`; typical execution times for values of `nits` on a PC are given in Table A7.5.5.

Table A7.5.5. Typical execution times for plotMSY, recorded for R version 2.10.1 running under XP 32 bit on a 2.3Ghz processor with 3.45GB RAM

nits	Total execution time (min:sec)
10	0:24
100	1:49
1000	15:50

Output files

The function creates the files described below and invisibly returns a list to R. The list contains the same data as in the [stock].txt file, except the header information. The contents of the image files (those marked with '*' are not produced when running with the 'onlyYPR' option) and the files produced are as follows ('[stock]' is replaced by the name of the stock given to the function):

- **[stock]_SRR.png*** illustrates the uncertainty inherent in the estimation of the stock and recruitment curves. The left hand curves in each figure illustrate the confidence intervals from X/`nits` resamples (printed at the bottom of the legend) from the MCMC chain; where X (recorded in the legend) represents the number of samples that have feasible parameter estimates (i.e. alpha and beta are positive for the usual parameterization of the functions). The right hand figures present curves plotted from the first `nhair` resamples for illustration. In this, and the following plots, the blue line indicates a deterministic estimate, separate from the MCMC chain.
- **[stock]_diagnostics.png*** presents the range and correlation of the alpha and beta parameters for each stock and recruit function, the figures on the left as estimated using a transformation to increase orthogonality, on the right as defined for the original formulations of each of the curves. The transformation may reduce the correlation between the parameters allowing an improved estimate for both the Ricker and Beverton–Holt curve parameters.
- **[stock]_Yield_Ri.png*** presents for the fit of the Ricker curve:

a) box plots of the estimated F_{MSY} fishing mortality with proxies for F_{MSY}, based on the yield-per-recruit definitions of F_{max}, $F_{0.1}$, $F_{35\%}$ and $F_{40\%}$, and also F_{lim}, F_{pa} and F in the final year, for comparison;

b) the equilibrium landings vs. fishing mortality plot based on the fitted stock and recruit plot and the selection, maturity and weight at age data. The left hand figure illustrates the percentiles from re-sampling the MCMC chain with the assessment data points, the right hand figure the first nhair re-samples of the estimated relationship;

c) the equilibrium SSB vs. fishing mortality relationship for the fitted stock and recruit plot, selection, weight and maturity-at-age data, with the assessment data points.

- **[stock]_Yield_BH.png*** – as stock_Yield_Ri.wmf for Beverton–Holt
- **[stock]_Yield_HS.png*** – as stock_Yield_Ri.wmf for Hockey-stick
- **[stock]_YPR.png** presents the yield-per-recruit output from the model:
  a) The estimates of F_{max}, $F_{0.1}$, $F_{35\%}$ and $F_{40\%}$ SPR with F_{lim}, F_{pa} and the final year F.
  b) The human consumption yield-per-recruit at specified levels of fishing mortality.
  c) The spawner biomass per recruit at the specified level of fishing mortality.
- **[stock]_Fmsy.png*** contains a histogram of the F_{MSY} values estimated by the three stock–recruit models, weighting each model equally, with quantiles for the overall distribution.
- **[stock]_Fmsy2.png*** contains a histogram of the F_{MSY} values estimated by the three stock–recruit models, weighting each model either by its likelihood or by manually imposed weights, with quantiles for the overall distribution. The procedure for weighting by likelihood is to calculate the harmonic mean H_i for each model i using the number of samples given by `nits`, then to allocate a weighting to model i as follows: $H_i/\Sigma_i H_i$. A model can be ignored by either method (likelihood or manual weighting) by allocating a zero to it in the `srweights` vector.
- **[stock]_Fmsy3.png*** is plotted if B_{lim} is specified. This plot gives the probability of SSB being below B_{lim} at different values of F using the weighted combination of stock–recruit models for whichever choice of weighting is used in the file [stock]_Fmsy2.png. This is done by sampling, at different values of F, a number of SSB values from each model in proportion to the relevant weighting, and calculating the proportion of SSB values from the combined set that are below B_{lim}. The 5%-ile and corresponding F-value are shown as an indication of F values consistent with the precautionary approach.
- **[stock].txt** is a tab delimited file (for Excel or similar spreadsheet packages) containing a summary of the output plotted in the images. This is split into three sections:
  a) A header, listing the stock name, senfile used, pf and pm or the index file used to find them, the number of MCMC iterations saved, whether variation in biological parameters is simulated and whether the SR relationships are constrained to be physically plausible. These all coincide with input parameters.
  b) For each Stock Recruitment relationship, the name of the SR relationship is followed by the number of MCMC iterations that produced feasible stock–recruit parameters, and then a table indicating the estimated values of F_{crash}, F_{MSY}, MSY, B_{MSY}, the transformed alpha and beta and their untransformed counterparts, and AICc. For each value, the deterministic value, mean, selected percentiles and coefficient of variation are given. Also included is N,

the number of iterations used to derive the statistic (the remainder having been discarded because of a boundary issue, such as F hitting an upper permitted bound, here 5 for F_{crash} and 3 for F_{MSY}).

c) A table of per recruit statistics, giving the same statistics as in the previous table for $F_{20\%}$, $F_{25\%}$, $F_{30\%}$, $F_{35\%}$, $F_{40\%}$, $F_{0.1}$, F_{max} B_{MSYpr}, MSY_{pr}, F_{pa} and F_{lim}. F_{pa} and F_{lim} are provided as arguments to the function, rather than estimated by this, so there is no estimate of their variability.

d) Aggregated percentiles of F_{MSY}, F_{crash}, MSY and B_{MSY} are shown with models equally weighted and weighted either manually or proportionally to the likelihood of the model (labelled with _w), whichever of these weighting choices has been made. The weights applied to each model for the manual or likelihood weighting are also given.

- **[stock]_trim_diag.png** is plotted if `trimming` is `NA`, it shows the weights allocated to the three stock–recruit functions under different levels of trimming.
- **[stock] _trim_diag.csv** is a csv file produced if `trimming` is `NA`, containing a table of the weights allocated to the three stock–recruit functions under different levels of trimming.

Weighting and trimming

Where there is no *a priori* information about the likelihood of each of the stock–recruit relationships being fitted to the data, the likelihood of each model can be assessed by taking the harmonic mean of the likelihoods of individual iterations of each stock–recruit function (E.J. Simmonds, personal communication). Within this program, this is done by setting the `srweights` of two or three of the models to `NA`, this is referred to in this guide as automatic weighting.

The harmonic mean of likelihoods is numerically unstable, because a single low likelihood iteration can significantly alter the weights allocated to each model. To correct for this, the program allows the user to select a level of trimming which removes this proportion of the least likely iterations before calculating the harmonic mean. To allow the user to choose a suitable value of `trimming`, a diagnostic is available, produced with `trimming=NA`. This produces a plot and table showing the effect of different levels of trimming as is shown in Figure A7.5.1. A suitable choice of `trimming` would be the lowest value where the weights seem to have stabilized after the initial variability at low levels of trimming, perhaps 2% in this case. E.J. Simmonds (personal communication) suggested identifying the trimming value as the lowest value of `trimming` such that the maximum percentage difference by trimming an extra point is less than 1000/`nits`%. For example, Table A7.5.6 shows the start of a trim diagnostics file for a simulation with `nits=1000`, so the least acceptable trim percentage is where the relative changes from one row to the next are all less than 1%. The percentage change in BH weight from 0.3-0.4 is 2.2%, but none of the percentage changes from 0.4-0.5 are greater than 1%, so a trim value of 0.4% would be chosen.

To summarize the use of stock–recruit weights and trimming, a flow chart is shown in Figure A7.5.2, indicating a possible approach to identifying suitable values of these parameters for a stock.
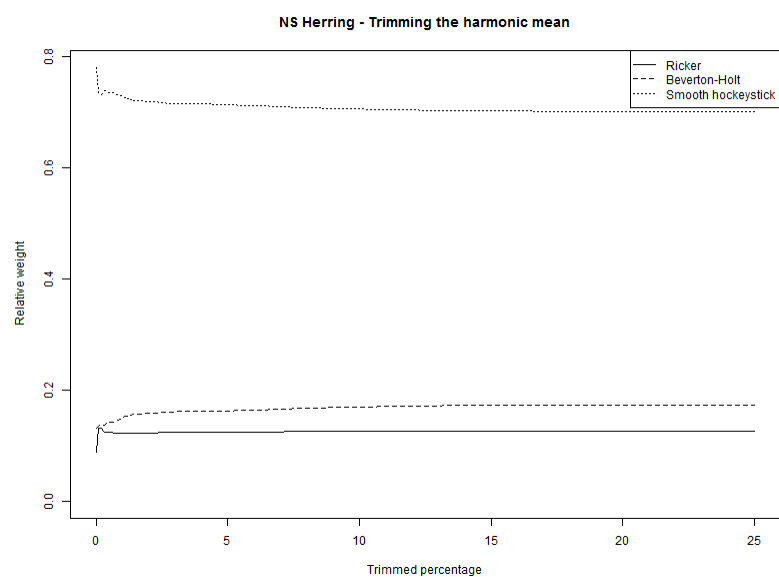
Figure A7.5.1. Weights given to Stock–recruit functions under different levels of trimming.

Table A7.5.6. Extract from an example trim diagnostics table.

Trim Percentage	Ricker	Beverton–Holt	Smooth Hockey–stick
0	0.088663003	0.130909267	0.78042773
0.1	0.131280931	0.134228228	0.73449084
0.2	0.130347436	0.137496333	0.732156231
0.3	0.123401989	0.137162076	0.739435935
0.4	0.123312989	0.140222716	0.736464295
0.5	0.12340671	0.141063786	0.735529504
…	…	…	…

```
                          ┌──────────┐
                          │  START   │
                          └──────────┘
                               │
        ┌──────────────────────────────────────┐
        │ Is there a knowledge about the       │
        │ likelihood of different stock recruit│          ┌──────────────────────┐
        │ forms beyond the stock-recruit pairs │   Yes    │ Use this information │
        │ in the .sen file?                    │─────────▶│ to set srweights     │
        └──────────────────────────────────────┘          └──────────────────────┘
                               │
                              No
                               │
        ┌──────────────────────────────────────────────────────────────────────┐
        │ How many of the stock recruit forms are compatible with knowledge of  │
        │ the stock                                                             │
        └──────────────────────────────────────────────────────────────────────┘
              0            1            2            3
```

Is there a knowledge about the likelihood of different stock recruit forms beyond the stock-recruit pairs in the .sen file?

Yes → Use this information to set srweights

No

How many of the stock recruit forms are compatible with knowledge of the stock

0
Use yield per recruit statistics
`onlyYPR=TRUE`

1
Use one SR form
`onlyYPR=FALSE`
`srweights`
`    =c(1,0,0)`

2
Use two SR forms
`onlyYPR=FALSE`
`srweights`
`    =c(NA,NA,0)`
`trimming=NA`

3
Use all SR forms
`onlyYPR=FALSE`
`srweights`
`  =c(NA,NA,NA)`
`trimming=NA`

Use `trim_diag.csv` and `trim_diag.png` to investigate whether trimming a small percentage (e.g 1%) removes instability in the weights

Re-run with trimmed mean by setting `trim` to a suitable value, or `srweights` to the weights corresponding to the chosen `trim` value
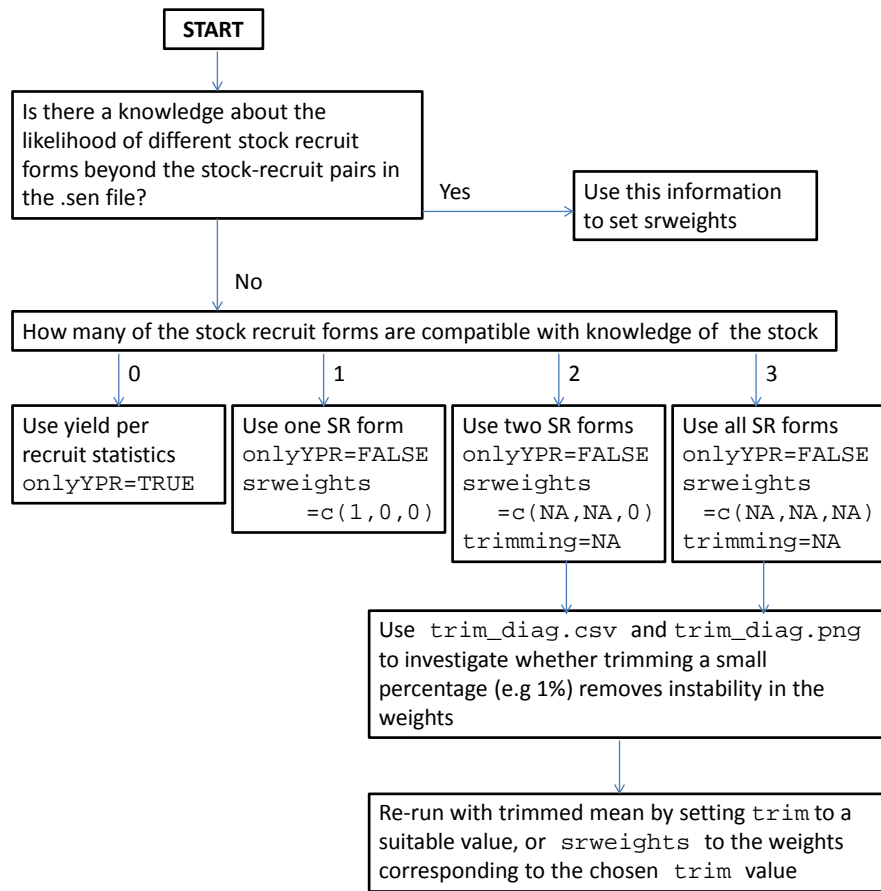
Figure A7.5.2. Flow chart as a guideline to help with the choice of relative stock–recruit function weights and appropriate level of trimming.

Annex 8: Method 2: EqSim

This section is taken from an online pdf document that can be found at:

https://github.com/wgmg/msyExamples

To install the msy package the best way is to install `devtools` and use the function `install_github`. If you are using windows you will also need to install Rtools.exe which is a collection of software which enables you to compile R packages from source code. Run the following lines to install the latest version of msy; any other packages that you require will automatically be downloaded from CRAN, the R package repository. However, `FLCore` is also installed from github.

```
library(devtools)
install_github("msy", "wgmg")
install_github("FLCore", "flr")
```

A8.1. Exploring Maximum Sustainable Yield of North Sea Cod using EqSim

First load the library and load in some data. The North Sea cod data has been preloaded as an `FLStock` object. The `EqSim` method requires an `FLStock` to work.

```
library(msy)
load("data/codNS.rData")
```

In the following subsections, we will simulate the North Sea cod stock into the future under some basic assumptions. For the simulations, we need to choose which years we will use to generate noise in the quantities:

- weight at age
- maturity-at-age
- natural mortality-at-age
- selection pattern.

We also need to choose a set of Fbar values to simulate over in order estimate F reference points. A convenient way to store this set up information is to contain it in a list.

```
codsetup <- list(
  data = codNS,
  wt.years = c(2008, 2012),
  Fscan = seq(0, 1.5, len = 40),
  Bpa = 150000,
  Blim = 70000,
  Btrigger = 150000,
  verbose = FALSE) # set verbose = TRUE to see simulation progress
```

Segmented regression (Hockey-stick) worked example

Using the settings defined above we can run the three components of the simulation approach for estimating MSY reference points. The components are:

1. Estimate the stock recruitment relationship
2. Simulate a stock to equilibrium and continue simulating for some years
3. Calculate reference points from the simulated stock at equilibrium

This is done in one go with the code

```
codsg <- within(codsetup, {
  fit <- fitModels(data, nsamp = 2000, model = "segreg")
  sim <- EqSim(fit, wt.years = wt.years, Fscan = Fscan,
    verbose = verbose)
  ref <- Eqplot(sim, fit, Blim = Blim, Bpa = Bpa, plot = FALSE)
})
```

The reference points can be accessed by

```
t(codsg$ref$Refs)
## F SSB Catch
## Flim 0.7723 193985.6 322413
## Flim10 0.7817 181018.7 305683
## Flim50 0.8330 68887.8 125793
## MSY:median 0.3462 765573.4 407897
## Maxmeanland 0.3077 891186.0 410688
## FCrash5 0.8077 145367.5 259684
## FCrash50 0.8846 827.4 1714
```

and summary plots are obtained by calling the `Eqplot` function again

```
with(codsg, Eqplot(sim, fit, Blim = Blim, Bpa = Bpa))
```

The stock recruitment fit is returned by `fitModels` and is plotted using the `SRplot` function

```
SRplot(codsg$fit)
```

These are the main functions of the `EqSim` approach. The following paragraphs will cover each step in more detail.

Model fitting

Model fitting is done by maximum likelihood using the `nlminb` optimizer in R. By refitting to non-parametric bootstrap resamples of the stock and recruit pairs, samples from the approximate joint distribution of the model parameters can be made. This all happens in the `fitModels` function. The `fitModels` function first sets up the stock and recruit pairs based on the information in the `FLStock` object and removes any incomplete pairs before proceeding to the model fitting / averaging algorithm chosen. Currently only a bootstrap based model averaging method called smooth AIC is implemented fully. The details can be found in `fitModelsBuck`. The algorithm implemented is:

1. take a resample with replacement from the stock and recruit pairs
2. fit every stock–recruit model under consideration and store the AIC of each
3. retain the parameter estimates from the best model
4. repeat

This process provides a robust way to average over several models, as long as the bootstrap resampling procedure provides an adequate approximation to the empirical distribution of the stock and recruits pairs.

The arguments to the fitting function are

```
args(fitModels)
## function (stk, nsamp = 5000,
##   models = c("ricker", "segreg", "bevholt"),
##   method = "Buckland", runid = NULL, remove.years = NULL,
##   delta = 1.3, nburn = 10000)
```

where

- `stk` is an `FLStock`,

- `nsamp` is the number of simulations to run a simulation for,
- `models` is the models to average over (one model may be supplied),
- `remove.years` is used to remove outlying years from the fit,
- `delta` and `nburn` are related to an MCMC based fitting procedure that is not complete,
- `runid` is an opportunity for the user to name the fit.

The results from the fitting process are returned to the user as a list

```
str(codsg$fit, 2)
## List of 6
## $ fit :'data.frame': 2000 obs. of 4 variables:
## ..$ a : num [1:2000] 6.22 6.33 4.8 5.59 4.96 ...
## ..$ b : num [1:2000] 166604 161872 240825 190059 285356 ...
## ..$ cv : num [1:2000] 0.438 0.432 0.419 0.452 0.407 ...
## ..$ model: chr [1:2000] "segreg" "segreg" "segreg" "segreg"
## $ pred : num [1:2000, 1:49] 135847 138191 104869 122097 ...
## $ fits :'data.frame': 1 obs. of 4 variables:
## ..$ a : num 6.09
## ..$ b : num 177048
## ..$ cv : num 0.463
## ..$ model: Factor w/ 1 level "segreg": 1
## $ data :'data.frame': 49 obs. of 3 variables:
## ..$ rec : num [1:49] 845768 1067681 1375049 1274418 ...
## ..$ ssb : num [1:49] 153588 165474 204933 228076 252322 ...
## ..$ year: num [1:49] 1964 1965 1966 1967 1968 ...
## $ stknam: chr "North Sea/Skagerrak/Eastern Channel …
## $ stk :Formal class 'FLStock' [package "FLCore"] with 20 slots
```

where

- `fit` is a sample from the joint distribution of the estimated model and parameters,
- `pred` is an associated sample from the predictive distribution of recruitment based on the model and parameters in `fit` and the SSB values used ,
- `fits` contains the fitted parameters to the observed data,
- `data` contains the data used,
- `stknam` holds the name of the stock for plotting later on,
- `stk` retains the original `FLStock` object.

Simulating forward

Simulating forwards is done using the `EqSim` function. The function takes as input the output from the `fitModel` function. Simulations are run independently for each sample from the distribution of model and parameters. This is done for a range of Fbar values. For example if we scanned over 10 values of Fbar and had taken 200 samples from the stock–recruit relationship then 2000 simulations would be run in total. These simulations run for 200 years, say, and the last 50 years are retained to calculate summaries, such as the proportion of times the stock crashes at a given level of F. It is important to note that each simulation is conditioned on a single stock recruit relationship with fixed parameters (including CV). Error is introduced within the simulations randomly generating process error about the constant stock–recruit fit, and by using historical variation in maturity, natural mortality, weight at age etc. Note that if there is no variability in these quantities in the stock object then no variability will be taken into the simulations.

The arguments to the simulation function are

```
args(EqSim)
```

```
## function (fit, Nrun = 200, wt.years = c(2007, 2011),
##   Fscan = seq(0, 1, len = 20), process.error = TRUE,
##   verbose = TRUE, Btrigger = 0)
```

where

- `fit` is the output from `fitModels`,
- `Nrun` is the number of years to simulate forward; note thet currently, the last 50 are used for summarizing equilibrium conditions,
- `wt.years` is the start and end year from which to generate the noise in weight at age etc.,
- `Fscan` is the range of Fbar values to scan over,
- `process.error` allows the simulations to be run using the predictive distribution of recruitment or the mean recruitment,
- `verbose = TRUE` shows a progress bar to the user,
- `Btrigger` is the location of the ramp in a simple HCR; if `Btrigger = 0`, this is like having no HCR present.

The results from the simulation process are returned to the user as a list

```
str(codsg$sim, 2)
## List of 14
## $ ssbs : num [1:7, 1:40] 3594589 3760648 4366111 4904481
## $ cats : num [1:7, 1:40] 0 0 0 0 0 ...
## $ recs : num [1:7, 1:40] 444087 516098 819854 1131301 ...
## $ ssbsa: num [1:40, 1:50, 1:2000] 4478184 3179649 2533362
## $ catsa: num [1:40, 1:50, 1:2000] 0 153849 256893 366760
## $ recsa: num [1:40, 1:50, 1:2000] 905941 1319530 548875
## $ Mat : Named num [1:6] 0.01 0.05 0.23 0.62 0.86 1
## ..- attr(*, "names")= chr [1:6] "1" "2" "3" "4" ...
## $ M : Named num [1:6] 1.038 0.697 0.489 0.233 0.2 ...
## ..- attr(*, "names")= chr [1:6] "1" "2" "3" "4" ...
## $ Fprop: Named num [1:6] 0 0 0 0 0 0
## ..- attr(*, "names")= chr [1:6] "1" "2" "3" "4" ...
## $ Mprop: Named num [1:6] 0 0 0 0 0 0
## ..- attr(*, "names")= chr [1:6] "1" "2" "3" "4" ...
## $ west : num [1:6, 1:5] 0.322 0.918 2.292 4.108 6.065 ...
## $ weca : num [1:6, 1:5] 0.322 0.918 2.292 4.108 6.065 ...
## $ sel : num [1:6, 1:5] 0.248 0.794 1.076 1.13 1.154 ...
## $ Fscan: num [1:40] 0 0.0385 0.0769 0.1154 0.1538 ...
```

where

- `ssbs`, `cats` and `recs` contain the 0.025, 0.05, 0.25, 0.5, 0.75, 0.95, 0.975 percentiles of the simulations of SSB, catch and recruitment for each `Fscan` value.
- `ssbsa`, `catsa` and `recsa` contain, for each `Fscan`, the final 50 years of each simulation of SSB, catch and recruitment.
- The remaining values show the range of variability included for maturity, natural mortality etc. and the Fbar values used.

Reference points

Reference points are derived from the output of `EqSim`.

Some code to fit different stock recruit models and apply different simulation settings

The remainder of this section presents code to use to generate the fits presented for cod in the main report.

Beverton–Holt

```
codbh <- within(codsetup, {
  fit <- fitModels(data, nsamp = 2000, model = "bevholt")
  sim <- EqSim(fit, wt.years = wt.years, Fscan = Fscan,
    verbose = verbose)
  ref <- Eqplot(sim, fit, Blim = Blim, Bpa = Bpa, plot = FALSE)
})
```

Ricker

```
codrk <- within(codsetup, {
  fit <- fitModels(data, nsamp = 2000, model = "bevholt")
  sim <- EqSim(fit, wt.years = wt.years, Fscan = Fscan,
    verbose = verbose)
  ref <- Eqplot(sim, fit, Blim = Blim, Bpa = Bpa, plot = FALSE)
})
```

Model averaging

```
codall <- within(codsetup, {
  fit <- fitModels(data, nsamp = 2000,
    model = c("segreg", "bevholt", "ricker"))
  sim <- EqSim(fit, wt.years = wt.years, Fscan = Fscan,
    verbose = verbose)
  ref <- Eqplot(sim, fit, Blim = Blim, Bpa = Bpa, plot = FALSE)
})
```

Model averaging with extra bits

```
codall_variations <- within(codall, {
# simulate without process error in the recruitment predictions
  sim2 <- EqSim(fit, wt.years = wt.years, Fscan = Fscan,
    process.error = FALSE, verbose = verbose)
# simulate with process error (i.e. using predictive distrution
# of recruitment) and include a simple HCR
  sim3 <- EqSim(fit, wt.years = wt.years, Fscan = Fscan,
    Btrigger = Btrigger, verbose = verbose)
# simulate without process error (i.e. using model and
# parameter error only, not including 'observation' error)
# and include a simple HCR
  sim4 <- EqSim(fit, wt.years = wt.years, Fscan = Fscan,
    process.error = FALSE, Btrigger = Btrigger, verbose = verbose)
# now calculate the reference points for each simulation
  ref2 <- Eqplot(sim2, fit, Blim = Blim, Bpa = Bpa, plot = FALSE)
  ref3 <- Eqplot(sim3, fit, Blim = Blim, Bpa = Bpa, plot = FALSE)
  ref4 <- Eqplot(sim4, fit, Blim = Blim, Bpa = Bpa, plot = FALSE)
})
```

A8.2. The code behind the fitting and simulations

fitModels

```
## function (stk, nsamp = 5000,
##   models = c("ricker", "segreg", "bevholt"),
##   method = "Buckland", runid = NULL, remove.years = NULL,
##   delta = 1.3, nburn = 10000)
## {
##   dms <- dims(stk)
##   rage <- dms$min
##   if (rage == 0) {
```

```
##      data <- data.frame(rec = stock.n(stk)[1, drop = TRUE],
##        ssb = ssb(stk)[drop = TRUE], year = with(dms, 1:year +
##        minyear - 1))
##    }
##    else {
##      data <- data.frame(rec = stock.n(stk)[1, -seq(rage),
##        drop = TRUE], ssb = ssb(stk)[1, seq(dms$year - rage),
##        drop = TRUE], year = with(dms, (rage + 1):year +
##        minyear - 1))
##    }
##    if (!is.null(remove.years)) {
##      data$ssb[data$year %in% remove.years] <- NA
##    }
##    data <- data[complete.cases(data), ]
##    if (is.null(runid))
##      runid <- name(stk)
##    method <- match.arg(method, c("Buckland", "Simmonds", "King",
##      "Cadigan"))
##    if (!is.character(models))
##      stop("models arg should be character vector giving names of
##      stock recruit models")
##    if (method == "Buckland") {
##      c(fitModelsBuck(data, runid, nsamp, models), list(stk = stk))
##    }
##    else {
##      cat("The", method, "is not ready yet! Working on it!\n")
##    }
## }
## <environment: namespace:msy>
```

fitModelsBuck

```
## function (data, runid, nsamp = 5000, models = c("ricker",
##   "segreg", "bevholt"), ...)
## {
##    nllik <- function(param, ...) -1 * llik(param, ...)
##    ndat <- nrow(data)
##    fit <- lapply(1:nsamp, function(i) {
##      sdat <- data[sample(1:ndat, replace = TRUE), ]
##      fits <- lapply(models, function(mod) nlminb(initial(mod,
##        sdat), nllik, data = sdat, model = mod, logpar = TRUE))
##      best <- which.min(sapply(fits, "[[", "objective"))
##      with(fits[[best]], c(a = exp(par[1]), b = exp(par[2]),
##        cv = exp(par[3]), model = best))
##    })
##    fit <- as.data.frame(do.call(rbind, fit))
##    fit$model <- models[fit$model]
##    pred <- t(sapply(seq(nsamp),
##      function(j) exp(match.fun(fit$model[j])(fit[j,], sort(data$ssb)))))
##    fits <- do.call(rbind, lapply(models,
##      function(mod) with(nlminb(initial(mod,data), nllik, data = data,
##      model = mod, logpar = TRUE), data.frame(a = exp(par[1]),
##      b = exp(par[2]), cv = exp(par[3]), model = mod))))
##    list(fit = fit, pred = pred, fits = fits, data = data, stknam = runid)
## }
## <environment: namespace:msy>
```

SRplot

```
## function (fit)
## {
##    modset <- fit$fit
##    data <- fit$data
##    ssb <- data$ssb
##    rec <- data$rec
##    mn <- length(ssb)
##    minSSB <- min(ssb, max(ssb) * 0.05)
##    maxSSB <- max(ssb) * 1.1
##    maxrec <- max(rec * 1.5)
##    plot(ssb, rec, xlim = c(0, maxSSB), ylim = c(0, maxrec),
##      type = "n", xlab = "SSB ('000 t)", ylab = "Recruits",
```

```
##     main = paste("Predictive distribution of recruitment\nfor",
##     fit$stknam))
##   out <- do.call(rbind, lapply(sample(1:nrow(modset), 500),
##     function(i) {
##       fssb <- runif(500, minSSB, maxSSB)
##       FUN <- match.fun(modset$model[i])
##       frec <- exp(FUN(modset[i, ], fssb) + rnorm(500, sd = modset$cv[i]))
##       points(fssb, frec, pch = 20, col = paste0(grey(0),
##       "05"), cex = 0.0625)
##       data.frame(ssb = fssb, rec = frec)
##     }))
##   out$grp <- with(out, floor(10 * (ssb - min(ssb))/(max(ssb) -
##     min(ssb) + 0.001)))
##   out$mid.grp <- with(out, (grp + 0.5)/10 * (max(ssb) - min(ssb)) +
##     min(ssb))
##   summ <- with(out, t(simplify2array(tapply(rec, grp, quantile,
##     c(0.5, 0.05, 0.95)))))
##   mid.grp <- sort(unique(out$mid.grp))
##   lines(mid.grp, summ[, 1], col = 7, lwd = 3)
##   lines(mid.grp, summ[, 2], col = 4, lwd = 3)
##   lines(mid.grp, summ[, 3], col = 4, lwd = 3)
##   x <- fit$fits
##   y <- seq(1, round(max(ssb)), length = 100)
##   sapply(1:nrow(x), function(i) lines(y,
##     exp(match.fun(as.character(x$model[i]))(x[i,], y)), col = "black",
##     lwd = 2, lty = i))
##   lines(ssb, rec, col = 10)
##   points(ssb, rec, pch = 19, col = 10, cex = 1.25)
## }
## <environment: namespace:msy>
```

EqSim

```
## function (fit, Nrun = 200, wt.years = c(2007, 2011),
##   Fscan = seq(0,1, len = 20), process.error = TRUE,
##   verbose = TRUE, Btrigger = 0)
## {
##   btyr1 <- wt.years[1]
##   btyr2 <- wt.years[2]
##   flgsel <- 0
##   flgmatwt <- 0
##   keep <- min(Nrun, 50)
##   SR <- fit$fit
##   data <- fit$data
##   stk <- fit$stk
##   stk.win <- window(stk, start = btyr1, end = btyr2)
##   west <- matrix(stock.wt(stk.win), ncol = btyr2 - btyr1 + 1)
##   weca <- matrix(catch.wt(stk.win), ncol = btyr2 - btyr1 + 1)
##   sel <- matrix(harvest(stk.win), ncol = btyr2 - btyr1 + 1)
##   Fbar <- matrix(fbar(stk.win), ncol = btyr2 - btyr1 + 1)
##   sel <- sweep(sel, 2, Fbar, "/")
##   if (flgsel == 0) {
##     sel[] <- apply(sel, 1, mean)
##   }
##   if (flgmatwt == 0) {
##     west[] <- apply(west, 1, mean)
##     weca[] <- apply(weca, 1, mean)
##   }
##   Mat <- apply(mat(stk.win), 1, mean)[drop = TRUE]
##   M <- apply(m(stk.win), 1, mean)[drop = TRUE]
##   Fprop <- apply(harvest.spwn(stk.win), 1, mean)[drop = TRUE]
##   Mprop <- apply(m.spwn(stk.win), 1, mean)[drop = TRUE]
##   Nmod <- nrow(SR)
##   NF <- length(Fscan)
##   ages <- dims(stk)$age
##   ssby <- array(0, c(Nrun, Nmod))
##   Ny <- Fy <- WSy <- WCy <- Cy <- Wy <- array(0, c(ages, Nrun,
##     Nmod))
##   rsam <- array(sample(1:ncol(weca), Nrun * Nmod, TRUE), c(Nrun,
```

```
##      Nmod))
##    Wy[] <- c(weca[, c(rsam)])
##    R <- mean(data$rec)
##    ssbs <- cats <- recs <- array(0, c(7, NF))
##    pssb1 <- pssb2 <- array(0, NF)
##    ssbsa <- catsa <- recsa <- array(0, c(NF, keep, Nmod))
##    begin <- Nrun - keep + 1
##    if (verbose)
##      loader(0)
##    for (i in 1:NF) {
##      Fbar <- Fscan[i]
##      Zpre <- (Fbar * Fprop * sel[, rsam[1, ]] + M * Mprop)
##      Zpos <- (Fbar * (1 - Fprop) * sel[, rsam[1, ]] + M *
##        (1 - Mprop))
##      Zcum <- c(0, cumsum(Fbar * sel[c(1:ages, rep(ages, 49 -
##        ages)), rsam[1, ]] + M[c(1:ages, rep(ages, 49 - ages))]))
##      N1 <- R * exp(-unname(Zcum))
##      Ny[, 1, ] <- c(N1[1:(ages - 1)], sum(N1[ages:50]))
##      ssby[1, ] <- colSums(Mat * Ny[, 1, ] * west[, rsam[1,]]/
##        exp(Zpre))
##      for (j in 2:Nrun) {
##        SSB <- ssby[j - 1, ]
##        if (process.error) {
##          allrecs <- sapply(unique(SR$mod),
##            function(mod) exp(match.fun(mod)(SR,SSB) +
##              rnorm(Nmod, 0, SR$cv)))
##        }
##        else {
##          allrecs <- sapply(unique(SR$mod),
##            function(mod) exp(match.fun(mod)(SR,SSB)))
##        }
##        select <- cbind(seq(Nmod), as.numeric(factor(SR$mod,
##          levels = unique(SR$mod))))
##        Ny[1, j, ] <- allrecs[select]
##        Fnext <- Fbar * pmin(1, SSB/Btrigger)
##        Zpre <- rep(Fnext, each = length(Fprop)) * Fprop *
##          sel[, rsam[j, ]] + M * Mprop
##        Fy[, j - 1, ] <- rep(Fnext, each = ages) * sel[,
##          rsam[j - 1, ]]
##        Ny[-1, j, ] <- Ny[1:(ages - 1), j - 1, ] *
##          exp(-Fy[1:(ages - 1), j - 1, ] - M[1:(ages - 1)])
##        Ny[ages, j, ] <- Ny[ages, j, ] + Ny[ages, j - 1, ] *
##          exp(-Fy[ages, j - 1, ] - M[ages])
##        ssby[j, ] <- apply(array(Mat * Ny[, j, ] * west[,
##          rsam[j, ]]/exp(Zpre), c(ages, Nmod)), 2, sum)
##        Cy[, j, ] <- Ny[, j - 1, ] * Fy[, j - 1, ]/(Fy[,
##          j - 1, ] + M) * (1 - exp(-Fy[, j - 1, ] - M))
##      }
##      Cw <- Cy * Wy
##      Cat <- apply(Cw, 2:3, sum)
##      quants <- c(0.025, 0.05, 0.25, 0.5, 0.75, 0.95, 0.975)
##      ssbs[, i] <- quantile(ssby[begin:Nrun, ], quants)
##      cats[, i] <- quantile(Cat[begin:Nrun, ], quants)
##      recs[, i] <- quantile(Ny[1, begin:Nrun, ], quants)
##      ssbsa[i, , ] <- ssby[begin:Nrun, ]
##      catsa[i, , ] <- Cat[begin:Nrun, ]
##      recsa[i, , ] <- Ny[1, begin:Nrun, ]
##      if (verbose)
##        loader(i/NF)
##    }
##    list(ssbs = ssbs, cats = cats, recs = recs, ssbsa = ssbsa,
##      catsa = catsa, recsa = recsa, Mat = Mat, M = M,
##      Fprop = Fprop,Mprop = Mprop, west = west, weca = weca,
##      sel = sel, Fscan = Fscan)
## }
## <environment: namespace:msy>
```

Eqplot

```
## function (sim, fit, Blim, Bpa = 1.4 * Blim, ymax = c(NA, NA,
## NA), plot = TRUE)
## {
##    stk <- fit$stk
##    Nmod <- dim(sim$ssbsa)[3]
##    Nyrs <- dim(sim$ssbsa)[2]
##    Fscan <- sim$Fscan
##    catm <- apply(sim$catsa, 1, mean)
##    maxcatm <- which.max(catm)
##    catsam <- apply(sim$catsa, c(1, 3), mean)
##    maxpf <- apply(catsam, 2, which.max)
##    fmsy <- Fscan[maxpf]
##    msym <- mean(fmsy)
##    vcum <- median(fmsy)
##    fmsy.dens <- density(fmsy)
##    vmode <- fmsy.dens$x[which.max(fmsy.dens$y)]
##    pssb1 <- apply(sim$ssbsa > Blim, 1, mean)
##    pssb2 <- apply(sim$ssbsa > Bpa, 1, mean)
##    pp1 <- max(which(pssb1 > 0.95))
##    grad <- diff(Fscan[pp1 + 0:1])/diff(pssb1[pp1 + 0:1])
##    flim <- Fscan[pp1] + grad * (0.95 - pssb1[pp1])
##    maint <- fit$stknam
##    rec <- fit$data$rec
##    ssb <- fit$data$ssb
##    Catchs <- catch(stk)[, 1:length(ssb), drop = TRUE]
##    FbarO <- fbar(stk)[, 1:length(ssb), drop = TRUE]
##    recs <- sim$recs
##    ssbs <- sim$ssbs
##    cats <- sim$cats
##    ssbsa <- sim$ssbsa
##    NF <- length(Fscan)
##    pp1 <- max(which(pssb1 > 0.5))
##    grad <- diff(Fscan[pp1 + 0:1])/diff(pssb1[pp1 + 0:1])
##    flim50 <- Fscan[pp1] + grad * (0.5 - pssb1[pp1])
##    pp1 <- max(which(pssb1 > 0.9))
##    grad <- diff(Fscan[pp1 + 0:1])/diff(pssb1[pp1 + 0:1])
##    flim10 <- Fscan[pp1] + grad * (0.9 - pssb1[pp1])
##    maxcatm <- which.max(catm)
##    if (plot) {
##      op <- par(mfrow = c(2, 2), mar = c(2.5, 4, 1.5, 1),
##        oma = c(0, 0, 0, 0), cex.axis = 0.75, tcl = 0.25,
##        mgp = c(0, 0.25, 0), las = 1)
##      xmax <- max(Fscan)
##      y.max <- if (!is.na(ymax[1])) ymax[1]
##        else max(recs[7, ], rec)
##      plot(Fscan, recs[7, ], type = "l", lty = 4, ylim = c(0,
##        y.max), xlim = c(0, xmax), ylab = "", xlab = "")
##      title(ylab = "Recruitment", xlab = "F bar", cex.lab = 0.75,
##        line = 2.5, cex.main = 0.75)
##      mtext(text = paste(maint, " a) Recruits"), cex = 0.75,
##        side = 3, line = 0.5)
##      lines(Fscan, recs[6, ], lty = 3)
##      lines(Fscan, recs[5, ], lty = 2)
##      lines(Fscan, recs[4, ], lty = 1)
##      lines(Fscan, recs[3, ], lty = 2)
##      lines(Fscan, recs[2, ], lty = 3)
##      lines(Fscan, recs[1, ], lty = 4)
##      points(FbarO, rec, pch = 21, cex = 0.75, bg = 1)
##      lines(c(flim, flim), c(0, y.max), col = 3)
##      y.max <- if (!is.na(ymax[2])) ymax[2]
##        else max(ssbs[7, ])
##      plot(Fscan, ssbs[7, ], type = "l", lty = 4, ylim = c(0,
##        y.max), xlim = c(0, xmax), ylab = "", xlab = "")
##      title(ylab = "SSB", xlab = "F bar", cex.lab = 0.75,
##        line = 2.5, cex.main = 0.75)
##      mtext(text = "b) Spawning Stock Biomass", cex = 0.75,
```

```
##      side = 3, line = 0.5)
##      lines(Fscan, ssbs[6, ], lty = 3)
##      lines(Fscan, ssbs[5, ], lty = 2)
##      lines(Fscan, ssbs[4, ], lty = 1)
##      lines(Fscan, ssbs[3, ], lty = 2)
##      lines(Fscan, ssbs[2, ], lty = 3)
##      lines(Fscan, ssbs[1, ], lty = 4)
##      lines(c(0, xmax), c(Blim, Blim))
##      text(x = 0.1, y = Blim * 1.1, "Blim", cex = 0.7)
##      points(FbarO, ssb, pch = 21, cex = 0.75, bg = 1)
##      lines(c(flim, flim), c(0, y.max), col = 3)
##    }
##    FCrash5 <- Fscan[which.max(cats[2, ]):NF][which(cats[2,
##      which.max(cats[2, ]):NF] < 0.05 * max(cats[2, ]))[1]]
##    FCrash50 <- Fscan[which.max(cats[4, ]):NF][which(cats[4,
##      which.max(cats[4, ]):NF] < 0.05 * max(cats[4, ]))[1]]
##    if (plot) {
##      y.max <- if (!is.na(ymax[3])) ymax[3]
##        else max(cats[7, ])
##      plot(Fscan, cats[7, ], type = "l", lty = 4, ylim = c(0,
##        y.max), xlim = c(0, max(Fscan)), ylab = "", xlab = "")
##      title(ylab = "Catch", xlab = "F bar", cex.lab = 0.75,
##        line = 2.5, cex.main = 0.75)
##      mtext(text = "c) Catch", cex = 0.75, side = 3, line = 0.5)
##      lines(Fscan, cats[7, ], lty = 4)
##      lines(Fscan, cats[6, ], lty = 3)
##      lines(Fscan, cats[5, ], lty = 2)
##      lines(Fscan, cats[4, ], lty = 1)
##      lines(Fscan, cats[3, ], lty = 2)
##      lines(Fscan, cats[2, ], lty = 3)
##      lines(Fscan, cats[1, ], lty = 4)
##      points(FbarO, Catchs, pch = 21, cex = 0.75, bg = 1)
##      lines(c(flim, flim), c(0, y.max), col = 3)
##      lines(c(FCrash5, FCrash5), c(0, y.max), col = 5)
##      lines(c(FCrash50, FCrash50), c(0, y.max), col = 5)
##      lines(Fscan, catm, lty = 1, col = 2)
##      lines(rep(Fscan[maxcatm], 2), c(0, y.max), lty = 1, col = 5)
##      plot(Fscan, 1 - pssb1, type = "l", lty = 2, ylim = c(0, 1),
##        xlim = c(0, max(Fscan)), ylab = "", xlab = "")
##      title(ylab = "Prob MSY, SSB<Bpa or Blim", xlab = "F bar",
##        cex.lab = 0.75, line = 2.5, cex.main = 0.75)
##      mtext(text = "d) Prob MSY and Risk to SSB", cex = 0.75,
##        side = 3, line = 0.5)
##      lines(Fscan, 1 - pssb2, lty = 4)
##      text(x = max(Fscan[pssb2 > 0.5]) - 0.05, y = 0.5, "SSB<Bpa",
##        cex = 0.75)
##      text(x = max(Fscan[pssb1 > 0.7]) + 0.1, y = 0.3, "SSB<Blim",
##        cex = 0.75)
##      lines(c(flim, flim), c(0, 1), col = 3)
##      lines(c(0, flim), c(0.05, 0.05), lty = 2, col = 3)
##      text(x = 0.1, y = 0.075, "5%", cex = 0.75, col = 3)
##      lines(c(flim10, flim10), c(0, 1), col = "darkgreen")
##      lines(c(0, flim10), c(0.1, 0.1), lty = 2, col = "darkgreen")
##      text(x = 0.05, y = 0.125, "10%", cex = 0.75,
##        col = "darkgreen")
##      lines(fmsy.dens$x, cumsum(fmsy.dens$y *
##        diff(fmsy.dens$x)[1]), col = 4)
##      text(x = 0.9, y = 0.8, "Prob of Fmsy", cex = 0.75, col = 4)
##      lines(rep(vcum, 2), c(0, 1), lty = 1, col = 4)
##      lines(c(Fscan[maxcatm], Fscan[maxcatm]), c(0, 1), col = 5)
##    }
##    out <- c(Blim, Bpa)
##    outF <- c(flim, flim10, flim50, vcum, Fscan[maxcatm], FCrash5,
##      FCrash50)
##    outB <- approx(Fscan, ssbs[4, ], xout = outF)$y
##    outC <- approx(Fscan, cats[4, ], xout = outF)$y
##    outTable <- rbind(outF, outB, outC)
##    rownames(outTable) <- c("F", "SSB", "Catch")
```

```
##    colnames(outTable) <- c("Flim", "Flim10", "Flim50",
##      "MSY:median","Maxmeanland", "FCrash5", "FCrash50")
##    list(Blim = Blim, Bpa = Bpa, Refs = outTable)
## }
## <environment: namespace:msy>
```

Annex 9: Method 3: StochSim

Most processes that need to be taken into account in Harvest Control Rule simulations are correlated in time. Ignoring those correlations leads to underestimation of risk and a higher acceptable fishing mortality as demonstrated by simulations done for Icelandic haddock and saithe.

Introduction

In recent years Harvest Control Rules have been evaluated for many fish stocks. Typically a group of scientist working with the stocks makes a series of stochastic simulation, their work then being reviewed by another group of scientist appointed by organizations like ICES. The official stamp is usually that the Harvest Control Rule is "precautionary and in accordance with the ICES MSY approach".

Most of HCR evaluations done so far are single species. Some of them are done by what is called "full model" where biological model, observation model and assessment model are linked in a closed loop. Simpler models are stochastic simulation models where dynamics of the stock are simulated forward, including stochasticity in weights at age, residuals from the stock recruitment function, assessment uncertainty etc. The main problem here is to include appropriate uncertainty in the simulations, both in terms of magnitude and autocorrelation. In addition, the uncertainty in both the form and actual parameters of the stock recruitment function needs to be included, but for most stocks available data are very limited in this context.

Stochastic simulations can in principle be used to evaluate MSY. When fishing mortality or harvest rate exceeds a certain level, a higher and larger proportion of the stochastic simulations lead to spawning stock depleted to a level where reduced recruitment is predicted, resulting in lower yields.

Material and methods.

The stocks investigated were Icelandic haddock and saithe. (Björnsson 2013, Hjörleifsson and Björnsson 2013). Data on catch in number and catch weights are available since 1979. The two surveys used in the assessment commenced in 1985 and 1996 respectively, so estimates of assessment uncertainty are based on a relatively short time-series.

The simulations were done by an assessment and prognosis model written in AD model builder. Parameters of the stock recruitment function, selection and current stock size are estimated from available data. The variance-covariance matrix of the estimated parameters is used to generate stochastic replicates that are saved and used in the stochastic simulations of the Harvest Control Rule.

Autocorrelation of the residuals from the stock–recruitment model were modelled by a first order AR model.

$$\varepsilon_{t+1} = \rho_R \varepsilon_t + \xi_t \tag{A9.1}$$

Where ξ_t is normally distributed white noise with mean 0 and standard deviation $\sigma\sqrt{(1-\rho_R^2)}$. The parameter ρ_R had to be fixed in the model as it was not estimable in addition to the 2 parameters of the stock recruitment function and standard deviation of the residuals. Different types of stock–recruitment relationship were tested, but the results presented are based on the Hockey-stick function. Assessment errors were

modelled in the same way, with parameters based on empirical assessment performance and analytical retrospective pattern. Stochasticity in mean weight at age was modelled by a common year factor applied to all age groups. The year factor is also modelled by a first order AR model, with parameters estimated from data for the most important age groups. Criteria that results of the simulations were tested against were $P(SSB < B_{\text{lim}}) < 0.05$ and maximum average yield (HMSY). According to ICES standards (ICES-WKGMSE, 2013) $P(SSB < B_{\text{lim}})$ should not exceed 0.05 in any year (type 3 risk).

Results and discussions

Mean yield and the fifth percentile of SSB show that H_{MSY} is usually higher than the harvest ratio corresponding to $P(SSB < B_{\text{lim}}) < 0.05$ (Figure A9.1). Using only white noise leads to a considerably higher acceptable harvest ratio than when correlated noise is included: 0.27 vs. 0.216 for saithe and 0.52 vs. 0.44 for haddock. For both species, the harvest rate giving maximum yield is higher than that fulfilling the precautionary criterion $P(SSB < B_{\text{lim}})$.
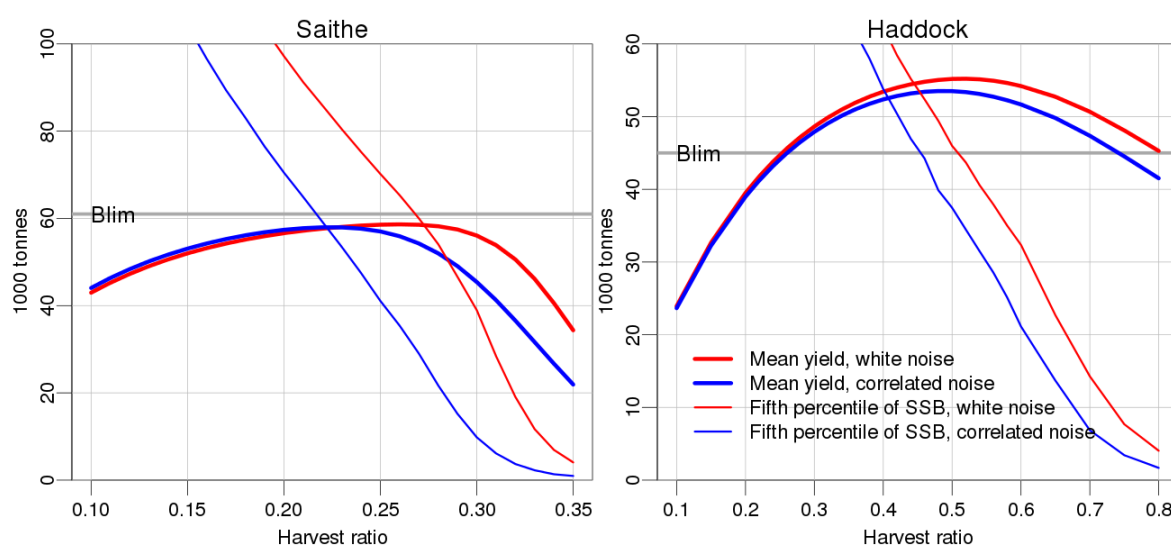
Figure A9.1. Average yield and the fifth percentile of spawning stock as function of harvest ratio for Icelandic saithe and haddock.

The characteristics of the two stocks are different: stock assessment of haddock is much more precise than that for saithe but with greater variability in recruitment. Results for haddock are therefore very sensitive to the value of ρ_R. Including uncertainty in ρ_R would be an appropriate action but is not easily done with available data for only 30 years. For saithe, uncertainty assessment error is high, and uncertainty about its magnitude and autocorrelation important. For both stocks the proposed harvest ratios - 0.2 for saithe and 0.4 for haddock - are lower than that resulting in MSY, but perhaps not so low taking into account unaccounted uncertainty.

Annex 10: Method 4: NSR

A10.1. Introduction

Cadigan (2013) presented a nonparametric approach to estimate stock–recruitment (SR) relationships. The approach preserves compensatory density-dependence in which the recruitment rate monotonically decreases as stock size increases, which is a basic assumption of commonly used parametric SR models. This is sometimes referred to as the compensatory mortality property (CMP; e.g. Quinn and Deriso, 1999). The CMP ensures that for any level of F there is a unique equilibrium stock size in projections. CMP ensures the equilibrium yield curve (i.e. Catch vs. F) is continuous with a well-defined maximum at F_{MSY}. Cadigan (2013) used this approach to fit nonparametric SR curves with CMP and to derive "SR-nonparametric" equilibrium yield curves. A simple bootstrap procedure was used to characterize the uncertainty in the SR model, including model uncertainty, and to derive confidence intervals for MSY reference points based on uncertainty in the SR relationship.

In this section the nonparametric SR model (i.e. NSR) is applied to two case studies, North Sea cod and herring. The approach is also extended to include a time-series bootstrap methodology to account for the additional uncertainty due to autocorrelated SR residuals. In addition, additional information and implementation details are provided.

Time–series bootstrap

Cadigan (2013) used a regression bootstrap approach in which the stock–recruit model residuals were re-sampled and added to predictions to generate bootstrap datasets. This approach is extended in this section to use time-series bootstrap residuals to account for autocorrelation in the model residuals. Such autocorrelation is a common feature. Not accounting for autocorrelation can lead to bootstrap confidence intervals that are too narrow. The program "tsbootstrap" in the "tseries" R package (Adrian and Hornik, 2012) was used, with default settings.

A10.2. Case Studies

The *scam* package (Pya, 2012) in R was used to fit the nonparametric SR curves. However, there were convergence problems for both case studies. This problem occurred when fitting models with a fixed smoothing parameter selected to give a prespecified degrees-of-freedom (df), such as df=3 or 4 (see Cadigan, 2013). Convergence problems did not seem to occur when the *scam* package estimated the smoothing parameter; however, convergence problems did occur even when the smoothing parameter was fixed at the same value as selected by the *scam* package which suggests that there is a bug in the package. Hence, only results based on the option with convergence (i.e. internal smoothing parameter selection) are presented in this section. Note that after this work was completed the *scam* package developer proposed a solution to this problem which is described in Section A10.3. Bootstrap procedures included estimation of the smoothing parameter, which is also different from Cadigan (2013) where this parameter was fixed when generating bootstrapped data.

North Sea herring

The autocorrelation structure of the NSR raw residuals (Figure A10.2.1) is very different from the autocorrelation structure of an example of simple (i.e. iid) boot-

strapped residuals. However, the autocorrelation structure of an example of time-series bootstrapped residuals was much more similar to the NSR raw residuals.
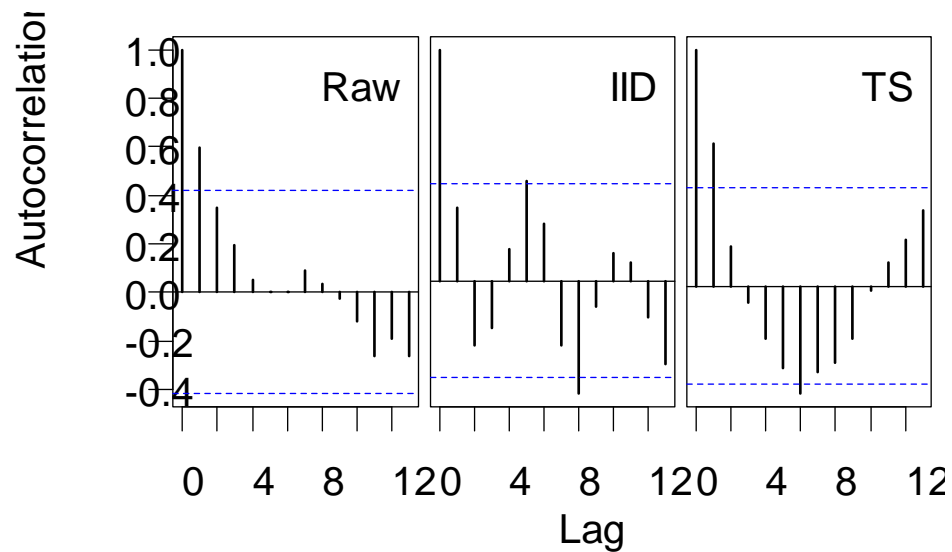

Figure A10.2.1. Autocorrelation function (ACF) for the NSR raw residuals (left panel), an example of simple bootstrap IID NSR residuals (middle panel) and an example of time-series (TS) bootstrap NSR residuals (right panel).

The smoothing parameter selected by the *scam* package was large (175.8). In this case the NSR is basically the same as a Ricker function (see Cadigan, 2013). The NSR curve (Figure A10.2.2) was virtually identical. However, the NSR bootstrap confidence intervals were wide, and the time-series intervals were somewhat wider than confidence intervals based on simple bootstrapped residuals. All methods fit the data almost equally as well (Table A10.2.1) although the Hockey-stick model fit best and the Beverton–Holt fit worst.
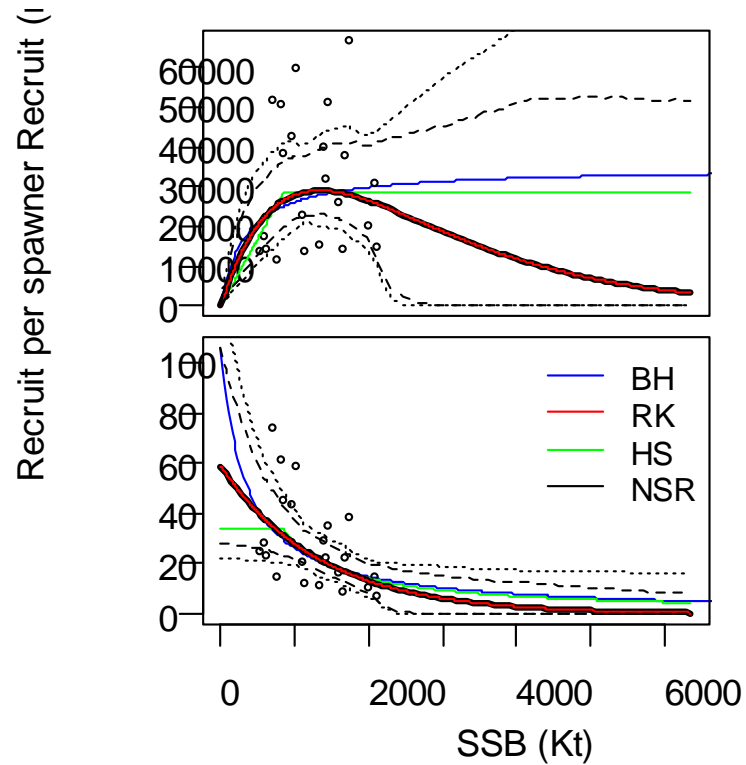
Figure A10.2.2. A comparison of NSR (black), Ricker (RK; red), Beverton–Holt (BH; blue) and Hockey-stick (HS; green) estimated stock recruit curves. Data are shown as points. Dashed lines indicate 95% simple NSR bootstrap confidence intervals. Dotted lines indicate 95% time-series NSR bootstrap confidence intervals. Top panels: recruits. Bottom panel: recruits per spawner.

Table A10.2.1. Fit statistics; MSE (mean-square error) and GCV (generalized cross validation). The degrees of freedom (df) of each method is also provided.

	MSE	df	GCV
NSR	0.284	2.0	0.344
HS	0.275	2.0	0.333
BH	0.300	2.0	0.363
RK	0.284	2.0	0.344

Equilibrium yields inferred from the four stock recruit curves were similar (Figure A10.2.3), although the F_{MSY}'s differed substantially (Table A10.2.2). Time-series bootstrap confidence intervals were wider than intervals based on the simple bootstrap.
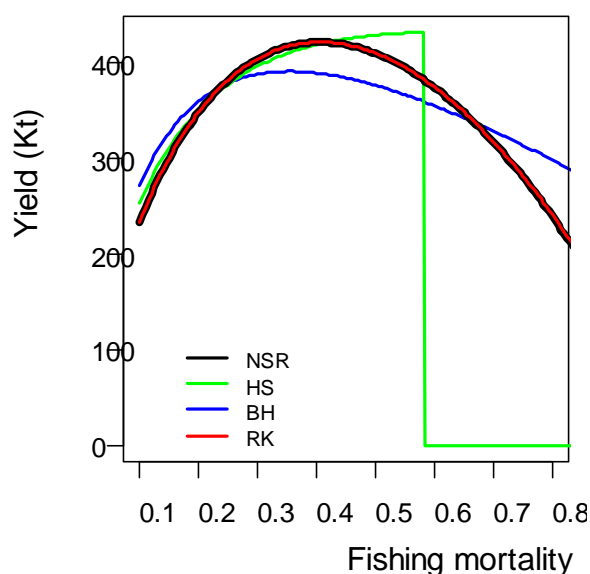
Figure A10.2.3. A comparison of equilibrium yields inferred from four stock–recruit curves: NSR (black), Ricker (RK; red), Beverton–Holt (BH; blue) and Hockey-stick (HS; green).

Table A10.2.2. MSY reference points inferred from four stock–recruit curves, with lower (LCI) and upper (UCI) 95% bootstrap confidence intervals. The NSR intervals are based on the simple bootstrap method, with time-series bootstrap intervals in the next row.

Method	F_{MSY}			B_{MSY}		
	Est	LCI	UCI	Est	LCI	UCI
NSR	0.40	0.21	0.67	1118	843	2620
TS Boot		0.15	0.83		756	6365
HS	0.58	0.35	0.61	845	677	1378
BH	0.35	0.22	0.61	1160	667	2044
RK	0.41	0.22	0.70	1115	832	2145

North Sea cod

There is little autocorrelation in NSR raw residuals (Figure A10.2.4) and its autocorrelation structure is similar to the simple bootstrapped residuals and the time-series bootstrapped residuals. Hence, the simple bootstrap method is appropriate and one would not expect the time-series bootstrap confidence intervals to differ much compared to the simple approach. This is basically what was observed for the stock–recruit confidence intervals (Figure A10.2.5).
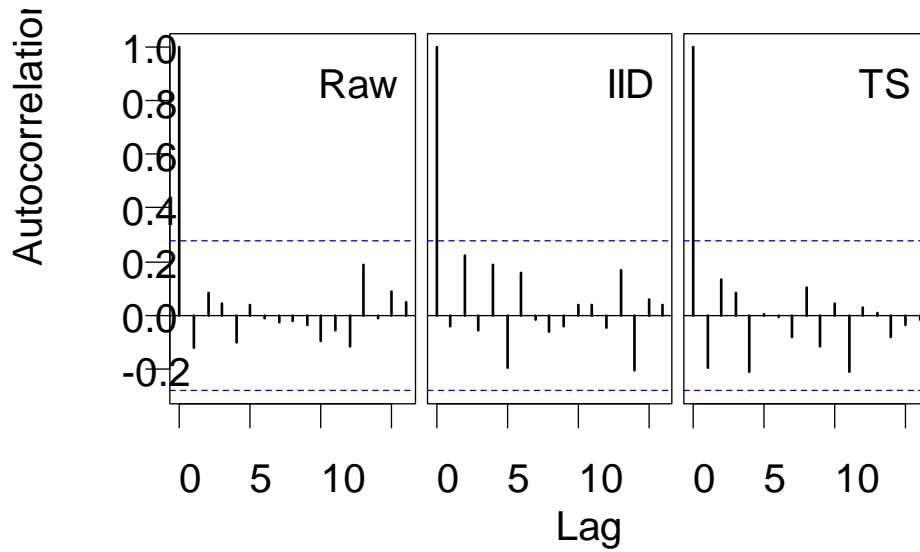
Figure A10.2.4. Autocorrelation function (ACF) for the NSR raw residuals (left panel), an example of simple bootstrap IID NSR residuals (middle panel) and an example of time-series (TS) bootstrap NSR residuals (right panel).
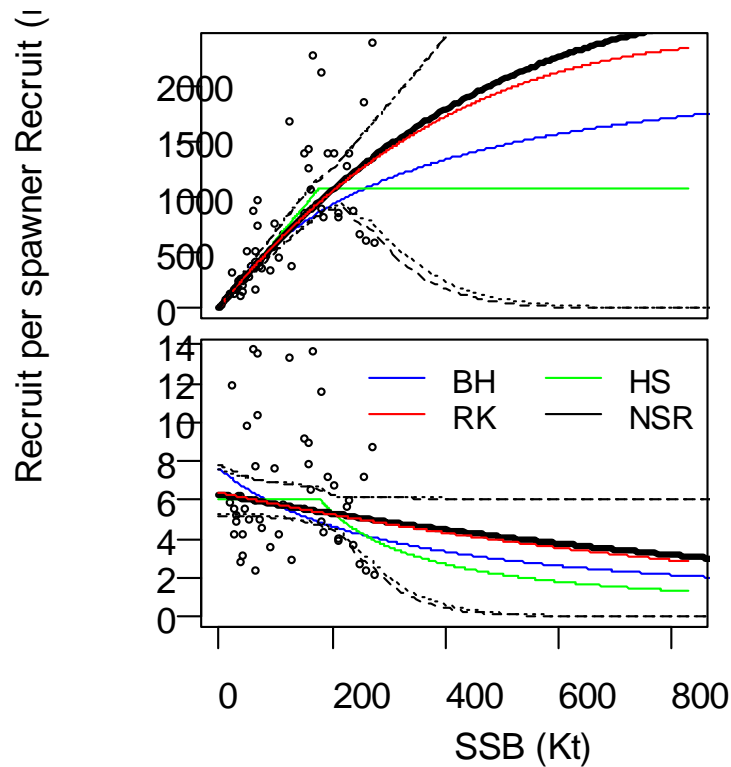

Figure A10.2.5. A comparison of NSR (black), Ricker (RK; red), Beverton–Holt (BH; blue) and Hockey-stick (HS; green) estimated stock recruit curves. Data are show as points. Dashed lines indicate 95% simple NSR bootstrap confidence intervals. Dotted lines indicate 95% time-series NSR bootstrap confidence intervals. Top panels: recruits. Bottom panel: recruits per spawner.

The smoothing parameter selected by the *scam* package was 3.9 which is intermediate in value. The NSR curve differed only slightly from the estimated Ricker (Figure A10.2.5). All methods fit the data almost equally as well (Table A10.2.3) although the Hockey-stick model fit best and the Beverton–Holt fit worst, similar to North Sea herring.

Table A10.2.3. Fit statistics; mean-square error (MSY) and GCV (generalized cross validation). The degrees of freedom (df) of each method is also provided.

	MSE	df	GCV
NSR	0.232	2.0	0.252
HS	0.214	2.0	0.233
BH	0.249	2.0	0.270
RK	0.232	2.0	0.253

Equilibrium yields inferred for the NSR, Beverton–Holt, and Ricker stock recruit curves were similar to each other but not to the yield curve derived from the Hockey-stick model (Figure A10.2.6). Estimates of F_{MSY}'s differed substantially (Table A10.2.4) among methods. Time-series and simple bootstrap confidence intervals were similar and both were substantially wider than intervals based on parametric models.
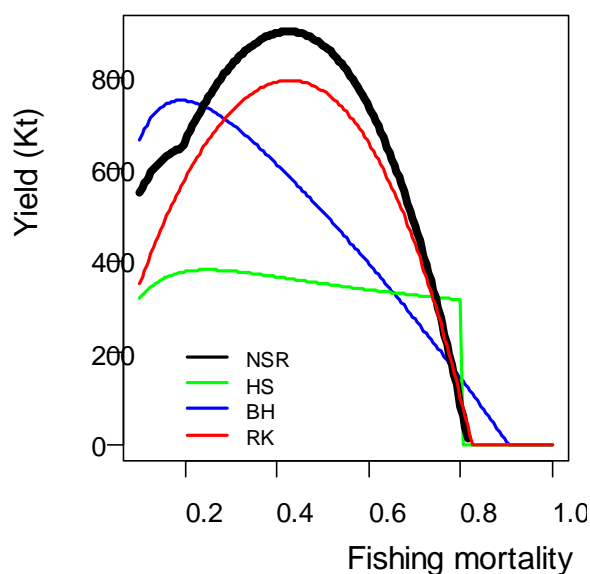

Figure A10.2.6. A comparison of equilibrium yields inferred from four stock–recruit curves: NSR (black), Ricker (RK; red), Beverton–Holt (BH; blue) and Hockey-stick (HS; green).

Table A10.2.4. MSY reference points inferred from four stock–recruit curves, with lower (LCI) and upper (UCI) 95% bootstrap confidence intervals. The NSR intervals are based on the simple bootstrap method, with time-series bootstrap intervals in the next row.

Method	F_{MSY}			B_{MSY}		
	Est	LCI	UCI	Est	LCI	UCI
NSR	0.42	0.25	0.76	1309	199	15204
TS Boot		0.25	0.76		199	15351
HS	0.25	0.25	0.25	1096	879	1525
BH	0.19	0.18	0.20	2910	1555	2958
RK	0.43	0.40	0.49	1145	423	1284

Conclusions

Model-uncertainty in MSY reference points was large for the two case studies. We look forward to future versions of the *scam* package.

A10.3. Additional information

SCAM R package background

The *scam* package is similar to the R *mgcv(gam)* package for fitting GAMs (generalized additive models), except that *scam* allows for a variety of shape constraints on the component functions of the linear predictor of the GAM. The constraints involve monotonicity (increasing or decreasing) with options to specify convex or concave shapes. *Scam* uses spline smoothers for nonparametric regression. Data are assumed to be independent and from an exponential family distribution with mean μ that is a partially linear function of covariates, $g(\mu) = \theta_0 + \sum_{k=1}^{p_l} \theta_k x_k^* + \sum_{j=1}^{p_n} f_j(x_j)$, where g is a smooth monotone link function and the $f_j(x_j)$'s are unknown smooth functions of the x_j covariates. θ_k's and $f_j(x_j)$'s must be estimated.

The *scam* package uses spline approximations for the $f_j(x_j)$'s; $f(x) = \sum_{i=1}^{q} B_i^m(x) \gamma_i$, where $\gamma_1, ..., \gamma_q$ are unknown spline parameters to estimate and $B_1^m(x), ..., B_q^m(x)$ are known spline basis functions. The *scam* package uses B-spline basis functions. Knots determine the location and shape of the polynomial. The knots are evenly spaced and cover the range of x. The shape constraints are based on evenly spaced knots; these constraints are difficult to specify otherwise. The number of knots (q) should be large to avoid over-smoothing/under-fitting; however, this could result in over-fitting of the data.

A penalty function is used to control the variation in the γ's. A smoothing parameter determines the contribution of the smoothing penalty function to the total fit function. The *scam* package uses generalized cross-validation or the Akaike information criterion to determine the value of the smoothing parameter. P-splines are penalized B-splines. The *scam* package uses various shape restrictions on the γ spline parameters to ensure the correct shape restrictions on *f*. For example, if *f(x)* is strictly monotone increasing in *x*, and since all B-spline basis functions are nonnegative, then a sufficient condition for this shape constraint (i.e. monotone increasing) is $\gamma_i > \gamma_{i-1}$. This

is achieved by redefining the γ parameters as $\gamma_1 = \beta_1$, $\gamma_j = \beta_1 + \sum_{i=2}^{j} \exp(\beta_j)$, for $j = 2,\ldots,q$. The β_i's are unconstrained parameters to estimate. The penalty function is based on the squared differences of $\beta_2,\ldots,\beta_q$. However, the shape restrictions themselves add much smoothing and model results are usually not that sensitive to the choice of smoothing parameter.

Implementation

The *scam* package option *bs='mpd'* produces a monotone decreasing spline smoother. The *scam* code is simple to use. If the SR data are contained in a R dataframe called dat, then the R code

scam(log.recruit ~ s(stock.size,bs="mpd" ,m=2) + offset(log(stock.size)),data=dat)

will provide nonparametric estimates of a SR curve with the CMP. By default the *scam* link function is the identity function, and the default error distribution is Gaussian. This R code is more appropriate when recruitment is lognormally distributed. The *s(.)* term represents $log\{\mu(S)/S\}$ which is assumed to be a monotonic decreasing function of *S*. The offset term is added to *s(.)* so that the right-hand side of the *scam* equation represents $log\{\mu(S)\}$. The number of spline knots can be determined by *scam* or user-specified within the *s()* code; that is, *s(k=nknots,….)*, where *nknots* is the number of knots. The *scam* developer has recently indicated that the smoothing parameter should also be specified in the *s()* code, such as *s(sp=λ,…)* where λ is the externally supplied smoothing penalty weight. This is different than described by the *scam* documentation.

Predictions of the SR relationship over a fine mesh of *S* values that can exceed the range of observed *S*'s are required to calculate MSY RPs. Cadigan (2013) encountered problems with the *predict.scam* function and used a different approach to extrapolate the SR function for MSY RP calculations. However, these problems seem to have been fixed in the most recent version of the software and *predict.scam* was used in the two case studies in this section.

Cadigan (2013) fixed the number of knots (*q*) at 20 as a compromise between spline flexibility and computational speed for bootstrapping. *q* is an upper limit on the model degrees of freedom (df's) so this number should be large enough that the smoother has sufficient flexibility. There is little harm, other than computational inefficiency, in setting *q* to be too large because both the shape constraint and the smoothing penalty reduce unnecessary smoother flexibility. Results were not sensitive when *q* was increased to 40, although there were some differences in recruitment extrapolations.

Annex 11: Influence of implicit priors in plotMSY

This Annex investigates the influence of implicit priors on the posterior marginal distributions for estimable parameters of the smooth Hockey-stick model in the plotMSY software (Annex 7). It does this by declaring the parameters on the original scale (in ADMB, estimable parameters *ap* and *bp* are declared as "*init_number ap*" and "*init_number bp*") and then alternatively on the log scale and then back-transforming ("*init_number lnap*" and "*init_number lnbp*", then set "*ap=exp(lnap)*" and "*bp=exp(lnbp)*"). The program was compiled and run with the arguments "*-mcmc 10000000 –mcsave 1000*". MCMC diagnostics are shown in Figures A11.1-4, with similar behaviour, whether the implicit priors are on the original or log scales. Figure A11.5 shows negligible difference in the marginal posterior distributions for the two methods, indicating that the implicit priors are having a negligible effect on the plotMSY estimates.
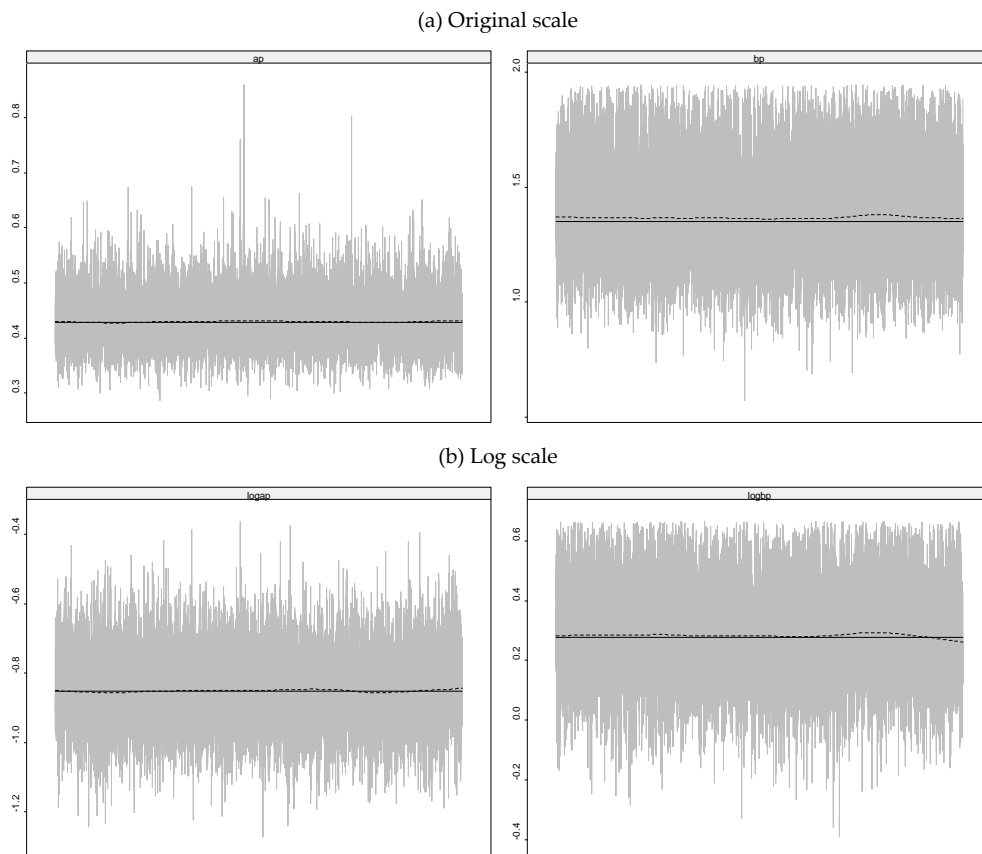

(a) Original scale

(b) Log scale

Figure A11.1. MCMC traces on estimable parameters *ap* and *bp* on the (a) original and (b) log scale. This diagnostic plot is used to decide whether there are undesirable trends.

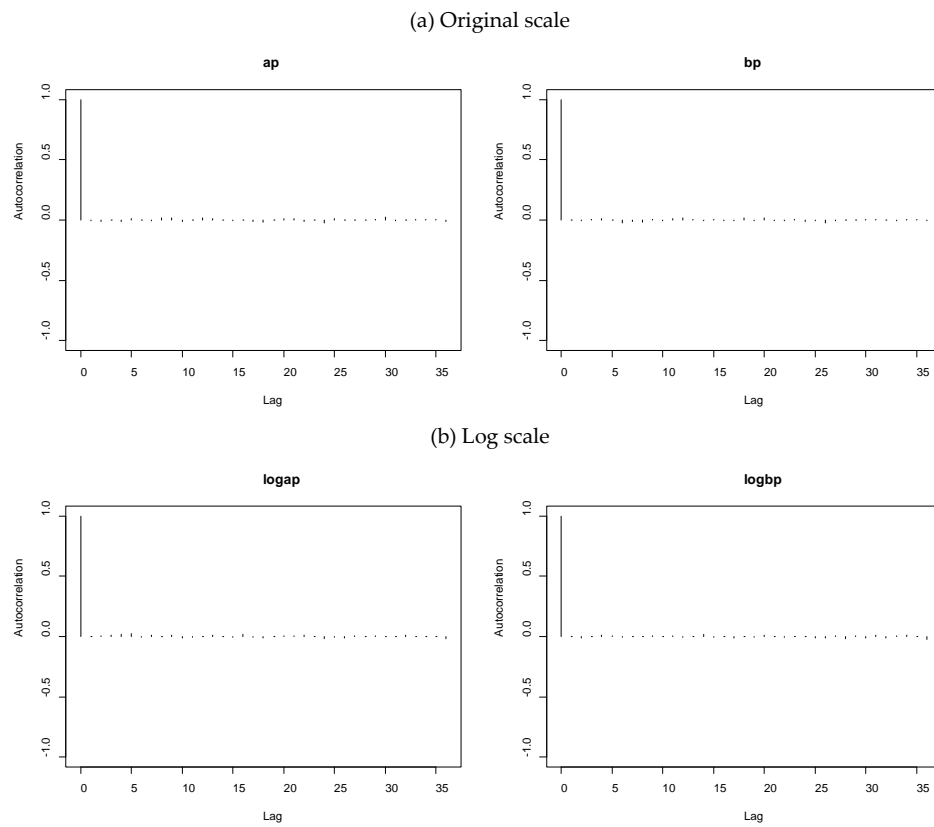(a) Original scale

(b) Log scale

Figure A11.2. MCMC autocorrelation over a range of lag values for estimable parameters *ap* and *bp* on the (a) original and (b) log scale. This diagnostic plot is used to decide whether the MCMC chain needs further thinning.
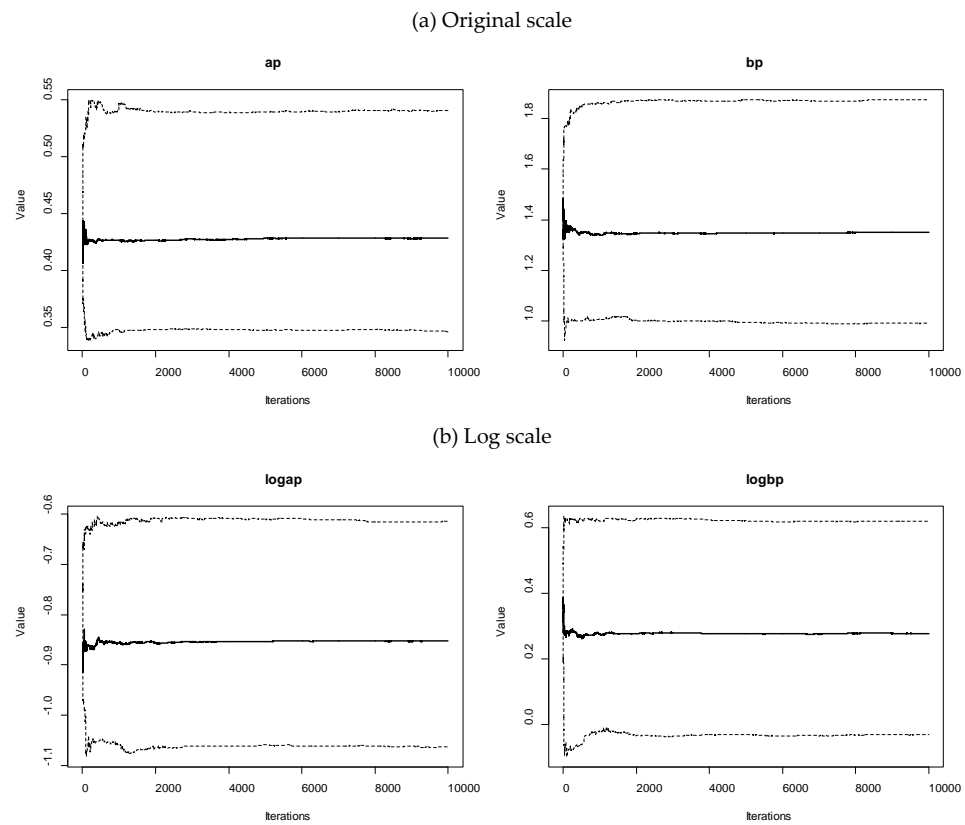
(a) Original scale

(b) Log scale

Figure A11.3. MCMC cumulative quantiles for estimable parameters *ap* and *bp* on the (a) original and (b) log scale. This diagnostic plot is used to decide whether the MCMC chain has converged.
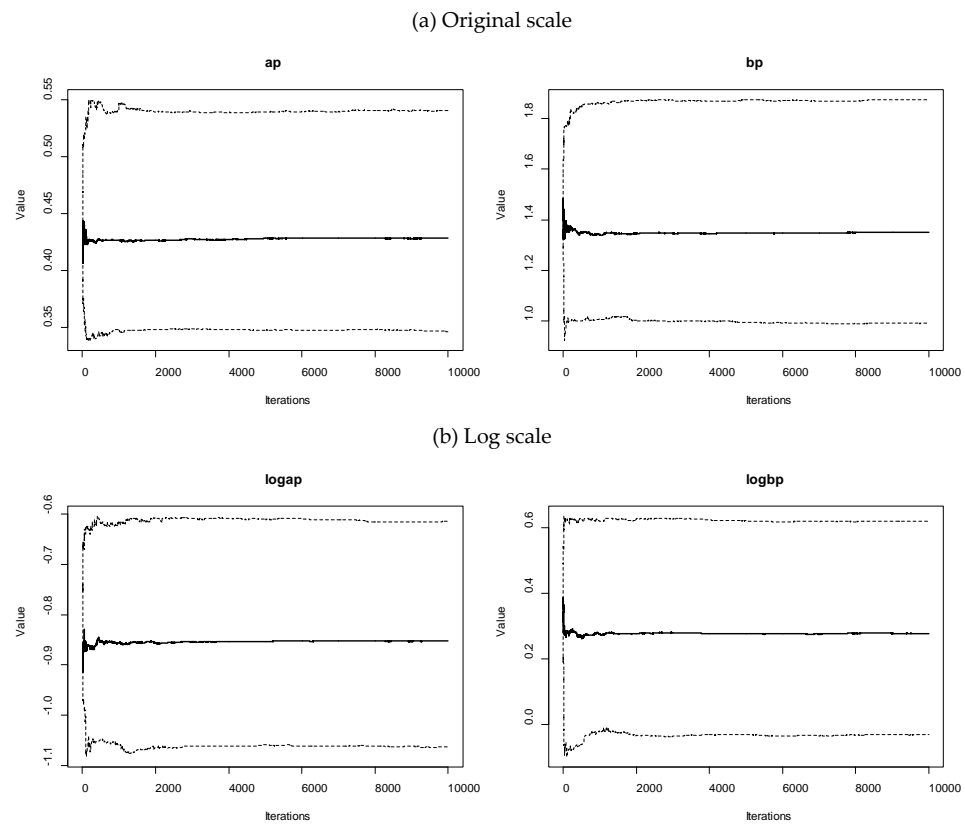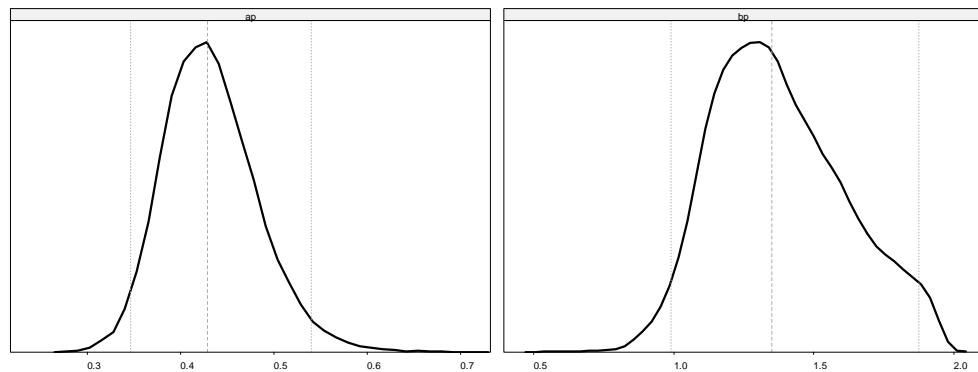
(a) Original scale

(b) Log scale

Figure A11.4. MCMC cumulative quantiles for estimable parameters *ap* and *bp* on the (a) original and (b) log scale. This diagnostic plot is used to decide whether the MCMC chain has converged.
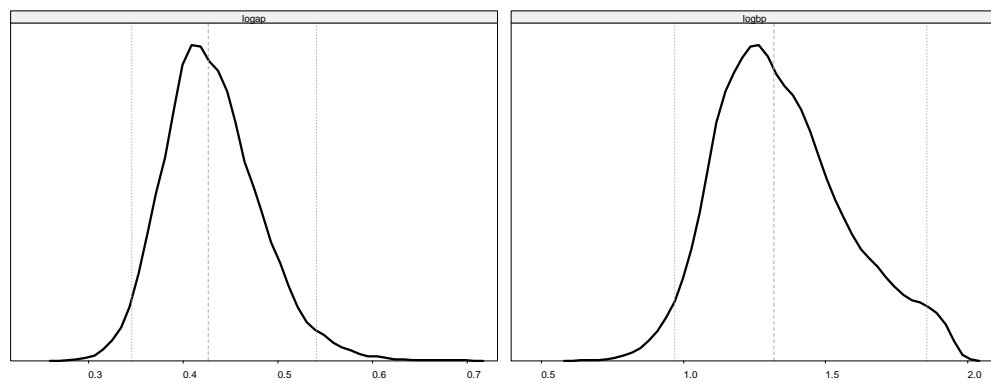
(a) Original scale

(b) Log scale

Figure A11.5. MCMC density for estimable parameters *ap* and *bp* on the (a) original and (b) log scale. This diagnostic plot provides an approximation to the marginal posterior probability density function for these estimable parameters. In (b), the plot shows the estimates back-transformed to the original scale for comparison with (a).