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Report of the Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE IV)

27–31 October 2014

Lisbon, Portugal

International Council for the Exploration of the Sea

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Executive summary

The fourth **Workshop on the Development of Quantitative Assessment Methodologies based on Life-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (**WKLIFE IV**)**, chaired by Carl O'Brien (UK) and Manuela Azevedo (Portugal) was held at IPMA, Lisbon, from 27–31 October 2014. The work conducted addressed five Terms of Reference concerning a collation of the simulation testing of methods undertaken from 2010 to date and based on ICES work carried out in several expert groups, a comprehensive review of data-limited assessment methods and of simulation-tested HCRs that could be used in data-poor circumstances and the development of length-based targets, F-based proxies, size-based assessment methods within DLS and methods using survey data and MSY-based exploitation proxies for Category 3 stocks.

One of the primary conclusions from the simulation work undertaken to date is that the current widely used DLS category 3.2 HCR cannot be applied on its own, particularly when stocks are overexploited, as it fails to recover such stocks. This HCR needs to work in conjunction with a target, and several options have been tested. One area that needs further investigation is the use of the precautionary (PA) buffer, both its magnitude (which may differ depending on DLS category) and duration of application. The goal for the application of the PA buffer is to conserve stocks when there is uncertainty, hence its application should be related to the level of perceived risk. Information on the stock productivity and resilience can provide guidance on the duration of the period between PA buffer applications while guidance on acceptable range of PA buffer should be made by managers, taking into account the economic, biodiversity and ecosystem risks.

Stocks assigned to DLS Category 3 and Category 4 methods have a problem when SSB is declining and when a stock is overexploited. Category 3 methods are the most used this year by ICES in its advice but all the Category 3 HCRs tested lead to increasing biological risk over time and need a target to track movement towards MSY, as a priority. New methods were explored, principally, survey-based methods based on the DATRAS database. Results are consistent for the examples explored. Catch-based methods (CMSY method) were explored further but the outstanding issue of which r-k to use remains an issue and further guidance is a priority. Size-based methods are being validated and all new methods could be applied systematically to all DLS to compare estimates of MSY proxies and then expertise used to reach consensus on appropriate values. However, for length-based methods it is necessary to identify available data and any gaps for which further data collection is necessary before the methods can become operational.

1 Introduction

1.1 Terms of reference (ToR)

The **Workshop on the Development of Quantitative Assessment Methodologies based on Life-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks** (WKLIFE IV), chaired by Carl O'Brien (UK) and Manuela Azevedo (Portugal) will meet in Lisbon, Portugal 27–31 October 2014 to focus on:

1) Collation of the simulation work undertaken to date and based on ICES work carried out in several expert groups; e.g. WKFRAME, WKLIFE, RGLIFE, WKLIFE 2 and WKLIFE III. Based on this collation, define a timetable, methods and tasks to test through simulations the ICES DLS approach. Review past international work on the use of the precautionary buffer, the number of years the precautionary buffer should be applied when giving advice and its magnitude.

2) Further develop the identification of length-based targets and F-based proxies; defining operational procedures for size-based assessment methods within DLS.

3) Continue the development of life-history informed assessments, especially for short-lived species.

4) Continue developing the use of survey data and MSY-based exploitation proxies for Category 3 stocks.

5) Review the FAO technical report (Rosenberg et al., 2014) on data-limited methods development and identify appropriate methods to investigate further with respect to the ICES DLS Categories 5 and 6.

1.1.1 References

Rosenberg, A. A., Fogarty, M. J., Cooper, A. B., Dickey-Collas, M., Fulton, E. A., Gutiérrez, N. L. *et al*. 2014. Developing new approaches to global stock status assessment and fishery production potential of the seas. FAO Fisheries and Aquaculture Circular No. 1086. Rome, FAO. 175 pp.

WKLIFE IV will report by 30 November 2014 for the attention of ACOM.

1.2 Background

WKLIFE IV follows on from the third WKLIFE meeting held in Copenhagen in October 2013 (ICES CM 2013/ACOM:35) and the second WKLIFE meeting and its review (ICES 2012b).

1.3 Conduct of the meeting

The workshop participants made available a number of working documents and presentations which subsequently, formed the basis of the workshop's investigations during the week.

The following working documents were presented:

WD1 - Analysis of Simulated Catch Data with the Latest Version of CMSY. Rainer Froese

WD2 - Evaluation of the Performance of the CMSY Method Against Global Stocks. Rainer Froese

WD3 - Assessing the fishing status of by-catch species using a size-based assessment method. Alexandros Kokkalis

WD4 - Data-poor/limited methods review. Nicola D. Walker, Timothy J. Earl, Jonathan P. Gillson, José A. A. De Oliveira

The following speakers presented the talks indicated:

José de Oliveira – Summary of simulation work.

Helena Geromont – Generic Management Procedures for data-poor fisheries: forecasting with few data.

Helena Geromont – FAO review: data-poor assessment and management methods.

Gianpaolo Coro – Estimating resilience and productivity from catch-biomass trends.

Rainer Froese – Evaluation and simulation testing of CMSY.

Manuela Azevedo – more on … Harvest control rules for data limited stocks using length-based reference points and survey biomass indices.

Manuela Azevedo (on behalf of Giacomo Chato Osio) – Assessing the vulnerability of Mediterranean demersal stocks and predicting exploitation status of un-assessed stocks.

Alexandros Kokkalis (presented via WebEx) – Assessing the fishing status of by-catch species using a size-based assessment method.

During the workshop participants were divided into two subgroups: a length-based assessment and reference points that addressed aspects of ToR 2) and 3) and a catch-based and HCR methods subgroup that addressed ToRs 2) and 4). A set of data-limited stocks, encompassing a diversity of life-history traits, including: pelagic, demersal, elasmobranch, and crustaceans, were used as case-studies to illustrate the application of a suite of data-limited assessment methods.

1.4 Structure of the report

The structure of the report is as follows:

- Section 2 presents the simulation work undertaken to date and based on ICES´ work (ToR 1).
- Section 3 presents a review of data-limited methods (ToR 5).
- Section 4 examines catch-, length- and survey-based methods for ICES stocks in assessment categories 3, 4, 5, and 6 (ToRs 2, 3, and 4)
- Section 5 demonstrates harvest control rules for data-limited stocks (ToRs 2, 3 and 4)
- Section 6 discusses the precautionary buffer's application and risk assessment methods
- Section 7 - discussions and conclusions.

1.5 Recommendations from ICES Expert Groups in 2014

Two expert groups (WGNSSK and WGEF) raised issues that this meeting of WKLIFE has been requested to comment on.

1.5.1 WGNSSK

Issue: *The current rules for category 3 stocks treating survey information as point estimates can lead to substantial changes in advice from year to year despite the TAC constraint of +/-20%. However, an appropriate signal to noise ratio needs to be ensured as basis for advice. Smoothing of time-series or similar methods should be considered. Same issues arise when checking the need for an update of advice for biennial stocks. Agreed guidelines on how to determine whether the perception of the stock has changed given the noise in time-series would avoid subjective interpretations. In general, the absence of biomass or Fproxy targets for category 3 stocks can make the approach less precautionary than for category 2 (e.g. turbot in IV: decrease in TAC with category 2, but increase with category 3, ple-eche: same as for turbot). This also needs further investigation.*

WKLIFE IV response: The identification of MSY proxies for Category 3 and Category 4 stocks is a priority for the next scheduled meeting of WKLIFE using the methods trialled at this fourth meeting of WKLIFE.

1.5.2 WGEF

Issue: *WGEF requires further clarification and scope and objective of PSA analysis applied to the elasmobranch fish and fisheries.*

WKLIFE IV response: ACOM's December 2014 meeting discussed a roadmap to advice on risk to sensitive species, sensitive habitats and key trophic guilds prepared by the chairs of ICES WGSAM, WGMIXFISH, WGNSSK and WGECO. To WGBYC:

Identify sensitive species, such as elasmobranchs, in the North Sea and Celtic Sea for which advice should ideally be given by WGMIXFISH, reference points based on life-history parameter and where possible, provide data on catch by fleet. This is considered a more fruitful activity than pursuing PSA analysis.

1.6 Follow-up process within ICES

The results of this fourth meeting of WKLIFE were presented at ACOM's December 2014 meeting and it was agreed that there will be a fifth meeting of WKLIFE in Lisbon, Portugal on 5-9 October 2015. The initial proposed ToRs are given in Section 7.1.

2 Simulation work undertaken to date and based on ICES´ work (ToR 1)

2.1 European Commission's (EC) Annex IV Evaluations

2.1.1 Evaluation of Category 3 and 4 methods

The EC Communication entitled: Consultation on Fishing Opportunities for 2011 [COM (2010) 241] gave rules for setting TACs (Annex III of the EC Communication) according to 11 stock categories. Some of these rules applied to stocks where it was not possible to provide advice based on a catch forecast in relation to precautionary limits, except for naturally short-lived species. Following a request to ICES to evaluate the Annex IV rules, De Oliveira *et al*. (2010) evaluated the F-based and biomass-based Harvest Control Rules (HCRs) specified in the Annex, using cod and herring-like simulated populations. The F-based HCRs, based on a Pseudocohort analysis and an untuned VPA, were applied with the aim of achieving a previously estimated MSY F. The biomass-based HCRs applied a step function where the TAC was adjusted by a fixed percentage if the change in a biomass index was large enough, and a linear transition function where the TAC was adjusted in proportion to the biomass index, up to a lower and upper limit on the TAC change. The key findings were as follows:

Annex IV rules 1 and 2 (F-based rules):

- Under severely limited data conditions (only 3-year catch-at-age data available), Annex IV rules 1 and 2 (F-based rules) performed exceptionally poorly in terms achieving their intended target of MSY F.

Annex IV rules 4 and 5 a/b (biomass-based rules)

- The current set of Annex IV rules 4 and 5 a/b (biomass-based rules), based on a step function, performed poorly because it did not respond to changes in total biomass when these changes are too small, i.e. less than the 20% threshold which triggered a TAC change. A modification based on a linear transition rather than a step function, was more responsive to changes in total biomass and therefore performed better overall, in terms of achieving a stable SSB, when the biomass index was reliable in terms of trend.
- The objective of keeping SSB stable did not deal with the question of whether that SSB level was appropriate or would lead to optimal yields over time – i.e. it was not necessarily a good place to be. The biomass-based rules did not deal with this concern.
- Performance deteriorated for both biomass-based rules when the survey trend was problematic (e.g. there was a gradual increase in survey catchability over time not accounted for by the HCR).

None of the rules considered in this study delivered in terms of compatibility with maximum sustainable yield; not the F-based rules because they had no control overfishing mortality, nor the biomass-based rules because they were essentially designed to achieve a stable level of biomass, but without a mechanism to also ensure that this level was compatible with MSY.

2.2 Initial WKLIFE meeting

2.2.1 Evaluation of WKFRAME 3 catch rule

This work (De Oliveira *et al*., 2012) evaluated the catch rule proposed by WKFRAME3 in terms of its ability to meet MSY objectives. The catch rule relied on the availability of a time-series of a survey biomass index, and combined three factors in order to provide TAC advice, namely a survey biomass trend factor, a precautionary scale-down factor relating current biomass to a trigger level, and a factor relating current exploitation to MSY levels. The catch rule was intended to be used in circumstances where no analytical assessment existed, so scaling to true stock size became a problem, and the rule relied on proxies for current stock size and MSY levels. Although this study did not help with the problems associated with estimating the three factors, in particular with scaling the biomass index and using suitable proxies, it did explore the behaviour of the catch rule, both when the scaling and proxies were appropriate, and when they were not, and under scenarios representing a limited range of uncertainties. The main conclusions were:

- unbiased estimates of the ratio MSY/B_{MSY} (the MSY rate), exploitation rate and survey catchability were needed in order to deliver MSY targets;
- where a time-lag in the factor relating current exploitation to MSY levels was unavoidable, a TAC constraint was needed to stabilise the catch rule, and a substantially higher risk of unintended stock depletion to low levels was evident;
- when applying the precautionary scale-down factor, it was better to set the biomass trigger level too high than too low.

2.2.2 Evaluation of category 2 and 4 methods

This work was done following the first WKLIFE meeting (at the request of that meeting) but was never formally included in any report. The working document produced at the time is therefore included in Annex 3 to complete the record of simulation work. The work was intended to consider rules that could be used under ICES DLS Categories 2 and 4.

Under Category 2, the simulation work evaluated the case of an assessment that was indicative of trends only by considering biased catch-at-age data (single bias factor applied to all ages and years), and including estimation of an F_{MSY} proxy ($F_{0.1}$ was used), so that application of the HCR (comprising a short-term forecast and the F_{MSY} proxy as a target) was on a relative scale. The analysis also considered different lengths of transition between current F and the F_{MSY} proxy. This analysis found that the HCR would miss its target in the presence of a catchability trend in the tuning index, or when scaling was an issue (catch bias other than 1), and would take longer to reach its target when the stock was overexploited or less productive, or when the transition period was longer. TAC constraints had some stabilizing effect on the HCR. Finally, the analysis found that when scaling is uncertain, a more conservative HCR may be needed, but this could be achieved by using the conservative F_{MSY} proxy of $F_{0.1}$ (though not always).

Under Category 4, the simulation work evaluated two rules using “data-limited” assessment methods, one based on catch curves and another using an un-tuned VPA, that were applied to a full catch-at-age matrix, and derived TAC advice based directly on stock status and exploitation estimates from these assessment methods; this included estimating the F_{MSY} proxy, $F_{0.1}$, in the first year of implementation. Each rule considered either an annual or a multi-annual implementation (the latter based on the number of years to 50% maturity). These HCRs were failures, likely because the assessments they were based on "informed" the HCR on stock status, and more than just catch data are required for this.

2.2.3 Further evaluation of category 2 and 3 methods

This work was requested by RGLIFE, the ICES Review Group that considered the first WKLIFE Report (ICES 2012), and the subsequent analysis reported in Section 2.2.2. The working document produced at the time was not formally incorporated into any report, and is therefore included in Annex 3 to complete the record of simulation work. The work was intended to further evaluate the Category 2 analyses reported in Section 2.2.2, but also Category 3 rules that can use information on current exploitation relative to reference points (e.g. the F_{MSY} proxy of $F_{0.1}$), including reducing exploitation when the biomass index is below a threshold level (e.g. the smallest value over a fixed historic period).

Under Category 2, the evaluation considered a refinement the catch bias in Section 2.2.2, where a "discard" catch bias was applied (bias factors of 0.3 and 0.7 applied to ages 1 and 2 only), and found that although biomass MSY targets were missed, it was possible to achieve F-based MSY targets under both well-managed and overexploited scenarios in the absence of trends in catchability in the tuning index.

Under Category 3, targets were surpassed (even when the stock was overexploited) when introducing information on current exploitation and stock status, with increasing error in the information on exploitation slightly eroding the extent to which targets were surpassed. The behaviour of the Category 3 rules, when used in conjunction with information on exploitation, underlines the importance of including targets in these rule in order to e.g. recover depleted stocks. However, this analysis did not specify (or test for) how these estimates of current exploitation and stock status were derived. Furthermore, the extent to which targets were surpassed indicates a need to "tune" HCRs to the level of information available, and given prevailing uncertainties, to better achieve objectives.

2.3 WKLIFE 3 meeting

2.3.1 Evaluation of the robustness of the DLS framework for providing advice

This work is described in both ICES 2013a and ICES 2013b, and considers whether the ICES DLS framework provides more precautionary advice as one moves down the ICES DLS categories (from the data-rich end of the spectrum to the data-poor end). The simulation work considered a data-rich stock, and systematically stripped data away to force the stock to lower DLS categories, and then compare the catch advice that would result for this stock under each of the DLS categories. For this initial work, feedback was not considered important (i.e. the catch advice did not affect the underlying population); rather, the focus was on keeping identical stock conditions, but changing the amount of information available to the DLS framework, as a means to compare catch advice directly amongst the categories. General conclusions were as follows (ICES 2013b):

- Under a well-managed stock scenario, the DLS framework delivers, in most cases (but not all) more conservative catch advice when there is less data available (i.e. as one moves down the DLS categories) – the one exception is the case where the terminal F assumption is an underestimate in the case where a separable VPA method is used for Category 4.
- 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 provided less conservative catch advice than Category 1.

2.3.2 Evaluation of variants of the category 3.2 method

2.3.2.1 Simple alternatives

An evaluation of variants of the current DLS category 3.2 HCR (the most commonly applied DLS method in categories 2-6) was undertaken during WKLIFE 3, and presented in ICES (2013b). The current HCR does not explicitly use information about the precision of annual estimates of the age-aggregated abundance index (here total biomass was used), and the idea of these simulations was to test whether its performance could be improved if such information were included. The variants were: (a) the HCR was applied only when the change in the index (recent two years compared to preceding three) was significant at the 5% level, (b) a weighted-mean version of the HCR was used, where the weights were the CVs from the index, and (c) a smoother was fitted to the index time-series (a weighted smoothing spline, with the weights being the squared inverse of the survey CVs), with the smoothed values replacing the original values in the HCR. The results were not encouraging, with all four HCRs leading to increased biological risk over time, none of them being considered precautionary in the medium- to long-term, although they all appeared to stabilise SSB and F in the short term (~5 years). This indicates that these HCRs can be used as a stop-gap in the short term until more appropriate HCRs (e.g. those with targets that can recover exploited stocks) have been developed and implemented.

Variants of the DLS category 3.2 HCR that introduced a length-based target ($L_{SQ}/L_{F=M}$), based on life-history information (ICES 2013a and b; see also Jardim *et al*., In press, and Section 5), led to improved performance of the HCR, and in particular was able to move most stocks that were depleted towards recovery. However, the approach relies on the suitability of $L_{F=M}$ as a target, and the quality of life-history information used, and may be hampered by delayed response.

The use of Fproxy methods are another way of introducing targets, and it can be shown that the current DLS category 3.2 HCR is in fact an Fproxy rule with a moving target (ICES 2013a and ICES 2013b). Fixed targets are required, and this can be achieved by e.g. selecting from amongst historic harvest ratios (catch as proportion of stock biomass) which do not appear to have negatively affected the resource.

2.3.2.2 Variants that include learning

ICES 2013a and b considered an HCR that adjusts status quo catches on the basis the variability of biomass index, increasing/decreasing catch advice when the biomass was above/below confidence intervals derived from the biomass index time-series, where this confidence interval was updated as future biomass indices became available, thus “learning”. When the confidence intervals and extent of adjustments were symmetrical, and in the absence of a target adjustment, the HCR led to some improvement in the “development” scenario, but to no improvement in the “overexploited” scenario compared to the DLS category 3.2 HCR. However, Jardim *et al*. (in press; see also Section 5) showed through simulation testing that with asymmetrical confidence intervals and adjustments, substantial improvements in the performance of this survey interval-based HCR was possible.

2.3.3 Length-based alternatives for categories 4 and 5

Length-based targets were used in conjunction with the DLS category 3.2 HCR (Section 2.3.2.1), but Jardim *et al*. (in press; see also Section 5) also evaluated (through simulation tests) the use of the length-based targets (F_{SQ}/F_{MSY}) on their own to adjust status quo catches, and found that they were able to reverse declining trends in biomass, albeit with levels of catches below MSY. Nevertheless, this approach did not prevent some stock declining when they were overexploited. Further simulation-tested HCRs for data-poor circumstances are considered in Section 5.

2.4 Conclusions and future work

This sections summarises the simulation testing of methods that has been conducted since evaluations of the 2010 Annex IV rules were first requested form ICES by the European Commission. One of the primary conclusions from this work is that the current widely used DLS category 3.2 HCR cannot be applied on its own, particularly when stocks are overexploited, as it fails to recover such stocks. This HCR needs to work in conjunction with a target, and several options have been tested. Simulation testing is never “complete”. One area that needs further investigation is the use of the precautionary buffer, both its magnitude (which may differ depending on DLS category) and duration of application. Further simulation testing could help with these questions, but possible combinations (magnitude and duration) would need to be narrowed down to acceptable alternatives in order to make the number of options considered tractable (see also Section 6).

2.5 References

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3 Review of methods for data-limited stocks (ToR5)

3.1 Review of existing methods

3.1.1 Data-limited methods review

A review was conducted of data-limited methods, and this review is given in Annex 4, along with Table A.4.1 summarizing the methods, data requirements, assumptions, outputs and caveats, as well as any testing that was conducted of a given method (including simulation testing). A range of data-limited methods were covered, including methods based on catch data only, but with supplementary life-history information, methods that in addition include supplementary data (e.g. length), life-history and size-based methods, and graphical/empirical methods and alternative approaches (Annex 4, Table A.4.1). In addition to these methods were simulation-tested HCRs that could be used in data-poor circumstances (included in Annex 4, and discussed in Section 5).

3.1.2 Other work

Geromont and Butterworth are currently conducting a review of world practices in fisheries assessment methods for FAO, and part of this work is a review of data-poor assessment methods and their application to management (Geremont, H., presentation in Section 1.3). There is considerable overlap between this work and that in Section 3.1.1, although the FAO review also covers other approaches (e.g. the per-recruit approaches of Beverton and Holt, 1975, and Gedamke and Hoenig, 2006; the length-based approaches of Cope and Punt, 2009; Daan *et al*., 2005 and Prince, 2010; the catch-based approach of Berkson *et al*., 2011; the index-based approaches of Wayte, 2009; Prince *et al*., 2011; Deriso, 1980; Shepherd, 1984; Pope, 1984; Prager, 1992; 1994 and McAllister and Babcock, 2003; and the MPA approaches of Babcock and MacCall, 2011 and Wilson *et al*., 2010). It also cover the method AIM (NOAA Fisheries toolbox: http://nft.nefsc.noaa.gov/AIM.html).

Following the review described in Section 3.1.2, another paper evaluating data-poor methods within an MSE framework came to light, namely Carruthers *et al*. (2014). This paper quantifies the performance of a number of data-limited methods, and found that for most life-histories, methods that made use of only historical catches often performed worse than maintaining current fishing levels. Furthermore, only those methods that dynamically accounted for changes in abundance and/or depletion performed well at low stock sizes, and the use of effort data in addition to historic catches did not necessarily lead to improved performance compared to the simpler methods based on fewer data. The paper also found that there was a high value attached to additional information on stock depletion, historic fishing effort and current abundance when only catch data are available.

3.1.3 Approaches that could inform data-limited methods

The work of Cope *et al*. (2014) (included as part of the review in Annex 4) provides an example of an approach (here PSA) that could inform data-limited approaches (here by using the relationship between vulnerability and depletion to derive priors on depletion for the data-limited method, DB-SRA), and thus improve performance of those methods.

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For other references, see Annex 4: Data-poor/limited methods review.

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4 Catch-, length- and survey-based methods for ICES stocks in assessment categories 3, 4, 5 and 6 (ToR 2, 3 and4)

4.1 Introduction

Information available for ICES stocks in assessment category 3 (stocks for which survey-based assessments indicate trends), category 4 (stocks for which reliable catch data are available), category 5 (data-poor stocks) and category 6 (negligible landings stocks and stocks caught in minor amounts as bycatch) (ICES, 2012a) is of different type and quality. However, it is recognized that stocks within each assessment category may have more data than currently used for assessment purposes, such as survey and/or catch/landings length composition as well as information on life-history traits. During the workshop eight ICES DLS stocks currently assessed with method 3.2 (category 3) and two Icelandic stocks not assessed by ICES were used as case-studies to apply several catch-, length- and survey-based methods. Two criteria were used to select the pelagic, demersal, deep, elasmobranchs and shellfish case-study stocks: having stock expertise present at the workshop and stocks representing different life-history traits. The DLS methods were also applied to three ICES data-rich stocks (category 1, quantitative assessments). Table 4.1.1 presents the type of data available and the DLS methods applied for each stock.

Table 4.1.1. The type of data available and the DLS methods applied for a selected group of stocks in WKLIFE IV.

				Data available			Harvest control rules (HCRs)									
Stock code	Species	Functional group	ICES category	Catch / Landings	Biomass index	Length	CMSY	HS-cpue	LCA	LRPs	Length-based	DCAC	I_{ratio}	L_{target}	I_{slope}	I_{target}
nep-2829	*Nephrops*	Crustacean	3	C	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
pand-bor1	*Pandalus*	Crustacean	3	C	Y	NA	Y	N	N	N	N	N	N	N	N	N
pand-bor2	*Pandalus*	Crustacean	3	C	Y	NA	Y	N	N	N	N	N	N	N	N	N
rjh-pore	Blonde ray	Elasmobranch	3	C	Y	Y	Y	N	Y	Y	N	N	N	N	N	N
rjh-347d	Thornback ray	Elasmobranch	3	L	Y		Y	N	N	N	N	N	N	N	N	N
gfb-comb	Greater forkbeard	Deep-water	3	L	Y		Y	Y***	N	N	N	N	N	N	N	N
usk-oth	Tusk	Deep-water	3	C	Y		Y	N	N	N	N	N	N	N	N	N
lem-nsea	Lemon sole	Demersal	3	L	Y	Y	Y	Y	Y	Y**	N	N	N	N	N	N
bll-nsea	Brill	Demersal	3	L	Y	NA	Y	Y	N	N	N	N	N	N	N	N
sar-78	Sardine	Pelagic	3	C	Y	Y	Y	N	Y	Y	N	N	N	N	N	N
dgs-nea	Spurdog	Elasmobranch	1	L	Y	Y	Y	N	N	Y**	N	N	N	N	N	N
her-47d3	Herring	Pelagic	1	C	Y	Y	Y	N	N	N	N	N	N	N	N	N
cod-347d	Cod	Demersal	1	C	Y	Y	Y	N	N	N	N	N	N	N	N	N

***Y Method applied / data available and used in the method. NA Data not available.**

**** Subset data.**

***** Data not suitable.**

4.2 Survey-based method: Hockey stick cpue

4.2.1 Introduction

At WKLIFE IV, a subgroup evaluated the hockey stick cpue method (hscpue), i.e. the method used by Froese et al. (2015) and Froese and Sampang (2013) to classify the environmental status of data-limited stocks in German marine waters. The concept was explained using the example of North Sea cod (*Gadus morhua*) (Figure 4.2.1.1).

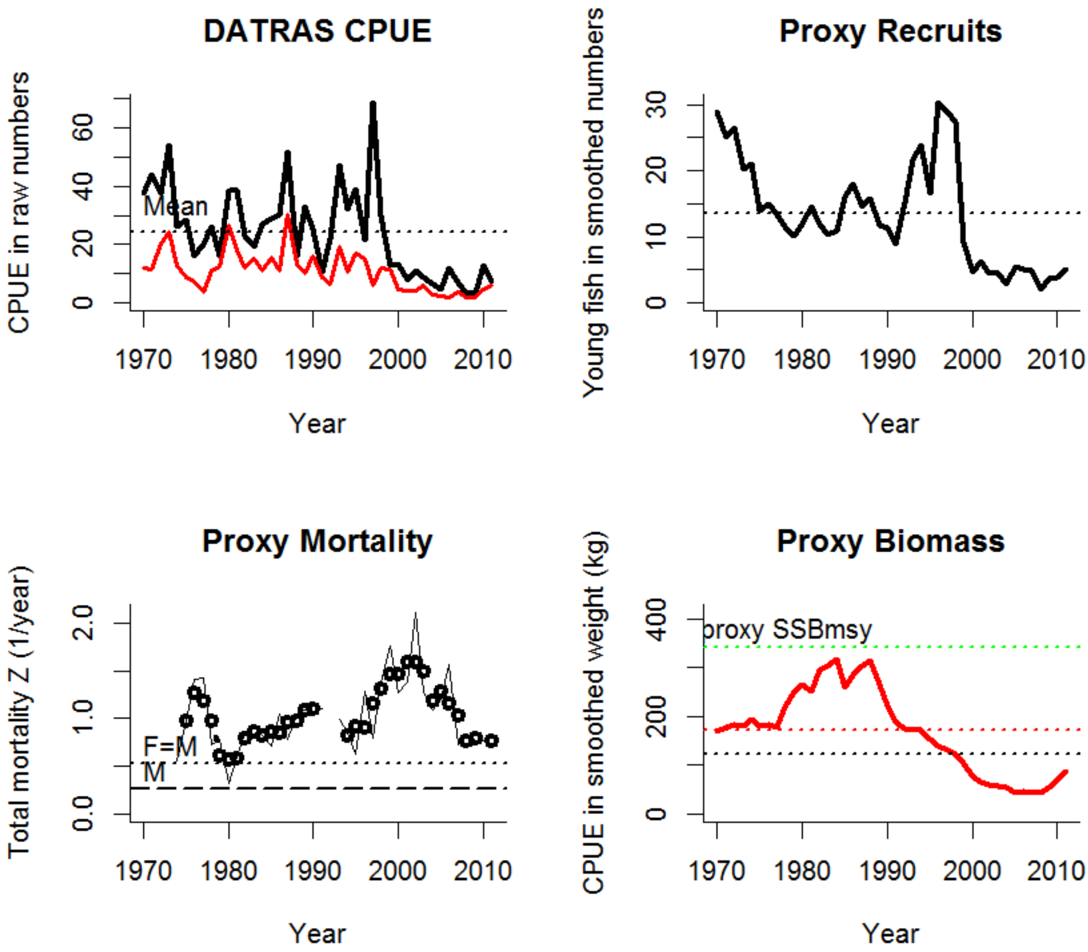

Figure 4.2.1.1. Example of the output of hsCPUE, here for North Sea cod. The "DATRAS cpue" graph shows total cpue in numbers per hour as well as number of mature individuals (red curve). The "Proxy Recruits" graph shows cpue of immature individuals, treated as recruits. The "Proxy Biomass" graph shows the summed-up weight of the mature individuals, treated as proxy for spawning–stock biomass, relative to proxies for Blim and Bpa and 2*Bpa as proxy for Bmsy. The "Proxy Mortality" graph shows estimates of total mortality Z in a framework of M and Z if F=M.

Basically, hsCPUE uses DATRAS SMALK data to obtain a length–weight relationship, von Bertalanffy growth parameters, and a length-at-maturity ogive. An estimate of natural mortality *M* is also needed. hsCPUE then analyses DATRAS cpue-per-Length-per-Area data for a given stock. It uses length at 50% maturity to split cpue in numbers into numbers of immature and mature specimens. The length-weight relationship is then used to turn the length of the mature specimens into weight. Multiplied with numbers at length and summed up, this gives a proxy for spawning-stock biomass. The number of immature fish are considered as proxy-recruits and a plot of proxy recruits over proxy spawning biomass in the year when the recruits were born then gives a stock–recruitment plot. A rule-based hockey stick is fitted to that plot and gives proxies for B_{lim} and B_{pa}, which can be used to evaluate current stock status (Figure 4.2.1.2).

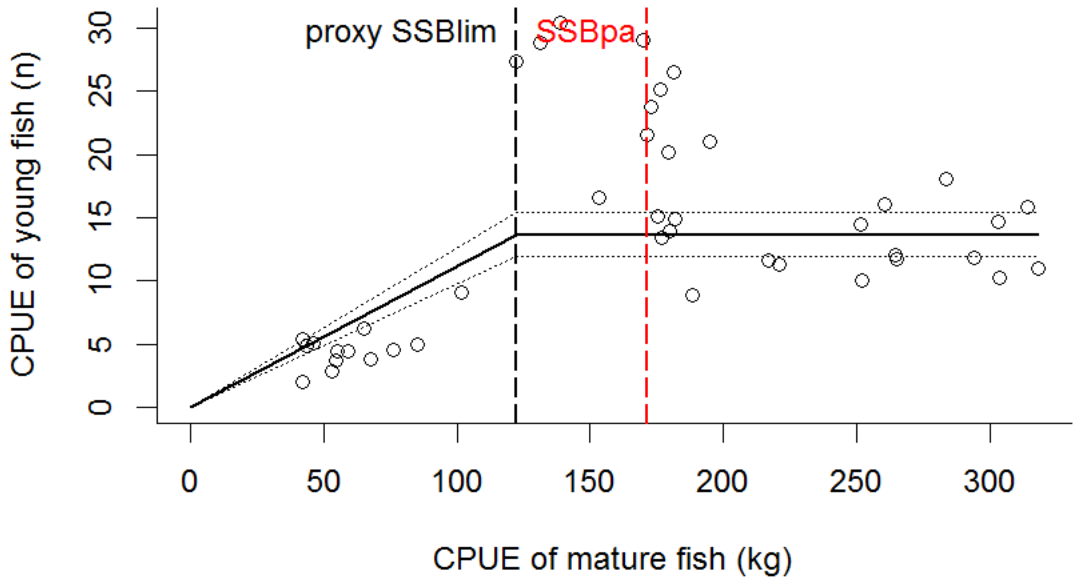

Figure 4.2.1.2. Rule-based hockey stick fitted to proxy recruits and proxy spawners, with indication of proxies for B_{lim} and B_{pa}.

The trends for biomass and exploitation shown in Figure 4.2.1.1 for North Sea cod are in reasonable agreement with the full assessment for this stock (see http://www.ices.dk/sites/pub/Publication%20Reports/Advice/2014/2014/cod-347d.pdf).

4.2.2 Application to selected stocks

The group then tried to apply this method to some of the selected data-limited stocks (Table 4.1.1). Examples are shown below for Lemon sole (*Microstomus kitt*) (Figure 4.2.2.1 and Figure 4.2.2.2) and for North Sea brill (*Scophthalmus rhombus*) (Figure 4.2.2.3 and Figure 4.2.2.4). DATRAS data were insufficient for the application of the method to Great Forkbeard (*Phycis blennoides*).

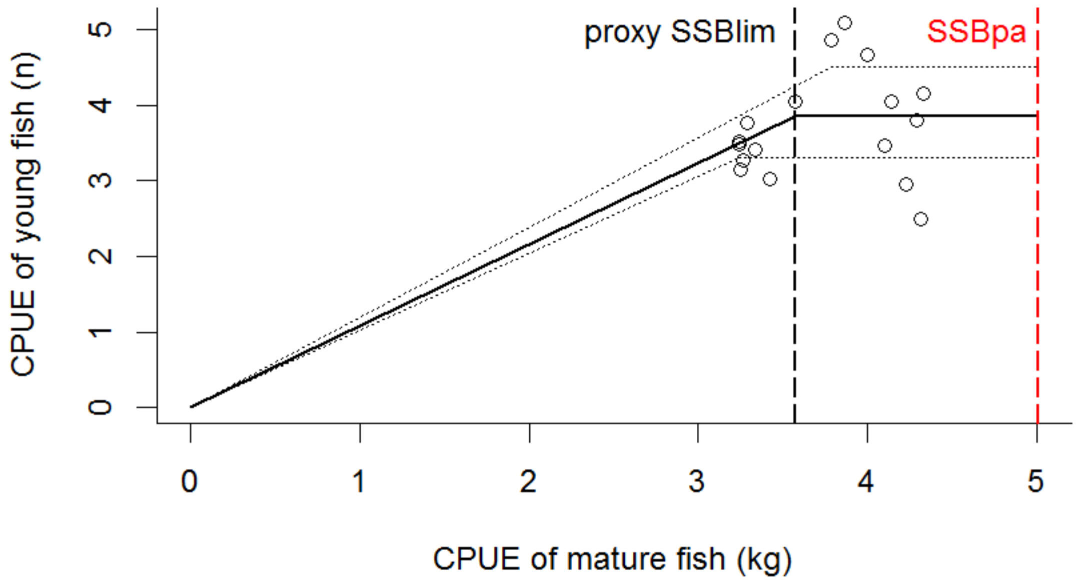

Figure 4.2.2.1. Proxy stock–recruitment relationship for Lemon sole.

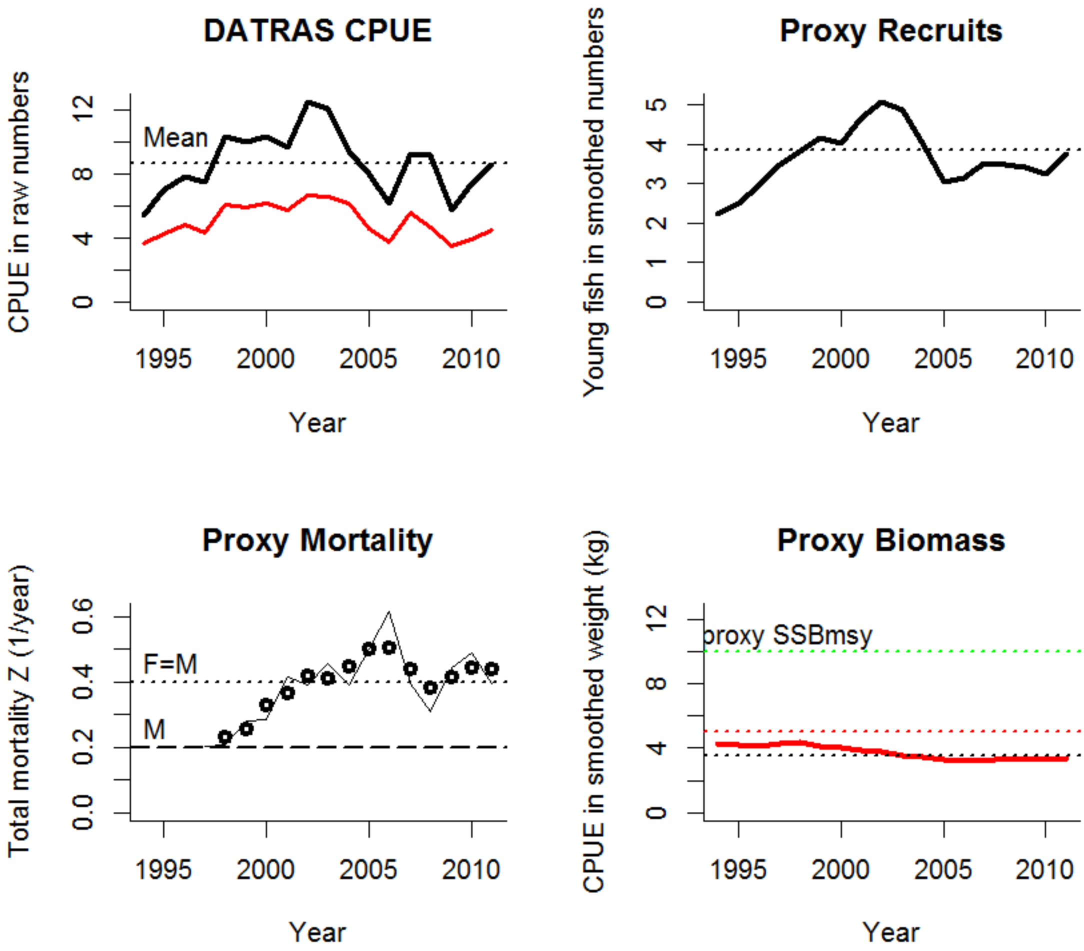

Figure 4.2.2.2. Results of hsCPUE analysis for Lemon sole.

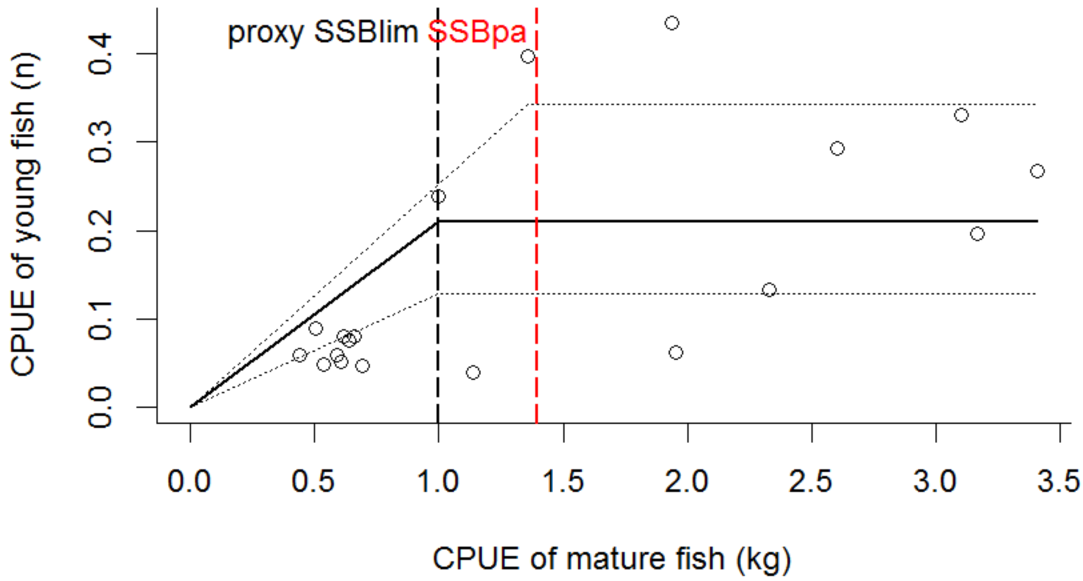

Figure 4.2.2.2. Hockey stick fitted to cpue data for North Sea Brill.

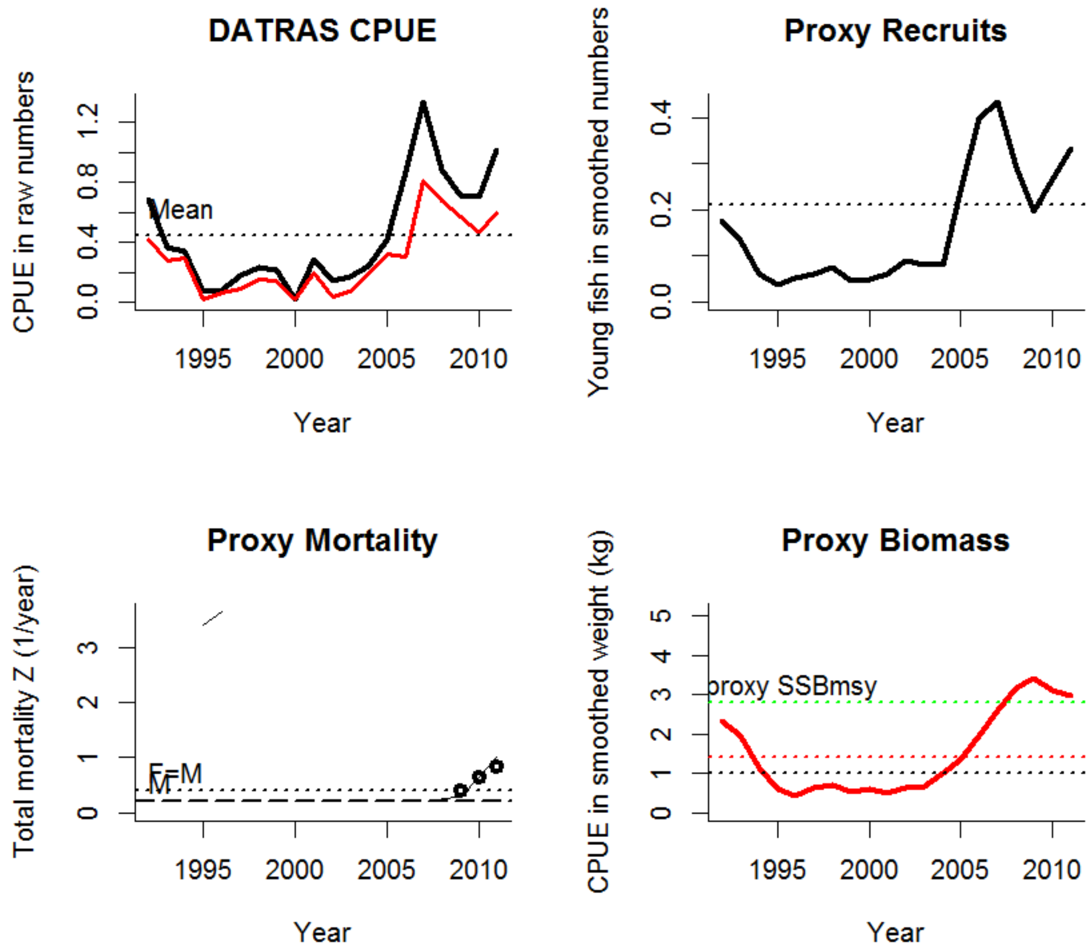

Figure 4.2.2.3. Results of the hsCPUE analysis for North Sea Brill.

4.2.3 Conclusions and future work

The results for lemon sole and North Sea brill seem consistent with other assessment, but clearly more testing is needed. For example, it is well known that cpue data vary widely between areas and even quarters. It is therefore important to decide before the hsCPUE analysis which area(s) and quarter (only one!) is to be used consistently for a given stock. There were also concerns about the determination of recruits when the length at full selection by the gear overlapped with the length at first maturity.

The hsCPUE code used at the workshop was apparently not the latest version, which should instead be tested. For example, the hockey stick did not fit the data in at least one example. In summary, while this approach appears promising and makes good use of available data, it needs more scrutiny and maybe recoding of the R-code before it can be used on a regular basis.

4.3 Catch-based method CMSY

4.3.1 Introduction

CMSY is a method for estimating maximum sustainable yield (*MSY*) and related fisheries reference points from catch data and resilience. It is an advanced implementation of the Catch-MSY method of Martell and Froese (2013). If managers, experts or stakeholders have a perception about the depletion history and the current status of a given stock, then CMSY can test the compatibility of such hypothesis against observed catches and the known resilience of the species. If combinations of productivity and stock size are found that are compatible with catches and resilience, then the stock status and exploitation rate are presented in an MSY-framework.

As with the Catch-MSY method, prior parameter ranges for the maximum intrinsic range of population increase (*r*) and for unexploited population size or carrying capacity (*k*) are filtered with a Monte Carlo approach to detect 'viable' *r-k* pairs. A parameter pair is 'viable' if the corresponding biomass trajectories calculated with a Schaefer model are compatible with the observed catches, in the sense that they do not overshoot carrying capacity nor crash the stock. Also, predicted biomass shall be compatible with prior estimates of relative biomass ranges for the beginning and the end of the respective time-series. Optionally, a third intermediate prior biomass range can be provided to reflect extraordinary year classes or stock depletions. Also optionally, an indication whether the stock is likely to crash within three years if current catches continue can be given. This will improve the estimation of biomass in the final years.

A plot of viable *r-k* pairs typically results in a triangular-shaped cloud in log-space. CMSY differs from the Catch-MSY method by searching the most probable *r* not in the center but rather in the tip-region of the triangle, because it is the mean of maximum viable *r*-values that is sought. The final CMSY algorithm is still under development.

4.3.2 Material and methods

CMSY is written in R and the version used at the workshop was CMSY_22.r. This was made available from the share point to participants, several of whom installed it on their PCs and were able to run the software successfully, after installation of RJAGS and some required libraries.

The CMSY method requires prior information about the range of possible *r*-values for the considered species. As a proxy for *r*-ranges, the resilience of the species as stated in FishBase (www.fishbase.org) can be used. Similar to the original Catch-MSY method by Martell and Froese (2013), *R*-ranges shown in Table 4.3.2.1 were used as corresponding to the respective resilience category. In a real CMSY application for stock assessment, experts are of course free to use more suitable prior ranges for *R*.

Table 4.3.2.1. Prior ranges for parameter *R*, based on classification of resilience.

Resilience	Prior *R* range
High	0.6 – 1.5
Medium	0.2 – 0.8
Low	0.05 – 0.5
Very low	0.015 – 0.1

The CMSY method requires prior estimates of relative biomass at the beginning and end of the time-series, and optional also in the middle. For the purpose of this test, one of the possible two broad ranges shown in Table 4.3.2.2 was applied. The stocks assessed at WKLIFE 4 were selected such that experts could provide guidance on stock depletion history and current status and whether the stock was likely to crash within 3 years if current catches were to continue. In a real CMSY application for stock assessment, experts are of course free to use more suitable prior ranges for relative biomass.

Table 4.3.2.2. Prior relative biomass ranges *B/k* used by CMSY for analysing the simulated data.

Point in time-series	Strong depletion	Low depletion
Beginning	0.1 – 0.5	0.5 – 0.9
Intermediate	0.01 – 0.4	0.3 – 0.9
End	0.01 – 0.4	0.4 – 0.8

CMSY input data are contained in two files, here WKLIFE4Stocks.csv and WKLIFE4ID.csv. The first file contains time-series of catch and total biomass, with mandatory headers for the stock ID "stock" (e.g. "her-47d3"), a column for the years with available data "yr" (e.g. 1947..2013), a column for catches "ct" (e.g. 581760..511416) and an optional column for total (=exploited) biomass or cpue "TB" (e.g. 7053207..3937277). The second file contains information about the stock and the priors to be used for *r, k*, initial relative biomass and final relative biomass, and the "FutureCrash" indicator with options "Possible" or "No". A column with header "Btype" classifies available total biomass data as "observed", "simulated", "cpue", or "None", i.e. CMSY can also be used if no biomass or cpue data are available.

In order to obtain suitable reference points for the evaluation of the quality of CMSY prediction, we also fitted a full Schaefer model using a Bayesian approach. In this case, the Schaefer function is taken as the model for estimating the most probable *r-k* pair from biomass and catch trends. The Bayesian model fits the real data by modifying the estimation of likelihood and prior density functions, which model the distribution of random variables associated to r and k. Once the model has estimated the probability densities of r and k, it calculates their most probable values. Differently from other approaches (e.g. MacAllister *et al*., 2001), our Bayesian model uses prior expert knowledge about the resilience of a species and the initial and final biomass status to restrict the search for the optimal pair in the r-k space. We implemented the Bayesian model using the JAGS package of the R programming language and the BUGS formalism. Although the applicability of the full Schaefer is limited to the cases in which a biomass trend is available, the model produces precise confidence levels, thus it can be considered a good reference against which the results of CMSY can be compared.

4.3.3 Results

CMSY was applied at the workshop to altogether 17 stocks, including fully assessed stocks (D1), data-limited stocks (D3.2), and simulated stocks. The results are summarized in Table 4.3.3.1 and are given in full detail in Annex 5. For every analysed stock, CMSY produces a screen printout describing the analysed data, the priors, the results of the full Schaefer analysis, and the results of CMSY. For visual examination, CMSY also produces standardized graphs. Figure 4.3.3.1 shows such graph for North Sea herring (*Clupea harengus*, her-47d3).

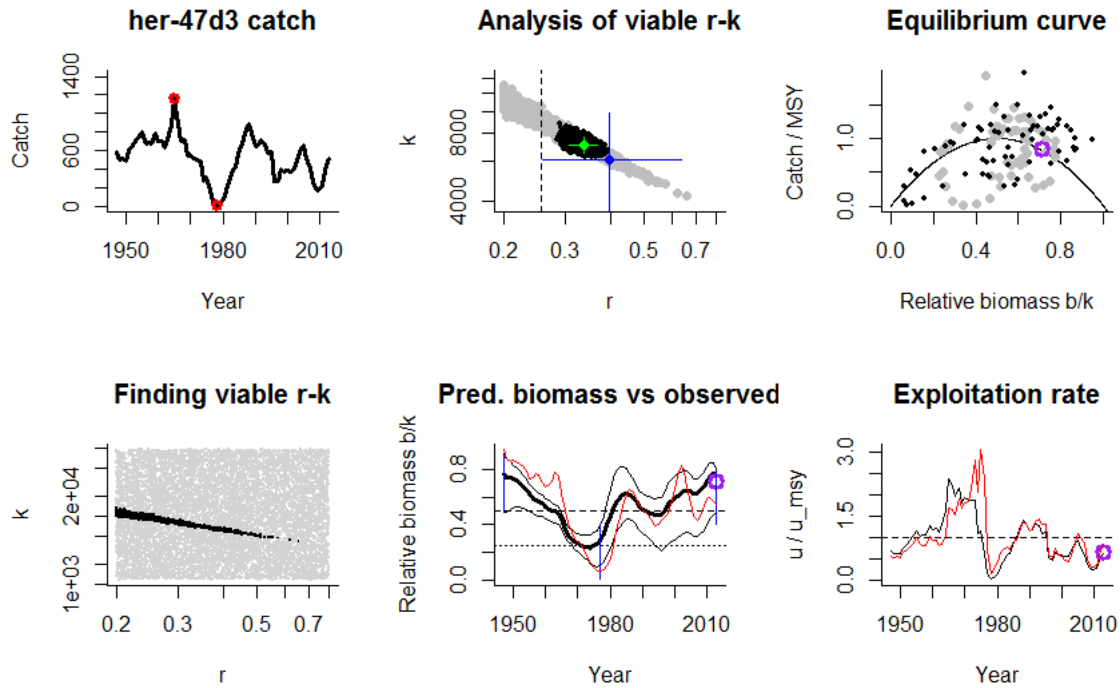

Figure 4.3.3.1. Graphical output of CMSY applied to the fully assessed North Sea herring stock.

The “[stock] catch” graph in the upper left indicates the acronym used for the stock by the assessment working group (here: her-47d3), and shows the time-series of catch data used by CMSY. The red circles indicated the highest and the lowest catch, respectively. If the user does not provide prior information on biomass ranges, simple prior rules are applied to catch relative to maximum and minimum catch, and are used to establish likely relative biomass ranges for the beginning and the end of the time-series, as well as for an intermediate year (blue vertical lines in in the “Pred. biomass vs. observed” graph.

The “Finding viable r-k” graph shows the filtered log-r-k-space, with viable r-k pairs in black and initially tested pairs in grey. While CMSY is executed, this graphs shows progress by adding black dots as viable r-k pairs are found. This search for viable r-k pairs is the most time-demanding part of CMSY.

The “Analysis of viable r-k” graph shows the result of the CMSY-analysis, with viable pairs in grey and the predicted most probable r-k pair in blue, with 95% confidence limits. The black dots are viable pairs identified by the Bayesian implementation of the full Schaefer model, with the green dot showing the predicted most probably r-k pair, with 95% confidence limits. The green dot from the full Schaefer analysis is deemed more reliable and is used as reference for the blue dot from CMSY. The r-k pairs to the left of the vertical dashed line are excluded from the analysis, as this section of the viable r-k space is not expected to contain the maximum intrinsic rate of population increase.

The “Pred. biomass vs. observed” graph shows in bold the median relative biomass trajectory predicted by CMSY, with 2.5th and 97.5th percentiles. The red line shows the biomass trajectory from the assessment relative to the k estimated by the full Schaefer method. The dashed horizontal line at 0.5 k indicates B_{msy} and the horizontal dotted line at 0.25 k indicates the border to stock sizes that may result in reduced recruitment.

The blue vertical lines show the prior biomass ranges set by the user or by prior rules applied to the catch pattern. In the example of Figure 1, it was assumed that the user knew that the herring stock was, high (0.5–0.9 k) after World War II, low (0.01–0.4 k) in the 1970s, and high (0.4–0.8 k) again at the end of the time-series. The purple point in the final year indicates the 25th percentile of predicted biomass, which could be used as precautionary starting point for harvest control rules.

The "Equilibrium curve" graph shows the Schaefer parabola with catch expressed relative to MSY on the Y-axis and biomass relative to k on the X-axis. Grey dots are catch over biomass predicted by the CMSY method. Black dots are catch relative MSY from the full Schaefer model over biomass from the assessment over k from the full Schaefer model. Dots falling on the parabola indicate catches that will maintain the corresponding biomass. Dots above the parabola will shrink the biomass; dots below the parabola allow the biomass to increase. The purple point shows the catch in the last year over the 25th percentile of predicted biomass.

The "Exploitation rate" graph shows the time-series of the catch/biomass ratio (u) relative to the ratio corresponding to MSY, where $u_{msy} = 1 - e^{-r/2}$. This conversion accounts for the fact that r relates catches to the average annual biomass, whereas the biomass data used in assessments represent biomass at the beginning of the year. The black curve is the exploitation rate resulting from catch relative to biomass predicted by CMSY. The red curve relates catch to the biomass from the assessment, scaled by using the r estimated by the full Schafer model. The dashed horizontal line indicates the maximum sustainable exploitation rate. The purpule pont in the final year shows catch over the 25th percentile of predicted biomass, as a potential precautionary starting point for harvest control rules.

Figure 4.3.3.2 shows an example for a data-limited stock (here: tusk, *Brosme brosme*, usk-oth), where only catch and catch-per-unit-of-effort data from standardized surveys were available. In such stocks, the full Schaefer model was not applied because the quality of the cpue data was not considered reliable enough. Therefore, no reference point is available in the "Analysis of viable r-k" graph and no black dots are shown in the "Equilibrium curve" graph. Instead, the cpue data are plotted on a second Y-axis (in red) in the "Predicted biomass vs. cpue" graph and in the "Exploitation rate" graph. Here, we would expect the biomass trajectory predicted by CMSY to show a similar trend as the cpue data, and the exploitation rate trajectory predicted by CMSY to show a similar trend as the catches relative to cpue. If these trends are similar, as in the example shown in Figure 4.3.3.1, then this builds confidence in the CMSY-predictions.

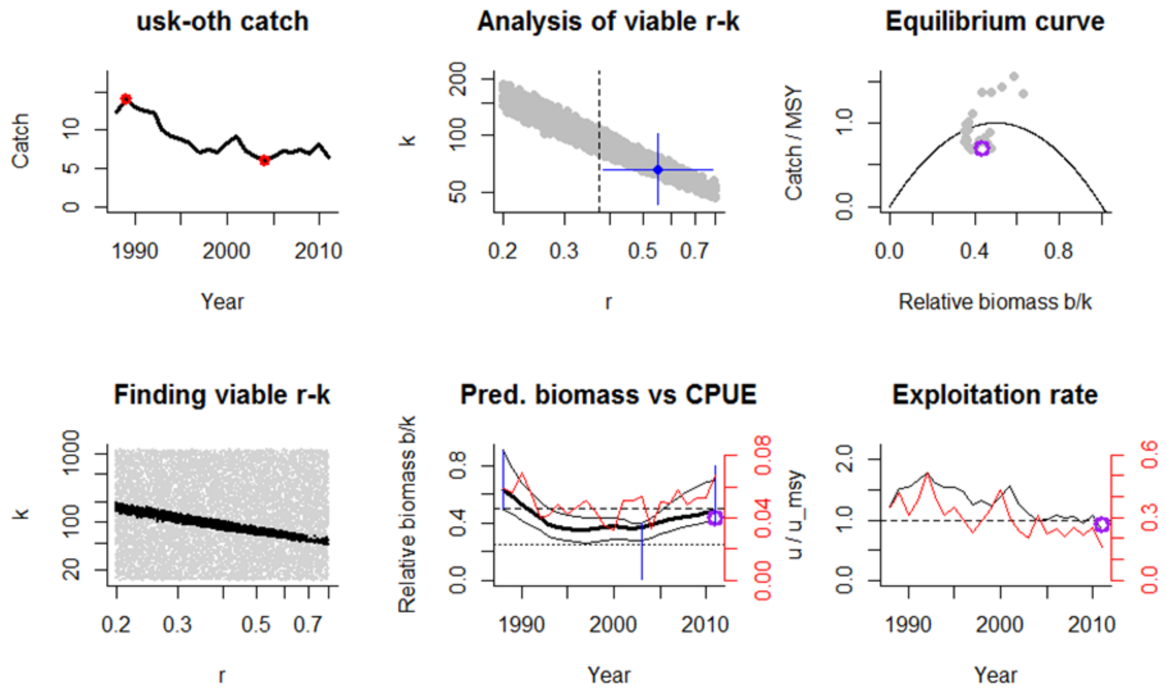

Figure 4.3.3.2. Tusk (*Brosme brosme*) as an example of CMSY graphical output for a stock where only catch and cpue data are available. Cpue data are shown directly on a second Y-axis in red in the "Pred. biomass vs. cpue" graph. In the "Exploitation rate" graph, the catch/cpue ratio is shown in red against a second Y-axis. Note that the trends for biomass and exploitation rate predicted by CMSY correspond well with the respective trends based on cpue.

In the remaining figures (Figures 4.3.3.3–4.3.3.11) we report the results for the other stocks indicated in Table 4.3.3.1. Detailed results and estimations are given in Annex 5.

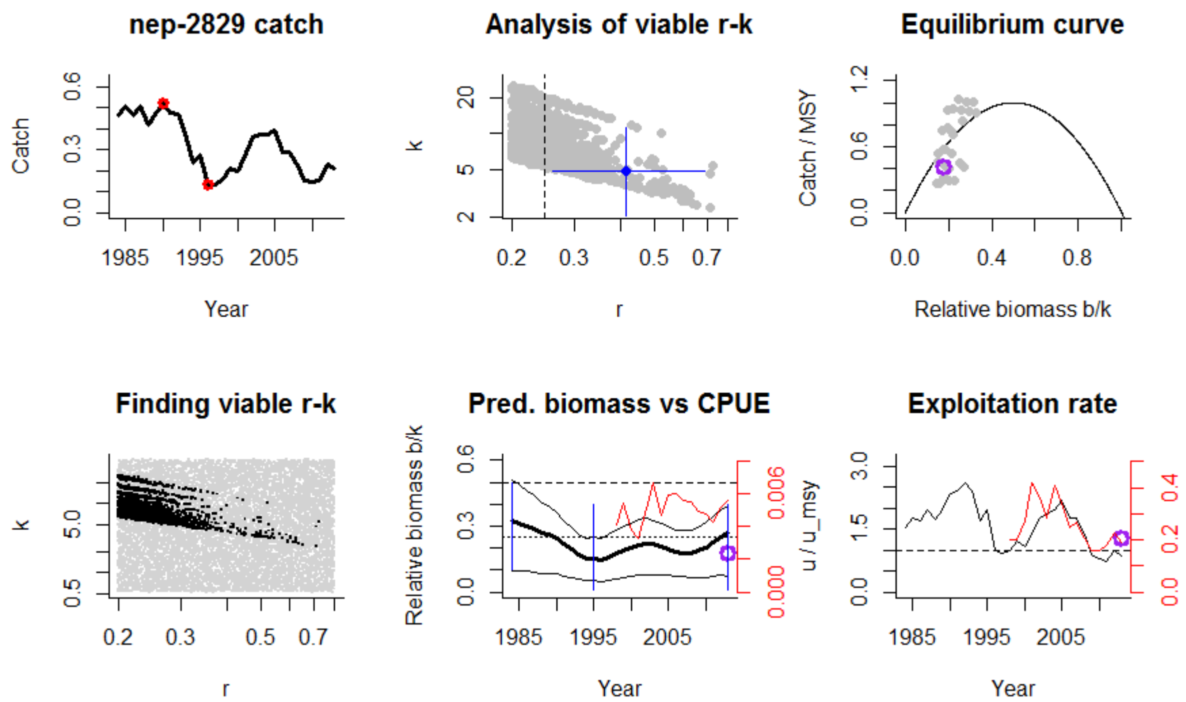

Figure 4.3.3.3. CMSY results for *Nephrops* in Functional Units 28 and 29 (nep-2829).

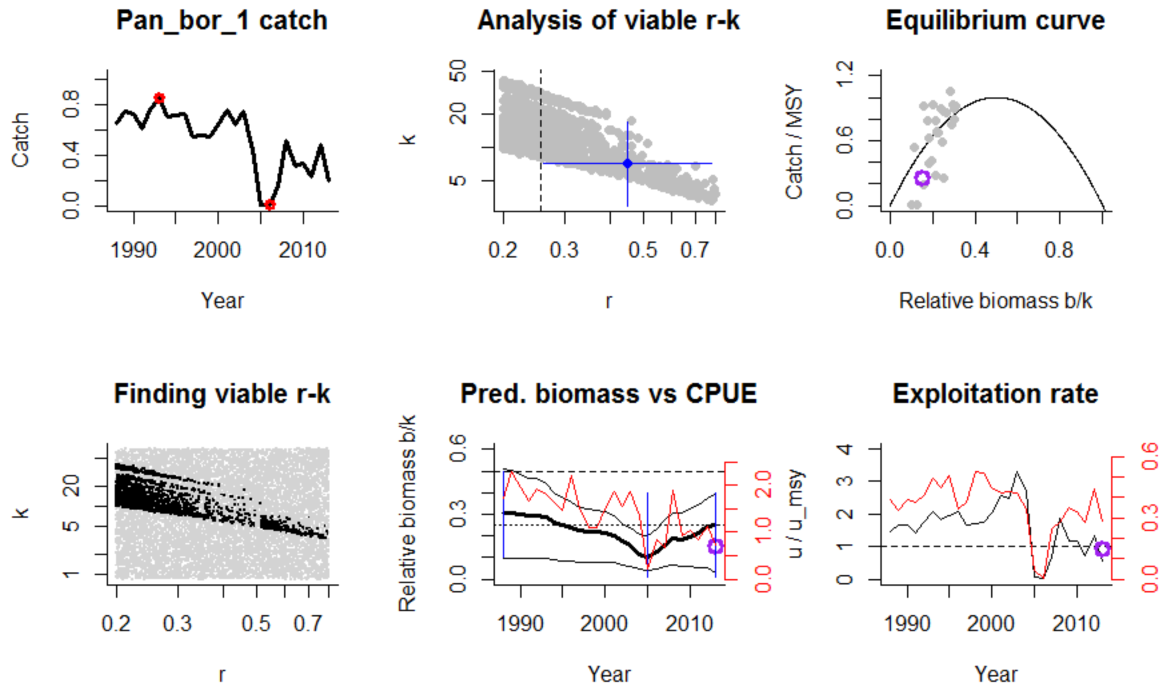

Figure 4.3.3.4. CMSY results for an Icelandic *Pandalus* (pand-bor_1).

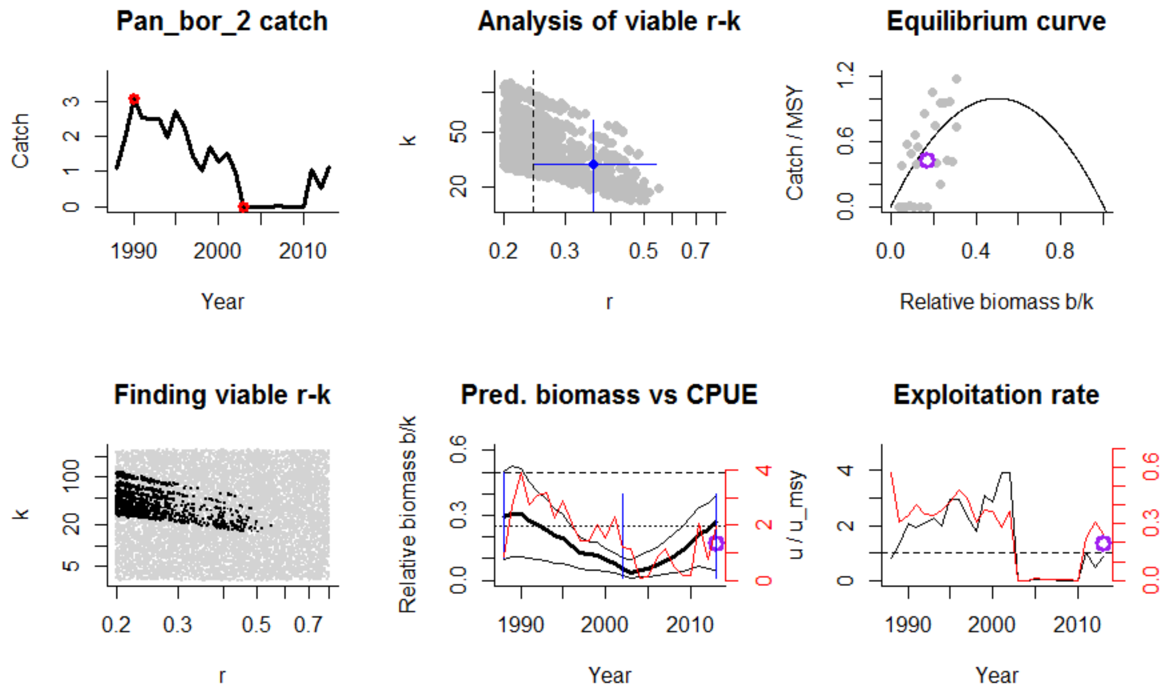

Figure 4.3.3.5. CMSY results for an Icelandic *Pandalus* (pand-bor_2).

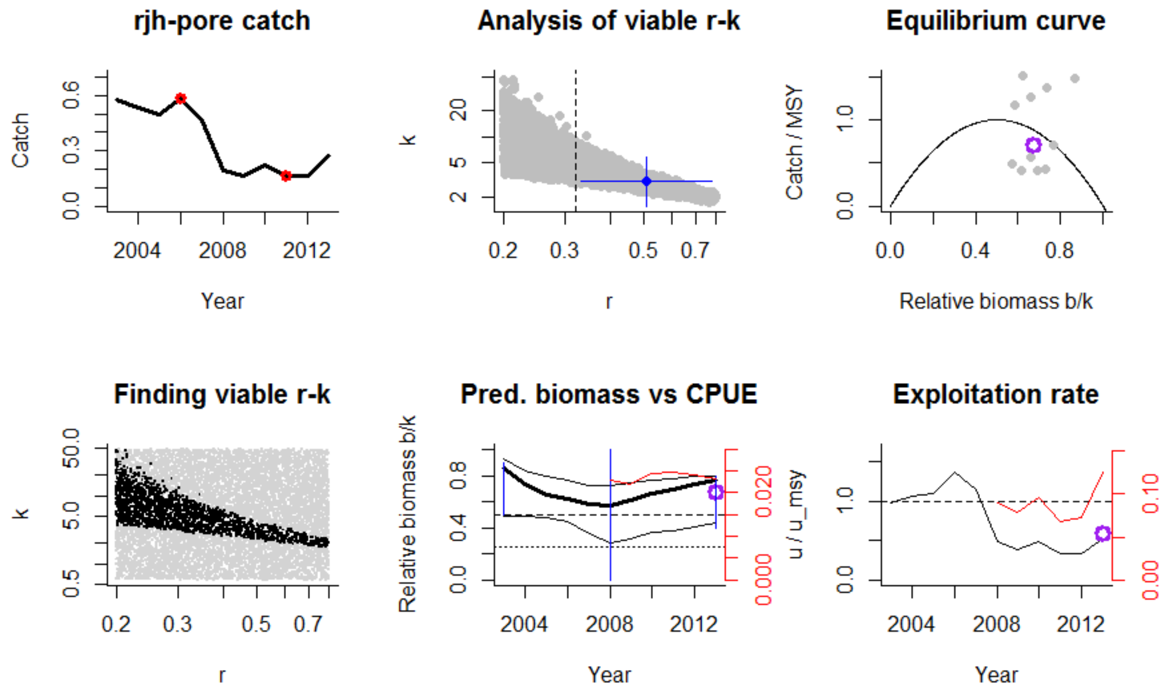

Figure 4.3.3.6. The CMSY results for Blonde ray (rjh-pore).

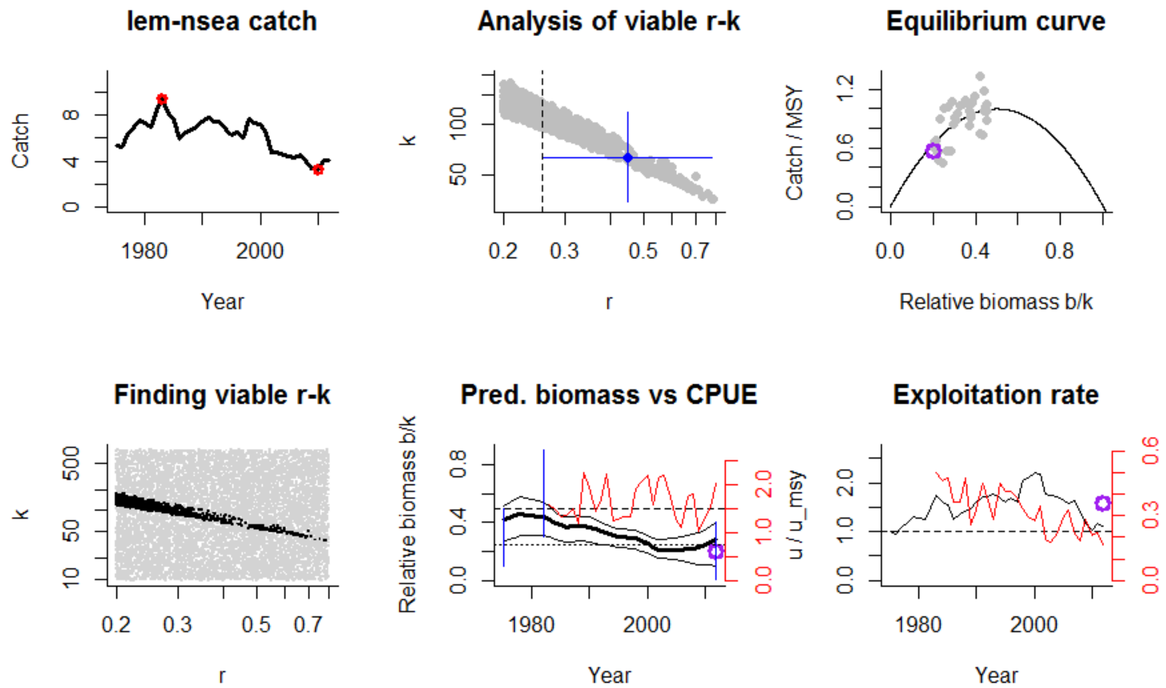

Figure 4.3.3.7. The CMSY results for Lemon sole in the North Sea (lem-nsea).

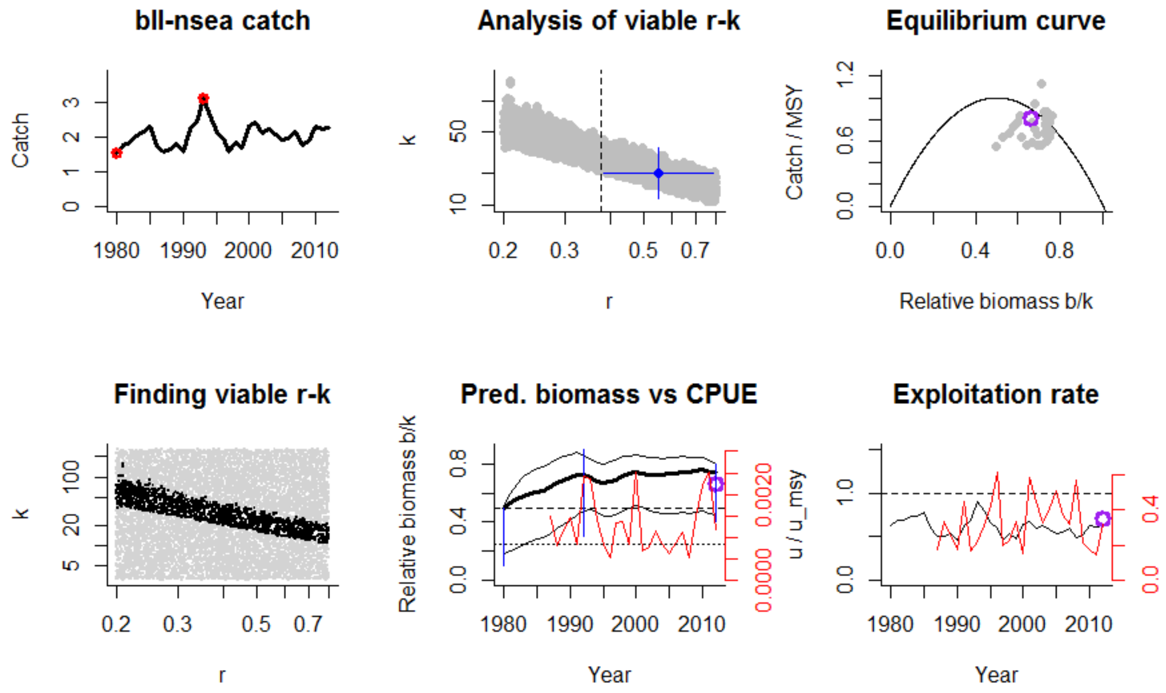

Figure 4.3.3.8. The CMSY results for Brill in the North Sea (bll-nsea).

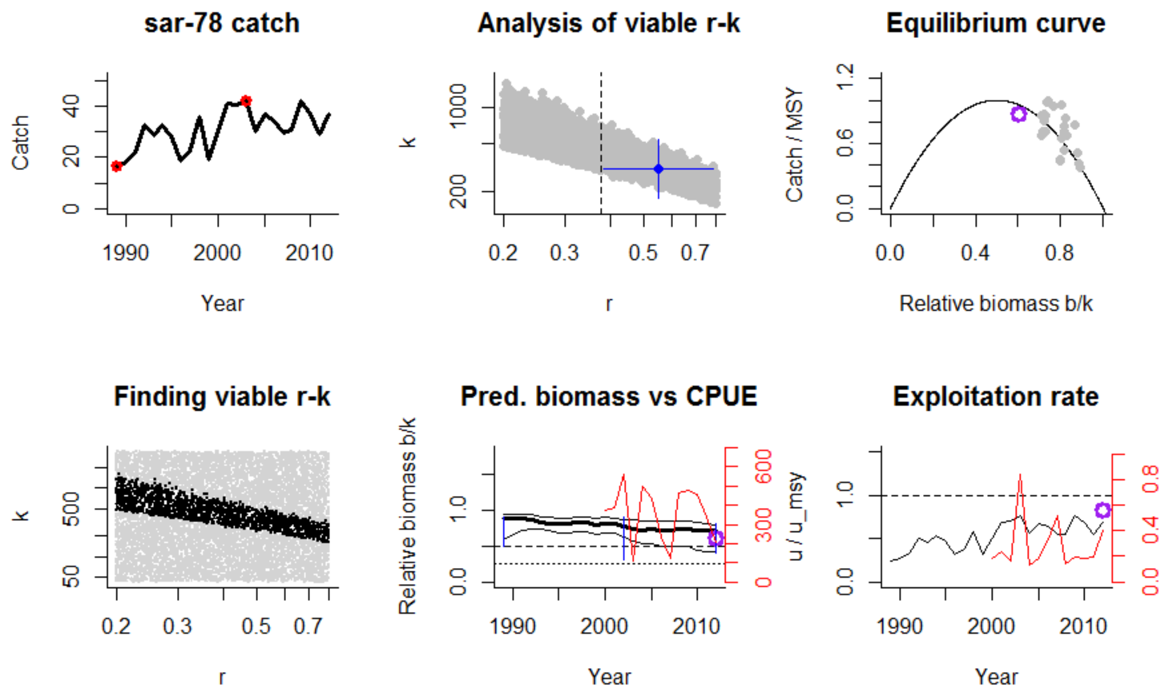

Figure 4.3.3.9. The CMSY results for Sardine in areas 7 and 8 (sar-78).

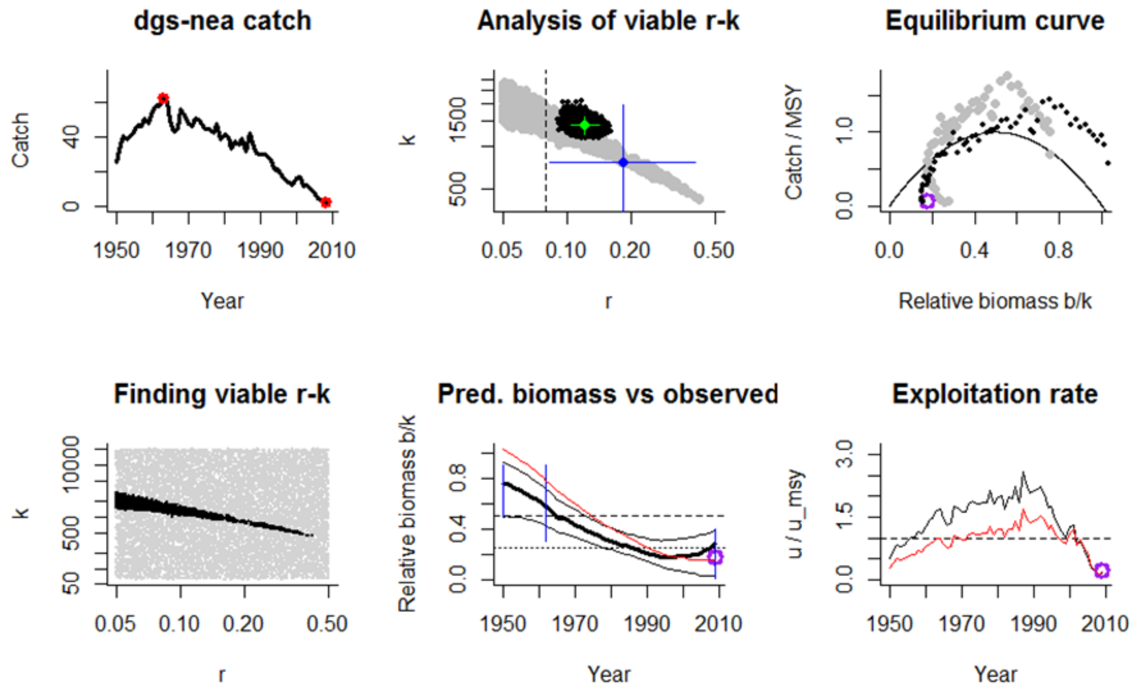

Figure 4.3.3.10. The CMSY results for Spurdog in the Northeast Atlantic (dgs-nea).

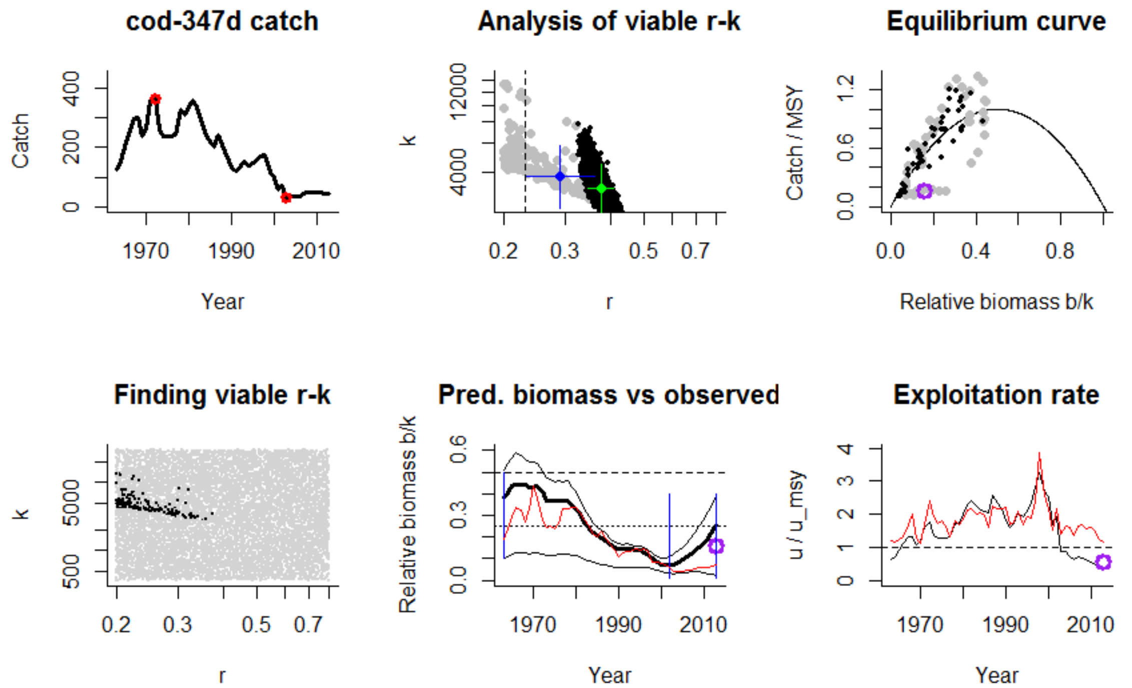

Figure 4.3.3.11. The CMSY results for North Sea Cod (cod-347d).

Table 4.3.3.1. Overview of stocks assessed with the CMSY method at WKLIFE IV, with a summary of the assessment relative to the MSY framework, and some comments as to the perceived goodness of the assessment. Data-limited stocks are marked with an asterisk in the first column.

Stock	Name	Species	Biomass	Exploitation	Comment
bll-nsea*	Brill	*Scophthalmus rhombus*	Above B_{msy}	Below F_{msy}	Consistent with cpue
cod-347d	Cod	*Gadus morhua*	At half B_{msy}	Below F_{msy}	Good fit with observed biomass; too optimistic in last years where B <= $0.5B_{msy}$
dgs-nea	Spurdog	*Squalus acanthias*	At half B_{msy}	Below F_{msy}	Reasonable fit with observed biomass, too optimistic in last years where B <= 0.5 B_{msy}
her-47d3	Herring	*Clupea harengus*	Above B_{msy}	Below F_{msy}	Good fit with observed biomass
had-346a	Haddock	*Melanogrammus aeglefinus*	Below half B_{msy}	Below F_{msy}	Catch data used; good fit with observed biomass
had-346a	Haddock	*Melanogrammus aeglefinus*	Below half B_{msy}	Below F_{msy}	Landings data used; same relative assessment as with catch
HLH_M	HLH_M	Simulated medium resilience, high-low-high biomass	Above B_{msy}	Below F_{msy}	Simulated catch used, good fit with simulated data
HLH_M07	HLH_M	Simulated medium resilience, high-low-high biomass	Above B_{msy}	Below F_{msy}	Simulated landings = 0.7*catch used; same relative assessment as with catch data
gfb-comb*	Great Forkbeard	*Phycis blennoides*	Near half B_{msy}	At F_{msy}	Good fit with cpue; maybe too optimistic in last years where B <= 0.5 B_{msy}
lem-nsea*	Lemon sole	*Microstomus kitt*	Near half B_{msy}	At F_{msy}	Reasonable fit with cpue; maybe too optimistic in last years because B <= 0.5 B_{msy}
nep-2829*	Nephrops	*Nephrops norwegicus*	Near half B_{msy}	Near F_{msy}	Reasonable fit with cpue trends; maybe too optimistic in last years because B <= 0.5 B_{msy}
Pan_bor_1*	Northern shrimp	*Pandalus borealis*	Near half B_{msy}	Near F_{msy}	Reasonable fit with cpue trends; maybe too optimistic in last years because B <= 0.5 B_{msy}
Pan_bor_1*	Northern shrimp	*Pandalus borealis*	Near half B_{msy}	Near F_{msy}	Reasonable fit with cpuetrends; maybe too optimistic in last years because B <= 0.5 B_{msy}

Stock	Name	Species	Biomass	Exploitation	Comment
ple-nsea	Plaice	*Pleuronectes platessa*	Above B_{msy}	BelowF_{msy}	Reasonable fit with recent exploitation, but catches before 1984 are not compatible with observed biomass
rjh-pore*	Blond ray	*Raja brachyuran*	Above B_{msy}	Below F_{msy}	Same trends as in cpue
sar-78*	Sardine	*Sardina pilchardus*	Above B_{msy}	Below F_{msy}	Similar trends as in cpue
usk-oth*	Tusk	*Brosme brosme*	Near B_{msy}	Near F_{msy}	Good fit with cpue trends

4.3.4 Discussion

4.3.4.1 CMSY Evaluation of fully assessed stocks and simulated stocks

CMSY predictions for relative biomass and relative exploitation rate were compared with those for several fully assessed stocks. Figure 4.3.3.1 showed good agreement between assessments for North Sea herring. A similar satisfying agreement between CMSY and full assessments with regard to relative biomass and relative exploitation rate was obtained for North Sea haddock and for the simulated stock HLH_M. These workshop results confirm the results of previous testing against 24 simulated stocks and 114 global fully assessed stocks (see documents made available for the workshop), where confidence limits of *r, k, MSY* and final biomass overlapped in more than 90% of the stocks. For North Sea plaice a reasonable CMSY prediction of biomass was only obtained for the years after 1985. For preceding years, the CMSY productivity of $r \sim 0.5$, which is confirmed by the full Schaefer model and the current official estimate of $F_{msy} = 0.25$, would predict much higher biomass given the catches.

4.3.4.2 Warning about reduced recruitment at low stock sizes

Productivity models such as used by CMSY assume average recruitment across all stock sizes, including stock sizes below half of B_{msy}, where fisheries textbooks predict an increased risk of reduced recruitment. In other words, if recruitment is indeed reduced, then production models and CMSY will overestimate production of new biomass and will underestimate exploitation rates. This is visible in Figure 4.3.3.1 for North Sea herring in the 1970s. It is also prominently visible for North Sea cod (see Annex 5). Thus, if the final biomass predicted by CMSY is below or close to half of B_{msy}, then extra precaution should be applied if CMSY is used for management. For example, instead of the median a lower percentile of predicted biomass could be used, such as the 25^{th} percentile or even less. Stock recovery predicted by CMSY from low biomass should always be confirmed by independent data, such as cpue.

4.3.4.3 Impact of using landings instead of catch

Whenever possible, stock assessment is based on true removals from the stock, i.e. including discards and other unallocated removals. But for data-limited stocks, estimates of discard are typically not available and only the reported landings can be used as indicator of removals. The effect of using landings instead of catch for CMSY assessment was explored in a simulated stock and also in North Sea haddock. For the simulated stock (HLH_M), the true catches corresponding to *r, k* and true biomass were reduced by 30%, and the CMSY analysis was rerun with all other data being the same

(HLH_M07). As a result, the estimate of *r* remained practically unaffected, but the estimates of *MSY*, *k* and biomass were reduced by about 30%. However, the relative estimates of *b*/*k* and *c*/*b* remained unchanged (compare assessments of HLH_M and HLH_M07 in Annex 5). Similar results were obtained for the case of North Sea haddock, where discards constitute about 40% of the catch. Again, the CMSY estimate of *r* remained nearly unchanged, whereas the estimates o*f MSY*, *k* and predicted biomass decreased by about 40%. The relative assessments, however, remained largely unchanged (compare assessments of had-346a and had-346a-land in Annex 5). Thus, the CMSY methods seems capable of providing reliable relative assessments for stocks for which only landing data are available.

4.3.4.4 CMSY evaluation of data-limited stocks

At WKLIFE IV, CMSY was applied to nine data-limited stocks, including three invertebrates and one elasmobranch (see Table 4.3.3.1). Trends in cpue data were compared with the trends in CMSY predictions for relative biomass and relative exploitation rate. Note that in the CMSY graphical output, cpue and catch/cpue are plotted on a second axis, i.e. the height and spread of the cpue-based trajectories cannot be directly compared with the CMSY prediction, only the respective trends. There was no case of clearly contradictory trends, such as cpue clearly increasing while CMSY predicted biomass was clearly decreasing. Rather, the trends were very similar, thus building confidence in the CMSY prediction (see summary in Table 4.3.3.1). In five of the data-limited stocks, final biomass predicted by CMSY was near half of B_{msy}, i.e. reduced recruitment cannot be ruled out and in these cases the CMSY prediction may be too optimistic.

4.3.5 Conclusion

The CMSY method produce reasonable predictions for relative biomass and relative exploitation rate when compared with fully assessed stocks, simulated stocks and data-limited stocks for which cpue data were available. Application to stocks for which only landings data are available should not be a problem as long as the proportion of discards can be expected to be about the same throughout the time-series. Confirmation of predictions should then be obtained from, e.g. length-based methods. Extra caution need to be applied when the assumption of average recruitment is likely to be incorrect, e.g. at stock sizes below half B_{msy} or during periods known to be unfavourable for recruitment.

4.4 Length-based assessment methods

Many biological and fishery processes are primarily related to size (e.g. fecundity, fisheries selection, susceptibility to predation [i.e. M]) and in some cases to both age and length (e.g. maturity). Length (or any linear size) data therefore contain substantial information regarding stocks and fisheries impacting on them (Blanchard *et al.*, 2005). Further, length data are relatively cheap and straightforward to obtain and usually form one of the base datasets from which catch numbers-at-age are derived. Size frequency data are the primary data collected under the DCF.

In the absence of age–length keys, temporal dimensions (i.e. age and cohort structure) of length frequency data are obscured and difficult to identify (other than exceptional strong/weak year classes). Thus different parts of a length frequency distribution represent individuals that (may/will) have experienced different environmental and fishery conditions through their lifetime. In order to overcome this, simpler length-based approaches rely on steady state assumptions (i.e. stable exploitation (pattern and level), year-class strength and biological parameters) and length frequency data may be averaged over a number of years in order to reduce the magnitude of annual variations. These assumptions permit a (single) length frequency distribution to be considered representative of the exploitation history of a (typical) cohort and hence the derivation of metrics which characterise it. When using these methods it should be borne in mind that these steady state assumptions will frequently be violated and the methods have been criticised in this respect (e.g. Hilborn and Walters, 1992).

Although not their intended use, application of steady state methods to time-series data may provide additional information on trends. Other approaches are available, such as age/length slicing and age structured assessment which would likely better capture information on year class and dynamic length-based models which explicitly model size structure through time, but are often complex and may not be tractable for many data-limited stocks.

Participants at the workshop explored the performance of some length-structured approaches assuming steady state conditions, by applying them to data from stocks currently considered category 3 in the ICES data-limited classification. Length data were obtained for five stocks covering a range of species (*Nephrops*, sardine, blonde ray, lemon sole, spurdog), exploitation states and data qualities. In theory it should have been possible to obtain length data for a wider range of case studies, but aggregated catch numbers at length data were not always presented in ICES advice or working group reports.

Data for *Nephrops* males in fisheries units 28 and 29, blonde rays in Portugal and sardine in ICES Areas VII & VIII were analysed using length cohort analysis and per recruit analysis, length-structured catch curve analysis and using a length-based reference points approach suggested in WKLIFE2 (ICES, 2012c). These comparisons used essentially identical data, except that the first two also needed an estimate/assumption for natural mortality rate (M). Comparisons with methods using other data sources were also made for the *Nephrops* stock. In general the methods were applied ‘blindly’ to provide an initial interpretation of the results, then where possible expert knowledge relating to the fisheries and stocks was incorporated to modify this interpretation where and when appropriate. In some cases (e.g. blonde rays) this highlighted the danger of applying methods to data without an understanding or consideration of its background.

Size-based methods are of particular importance for crustacean species such as *Nephrops* that moult and where solid structures to permit direct ageing of individuals are generally unavailable, although note that recent work (e.g. Kilada *et al*., 2012) has suggested that some hard structures may contain age information even though they are not retained through the moult. They are also very important in tropical fisheries, where reduced seasonality generally limits contrast in deposition of hard structures.

A new size- (in weight) based method was also introduced to the group by teleconference and applied to a number of bycatch species in the Skagerrak and to *Nephrops* (males) in FU 28–29 (Section 4.4.4).

4.4.1 4.4.1 Length cohort analysis (LCA) and catch curve analysis

4.4.1.1 Methods

The EU Data Collection Framework sampling program includes the routine collection of length data from fish stocks at the landing ports. Under the assumptions that: i) the species' growth follows the von Bertalanffy growth model, ii) the population is in a steady state with constant exponential mortality, iii) there are no changes in the selection pattern of the fishery and iv) recruitment is constant, catch length data can be used to estimate total mortality (Z). This is done based on the general model according to which the number of survivors from a cohort at the instant t (N_t) that have been subject to the total mortality Z between ages t_j and t_k can be estimated as:

$$N_t = N_a e^{-Z(t_j - t_k)} \tag{1}$$

However if only length data are available it is necessary to determine relative ages (t_i*) which are related to absolute ages (t_i) by a constant age (t_a). Relative ages can be calculated following Cadima (2003) as:

$$\mathrm{t}_i^* = -\frac{1}{K}.ln\frac{(L_\infty - L_i)}{(L_\infty - L_a)} \text{ or } \mathrm{t}_i^* = -\frac{1}{K}.ln\left[1 - \frac{(L_i - L_a)}{(L_\infty - L_a)}\right] \tag{2}$$

where:

$L_\infty$is the assimptotic growth;

K is growth rate.

Jones' (1981) length cohort analysis (LCA) is one of the methods that estimate fishing mortality and population size based on length data. LCA is considered a satisfactory method for stocks with values of the natural mortality, M, up to 0.3 and of fishing mortality, F, up to 1.2 (Pope, 1972).

LCA requires an estimate of the steady-state of the total catch-at length distribution together with parameter estimates describing natural mortality and growth. However in some applications, a quasi-steady-state length distribution is constructed from the average of the catch-at-length distributions over a number of years and LCA is then applied.

In LCA the number of fishes at the lower limit of the length interval, N_i, is given by:

$$N_i = N_{i+\Delta t} e^{-M\Delta t/2} + C_i e^{-M\Delta t/2} \tag{3}$$

where Δt refers to the time required to grow from the lower to the upper limit of the length interval [L_i, L_j]. Based on von Bertallanfy growth parameters estimates, Δt can be determined as:

$$\Delta t = t_j - t_i = \frac{1}{K}.\ln\left(\frac{(L_\infty - L_i)}{(L_\infty - L_j)}\right) \; L_j > L_i \tag{4}$$

Using this expression, equation (3) can be modified as:

$$N_i = \left(N_j X_L + C_{i,j}\right) X_L \tag{5}$$

where:

$C_{i,j}$ is the number of fishes caught with lengths between L_i and L_j

$$X_L = \left(\frac{(L_\infty - L_i)}{(L_\infty - L_j)}\right)^{M/2K} \tag{6}$$

Following the LCA procedure the number of fishes reaching the length corresponding to the beginning of the largest length group is first estimated and then the numbers of fish reaching a particular length for successively smaller sizes are calculated backwards by continuously applying equation (5).

The largest length group refers to individuals greater than a particular length so that for calculating the number at the beginning of this interval it is necessary to know, or to assume, a value of exploitation rate, E=F/Z, for this length group. The value of E is dependent on the level of exploitation of the stock; if the stock is heavily exploited the choice of E is not likely to affect the calculation critically. However, significantly different results arise when the final value of E becomes very small, i.e. for stocks only lightly exploited. So if the value of E is quite unknown and if it happens to be very small cohort analysis shall not be used (Jones, 1981).

Length catch curve analysis (CCA_1) is other method that allows estimate Z. Assuming that Z is constant within a length interval (L_i, L_{i+Ti}) whose ages correspond to:

$$i = a + \frac{1}{K}\ \ln\left(\frac{(L_\infty - L_a)}{(L_\infty - L_i)}\right) \qquad \text{and} \qquad i + Ti = a + \frac{1}{K}\ \ln\left(\frac{(L_\infty - L_a)}{(L_\infty - L_{i+Ti})}\right) \tag{7}$$

based on this

$$Ti = -\frac{1}{K}\ \ln\left(\frac{(L_\infty - L_{i+Ti})}{(L_\infty - L_i)}\right) \tag{8}$$

or equivalently

$$i + \frac{Ti}{2} = constant - \frac{1}{K}\frac{\ln(L_\infty - L_i) + \ln(L_\infty - L_{i+Ti})}{2} = constant - \frac{1}{K}\overline{\ln(L_\infty - L_\iota)} \tag{9}$$

Considering that F is constant, the catch, C_i, is given by

$$C_i = F.\bar{N}_i T_i \tag{10}$$

$$ln(C_i/T_i) = [ln(F) + ln(N_a).Z_a].Z(i + T_i/2) \tag{11}$$

Based on (8), the equation (11) can be reformulated as:

$$ln(C_i/T_i) \cong const + \frac{Z}{k}\overline{\ln(L_\infty - L_\iota)} \tag{12}$$

The Jones and van Zalinge cumulative plot is a variant of the length-converted catch curve approach (CCA_2), but rests on slightly different assumptions. Considering that the age t_{i+1} takes a very high value (i.e. ti+1 = ∞), and adopting $C_{i,\infty}$ to denote all fish caught at age t_i and older, Jones and van Zalinge (1981) propose the following linear relationship:

$$ln(C_{i,\infty}) = d - Z.t_i \tag{13}$$

If the age t_i is replaced by the inverse of the von Bertalanffy model the equation (13) will be:

$$ln(C_{i,\infty}) = d - Z\{t_0 - (1/k).ln[1 - (L_i/L_\infty)]\} \tag{14}$$

which can be reduced to:

$$ln(C_{i,\infty}) = a + \left(\frac{Z}{K}\right) ln(L_\infty - L_i) \tag{15}$$

where

$C_{i,\infty}$ - the cumulative catch (computed from the highest length class with non-zero catch) corresponding to a given length class; where the subscript i is he lower limit of that length class.

The Jones and van Zalinge (1981) method is extremely sensitive to the values of the catches in the largest length groups, even when they are not included in the linear regression. Thus, it should not be used when the catch composition data were obtained from gears that are markedly selective for or against very large fish. Also, the statistics of the plot (correlation coefficient, confidence intervals, etc.) must be taken with scepticism, since they are based on data points that are not independent of each other. Finally, the method does not take account of seasonal growth oscillations, and thus shall not be used when such oscillations are known to occur (Gayanilo and Pauly, 1997).

It is important to note that in order to verify if the assumptions of the methods are acceptable it is recommended that before applying either CCA_1 or CCA_2 a graphical representation of the data be done (Cadima, 2003). This analysis will also allow to determine the adequate length interval to be used to estimate Z, i.e. to visually select the points representing the fully selected and recruited fishes.

Beverton and Holt (1964) developed a general version of Yield-per-recruit (Y/R) based on the relative differences of Y/R for different values of F. The “relative” Y/R model has the advantage of requiring fewer parameters being especially suitable for assessing the effect of mesh size regulations.

Let Lc be the 50% retention length, i.e. the length at which 50% of the fish are retained by the gear, and the auxiliary variables U and m be defined as:

$$U = 1 - \left(\frac{L_c}{L_\infty}\right) \tag{16}$$

$$m = \frac{(1-E)}{M/K} = \frac{K}{Z} \tag{17}$$

the "relative" yield-per-recruit (Y'/R), as proposed by Beverton and Holt (1964), is determined as:

$$\frac{Y'}{R} = E.U^m \left[1 - \frac{3U}{1+m} + \frac{(3U)^2}{1+2m} - \frac{(U)^3}{1+3m}\right] \tag{18}$$

The Y'/R is a proportional to Y/R and is given by:

$$\frac{Y'}{R} = \frac{Y}{R}.e^{M(t_r-t_a)/W_\infty} \tag{19}$$

where

tr – is the age of recruitment here considered as age corresponding to the length of recruitment (≅ 10% of the catch cumulative proportion by length).

Based on the Y/R model, long-term (or equilibrium) biological reference points can thus be defined. Among these $F_{0.1}$, is a reference point viewed as a surrogate for maximum economic yield that corresponds to 1/10th of the rate of increase of yield-per-recruit that can be obtained by changing F at low levels of F (Gulland and Boerema, 1973).

4.4.1.2 Applications

LCA, CCA_1 and CCA_2 were applied for several selected stocks. Table 4.4.1.2.1 presents the input data for each stock.

Table 4.4.1.2.1. Input data used for the different length data methods applied on the different stocks. M – natural mortality; k – growth rate ($year^{-1}$ von Bertalanffy parameter); L_∞ .- asymptotic length (von Bertalanffy parameter); weight/length relationship parameters $W=aL^b$ (W body weight; L length); tr – age of recruitment and tc- age of fully recruited fish.

Stock Code	M	K	L_∞	A	B	T_R	T_C
nep-2829 (males)	0.3 $year^{-1}$	0.2 $year^{-1}$	70 mm (CL)	0.0003	3.2	1.9 year	2.8 year
rjh-pore	0. 19 $year^{-1}$	0.13 $year^{-1}$	154.7 cm (TL)	0.0020	3.2	1.63 year	3 year
sar-78	0.3 $year^{-1}$ (sar-9a)	0.34 $year^{-1}$	26 cm (TL)	0.0059	3.1	0.5 year	1.9 year
lem-nsea	0. 41 $year^{-1}$ (King *et al.*, 2006)	0.14 $year^{-1}$	45 cm (TL)	0.0051	3.2	0.97 year	2.2 year

4.4.1.3 Results

The LCA assessment and CCA_1 and CCA_2 results are presented for each selected stock in the Table 4.4.1.3.1. This table includes the reference period, i.e. the period during which the stock was in a steady state.

Table 4.4.1.3.1. Results obtained by the application of the different length methods (CCA_1; CCA_2; LCA) with indication of the length range adopted for calculation of total mortality; last column presents reference points derived from Y/R model.

Stock Code	Reference period	LCA	LCA Length range	CCA_1	CCA_2	CCA_1 & CCA_2 Length range	Reference Points
nep-2829	2011–2013	F=0.9M	[30, 56mm] (CL)	F=1.2M	F=M	[30, 56mm] (CL)	F=M=0.3 F0.1=0.8M Fmax=NC
rjh-pore	2008–2013	F=0.7M	[58, 100 cm]	F=0.7M	F=3.6M	[58, 100 cm]	F=M=0.19 F0.1=0.7M Fmax=1.1M
sar-78	2013	F=1.7M	[15.5-23 cm]	F=0.13M	F=1.5M	[15.5–23 cm]	F=M=0.3 F0.1=1.4M Fmax=NC
lem-nsea	2011 (subset sample)	NA	-	F=0.1M	F=0.3M	[22–36 cm]	F=M=0.4 F0.1=M Fmax=NC

NA Not applicable; NC Not converged

4.4.1.4 Discussion

Stock: nep-2829 males

Nephrops males are available for fishing during the whole year whereas females are hidden in the burrows during egg-bearing period. The male component is thought more vulnerable to fishing pressure and was selected as one of the case studies. Estimates of F derived from the different methods varied, however all suggested that the current F is slightly above $F_{0.1}$ and around the level of M. For this stock the Y/R curve is flat topped and F_{MAX} could not be defined.

Stock: rjh-pore

F estimates obtained with LCA and CCA_1 were similar, while the estimate of F obtained using CCA_2 method was much higher, probably reflecting one of the drawbacks of the method associated with gear selectivity and mentioned by Jones and van Zalinge (1981). According to these authors CCA_2 method should not be used when the catch composition data are obtained from gears that are markedly selective for or against very large fish. The latter situation seems to occur in the case of stock rjh-pore as can be seen in Figure 4.4.1.4.1. The estimates of fishing mortality obtained from LCA and CCA_1 were 70% of natural mortality, at the level estimated for $F_{0.1}$.

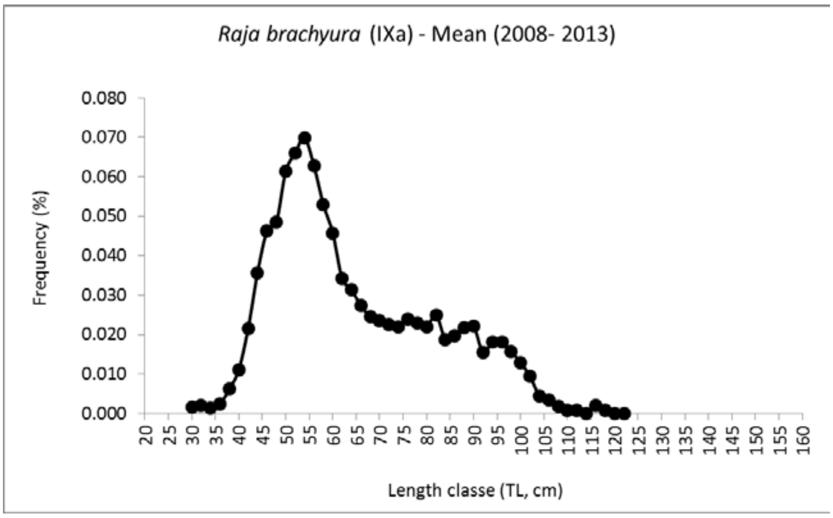

Figure 4.4.1.4.1. ***Raja brachyura*** **Length–frequency distribution derived from Portuguese catches (ICES Division IXa).**

Stock: sar-78

The estimates of F obtained with LCA and CCA_2 were similar and both were much higher than the value of F estimated using method CCA_1. The discrepancies on F estimates are probably associated with the fact mentioned by Pauly and Morgan (1987) that the use of length-based methods in short-lived species essentially involves a "dynamic non-equilibrium" situation. In these species either the biomass or the abundance may change greatly seasonally, and this may also be reflected on the annual catch size structure of those species.

Stock: lem-nsea

The LCA method could not be applied on lem-nsea stock because the length data available was not extrapolated to the whole catch. Furthermore, this method is not satisfactory for stocks with values of the natural mortality M>0.3 (Csirke *et al.* in Pauly and Morgan, 1987).

The estimates of F from CCA_1 and CCA_2 methods were obtained based on the assumption that the length data available was representative of the exploited population. The CCA_2 may lead to inconsistent results if length data suggest the existence of two more or more cohorts, which seems to be the case of lem-nsea stock (Figure 4.4.1.4.2). As mentioned by Pauly and Morgan (1987) variations in recruitment strength may serious bias the F vectors when these are expressed in terms of length.

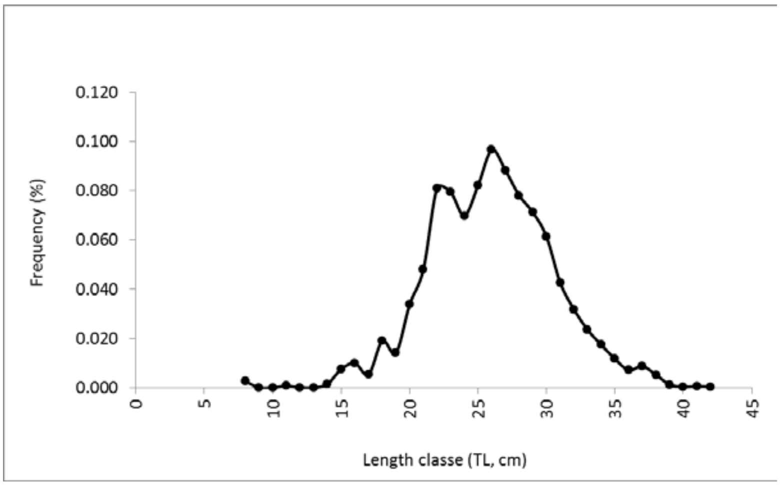

Figure. 4.4.1.4.2. Length–frequency distribution of lemon sole (*Microstomus kitt*) in the North Sea.

4.4.2 Length-based reference points (LRPs)

4.4.2.1 Methods

WKLIFE2 (ICES, 2012c) discussed an approach to develop reference points based on length frequency information and biological parameters, citing the ICES on line database of trawl surveys (DATRAS) and FishBase as potential data sources. Population and fishery metrics needing to be characterised include:

- length (L_{mat}) at 50% maturity
- von Bertalanffy growth parameters (L_{inf}(L_∞), K, t_0)
- mean length at first capture (L_c)
- length where growth rate in weight peaks, where cohort biomass has a maximum in the unexploited stock and therefore where egg-production has a maximum, where a given F obtains the highest catch, and where a given catch causes the lowest F (Cope & Punt, 2009; ICES, 2012) (L_{opt})
- theoretical mean length resulting from fishing with F = M ($L_{F=M}$)

Length at first capture (L_c) and mean length in the catch (L_{mean}) are used as indicators of current status and can be compared against length-based reference points derived from the stock characteristics. WKLIFE II provided some example case studies illustrating how length at first capture and mean length in the catch could be calculated (Figure 4.4.2.1.1), noting that L_{mean} was calculated as the mean length of fish larger than the length at first capture (L_c).

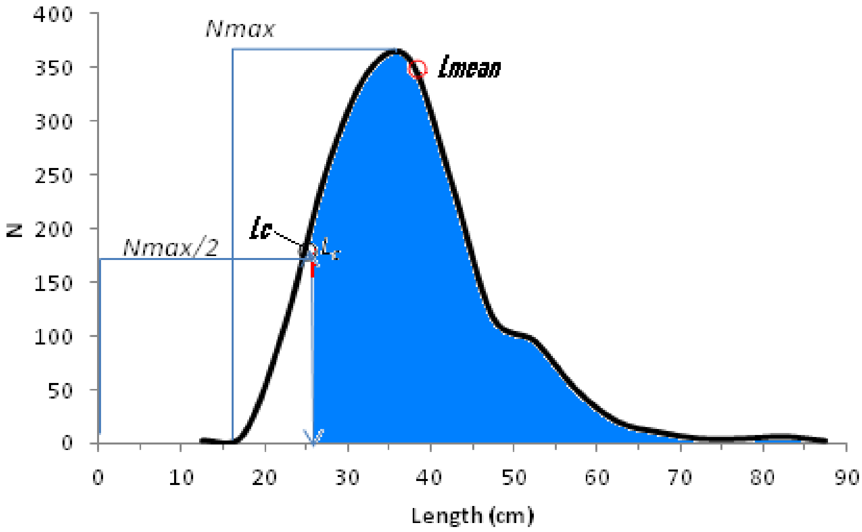

Figure 4.4.2.1.1. Length–frequency distributions showing calculation of L_c and L_{mean}; area shaded used to calculate L_{mean} (from Figure 3.4.5.3 *in* ICES, 2012).

i) Length at maturity (L_{mat}) compared with length at first capture (L_c) and central metrics in the commercial catch length distribution (e.g. mean length).

L_{mat} is typically determined from the inflection point of a maturity ogive (an S-shaped curve representing the proportion of the female (or male) population that is mature). The female maturity ogive is usually considered more relevant as the determinant of future progeny and sustainability. Some authors (e.g. Froese and Sampang, 2012) have suggested increasing this size by a multiplier of around 1.2 because although small females may show clinical signs of maturation their contribution to future recruitment is actually low because of their small size and relatively low fecundity. Other authors (e.g. Froese and Binohlan, 2000; Gislason *et al*., 2008; Le Quesne and Jennings, 2012) have developed empirical relationships for size at maturity based on asymptotic length (L_{inf}).

L_c is defined as the length at which 50% of individuals are vulnerable to/retained by the fishing gear. Length at first capture was determined as the length at half the maximum frequency in the ascending part of a length frequency distribution representing the commercial catch. Myers and Mertz (1998) state that overfishing is theoretically impossible if all individuals are allowed to re-produce at least once, hence, if length at first capture is above length at maturity (for a period of around generation time) biomass is likely to be above the biomass that produces MSY. A reasonable approximation for generation time (the average age of spawners in an unexploited stock) is the age at L_{opt} which is given by:

$$t_{opt} = \ln(3)/K + t_0 \quad \approx 1.1/K \qquad \text{(ICES, 2012)}$$

If the mean length in the catch (over a sustained period of time such as a generation time) is below the length at first maturity there are more juveniles than adults in the catch and biomass is likely to be below that corresponding to MSY and possibly at levels where recruitment will be impaired. In contrast if L_{mean} is above L_{mat} the stock is likely to be above the level where recruitment is impaired.

ii) Asymptotic length (L_{inf}; L_{∞}) and length where growth rate is maximum (L_{opt}) as reference points.

L_{inf} is a parameter of the von Bertalanffy growth model or if this is unavailable may be approximated by the largest specimens found in survey databases, which are often fish that have managed to avoid capture by fisheries. L_{inf} is generally not (much) smaller than the largest specimens found. Comparing metrics characterising the central or upper portions of the catch length frequency distribution with asymptotic length provides an indication of the degree of truncation of the population size structure, e.g. few or no individuals reach large size.

However, the length where growth rate is maximum (L_{opt}), was considered a better reference point as it represents the point where cohort biomass and egg production are maximal in an unexploited state and where catch is maximal for a given F, or F minimal for a given catch(i.e. the optimum harvest length) (Cope and Punt, 2009; ICES, 2012c). It is empirically defined as:

$$L_{opt} = 2 * L_{inf} / 3$$

If L_{mean} is close to L_{opt}, then either the stock is very lightly exploited or the fishery is operating with a target length that is sustainable and close to MSY.

iii) Length where F=M ($L_{F=M}$) as a reference point.

Rearranging and simplifying Beverton and Holt's (1956) equation for mean length in the catch as a function of the von Bertalanffy growth parameters, length at first capture and natural and fishing mortality gives an equation for the mean length in the catch that would result from fishing at F=M in the long term.

$$L_{F=M} = (3L_c+L_{inf})/4$$

F=M is a proxy for MSY, hence $L_{F=M}$ is a length-based MSY proxy reference point that can be used to compare against current exploitation levels expressed by mean length in the catch (L_{mean}). Thus, if L_{mean} is less than $L_{F=M}$ then fishing mortality is likely to be larger than M and F_{MSY}.

These empirical length-structured reference points and length-based indicators of current status seem eminently suited to the provision of initial assessments of stock status for many data-limited stocks where data are restricted to length distributions, but some estimates of biological parameters are available and they have been used to indicate whether biomass is above reference levels (Jennings and Dulvy, 2005; Cope and Punt, 2009). However, it should also be noted that growth parameters are far more difficult to obtain and may be uncertain for species that are difficult to age (i.e. many shellfish species, particularly crustaceans).

4.4.2.2 Method implementation

An R script implementing a length-based reference points analysis based on WKLIFE_2 that had been developed as part of a UK Defra funded research and development project (UK Department for Environment, Food and Rural Affairs, Defra, Project MF0234 - Enhancing the ability to provide advice on data limited shellfish stocks) was available to the workshop and was used with some *in situ* modifications to carry out the analysis. A second similar script was independently produced by another workshop participant to provide a degree of quality control and to present the results for the *Nephrops* length–frequency time-series (Figure 4.4.2.3.2).

Length-based indicators of exploitation that were estimated included: two estimates of mean length (one using the full length distribution and one only length classes above L_c) (L_{mean} or Mu_L), median (L_{median} or L_{Med}), the 25th, 75th and 95th percentiles, maximum observed length in the distribution (L_{max}) and two estimates for length at first capture L_c. Both estimates of length at first capture were based on using a mode in the distribution to indicate the size at full selection and then estimated the length (or length class) where a frequency of 50% of the modal frequency occurred. One approach used the 'raw' frequencies by length class, while another fitted a stiff smoother (loess, span=0.95) and used predictions from this. For multimodal distributions it was possible for the user to manually set the mode to be used for L_c estimation. One further central metric was calculated; the length class contributing the most to the catch in weight (biomass) to the length distribution (L_{MaxY} or LC_{MaxY}).

Length-based reference points were based on published life-history characteristics and parameters of the von Bertalanffy growth equation, i.e. size at 50% maturity (L_{mat}), asymptotic length (L_{inf} or L_{∞}), and L_{opt}, which is the length class which would provide maximal biomass in the unexploited population state (Cope and Punt, 2009; ICES, 2012). In addition to the empirical formulation for L_{opt}, an analytical calculation using the von Bertalanffy growth and length-weight relationship parameters was made where L_{opt} was the length class where the increase in growth in weight per unit time was maximal. As an FMSY proxy the empirical formula for length at F equals M (L_{FeM}) was used.

Outputs from the R script included a palette of three graphs:

- The upper graph focusing on conservation and sustainability by comparing the reference points length at first maturity (and L_{mat} *1.2) and L_{inf} with indicators from the lower (L_c and $L_{25\%}$) and upper ($L_{95\%}$ and L_{max}) portions of the length distribution, respectively.
- The central graph focusing on optimal yield and presenting estimates of the reference point L_{opt} in comparison with central metrics from the length distribution (L_{mean}, L_{med}, L_{MaxY} and the upper and lower quartiles). Cumulative yield was also presented on the right axis of this plot to provide an indication of where (and how rapidly) most yield was taken.
- The lower graph focusing on MSY and presenting central metrics (L_{mean}, L_{med} and the upper and lower quartiles) in comparison with the FMSY proxy, the empirical L_{FeM}.

Tabular outputs of the length-based metrics and reference points were manually extracted from the R analysis. For *Nephrops* the script was modified to run over a time-series of length distributions, in each case analysing a simple 3 year average of the frequencies.

Stocks analysed

Selected stock units included;

- *Nephrops norvegicus* (FU 28–29, males only, average 2011–2013),
- Sardine, *Sardina pilchardus* (Division VIII, unsexed, 2012),
- Blonde ray, *Raja brachyuran* (Division IXa, unsexed, 2008–2013),
- Spurdog, *Squalus acanthi* (NE Atlantic, females and males, 1999–2001), and
- Lemon sole, *Microstomus kitt* (North Sea, subset of UK observer data, unsexed, 2011).

A summary of indicators and reference points for three of the stocks (*Nephrops*, sardine and blonde ray) is provided in the results section. The two further stocks that did not necessarily represent the full catch (lemon sole in the North Sea, for which only a subset of observer data were available, and Northeast Atlantic spurdog for which length distributions for targeted and non-targeted fisheries were available separately by sex) required multiple runs and are presented in Annex 6, along with more detail on the analyses for the *Nephrops*, sardine and blonde ray.

4.4.2.3 Results

Summary of single-stock interpretations

Three stocks for which aggregated length distributions were available for the fishery are considered initially, with *Nephrops* data consisting of males only.

Calculated length-based indicators and reference points for sardine suggested that the level of exploitation on the stock was below potential F_{MSY} targets of $L_{F=M}$ or L_{opt}. L_c was above L_{mat} indicating opportunity to spawn prior to entry to the fishery and there was little evidence of depletion of large animals as L_{max} was close to L_{inf}. The general stock prognosis was favourable.

For *Nephrops* males there were indications of not being harvest optimally nor at MSY, with L_{opt} above all central metrics and $L_{75\%}$ and $L_{F=M}$ close to $L_{75\%}$. L_c was estimated above L_{mat} suggesting that spawning opportunities exist before entry to the fishery and large individuals with sizes close to asymptotic size were present in the catches although the 95th percentile of the length distribution for *Nephrops* was quite far below from L_{inf}, indicating some depletion of large individuals (Figure 4.4.2.3.1).

A time-series of length distributions for the selected *Nephrops* stock was also analysed producing time-series for indicators of exploitation and the reference points (Figure 4.4.2.3.2). Most of the length-based exploitation indicators were relatively stable and had low variation over time, with exceptions L_{MaxY} and L_{max} which were more variable. $L_{95\%}$ (or another high percentile) could provide a more stable indicator for the presence of large individuals, rather than the extreme point L_{max}. There was a slight increase in the proportion of the largest 5% in the catch since the late 1990s. The central metrics have been below L_{opt}, but above L_{mat} throughout the time-series. Most of the length-based indicators of exploitation show a slight increase through time, potentially equating to a slight decline in fishing mortality.

A general prognosis for *Nephrops* was that it was being fished sustainably but exploitation level was above that required for MSY (and optimal yield).

In contrast, for the blonde ray stock length-based indicators pointed to exploitation of immature individuals, a truncation of the length distribution at large sizes and exploitation (level and pattern) that failed to achieve MSY or optimal yield. However, background knowledge relating to this fishery suggested the length distribution was unlikely to accurately represent the ray population (see discussion), because of domed selection pattern by the fishery. This renders inference regarding stock status inappropriate, but it is still possible to state that the selection pattern of the fishery exploits rays before they have opportunity to spawn and at sizes below those which would optimise yield.

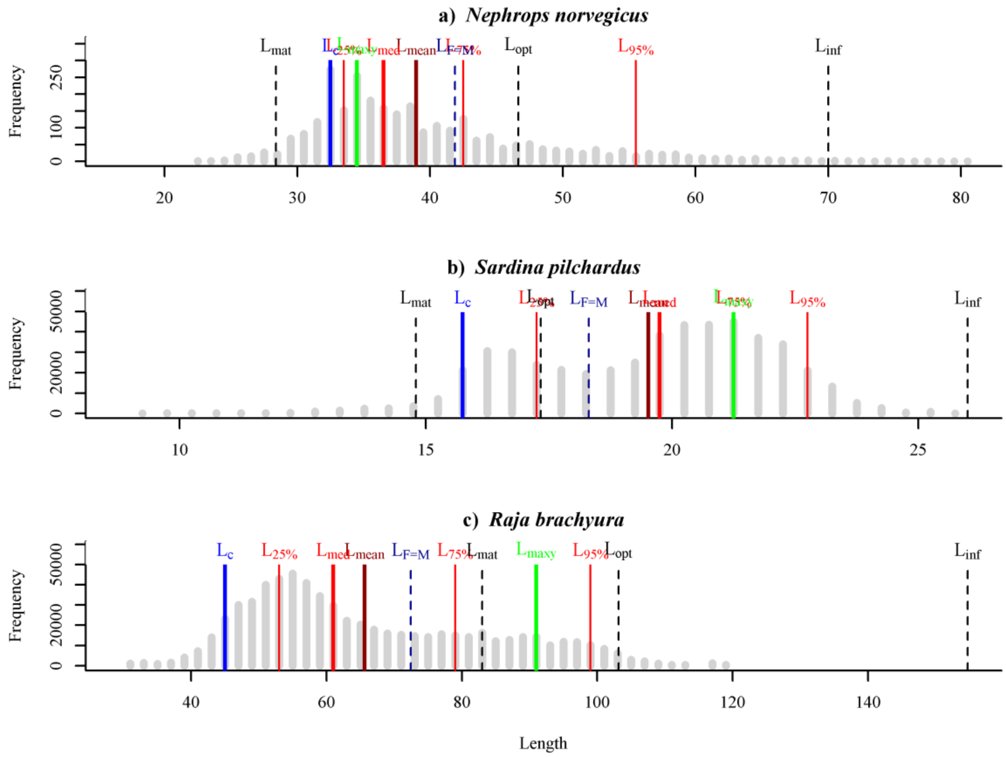

Figure 4.4.2.3.1. Length–frequency distributions for a) *Nephrops*, b) sardine and c) blonde ray of the recent years with length-based indicators and reference points.

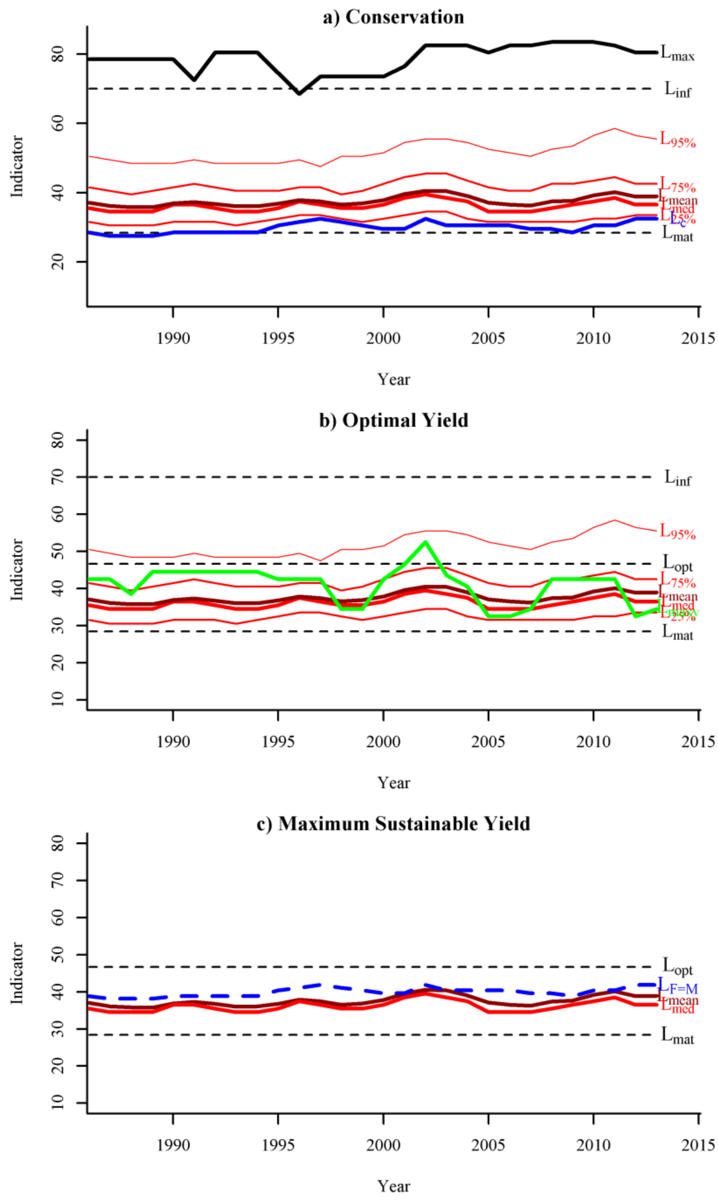

Figure 4.4.2.3.2. Time-series of length-based indicators and reference points for *Nephrops* (1987-2013), smoothed taking the three year simple average of frequencies.

4.4.2.4 Discussion

The three species considered differ in their life-history characteristics (growth, maturation, reproductive strategy, longevity and habitat). Of the three considered stocks, two were finfish species and one a crustacean. Sardine are pelagic, relatively small with low to moderate longevity, mature early as batch spawners with indeterminate annual fecundity (estimated to be c. 50–60 K eggs per annum) and planktonic eggs and larvae. In contrast, blonde rays are demersal, long-lived and relatively large, mature late with low fecundity, but internal fertilization, large egg and juvenile size with no planktonic stage reduce larval/juvenile natural mortality. *Nephrops* are demersal/benthic have small asymptotic size and low to moderate longevity, mature at relatively small size with low to moderate fecundity and brood eggs before releasing relatively large larvae to the plankton.

The three stocks considered also differ in their exploitation characteristics, with sardine in areas VII & VIII a target catch taken by pelagic gears primarily purse-seine, but also trawl, while blonde ray in Division IXa are primarily a bycatch in a demersal fixed (trammel) net fishery targeting smaller demersal fish (e.g. sole) and *Nephrops* in FU 28–29 are taken as a valuable component of a mixed species demersal trawl fishery.

The favourable general prognosis for sardines obtained from the length-based reference points approach was in broad agreement with findings from WKPELA (ICES, 2013) where three assessment approaches (TASACS, catch curve analysis and AMAK) applied to data from Biscay suggested low exploitation rates. However WKPELA noted that the models suffered from lack of input data and were sensitive to assumptions made without sufficient tuning data to validate them and were not considered sufficiently quality assured to serve as a basis for advice.

The length-based reference point analyses for *Nephrops* suggested sustainability, but harvesting that was not optimal, but appeared to be improving through time, most notably during the late 1990s and early 2000s. This *Nephrops* functional unit is assessed through WGBIE (ICES, 2014) on the basis of survey and fishery cpue and effort trends. Iberian *Nephrops* stocks have been subject to a recovery plan since 2006. WGBIE indicates that standardized fishing effort shows a consistent declining trend since 2005 to historic lows in 2009-2010, then rises slightly, while fleet standardised cpue used as index of biomass, increased in the early 2000s, decreased in the period 2006-2011 and increased in 2012 and 2013. Technical issues prevented use of survey cpue. These two perceptions show some similarities and other disparities. The increase in cpue in the early 2000s to some extent matches the increase in length-based metrics during this time period, however, the general prognosis from the length-based reference points approach suggests slight to moderate overexploitation, rather than the recovery plan status documented in WGBIE. Further, it should be noted that WGBIE does not provide a clear perception of stock status, while the male only reference points assessment here also needs to be treated with caution given the absence of information relating to females, which are likely to be more relevant with regards to stock sustainability.

Application of the length-based reference points approach to blonde ray suggested overexploitation of recruits and truncated population structure. However, in this case the frequency distribution was calculated from sampling bycatch, taken by fixed nets (principally trammelnets) targeting smaller species and it is unlikely that the distribution provides an accurate perception of the stock status, because such nets are known to have highly domed selection patterns (Hovgard and Lassen, 2000). Hence the approach was not applicable in its entirety; however it could be noted that the bycatch fishery captured rays before maturity and was not optimal with regards to maximising yield of blonde rays.

For a subset of lemon sole data, the length-based reference points approach suggested that the stock appeared to be fished sustainably, but that there was some evidence of reduced numbers of large fish and exploitation exceeded the level for maximising yield and was slightly above an F_{MSY}. ICES advice indicated that landings have declined since the late 1980s, while a mature biomass index was noisy but broadly stable over the same time period. Recent ICES advice was for no increase in landings or no more than 16% increase in landings. Perceptions from the different approaches were not dissimilar, indicating minor rather than major changes in TAC.

For spurdog the length-based reference points approach was difficult due to sexual dimorphism and data disaggregated for target and non-target fisheries. However all components had generally favourable prognoses. This perception differs markedly from that in the ICES advice which shows a 10 fold decrease in SSB and an accompanying fivefold decrease in recruitment over a 100 year time-series, with the low point occurring around the time of the assessment (2001).

The length-based reference points approach provides a very simple methodology with low data requirements which may provide an indication of stock status under steady state assumptions. In this comparative exercise it appeared to perform with reasonable consistency for sardine, less so for *Nephrops* (males only) and was not really applicable given data that (due to fishery selection characteristics) did not represent the population for blonde rays, but was still useful in highlighting potential problems with this fisheries exploitation pattern. It seemed to provide a similar perception to ICES advice given a subset of data for lemon sole, but gave wildly optimistic perceptions for spurdogs in comparison to the ICES advice. The latter may reflect selection characteristics of the gears used and the ability of fisheries to target aggregations of mature individuals.

The length-based reference points approach utilises a number of metrics and reference points that have to some extent been discussed in the methods section. However a few further points may deserve mention here:

- Several of the reference points calculated were empirical and based on the von Bertalanffy growth parameter L_{inf}. Clearly it is important that representative growth parameters are used in the approach. In some cases the method may highlight inconsistent growth parameters, for example if L_{max} is substantially larger than L_{inf}.
- A note of caution may also be advised in using the LF=M empirical formula, which includes a term for length at first capture, L_c. There is a danger that changing fishery exploitation successively targeting smaller and smaller fish could lead to a downward spiral of the target value. A check on L_c relative to L_{mat} was included in this analysis as one of the sustainability indicators.
- Two outputs for L_{opt} were presented in the detailed results, one based on the empirical formula and a second based on calculating the length class in which von Bertalanffy growth (in weight) was maximal. The latter does not equate exactly with the yield-per-recruit theory where yield is maximised if the population is taken instantaneously at the point where population growth ceases (i.e. growth = natural mortality), because 1) it uses the length class where growth is maximal and 2) it takes no account of natural mortality. In examining the positions of these two alternative reference points it can be noted that a) they were always close together, and b) they did not vary consistently (the empirical version was generally but not always smaller, 4 of 5 occasions).
- In this approach a length distribution is used to characterise aspects of both the fishery and the stock and consideration needs to be given as to whether this can be justified. In the blonde ray case study it was felt that although the length distribution provided information on the fishery exploitation pattern, it probably did not accurately reflect population demographics and therefore could not reliably inform on status.
- With regards to estimation and use of size at first capture as a fishery metric, clearly the length distribution must represent catch (rather than landings only) if discards occur and their survival is other than high. In the lemon sole case study (Annex 6) removal of discards made little difference to the overall status estimation, but this was because the size at maturity (in this

case) was far below size at first capture whether or not discards were included.

- It has sometimes been remarked that central metrics of length distributions can be insensitive to changes in the population and potentially slow and/or ineffective in identifying changes in status. In this case study a number of central metrics were used including L_{maxy} which was intended to identify most important length class relating to yield. This metric was found to exhibit more variability than other central metrics in the *Nephrops* case study, although whether this was noise or a genuine signal is not clear, but this could be investigated, along with the performance of other length based metrics, through simulation. Simulation studies detailed elsewhere in this report have found length-based metrics and reference points to work effectively in HCRs.
- As noted above, with regards to status evaluation, there is a danger that some reference point may change in response to changes in selection and this also applies to their use in HCRs. A two reference point approach might also prove appropriate in this context, such that L_c was maintained close to or above L_{mat} and a central metric (e.g. L_{mean}) is kept close to or above an MSY target. Again simulation studies could be used to evaluate such approaches, although the management response to improve exploitation pattern may require alternatives to TAC control.
- TAC control has been considered as the primary control measure for management in most of the work of WKLIFE. However for some data-limited species of high economic importance that currently fall outside the EU CFP TAC system and ICES assessment remit (e.g. scallops, edible crabs, lobsters), other control measures may be more appropriate and TAC systems may not be in place. MLS remains the major control measure for several important species and can be effective where discard survival is high.

Sexually dimorphic species with life histories differing between sexes, often pose problems for stock assessment .Evaluating sexes separately may provide assessments that are internally consistent, but there may still be issues with regards to obtaining an overall status assessment if the results differ by sex. In general females are considered more relevant with regards to sustainability, as reproductive potential is generally dependent on female biomass. However, this may not always be the case and sperm limitation has been postulated as an issue for some male-only crustacean fisheries.

Two of case studies considered here included species exhibiting significant sexual dimorphism, *Nephrops*, where in this case only males were considered and spurdog, where both sexes were analysed, but results for males were not thought to be reliable and only results for females considered as the basis of assessing stock status.

4.4.3 Comparison of results obtained from various length-based methods assuming equilibrium conditions

4.4.3.1 Methods

Outputs summarizing stock status were derived from the length-based reference points approach, length cohort analysis and length-based catch curves (along with an assumption of natural mortality, M). These were compared to provide some evaluation of consistency or otherwise between methods using essentially the same data.

The level of fishing mortality was presented relative to three reference points: an MSY proxy F=M and two yield-per-recruit references (F_{max} and $F_{0.1}$), i.e. F_{sq}/F_{ref}. A generalized yield-per-recruit approach (Beverton and Holt, 1964) was used following the LCA and catch curve analyses, which uses an aggregate estimate for F rather than a full length structured per recruit analysis (which could be applied following LCA). The length-based reference points and metrics operate in the inverse direction so the comparable relationship is L_{ref}/L_{sq}. The length-based MSY proxy $L_{F=M}$ (L_{FeM}) was directly analogous between assessment methods. The length-based reference point L_{opt} was used to compare with the yield-per-recruit reference points, although it is not clear that this is directly comparable with either F_{max} or $F_{0.1}$ and two slightly different estimates of L_{opt} (empirical and based on von Bertalanffy growth parameters but not accounting for M) were used (see also discussion, Section 4.4.2.4).

For the length-based reference points approach, mean length over the entire length distribution (MuL_All) was used as the default metric characterizing exploitation level, but a range of other central metrics were also presented for comparison, including:

- Mean length of sizes above the length at first capture (MuL_Lc50)
- Median length in the full length distribution (LMed)
- The length class which provided the maximum biomass (weight) to the catch (LCMaxY)
- The inter-quartile range (L25% - L75%) was considered a representation of the limits of central metrics.

4.4.3.2 Results

Nephrops

The length-based reference points approach suggests that *Nephrops* were fished at a level close to or just above the F_{MSY} proxy (F=M), with other central length metrics (LMed and LMaxY) more conservative than the default (MuL_All) (Table 4.4.3.2.1). Ratios of $F/F_{MSYProxy}$ produced by length cohort analysis and the Jones and van Zalinge length catch curve analysis were lower, indicating $F<F_{MSY}$, while the length catch curve method suggested F was above F_{MSY}. These results were broadly, but not entirely consistent, with LCA and the Jones and van Zalinge catch curve results (slightly) more optimistic than the length-based reference points and the (CCA_1) catch curve method.

Length-based per recruit analysis from the LCA output showed a flat topped yield curve and F_{max} was poorly determined and high, hence F/F_{max} would be well below 1. $F_{0.1}$ was better determined and current fishing mortality was just above this level. Thus LCA and per recruit analysis suggest F is just above $F_{0.1}$ and F_{max} is poorly determined, so yield-per-recruit will be near maximal. By comparison, the length-based reference points approach was again more pessimistic, suggesting the fishery was fished above the L_{opt} level for yield, although it is not entirely clear that L_{opt} represents maximal yield, or more likely some other point further to the left of the YPR curve (see discussion, Section 4.4.2.4).

Table 4.4.3.2.1. Comparison of status indicators from length-based reference points, LCA and length catch curve approaches applied to Nephrops. Note the colour coding was for illustration only and should not be interpreted as definitive in any way.

	LENGTH BASED REFERENCE POINTS APPROACH								LENGTH COHORT ANALYSIS AND LENGTH BASED CATCH CURVE APPROACH			
	$F/F_{MSYProxy}$		Other $F/F_{MSYProxy}$						$F/F_{MSYProxy}$			
	LFeM/MuL_All		LFeM/MuL_Lc50	LFeM/LMed	LFeM/LMaxY	LFeM/L25%	LFeM/L75%		F/M (LCA)		F/M (LCC)	F/M (JvZ)
Nephrops	1.07		1.04	1.15	1.21	1.25	0.99		0.87		1.17	0.97
	F/F_{max} or $F/F_{0.1\ proxies}$		Other F/F_{max} or $F/F_{0.1\ proxies}$									
	Lopt_emp/MuL_All		Lopt_emp/MuL_Lc50	Lopt_emp/LMed	Lopt_emp/LMaxY	Lopt_emp/L25%	Lopt_emp/L75%		F/F_{max}			
Nephrops	1.20		1.16	1.28	1.35	1.39	1.10		na			
	F/F_{max} or $F/F_{0.1\ proxies}$		Other F/F_{max} or $F/F_{0.1\ proxies}$									
	Lopt_calc/MuL_All		Lopt_calc/MuL_Lc50	Leopt_calc/LMed	Lopt_calc/LMaxY	Lopt_calc/L25%	Lopt_calc/L75%		$F/F_{0.1}$			
Nephrops	1.23		1.19	1.32	1.39	1.43	1.13		1.08			

Other stocks

Similar analyses were carried out for other stocks including blonde rays in Portugal (rjh_pore), sardines (Area VII & VIII) and a subset of UK observer data for lemon sole in the North Sea. Data constraints (e.g. subset) and features of the length distributions caused problems for the LCA and catch curve approaches and as a result comparisons were less comprehensive (Table 4.4.3.2.2).

Table 4.4.3.2.2. Comparison of status indicators from length-based reference points, LCA and length catch curve approaches. Note the colour coding was done arbitrarily for illustration only and should not be interpreted as definitive in any way.

	$F/F_{MSYProxy}$	Other $F/F_{MSYProxy}$							
	LFeM/MuL_All	LFeM/MuL_Lc50	LFeM/LMed	LFeM/LMaxY	LFeM/L25%	LFeM/L75%	F/M (LCA)	F/M (LCC)	F/M (JvZ)
Sardine	0.94	0.93	0.93	0.86	1.06	0.86	1.73	0.13	1.53
	F/F_{max} or $F/F_{0.1\ proxies}$	Other F/F_{max} or $F/F_{0.1\ proxies}$							
	Lopt_emp/MuL_All	Lopt_emp/MuL_Lc50	Lopt_emp/LMed	Lopt_emp/LMaxY	Lopt_emp/L25%	Lopt_emp/L75%	F/F_{max}		
Sardine	0.89	0.88	0.88	0.82	1.00	0.82	nc		
	F/F_{max} or $F/F_{0.1\ proxies}$	Other F/F_{max} or $F/F_{0.1\ proxies}$							
	Lopt_calc/MuL_All	Lopt_calc/MuL_Lc50	Leopt_calc/LMed	Lopt_calc/LMaxY	Lopt_calc/L25%	Lopt_calc/L75%	$F/F_{0.1}$		
Sardine	0.87	0.86	0.86	0.80	0.99	0.80	1.24		
	$F/F_{MSYProxy}$	Other $F/F_{MSYProxy}$							
	LFeM/MuL_All	LFeM/MuL_Lc50	LFeM/LMed	LFeM/LMaxY	LFeM/L25%	LFeM/L75%	F/M (LCA)	F/M (LCC)	F/M (JvZ)
Lemon sole	1.03	1.00	1.03	0.93	1.16	0.93	na	0.12	0.27
	F/F_{max} or $F/F_{0.1\ proxies}$	Other F/F_{max} or $F/F_{0.1\ proxies}$							
	Lopt_emp/MuL_All	Lopt_emp/MuL_Lc50	Lopt_emp/LMed	Lopt_emp/LMaxY	Lopt_emp/L25%	Lopt_emp/L75%			
Lemon sole	1.13	1.10	1.13	1.02	1.28	1.02	na		
	F/F_{max} or $F/F_{0.1\ proxies}$	Other F/F_{max} or $F/F_{0.1\ proxies}$							
	Lopt_calc/MuL_All	Lopt_calc/MuL_Lc50	Leopt_calc/LMed	Lopt_calc/LMaxY	Lopt_calc/L25%	Lopt_calc/L75%		$F/F_{0.1}$	$F/F_{0.1}$
Lemon sole	1.17	1.13	1.17	1.05	1.32	1.05	na	0.12	0.27
	$F/F_{MSYProxy}$	Other $F/F_{MSYProxy}$							
	LFeM/MuL_All	LFeM/MuL_Lc50	LFeM/LMed	LFeM/LMaxY	LFeM/L25%	LFeM/L75%	F/M (LCA)	F/M (LCC)	F/M (JvZ)
Blonde ray	1.10	1.08	1.19	0.80	1.37	0.92	0.74	0.74	1.89
	F/F_{max} or $F/F_{0.1\ proxies}$	Other F/F_{max} or $F/F_{0.1\ proxies}$							
	Lopt_emp/MuL_All	Lopt_emp/MuL_Lc50	Lopt_emp/LMed	Lopt_emp/LMaxY	Lopt_emp/L25%	Lopt_emp/L75%	F/F_{max}		
Blonde ray	1.57	1.54	1.69	1.13	1.95	1.31	0.67		
	F/F_{max} or $F/F_{0.1\ proxies}$	Other F/F_{max} or $F/F_{0.1\ proxies}$							
	Lopt_calc/MuL_All	Lopt_calc/MuL_Lc50	Leopt_calc/LMed	Lopt_calc/LMaxY	Lopt_calc/L25%	Lopt_calc/L75%	$F/F_{0.1}$		
Blonde ray	1.61	1.59	1.74	1.16	2.00	1.34	1.00		

For sardine the length-based reference points approach suggested the stock was fished at levels below the F_{MSY} proxy F=M and below the levels associated with both L_{opt} references. This result was consistent across all the central metrics used to express exploitation rate. LCA and one catch curve estimate suggested F was high for this stock while the Jones and van Zalinge (1981) catch curve method suggested F was low; the former indicating F well above the MSY proxy of F=M (0.3), while the latter indicating F well below the MSY proxy. These inconsistent results probably reflect difficulties in selecting the range of length classes over which to calculate an average level for F in the LCA (or Z in the catch curve case). The length ranges were chosen consistently to provide a comparison between methods, but the bimodality of the sardine length distribution over this range is likely to have caused severe problems for the catch curve analyses. The LCA and per recruit estimate of status relative suggests that F is just above $F_{0.1}$. In general the length-based reference points approach and length catch curve method suggested more optimistic status prognoses than LCA and Jones and van Zalinge (1981) catch curve analysis. This overall result was the converse of that for *Nephrops*.

For lemon sole the length-based reference point approach suggests that F is around or just above the level of F_{MSY} (F=M proxy) and this result is consistent over most central metrics, with the possible exception of LCMaxY. F was estimated to be (either slightly or substantially) above the L_{opt} reference levels by all central metrics in the length reference points approach. It was not considered appropriate to apply LCA to the sampled subset of data, but catch curves suggested that F was much lower than M and the reference point $F_{0.1}$ was estimated to be equal to M. These results differed substantially with the length-based reference points suggesting F was close to F_{MSY} while catch curves suggested F was far below M and $F_{0.1}$. Whether this reflects differences in perception of F or M is not clear as the length-based reference point approach does not explicitly use M as a parameter and does not explicitly consider F. However, the approximation for $L_{F=M}$ (i.e. $=0.75L_c+0.25L_{inf}$) is considered reliable and does implicitly consider natural mortality and the growth parameter K. Some concern was expressed that the growth parameters used for this species may have indicated higher growth than is actually the case for this species.

For Blonde ray in Portugal the length-based reference points approach suggested that F was (slightly to substantially) above the F_{MSY} proxy level (F=M). This result held for most central metrics, with the exceptions of the upper quartile and the length class contributing maximum biomass (LCMaxY). Fishing mortality was estimated to be well above L_{opt} levels irrespective of which of central length metrics was used. LCA and length catch curve analysis suggested that fishing mortality was 25% below F_{MSY} proxy levels (F=M), while the Jones and van Zalinge (1981) catch curve analysis suggested it was far above this level. LCA suggested fishing mortality was well below F_{max}, at $F_{0.1}$. **Although this length distribution was not considered suitable to provide advice on sustainability** (see Annex 6, A.6.4)**,** comparisons between outputs from methods are still valid. Results from the length-based reference points approach and LCA and catch curve analyses showed poor consistency, with, the former suggesting poor status, LCA and catch curve analysis suggesting good status and Jones and van Zalinge (1981) catch curve analysis suggesting very poor status although it was not considered well suited to the situation for this fishery.

4.4.3.3 Discussion

For *Nephrops* there was broad agreement between the length-based reference points regarding optimal harvest and harvest at MSY and the CCA_1 method, while the LCA and CCA_2 methods gave slightly more optimistic perceptions of status. For sardine there was poor agreement between methods, with the length-based reference points approach suggesting exploitation rates just below MSY proxy levels, while LCA and CCA_2 suggested high exploitation (>$F_{MSYproxy}$) and CCA_1 suggested very low exploitation far below the MSY proxy level. For lemon sole no LCA was carried out but results for the length-based reference points approach differed from the catch curves, the former suggesting exploitation rates near the MSY proxy level while the latter suggested very low exploitation rates. For blonde rays results again differed substantially with the length-based reference points approach indicating very poor status, modified in the light of background information on fishery selection, to no advice on status, but a warning that the fishery exploitation pattern was poor with respect to blonde rays. The LCA and CCA_1 approaches suggested good status while the CCA_2 method indicated poor status.

In summary, results from the 4 different approaches were rarely in agreement, the closest being for *Nephrops*. The CCA_2 method (Jones and van Zalinge, 1981) often differed from the CCA_1 catch curve approach and the analysts at the working group noted the sensitivity of this method in the methods section (4.4.1.1). Additional diagnostics showing some of the regression fits or exploitation patterns derived from LCA may have been useful in identifying some of the reasons for the differences between methods. In the case study for blonde rays the length range used for the LCA and catch curve analyses (58-100cm) started above the main peak of the distribution and finished before the rapid decline in numbers in the right-hand tail of the distribution. It seems likely then that F estimated over the relatively flat middle section of the distribution will be lower than Fs estimated around the peak at small sizes or in the right hand tail of the distribution. However in the other case studies the length ranges used did broadly cover most of the length distribution and results were still inconsistent. Bimodality in both the sardine and lemon sole length distributions may have caused problems with the catch curve analyses.

Although using the same basic length data results and interpretations of status from the different approaches differed, sometimes substantially. Possible reasons for this include:

- Additional parameters in some of the methods (e.g. M in the LCA, yield-per-recruit analyses and *post hoc* in the catch curve analyses and ages/lengths at recruitment and full capture in the yield-per-recruit analyses).
- Assumptions regarding ranges of length classes over which apply the LCA and calculate Fbar or over which to carry out regression for catch curves.
- Differences in the assumptions underlying the different methods.

The length based reference points approach uses the length distribution in its raw form and does not include explicit modelling of age or mortality (natural or fishing), its characterising metrics are standard statistical measures (e.g. mean and quantiles) and its reference points are derived primarily from externally derived biological parameters (growth and maturity). By contrast the catch curves and LCA explicitly model mortality as the exponential decline in catch numbers after rescaling the length classes into 'pseudo' age classes. In the former an average total mortality is estimated, by assuming the catch numbers are representative of population decline and fitting a linear model (to the logarithm of numbers) to estimate the rate of decline (Z). In LCA, starting with an estimate of exploitation rate for the terminal length class and with an assumption for natural mortality rate, (starting) numbers and fishing mortality are calculated sequentially for each preceding length class in the length distribution. In both cases, the steepness of the downward slope in the right-hand limb of the length distribution determines the rate of mortality, as an average in the catch curves methodology and explicitly by length class in LCA, the latter having the advantage that it can cope better with non-linearity in the decline of log catch numbers, which is common place.

Taking the blonde ray case study as an example, the length based reference points approach (applied blindly) suggests a very poor status, but when the shape of the length distribution is taken into account, the relatively flat plateau in the middle of the distribution and shallow overall slope of the right-hand limb (which would be even shallower when rescaled to represent age) point to low levels of mortality on these sizes.

One conclusion from this would be that rescaling the length distribution and explicitly considering the decline in numbers as an indication of exponential mortality rates can provide considerably more information than a simple consideration of the length distribution *per se*.

Differences between the performance of LCA and the catch curve approaches are also likely to be driven by the assumptions behind the methods and the particular features of the length distributions. The Jones and van Zalinge (1981) method was noted in the methods (Section 4.4.4.1) to be extremely sensitive and in general both catch curve methods are likely to suffer when the length distributions are other than unimodal, which was the case for all the distributions considered here with the exception of *Nephrops*; the case study in which most consistency was apparent.

4.4.4 Size-based method

4.4.4.1 Introduction

The assessment of the status of fish stocks that are caught mainly as bycatch can be challenging because of limited available information. There is rarely information on age, or time-series of commercial catches. A new size based method for data-limited stock assessment is used to assess three bycatch species in Skagerrak. The data limited assessment method is presented in Kokkalis et al. (In press) along with a simulation analysis and discussion about its limits. It is based on a theoretical size-based framework of exploited fish stocks (Andersen and Beyer, 2013). It requires little input data, i.e. catch-at-size from commercial catches or surveys, to estimate the status of fish stocks. The stock status is quantified by the ratio of fishing mortality (F) and the reference point Fmsy. The method is novel in two aspects. Firstly, it does not estimate the fishing mortality directly, but the ratio of current fishing mortality and Fmsy. Secondly, it includes a stock–recruitment relationship, thus it is not a per-recruit method. Not all of the parameters can be estimated, thus, a Robin Hood approach (Punt et al., 2011) is used; information from data-rich well assessed stocks is utilized to parametrize the data-poor method. The estimation is mostly sensitive to the value of one life-history parameter, the physiological mortality (i.e. ratio of natural mortality and growth). Since this parameter is not easily measured, its uncertainty is included in the estimation, resulting to "sensitivity intervals" of the stock status. These intervals represent the uncertainty of the result.

The "Sustainable Bycatch" project identified important bycatch species in Skagerrak. For three of the species length data were available from the North Sea International Bottom Trawl Survey (NS-IBTS). The assessment presented here provides a first indication of the fishing status of these species that can be used for management decisions. However, further investigation, using more data, is necessary to inform on sustainable harvesting.

The method is also used to assess the status of the *Nephrops* in Southwest and South Portugal (nep-2829) using yearly length compositions from landings of male *Nephrops*.

4.4.4.2 Methods

Survey data

Survey data were obtained from the NS-IBTS for ling (*Molva molva*), long rough dab (*Hippoglossoides platessoides*) and witch flounder (*Glyptocephalus cynoglossus*). The data were acquired from the ICES database of trawl surveys (DATRAS) for years 1991 to 2013. The assessment model works using weight as the population structuring parameter. Thus, the length data are transformed to weight using weight-length relationships. For ling and witch, survey data were used to estimate the weight-length relationships. For long rough dab survey weight data were not available; a weight-length relationship from the literature was used.

Yearly length composition of male *Nephrops* from landings is used to estimate fishing status. The weight–length relationship from the WGBIE working group report (ICES, 2014) is used to transform the length to weight. The estimation for each year is done using aggregated data from the last five years. This is done to get an equilibrium snapshot of the stock.

Assessment

The assessment was done using the single species data-poor assessment model described in Kokkalis *et al.* (*In press*). The model describes the equilibrium population size spectrum using size specific growth and mortality equations and Beverton–Holt stock–recruitment relationship. Three parameters of the model are estimated: the fishing mortality, the 50% retainment size and the asymptotic weight. The other life-history parameters describing the growth, maturation and mortality of the population are borrowed from well assessed stocks in a Robin Hood approach. The yield function is maximized with respect to fishing mortality to estimate the Fmsy reference point. The estimated ratio of fishing mortality and F_{msy}, i.e. the stock status, is the output of the model. If the stock status is larger than "1", the stock is fished at rates higher than F_{msy} and if it is below "1" the stock is underexploited.

Simulation analysis (Kokkalis *et al.*, In press) revealed that estimations are mostly sensitive to the physiological mortality, a life-history invariant defined as the ratio of natural mortality and available energy, related to the M/K Beverton–Holt life-history invariant. The estimation is repeated for many values of the physiological mortality, sampled from its empirical distribution, i.e. the observed distribution among well assessed stocks.

4.4.4.3 Results and discussion

Ling

The weight–length relationship was estimated from survey data and used to transform the length data to weight. The assessment of the stock status of each year was done by aggregating the current year with the previous four years. This was done to accommodate for the low number of samples and to get a steady state snapshot of the size distribution. The stock seems to be fished below F_{msy} for most of the studied period (Figure 4.4.4.3.1).

Long rough dab

The survey data did not include weight, thus the weight-length relationship from Coul *et al*. (1989) was used to transform length to weight. The stock status was assessed using only data of each year separately, assuming a steady state snapshot of the size/distribution. The long rough dab seems to be exploited at rates near the F_{MSY} reference point, with a declining trend during recent years (Figure 4.4.4.3.2).

Witch flounder

The weight–length relationship was estimated using survey data, and was used to transform length data to weight. Data from the previous five years were aggregated to estimate each year's stock status, due to small yearly sample size. The stock seems to be fished at levels below or at F_{MSY} during recent years (Figure 4.4.4.3.3).

Nephrops

The weight–length relationship from the WGBIE working group (ICES, 2014) was used to transform length data to weight. Aggregated data from the last five years were aggregated to perform the assessment of each year. The stock was harvested at levels around Fmsy in the early 2000, and there is an increasing trend of F/F_{MSY} during recent years (Figure 4.4.4.3.4).

In summary, the novel data-poor method provides an assessment of fishing status for three stocks in the North Sea (ling, long rough dab and witch flounder) and *Nephrops* in Southwest and South Portugal (nep-2829). The results indicate that ling and witch flounder are exploited below or at MSY, while long rough dab is exploited close to MSY with a declining trend. *Nephrops* in FU 28–29 seems to be undergoing overfishing in the recent years, with its status trending away from MSY.

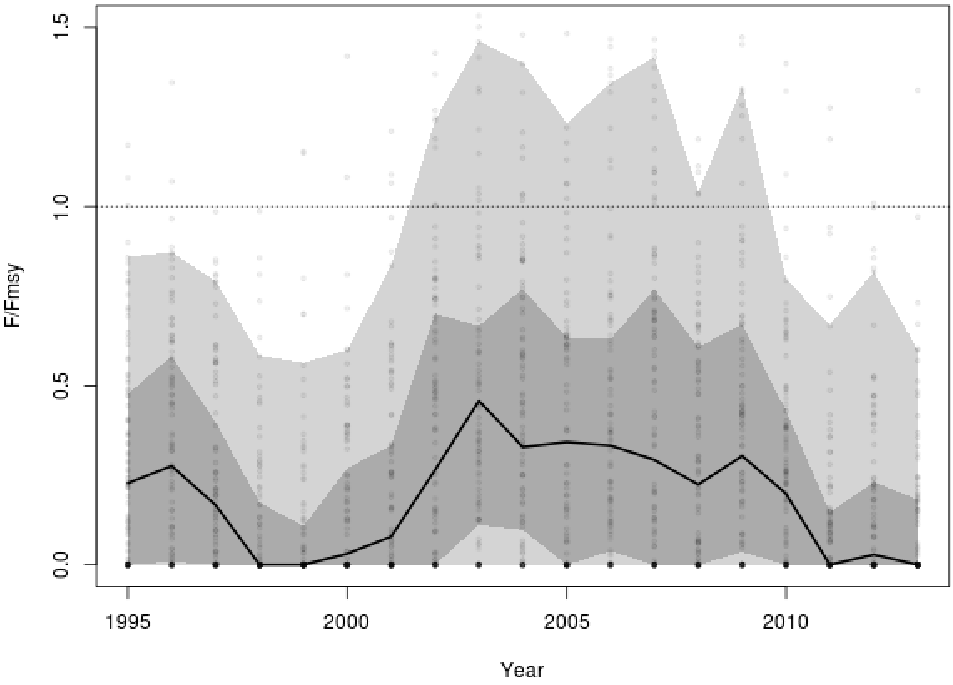

Figure 4.4.4.3.1. Status of North Sea ling stock estimated using survey data. The estimation for each year is done using data from the last five years. The solid line is the estimation using the default physiological mortality (a = 0.35). Sensitivity intervals were created by using random values for a. The dots show all results, the dark grey area shows the 50% sensitivity interval and the light grey area shows the 90% sensitivity interval.

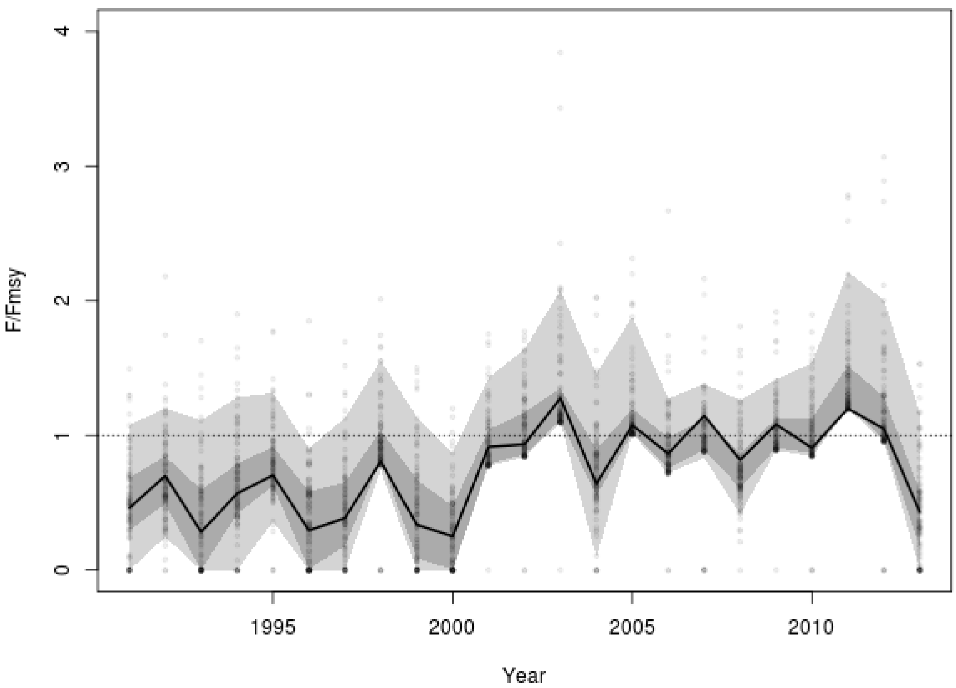

Figure 4.4.4.3.2. The status of the North Sea long rough dab stock estimated using survey data. The solid line is produced using the default parameter values. The shaded areas show the sensitivity intervals for different values of physiological mortality. The dark grey area shows the 50% sensitivity interval and the light grey area shows the 90% sensitivity interval and the dots show all results.

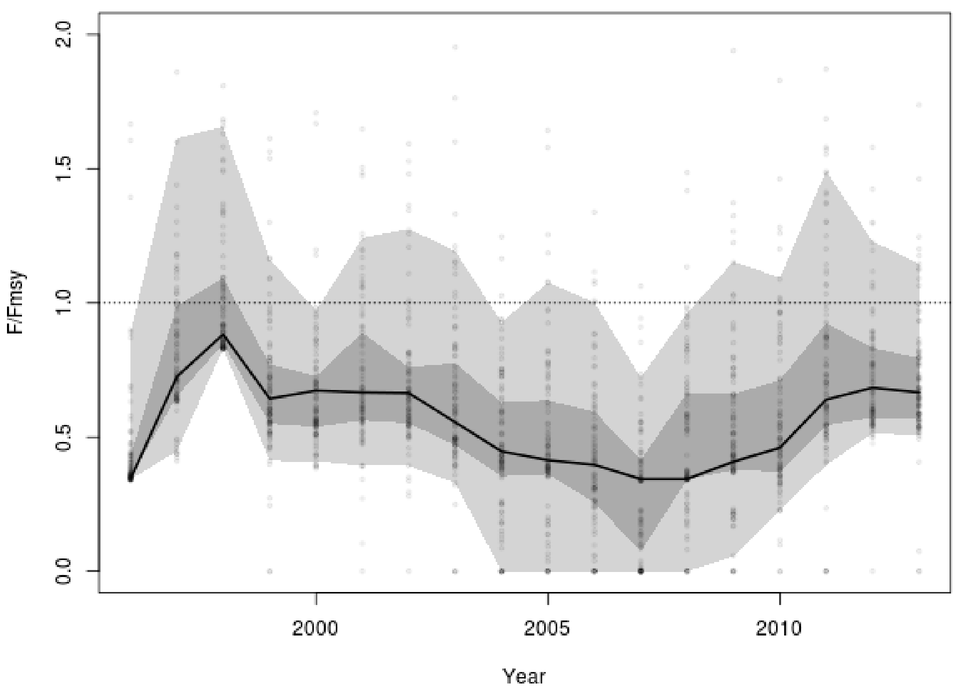

Figure 4.4.4.3.3. The status of the North Sea witch flounder stock estimated using survey data. The solid line is produced using the default parameter values and 50% retention size relative to the asymptotic weight equal to 0.05. The shaded areas show the sensitivity intervals for different values of physiological mortality. The dark grey area shows the 50% sensitivity interval and the light grey area shows the 90% sensitivity interval and the dots show all results.

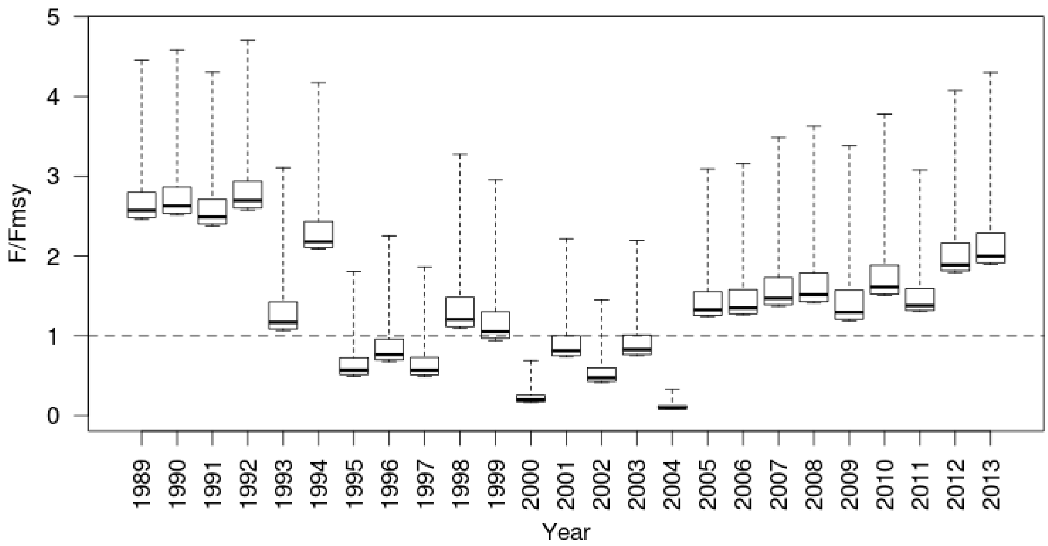

Figure 4.4.4.3.4. The status of the *Nephrops* (nep-2829) estimated using commercial landings of males. A box plot is presented for each year, showing the upper and lower 5th and 25th quantiles and the median of all estimated F/Fmsy. The different estimations are done using different values of physiological mortality and give a sense of the uncertainty of the results (due to sensitivity).

4.4.4.4 Future work

The size-based assessment method presented here is undergoing validation. The first step was using a simulation analysis which revealed the limits of the method. The next necessary step is validation using real data. This is currently being done treating well assessed stocks as data-limited. The results can be compared to the official assessment to reveal agreements and disagreements.

The method is currently being implemented as an R package called *s6model* (Single-species, size-based, steady-state model). The package is currently actively developed and it should be used with caution. It is expected to be in a stable well documented state in the first quarter of 2015. The source code is available in github (https://github.com/alko989/s6model) and the latest version can be installed using the *devtools* package by running:

devtools::install_github("alko989/s6model")

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5 HCRs for data-limited stocks (ToR 2, 3 and 4)

5.1 Management strategy evaluation of HCRs for *Nephrops* 28–29

This section provides an initial investigation when applying a number of harvest control rules with the aim to generate TAC advice for the *Nephrops* in Functional Units 28 and 29. The operating model used to simulate the underlying dynamics of the stock is an age-structured production model (ASPM), described in Annex 7. Four sources of uncertainty are incorporated: model uncertainty, process error, observation error and implementation error. Model parameters and associated distributions assumed for these simulations are summarized in Table 5.1.1 and Table 5.1.2. The time-series data (catch, cpue and mean length of catch) are summarized in Table 5.1.1.1 and plotted in Figure 5.1.1.1.

Ten-year projections were also performed under the five alternative HCRs. A thousand simulations were done to better incorporate the full extent of uncertainty. Simulation results are summarized in Table 5.1.3.2.

Table 5.1.1. Parameter estimates for *Nephrops* in 28–29 used to condition the operating model (see Annex 7 for technical details).

Parameter	Point estimate (as provided by Christina Silva pers comm.)	Distribution assumed for base case simulations
Minimum age	0 years	
Maximum age	10 years	
Age-at-50% maturity	2 years	
Growth: L_∞	70 mm	Simulated values for growth parameters are derived from natural mortality sampled from a uniform distribution:
Growth: κ	0.2 yr^{-1}	$\hat{\kappa} = \hat{M} / (M / \kappa) = \hat{M} / 1.25$
Growth: t_0	0 years	$\ln \hat{L}_\infty = \ln \hat{\kappa} (\ln L_\infty / \ln \kappa) = -2.64 \ln \hat{\kappa}$
Weight-length: a	0.00028 g mm^{-1}	Log-normal with CV=0.1
Weight-length: b	3.2229	Log-normal with CV=0.1
Natural mortality rate: M	0.25 yr^{-1}	$U[0.2, 0.3]$
Steepness *h*	Fairly constant recruitment	$U[0.7, 0.9]$
B^{sp} / K	Not very depleted as it is not the target species	$U[0.3, 0.5]$
Implementation error:	Assumed negatively biased	Residuals: N(0.1,0.2^2)
Process error:	Knife-edge selectivity	Log-normal with CV=0.4, $\rho = 0.5$
	B–Holt recruitment with high *h*	Log-normal with CV=0.5
Observation error:	Mean length data	Log-normal with CV=0.2
	cpue data	Log-normal with CV=0.2

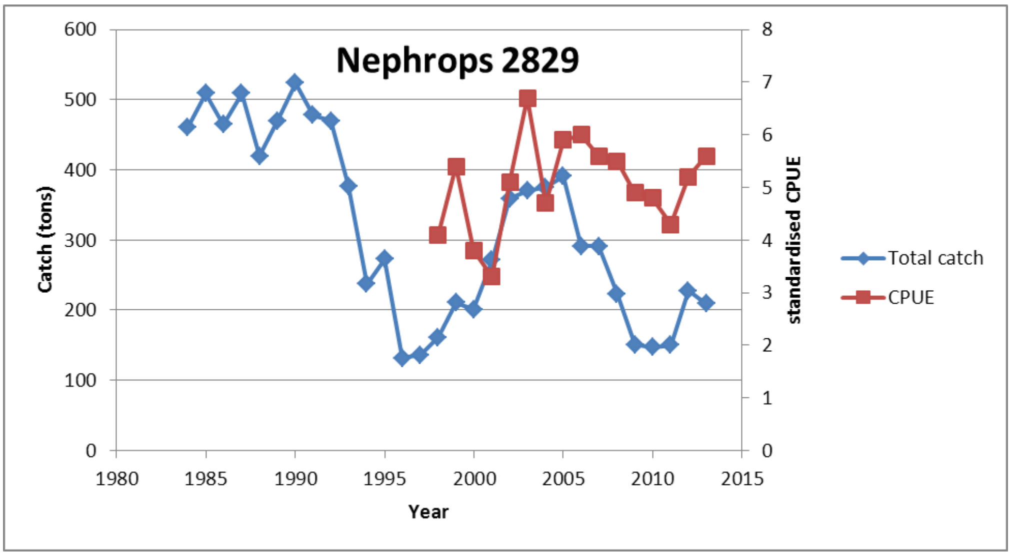
Table 5.1.2. Knife-edged fishing selectivity-at-age is assumed for the *Nephrops* in 28–29 for simplicity.

Age	0	1	2	3	4	5	6	7	8	9	10
S_a	0	0	1	1	1	1	1	1	1	1	1

5.1.1 Data

Table 5.1.1.1. Time-series data for the *Nephrops* in 28–29 stock as provided by the WKLIFE IV.

Year	Catch (tonnes)	cpue	Mean Length (mm)
1984	461	0	0
1985	509	0	0
1986	465	0	37
1987	509	0	36
1988	420	0	36
1989	469	0	36
1990	524	0	37
1991	478	0	37
1992	470	0	37
1993	377	0	36
1994	237	0	36
1995	273	0	37
1996	132	0	38
1997	136	0	37
1998	161	4.1	37
1999	211	5.4	37
2000	201	3.8	38
2001	271	3.3	40
2002	359	5.1	41
2003	370	6.7	40
2004	375	4.7	39
2005	391	5.9	37
2006	291	6	37
2007	291	5.6	36
2008	223	5.5	37
2009	151	4.9	38
2010	147	4.8	39
2011	150	4.3	40
2012	228	5.2	39
2013	209	5.6	39



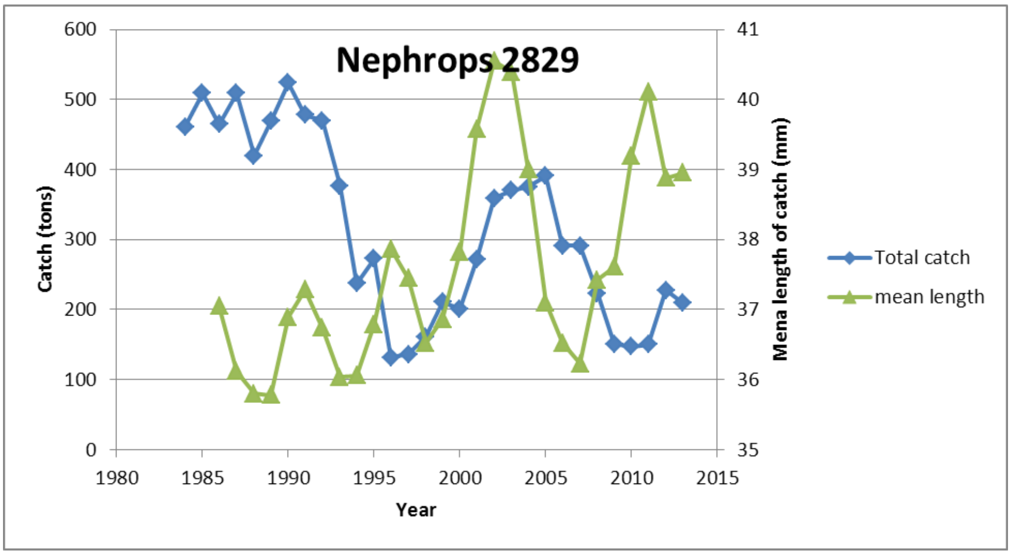


Figure 5.1.1.1. Annual landings of the *Nephrops* 28–29 fishery are indicated by the blue diamonds. The total catches prior to 1984 are excluded as these are not well known. The total catches after 1984 are not reliable as the Spanish catches may not be reported correctly. The standardized cpue index is indicated by the red squares (top plot). Contrary to expected, the cpue data follows catch trends. The mean length of catch time-series is shown in the bottom plot (green diamonds).

5.1.2 Harvest Control Rules (HCRs)

Five candidate harvest control rules (HCRs), summarized in Table 5.1.3.1, were evaluated. Prior to performing simulation trials, the candidate HCRs were first applied to the data using the preselected tuning parameters indicated in Table 5.1.3.1. This exercise was done to determine the TAC advice for 2014 according to these "off-the-shelf" control rules.

- The depletion-corrected average catch relies on estimates of relative depletion, Δ, to determine the DCAC (MacCall, 2009). While it is thought that the *Nephrops* in FU 28–29 stock has declined since 1984, the stock is nevertheless thought to be in a healthy state. Values for relative depletion of 0.0, 0.2 and 0.5 were applied, with corresponding DCAC's of 316, 297 and 271 tons, respectively.

- The ICES ratio rule (ICES, 2012) does not depend on estimates of relative depletion, but simply adjusts the TAC up or down if the recent average cpue is above or below the previous average. According to this rule a TAC of 264 tonnes was generated for 2014.
- The length-based rule adjusts the TAC up/down from a target TAC depending if the recent mean length is above or below the target mean length (Geromont and Butterworth 2014). The target mean length was set equal to the estimated length when the stock is at MSY level (Mike Smith pers. comm). The target TAC was set equal to the DCAC when assuming a relative depletion of 0.5. The TAC for 2014 generated by this rule is 264 tonnes, the same as that generated by the ratio rule.
- The fourth HCR considered is a simple cpue slope rule where the TAC is moved up or down if the slope of the most recent years of cpue data is positive or negative (Geromont and Butterworth, 2001). The resultant TAC advice for 2014 for $\lambda = 0.4$ is 224 tonnes. This relatively low value is due to the low catch estimate for 2013.
- The last HCR investigated is target rule based on a cpue index (Geromont and Butterworth, 2014; Wayte, 2009). This rule adjusts the TAC up or down from a target TAC if the recent average cpue is above or below a target index value. The DCAC for a relative depletion of 0.5 was adopted as the target TAC. The target cpue was simply set to the maximum historic value. The resulting TAC advice for 2014 is 236 tonnes.

5.1.3 Simulation trials

Table 5.1.3.1 shows medians and 90% probability intervals for relative depletion and spawning biomass relative to MSY level at the start and end of the projection period. The Table 5.1.3.1 also shows median estimates for average TAC, average interannual variation in TAC, and average "true" catch, which incorporates implementation error, over the ten-year projection period. In addition to the five candidate HCRs summarized in Table 5.1.3.1, projections were also performed when taking zero future catch as well as a high constant catch of 500 tons for comparison. The candidate HCRs were not tuned to achieve improved performance. Rather, the same control parameters were used as for the direct applications in the subsection above. A limit on the interannual change in TAC of 15% was applied for all simulations.

All five candidate HCRs are able to maintain the mean relative depletion at about 40% of the biomass at the beginning of the assessment period, and keeping the minimum estimates for depletion above 0.2 for 95% of the time. Average mean TAC generated by the HCRs range from 250 to 270 tons, while the "true" median catches range from 280 to 300 tonnes.

Figure 5.1.3.1 shows ten-year projections for the biomass, TAC and "true" catch trajectories under the five candidate HCRs: DCAC at the top, L_{target}, I_{ratio}, I_{slope} and I_{target} at the bottom. Although the projected TACs differ appreciably between alternative control rules, these differences are obscured once implementation error is reflected in the "true" catches.

Summary statistics are compared in Figure 5.1.3.2. While all control rules are able maintain spawning biomass levels throughout the projection period, the main difference in performance is related to the interannual fluctuations in TAC advice: the ratio rule resulted in the highest variability in TAC advice, but without the benefit of reducing the risk of stock depletion. Figure 5.1.3.3 compares the yield-risk trade-offs for the alternative rules. The "best performing" rule will lie towards to top right-hand corner of the plot (higher yield and biomass). Accordingly, the slope rule appears to achieve the best risk-yield trade-offs. However, it should be kept in mind that none of the rules were tuned to achieve maximum performance.

Table 5.1.3.1. MP generated TAC advice (in tonnes) when applying the four candidate MPs directly to data from the *Nephrops* in FU 28–29 without tuning of control rule parameters. Data were provided by Cristina Silva and Mike Smith. Note that the *Nephrops* in FU 28-29 is not at virgin biomass at the start of the assessment period in 1984 (the preceding years are typified by high, but uncertain, catches by the Spanish fleet).

HCR generated TAC advice	HRCs and tuning parameters
Depletion Corrected Average Catch (DCAC): $\Delta = (B_{84}/K - B_{13}/K) = 0.5$: DCAC =271tons $\Delta = (B_{84}/K - B_{13}/K) = 0.2$: DCAC =297tons $\Delta = (B_{84}/K - B_{13}/K) = 0$: DCAC =316 tons	$DCAC = \dfrac{\sum_{1983}^{2013} C_y}{n + \Delta/(MSYL \times c \times M)}$ where $\Delta = (B_{1984} - B_{2013})/K$ is the final depletion relative to the start of the assessment period, $n = 30$, $MSYL = 0.4$, $M = 0.25$, and $c = 1$.
Index ratio (Iratio): Iratio=264	$TAC_{2014} = TAC_{2012} \dfrac{1/2\sum_{2012}^{2013} I_y}{1/3\sum_{2009}^{2011} I_y}$
Length-based target MP (Ltarget): Catch and mean length time-series. TAC Ltarget=264 tons	$TAC_{y+1} = 0.5TAC^*[1 + (\dfrac{L_y^{recent} - L^0}{L^{target} - L^0})]$ L^{recent} is average index over the most recent 5 years, $L^{target} = L_{F=M}$ =41mm, $L^0 = 0$, and $TAC^* = DCAC$ with $\Delta = 0.5$
Index slope (Islope) TAC Islope=224 tons	$TAC_{y+1} = TAC_y(1 + \lambda s_y)$ where $\lambda = 0.4$ and s_y is the slope of the cpue over the last five years.
Target MP (Itarget): TAC Itarget=236 tons	$TAC_{2014} = 0.5TAC^*[1 + (\dfrac{I_y^{recent} - I^0}{I^{target} - I^0})]$ where I^{recent} is average index over the most recent five years. I^{target} is the maximum historic cpue value, $I^0 = 0$ and $TAC^* = DCAC$ with $\Delta = 0.5$.

Table 5.1.3.2. Medians and 90% probability intervals for management quantities for a 1000 simulations when projecting forward for ten years under alternative control rules. The operating model allows for different sources of uncertainty as summarized in Table 5.1.1.1. Units are tonnes where applicable.

	TAC=0	TAC=500	DCAC	LTARGET	IRATIO	ISLOPE	ITARGET
B_n^{sp} / B_1^{sp}	0.40 (0.31, 0.49)	0.40 (0.31, 0.49)	0.40 (0.31, 0.49)	0.40 (0.31, 0.49)	0.40 (0.31, 0.49)	0.40 (0.31, 0.49)	0.40 (0.31, 0.49)
$B_{final}^{sp} / B_1^{sp}$	0.85 (0.66, 1.10)	0.03 (0.01, 0.27)	0.40 (0.18, 0.69)	0.41 (19, 69)	0.43 (0.22, 0.67)	0.43 (0.24, 0.68)	0.42 (0.21, 0.68)
Min depletion	0.4 (0.31, 0.49)	0.033 (0.01, 0.27)	0.35 (0.18, 0.47)	0.35 (0.18, 0.47)	0.35 (0.21, 0.48)	036 (0.23, 0.48)	0.35 (0.20, 0.48)
B_n^{sp} / B_{MSY}^{sp}	1.28 (0.97, 1.62)	1.28 (0.97, 1.62)	1.28 (0.97, 1.62)	1.28 (0.97, 1.62)	1.28 (0.97, 1.62)	1.28 (0.97, 1.62)	1.28 (0.97, 1.62)
$B_{final}^{sp} / B_{MSY}^{sp}$	2.71 (2.05, 3.67)	0.11 (0.03, 0.09)	1.30 (0.57, 2.27)	1.34 (0.59, 2.23)	1.40 (0.72, 2.34)	1.36 (0.75, 2.23)	1.34 (0.66, 2.26)
$\overline{TAC}_{future}$	0	500	267 (267, 267)	260 (252, 268)	252 (179, 340)	254 (225, 291)	252 (213, 325)
AAV	0.1	0.14	0.03	0.03 (0.03, 0.04)	0.12 (0.09, 0.14)	0.04 (0.03, 0.06)	0.04 (0.02, 0.08)
$\overline{C}_{future}$ (implementation error)	0	554 (499, 614)	296 (267, 329)	288 (257, 322)	278 (191, 383)	281 (237, 333)	281 (231, 370)

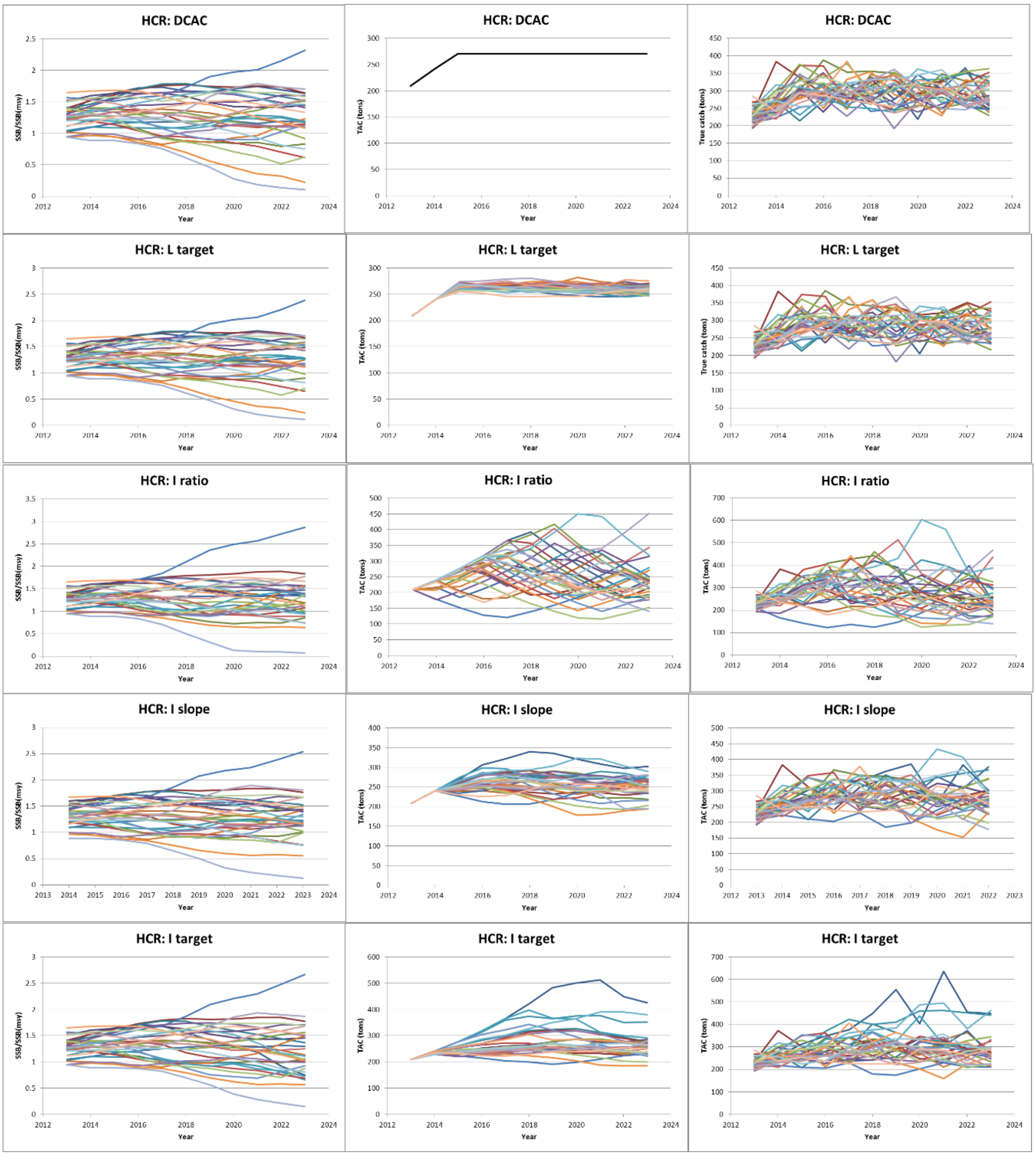


Figure 5.1.3.1. Spawning biomass, TAC and catch projections under alternative HCRs. Thirty simulations of a total of one thousand are shown. The true catch is estimated from the TAC advice by adding bias and noise. The extent of uncertainty incorporated by the operating model (in particular observation and implementation error) obscures trends in the data as well as the effects of adjusting the TAC advice up or down, so that the resultant performance of the control rules are similar.

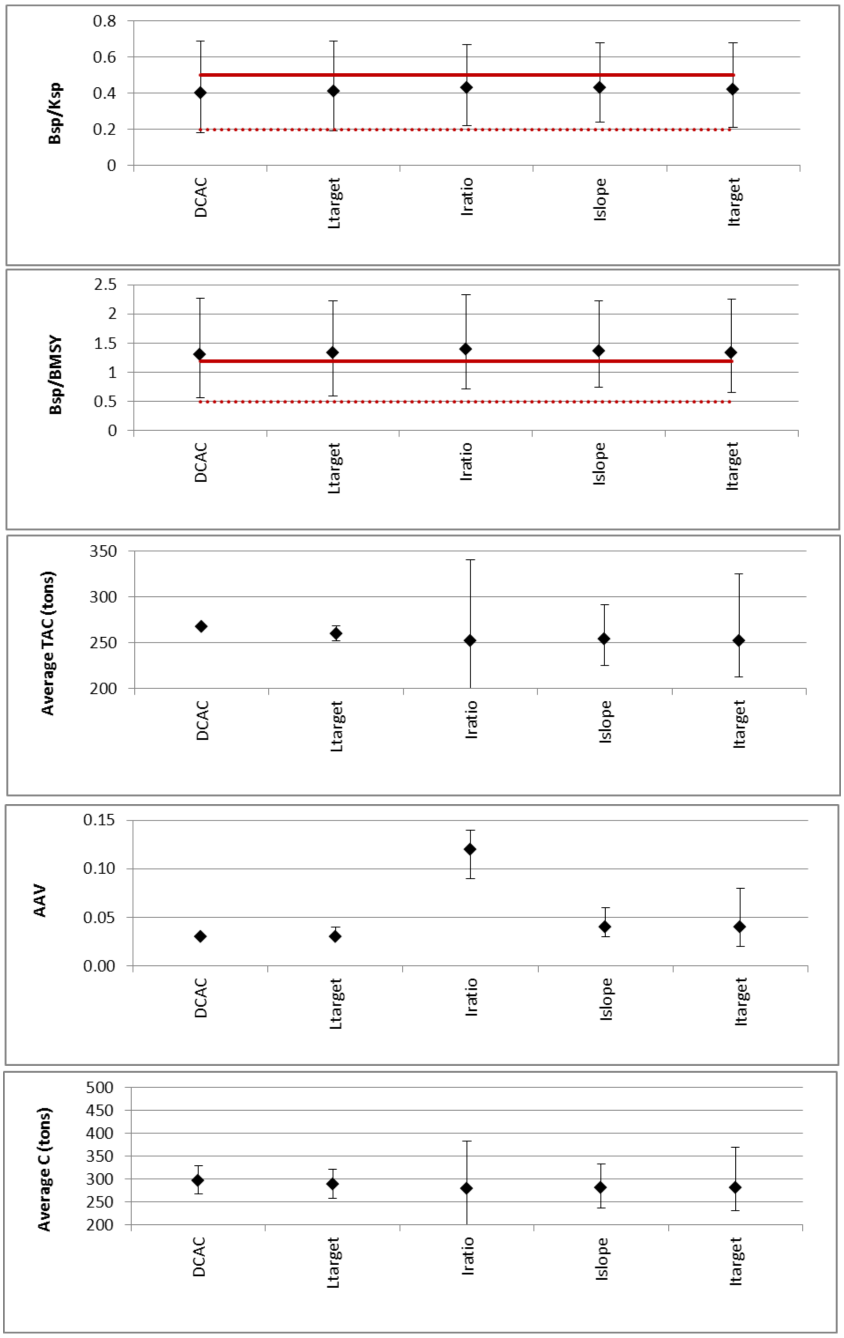


Figure 5.1.3.2. Comparison of performance statistics (medians and 90% probability intervals for a thousand simulations) for the base case operating model with model parameters distributions summarized in Table 5.1.1.1. Notable is that the TAC advice generated by the ratio type HCR fluctuates far more than that generated by the other candidates. From a risk point of view, the slope rule seems to perform best.

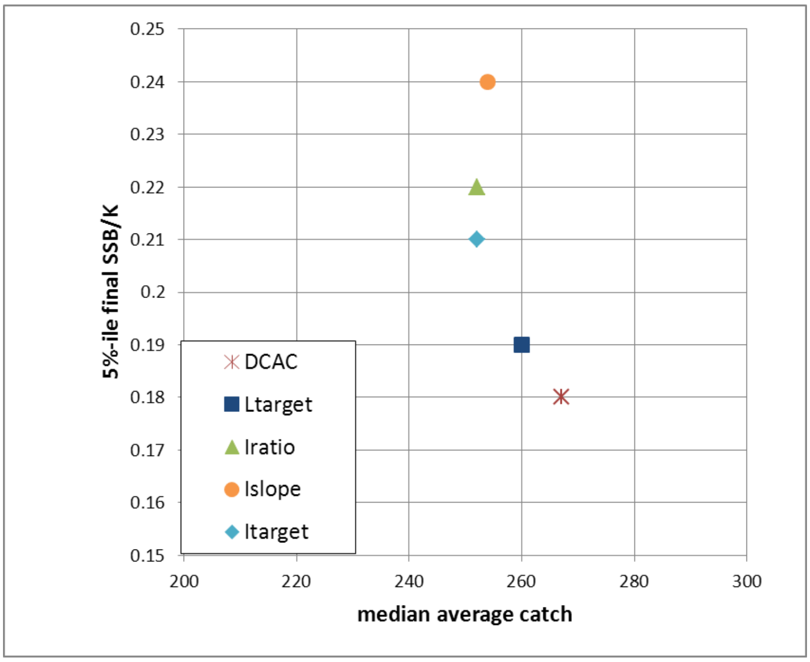


Figure 5.1.3.3. Comparing median yield/risk trade-offs for the five candidate control rules. Here the 5%-ile of the probability interval for final biomass depletion is plotted against median estimates for average catch. The values lying towards the top right-hand side of the plot performs best.

5.1.4 Conclusion and discussion

- The performance of these HCRs were largely over-shadowed by observation and implementation error: small adjustments in TAC advice were not effective to drive biomass levels.
- Of the control rules tested here, the slope-type rule shows the most promise: the simplicity with which it tracks the biomass works particularly well for stocks that are not overexploited and severely depleted.
- The mean length index was not adequately informative and the length-based HCR is therefore not adequately reactive.
- Other HCRs, as well as different tunings of the current rules, need to be simulation tested. For example, a stepwise constant catch type rule which adjusts the TAC up or down by a step only when there is overwhelming evidence in the index to support such an increase/decrease, should also be evaluated.
- The operating models are conditioned on the assumption that current depletion is 30–50% of the level in the first year of the assessment. The simulation trials need also be repeated for other depletion ranges.

5.2 Simulation testing of survey- and length-based HCRs

For many data-limited stocks a considerable amount of data and information may indeed be available, like length frequencies of catch/landings and/or abundance indices from scientific surveys (e.g. in compliance with the European Data Collection Framework), as well as information on life-history parameters. Jardim et al. (*in press*) simulation tested the performance of three HCRs driven by indicators derived from fisheries key monitoring data to obtain catch advice for data-limited stocks that are able to recover the stock if it is depleted and minimize the risk of stock depletion. HCR1 and

HCR2 are survey-based HCRs while HCR3 is length-based. HCR1 is based on short-term changes in survey abundance/biomass (used by ICES to provide catch advice for DLS stocks, method 3.2; ICES, 2012). HCR2 is based on the confidence interval of the mean abundance of the survey, parametrized with asymmetric confidence intervals in a "fast down/low up" (-25%, +5%) catch changes approach. HCR3 requires data on the catch length composition and information on life-history parameters to compute the ratio between the mean length in the catch (used as a proxy for current fishing mortality, F_{SQ}) and the mean catch length when F=M (used as a proxy for F_{MSY}).

Simulation testing was performed within an MSE framework (age-structured operating model, uncertainty accounting for observation, process and implementation error, 250 simulations ran by stock) applied to 50 data-limited stocks under two fishery scenarios: "development ("dev") and overexploitation ("hi"). In the "dev" fishery scenario the stocks were subject, during 15 years (years: -14 to 0), to a linear increase in fishing mortality from F=0 to F=2F_{MSY} while in the "hi" scenario the fishing mortality was kept at 2F_{MSY} for 25 years, although only the last 15 years (years: -14 to 0) were used in the simulation study. The HCRs were applied for 25 years (years: 1 to 25).

A summary of data and information requirements, assumptions, simulation framework and main results of the study is presented in Annex 4.

5.2.1 Results

This section presents the results of the simulation testing of the performance of the HCRs applied to Lemon sole in the North Sea (lem-nsea) and *Nephrops* in Functional Units 28–29 (nep-2829). Lem-nsea and nep-2829 were selected among the 50 simulated stocks in the study because both stocks were used as case-studies during WKLIFE IV (Table 4.1.1). Table 5.2.1.1 presents the life-history parameters used to simulate these stocks and intended to loosely represent the biology of these species. Figure 5.2.1.1 show the trends in the spawning–stock biomass (ssb) from years -14 to 25 and the catch and catch multiplier for years 1 to 25 (application of the HCRs) for lem-nsea and nep-2829.

Table 5.2.1.1. Life-history parameters used to simulate the stocks of Lemon sole in the North Sea (lem-nsea) and *Nephrops* FU 28–29 (nep-2829) (from Table 1 *in* Jardim et al., *in press*).

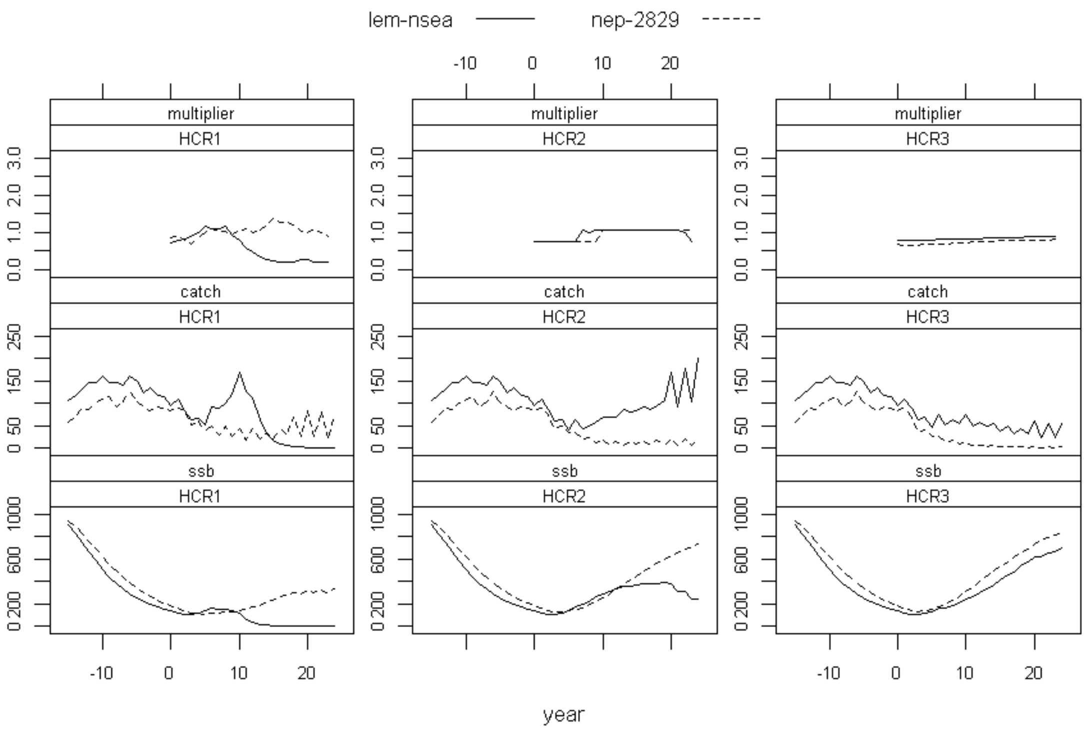
Stock	a	b	a50%	A_0	K	L_{inf}	F_{MSY}	M
lem-nsea	0.076	3.142	2.6	-0.1	0.30	40	0.30	0.51
nep-2829	< 0.001	3.000	3.7	-0.1	0.20	70	0.18	0.37

a,b: parameters of the length-weight relationship; a50%: age of first maturity; a_0, K, L_{inf}: parameters of the v. Bertalanffy growth model; F_{MSY}: fishing mortality at MSY (Beverton and Holt S–R relationship with steepness of 0.75 and virgin biomass of 1000 t); M: natural mortality (calculated from Gislason *et al.*, 2010).

The results from the simulated stock of lemon sole indicate that HCR1 (survey-based; short-term changes in biomass indices) is not risk-averse in both fishery scenarios (Figure 5.2.1.1). HCR1 is unable to recover the depleted stock in the "hi" scenario. In the "dev" scenario the catch multiplier increases in the first 10 years of the projected period and the stock biomass is stabilized at very low levels; despite a decrease in catches after year 10 the stock biomass is further reduced to a depleted level. HCR3 (length-based reference points) showed the best performance in terms of biological risk since it was able to reverse the decreasing trend in biomass in the "dev" scenario and to increase the depleted biomass in the "hi" scenario. HCR2 (survey-based; confidence intervals with "fast down/slow up" approach) was able to reverse the decreasing trend in biomass in the "dev" scenario (despite a decrease in the stock biomass after year 15) but was not risk-averse in the "hi" scenario.

In the case of the simulated *Nephrops* (nep-2829) all tested HCRs resulted in an increase ("dev") or recovery ("hi") of the stock biomass although at different time-lags and to distinct biomass levels. With HCR1 the low biomass in the "dev" scenario is stabilized at the recent low levels until year 10, after which increases to moderate levels at the end of the projected period; in the "hi" scenario the biomass increases after year 5 but at the end of the projected period is also at moderate levels. HCR2 and HCR3 correctly identify the stock to be overexploited in both scenarios, the catches are reduced quickly enough initially and the stock biomass increases to high levels at the end of the projected period (Figure 5.2.1.1).

(a)



(b)

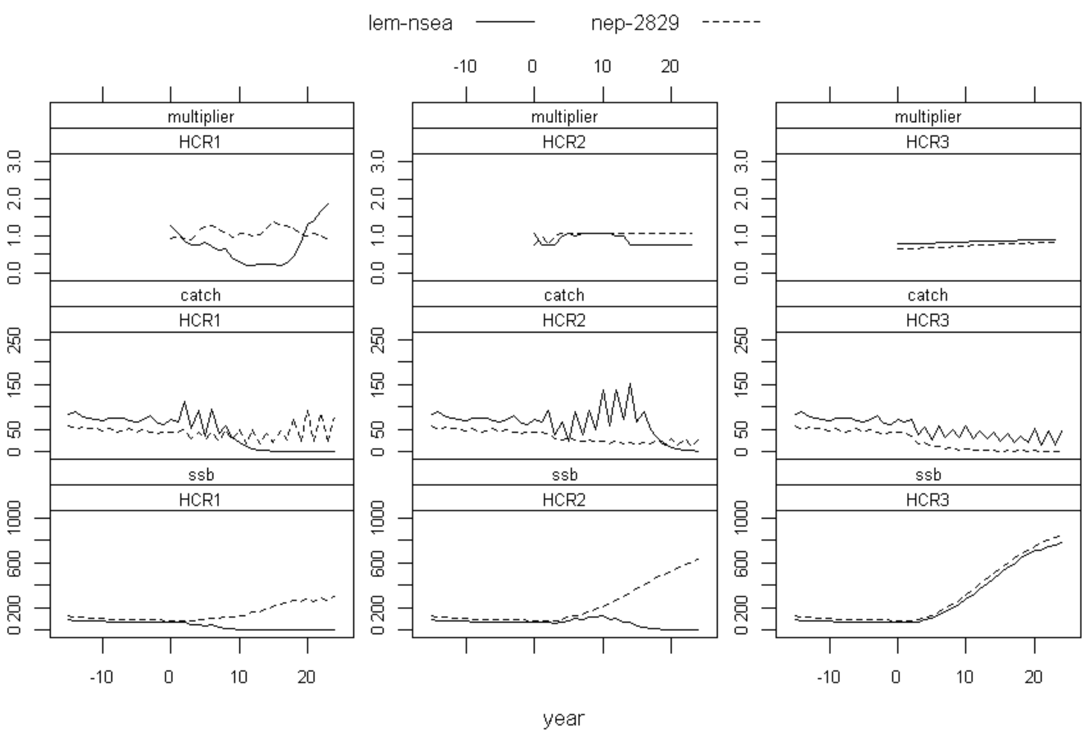


Figure 5.2.1.1. Trends in spawning–stock biomass (ssb), catch and multiplier (which defines the multiplier to the catch in year y-1 that derives the catch advice for year y +1) for the simulated stocks of Lemon sole in the North Sea (lem-nsea) and *Nephrops* in Functional Units 28–29 (nep-2829) by HCR and fishery scenario: (a) development and (b) overexploitation scenarios.

5.2.2 Conclusions and future work

The results presented for lem-nsea and nep-2829 are merely indicative of the relative performance of the three HCRs to deliver catch advice for data-limited stocks that is risk-averse. In terms of biological risk HCR1 showed the poorest performance for lem-nsea while HCR3 showed the best performance, although the latter with levels of catch well below MSY. In the case of the nep-2829 both HCR2 and HCR3 were less risk-averse than HCR1 once the stock catches are reduced to lower levels.

The amount and quality of information available differ among the data-limited stocks. HCR1 and HCR2 can be used to provide catch advice if survey data exists (DLS category 3), while HCR3 can be used if only catch length composition is available (DLS categories 4–6). If both information sources exist, combinations of these HCRs can be explored.

Jardim et al (*in press*) discuss the overall performance of the three HCRs and recommends to tune these HCRs to the specificities of the data-limited stock and fisheries subject to management, which can be done with the MSE framework used in the study.

5.3 References

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6 Precautionary buffer application and risk

6.1 Precautionary Approach buffer

In the ICES Data Limited Stock (DLS) Guidance (ICES, 2012) a 'precautionary buffer' (PA buffer) or 'precautionary margin' is defined as a reduction of -20% in the advised catch applied after the 20% 'uncertainty cap' or 'change limit'. The PA buffer is designed to make advice based on uncertain information more precautionary.

The DLS method requires the calculation of the indicated increase or decrease in catches based on the method for the appropriate category; changes in survey indices, catches or other method. The uncertainty cap is then applied, limiting the advised change to ±20% prior to the application of the precautionary buffer. The PA buffer is then applied, which would reduce the resulting catch by a further 20%. Thus the maximum reduction in advised catch could be up to 36% after application of the 20% uncertainty cap to an estimated decrease in catches ≥20%, followed by the precautionary buffer of -20%. The minimum decrease in catches would be 4% after application of an uncertainty cap of 20% to an indicated increase in catches of ≥20% followed by a precautionary buffer of -20%. After the implementation of the PA buffer the intention is to monitor the stock for a period (duration) to see if there is some improvement in the status of the stocks before further control measures such as further reduction in TACs are required.

The precautionary buffer is applied when there is uncertainty in relation to the stock status in relation to candidate reference points in relation to stock size or exploitation is unknown. Exceptions to this rule have been made where expert judgement determines that the stock is not reproductively impaired, and where there is evidence that stock size is increasing or that exploitation has reduced significantly.

This means that the expert groups carrying out the assessments have been able to use judgment in the application of the precautionary buffer. Table 6.1.1 shows a breakdown of the numbers of stocks where the PA buffer has been applied as applied to ICES advice in 2014. These results showed that the PA buffer was applied in 61 out of the 118 stocks for which it could have been applied to and that the most common reason, 54 out of the 61 was that the abundance or exploitation was unknown.

With so many stocks being eligible for the PA buffer there is a need to refine the advice on PA buffers, drawing on international experience of their use. This section aims to review past international work on the use of precautionary buffers. It discusses the advice framework within which the precautionary buffer should be applied in terms of its magnitude and the intervals (duration) between applications. It discusses how risk assessments can contribute to this process, and the information requirements to support the precautionary buffer framework.

Firstly we briefly review the application of precautionary buffers in America and Australia then we review risk assessment methods and their application.

6.1.1 Context in the United States

In the US system, management plans define probability-based catch levels. Peer reviewed estimates of Maximum Sustainable Yield (MSY) or Over Fishing Level (OFL; level of harvest that if exceeded would constitute overfishing) are used by the Science and Statistical committee (SSC) (Cieri, 2013). US Regional Fisheries Management Councils (RFMCs) have generally adopted Tier systems to which stocks are assigned. The Tiers depend on data availability and differ in terms of the OFL control rule (Punt *et al.*, 2012). The Groundfish tier system is based on 6 tiers based on the information availability. The tiers which would match with ICES data limited stocks are tier 5 based on current biomass and natural mortality rate and tier 6 based usually on catch time-series and other measures if appropriate. The Crab tier system is based on 5 tiers, with tier 5 used for stocks with no biomass estimate and only reliable catch information. In all, a first buffer is applied on the OFL to account for scientific uncertainty around current stock estimates, with larger reduction in case of larger uncertainty.

In the groundfish tier system the scientific uncertainty depends either on the retrospective level of uncertainty in spawning biomass, or the level of uncertainty estimated from the current stock assessment result. Minimum buffer in tier 1 varies directly with FMSY. Minimum buffers in tiers 2-6 are "fixed": estimates are used to create a probability distribution for the OFL, which allows the selection of a "P*" representing the estimated probability that the specified catch will be in excess of the OFL. This P* must be <50% by law (a minimum buffer between OFL and ABC is also prescribed for all tiers), and is very important in calculating the recommended catch target, particularly the lower quartiles (Stewart et al., 2013). According to the OFL and the P*, an ABC (allowable biological catch), equal or above the ACL (allowable catch limit) is produced. A new buffer is then applied to account for management uncertainty, which leads to the ACT (annual catch target).

For all tiers from the crab tier system, a 10% buffer between the OFL and ABC is applied.

Data-limited (tier 6) methods

One example of a tier 6 implementation: assessment of the shark stock complex in the Bering Sea and Aleutian Islands (BSAI). Historical catches of sharks in the BSAI are composed entirely of incidental catch. Sharks in the BSAI are managed under Tier 6, so no stock assessment modelling is performed. Sharks have been considered a Tier 6 species because they are not targeted and only limited data are available. For the 2012-2013 recommendations, the OFL was the maximum annual shark catch from the period 1997-2007, and the ABC was set as ABC = OFL*0.75 (Tribuzio *et al.*, 2012). There are a number of different methods used in various management plans, see Carruthers et al., (2014) for details.

The NPFMC (North Pacific Fishery Management Council) used for BSAI red crab fishery (a tier 3 fishery recruitment, biomass, and fishing mortality estimated) ABC control rule a function of the estimated uncertainty of the OFL and P* (probability that the ABC exceeds the true OFL). Punt *et al.* (2012) defined P* as the sum of the uncertainty which can be quantified using the stock assessment and the unquantifiable uncertainty which is specified based largely on expert opinion and comparisons with other stocks. Bayesian methods were used to quantify the uncertainty associated with fitting the model. Different buffers and P* are tested to see the implications for biomass, for probability of overfishing as well as for projected catches and estimated revenue.

The size of the buffer implemented is larger (so the ABC decreases as a proportion of OFL) when there is more uncertainty. In terms of biomass, larger buffers lead to larger modelled stock sizes. Long-term catches under small buffers may be similar to those under larger buffers. In the short term the revenue is greater for smaller buffers. The probability of overfishing and of the stock being overfished decreases as the size of the buffer is increased. This leads to lower annual catches and economic value. Compared with no buffer, a relatively small increase in the buffer leads to a large reduction in the probability of overfishing, but a relatively small reduction in the economic value. There is an evident trade-off between reducing the probability of overfishing and the consequential reduction in catches and hence fishery revenues (Punt *et al*., 2012).

6.1.2 Context in Australia

In Australia, fisheries management is undertaken by governments in all national jurisdictions. All have adopted ecosystem-based fisheries management (EBFM) approaches as a means of implementing the principles of ecologically sustainable development.

Assessment is made at fishery level. Under EBFM, ecological risk analysis as assessment framework applied to fisheries (ERAEF), which includes the PSA at level 2, are currently in place (Hobday *et al*., 2011). Key species are chosen for monitoring based on this assessment and the species' commercial value (Smith et al., 2009). Monitoring of catches, collection of otoliths, length and sex distributions, detailed logbooks and observer coverage is carried out routinely for key species. However, these data are only analysed and assessments conducted if exploitation levels as defined by pre agreed trigger levels related to changes in catches are reached.

Since 2007, federally managed fisheries also follow a formal harvest strategy policy (HSP), comprising monitoring, assessment, and decision rules (the latter also known as harvest control rules) for key commercial species, where explicit standards for risk are adopted (Smith *et al*., 2014). The HSP specifies target and limit biomass reference points (B_{TARG} and B_{LIM} respectively). The B_{TARG} is the biomass corresponding to maximum economic yield, and the B_{LIM} is half of the biomass corresponding to the maximum sustainable yield (Smith et al., 2014). The lack of economic data for data-poor fisheries is a problem for B_{TARG} estimations. Therefore, stakeholder should be involved in processes such as co-management (Smith *et al*., 1999; Mapstone *et al*., 2008). For data-poor species, proxies relating to spatial distribution or regularity in fishing were identified as indirect proxies for biomass abundance and fishing mortality.

HSP encourages the use of a tiered approach to control rules in order to accommodate for different levels of certainty about a stock (Anon., 2007). Each species is assigned to one of a number of Tier levels depending on the amount and type of information available to assess stock status, where Tier level 1 represents the highest quality of information available (e.g. a robust quantitative stock assessment). Each stock is assigned to a Tier based on the quality of information available to assess stock status, and the control rules associated with each Tier are designed to be increasingly precautionary as the Tier level increases (uncertainty increases) (Anon., 2007).

In the Southern and Eastern Scalefish and Shark Fishery Harvest Strategy, catch reduction of 5 and 15% are applied to TACs derived from Tiers 3 and 4 assessments, respectively. These discount factors have to be justified. If using ERAEF, uncertainty estimates can be derived directly from level 3 analysis (e.g. SAFE) (Hobday et al., 2011) this is carried out.

After five years of HSP implementation, the proportion of federally managed stocks subject to overfishing has been reduced, as well as the proportion of stocks of uncertain status. The adoption of the HSP has improved both the biological and economic performance of the fisheries.

6.2 Risk assessment methods and vulnerability matrix

There have been several methods developed to assess relative risk in fisheries. The methods take various forms but in essence they:

- **Assess relative susceptibility**; information from the intersection of the fishing activities with the stock, which broadly relate to spatial and temporal factors in relation to the fishery encountering the stock and the intensity of the interaction. These relative attributes are assessed and scored using expert judgement.
- **Assess relative productivity;** here, the rate at which the stock can replenish once it has been affected by fishing. Growth rates, reproduction in terms of fecundity and other features of the stock are assessed and scored. One approach would be to obtain an index of relative productivity which can be related across different stocks and ecosystem components. One possibility is the resilience index from fishbase.org. This index relates a species' (or stock's) ability to recover from low levels; it uses von Bertalanffy K, age at maturity and maximum age, to assign a resilience category. The advantage is that it can be estimated for many species, both exploited and unexploited, so can be favoured for ecosystem risk assessment.

For Productivity and Susceptibility Analysis (PSA) the two scores are plotted in two dimensions (Productivity x axis (high to low), Susceptibility y axis) and the 'vulnerability score' taken from the Euclidian distance from the origin of the plot (see the report of the first WKLIFE (ICES 2012) for a generalised description of the process, and WKLIFE III report for an example of implementation in the Mediterranean fisheries, see also McCully *et al*. (2013) for an implementation in Northeast Atlantic fisheries). A more generalised version, termed ecological risk screening, where interaction between fisheries and the ecosystem components are scored (where feasible) for their most sensitive attribute, is described in Cotter *et al*. (2014).

Other methods to assess risk include monitoring changes in species composition of catches; expansion or contraction in the catch of species, changes in effort levels leading to the expansion or contraction of the fishery would trigger further investigation. Smith *et al*. (2009) discuss these aspects in Australian fisheries. Trawl surveys can be used to understand temporal and spatial trends in ecosystem components. Of relevance here are changes in the distribution of the population and the size composition of the components over time; this is discussed using survey data in Cotter *et al*. (2009).

The ability to draw on stakeholder knowledge and relate it to observations in the catches and in the survey data are a key theme of risk assessment (discussed in Smith *et al*., 2009; Cotter *et al*., 2014). The use of interdisciplinary working groups, enabling stakeholders to participate in the assessment and the design of surveys and measures to control risks is an important theme. Such working groups need common principles such as the ICES MSY framework and/or the Marine Strategy Framework Directive to derive the risk assessments.

These methods enable a relative ranking of the risk to ecosystem components including stocks. In deciding the course of action to be taken for the at most risk components all the information should be considered including temporal and spatial trends, stakeholder knowledge, size distributions in the catches and surveys. The methods prioritise obtaining more information on certain components as in Defra's 'shark bywatch' and related projects (Defra, 2014). To translate this risk assessment into quantitative advice for management there is a requirement to make a more quantitative assessment of risk.

6.2.1 Advances in the use of risk analysis in the assessment of data-limited stocks

Osio *et al*. (2014) use the PSA susceptibility and productivity scores and information on data-rich species (specifically F/F_{MSY}) to predict the exploitation status of un-assessed stocks, in special those with high vulnerability scores and high economic value, which require more attention in terms of stock assessment. Additive mixed models were applied to training datasets composed of data rich species (including the variables: susceptibility scores, productivity scores and area) and then results were used to predict for un-assessed stocks. The PSA combined with "Robin Hood" approaches where information from related stocks is used to help advise on stocks with poor information, seem promising to give an indication on exploitation status of data-poor species without landings information. Further exploration of this method should be carried out with learning data comprising stocks from different taxa at different level of exploitation and other variables that can reflect fishing pressure within each area, as, for example, depth.

Cope *et al*. (2014) develops and introduces a prior on relative stock status using PSA vulnerability scores. This method was applied to stock reduction analysis, which are quite sensitive to the treatment of the stock status prior, relaxing these models from the following assumptions: i) stock status is defined in the terminal year of the time-series and ii) that it was set at 40% of the initial stock biomass. The authors define retrospective vulnerability as the vulnerability of the stock at the latest year before management had significant impact on removals and build vulnerability reference points based on these retrospective vulnerability scores. Comparisons between retrospective vulnerabilities and category 1 stock assessment estimates in the year 2000 (SB_{2000}/SB_0, where SB_{2000} is the spawning biomass in the year 2000 and SB_0 is the initial spawning biomass) for the same year showed a conspicuous relationship, with higher vulnerability corresponding to lower stock status. Model outputs using the priors produced in vulnerability –based stock status general presented less biased results relative to full stock assessments. The variety of data-limited methods being developed that require some estimate of relative stock status can benefit from the approach presented.

6.3 Potential use of risk assessment methods to estimate magnitude and duration of PA buffer

In the above we focus on the need to use risk assessment methods to sensibly estimate the magnitude of the PA buffer.

The risk assessment methods described above produce ranked risk assessments against pre agreed principles and goals for example ICES MSY, Precautionary Approach (PA) and EU MSFD. The goal for the application of the PA buffer is to conserve stocks when there is uncertainty. Therefore its application should be related to the level of perceived risk; when there is uncertainty there is increased risk. WKLIFE III report in 2013 highlighted how the PSA vulnerability score could be used to decide the level of the precautionary buffer in cases where the PSA is produced for the main fishery taking that stock, suggesting higher precautionary buffers for high vulnerable species. The Marine Resources Assessment Group (MRAG) Americas also suggested the use of PSA vulnerability scores to define the Annual Biological Catch, i.e. to define the scientific uncertainty, where species with low vulnerability should have a smaller buffer size (Rosenberg *et al*., 2009).

On the other hand, because not all components are assessed, the emphasis is on 'Robin Hood' methods where information from data rich stocks can be used to inform assessments for data-poor species and hence the magnitude of the PA buffer (see Osio *et al.*, 2014).

6.3.1 Magnitude of the PA buffer

Currently the ICES PA buffer set at 20%. The setting of this level is an issue relating to the level of societal risk which managers are willing to take. For commercial species this would relate primarily to economic risk: the discussion of the BSAI red crab fishery above shows that there is a trade-off between economic and stock risks (Punt et al., 2012). Note that the risks to stocks were not linearly related to the magnitude of the buffer. For non-commercial components, which would be managed under biodiversity and ecosystem objectives, there would be other trade-offs. However, for many of these components the information available is very sparse. There is a need for guidelines from managers on what range of PA buffer would be acceptable taking into account the economic, biodiversity and ecosystem risks.

6.3.2 Duration of the application of the PA buffer

Currently there are no guidelines relating to the time ('duration') after the first implementation of the PA buffer, the stock should be monitored for signs of recovery or deterioration before further control measures, such as a further reduction in TAC, should be implemented.

The productivity of a species relates to the length of time it would be expected to take to recover. Hence it would relate to the length of time after application of the precautionary buffer or other measure it would take before a response would be expected in the biomass index. Thus for long lived late maturing species (low resilience) several years would be required, so infrequent applications of the buffer would be expected with a period of time allowed to see if there is stock recovery before the application of more measures. Those species which grow more rapidly and mature at a smaller size (high resilience; high productivity) should require less time to recover so further measures should be considered more frequently if there is no response from the stock. By the application of information on productivity and resilience (see above) it should be possible for scientists to provide guidance on the duration of the period between PA buffer applications.

6.4 Future work

There is a need to simulate different magnitudes and duration of the PA buffer based on varying stock resilience and status, based on information from managers and scientists. Existing time-series of biomass indices could be used as a starting point and the PSA and Bayesian approaches discussed above have potential to assist in this process although an approach based on low, medium and high resilience and low medium and high PA buffers would be a good starting point.

For category 5 and 6 stocks and non-commercial components where there is no biomass index available to judge the effectiveness of the PA Buffer on the recovery of the stock. Therefore the above framework is not easy to apply unless some other index of stock health can be ascertained. Carruthers *et al.* (2014) found that where catch only data were available there was a high value in knowing stock depletion levels, historical fishing effort levels and an index of current abundance. Without these data and the ability to link those through dynamic models catch only methods performed poorly when stocks were depleted.

Therefore the most difficult assessments would be for stocks which are known to be vulnerable (e.g. blonde ray) where trends in survey indices are very variable and time-series of catches are short or non-existent as for the zero TAC (examples; common skate, black skate, deep-water sharks) or protected (white skate, angel shark and other species). Minor components of bycatch are also difficult to manage in the context of TACs since changes in TACs do not necessarily result in changes in catches.

In summary, it is considered important:

- To simulate in collaboration with managers the use of differing levels of PA buffer on stocks with varying levels of resilience (or productivity). The results obtained would be used to provide guidance on the magnitude and duration of the application of PA buffers in relation to the resilience of the stocks under consideration; and
- To produce guidelines for using data from risk assessments, stakeholder data and information, surveys and other sources to inform on stock depletion levels, historical fishing effort levels, spatial distribution of stocks and indices of abundance. The context should be not only to inform on PA buffers applied to TACs but also potential for alternative management strategies as appropriate to the stocks under consideration.

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Table 6.1.1. Application of the Precautionary Approach (PA) buffer to ICES stocks in 2014. Of the 273 stocks in the table in Annex 8 the PA buffer applies to 118 stocks. The PA buffer was not applied to all these stocks; here are the generic reasons for non-application and application the number of stocks in each category.

PA buffer not applied because....	N	PA buffer applied because....	N
Decreasing effort	5	Effort increase	1
Low exploitation rate		Overexploitation	2
Declining harvest rate	4	Uncertainty in stock status	1
Decreasing effort in target fishery	3	Unknown abundance or exploitation	41
Exploitation is not detrimental	4	Unknown exploitation	13
Increasing abundance	6	No reason	3
Increasing abundance and no overexploitation	1	**Total**	**61**
Increasing biomass	3		
Increasing biomass and low exploitation	1		
Increasing biomass and low exploitation in target fishery	4		
Low exploitation rate	2		
Low fishing effort	1		
Reduced exploitation in target fishery	5		
Underexploited	1		
Unknown exploitation	1		
No reason	15		
Total	**56**		

7 Discussion and conclusions

7.1 Future terms of reference (ToRs)

The **Workshop on the Development of Quantitative Assessment Methodologies based on Life-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks** (WKLIFE V), chaired by Carl O'Brien (UK) and Manuela Azevedo (Portugal) will meet in Lisbon, Portugal, 5–9 October 2015 to focus on:

a) Identification and proposal of MSY proxies for all Category 3 and Category 4 stocks for which ICES provides advice. For those stocks where this is not possible, describe the current difficulties to the provision of MSY proxies and detail a roadmap to deliver such values as a matter of priority.

b) Provide operational guidance to EGs on the exploitation status of data-limited stocks.

c) Assessment methods to apply to stocks within a framework to find an optimal trade-off, including CMSY, size-based, and HCR simulation testing.

d) Develop a framework that would aid in decision-making on the appropriate HCR to use by stock, if possible, or DLS Category, if not.

e) Analysis of basic data available under the DCF (e.g. length composition) and method development.

WKLIFE V will report by 13 November 2015 for the attention of ACOM.

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Annex 2: Recommendations

RECOMMENDATION	FOR FOLLOW UP BY:
Sections 4 and 5: EGs should compile length data	ACOM
Sections 4 and 5: ICES databases should maintain length and discard data	ACOM and ICES Data Center

Annex 3: Simulation work

Annex 3 presents two working documents:

1) Further evaluations: WKLIFE, José De Oliveira, Chris Darby and Timothy Earl. February 2012.

2) Further evaluations requested by RGLIFE, José De Oliveira. February 2012.

Annex 4: Data-poor/limited methods review

Working Document presented to WKLIFE 4, October 2014 authored by Nicola D. Walker, Timothy J. Earl, Jonathan P. Gillson, and José A. A. De Oliveira.

A.4.1 Introduction

This Working Document was presented to WKLIFE 4 and attempts to summarise the methods that could be applied to data-poor stocks. The document is organised into a number of categories, loosely representing available data and type of methodology, and includes studies that simulation tested these methods, where available, and Harvest Control Rules that have been simulation tested. Table 1 summarises the methods, data requirements, main assumptions and caveats of methods other than simulation-tested HCRs and data-moderate approaches.

A.4.2 Catch-only methods with supplementary life-history information

A.4.2.1 MacCall, A. D. 2009. Depletion-corrected average catch: a simple formula for estimating sustainable yields in data-poor situations. ICES J. Mar. Sci. 66:2267–2271.

Abstract: The depletion-corrected average catch (DCAC) formula is an extension of the potential-yield formula, and it provides useful estimates of sustainable yield for data-poor fisheries on long-lived species. Over an extended period (e.g. a decade or more), the catch is divided into a sustainable yield component and an unsustainable "windfall" component associated with a one-time reduction in stock biomass. The size of the windfall is expressed as being equivalent to a number of years of sustainable production, in the form of a "windfall ratio". The DCAC is calculated as the sum of catches divided by the sum of the number of years in the catch series and this windfall ratio. Input information includes the sum of catches and associated number of years, the relative reduction in biomass during that period, the natural mortality rate (M, which should be <0.2 $year^{-1}$), and the assumed ratio of F_{MSY} to M. These input values are expected to be approximate, and based on the estimates of their imprecision, the uncertainty can be integrated by Monte Carlo exploration of DCAC values.

Data/information requirements:

- The sum of catches over the time-series.
- The number of years in the time-series.
- The following parameters (with an associated probability distribution and standard deviation for Monte Carlo):
  - An estimate of the relative reduction in biomass over the time-series (Δ).
  - Natural mortality (M).
  - An assumed ratio (c) of F_{MSY} to M.

Assumptions:

- Modified potential yield assumptions:
  - B_{MSY}=0.4B_0, i.e. B_{MSY} is 0.4 times the unfished vulnerable biomass.
  - F_{MSY}=cM where c < 1, i.e. F_{MSY} is proportional to natural mortality.
- Assuming, on average, each year produces one unit of sustainable yield, the catch is divided into a sustainable yield component and an unsustainable

"windfall" component associated with a one-time reduction in stock biomass (which is assumed to be the relative reduction in vulnerable stock biomass over the duration of the catch time-series).

- The "windfall ratio" expresses the size of the windfall equivalent to a number of years of sustainable production (Windfall/Potential yield).
- The Depletion-corrected average catch (DCAC) divides the sum of catches by the number of years in the catch series plus the windfall ratio, to give an average (sustainable catch) that accounts for changes in the underlying resource abundance.

Outputs expected:

- An estimate of sustainable yield over the catch period (this is expected to be moderately high while having a low probability of greatly exceeding MSY).
- Estimates of confidence intervals (if using Monte Carlo).

Method of operation:

- The DCAC can be calculated as a point estimate using the most likely values of the inputs, but this is not recommended.
- Should be used with Monte Carlo exploration of DCAC estimates to provide information on precision and bias.

Testing:

- DCAC was used on two stocks (widow rockfish off the west coast of the United States and redfish in the Gulf of Maine and Georges Bank) where full age-structured stock assessments had been carried out. The DCAC results were compared to the independently derived estimates of MSY from the stock assessments.
  - The DCAC performed well in both cases. In practice the DCAC is often near MSY.

Caveats:

- Works better for longer time-series (e.g. a decade or more).
- Should not be used if $M > 0.2$ year^{-1}.
- In data-poor circumstances it can be difficult to estimate the relative depletion over the duration of the catch series.
- DCAC is not suitable for specifying catches in a stock-rebuilding plan.

A.4.2.2 Walters, C. J., Martell, S. J. D. and Korman, J. 2005. A stochastic approach to stock reduction analysis. Can. J. Fish. Aquat. Sci 63: 212–-223.

Abstract: Stock reduction analysis (SRA) can complement more detailed assessment methods by using long-term historical catches to estimate recruitment rates needed to have produced those catches, yet still end up with stock sizes near those estimated by the detailed methods. A longer historical perspective can also add information to the estimation of reference points such as unfished biomass (B_0) or target biomass (B_{MSY}). Deterministic SRA models provide a single-stock size trajectory that is vanishingly unlikely to have actually occurred, while stochastic SRA attempts to provide probability distributions for stock size over time under alternative hypotheses about unfished recruitment rates and about variability around assumed stock–recruitment relationships. These distributions can be generated with age-structured population models by doing

large numbers of Monte Carlo simulation trials and retaining those sample trials for which the stock would not have been driven to extinction by historical catches. By resampling from these trials using likelihood weights (sampling–importance resampling method), it is possible to move into fully Bayesian, state–space assessment modelling through a series of straightforward steps and to provide understandable visualization of how much the data help to reduce uncertainty about historical fishing impacts and stock status.

Data / information requirements:

- Time-series of total catch data – ideally going back close to virgin biomass – preferably as numbers, if not, numbers can be estimated from total weight and mean individual weight.
- Estimate of natural mortality M
- Estimate of stock–recruit steepness at low stock size (index, cpue, tagging etc.)

Assumptions:

- Known constant M.
- Known stock–recruit steepness at low stock size and a Beverton–Holt recruitment relationship
- Fishery selection

Outputs expected:

- Estimates of harvest ratio (catch/vulnerable biomass)
- Probability distribution of current depletion level relative to Virgin Biomass

Method of operation:

- In deterministic SRA, stock numbers-at-age are projected forward from an initial recruitment of R_0. Using estimates of M, and historic catch data, divided among the age classes proportional to the total selected weight at each age. If there are years where catch is greater than estimated vulnerable biomass, this is a strong indication that the initial biomass or recruitment steepness are too low. This method places no upper bound on the steepness or initial biomass, but information about relative abundance may be used to inform an upper bound on these parameters.
- Bayesian fitting of the SRA model uses historic catch data to investigate a range of Virgin Biomass and recruitment assumptions to find feasible parameter space, acknowledging that recruitment is variable between years, by taking a large number of simulations with randomly generated deviations from the stock–recruit relationship. Autocorrelation can be added to these deviations. The authors suggest that the Bayesian SRA can be considered as a stepping-stone to a full assessment as more sources of data become available and are integrated into the method.

Testing:

- Fraser River white sturgeon is used as an example of fitting in the deterministic case. In this case, as well as the time-series of catches, there are individual weight measurements that indicate a roughly tenfold reduction in mean body weight due to the truncated age structure caused by past exploitation

- Data from the Fraser River white sturgeon is used for an example of deterministic stock reduction analysis. The parameters were varied to achieve a current vulnerable biomass estimate of 40 000–60 000 fish, and to follow recent trends indicated by mark–recapture analysis. This implied virgin recruitment around 21 600, which has fallen to around 7500 in recent years. Comparable results are not shown for the Bayesian method, but they show probability distributions of output quantities such as depletion level given the assumptions about input parameters.
- The fit of the model to the data can either be judged by comparing to some measure of abundance trend, or by evaluating the probability of extinction given the observed catches; if this is high, then the initial parameter estimates should be reviewed.

Caveats:

- Autocorrelation in estimates of recruitment deviates lead to high uncertainty in stock size; this might be particularly the case if there is a regime shift due to environmental factors, where effectively one stock–recruit relationship is used to model two substantially different ones.
- Small populations may have high uncertainty if a small number of large fish contribute substantially to the biomass.

A.4.2.3 Dick, E. J. and MacCall, A. D. 2011. Depletion-based stock reduction analysis: a catch-based method for determining sustainable yields for data-poor fish stocks. Fish. Res. 110:331–341.

Abstract: We describe a method for determining reasonable yield and management reference points for data-poor fisheries in cases where approximate catches are known from the beginning of exploitation. The method, called Depletion-Based Stock Reduction Analysis (DB-SRA), merges stochastic Stock-Reduction Analysis with Depletion-Corrected Average Catch. Data requirements include estimates of historical annual catches, approximate natural mortality rate and age at maturity. A production function is specified based on general fishery knowledge of the relative location of maximum productivity and the relationship of MSY fishing rate to the natural mortality rate. This leaves unfished biomass as the only unknown parameter, which can be estimated given a designated relative depletion level near the end of the time-series. The method produces probability distributions of management reference points concerning yield and biomass. Uncertainties in natural mortality, stock dynamics, optimal harvest rates, and recent stock status are incorporated using Monte Carlo exploration. Comparison of model outputs to data-rich stock assessments suggests that the method is effective for estimating sustainable yields for data-poor stocks.

Data/information requirements:

- Time-series of historical catches from the beginning of exploitation.
- The following parameters with an associated probability distribution and standard deviation:
  - Natural mortality (M).
  - Ratio of F_{MSY} to M.
  - Relative biomass at maximum latent productivity B_{MSY}/K (assumed 0.4 in DCAC above).
  - Relative depletion level in a recent year (Δ for DCAC = 1-depletion).

- Age at maturity.

Assumptions:

- Depletion-based stock reduction analysis (DB-SRA) is implemented using a delay-difference production model.
- This implementation uses a hybrid Schaefer-PTF model for the latent production function; this function has the form of a Pella-Tomlinson-Fletcher (PTF) production model for abundances above a join point and the form of a Schaefer model below the join point. The value of the join point is chosen to give a good approximation to the Beverton–Holt stock–recruit model.

Outputs expected:

A set of plausible trajectories giving probability distributions of:

- Estimated biomass
- Reference points:
    - MSY
    - B_{MSY}
    - C_{FMSY} or OFL (overfishing limit)

Method of operation:

- A Monte Carlo approach is used to draw input parameters (natural mortality, F_{MSY}/M, relative biomass at latent productivity and the relative depletion level) from prior probability distributions. Given the time-series of historical catch, the delay-difference model is applied sequentially over the years of the time-series, and the value of K (unfished biomass) is determined by a numerical solution that gives the recent relative depletion level. This is run 10 000 times to produce the probability distributions above.

Testing:

- DB-SRA was used on 31 data-rich assessed species of groundfish managed by the Pacific Fishery Management Council (PFMC) on the west coast of the United States, assuming current stock biomass is 40% of the unfished biomass. The maximum posterior density (MPD) estimates from the full stock assessment were taken as benchmarks to compare the performance of DB-SRA.
    - Median estimates of MSY and K from DB-SRA tend to be between one half and double the assessment value.
    - DB-SRA estimates of MSY are most consistent with data-rich results (compared to the estimates of C_{FMSY} and K).
- The sensitivity of the model to the relative depletion level was tested by applying the model to the 31 assessed species at nine different depletion levels.
    - Estimates of MSY, C_{FMSY} and K based on low relative depletion levels tended to minimise the absolute relative error between the DB-SRA median and the assessment MPD.

Caveats:

- Well suited to cases with nearly monotonic declines in abundance.

- Gives implausibly high estimates of MSY if the stock is close to its unfished biomass in recent years. DB-SRA gives better estimates if falsely given a much lower value.
- Requires knowledge of the entire history of catches, which may be poorly documented for early years.
- Uncertainty in historical catches is not addressed adequately.

A.4.2.4 Martell, S. And Froese, R. 2013. A simple method for estimating MSY from catch and resilience. Fish. 14: 504–514.

Abstract: The Law of the Sea requires that fish stocks are maintained at levels that can produce the maximum sustainable yield (MSY). However, for most fish stocks, no estimates of MSY are currently available. Here, we present a new method for estimating MSY from catch data, resilience of the respective species, and simple assumptions about relative stock sizes at the first and final year of the catch data time-series. We compare our results with 146 MSY estimates derived from full stock assessments and find excellent agreement. We present principles for fisheries management of data-poor stocks, based only on information about catches and MSY.

Data / information requirements:

- Time-series of catch
- Prior ranges of *r* (intrinsic growth) and *k* (carrying capacity)
- A range of possible initial and current depletion levels
- Standard deviation in process errors (if including a stochastic component)

Assumptions:

- The stock-productivity relationship follows the Schaefer model.
- A stationary production function, i.e. constant model parameters.
- Process errors are assumed lognormal, independent and identically distributed.

Outputs expected:

- An estimate of MSY with error margins

Method of operation:

- The Schaefer production model is used to calculate annual biomasses for *r*-*k* pairs randomly drawn from the prior distributions. *r*-*k* pairs that have never collapsed the stock or exceeded carrying capacity, and that result in a final relative biomass estimate between the values specified in the inputs are accepted and used to calculate MSY.
- Here the prior distribution range for *k* was taken as the maximum catch in the time-series and 100 times the maximum catch. The prior distribution range for *r* was obtained using resilience estimates from FishBase. However, the best available knowledge about the stocks should be used to obtain these priors.
- The geometric means of the resulting density distributions of *r*, *k* and MSY were taken as the most probable values.

Testing:

- The method was demonstrated on Greenland halibut and Strait of Georgia lingcod.
- Catch-MSY was applied to 48 Northeast Atlantic stocks and compared to independent estimates of MSY from a previous study.
    - A log-log linear regression accounted for 98.6% of the variability of Catch-MSY estimates relative to full assessment assessments of MSY, with an intercept not significantly different from zero and a gradient not significantly different from one.
    - The 95% confidence limits of MSY provided by the assessments overlapped with 42 out of the 48 stocks, suggesting that the Catch-MSY estimates were not significantly different.
- Catch-MSY was applied to 98 global stocks with MSY estimates derived from full stock assessments.
    - Suitable *r*-*k* combinations were not found for about ten of the 98 stocks. These stocks had intermediate resilience or were very lightly exploited.
    - Most of the Catch-MSY estimates fell within a range of 0.5–1.5 of the assessment estimates.
- The *r* and *k* estimates of the Catch-MSY method were compared to related fisheries reference points.
    - The Catch-MSY method tends to overestimate *k* by about 10%.
    - The Catch-MSY method tends to underestimate *r* and derived reference points such as F_{MSY}, but is better matched with $F_{0.1}$.
    - *r* and *k* estimates strongly depend on the lower prior for *r*.

Caveats:

- The Catch-MSY method should not be applied to very lightly exploited fish stocks as the time-series of catches will not contain sufficient information about productivity.
- It will be difficult to define the upper bound on *k* in a developing fishery or a fishery that has a continuous increase in catch as the maximum potential has yet to be realised.

A.4.2.5 Vasconcellos, M. and Cochrane, K. 2005. Overview of world status of data-limited fisheries: inferences from landing statistics. In G.H. Kruse, V.F. Gallucci, D.E. Hay, R.I. Perry, R.M. Peterman, T.C. Shirley, P.D. Spencer, B. Wilson and D. Woodby, eds. Fisheries assessment and management in data-limited situations, pp. 1–20. Fairbanks, USA, Alaska Sea Grant College Program.

Abstract: Data-limited fisheries are here considered to be fisheries lacking sufficiently reliable biological information to infer the exploitation status of the targeted stocks. Considering species-specific catch data as the common minimum available data for assessing the status of a stock, in this paper we use the taxonomic breakdown of the reported landings statistics to FAO to make an approximate inference of data limitation of fisheries by region, country, and taxonomic groups. The paper also explores the possibility of extracting meaningful biological information from fisheries landings by applying a Bayesian approach to two selected fisheries. The contribution of data-poor fisheries to the world landings from marine capture fisheries is relatively low, but increasing (from 20 to 30% of world landings in the last 50 years). However, data limitation can be a substantial problem at the regional and country level, especially in areas

with high species diversity, small stock sizes, and where fisheries play an important role for food security. Preliminary modelling results indicate that catch data, when combined with prior information about the dynamics of similar species/stocks and fisheries, could be useful for informing fisheries management in data-limited situations.

Data / information requirements:

- Time-series of catch
- Priors for:
  - Intrinsic growth rate, r
  - Carrying capacity, K
  - Bioeconomic equilibrium as a proportion of K, a
  - Increase of harvest rate over time, x
- Process error variability

Assumptions:

- Fisheries follow a pattern where the relative rate of increase in catch increases rapidly during a development stage, drops to zero when a mature stage has been reached and becomes negative during a senescent phase (Vasconcellos and Cochrane, 2005).
- Time-series of catch data contain information on both fishing effort and stock biomass dynamics (Vasconcellos and Cochrane, 2005).
- Initial catch is equal to the first observed catch in the time-series and is assumed to be measured without error.
- Initial biomass is equal to the carrying capacity.
- Either no harvest control regulations are in place or any existing regulations have only negligible effects so that the harvest rate dynamics respond only to the economic / market stimulus.
- Observed catches follow a lognormal likelihood function.
- The variability parameter is assumed known and equal to 0.4.

Outputs expected:

- Stock status
- Production
- Exploitation rate

Method of operation:

- The model predicts catches based on a combination of a biomass dynamics model and a harvest rate dynamics model. The biomass dynamics model follows the Schaefer surplus production model and the harvest rate dynamics model follows a logistic model.
- The Bayesian algorithm sampling importance resampling is used to fit the model to the catch time-series by estimating four model parameters: r, K, a and x.

A.4.2.6 Thorson, J. T., Minto, C., Minte-Vera, C. V., Kleisner, K. M. And Longo, C. 2013. A new role for effort dynamics in the theory of harvested populations and data-poor stock assessment. Can. J. Fish. Aquat. Sci. 70: 1829–1844.

Abstract: Research shows that population status can be predicted using catch data, but there is little justification for why these predictions work or how they account for changes in fisheries management. We demonstrate that biomass can be reconstructed from catch data whenever fishing mortality follows predictable dynamics over time (called “effort dynamics”), and we develop a state-space catch only model (SSCOM) for this purpose. We use theoretical arguments and simulation modelling to demonstrate that SSCOM can, in some cases, estimate population status from catch data. Next, we use meta-analysis to estimate effort dynamics for US West Coast groundfishes before and after fisheries management changes in the mid-1990s. We apply the SSCOM using meta-analytic results to data for eight assessed species and compare results with stock assessment and data-poor methods. Results indicate general agreement among all three methods. We conclude that effort dynamics provides a theoretical basis for using catch data to reconstruct biomass and has potential for conducting data-poor assessments. However, we still recommend that index and compositional data be collected to allow application of data-rich methods.

Data/information requirements:

- A time-series of catch data
- Prior distributions for model parameters

Assumptions:

- B_{MSY} is equal to half of the average unfished biomass.
- Effort enters and exits the fishery as a function of the difference between current biomass and biomass at bioeconomic equilibrium, and follows semi-predictable dynamics.
- There is a yield that will produce both a biological and economic (average revenue equals average costs) equilibrium.
- Nominal effort is proportional to fishing mortality, where either the catchability coefficient is constant or fluctuates around an average value due to random variation in fish vulnerability and fishing efficiency.
- Process error parameters (for effort, biomass and catchability) are independently and lognormally distributed, and have equal magnitude to each other.
- The population begins at average unfished biomass.

Outputs expected:

- Information regarding depletion
- An estimate of stock status and productivity

Method of operation:

- A two-parameter effort dynamics model is combined with a conventional surplus production model to create a coupled population- and effort-dynamics model.
- A time-series of catch data is analysed using Takens’ Theorem to recover trajectories that resemble the original effort and biomass time-series. The

model is fit to the time-series of catch data and parameters representing effort dynamics, population dynamics and catchability are estimated using standard statistical methods.

- An index of abundance or fishing effort could be added by including an additional model component.

Testing:

- Simulation was used to explore model sensitivity to the magnitude of errors and to show the performance of the model with and without a prior on final depletion.
  - Increasing the magnitude of errors causes the trajectory to become more irregular.
  - The model results in imprecise estimates of final depletion with no prior and gets progressively worse with increased variability. Including a prior results in improved estimates of final depletion and enhanced reconstruction of the entire effort and biomass trajectory.
  - MSY estimates are accurate and precisely estimated without a prior on final depletion when variability is low. Increasing the error magnitude without a prior on final depletion generally decreases the precision for all estimated parameters and increases the magnitude of bias in final depletion. Therefore, a prior on final depletion improves performance in the high variability case, but is not necessary for accurate MSY estimates in the low and medium variability cases.
- The method was applied to US West Coast groundfishes that were subject to management changes during the time-series. The results for eight species were compared to stock assessment estimates using both Stock Synthesis (data-rich method) and DB-SRA (data-limited method; Dick and MacCall, 2011).
  - SSCOM obtains similar estimates of exploitation rate and relative biomass in the final year to both DB-SRA and the assessment.

Caveats:

- The model is highly dependent upon contrast in the catch time-series and must reach a peak and subsequently decline.
- Datasets that egregiously violate the model assumptions of either Schaefer biomass dynamics or the effort-dynamics model (e.g. bycatch species, highly mixed fisheries and subsistence-recreational fisheries) will be poorly reconstructed.
- The performance of the model when sequentially applied in a control-rule management scenario is unknown.

A.4.2.7 Cope, J.M. 2012. Implementing a statistical catch-at-age model (Stock Synthesis) as a tool for deriving overfishing limits in data-limited situations. Fish. Res. doi:10.1016/j.fishres.2012.03.006.

Abstract: Stock Synthesis (SS) is a likelihood-based statistical catch-at-age modelling environment allowing multiple data sources to be used to characterize population dynamics through time. While it is typically applied in data-rich circumstances, its suitability in data-limited situations is investigated in this work. Two "Simple Stock Synthesis" (SSS) approaches are outlined, each developed to mimic the Depletion-

Based Stock Reduction Analysis (DB-SRA) estimation of overfishing limits (OFLs) currently applied to data-limited US west coast groundfish species. SSS-MC uses Monte Carlo draws of natural mortality, steepness, and stock depletion and estimates initial recruitment, while SSS-MCMC estimates natural mortality, steepness, and initial recruitment while fitting to an artificial abundance survey representing stock depletion with an error distribution equivalent to the stock depletion prior used in DB-SRA. These approaches are applied to 45 species of unassessed groundfishes in the Pacific Fishery Management Council Groundfish Fishery Management Plan, and the OFL estimates are compared to corresponding DB-SRA estimates. Despite model structure and parameter specification differences, SSS led to results comparable to DB-SRA over a wide range of species and life histories. SSS models with sex-specific life-history parameters and growth variability are also presented as examples of how the inherent flexibility of SS can be used to account for more uncertainty in derived quantities. SSS-MCMC, while exhibiting statistically undesirable traits due to the inclusion of the artificial survey, readily includes data-informed abundance surveys into an assessment framework consistent with more complex, data-informed assessments. Establishment of viable data-limited approaches in SS is a convenient first steps in "building-up" stock assessments towards fuller implementation in SS when additional data become available, while also providing a way to inform management in data-limited situations.

Data/information requirements:

- Time-series of total catch weight
- Estimate of depletion level from virgin biomass as a distribution
- Growth parameters (possibly by sex)
- Weight-at-length
- Natural mortality (M)

Assumptions

- Prior on stock–recruit steepness set to truncated beta distribution on 0.25–0.99.

Outputs expected:

- An estimate of the overfishing limit for the stock which can be compared with that from DB-SRA.

Method of operation:

- The authors present an investigation of the utility of stock synthesis (an age-structured assessment method) for assessments of data-poor stocks, which they define as having a catch time-series, and estimates of a few key biological parameters which can be implied from similar stocks. While it may seem to be a particularly complicated way to use these data, they point out that it has the advantage of being able to build up the assessment progressively if more data sources become available, providing a route towards a fully assessed stock.
- The model recognises that there is uncertainty in input parameters, this can either be used in the model by generating Monte Carlo realisations of the input parameters, and performing effectively a deterministic assessment on each set, or alternatively uncertainty in output parameters can be assessed by MCMC methods (Markov chain Monte Carlo).

Testing:

- The model was set up to closely resemble depletion based SRA, and tested on 45 assessments where DB-SRA can also be applied.
    - For the great majority of the stocks, SS produced higher estimates of the overfishing limit, but there was greater uncertainty about these values than for DB-SRA in all cases.

Caveats:

- The MCMC method of assessing uncertainty in model fit should mimic priors for parameters about which the data are uninformative – this doesn't happen in all the stocks, in particular the posterior distribution of depletion is influenced by the prior for R_0, and so the authors acknowledge that the MCMC fits need further investigation.

A.4.3 Catch-only methods with supplementary data (e.g. length) and life-history information

A.4.3.1 Thorson. J. T. And Cope, J. M. 2014. Catch curve stock-reduction analysis: An alternative solution to the catch equations. Fish. Res. http://dx.doi.org/10.1016/j.fishres.2014.03.024.

Abstract: Legislative changes in the United States and elsewhere now require scientific advice on catch limits for data-poor fisheries. The family of stock reduction analysis (SRA) models is widely used to calculate sustainable harvest levels given a time-series of harvest data. SRA works by solving the catch equation given an assumed value for spawning biomass relative to unfished levels in the final (or recent) year, and resulting estimates of recent fishing mortality are biased when this assumed value is mis-specified. We therefore propose to replace this assumption when estimating stock status by using compositional data in recent years to estimate a catch curve and hence estimating fishing mortality in those years. We compare this new "catch-curve stock reduction analysis" (CC-SRA) with an SRA or catch curve using simulated data for slow or fast life histories and various magnitudes of recruitment variability. Results confirm that the SRA yields biased estimates of current fishing mortality given mis-specified information about recent spawning biomass, and that the catch curve is biased due to changes in fishing mortality over time. CC-SRA, by contrast, is approximately unbiased for low or moderate recruitment variability, and less biased than other methods given high recruitment variability. We therefore recommend CC-SRA as a data-poor assessment method that incorporates compositional data collection in recent years, and suggest future management strategy evaluation given a data-poor control rule.

Data/information requirements:

- A time-series of catch data
- Priors for life-history parameters

Assumptions:

- Fishery selection is age-specific and follows a logistic curve.
- Fishery catch-at-age follows the Baranov catch equation and population numbers decay exponentially.
- Recruitment is variable around a stock–recruit relationship. There exists some prior information regarding the strength of density-dependent recruitment and the true magnitude of variability in recruitment is known.
- Fishing mortality is variable and follows no specified parametric function.

- Abundance at age at the beginning of available catch data is from an approximately unfished state.
- Age composition sampling is available for the final year of catches. This represents a catch-curve on a synthetic cohort allowing estimation of fishing mortality in the final year. This fishing mortality estimate replaces the requirement of pre-specifying depletion in conventional stock-reduction analysis.
- Maturity-at-age and weight-at-age are known without error.

Outputs expected:

- Estimates of fishing mortality
- Estimates of stock status

Method of operation:

- The CC-SRA model is fit to a time-series of catch data, with the estimable parameters being annual recruitment and fishing mortality rates, the stock–recruit parameters, the selectivity parameters and natural mortality (given prior). Maximum penalised likelihood is used to estimate the parameters. The implementation uses an "explicit-F" parameterisation to solve for the levels of fishing mortality that would generate the given catch time-series.

Testing:

- Simulation modelling was used to evaluate the performance of CC-SRA, compared to catch curves and stock-reduction analysis (SRA), when estimating spawning biomass relative to unfished levels and fishing mortality. Two life-history types were simulated: a "fast" or "opportunistic" type modelled on Pacific sardine, and a "slow" or "periodic" type modelled on red snapper. Three levels of recruitment variability were explored for each life-history type.
    - The CC-SRA has wider confidence intervals that SRA for estimates of final spawning biomass but more closely matches the true spawning biomass relative to unfished levels for the "periodic" species. The catch curve does not provide a measure of stock status.
    - The catch curve provides the most accurate estimate of fishing mortality for the "periodic" species. CC-SRA provides a similar estimate of final fishing mortality to the SRA.
    - For the "periodic" species CC-SRA is least biased and has lowest errors given low recruitment variability. SRA produced biased estimates of spawning biomass relative to unfished levels and final fishing mortality for both life histories, but had the lowest error in estimates of terminal fishing mortality for the "fast" life-history type. The catch curve was positively biased in fishing mortality for all scenarios. The CC-SRA largely eliminates this bias.
    - The catch curve and CC-SRA perform significantly worse for the "fast" life history than the "slow".

Caveats:

- CC-SRA and other data-poor methods require additional testing prior to use for management of data-poor fisheries.
- Model performance will likely degrade in the following situations:

- Fishery selection is non-asymptotic
- Natural mortality is age specific
- Misspecification of life-history parameter priors

A.4.4 Life-history and size-based methods

A.4.4.1 Brooks, E. N., Powers, J. E. and Cortés, E. 2010. Analytical reference points for age-structured models: application to data-poor fisheries. ICES Journal of Marine Science, 67:165–175.

Abstract: Analytical solutions for biological reference points are derived in terms of maximum lifetime reproductive rate. This rate can be calculated directly from biological parameters of maturity, fecundity, and natural mortality or a distribution for this rate can be derived from appropriate metadata. Minimal data needs and assumptions for determining stock status are discussed. The derivations lead to a re-parameterization of the common stock–recruit relationships, Beverton–Holt and Ricker, in terms of spawning potential ratio. Often, parameters in stock–recruit relationships are restricted by tight prior distributions or are fixed based on a hypothesized level of stock resilience. Fixing those parameters is equivalent to specifying the biological reference points. An ability to directly calculate reference points from biological data, or a meta-analysis, without need of a full assessment model or fisheries data, makes the method an attractive option for data-poor fisheries. The derivations reveal an explicit link between the biological characteristics of a species and appropriate management. Predicted stock status for a suite of shark species was compared with recent stock assessment results, and the method successfully identified whether each stock was overfished.

Data/information requirements:

- Estimates of stock–recruit relationship parameters
- Estimates of current fishing mortality and spawning-stock biomass (i.e. from indices of abundance) if estimates of stock status (depletion and exploitation) required.
- A management specification about the proportion below optimal depletion where the stock is considered overfished.

Assumptions:

- Knowledge of the stock–recruit form, either Ricker or Beverton–Holt
- All age classes beyond recruitment are fully selected by the fishery

Outputs expected:

- Spawners per recruit as a function of F, allowing reference point proxies (e.g. F40%) to be estimated.
- Maximum excess recruitment (MER) – numbers that can potentially be fished (as opposed to MSY giving weight)
- Depletion at MER (S_{MER}/S_0)

Method of operation:

- The authors formulate the analytical solution for SPR_{MER} for both the Beverton–Holt and Ricker stock–recruit functions in terms of maximum lifetime reproductive rate and steepness. They then derive analytical reference points for depletion at MER (S_{MER}/S_0) for which relative indices of abundance can be compared to obtain stock status.

Testing:

- A simulation study was conducted to evaluate how analytical values of SPR_{MER} compared with numerical estimation of SPR_{MSY}. A standard age-structured population dynamics model was used for the simulation and MSY was estimated across a range of age-constant natural mortality rates and steepness levels.
  - When all ages are fully selected $F_{MER} > F_{MSY}$, although the disparity was greatly reduced at lower levels of steepness.
  - The rule of thumb that $F_{MSY} \approx M$ was only true at the highest levels of steepness when all ages were fully selected.
  - When the selectivity ogive was equal to the maturity ogive there were more cases where F_{MSY} or F_{MER} exceed M.
  - When selectivity occurred at 75% of the age of maturity results were similar to when all ages are fully selected, except that F_{MSY} and F_{MER} only exceeded M for h >0.75.
  - When the selectivity ogive was shifted to the right of the maturity ogive only the lowest levels of steepness had F_{MSY} or F_{MER} less than M.
- As an example the method was applied to Dusky sharks for which biological information was available to calculate the SPR-based reference points and a fisheries-independent index of abundance was available to provide information on relative depletion. The analytical prediction was compared to results from multiple stock assessment methodologies.
  - The conclusions were in agreement with the results of the stock assessment methodologies.
- Results from recently assessed shark stocks were compared with analytically predicted spawner depletions.
  - For all nine cases the predictions from the analytic methodology consistently matched those from the stock assessments.

Caveats:

- Using the analytical result for SPR_{MER} in place of SPR_{MSY} produces reference points that are biased low.
- Bias in any of the life-history parameter estimates could have a small effect on SPR.
- The derived values of SPR_{MER} are deterministic but the biological parameters that go into it are expected to have variability associated with them.
- The best scientific advice about the individual components of maturity, fecundity and survival can sometimes produce implausible values for steepness.

A.4.4.2 Hordyk, A., Ono, K., Sainsbury, K., Loneragen, N., and Prince, J. 2014a. Some explorations of the life history ratios to describe length composition, spawning-per-recruit and the spawning potential ratio. ICES Journal of Marine Science. Doi:10.1093/icesjms/fst235.

Abstract: Evaluating the status of data-poor fish stocks is often limited by incomplete knowledge of the basic life-history parameters: the natural mortality rate (M), the von

Bertalanffy growth parameters (L_∞ and k), and the length at maturity (L_m). A common approach to estimate these individual parameters has been to use the Beverton–Holt life-history invariants, the ratios M/k and L_m/L_∞, especially for estimating M. In this study, we assumed no knowledge of the individual parameters, and explored how the information on life-history strategy contained in these ratios can be applied to assessing data-poor stocks. We developed analytical models to develop a relationship between M/k and the von Bertalanffy growth curve, and demonstrate the link between the life-history ratios and yield- and spawning-per-recruit. We further developed the previously recognized relationship between M/k and yield- and spawning-per-recruit by using information on L_m/L_∞, knife-edge selectivity (L_c/L_∞), and the ratio of fishing to natural mortality (F/M), to demonstrate the link between an exploited stock's expected length composition, and its spawning potential ratio (SPR), an internationally recognized measurement of stock status. Variation in length-at-age and logistic selectivity patterns were incorporated in the model to demonstrate how SPR can be calculated from the observed size composition of the catch; an advance which has potential as a cost-effective method for assessing data-poor stocks. A companion paper investigates the effects of deviations in the main assumptions of the model on the application of the analytical models developed in this study as a cost-effective method for stock assessment [Hordyk, A. R., Ono, K., Valencia, S., Loneragan, N. R., and Prince, J. D. this issue. A novel length based empirical estimation method of spawning potential ratio (SPR), and tests of its performance, for small-scale, data-poor fisheries. ICES Journal of Marine Science].

Data/information requirements:

- Knowledge of the proportion of population that survive to some maximum age t_{max} in virgin state, which is used to estimate M.
- Estimate of exponent from length–weight relationship, b (typically around 3).

Assumptions:

- Relationship between Beverton–Holt life-history invariants and YPR/SPR reference points.
- Selectivity either flat or knife-edged

Outputs expected:

- Spawning potential ratio (eggs per spawner compared to virgin eggs per spawner) and length distribution.
- A ratio F/M which optimises SPR values.

Method of operation:

- Numbers per recruit surviving to age x can be approximated in the virgin stock by $(1-\tilde{L}_x)^{M/k}$ where $\tilde{L}_x$ is length relative to L_∞ and $M/_k$ can be inferred from similar stocks. Length at maturity is estimated from $M/_k$ and b. These, combined with a selectivity ogive allow yield to be calculated as a function of F, and an optimum found.
- Variation in growth between individuals can be incorporated by specifying L_∞ as being drawn from a normal distribution and solved analytically. When selectivity-at-length is modelled as varying, there is no known analytical solution, and numerical methods or simulation are required.

Testing:

- Results are based on simulation testing rather than application to particular stocks.

Caveats:

- Knife-edged maturity assumed at a single length dependent on $M/_k$ and b.
- If the knife-edged selectivity occurs at a longer length than maturity, high (effectively infinite) F values may optimise SPR.

A.4.4.3 Kokkalis, A., Thygesen, U.H., Nielsen, N., Andersen, K.H. In press. Limits to the reliability of size-based fishing status estimation for data-poor stocks. Fisheries Research Special Issue on data-poor methods.

Abstract: For stocks which are considered "data-poor" no knowledge exist about growth, mortality or recruitment. The only available information is from catches. Here we examine the ability to assess the level of exploitation of a data-poor stock based only on information of the size of individuals in catches. The model is a formulation of the classic Beverton–Holt theory in terms of size where stock parameters describing growth, natural mortality, recruitment etc. are determined from life-history invariants. A simulation study was used to compare the reliability of assessments performed under different information availability scenarios, from data-limited, where none of the parameters are known beforehand, to different degrees of information availability cases where one or more parameters are known. If no parameters are known it is possible to correctly assess whether the fishing mortality is below F_{MSY} in more than 60% of the cases, and almost always correctly assess whether a stock is subject to overfishing. Adding information about age, i.e. assuming that growth rate and asymptotic size are known, does not improve the estimation. Only knowledge of the ratio between mortality and growth led to a considerable improvement in the assessment. Overall, the simulation study demonstrates that it may be possible to classify a data-poor stock as undergoing over- or under-fishing, while the exact status, i.e. how much the fishing mortality is above or below F_{MSY}, can only be assessed with a substantial uncertainty. Limitations of the approach are discussed.

Data/information requirements:

- Catches of fish (numbers) as a function of size (weight) for one year (no requirement for time-series, although the approach could be used to derive estimates for each year of available data). Size-based information can also come from surveys.
- Case-specific life-history parameters characterising growth, mortality and recruitment, if available (otherwise a "Robin-Hood" approach, e.g. Punt *et al.*, 2011, is used).

Assumptions:

- Model follows the size-based theory of exploited fish stocks (Andersen and Beyer, 2013)
- A species-independent set of life-history parameters together with asymptotic size W_∞ define a stock
- The model assumes steady-state, and uses a Beverton–Holt stock–recruit function, von Bertalanffy growth parameters, size-dependent M, and a sigmoid curve for selection.

Outputs expected:

- Distribution of F/F_{MSY} (with sensitivity intervals defined by scanning over a range of plausible physiological mortality values) for each year of available catch-at-size data.

Method of operation:

- Given catch-at-size data and a life-history parameter set (if available), the model estimates only three parameters, namely fishing mortality, asymptotic weight W_∞ and the size at 50% retainment. All other parameters are constant during the estimation.

Testing:

- Simulation testing was based on 100 artificial stocks, with 20 catch-at-size datasets (each with 10 000 individuals) with varying fishing mortality (ranging from $0.1F_{MSY}$ to $2F_{MSY}$) generated for each. The analysis was repeated for three asymptotic weights (0.1, 1 and 10 kg).
- Estimation was repeated for the case where none of the life-history parameters were known (and therefore default values assumed), where all of the life-history parameters were known, and for cases in between (varying amounts of life-history parameters known.
- While estimation of a specific F or how much above or below F_{MSY} a stock was quite uncertain, simulation testing showed that the method was able to correctly classify whether the stock was undergoing over- or underexploitation better than random classification.
- Physiological mortality, which corresponds to the classical M/K invariant, was the most important parameters in the life-history set for the estimation.

Caveats:

- During testing, the same model was used for simulation and estimation, so the reliability of the method is optimistic and results cannot be generalised to real situations without further investigation. However, subsequent to the paper, the method was applied to a couple of data-rich stocks for comparison, and revealed broadly similar trends in relative exploitation to the data-rich assessments. It has also been applied to a handful of data-poor stocks.
- Misspecification of the selection function and inaccuracies in the estimation of asymptotic size can have severe consequences for the estimation of fishing mortality and reference points.
- Asymptotic size is difficult to estimate when the largest individuals are not selected, and may need additional information (e.g. local knowledge or information from other stocks of the same species).

A.4.5 Graphical/empirical and alternative approaches

A.4.5.1 Froese, R. And Kesner-Reyes, K. 2002. Impact of fishing on the abundance of marine species. ICES Document CM 2002/L: 12, 15 pp.

Abstract: The Census of Marine Life program aims to document the existence, distribution and abundance of marine organisms using all suitable data sources. In this study we analysed time-series of catch data published by ICES and FAO in respect to trends in the resilience of species towards fishing. For this purpose we classified the

fishing status of over 900 exploited species into undeveloped, developing, fully exploited, overfished, and collapsed or closed, where the sequence of the last three stages usually corresponds to a decline in species abundance. In world fisheries the percentage of species being overfished within ten years after start of full exploitation increased from 26% in the 1950ies to 35% in the 1980s. In 1999 the status of 50% of the exploited species was overfished, collapsed or closed. The number of species with low or very low resilience to fishing has been increasing from 80 (26%) in 1950 to 155 (32%) in 1999. Of 24 species reaching full exploitation in 1998 or 1999 for the first time, eight had low and eight had very low resilience to fishing. Of 25 species that had sustained 30 or more years of full exploitation before 1989, eleven species reached overfished or collapsed status thereafter. An analysis of length–frequency studies of commercial landings showed that in most cases mean length was below length at first maturity. In the ICES area 46% of the species were overfished within ten years after start of full exploitation and in 1999 the status of 60% of the species were overfished, collapsed or closed. We suggest an alternative management regime that would allow fish to spawn at least once before being caught. A census of marine life conducted in an exploited area will still largely be able to detect the evolutionary species composition, but will not be able to determine the evolutionary relative abundance of species and their respective roles in the ecosystem.

Data/information requirements:

- A time-series of catch data.

Assumptions:

- Assumes a model in which catches for a fish population increase during fisheries development and subsequently decline as fisheries become increasingly exploited.
- Given a time-series of catch data, the total production per year is calculated. This is then used to classify the status of the fishery in any given year into one of the following (arbitrary) development stages:
  - Undeveloped: C_{cur} before C_{max} and $C_{cur} < 0.1\ C_{max}$.
  - Developing: C_{cur} before C_{max} and $0.1\ C_{max} < C_{cur} < 0.5\ C_{max}$.
  - Fully exploited: $C_{cur} > 0.5\ C_{max}$.
  - Overfished: C_{cur} after C_{max} and $0.1\ C_{max} < C_{cur} < 0.5\ C_{max}$.
  - Collapsed/Closed: C_{cur} after C_{max} and $C_{cur} < 0.1\ C_{max}$.

Where C_{cur} is the current catch and C_{max} is the maximum catch in the time-series.

- The first and last year are excluded as the 'after maximum year' and 'before maximum year' criteria cannot be applied to them.
- Assumes catch data are representative of changes in abundance.

Outputs expected:

- A stock-status plot showing the percentage of stocks by status over time.

Testing:

- No testing described here. Tested by Carruthers *et al.* (2012) below.
- Applied to time-series of catch data published by FAO (Fisheries production time-series 1950–1999) and ICES (catch data for NE Atlantic 1973–1999).

Caveats:

- By definition, the percentage of undeveloped or developed stocks is zero in the final year of the time-series (Kleisner and Pauly, 2011).
- The stock-status plots do not take recovery into account (Kleisner and Pauly, 2011). Recovery is automatically classified as a 'developing' stock.

A.4.5.2 Kleisner, K. And Pauly, D. 2011. Stock-status plots of fisheries for regional seas. In: Christensen, V. Lai, S., Palomares, M. L. D., Zeller, D. and Pauly, D. (Eds.). The State of Biodiversity and Fisheries in Regional Seas. Fisheries Centre Research Reports 19(3). Fisheries Centre, University of British Columbia, pp. 37–40, ISSN 1198-6727.

Abstract: Stock-status plots are bivariate graphs summarizing the status ('underdeveloped', 'developing', 'fully exploited', 'overexploited', etc.), through time, of the multispecies fisheries of an area or ecosystem. Given that the limitations of these plots are understood, they are very useful for communicating, at a glance, the evolving status of multispecies fisheries in Regional Seas. Here, we present a new version of this approach that addresses some previous concerns.

Data/information requirements:

- A time-series of catch data.

Assumptions:

- This model makes the same assumptions and uses the same classification system as Froese and Kesner-Reyes (2002), except:
  - There is no 'undeveloped stage'. This is combined with the 'developing' stage.
  - Stocks that have a peak in catch in the final year of the time-series are classified as 'developing'.
  - An additional category 'recovery', which is a form of stock (re-) development, is defined as: C_{cur} & C_{min} after C_{max}, C_{cur} after C_{min}, C_{min} <0.1 C_{max} and C_{cur} <0.5 C_{max}. Where C_{min} is a 'post-maximum minimum', i.e. the minimum landing occurring after the maximum landing.

Outputs expected:

- A stock-status plot showing the percentage of stocks by status over time.
- A stock-catch status plot showing percentage catch by stock-status over time.

Method of operation:

- A three-year running average was used to smooth curves and remove anomalous peaks in the stock-status plots.

Testing:

- No testing described here. Tested by Carruthers *et al.* (2012) below.
- Applied to the Norwegian Exclusive Economic Zone (EEZ) as an example.

Caveats:

- Interpretation of stock-catch status plots can be problematic as they are based on catch, and not population size estimates.

A.4.5.3 Costello, C., Ovando, D., Hilborn, R., Gaines, S. D., Deschenes, O. and Lester, S. E. 2012. Status and solutions for the world's unassessed fisheries. Science, 338(6106): 517–520.

Abstract: Recent reports suggest that many well-assessed fisheries in developed countries are moving toward sustainability. We examined whether the same conclusion holds for fisheries lacking formal assessment, which comprise >80% of global catch. We developed a method using species' life-history, catch, and fishery development data to estimate the status of thousands of unassessed fisheries worldwide. We found that small unassessed fisheries are in substantially worse condition than assessed fisheries, but that large unassessed fisheries may be performing nearly as well as their assessed counterparts. Both small and large stocks, however, continue to decline; 64% of unassessed stocks could provide increased sustainable harvest if rebuilt. Our results suggest that global fishery recovery would simultaneously create increases in abundance (56%) and fishery yields (8 to 40%).

Data / information requirements:

- Time-series of catch
- Broad life-history and fishing history information

Assumptions:

- The status of a population is a function of its life-history traits and harvest history, and the manner in which these variables collectively affect fishery status is consistent across species with similar characteristics (Costello *et al.*, 2012).

Outputs expected:

- An estimate of B/B_{MSY} with 95% confidence intervals

Method of operation:

- mPRM is a regression model that estimates $\log(B/B_{MSY})$ from predictors of stock status, and was trained on a subset of assessed fisheries from the RAM Legacy database. This model is used to predict the status of unassessed fisheries using the same regression coefficients as estimated for the assessed species.
- The mPRM only uses the "developed" period of a fishery, which is defined as the period that begins once catch exceeds 15% of the maximum catch recorded for that fishery.
- It is necessary to correct for a retransformation bias as mPRM predicts $\log(B/B_{MSY})$.

Caveats:

- This approach is not suitable for formal assessment as it does not produce precise estimates for individual fisheries (Costello *et al.*, 2012).

A.4.5.4 Karnauskas, M., McClellan, D. B., Wiener, J. W., Miller, M. W. and Babcock, E. A. 2011. Inferring trends in a small-scale, data-limited tropical fishery based on fishery-independent data. Fish. Res. 111: 40–52.

Abstract: Size-based indicators have emerged as useful tools to analyse the status of fisheries which lack fishery-dependent data over long time-series, such as many coral reef fisheries. In this study, we calculate a number of size-based indicators for the Haitian fishery at the remote Navassa Island, where a reef fish visual census (RVC) dataset is available over an eight year study period (2002–2009). We also calculate the slope of

the size spectrum indicator within a Bayesian framework, which allows for potential biases inherent in the RVC method to be accounted for in credibility intervals around parameter estimates. Results of our analyses suggest that stocks targeted by traps declined from 2002 to 2004, followed by a period of increase from 2006 to 2009. The slope of the size spectrum declined from 2002 to 2004 and remained constant for the remainder of the study period, and this pattern was driven by a decrease in abundance of larger species targeted by hook and line. Analysis of the LMAX spectrum also indicated a decrease in the occurrence rates of larger species throughout the study period. Our methods can be applied to fisheries in other areas where limited fishery-independent data and no fishery-dependent data are available.

Data/information requirements:

- Limited fishery-independent data
    - Number of fish
    - Minimum, maximum and average size observed
    - Observations of fishing activity (optional: used here to define sub-communities)

Assumptions:

- The size distribution of fish species is assumed to follow a Poisson distribution with the mean equal to the average size observed and with maximum and minimum values truncated according to observations.
- The observed number of individuals in each length bin for fish communities is assumed to follow a multinomial distribution.

Outputs expected:

- Size-based indicators (SBIs)
    - Time-series of mean length and density for individual species
    - Time-series of density for fish communities
    - Slope of size spectrum indicator for fish communities
    - LMAX spectra for fish communities

Method of operation:

- A three-way mixed-effects analysis of variance (ANOVA) is used to analyse changes in length for each species.
- A three-way ANOVA was used on log-transformed densities to analyse changes in mean density over time for the entire fished community and some sub-communities. For individual species and one sub-community the delta lognormal method was used to test for trends due to the large number of zero counts.
- The size spectrum slope indicator is calculated using a Bayesian hierarchical model to account for potential biases inherent in the sampling method.
- Fish species were assigned to one of six LMAX classes. The changes in mean density were analysed for each group using a three-way ANOVA and the delta lognormal method on log-transformed densities.
- The analysis was run using both the full dataset from the unbalanced survey design and on a balanced subsample of the dataset. There was little difference in the results.

- Five models were considered for the slope of the size spectrum for the entire fished community. The final model was chosen based on the lowest deviance information criterion (DIC) value.

Testing:

- The analysis was applied to the Haitian fishery at Navassa Island using a reef fish visual census (RVC) dataset over an eight year period.

Caveats:

- Trends at the species level can be detected only when occurrence is high (>20%).
- The slope of the size spectrum should only be calculated for size classes well-selected by the sampling methodology, often excluding upper and lower size classes. Therefore this indicator is unable to account for information contained in some of the larger size classes that are excluded due to poor representation in the survey.
- Length distributions and densities of individual fish populations may fluctuate dramatically due to a range of factors in addition to fishing pressure e.g. large stochastic recruitment and environmental conditions. Community level indicators may be less influenced by stochastic recruitment and may be more favourable over species-specific indicators to detect fishing impacts in data-limited situations.

A.4.5.5 Scandol, J. 2005. Use of quality control methods to monitor the status of fish stocks. In G.H. Kruse, V.F. Gallucci, D.E. Hay, R.I. Perry, R.M. Peterman, T.C. Shirley, P.D. Spencer, B. Wilson and D. Woodby. (Eds.) Fisheries assessment and management in data-limited situations, pp. 213–231. Fairbanks, USA, Alaska Sea Grant College Program.

Abstract: Many fisheries that are data-limited are also of low economic value. Therefore, not only are the fisheries data-limited, but there are limited human resources available for undertaking stock assessment. Qualitative methods such as "eyeballing" the data are then often used to assess such systems. Quantitative methods need to be developed that are objective, but less demanding than dynamic stock assessment models. In particular, simple methods that can signal trends in empirical stock-status indicators need to be explored. One such approach is the use of quality control methods such as Shewhart, moving-average, and CUSUM (cumulative sum) control charts. Originally designed for industrial quality control, these methods can be parameterized to detect transient or persistent causes with specific false-positive and false-negative error rates. These signals can be interpreted within a managerial context as trigger reference points.

Results of a simulated study of yellowfin bream (*Acanthopagrus australis*) stocks from New South Wales (Australia) are presented. Empirical stock-status indicators including catch, catch per unit of effort, mean age, mean length, recruitment fraction, total mortality, and fishery-independent surveys were processed using quality control methods. Performance of these indicators and algorithms were measured with receiver-operator characteristic curves, which captured both false-positive and false-negative error rates. Biomass surveys performed best, followed by mean age and length, and recruitment fractions. Commercial catch rates and catch had the worst performance but were still acceptable. Age-based total mortality performed poorly unless very large numbers of samples were taken. Potential applications of these methods in-

clude a rapid diagnostic tool in data-limited situations, development of empirical reference points, and empirical rule-based management systems. These methods are easily applied even when there is a short time-series of low-contrast data but a range of caveats must always be considered.

Data/information requirements:

- An empirical stock-status indicator standardised using a control mean and standard deviation
- Parameters:
  - Decision interval, *h*, outside of which to raise a signal
  - Number of observations to average, *w* (moving-average control chart only)
  - Chart tolerance / variation that is ignored, *k* (CUSUM only)

Outputs expected:

- A quality control chart that signals uncharacteristic processes

Method of operation:

- *Shewhart Control Chart*: The Shewhart control algorithm raises a signal at any time when the value of the standardised indicator leaves the decision interval *h*.
- *Moving-Average Control Chart*: The moving average control algorithm calculates the moving average of the last *w* observations of the indicator and applies the Shewhart control algorithm to the smoothed values, raising a signal if the absolute value of the indicator is greater than the decision interval *h*.
- *CUSUM Control Chart*: The cumulative sum control method calculates the cumulative sum of the deviations of observations from the mean and raises a signal when this is leaves the decision interval *h*.

Testing:

- An operating model was used to generate observations that were transformed into nine stock-status indicators: cpue, commercial catch, biomass surveys, mean age, mean length, total mortality from age, total mortality from length and recruitment fractions by age and length. Time-series of the indicators were analysed for transient and persistent causes using the three quality control (QC) methods. The overall performance of an indicator and a QC algorithm was measured as the area under the ROC curve.
  - There was a strong correlation with the survey indicator and relative biomass, but commercial catch did not indicate biomass in a robust way.
  - The choice of control chart did not have a large effect upon performance of an indicator, though the CUSUM performed marginally better.
  - Biomass surveys performed best, followed by mean age and length, and recruitment fractions. Commercial catch rates averaged lower performance across all QC methods than these previous indicators but performed better than commercial catch and total mortality from age. Total mortality from length was biased but superior to total mortality from age.

- Performance of indicators as a function of (1) the value of the relative biomass reference point and (2) the probability of an impact occurring during the historical phase was estimated using the CUSUM scheme.
  - As the effect size decreased (larger values of relative biomass) the performance of all indicators decreased except surveys. Large effects degraded the performance of the survey indicator.
  - Performance of total mortality from age degraded badly when attempting to detect small changes to the underlying stock.
  - Large amounts of historical variation degrade the performance of all indicators.
- Using the CUSUM, sensitivity analyses were carried out for the number of fish aged, the number of fish measured, recruitment variability and the steepness of the stock–recruitment parameter.
  - Increasing the numbers of fish aged and measured increased the precision and accuracy of all the age- and length-based indicators except total mortality from length which was always biased. Most of the increase in performance was obtained within 100~200 fish except for total mortality from age which continued to increase in performance until 10 000 fish.
  - Performance of indicators was robust to changes in the steepness of the stock–recruitment parameter.
  - Only very large values of the coefficient of variation of recruitment appeared to degrade the performance of the indicators.

Caveats:

- QC algorithms are simple and numerically stable but cannot provide the same insight into a fishery that a dynamic model can.

A.4.6 Additional simulation testing of methods

A.4.6.1 Wetzel, C. R. and Punt, A. E. 2011. Model performance for the determination of appropriate harvest levels in the case of data-poor stocks. Fish. Res. 110:342–355.

Abstract: The determination of harvest limits for data-poor and data-limited stocks poses unique challenges for traditional complex stock assessment methods. Simulation is used to examine the performance of two new data-poor assessment methods, Depletion Corrected Average Catch (DCAC) and Depletion-Based Stock Reduction Analysis (DB-SRA), and a more complex catch-at-age method, Stock Synthesis (SS), in terms of estimating harvest levels for two life-history types (US west coast flatfish and rockfish) under varying mis-specifications of parameter distributions. DCAC and DB-SRA are fairly robust to mis-specification of the distributions for natural mortality and the productivity parameter (the fishing mortality rate that corresponds to maximum sustainable yield relative to natural mortality) for the flatfish life-history, but led to greater error for the rockfish life-history when estimating harvest levels that would not result in overfishing. SS estimates of the harvest level increased when natural mortality was set to a higher value than the true value for both life-histories. Both DCAC and DB-SRA were highly sensitive to the assumed distribution for the ratio of the current to starting biomass and provided overestimates of the harvest level when based on an overly optimistic value for this ratio.

Summary:

The aim of this paper was to use simulation to test the performance of Depletion-Corrected Average Catch (DCAC; MacCall, 2009), Depletion-Based Stock Reduction Analysis (DB-SRA, Dick and MacCall, 2011), and the more complex catch-at-age method Stock Synthesis (SS) in terms of estimating harvest levels (HLs) under mis-specifications of the parameter distributions.

Testing:

An operating model was used to simulate the population dynamics of two life-histories, flatfish and rockfish, common on the US west coast. The HLs estimated by DCAC, DB-SRA and SS (10 000 parameter draws) were compared to the true overfishing level (OFL) for each life history.

- Four cases were created to explore the effect of mis-specifications of the biology-based parameters (natural mortality, M, and the ratio of F_{MSY} to M) for the two life-histories: (1) M and F_{MSY}/M were centred about the true values, (2) F_{MSY}/M was centred about an incorrect value, (3) M was centred about an incorrect value and (4) M and F_{MSY}/M were centred about incorrect values. Three catch histories were used to examine the effect of catch history on estimation performance: (1) constant catch, (2) ramp up and (3) ramp and decline. Three additional analyses were applied to DCAC to explore the implications of truncating the catch history: use only the years where the catches were at least (1) 10%, (2) 20% and (3) 30% of the maximum.
    - DCAC and DB-SRA were robust to mis-specification of the biology-based parameters for the flatfish life history with estimates of the HL low relative to the true OFL values.
    - DCAC and DB-SRA were more sensitive to mis-specification of the distribution of M for the rockfish life history, especially when both biology-based parameters were mis-specified.
- A fifth case was created to examine the effect of an underestimation in the final depletion.
    - Both DCAC and DB-SRA were highly sensitive to the assumed distribution of final depletion, and the probability of overestimating the HL greatly increases when this is assumed incorrectly.
- Performance of each model was evaluated by calculating relative errors based on a summary statistic that compares the median value of the 10 000 model estimates with 100 operating model values.
    - Both DCAC and DB-SRA were ranked poorly by the performance statistic. However, the authors acknowledge that their statistic may not be the most appropriate for judging model performance.

Method of operation:

- Multiple runs examining the impact of assumed depletion should be conducted routinely to determine the potential range of HLs when using DCAC or DB-SRA.
- The analysis should examine various parameter distributions for the biology-based parameters (natural mortality and the ratio F_{MSY}/M).

A.4.6.2 Arnold, L. M. And Heppell, S. S. 2014. Testing the robustness of data-poor assessment methods to uncertainty in catch and biology: a retrospective approach. ICES J. Mar. Sci. doi: 10.1093/icesjms/fsu077.

Abstract: The quality and quantity of data affect the reliability of all stock assessments. Over time, we expect data to improve and assessment predictions to become more reliable. There is a potential for strong bias in estimates of sustainable yield if the available data are not a good representation of stock dynamics, particularly for catch-based data-poor methods that rely on limited information and assumptions about stock status. We retrospectively investigated the interaction of data quantity and quality through time using the "real-world" data for a stock as it progressed from data-poor to data-rich. For this analysis, we chose a currently data-rich and overfished stock with historical assessments representing both a data-poor and data-moderate state, the canary rockfish (*Sebastes pinniger*). We asked how changes in the catch history and biological parameters over time affected the estimates of sustainable yield and the overfishing limit (OFL) predicted by two data-poor assessment tools, depletion-corrected average catch (DCAC) and depletion-based stock reduction analysis (DB-SRA). We found that both of these methods underestimated the "true" OFL in simulations with catch error alone. While there was slightly less bias for DB-SRA than DCAC, increasing error in the catch led to a more rapid increase in the variance of the DB-SRA harvest limit (HL). Our retrospective analysis showed that the expectation for a more accurate HL estimate between the data-poor and data-moderate canary rockfish assessments does not come from an increase in the quantity or quality of the catch data alone; a decrease in the quality of the biological data between assessments had the greatest impact. By evaluating these methods with historical data, our retrospective approach highlighted the impact of change in data quality and quantity on HL estimates for a long-lived rockfish, and could be used to define the amount and type of error included in simulation studies that further evaluate data-poor methods.

Summary:

The aim of this paper was to test the robustness of the Depletion-Corrected Average Catch (DCAC; MacCall, 2009) and Depletion-Based Stock Reduction Analysis (DB-SRA, Dick and MacCall, 2011) methods using a retrospective analysis of a data-rich stock (canary rockfish) using the data that were available to past assessments, when the stock was considered data-moderate or poor.

Assumptions:

- The current data-rich assessment is considered the truth and serves as the baseline to compare DCAC and DB-SRA harvest limits (HLs).

Testing:

- The effect of error on performance of DCAC and DB-SRA was evaluated by using the true canary catch history to simulate catch histories with increasing error. The error scenarios considered were biological parameter error (PE) only, catch error (CE) only and combined catch and parameter error (CPE).
    - Both DCAC and DB-SRA underestimated the true OFL in CE simulations alone. There was slightly less bias for DB-SRA but increasing catch error led to a more rapid increase in the variance of the DB-SRA HL.
    - In the PE and CPE simulations, DCAC was a less biased estimator of the OFL and was less sensitive to the addition of PE.

- The retrospective analysis estimated harvest limits (HLs) using DCAC and DB-SRA with the biological parameters and catch data that were available in the years of the first (1984, data poor) and second (1990, data moderate) assessments. The response of the model estimated HLs was investigated under the three types of error above (PE, CE and CPE) and two levels of biomass change (Δ, low=0.6, high=0.8). The performance of each model was assessed by comparing the true overfishing limit (OFL) to the estimated HLs with a percent relative error statistic.
    - DCAC and DB-SRA HLs are robust to error in the catch time-series, but overestimate the true OFL with mis-specified biological and production parameters. An increase in the quantity and quality of data from the 1984 to the 1990 assessment did not improve the HL estimates when paired with parameter misspecification (M).
    - DCAC provides a more conservative HL with less sensitivity to the type of error and assumed depletion when biological parameters are highly uncertain.
    - DB-SRA provides a more precautionary HL when the stock was highly depleted. The relative influence of the error scenarios is reduced at high depletion for DB-SRA.

Other relevant information:

The DCAC and DB-SRA methods are approved by the Pacific Fisheries Management Council (PFMC) for the evaluation of data-poor stocks on the US west coast, and they are the first two methods recommended for Only Reliable Catch Stocks (ORCS) by the National Oceanic and Atmospheric Administration.

A.4.6.3 Rosenberg, A. A., Fogarty, M. J., Cooper, A. B., Dickey-Collas, M., Fulton, E. A., Gutiérrez, N. L., Hyde, K. J. W., Kleisner, K. M., Kristiansen, T., Longo, C., Minte-Vera, C., Minto, C., Mosqueira, I., Chato Osio, G., Ovando, D., Selig, E. R., Thorson, J. T. and Ye, Y. 2014. Developing new approaches to global stock status assessment and fishery production potential of the seas. FAO Fisheries and Aquaculture Circular No. 1086. Rome, FAO. 175 pp.

Abstract: Stock status is a key parameter for evaluating the sustainability of fishery resources and developing corresponding management plans. However, the majority of stocks are not assessed, often as a result of insufficient data and a lack of resources needed to execute formal stock assessments. The working group involved in this publication focused on two approaches to estimating fisheries status: one based on single-stock status, and the other based on ecosystem production.

For the single-stock status work, a fully factorial simulation testing framework was developed to assess four potential data-limited models. The results suggest that Catch-MSY, a catch-based method, was the best performer, although the different models performed similarly in many cases. Catch-MSY was more effective in estimating status over short time-scales and could be particularly applicable for use in developing countries where data time-series are often shorter. Harvest dynamics was the most important explanatory variable in determining performance, which emphasizes the importance of having accurate information on fishing effort and total removals.

For the ecosystem-level production analysis, the working group used satellite-based estimates of primary productivity by size classes and a more complete foodweb, which included more complete microbial pathways than earlier approaches. The working group also assembled estimates of ecological transfer efficiencies from a large number of energy flow network models to characterize uncertainty. The first-order estimates of fishery production potential indicated a potential yield of up to 180 million tonnes of fish, which could vary depending on the capacity to sustainably diversify the suite of species that are currently exploited. Planktivorous species provide the largest scope for growth. However, consideration of factors such as the ecological impact on other foodweb components, profitability of harvest operations, and marketability for these species must first be resolved. The realized production potential for planktivores may be much lower than their potential levels depending on the outcome of these considerations. The working group estimated that up to 50 million tonnes of benthic production could be potentially harvested, although this estimate is subject to similar constraints as those for planktivores. The greatest scope for growth in the benthic component may be found in the mariculture sector, subject to suitable environmental safeguards.

Ecosystem exploitation rates should not exceed 20–25 percent of available production, considering basic energetic constraints in marine ecosystems. Current harvest levels for benthivorous and piscivorous species (principally fish) exceeded these levels in higher-latitude ecosystems (subarcticboreal and temperate) and were near or slightly below them in lower latitudes and upwelling systems. The estimates of the ratio of current catches to available production for planktivorous species are substantially lower, reflecting the production potential of currently underutilized species. However, targeted harvesting of selected planktivorous species does lead to relatively high exploitation rates for some species. Together, these results provide globally applicable methods for estimating fish stock status and fishery production potential.

Summary

This document tests the performance of four data-limited models: modified panel regression (mPRM), catch-MSY (CMSY), catch only model – sampling importance resampling model (COM-SIR) and state–space catch only model (SSCOM).

Modified panel regression (mPRM)

See review of Costello *et al*. (2012). This implementation was modified here to omit all life-history information except fixed effects for three life-history categories: demersal, small pelagic and large pelagic.

Catch–MSY (CMSY)

See review of Martell and Froese (2013).

- The implementation here assumes zero process errors, so the model is deterministic.
- The model was extended to produce biomass and B/B_{MSY} time-series.

Catch only model – sampling importance resampling (COMSIR)

See review of Vasconcellos and Cochrane (2005). This implementation uses sampling importance resampling to estimate the parameters.

State–space catch only model (SSCOM)

See review of Thorson *et al.* (2013).

Testing (all models)

A fully factorial two-stage simulation testing framework with both a deterministic and a stochastic set of simulations was developed to assess the four data-limited models. 72 stocks were generated for full factorial interactions between life history (three levels), initial depletion (three levels), harvest dynamics (four levels) and time-series length (two levels). Stochasticity was incorporated through recruitment variability (two levels), autocorrelation on recruitment residuals (two levels) and measurement error on catch (two levels). A total of 5760 stocks were simulated for the stochastic set.

Proportional error (PE) and mean proportional error (MPE) were used to estimate the bias of the methods. Absolute proportional error (APE) and mean absolute proportional error (MAPE) were used to estimate both the bias and the precision of the methods.

- Overall performance:
  - All models had positive bias as judged by the MPE. CMSY had the smallest bias, followed by mPRM, COM-SIR and then SSCOM.
  - CMSY had the lowest MAPE. mPMR and COM-SIR had similar MAPEs and SSCOM had the largest MAPE. CMSY, COM-SIR and SSCOM all had similar median absolute proportional errors while mPMR had a larger median absolute proportional error.
  - CMSY performs the best as judged by the mean PE or APE. COM-SIR had the lowest bias when median proportional errors were used.
- Frequency of best performance:
  - CMSY had the highest frequency of best performance when MPE was used, followed by COM-SIR and mPRM, then SSCOM.
  - CMSY remained the top-performing method when using MAPE, and was the best performer when using MAPE and MPE over the last five years of the time-series.
- Tile plots:
  - According to MAPE and MPE the CMSY performed the best for short time-series (20 years), except for flat harvest dynamics when COM-SIR was the best performer.
  - CMSY was also the best performer for scenarios with long time-series (60 years), one-way trip harvest dynamics and no autocorrelation. With addition of autocorrelation the mPRM performed the best.
  - The mPRM performed best for long time-series and rollercoaster harvest dynamics.
  - There are no models that dominate as the top performer within the majority of stochastic scenarios.
- Performance maps:
  - CMSY was the most frequent best performer when looking at performance maps for both the full time-series and the last five years.
  - No model was clearly superior in all scenarios.
  - CMSY performed best in cases of high initial depletion as the other methods (COM-SIR and SSCOM) assume no initial depletion.
- Performance across models – Regression trees:

    - Harvest dynamics was the factor that contributed the most to the variability, followed by time-series length across all years, and life history for the last five years.
    - For the MPE tree model choice explained some of the variability in only 6% scenarios. For APE model choice was not a factor.
- Determinants of performance for each of the four models – regression tress:
    - Modified panel regression model (mPMR):
        - Harvest dynamics was the most important explanatory variable affecting performance for PE and APE.
        - For APE the strength of autocorrelation in recruitment was the most important variable explaining performance over the last five years and was of secondary importance for PE as well.
    - Catch-MSY (CMSY)
        - No variables appeared to affect performance consistently for APE, or PE in the last five years.
        - Harvest dynamics was the only variable affecting performance in PE for all years; the performance for rollercoaster harvest dynamics was considerably poorer with the method overestimating relative biomass by an average of 68%.
    - Catch-only model (COM-SIR):
        - Harvest dynamics was the main variable that affected performance of the COM-SIR.
        - Time-series length was the second most important variable as judged by PE and APE across all years only. No variables other than harvest dynamics affected the performance of COM-SIR over the last five years of the time-series.
    - State–space catch only model (SSCOM):
        - Harvest dynamics was the main variable influencing the performance of SSCOM, with rollercoaster harvest dynamics resulting in the lowest performance for all years and both rollercoaster and one-way trip harvest dynamics having low performance for the last five years of the time-series.

A.4.6.4 Carruthers, T. R., Walters, C. J. And McAllister, M. K. 2012. Evaluating methods that classify fisheries stock status using only fisheries catch data. Fish. Res. 119–120: 66–79.

Abstract: Methods that use only fisheries catch records to determine the status of exploited fish populations have been used to draw important conclusions regarding the world's fisheries. The reliability of two such approaches is evaluated by simulating a range of fisheries development and overfishing scenarios. The success rate and bias of stock status classification by two catch-based methods is compared with those of two stock assessment methods that explicitly model population dynamics and use additional fishing effort data. On average the catch-based methods correctly classified the status of stocks in 31% and 34% of the cases considered. Two simple stock assessments successfully classified stock status in 57% and 59% of the cases. The catch-based methods and the surplus production stock assessment were negatively biased and on average provided overly pessimistic conclusions regarding stock status. Catch-based methods were more negatively biased on average than the stock assessment approaches.

The aim of this paper was to use simulation to test the reliability of the Froese and Kesner-Reyes (2002) and Kleisner and Pauly (2011) catch-based methods, and compare this to the reliability of two stock assessment methods that use additional fishing effort data.

Testing:

This paper evaluates the reliability of the Froese and Kesner-Reyes (2002) and Kleisner and Pauly (2011) catch-based methods under a range of simulated fishery development and exploitation scenarios. Success rate and bias were quantified by comparing the stock status (final year) conclusions of the two catch-based methods to reference points (B_{MSY} and F_{MSY}) obtained from the simulated 'truth'.

- Success rate was calculated as the fraction of simulations the methods correctly classified.
    - The success rate of the Froese and Kesner-Reyes (2002) method was 34% and the success rate of the Kleisner and Pauly (2011) method was 31%. Hence both methods are error-prone, but average success rates are above the 20% that could be expected by random selection of stock classification.
    - Both models were unable to achieve success rates appreciably higher than random selection when the current spawning stock level is higher than 10% unfished biomass.
- Stock status was ranked in terms of depletion and used to quantify bias of the two catch-based methods.
    - Both methods were generally pessimistic (negatively biased).
    - The method of Kleisner and Pauly (2011) was slightly less biased on average than Froese and Kesner-Reyes (2002).
    - To some extent both methods were on average positively biased when 'crashed' stocks were simulated, as there is no classification level below 'crashed'. The Kleisner and Pauly (2011) method was more biased and erroneously reported 'recovering' in the majority of these cases.
    - Because both methods tend to draw 'overexploited' and 'crashed' (pessimistic) conclusions, the methods were least biased and most successful when simulated conditions were 'crashed' or 'overexploited'.
- A linear model was fitted to the final half of the effort time-series to assess whether classification success or bias is affected by the general trajectory of recent fishing effort.
    - With increasing effort the success rate of Froese and Kesner-Reyes (2002) was 35% and the success rate of Kleisner and Pauly (2011) was 30%.
    - The success rate of Kleisner and Pauly (2011) decreased to 25% under decreasing effort trends.
    - On average, both methods were pessimistic (negatively biased) under all three effort scenarios.
- The performance of two stock assessment models (a non-equilibrium time-dynamic Schaefer model and a delay-difference model) was evaluated to provide a reference for the catch based methods.
    - The surplus production and delay-difference methods had success rates 57% and 59% respectively.

- Stock classification by the surplus production model was generally negatively biased, but to a lesser extent than the catch-based methods.
- The success rates of the stock assessments were negatively related to the effort trajectory, unlike for the catch-based methods.

A.4.6.5 Hordyk, A., Ono, K., Valencia, S., Loneragan, N., and Prince, J. 2014b. A novel length-based empirical estimation method of spawning potential ratio (SPR), and tests of its performance, for small-scale, data-poor fisheries. ICES Journal of Marine Science, doi:10.1093/icesjms/fsu004.

Abstract: The spawning potential ratio (SPR) is a well-established biological reference point, and estimates of SPR could be used to inform management decisions for data-poor fisheries. Simulations were used to investigate the utility of the length-based model (LB-SPR) developed in Hordyk et al. (this issue. Some explorations of the life-history ratios to describe length composition, spawning-per-recruit, and the spawning potential ratio. ICES Journal of Marine Science) to estimate the SPR of a stock directly from the size composition of the catch. This was done by (i) testing some of the main assumptions of the LB-SPR model, including recruitment variability and dome-shaped selectivity, (ii) examining the sensitivity of the model to error in the input parameters, and (iii) completing an initial empirical test for the LB-SPR model by applying it to data from a well-studied species. The method uses maximum likelihood methods to find the values of relative fishing mortality (F/M) and selectivity-at-length that minimize the difference between the observed and the expected length composition of the catch, and calculates the resulting SPR. When parameterized with the correct input parameters, the LB-SPR model returned accurate estimates of F/M and SPR. With high variability in annual recruitment, the estimates of SPR became increasingly unreliable. The usefulness of the LB-SPR method was tested empirically by comparing the results predicted by the method with those for a well-described species with known length and age composition data. The results from this comparison suggest that the LB-SPR method has potential to provide a tool for the cost-effective assessment of data-poor fisheries. However, the model is sensitive to non-equilibrium dynamics, and requires accurate estimates of the three parameters (M/k, L_∞, and $CV_{L\infty}$). Care must be taken to evaluate the validity of the assumptions and the biological parameters when the model is applied to data-poor fisheries.

Summary:

This paper tests the LB-SPR method developed in Hordyk *et al.* (2014a) using an age-structured operating model with constant selectivity.

Testing:

- Operating model:
  - Beverton–Holt stock–recruitment with lognormally distributed error
  - Length-at-age modelled with von Bertalanffy growth curve with increasing variability at longer lengths
  - Maturity-at-age follows logistic pattern, converted to maturity at length
  - Selectivity-at-age was either asymptotic or dome shaped, and converted to length
- Parameter values used by assessment model
  - Chosen to be typical of sand sole, Puget Sound rockfish, yellowtail rockfish and Pacific Saury

- Generally the model was provided with OM values of $M/_k$, L_∞ and CV_{L_∞}, except where sensitivity to these parameters was being tested, in which case they varied randomly between 75% and 125% of the OM value.
- recruitment variability set to 0, except where being explicitly investigated

- Simulation results:
  - The model is very sensitive to mis-specification of L_∞ , which can results in any value of the SPR between 0 and 1 for a 30% error in L_∞.
  - $M/_k$ mis-specification leads to a smaller, but still substantial error in SPR, but the estimates of SPR are relatively insensitive to a mis-specified CV_{L_∞}.
  - Errors in $F/_M$ followed a similar pattern to the errors in SPR.
  - Large variability in recruitment led to poor estimates of $F/_M$, but generally lower errors in estimating SPR.

A.4.7 Simulation–tested Harvest Control Rules (HCRs)

A.4.7.1 Klaer, N. L., Wayte, S. E. and Fay, G. 2012. An evaluation of the performance of a harvest strategy that uses an average–length-based assessment method. Fish. Res. 134–136: 42–51.

Abstract: The average length of the catch has long been used as a simple indicator of stock condition. Previous studies have evaluated the fishery conditions and species' biological characteristics where such an indicator performs best. This study uses a management strategy evaluation framework to test the combination of an average length-based assessment with a target- and limit-based harvest control rule in terms of achieving specific long-term management objectives. Results show that the average length-based harvest strategy performs acceptably well for typical Australian demersal temperate trawl species with relatively high productivity. It is essential that the assessment takes the variability in length-at-age into account for this harvest strategy to work effectively.

Data/information requirements:

- Information on recent catch history
- Average length of the catch above L_{ref} (length where full selection can be expected)
- Biological parameters
  - Von Bertalanffy growth parameters
  - Natural mortality
  - Steepness
  - Selectivity
  - Length–weight
  - Maturity
  - CV of length-at-age

Assumptions:

- Knife-edge selectivity

- Logistic selectivity
- Assessment uses assumed values for the biological parameters

Outputs expected:

- Estimates of:
  - Current fishing mortality rate
  - Next years fishing mortality rate
  - Recommended biological catch

Method of operation:

- The assessment compares the average length of the catch above L_{ref} to the expected average catch lengths, obtained from a yield-per-recruit procedure, to calculate current fishing mortality. This is compared to the limit (F_{20}), and breakpoint (F_{40}) fishing mortality reference levels in the harvest control rule to give the intended fishing mortality rate for the following year. A ratio that includes the current and intended fishing mortalities is then used in conjunction with an appropriate estimate of recent catches to determine the recommended biological catch (RBC) for the following year.
- The calculations are based on the biological parameters for females when there are considerable differences in growth between males and females.

Testing:

- Management strategy evaluation is used to test the combination of the average length-based assessment with the target- and limit-based harvest control rule in terms of achieving management objectives for three major Southern and Eastern Scalefish and Shark Fishery (SESSF) species with different life histories: tiger flathead (long-lived with relatively constant recruitment), jackass morwong (long-lived with low recruitment in recent years) and school whiting (short-lived with highly variable recruitment). One hundred simulations were conducted for each of the scenarios below.
- Two initial stock status levels were tested for each species: the stock was either below (35% unfished SSB) or above (60% unfished SSB) the target stock size at the start of the period in which the harvest control rule was applied.
  - The average length-based harvest strategy performs well and can achieve management policy objectives with an acceptable level of risk; the final relative SSB is close to target levels, the minimum relative SSB was above the limit level for most simulations and the proportion of years where the SSB goes below the limit reference point is below 10% for almost all simulations.
  - The year-to-year catch variability is very high.
  - The range of final relative SSB levels was wide for all scenarios.
- A scenario was run for each species where the assumed length-at-age CV was set to zero.
  - The model performs poorly when variability in length-at-age is ignored.
- A number of robustness test scenarios were conducted to examine the behaviour of the average length harvest strategy when biological parameters were mis-specified.

    - The performance was fairly insensitive to the value of the stock–recruit steepness parameter.
    - Using the wrong value of natural mortality led to poor outcomes.
    - Results were relatively sensitive to the value assumed for the CV of length-at-age.
- A comparison was made of the performance of this length-based model with a similar model that uses age composition (Wayte and Klaer, 2010).
    - The performance of the two models is reasonably similar.
    - The average length method leads to slightly lower average annual catches and slightly higher SSB levels.
    - The average length method leads to considerably more interannual variability in catches.

Caveats:

- The method must account for variability in length-at-age to perform adequately. It is important that estimates of variability in length-at-age are likely to be accurate.
- An appropriate natural mortality value needs to be selected for the harvest strategy to perform effectively.
- The method cannot be used as described if selectivity is assumed to be dome-shaped, because fishing mortality will be overestimated.

A.4.7.2 Geromont, H. F., and Butterworth, D. S. In press. Generic management procedures for data-poor fisheries: forecasting with few data. ICES Journal of Marine Science, doi:10.1093/icesjms/fst232.

The majority of fish stocks worldwide are not managed quantitatively as they lack sufficient data, particularly a direct index of abundance, on which to base an assessment. Often these stocks are relatively “low value”, which renders dedicated scientific management too costly, and a generic solution is therefore desirable. A management procedure (MP) approach is suggested where simple harvest control rules are simulation tested to check robustness to uncertainties. The aim of this analysis is to test some very simple “off-the-shelf” MPs that could be applied to groups of data-poor stocks which share similar key characteristics in terms of status and demographic parameters. For this initial investigation, a selection of empirical MPs is simulation tested over a wide range of operating models (OMs) representing resources of medium productivity classified as severely depleted, to ascertain how well these different MPs perform. While the data-moderate MPs (based on an index of abundance) perform somewhat better than the data-limited ones (which lack such input) as would be expected, the latter nevertheless perform surprisingly well across wide ranges of uncertainty. These simple MPs could well provide the basis to develop candidate MPs to manage data-limited stocks, ensuring if not optimal, at least relatively stable sustainable future catches.

Data/information requirements:

- Data-limited HCRs: mean length in the catch
- Data-moderate HCRs: direct index of abundance (commercial cpue or from surveys)

Assumptions:

- For data-limited HCRs: mean length in the catch is a quantitative, though indirect, indicator of the trend in resource abundance

- For data-moderate HCRs: index of abundance reflects unbiased population trends
- All these data have reasonable information content and the associated observation error is not too large

Outputs expected:

- HCRs that can be applied to obtain catch advice in both data-limited and data moderate scenarios that are able to recover the stock if it is depleted, and minimise the risk of stock depletion

Method of operation:

- Data-limited: rules ranging from simple constant catch to step up/down constant catch strategies as a function of the current mean length of the catch, and a target rule based on current mean length as a function of target mean length
- Data-moderate: slope and target rules based on the index of abundance
- The TAC each year is adjusted up or down from the previous year's TAC or recent years average catch depending on either the rate of increase or decrease in the size of the resource or whether it is above or below some target level indicated by data
- The success of a rule depends on how much information, rather than noise due to observation error, dataseries contain

Testing:

- Testing within an MSE framework, accounting for observation error (when generating future abundance indices and length data), process error (recruitment and fishing selectivity) and implementation error.
- Age-structured production model used as the operating model, parameterised using a Bayes-like approach (integrating over ranges specified for model variables such as current depletion B/K, stock–recruit steepness h, and natural mortality M). Parameter distributions are chosen to reflect qualitative information typically available, while allowing for the amount of model uncertainty expected.
- Fish stocks grouped into "baskets" according to perceived level depletion (severely depleted, moderately depleted, near target) and productivity (low, medium and high). However, for the paper only one of the baskets is considered (severely depleted of medium productivity).
- Simple empirical rules lack used in data-limited situations lack estimates of stock status and quantities such as MSY on which to base TACs, so additional caution is needed to avoid undetected resource depletion. Therefore, if little information is known about stock status, the starting point of these empirical rules should correspond to an appropriately precautionary level of catch.
- As expected, data-moderate rules performed better than data-limited ones; nevertheless, the data-limited rules performed surprisingly well across a wide range of uncertainty. The rules were not robust to misclassification of the depletion/productivity "basket", suggesting that correct classification is key for HCRs to meet their objectives.

Caveats:

- The generic HCRs cannot be applied "as is" in practice without further testing to account for the full extent of uncertainty for the group of stocks under consideration.
- The simulations assumed the availability of reliable direct/indirect indices of population abundance and trends – reliable indices may not be available, so robustness to biases in available indices would need to be demonstrated.
- Simulation study only considered severely depleted stocks of medium productivity (only one of the nine "baskets").
- Classification of "depletion" is challenging and may need to be supported by use of classification approaches such is in FAO (2011).
- The extent of uncertainty, as reflected by prespecified distributions, may need to be closely examined by stakeholders to ensure acceptance.

A.4.7.3 Jardim, E., Azevedo, M., and Brites, N.M. Submitted. Harvest Control Rules for data limited stocks using length-based reference points and survey biomass indices. Fisheries Research Special Issue on data-poor methods.

Abstract: There are a large number of commercially exploited stocks lacking quantitative assessments and reliable estimates of stock status. Providing MSY-based advice for these data limited stocks remains a challenge for fisheries science. For many data-limited stocks, catch length composition and/or survey biomass indices or catch-per-unit effort (cpue) are available. Information on life-history traits may also be available or borrowed from similar species/stocks. In this work we present three harvest control rules (HCRs), driven by indicators derived from key monitoring data. These were tested through simulation using two exploitation scenarios (development and overexploitation) applied to 50 stocks (pelagic, demersal, deep-sea species and *Nephrops*). We examine the performance of the HCRs to deliver catch-based advice that is risk adverse and drives stocks to MSY. The HCR with a biomass index-adjusted status quo catch, used to provide catch-based advice for several European data-limited stocks, showed the poorest performance, keeping the biomass at low or very low levels. The HCRs that adjust the status quo catch based on the variability of the biomass index time-series was able to drive most of the stocks to MSY, showing low to moderate biological risk. The recovery of biomass required asymmetric confidence intervals for the biomass index and larger decreases in status quo catch than increases. The HCR based on length reference points as proxies for the F_{SQ}/F_{MSY} ratio was able to reverse the decreasing trend in biomass but with levels of catch below MSY. This HCR did not prevent some of the stocks declining when subject to overexploitation. For data-limited stocks, the empirical HCRs tested in this work can provide the basis for catch advice. Nevertheless, applications to real life cases require simulation testing to be carried out to tune the HCRs. Our approach to simulation testing can be used for such analysis.

Data/information requirements:

- For survey-based HCRs: time-series of survey biomass indices (survey-based HCR)
- For length-based HCR: current mean length in the catch, mean length at first capture (L_c), and the von Bertalanffy growth parameters L_∞.

Assumptions:

- For survey-based HCRs: Survey biomass indices reflect unbiased population trends

- For length-based HCR: mean length in the catch reasonably reflects population status; $L_{SQ}/L_{F=M}$ is used as a proxy for F_{SQ}/F_{MSY}

Outputs expected:

- HCRs that can be applied to obtain catch advice in data-limited scenarios that are able to recover the stock if it is depleted, and minimise the risk of stock depletion

Method of operation:

- Survey-based HCR1: calculate the ratio of the mean of the most recent two years relative to the mean of the three preceding years for the survey biomass index, and apply this ratio to recent catch to obtain catch advice
- Survey-based HCR2: compare the most recent survey index to survey confidence intervals based on survey means and standard deviations that are continuously updated with new data, and apply a multiplier depending on whether the recent index is above or below the survey confidence interval. Apply this multiplier to recent catch to obtain catch advice. The interval need not be symmetrical, nor the multipliers equal.
- Length-based HCR3: calculate the ratio of the current mean length in the catch (L_{SQ}) o the mean length used as a proxy for the mean catch length at MSY ($L_{F=M}$=$0.75L_c$+$0.25L_\infty$), and apply this ratio to recent catch to obtain catch advice

Testing:

- Testing within an MSE framework (FLR), accounting for observation, process and implementation error.
- Tested under two exploitation scenarios: development and overexploitation
- Applied to 50 stocks (pelagic, demersal, deep-sea, *Nephrops*).
- Steepness of h=0.75 used for all stocks, with M calculated from Gislason *et al*. (2010) and von Bertalanffy growth parameters from ICES (2012).
- Fleet selectivity modelled as double-normal with a mode at 50% maturity, with survey selectivity modelled as asymptotically flat-topped.
- Operating model was age-structured, with mean length in the catch calculated as a weighted average of length-at-age with the weights being catch-at-age. Mean length at first capture calculated using von Bertalanffy growth parameters assuming age at first capture at 25% maturity.
- Results indicated that HCR1 was unable to recover depleted stocks. HCR3 was able to reverse decreasing trends in biomass, but with levels of catch below MSY; in some cases, HCR3 was unable to prevent stocks that were overexploited from declining further. HCR2 required the use of asymmetric intervals and multipliers (resulting in larger decreases than increases) in order to drive stocks towards MSY levels and secure low to moderate levels of biological risk.

Caveats:

- Application to real-life scenarios requires that the HCRs be "tuned" in order to ensure reasonable performance under the specific scenario
- How reliable the performance of an HCRs is for a given stock scenario depends on the appropriateness of testing assumptions

A.4.8 Approaches that could provide supplementary information to other methods

A.4.8.1 Cope, J. M., Thorson, J. T., Wetzel, C. R. and DeVore, J. 2014. Evaluating a prior on relative stock status using simplified age-structured models. Fish. Res. http://dx.doi.org/10.1016/j.fishres.2014.07.018

Abstract: Fisheries management aimed to support sustainable fisheries typically operates under conditions of limited data and analytical resources. Recent developments in data-limited analytical methods have broadened the reach of science informing management. Existing approaches such as stock reduction analysis and its extensions offer simple ways to handle low data availability, but are particularly sensitive to assumptions regarding relative stock status. This study develops and introduces a prior on relative stock status using Productivity-Susceptibility Analysis vulnerability scores. Data from US west coast groundfish stocks (n = 17) were used to develop and then test the performance of the new relative stock status prior. Traditional simulation testing via an operating model was not possible because vulnerability scoring could not be simulated; we instead used the "best available scientific information" (BASI) approach. This approach uses fully realized stock assessments (deemed the best available scientific information by management entities) and reduces data content available to simpler models. The Stock Synthesis statistical catch-at-age framework was used to nest within the full assessment two simpler models that rely on stock status priors. Relative error in derived estimates of biomass and stock status were then compared to the BASI assessment. In general, the new stock status prior improved performance over the current application of stock status assumed at 40% initial biomass. Over all stocks combined, stock status showed the least amount of bias, while initial biomass was better estimated than current biomass. The BASI approach proved a useful and possibly complimentary approach to simulation testing with operating models in order to gain insight into modelling performance germane to management needs, particularly when system components (e.g. susceptibility scoring) cannot be easily simulated.

Data / information requirements:

- Time-series of catches
- Priors on:
  - Natural mortality
  - Steepness
  - Relative stock status – derived from Productivity-Susceptibility Analysis (PSA) vulnerability scores
- An index of abundance (optional)

Assumptions:

- Frees the assumptions of previous stock reduction analysis (SRA) type models. Those being (1) that stock status is defined in the final year of the time-series and (2) relative stock status is set at 40% of the initial stock biomass.

- The relationship of vulnerability to stock status assumes that a long period of relatively constant vulnerability has occurred.

Outputs expected:

- Spawning–stock biomass
- Relative stock status

Method of operation:

- Data-limited and moderate assessments were ran with the nested Stock Synthesis models Simple Stock Synthesis (SSS; catch only data) and extended Simple Stock Synthesis (XSSS; index of abundance available) using a PSA derived prior for relative stock status.
- A Productivity-Susceptibility Analysis (PSA) is carried out on stocks with full assessments to obtain retrospective vulnerabilities for a year prior to any significant management impact on removals. A logit-linear model can then constructed to predict relative stock status from retrospective vulnerability, and fit to the assessed species data using Markov Chain Monte Carlo sampling. This model is used to formulate the stock-status priors for the data limited and moderate assessments.

Testing:

- The vulnerability-based stock status priors for each of 17 fully assessed US West Coast groundfish species were compared to the defaults assumed in standard SRA type models (mean of 0.4 and standard deviation 0.2).
    - The vulnerability stock status priors showed appreciable differences across stocks to the default priors and demonstrated similar or greater uncertainty.
- The performance of the vulnerability-based stock status prior was tested in data-reduced applications of the Stock Synthesis framework. The framework reduced the data content of the full stock assessment to that of an SRA-type analysis that uses either catch-only (SSS) or catch and biomass index data (XSSS). Model performance was compared against the fully specified assessment for several model-derived outputs (initial and terminal spawning biomass and stock status) under the two different stock status priors: the vulnerability stock status prior and the commonly applied mean of 0.4 and standard deviation of 0.2.
    - Models using the vulnerability-based stock status priors generally produced less biased or more negatively biased results relative to the full stock assessment when compared to the default prior, translating to better or more conservative performance. These results were most apparent in stocks with higher vulnerability or lower relative stock status.
    - Variance in relative error tended to decrease when using the vulnerability-based stock status prior.
    - XSSS models typically produced results with less bias and variance in error relative to the SSS models. Cases which did not show much difference between XSSS and SSS are indicative of uninformative biomass indices.
    - Initial spawning biomass and relative stock status showed less bias and variance compared to the terminal year biomass.

- Relative stock status was the best performing of the derived quantities across all prior types and modelling approaches.

A.4.9 Data-moderate methods

A.4.9.1 McGarvey, R., Punt, A. E. and Matthews, J. M. 2005. Assessing the Information Content of Catch-in-Numbers: A Simulation Comparison of Catch and Effort Data Sets Fisheries Assessment and Management in Data-Limited Situations Alaska Sea Grant College Program AK-SG-05-02.

Abstract: The fishing industry provides totals for landed catch-in-weight and fishing effort in skippers' logbooks. Because this data-gathering infrastructure is in place, one potentially inexpensive source of additional information could be the catch reported in numbers of individuals landed. The performance of stock assessment models based on three logbook datasets,

(1) catch-in-weight and fishing effort, (2) that of (1) plus catch in numbers, and (3) catch-in-weight and catch in numbers (no effort), was evaluated by means of simulation. Simulated datasets were generated from an individual-based model of a lobster fishery and used to test the ability of these three datasets to estimate recruitment, biomass, population numbers, and exploitation rate. The agreement of estimates from two different delay-difference models with true simulation values were quantified. With perfect knowledge of growth and natural mortality, and under nineteen simulated variations from perfect knowledge, adding catch in numbers to the traditional dataset of catch-in-weight and effort substantially improved the precision and accuracy of the yearly population estimates.

Data/information requirements

- Time-series of catch weight
- Time-series of catch numbers
- Time-series of effort
- estimate of natural mortality M

Assumptions:

- Either exact catch or exact cpue (depending on model setup).
- Stock can be represented as a recruitment (to the fishery) age class, followed by a plus group. In the first delay difference model (DD1), numbers in a year only depend on numbers in the previous year and recruitment in the previous year. In the second model (DD2), the numbers may depend on the stock state in the previous two years.
- Von Bertalanffy growth parameters

Output:

- Time-series of harvest rate, biomass, population numbers and recruitment.
- Potentially enough data to perform limited forward projections, and hence define reference points.

Method of operation:

- The two different delay-difference models are fitted to simulated data to investigate the importance of having three time-series of data in the assessment (catch weight, catch numbers and effort). Three different scenarios of data availability were investigated:

1) CwCnE: catch weight, number and effort time-series are available
2) CwE: catch weight and effort time-series are available
3) CwCn: catch weight and catch numbers time-series are available

Data were simulated with varying mis-specification to represent a possible stock of South Australian rock lobster.

Testing:

- Twenty scenarios were tested, for 100 runs each, including a base case with no model mis-specification.
    - In the well specified situation, all three series were required to be able to recreate the 'truth' assumed in simulation.
    - If catch numbers were omitted, trends were correctly modelled by DD1 (on the few occasions that it converged), but not scaled correctly, whereas DD2 did not even capture the trends.
    - Where effort data were omitted, the models typically fitted well over the majority of the time period, but with substantial error in the most recent year. The authors hypothesise that this is due to increases in mean weight (which is effectively what the data provide together) being possible due to either decreasing fishing effort leading to greater survival, or to low recruitment, and it takes observations over a few subsequent years to correctly detect which is happening.
- Given the demonstrated importance of having all three time-series, the results for the majority of scenarios are only presented for the case where all three sources of data are available (CwCnE). In these cases, the authors report poor model fitting in the following situations:
    - High variability in recruitment (cv=1)
    - High noise in effort-exploitation relationship (cv=0.4)
    - Low exploitation rates (harvest rate of 5% and 10%)

Caveats:

- Despite the large number of simulations run, they were effectively based around a single life history, and the conclusions may not extend beyond this species.
- Under some forms of mis-specification, the model had a high rate of failure to converge when applied to the simulated data. This was particularly true when the catch number time-series was excluded.
- Only one of the simulation sets included variation in time of the individual growth function parameters.

A.4.9.2 Jardim, E., Millar, C. P., Mosqueira, I., Scott, F., Osio, G. C., Ferretti, M., Alzorriz, N. And Orio, A. In Press. What if stock assessment is as simple as a linear model? The a4a initiative. ICES J. Mar. Sci. DOI:10.1093/icesjms/fsu050.

Abstract: This manuscript discusses the benefits of having a stock assessment model that is intuitively close to a linear model. It creates a case for the need of such models taking into account the increase in data availability and the expansion of stock assessment requests. We explore ideas around the assessment of large numbers of stocks and the need to make stock assessment easier to run and more intuitive, so that more scientists from diverse backgrounds can be involved. We show, as an example, the model

developed under the European Commission Joint Research Center's 'Assessment for All' Initiative (a4a) and how it fits the a4a strategy of making stock assessment simpler and accessible to a wider group of scientists.

Data/information requirements:

- Exploitation
  - Volume of catch
  - Length frequencies of the catches, landings or discards
  - Nominal effort (optional)
- Biology
  - Estimated maturity ogive
  - Estimated growth model and parameters
  - Estimated length–weight relationship
- Abundance
  - Index of abundance

Assumptions:

- The statistical catch-at-age model is based on the Baranov catch equation.
- Population numbers are assumed to decay exponentially.
- Errors of catches and abundance indices are assumed lognormal.

Outputs expected:

- Two output objects may be obtained. The basic model output class (a4aFit) contains fitted values of:
  - Stock numbers
  - Fishing mortality
  - Catch numbers
  - Indices

The full assessment model output class (a4aFitSA) contains model summaries and the model parameters in addition to the fitted values above.

- Commands are available to obtain:
  - The standardised residuals.
  - A stock summary plot showing time-series of recruitment, SSB, catch and fishing mortality.

Method of operation:

- The stock assessment model framework is a non-linear statistical catch-at-age model implemented in R, making use of the FLR platform and using automatic differentiation in ADMB.
- Submodels for fishing mortality (F), survey catchability (Q) and recruitment (R) have to be given structure by the user, in the form of log-linear models. This choice should be based on knowledge of the biology of the stock, environmental conditions of the region, fishing gears and major management events.

Testing:

- It is stated that "The methods being developed are subject to extensive testing to evaluate their performance and to identify the appropriate configurations for different situations, as well as robust default settings". However, no further details are given.

Caveats:

- The flexibility introduced in the model increases the possibility of over-parameterisation.
- Users will need to know how to operate R.

A.4.9.3 Millar, C. P., Jardim, E., Scott, F., Osio, G. C., Mosqueira, I. And Alzorriz, N. In Press. Model averaging to streamline the stock assessment process. ICES J. Mar. Sci. DOI:10.1093/icesjms/fsu043.

Abstract: The current fish stock assessment process in Europe can be very resource- and time-intensive. The scientists involved require a very particular set of skills, acquired over their career, drawing from biology, ecology, statistics, mathematical modelling, oceanography, fishery policy, and computing. There is a particular focus on producing a single "best" stock assessment model, but as fishery science advances, there are clear needs to address a range of hypotheses and uncertainties, from large-scale issues such as climate change to specific ones, such as high observation error on young hake. Key to our discussion is the use of the assessment for all frameworks to translate hypotheses into models. We propose a change to the current stock assessment procedure, driven by the use of model averaging to address a range of plausible hypotheses, where increased collaboration between the varied disciplines within fishery science will result in more robust advice.

Data/information requirements:

- Exploitation
  - Volume of catch
  - Length frequencies of the catches, landings or discards
  - Nominal effort (optional)
- Biology
  - Estimated maturity ogive
  - Estimated growth model and parameters
  - Estimated length–weight relationship
- Abundance
  - Index of abundance

Assumptions:

- The a4a assumptions of Jardim *et al.* (2014).
- Attention is restricted to lognormally distributed data.

Outputs expected:

- Standard stock assessment outputs that incorporate uncertainty due to different plausible states of nature, defined through the input models.

Method of operation:

- An initial suite of plausible models, chosen to represent possible "states of nature", is defined for each stock. The a4a framework is used to set up the population dynamics and fishery models as it gives easy access to a variety of fishing mortality, catchability, recruitment and variance models.
- Stock assessment results are obtained through model averaging; all models contribute to the final estimates of stock status and uncertainty and to other standard outputs from stock assessment. The weight that each model receives in the output depends on the fit of the model to the data.

Testing:

- No testing described.

Caveats:

- A flexible and intuitive interface is the key to success. A4a is suggested as such an interface but requires the user to be familiar with linear modelling and working with splines to get the most out of the interface.
- Model averaging may result in bimodal distributions due to competing hypotheses / models.
- Model averaging is not easy. Simpler methods make more assumptions, while more complex methods, such as Bayesian treatment through reversible jump MCMC, are very difficult.

A.4.10 Other approaches of interest

A.4.10.1 A'mar, Z. T. and Punt, A. E. 2005. Minimum stock size thresholds: how well can we detect whether stocks are below them? In G.H. Kruse, V.F. Gallucci, D.E. Hay, R.I. Perry, R.M. Peterman, T.C. Shirley, P.D. Spencer, B. Wilson and D. Woodby. Eds. Fisheries assessment and management in data-limited situations, pp. 213–231. Fairbanks, USA, Alaska Sea Grant College Program.

Abstract: Management of marine fisheries in US waters is based on the Magnuson-Stevens Fishery Conservation and Management Act. Rebuilding plans need to be developed for fish stocks that have been depleted to below a minimum stock size threshold, MSST. Whether a stock is below MSST is based on the results from a stock assessment. Two types of error can arise when a stock is assessed relative to MSST: (a) it can be assessed to be above MSST when it is not, or (b) it can be assessed to be below MSST when it is not. Simulation is used to assess the likelihood of making these two types of errors as a function of the true status of the resource, the stock assessment method applied, and the quality and quantity of the data available for assessment purposes. All three of the methods of stock assessment considered in this study (two age-structured methods and a production model) make the two errors, especially when the true status of the resource is close to MSST. The major factor influencing the likelihood of under- and over-protection errors is the extent of variability in recruitment, the impact of which is larger than that of data quality and quantity, at least within the range for data quality and quantity considered in this paper.

Summary:

This paper uses simulation to assess the likelihood of three models (two age-structured models and a surplus production model) assessing a stock to either be below the minimum stock size threshold (MSST) when it is not or above the MSST when it is not as a function of the true stock status, the stock assessment method and the quality and quantity of the data available.

Methods:

- Age-structured assessments
- Schaefer surplus production model

Testing:

- An artificial dataset was generated for which the true status of the stock relative to S_{MSY} (spawning output) and MSST (0.5 S_{MSY}) is known. It was assessed how often each assessment method correctly determined the status of the stock relative to the true S_{MSY} and MSST and their proxies (0.4 S_0 is the proxy for S_{MSY} and 0.25 S_0 is the proxy for MSST).
- The fully integrated age-structured population model was run with four levels of available data: data-rich, data-moderate, data-poor and no-age data.
    - The probability of an under-/over protection error is greatest when the actual depletion is close to the threshold depletion level.
    - There was little difference among the data scenarios for the probability of being below S_{MSY}. The performance of the no-age data scenario was worse than that of the other scenarios for the other three thresholds (MSST and the two proxies).
    - Performance at detecting whether the resource is below the proxies is superior to detecting whether the resource is below S_{MSY} and MSST for the three age-data scenarios.
    - The distributions for the estimates of the depletion of the stock are wider for the data-poor scenario than for the data-rich scenario.
- The performance of the three models (two age-structured models and a Schaefer surplus production model) was compared for the data-rich scenario. The results for the data-moderate and data-poor scenarios were qualitatively identical.
    - The Schaefer model assesses the stock to be below S_{MSY} much more frequently than the two age-structured models, resulting in less frequent underprotection errors and more frequent over-protection errors.
    - The Schaefer production model estimates the resource to be below the two proxies more frequently than the two age-structured models, but the effect is much smaller than for S_{MSY} and MSST.
- Analyses were conducted in which: (a) the values of MSYR (the ratio of MSY to B_{MSY}) and MSYL (the ratio of exploitable biomass at MSY to the average exploitable biomass in an unfished state) were varied, (b) the extent of variation in recruitment was changed, (c) the catch history was changed and (d) the age-at-maturity and the age-at-50%-recruitment were changed in the operating model.
    - The impact of different values for recruitment variability is case-specific with much larger impacts for the data-rich scenario compared to the data-poor scenario.
    - Changing MSYL, the age-at-maturity and the age-at-50%-recruitment have almost no impact on the ability to correctly detect whether a resource is above or below any of the thresholds.

- The frequency with which the resource is found to be below all four thresholds gets lower when the resource is less productive, but the size of the effect is small.
- The results are insensitive to the catch series, although the frequency of determining the resource to be below S_{MSY} is higher for a stable catch history (compared to an increasing catch history or an increase followed by a decline).

A.4.10.2 Berkson, J. and Thorson, J. 2014. The determination of data-poor catch limits in the United States: is there a better way. ICES Journal of Marine Science. Doi: 10.1093/icesjms/fsu085.

Abstract: Methods for determining appropriate management actions for data-poor stocks, including annual catch limits (ACLs), have seen an explosion of research interest in the past decade. We perform an inventory of methods for determining ACLs for stocks in the United States, and find that ACLs are assigned to 371 stocks and/or stock complexes with 193 (52%) determined using methods involving catch data only. The proportion of ACLs involving these methods varies widely among fisheries management regions, with all the 67 ACLs in the Caribbean determined using recent catch when compared with 1 of 33 ACLs in the New England region (US Northeast). Given this prevalence of data-poor ACLs, we recommend additional research regarding the potential effectiveness of simple management procedures for data-poor stocks that are currently managed using ACLs. In particular, simple management procedures may allow a broader range of data types and management instruments that better suit the particulars of individual regions and stocks.

Summary:

A review of existing Annual Catch Limits showed that there were 371 ACLs for management (some covering multiple species), of which 193 were based on catch only methods. The authors consider that catch only methods are incompatible with an MSY approach unless additional data are included (catch composition or an index of abundance), an alternative would be to base targets on achieving high average yield and/or low risk of depletion.

An alternative to a full assessment is to use a simple management plans (Butterworth, 1997; Rademeyer *et al*., 2007) based on an indicator (such as average length), although this still needs an operating model to estimate suitable action points. As with catch only assessments, these would not be compatible with an MSY approach, but could be part of a risk based approach. The reason that simple management plans may be more suitable than assessments for some stocks is that they can use a wider variety of data than is used in traditional stock assessments.

Methods:

- Scaling past catches, e.g. 75% of previous catches over past decade, depending on judgement of stock state.
- DCAC (MacCall, 2009)
- DB-SRA (Dick and MacCall, 2011)
- Taking biological parameters from other stocks

Caveats:

- To calibrate a model-free management plan, it is necessary to create some model of the stock to test the plan, so assumptions about the stock and fishery still need to be made.

A.4.10.3 Cope *et al*. 2011. An approach to defining stock complexes for US West Coast groundfishes using vulnerabilities and ecological distributions. North American Journal of Fisheries Management 31: 589–604.

Abstract: The Magnuson–Stevens Fishery Conservation and Management Act (MSA) requires active management of all stocks at risk of overfishing or otherwise in need of conservation and management. In the Pacific Fishery Management Council groundfish fishery management plan, about two-thirds of the more than 90 managed stocks are currently without traditional assessments to help define stock status in relation to management targets. Stock complexes are often employed for management purposes in such situations. The guidelines issued in response to the 2006 MSA amendments defined a complex as a group of stocks with similar geographic distributions, life histories, and vulnerabilities to fisheries. This work uses productivity–susceptibility analysis (PSA) to measure the vulnerabilities of 90 managed groundfish stocks, 64 of which are currently managed within stock complexes. These stock complexes are re-evaluated by first using a partitioning cluster analysis to group the stocks by depth and latitude. Vulnerability reference points are then established based on the PSA results to determine vulnerability groups of low, medium, high, and major concern within each ecological group. This method is a simple and flexible approach to incorporating vulnerability measures into stock complex designations while providing information with which to prioritize stock and complex-specific management.

Approach:

Productivity-susceptibility analysis (PSA) is a semi-quantitative risk assessment model that has proven fruitful in evaluating the vulnerability of finfish and shellfish stocks to fishing activities in data limited situations (Cortés *et al*., 2010; Arrizabalaga *et al*., 2011; Devine *et al*., 2012). PSA was originally developed to examine bycatch sustainability in the Australian Northern prawn trawl fishery (Milton, 2001; Stobutzki *et al*., 2001), and has been recommended as an effective tool to provide information on the ecological risks of fishing for the purposes of ecosystem-based fishery management (Hobday *et al*., 2011). Since its initial development, PSA has generated a history of application as a flexible risk assessment technique in many fisheries throughout the world (Griffiths *et al*., 2006; Cope *et al*., 2011; Ormseth and Spencer, 2011). The PSA approach has been modified and applied to fish stocks in the United States (Patrick *et al*., 2010), bycatch species in Atlantic tuna fisheries (Arrizabalaga *et al*., 2011) and grenadier stocks in the deep-seas (Devine *et al*., 2012). Understanding the vulnerability of data limited stocks to fishing activities is essential to devise effective management strategies that ensure sustainable exploitation when traditional stock assessments are lacking.

PSA has been used to re-evaluate the validity of groundfish stock complexes on the west coast of North America (Cope *et al*., 2011). In this study, PSA was applied to 90 groundfish stocks listed in the Pacific fishery management council's fisheries management plan to evaluate stock vulnerability to fishing activities and refine stock complexes. The authors followed the PSA approach outlined by Patrick *et al*. (2009; 2010); except that the first susceptibility attribute ("management strategy) was modified to better reflect the specific qualities of west coast groundfish management in North America. Vulnerability scores were firstly used to indicate whether a stock is "in the fishery" (stocks that would be overfished in the absence of conservation measures), an "ecosystem component stock" (non-target and non-retained stocks not likely to become overfished in the absence of management) or should be removed from the fisheries management plan. Vulnerability reference points were then defined to group stocks by vulnerability scores. Existing stock complexes were reclassified based on vulnerability groupings and information on ecological distributions. The reclassified stock complexes were compared to former complexes and subsequent advice on interpreting and applying vulnerability scores for the purpose of defining stock complexes was provided.

An iterative approach was used to assign productivity and susceptibility scores for each attribute of the stocks considered. Each of the authors was provided with a set of unique stocks to score. All scorers were encouraged to score every productivity and susceptibility attribute that was scoreable and record the data quality to reflect their confidence in that score. Once attribute scoring was completed for all stocks, the scores were retrospectively evaluated by the entire scoring team to (1) ensure that a consistent scoring approach was applied, (2) rectify any perceived discrepancies, and (3) identify stocks with poor data quality scores for further consideration. The productivity and susceptibility scores were then further reviewed and updated by relevant experts before being finalised by the scoring team. All scoring was completed using the Productivity-Susceptibility Analysis (version 1.4) module of the NOAA Fisheries Toolbox (http://nft.nefsc.noaa.gov/PSA.html).

Vulnerability scores were then applied to identify stocks "in the fishery" and define "ecosystem component stocks". Stocks were considered an "ecosystem component stock" if (1) an appreciable proportion of the population inhabits the management area, (2) they have low vulnerability scores, and (3) they are neither targeted nor retained in a fishery.

Stock complexes were re-evaluated using multivariate partitioning cluster analysis in the R statistical environment. A stepwise approach to clustering stocks was used based on (1) ecological distribution (e.g. depth and latitude), (2) grouping within ecological distribution clusters based on vulnerability scores, and (3) the final groups were evaluated based on fishery interactions (i.e. separating groups further by associations in particular fisheries). For each cluster analysis, a k-medoids partitioning analysis based on Euclidean distance was used. The number of clusters best supported by the data were identified using silhouette and Hubert's gamma cluster validity diagnostics. In instances where stocks co-occurred within the same depth range, the following grouping approach was used: firstly all stocks were clustered by depth, then latitude, and finally grouped by vulnerability reference points.

Vulnerability (V) reference points were defined as follows: V = ≥ 2.2 indicated stocks of major concern; V = 2.0–2.2 indicated stocks of high concern; V = 1.8–2.0 indicated stocks of medium concern; and V = <1.8 indicated stocks of low concern.

Data/Information requirements:

Productivity (*p*) and susceptibility (*s*) indices are constructed for individual stocks by ranking a series of attributes that can be weighted according to their relative importance to the fishery. Productivity is determined by life-history attributes such as longevity, growth rate, fecundity, recruitment and natural mortality. In contrast, susceptibility to fishing activities is estimated from fishery attributes such as stock distribution, catchability, selectivity and post-capture mortality. Both the selection and scoring of attributes is based on published information where possible and the guidance of expert opinion. Attribute scores range from 1 (low), 2 (medium) or 3 (high). As a precaution, missing attributes are scored as a 3 (high risk) by default. Stock vulnerability to fishing activities is explored by displaying the mean weight of the productivity and susceptibility scores onto an x-y scatterplot. Stocks with low productivity scores and high susceptibility scores are considered the most vulnerable to fishing activities, while stocks with high productivity scores and low susceptibility scores are considered the least vulnerable. Vulnerability scores (v) are estimated by calculating the Euclidean distance from the origin of the plot to the datum point using Pythagoras' theorem. A data-quality index constructed from the weighted average of the productivity and susceptibility scores estimates the degree of uncertainty underlying the vulnerability scores.

Cope *et al*. (2011) used ten productivity and twelve susceptibility attributes scored on a three point scale (low, medium and high), with each attribute assigned a weighting value (default of two) relative to its perceived contribution to the overall productivity or susceptibility score. Information sources used to inform attribute scoring included stock assessments, peer-reviewed literature, the Pacific Shark Research Centre elasmobranch life-history matrix and FishBase.

Productivity attributes for each stock included:

- Intrinsic population growth rate (r)
- Maximum age
- Maximum size
- von Bertalanffy growth coefficient (k)
- Natural mortality (M)
- Fecundity
- Breeding strategy
- Recruitment pattern
- Age-at-maturity
- Mean trophic level

Susceptibility attributes for each stock included:

- Management strategy
- Areal overlap with the fishery
- Geographic concentration
- Vertical overlap with the fishery
- Fishing mortality (F)/Natural mortality (M)
- Relative spawning biomass (current biomass/B_0 or maximum biomass estimate from the time-series)
- Seasonal migrations
- Schooling, aggregation and other behavioural responses
- Morphology affecting capture
- Survival after capture and release
- Desirability
- Fishery impact on essential fish habitat (EFH) or habitat in general for non-target species

The level of confidence associated with each productivity and susceptibility score was obtained by scoring data quality on a five point scale, with lower scores reflecting increased confidence. Stocks with low data quality scores were flagged as either needing revised scoring or indicating that information is generally lacking. Three species groups were considered to coordinate attribute weighting for productivity attributes (“elasmobranchs”, “flatfish” and “rockfishes and other fishes”), and two susceptibility attributes were used to coordinate attribute weighting for susceptibility attributes (“assessment” and “no assessment”).

Assumptions:

The PSA adopts a precautionary approach to data-limited situations by giving stocks with missing data for particular attributes a high vulnerability (risk) score, thereby decreasing the possibility of generating false negative results (i.e. stock vulnerability to fishing is lower than in reality) and increasing the probability of generating false positive results (i.e. stock vulnerability to fishing is higher than in reality), which can be screened out as additional information becomes available to update the attribute scores. In instances where stock-specific information is lacking, a score can be applied to a particular attribute based on information from a surrogate species or stock with similar life-history characteristics (e.g. congeners or species of the same family). Caution is warranted, however, when assigning attributes across species groups or entire genera with differing life-history characteristics (Cotter and Lart, 2011).

Outputs expected:

PSA estimates the productivity of a stock and its susceptibility to fishing activities to provide a vulnerability score indicating the degree of ecological risk associated with current levels of fishing pressure.

The PSA approach adopted by Cope *et al*. (2011) generated the following outputs for each stock:

- Productivity and susceptibility scores
- Vulnerability scores and vulnerability reference points
- Data quality scores

Method of operation:

The PSA does not directly assess the sustainability of a fishery, but instead provides a conceptual tool to highlight vulnerable stocks, establish appropriate management strategies and direct future research efforts. This approach hierarchically rank stocks based on their relative vulnerability to fishing activities.

Cope *et al*. (2011) used PSA for four purposes:

- Re-evaluating the validity of stock complexes in a stepwise manner based on depth, latitude, vulnerability to fishing activities and shared fishery interactions
- Clarifying stocks as either “in the fishery” or “ecosystem component stocks”, and therefore identifying stocks for which annual catch limits and accountability measures are required
- Quantifying stock vulnerability to fishing activities and deriving vulnerability reference points
- Prioritising data collection activities using data quality scores to highlight stocks in need of basic biological or fisheries data

Testing:

Cope *et al*. (2011) compared stock vulnerability scores from the PSA to the results of Dick and MacCall (2010) who estimated the probability of overfishing occurring among several data-limited stocks using depletion-based stock reduction analysis (DB-SRA). Stocks with a vulnerability score over 2.2 demonstrated ~50% chance of current catch exceeding the DB-SRA based estimate of the overfishing limit. A comparison of stock vulnerability scores from the PSA with the DB-SRA output provided guidance on the derivation of vulnerability reference points.

Cope *et al*. (2011) found that the life histories of many rockfishes and elasmobranchs increased the probability of overfishing, corroborating with the findings of Dick and MacCall (2010). Findings from these two studies were relatively consistent, with many of the stocks identified as having the highest vulnerability to fishing activities in the PSA were also identified as the most likely to have undergone overfishing from recent catch levels in the DB-SRA.

Caveats:

A limitation of PSA is that it estimates relative rather than absolute levels of vulnerability (Hobday *et al*., 2011). The vulnerability scores are fishery-specific, and therefore ignore the cumulative effects of interactions with other fisheries and environmental disturbance. Interactions between the stock complex and the fishery under investigation will determine the scale of relative vulnerability in the PSA. More importantly, the relevance of the vulnerability scores depends on how appropriately the productivity and susceptibility attributes reflect the resilience of the stock and the operational characteristics of the fishery. Attributes can be tailored according to data availability and the current state of knowledge. Caution should be exercised, however, when devising appropriate susceptibility attributes to ensure that they are pertinent to the stock and fishery under investigation (Devine *et al*., 2012). In some instances, susceptibility attributes may need to be modified to better reflect interactions between the stock and the fishery by including additional characteristics such as the degree of commercialisation (e.g. targeted or bycatch species), the current management strategy and the extent of monitoring activities (McCully *et al*., 2013).

An issue regarding PSA is that difficulties can arise when assigning weightings to attributes in data limited situations. A complete understanding of the relevance of an attribute for estimating the productivity and susceptibility of data limited stocks is often lacking (Patrick *et al*., 2010). Consequently, the influence of an attribute on the productivity and susceptibility of a stock can be inadvertently underestimated or overestimated in the PSA. Most studies using PSA attempt to overcome this uncertainty by assigning close to equal weightings for attributes in data limited situations.

Another potential issue underlying PSA is that K-selected species with low fecundity (e.g. elasmobranchs) could receive a higher vulnerability score than r-selected species with high fecundity (e.g. Atlantic herring, ***Clupea harengus***). K-selected species produce relatively few offspring providing low population resilience to fishing mortality compared to r-selected species that broadcast spawn a large number of planktonic eggs with the potential to provide greater population resilience to fishing mortality. However, both rates of natural mortality for early life-history stages and the number of individuals recruiting to the fishery may be vastly different between r- and k-selected species, effectively cancelling out the seeming imbalances in stock vulnerability. In some instances, PSA may overstate the vulnerability of low fecundity, K-selected species to fishing activities and thereby exaggerate the position of the stock in vulnerability hierarchy.

Cope *et al*. (2011) stressed that PSA is not a substitute for stock assessment, but can be used as a flexible risk assessment technique to focus research and management efforts. Maintaining consistency in attribute scoring was challenging when multiple individuals scored attributes independently. A quality assurance process was, therefore, adopted where attribute scores were retrospectively reviewed and refined by the entire scoring team to overcome any potential scoring inconsistencies. Scoring susceptibility attributes proved the most difficult, especially attributes addressing the aerial and spatial overlap with the fishery, as well as the geographic concentration of the stock. Data quality scores were used to highlight attributes that required rescoring and further consideration. The authors noted that scoring should be updated on regular basis to reflect changes in susceptibility or increased knowledge of productivity attributes.

Another issue with the PSA approach adopted by Cope *et al*. (2011) was that a trade-off existed when determining the appropriate resolution for stock complexes. Including too much information in the stock groupings resulted in the formation of too many stock complexes, while including insufficient information in the stock groupings resulted in the formation of too few stock complexes to maintain management flexibility and applicability. Grouping stocks in stepwise manner (e.g. depth, latitude and then vulnerability scores) and presenting the final stock complexes with each level of detail explicit overcame this resolution issue by allowing managers to assemble complexes in a manner most useful to their needs. Attribute scores and groupings can be tailored to suit the specific resolution required by fisheries management.

Frameworks:

- In Europe, ICES recommends that PSA be applied to stocks in Data Categories 5 (data-limited stocks; only landings data available) and 6 (negligible landings and minor bycatch stocks)
- In Australia, PSA has been traditionally applied to stocks within data-poor tiers 6 and 7 in the harvest strategy framework. Below these data-poor tiers, PSA has been included as a semi-quantitative approach for Level 2 analysis of data-limited stocks within the ecological risk assessment for the effects of fishing framework (Hobday *et al.*, 2011)
- In the USA, PSA can be applied to stocks within data-poor tiers 5 and 6 of the regional fisheries management council's fisheries management plan

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Table A.4.1. Summary of the methods, data requirements, main assumptions and caveats.

	Acronym	Full name	Reference	Data	Other inputs	Assumptions	Outputs	Method testing	Caveats	Additional Simulation testing	Some findings from additional testing
Catch-only methods with supplementary life-history information											
1	DCAC	Depletion-Corrected Average Catch	MacCall (2009)	Catch	Priors for relative depletion, M, Fmsy/M	Bmsy/B0=0.4 Fmsy/M<1	Sustainable Yield + confidence intervals	Applied to 2 data-rich stocks for cross-comparison	Once-off calculation (not annual) Not suitable for rebuilding Don't use if M>0.2	Wetzel and Punt (2011), testing DCAC, DB-SRA & SSS Arnold and Heppell (2014), testing DCAC & DB-SRA	Robust to misspecification of distributions for M & Fmsy/M Highly sensitive to assumed distribution of relative depletion
2	DB-SRA	Depletion-Based Stock Reduction Analysis	Dick and MacCall (2011)	Catch (full)	Priors for relative depletion (recent year), M, Fmsy/M, Bmsy/B0 Age at maturity	Uses delay-difference production model, with a hybrid Schaefer & Pella-Tomlinson-Fletcher to achieve good approximation of Beverton–Holt stock–recruit model	Probability distributions for estimated biomass, MSY, Bmsy, Cfmsy	Applied to 31 data-rich stocks for cross comparison	Works well for near-monotonic declines in abundance Not suitable for stocks close to unfished biomass in recent years Early catch history may be less reliable	Wetzel and Punt (2011), testing DCAC, DB-SRA & SSS Arnold and Heppell (2014), testing DCAC & DB-SRA	Robust to misspecification of distributions for M & Fmsy/M Highly sensitive to assumed distribution of (recent) relative depletion

	Acronym	Full name	Reference	Data	Other inputs	Assumptions	Outputs	Method testing	Caveats	Additional Simulation testing	Some findings from additional testing
3	Catch-MSY	Catch-MSY	Martell and Froese (2013)	Catch	Priors for r, K Range of possible initial and current depletion levels Process error standard deviation	Stationary Schaeffer stock production Process errors are iid lognormal	Probability distributions for MSY	Comparison with 146 MSY estimates from fully assessed stocks	Do not use for lightly exploited stocks. Won't work well for continuously increasing catch (developing fisheries). Overestimates K, underestimates r & Fmsy. Sensitive to lower prior on r.	Rosenberg *et al*. (2014), testing mPRM, Catch-MSY, COMSIR & SSCOM - using Proportional Error (PE), Mean PE (MPE), Absolute Proportional Error (APE), Mean APE (MAPE)	Overall best performance of the four methods: smallest MPE and MAPE

	Acronym	Full name	Reference	Data	Other inputs	Assumptions	Outputs	Method testing	Caveats	Additional Simulation testing	Some findings from additional testing
4	COMSIR	Catch-Only Model - Sampling Importance Resampling	Vasconcellos and Cochrane (2005)	Catch (full)	Process error variability = 0.4 Priors for intrinsic growth rate r, carrying capacity K, bioeconomic equilibrium as a proportion of K, and increase of harvest rate over time	Rate of increase in catches first positive (development), then zero (mature), then negative (senescence), and catches contain information on both fishing effort and stock biomass Start at pre-exploitation levels Harvest dynamic respond only to economic/market stimulus Observed catches lognormal	Stock status Production Exploitation rates	Method tested using data from two previously assessed fisheries (yellowfin tuna and Namibian hake)	Performance sensitive to assumptions about effort dynamics and information contents of catch data (e.g. more information about stock status from "senescent" fisheries)	Rosenberg et al. (2014), testing mPRM, Catch-MSY, COMSIR & SSCOM - using Proportional Error (PE), Mean PE (MPE), Absolute Proportional Error (APE), Mean APE (MAPE)	Neither best nor worst of the four methods

	Acronym	Full name	Reference	Data	Other inputs	Assumptions	Outputs	Method testing	Caveats	Additional Simulation testing	Some findings from additional testing
5	SSCOM	State-Space Catch-Only Model	Thorson et al. (2013)	Catch	Priors for: average unfished biomass B0, initial effort, parameters of effort-dynamics model, magnitude of process errors	F follows predictable dynamics over time, process errors have equal magnitude, Bmsy is half B0, initial biomass=B0	Estimates of stock status and productivity	Simulation testing for sensitivity to magnitude of errors and reliance on priors for final depletion. Method applied to eight US West Coast groundfish stocks that were subject to management changes.	Highly dependent on good contrast in catch data (must reach peak & decline) Poor performance when model assumptions (Shaeffer & effort-dynamics) violated Many species show little predictive relationship between past and future changes in fishing effort	Rosenberg et al. (2014), testing mPRM, Catch-MSY, COMSIR & SSCOM - using Proportional Error (PE), Mean PE (MPE), Absolute Proportional Error (APE), Mean APE (MAPE)	Overall performance weakest of four methods tested: largest MPE and MAPE
6	SSS	Simple Stock Synthesis	Cope (2012)	Catch	Priors for depletion, M and steepness growth parameters weight-length relationship	growth parameters assumed known 2cm length bins used	Probability distributions for OFL	Tested on 45 assessments and compared to DB-SRA	MCMC needs further investigation as posterior on depletion influenced by prior on R0	Wetzel and Punt (2011), testing DCAC, DB-SRA & SSS	Estimated harvest levels increased when M set too high
Catch-only methods with supplementary data (e.g. length) and life-history information											

	Acronym	Full name	Reference	Data	Other inputs	Assumptions	Outputs	Method testing	Caveats	Additional Simulation testing	Some findings from additional testing
7	CC-SRA	Catch-Curve Stock Reduction Analysis	Thorson and Cope (in press, Fisheries Research Special Issue)	Catch (full) Recent compositional data	Priors for life-history parameters	Logistic fishing selection Combines SRA and catch-curve analysis Recruitment variability assumed known	Fishing mortality and stock status	CC-SRA vs. catch curves & SRA Sardine-like fast & opportunistic Red snapper-like slow & periodic 3 levels of recruitment variability	Model performs will degrade under: non-asymptotic fishery selection age-specific M misspecification of life-history priors	None	
Life-history and size-based methods											
8	Brooks method	SPR-based method	Brooks et al. (2010)	Method requires additional data for estimating stock status	Life-history parameters Current depletion: additional information, such as scaled index of abundance Current exploitation: additional information on mean length or from short-term tagging studies	Stock–recruit relationship follows Beverton–Holt or Ricker All ages beyond recruitment are fully selected by the fishery	SPR as a function of F, allowing for F reference point proxies Depletion at MER: SPR_{MER}/S_0 With additional information, stock status (depletion and exploitation)	Simulation study to compare SPR_{MER} with SPR_{MSY}. Compare results to those for multiple stock assessment methodologies applied to Dusky sharks.	Using SPR_{MER} instead of SPR_{MSY} biases reference points low. Best science for maturity, fecundity and survival, taken individually, can lead to implausible values for steepness. Bias in life-history parameters can affect SPR.	None	

	Acronym	Full name	Reference	Data	Other inputs	Assumptions	Outputs	Method testing	Caveats	Additional Simulation testing	Some findings from additional testing
9	LB-SPR	Length-Based Spawning Potential Ratio	Hordyck et al. (2014a)	Observed length composition of catch	Life-history ratios M/k and L_m/L_∞, and knife-edge selection L_c/L_∞, $CV(L_\infty)$	Equilibrium-based model. Relationships between life-history ratios and YPR/SPR reference points. Selectivity is either flat or knife-edge. Observed length does not differ from expected length due to variability in recruitment or mortality, and is representative of the population.	Estimation of F/M and SPR	See Hordyck *et al*. (2014b)	Gives biased results of F/M and SPR if length data from dome (instead of asymptotic) selection.	Hordyck *et al*. (2014b), using an age-structured operating model with constant selectivity	Very sensitive to mis-specification of L_∞ and M/k (less for latter) SPR insensitive to mis-specification in $CV(L_\infty)$ Errors in F/M and SPR follow similar patterns. Large variability in recruitment leads to poor estimates of F/M, but lower errors in estimating SPR

	Acronym	Full name	Reference	Data	Other inputs	Assumptions	Outputs	Method testing	Caveats	Additional Simulation testing	Some findings from additional testing
10	Kokkalis method	Catch-at-size-based life-history method	Kokkalis *et al*. (in press, Fisheries Research Special Issue)	Catches of fish (numbers) as a function of size (weight) for one year at least (fishery or survey).	Case-specific life-history parameters characterising growth, mortality and recruitment, if available (otherwise use "Robin Hood" approach	Model follows size-based theory of exploited fish stocks. A species-independent set of life-history parameters and assymptotic size W_∞ define a stock. Assumes steady-state, with Beverton–Holt stock–recruit, von Bertalanffy growth, size-dependent M and sigmoid selection.	Distribution of F/Fmsy for each year of catch-at-size data, with sensitivity intervals derived by scanning over a range of plausible physiological mortality values.	Tested on 100 artificial stocks with 20 catch-at-size datasets for varying Fs and 3 assymptotic sizes. Estimation repeated for a range of "knowledge", where none to all life-history paramters were known. Method correctly classified exploitation status better than random classification. Physiological mortality was most important life-history parameter.	For testing, same model used for simulation and estimation; however, subsequet to paper, method was compared to data-rich stock assessments and compared well. Misspecification of selection and inaccuracies in W_∞ can have severe consequences for estimating F and Fmsy. W_∞ difficult to estimate when largest individuals not selected	Not formally publised (but see caveats)	
Graphical/empirical and alternative approaches											

	Acronym	Full name	Reference	Data	Other inputs	Assumptions	Outputs	Method testing	Caveats	Additional Simulation testing	Some findings from additional testing
11	SSP-1	Stock-status Plots Version 1	Froese and Kesner-Reyes (2002)	Catch time-series	Classification of stock status by fishery development stage	Catches are representative of changes in abundance Using catches, stock status can be ascribed to 5 stages: undeveloped, developing, fully exploited, overfished and collapsed/closed	Stock status plot showing percentage of stocks by status over time	No testing described	Percentage of undeveloped or devloped stocks is zero in the final year, by construct	Caruthers *et al*. (2012)	Correct classification of stock status 34% of the time, and on average provided overly pessimistic conclusions on stock status. Method was more negatively biased on average than stock assessment approaches

	Acronym	Full name	Reference	Data	Other inputs	Assumptions	Outputs	Method testing	Caveats	Additional Simulation testing	Some findings from additional testing
12	SSP-2	Stock-status Plots Version 2	Kleisner and Pauly (2011)	Catch time-series	Classification of stock status by fishery development stage	As for SSP-1, but "undeveloped" and "devloping" stages combined, stocks with a peak in catch in the final year classified as "developing", and additional "recovery" category added.	Stock status plot showing % of stocks by status over time. Stock-catch status plot showing % catch by stock-status over time.	No testing described, but applied to Norwegian EZZ as an example.	Interpretation of stock-catch status plots can be problematic as they are based on catch and not population size estimates.	Caruthers *et al*. (2012)	Correct classification of stock status 31% of the time, and on average provided overly pessimistic conclusions on stock status. Method was more negatively biased on average than stock assessment approaches

	Acronym	Full name	Reference	Data	Other inputs	Assumptions	Outputs	Method testing	Caveats	Additional Simulation testing	Some findings from additional testing
13	mPRM	modified Panel Regression Method	Costello *et al*. (2012)	Catch time-series	Broad life-history and fishing history information	Population status is a function of life-history traits and harvest history. The manner in which variables collectivley affect population status is consistent across species with similar characteristics.	Estimate of B/Bmsy with 95% confidence intervals, derived without specifying a structural model between population variables and stock status. Provides method for estimating the status of collections of previously unassessed stocks.	Consider 1793 distinct unassessed fisheries (finfish only and aggregating across countries for highly mobile species). Use of 5 approaches to validate model predictions, which generally supported the value of mPRM as a tool.	Not suitable for formal assessments as it does not produce precise estimates for individual fisheries. Use of the FAO landings database has strong associated caveats.	Rosenberg *et al*. (2014), testing mPRM, Catch-MSY, COMSIR & SSCOM - using Proportional Error (PE), Mean PE (MPE), Absolute Proportional Error (APE), Mean APE (MAPE)	Performed best of 4 methods in the presence of autocorrelation, and for long time-series and rollecoaster harvest dynamics

	ACRONYM	FULL NAME	REFERENCE	DATA	OTHER INPUTS	ASSUMPTIONS	OUTPUTS	METHOD TESTING	CAVEATS	ADDITIONAL SIMULATION TESTING	SOME FINDINGS FROM ADDITIONAL TESTING
14	SBI	Size-based indicators	Karnauskas *et al*. (2011)	Limited fishery-independent data: number of fish; minimum, maximum and average size of fish No fishery-dependent data	Optional information used to define sub-communities (e.g. observation of fishing activity)	Size-distributions of fish species follow Poisson (mean=ave size, min/max used for truncation) Observed numbers of individuals in each length bin for fish communities follow multinomial	Size-based indicators: time serie of mean length and densitiy for individual species, and density for fish communities; slope of size spectrum and L_{max} spectra for fish communities	No testing described, but method was applied to Haitian fishery using a reef fish visual census dataset	Trends at species level detected only when occurrence high Calculate slope of size spectrum only for size classes well-selected by sampling Community-level indicators may better detect fishing impacts in data limited situations	None	

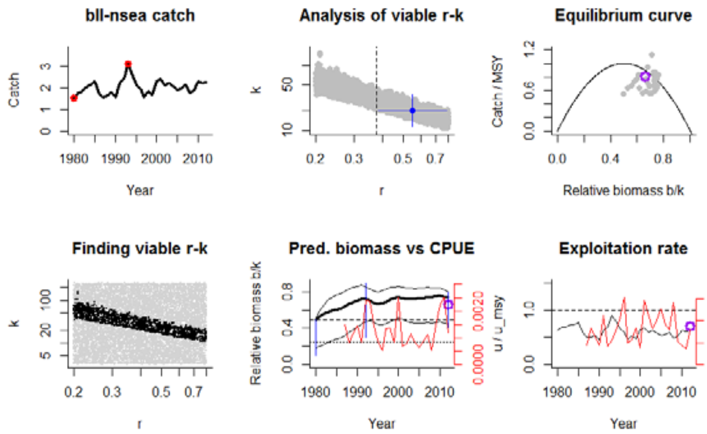
	Acronym	Full name	Reference	Data	Other inputs	Assumptions	Outputs	Method testing	Caveats	Additional Simulation testing	Some findings from additional testing
15	QCM	Quality Control Method	Scandol (2005)	Standardised empirical stock status indicator	Specification of decision interval outside which signal is raised	Assumptions underlying statistical quality control theory	QC chart that signals uncharacteristic processes	Operating model generated observations transformed into 9 stock status indicators as a basis for testing the ability of QC algorithms to detect signals in these indicators. Those using average age and length performed well.	Quality Control algorithms are simple and numerically stable but cannot provide the same insight into a fishery that a dynamic model can	None	

Annex 5: CMSY

A.5.1 Results of applying CMSY to seventeen stocks in the ICES area

Species: *Scophthalmus rhombus*

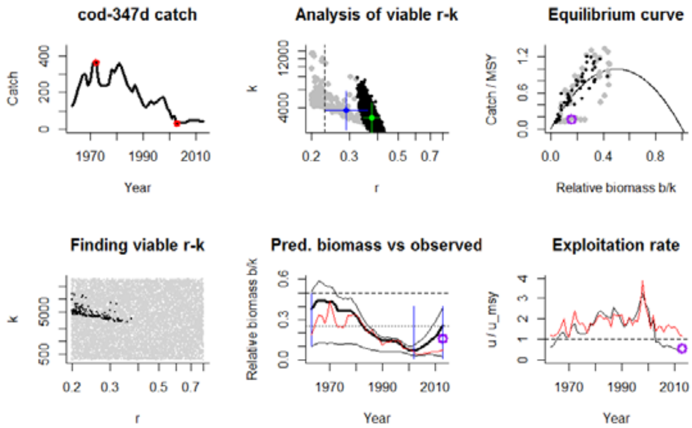
Name: Brill
Region: Brill in Subarea IV, Divisions IIIa and VIId,e
Stock: **bll-nsea**
Catch data used from years 1980–2012, biomass = cpue
Prior initial relative biomass = 0.1–0.5
Prior intermediate rel. biomass= 0.3–0.9 in year 1992
Prior final relative biomass = 0.4–0.8
Future crash with current catches? No
Prior range for r = 0.2–0.8, prior range for k = 3.14–251



Results of CMSY analysis with altogether 1648 unique viable r-k pairs
845 r-k pairs above the initial geometric mean of r = 0.379 were analysed
r = 0.549, 95% CL = 0.384–0.784
k = 20.2, 95% CL = 11.6–35.2
MSY = 2.78, 95% CL = 1.88–4.09
Predicted biomass last year = 0.744 2.5th perc = 0.448 97.5th perc = 0.799
Predicted biomass next year = 0.742 2.5th perc = 0.439 97.5th perc = 0.818

Species: *Gadus morhua*

Name: Atlantic cod
Region: Cod in Subarea IV, Division VIId & Division IIIa (Skagerrak)
Stock: **cod-347d**
Catch data used from years 1963–2013, biomass = observed
Prior initial relative biomass = 0.1–0.5
Prior intermediate rel. biomass= 0.01–0.4 in year 2002
Prior final relative biomass = 0.01–0.4
Future crash with current catches? Possible
Prior range for r = 0.2–0.8, prior range for k = 367–29 327

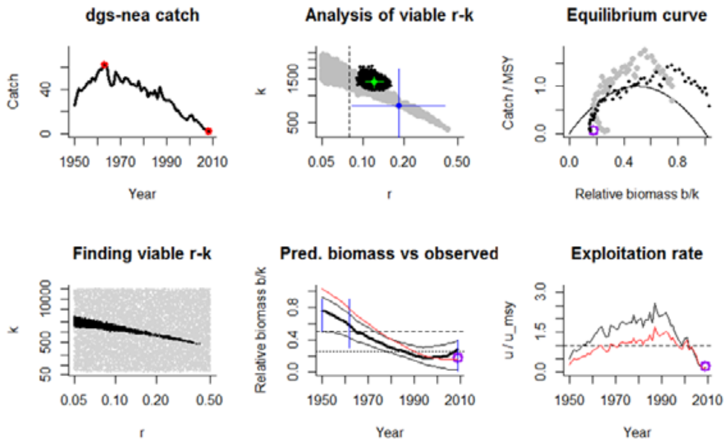


Results from Bayesian Schaefer model using catch & biomass
r = 0.377, 95% CL = 0.348–0.41
k = 3219, 95% CL = 2312–4483
MSY = 304, 95% CL = 231–400
Mean catch / MSY = 0.589
Results of CMSY analysis with altogether 147 unique viable r-k pairs
71 r-k pairs above the initial geometric mean of r = 0.23 were analysed
r = 0.289, 95% CL = 0.233–0.363
k = 3797, 95% CL = 2459–5815
MSY = 275, 95% CL = 183–413
Predicted biomass last year = 0.258 2.5th perc = 0.0248 97.5th perc = 0.39

Predicted biomass next year = 0.296 2.5th perc = 0.0217 97.5th perc = 0.442

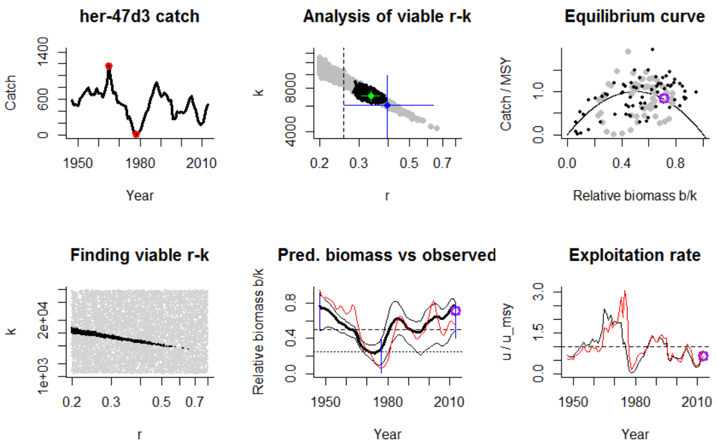
Species: *Squalus acanthias*

Name: Spurdog
Region: Spurdog in Northeast Atlantic
Stock: **dgs-nea**
Catch data used from years 1950–2009, biomass = observed
Prior initial relative biomass = 0.5–0.9
Prior intermediate rel. biomass= 0.3–0.9 in year 1962
Prior final relative biomass = 0.01–0.4
Future crash with current catches? Possible
Prior range for r = 0.05–0.5, prior range for k = 62.3–19 932



Results from Bayesian Schaefer model using catch & biomass
r = 0.122, 95% CL = 0.104–0.142
k = 1409, 95% CL = 1227–1617
MSY = 42.9, 95% CL = 36–51.2
Mean catch / MSY = 0.802
Results of CMSY analysis with altogether 2369 unique viable r-k pairs
1170 r-k pairs above the initial geometric mean of r = 0.0795 were analysed
r = 0.183, 95% CL = 0.0834–0.4
k = 774, 95% CL = 307–1951
MSY = 35.3, 95% CL = 26.8–46.6
Predicted biomass last year = 0.28 2.5th perc = 0.0316 97.5th perc = 0.395
Predicted biomass next year = 0.301 2.5th perc = 0.0325 97.5th perc = 0.423

Species: *Clupea harengus*
Name: Atlantic herring
Region: Herring in Subarea IV, Divisions VIId & IIIa (autumn-spawners)
Stock: **her-47d3**
Catch data used from years 1947–2013, biomass = observed
Prior initial relative biomass = 0.5–0.9
Prior intermediate rel. biomass= 0.01–0.4 in year 1977
Prior final relative biomass = 0.4–0.8
Future crash with current catches? No
Prior range for r = 0.2–0.8, prior range for k = 1169–93 504

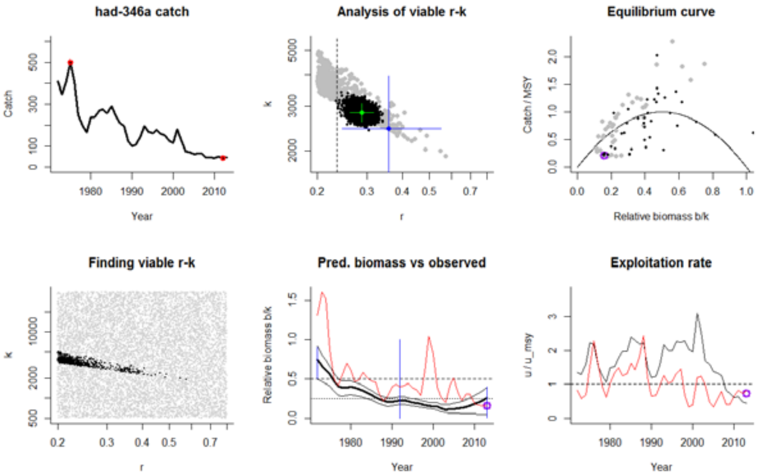


Results from Bayesian Schaefer model using catch & biomass
r = 0.336, 95% CL = 0.307–0.369
k = 7094, 95% CL = 6528–7710
MSY = 596, 95% CL = 547–650
Mean catch / MSY = 0.871
Results of CMSY analysis with altogether 1393 unique viable r-k pairs
566 r-k pairs above the initial geometric mean of r = 0.257 were analysed
r = 0.397, 95% CL = 0.259–0.639
k = 6140, 95% CL = 3648–9828
MSY = 609, 95% CL = 559–662

Predicted biomass last year = 0.765 2.5th perc = 0.487 97.5th perc = 0.799
Predicted biomass next year = 0.751 2.5th perc = 0.494 97.5th perc = 0.801

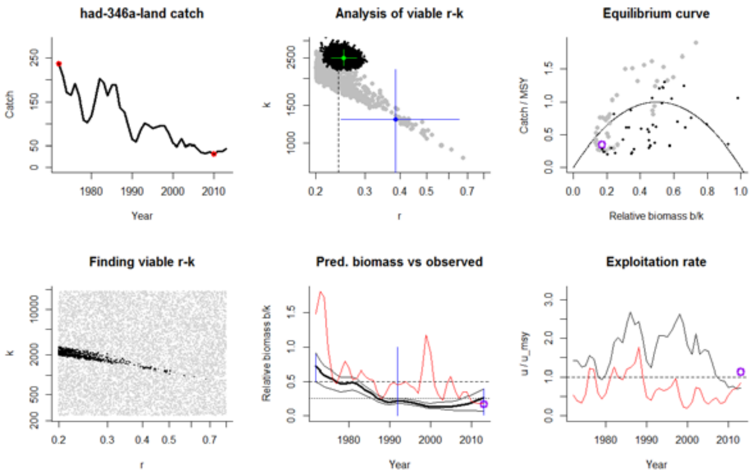
Species: *Melanogrammus aeglefinus*

Name: Haddock
Region: Haddock in the North Sea
Stock: **had-346a**
Catch data used from years 1972–2013, biomass = observed
Prior initial relative biomass = 0.5–0.9
Prior intermediate rel. biomass= 0–1 in year 1992
Prior final relative biomass = 0.01–0.4
Future crash with current catches? No
Prior range for r = 0.2–0.8, prior range for k = 500–39 992



Results from Bayesian Schaefer model using catch & biomass
r = 0.287, 95% CL = 0.26–0.316
k = 2831, 95% CL = 2602–3080
MSY = 203, 95% CL = 182–227
Mean catch / MSY = 0.891
Results of CMSY analysis with altogether 605 unique viable r-k pairs
323 r-k pairs above the initial geometric mean of r = 0.235 were analysed
r = 0.359, 95% CL = 0.245–0.552
k = 2447, 95% CL = 1440–3953
MSY = 219, 95% CL = 180–267
Predicted biomass last year b/k = 0.259 2.5th perc b/k = 0.0486 97.5th perc b/k = 0.393
Precautionary 25th percentile b/k = 0.158

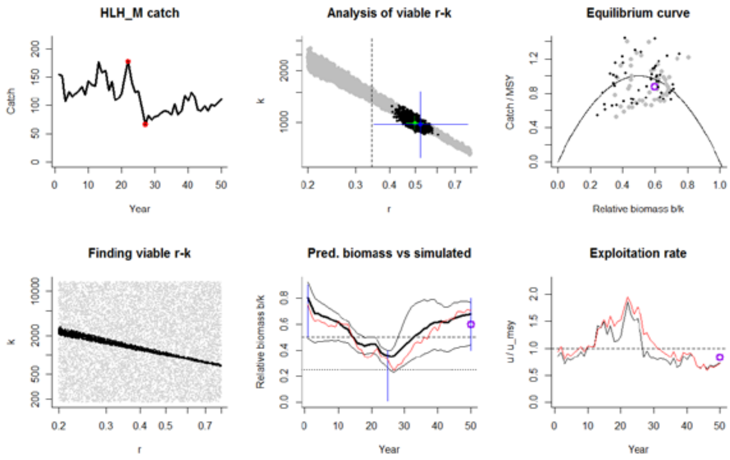
Species: *Melanogrammus aeglefinus*
Name: Haddock
Region: Haddock in the North Sea
Stock: **had-346a-land**
Landings data used from years 1972–2013, biomass = observed
Prior initial relative biomass = 0.5–0.9
Prior intermediate rel. biomass= 0–1 in year 1992
Prior final relative biomass = 0.01–0.4
Future crash with current catches? No
Prior range for r = 0.2–0.8, prior range for k = 237–18 936



Results from Bayesian Schaefer model using catch & biomass
r = 0.252, 95% CL = 0.227–0.28
k = 2498, 95% CL = 2291–2723
MSY = 157, 95% CL = 140–177
Mean catch / MSY = 0.665
Results of CMSY analysis with altogether 591 unique viable r-k pairs
343 r-k pairs above the initial geometric mean of r = 0.241 were analysed
r = 0.387, 95% CL = 0.246–0.655
k = 1294, 95% CL = 702–2211
MSY = 125, 95% CL = 106–148

Predicted biomass last year b/k = 0.265 2.5th perc b/k = 0.0647 97.5th perc b/k = 0.395
Precautionary 25th percentile b/k = 0.168

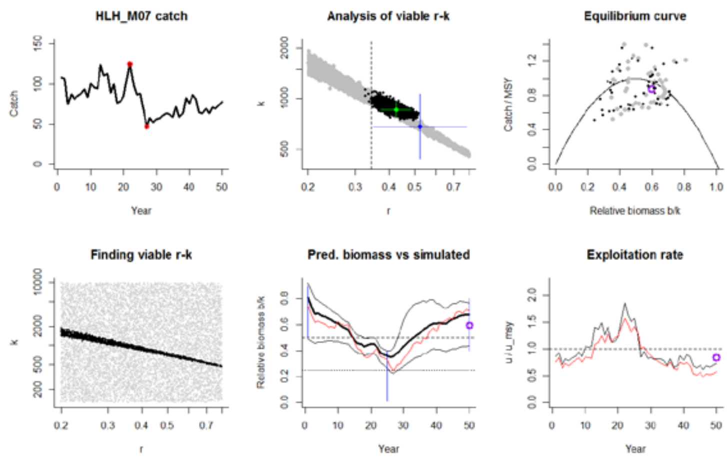
Species: Simulated stock with medium resilience and high-low-high biomass



Name: NA
Region: NA
Stock: **HLH_M**
Catch data used from years 1–50, biomass = simulated
Prior initial relative biomass = 0.5–0.9
Prior intermediate rel. biomass= 0.01–0.4 in year 25
Prior final relative biomass = 0.4–0.8
Future crash with current catches? No
Prior range for r = 0.2–0.8, prior range for k = 178–14 236

Results from Bayesian Schaefer model using catch & biomass
r = 0.497, 95% CL = 0.461–0.537
k = 994, 95% CL = 907–1089
MSY = 124, 95% CL = 115–132
Mean catch / MSY = 0.934
Results of CMSY analysis with altogether 1933 unique viable r-k pairs
1066 r-k pairs above the initial geometric mean of r = 0.344 were analysed
r = 0.522, 95% CL = 0.349–0.782
k = 974, 95% CL = 623–1520
MSY = 127, 95% CL = 117–138
Predicted biomass last year b/k = 0.679 2.5th perc b/k = 0.444 97.5th perc b/k = 0.769
Precautionary 25th percentile b/k = 0.597

Species: Simulated stock with medium resilience and high-low-high biomass



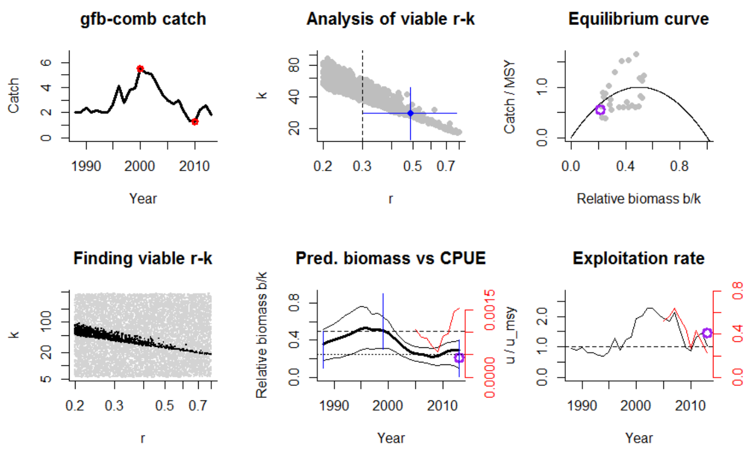
Name: NA
Region: NA
Stock: **HLH_M07**
Landings obtained as catches -30% of HLH_M used from years 1–50, biomass same as HLH_M
Prior initial relative biomass = 0.5–0.9
Prior intermediate rel. biomass= 0.01–0.4 in year 25
Prior final relative biomass = 0.4–0.8
Future crash with current catches? No
Prior range for r = 0.2–0.8, prior range for k = 125–9965

Results from Bayesian Schaefer model using catch & biomass
r = 0.425, 95% CL = 0.373–0.483
k = 863, 95% CL = 783–952
MSY = 91.7, 95% CL = 83.9–100
Mean catch / MSY = 0.881
Results of CMSY analysis with altogether 1970 unique viable r-k pairs
1096 r-k pairs above the initial geometric mean of r = 0.344 were analysed
r = 0.522, 95% CL = 0.349–0.782

k = 683, 95% CL = 438–1063
MSY = 89.1, 95% CL = 82.5–96.2
Predicted biomass last year b/k = 0.679 2.5th perc b/k = 0.436 97.5th perc b/k = 0.767
Precautionary 25th percentile b/k = 0.597

Species: *Phycis blennoides*

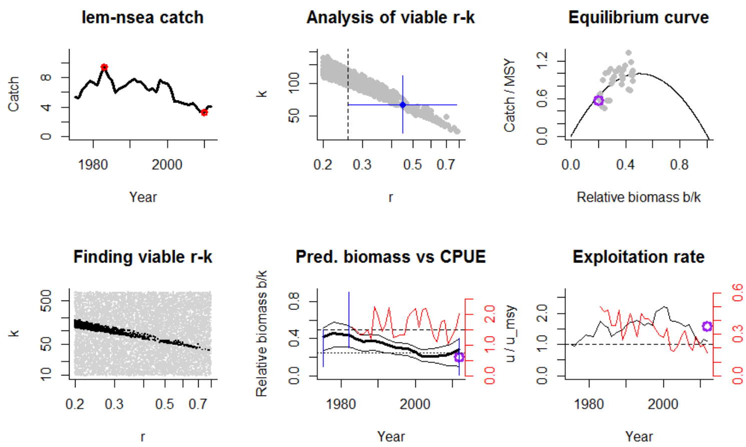
Name: Great Forkbeard
Region: Great Forkbeard in Northeast Atlantic
Stock: **gfb-comb**
Catch data used from years 1988–2013, biomass = cpue
Prior initial relative biomass = 0.1–0.5
Prior intermediate rel. biomass= 0.3–0.9 in year 1999
Prior final relative biomass = 0.01–0.4
Future crash with current catches? No
Prior range for r = 0.2–0.8, prior range for k = 5.52–442



Results of CMSY analysis with altogether 1071 unique viable r-k pairs
629 r-k pairs above the initial geometric mean of r = 0.298 were analysed
r = 0.484, 95% CL = 0.301–0.779
k = 27.7, 95% CL = 15.5–49.6
MSY = 3.35, 95% CL = 2.72–4.13
Predicted biomass last year = 0.295 2.5th perc = 0.1 97.5th perc = 0.396
Predicted biomass next year = 0.318 2.5th perc = 0.0837 97.5th perc = 0.442

Species: *Microstomus kitt*

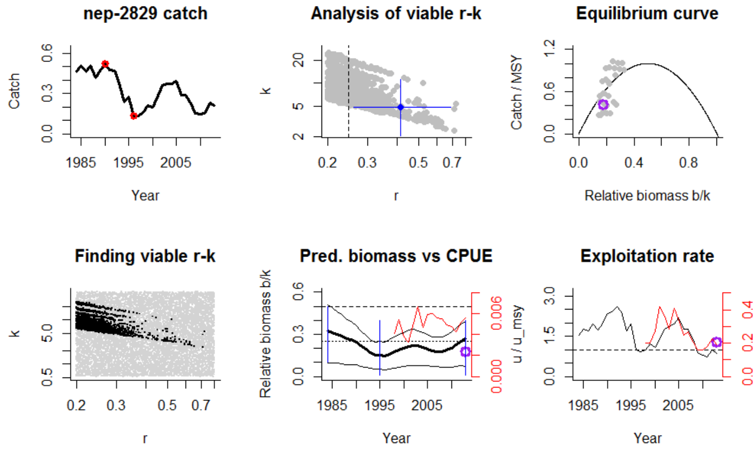
Name: Lemon sole
Region: Lemon sole in Subarea IV (North Sea) and Divisions IIIa (Skagerrak–Kattegat) and VIId (Eastern Channel)
Stock: **lem-nsea**
Catch data used from years 1975–2012, biomass = cpue
Prior initial relative biomass = 0.1–0.5
Prior intermediate rel. biomass= 0.3–0.9 in year 1982
Prior final relative biomass = 0.01–0.4
Future crash with current catches? No
Prior range for r = 0.2–0.8, prior range for k = 9.51–761



Results of CMSY analysis with altogether 1151 unique viable r-k pairs
615 r-k pairs above the initial geometric mean of r = 0.258 were analysed
r = 0.449, 95% CL = 0.26–0.776
k = 63.6, 95% CL = 34.2–118
MSY = 7.15, 95% CL = 6.17–8.29
Predicted biomass last year = 0.282 2.5th perc = 0.0943 97.5th perc = 0.396
Predicted biomass next year = 0.3 2.5th perc = 0.0777 97.5th perc = 0.434

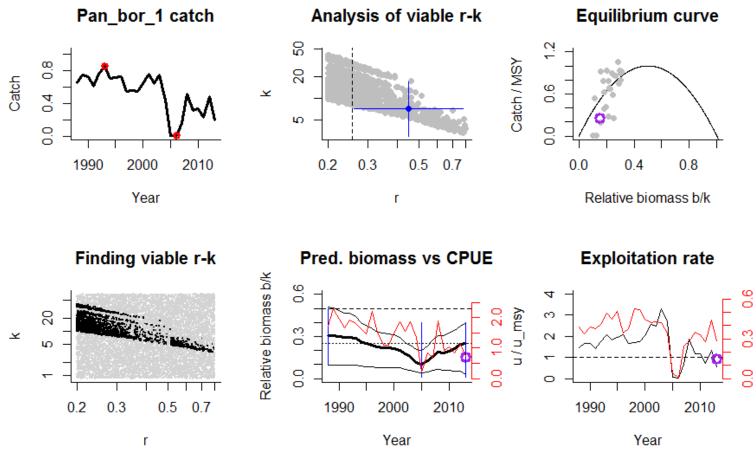
Species: *Nephrops norvegicus*

Name: *Nephrops*
Region: Nephrops in FUs 28 and 29
Stock: **nep-2829**
Catch data used from years 1984–2013, biomass = cpue
Prior initial relative biomass = 0.1–0.5
Prior intermediate rel. biomass= 0.01–0.4 in year 1995
Prior final relative biomass = 0.01–0.4
Future crash with current catches? No
Prior range for r = 0.2–0.8, prior range for k = 0.524–41.9



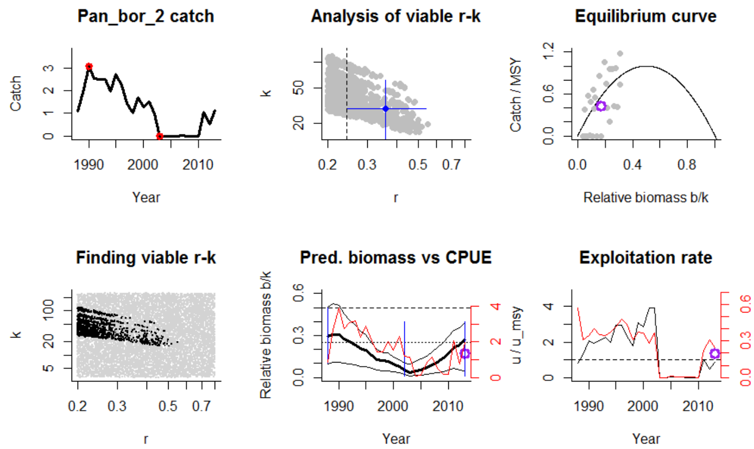
Results of CMSY analysis with altogether 1915 unique viable r-k pairs
1159 r-k pairs above the initial geometric mean of r = 0.247 were analysed
r = 0.417, 95% CL = 0.259–0.687
k = 4.85, 95% CL = 2.06–11.1
MSY = 0.505, 95% CL = 0.252–1.01
Predicted biomass last year = 0.269 2.5th perc = 0.0711 97.5th perc = 0.395
Predicted biomass next year = 0.292 2.5th perc = 0.0643 97.5th perc = 0.43

Species: *Pandalus borealis*
Name: Northern shrimp
Region:
Stock: **Pan_bor_1**
Catch data used from years 1988–2013, biomass = cpue
Prior initial relative biomass = 0.1–0.5
Prior intermediate rel. biomass= 0.01–0.4 in year 2005
Prior final relative biomass = 0.01–0.4
Future crash with current catches? Possible
Prior range for r = 0.2–0.8, prior range for k = 0.853–68.2



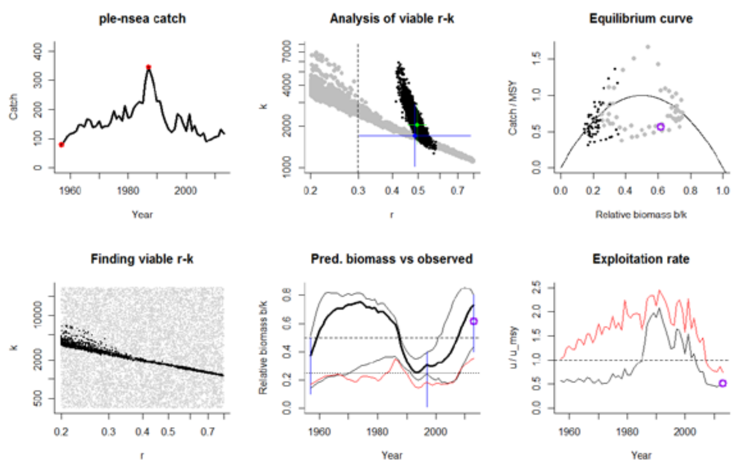
Results of CMSY analysis with altogether 1992 unique viable r-k pairs
1093 r-k pairs above the initial geometric mean of r = 0.255 were analysed
r = 0.449, 95% CL = 0.26–0.776
k = 7.2, 95% CL = 3.01–17.2
MSY = 0.808, 95% CL = 0.426–1.53
Predicted biomass last year = 0.253 2.5th perc = 0.0269 97.5th perc = 0.394
Predicted biomass next year = 0.288 2.5th perc = 0.018 97.5th perc = 0.462

Species: *Pandalus borealis*



Name: Northern shrimp
Region: Isafjardardjup
Stock: **Pan_bor_2**
Catch data used from years 1988–2013, biomass = cpue
Prior initial relative biomass = 0.1–0.5
Prior intermediate rel. biomass= 0.01–0.4 in year 2002
Prior final relative biomass = 0.01–0.4
Future crash with current catches? Possible
Prior range for r = 0.2–0.8, prior range for k = 3.1–248

Results of CMSY analysis with altogether 1236 unique viable r-k pairs
669 r-k pairs above the initial geometric mean of r = 0.244 were analysed
r = 0.359, 95% CL = 0.245–0.541
k = 29.2, 95% CL = 13.2–62.4
MSY = 2.62, 95% CL = 1.24–5.51
Predicted biomass last year = 0.267 2.5th perc = 0.0482 97.5th perc = 0.394
Predicted biomass next year = 0.284 2.5th perc = 0.0288 97.5th perc = 0.436

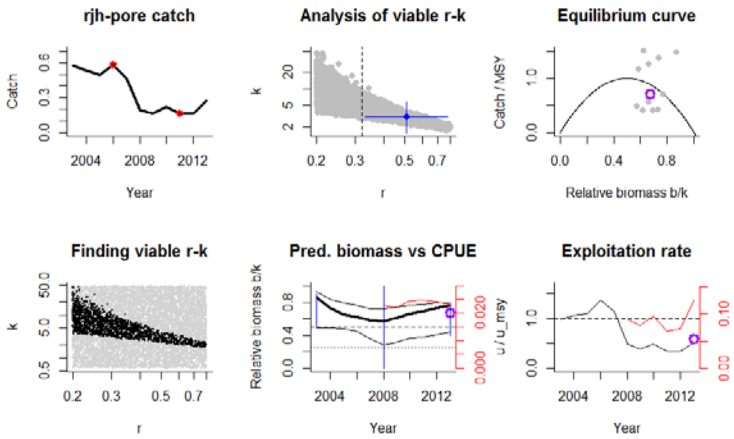


Species: *Pleuronectes platessa*
Name: Plaice
Region: Plaice in the North Sea
Stock: **ple-nsea**
Catch data used from years 1957–2013, biomass = observed
Prior initial relative biomass = 0.1–0.5
Prior intermediate rel. biomass= 0.01–0.4 in year 1997
Prior final relative biomass = 0.4–0.8
Future crash with current catches? No
Prior range for r = 0.2–0.8, prior range for k = 346–27 650

Results from Bayesian Schaefer model using catch & biomass
r = 0.495, 95% CL = 0.457–0.537
k = 2057, 95% CL = 1478–2864
MSY = 255, 95% CL = 196–332
Mean catch / MSY = 0.632
Results of CMSY analysis with altogether 2604 unique viable r-k pairs
745 r-k pairs above the initial geometric mean of r = 0.298 were analysed
r = 0.484, 95% CL = 0.301–0.779
k = 1715, 95% CL = 1019–2888
MSY = 208, 95% CL = 190–227
Predicted biomass last year b/k = 0.73 2.5th perc b/k = 0.434 97.5th perc b/k = 0.799
Precautionary 25th percentile b/k = 0.616

Species: *Raja brachyura*

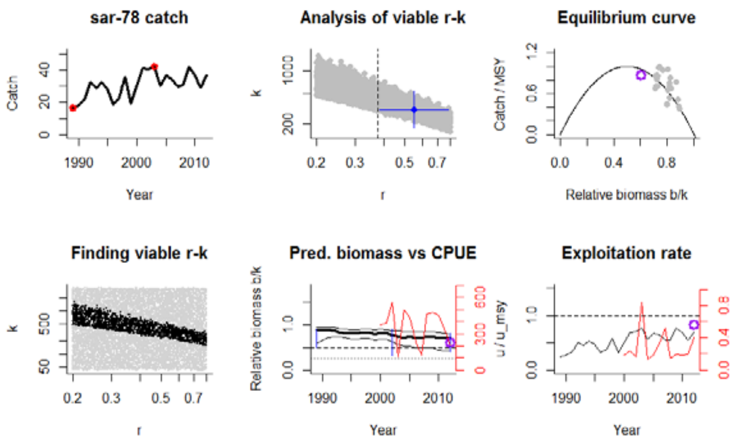
Name: Blond ray
Region: Blond ray in Division IXa
Stock: **rjh-pore**
Catch data used from years 2003–2013, biomass = cpue
Prior initial relative biomass = 0.5–0.9
Prior intermediate rel. biomass= 0–1 in year 2008
Prior final relative biomass = 0.4–0.8
Future crash with current catches? No
Prior range for r = 0.2–0.8, prior range for k = 0.586–46.9



Results of CMSY analysis with altogether 2002 unique viable r-k pairs
1153 r-k pairs above the initial geometric mean of r = 0.32 were analysed
r = 0.509, 95% CL = 0.332–0.781
k = 3.06, 95% CL = 1.6–5.87
MSY = 0.389, 95% CL = 0.251–0.604
Predicted biomass last year = 0.765 2.5th perc = 0.434 97.5th perc = 0.799
Predicted biomass next year = 0.768 2.5th perc = 0.428 97.5th perc = 0.83

Species: *Sardina pilchardus*

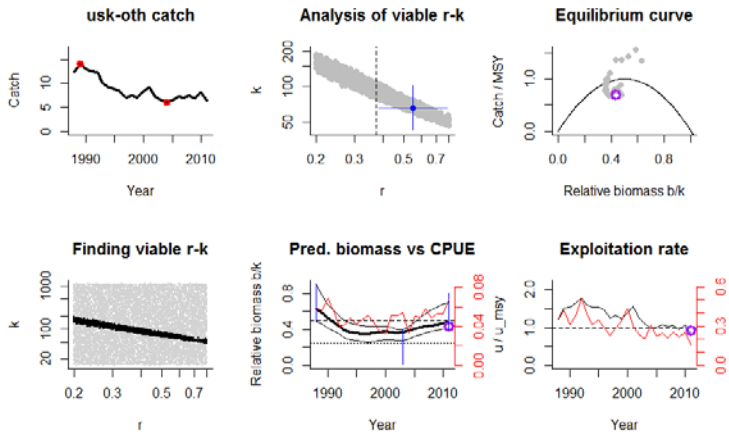
Name: Sardine
Region: Sardine in Divisions VIIIa,b,d and Subarea VII
Stock: **sar-78**
Catch data used from years 1989–2012, biomass = cpue
Prior initial relative biomass = 0.5–0.9
Prior intermediate rel. biomass= 0.3–0.9 in year 2002
Prior final relative biomass = 0.4–0.8
Future crash with current catches? No
Prior range for r = 0.2–0.8, prior range for k = 42.5–3397



Results of CMSY analysis with altogether 1841 unique viable r-k pairs
972 r-k pairs above the initial geometric mean of r = 0.379 were analysed
r = 0.549, 95% CL = 0.384–0.784
k = 313, 95% CL = 177–552
MSY = 42.9, 95% CL = 28.3–65
Predicted biomass last year = 0.722 2.5th perc = 0.413 97.5th perc = 0.798
Predicted biomass next year = 0.711 2.5th perc = 0.382 97.5th perc = 0.814

Species: *Brosme brosme*

Name: Tusk
Region: Tusk in Divisions IIIa, Vb, VIa, and XIIb and Subareas IV, VII, VIII, and IX (other areas).
Stock: **usk-oth**
Catch data used from years 1988–2011, biomass = cpue
Prior initial relative biomass = 0.5–0.9
Prior intermediate rel. biomass= 0.01–0.4 in year 2003
Prior final relative biomass = 0.4–0.8
Future crash with current catches? Possible
Prior range for r = 0.2–0.8, prior range for k = 14.1–1130



Results of CMSY analysis with altogether 2041 unique viable r-k pairs
1033 r-k pairs above the initial geometric mean of r = 0.373 were analysed
r = 0.549, 95% CL = 0.384–0.784
k = 66.3, 95% CL = 42.9–103
MSY = 9.1, 95% CL = 7.79–10.6
Predicted biomass last year = 0.48 2.5th perc = 0.403 97.5th perc = 0.693
Predicted biomass next year = 0.503 2.5th perc = 0.412 97.5th perc = 0.729

Annex 6: Detailed descriptions of single-stock length-based reference points analyses

A.6.1 *Nephrops* in FU 28–29

Graphical output from a length-based reference point R script (Figure A.5.1.1) applied to length data averaged over three years for males only show:

Upper panel (conservation/sustainability) - two estimates of length at first capture (L_c and L_{c_s}) are both above L_{ma}t suggesting that most individuals have opportunity to breed at least once. However these indices of exploitation are both below 1.2*L_{mat}, which has been suggested as an alternative reference level (Froese and Sampang, 2012). The maximum sampled length (L_{max}[1]) is above L_{inf}, indicating that large individuals are present in the population, however the 95 percentile of length ($L_{95\%}$) is below L_{inf}, indicating these large animals are scarce; the upper tail of the distribution is extended. The lower tail of the distribution rises slowly at first then rapidly to the first mode; the raw estimate of length at first capture occurs in this mode. This relatively sharp increase was initially thought possibly indicative of manual onboard selection (i.e. to an MLS) but it is at a size well above MLS and experts on this stock indicate that discarding in this area is minimal due to the high value and relative scarcity of *Nephrops*.

Central panel (yield optimisation) – Central metrics of the length distribution (mean length (MuL_All), mean length of animals above the length at first capture (MuL), 25th percentile (25%), median length (L_{med}), 75th percentile (75%) and the length class with the highest yield (LMaxY)) are all below two estimates for the reference point Lopt, which is indicative of maximum yield potential. This suggests exploitation is higher than optimal. Cumulative yield (dashed red line and right-hand axis) indicates that most yield is taken below L_{opt}.

Lower panel (MSY proxy) – Central metrics are below the empirical estimate for length where fishing mortality equals natural mortality (LFeM), an F_{MSY} proxy, indicating that exploitation is above the MSY level. LFeM falls just within the 75th percentile.

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[1] The R script implementation (used here) introduced small errors in quantiles where frequencies were fractions. This has been updated to correct this and return quantiles as mid-class lengths.

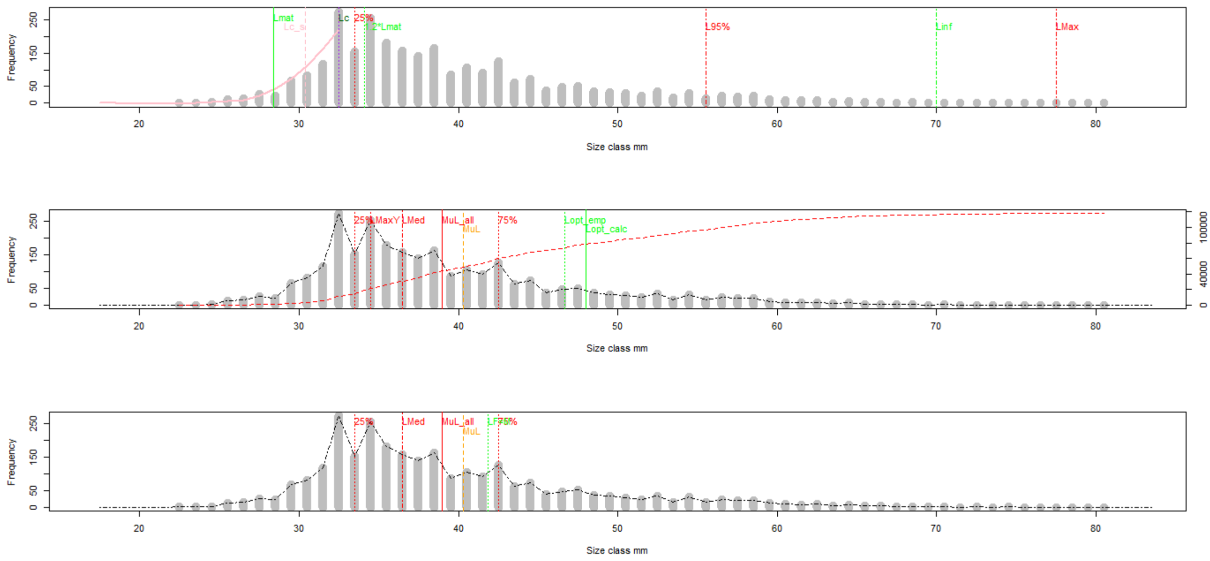

Figure A.6.1.1. Length-based reference points output for male *Nephrops* in FU 28 & 29.

Length-based metrics and reference points are detailed in Table A.6.1.1.

Table A.6.1.1. Length-based reference points and indicators of exploitation for male *Nephrops* in FU 28–29.

Lc50_raw	Lc50_s	MuL_all	MuLLc50	L25%	LMed	L75%	LMax	L95%	LCMaxY	L50mat	Lopt_emp	LoptCalc	LFeM	Linf
32.50	30.40	38.95	40.30	33.50	36.50	42.50	77.50	55.50	34.50	28.40	46.67	48.00	41.88	70.00

General prognosis (Table A.6.1.2) – The stock appears to be fished with pattern and level that permits maturation before substantial harvest and has not removed all large individuals from the population. However, it appears to be fished above levels that would maximize yield and slightly to moderately above the level representative of MSY (i.e. F=M).

Table A.6.1.2. Summary of status for male *Nephrops* in FU 28-29 as suggested by length-based reference points approach (note colour coding is for illustration only).

Lmat/Lc	Lopt/MuL	LFeM/MuL	Linf/Lmax	Lmat/Lc_s	Lopt/MuLlc50	Lopt/LCMaxy	LFeM/Lmed	Linf/L95
0.87	1.20	1.07	0.90	0.93	1.16	1.35	1.15	1.26

The length-based reference points approach was also applied to a time-series of length distributions for *Nephrops*. This may permit trends and other characteristics of the metrics and reference points to be explored over time, thereby adding additional information. There was a slight increase in many of the metrics suggesting general improvement in status through the time-series.

A.6.2 Length-based reference point analyses for other stocks

A.6.3 Sardine in Areas 7 and 8

Graphical output from a length-based reference point R script (Figure A.6.3.1) applied to length data for 2012 only shows:

Upper panel (conservation/sustainability) - two estimates of length at first capture (L_c and L_{c_s}) are both above L_{mat} suggesting that most individuals have opportunity to breed at least once. However, these indices of exploitation are both below 1.2*L_{mat}, which lies just above the 25th percentile of length. Maximum length (L_{max}) is above L_{inf}, indicating that large individuals are present in the population, however the 95 percentile of length ($L_{95\%}$) is below L_{inf}, indicating these large animals are relatively scarce. The length frequency distribution is bi-modal; the first mode being used to estimate lengths at first capture. The first mode is mainly below the lower quartile and may be influenced by recruitment. A stock expert indicated that this bi-modality was also present in survey data suggesting it is a population characteristic, rather than representative of fisheries with different selectivities acting on the stock.

Central panel (yield optimisation) – Central metrics of the length distribution are all substantially above L_{opt}, the length representing maximum yield potential. This suggests exploitation may be lower than optimal, but is good in terms of stock sustainability. Cumulative yield (dashed red line and right-hand axis) indicates that little yield has been taken around the L_{opt} level.

Lower panel (MSY proxy) – Central metrics are above the empirical estimate for the MSY proxy (LFeM) suggesting that exploitation is below the MSY level. LFeM falls midway between the 25th percentile and central metrics.

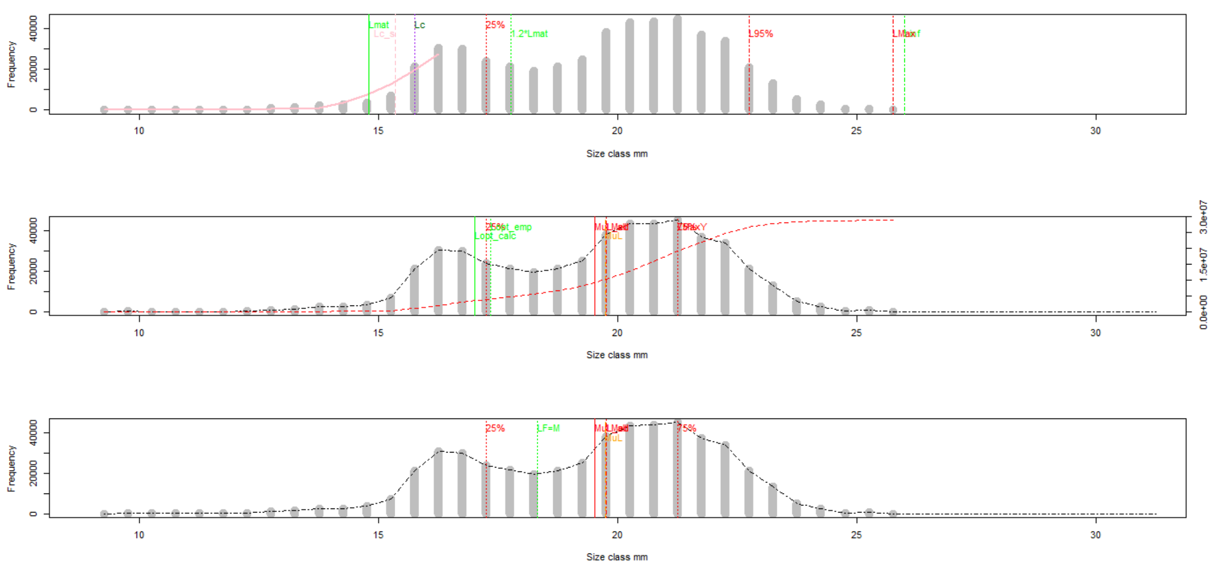

Figure A.6.3.1. Length-based reference points output for sardine in Areas 7 and 8.

Table A.6.3.1. Length-based reference points and indicators of exploitation for sardine in ICES Areas 7 and 8.

Lc50_raw	Lc50_s	MuL_All	MuLLc50	L25%	LMed	L75%	LMax	L95%	LCMaxY	L50mat	Lopt_emp	LoptCalc	LFeM	Linf
15.75	15.35	19.52	19.74	17.25	19.75	21.25	25.75	22.75	21.25	14.80	17.33	17.00	18.31	26.00

General prognosis (Table A.6.3.2) – The stock appears to be fished with pattern and level that permits maturation before substantial harvest and has not eradicated large individuals from the population. Fishing mortality is likely sustainable, at levels below F_{MSY}, however there might be potential to increase yields without exceeding MSY.

Table A.6.3.2. Summary of status for sardine in ICES Areas 7 and 8 as suggested by length-based reference points approach (note colour coding is for illustration only).

Lmat/Lc	Lopt/MuL	LFeM/MuL	Linf/Lmax	Lmat/Lc_s	Lopt/MuLlc50	Lopt/LCMaxy	LFeM/Lmed	Linf/L95
0.94	0.89	0.94	1.01	0.96	0.88	0.82	0.93	1.14

A.5.4 Blonde ray in Portugal

Graphical output from a length-based reference point R script (Figure A.6.4.1) applied to length data aggregated from 2008–2013 for blonde rays shows:

Upper panel (conservation/sustainability) - two estimates of length at first capture (L_c and L_{c_s}) are both well below L_{mat} suggesting that substantial harvesting occurs before individuals have the opportunity to breed at least once. Ninety five percent of the catch is taken below the more conservative maturity reference point, 1.2*L_{mat}. Maximum length (L_{max}) is well below L_{inf}, suggesting that large individuals are absent or rare in the population.

Central panel (yield optimisation) – Central metrics of the length distribution are all substantially below tow estimates for L_{opt}, the length representing maximum yield potential. This suggests exploitation is higher than is optimal and is also excessive in terms of stock sustainability. Cumulative yield (dashed red line and right-hand axis) indicates that virtually all yield has been taken before the L_{opt} level.

Lower panel (MSY proxy) – Central metrics are below the empirical estimate for the MSY proxy (LFeM) suggesting that exploitation is above the MSY level. LFeM falls midway between the central metrics and the 75th percentile.

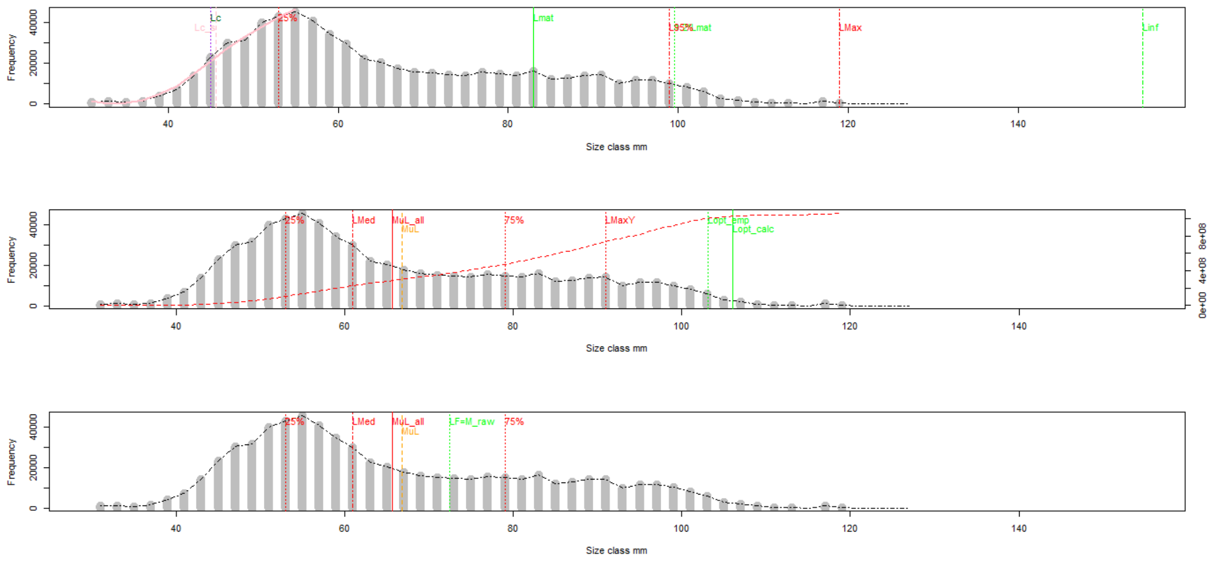

Figure A.6.4.1. Length-based reference points output for blonde rays in Portugal.

Table A.6.4.1. Length-based reference points and indicators of exploitation for blonde rays in Portugal.

Lc50_raw	Lc50_s	MuL_All	MuLLc50	L25%	LMed	L75%	Lmax	L95%	LCMaxY	L50mat	Lopt_emp	LoptCalc	LFeM	Linf
45.00	45.60	65.65	66.86	53.00	61.00	79.00	119.00	99.00	91.00	83.00	103.13	106.00	72.43	154.70

General prognosis (Table A.6.4.2) – The stock appears to be fished with pattern and level where substantial harvesting occurs before maturation and large individuals are eradicated from the population. It appears to be fished at a level substantially above that which would maximize yield and also above that corresponding to F_{MSY}. Based on this length distribution, the stock appears over exploited in terms of sustainability and yield.

Note: Consultation with scientists with knowledge of this fishery indicated that these rays are taken as untargeted bycatch in a fixed net fishery primarily using trammelnets and targeting smaller demersal species (e.g. sole). Fixed gillnets are known to have strongly domed selection patterns and although trammelnets retain some larger fish they also have a domed selection (Hovgard and Lassen, 2000). This means that the length distribution reflects the selection of the fishery rather than the population. Externally derived metrics and size at first capture are still relevant, but other metrics intended to capture population characteristics (e.g. mean sizes and quantiles) may be more representative of the selection characteristics of the gear rather than the population.

Therefore the length distribution is not considered representative of the population and advice would need to be reframed to take account of the bycatch nature of the fishery. It is still relevant to say that the selection pattern of this untargeted bycatch fishery harvests blonde rays before they are mature and at sizes that are not optimal in terms of optimising yield. However its impact, in terms of sustainability cannot be assessed using these data alone.

Table A.6.4.2. Summary of status for blonde ray in Portugal as suggested by length-based reference points approach (note colour coding is for illustration only).

Lmat/Lc	Lopt/MuL	LFeM/MuL	Linf/Lmax		Lmat/Lc_s	Lopt/MuLlc50	Lopt/LCMaxy	LFeM/Lmed	Linf/L95
1.84	1.57	1.10	1.3		1.82	1.54	1.13	1.19	1.56

A.6.5 Lemon sole in the North Sea

For this stock, only a subset of data was available for analysis. These consisted of UK observer samples by quarter for 2013 and were summed to provide the aggregate distribution. This distribution may therefore not be representative of the commercial catch as a whole or the population.

The length distribution was slightly bimodal, so two permutations for selecting the mode from which to determine the size at 50% selection were used and a third run was used based on the landed component only.

Graphical output from the length-based reference point R script (Figure A.6.5.1) with the length class for estimation of length at first capture manually fixed at 22 cm to take account of bimodality showed:

Upper panel (conservation/sustainability) - two estimates of length at first capture (L_c and L_{c_s}) are both well above L_{mat} (and 1.2*L_{mat}) suggesting that many individuals have the opportunity to breed at least once before harvesting occurs. Maximum length (L_{max}) is below L_{inf}, suggesting that large individuals may be scarce in the population.

Central panel (yield optimisation) – Central metrics of the length distribution are all substantially below two estimates for L_{opt}, the length representing maximum yield potential. This suggests exploitation is higher than is optimal and is also excessive in terms of stock sustainability. Cumulative yield (dashed red line and right-hand axis) indicates that the majority of yield has been taken before the L_{opt} level.

Lower panel (MSY proxy) – Central metrics are slightly below the empirical estimate for the MSY proxy (LFeM) suggesting that exploitation is slightly above the MSY level.

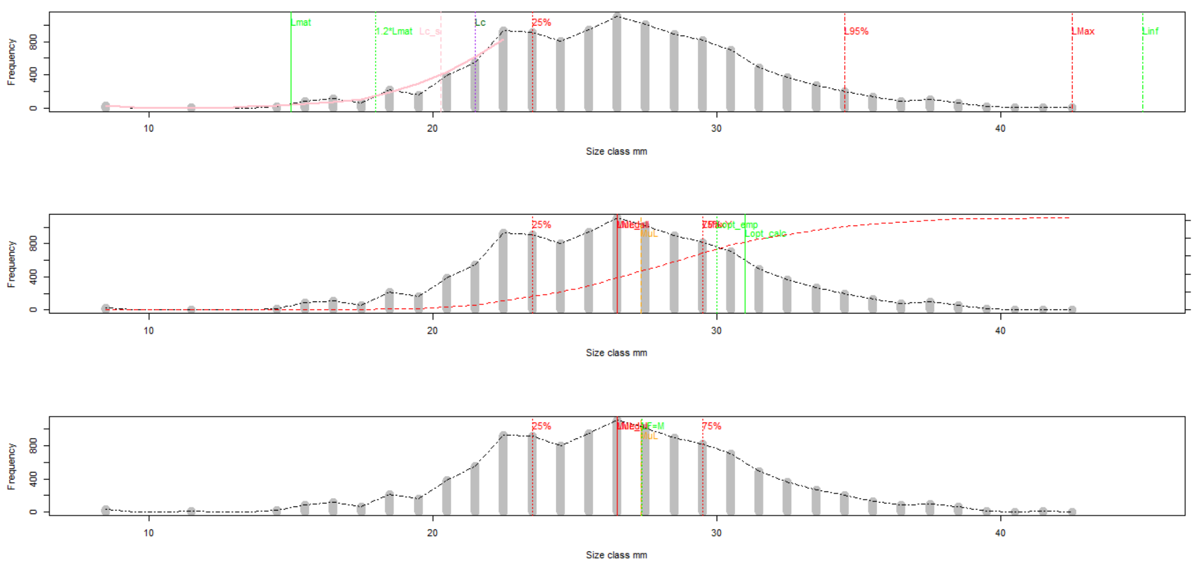

Figure A.6.5.1. Length-based reference points output for Lemon sole in the North Sea (UK observer sampled data, not aggregated commercial catch).

A second run with L_c estimated automatically (Figure A.6.5.2) showed minor differences in length at first capture, and metrics or reference points using this, i.e. mean size of animals greater than the size at first capture (MuL_LC50) and the reference point length where F = M (LFeM) (Table A.6.5.1).

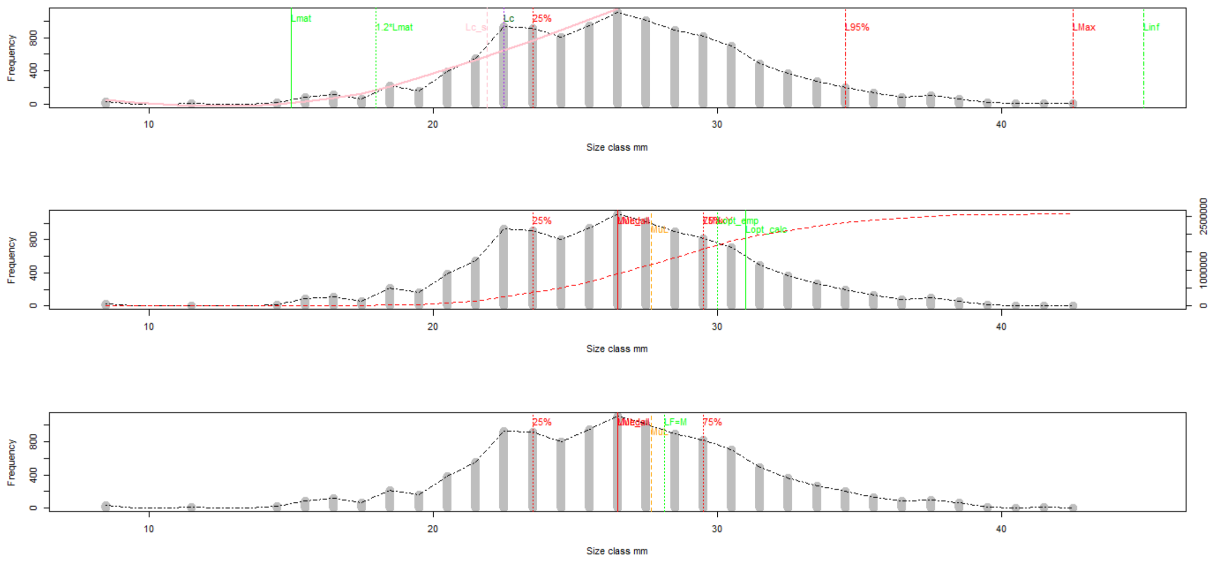

Figure A.6.5.2. Length-based reference points output for lemon sole in the North Sea (UK observer sampled data, not aggregated commercial catch).

Output from an analysis where discards were excluded (Figure A.6.5.3) showed more substantial differences as all metrics and reference points using data from the length distribution were changed. Obviously, use of the estimate of size at first capture becomes irrelevant if discards are excluded and known to be substantial and other metrics summarising the length distribution will be biased upwards, suggesting lower relative fishing mortality. However, it would still be valid to use the maximum observed length in comparison with L_{inf} to evaluate depletion of large individuals from the population.

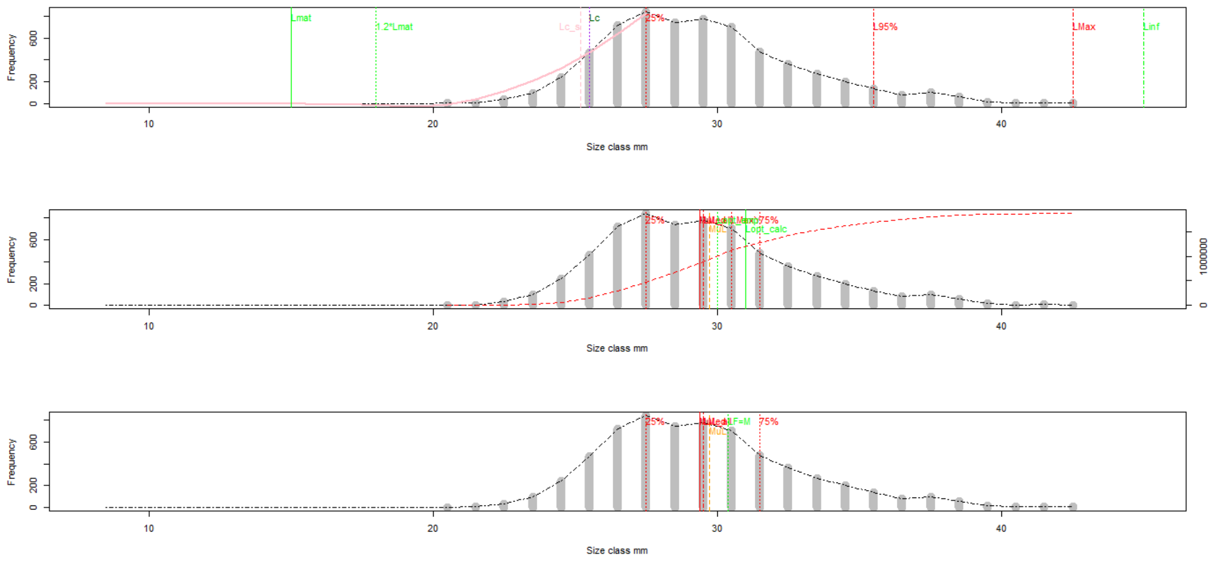

Figure A.6.5.3. Length-based reference points output for Lemon sole in the North Sea (UK observer sampled data, not aggregated commercial catch – retained component only).

Table A.6.5.1. Length-based reference points and indicators of exploitation for lemon sole in the North Sea using different data and length at first capture combinations.

Lc50_raw	Lc50_s	MuL_All	MuLLc50	L25%	LMed	L75%	LMax	L95%	LCMaxY	L50mat	Lopt_emp	LoptCalc	LFeM	Linf
21.50	20.30	26.50	27.33	23.50	26.50	29.50	42.50	34.50	29.50	15.00	30.00	31.00	27.38	45.00
22.50	21.90	26.50	27.66	23.50	26.50	29.50	42.50	34.50	29.50	15.00	30.00	31.00	28.13	45.00
25.50	25.20	29.39	29.74	27.50	29.50	31.50	42.50	35.50	30.50	15.00	30.00	31.00	30.38	45.00

Top row: all data, mode for Lc50% determination manual (22 cm).

Top row: all data, mode for Lc50% determination automatic (26 cm).

Top row: landings only, mode for Lc50% determination automatic (27 cm).

General prognosis (**Table A.6.5.2**) – The general prognosis was remarkably similar over the three scenarios, although as expected, generally biased to a more favourable perception when discards were excluded. The stock appeared to be fished with pattern and level where little harvesting took place before maturation, but large individuals were not well represented in the population. It appears to be fished at a level above that which would maximize yield and also slightly above that corresponding to F_{MSY}, i.e. (slightly) over exploited in terms of both sustainability and yield.

Table A.6.5.2. Summary of status for lemon sole in the North Sea as suggested by length-based reference points approach (note colour coding is for illustration only).

Lmat/Lc	Lopt/MuL	LFeM/MuL	Linf/Lmax		Lmat/Lc_s	Lopt/MuLlc50	Lopt/LCMaxy	LFeM/Lmed	Linf/L95
0.70	1.13	1.03	1.06		0.74	1.10	1.02	1.03	1.30
0.67	1.13	1.06	1.06		0.68	1.08	1.02	1.06	1.30
0.59	1.02	1.03	1.06		0.60	1.01	0.98	1.03	1.27

Top row: all data, mode for Lc50% determination manual (22 cm).

Top row: all data, mode for Lc50% determination automatic (26 cm).

Top row: landings only, mode for Lc50% determination automatic (27 cm).

A.6.6 Spurdog in the Northeast Atlantic

It was not possible to obtain an aggregated length distribution for the catch of this species, but length historical distributions were available for targeted and non-targeted fishery components, both of which were separate by sex because growth and maturity parameters differ in this respect. This complicated the analysis which required multiple scenarios and also the inference because data on the relative contributions of each (target/non-target and sex) component were not readily available. Data were averaged length distributions for the period 1999–2001.

A.6.6.1 Targeted fishery-females

The length-based reference point R script was applied to the targeted fishery distribution for females and graphical output (Figure A.6.6.1.1) showed:

Upper panel (conservation/sustainability) - two estimates of length at first capture (L_c and L_{c_s}) were just above L_{mat} (but below well below 1.2*L_{mat}) suggesting that some individuals have the opportunity to breed at least once before harvesting occurs. Maximum length (L_{max}) was above L_{inf} and the 95% quantile of the length distribution slightly below L_{inf}, suggesting that large individuals are not particularly scarce in the population.

Central panel (yield optimisation) – Central metrics of the length distribution were all substantially above two estimates for L_{opt}, the length representing maximum yield potential, which was near the 25 percentile. This suggests exploitation may be lower than is optimal for yield but is good with regard to stock sustainability. Cumulative yield (dashed red line and right-hand axis) indicates that very little yield has been taken before the L_{opt} level.

Lower panel (MSY proxy) – Central metrics are above the empirical estimate for the MSY proxy (LFeM) suggesting that exploitation is below the F_{MSY} level.

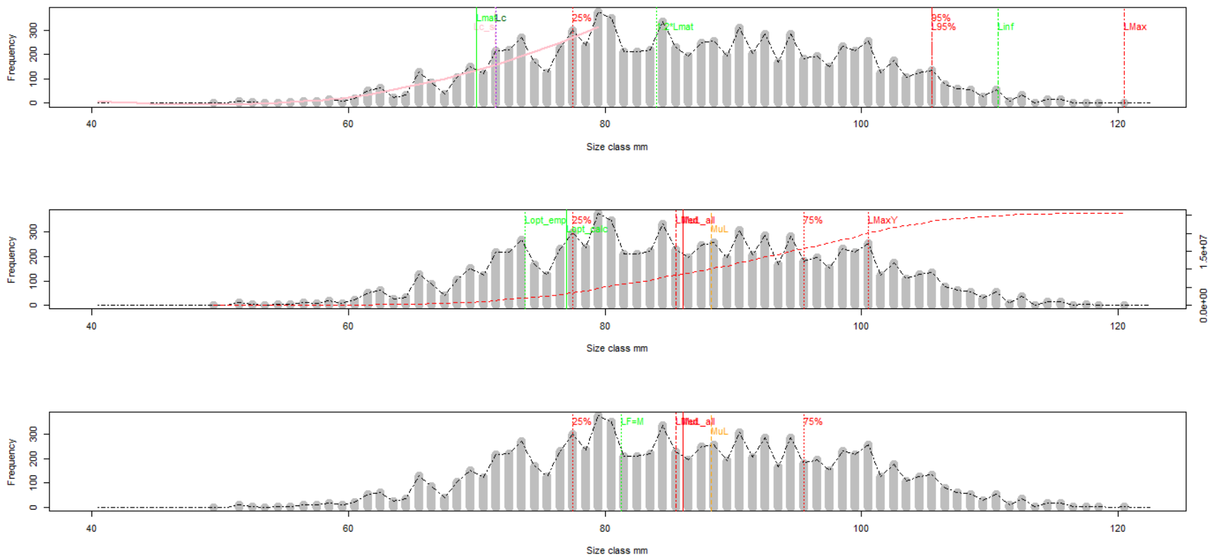

Figure A.6.6.1.1. Length-based reference points output for spurdog females targeted fishery.

A.6.6.2 Non-targeted fishery-females

Graphical output from the length-based reference point R script applied to the non-targeted fishery distribution for females (Figure A.6.6.2.1) showed:

Upper panel (conservation/sustainability) - two estimates of length at first capture (L_c and L_{c_s}) were well below L_{mat} (and 1.2*L_{mat}) which was close to the 25th percentile of the distribution indicating that a substantial part of the catch is harvested before having the opportunity to breed. Maximum length (L_{max}) was at L_{inf} but the 95% quantile of the length distribution was well below L_{inf}, suggesting that large individuals are present but possibly scarce in the population.

Central panel (yield optimisation) – Central metrics of the length distribution were all close to two estimates for L_{opt}, the length representing maximum yield potential, suggesting exploitation close to the level that is optimal for yield. Cumulative yield (dashed red line and right-hand axis) indicates that around half the yield has been taken before the L_{opt} level.

Lower panel (MSY proxy) – Central metrics are around the empirical estimate for the MSY proxy (LFeM) suggesting that exploitation is close to the F_{MSY} level.

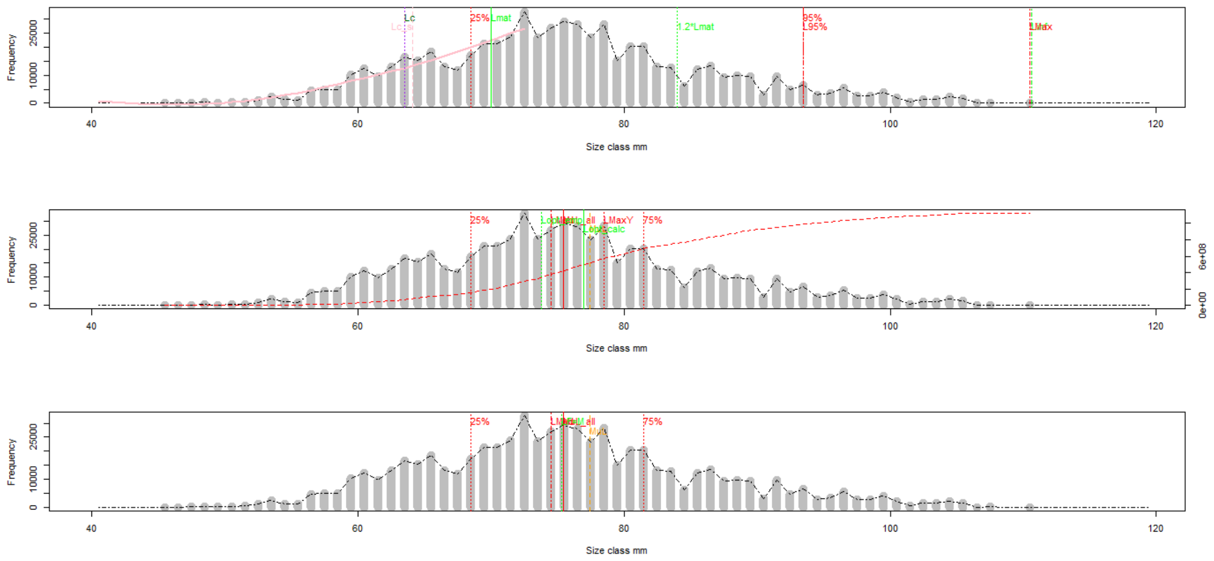

Figure A.6.6.2.1. Length-based reference points output for spurdog females non-targeted fishery.

A.6.6.3 Targeted fishery-males

Graphical output from the length-based reference point R script applied to the targeted fishery distribution for males (Figure A.6.6.3.1) showed:

Upper panel (conservation/sustainability) – Only the L_{mat} for females was available and it was not considered particularly useful to compare male length at first capture against this level. The maximum size was far above L_{inf}, which was below the 95th percentile of the distribution, raising doubts about the validity of the male growth parameters. Subsequent investigation indicated the maximum size was the result of a few outlying sampled points and therefore not really representative. Nonetheless, the fact that the 95 percentile is above L_{inf} does suggest that this growth parameter may be low. As a result additional runs were carried out, replacing the L_{inf} parameter with the larger 95 percentile from the two male spurdog components. It should also be noted that the reproductive potential and status of the stock is likely to be more dependent on females than males, hence this component may have less overall relevance.

Central panel (yield optimisation) – Central metrics of the length distribution were all far above two estimates for L_{opt}, the length representing maximum yield potential, suggesting exploitation below the level optimal for yield, but good in terms of sustainability. Cumulative yield (dashed red line and right-hand axis) indicates that almost no yield has been taken before the L_{opt} level. L_{opt} is dependent on growth parameters and this result may again suggest that the parameters used were not appropriate.

Lower panel (MSY proxy) – Central metrics were above the empirical estimate for the MSY proxy (LFeM) suggesting that exploitation was below the F_{MSY} level.

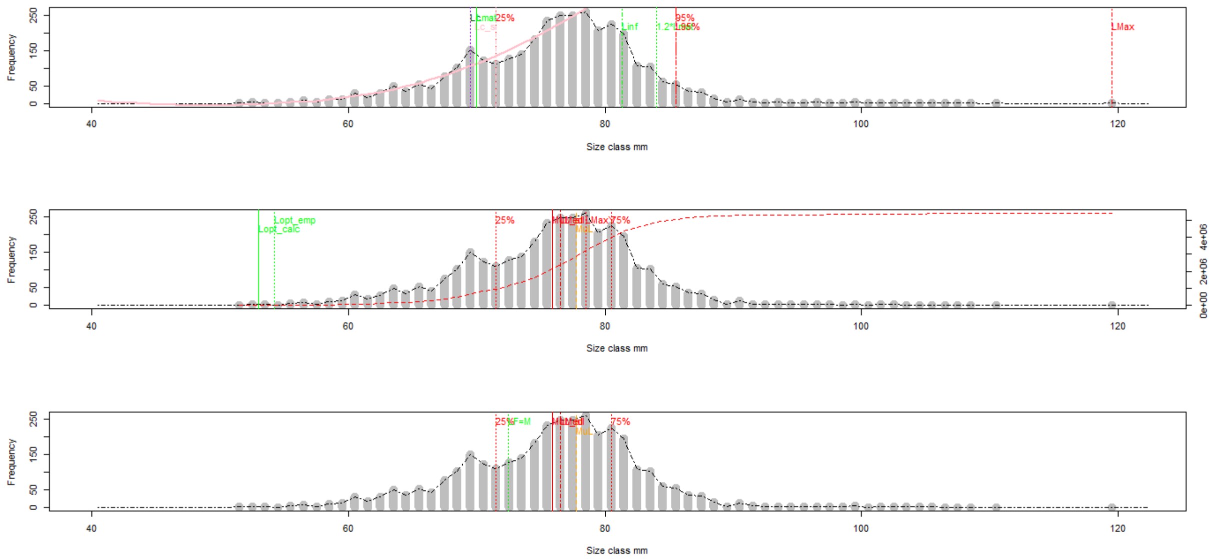

Figure A.6.6.3.1. Length-based reference points output for spurdog males targeted fishery.

A.6.6.4 Non-targeted fishery-males

Graphical output from the length-based reference point R script applied to the non-targeted fishery distribution for males (Figure A.6.6.4.1) showed:

Upper panel (conservation/sustainability) – The female L_{mat} was not considered relevant. Male L_{mat} is likely to be lower and hence below size at first capture. The maximum size was far above L_{inf}, which was around the 95th percentile of the distribution, again raising doubts about the validity of the male growth parameters.

Central panel (yield optimisation) – Central metrics of the length distribution were all far above two estimates for L_{opt}, which as in the targeted fishery was at the lower margin of the distribution. This suggests that the fishery exploitation level is far below that which would maximize yield or the growth parameters are inappropriate.

Lower panel (MSY proxy) – Central metrics were close to the empirical estimate for the MSY proxy (LFeM) suggesting that exploitation was at the F_{MSY} level. The empirical LFeM reference point is dependent on the growth parameters so should be treated with some caution due to the doubts raised above.

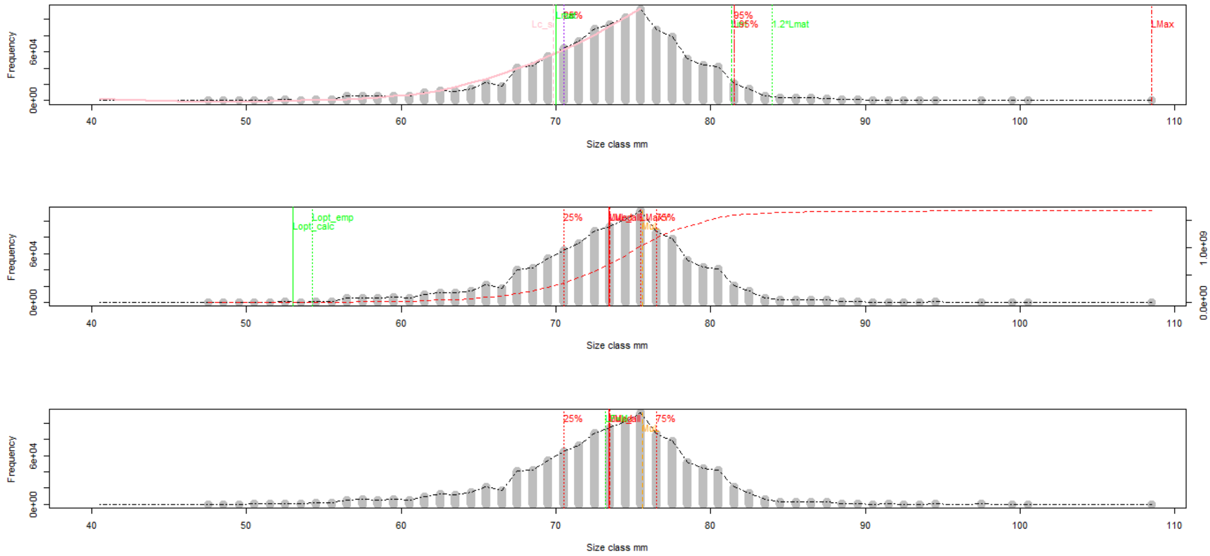

Figure A.6.6.4.1. Length-based reference points output for spurdog males non-targeted fishery.

A.6.7 Additional runs for males using an alternative estimate for L_{inf}

Two additional runs were carried out using the larger 95th percentile from the two male distributions as a proxy for L_{inf}. Using the maximum had been proposed but because this was dependent on a few outlying points a high percentile was considered more appropriate. The new estimate for L_{inf} was 85.5cm around 5% higher than previously. With hindsight a higher percentile than the 95th may have been preferable, but this is subjective. As expected this resulted in a slightly worse perception against reference points derived from L_{inf} (Figure A.6.7.1 and Figure A.6.7.2), but the changes were insignificant with regards to status (Table A.6.7.1).

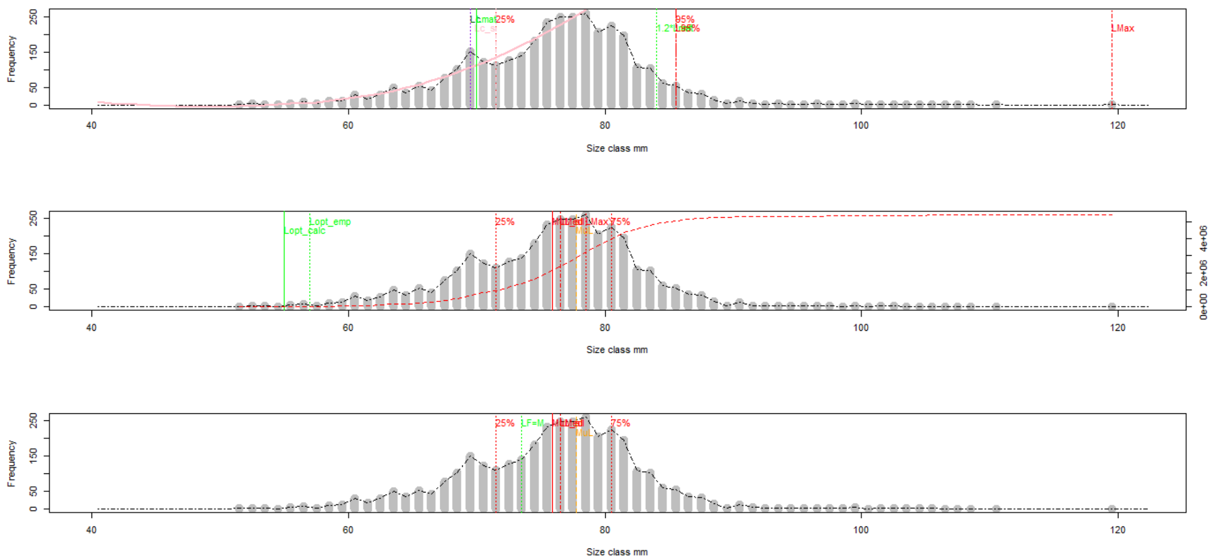

Figure A.6.7.1. Length-based reference points output for spurdog males targeted fishery L_{inf}=$L_{95\%}$.

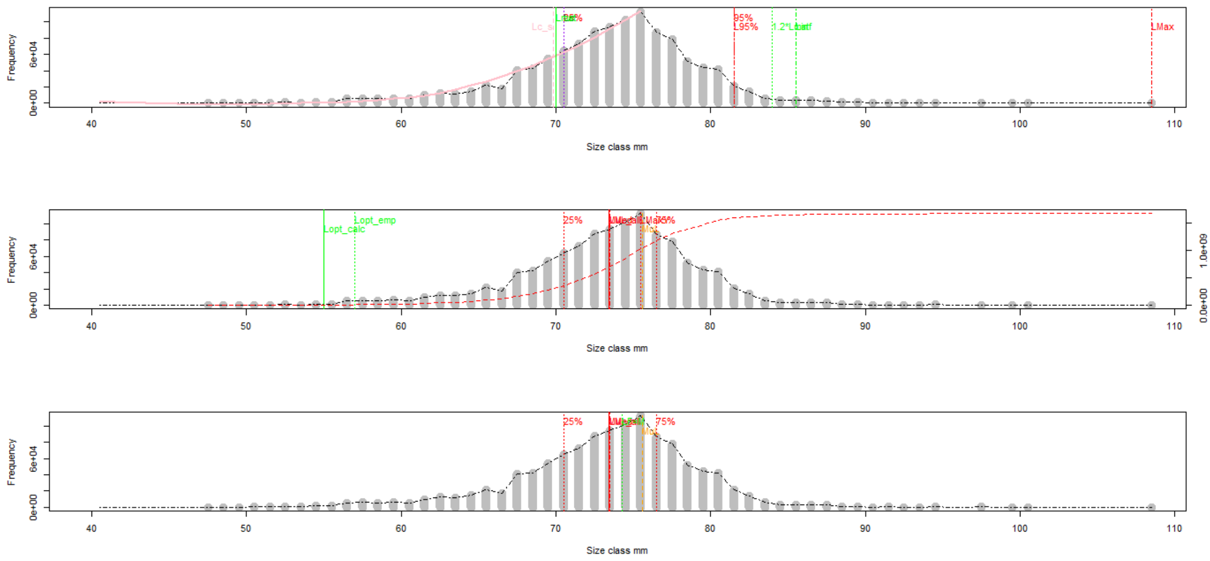

Figure A.6.7.2. Length-based reference points output for spurdog males non-targeted fishery L_{inf}=$L_{95\%}$.

Table A.6.7.1. Length-based reference points and indicators of exploitation for Northeast Atlantic spurdog (1999–2001) by fishery sex components. Female L_{50mat} in all cases.

Lc50_raw	Lc50_s	MuL_All	MuLLc50	L25%	LMed	L75%	LMax	L95%	LCMaxY	L50mat	Lopt_emp	LoptCalc	LFem	Linf
71.50	71.40	86.08	88.30	77.50	85.50	95.50	120.50	105.50	100.50	70.00	73.77	77.00	81.29	110.66
63.50	64.10	75.47	77.43	68.50	74.50	81.50	110.50	93.50	78.50	70.00	73.77	77.00	75.29	110.66
69.50	71.50	75.89	77.73	71.50	76.50	80.50	119.50	85.50	78.50	70.00	54.24	53.00	72.47	81.36
70.50	69.80	73.39	75.61	70.50	73.50	76.50	108.50	81.50	75.50	70.00	54.24	53.00	73.22	81.36
69.50	71.50	75.89	77.73	71.50	76.50	80.50	119.50	85.50	78.50	70.00	57.00	55.00	73.50	85.50
70.50	69.80	73.39	75.61	70.50	73.50	76.50	108.50	81.50	75.50	70.00	57.00	55.00	74.25	85.50

Top row: female only, targeted fishery.

2nd row: female only, non-targeted fishery.

3rd row: male only, targeted fishery.

4th row: male only, non-targeted fishery.

5th row: male only, targeted fishery, L_{inf} set at 95th percentile of the target component.

Bottom row: male only, non-targeted fishery, L_{inf} set at 95th percentile of the target component.

General prognosis (Table A.6.7.2) – Combining the interpretations from the four components is not straightforward especially without knowledge relating to the stock and its fisheries and the relative importance of each fishery and sex. The prognoses for both male components were generally good, but males are considered less important in the context of sustainability, the male size at maturity parameter was not available and there were some concerns regarding the validity of growth parameters, so the analyses for males are not considered further at present. The prognoses for females were also broadly favourable, especially for the targeted fishery and slightly less so for the non-targeted fishery, in which there could be concerns regarding sustainability from both fishing before females mature and removal of large animals from the population. In terms of yield optimization and MSY proxy, performance metrics were favourable relative to reference points.

The primary methods of capture of these fisheries is not known to the analysts at the present time, but it is thought that static gears including longlines and fixed nets may be important for the target fishery. As with the case of blonde rays in Portugal and Spain this would lead to some concerns as to whether the catch was representative of the population or not. However, in the target fishery (unlike the ray bycatch fishery) these would be expected to have mesh (or hook) sizes effective for the large fish, and would be less of a concern. Perhaps a bigger concern relates to the schooling behaviour of this species, which potentially makes it vulnerable to capture especially when the large animals are spatially aggregated for breeding. Such circumstances could potentially permit heavy exploitation of the mature part of the population.

Table A.6.7.2. Summary of status for Northeast Atlantic spurdog (1999–2001) as suggested by length-based reference points approach (note colour coding is for illustration only).

Lmat/Lc	Lopt/MuL	LFeM/MuL	Linf/Lmax		Lmat/Lc_s	Lopt/MuLlc50	Lopt/LCMaxy	LFeM/Lmed	Linf/L95
0.98	0.86	0.94	0.92		0.98	0.84	0.73	0.95	1.05
1.10	0.98	1.00	1.00		1.09	0.95	0.94	1.01	1.18
1.01	0.71	0.95	0.68		0.98	0.70	0.69	0.95	0.95
0.99	0.74	1.00	0.75		1.00	0.72	0.72	1.00	1.00
1.01	0.75	0.97	0.72		0.98	0.73	0.73	0.96	1.00
0.99	0.78	1.01	0.79		1.00	0.75	0.75	1.01	1.05

Top row: female only, targeted fishery.

2nd row: female only, non-targeted fishery.

3rd row: male only, targeted fishery.

4th row: male only, non-targeted fishery.

5th row: male only, targeted fishery, Linf set at 95th percentile of the target component.

Bottom row: male only, non-targeted fishery, Linf set at 95th percentile of the target component.

Annex 7: Harvest control rule operating model

An age-structured production model (ASPM) is used to model the resource dynamics. Fishing is assumed to be continuous throughout the year, so that the population dynamics are described by the equations:

$$N_{y+1,a\min} = R_{y+1} \tag{A.1}$$

$$N_{y+1,a+1} = N_{y,a} e^{-(M_a + S_{y,a} F_y)} = N_{y,a} e^{-Z_{y,a}} \text{ for } 0 < m-2 \tag{A.2}$$

$$N_{y+1,m} = N_{y,m-1} e^{-(M_{m-1} + S_{y,m-1} F_y)} + N_{y,m} e^{-(M_m + S_{y,m} F_y)} \tag{A.3}$$

Where:

$N_{y,a}$ is the number of fish of age *a* at the start of year *y*,

M_a denotes the natural mortality rate for fish of age *a* (for the analyses of this paper age-independence is assumed),

$S_{y,a}$ is the age-specific selectivity for year *y* and set to 1 for the age at which there is full selectivity,

F_y is the fishing mortality for year *y*,

m is the maximum age considered (taken to be a plus-group).

The total number of fish caught of age a in year *y* is given by the Baranov equation:

$$C_{y,a} = N_{y,a} \frac{S_{y,a} F_y}{Z_{y,a}} (1 - e^{-Z_{y,a}}) \tag{A.4}$$

where $Z_{y,a} = M_a + S_{y,a} F_y$ is the total mortality for fish of age *a* in year *y*.

The corresponding total catch by mass for each year is given by:

$$C_y = \sum_{a=0}^{m} w_{a+1/2} \, C_{y,a} \tag{A.5}$$

where $w_{y,a+1/2}$ denote the mid-year weights-at-age of fish caught in year *y*.

Stock–recruitment relationship

The number of recruits at the start of year *y* (for *y>1*) is related to the spawning–stock size by a Beverton–Holt stock–recruitment relationship:

$$R_y = \frac{\alpha\, B_y^{sp}}{\beta + B_y^{sp}} e^{\varsigma_y - \sigma_R^2/2} \tag{A.6}$$

where

α and β are spawning biomass-recruitment parameters,

$\varsigma_y \sim N(0,\sigma_R^2)$ reflect fluctuations about the expected recruitment for year *y*,

σ_R is the standard deviation of the log-residuals, and

B_y^{sp} is the spawning biomass at the start of year y, given that:

$$B_y^{sp} = \sum_{a=0}^{m} f_a w_a N_{y,a} \tag{A.7}$$

where w_a is the begin-year mass of fish of age *a* (spawning is assumed to take place at the start of the year) and f_a is the proportion of fish of age *a* that are mature.

In order to work with estimable parameters that are more meaningful biologically, the stock–recruitment relationship is re-parameterised in terms of the pre-exploitation equilibrium spawning biomass, K^{sp}, and the "steepness" of the stock–recruitment relationship, *h* (recruitment at $B^{sp} = 0.2K^{sp}$ as a fraction of recruitment at $B^{sp} = K^{sp}$):

$$\alpha = \frac{4hR_K}{5h-1} \tag{A.8}$$

and

$$\beta = \frac{K^{sp}(1-h)}{5h-1} \tag{A.9}$$

where the pristine equilibrium recruitment R_K is given by

$$R_K = K^{sp} / [\; f_0 w_0 + \sum_{a=1}^{m-1} f_a w_a e^{-(\sum_{a'=a\min}^{a-1} M_{a'})} + f_m w_m \frac{e^{-(\sum_{a'=a\min}^{m-1} M_{a'})}}{1-e^{-M_m}} \;] \tag{A.10}$$

Biomass

The model estimate of the exploitable ("available" to the fishing fleet) component of biomass is given by:

$$B_y^{\exp} = \sum_{a=0}^{m} w_a S_{y,a} N_{y,a} \qquad \text{for begin-year biomass, and} \tag{A.11}$$

$$B^{\exp}_{y+1/2} = \sum_{a=0}^{m} w_{a+1/2} S_{y,a} N_{y,a} e^{-Z_{y,a}/2} \text{ for the mid-year biomass} \quad (A.12)$$

where w_a denote the begin-year weights-at-age of fish caught in year y, and $w_{a+1/2}$ are the mid-year weights-at-age.

The age-structure of B_1^{sp} is taken here to be that corresponding to the equilibrium with no fishing mortality.

A.7.1 Model parameters

A.7.1.1 Natural mortality rate

The natural mortality rate, M, is assumed to be constant over all ages and years.

A.7.1.2 Fishing selectivity

Lognormally distributed variability about fishing selectivity values is taken to be correlated across both ages and years such that:

$$S_{y,a} = S_a e^{\tau_{y,a} - \sigma_\tau^2/2} \quad (A.13)$$

where

$\tau_{1,a_{\min}} \sim N(0, \sigma_\tau{}^2)$ is the log-residual for the first year and minimum age,

$\tau_{y,a} = \rho \tau_{y,a-1} + \sqrt{1-\rho^2}\, \chi_{y,a}$ is the log-residual for year y and year a, which is generated for ages a= *1* to m and years y,

$\tau_{y,0} = \rho \tau_{y-1,0} + \sqrt{1-\rho^2}\, \chi_{y,0}$ is the residual for the minimum age *0* and year y,

$$\chi_{y,a} \sim N(0, \sigma_\tau^2),$$

σ_τ is the standard deviation of the log-residuals ($\sigma_\chi = 0.4$ is used here), and

ρ is the serial correlation coefficient ($\rho = 0.5$ is assumed for these calculations).

A.7.1.3 Weight-at-age

The mass (w) of a fish at-age (a) is assumed to be related to a von Bertalanffy growth equation:

$$w_a = \alpha\, [l_\infty (1 - \exp(-\kappa(a - t_0)))\,]^\beta \quad (A.14)$$

A.7.2 Data generated by operating model

A.7.2.1 Mean length data

The annual mean length of the catch, when allowing for observation error, is given by:

$$\hat{L}_y = \sum_{a=0}^{m} \hat{P}_{y,a} \; L_a \tag{A.15}$$

where

L_a is the length of fish of age a as per the von Bertalanffy growth curve given by equation (A.14), and

$\hat{P}_{y,a} = P_{y,a} \; e^{\varphi_{y,a} - \sigma_l^2/(2P_{y,a})}$ is the model-generated proportion of fish caught of age a in year y which is renormalized such that $\sum_{a=0}^{m} \hat{P}_{y,a} = 1$.

In the above formulation $P_{y,a}$ denotes the proportion of fish of age a caught in year y of the simulation, given by:

$$P_{y,a} = \frac{C_{y,a}}{\sum_{a'=0}^{m} C_{y,a'}}$$

where $C_{y,a}$ is the total number of fish caught of age a in year y, given by equation (A.4), and

$\varphi_{y,a} \sim N(0, \sigma_l^2 / P_{y,a})$ reflect the variability for which the variance is assumed to be greater for those ages where sample sizes are smaller, where σ_l is the coefficient of variation (CV) associated with the mean length data.

A.7.2.2 Index of abundance

The cpue data are generated assuming that the abundance index is lognormally distributed about its expected value such that:

$$I_y = \hat{I}_y e^{\varepsilon_y} \tag{A.16}$$

where

I_y is the abundance index generated for year y,

$\hat{I}_y = \hat{q} \; \hat{B}_y$ is the corresponding model value, where $\hat{B}$ is the model value for exploitable biomass given by equation (A.12),

$\hat{q}$ is the constant of proportionality for the abundance series, and

$\varepsilon_y \sim N(0, \sigma_I^2)$ where σ_I is the coefficient of variation (CV) associated with the resource abundance index.

A.7.2.3 Annual catches

A key uncertainty for data-poor stocks is associated with the reliability of the historical catch series. Rather that assume that the historical catches are known without error, simulated catch data are generated assuming that total removals are lognormally distributed about the reported historical catches, i.e.

$$C_y = \hat{C}_y e^{\varepsilon_y^C - \sigma_C^2/2} \tag{A.17}$$

where

C_y is the true catch in year y,

$\hat{C}_y$ is the reported catch for year y, which is input, and

$\varepsilon_y^C \sim N(\mu, \sigma_C^2)$ where σ_C is the standard deviation of the log-residuals, and

$\mu \sim U[0, 0.1]$ is the mean which is sampled from a uniform distribution to account for negative bias.

Bias and noise are taken forward and incorporated in future catches in the same manner:

$$C_y = TAC_y e^{|\varepsilon_y^C| - \sigma_C^2/2} \tag{A.18}$$

where TAC_y is the TAC generated by the MP for year y.

Annex 8: Stocks assessed with ICES data-limited stock methods

The ICES approach to data-limited stocks was first implemented in the 2012 assessments and advice. In 2014 ICES provided advice on 254 stocks, of which 64% of stocks used data-limited methods. Table A.8.1 details the data category used in the ICES advice for each of these stocks over time. In addition, the current target category is provided for each stock. The target category is the data category that ICES scientists think is reasonably obtainable using data sources that are currently available or coming online shortly or planned methods benchmarks on a stock-by-stock basis. Table A.8.2 provides insight into how stocks move among data categories from one assessment year to the next. The majority of ICES data-limited stocks are in data category 3; using survey or cpue time-series along with catch/landings data to provide a catch advice. Table A.8.2 shows that there were eighty-five and ninety-four stocks using data category 3 in 2013 and 2014, respectively. Between 2013 and 2014, seventy stocks continued with category 3 assessments, while three stocks moved to fully accepted analytical assessments (category 1) and three moved to category 5 and 6 (advice based on recent catch or landings data only).

Figure A.8.1 shows the proportion of stocks assessed by ICES in each assessment category; 2, 3, 4, 5 and 6 since the ICES data-limited approach was implemented in the 2012 assessment year.

Table A.8.1. All stocks assessed by ICES in 2014 and the data categories, as used in the advice over time and their near-term target data category.

					ICES Data Category			
Stock code	Species	EcoRegion	Scientific Name	ICES Stock name	2012	2013	2014	Target
cod-2224	Cod	Baltic Sea	*Gadus morhua*	Cod in Subdivisions 22–24	1.00	1.00	1.00	1.00
her-2532-gor	Herring	Baltic Sea	*Clupea harengus*	Herring in Subdivisions 25–29 and 32 (excluding Gulf of Riga herring)	1.00	1.00	1.00	1.00
her-30	Herring	Baltic Sea	*Clupea harengus*	Herring in Subdivision 30 (Bothnian Sea)	1.00	1.00	1.00	1.00
her-riga	Herring	Baltic Sea	*Clupea harengus*	Herring in Subdivision 28.1 (Gulf of Riga)	1.00	1.00	1.00	1.00
spr-2232	Sprat	Baltic Sea	*Sprattus sprattus*	Sprat in Subdivisions 22–32 (Baltic Sea)	1.00	1.00	1.00	1.00
cap-bars	Capelin	Barents Sea & Norwegian Sea	*Mallotus villosus*	Capelin in Subareas I and II, excluding Division IIa west of 5°W (Barents Sea capelin)	1.00	1.00	1.00	1.00
cod-arct	Cod	Barents Sea & Norwegian Sea	*Gadus morhua*	Cod in Subareas I and II (northeast Arctic cod)	1.00	1.00	1.00	1.00
had-arct	Haddock	Barents Sea & Norwegian Sea	*Melanogra-mmus aeglefinus*	Haddock in Subareas I and II (Northeast Arctic)	1.00	1.00	1.00	1.00
pan-barn	Northern shrimp/ prawn	Barents Sea & Norwegian Sea	*Pandalus borealis*	Northern shrimp (*Pandalus borealis*) in Subareas I and II (Barents Sea)	1.00	1.00	1.00	1.00
anb-8c9a	Black-bellied anglerfish	Bay of Biscay & Atlantic Iberian waters	*Lophius budegassa*	Black-bellied anglerfish (*Lophius budegassa*) in Divisions VIIIc and IXa	1.00	1.00	1.00	1.00

					ICES Data Category			
Stock code	Species	EcoRegion	Scientific Name	ICES Stock name	2012	2013	2014	Target
anp-8c9a	White anglerfish	Bay of Biscay & Atlantic Iberian waters	*Lophius piscatorius*	White anglerfish (Lophius piscatorius) in Divisions VIIIc and IXa	1.00	1.00	1.00	1.00
hke-soth	Hake	Bay of Biscay & Atlantic Iberian waters	*Merluccius merluccius*	Hake in Divisions VIIIc and IXa (Southern stock)	1.00	1.00	1.00	1.00
mgb-8c9a	Four-spot megrim	Bay of Biscay & Atlantic Iberian waters	*Lepidorhom-bus boscii*	Four-spot megrim (Lepidorhombus boscii) in Divisions VIIIc and IXa	1.00	1.00	1.00	1.00
mgw-8c9a	Megrim	Bay of Biscay & Atlantic Iberian waters	*Lepidorhom-bus whiffiagonis*	Megrim (Lepidorhombus whiffiagonis) in Divisions VIIIc and IXa	1.00	1.00	1.00	1.00
sol-bisc	Sole	Bay of Biscay & Atlantic Iberian waters	*Solea solea*	Sole in Divisions VIIIa, b (Bay of Biscay)	1.00	1.00	1.00	1.00
ane-bisc	Anchovy	Bay of Biscay & Atlantic Iberian waters	*Engraulis encrasicolus*	Anchovy in Subarea VIII (Bay of Biscay)	1.00	1.00	1.00	1.00
hom-soth	Horse mackerel	Bay of Biscay & Atlantic Iberian waters	*Trachurus trachurus*	Horse mackerel (*Trachurus trachurus*) in Division IXa (Southern stock)	1.00	1.00	1.00	1.00
sar-soth	Sardine	Bay of Biscay & Atlantic Iberian waters	*Sardina pilchardus*	Sardine in Divisions VIIIc and IXa	1.00	1.00	1.00	1.00

					ICES Data Category			
Stock code	Species	EcoRegion	Scientific Name	ICES Stock name	2012	2013	2014	Target
cod-7e-k	Cod	Celtic Sea & West of Scotland	*Gadus morhua*	Cod in Divisions VIIe–k (Celtic Sea cod)	1.00	1.00	1.00	1.00
cod-scow	Cod	Celtic Sea & West of Scotland	*Gadus morhua*	Cod in Division VIa (West of Scotland)	1.00	1.00	1.00	1.00
had-7b-k	Haddock	Celtic Sea & West of Scotland	*Melano-grammus aeglefinus*	Haddock in Divisions VIIb,c,e–k	1.00	1.00	1.00	1.00
had-rock	Haddock	Celtic Sea & West of Scotland	*Melano-grammus aeglefinus*	Haddock in Division VIb (Rockall)	1.00	1.00	1.00	1.00
her-irls	Herring	Celtic Sea & West of Scotland	*Clupea harengus*	Herring in Division VIIa South of 52° 30′ N and VIIg,h,j,k (Celtic Sea and South of Ireland)	1.00	1.00	1.00	1.00
her-nirs	Herring	Celtic Sea & West of Scotland	*Clupea harengus*	Herring in Division VIIa North of 52º 30′N (Irish Sea)	1.00	1.00	1.00	1.00
her-vian	Herring	Celtic Sea & West of Scotland	*Clupea harengus*	Herring in Division VIa (North)	1.00	1.00	1.00	1.00
meg-4a6a	Megrim	Celtic Sea & West of Scotland	*Lepidorhombus* spp.	Megrim (*Lepidorhombus spp.*) in Divisions IVa and VIa	1.00	1.00	1.00	1.00
nep-11	Norway lobster	Celtic Sea & West of Scotland	*Nephrops norvegicus*	*Nephrops* in North Minch (FU 11)	1.00	1.00	1.00	1.00
nep-12	Norway lobster	Celtic Sea & West of Scotland	*Nephrops norvegicus*	*Nephrops* in South Minch (FU 12)	1.00	1.00	1.00	1.00
nep-13	Norway lobster	Celtic Sea & West of Scotland	*Nephrops norvegicus*	*Nephrops* in the Firth of Clyde (FU 13)	1.00	1.00	1.00	1.00

					ICES Data Category			
Stock code	Species	EcoRegion	Scientific Name	ICES Stock name	2012	2013	2014	Target
nep-14	Norway lobster	Celtic Sea & West of Scotland	*Nephrops norvegicus*	*Nephrops* in Irish Sea East (FU14)	1.00	1.00	1.00	1.00
nep-15	Norway lobster	Celtic Sea & West of Scotland	*Nephrops norvegicus*	*Nephrops* in Irish Sea West (FU 15)	1.00	1.00	1.00	1.00
nep-16	Norway lobster	Celtic Sea & West of Scotland	*Nephrops norvegicus*	*Nephrops* on Porcupine Bank (FU 16)	1.00	1.00	1.00	1.00
nep-17	Norway lobster	Celtic Sea & West of Scotland	*Nephrops norvegicus*	*Nephrops* on Aran Grounds (FU 17)	1.00	1.00	1.00	1.00
nep-19	Norway lobster	Celtic Sea & West of Scotland	*Nephrops norvegicus*	*Nephrops* off the southeastern and southwest coasts of Ireland (FU 19)	1.00	1.00	1.00	1.00
nep-22	Norway lobster	Celtic Sea & West of Scotland	*Nephrops norvegicus*	*Nephrops* in the Smalls (FU 22)	1.00	1.00	1.00	1.00
ple-echw	Plaice	Celtic Sea & West of Scotland	*Pleuronectes platessa*	Plaice in Division VIIe (Western Channel)	1.00	1.00	1.00	1.00
sol-celt	Sole	Celtic Sea & West of Scotland	*Solea solea*	Sole in Divisions VIIf,g (Celtic Sea)	1.00	1.00	1.00	1.00
sol-echw	Sole	Celtic Sea & West of Scotland	*Solea solea*	Sole in Division VIIe (Western Channel)	1.00	1.00	1.00	1.00
sol-iris	Sole	Celtic Sea & West of Scotland	*Solea solea*	Sole in Division VIIa (Irish Sea)	1.00	1.00	1.00	1.00
whg-7e-k	Whiting	Celtic Sea & West of Scotland	*Merlangius merlangus*	Whiting in Divisions VIIe–k	1.00	1.00	1.00	1.00
whg-scow	Whiting	Celtic Sea & West of Scotland	*Merlangius merlangus*	Whiting in Division VIa (West of Scotland)	1.00	1.00	1.00	1.00

					ICES Data Category			
Stock code	Species	EcoRegion	Scientific Name	ICES Stock name	2012	2013	2014	Target
cod-farp	Cod	Faroe Plateau Ecosystem	*Gadus morhua*	Cod in Subdivision Vb_1 (Faroe Plateau)	1.00	1.00	1.00	1.00
had-faro	Haddock	Faroe Plateau Ecosystem	*Melano-grammus aeglefinus*	Haddock in Division Vb	1.00	1.00	1.00	1.00
sai-faro	Saithe	Faroe Plateau Ecosystem	*Pollachius virens*	Saithe in Division Vb	1.00	1.00	1.00	1.00
ghl-grn	Halibut	Iceland & East Greenland	*Reinhardtius hippogloss-oides*	Greenland halibut in Subareas V, VI, XII, and XIV	1.00	1.00	1.00	1.00
cap-icel	Capelin	Iceland & East Greenland	*Mallotus villosus*	Capelin in Subareas V and XIV and Division IIa west of 5°W (Iceland–East Greenland–Jan Mayen area)	1.00	1.00	1.00	1.00
cod-iceg	Cod	Iceland & East Greenland	*Gadus morhua*	Cod in Division Va (Icelandic cod)	1.00	1.00	1.00	1.00
had-iceg	Haddock	Iceland & East Greenland	*Melano-grammus aeglefinus*	Haddock in Division Va (Icelandic haddock)	1.00	1.00	1.00	1.00
her-vasu	Herring	Iceland & East Greenland	*Clupea harengus*	Herring in Division Va (Icelandic summer-spawning herring)	1.00	1.00	1.00	1.00
sai-icel	Saithe	Iceland & East Greenland	*Pollachius virens*	Saithe in Division Va (Icelandic saithe)	1.00	1.00	1.00	1.00
her-47d3	Herring	North Sea	*Clupea harengus*	Herring in Subarea IV and Divisions IIIa and VIId (North Sea autumn spawners)	1.00	1.00	1.00	1.00
san-ns1	Sandeel	North Sea	*Ammodytes* spp.	Sandeel in the Dogger Bank area (SA 1)	1.00	1.00	1.00	1.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
san-ns2	Sandeel	North Sea	*Ammodytes* spp.	Sandeel in the Southeastern North Sea (SA 2)	1.00	1.00	1.00	1.00
san-ns3	Sandeel	North Sea	*Ammodytes* spp.	Sandeel in the Central Eastern North Sea (SA 3)	1.00	1.00	1.00	1.00
sol-kask	Sole	North Sea	*Solea solea*	Sole in Division IIIa and Subdivisions 22–24 (Skagerrak, Kattegat, and the Belts	1.00	1.00	1.00	1.00
cod-347d	Cod	North Sea	*Gadus morhua*	Cod in Subarea IV (North Sea) and Divisions VIId (Eastern Channel) and IIIa West (Skagerrak)	1.00	1.00	1.00	1.00
had-34	Haddock	North Sea	*Melano-grammus aeglefinus*	Haddock in Subarea IV (North Sea) and Division IIIa North (Skagerrak)	1.00	1.00	1.00	1.00
nep-3-4	Norway lobster	North Sea	*Nephrops norvegicus*	*Nephrops* in Division IIIa	1.00	1.00	1.00	1.00
nep-6	Norway lobster	North Sea	*Nephrops norvegicus*	*Nephrops* in Farn Deeps (FU 6)	1.00	1.00	1.00	1.00
nep-7	Norway lobster	North Sea	*Nephrops norvegicus*	*Nephrops* in Fladen Ground (FU 7)	1.00	1.00	1.00	1.00
nep-8	Norway lobster	North Sea	*Nephrops norvegicus*	*Nephrops* in Firth of Forth (FU 8)	1.00	1.00	1.00	1.00
nep-9	Norway lobster	North Sea	*Nephrops norvegicus*	Nephrops in Moray Firth (FU 9)	1.00	1.00	1.00	1.00
nop-34 june	Norway pout	North Sea	*Trisopterus esmarkii*	Norway pout in Subarea IV (North Sea) and Division IIIa (Skagerrak–Kattegat) June advice	1.00	1.00	1.00	1.00
ple-nsea	Plaice	North Sea	*Pleuronectes platessa*	Plaice in Subarea IV (North Sea)	1.00	1.00	1.00	1.00

					ICES Data Category			
Stock code	Species	EcoRegion	Scientific Name	ICES Stock name	2012	2013	2014	Target
sai-3a46	Saithe	North Sea	*Pollachius virens*	Saithe in Subarea IV (North Sea), Division IIIa (Skagerrak), and Subarea VI (West of Scotland and Rockall)	1.00	1.00	1.00	1.00
sol-eche	Sole	North Sea	*Solea solea*	Sole in Division VIId (Eastern Channel)	1.00	1.00	1.00	1.00
sol-nsea	Sole	North Sea	*Solea solea*	Sole in Subarea IV (North Sea)	1.00	1.00	1.00	1.00
whg-47d	Whiting	North Sea	*Merlangius merlangus*	Whiting in Subarea IV (North Sea) and Division VIId (Eastern Channel)	1.00	1.00	1.00	1.00
nop-34-oct	Norway pout	North Sea	*Trisopterus esmarkii*	Norway pout in Subarea IV (North Sea) and Division IIIa (Skagerrak–Kattegat) October advice	1.00	1.00	1.00	1.00
her-3a22	Herring	North Sea & Baltic Sea	*Clupea harengus*	Herring in Division IIIa and Subdivisions 22–24 (western Baltic spring spawners)	1.00	1.00	1.00	1.00
her-noss	Herring	Widely Distributed	*Clupea harengus*	Herring in the Northeast Atlantic (Norwegian spring-spawning herring)	1.00	1.00	1.00	1.00
hke-nrth	Hake	Widely Distributed	*Merluccius merluccius*	Hake in Division IIIa, Subareas IV, VI, and VII, and Divisions VIIIa,b,d (Northern stock)	1.00	1.00	1.00	1.00
hom-west	Horse mackerel	Widely Distributed	*Trachurus trachurus*	Horse mackerel (*Trachurus trachurus*) in Divisions IIa, IVa, Vb, VIa, VIIa–c,e–k, and VIIIa–e (Western stock)	1.00	1.00	1.00	1.00
whb-comb	Blue whiting	Widely Distributed	*Micromes-istius poutassou*	Blue whiting in Subareas I–IX, XII, and XIV	1.00	1.00	1.00	1.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
rng-5b67	Roundnose grenadier	Widely Distributed	*Coryphaen-oides rupestris*	Roundnose grenadier (*Coryphaenoides rupestris*) in Subareas VI and VII, and Divisions Vb and XIIb	1.00	1.00	1.00	1.00
usk-icel	Tusk	Widely Distributed	*Brosme brosme*	Tusk (*Brosme brosme*) in Division Va and Subarea XIV	1.00	1.00	1.00	1.00
cod-2532	Cod	Baltic Sea	*Gadus morhua*	Cod in Subdivisions 25–32	1.00	1.00	3.20	1.00
had-scow	Haddock	Celtic Sea & West of Scotland	*Melano-grammus aeglefinus*	Haddock in Division VIa (West of Scotland)	1.00	1.00	na	1.00
smn-arct	Beaked redfish	Barents Sea & Norwegian Sea	*Sebastes mentella*	Beaked redfish (*Sebastes mentella*) in Subareas I and II	1.00	2.00	1.00	1.00
sai-arct	Saithe	Barents Sea & Norwegian Sea	*Pollachius virens*	Saithe in Subareas I and II (Northeast Arctic)	1.00	2.00	1.00	1.00
mac-nea	Mackerel	Widely Distributed	*Scomber scombrus*	Mackerel in the Northeast Atlantic (combined Southern, Western, and North Sea spawning components)	1.00	na	1.00	1.00
bli-5b67	Blue ling	Widely Distributed	*Molva dypterygia*	Blue ling (*Molva dypterygia*) in Division Vb and Subareas VI and VII	2.00	2.00	1.00	2.00
smr-arct	Golden redfish	Barents Sea & Norwegian Sea	*Sebastes marinus*	Golden redfish (*Sebastes marinus*) in Subareas I and II	2.00	2.13	2.13	2.00
cod-iris	Cod	Celtic Sea & West of Scotland	*Gadus morhua*	Cod in Division VIIa (Irish Sea)	2.13	2.13	1.00	1.00
cod-kat	Cod	North Sea	*Gadus morhua*	Cod in Division IIIa East (Kattegat)	2.13	2.13	1.00	1.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
her-irlw	Herring	Celtic Sea & West of Scotland	*Clupea harengus*	Herring in Divisions VIa (South) and VIIb,c	2.13	2.13	2.13	1.00
whg-iris	Whiting	Celtic Sea & West of Scotland	*Merlangius merlangus*	Whiting in Division VIIa (Irish Sea)	2.13	2.13	2.13	1.50
boc-nea	Boarfish	Widely Distributed	*Capros aper*	Boarfish in the Northeast Atlantic	3.00	1.00	3.00	1.00
smr-5614	Golden redfish	Iceland & East Greenland	*Sebastes marinus*	Golden redfish (*Sebastes marinus*) in Subareas V, VI, XII, and XIV	3.00	2.11	1.00	1.00
cod-coas	Cod	Barents Sea & Norwegian Sea	*Gadus morhua*	Cod in Subareas I and II (Norwegian coastal waters cod)	3.00	3.00	3.00	1.00
ghl-arct	Halibut	Barents Sea & Norwegian Sea	*Reinhardtius hippogloss-oides*	Greenland halibut in Subareas I and II	3.00	3.00	3.00	1.00
smn-grl	Beaked redfish	Iceland & East Greenland	*Sebastes mentella*	Beaked redfish (*Sebastes mentella*) in Subareas V, XII, and XIV and NAFO Subareas 1+2 (Deep pelagic stock > 500 m)	3.00	3.00	3.00	3.00
smn-sp	Beaked redfish	Iceland & East Greenland	*Sebastes mentella*	Beaked redfish (*Sebastes mentella*) in Subareas V, XII, and XIV and NAFO Subareas 1+2 (Shallow pelagic stock < 500 m)	3.00	3.00	3.00	3.00
smn-dp	Beaked redfish	Iceland & East Greenland	*Sebastes mentella*	Beaked redfish (*Sebastes mentella*) in Division XIVb (Demersal)	3.00	3.00	3.10	3.00
ple-eche	Plaice	North Sea	*Pleuronectes platessa*	Plaice in Division VIId (Eastern Channel)	3.10	2.11	2.11	1.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
ple-2123	Plaice	Baltic Sea	*Pleuronectes platessa*	Plaice in Subdivisions 21, 22, and 23 (Kattegat, Belts, and Sound)	3.10	3.10	3.20	1.00
ple-skag	Plaice	North Sea	*Pleuronectes platessa*	Plaice in Subdivision 20 (Skagerrak)	3.12	3.20	3.20	1.00
cod-farb	Cod	Faroe Plateau Ecosystem	*Gadus morhua*	Cod in Subdivision Vb_2 (Faroe Bank)	3.13	3.13	3.13	1.00
dgs-nea	Spurdog	Widely Distributed	*Squalus acanthias*	Spurdog (*Squalus acanthias*) in the Northeast Atlantic	3.14	3.14	1.00	1.00
nep-25	Norway lobster	Bay of Biscay & Atlantic Iberian waters	*Nephrops norvegicus*	*Nephrops* in North Galicia (FU 25)	3.14	3.14	3.14	3.00
nep-2627	Norway lobster	Bay of Biscay & Atlantic Iberian waters	*Nephrops norvegicus*	*Nephrops* in West Galicia and North Portugal (FUs 26–27)	3.14	3.14	3.14	3.00
nep-31	Norway lobster	Bay of Biscay & Atlantic Iberian waters	*Nephrops norvegicus*	*Nephrops* in the Cantabrian Sea (FU 31)	3.14	3.14	3.14	3.00
rjb-celt	Common skates	Celtic Sea & West of Scotland	*Dipturus* spp.	Common skate (*Dipturus batis*) complex (flapper skate (*Dipturus cf. flossada*) and blue skate (*Dipturus cf. intermedia*)) in Subareas VI and VII (excluding VIId)	3.14	3.14	3.14	3.00
cod-ewgr	Cod	Iceland & East Greenland	*Gadus morhua*	Offshore cod in ICES Subarea XIV and NAFO Subarea 1 (Greenland cod)	3.14	3.14	3.14	3.00

					ICES Data Category			
Stock code	Species	EcoRegion	Scientific Name	ICES Stock name	2012	2013	2014	Target
ele-nea	European eel	Widely Distributed	*Anguilla anguilla*	European eel	3.14	3.14	3.14	1.00
guq-nea	Leafscale gulper shark	Widely Distributed	*Centrophorus squamosus*	Leafscale gulper shark (*Centrophorus squamosus*) in the Northeast Atlantic	3.14	3.14	5.30	3.00
cyo-nea	Portuguese dogfish	Widely Distributed	*Centroscym-nus coelolepis*	Portuguese dogfish (*Centroscymnus coelolepis*) in the Northeast Atlantic	3.14	3.14	6.30	3.00
pan-sknd	Northern shrimp/ prawn	North Sea	*Pandalus borealis*	Northern shrimp (*Pandalus borealis*) in Divisions IIIa and IVa East (Skagerrak and Norwegian Deep)	3.20	1.00	1.00	1.00
bsf-89	Black scabbardfish	Widely Distributed	*Aphanopus carbo*	Black scabbardfish (*Aphanopus carbo*) in Subareas VIII and IX	3.20	3.20	3.00	2.00
bsf-nrtn	Black scabbardfish	Widely Distributed	*Aphanopus carbo*	Black scabbardfish (*Aphanopus carbo*) in Subareas VI, VII, and Divisions Vb and XIIb	3.20	3.20	3.00	2.00
bll-2232	Brill	Baltic Sea	*Scophthal-mus rhombus*	Brill in Subdivisions 22–32 (Baltic Sea)	3.20	3.20	3.20	3.00
dab-2232	Dab	Baltic Sea	*Limanda limanda*	Dab in Subdivisions 22–32 (Baltic Sea)	3.20	3.20	3.20	3.00
fle-2223	Flounder	Baltic Sea	*Platichthys flesus*	Flounder in Subdivisions 22–23 (Belts and sound)	3.20	3.20	3.20	2.00
fle-2425	Flounder	Baltic Sea	*Platichthys flesus*	Flounder in Subdivisions 24–25 (Southern Baltic Sea)	3.20	3.20	3.20	2.00
fle-2628	Flounder	Baltic Sea	*Platichthys flesus*	Flounder in Subdivisions 26 and 28 (Eastern Gotland and Gulf of Gdańsk)	3.20	3.20	3.20	2.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
fle-2732	Flounder	Baltic Sea	*Platichthys flesus*	Flounder in Subdivisions 27 and 29–32 (Northern Baltic Sea)	3.20	3.20	3.20	2.00
her-31	Herring	Baltic Sea	*Clupea harengus*	Herring in Subdivision 31 (Bothnian Bay)	3.20	3.20	3.20	2.00
ple-2432	Plaice	Baltic Sea	*Pleuronectes platessa*	Plaice in Subdivisions 24-32 (Baltic Sea)	3.20	3.20	3.20	3.00
tur-2232	Turbot	Baltic Sea	*Scophthal-mus maximus*	Turbot in Subdivisions 22–32 (Baltic Sea)	3.20	3.20	3.20	3.00
nep-2324	Norway lobster	Bay of Biscay & Atlantic Iberian waters	*Nephrops norvegicus*	*Nephrops* in Division VIIIab (Bay of Biscay, FUs 23–24)	3.20	3.20	3.20	1.00
nep-2829	Norway lobster	Bay of Biscay & Atlantic Iberian waters	*Nephrops norvegicus*	*Nephrops* in Southwest and South Portugal (FUs 28–29)	3.20	3.20	3.20	1.00
nep-30	Norway lobster	Bay of Biscay & Atlantic Iberian waters	*Nephrops norvegicus*	*Nephrops* in the Gulf of Cadiz (FU 30)	3.20	3.20	3.20	1.00
rjc-bisc	Thornback ray	Bay of Biscay & Atlantic Iberian waters	*Raja clavata*	Thornback ray (*Raja clavata*) in Subarea VIII (Bay of Biscay and Cantabrian Sea)	3.20	3.20	3.20	3.00
rjn-8c	Cuckoo ray	Bay of Biscay & Atlantic Iberian waters	*Leucoraja naevu*	Cuckoo ray (*Leucoraja naevus*) in Division VIIIc (Cantabrian Sea)	3.20	3.20	3.20	3.00

					ICES Data Category			
Stock code	Species	EcoRegion	Scientific Name	ICES Stock name	2012	2013	2014	Target
syc-8c9a	Lesser-spotted dogfish	Bay of Biscay & Atlantic Iberian waters	*Scyliorhinus canicula*	Lesser-spotted dogfish (*Scyliorhinus canicula*) in Divisions VIIIc and IXa (Atlantic Iberian waters)	3.20	3.20	3.20	3.00
syc-bisc	Lesser-spotted dogfish	Bay of Biscay & Atlantic Iberian waters	*Scyliorhinus canicula*	Lesser-spotted dogfish (*Scyliorhinus canicula*) in Divisions VIIIa,b,d (Bay of Biscay)	3.20	3.20	3.20	3.00
anb-78ab	Black bellied anglerfish	Celtic Sea & West of Scotland	*Lophius budegassa*	Anglerfish (*L. budegassa*) in Divisions VIIb–k and VIIIa,b,d	3.20	3.20	3.20	1.00
anp-78ab	White Anglerfish	Celtic Sea & West of Scotland	*Lophius piscatorius*	Anglerfish (*Lophius piscatorius*) in Divisions VIIb–k and VIIIa,b,d	3.20	3.20	3.20	1.00
had-iris	Haddock	Celtic Sea & West of Scotland	*Melanogra-mmus aeglefinus*	Haddock in Division VIIa (Irish Sea)	3.20	3.20	3.20	3.00
meg-rock	Megrim	Celtic Sea & West of Scotland	*Lepidorhom-bus spp.*	Megrim (*Lepidorhombus* spp.) in ICES Division VIb (Rockall)	3.20	3.20	3.20	3.00
mgw-78	Megrim	Celtic Sea & West of Scotland	*Lepidorhom-bus whiffiagonis*	Megrim (*Lepidorhombus whiffiagonis*) in Divisions VIIb–k and VIIIa,b,d	3.20	3.20	3.20	1.00
ple-celt	Plaice	Celtic Sea & West of Scotland	*Pleuronectes platessa*	Plaice in Divisions VIIf,g (Celtic Sea)	3.20	3.20	3.20	3.00
ple-iris	Plaice	Celtic Sea & West of Scotland	*Pleuronectes platessa*	Plaice in Division VIIa (Irish Sea)	3.20	3.20	3.20	3.00
rjc-7afg	Thornback ray	Celtic Sea & West of Scotland	*Raja clavata*	Thornback ray (*Raja clavata*) in Divisions VIIa, f, g (Irish and Celtic Sea)	3.20	3.20	3.20	3.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
rjc-VI	Thornback ray	Celtic Sea & West of Scotland	*Raja clavata*	Thornback ray (*Raja clavata*) west of Scotland (Subarea VI)	3.20	3.20	3.20	3.00
syc-celt	Lesser-spotted dogfish	Celtic Sea & West of Scotland	*Scyliorhinus canicula*	Lesser-spotted dogfish (*Scyliorhinus canicula*) in Subarea VI and Divisions VIIa–c, e–j (Celtic Seas and west of Scotland)	3.20	3.20	3.20	3.00
ang-ivvi	Anglerfish	Celtic Sea, West of Scotl& & North Sea	*Lophius* spp.	Anglerfish (*Lophius piscatorius* and *L. budegassa*) in Division IIIa, and Subareas IV and VI	3.20	3.20	3.20	1.00
smn-con	Beaked redfish	Icel& & East Greenland	*Sebastes mentella*	Beaked redfish (*Sebastes mentella*) in Division Va and Subarea XIV (Icelandic slope stock)	3.20	3.20	3.20	3.00
syc-347d	Lesser-spotted dogfish	North Sea	*Scyliorhinus canicula*	Lesser-spotted dogfish (*Scyliorhinus canicula*) in Subarea IV, and Divisions IIIa and VIId (North Sea, Skagerrak, Kattegat, and Eastern English Channel)	3.20	3.20	3.20	3.00
san-ns4	Sandeel	North Sea	*Ammodytes* spp.	Sandeel in the Central Western North Sea (SA 4)	3.20	3.20	3.20	5.00
rjc-347d	Thornback ray	North Sea	*Raja clavata*	Thornback ray (*Raja clavata*) in Subarea IV, and Divisions IIIa and VIId (North Sea, Skagerrak, Kattegat and eastern English Channel)	3.20	3.20	3.20	3.00
arg-oth	Greater silver smelt	Widely Distributed	*Argentina silus*	Greater silver smelt (*Argentina silus*) in Subareas I, II, IV, VI, VII, VIII, IX, X, XII, and XIV, and Divisions IIIa and Vb (other areas)	3.20	3.20	3.20	3.00

					ICES Data Category			
Stock code	Species	EcoRegion	Scientific Name	ICES Stock name	2012	2013	2014	Target
gfb-comb	Greater forkbeard	Widely Distributed	*Phycis blennoides*	Greater forkbeard (*Phycis blennoides*) in the Northeast Atlantic	3.20	3.20	3.20	3.00
raj-mar	Rays and skates	Widely Distributed		Rays and skates (mainly thornback ray) in the Azores and Mid-Atlantic Ridge	3.20	3.20	3.20	3.00
trk-nea	Smooth hounds	Widely Distributed	*Mustelus* spp.	Starry smooth-hound (*Mustelus* spp.) in the Northeast Atlantic	3.20	3.20	3.20	3.00
lin-faro	Ling	Widely Distributed	*Molva molva*	Ling (*Molva molva*) in Division Vb	3.20	3.20	3.20	1.00
lin-oth	Ling	Widely Distributed	*Molva molva*	Ling (*Molva molva*) in Divisions IIIa and IVa, and in Subareas VI, VII, VIII, IX, XII, and XIV (other areas)	3.20	3.20	3.20	3.00
sbr-x	Red sea bream	Widely Distributed	*Pagellus bogaraveo*	Red (=blackspot) sea bream (*Pagellus bogaraveo*) in Subarea X (Azores region)	3.20	3.20	3.20	3.00
usk-oth	Tusk	Widely Distributed	*Brosme brosme*	Tusk (*Brosme brosme*) in Divisions IIIa, Vb, VIa, and XIIb, and Subareas IV, VII, VIII, and IX (other areas)	3.20	3.20	3.20	3.00
usk-rock	Tusk	Widely Distributed	*Brosme brosme*	Tusk (*Brosme brosme*) in Division VIb (Rockall)	3.20	3.20	3.20	3.00
rjm-347d	Spotted ray	North Sea	*Raja montagui*	Spotted ray (*Raja montagui*) in Subarea IV, and Divisions IIIa and VIId (North Sea, Skagerrak, Kattegat, and Eastern English Channel)	3.20	3.20	5.20q	3.00
fle-2232	Flounder	Baltic Sea	*Platichthys flesus*	Flounder in Subdivisions 22–32 (Baltic Sea)	3.20	3.20	na	2.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
ang-78ab	Anglerfish	Celtic Sea & West of Scotland	*Lophius* spp.	Anglerfish (*Lophius piscatorius* and *L. budegassa*) in Divisions VIIb–k and VIIIa,b,d	3.20	3.20	na	1.00
rjm-7afg	Spotted ray	Celtic Sea & West of Scotland	*Raja montagui*	Spotted ray (*Raja montagui*) in Divisions VIIa, f, g	3.20	3.20	na	3.00
rjm-VI	Spotted ray	Celtic Sea & West of Scotland	*Raja montagui*	Spotted ray (*Raja montagui*) in Subarea VI	3.20	3.20	na	3.00
rjn-celt	Cuckoo ray	Celtic Sea & West of Scotland	*Leucoraja naevu*	Cuckoo ray (*Leucoraja naevus*) in Subarea VI and Divisions VIIa–c, e–j	3.20	3.20	na	3.00
rjc-347de	Thornback ray	North Sea	*Raja clavata*	Thornback ray (*Raja clavata*) in Subarea IV and in Divisions IIIa and VIId, e (North Sea, Skagerrak, Kattegat, and English Channel)	3.20	3.20	na	3.00
rjn-347d	Cuckoo ray	North Sea	*Leucoraja naevu*	Cuckoo ray (*Leucoraja naevus*) in Subarea IV and in Divisions IIIa and VIId (North Sea, Skagerrak, Kattegat, and eastern English Channel)	3.20	3.20	na	3.00
rjr-347d	Starry ray	North Sea	*Amblyraja radiata*	Starry ray (*Amblyraja radiata*) in Subarea IV and in Divisions IIIa and VIId (North Sea, Skagerrak, Kattegat, and eastern English Channel)	3.20	3.20	na	3.00
lin-icel	Ling	Widely Distributed	*Molva molva*	Ling (*Molva molva*) in Division Va	3.30	3.30	1.00	1.00
arg-icel	Greater silver smelt	Widely Distributed	*Argentina silus*	Greater silver smelt (*Argentina silus*) in Division Va	3.30	3.30	3.30	3.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
bli-5a14	Blue ling	Widely Distributed	*Molva dypterygia*	Blue ling (*Molva dypterygia*) in Division Va and Subarea XIV (Iceland and Reykjanes ridge)	3.30	3.30	3.30	3.00
pol-celt	Pollack	Celtic Sea & West of Scotland	*Pollachius pollachius*	Pollack in Subareas VI and VII (Celtic Sea and West of Scotland)	4.12	4.12	4.12	4.00
ple-7h-k	Plaice	Celtic Sea & West of Scotland	*Pleuronectes platessa*	Plaice in Divisions VIIh–k (Southwest of Ireland)	4.13	3.20	3.20	3.50
sol-7h-k	Sole	Celtic Sea & West of Scotland	*Solea solea*	Sole in Divisions VIIh–k	4.13	3.20	3.20	3.50
nep-2021	Norway lobster	Celtic Sea & West of Scotland	*Nephrops norvegicus*	*Nephrops* in the FU 20–21 (Labadie)	4.14	4.14	4.14	1.00
nep-10	Norway lobster	North Sea	*Nephrops norvegicus*	*Nephrops* in Noup (FU 10)	4.14	4.14	4.14	4.00
nep-32	Norway lobster	North Sea	*Nephrops norvegicus*	*Nephrops* in the Norwegian Deep (FU 32)	4.14	4.14	4.14	1.00
nep-33	Norway lobster	North Sea	*Nephrops norvegicus*	*Nephrops* off Horn's Reef (FU 33)	4.14	4.14	4.14	1.00
nep-34	Norway lobster	North Sea	*Nephrops norvegicus*	*Nephrops* in Devil's Hole (FU 34)	4.14	4.14	4.14	1.00
nep-5	Norway lobster	North Sea	*Nephrops norvegicus*	*Nephrops* in Botney Gut–Silver Pit (FU 5)	4.14	4.14	4.14	1.00
sbr-678	Red sea bream	Widely Distributed	*Pagellus bogaraveo*	Red (=blackspot) sea bream (*Pagellus bogaraveo*) in Subareas VI, VII, and VIII	4.20	4.20	6.30	4.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
bsf-oth	Black scabbardfish	Widely Distributed	*Aphanopus carbo*	Black scabbardfish (*Aphanopus carbo*) in other areas (Subareas I, II, IV, X, XIV, and Divisions IIIa and Va)	5.00	5.00	3.00	5.00
spr-nsea	Sprat	North Sea	*Sprattus sprattus*	Sprat in Subarea IV (North Sea)	5.20	1.00	1.00	1.00
bss-47	Sea bass	Celtic Sea, West of Scotl& & North Sea	*Dicentrar-chus labrax*	European sea bass in Divisions IVbc, VIIa and VIId-h (Irish Sea, Celtic Sea, English Channel and southern North Sea)	5.20	3.20	1.00	1.00
spr-ech	Sprat	Celtic Sea & West of Scotland	*Sprattus sprattus*	Sprat in Divisions VIId,e	5.20	3.20	3.20	3.00
spr-kask	Sprat	North Sea	*Sprattus sprattus*	Sprat in Division IIIa (Skagerrak – Kattegat)	5.20	3.20	3.20	3.50
mur-347d	Striped red mullet	North Sea	*Mullus surmuletus*	Striped red mullet in Subarea IV (North Sea) and Divisions VIId (Eastern English Channel) and IIIa (Skagerrak–Kattegat)	5.20	3.20	3.20	3.00
jaa-10	Blue jack mackerel	Bay of Biscay & Atlantic Iberian waters	*Trachurus picturatus*	Blue jack mackerel (Trachurus picturatus) in Subdivision Xa2 (Azores)	5.20	5.20	3.00	4.00
hom-nsea	Horse mackerel	North Sea	*Trachurus trachurus*	Horse mackerel (*Trachurus trachurus*) in Divisions IIIa, IVb,c, and VIId (North Sea stock)	5.20	5.20	3.00	1.00
lin-arct	Ling	Widely Distributed	*Molva molva*	Ling (*Molva molva*) in Subareas I and II	5.20	5.20	3.20	3.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
sbr-ix	Red sea bream	Widely Distributed	*Pagellus bogaraveo*	Red (=blackspot) sea bream (*Pagellus bogaraveo*) in Subarea IX	5.20	5.20	3.20	3.00
bss-8ab	Sea bass	Bay of Biscay & Atlantic Iberian waters	*Dicentrar-chus labrax*	European sea bass in Divisions VIIIa,b (Bay of Biscay)	5.20	5.20	5.20	4.00
bss-8c9a	Sea bass	Bay of Biscay & Atlantic Iberian waters	*Dicentrar-chus labrax*	European sea bass in Divisions VIIIc and IXa (Atlantic Iberian waters)	5.20	5.20	5.20	5.00
raj-89a	Other skates	Bay of Biscay & Atlantic Iberian waters		Other skates and rays in Subarea VIII and Division IXa (Bay of Biscay and Atlantic Iberian waters)	5.20	5.20	5.20	5.00
spr-celt	Sprat	Celtic Sea & West of Scotland	*Sprattus sprattus*	Sprat in Subarea VI and Divisions VIIa–c and f–k (Celtic Sea and West of Scotland)	5.20	5.20	5.20	5.00
san-ns6	Sandeel	North Sea	*Ammodytes* spp.	Sandeel in Division IIIa East (Kattegat, SA 6)	5.20	5.20	5.20	5.00
whg-kask	Whiting	North Sea	*Merlangius merlangus*	Whiting in Division IIIa (Skagerrak – Kattegat)	5.20	5.20	5.20	3.00
rng-1012	Roundnose grenadier	Widely Distributed	*Coryphaenoi-des rupestris*	Roundnose grenadier (*Coryphaenoides rupestris*) on the Mid-Atlantic Ridge (Divisions Xb and XIIc, and Subdivisions Va_1, $XIIa_1$, and $XIVb_1$)	5.20	5.20	5.20	5.00
gag-nea	Tope	Widely Distributed	*Galeorhinus galeus*	Tope (*Galeorhinus galeus*) in the Northeast Atlantic	5.20	5.20	5.20	4.00
mur-west	Striped red mullet	Widely Distributed	*Mullus surmuletus*	Striped red mullet in Subarea VI, VIII and Divisions VIIa–c, e–k and IXa (Western area)	5.20	5.20	5.20	4.00

					ICES Data Category			
Stock code	Species	EcoRegion	Scientific Name	ICES Stock name	2012	2013	2014	Target
usk-arct	Tusk	Widely Distributed	*Brosme brosme*	Tusk (*Brosme brosme*) in Subareas I and II (Arctic)	5.20	5.20	5.20	3.00
pol-nsea	Pollack	North Sea	*Pollachius pollachius*	Pollack in Subarea IV and Division IIIa	5.20	5.20	5.20 and 3.14	3.00
rjc-pore	Thornback ray	Bay of Biscay & Atlantic Iberian waters	*Raja clavata*	Thornback ray (*Raja clavata*) in Division IXa (west of Galicia, Portugal, and Gulf of Cadiz)	5.20q	5.20q	3.20	3.00
rjh-pore	Blonde ray	Bay of Biscay & Atlantic Iberian waters	*Raja brachyura*	Blonde ray (*Raja brachyura*) in Division IXa (west of Galicia, Portugal, and Gulf of Cadiz)	5.20q	5.20q	3.20	3.00
rjm-bisc	Spotted ray	Bay of Biscay & Atlantic Iberian waters	*Raja montagui*	Spotted ray (*Raja montagui*) in Subarea VIII (Bay of Biscay and Cantabrian Sea)	5.20q	5.20q	3.20	4.00
rjm-pore	Spotted ray	Bay of Biscay & Atlantic Iberian waters	*Raja montagui*	Spotted ray (*Raja montagui*) in Division IXa (west of Galicia, Portugal, and Gulf of Cadiz)	5.20q	5.20q	3.20	4.00
rjn-pore	Cuckoo ray	Bay of Biscay & Atlantic Iberian waters	*Leucoraja naevu*	Cuckoo ray (*Leucoraja naevus*) in Division IXa (west of Galicia, Portugal, and Gulf of Cadiz)	5.20q	5.20q	3.20	3.00
pol-89a	Pollack	Bay of Biscay & Atlantic Iberian waters	*Pollachius pollachius*	Pollack (*Pollachius pollachius*) in Subarea VIII and Division IXa	5.20q	5.20q	5.20	5.00
rjf-celt	Shagreen ray	Celtic Sea & West of Scotland	*Leucoraja fullonica*	Shagreen ray (*Leucoraja fullonica*) in Subareas VI and VII (Celtic Sea and West of Scotland)	5.20q	5.20q	5.20	4.00

					ICES Data Category			
Stock code	Species	EcoRegion	Scientific Name	ICES Stock name	2012	2013	2014	Target
rjh-7afg	Blonde ray	Celtic Sea & West of Scotland	*Raja brachyura*	Blonde ray (*Raja brachyura*) in Divisions VIIa, f, g (Irish and Celtic Sea)	5.20q	5.20q	5.20	3.00
rji-celt	Sandy ray	Celtic Sea & West of Scotland	*Leucoraja circularis*	Sandy ray (*Leucoraja circularis*) in Subareas VI and VII (Celtic Sea and West of Scotland)	5.20q	5.20q	5.20	4.00
rjh-7e	Blonde ray	Celtic Sea & West of Scotland	*Raja brachyura*	Blonde ray (*Raja brachyura*) in Division VIIe (western English Channel)	5.20q	5.20q	5.20	3.00
raj-347d	Other skates and rays	North Sea	*Rajadai*	Other skates and rays in the North sea ecoregion (Subarea IV, and Divisions IIIa and VIId)	5.20q	5.20q	5.20	5.00
ple-89a	Plaice	Bay of Biscay & Atlantic Iberian waters	*Pleuronectes platessa*	Plaice in Subarea VIII and Division IXa	5.20q	5.20q	5.20q	4.00
whg-89a	Whiting	Bay of Biscay & Atlantic Iberian waters	*Merlangius merlangus*	Whiting in Subarea VIII and Division IXa	5.20q	5.20q	5.20q	4.00
gur-comb	Red gurnard	Widely Distributed	*Aspitrigla cuculus*	Red gurnard in the Northeast Atlantic	5.20q	5.20q	6.20q	4.00
rjh-VI	Blonde ray	Celtic Sea & West of Scotland	*Raja brachyura*	Blonde ray (*Raja brachyura*) in Subarea VI	5.20q	5.20q	na	4.00
rjh-4c7de	Blonde ray	North Sea	*Raja brachyura*	Blonde ray (*Raja brachyuran*) in Divisions IVc and VIId, e (Southern North Sea and English Channel)	5.20q	5.20q	na	4.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
rjh-4c7d	Blonde ray	North Sea	*Raja brachyura*	Blonde ray (*Raja brachyura*) in Divisions IVc and VIId (Southern North Sea and eastern English Channel)	5.20q	5.20q	NA	4.00
sck-nea	Kitefin shark	Widely Distributed	*Dalatias licha*	Kitefin shark (*Dalatias licha*) in the Northeast Atlantic	5.30	5.30	3.14	6.00
bli-oth	Blue ling	Widely Distributed	*Molva dypterygia*	Blue ling (*Molva dypterygia*) in Divisions IIIa and Iva, and Subareas I, II, VIII, IX, and XII	5.30	5.30	5.30	4.00
por-nea	Porbeagle	Widely Distributed	*Lamna nasus*	Porbeagle (*Lamna nasus*) in the Northeast Atlantic	5.30	5.30	5.30	4.00
rjb-89a	Common skates	Bay of Biscay & Atlantic Iberian waters	*Dipturus* spp.	Common skate (*Dipturus batis*-complex) in Subarea VIII and Division IXa (Bay of Biscay and Atlantic Iberian waters)	5.30	5.30	6.30	6.00
alf-comb	Golden eye perch	Widely Distributed	*Beryx* spp.	Alfonsinos/Golden eye perch (*Beryx* spp.) in the Northeast Atlantic	6.20	6.20	5.20	6.00
bss-wosi	Sea bass	Celtic Sea & West of Scotland	*Dicentrar-chus labrax*	European sea bass in Divisions VIa, VIIb and VIIj (West of Scotland and Ireland)	6.20	6.20	6.20	5.00
cod-rock	Cod	Celtic Sea & West of Scotland	*Gadus morhua*	Cod in Division VIb (Rockall)	6.20	6.20	6.20	6.00
ple-7b-c	Plaice	Celtic Sea & West of Scotland	*Pleuronectes platessa*	Plaice in Divisions VIIb,c (West of Ireland)	6.20	6.20	6.20	6.00
sol-7b-c	Sole	Celtic Sea & West of Scotland	*Solea solea*	Sole in Divisions VIIb,c (West of Ireland)	6.20	6.20	6.20	6.00
whg-rock	Whiting	Celtic Sea & West of Scotland	*Merlangius merlangus*	Whiting in Division VIb (Rockall)	6.20	6.20	6.20	6.00

					ICES Data Category			
Stock code	Species	EcoRegion	Scientific Name	ICES Stock name	2012	2013	2014	Target
rng-oth	Roundnose grenadier	Widely Distributed	*Coryphaen-oides rupestris*	Roundnose grenadier (*Coryphaenoides rupestris*) in all other areas (Subareas I, II, IV, VIII, and IX, Division XIVa, and Subdivisions Va2 and XIVb2)	6.20	6.20	6.20	6.00
gug-347d	Grey gurnard	North Sea	*Eutrigla gurnardus*	Grey gurnard in Subarea IV (North Sea) and Divisions VIId (Eastern Channel) and IIIa (Skagerrak–Kattegat)	6.20q			
sol-8c9a	Sole	Bay of Biscay & Atlantic Iberian waters	*Solea solea*	Sole in Divisions VIIIc and IXa	6.20q	6.20q	5.20	4.00
rje-7ech	Small-eyed ray	Celtic Sea & West of Scotland	*Raja microocellata*	Small-eyed ray (*Raja microocellata*) in the English Channel (Divisions VIId,e)	6.20q	6.20q	5.20	4.00
gug-89a	Grey gurnard	Bay of Biscay & Atlantic Iberian waters	*Eutrigla gurnardus*	Grey gurnard in Subarea VIII and Division IXa	6.20q	6.20q	6.20q	6.00
gug-celt	Grey gurnard	Celtic Sea & West of Scotland	*Eutrigla gurnardus*	Grey gurnard in Subarea VI and Divisions VIIa-c and e-k (Celtic Sea and West of Scotland)	6.20q	6.20q	6.20q	5.00
raj-ech	Small-eyed ray	North Sea	*Raja microocellata*		6.20q	6.20q	na	4.00
san-ns5	Sandeel	North Sea	*Ammodytes* spp.	Sandeel in the Viking and Bergen Bank areas (SA 5)	6.30	6.30	5.30	6.00
san-ns7	Sandeel	North Sea	*Ammodytes* spp.	Sandeel in the Shetland area (SA 7)	6.30	6.30	5.30	6.00
ang-nea	Angel shark	Widely Distributed	*Squatina squatina*	Angel shark (*Squatina squatina*) in the Northeast Atlantic	6.30	6.30	5.30	6.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
bsk-nea	Basking shark	Widely Distributed	*Cetorhinus maximus*	Basking shark (Cetorhinus maximus) in the Northeast Atlantic	6.30	6.30	5.30	6.00
raj-celt	Other skates	Celtic Sea & West of Scotland		Other skates and rays in Subareas VI and VII (excluding VIId)	6.30	6.30	6.20	5.00
rju-8ab	Undulate ray	Bay of Biscay & Atlantic Iberian waters	*Raja undulata*	Undulate ray (*Raja undulata*) in Divisions VIIIa,b (Bay of Biscay)	6.30	6.30	6.30	unknown
rju-8c	Undulate ray	Bay of Biscay & Atlantic Iberian waters	*Raja undulata*	Undulate ray (*Raja undulata*) in Divisions VIIIc (Cantabrian Sea)	6.30	6.30	6.30	unknown
rju-9a	Undulate ray	Bay of Biscay & Atlantic Iberian waters	*Raja undulata*	Undulate ray (*Raja undulata*) in Division IXa (west of Galicia, Portugal, and Gulf of Cadiz)	6.30	6.30	6.30	unknown
rju-ech	Undulate ray	Celtic Sea & West of Scotl&	*Raja undulata*	Undulate ray (*Raja undulata*) in Divisions VIId, e (English Channel)	6.30	6.30	6.30	6.00
rju-7bj	Undulate ray	Celtic Sea & West of Scotland	*Raja undulata*	Undulate ray (*Raja undulata*) in Divisions VIIb,j (Southwest of Ireland)	6.30	6.30	6.30	6.00
san-scow	Sandeel	Celtic Sea & West of Scotland	*Ammodytes* spp.	Sandeel in Division VIa	6.30	6.30	6.30	6.00
nop-scow	Norway pout	Celtic Sea & West of Scotland	*Trisopterus esmarkii*	Norway pout in Division VIa	6.30	6.30	6.30	6.00
pan-flad	Northern shrimp/prawn	North Sea	*Pandalus borealis*	Northern shrimp (*Pandalus borealis*) in Division IVa (Fladen Ground)	6.30	6.30	6.30	6.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
rjb-34	Common skates	North Sea	*Dipturus* spp.	Common skate (*Dipturus batis*-complex) in Subarea IV and Division IIIa (North Sea and Skagerrak)	6.30	6.30	6.30	4.00
ory-comb	Orange roughy	Widely Distributed	*Hoplostethus atlanticus*	Orange roughy (*Hoplostethus atlanticus*) in the Northeast Atlantic	6.30	6.30	6.30	4.00
rng-kask	Roundnose grenadier	Widely Distributed	*Coryphaen-oides rupestris*	Roundnose grenadier (*Coryphaenoides rupestris*) in Division IIIa	6.30	6.30	6.30	3.00
usk-mar	Tusk	Widely Distributed	*Brosme brosme*	Tusk (*Brosme brosme*) in Subarea XII, excluding Division XIIb (Mid-Atlantic Ridge)	6.30	6.30	6.30	6.00
rjb-347d	Common skates	North Sea	*Dipturus* spp.	Common skate (*Dipturus batis*) complex (Dipturus cf. flossada and Dipturus cf. intermedia) in Subarea IV and in Divisions IIIa and VIId (North Sea, Skagerrak, Kattegat, and eastern English Channel)	6.30	6.30	na	4.00
tur-nsea	Turbot	North Sea	*Scophthal-mus maximus*	Turbot in Subarea IV	na	2.11	2.11	1.00
sar-78	Sardine	Bay of Biscay & Atlantic Iberian waters	*Sardina pilchardus*	Sardine in Divisions VIIIa,b,d and Subarea VII	na	3.20	3.20	3.00
cod-ingr	Cod	Iceland & East Greenland	*Gadus morhua*	Inshore cod in NAFO Subarea 1 (Greenland cod)	na	3.20	3.20	3.00
bll-nsea	Brill	North Sea	*Scophthal-mus rhombus*	Brill in Subarea IV and Divisions IIIa and VIId,e	na	3.20	3.20	1.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
dab-nsea	Dab	North Sea	*Limanda limanda*	Dab in Subarea IV and Division IIIa	na	3.20	3.20	3.00
fle-nsea	Flounder	North Sea	*Platichthys flesus*	Flounder in Division IIIa and Subarea IV	na	3.20	3.20	3.00
lem-nsea	Lemon sole	North Sea	*Microstomus kitt*	Lemon sole in Subarea IV and Divisions IIIa and VIId	na	3.20	3.20	1.00
wit-nsea	Witch	North Sea	*Glyptoceph-alus cynoglossus*	Witch in Subarea IV and Divisions IIIa and VIId	na	3.20	3.20	1.00
tur-kask	Turbot	North Sea	*Scophthal-mus maximus*	Turbot in Division IIIa	na	3.20	3.20	3.00
sal-2231	Salmon	Baltic Sea	*Salmo salar*	Salmon in Subdivisions 22-31 (Main Basin and Gulf of Bothnia)	na	na	1.00	na
sal-na	Salmon	Salmon	*Salmo salar*	Atlantic salmon from North America	na	na	1.00	na
sal-nea	Salmon	Salmon	*Salmo salar*	Atlantic salmon from the Northeast Atlantic	na	na	1.00	na
sal-wg	Salmon	Salmon	*Salmo salar*	Atlantic salmon at West Greenland	na	na	1.00	na
sal-32	Salmon	Baltic Sea	*Salmo salar*	Salmon in Subdivision 32 (Gulf of Finland)	na	na	3.00	na
trt-bal	Sea trout	Baltic Sea	*Salmo trutta*	Sea trout	na	na	3.00	na
ane-pore	Anchovy	Bay of Biscay & Atlantic Iberian waters	*Engraulis encrasicolus*	Anchovy in Division IXa	na	na	3.00	3.00
bsf-nea	Black scabbardfish	Widely Distributed	*Aphanopus carbo*	Black scabbardfish (*Aphanopus carbo*) in the Northeast Atlantic: Subareas I, II, IV, VI, VII, VIII, X, and XIV, and Divisions IIIa, Va, Vb, IXa, and XIIb.	na	na	3.00	2.00

					ICES Data Category			
Stock code	**Species**	**EcoRegion**	**Scientific Name**	**ICES Stock name**	**2012**	**2013**	**2014**	**Target**
rjn-678abd	Cuckoo ray	Celtic Sea & West of Scotland	*Leucoraja naevus*	Cuckoo ray (*Leucoraja naevus*) in Subareas VI, VII (Celtic Sea and West of Scotland) and Divisions VIIIa,b,d (Bay of Biscay)	na	na	3.20	3.20
rjm-67bj	Spotted ray	Celtic Sea & West of Scotland	*Raja montagui*	Spotted ray (*Raja montagui*) in Subarea VI and Divisions VIIb,j (west of Scotland and Ireland)	na	na	3.20	3.00
rjm-7aeh	Spotted ray	Celtic Sea & West of Scotland	*Raja montagui*	Spotted ray (*Raja montagui*) in Divisions VIIa and VII e-h (southern Celtic seas)	na	na	3.20	3.00
rje-7fg	Small-eyed ray	Celtic Sea & West of Scotland	*Raja microocellata*	Small-eyed ray (*Raja microocellata*) in Divisions VIIf, g (Bristol Channel)	na	na	3.20	3.00
rjn-34	Cuckoo ray	North Sea	*Leucoraja naevus*	Cuckoo ray (*Leucoraja naevus*) in Subarea IV and Division IIIa (North Sea and Skagerrak and Kattegat)	na	na	3.20	3.00
rjr-234	Starry ray	North Sea	*Amblyraja radiata*	Starry ray (*Amblyraja radiata*) in Subareas II, IIIa and IV (Norwegian Sea, Skagerrak, Kattegat and North Sea)	na	na	3.20	na
rjc-echw	Thornback ray	Celtic Sea & West of Scotland	*Raja clavata*	Thornback ray (*Raja clavata*) in Division VIIe (Western English Channel)	na	na	5.20	na
rja-nea	White skate	Widely Distributed	*Rostroraja alba*	White skate (*Rostroraja alba*) in the Northeast Atlantic	na	na	6.30	na

Table A.8.2.Movement of stock assessments among ICES data categories from the 2013 to the 2014 assessment years.

		2014							
		Data Category						# changed	Total # stocks
Data category		1	2	3	4	5	6		
	1	78		2				1	81
	2	6	5						11
	3	3		70		2	1	9	85
	4				7		1		8
	5			11		21	2	3	37
	6			1		7	21	2	31
	# changed	5		9		1	1	3	19
2013	**Total # of stocks**	**92**	**5**	**93**	**7**	**31**	**26**	**18**	**272**

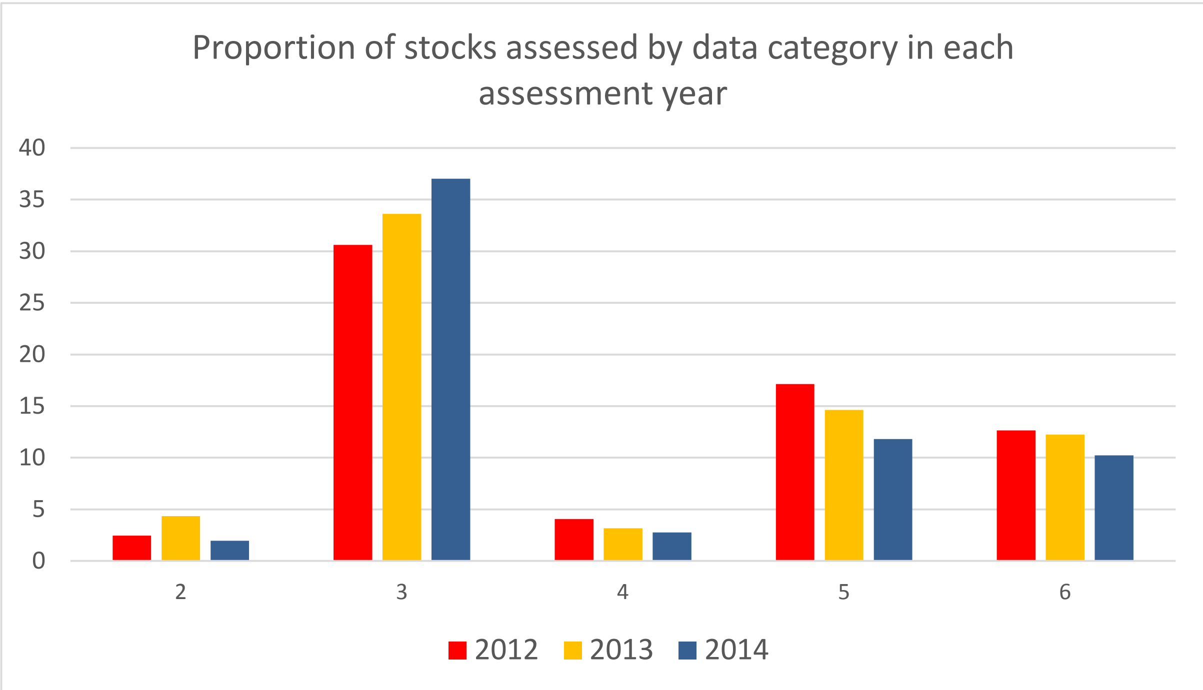

Figure A.8.1. Proportion of stocks by ICES assessment category in each assessment year. Stocks that have fully accepted analytical assessments (category 1) are not shown.