NINTH WORKSHOP ON THE DEVELOPMENT OF QUANTITATIVE ASSESSMENT METHODOLOGIES BASED ON LIFE-HISTORY TRAITS, EXPLOITATION CHARACTERISTICS, AND OTHER RELEVANT PARAMETERS FOR DATA-LIMITED STOCKS (WKLIFE IX)

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

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Editors

Manuela Azevedo • Carl O'Brien

Authors

Manuela Azevedo • Casper Berg • Alain Biseau • Simon Fischer • John Hoenig • Laurence Kell • Alexandros Kokkalis • Guillermo Martin • Tanja Miethe • Tobias Mildenberger • Carl O'Brien • Cristina Silva • Maria Soto • Marc Taylor • Katie Thomas • Robert Thorpe • Andrés Uriarte • Nicola Walker

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

Contents

i Executive summary

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) focuses on the provision of sound advice rules for data-limited stock (DLS) assessments that are within the ICES MSY framework. This ninth workshop was convened to further address the challenges to the evidence base for the provision of ICES advice with specific reference to DLS. The reviewers' report of WKLIFE VIII (ICES, 2018) was used as the basis to draft ICES technical guidance on advice rules for stocks in Categories 3 and 4 following the meeting in 2018. The draft document reflected the conclusions of the WKLIFE VIII meeting report but in order to provide a good guidance document to the ICES community, some of the text and steps identified required further elaboration. The intersessional work undertaken ahead of this WKLIFE IX meeting provided a basis to revise the draft and during this WKLIFE IX meeting, the draft technical guidance was revised and updated. The draft report of, and recommendations from, the ICES workshop on data-limited stocks of short-lived species (WKDLSSLS) was reviewed and additional simulation studies undertaken during WKLIFE IX, and the need for specific advice rules for these stocks examined. Annex 3 to this report contains the revised and agreed text by the participants at WKLIFE IX. Specifically, the draft ICES technical guidance was revised and amended based on the work presented at WKLIFE IX and its previous workshops with respect to short-term forecasts utilising a surplus production model (*SPiCT* – Stochastic Production model in Continuous Time), and harvest control rules for length-based approaches, for short-lived species, and for bycatch elasmobranch stocks.

ii Expert group information

Expert group name	**Workshop on the Development of Quantitative Assessment Methodologies based on Life-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE IX)**
Expert group cycle	Annual
Year cycle started	2019
Reporting year in cycle	1/1
Chairs	Carl O’Brien, UK
	Manuela Azevedo, Portugal
Meeting venue and dates	30 September–4 October 2019 (19 participants, including three remotely by WebEx)

1 Introduction

1.1 Terms of Reference

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 IX), chaired by Carl O'Brien (UK) and Manuela Azevedo (Portugal) met in Lisbon, Portugal, 30 September–4 October 2019, to further develop methods for stock assessment and catch advice for stocks in Categories 3–6, focusing on the provision of sound advice rules that are within the ICES MSY framework.

Specifically, the workshop was tasked with addressing the following Terms of Reference (ToRs):

a) Evaluate potential improvements to the performance of the WKMSYCat34 catch rule 3.2.1 (ICES, 2017) as follows:
   1. Investigate the impact of relative weighting of the r, f and b components of the rule on the performance of the rule;
   2. Investigate more extensively the time-lag properties of the r component, including alternative formulations;
   3. Explore the setting of appropriate reference levels in the f and b component of the rules, and the extent to which this could be done with tuning that depends on life-history traits and/or the nature of the time-series;
   4. Investigate the use of trends in an index without a reference level.

b) Evaluate *MSY-PA* advice rules (WKLIFE VIII; ICES, 2018) for stock production models (e.g. SPiCT) and develop recommended guidelines for use in determining catch advice.

c) Establish relationships between simple measures of the life-history (e.g. M, K, L_{mat}) and %SPR reference points to estimate data-limited proxies corresponding to F_{MSY} and F_{lim}.

d) Review and further investigate modelling approaches that incorporate both data-rich and data-limited stocks within mixed fisheries/multi-species frameworks and their ability to provide sea area-based stock assessments and catch advice.

e) Review the draft report of, and recommendations from, the ICES workshop on data-limited stocks of short-lived species (WKDLSSLS) and the need for specific advice rules for these stocks.

WKLIFE IX will report to ACOM no later than 18 November 2019.

1.2 Background

ICES provides advice on more than 260 stocks on an annual basis and more than sixty percent of these stocks are in Categories 3–6. Further developments of the approaches used in providing advice on fishing opportunities for these stocks are needed. WKLIFE is the premier venue for method development and discussion of stock assessments and advice approaches for stocks in Categories 3–6.

There is an increasing number of fish stocks in Categories 3 and 4 for which assessment of status relative to MSY proxy reference points is available but for which short-term forecasts and MSY-based advice are not available. As for last year's meeting of WKLIFE, ICES wishes to further address this issue.

The report of this workshop provides a description of advice rules developed by the Workshop on the Development of the ICES Approach to Providing MSY Advice for Category 3 and 4 stocks (WKMSYCat34-ICES, 2017), and the Eighth and Ninth Workshop on the Development of Quantitative Assessment Methodologies based on Life-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE VIII-ICES, 2018), and the Workshop on Data-Limited Stocks of Short-Lived Species (WKDLSSLS-ICES, 2019). These are harvest control rules used by ICES for stocks in Categories 3 and 4, with additional specifications for short-lived species and elasmobranch stocks in Categories 3 and 4.

The objective of WKMSYCat34, and WKLIFE VIII and IX, and WKDLSSLS was to investigate the performance of harvest control rules across life-history types through simulation and management strategy evaluation (MSE). This would identify the potential approaches that best meet the goals of management; i.e. maximizing long-term yield while minimizing the probability of stocks falling below biologically sustainable limits.

1.3 Conduct of the meeting

The list of participants and agenda for the workshop are presented in Annex 1 and Annex 2, respectively.

No working documents were received prior to the meeting but presentations were made by the participants which subsequently, formed the basis of the workshop's investigations during the week. However, one working document was produced during the meeting and is presented in Annex 4 for ease of reference. The working document presents a testing of length-based reference points for elasmobranchs; specifically, cuckoo ray and thornback ray.

Much intersessional work had taken place ahead of the WKLIFE IX meeting by its participants, and this was presented during the first day, the afternoon of the second day and the morning of the third day of the workshop. The presentations were used to define the work programme for the remainder of the workshop and the identification of virtual subgroups; two of which were identified:

- Subgroup 1 – focused on short-lived species; and
- Subgroup 2 – focused on catch rules.

Three participants worked by correspondence during the meeting and the facilities of WebEx were relied upon for their full contribution to the workshop's plenary discussions. This worked well, and lively discussions resulted from this interaction; together with the development of the working document presented in Annex 4.

Given ICES role as a knowledge provider, it is essential that experts contributing to ICES science and advice maintain scientific independence, integrity and impartiality. It is also essential that their behaviours and actions minimise any risk of actual, potential or perceived Conflicts of Interest (CoI).

To ensure credibility, salience, legitimacy, transparency and accountability in ICES work, to avoid CoI and to safeguard the reputation of ICES as an impartial knowledge provider, all contributors to ICES work are required to abide by the ICES Code of Conduct. The ICES Code of Conduct document dated January 2019 was brought to the attention of participants at the workshop and no CoI was reported.

1.4 Relevant on-going activities outside of ICES

During WKLIFE IX, one project was briefly presented that is of relevance to the activities of ICES in the development of methods for data-limited stocks (DLS):

- PROBYFISH (Protecting bycaught species in mixed fisheries) - One of the tasks of the project is to identify candidate indicators and appropriate trigger values for use in evaluating the status of data-limited stocks. Within this task, the project aims to test the performance of reference points, indicators and trigger values as derived by various data-poor stock assessment methods. An individual-based model (FLIBM) was presented during this meeting of WKLIFE IX that is being used to generate various data types (length-based, catch-only, catch plus index etcetera) for these analyses.

1.5 Structure of the report

The structure of the report is as follows:

- Section 2 focuses on advice rules for harvest control rules for short-lived species (stock Categories 3 and 4) – ToR e);
- Section 3 focuses on advice rules for harvest control rules for bycatch elasmobranch stocks – ToR c);
- Section 4 focuses on advice rules for harvest control rules for length-based approaches – ToR a);
- Section 5 focuses on advice rules for short-term forecasts utilizing a surplus production model – ToR b);
- Section 6 focuses on the combined modelling of both data-rich and data-limited stocks – ToR d); and
- Section 7 focuses on future directions of work for data-limited stocks (DLS).

Instead of providing conclusions from the workshop at the end of the report as is customary with ICES reports, each of the Sections 2–6 provides a synthesis of the material presented within each Section in either a summary or future work Section.

1.6 Recommendations of WKLIFE VIII and its review process

The reviewers' report of WKLIFE VIII (ICES, 2018) was used as the basis to draft ICES technical guidance on advice rules for stocks in Categories 3 and 4 following the meeting in 2018. The draft document reflected the conclusions of the WKLIFE VIII meeting report but in order to provide a good guidance document to the ICES community, some of the text and steps identified required further elaboration. The intersessional work undertaken ahead of this WKLIFE IX meeting provided a basis to revise the draft and during this WKLIFE IX, the draft technical guidance was revised and updated. Annex 3 to this report contains the revised and agreed text by WKLIFE IX participants.

1.7 Follow-up process within ICES

The participants at WKLIFE IX agreed to provide text for the draft workshop report by Friday 18th October 2019 and to then comment on the compiled draft report no later than 1st November 2019; when the report can be finalised by the Chairs and formatted by the ICES Secretariat.

Recommendation: It is recommended by WKLIFE IX that there be a tenth meeting of WKLIFE in Lisbon, Portugal 21st–25thSeptember 2020, whose draft ToRs are proposed in this report for the consideration of ACOM.

The work of WKDLSSLS is considered incomplete and the participants at WKLIFE IX support a second meeting of WKDLSSLS to further develop and refine advice rules for short-lived species.

1.8 References

ICES. 2017. Report of the Workshop on the Development of the ICES approach to providing MSY advice for category 3 and 4 stocks (WKMSYCat34), 6–10 March 2017, Copenhagen, Denmark. ICES CM 2017/ACOM:47. 53 pp.

ICES. 2018. Report of the Eighth Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE VIII), 8–12 October 2018, Lisbon, Portugal. ICES CM 2018/ACOM:40. 172 pp.

ICES.2019. Workshop on Data-limited Stocks of Short-Lived Species(WKDLSSLS). ICES Scientific Reports. 1:73. 166pp. http://doi.org/10.17895/ices.pub.5549.

2 Short-lived species

2.1 Introduction

This Section focuses on the need for specific advice rules for stocks of short-lived species; namely, ToR e). The current advice rule for Category 3–6 is targeted at stocks of medium- to long-lived species and has proven difficult to apply for stocks of short-lived species. WKLIFE IX reviewed the draft report of WKDLSSLS presented by one of its chairs, Andrés Uriarte, and revised the draft ICES technical guidance on advice rules for stocks in Categories 3 and 4 (Annex 3).

Prior to WKLIFE IX in September 2019, the ICESWorkshop on Data-Limited Stocks of Short-Lived Species (WKDLSSLS), chaired by Andres Uriarte, Spain and Mollie Brooks, Denmark was held in San Sebastian; aimed at finding alternatives to the current advice rules for data-limited stocks (Categories 3 and 4) used within ICES.

A summary of the major findings from WKDLSSLS were presented in plenary at WKLIFE IX and the general conclusions of those discussions are presented in the remainder of this Section 2.

2.2 Work on assessment methods for short-lived species and estimation of MSY proxies for Category 3–4 short-lived species

In relation to assessment methods for short-lived data-limited stocks and estimation of biological and MSY proxy reference points, the workshops did not explore other methods than SPiCT (Pedersen and Berg, 2016).

Guidelines for the use of the stochastic production model in continuous time (SPiCT)

ICES Category 3 stocks can be managed using the official advice rules based on the stochastic production model in continuous time (SPiCT; Pedersen and Berg, 2017; 3.1.1 and 3.1.2 in ICES, 2018). These advice rules require the acceptance of a SPiCT assessment. A condensed summary with specific guidelines for the use of SPiCT has been developed within the frame of WKDLSSLS and WKLIFE. The document is a living document and part of the SPiCT package. It can be accessed through github and downloaded here (https://github.com/DTUAqua/spict). The WKDLSSLS endorsed the application of SPiCT provided the quality and properties of the data are good enough as to allow a successful model fit.

In the last years, the SPiCT HCRs to manage stocks have been improved (WKLIFE VII and VII) by including either SPICT - fractile rule (to departure from median of the Biomass and F safeguards ratios in the recent past to a more precautionary fractiles) or by using SPICT - PA rules by including modification of normal advisable MSY SPiCT advice to accommodate to precautionary levels of risks concerning the likelihood of biomass being above B_{lim}in the management year. For the optimal SPiCT advice rule, users should refer to the update ICES guidelines following after this WKLIFE IX.

During the workshop,SPiCT assessments to Anchovy in 9a South, Anchovy 9a West and to Sprat in 7de were essayed, ending up with a satisfactory application to Anchovy in 9a South (Rincon *et al*. 2019, WD to WKDLSSLS). Results for Sprat 7de and Anchovy 9aWest were still too imprecise as to be acceptable. In addition, there were some presentations on applications of SPiCT to several cephalopod populations.

No alternative setting of Reference points for management were produced by WKDLSSLS, other than those already available from SPICT assessment. Length-based indicators of stock status are known to be generally not suitable for short-lived species where recruitment induce interannual major changes in the length distribution of catches (ICES reference points for stocks in Categories 3 and 4).

Perspective for future: Explore methods to assess initial stock status either from catch only trend or from the survey trends. The two-stage approaches need further work. A provisional application was presented for Sprat in 7de (Rousa Ourens *et al*. WD), but results were still provisional.

2.3 Work on testing the performance of harvest control rules through MSE for management

During the Workshop the performance of 1-over-2 and 2-over-3 for normal timing of the advice (which is the ICES default advice for a January to December management calendar, including an interim year when the advice is produced) and for in-year advice were tested, both for symmetrical and asymmetrical uncertainty cap restrictions on interannual advices, and either supplemented or not with a Biomass indicator safeguard (case studies for anchovy and sardine/sprat like stocks,Uriarte*et al*., WD to WKDLSSLS and for sprat like stocks; Walker WD to WKDLSSLS and Brooks WD to WKDLSSLS).

The main results are the following:

- Regarding the **<u>coupling in time between assessment, advice and management</u>**: The shorter the lag between observations, advice and management, the bigger the catches and the smaller are the risks. This means that in-year advice should always be preferred over the normal calendar (with an interim) year advice. Results are very consistent across the different OM essayed.
- **<u>Initialization of the advice</u>** in the first year of the management period either with the last year catch or with the mean of the last year catches corresponding with those in the denominator of the HCR did not produce relevant differences in the performance of the HCRs. We suggest using the latter option to start with some mean harvest rate over a recent set of years to filter out some of the inherent noise coming from fluctuations in the interannual catchability of the fishery before the starting of management.
- Regarding the **<u>trend-based HCRs</u>**: Globally, for all simulations (except the North Sea sprat), in the short, medium and long term 1-over-2 outperformed 2-over-3 (ICES default rule). For quite similar level of catches, 1-over-2 has a bit lower risk than 2-over-3, although often above 0.05 (particularly for full or high harvest levels before the start of management). This is valid for all uncertainty caps tested (including no uncertainty cap).

  This is true for both the in-year advice and the normal calendar advice of ICES. Figure 2.3.1 shows an example tested for Sprat 7de, where applying 1-over-2 rule results in higher catches and lower risks, clearly seen in the medium and long term, while in the short term, there are some exceptions at high exploitation levels (FH2) where 2-over-3 rule might be better than HCR(1/2). This figure also serves to support again the better performance of the in-year versus the normal calendar advice procedure of ICES. This example shows that for Sprat 7de, the risks in the long term are more than twice as large with the 2-over-3 rule than with the 1-over-2. Notice therefore, that the current procedure for providing advice for sprat in 7de (annual HCR(2/3) rule with 20% uncertainty cap) is not precautionary and resulted in high levels of risk and collapse.

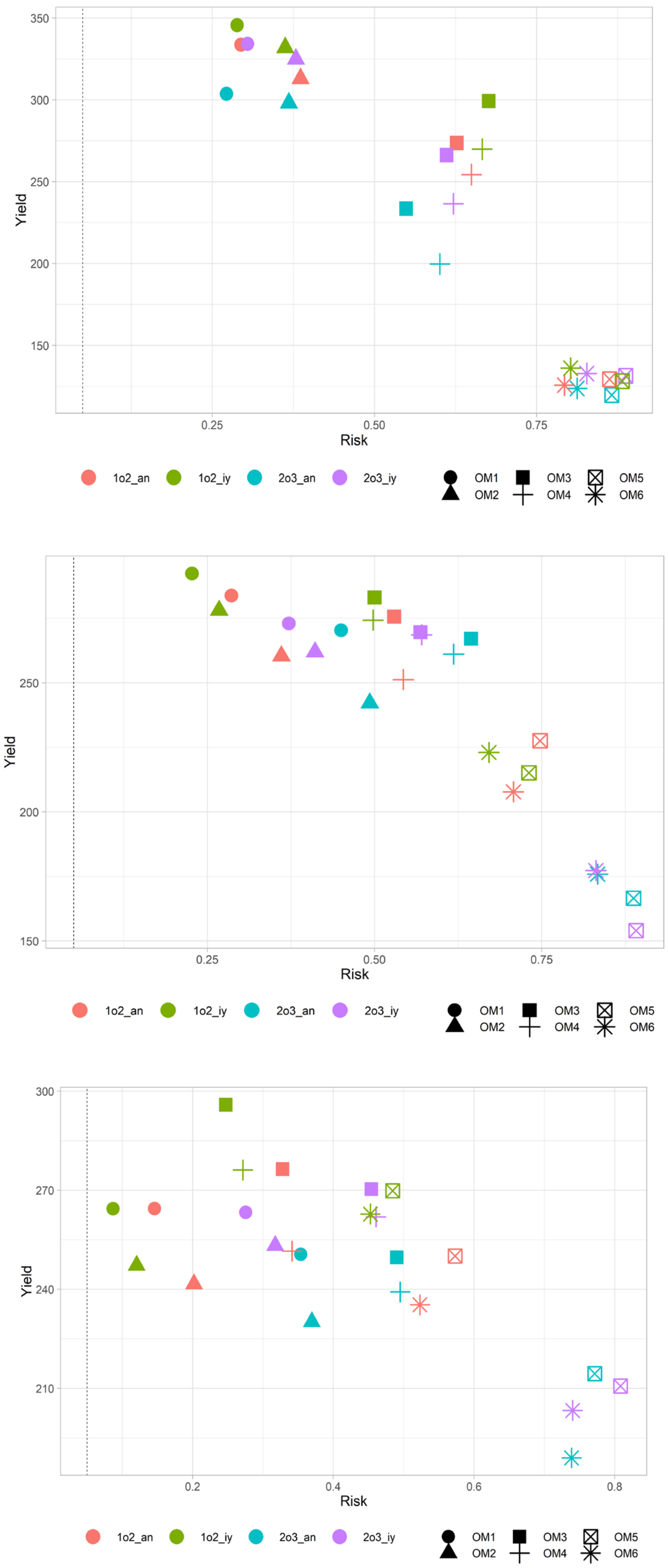

Figure 2.3.1. Short-, medium- and long-term plots of yield against risk for the 1-over-2 (1o2) and 2-over-3 (2o3) rules following annual (an) and in-year (iy) advice schedules. From Walker WD in WKDLSSLS report (ICES, 2019).

In the sardines/Sprat and anchovy like stocks benefits in the in-year advice of 1-over-2 rule compared with the 2-over-3 rule were clear at all periods of projections and particularly in the short and medium term (i.e. at least for the ten years after starting the management). Figure 2.3.2

allows comparing rules 1-over-2 with the 2-over-3 in terms of catches and risks for the same uncertainty cap levels (compare the empty symbols -1o2- with the same coloured symbols -2o3- in Figure 2.3.2 by periods and stocks), showing that for rather similar levels of catches (or slightly smaller) at a given uncertainty cap level, the former rule results in smaller levels of risks

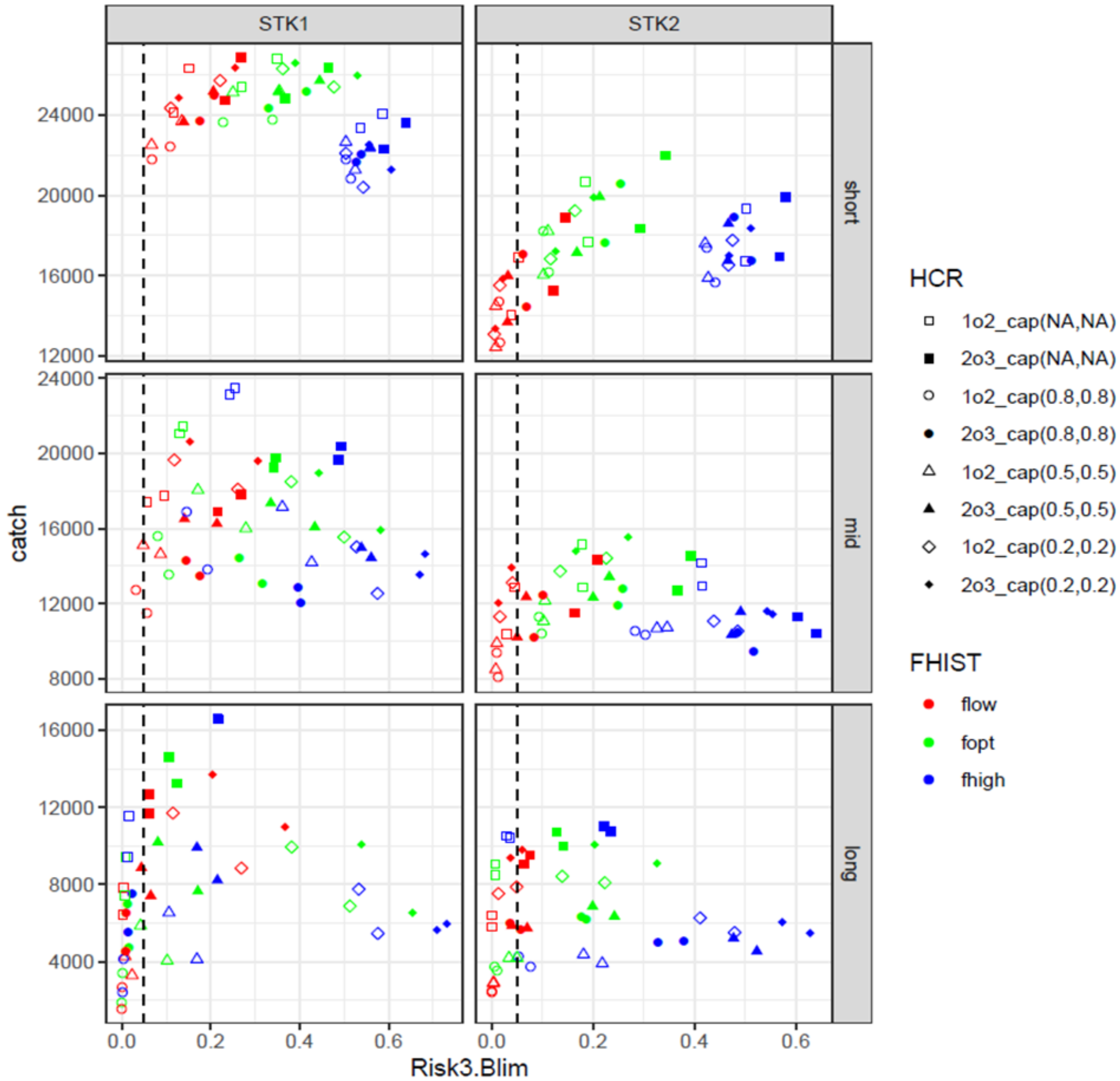

Figure 2.3.2. Median catch versus Risk3 of falling below B_{lim}, in the short (upper graphs), medium (middle graphs) and long term (bottom graphs), by stocks (anchovy like -right panels- and sardine/sprat like -left panels) for each HCR combined with various uncertainty cap levels (see right upper legend) and for historical fishing mortality F levels (F_{high}: 2*F_{MSY} -blue-; F_{low}: 0.5*F_{MSY} -red-; and F_{opt}: F_{MSY} -green-). There are two repeated values with the same form and colour which correspond to alternative standard deviations for the recruitment (0.5 or 0.75). From Uriarte *et al*. WD in WKDLSSLS report (ICES, 2019).

When rules are applied with some interannual Uncertainty Cap constraint, the former results hold on because for in-year advice and with the same Ucap level 1-over-2 overcomes 2-over-3 rules producing similar or bigger catches with smaller risks (see Figure 2.3.2).

- Application of some **uncertainty caps** to constraint the interannual variability in the advice leads to a reduction of catches and risks, but up to an intermediate uncertainty level beyond which risks start to increase again:

When the Uncertainty cap is applied symmetrically for upward and downward revision, a 20% uncertainty cap is the riskiest approach and differences with other uncertainty cap levels increase with time, with a few exceptions at low exploitations (Figure 2.3.2). Globally, in the short and medium term, 80% uncertainty cap overcomes the performance of any other uncertainty cap in terms of lesser risks for minor reductions of catches, whilst in the long term, 1-over-2 rule with no uncertainty cap produce higher catches than with the 80% uncertainty cap for similar levels of risks. Therefore, the benefits of applying the 80% Ucap are particularly noticeable in the short- and medium-term levels. Figure 2.3.2 allows verifying the previous comparisons between the various uncertainty cap levels for the 1-over-2 rule (by comparing for the 1o2 the empty circles - 1o2 with 80% uncertainty cap- with the other empty symbols of the same colours; i.e. for the same historical exploitation levelsby periods and stocks).And the same for 2-over-3 rule (by comparing the filled circles, 2o3 with 80% uncertainty cap with the other filled symbols of the same colours, with minor exceptions for this rule).

Asymmetrical application of the Uncertainty Caps was tested for sprat like stocks (Walker WD to WKDLSSLS and Brooks WD to WKDLSSLS). The maximum upward revisions were fixed to 1.2 times the former advice, but a maximum a different percentage of reductions (X%) from former advices were allowed. The analysis shows that for in-year advice allowing maximum reductions of 60% or higher levels of Uncertainty Caps results in smallest risks and very similar catch levels for the different historical exploitation trajectories before management in the long term (Figure 2.3.3). For normal (calendar) similar results were obtained but with optima at 70% Ucap or higher levels.

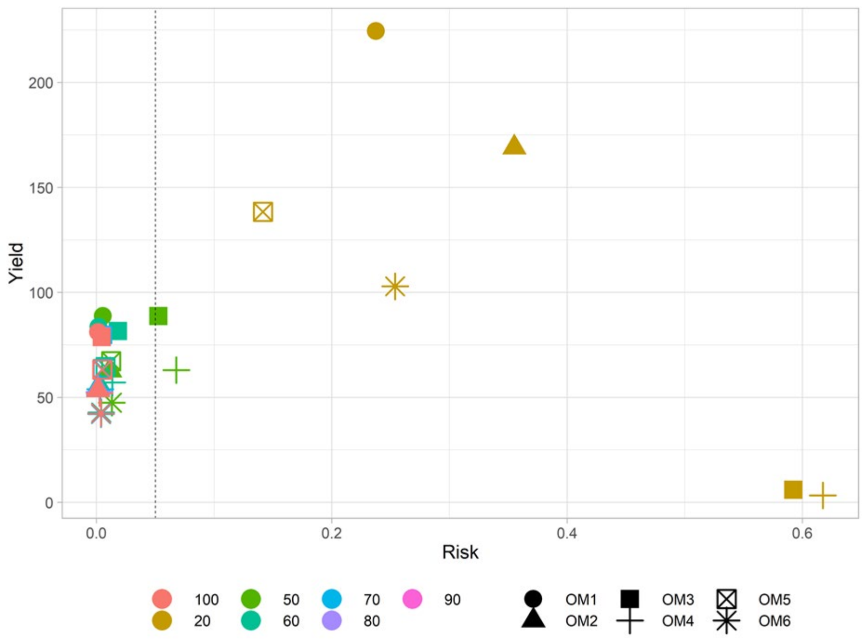

Figure 2.3.3. Long-term yield against risk for the 1-over-2 rule on an in-year advice basis with asymmetric uncertainty caps levels (colours of the symbols indicating the maximum downward revisions of interannual advices, for maximum upward revisions of 20% Ucap) and for several historical exploitation trajectories (different symbols). (Case study of Sprat in 7de, taken from Walker WD in WKDLSSLS report (ICES, 2019)).

- Role of **historical fishing mortality** prior to management: The greater the historical exploitation, the greater the risks (different symbols in Figure 2.3.4). Actually, this is the major driver of risks associated to any harvest control rule. This implies that getting some initial assessment of the status of the stock regarding BRPs (before starting the management) would allow deciding on the convenience of applying the 20% precautionary buffer.

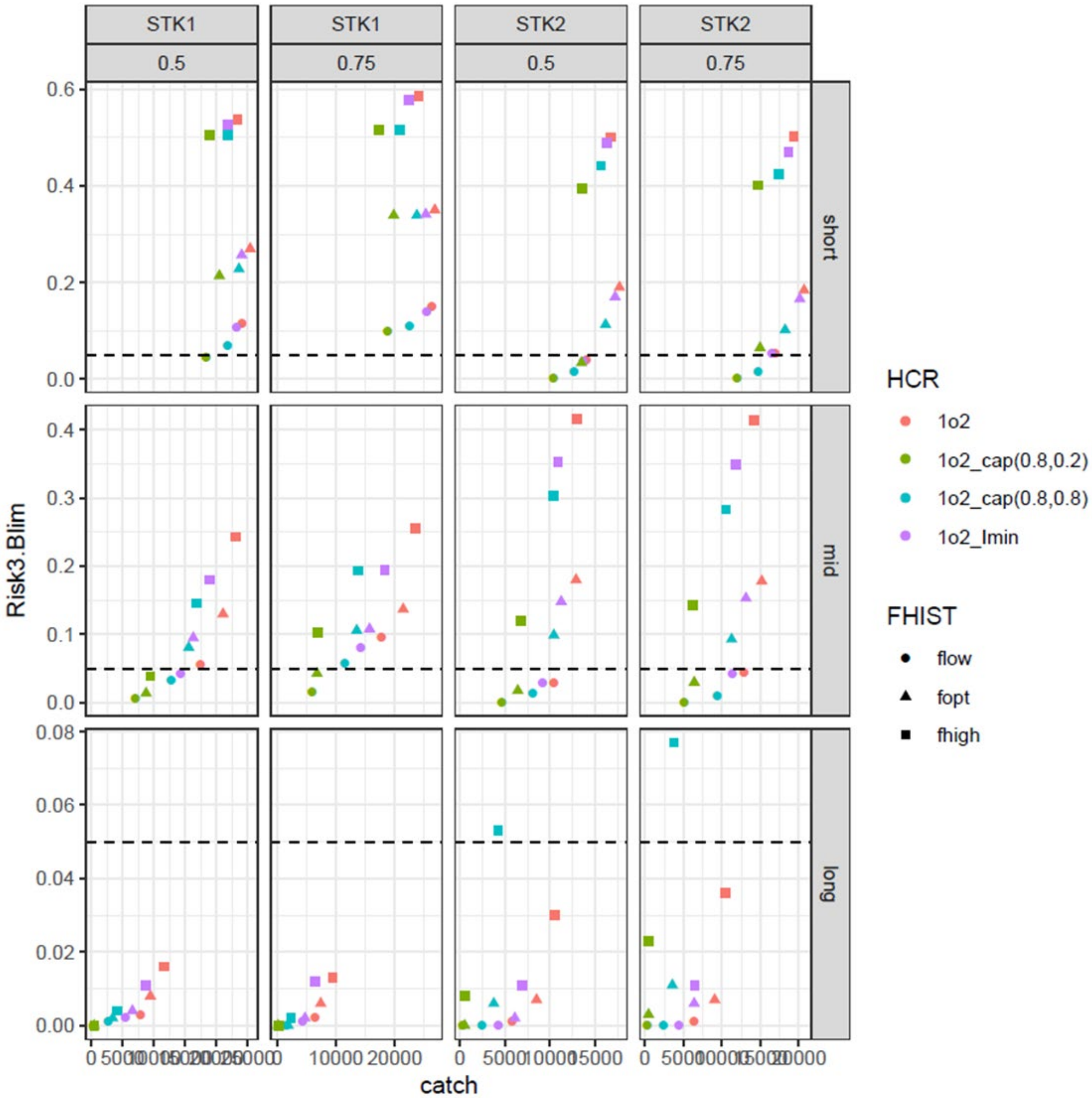

Figure 2.3.4. Risk3 of falling below B_{lim} versus median catch for alternative historical F levels (circle - F_{low}: 0.5*F_{MSY}; triangle - F_{opt}: F_{MSY}; and square - F_{high}: 2*F_{MSY}), HCRs (red – 1o2: 1-over-2 without uncertainty cap; green – 1o2_cap(0.8,0.2): 1-over-2 with lower and upper uncertainty caps of 80% and 20%, respectively; blue – 1o2_cap(0.8,0.8): 1-over-2 with symmetric uncertainty cap of 80%; and purple – 1o2_Imin: 1-over-2 with biomass safeguard), stock types (STK1: anchovy-like; STK2: sardine-like), standard deviation for the recruitment (0.25 or 0.75) and timeframes (short: years 31–35; medium: years 36–40; and long-term: years 51–60).

- Regarding the application of the Rules with a **biomass safeguard:**

For the Biomass safeguard, in the context of these Category 3-4 stocks, in the absence of B_{lim} (WKLIFE VI and VII and WKMSY) a provisional approach to have a Biomass indicator for management (like but not equal to B_{lim} or B_{pa}) has been used in WKDLSSLS. The harvest control rules included a biomass trigger point at the lowest of the available Index series prior to start the management (I_{lim}) (and for sprat in 7.de also at 1.4 this value - Itrigger) that acted as a biomass safeguard.

For sprat like in 7.de, Figure 2.3.5 shows that applying a biomass safe guard to in-year advice (either on I_{lim} or Itrigger at 1.4*I_{lim}) to 1-over-2 rule without uncertainty Cap results in bigger catches and risks than 1-over-2 rule with asymmetrical uncertainty caps and in smaller catches and risks than the 1-over-2 rule without uncertainty Cap. Between the two biomass safeguard options I_{lim} (threshold Indicator taken from the minimum previously observed index in the available series) leads to some bigger catches and risks than Itrigger. Care should be taken with a direct application of these rules, as the relationship between PELTIC index biomass and stock status is still uncertain.

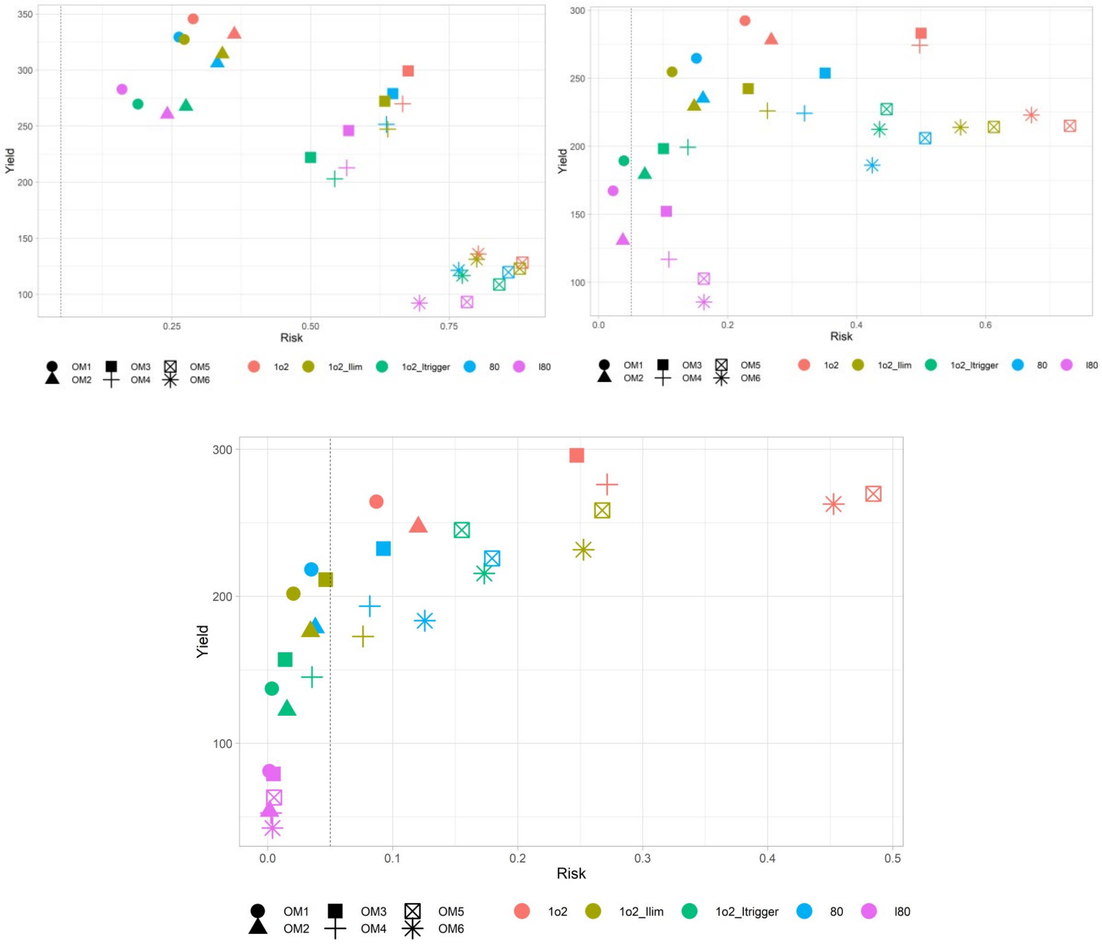

Figure 2.3.5. Short-, medium- and long-term plots of yield against risk for the 1-over-2 rule (1o2) and 1-over-2 rule with select mechanisms (Ilim = Ilim safeguard; Itrigger = Itrigger safeguard; 80 = 80% symmetric uncertainty cap; I80 = asymmetric uncertainty cap with 20% upper bound and 80% lower bound) following an in-year advice schedule.

For Anchovy and Sardine/Sprat like stocks the Figure 2.3.5 (above) shows for In-year advice that adding a biomass safe guard (on I_{lim}) to the 1-over-2 rule without any uncertainty cap, leads it to have an intermediate performance between that rule with 80% uncertainty cap (which would have smaller catches and risks) and the original rule without any uncertainty cap or biomass safeguard (which would have bigger catches and risks), at any time horizon. So for these Operating models Imin was a bit less risk averse than the analysis resulting for the Sprat 7.de.

Another analysis with North Sea Sprat (Brooks WD to WKDLSSLS) shows that combining the biomass safeguards with any of the former HCR makes them more risk averse.

In summary, that last two figures evidence for these operating models that for interim year advice 1-over-2 rule with asymmetrical uncertainty cap (0.8,0.2) leads to smallest risks, but also at the expense of allowing the smallest catches at any time frame and become almost equal to 0 t in the long term (i.e. fishery is almost closed). Opposite to this, the 1-over-2 without uncertainty cap results in the highest catches and risks, particularly in the short and medium term, while the risk would be reduced to precautionary levels in the longterm.Therefore, some rule showing an intermediate behaviour might be put forward for management consideration. Intermediate rules in terms of balance between catches and risks are the 1-over-2 with symmetrical 80% uncertainty cap (1o2_cap(0.8,0.8)) and the 1-over-2 with biomass safeguard (1o2_Imin or Itrigger). Rule with the 80% uncertainty cap (1o2_cap(0.8,0.8)) results to be a bit more precautionary in the short and medium term, without major loses of catches compared to the other rule, though the drop in catches in the long term is a bit more pronounced. The 1-over-2 rule with symmetrical 80% uncertainty cap might be preferred over the asymmetrical with 80% lower and 20% upper uncertainty caps for a better compromise in terms of catches versus risks in the short and medium term. Although given the trade-off between risks and catches (for the short, medium and long term) this discussion should be partly passed to managers and stakeholders.

- A management strategy of exploiting Sprat 7.de at a **Constant Harvest rate** of about 0.17 of survey estimates leads to highest levels of catches compared with HCR(1/2) with biomass safe guards resulting in risks below 0.05. Such result is conditioned to the assumed catchability of the survey, and the result applied only to in-year advice. Further research is required on the rules based on constant harvest rates.

2.4 Main Conclusions (extract from WKDLSSLS report)

- Short-lived ICES Category 3 stocks can be managed using the official advice rules based on the stochastic production model in continuous time (SPiCT) conditioned upon a successful SPiCT fitting, according to the specific guidelines for the use of SPiCT developed within the frame of WKDLSSLS and WKLIFE.

If not, go for trend-based HCRs:

- The lag between abundance index, advice and management should be minimized, this leads to In-Year advice, even if this implies that the management year is not equal to the annual calendar.
- The time-lag between abundance index, advice and management should be minimized, this leads to select in-year advice, implying that the management year (i.e. TAC year) generally differs from the calendar year.
- Major drivers of risks are (in order of relevance): historical exploitation level (and trajectory), and the harvest control rule (HCR) with uncertainty cap (Ucap). This emphasizes the relevance of trying an initial assessment of the relative status of the stock regarding optimal exploitation to judge if a precautionary buffer is required to start management.
- Regarding the trend-based HCRs: For all simulations except the North Sea sprat, in the short, medium and long term 1-over-2 outperformed 2-over-3 (ICES default rule). For quite similar level of catches, 1-over-2 has a bit lower risk than 2-over-3. This is valid for all uncertainty caps tested (including no uncertainty cap).
- Application of some uncertainty caps to constrain interannual variability in the advice led to a reduction of catches and risks, only up to an intermediate uncertainty cap beyond which risks start to increase again:
    - For symmetrical uncertainty caps: Best performance (least risks for minimum reduction of catches) was from 1-over-2 with symmetric 80% Ucap. The most risk prone performance was from a symmetric 20% uncertainty cap, both for 1-over-2 and 2-over-3, and the performance worsens with time.
    - For asymmetrical uncertainty caps tested for rules with a maximum interannual upward revision of 20%, optimal performance was achieved when allowing reductions of 60% or more from the previous advice for in-year advice, and of 70% or more for calendar-year advice.

- Biomass safeguards (based on the minimum historical abundance index -I_{lim}- or on the 5th percentile of the historical index) show a rather good performance, generally reducing risk without too much reduction in catch, when applied to any HCR, possibly in combination with uncertainty caps.
- The constant rate HCRs can be appropriate but require a good knowledge of the catchability/error/properties of the index. This should be studied in a case-by-case basis and deserves further simulations.
- There is a strong trade off between risks and catches. The 1-over-2 rule with asymmetric Ucap (0.8,0.2) has the lowest risks through a progressive strong reduction of catches (maximum reduction in the long term). The 1-over-2 rule with no Ucap produce the highest catches with long-term risk being at precautionary levels for some operating models tested. Intermediate rules in terms of balancing catches and risks are: 1-over-2 with Ucap (0.8,0.8) and 1-over-2 with biomass safeguard (Imin).
- While 1-over-2 with Ucap (0.8,0.2) is the lowest risk rule, in order to avoid excessive reductions of catches, 1-over-2 with Ucap (0.8,0.8) might be preferred as a good compromise between risk and catches. Application of the symmetric 80% Ucap can lead to major reduction of catches in the long term. So, its implementation should be temporary while aiming at achieving a better management of the stock in 8–10 years.
- Given the trade off between competing rules, it seems that selection of a rule should be made in consultancy with managers and stake holders.
- The work of WKDLSSLS is considered unfinished. Further research on the definition of optimal harvest control rules for data-limited short-lived stocks is ongoing. Therefore, the suggested rule (1-over-2 with symmetrical 80% Ucap) should be taken as an interim (provisional) proposal while guidelines are refined in 2020 for 2021.

2.5 Future work (extract from WKDLSSLS report)

Future work

- Further work on assessment methods of initial stock status relative to MSY with simpler analysis of historical catches, the abundance indices or from expert knowledge is of relevance.
- Further research/suggestions on SPICT:
  - Borrowing parameters between SPiCT assessments (including prior sensitivity testing).
  - Testing further the SPiCT advice rules for management for these short-lived species.
  - Include the SPiCT in an interactive tool similar to the one being developed in the EU's Horizon 2020 research and innovation programme project FarFish, or develop a new one.
- Testing properly the precautionary buffer role in terms of mitigating short-term risks but keeping long-term benefits for the different harvest control rules and historical exploitation trajectories.
- Further exploring the benefits of adding a biomass safeguard of minimum observed index or at a fractile of available index series to the rules either alone or in combination to uncertainty cap levels.
- Further testing of asymmetric uncertainty caps with variable upper and lower bounds.
- Testing the effect of shifting the uncertainty cap from 80% to no uncertainty cap in time (for instance after 8-10 years of application of the 80% uncertainty cap).
- Constant or variant harvest rate strategies instead of the trend-based rules (aligned with HCR 3.2.2 Catch rule based on applying an F_{proxy} (WKMSYCat34)). Harvest rates and how they vary with assumed catchability. Further testing of harvest rates under a range of catchability, uncertainty and life history assumptions and across modelling platforms.

2.6 References

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3 Bycatch elasmobranch stocks

This section focuses on the ToRc) and the revision of the draft ICES technical guidance on advice rules for stocks in Categories 3 and 4 (Annex 3).

3.1 Introduction

Elasmobranchs are cartilaginous fish most of which are k-selected species with relatively slow growth, late maturity, large adult size, and few developed juveniles. The species most vulnerable to overexploitation tend to be larger sized, slow growing, latematuring and longlived (Smith *et al.*, 1998; Dulvy *et al.*, 2000).

In particular, stocks with maturation occurring at relatively large size and slow growth, are vulnerable to recruitment failure as the size range of mature individuals become truncated and decimated, size classes are slowly replenished due to long generation time. In contrast, small-bodied species tend to be more productive with a higher rebound potential (Stevens *et al.*, 2000). Elasmobranchs recruitment is closely linked to the number of mature females, which leads to a fast reduction in recruitment with decreasing number of mature females in the populations, and limits the recovery from overfishing when SSB is low and the potential of replenishment by large incoming cohorts is small (Cailliet *et al.*, 2005). Instead of maximizing yield, the focus of management for elasmobranch stocks should therefore be on the protection of the reproductive potential.

Currently, harvest control rules suggested by WKLIFE use the length-based reference point $L_{F=M}$. It has been shown that this reference point may not perform well in terms of providing risk-adverse catch advice for stocks with late maturity and when $L_c<L_{mat}$(Jardim *et al.*, 2015). For many elasmobranch stocks L_c is typically lower than L_{mat}(ICES, 2018b). Harvest control rules combining length-based indicators with a CPUE-based stock index and TAC constraints show an improved performance (ICES, 2018a; Annex 4 WD).

For the example of cuckoo ray, *Leucoraja naevus*, and thornback ray, *Raja clavata*, the length-based reference point $L_{F=M}$ is compared to SPR-based reference points, which take into account the respective maturation schedule (L_{mat}). We compare the effect of different values of natural mortality and L_{mat} on the length-based reference points and $F_{40\%SPR}$.

3.2 Methods

The derivation of the reference point for $\bar{L}$, $L_{F=M}$, requires the assumptions that the population is at equilibrium with individuals following deterministic von Bertalanffy growth, with constant recruitment, that natural mortality is independent of size and fishing mortality occurs with knife-edged selectivity. An analytical expression for the calculation of the reference point $L_{F=M}$was presented by Jardim *et al.* (2015), with $\theta = \frac{k}{M}$and $\gamma = \frac{F}{M} = 1$:

$$L_{F=\gamma M,k=\theta M} = \frac{\theta L_\infty + (\gamma + 1)L_c}{\theta + \gamma + 1}$$

The reference point depends on L_c and stock-specific with life-history parameters L_∞, M, and k.

Alternatively, the expected mean length in the catch and mean length of the largest 5% in the catch can be calculated for a particular level of spawning potential ratio (SPR, 40%), based on basic life-history characteristics under assumptions of equilibrium conditions and constant recruitment (Miethe *et al.*, 2019). In the paper by Miethe *et al.* (2019), a method is described to calculate length-based reference points assuming a particular level of SPR. The respective fishing mortality at an SPR of 40% ($F_{40\%SPR}$) can be calculated and compared to the assumption of F=M. Life-history parameters for these two stocks are listed in Table 3.2.1. For reference point calculation, female (larger sex) life-history characteristics are used. The necessary level of SPR to ensure sustainable exploitation of stocks can differ depending on the spawning–stock-recruitment relationship.

Table 3.2.1. Life-history parameters for cuckoo ray RJN, thornback ray RJC.

Description	parameter	Value RJN	Value RJC	unit	reference
Von Bertalanffy growth	K (male)	0.294	0.135		Gallagher *et al.* (2005)
	K (female)	0.197	0.093		Irish Sea
	L_∞ (male)	746	1065	mm	
	L_∞ (female)	839	1395	mm	
Variability in L_∞	CV(L_∞)	≈ 0	≈ 0		
Natural mortality	M (male)	0.406	0.205		Then *et al.* (2015)
	M (female)	0.292	0.143		
Length-weight relationship	b (male)	3.105	3.106	g cm^{-b}	McCully *et al.* (2012)
	b (female)	3.147	3.162	g cm^{-b}	Celtic Sea
Size at 50% maturity	L_{mat} (males)	569	657	mm	Gallagher *et al.* (2005)
	L_{mat} (females)	562	718	mm	

3.3 Results

In Figures 3.3.1 and 3.3.2, the reference points are illustrated for both stocks. Comparing $L_{F=M}$ and SPR 40% reference points (right panel), shows that for both stocks, we expect $L_{F=M}$ to deliver SPR ratios lower than 40% in the longterm if L_c is substantially below L_{mat} (red line below black line). On the other hand, the reference points are overly precautionary at large values of L_c, leading to SPR ratios larger than 40% (red line above black line).

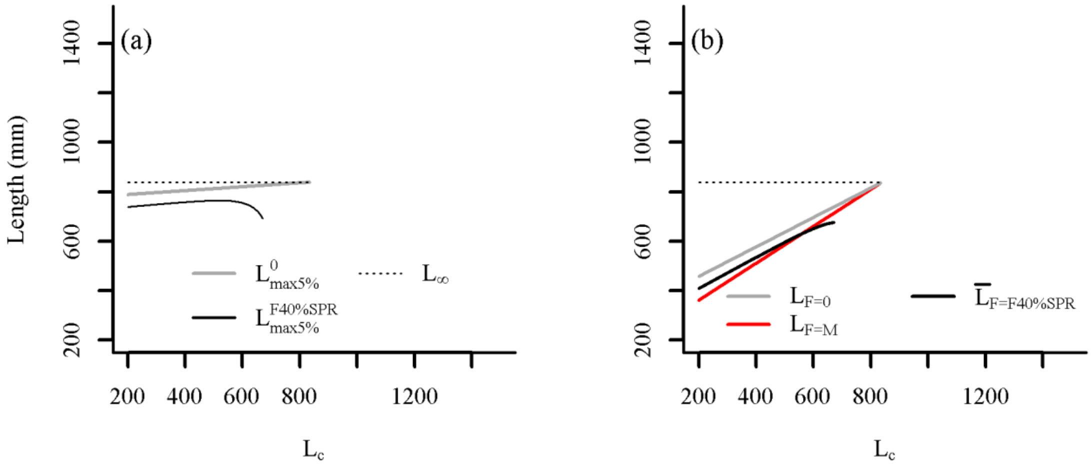

Figure 3.3.1. Reference points (40% SPR in black, $L_{F=M}$ in red, expected values for nearly unexploited status in grey) for cuckoo ray. Mean length of the largest 5% in the catch on the left, mean length in the catch on the right.

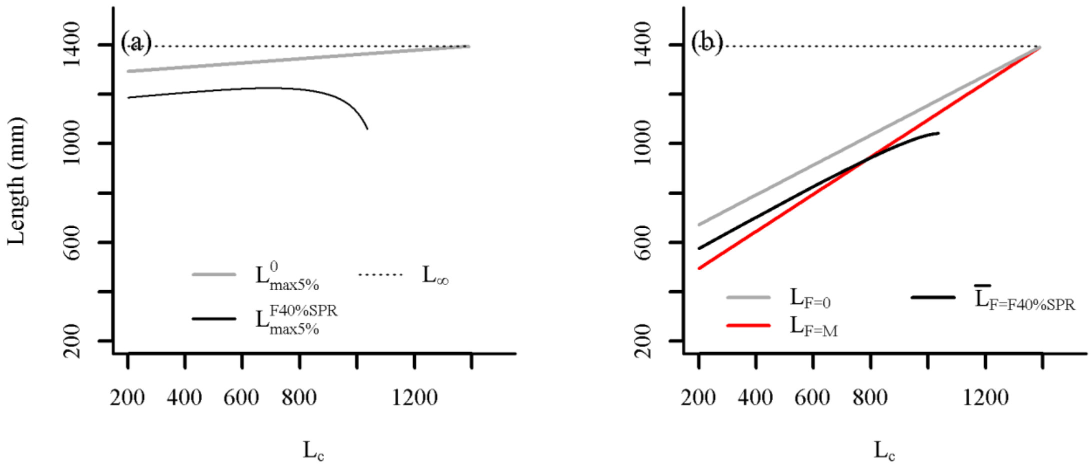

Figure 3.3.2. Reference points (40% SPR in black, $L_{F=M}$ in red, expected values for nearly unexploited status in grey) for thornback ray. Mean length of largest 5% in the catch on the left, mean length in the catch on the right.

Using smaller or larger values of M leads to a change in $L_{F=M}$ reference points (Figure 3.3.3). This change is larger at smaller values of L_c, as stock length distribution are affected by a different level of M (change of M/k as k is constant). For F=M, the reduction in M is directly translated to a reduction in F lowering the exploitation across more targeted size classes if L_c is small. Similarly, M affects SPR-based reference points (Figure 3.3.4). A lower value of M allows for a more extended length distribution and higher length-based reference points. A reduction M causes a stronger change in reference point level at low values of L_c.

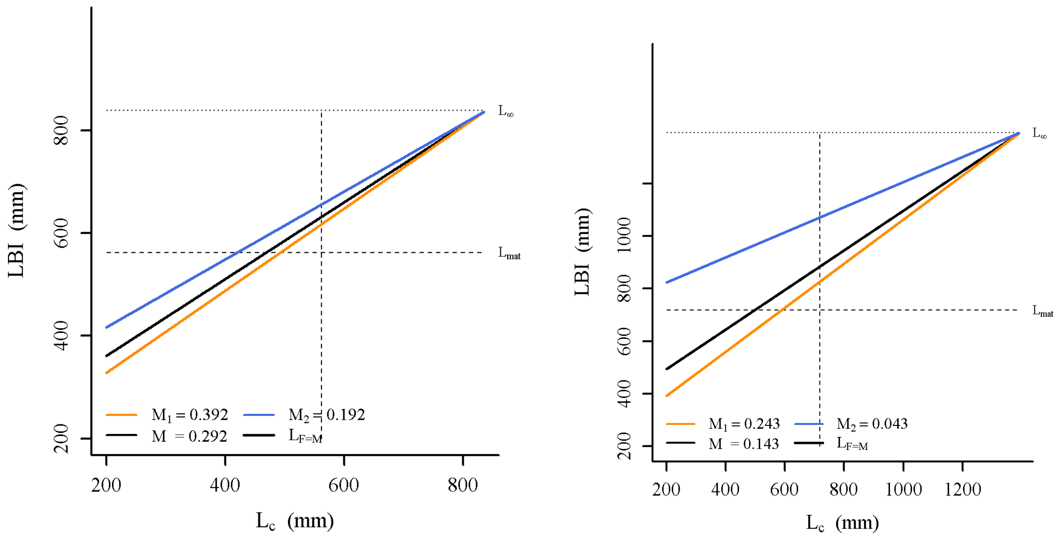

Figure 3.3.3. Reference points $L_{F=M}$ for cuckoo ray (left) and thornback ray (right), and for alternative values of M.

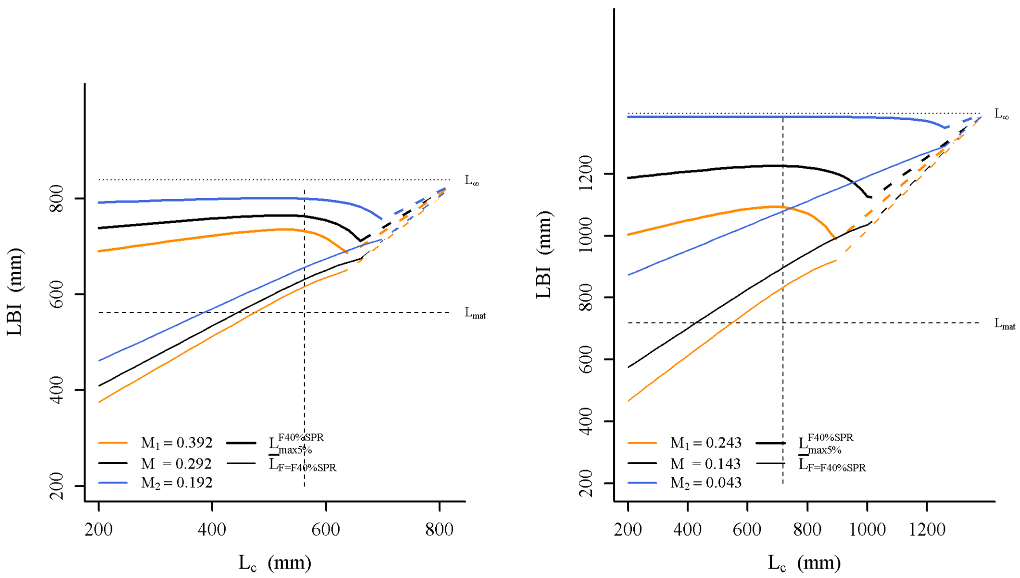

Figure 3.3.4. Reference points for SPR 40% using alternative values of M for cuckoo ray on the left and thornback ray on the right.

In Figure 3.3.5, the respective values of $F_{40\%SPR}$ (relating to Figure 3.3.4) are illustrated. For cuckoo ray (Figure 3.3.5, left panel) the relationship is similar across different values of M, with F=M at SPR of 40% as L_c is equal to L_{mat}. The F/M ratio decreases below 1 as $L_c$decreases, and increases to infinity as the L_c increases beyond L_{mat} (majority of size classes protected allowing higher F while SPR is at or even above 40% SPR).

In contrast for thornback ray the relationship appears to be less clear. The ratio F/M is equal to 1 at 40% SPR only at L_c>L_{mat} , at varying value of L_c depending on M (Figure 3.3.5 right panel). For this species the value of M (alternative M_2) is relatively low.

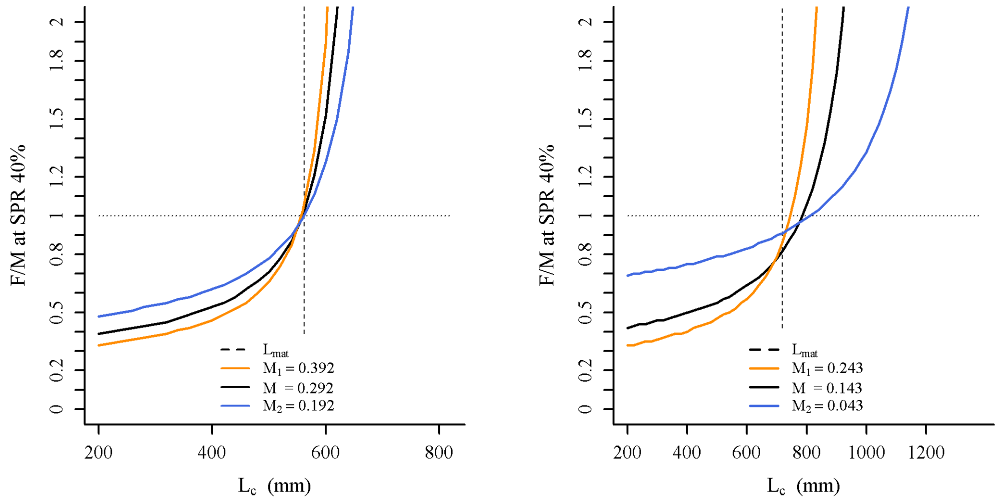

Figure 3.3.5. Reference points for SPR 40% using more alternative values of M for cuckoo ray on the left and thornback ray on the right.

We can compare the reference points for more values of M (Figure 3.3.6). While the lines generally intersect for 40% SPR and F=M at around L_{mat}, it is illustrated in Figure 3.3.6 that for low values of M, 40%SPR is reached at L_c either slightly above or slightly below L_{mat}. The F/M ratio decreases down to value of 0.2 for low values of $L_c$and high values of M while ensuring an SPR of 40%. F/M tends to infinity as L_c increases and a substantial part of mature biomass is not targeted by fishing (hence ensuring at least 40%SPR whatever the fishing intensity).

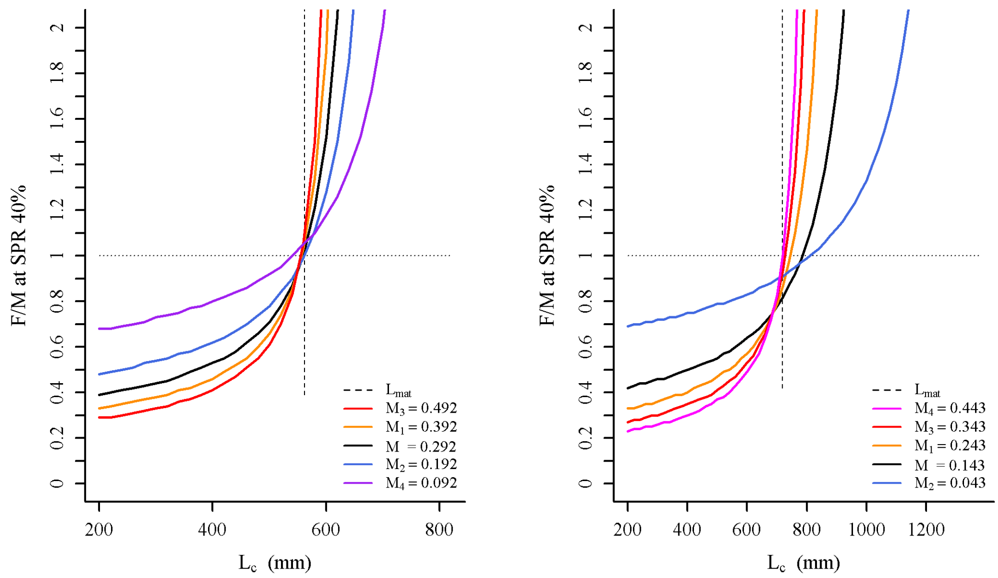

Figure 3.3.6. Reference points for SPR 40% using more alternative values of M for cuckoo ray on the left and thornback ray on the right.

Using alternative values of L_{mat}, the reference points change according to Figure 3.3.7. Reference points increase slightly with increasing L_{mat}. The respective values of F/M at 40% SPR are illustrated in Figure 3.3.8. At a particular level of L_c, if $L_{mat}$is lower the SSB is calculated over a wider range of size classes which allows higher values of fishing mortality (F/M). The pattern is consistent in both ray stocks and across a wide range of values of L_{mat} (Figure 3.3.9). The change is stronger in cuckoo ray than in thornback ray.

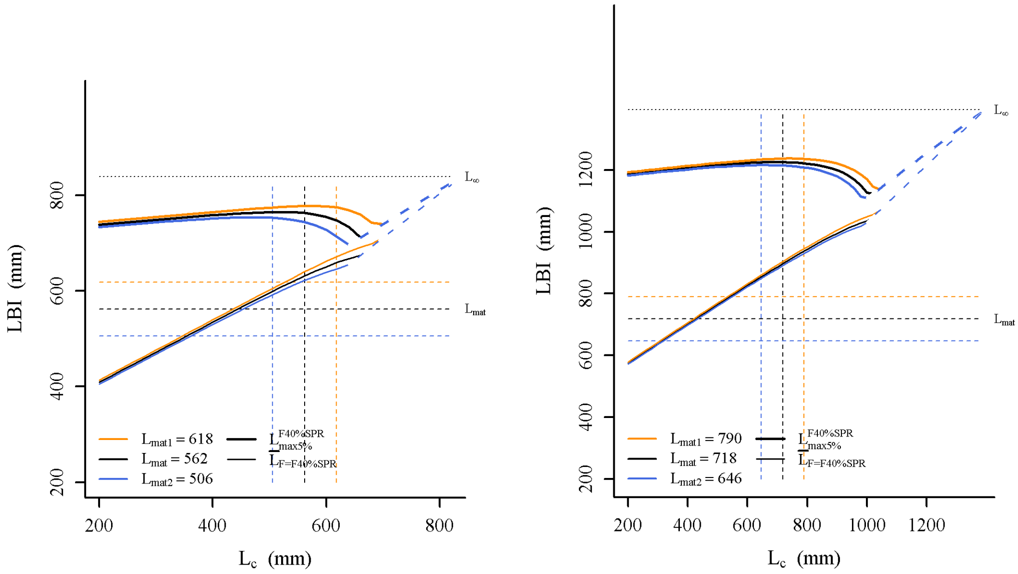

Figure 3.3.7. Reference points for SPR 40% using alternative values of L_{mat} for cuckoo ray on the left and thornback ray on the right.

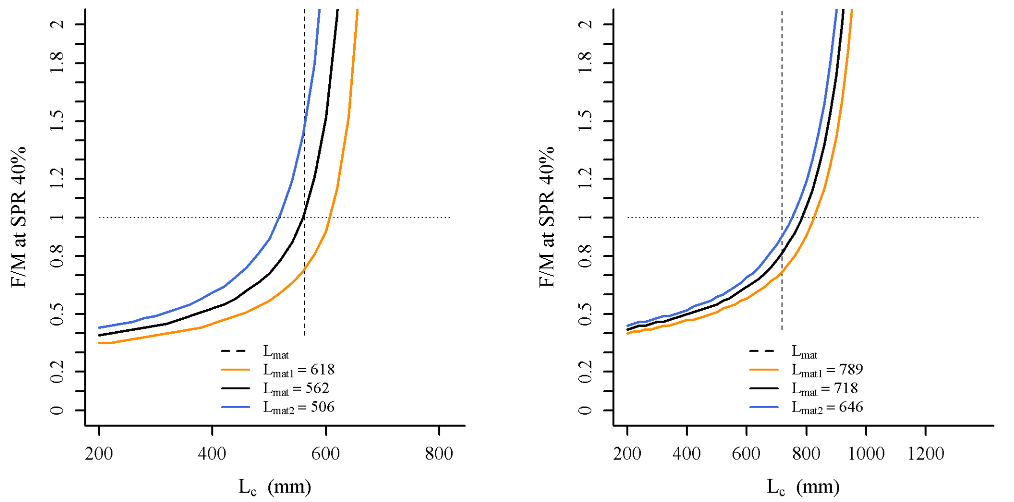

Figure 3.3.8. F/M at 40% SPR using alternative values of L_{mat} for cuckoo ray on the left and thornback ray on the right, relating to Figure 3.3.7.

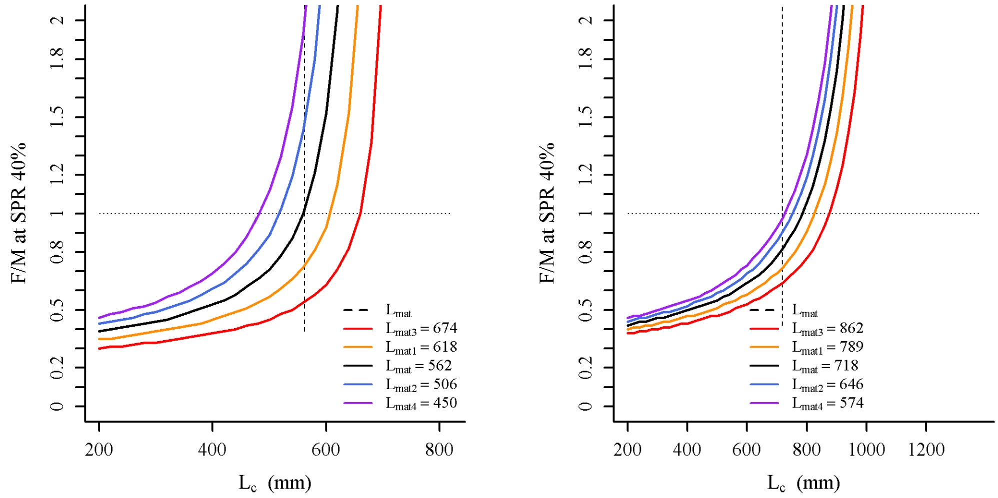

Figure 3.3.9. Reference points for SPR 40% using more alternative values of L_{mat} for cuckoo ray on the left and thornback ray on the right. Dashed line L_{mat} (baseline).

3.4 Discussion

It has been shown (also see working document in Annex 4), that the performance of $L_{F=M}$as a reference point is expected to vary depending on the life history, selectivity and spawning–stock recruitment relationship.The length-based indicator calculation is affected by recruitment dynamics, in particular for low values of L_c. The performance of harvest control rulescan be improved by combining length-based indicators with a CPUE-based stock index.

For elasmobranchs, $L_c$is typically below L_{mat}. This can lead to overexploitation of immature individuals and thereby diminishing the number of mature individuals in the stock needed for reproduction. The reference point $L_{F=M}$ does not depend on L_{mat}. It is therefore possible that for low values of L_c , $L_{F=M}$, the expected mean length in the catch when F=M, is actually below L_{mat}. Ideally, the mean length in the catch should be above $L_{mat}$to limit the risk of SSB to fall below biomass thresholds. To ensure and SPR of at least 40%, fishing mortality may need to be below M if L_c<L_{mat} (Figure 3.3.6).

The mean length in the catch is strongly affected by selectivity of the fishery (L_c, Figure 3.3.2). Due to the “sampling effect” (Miethe *et al.*,2019) even at infinitesimally low level of fishing mortality, changing L_c changes the expected mean length in the catch. With uncertainty in L_c, it is difficult to determine a precautionary reference point across various values of L_c. The option of choosing L_{mat} as the reference point for the mean in the catch, has been discussed in the workshop. While L_{mat} may bean (overly) precautionary reference point for low values of L_c, but it may not be precautionary for higher values of L_c. At some high values of L_c, the mean length in the catch expected even from a virtually unexploited stock may exceed L_{mat}. Further, work is necessary to account for uncertainty in L_c when estimating a reference point for mean length.

In comparison, $L_{max5\%}$ the mean length of the largest 5% in the catch changes less with L_c (Figure 3.3.2). For $L_{max5\%}$, it possible to define a precautionary reference point which can be applied even with high uncertainty in L_c. For example, the maximum value of the reference point across a wide range of different values of L_c, which ensure 40% SPR can be used (maximum of curve $L_{max5\%40\%SPR}$ in Figure 3.3.2a).

3.5 References

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4 Length-based approach

4.1 Introduction

This section focuses on the ToRa) and the revision of the draft ICES technical guidance on advice rules for stocks in Categories 3 and 4 (Annex 3).

4.2 Optimisation of WKMSYCat34 catch rule 3.2.1

4.2.1 Management Strategy Evaluation

The operating models were based on the work presented during WKLIFE VII (ICES, 2017a) and WKLIVE VIII (ICES, 2018) and the same life-history parameters were used to simulate them. The operating models were created using the FLR package FLife (https://github.com/flr/FLife) developed under the MyDas project. A total of 28 stocks were simulated. The previously highest k stock (sandeel with $k = 1$) was not included because with the latest version of FLife, this stock appeared to be overly productive; i.e. could not be fished down sufficiently during the creation of the operating model. Simulations were conducted with FLR's "mse" R package (https://github.com/flr/mse) with minor modifications so that it could be used in a data-limited context (https://github.com/shfischer/mse/tree/mseDL). Previously, two fishing histories ("one-way" and "roller-coaster") were used, both representing severely depleted stocks (one of which was starting to recover). For this workshop, a new fishing history was simulated, covering a wide range of depletion levels (Figure 4.2.1).

The fishing mortality associated with each of the 500 replicates (i) at the start of the projection period was drawn from a lognormal distribution centred around F_{MSY}:

$$F_{i,y=0} = F_{MSY}e^{\varepsilon_i}, \text{where } \varepsilon_i \sim N[0,1] (equation\ 4.2.1)$$

Additionally, the fishing mortality was varied randomly over a period of 100 years (y) for each replicate:

$$F_{i,y} = F_{i,y=0}e^{\varepsilon_y}, \text{where } \varepsilon_y \sim N[0,0.25] (equation\ 4.2.2)$$

This fishing mortality pattern was then used for all simulated stocks to create the stock-specific fishing history.

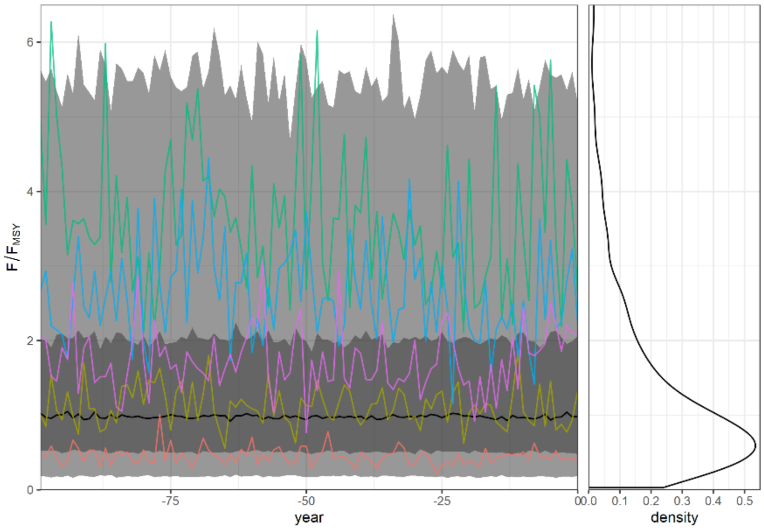

Figure 4.2.1. Fishing history for the operating models, as used for all simulated stocks. The left plot shows the targeted fishing mortality with the median of the 500 replicates in black, 50% and 90% confidence intervals and five individual replicates in colour (the same replicates are highlighted in subsequent figures). The right plot shows the density of the targeted fishing mortalities.

The application of this fishing history meant that at the end of the fishing history approximately half of the stocks were below and half above B_{MSY}.

Recruitment was implemented as previously, with a CV of 0.3.

The operating models were created with 500 replicates ("iterations" in FLR). The projection period (duration for the application of the catch rule) was set to 50 years with a biennial TAC. Compared to previous WKLIFE simulation for this catch rule, the MSE design was simplified for computational efficiency. The biomass index was created with a selectivity corresponding to maturity; therefore, the biomass index is effectively the SSB. For the observation error model, a lognormal noise term was introduced to the SSB to get the observed index value (I_y):

$$I_y = SSB_y e^{\varepsilon_y}, \text{where } \varepsilon_y \sim N[0, 0.2] (equation\ 4.2.3)$$

For the generation of the mean length in the catch (L_{mean}) above L_C (first length class at or above 50% of modal abundance in the catch), catch length frequencies were first created by converting ages into lengths deterministically, and then uncertainty was included the same way as for the index:

$$L_{meanobserved,y} = L_{mean,y} e^{\varepsilon_y}, \text{where } \varepsilon_y \sim N[0, 0.2] (equation\ 4.2.4)$$

B_{lim} was defined, as previously (ICES, 2017b; 2018), as the SSB from the stock–recruitment function where recruitment is at 70% of virgin recruitment.

4.2.2 Catch rule

The subject of analysis was WKNSMSYCat34 catch rule 3.2.1 (ICES, 2017b):

$$C_{y+1} = C_{current}\ r\ f\ b\ (equation\ 4.2.5)$$

Where C_{y+1} is the newly advised catch, $C_{current}$ is the recent catch, r is the trend in the biomass index, f is an exploitation proxy from catch length data and b is a biomass safeguard. Previously, additional elements (catch constraints and a multiplier) were included but were not considered here. Different options for the components are available and previous testing during WKLIFE narrowed it down to the following options: $C_{current} = C_{y-1}$ (i.e. the last available catch), $r = \frac{\sum_{i=y-2}^{y-1} I_i/2}{\sum_{i=y-5}^{y-3} I_i/3}$ (the "2 over 3" rule applied to an biomass index I), $f = \bar{L}_{y-1}/L_{F=M}$ with $L_{F=M} = 0.25L_c + 0.75L_\infty$ derived by assuming $M/k = 1.5$ and $b = min\left\{1, \frac{I_{current}}{I_{trigger}}\right\}$ with $I_{trigger} = 1.4I_{loss}$, where I_{loss} is the lowest observed index value in the 25 years prior to the start of the projection. To make the rule more flexible additional elements were introduced:

$$C_{y+1} = C_{current} r^{e_r} f^{e_f} b^{e_b} (equation\ 4.2.6)$$

The newly introduced exponents e_r, e_f and e_b allow the weighting of the three components. Setting all to 1 corresponds the default catch rule (no weighting), setting $e_x < 1$ reduces the weight of the component and makes it less reactive, with $e_x = 0$ removing it altogether and setting $e_x > 1$ gives the component more weight by making it more reactive. The recent catch was modified so that it corresponded to an average of the N previous years:

$$C_{current} = \sum_{n=1}^{N} \frac{C_{y-n}}{N} \ (equation\ 4.2.7)$$

The r component was adapted so that it corresponded to an average of l_1 divided by l_2 years and the most recent year was defined as an offset s to the intermediate (assessment) year y:

$$r = \frac{\sum_{i=y-s-l_1+1}^{y-s} \frac{I_i}{l_1}}{\sum_{i=y-s-l_1-l_2+1}^{y-s-l_1} \frac{I_i}{l_2}} (equation\ 4.2.8)$$

The remaining components (f, b) were not altered.

4.2.3 Optimisation procedure

The modifications of the catch rule made the rule very flexible but introduced seven more parameters, making it difficult optimise. A Genetic Algorithm (GA) was used as optimisation procedure, mimicking evolutionary principles (mutation, crossover, selection). The R package "GA" (Scrucca, 2013) was used for this, but slightly modified to allow for massive parallelisation on high performance computing (HPC) systems (https://github.com/shfischer/GA). This approach allowed to improve the performance of the catch rule efficiently. However, in a GA approach, the fitness function has to be designed such that the fitness of an individual (here one MSE simulation with one set of parameters) is evaluated. The catch rule is designed with a length target ($L_{F=M}$) approximating MSY, and so it is expected to lead to B_{MSY}; therefore, a first fitness function was defined as the deviation of the SSB from B_{MSY} during the MSE simulation, summed up over the replicate i and year y dimensions:

$$fitness_{MSY} = -\sum_{y=1}^{50} \sum_{i=1}^{500} \left(SSB_{y,i} - B_{MSY}\right)^2 \ (equation\ 4.2.9)$$

A minus sign was added to the fitness function because the algorithm used maximises the fitness; i.e. the deviation is minimised. An additional fitness function was defined for the case when the catch rule was applied in a reduced form, without trigger or target reference values ($C_{y+1} = C_{current}\ r$). In this case, the fitness function measured the deviation of the SSB from the initial SSB at the beginning of the MSE simulation with the reasoning that the "2 over 3" rule was originally implemented as a means of keeping the stocks at *status quo*. Additionally, a penalty term was added, penalising the fitness (moving it away from 0) if the B_{lim} risk increased during the simulation compared to the beginning of the simulation.

$$fitness_{sq} = -\left[\sum_{y=1}^{50}\sum_{i=1}^{500}\left(SSB_{y,i} - SSB_{y=0,i}\right)^2\right] \times \frac{risk_{projection}}{risk_{start}} (equation\ 4.2.10)$$

where$risk_{start}$ is the risk of the stock being below B_{lim} at the start of the simulation (year 0) and $risk_{projection}$ is the risk of the stock being below B_{lim} during the entire projection (years 1–50).

Setting parameters for a genetic algorithm optimisation procedure is a difficult task, and there is no obvious solution. Here, the settings were chosen based on computational limitations, because each fitness evaluation was a stochastic full feedback MSE projection and could, depending on the stock, take several CPU hours computing time. The initial population size (i.e. the number of MSE projections in one generation) was set to 40. The optimisation procedure was terminated if either (i) no improvement was reached within the last ten generations, (i.e. that the best performing individual per generation did not show any improvement), or (ii) 50 generations were reached (i.e. after a maximum of 40*50=200 scenarios). Please note that a genetic algorithm does not necessarily reach a global optimum; however, the result obtained is usually a substantial improvement.

The parameters values optimised in the genetic algorithm can take any real number. However, to make it more realistic, constraints were applied. The parameters expressing years (N, s, l_1, l_2, see equations 4.2.7 and 4.2.8) were rounded to the nearest full year (integer) and the exponents (e_r, e_f, e_b, see equation 4.2.6) were rounded to one decimal digit for computational efficiency. Furthermore, the following limits were imposed:

- catch range: N = 1, 2, …, 5
- biomass index: s = 0, 1, 2, … 5; l_1, l_2 = 1, 2, …, 5
- exponents: e_r, e_f, e_b = 0, 0.1, 0.2, …, 2

With these possible values, there are around seven million possible combinations (per stock).

Despite the modifications to make the simulations computationally more efficient, they are still computationally expensive. For most stocks, one optimisation procedure run took a few hundred CPU hours, but the run time could be reduced to a few hours by making use of massive parallelisation on HPC systems.

4.2.4 Results

Catch rule without observation error

Firstly, the genetic algorithm (GA) was used to optimise the catch rule assuming perfect observations; i.e. the biomass index corresponded to the SSB from the operating model, the mean catch length (above length of first capture L_c) was known without error ($\varepsilon_y = 0$ in equations 4.2.3–4.2.4) and the $I_{trigger}$ value used in the biomass safeguard component of the catch rule (b) was set to B_{lim}, taken from the operating model. The reference length used in the f component was nevertheless set to $L_{F=M}$. Figure 4.2.2 shows the GA progress for one example stock (pollack), for which the GA terminated after 25 generations. Figure 4.2.3 shows pollack when subjected to the catch rule with default parameters (i.e. catch of the last $N = 1$ years, the index trend is calculated with a time-lag$s = 1$, using the “2 over 3” rule $l_1 = 2$, $l_2 = 3$ and the exponents are all set to $e_r = e_f = e_b = 1$), Figure 4.2.4 shows pollack when used with optimised parameters ($N = 2$, $s = 0$, $l_1 = 3$, $l_2 = 2$, $e_r = 1.4$, $e_f = 1.8$ and $e_b = 0.3$). When the catch rule was implemented with default parameters, the SSB moved above B_{MSY} after the implementation of the catch rule and maintained a large range of SSBs around the median. However, when subjected to the optimised catch rule, the individual replicates converged towards B_{MSY} and the range of SSBs narrowed substantially over time. Figure 4.2.5 shows the SSBs for all simulated stocks with the default catch rule, and Figure 4.2.6 for the optimised (stock-specific) parameters. With default parameters, most lower $k$stocks stayed around BMSY (but with high spread) whereas the higher k stocks frequently moved away from BMSY. The optimised parameters resulted in SSB trajectories converging towards BMSY in most cases. In general, for the higher k stocks, a large range of SSB values is maintained throughout the simulated period and the SSB shows higher variability in individual replicates, which is also observed in the median SSB.

Table 4.2.1 shows a summary of the improvement (fitness function value and deviation from BMSY) through the optimisation procedure. The optimised parameters resulted in an improved of the fitness function for all stocks of between 30–87% and catch, F and SSB were generally closer to their MSY reference value (performance statistics not shown). However, Blim risk increased for 25 out of the 28 stocks and inter-annual catch variability increased for 21 stocks (not shown). The optimised catch rule parameters are stock-specific, but some general trends were visible. The lag between the intermediate year and the most recent year used from the biomass index (s), was 1 for 5 stocks and 0 for the remaining 23; i.e. an index from the beginning of the intermediate year is used. The number of years used in the numerator (l_1) was between 1–4, dominated by two years for 18 of the stocks, and between 2–4 for the denominator (l_2) dominated by three years for 19 stocks. Then number of years used to calculate the current catch (N) was between 1–5, but most stocks (17) had two years. The exponent for component r (e_r) was always 1 or higher with a mean of 1.5, e_f ranged from 0.5–1.9 with mean 1.6 and e_b was in the range 0.2–0.7 with mean 0.3.

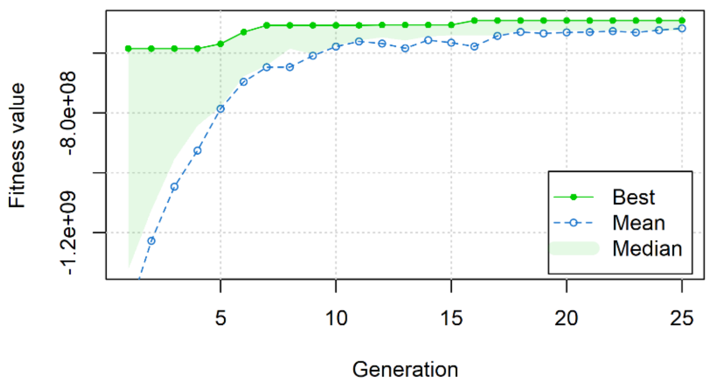

Figure 4.2.2. Result of running the GA for pollack without uncertainty. Shown is the progress of the optimisation procedure over generations. Please note that "Median" shows the spread between the maximum fitness ("Best") and the median fitness; i.e. the bottom of the green area corresponds to the actual median value.

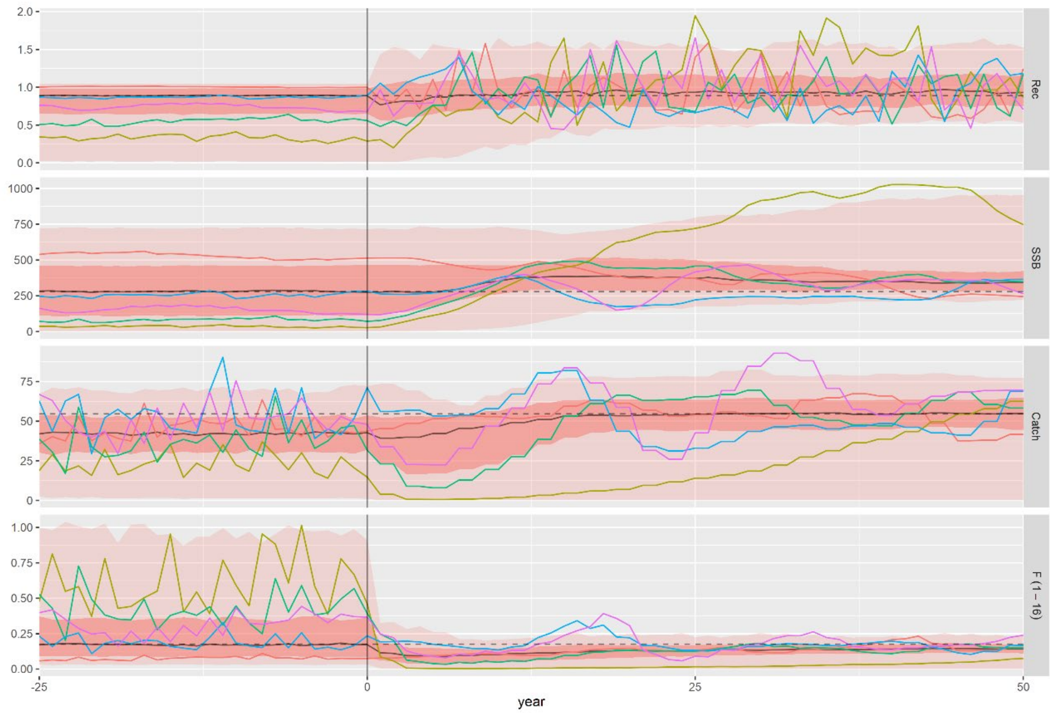

Figure 4.2.3. Results of the application of the catch rule to pollack with default parameters (not tuned). Shown are recruitment, SSB, catch and fishing mortality. The vertical line indicates the start of the implementation of the catch rule, the dashed horizontal lines indicate MSY reference values. Shown are the median (black line), surrounded by 50% and 90% intervals and five replicates (coloured).

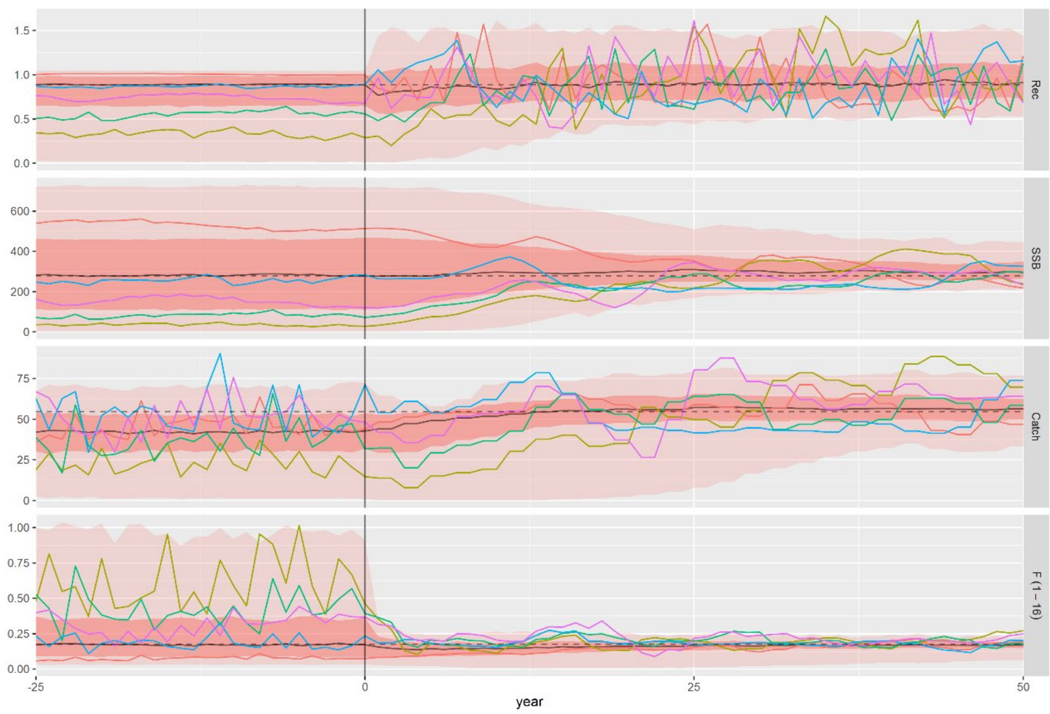

Figure 4.2.4. Results of the application of the catch rule to pollack with optimised parameters. See Figure 4.2.3 for more details.

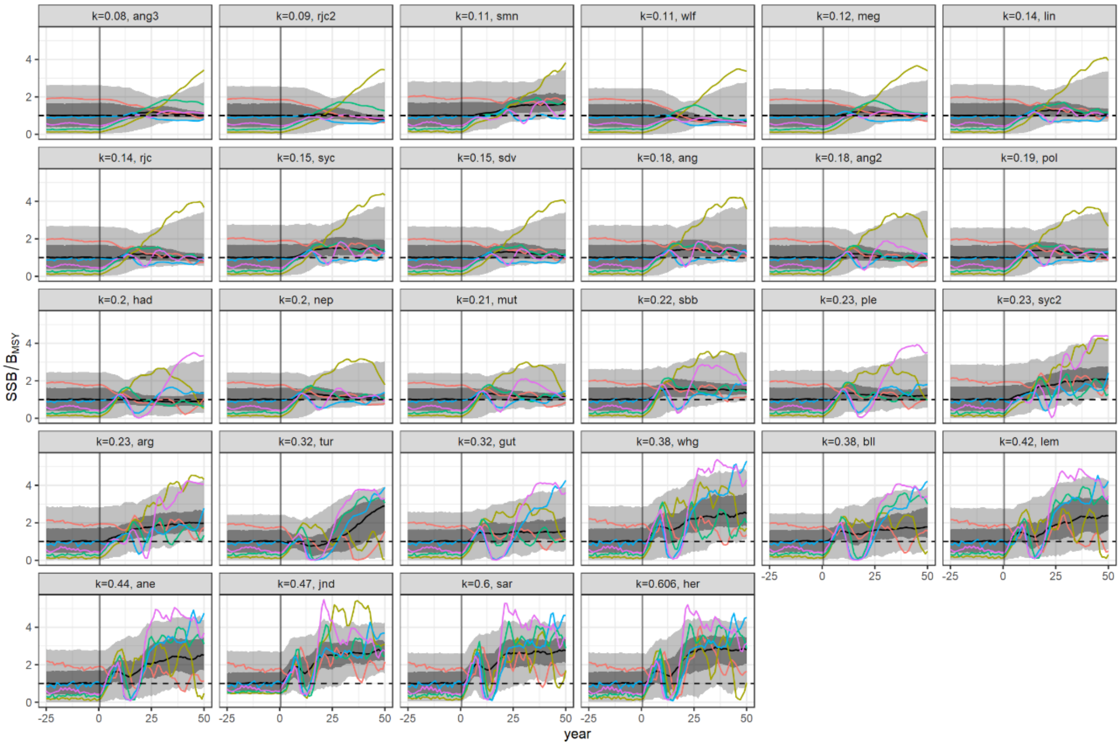

Figure 4.2.5. SSBs for the 28 simulated stocks when subject to the catch rule with default (not tuned) parameters. Shown are the medians (solid curve), surrounded by 50% and 90% intervals and five of the 500 replicates (coloured curves). The vertical solid line indicates the start of the implementation of the catch rule and the dashed horizontal line corresponds to B_{MSY}.

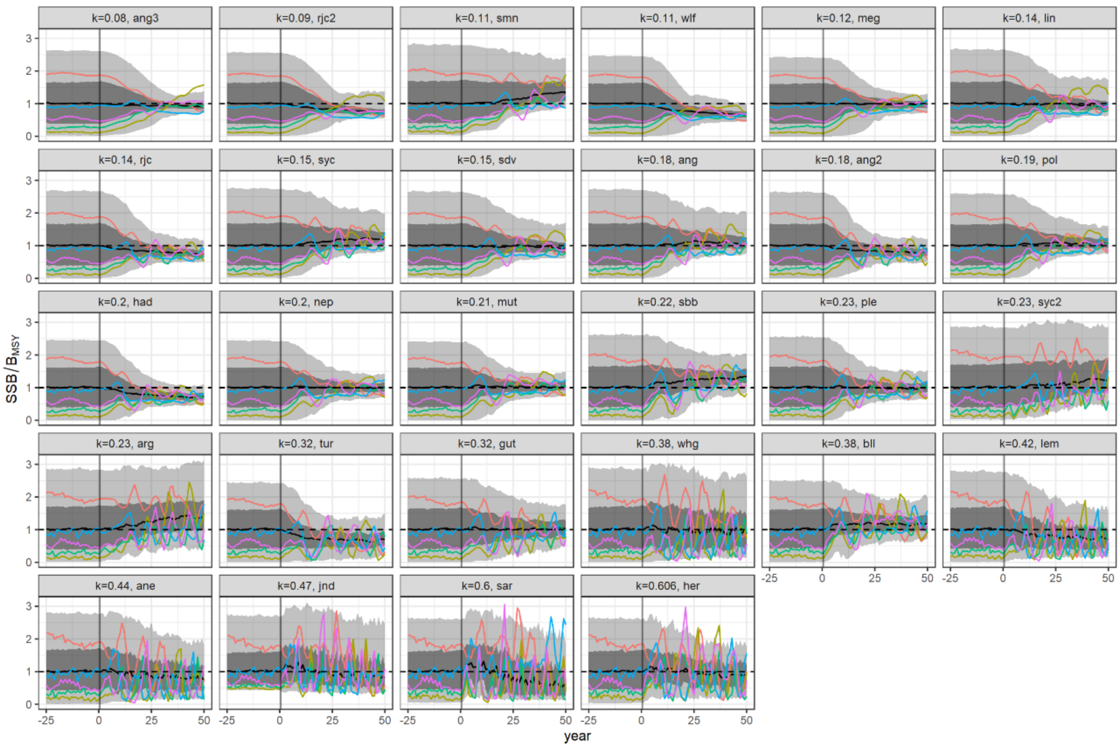

Figure 4.2.6. SSBs for the 28 simulated stocks when subject to the catch rule with optimised parameters. See Figure 4.2.5 for more details.

Table 4.2.1. Improvement of the catch rule without observation error, with optimised parameters in comparison to default parameters.

		optimised catch rule parameters							**fitness**			**deviation from B_{MSY}**		
k	stock	s	l_1	l_2	N	e_r	e_f	e_b	default	optimised	improvement [%]	default	optimised	improvement [%]
0.08	ang3	1	2	3	2	1.4	1.9	0.2	-7.42E+08	-4.62E+08	38	74	56	25
0.09	rjc2	1	3	3	2	1.4	1.9	0.4	-7.83E+08	-5.14E+08	34	84	82	3
0.11	smn	0	2	3	2	1.4	1.9	0.4	-1.18E+09	-7.83E+08	34	121	93	23
0.11	wlf	1	3	4	2	1.4	1.6	0.5	-8.15E+08	-5.66E+08	30	106	102	5
0.12	meg	0	4	3	2	1.4	1.8	0.4	-9.43E+08	-5.03E+08	47	73	59	18
0.14	lin	1	2	3	2	1.4	1.9	0.4	-1.01E+09	-5.28E+08	48	84	66	21
0.14	rjc	0	2	3	1	1.3	1.8	0.3	-9.31E+08	-4.48E+08	52	79	77	2
0.15	syc	0	2	2	1	1.5	1.8	0.3	-1.38E+09	-6.74E+08	51	123	82	33
0.15	sdv	1	2	3	2	1.4	1.9	0.3	-1.07E+09	-5.43E+08	49	90	70	21
0.18	ang	0	2	3	2	1.4	1.9	0.4	-1.30E+09	-6.22E+08	52	108	71	35
0.18	ang2	0	2	3	1	1.4	1.8	0.3	-9.87E+08	-4.34E+08	56	80	73	9
0.19	pol	0	3	2	2	1.4	1.8	0.3	-1.25E+09	-5.73E+08	54	103	66	36
0.2	had	0	2	3	2	1.6	1.3	0.2	-1.09E+09	-5.37E+08	51	102	95	7
0.2	nep	0	3	3	2	1.3	1.7	0.2	-1.11E+09	-5.22E+08	53	89	65	27
0.21	mut	0	2	3	2	1.7	1.7	0.2	-1.13E+09	-4.99E+08	56	96	62	36
0.22	sbb	0	3	3	2	1.4	1.9	0.4	-1.69E+09	-7.78E+08	54	157	100	36

		optimised catch rule parameters							**fitness**			**deviation from B_{MSY}**		
k	stock	s	l_1	l_2	N	e_r	e_f	e_b	default	optimised	improvement [%]	default	optimised	improvement [%]
0.23	ple	0	2	3	2	1.4	1.8	0.2	-1.32E+09	-4.91E+08	63	107	63	41
0.23	syc2	0	1	4	3	1.8	1.1	0.2	-2.13E+09	-1.07E+09	50	185	117	37
0.23	arg	0	2	3	3	1.4	1.5	0.3	-2.09E+09	-1.09E+09	48	181	118	35
0.32	tur	0	2	4	3	1.5	1.2	0.2	-3.43E+09	-7.29E+08	79	230	119	48
0.32	gut	0	2	3	2	1.7	1.7	0.2	-2.16E+09	-7.20E+08	67	165	97	41
0.38	whg	0	3	3	3	1.8	1.2	0.2	-3.76E+09	-1.03E+09	73	244	140	43
0.38	bll	0	2	2	2	1.6	1.6	0.4	-2.82E+09	-7.75E+08	73	204	87	58
0.42	lem	0	3	3	3	1.6	1.8	0.3	-3.30E+09	-7.00E+08	79	208	109	47
0.44	ane	0	3	3	3	1.7	1.6	0.2	-3.69E+09	-7.86E+08	79	232	124	47
0.47	jnd	0	2	2	5	1.9	0.5	0.4	-3.86E+09	-9.12E+08	76	313	107	66
0.6	sar	0	2	2	4	1.9	1.5	0.7	-5.44E+09	-1.16E+09	79	360	166	54
0.606	her	0	2	2	2	1.6	1.8	0.3	-5.48E+09	-7.26E+08	87	333	115	66

Catch rule with observation error

In a second step, the optimisation procedure was repeated with an observation error. Observation uncertainty was implemented for the index (equation 4.2.3) and the mean length (equation 4.2.4). Furthermore, $I_{trigger}$ as used in the b component of the catch rule, was set to $1.4 I_{loss}$. The addition of observation error resulted in higher uncertainty after implementation of the default catch rule for pollack (Figure 4.2.7) and the optimisation procedure yielded a smaller reduction in the spread of trajectories (Figure 4.2.8). Figures 4.2.9 and 4.2.10 show the SSB trajectories for all simulated stock for the default and the optimised stock-specific parameters respectively. In general, when including observation error, the improvement in the catch rule performance is less pronounced compared to the runs without observation error. However, the default parameters frequently moved the stocks above B_{MSY} during the simulated period, and this behaviour could be averted with the optimised parameters. However, for some of the higher k stocks, the median SSB dropped markedly below B_{MSY}. Tables 4.2.2–4.2.4 show a summary of the improvement obtained with the optimisation procedure, and the summary statistics for the scenarios with default and optimised parameters. The optimised parameters resulted in an improved of the fitness function for all stocks of between 39–84% and catch, F and SSB were closer to their MSY reference value. However, B_{lim} risk always increased and inter-annual catch variability increased for 26 out of the 28 stocks. The optimised catch rule parameters are stock-specific, but some general trends were visible, as before. The lag between the intermediate year and the most recent year used from the biomass index (s), was 1 for three stocks and 0 for the remaining 25; i.e. an index from the beginning of the intermediate year is used. The number of years used in the numerator (l_1) was always 2 and between 1 and 4 for the denominator (l_2); however, for most stocks (17), this value was also 2. The number of years used to calculate the current catch (N) was between 2–5, but most stocks were in the range 3–4 (14 and 12 respectively). The exponent for component r (e_r) was always 1 or higher with a mean of 1.4, e_f ranged from 0.5-1.9 with mean 1.4 and e_b was in the range 0.1–0.4 with mean 0.25.

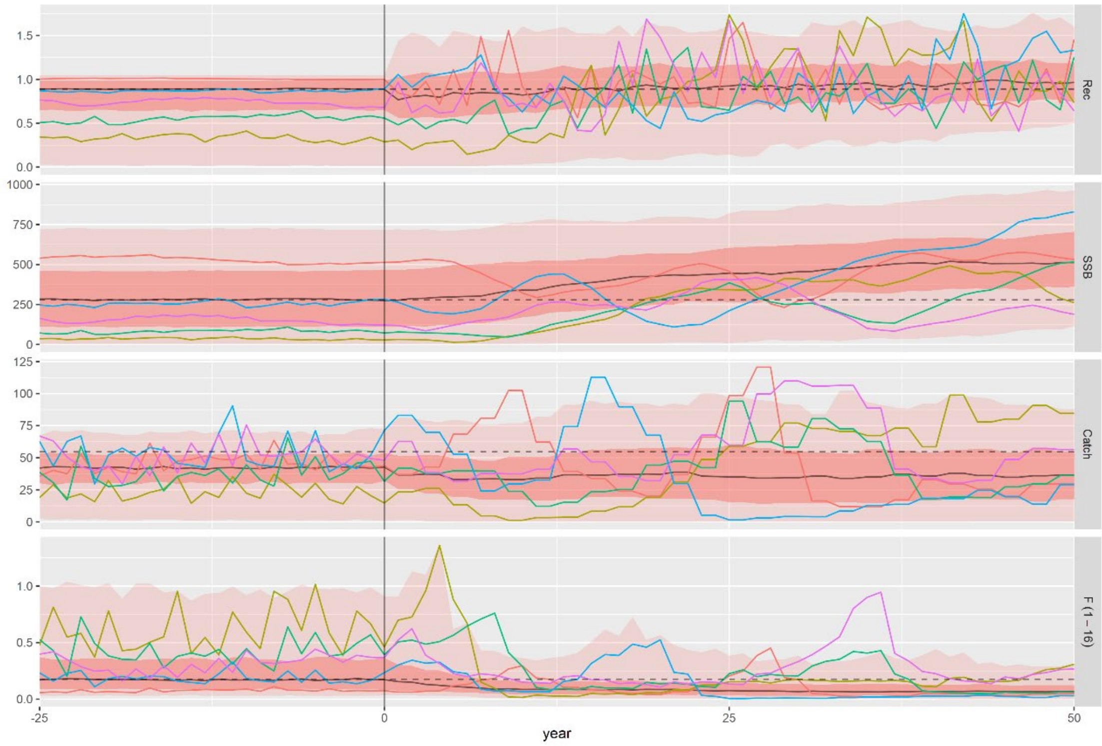

Figure 4.2.7. Results of the application of the catch rule to pollack with default parameters and observation uncertainty. See Figure 4.2.3 for more details.

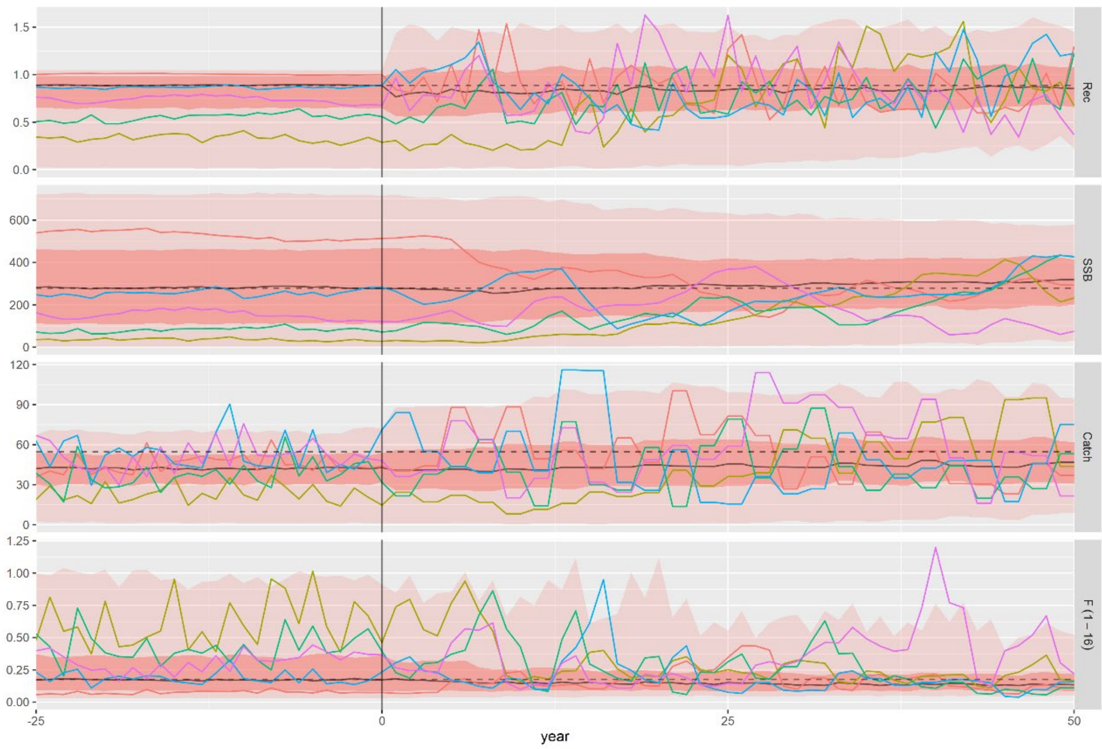

Figure 4.2.8. Results of the application of the catch rule to pollack with optimised parameters and observation uncertainty. See Figure 4.2.3 for more details.

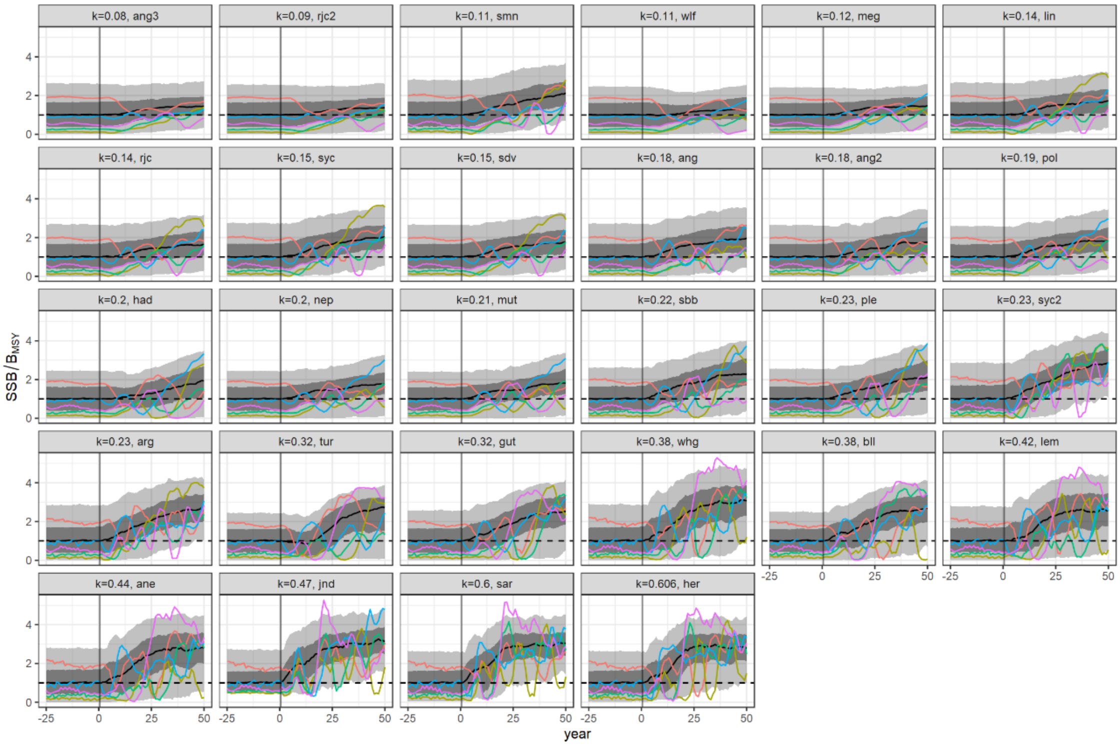

Figure 4.2.9. SSBs for the 28 simulated stocks when subject to the catch rule with default parameters and observation uncertainty. See Figure 4.2.5 for more details.

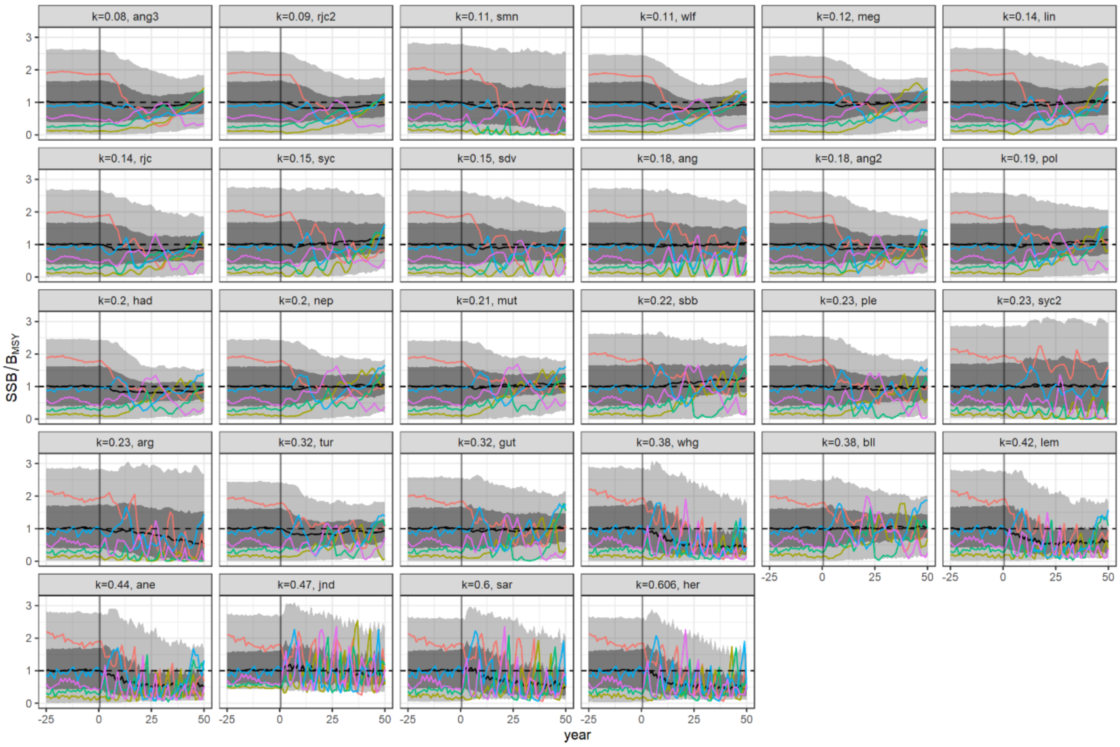

Figure 4.2.10. SSBs for the 28 simulated stocks when subject to the catch rule with optimised parameters and observation uncertainty. See Figure 4.2.5 for more details.

Table 4.2.2. Improvement of the catch rule with observation error and optimised parameters in comparison to default parameters.

		optimised catch rule parameters							fitness			deviation from B_{MSY}		
k	stock	s	l_1	l_2	N	e_r	e_f	e_b	default	optimised	improvement [%]	default	optimised	improvement [%]
0.08	ang3	1	2	2	4	1	1.9	0.3	-1.26E+09	-7.29E+08	42	159	118	26
0.09	rjc2	0	2	3	2	1.3	1.8	0.3	-1.26E+09	-7.70E+08	39	160	123	23
0.11	smn	0	2	1	4	1.4	1.4	0.3	-1.89E+09	-1.03E+09	46	188	156	17
0.11	wlf	0	2	3	3	1.2	1.6	0.4	-1.22E+09	-7.34E+08	40	159	116	27
0.12	meg	0	2	2	3	1.7	1.6	0.3	-1.42E+09	-7.67E+08	46	173	115	33
0.14	lin	1	2	2	4	1	1.6	0.3	-1.65E+09	-8.92E+08	46	182	134	27
0.14	rjc	0	2	3	3	1.1	1.7	0.2	-1.58E+09	-7.86E+08	50	175	127	27
0.15	syc	0	2	4	3	1	1.5	0.1	-2.05E+09	-1.05E+09	49	202	137	32
0.15	sdv	1	2	3	3	1.4	1.6	0.2	-1.76E+09	-9.28E+08	47	189	136	28
0.18	ang	0	2	4	4	1.3	1.6	0.3	-2.05E+09	-9.79E+08	52	201	139	31
0.18	ang2	0	2	4	3	1.1	1.6	0.2	-1.85E+09	-7.44E+08	60	191	120	37
0.19	pol	0	2	4	4	1.2	1.7	0.3	-2.11E+09	-9.44E+08	55	213	136	36
0.2	had	0	2	2	3	1.4	1.1	0.2	-2.14E+09	-7.22E+08	66	217	113	48
0.2	nep	0	2	2	3	1.5	1.4	0.2	-2.07E+09	-8.38E+08	60	217	123	43
0.21	mut	0	2	2	3	1.7	1.3	0.3	-2.22E+09	-8.24E+08	63	224	119	47
0.22	sbb	0	2	2	3	1.6	1.3	0.3	-3.09E+09	-1.05E+09	66	261	144	45

		optimised catch rule parameters							fitness			deviation from B_{MSY}		
k	stock	s	l_1	l_2	N	e_r	e_f	e_b	default	optimised	improvement [%]	default	optimised	improvement [%]
0.23	ple	0	2	2	3	1.6	1.4	0.2	-2.71E+09	-8.19E+08	70	238	128	46
0.23	syc2	0	2	2	3	1.1	0.5	0.2	-3.24E+09	-1.29E+09	60	242	166	31
0.23	arg	0	2	1	4	1.1	1.1	0.2	-3.15E+09	-1.25E+09	60	236	185	22
0.32	tur	0	2	4	4	1.1	1.1	0.4	-4.05E+09	-8.34E+08	79	289	128	56
0.32	gut	0	2	2	3	1.5	1.4	0.2	-3.91E+09	-1.03E+09	74	281	150	47
0.38	whg	0	2	2	4	1.8	1.7	0.2	-4.76E+09	-9.22E+08	81	311	158	49
0.38	bll	0	2	2	3	1.5	1.1	0.1	-4.68E+09	-9.81E+08	79	297	136	54
0.42	lem	0	2	2	4	1.5	1.5	0.3	-4.04E+09	-8.17E+08	80	252	146	42
0.44	ane	0	2	2	4	1.8	1.4	0.3	-4.52E+09	-8.73E+08	81	293	151	48
0.47	jnd	0	2	2	5	1.8	0.7	0.3	-5.27E+09	-8.33E+08	84	381	106	72
0.6	sar	0	2	2	4	1.7	1	0.2	-6.38E+09	-1.17E+09	82	420	173	59
0.606	her	0	2	2	4	1.7	1.3	0.2	-5.82E+09	-9.73E+08	83	377	170	55

Table 4.2.3. Summary statistics for catch rule with observation errorand default parameters.

		default catch rule parameters							summary statistics									
k	stock	s	l_1	l_2	N	e_r	e_f	e_b	fitness	B_{MSY} deviation	B_{lim} risk	B_{MSY} risk	$0.5B_{MSY}$ risk	collapse risk	catch/MSY	SSB/B_{MSY}	F/F_{MSY}	ICV
0.08	ang3	1	2	3	1	1	1	1	-1.26E+09	159	0.20	0.36	0.11	0.019	0.67	1.29	0.58	0.23
0.09	rjc2	1	2	3	1	1	1	1	-1.26E+09	160	0.21	0.39	0.12	0.029	0.69	1.23	0.63	0.24
0.11	smn	1	2	3	1	1	1	1	-1.89E+09	188	0.19	0.28	0.10	0.007	0.56	1.60	0.35	0.25
0.11	wlf	1	2	3	1	1	1	1	-1.22E+09	159	0.21	0.42	0.12	0.037	0.69	1.15	0.65	0.27
0.12	meg	1	2	3	1	1	1	1	-1.42E+09	173	0.15	0.33	0.09	0.036	0.70	1.33	0.54	0.26
0.14	lin	1	2	3	1	1	1	1	-1.65E+09	182	0.19	0.33	0.11	0.023	0.66	1.44	0.49	0.26
0.14	rjc	1	2	3	1	1	1	1	-1.58E+09	175	0.21	0.35	0.11	0.026	0.67	1.38	0.52	0.27
0.15	syc	1	2	3	1	1	1	1	-2.05E+09	202	0.17	0.27	0.10	0.017	0.62	1.61	0.40	0.26
0.15	sdv	1	2	3	1	1	1	1	-1.76E+09	189	0.19	0.32	0.11	0.023	0.65	1.47	0.47	0.26
0.18	ang	1	2	3	1	1	1	1	-2.05E+09	201	0.18	0.29	0.10	0.024	0.65	1.58	0.43	0.27
0.18	ang2	1	2	3	1	1	1	1	-1.85E+09	191	0.20	0.33	0.11	0.031	0.65	1.43	0.49	0.31
0.19	pol	1	2	3	1	1	1	1	-2.11E+09	213	0.17	0.29	0.10	0.031	0.65	1.55	0.45	0.28
0.2	had	1	2	3	1	1	1	1	-2.14E+09	217	0.21	0.37	0.14	0.040	0.55	1.33	0.42	0.39
0.2	nep	1	2	3	1	1	1	1	-2.07E+09	217	0.16	0.30	0.11	0.037	0.65	1.47	0.45	0.31
0.21	mut	1	2	3	1	1	1	1	-2.22E+09	224	0.15	0.29	0.11	0.036	0.63	1.48	0.42	0.33
0.22	sbb	1	2	3	1	1	1	1	-3.09E+09	261	0.15	0.24	0.11	0.035	0.58	1.81	0.33	0.31

		default catch rule parameters							summary statistics									
k	stock	s	l_1	l_2	N	e_r	e_f	e_b	fitness	B_{MSY} deviation	B_{lim} risk	B_{MSY} risk	$0.5B_{MSY}$ risk	collapse risk	catch/MSY	SSB/B_{MSY}	F/F_{MSY}	ICV
0.23	ple	1	2	3	1	1	1	1	-2.71E+09	238	0.17	0.28	0.11	0.031	0.59	1.61	0.38	0.34
0.23	syc2	1	2	3	1	1	1	1	-3.24E+09	242	0.15	0.20	0.09	0.010	0.50	2.05	0.24	0.28
0.23	arg	1	2	3	1	1	1	1	-3.15E+09	236	0.15	0.21	0.09	0.011	0.53	2.01	0.26	0.29
0.32	tur	1	2	3	1	1	1	1	-4.05E+09	289	0.22	0.34	0.16	0.033	0.22	1.61	0.18	0.55
0.32	gut	1	2	3	1	1	1	1	-3.91E+09	281	0.16	0.25	0.11	0.036	0.50	1.88	0.27	0.34
0.38	whg	1	2	3	1	1	1	1	-4.76E+09	311	0.17	0.21	0.11	0.027	0.46	2.34	0.21	0.36
0.38	bll	1	2	3	1	1	1	1	-4.68E+09	297	0.14	0.22	0.10	0.024	0.42	1.98	0.22	0.38
0.42	lem	1	2	3	1	1	1	1	-4.04E+09	252	0.19	0.26	0.12	0.022	0.50	2.03	0.26	0.40
0.44	ane	1	2	3	1	1	1	1	-4.52E+09	293	0.17	0.23	0.11	0.021	0.48	2.20	0.23	0.38
0.47	jnd	1	2	3	1	1	1	1	-5.27E+09	381	0.07	0.12	0.01	0.000	0.54	2.62	0.17	0.32
0.6	sar	1	2	3	1	1	1	1	-6.38E+09	420	0.09	0.14	0.06	0.000	0.41	2.55	0.15	0.35
0.606	her	1	2	3	1	1	1	1	-5.82E+09	377	0.12	0.18	0.08	0.003	0.42	2.40	0.17	0.41

Table 4.2.4. Summary statistics for catch rule with observation errorand optimised parameters.

		optimised catch rule parameters							summary statistics									
k	stock	s	l_1	l_2	N	e_r	e_f	e_b	fitness	B_{MSY} deviation	B_{lim} risk	B_{MSY} risk	$0.5B_{MSY}$ risk	collapse risk	catch/MSY	SSB/B_{MSY}	F/F_{MSY}	ICV
0.08	ang3	1	2	2	4	1	1.9	0.3	-7.29E+08	118	0.30	0.56	0.14	0.023	0.75	0.91	0.89	0.39
0.09	rjc2	0	2	3	2	1.3	1.8	0.3	-7.70E+08	123	0.31	0.59	0.15	0.033	0.76	0.86	0.99	0.36
0.11	smn	0	2	1	4	1.4	1.4	0.3	-1.03E+09	156	0.43	0.56	0.28	0.063	0.73	0.84	1.00	0.52
0.11	wlf	0	2	3	3	1.2	1.6	0.4	-7.34E+08	116	0.26	0.60	0.12	0.038	0.80	0.86	1.00	0.36
0.12	meg	0	2	2	3	1.7	1.6	0.3	-7.67E+08	115	0.20	0.52	0.10	0.039	0.79	0.97	0.86	0.45
0.14	lin	1	2	2	4	1	1.6	0.3	-8.92E+08	134	0.31	0.51	0.16	0.035	0.78	0.97	0.85	0.37
0.14	rjc	0	2	3	3	1.1	1.7	0.2	-7.86E+08	127	0.36	0.58	0.18	0.035	0.79	0.85	0.97	0.39
0.15	syc	0	2	4	3	1	1.5	0.1	-1.05E+09	137	0.29	0.47	0.15	0.023	0.78	1.07	0.76	0.34
0.15	sdv	1	2	3	3	1.4	1.6	0.2	-9.28E+08	136	0.32	0.53	0.17	0.035	0.76	0.94	0.81	0.42
0.18	ang	0	2	4	4	1.3	1.6	0.3	-9.79E+08	139	0.32	0.50	0.18	0.034	0.77	0.99	0.78	0.45
0.18	ang2	0	2	4	3	1.1	1.6	0.2	-7.44E+08	120	0.32	0.56	0.15	0.034	0.83	0.90	0.96	0.36
0.19	pol	0	2	4	4	1.2	1.7	0.3	-9.44E+08	136	0.26	0.47	0.14	0.038	0.80	1.05	0.82	0.40
0.2	had	0	2	2	3	1.4	1.1	0.2	-7.22E+08	113	0.26	0.61	0.12	0.039	0.87	0.85	1.04	0.38
0.2	nep	0	2	2	3	1.5	1.4	0.2	-8.38E+08	123	0.20	0.50	0.11	0.038	0.82	1.00	0.86	0.41
0.21	mut	0	2	2	3	1.7	1.3	0.3	-8.24E+08	119	0.17	0.47	0.09	0.038	0.83	1.04	0.82	0.45
0.22	sbb	0	2	2	3	1.6	1.3	0.3	-1.05E+09	144	0.23	0.42	0.13	0.041	0.79	1.14	0.74	0.45

		optimised catch rule parameters							summary statistics									
k	stock	s	l_1	l_2	N	e_r	e_f	e_b	fitness	B_{MSY} deviation	B_{lim} risk	B_{MSY} risk	$0.5B_{MSY}$ risk	collapse risk	catch/MSY	SSB/B_{MSY}	F/F_{MSY}	ICV
0.23	ple	0	2	2	3	1.6	1.4	0.2	-8.19E+08	128	0.29	0.54	0.15	0.036	0.81	0.93	0.90	0.47
0.23	syc2	0	2	2	3	1.1	0.5	0.2	-1.29E+09	166	0.39	0.49	0.25	0.058	0.78	1.02	0.78	0.37
0.23	arg	0	2	1	4	1.1	1.1	0.2	-1.25E+09	185	0.47	0.56	0.34	0.080	0.70	0.80	0.98	0.49
0.32	tur	0	2	4	4	1.1	1.1	0.4	-8.34E+08	128	0.28	0.59	0.14	0.033	0.85	0.87	0.94	0.41
0.32	gut	0	2	2	3	1.5	1.4	0.2	-1.03E+09	150	0.30	0.51	0.18	0.041	0.78	0.97	0.83	0.48
0.38	whg	0	2	2	4	1.8	1.7	0.2	-9.22E+08	158	0.59	0.70	0.38	0.040	0.65	0.54	1.06	0.71
0.38	bll	0	2	2	3	1.5	1.1	0.1	-9.81E+08	136	0.24	0.48	0.13	0.028	0.83	1.03	0.80	0.47
0.42	lem	0	2	2	4	1.5	1.5	0.3	-8.17E+08	146	0.53	0.69	0.31	0.026	0.71	0.61	1.04	0.66
0.44	ane	0	2	2	4	1.8	1.4	0.3	-8.73E+08	151	0.54	0.70	0.33	0.031	0.67	0.60	1.04	0.74
0.47	jnd	0	2	2	5	1.8	0.7	0.3	-8.33E+08	106	0.33	0.52	0.05	0.000	0.85	0.97	0.89	0.66
0.6	sar	0	2	2	4	1.7	1	0.2	-1.17E+09	173	0.47	0.64	0.27	0.000	0.72	0.67	0.98	0.72
0.606	her	0	2	2	4	1.7	1.3	0.2	-9.73E+08	170	0.53	0.71	0.32	0.003	0.70	0.56	1.14	0.73

Catch rule without components *f* and *b*

Figure 4.2.11 show the stocks trajectory for pollack when the catch rule is used with default parameters and observation error but without components *f* and *b*; i.e. the "2 over 3 rule" and Figure 4.2.12 the results for the same stock but with optimised parameters. Figure 4.2.13 shows the SSB trends for all simulated stocks with default parameters and Figure 4.2.14 with optimised parameters. With default parameters, most lower *k* stocks remained, on average, around B_{MSY} during the simulation; i.e. the initial SSB was maintained. However, some of the medium-to-higher *k* stocks moved away from B_{MSY}, typically to higher levels, and the replicates exhibited high oscillations. The summary statistics for the scenarios with default and optimised parameters and a comparison is found in Tables 4.2.5–4.2.7. The fitness function value, accounting for deviation of SSB to starting SSB and also for risk, was improved for all stocks and the improvement ranged from 53% to 82% with optimised parameters. However, the deviation of SSB to B_{MSY} was not reduced in all cases because it was not part of the fitness function evaluation. The catch was increased for all stocks between 4% and 26%, F and SSB moved closer to their corresponding MSY reference point, inter-annual catch variability was reduced for 26 out of the 28 stocks. Despite including a risk penalty in the fitness function, B_{lim} risk increased for all stocks between 5% and 91% because the fitness value was dominated by the deviation of the SSB, and the risk component did not have enough influence.

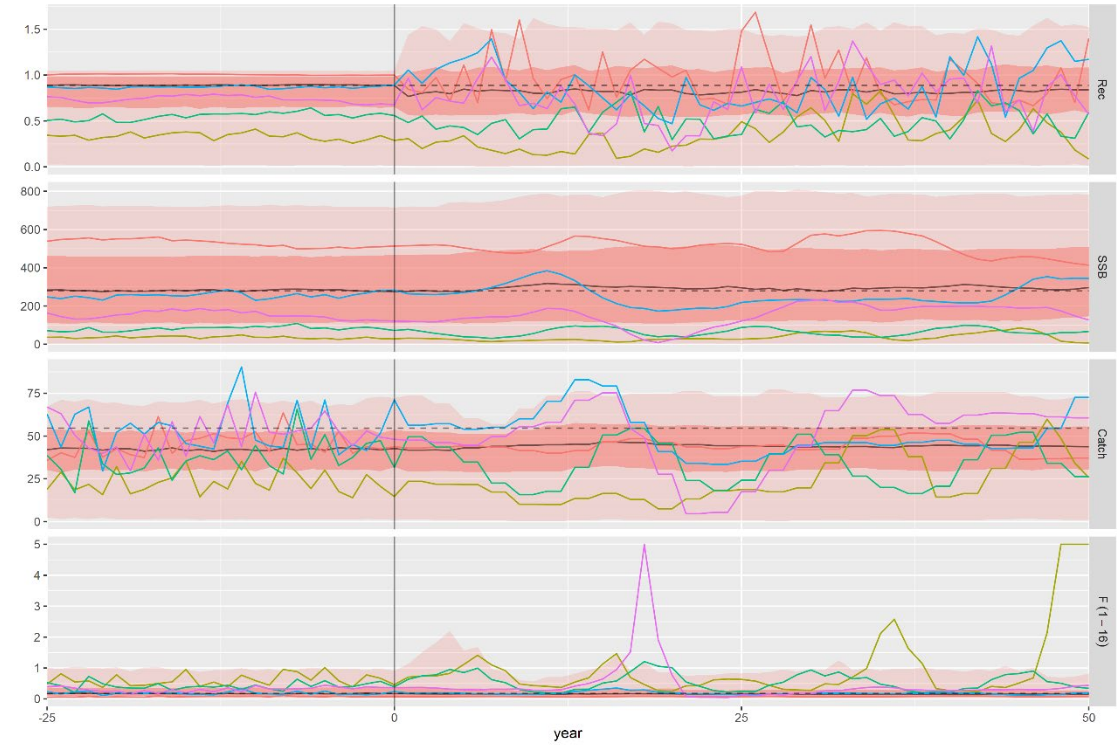

Figure 4.2.11. Results of the application of the catch rule without component f and b to pollack with default parameters and observation error. See Figure 4.2.3 for more details.

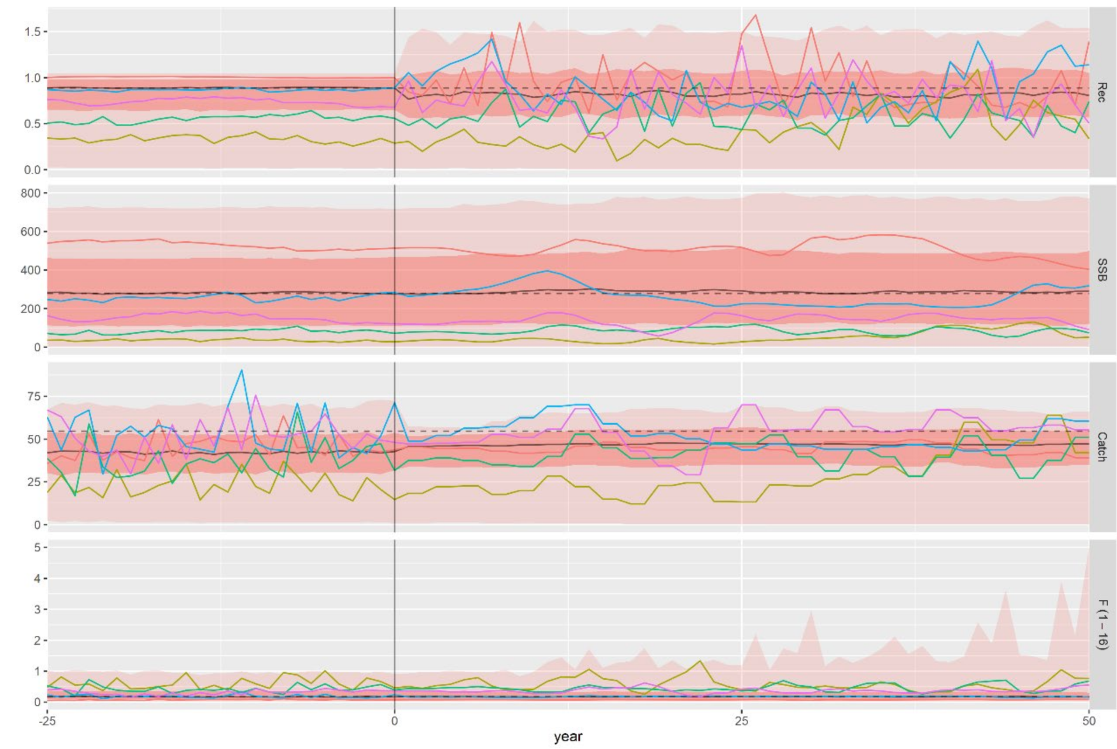

Figure 4.2.12. Results of the application of the catch rule without component f and b to pollack with default parameters and observation error. See Figure 4.2.3 for more details.

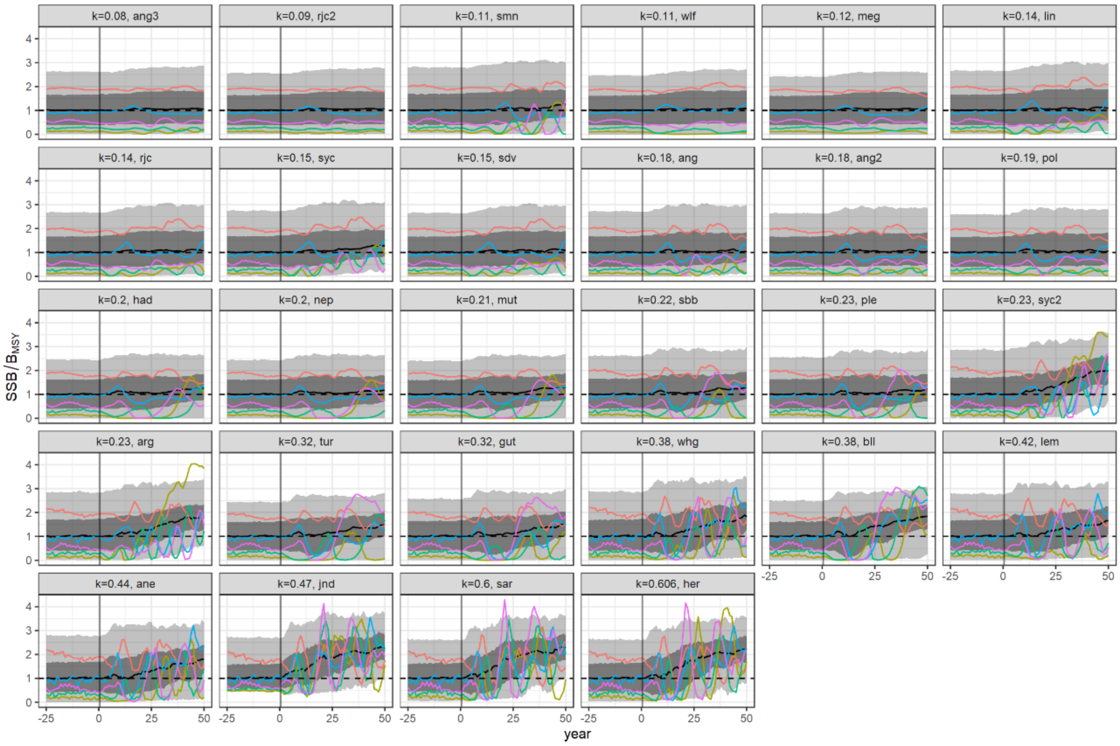

Figure 4.2.13. SSBs for the 28 simulated stocks when subject to the catch rule without components f and b, with default parameters and observation error. See Figure 4.2.5 for more details.

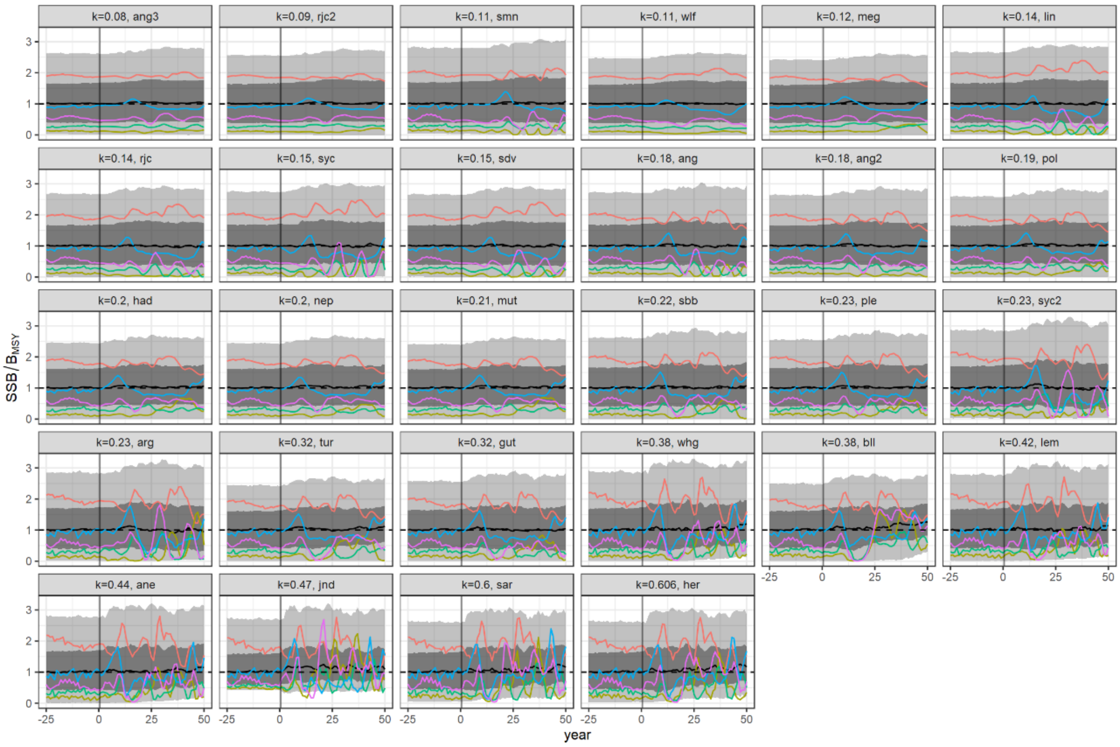

Figure 4.2.14. SSBs for the 28 simulated stocks when subject to the catch rule without components f and b, with optimised parameters and observation error. See Figure 4.2.5 for more details.

Table 4.2.5. Improvement of the catch rule without component f and b, with observation errorand with optimised parameters in comparison to default parameters.

		optimised catch rule parameters				fitness			deviation from B_{MSY}		
k	stock	s	l_1	l_2	N	default	optimised	improvement [%]	default	optimised	improvement [%]
0.08	ang3	0	4	5	3	-1.04E+08	-3.95E+07	62	182	177	3
0.09	rjc2	1	4	4	4	-1.14E+08	-4.22E+07	63	192	189	2
0.11	smn	0	2	3	4	-1.93E+08	-6.30E+07	67	153	161	-6
0.11	wlf	0	4	4	4	-1.39E+08	-5.17E+07	63	205	197	4
0.12	meg	1	4	4	4	-1.63E+08	-7.04E+07	57	208	206	1
0.14	lin	0	4	4	3	-1.63E+08	-7.03E+07	57	172	177	-3
0.14	rjc	0	4	4	4	-1.59E+08	-6.67E+07	58	173	178	-3
0.15	syc	0	4	4	3	-2.47E+08	-9.55E+07	61	153	164	-8
0.15	sdv	0	4	4	3	-1.74E+08	-7.69E+07	56	171	178	-4
0.18	ang	0	4	5	4	-1.98E+08	-9.33E+07	53	166	176	-6
0.18	ang2	0	4	4	4	-1.94E+08	-9.14E+07	53	184	186	-1
0.19	pol	0	2	4	4	-2.12E+08	-9.90E+07	53	190	183	4
0.2	had	0	2	4	4	-4.03E+08	-1.21E+08	70	206	194	6
0.2	nep	0	2	4	3	-3.33E+08	-1.16E+08	65	205	195	5
0.21	mut	0	2	4	4	-4.87E+08	-1.34E+08	72	212	198	7
0.22	sbb	0	2	5	4	-4.50E+08	-1.44E+08	68	196	180	8

		optimised catch rule parameters				fitness			deviation from B_{MSY}		
k	stock	s	l_1	l_2	N	default	optimised	improvement [%]	default	optimised	improvement [%]
0.23	ple	0	2	4	4	-3.87E+08	-1.41E+08	64	195	189	3
0.23	syc2	5	2	4	4	-1.04E+09	-1.87E+08	82	182	163	11
0.23	arg	4	2	4	4	-8.86E+08	-1.92E+08	78	176	164	7
0.32	tur	0	2	4	3	-8.30E+08	-2.25E+08	73	226	191	16
0.32	gut	0	2	4	4	-7.08E+08	-2.06E+08	71	214	200	7
0.38	whg	0	2	4	3	-9.91E+08	-2.78E+08	72	194	155	20
0.38	bll	0	2	4	3	-1.58E+09	-4.25E+08	73	249	175	30
0.42	lem	0	2	4	3	-8.08E+08	-2.62E+08	68	190	161	16
0.44	ane	0	2	4	3	-1.03E+09	-3.11E+08	70	198	157	21
0.47	jnd	0	2	2	3	-2.11E+09	-4.89E+08	77	216	105	51
0.6	sar	0	2	3	3	-3.02E+09	-6.20E+08	79	249	163	34
0.606	her	0	2	3	3	-2.64E+09	-6.17E+08	77	243	162	33

Table 4.2.6. Summary statistics for catch rule without component f and b, with observation errorand default parameters.

		default catch rule parameters				summary statistics									
k	stock	s	l_1	l_2	N	fitness	B_{MSY} deviation	B_{lim} risk	B_{MSY} risk	$0.5B_{MSY}$ risk	collapse risk	catch/MSY	SSB/B_{MSY}	F/F_{MSY}	ICV
0.08	ang3	1	2	3	1	-1.04E+08	182	0.32	0.48	0.19	0.032	0.78	1.05	0.85	0.15
0.09	rjc2	1	2	3	1	-1.14E+08	192	0.31	0.48	0.19	0.048	0.78	1.05	0.93	0.15
0.11	smn	1	2	3	1	-1.93E+08	153	0.31	0.45	0.18	0.019	0.76	1.12	0.65	0.20
0.11	wlf	1	2	3	1	-1.39E+08	205	0.29	0.48	0.19	0.065	0.77	1.05	0.90	0.15
0.12	meg	1	2	3	1	-1.63E+08	208	0.28	0.48	0.18	0.075	0.77	1.06	0.80	0.16
0.14	lin	1	2	3	1	-1.63E+08	172	0.31	0.48	0.17	0.031	0.78	1.07	0.78	0.18
0.14	rjc	1	2	3	1	-1.59E+08	173	0.32	0.48	0.18	0.033	0.78	1.07	0.80	0.18
0.15	syc	1	2	3	1	-2.47E+08	153	0.28	0.44	0.15	0.022	0.78	1.13	0.68	0.20
0.15	sdv	1	2	3	1	-1.74E+08	171	0.31	0.47	0.17	0.031	0.78	1.07	0.77	0.19
0.18	ang	1	2	3	1	-1.98E+08	166	0.32	0.47	0.17	0.032	0.78	1.08	0.76	0.20
0.18	ang2	1	2	3	1	-1.94E+08	184	0.31	0.47	0.19	0.047	0.77	1.07	0.82	0.19
0.19	pol	1	2	3	1	-2.12E+08	190	0.30	0.47	0.19	0.051	0.76	1.07	0.80	0.19
0.2	had	1	2	3	1	-4.03E+08	206	0.25	0.44	0.19	0.080	0.74	1.16	0.60	0.21
0.2	nep	1	2	3	1	-3.33E+08	205	0.26	0.45	0.19	0.073	0.74	1.12	0.64	0.20
0.21	mut	1	2	3	1	-4.87E+08	212	0.24	0.43	0.19	0.082	0.73	1.18	0.58	0.21
0.22	sbb	1	2	3	1	-4.50E+08	196	0.28	0.42	0.19	0.055	0.73	1.19	0.59	0.25
0.23	ple	1	2	3	1	-3.87E+08	195	0.27	0.44	0.19	0.051	0.74	1.15	0.62	0.24

		default catch rule parameters				summary statistics									
k	stock	s	l_1	l_2	N	fitness	B_{MSY} deviation	B_{lim} risk	B_{MSY} risk	$0.5B_{MSY}$ risk	collapse risk	catch/MSY	SSB/B_{MSY}	F/F_{MSY}	ICV
0.23	syc2	1	2	3	1	-1.04E+09	182	0.23	0.32	0.13	0.014	0.68	1.52	0.43	0.27
0.23	arg	1	2	3	1	-8.86E+08	176	0.23	0.32	0.14	0.013	0.70	1.47	0.46	0.27
0.32	tur	1	2	3	1	-8.30E+08	226	0.24	0.39	0.18	0.050	0.69	1.28	0.52	0.26
0.32	gut	1	2	3	1	-7.08E+08	214	0.27	0.41	0.19	0.049	0.70	1.27	0.53	0.29
0.38	whg	1	2	3	1	-9.91E+08	194	0.29	0.37	0.20	0.040	0.68	1.47	0.47	0.36
0.38	bll	1	2	3	1	-1.58E+09	249	0.22	0.32	0.16	0.036	0.67	1.51	0.43	0.29
0.42	lem	1	2	3	1	-8.08E+08	190	0.28	0.39	0.18	0.033	0.71	1.36	0.52	0.33
0.44	ane	1	2	3	1	-1.03E+09	198	0.27	0.37	0.18	0.034	0.69	1.44	0.48	0.35
0.47	jnd	1	2	3	1	-2.11E+09	216	0.13	0.22	0.02	0.000	0.75	1.92	0.34	0.32
0.6	sar	1	2	3	1	-3.02E+09	249	0.17	0.25	0.11	0.000	0.65	1.88	0.32	0.36
0.606	her	1	2	3	1	-2.64E+09	243	0.19	0.27	0.12	0.004	0.64	1.81	0.34	0.36

Table 4.2.7. Summary statistics for catch rule without component f and b, with observation errorand optimised parameters.

		optimised catch rule parameters				summary statistics									
k	stock	s	l_1	l_2	N	fitness	B_{MSY} deviation	B_{lim} risk	B_{MSY} risk	$0.5B_{MSY}$ risk	collapse risk	catch/MSY	SSB/B_{MSY}	F/F_{MSY}	ICV
0.08	ang3	0	4	5	3	-3.95E+07	177	0.34	0.49	0.20	0.040	0.82	1.03	0.94	0.11
0.09	rjc2	1	4	4	4	-4.22E+07	189	0.32	0.50	0.21	0.058	0.83	1.01	1.02	0.11
0.11	smn	0	2	3	4	-6.30E+07	161	0.39	0.50	0.23	0.046	0.83	0.99	0.97	0.22
0.11	wlf	0	4	4	4	-5.17E+07	197	0.31	0.50	0.19	0.071	0.83	1.01	1.02	0.11
0.12	meg	1	4	4	4	-7.04E+07	206	0.30	0.49	0.20	0.102	0.82	1.02	0.93	0.12
0.14	lin	0	4	4	3	-7.03E+07	177	0.35	0.50	0.21	0.042	0.82	1.01	0.89	0.14
0.14	rjc	0	4	4	4	-6.67E+07	178	0.35	0.50	0.22	0.047	0.83	1.00	0.93	0.14
0.15	syc	0	4	4	3	-9.55E+07	164	0.36	0.50	0.21	0.035	0.82	1.01	0.80	0.16
0.15	sdv	0	4	4	3	-7.69E+07	178	0.35	0.50	0.21	0.041	0.82	1.01	0.88	0.14
0.18	ang	0	4	5	4	-9.33E+07	176	0.37	0.50	0.23	0.043	0.81	1.00	0.89	0.15
0.18	ang2	0	4	4	4	-9.14E+07	186	0.35	0.51	0.23	0.065	0.81	0.98	1.01	0.14
0.19	pol	0	2	4	4	-9.90E+07	183	0.33	0.50	0.20	0.061	0.82	1.00	1.00	0.21
0.2	had	0	2	4	4	-1.21E+08	194	0.30	0.50	0.18	0.104	0.82	1.01	0.92	0.20
0.2	nep	0	2	4	3	-1.16E+08	195	0.29	0.49	0.17	0.079	0.81	1.04	0.93	0.19
0.21	mut	0	2	4	4	-1.34E+08	198	0.29	0.50	0.18	0.108	0.81	1.01	0.91	0.21
0.22	sbb	0	2	5	4	-1.44E+08	180	0.32	0.49	0.19	0.072	0.81	1.03	0.90	0.21
0.23	ple	0	2	4	4	-1.41E+08	189	0.33	0.50	0.21	0.092	0.81	0.99	0.98	0.22

		optimised catch rule parameters				summary statistics									
k	stock	s	l_1	l_2	N	fitness	B_{MSY} deviation	B_{lim} risk	B_{MSY} risk	$0.5B_{MSY}$ risk	collapse risk	catch/MSY	SSB/B_{MSY}	F/F_{MSY}	ICV
0.23	syc2	5	2	4	4	-1.87E+08	163	0.40	0.51	0.25	0.026	0.81	0.98	0.81	0.24
0.23	arg	4	2	4	4	-1.92E+08	164	0.39	0.50	0.25	0.025	0.81	1.00	0.79	0.24
0.32	tur	0	2	4	3	-2.25E+08	191	0.27	0.48	0.17	0.060	0.80	1.05	0.84	0.22
0.32	gut	0	2	4	4	-2.06E+08	200	0.35	0.51	0.24	0.109	0.78	0.97	0.96	0.25
0.38	whg	0	2	4	3	-2.78E+08	155	0.36	0.48	0.20	0.038	0.80	1.06	0.80	0.28
0.38	bll	0	2	4	3	-4.25E+08	175	0.24	0.43	0.14	0.039	0.81	1.14	0.73	0.25
0.42	lem	0	2	4	3	-2.62E+08	161	0.34	0.48	0.19	0.032	0.80	1.04	0.84	0.26
0.44	ane	0	2	4	3	-3.11E+08	157	0.34	0.48	0.18	0.030	0.80	1.06	0.80	0.27
0.47	jnd	0	2	2	3	-4.89E+08	105	0.26	0.45	0.04	0.000	0.91	1.08	0.89	0.30
0.6	sar	0	2	3	3	-6.20E+08	163	0.29	0.46	0.15	0.000	0.82	1.08	0.81	0.33
0.606	her	0	2	3	3	-6.17E+08	162	0.28	0.46	0.15	0.005	0.81	1.10	0.80	0.31

4.2.5 Discussion

The outcome of the catch rule with default parameters appears to be somewhat different in terms of terminal SSB compared to results presented previously (ICES, 2017a; 2018). This outcome is caused by different condition at the beginning of the implementation of the catch rule. Previously, highly depleted starting conditions have been used, while the current simulations are based on less depleted conditions. Previously, medium to high k stocks collapsed early during the simulation period due their high variability and the feature of the catch rule that the newly advised catch is based on the previous catch.

The optimisation of the catch rule parameters led to improvement for all stocks and simulated scenarios. However, the improvement is only as good as the definition of the fitness function, and the optimisation is purely based on evaluating this fitness function, ignoring any other feature. Therefore, the improvement was frequently only observed in the fitness function (i.e. deviation of SSB to B_{MSY} for the full catch rule), whereas other performance statistics such as risks and interannual catch variability increased. Nevertheless, stock characteristics such as F, SSB and catch, tended to move closer to their MSY reference levels. This trade-off between desirable and undesirable changes in summary statistics is a result of the definition of the fitness function, which only considered SSB and is aimed at moving it closer to B_{MSY}, neglecting risks and stability in catch.

Furthermore, it should be noted that the used optimisation procedure with a genetic algorithm did improve the performance, but the optimised solution does not necessarily correspond to a global optimum and could as well simply be a local optimum. Due to the high number of possible parameter combinations (around 7 million), it is computationally infeasible to run all of them. Allowing the genetic algorithm to iterate through more generations or increasing the population size could potentially improve the optimisation. However, running more simulations comes at a high computational cost and looking at the progress during the genetic algorithm (see e.g. Figure 4.2.2) indicated that the best solution per generation already showed a relatively flat curve.

Catch rule including observation error

For the full catch rule (including components r, f and b and their exponents), the optimised parameters were stock-specific without showing a clear pattern. For most stocks, the time-lag of the biomass index was reduced (i.e. including the intermediate year index value). The components r and f of the catch rule were made more reactive and given a higher influence on the catch advice (exponents above 1 and on average 1.4 for both) whereas component b (biomass safeguard) was always downweighed. This can be explained by the fact that the optimisation procedure included only an SSB target and ignored safety considerations, and therefore there was no reward for reducing the catch below $I_{trigger}$. In the scenarios were $I_{trigger}$ was based on the lowest observed index value in the recent past, b was downweighed even further because for many of the replicates, $I_{trigger}$ was set to high (around half of the replicates were above B_{MSY}during the historical fishing period, and hence so was $I_{trigger}$) and would otherwise always tend to reduce catch.

Catch rule without component f and b

The performance of the catch rule without components f and b could be substantially improved with regards to the fitness function, in particular for medium to higher k stocks. Originally, the "2 over 3" rule was designed to keep a stock at status quo by adjusting the current catch with the trend from the biomass index (ICES, 2012). However, as shown previously by WKLIFE and again here, the default "2 over 3" rule frequently moves the SSB away from the initial SSB. By optimising the catch rule parameters, this behaviour can be avoided, and the stocks stay, on average, where they started, but the optimised parameters are stock-specific. This also worked for the higher *k* stocks, however, the individual replicates still exhibited large SSB oscillations which might not be a desired feature of a catch rule.

In conclusion, it can be said that WKMSYCat34 catch rule 3.2.1, or parts of it, seem to perform satisfactorily for low to medium *k* stocks. For higher *k* stocks (either short-lived or other fast-growing species) additional modifications are required, which can cause unwanted effects, and even then, the catch rule does not necessarily live up to its expectations in these cases. The optimisation procedure can improve the performance of the rule for all stocks, but the parameters become stock-specific.

4.3 Receiver Operating Characteristic (ROC) curves used to explore the setting of appropriate reference levels in the *f* and *b* component of the catch rule

This section addresses ToRa(iii) "Setting of appropriate reference levels in the f and b component of the rules, and the extent to which this could be done with tuning that depends on life-history traits and/or the nature of the time-series". Appropriate reference levels for a range of indicators, reference points and reference levels were evaluated using tools developed under the [MyDas]() project. The aim of MyDas is to develop and test a range of assessment models and methods to establish Maximum Sustainable Yield (MSY), or proxy MSY reference points across the spectrum of data-limited stocks.

To tune a catch rule of the form $C_{y+1} = C_{current} r\, f\, b$, requires selecting time-series for use as indicators and reference points for the *r* and *f* components. Then to choose multipliers and thresholds to combine the components into the catch rule. Applying a generic rule across life-history types and fisheries, however, may result in increased risk of stock collapse for some stocks unless the rule is tuned to be conservative with a consequent loss of yield. The alternative is to conduct MSE on a stock-specific basis to tune rules. This can take considerable time, especially as a variety of indicators and reference points can be used. Therefore, a method for screening potential indicators and reference levels was developed using Receiver Operating Characteristic or ROC curves (Green and Swets, 1966). An example is provided based on the *f* component.

The *f* component is a proxy for the ratio of current exploitation to F_{MSY},and normally makes use of an indicator based on length samples. For example, Fischer *et al*. (submitted) used L_{mean}, the mean length of individuals>L_c, where L_c is the length at 50% of modal abundance in the catch, relative to the reference point $L_{F=M}$=($0.75L_c + 0.25L_\infty$).

In the ICES Technical guidelines (16.4.3.2 ICES reference points for stocks in categories 3 and 4) if $L_{mean}/L_{F=M} < 1$ then the stock is said to be undergoing overfishing. Indicators and reference points, however, are likely to be biased and/or have poor precision due to uncertainty about life-history parameters, lags between exploitation levels and size distribution, variability in recruitment, and resonant cohort effects that can produce long-term fluctuation (Botsford*et al*., 2014; Bjørnstad*et al*., 2004). Therefore, the reference level (i.e. the discrimination threshold) that can best identify the system state is unlikely to be $L_{mean}/L_{F=M}$ but some multiple of it. Risks are also asymmetric, since the risk of indicating overfishing when the stock is actually being sustainably exploited is not the same as the risk of failing to identify overfishing. A ROC analysis addresses these problems by comparing the true positive rate (TPR) the false positive rate (FPR) for various reference levels; i.e. threshold settings.

The ROC curve can be thought of as a plot of power as a function of the Type 1 Error of the decision rule. When the probability distributions for both detection and false alarm are known, the ROC curve is generated by plotting the cumulative distribution function (area under the probability distribution from to the discrimination threshold) of the detection probability in the y-axis versus the cumulative distribution function of the false-alarm probability on the x-axis. ROC analysis therefore provides a tool to select the best candidate indicators. To construct the ROC curves, an Operating Model (OM) was conditioned on the life-history characteristics of pollack (*Pollachius pollachius*) and an Observation Error Model (OEM) used to simulate length samples (i.e. a sim–sam procedure). This allowed the cumulative true positive and false positive rates to be calculated.

The base case OM conditioned on pollack life-history characteristics assumed the steepness of the Beverton and Holt stock–recruitment relationship equal to 0.9, natural mortality was modelled by the Gislason functional form, and the fishery was conducted on spawners (i.e. the selection pattern was the same as maturity ogive). To evaluate robustness, five sensitivity OM scenarios were developed, along with the **Base:** base case; namely **h=0.7:** steepness = 0.7; **M:** natural mortality constant at all ages and equal to M at L_∞; **Dome:** reduced selectivity at older ages; **Flat:** selection pattern the same at for ages; and **Sample Size:** effective sample size used in the OEM of length samples halved.

Six indicators were simulated; i.e. L_{95}, L_{25}, L_{max5}, P_{mega}, L_{mean} and L_{bar}. Where L_{95} is the 95th percentile of the length distribution, L_{25} the 25th percentile of the length distribution, L_{max5} the mean length of largest 5%, P_{mega} the proportion of individuals above L_{opt}+10%, L_{mean} the mean length of individuals >L_c where L_c is length at 50% of modal abundance, and L_{bar} is mean size.

To assess stock status, various life-history parameters are used as reference points; i.e.L_{mat} (length-at-maturity), L_{opt} ($2/3L_\infty$) and $L_{F=M}$ ($0.75L_c + 0.25L_\infty$). In these examples the reference points were not used, instead the appropriate reference levels were estimated from the ROC curves and compared to the candidate reference points.

Figure 4.3.1 shows the base case OM, and Figure 4.3.2 the corresponding simulated indicators. In the OM, fishing was initially low then increased to $2.5F_{MSY}$, following which a recovery plan was implemented in order to reduce F to F_{MSY}. The coloured regions in Figure 4.3.2 indicate exploitation levels $F \leq F_{MSY}$ (green), $F_{MSY}<F \leq 1.5F_{MSY}$ (yellow), and $F>1.5F_{MSY}$ (red).

ROC curves and discrimination thresholds for the overfishing phase (yellow to red) are plotted in Figures 4.3.3 and 4.3.4. The ROC curves distinguish between the period 80 to 90 when $F_{MSY}<F \leq 1.5F_{MSY}$) and 91 to 100 when $F>1.5F_{MSY}$. Figures 4.3.5 and 4.3.6 are the corresponding figures for the recovery phase; i.e. to distinguish between the period 91 to 100 and 111 to 115 when fishing was at F_{MSY}.

Figures 4.3.3 and 4.3.5 can be used to evaluate the performance of the different indicators (lines) and their robustness for each OM scenario (panels). Comparison of lines within a panel allows the relative performance of the indicators to be evaluated, and comparison across panel allows the robustness of the indicators to uncertainty to be evaluated. For an indicator to be robust, the choice of the discrimination threshold should not vary across scenarios. The L_{95}, L_{max5}, $L_{F=M}$ and L_{bar} indicators exhibit good performance, with high TPR and low FPR; all scenarios other than the flat selection pattern perform well. There is a slight degradation in performance with a reduction in sample size. There is some difference between identification of recovery compared to overfishing, although relative performance of indicators is similar.

Figures 4.3.4 and 4.3.6 compare the discrimination thresholds for each indicator (panel) by OM scenario. To help in specification of indicators and reference points ideally the discrimination threshold should align with a life history parameter. It should be noted, however, that life history parameters are not independent, because P_{mega} is set in the guidelines as a multiple of L_{opt}, which in turn is a multiple of L_∞. For the overfishing phase (Figure 4.3.4) the discrimination thresholds for L_{bar} and $L_{F=M}$ approximate to L_{mat}. For the flat-topped selection pattern scenario, the discrimination threshold should be decreased, and for constant M and steepness=0.7 increased. For the identification of recovery (Figure 4.3.6) M and steepness are less important for the choice of reference point than the form of selection pattern.

For an indicator to be robust the threshold should not vary across scenarios, if they represent equally plausible hypotheses. The flat selection pattern shows the biggest divergence from the mean value, in practice this scenario could potentially be discounted by collection of more data. Other scenarios such as steepness will be difficult to discount, and so indicators should not depend on the assumed value. Due to the non-independence of reference points and difference in reference levels across scenarios, the problem resolves into finding discrimination threshold by tuning, where tuning is used to set the threshold at a level that best meets agreed management objectives. The ROC analysis can assist by providing an objective function; i.e. a reward to be used in parameter selection using non-linear optimisation.

Section 4.2 explored the benefits of implementing alternative control rules. Future steps should involve an evaluation of the relative value-of-information and the value-of-control. The former case involves demonstrating the benefit of obtaining better knowledge and data; i.e. to move a stock between categories, and the later involves considering alternative forms of indicators and control rules to develop robust advice. ROC curves are related in a direct and natural way to a cost/benefit analysis of diagnostic decision making; i.e. they can be used to identify the value of control and the value of information. For risks to be managed in a consistent way, given the range of uncertainties across the ICES stock categories (see Sections 5), requires OMs to be conditioned on appropriate processes (see Section 1.4).

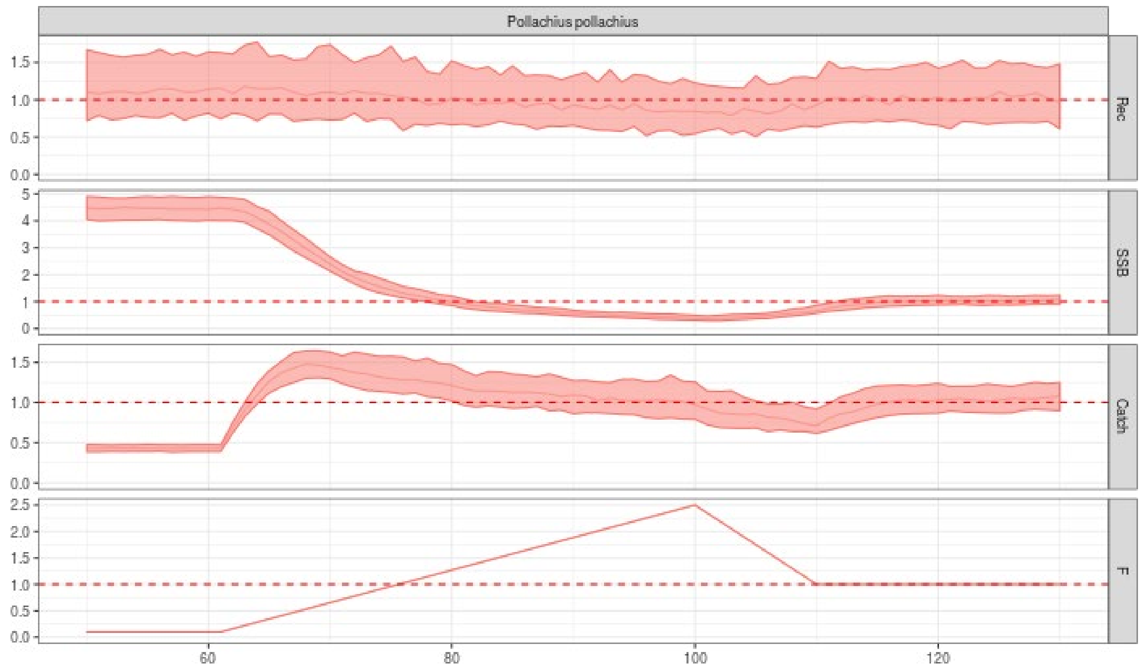

Figure 4.3.1. Operating model for pollack; all values relative to MSY benchmarks, for recruitment this is the expected recruitment at MSY.

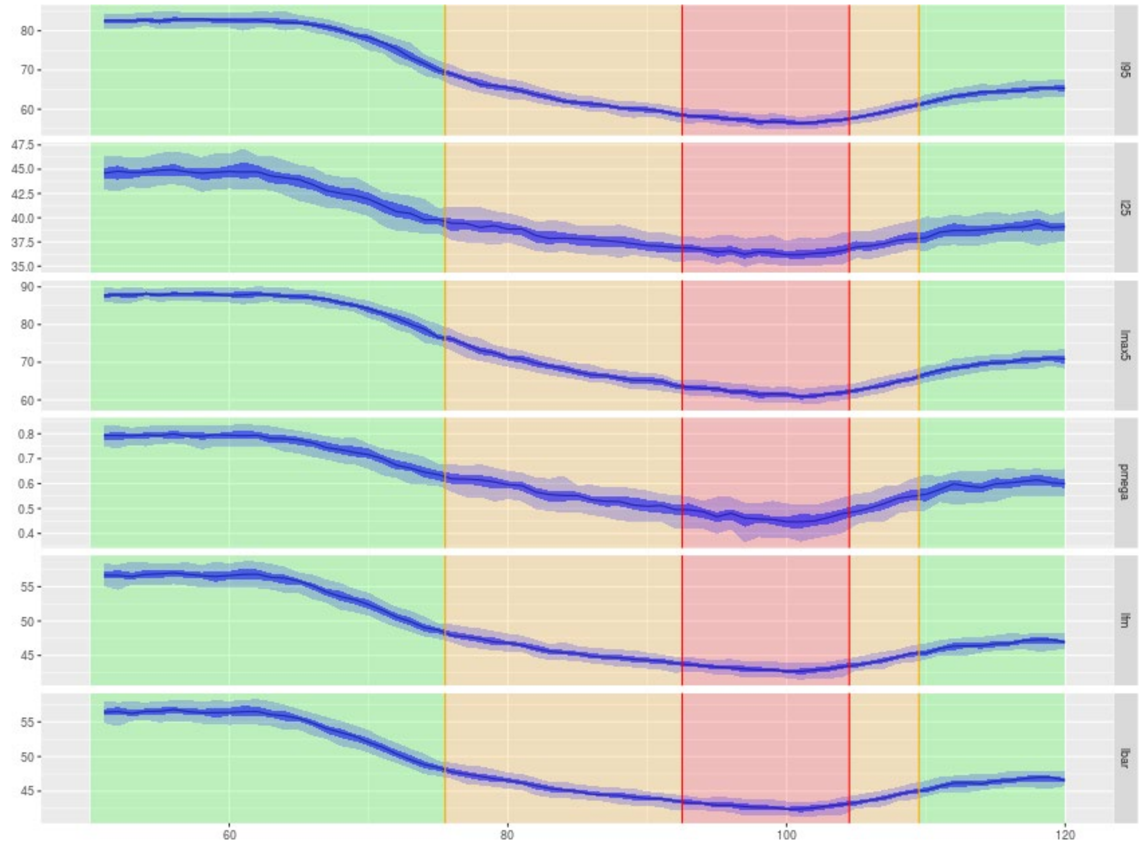

Figure 4.3.2. Indicators without reference levels. The coloured regions indicate exploitation levels; i.e. green $F \leq F_{MSY}$, yellow $F_{MSY} < F \leq 1.5F_{MSY}$, red $F > 1.5F_{MSY}$.

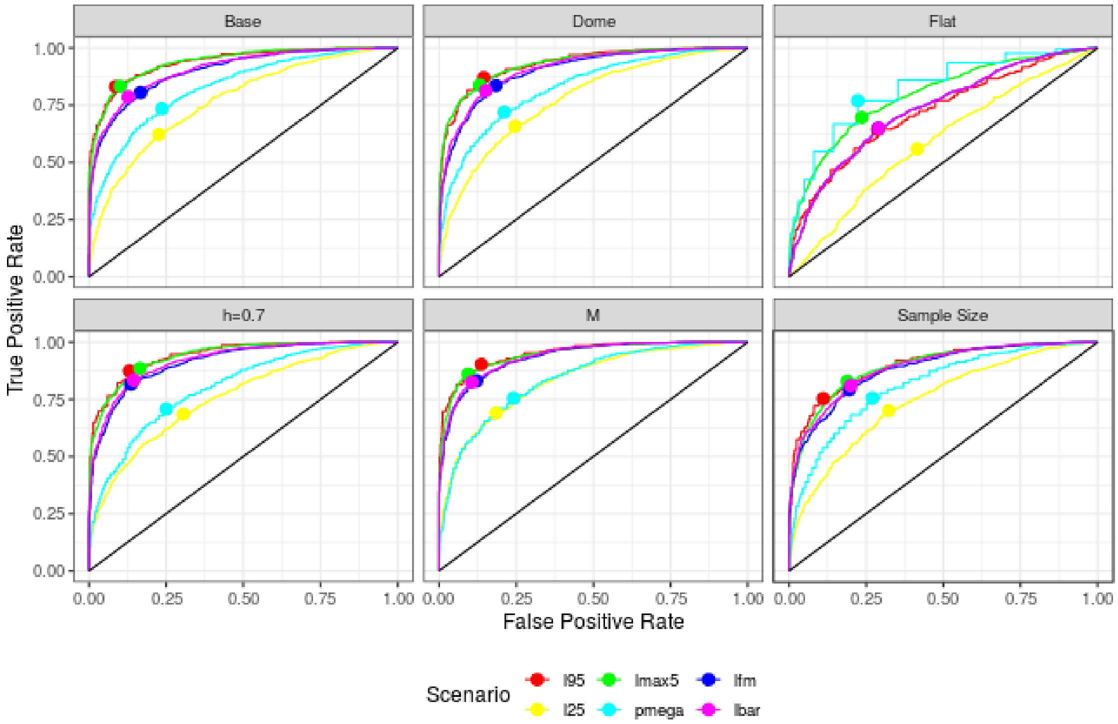

Figure 4.3.3. Receiver Operating Characteristic (ROC) curves for pollack for the overfishing phase, each panel represents a different indicator and curves are for the six scenarios. The black line is the Y=X line provided as a reference since this represents a model with no prediction skill (i.e. a coin toss) and the points represent the optimum discrimination where TPR*(1-FPR) is maximised.

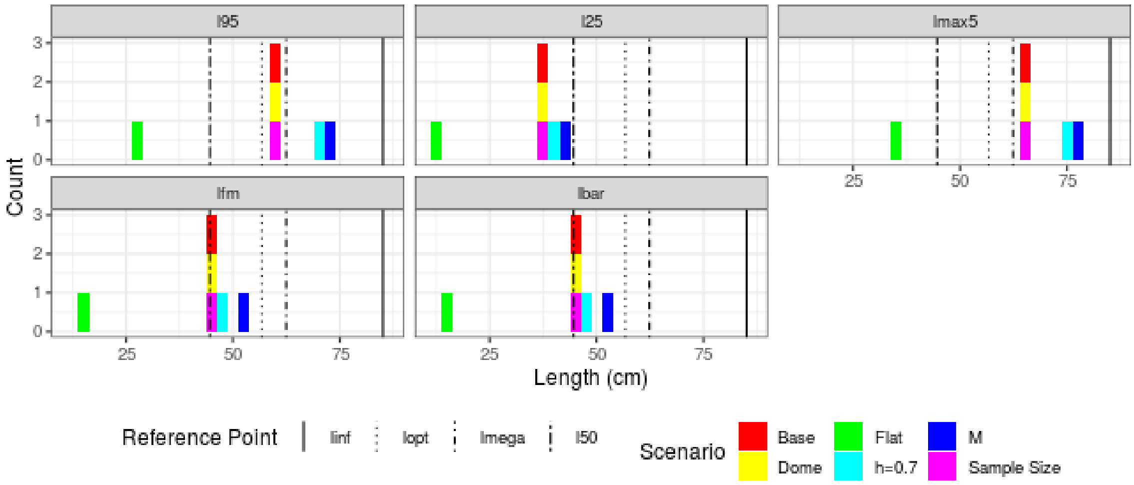

Figure 4.3.4. Discrimination thresholds for each indicator for the overfishing phase. Each panel represents a different indicator, colours are for the six scenarios, and lines are the potential life-history indicators. P_{mega} is not included as it uses proportion and not length.

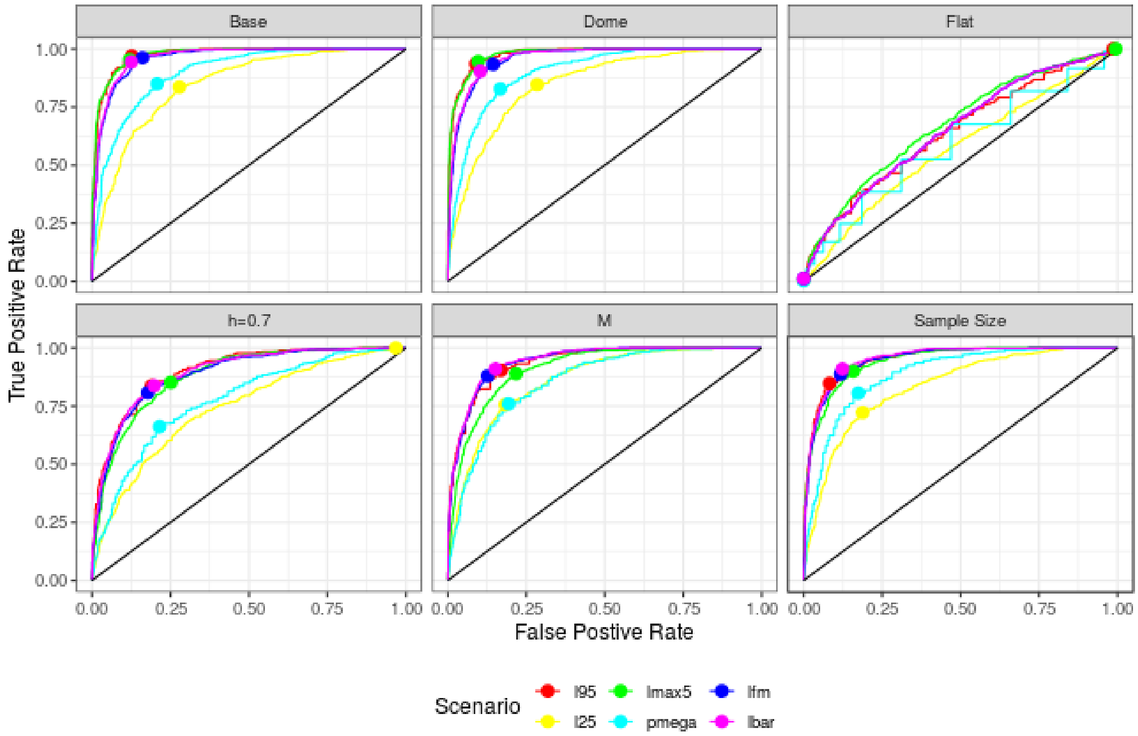

Figure 4.3.5. Receiver Operating Characteristic curves for pollack for the recovery phase, each panel represents a different indicator and curves are for the six scenarios. The black line is the Y=X line provided as a reference since this represents a model with no prediction skill (i.e. a coin toss) and the points represent the optimum discrimination where TPR*(1-FPR) is maximised.

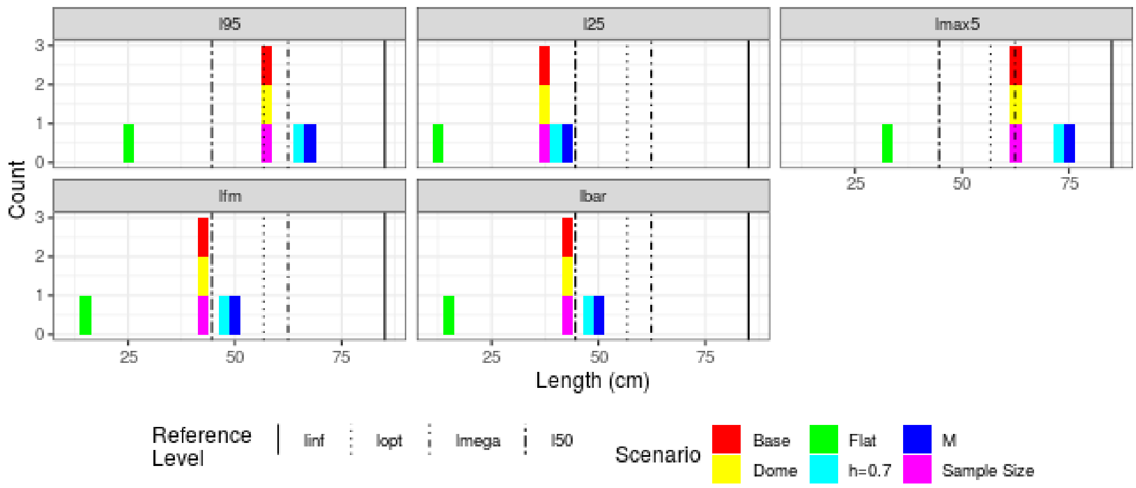

Figure 4.3.6. Discrimination thresholds for each indicator for the recovery phase. Each panel represents a different indicator, colours are for the six scenarios, and lines are the potential life-history indicators. P_{mega} is not included as it uses proportion and not length.

4.4 The use of trends in an index without a reference level

The use of trends in an index without a reference level (ToR iv) were explored using methods developed under the MyDas project. To do this, a Management Strategy Evaluation (MSE) was conducted to evaluate an empirical harvest control rule (HCR) based on a trend in an index of abundance.

The Operating Model (OM) was conditioning on turbot life-history characteristics and the HCR was based on that used by the Commission for the Conservation of Southern Bluefin Tuna (CCSBT). The HCR has several parameters that require tuning (Hillary *et al.*, 2016). When tuning an HCR the parameters are found by choosing values that best meet the objectives of asset and stakeholders; i.e. optimises the outcomes modelled as a reward function.

The HCR was modelled as part of a Management Procedure (MP) where catches are increased when the trend in an index of abundance is positive, and decreased if the trend is negative, namely:

$$TAC^1_{y+1} = TAC_y \times \begin{cases} 1 - k_1|\lambda|^\gamma \text{for } \lambda < 0 \\ 1 - k_2\lambda \quad\quad \text{for } \lambda \geq 0 \end{cases}$$

whereλ is the slope in the regression of lnI_y against year for the most recent n years and k_1 and k_2 are the tuneable parameters andγactions asymmetry so that decreases in the index do not result in the same relative change as an increase.

When tuning an empirical MP, it is run for a range of control parameters values (i.e. fork_1,$k_2$and λ). These are then chosen based on the performance of the MP; i.e. maximising a reward function based on management objectives. It can be difficult, however, to specify a single reward function, due to trade-offs between multiple objectives. Deciding which is the "best" MP therefore requires an iterative process involving managers, asset holders, stakeholders and scientists.

Once objectives are agreed the traditional way to find the control parameters is to perform a grid search; i.e. an exhaustive search through a manually specified set of control parameters. Even for a limited number of control parameters this can take a substantial amount of computing time. Tuning was performed using random search where control parameters are selected from all the potential combinations at random. Random search has proven to yield better results in comparison to grid search. Drawbacks of random search are that it may yield high variance during computing and since the selection of parameters is completely random no intelligence is used to sample the combinations and so luck plays its part.

Trade-offs between multiple objectives were evaluated by identifying pareto-optimal solutions (Mishra *et al.*, 2002) using support vector regression (SVR, Smola and Schölkopf, 2004). The best HCR parameters were then identified using a Genetic Algorithm (GA, Whitley, 1994). Both SVR and GAs are machine learning techniques.

In optimisation studies with multi-objectives the focus is usually on finding a global optimum; i.e. the global Pareto-optimal frontier, representing the best possible objective values (Deb and Gupta, 2005). However, in fisheries there is usually high uncertainty about resource dynamics and solutions are therefore sensitive to the assumptions and environmental variability. Therefore, rather than finding global solution it is more important to find robust solutions which are insensitive to uncertainty about processes.

Figure 4.4.1 shows the trade-off between yield (Yield:MSY) and safety (the minimum expected recruitment relative toR_{virgin}). Individual MSE (blue) results are highly variable due to variablity in recruitment and the index of abundance used in the MP. The pareto frontier derived from SVR are shown (red) and an example of an optimal solution highlighted (large dot).

Figure 4.4.2 shows the calibration curves, obtained using the GA for the control parameters $k_1$and k_2. This was obtained from the pareto frontiers by finding the values that corresponded to the optimal solution. If the management objectives are agreed the corresponding control value can be read off from the Y-axes. The scatter of points reflects that the Pareto frontiers are hyper-dimensional surfaces projected into two dimensions.

Once the control parameters that best met the management objectives were found, the MSE was run for the control parameters for two scenarios corresponding to the index of abundance CV (10%, 20% and 30%) and the number of years (3, 5, and 7 column) used in the regression to estimate the trend in the index; the summary statistics are shown in Figure 4.4.3.

An objective of the approach was to develop a risk-based framework for conducting MSE, by allowing asset and stakeholders to more easily to evaluate the trade-offs between management objectives and the impact of uncertainty when conducting MSE. The framework also provides an efficient way of tuning Management Procedures so that case specific management strategies can more easily be developed. However, since random search was used the outcomes partly depend on chance, the next step is to add intelligence by using machine learning to choose the control parameters.

The approached used demonstrates a potential stepwise procedure for conducting MSE namely:

- First a single MSE is run using random search and the Pareto frontiers found.
- Objectives can be elicited from asset and stakeholders, and the trade-offs between them evaluated.
- Using the Pareto frontiers, the control parameters can be derived by calibration.
- Next a set of robustness trials, can be developed for an agreed set of OMs that reflect the main uncertainties and the corresponding Pareto frontiers derived.
- A final set of control parameters can then be agreed following dialogue with asset and stakeholders.

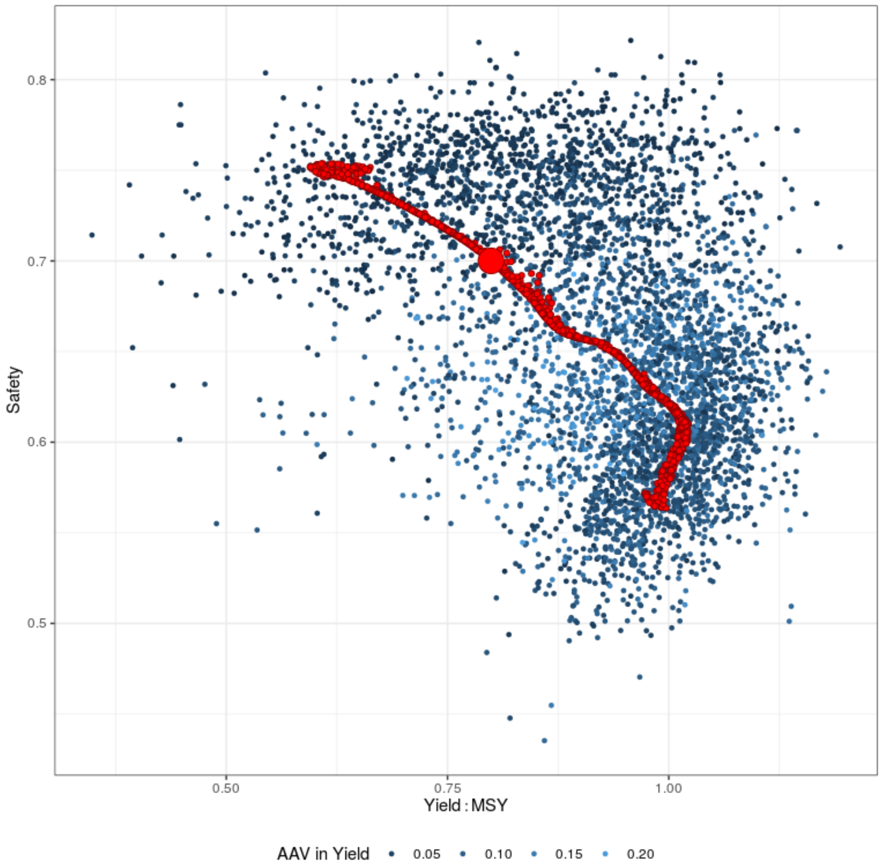

Figure 4.4.1. The trade-off between yield (Yield:MSY) and the average SSB relative to SSB_{virgin} are shown for the individual management strategy evaluations (blue) along with the pareto frontier (red).

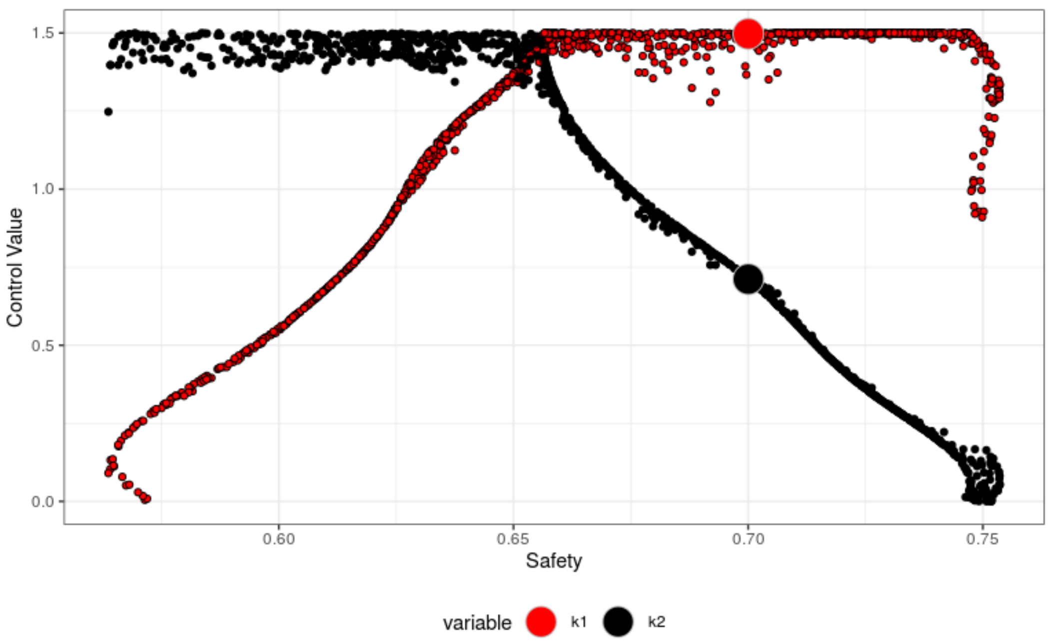

Figure 4.4.2. Calibration regression values for the control parameters K1 and K2 for the pareto frontier for B_{lim}, large point is for safety~0.7.

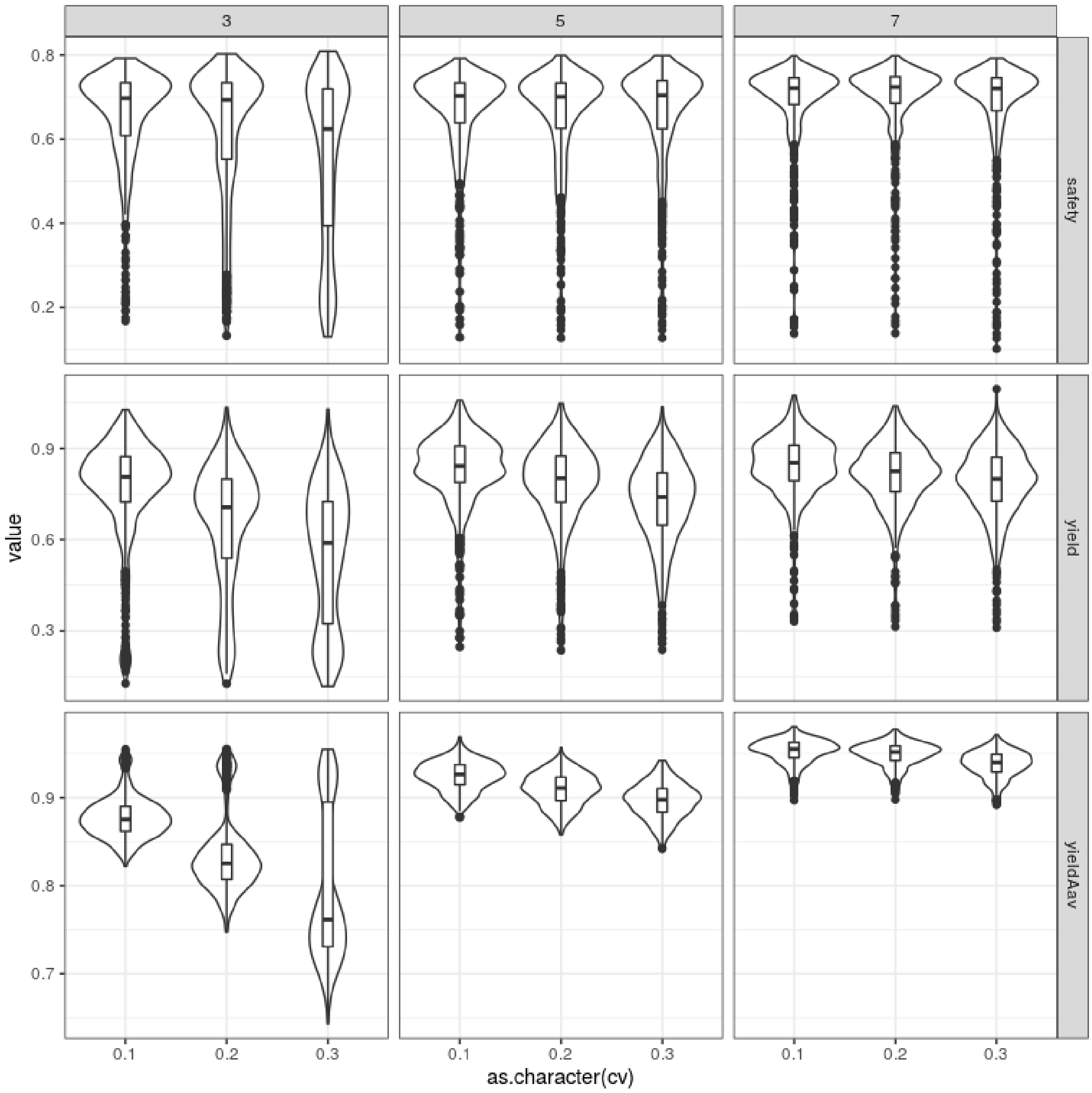

Figure 4.4.3. Summary statistics from MSE.

4.5 Conclusions

This work builds on the evaluation of the catch rule presented in ICES (2018) to deal with ToRs a(i), a(ii) and a(iv), using the same MSE framework with some adjustments to the operating models, and makes use of Receiver Operating Characteristic (ROC) curves to explore ToR a(iii).

Weighting of the individual components of the catch rule (ToRa(i)) was achieved by adding an exponent to each of the individual component (*r*, *f* and *b*). The time-lag properties of the *r* component (ToRa(ii)) was explored by varying the number of years used for the *r* component (both the denominator and numerator), and the most recent year used in the *r* component. Furthermore, the number of years used for the current advised catch, to which the *r*, *f* and *b* components are applied, was also varied. This gave a total of seven parameters to tune the catch rule to achieve MSY; the objective function minimises the negative sum of squares between SSB and B_{MSY}. A genetic algorithm (R package GA) was used to explore the 7-dimensional parameter space in order to find the combination of parameters that maximises the reward function (i.e. minimises the objective function). The main conclusions were:

1. The performance of the catch rule in terms of achieving MSY can be substantially improved on a case-by-case basis, both by weighting of the different components of the rule, and through changing the lags in the indices used in the rule, and in setting the catch. Further work should focus on:
   a) Exploring alternative reward functions that better capture management objectives and the trade-offs between them. Thus far, the genetic algorithms only dealt with achieving MSY, by minimising differences between SSB and B_{MSY}, which resulted in better yields but also an increase in interannual catch variability and risk. Objectives could include a low probability of falling below B_{lim} and F varying randomly around F_{MSY} with no apparent trend.
   b) Exploration of rules with components that take into account the dynamics and life-histories of stocks in order to maintain generality while improving performance.
2. In cases where only the *r* component is used i.e. without the biomass safeguard and reference level, the rule could be improved with additional tuning (in this case, varying the lag components of the rule), but further work is needed in terms of achieving multiple objectives and maintaining generality (as in 1 above).
3. The additional simulations confirmed (on the basis of operating models that included a wider range of catch histories than presented for ICES (2018)) that the catch rule should not be used for k>0.32, despite further tuning. Further work is needed to explore alternative rules for these cases. In the meantime, the current approach (“2 over 3” rule with the PA buffer and uncertainty cap) should be used for these cases, except for short-lived species (see Section 2: Short-lived species).
4. To ensure robustness, alternative operating models should be explored, e.g. variation in selection pattern relative to age-at-maturity.

4.6 Future directions

WKMSYCat34 catch rule 3.2.1 in its current form has been extensively tested during previous WKLIFE workshops. The work presented during WKLIFE IX showed that the performance of the rule can be improved on a case-specific basis. The simulations so far, however, were based on a selected set of life-history parameters and the operating models can be thought of as a reference set. In general, the catch rule seems to perform satisfactorily for stocks with low to medium k ($k \leq 0.32$). Further research is required to understand the reasons for this behaviour and why higher k stocks ($k > 0.32$) perform poorly with the catch rule. This will require investigating the characteristics of the operating models. Importantly, future work should focus on stocks for which the current catch rule did not work (eight stocks in total with $k > 0.32$) and evaluation of forms of rules based on trends, without reference levels that take into account resource dynamics (e.g. Botsford *et al.*, 2014).

When tuning catch rules, the options are evaluated in terms of summary statistics, e.g. maximising yield while maintaining acceptable risk levels and moving the stocks towards B_{MSY}, or keeping F fluctuating around F_{MSY} with no trend. Such evaluations require the agreement of management objectives from which a reward function can be derived and used in automated approaches based on Machine Learning or genetic algorithms. The key management objectives involve, for example, trade-offs between risk, interannual catch variability and yield, while aiming to fish around F_{MSY}.

The results and lessons learnt from the simulations so far show that the performance of simple catch rules depends on the operating models used to evaluate them. The operating models have been conditioned on a set of fixed parameters without considering uncertainty in processes, for example related to the form of compensation; Individual Based Models (c.f. FLIBM in Section 1.4 of this report, PROBYFISH) could be used to condition OMs. Therefore, future operating models should explore the option of including variability in life-history information and how this affects the operating model characteristics (such as reference levels, productivity, and the time-series of observable states) and ultimately the performance of the catch rules.

The analysis into the timing of data used (in particular, the information from the biomass index) to scale catch showed that the current formulation of the catch rule might be too restrictive. Alternative formulations allowing wider options, such as asymmetric gain terms depending on the direction of the change (up/down) or using entirely different metrics from the biomass index to quantify changes in the stock which can be converted into corresponding changes in catch.

Previously stated aspects to consider for data-limited catch rules should be further investigated as a next step, and these include:

a) focusing on the nature of time-series and developing diagnostics that could help determine the rules that would work well under alternative characterisations of the nature of the time-series, and aspects such as quality of data used by the rules (and hence ability to detect signals), ability to set appropriate reference points, etc.
b) Linking life-history traits and fishery characteristics (e.g. including fishery selectivity) to the nature of resulting time-series.
c) Develop guidance for use of catch rules by linking the two previous points.
d) Avoiding the shot-gun approach to simulation testinge.g. by making more extensive use of sensitivity (elasticity) analysis to highlight factors that are most important in determining the time-series behaviour of stocks.

Finally, in practice, the application of simple empirical catch rule is simpler and less time consuming compared to model-based management procedures, particularly if operational effort is considered. Therefore, in the longterm, it might be useful to consider performing comparisons of the performance of catch rules under investigation with more complex model-based management procedures that are used in a data-limited context as well as in more data-moderate or rich situations. Conversely, in data-limited situations, stocks are usually simulated based on limited number of parameters. Lessons could be learned by using data or assessment results from data-rich stocks and their assessments.

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5 Stochastic surplus production models

This section of the report focuses on the ToR b) and the revision of the draft ICES technical guidance on advice rules for stocks in Categories 3 and 4 (Annex 3).ICES Category 3 stocks can be managed using the official advice rules based on the stochastic production model in continuous time (SPiCT; Pedersen and Berg, 2017; Sections 3.1.1 and 3.1.2 in ICES, 2017). These advice rules require the acceptance of a SPiCT assessment.

5.1 Introduction

The stochastic production model in continuous time (SPiCT; Pedersen and Berg, 2017) is one of the official assessment methods for stocks in ICES category 3 stocks (hereafter referred to as data-limited stocks; ICES, 2018a). SPiCT is a state–space re-parameterized version of the Pella-Tomlinson surplus production model (Pella and Tomlinson, 1969); i.e. quantifies observation and process errors and estimates stock status and reference levels with associated confidence intervals.

The Workshop on the Development of the ICES approach to providing MSY advice for Category 3 and 4 stocks (Section 3.1, WKMSYCat34; ICES, 2017) suggested equations 1 and 2 for management advice based on SPiCT assessments (“median rule”):

Equation 1

$$\boldsymbol{TAC_{y+1} = median(C_{y+1})}$$

Equation 2

$$F_{y+1} = F_y \frac{min\left(1, median\left(\frac{B_{y+1}}{MSYB_{trigger}}\right)\right)}{median\left(\frac{F_y}{F_{MSY}}\right)}$$

By means of simulation testing, WKLIFE VII and VIII found that the median rule does not meet the precautionary thresholds in a few scenarios, and thus introduced two modifications to the median rule that allow to account for the assessment uncertainty (ICES, 2018b; ICES, 2018c): (i) the precautionary rule (MSY-PA) allows to adjust the TAC dependent on the predicted risk ($P(B_{pred}>B_{lim})$); and (ii) the percentilerule (MSY-F) uses certain percentiles other than the median for the distributions C_{pred}, F/F_{MSY}, and B/B_{MSY}. Simulations confirmed that these rules are more precautionary than the median rule (ICES, 2018c). However, the performance of the MSY-PA rule fully depends on the definition of B_{lim}. Within ICES, this biomass limit reference level is often defined as the break point of the hockey-stick stock–recruitment relationship or as 70% of the virgin biomass for data-limited situations, respectively (ICES, 2017). These definitions of B_{lim} do not guarantee that the limit reference level is more precautionary than the target reference level (B_{MSY}); i.e. in theory, B_{lim} could be larger than B_{MSY} (Mesnil and Rochet, 2010). A universal definition of B_{lim} is needed which ensures that the limit reference levels are more precautionary than the target reference levels. By contrast, the percentile rule does not require any definition of B_{lim} but uses the distributions of the target reference levels to scale the TAC. The MSY-percentilerule is defined as:

Equation 3

$$C_{y+1} = q_C(p)$$

Equation 4

$$F_{y+1} = F_y \frac{min\big(1, q_B(p)\big)}{q_F(100-p)}$$

where the advised catch (C) for forecast year y + 1 corresponds to the predicted catch given the fishing mortality trajectory in the forecast year, and where F_y and $F_{y+1}$are the fishing mortalities at the beginning and the end of the forecast year, respectively. Components are defined as follows:

Table 5.1.1. Description of the different components of equations 2 and 3.

Components	Definition and purpose
q$_C$	**Function that takes a percentile and returns the corresponding predicted catch C_{y+1} given the fishing mortality trajectory during the forecast year y+1; i.e.$q_C = \Phi^{-1}_{(C_{pred} \vee F=F_y \dots F_{y+1})}$**
q$_B$	**Function that takes a percentile and returns the corresponding predicted $\frac{B_{y+1}}{MSYB_{trigger}}$ at the beginning of the forecast year and $MSYB_{trigger} = \frac{B_{MSY}}{2}$; i.e.$q_B = \Phi^{-1}_{\left(2\frac{B_{y+1}}{B_{MSY}}\right)}$**
q$_F$	**Function that takes a percentile and returns the corresponding predicted $\frac{F_y}{F_{MSY}}$ at the beginning of the forecast year y+1; i.e.$q_F = \Phi^{-1}_{\left(\frac{F_y}{F_{MSY}}\right)}$**
p	**Specific percentile of the respective distributions, e.g. 35 (this report).**

where the different quantities can be depicted on a timeline as follows:

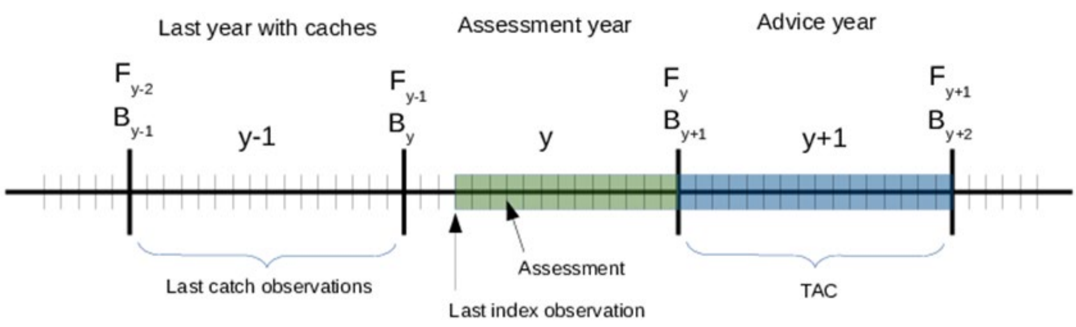

Figure 5.1.1. A timeline defining the continuous time quantities of SPiCT in relation to the discrete time of assessment and advice years in fisheries management. The small vertical bars represent the dt$_{Euler}$time-steps (here: 16 per year). The green area depicts the projection period between the last observation (here: index observation) and the start of the management period. The blue area depicts the period for which the TAC is going to be calculated.

In this report, we describe the work performed in preparation for and during WKLIFE IX, which aimed at providing guidelines on the use of SPiCT for stock assessment and fisheries management. Due to above mentioned points regarding the MSY-PA rule, we focus the MSE simulations on the MSY percentilerule.

5.2 Guidelines for the use of the stochastic production model in continuous time (SPiCT)

Any advice rule for the management of an ICES Category 3 stock using SPiCT requires the acceptance of a SPiCT assessment. A condensed summary with specific guidelines for the use of SPiCT has been developed within the frame of WKDLSSLS (ICES, 2019) and WKLIFE IX. In particular, the guidelines document contains:

- the main assumptions and data requirements of SPiCT,
- a checklist for the acceptance of a SPiCT assessment,
- options for assessment tuning, and
- harvest control rules for SPiCT assessments.

Target audience of this document are stock assessors and members of assessment groups who apply SPiCT and are responsible for deciding on accepting or rejecting a SPiCT assessment. The summary is a living document and may as such be subject to future changes. The document is part of the SPiCT package (vignette: “spict_guidelines”). It can be accessed and downloaded here (https://github.com/DTUAqua/spict/vignettes/spict_guidelines.pdf).

5.3 Management strategy evaluation

The relative and absolute performance of the different advice rules were evaluated within an MSE framework (Smith, 1994; Punt *el al*., 2016). The details of which are explained in the following sections.

5.3.1 Methods

5.3.1.1 Operating model

The age-structured population model with yearly time-steps from the DLMtool package was used as the underlying operating model within the MSE framework (Carruthers and Hordyk, 2018a). This operating model differs substantially from the tested assessment model (biomass dynamic model without age structure). More details about the model assumptions and governing equations can be found in the supporting material of Carruthers and Hordyk (2018b).

5.3.1.2 Stocks

The MSE simulations were parameterised according to three stocks with various life-history strategies: (i) anchovy in Biscay-Iberia representing a fast-growing species, (ii) haddock in the Celtic Seas representing intermediate growing species, and (iii) widely distributed ling representing a slow growing species. The biological parameters were based on the data-limited stocks included in Jardim *et al*. (2015), however, most parameters were updated based on the most recent analyses and/or expert knowledge.

Table 5.3.1.2.1. Updated population mean biological parameters for the three stocks used in the MSE simulations. The parameter labels correspond to the nomenclature of the DLMtool package (Carruthers and Hordyk, 2019).

Parameter	Anchovy	Haddock	Ling
Max age	6	9	20
Linf	18.69	45.5	160
K	0.89	0.428	0.09
t0	-0.02	-0.092	-0.1
M	1.2, 0.8, 1.2, 1.2, 1.2, 1.2	2.44, 0.92, 0.62, 0.49, 0.42, 0.38, 0.35, 0.33, 0.33	2.95, 1.12, 0.64, 0.44, 0.33, 0.26, 0.22, 0.19, 0.17, 0.15, 0.14, 0.13, 0.12, 0.11, 0.11, 0.10, 0.10, 0.09, 0.09, 0.09
a	3.13e-06	0.0065	0.0033
b	3.278	3.108	3.1311
h	0.62	0.74	0.79
L50	12	31.5	75
L50_95	0.3	3	25
L5	0.3	1	50
LFS	12	40	135

It is important to note that the parameters in Table 5.3.1.2.1 represent population mean values. The operating model resamples all biological parameters from uniform distributions. If no informative evidence about the variability of these parameters was available, a default range of ±5% around the population mean values was assumed to define the uniform distributions. In other words, due to the parameter ranges, the operating model simulates "anchovy-like", "haddock-like", and "ling-like" stocks rather than specific stocks. Among the three stocks, not only the life-history strategies vary, but also the relation of the selectivity to the maturity ogive (Figure 5.3.1.2.1).

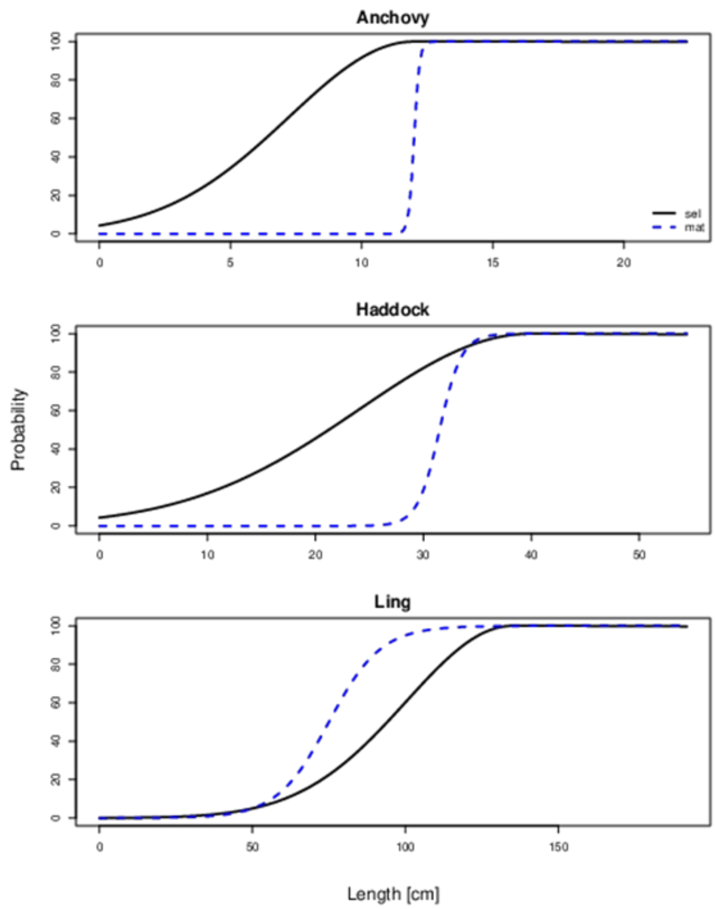

Figure 5.3.1.2.1. Selectivity and maturity as a function of length for the three stocks.

For all stocks, the Beverton and Holt stock–recruitment-relationship (Beverton and Holt, 1957) was assumed. The steepness parameters (h) were taken from Myers *et al*. (1999).

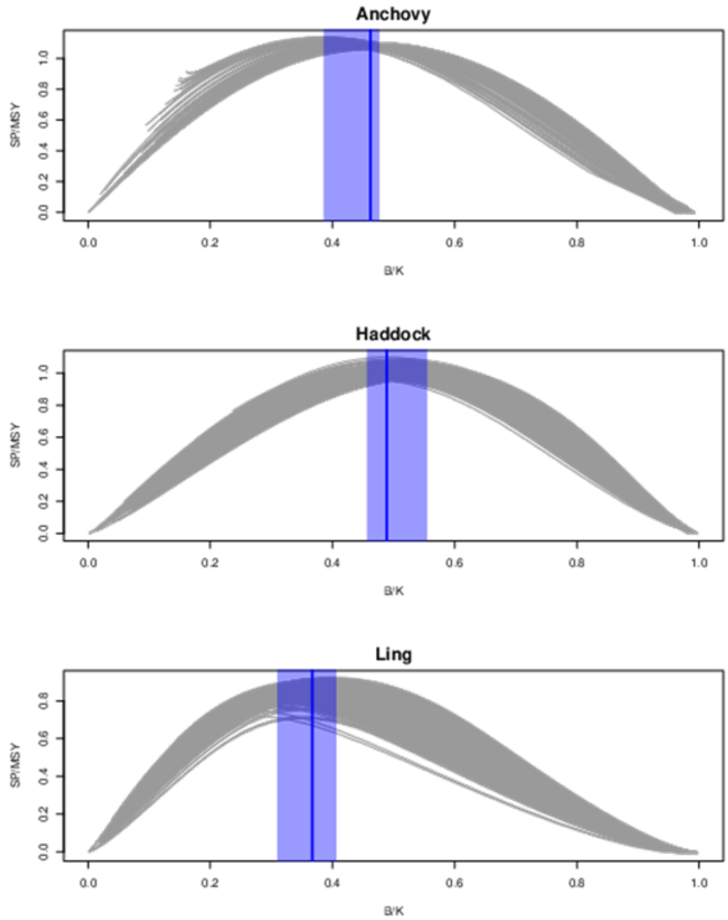

Figure 5.3.1.2.2. Production curves for the three stocks calculated from the operating model.

5.3.1.3 Scenarios

For the three stocks, we tested the performance of the different HCRs under perfect conditions (long time-series of 40 years with high contrast and low observation and process errors) and under data poor conditions (short time-series of 20 years with low contrast and high observation and process errors; S1–S2 and S5–S8 in Table 5.3.1.3.1, respectively). Additionally, we evaluated the performance of the rules when the haddock-like stocks are underexploited (S3 and S4). Scenarios S9 and S10 are additional, rather unrealistic scenarios that allow to test (i) the performance of the rules when approaching the limits of the data requirements for SPiCT and (ii) the performance of the tighter Schaefer-like prior when the underlying stock has a right skewed production curve (Figure 5.3.1.3.2), respectively.

Table 5.3.1.3.1. Scenario settings. The parameter ranges represent the lower and upper limits of the uniform distributions. The F pattern corresponds to the effort patterns during the historic years depicted in Figure 5. For scenario 10, K is lowered to 0.1 to force a right-skewed production curve (Figure 5.3.1.3.1).

Scenario number	Species	SigmaR	SigmaC	SigmaI	Depletion level	Number of years	Autocorrelation in SR	F pattern
S1	Haddock	[0.01,0.05]	[0.05,0.05]	[0.05,0.05]	[0.03,0.3]	40	[0.1,0.3]	incr
S2	Haddock	[0.4,0.6]	[0.25,0.25]	[0.25,0.25]	[0.03,0.3]	20	[0.1,0.3]	incr
S3	Haddock	[0.01,0.05]	[0.05,0.05]	[0.05,0.05]	[0.4,0.7]	40	[0.1,0.3]	decr
S4	Haddock	[0.4,0.6]	[0.25,0.25]	[0.25,0.25]	[0.4,0.7]	20	[0.1,0.3]	decr
S5	Anchovy	[0.01,0.05]	[0.05,0.05]	[0.05,0.05]	[0.03,0.3]	40	[0.1,0.3]	incr
S6	Anchovy	[0.4,0.6]	[0.25,0.25]	[0.25,0.25]	[0.03,0.3]	20	[0.1,0.3]	incr
S7	Ling	[0.01,0.05]	[0.05,0.05]	[0.05,0.05]	[0.03,0.3]	40	[0.1,0.3]	incr
S8	Ling	[0.4,0.6]	[0.25,0.25]	[0.25,0.25]	[0.03,0.3]	20	[0.1,0.3]	incr
S9	Haddock	[0.6,0.8]	[0.4,0.4]	[0.8,0.8]	[0.03,0.3]	20	[0.1,0.3]	incr
S10	Haddock	[0.4,0.6]	[0.25,0.25]	[0.25,0.25]	[0.03,0.3]	20	[0.1,0.3]	incr

Additional MSE settings were held constant across all scenarios:

- Projection years = 20;
- Number of simulations per scenario = 200;
- Annual assessment and TAC calculation;
- Intermediate (assessment) year between last observations and advice year (c.f. Figure 5.3.1.2.1);
- No observation biases;
- No implementation errors/biases.

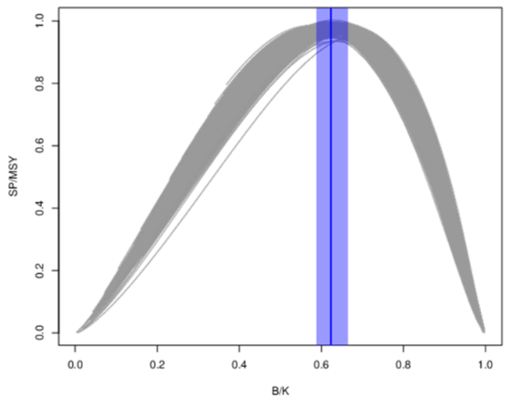

Figure 5.3.1.3.1. Production curve for scenario 10 calculated from the operating model.

Figure 5.3.1.3.2 depicts the effort time-series in the historic years used for simulation. The vertical dashed lines represent the part of the time-series available to the assessment models in the data poor scenarios (S2,S4,S6,S8,S9,S10).

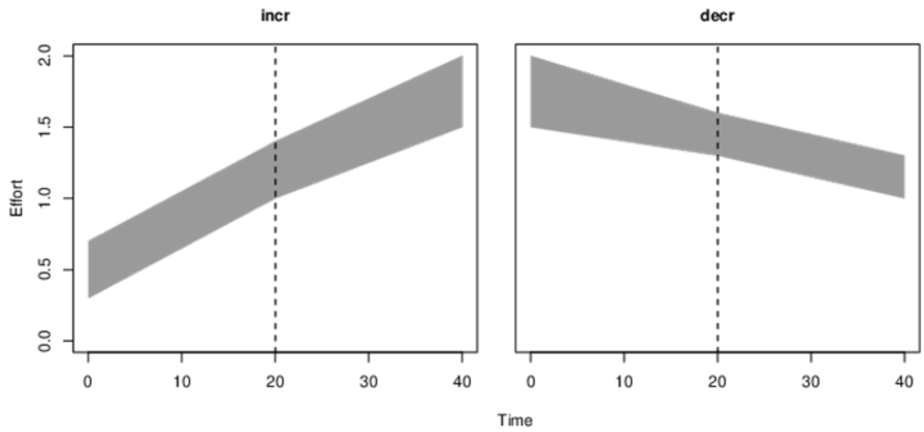

Figure 5.3.1.3.2. Effort during the 40 historic years. Vertical lines show the start of the historic effort time-series available for the scenarios S2,S4,S6,S8,S9 andS10 that use short time-series of 20 years.

5.3.1.4 Harvest control rules (HCRs)

For each scenario, we compared the performance of 19 different harvest control rules (HCRs), which comprise the optimal harvesting strategy of the operating model, various variations of index-trend rules; i.e. 1/2 and 2/3 rules, and different MSY percentilerules based on a SPiCT assessment. The 2/3 rule is based on the trend in the survey index by dividing the average of the last two observations in the index by the average of the preceding three observations. Comparatively, the 1/2 rule is based on the last observation in the index divided by the average of the preceding two observations. These index-trend rules are one of the factors ("r") of the advice rule 3.2.2 in ICES (2017). The factors "f" and "b" of this rule were not tested here. However, the index-trend rules were tested with and without a ±20% uncertainty cap, which limits the change in the advice between 80% and 120% of the TAC in the preceding year. Furthermore, we tested the addition of a precautionary buffer, which lowers the TAC by 20% every three years (ICES, 2017). The types of HCRs tested comprise (with labels in brackets):

- F_{MSY} of operating model (**ref**)
- 2/3 rules
  - standard (**2/3**)
  - with uncertainty cap (**2/3_uC**)
  - with uncertainty cap and precautionary buffer (0.2 reduction every 3 years) (**2/3_uC_PA3**)
- 1/ 2 rules
  - standard (**1/2**)
  - with uncertainty cap (**1/2_uC**)
  - with uncertainty cap and precautionary buffer (0.2 reduction every 3 years) (**1/2_uC_PA3**)
- SPiCT percentile rules (50, 45, 35, 25 percentiles)
  - default settings (**MSY50, MSY45, MSY35, MSY25**)
  - default settings plus tighter prior on n
    - sdn = 0.5 (**MSY50-S05, MSY45-S05, MSY35-S05, MSY25-S05**)
    - sdn = 0.1 (**MSY50-S01, MSY45-S01, MSY35-S01, MSY25-S01**)

All SPiCT based HCRs assume an Euler discretization time-step of 1/16 and can be calculated using the get.TAC() function within the SPiCT package.

5.3.1.5 Performance metrics

The performance of the advice rules was compared among rules and between scenarios based on following performance metrics:

- Risk 1: average probability that SSB is below B_{lim} where the average (of the annual probabilities) is taken across x number of years (ICES, 2013);
- Mean relative yield;
- Median inter-annual variability of yield (MIAVY);
- Proportion of converged simulations.

Where the true B_{lim} for performance evaluation is defined as 30% of the true B_{MSY} and the mean relative yield refers to the yield relative to the yield obtained by fishing according to the true F_{MSY} (from the operating model) in the last five years (Carruthers and Hordyk, 2019). Simulations where any SPiCT based HCR did not converge, were excluded for the calculation of the performance metrics for all HCRs (including index-trend based rules). All metrics are evaluated over the whole projection time-series (years 1–20).

5.3.2 Results

The results indicate that the absolute performance of the HCRs depends on the scenario and thus on the life-history parameters, data quality and quantity, process and observation errors, and the fishing effort pattern. Overall, the MSY percentilerules show a good performance with a high relative yield, a low risk level, and low median interannual variability of yield (Figures 5.3.2.1–5.3.2.3). In contrast, the 2/3 and 1/2 rules show low average relative yield levels, higher risk levels, and higher variabilities of yield (Figures 5.3.2.1–5.3.2.3). The results indicate that overall the tested percentile rules outperform the tested 2/3 and 1/2 rules.

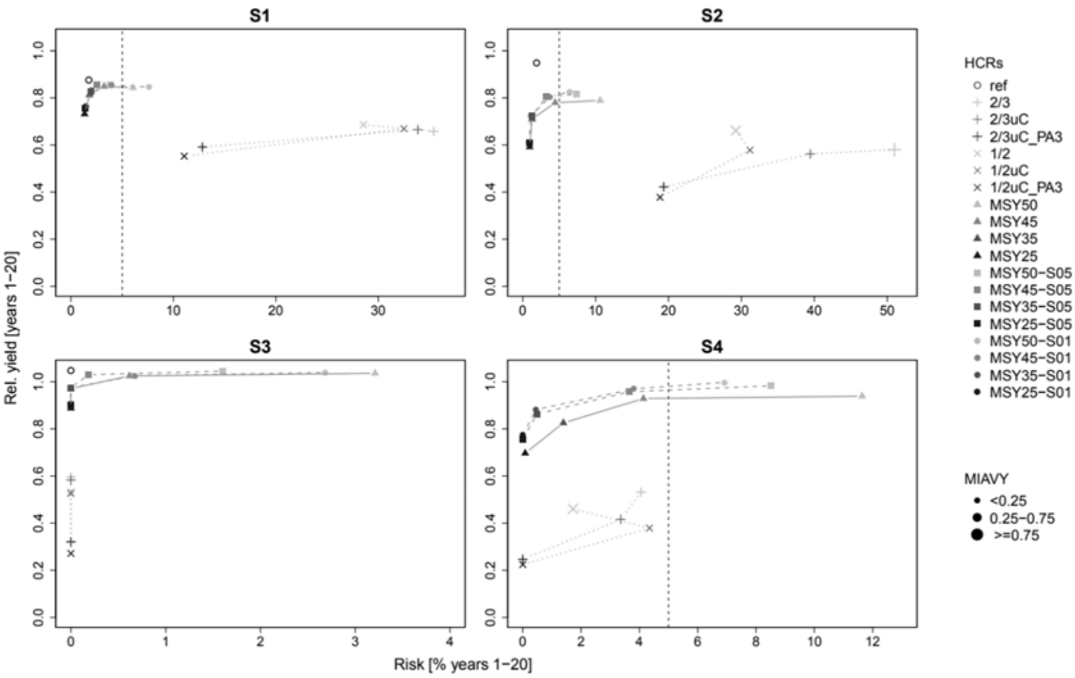

Figure 5.3.2.1. Trade-off of relative yield, risk, and MIAVY for scenarios 1–4. Vertical line represents the reference level of a 5% risk. Lines connecting symbols represent HCRs of a similar type, e.g. only differing in the percentile.

Across all scenarios the percentilerules are more precautionary (lower risk) than the median rule. The difference in risk depends on the percentile. While the difference in risk between the median rule and the MSY-45 rule can be substantial (e.g. eight units for S4), the loss in relative yield with the 45th percentile is minor (highest for ling, see Figure 5.3.2.3). For the anchovy-like stocks, the relative yield of MSY-45 is even slightly larger than of the median rule (Figure 5.3.2.2). On the other hand, the difference in relative yield between the 25th and 35th percentile rule outweighs the difference in risk between these rules. These findings indicate that there might be an optimal percentile between the 25th and 45th percentile. The tested 35th percentile shows high relative yield and is below the reference risk level of 5% for all main scenarios (S1–S8). For most scenarios, higher percentiles than 35th show higher levels of risk while pertaining same levels of relative yield, while lower percentiles show a decrease in yield with little change in risk. The 35th percentile rule is thus the best performing percentilerule of all tested rules.

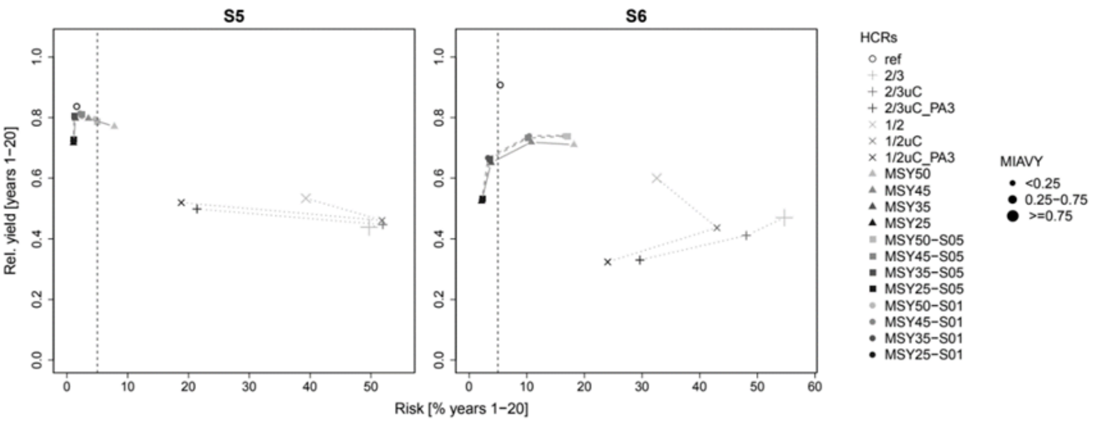

Figure 5.3.2.2. Trade-off of relative yield, risk, and MIAVY for scenario 5 and 6. Vertical line represents the reference level of a 5% risk. Lines connecting symbols represent HCRs of a similar type, e.g. only differing in the percentile.

Across all scenarios, the SPiCT HCRs with a tighter prior on the shape of the production curve (parameter "n") are more precautionary than with default priors. Interestingly, even for scenario 10 with a right-skewed production curve, the Schaefer like prior is more precautionary.

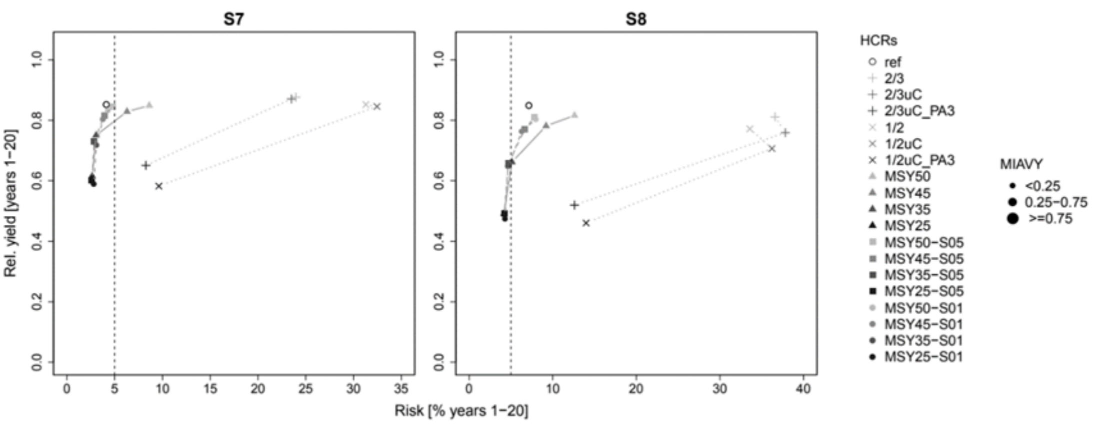

Figure 5.3.2.3. Trade-off of relative yield, risk, and MIAVY for scenarios 7 and 8. Vertical line represents the reference level of a 5% risk. Lines connecting symbols represent HCRs of a similar type, e.g. only differing in the percentile.

The scenarios with the shorter time-series reveal that the 1/2 rule with uncertainty cap has a higher risk and lower yield than without the uncertainty cap (Figures 5.3.2.1–5.3.2.3). For haddock and ling-like stocks the 2/3 rule outperforms the 1/2 rule (Figures 5.3.2.1 and 5.3.2.3), while for the anchovy-like stock, the 1/2 rule outperforms the 2/3 rule (Figure 5.3.2.2). These finding confirm the results of the WKDLSSLS (ICES, 2019).

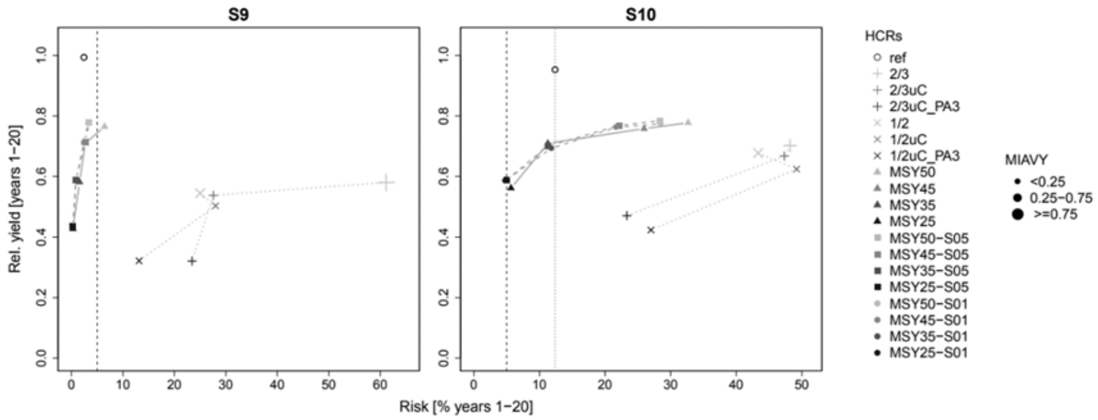

Figure 5.3.2.4. Trade-off of relative yield, risk, and MIAVY for scenarios 9 and 10. Vertical dashed line represents the reference level of a 5% risk. The vertical dotted line represents the risk level of the optimal HCR. Lines connecting symbols represent HCRs of a similar type, e.g. only differing in the percentile.

The additional scenario S9 shows that high observation errors of a CV of 0.4 and 0.8 for catch and index observations, respectively, a high process error of a CV of 0.6–0.8, together with a short time-series (20 years) decreases the convergence rate (Table 5.3.2.1), but converged simulations still show a good performance with low risk levels (Figure 5.3.2.4). Scenario S10 with a manually changed growth coefficient (K=0.1) shows large differences to the comparative scenario S2 (Figure 5.3.2.4 vs 5.3.2.1). The risk for all HCRs is much higher for S10 than for S2, so that even the 35th percentile rule is not below the reference risk level of 5%. However, it is important to note that also the optimal harvest strategy informed by operating model ("ref") is above 5% and MSY-35 has a lower risk than the reference HCR (Figure 5.3.2.4).

Table 5.3.2.1. Percentage of non-converged simulations for each harvest control rule (HCR) and scenario. A simulation was categorised as non-converged if at least one assessment in the 20 years projection period did not converge.

HCR	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
MSY50	14.5	37	8.5	29	11	30	1.5	23	67	33
MSY45	10	42	7	28	11	28.5	5.5	33	69.5	35
MSY35	10.5	33	6.5	23	6.5	18.5	5.5	27.5	64	31.5
MSY25	8	27	7	16.5	7.5	14	5.5	28	59.5	30.5
MSY50-S05	4	25.5	8	16.5	10	24.5	2	5.5	62.5	17
MSY45-S05	4.5	24	5	12	9	20	3	12.5	59.5	22
MSY35-S05	2	18	4.5	10	7.5	11	3.5	9.5	57.5	18
MSY25-S05	2.5	11.5	2	3	6	4	3.5	10.5	51.5	12
MSY50-S01	2.5	22.5	3	11	6.5	21.5	1.5	1	63.5	12.5
MSY45-S01	5	22	2	11	5	22	1	9	61	18
MSY35-S01	3.5	14.5	3.5	7.5	4	9.5	3.5	7.5	47.5	13
MSY25-S01	2.5	10	1.5	3	7	3	2.5	7	49	10

Table 5.3.2.1 shows the percentage of simulations, where SPiCT failed to converge in at least one year of the 20 projection years. The number of non-converged simulations is higher for the data-poor scenarios in comparison to respective data moderate scenarios (c.f. e.g. S2 and S1) and for anchovy and haddock-like stock in comparison to ling stocks (Table 5.3.2.1). Overall, the number of iterations to convergence can be increased with a tighter prior on the shape of the production curve by up to a factor of 2. Increasing the observation and process errors to very high levels (S9) shows high numbers of non-converged simulations of up to 70%, which can be decreased with a tighter prior on n to 63%. The numbers for the stocks with a right-skewed production curve (S10) are similar to comparative scenario S2.

5.3.3 Conclusion

Within the context of WKLIFE IX, guidelines for the application of SPiCT for stock assessment and management have been developed. These guidelines offer specific criteria for the acceptance of a SPiCT assessment, tuning of assessments, as well as options for the estimation of the TAC. The guidelines are available as a living document maintained by the developers of SPiCT and part of the R package (Mildenberger *et al*., 2019).

Furthermore, stochastic harvest control rules introduced and tested in WKLIFE VII and WKLIFE VIII, were further tested. By considering any percentilelarger than the median for the distribution of F/F_{MSY} and smaller than the median for the distribution of B/B_{MSY} and C_{pred}, the percentilerules allow to account for the assessment uncertainty. While the trade-off between relative yield and risk aversion is dependent on the specific percentiles, the results indicate that the 35th percentile rule gives a high yield while meeting the risk aversion levels across all main scenarios. In theory, with increasing time-series lengths and decreasing observation error, the estimated catch with the MSY-35th percentile rule approximates the median rule suggested by WKM-SYCat34 while being more precautionary. The MSY-35 rule is defined as:

Equation 5

$$C_{y+1} = q_C(35)$$

Equation 6

$$F_{y+1} = F_y \frac{min\left(1, q_B(35)\right)}{q_F(65)}$$

where the components are explained in Table 5.1.1. Different options can be explored to stabilise SPiCT for data with low contrast or high observation errors. SPiCT allows the use of prior distributions, for example on the shape of the production curve or the initial depletion level, which can help stabilise the optimisation procedure. However, using priors with lower standard deviations affects the results (confidence intervals and parameter estimates). The SPiCT developers emphasise that stock-specific MSEs should be used for the comparison of precautionary levels of different advice rules.

Caveats

All results are subject to the assumptions of the operating model, which is in this case an age-structured population model with a yearly time-step.

The effect of a tighter Schaefer-like prior should be evaluated with a stock that has an even more right skewed production curve (c.f. Figure 5.3.1.3.2).

The performance of the SPiCT-based rules might be better, when correcting the survey index by the exploitable part of the stock. In the results presented here, the total stock biomass is used. Furthermore, instead of extrapolating the F process in the assessment year, the catch should be set to last year's advice ($C_y = TAC_{y-1}$).

The performance of the index-trend based rules might in theory be slightly better if the other factors of the catch rule 3.2.2 are considered ("f" and "b"; ICES, 2017). In practice, however, these factors are rarely used for management advice.

5.4 Future work

The SPiCT-based advice rules should be implemented within another MSE framework. This would allow to compare the here presented results with an operating model based on different assumptions. The introduced individual-based operating model (FLIBM) within the FLR framework poses a promising candidate for such simulation testing. This would also allow to simulate stocks with a finer temporal resolution such as quarterly or monthly time-steps. The impact of additional aspects and settings of the operating model, like fleet selectivity, implementation error, hyperstability/hyperdepletion of indices, the use of biannual indices, etc. should be explored. In particular, the effect of the relationship of selectivity to maturity functions on the productivity of the stocks, estimated reference levels and thus the performance of the HCRs should be explored further.

The relationship between the performance of SPiCT-based advice rules and tightening the prior on the shape parameter of the production curve ('n') has to be evaluated in more detail and with more right skewed production curves, which might be hard to find in nature despite for whales. As discussed earlier, this parameter is hard to estimate, but can be fixed or informed by a prior in data-limited cases. However, the prior affects the size of the confidence intervals of predicted stock status and thus the advice rules.

The results should be compared to fractile rules which assume the catch in the assessment year equal to the TAC estimated in the previous year, instead of extrapolating the F process. Furthermore, the other components (*f* and *b*) of the index-trend rules should be tested.

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6 Combined modelling of both data-rich and data-limited stocks

6.1 Introduction

This section focuses on the ToR d); namely, a review and investigation of modelling approaches that incorporate both data-rich and data-limited stocks within mixed fisheries/multispecies frameworks and their ability to provide sea area-based stock assessments and catch advice. Sea area is used in the sense that a mixed fisheries approach is being developed by ICES separately by sea area: e.g. for the North Sea and Celtic Sea.

Currently within ICES, the focus is very much on the use of single species assessments to provide advice on a stock by stock basis. Three additional products, a) ecosystem overviews, b) multi-species advice, and c) mixed fisheries advice, are generated, but are not produced for all ecosystems, and their take up has been limited. The first product provides a broad overview, and tends to draw information from a wide variety of sources, and is useful for framing the big picture, but does not impact directly on advice. The second is typically provided for the Baltic and North Seas using the SMS model. The model outputs directly impact on the assessment process by providing boundary conditions on mortality for single species assessments, but the multispecies biomass projections are not used per se. The mixed fisheries advice is a useful item to inform negotiations but is again in general not used for issuing specific advice.

In reality, stocks cannot be considered in isolation from the foodweb that they are part of, or the fisheries that harvest them, and it makes sense to treat stocks together in a mixed fisheries and multispecies framework. Not only is this biologically and economically more realistic than the fiction of a single species in isolation, but offers the potential benefits of a) maximising the utility of stock data by enabling data on one stock to be used in constraining the assessments of many, and b) providing a single self-consistent picture of the ecosystem and offering greater clarity for decision-makers on the trade-offs involved.

In this section we present and discuss some work done in this direction, where we use an existing multispecies and mixed fisheries model of the North Sea to look at the impacts of managing data-poor and data-rich stocks within a common framework. The North Sea is an appropriate case study region because it is relatively data rich (some ten stocks with full analytical assessments), whilst also having complex mixed fisheries, and a number of important data-limited stocks (including ones such as grey gurnard that may have significant impacts on commercial stocks via the foodweb).

6.2 Methods

We used a length-structured multispecies model to consider the effects of managing data-rich and data-limited stocks together, using a management strategy evaluation framework. Because it would be impractical to embed >20 single species assessments models within the MSE framework, we used a "short-cut" approach in which the assessment process is approximated by adding process error to the modelled biomasses. In the study of Thorpe and De Oliveira(2019) this was done by adding white noise with a given variance, but here we follow Thorpe (2019) in using red noise with the statistical properties of the North Sea cod assessment, assuming that this is an unbiased estimator in the long term. We chose cod *a priori* because of its cultural value to the UK rather than for any impact such a choice might have had on the MSE. The statistical properties of this assessment are then assumed to apply to all 21 stocks, data rich and data poor alike. The MSE is used to estimate the expected long-term outcomes of managing to different F_{MSY} targets across the fish community. Three different types of targets were considered. In the first case, we looked at F estimates based on assessment products, using assessed Fs where available, and Fs emerging from mixed fisheries constraints for the data-poor stocks. In the second case, we calculated a Nash Equilibrium (NE) and used that as the F_{MSY} target. This depends only on the dynamics of the operating model, and so does not depend directly upon the availability of assessments. And thirdly, we used a set of 238 ICES-style harvest control rules, which aim for a certain level of fishing (F-LIMIT), but scaling back from that if stock status deteriorates (B <B-TARGET, representingthe ICES reference point $B_{trigger}$, here a given fraction of the virgin biomass B_0). Outcomes were evaluated in terms of expected catch value, risk of stock depletion, income variability, and notional profit (on the basis of the imputed mixed fishery). In this way we could compare the performance of the assessment-based targets with those that were more data poor.

The method has five main components, a multispecies model, an MSE approach, definition of the target Fs, setting of the data-poor harvest control rules, and characterisation and comparison of the MSY outcomes. Each is considered in more detail in the following subsections.

6.2.1 The multispecies model

We use the LeMans multispecies model, which was originally designed by Hall *et al.*, 2005 for the Georges Bank, adapted for the North Sea by Rochet *et al.* (2011) and further developed by Thorpe *et al.* (2015; 2016; 2017). The model is a fish community model structured by species and length. It is broadly similar to SMS, albeit structured by length rather than age, with some of the parameter choices being replaced by life-history invariants. This means that the model is less good at reproducing today's stock status than SMS, but may be better at making future projections. In comparison, both SMS and LeMans are quite different from Ecopath, which covers the whole ecosystem, but does not explicitly represent size-structured processes (Figure 6.2.1.1).

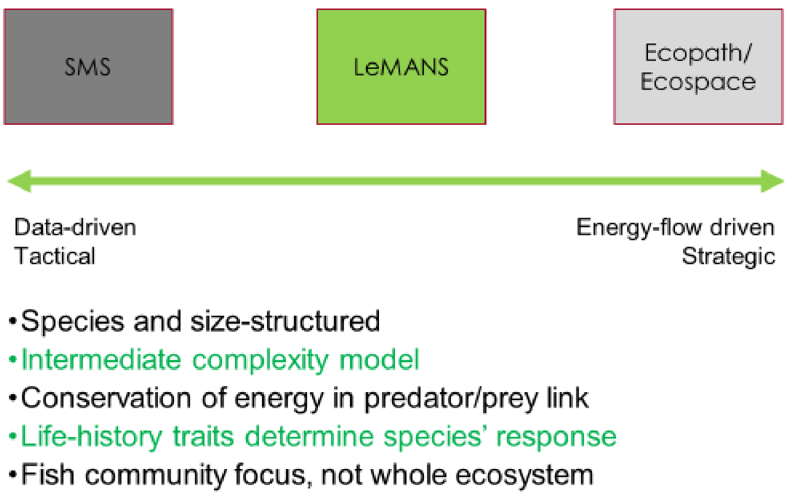

Figure 6.2.1.1. Schematic comparing LeMans with SMS and with Ecopath.

6.2.2 The MSE approach

We use an ensemble of 63 LeMans variants as the operating model. The 63 variants have the same model structure but different parameter settings, and represent the effect of uncertainty in key processes such as recruitment, natural mortality, the preferred length ratio of predator and prey, life-history traits and growth efficiency.

The parameters are chosen because of 78 125 combinations tried, they are best able to replicate observed abundance patterns between 1990 and 2010 to an acceptable degree (Thorpe *et al.*, 2017; Figure 6.2.2.1)

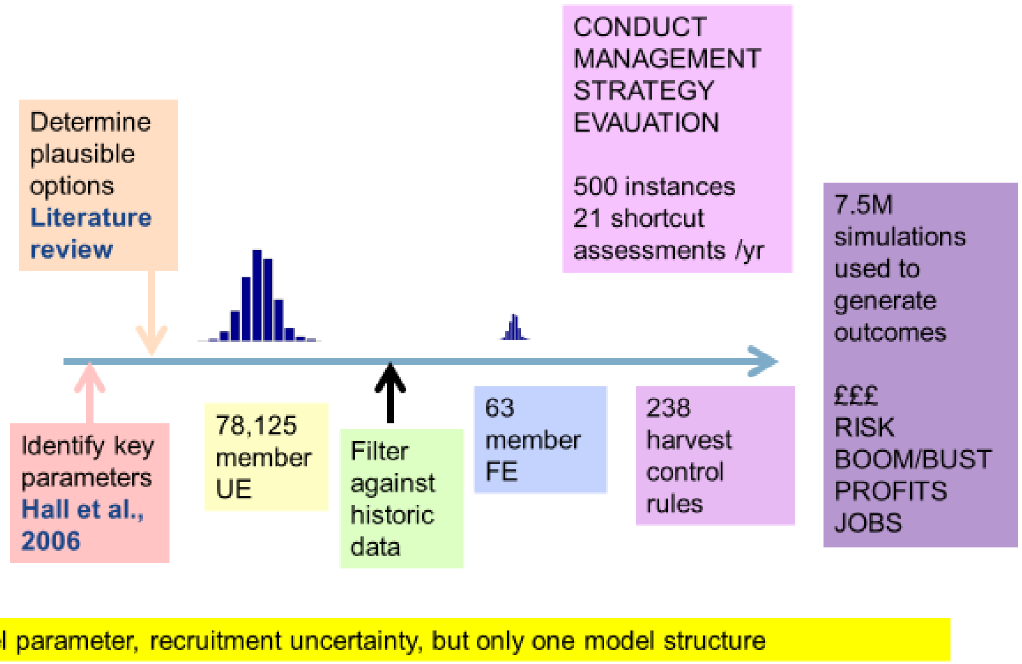

Figure 6.2.2.1. Schematic showing experimental set up; model parameter sets that match historic data for the period 1990–2010 are used to drive an MSE evaluation of 5 multispecies MSY proxies and 238 data-limited harvest control rules.

The evaluation is by way of an MSE (Figure 6.2.2.2), using averages for the last 50 years of 100 simulations to represent the expected long-term outcomes, assuming a constant strategy and environment. Management is on the basis of a simple harvest control rule with a target F and limit biomass, below which fishing is scaled back linearly with abundance, such that zero F would be associated with zero observed biomass. Targets are set with a two-year lag, reflecting delays in the assessment process, so that the previous year's biomass status provides the basis for the subsequent year's catch. Assessment error has properties of variance and autocorrelation (~80%, consistent with Wiedenmann*et al.*, 2015) associated with the North Sea cod assessment, assuming no long-term bias (Thorpe, 2019) and this is applied to all stocks. Implementation error is assumed to be unbiased white noise, with a coefficient of variance of 0.3.

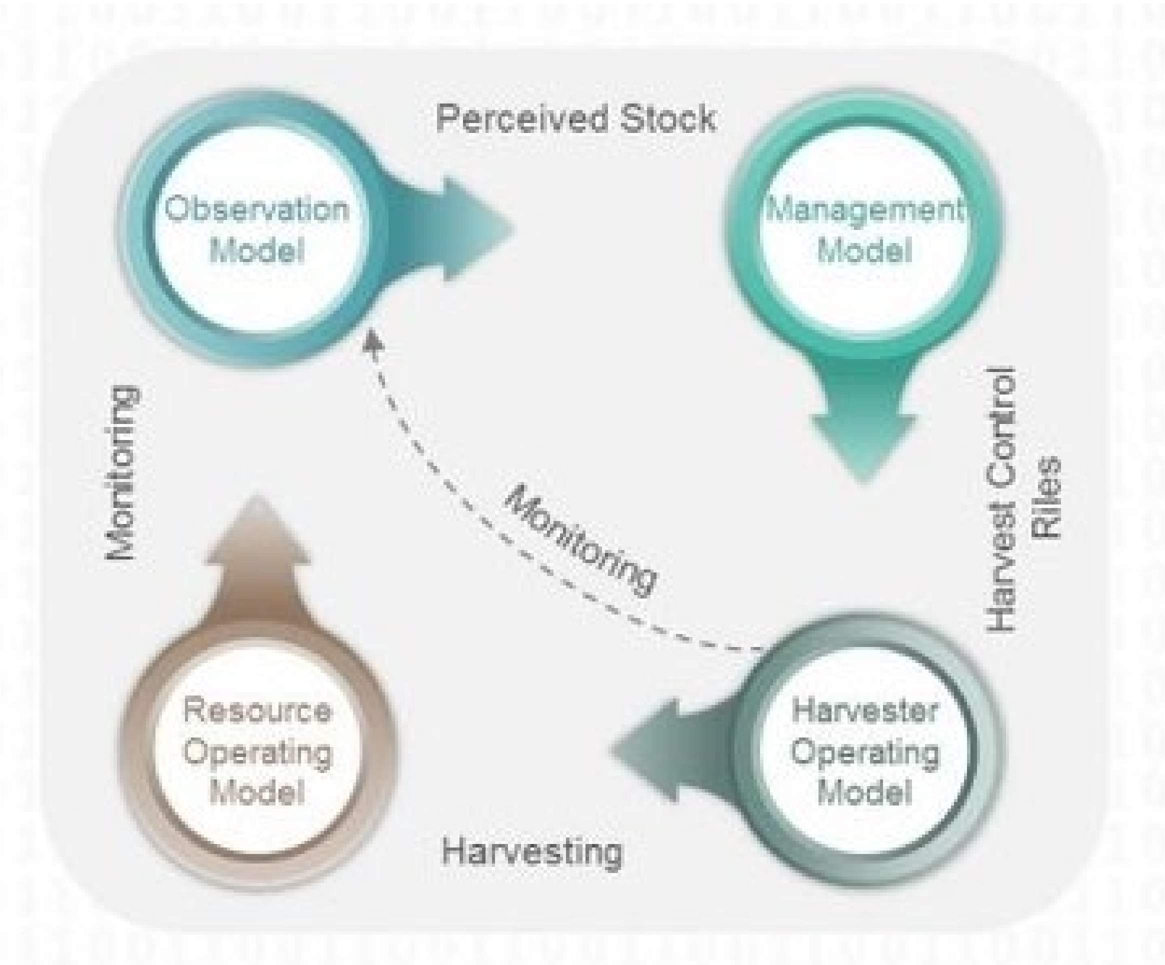

Figure 6.2.2.2. Schematic of the MSE approach used. The LeMans model is the resource operating model, a short-cut assessment based on the cod assessment is the observation model, and harvest control rules with an effective two-year lag are then used to determine the harvesting strategy applied to the operating model.

6.2.3 Defining the target Fs

Three types of target Fs were considered; in decreasing order of data requirements they were i) assessment-based Fs in which assessed Fs were used where available, with other stocks being constrained through mixed fisheries interactions (Thorpe and De Oliveira, 2019; Table 6.2.3.1), ii) a stochastic Nash Equilibrium (Thorpe *et al*., 2017) being a representative of a true multispecies reference point, and iii) arbitrary target Fs that are common to all stocks, ranging from F=0.05 to F=2.5, and thus covering very light to very heavy fishing activity.

Table 6.2.3.1. Target fishing mortalities by species and scenario (from Thorpe and De Oliveira, 2019).

Stock	COD	DAB	GUG	HAD	HER	HOM	LEM	MAC	MON	NOP	PLA	PLE	POD	POK	RJN	RJR	SAN	SPR	SOL	WHG	WIT
2012 Single species FMSY (ICES, 2012c; Thorpe *et al.*, 2015)	0.19	0.41	0.25	0.30	0.25	0.50	0.33	0.32	0.10	0.35	0.60	0.25	0.72	0.30	0.11	0.15	0.35	1.30	0.22	0.21	0.27
Nash equilibrium (Thorpe *et al.*, 2017)	0.20	0.52	0.42	0.38	0.46	0.52	0.45	0.42	0.21	0.61	0.49	0.18	0.56	0.28	0.14	0.29	0.46	0.65	0.37	0.39	0.34
U-PGY	0.46	0.24	0.26	0.19	0.39	0.73	0.24	0.77	0.26	0.59	0.24	0.30	0.26	0.49	0.24	0.24	0.71	1.33	0.37	0.15	0.24
M-PGY	0.31	0.17	0.19	0.19	0.33	0.53	0.17	0.56	0.19	0.43	0.17	0.21	0.19	0.36	0.17	0.17	0.51	0.96	0.20	0.14	0.17
L-PGY	0.20	0.12	0.13	0.17	0.24	0.37	0.12	0.39	0.13	0.30	0.12	0.15	0.13	0.21	0.12	0.12	0.36	0.67	0.11	0.14	0.12

The basis for the single species estimates is explained in Thorpe *et al.* (2015), and the 21-stock Nash equilibrium is calculated in Thorpe *et al.* (2017). The PGY range mortalities, U-PGY, M-PGY, and L-PGY, are calculated as follows: (i) ICES PGY range advice is directly applied where available, (ii) the central range estimate (M-PGY) is determined from the simple 4-fleet fishery (beam, otter, industrial, and pelagic) of Thorpe *et al.* (2016) by maximizing F subject to the constraints that the values in Table 3 are not exceeded, and the relative effort of the least and most active fleets does not diverge by a factor of >3 from 1990 to 2010 average values. U-PGY for the stocks that lack range advice is calculated by multiplying M-PGY by 1.37, and L-PGY is taken as U-PGY/2, reflecting the average spread of the seven published ranges.
Following Thorpe *et al.* (2015), we group stocks for which there is no assessment together with the assessed stock or stocks, which is or are deemed to be most similar in order to estimate the appropriate F for that stock. PLA, DAB, LEM, WIT, RJR, RJN, are grouped with plaice (PLE). POD, GUG, and MON are grouped with COD, HAD, and WHG (details in Thorpe *et al.*, 2015), leading to some F estimates being common to >1 stock. The stocks are mainly in the North Sea (ICES Subarea 4); however, if the assessment unit includes ICES Division 3a, it is 4 and 3a, and if the stock is more widely ranging, values have been imputed for the portion of it in the North Sea.

6.2.4 Setting the harvest control rules (HCRs)

Harvest control rules were assumed to be of the ICES hockey-stick type, with a proposed F, and a biomass reference point, below which fishing effort would be scaled back to prevent the stock becoming depleted (Figure 6.2.4.1).

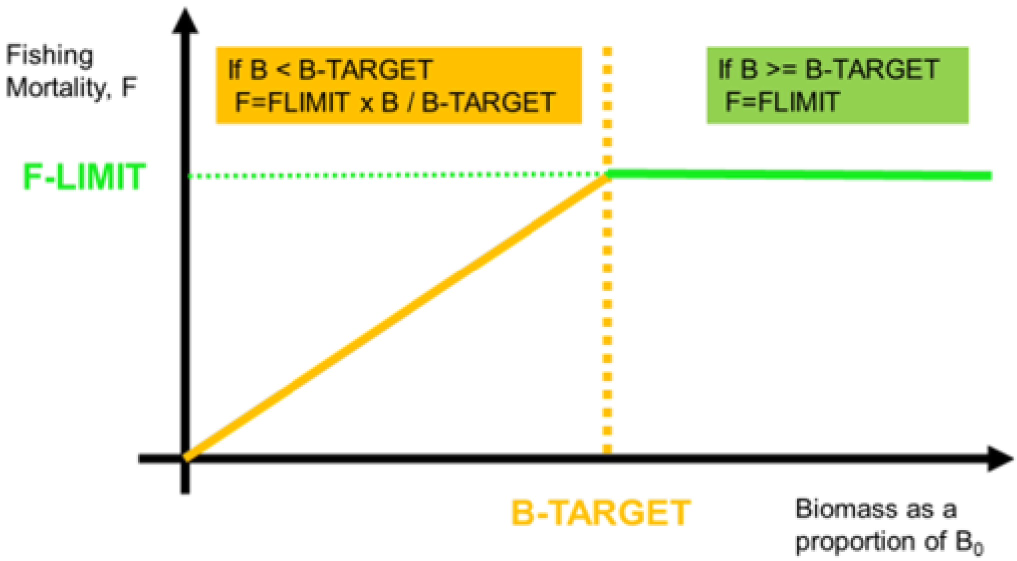

Figure 6.2.4.1. Schematic of the harvest control rule, showing the proposed fishing level, and how it is scaled back if the biomass falls below a certain threshold, expressed as a fraction of the unfished or virgin biomass. B-TARGET represents MSY $B_{trigger}$ in the ICES framework.

17 different F levels and 14 different biomass thresholds were independently considered, giving a total of 238 possible harvest control rules. These cover a wide variety of fishing approaches, including very high and very low levels of fishing, and high levels of fishing if stock status was healthy, and low if it was not. The spread of rules provides a wide range of possible outcomes against which to compare the results of fishing to specific Fs, either assessment-based, or using the model-based Nash equilibrium.

6.2.5 Characterisation of the MSY outcomes

When comparing the results of the target Fs and harvest control rules, we need a way of thinking about what "MSY" means in a community sense so that we can sort the good outcomes from the less good. For a single species in isolation, MSY is that intermediate level of fishing that maximises total yield in the long term (Figure 6.2.5.1) but that's more problematic for a community because not all stocks can simultaneously have their yield maximised; there are trade-offs that have to be made.

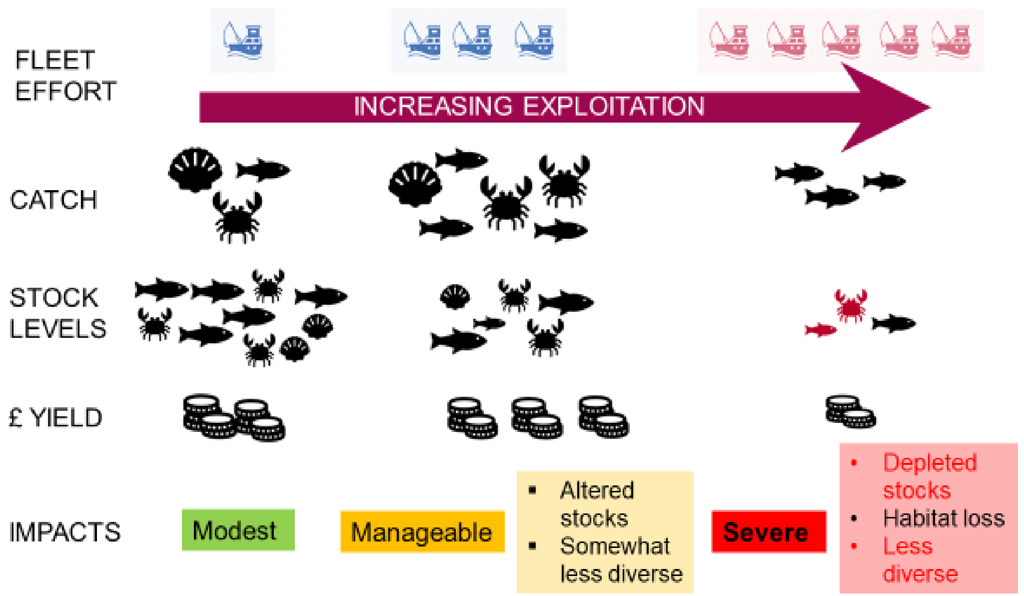

Figure 6.2.5.1. Schematic illustrating MSY for a fish community; but whilst the concept is clear, implementation is difficult on account of the many trade-offs involved.

We framed the outcomes in terms of community levels of risk and reward. Reward is simply the catch (or catch value) summed across all the stocks in the fish community. Risk, however, cannot simply be added up, because a 100% risk of depletion of one stock is not the same as a 10% risk against ten stocks, so we develop a fish community risk metric which is defined as follows:

$$\boxed{CR = \frac{\sum_{i=1}^{n} (R_i * i^{-t})}{\sum_{i=1}^{n} i^{-t}}}$$

Where n is the number of stocks, Ri is the risk of depletion of stock i, where the stocks are ordered in terms of their risk; i.e. R1 > R2 > R3 > … Rn, and t is the measure of society's willingness to tolerate concentration of risk against a few stocks. If t=0, the community risk will be the mean risk. As t→ infinity, the risk metric defaults to the worst risk. We used t=1, the largest value for which the denominator is unbounded as n increases (i.e. each risk contributes at least something to the overall measure), i.e. the most risk averse setting consistent with every risk value making a contribution to the overall risk.

The effect of this formula is shown in Table 6.2.5.1, taken from Thorpe and De Oliveira (2019).

Table 6.2.5.1. Community risks as calculate for some idealised risk profiles in a 21-stock fish community. Green = precautionary, orange and red = not precautionary.

	Scenario risk profile for a hypothetical 21-stock fish community			
	5% risk of depletion across the community All stocks $R = 0.05$	One stock depleted, others untouched. One stock has $R = 1.0$ All other stocks $R = 0$	5 stocks have $R = 0.2$ 17 stocks have $R = 0$	10 stocks have $R = 0.1$ 11 stocks have $R = 0$
Mean risk to stocks	0.050	0.048	0.048	0.048
$t = 1$: this study	0.050	0.270	0.125	0.085
$t = \text{inf}$: defaults to highest risk	0.050	1.000	0.200	0.100
$t = 0$: defaults to mean risk	0.050	0.048	0.048	0.048

Having defined suitable risk and reward metrics, it is then easy to visualise whether a multispecies MSY has been achieved by projecting outcomes into this space, as per Figure 6.2.5.2, where the purple region can be considered as producing outcomes consistent with multispecies MSY.

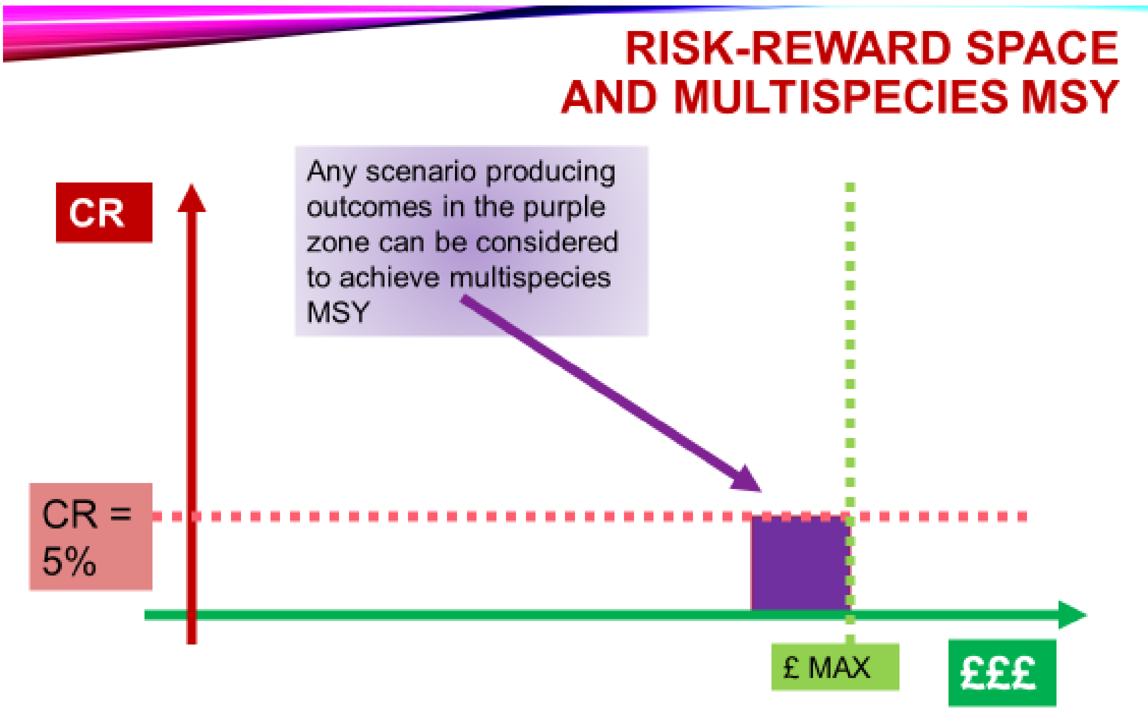

Figure 6.2.5.2. Schematic diagram of the risk/reward space. Risk is defined using the community risk metric, and the purple zone represents outcomes consistent with multispecies MSY.

6.3 Results

We compared long-term outcomes for the five MSY proxies, based upon a) 2012 assessments (black), b) upper "pretty good yield" (PGY) ranges (Hilborn, 2010; Rindorf *et al.*, 2017) for 2017 (magenta), c) mid PGY ranges for 2017 (cyan), d) lower PGY ranges for 2017 (green), and e) F_{MSY} based on the model's internal Nash equilibrium (gold). Figure 6.3.1 shows the outcomes for b)–e) expressed relative to the 2012 assessments, which would appear at the origin.

Outcomes in the lower right quadrant are higher yielding and lower risk, hence better; those in the top level are lower yielding and those in the other quadrants could be considered better or worse, depending upon the societal appetite for risk.

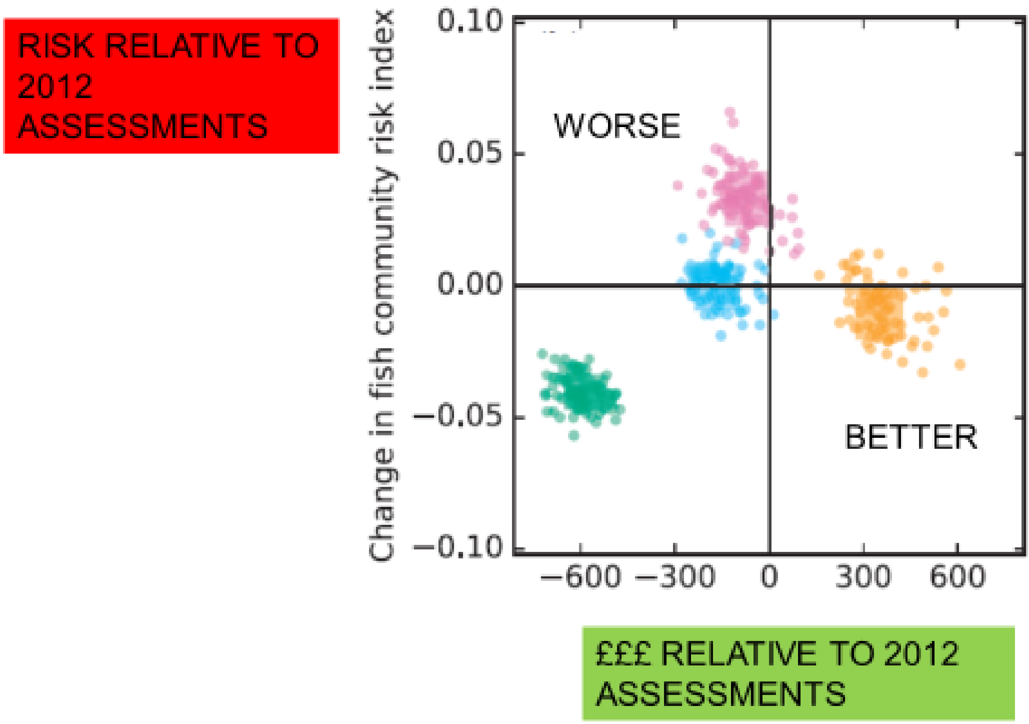

Figure 6.3.1. Expected long-term risk vs reward outcomes for a) upper PGY ranges (magenta), b) central PGY ranges (blue), c) lower PGY ranges (green), and d) Nash equilibrium (gold), relative to the 2012 assessments (black, origin).

We find that relative to the 2012 assessments, the central PGY ranges perform similarly (as expected), the upper part of the ranges is worse (consistent with Thorpe *et al.*, 2017), and the lower part of the ranges safer. The outcomes for the Nash equilibrium were expected to be better, with both higher yield and lower risk. This is consistent with other studies on the utility of Nash Equilibria as multispecies reference points (Norrstrom *et al.*, 2017; Farcas and Rossberg, 2016).

We also compared all five outcomes with the 238 harvest control rules (Figure 6.3.2). The HCRs cover a wide range of outcomes but collectively draw out a frontier. The Nash results lie on or beyond the frontier, the other outcomes clearly inside it. The surprising finding is that the HCRs with a fixed F-target can be competitive with the tailored Fs based upon the assessment process, the implication being that losses associated with not taking into account multispecies dynamics can be as great as or greater than those caused by ignorance about the best F for each stock, if we assume that we know enough about the stock biomass status to be able to respond quickly enough if it deteriorates.

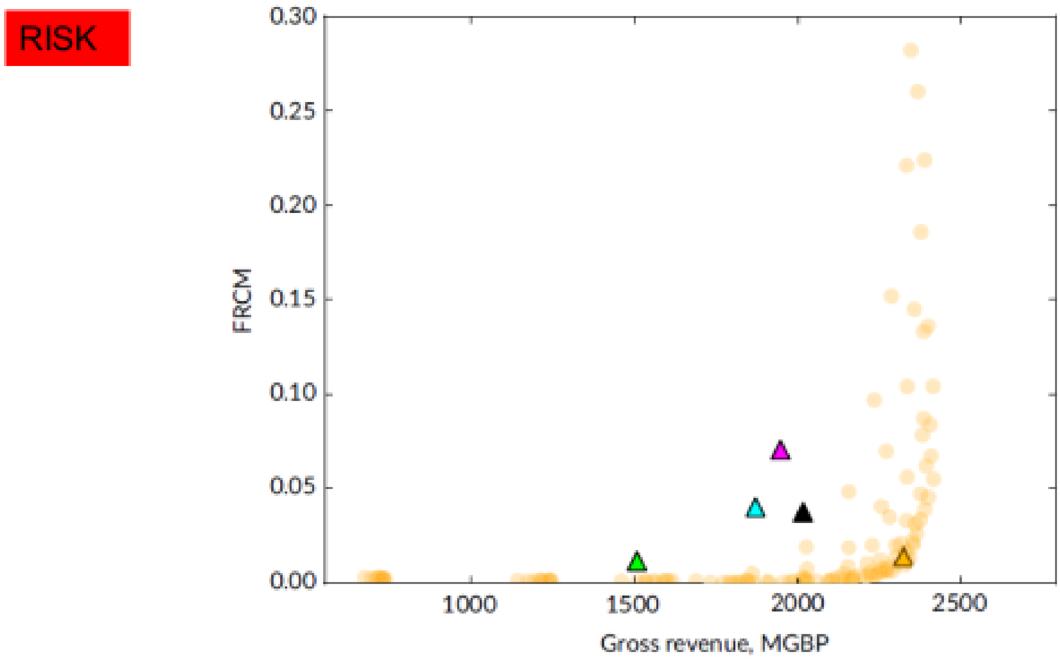

Figure 6.3.2. Expected risk/reward outcomes for the five community F_{MSYS} (triangles) and the 238 harvest control rules (orange dots).

In general, we found that outcomes from the HCRs were very variable (consistent with the very different fishing strategies they cover). Catch yields and profits aligned reasonably well, but there were strong tensions with income variability and even stronger ones between risk and effort, with a small region providing good, profits, yield, and modest income variability, whilst being precautionary (Figure 6.3.3).

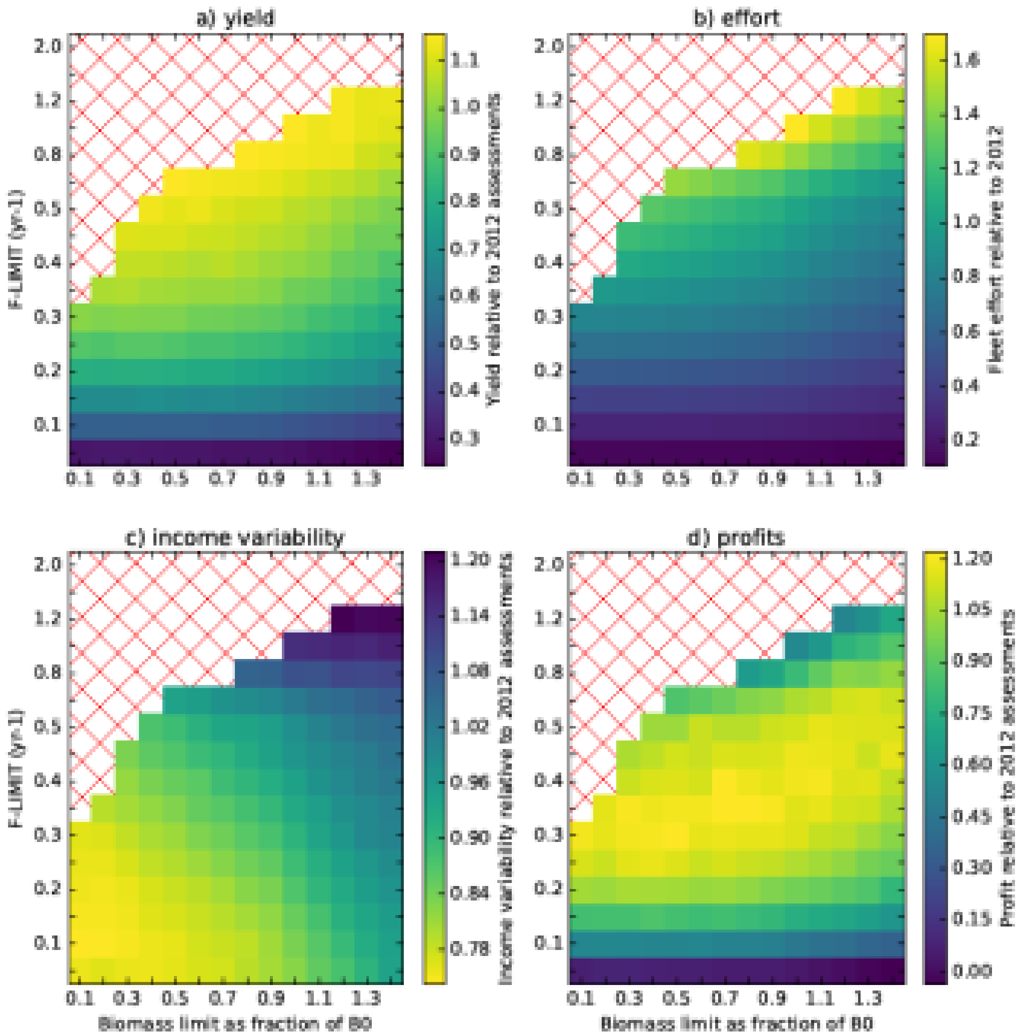

Figure 6.3.3. Expected management outcomes from the 238 harvest control rules. Yellow colours indicate good outcome, and dark blue, poor ones. The red hashed area is not precautionary. Effort can be thought of as a proxy for employment.

Next, we compared the HCR outcomes from the five F_{MSY} targets used. Individual HCR outcomes were deemed to be better if they had higher catch and higher profits, and lower income variability, whilst remaining precautionary. The number of different HCRs that managed to beat the F_{MSY} target was taken to be a measure of the optimality of the target, as the better it is, the harder it will be to beat, and the fewer HCRs that will do better. The results are shown in Figure 6.3.4.

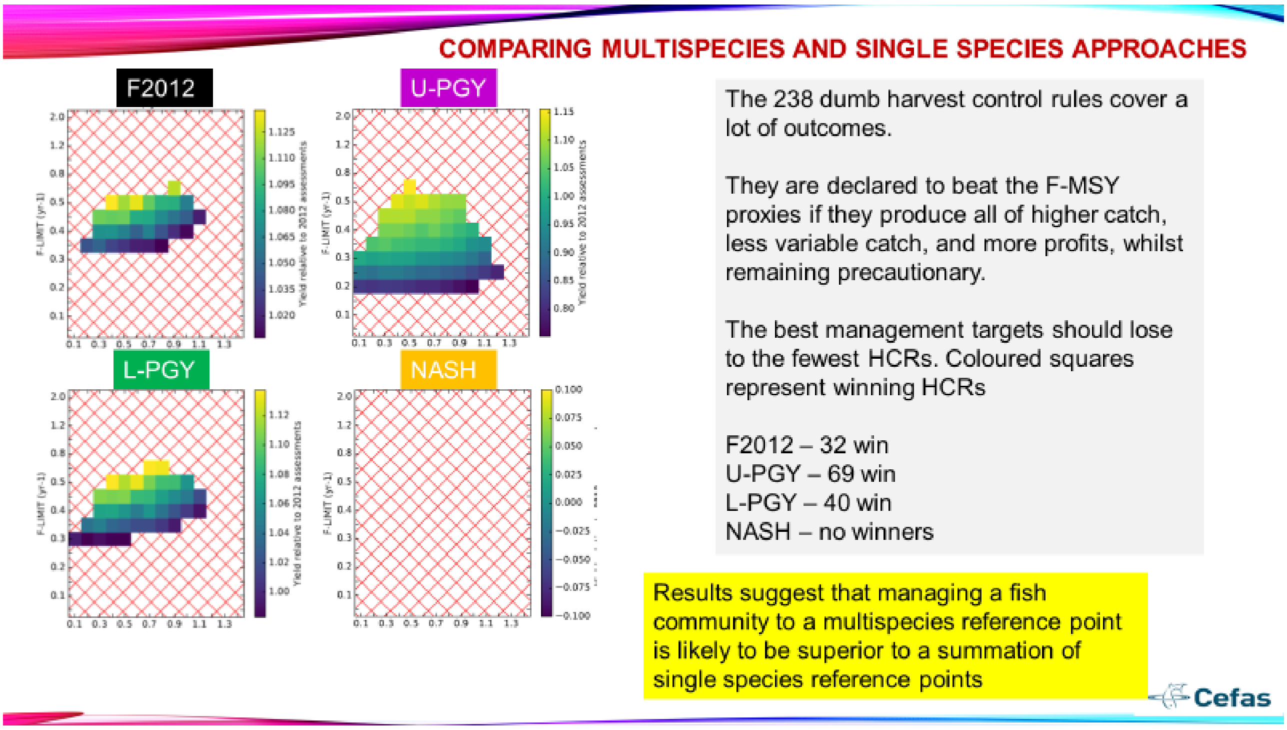

Figure 6.3.4. Comparison of the F_{MSY} targets with the HCR outcomes, the smaller the coloured space, the fewer HCRs are superior, and the better the F_{MSY} is as a management target.

We find a clear order of performance, U-PGY < L-PGY < F2012 (or central PGY) << NASH, with none of the HCRs being clearly better than the Nash Equilibrium. We can conclude from this that a genuine multispecies management target may be superior because it respects the multispecies dynamics.

Finally, we looked at what this might mean for individual stocks (Figure 6.3.5).

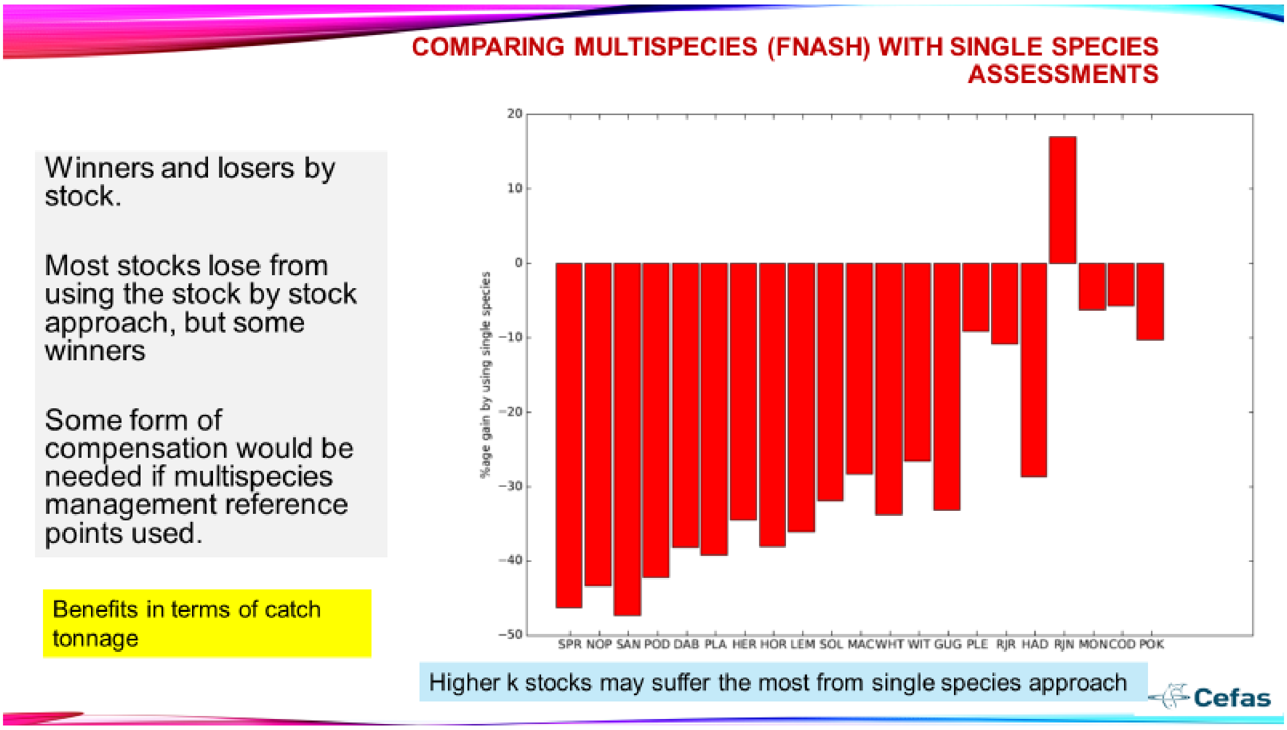

Figure 6.3.5. Relative superiority of single species approach by stock compared with the Nash equilibrium multispecies reference points. Above the zero horizontalline, single species approaches are expected to do better, below it, to do worse.

Most, but not all stocks gain from a multispecies approach, but some may lose, so if management does take this approach, there will need to be a mechanism to compensate the losers and ensure management "buy-in".

6.4 Summary

We have conducted a management strategy evaluation using a multispecies fish community model of the North Sea, structured by species and size (length). We have compared F targets based on assessments (where available, and mixed fishery interactions where not) with one based on the operating model dynamics (a Nash Equilibrium) and 238 ICES-type harvest control rules, using pre-determined reference points that are common to all stocks. We have assumed that it is possible to estimate a virgin biomass that can be used to determine stock status when operating the rules.

When characterising the outcomes in terms of risk (via a fish community risk metric) and reward, we find that the data-limited harvest control rules can be competitive, and that a small subset can sometimes do better than the assessment-based F_{MSY} targets, though not the Nash Equilibrium, which is a true multispecies reference point. Our results suggest that it may be best to manage data-rich and data-limited stocks together as a single community, as there will be more winners than losers if we do this.

6.5 Future work

The obvious next step is to use this approach to test other more data-limited rules in a multi-species setting, particularly the variants of the 2/3 rule discussed at WKLIFE IX. In addition, this study leads to the following further questions:

a) We used a short-cut assessment in the MSE, as running 21 stock assessment models within the MSE might have been prohibitive. We assumed that the cod assessment was an unbiased estimator in the longterm and used the auto-correlation and variance properties associated with that assumption to model assessment error for all stocks. However, is there a better way of performing a short-cut approximation, in the absence of a full assessment?

b) We used ICES-style harvest control rules with a single target F and biomass reference point, taken as a certain fraction of the virgin biomass, but is this realistic?

c) We characterised income variability by way of a coefficient of variance, but this would not be the most resonant concept with the policy maker. Is the expected number of large income drops in say a 20-year period a better measure?

d) How can we best take account of structural uncertainty (seee.g. Spence *et al*., 2018)?

e) What doesit mean for a stock to be depleted in the absence of an assessment B_{lim}? Can we use proxies based on virgin biomass estimates?

We hope to address some of these issues in future work.

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7 Future directions for data-limited stocks (DLS)

7.1 Relationships between life-history parameters and %SPR reference points

A method for estimating fishing mortality and exploitation status was presented to WKLIFE IX but requires further work and development. The method derives empirical estimates of:

i. Fishing mortality from the area swept by towed gears, the efficiency of those gears and modelled species distributions; and
ii. %SPR from life-history parameters (LB-SPR, Walker *et al.*, 2019).

The method may be useful to ICES when existing length-based approaches are hindered by poor or unrepresentative commercial length–frequency data and is also capable of community-wide comparative status assessment. However, further work is required to derive appropriate %SPR reference points and the method remains to be tested on stocks.

With SPR methods, stock status is currently assessed by comparing %SPR with a fixed (often 40%SPR) reference point adopted with the objective of obtaining a large fraction of MSY or a limit reference point (often 20%SPR). These reference points were based on data for commercially important species with the *typical demersal* life-history. However, a fixed %SPR reference point does not account for links between lifehistories and parameters of spawner–recruit relationships and is likely not valid for species with slower lifehistory and lower slopes at the origin of the spawner–recruit relationship. Estimation of %SPR from a simple measure of life history will address its dependency on the spawner–recruit relationship and improve rigour of application.

<u>Recommendation</u>: It is recommended by WKLIFE IX that the exploratory studies undertaken with respect to ToR c) this year be further explored, if possible.

7.2 Data-limited stocks in northwest African waters

European fleets operate in northwest African waters under sustainable Partnership Fisheries Agreements between EU and African countries. In the region, black hakes are caught by the Spanish trawling fleet, other pelagic European fleets and local fleets. All target species of black hake, *Merluccius polli* and *Merluccius senegalensis,* are data-limited stocks not identified to species in declared catches and are assessed by CECAF as a single stock: i.e. *Merluccius* spp. Estimates of discards by these fleets are highly uncertain and are an important component of the total catch (retained and discarded). The Spanish trawling fleet is the only fleet with continuous monitoring since the eighties and the CPUE of this fleet is used to tune the assessment production model used (BIODYN). On-board observer data from commercial surveys from 2016 to 2018 provide a detailed source of scientific information about catches, discards, effort and technical factors in this fleet. From this information, two lines of modelling have been initiated: the first one, regarding the quantification of discards in the fleet that accounts for around 40% of the catches; and the second one, regarding the improvement of biological knowledge about growth from microstructure of otoliths. Observer programmes are supported by the Data Collection Framework and should be reinforced to guarantee the continuity of these studies. Implementation of logbook improvements at geo-referenced level and provide information on retained and discarded data is also needed. The participants at WKLIFE IX made the following suggestions to help in developing improved assessment methodologies and species identification through simulation techniques.

1. How to improve the assessment of *Merluccius* spp: Using SPiCT as the assessment method to develop an OM (Fischer *et al*., submitted) to pose alternative hypotheses about the nature of discarding (e.g. percentage of misreporting in hake discards) and then simulate datasets to evaluate the impact on estimates of stock status and reference points (e.g. Omori *et al*., 2016).
2. Quality of observer datarequired: how good are the observer data to apply to the whole fleet for separating retained and discarded catches and for separating species *Merluccius senegalensis* and *Merluccius polli* in catches of the whole fleet? First, explore existing data to identify potential covariates related to species and fishing effort distribution (e.g. Okamoto, *to appear*). Develop a two species OM (hake - discards and *Merlucciuspolli-Meluccius senegalensis*) using FLife developed under the MyDas project to explore robustness of current production models assessment approach (e.g. Kell *et al*., 2009).
3. Growth: It is not possible currently to provide growth curves by species as more otolith readings are needed to evidence different life strategies. Meanwhile, the first step is to try to estimate a robust model VBGM and provide age-length keys for *Merluccius* spp. Then separate data by ages to help conduct age-based assessments and develop length-based indicators.

7.3 Online App development for data-limited, data-moderate and data-rich fisheries

After the WKLIFE IX meeting, Tom Carruthers, Institute for the Oceans and Fisheries, Vancouver, Canada contacted the UK chair of WKLIFE with details of MERA (Method Evaluation and Risk Assessment) an open-source tool for analysing risk, guiding fishery improvement projects, and evaluating management strategies for certification (www.merafish.org). MERA links to DLMtool (previously, investigated at WKLIFE meetings) and MSEtool libraries to calculate population status and management performance. The App has potential within the ICES community and would be worth exploring at future meetings of WKLIFE.

Recommendation: WKLIFE chairs to liaise with Tom Carruthers and his colleagues to ensure their participation at the next meeting of WKLIFE X, if ACOM consider that online App development is worth exploring further.

7.4 Short-cut versus full-feedback MSE

When combining modelling approaches incorporating data-rich, data-moderate and data-limited stocks, there may be a need for undertaking MSE using short-cut approaches rather than full-feedback evaluation, as in the modelling presented in Section 6. Guidelines on the appropriateness of such an approach would greatly benefit future advisory work both within, and outside, ICES.

7.5 ToRs for WKLIFE X

Section 2 of this report focused on advice rules for harvest control rules for short-lived species. Short-lived ICES Category 3 stocks can be managed using the official advice rules based on the stochastic production model in continuous time (SPiCT) conditioned upon a successful SPiCT fitting, according to the specific guidelines for the use of SPiCT developed within the frame of

WKDLSSLS and WKLIFE. The work of WKDLSSLS is considered unfinished and a second workshop would be preferable. Further research on the definition of optimal harvest control rules for data-limited short-lived stocks is ongoing and the following draft ToRs are proposed for the next meeting of WKLIFE X:

- Continue the development of appropriate methods for the assessment and provision of fishing opportunities for data-limited short-lived species stocks.
- Further review the application of harvest control methods exploring the implementation of additional precautionary measures where necessary such as an asymmetric precautionary buffer and/or biomass safeguards; i.e. reducing advice when below reference point(s).

Section 4 of this report focused on advice rules for harvest control rules for length-based approaches. WKMSYCat34 catch rule 3.2.1 in its current form has been extensively tested during previous WKLIFE workshops. The work presented during WKLIFE IX showed that the performance of the rule can be improved on a case specific basis. In general, the catch rule seems to perform satisfactorily for stocks with low to medium k ($k \leq 0.32$). Further research is required to understand the reasons for this behaviour and why higher k stocks ($k > 0.32$) perform poorly with the catch rule. This will require investigating the characteristics of the operating models. With this in mind, the following draft ToRs are proposed for the next meeting WKLIFE X:

- Evaluate further improvements to the performance of the WKMSYCat34 catch rule 3.2.1. Focus on improving the catch rule for stocks with von Bertalanffy growth parameter k>0.32, investigate more extensively the definition of the catch rule components and their impact on performance, and investigate the possibility of alternative catch rules.
- Explore the operating model set-up for data-limited simulations, including sensitivity analyses based on the Jacobian; e.g. elasticity analysis, on how the different life-history and fishery parameters affect the simulated stock behaviour under exploitation, an analysis of the nature of time-series and trends of observable stock characteristics (such as fishery-dependent and -independent metrics) and how the knowledge gained can be used to further improve the performance of catch rules.

Section 6 of this report focused on the combined modelling of both data-rich and data-limited stocks. The obvious next step is to use this modelling approach to test data-limited rules in a multispecies setting, particularly the variants of the 2/3 rule discussed at WKLIFE IX, and the following ToR is proposed for the next meeting WKLIFE X:

- Further explore and develop methods appropriate for data-limited, data-moderate and data-rich fisheries such as MERA, DLMtool and MSEtool libraries; together with emerging multispecies approaches both within and outside the ICES' community.

In Section 7.2 of this report, the participants at WKLIFE IX made suggestions to help in developing improved assessment methodologies with respect to black hake fisheries operating in northwest African waters. The following draft ToR is proposed for the next meeting WKLIFE X:

- Evaluate the robustness of SPiCT based upon the development of Operating Models of African black hakes using FLife developed under the MyDas project and compare results from SPiCT to the age-based a4a assessment model.

7.6 References

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Annex 1: List of participants

Name	Institute	Country	E-mail
Manuela Azevedo Chair	Instituto Português do Mar e da Atmosfera (IPMA)	Portugal	mazevedo@ipma.pt
Casper Berg (by correspondence)	National Institute of Aquatic Resources Technical University of Denmark	Denmark	cbe@aqua.dtu.dk
Alain Biseau	Ifremer	France	alain.biseau@ifremer.fr
Liese Carleton	International Council for the Exploration of the Seas (ICES)	Denmark	liese.carleton@ices.dk
Simon Fischer	Centre for Environment, Fisheries and Aquaculture Science (Cefas)	UK	simon.fischer@cefas.co.uk
John Hoenig	Virginia Institute of Marine Science	US	hoenig@vims.edu
Laurence Kell	Sea++	UK	laurie@seaplusplus.co.uk
Alexandros Kokkalis	National Institute of Aquatic Resources Technical University of Denmark	Denmark	alko@aqua.dtu.dk
Guillermo Martin	Marine Institute	Ireland	guillermo.martin@marine.ie
Tanja Miethe (by WebEx and correspondence)	Marine Scotland Science (MSS)	UK	t.miethe@marlab.ac.uk
Tobias Mildenberger	National Institute of Aquatic Resources Technical University of Denmark	Denmark	tobm@aqua.dtu.dk
Carl O'Brien Chair	Centre for Environment, Fisheries and Aquaculture Science (Cefas)	UK	carl.obrien@cefas.co.uk
Cristina Silva	Instituto Português do Mar e da Atmosfera (IPMA)	Portugal	csilva@ipma.pt
Maria Soto	Instituto Español de Oceanografía (IEO)	Spain	maria.soto@ieo.es
Marc Taylor	Thünen Institute	Germany	marc.taylor@thuenen.de
Katie Thomas	Marine Institute	Ireland	katie.thomas@marine.ie
Robert Thorpe	Centre for Environment, Fisheries and Aquaculture Science (Cefas)	UK	robert.thorpe@cefas.co.uk
Andrés Uriarte	AZTI-Pasaia	Spain	auriarte@azti.es
Nicola Walker (by WebEx and correspondence)	Centre for Environment, Fisheries and Aquaculture Science (Cefas)	UK	nicola.walker@cefas.co.uk

Annex 2: Workshop agenda

Ninth Workshop on the Development of Quantitative Assessment Methodologies based on Life-history traits, exploitation characteristics, and other relevant parameters for data-limited stocksWKLIFE IX

IPMA, Lisbon, 30th September-4th October 2019

Draft Agenda

Daily schedule (except 30 September, start at 09:30 and 4 October,finish at 13:00):

09:00	start
11:00	Coffee-break
13:00	Lunch
16:00	Coffee-break
18:00	end

30 September (Monday)

09:30–10:00

- General meeting set-up, accessing WiFi, meeting facility orientation, introductions& meeting ToRs.

10:00–13:00

- Presentation & plenary discussion:

  Simon Fisher &JoséDe Oliveira – Linking the performance of a data-limited empirical catch rule to life-history traits updates for WKLIFE IX: ToR a)

  Simon Fisher &JoséDe Oliveira – Performance of the WKMSYCat34 catch rule 3.2.1: ToR a)

14:00–18:00

- Presentation & plenary discussion:

  Laurie Kell – Establish relationships between life-history parameters and biological reference points in order to develop robust proxies MSY reference points: ToR c)

  Andres Uriarte–´Workshop on data limited stocks of short-lived species (WKDLSSLS)´: ToR e)

1 October (Tuesday)

09:00–11:00

- Subgroups work (WKDLSSLS).

11:30–13:00

- Subgroups work

14:00–18:00

- Presentation & plenary discussion:

  TobiasMildenberger –SPiCT and MSE testing of catch rules: ToR b)
  Robert Thorpe – Data-rich/data-limited and modelling approaches for multi-species/mixed fisheries: ToR d)
  Marc Taylor– Evaluation of data-limited assessment performance using an individual-based operational model: ToR a)

20:00 WKLIFE group dinner (Tasca do Manel, Rua da Barroca, 24, Bairro Alto)
https://www.google.com/maps/place/Tasca+do+Manel/@38.7113782,-9.1466396,17z/data=!4m5!3m4!1s0x0:0xe9fa3c35020ede26!8m2!3d38.7113456!4d-9.1444505

2 October (Wednesday)

09:00–11:00

- Presentation & plenary discussion:

  María Soto – Discard estimation in DLS.
  NicolaWalker– Relationships between life-history parameters and %SPR reference points: ToR c)
  Tanja Miethe – Relationships between life-history parameters and %SPR reference points: ToR c)

11:30–17:00

- Subgroups work.

17:00–18:00

- Plenary session: subgroup work progress and discussion.

3 October (Thursday)

09:00–18:00

- Subgroups work.
- Report writing and collation.

4 October (Friday)

09:00–13:00

- Plenary session: conclusions & report adoption.


INSTITUTO PORTUGUÊS DO MAR E

Annex 3: ICES technical guidance on advice rules for stocks in Categories 3 and 4

Introduction

This document provides a description of advice rules developed by the Workshop on the Development of the ICES Approach to Providing MSY Advice for Category 3 and 4 stocks (WKMSYCat34 – ICES, 2017a), the Eighth and Ninth Workshops on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE VIII – ICES, 2018a; WKLIFE IX – ICES, 2019a), and the Workshop on Data-Limited Stocks of Short-Lived Species (WKDLSSLS – ICES, 2019b).These are harvest control rules used by ICES for stocks in categories 3 and 4, with additional specifications for short-lived species and elasmobranch stocks in categories 3 and 4.

Background

The objective of WKMSYCat34, WKLIFE VIII and IX, and WKDLSSLS was to investigate the performance of harvest control rules across life-history types through simulation and management strategy evaluation (MSE). This would identify the potential approaches that best meet the goals of management; i.e. maximizing long-term yield while minimizing the probability of stocks falling below biologically sustainable limits.

Advice rules for short-term forecasts utilizing a surplus production model (SPiCT)

WKMSYCat34 developed an MSY harvest control rule (“median rule”) for assessments using the stochastic surplus production model in continuous time (SPiCT; Pedersen and Berg, 2017) (Section 3.1, WKMSYCat34; ICES, 2017a). WKLIFE VIII and IX did simulation testing of multiple modifications to this harvest control rule that account for the assessment uncertainty; additional comparisons were performed with the currently used “2-over-3" rule (ICES DLS Method 3.2; ICES, 2012).

For stocks that have an accepted SPiCT assessment, ICES recommends to use the MSY-35th percentile rule (MSY-35). In theory, with increasing time-series lengths and decreasing observation error, the estimated catch with the MSY-35th percentile rule approximates the median rule suggested by WKMSYCat34 while being more precautionary. The technical criteria to accept a SPiCT assessment are given below; more detailed information and example code is included in the SPiCT technical guidelines (Mildenberger *et al.*, 2019), which is a living document maintained by the developers of SPiCT.

The MSY-35 rule is defined as:

$$C_{y+1} = q_C(p)$$

$$F_{y+1} = F_y \frac{\min(1, q_B(p))}{q_F(100 - p)}$$

where the advised catch (C) for forecast year $y + 1$ corresponds to the predicted catch given the fishing mortality trajectory in the forecast year, and where F_y and $F_{y+1}$are the fishing mortalities at the beginning and the end of the forecast year, respectively. Components are defined as follows:

Components	Definition and purpose
q_C	Function that takes a percentile and returns the corresponding predicted catchC_{y+1} given the fishing mortality trajectory during the forecast year y+1; i.e.$q_C = \Phi^{-1}_{(C_{pred} \mid F=F_y \dots F_{y+1})}$
q_B	Function that takes a percentile and returns the corresponding predicted $\frac{B_{y+1}}{\text{MSY B}_{\text{trigger}}}$ at the beginning of the forecast year and $\text{MSY B}_{\text{trigger}} = \frac{B_{MSY}}{2}$; i.e.$q_B = \Phi^{-1}_{(2\frac{B_{y+1}}{B_{MSY}})}$
q_F	Function that takes a percentile and returns the corresponding predicted $\frac{F_y}{F_{MSY}}$ at the beginning of the forecast year y+1; i.e.$q_F = \Phi^{-1}_{(\frac{F_y}{F_{MSY}})}$
p	Specific percentile of the respective distributions, e.g. 35 (WKLIFE IX, ICES 2019a).

The above advised catch can be calculated using the get.TAC() function within the spict package in R.

Technical criteria for accepting a SPiCT assessment

When determining harvest limits using output from SPiCT, appropriate application first depends on model performance. An accepted assessment using SPiCT has to fulfil all of the following criteria:

1. The assessment converged.
2. All variance parameters of the model parameters are finite.
3. No violation of model assumptions based on one-step-ahead residuals (bias, autocorrelation, normality). This means that p-values of the relevant statistical tests, implemented in SPiCT, are insignificant ($p \leq 0.05$). Slight violations of these assumptions do not necessarily invalidate model results.
4. Consistent patterns in the retrospective analysis. This means that there is no tendency of consistent under- or overestimation of the relative fishing mortality (F/F_{MSY}) and relative biomass (B/B_{MSY}) in successive assessment. The retrospective trajectories of those two quantities should be inside the confidence intervals of the base run.
5. Realistic production curve. The shape of the production curve should not be too skewed (B_{MSY}/K, where K is the carrying capacity estimate, should be between 0.1 and 0.9). Low values of B_{MSY}/K allow for an infinite population growth rate.
6. The main variance parameters (i.e. of the biomass and fishing mortality processes, and the catch and index observations) should not be unrealistically high. Confidence intervals for B/B_{MSY} and F/F_{MSY} should not span more than 1 order of magnitude. High assessment uncertainty can indicate a lack of contrast in the input data or violation of the ecological model assumptions.
7. Initial values do not influence the parameter estimates. The optimisation should converge to the same estimates when starting from different initial parameter values.

Caveats

Different options can be explored to stabilise SPiCT for data with low contrast or high observation errors. SPiCT allows the use of prior distributions, for example on the shape of the production curve or the initial depletion level, which can help stabilise the optimisation procedure. However, using priors with lower standard deviations affects the results (confidence intervals and parameter estimates). Several options to stabilise SPiCT assessments have been explored and tested within WKLIFE VIII and IX and are described in detail in the SPiCT technical guidelines (ICES 2019a; Mildenberger *et al*., 2019).

The harvest control rule described above accounts for the assessment uncertainty in the MSY SPiCT median advice rule proposed by WKMSYCat34. This is done by using a percentile lower than 50 (i.e. median) for relative biomass and catch, and higher than 50 for relative fishing mortality. In the simulation testing done during WKLIFE IX, the same percentile (p) was used for biomass and catch; for fishing mortality the percentile was equal to 100 - p. Management strategy evaluation simulations tested the harvest control rule for different quantiles of the distributions of fishing mortality, biomass, and catch. The results show that across all tested scenarios and harvest control rules, management with the MSY-35 rule leads to high levels of relative yield while retaining the risks at low levels. Higher percentiles than 35th show higher levels of risk while achieving similar levels of relative yield, while lower percentiles show a decrease in yield with small change in risk (WKLIFE IX, ICES 2019a).The SPiCT developers emphasise that stock-specific MSEs should be used for the comparison of precautionary levels of different advice rules.

Advice rules for harvest control rules for length-based approaches

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

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

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

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

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

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

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

Application of the length-based harvest control rule

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

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

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

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

Caveats

The performance (i.e. maintaining the stock near the target biomass and reducing the risk of the stock declining below B_{lim}) of the harvest control rule varies based on life-history traits of the species, the nature of recruitment dynamics, and on the assumed reference level of b, the $I_{trigger}$ component.

The $I_{trigger}$= 1.4 I_{loss} component of the harvest control rule should be set to the breakpoint below which, the state of the stock in question would deteriorate to an undesirable level (i.e. a decline below B_{lim}, resulting in reduced yield and an increased probability of stock collapse). That limit is often identified by fisheries management as 0.5 B_{MSY}. The harvest control rule generally maintains a target or near-target biomass for slow and medium life-history stocks, when the $I_{trigger}$ value is set equal to 0.5 B_{MSY}. Setting I_{loss} equal to the lowest observed index value may not be appropriate if the stock has not been heavily exploited, or if the index period does not cover a period of low biomass levels in the stock. In these instances, the harvest control rule may be overly precautionary. The $I_{trigger}$ component of the harvest control rule should reflect a true limit biomass level for the stock in question. Care should be taken when determining this value based on the stock productivity, as well as its susceptibility to the effects from fishery-specific activities.

Advice rules for harvest control rules for short-lived species (stock categories 3 and 4)

The risk of harvesting short-lived stocks that have high interannual variability of biomass is inherently higher than long-lived species, given their dynamics. This means that the harvest control rules applied to short-lived stocks need to be designed in a manner that incorporates the dynamics of these specific stocks. Guidance is provided for short-lived stock harvest control rules that determine next year's catch based on the last advised catch.

The harvest control rule is defined as:

$$C_{y+1} = \begin{cases} 0.2\, C_y & \dfrac{I_y}{\sum_{y-1}^{y-2} I_y/2} < 0.2 \\ C_y \dfrac{I_y}{\sum_{y-1}^{y-2} I_y/2} & 0.2 \le \dfrac{I_y}{\sum_{y-1}^{y-2} I_y/2} < 1.8 \\ 1.8\, C_y & \dfrac{I_y}{\sum_{y-1}^{y-2} I_y/2} \ge 1.8 \end{cases}$$

whereC_y and I_y represent the advised catch and the biomass indicator for year y, respectively. Note that $\frac{I_y}{\sum_{y-1}^{y-2} I_y/2}$should be replaced by $\frac{I_{y+1}}{\sum_{y}^{y-1} I_y/2}$in the formula above if the index is available at the beginning of the management year y+1, instead of being available at the end of the interim (management) year y. The first and third cases of the formula correspond to the application of an 80% symmetrical uncertainty cap.

The notation of these rules is for in-year advice where the advised catch for the current year is based on last year's advised catch adjusted by the trend in the most recent abundance index, I_y, relative to the average of the index value in the previous two years. An uncertainty cap is applied to limit the change in the index trend, the I_y component of the harvest control rule, to ±80%, which allows the current years advised catch to increase or decrease up to 80% relative to the previous years advisedcatch.

Application of the harvest control rule

For some short-lived species, assessments are so sensitive to incoming recruitment that information on the incoming year class is essential to assessment and management. Therefore for these species, the management year should be coupled as closely as possible to the time when the abundance index becomes available. For most of the stocks concerned such data are obtained just before the fishery starts (or during the fishing year). Therefore, the advice on fishing possibilities is often given just prior to the start of the fishing season or after the fisheries have started, which corresponds with the two formulations provided above. In the case where the survey is at the beginning of the management year, the fishery would start with a provisional catch to be updated when the abundance index is available.

The harvest control rule for short-lived stocks is composed of three components: the advised catch in the previous year, the trend in the index, and the uncertainty cap. The trend in the index performs best for short-lived stocks when the most recent years, including data from the current year, are applied. It is recommended to use the most recent year of data divided by the average of the index over the preceding two years, termed 1-over-2. The rule has greatest performance when a large fraction of the harvested population in the management year is covered by the index.

The first time this rule is applied to a stock, the initial catch should be taken from the mean of the catch from the previous two years (WKDLSSLS ICES, 2019b).

Short-lived stocks with high interannual variability of biomass can show large biomass fluctuations from one year to the next. A symmetrical 80% uncertainty cap allows appropriate adjustment of the harvest control rule accordingly from year to year. Large reductions in catch may be necessary between years to respond accordingly to reductions in the underlying stock biomass.

Caveats

For stocks heavily exploited in the past, the rule does not necessary lead to precautionary levels of risks in the short-term but gradually leads to sustainable exploitation in the long term.

Application of the uncertainty cap can lead to major reduction of catches in the long term, and it is recommended that the harvest control rule be periodically re-evaluated.

Advice rules for harvest control rules for bycaught elasmobranch stocks

The catch for elasmobranch stocks taken as bycatch is defined as:

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

where the components are defined as:

Component	Definition and use
r	The rate of change in the catch per unit of effort (CPUE), based on the average of the two most recent years of data (*y*−2to *y*−1) relative to the average of the five years prior to the most recent two (*y*−3to *y*−8), termed the “2-over-5” rule.
f	The ratio of the mean length in the observed catch that is above the length of first capture relative to the target reference length (mean length/target reference length).The target reference length is $L_{F=M} = 0.75L_c + 0.25L_\infty$, where L_c is defined as length at 50% of modal abundance (ICES 2018b)*.
Stability clause	Limits the amount the advised catch can change upwards or downwards between years. The recommended values are +5% and -25%, where the catch would be limited to increase by 5% or decrease by 25% relative to the previous year’s catch.

*** The equation for $L_{F=M}$ relies on the assumption of M/k=1.5 (natural mortality M, growth rate k) for data-limited stocks.**

Application of the harvest control rule

The performance of the harvest control rule depends on the accuracy of the CPUE, and on how correctly the target reference length is determined. The CPUE is used to identify the trend in the biomass relative to previous years. Determining the trend in biomass based on the CPUE performs well with the 2-over-5 rule. Elasmobranch species generally have lower natural mortality rates and low fecundity compared to fish species; in this case the 2-over-3 approach is therefore better at capturing the trend in biomass over a longer time period. Applying the longer term index rule also reduces risk when there is increased uncertainty in the CPUE data.

The fishery should be managed in such a way that, if possible, the length of first capture is greater than the length of maturity for bycaught elasmobranch species. The *f* component of the harvest control rule adjusts the catch upwards or downwards, based on the average length of captured individuals relative to the target length which is, in turn, based on biology and life history. The harvest control rule will result in lower catch limits if the fishery is selecting a large proportion of immature individuals.

Elasmobranch species are often slow growing and with low fecundity, making them slow to recover if overexploited. The harvest control rule should, when warranted, make it possible to apply larger reductions to the catch, based on the CPUE and length data relative to the amount allowed for increases in the catch. Therefore, it is recommended that an asymmetric stability clause governing the percentage of change allowed in the catch between years be applied. This clause should allow for reductions up to 25% downwards or an increase up to 5% in the catch for next year, relative to the current year’s catch.

Caveats

Several factors can affect the performance, in terms of risk to fall below SSB thresholds, of the harvest control rule for elasmobranch stocks. Elasmobranch species often have dimorphic growth between the sexes, and it is recommended that calculation of the target reference length is based on the biology of the larger-growing sex. Additionally, if the fishery mainly exploits immature individuals, the sustainable catch from the population will be lower, leading to a reduced catch based on the harvest control rule.

For stocks where $L_c<L_{mat}$, values of reference point $L_{F=M}$ may be below L_{mat}, affecting the performance of harvest control rules negatively.

As with species taken as bycatch, the performance of the harvest control rule for elasmobranch stocks depends on data from the target fisheries to adequately capture the dynamics of individual stocks. Uncertainty in the CPUE may result in such data being less informative regarding the trend in elasmobranch stocks. Furthermore, uncertainty in length measurements (i.e. observation error) and limited sample sizes may result in the harvest control rule being more reactive to non-representative length samples, leading to unwarranted reductions or increases in the advised catch.

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Annex 4: Working document

Testing length-based reference points for two elasmobranchs: cuckoo ray (*Leucoraja naevus*) and thornback ray (*Raja clavata*)

Tanja Miethe and Helen Dobby, Marine Scotland Science, Marine Laboratory, PO Box 101, Victoria Road 375, AB11 9DB Aberdeen, UK, E-mail: t.miethe@marlab.ac.uk

Introduction

The maximum size of species of Rajidae was suggested as an indicator of resilience (Walker and Hislop, 1998; Frisk *et al.*, 2001). In the North Sea, the abundance of the larger common skate and thornback ray declined since the 1960s-70s and a concomitant increase in smaller-bodied rays, starry and spotted ray (Chevolot *et al.*, 2008; Sguotti *et al.*, 2016). Rays, Rajidae, exhibit M/k similar to bony fish (Frisk *et al.*, 2001). The ratio of natural mortality M and growth rate k determines the equilibrium size distribution in an unexploited stock. With truncation of population size distributions and thereby catch size distributions, the effect of fishing mortality on populations may be determined from catch size distributions.

A number of length-based indicators are available and some have been identified as potential suitable to summarize catch–length distributions with regard to exploitation of juveniles, large adults and optimal yield (ICES, 2015; Miethe and Dobby, 2015; Miethe *et al.*, 2016; ICES, 2018b). The mean length in the catch with a reference point based on F=M proxy for MSY has been suggested (Jardim *et al.*, 2015). The reference point is derived accounting for $L_c$and M/k. However, it was found that $\bar{L}$and its respective reference point $L_{F=M}$ perform well only if the length at first capture L_c>L_{mat} (Jardim *et al.*, 2015; Miethe and Dobby, 2016). For many elasmobranch stocks L_c is typically lower than L_{mat} (ICES, 2018c). As an alternative reference point the expected mean length at an spawning potential ratio (SPR) of 40% can be calculated, based on basic life-history characteristics under equilibrium conditions (Miethe *et al.*, 2019).

Cuckoo ray, *Leucoraja naevus*, with demersal habitat in the Northeast Atlantic, is wide-spread, small-bodied ray. Spawning can occur throughout the year, but was observed to be typically highest in the beginning of the year (Maia *et al.*, 2012). Rays are often caught offshore as bycatch in mixed demersal fishery for roundfish and flatfish (ICES, 2017; ICES, 2018b). Stock structure in the Celtic Sea is uncertain. Currently, Cuckoo ray in the West of Scotland, Celtic Sea and Bay of Biscay are considered to form a single stock (ICES, 2018b).

Thornback ray, *Raja clavata,* is one of the most important commercial species in the inshore fishing grounds of the Celtic Seas (ICES, 2018b). Thornback ray are assessed as separate stocks in the West of Scotland and Celtic Sea. A low level of population differentiation was observed for *R. clavata* in southern North Sea, English Channel and Irish Sea (Chevolot *et al.*, 2006). Life-history data for thornback ray and cuckoo ray in the Celtic and Irish Sea was used to parameterize the model (Table A.1).

Estimates of natural mortality for these stocks are typically scarce. Values of around 0.3 for females and 0.4 for males of Cuckoo ray, and 0.14 for females and 0.2 for males of Thornback ray have been suggested (Pauly, 1980; Gallagher *et al.*, 2005a; Then *et al.*, 2015).

With help of length-based population models and management strategy evaluation (MSE), we test the use of length-based indicator $\bar{L}$together with respective reference points in harvest control rules (HCRs) to recover an overexploited stock of Cuckoo ray and Thornback ray. We compare the performance of the length-based reference point $L_{F=M}$ to SPR-based reference points for both example stocks. Harvest control rules are based on length-based indicators and a CPUE-based stock index.

Methods

Population model

A length-based modelling approach allows for a direct implementation of length-dependent life-history processes and length-dependent fishing mortality. The general population model operates in discrete time and can be written in matrix notation:

$$N_{t+1} = \mathbf{A_t} N_t, \tag{1}$$

whereN_t is a vector of the numbers-at-length at time t, including each sex separately. The transition matrix $\mathbf{A_t}$ contains sex-specific survival, growth rates and fecundities. The population is subject to both fishing and natural mortality, which occur simultaneously and continuously through time. Growth occurs instantaneously at the end of each time-step and is irreversible.

Discrete length-structured models often make use of size classes with constant bin width (Drouineau *et al.*, 2008). However, in this model we construct bins with varying length bin width such that individuals grow into the next length class within a single time-step as described by Andrews *et al.* (2006), Gurney *et al.* (2007) and Speirs *et al.* (2010). This results in a parsimonious number of length classes for each sex. The use of very small time-steps or many narrow length classes can thereby be avoided, improving computational efficiency. In order to create the length bins, we first define for each sex a development index, q, which is a function of length (Speirs *et al.*, 2010). At the minimum length at which recruits are assumed to enter the population, L_{min}, q is zero. Following von Bertalanffy growth, q increases linearly with length. Since q tends to infinity as the individual length approachesL_∞, we define a maximum length L_{max} which is less than L_∞ to ensure a finite q_{max}. The number of length classes J is calculated, for each sex separately, as:

$$J = \frac{q_{max}}{\Delta q} \tag{2}$$

The maximum development index, q_{max}, at L_{max} is defined as:

$$q_{max} \equiv -\ln\left(\frac{L_\infty - L_{max}}{L_\infty - L_{min}}\right), \tag{3}$$

whereL_∞ is the asymptotic length. Classes are of fixed q width (Δq) but varying length width: classes are wider (in length) early in life when the individual growth rate is high and decrease as growth slows later in life, when individuals approach asymptotic size.

The increment Δq is set according to the growth rate k of the von Bertalanffy growth equation, growth variability coefficient p and the time-stepΔt of the model (Speirs *et al.*, 2010):

$$\Delta q = \frac{k\Delta t}{p}, \tag{4}$$

To incorporate variability in growth into the model, we assume that only a fraction, p, of individuals in a length class grows to the next size class within any time-step and the remaining fraction, (1-p), of individuals stay at their current size for another time-step(Gurney *et al.*, 2007; Speirs *et al.*, 2010).

The left-hand (lower) boundary of each length class j in terms of the development index is:

$$L_j = L_\infty - (L_\infty - L_{min})\, e^{(-(j-1)\Delta q)}. \tag{5}$$

The midpoint of each length class, l_i, is calculated as the mean length of the lower boundary (Equation 4) and the lower boundary of the next larger length class. For the maximum length class of each sex, the respective L_∞ is used as the upper boundary to calculate the midpoint. We select a conservative value of p=0.9, allowing only 10 % of individuals to remain in their current length class after one time-step while keeping the general growth pattern close to the respective von Bertalanffy growth equation.

Using $N_{i,t}$ to denote the number of individuals in size class i at time t, we can express the population model (equation 1) in difference equations for two sexes and n length classes, with $n=n_m+n_f$, the sum of the number of male and female length classes:

$$\begin{aligned}
N_{i,t+1} &= s_{i,t}(1-p)N_{i,t} + \frac{1}{2}R && \text{if } i = 1 \text{ or } i = (n_m + 1) \\
N_{i,t+1} &= s_{i-1,t}pN_{i-1,t} + s_{i,t}(1-p)N_{i,t} && \text{if } 1 < i < n_m \text{ or } (n_m + 1) < i < n \\
N_{i,t+1} &= s_{i-1,t}pN_{i-1,t} + s_{i,t}N_{i,t} && \text{if } i = n_m \text{ or } i = n
\end{aligned} \tag{6}$$

Recruits are split equally between males and females (entering only the smallest length class). Individuals reaching the maximum modelled size class for each sex cannot grow larger and survivors remain in that class.

Mortality

The population is subject to both fishing and natural mortality, which occur simultaneously and continuously through time. Natural mortality is assumed to be constant over time, length and for both sexes. Natural mortality is estimated for each sex separately using the length-based updated Pauly estimator recommended by Then *et al.* (2015):

$$M = 4.118k^{0.73}(L_\infty/10)^{-0.33} \qquad (L_\infty \text{ in mm}) \tag{7}$$

Fishing mortality at time t and length i, $F_{i,t}$, is assumed to be separable and can be written as the product of a length-dependent selectivity ogive (logistic curve) and a time-dependent component, f_t, related to the level of fishing effort in the fisheries:

$$F_{i,t} = f_t \frac{1}{1+e^{-v(l_i-L_{50\%})}} e^{\varepsilon_{i,t}} . \tag{8}$$

where $L_{50\%}$, the length at 50% retention, is the inflection point and v is a constant describing the steepness of the selectivity ogive. The selectivity ($L_{50\%}$) of the fishery is held constant over time resulting in a constant L_c, calculated from the resampled catch–length distributions.

A lognormal error is included to allow for some variability in fisheries selectivity, with $\varepsilon_{t,i}$ being normally distributed with $N(0, \sigma_F^2)$ (Figure A.1).

The use of sex-specific growth parameters results in different length bin widths and midpoints and hence different mortality curves for the male and female components of the population.

Survival at length i and time t, $s_{i,t}$, is defined as:

$$s_{i,t} = e^{-(M_i+F_{i,t})} . \tag{9}$$

Catch in numbers by length class at time t are calculated according to the Baranov catch equation:

$$C_{i,t} = \frac{F_{i,t}}{M_i + F_{i,t}}\left(1 - s_{i,t}\right)N_{i,t}\,. \tag{10}$$

The yield should be equal to TAC, assuming that the TAC is fully used:

$$TAC_t = \sum_{i=1}^{n} w_i\, C_{i,t} \tag{11}$$

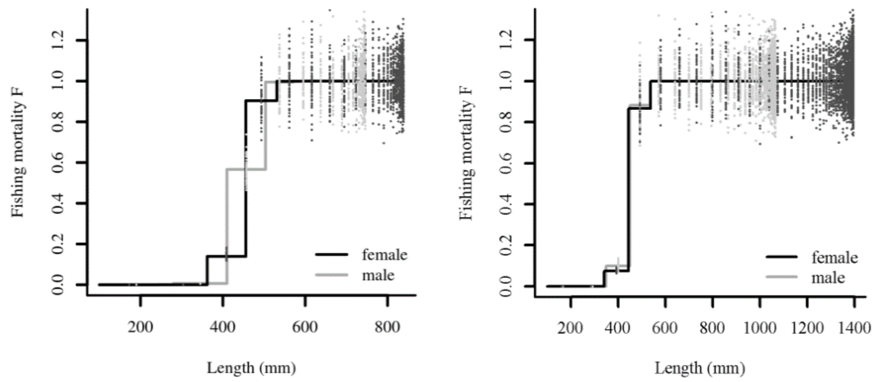


Figure A.1. Selectivity for cuckoo ray (left) and thornback ray (right) using an L_{50} of 450 mm.

Reproduction

In this model, mature individuals produce offspring at the beginning of the time-step and only in the following time-step do recruits enter the smallest length class of the population.

The maturity ogive is defined as a logistic function with an inflection point around the sex-specific length at 50% maturity, L_{mat} and calculated for the midpoint of each length class (Figure A.2):

$$Mat_i = \frac{1}{1 + e^{-u(l_i - L_{mat})}} \tag{12}$$

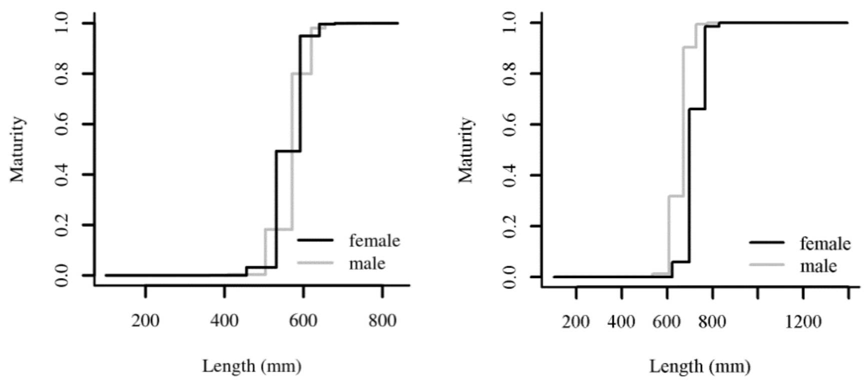


Figure A.2. Maturity ogives by sex for cuckoo ray (left) and thornback ray (right).

Spawning–stock biomass is calculated as the sum of individual weights of all mature individuals in the stock:

$$\mathrm{SSB_t} = \sum_{i=1}^{n} \mathrm{Mat_i N_{i,t} w_i}\,, \tag{13}$$

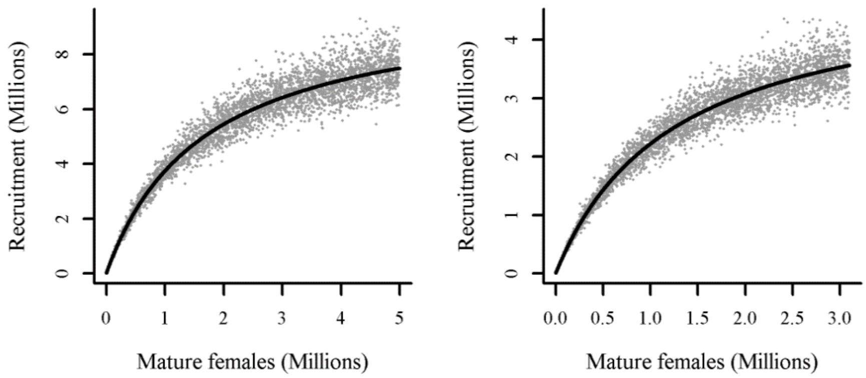
The individual weights at length, w_i, are estimated using sex-specific exponential length–weight relationships that are constant over time:

$$\mathrm{w_i} = \mathrm{a l_i^b} \tag{14}$$

Recruitment is related to the number of mature females in the previous year and is assumed to follow the Beverton–Holt stock–recruitment relationship with multiplicative lognormal error (Figure A.3):

$$\mathrm{R_{t+1}} = \frac{\mathrm{c}\sum_{i=1}^{n_f} \mathrm{Mat_i N_{i,t}}}{1 + \mathrm{d}\sum_{i=1}^{n_f} \mathrm{Mat_i N_{i,t}}} e^{\left(\varepsilon_{t+1} - \frac{\sigma_R^2}{2}\right)} \tag{15}$$

The error ε_{t+1} is normally distributed with $N(0, \sigma_R^2)$ and has a bias correction term (Thorson and Kristensen, 2016). In the basic scenario, the spawning–stock recruitment relationship is parameterized to generate unexploited stable population equilibrium with a steepness that allows for a reduction of recruitment as SSB decreases (Figure A.3). The specific life-history parameters used in the model are listed in Table A.1.



A.3.Spawner–recruitment relationship, cuckoo ray (left) and thornback ray (right).

Table A.1. Parameters *L.naevus* (RJN) and *R.clavata*(RJC), using life-history characteristics.

Description	parameter	Value RJN	Value RJC	unit	reference
Von Bertalanffy growth	K (male)	0.294	0.135		Gallagher *et al.* (2005b)
	K (female)	0.197	0.093		Irish Sea
	L_∞ (male)	746	1065	mm	
	L_∞ (female)	839	1395	mm	
Variability in L_∞	CV(L_∞)	0	0		
Maximum length to determine number of classes	L_{max} (male)	745.5	1064.5	mm	0.5mm below L_∞
	L_{max} (female)	838.5	1394.5	mm	
Minimum modelled length	L_{min}	100	100	mm	
Growth variability constant	p	0.9	0.9		
Times-step	Δt	1	1		
Natural mortality	M(male)	0.406	0.205		Then *et al.* (2015)
	M(female)	0.292	0.143		
Length at 50% retention	$L_{50\%}$	450	450	mm	
Selectivity ogive constant	v	0.07	0.07		
Standard deviation of $\varepsilon_{t,i}$ (fishing mortality)	σ_F	0.1	0.1		
Length–weight relationship	a (male)	0.0041	0.0042	g cm^{-b}	McCully *et al.* (2012)
	a (female)	0.0036	0.0036		Celtic Sea
	b (male)	3.105	3.106	g cm^{-b}	to mm: $a'=a10^{-b}$
	b (female)	3.147	3.162		
Size at 50% maturity	L_{mat} (males)	569	657	mm	Gallagher *et al.* (2005b)
	L_{mat} (fe-males)	562	718	mm	
Maturity ogive constant	u	0.06	0.06		
Recruitment relationship	c	6	4		
	d	$6*10^{-7}$	$8*10^{-7}$		
Standard deviation of ε_{t+1} (fecundity)	σ_{Rec}	0.08	0.08		

Reference points

The derivation of the reference point for $\overline{L}$, $L_{F=M}$, requires the assumptions that the population is at equilibrium with individuals following deterministic von Bertalanffy growth, constant recruitment, natural mortality is independent of size, fishing mortality occurs with knife-edged selectivity. An analytical expression for the calculation of the reference point $L_{F=M}$ was presented by Jardim *et al.* (2015), with $\theta = \frac{k}{M}$ and $\gamma = \frac{F}{M} = 1$,:

$$L_{F=\gamma M,k=\theta M} = \frac{\theta L_\infty + (\gamma+1)L_c}{\theta+\gamma+1} \tag{16}$$

The reference point depends on L_c and stock-specific biological parameters of L_∞, M, and k (larger sex females, Table A.1). The respective values of L_c are calculated from the 'sampled' catch-at-length data generated with the simulation model. From the catch–length distribution in each year and simulation run, 0.1% of catches are resampled. Alternative expected values for the mean length in the catch can be calculated for any given k/M. The reference point is independent of the maturation process.

Alternative reference points can be calculated based on the spawning potential ratio (SPR). We can calculate reference points based on $F_{40\%SPR}$ using analytical models (Miethe *et al.*, 2019). Methods allow for the estimation of the expected catch–length distribution at a particular level of SPR, depending on L_c (size at first capture) and stock-specific biological parameters of L_∞ (asymptotic size), L_{mat} (size at first maturation), M (natural mortality), k (growth) and b (length–weight relationship) for females. The respective mean length in the catch (total mean length, mean length of largest 5%). Assumptions are von Bertalanffy growth, equilibrium dynamics and constant recruitment. Due to the set-up of the population model (limited by L_∞) the coefficient of variation $CV_{L_\infty} \approx 0$ for calculation of the reference points.

Harvest control rules (HCRs)

To evaluate the performance of indicator-based HCRs, we make use of an MSE framework and consider a number of different reference points. We run scenarios with an $L_{50\%}$ of 450mm (i.e. smaller than L_{mat}) for two elasmobranch species. As length-based indicators, we calculate the mean length in the catch (larger than L_c) and the mean length of the largest 5% in the catch, $L_{max5\%}$(Probst *et al.*, 2013).

Each scenario is simulated 1000 times. The simulations are run for a total of 200 years. All simulations are carried out in R (R Core Team, 2017). Each simulation is initiated with a stock at the unexploited equilibrium and with stochastic recruitment. After ten years without exploitation, the fishery is assumed to begin, initially with a constant catch (TAC) at a level which causes the stock to be overexploited (SPR<40% by year 40). Then after year 40, when a TAC management is implemented, catch is defined by an indicator-based HCR.

Two alternative length-based HCRs, which update the TAC on a quadrennial basis, are tested within the MSE framework.In each HCR, the future TAC is assumed to be proportional to the current TAC (year t) and a time-dependent multiplier. In the first rule, the multiplier is calculated as the ratio of the average of the length-based indicator (LBI) to the respective reference point (Ref) in the in the previous four years:

$$TAC_{t+1} = \frac{\frac{1}{4}\sum_{k=t-4}^{t-1} LBI}{\frac{1}{4}\sum_{k=t-4}^{t-1} Ref} \times TAC_t \qquad \text{where } t = 41, 45, 49, \ldots \tag{17}$$

With this rule, the annual TAC change is limited to ±15 %. Truncation of the length distribution will first be visible in the larger sex (here females) if both sexes are exploited equally. Therefore the HCRs are based only on the indicators and reference points of females. Alternatively, we test a combined HCR which uses the LBI ratio together with a stock index based on CPUE (2-over-5 rule) to adjust catches:

$$\mathrm{TAC}_{t+1} = \frac{\frac{1}{4}\sum_{k=t-4}^{t-1}\mathrm{LBI}}{\frac{1}{4}\sum_{k=t-4}^{t-1}\mathrm{Ref}} \times \frac{\mathrm{CPUE}_2}{\mathrm{CPUE}_5} \times \mathrm{TAC}_t \qquad \text{where } t = 40, 44, 48, \ldots \tag{18}$$

CPUE is calculated as the ratio of catch weight (yield) and fishing mortality level (f_t) from the model output. Observation error in the CPUE index is included using a lognormal error $\varepsilon_{cpue,t}$ with N(0,σ_{CPUE}):

$$\mathrm{CPUE}_t = \frac{\mathrm{Yield}_t}{f_t \times e^{\varepsilon_{cpue,t}}} \tag{19}$$

In a 2-over-5 rule the ratio of the mean CPUE in the most recent two years and the previous five years is calculated (ICES, 2018b). Following results from WKLIFE 2018 (ICES, 2018a), we use asymmetric annual constraints on TAC (-25%, 5%).

For a given TAC, the annual fishing mortality multiplier, f_t (equation 19), is derived by numerically solving equation 7–11. The value of f_t is limited to a maximum of 2.0, to avoid infinite values of fishing mortality as the population declines to zero. The numerically derived f_t is then used to calculate catch-at-length data and project the population for the next time-step. To account for observation error introduced through the sampling process, 'sampled' catch-at-length data are generated by randomly selecting 0.1 % of the total number of individuals in the catch from the model-simulated empirical catch–length distribution.

Length-based indicators, $L_{max5\%}$ and $\bar{L}$, are calculated from the 'sampled' catch-at-length data for use in the HCR. $\bar{L}$ is calculated as the mean length of individuals larger than L_c (the length at first capture), the length at which the frequency reaches 50 % of the mode on the left hand side of the distribution (Jennings *et al.*, 2001; ICES, 2012). L_c of the 'sampled' catches is then equivalent to the $L_{50\%}$of the selectivity ogive, but it corresponds to length classes and midpoints of the analytical model for the respective species.

We calculate the annual probability of being below 0.25 SSB_0 (25% of unexploited spawning–stock biomass) and 0.4 SSB_0. The risk of falling below 0.25 SSB_0 and 0.4 SSB_0 after implementation of the HCR (year 40) is determined for each ten-year period as the maximum annual probability of being below the respective SSB threshold and for the final 50 years of the simulation. The time to recovery is measured in number of years until median SSB reaches 0.4 SSB_0 with implementation of the HCRs. Median yield at the end of the simulation period (years 195–200) is calculated together with standard deviation (SD).

Results

Cuckoo ray results

In the baseline scenario the simulated stock, cuckoo ray, collapses after a period of high constant catch taken annually at L_{50}=450 (fishing below L_{mat}), with risk to fall below 0.25SSB_0 at the end of the simulation period of 100% (Figure A.8). Using a simple indicator-based harvest control rule ($L_{F=M}$) improves stock status in some of the simulations (Table A.2). However, the risk to fall below 0.25SSB_0 at the end of the simulation period is above 70%. The simple HCR using $\bar{L}_{SPR40\%}$ succeeds in recovering an overexploited stock with risks below 5% in the longterm. Simulation results of the scenarios are detailed in Figures A.8–A.12 for cuckoo ray.

A combined HCR (LBI and CPUE, Equation 19) is better suited to recover overexploited stocks under non-equilibrium dynamics and with a spawner–recruitment relationship that allows for strong reduction recruitment as the number of spawners decrease (Table A.2). By taking into account a CPUE index, the combined HCRs account for changes in stock size which is of particular importance when L_c<L_{mat}, and length-based indicator calculation is strongly influenced by recruitment variability (including trends in recruitment). For all combined HCRs, risks to fall below $0.25SSB_0$ remain below 5% for cuckoo ray. For cuckoo ray, the $\bar{L}_{SPR40\%}$ indicator is best suited for use in a harvest control rule when L_c<L_{mat} (Table A.5, Figure A.4). Recovery duration is shortest when applying a HCR combining $\bar{L}_{SPR40\%}$ indicator with a CPUE index but lower long-term yield (Table A.6).

If L_c is above L_{mat} (L_{50}=600), the simple HCRs perform better in terms of risk and all tested HCRs succeed in recovering an overexploited stock. Here at higher value of L_c, recruitment variability has less effect on indicator calculation. The reference point $L_{F=M}$ is more precautionary when L_c>L_{mat}, as anticipated from analysis presented in Section 3.

Median values of SSB/SSB_0, recruitment and length-based indicators are summarized for different HCRs in Figures A.4 and A.5.

Table A.2. Cuckoo ray, risk3 (maximum annual probability to fall below $0.25SSB_0$) in years 151–200.

LBI	Simple HCR, L_{50}=450	combined HCR L_{50}=450	Simple HCR, L_{50}=600	combined HCR L_{50}=600
$L_{max5\%SPR40\%}$	100	1.1	0.2	0.2
$L_{max5\%SPR60\%}$	71	0	0	0
$\bar{L}_{SPR40\%}$	0.8	0	3.3	0
$L_{F=M}$	73	0	0	0

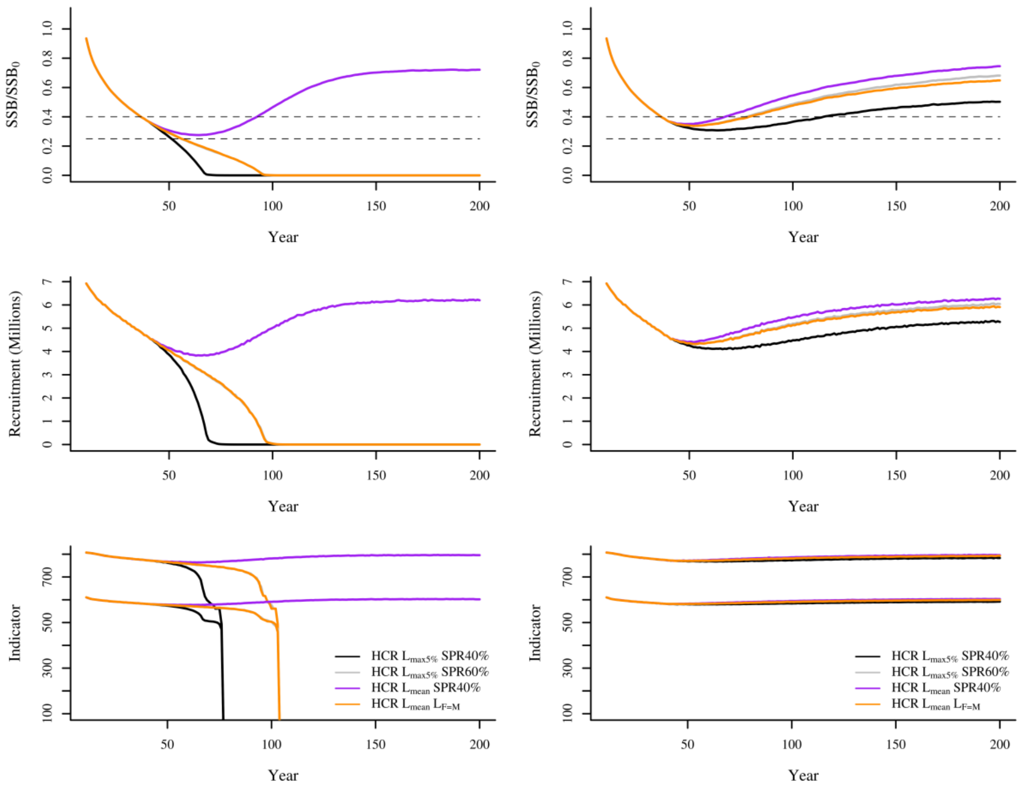


Figure A.4. Cuckoo ray, initial TAC 700t, L_{50}=450 mm, simple (LBI) HCRs in the left panel, combined (LBI, CPUE) HCRs right panel.

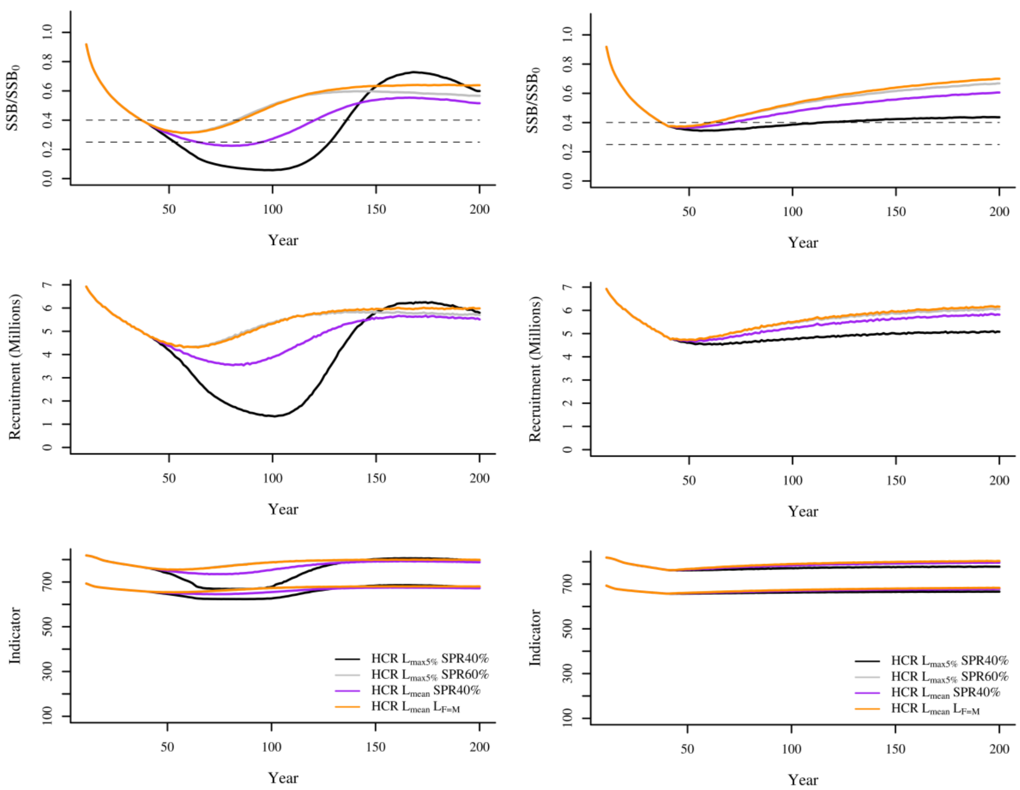


Figure A.5. Cuckoo ray, initial TAC 825t, L_{50}=600mm, simple (LBI) HCRs in the left panel, combined (LBI, CPUE) HCRs right panel.

Thornback ray results

In the baseline scenario the simulated stock, thornback ray, collapses after a period of high constant catch taken annually with risk to fall below $0.25SSB_0$ at the end of the simulation period of 100% (Figure A.13). Using a simple indicator-based harvest control rule with $L_{max5\%SPR60\%}$ or $\bar{L}_{SPR40\%}$ at L_{50}=450 (fishing below L_{mat}), improves stock status with risk to fall below $0.25SSB_0$ at 0% in the long-term. However, for this stock the risk to fall below $0.25SSB_0$ is above 90% when using a simple length-based indicator HCR with $L_{max5\%SPR40\%}$ and $L_{F=M}$ (Table A.3). Simulations of the scenarios are detailed in Figures A.13–A.15 for thornback ray.

A combined HCR is better suited to recover overexploited stocks under non-equilibrium dynamics and the respective spawner–recruitment relationship (Table A.3, Figures A.16–A.17). All combined HCRs succeed in recovering an overexploited stock, with risks below 5%. The use of a combined HCR using $L_{F=M}$ as a reference point still results in a long-term risk of 4.1%. This value is relatively close to 5%, such that small changes in the simulation set up could lead to the risk being above 5%. In comparison to cuckoo ray, at L_{50}=450 for thornback ray $L_{F=M}$ performs worse than other HCRs.

At L_c>L_{mat}, all tested HCRs are successful in recovering an overexploited stock. For thornback ray, the indicators $\bar{L}_{SPR40\%}$ and $L_{max5\%SPR60\%}$ are best suited for use in a harvest control rule for different levels of L_c.

Table A.3. Thornback ray, Risk3 (maximum annual probability to fall below $0.25SSB_0$) in years 151–200.

LBI	Simple HCR, L_{50}=450	CPUE based HCR L_{50}=450	Simple HCR, L_{50}=800	CPUE based HCR L_{50}=800
$L_{max5\%SPR40\%}$	91	0	0	0
$L_{max5\%SPR60\%}$	0	0	0	0
$\bar{L}_{SPR40\%}$	0	0	0	0
$L_{F=M}$	100	4.1	0	0

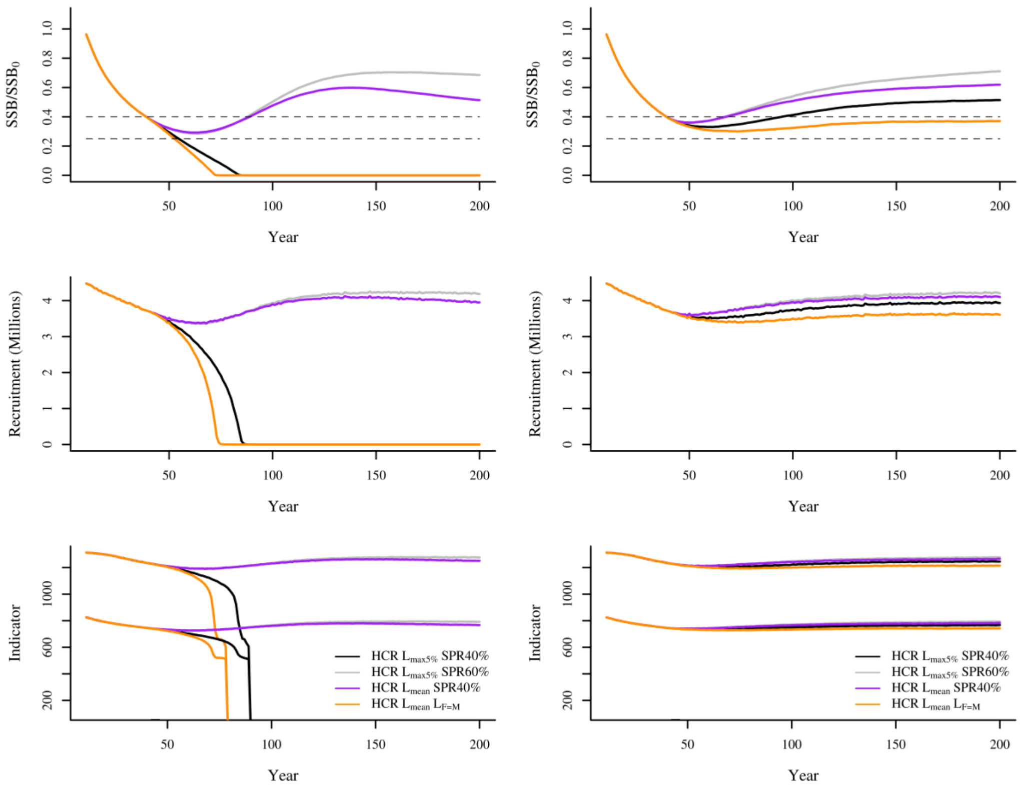


Figure A.6. Thornback ray, initial TAC 2300t, L_{50}=450mm, simple (LBI) HCRs in the left panel, combined (LBI, CPUE) HCRs right panel.

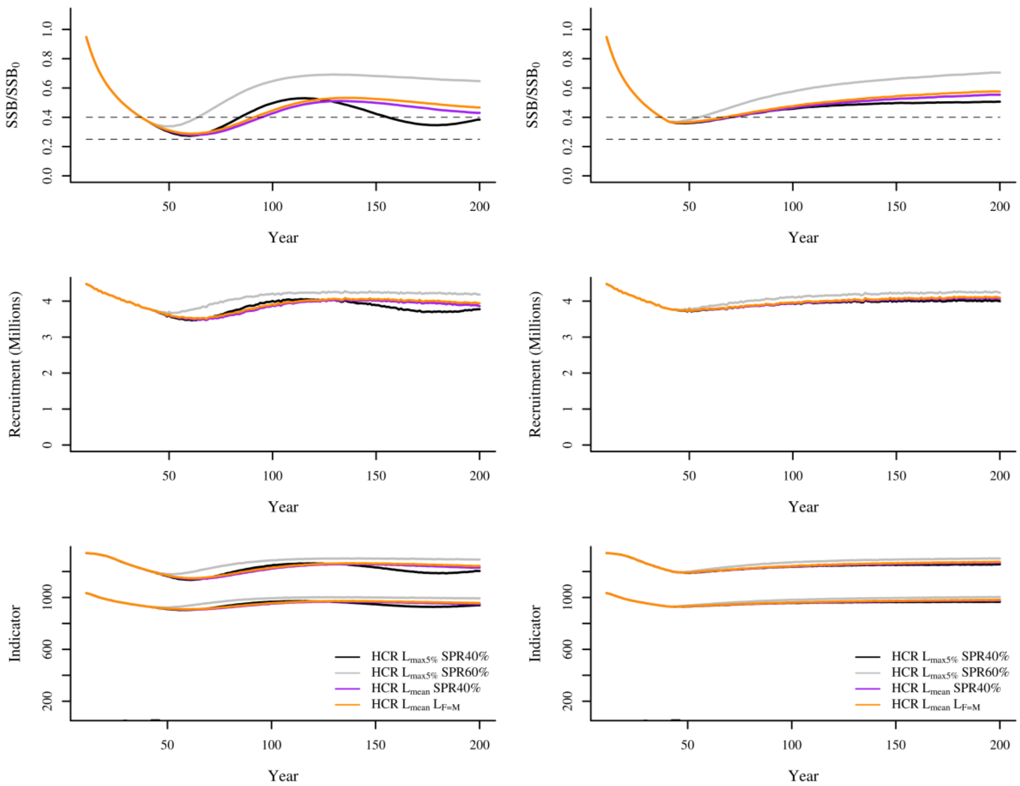


Figure A.7. Thornback ray, initial TAC 3000t, L_{50}=800mm, simple (LBI) HCRs in the left panel, combined (LBI, CPUE) HCRs right panel.

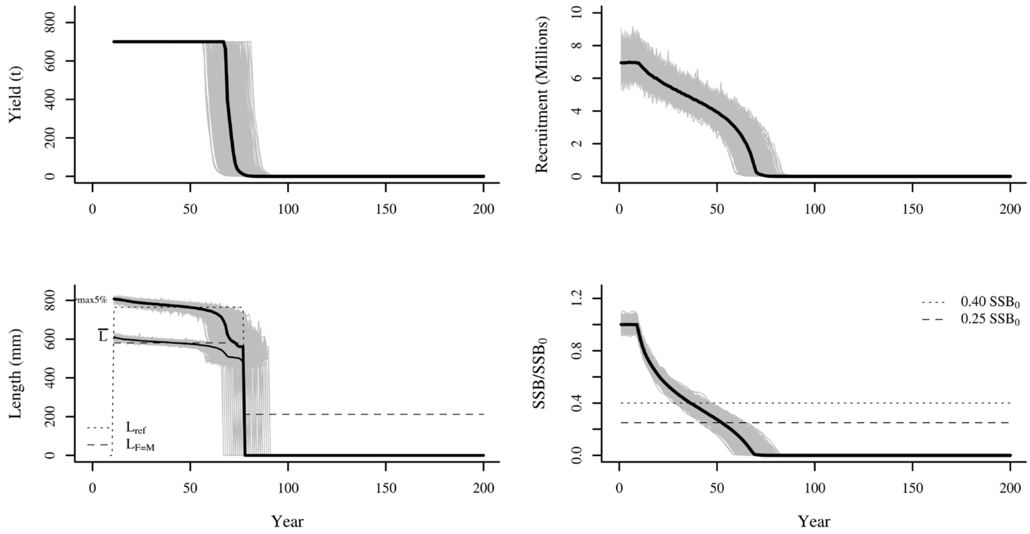


Figure A.8. Cuckoo ray, initial TAC 700t, L_{50}=450mm, no HCR.

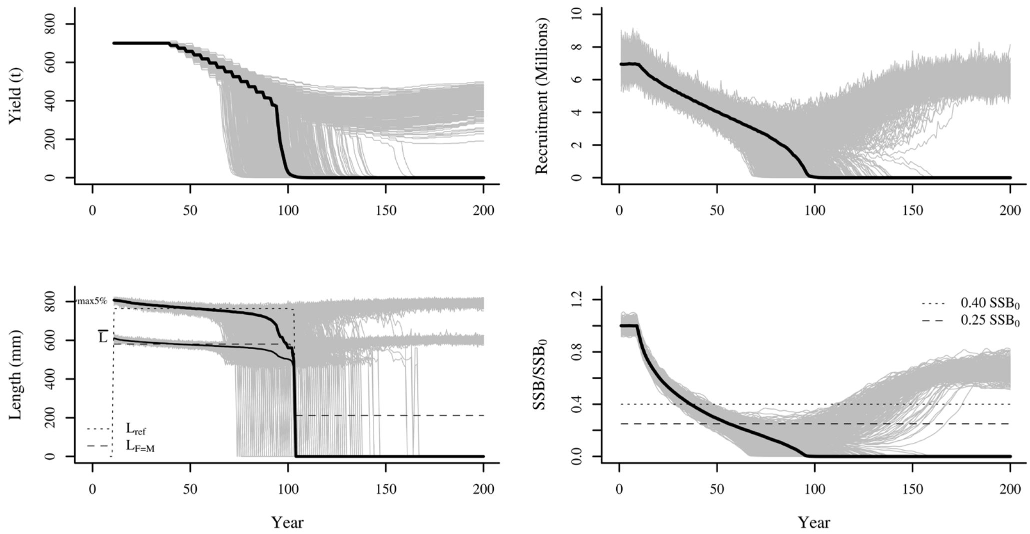


Figure A.9. Cuckoo ray, initial TAC 700t, L_{50}=450mm, HCR $L_{F=M}$.

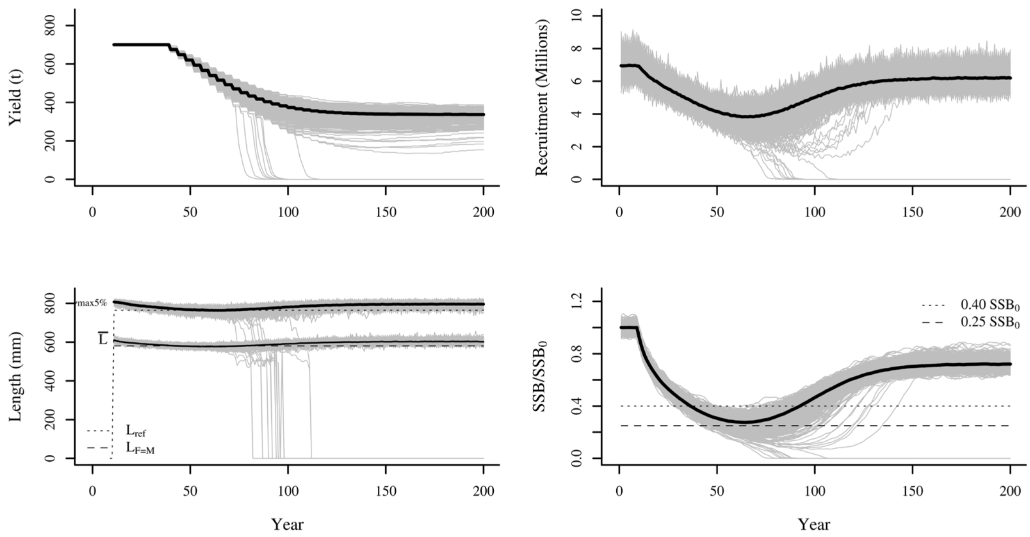


Figure A.10. Cuckoo ray, initial TAC 700t, L_{50}=450mm, HCR $\bar{L}$ 40%SPR.

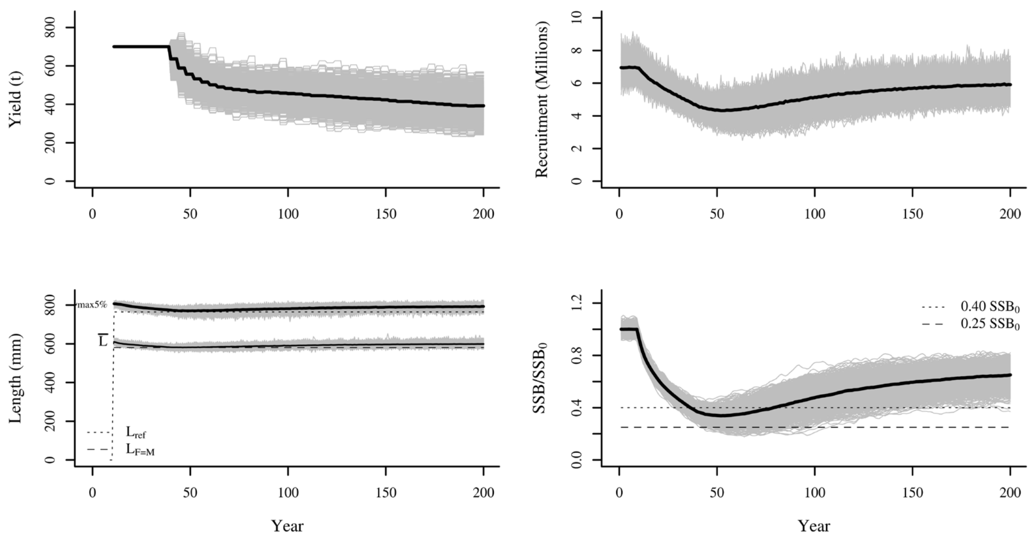


Figure A.11. Cuckoo ray, initial TAC 700t, L_{50}=450mm, HCR $L_{F=M}$ CPUE.

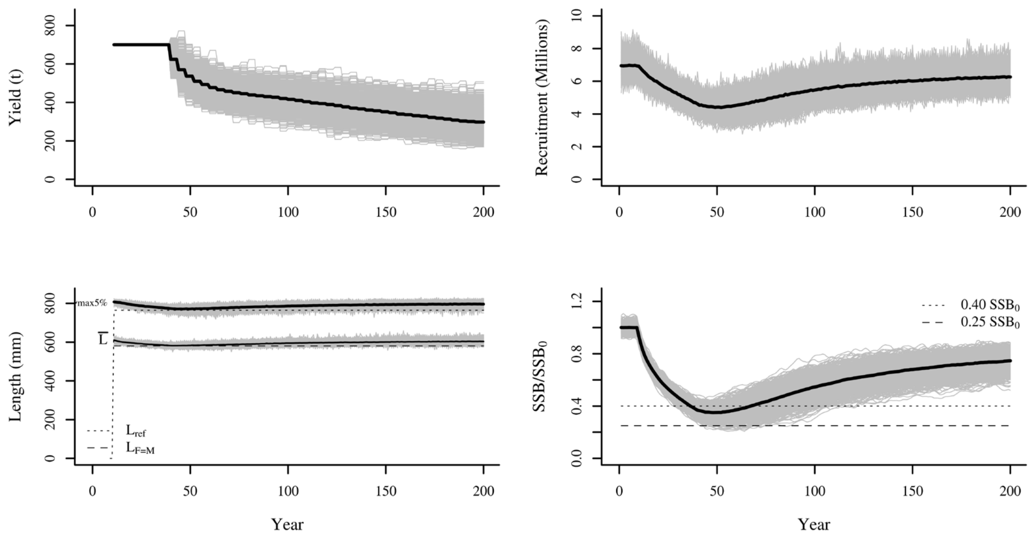


Figure A.12. Cuckoo ray, initial TAC 700t, L_{50}=450mm, HCR $\overline{L}$ 40%SPR CPUE.

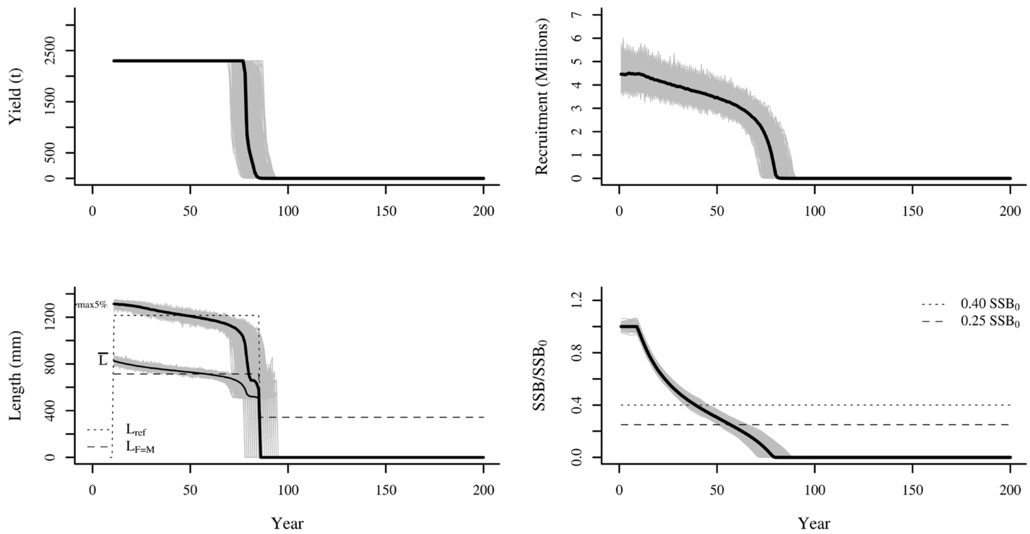


Figure A.13. Thornback ray, initial TAC 2300t, L_{50}=450mm, no HCR.

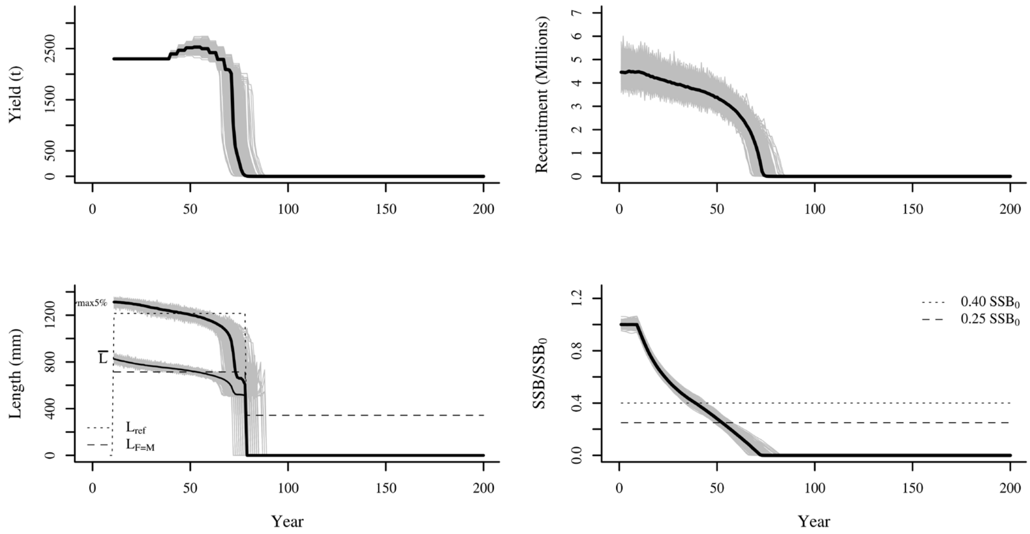


Figure A.14. Thornback ray, initial TAC 2300t, L_{50}=450mm, HCR $L_{F=M}$.

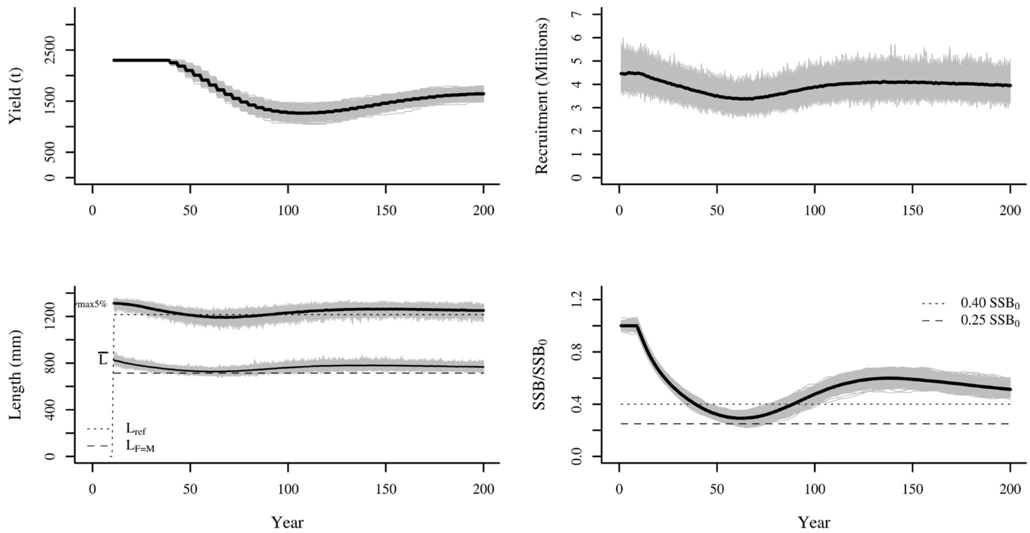


Figure A.15. Thornback ray, initial TAC 2300t, L_{50}=450mm, HCR $\bar{L}$ 40%SPR.

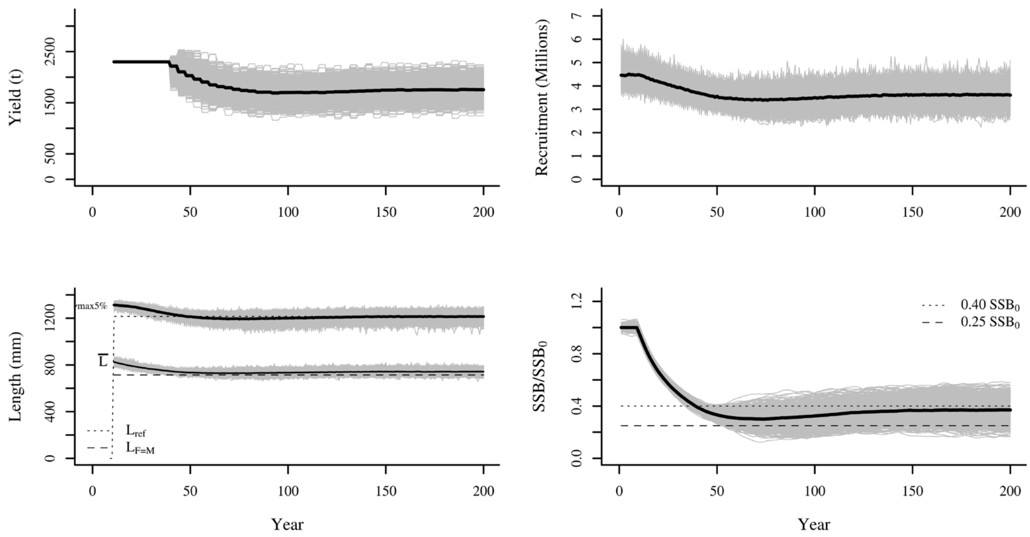


Figure A.16. Thornback ray, initial TAC 2300t, L_{50}=450mm, HCR $L_{F=M}$ CPUE.

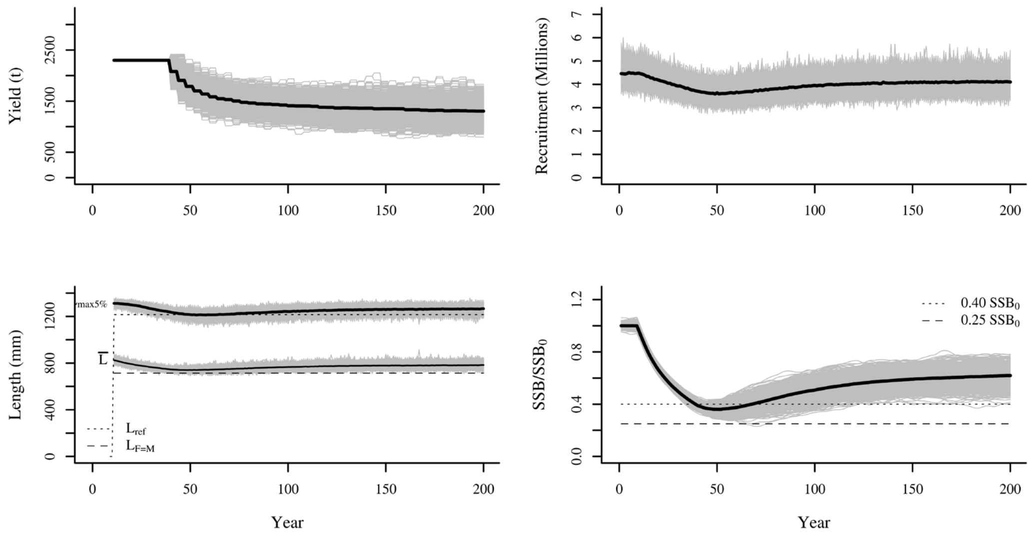


Figure A.17. Thornback ray, initial TAC 2300t, L_{50}=450mm, HCR $\bar{L}$ 40%SPR CPUE.

Discussion

The MSE simulations confirmed for two stocks with different life histories that a combined HCRs, making use of a CPUE index together with a length-based indicator, are best suited to manage overexploited elasmobranch stocks, in particular since L_c is often below L_{mat}. The reduction in recruitment with decreasing spawner numbers affects length-based indicators. A decreasing number of small individuals in the catch can lead to higher length-based indicator values (larger mean length, larger mean length of the largest 5%) than expected under a constant recruitment. The reference points are calculated with the assumption of constant recruitment and equilibrium dynamics. Under non-equilibrium dynamics, trends in stock abundance, indicated by a low CPUE index, can occur and should be taken into account, for example by using a combined HCR.

The reference point $L_{F=M}$ is expected to perform worse in terms of risk to fall below biomass thresholds when L_c<L_{mat}(Jardim *et al.*, 2015). Here, it was found that $L_{F=M}$ performs worse for thornback ray than cuckoo ray, which should be due to differences in life history and exploitation characteristics. In Table A.4, a number of relevant life-history ratios and reference points are compared. We find that while both stocks have a similar ratio of M/k, fishing with L_{50}=450 mm relates differently to the respective L_{mat}. While in relative terms (relative to L_∞) maturity occurs at smaller size in thornback ray, the absolute size at first maturation is larger than for cuckoo ray. So for the same L_{50}, fisheries targets immature individuals in thornback rays at relatively lower size making the stock more vulnerable to overexploitation. SPR-based reference point take into account the maturity and fishing selectivity. The reference point $L_{F=M}$ does not depend on L_{mat}, such that for thornback ray the expected mean length at F=M ($L_{F=M}$) is slightly below L_{mat}. In contrast, for cuckoo ray both $L_{F=M}$ and $\bar{L}_{SPR40\%}$ as well as $\bar{L}_{SPR40\%}$ for thornback ray are larger than the respective L_{mat}. Ideally, the mean length in the catch should not be below L_{mat} to ensure that a sufficient number of individuals survive to reach maturity and reproduce.

Table A.4. Life-history ratios and reference points (L_{50}=450, resulting in L_c=493 (RJN), L_c=492 (RJC)).

	Cuckoo ray	Thornback ray
M/k (female)	1.48	1.54
L_{mat}/L_∞ (female)	0.67	0.52
$L_{50\%}/L_{mat}$(female)	0.8	0.63
$L_{max5\%}$40%SPR / L_∞	0.91	0.87
$L_{max5\%}$60%SPR / L_∞	0.94	0.91
$L_{F=M}/ L_\infty$	0.69	0.51
$\bar{L}_{SPR40\%}/ L_\infty$	0.71	0.54
$L_{F=M}/ L_{mat}$	1.03	0.99
$\bar{L}_{SPR40\%}/ L_{mat}$	1.05	1.06

Additional tables and figures

Table A.5. Risks, cuckoo ray, L_{50}=450, initial TAC =700t.

	101–110 years	111–120 years	121–130 years	131–140 years	141–150 years	151–200 years	HCR
0.25 SSB	93.7	87.3	80.5	76.4	74.1	73.2	$L_{F=M}$
0.40 SSB	100	99.7	96.3	85.1	77.1	74.2	
0.25 SSB	2	1.4	1	0.9	0.8	0.8	$\bar{L}_{SPR40}$
0.40 SSB	11.9	2.3	1.4	0.9	0.9	0.8	
0.25 SSB	100	100	100	100	100	100	$L_{max5\%\ 40\%SPR}$
0.40 SSB	100	100	100	100	100	100	
0.25 SSB	91.9	83.6	77.1	73.7	71.2	70.8	$L_{max5\%\ 60\%SPR}$
0.40 SSB	99.9	99	92.7	79.8	74.1	71.2	
0.25 SSB	0.2	0	0	0	0	0	$L_{F=M}$
0.40 SSB	17.3	10.3	5.2	2.3	1.2	0.4	CPUE
0.25 SSB	0	0	0	0	0	0	$\bar{L}_{SPR40}$
0.40 SSB	1.9	0.3	0.1	0	0	0	CPUE
0.25 SSB	10.7	8.1	6.2	4.2	2.4	1.1	$L_{max5\%\ 40\%SPR}$
0.40 SSB	64.7	55	44.4	37.5	32.3	27.1	CPUE
0.25 SSB	0.2	0	0	0	0	0	$L_{max5\%\ 60\%SPR}$
0.40 SSB	14.3	7.6	3.4	1.5	0.6	0.1	CPUE

Table A.6. Recovery, cuckoo ray, L_{50}=450, initial quota 700t.

HCR	Duration recovery (median SSB>0.4SSB$_0$)	Median yield (195-200)	SD in yield (195-200)
$L_{F=M}$	NA	0	183
$\bar{L}_{SPR40}$	53	337	37.1
$L_{max5\%\ 40\%SPR}$	NA	0	0
$L_{max5\%\ 60\%SPR}$	NA	0	162
$L_{F=M}$ CPUE	39	392	62.1
$\bar{L}_{SPR40}$ CPUE	28	298	58.5
$L_{max5\%\ 40\%SPR}$ CPUE	75	487	57.5
$L_{max5\%\ 60\%SPR}$ CPUE	38	360	66.1

Table A.7. Risks thornback ray, L_{50}=450, initial TAC =2300t.

	101–110 years	111–120 years	121–130 years	131–140 years	141–150 years	151–200 years	HCR
0.25 SSB	100	100	100	100	100	100	$L_{F=M}$
0.40 SSB	100	100	100	100	100	100	
0.25 SSB	0	0	0	0	0	0	$\bar{L}_{SPR40}$
0.40 SSB	0	0	0	0	0	0	
0.25 SSB	99.9	98.3	94.4	91.9	91.3	91	$L_{max5\%\ 40\%SPR}$
0.40 SSB	100	100	98.9	93.3	91.8	91.2	
0.25 SSB	0	0	0	0	0	0	$L_{max5\%\ 60\%SPR}$
0.40 SSB	0	0	0	0	0	0	
0.25 SSB	10.3	7.8	5	3.7	3.1	4.1	$L_{F=M}$
0.40 SSB	87.4	82.9	80.5	75.2	72.3	69.9	CPUE
0.25 SSB	0	0	0	0	0	0	$\bar{L}_{SPR40}$
0.40 SSB	2.8	0.9	0.1	0	0.1	0.1	CPUE
0.25 SSB	0.7	0.2	0	0	0	0	$L_{max5\%\ 40\%SPR}$
0.40 SSB	40.2	27.3	19.3	13.3	10	8.4	CPUE
0.25 SSB	0	0	0	0	0	0	$L_{max5\%\ 60\%SPR}$
0.40 SSB	1.1	0.1	0	0	0	0	CPUE

Table A.8. Recovery, thornback ray, L_{50}=450, initial TAC =2300t.

HCR	Duration recovery (SSB>0.4SSB$_0$)	Median yield (195–200)	SD in yield
$L_{F=M}$	NA	0	0
$\bar{L}_{SPR40}$	49	1641	53.9
$L_{max5\%\ 40\%SPR}$	NA	0	380.7
$L_{max5\%\ 60\%SPR}$	48	1177	61.4
$L_{F=M}$ CPUE	NA	1755	161.6
$\bar{L}_{SPR40}$ CPUE	28	1305	180.2
$L_{max5\%\ 40\%SPR}$ CPUE	55	1548	188.2
$L_{max5\%\ 60\%SPR}$ CPUE	28	1019	193.2

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Annex 5: Recommendations

Recommendation	For follow up by:
It is recommended by WKLIFE IX that there be a tenth meeting of WKLIFE in Lisbon, Portugal 21st–25th September 2020, whose draft ToRs are proposed in this report for the consideration of ACOM. 1. Continue the development of appropriate methods for the assessment and provision of fishing opportunities for data-limited short-lived species stocks. 2. Further review the application of harvest control methods exploring the implementation of additional precautionary measures where necessary such as an asymmetric precautionary buffer and/or biomass safeguards; i.e. reducing advice when below reference point(s). 3. Further explore and develop methods appropriate for data-limited, data-moderate and data-rich fisheries such as MERA, DLMtool and MSEtool libraries; together with emerging multispecies approaches both within and outside the ICES' community. 4. Evaluate the robustness of SPiCT based upon the development of Operating Models of African black hakes using FLife developed under the MyDas project and compare results from SPiCT to the age-based a4a assessment model. 5. Evaluate further improvements to the performance of the WKMSYCat34 catch rule 3.2.1. Focus on improving the catch rule for stocks with von Bertalanffy growth parameter k>0.32, investigate more extensively the definition of the catch rule components and their impact on performance, and investigate the possibility of alternative catch rules. 6. Explore the operating model set-up for data-limited simulations, including sensitivity analyses based on the Jacobian; e.g. elasticity analysis, on how the different life-history and fishery parameters affect the simulated stock behaviour under exploitation, an analysis of the nature of time-series and trends of observable stock characteristics (such as fishery dependent and independent metrics) and how the knowledge gained can be used to further improve the performance of catch rules.	ACOM
The work of WKDLSSLS is considered incomplete and the participants at WKLIFE IX support a second meeting of WKDLSSLS to further develop and refine advice rules for short-lived species.	ACOM
It is recommended by WKLIFE IX that the exploratory studies undertaken with respect to ToR c) this year be further explored, if possible.	ACOM
ICES should explore the on-line App developments for data-limited, data-moderate and data-rich fisheries; e.g. MERA (Method Evaluation and Risk Assessment) an open-source tool for analysing risk, guiding fishery improvement projects, and evaluating management strategies for certification which links to DLMtool (previously, investigated at WKLIFE meetings) and MSEtool libraries to calculate population status and management performance. The App has potential within the ICES community and would be worth exploring at future meetings of WKLIFE.	ACOM
When combining modelling approaches incorporating data-rich, data-moderate and data-limited stocks, there may be a need for undertaking MSE using short-cut approaches rather than full-feedback evaluation, as in the modelling presented in Section 6. Guidelines on the appropriateness of such an approach would greatly benefit future advisory work both within, and outside, ICES.	ACOM