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

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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 X), chaired by Carl O'Brien (UK) and Manuela Azevedo (Portugal) met virtually 5–9 October 2020, to further develop methods for stock assessment and catch advice for stocks in Categories 3 and 4, focusing on the provision of sound advice rules that are within the ICES MSY framework. This tenth workshop was convened to further address the challenges to the evidence base for the provision of ICES advice with specific reference to data-limited stocks. 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. For assessments using the stochastic surplus production model in continuous time (SPiCT), WKLIFE X developed and evaluated 'fractile rules' that account for uncertainty and allow to consider any percentile and demonstrated that 'fractile rules' are more effective and precautionary than the median rule (50th percentile) and the '2-over-3' rule. Additional work on advice rules for stocks in Category 3 based on life-history traits (k), tested through simulation and management strategy evaluation (MSE), showed that the addition of specific multipliers based on the stock's life-history characteristics decreases the risk of the control rule´s performance. Annex 3 to this report contains the revised technical guidance on methods and advice rules for stocks in Category 3. The revision of the accumulated decade of ICES documentation on methods and advice for data-limited stocks into a stand-alone technical guidance document requires significant effort and dedicated work beyond the time available at the WKLIFE X meeting. It is proposed that a dedicated workshop be established to undertake and complete the updating and revision into a single reference document.

ii Expert group information

Expert group name	Tenth Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE X)
Expert group cycle	Annual
Year cycle started	2012
Reporting year in cycle	1/1
Chairs	Manuela Azevedo, Portugal
	Carl O'Brien, UK
Meeting venue and dates	5–9 October 2020, Online meeting (30 participants)

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 virtually by WebEx and MS Teams, 5–9 October 2020, 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) Continue the development of appropriate methods for the assessment and provision of fishing opportunities for data-limited short-lived species stocks.
b) 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).
c) 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.
d) 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.
e) 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.
f) 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.

WKLIFE X will report to ACOM no later than 16 October 2020.

1.2 Background

ICES provide 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 recent meetings of WKLIFE, ICES wishes to further address this issue.

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. However, further research on the definition of optimal harvest control rules for data-limited short-lived stocks is ongoing and WKLIFE X should review such developments (ToRs a and b).

ICES wishes to evaluate the robustness of SPiCT based upon the development of Operating Models using FLife developed under the MyDas project and compare results from SPiCT to the age-based a4a assessment model, using African black hakes, presented at WKLIFE IX, as case study (ToR c).

The work presented during WKLIFE IX showed that the performance of the WKMSYCat34 catch rule 3.2.1 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. ICES wishes to address this issue during WKLIFE X meeting by investigating the characteristics of the operating models (ToRs d and e).

Combined modelling of both data-rich and data-limited stocks has been largely neglected within the ICES community and WKLIFE IX attempted to rectify this deficiency. An obvious next step is to use modelling approaches to test data-limited rules in a multispecies/mixed-fisheries setting at WKLIFE X (ToR f).

1.3 Conduct of the meeting

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

Two working documents were received prior to the meeting (Annex 4) and presentations were made by the participants which subsequently, formed the basis of the workshop's investigations during the week.

Much intersessional work had taken place ahead of the WKLIFE X meeting by its participants, and this was presented during the afternoon of the first day, the morning 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; three of which were identified:

- Subgroup 1 – focused on a revision of the ICES guidelines for data-limited stocks;
- Subgroup 2 – focused on short-lived species and catch rules; and
- Subgroup 3 – focused on approaches for data-limited, data-moderate and data-rich fisheries.

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 October 2018 was brought to the attention of participants at the workshop and no CoI was reported.

1.4 Plenary presentations

Eleven presentations were given during the plenary sessions of WKLIFE X; presenter, title and synopsis or relevant section of the report indicated below.

José De Oliveira – Using a genetic algorithm to optimise a data-limited catch rule

See Section 3.3.1

Laurie Kell – ROC curves for length indicators and the use of machine learning in MSE

The use of Receiver Operating Characteristic (ROC) curves was discussed at WKLIFE IX (ICES, 2019) and a follow-up presentation describing on-going work was given this year at WKLIFE X. To evaluate data-limited methods, the author conditioned an Operating Model (OM) on life-history characteristics and then simulated a variety of data types (e.g. length, catch, and catch per unit of effort) which were then used to fit a number of different assessment methods. The predictions from the assessment methods are compared to the OM using the Mean Absolute Scaled Error (MASE) and the ability of the methods to assess stock status to target and limit reference points using ROC curves. The overall aim 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.

Simon Fischer – The rfb-rule and the ICES precautionary approach

See Section 3.3

Simon Fischer – Constant harvest rates revisited

See Section 3.4

Henrik Sparholt – Obtaining F_{MSY} from L_∞, K and a50mat

See Annex 4

Jan Horbowy –Survey-based estimates of F_{MSY} and its proxies

The methodology and selected results shown in the paper recently published by Horbowy and Hommik (2020) were presented to the group.

The basis of the approach were formulae for equilibrium yield and biomass developed by Horbowy and Luzeńczyk (2012). Similar equations were presented earlier by Mace (1994). The equations have been developed by combining yield-per-recruit (YPR) and spawning stock per recruit (SPR) with parameters of Beverton and Holt (B&H) and Ricker stock–recruitment (S–R) relationships.

If Beverton and Holt S–R relationship is parameterised as R=B/(a+b*B) then the equilibrium yield and biomass may be presented as functions of fishing mortality in the form:

$$Y_{eq}(F) = YPR(F)\frac{SPR(F)-a}{b*SPR(F)} \quad (1a)$$

$$B_{eq}(F) = \frac{SPR(F)-a}{b} \quad (1b)$$

where R is recruitment, a and b are parameters of S–R relationship, **Y** is yield, **B** is spawning–stock biomass, **F** is fishing mortality, and $_{eq}$ stands for equilibrium (Horbowy and Luzeńczyk, 2012).

In case of Ricker S–R relationship R = a*B*exp(-b*B) and then the equilibrium yield and biomass take the form:

$$Y_{eq}(F) = YPR(F)\frac{\ln(a*SPR(F))}{b*SPR(F)} \quad (2a)$$

$$B_{eq}(F) = \frac{\ln(a*SPR(F))}{b} \quad (2b)$$

The right-hand side terms in eq. 1a, 2a. represent equilibrium recruitment at given fishing mortality (Yeq (F)=YPR(F)*Req (F)). Having equations for equilibrium yield and biomass, it is easy to estimate F_{msy} and some other proxies, e.g. $F_{40\%ssb}$. This is simple analytical approach, developed in deterministic mode, but stochasticity may be added to the model as random noise in recruitment and variables used in YPR and SPR (weight, natural mortality, maturity, selectivity). The method differs from standard ICES approach, which uses long-term stochastic simulations and often harvest control rules to estimate F_{MSY}.

In the recent paper by Horbowy and Hommik (2020) it was shown, that under some assumptions the above approach can also be used when analytical estimates of stock size and recruitment are not available, and instead of this the S–R relationship is fitted to survey indices of stock size and recruitment.

Thus, assume that survey indices of biomass, $\mathbf{B}_S$, and survey indices of recruitment, $\mathbf{R}_S$ are proportional to "true" (analytically estimated) spawning–stock biomass and recruitment as:

$B_S = q_B*B$, and $R_S = q_R*R$

where $\mathbf{q}_B$ and $\mathbf{q}_R$ are the survey catchabilities for spawning biomass and recruitment, respectively. Then, after scaling the survey recruitment by the ratio $\mathbf{q}_B/\mathbf{q}_R$ and fitting S–R relationship to survey data, the survey-based equilibrium recruitment, $R_{s,eq}$, is proportional to the analytical equilibrium recruitment for both the Beverton and Holt and Ricker S–R relationships and thus equilibrium yield (eq. 1a, 2a) basing on survey S–R has the same maximum (F_{MSY}) as equilibrium yield using S–R from analytical assessment (see Horbowy and Hommik (2020) for details). Similar refers to some F_{MSY} proxies, e.g. $F_{40\%ssb}$.

There is no need to estimate survey catchabilities separately but their ratio must be estimated if catchabilities of recruitment and spawners differ. In the paper, an approximate method to estimate catchability is presented.

The method may be applied also to results of assessments considered as "indicative of trends" only as we may consider them as proportional to "true" values with the same proportionality coefficient (catchability) for recruitment and biomass, so $\mathbf{q}_B/\mathbf{q}_R$ ratio may be assumed 1.

The approach was tested in two ways:

a) on generated stock (assessment datasets), assuming two options for catchabilities: $q_B = q_R$ and $q_B = 2q_R$

b) on selected stocks; for part of them analytical assessment was available, so it was possible to apply the method using both analytical and survey-based S–R, estimate F_{MSY} and $F_{40\%ssb}$ in both cases, and compare the results.

For generated stock, the "survey" samples were taken at random from generated data and S–R models were fitted to both generated recruitment and biomass and "survey" indices of recruitment and biomass. Next, equilibrium yields and biomasses were derived using eq. 1-2, and F_{MSY} and $F_{40\%\ ssb}$ have been estimated. The "survey"-based method quite well reproduces F_{MSY} and $F_{40\%ssb}$ from generated data, relative difference between estimates were mostly below 20%. The precision of $F_{40\%ssb}$ was higher than the precision of F_{MSY}. For option $q_B = 2q_R$ the median q_B/q_R ratio was 2.15, and its 90% confidence interval contained exact value of 2.

The survey-based method was also tested on a few stocks, e.g. central Baltic herring (CBH, analytical assessment and F_{MSY} available) and sole in 7h–k (in 2019 assessment considered by ICES as "indicative of trends" only). For CBH assuming B&H S–R relationship, the survey-based estimates of F_{MSY} and $F_{40\%ssb}$ were 0.20 and 0.17, respectively, while the assessment-based values were equal to 0.21 and 0.20. In case of sole assuming B&H S–R relationship the F_{MSY} and $F_{40\%ssb}$ were estimated at 0.17 and 0.14, respectively, while F_{MSY} estimated by ICES in 2016 was 0.16.

References

Horbowy, J., Luzeńczyk, A. 2012. The estimation and robustness of F_{MSY} and alternative fishing mortality reference points associated with high long-term yield. Can. J. Fish. Aquat. Sci. 69, 1468–1480

Horbowy, J., Hommik, K. 2020. Survey-based estimates of F_{MSY} and its proxies. Fisheries Research 229 (2020) 105607, https://doi.org/10.1016/j.fishres.2020.105607.

Mace, P.M. 1994. Relationships between common biological reference points used as thresholds and targets of fisheries management strategies. Can. J. Fish. Aquat. Sci. 51(1): 110–122. doi:10.1139/f94-013.

Tobias Mildenberger – Probability-based HCRs

See Section 3.2.

Santiago Cerviño - IMPRESS project

See Section 5.3

Tobias Mildenberger – Alternative SPiCT-based HCR to the 2/3 rule

See Section 3.8.

Andrés Uriarte –Workshop on data-limited stocks of short-lived species

See Section 2.2.

María Soto – Effects of under-estimating discards in production models: improving the assessment of *Merluccius spp*. in NW Africa

See Section 4.2.

1.5 Structure of the report

The structure of the report is as follows:

- Section 2 focuses on short-lived species – ToRs a) and b);
- Section 3 focuses on improvements to the performance of the WKMSYCat34 catch rule 3.2.1 – ToRs d) and e);
- Section 4 focuses on stochastic surplus production models – ToR c);
- Section 5 focuses on approaches for data-limited, data-moderate and data-rich fisheries stocks – ToR f); and
- Section 6 focuses on the ICES guidelines for data-limited stocks – this was not included in the ToRs for WKLIFE X but was added as a follow-up to the guidelines drafted at last year's WKLIFE IX meeting.

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 Follow-up process within ICES

The participants at WKLIFE X agreed to provide text for the draft workshop report by Friday 6th November 2020 and to then comment on the compiled draft report no later than 13th November 2020; when the report can be finalised by the Chairs and formatted by the ICES Secretariat.

1.6.1 Recommendations

It is recommended by WKLIFE X that there be a eleventh meeting of WKLIFE in Lisbon, Portugal 4–8 October 2021 or virtually, whose draft ToRs are proposed in this report for the consideration of ACOM (Annex 5). It is also recommended by WKLIFE X that ICES hold a workshop on technical guidelines for data-limited stocks in early 2021 (Annex 5). The work of WKDLSSLS is considered incomplete and the participants at WKLIFE X support a third meeting of WKDLSSLS to further develop and refine advice rules for short-lived species.

1.7 References

ICES. 2019. 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). ICES Scientific Reports. 1:77. 131 pp. http://doi.org/10.17895/ices.pub.5550.

2 Short-lived species

2.1 Introduction

This Section focusses on the need for specific advice rules for stocks of short-lived species; namely, ToRs a) and b).

2.2 Advances from WKDLSSLS in 2020

The Workshop on Data-Limited Stocks of Short-Lived Species WKDLSSLS met in September 14–18, 2020, by video conference to address its ToRs:

1. Test different assessment methods for data-limited short-lived species (seasonal SPiCT, others) and provide guidelines on the estimation of MSY proxy reference points for category 3–4 short-lived species.
2. Further explore the appropriateness of the management procedures currently in use for short-lived species by means of Long-Term Management Strategy Evaluations (LT-MSE).

- Regarding ToR 1: Test different assessment methods for data-limited short-lived species (seasonal SPiCT, others) and provide guidelines on the estimation of MSY proxy reference points for cat 3–4 short-lived species:

No further progress on assessment methods of initial stock status relative to MSY was done other than applying surplus production models (SPiCT mainly).

The WK explored the application of Surplus production models like SPICT (Pedersen and Berg, 2016) and other similar methods.

Several Applications were presented and improved during the workshop for:

- Anchovy in 9.a West: essays on SPiCT and on testing harvest rate strategies (Wise *et al.*)
- Anchovy in 9.a South: Comparison of SPiCT vs Gadget (Rincón *et al.*)
- Octopus in Asturias (North of Spain): Interannual Pella-Tomlinson surplus production model and intraannual decay depletion model (CatDyn) (Roa-Ureta).
- Cuttlefish (*Sepia officinalis*) in the English Channel (Larivain).

As these works do not change the procedures for estimation of MSY proxy reference points for management, they are not further detailed in this report. For further detail on these works consult the WKDLSSLS2 report.

In addition, some ideas on the general production curves applicable to North Sea sprat were presented for discussion (Brooks). And general ideas and essays on risk averse harvest control rules (HCR) built upon a SPiCT assessment for the management of short-lived species were presented by Mildenberger, but they are further tested and presented in another section of this WKLIFEX report.

The group agreed that for short-lived stocks with sufficient long dataseries (and with enough contrast of biomasses and production in the series) surplus production models will be applicable (can be fitted) and the advice can be formulated on the basis of F_{MSY} (rather than on constant catch at MSY), or preferably less than F_{MSY} (accounting for the strong fluctuations of these short-lived species).

Such F_{MSY} rule would be more successful if applied to an assessment including an indicator of the biomass abundance just prior to the management calendar (and including most of the harvestable population age classes). A year lag between assessment and management would worsen the performance of the management for short-lived species, and this should be evaluated in comparison with other potential MPs.

Basically, results endorsed the conclusions produced in WKDLSSLS-1.

- Regarding ToR 2: 2): Further explore the appropriateness of the management procedures currently in use for short-lived species by means of Long-Term Management Strategy Evaluations (LT-MSE)

Here, several <u>subtasks</u> were included to cover:

a) revision of past year harvest control rules, b) revision of the effectiveness of the precautionary buffer (PA), c) or effectiveness of adding a biomass safeguard, d) sensitivity to the time-lag between assessment and enforcement of the TAC advice, e) exploring the suitability and magnitude of the uncertainty caps, and f) constant or variable harvest rate strategies instead of the trend-based, etc.

No major advance was produced on assessing the effectiveness of the <u>precautionary buffer</u> (PA), other than its effect on constant harvest rates, which will be detailed when dealing with subtask 2.f.

In WKDLSSLS-1 and 2, the relevance of the <u>time-lag between the survey, the advice and the management</u> was assessed, in both workshops all simulations proved that the shorter the lag between observations, advice, and management the smaller will be risks, usually for higher (or similar) catches. This means that the in-year advice should always be preferred over the normal calendar year advice (with one interim year lag). Results were very consistent across different operating models (no figure shown in this case, but see the original WKDLSSLS reports).

<u>Trend rules</u> based on the most recent survey indexes using the 2-over-3 and 1-over-2 ratios were compared alone and coupled with uncertainty cap levels to constrain the interannual variability of TACs. In addition, provision of advice through a constant harvest rate applied to the most recent survey index at the beginning of the management year was preliminary tested. Such harvest strategy was already proposed as a promising follow up management procedure to be further tested by MSE after WKDLSSLS-1, and it came also a recommendation to WKDLSSLS-2 from the ICES WGHANSA as a result of some rigid performance of the 1-over-2 HCR for the anchovy in 9.aW (a population with very large interannual fluctuations).

Case studies were anchovy, sardine/sprat-like stocks.

<u>New comparisons between the trend rules 2-over-3 and 1-over-2 ratios for different Uncertainty cap values</u>:

Figure 2.2.1 shows that the historical exploitation level conditions the initial risks and its trajectory after management (columns), so that the bigger the historical exploitation, the bigger the initial risk.

Rule 2-over-3 results in higher risks levels for the same catch levels as the 1-over-2 rules (symbols: squares and crosses versus the other point forms).

The use of these trend-based HCRs taking geometric means instead of arithmetic means results in higher risks, because of the lesser reduction of catches in time.

Concerning the uncertainty caps (colours):

- The Riskiest → UC(0.2,0.2)
- Safest → UC(0.8,0.8)
- Intermediate risks → UC(NA,NA) & UC(0.8,4)

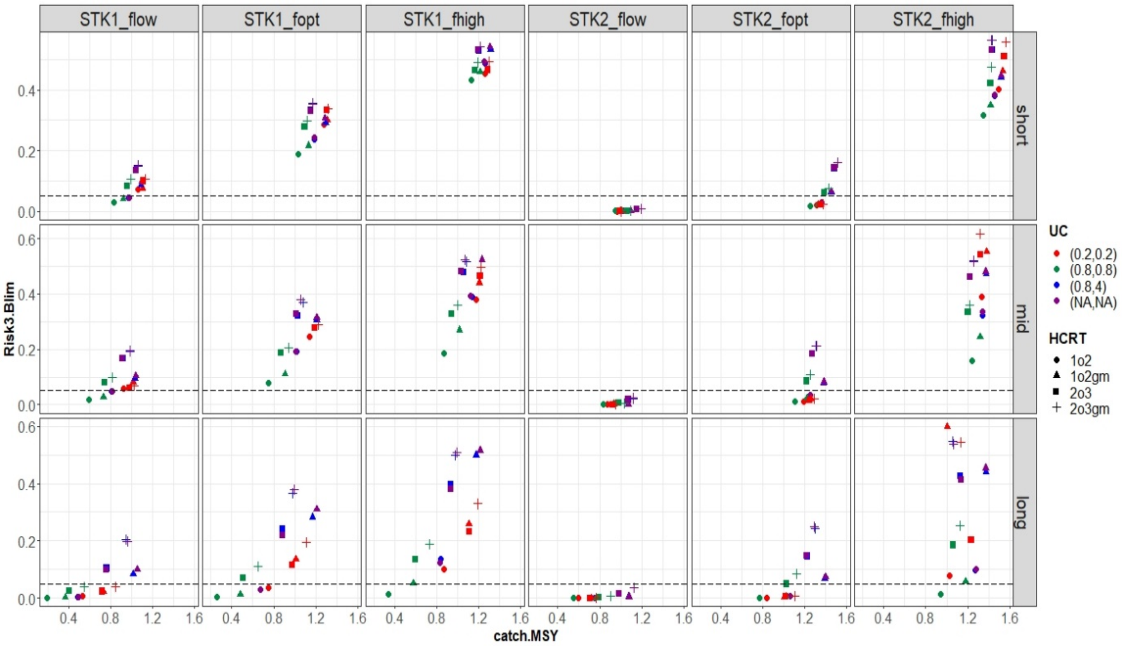


Figure 2.2.1. Risk3 (maximum probability of falling below B_{lim}) versus relative yields (catch/MSY) in the short (first five projection years - upper graphs), medium (next five projection years - middle graphs) and long-term (last ten projection years - bottom graphs) for each HCR (standard 1-over-2 and 2-over-3 rules and same rules with geometric means instead of arithmetic means, see right lower legend) combined with various uncertainty cap levels (see right upper legend). In columns, combination of stock-types and their historical fishing mortality levels (STK1 and STK2, correspond to anchovy-like and sardine/sprat-like stocks, respectively; and flow: Fhist=0.5*F_{MSY}, fopt: Fhist=F_{MSY} and fhigh: Fhist=2*F_{MSY}). Based on Sánchez *et al.* (in prep.).

Regarding the biomass safeguard:

Figure 2.2.2 shows biomass safeguards applied to the Sprat in 7.d–e make the 1-over-2 rule more precautionary (black symbols versus the rest).

Using biomass safeguards either based on the following I reference levels: Imin (= historical minimum value), Itrig (= 1.4 Imin) or Istat (=$geometricMean(I_{hist}) \cdot exp(-1.645 \cdot sd(log\ (I_{hist}))$), makes little difference in the global effects, though they could be ranked in terms of reductions of risks as:

Risk(Itrigger) < Risk(Istat) < Risk(Ilim)

It is noticeable as well, that extreme fishing histories like FH2 (historical gradual increase to 1.5Fopt) and FH3 (gradual increase to 1.5FPt in 15 years, five years at 1.5FP and then decreased exponentially to FP (corresponding to Patterson's exploitation rate, E = 0.4 = F/Z considered an appropriate level) in five years until the end of the 25-year historic period) make biomass safe-guards less reactive.

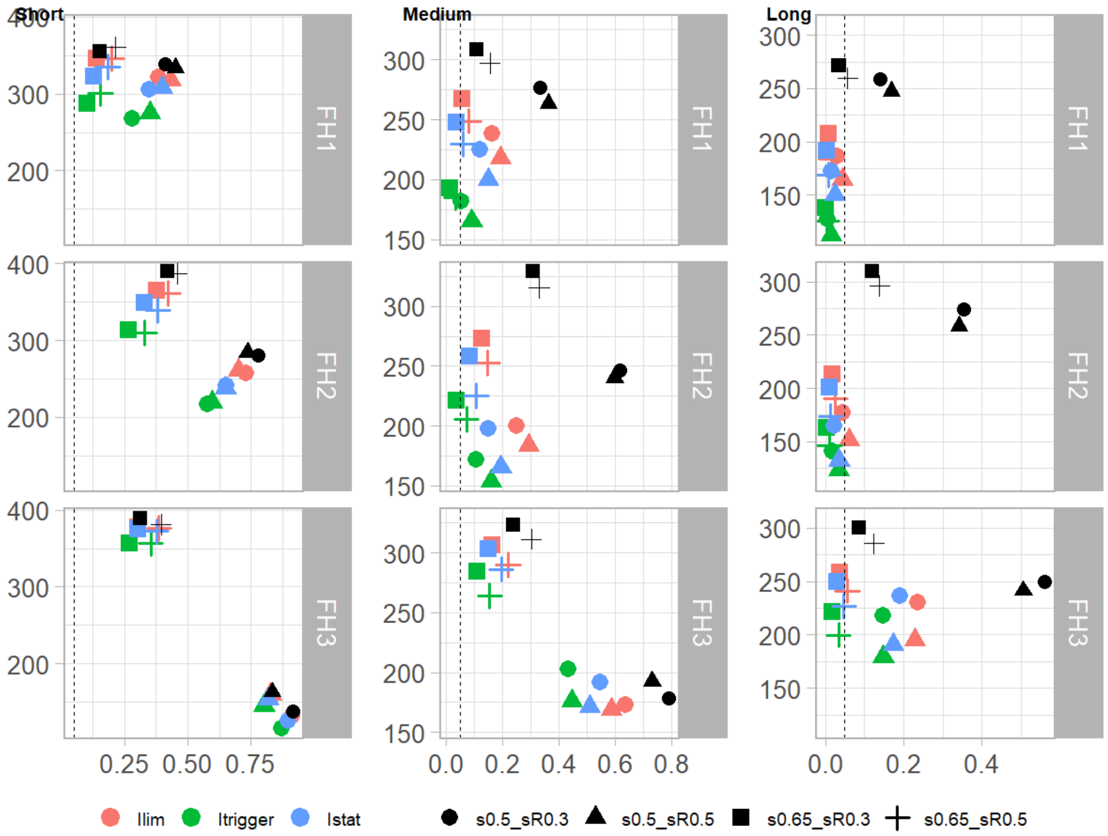


Figure 2.2.2. Short, medium and long-term plots of yield against risk (Risk1 -- mean probability of falling below B_{lim}) for the 1-over-2 rule alone (black points) or coupled to a biomass safeguard multiplier, either based on Ilim, Itrigger or Istat, (colours) across several variants of a sprat like stock operating models (point forms, varying according to the recruitment parameters, steepness and variability; s0.5_sR0.3: steepness=0.5 and sigmaR=0.3; s0.5_sR0.5: steepness=0.5 and sigmaR=0.5; s0.65_sR0.3: steepness=0.65 and sigmaR=0.3; s0.5_sR0.65: steepness=0.65 and sigmaR=0.5;.) and historical exploitation levels (FH1:Historical gradual increase to Fopt, FH2: historical gradual increase to 1.5Fopt and FH3: roller coaster: gradual increase to 1.5FP in 15 years, stay there for 5 years and then decreased exponentially to FP in five years until the end of the 25-year historic period).

Very similar results were obtained in WKDLSSLS (ICES, 2019) when applying biomass safeguards for anchovy and sprat/sardine like stocks complementing the application of the 1-over-2 rule applied either alone or with uncertainty caps (symmetric and asymmetric ones). Though minor improvements were seen for this rule when applying the biomass safeguard in combination with the last year recommended 80% symmetrical uncertainty cap UC(0.8, 0.8). It was also found that applying the biomass safeguard with either the Imin, Itrig or Istat, made little difference. And Istat is put forward for the standard application as its behaviour is similar to the Imin, but it may result in better statistical properties if that value is sought to be updated every year.

All former results confirm past year conclusion that the best performing rule in terms of trade-offs between biological risks and relative yields in the long and medium term are the 1-over-2 rule with 80% symmetric uncertainty cap, preferably with biomass safeguard.

Regarding <u>constant harvest rates</u>:

Figure 2.2.3 shows the results of searching a constant harvest rate (hr) for the sprat in 7.d–e by increasing the hr until all of the risk statistics in the short, medium-and long-term risks exceeded 5%. It is evidenced that the hr changes as a function of:

- Survey catchability (rows)
- The operating model (steepness and Sigma R) (columns)

- Growth parameters (VB1 with Linf=16 and k=0.6, VB2 with Linf=16 and k=0.4, and VB3 with Linf=13 and k=0.6 in the X axes).

In addition, it is shown that hr appears relatively insensitive to past exploitation and stock status at the beginning of simulations when management is implemented (colours).

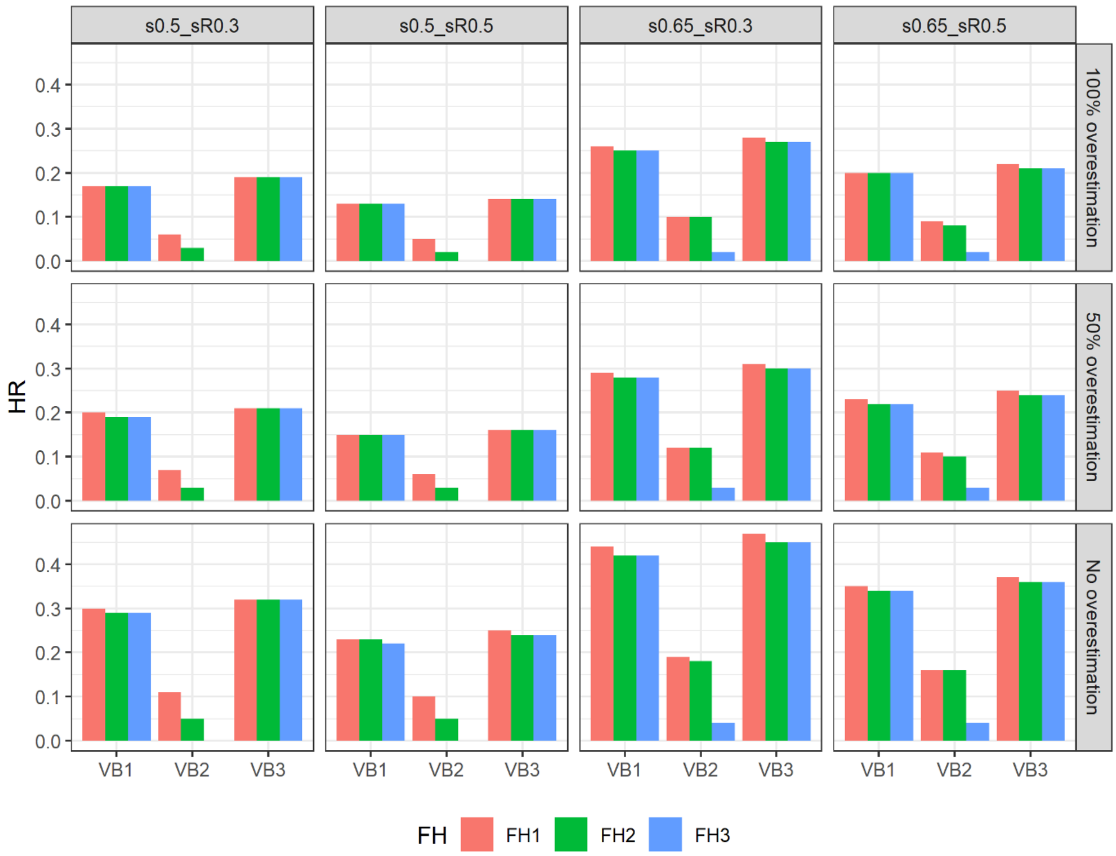


Figure 2.2.3. The maximum precautionary harvest rate (i.e. the maximum harvest rate for at least one of the risk statistics to be <5%) under a range of different life histories (columns), survey catchabilities (rows) and fishing histories (colours).

The performance managing the anchovy and sprat/sardine-like stocks with constant harvest rates, just taken from the average of the last five years before management, with different initial precautionary buffer multipliers (= 0.75, 0.8 and 1) in combination with biomass safeguard (Istat) are shown in Figure 2.2.4 and compared to the 1-over-2 alone or combined with the 80% symmetrical uncertainty cap. There it is again confirmed that application of biomass safe guard can produce a reduction of risk in time, even for the constant harvest rates, by gradually reducing catches as well. However, risks remain above 0.05 at any time horizons particularly for stocks heavily exploited in the past. Therefore, taking the average harvest rate of recent years as the reference harvest rate cannot be sustainable, as the risk would depend on how much the stock has been exploited before management starts. In addition, such reductions of risks and catches are less intense that the one achieved by the 1-over-2 rule alone or with 80% symmetrical uncertainty cap combined with the biomass safeguards.

Overall, again the better performance in the medium term (years 6–10 of the management period) of the 1-over-2 with UC(0.8,0.8), combined with the biomass safeguards, in reducing risks supports its election as the best one.

It should be noted that constant HR rules may be affected by the survey catchability parameter and the CV of such survey index. The interaction between these two factors affecting survey index may require *ad hoc* tunning of the performance of the constant harvest rate rules devised to be applied to a particular stock and monitoring system.

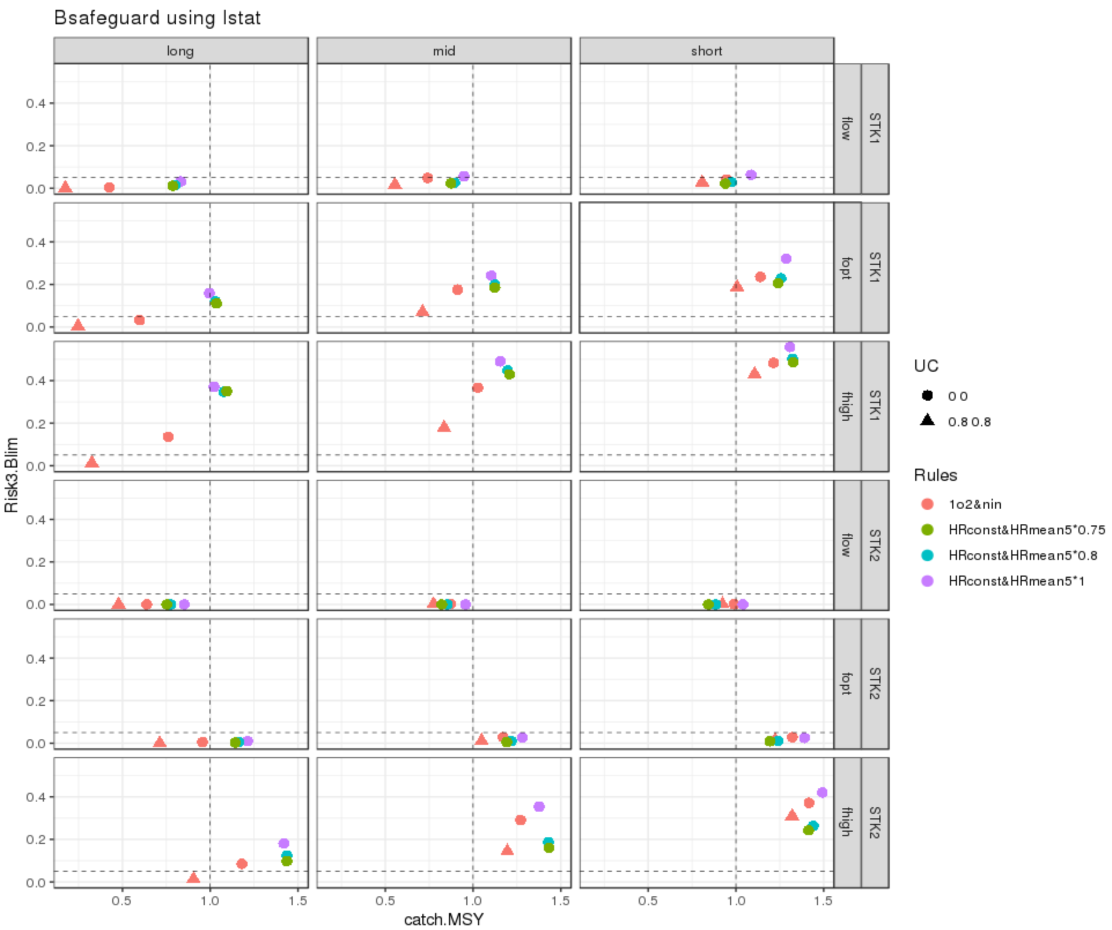


Figure 2.2.4. Risk3 of falling below B_{lim} versus relative catch respect to MSY for alternative historical F levels (Flow: 0.5*F_{MSY}, F_{opt}: F_{MSY} and F_{high}: 2*F_{MSY}), HCRs (red circle and triangle – 1o2 without uncertainty cap UC(0,0) and 1o2 with uncertainty cap UC(0.8,0.8); greenbrown circle –constant HR with the starting refHR=0.75*historical HRmean(last five years); blue circle –constant HR with the starting refHR=0.8*historical HRmean(last five years) without uncertainty cap; purple circle –constant HR with the starting refHR=historical HRmean(last five years) without uncertainty cap, all of them with a biomass safeguard factor (I=Istat), and for the stock types (STK1: anchovy-like; STK2: sardine-like), standard deviation for the recruitment= 0.75 and timeframes (short: years 31–35; medium: years 36–40; and long term: years 51–60). Based on Citores and Sánchez *et al*. (in prep.).

2.3 Summary and conclusions

- For short-lived stocks with sufficient long dataseries (and with enough contrast of biomasses and production in the series) surplus production models will be applicable (can be fitted) and the advice can be formulated on the basis of F_{MSY} with the additional use of a precautionary approach (probability-based harvest control rule and biomass threshold), rather than on constant catch at MSY.
- Such F_{MSY} rule would be most successful if applied to an assessment including an indicator of the biomass population just prior to the management calendar (and including most of the harvestable population age classes). A year lag between assessment and management would worsen the performance of the management for short-lived species.

- For data-limited short-lived stocks (DLSSLS) with a survey monitoring system, a constant harvest rate strategy can be the best management procedure conditioned to a careful setting of such level according to a prior good knowledge on the distribution of potential catchability of the survey. Definition of such constant harvest rate is to be made by MSE covering a range of uncertainties on life-history characteristics, survey catchabilities, CV of surveys, etc.
  - A preliminary assessment of such constant HR has been made for the sprat in 7.d–e.
  - Other analyses have shown that just taking the mean of recent HR from the fishery history (with some buffers) is not necessarily sustainable as this would depend heavily on the exploitation the fishery has exerted historically on the stock.
  - The potential of this approach would also depend upon the observation error of the survey.
- When knowledge on the catchability or the uncertainties are so poor as to preclude the definition of constant harvest rates, then trend-based harvest control rules (according to the recent indications of biomass) can be applied, coupled preferably to some uncertainty cap constraints and to biomass safeguards, as follows:
  - The WK recommends for short-lived small pelagic fish stocks the trend rule 1-over-2 coupled with an 80% symmetric uncertainty cap and with biomass safeguard (Istat): The analysis shows that this rule allows decreasing the biological risks (of falling below B_{lim}) for anchovy and sardine/sprat like stocks in the long term to around 0.05, or below, with moderate losses of catches and reducing the risks below 0.2 in the medium term (for the stocks exploited at or above F_{MSY}), but losses of catches are more pronounced in the long term.
  - Asymmetric uncertainty caps: An asymmetric uncertainty cap (specifically -80% and +400%) with a biomass safeguard can prevent losses of yield by allowing fast recovery of catches to past levels, but it may not be precautionary for less resilient or for depleted stocks. This conclusion is based on simulating sprat- and anchovy-like life histories rather than on specific stocks *per se*.
  - The 1-over-2 rule with a symmetric 20% uncertainty cap is not sustainable in the long term (implying risks of falling below B_{lim} well above 0.05). Adding a biomass safeguard greatly improves its performance, but without outperforming the 1-over-2 rule with 80% symmetrical uncertainty cap and biomass safeguard.
- The shorter the lag between assessment, advice and management, the better the performance of all of these rules (constant harvest rate or trend based rules). The performance is optimized if based on an indication of the population (from surveys) just around the start of the management years, or with a shorter than a half year gap (in-year advice). For lags of a year or more, the performance of the rules worsens.
- The risk reduction properties of this rule over time are due to the reduction of implied catch. This means that trend-based rules should be considered as a provisional HCR with the aim of achieving a better management system.

2.4 Future work

The WKDLSSLS-2 has not finished its work yet and the participants at WKLIFE X support a third meeting of WKDLSSLS to further develop and refine advice rules for short-lived species.

2.5 References

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

Pedersen, M. W., and Berg, C. W. 2017. A stochastic surplus production model in continuous time. Fish and Fisheries, 18: 226–243.

3 Further developments of WKMSYCat34 catch rules 3.1 (the SPiCT rule), 3.2.1 (the rfb rule) and 3.2.2 (the chr rule)

3.1 Introduction

This section focusses on the ToRs d) and e). It covers further development and testing, within an MSE framework, of the various advice rules proposed by WKMSYCat34.

3.2 Further development of probability-based rules using SPiCT (WKMSYCat34 catch rule 3.1)

The stochastic surplus production model in continuous time (SPiCT; Pedersen and Berg, 2017) is one of the official assessment methods for stocks in ICES category 3 (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, 2017c) suggested equations 1 and 2 for management advice based on SPiCT assessments ("median rule"):

Equation 1

$$\mathrm{TAC} = C_{y+1},$$

Equation 2

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

ICES WKLIFE workshops VII–IX demonstrated that this advice rule can lead to high risk of overfishing in the face of high uncertainty, and highlighted that the time notation of the equations are difficult to interpret for SPiCT due to the in-year time steps of SPiCT (ICES, 2017a; ICES, 2018; ICES, 2019). Therefore, the workshops proposed new equations, which allow to consider any percentile other than the median (50th percentile) for the three distributions (C_{y+1}), relative fishing mortality (F/F_{MSY}), and relative exploitable biomass ($B/\mathrm{MSY}B_{\mathrm{trigger}}$) in the short-term forecast. Here, we present the same equations with an improved time notation that accounts for discrepancies of discrete and continuous time as well as multiannual assessment intervals. Instead of using $y+1$ to refer to the advice period, we use the subscript "pred" to refer to any prediction period $[p_1, p_2]$. Thus, p_1 and p_2 define the start and end of the advice (or prediction) period. This notation accounts for the fact that the advice period is in fact two years for most data-limited stocks in ICES (ICES, 2018a). Combining the two aspects (various percentiles and time notation), the equations 1 and 2 can be written as follows:

Equation 3 $$\text{TAC} = \Phi^{-1}_{(C_{\text{pred}}|F^{\tau}_{\text{pred}})}(f^{\text{C}}),$$

where Φ^{-1} is the inverse distribution function, C_{pred} is the catch during the prediction period, F^{τ}_{pred} is the target fishing mortality during the prediction period, and f^{C} is the "risk fractile" determining the percentile of the predicted catch distribution.

Equation 4 $$F^{\tau}_{\text{pred}} = F_{p_1} \frac{\min\left(1, \Phi^{-1}_{\left(\frac{B_{p_2}}{\text{MSY}B_{\text{trigger}}}\right)}(f^{\text{B}})\right)}{\Phi^{-1}_{\left(\frac{F_{p_1}}{F_{\text{MSY}}}\right)}(f^{\text{F}})},$$

where Φ^{-1} is the inverse distribution function, C_{pred} is the catch during the prediction period, F^{τ}_{pred} is the target fishing mortality during the prediction period, and f^B, f^F are the "risk fractiles" determining the percentile of the predicted biomass and fishing mortality distributions, respectively. We refer to the advice rules defined by equations 3 and 4 as "fractile rules" (referred to as "percentile rules" in previous reports). In contrast to equations 1 and 2 that define a single rule, fractile rules rather describe a suit of rules which can vary by choosing various risk fractiles for the three distributions.

For WKLIFE X, we extended the simulations from the last workshops (ICES, 2017a, 2018; ICES 2019) by (i) additional reference stocks, (ii) a wider variety of HCRs, and (iii) using a new fully stochastic operating model with subannual time-steps. We revised and updated the life-history parameters of the anchovy and haddock stock with detailed information from the stock assessments and personal communication of the stock assessors. Besides the HCRs tested in WKLIFE VIII and IX, we evaluated various $\text{MSY}B_{\text{trigger}} = xB_{\text{MSY}}$ levels for $x \in [0, 3]$. Furthermore, we included more combinations of percentiles on various distributions. Lastly, we used a different operating model to simulate the population and fisheries dynamics than used in WKLIFE VIII and IX. The operating model with quarterly time-steps allowed to simulate multiple surveys at different times of the year, test different data and assessment timing scenarios, and model the fast dynamics of fast-growing stocks more realistically. Overall, the results confirm the findings of previous WKLIFE workshops demonstrating the value of probability-based HCRs (HCRs that account for uncertainty). The details and results of the additional simulations are described in detail in Mildenberger *et al*. (2020).

3.3 Further development of the rfb-rule (WKMSYCat34 catch rule 3.2.1)

The simulation work on the *rfb*-rule presented during the previous WKLIFE workshops (ICES, 2017a; 2018; 2019) has been peer-reviewed and published in the ICES Journal of Marine Science (Fischer *et al*., 2020). Fischer *et al*. (2020) also provide extensive robustness tests and a detailed description of the set-up of the operating model. Additional sensitivity analyses are presented in this report in Section 3.5. The *rfb*-rule has the following form:

$$A_{y+1} = C_{y-1}\, r\, f\, b,$$

where A_{y+1} is the advised catch, C_{y-1} is the previous catch, r corresponds to the trend in the biomass index (as in the current ICES "2 over 3" rule), f is a proxy for the exploitation (mean catch length divided by an MSY reference length) and *b* a biomass safeguard (reducing the catch when the biomass index drops below a trigger value).

The MSE simulations were conducted using FLR (Kell *et al*., 2007) and FLR's mse package. The source code for the simulation in this section is available from GitHub at https://git.io/JTF9q (there are several branches of this repository for different analyses).

3.3.1 Optimisation of the rfb-rule towards MSY

Following on from the initial explorations of a genetic algorithm to optimise the *rfb*-rule at WKLIFE IX (ICES, 2019), this work was progressed and presented to WKLIFE X. A working document is available in the ICES WKLIFE X SharePoint site. The following is a summary extracted from Fischer *et al.* (in press):

> Many data-limited fish stocks worldwide require management advice. Simple empirical management procedures have been used to manage data-limited fisheries but do not necessarily ensure compliance with maximum sustainable yield objectives and precautionary principles. This study focuses on an empirical catch rule and explores the application of a genetic algorithm to improve the performance of the rule by adding an additional optimisation procedure to a management strategy evaluation framework. The optimisation procedure was able to improve the performance of the catch rule against predefined objectives. The optimised rule and the magnitude of the improvement, however, are dependent on the specific stock, stock status and definition of the fitness function. The genetic algorithm proved to be an efficient and automated method for tuning the catch rule and removed the need for manual intervention during the process. Therefore, we conclude that the approach could also be applied to other management procedures, is of particular importance for case-specific tuning, and could be used for data-rich stocks. Finally, we recommend the phasing out of the current generic ICES "2 over 3" advice rule in favour of case-specific catch rules of the form tested here, although neither work well for fast-growing stocks.

3.3.2 Optimisation of the rfb-rule towards the ICES precautionary approach

Section 3.3.1 summarised the work for optimising the rfb-rule towards MSY objectives. However, for application within ICES, the ICES interpretation of the precautionary approach has to be considered, usually defined as: the risk of dropping below B_{lim} should not exceed 5%.

Using an absolute risk metric and threshold is challenging to justify in a data-limited situation because, as a result of the lack of data, specific assumptions have to be made when setting up the operating models and MSE projections. Exploration for one example stock (pollack) revealed that when the *rfb*-rule is applied, the absolute risk level is dependent on, e.g.:

- the length of the projection period (number of years);
- the period over which summary statistics are calculated (short-, medium-, long-term, full period);
- observation uncertainty (e.g. for the biomass and length index);
- stock status at the beginning of the simulation;
- the definition of the limit biomass reference point (B_{lim}).

Therefore, all optimisation ("tuning") towards achieving specific objectives are conditional on the simulation specifications.

In order to include the precautionary approach, the risk component of the fitness function used in the genetic algorithm was adapted and a new MSY-PA fitness function created:

$$\Phi_{MSY-PA} = \Phi_{\mathrm{SSB}} + \Phi_{\mathrm{Catch}} + \Phi_{\mathrm{riskPA}} + \Phi_{\mathrm{ICV}}$$

Φ_{SSB} and Φ_{Catch} represented the deviation of the metric from the MSY target (e.g. Φ_{SSB} = -|SSB/B_{MSY} -1|; negative because the optimisation maximised the fitness) and Φ_{ICV} was the value of the interannual catch variability. The new element was Φ_{riskPA}, which was based on a sigmoid curve as a function of the B_{lim} risk (Figure 3.3.2.1). This element of the fitness function is inactive as long as the risk stays below 5%. However, a penalty is applied when the risk exceeds 5%. The penalty curve after 5% was steep and quickly reached its asymptote because this area should be avoided and therefore has a large penalty.

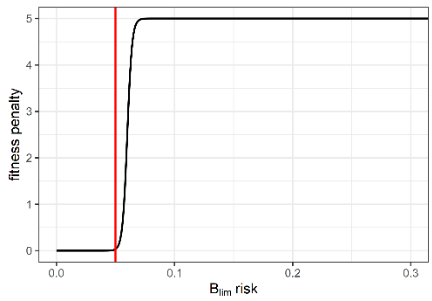


Figure 3.3.2.1. Fitness penalty of the genetic algorithm as a function of B_{lim} risk.

For the simulations for the optimisation based on the MSY-PA fitness function, the same simulation conditions as used for the MSY fitness function optimisation (Section 3.3.1) were recycled (e.g. fishing histories, 500 replicates, 50-year projections, observations uncertainty for biomass index and mean catch length index with CV=0.2, 29 stocks).

The first explorations of this penalty function were conducted for Pollack, and are summarised in Figure 3.3.2.2. The risk could be reduced to fall within the 5% limit by including a catch multiplier. This optimisation led, however, to a substantial deterioration in other metrics (the SSB overshot B_{MSY} and the catch was low). The inclusion of the remaining *rfb*-rule tuning parameters alleviated these trade-offs, while still keeping the risk within the 5% threshold. Adding an uncertainty cap (with the possibility of asymmetric constraints) did not improve the performance, neither when included on its own, nor in combination with the multiplier or the remaining parameters.

Subsequently, the optimisation of the rfb-rule was applied to all 29 stocks (Figure 3.3.2.3). The results were similar to the ones obtained for pollack, i.e. inclusion of the multiplier was enough to limit the risk to the 5% threshold but came at the cost of low yields, but this situation could be improved by including more tuneable parameters. For the higher-*k* stocks (k≥0.32 yr^{-1}), the risk could be reduced to 5%, but at the cost of zero or very low catch.

Figure 3.3.2.2. Exploration of the MSY-PA fitness function for pollack; "default" corresponds to the default rfb-rule, the remaining options show optimised results when components of the rule are added as tuneable parameters to the optimisation procedure (options with GA prefix; "all w/o cap" refers to the *rfb*-rule with all components but without the uncertainty cap and "all" includes all components and the uncertainty cap).

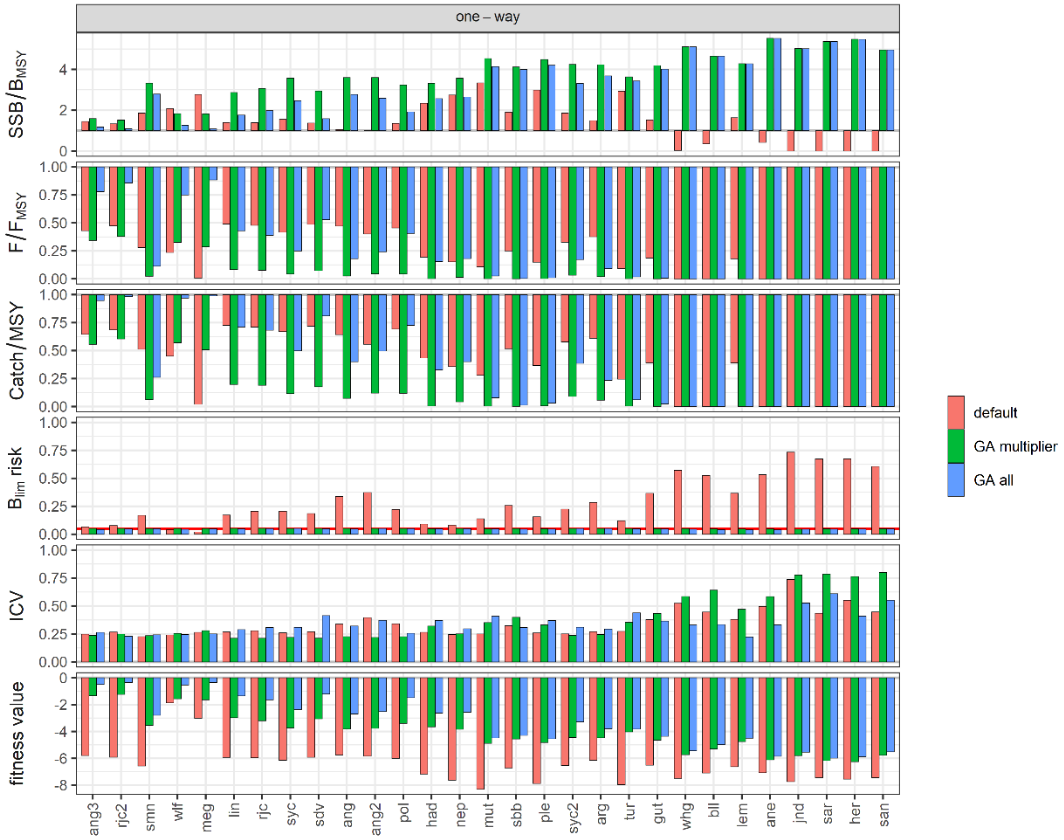


Figure 3.3.2.3. Application of the genetic algorithm optimisation with the MSY-PA fitness function for 29 stocks. "default" corresponds to the default rfb-rule, "GA multiplier" includes the multiplier as a tuneable parameter and "GA all" all parameters, including the uncertainty cap.

3.4 Further development of the chr-rule (WKMSYCat34 catch rule 3.2.2)

The rfb-rule, as discussed in Fischer *et al.* (2020; in press) and in Section 3.3, exhibits unsatisfactory performance for higher-*k* stocks ($k \geq 0.32$ yr^{-1}) with high risks and low yields. Therefore, alternatives have to be explored. One such alternative is a constant harvest rate (chr) rule. An example of such a constant harvest rate rule is the "WKMSYCat34 rule 3.2.2", also called "F_{proxy} rule" or "Icelandic rule", which has already been explored during previous WKLIFE workshops (ICES, 2017b; 2017a). The difficulty with this rule is that a target proxy harvest rate needs to be defined, which is challenging in a data-limited situation. WKLIFE VI (ICES, 2017b) explored the use of a proxy harvest rate, which was derived when stocks were fished deliberately at F_{MSY}, but concluded that this parameterisation showed poor performance for higher-*k* stocks. WKLIFE VII (ICES, 2017a) tested a different proxy harvest rate by fishing the stocks until the mean catch length matched the $L_{F=M}$ MSY proxy length, and then targeted a harvest rate derived from this equilibrium situation. These target harvest rates proved inaccurate, and the performance was also poor for higher-*k* stocks. Furthermore, these two examples are difficult to implement in reality.

The code for the MSE simulations in this section is available from GitHub at https://git.io/JTFS5.

3.4.1 Exploration of constant harvest rate-type rules

First, the applicability of constant harvest rates for higher-k stocks was explored. For this purpose, the operating models with the "random" fishing history were expanded to 10 000 replicates. Then, a simple constant harvest rate was applied:

$$C_{y+1} = I_{tsb,y-1}\, H$$

where $I_{tsb,y-1}$ is a total biomass index (with an observation uncertainty CV of 0.2) and H the harvest rate drawn randomly from $U(0,1)$. This rule was implemented with an annual TAC and for a period of 100 years. A large number of replicates and harvest rates allowed an analysis of the results depending on initial stock status and target harvest rate. The results are summarised in Figure 3.4.1.1. When only the initial ten years of the simulation were considered, the realised catch was dependent on the initial stock status (first row of Figure 3.4.1.1). When using the full 100-year projection, the initial stock status did not influence the long-term catch. For the stocks simulated, there was a specific harvest rate for which the long-term catch was maximised. However, this rate was stock dependent and generally lower for the very high-k stocks (the optimum harvest rate correlated to k with $\rho = -0.90; p \leq 0.001$). These results indicated that constant harvest rates were a promising option for managing high-k stocks, but excluding the very high-k stocks.

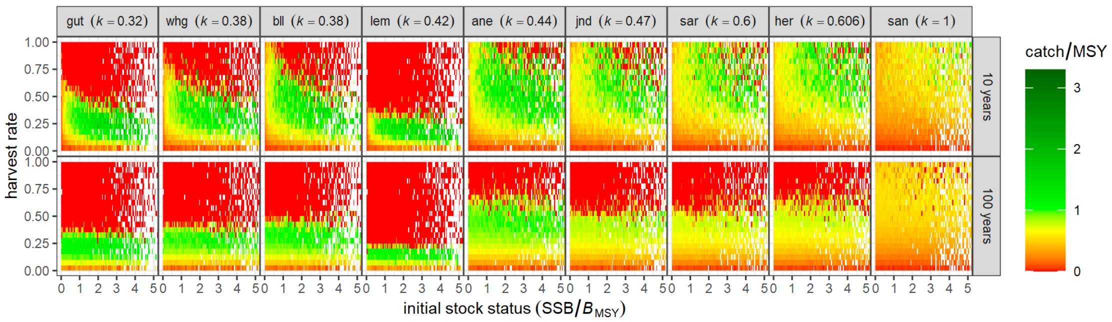


Figure 3.4.1.1. Application of a constant harvest rate rule for the higher-*k* stocks. Shown is the yield relative to MSY for two reporting periods (10 years, i.e. year 1 to 10 and 100 years, i.e. year 1 to 100). The x-axis shows the relative stock status prior to the implementation of the rule, and the y-axis the target harvest rate.

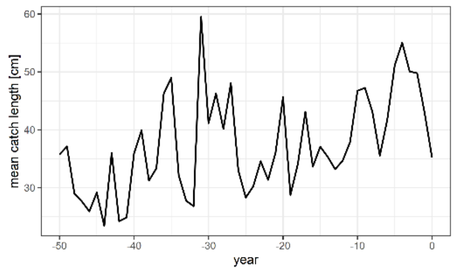
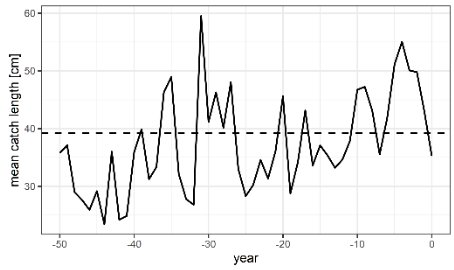
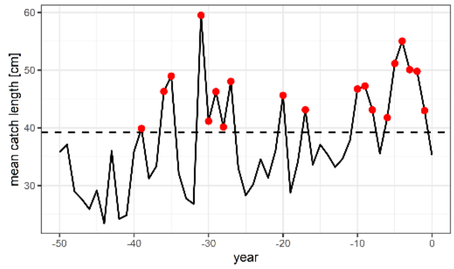
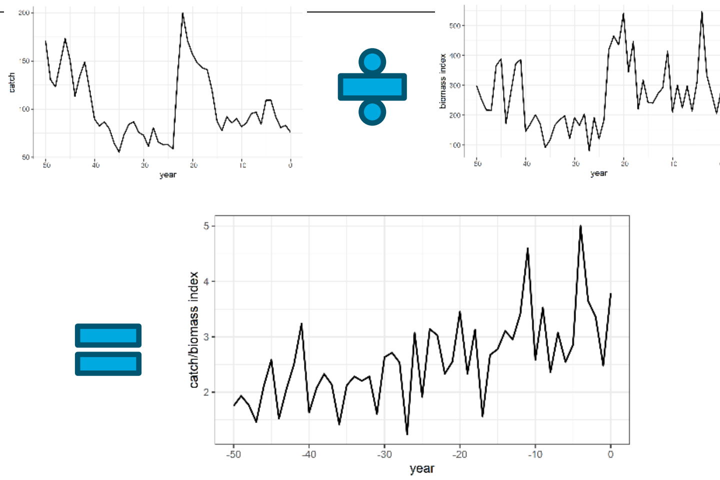
3.4.2 The proposed chr-rule

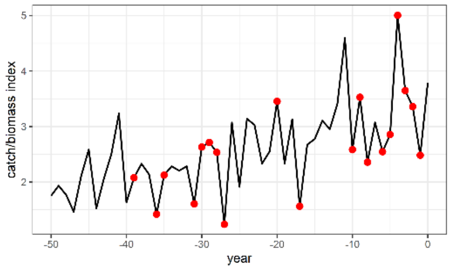
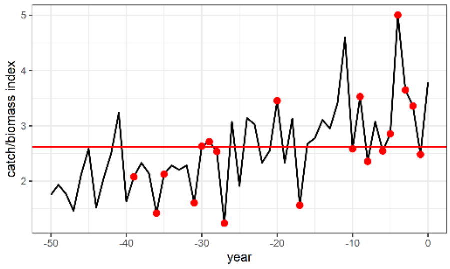
For a constant harvest rate rule to be applicable in reality, the harvest rate needs to be defined relative to an index. Therefore, the "F_{proxy} rule" was revisited, now called the chr-rule:

$$C_{y+1} = I_{y-1}\, F_{\text{proxy,MSY}}\, b\, m,$$

where C_{y+1} is the new catch advice, I_{y-1} a total biomass index, $F_{\text{proxy,MSY}}$ the target harvest rate, b the biomass safeguard (defined identical to the rfb-rule, i.e. $b = min(1, I_{y-1}/I_{\text{trigger}})$ and $I_{\text{trigger}} = 1.4\, I_{\text{loss}}$), and m a multiplier $\leq$1). A procedure to derive the target harvest rate from empirical data was devised, and is described in Table 3.4.2.1.

Table 3.4.2.1. Description of the procedure for deriving a target harvest rate from empirical data as part of the chr-rule.

Step	Description	Visualisation (example)
1	Calculate time-series of mean catch length $\overline{L}_y$ (above the length of first capture L_c)	
2	Calculate MSY proxy reference catch length: $$L_{F=M} = 0.75L_c + 0.25L_\infty$$ where $L_c$is the length at first capture and L_∞ the von Bertalanffy asymptotic length	
3	Identify years where $\overline{L}_y \geq L_{F=M}$	
4	Calculate the historical harvest rate by dividing the catch time-series by the biomass index time-series	

Step	Description	Visualisation (example)
5	Take the years from step 3 and extract these years from the harvest rate time-series	
6	Calculate the mean of the values from step 5	

This chr-rule was then simulated in an MSE based on the "random" fishing history for a projection period of 50 years, with 500 replicates and an annual TAC. By default, there is a 1-year time-lag between the assessment year and the last data year for the index (i.e. I_{y-1} is used). The effect of reducing this lag was tested (i.e. I_y). Furthermore, multipliers in the range [0, 1] were explored. The results are shown in Figure 3.4.2.1. For all stocks, a catch maximum was observed for a multiplier $m < 1$. The location of this catch maximum was dependent on the stock and the time-lag in the index. The performance of the rule for the tested stocks was generally good, apart from the very high-k stocks.

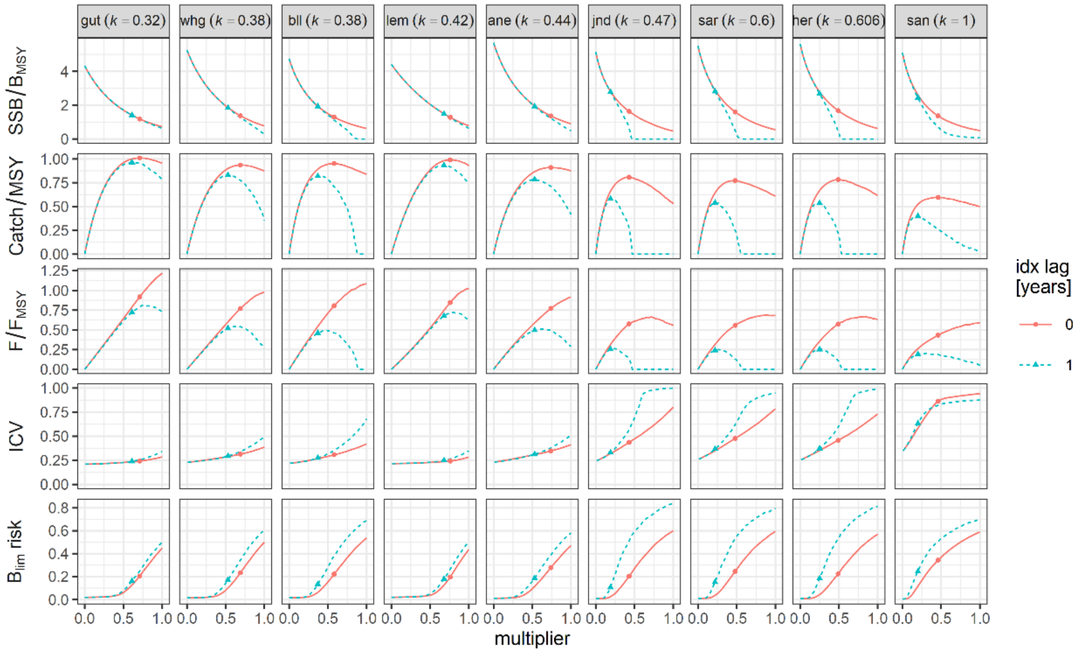


Figure 3.4.2.1. Summary statistics for the application of the chr-rule for the higher-*k* stocks. The points and triangles indicate the location of the maximum catch.

3.5 Sensitivity analysis for the operating models used to test empirical rules

3.5.1 Introduction

The operating models generated for the testing of the rfb rule (also known as the WKMSYCat34 catch rule 3.2.1; ICES, 2017c) and later for the optimisation of the rule with a genetic algorithm were based on few primary input parameters (for details, see Fischer *et al.*, 2020). These life-history parameters are usually available for data-limited stocks and can sufficiently define a fish stock in order to generate an age-structured operating model, which captures its intrinsic dynamics and behaviour towards extrinsic forces such as fishing. Fischer *et al.* (2020) found that the von Bertalanffy growth parameter *k* was the most important factor influencing the performance of the catch rule when applied to the simulated stocks. This raises the question about whether this is only true for this specific catch rule's performance, or which other parameters are most influential for the operating models.

The influence of parameters in a model can be evaluated with an elasticity analysis. In an elasticity analysis, the influence of input parameters of a model is evaluated, e.g. by calculating the first order derivates of one or more important model output parameters with respect to model input parameters, which can be represented with a Jacobian matrix.

The generation of operating models is a complex process and requires the inclusion of assumptions, e.g. about life-history invariants (Beverton and Holt, 1959; Beverton, 1992; Prince *et al.*, 2015). Furthermore, this process includes numerical optimisations, e.g. for the calculation of MSY levels. Therefore, operating model parameters cannot be purely algebraically linked to the primary input parameters. Consequently, the gradients of the elasticity analysis have to be approximated numerically.

3.5.2 Methods

From the total list of 29 stocks, two example stocks were selected for the elasticity analysis. These stocks comprised the large demersal medium-k stock pollack (*Pollachius pollachius*) and the pelagic high-k stock herring (*Clupea harengus*). The primary input parameters for these are given in Table 3.5.1.

Table 3.5.1. Primary input parameters for the two example stocks used in the elasticity analysis.

Primary input parameters	Pollack (pol)	Herring (her)
Length–weight parameters		
$\boldsymbol{a}$	0.0076	0.0048
$\boldsymbol{b}$	3.069	3.198
von Bertalanffy growth parameters		
$\boldsymbol{k}$ [year^{-1}]	0.19	0.606
$\boldsymbol{L_\infty}$ [cm]	85.6	33
$\boldsymbol{t_0}$ [years]	-0.1*	-0.1*
maturity		
$\boldsymbol{a_{50}}$ [years]	4.11**	1.87**
steepness		
$\boldsymbol{h}$	0.75*	0.75*

*** Default parameter value in the absence of empirical data.**

**** These values have been calculated from L_{50} with the von Bertalanffy growth function.**

These input parameters were then used to create operating models with the FLR (Kell *et al.*, 2007) package FLife. An elasticity analysis of the influence of these primary input parameters on important output parameters describing the characteristics of the operating models was then conducted. The output parameters considered were the Beverton–Holt stock–recruitment parameters (α, β), the MSY reference points for fishing mortality (F_{MSY}), SSB (SSB_{MSY}), total stock biomass (B_{MSY}), recruitment (R_{MSY}) and catch (MSY), unfished reference points for total stock biomass (B_0) and recruitment (R_0), instantaneous growth rate at the limit of zero stock size (g) and conditional growth rate at MSY (g_c), spawning potential ratio at zero stock size (SPR_0) and at MSY (SPR_{MSY}), natural mortality (M) and the ratios F_{MSY}/M and M/k.

The elasticity analysis was conducted by numerically approximating the gradient of the output parameters at the value of the primary input parameters, i.e. the first order derivates.

3.5.3 Results

Table 3.5.2 shows the results of the elasticity analysis in the form of the Jacobian matrices for the two stocks, pollack and herring.

Table 3.5.2. Jacobian matrices for the elasticity analysis of pollack and herring. Columns correspond to the input parameters used in the creation of the operating models and rows show the generated operating model parameters. The row and column labelled "default" represent the default values for the input and output parameters for comparison.

	default	L_∞	k	t_0	a	b	a_{50}	h
Pollack								
default		85.6	0.19	-0.1	0.0076	3.069	4.1	0.75
α	4.6	-0.2	-47.3	19.0	-598.8	-19.3	0.4	-2.2
β	90.9	0.0	0.0	0.0	0.0	0.0	0.0	-528.9
F_{MSY}	0.2	0.0	1.4	0.0	0.0	-0.1	0.0	0.6
SSB_{MSY}	253.6	0.2	-287.3	6.1	-1.6	27.8	-5.1	-434.6
B_{MSY}	575.5	-2.2	1678.1	209.3	-2.1	-278.5	103.2	-251.6
R_{MSY}	3.4	-0.2	-35.8	14.0	-440.8	-14.1	0.3	2.0
MSY	65.3	-0.2	397.1	-3.1	0.0	-13.0	3.8	93.2
B_0	1404.8	-3.1	2624.0	249.8	0.0	-395.6	137.2	0.0
R_0	4.2	-0.2	-43.3	17.4	-548.9	-17.7	0.4	0.0
r	0.3	0.0	0.7	0.0	0.0	0.0	0.0	0.8
r_c	0.1	0.0	0.4	0.0	0.0	0.0	0.0	0.3
SPR_0	239.7	11.3	2490.8	-998.5	31541.9	1015.9	-23.4	0.0
SPR_{MSY}	75.7	3.6	723.6	-314.0	9962.0	327.0	-8.5	-175.0
M	0.2	0.0	0.4	0.0	0.0	0.0	0.0	0.0
F_{MSY}/M	0.9	0.0	4.6	-0.2	0.0	-0.3	0.1	2.8
M/k	1.2	0.0	-3.8	0.1	0.0	0.0	-0.1	0.0
Herring								
default		33	0.606	-0.1	0.0048	3.198	1.9	0.75
α	26.3	-3.0	-36.5	68.0	-5475.5	-86.6	13.6	-12.7
β	90.9	0.0	0.0	0.0	0.0	0.0	0.0	-528.9
F_{MSY}	1.9	0.0	5.9	1.4	0.0	-1.0	-0.5	12.2
SSB_{MSY}	154.6	1.0	-76.2	-96.5	-3.8	31.2	1.7	-619.5
B_{MSY}	752.3	-5.3	1020.0	14.4	-10.3	-183.4	628.8	-788.6
R_{MSY}	16.6	-1.8	-26.0	39.0	-3448.1	-53.3	8.6	3.1
MSY	446.6	-6.3	1141.5	267.3	0.0	-137.7	-44.0	1184.0
B_0	1965.6	-13.0	2094.1	403.5	0.0	-421.0	1014.5	0.0

	default	L_∞	k	t_0	a	b	a_{50}	h
R_0	24.1	-2.7	-33.5	62.3	-5019.2	-79.3	12.4	0.0
r	1.0	0.0	0.7	0.1	0.0	-0.1	-0.4	2.6
r_c	0.5	0.0	0.5	0.2	0.0	-0.1	-0.2	1.7
SPR_0	41.5	4.7	57.7	-107.4	8647.4	136.7	-21.4	0.0
SPR_{MSY}	9.3	1.1	10.1	-27.8	1946.0	32.0	-4.8	-39.2
M	0.8	0.0	0.6	0.2	0.0	0.0	-0.1	0.0
F_{MSY}/M	2.5	0.0	5.7	1.4	0.1	-1.3	-0.4	16.2
M/k	1.2	0.0	-1.1	0.3	0.0	0.0	-0.2	0.0

The comparison of absolute values of the different derived operating model parameters is meaningless due to different units and only a comparison to the default value is interpretable.

In general, the primary input parameters k (von Bertalanffy growth parameter) and h (recruitment steepness) appeared most influential on most operating model characteristics such as MSY reference points (F_{MSY}, SSB_{MSY}) and growth rate (r) for both stocks.

The effects of k on the operating models are visualised in Figure 3.5.1 for pollack and Figure 3.5.2 for herring.

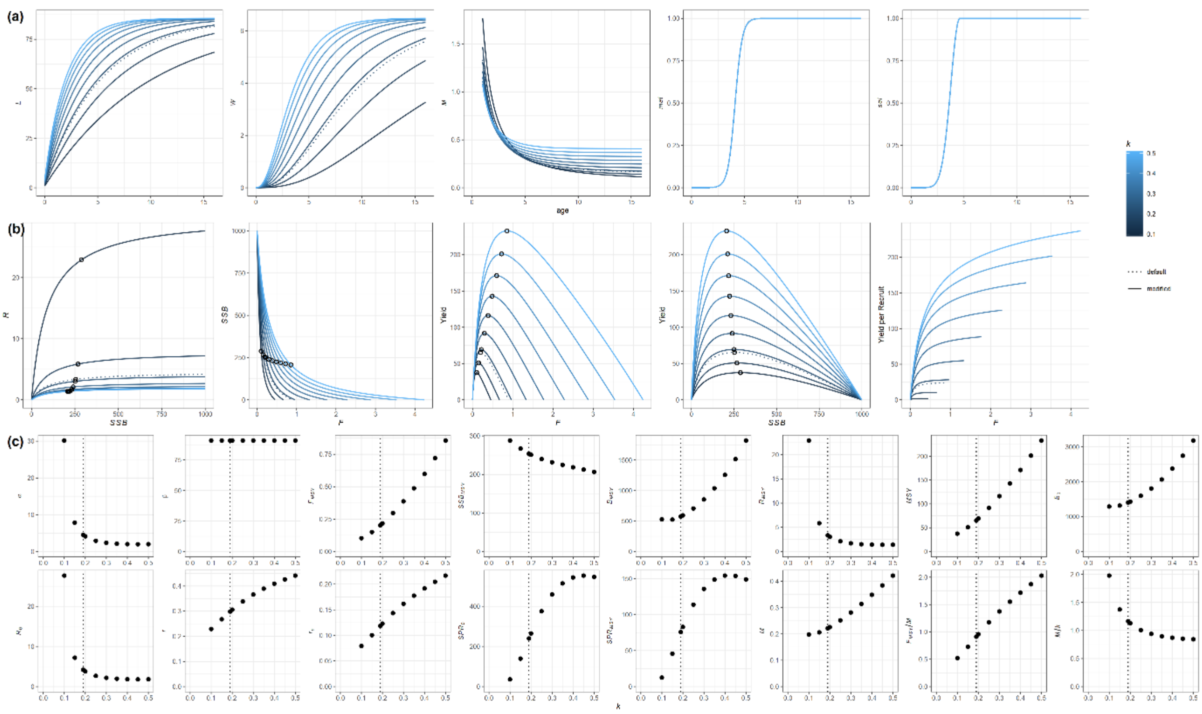


Figure 3.5.1. Effect of the von Bertalanffy growth parameter k on the pollack operating model. (a) shows the basic age-dependent relationships of individual length (L) and weight (W), natural mortality (M), maturity (mat) and fisheries selectivity (sel); (b) the equilibrium dynamics with the MSY levels indicated by circles and (c) the operating model parameters as a function of k, where the location of the values from the Jacobian matrix from Table 1 are indicated by dashed vertical lines.

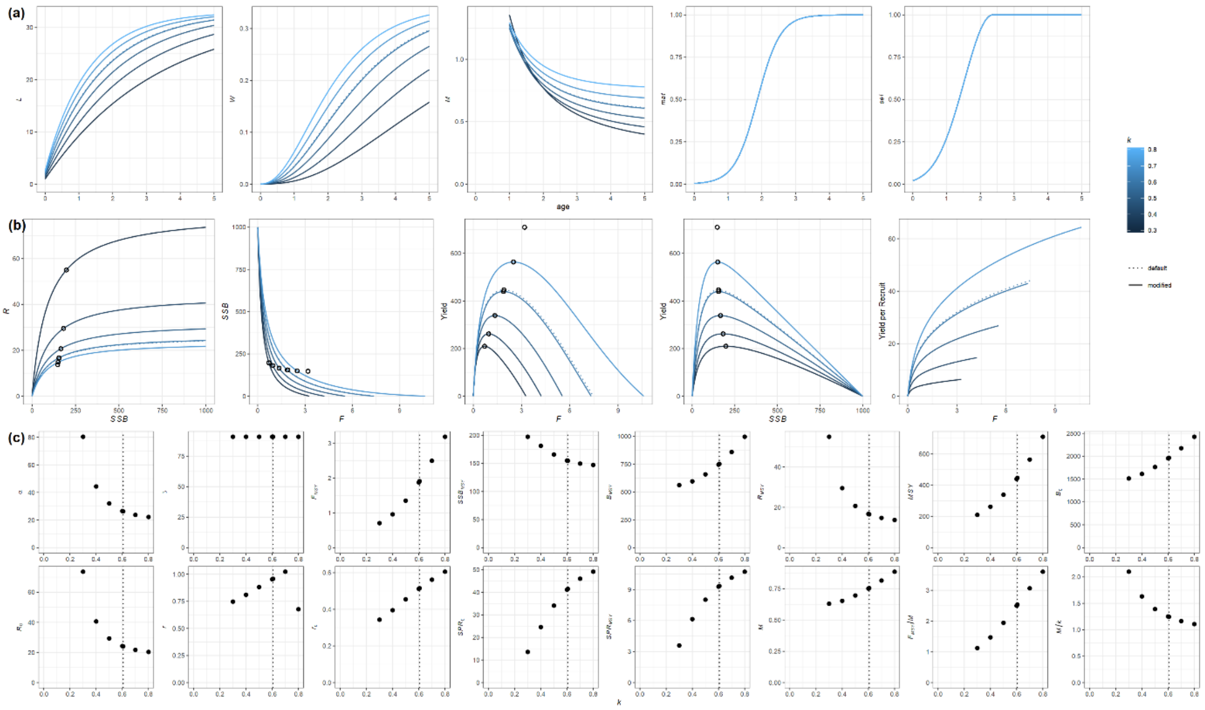


Figure 3.5.2. Effect of the von Bertalanffy growth parameter k on the herring operating model. See Figure 3.5.1 for more details.

3.5.4 Discussion

The elasticity analysis conducted here provided insights into which primary input parameters are important for the definition of operating models.

The analysis revealed that the von Bertalanffy growth parameter k and recruitment steepness h were most influential for the majority of operating model parameters. For some operating model parameters, additional input parameters appeared as important, e.g. for the Beverton–Holt recruitment model parameter α, the allometric length–weight parameter a is highly influential. However, this can be explained with the fact that the allometric a works like a scaling factor, linking the weight-at-age and length. Therefore, a scaling of the allometric a also causes a scaling of the biomass of the stock, which in turn modifies the recruitment parameter without changing the operating model characteristics apart from the absolute scale of biomass.

The steepness of the stock–recruitment model was unsurprisingly one of the most influential parameters. Changes in the steepness cause direct changes in the productivity of a stock, e.g. a higher steepness will inevitably lead to higher productivity at lower stock sizes and therefore MSY reference points change.

Regarding the von Bertalanffy growth parameters, k was more important than L_∞. It is more important how fast an individual approaches its asymptotic size L_∞, as expressed by k, than the absolute value of L_∞. The parameter t_0 is used to shift the entire growth curve along the age-axis. For many of the simulated stocks, this value is poorly estimated or not available and a default of $t_0 = -0.1$ was implemented instead. The elasticity analysis provides reassurance about the appropriateness of using a default value, because t_0 had only a minor effect on the operating models.

Previous analyses found that the performance of the new catch rule was dependant on the value of k (Fischer *et al.*, 2020) of the operating models. The elasticity analysis conducted here supports this finding and yields further evidence that k is a crucial factor suitable for describing the characteristics of a fish stock. k is important to distinguish between species but also the specific value of k for a stock is important and the estimation procedure of k from empirical data should be scientifically sound to ensure realism in simulations.

3.6 Generic application of the empirical rules

This section was updated in September 2021.

This section describes the work conducted during WKLIFE X on the empirical rules, on which the guidelines in Annex 3 are based.

The previous sections described how the empirical rules (rfb-rule and chr-rule) can be optimised and their performance improved depending on life history of fish stocks. For the application to stocks within ICES, the ICES interpretation of the precautionary approach has to be considered, i.e. the B_{lim} risk should not exceed 5%. The rules were tuned with a multiplier so that this risk condition was met. Unless stated otherwise, the rules were tested with a biennial TAC. An additional asymmetric stability measure (the uncertainty cap) was included for the rules, which limited the catch advice increase to +20% and the decrease to -30%, based on the considerations of Fischer *et al.* (2020). The application of the uncertainty cap was ceased as soon as the biomass safeguard (component *b*) fell below 1, i.e. when the biomass index fell below its trigger value.

Simulation conditions were identical for all stocks and rules and similar to the ones on which the preliminary evaluations in WKLIFE VIII (ICES, 2018) were based. Detailed descriptions of the operating models can be found in Fischer *et al.* (2020). Two fishing histories were used, the "one-way" scenario representing an overfished state, and the "random" fishing history, covering a wide range of possible exploitation patterns. The MSE projections were conducted over a period of 100 years and with 500 simulation replicates. Observation uncertainty was added to the aggregated biomass index and the mean catch length index, both with a CV of 0.2. Recruitment variability (σ_R) was set to 0.6. B_{lim} was defined as the SSB where recruitment was impaired by 30%.

As already described in Section 3.3.2, risk and uncertainty in a simulation are closely related, which poses challenges for data-limited situations, particularly if absolute risk thresholds are used, such as the 5% here. Therefore, we have to re-iterate that the tuning performed here is specific to the simulated conditions. However, the simulations include a reasonable amount of uncertainty, contain an over-exploitation scenario (the "one-way" fishing history), and the proposed rules are a step forward from the currently applied "2 over 3" rule, which was initially only meant to be an interim solution.

3.6.1 Generic application of the rfb-rule

Fischer *et al.* (2020; in press) showed that the rfb-rule only performs satisfactorily for stocks with von Bertalanffy growth parameter k≤0.32 yr^{-1}. Therefore, this section only considers the following stocks: blackbellied angler (ang3, k=0.08 yr^{-1}), thornback ray (rjc, k=0.09 yr^{-1}), Atlantic wolffish (wlf, k=0.11 yr^{-1}), golden redfish (smn, k= 0.11 yr^{-1}), megrim (meg, k=0.12 yr^{-1}), ling (lin, k=0.14 yr^{-1}), thornback ray (rjc2, k=0.14 yr^{-1}), starry smooth-hound (sdv, k=0.15 yr^{-1}), lesser spotted dogfish (syc, k=0.15 yr^{-1}), angler (ang2, k=0.18 yr^{-1}), angler (ang, k=0.18 yr^{-1}), pollack (pol, k=0.19 yr^{-1}), haddock (had, k=0.20 yr^{-1}), Norway lobster (nep, k=0.20 yr^{-1}), striped red mullet (mut, k=0.21 yr^{-1}), black seabream (sbb, k=0.22 yr^{-1}), greater argentine (arg, k=0.23 yr^{-1}), European plaice (ple, k=0.23 yr^{-1}), lesser spotted dogfish, (syc2, k=0.23 yr^{-1}) and turbot (tur, k=0.32 yr^{-1}). Furthermore, these stocks were grouped into two k-groups: low-k (0.08≤k<0.20 yr^{-1}) and medium-k (0.20≤k≤0.32 yr^{-1}).

[Note, for the purpose of the flowchart shown in Annex 3, the grouping is modified to k<0.2 yr^{-1} and 0.20≤*k*<0.32 yr^{-1} to avoid ambiguity in application.]

The outcome of the application of the rfb-rule is summarised in Figures 3.6.1.1 and 3.6.1.2. The median line for the B_{lim} risk of the low-*k* stocks exceeds 5% just below a multiplier of 0.95 and for the medium-*k* stocks at a multiplier of 0.9. Therefore, we recommend the use of these multipliers if case-specific tuning is not performed.

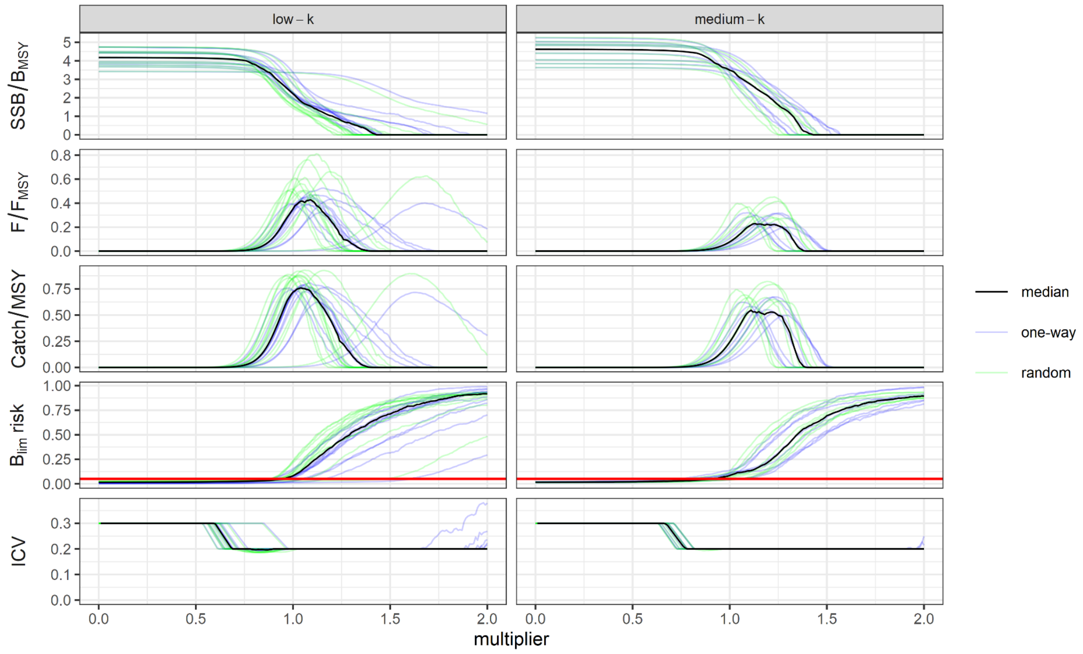


Figure 3.6.1.1. Results of the application of a multiplier to the rfb-rule on summary statistics. On the left are the low-*k* (0.08≤*k*<0.2 yr^{-1}) stocks, on the right the medium-*k* (0.20≤*k*≤0.32 yr^{-1}) stocks. The blue curves show the results from the one-way fishing history, the green curves from the random fishing history and the black curve is the median of all stocks and fishing histories.

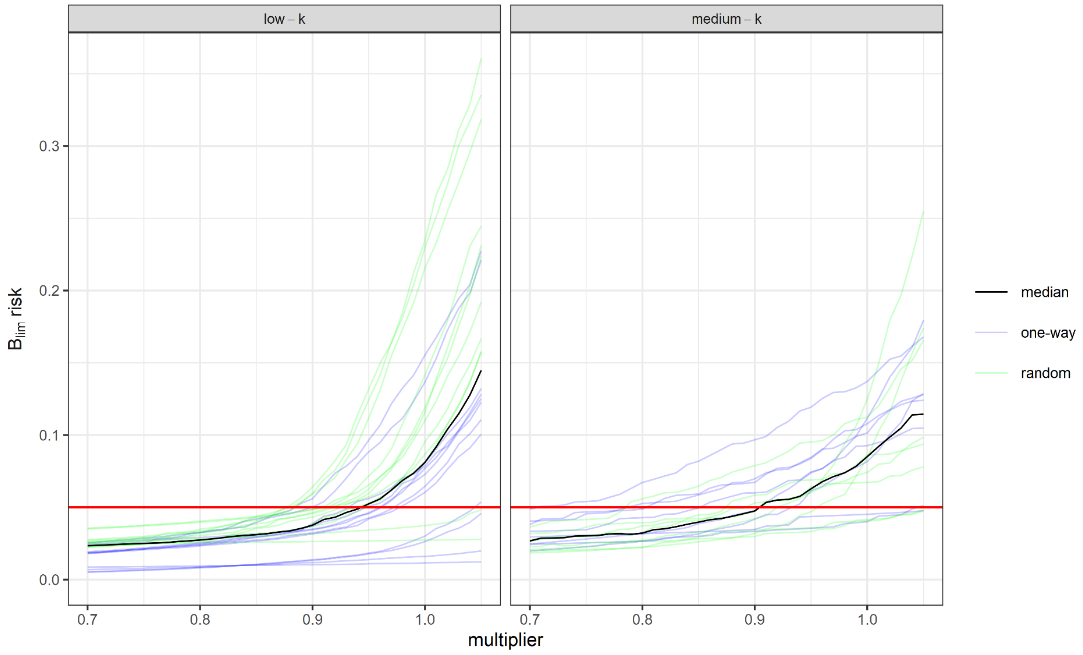


Figure 3.6.1.2. The same as Figure 3.6.1.1 zoomed in onto the B_{lim} risk.

3.6.2 Generic application of a rb-rule

There are situations where the rfb-rule, as described in Section 3.6.1, might not be applicable. This might be because the mean catch length is not available or considered too unreliable, so that the *f* component of the rule cannot be included. In such cases, we propose a simplification of the rfb-rule, where the *f* component is removed, i.e. an rb-rule.

This rb-rule has been tested for all 29 stocks, but without separating them into *k*-groups. The results are presented in Figure 3.6.2.1. The median curve for the B_{lim} risk exceeds 5% at around 0.9. However, there is a large spread around this median, and some curves never fall below 5% (mainly the smaller short-lived stocks: European pilchard, herring and sandeel, but also John Dory). Therefore, we recommend the use of a precautionary multiplier of 0.5 if no case-specific tuning is performed.

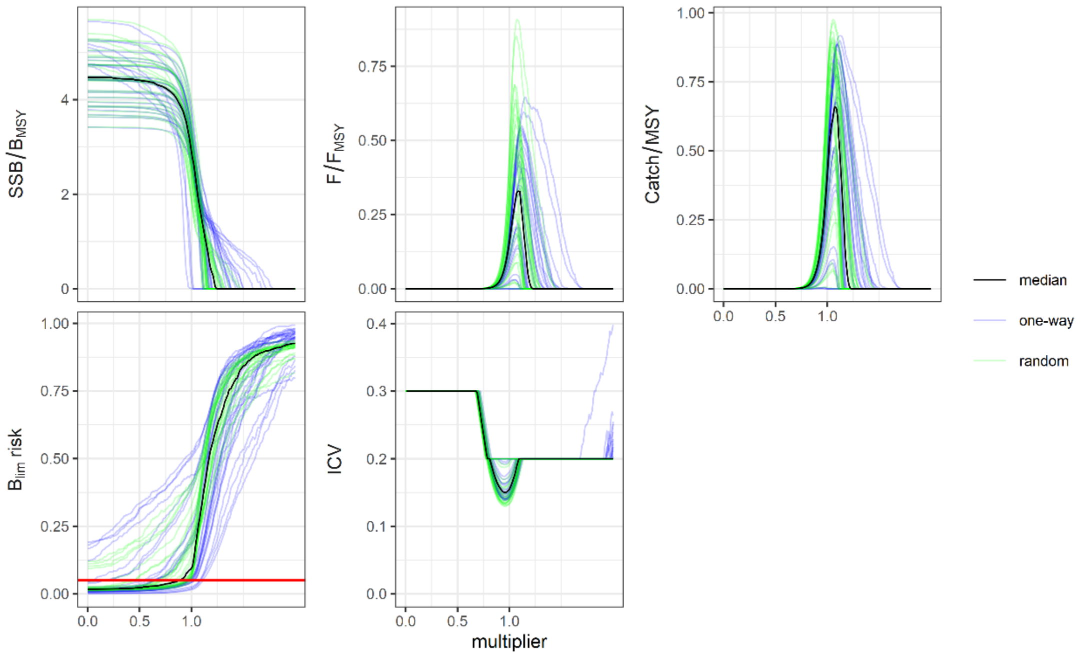


Figure 3.6.2.1. Results of the application of a multiplier to the *rb*-rule (without the *f* component) on summary statistics. Shown are the results for all 29 stocks. The blue curves show the results from the one-way fishing history, the green curves from the random fishing history and the black curve is the median of all stocks and fishing histories.

3.6.3 Generic application of the chr-rule

For stocks with $k \geq 0.32$ yr^{-1}, the rfb-rule should not be applied because of poor performance and high risks. Alternatively, the constant harvest rate (chr) rule could be applied. This rule in combination with a multiplier and annual catch advice was tested for the following higher-k stocks: tub gurnard (gut, k=0.32 yr^{-1}), whiting (whg, k=0.38 yr^{-1}), brill (bll, k=0.38 yr^{-1}), lemon sole (lem, k=0.42 yr^{-1}) and anchovy (ane, k=0.44 yr^{-1}). The very high-k stocks are excluded.

The results are summarised in Figure 3.6.3.1. The median curve for the B_{lim} risk exceeds 5% just above a multiplier of 0.5. Therefore, we recommend the use of a multiplier of 0.5 if no case-specific tuning is performed.

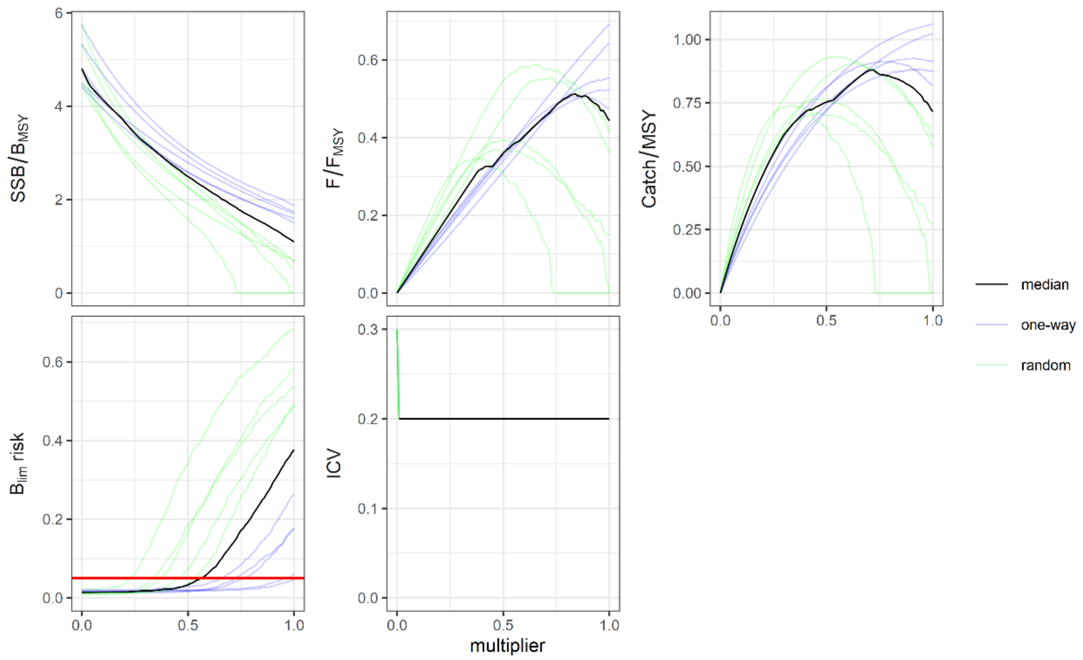


Figure 3.6.3.1. Results of the application of a multiplier to the chr-rule. Shown are the results for stocks with 0.32≤k≤0.44 yr^{-1}. The blue curves show the results from the one-way fishing history, the green curves from the random fishing history and the black curve is the median off all stocks and fishing histories.

3.6.4 Rules for bycaught elasmobranch stocks

The draft of the "ICES technical guidance on advice rules for stocks in Categories 3 and 4" (Annex 3 of ICES, 2019) included a section about "advice rules for harvest control rules for bycaught elasmobranch stocks" in which an adapted version of the rfb rule (without the *b* component, i.e. an rf rule) was suggested. This rf-rule included a "2 over 5" ratio for a biomass index and a restrictive uncertainty cap (limit catch advice changes to +5% and -25%). The application of this rule was discussed again at WKLIFE X, and concerns expressed about the formulation of the rule. The uncertainty caps are restrictive, and a justification for the omission of the biomass safeguard (the *b* component of the rfb rule), or alternative safety measures such as the PA buffer associated with the "2 over 3" rule, are lacking. The biomass safeguard is the primary component safeguarding a stock in case of low stock levels.

At WKLIFE X, the performance of the rf-rule (including the constraints) was compared to the rfb-rule. The rfb-rule tested included the +20/-30% constraints and a multiplier as proposed, depending on *k*. This evaluation was done for the five elasmobranch stocks included in the simulations for the rfb-rule: thornback rays (rjc2, *k*=0.09 yr^{-1} and rjc, *k*=0.14 yr^{-1}), starry smooth-hound (sdv, *k*=0.15 yr^{-1}) and lesser spotted dogfish (syc, *k*=0.15 yr^{-1} and syc2, *k*=0.23 yr^{-1}).

The B_{lim} risk for the two rules is compared in Figure 3.6.4.1. The B_{lim} risk of the rf-rule is dependent on the fishing history (i.e. on the initial stock status), with high-risk values for all elasmobranch stocks in the "one-way" fishing history, several times as high as for the rfb-rule. The rfb-rule resulted in more stable risks, irrespective of the fishing history.

Therefore, we conclude that the rf-rule, in its suggested parameterisation, should not be used and be removed from the guidelines. Instead, the rfb-rule can be used for elasmobranch stocks, which are generally slow-growing stocks, for which the rfb-rule performed best.

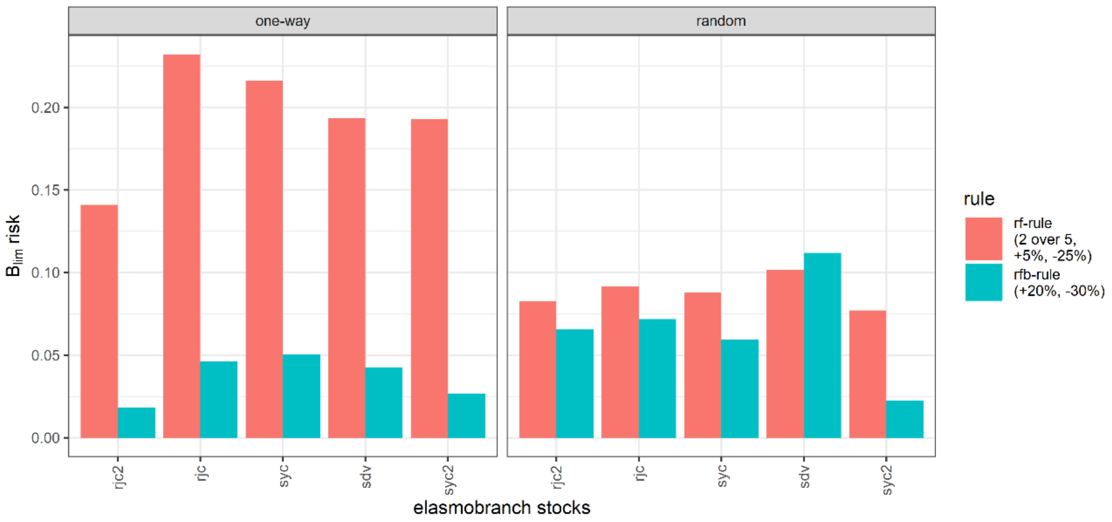


Figure 3.6.4.1. Comparison of the B_{lim} risk of the rf- and rfb-rule for elasmobranch stocks.

3.7 Summary and conclusions

- SPiCT

Simulation testing carried out in the frame of WKLIFE X revealed that MSY-based harvest control rules (HCRs) based on a SPiCT assessment ideally include two components in addition to MSY reference points. The first relates to the use of a biomass threshold (MSY $B_{trigger}$) similar to the HCR for data-rich stocks within ICES (ICES stock categories 1-2). The fishing mortality is set equal to F_{MSY} when the biomass is above the threshold, but is reduced linearly to zero with declining biomass. ICES guidelines define MSY $B_{trigger}$ as 50% of B_{MSY} for surplus production models. Our simulations indicate that larger fractions of B_{MSY} reduce the risk even more and show a generally good performance. Future research should evaluate different definitions of the biomass threshold (see below in Subsection 3.8). The second relates to the quantification and consideration of uncertainty in the calculation of the advised catch (TAC). This is done by considering the short-term forecast of the catch distribution and calculating the TAC using a percentile lower than the median (fractile rule). Both the biomass threshold and the fractile rule reduce the risk of overfishing, which is linked to a short-term loss in yield, but not necessarily to a loss in the long term.

Our generic MSE work indicated that risk fractiles in the range of 0.15–0.45 for the predicted catch distribution (f^{C}) describe a meaningful trade-off of risk, yield and interannual variability in yield. Very small fractiles ($f^{C} < 0.05$) can lead to large variability in yield and should be avoided. The choice of the actual risk fractile depends on fisheries objectives and the stakeholders' willingness to take risk. These results do not replace the application of stock-specific simulations and we highly recommend to apply stock-specific MSEs to derive the most effective risk fractiles. Only when stock-specific MSEs are not feasible and until further research indicates differently, we recommend the use of the probability-based threshold HCR with MSY $B_{trigger}$ = 50% B_{MSY} and the 35th percentile of the predicted catch distribution ($f^{C} = 0.35$). These recommendations are also summarised in Annex 3 Method 1. This work is described and discussed in detail in Mildenberger *et al*. (2020).

- Empirical rules based on life history

Further work on the rfb rule showed that performance could be improved by tuning towards specific objectives (MSY or Precautionary Approach), using tools such as genetic algorithms, but this would require stock-specific analyses. Generally, further optimisation suggested a reduction of lags (so as to use more recent information) and more flexible constraints (uncertainty caps were effectively removed), and as a result led to a substantial improvement in performance related to management objectives, but this can only be recommended when stock-specific analyses are possible. However, we cannot recommend the use of the rfb rule for fast-growing stocks ($k \geq 0.32\ yr^{-1}$). Additional analyses considered a constant harvest rate (chr) rule, and this appeared to be suitable for faster-growing stocks ($0.32<k<0.45\ yr^{-1}$), but not for short-lived and very fast growing stocks ($k \geq 0.45\ yr^{-1}$). The chr rule required the use of empirical data (the mean of the ratio of the catch relative to the index for the cases where the mean length in the catch was above $L_{F=M}$) to characterise a harvest rate that could be used as a proxy for an MSY harvest rate (Section 3.4 and Annex 3).

In order to ensure compliance with the ICES 5% risk threshold, a multiplier (m<1) is applied to the catch rules. Because of a need to perform generic testing to ensure adequate performance of the rules across a wide range of conditions (related to life history and stock depletion) in meeting this criterion, there is inevitably a loss in performance of the rule. This drawback could be addressed through stock-specific simulation testing. This additional work led to a revision of the guidelines (Annex 3 of WKLIFE IX), including specification of multipliers depending on life-history traits (k) given in Annex 3 of this report.

3.8 Future work

- General

So far, most MSE work assumed unbiased independent randomly distributed noise/uncertainty/errors for processes and observations (usually lognormal, normal or uniform distributed). However, another important component of uncertainty is often neglected: bias. Bias can be present and should be simulated for catch observations (landings vs. discards, misreporting), effort observations (selectivity/gear changes), abundance index observations (hyperstability), or length–frequency distributions which are used, e.g. for the estimation of the stock-status proxies (non-representative samples).

Further work should revisit the definition of B_{lim} in the OM. Ideally, the definition considers life-history traits of the stock as well as all density-dependent processes and stock-specific process uncertainty (natural stock variability, recruitment variability).

There is a strong need for a software package that allows fast and straight-forward application of stock-specific MSEs. The package should (i) include several operating models with different assumptions regarding for instance the assumptions of density-dependence (production models vs. age-based models), (ii) include all ICES HCRs, (iii) allow for straight-forward conditioning of the MSE from a the stock assessment, (iv) be well-documented, user-friendly, and open-access.

- SPiCT

Further research regarding the HCR for SPiCT assessments should evaluate the performance of different biomass thresholds. If defined as a fraction of B_{MSY}, values in the range of 50–100% should be considered for stocks with different life-history traits. The implications of an additional biomass limit reference point in the HCR, such as in the 40–10 rule, should be explored.

A novel data-limited HCR as an alternative to the ⅔ rule was introduced in WKLIFE X: the 'Bref rule'. Similar to the ⅔ rule, the Bref rule aims at stabilising the biomass. However, it is based on the biomass estimated by SPiCT relative to a reference biomass (Bref) instead of raw index observations. The reference biomass could be defined as the biomass (estimated by SPiCT) at any point in time or any period of time. Preliminary results presented to WKLIFE X show a good performance in terms of the risk-yield trade-off of the rule, but further simulations are required. In particular, the performance of the method has to be correlated to the level of contrast in the available data.

- Empirical rules based on life history

OMs more suitable for short-lived cases (e.g. with subannual time-steps) should be explored and developed so that testing can be done in a consistent way across a wide range of scenarios.

Consider additional work on constant harvest rate based rules.

A framework for investigating risk equivalency should be explored and developed to ensure more uncertainty is associated with more precautionary advice across the different ICES categories, and to evaluate the value of information.

More case-specific work is needed to condition the OMs more closely to historical data (rather than the generic testing explored so far), so that the rules developed can undergo for further testing to confirm these rules are robust, given actual data. Such conditioning of OMs should account for model fit and prediction skill. Case-specific work has not been possible to date due the data-limited nature of the cases examined so far.

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4 Stochastic surplus production models

This Section of the report focusses on the ToR c).

4.1 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 level 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). Onboard 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.

4.2 Effects on under-estimating discards in production models: improving the assessment of African black hakes

Assessment of black hake (*Merluccius spp*.) in CECAF group is based on the Biodyn model fitted in EXCEL with Solver. WKLIFE IX established as a ToR to improve assessment of this DLS based on SPICT incorporating uncertainty process and observation errors to develop operating models and then to test uncertainties produced by unknown discards in the black hake fisheries. Based on recent work about discards in the Spanish fresh trawling fishery (Soto *et al*., 2020) initial simulated underreported discards scenarios were proposed adding constantly percentages of catches (0%, 10%, 20%, 30%) during the period of the assessment representing constant levels of discards, bycatch and non-declared catches (Table 4.2.1).

The first limitation to fit the production models to black hake is the absence of a standardized index of abundance. During years, the nominal CPUE of the Spanish fresh trawling fleet has been used as input for Biodyn, without applying any standardization procedure. This series of CPUE is the only one available and Generalized Linear Models (GLMs) have been used to provide standardized CPUE index as input of the SPiCT and JABBA models. Nevertheless, the original catch and effort data are collected at trip-country level, which limits the effectiveness of the standardization.

Three alternatives in initial parameters and priors of SPiCT (Pedersen and Berg, 2017) were fitted to the four scenarios (Table 4.2.1). To evaluate the effect of discards scenarios on the estimates relative to Biodyn current assessment outputs Model 1 is fitted with parameters based on Biodyn estimates and n=2 fixed (Schaefer model) and with default priors for α and β. Model 2 uses priors for α, β, n, B0/K, q and K with normal distribution with mean obtained from estimates of Model 1 and σ=2. Model 3 is fitted to scenarios without constraints in initial parameters and default priors for α, β, n. Alternative assessments were done with JABBA model (Winker *et al*., 2018) to complement analysis with a Bayesian surplus model (see Section 5.5).

Effects of different scenarios of discards were observed mainly in K, B_{MSY} and MSY, increasing in the same proportion of percentage of discards between scenarios. This is due to the constant increase in the discards rate introduced (Figure 4.2.2). The group suggested introducing more refined patterns of discards trends to perceive different changes between scenarios estimates.

Also, potential dependency in the standardised CPUE index, due to space-time effects should be investigated to compare results and improve diagnostics in the surplus models. Possible frameworks to implement these correlation structures include traditional approaches such as glm's, gam's and their mixed effect extensions (glmm; gamm) although other approaches should be considered including: Integrated Nested Laplace Approximation (INLA) (Rue, H., 2009), Template Model Builder (TMB) (Kristensen *et al*., 2016) and Vector Autoregressive Spatio-Temporal Model (VAST) (Thorson, 2019a,b). Effect of discards scenarios are also shown in Figure 4.2.3 production curves of JABBA models.

Results from biomass dynamic stock assessments will be used to condition an operating model for African black hakes using FLife (https://github.com/flr/FLife/issues). Trends in relative reference quantities, B/B_{MSY} and F/F_{MSY} are shown in Figure 4.2.1. Compared with Biodyn assessment, state–space models showed higher levels of relative current F/F_{MSY} and moderate higher levels of relative biomass B/B_{MSY}.

Table 4.2.1. Models and scenarios fitted to black hake data.

Scenarios and Models			**SPiCT1**	**SPiCT2**	**SPiCT3**	**JABBA**
Scenario	Unreported Discards	Model input	Schaefer	Pella-Tomlinson	Pella-Tomlinson	Schaefer
S1 S2 S3 S4	0% 10% 20% 30%	Total declared catches CPUE Standarized	Initial values From Biodyn assessment: B_0/K=0.58, r=0.66, K=60902, q=0.1 Priors: default α and β	Priors: α, β, n, B_0/K, q, K ~ N(estimates SPiCT1, σ=2)	No in initial values Default priors for α, β, n	Initial values from Biodyn assessment B_0/K=0.58, r=0.66, K=60902, q=0.1

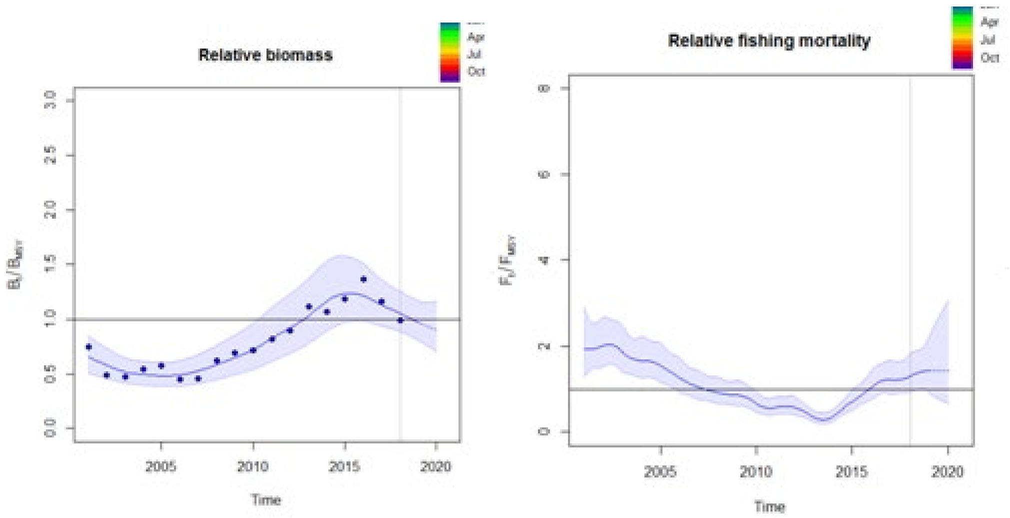

Figure 4.2.1. Relative biomass and relative fishing mortality obtained by SPiCT1 model.

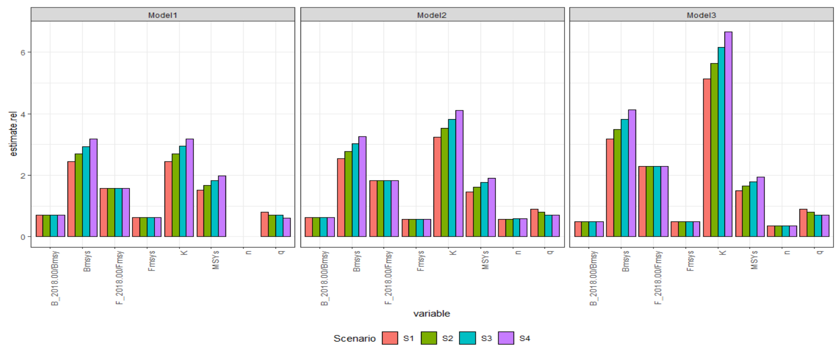

Figure 4.2.2. Comparison of the estimated quantities relative to Biodyn estimates from models SPiCT1, SPiCT2 and SPiCT3 for Scenarios 1,2,3 and 4.

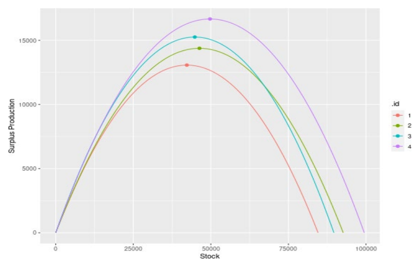

Figure 4.2.3. Comparison of the production curves from JABBA model for each discard scenario.

4.3 Summary and conclusions

Improvements in assessment of black hakes have been addressed using state–space models SPiCT and JABBA based on Pella Tomlinson productivity function. Limitations in the standardized index bring out the necessity of collecting data more disaggregated and geo-referenced for catch and effort. SPiCT is appropriate to assess black hake stock, providing estimates of process and observation errors and confidence bounds for stock status and reference levels. Also, JABBA is applicable as well, where assessments acceptance are checked through several criteria such that convergence, variance of parameters, retrospective analysis and residual analysis. Assessment results for SPiCT and JABBA are consistent with Biodyn in EXCEL, showing similar trends in relative biomass and fishing mortality. But also, generate replicable results, increase transparency in the assessments and, in particular, SPiCT provides functions to develop operating models and harvest control rules. Both libraries are available in R with detailed tutorials, which are key issues to make assessment methods available for all fishery scientists.

Regarding discards scenarios, more accurate trends in underreporting percentages must be investigated to observe the sensitivity of model parameters and management quantities to no declared discards. For all simulations, the K parameter is the more sensible to variations in the percentages of discards. Also, B_{MSY} and MSY are the values that showed more differences between scenarios.

4.4 Future work

CPUE indices of abundance of black hake base on commercial data will be developed based on INLA, TMB and VAST approaches.

Explore more detailed assessments through SPiCT and JABBA with variations between CPUE indices or effort, timing the index in the middle of the year or constraining some parameters to prevent no convergence in some trials to provide a consistent assessment to set the basis for the development of an operating model of black hake.

More refined underreported discards and total catches will be explored to evaluate sensibility of parameters and reference point used for management.

Biological information on growth parameters will continue being investigated through microstructure in otoliths to generate life-history traits based on k and Linf parameters.

Develop an operating model for black hakes based on life-history traits of a SPiCT MSE framework.

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5 Approaches for data-limited, data-moderate and data-rich fisheries

5.1 Introduction

This section focusses on the ToR f) namely, further explore and develop methods appropriate for data-limited, data-moderate and data-rich fisheries such as MyDas, MERA, DLMtool and MSEtool libraries; together with emerging multispecies approaches both within and outside the ICES community (e.g. in the tuna RFMOs, GCFM, NEAFC and CECAF); and ToR c), namely, evaluate the robustness of biomass dynamic assessment models (e.g. SPiCT and JABBA) based upon the development of Operating Models for African black hakes using FLife developed under the MyDas project and compare results with age-based assessment model, e.g. a4a.

Currently within ICES, single-stock assessment is the main tool used to provide scientific advice to annual catch options in European waters. Three additional products, a) ecosystem overviews, b) multispecies advice, and c) mixed-fisheries advice, are generated, although are not produced for all ecosystems. The ecosystem overviews provide a big picture of the ecosystem, but does not impact directly on advice. Multispecies advice is provided for the Baltic and North Seas using the SMS model. Multispecies models have also been developed for other ICES areas using a variety of models, e.g. LeMans for the North and Irish Seas, and GADGET for Iceland, West of Scotland, Iberian waters as well and the Baltic.

SMS 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. For the mixed fisheries, there are two ICES WGs (WGMIXFISH ADVICE and METHODS), where different methodologies are being developed and implemented in different areas. However, although the mixed-fisheries scenarios provided by ICES are used to inform international fisheries negotiations, they are not specific advice, but are used to guide management decisions by ICES clients.

Nowadays, there are two main different modelling strategies in fisheries science: one is to develop ecosystem models considering multiple interactions whose complexity can vary from Minimum Realistic Ecosystem Models (MICE models), such as Multispecies Production Models (MSPM, Horbowy, 2005; Bauer *et al*., 2019) or the Globally Applicable Disaggregated General Ecosystem Toolbox (GADGET, Beagle and Howell, 2004) or the Multispecies Virtual Population Analysis Model (MSVPA, Helgason and Gislason, 1979), which consider a few ecosystem interactions. On the other side ecosystem models like Ecopath (Christensen and Walters, 2004) or End-to-End models like ATLANTIS (Fulton *et al*., 2004) consider all parts of marine ecosystems (biophysical, economic and social). However, these complex models are rarely used for management purposes. The second option is to develop very accurate single-species stock assessment models that, as mentioned above, nowadays are the main tool for management. Problems are how to validate these models and how to use them to evaluate single-species advice, especially as many take inputs from single-species assessments.

Among the single-stock assessment models, and depending on the availability of information conditions, we can distinguish between “data-limited” and “data-rich” methods. There is no clear demarcation line between data-limited and data-rich methods, but following Newman *et al*. (2015), the former is used to describe a fishery that has few available data, while the latter are characterized by having multiple sources of information available regarding catch, abundance, and life-history characteristics. More in details:

Data-limited methods are used to describe a fishery that has little information available, data of poor quality, or, in some cases, available raw data that need to be processed into a usable format for conducting a conventional stock assessment. The stock assessment system has been historically directed to the stocks with more relevance (bigger amounts of landings, economic relevance, etc.). However, there has been a need to increase the assessed stocks in recent years. This decision has raised the problem of performing an assessment for stocks with not enough available information for the usual assessment methods. Under these circumstances fishery research has focused on developing assessment methods for data-limited stocks. Examples of data-limited methods can go from simple overfishing length indicators (Froese, 2004) to more elaborated models based on length distribution (Carruthers *et al.*, 2014) or on catch-curve stock reduction analysis (Thorson and Cope, 2015). Most of these models rely on equilibrium assumptions (e.g. constant recruitment and fishing mortality) and the recent work is focusing on relaxing these assumptions (Hordyk *et al.*, 2014) or reducing them, using Bayesian priors (Cope *et al.*, 2015).

Data-rich methods usually include long time-series of data with different levels of complexity depending on the available information. In its simple format (Biomass dynamic models or Surplus production models) only catch and effort time-series are needed (Pedersen and Berg, 2016). Age structured models (XSA, ADAPT, a4a, etc.) is the next level in model complexity. In its more complex format (Integrated Assessment Models) most available data (biological processes, surveys, CPUEs, age or length structure, tagging, etc.) can be considered as in models such as Stock Synthesis (Methot and Wetzel, 2013) or GADGET (Begley and Howell, 2004) which can be used for different single-stock assessment and then combined for multispecies fishery. Integrated assessment model have usually three components: (1) a parametric model to simulate the population, (2) an observation model that creates predictions from the population model based on true observations (surveys indices, size composition, etc.) and (3) a statistical model that compares and scores the differences between the observation model and the population model. How closely the model fits the actual data indicates the reliability of the historical estimates and its prediction skill (Kell *et al.*, in revision).

Despite the lack of progress in some methods, a great effort is being made to improve the majority of the methods in both single-species and multi-and mix-species stock assessment models. Within this context, in the sections below we are going to present and discuss some work done in this direction.

5.2 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. MERA is intended to better account for uncertainty in the fishery system, prioritizing robust management options and identifying value in alternative data collection and research programs. By focusing on operational modelling, MERA can provide quantitative outputs that are central to fishery legal frameworks and eco-certification standards, for example probabilistic estimates of stock status relative to reference levels. MERA lessens the reliance on subjective, qualitative scoring systems, increasing transparency and accountability in decision-making.

Furthermore, since the App is compatible with the R statistical software operating models, management procedures and diagnostics are all customizable allowing for bespoke state-of-the art closed-loop simulation including MSE.

The App has potential within the ICES community and would be worth exploring at future meetings of WKLIFE.

5.3 Improving scientific advice to fishery management for resources of interest for Spain in Atlantic waters (IMPRESS)

The IMPRESS project (https://impressproject.github.io/PROJECTIMPRESS/) is a Spanish project of three years (2019–2021) to tackle the issues identified in the stock assessment of the Spanish Northwest Atlantic species and to substantially improve their fisheries management. In particular, this main objective will be achieved through four working packages and many tasks. The ones more relevant for the WKLIFE work are:

1. Testing how life-history parameter estimations could affect the assessment results for different Iberian stocks and also thought simulation;
2. Development of Bayesian spatial-temporal models to generate new relative abundance indexes that include intrinsically the spatial and environmental variability, as well as reduce uncertainties;
3. Understanding the sensitivity of the parameter's estimation (e.g. Schaefer curve) of the Surplus production in continuous-time (SPiCT, Pedersen and Berg, 2017) model using both simulated data and real case studies (e.g. elasmobranchs, crustaceans, demersal and pelagic species);
4. Assessing the sensitivity of the parameter's estimations (e.g. L50 and M/K) of the Length Based Indicator (LBI) and Length-Based Spawning Potential Ratio (LBSPR) methods using real case studies (e.g. elasmobranchs, crustaceans, demersal and pelagic species);
5. Comparing the stock assessment results and derived reference points of different Iberian stocks that are normally evaluated with data-rich models (e.g. GADGET, SS3, a4a) with the SPiCT model;
6. Development of a new R package, the Rfishpop (available on https://github.com/IMPRESSPROJECT/Rfishpop) for analysing exploited populations under uncertainty. More precisely, Rfishpop develops an exploited population simulator that allows the classical implementation of a Management Strategy Evaluation (MSE) cycle, where the operating model can be parameterized process by process or from stock assessment results. In addition, this package allows to quantify the uncertainty in processes, observation, assessment and management. This package does not implement any assessment models; the idea is to use available assessment models. The package contains specific functions to change the format of the data into the required format of the assessment model. Now, the package contains such functions for the methods such as LBI, LB-SPR and Surplus-Production model Incorporating Covariates (ASPIC) and SPiCT.

Recently, a FLBEIA modelling framework (Bio economic Impact Assessment implemented in FLR) (García *et al*., 2017) was developed for mixed fisheries in the Atlantic Iberian waters (AIW) to evaluate management strategies. In particular, FLBEIA is a stochastic model that allows simulating simultaneously multiple stocks and multiple fleets (ICES, 2019). The AIW FLBEIA model included four stocks: hake, four-spot megrim, megrim and white anglerfish whose conditioning was based on the single-stock assessment. Within this framework, the aims of IMPRESS will be to improve the current AIW FLBEIA model increasing the number of demersal stocks and in particular trying to add data-poor species as the common sole.

5.4 Advances in the Surplus Production in Continuous-Time (SPiCT)

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.

SPiCT is in continuous development adding new features. The most important recent developments include:

- Time-varying productivity, that allows the stock productivity to vary seasonally or in the long term, in a stepwise or gradual way. More details, simulation testing and a case study are given in Mildenberger *et al.* (2020a).
- Probabilistic harvest control rules allow for inclusion of estimated uncertainty in the short-term forecast and the projection of the TAC. Simulations in a management strategy evaluation framework showed that such probabilistic harvest control rules, which include a biomass threshold, are performing best considering the trade-off between risk, yield and yield variability. A summary of these developments is given in Section 3.2 of this report and in Mildenberger *et al.* (2020b).
- The package is now in version 1.3.0. In the latest release, the management and short-term forecast functionality was improved and made more flexible. Functions were added that allow probabilistic harvest control rules, biomass thresholds and user-defined intermediate year assumptions.
- Data-limited harvest control rules based on SPiCT assessments are tested in a management strategy evaluation. SPiCT is used where the available time-series are relatively short and uninformative in a qualitative way. The rules aim to keep the biomass of the stock at current levels, to target a period of high biomass estimates, or to avoid a period of low biomass estimates. A summary of first results is given in Section 3.8.

5.5 Bayesian State–Space biomass dynamic assessment (JABBA)

JABBA like SPiCT is a biomass dynamic model, based on a Pella Tomlinson production function that allows alternative assumptions about productivity and density-dependence to be modelled. Biomass dynamic models therefore require the estimation, fixing and development of priors for fewer parameters than aged based assessments. JABBA presents a unifying, flexible framework for biomass dynamic modelling, runs quickly, and generates reproducible stock status estimates (Winker, 2018). It has also been used as a Management Procedure in both data-rich and data-poor case studies. In the latter case, it has been configured as a catch only method, where rather than using an index of abundance priors were used for final depletion (Kell *et al.*, 2020).

Biomass dynamic assessment models make no explicit assumption about the form of density-dependence, since recruitment, natural mortality, spawning reproduction potential and growth are all modelled by a production function with parameters for shape, productivity and carrying capacity. In a state–space model like JABBA exogenous processes like environmental forcing, or processes not included in the model structure are partitioned into process error.

Although JABBA is a Bayesian model many of the criteria used to assess acceptance for SPiCT assessments can be applied, e.g. convergence, variance of parameters, retrospective analysis and residual analysis. JABBA has been extended to allow selectivity-at-age to be modelled (Winker *et al*., 2020). JABBA therefore provides a framework that can span data-poor and data-rich case studies. This will allow a risk based framework to be developed that can be used to show the value-of-information, by comparing estimates of uncertainty based on different datasets and priors.

An example of the types of diagnostics available when using JABBA was presented to WKLIFE by L. Kell. These are based on those used for SPiCT but include additional methods such as hindcasting to assess prediction skill and non-stationarity.

Although JABBA is a Bayesian state–space model, the same issues have to be addressed when considering goodness of fit diagnostics and model validation, although the ways to do this may vary. For example, convergence is assessed by comparing multiple chains while bounds on initial starting values of parameters are set using priors which are then compared to the distributions of posteriors.

5.6 Summary and conclusions

Although a big effort is being done to improve single-stock assessment models, especially developing data-limited methods for species with poor information, it is clear that a shift from single-species to multispecies and mixed-fisheries model is needed. Traditionally the fishery management advice has been given using a single-species approach through Total Allowable Catch (TAC). Since 2002, some of the limitations in implementing this advice have been brought to light suggesting that in the long term, it would be desirable to give advice that accounts for mixed-fishery and multispecies effects that is both scientifically robust and meaningful for managers. In addition, the requirement of the mixed-fisheries approach has been emphasized recently with the imminent implementation of the landing obligation and the associated problem of the choke species. Additionally, populations are regulated by competition (food limitation), predation, and environmental variability. Each factor may influence different life-history stages, locally or regionally. Multispecies models that incorporate all these important interactions at specific stages and scales will be necessary if they are to continue to supplement the information provided by single-species models.

5.7 Future work

- ICES should liaise with the advice requestors to determine their needs and what ICES can provide/develop to increase the utility of our advice;
- Exploring the use of the on-line MERA app into the ICES community and in the WKLIFE;
- Monitoring the IMPRESS project progresses in terms of comparison between data-poor and data-rich methods, improving the AIW mixed-fisheries model with data-poor species and testing the sensitivity of parameters estimations in the ASPIC, SPiCT, LBI and LB-SPR. Results will be presented in the next meeting of WKLIFE.

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6 ICES guidelines for data-limited stocks

6.1 Introduction

This section does not address a specific ToR of WKLIFE X but is important to the transparency of ICES methods and advice for data-limited stocks.

6.2 A decade of ICES documentation

Earlier this year, ICES produced a helpful infographic showing their decade of development of stock status, assessment and advice rules for data-limited stocks:

6.3 Proposal to establish WKTGDLS

It became apparent during the discussions within WKLIFE X that the revision of the accumulated decade of ICES documentation on methods and advice for data-limited stocks into a stand-alone technical guidance document required significant effort and dedicated work beyond the time available at the WKLIFE X meeting.

WKLIFE X discussed the potential for updating and revising existing documentation but there is a clear need for a dedicated workshop to complete this task. WKLIFE has an established core of participants who work well together and are continuing to advance ICES methods and it is imperative that this momentum and energy is not lost. Hence, an additional dedicated workshop is proposed to undertake and complete the updating and revision tasks:

Workshop on ICES Technical Guidelines for Data-Limited Stocks (WKTGDLS)

Co-chairs: Carl O'Brien (UK) and Manuela Azevedo (Portugal)

Participants: Anne Cooper (ICES), José De Oliveira (UK), Jenni Grossmann (UK), Tobias Mildenberger (DK), Cristina Ribeiro (EU), Andrés Uriarte (ES), Deirdre Hoare (IRE), Lisa Borges (PT), Alain Biseau (F), Fátima Borges (PT) and Alexandros Kokkalis (DK).

Virtual meeting in early 2021 before WGCHAIRS.

The following ToRs are proposed:

a) to produce a new guidance document for ACOM's approval and adoption for the advice in 2021; and
b) to outline the structure for a full, in-depth handbook as an ICES Cooperative Research Report (CRR).

ICES CRR to be completed by year-end 2021, if practicable but otherwise as soon as possible. The report will document ICES decade of development and relevant linkages to activities outside of ICES that participants to WKLIFE have contributed to; e.g. the PROBYFISH (EASME/EMFF/2017/022), DRuMFISH and MYDAS projects.

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
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Ching Villanueva	Ifremer	France	Ching.Villanueva@ifremer.fr

Annex 2: Workshop agenda

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

WKLIFE X

5–9 October 2020 (online)

http://community.ices.dk/ExpertGroups/wklife/SitePages/HomePage.aspx

PLEASE NOTE: time table = Copenhagen time

Agenda

5 Oct (Monday)

14:00–14:30

- Introductions & CoC, meeting ToRs.

14:30–16:30

- Presentation & plenary discussion:

  José De Oliveira – 'Using a genetic algorithm to optimise a data-limited catch rule'
  Laurie Kell – 'ROC curves for length indicators and the use of machine learning in MSE'
  Simon Fischer – 'The rfb-rule and the ICES precautionary approach '

16:30–16:45 Coffee-break

16:45–18:00

- Presentation & plenary discussion:

  Simon Fischer – 'Constant harvest rates revisited'
  Henrik Sparholt – 'Obtaining F_{MSY} from L_{∞}, K and a50mat'

06 Oct (Tuesday)

10:00–13:00

- Presentation & plenary discussion:

  Jan Horbowy –'Survey-based estimates of F_{MSY} and its proxies'
  Tobias Mildenberger – 'Probability-based HCRs'
  Santiago Cerviño - IMPRESS project

- Planning of subgroups' work
- Subgroups' work

07 Oct (Wednesday)

10:00–11:00

- Presentations & plenary discussion:

  María Soto – 'Effects of under-estimating discards in production models: improving the assessment of *Merluccius* spp. in NW Africa'

11:00–16:00

- Subgroups' work

16:00–18:00

- Plenary session: Presentations and subgroups' work progress
  Andres Uriarte –´Workshop on data-limited stocks of short-lived species'

08 Oct (Thursday)

09:00–14:00

- Subgroups work; Report writing and collation

14:00–15:00

- Plenary session: Presentations and sub-groups work progress
  Tobias Mildenberger – 'Alternative SPICT-based HCR to the 2/3 rule'

14:00–18:00

- Subgroups work & report writing and collation

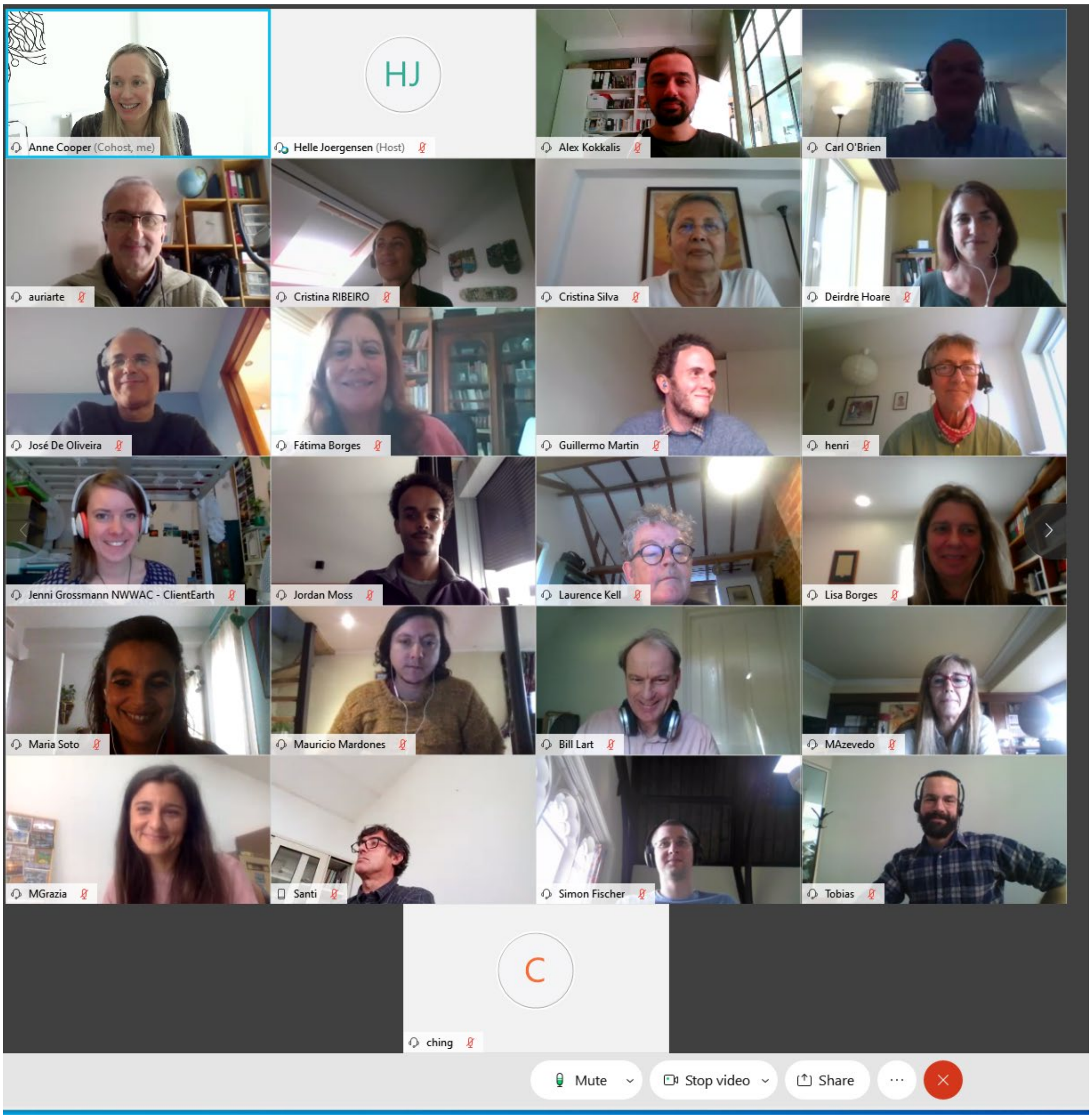
09 Oct (Friday)

10:00–14:00

- **Plenary session**: subgroup work progress
- Report writing and collation

14:00–18:00

- Plenary session: conclusions & report adoption



HJ
Anne Cooper (Cohost, me)
Helle Joergensen (Host)
Alex Kokkalis
Carl O'Brien
auriarte
Cristina RIBEIRO
Cristina Silva
Deirdre Hoare
José De Oliveira
Fátima Borges
Guillermo Martin
henri
Jenni Grossmann NWWAC - ClientEarth
Jordan Moss
Laurence Kell
Lisa Borges
Maria Soto
Mauricio Mardones
Bill Lart
MAzevedo
MGrazia
Santi
Simon Fischer
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Annex 3: ICES technical guidance on advice rules for stocks in Category 3

This annex was updated in September 2021.

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, Ninth and Tenth 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; WKLIFE X), 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 Category 3, with additional specifications for short-lived species Category 3. The application for Category 3, and not 4, is because all harvest control rules considered below rely on an index of abundance or biomass.

These advice rules have been tested by MSE. Although the intention of an MSE is to apply a feedback control rule that can be run for an extended period, it is still a requirement to conduct some form of assessment to check stock status, although it is not always possible for such an assessment to be based on a stock assessment model. However, in many cases, Operating Models (OMs) are conditioned on data using a stock assessment paradigm. An important part of conditioning an Operating Model in such cases is checking fits to the data, and the plausibility of model estimates and predicted dynamics. The criteria for accepting an assessment (see Method 1 below) are therefore important.

In ICES, often the OM is the same as the assessment used in the Management Procedure. In this case, reviewing the actual performance of an HCR after implementation is relatively easy, since it entails repeating the assessment used in the OM/MP, following the "acceptance criteria". A problem is when the OM has been conditioned on multiple reference cases, e.g. using an ensemble (e.g. ICES WKENSEMBLE meeting, 11–15 May 2020). In addition, there is a continuum across assessment models, e.g. when using flexible frameworks based on integrated models, or Bayesian frameworks like JABBA, that can span catch-only, biomass-based, and age-based models. Furthermore, even when an empirical rule has been used for the HCR, it is still necessary to perform a review/assessment in the future. It is therefore important that acceptance criteria can apply across a range of models.

Background

The objective of WKMSYCat34, WKLIFE VIII, IX, X, WKDLSSLS and WKDLSSLS II 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.

Figure A3.1 provides a flowchart for how the rules presented in this Annex could be applied.

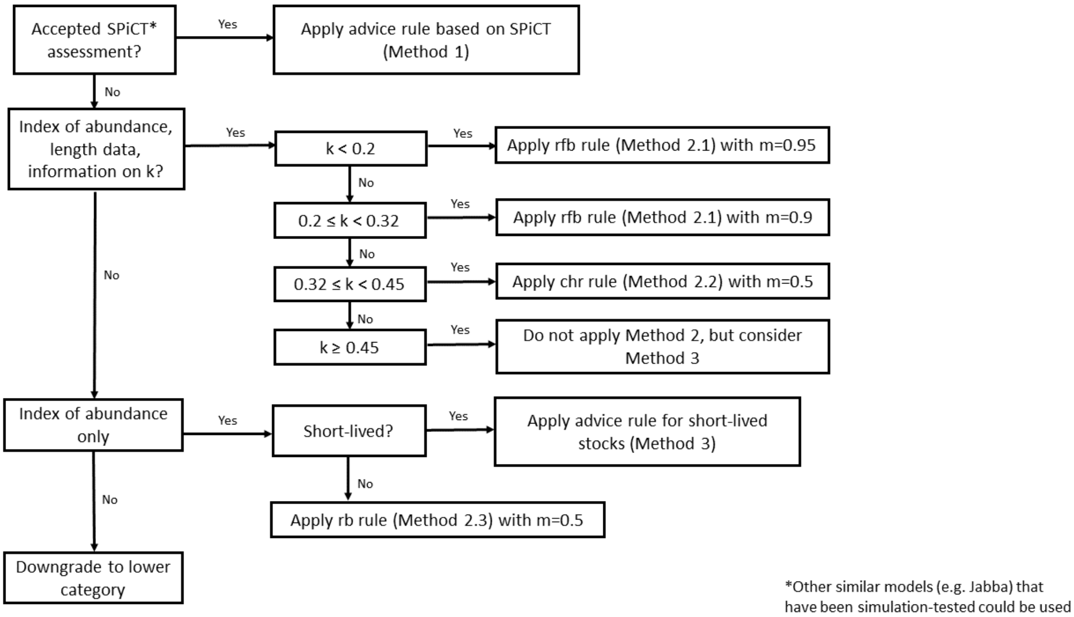

Figure A3.1. Flowchart of how the rules could be applied. The left-hand boxes refer to the reliable data and information to be used in the provision of advice; k refers to the von Bertalanffy growth parameter *k* (unit: yr^{-1}). *Other similar models (e.g. Jabba) that have been simulation-tested could be used.

Method 1: 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). Based on the median rule, WKLIFE VII-X developed and evaluated the "fractile rules" that account for uncertainty and demonstrated that the fractile rules are more effective and precautionary than the median rule and the "2-over-3" rule (ICES DLS Method 3.2; ICES, 2012; ICES 2017b, 2018a; ICES 2019a).

For stocks that have an accepted SPiCT assessment, ICES recommends to use the fractile rule with 35th percentile of the predicted catch distribution ($f^{C}_{0.35}$). In theory, with increasing time-series lengths and decreasing observation error, the estimated catch with the $f^{C}_{0.35}$ 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 $f^{C}_{0.35}$ rule recommends the TAC based on the 35th percentile of the predicted catch distribution given the target fishing mortality F^{τ}_{pred} during the prediction year.

$$\text{TAC} = \Phi^{-1}_{(C_{\text{pred}}|F^{\tau}_{\text{pred}})}(0.35),$$

where Φ^{-1} is the inverse distribution function, thus $\Phi^{-1}_{(C_{pred}|F^{\tau}_{pred})}(0.35)$, is the catch that corresponds to the 35th percentile of the estimated catch distribution. The target fishing mortality, F^{τ}_{pred}, during the prediction period $[p_1, p_2]$ depends on the median expected relative biomass at the end of the prediction period ($\frac{B_{p_2}}{MSY\ B_{trigger}}$) and the median relative fishing mortality at the start of the prediction period ($\frac{F_{p_1}}{F_{MSY}}$). Thus, the target fishing mortality corresponds to the median rule proposed by WKMSYCat34 (ICES, 2017a), i.e.

$$F^{\tau}_{pred} = F_{y+1} \frac{\min\left(1, \Phi^{-1}_{\frac{B_{p_2}}{MSY\ B_{trigger}}}(0.5)\right)}{\Phi^{-1}_{\frac{F_{p_1}}{F_{MSY}}}(0.5)}.$$

This advice rule is one of the default management scenarios included in the "`manage()`" function in the spict R package. In addition, the TAC based on this rule can be estimated by "`get.TAC(rep, fractiles = list(catch=0.35), breakpointB=0.5)`".

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 optimisation has 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. Note that this does not hold for short-lived, fast-growing species, where the confidence intervals are expected to be larger. 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).

Method 2: Advice rules for empirical approaches based on life-history traits

The advice rules presented here have been tested for the type of data that are typically available, including when these data are available. The testing has been done generically to ensure wider application of the rules. However, extensive testing, using genetic algorithms, has shown that it is possible to substantially improve the performance of the rules presented if time-lags were reduced (so that more recent information is used), constraints applied more flexibly, individual components of the rule weighted differentially, and stock-specific testing were conducted. In the absence of such additional simulation testing, it is recommended that the rules presented below, with associated multipliers, be applied.

Incorporating a multiplier (m) less than 1 will decrease risk of the 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. Section 3.6 of WKLIFE X provides the justification for the multipliers associated with each method 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 empirical rules, as long as the biomass safeguard $b = 1$. It is recommended that the stability clause be abandoned whenever $b < 1$.

Method 2.1 (the rfb rule)

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

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

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

Each component of the harvest control rule is combined (multiplied together), in order to determine next year's catch advice by adjusting this year's catch advice upwards or downwards. This is based on the trend in the index (i.e. whether the stock is going up or down, *r*), the observed mean length in the catch relative to the target mean length (*f*), and a factor to adjust catch downwards if the current stock falls below a threshold index value (*b*), defined as $I_{\text{trigger}} = 1.4I_{\text{loss}}$. 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. $0.5B_{\text{MSY}}$).

For the harvest estimate for longer lived stocks with low natural mortality and low growth rates (von Bertalanffy $k < 0.2$ yr^{-1}, e.g. redfish or ling), a multiplier of 0.95 should be applied to the control rule ($C_{y+1} = C_y \times r \times f \times b \times 0.95$), i.e. by setting the estimated catch for the following year to 95% of the estimated yield, based on the control rule. Medium lived stocks with $0.2 \le k < 0.32$ yr^{-1} (e.g. plaice, red mullet) should apply a multiplier of 0.9 to next year's estimated catch. If there is no reliable information about k, but k is considered to be less than 0.32 yr^{-1}, then a multiplier of 0.9 should be used. The constant harvest rate (chr) rule (Method 2.2) has been developed to deal with some of the cases where $k \ge 0.32$ yr^{-1}. [See Section 3.6.1 of WKLIFE X for a justification of the multipliers.]

Method 2.2 (the chr rule)

The constant harvest rate (chr) rule, also called the Fproxy rule (ICES, 2017a), or even the "Icelandic" rule, was originally proposed by WKMSYCat34. It applies a constant harvest rate ($F_{proxy,MSY}$) that is considered a proxy for an MSY harvest rate, and applies this to the index. WKMSYCat34 proposed that historical data be used to define $F_{proxy,MSY}$, so the approach used here is to extract the ratio C_y/I_y from those historical years for which the quantity $f > 1$, where f is the ratio of mean length above L_c relative to $L_{F=M}$, and to calculate the mean of this C_y/I_y ratio. Simulation testing of this rule found it was suitable for stocks where $0.32 \leq k$ 0.45 yr^{-1} (see Section 3.4 of this report).

$$C_{y+1} = I_{y-1} \times F_{proxy,MSY} \times b \times m$$

Component	Definition	Description and use
I_{y-1}		The index in year y−1.
$F_{proxy,MSY}$	$\frac{1}{u}\sum_{y \in U} C_y/I_y$	Is the mean of the ratio C_y/I_y for the set of historical years U for which the quantity $f > 1$, and u is the number of years in the set U. The quantity f is 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	$\min\left\{1, \frac{I_{y-1}}{I_{\mathrm{trigger}}}\right\}$	Biomass safeguard. Adjustment to reduce catch when the most recent index data I_{y-1} is less than $I_{trigger} = 1.4I_{loss}$ such that b is set equal to $I_{y-1}/I_{\mathrm{trigger}}$. When the most recent index data I_{y-1} is greater than I_{trigger}, b is set equal to 1. I_{loss} is generally defined as the lowest observed index value for that stock.
m	[0,1]	Multiplier applied to the harvest control rule to maintain the probability of the biomass declining below B_{lim} to less than 5%. May range from 0 to 1.0.
Stability clause	$min\{max(0.7C_y, C_{y+1}), 1.2C_y\}$	Limits the amount the advised catch can change upwards or downwards between years. The recommended values are +20% and −30%; i.e. the catch would be limited to a 20% increase or a 30% decrease relative to the previous year's advised catch. The stability clause does not apply when $b < 1$.

For medium to shorter lived stocks with $0.32 \leq k < 0.45$ yr^{-1} (e.g. brill, whiting), a multiplier of 0.5 should be applied to next year's estimated catch. [See Section 3.6.3 of WKLIFE X for a justification of the multiplier.]

For stocks for which $k \geq 0.45$, it is proposed that the method for short-lived stocks be use (Method 3).

Method 2.3 (the rb rule)

The rb rule is a simpler version of the rfb rule and is meant to cover those cases where length data are not available. The rule is decoupled from the life-history parameter k, and is tuned to ensure that the 5% risk threshold is met across a broad range of k values. It is intended as a replacement for the widely-used "2 over 3" rule, for the cases where Methods 2.1 and 2.2 cannot be used The "2 over 3" rule (coupled with an uncertainty cap and precautionary buffer) has consistently been shown to deliver poor performance when compared to alternative rules (such as the rfb rule).

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

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

The use of the rb rule should be accompanied by a multiplier of 0.5, applied to next year's estimated catch. [See Section 3.6.2 of WKLIFE X for a justification of the multiplier.]

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 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 $I_{\mathrm{trigger}} = 1.4I_{\mathrm{loss}}$ component of the 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 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 category 3)

The risk of harvesting short-lived stocks that have high interannual variability of biomass is inherently higher than long-lived species, given their dynamics. As such, the harvest control rules applied to short-lived stocks are designed in a manner that incorporates the dynamics of these specific stocks.

Method DLSSL 1 - SPICT for short-lived stocks

For data-limited short-lived stocks (SLDLS) with sufficiently long dataseries and contrast in biomass and production, surplus production models can be fitted and the advice can be formulated on the basis of F_{MSY} (rather than on constant catch at MSY), or possibly less than F_{MSY} to account for the strong fluctuations of these short-lived species.

Such a F_{MSY} rule would be most successful if applied to an assessment including an indicator of the biomass population just prior to the management calendar while including most of the harvestable population age classes. A year lag between the assessment and management years worsens the performance of the management for short-lived species and this should be evaluated in comparison with other potential HCRs. Refer to the report section on SPiCT for further details on this method and its caveats.

Method DLSSL 2 – Constant harvest rate

If a SPiCT model cannot be fitted to a SLDLS, and the stock has an accepted survey, the best way to adjust catches to the highly fluctuating nature of these stocks may be achieved by removing a constant fraction of the stock every year, corresponding with a sustainable harvest rate (*HRmsy.proxy*), applicable to the abundance indicator of the stock ($I_{current}$), so that risk of falling below B_{lim} is kept <0.05.

$$TAC_{y+1} = I_{current} \cdot HR_{msy.proxy}$$

The constant harvest rate HCR can be complemented with a biomass safe guard factor (**b factor**) based on a trigger index value, below which the advice should be corrected downwards in proportion to the drop of the most recent abundance index over the $I_{trigger}$ value.

Application of the method

A stock-specific management strategy evaluation (MSE) process should be conducted when implementing this method. The MSE should: (1) determine the constant harvest rate that is most robust to the OM and observation system uncertainties; (2) consider the time-lag between the index availability and management implementation; and, (3) determine the $I_{trigger}$ value, aiming at assuring allowable risk levels.

Caveats

This constant harvest rate HCR is dependent on the actual life history of the stock and it is conditioned on the survey catchability and observation error. Therefore, the degree of prior knowledge on the range of potential catchabilities and the likely magnitude of observation errors should be taken into account when considering this as a risk-averse HCR.

The application of a constant harvest rate can only be achieved for a management calendar triggered immediately after the abundance index becomes available (either from the survey or from the fishery). The longer the lag in time between the availability of the abundance index and the implementation of the management decision the lower would be the sustainable harvest rate.

Method DLSSL 3 – 1-over-2 rule

When knowledge of catchability and abundance is so poor as to preclude the selection of a robust harvest rate, a HCR that determines next year's catch based on the last advised catch can be used.

The harvest control rule is defined as:

$$C_{y+1} = \left\{ \begin{cases} 0.2\, C_y & \dfrac{I_y}{\sum_{y-1}^{y-2} I_y/2} < 0.2 \\ C_y \dfrac{I_y}{\sum_{y-1}^{y-2} I_y/2} & 0.2 \le \dfrac{I_y}{\sum_{y-1}^{y-2} I_y/2} < 1.8 \\ 1.8\, C_y & \dfrac{I_y}{\sum_{y-1}^{y-2} I_y/2} \ge 1.8 \end{cases} \right\} \cdot \left[min\left(1, \frac{I_{current}}{I_{trig}}\right) \right]$$

where C_y and I_y represent the advised catch and the biomass indicator for year y, respectively.

The first and third cases of the formula correspond to the application of an 80% symmetrical uncertainty cap.

The last term in the equation refers to the biomass safe guard based on a trigger index value, below which the advice would be corrected downwards in proportion to the drop of the most recent abundance index over the $I_{trigger}$ value. This is a term, which has been shown to further reduce the risks associated to this management system. A recommendation is made to take $I_{trigger}$ as $I_{stat} = geometric(I\_hist)\ \exp(-1.645 \cdot sd(\log(I\_hist)))$, where I_hist is the available historical series of the abundance index.

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 advised catch.

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*.

Caveats

This is a blind HCR as it does not necessarily lead to MSY exploitation, but it implies a decreasing trend of catch options in time after repeated applications, particularly when coupled to the 80% symmetrical uncertainty cap constraint, whereby for stocks substantially exploited (around or above F_{MSY}) it will decrease risks of falling below 20%B_0 below 0.2 in about ten years, and to levels around 0.05 or below after 20–30 years of applications. Therefore, this trend-based rule should be considered a provisional HCR with the aim of achieving a better management approach within ten years. Long-term application of this HCR may lead to major losses of yield.

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 quota year should be coupled as closely as possible to the availability of the abundance index. 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 could 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 (ICES, WKDLSSLS 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.

Precautionary buffer will certainly reduce the initial risks associated to a past substantial exploitation of the stock (above F_{MSY}), though is probably unnecessary for lightly exploited stocks. The performance of the rule has been tested without any precautionary buffer. Therefore, the convenience of applying such a precautionary buffer would depend on an early assessment of the exploitation levels and depletion of the resource.

Caveats

For stocks that were heavily exploited in the past, the rule does not necessary lead to precautionary levels of risk in the short term, but rather it 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. It is recommended that this harvest control rule be periodically re-evaluated.

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Annex 4: Working documents presented

WD1: Using a genetic algorithm to optimise a data-limited catch rule, Simon H. Fischer, José A. A. De Oliveira1, John D. Mumford and Laurence T. Kell.

WD2: Obtaining F_{MSY} from L_∞, K, and age-at-50% maturity, Henrik Sparholt.

For data-poor stocks some life-history parameters like Loo, K, and age-at-50% maturity, are often available. These can be used to get F_{MSY}, based on the observed relation for data-rich stocks between F_{MSY} and life-history parameters. If, for instance, for a data-poor stock, only a short time-series of catch-at-age is available so that ordinary methods for calculation F_{MSY} is not possible, the approach proposed here might be used to obtain a sound F_{MSY} value to use in management. Also in cases where only a short time-series of catch and stock biomass are available so that surplus production models can be difficult to estimate with a useful precision, the F_{MSY} can be obtained from the approach proposed (but then a transformation from F_{MSY} expressed in the ICES F-'currency', i.e. mean F over some age groups, need to be translated to the SPM F-'currency' i.e. catch biomass divided by stock biomass).

F_{MSY} has often been linked to life-history parameters such as natural mortality and growth rate. Sparholt *et al*.)2019a-c) used General Linear Models (GLM) coded in R, for this purpose. Based on the F_{MSY} estimates from the F_{MSY}-project (www.fmsyproject.net, of 53 data-rich ICES stocks they tested a set of relevant life-history parameters: age at 50% maturity – "a50mat", natural mortality of mature fish – "natM", $L_\infty \times K$ from the von Bertalanffy growth models – "Linf_K", preferred temperature –"prefT", trophic level of adult fish – "troph"). The life-history parameter values were based on ICES current input data to fish stocks assessments (ICES, 2018 and reference therein) supplemented with data from FishBase (Froese and Pauly, 2018). A few relevant groupings of species were tested and it was found that a five-category grouping of species "taxg3" [cod and hake, other gadoids, flatfish, herring, and sprat, and others] worked well with the model. Only a few parameters can be included in the model as we only have 53 F_{MSY} "observations". Several relevant GLM models were tested. Across most of the models, they found (a) a positive influence on F_{MSY} of "natM" and, to a lesser degree, of "Linf_K"; (b) a negative influence on F_{MSY} of "a50mat" and, to a lesser degree, of "prefT"; and (c) "troph" was correlated with both "a50mat" and "Linf_K" and did not add much to the model when both of these were included. "Linf_K" was preferred to "natM" because it is easier to estimate with good precision for most stocks. Because estimates of Linf and K is very often strongly correlated these were combined into one parameter Linf*K. This also served the objective of parsimony. The final GLM model was:

$$\log(F_{MSY}) = \log(a50mat) + \log(Linf\_K) + taxg3$$

It was assumed that F_{MSY} is log-normally distributed. The above GLM models were fitted to F_{MSY} estimates, one datapoint for each stock obtained as the mean by stock from the SPMs (Surplus Production Models), ecosystem, multispecies, and dynamic pool models (column "i" in Table 1).

The GLM model based on life-history parameters explained 59% of the variation in the F_{MSY} values. A model without the "taxg3" factor was almost as good, explaining 46% of the variation, while requiring only two parameters (see Supplementary material). However, the AICc was higher (50.9 vs. 45.8) than for the model including "taxg3". Linf_K was not significant at the 5% level, but leaving it out gave higher AICc scores (47.0), and the above-mentioned two-parameter model gave highly significant effects of Linf_K, indicating it was an influential parameter. Diagnostics from the run can be found in Table 2. Plots of model-predicted estimates of F_{MSY} vs. "observed" F_{MSY} and residuals vs. "observed" F_{MSY} are presented in Figure 1.

Table 1. Estimates of F_{MSY} by stock and method. Stock names from ICES Stock Assessment Database. [19/11-2019]. http://standardgraphs.ices.dk. From the F_{MSY} project (www.fmsyproject.net).

	Column identifier	a	b	c	d	e	f	g	h	i	j	
#	Stock name - short	ICES 2018	Froese *et al.* SPM	RAM Legacy Data-base. Schaefer	RAM Legacy Data-base. Thorson "Taxo-nomic"	RAM Legacy Data-base. Thorson "general"	Eco-system model	Dynamic pool mo-dels, e.g. PROST	Average of b, average (c-e), f and g	GLM of h, based on life history para-meters	Final recom-mended Fmsy values - column i unless there are ecosystem or dynamic pool estimates then a mean of column h and i	Full stock name (truncated to save space)
1	reb.27.1-2		0.06	0.14	0.20	0.15			0.11	0.13	0.13	Beaked redfish in subareas 1 and 2 (Northeast Arctic)
2	bli.27.5b67	0.12	0.11						0.11	0.22	0.22	Blue ling in subareas 6-7 and Division 5.b (Celtic Seas, English ...
3	whb.27.1-91214	0.32	0.37	0.31		0.28			0.33	0.44	0.44	Blue whiting in subareas 1-9, 12, and 14 (Northeast Atlantic and ...
4	cod.27.5a		0.63	0.45	0.39	0.44		0.70	0.59	0.43	0.51	Cod in Division 5.a (Iceland grounds
5	cod.27.7a	0.44	0.95	0.75		0.66			0.83	0.76	0.76	Cod in Division 7.a (Irish Sea)
6	cod.27.7e-k	0.35	0.56	0.51		0.47			0.52	0.63	0.63	Cod in divisions 7.e-k (eastern English Channel and southern ...
7	cod.27.47d20	0.31	0.70	0.73	0.41	0.68	0.87	0.70	0.72	0.71	0.71	Cod in Subarea 4, Division 7.d, and Subdivision 20 (North Sea, ...
8	cod.27.1-2	0.40	0.55	0.51	0.46	0.50		0.60	0.55	0.38	0.47	Cod in subareas 1 and 2 (Northeast Arctic)
9	cod.27.5b1	0.32	0.36	0.57	0.52	0.57			0.46	0.60	0.60	Cod in Subdivision 5.b.1 (Faroe Plateau)
10	cod.27.22-24	0.26	0.62						0.62	0.51	0.51	Cod in subdivisions 22-24, western Baltic stock
11	ldb.27.8c9a	0.193	0.33	0.33	0.24	0.32			0.31	0.44	0.44	Four-spot megrim in divisions 8.c and 9.a (southern Bay of Biscay ...
12	reg.27.1-2	0.0525	0.10						0.10	0.14	0.14	Golden redfish in subareas 1 and 2 (Northeast Arctic)
13	reg.27.561214	0.097	0.14	0.11	0.08	0.10			0.12	0.14	0.14	Golden redfish in subareas 5, 6, 12, and 14 (Iceland and Faroes ...
14	had.27.5a		0.47	0.33		0.31			0.40	0.38	0.38	Haddock in Division 5.a (Iceland grounds)
15	had.27.5b	0.165	0.28	0.39	0.36	0.39			0.33	0.46	0.46	Haddock in Division 5.b (Faroes grounds)
16	had.27.6b	0.20	0.31						0.31	0.39	0.39	Haddock in Division 6.b (Rockall)
17	had.27.7a	0.27	0.41						0.41	0.43	0.43	Haddock in Division 7.a (Irish Sea)
18	had.27.7b-k	0.40	0.87						0.87	0.67	0.67	Haddock in divisions 7.b-k (southern Celtic Seas and English ...
19	had.27.46a20	0.19		0.47	0.71	0.51	0.58		0.57	0.35	0.46	Haddock in Subarea 4, Division 6.a, and Subdivision 20 (North Sea, ...
20	had.27.1-2	0.35	0.43	0.30	0.24	0.29			0.35	0.26	0.26	Haddock in subareas 1 and 2 (Northeast Arctic)
21	hke.27.8c9a	0.25	0.59	0.51	0.43	0.50			0.54	0.65	0.65	Hake in divisions 8.c and 9.a, Southern stock (Cantabrian Sea and ...
22	hke.27.3a46-8abd	0.28	0.82	0.42	0.28	0.40			0.59	0.64	0.64	Hake in subareas 4, 6, and 7, and divisions 3.a, 8.a-b, and 8.d, ...
23	her.27.5a	0.22	0.23	0.25	0.29	0.26			0.25	0.28	0.28	Herring in Division 5.a, summer-spawning herring (Iceland grounds)
24	her.27.nirs	0.27	0.43	0.57	0.66	0.58			0.52	0.32	0.32	Herring in Division 7.a North of 52°30′N (Irish Sea)
25	her.27.irls	0.26	0.34	0.30	0.41	0.32			0.34	0.40	0.40	Herring in divisions 7.a South of 52°30′N, 7.g-h, and 7.j-k (Irish Sea, ...
26	her.27.3a47d	0.26	0.58	0.23	0.29	0.24	0.50		0.45	0.32	0.38	Herring in Subarea 4 and divisions 3.a and 7.d, autumn spawners ...
27	her.27.1-24a514a	0.157		0.16	0.13	0.16			0.15	0.23	0.23	Herring in subareas 1, 2, 5 and divisions 4.a and 14.a, Norwegian ...
28	her.27.28	0.32	0.34	0.53	0.52	0.53			0.43	0.31	0.31	Herring in Subdivision 28.1 (Gulf of Riga)
29	her.27.20-24	0.31	0.33	0.29		0.27			0.30	0.30	0.30	Herring in subdivisions 20-24, spring spawners (Skagerrak, ...
30	her.27.25-2932	0.22	0.21	0.18	0.15	0.18	0.35		0.24	0.25	0.25	Herring in subdivisions 25-29 and 32, excluding the Gulf of Riga ...
31	her.27.3031	0.21		0.19	0.17	0.19			0.19	0.30	0.30	Herring in subdivisions 30 and 31 (Gulf of Bothnia)
32	lin.27.5a	0.286	0.34	0.43					0.39	0.32	0.32	Ling in Division 5.a (Iceland grounds)
33	mac.27.nea	0.21	0.36	0.37	0.39	0.37		0.40	0.38	0.39	0.39	Mackerel in subareas 1-8 and 14 and Division 9.a (the Northeast ...
34	meg.27.7b-k8abd	0.191	0.37	0.35	0.34	0.35			0.36	0.33	0.33	Megrim in divisions 7.b-k, 8.a-b, and 8.d (west and southwest of ...
35	meg.27.8c9a	0.191	0.15	0.18					0.17	0.34	0.34	Megrim in divisions 8.c and 9.a (Cantabrian Sea and Atlantic ...
36	ple.27.7a	0.169	0.21	0.42	0.57	0.45			0.35	0.29	0.29	Plaice in Division 7.a (Irish Sea)
37	ple.27.7d	0.25	0.27						0.27	0.29	0.29	Plaice in Division 7.d (eastern English Channel)
38	ple.27.420	0.21	0.47	0.36	0.30	0.35			0.40	0.35	0.35	Plaice in Subarea 4 (North Sea) and Subdivision 20 (Skagerrak)
39	ple.27.21-23	0.37	0.55						0.55	0.28	0.28	Plaice in subdivisions 21-23 (Kattegat, Belt Seas, and the Sound)
40	pok.27.5a		0.31	0.19		0.17			0.25	0.31	0.31	Saithe in Division 5.a (Iceland grounds)
41	pok.27.5b	0.30	0.37	0.34	0.25	0.32			0.34	0.34	0.34	Saithe in Division 5.b (Faroes grounds)
42	pok.27.1-2		0.49	0.32	0.30	0.32			0.40	0.32	0.32	Saithe in subareas 1 and 2 (Northeast Arctic)
43	pok.27.3a46	0.36	0.54				0.33		0.44	0.33	0.38	Saithe in subareas 4, 6 and Division 3.a (North Sea, Rockall and ...
44	sol.27.7a 1.2	0.20	0.18	0.27	0.17	0.26			0.21	0.36	0.36	Sole in Division 7.a (Irish Sea)
45	sol.27.7d	0.256	0.48	0.63		0.68			0.57	0.34	0.34	Sole in Division 7.d (eastern English Channel)
46	sol.27.7e	0.29	0.26	0.21		0.20			0.23	0.33	0.33	Sole in Division 7.e (western English Channel)
47	sol.27.7fg	0.27	0.31	0.44	0.60	0.47			0.41	0.31	0.31	Sole in divisions 7.f and 7.g (Bristol Channel, Celtic Sea)
48	sol.27.8ab	0.33	0.43	0.38	0.27	0.36			0.39	0.32	0.32	Sole in divisions 8.a-b (northern and central Bay of Biscay)
49	sol.27.4	0.20	0.38	0.40	0.38	0.40			0.39	0.32	0.32	Sole in Subarea 4 (North Sea)
50	sol.27.20-24	0.23	0.38	0.28	0.22	0.27			0.32	0.32	0.32	Sole in subdivisions 20-24 (Skagerrak and Kattegat, western Baltic ...
51	spr.27.22-32	0.26	0.42	0.30	0.34	0.31	0.40	0.45	0.40	0.38	0.39	Sprat in subdivisions 22-32 (Baltic Sea)
52	mon.27.78abd	0.28	0.41						0.41	0.30	0.30	White anglerfish in Subarea 7 and divisions 8.a-b and 8.d (Celtic ...
52	mon.27.8c9a	0.24	0.63	0.27	0.21	0.26			0.44	0.30	0.30	White anglerfish in divisions 8.c and 9.a (Cantabrian Sea and ..

Table 2. Diagnostics of the GLM model log(F_{MSY}) = log(a50mat) + log(Linf_K) + taxg3, used to link life-history parameters to F_{MSY}.

Variable name	Coefficient	Standard error	*t*-value	*P*-value
Intercept	–0.3807	0.3881	–0.981	0.3318
taxg3 (flatfish)	–0.6295	0.1906	–3.302	0.0019**
taxg3 (forage fish)	–0.7003	0.1880	–3.724	0.0005***
taxg3 (other gadoids)	–0.3984	0.1513	–2.634	0.0115*
taxg3 (other taxonomic groups)	–0.5154	0.2258	–2.258	0.0271*
Linf_K	0.2091	0.1145	1.826	0.0744
a50mat	–0.5800	0.1125	–5.156	0.0000***
Null deviance	12.7648 on 52 degrees of freedom			
Residual deviance	5.2618 on 46 degrees of freedom			
AIC	43.987			
AICc	45.813			
Significance codes: * < 0.05, **<0.01, ***<0.001				

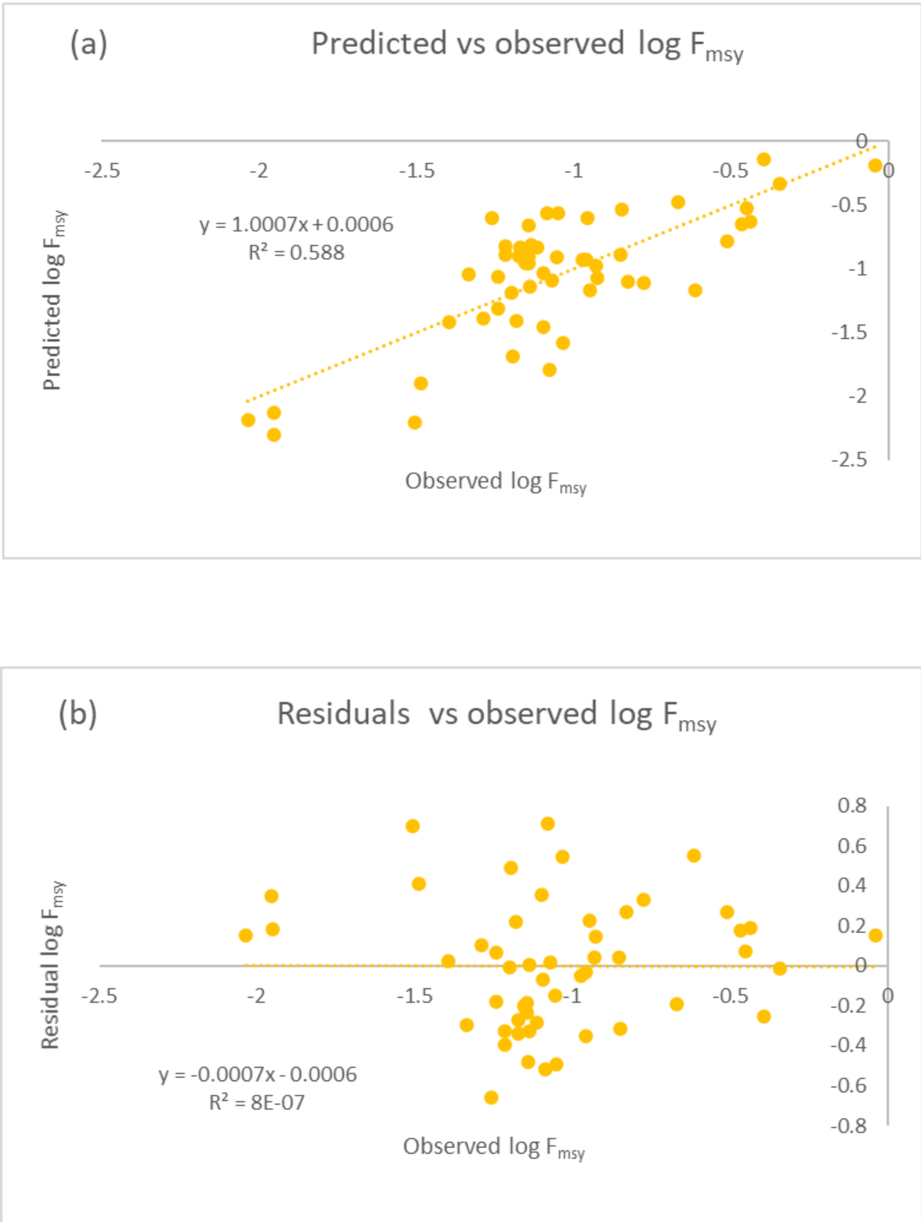

Figure 1. Model predicted log(F_{MSY}) vs. "observed" log(F_{MSY}) from a GLM model: log(F_{MSY}) = log(a50mat) + log(Linf_K) + taxg3, used to link life-history parameters to F_{MSY} (a), and residual vs. "observed" log(F_{MSY}) values (b).

Of course alternative GLMs using for instance Linf and K as separate parameters can be attempted and it might be interesting and useful to avoid the taxonomic groupings if possible. However, the results are not expected to be wildly different from the GLM results presented here in terms of the F_{MSY} value for a given data-poor stock.

If only an SPR is possible for a given data-poor stock the new F_{MSY} value could be used if there is a translation from F_{MSY} expressed in the ICES F-'currency', i.e. mean F over some age groups, to the SPM F-'currency' i.e. catch biomass divided by stock biomass. Translations factors could be obtained from the data-rich stocks based on F_{MSY} expressed in the ICES F-'currency' from Table 1 combined with F_{MSY} expressed in the SPM F-'currency' in Froese *et al*. (2016). One would expect the factor to be dependent on the F level so a linear relationship between the factor and F should probably be attempted.

Conclusion: The above formula and the parameter values given in Table 2 can be used to obtain a scientifically sound estimate of F_{MSY}, for data-poor stocks where Loo, K and age-at-50%-maturity are available.

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Annex 5: Recommendations

Recommendation	For follow up by:
It is recommended by WKLIFE X that there be an eleventh meeting of WKLIFE either in Lisbon, Portugal 4–8 October 2021, or meeting virtually at the same time whose draft ToRs are proposed in this report for the consideration of ACOM. It is recommended that ToRs be developed in consultation with the ACOM Leadership but as a starting point for discussion might include: For ICES stocks in Categories 5 and 6 where fishery-independent time-series are not currently available, re-consider and evaluate methods for application of the Precautionary Buffer, and propose a rules-based approach to its application in advice based on life-history characteristics. The HCR for SPiCT assessments to be evaluated wrt the performance of different biomass thresholds. If defined as a fraction of B_{MSY}, values in the range of 50–100% could be considered as a starting point for stocks with different life-history traits. The implications of an additional biomass limit reference point in the HCR should be explored. A novel data-limited HCR as an alternative to the ⅔ rule was introduced in WKLIFE X: the *Bref rule*. Similar to the ⅔ rule, the *Bref rule* aims at stabilising the biomass. However, it is based on the biomass estimated by SPiCT relative to a reference biomass (Bref) instead of raw index observations. The reference biomass could be defined as the biomass (estimated by SPiCT) at any point in time or any period of time. Preliminary results presented to WKLIFE X show a good performance in terms of the risk-yield trade-off of the rule, but further simulations are required and the performance of the method has to be correlated to the level of contrast in the available data. Explore and develop a framework for investigating risk equivalency to ensure that more uncertainty is associated with more precautionary advice across the different ICES categories, and link to the evaluation of the value of information. 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.	ACOM
It is recommended by WKLIFE X that ICES benchmark assessment for data-limited and data-rich mixed fisheries developed by WGMIXFISH-Methods.	BOG, WGMIXFISH-Methods
It is recommended by WKLIFE X that ICES hold a workshop on technical guidelines for DLS in early 2021.	ACOM
It is recommended by WKLIFE X that an ICES Cooperative Research Report (CRR) be prepared and published as an in-depth handbook detailing the decade of ICES development of stock status, assessment and advice rules for data-limited stocks.	ACOM, SCICOM