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Original Article

Application of explicit precautionary principles in data-limited fisheries management

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Many management bodies require applying the precautionary approach when managing marine fisheries resources to achieve sustainability and avoid exceeding limits. For data-limited stocks, however, defining and achieving management objectives can be difficult. Management procedures can be optimized towards specific management objectives with genetic algorithms. We explored the feasibility of including an objective that limited the risk of a stock falling below various limit reference points in the optimization routine for an empirical data-limited control rule that uses a biomass index, mean catch length, and includes constraints (the "rfb-rule"). This was tested through management strategy evaluation on several fish stocks representing various life-history traits. We show that risk objectives could be met, but more restrictive risk limits can lead to a potential loss of yield. Outcomes were sensitive to simulation conditions such as observation uncertainty, which can be highly uncertain in data-limited situations. The rfb-rule outperforms the method currently applied by ICES, particularly when risk limitation objectives are considered. We conclude that the application of explicit precautionary levels is useful to avoid overfishing. However, we caution against the indiscriminate use of arbitrary risk limits without scientific evaluation to analyse their impact on stock yields and sustainability.

Keywords: data-limited, empirical management procedure, FLR, genetic algorithm, ICES, management strategy evaluation, precautionary approach, risk

Introduction

One of the main objectives of fisheries management is to ensure the long-term sustainability of the resources being exploited. An imperative for the successful management of fish stocks is the existence of clearly defined management objectives and robust ways to achieve them. However, for many of the world's fish stocks, there are insufficient data and knowledge to conduct reliable quantitative stock assessments (Rosenberg *et al.*, 2014). The limitations do not solely impact data and knowledge of managed resources but can extend to the management objectives themselves. Management goals for data-limited fish stocks are frequently vague and might only be formulated to ensure precautionary exploitation without specific performance metrics or guidelines.

Management measures for many fish stocks in the Northeast Atlantic are based upon scientific recommendations from ICES. ICES applies an advice framework for data-rich stocks that considers both maximum sustainable yield (MSY) and precautionary principles (ICES, 2019a). Within this framework, catch advice is derived from short-term forecasts, typically with a target fishing mortality at the level that would achieve MSY (F_{MSY}). Precautionary considerations require that limit reference points are also defined to ensure that low stock size and unsustainable fishing mortality are avoided with a high probability.

The precautionary approach was first introduced in ICES in the late 1990s and is based on the principle that a fish stock should not fall below a point where recruitment or productivity is impaired (Lassen *et al.*, 2014). For data-rich stocks, this point is typically defined as a spawning stock biomass (SSB) limit reference point (B_{lim}). ICES technical guidelines state that management must ensure that the probability of SSB falling below B_{lim} must not exceed 5% (ICES, 2017a, 2019a). The precautionary principle is implicitly implemented in ICES advice by defining threshold reference points (such as B_{pa}) that ensure that the limit reference points are avoided with a high probability (Hauge *et al.*, 2007). The ICES MSY advice rule itself (fish at F_{MSY} unless SSB < MSY $B_{trigger}$, in which case reduce F linearly to zero by the extent that SSB < MSY $B_{trigger}$) is designed to ensure that stocks are capable of producing MSY, but the constraint that MSY $B_{trigger} \geq B_{pa}$ ensures this rule is consistent with the precautionary principle. Alternatives to the ICES MSY advice rule are possible but need to demonstrate that they comply with the precautionary 5% risk limit. To do this, evaluations are preferably conducted using management strategy evaluation (MSE), and recent examples of this procedure are the evaluations of long-term management strategies for North Sea stocks (cod, haddock, saithe, whiting, and herring; ICES, 2019b) or Northeast Atlantic mackerel (ICES, 2020c).

In data-limited cases, quantitative assessment models are often unavailable and knowledge about stock development and status does not exist. Consequently, stock size or fishing mortality cannot be judged relative to target or limit reference points, impairing risk considerations. For such cases, ICES applies a precautionary framework aimed at ensuring sustainable catch advice by using all available information (ICES, 2019a). Despite this overarching precautionary principle, there are no specific definitions or guidelines about what constitutes precaution or how this could be measured. Instead, ICES classifies fish stocks into six categories depending on the extent of data limitations and provides a set of possible methods to derive catch advice and evaluate stock status relative to MSY proxy reference levels, if possible (ICES, 2012a, 2018).

Stocks for which there is no quantitative assessment, but for which an index of relative abundance exists, are defined as category 3 stocks. For these stocks, ICES catch advice is currently derived in most cases from a simple "2 over 3" rule, which sets the catch advice by multiplying the most recent advised catch by the average of the last two index values divided by the average of the three preceding index values (ICES, 2012a, 2018, 2019a). This approach is complemented by an uncertainty cap limiting the change between advised catches to no more than 20%. Additionally, a precautionary buffer reduces the catch advice by 20% when the stock is judged to be in an unfavourable condition (if either biomass is thought to be below a possible biomass limit, usually 50% of a B_{MSY} proxy value, or fishing mortality is thought to be above an F_{MSY} proxy value) or unknown, but can only be applied once in a three-year period. At best, this rule can maintain the current stock status because it lacks a target.

Since the first implementation of the 2 over 3 rule in 2012, it was only meant as an interim solution until better options could be developed. Despite some early simulation testing (De Oliveira *et al.*, 2010; ICES, 2012b), it was never shown that the 2 over 3 rule provided precautionary advice or was, in fact, compliant with the principles of the ICES precautionary approach. Currently, alternative management approaches are being considered for implementation into the ICES advice framework. The prime forum for developing and testing alternative data-limited approaches in ICES is the WKLIFE workshop (ICES, 2012b), which has been running since 2012, with the tenth meeting in the series held in 2020 (ICES, 2020a).

Two main strains of methods for category 3 stocks are being considered; model-based and model-free. The model-based strain considers control rules based on a surplus production model (SPiCT; Pedersen and Berg, 2017), including short-term forecasting. To account for uncertainty and provide precautionary advice, percentiles different from 50% of model estimates are deployed (Mildenberger *et al.*, 2021). However, it is common that stock assessment models cannot be used for data-limited stocks, e.g. because of convergence issues or insufficient data. Simpler models relying on fewer data, such as catch only methods, exist, but are only considered for stocks with more severe data limitations (category 4 and higher). The alternative is a model-free empirical rule, and ICES considers the *rfb*-rule for these cases, which includes additional elements for providing catch advice: in addition to the 2 over 3 component (r), there is an exploitation proxy target derived from the mean length in the catch (f), and a biomass safeguard reducing the catch advice once the stock falls below a threshold (b). New guidelines with these rules have been drafted (Annex 3 of ICES, 2020a) and are intended to replace current methods. Simple empirical management procedures are a viable possibility for managing fisheries, are easier to implement, cheaper because they rely on fewer data, and their management performance can match more complex stock assessment frameworks (Geromont and Butterworth, 2015a, b; Carruthers *et al.*, 2016). Another benefit is that they are less susceptible to environmental changes, such as those induced by climate change, because management follows trends in the stock instead of chasing the expensive "best assessment" approach.

Early simulation testing of the *rfb*-rule (Fischer *et al.*, 2020) showed that its performance depended on the individual growth rate of the managed stock and the performance was poor, with high risks of stock collapses, for fast-growing stocks (von Bertalanffy $k \geq 0.32\ \text{year}^{-1}$). For slow- to medium-growing stocks, the *rfb*-rule performed reasonably but often led to stock levels above B_{MSY} and therefore forfeited yield. However, the performance could be improved by optimizing the rule towards MSY (Fischer *et al.*, 2021).

Fischer *et al.* (2021) established a procedure to optimize the *rfb*-rule to meet specific management objectives by applying a genetic algorithm (Holland, 1992), and the principle is visualized in Figure 1. For the optimization, the objectives need to be defined mathematically in the form of a fitness function. Fischer *et al.* (2021) deployed a generic fitness function to achieve MSY while also reducing the risk of stocks falling below limit biomass reference levels and catch variability. Furthermore, Fischer *et al.* (2021) evaluated the performance of the 2 over 3 rule and compared it to the *rfb*-rule. The results showed that the 2 over 3 rule's performance crucially depends on the stock status before its implementation; it merely maintains that level and does not provide precautionary management advice. The *rfb*-rule outperforms the 2 over 3 rule, in particular when optimized for a specific stock.

In this study, we explore including explicit precautionary elements in data-limited fisheries management with the example of the empirical *rfb*-rule. This includes considerations of the definition of risk levels and how MSE simulation conditions, such as historical fishing patterns, the length of the simulation, or the levels of uncertainty and variability, can affect the selection of management options. Then, we explore how the *rfb*-rule can be optimized to meet specific precautionary considerations and discuss their trade-offs.

Methods

MSE

The age-structured operating models developed by Fischer *et al.* (2020) in FLR (Kell *et al.*, 2007), and as parameterized in Fischer *et al.* (2021), were redeployed. These comprised 29 stocks generated from life-history parameters covering a wide range of life-history traits (Supplementary Table S1). There were two distinct 100-year fishing histories; a *one-way* fishing history (fished at $0.5F_{MSY}$ for 75 years, then increase fishing mortality exponentially to $0.8F_{crash}$

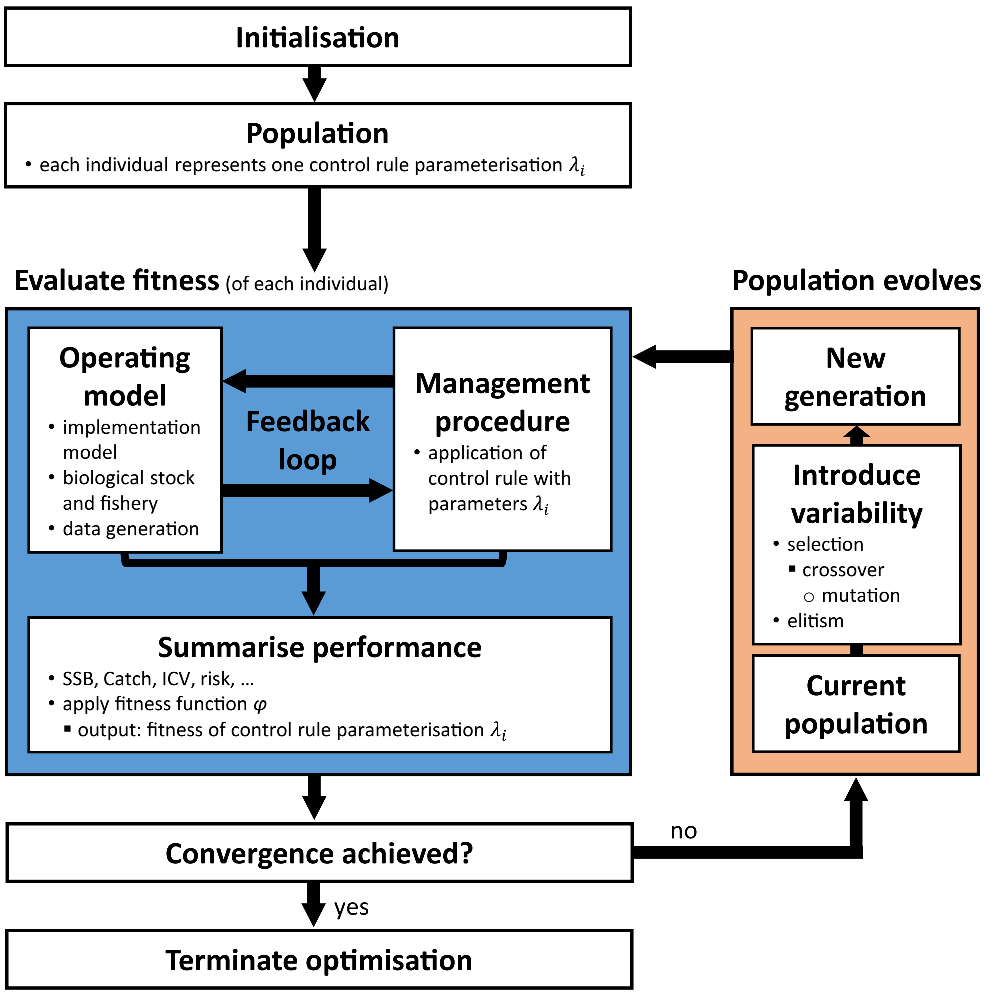

Figure 1. Principle of using a genetic algorithm to optimize a management procedure in an MSE.

over 25 years, where F_{crash} is defined as the lowest fishing mortality that causes the stock to collapse in equilibrium), and a *random* fishing history with arbitrary fishing mortality trajectories [$F_{y=-99} = 0$, and two points in time where fishing mortality is drawn from independent uniform distributions: $F_{y=-50} \sim U(0, F_{\text{crash}})$ and $F_{y=0} \sim U(0, F_{\text{crash}})$, with linear interpolations in-between]. These two fishing histories offered insights into situations with a strong initial depletion (one-way) and an alternative with a wide range of depletion (random). Errors were assumed to be log-normal, and each stock consisted of 500 independent simulation replicates. Recruitment was simulated by a Beverton–Holt model with steepness $h = 0.75$ and recruitment variability $\sigma_R = 0.6$. Subsequent to the fishing history, a management procedure was implemented for 50 years. Observation errors were implemented to the aggregated biomass index and mean catch length index with $\sigma_{\text{obs}} = 0.2$. Full specifications of the operating models and simulation conditions are available from Fischer *et al.* (2020, 2021).

Management procedure

The management procedure was based on the *rfb*-rule (ICES, 2017b; Fischer *et al.*, 2020):

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

where the newly advised catch A_{y+1} in year $y + 1$ is based on the previously realised catch C_{y-1}, multiplied by three components corresponding to the stock trend (r) from a biomass index, an exploitation proxy (f) derived from the mean catch length and a biomass safeguard (b) protecting the stock when the biomass index falls below a critical threshold. Fischer *et al.* (2021) expanded the *rfb*-rule for optimization purposes:

$$A_{y+1} = C_{y-1} \left(\frac{\sum_{i=y-n_0-n_1+1}^{y-n_0} (I_i/n_1)}{\sum_{i=y-n_0-n_1-n_2+1}^{y-n_0-n_1} (I_i/n_2)} \right)^{e_r} \left(\frac{\bar{L}_{y-1}}{L_{F=M}} \right)^{e_f} \times \left(\min \left\{ 1, \frac{I_{y-n_0}}{I_{\text{trigger}}} \right\} \right)^{e_b} x. \tag{2}$$

The parameters of this rule are defined in Table 1. A total of seven of the parameters in Equation (2) were tuneable (n_0, n_1, n_2, e_r, e_f, e_b, and x), i.e. could be changed during the optimization process. Additionally, the catch advice interval v defines the number of years for which the advice is kept constant before the *rfb*-rule is applied again. Finally, an uncertainty cap can limit the allowed increase (u_u) and decrease (u_l) in the catch advice A_{y+1} relative to the previously realised catch C_{y-1}. The inclusion of these additional parameters resulted in 10 tuneable parameters that could be used in the optimization.

Table 1. Parameters of the flexible *rfb*-rule (as shown in Equation (2) and described in subsequent text).

Parameter	Definition	Default
Generic parameters		
y	Assessment year	
A	Catch advice	
C	Realised catch	
I	Biomass index	
$\bar{L}$	Mean catch length above the length of first capture (L_c)	
$L_{F=M}$	Theoretical proxy MSY reference length assuming $F = M$ and $M/k = 1.5$	
I_{trigger}	Biomass safeguard reference value, set to 1.4 I_{loss}, where I_{loss} is the lowest observed historical value	
Tuneable parameters		
n_0	Offset between last biomass index year and assessment year	1
n_1, n_2	Number of biomass index years in the numerator and denominator of component r	$n_1 = 2, n_2 = 3$
e_r, e_f, e_b	Exponents for weighting of components r, f and b	1
x	Multiplier, scaling the catch advice	1
v	Catch advice interval, number of years for which the catch advice is kept constant	2 (biennial)
u_u, u_l	Catch constraint (upper and lower limit), restricting the allowed change in the catch advice A_{y+1} relative to the previously realised catch C_{y-1}	$u_u = \infty, u_l = 0$

Genetic algorithm

The genetic algorithm as applied and parameterized by Fischer *et al.* (2021) was used to optimize the *rfb*-rule. The population size of the algorithm was set to 100 individuals. Each of these individuals was characterized by a specific parameterization of the 10 tuneable parameters of the *rfb*-rule described above. This projection was summarized in a single value using a fitness function. Those individuals with the highest fitness were selected and formed the reproductive population. The next generation was generated by including natural variability through genetic operators (crossover with a probability of $p = 0.8$ and mutation with $p = 0.1$) working on the 10 tuneable parameters of the *rfb*-rule. Additionally, an elitist strategy allowed the survival of those 5% of individuals with the highest fitness. This iterative process was repeated for every subsequent generation until either (i) a limit of 100 generations was reached or (ii) due to stationarity of the best fitness value in a generation for 10 consecutive generations.

Precautionary considerations

Fischer *et al.* (2021) defined a fitness function that included four components:

$$\phi_{\text{MSY}} = \phi_{\text{SSB}} + \phi_{\text{Catch}} + \phi_{\text{risk}} + \phi_{\text{ICV}}, \tag{3}$$

where the individual components were

$$\phi_{\text{SSB}} = -\left|\frac{\text{SSB}}{B_{\text{MSY}}} - 1\right|, \tag{4}$$

$$\phi_{\text{Catch}} = -\left|\frac{\text{Catch}}{\text{MSY}} - 1\right|, \tag{5}$$

$$\phi_{\text{risk}} = -B_{\text{lim}}\ \text{risk, and} \tag{6}$$

$$\phi_{\text{ICV}} = -\text{ICV}. \tag{7}$$

The summary statistics used in these fitness elements were calculated over the 50-year projection and 500 simulation replicates. SSB/B_{MSY} and Catch/MSY were the medians of their respective distributions and B_{lim} risk the proportion of the SSB values falling below the biomass limit reference point B_{lim} (defined as the SSB corresponding to a recruitment impairment of 30%). The inter-annual catch variability (ICV) was the median of $|(C_y - C_{y-v})/C_{y-v}|$ (exclusive of undefined values due to division by zero) calculated every v years, where C_y is the catch for the year y and v the frequency of advice, e.g. $v = 2$ for a biennial advice. Effectively, this fitness function was aimed at reaching MSY reference levels for SSB and catch, while at the same time reducing risk and ICV.

The ICES precautionary criterion generally states that the probability of SSB falling below B_{lim} should not exceed 5%. Therefore, ϕ_{MSY} is not entirely aligned towards the ICES precautionary approach, and ϕ_{risk} will need to be changed. Compliance with the precautionary approach can be achieved by including a penalty in the fitness when the risk exceeds 5%, which was implemented by replacing ϕ_{risk} with a fitness function component for which the fitness value was linked to the B_{lim} risk (=P) via a penalty function Ω:

$$\phi_{\text{risk-PA}} = -\Omega(P), \tag{8}$$

and

$$\Omega(P) = \frac{\tau_m}{1 + e^{-(P-\tau_i)\tau_s}}. \tag{9}$$

This function has a sigmoid shape (Figure 2) and is characterized by three parameters; τ_m defines the maximum penalty, τ_i the inflection point and τ_s the steepness of the curve. The three parameters' values were based on considerations for one example stock (pollack, *Pollachius pollachius*). When pollack was projected forward with zero catch, the sum of $\phi_{\text{SSB}} + \phi_{\text{Catch}} + \phi_{\text{ICV}}$ [Equations (4), (5), and (7)] had an absolute value of just below 5. Therefore, the maximum penalty τ_m was set to 5. This parameterization had the effect that the *rfb*-rule parameterization leading to zero-catch always had a higher fitness than the *rfb*-rule parameterizations where B_{lim} risk exceeded 5%. The penalty curve inflection point was set to $\tau_i = 0.06$ so that the risk could slightly exceed 5% without immediately incurring the maximum penalty. The penalty steepness was set to $\tau_s = 500$ so that the penalty quickly reached its maximum value but avoided a knife-edge which might cause problems during the optimization.

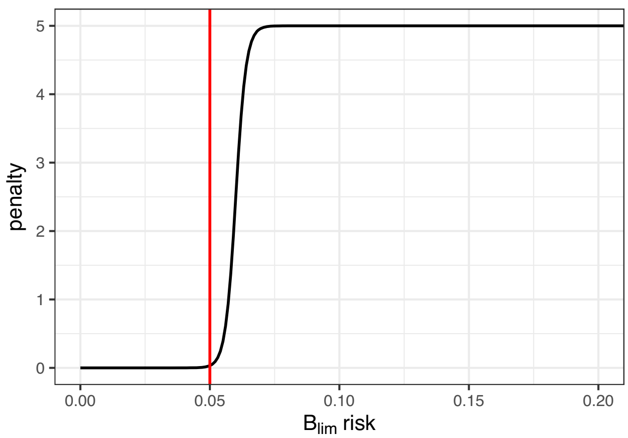

Figure 2. Fitness penalty (Ω) as a function of B_{lim} risk (P), as defined in Equation (9). The vertical red line represents the B_{lim} risk limit of 5%.

The final fitness function, which included MSY objectives for catch and SSB and included precautionary considerations for the risk, was defined as:

$$\phi_{\text{MSY-PA}} = \phi_{\text{SSB}} + \phi_{\text{Catch}} + \phi_{\text{risk-PA}} + \phi_{\text{ICV}}. \tag{10}$$

Each of the elements in $\phi_{\text{MSY-PA}}$ is negative because the genetic algorithm maximized the fitness. The fitness value of $\phi_{\text{MSY-PA}}$ quantifies the management performance of the simulation results (see e.g. Figures 5 and 7, described in the Results section). Fitness values closer to 0 (less negative) indicate better performance. The aim of the optimization procedure was to provide precautionary management solutions, and options where risk exceeds 5% are clearly indicated by red shading.

Scenarios

The scenarios explored were:

(1) Sensitivity. Pollack was chosen as a typical example stock ($k = 0.19$ year^{-1}, a medium value within the range for which the *rfb*-rule performed reasonably; Fischer *et al.*, 2020). As a baseline, the *rfb*-rule was tuned solely with the multiplier [x in Equation (2)] and all remaining parameters set to their default values (see Table 1) so that the B_{lim} risk was 5%. Subsequently, the sensitivity of the B_{lim} risk to the following simulation conditions was explored: the definition of B_{lim}, the starting condition of the stock before the implementation of the *rfb*-rule, the length of the projection period, the observation uncertainty (for biomass index and mean catch length, σ_{obs}), recruitment variability (σ_R) and recruitment steepness (h). For the runs considering the B_{lim} definition and the stock status ($\text{SSB}_{y=0}/B_{\text{MSY}}$), the number of simulation replicates was increased from 500 to 10 000 so that they could be split into groups (with steps of $0.1B_{\text{MSY}}$), and sufficient replicates in each group were available to calculate B_{lim} risk (>200 replicates for all groups with $\text{SSB}_{y=0}/B_{\text{MSY}} \leq 1.5$).

(2) Short- vs. long-term optimization. The standard simulation period for the *rfb*-rule was 50 years and the optimization considered the performance over the full period. The impact of this simulation period on B_{lim} risk and catch was explored by considering three time horizons; the first 10 years (years 1–10), the last 10 years (years 41–50), and all years (years 1–50).

(3) *rfb*-rule parameters. The impact of using all or a subset of the 10 tuneable parameters of the *rfb*-rule on achieving the precautionary management objectives (SSB, catch, B_{lim} risk, and ICV, summarized by $\phi_{\text{MSY-PA}}$) was explored for the example stock (pollack).

(4) Risk limit. The sensitivity of the optimization (SSB, catch, B_{lim} risk, and ICV) to the 5% B_{lim} risk limit was explored for all 29 stocks. For this purpose, the *rfb*-rule was tuned with the multiplier (x), and the remaining parameters were set to their default values. A comparison was made between the default 5% risk limit, doubling the risk to 10%, and an additive 5% point risk increase, defined as the stock-specific B_{lim} risk under no fishing and adding 5% points on top of that.

(5) Stock-specific optimization. The genetic algorithm was applied to optimize the full *rfb*-rule using $\phi_{\text{MSY-PA}}$ for all 29 stocks and the management performance was summarized with the value of $\phi_{\text{MSY-PA}}$.

(6) Comparison to MSY and ICES rule. The results of the optimization process from the previous step (including all *rfb*-rule parameters) were compared to the results of Fischer *et al.* (2021), who applied the ϕ_{MSY} fitness function and also tested the current ICES 2 over 3 advice rule for category 3 data-limited stocks. The 2 over 3 rule is essentially a simplification of the *rfb*-rule (with $n_0 = 1$, $n_1 = 2$, $n_2 = 3$, $e_r = 1$, $e_f = 0$, $e_b = 0$, $v = 2$, $x = 1$, $u_u = 1.2$, and $u_l = 0.8$) but includes a precautionary buffer. This buffer reduces the catch advice by 20% if either fishing mortality is above its MSY reference level, or biomass below half its MSY reference level, based on MSY proxy reference evaluations, such as with the surplus production in continuous time model (SPiCT; Pedersen and Berg, 2017), and can be applied once every three years (see Fischer *et al.*, 2021, for details on the implementation).

(7) Uncertainty cap. The optimizations of the *rfb*-rule in the previous points either did not include the uncertainty cap, or the values of the uncertainty cap were part of the optimization procedure. Fisheries managers might insist on the inclusion of an uncertainty cap to avoid large catch variability. Therefore, a final set of simulations was conducted where the uncertainty cap in the optimization was fixed to the values (+20%, −30%) suggested by Fischer *et al.* (2020).

Results

Sensitivity

Figure 3 summarizes the influence of the simulation specifications on B_{lim} risk for pollack in the random fishing history. A B_{lim} risk of 5% was achieved when setting the multiplier $x = 0.75$ (Figure 3a), and this parameterization was used as the baseline for the sensitivity analyses. B_{lim} risk was sensitive to the definition of B_{lim} (larger reference points reduced the risk), the initial stock status before the implementation of the *rfb*-rule (stronger initial depletion caused higher risks), the length of the MSE projection (risk declined over time), observation uncertainty for the biomass index and mean catch length (higher uncertainty increased the risk), and recruitment steepness (higher steepness reduced the risk, Figure 3b–e, g). The B_{lim} risk was insensitive to recruitment variability for $x = 0.75$; however, with larger multipliers (e.g. $x = 1$), the risk increased with increasing recruitment variability (Figure 3f).

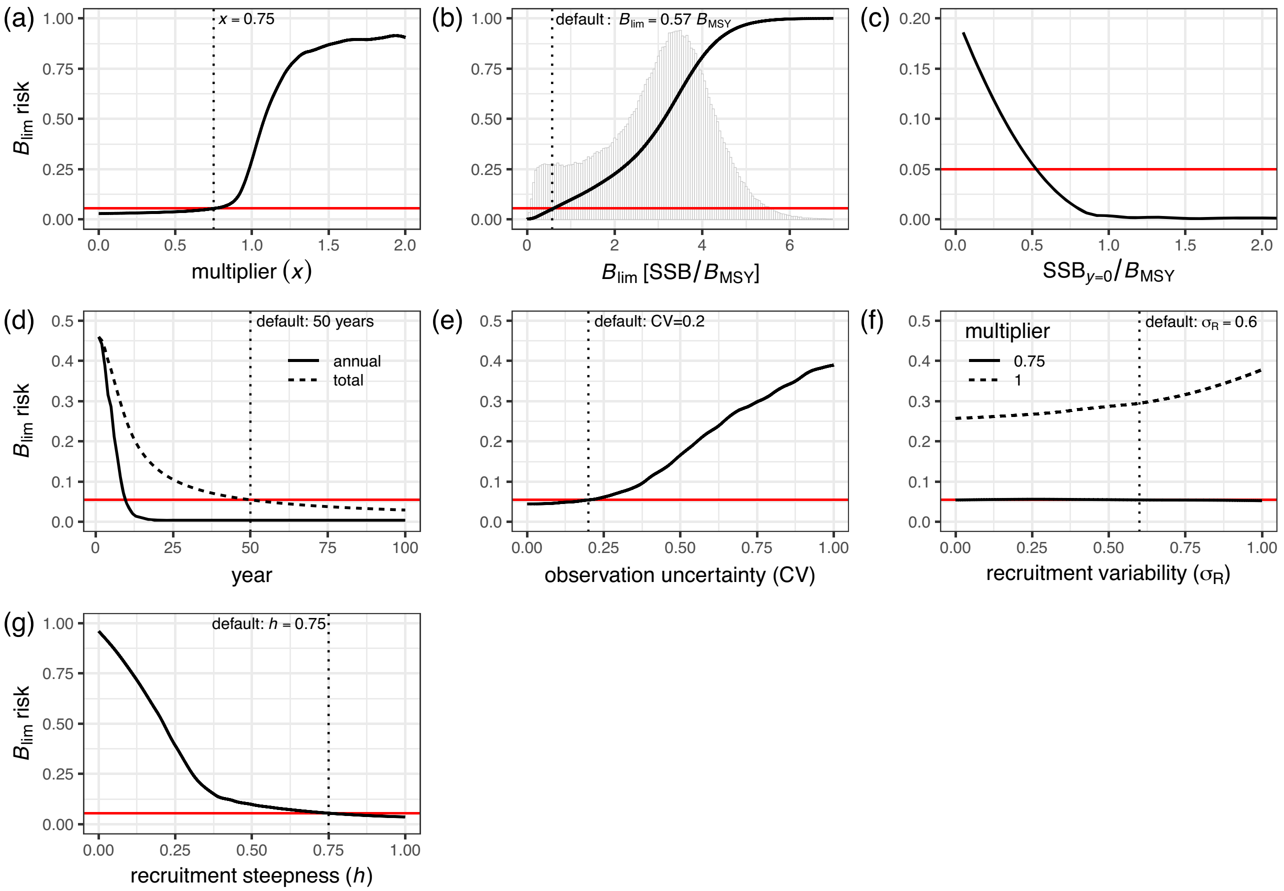

Figure 3. Summary of the sensitivity analyses of B_{lim} to simulation conditions for pollack under the random fishing history. B_{lim} risk reaches 5% for a multiplier of $x = 0.75$ of the *rfb*-rule (a), which is used for the remaining sensitivity analyses. Shown is the B_{lim} risk depending on the definition of B_{lim}, including a histogram of the distribution of SSB values (b), the initial stocks status before the implementation of the *rfb*-rule (c), the simulation period (d), the level of observation uncertainty for both the biomass index and mean catch length (e), recruitment variability (f), and recruitment steepness (g). The solid red horizontal line indicates the 5% risk limit, and the dotted vertical line the default parameterizations. In (d), shown are both the "annual" risk and the "total" risk from the start of the projection to the current year. The risk curve for recruitment variability (f) is flat for $x = 0.75$, and therefore sensitivity is also illustrated for $x = 1$.

Short- vs. long-term optimization

The selection of the time period over which the summary statistics are calculated influenced the selection of an *rfb*-rule parameterization so that the 5% B_{lim} risk limit was met. This is shown for two stocks in Figure 4. For pollack, in the one-way fishing history, $x = 0.76$ met the risk requirement when the full 50-year projection is considered. When only the last 10 years of the projection were taken into account, the multiplier could increase to $x = 0.92$. However, for the first 10 years of the simulation, no multiplier led to B_{lim} risk $\leq 5\%$. Short-term (first 10 years) risk for none of the faster-growing species ($k \geq 0.32$ year^{-1}) could be reduced to 5%. The short-term risk was more influenced by the starting condition of the simulation (i.e. fishing history), compared to calculating risk over a longer time.

[x, see Equation (2) and Table 1] was sufficient to reduce the B_{lim} risk to 5% with the $\phi_{MSY\text{-}PA}$ fitness function of the genetic algorithm. However, this risk reduction led to a substantial loss of catch and high SSB compared to the default (i.e. not optimized) *rfb*-rule parameterization. The performance could be substantially improved (higher yield while staying within the 5% risk limit) when more elements of the rule were introduced (n_0, n_1, n_2, e_r, e_f, e_b, and v). The uncertainty cap (restricting the difference of the catch advice compared to the previously realised catch; u_u and u_l) on its own could not reduce the risk to 5%. Including the uncertainty cap in combination with other *rfb*-rule parameters (either with the multiplier or with all parameters) did not affect the optimization and the optimized parameterization kept the default uncertainty cap (i.e. no cap).

rfb-rule parameters

The outcome of including different elements of the *rfb*-rule in optimizing the rule for pollack is shown in Figure 5, and the optimized parameterizations are listed in Supplementary Table S2. The results were similar for both fishing histories. Including only the multiplier

Risk limit

The selection of the B_{lim} risk limit had a substantial impact on the optimized *rfb*-rule parameterization. An analysis of the risk limits related to the selection of the rule's multiplier x is shown in Figure 6 for four example stocks (the remaining stocks are presented in

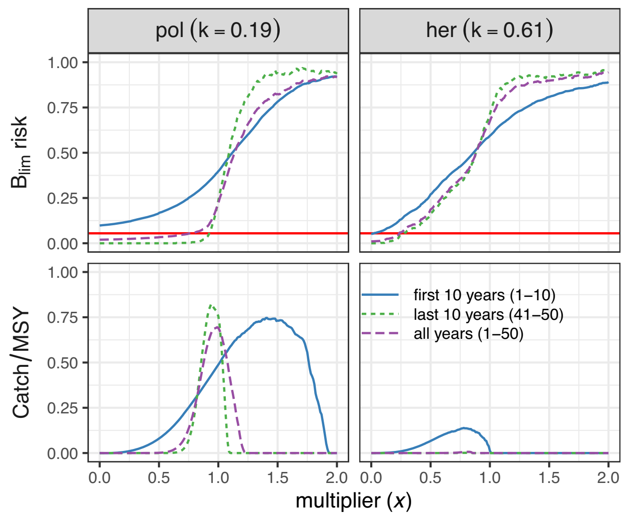

Figure 4. Impact of the time period used for calculating summary statistics. Results are shown for two stocks; pollack (pol) and herring (her) in the one-way fishing history. The red horizontal line indicates the 5% risk limit. Results for the remaining stocks are included in Supplementary Figure S1.

Supplementary Figure S2). It was possible for all 29 stocks (and both fishing histories) to set a multiplier that reduced the risk to $\leq$ 5%. An explicit 5% risk limit was the most restrictive for all stocks and resulted in the lowest long-term catch, followed by the additive 5% point and the 10% limits.

Stock-specific optimization

Figure 7 shows the management performance of the *rfb*-rule for the various optimizations, a comparison with the results of Fischer *et al.* (2021, optimization without the risk limit, and the 2 over 3 rule) and a zero fishing option. The performance is expressed through the fitness [$\phi_{\text{MSY-PA}}$, Equation (10)] and non-precautionary parameterizations (B_{lim} risk > 5%) are clearly highlighted in red. The fitness split into its elements (SSB, catch, ICV, and risk penalty) is available from Supplementary Figure S3.

For all 29 stocks and both fishing histories, the B_{lim} risk could be reduced to 5%, both when using only the multiplier (f in Figure 7) or all *rfb*-rule parameters in the optimization (g in Figure 7) with the genetic algorithm. When using only the multiplier, the catches were often low and SSB well above B_{MSY}. Including all *rfb*-rule parameters in the optimization improved performance for most stocks, with higher catches while keeping B_{lim} risk within the 5% limit. The performance of the rule for the higher-*k* stocks ($k \geq 0.32\ \text{year}^{-1}$) was poor (high B_{lim} risk, low catch/MSY), and meeting the 5% risk limit was only possible by reducing catches to zero or near-zero. The optimized *rfb*-rule parameterizations were specific to the stock and fishing history and are summarized in Supplementary Table S2.

Comparison to MSY and ICES rule

Figure 7 includes a comparison of the performance of the $\phi_{\text{MSY-PA}}$-optimized *rfb*-rule (f and g) to the optimization with ϕ_{MSY} (d and e) of Fischer *et al.* (2021) and the ICES 2 over 3 rule (b). The ICES 2 over 3 rule often led to high B_{lim} risks and risk was always > 5%. There were clear trade-offs between the ϕ_{MSY}-optimized and the $\phi_{\text{MSY-PA}}$-optimized *rfb*-rule, where the first delivered highest yields close to B_{MSY} but B_{lim} risks above 5%, whereas the latter resulted in B_{lim} risks within the 5% limit, but with markedly lower yields.

Uncertainty cap

For all but two stocks (lesser spotted dogfish, syc2 and golden redfish, smn), fixing the uncertainty cap (limiting catch advice increase to +20% and the decrease to −30%) meant that the optimization of the *rfb*-rule with $\phi_{\text{MSY-PA}}$ and the multiplier was impaired and the risk could not be reduced to 5% in at least one of the fishing histories (h in Figure 7). To overcome this problem, the *rfb*-rule was tested with a conditional uncertainty cap, where the cap is only applied when the biomass index is above its threshold level [$I \geq I_{\text{trigger}}$ in Equation (2)]. The results of these optimizations (i and j in Figure 7) show that the 5% risk limit could be met for most stocks, at least when the optimization was conducted with all parameters. Exceptions are the four fastest-growing species (John Dory, jnd, European pilchard, sar, herring, her, and sandeel, san), where the inclusion of the conditional uncertainty cap did not allow the risk to meet the 5% limit. In some cases (see, e.g. plaice, ple, and turbot, tur, in Figure 7), the introduction of the conditional cap resulted in a better fitness when the optimization included all parameters (j), compared to the free selection of the (unconditional) cap (g).

Discussion

The outcomes of this study were manifold, and the main results are summarized in Figure 7. The key message is that explicit precautionary consideration (such as the 5% risk limit) could be incorporated into data-limited fisheries management, shown here with the example of the *rfb*-rule and through the application of a genetic algorithm. This approach allowed the specification of management objectives and the exploration of trade-offs. The level of complexity of a decision rule can impact the overall management performance and more complex case-specific adaptions delivered higher yield while remaining precautionary.

Results of any simulation study depend on the simulation specifications, and models are simplifications of reality (Burnham, 2002). The present study is no exception, and the sensitivity analysis reiterated this by showing that the presumed precautionary management performance of the *rfb*-rule (quantified through the B_{lim} risk) was influenced by simulated conditions such as the initial stock status. The MSE concept inherently relies on simulations and associated assumptions, which can lead to criticism (Rochet and Rice, 2009, 2010; Kraak *et al.*, 2010), but following best practices (e.g. Punt *et al.*, 2016) and including a wide range of uncertainties can restore confidence in the conclusions (Butterworth *et al.*, 2010).

Uncertainty is exacerbated for simulations of the *rfb*-rule because the rule is meant to be applied in data-limited situations. For example, the biomass limit reference point (B_{lim}) was defined in terms of recruitment impairment (Fischer *et al.*, 2020) and is therefore dependent on recruitment steepness, which is difficult to estimate even for data-rich stocks. However, the value of B_{lim} relative to unfished biomass, $0.16B_0$, closely resembles the generic value of $0.2B_0$ adopted by other management bodies such as the International Whaling Commission (IWC), the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR), and Australia and New Zealand (Preece *et al.*, 2012).

A 5% limit is commonly used in many scientific fields to describe rare events or to safeguard against their occurrence, e.g. by

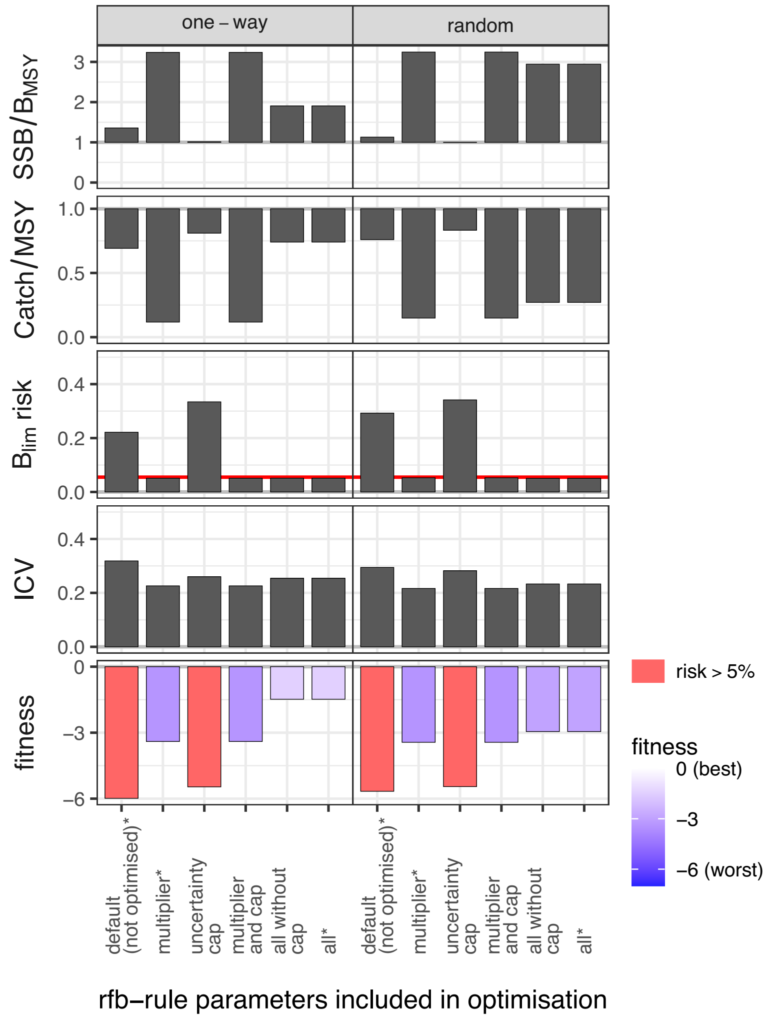

Figure 5. Results of using different elements of the *rfb*-rule in the optimization procedure (with $\phi_{\mathrm{MSY\text{-}PA}}$) for pollack for two fishing histories (one-way and random). All optimizations apart from the default use the genetic algorithm. The red horizontal line in the third row of plots highlights the 5% B_{lim} risk limit. Fitness values (last row) where the risk exceeds 5% are highlighted in red. Results marked with * are shown again in Figure 7 (c, f, and g) for comparison.

defining that statistical analyses are significant for $p \leq 0.05$. However, this limit itself is controversial in the scientific community (Wasserstein and Lazar, 2016; Amrhein *et al.*, 2019). The origin of the 5% limit used in the ICES interpretation of the precautionary approach is somewhat opaque. The approach was initially introduced into the ICES fisheries advice framework without specific risk limits, and stated that limit reference points should be avoided with a high probability (ICES, 1997), with reference to a United Nations agreement on the implementation of the precautionary approach (UN, 1995). Subsequently, referring to the considerations of Butterworth and Bergh (1993) on precautionary decision rules, ICES (1998) note that an “example of a precautionary criterion for management might be [defined as a] probability of less than 5% of reducing the resource below B within 10 years”, without specifying or giving justifications for the 5%, the reference point B or the 10-year period. Such risk levels were originally meant as interim solutions until more appropriate risk levels had been agreed among stakeholders. However, this value has not changed since then and is currently enshrined into the ICES advice framework (ICES, 2019a) and also recommended for MSE testing of data-limited management procedures (ICES, 2017b). ICES (2020b) note that the appropriateness of the 5% risk limit was queried again with advice recipients in 2020 and recipients expressed their satisfaction about using this value without suggesting alternatives.

In other parts of the world, risk considerations similar to the ICES precautionary approach are applicable. For example, the harvest strategy standard for New Zealand fisheries (Ministry of Fisheries, 2008) includes a clause stipulating that management procedures need to ensure that breaching a soft limit does not exceed 5%. The justification of using specific risk limits is always challenging and can easily draw criticism. The benefit of using a modelling approach is that different risk limits can be tested and their implications on management performance can be illustrated, which in turn allows an informed judgement about the acceptability of a particular risk limit.

Specific risk values crucially influence management rules and decisions. As shown here for the *rfb*-rule, doubling the allowed risk to 10% had a large impact on the optimized rule’s performance and resulted in much higher long-term catches while being precautionary at a 10% risk level. Relative risk metrics might be considered a

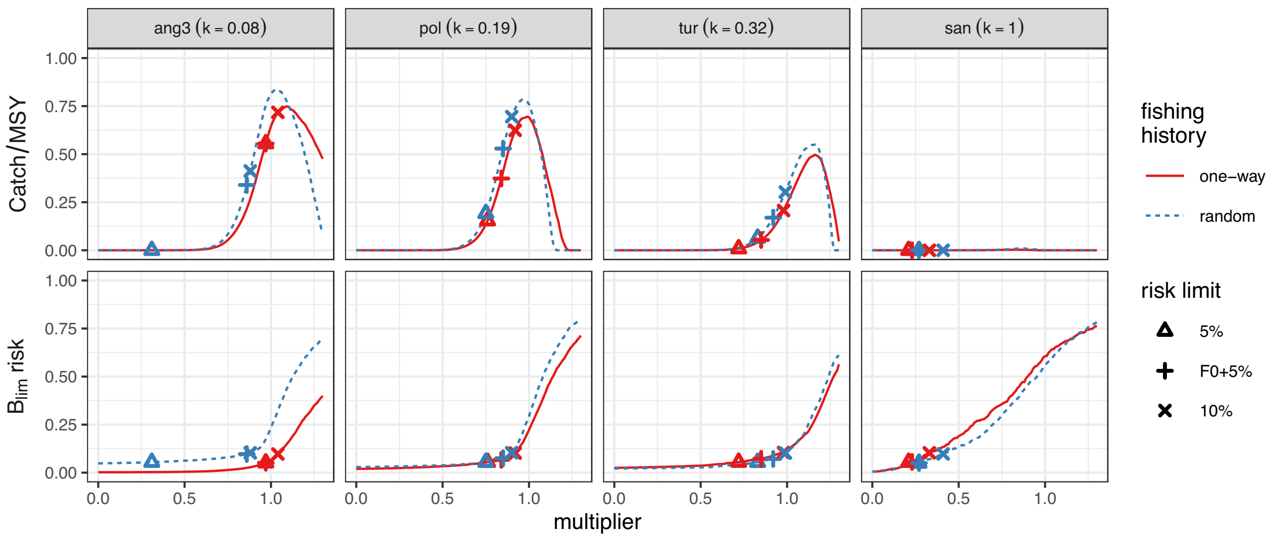

Figure 6. Impact of different precautionary B_{lim} risk limits on summary statistics in optimizing the *rfb*-rule with a multiplier (the remaining parameters are set to their default values of Table 1). Results are shown for four example stocks; blackbellied angler (ang3), pollack (pol), turbot (tur), and sandeel (san). The optimized solutions are highlighted with symbols. F0+5% indicates the additive 5% point risk limit increase compared to no fishing. The "5%" risk limit optimization results (triangles) for pollack correspond to the "multiplier" optimization in Figure 5.

plausible alternative to absolute risk. Relative risk can be defined as the risk relative to some baseline risk, such as the risk without any fishing activity. The benefit of this approach is that natural variability is explicitly considered, e.g. when a fish stock naturally exhibits high fluctuations and, therefore, the risk of falling below a limit reference point is high, even without any fishing activity. One example explored here for the *rfb*-rule was an additive risk of 5% points, added on top of the risk without fishing. On the other hand, defining the risk increase of 5% points is arbitrary in the same way as defining an absolute risk limit. Another alternative to quantify risk is the approach used for South African short-lived pelagic species where the shift of the biomass distribution of a stock is compared to the distribution under no fishing (de Moor *et al.*, 2011), but generally only possible if such information is available. The definition and usefulness of risk criteria in fisheries management should be explored further, in particular whether the same approach should be applied irrespective of life history or other stock characteristics. Tools such as genetic algorithms can be useful because they allow the exploration of management solutions and illustrate trade-offs.

Fischer *et al.* (2020) developed the operating models for the 29 stocks used in the simulations, and provided extensive sensitivity analyses on their assumptions and parameterizations, including the appropriateness of levels of uncertainty. The simulation approach used here can be considered generic, but conditioned on life-history traits. Generic simulations need to account for additional uncertainty, which was implemented here by considering two alternative fishing histories, one where the starting condition implied a high stock depletion, and the other provided a large spread of different depletion levels. For optimum performance of any decision rule, more data should be collected to enable case-specific testing and optimization.

For all 29 stocks and both fishing histories simulated in this study, projecting forward with zero fishing led to B_{lim} risks below 5%, which meant that there was scope for fishing activities while remaining within the 5% risk limit. The 2 over 3 rule generally resulted in high B_{lim} risks (16–73%), and its performance was strongly dependent on the initial stock status. Therefore, the current management of ICES category 3 data-limited stocks based on the 2 over 3 rule with uncertainty cap and precautionary buffer cannot be considered precautionary. Except for two slow-growing stocks (Atlantic wolffish and megrim in the one-way fishing history), applying the default *rfb*-rule parameterization led to risks above 5%.

However, when the *rfb*-rule was optimized with the genetic algorithm, and the fitness function included the 5% risk limit, an optimized parameterization of the *rfb*-rule was found, which complied with the risk limit, both when only modifying the rule's multiplier or the complete set of parameters. However, clear trade-offs between the two solutions were evident. The parameterization based on the multiplier achieved risk compliance by reducing the catch advice and forfeiting much of the long-term catch. On the other hand, the solution with all of the *rfb*-rule's parameters tuned resulted in better performance with higher catches. The comparison of the optimized *rfb*-rule with (this study) and without the 5% risk limit (Fischer *et al.*, 2021) revealed that the inclusion of the limit was restrictive and led to lower yields. The decision on which approach should be implemented in reality is essentially up to managers. Including risk limits can be restrictive; however, this might be considered necessary to ensure precautionary management. An interesting observation was made about the implementation of the uncertainty cap. For pollack, the inclusion of the cap did not improve management performance, and the optimization procedure selected the parameterization, which turned off the cap. When a fixed cap (+20% and −30%) was enforced, for most stocks, this meant that the 5% risk limit could not be met. To avoid this, we suggest implementing a conditional uncertainty cap (+20% and −30%), which is only activated when the biomass index is at or above its trigger value.

Previous work showed that the *rfb*-rule resulted in poor performance with high risks of stock collapses and low yields for faster-growing stocks (with von Bertalanffy growth parameter $k \geq 0.32\ \text{year}^{-1}$; Fischer *et al.*, 2020), and even optimizing the rule towards MSY objectives did not markedly improve the outcome

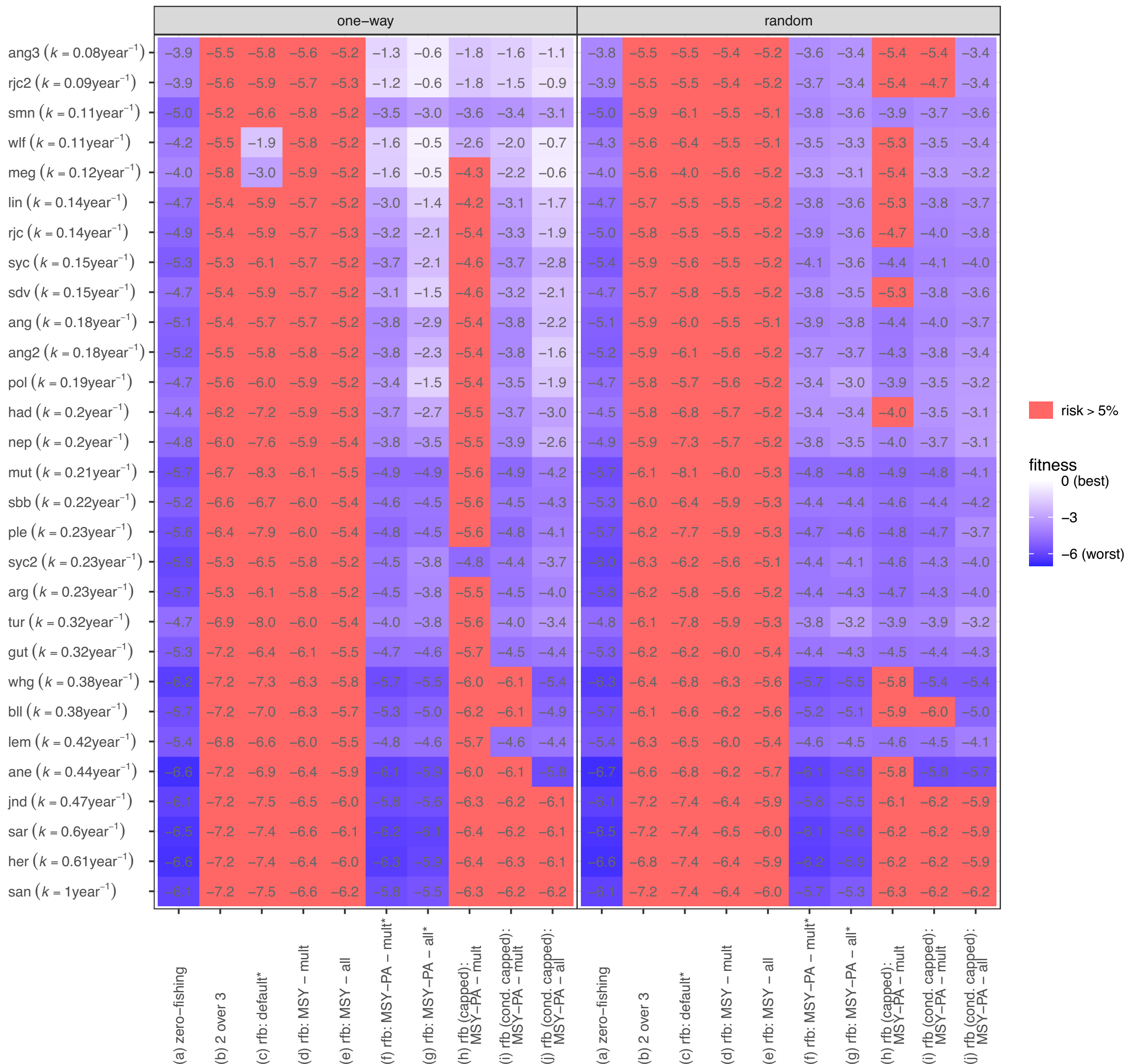

Figure 7. Fitness ($\phi_{\text{MSY-PA}}$) as a measure of management performance of the *rfb*-rule, achieved through optimization with the genetic algorithm, and comparison to a "zero-fishing" option (a) and the 2 over 3 rule (b, from Fischer *et al.*, 2021). Non-precautionary management (risk exceeds 5%) is highlighted in red. "rfb: default" denotes the non-optimized parameterization (c), "rfb: MSY" are the parameterizations optimized without the risk limit (d and e, from Fischer *et al.*, 2021), "rfb: MSY-PA" include the 5% risk limit (f–j), "rfb (capped)" indicates that the uncertainty cap is fixed (+20% and −30%, h) and for "rfb (cond. capped)" the cap is conditional and only implemented when $I \geq I_{\text{trigger}}$ in Equation (2) (i and j). The "mult" indicates optimization with only the multiplier of the *rfb*-rule (d, f, h, and i) and "all" with all parameters (e, g, and j). The labels highlighted by * (c, f, and g) refer to the same optimizations shown in Figure 5 for pollack.

(Fischer *et al.*, 2021). The general conclusion was that the *rfb*-rule should not be implemented for such fast-growing stocks because of their highly variable populations dynamics and dependence on recruitment success (see, e.g. Cury *et al.*, 2014). The present work supports this recommendation. The *rfb*-rule could be optimized to meet a specific precautionary criterion (constraining the risk of the stock falling below B_{lim} to a specific limit). Nevertheless, meeting this criterion was only possible by accepting an extreme trade-off for the yield, i.e. advising very low precautionary catch levels. Alternative management procedures, e.g. based on harvest rates or escapement strategies (ICES, 2020a), appear more suitable and are a subject of future work.

The main recommendation from this work is to replace the 2 over 3 rule with the *rfb*-rule for ICES category 3 data-limited stocks with slow to medium individual growth ($k \leq 0.32$ year^{-1}). If case-specific simulations are not possible, the *rfb*-rule can be applied with generic multipliers meant to ensure precautionary management, as proposed by ICES (2020a). The *rfb*-rule was already applied this way to the first two stocks in the 2021 ICES advice (ICES, 2021b, c), and a further rollout is anticipated for 2022. Ideally, case-specific simulations are conducted and should consider stock characteristics, such as adapting the simulation period to life history, using more specific uncertainty estimates (e.g. correlation structure of residuals), and alternative operating models. An example for such a situation is the western English Channel plaice stock, where ICES advice is currently based on the 2 over 3 rule (ICES, 2021a), but this stock is relatively data-rich, facilitating case-specific simulations. Case-specific analyses are likely to lead to better overall management performance while maintaining precautionary principles.

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Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

Data availability

Input data, software code and summarised results presented in this study are available from GitHub at https://git.io/JCEbw.

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