ICES Journal of Marine Science, 2022, **00**, 1–12
DOI: 10.1093/icesjms/fsac103
Original Article

ICES CIEM
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Exploring a relative harvest rate strategy for moderately data-limited fisheries management

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Moderately data-limited fisheries can be managed with simple empirical management procedures without analytical stock assessments. Often, control rules adjust advised catches by the trend of an abundance index. We explored an alternative approach where a relative harvest rate, defined by the catch relative to a biomass index, is used and the target level derived from analysing historical catch length data. This harvest rate rule was tested generically with management strategy evaluation. A genetic algorithm was deployed as an optimisation procedure to tune the parameters of the control rule to meet maximum sustainable yield and precautionary management objectives. Results indicated that this method could outperform trend-based strategies, particularly when optimised, achieving higher long-term yields while remaining precautionary. However, optimum harvest rate levels can be narrow and challenging to find because they depend on historical exploitation and life history characteristics. Misspecification of target levels can have a detrimental impact on management. Nevertheless, harvest rates appear to be a suitable management option for moderately data-limited resources, and their application has modest data requirements. Harvest rate strategies are especially suitable for stocks for which case-specific analyses can be conducted.

Keywords: data-limited, empirical catch rules, FLR, genetic algorithm, harvest rate, ICES, management strategy evaluation, precautionary approach, risk.

Introduction

Fisheries management should ensure the sustainable exploitation of harvested fish stocks (Hilborn and Walters, 1992). Management principles such as maximum sustainable yield (MSY, i.e. keeping the stock at or above a level where it is most productive) or the precautionary approach (i.e. reduce the risk of stock depletion; Garcia, 1996) are often mandated through national or international legislation, such as the European Union's common fisheries policy (EU, 2013). However, most of the world's fish stocks are considered data-limited and complex stock assessments or forecasts do not exist (Rosenberg *et al.*, 2014). For such stocks, simpler stock assessment models can sometimes be used to help comply with these management principles. Alternatively, model-free management procedures relying only on empirical data have been shown to be viable management options (Geromont and Butterworth, 2015b; Carruthers *et al.*, 2016).

ICES is the provider of scientific advice on fishing opportunities for many fish stocks in the Northeast Atlantic (ICES, 2021a) and classifies stocks into six categories (Table 1). According to their stock assessment database (ICES, 2021e), ICES provided advice for 175 fish stocks in 2020, of which around 50% were considered data-limited (ICES categories 3–6). Of these data-limited stocks, 55% were classified as category 3. For category 3 stocks, catches, including catch length data, as well as a stock index (often from a scientific survey), exist (ICES, 2021a). While the data might be enough to apply surplus production or integrated assessment models, these models are not used because of insufficiently long time series, lack of contrast in the data to inform models, violations of model assumptions, model convergence issues, unacceptably high uncertainty estimates, or because models fail acceptance criteria (Punt *et al.*, 2020). We follow the ICES interpretation of the term "data-limited", which might be considered as "data-moderate" or even "data-rich" elsewhere, and category 3 is the focus of this paper.

There are two main approaches to how empirical management procedures generate catch advice: (i) indicator-adjusted catch rules which adjust the previous catch by a multiplier derived from an indicator such as the trend from a stock index, and (ii) by defining a harvest rate and applying this to a biomass estimate. ICES is currently in the process of revising its data-limited management framework from 2012 (ICES, 2012) and is replacing methods for category 3 stocks (ICES, 2020, 2022). One of the replacement methods is the rfb rule (Fischer *et al.*, 2020, 2021a, b), an indicator-adjusted catch rule in which the catch advice is adjusted by the trend in a relative biomass index and the signal from length data. However, indicator-adjusted catch rules can be problematic because the new advice is directly linked to the previous value, which can induce oscillatory behaviour, restrict flexibility, or react slowly to changes in the stock if the index trend is estimated over several historical years.

The use of harvest rates can overcome some of the shortcomings of indicator-adjusted catch rules. In its simplest form, a harvest rate is the catch divided by the abundance of an exploited stock, e.g. derived from a stock index. This allows the definition of a target harvest rate, implemented by multiplying it with the current index value to calculate a new catch limit. A potential benefit of such an approach is that a new catch advice can be set independently of the previous catch. A main challenge for harvest rate-based management

Received: January 24, 2022. **Revised:** April 8, 2022. **Accepted:** May 12, 2022

Table 1. Overview of the ICES data categories. Data and advice method columns describe typical scenarios but deviations from these exist. Revisions for category 2 and 3 suggested by ICES (2020, 2022) are included.

Category	Description (ICES, 2021a)	Typical data	Typical advice method
1	*Stocks with quantitative assessments*	Catch and survey data (mostly age-structured)	Stock assessment & short-term forecast
2	*Stocks with analytical assessments and forecasts that are only treated qualitatively*	Catch and survey data (mostly age-aggregated)	Stock assessment & short-term forecast
3	*Stocks for which survey-based assessments or exploratory assessments indicate trends*	Catch (with length data) and stock index (survey/commercial) without age structure, life-history information	Empirical (model-free) methods
4	*Nephrops stocks where information on possible abundance can be inferred*	Catch, recent survey index value, biological data (can be borrowed)	Precautionary MSY harvest rate applied to index
5	*Stocks for which either only data on landings or a short time-series of catch are available*	Landings	Recent advice kept or reduced (if previous reduction was more than 3 years ago)
6	*Stocks for which there are negligible landings and stocks caught in minor amounts as bycatch*	Unreliable catch	Recent advice kept or reduced (if previous reduction was more than 3 years ago)

in a data-limited situation is the definition of the target level. Here, we consider the situation where the target harvest rate is derived empirically (as opposed to using a model in data-rich situations).

The use of harvest rates for data-limited fisheries management is not new. The 2012 ICES framework for data-limited stocks includes an F_{proxy} rule (method 3.3. of ICES, 2012). This rule can be considered a variant of a harvest rate rule, where a target is set based on historical F_{proxy} values (catch divided by stock index) and used to derive catch advice for the next year, with an uncertainty cap (limiting changes in catch advice to 20%) and a precautionary buffer (reducing the catch advice by 20%). This rule has occasionally been used in ICES (ICES, 2021e), e.g. for East and South Greenland cod (*Gadus morhua*, 2016-2017; ICES, 2017a), East Greenland and Iceland grounds greater silver smelt (*Argentina silus*, 2012-2019; ICES, 2021c) and blue ling (*Molva dypterygia*, 2012-2018; ICES, 2021b). In these cases, the management target was largely based on expert judgement. This included selecting a time period of several years based on considerations such as whether F_{proxy} values appeared stable or a stock index indicated a generally stable or increasing trend for stock biomass. The target harvest rate was then defined as the average F_{proxy} for these years.

Harvest rates are commonly used for data-rich fisheries management and this is often associated with running stock assessment models to estimate the stock size. The ICES advisory framework for data-rich stocks goes one step further by conducting short-term forecasts and setting catch limits based on a hierarchy of advice rules (ICES, 2019, 2021a). Previous data-limited simulation studies considered the applicability of control rules by comparing stock index values relative to a target value, but either used the comparison to adjust a previous catch (Geromont and Butterworth, 2015b; Carruthers *et al.*, 2016) or to move the current catch towards a target level (Geromont and Butterworth, 2015a). The direct application of harvest rates based on a stock index has not been considered for data-limited fisheries management recently.

This paper explores the applicability of a relative harvest rate rule for moderately data-limited fisheries management, in particular how it could complement the current set of rules, especially where current approaches are inadequate and do not follow required management principles. To accomplish this, we use management strategy evaluation (MSE; Punt *et al.*, 2016), in the sense of a closed-loop simulation for evaluating management procedures but without extensive stakeholder engagement.

MSE (Smith, 1994; Punt *et al.*, 2016) is widely considered the state-of-the-art for exploring management strategies. It is crucial that candidate management procedures are simulation tested before implementation to ensure their robustness to a range of uncertainties. Many MSEs are conducted on a case-specific basis for well monitored and commercially important species, e.g. international tuna stocks (Sharma *et al.*, 2020). The simulation of stocks with limited data can be more challenging due to the lack of data and knowledge. Nevertheless, notable studies screened various data-limited methods (Geromont and Butterworth, 2015b; Jardim *et al.*, 2015; Carruthers *et al.*, 2016).

To conduct the MSE, we used the generic operating models developed by Fischer *et al.* (2020) because these cover a wide range of life-history traits. Furthermore, Fischer *et al.* (2021a) showed that the performance of control rules could be substantially improved through tuning with a genetic algorithm. A genetic algorithm is a computationally efficient method for solving multi-dimensional optimisation problems, and works by mimicking principles of biological evolution by introducing variability into the tuneable parameters and subjecting parameterisations to a competitive environment where selection favours individuals with higher fitness (Holland, 1992). In the context of a fisheries management procedure, the elements of a control rule are the tuneable parameters, and the fitness can be measured as the management performance relative to agreed management objectives, such as long-term sustainable exploitation. This can include explicit precautionary considerations (Fischer *et al.*, 2021b), such as the 5% risk limit that is part of the ICES precautionary approach (ICES, 2019, 2021d).

Specifically, this paper explores an approach in which a target harvest rate is linked to empirical data (mean catch length as a proxy for fishing pressure). The resultant management procedure is simulation tested using MSE, and then optimised

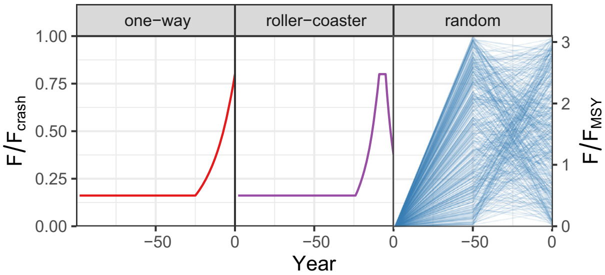

Figure 1. The three fishing histories of the operating models.

considering the ICES precautionary approach and MSY. Finally, we compare the relative harvest rate rule with other more traditional ICES data-limited fisheries management approaches.

Methods

Operating models

The age-structured operating models developed by Fischer *et al.* (2020) in the Fisheries Library in R (FLR; Kell *et al.*, 2007), and as parameterised in Fischer *et al.* (2021a), were used. These operating models were generated from life-history parameters and considerations of life-history relationships, and comprised 29 generic stocks, covering a wide range of life-history traits (see Supplementary Table S1). All operating models were subjected to three 100-year fishing histories (Figure 1; Fischer *et al.*, 2020, 2021a). In the *one-way* fishing history, fishing mortality (F) was increased exponentially, in the *roller-coaster* history, F was first increased but then decreased again, and in the *random* history, random F trajectories occurred, leading to a range of depletion levels at the beginning of the MSE. The operating models were stochastic and uncertainty was included in 500 simulation replicates through a log-normal process (recruitment error $\sigma_R = 0.6$, added to the Beverton-Holt stock-recruitment model) and observation errors ($\sigma_{\text{obs}} = 0.2$, added to the aggregated total biomass and mean catch length indices). Details of the operating models are described in the Supplementary Material.

Relative harvest rate management procedure

A relative harvest rate H can be defined as the ratio of the catch C divided by a stock size indicator I, e.g. a biomass index:

$$H_y = C_y/I_y, \tag{1}$$

for year y. I can be a relative index and does not need to represent the total stock biomass because it is only used relative to the catch. For simplicity, I was assumed to be a total biomass index in the simulations. Figure 2 explains how a target harvest rate can be derived purely from empirical data. The procedure consists of determining reference years where historical mean catch length is above a reference length, calculating the relative harvest rates for these years, and taking their average to define a target harvest rate H_{target}. We used the MSY proxy reference length defined by Jardim *et al.* (2015):

$$L_{F=M} = 0.75L_c + 0.25L_\infty, \tag{2}$$

where L_c is the length at first capture and L_∞ the von Bertalanffy asymptotic length. This reference length assumes $M/k = 1.5$ (where k is the von Bertalanffy growth parameter) and fishing at the natural mortality rate $F = M$ as a proxy for F_{MSY}, and follows the concepts of Beverton and Holt (1957). The length data are only required for setting H_{target} and not used later in the implementation of the management procedure.

This target harvest rate H_{target} can then be used to determine the advised catch for the next year A_{y+1}:

$$A_{y+1} = I\, H_{\text{target}}, \tag{3}$$

where I is the recent index value. Additional precaution can be introduced with a biomass safeguard b, which reduces the targeted harvest rate when the index falls below an index trigger value, I_{trigger} (see Table 2). The biomass safeguard b essentially imposes a hockey-stick functional form on the control rule (Figure 3), similar to the ICES MSY advice rule used for category 1 data-rich stocks (ICES, 2019).

I_{trigger} can be linked to the lowest observed index value I_{loss} through a multiplicative buffer w (see Table 2), often set to $w = 1.4$ in the absence of better knowledge (ICES, 2017b, 2021d).

In order for the harvest rate control rule to be optimised, the components of the rule can be made more flexible by adding additional parameters. This allows the components to be calibrated for best performance:

$$A_{y+1} = \sum_{i=y-n_0-n_1+1}^{y-n_0} \left(\frac{I_i}{n_1}\right) H_{\text{target}}\, b\, x. \tag{4}$$

We refer to this relative harvest rate management procedure of Equation (4) as "harvest rate rule". See Table 2 for details and descriptions of all parameters. The multiplier x is applied to the entire control rule. However, because the elements of the control rule are multiplicative, it can also be thought of as being part of the harvest rate ($H'_{\text{target}} = x\, H_{\text{target}}$), i.e. changing the target level of the rule.

Finally, the catch advice can be set constant for an interval of v years before the control rule is applied again, and catch constraints (called uncertainty caps in ICES) limit the allowed increase (u_u) and decrease (u_l) of the catch advice. This leads to a total of seven tuneable parameters (x, n_0, n_1, w, v, u_u, u_l).

Optimisation

Fischer *et al.* (2021a, b) showed that a genetic algorithm effectively optimises empirical management procedures towards specific management objectives and defined two fitness functions:

$$\phi_{\text{MSY}} = -\left|\overline{B}/B_{\text{MSY}} - 1\right| - \left|\overline{C}/\text{MSY} - 1\right| - \overline{\text{ICV}} - B_{\text{lim}}\text{ risk} \tag{5}$$

and

$$\phi_{\text{MSY-PA}} = -\left|\overline{B}/B_{\text{MSY}} - 1\right| - \left|\overline{C}/\text{MSY} - 1\right| - \overline{\text{ICV}} - \Omega\left(B_{\text{lim}}\text{ risk}\right), \tag{6}$$

where $\overline{B}$, $\overline{C}$, and $\overline{\text{ICV}}$ are the medians of spawning stock biomass (SSB), catch, and inter-annual catch variability (calculated over a 50-year projection and 500 simulation replicates), B_{MSY} and MSY the MSY reference values, B_{lim} risk the risk of the SSB falling below the biomass limit reference point (defined as the SSB where recruitment is impaired by 30%, i.e. $B_{\text{lim}} = B_{R=0.7R_0}$), and Ω a penalty function reducing ϕ when

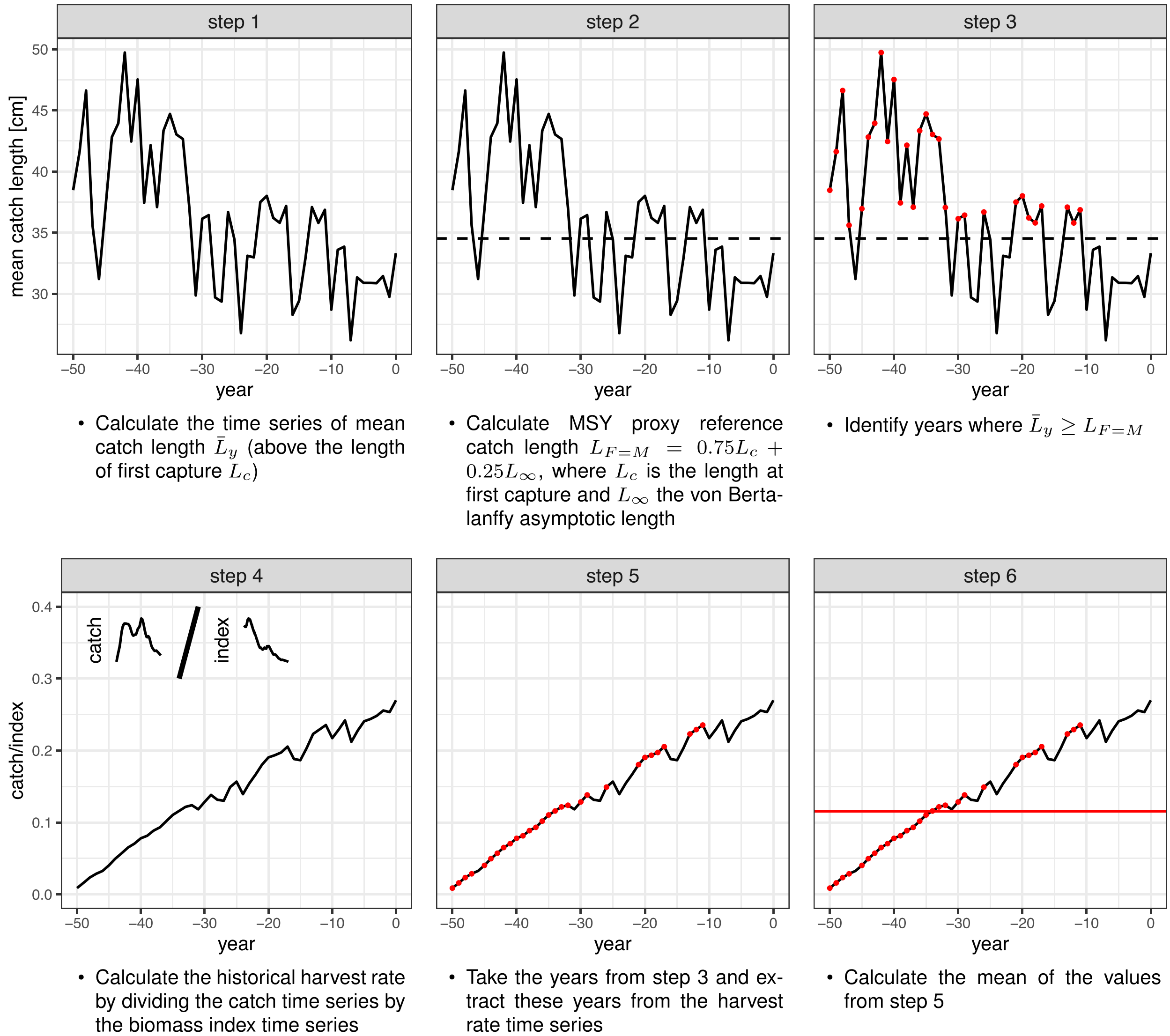

Figure 2. Derivation of a target harvest rate from empirical data. Shown is one example simulation replicate for pollack. Please note that the index can be a relative index.

Table 2. Parameters of the flexible harvest rate rule (as shown in Equation (4) and described in the subsequent text).

Parameter	Description	Definition	Default
Components of the harvest rate rule			
A	Catch advice	See Equation (4)	
I_y	Index value	Index value in year y	
H_{target}	Harvest rate target	C_y/I_y for reference years y	
b	Biomass safeguard	$b = \min(1, I_{y-n_0}/I_{\text{trigger}})$	
x	Multiplier		$x = 1$
Generic parameters			
y	Year	Year relative to assessment year	
n_0	Time lag	Offset between last biomass index year and assessment year	$n_0 = 1$
n_1	Index range	Number of index years	$n_1 = 1$
I_{trigger}	Index trigger	Value below which the biomass safeguard reduces catch advice $I_{\text{trigger}} = wI_{\text{loss}}$	
I_{loss}		Lowest observed index value	
w	Index trigger buffer	Connects I_{loss} to I_{trigger}	$w = 1.4$
Additional parameters			
v	Interval	Number of years for which the catch advice is kept constant	$v = 1$
u_u, u_l	Upper and lower uncertainty cap	Catch constraint (upper and lower limit), restricting the allowed change in the catch advice A_{y+1} relative to last advice A_y, implemented after deriving A_{y+1} from Equation (4): $\min\{\max(u_l A_y, A_{y+1}), u_u A_y\}$	$u_u = \infty$, $u_l = 0$

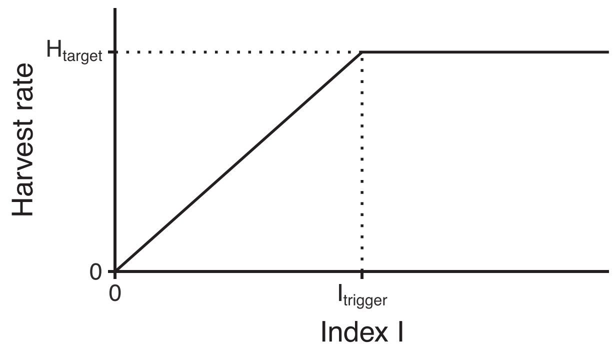

Figure 3. Hockey-stick principle of the harvest rate control rule. The harvest rate shown is the $H_{\text{target}}\, b$ component of Equation (4) and the shape of the curve is determined by the biomass safeguard b.

B_{lim} risk exceeds 5% (i.e. formalised the ICES precautionary criterion, $\Omega\left(B_{\text{lim}} \text{ risk}\right) = 5/\left(1 + e^{-500(B_{\text{lim}} \text{ risk} - 0.06)}\right)$). ICV was defined as $|(C_y - C_{y-v})/C_{y-v}|$ for years y in which a new advice was set and the advice interval v. The fitness function ϕ_{MSY} measured MSY management performance by including all four summary statistics, i.e. its aim was to move SSB to B_{MSY}, catch to MSY, and reduce ICV and risk. In $\phi_{\text{MSY-PA}}$, a penalty was applied when risk exceeded 5%. Elements of ϕ are negative because ϕ was maximised with the genetic algorithm and a maximum fitness of zero implies SSB is at B_{MSY}, catch at MSY, and ICV is zero, and furthermore, that risk is zero (for ϕ_{MSY}) or well below 5% (for $\phi_{\text{MSY-PA}}$).

Scenarios

The scenarios explored were:

(1) **Pure harvest rate**

First, the pure harvest rate from Equation (3) was explored. For this purpose, the harvest rate was implemented for 100 years and simulations were based on the random fishing history. The index was a total biomass index at the beginning of the year for which the catch advice was given ($I = I_{y+1}$) and without any observation uncertainty.

The target harvest rate was defined with a uniform distribution $H \sim U(0, 1)$. This allowed an analysis of the performance of the pure harvest rate, depending on initial stock depletion and the level of the harvest rate. The number of simulation replicates was increased to 10,000 to ensure enough replicates for subsets of harvest rates and depletion levels. These initial simulations served as a baseline to explore the scope of the harvest rate principle.

(2) **Sensitivity analysis**

The sensitivity of the harvest rate rule to the assumed conditions was analysed for the three main summary statistics (SSB, catch, B_{lim} risk). The baseline was the default harvest rate rule [Equation (4), Table 2], calculating the target harvest rate according to Figure 2, applied for 50 years and with 500 simulation replicates, and for the three fishing histories (one-way, roller-coaster, random). Pollack (pol, *Pollachius pollachius*), a medium-fast growing species ($k = 0.19$ year^{-1}), was chosen as an example stock. The sensitivity analysis considered recruitment variability ($0 \le \sigma_R \le 1$, default $\sigma_R = 0.6$), recruitment steepness ($0.2 \le h \le 1$, default $h = 0.75$ year^{-1}), recruitment auto-correlation ($0 \le \rho_R < 1$, default $\rho_R = 0$), observation uncertainty (length and biomass index, $0 \le \sigma_{\text{obs}} \le 1$, default $\sigma_{\text{obs}} = 0.2$), observation auto-correlation ($0 \le \rho_{\text{obs}} < 1$, default $\rho_{\text{obs}} = 0$), and the duration of the implementation (1–100 years, default 50 years). Additionally, the sensitivity to stock status prior to implementing the rule ($\text{SSB}_{y=0}/B_{\text{MSY}}$) was evaluated. For this purpose, the random fishing history was used and the number of simulation replicates increased from 500 to 10,000. Subsequently, the simulation replicates were sorted by $\text{SSB}_{y=0}/B_{\text{MSY}}$ and split into groups corresponding to different stock status levels ($0{-}1.7B_{\text{MSY}}$ in groups of $0.1B_{\text{MSY}}$). This way, each group contained >200 replicates, sufficient to calculate summary statistics.

Lastly, the sensitivity of the harvest rate rule to the index selectivity was evaluated. The performance of the harvest rate rule with the default index (a total biomass index) was compared to scenarios where the index selectivity matched maturity (SSB index), fishery selectivity (commercial index), and for an index with dome-shaped selectivity (Supplementary Figure S4).

(3) **Harvest rate level**

The impact of the level of the target harvest rate on the performance of the harvest rate rule was explored by implementing the rule with multipliers $0 \le x \le 2$ in steps of 0.01 [but otherwise default parameters of Equation (4)] and with default simulation dimensions (50 years, 500 replicates) for all stocks.

(4) **Parameters of the harvest rate rule**

The impact of the various parameters of the harvest rule on the optimisation procedure with the genetic algorithm was explored for pollack. The optimisation was performed individually for each parameter (x, n_0, n_1, w, v, u_u, or u_l), combining both uncertainty caps (u_u and u_l), all parameters without the uncertainty cap (x, n_0, n_1, w, and v), and all parameters (x, n_0, n_1, w, v, u_u, and u_l). Following the conclusion of Fischer *et al.* (2021b) that uncertainty caps can impair the recovery of depleted stocks and make it impossible to meet risk thresholds, additional optimisations with conditional uncertainty caps (fixed at $u_u = 1.2$, $u_l = 0.7$), only implemented when $I \ge I_{\text{trigger}}$, were conducted for the multiplier and all parameters. The optimisation was performed for the fitness function aiming at MSY [ϕ_{MSY}, Equation (5)] and the fitness function including the precautionary risk limit [$\phi_{\text{MSY-PA}}$, Equation (6)].

(5) **Optimisation for all stocks**

The optimisation procedure with the genetic algorithm is computationally complex; therefore, the full optimisation for all stocks was limited to the $\phi_{\text{MSY-PA}}$ fitness function. Finally, the harvest rate rule was compared to two indicator-adjusted catch rules; the 2 over 3 rule as simulated by Fischer *et al.* (2021a) and the rfb rule from Fischer *et al.* (2021b). The 2 over 3 rule was the standard ICES method for category 3 stocks until 2021 and adjusts the catch based on the trend from a biomass index. The rfb rule is intended to replace the 2 over 3 rule and, in addition to the biomass index trend, also uses catch length data to inform on fishing pressure. Full details of these two catch rules are provided in the Supplementary material.

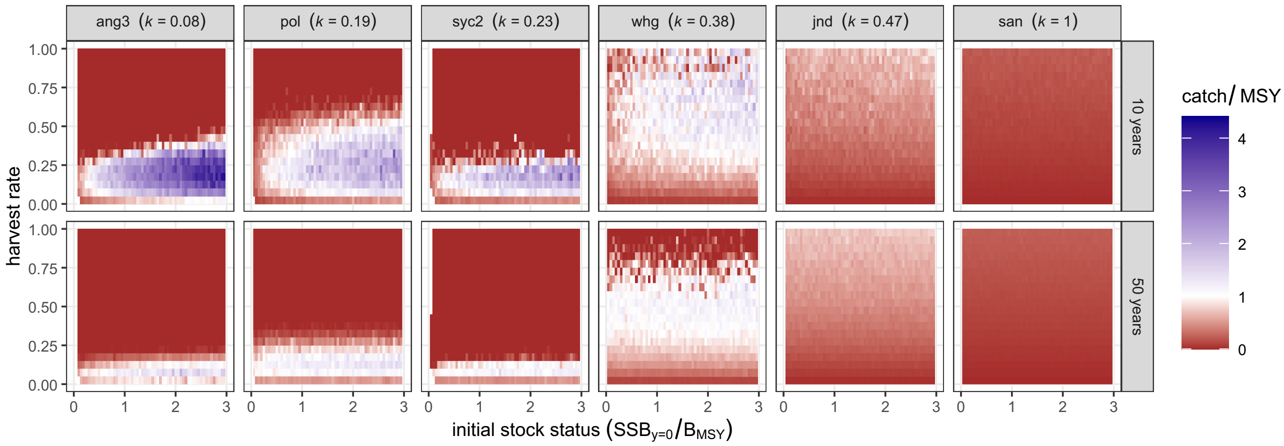

Figure 4. Realised catch for a pure harvest rate management procedure, depending on the level of the harvest rate, the stock status prior to implementing the rule, and the simulation period. In this management procedure, the index corresponded to the total biomass at the beginning of the advice year and no biomass safeguard was used. Shown is the catch relative to MSY, averaged over two simulation periods (10 and 50 years), and for six example stocks: blackbellied anglerfish (ang3), pollack (pol), lesserspotted dogfish (syc2), whiting (whg), John Dory (jnd), and sandeel (san), sorted by von Bertalanffy growth rate k (unit: year^{-1}). The results for the remaining stocks are included in Supplementary Figure S2.

Results

Pure harvest rate

When the pure harvest rate was implemented for only 10 years (first row of Figure 4), the realised catch over this period was affected by the initial stock status, with lower catches in cases of higher depletion but this effect disappeared when the rule was implemented for more years. Short-term catches could be substantially above MSY, but could not be sustained in the longer term.

There was a harvest rate that returned the highest catches; however, the level and spread of this harvest rate were stock-specific. In general, this high-catch area was at lower harvest rates for slower-growing stocks and at higher harvest rates for faster-growing stocks. For example, the harvest rate for blackbellied angler (ang3) resulting in catches >0.9MSY in the longer term was in a narrow range with $H < 0.15$, but for whiting (whg) $0.2 \leq H \leq 0.6$. For the fastest-growing stock (sandeel; san), the catch was always low and <0.3 MSY.

There are some exceptions to the general trend, e.g. a lower harvest rate for the very late maturing lesserspotted dogfish (syc2 in Figure 4) or a higher harvest rate for the early maturing Atlantic wolffish (wlf in Supplementary Figure S2). This behaviour can be explained by the fact that fishery selectivity was linked to maturity and the harvest rate was proportional to the total (not exploitable) biomass index. This meant, for example, that for the lesserspotted dogfish, it was not possible to fish a larger proportion of the stock because younger ages were not available to the fishery but contributed to the stock biomass (see Supplementary Figure S3). In contrast, for Atlantic wolffish, more age classes could be fished and this allowed taking a higher proportion of the stock.

Sensitivity analysis

The results of the sensitivity analysis for pollack are summarised in Figure 5. Higher recruitment variability (i.e. larger recruitment events due to log-normal distributed residuals) or steepness (i.e. higher productivity at lower stock size) led to higher SSB and catch, and lower risk. However, for the one-way fishing history, the risk was low (0.03) and unaffected by recruitment variability, only increasing substantially when the steepness was very low ($h < 0.5$, default $h = 0.75$). Increasing observation uncertainty (i.e. representing a more data-limited situation) caused a lower SSB and catch, and higher risk. Including temporal auto-correlation for recruitment or observation residuals had negligible effects. The initial stock status prior to implementing the harvest rate rule correlated positively and almost linearly with the averaged SSB after implementing the rule and negatively with risk, meaning that a depleted stock stayed depleted during the application of the rule with default settings. Regarding the implementation period, the summary statistics showed little variability and stabilised after around 10 years in the random fishing history. Conversely, for the one-way and roller-coaster fishing history, SSB and catch were initially low ($SSB/B_{MSY} = 0.5$ and catch/MSY $= 0.5$), increased after the implementation of the harvest rate rule and stabilised subsequently, leading to a reduction of the initially high risk.

The harvest rate rule was relatively robust to alternative index selectivities because using a different survey in the projection also meant that the target harvest rate, derived from historical observations, was changed accordingly. The influence on the long-term performance was negligible, but slight differences in behaviour in the first few years after implementing the harvest rate rule occurred (Figure 6 and Supplementary Figure S5). For example, an SSB index detected the depletion of the one-way fishing history earlier, resulting in stronger initial catch reductions and faster stock recovery than the total biomass index.

Harvest rate level

The inclusion of a multiplier had a substantial effect on the performance of the full harvest rate control rule. A catch maximum was observed for each stock, but the location (i.e. the multiplier leading to the catch maximum) and catch value depended on the stock and fishing history (Figure 7a). The general pattern was the same as for the pure harvest rate, and for slower-growing species, the optimum harvest rate (expressed through the multiplier) and the realised catch were higher than for faster-growing species. This relationship can be illustrated

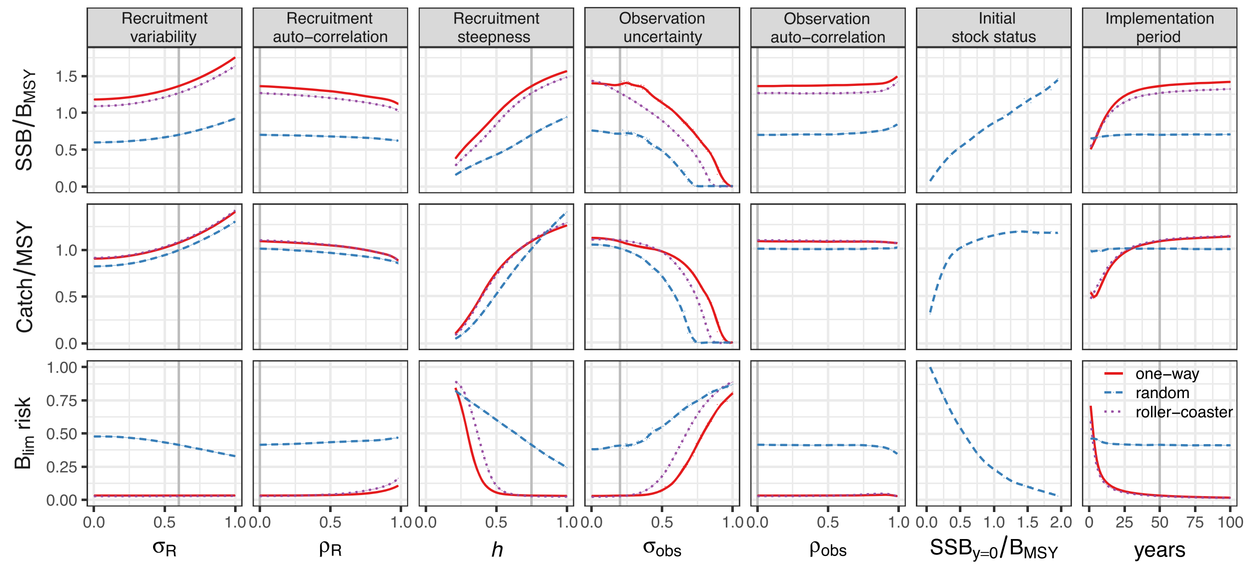

Figure 5. Summary of the sensitivity analysis for pollack. Shown are summary statistics (SSB, catch and B_{lim} risk) as a result of applying the default harvest rate rule and depending on simulated conditions (recruitment variability, steepness, observation uncertainty, initial stock status, and implementation period). Dots are simulation outcomes and the lines are the result of applying a smoother. Vertical lines indicate default values. For the initial stock status, simulation replicates where increased from 500 to 10,000 and results are only shown for the random fishing history. B_{lim} risk for the implementation period is the risk up to the respective year.

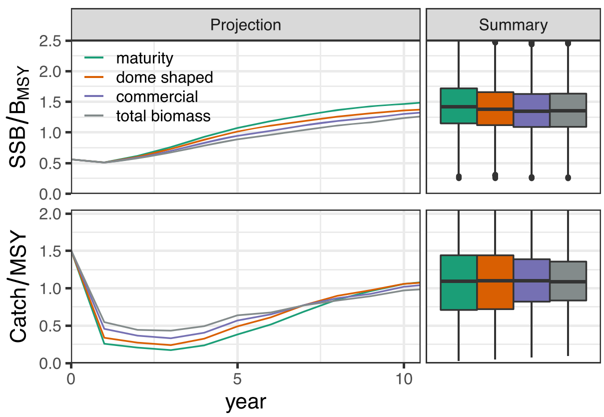

Figure 6. Impact of the index selectivity on the harvest rate rule for pollack for the one-way fishing history. The projections (left) show the first 10 years, the summary boxplots (right) the full 50-year projections.

with the von Bertalanffy k parameter of the stocks (Figure 7b). Pearson correlation coefficients indicated a negative correlation between the multipliers where the catch was maximised ($\rho \leq -0.89$, $p \leq 7.5 \times 10^{-11}$) and between the maximum catch and k ($\rho \leq -0.86$, $p \leq 3.5 \times 10^{-9}$).

The results for the one-way and roller-coaster fishing histories were very similar, which was also the case for the previous sensitivity analysis. Therefore, the following sections only consider the one-way and random fishing histories.

Parameters of the harvest rate rule

When considering the impact of the individual parameters of the harvest rate rule for pollack, the time lag (n_0) and interval (v) had negligible influence, while the index trigger buffer (w) and index range (n_1) led to small improvements (Figure 8). Although the uncertainty caps (u_l, u_u) had little or no influence on their own when considering a risk limit in the fitness function ($\phi_{\text{MSY-PA}}$; Figure 8b), they had a stronger impact (either individually or together) when a risk limit was not included (ϕ_{MSY}; Figure 8a). The use of a multiplier (x) had a strong impact on its own in all cases, apart from the one-way fishing history when a risk limit was not included.

The improvement was generally better when the optimisation was conducted for several parameters. The addition of uncertainty caps led to no or minor performance improvement compared to the optimisation with all parameters excluding the uncertainty caps and the optimisation selected either no or very wide caps (Supplementary Table S2). This is an important result for the industry, which prizes more stable catch advice (compare "all" and "all (cond. cap)" to "all without caps"). The default harvest rate resulted in a risk above 5% for the random fishing history. In the optimisation scenarios where the fitness function included the risk limit ($\phi_{\text{MSY-PA}}$; Figure 8b), this risk could only be reduced sufficiently when the multiplier was included, either on its own, or in combination with other parameters.

Optimisation for all stocks

The magnitude of the fitness improvement was stock-specific. Figure 9 shows the optimisation results for all stocks (including the conditional uncertainty cap) and a comparison to the results of Fischer *et al.* (2021a, b). The inclusion of all parameters in the optimisation of the harvest rate rule resulted only in marginal improvements compared to the optimisation with multiplier.

Fitness values were highest for the one-way fishing history (stronger but narrow initial depletion) compared to the random fishing history (large spread of initial depletion). In the one-way history, fitness appeared to be correlated to individual growth with the best management performance for the slowest-growing species. In the random history, management performance seemed best for species in the middle of the range

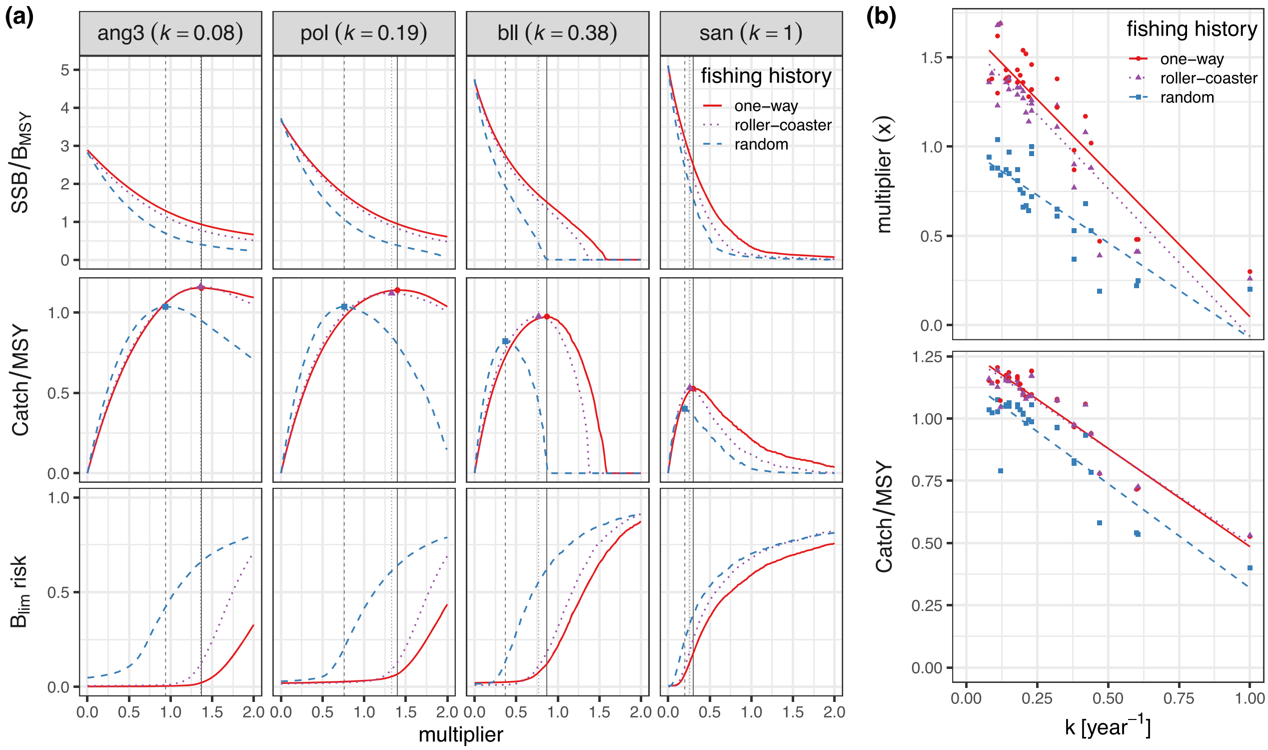

Figure 7. Impact of a harvest rate multiplier on the performance of the harvest rate rule. (a) shows the summary statistics for four example stocks; anglerfish (ang3), pollack (pol), brill (bll) and sandeel (san). The location of the maximum catch (second row) is indicated by small points and vertical lines corresponding to the multiplier. (b) shows the correlation between the location of the maximum catch in terms of the multiplier in (a) and the von Bertalanffy k, and between the maximum catch level of (a) and k, for all 29 simulated stocks for three fishing histories.

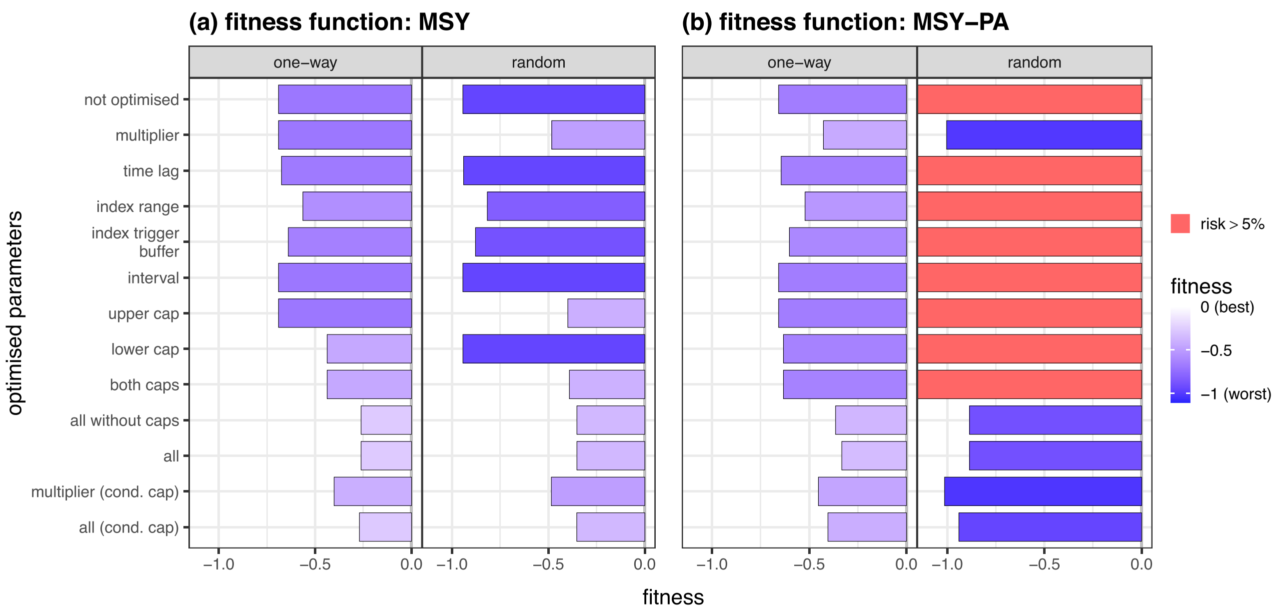

Figure 8. Fitness values as a proxy for management performance for the harvest rate rule when including single or combinations of the rule's parameters into the optimisation with the genetic algorithm for pollack. Shown are optimisation for the fitness function without a risk limit (a) and with a risk limit (b). The following parameter combinations were tested: multiplier (x), time lag (n_0), index range (n_1), index trigger buffer (w), interval (v), upper cap (u_u), lower cap (u_l), both caps (u_u, u_l), all parameters without the caps (x, n_0, n_1, w, v), all parameters (x, n_0, n_1, w, v, u_u, u_l), multiplier with conditional caps (x, $u_u = 1.2$, $u_l = 0.7$), and all parameters with conditional caps (x, n_0, n_1, w, v, $u_u = 1.2$, $u_l = 0.7$). Shorter bars indicate better performance. In (b), optimisations where risk exceeds 5% are coloured in red, and bars are cut off on the left because fitness values are < -5 due to the risk penalty. The split of the fitness function into its elements is illustrated in Supplementary Figure S6.

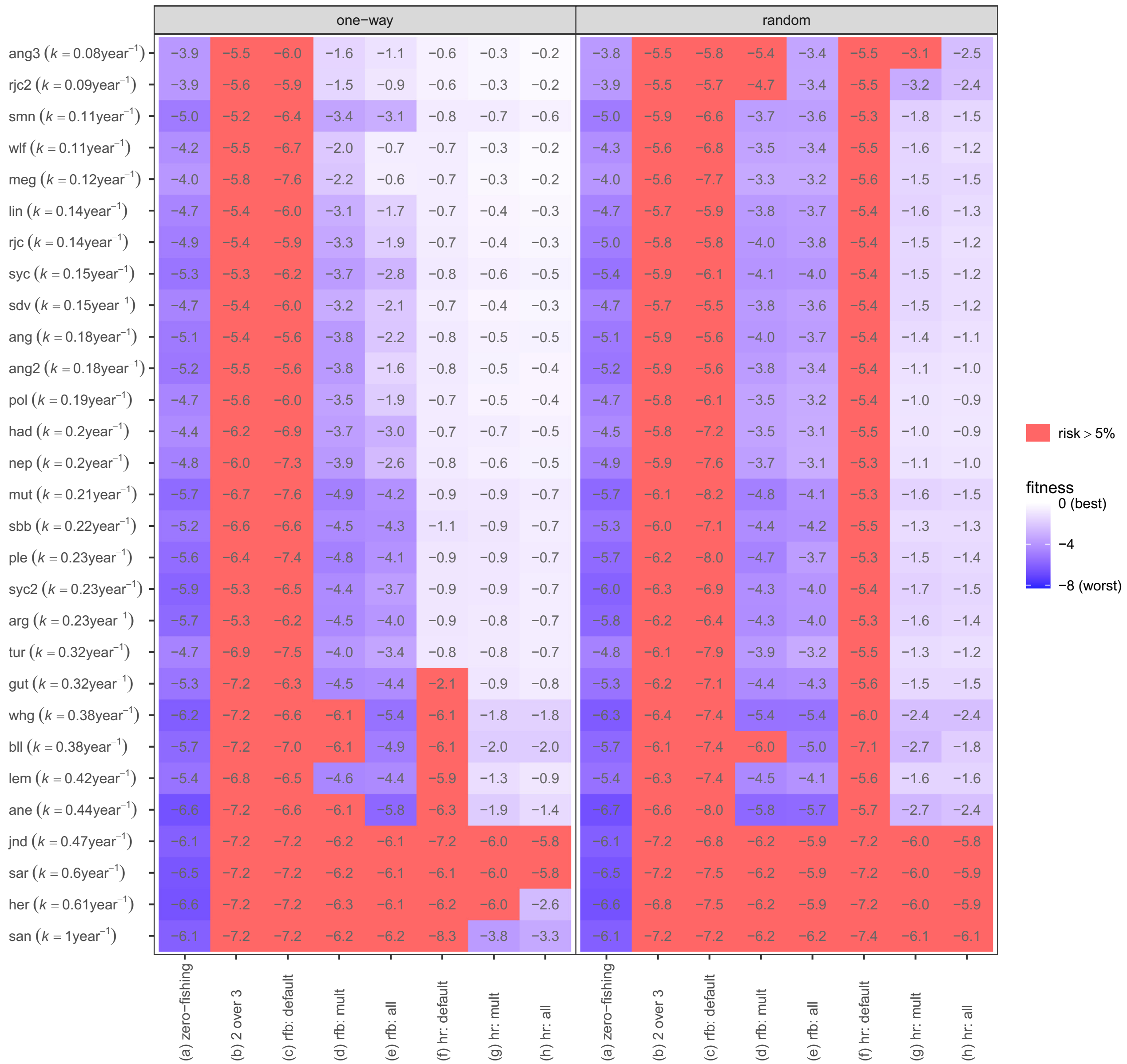

Figure 9. Fitness ($\phi_{\text{MSY-PA}}$) as a measure of management performance of the harvest rate rule, achieved through optimisation with the genetic algorithm and a comparison with other management options. Non-precautionary management (risk exceeds 5%) is highlighted in red. Shown are a "zero-fishing" option (a), the 2 over 3 rule (b, from Fischer *et al.*, 2021a), the rfb rule (c-e, from Fischer *et al.*, 2021b) and the harvest rate rule (f-h). For the rfb and harvest rate rules, three options are shown; the default rules (c, f, not optimised), optimisation with a multiplier (d, g), and optimisations where all parameters are included (e, h). For c-h a conditional uncertainty cap (+20%, -30%) is included. Optimised parameterisations of the harvest rate rule are available from Supplementary Table S2.

tested, with a clear deterioration (i.e. poorer management performance and increased risk) for the faster-growing species, but also the slowest-growing species. For example, for the slowest growing stock (blackbellied angler, ang3), when the optimisation was performed only with a multiplier in the random fishing history, no multiplier could reduce risk to 5% and the optimised solution was not precautionary (Figure 9). However, this was caused by the restriction of the conditional uncertainty cap, and if the cap was removed, a precautionary solution is possible (see Supplementary Figure S7). Figure 10 visualises the optimised multipliers (option "(g) hr: mult" in Figure 9).

The harvest rate rule always outperformed the corresponding rfb rule (apart from sandeel for the default configuration), although it could not always provide precautionary management for the fastest-growing species for the fully optimised configuration in both fishing histories (Figure 9).

Discussion

The key message is that the application of harvest rates through a biomass index is a suitable method for the management of moderately data-limited fisheries. However, this requires first finding a harvest rate level corresponding to the desired management objectives, for example, with empirical data. Simple modifications of a harvest rate rule, such as including a multiplier, can be sufficient to meet these objectives.

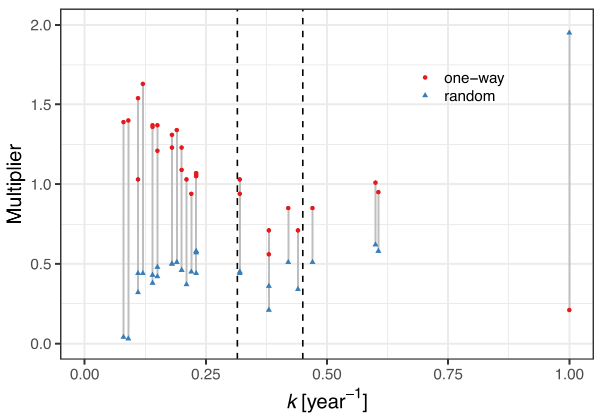

Figure 10. Optimised multiplier values of the harvest rate for all 29 stocks. The values shown correspond to option "(g) hr: mult" in Figure 9 and are sorted by von Bertalanffy *k*. Multipliers for the same stocks are connected with vertical grey lines. The dashed vertical lines indicate the area 0.32 year^{-1} $\leq k <$ 0.45 year^{-1}, which is the area for which ICES suggests considering a harvest rate approach (ICES, 2020, 2022).

In the present work, uncertainty was addressed by simulating many species, conducting a sensitivity analysis, and including alternative historical fishing histories. In the one-way fishing history, the initial stock status was narrow but strongly depleted. This condition allowed the exploration of a recovery phase. The alternative random fishing history offered a wide spread of depletion levels. This alternative history might be regarded as a more favourable starting state; however, it proved rather challenging because both MSY and precautionary principles were needed, i.e. a management procedure needed to limit risk (avoid low stock size) and deliver good long-term yields. The results indicated that the desired harvest rate parameterisation can differ substantially between fishing histories, even when implemented over a long time. Consequently, we recommend caution when applying a harvest rate rule generically and encourage considering exploitation information and conducting stock-specific analyses.

The quantities explored in the sensitivity analyses cover essentially different elements of the simulation, and the impact of specific quantities has different management implications. For example, recruitment variability is a proxy for process error which is given by the underlying population dynamics—this is something we have to live with. On the other hand, observation uncertainty is an observation error and could be reduced through better sampling, while uncertainty about steepness can be dealt with by building rules robust to it, or conducting further research to reduce uncertainty. Larger observation uncertainty degraded management performance (reduced stock size, higher risk of falling below the biomass limit, and reduced catch) and could correspond to a more severely data-limited situation. Consequently, a more conservative harvest rate would need to be used to avoid exceeding risk limits in such a situation.

The harvest rate principle is straightforward and, crucially, does not rely on knowledge about the absolute size of a fish stock, such as through the use of a stock assessment or an estimate of the index catchability, and can instead be used on a relative basis. The challenge is setting a harvest rate target corresponding to the desired management objectives. Our proposal of using empirical data (mean catch length) appeared to work well to inform on historical exploitation. Nevertheless, this is just one option, and other methods can be considered, e.g. simple biomass models. For some stocks, acoustic surveys might exist, providing an estimate of absolute biomass, making the application of a harvest rate strategy simpler because absolute management thresholds could be set.

If a target level is set too low, this will lead to lighter exploitation than expected, but conversely, if the target harvest rate is too high, this quickly leads to overfishing. Therefore, setting target harvest rates should be considered with utmost care. This is particularly important for cases when the target is set based on historical observations. For example, if overfishing has occurred during the entire historical period for which data are available, an appropriate reference that does not lead to overfishing is unlikely to be found. On the other hand, if a stock has only been lightly exploited, selecting a target value does not cause issues for stock conservation but some yield might be forfeited.

A crucial assumption in implementing a relative harvest rate strategy is that the biomass index is an adequate measure of the stock biomass and captures trends. The absolute scale of the index is not important because the harvest rate is defined relative to the index. This means that a systematic bias in either catch or index will not affect management as long as the bias does not change over time. When exploring different index selectivities, we found that this had negligible long-term impacts on the management performance of the harvest rate rule. This outcome was not surprising because the target harvest rate (defined by reference years and not index values) was scaled accordingly when an alternative index was used. However, this requires a standardised index (e.g. from a scientific survey or a standardised index of commercial catch per unit effort). Any temporal changes to the index (or fishery) selectivity or survey design are likely to negatively impact fisheries management because translating the relative target harvest rate with the index into a catch value does not return the correct absolute scale. Consequently, the proposed harvest rate rule is only applicable in cases where a standardised index exists and continues into the future.

The application and optimisation of the harvest rate rule in the generic context was not successful for the few fastest-growing species. Such species mainly include short-lived species, small pelagics, or fish with otherwise very high growth rates. Modelling such populations can be complex, but it is feasible given sufficient considerations (Siple *et al.*, 2021). The fast dynamics (boom and bust; de Moor *et al.*, 2011) might warrant alternative modelling approaches where sub-annual dynamics are explicitly considered. Consequently, more case-specific models and alternative management procedures, such as escapement strategies, might be useful to consider.

The new guidelines of the ICES data-limited methods framework (ICES, 2022) recommend the empirical rfb rule, for which new catch advice is derived by adjusting the previous advice by the trend of a biomass index, the mean of length of fish in the catch and a biomass safeguard. This rule is restricted to species with slow to medium individual growth (von Bertalanffy k < 0.32 year^{-1}). The rfb rule appears to struggle with the rapid population dynamics of faster-growing species and cannot provide long-term sustainable management unless the catch is reduced to very low levels (Fischer *et al.*, 2021b, a). ICES (2022) already suggested a harvest rate rule for faster-growing species (0.32 year^{-1} $\leq k <$ 0.45 year^{-1})

with a generic precautionary multiplier of $x = 0.5$, and the present study supports this conclusion.

Furthermore, the comparison of the harvest rate rule to the rfb rule (Figure 9) showed that, when optimised, the harvest rate rule appears to outperform the rfb rule, with higher catches while offering the same level of precaution. The biggest improvement in the harvest rate rule's performance was by introducing a multiplier. In most cases, introducing more parameters led to only minor further improvements, but came at the cost of making the rule much more complex. Nevertheless, the challenge of setting a multiplier value remained, as illustrated in Figure 10, where the multiplier levels for the same stocks depend on the fishing history, although a generic precautionary multiplier of $x = 0.5$ appears precautionary for all stocks with $k < 0.45\,\text{year}^{-1}$. This precautionary value might forfeit some of the yields for slower-growing species, but this could be ameliorated with case-specific simulations. Such case-specific analyses could also explore management trade-offs in more detail, ideally with stakeholder engagement.

In conclusion, we recommend that harvest-rate-based management be considered for moderately data-limited fisheries management. Developing a generic one-size-fits-all parameterisation for a relative harvest rate rule is challenging; therefore, case-specific simulations may be needed. A key benefit is that applying a harvest rate strategy, once set up, requires few data apart from an index, and is, therefore, suitable for many moderately data-limited stocks. Nevertheless, we suggest continued monitoring of stock status and exploitation to ensure the harvest rate rule performs as expected.

Supplementary data

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

Author contributions

SHF: methodology, software, formal analysis, investigation, visualisation, and writing (original draft, revisions). SHF, JAADO, JDM, and LTK: conceptualisation, discussion, writing (review and editing), and final approval.

Data availability statement

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

Funding

This work was supported by UK Department for Environment, Food & Rural Affairs (Defra) project FRD016. The views and opinions expressed in this article are those of the authors and do not necessarily reflect any funding body's official policy or position.

Acknowledgements

The authors would like to thank the ICES WKLIFE (Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks) workshop series, which played an important part in this work, and four anonymous reviewers for their constructive comments. The simulations were run on the high-performance computing system of the Imperial College Research Computing Service (www.doi.org/10.14469/hpc/2232).

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Handling Editor: M.S.M Siddeek