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Original Article

Linking the performance of a data-limited empirical catch rule to life-history traits

Simon H. Fischer [1,2]*, José A. A. De Oliveira[1], and Laurence T. Kell[2]

[1]Centre for Environment, Fisheries and Aquaculture Science (Cefas), Pakefield Road, Lowestoft, Suffolk NR33 0HT, UK
[2]Centre for Environmental Policy, Imperial College London, Weeks Building, 16-18 Princes Gardens, London SW7 1NE, UK

*Corresponding author: tel: +44 (0)1502 521326; e-mail: simon.fischer@cefas.co.uk.

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Worldwide, the majorities of fish stocks are data-limited and lack fully quantitative stock assessments. Within ICES, such data-limited stocks are currently managed by setting total allowable catch without the use of target reference points. To ensure that such advice is precautionary, we used management strategy evaluation to evaluate an empirical rule that bases catch advice on recent catches, information from a biomass survey index, catch length frequencies, and MSY reference point proxies. Twenty-nine fish stocks were simulated covering a wide range of life histories. The performance of the rule varied substantially between stocks, and the risk of breaching limit reference points was inversely correlated to the von Bertalanffy growth parameter k. Stocks with $k > 0.32$ year^{-1} had a high probability of stock collapse. A time series cluster analysis revealed four types of dynamics, i.e. groups with similar terminal spawning stock biomass (collapsed, B_{MSY}, $2B_{MSY}$, $3B_{MSY}$). It was shown that a single generic catch rule cannot be applied across all life histories, and management should instead be linked to life-history traits, and in particular, the nature of the time series of stock metrics. The lessons learnt can help future work to shape scientific research into data-limited fisheries management and to ensure that fisheries are MSY compliant and precautionary.

Keywords: data-limited, empirical catch rules, FLife, FLR, life history, management strategy evaluation, MSY, precautionary

Introduction

When managing fisheries, decisions must be made with incomplete knowledge, which is why international agreements request the adoption and implementation of the Precautionary Approach (Garcia, 1996). In addition, fish retailers and consumers are increasingly looking for assurances that the food they buy is sustainably produced. Therefore, many regional fisheries management organizations have implemented management frameworks based on target and limit reference points to prevent overfishing and ensure targets are achieved. Despite this, most fisheries and commercially exploited stocks still lack reliable estimates of stock status and effective management due to poor data, limited knowledge, and insufficient resources (Jardim *et al.*, 2015; Fitzgerald *et al.*, 2018).

Since 2012, ICES has applied a framework to provide catch advice for the European data-limited stocks (ICES, 2012a, 2013a). The increasingly sophisticated methods developed for stock assessment are not always suited to data-poor fisheries (Bentley, 2015). Therefore, recently, many data-limited approaches have emerged and re-emerged to meet the increasing demand for science-based fisheries management for data-limited stocks (Wetzel and Punt, 2011; Costello *et al.*, 2012; Dowling *et al.*, 2015, 2016; Chrysafi and Kuparinen, 2016; Rosenberg *et al.*, 2018). However, in a review of data-limited methods, Dowling *et al.* (2019) noted the dangers in the indiscriminate use of generic methods and recommended obtaining better data, using care in acknowledging and interpreting uncertainties, developing harvest strategies that are robust to the higher levels of uncertainty, and tailoring them to the specific species' and fisheries' data and context.

One way to do this is to evaluate candidate data-limited management frameworks using management strategy evaluation

(MSE; Smith, 1994; Punt *et al.*, 2016). MSE uses an operating model (OM) to represent a fish stock and the fisheries operating on it. The OM is used to simulate resource dynamics in simulation trials and to generate pseudo data to evaluate the performance of a management procedure (MP). The MP is the combination of pre-defined data, together with an algorithm to which such data are input to set a management measure, such as a total allowable catch (TAC). This in turn is converted into a catch that is removed from the OM in a feedback loop (Punt *et al.*, 2016).

The application of MSEs has been mainly focused on data-rich situations, where enough data are available to condition the OM using stock assessment models. An MP may be either model-based, where a stock assessment is used to estimate stock status and set management measures (e.g. Kell *et al.*, 2005), or empirical where a trend in an indicator is used to set the catch (Hillary *et al.*, 2016). MSEs for data-limited purposes are somewhat rarer, although there are notable studies. For example, Carruthers *et al.* (2012) evaluated methods based on catch data alone and found that catch-based methods were, on average, more negatively biased than stock assessment methods that explicitly model population dynamics and use additional fishing effort data. In a subsequent study, Carruthers *et al.* (2014) found that methods that rely only on historical catches performed worse than maintaining current fishing levels and that only methods that dynamically accounted for changes in abundance and/or depletion performed well at low stock sizes. Geromont and Butterworth (2015a) tested a range of simple catch rules based on historical catches, length data, or survey index data and found that such simple rules perform well and could be used in practice. Punt *et al.* (2001) explored a range of empirical indicators and noted that length- or weight-based indicators outperform catch rate indicators; however, caution needs to be exercised about reference levels. A review of data-poor empirical harvest strategies can be found in Dowling *et al.* (2015).

Within ICES, simple catch rules have been developed for data-limited stocks (ICES, 2012a). For example, the "2 over 3" rule aims to keep stocks at their current level by multiplying recent catches by the trend in a biomass index:

$$A_{y+1} = A_{y-1}\frac{\sum_{i=y-2}^{y-1} I_i/2}{\sum_{i=y-5}^{y-3} I_i/3}, \tag{1}$$

where A_{y+1} is the newly advised catch for year $y+1$, A_{y-1} is the previously advised catch [note: this could be observed catch, C_{y-1}, e.g. when the advice is first produced, or when the advised catch is no longer appropriate because a stock has undergone a benchmark; for the purposes of this study, we used C_{y-1}, following the original definition in ICES (2012a)] and I is a biomass index. This rule, in combination with an uncertainty cap (limiting change in catch advice to no more than 20%) and precautionary buffer (which reduces the catch advice by 20% if the stock is judged to be outside safe biological levels), is currently applied to give catch advice within ICES for category 3 data-limited stocks (ICES, 2018a).

The ICES "2 over 3" rule lacks a management target, can induce oscillatory behaviour resulting in increased biological risk over time, and includes a time lag in the translation of changes in the biological stock into advice (ICES, 2013b, 2017a). An alternative catch rule, making use of more data sources, has therefore been proposed (ICES, 2012b):

$$A_{y+1} = C_{y-1}\ r\ f\ b, \tag{2}$$

where the advised catch A_{y+1} is based on the previous observed catch C_{y-1}, multiplied by three components r, f, and b, each representing a stock characteristic. Component r corresponds to the trend in a biomass index (I), component f is a proxy for the ratio F_{MSY} divided by the current exploitation based on length data from the catch, and component b is a biomass safeguard that protects the stock once the biomass index drops below a threshold. Initially, this catch rule was merely a concept without specifying what data should be used and how the components could be derived from them (ICES, 2012b). Recently, the rule has been revisited by ICES (2017b) and suggestions made for simulation testing and application to actual stocks. Several options for the three components have been proposed, and initial simulation testing narrowed it down to only one option per component (ICES, 2017a). This catch rule is the focus of the present study, where we aim to (i) establish procedures to simulate data-limited fish stocks based on life-history parameters, (ii) simulation-test the aforementioned catch rule, (iii) associate the performance of the catch rule to life-history parameters, and (iv) provide guidance on the application of the catch rule and thereby advancing the management of data-limited stocks.

Jardim *et al.* (2015) tested a simplified version of the rule where components r and f were tested one-at-a-time and component b excluded and concluded that the rule based on r [Equation (1)] performed the poorest, and while the rule based on f was able to reverse decreasing trends in biomass, it resulted in catch levels below MSY and could not prevent some stocks declining when subject to over-exploitation.

As the purpose of this study is to test catch rules for data-limited stocks, assumptions and approximations must be made. We use a similar approach to Jardim *et al.* (2015) where stocks are simulated based on a set of life-history parameters and where fishing scenarios are developed. The simulations were conducted in the Fisheries Library in R (FLR, Kell *et al.*, 2007) software suite, within an MSE framework originally developed by Jardim *et al.* (2017) for data-rich stocks but adapted and extended to accommodate data-limited stocks. Furthermore, the FLR package FLife is used to simulate stocks based on life-history parameters.

The study stocks are given in Table 1; there are 29 data-limited stocks from European waters (North Sea region, Celtic Sea region, Bay of Biscay, and widely distributed stocks) and they encompass a wide range of life histories, including roundfish, flatfish, elasmobranchs, shellfish, and demersal as well as pelagic species. Jardim *et al.* (2015) used averaged life-history parameters for species to simulate stocks; in contrast, in the present study, we chose stock-specific parameters, so that simulated stocks resemble real stocks in terms of biology (growth, productivity, etc.). As this is a data-limited simulation approach, however, artificial fishing histories had to be developed.

There is a plethora of approaches on how to analyse the results of an MSE, and this study focuses on the time series of stock metrics such as spawning stock biomass (SSB) and on summary statistics derived from stock metrics over the course of the projection period. To determine which of the OM parameters could explain the performance of the catch rule for a specific stock, a penalized regression model (glmnet, Friedman *et al.*,

Table 1. The 29 stocks on which the operating models are based.

Scientific name	Common name	ID	k (year^{-1})
Lophius budegassa	Blackbellied angler	ang3	0.08
Raja clavata	Thornback ray	rjc	0.09
Anarchias lupus	Atlantic wolffish	wlf	0.11
Sebastes norvegicus	Golden redfish	smn	0.11
Lepidorhombus whiffiagonis	Megrim	meg	0.12
Molva molva	Ling	lin	0.14
Raja clavata	Thornback ray	rjc2	0.14
Mustelus asterias	Starry smooth-hound	sdv	0.15
Scyliorhinus canicula	Lesser spotted dogfish	syc	0.15
Lophius piscatorius	Angler	ang	0.18
Lophius piscatorius	Angler	ang2	0.18
Pollachius pollachius	Pollack	pol	0.19
Melanogrammus aeglefinus	Haddock	had	0.2
Nephrops	Norway lobster	nep	0.2
Mullus surmuletus	Striped red mullet	mut	0.21
Spondyliosoma cantharus	Black seabream	sbb	0.22
Argentina silus	Greater argentine	arg	0.23
Pleuronectes platessa	European plaice	ple	0.23
Scyliorhinus canicula	Lesser spotted dogfish	syc2	0.23
Scopthalmus maximus	Turbot	tur	0.32
Chelidonichtys lucerna	Tub gurnard	gut	0.32
Merlangius merlangus	Whiting	whg	0.38
Scophthalmus rhombus	Brill	bll	0.38
Microstomus kitt	Lemon sole	lem	0.42
Engraulis encrasicolus	Anchovy	ane	0.44
Zeus faber	John Dory	jnd	0.47
Sardina pilchardus	European pilchard	sar	0.6
Clupea harengus	Herring	her	0.606
Ammodytes spp.	Sandeels	san	1

Given are the scientific and common names, a unique stock ID and the von Bertalanffy growth parameter *k*.

2010) was deployed, because such a model allowed the inclusion of correlated parameters (a particular feature of the OMs) by imposing a penalty on them. In addition, penalized regression allows fitting the entire elastic-net regularization path from lasso to ridge regression (Hoerl and Kennard, 1988; Tibshirani, 1996; Zou and Hastie, 2005), where a lasso regression rejects non-crucial parameters and a ridge regression retains all parameters but reduces their influence by penalizing them, if necessary. Another approach used is to find patterns in resultant time series. Simple groupings might become apparent on visual inspection; we employed time series cluster analysis because it provides an objective statistical approach to grouping the results into clusters with similar trajectories when no prior information about the clusters exists.

Methods

Simulation of stocks

OMs were conditioned for 29 stocks, simulated based on a limited set of life-history parameters: allometric parameters for length–weight conversion, a and b, von Bertalanffy growth model parameters L_∞, k, and t_0 (Von Bertalanffy, 1950), and age at 50% maturity a_{50}. Based on these data, using the FLR (Kell *et al.*, 2007) package FLife, and closely following the approach of Jardim *et al.* (2015), age-structured OMs were created. Growth was modelled with the von Bertalanffy growth equation, recruitment by a Beverton–Holt stock recruit function with steepness $h = 0.75$ (for the default scenario), virgin SSB set to 1000 (units) for all stocks, the maximum age a_{max} and plus-group set as the age (rounded up) where the stock reached 95% of L_∞, maturity modelled with a sigmoid function centred on a_{50}, and fisheries selectivity modelled with a sigmoid function where the first age at full selectivity equalled a_{50}. Natural mortality M was length dependent, following Gislason *et al.* (2010), but converted to age using the von Bertalanffy growth equation. Survey selectivity was modelled with a sigmoid function and the inflection point set to $0.1a_{max}$, and the biomass index was derived by summing the survey catch biomass over all ages. Catch length frequencies were generated by applying a simulated inverse age-length key to the catch at age distribution. Full specifications, including equations, are given in the Supplementary Material.

Two fishing histories were created for all simulated stocks. Initially, the stocks where fished at $0.5F_{MSY}$ for 75 years, and subsequently for another 25 years in a roller-coaster or a one-way fishing scenario (Figure 1). In the one-way scenario, the fishing mortality was increased from $0.5F_{MSY}$ to $0.8F_{crash}$ within 25 years, with F_{crash} defined as the lowest fishing mortality that causes the stock to collapse in equilibrium. In the roller-coaster scenario, the fishing mortality was increased from $0.5F_{MSY}$ to $0.75F_{crash}$, kept at $0.75F_{crash}$ for 5 years, and then reduced to F_{MSY} by the end of the 25 years. After both fishing scenarios, the stocks were severely depleted; however, in the one-way scenario, the stocks were at their lowest levels and declining, whereas in the roller-coaster scenario the stocks had started to recover. This exploitation state was then used as starting point for the MSE simulation.

Catch rule

The main catch rule tested sets catch advice by multiplying recent catch with three factors corresponding to perceptions of stock characteristics based on catch and survey data [Equation (2)]. Component r corresponds to the trend in a biomass index and is based on the "2 over 3" rule [Equation (1)]:

$$r = \frac{\sum_{i=y-2}^{y-1} I_i/2}{\sum_{i=y-5}^{y-3} I_i/3}, \tag{3}$$

where I is the biomass index. Component f is a proxy for the ratio F_{MSY} divided by the current exploitation based on length data from the catch:

$$f = \frac{\bar{L}_{y-1}}{L_{F=M}}, \tag{4}$$

where $\bar{L}_{y-1}$ is the mean length in the catch above the length of first capture (L_c), weighted by catch numbers at length, with L_c defined as the first length class having at least 50% of the mode in the observed catch length frequency. The reference length $L_{F=M}$ is a proxy for the length at MSY proposed by Beverton and Holt (1957), under the assumption that $F = M$. Using the simplification that $M/k = 1.5$, the reference length can be calculated as:

$$L_{F=M} = 0.75L_c + 0.25L_\infty. \tag{5}$$

Finally, component b of the catch rule is a biomass safeguard protecting the stock when the biomass index drops below a threshold:

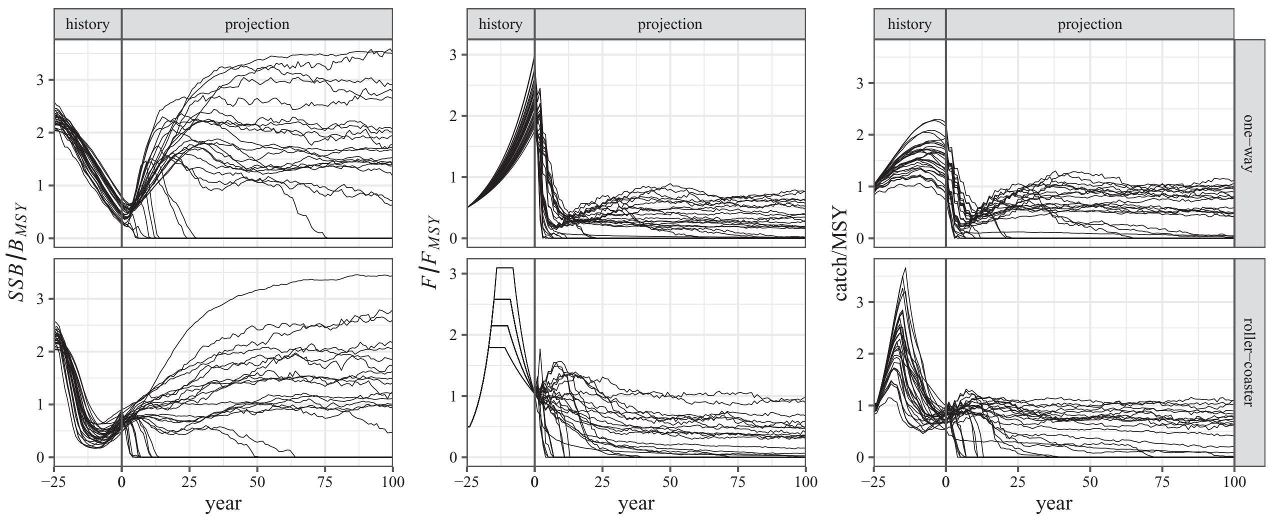

Figure 1. Median trajectories for SSB, mean fishing mortality, and catch relative to MSY reference points for the 29 simulated stocks. Shown are the historical fishing period ("history", years −25 to 0) and the results of subsequently applying the catch rule (years 1 to 100). The top row shows the one-way fishing history and the bottom row the roller-coaster fishing history.

$$b = \min\left\{1, \frac{I_{y-1}}{I_{\text{trigger}}}\right\}. \tag{6}$$

I_{trigger} was based on the lowest historical biomass index value I_{loss} and defined as $I_{\text{trigger}} = 1.4 I_{\text{loss}}$.

Projection

The OM was projected forward for a period of 100 years. Errors were implemented with a log-normal distribution and included for the biomass index ($SD = 0.2$), recruitment ($SD = 0.6$), life-history parameter L_∞ ($SD = 0.1$), which is used both in the calculation of catch length frequencies and in the calculation of the length reference point $L_{F=M}$, catch numbers at length ($SD = 0.2$), and implementation of the advice into catch ($SD = 0.1$). Note that no additional uncertainty is included for L_c, which is already calculated from simulated observed data. The error distributions were set prior to running the simulation, and random number deviates were identical for all stocks. Based on these uncertainties, 500 replicates were created for each stock.

Modifications to the catch rule

Various modifications of the catch rule were explored and are detailed in Table 2. One option tested was the addition of a multiplier x to the catch rule:

$$A_{y+1} = C_{y-1}\ r\ f\ b\ x. \tag{7}$$

In addition, the impact of including catch constraints was examined by including upper constraints (maximum allowed increase in catch advice compared to previous advice), lower constraints (maximum allowed decrease) and their combinations of upper and lower constraints.

By default, the management simulated here followed the ICES assessment cycle for data-limited stocks (ICES, 2012a, 2018a). This meant that the catch rule was applied in an intermediate (assessment) year y based on data up to the previous year ($y-1$) and the TAC was set biennially for the following 2 years $y+1$ and $y+2$. The data used in the catch rule were from the years up to the year before the intermediate year; i.e. $y-1$ for the catch data for components C_{y-1} and f, $y-1$ for the index for b, and years $y-5 \ldots y-1$ for r. The effect of time lags on management was explored by including more recent data and also setting the TAC annually (Table 2).

Sensitivity to OM assumptions

A sensitivity analysis of the performance of the catch rule to OM assumptions was conducted. This included investigations into steepness, recruitment variability, and observation uncertainties (see Table 2). Full details and results of this analysis are provided in the Supplementary Material.

Perfect information scenario

Finally, to check whether the catch rule worked when all the information available to it was available without error, an additional scenario was run for all the simulated stocks and fishing histories. For these scenarios, only recruitment variability was implemented. The survey index was replaced with the SSB from the OM to remove the impact of survey selectivity, I_{trigger} was set to B_{trigger}, which, in agreement with ICES data-limited guidelines (ICES, 2018b), was set to $0.5B_{\text{MSY}}$. This modification meant that the biomass threshold was set irrespective of the historical exploitation and was comparable for all stocks. The reference length for the f component of the catch rule was defined as the equilibrium length obtained in the OM when fishing at F_{MSY}.

Performance of the catch rule

The performance of the catch rule was assessed based on six performance statistics, computed over the entire 100-year projection period and 500 replicates:

(i) catch/MSY: the median of the distribution of catch/MSY,

Table 2. Explored modifications of the catch rule and sensitivity analysis of operating model parameterization on the performance of the catch rule.

Modification	Default value	Alternative values
Catch rule modifications		
Catch rule multiplier	1	0.5, 0.6, 0.7, 0.8, 0.85, 0.9, 0.95
Catch constraints (including combinations)		
Upper	∞	1.1, 1.15, 1.2, 1.25, 1.3, 1.5
Lower	0	0.5, 0.6, 0.7, 0.75, 0.8, 0.85, 0.9
Timing (relative to intermediate year *y*, including combinations)		
Biomass index	$y-1$	y, $y+1$
Recent catch	$y-1$	y
TAC interval (years)	2 (biennial)	1 (annual)
Parameter	**Default value**	**Alternative parameterizations**
Sensitivity analysis (explored in Supplementary Material)		
Steepness *h*		
Fixed	0.75	0.6, 0.9
Functional relationships	Constant	Linked to *k*, linked to L_{50}/L_∞ (Wiff *et al.*, 2018)
Borrowed values	0.75	Species specific *h* from Myers *et al.* (1999)
Uncertainty and variability		
Recruitment variability (*SD*)	0.6	0.3, 0.9
Biomass index uncertainty (*SD*)	0.2	0.4, 0.6
Length-frequency uncertainty (*SD*)	0.2	0.4, 0.6

(ii) collapse risk: risk of stock collapse, i.e. the proportion of the projected stock where the stock is <0.1% of virgin SSB,

(iii) B_{lim} risk: risk of the stock falling below B_{lim} [proportion of the projected stock where the stock is below B_{lim}, defined as the stock level where recruitment is at 70% of the recruitment achieved at virgin SSB, i.e. 16.3% of virgin SSB for all stocks, because they had the same value of steepness (h) for the Beverton–Holt stock recruitment relationship],

(iv) ICV: the median of the distribution of inter-annual variability in catch, calculated as follows:

$$(C_y - C_{y-n})/C_{y-n},$$

where C_y is the catch for the year y in which a TAC has been set and n is the TAC period, e.g. $n = 2$ for a biennial TAC, and

(v) SSB/B_{MSY} and F/F_{MSY} : the median of the distribution of stock status (SSB and F relative to MSY reference points B_{MSY} and F_{MSY}, respectively).

Initial analysis revealed that, for some stocks and scenarios, the stocks collapsed, and catches were reduced to zero as a result. Depending on the stock productivity, some stocks subsequently recovered towards virgin biomass due to the zero catch. This behaviour was deemed inappropriate for further exploration of the performance as it implied a reduced risk. Consequently, when running the simulations once a replicate of a scenario had collapsed, the stock level and catch in subsequent simulation years were both set to zero.

Penalized regression

Many of the life-history parameters (both primary parameters used to create stocks and parameters derived from the simulated stocks) are highly correlated. For example, natural mortality M, von Bertalanffy growth model parameter k, F_{MSY}, MSY, population growth rate g (at the limit of zero stock size), and conditional growth rate g_c (growth rate at MSY) had positive Pearson correlation coefficients $\rho \geq 0.92$ between each other, and k and L_∞ correlated negatively with $\rho = -0.70$.

Therefore, to determine which of the stock characteristics influenced the performance of the catch rule, a penalized regression model was applied (glmnet, Friedman *et al.*, 2010). A multi-response Gaussian model (Simon *et al.*, 2013) was applied that selected the predictor variables that could explain all six performance statistics (catch/MSY, collapse risk, B_{lim} risk, ICV, SSB/B_{MSY} and F/F_{MSY}). First, only the primary input parameters were used as predictor variables: a, b (length–weight relationship), L_{inf}, k, t_0 (von Bertalanffy growth model parameters), and a_{50} (age at 50% maturity). Second, the analysis was repeated with additional derived parameters: α, β (Beverton–Holt stock recruitment model parameters), spr0 (spawning potential ratio), L_{opt} (mean length when the stock is at MSY level), g, g_c (population growth rates), M (natural mortality), M/k, F_{MSY}/M, and B_{MSY}/B_0 (B_{MSY} relative to virgin biomass, i.e. location of peak in production curve).

Clustering

A cluster analysis of the relative stock status SSB/B_{MSY} time series was conducted using the dynamic time warping (DTW) technique (Berndt and Clifford, 1994; Aghabozorgi *et al.*, 2015) as distance measure. Several clustering algorithms (partitional, fuzzy, hierarchical) were trialled. Partitional and fuzzy clustering imply stochasticity, because the results depend on the random location of where the algorithm starts. This proved unreliable for the cluster analysis presented here, because the results were unstable, and even iterating the analysis did not lead to stable clusters. Hierarchical clustering on the other hand does not rely on stochasticity for the formation of the clusters. In addition, once a hierarchical cluster analysis is conducted, the output can be visualized in a dendrogram and any arbitrary number of clusters can be pursued without having to rely on potentially biased cluster validity indices to select the optimum number of clusters.

Results

Figure 1 shows the median trajectories for the 29 simulated stocks when the catch rule was implemented for the two fishing history scenarios. In the one-way scenario, 10 (anchovy, black seabream, brill, herring, John Dory, lemon sole, sandeels, European pilchard, tub gurnard, and whiting) out of the 29 stocks collapsed by the end of the 100-year simulation period. In the roller-coaster scenario, two additional stocks (angler and pollack) collapsed. The remaining stocks survived and displayed stock-specific long-term oscillations. One stock, megrim, approached virgin SSB and the other stocks reached terminal biomass values between 12 and 74% of virgin SSB.

In general, the catch rule was influenced most by component r [Equation (3)]. Figure 2 shows the time series of the individual components for two example stocks (pollack and herring). In the beginning, after the implementation of the catch rule, component b [Equation (6)] acted and reduced the catch; however, this effect lasted only for a few years. Component f [Equations (4) and (5)] gave some information throughout the entire simulation period, but at a markedly lower magnitude compared to r. Figure 3 presents the SSB and the catch for the two stocks, including individual simulation replicates.

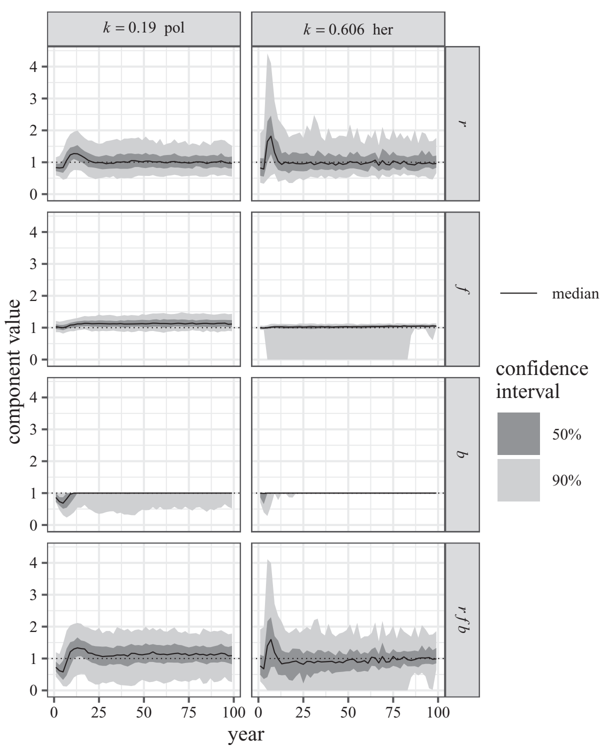

Figure 2. Components of the catch rule (r, f, and b) and their product ($r\ f\ b$, which scales the recent catch) for two example stocks: herring (her) and pollack (pol). The higher the deviation of a component from one (up or down), the higher is its contribution in the catch rule. Please note that for herring, the stock collapsed in most simulated replicates (the median SSB collapsed after 6 years) and in the distributions shown for the components, these collapsed replicates were excluded because they did not provide any stock status information.

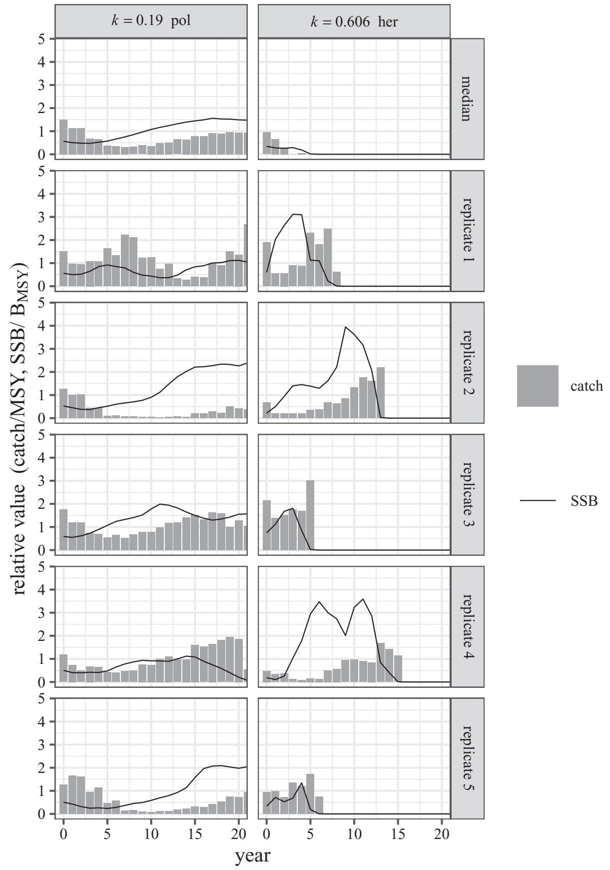

Figure 3. Catch and SSB for two stocks, pollack (pol) and herring (her), for the first 20 years of the projection period. Shown are the median of the 500 simulation replicates (first row) and 5 example replicates (subsequent rows).

Penalized regression

Performing a lasso regression with the primary input and the full parameter set (including derived parameters) both resulted in a model fit that selected solely the von Bertalanffy growth parameter k to explain the six performance statistics for the one-way fishing scenario (Figure 4). Allowing elastic-net regularization in the penalized regression model led to minor improvements in the model fit (the mean squared error was reduced from 0.85 to 0.73) but came at the cost of adding complexity to the model by returning non-zero coefficients for all supplied input parameters. Consequently, k was selected as the single most important factor for the performance of the catch rule for the simulated stocks. Higher values of k were linked to higher risks (both collapse risk and B_{lim} risk) and catch variability and lower or zero long-term catch, F/F_{MSY} and SSB/B_{MSY}. The results were similar for the roller-coaster scenario.

Clustering

Clustering was performed on the time series of the annual medians of $\mathrm{SSB}/B_{\mathrm{MSY}}$ of the entire 100-year projection period for the 29 simulated stocks. Figure 5 shows the results from the hierarchical clustering for up to four clusters for the one-way fishing history. Hierarchical clustering does not compute centroids for the clusters; for plotting purposes (Figure 5b), centroids for the clusters were calculated *post hoc* as the annual average of the

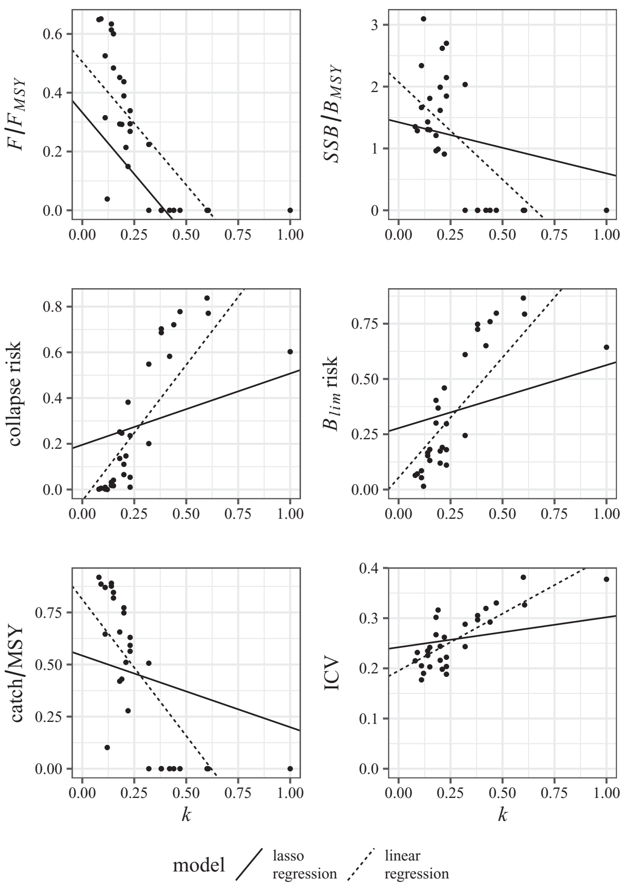

Figure 4. Six performance statistics vs. the von Bertalanffy growth model parameter *k* for the tested catch rule and the one-way fishing history for all 29 stocks. The solid lines show the fit from the lasso regression model, and the dotted lines show a linear regression for each individual performance statistic.

SSB/B_{MSY} values of all stocks within a cluster. If all stocks were kept in a single cluster, the centroid SSB/B_{MSY} trend showed a recovery after the start of the MSE simulation and equilibrated at a level slightly>1. The first separation in the hierarchical cluster distinguished between two distinct patterns (second row in Figure 5b); the first cluster was composed of stocks that experienced early peaks and collapsed within ∼25 years, whereas the stocks in the second cluster survived (apart from one exception; black seabream). This split corresponds well to the von Bertalanffy *k* values for these stocks (Figure 5c). The first cluster (collapsed) is comprised of stocks with $k \geq 0.32\,\text{year}^{-1}$. On the other hand, the stocks with lower *k* ($k \leq 0.32\,\text{year}^{-1}$) survived. There is an overlap for the $k = 0.32\,\text{year}^{-1}$ stocks: one survived (turbot) and one collapsed (tub gurnard).

Following the dendrogram further, the next two splits occurred within the cluster of surviving stocks. First, there is a separation of stocks that stay $\sim 1.5B_{\text{MSY}}$ in the long term and the ones that end up $\sim 3B_{\text{MSY}}$ (third row of Figure 5b). Second, the stocks reaching levels $\sim 1.5B_{\text{MSY}}$ are divided further into one cluster where the SSB converged at $\sim 2B_{\text{MSY}}$ and one cluster where the SSB stays ∼B_{MSY} (fourth row of Figure 5b). In terms of *k*, these stocks overlap when there are four clusters and no clear distinction is evident. Moving further along the dendrogram, these clusters are divided further; however, clusters increasingly represent individual stocks instead of general trends, because stocks are singled out as the number of clusters grows. The clusters in Figure 5 are colour-coded, and this colour-code is maintained throughout the study. Results in this figure are for the one-way trip scenario, but results for the roller-coaster scenario are almost identical when considering four clusters.

Modifications to the catch rule

Adding a multiplier [*x* in Equation (7)] of less than one to the catch rule reduced the risk (both collapse risk and B_{lim} risk) for all stocks and for both fishing scenarios (Figure 6). This risk reduction was a result of higher terminal SSB values: the smaller the multiplier, the higher the SSB values, capped at the top at the virgin biomass level. For the stocks where the median SSB collapsed during the simulation period (cluster 1), adding the multiplier delayed this collapse, and by reducing the multiplier further, the collapse was avoided altogether. This behaviour of the SSB trajectory was stock specific. For example, in the default catch rule, the median SSB of anchovy in the one-way fishing scenario reached zero 12 years after the start of the simulation and adding a multiplier of only 0.9 avoided this collapse. On the other hand, pilchard and John Dory collapsed in the roller-coaster fishing scenario after 5 years and this collapse could only be averted by implementing a multiplier ≤0.7.

The performance of the catch rule for these cluster 1 stocks was highly sensitive to small changes in the multiplier. Once a threshold multiplier was reached, the long-term stock levels increased rapidly and overshot B_{MSY}, thereby foregoing catch. Stocks in cluster 2 were kept ∼B_{MSY} in the long term when the catch rule was applied without a multiplier. Introducing the multiplier for these stocks reduced their risks but moved them above B_{MSY}. Stock levels for stocks from clusters 3 and 4 were shifted further above B_{MSY} when the multiplier was added. In the one-way scenario, for 13 of the 29 stocks tested, adding the multiplier reduced the catch; this was also the case for 8 stocks in the roller-coaster scenario. The maximum catch for cluster 1 (collapsed) stocks occurred at multiplier levels between 0.7 and 0.9, but the peak was substantially below MSY. For the remaining stocks, the catch peaked at multipliers ≥0.9. When considering all stocks together, there does not seem to be a single multiplier that increases risk performance for all stocks without jeopardizing catch for some.

Implementing an upper catch constraint reduced the risks for all stocks, and more restrictive constraints led to lower risks (Figure 7a). The upper constraint leading to the maximum catch was stock specific and occurred at constraints between 1.1 and no constraint. However, for most stocks the catch is relatively stable for constraints ≥1.2 and this value seems to be a reasonable compromise between risk reduction and maximizing catch. Including a lower constraint on the catch increased the risk of stock collapse and resulted in subsequent reduction in catch. If the lower constraint was implemented in combination with an upper constraint, for some stocks a small peak in catch was observed at lower constraint levels>0 and <1. Figure 7b shows the effect of including lower catch constraints on the performance of the catch rule in combination with an upper constraint of 1.2. More restrictive lower constraints (i.e. restricting catch reductions) caused a large increase in risks and a large decrease in catch, with this behaviour

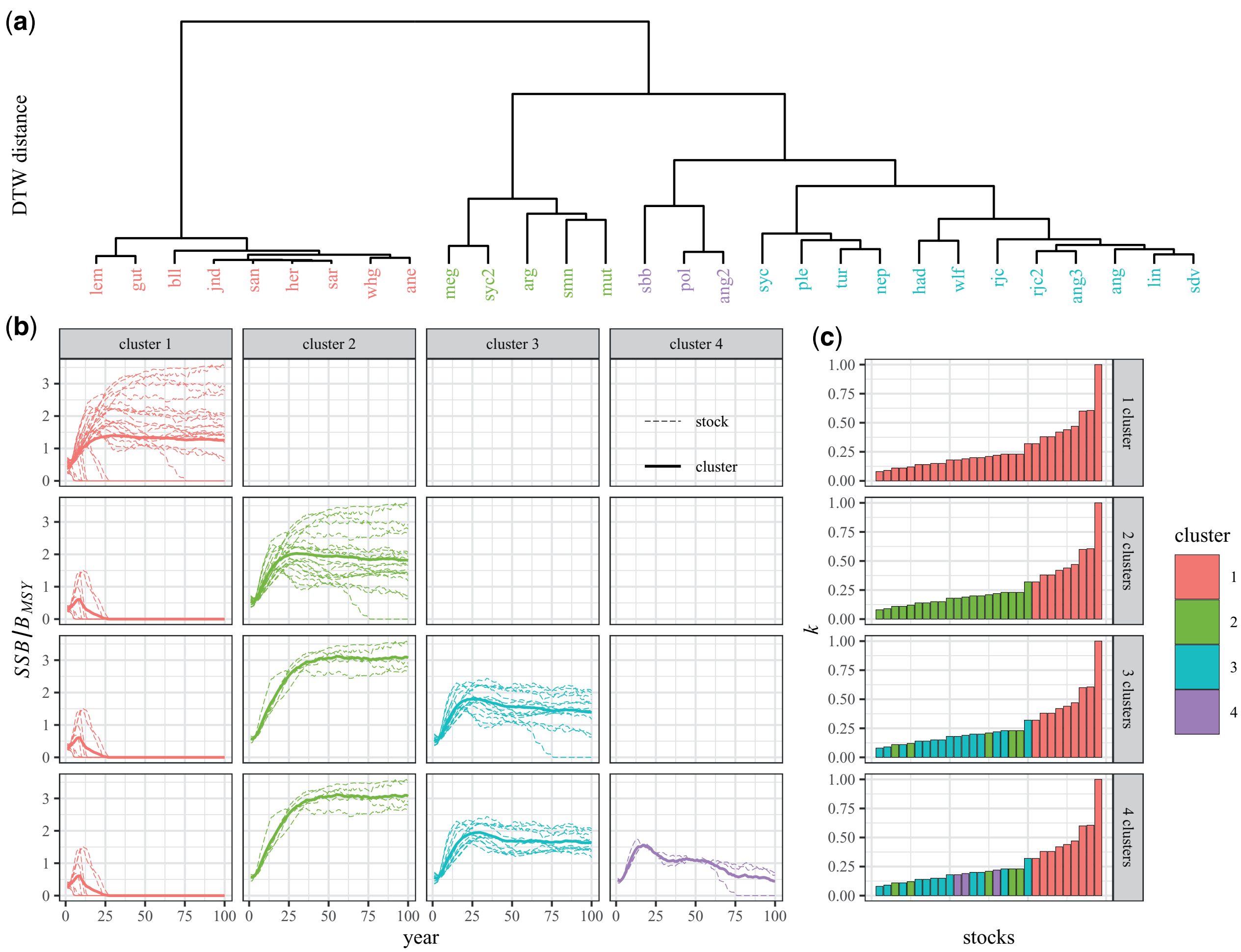

Figure 5. Results of the hierarchical clustering analysis of relative SSB for the one-way fishing history. (a) A dendrogram of the time series for the 29 simulated stocks, the names correspond to the stock IDs defined in Table 1. The *y*-axis corresponds to the DTW distance between the time series. (b) The median SSB/B_{MSY} times series for all stocks (dashed lines) and the centroids (solid bold line). Rows represent the number of clusters, and each column is one cluster. (c) von Bertalanffy growth model parameter *k* for all stocks, sorted in ascending order and colour-coded for the clusters shown in (b).

being particularly pronounced at constraint levels>0.7. Below 0.7, the risks and catches were relatively stable.

For the stocks surviving the default implementation of the catch rule ($k \leq 0.32\,\text{year}^{-1}$), using more recent data and setting the TAC more frequently improved performance by reducing oscillations and reaching final biomass values earlier (Figure 8). The lowest fluctuations were observed when the TAC was set annually, the catch data provided up to the intermediate year, and the survey data up to the beginning of the advice year. The terminal biomass values were similar irrespective of the timing. One exception is black seabream (not shown), which collapsed when the catch rule was implemented with default parameters, but all tested combinations resulted in stock levels just above B_{MSY}. Some of the high-*k* stocks (cluster 1) could be saved; however, three stocks (John Dory, pilchard, and herring) still collapsed even if the TAC was set annually and the most recent data were used.

Perfect information scenario

When the catch rule was implemented with perfect information and knowledge (i.e. the SSB from the OM was used as the index and $I_{trigger}$ set to $0.5B_{MSY}$ from the OM), the performance of the catch rule was substantially improved for the low-to-medium-*k* stocks ($k \leq 0.32\,\text{year}^{-1}$) and most converged towards B_{MSY}, indicating that the catch rule did work under these unrealistically perfect conditions (Figure 9). Performance was not improved for the higher-*k* stocks from cluster 1. These stocks still collapsed early and only the highest-*k* stock, sandeel, showed a recovery to very high biomass levels, but this behaviour could be attributed to the stock being close to collapse, with catches reduced to very low levels, and consequently the stock could recover with almost no fishing activity.

Discussion

This study simulation tested a simple catch rule, making use of proxy MSY reference points for a range of data-limited fish stocks. The main result was that the performance of the catch rule was stock specific and could broadly be linked to life-history characteristics, with the von Bertalanffy growth parameter *k* emerging as the most important one from a penalized regression model.

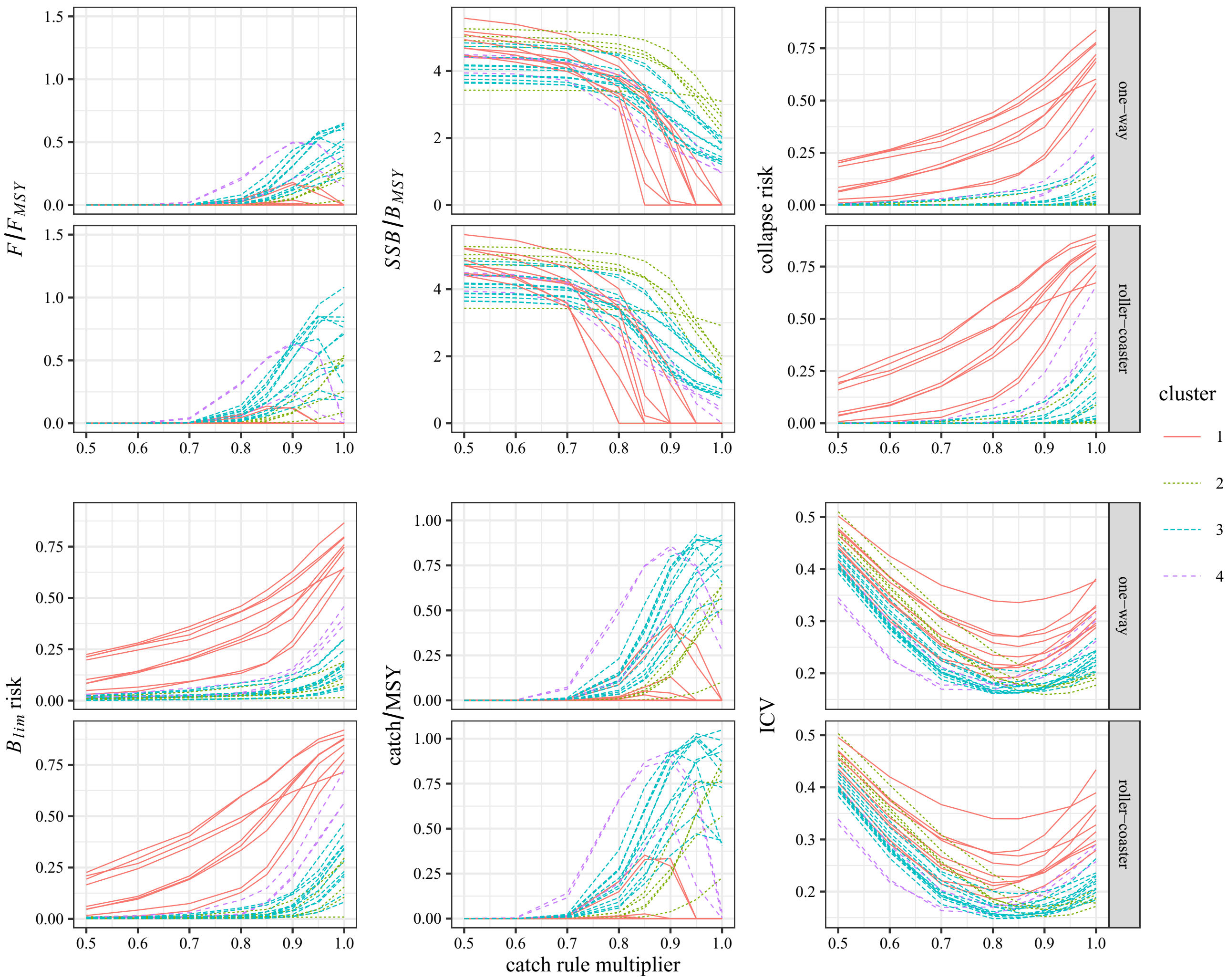

Figure 6. Effect of implementing a multiplier to the catch rule on the six performance statistics for the 29 simulated stocks and both fishing histories. The clusters correspond to the ones defined in Figure 5.

It was clear from a visual inspection of the results that the response of stocks to the application of the catch rule could be organized into different groups and, therefore, a time series clustering approach using DTW was adopted. The relative stock status SSB/B_{MSY} was selected as a time series index because it provided the overall best indicator of the performance of the catch rule over time. Biomass was used in relative terms because the catch rule's long-term target is MSY, and consequently both undershooting (overfishing) and overshooting (loosing yield through fishing below MSY) of B_{MSY} could be identified and was comparable across all simulated stocks. Both the clustering analysis and the penalized regression approach indicated that there is a clear relationship between the life histories of the simulated stocks and the performance of the catch rule. The most important finding is the separation of the simulation trajectories into two groups based on the results of the cluster analysis: one where the stocks collapsed during the simulation and the other where the stocks survived and ended up at or above B_{MSY}. The split corresponded well to the von Bertalanffy growth parameter k and the catch rule seemed to perform reasonably for stocks with $k < 0.32\,\text{year}^{-1}$, but very poorly for stocks with $k > 0.32\,\text{year}^{-1}$. The $k < 0.32\,\text{year}^{-1}$ stocks reached levels of between B_{MSY} and $3B_{MSY}$, i.e. stock collapses were avoided in all but one case, but frequently there was a loss in yield compared to the yield achieved when fishing at F_{MSY}.

The result that the catch rule performed worse for the more productive stocks (with higher k) compared to the less productive stocks (with lower k) might at first glance appear counter intuitive. The performance of the catch rule as measured by the summary statistics, however, is an emergent property of the interaction between the OM and the catch rule. The advised catch was mainly influenced by the r component of the rule (the trend in the relative index of abundance; Figure 2), and stocks with higher k are inherently more variable, which in turn leads to higher fluctuations in catch. When subjected to the catch rule, the higher-k stocks collapsed early during the simulation. This behaviour can be attributed to an initial rapid recovery, which resulted in an increase in catch (Figure 3). Once the stocks started to decline again, however, catch was not reduced quickly enough to avoid stock collapse. This undesirable feature is caused by the design of the catch rule, which bases the newly advised catch on the previous catch and observed data with a time lag. Since the

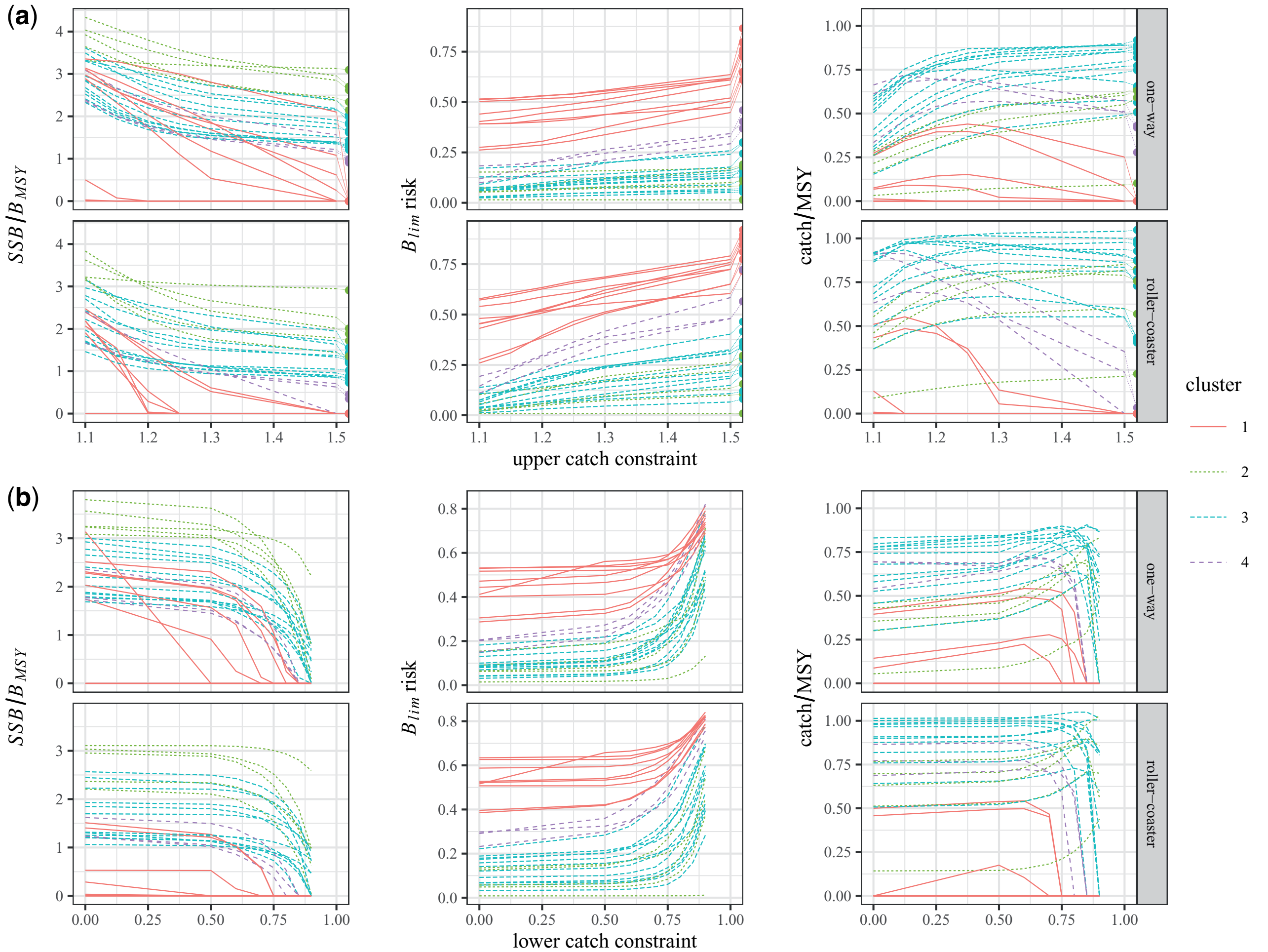

Figure 7. Effect of catch constraints on three performance statistics. (a) The effect of upper catch constraints without a lower constraint. The points above an upper catch constraint of 1.5, connected with thin lines, indicate the performance when no upper catch constraint was implemented. (b) The effect of lower catch constraints in combination with an upper catch constraint of 1.2. The clusters correspond to the ones defined in Figure 5.

less productive stocks (those with low k) were also less variable, the catch rule was sufficiently reactive to avoid stock collapse.

Previous studies have tested simple empirical data-limited catch rules with various simulated stocks (e.g. Jardim *et al.*, 2015), or based OMs on knowledge from fully analytical stock assessments (e.g. Geromont and Butterworth, 2015a; Carruthers *et al.*, 2016). In the simulation exercise of Carruthers *et al.* (2016), various data-limited methods have been tested, but only three stocks (Pacific herring, Atlantic bluefin tuna, and Pacific canary rockfish) were simulated and, therefore, possible inferences from life histories were limited. Jardim *et al.* (2015) tested a simplified version of the catch rule tested here, including only a single component at a time (either r using survey data or f using length-frequency data). The results from their simulation study are in agreement with the current work, showing a wide range of stock trajectories and yields often below MSY. The basis for the simulation of the stocks in Jardim *et al.* (2015) was averaged life-history parameters to generate a variety of life-history traits. For the work presented here, we went one step further and used life-history parameters from real stock units; by doing so, we were able to link the performance of the catch rule back to the original life-history parameters.

Modifications to the catch rule (multipliers, catch constraints, using more recent data) were able to improve the performance of the catch rule. However, the improvement was stock specific and a trade-off between yield and risk was evident. Although application of the multiplier always reduced the risk, the stocks frequently ended up above B_{MSY} and the catch rule was overly reactive to minor changes in the multiplier for higher-k stocks, not a good feature in a situation of high uncertainty. For stocks for which the catch rule kept the stock at or above B_{MSY} in the long term, the multiplier moved the stock level further away from B_{MSY} and reduced yield. Stocks that collapsed when the default catch rule was applied (the higher-k stocks) could be saved, but only at the cost of moving the stocks far above B_{MSY} and losing yield.

Regarding the catch constraint, an upper limit of 1.2 was deemed appropriate because the long-term yield hardly changed for most stocks if less restrictive constraints were implemented; furthermore, this value provides an important reduction in risk compared to the application of the catch rule without any constraints. For this level of upper constraint, a lower constraint of

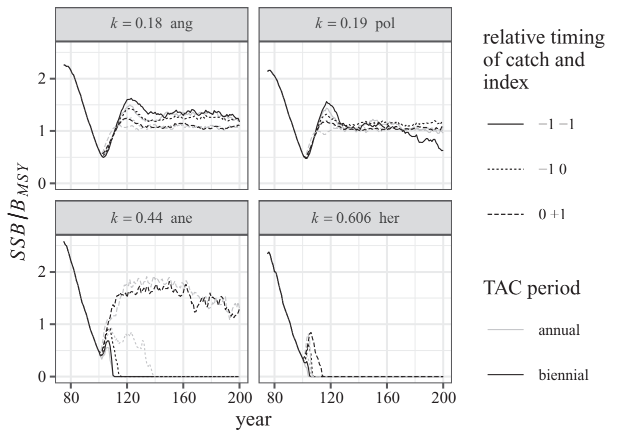

Figure 8. Effect of time lags for the data used in the catch rule and periodicity of TAC setting (annual vs. biennial) for four example stocks (sorted by von Bertalanffy k) in the one-way fishing scenario. The timing is relative to the intermediate year (0); -1 refers to the year before the intermediate year and $+1$ refers to the year after the intermediate year. Relative timing is distinguished by line type, and TAC period by line shading.

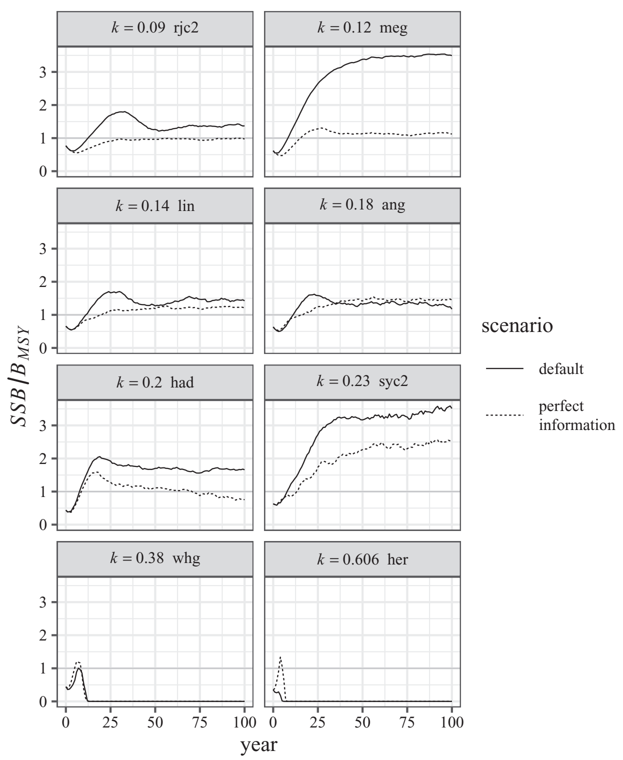

Figure 9. Application of the catch rule with and without perfect information for eight example stocks (as defined in Table 1) for the one-way fishing history. In the perfect information scenario, no uncertainty, apart from recruitment variability, has been implemented; the survey is an exact representation of the SSB and $I_{trigger} = 0.5B_{MSY}$.

0.7 seemed to be a suitable choice because implementing more restrictive lower constraints would cause a large increase in risk and a drop in yield. Less restrictive lower constraints did not have much impact on either yield or risk.

As could be expected, more recent data did improve the performance of the catch rule, mainly by reducing oscillations, but this approach did not prove successful for all high-k stocks.

Challenges remain for the catch rule tested here. For example, the components of the catch rule make use of different commercial and scientific data and are designed to account for stock dynamics. However, if just one of the components of the catch rules fails or produces very low (close to zero) or high values, it will inevitably overrule the other components and dominate the final catch advice; in such circumstances, the use of the catch constraints becomes important. The analysis into the components of the catch rule showed that the rule is mainly dominated by the trend in the index, frequently masking information from the other components. The biomass safeguard is important to recover the stock above a threshold, but depending on how this level is set, it may not be effective enough (e.g. if the threshold is set too low). The problem of dominant components of the rule could be dealt with through variable weighting of the different components and is a subject of future work.

If there is perfect information available (catch data, survey index, mean length in the catch) and reference points were set correctly according to MSY, then the catch rule performed well and approached the desired MSY target for low-to-medium-k stocks. The results from these perfect information scenarios showed the importance of setting reference points appropriately, because, for example setting the index trigger value dependant on the fishing history based on the lowest ever observed value governed where the biomass ended up. The lower-k stocks were less depleted relative to B_{MSY} and, therefore, the trigger point in the b component of the catch rule was higher, which in turn resulted in a higher terminal biomass when the stocks were subjected to the catch rule. In a real-life application of the catch rule to data-limited stocks, reference values are uncertain, possibly impeding the performance of the rule.

During this work, concerns were raised about the appropriateness of the OM assumptions. This study simulated data-limited stocks, and assumptions were needed due to a lack of information. However, extensive sensitivity tests of the results to OM assumptions have been conducted (Table 2) and are described in the Supplementary Material. One assumption was to use a constant steepness of 0.75 in the recruitment model for all stocks. Steepness is notoriously difficult to estimate, particularly for data-limited stocks for which no analytical assessments exist. This issue was addressed by conducting additional sensitivity runs with different steepness levels (lower and higher), borrowing values from previous studies, and imposing relationships between steepness and life-history parameters. The results were generally insensitive to the steepness assumptions. The additional sensitivity tests on variability and uncertainty showed that the results of this study are largely robust and the conclusions valid irrespective of these model assumptions.

The starting point for the simulations in this study represented highly depleted stocks and might be considered as a worst case. We used this condition to examine whether the catch rule was able to correctly identify the depletion and recover stocks. In addition, due to the long simulation period (100 years), all stocks moved away from their initial state during the simulation and this provided insight into whether a long-term equilibrium was reached.

Trends and fluctuations in populations are determined by complex interactions between extrinsic forcing and intrinsic dynamics. For example, stochastic recruitment can induce low-frequency variability, i.e. "cohort resonance", which can result in trends in abundance; such low-frequency fluctuations can potentially mimic or cloak critical variation in abundance linked to environmental change, over-exploitation, or other types of anthropogenic forcing (Bjørnstad *et al.*, 2004). Although important, these effects can be difficult to disentangle. The simulations so far show that life histories are important and should be used to help condition OMs to ensure robust feedback-control rules. MSE is important to help develop these robust feedback-control rules and to help identify appropriate observational systems.

Although the performance of the catch rule depended on the life-history characteristic, it was not in the way initially expected, i.e. the outcomes could not be grouped solely by whether the OMs represented fast-growing vs. late-maturing species, or demersal vs. pelagic stocks. What was important was the nature of the dynamics, i.e. how variable the stock was between years; for example a stock could exhibit high inter-annual variability if natural mortality and recruitment variability were high, regardless of the values of k, L_∞, and L_{50}. The nature of the indices is also important; for example even if a stock had low inter-annual variability, an index could be highly variable if it was based on juveniles or there were large changes in spatial distribution between years. It is therefore necessary to look at the robustness of management strategies to the nature of the time series of the stock (as represented by the OM) and to the characteristics of the data collected from it. This will require tuning by constructing a reference set of OMs and then tuning the management strategy to secure the desired trade-offs. The work so far can be considered as focusing first on developing management strategies that perform satisfactorily for a reference set; the next step is to develop case-specific strategies.

Finally, simple empirical MPs are usually considered in a data-limited context; such simple rules can sometimes achieve similar performance compared to MPs based on fully analytical assessments (e.g. shown by Carruthers *et al.*, 2014; Geromont and Butterworth, 2015b) or even outperform them, particularly if the operational effort is included.

Supplementary data

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

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References

Aghabozorgi, S., Shirkhorshidi, A. S., and Wah, T. Y. 2015. Time-series clustering—a decade review. Information Systems, 53: 16–38.

Bentley, N. 2015. Data and time poverty in fisheries estimation: potential approaches and solutions. ICES Journal of Marine Science, 72: 186–193.

Berndt, D. J., and Clifford, J. 1994. Using Dynamic Time Warping to Find Patterns in Time Series. *In* Workshop on Knowledge Discovery in Databases. AAAI Technical Report WS-94-03, pp. 359–370. Association for the Advancement of Artificial Intelligence, Menlo Park, California.

Beverton, R. J. H., and Holt, S. J. 1957. On the Dynamics of Exploited Fish Populations. HMSO for Ministry of Agriculture, Fisheries and Food, London.

Bjørnstad, O. N., Nisbet, R. M., and Fromentin, J.-M. 2004. Trends and cohort resonant effects in age-structured populations. Journal of Animal Ecology, 73: 1157–1167.

Carruthers, T. R., Walters, C. J., and McAllister, M. K. 2012. Evaluating methods that classify fisheries stock status using only fisheries catch data. Fisheries Research, 119–120: 66–79.

Carruthers, T. R., Punt, A. E., Walters, C. J., MacCall, A., McAllister, M. K., Dick, E. J., and Cope, J. 2014. Evaluating methods for setting catch limits in data-limited fisheries. Fisheries Research, 153: 48–68.

Carruthers, T. R., Kell, L. T., Butterworth, D. D. S., Maunder, M. N., Geromont, H. F., Walters, C., McAllister, M. K. *et al.* 2016. Performance review of simple management procedures. ICES Journal of Marine Science, 73: 464–482.

Chrysafi, A., and Kuparinen, A. 2016. Assessing abundance of populations with limited data: lessons learned from data-poor fisheries stock assessment. Environmental Reviews, 24: 25–38.

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

Dowling, N. A., Dichmont, C. M., Haddon, M., Smith, D. C., Smith, A. D. M., and Sainsbury, K. 2015. Empirical harvest strategies for data-poor fisheries: a review of the literature. Fisheries Research, 171: 141–153.

Dowling, N. A., Wilson, J. R., Rudd, M. B., Babcock, E. A., Caillaux, M., Cope, J., Dougherty, D. *et al.* 2016. FishPath: A Decision Support System for Assessing and Managing Data- and Capacity-Limited Fisheries. *In* Assessing and Managing Data-Limited Fish Stocks. Alaska Sea Grant, University of Alaska Fairbanks.

Dowling, N. A., Smith, A. D. M., Smith, D. C., Parma, A. M., Dichmont, C. M., Sainsbury, K., Wilson, J. R. *et al.* 2019. Generic solutions for data-limited fishery assessments are not so simple. Fish and Fisheries, 20: 174–188.

Fitzgerald, S. P., Wilson, J. R., and Lenihan, H. S. 2018. Detecting a need for improved management in a data-limited crab fishery. Fisheries Research, 208: 133–144.

Friedman, J., Hastie, T., and Tibshirani, R. 2010. Regularization paths for generalized linear models via coordinate descent. Journal of Statistical Software, 33: 1–20.

Garcia, S. M. 1996. The precautionary approach to fisheries and its implications for fishery research, technology and management: an updated review. *In* Precautionary Approach to Fisheries. Part 2: Scientific Papers. FAO Fisheries Technical Paper, No. 350, Part 2, pp. 1–75. FAO, Rome.

Geromont, H. F., and Butterworth, D. S. 2015a. Generic management procedures for data-poor fisheries: forecasting with few data. ICES Journal of Marine Science, 72: 251–261.

Geromont, H. F., and Butterworth, D. S. 2015b. Complex assessments or simple management procedures for efficient fisheries management: a comparative study. ICES Journal of Marine Science, 72: 262–274.

Gislason, H., Daan, N., Rice, J. C., and Pope, J. G. 2010. Size, growth, temperature and the natural mortality of marine fish. Fish and Fisheries, 11: 149–158.

Hillary, R. M., Preece, A. L., Davies, C. R., Kurota, H., Sakai, O., Itoh, T., Parma, A. M. *et al.* 2016. A scientific alternative to moratoria for rebuilding depleted international tuna stocks. Fish and Fisheries, 17: 469–482.

Hoerl, A., and Kennard, R. 1988. Ridge regression. *In* Encyclopedia of Statistical Sciences, 8. Regressograms—St. Petersburg Paradox. Ed. by S. Kotz, N. L. Johnson, and C. B. Read Wiley, New York.

ICES. 2012a. ICES Implementation of Advice for Data-limited Stocks in 2012 in its 2012 Advice. ICES Document CM 2012/ACOM: 68. 42 pp.

ICES. 2012b. Report of the Workshop 3 on Implementing the ICES Fmsy Framework, 9-13 January 2012, ICES Headquarters. ICES Document CM 2012/ACOM: 39. 33 pp.

ICES. 2013a. Advice basis June 2013. Report of the ICES Advisory Committee 2013. ICES Advice, 2013. Book 1. 20 pp.

ICES. 2013b. Report of the Workshop on the Development of Quantitative Assessment Methodologies Based on LIFE-history Traits, Exploitation Characteristics, and Other Key Parameters for Data-limited Stocks (WKLIFE III), 28 October–1 November 2013, Lisbon. ICES Document CM 2013/ACOM: 35. 98 pp.

ICES. 2017a. Report of the ICES Workshop on the Development of Quantitative Assessment Methodologies Based on Life-history Traits, Exploitation Characteristics, and Other Relevant Parameters for Data-limited Stocks in Categories 3-6 (WKLIFE VII), 2-6 October 2017, Lisbon, Portugal. ICES Document CM 2016/ACOM: 59. 106 pp.

ICES. 2017b. Report of the Workshop on the Development of the ICES Approach to Providing MSY Advice for Category 3 and 4 Stocks (WKMSYCat34), 6–10 March 2017, Copenhagen, Denmark. ICES Document CM 2017/ACOM: 47. 53 pp.

ICES. 2018a. ICES Advice Basis. Report of the ICES Advisory Committee 2018. ICES Advice 2018. 13 pp.

ICES. 2018b. ICES reference points for stocks in categories 3 and 4. ICES Technical Guidelines. Report of the ICES Advisory Committee 2018. ICES Advice 2018. Book 12. 50 pp.

Jardim, E., Azevedo, M., and Brites, N. M. 2015. Harvest control rules for data limited stocks using length-based reference points and survey biomass indices. Fisheries Research, 171: 12–19.

Jardim, E., Scott, F., Mosqueira, I., Citores, L., Devine, J., Fischer, S., Ibaibarriaga, L. *et al.* 2017. Assessment for All initiative (a4a) Workshop on Development of MSE Algorithms with R/FLR/a4a. EUR 28705 EN. Publications Office of the European Union, Luxembourg.

Kell, L. T., Pilling, G. M., Kirkwood, G. P., Pastoors, M., Mesnil, B., Korsbrekke, K., Abaunza, P. *et al.* 2005. An evaluation of the implicit management procedure used for some ICES roundfish stocks. ICES Journal of Marine Science, 62: 750–759.

Kell, L. T., Mosqueira, I., Grosjean, P., Fromentin, J.-M., Garcia, D., Hillary, R., Jardim, E. *et al.* 2007. FLR: an open-source framework for the evaluation and development of management strategies. ICES Journal of Marine Science, 64: 640–646.

Myers, R. A., Bowen, K. G., and Barrowman, N. J. 1999. Maximum reproductive rate of fish at low population sizes. Canadian Journal of Fisheries and Aquatic Sciences, 56: 2404–2419.

Punt, A. E., Campbell, R. A., and Smith, A. D. M. 2001. Evaluating empirical indicators and reference points for fisheries management: application to the broadbill swordfish fishery off eastern Australia. Marine and Freshwater Research, 52: 819–832.

Punt, A. E., Butterworth, D. S., de Moor, C. L., De Oliveira, J. A. A., and Haddon, M. 2016. Management strategy evaluation: best practices. Fish and Fisheries, 17: 303–334.

Rosenberg, A. A., Kleisner, K. M., Afflerbach, J., Anderson, S. C., Dickey-Collas, M., Cooper, A. B., Fogarty, M. J. *et al.* 2018. Applying a new ensemble approach to estimating stock status of marine fisheries around the world. Conservation Letters, 11: e12363.

Simon, N., Friedman, J., and Hastie, T. 2013. A Blockwise Descent Algorithm for Group-penalized Multiresponse and Multinomial Regression. arXiv: 1311.6529.

Smith, A. D. M. 1994. Management strategy evaluation—the light on the hill. *In* Population Dynamics for Fisheries Management, Australian Society for Fish Biology Workshop Proceedings. August 24–25, 1993, Perth, WA, pp. 249–253. Australian Society for Fish Biology, Perth, WA.

Tibshirani, R. 1996. Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society: Series B (Methodological), 58: 267–288.

Von Bertalanffy, L. 1950. An outline of general system theory. The British Journal for the Philosophy of Science, I: 134–165.

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

Wiff, R., Flores, A., Neira, S., and Caneco, B. 2018. Estimating steepness of the stock-recruitment relationship in Chilean fish stocks using meta-analysis. Fisheries Research, 200: 61–67.

Zou, H., and Hastie, T. 2005. Regularization and variable selection via the elastic net. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 67: 301–320.

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