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Complete List of Authors:	Fischer, Simon; Centre for Environment Fisheries and Aquaculture Science; Imperial College London, Centre for Environmental Policy De Oliveira, José; Centre for Environment Fisheries and Aquaculture Science Kell, Laurence; Imperial College London, Centre for Environmental Policy
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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], 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 1N, UK

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Contact author: Simon H. Fischer, Centre for Environment, Fisheries and Aquaculture Science (Cefas), Pakefield Road, Lowestoft, Suffolk, NR33 0HT, UK, Email: simon.fischer@cefas.co.uk

ABSTRACT

Worldwide, the majority 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 catches 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 had a high probability of stock collapse. A time-series cluster analysis revealed four types of dynamics, i.e. groups with similar stock trajectories (collapse, 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. The lessons learnt can help future work to shape scientific research into data-limited fisheries management and to ensure fisheries are MSY-compliant and 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, 1995). In addition, fish retailers and consumers are increasingly looking for assurances that the food they buy is sustainably produced. Therefore, many regional fisheries management Organisations (RFMOs) 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 in order to evaluate the performance of a Management Procedure (MP),~~.~~ ~~W~~where 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 catches (TAC). This in turn is converted into a catch that is removed from the operating model 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 model free, where a trend in an empirical indicator is used to set the catch (Hillary *et al.*, 2016). ~~The~~ 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~~e~~ 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.

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:

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

where C_{y+1} is the newly advised catch for year $y + 1$, C_{y-1} is the last advised catch and I is a biomass index. This rule, in combination with an uncertainty cap (limiting change to no more than 20%) and precautionary buffer (which reduces the catch by 20% if the stock is judged to be outside safe biological levels), is currently applied to give catch advice within ICES for many 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, 2017b). An alternative catch rule, making use of more data sources, has therefore been proposed (ICES, 2012b):

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

where the advised catch C_{y+1} is based on the previous 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 which protects the stock once the biomass index drops below a threshold. Initially, this catch rule was merely a concept without specification about what data should be used and how the components could be derived from them (ICES, 2012b). Recently, the rule has been revisited by ICES (2017c) 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, 2017b). 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 paper is to test catch rules for data limited stocks, assumptions and approximations must be made. We used 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 stock 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 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 parameters from particular stock units, 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.

METHODS

Simulation of stocks

Operating models were conditioned for twenty-nine 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 operating models were created. Growth was modelled with the von Bertalanffy growth equation, recruitment by a Beverton-Holt stock recruit function with steepness $h = 0.75$, virgin recruitment 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). 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 calculated based on the age distribution in the catch. Weights at age were converted first into discrete length classes using the allometric length-weight relationship, then numbers at length were created assuming a normal distribution around the discrete length classes. The final length distribution was derived by aggregating numbers at age in 1cm steps. Full specifications, including equations are given in the online 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. 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

149 were at their lowest levels and declining, whereas in the roller-coaster scenario the stocks had started

150 to recover. This exploitation state was then used as starting point for the MSE simulation.

151 *Catch rule*

152 The main catch rule tested sets catch advice based on the recent catch multiplied by three factors

153 corresponding to perceptions of stock characteristics based on catch and survey data (equation 2).

154 Component r corresponds to the trend in a biomass index, and is based on the “2 over 3” rule (equation

155 1):

156 $$r = \frac{\sum_{i=y-2}^{y-1} I_i/2}{\sum_{i=y-5}^{y-3} I_i/3} \quad (3)$$

157 where I is the biomass index. Component f is a proxy for the ratio F_{MSY} divided by the current

158 exploitation based on length data from the catch:

159 $$f = \frac{\bar{L}_{y-1}}{L_{F=M}} \quad (4)$$

160 where $\bar{L}_{y-1}$ is the mean length in the catch above the length of first capture (L_c), weighted by catch

161 numbers at length, with L_c defined as the first length class having at least 50% of the mode in the catch

162 length frequency. The reference length $L_{F=M}$ is a proxy for the length at MSY proposed by Beverton

163 and Holt (1957), under the assumption that $F = M$. Using the simplification that $M/k = 1.5$ the

164 reference length can be calculated as:

165 $$L_{F=M} = 0.75L_c + 0.25L_\infty \quad (5)$$

166 Finally, component b of the catch rule is a biomass safeguard protecting the stock when the biomass

167 index drops below a threshold:

168 $$b = min\left\{1, \frac{I_{y-1}}{I_{trigger}}\right\} \quad (6)$$

169 $I_{trigger}$ was based on the lowest historical biomass index value I_{loss} and defined as $I_{trigger} = 1.4I_{loss}$.

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 ($sd = 0.2$, implemented individually on each age before compiling them into the biomass index), recruitment ($sd = 0.3$ and autocorrelation with $\rho = 0.2$), reference points ($sd = 0.1$), life-history parameters used in the calculation of catch length frequencies ($sd = 0.1$), catch numbers at length ($sd = 0.2$) and implementation of the advice into catch ($sd = 0.1$). 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.

Performance of the catch rule

The performance of the catch rule was assessed based on six performance statistics:

- catch/MSY: the catch (averaged over the simulated period), expressed as a proportion of the catch when fishing at F_{MSY},
- collapse risk: risk of stock collapse, i.e. the proportion of the projected stock where the stocks is below 0.1% of virgin spawning stock biomass (SSB),
- 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 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),
- ICV: inter-annual variability in catch, calculated as follows:

$$\text{ICV} = \text{median over 500 replicates of} \frac{1}{n}\sum_{y \in Y}\left|(C_y - C_{y-1})/C_{y-1}\right|$$

  where Y is the set of n years in the projection period for which a TAC is set (which could be a biennial TAC)
- SSB/B_{MSY} and F/F_{MSY}: stock status (SSB and F relative to MSY reference points B_{MSY} and F_{MSY}, respectively, averaged over simulation period)

Initial analysis revealed that for some stocks and scenarios the stocks collapsed, and catches were reduced to zero as a result. Depending on 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, 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, and population growth rate g and conditional growth rate g_c had positive Pearson correlation coefficients $\rho \geq 0.92$ between each other, and k and L_∞ correlated negatively with $\rho = -0.70$. Therefore, in order to determine which of the stock characteristics influenced the performance of the catch rule, ordinary linear models were of limited value for the analysis. Consequently, a penalized regression model was applied (glmnet, Friedman *et al.*, 2010) because this provides procedures for fitting the entire elastic-net regularization path from lasso to ridge regression (Hoerl and Kennard, 1988; Tibshirani, 1996; Zou and Hastie, 2005). A multi-Gaussian model was applied that selected the predictor variable(s) that could explain all six performance statistics (catch/MSY, collapse risk, B_{lim} risk, ICV, $^{SSB}/_{B_{MSY}}$ and $^{F}/_{F_{MSY}}$). Firstly, 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), a_{50} (age at 50% maturity). Secondly, 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 rate and conditional growth rate at MSY), M (natural mortality), M/k, F_{MSY}/M (F_{MSY} relative to M) and B_{MSY}/B_0 (B_{MSY} relative to virgin biomass, i.e. location of peak in production curve).

Clustering

In order to identify groups of similar-performing stocks for the range of life histories tested, a time-series clustering approach was adopted. The Dynamic Time Warping technique (DTW, Berndt and Clifford, 1994; Aghabozorgi *et al.*, 2015) was selected as a distance measure and clustering performed on the relative stock status SSB/B_{MSY}. 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. Additionally, once a hierarchical cluster analysis is conducted, the output can be visualised 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.

Modifications to the catch rule

Various modifications of the catch rule were explored. One option tested was the addition of a multiplier x to the catch rule:

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

Multipliers of $x =$ 0.5, 0.6, 0.7, 0.8, 0.85, 0.9, and 0.95 were evaluated.

By default, the catch rule does not include any constraints on the catch advice. In order to examine the impact of constraints on the performance of the catch rule, inter-annual limits on the relative variation in catches were evaluated. The constraints were defined as the maximum change in the advised catch compared to the last catch. Eight lower limits (0, i.e. no constraint, 0.5, 0.6, 0.7, 0.75, 0.8, 0.85 and 0.9), seven upper limits (1.1, 1.15, 1.2, 1.25, 1.3, 1.5 and no limit) and all combinations of these (56 combinations in total) were implemented.

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 two 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 $(y-1)$, 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 data in the catch rule up to the intermediate year y. The survey index was calculated based on the stock at the beginning of a given year and could therefore be extended two years up to the advice year $y+1$. Additionally, setting the TAC annually instead of biennially was explored.

Perfect information scenario

Finally, to check whether the catch rule worked when all the information available to the catch rule 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 operating model to remove the impact of survey selectivity, $I_{trigger}$ was set to exactly $B_{trigger}$, which, in agreement with ICES data limited guidelines (ICES, 2018b), was set to $0.5B_{MSY}$. This modification meant that the biomass threshold was set irrespective of the historical exploitation and comparable for all stocks. The reference length for the f component of the catch rule was defined as the equilibrium length obtained in the operating model when fished at F_{MSY}.

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, seven (anchovy, brill, herring, John Dory, lemon-sole, sandeels, European pilchard 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 (tub gurnard and black seabream) 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 7% - 63% 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. 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 4-5) gave some information throughout the entire simulation period but at a markedly lower magnitude compared to r.

Penalized regression

Performing a lasso regression with the primary input parameters resulted in a model fit that selected only the von Bertalanffy growth parameter k to explain the six performance statistics for the one-way fishing scenario (Figure 3). Allowing elastic-net regularization in the penalized regression model led to minor improvements in the model fit (the mean squared error was reduced from 0.45 to 0.41), 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. This was particularly evident for the risk and catch. Higher values of k were linked to higher risks (both collapse risk and B_{lim} risk) and lower long-term catch. Stocks with very low collapse risks were clustered at $k \leq 0.32$ whereas collapse risks above 20% were only observed for stocks with $k > 0.32$. When also using ~~also~~ derived input parameters as predictor variables, the lasso regression selected only the conditional population growth rate at MSY (g_c) and using the elastic-net regularization resulted in minor improvements but retained all provided input parameters.

Clustering

Clustering was performed on the median of the SSB/B_{MSY} time-series for the 29 simulated stocks. Figure 4 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 4B), centroids for the clusters were calculated post-hoc as the annual average of the 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 above

1. The first separation in the hierarchical cluster distinguished between two distinct patterns (second row in Figure 4B); the first cluster was composed of stocks that experienced early peaks but collapsed by the end of the simulation period, whereas the stocks in the second cluster survived. This split corresponds well to the von Bertalanffy k values for these stocks (Figure 4C). The first cluster (collapsed) is comprised of stocks with $k > 0.32$. On the other hand, the stocks with lower k ($k \leq 0.32$) survived.

Following the dendrogram further, the next two splits occurred within the cluster of surviving stocks. Firstly, there is a separation of stocks that stay around B_{MSY} in the long term and ~~the~~ ones that end up markedly above B_{MSY} (third row of Figure 4B). These stocks are mainly characterised by k values around the median of the simulated range, although two of the stocks inside this cluster have k values at the lower end of the total range (megrim and redfish). For megrim, the catch was reduced substantially at the beginning of the simulation and approaches zero; consequently, the stock moves towards virgin biomass. Redfish displayed a similar behaviour; however, the catch recovered later in the simulation and the stock declined again from very high levels. Secondly, the stocks reaching levels above B_{MSY} are divided further into one cluster where the SSB converged at around $2B_{MSY}$ and one cluster where the SSB approaches levels close to $3B_{MSY}$ (fourth row of Figure 4B). In terms of k, these stocks overlap 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 4 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 5). This risk reduction was a result of higher terminal SSB values, and 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 roughly 40 years after the start of the simulation and adding a multiplier of only 0.95 avoided this collapse. On the other hand, pilchard and John Dory collapsed in the roller-coaster fishing scenario within approximately five years, and this collapse could only be averted by implementing a multiplier of 0.8 or below.

The performance of the catch rule for these cluster 1 stocks was highly sensitive to small changes of 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 around 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 where shifted further above B_{MSY} when the multiplier was added. For 16 of the 29 stocks tested, adding the multiplier reduced the catch. For the remaining 13 stocks, the maximum was achieved within a range 0.9–0.95. When considering all stocks together, there does not seem to be a 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 6A). For most stocks, the catch was reduced when upper catch constraints were used. An exception was for the stocks from cluster 1. For the one-way fishing history, the catch peaked at upper constraints between 1.15 and 1.3, and for the roller-coaster scenario, the catch increased up to the most restrictive constraint (1.1). For most of the remaining stocks, the catch is relatively stable for constraints at or above 1.2, and this value seems to be a reasonable compromise between risk reduction and maximising catch. In general, including a lower constraint on the catch increased the risk of stock collapse and resulted in subsequent reductions 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 above 0 and below 1. Figure 6B 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 being particularly pronounced at constraint levels above 0.7. Below 0.7, the risks and catches were relatively stable.

For the stocks surviving the default implementation of the catch rule ($k \leq 0.32$), using more recent data and setting the TAC more frequently improved performance by reducing oscillations and reaching final biomass values earlier (Figure 7). 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. Some of the high k stocks (cluster 1, $k > 0.32$) could be saved; however, two stocks (John Dory and herring) still collapsed even if the TAC was set annually and the most recent data was used.

Perfect information scenario

When the catch rule was implemented with perfect information ~~and knowledge~~ (i.e. the SSB from the operating model was used as the index and $I_{trigger}$ set to $0.5B_{MSY}$ from the operating model), the performance of the catch rule was substantially improved and most stocks converged towards B_{MSY}, indicating that the catch rule did work under these unrealistically perfect conditions (Figure 8). However, stocks with higher k values generally displayed a stronger oscillatory behaviour. Among the high k stocks ($k > 0.32$), three stocks survived (brill, whiting and lemon sole) in the one-way fishing history scenario but the remaining stocks, and all high k stocks in the roller-coaster fishing scenario, showed poor performance with collapses. The highest k stock, sandeel, showed a recovery to very high biomass levels, but this behaviour could be attributed to the fact that this stock was at the brink of stock 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. When also using derived input parameters, the conditional growth rate at MSY (g_c) appeared as crucial factor determining the performance of the catch rule. However, this parameter might not always be readily available and is computed from the primary input parameters. Therefore, we focused the analysis on k.

It was clear from a visual inspection of the results that the response of stocks to the application of the catch rule could be organised into different groups, and therefore a time series clustering approach using dynamic time warping 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: 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 $k \leq 0.32$, but very poorly for stocks with $k > 0.32$. The $k \leq 0.32$ stocks reached levels of between B_{MSY} and $3B_{MSY}$, i.e. stock collapses were avoided, but frequently there was a loss of~~n~~ yield compared to the yield achieved when fishing at F_{MSY}.

The result that the catch rule performed worse for more productive stocks ($k \geq 0.32$) compared to less productive stocks ($k \leq 0.32$) might at first glance appear counter-intuitive. However, the performance of the catch rule, as measured by the summary statistics, is an emergent property of the interaction between the operating model and the catch rule. We showed that the advised catch was mostly influenced by the r component of the rule (the stock trend) and stocks with higher k are inherently more variable, which led to higher fluctuations in the catch. When subjected to the catch rule, the higher k stocks collapsed on average early during the simulation. This behaviour can be attributed to an initial rapid recovery, also causing the catch to increase, but once the stocks started to decline again, the 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. The less productive stocks were also less variable, and 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 operating models on knowledge from fully ~~analytical~~ quantitative 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) were 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 of 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 which 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 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 the 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 become 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.

One concern raised during this work was the appropriateness of using a constant steepness of 0.75 in the recruitment model for all stocks. We addressed this issue by conducting additional sensitivity runs (detailed in the supplementary online material) and found that changing steepness to 0.9 or imposing a positive linear relationship between steepness and k did not affect the conclusions.

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. If a catch rule works in such harsh conditions, the rule is likely to work well in less depleted states. Additionally, 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 induce apparent trends in abundance and may be common in age-structured populations; 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 operating models 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 HCR 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 operating models 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 was the stock between years; for example, a stock could exhibit high interannual variability if natural mortality and recruitment variability was high, regardless of the values of k, L_{inf}, L_{50}. The nature of the indices is also important; for example, even if a stock had low interannual 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 operating model), and to the characteristics of the data collected from it. This will require tuning by constructing a reference set of operating models 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 management procedures are usually considered in a data-limited context; such simple rules can sometimes achieve similar performance compared to management procedures based on fully ~~analytical~~ quantitative assessments (e.g. shown by Carruthers *et al.*, 2014; Geromont and Butterworth, 2015b) or even out-perform them, particularly if operational effort is included.

SUPPLEMENTARY MATERIAL

The following supplementary material is available at ICESJMS online: A document describing the operating models, including input parameters and equations and an analysis of the sensitivity of the study to the stock recruitment model steepness and variability.

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614 **TABLES**

615 **Table 1**. The 29 stocks on which the operating models are based. Given are the scientific and
616 common names, a unique stock ID and the von Bertalanffy growth parameter k.

Scientific name	Common name	ID	k
Ammodytes spp.	sandeels	san	1
Anarchias lupus	Atlantic wolffish	wlf	0.11
Argentina silus	greater argentine	arg	0.23
Chelidonichtys lucerna	tub gurnard	gut	0.32
Clupea harengus	herring	her	0.606
Engraulis encrasicolus	anchovy	ane	0.44
Lepidorhombus whiffiagonis	megrim	meg	0.12
Lophius budegassa	blackbellied angler	ang3	0.08
Lophius piscatorius	angler	ang	0.18
Lophius piscatorius	angler	ang2	0.18
Melanogrammus aeglefinus	haddock	had	0.2
Merlangius merlangus	whiting	whg	0.38
Microstomus kitt	lemon sole	lem	0.42
Molva molva	ling	lin	0.14
Mullus surmuletus	striped red mullet	mut	0.21
Mustelus asterias	starry smooth-hound	sdv	0.15
Nephrops	Norway lobster	nep	0.2
Pleuronectes platessa	European plaice	ple	0.23
Pollachius pollachius	pollack	pol	0.19
Raja clavata	thornback ray	rjc2	0.14
Raja clavata	thornback ray	rjc	0.09
Sardina pilchardus	European pilchard	sar	0.6
Scophthalmus rhombus	brill	bll	0.38
Scopthalmus maximus	turbot	tur	0.32
Scyliorhinus canicula	lesser spotted dogfish	syc	0.15
Scyliorhinus canicula	lesser spotted dogfish	syc2	0.23
Sebastes norvegicus	golden redfish	smn	0.11
Spondyliosoma cantharus	black seabream	sbb	0.22
Zeus faber	John Dory	jnd	0.47

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FIGURES

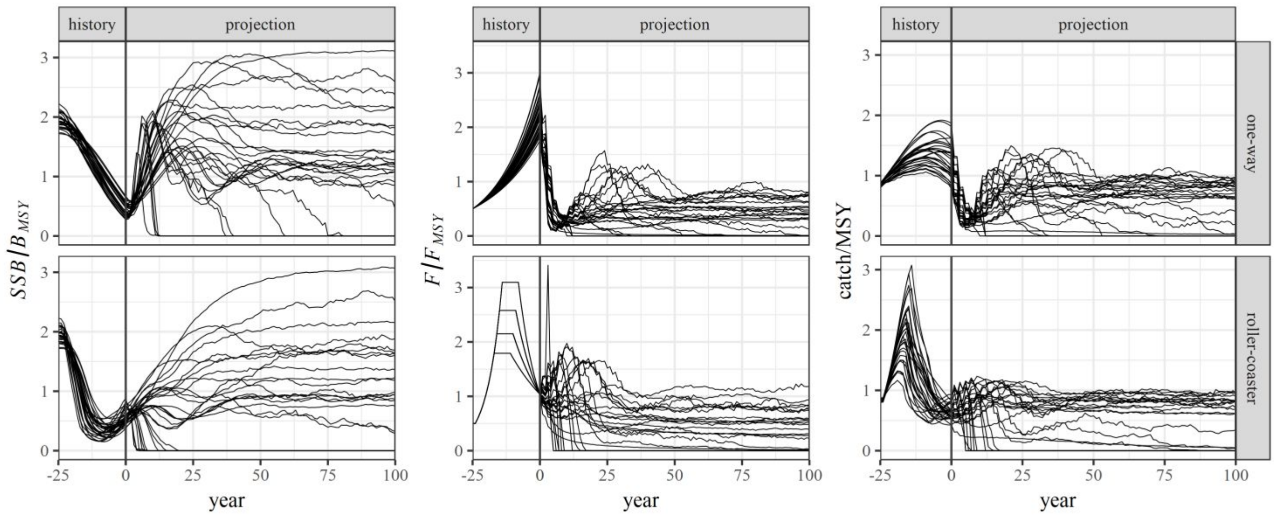


Figure 1. Median trajectories for spawning stock biomass (SSB), mean fishing mortality and catch relative to MSY reference points for the 29 simulated stocks. Shown are the historical fishing period ("history", years -25-0) and the results of subsequently applying the catch rule (years 1-100). The top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

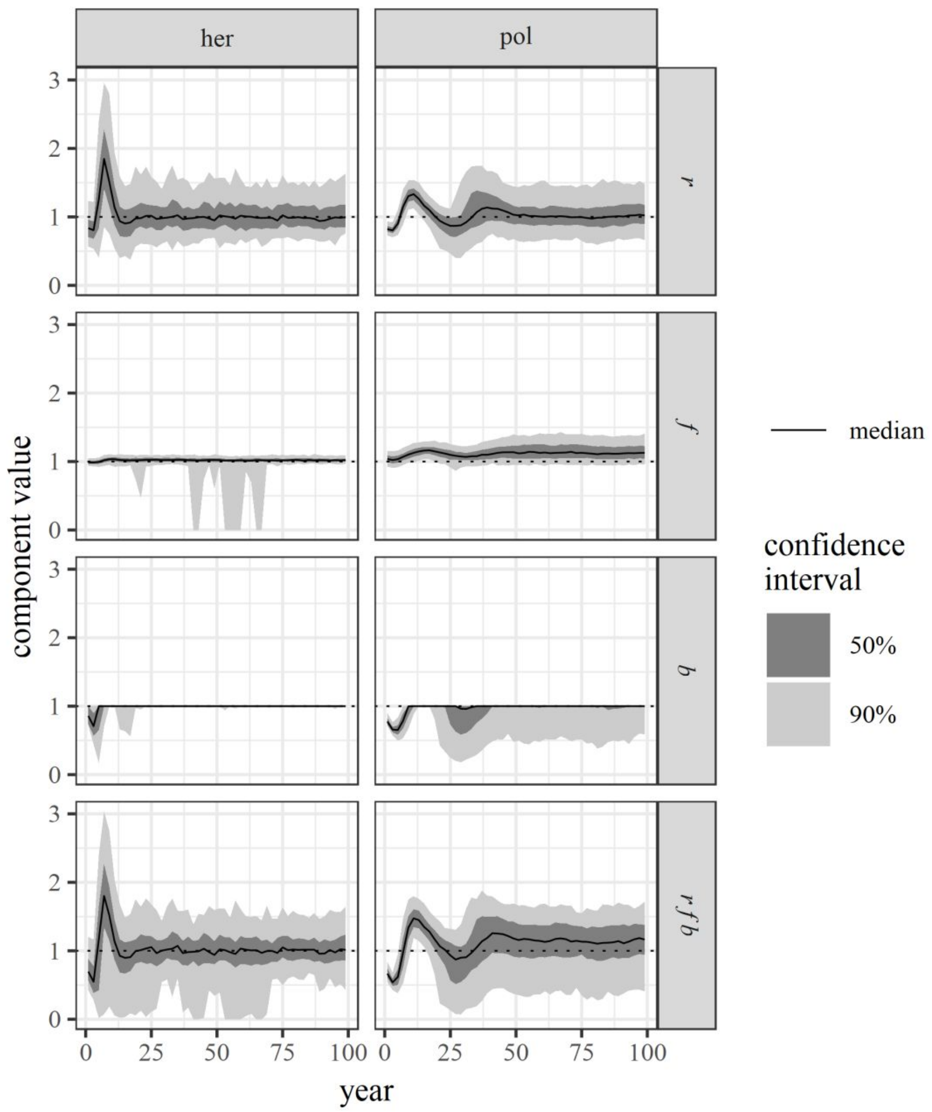


Figure 2. Components of the catch rule (r, f and b) and their product ($r\ f\ b$, which scales the recent catch) for two example stocks: herring (her) and pollack (pol). The higher the deviation of a component from one (up or down), the higher is its contribution in the catch rule. Please note that for herring, the stock collapsed in most simulated replicates (the median SSB collapsed after 13 years) and in the distributions shown for the components, these collapsed replicates were excluded because they did not provide any stock status information.

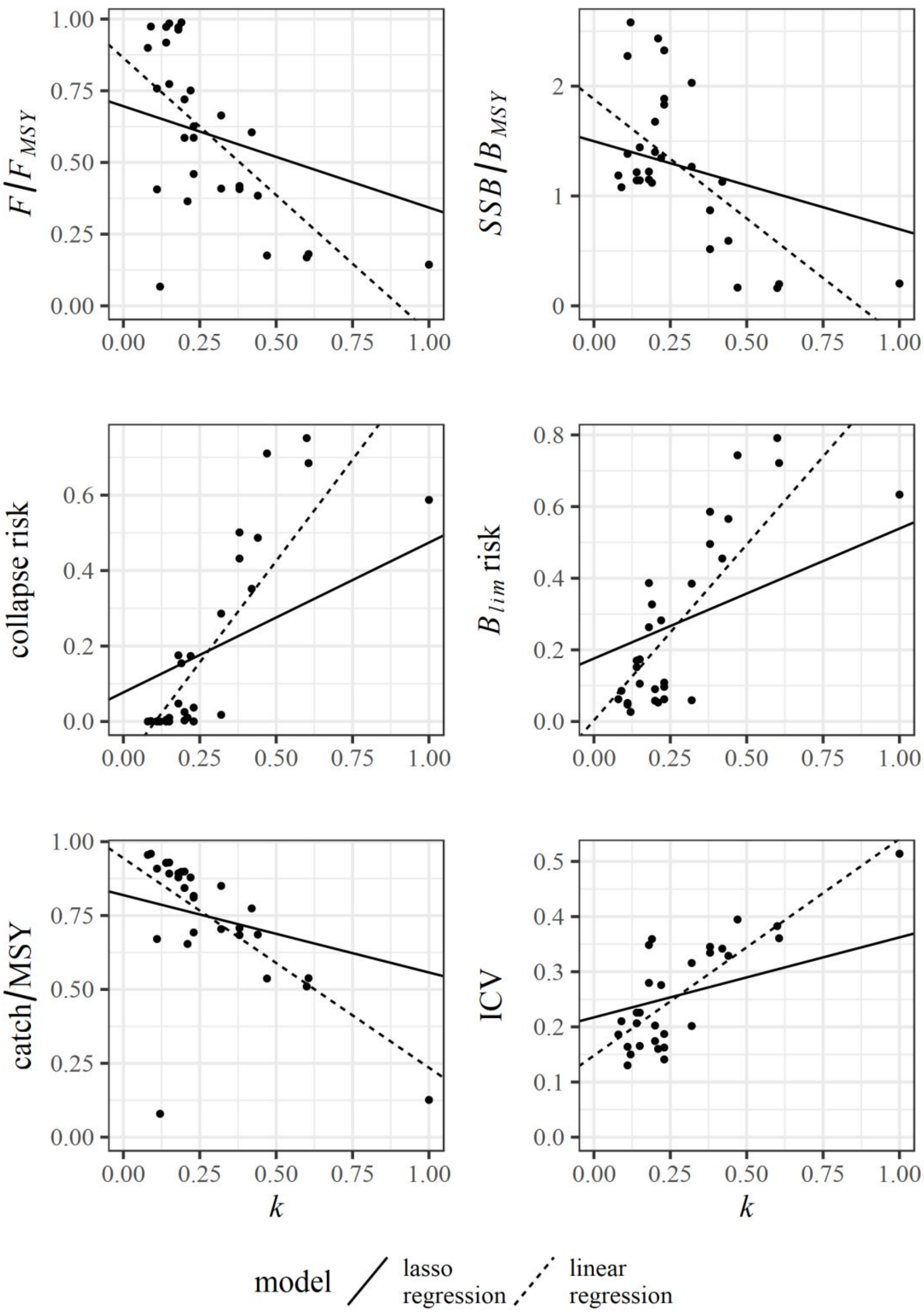


Figure 3. Six performance statistics versus the von Bertalanffy growth model parameter k for the tested catch rule and the one-way fishing history for all 29 stocks. The solid lines show the fit from the lasso regression model, and the dotted lines a linear regression of the data.

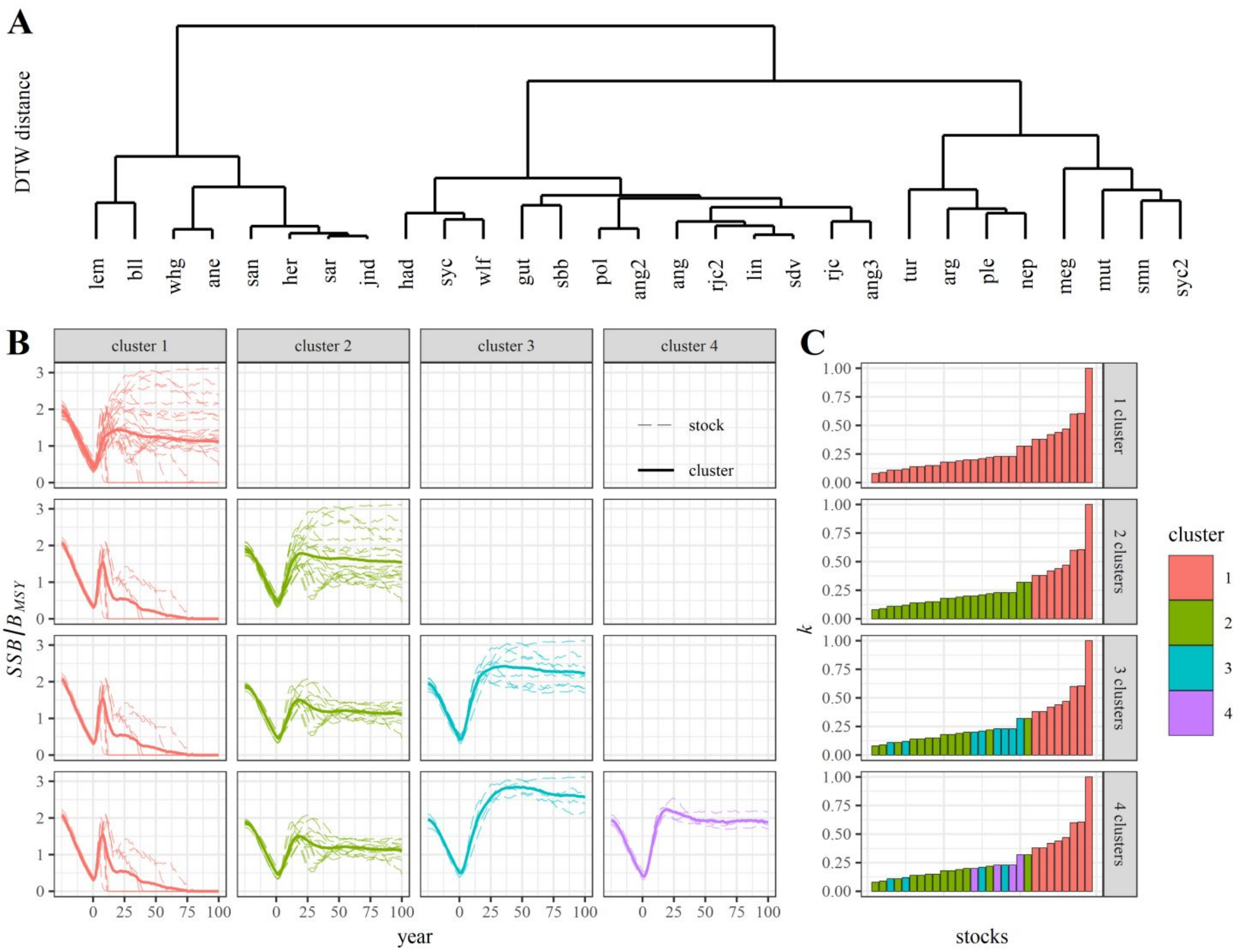


Figure 4. Results of the hierarchical clustering approach of relative SSB for the one-way fishing history. A shows a dendrogram of the time series for the 29 simulated stocks, the names correspond to the stock IDs defined in Table 1. The y-axis corresponds to the dynamic time warping (DTW) distance between the time series. B represents 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 shows von Bertalanffy growth model parameter k for all stocks, sorted in ascending order and colour-coded for the clusters shown in B.

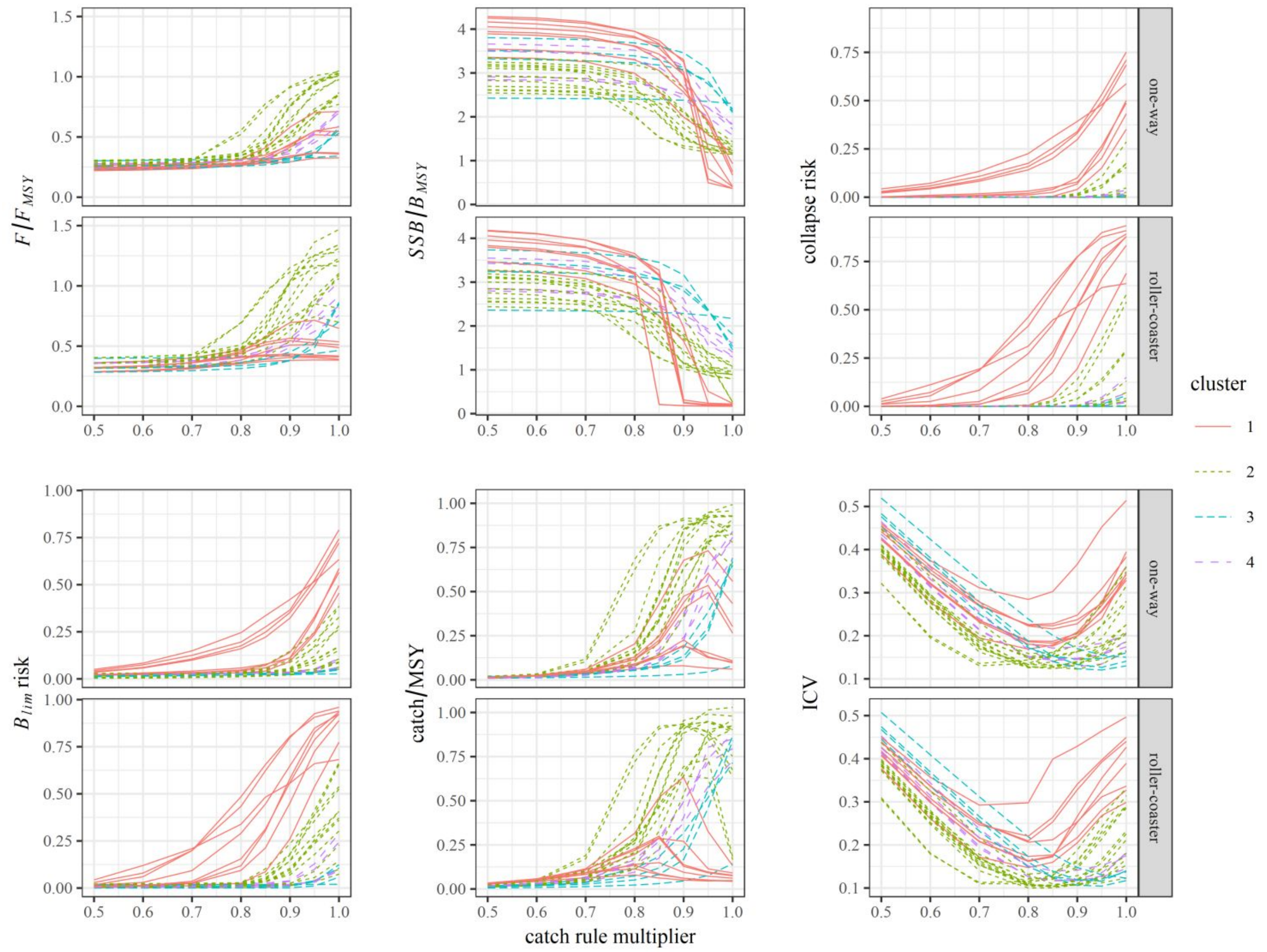


Figure 5. Effect of implementing a multiplier to the catch rule on the six performance statistics for the 29 simulated stocks and both fishing histories. The clusters correspond to the ones defined in Figure 4.

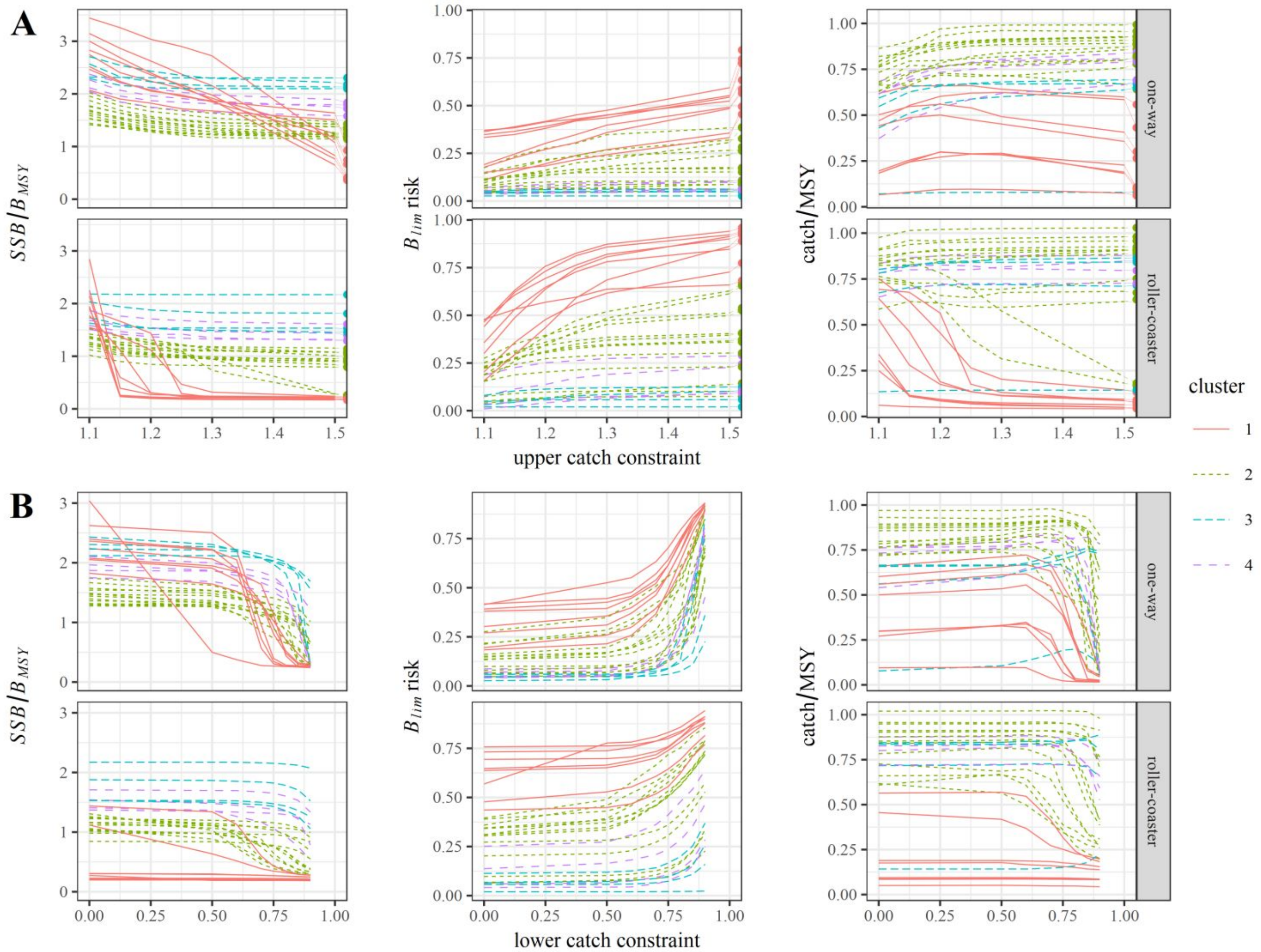
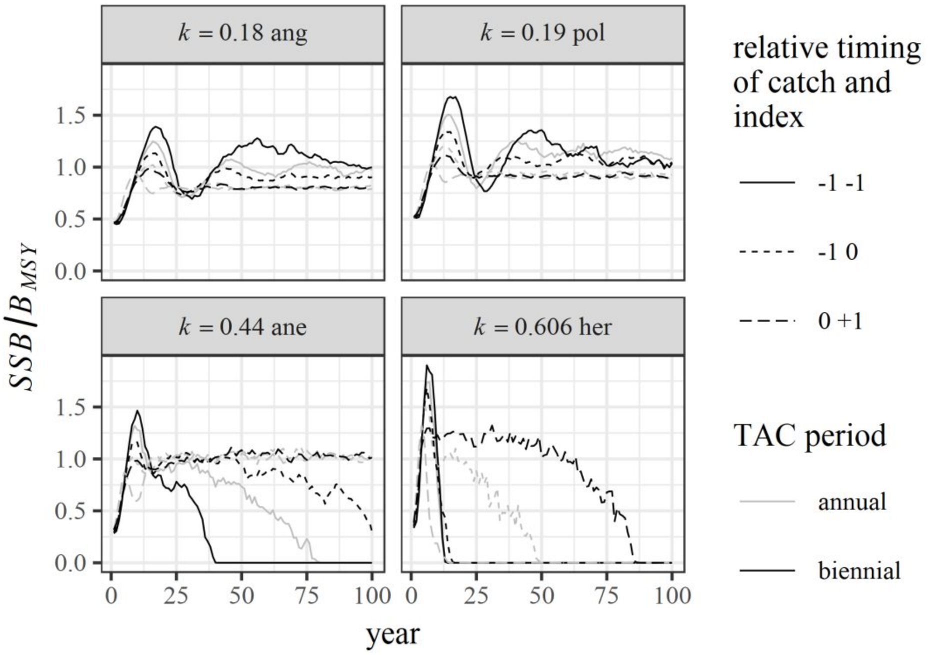


Figure 6. Effect of catch constraints on three performance statistics. **A** shows the effect of upper catch constraints. The points above an upper catch constraint of 1.5, connected with thin lines, indicate the performance when no upper catch constraint was implemented. **B** shows the effect of lower catch constraints in combination with an upper catch constraint of 1.2. The clusters correspond to the ones defined in Figure 4.

661 

662 **Figure 7.** Effect of time-lags for the data used in the catch rule and periodicity of TAC-setting (annual
663 vs. biennial) for four example stocks (sorted by von Bertalanffy k) in the one-way fishing scenario. The
664 timing is relative to the intermediate year (0) and -1 refers to the year before, +1 to year after the
665 intermediate year.

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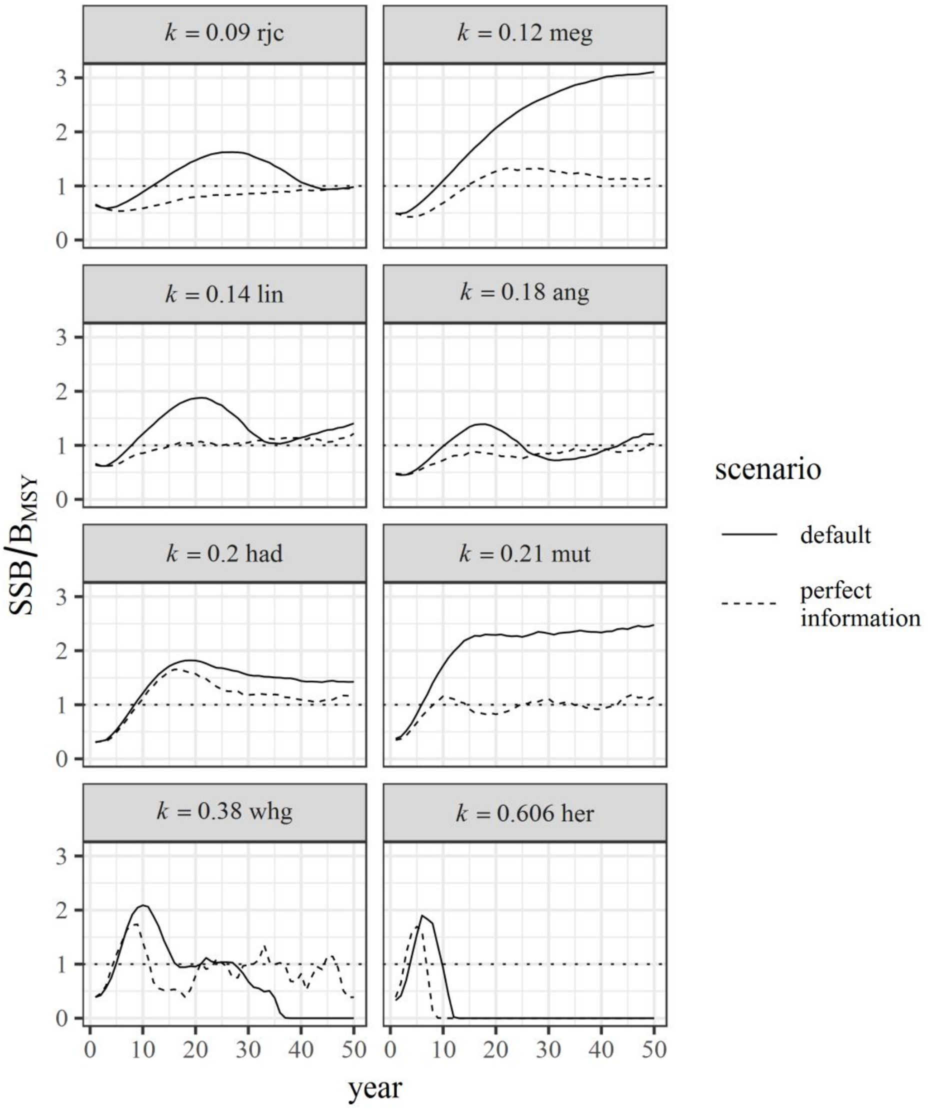

Figure 8. Application of the catch rule with and without perfect information for eight example stocks (as defined in Table 1) for the one-way fishing history. In the perfect information scenario, no uncertainty, apart from recruitment variability, has been implemented; the survey is an exact representation of the spawning stock biomass and $I_{trigger} = 0.5B_{MSY}$.