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Risk equivalence in data-limited and data-rich fisheries management: An example based on the ICES advice framework

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Abstract

Fisheries management needs to ensure that resources are exploited sustainably, and the risk of depletion is at an acceptable level. However, often uncertainty about resource dynamics exists, and data availability may differ substantially between fish stocks. This situation can be addressed through tiered systems, where tiers represent different data limitations, and tier-specific stock assessment methods are defined, aiming for risk equivalence across tiers. As case studies, we selected stocks of European plaice, Atlantic cod and Atlantic herring, where advice is provided by the International Council for the Exploration of the Sea (ICES). We conducted a closed-loop simulation to compare risk equivalence between the data-rich ICES MSY rule, based on a quantitative stock assessment, and the revised data-limited empirical management procedures of the ICES advice framework. The simulations indicated that the data-limited approaches were precautionary and did not lead to a higher risk of depletion than the data-rich approach. Although the catch based on generic data-limited approaches was lower, stock-specific optimisation improved management performance with catch levels comparable with the data-rich approach. Furthermore, the simulation indicated the ICES MSY rule can fail to meet management objectives due to increased depletion risk when management reference points are set suboptimally. We conclude that the recent revisions of the ICES system explicitly account for risk equivalence for data-limited fisheries management and are a major step forward. Finally, we advocate further consideration of simple empirical management procedures irrespective of data limitations due to their ability to meet fisheries management objectives with greater simplicity.

KEYWORDS
empirical, genetic algorithm, management procedure, management strategy evaluation, optimisation, precautionary approach

1 | INTRODUCTION

Assessing possible impacts of anthropogenic influences on ecosystems is important, and this is often formalised with risk assessments, widely used in many fields of environmental management (Burgman, 2005). The exploitation of marine living resources is no exception and has spawned the management strategy evaluation approach (MSE; Smith, 1994), which is considered the best practice for the evaluation of the impact of management strategies (Punt et al., 2016). According to Punt et al. (2016), MSE comprises (1) the identification of management objectives, (2) identification of uncertainties, (3) development and (4) conditioning of operating models (OMs), which represent the resource dynamics and the fishery, (5) identification of candidate management procedures (MPs), (6) a closed-loop simulation of MPs for the OMs and (7) interpretation of results. Uncertainty about resource dynamics is included by considering alternative hypotheses in the form of alternative OMs because the underlying reality is unknown and can only be inferred from observations (Kell et al., 2021).

MSE approaches frequently include stakeholder engagement, considered a defining characteristic of the process (Miller et al., 2019). The interpretation and extent of what constitutes MSE can differ between regions and management bodies. In this paper, we focus on the closed-loop simulation without extensive stakeholder engagement. Consequently, this might be considered a pure management procedure evaluation (MPE) instead of a comprehensive MSE.

Assessing risks requires a definition of what constitutes risk. Roux et al. (2022) define risk as the probability of exceeding reference levels leading to potential adverse consequences (biological, ecological, social or economic). In fisheries management, risk is often defined as the probability of the exploited resource being overfished (Dichmont et al., 2016) and failing to meet targets, i.e. management objectives. Uncertainty in the understanding of processes is explicitly considered in the precautionary approach to fisheries management (Garcia, 1996), which aims to reduce the risk of adverse consequences. MSE can be used as a tool to identify where a reduction in scientific uncertainty could improve fisheries management (Fromentin et al., 2014).

The availability of data and knowledge can differ substantially between fish stocks, requiring the application of different methods to derive scientific management advice. Tiered systems, which classify fish stocks into tiers or categories depending on the available data, have been developed to account for this discrepancy. Such tiered systems are, for example, used in Australia (Department of Agriculture and Water Resources, 2018), the United States of America (PFMC, 2014) and Europe (ICES, 2012a). The general aim of such frameworks is to provide more precautionary advice when there are fewer data (i.e. more uncertainty), e.g. through the inclusion of buffers depending on the stock category (Dichmont et al., 2016). This implies that there is a benefit of improving data collection and knowledge because more data could increase the yield.

Ideally, tiered fisheries management frameworks ensure risk equivalence between categories, i.e. in a situation with poor or limited data and consequently higher uncertainty, management should not permit higher risks. Dichmont et al. (2016) reviewed the tier approaches of Australia's Southern and Eastern Scalefish and Shark Fishery, the US west coast groundfishery, the US Alaskan crab fishery and the European Union fisheries. They found that none of the systems achieved complete risk equivalency, and only the Australian system explicitly aimed towards it. Dichmont et al. (2017) then subjected the Australian system with its tiers to a closed-loop simulation with a full ecosystem model and found that risk equivalence was not achieved. However, Fulton et al. (2016) noted that introducing buffers similar to the one applied on the US west coast could move the Australian system closer to full risk equivalence between the tiers. Other studies comparing methods among tiers exist, but these compared generic methods rather than specific management frameworks (e.g. Carruthers et al., 2014; Geromont & Butterworth, 2015b).

The International Council for the Exploration of the Sea (ICES) provides catch advice for fish stocks in the Northeast Atlantic (ICES, 2021a). Since 2012, ICES classified fish stocks into six categories depending on available data and applicable methods (ICES, 2012a), from category 1 (most data-rich) to the most data-limited category 6.

Stocks in category 1 are usually assessed with age-structured stock assessments, and the catch advice is based on a short-term forecast. In most cases, this advice is based on the ICES MSY rule (ICES, 2021a), which is a harvest control rule aiming at the fishing mortality corresponding to the maximum sustainable yield (MSY), F_{MSY}, but with F reduced when the spawning stock biomass (SSB) is estimated to be below a trigger value ($MSYB_{trigger}$). Guidelines specify how these management reference points should be derived (ICES, 2021f), and this usually involves a stochastic long-term simulation assuming stationarity ('EqSim' software; Simmonds et al., 2022). EqSim is conditioned on the point estimates from a stock assessment and only includes limited uncertainty considerations.

The 2012 ICES data-limited stock assessment framework (ICES, 2012a) is a collection of methods for stocks in categories 2–6, i.e. for those without absolute estimates of biomass and fishing mortality. Category 2 was originally meant for stocks with quantitative assessments, which were considered to provide only relative estimates due to large uncertainty. For stocks in categories 3–6, there is typically no stock assessment due to data limitations or because assessment models do not meet acceptance criteria. For category 3 stocks, a survey or catch per unit effort index exists and can indicate stock trends. The standard method for this category is a status quo catch rule, which adjusts the recently advised catch by the trend in a stock index, typically a '2 over 3' rule, where the trend is defined as the average of the two most recent index values divided by the average of the three preceding values. The remaining stocks are classified as category 4 (stocks with a time series of reliable catch, including discard estimates, which can be used in catch-only models), 5 (stocks with only landings or short catch time series insufficient for catch-only models) and 6 (stocks with negligible landings or bycatch). According to the ICES stock assessment database (ICES, 2022b), ICES provided advice for 179 stocks in 2021, of which 99, 6, 55, 1, 13 and 5 were in categories 1–6, respectively.

Although the 2012 ICES data-limited framework aimed to provide advice following a precautionary approach, this was never shown to be the case. Recently, there have been developments to revise the ICES data-limited framework, guidelines were proposed in ICES (2020a) and published in ICES (2022c) to overhaul the system for category 3 stocks. Figure 1 illustrates the revised framework. The first step is to check whether a surplus production model (e.g. SPiCT; Pedersen & Berg, 2017) can be fit. If such a model fit meets acceptance criteria, the stock can be upgraded to category 2 and a fractile rule (Mildenberger et al., 2022) is applied. The fractile rule involves taking the SPiCT model fit and running a stochastic short-term forecast targeting F_{MSY}, resulting in a distribution of catch values in the forecast year. Instead of using the median of this distribution, a percentile below 50%, e.g. the 35th percentile, is then used for the catch advice. This approach accounts for model uncertainty and larger uncertainty leads to lower catch advice, similar to the P* approach used in the United States of America (Prager & Shertzer, 2010; Privitera-Johnson & Punt, 2020).

In the absence of quantitative stock assessments, empirical (model-free) MPs were developed through testing with generic simulations and tuning to achieve precautionary criteria for a wide range of life histories and uncertainties. One of the new empirical MPs is the 'rfb rule' (Fischer et al., 2020, 2021a, 2021b), which derives advice by adjusting the previous catch advice by the trend from a biomass index, the catch length data as a proxy for fishing pressure and a biomass safeguard protecting against low stock size. Another suggested MP is a harvest rate rule, which sets catch advice by targeting a relative harvest rate (catch divided by a biomass index; Fischer et al., 2022). The rfb rule was already applied to two stocks in 2021 (ICES, 2021h, 2021i) and in the first half of 2022, the rfb and harvest rate rules were applied to five stocks each (ICES, 2022a), with a further rollout being anticipated.

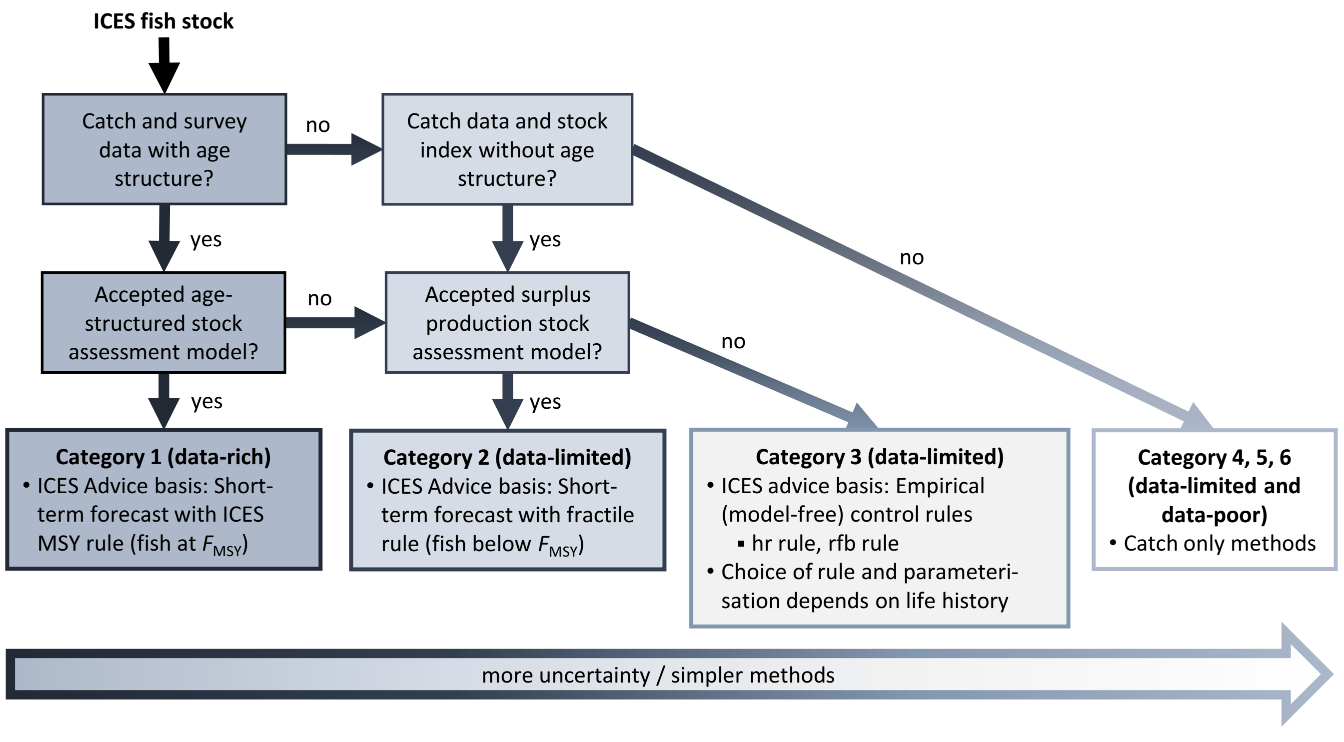

FIGURE 1 Simplified illustration of the revised ICES advice framework following the revisions for categories 2 and 3 by ICES (2022c). The figure shows typical situations, but deviations exist, e.g. for short-lived species.

The aim of this study was to compare the risks of data-limited category 3 approaches with the data-rich category 1 approach. Statements on the comparison of risk or other management performance metrics for a specific stock are only useful if approaches are compared under equivalent conditions. Consequently, we developed a framework that allows closed-loop simulations to be conducted for data-limited and data-rich MPs. Evaluations should include several life histories, initial stock conditions and sources of uncertainty. Consequently, we selected three ICES stocks as case studies for which OMs could be generated.

The first case study stock was a flatfish, European plaice (*Pleuronectes platessa*, Pleuronectidae) in the western English Channel (ICES, 2021g). This stock was historically treated as a category 1 stock, and the advice was based on the age-structured extended survivors analysis (XSA; Shepherd, 1999), a computationally efficient version of a virtual population analysis (VPA) with survey tuning. However, in 2015, this stock was downgraded to category 3 due to high assessment uncertainty (ICES, 2015). Nevertheless, the assessment was retained, and its SSB estimates were used as the index for the 2 over 3 rule. Since then, the data situation of the stock has improved substantially, sampling levels are at or above levels seen for other data-rich stocks, and this stock offers an opportunity to condition a case-specific OM to a data-limited stock.

The other two case studies were commercially important and well-researched category 1 stocks; Atlantic cod (*Gadus morhua*, Gadidae) in the North Sea, eastern English Channel and Skagerrak (ICES, 2021c), a demersal roundfish, and finally, autumn spawning Atlantic herring (*Clupea harengus*, Clupeidae) in the North Sea, Skagerrak, Kattegat and eastern English Channel (ICES, 2021d), a medium-sized fast-growing pelagic species.

The objectives of this study were to (i) conduct closed-loop simulations for three case study stocks and evaluate both the new ICES data-limited approach (generic empirical MPs) and the traditional ICES data-rich approach (the ICES MSY rule), (ii) compare management performance of these approaches, particularly considering meeting management objectives and risk equivalence, and (iii) explore the benefit of case-specific tuning of the generic empirical MPs. Our work illustrates that data-limited approaches can work well and even exceed the management performance of more complex data-rich approaches.

2 | METHODS

An MSE framework using the Fisheries Library in R (FLR; Kell et al., 2007) was developed to evaluate data-rich and data-limited MPs.

2.1 | Operating models

Age-structured stochastic operating models (OMs) were conditioned for three contrasting fish stocks from the Northeast Atlantic (plaice, cod, herring, Table 1). OMs were based on the model fits of the state-space stock assessment model (SAM; Nielsen & Berg, 2014), which estimates processes (stock numbers at age, recruitment, fishing mortality), observations (catch numbers, survey indices), as well as uncertainties and uncertainty structures of estimated parameters. Uncertainty was introduced into the OMs by sampling from the variance–covariance matrix of the SAM model fit and generating 1000 different (but internally consistent) simulation replicates, each representing one possible outcome. Full details of this approach are available from ICES (2019b). For cod and herring, OMs were based on the latest stock assessments conducted by ICES working groups and accepted by ICES for advice purposes in 2021 (ICES, 2021c, 2021d). For plaice, the OM was based on an exploratory assessment from ICES (2021g), with full catch data including discards. Although the OMs are conditioned on real stock units, they might not exactly represent the ICES benchmarked assessments for these due to small changes (Table 1), but the OMs are very similar to the accepted ICES assessments (Figure 2).

Recruitment was modelled by fitting stock-recruitment models to historical SSB-recruitment pairs and following decisions of ICES expert groups (Table 1). Variability in future recruitment values (process error) was introduced by taking model log residuals, fitting a kernel density smoother to residuals and sampling from this distribution (Figure 3). This process allowed a wider range of residuals to be generated compared with bootstrapping residuals. Autocorrelation of future residuals was included if autocorrelation was significant in historical residuals. The model fitting and sampling were done independently for each simulation replicate.

The OMs based on the SAM model fits (referred to as baseline OMs) describe the historical dynamics of the three stocks. These OMs were used as the basis for the projections in the closed-loop simulations. Future variability in biological parameters (weights at age, natural mortality, maturity, etc.) and fishery selectivity was modelled by resampling from the historical period for each replicate (see Table 1). Process error was included for recruitment (through recruitment residuals) and for older age classes with survival and other process error structure estimated by SAM.

Observations were generated for all survey indices used in the conditioning of the OMs (Table 1). Biomass indices were created by multiplying survey index numbers at age with survey weights and aggregating these. Uncertainty for index and catch observations was modelled based on the SAM estimates of observation error and observation error structure (see ICES, 2019b, for details). Catch length frequencies were derived by applying stochastic age-length keys to the observed catch numbers at age.

OM MSY reference points were estimated using the simulation framework (including process error) and projecting forward for 100 years with constant *F*s. MSY was derived by maximising the long-term catch (median of the last 10 years). The biomass limit reference point (B_{lim}) is meant to represent the SSB below which recruitment is impaired (ICES, 2021f). Consequently, B_{lim} was set to the breakpoint of the hockey-stick model for cod and herring. This approach was not applicable to the Beverton-Holt model used for

TABLE 1 The three baseline operating models

	Plaice	Cod	Herring
Species	European plaice *Pleuronectes platessa*	Atlantic cod *Gadus morhua*	Atlantic herring *Clupea harengus*
Stock unit	western English Channel	North Sea, eastern English Channel and Skagerrak	North Sea, Skagerrak, Kattegat and eastern English Channel
Stock ID	ple.27.7e	cod.27.47d20	her.27.3a47d
Last stock assessment	2021 (ICES, 2021g)	2021 (ICES, 2021c)	2021 (ICES, 2021d)
Operating model specifications			
Time series	Full (1980–2020)	Full (1963–2021)	Full (1947–2021)
Ages	2–10	1–6	0–8
Stock-recruitment model	Beverton-Holt, fitted to full-time series, with residual autocorrelation $\rho = 0.6$	Hockey-stick, fitted to 1998–2021 (following ICES, 2019b, 2021b, 2021k)	Hockey-stick, fitted to 2002–2021 and breakpoint fixed to B_{lim} (following ICES, 2021e)
Survey indices	2: UK-FSP Q3 (beam trawl) ages 2–8; UK-Q1SWBeam (beam trawl) ages 2–9	3: IBTS Q1 (bottom trawl) ages 1–5; IBTS Q3 (bottom trawl) ages 1–4; IBTS Q3 (bottom trawl) age 0	4: IBTS Q1 (bottom trawl) age 1; IBTS Q1 (herring larva index) age 0; IBTS Q3 (bottom trawl) ages 0–5; HERAS (acoustic) ages 1–8
Biomass index	UK-FSP Q3	IBTS Q3	HERAS
Length data source	Commercial catch sampling and Q1SWBeam	IBTS Q1 and Q3	HERAS
Resampling period used in projection	Last 5 years	Last 5 years (ICES, 2019b, 2021b)	Last 10 years (ICES, 2019b, 2021e)
Deviation from stock assessment	Used exploratory assessment from ICES (2021j)	Removed maturity estimation from the model and provided as input (faster model, negligible difference); removed survey age correlation (computational complexity reduced, negligible difference)	Removed LAI SSB index (faster model, negligible difference) following ICES (2019b)

plaice. As an alternative, the principle used by ICES for determining management reference points (ICES, 2021f) was followed, and the lowest observed SSB was selected. This value was then linked to the recruitment model and corresponded to 77% of the unfished recruitment, similar to the 70% used by Fischer et al. (2021a). The MSY estimates derived from the baseline OMs through stochastic projections are summarised in Table 2.

Using the stochastic OM projections to estimate reference points led to reference points matching the structure and dynamics of these OMs. However, details adopted for projections may not exactly match those adopted by the ICES expert groups when calculating ICES management reference points. Therefore, there are differences between the baseline OM reference points and ICES-derived management reference points (Table 2), as already shown by ICES (2019b). For example, F_{MSY} estimates for cod and herring were higher than their corresponding ICES estimates.

The previous sections described the 'baseline' OMs for the three stocks, which were based on their respective ICES assessments. These baseline OMs were used for the initial evaluation of MPs and their optimisation (described below). A range of alternative OMs was created to cover different assumptions made in the condition of the baseline OM in the sense of robustness tests (tRFMO, 2018) so that the robustness of MPs could be evaluated (Table 3). These OMs were conditioned individually following the processes described above and covered considerations such as recruitment (failure, higher recruitment), natural mortality or discards. Reference points were estimated for each alternative OM. Alternative OMs were considered separately and not combined.

2.2 | Management procedures

The tested MPs are detailed in Table 4 and included the data-rich (ICES category 1) MSY rule (ICES, 2021f), the data-limited (ICES category 3) empirical 2 over 3 rule (ICES, 2012a), the rfb rule (Fischer et al., 2020, 2021a, 2021b) and the hr rule (Fischer et al., 2022). The ICES MSY rule MP mimicked the process conducted by ICES working groups, including a SAM assessment and a short-term forecast. The ICES management reference points (Table 2) were used for this process and not the OM-specific values. A slight deviation was done for herring because the ICES advice is based on a deterministic multifleet short-term forecast following a single fleet SAM model. For the simulation conducted here, this was simplified to a single fleet forecast because the aim was to evaluate the performance of the MP for a fast-growing pelagic species and not to consider individual fleet behaviour. The rfb and hr rules were tested for all stocks. The 2 over 3 rule was only tested for plaice because this is the method currently used for producing ICES advice for this stock (ICES, 2021g). All MPs were implemented for 20 years.

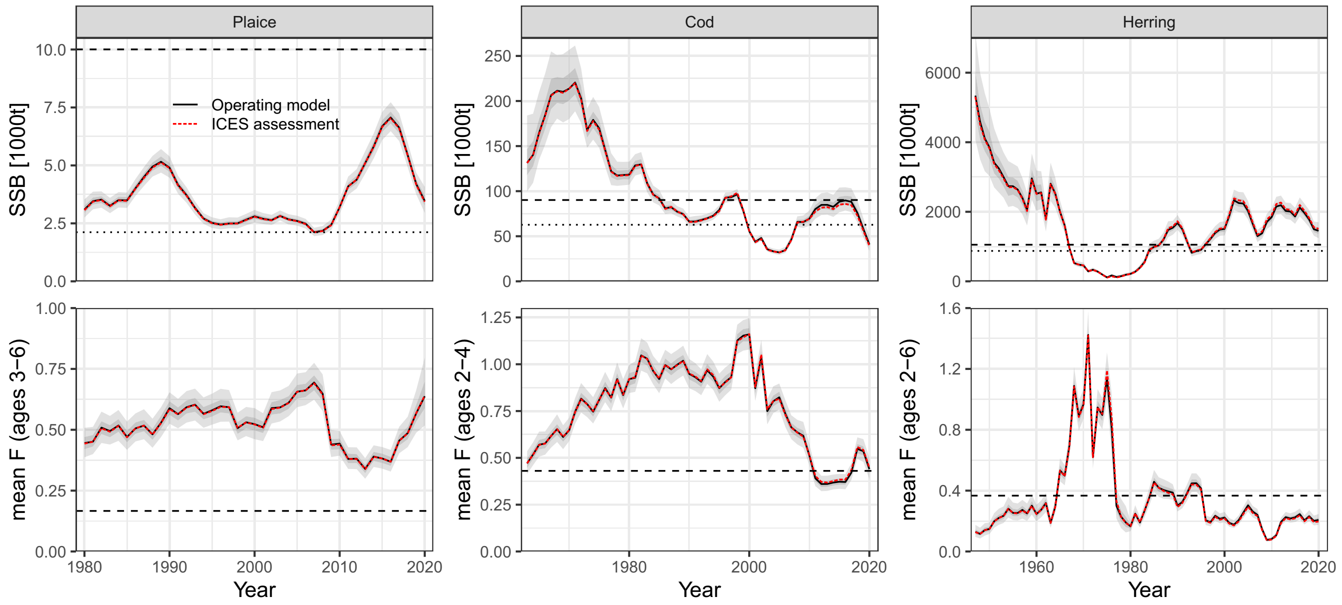

FIGURE 2 Comparison of spawning stock biomass (SSB) and fishing mortality (F) of baseline operating models (OMs) to ICES assessments. Shaded areas are 50% and 90% confidence intervals of the OMs. Horizontal dashed lines indicate OM MSY levels (B_{MSY}, F_{MSY}) and horizontal dotted lines B_{lim}.

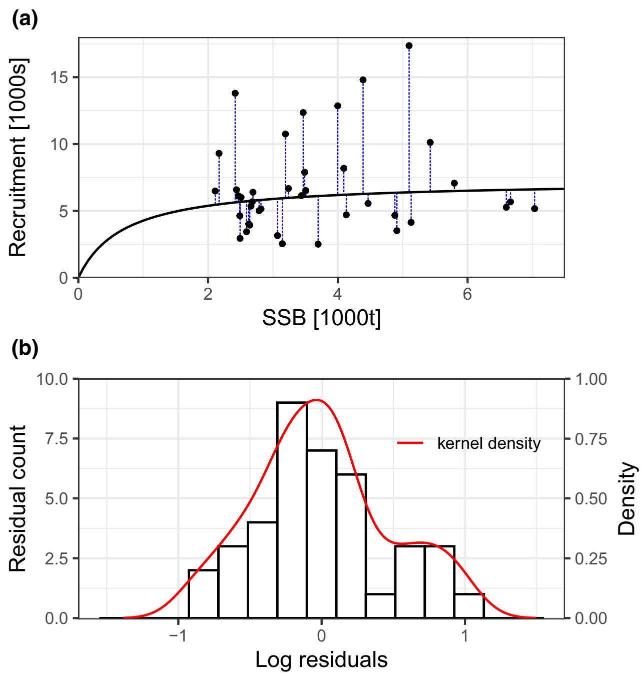

FIGURE 3 Visualisation of recruitment modelling for plaice. Shown are the Beverton-Holt recruitment model fit (solid black curve in a; points are stock-recruit pairs) and the distribution of log residuals (bars in b). Residuals for the projection are sampled from the kernel density distribution (red curve in b).

The inclusion of the ICES category 2 fractile rule (Mildenberger et al., 2022) into the study was considered. However, this MP requires a surplus production model and the suggested SPiCT model (Pedersen & Berg, 2017) has been repeatedly shown to fail to model the dynamics of the plaice stock (ICES, 2021j). Furthermore, attempts to fit it to cod resulted in unacceptably high uncertainty, and for both cod and herring, acceptance criteria were not met (see Appendix S1 for details). This means that acceptance criteria for a SPiCT assessment were not met for any of the three case study stocks considered here, and the category 2 fractile rule would not be applied by ICES. In the absence of an age-structured category 1 stock assessment, these stocks would then be downgraded and the advice based on the category 3 empirical MPs.

2.3 | Performance statistics

Management performance of the MPs was evaluated through three main metrics: stock size (SSB relative to B_{MSY}), depletion risk (called B_{lim} risk, $P_{B_{lim}}$, the proportion of simulation replicates for which the stock is below the biomass limit reference point B_{lim}) and catch (relative to MSY). These metrics were calculated for the long term (the last 10 years of a 20-year projection). For stock size and catch, medians (of the 10 years and 1000 simulation replicates) and distributions were considered; for $P_{B_{lim}}$, the 10 annual values and their maximum were considered. These metrics allowed a summary of the management performance of the MPs, including both biological (stock size, depletion risk) and economic (catch) quantities.

2.4 | Optimisation

The rfb and hr rules were optimised with a genetic algorithm following the approach developed by Fischer et al. (2021a, 2021b). This approach essentially mimics evolution, and individuals (MP parameterisations) are subjected to natural variability in a

TABLE 2 Reference points of the baseline operating models and comparison with ICES reference points

	Operating model reference points					ICES reference points		
Stock	B_0 [t]	F_{MSY}	MSY [t]	B_{MSY} [t]	B_{lim} [t]	F_{MSY}	MSY $B_{trigger}$ [t]	B_{lim} [t]
Plaice	38,340	0.167	1703	10,005	2119	0.24	2443	2110
Cod	415,979	0.430	55,391	90,187	62,734	0.28	97,777	69,841
Herring	3,621,774	0.367	403,512	1,052,763	874,198	0.31	1,232,828	874,198

TABLE 3 Alternative operating models

	Plaice	Cod	Herring
Recruitment	• *R: failure*: recruitment failure (2021–2025) • *R: no AC*: without recruitment residual autocorrelation	• *R: failure*: recruitment failure (2021–2025) • *R: higher*: higher recruitment (model fitted to 1988–2021)	• *R: failure*: recruitment failure (2021–2025) • *R: higher*: higher recruitment (model fitted to 1947–2021)
Natural mortality (*M*)	• *M: high*: *M* +50% • *M: low*: *M* −50% • *M: Gislason*: age-dependent *M* (Gislason et al., 2010)	• *M: dens. dep.*: density-dependent *M* through cannibalism (ICES, 2017a, 2019b) • *M: no migr.*: removed inflated *M* for ages 3+ accounting for migration	• *M: high*: *M* +50% • *M: low*: *M* −50%
Catch	• *Catch: no disc.*: assume 100% discard survival		

selective environment, favouring individuals with higher fitness (better management performance). In the generic simulations of Fischer et al. (2021b), the fitness was defined with a fitness function aiming to move the stock towards MSY while keeping $P_{B_{lim}}$ low. The ICES precautionary approach requires an MP to deliver management that ensures $P_{B_{lim}} \leq 5\%$ (ICES, 2016, 2021a); otherwise, the management is considered non-precautionary. In the present analysis for plaice, cod and herring, the fitness function aimed to maximise long-term catch relative to MSY (C_{lt}) but with a penalty if $P_{B_{lim}}$ exceeded 5%, following the concept adopted by ICES for case-specific MSEs (e.g. ICES, 2019b, 2020b):

$$\phi = C_{lt} - \frac{1}{1 + e^{-\left(P_{B_{lim}} - 0.06\right)500}} \tag{1}$$

The genetic algorithm was set up with a population size of 1000 individuals. Variability was introduced through two genetic operators, crossover with $p = .8$ and mutation with $p = .1$, as well as elitism with $p = .05$ (Fischer et al., 2021a). Convergence of the optimisation was achieved when either a maximum of 100 generations was reached or no further improvement was achieved within 10 generations.

This optimisation was conducted first with the multiplier x (Table 4) and then with all MP parameters (n_0, n_1, n_2, e_r, e_f, e_b, x, v for the rfb rule, n_0, n_1, w, x, v for the hr rule) for all three stocks and the baseline OMs. The conditional uncertainty caps restricting changes in catch advice were kept fixed at +20% and −30% following the considerations of Fischer et al. (2020, 2021b, 2022) and ICES (2022c) because this is often requested by the fishing industry and can restrict large changes due to noisy data.

The optimisation was conducted with the baseline OMs for the three stocks (plaice, cod and herring). The optimised parameterisations were then subjected to the alternative OMs.

3 | RESULTS

3.1 | Management procedures in the baseline operating model

The ICES MSY rule induced non-precautionary long-term management for all three stocks (Figures 4 and 5), but catch and SSB were close to their MSY reference values for cod and herring. For plaice, using the ICES MSY rule led to a long-term $P_{B_{lim}}$ of 39.8%, and the SSB remained well below B_{MSY}. For plaice, this outcome was because the ICES management reference point target F_{MSY} was higher than the OM F_{MSY} (Table 2), leading to overfishing, and worse performance (lower catch, higher $P_{B_{lim}}$) than the optimised rfb and hr rules. For cod and herring, the management target was lower than the OM F_{MSY} (Table 2) and the ICES MSY rule did not cause overfishing, on average. Nevertheless, the rule did not lead to precautionary management because despite the SSB being above B_{MSY}; the uncertainty in the simulation was large enough to result in $P_{B_{lim}} > 5\%$. It should be noted that the ICES MSY rule applied here used non-tuned ICES management reference points, as is standard practice in ICES. If the ICES MSY rule had been tuned, as was done for the empirical MPs, this might have improved management performance.

For plaice, the 2 over 3 rule used with a biomass index led to a maximum $P_{B_{lim}}$ of 13.4% (Figure 4), and despite an increase in the

TABLE 4 Evaluated management procedures (MPs)

MP	Equation and description	References
Data-rich MPs		
ICES MSY rule	$F_{y+1} = F_{target}\ \min(1, B_{y+1} / B_{trigger})$, where F_{y+1} is the fishing mortality targeted in the advice year, F_{target} and $B_{trigger}$ the management target (F_{MSY}) and trigger ($MSYB_{trigger}$), respectively, defined by ICES, B_{y+1} the SSB at the beginning of the advice year.	ICES (2021a)
Data-limited MPs		
2 over 3 rule	$A_{y+1} = A_y\ r\ b_{PA}$ with the new catch advice A_{y+1}, previous catch advice A_y, biomass index trend r and precautionary buffer b_{PA}: $r = \frac{\sum_{i=y-2}^{y-1} (I_i / 2)}{\sum_{i=y-5}^{y-3} (I_i / 3)}$ $b_{PA} = \begin{cases} 1, & \text{if both } F \leq F_{MSY}\ \&\ B \geq 0.5 B_{MSY}, \text{ OR} \\ & \text{if } b_{PA} = 0.8 \text{ within last two years} \\ 0.8 & \text{otherwise} \end{cases}$ where I is the biomass index, and F and B are estimated relative to MSY levels with a proxy MSY method, such as a surplus production model. The rule is applied every second year ($v = 2$). The change in catch advice is limited to 20% through an uncertainty cap ($u_u = 1.2$, $u_l = 0.8$).	ICES (2012a)
2 over 3 rule with XSA	Same as 2 over 3 rule above, except: the SSB estimates from XSA are used as biomass index, the F and B evaluation is done with SSB estimates relative to ICES management reference points (F_{MSY} and $MSYB_{trigger}$), and the rule is applied every year.	ICES (2021j)
rfb rule	$A_{y+1} = A_y\ r\ f\ b$ with the new catch advice A_{y+1}, previous catch advice A_y, biomass index trend r, fishing proxy f and biomass safeguard b: $r = \left(\frac{\sum_{i=y-n_0-n_1+1}^{y-n_0} (I_i/n_1)}{\sum_{i=y-n_0-n_1-n_2+1}^{y-n_0-n_1} (I_i/n_2)} \right)^{e_r}$ $f = \left(\frac{\bar{L}_{y-1}}{L_{F=M}} \right)^{e_f} x$ $b = \left(\min\left\{ 1, \frac{I_{y-n_0}}{I_{trigger}} \right\} \right)^{e_b}$ where I is the biomass index, $\bar{L}$ the mean catch length above the length of the first capture L_c, $L_{F=M}$ an MSY proxy reference length, $I_{trigger}$ an index trigger value calculated from the lowest observed index value I_{loss} via an index trigger buffer w ($I_{trigger} = wI_{loss}$, default $w = 1.4$), n_0 the offset between last biomass index year and assessment year (default $n_0 = 1$), n_1 and n_2 the number of biomass index years in the numerator and denominator of r (default $n_1 = 2$, $n_2 = 3$), x a multiplier for scaling the advice (default $x = 0.95$ for stocks with von Bertalanffy $k < 0.2\ \text{year}^{-1}$, $x = 0.9$ for stocks with $0.2 \leq k < 0.32\ \text{year}^{-1}$), and e_r, e_f, e_b exponents for weighting r, f and b (default $e_r = e_f = e_b = 1$). The default advice interval is biennial ($v = 2$) and changes in catch advice are limited with an uncertainty cap to an increase of +20% ($u_u = 1.2$) and decrease of −30% ($u_l = 0.7$), but the application of the cap is conditional on $I_{y-n_0} \geq I_{trigger}$.	Fischer et al. (2020, 2021a, 2021b); ICES (2020a, 2022c)
hr rule	$A_{y+1} = I\ H\ b$ with new catch advice A_{y+1}, biomass index value I, target harvest rate H and biomass safeguard b: $I = \sum_{i=y-n_0-n_1+1}^{y-n_0} (I_i / n_1)$ $H = C_{ref} / I_{ref}\ x$ $b = \min\left(1, \frac{I_{y-n_0}}{I_{trigger}}\right)$ where I is the biomass index, n_0 the offset between last biomass index year and assessment year (default $n_0 = 1$), n_1 the number of biomass index years used in I (default $n_1 = 1$), C the realised catch, C_{ref} / I_{ref} the harvest rate from a reference period (using historical mean catch length as a proxy for fishing pressure to define this period), x a multiplier for scaling H (default $x = 0.5$) and $I_{trigger}$ an index trigger value calculated from the lowest observed index value I_{loss} via an index trigger buffer w ($I_{trigger} = wI_{loss}$, default $w = 1.4$). The default advice interval is annual ($v = 1$) and changes in catch advice are limited with an uncertainty cap to an increase of +20% ($u_u = 1.2$) and decrease of -30% ($u_l = 0.7$), but the application of the cap is conditional on $I_{y-n_0} \geq I_{trigger}$.	ICES (2020a, 2022c); Fischer et al. (2022)

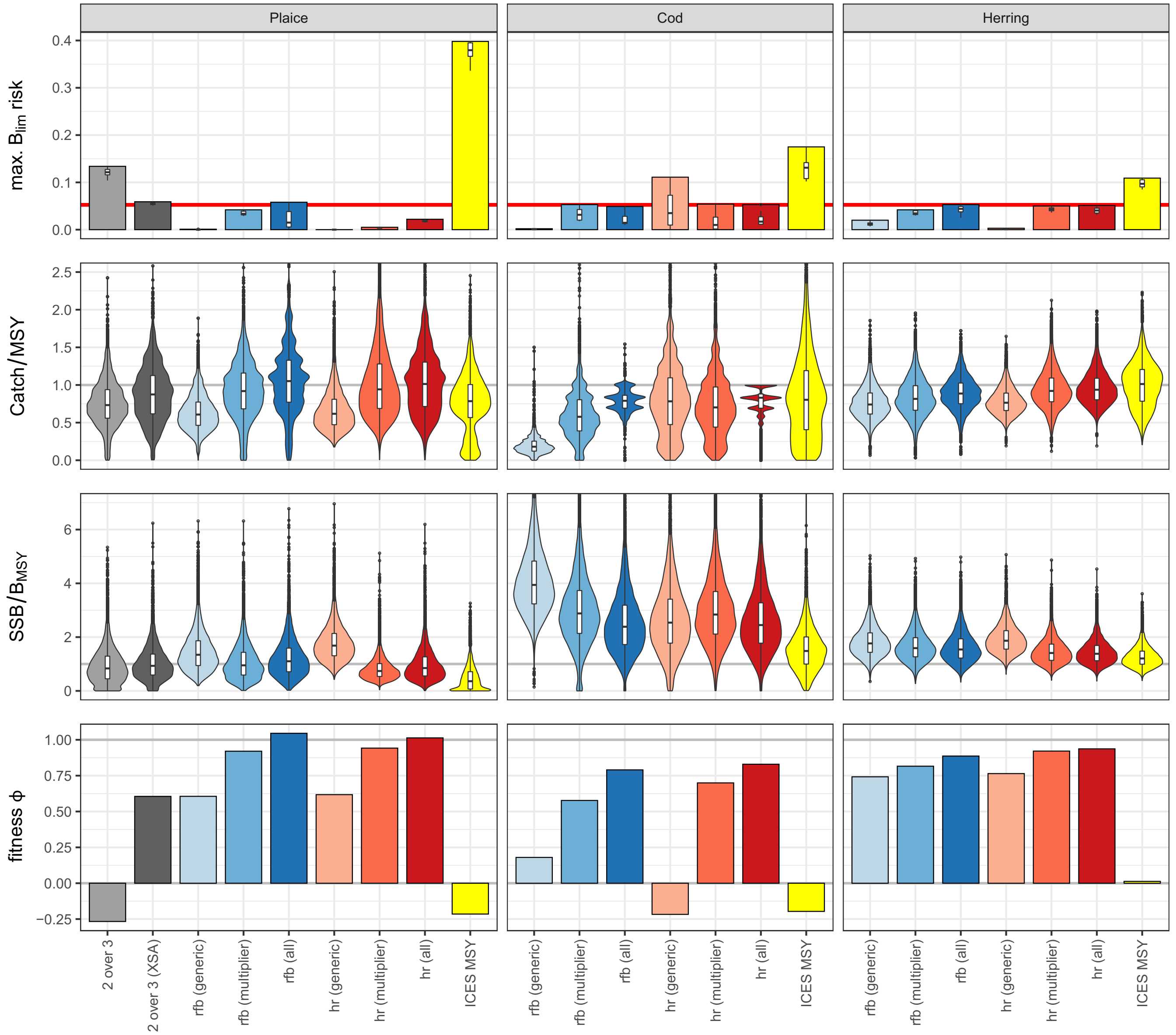

FIGURE 4 Summary statistics of all tested management procedures for all three stocks under their respective baseline operating models. Management procedures are colour-coded (2 over 3 rule in grey, rfb rule in blue, hr rule in red, and ICES MSY rule in yellow). For the rfb and hr rule, three options are shown: The generic parameterisations ('generic', light shading), the parameterisation obtained by optimising with a multiplier ('multiplier', medium shading) and the optimised parameterisation with all parameters ('all', dark shading). The risk is the maximum annual risk over the last 10 years, with the distribution of annual values shown inside the bars, catch and SSB show the distribution of the long-term (last 10 years, relative to their respective MSY values), and the fitness is a single value defined by equation (1), where larger (more positive) values indicate better management performance.

median SSB over time, $P_{B_{lim}}$ increased continuously due to increasing uncertainty (Figure 5). When used in combination with the XSA assessment, the $P_{B_{lim}}$ was 5.9%, with slightly higher catches and stock size.

The generic (non-optimised) rfb rule resulted in precautionary management with $P_{B_{lim}} < 5\%$ for all stocks but with relatively low catch and SSB generally above B_{MSY} (Figure 4). The optimisation of the rule purely with a multiplier substantially improved performance, with higher catches and SSB trajectories closer to B_{MSY} (Figure 5), and this improvement was larger when all control rule parameters were included.

Similar to the rfb rule, the generic hr rule provided precautionary management for plaice and herring with SSB overshooting B_{MSY}, with the optimisation using the multiplier increasing the catch and with a further slight increase when including all control rule parameters (Figure 4). The generic hr rule was not precautionary for cod with a $P_{B_{lim}}$ of 11% because once the SSB started to recover, catches increased quickly, reversing the trend and reducing SSB again (Figure 5). However, the optimisation made the hr rule precautionary by reducing the harvest rate target in the optimisation with the multiplier or reducing the time lag for the optimisation with all parameters (Table 5) while retaining a similar long-term catch level (Figure 4).

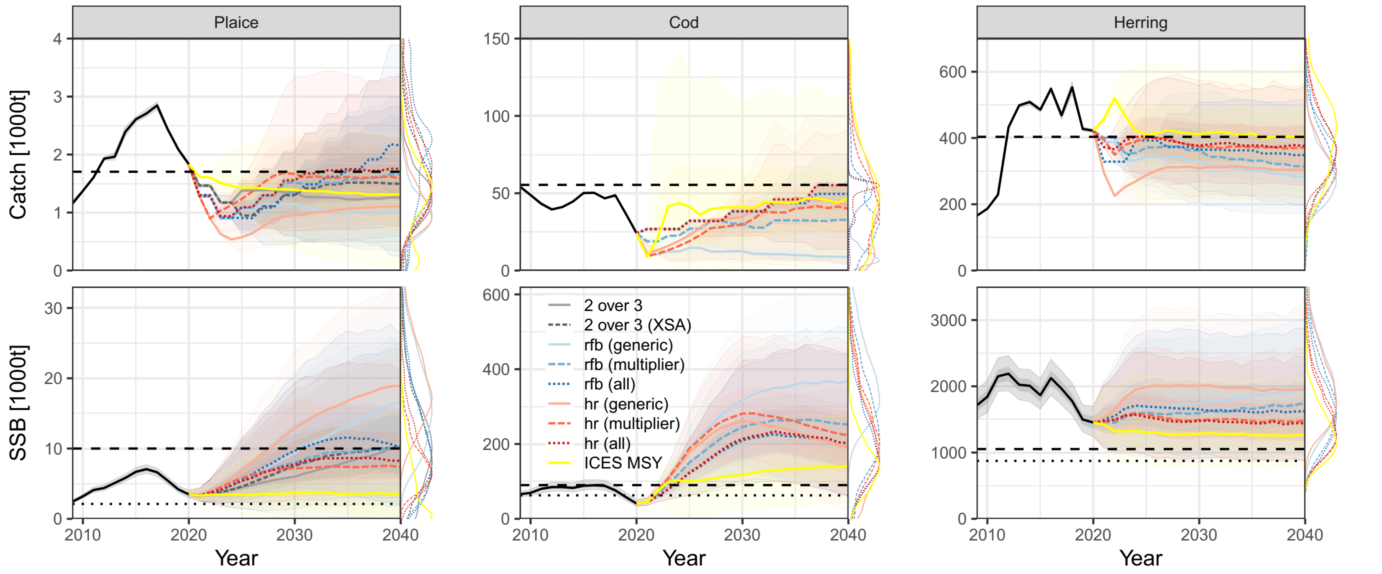

FIGURE 5 Projections corresponding to the management procedures shown in Figure 4 for the baseline operating models. The curves represent medians, surrounded by 50% and 90% confidence intervals (shaded areas). The dashed horizontal lines indicate MSY reference values (MSY, B_{MSY}), and the dotted lines are the biomass limit reference value (B_{lim}). The lines on the right of the panels show the distribution in the last simulation year (2040).

3.2 | Robustness to alternative operating models

The relative performance of the MPs was similar between the OMs (Figure 6). Different *M* assumptions for the plaice and herring OMs resulted mainly in shifts of all summary statistics, with lower SSB in case of lower *M* and vice versa in case of higher *M* (or age-dependent *M* for plaice). Assuming discard survival for plaice had a minor influence on the empirical MPs but avoided the poor performance of the ICES MSY rule. Turning off the recruitment autocorrelation led to negligible differences.

For cod, assuming density-dependent *M* due to cannibalism led to a higher $P_{B_{lim}}$ for all MPs. On the other hand, removing the migration adjusted *M* of older fish meant that the $P_{B_{lim}}$ for all MPs dropped below 5% because this meant that fewer older fish had died. This in turn means that fishing at the same *F* led to a higher SSB, representing a more productive stock scenario (see Figure S4 and Table S1 in Appendix S1). Similarly, assuming a higher recruitment regime resulted in a lower $P_{B_{lim}}$ and larger SSB for cod and herring.

Reduced recruitment at the beginning of the projection resulted in lower stock sizes and reduced catches for all stocks. The impact of this recruitment failure scenario is illustrated for cod in Figure 7. The reduced recruitment impaired initial stock recovery, and the SSB started to decline after 2–3 years. The rfb rule appeared to struggle under these conditions, and the catch advice was only reduced at the end of the recruitment failure period after the SSB reached a very low level. Once the catch advice had been reduced to very low levels, the SSB started to recover; however, the catch advice had already reached very low levels and stayed there until the end of the projection. The hr rule coped better than the rfb rule and after the stock started to recover, the catch increased again, but it took until the end of the projection for previously seen catch levels to be reached. The ICES MSY rule recovered catches the fastest, but this reduced stock recovery and kept the risk high.

4 | DISCUSSION

The main aim of this study was to test data-limited empirical MPs and compare their performance to data-rich MPs to evaluate risk equivalence for three case study stocks. The key outcome was that while the data-rich and data-limited approaches have the same theoretical management objectives (maximise yield while restricting risk, following the precautionary approach), in our simulation, the precautionary element was only met for the data-limited empirical MPs. However, when applied generically, the data-rich MPs resulted in higher catches, although case-specific tuning of the data-limited MPs could increase yield to a similar level.

The testing of MPs with closed-loop simulations can be broadly divided into generic MP testing and case-specific evaluations. In generic MP testing, MPs are tested and possibly refined across a range of OMs (e.g. Carruthers et al., 2016; Geromont & Butterworth, 2015b; Jardim et al., 2015; Mildenberger et al., 2022; Wetzel & Punt, 2011). While generic testing is useful for screening MPs and tuning generically to specific life histories, evaluations of management performance for specific stocks and conditions are limited. This requires case-specific analyses with OMs conditioned to the stock (e.g. Bergh & Butterworth, 1987; De Oliveira & Butterworth, 2004; Kell et al., 2005; Sharma et al., 2020). This study adopted a case-specific approach and simulation tested previously developed generic MPs (Fischer et al., 2021a, 2021b, 2022) to evaluate whether the outcomes from the generic testing are valid.

TABLE 5 Default and optimised parameterisations for the rfb and hr rule. '–' indicates the default parameterisation, 'mult' the optimisation with the multiplier and 'all' the optimisation with all parameters. 'Generations' is the number of generations in the optimisation until convergence was achieved. 'Improvement' is the improvement in fitness relative to the default parameterisation. For a definition of the control rule parameters, see Table 4. Italicised values indicate values included in the optimisation.

Stock	Optimisation	Generations	Improvement [%]	Control rule parameters									
rfb rule				n_0	n_1	n_2	e_r	e_f	e_b	v	x	u_u	u_l
Plaice	–	–	–	1	2	3	1	1	1	2	0.95	1.2	0.7
	mult	1	52	1	2	3	1	1	1	2	*1.16*	1.2	0.7
	all	11	73	*0*	*5*	*4*	*1.7*	*1.7*	*1.9*	*2*	*1.65*	1.2	0.7
Cod	–	–	–	1	2	3	1	1	1	2	0.95	1.2	0.7
	mult	1	221	1	2	3	1	1	1	2	*1.73*	1.2	0.7
	all	13	339	*0*	*4*	*3*	*0.1*	*1.3*	*0.4*	*4*	*1.06*	1.2	0.7
Herring	–	–	–	1	2	3	1	1	1	2	0.90	1.2	0.7
	mult	1	10	1	2	3	1	1	1	2	*0.93*	1.2	0.7
	all	18	20	*0*	*2*	*3*	*1.2*	*1.5*	*1.4*	*3*	*0.94*	1.2	0.7
hr rule				n_0	n_1				w	v	x	u_u	u_l
Plaice	–	–	–	1	1				1.4	1	0.50	1.2	0.7
	mult	1	53	1	1				1.4	1	*1.23*	1.2	0.7
	all	22	64	*1*	*2*				*0.8*	*2*	*1.28*	1.2	0.7
Cod	–	–	–	1	1				1.4	1	0.50	1.2	0.7
	mult	1	422	1	1				1.4	1	*0.42*	1.2	0.7
	all	11	482	*0*	*1*				*1.0*	*4*	*0.83*	1.2	0.7
Herring	–	–	–	1	1				1.4	1	0.50	1.2	0.7
	mult	1	21	1	1				1.4	1	*0.78*	1.2	0.7
	all	14	23	*0*	*2*				*1.0*	*1*	*0.85*	1.2	0.7

For the three case study stocks considered in this study, model fits of the state-space SAM model (Nielsen & Berg, 2014) were readily available and allowed the rapid conditioning of OMs. SAM is increasingly used in Europe (despite occasional criticism such as Aldrin et al., 2019) and could facilitate MSE development for many stocks, and has already been used by ICES (2019b, 2020b) and Goto et al. (2022). However, for most data-limited stocks, the data required to fit such a model are typically unavailable. In many scientific disciplines, model validation is common (e.g. Balmaseda et al., 1995; Jin et al., 2008; Weigel et al., 2008). In fisheries science, model validation of state-space models can be difficult because validation requires that the system is observable and measurable (Hodges & Dewar, 1992).

The ICES MSY rule is the main harvest control rule used for most data-rich stocks in the Northeast Atlantic (ICES, 2021a). The principle of targeting F_{MSY} and reducing this when a stock moves below a biomass trigger value has been widely adopted. Nevertheless, the ICES MSY rule led to non-precautionary management for all three stocks tested in this study, and the same was found previously for North Sea whiting and herring by ICES (2019b). This outcome appears to be caused less by the formulation of the ICES MSY rule and more by how it is operationalised.

The management reference points such as F_{MSY} are estimated with stochastic long-term projections (ICES, 2021f), and uncertainties, even when available from a stochastic stock assessment, are largely ignored. Furthermore, there can be spurious assumptions in the estimation of ICES management reference points. For example, natural mortality in the current North Sea cod stock assessment is inflated ('corrected') for ages 3+ to account for an assumed migration of older fish out of the stock area and might be better considered as a case of 'retrospective pattern hacking' so that the assessment passes acceptance criteria (ICES, 2021b). However, while this correction is considered for the recent historical period, it is ignored in the MSY estimation by ICES, leading to a considerable step change in the inputs used for the MSY calculations compared with the recent historical period.

It should be noted that the ICES MSY rule's parameters used in the present study were not tuned through closed-loop simulations and, instead, the values recommended by ICES were adopted. If these parameters had been tuned, the management performance of the ICES MSY rule might have been better than presented here. Future studies might consider a situation where both data-rich and data-limited MPs are tuned.

The OMs were conditioned on SAM, which implies that SAM describes nature almost perfectly and that the model structure is correct. This could be considered an unfair advantage for the MP based on SAM. Nevertheless, the performance of this MP was only moderate, and it resulted in high risks. Potentially, this could mean that the

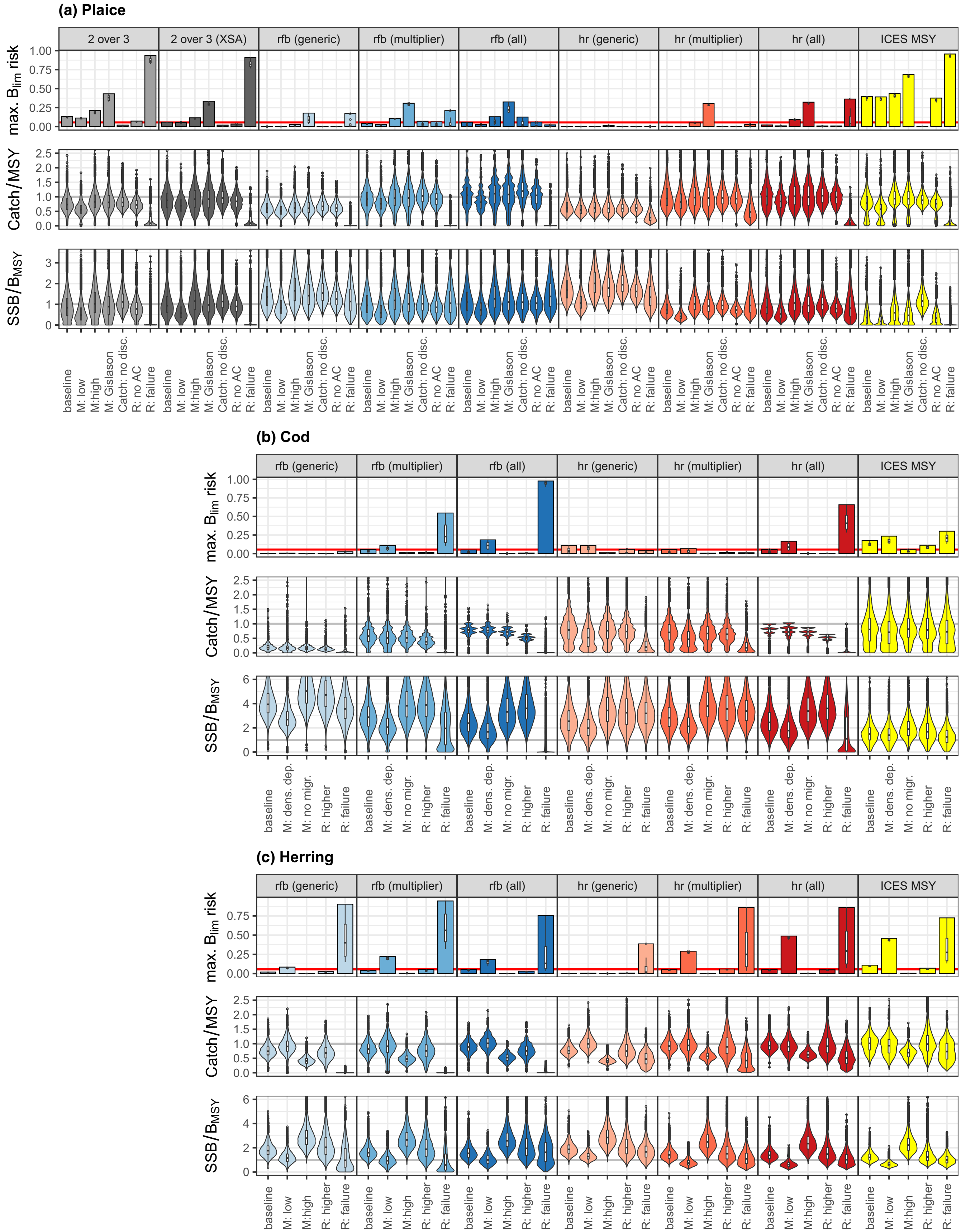

FIGURE 6 Summary statistics of all tested management procedures for all stocks and all alternative operating models. See Figure 4 for details on the presentation and Table 3 for operating model definitions.

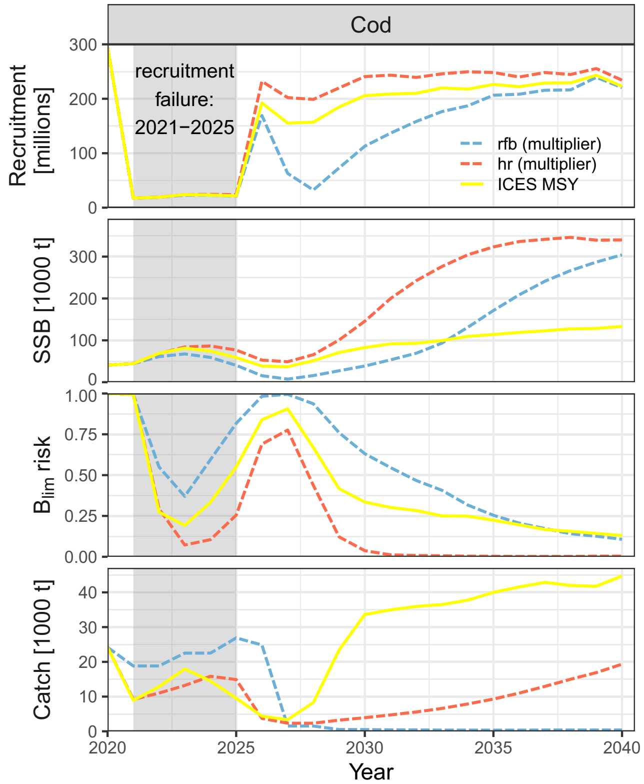

FIGURE 7 Impact of the recruitment failure alternative operating model on the management procedures, illustrated for cod.

performance might be further impaired when the reality was not as simple as implied by SAM and when more realistic representations of uncertainty were to be considered (Kell et al., 2006).

The outcomes of MSE exercises can be lost quickly in ICES. For example, North Sea cod, saithe and herring were included in a time and capacity-intensive MSE evaluation in ICES (2019b), including recommendations on management reference points. Since then, ICES conducted benchmarks (a process where new stock assessment models or model configurations are agreed upon for the provision of advice) for these stocks, and benchmarks were also tasked with updating management reference points. However, the time and scope for such benchmarks are typically limited and do not allow updating closed-loop simulations. Consequently, reference points were calculated with the standard ICES approach (EqSim; Simmonds et al., 2022, which could be considered a short-cut MSE), despite emerging alternatives that consider uncertainty more holistically (e.g. Trijoulet et al., 2022). Furthermore, the data-rich ICES MSY rule might not always be such a good choice for providing management advice, especially if the rule and management reference points were not simulation tested.

Three data-limited MPs were tested, the 2 over 3 rule, the rfb rule and the hr rule. The 2 over 3 rule performed worst for plaice, was not precautionary and had the undesirable feature of increasing risk over time. This outcome is not surprising because the 2 over 3 rule adjusts the catch based on the five-year trend of a biomass index. Essentially, this rule is aimed at moving the stock towards the average index value of the first 3 years of the period considered. However, this is a moving target, which changes every time the rule is applied, i.e. the rule does not include a long-term target, and the moving target is likely a poor measure of MSY. Currently, the 2 over 3 rule is used for plaice but in combination with an XSA assessment. This MP performed slightly better but exceeded the 5% risk limit of the ICES precautionary approach. Furthermore, both versions of the 2 over 3 rule were highly susceptible to the recruitment failure scenario, with $P_{B_{lim}}$ above 90%. Consequently, this study provides further reassurance to phase out the 2 over 3 rule because it is not fit for purpose.

Generic (not tuned) parameterisations of the rfb and the hr rule resulted in long-term precautionary management, except for the hr rule for cod. However, this precaution was achieved by reducing catch and stocks moving to high levels. Such a management approach might be perceived as overly cautious but is necessary in case of data limitations to ensure compliance with the precautionary approach and follows the principle of a risk-equivalent framework where better knowledge can reduce uncertainty and increase yield. In general, while the hr rule might achieve higher yields and is less susceptible to adverse events such as recruitment failures, it is crucially dependent on defining a target harvest rate appropriate for the stock. Here, we used the historical mean catch length to define a reference for the target harvest rate, which might not be successful for every stock (ICES, 2022c). Therefore, the hr rule may require more in-depth analyses to ensure future management is precautionary.

In their generic evaluation of the rfb rule, Fischer et al. (2021b) concluded that the management performance of the rfb rule could be substantially improved through tuning, but this would require case-specific analyses. This was done here for the rfb and the hr rule and three case study stocks (plaice, cod, herring) using a genetic algorithm as an optimisation procedure. Including only a multiplier improved the rules markedly and increased catches. Optimising over more control rule parameters led to further improvements but came at the cost of much higher complexity and made the management often more susceptible to different assumptions, as tested with the alternative OMs. This is because the optimisation was only performed with the baseline OM and alternative OMs were only considered for exploring the robustness of generic and optimised MPs. For additional precaution, a reference set, i.e. an ensemble of OMs to reflect a broader range of uncertainties, could be defined and deployed in the optimisation. However, the process of deciding which OMs to include in a reference set can be time-consuming and is likely infeasible to carry out for the dozens of fish stocks for which ICES provides advice. Additionally, optimising over a large ensemble of OMs further increases computational complexity.

The definition of the objective function (or fitness function in the genetic algorithm) needs to be carefully considered. Here, the objective was long-term sustainability, i.e. the initial simulation period only indirectly influenced the optimisation objectives through stock dynamics, and was not included in the objective function. This approach decoupled the initial conditions from the optimisation, and this was, for example, useful for cod, which started below

B_{lim}, and could therefore not possibly meet precautionary criteria. Furthermore, the optimisation considered the long-term average catch (last 10 years of a 20-year projection), without considering trends or variability. This meant, for example, that in the rfb rule's optimisation with all parameters for plaice, the catch was still increasing at the end of the simulation because this solution provided the highest precautionary average catch. The incorporation of such performance statistics is common practice in MSE. For example, the International Commission for the Conservation of Atlantic Tunas (ICCAT, 2021) includes the depletion at the end of a 30-year projection as a tuning target for candidate MPs.

When comparing the rfb and hr rules, the generic rfb rule appears to offer a more reliable precautionary management option than the hr rule, but this comes at the cost of potentially low catch for the sake of precaution. On the other hand, the hr rule, particularly if optimised, can deliver higher yields but requires more consideration when choosing the target harvest rate, and the generic parameterisation might not always provide a precautionary management solution, as shown for cod. However, if more data are available and case-specific analyses can be conducted, as was the case for the plaice stock, then the hr rule appears to provide excellent management advice and has the potential to outperform much more complex options such as the ICES MSY rule.

New ICES guidelines recommend the generic application of the rfb rule for stocks with slow to medium individual growth (von Bertalanffy growth parameter $k < 0.32$ year^{-1}) and the hr rule for stocks with faster individual growth ($k < 0.45$ year^{-1}) but excluding very fast-growing and short-lived species (ICES, 2022c). Our study supports this recommendation but goes beyond that by suggesting that both rules might be applied beyond their generic limits, as shown here for herring, a fast-growing, but relatively long-lived pelagic species, for which both rules appeared suitable. However, applying the rules beyond their generic limits should be accompanied by case-specific testing.

Simulating different MPs in a common simulation framework allows direct comparison and statements about risk equivalence. While this was tested for management frameworks in regions such as Australia (Dichmont et al., 2017; Fulton et al., 2016), it had not been done before for ICES, apart from Geromont and Butterworth (2015a), who conducted a hindcast analysis and concluded that simple, but theoretical empirical rules can achieve similar performance to complex assessments.

The ICES data-limited system has been subject to only limited development over the past 10 years, despite attempts to improve it, e.g. through a dedicated workshop series on data-limited methods (ICES, 2012b). However, a revision of the ICES system has now started, and the changes are substantial (ICES, 2022c). The new generic data-limited MPs were designed to meet the same precautionary criteria as used in data-rich considerations, which means they explicitly consider risk equivalence, and this was confirmed with case-specific testing in our study. This approach follows the recommendations of Dichmont et al. (2016) that risk-equivalent frameworks should be tested with closed-loop simulations, ideally with case-specific analyses, but in their absence, generic simulations can be used.

5 | CONCLUSIONS AND RECOMMENDATIONS

1. The new empirical ICES MPs for moderately data-limited fish stocks (ICES category 3) have undergone extensive simulation testing and review in the past years (Fischer et al., 2020, 2021a, 2021b, 2022; ICES, 2017b, 2018, 2019a, 2020a, 2022c). The MPs' ability to meet management objectives is further strengthened with the case studies of the present study. Consequently, we endorse the further rollout of the generic empirical rules in ICES scheduled for 2022. Furthermore, for stocks for which case-specific analyses are possible, such as the plaice stock, this can be done to improve realised catch without jeopardising precaution. The inclusion of risk equivalence in the ICES system is a major step forward and moves the ICES data-limited framework on par with other parts of the world, where this is already included.
2. More generally, we recommend that risk equivalence be considered in any changes to an advice framework to ensure that alternative management approaches or higher uncertainty due to, for example, data limitations, do not compromise conservation. Additionally, accounting for risk equivalence mandates the definition of an acceptable risk limit. Once such a limit is set, a benefit is that alternative management strategies can be selected based on, for example, socio-economic criteria, as long as they are risk-equivalent. The approach of, firstly, conducting generic MP testing to identify and tune suitable MPs and, secondly, conducting case-specific simulations to confirm the performance of the generic MPs, appeared to work well. Therefore, we argue for this approach to be adopted more widely, both for revisions of data-rich and data-limited fisheries management. The evaluation of risks is particularly important in the light of changes in the environment, e.g. caused by climate change, which can lead to a shifting baseline, and such effects should be considered in future studies.
3. Finally, we would like to promote using simple empirical strategies for managing fisheries resources, independently of their data limitations, as pursuing the best assessment approach will not always be necessary. Complex procedures, including analytical stock assessments and projections, might appear tempting but can easily lead to issues (e.g. non-precautionary management) when implemented suboptimally or when target and reference levels are set incorrectly. Such issues could be avoided by conducting full MSEs, including robustness tests. On the other hand, empirical MPs have major benefits such as being simpler to test and optimise in simulation studies, easier to apply to data, potentially cheaper due to reduced frequency of data requirements, can reach equivalent catch levels and are more straightforward to communicate to stakeholders and managers than much more complex approaches. This does not mean that we advocate dropping stock

assessments entirely because they are still required for assessing the stock status and conditioning OMs for simulations, but they could potentially be performed less frequently.

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DATA AVAILABILITY STATEMENT

Input data, software code and summarised results (including worm plots for all MPs) are available from GitHub at https://github.com/shfischer/MSE_risk_comparison, and the version of this publication is recorded in Fischer (2022). The stock assessment data for the three stocks used for conditioning the OMs are stored in the ICES Transparent Assessment Framework (TAF, https://taf.ices.dk) and were obtained by contacting the ICES stock coordinators.

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REFERENCES

Aldrin, M., Aanes, S., & Subbey, S. (2019). Comments on incongruous formulations in the SAM (state-space assessment model) model and consequences for fish stock assessment. *Fisheries Research*, *210*, 224–227. https://doi.org/10.1016/j.fishres.2018.08.001

Balmaseda, M. A., Davey, M. K., & Anderson, D. L. T. (1995). Decadal and seasonal dependence of ENSO prediction skill. *Journal of Climate*, *8*(11), 2705–2715. https://doi.org/10.1175/1520-0442(1995)008%3C2705:DASDOE%3E2.0.CO;2

Bergh, M. O., & Butterworth, D. S. (1987). Towards rational harvesting of the south African anchovy considering survey imprecision and recruitment variability. *South African Journal of Marine Science*, *5*, 937–951. https://doi.org/10.2989/025776187784522702

Burgman, M. (2005). *Risks and decisions for conservation and environmental management*. Cambridge University Press. https://doi.org/10.1017/CBO9780511614279

Carruthers, T. R., Kell, L. T., Butterworth, D. S., Maunder, M. N., Geromont, H. F., Walters, C., McAllister, M. K., Hillary, R., Levontin, P., Kitakado, T., & Davies, C. R. (2016). Performance review of simple management procedures. *ICES Journal of Marine Science*, *73*, 464–482. https://doi.org/10.1093/icesjms/fsv212

Carruthers, T. R., Punt, A. E., Walters, C. J., MacCall, A., McAllister, M. K., Dick, E. J., & Cope, J. M. (2014). Evaluating methods for setting catch limits in data-limited fisheries. *Fisheries Research*, *153*, 48–68. https://doi.org/10.1016/j.fishres.2013.12.014

De Oliveira, J. A. A., & Butterworth, D. S. (2004). Developing and refining a joint management procedure for the multispecies south African pelagic fishery. *ICES Journal of Marine Science*, *61*, 1432–1442. https://doi.org/10.1016/j.icesjms.2004.09.001

Department of Agriculture and Water Resources. (2018). *Guidelines for the implementation of the commonwealth fisheries harvest strategy policy*. 80 pp. Australian Government. https://www.awe.gov.au/sites/default/files/sitecollectiondocuments/fisheries/domestic/harvest-strategy-policy-guidelines.pdf

Dichmont, C. M., Fulton, E. A., Gorton, R., Sporcic, M., Little, L. R., Punt, A. E., Dowling, N., Haddon, M., Klaer, N., & Smith, D. C. (2017). From data rich to data-limited harvest strategies—Does more data mean better management? *ICES Journal of Marine Science*, *74*, 670–686. https://doi.org/10.1093/icesjms/fsw199

Dichmont, C. M., Punt, A. E., Dowling, N., De Oliveira, J. A. A., Little, L. R., Sporcic, M., Fulton, E., Gorton, R., Klaer, N., Haddon, M., & Smith, D. C. (2016). Is risk consistent across tier-based harvest control rule management systems? A comparison of four case-studies. *Fish and Fisheries*, *17*, 731–747. https://doi.org/10.1111/faf.12142

Fischer, S. H. (2022). *Shfischer/MSE_risk_comparison GitHub repository*. Zenodo. https://doi.org/10.5281/zenodo.7334634

Fischer, S. H., De Oliveira, J. A. A., & Kell, L. T. (2020). Linking the performance of a data-limited empirical catch rule to life-history traits. *ICES Journal of Marine Science*, *77*, 1914–1926. https://doi.org/10.1093/icesjms/fsaa054

Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D., & Kell, L. T. (2021a). Using a genetic algorithm to optimize a data-limited catch rule. *ICES Journal of Marine Science*, *78*, 1311–1323. https://doi.org/10.1093/icesjms/fsab018

Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D., & Kell, L. T. (2021b). Application of explicit precautionary principles in data-limited fisheries management. *ICES Journal of Marine Science*, *78*, 2931–2942. https://doi.org/10.1093/icesjms/fsab169

Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D., & Kell, L. T. (2022). Exploring a relative harvest rate strategy for moderately data-limited fisheries management. *ICES Journal of Marine Science*, *79*, 1730–1741. https://doi.org/10.1093/icesjms/fsac103

Fromentin, J.-M., Bonhommeau, S., Arrizabalaga, H., & Kell, L. T. (2014). The spectre of uncertainty in management of exploited fish stocks: The illustrative case of Atlantic bluefin tuna. *Marine Policy*, *47*, 8–14. https://doi.org/10.1016/j.marpol.2014.01.018

Fulton, E. A., Punt, A. E., Dichmont, C. M., Gorton, R., Sporcic, M., Dowling, N., Little, L. R., Haddon, M., Klaer, N., & Smith, D. C. (2016). Developing risk equivalent data-rich and data-limited harvest strategies. *Fisheries Research*, *183*, 574–587. https://doi.org/10.1016/j.fishres.2016.07.004

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*. 75 pp. FAO. http://www.fao.org/3/W1238E/W1238E01.htm#ch1

Geromont, H. F., & Butterworth, D. S. (2015a). Complex assessments or simple management procedures for efficient fisheries management: A comparative study. *ICES Journal of Marine Science*, *72*, 262–274. https://doi.org/10.1093/icesjms/fsu017

Geromont, H. F., & Butterworth, D. S. (2015b). Generic management procedures for data-poor fisheries: Forecasting with few data. *ICES Journal of Marine Science*, *72*, 251–261. https://doi.org/10.1093/icesjms/fst232

Gislason, H., Daan, N., Rice, J. C., & Pope, J. G. (2010). Size, growth, temperature and the natural mortality of marine fish. *Fish and Fisheries*, *11*, 149–158. https://doi.org/10.1111/j.1467-2979.2009.00350.x

Goto, D., Devine, J. A., Umar, I., Fischer, S. H., De Oliveira, J. A. A., Howell, D., Jardim, E., Mosqueira, I., & Ono, K. (2022). Shaping sustainable harvest boundaries for marine populations despite estimation bias. *Ecosphere*, *13*, 14. https://doi.org/10.1002/ecs2.3923

Hodges, J. S., & Dewar, J. A. (1992). *Is it you or your model talking? A framework for model validation*. 32 pp. http://www.rand.org/content/dam/rand/pubs/reports/2006/R4114.pdf

ICCAT. (2021). *Specifications for MSE trials for Atlantic bluefin tuna. Version 21–01: June 2 2021*. 40 pp. https://www.iccat.int/Documents/Meetings/Docs/2021/ADD/2021_BFT1_APP_7.pdf

ICES. (2012a). *ICES Implementation of Advice for Data-limited Stocks in 2012 in its 2012 Advice. ICES CM 2012/ACOM 68*. https://doi.org/10.17895/ices.pub.5322

ICES. (2012b). *Report of the Workshop on the Development of Assessments based on LIFE history traits and Exploitation Characteristics (WKLIFE), 13–17 February, Lisbon, Portugal. ICES CM 2012/ACOM:36*. 140 pp. http://www.ices.dk/sites/pub/PublicationReports/ExpertGroupReport/acom/2012/WKLIFE/WKLIFE2012.pdf

ICES. (2015). *Report of the second inter-benchmark protocol on west of channel flatfish (IBPWCFlat2). ICES CM2015/ACOM:55*. 142 pp. https://doi.org/10.17895/ices.pub.19283303

ICES. (2016). ICES criteria for defining multi-annual plans as precautionary. ICES Advice Technical Guidelines. 3 pp. https://doi.org/10.17895/ices.advice.8343

ICES. (2017a). *Interim Report of the Working Group on Multispecies Assessment Methods (WGSAM). ICES CM 2017/SSGEPI:20*. 395 pp. https://doi.org/10.17895/ices.pub.5306

ICES. (2017b). *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). ICES CM 2017/ACOM:43*. 221 pp. http://ices.dk/sites/pub/PublicationReports/ExpertGroupReport/acom/2017/WKLIFEVII/wklife_2017.pdf

ICES. (2018). *Report of the Eighth Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE VIII). ICES CM 2018/ACOM:40*. 172 pp. http://ices.dk/sites/pub/PublicationReports/ExpertGroupReport/acom/2018/WKLIFEVIII/WKLIFEVIII_2018.pdf

ICES. (2019a). Ninth Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE IX). *ICES Scientific Reports*, *1*(77), 131 pp. https://doi.org/10.17895/ices.pub.5550

ICES. (2019b). Workshop on North Sea stocks management strategy evaluation (WKNSMSE). *ICES Scientific Reports*, *1*(12), 378 pp. https://doi.org/10.17895/ices.pub.5090

ICES. (2020a). Tenth workshop on the development of quantitative assessment methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE X). *ICES Scientific Reports*, *2*(98), 72 pp. https://doi.org/10.17895/ices.pub.5985

ICES. (2020b). Workshop on management strategy evaluation of mackerel (WKMSEMAC). *ICES Scientific Reports*, *2*(74), 175 pp. https://doi.org/10.17895/ices.pub.7445

ICES (2021a). Advice on fishing opportunities. In *Report of the ICES advisory committee, 2021. ICES advice 2021*. 9 pp. International Council for the Exploration of the Sea. https://doi.org/10.17895/ices.advice.7720

ICES. (2021b). Benchmark workshop on North Sea stocks (WKNSEA). *ICES Scientific Reports*, *3*(25), 756 pp. https://doi.org/10.17895/ices.pub.7922

ICES (2021c). Cod (Gadus morhua) in subarea 4, division 7.d, and subdivision 20 (North Sea, eastern English Channel, Skagerrak). In *Report of the ICES advisory committee, 2021. ICES advice 2021*. 14 pp. International Council for the Exploration of the Sea. https://doi.org/10.17895/ices.advice.7746

ICES (2021d). Herring (Clupea harengus) in subarea 4 and divisions 3.a and 7.d, autumn spawners (North Sea, Skagerrak and Kattegat, eastern English Channel). In *Report of the ICES advisory committee, 2021. ICES advice 2021*. 11 pp. International Council for the Exploration of the Sea. https://doi.org/10.17895/ices.advice.7770

ICES. (2021e). Herring assessment working Group for the Area South of 62 N (HAWG). *ICES Scientific Reports*, *3*(12), 917 pp. https://doi.org/10.17895/ices.pub.8214

ICES (2021f). ICES fisheries management reference points for category 1 and 2 stocks. In *ICES technical guidelines. ICES advice 2021*. 19 pp. International Council for the Exploration of the Sea. https://doi.org/10.17895/ices.advice.7891

ICES (2021g). Plaice (*Pleuronectes platessa*) in division 7.e (western English Channel). In *Report of the ICES advisory committee, 2021. ICES advice 2021*. 7 pp. International Council for the Exploration of the Sea. https://doi.org/10.17895/ices.advice.7822

ICES (2021h). Sole (Solea solea) in divisions 8.c and 9.A (Cantabrian Sea and Atlantic Iberian waters). In *Report of the ICES advisory committee, 2021. ICES advice 2021*. 5 pp. International Council for the Exploration of the Sea. https://doi.org/10.17895/ices.advice.8528

ICES (2021i). Plaice (Pleuronectes platessa) in divisions 7.h–k (Celtic Sea south, southwest of Ireland). In *Report of the ICES advisory committee, 2021. ICES advice 2021*. 6 pp. International Council for the Exploration of the Sea. https://doi.org/10.17895/ices.advice.7824

ICES. (2021j). Working Group for the Celtic Seas Ecoregion (WGCSE). *ICES Scientific Reports*, *3*(56), 1082 pp. https://doi.org/10.17895/ices.pub.8139

ICES. (2021k). Working group on the assessment of demersal stocks in the North Sea and Skagerrak (WGNSSK). *ICES Scientific Reports*, *3*(66), 1281 pp. https://doi.org/10.17895/ices.pub.8211

ICES. (2022a). *ICES Advice 2022. A collection of all ICES Advice released in 2022, version 33*. https://doi.org/10.17895/ices.pub.c.5796935.v33

ICES. (2022b). *ICES Stock Assessment Database*. Retrieved April 30, 2022. https://standardgraphs.ices.dk

ICES (2022c). ICES technical guidance for harvest control rules and stock assessments for stocks in categories 2 and 3. In *Report of ICES advisory committee, 2022. ICES advice 2022, section 16.4.11*. 20 pp. International Council for the Exploration of the Sea. https://doi.org/10.17895/ices.advice.19801564.v1

Jardim, E., Azevedo, M., & 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. https://doi.org/10.1016/j.fishres.2014.11.013

Jin, E. K., Kinter, J. L., Wang, B., Park, C.-K., Kang, I.-S., Kirtman, B. P., Kug, J.-S., Kumar, A., Luo, J.-J., Schemm, J., Shukla, J., & Yamagata, T. (2008). Current status of ENSO prediction skill in coupled ocean–atmosphere models. *Climate Dynamics*, *31*(6), 647–664. https://doi.org/10.1007/s00382-008-0397-3

Kell, L. T., De Oliveira, J. A. A., Punt, A. E., McAllister, M. K., & Kuikka, S. (2006). Chapter 15 operational management procedures: An introduction to the use of evaluation frameworks. *Developments in aquaculture and fisheries science*, *36*, 379–407. https://doi.org/10.1016/S0167-9309(06)80018-9

Kell, L. T., Mosqueira, I., Grosjean, P., Fromentin, J.-M., Garcia, D., Hillary, R., Jardim, E., Mardle, S., Pastoors, M. A., Poos, J. J., Scott, F., & Scott, R. D. (2007). FLR: An open-source framework for the evaluation and development of management strategies. *ICES Journal of Marine Science*, *64*, 640–646. https://doi.org/10.1093/icesjms/fsm012

Kell, L. T., Pilling, G. M., Kirkwood, G. P., Pastoors, M., Mesnil, B., Korsbrekke, K., Abaunza, P., Aps, R., Biseau, A., Kunzlik, P., Needle, C., Roel, B. A., & Ulrich-Rescan, C. (2005). An evaluation of the implicit management procedure used for some ICES roundfish stocks. *ICES Journal of Marine Science*, *62*, 750–759. https://doi.org/10.1016/j.icesjms.2005.01.001

Kell, L. T., Sharma, R., Kitakado, T., Winker, H., Mosqueira, I., Cardinale, M., & Fu, D. (2021). Validation of stock assessment methods: Is it me or my model talking? *ICES Journal of Marine Science*, *78*(6), 2244–2255. https://doi.org/10.1093/icesjms/fsab104

Mildenberger, T. K., Berg, C. W., Kokkalis, A., Hordyk, A. R., Wetzel, C., Jacobsen, N. S., Punt, A. E., & Nielsen, J. R. (2022). Implementing the precautionary approach into fisheries management: Biomass reference points and uncertainty buffers. *Fish and Fisheries*, *23*, 73–92. https://doi.org/10.1111/faf.12599

Miller, S. K., Anganuzzi, A., Butterworth, D. S., Davies, C. R., Donovan, G. P., Nickson, A., Rademeyer, R. A., & Restrepo, V. (2019). Improving communication: The key to more effective MSE processes. *Canadian Journal of Fisheries and Aquatic Sciences*, *76*, 643–656. https://doi.org/10.1139/cjfas-2018-0134

Nielsen, A., & Berg, C. W. (2014). Estimation of time-varying selectivity in stock assessments using state-space models. *Fisheries Research*, *158*, 96–101. https://doi.org/10.1016/j.fishres.2014.01.014

Pedersen, M. W., & Berg, C. W. (2017). A stochastic surplus production model in continuous time. *Fish and Fisheries*, *18*(2), 226–243. https://doi.org/10.1111/faf.12174

PFMC. (2014). *Status of the pacific coast groundfish fishery. Stock assessment and fishery evaluation*. 280 pp. Pacific Fishery Management Council.

Prager, M. H., & Shertzer, K. W. (2010). Deriving acceptable biological catch from the overfishing limit: Implications for assessment models. *North American Journal of Fisheries Management*, *30*, 289–294. https://doi.org/10.1577/M09-105.1

Privitera-Johnson, K. M., & Punt, A. E. (2020). Leveraging scientific uncertainty in fisheries management for estimating among-assessment variation in overfishing limits. *ICES Journal of Marine Science*, *77*, 515–526. https://doi.org/10.1093/icesjms/fsz237

Punt, A. E., Butterworth, D. S., de Moor, C. L., De Oliveira, J. A. A., & Haddon, M. (2016). Management strategy evaluation: Best practices. *Fish and Fisheries*, *17*, 303–334. https://doi.org/10.1111/faf.12104

Roux, M., Duplisea, D. E., Hunter, K. L., & Rice, J. (2022). Consistent risk Management in a Changing World: Risk equivalence in fisheries and other human activities affecting marine resources and ecosystems. *Frontiers in Climate*, *3*, 1–30. https://doi.org/10.3389/fclim.2021.781559

Sharma, R., Levontin, P., Kitakado, T., Kell, L., Mosqueira, I., Kimoto, A., Scott, R., Minte-Vera, C., De Bruyn, P., Ye, Y., Kleineberg, J., Walton, J. L., Miller, S., & Magnusson, A. (2020). Operating model design in tuna regional fishery management organizations: Current practice, issues and implications. *Fish and Fisheries*, *21*, 940–961. https://doi.org/10.1111/faf.12480

Shepherd, J. (1999). Extended survivors analysis: An improved method for the analysis of catch-at-age data and abundance indices. *ICES Journal of Marine Science*, *56*, 584–591. https://doi.org/10.1006/jmsc.1999.0498

Simmonds, J., Hjorleifsson, E., Fernandez, C., & Millar, C. (2022). msy: Estimation of equilibrium reference points for fisheries. R package version 0.1.19. http://github.com/ices-tools-prod/msy

Smith, A. D. M. (1994). Management strategy evaluation – the light on the hill. In D. A. Hancock (Ed.), *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. http://hdl.handle.net/102.100.100/239946

tRFMO. (2018). *Report of the 2018 joint tuna RFMO management strategy evaluation working group meeting, Seattle, USA, 13–15 June 2018*. 24 pp.

Trijoulet, V., Berg, C. W., Miller, D. C. M., Nielsen, A., Rindorf, A., & Albertsen, C. M. (2022). Turning reference points inside out: Comparing MSY reference points estimated inside and outside the assessment model. *ICES Journal of Marine Science*, *79*, 1232–1244. https://doi.org/10.1093/icesjms/fsac047

Weigel, A. P., Liniger, M. A., & Appenzeller, C. (2008). Can multi-model combination really enhance the prediction skill of probabilistic ensemble forecasts? *Quarterly Journal of the Royal Meteorological Society*, *134*(630), 241–260. https://doi.org/10.1002/qj.210

Wetzel, C. R., & 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. https://doi.org/10.1016/j.fishres.2011.04.024

SUPPORTING INFORMATION

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