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Generic management procedures for data-poor fisheries: forecasting with few data

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The majority of fish stocks worldwide are not managed quantitatively as they lack sufficient data, particularly a direct index of abundance, on which to base an assessment. Often these stocks are relatively "low value", which renders dedicated scientific management too costly, and a generic solution is therefore desirable. A management procedure (MP) approach is suggested where simple harvest control rules are simulation tested to check robustness to uncertainties. The aim of this analysis is to test some very simple "off-the-shelf" MPs that could be applied to groups of data-poor stocks which share similar key characteristics in terms of status and demographic parameters. For this initial investigation, a selection of empirical MPs is simulation tested over a wide range of operating models (OMs) representing resources of medium productivity classified as severely depleted, to ascertain how well these different MPs perform. While the data-moderate MPs (based on an index of abundance) perform somewhat better than the data-limited ones (which lack such input) as would be expected, the latter nevertheless perform surprisingly well across wide ranges of uncertainty. These simple MPs could well provide the basis to develop candidate MPs to manage data-limited stocks, ensuring if not optimal, at least relatively stable sustainable future catches.

Keywords: Bayes, data-poor, generic, management procedures, simulations, target/limit reference points, uncertainty, yield/risk trade-offs.

Introduction

The majority of the world's most valuable living marine resources are managed on the basis of advice generated using quantitative scientific techniques. These quantitative approaches provide the basis for scientific recommendations which aim to ensure the long-term sustainable exploitation of fish stocks. The traditional and widely used approach for the provision of such scientific advice is stock assessment, where statistical and mathematical models which describe the underlying dynamics of the fishery and resource are fitted to fisheries data to produce estimates of current stock abundance and sustainable yield.

A variety of stock assessment methods have been developed over the years and are conveniently grouped in terms of their data requirements by ICES (2012). These typically include virtual population analysis, integrated analysis, and statistical catch-at-age models, which are based on age or length data as well as one or more indices of abundance. In the absence of catch-at-age data, simpler age-aggregated models such as production models (e.g. Schaefer or Pella–Tomlinson), fitted to one or more indices of abundance, are typically used to estimate pertinent resource management quantities.

A cornerstone of successful modelling is reliable data. However, for most fish stocks, and particularly for low-value resources, reliable data are in short supply. With the lack of knowledge and greater uncertainty associated with the majority of exploited marine stocks, sustainable resource management becomes difficult, if not impossible, if one seeks to base this on traditional stock assessment methods. The question is: how to achieve effective management in the absence of reliable data, which rules out the use of traditional assessment techniques?

An alternative, called the management procedure (MP), approach, which was first developed by the International Whaling Commission's (IWC's) Scientific Committee (Punt and Donovan, 2007), has found favour with marine scientists and fisheries managers seeking a more comprehensive resource management paradigm. [An inclusive and holistic approach to fisheries management, involving full quantitative recognition of underlying uncertainty as well as including all stakeholders (scientists, industry,

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and managers) in the management process, thereby seeking to ensure that biological and economic goals are met in the long run.] This approach, described in the Supplementary material, has been adopted to provide scientific recommendations for management measures for the exploitation of some high-value stocks in the southern hemisphere, e.g. the South African demersal hake fishery, the pelagic fishery for sardine and anchovy, and the lobster fishery (Punt, 1992; Johnston, 1998; Geromont *et al.*, 1999; De Oliveira, 2003; De Oliveira and Butterworth, 2004; Rademeyer, 2012). Known as Management Strategy Evaluation in Australia, this approach provides a platform to simulation test a variety of management options for fish stocks ranging from data-rich to data-poor (Wayte, 2009).

Compared with complex annual stock assessments, MPs (harvest control rules that have been simulation tested to check robustness to uncertainties about resource dynamics) are often very simple empirical algorithms that are much more easily understood by stakeholders such as the fishing industry, thus enhancing the credibility of fishery scientists with these stakeholders (Geromont *et al.*, 1999). An additional advantage of the MP approach is its multiyear cyclical implementation, which is particularly advantageous for managing data-poor stocks for which scientific person-power and financial support are typically sorely lacking. (Although it can be argued that all fish stocks are data-poor to some degree due to unavoidable uncertainty about both the resource dynamics and the associated data, "data-poor" refers here to stocks for which a statistical assessment is not possible due to insufficient data.) One further advantage of the approach is related to the important resource management concern of long-term trade-offs (between, for example, the mutually conflicting objectives of maximizing catch and minimizing the risk of overexploitation of the resource). These are basic to the MP selection process, though generally ignored in the traditional "best" assessment approach. These advantages notwithstanding, the key advantage of the MP approach, compared with the traditional annual stock assessment approach, is its ability to incorporate uncertainty in the modelling exercise explicitly, thereby ensuring consistency with the precautionary approach (PA; Butterworth, 2007), which is an important consideration when dealing with all marine resources, and even more so with data-poor stocks.

At present, there are as yet no quantitative measures in place to manage the majority of low-value fish stocks, mainly due to this lack of reliable data. In South Africa, management reference points have been estimated for data-poor species using spawning biomass-per-recruit analyses (Griffiths *et al.*, 1999); however, the reliability of these estimates is questionable as they rely on the estimates of natural mortality whose accuracy is debatable. Another possible management option for data-poor stocks is a simple "traffic light" framework based on qualitative information, or "expert judgement" (Caddy, 1998, 1999). However, the problem with management decisions that are based on such "expert judgement" is that their underlying rationale can hardly be subjected to scientific scrutiny and, more specifically and importantly, they therefore cannot be simulation tested to demonstrate their robustness in the presence of uncertainty (Butterworth *et al.*, 2010). A "Robin Hood" approach (taking from the rich to benefit the poor) has been proposed by Smith *et al.* (2009) where information from data-rich stocks/fisheries is used when developing harvest control rules to manage data-poor stocks/fisheries.

To manage data-poor resources successfully (and defensibly from a scientific stand-point), some very simple quantitative harvesting rules are desirable, where these have been shown to be robust by subjecting them to comprehensive simulation testing to ensure that management objectives are reasonably met despite the uncertainties about the underlying dynamics. Rather than attempt the impossible task of developing and simulation testing many species-specific MPs, it seems more reasonable to try to develop generic MPs that can be applied to several similar data-poor low-value stocks. Based on available quantitative and qualitative data, different sets of generic operating models (OMs) can be specified for the different groups of resources. Having defined the range of OMs that would encompass the uncertainty associated with such a selection of resources, robustness trials can then be undertaken for the chosen set of MPs depending on the data typically available. The generic MP most appropriate for a group of resources sharing similar characteristics can then be chosen by comparing performance statistics.

The aim of this work is therefore to design and test some very simple "off-the-shelf" MPs that could be applied to a group of data-poor fisheries which share some key characteristics in terms of demographic parameters.

Methods

Building on preliminary work by Butterworth *et al.* (2010), this paper looks at more extensive comparative testing of a selection of empirical MPs on a wider range of OMs representing the underlying dynamics of the resource. In the absence of a direct index of abundance, how well can these MPs perform?

Rather than test the MPs on data forthcoming from an existing fishery, simulated data are generated from a range of OMs encompassing the extent of uncertainty expected in reality. A generic approach is required for data-poor stocks where similar species are grouped together in "baskets" (Smith *et al.*, 2009) according to their longevity/productivity and perceived depletion levels. Similar to the FAO (2011) categories in terms of exploitation level, stocks are grouped here into three broad categories depending on the perceived level of resource depletion: "severely depleted" (current biomass B_n^{sp}/K^{sp} between 10 and 30% of the pre-exploitation level), "moderately depleted" (corresponding to a less pessimistic range for depletion of B_n^{sp}/K^{sp} of 30–50%), and "near target" (depletion in the range of 50–70% of the pre-exploitation level). In addition, stocks are grouped in terms of their level of productivity so that the categorization results in nine large "baskets" (Table 1). [The Food and Agriculture Organisation of the United Nations (FAO, 2011) defines three general categories similar to those adopted here: overexploited, fully exploited and non-fully exploited corresponding to current biomass less than 40%, between 40 and 60%, and more than 60% of the pre-exploitation level, respectively.] A different generic suite of OMs needs to be developed for each of the nine "baskets", with different MPs being appropriate for each. However, for this initial study whose primary purpose is illustrative, the analysis here considers only at a group of stocks of "medium productivity" deemed to be "severely depleted".

Two data-poor scenarios are considered. The "data-limited" scenario is typified by the lack of any index of abundance (such as catch per unit effort, cpue), with only the mean length of catch data available as a quantitative though an indirect indicator of the trend in resource abundance. In contrast, the "data-moderate" scenario corresponds to a fishery for which a direct index of abundance is available. For the data-limited scenario, where stock assessments are not possible due to the lack of quantitative data, a number of empirical MPs are simulation tested, ranging from a conservative constant catch (CC) to a step up/down CC strategy depending on the value of

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Table 1. Fish stocks grouped into nine "baskets" according to their perceived level of depletion and productivity.

	Low productivity	Medium productivity	High productivity
Severely depleted	$M \sim U[0.05, 0.2]$ $B^{sp}/K^{sp} \sim U[0.05, 0.2]$	$M \sim U[0.2, 0.4]$ $B^{sp}/K^{sp} \sim U[0.05, 0.2]$	$M \sim U[0.4, 1.0]$ $B^{sp}/K^{sp} \sim U[0.05, 0.2]$
Moderately depleted	$M \sim U[0.05, 0.2]$ $B^{sp}/K^{sp} \sim U[0.3, 0.5]$	$M \sim U[0.2, 0.4]$ $B^{sp}/K^{sp} \sim U[0.3, 0.5]$	$M \sim U[0.4, 1.0]$ $B^{sp}/K^{sp} \sim U[0.3, 0.5]$
Near target	$M \sim U[0.05, 0.2]$ $B^{sp}/K^{sp} \sim U[0.5, 0.7]$	$M \sim U[0.2, 0.4]$ $B^{sp}/K^{sp} \sim U[0.5, 0.7]$	$M \sim U[0.4, 1.0]$ $B^{sp}/K^{sp} \sim U[0.5, 0.7]$

For the analyses of this paper, values are drawn from uniform distributions across the ranges shown.

the current mean length of the catch, and a target-type MP based on this mean length as a function of a target mean length. For comparative purposes, empirical MPs corresponding to the data-moderate scenario are also tested, including slope and target MPs based on a direct index of abundance (e.g. from a survey or cpue). Summary statistics and plots are shown to compare performance statistics across the candidate MPs.

Operating models

A Bayes-like approach has been adopted for this generic data-poor MP evaluation exercise. The OMs that form the basis of this exercise are age-structured production models. They include model uncertainty (by effectively integrating over the ranges specified for model parameter values); this is in addition to "observation" error (taken into account by including stochastic components when generating future abundance index and length data), as well as "process" error (past and future recruitment and fishing selectivity fluctuations are included for each simulation). These three sources of uncertainty are incorporated explicitly into the generic MP approach adopted here for a group of similar data-poor resources: simulated trajectories are generated by sampling from prespecified distributions for key model variables such as the current depletion B_n^{sp}/K^{sp} (from which the pre-exploitation equilibrium spawning biomass, K^{sp}, is back-calculated), the "steepness" of the stock–recruit relationship h and an age-independent natural mortality rate M, as well as for selectivity and stock–recruit residuals. The distributions chosen are intended to reflect some of the qualitative information which would typically be available for a resource or a group of stocks of the same or similar species, while still allowing for the extent of model uncertainty which would be expected in an application for an actual resource.

The specific distributions used for model variables/parameters are based on typical ranges expected for other similar stocks of intermediate size and longevity for which data and assessments are readily available, in this case South African hake and horse mackerel (Johnston and Butterworth, 2007):

- steepness of the Beverton–Holt stock–recruitment relationship: sampled from a wide uniform distribution $h \sim U[0.5, 0.9]$;
- age-independent natural mortality: sampled from a uniform distribution $M \sim U[0.2, 0.4]$ year^{-1};
- selectivity residuals: generated from lognormal fluctuations about the expected fishing selectivity-at-age vector, with a s.d. of the log-residuals of 0.4: $\tau_{y,a} \sim N(0, 0.4^2)$ where a is the age and y the year;
- stock–recruit residuals: generated from lognormal fluctuations about the recruitment expected in terms of the stock–recruitment relationship, with a s.d. of the log-residuals of 0.5: $\zeta_y \sim N(0, 0.5^2)$;
- data for MPs: pseudo mean length and cpue data are generated from lognormal fluctuations about the expected indices, with s.d. of the log-residuals of $\sigma_l = 0.25$ and $\sigma_{cpue} = 0.2$, respectively.

Furthermore, as the focus here is a group of "severely depleted" stocks, the current (year n) intended spawning biomass may lie between 10 and 30% of its pre-exploitation level and is sampled from a uniform distribution: $B_n^{sp}/K^{sp} \sim U[0.1, 0.3]$.

A large set of biomass trajectories is generated by sampling from these distributions. Each population biomass trajectory, or simulation, corresponds to a plausible reality. To ensure comprehensive sampling from these distributions, 8000 simulations are generated. The pre-management period is taken to span $n = 40$ years, followed by a projection period of 10 years. [A 10-year period is consistent with typical rebuilding periods selected for species of medium productivity and is also as advocated at the World Summit on Sustainable Development held in 2002 (UN, 2002).] Annual historical catches are assumed to be known exactly (Table A.1), while direct (cpue) and indirect (mean length) indices of abundance are available for only the past 10 years.

Technical specifications of the OM, parameters, and pseudo data are detailed in Supplementary material.

MPs considered

A variety of total allowable catch (TAC)-based harvest control rules, suitable for data-poor resource management, are simulation tested. These simple empirical MPs are easy to code and would be readily understood by all parties typically involved in the management of the resource. Limited data are used in the formulae: it is assumed that these data have reasonable information content and that the associated observation error is not too large. Given these premises, it is reasonable to assume that any trend in the data is a fairly reliable indicator of trend in resource abundance. The idea underlying these empirical MPs is that the TAC each year is adjusted up or down from the previous year's TAC depending on either the rate of increase or decrease in the size of the resource or whether it is above or below some target level as indicated by the index of abundance. The success of this rule depends on how much information, rather than noise due to observation error, the dataseries contains, i.e. whether the MP is reacting to real trends in biomass or simply following noise.

An unavoidable disadvantage of these simple empirical MPs is the lack of estimates of resource abundance and other management quantities such as MSY on which to base TACs. While not problematic for a data-rich scenario for which estimates of resource depletion are readily available, this poses an obvious problem for the data-limited case for which there are not sufficient data to obtain reliable estimates of current resource status, rendering optimum resource management difficult if not impossible. In the absence of a formal assessment to provide an estimate of stock status, the FAO (2011) suggests that

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data/information be collected from "grey literature" or "black literature" to assist with classification of data-poor stocks. ("Grey literature refers to working papers, local government reports, and regional fisheries management reports and projects. "Black literature" refers to personal communications, reports of local meetings, newspaper articles, and so forth.) If little is known about the resource status particular caution needs to be taken to avoid undue (and undetected) resource depletion as a result of unsustainable use of the stock. It is therefore important that the starting point of such an empirical MP corresponds to an appropriate level of catch (TAC); the starting point (expressed as a percentage of the average catch taken over the last 5 years) is a key control parameter of all the MPs, which is chosen to ensure adequate recovery within the selected period; the feedback nature of the MP would adjust if this starting point is too low/too high.

For illustrative purposes, these empirical MPs are divided here into two classes appropriate to the different levels of quantitative data availability:

(i) data-limited: no quantitative data except for the catch history (which is assumed to be known exactly), and possibly some mean length of catch data;

(ii) data-moderate: an index of abundance (cpue) in addition to the above.

cpue and mean length of catch data are generated by the OM for each simulation, i.e. each dataset generated corresponds to a different set of parameter values sampled from the input distributions. Technical specifications of the process for generating the pseudo data are provided in Supplementary material.

Data-limited MPs

A CC rule is tested to give some idea of what level of TAC can be supported by the resource in the absence of quantitative data (other than the historical catches); this provides a benchmark against which to compare feedback-control MPs. The CC sought is that which would move the resource biomass to above the MSY level within the projection period of 10 years. CC strategies, where future TAC is fixed to some percentage (100%, 90%, 80%, etc.) of the average TAC over the last 5 years, are tested. The downside of this type of MP is that it may require an unacceptably large drop in TAC in the first year of implementation and, more important, that there is no feedback control.

When mean length of catch data are available, empirical rules are employed in which the mean length of fish caught is taken to be an indirect index of abundance. These MPs include a simple CC strategy in which the TAC is stepped up or down by a fixed amount depending on whether certain thresholds are crossed. The idea is that unless there is a strong quantitative signal from the length data, the TAC is better left where it is so as to avoid the possibility of tracking noise rather than signal in a data-poor situation. Target-based MPs, similar in form to those investigated in Wayte (2009), are tested for comparison. For this class of MPs, the TAC is adjusted up or down depending on whether the recent mean length is above or below a target mean length.

Data-moderate MPs

For the data-moderate case where cpue data are available, some simple empirical MPs based on the recent slope of the cpue series and on the difference of the recent cpue from some target level are considered. Although these MPs would normally not be applicable to data-poor resources because such data are typically absent, they are included here in an attempt to illustrate the possible benefit of the availability of a direct index of abundance for management use.

The MPs are summarized in Table 2 with full technical specifications given in Supplementary material.

Results and discussion

To assist realism, the results are shown as if the pre-management period of $n = 40$ years corresponded to starting in 1970 and ending in 2009. This is followed by a rebuilding period under the MP which allows only 10 years to reach the management targets, i.e. from 2010 to 2019. The values of the control parameters used to tune the five MPs of Table 2 are chosen to achieve adequate biomass recovery (see below) for a "severely depleted" stock within the 10-year projection period.

The spawning biomass target and limit reference points proposed in Smith *et al.* (2009) have been adopted here. Specifically, the MP sought is one which would move the resource biomass to 20% above the MSY level (i.e. the target is $1.2B^{sp}_{MSY}$) within the projection period of 10 years. In terms of risk of further resource depletion, the MP must ensure that the spawning biomass is maintained above 50% of B^{sp}_{MSY} (the limit reference point) for 90% of the time. Therefore, assuming that B^{sp}_{MSY} is achieved when the resource biomass is at ~40% of its pre-exploitation biomass level K^{sp}, the target biomass (in median terms) to be achieved at the end of the projection period is $\tilde{0}.5K^{sp}$, with a 10 percentile of $0.2K^{sp}$ to meet the risk threshold. A complete set of results is provided in Supplementary material.

Summary statistics

Pertinent management quantities for the five types of MPs, each tested over a range of control parameters, are shown in Figure 1 to facilitate comparison. The key statistics reported are medians and 90 percentiles of spawning biomass depletion B^{sp}/K^{sp}, spawning biomass in terms of MSY, B^{sp}/B^{sp}_{MSY} at the end of the 10-year projection period, the average annual future TAC, and the average inter-annual variation in TAC.

Noticeable from the top two plots in Figure 1 is that all five MPs can be tuned to give comparable performance in terms of the risk statistics with perhaps marginally narrower probability intervals for the data-moderate MPs based on cpue data (the "Islope" and "Itarget" candidates). Summary statistics for the best-performing candidates (considered to be those that maximize catch while satisfying both target and limit abundance reference points) are compared in Figure 2. The difference in performance between these MPs lies mainly in the extent of fluctuation in TAC that can be tolerated by the fishery, and the total average future yield to be expected under a particular MP.

For comparative purposes, and to show the bound on the maximum recovery possible by the simulated stock over the period considered, summary statistics are also shown for a future catch of zero (CC0).

Biomass and catch projections

Spawning biomass and TAC trajectories corresponding to the best performing MPs in each category are shown in Figure 3.

The top two plots of Figure 3 show simulation results for the best performing CC harvesting strategy, which requires a large drop in TAC from 500 to 350 t in the first year of implementation. This provides a benchmark against which to compare the feedback-based MPs that follow.

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Table 2. Summary of the five types of empirical MPs considered for data-poor stocks.

Summary of candidate MPs	
CC: CC0: $\text{TAC}^* = 0$ CC1: $\text{TAC}^* = C^{\text{ave}}$ CC2: $\text{TAC}^* = 0.9C^{\text{ave}}$ CC3: $\text{TAC}^* = 0.8C^{\text{ave}}$ CC4: $\text{TAC}^* = 0.7C^{\text{ave}}$ CC5: $\text{TAC}^* = 0.6C^{\text{ave}}$	$\text{TAC}_{y+1} = \text{TAC}^* = (1-x)C^{\text{ave}}$ where x lies between 0 and 1, and $C^{\text{ave}} = 1/5\sum_{y=n-4}^{n} C_y$
Stepwise CC (length data): LstepCC1: $\text{TAC}^* = C^{\text{ave}}$ LstepCC2: $\text{TAC}^* = 0.9C^{\text{ave}}$ LstepCC3: $\text{TAC}^* = 0.8C^{\text{ave}}$ LstepCC4: $\text{TAC}^* = 0.7C^{\text{ave}}$ LstepCC5: $\text{TAC}^* = 0.6C^{\text{ave}}$	$\text{TAC}_{y+1} = \text{TAC}_y \pm \text{step}$ where step $= 5\%C^{\text{ave}}$, and TAC* is the starting point defined above
Length target (length data): Ltarget1: $L_{\text{target}} = 1.05L^{\text{ave}}, \text{TAC}^* = C^{\text{ave}}$ Ltarget2: $L_{\text{target}} = 1.1L^{\text{ave}}, \text{TAC}^* = C^{\text{ave}}$ Ltarget3: $L_{\text{target}} = 1.15L^{\text{ave}}, \text{TAC}^* = C^{\text{ave}}$ Ltarget4: $L_{\text{target}} = 1.15L^{\text{ave}}, \text{TAC}^* = 0.8C^{\text{ave}}$	$\text{TAC}_{y+1} = 0.5\text{TAC}^*\left[1 - \left(\frac{L_y^{\text{recent}} - L^0}{L^{\text{target}} - L^0}\right)\right]$ if $L_y^{\text{recent}} \geq L^0$, or $\text{TAC}_{y+1} = 0.5\text{TAC}^*\left[\frac{L_y^{\text{recent}}}{L^0}\right]^2$ if $L_y^{\text{recent}} < L^0$, where $L^0 = 0.9L^{\text{ave}}$, L_y^{recent} is the average length for the most recent 5 years, and L_{ave} is the historical mean length
Index slope (cpue index of abundance): Islope1: $\lambda = 0.4, \text{TAC}^* = 0.8C^{\text{ave}}$ Islope2: $\lambda = 0.4, \text{TAC}^* = 0.7C^{\text{ave}}$ Islope3: $\lambda = 0.4, \text{TAC}^* = 0.6C^{\text{ave}}$ Islope4: $\lambda = 0.2, \text{TAC}^* = 0.6C^{\text{ave}}$	$\text{TAC}_{y+1}^{\text{slope}} = \text{TAC}_y(1 + \lambda s_y)$ where s_y is the cpue slope (gradient of a log-linear regression) for the most recent 5 years
Index target (cpue index of abundance): Itarget1: $I_{\text{target}} = 1.5I^{\text{ave}}, \text{TAC}^* = C^{\text{ave}}$ Itarget2: $I_{\text{target}} = 2I^{\text{ave}}, \text{TAC}^* = C^{\text{ave}}$ Itarget3: $I_{\text{target}} = 2.5I^{\text{ave}}, \text{TAC}^* = C^{\text{ave}}$ Itarget4: $I_{\text{target}} = 2.5I^{\text{ave}}, \text{TAC}^* = 0.7C^{\text{ave}}$	$\text{TAC}_{y+1} = 0.5\text{TAC}^*\left[1 + \left(\frac{I_y^{\text{recent}} - I^0}{I^{\text{target}} - I^0}\right)\right]$ if $I_y^{\text{recent}} \geq I^0$, or $\text{TAC}_{y+1} = 0.5\text{TAC}^*\left[\frac{I_y^{\text{recent}}}{I^0}\right]^2$ if $I_y^{\text{recent}} < I^0$, where $I^0 = 0.8I^{\text{ave}}$, I_y^{recent} is the average cpue for the most recent 5 years, and I^{ave} is the historical average cpue

Full specifications for these MPs are given in the supplementary material.

Spawning biomass trajectories for MPs based on a stepwise CC strategy (linked to some threshold) show improved behaviour to the CC MPs for the equivalent starting point of 70% of recent catches (second row, Figure 3), with marginally less spread in the final spawning biomass distribution. However, this improvement comes at the price of a much greater spread in future catch trajectories (100–600 t).

Spawning biomass and TAC trajectories corresponding to the target length-based MP are shown in the third row of plots of Figure 3. Compared with the TAC trajectories of the stepwise CC strategy, this MP results in less interannual TAC variability to achieve the biological target and reference points (Figure 2).

Spawning biomass and catch trajectories corresponding to the data-moderate MPs based on trend in recent cpue data are shown in the fourth row of plots in Figure 3. To achieve the biomass target and limit reference points, the slope-type MP requires a rather sharp drop in catch in the first year of the projection period. By comparison, the initial decrease in catch is more gradual for the target-type MP (bottom two plots), but here future TACs are more widely spread than for the slope MP, with a correspondingly narrower distribution for final spawning biomass at the end of the projection period.

Yield-risk trade-offs

While the summary statistics in Figure 1 give useful information regarding spread of results and the trade-offs under different strategies, Figure 4 provides a better visual aid when comparing risk/return performance statistics. Here, the median average future TAC is plotted against the 10 percentile estimates for spawning biomass depletion under different harvesting strategies and their corresponding control parameter values. If the objective is to maximize future catch while at the same time minimizing the risk of resource depletion, then one seeks points that lie furthest to the top right of Figure 4. The yield-risk trade-off choice would be then be made from among these points.

Considering the trendlines drawn for each type of harvesting strategy, it is clear that the C) benchmark strategy performs worst as would be expected. In the absence of an index of abundance, the stepwise CC (LstepCC) strategy, based on mean length data, performs best. The best performing MPs overall are the cpue-based MPs, which achieve a higher yield in terms of median average TAC for the same level of risk of resource depletion, when compared with the length-based ones.

These results accentuate the importance of the role of a reliable abundance index, such as provided by cpue data, for fishery

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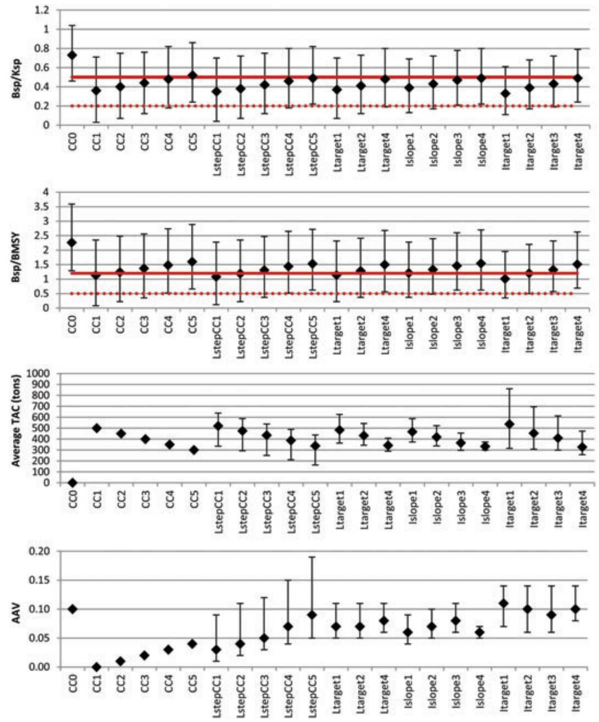

Figure 1. Medians and 90% probability intervals for final spawning biomass depletion (top), final spawning biomass in terms of the MSY level (second), average future annual TAC (third), and average interannual variation in TAC (bottom) for the various candidate MPs tested (see text for definitions). The solid horizontal lines correspond to the target reference points ($0.5K^{sp}$ and $1.2B_{MSY}$), whereas the dotted horizontal lines correspond to the limit reference points ($0.2K^{sp}$ and $0.5B_{MSY}$).

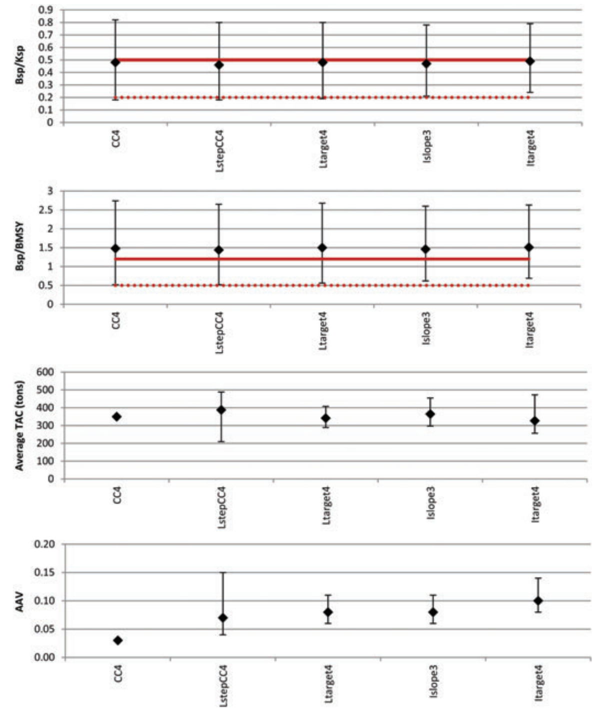

Figure 2. As for Figure 1, but here comparing the best performing MPs in each category (where "best" is defined here as maximizing catch subject to satisfying the spawning biomass limit reference point at the 10th percentile).

management purposes. For the cpue-based MP, a median future TAC of ~475 t is achievable for only 10% chance of being below a stock depletion level of 20% of the pre-exploitation biomass, which is indicated by the black vertical line in Figure 4. The potential yield corresponding to the stepwise CC MPs is somewhat less at ~425 t, with the benchmark CC strategy yielding only 400 t for the same level of risk. Hence, in the absence of an index of abundance, the potential yield foregone is more than 15% when comparisons are made for the same level risk. From a strategic point of view, the management authority therefore needs to decide if the extra tonnage warrants the effort that is required to obtain the additional data.

While data-moderate MPs based on a direct index of abundance (cpue) perform better than the data-limited length-based strategies as might be expected, these initial results show that nevertheless the very simple empirical MPs perform surprisingly well given the wide range of uncertainty associated with key parameters and could well be candidates to manage some of the world's many data-poor stocks, ensuring perhaps not optimum, but at least some form of management to ensure relatively stable and sustainable future catches.

Robustness trials

Thus far, the results reflect the performance of MPs which have been simulation tested across a suite of base case OMs with prespecified parameter distributions as detailed in "Operating models". An important aspect not yet covered in the previous sections is that no allowance is made for implementation error: TAC and total removals are taken to be the same, with annual historical catches assumed to be known exactly. This section examines robustness of the best performing MPs to further uncertainties and in particular implementation error. The robustness tests are summarized in Tables 1 and 3. Tables of summary statistics for these robustness trials are given in Section 4 of Supplementary material.

Figure 5 shows summary statistics for the best performing MPs in each of the five categories when making allowance for lognormally distributed implementation error (robustness test OM1). The performance of all five MPs are largely unaffected by these random differences from the assumed catches, with risk-related limit and target reference points being met always. To visualize the extent of the differences between actual and reported catches (and TACs), trajectories of "true" catches are shown in Figure 6, along with associated spawning biomass trajectories.

Rather than submit all the MPs to all nine robustness tests listed in Table 3, a target-type MP which relies only on mean length data (the data-limited scenario) was selected for further projections; this MP was selected based on its performance across the range of base case OMs (Figures 2 and 3). A comparison of summary statistics when subjecting the Ltarget4 MP to all robustness tests is shown in Figure 7. The combined tests (OM2 plus OM4 and OM5) investigate both bias and variability in the reported catches. Of particular note is that this MP is surprisingly robust across the range of uncertainty encompassed by these trials, except robustness tests OM6 and OM7; this is not surprising as these fall outside the "basket" for which the MPs were designed. This suggests that the correct classification of stocks within baskets in terms of their depletion and productivity levels is key to these MPs achieving their objectives. Therefore, when dealing

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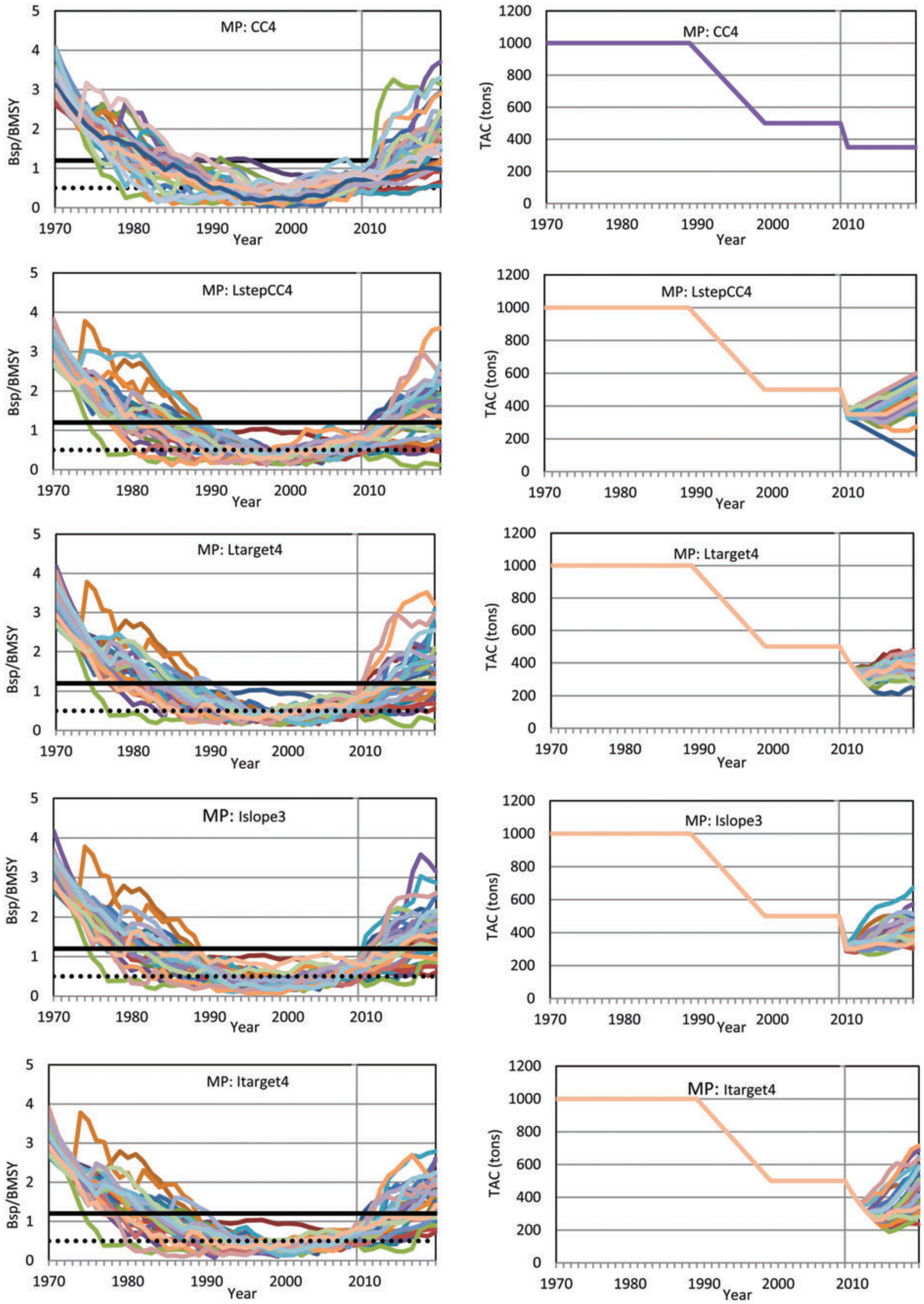

Figure 3. Spawning biomass in terms of the MSY level (left) and TAC (right) trajectories for 30 from a total of 8000 simulations are shown for the best performing data-poor strategies: CC (CC4, top row), stepwise CC (LstepCC4, second row), length-based target (Ltarget4, third row), slope (Islope3, fourth row), and target (Itarget4, bottom row) MPs. The horizontal lines on the left-hand plots correspond to the spawning biomass target (solid) and limit (dotted) reference points. A subset of 30 simulations from a total of 8000 performed are shown so as to clearly reflect the extent of variation and uncertainty incorporated into the population models.

with stocks that fall in the "severely depleted" and/or "low productivity" basket, different generic MPs would need to be developed which are more conservative than the Ltarget4 considered here to avoid further depletion of the stock.

Future work

The generic MPs developed and the simulation tested in this paper are intentionally simple to illustrate some basic principles of the approach. The purpose of these analyses is first to show how an

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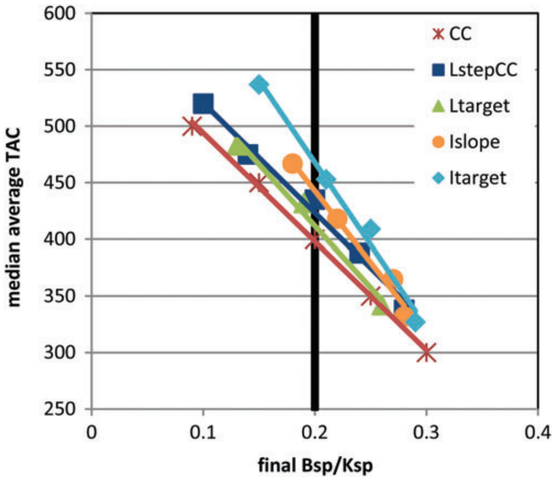

Figure 4. Medians average future TAC plotted against 10th percentile values for final spawning biomass depletion distributions for the five MPs tested across a selection of tuning parameters for each: five CC strategies (stars), five stepwise CC strategies (squares), three length-based target strategies (triangles), four cpue slope strategies (dots), and four cpue target strategies (diamonds). Linear trend lines are shown for each MP type to facilitate comparisons. The vertical solid black line indicates the limit reference point used in selecting the best performing MPs.

Table 3. Summary of robustness tests.

Robustness tests	Notable performance difference from base case OMs: Risk	Yield
OM1: undetected implementation error $\varepsilon_y^C \sim N(0, 0.2^2)$	No	No
OM2: detected implementation error $\varepsilon_y^C \sim N(0, 0.2^2)$	No	No
OM3: detected implementation error with bias $\varepsilon_y^C \sim N(0.1, 0.2^2)$	Marginal −	Yes +
OM4: undetected 40% positive bias in reported catches	Marginal −	Marginal +
OM5: undetected 40% negative bias in reported catches	Marginal +	Marginal −
OM5k: same as above, but here detected		
OM6: $B^{sp}/K^{sp} = 0.05$ (outside base case basket)	Yes −	Yes −
OM7: $M = 0.1$ (outside base case basket)	Yes −	Yes −
OM8: $\sigma_{cpue} = 0.3$; $\sigma_L = 0.35$	No	No
OM9a: shift in selectivity ($S_a = 1$ from a = 4) over projections period	No	No
OM9b: shift in selectivity ($S_a = 1$ from a = 8) over projections period	Yes −	Yes +
OM2 + OM4: detected variations and undetected positive bias	Marginal−	Marginal +
OM2 + OM5: detected variations and undetected negative bias	Marginal+	Marginal−
OM2 + OM5k: detected variations and detected negative bias	Yes −	Yes +

MP approach could be applied to data-limited resources, and, second, to highlight the emphasis placed on forecasting, with long-term management objectives defined in terms of target and limit

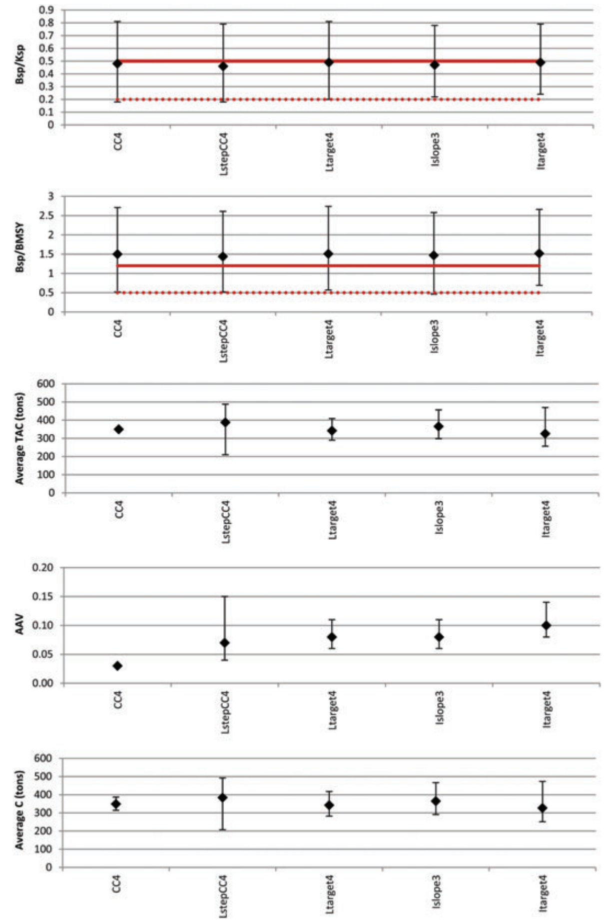

Figure 5. As for Figure 2, but here allowing for implementation error in catches which is random and unbiased (OM1).

reference points with decision-making based on yield-risk trade-offs, and, lastly, to emphasize the potential value in terms of extra yield for extra data.

These generic MPs can of course not be adopted for practical implementation in their present form. In particular, before practical application might be considered, the full extent of uncertainty (model structure uncertainty, process error, observation error, and implementation error) for the group of stocks under consideration would need to be addressed. While these sources of error are incorporated to some extent in the analyses reported here, a wider range of testing would be needed. For example, robustness to uncertainty regarding the somatic growth parameters and their correlation with natural mortality should be considered. In addition, different stock–recruitment relationships, such as a Ricker model, need to be examined.

Furthermore, the MPs investigated here rely on a direct or indirect index of abundance to set the TAC for the following year, based on the assumption that any trend in the index of abundance is a reliable indicator of the trend in resource biomass. However, reliable data may not be available for data-limited stocks and robustness to bias in these indices need to be demonstrated.

At this stage, the range of OMs used for trials corresponds only to "severely depleted" resources of medium productivity. Ideally, these generic analyses need to be repeated, for MPs with different control parameter choices, for groups of stocks that fall in the other eight

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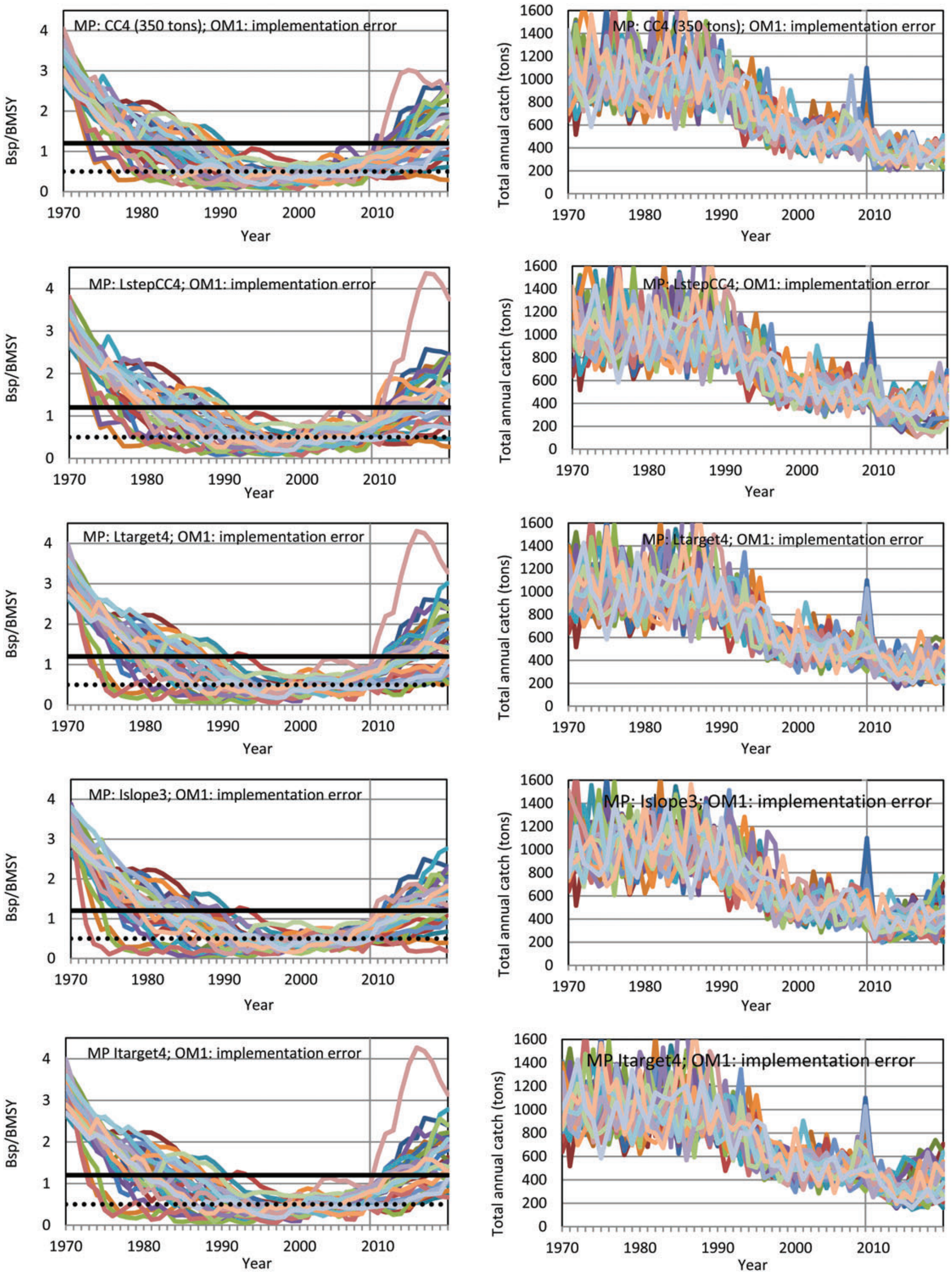

Figure 6. As for Figure 3, but here making allowance for implementation error in catches which is random and unbiased (OM1).

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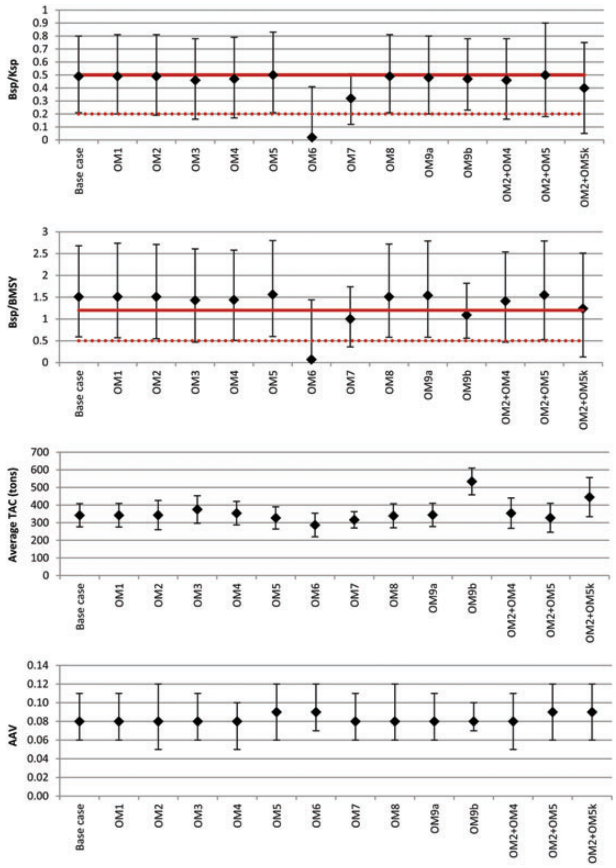

Figure 7. Summary statistics of various robustness tests when projecting with the length based MP: Ltarget4.

"baskets" depicted in Table 1, together with associated alternative historical catch series and cpue/length data availability scenarios. An unavoidable difficulty for data-limited stocks is the need to categorize stocks into "baskets" according to productivity levels and depletion. The former may not be too problematic, given results from research on similar stocks and species, but the latter presents greater challenges. A possible approach would be to follow a procedure similar to the FAO (2011) classification system which relies on "grey" and "black" literature. With few data (and an absence of quantitative assessments) to inform reliable categorization of stocks, a more PA is required, particularly for low productive longer-lived species that have been under severe fishing pressure.

Finally, the extent of uncertainty, as reflected by the prespecified distributions, needs to be closely examined and accepted by all stakeholders before these simple MPs could be considered for application in practice.

Supplementary material

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

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Appendix: Data

For purposes of this exercise, a pseudo stock has been selected that has been depleted to well below the maximum sustainable level, with historical catches having been high at the start of the fishery after which they are reduced later to prevent further resource depletion. The historical catches assumed for the pseudo fishery for the pre-management period ($y = 1$ to $n = 40$) are given in Table A1.

Table A1. Annual historical catches in tonnes assumed for the base case analyses.

Year	Catch (metric tonnes)	Year	Catch (metric tonnes)
1	1 000	21	950
2	1 000	22	900
3	1 000	23	850
4	1 000	24	800
5	1 000	25	750
6	1 000	26	700
7	1 000	27	650
8	1 000	28	600
9	1 000	29	550
10	1 000	30	500
11	1 000	31	500
12	1 000	32	500
13	1 000	33	500
14	1 000	34	500
15	1 000	35	500
16	1 000	36	500
17	1 000	37	500
18	1 000	38	500
19	1 000	39	500
20	1 000	40	500

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