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John Wiedenmann [a b], Michael J. Wilberg [a] & Thomas J. Miller [a]

[a] Chesapeake Biological Laboratory, University of Maryland Center for Environmental Sciences, Post Office Box 38, Solomons, Maryland, 20688, USA

[b] Institute of Marine and Coastal Sciences, Rutgers, State University of New Jersey, 71 Dudley Road, New Brunswick, New Jersey, 08901, USA

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ARTICLE

An Evaluation of Harvest Control Rules for Data-Poor Fisheries

John Wiedenmann,*[1] Michael J. Wilberg, and Thomas J. Miller
Chesapeake Biological Laboratory, University of Maryland Center for Environmental Sciences, Post Office Box 38, Solomons, Maryland 20688, USA

Abstract
For federally managed fisheries in the USA, National Standard 1 requires that an acceptable biological catch be set for all fisheries and that this catch avoid overfishing. Achieving this goal for data-poor stocks, for which stock assessments are not possible, is particularly challenging. A number of harvest control rules have very recently been developed to set sustainable catches in data-poor fisheries, but the ability of most of these rules to avoid overfishing has not been tested. We conducted a management strategy evaluation to assess several control rules proposed for data-poor situations. We examined three general life histories ("slow," "medium," and "fast") and three exploitation histories (under-, fully, and overexploited) to identify control rules that balance the competing objectives of avoiding overfishing and maintaining high levels of harvest. Many of the control rules require information on species life history and relative abundance, so we explored a scenario in which unbiased knowledge was used in the control rule and one in which highly inflated estimates of stock biomass were used. Our analyses showed that no single control rule performed well across all scenarios, with those that performed well in the unbiased scenario performing poorly in the biased scenarios and vice versa. Only the most conservative data-poor control rules limited the probability of overfishing across most of the life history and exploitation scenarios explored, but these rules typically required very conservative catches under the unbiased scenarios.

In many fisheries, management actions are based on estimates of stock biomass and management targets (biological reference points [BRPs]) produced from stock assessment models. Such models typically require long time series of catch and relative abundance by age and often life history information, and stocks for which there is such information are considered "data rich." For many stocks, however, this information is lacking, preventing the use of a data-driven assessment model. Such stocks are considered "data poor," and they pose a challenge to fisheries managers.

In the USA, fisheries managers are now confronting this challenge due to the Magnuson–Stevens Fishery Conservation and Management Reauthorization Act (MSFCMRA). The act requires that the Statistical and Scientific Committees of each of the eight regional fisheries management councils recommend acceptable biological catch (ABC) levels for all stocks under a fisheries management plan. National Standard 1 of the MSFCMRA further requires that the ABC prevent overfishing (i.e., when the fishing mortality rate exceeds that which produces the maximum sustainable yield, or F_{MSY}), while still attempting to achieve optimum yield for the fishery. To prevent overfishing, the ABC must have a probability of overfishing (P_{OF}) that does not exceed 50%. Scientific uncertainty must also be considered in the selection of an ABC, with the goal of achieving a specific, acceptable probability of overfishing. Importantly, the ABCs constrain the council's annual catch limits, which may not exceed the ABC.

For data-rich stocks, approaches have been developed for selecting a catch level that is expected to achieve a specified probability of overfishing, or P* (Shertzer et al. 2008). Although

*Corresponding author: john.wiedenmann@gmail.com
[1]Present address: Institute of Marine and Coastal Sciences, Rutgers, State University of New Jersey, 71 Dudley Road, New Brunswick, New Jersey 08901, USA.
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National Standard 1 does not mandate the use of the P^* approach, many councils have adopted some variant of this technique for setting ABCs (e.g., Prager and Shertzer 2010; Ralston et al. 2011). The challenge in setting an ABC with the P^* approach lies in determining whether scientific uncertainty has been adequately accounted for in estimating stock biomass and BRPs.

For data-poor stocks, however, implementation of the P^* approach is impossible, and setting ABCs that prevent overfishing for these stocks is challenging (Wetzel and Punt 2011). Recently, a number of approaches for setting ABCs for data-poor stocks have been developed. These approaches are called harvest control rules, as they specify a rule or set of rules for setting harvests in response to various factors, such as stock abundance (Deroba and Bence 2008). Data-poor harvest control rules were reviewed and ranked by Berkson et al. (2011), who recommend using a depletion-based stock reduction analysis (DB-SRA; Dick and MacCall 2011) when a catch series spanning the entire history of the fishery is available. If such catch data are not available, Berkson et al. (2011) recommend using a depletion-corrected average catch analysis (DCAC; MacCall 2009). MacCall (2009) advises that DCAC only be used for stocks with low natural mortality rates (M) and values of F_{MSY} at or below M. In cases in which DCAC is not appropriate, Berkson et al. (2011) recommend using a general framework they developed called the only reliable catch series (ORCS) approach.

The rankings described above were not based on a formal evaluation of how these control rules performed with respect to preventing overfishing. Wetzel and Punt (2011) conducted a simulation analysis to explore how well DB-SRA and DCAC estimated the catch that achieves F_{MSY} (called the overfishing limit, or OFL) for species with life histories typical of groundfishes, principally flatfishes (order Pleuronectiformes) and members of the genus *Sebastes*, found off the western USA. They found that both DB-SRA and DCAC generally produced estimates of the OFL at or below the true values. However, Wetzel and Punt (2011) did not look at the long-term effects of applying each control rule to the population. Although Wetzel and Punt (2011) showed that DCAC and DB-SRA can be effective at limiting overfishing, these control rules cannot be applied in all situations due to the limitations described above. Therefore, a broader examination of data-poor control rules is needed.

In this study, we used simulation testing (also called management strategy evaluation) to explore the performance of a suite of data-poor harvest control rules over a 20-year period for a range of fishing pressures and species' life histories. We calculated different performance measures associated with each control rule but focused on identifying control rules that were robust at preventing overfishing across the range of scenarios we explored. Our analysis included the control rules recommended by Berkson et al. (2011) as well as other rules because we wanted to evaluate a broad spectrum of potential data-poor approaches to provide quantitative advice in managing fisheries. To our knowledge no formal approach for updating the control rules has been proposed, but we reapplied control rules sequentially over the 20-year period, as this allowed us to evaluate how they perform when updated with new information.

METHODS

Model Structure

Our simulation study included an operating model and a management model. The operating model represented the true population dynamics of the stock, whereas the management model determined the annual catch harvested from the stock by applying a particular control rule. Each model run represented a 60-year period divided into two phases. During the first 40 years, an unregulated fishery harvested the population. The remaining 20 years represented the data-poor management phase, in which control rules were applied every 4 years to determine the ABC for the stock (Figure 1). An amount equivalent to the ABC was then harvested from the stock each year (if sufficient biomass was available), which in turn affected stock size in subsequent years. At the end of each run, the performance of the control rule was summarized over the 20-year period. The simulation was repeated 1,000 times for each control rule.

Operating model.—We used an age-structured population model to generate population dynamics. The equations governing the population dynamics are defined in Table 1 and variable definitions are provided in Table 2. Hereafter, the equations used in the model are referenced by their number in Table 1, such that, for example, the numerical abundance at age is referred to as equation T1.1. The annual abundances of a recruited age was determined from the abundance of that cohort in the previous year, as decreased by continuous natural and fishing mortality (equation T1.1). Recruitment to the population followed the Beverton–Holt stock–recruit relationship, with bias-corrected lognormal stochasticity (equation T1.2). The parameters for the Beverton–Holt model were derived from the unfished spawning biomass, the unfished recruitment, and the steepness parameter (equation T1.3), where steepness represents the fraction of unfished recruitment that results when the spawning biomass is reduced to 20% of the unfished level. Total spawning biomass in a given year was calculated by summing the product of the

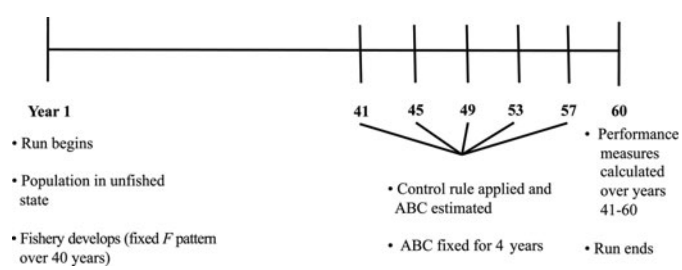

FIGURE 1. Timeline of events in the simulations. For each scenario explored, this timeline was repeated 1,000 times for each control rule to account for the variability in the population dynamics. The abbreviation ABC stands for acceptable biological catch.

TABLE 1. Equations characterizing the age-structured population and fishing dynamics in the operating model (see Quinn and DeRiso 1999 for more details).

	Equation	Description
	Population dynamics	
1	$N(a,t) = \begin{cases} R(t) & a = a_R \\ N(a-1, t-1)e^{[-M - s(a-1)F(t-1)]} & a_R < a \leq a_{\max} \end{cases}$	Numerical abundance at age
2	$R(t) = \frac{S(t-a_R)}{\alpha+\beta S(t-a_R)} e^{\theta_R - 0.5\sigma_R^2}$	Stock–recruit relationship
3	$\alpha = \frac{S_0(1-h)}{4hR_0}$ $\beta = \frac{5h-1}{4hR_0}$	Stock–recruit parameters
4	$S(t) = \sum_{a=a_R}^{a_{\max}} m(a)w(a)N(a,t)$	Spawning biomass
	Life history	
5	$L(a) = L_\infty(1 - e^{-k(a-a_0)})$	Length at age
6	$w(a) = bL(a)^c$	Weight at length
7	$m(a) = \dfrac{1}{1 + e^{-(\frac{a - m_{50\%}}{m_{slope}})}}$	Maturity at age
	Fishing dynamics	
8	$s(a) = \dfrac{1}{1 + e^{-(\frac{a - s_{50\%}}{s_{slope}})}}$	Selectivity at age in the fishery
9	$C(t) = \sum_a \frac{s(a)F(t)}{M + s(a)F(t)} w(a)N(a,t)(1 - e^{-M - s(a)F(t)})$	Total catch

proportion mature, weight at age, and abundance at age over all recruited age-classes (equation T1.4). Weight at age was an allometric function of length at age, which followed a von Bertalanffy growth function (equations T1.5 and T1.6). The proportion mature at age was calculated using a logistic function (equation T1.7). Length, weight, and maturity at age were fixed for a given species' life history.

The model contained a single fishery, with selectivity at age calculated using a logistic function (equation T1.8). Because we assumed that both natural (M) and fishing mortality (F) occurred continuously throughout the year, catch was calculated using the Baranov catch equation (Quinn and Deriso 1999; equation T1.9). We initialized the population in an unfished state. The unfished abundance at age was calculated using equation T1.1 assuming that the abundance of recruits was the unfished equilibrium recruitment (R_0; specified in Table 2), and abundance of older cohorts was calculated assuming a stable age distribution under $F = 0$. The unfished spawning biomass (S_0) was calculated using equation T1.4 using estimates of unfished abundance. Subsequently, F increased linearly for the first 20 years, and then reached a plateau for the remaining years (Figure 2). We applied three levels of fishing pressure during this initial 40 years: light, moderate, and heavy. These different fishing pressures resulted in median population sizes in year 41 (when the control rules were first applied) of 165, 96, and 40% of the spawning stock biomass at maximum sustainable yield (S_{MSY}), corresponding to underexploited, fully exploited, and overexploited populations (Table 2).

In year 41 a particular control rule was applied to estimate the ABC, and in most cases it was reapplied every 4 years throughout the final 20-year period. In a few cases a fixed catch was applied for the entire time period, or catches estimated from projections were applied across years. Target catches were converted to fishing mortality rates by solving equation T1.9 numerically. The true catch series (i.e., no error in determining annual catch) was used for each control rule. The ABC was fixed at the estimated value for the four-year interval before the reapplication of the control rule. It is possible for control rules in our model to set the ABC above the exploitable biomass. To prevent a control rule from removing all exploitable biomass from the population in a year, we set the achieved catch to 75% of the exploitable biomass in that year in cases in which the ABC exceeded the exploitable biomass.

We ran the model for three different life histories, which we labeled "slow," "medium," and "fast." The definitions for the slow, medium, and fast life histories were based on the characteristics of the Spiny Dogfish *Squalus acanthia*s, Summer Flounder *Paralicthys dentatus*, and Butterfish *Peprilus triacanthus*, respectively, species of importance in the Mid-Atlantic Bight of the USA. The slow life history had slow growth, late maturation, and low productivity. In contrast, the fast life history had rapid growth, early maturation, and high productivity. The medium life history was intermediate between the slow and fast life histories. The parameter values used to represent these life histories were obtained from the most recent stock assessments (NEFSC 2006, 2008, 2010) and FISHBASE

TABLE 2. Parameter values for the slow, medium, and fast life histories modeled in the data-poor simulation. Important quantities derived from these parameters that were used in the analyses are also listed. The slow, medium, and fast life histories are parameterized roughly using values for Spiny Dogfish (NEFSC 2006), Summer Flounder (NEFSC 2008), and Butterfish (NEFSC 2010). Some parameters were not available for every species (like steepness) or were modified slightly from the assessment values. Therefore, reference points do not exactly match those reported in the assessments. In cases in which parameter values could not be obtained from the stock assessment, we used FISHBASE (www.fishbase.org), although for steepness we used Myers et al. (1999) as a guide.

		Life history		
Parameter	Description	Slow	Medium	Fast
	Specified			
a_R	Age at recruitment (to population)	1	1	1
$a_{\max}$	Maximum age	30	15	7
M	Natural mortality rate	0.1	0.25	0.65
R_0	Unfished recruitment	1×10^6	1×10^6	1×10^6
h	Steepness	0.45	0.65	0.85
σ_R	Standard deviation of recruitment variability	0.4	0.4	0.4
a_0	Age at length = 0	−2	0	−0.214
L_∞	Maximum length	105	90	19.19
k	Growth rate	0.15	0.35	0.4
b	Length–weight scalar	2.98×10^{-7}	3.5×10^{-6}	4.27×10^{-5}
c	Length–weight exponent	3.6	3.15	2.8
m_{50}	Age at 50% maturity	5	2	1.4
m_{slope}	Slope of maturity function	0.5	0.36	0.1
s_{50}	Age at 50% selectivity	6	2.5	1
s_{slope}	Slope of selectivity function	0.5	0.34	0.2
	Derived			
S_0	Unfished spawning biomass	2,045,034	717,120	6,825
S_{MSY}	Spawning biomass that produces MSY	821,080	259,329	2,054
S_{MSY}/S_0	Ratio of S_{MSY} to S_0	0.4	0.36	0.3
F_{MSY}	Fishing mortality that produces MSY	0.07	0.25	0.75
MSY	Maximum sustainable yield	50,520	48,026	1,065
F_{MSY}/M	Ratio of F_{MSY} to M	0.7	1	1.15
$F_{\text{init}}/F_{\text{MSY}}$	Maximum F in the initial period to F_{MSY} for the under-, fully, and overexploited runs, respectively	0.5, 1.02, 2.0	0.45, 1.01, 2.2	0.54, 1.25,2.65

(http://www.fishbase.org; Table 2). Steepness values for Spiny Dogfish and Butterfish were based on the meta-analysis of Myers et al. (1999). We set steepness for the medium life history between the those for the slow and fast life histories, as the values for flatfishes from Myers et al. (1999) were similar to that for Butterfish. Recruitment variability was fixed across species ($\sigma_R = 0.4$). In addition, we used the same R_0 for each species, which resulted in BRPs for each stock that are not comparable to the assessment-estimated values. We calculated the maximum sustainable yield (MSY)–based BRP (Table 2) for each stock following the standard yield-per-recruit and spawning biomass-per-recruit approach (Shepherd 1982; NEFSC 2002).

Management model.—The control rules that we tested varied greatly in the level of information required to estimate the ABC (Table 3). Some control rules only required a catch series (which need not cover the entire history of the fishery), while others required additional information on life history and relative abundance. Given that these control rules are to be applied to data-poor stocks, relative abundance and general life history characteristics may be difficult to ascertain. For relative abundance, some control rules required that a stock be classified in broad categories (e.g., under-, fully, or overexploited), while others required a more exact measure of depletion. Like those for life history traits, some control rules required a species to be broadly categorized based on productivity (e.g., low, medium, or high), while others required specific values for parameters. These requirements pose a challenge for scientists, and expert opinion is often required.

In our application of the control rules, we explored two scenarios. In the first scenario, unbiased (i.e., perfect) information on stock biomass and life history was used in the control rule. In the second scenario, we again used unbiased information on life history, but stock biomass was assumed to be inflated (biased upward). We call these scenarios the unbiased and biased runs, respectively. We describe the specifics of these runs when discussing each control rule, as using inflated estimates of abundance required different approaches for different control rules.

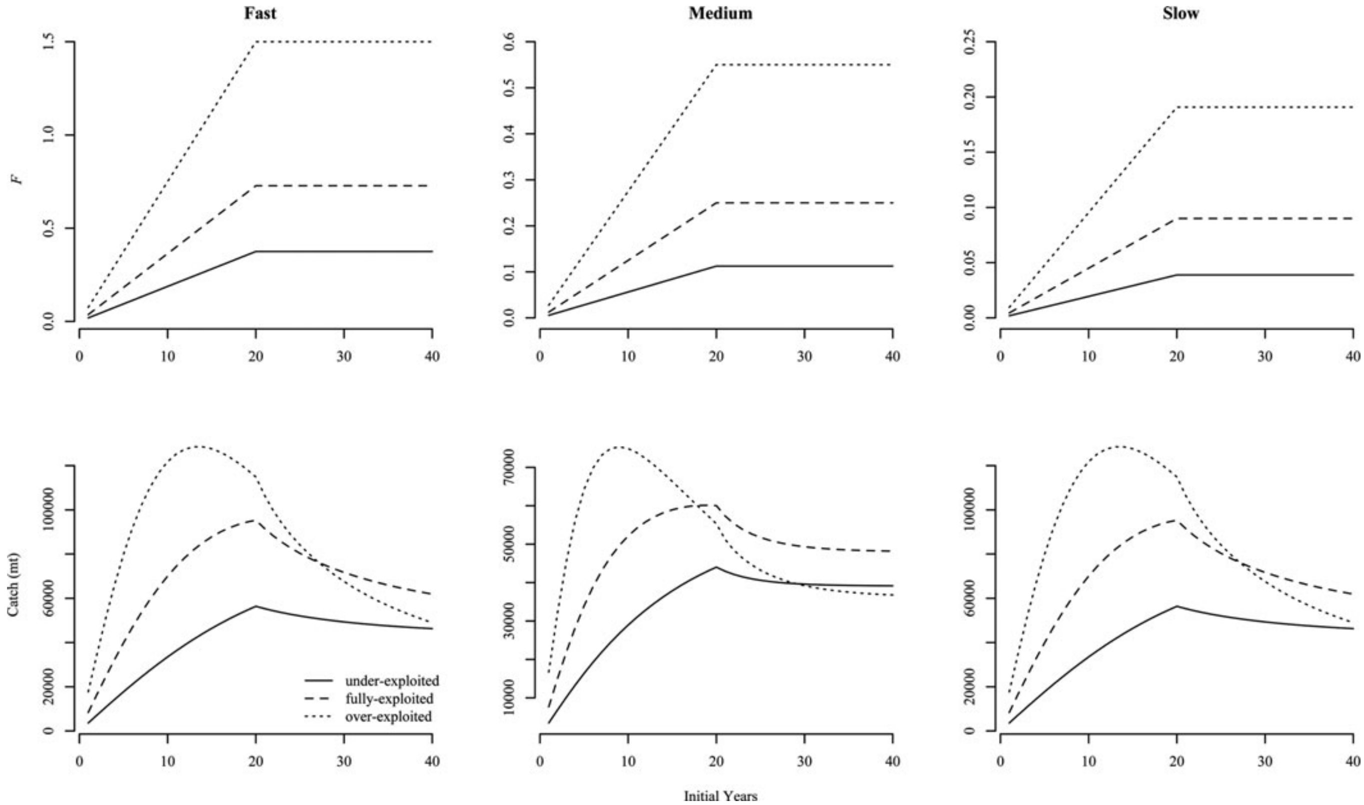

FIGURE 2. Fishing mortality rates (F) and catch histories during the initial period in the simulations for the slow, medium, and fast life histories. The values shown are for model runs with no stochasticity in recruitment during the initial phase.

The control rules that we explored vary with respect to the catch that is estimated, with some explicitly estimating the OFL and others estimating the ABC. In some cases, the control rule is used to estimate a sustainable catch (not necessarily the OFL or ABC). For each rule described below, we explicitly state whether we assumed that the catch was the OFL or the ABC.

TABLE 3. Level of catch and life history knowledge required and how stock abundance is determined for the control rules used in the analyses. Complete catch series refers to whether or not an entire catch history (starting in the unfished state) is needed for the control rule. Life history and stock abundance refer to the level of knowledge of the species' life history and current abundance, with basic meaning that a species is broadly categorized (e.g., as being of low or high productivity for life history, and under- or overexploited for abundance); detailed indicates that specific values (in the form of values drawn from specified probability distributions) are required as inputs. For the control rules, ORCS refers to the only reliable catch series, DCAC to the depletion-corrected average catch, and DB-SRA to depletion-based stock reduction analysis.

Control rule	Complete catch series?	Life history knowledge	Stock abundance
Mean/median catch	No	None	None
Percent of the mean/median catch	No	None	None
ORCS	No	Basic	Basic
Restrepo	No	None	Basic
DCAC	No	Detailed	Detailed
DB-SRA	Yes	Detailed	Detailed

Although councils are required to annually specify ABCs, the 4-year interval between updates to each control rule may be unrealistically short. The data-poor control rules we are testing were not necessarily designed to be updated on a semiannual basis unless new information becomes available to justify an update in the catch limit. We selected an interval of 4 years for two reasons. First, while longer intervals may make more sense given the limited data, there will likely be pressure from stakeholders to update catch targets that are deemed too low or too high, even in cases in which data are not available to support their claims. Second, we wanted to explore how the control rules performed under a best-case scenario, and having control rules updated with the true information every fourth year seemed reasonable, as updates for data-poor stocks would not likely occur more frequently even with data available to inform the control rule. In updating the data-poor control rules, we are illustrating how these rules would perform if updated and are not providing insight into how one would go about updating them.

Harvest Control Rules

Summary catch statistic.—In many situations, only catch data are available for a particular stock, and it is not possible for scientists or managers to determine the status of the stock. In such cases, a summary catch statistic may be used to set future catches. A summary catch statistic can be any metric calculated from the catch history. For our analyses, we used the median of the catch history as well as 50% and 75% of the median as our summary statistics and set these as the ABC. Because the summary catch statistic does not use any information regarding stock size, there is no effect of having a biased perception of stock abundance.

An important issue when calculating a summary catch statistic is whether or not to update the catch history using the catches produced from a particular control rule, as using an updated catch series can have a ratcheting effect. For example, if the control rule is to use 50% of the median catch as the ABC and the catch history used to calculate the median is updated, the median catch will decrease over time. Therefore, the ABC that is estimated using 50% of the median catch will also decline over time. This effect also works in the other direction if the ABC is greater than the median catch. For analyses that required a summary catch statistic, we did not update the catch series, as we felt that the ratcheting was unrealistic.

Only reliable catch series (ORCS) approach.—An extension of the summary catch statistic control rule is to adjust the statistic based on the available evidence. For example, if a population is believed to be underexploited, the ABC may be set at some multiple of the median catch. Berkson et al. (2011) proposed a general framework for developing a control rule to be used when additional information is available, but it is not possible to use more information-intensive control rules (i.e., DCAC and DB-SRA). This framework, called the ORCS approach, is extremely flexible in its application, and we note that we are only testing a few possibilities.

The ORCS framework requires that stock abundance first be put into into three broad categories: (1) underexploited, (2) fully exploited, and (3) overexploited. Berkson et al. (2011) suggest that stocks with a spawning biomass below 19% of S_0 be classified as overexploited, that stocks with a spawning biomass more than 65% of S_0 be classified as lightly exploited, and that stocks in between be classified as fully exploited. The justification for these biomass classification thresholds comes from Hilborn (2008), who showed that between these thresholds a "pretty good yield" (≥80% of MSY) could be sustainably removed. We used these classification groups, but other groups or different boundaries may also be appropriate. Given a classification of abundance for a stock, the next step in the ORCS approach is to adjust the summary catch statistic (e.g., the mean or median, denoted $\hat{C}$) to generate an estimate for the OFL. Berkson et al. (2011) recommend multipliers of 0.5, 1, or 2 for the over-, fully, and underexploited stocks, respectively, to generate an OFL estimate, such that

$$\mathrm{OFL} = \begin{cases} 2\hat{C} & S(t) \geq S_{65\%} \\ \hat{C} & S_{19\%} \leq S(t) < S_{65\%} \\ 0.5\hat{C} & S(t) < S_{19\%} \end{cases}. \tag{1}$$

TABLE 4. Overfishing limit (the catch at F_{MSY}) buffering options (θ) in relation to risk presented used with the only reliable catch series (ORCS) control rule.

Risk level (productivity)	θ_1	θ_2	θ_3
Low risk (high productivity)	0.9	0.8	0.7
Moderate risk (moderate productivity)	0.8	0.65	0.5
High risk (low productivity)	0.7	0.5	0.3

The ABC is then calculated by multiplying the OFL by a scalar ($\theta \leq 1$) based on the perceived level of "risk" for the stock ($\mathrm{ABC} = \theta \times \mathrm{OFL}$). The risk for a stock may be based on its assumed productivity (i.e., how fast biomass can recover) or susceptibility to the fishery (i.e., how easily a stock can be affected by a fishery), or both (see Patrick et al. 2009 for an example of classifying stocks using productivity–susceptibility analysis). Berkson et al. (2011) suggest that the amount of buffer should depend on the life history of the stock, with a high-productivity stock receiving a smaller buffer than a low-productivity stocks. They also provide a range of different possible values for θ based on risk. Berkson et al. (2011) do not explicitly state which summary catch statistic to choose but mention the median and the 75th percentile of the catch history as two possibilities. Therefore, we applied the ORCS approach using both the median and the 75th percentile of the catch, and we explored three θs (denoted θ_1, θ_2, and θ_3; Table 4). For the unbiased model run, the stocks are correctly classified according to the categories in equation (1). For the biased model run, the stocks are incorrectly classified into the adjacent-less-depleted category. That is, if the stock is overexploited it is classified as being fully exploited, and if it is fully exploited it is classified as underexploited. The biased model run is meant to be a worst-case scenario, and in this instance the population is never assumed to be overexploited.

The Restrepo rule.—Restrepo et al. (1998) developed guidance for specifying catch limits in data-poor situations for the 1996 reauthorization of the Magnuson–Stevens Act (we refer to their approach as the Restrepo rule). Like the ORCS approach, their approach requires classifying a stock into under-, fully, and overexploited categories (although the biomass thresholds defining these categories are slightly different, using the overfished and recovery thresholds of $0.5 \times S_{\mathrm{MSY}}$ and S_{MSY}, respectively) and adjusting a summary catch statistic to calculate the ABC:

$$\mathrm{ABC} = \begin{cases} 0.75\hat{C} & S(t) \geq S_{\mathrm{MSY}} \\ 0.5\hat{C} & 0.5S_{\mathrm{MSY}} \leq S(t) < S_{\mathrm{MSY}} \\ 0.25\hat{C} & S(t) < 0.5S_{\mathrm{MSY}} \end{cases}. \tag{2}$$

A key difference between the Restrepo and ORCS approaches is in the adjustment of $\hat{C}$, with the Restrepo rule being much more conservative as it decreases $\hat{C}$, even for an underexploited stock. Restrepo et al. (1998) recommended using recent stable catches to estimate $\hat{C}$, so we used recent stable catches as well as the median catch in our exploration of the Restrepo rule. Recent stable catches are defined in our model as those occurring in the most recent 5-year period in which the coefficient of variation (CV) of the catch series is at or below 5%. If no such period existed, we increased the CV to 10%, 15%, and so on. If there was no period with a CV below 30%, we used the mean catch in the most recent 5-year period.

Depletion-corrected average catch (DCAC).—MacCall (2009) developed DCAC as a way to calculate a sustainable yield in data-poor situations using a catch time series and assumptions about the life history parameters and relative status of the stock. The formula for calculating the target catch using DCAC requires a catch series (C_{obs}) spanning some period between t_{first} and t_{last} and assumptions about the relative decline in biomass over this period ($\Delta = [S\{t_{\text{first}}\} - S\{t_{\text{last}}\}]/S_0$), M, the ratio of F_{MSY} to M, and the ratio of S_{MSY} to S_0. In practice, assumptions can be made about the two ratios (Thorson et al. 2012b; Zhou et al. 2012) and M can be estimated from longevity information. Information on current depletion can be based on an index of abundance or expert opinion. The generic formula for calculating the target catch $C(t)$ in year t ($>t_{\text{last}}$) using DCAC is

$$C(t) = \frac{\sum_{t_{\text{first}}}^{t_{\text{last}}} C_{\text{obs}}(t)}{n + \frac{\Delta}{\left(\frac{S_{\text{MSY}}}{S_0}\right)\left(\frac{F_{\text{MSY}}}{M}\right)M}}, \quad (3)$$

where n is the number of years of catch data. Given the inherent uncertainty in these inputs, particularly for data-poor stocks, MacCall (2009) suggests that DCAC be calculated using a Monte Carlo approach. For the Monte Carlo simulation we drew values for M, F_{MSY}/M, and S_{MSY}/S_0 from a lognormal distribution with means equal to the true values and CVs of 50, 25, and 15%, respectively. For the unbiased model run, Δ was drawn from a normal distribution (allowing for negative values) with the mean equal to the true value and a CV of 30%. For the biased model run, Δ was drawn from a normal distribution with a mean calculated assuming that $S(t_{\text{last}})$ is 50% greater than the true value (i.e., $[S\{t_{\text{first}}\} - 1.5 \times S\{t_{\text{last}}\}]/S_0$) and a CV of 30%. We set a maximum value of 0.98 for Δ. The CVs assumed for M, F_{MSY}/M, and Δ are consistent with the values suggested by MacCall (2009), and our CV for S_{MSY}/S_0 matched that used by Wetzel and Punt (2011). MacCall (2009) recommends that DCAC not be used for species with an M above 0.2 and an F_{MSY}/M above 1. The constraint on M was based on the derivation of DCAC and the concept of a "windfall harvest" (the amount needed to reduce the population from S_0 to S_{MSY} in a single year). At high values of M, the sustainable yield approaches the windfall harvest, such that the depletion correction becomes small (equations 3–7 in MacCall 2009). The constraint on F_{MSY}/M was based on the observations of the ratios for other stocks (e.g., Zhou et al. 2012) and the fact that in the absence of information it would be prudent to assume an F_{MSY}/M less than 1. The true M is greater than 0.2 for the medium and fast life histories, and F_{MSY}/M is above 1 for the fast life history (Table 2). Despite its being above the limits, we applied DCAC to these life histories to see how it performed in such cases and refer to this as the base DCAC run. We also applied DCAC with a fixed level of $\Delta = 0.6$ in all years, representing a decline in biomass from S_0 to 40% of S_0, which we call the fixed DCAC run. The purpose of this run was to explore the effects of an assumed depletion in cases in which a mean Δ could not be decided. Each time DCAC was used, we conducted 1,000 parameter draws to create a catch distribution. The catch distribution is not an explicit estimate of the OFL or the ABC, so we assumed that the median of the distribution was the ABC. For the base run the depletion level was updated every 4 years and a new ABC was calculated. For the fixed run, DCAC was only used once (at $t = 41$) and the ABC was fixed for the remainder of the period.

Depletion-based stock reduction analysis (DB-SRA).—Although DCAC is a way of adjusting the average catch based on current depletion and stock life history, DB-SRA (a combination of DCAC and stock reduction analysis [Walters et al. 2006] proposed by Dick and MacCall 2011) is a method for obtaining a distribution for the OFL in data-poor situations. It requires nearly the same inputs as DCAC, with assumptions being made about M, F_{MSY}/M, S_{MSY}/S_0, and Δ. An important distinction between DB-SRA and DCAC is that DB-SRA requires a complete catch history, starting at the unfished state. Thus, for DB-SRA $\Delta = 1 - S(t)/S_0$ and can only range between 0 and 1 (whereas Δ can be negative in DCAC).

Like DCAC, DB-SRA was applied using a Monte Carlo approach, with draws for each required quantity. Given a particular set of values, we then calculated $F_{\text{MSY}} = F_{\text{MSY}}/M \times M$ and the harvest fraction $U_{\text{MSY}} = (F_{\text{MSY}}/[F_{\text{MSY}} + M]) \times (1 - \exp[-M - F_{\text{MSY}}])$. Next, we iteratively solved for the unfished biomass, S_0, that resulted in the assumed current level of depletion, given the catch history and a modified Pella–Tomlinson production model (see Dick and MacCall 2011 for the reasons for using a modified production function). With an estimate of S_0, we then estimated $S_{\text{MSY}} = S_0 \times S_{\text{MSY}}/S_0$ and $S(t) = S_0\,(1 - \Delta)$, and finally the OFL with $C(t) = U_{\text{MSY}} \times S(t)$. The modified production model can be used to project the population biomass for a number of years by fishing at U_{MSY}, producing a time series of OFL estimates. The Monte Carlo approach produces a distribution for the OFL (in one or many years), such that one could take some percentile (e.g., $\leq$50%) to buffer the ABC away from the median OFL estimate.

As with DCAC, we drew values for M, F_{MSY}/M and S_{MSY}/S_0 from a lognormal distribution with mean equal to the true value and CVs of 50, 25, and 15%, respectively. Values for Δ were drawn from a beta distribution (constraining it between 0 and 1) with a CV of 30%, a mean equal to the true value in the unbiased run, and the mean calculated with $S(t)$ being 50% greater than the true value in the biased run. We set a maximum value of 0.98 for Δ. We explored three permutations of DB-SRA, each of which used 1,000 parameter sets. Under the first permutation (called the base run), DB-SRA was applied every

4 years and the ABC for the 4-year interval was fixed at the median of the OFL distribution for the current year. For the second permutation (called the projected run), DB-SRA was only applied in the first year ($t = 41$), and we generated a distribution of OFL over the remaining period by projecting the population biomass assuming that $U(t) = U_{\mathrm{MSY}}$ for all years. For the final permutation (called the fixed run), DB-SRA was only applied in the first year, with an assumed $\Delta = 0.6$ corresponding to an assumed biomass of 40% of S_0. This assumption was based on Dick and MacCall (2011), who noted that DB-SRA generally performed well when an assumed $\Delta = 0.6$ was used, regardless of the population size of the stocks they explored. For each year we set the ABC equal to the median of the OFL distribution for that year (i.e., there was no buffering).

Performance Measures

It is important to understand how each control rule performs with respect to objectives that are of interest to both managers and stakeholders, and how performance varies according to the life history and exploitation history of a population. We calculated performance measures for each control rule for each run (of the 1,000 total) for a given scenario (life history, exploitation history, and level of bias in estimated abundance). Managers must prevent overfishing under the MSFCMRA and revised National Standard 1, so we calculated the probability of overfishing (P_{OF}) across the 20-year period over which the control rules were applied (between years 41 and 60) as the proportion of years in which $F(t)$ exceeded F_{MSY}. Catches with a P_{OF} greater than 0.5 are more likely than not to result in overfishing and are not allowed under National Standard 1. Managers also want to prevent stocks from becoming overfished (or rebuild those that are), so we computed the ratio of the mean spawning biomass over the final 10 years to S_{MSY}. We used the final 10 years in the calculation to reduce the potential effect of transient dynamics in the initial years. Stakeholders are interested in the yield to the fishery, so we computed the mean ratio of the observed catch to the true MSY over the entire 20-year period the control rule was applied.

RESULTS

Control rules had variable performance across the life history and exploitation history scenarios, and no control rule was best across all scenarios. For the scenarios in which unbiased information was used when assessing stock abundance and life history (the unbiased runs), some patterns in harvest rates appeared across the range of life histories and exploitation histories we explored. For a given life history, many of the control rules resulted in the general trend of an increasing P_{OF} going from the underexploited population to the overexploited population (Figure 3; Table A.1 in the appendix). Many of the control rules we explored were extremely variable across exploitation scenarios, with the median P_{OF} near zero in the under- and fully exploited cases and above 0.5 in the overexploited cases (Figure 3; Table A.1). In addition, in the overexploited case P_{OF} was generally higher for the slow life history than for the medium and fast life histories for many of the control rules. An exception to these patterns was DB-SRA, which showed the greatest consistency in P_{OF} across life history and exploitation scenarios, with a median value between approximately 0.2 and 0.6 and the variation in the estimates increasing from the fast to slow life histories.

Control rule performance differed among scenarios with biased information. For the model runs in which the stock abundance was inflated, the P_{OF} for control rules using only a summary catch statistic (the median catch and 50% of the median catch) did not differ from those of the unbiased run, as these rules do not use any information on stock abundance (Figure 4). Control rules requiring classification of stock abundance generally resulted in higher P_{OF} than in the unbiased scenarios (Table A.2). For the fast life history, the difference in the P_{OF} for most of the control rules was small between the scenario in which the population was fully exploited (but assumed to be underexploited) and overexploited (but assumed to be fully exploited). For the medium life history, and particularly for the slow life history, most control rules resulted in higher P_{OF} when the population was overexploited than when it was fully exploited (Figure 4). The exception again was DB-SRA, which resulted in similar or slightly lower values of P_{OF} for the different life histories that were overexploited. For the medium and slow life histories, many of the control rules performed poorly, with many having a P_{OF} in excess of 0.8.

Estimates of P_{OF} only provide information on the frequency of overfishing, not the magnitude of the catches. Fishing close to F_{MSY} will result in catches being above, close to, or below MSY for under-, fully, and overexploited populations, respectively. Thus, a control rule that performed well (fishing close to F_{MSY}) would result in decreases in the ratio of mean catch to MSY going from the underexploited to the overexploited scenarios. However, we only observed this pattern for DB-SRA (Figure 5). For the underexploited runs, most control rules resulted in the catch being below MSY (Figure 5), causing the population biomass to be two to three times above S_{MSY} (Figure 6). In contrast, DB-SRA resulted in catches ranging between 100% and 150% of MSY and biomass between 50% and 150% of S_{MSY}. For the fully exploited scenarios, both the median catch and DB-SRA produced the highest catches for each life history, with the catch-to-MSY ratio generally close to 1 (Figure 5). The remaining control rules produced more conservative catches, resulting in biomass between 100% and 200% of S_{MSY} (Figures 5, 6). For the overexploited scenario there was less variation in catches despite considerable variation in P_{OF} (Figure 4) and stock size (Figure 6). Some control rules maintained high catches by allowing severe overfishing and driving biomass towards zero (the median catch and DCAC for the slow and medium life histories), while others were more conservative and allowed the population to rebuild, thus producing similarly higher catches (ORCS, Restrepo, and DB-SRA).

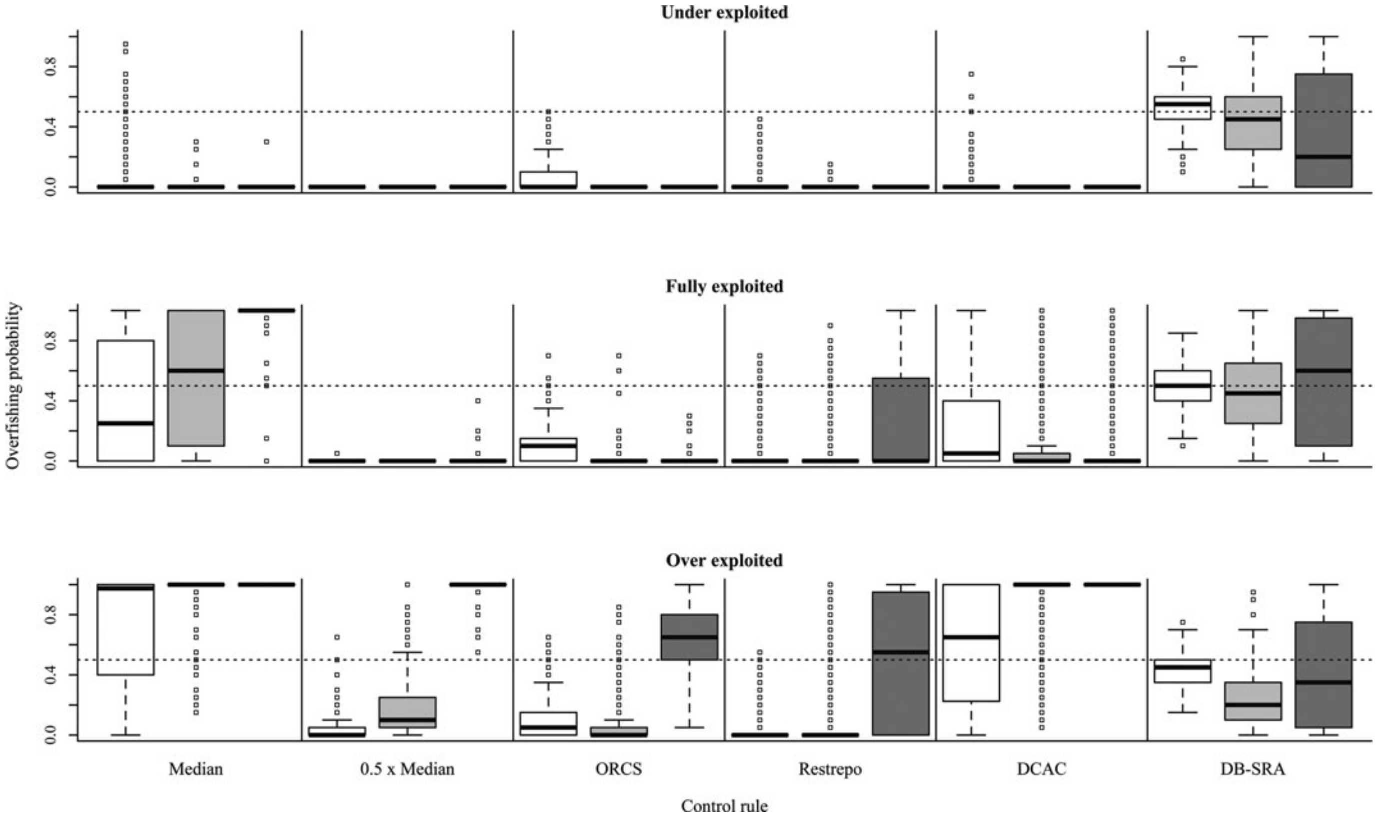

FIGURE 3. Probability of overfishing in the unbiased run across control rules and life histories for the three exploitation histories explored (underexploited, fully exploited, and overexploited). The life histories (fast, medium, and slow) are shown from left to right for each control rule and are distinguished by shading (none, light, and dark, respectively), although in some instances the shading is not evident because the range of outcomes was relatively small. The lower and upper edges of each box represent the first and third quartiles, respectively, with the solid horizontal line within each box representing the median. The whiskers represent ±1.5× the interquartile range, and the circles represent outliers. See the text for descriptions of the control rules.

For many of the alternative control rule variants we explored, the behavior was predictable from the reduced subset of control rules (Tables A.1, A.2). For example, across scenarios the more conservative ORCS option (θ_1) resulted in lower catch, higher biomass, and smaller P_{OF}, while using 75% of the median catch resulted in catch, biomass, and P_{OF} between the median and 50% of the median catch control rules (Tables A.1, A.2). For other variants, particularly for DCAC and DB-SRA, the responses were not as predictable. In addition to the base explorations of DCAC and DB-SRA, we explored situations in which biomass was assumed to be 40% of S_0 and a variant of DB-SRA in which the ABC in all years was based on projections done in the initial year. When projections were used for DB-SRA, there were instances in which this approach was more conservative than the base run of DB-SRA as well as instances in which it was less conservative. For the DB-SRA runs in which biomass was assumed fixed at 40% of S_0, catch estimates were generally more conservative than the base DB-SRA run when the true population was higher (the underexploited scenario); estimates were comparable when the population size was similar (the fully exploited scenario) and much greater when the true population size was less than the assumed value. This trend did not hold for the fast life history, however, where the fixed DB-SRA run resulted in higher instances of overfishing than in the base run across the exploitation scenarios (Table A.1). In contrast, assuming a fixed depletion for DCAC resulted in much smaller differences in performance measures across exploitation scenarios than in the base DCAC run. These differences were smaller for the medium and fast life histories, the result of smaller depletion corrections for high values of M and F_{MSY}/M (equation 3).

Both DCAC and DB-SRA produce a distribution of the catch estimate, and we selected the median value for all scenarios as the estimate of the ABC. Different percentiles of the distribution could be selected to reduce the probability of overfishing in cases in which these control rules resulted in values of P_{OF} greater than 0.5. For each year we calculated the percentile of the catch distribution that would achieve the OFL and then calculated the mean percentile across years for a particular scenario (Table 5). For DCAC, there were many instances in which the catch distribution barely overlapped (i.e., high or low percentiles) or did not overlap at all with the true OFL. In contrast, DB-SRA (for the base and projected runs) produced narrower ranges of percentiles between the 33rd and 87th percentiles (with most estimates between the 46th and 60th percentiles;

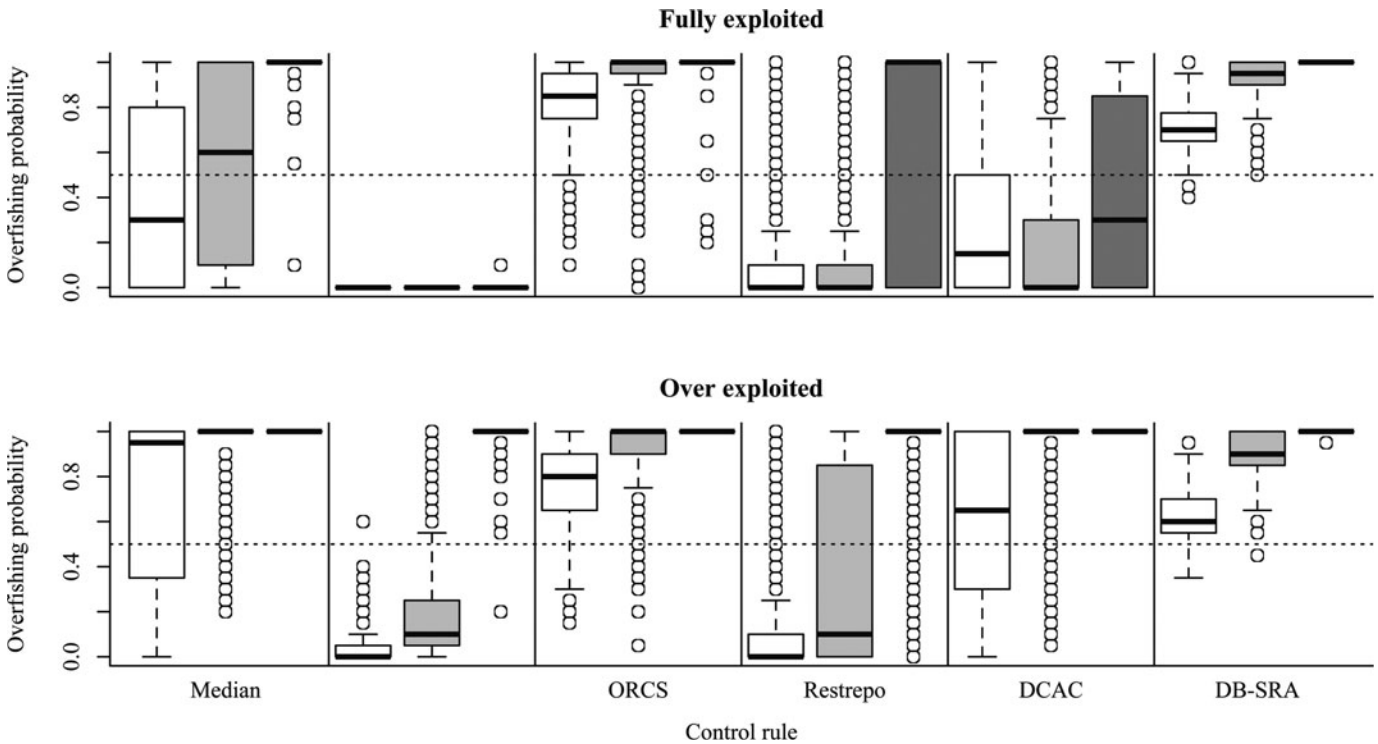

FIGURE 4. Probability of overfishing across control rules and life histories for the fully exploited and overexploited exploitation histories in the model run using inflated estimates of stock abundance in the control rules that require such information (called the biased scenario). The terms fully exploited and overexploited refer to the true abundance of the stock. See Figure 3 for additional details.

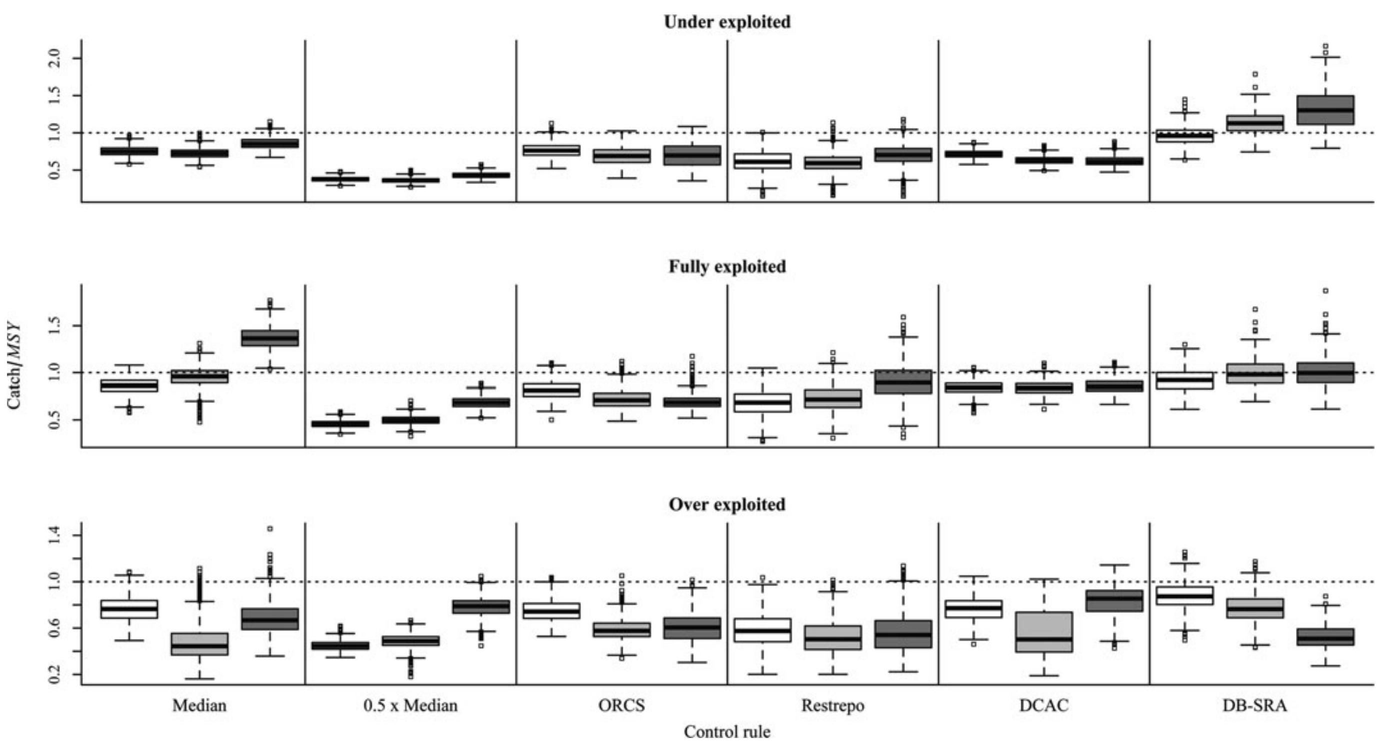

FIGURE 5. Mean catch relative to the maximum sustainable yield (MSY) across control rules for the different life histories and exploitation histories explored. See Figure 3 for additional details.

TABLE 5. The mean percentile of the catch distributions produced by DCAC (depletion corrected average catch) and DB-SRA (depletion-based stock reduction analysis) that achieves the true overfishing limit (OFL) across exploitation and life history runs. Values are presented as decimals, such that a value of 0.5 represents the 50th percentile of the distribution. A value of 0 indicates that the all values of the catch distribution were above the true OFL, while a value of 1 indicates all values were below the true OFL. Control rules were not applied to underexploited populations in the biased run, and we did not apply DCAC and DB-SRA assuming a fixed depletion in the biased run.

		Unbiased			Biased		
Harvest pressure	Control rule	Fast	Medium	Slow	Fast	Medium	Slow
Underexploited	DCAC	1.00	1.00	1.00			
	DCAC (fixed)	1.00	1.00	1.00			
	DB-SRA	0.46	0.52	0.53			
	DB-SRA (projected)	0.33	0.55	0.60			
	DB-SRA (fixed)	0.19	0.88	0.95			
Fully exploited	DCAC	0.80	0.91	0.84	0.75	0.85	0.58
	DCAC (fixed)	0.79	0.86	0.79			
	DB-SRA	0.48	0.51	0.49	0.23	0.16	0.13
	DB-SRA (projected)	0.39	0.52	0.48	0.13	0.07	0.04
	DB-SRA (fixed)	0.01	0.30	0.47			
Overexploited	DCAC	0.42	0.08	0.01	0.40	0.05	0.00
	DCAC (fixed)	0.42	0.04	0.00			
	DB-SRA	0.59	0.64	0.51	0.30	0.20	0.15
	DB-SRA (projected)	0.87	0.76	0.49	0.59	0.28	0.10
	DB-SRA (fixed)	0.00	0.00	0.00			

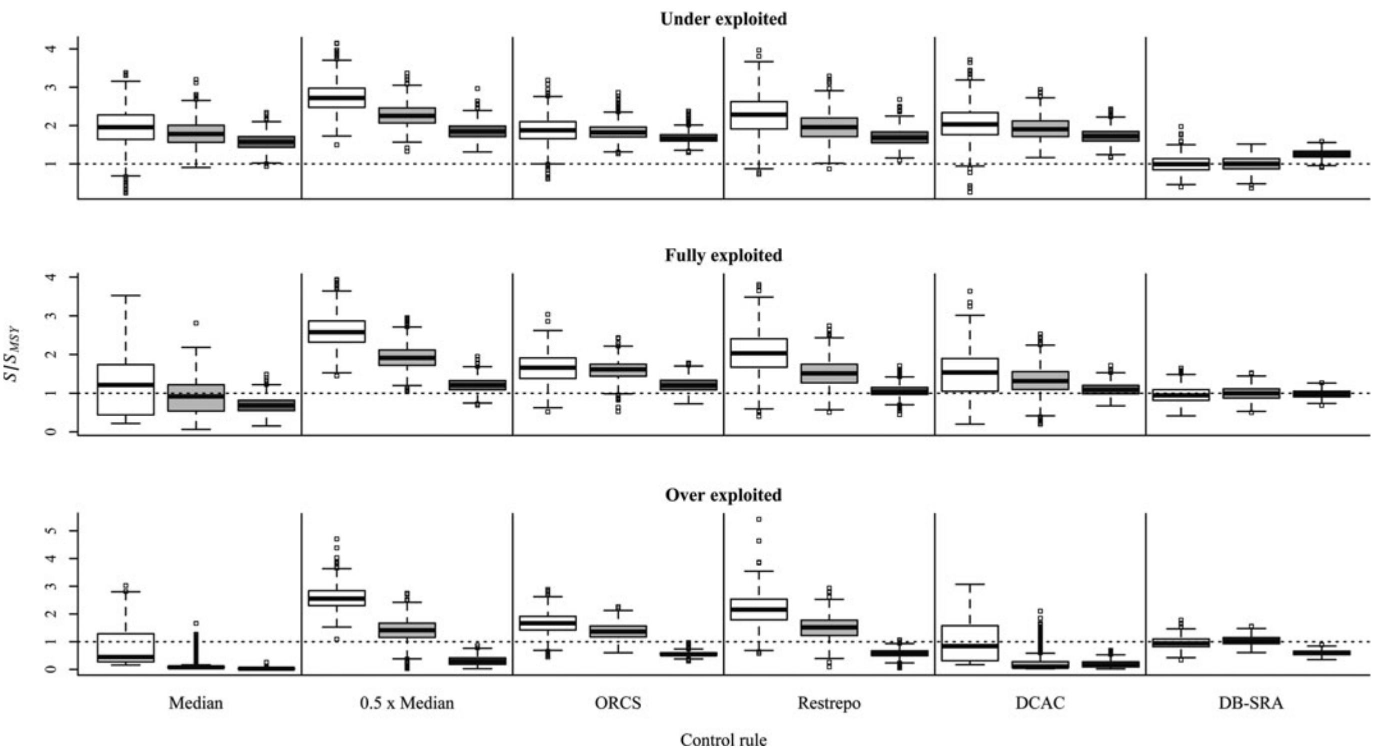

FIGURE 6. Mean spawning biomass (S) relative to the spawning biomass that produces the MSY (S_{MSY}) across control rules for the different life histories and exploitation histories explored. Each ratio was calculated using the mean spawning biomass from the final 10 years of the model run. See Figure 3 for additional details.

Table A.1). However, the catch distributions for DB-SRA assuming a fixed depletion ($\Delta = 0.6$) were less precise, particularly for the overexploited scenarios in which the distribution was always higher than the true OFL.

DISCUSSION

Although it is important to consider a wide range of performance measures in our analysis of harvest control rules, the MSFCMRA mandates that U.S. federal fisheries management avoid overfishing. National Standard 1 further requires that ABC control rules be developed in conjunction with the regional fishery management councils to achieve specific probabilities of overfishing ($\leq$0.5). Our analysis of data-poor control rules for specifying ABCs indicated that no single control rule performed best across all of the scenarios we explored. In the scenarios in which unbiased information on stock abundance was used, only the most conservative ORCS approach (option θ_1 using the median catch and the 75th percentile of the catch) and the Restrepo rule using recent stable catches resulted in a median P_{OF} less than 0.5 for all the exploitation and life history scenarios we explored. A number of rules resulted in P_{OF} values greater than 0.5 only for the overexploited species with a slow life history. For the scenarios in which biased (inflated) estimates of stock abundance were used in the control rules, no control rule resulted in a P_{OF} less than 0.5 for all of the exploitation and life history combinations we explored (Tables A.1, A.2).

Minimizing the risk of overfishing is not the only objective of management. Fishery managers must also try to achieve optimum sustainable yield. If a control rule were able to balance the trade-offs between a sizeable harvest and a low risk of overfishing, we would expect to see P_{OF} values somewhat lower than 0.5 across scenarios. Across exploitation scenarios, DB-SRA (both the base and projected runs) resulted in some of the highest catches but also in P_{OF} values above 0.5 in some scenarios, particularly when the stock was assumed to be in better condition than it actually was. However, DB-SRA performed well when unbiased information on stock abundance was used. An additional benefit to DB-SRA is that it produced accurate estimates of the OFL for the heavily exploited stocks across life histories. Greater accuracy for more depleted stocks was noted by Dick and MacCall (2011), and it is an extremely useful property, as it allows for more risk-averse harvesting in high-risk cases.

If a data-poor stock can be classified into the different life history and population status categories we explored, our results suggest it is possible to select a preferred control rule that performs consistently well. Our analyses, however, did not consider the full range of potential scenarios. For example, there are slower or faster life histories than those we used. Also, we did not explore all ranges of potential depletion, and stocks may be more or less depleted within a particular exploitation category. However, given that many of the control rules performed worse for the overexploited populations with the slow life history, the application of such control rules to populations with slower life histories that are more severely overfished will likely result in overfishing. Finally, our analyses did not consider a broad range of effort dynamics leading up to the use of a control rule, as we used the straightforward effort dynamics shown in Figure 2.

Many other potential catch histories could result in the different population sizes we explored (Vasconcellos and Cochrane 2005). Different dynamics would produce different catch histories, which could impact the performance of many of the control rules. For example, a constant catch that resulted in an overexploited stock might have a very different median catch than those resulting from the catch histories we used (Figure 2). Alternative catch histories may also influence DCAC and DB-SRA, as noted by Wetzel and Punt (2011). Therefore, a broader analysis of the effects of different catch histories on control rule performance is warranted.

Care is also needed when trying to select an appropriate control rule for a given stock, as there is the potential for error in classifying the stock into the different categories. Misclassification works in both directions (i.e., assumed biomass can be lower or higher than the true value, or the assumed life history can be slower or faster than assumed), but we only explored the effects of assuming that the population was higher than the true value, as we considered this a worst-case scenario. Many of the control rules that performed well when the true population abundance and life history were used performed poorly when the stock was assumed to be in better condition than it was. Having broad classification categories for a control rule (as in the ORCS or Restrepo rules) may reduce the likelihood of misclassifying a stock (as opposed to requiring a specific value, albeit from a distribution, for relative stock abundance, as in DCAC and DB-SRA), but there is still potential for error. Assuming a stock is more abundant than it actually is can have a large, negative impact on the population, as many control rules that were applied with inflated estimates resulted in large declines in biomass for the medium and slow life histories, in some cases driving the population to near extinction. Dick and MacCall (2011) showed, however, that for stocks with biomasses near S_0 the model performed better when biomass was assumed to be lower than the true value, making it problematic to assume that a stock is very lightly exploited. Thus, following Dick and MacCall's (2011) recommendation and assuming a greater depletion level for a stock that is believed to be near the unfished level would reduce or negate the effects of this misspecification.

A few control rules resulted in large declines in biomass when unbiased information was used for the species with the slow life history (the median catch, 50% of the median, and DCAC; Figure 6). Given these findings, it is important to identify when catches from a control rule are driving population biomass to such low levels. A formal analysis of methods to detect the status of data-poor stocks (e.g., Scandol 2003; Cope and Punt 2009) is beyond the scope of this paper, but it may be possible to use the trends in catches (Costello et al. 2012; Thorson et al. 2012a). For example, dramatic declines in catches may be a bellwether for a poorly performing control rule (in the absence of dramatic behavioral or regulatory changes). Another potential sign of a declining population is the inability of the fishery to reach the quota, although using this metric might result in an overreporting of the catch to prevent declines in the catch limit.

Various approaches have been proposed to obtain information on stock abundance and life history, such as using expert opinion based on similar species or trophic groups or from similar fisheries (MacCall 2009; Berkson et al. 2011). In cases in which it is not possible to classify a stock, one could assume that the population is in the worst possible category (i.e., overfished) or only some measure of the catch history may be used (e.g., the median or 50% of the median catch). We did not explore the effects of assuming a worst-case population in our analysis, but we did explore control rules that do not require abundance information. Such control rules are beneficial in that they make no assumptions about the current abundance of the stock. We explored three catch statistics: the median catch, 75% of the median, and 50% of the median as well as using DCAC and DB-SRA with a fixed estimate of stock abundance. None of these control rules resulted in $P_{OF} < 0.5$ in all of the scenarios explored, with the summary catch statistics often producing high P_{OF} values for the overexploited scenario. Thus, using very conservative catch statistics (e.g., $\leq$50% of the median) may be suitable when no information is available if one chooses to err on the side of caution. It is also possible to select lower assumed levels of depletion for DB-SRA ($\ll$40% of S_0), but this assumption may result in poor model performance in some cases, as our runs assuming a fixed depletion for the fast life history performed poorly in all the exploitation scenarios explored (Tables A.1, A.2). For DCAC, misspecification of the abundance had less of an effect on estimates than DB-SRA (Tables A.1, A.2), and this property of a control rule is beneficial. Assuming a fixed value for stock abundance often resulted in target catches that were below the OFL for underexploited stocks and above it for overexploited stocks. As a result, care is needed when applying this control rule, especially for overexploited populations.

Berkson et al. (2011) recommend using DB-SRA, if possible, followed by DCAC and then their own approach, which we called the ORCS approach. In addition to these rules we also evaluated the Restrepo rule, on which the ORCS approach is based. While DB-SRA and DCAC were the top-recommended control rules by Berkson et al. (2011) when stock status could be reliably determined, both resulted in $P_{OF} > 0.5$ for some scenarios (although the scenarios in which this occurred differed between them). Although DB-SRA resulted in overfishing in some scenarios, lower percentiles of the OFL distribution could be selected, resulting in a lower P_{OF} in such cases. Our analyses showed that choosing between the 30th and 40th percentiles would result in a P_{OF} below 0.5 for the unbiased model run but that much lower percentiles (between the 10th and 30th) were needed when inflated stock abundance was used (Table 5). Both the Restrepo rule and more conservative ORCS approaches we explored (θ_1 and θ_2) resulted in no or at most one scenario in which $P_{OF} > 0.5$ (the slow life history that was overexploited). For the biased scenarios, the Restrepo rule resulted in the fewest scenarios with P_{OF} greater than 0.5 because it used the largest buffer for the catch across all exploitation scenarios. If avoiding overfishing is the most important objective, the Restrepo rule or the more conservative variants of the ORCS rule might be appropriate.

In general, DCAC performed well (P_{OF} less than 0.5) in the under- and fully exploited scenarios when unbiased information was used, but it resulted in high harvest rates and occurrences of overfishing for the overexploited stocks, particularly for the medium and slow life histories. MacCall (2009) recommends using DCAC only for species with M less than 0.2 and F_{MSY}/M less than 1, but we applied it to populations with larger values (the medium and fast life histories). The DCAC approach did not result in P_{OF} exceeding 0.5 for these life histories when they were under- or fully exploited, but it did when the populations were overexploited. Our analysis suggests that restrictions on using DCAC be based on perceived population abundance (instead of life history), with DCAC use limited to populations believed to be under- or fully exploited. A caveat to using DCAC (for all life histories) is the effect of having a long time series of catches, as the total catch is adjusted based on the number of years (n) and the depletion correction factor (equation 3). For the same depletion correction factor, the overall effect on the estimated catch is less for larger values of n.

Our analysis of DCAC and DB-SRA generally agreed with Wetzel and Punt (2011), who evaluated the ability of these control rules to estimate the OFL. In their analysis, Wetzel and Punt (2011) estimated the OFL for two stocks with differing life histories (both with M at or below 0.2) for a range of scenarios, including catch histories, current abundance, and parameter misspecification. Our work differed in that we looked at the effects of the repeated application of each control rule over a 20-year period (whereas they compared OFL estimates with the true value in 1 year only), and we explored a broader range of life histories. As with our work, they showed that DCAC overestimated the OFL when the population was overfished and that the error was higher for the species with the slower life history (Wetzel and Punt 2011). For DB-SRA, Wetzel and Punt found instances of both over- and underestimation of the OFL and that the estimation was better for the slower life history.

In summary, no control rule performed best across the range of life histories, population abundance, and misclassification scenarios we explored. Stocks with slow life histories that had a history of overexploitation were particularly challenging unless an unbiased estimate of stock abundance could be obtained. While DB-SRA produced relatively accurate estimates of the OFL, it was sensitive to misspecification of current stock abundance. Selecting lower percentiles of the OFL distribution produced by DB-SRA may reduce the effect of assuming inflated stock abundance in many cases. Approaches that only require classification of abundance into broad categories (i.e., ORCS and Restrepo) may be a useful alternative, as the potential to incorrectly specify stock abundance is reduced. We only explored a few potential options for these rules, but the more conservative ORCS and Restrepo options were generally robust across scenarios, although the resulting ABCs were very conservative for the populations that had a history of underexploitation. Further refinement of these control rules (DB-SRA, ORCS, and Restrepo) is warranted based on our results, particularly refinement of the catch adjustment factors based on abundance and life history (ORCS and Restrepo approaches) and refinement of the methods of classifying current stock abundance (DB-SRA). Such refinements might result in a single control rule that is robust across the range of scenarios that may be encountered.

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Appendix: Detailed Results

TABLE A.1. Means and coefficients of variation (in parentheses) for the performance measures calculated for all control rules for the unbiased run across all of the life history and exploitation history scenarios explored. The control rules are as follows: ORCS = the only reliable catch series (with θ_1, θ_2, and θ_3 referring to the buffering options shown in Table 4), DCAC = the depletion-corrected average catch, and DB-SRA = the depletion-based stock reduction analysis. For the performance measures, C/MSY is the ratio of the mean catch to the true maximum sustainable yield and S/S_{MSY} is the ratio of the mean spawning biomass over the final 10 years in the simulation to the true spawning biomass that produces MSY.

		Fast			Medium			Slow		
Harvest pressure	Control rule	Overfishing probability	C/MSY	S/S_{MSY}	Overfishing probability	C/MSY	S/S_{MSY}	Overfishing probability	C/MSY	S/S_{MSY}
Underexploited	Median	0.02 (4.50)	0.75 (0.09)	1.95 (0.25)	0.00 (14.95)	0.72 (0.09)	1.79 (0.19)	0.00 (31.62)	0.86 (0.09)	1.58 (0.13)
	75% of median	0.00 (∞)	0.57 (0.09)	2.39 (0.17)	0.00 (∞)	0.54 (0.09)	2.04 (0.15)	0.00 (∞)	0.64 (0.09)	1.73 (0.12)
	50% of median	0.00 (∞)	0.38 (0.09)	2.74 (0.14)	0.00 (∞)	0.36 (0.09)	2.27 (0.13)	0.00 (∞)	0.43 (0.09)	1.86 (0.11)
	ORCS θ_1 (median)	0.08 (1.16)	0.82 (0.12)	1.73 (0.23)	0.00 (5.21)	0.78 (0.18)	1.71 (0.12)	0.00 (13.66)	0.85 (0.24)	1.58 (0.08)
	ORCS θ_1 (75th %)	0.19 (0.82)	0.90 (0.11)	1.43 (0.27)	0.03 (2.25)	0.86 (0.16)	1.56 (0.14)	0.03 (2.32)	0.95 (0.22)	1.51 (0.08)
	ORCS θ_2 (median)	0.05 (1.52)	0.77 (0.13)	1.88 (0.19)	0.00 (∞)	0.69 (0.18)	1.84 (0.12)	0.00 (∞)	0.69 (0.23)	1.69 (0.09)
	ORCS θ_2 (75th %)	0.13 (1.02)	0.86 (0.12)	1.59 (0.25)	0.00 (6.74)	0.77 (0.17)	1.73 (0.12)	0.00 (∞)	0.79 (0.24)	1.64 (0.08)
	ORCS θ_3 (median)	0.01 (2.53)	0.71 (0.13)	2.03 (0.17)	0.00 (∞)	0.58 (0.17)	1.99 (0.13)	0.00 (∞)	0.46 (0.20)	1.84 (0.10)
	ORCS θ_3 (75th %)	0.07 (1.32)	0.80 (0.13)	1.78 (0.22)	0.00 (∞)	0.66 (0.18)	1.88 (0.12)	0.00 (∞)	0.54 (0.21)	1.79 (0.10)
	Restrepo (median)	0.00 (31.62)	0.56 (0.09)	2.4 (0.17)	0.00 (∞)	0.54 (0.09)	2.05 (0.15)	0.00 (∞)	0.64 (0.09)	1.72 (0.12)
	Restrepo (stable)	0.01 (5.66)	0.62 (0.23)	2.28 (0.23)	0.00 (15.29)	0.6 (0.22)	1.96 (0.19)	0.00 (∞)	0.70 (0.20)	1.70 (0.13)
	DCAC (base)	0.01 (6.98)	0.71 (0.07)	2.06 (0.22)	0.00 (∞)	0.63 (0.09)	1.92 (0.15)	0.00 (∞)	0.62 (0.11)	1.73 (0.11)
	DCAC (fixed)	0.05 (7.78)	0.70 (0.07)	2.09 (0.22)	0.00 (∞)	0.59 (0.08)	1.97 (0.15)	0.00 (∞)	0.51 (0.07)	1.80 (0.12)
	DB-SRA (base)	0.52 (0.24)	0.89 (0.11)	1.00 (0.22)	0.44 (0.57)	1.01 (0.17)	1.00 (0.20)	0.37 (1.04)	1.25 (0.23)	1.26 (0.09)
	DB-SRA (projected)	0.65 (0.64)	0.96 (0.13)	0.85 (0.85)	0.37 (1.16)	1.13 (0.14)	1.07 (0.54)	0.26 (1.51)	1.31 (0.19)	1.32 (0.15)
	DB-SRA (fixed)	0.73 (0.39)	0.94 (0.13)	0.56 (0.83)	0.01 (5.75)	0.81 (0.09)	1.63 (0.20)	0.00 (∞)	0.62 (0.08)	1.73 (0.12)
Fully exploited	Median	0.40 (0.98)	0.86 (0.10)	1.19 (0.60)	0.55 (0.73)	0.95 (0.12)	0.9 (0.52)	0.99 (0.05)	1.37 (0.09)	0.69 (0.28)
	75% of median	0.03 (4.06)	0.68 (0.08)	2.10 (0.23)	0.04 (3.36)	0.75 (0.09)	1.49 (0.25)	0.65 (0.61)	1.03 (0.09)	0.96 (0.20)
	50% of median	0.00 (31.62)	0.46 (0.09)	2.60 (0.15)	0.00 (∞)	0.5 (0.09)	1.93 (0.16)	0.00 (17.73)	0.69 (0.09)	1.22 (0.15)
	ORCS θ_1 (median)	0.19 (0.87)	0.86 (0.12)	1.47 (0.27)	0.09 (2.13)	0.83 (0.12)	1.36 (0.21)	0.42 (0.99)	0.96 (0.09)	1.02 (0.18)
	ORCS θ_1 (75th %)	0.41 (0.53)	0.90 (0.12)	1.15 (0.35)	0.42 (0.86)	0.94 (0.11)	1.04 (0.34)	0.92 (0.24)	1.16 (0.08)	0.86 (0.23)
	ORCS θ_2 (median)	0.11 (1.1)	0.82 (0.12)	1.65 (0.23)	0.01 (5.91)	0.73 (0.14)	1.59 (0.16)	0.00 (15.14)	0.69 (0.11)	1.21 (0.15)
	ORCS θ_2 (75th %)	0.26 (0.77)	0.88 (0.12)	1.35 (0.31)	0.08 (2.28)	0.82 (0.13)	1.38 (0.22)	0.10 (2.53)	0.84 (0.09)	1.11 (0.17)
	ORCS θ_3 (median)	0.06 (1.37)	0.77 (0.13)	1.83 (0.21)	0.00 (∞)	0.62 (0.16)	1.78 (0.12)	0.00 (∞)	0.43 (0.16)	1.40 (0.13)
	ORCS θ_3 (75th %)	0.15 (0.99)	0.84 (0.12)	1.53 (0.27)	0.00 (6.77)	0.69 (0.15)	1.65 (0.14)	0.00 (∞)	0.52 (0.13)	1.35 (0.14)
	Restrepo (median)	0.01 (6.00)	0.65 (0.09)	2.15 (0.20)	0.00 (11.61)	0.71 (0.11)	1.60 (0.20)	0.17 (1.41)	0.89 (0.16)	1.07 (0.12)
	Restrepo (stable)	0.04 (2.78)	0.68 (0.19)	2.03 (0.26)	0.04 (3.31)	0.73 (0.19)	1.53 (0.23)	0.27 (1.28)	0.90 (0.21)	1.06 (0.15)
	DCAC (base)	0.23 (1.38)	0.84 (0.08)	1.44 (0.45)	0.11 (2.14)	0.84 (0.08)	1.33 (0.27)	0.06 (3.10)	0.86 (0.09)	1.10 (0.15)
	DCAC (fixed)	0.25 (1.35)	0.83 (0.09)	1.43 (0.46)	0.14 (1.90)	0.83 (0.08)	1.32 (0.30)	0.11 (2.34)	0.85 (0.07)	1.09 (0.17)
	DB-SRA (base)	0.51 (0.24)	0.86 (0.12)	0.96 (0.22)	0.45 (0.59)	0.94 (0.13)	1.00 (0.18)	0.53 (0.76)	1.02 (0.19)	0.98 (0.10)
	DB-SRA (projected)	0.61 (0.65)	0.92 (0.13)	0.83 (0.75)	0.47 (0.87)	1.00 (0.15)	0.96 (0.49)	0.54 (0.79)	1.00 (0.17)	0.98 (0.16)
	DB-SRA (fixed)	0.99 (0.04)	0.85 (0.12)	0.33 (0.19)	0.75 (0.46)	0.96 (0.17)	0.68 (0.69)	0.57 (0.73)	0.99 (0.07)	0.98 (0.20)
Overexploited	Median	0.72 (0.49)	0.76 (0.14)	0.79 (0.80)	0.98 (0.09)	0.48 (0.35)	0.13 (1.50)	1.00 (0.00)	0.69 (0.21)	0.03 (0.50)
	75% of median	0.23 (1.23)	0.66 (0.09)	1.88 (0.36)	0.76 (0.42)	0.58 (0.29)	0.53 (0.97)	1.00 (0.00)	0.77 (0.23)	0.07 (0.93)
	50% of median	0.03 (2.07)	0.45 (0.09)	2.58 (0.16)	0.20 (1.15)	0.49 (0.13)	1.38 (0.33)	1.00 (0.03)	0.78 (0.11)	0.31 (0.52)
	ORCS θ_1 (median)	0.15 (0.94)	0.79 (0.12)	1.52 (0.27)	0.26 (1.00)	0.68 (0.15)	1.11 (0.29)	0.97 (0.08)	0.69 (0.20)	0.45 (0.18)
	ORCS θ_1 (75th %)	0.35 (0.6)	0.85 (0.12)	1.15 (0.35)	0.75 (0.31)	0.75 (0.21)	0.66 (0.49)	1.00 (0.00)	0.79 (0.14)	0.30 (0.41)
	ORCS θ_2 (median)	0.10 (1.11)	0.75 (0.13)	1.67 (0.24)	0.06 (1.96)	0.59 (0.16)	1.36 (0.22)	0.64 (0.3)	0.60 (0.21)	0.56 (0.15)
	ORCS θ_2 (75th %)	0.23 (0.81)	0.82 (0.12)	1.35 (0.31)	0.40 (0.74)	0.71 (0.14)	0.97 (0.33)	0.961 (0.08)	0.67 (0.19)	0.46 (0.18)
	ORCS θ_3 (median)	0.06 (1.45)	0.70 (0.14)	1.84 (0.20)	0.01 (3.90)	0.49 (0.18)	1.61 (0.16)	0.02 (4.14)	0.40 (0.17)	0.72 (0.17)
	ORCS θ_3 (75th %)	0.15 (0.97)	0.78 (0.13)	1.52 (0.27)	0.07 (1.81)	0.60 (0.14)	1.35 (0.24)	0.41 (0.61)	0.52 (0.17)	0.63 (0.17)
	Restrepo (median)	0.01 (3.81)	0.59 (0.10)	2.18 (0.20)	0.01 (3.28)	0.57 (0.14)	1.45 (0.20)	0.626 (0.31)	0.60 (0.21)	0.56 (0.15)
	Restrepo (stable)	0.03 (2.87)	0.58 (0.23)	2.15 (0.27)	0.07 (2.85)	0.52 (0.28)	1.50 (0.27)	0.50 (0.82)	0.56 (0.29)	0.58 (0.25)
	DCAC (base)	0.61 (0.61)	0.76 (0.13)	0.99 (0.70)	0.93 (0.21)	0.55 (0.35)	0.27 (1.34)	1.00 (0.00)	0.83 (0.16)	0.19 (0.69)
	DCAC (fixed)	0.65 (0.55)	0.76 (0.13)	0.92 (0.76)	0.96 (0.15)	0.51 (0.36)	0.19 (1.52)	1.00 (0.00)	0.81 (0.21)	0.11 (0.88)
	DB-SRA (base)	0.44 (0.25)	0.73 (0.13)	0.96 (0.22)	0.24 (0.80)	0.67 (0.15)	1.04 (0.16)	0.42 (0.83)	0.55 (0.20)	0.60 (0.16)
	DB-SRA (projected)	0.15 (1.88)	0.88 (0.13)	1.69 (0.39)	0.22 (1.53)	0.77 (0.16)	1.17 (0.35)	0.56 (0.73)	0.53 (0.19)	0.60 (0.19)
	DB-SRA (fixed)	0.99 (0.01)	0.77 (0.13)	0.33 (0.20)	1.00 (0.01)	0.44 (0.27)	0.08 (0.84)	1.00 (0.00)	0.75 (0.24)	0.06 (0.98)

TABLE A.2. Means and coefficients of variation (in parentheses) for the performance measures calculated for all control rules for the biased run across all of the life history and exploitation history scenarios explored. Results are omitted for control rules that did not require stock classification (the median catch, 75% of the median, and 50% of median) as well as for those that had an assumed fixed stock abundance across years (DCAC and DB-SRA with assumed biomass of 40% of S_0). See Table A.1 for additional details.

		Fast			Medium			Slow		
Harvest pressure	Control rule	Overfishing probability	C/MSY	S/S_{MSY}	Overfishing probability	C/MSY	S/S_{MSY}	Overfishing probability	C/MSY	S/S_{MSY}
Fully exploited	ORCS θ_1 (median)	0.91 (0.12)	0.85 (0.15)	0.45 (0.55)	0.99 (0.02)	0.80 (0.23)	0.16 (0.85)	1.00 (0.00)	1.55 (0.13)	0.37 (0.35)
	ORCS θ_1 (75th %)	0.98 (0.06)	0.83 (0.14)	0.34 (0.39)	1.00 (0.00)	0.72 (0.20)	0.1 (0.51)	1.00 (0.00)	1.57 (0.14)	0.20 (0.56)
	ORCS θ_2 (median)	0.83 (0.19)	0.87 (0.15)	0.6 (0.56)	0.95 (0.14)	0.94 (0.20)	0.41 (0.70)	0.99 (0.05)	1.33 (0.1)	0.70 (0.28)
	ORCS θ_2 (75th %)	0.95 (0.09)	0.84 (0.15)	0.39 (0.53)	0.99 (0.02)	0.81 (0.23)	0.17 (0.84)	1.00 (0.00)	1.49 (0.12)	0.51 (0.30)
	ORCS θ_3 (median)	0.70 (0.28)	0.89 (0.14)	0.80 (0.51)	0.50 (0.72)	0.95 (0.10)	0.98 (0.38)	0.08 (2.82)	0.83 (0.08)	1.11 (0.17)
	ORCS θ_3 (75th %)	0.88 (0.15)	0.86 (0.15)	0.52 (0.56)	0.87 (0.26)	0.97 (0.17)	0.57 (0.61)	0.56 (0.75)	1.00 (0.08)	0.98 (0.20)
	Restrepo (median)	0.02 (3.76)	0.68 (0.08)	2.08 (0.21)	0.04 (3.45)	0.75 (0.09)	1.50 (0.24)	0.65 (0.60)	1.03 (0.08)	0.96 (0.20)
	Restrepo (stable)	0.13 (2.01)	0.71 (0.19)	1.88 (0.37)	0.15 (2.01)	0.77 (0.19)	1.43 (0.34)	0.61 (0.73)	1.06 (0.20)	0.92 (0.26)
	DCAC (base)	0.29 (1.18)	0.85 (0.09)	1.33 (0.49)	0.19 (1.54)	0.88 (0.09)	1.21 (0.28)	0.42 (0.96)	0.97 (0.10)	1.01 (0.16)
	DB-SRA (projected)	0.87 (0.32)	0.84 (0.14)	0.51 (0.91)	0.94 (0.20)	0.84 (0.20)	0.31 (1.23)	1.00 (0.00)	1.53 (0.16)	0.45 (0.41)
	DB-SRA (base)	0.70 (0.15)	0.90 (0.13)	0.70 (0.25)	0.93 (0.09)	0.95 (0.15)	0.54 (0.26)	1.00 (0.00)	1.32 (0.16)	0.64 (0.13)
Overexploited	ORCS θ_1 (median)	0.87 (0.16)	0.79 (0.17)	0.49 (0.59)	0.99 (0.04)	0.56 (0.35)	0.17 (1.03)	1.00 (0.00)	0.79 (0.20)	0.08 (0.89)
	ORCS θ_1 (75th %)	0.97 (0.06)	0.77 (0.15)	0.35 (0.41)	1.00 (0.00)	0.44 (0.28)	0.08 (0.50)	1.00 (0.00)	0.70 (0.19)	0.03 (0.43)
	ORCS θ_2 (median)	0.76 (0.23)	0.83 (0.16)	0.64 (0.54)	0.93 (0.13)	0.68 (0.29)	0.37 (0.76)	1.00 (0.00)	0.82 (0.15)	0.27 (0.46)
	ORCS θ_2 (75th %)	0.93 (0.11)	0.79 (0.16)	0.42 (0.51)	1.00 (0.01)	0.52 (0.35)	0.13 (0.93)	1.00 (0.00)	0.80 (0.20)	0.09 (0.86)
	ORCS θ_3 (median)	0.60 (0.36)	0.84 (0.15)	0.83 (0.51)	0.64 (0.45)	0.74 (0.17)	0.77 (0.43)	0.84 (0.18)	0.66 (0.21)	0.50 (0.15)
	ORCS θ_3 (75th %)	0.84 (0.19)	0.81 (0.17)	0.53 (0.59)	0.95 (0.09)	0.67 (0.31)	0.33 (0.77)	1.00 (0.00)	0.74 (0.16)	0.39 (0.25)
	Restrepo (median)	0.07 (1.72)	0.63 (0.10)	2.10 (0.22)	0.42 (0.77)	0.65 (0.15)	1.01 (0.38)	1.00 (0.00)	0.81 (0.14)	0.29 (0.46)
	Restrepo (stable)	0.13 (1.90)	0.61 (0.23)	2.05 (0.34)	0.35 (1.16)	0.56 (0.27)	1.12 (0.52)	0.95 (0.17)	0.73 (0.22)	0.34 (0.60)
	DCAC (base)	0.62 (0.57)	0.76 (0.14)	0.98 (0.70)	0.95 (0.16)	0.55 (0.37)	0.24 (1.31)	1.00 (0.00)	0.85 (0.17)	0.18 (0.69)
	DB-SRA (projected)	0.45 (0.94)	0.76 (0.12)	1.20 (0.64)	0.77 (0.43)	0.68 (0.22)	0.59 (0.82)	1.00 (0.03)	0.78 (0.18)	0.36 (0.32)
	DB-SRA (base)	0.61 (0.17)	0.86 (0.13)	0.73 (0.25)	0.90 (0.11)	0.81 (0.17)	0.61 (0.23)	1.00 (0.00)	0.68 (0.18)	0.44 (0.15)