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ARTICLE

An evaluation of acceptable biological catch (ABC) harvest control rules designed to limit overfishing

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Abstract: In this paper we developed a simulation model to evaluate a range of acceptable biological catch (ABC) control rules to determine their relative performance at achieving common fishery management objectives. We explored a range of scenarios to determine robustness of a control rule to different situations and found that across scenarios the control rules that used a buffer to account for scientific uncertainty when setting the ABC were able to limit the frequency of overfishing. Modest buffers when setting the ABC were generally effective at limiting overfishing, but larger buffers resulted in higher average biomass, similar long-term benefits to the fishery (high yield, low variability in yield), more rapid recovery of depleted populations, and a lower risk of the population being overfished, and these results were robust to the level of uncertainty in the assessment model estimates. In addition, fixing the ABC over the interval between assessments and having a short interval between assessments was generally more effective at meeting management objectives than using projections and having a long assessment interval.

Résumé : Nous avons développé un modèle de simulation pour évaluer différentes règles de contrôle de la quantité pêchée permise après étude biologique (ABC) afin de déterminer leur efficacité relative en ce qui concerne l'atteinte d'objectifs communs de gestion des pêches. Nous avons exploré différents scénarios afin d'établir la robustesse des différentes règles de contrôle dans différentes situations et constaté que, pour l'ensemble des scénarios, les règles de contrôle qui font appel à un tampon pour tenir compte de l'incertitude scientifique dans l'établissement de l'ABC sont en mesure de restreindre la fréquence de surpêche. Si l'intégration de tampons modestes dans l'établissement de l'ABC permet généralement de limiter la surpêche, des tampons plus importants se traduisent par une plus grande biomasse moyenne, des bénéfices à long terme pour la pêche semblables (haut rendement, faible variabilité sur le terrain), le rétablissement plus rapide de populations décimées et un plus faible risque de surpêche de la population, ces résultats étant robustes étant donné le degré d'incertitude dans les estimations découlant du modèle d'évaluation. En outre, l'atteinte des objectifs de gestion est généralement plus facile si l'ABC est établie sur l'intervalle entre les évaluations et si cet intervalle est court que si des projections sont utilisées et si l'intervalle entre les évaluations est long. [Traduit par la Rédaction]

Introduction

Uncertainty is an integral part of fisheries management, whether resulting from our lack of knowledge of and variation in either the biology of the species that is targeted or the response of the fishery itself to regulation. The importance of these two sources of uncertainty, scientific and management, may vary among systems and among the approach to management (single-species, multispecies, or ecosystem-based approaches), but they are ever present. Because it is likely that not all management tools are equally robust to uncertainty, it is important to understand how the performance of alternative fishery management tools responds to differing levels of uncertainty so that managers may adopt approaches with appropriate levels of precaution.

In the US, recent changes in federal fisheries legislation have required fisheries managers to explicitly consider uncertainty when setting harvest limits. The Magnuson–Stevens Fishery Conservation and Management Reauthorization Act of 2006 (MSFCMRA) aims to maintain healthy US fisheries by, among other things, limiting overfishing (NMFS 2006). In the revised National Standard 1 under the MSFCMRA, the Scientific and Statistical Committees (SSCs) of each of the eight regional management councils have been tasked with recommending acceptable biological catch (ABC) levels. Moreover, National Standard 1 requires that scientific uncertainty be used to guide the selection of an ABC by achieving a specific, acceptable probability of overfishing (≤50%; Federal Register 2009). Importantly, the ABCs recommended by the SSCs ultimately constrain the annual catch limit (ACL) set by the regional fishery management councils, as they cannot recommend a catch level above the ABC. Many control rules to manage fisheries have been developed and tested (reviewed in Deroba and Bence 2008), yet few of these satisfy the desired properties of the revised MSFCMRA. In particular, achieving a specified probability of overfishing has generally not been an explicit criterion for control rules. Overfishing occurs for a stock when the harvest rate, F, in a given year exceeds the limit rate that defines overfishing (F_{lim}), and managers try to achieve a desired harvest rate ($\leq F_{\mathrm{lim}}$) by setting a catch limit. For stocks where stock assessments are possible (i.e., data-rich), the overfishing limit (OFL) is the estimated catch achieved by fishing at the harvest rate F_{lim}, and it is calculated using estimates for the terminal year of the assessment model and often from stochastic stock projections for a number of years in the future to produce a distribution for possible OFL values over time (Shertzer et al. 2008). However, capturing all of the possible sources of uncertainty inherent in the estimation and projection processes is likely impossible, and as a result

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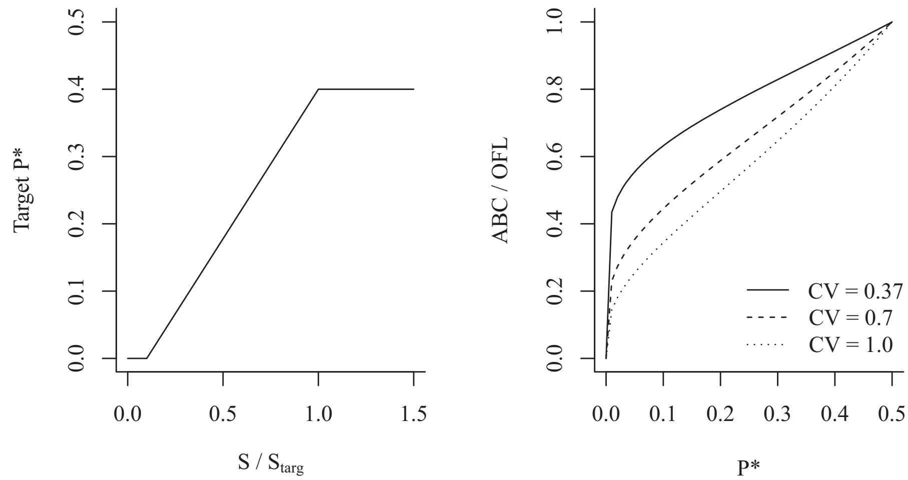
Fig. 1. (Left) An example biomass-dependent P^* control rule, where the target P^* declines linearly from a specified maximum as the estimated spawning biomass S falls below the S_{targ} target level. In this example, the specified maximum target $P^* = 0.4$, and the target $P^* = 0$ (and the fishery is closed) when $S/S_{\mathrm{targ}} \leq 0.1$. (Right) Buffer size (acceptable biological catch/overfishing limit ratio: ABC/OFL) as a function of the target P^* ($\leq$0.5) and the assumed CV of the distribution for the OFL.



the uncertainty in the OFL is likely underestimated. For example, Ralston et al. (2011) found that the uncertainty in population biomass estimated within an assessment is often less than the uncertainty in biomass estimated among repeated assessments for the same stock.

One approach to account for this underestimation of uncertainty is to estimate the uncertainty in the OFL distribution outside the stock assessment. In several regions of the US, the point estimate of the OFL in a given year is treated as the median of a lognormal distribution, with a coefficient of variation (CV) that is specified by the SSC (PFMC 2010; MAFMC 2011). Given a distribution for the OFL, the next step is to select a target probability of overfishing, or P^* (Shertzer et al. 2008). For example, with a P^* of 0.4, the 40th percentile of the OFL distribution would be selected as the ABC. Using this process, the buffer size between the ABC and the OFL increases as the target P^* decreases and as the assumed CV of the OFL distribution increases. The target P^* can be fixed or vary with estimated biomass in the control rule, but by having the target P^* decrease with decreasing biomass, the buffer between the ABC and the OFL will be greater for populations with low biomass (Fig. 1).

The P^* approach outlined above may be applied differently for different stocks, depending on the circumstances. For example, larger CVs may be selected for stocks with greater uncertainty in the assessment, such as a strong retrospective pattern (Mohn 1999). Alternatively, the target P^* might be fixed for a stock, or it could be varied in response to the changes in the estimated biomass, with a lower P^* for a more depleted stock (Fig. 1). Alternative approaches for implementing the P^* approach have been adopted across the US, but their relative performance has not been tested.

Here we developed a simulation model to evaluate a range of ABC control rules to determine their relative performance for achieving common fishery management objectives. We explored scenarios to determine robustness of a control rule to different situations, including a range of life histories, exploitation histories, and data and stock assessment quality. For each control rule, we measured performance in a variety of ways. One of the primary goals of the MSFCMRA is to avoid overfishing, and how well a control rule achieves this objective is thus an essential measure of its utility. But, ABC control rules must also balance the trade-offs between risk and reward, because minimizing the probability of overfishing may also minimize yield (Little et al. 2016). Thus, control rule performance was evaluated with respect to its impact on other fishery metrics in addition to the probability of overfishing.

Methods

To test the performance of alternative ABC control rules, we conducted a management strategy evaluation (MSE) over a range of scenarios encompassing different life histories, exploitation histories, and levels of assessment quality. The simulation model is a closed-loop MSE (Butterworth and Punt 1999; Milner-Gulland et al. 2010) with three main components (operating, assessment, and management submodels) and was developed in AD Model Builder (Fournier et al. 2011). The foundation of the MSE simulation is the operating model, which determines the population dynamics of the stock and how data are generated. Data generated in the operating model are based on the true state of the population with some specified amount of observation error. The operating model generated data on fishery harvests, as well as a fishery-independent index of abundance. These data were then used in the assessment model to estimate stock status and biological reference points. The assessment model was a statistical catch at age (SCAA) model (Fournier and Archibald 1982), and output from the assessment was used in the management model to determine the catch limit using a particular ABC control rule. The catch limit estimated in the management model was removed from the population, without implementation error, and the simulation loop continued for a set number of years. We did not include implementation error because our goal was to test performance of ABC control rules and not what the impacts are of going over or under the specified ABC. This process was repeated 1000 times stochastically for each scenario (e.g., life history, assessment quality, recruitment variability) to account for the variability in the population dynamics, data generation, and assessment estimation. At the end of each run, the true and estimated values summarizing the population and fishery dynamics were stored and used to evaluate the ability of a control rule to meet multiple management objectives.

Operating, assessment, and management models

The population dynamics in the operating model followed an age-structured model, with the equations governing these dynamics presented in Table 1, definitions of the variables in Table 2, and parameters defined in Table 3. Equations used in the model are referenced by their number in Table 1, such that the formula for calculating recruitment, for example, is referred to as eq. T1.1. The population began at unfished equilibrium abundance in year 1 of the simulation.

Table 1. Equations governing the population and data-generating dynamics in the operating model.

Equation		Description
Population, life history, and fishing dynamics		
T1.1	$R(t) = \dfrac{S(t - a_R)}{\alpha + \beta S(t - a_R)} e^{\varepsilon_R - 0.5\sigma_R^2}$	Stock–recruit relationship
	$\alpha = \dfrac{S_0(1 - h)}{4hR_0}, \quad \beta = \dfrac{5h - 1}{4hR_0}$	
	$\varepsilon_R(t) = \rho_R \varepsilon_R(t - 1) + \sqrt{1 - \rho_R^2}\varphi_R(t)$	
	$\varphi_R(t) \sim \mathrm{N}(0, \sigma_R^2)$	
T1.2	$S(t) = \sum_a m(a)w(a)N(a, t)$	Spawning biomass
T1.3	$N(a, t) = \begin{cases} R(t), & a = a_R \\ N(a - 1, t - 1)e^{-Z(a-1,t-1)}, & a_R < a < a_{max} \\ N(a - 1, t - 1)e^{-Z(a-1,t-1)} + N(a, t - 1)e^{-Z(a,t-1)}, & a = a_{max} \end{cases}$	Numerical abundance at age
T1.4	$Z(a, t) = M(t) + s(a, t)F(t)$	Total mortality
T1.5	$M(t) = \overline{M} e^{\varepsilon_M(t) - 0.5\sigma_M^2}$	Time-varying natural mortality
	$\varepsilon_M(t) = \rho_M \varepsilon_M(t - 1) + \sqrt{1 - \rho_M^2}\varphi_M(t)$	
	$\varphi_M(t) \sim \mathrm{N}(0, \sigma_M^2)$	
T1.6	$s(a, t) = \dfrac{1}{1 + e^{-\frac{a - s_{50}(t)}{s_{slope}}}}$	Selectivity at age in fishery or survey, with time-varying selectivity only in the fishery
	$s_{50\%}(t) = \bar{s}_{50\%} e^{\varepsilon_s(t) - 0.5\sigma_s^2}$	
	$\varepsilon_s(t) = \rho_s \varepsilon_s(t - 1) + \sqrt{1 - \rho_s^2}\varphi_s(t)$	
	$\varphi_s(t) \sim \mathrm{N}(0, \sigma_s^2)$	
T1.7	$L(a) = L_\infty[1 - e^{-k(a - a_0)}]$	Length at age
T1.8	$w(a) = bL(a)^c$	Mass at length
T1.9	$m(a) = \dfrac{1}{1 + e^{-\frac{a - m_{50}}{m_{slope}}}}$	Maturity at age
T1.10	$C(a, t) = \dfrac{s(a, t)F(t)}{Z(a, t)} w(a)N(a, t)[1 - e^{-Z(a,t)}]$	Annual catch at age and total catch
	$C(t) = \sum_a C(a, t)$	
Data-generating dynamics		
T1.11	$C_{obs}(t) = C(t)^{\varepsilon_C(t) - 0.5\sigma_C^2}$	Observed catch
	$\varepsilon_C(t) \sim \mathrm{N}(0, \sigma_C^2)$	
T1.12	$I(a, t) = q(t)s_s(a)N(a, t)$	True index of abundance
	$I(t) = \sum_a I(a, t)$	
	$q(t) = qe^{\varepsilon_q(t) - 0.5\sigma_q^2}$	
	$\varepsilon_q(t) \sim \mathrm{N}(0, \sigma_q^2)$	
T1.13	$I_{obs}(t) = I(t)^{\varepsilon_I(t) - 0.5\sigma_I^2}$	Observed index of abundance
	$\varepsilon_I(t) \sim \mathrm{N}(0, \sigma_I^2)$	
T1.14	$\boldsymbol{p}_{obs}(t) = \dfrac{1}{n}\boldsymbol{\Theta}(t)$	Observed vector of proportion at age in fishery *f*
	$\boldsymbol{\Theta}(t) \sim \mathrm{Multinomial}(n, p(t))$	
	$\boldsymbol{p}(t) = \dfrac{1}{I(t)}[I(a_R, t), \ldots, I(a_{max}, t)]$	

Recruitment followed the Beverton–Holt stock–recruit relationship, with bias-corrected, lognormally distributed, and autocorrelated deviations (eq. T1.1). Parameters controlling the degree of autocorrelation and variability in recruitment (Table 3) were based on the recruitment meta-analysis of Thorson et al. (2014). Total spawning biomass in a given year was calculated by summing the product of the proportion mature, mass at age, and abundance at age over all recruited age classes (eq. T1.2). Annual abundance of recruited ages was determined from the abundance of that cohort the previous year, decreased by continuous natural and fishing mortality (eq. T1.3). Total mortality at age was the sum of fishing and natural mortality (eq. T1.4). Natural mortality was independent of age, but varied over time following an autocorrelated process on the log scale (eq. T1.5). Fishing mortality at age was the product of fishing intensity of fully selected ages and selectivity at age, which followed an autocorrelated process on the log scale. The model contained a single fishery with a logistic selectivity function. The selectivity ogive varied over time as the parameter that determines the age at 50% selectivity varies annually in an autocorrelated manner (eq. T1.6), as selectivity in a fishery

Table 2. Description of the index and state variables used in equations in the model (presented in Table 1).

Symbol	Description
Index variables	
t	Year
a	Age
State variables	
N	Numerical abundance
S	Spawning biomass (kg)
L	Length (cm)
w	Mass (kg)
m	Maturity (proportion)
s_s	Survey selectivity (proportion)
s_f	Fishery selectivity (proportion)
F	Fishing mortality rate (year^{-1})
M	Natural mortality rate
Z	Total mortality rate (year^{-1})
C	Total fishery catch (kg)
C_{obs}	Observed fishery catch (kg)
p_C	Proportions at age in catch
$p_{C,obs}$	Observed proportion at age in catch
I	Survey numerical index of abundance
I_{obs}	Observed survey numerical index of abundance
q	Survey catchability
p_I	Proportions at age in survey
$p_{I,obs}$	Observed proportion at age in survey

Note: Parameter descriptions and values used are presented in Table 3.

can vary in response to changing regulations, fishing practices, or changes in growth, although the source for the changes was not modeled explicitly.

Mass at age was an allometric function of length at age, which followed a von Bertalanffy growth function (eqs. T1.7 and T1.8). The proportion mature at age was calculated using a logistic function (eq. T1.9). Length, mass, and maturity at age were fixed for a given species life history. Catch was calculated using the Baranov catch equation (Quinn and Deriso 1999; eq. T1.10).

Each model run was divided into two periods, the initial and management periods, covering 80 and 50 years, respectively. In the initial period, the population started in an equilibrium state and remained unfished for the first 50 years to allow for variability in biomass and age structure (due to recruitment only) at the start of fishing. In year 51 of the initial period, a single fishery developed during the next first 30 years following a fixed pattern of total fishing mortality, where F increased linearly for 15 years (until year 65) and was constant at its peak value for the remainder of the initial period. The combination of peak fishing intensity ($F = 0.5 \times F_{MSY}$, $1.0 \times F_{MSY}$, or $2.5 \times F_{MSY}$ for the light, moderate, or heavy exploitation scenarios, respectively), realized patterns of recruitment, fishery selectivity, and natural mortality during this period determined the abundance and age structure of the population at the start of the management period. The management period began in year 81, and the population was first assessed using 20 years of data generated during the initial period, starting in year 60, and with a 1-year lag between the last year of the data collected and when the assessment was done. Thus, the time series of catch and survey data did not cover the entire history of the fishery. The management period continued for 50 years to allow evaluation of the long-term effects of a given control rule, with stock assessments occurring every 2 years.

We assumed that a full catch history was not available for the assessment model as is common in the eastern US. The data used in the assessment were the fishery catch (both total and proportions at age) and a fishery-independent index of abundance (both total and proportions at age). These data sets were generated by applying observation error to the true values using lognormal errors for the total index and catch and multinomial distributions for the age compositions (eqs. T1.10–T1.14). The amount of observation error in the generation of the data was varied to explore the interactions between data quality and uncertainty in the assessment estimates.

The time series of catch and survey data were input into the SCAA model to estimate the abundance at age, fishing mortality rates in each year, and reference points for management. The estimated parameters were the abundance at age in the first year of the SCAA, recruitments and fishing mortality rates (across years), fishery selectivity parameters, survey selectivity parameters, and survey catchability. The SCAA used a maximum likelihood approach to estimate the parameters. Survey catchability and age at 50% selectivity in the fishery are assumed constant over time in the assessment model, even though they were varied with time in the operating model. Natural mortality was assumed to be constant over age and time at the mean value for the given life history (Table 3). All other required SCAA inputs (i.e., maturity and mass at age) are set to the true values specified in the operating model. The SCAA model also estimated the spawning potential ratio (SPR)-based reference points to determine stock status and target catch, because these are commonly used as proxies for MSY-based reference points due to the difficulties in estimating stock–recruit relationships needed for calculating MSY-based reference points (e.g., NEFSC 2002). We explored two SPR-based fishing mortality rates as the limit rate that defines overfishing ($F_{lim} = F_{35\%}$ and $F_{45\%}$) for all life histories, because they are within the range of commonly used values in the US. For example, the Pacific Fishery Management Council uses between $F_{30\%}$ and $F_{50\%}$ as the limit that defines overfishing for its groundfish species (PFMC 2015). The spawning biomass reference point was calculated by multiplying the spawning stock biomass-per-recruit by the mean estimate of recruitment over the time series (NEFSC 2002; Haltuch et al. 2008). Because maturity and mass at age were fixed at the true values, the SPR-based reference points varied across assessments based on the estimated fishery selectivity and the estimated mean recruitment.

For each life history we ran MSE simulations for two steepness values (0.6 and 0.85). We selected these values because they are representative of the range identified by Myers et al. (1999) for a number of Families (interquartile range at the Family level between 0.56 and 0.85). Punt et al. (2008) showed that the target SPR% is tightly correlated with the steepness of the stock–recruitment relationship, such that selecting a particular SPR% for a stock implies a certain level of steepness. Our steepness values do not perfectly match the target SPR%, such that the $F_{X\%} \neq F_{MSY}$. When $F_{lim} = F_{45\%}$, F_{lim} is close to the true F_{MSY} level for a steepness of 0.6, but is lower than F_{MSY} for a steepness of 0.85. Conversely, when $F_{lim} = F_{35\%}$, F_{lim} is close to the true F_{MSY} for a steepness of 0.85, but is higher than F_{MSY} when steepness is 0.6 ($F_{35\%}$, $F_{45\%}$, and F_{MSY} values are listed in Table 3). Thus, we are exploring the impact of defining overfishing with F_{lim} close to, below, and above F_{MSY}.

In the management model, a harvest control rule was applied using the estimated biomass projected 1 year past the terminal year and the F_{lim} from the assessment model to determine the ABC using the specified control rule. The projected biomass was calculated using the terminal abundance at age, fixed mass at age, assumed M and estimated F at age in the terminal year, with recruitment assumed equal to the mean level over the previous 10 years. Under the baseline model runs the ABC was constant for the interval between assessments (2 years), but we also explored the effects of using projections to set year-specific ABCs for the 2-year interval and over a 5-year interval. When projections were used, the same deterministic approach was used to calculate abundance at age in the projected year, assuming $F = F_{lim}$ in all years after the terminal year. Note that this approach ignores the changes in abundance that might occur by setting the ABC < OFL, which would result in $F < F_{lim}$ with accurate estimates of abundance. As a result, the deterministic projections provided more

Table 3. Parameter values used in the model and the biological reference points (BRPs) derived from the parameters.

A. Life-history-invariant parameters.

Parameter	Description	Value
σ_R	Standard deviation of stock–recruit relationship	0.77, 1.25
ρ_R	Autocorrelation in recruitment	0, 0.44
σ_M	Standard deviation of time-varying M	0.15
ρ_M	Autocorrelation in M	0.3, 0.9
σ_s	Standard deviation of age at 50% selectivity	0.1
ρ_s	Autocorrelation in selectivity	0.3, 0.9
σ_C	Standard deviation of catch estimates	0.15
σ_I	Standard deviation of survey estimates	0.29, 0.63
$\bar{q}$	Mean catchability in survey	5×10^{-5}
σ_q	Standard deviation of catchability random walk	0.05
n_C	Effective sample size of the catch	200, 50
n_I	Effective sample size of the survey	200, 50
h	Steepness	0.60, 0.85
SPR_{lim}	Spawning potential ratio that defines overfishing	0.35, 0.45

B. Life-history parameters for three life histories.

Parameter	Description	Short-lived	Medium-lived	Long-lived
a_R	Age at recruitment (to population)	1	2	5
a_{max}	Maximum age	7	12	20
$\bar{M}$	Mean natural mortality rate	0.4	0.2	0.1
R_0	Virgin recruitment	1×10^9	1×10^9	1×10^9
S_0	Unfished spawning biomass ($\times10^6$ t)	2.27	4.46	9.07
a_0	Age at length = 0	0	0	0
L_∞	Maximum length	90	90	90
k	Growth rate	0.27	0.13	0.07
b	Length–mass scalar	3.0×10^{-6}	3.0×10^{-6}	3.0×10^{-6}
c	Length–mass exponent	3	3	3
m_{50}	Age at 50% maturity	1.75	3.5	7
$\bar{s}_{f,50\%}$	Mean age at 50% selectivity in fishery	1.75	3.5	7
$\bar{s}_{s,50\%}$	Mean age at 50% selectivity in survey	1.3	2.6	5.3
m_{slope}	Slope of maturity function	1	1	1
s_{slope}	Slope of selectivity function (both survey and fishery)	1	1	1

C. BRPs.

Parameter	Description	Short-lived	Medium-lived	Long-lived
MSY	Maximum sustainable yield ($\times10^6$ t) for h = 0.6 and 0.85	0.16, 0.20	1.77, 2.31	2.03, 2.68
S_{MSY}	Spawning biomass that produces MSY ($\times10^6$ t) for h = 0.6 and 0.85	0.86, 0.75	1.64, 1.41	3.24, 2.70
F_{MSY}	F that produces MSY for h = 0.6 and 0.85	0.25, 0.38	0.13, 0.20	0.07, 0.11
$F_{X\%}$	F that results in an SPR of X% of unfished level (45%, 35%)	0.28, 0.39	0.13, 0.19	0.07, 0.11

Note: Life-history-invariant parameters are presented at the top, with multiple values explored for the assessments with "low" and "high" uncertainty. Multiple BRPs are shown for each life history due to the different values of steepness (h) of the stock–recruit relationship.

conservative estimates of the OFL because the F associated with the OFL is higher than the F associated with the ABC in most cases. The estimated ABC is then removed from the population the following year, and the resulting F is calculated using the Baranov catch equation (Quinn and Deriso 1999).

Control rules

We explored the performance of eight ABC control rules (Table 4). One control rule was used as a baseline to test the effect of using no buffer when setting the ABC (ABC = OFL). The other seven control rules applied different buffer sizes, with one doing so by setting a target F at 75% of F_{lim} (based on the work of Restrepo et al. 1998 and generally used for New England groundfish stocks not undergoing rebuilding; NEFMC 2009). The remaining six control rules were variations of the P^* approach (Shertzer et al. 2008), in which the distribution for the OFL was assumed to follow a lognormal distribution with different CVs. We explored three variations of the P^* approach with a fixed target P^* (i.e., P^* was independent of biomass) of 0.4 for CVs of 0.37, 0.7, and 1.0 and three variations with the same CVs but with a biomass-dependent target P^* that declines as biomass falls below S_{targ}, where P^* = 0 at

Table 4. Acceptable biological catch (ABC) control rules explored in this analysis.

Control rule name code	Target F	Target P^*	Assumed CV of OFL distribution	Buffer (ABC < OFL)
OFL	F_{lim}	—	—	No
75% of F_{lim}	0.75 F_{lim}	—	—	Yes
P^* threshold (0.37)	—	Varies	0.37	Yes
P^* threshold (0.70)	—	Varies	0.70	Yes
P^* threshold (1.00)	—	Varies	1.00	Yes
P^* fixed (0.37)	—	0.40	0.37	Yes
P^* fixed (0.70)	—	0.40	0.70	Yes
P^* fixed (1.00)	—	0.40	1.00	Yes

Note: P^* refers to a target probability of overfishing. The overfishing limit (OFL) is the catch achieved by fishing at the limit fishing mortality reference point (F_{lim}) given the projected abundance at age in the assessment model. Many of the control rules differed in the coefficient of variation (CV) assumed for a lognormal distribution about the OFL. The control rules that varied P^* did so using a biomass-dependent rule (Fig. 1).

$S/S_{targ} \leq 0.1$ (Fig. 1). The basis for the selection of a CV of 0.37 is Ralston et al. (2011), who conducted a meta-analysis of assessment error for stocks managed by the PFMC (note, however, that the PFMC uses a target P^* of 0.45 for many of their stocks; PFMC 2015). A CV of 1.0 was chosen because this value is used by the Mid-Atlantic Fishery Management Council (MAFMC) in their P^* control rule (MAFMC 2011), and 0.7 was chosen as an intermediate value. We selected a maximum target P^* of 0.4 because this is the value used by the MAFMC in their control rule and also because the differences in buffers between the ABC and OFL are small across the range of CVs we explored for target P^* values above 0.4 (Fig. 1).

Parameterization and model runs

We ran the model over a range of scenarios to identify factors affecting the performance of ABC control rules. For the baseline model runs we explored eight control rules over two levels of assessment uncertainty (low or high), two levels of recruitment variability (σ_R), two levels of recruitment autocorrelation (ρ_R), two steepness values (h), two SPR-based fishing mortality limits, three exploitation scenarios (light, moderate, and heavy historical fishing intensity), and three life histories (short-, medium-, and long-lived; see Table 3 for parameter values). We explored these different scenarios to determine whether control rule performance was robust across the different scenarios or performance was scenario-dependent (see Performance measures section below for how we quantified performance). For example, it is possible that the less conservative control rules do not provide sufficient buffers in cases of high assessment uncertainty, while control rules with larger buffers may be overly conservative in cases of low assessment uncertainty. Assessment uncertainty will be affected by the quality of the data going into the model, but it may also be influenced by the intensity of historical fishing pressure, as Wiedenmann et al. (2015) showed greater accuracy in assessment estimates for heavily exploited species, likely due to greater contrast in the data. Historical fishing pressure may interact with the life history of the species, as fast-growing, short-lived species may be more prone to collapse in cases of intense fishing (Pinsky and Byler 2015), while slow-growing, long-lived species will likely require longer time to rebuild if they become overfished (Benson et al. 2016), and these effects may be more or less severe depending on the variability and autocorrelation of recruitment events and how productive a population is at low biomass levels. We therefore evaluated control rule performance across these scenarios in a factorial manner, for a total of 288 scenario runs for each of the eight control rules, resulting in 2304 runs (each with 1000 stochastic iterations) in the baseline model.

The different life histories explored were short-lived, medium-lived, and long-lived (Table 3). The long-lived life history had relatively slow growth, late maturation, and later age at entry into the fishery. In contrast, the short-lived life history had rapid growth, early maturation, and early age at entry in the fishery. The medium-lived life history is between the long- and short-lived life histories. We used different maximum ages (assumed to be a plus group) for each life history (7, 12, and 20 years for the short-, medium- and long-lived life histories, respectively). Additionally, the mean natural mortality differed with life history, being higher for the short-lived life history. All other life history parameters were either fixed across life histories (L_∞ and the length–mass parameters b and c) or determined from the other parameters. The mean natural mortality rate was used to determine the growth rate, $k = M/1.5$, and age at 50% maturity, $m_{50\%} = M/1.4$ (Charnov and Berrigan 1991; Charnov et al. 1993; Frisk et al. 2001), which then determined the initial age at 50% selectivity in the fishery ($s_{f,50\%} = m_{50\%}$). For the survey, age at 50% selectivity was lower than that of the fishery, $s_{s,50\%} = 0.75\ s_{f,50\%}$, and this value was rounded down to the nearest integer to determine the age at recruitment to the population, $a_R = \lfloor s_{s,50\%} \rfloor$.

For the assessment uncertainty scenarios, we modeled "low" and "high" uncertainty cases where several factors were adjusted to affect assessment performance (Table 3). For each case we varied the CV of the observation error in the survey (lower for the good scenario), the number of samples collected to generate age-structured data (higher for the good case), and the amount of autocorrelation in the time-varying parameters (lower in the good scenario). Much of the error in poorly performing models is likely caused by poor structural assumptions (e.g., Deroba and Schueller 2013). We attempted to replicate poor assumptions by allowing fishery selectivity and natural mortality to vary over time in the operating model, but they were assumed to be constant over time in the assessment model. In addition, we explored two levels of recruitment variability and two levels of autocorrelation in recruitment, resulting in four total runs. The levels of variability and autocorrelation were based on the meta-analysis of Thorson et al. (2014).

In the baseline runs, the ABC was based solely on the most recent assessment. Large changes in the estimated abundance between assessments, either due to process variability (e.g., a strong year-class) or assessment uncertainty, result in large changes in the ABC. One alternative approach we explored to reduce the variability the ABC, often a concern of stakeholders, was calculating a weighted average between the current estimate ($ABC_{cur}(t)$) and the estimated ABC from the final year of the previous assessment period (ABC_{prev}). We assumed equal weight when averaging the ABC, such that $ABC(t) = 0.5 \times ABC_{cur}(t) + 0.5 \times ABC_{prev}$. We limited our analysis on averaging of the ABC to a subset of runs to reduce the amount of model output. As in the baseline runs, we explored two levels of assessment uncertainty and two levels of σ_R, but only for the medium-lived life history with $\rho_R = 0.44$, steepness = 0.85, and $F_{lim} = F_{35\%}$ and only for three control rules (OFL, P^* fixed with an assumed CV = 0.37, and the threshold P^* with an assumed CV = 0.7; Table 4). The effect of averaging the ABC likely interacts with the interval between assessments, and whether or not projections are done, so in addition to an assessment interval of 2 years, we explored a 5-year interval, both fixing the ABC over the interval or using projections to calculate a time-varying ABC between assessments.

Performance measures

At the end of each run, a range of performance measures was calculated to summarize the ability of each control rule to meet a suite of management objectives (Table 5). The primary performance measures we used to assess control rule performance were population size, fishery yield, variability in fishery yield, frequency of overfishing, magnitude of overfishing when it occurs, proportion of years below the stock size threshold ($S < 0.5S_{targ}$; calculated using all runs and also excluding runs where biomass started below the threshold), and years required to rebuild the population (calculated as the number of years for a population starting with below $0.5S_{targ}$ to increase to a level at or above S_{targ}). For most performance measures, we used the mean over a portion of the management period, such as the first 5 years or final 20 years, or over the entire management period. The probability of overfishing was calculated as the proportion of years during the management period in which F exceeded F_{lim}. We summarized year-to-year variability in fishery yield by calculating the average of the absolute value (AAV; Punt 2003) of difference in yield from one year to the next across the management period.

Results

A full summary of the model results across all combinations of runs is not feasible, and we provide a summary of some of the main conclusions here (more detailed output of the performance measures by scenarios can be found in Tables S1–S5 of the online

Table 5. Performance measures calculated for different time periods at the end of each model run.

Performance measure	Description	Time period
Long-term biomass	Mean spawning biomass relative to S_{MSY}	Final 20 years
Probability of being overfished	Proportion of years overfished ($S < 0.5S_{\mathrm{targ}}$)	All years
Initial catch	Mean catch relative to MSY	First 5 years
Long-term catch	Mean catch relative to MSY	Final 20 years
Catch AAV	Relative interannual variation in catch	All years
Overfishing magnitude	Mean fishing mortality rate relative to F_{lim} when overfishing occurs	Years when $F > F_{\mathrm{lim}}$
Probability of overfishing (P_{OF})	Proportion of years when $F > F_{\mathrm{lim}}$	All years
Rebuilding years	No. of years to rebuild (heavily exploited runs only)	From first year to year when $S > S_{\mathrm{targ}}$

Note: The AAV of the catch is calculated following Punt (2003) as AAV $= \sum_{t>1} C(t) - C(t-1) / \sum_t C(t)$.

Supplemental material[1]). Across scenarios, control rules that applied a buffer between the ABC and the OFL resulted in a probability of overfishing (P_{OF}) below the 0.5 threshold (above which overfishing is more likely to occur than not) for most model runs (Fig. 2). All control rules that accounted for uncertainty (i.e., ABC < OFL) were able to limit overfishing ($P_{\mathrm{OF}} < 0.5$), but the P_{OF} varied widely across control rules and depended on the particular scenario in many cases. In general, the interquartile range (IQR) in estimates of P_{OF} was below the 0.5 threshold, such that fewer than 25% of the runs resulted in frequent overfishing for most control rules. Only the OFL and the fixed P^* approach with the smallest buffer (assumed CV = 0.37) control rules had an IQR extend above 0.5 across scenarios, and the fixed P^* control rule with moderately sized buffer (assumed CV of 0.7) resulted in an IQR above 0.5 only for the runs with high recruitment variability (Fig. 2).

As might be expected, the median P_{OF} increased going from the long-lived to the short-lived life history (Fig. 2, top left panel), while the variability in P_{OF} increased going from the short- to the long-lived life histories. Overfishing occurred more frequently for the lightly exploited scenarios and was comparable between the moderate and heavy exploitation scenarios for the nonthreshold-based control rules (although variability in P_{OF} was reduced for the heavy exploitation scenario). Overfishing was less frequent for the heavy exploitation scenario for the threshold-based control rules that increased the buffer between the ABC and the OFL when biomass falls below S_{targ}. P_{OF} also varied by control rule for the different levels of steepness, with comparable or higher median P_{OF} (with greater variability) for the threshold-based control rules with a higher steepness and lower, less variable P_{OF} for the nonthreshold-based control rules with higher steepness (Fig. 2, middle left panel). In contrast, threshold-based control rules resulted in comparable rates of overfishing between the low and high assessment uncertainty runs, while the remaining control rules had higher rates of overfishing with greater assessment uncertainty. Increased recruitment variability increased the frequency of overfishing across control rules, while autocorrelation in recruitment had no effect (Fig. 2; Table 6).

For each run we calculated the mean yield to the fishery in the first 5 years of control rule implementation (called the "initial" yield), and the final 20 years (called the "long-term" yield). Threshold-based control rules had lower initial yield, with the lowest initial catches occurring with the largest assumed CVs and for the heavy exploitation scenarios (between 19% and 25% of MSY compared with 29% to 31% of MSY for the nonthreshold control rules; Table 6). In contrast, long-term yield was similar across exploitation scenarios and was slightly higher for the threshold control rules (66% of MSY compared with 64% of MSY for non-threshold options that buffered away from the OFL). Increasing the CV for the P^* approach did not alter the interannual variability in the catches (AAV), but AAV was slightly higher for the threshold-based control rules and for the light exploitation scenario (Table 6).

Mean spawning biomass (relative to S_{MSY}) in the final 20 years varied by control rule, with higher mean biomass for the more conservative control rules (larger buffers resulting from higher assumed CVs in the OFL distribution and threshold-based for a given CV), but was similar across exploitation scenarios for a given control rule (Table 6). We also calculated the proportion of years that biomass fell below the overfished threshold ($<0.5S_{\mathrm{targ}}$) as a measure of the probability of low biomass. The median probability of low biomass was greater than 0 only for the OFL and fixed P^* with CV = 0.37 control rules, with median proportions of 0.1 and 0.02 (Table 6). More conservative control rules also resulted in more rapid rebuilding of overexploited populations, with larger buffers (higher assumed CVs) decreasing rebuilding time by roughly 1 year, on average. Using a threshold-based control rule with a larger buffer at low population sizes reduced the rebuilding time by 2 to 3 years on average for a given assumed CV (Table 6).

The P_{OF} performance measure informs on how often overfishing occurs, but not on the magnitude of overfishing (i.e., how far F was above F_{lim}). We therefore calculated the mean F/F_{lim} in years when overfishing occurred. The magnitude of overfishing was generally lowest for the moderate exploitation scenario and highest for the heavy exploitation scenario across control rules (Table 6). This result is largely due to reduced future recruitment relative to the mean value used to calculate the ABC in the heavy exploitation scenario. For the nonthreshold control rules, the more conservative options reduced the magnitude of overfishing, whereas for the threshold-based control rules the magnitude of overfishing increased with the more conservative options.

Increased uncertainty in assessment estimates had predictable effects on the performance measures, resulting in a lower biomass, lower long-term yield, a greater proportion of years with low biomass, longer rebuilding times, more variable yield, and higher F/F_{lim} when overfishing occurred (Fig. 3). In general, the relative performance of the control rules was similar for both the low and high uncertainty scenarios. Interestingly, the differences in mean biomass between low and high assessment uncertainty was smaller for the threshold-based control rules (Fig. 3).

The effect that frequent overfishing has on long-term yield, as well as on the variability in yield, is shown in Fig. 4. The P_{OF} where yield is maximized depends on the steepness of the stock–recruit relationship and the target SPR. When the steepness and target SPR result in F_{lim} values close to the true F_{MSY} (h = 0.6 with SPR = 0.45 and h = 0.85 with SPR = 0.35), maximum long-term yield occurs at a P_{OF} between 0.4 and 0.45 and declines above a P_{OF} of 0.5. When $F_{\mathrm{lim}} > F_{\mathrm{MSY}}$ (h = 0.6 with SPR = 0.35), yield is maximized when P_{OF} = 0 and rapidly declines as P_{OF} increases. When $F_{\mathrm{lim}} < F_{\mathrm{MSY}}$ (h = 0.85 with SPR = 0.45), yield is highest at a $P_{\mathrm{OF}} \sim 0.6$,

[1]Supplementary data are available with the article through the journal Web site at http://nrcresearchpress.com/doi/suppl/10.1139/cjfas-2016-0381.

Fig. 2. Probability of overfishing (P_{OF}) across control rules for different life histories, exploitation histories, steepness values, assessment uncertainties, recruitment variability, and autocorrelation levels explored. The horizontal line at 0.5 represents the threshold where overfishing is more likely than not.

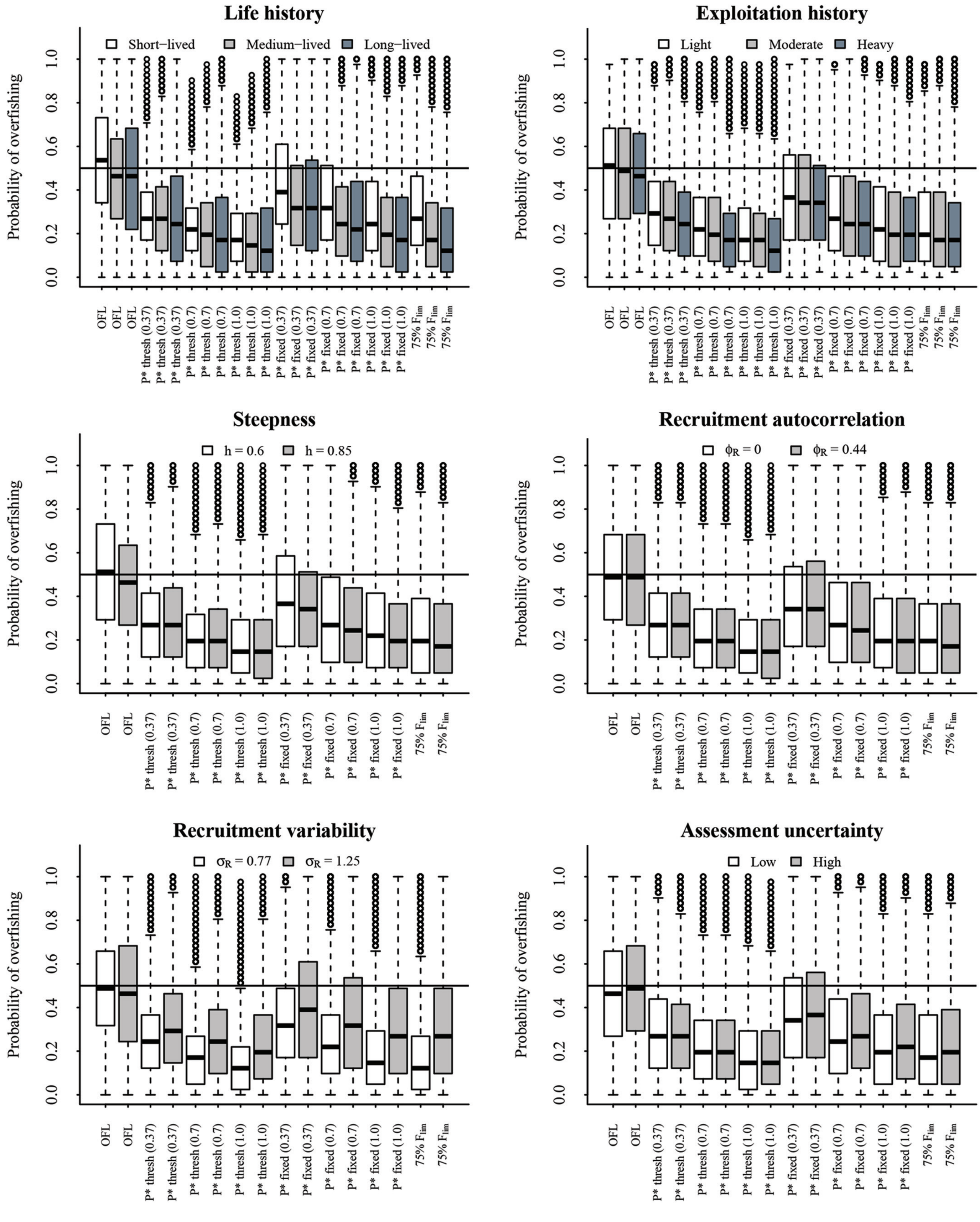


Table 6. Median performance measures across control rules and exploitation scenarios.

Control rule	Exploitation history	Long-term biomass (S/S_{MSY})	Prob. of overfishing (P_{OF})	Overfishing magnitude (F/F_{lim})	Initial catch (C/MSY)	Long-term catch (C/MSY)	Catch AAV	Rebuilding years	Prob. of low biomass ($S < 0.5S_{targ}$)
OFL	Light	0.63	0.51	1.61	1.08	0.66	0.16	—	0.12
	Moderate	0.62	0.49	1.45	0.69	0.65	0.13	—	0.07
	Heavy	0.63	0.46	1.55	0.33	0.58	0.13	16	0.20
	All	0.63	0.49	1.53	0.64	0.63	0.14	16	0.15
P^* threshold, CV = 0.37	Light	0.79	0.29	1.48	1.01	0.68	0.16	—	0
	Moderate	0.78	0.27	1.37	0.60	0.67	0.13	—	0
	Heavy	0.77	0.24	1.57	0.25	0.62	0.14	13	0.12
	All	0.78	0.27	1.48	0.56	0.66	0.14	13	0.07
P^* threshold, CV = 0.70	Light	0.87	0.22	1.43	0.95	0.68	0.16	—	0
	Moderate	0.85	0.20	1.35	0.55	0.67	0.14	—	0
	Heavy	0.84	0.17	1.64	0.22	0.62	0.14	12	0.12
	All	0.85	0.20	1.48	0.51	0.66	0.14	12	0.05
P^* threshold, CV = 1.00	Light	0.92	0.17	1.40	0.92	0.68	0.16	—	0
	Moderate	0.90	0.17	1.34	0.52	0.67	0.14	—	0
	Heavy	0.89	0.12	1.71	0.19	0.62	0.14	12	0.10
	All	0.90	0.15	1.49	0.48	0.66	0.14	12	0.05
P^* fixed, CV = 0.37	Light	0.72	0.37	1.49	1.01	0.67	0.15	—	0.02
	Moderate	0.72	0.34	1.37	0.64	0.66	0.12	—	0.02
	Heavy	0.72	0.34	1.54	0.31	0.59	0.12	15	0.17
	All	0.72	0.34	1.47	0.60	0.64	0.13	15	0.07
P^* fixed, CV = 0.70	Light	0.79	0.27	1.43	0.96	0.67	0.15	—	0
	Moderate	0.79	0.24	1.34	0.62	0.66	0.12	—	0
	Heavy	0.78	0.24	1.57	0.30	0.59	0.12	15	0.15
	All	0.79	0.27	1.46	0.57	0.64	0.13	15	0.10
P^* fixed, CV = 1.00	Light	0.84	0.22	1.40	0.92	0.67	0.14	—	0
	Moderate	0.83	0.20	1.33	0.60	0.66	0.12	—	0
	Heavy	0.83	0.20	1.62	0.29	0.59	0.12	14	0.12
	All	0.84	0.20	1.46	0.55	0.64	0.12	14	0.05
75% of F_{lim}	Light	0.86	0.20	1.41	0.91	0.67	0.14	—	0
	Moderate	0.85	0.17	1.34	0.59	0.65	0.12	—	0
	Heavy	0.85	0.17	1.67	0.29	0.59	0.12	14	0.12
	All	0.85	0.20	1.48	0.55	0.64	0.12	14	0.05

Note: For a given exploitation scenario, the median is calculated across all other scenarios (e.g., life histories, recruitment variability, etc.). "All" references when the different exploitation runs were aggregated to calculate the median for each performance measure. See Table 5 for specifics on the performance measures.

with a modest decrease in yield for P_{OF} above this level (Fig. 4). These differences result not only from where F_{lim} is relative to F_{MSY}, but also from the shape of the stochastic yield curve. Among life histories, yield is high across a wide range of F values around F_{MSY} when steepness is higher and declines more rapidly at high F values for the lower steepness (Fig. S1[1]). For all combinations of steepness and target SPR, variability in yield was lowest when $P_{OF} = 0$ and gradually increase with increasing P_{OF}. Interestingly, at higher P_{OF} (above 0.7), variability in yield rapidly increases when steepness is low, while it gradually decreases when steepness is high (Fig. 4).

Sensitivity runs

For the baseline model runs, the ABC calculated from a control rule was fixed for a 2-year interval between stock assessments. We evaluated setting the ABC using projections or fixing it over the interval and whether or not the ABC is a weighted average between the updated and previous assessments and how these different approaches interacted with the length of the assessment interval (2 or 5 years). Because of the large number of runs from the baseline analyses, these runs were conducted only for the medium life history using a subset of control rules (ABC = OFL, ABC set using the threshold P^* approach with an assumed CV for the OFL distribution of 0.7, and a fixed P^* of 0.4 with an assumed CV for the OFL of 0.37), and we focused only on the P_{OF}, long-term yield, and yield AAV performance measures. Fixing the ABC over the interval resulted in less frequent overfishing and less variable yield relative to runs using projections. Overfishing was also more frequent when the ABC was averaged using the previous and updated assessment, although this approach resulted in less variable yield compared with runs where the ABC was based solely on the updated assessment. The longer assessment interval also increased the frequency of overfishing and was exacerbated when using projections or averaging the ABC (Table 7).

Discussion

We evaluated alternative ABC harvest control rules over a range of scenarios to determine their effectiveness at achieving a suite of management objectives. An ideal control rule would limit overfishing, maintain or allow rebuilding to high stock biomass, and produce stable yields. Across the scenarios explored, the control rules that used a buffer when setting the ABC (<OFL) were able to limit the frequency of overfishing, with a probability of overfishing P_{OF} below the 0.5 threshold required for federal US management. On average, the more conservative control rules (larger buffers) resulted in a lower P_{OF} overall (often <0.3), high long-term biomass, similar or slightly higher long-term yield, similar variability in yield, fewer years with low biomass, and more rapid rebuilding compared with the less conservative control rules. The performance of the more conservative control rules was also robust to the different levels of assessment uncertainty we explored, such that the larger buffers performed as well or better than the smaller buffers, even when assessment uncertainty was low (i.e., they were not overly conservative). Thus, the more conservative control rules we explored appear well-suited to meet a range of long-term fisheries management objectives.

We explored eight control rules in this analysis, seven of which used a buffer when setting the ABC. The control rules that achieved the lowest P_{OF} explored in this analysis utilized the

Fig. 3. Median values for different performance measures across control rules explored for the low (solid line) and high (dashed line) assessment uncertainty runs. Median rebuilding years were calculated only for runs where the population started out overfished.

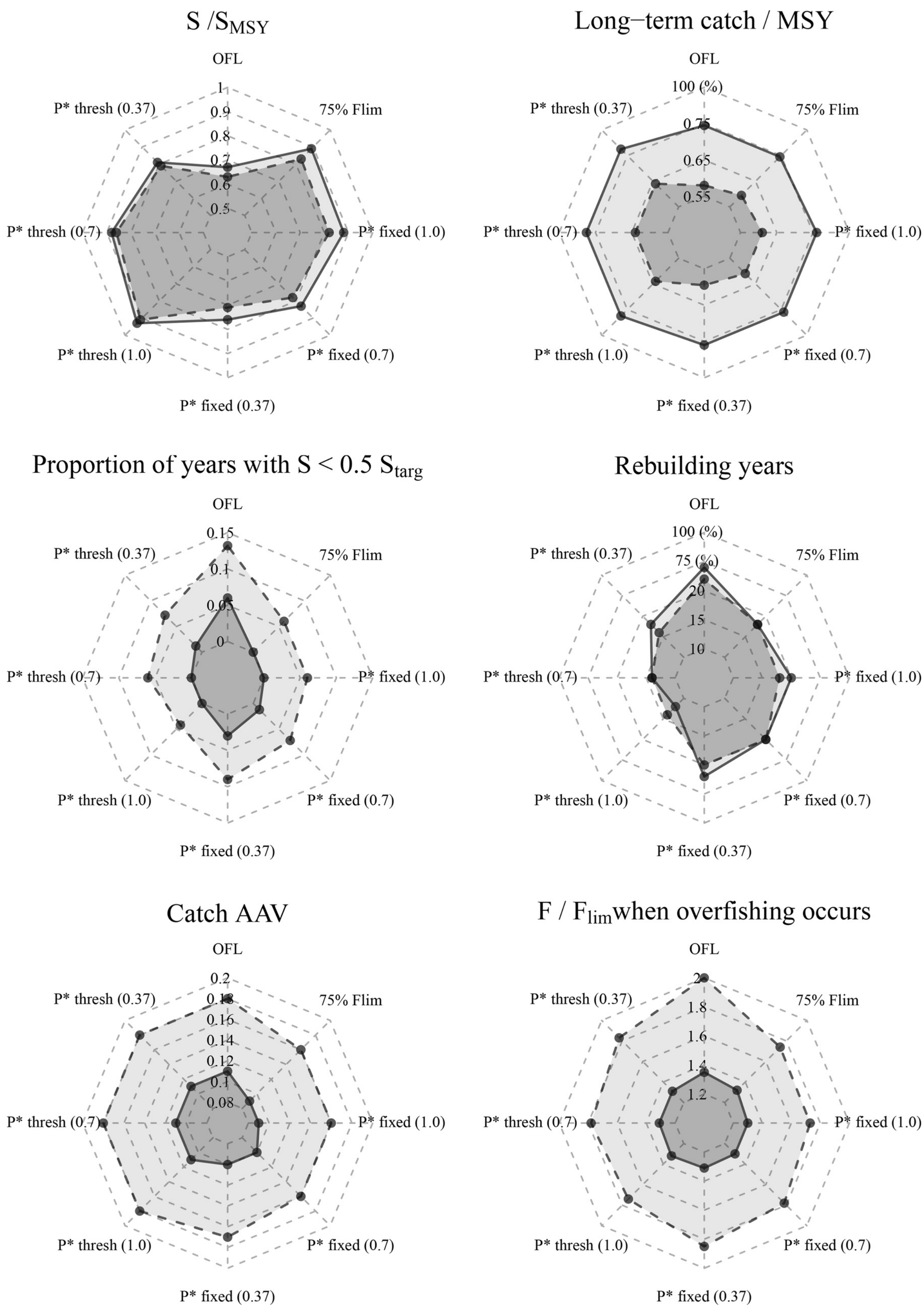


Fig. 4. The relationship between the mean long-term yield and P_{OF} (left) and mean catch variability (AAV) and P_{OF} (right) by the assumed steepness (h) of the stock–recruit relationship and target SPR used to set F_{lim}. The shaded region represents the density of results across all model runs, with darker regions representing more frequent model outcomes. Lines shown are the mean loess fit across all model runs for each combination of h and SPR. Thick and thin lines denote steepness (h = 0.85 and 0.6, respectively), and the solid and dashed lines denote the SPR limit (35% and 45%, respectively). The open circles on each line show where the loess fit for yield is maximized and AAV is minimized.

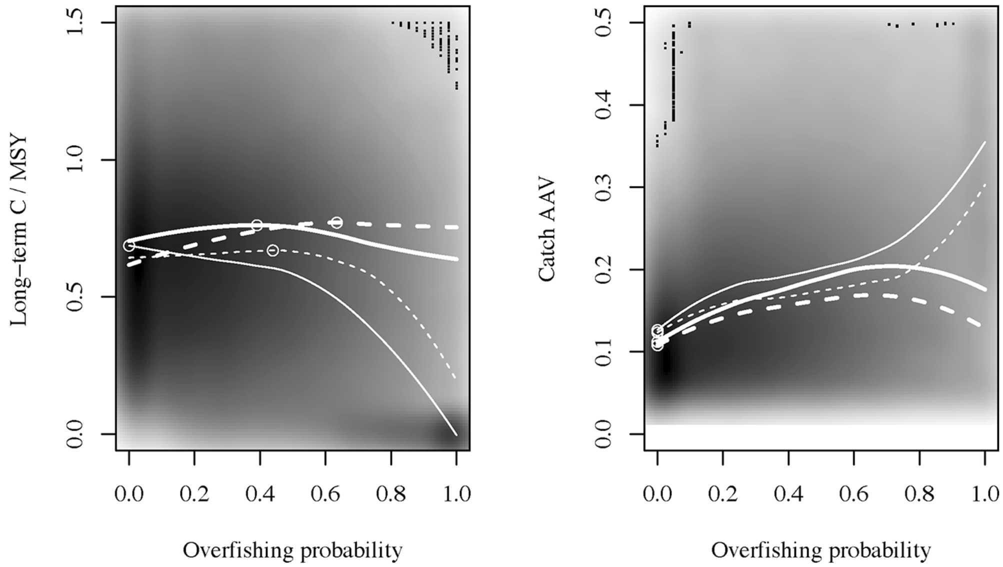


Table 7. Median overfishing probability (P_{OF}) and variability in catch (AAV) by exploitation history for the subset of control rules explored in the sensitivity runs using projections, a longer assessment interval, and a weighted averaging of the ABC for the medium-lived life history.

Control rule	Projections	ABC averaging	Assessment interval (years)	Prob. of overfishing (P_{OF})	Long-term catch (C/MSY)	Catch AAV
OFL	No	No	2	0.43	0.61	0.11
	No	No	5	0.47	0.57	0.08
	No	Yes	2	0.50	0.56	0.07
	No	Yes	5	0.60	0.51	0.05
	Yes	No	2	0.40	0.62	0.15
	Yes	No	5	0.50	0.55	0.11
	Yes	Yes	2	0.50	0.56	0.08
	Yes	Yes	5	0.60	0.49	0.06
P^* threshold, CV = 0.70	No	No	2	0.17	0.65	0.11
	No	No	5	0.20	0.63	0.08
	No	Yes	2	0.20	0.61	0.07
	No	Yes	5	0.27	0.59	0.05
	Yes	No	2	0.20	0.65	0.15
	Yes	No	5	0.20	0.62	0.11
	Yes	Yes	2	0.23	0.62	0.09
	Yes	Yes	5	0.27	0.59	0.06
P^* threshold, CV = 0.37	No	No	2	0.30	0.63	0.10
	No	No	5	0.33	0.59	0.07
	No	Yes	2	0.37	0.59	0.07
	No	Yes	5	0.47	0.56	0.04
	Yes	No	2	0.30	0.63	0.14
	Yes	No	5	0.33	0.58	0.10
	Yes	Yes	2	0.37	0.59	0.08
	Yes	Yes	5	0.47	0.55	0.06

biomass-dependent target P^* with the largest buffers (high assumed CVs for the OFL distribution). Additionally, the fixed P^* control rules with a CV of 0.7 and 1.0 and 75% of F_{lim} generally achieved P_{OF} at or below 0.3 for many of the scenarios. Our results agree with other studies that found biomass-based control rules were effective in maintaining high average yield while reducing the risk of low biomass (Punt et al. 2008; Irwin et al. 2008; Benson et al. 2016). Using a fixed P^* of 0.4 with CVs ≥0.37 or the approach using 75% of F_{lim} as the target F were also effective control rules for limiting overfishing, but often resulted in slightly lower long-term average yield than the threshold-based control rules.

Although the long-term yield (mean of the final 20 years of each run) of the more conservative control rules was similar to the less conservative control rules, the short-term effects on yield depended on the exploitation history. Yield during the first few years of control rule implementation was lower for the more conservative options, yet long-term yield was comparable across control rules that used buffers over the entire time period the control rule was applied. This was particularly apparent in the scenarios that began in an overexploited condition because the biomass-based control rules had the largest buffers to rebuild the population quickly. Beyond yield, there may be important, additional benefits to the more conservative options, such as more rapid rebuilding for overfished populations and higher long-term biomass.

One caveat to using more conservative control rules is that although overfishing was less frequent, when it did occur it was of a higher magnitude on average for the heavy exploitation scenarios compared with the less conservative control rules. One possible explanation is that there is some interaction between the pace of population growth and assessment uncertainty. Using the same operating and assessment model of this work, Wiedenmann et al. (2015) showed that variability in assessment estimates was higher when a harvest control rule was applied that caused larger changes in biomass over time and that autocorrelation in the error of assessment estimates was higher for short-lived, overfished stocks that increased in abundance. Another possibility is that the more rapid rebuilding of the threshold-based control rules increases the number of years with smaller buffers, although this mechanism only explains the slightly higher magnitude of overfishing between the threshold and nonthreshold options. Future work exploring the mechanisms behind this result is warranted.

Another caveat associated with the yield predictions for the conservative control rules is that they depend on how well the F_{lim} matches the steepness of the stock–recruit relationship. More conservative options had comparable or higher yield when F_{lim} was close to or above F_{MSY}, but when F_{lim} is below F_{MSY}, being too conservative can result in a considerable amount of forgone yield to the fishery (Little et al. 2016). Thorson et al. (2012) estimated that the stock size that would produce MSY was about 40% of the unfished level, which should correspond to F_{MSY} near $F_{40\%}$. This value is within the range we simulated in our study. Careful consideration of the interactions between the shape of the stochastic yield curve, plausible steepness values of the stock, and the SPR targets for a given stock is needed (if possible) when deciding on how conservative the control rule should be for that species. The control rules we explored here could also have an effect on the shape of the yield curve (Irwin et al. 2008), and future work will explore the yield curve shape across control rules.

ABCs must be set for a number of years in the future, depending on the length of the interval between stock assessments. Setting a fixed ABC in the future reduced the probability of overfishing, had comparable yield and lower variability in yield compared with using projections, both for the 2- and 5-year assessment intervals, and overfishing frequency was higher and yield lower for the longer (5-year) assessment interval, regardless of whether the ABC was fixed or based on projection. Using a weighted average of successive ABCs also resulted in a lower catch AAV, but a higher rate of overfishing and lower yield than the other methods. In the eastern US, projections are usually used to set catch limits for multiple years after an assessment, but our results suggest that fixing the ABC over the assessment interval may be more effective at achieving fishery objectives than using projections to set year-specific ABCs.

The control rules we explored that used buffers to set the ABC limited overfishing (P_{OF} < 0.5) across the range of sensitivity runs explored in this work, but there may be circumstances where their performance breaks down. For example, the size of the buffer needed to limit overfishing will depend on whether or not there may be bias in the assessment estimates. We included two scenarios of data quality that differed in the amount of observation and process error that generated the data sets, thereby affecting assessment accuracy, but these runs resulted in assessment estimates above and below the true values (i.e., variance but not bias). Assessment accuracy can degrade substantially if process uncertainties have trends over time (e.g., Wilberg and Bence 2006) or if the data are relatively uninformative about the population state (e.g., Bence et al. 1993). Frequent overestimation of biomass has been documented (Wiedenmann and Jensen 2015; Brooks and Legault 2016), and, in such cases, the buffers of the controls rules evaluated here may not be sufficient. For example, our analyses explored the 75% of F_{lim} control rule and found it to perform well across runs, and it was generally comparable to the fixed $P^* = 0.4$ approach with a CV between 0.7 and 1.0. The 75% of F_{lim} control rule has been used historically for many stocks in the New England groundfish complex (NEFMC 2009), but it has not been sufficient at limiting overfishing for many of these stocks, largely due to overestimation of terminal biomass (Wiedenmann and Jensen 2015). Accounting for estimation biases in assessment models is an important modification to consider in an MSE, and research into the sources and impacts of such biases is needed.

An additional source of error that we did not include in our simulations was implementation error, such that the specified ABC was removed from the population. We excluded implementation error from our models because our goal was to characterize ABC control rule performance rather than the performance of management for a given stock. For many fisheries, particularly those with large recreational sectors (e.g., Terceiro 2011), the ABC may frequently be exceeded by a large margin. There may also be interactions between the size of the ABC and the magnitude of implementation error, with larger overages occurring at low ABCs (Little et al. 2014). In such cases the control rules we explored would likely have resulted in greater P_{OF}, although it would depend on the pattern of implementation error. In federal US fisheries management, implementation error should be considered by managers when setting annual catch limits (ACL ≤ ABC), with larger buffers between the ACL and ABC when the error is large (Federal Register 2009). Because we were focused on the performance of ABC control rules, we did not consider implementation error in our model. Consideration of both factors in a broader analysis might reveal interesting patterns with respect to control rule performance, particularly if the goal is to test a management system for a specific fishery.

Another potential modification to the current model might be to add changes in stock productivity associated with a regime shift (Hare and Mantua 2000). MSE studies for species undergoing regime shifts have been conducted, although these studies generally focus on the development of specific control rules that include the effects of environmental covariates on recruitment and reference points (A'Mar et al. 2009). In general, attempts to account for changing environmental conditions in a harvest control rule result in greater variability in control rule performance, particularly when the projected changes do not occur (Punt et al. 2013). The control rules explored in this study do not attempt to account for changing environmental conditions, but control rules that do so may be important for stocks with well-understood linkages between stock productivity and climate variability.

Identifying harvest control rules that are robust to uncertainty is essential for effective fisheries management. This work showed that even modest buffers when setting the ABC are generally effective at limiting overfishing, in the sense that the limit fishing mortality rate is not frequently exceeded, but that more conservative control rules may result in higher average biomass, comparable yield long term, more rapid rebuilding, and lower risk of being overfished. Furthermore, it supports the notion that F_{MSY} (or proxy) be treated as a limit and not a target (Mace 2001). The results of this work may be used as a guide for managers in the selection of an appropriate ABC for their stock, and the flexible MSE framework developed here may be used to explore a wider range of control rules under different conditions or for particular case studies.

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References

A'Mar, Z.T., Punt, A.E., and Dorn, M.W. 2009. The evaluation of two management strategies for the Gulf of Alaska walleye pollock fishery under climate change. ICES J. Mar. Sci. **66**: 1614–1632. doi:10.1093/icesjms/fsp044.

Bence, J.R., Gordoa, A., and Hightower, J.E. 1993. Influence of age-selective surveys on the reliability of stock synthesis assessments. Can. J. Fish. Aquat. Sci. **50**(4): 827–840. doi:10.1139/f93-095.

Benson, A.J., Cooper, A.B., and Carruthers, T.R. 2016. An evaluation of rebuilding policies for U.S. fisheries. PLoS ONE, **11**(1): e0146278. doi:10.1371/journal.pone.0146278. PMID:26761442.

Brooks, E.N., and Legault, C.M. 2016. Retrospective forecasting – evaluating performance of stock projections for New England groundfish stock. Can. J. Fish Aquat. Sci. **73**(6): 935–950. doi:10.1139/cjfas-2015-0163.

Butterworth, D.S., and Punt, A.E. 1999. Experiences in the evaluation and implementation of management procedures. ICES J. Mar. Sci. **56**: 985–998. doi:10.1006/jmsc.1999.0532.

Charnov, E.L., and Berrigan, D. 1991. Dimensionless numbers and the assembly rules for life histories. Philos. Trans. R. Soc. B Biol. Sci. **332**: 41–48. doi:10.1098/rstb.1991.0031.

Charnov, E.L., Berrigan, D., and Shine, R. 1993. The *M*/*k* ratio is the same for fish and reptiles. Am. Nat. **142**: 707–711. doi:10.1086/285565. PMID:19425966.

Deroba, J.J., and Bence, J.R. 2008. A review of harvest policies: understanding relative performance of control rules. Fish. Res. **94**: 210–223. doi:10.1016/j.fishres.2008.01.003.

Deroba, J.J., and Schueller, A. 2013. Performance of stock assessments with misspecified age- and time-varying natural mortality. Fish. Res. **146**: 27–40. doi:10.1016/j.fishres.2013.03.015.

Federal Register. 2009. Magnuson–Stevens Act Provisions; Annual Catch Limits; National Standard Guidelines; final rule. 74:11, January 16. GPO, Washington, D.C. pp. 3178–3213.

Fournier, D. 2011. An introduction to AD Model Builder for use in nonlinear modeling and statistics. Version 10 [online]. Available from http://www.admb-project.org/docs/manuals/.

Fournier, D., and Archibald, C.P. 1982. A general theory for analyzing catch at age data. Can. J. Fish. Aquat. Sci. **39**(8): 1195–1207. doi:10.1139/f82-157.

Frisk, M.G., Miller, T.J., and Fogarty, M.J. 2001. Estimation and analysis of biological parameters in elasmobranch fishes: a comparative life history study. Can. J. Fish. Aquat. Sci. **58**(5): 969–981. doi:10.1139/f01-051.

Haltuch, M.A., Punt, A.E., and Dorn, M.W. 2008. Evaluating alternative estimators of fishery reference points. Fish. Res. **94**: 290–303. doi:10.1016/j.fishres.2008.01.008.

Hare, S.R., and Mantua, N.J. 2000. Empirical evidence for North Pacific regime shifts in 1977 and 1989. Prog. Oceanogr. **47**: 103–145. doi:10.1016/S0079-6611(00)00033-1.

Irwin, B.J., Wilberg, M.J., Bence, J.R., and Jones, M.L. 2008. Evaluating alternative harvest policies for yellow perch in southern Lake Michigan. Fish. Res. **94**: 267–281. doi:10.1016/j.fishres.2008.05.009.

Little, L.R., Parslow, J., Fay, G., Grafton, R.Q., Smith, A.D.M., Punt, A.E., and Tuck, G.N. 2014. Environmental derivatives, risk analysis, and conservation management. Conserv. Lett. **7**: 196–207. doi:10.1111/conl.12041.

Little, L.R., Punt, A.E., Dichmont, C.M., Dowling, N., Smith, D.C., Fulton, E., Sporcic, M., and Gorton, R.J. 2016. Decision trade-offs for cost-constrained fisheries management. ICES J. Mar. Sci. **73**: 494–502. doi:10.1093/icesjms/fsv206.

Mace, P.M. 2001. A new role for MSY in single-species and ecosystem approaches to fisheries stock assessment and management. Fish Fish. **2**: 2–32. doi:10.1046/j.1467-2979.2001.00033.x.

MAFMC. 2011. Omnibus Amendment [online]. Mid-Atlantic Fisheries Management Council. Available from www.nero.noaa.gov/nero/regs/frdoc/11/11OmnibusAmendmentEA&CommentsFinal.pdf [accessed November 2014].

Milner-Gulland, E.J., Arroyo, B., Bellard, C., Blanchard, J., Bunnefeld, N., Delibes-Mateo, M., Edwards, C., Nuno, A., Palazy, L., Reljic, S., Riera, P., and Skrbinsek, T. 2010. New directions in management strategy evaluation through cross-fertilization between fisheries science and terrestrial conservation. Biol. Lett. doi:10.1098/rsbl.2010.0588.

Mohn, R. 1999. The retrospective problem in sequential population analysis: an investigation using cod fishery and simulated data. ICES J. Mar. Sci. **56**: 473–488. doi:10.1006/jmsc.1999.0481.

Myers, R.A., Bowen, K.G., and Barrowman, N.J. 1999. Maximum reproductive rate of fish at low population sizes. Can. J. Fish. Aquat. Sci. **56**(12): 2404–2419. doi:10.1139/f99-201.

NEFMC. 2009. Final Amendment 16 to the Northeast Multispecies Fishery Management Plan [online]. New England Fishery Management Council. Available from http://www.nefsc.noaa.gov/publications/crd/crd0204/.

NEFSC. 2002. Final Report of the Working Group on Re-Evaluation of Biological Reference Points for New England Groundfish. US Department of Commerce, Northeast Fisheries Science Center, Reference Doc. 02-04. Available from http://www.nefsc.noaa.gov/nefsc/publications/ [accessed July 2010].

NMFS. 2006. Magnuson–Stevens Fishery Conservation and Management Reauthorization Act of 2006 [online]. National Marine Fisheries Service. Available from http://www.nmfs.noaa.gov/sfa/laws_policies/msa/.

PFMC. 2010. FMP amendment addresses National Standard 1 — annual catch limits, accountability measures [online]. Pacific Fishery Management Council. Pacific Council News, **34**(1): 5. Available from http://www.pcouncil.org/wp-content/uploads/Spring_2010_Newsletter.pdf.

PFMC. 2015. Harvest specifications and management measures for 2015–2016 and biennial periods thereafter [online]. Pacific Fishery Management Council. Available from http://www.pcouncil.org/groundfish/fishery-management-plan/fmp-amendment-24/.

Pinsky, M.L., and Byler, D. 2015. Fishing, fast growth and climate variability increase the risk of collapse. Proc. R. Soc. B Biol. Sci. **282**: 20151053. doi:10.1098/rspb.2015.1053.

Punt, A.E. 2003. Evaluating the efficacy of managing West Coast groundfish resources through simulations. Fish Bull. **101**: 860–873.

Punt, A.E., Dorn, M.W., and Haltuch, M.A. 2008. Evaluation of threshold management strategies for groundfish off the U.S. West Coast. Fish. Res. **94**: 251–266. doi:10.1016/j.fishres.2007.12.008.

Punt, A.E., A'mar, T., Bond, N.A., Butterworth, D.S., de Moor, C.L., De Oliveira, J.A.A., Haltuch, M.A., Hollowed, A.B., and Szuwalski, C. 2013. Fisheries management under climate and environmental uncertainty: control rules and performance simulation. ICES J. Mar. Sci. doi:10.1093/icesjms/fst057.

Quinn, T., and Deriso, R. 1999. Quantitative fish dynamics, Oxford University Press, New York.

Ralston, S., Punt, A.E., Hamel, O.S., DeVore, J.D., and Conser, R.J. 2011. A meta-analytic approach to quantifying scientific uncertainty in stock assessments. Fish. Bull. **109**: 217–231.

Restrepo, V.R., Thompson, G.G., Mace, P.M., Gabriel, W.L., Low, L.L., MacCall, A.D., Methot, R.D., Powers, J.E., Taylor, B.L., Wade, P.R., and Witzig, J.F. 1998. Technical guidance on the use of precautionary approaches to implementing National Standard 1 of the Magnuson–Stevens Fishery Conservation and Management Act. National Oceanic and Atmospheric Administration (US) Technical Memorandum NMFS-F/SPO-31.

Shertzer, K., Prager, M., and Williams, E. 2008. A probability-based approach to setting annual catch levels. Fish. Bull. **106**: 225–232.

Szuwalski, C.S., and Punt, A.E. 2012. Fisheries management for regime-based ecosystems: a management strategy evaluation for the snow crab fishery in the eastern Bering Sea. ICES J. Mar. Sci. doi:10.1093/icesjms/fss182.

Terceiro, M. 2011. The summer flounder chronicles II: new science, new controversy, 2001–2010. Rev. Fish Biol. Fish. **21**: 681–712. doi:10.1007/s11160-011-9207-9.

Thorson, J.T., Cope, J.M., Branch, T.A., and Jensen, O.P. 2012. Spawning biomass reference points for exploited marine fishes, incorporating taxonomic and body size information. Can. J. Fish. Aquat. Sci. **69**(9): 1556–1568. doi:10.1139/f2012-077.

Thorson, J.T., Jensen, O.P., and Zipkin, E.F. 2014. How variable is recruitment for exploited marine fishes? A hierarchical model for testing life history theory. Can. J. Fish. Aquat. Sci. **71**(7): 973–983. doi:10.1139/cjfas-2013-0645.

Wiedenmann, J., and Jensen, O. 2015. Catch advice methods for the Northeast multispecies fishery [online]. Final report to the New England Fishery Management Council. Available from http://s3.amazonaws.com/nefmc.org/2a-GF-Catch-Advice-Phase_3_report.pdf.

Wiedenmann, J., Wilberg, M.J., Sylvia, A., and Miller, T.J. 2015. Autocorrelated error in stock assessment estimates: implications for management strategy evaluation. Fish. Res. **172**: 325–334. doi:10.1016/j.fishres.2015.07.037.

Wilberg, M.J, and Bence, J.R. 2006. Performance of time-varying catchability estimators in statistical catch-at-age analysis. Can. J. Fish. Aquat. Sci. **63**(10): 2275–2285. doi:10.1139/f06-111.