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Developing Precautionary Reference Points for Fishery Management Using Robust Control Theory: Application to the Chesapeake Bay Blue Crab *Callinectes sapidus* Fishery

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Abstract

Most efforts to establish precautionary guidelines for fisheries management use essentially ad hoc impressions as to what constitutes conservative management. Such approaches, however, fail to take into account the magnitude of the uncertainty about particular systems. One alternative approach to precautionary management is robust control, in which decision makers attempt to maximize an outcome under the assumption that the conditions will be worse than expected. In this paper, we apply a robust optimization approach to estimate the maximum sustainable yield and other reference points for the Chesapeake Bay blue crab *Callinectes sapidus* fishery. This approach is relatively easy to implement in standard stock assessment models that use a maximum-likelihood approach to estimate model parameters. In addition, it has the advantage that a standard level of precaution can be chosen by decision makers and then applied to different fisheries with vastly different levels of data and analysis.

Precautionary management is one of the primary tenets of modern fisheries management (Pikitch et al. 2004; Francis et al. 2007). In practice, however, managers frequently lack a way to objectively characterize the extent to which their policies are precautionary, and efforts to establish precautionary guidelines rely on essentially ad hoc impressions as to what constitutes conservative management. Including a buffer between the target and limit reference points for uncertainty has become a priority in federal fisheries management (Shertzer et al. 2010) and has been recommended as good practice for some time (Caddy and Mahon 1995). While many regions of the world include precaution in management, the amount of precaution being applied is often based on ad hoc approaches. For example, Restrepo et al. (1998) recommended using a target fishing mortality rate of 75% of the limit fishing mortality rate. While approaches like this include precaution, it is unclear whether the degree of precaution is appropriate given the management objectives for the fishery. In some cases, such an approach may provide more precaution than is warranted, while in other cases it may provide too little.

In this paper we offer a new approach to developing precautionary reference points (either targets or thresholds) that applies insights from robust optimization to fisheries management. Under robust optimization, decision makers seek an optimal choice taking into account their uncertainty about important aspects of the underlying problem. Robust optimization has long been applied in engineering (Ben-Tal and Nemirovski 1998, 1999; Ben-Tal et al. 2009) and has been garnering attention among economists (Hansen et al. 2002, 2006; Hansen and Sargent 2007, 2011). Robust optimization methods typically posit a max–min optimization problem in which decision makers attempt to achieve the best possible outcome while acting as if the worst possible outcome will occur. In this way, the approach finds a maximum outcome (max) under a worst-case scenario (min).

There have been several applications of robust optimization to problems of natural resource management (Doyen and Béné 2003; Roseta-Palma and Xepapadeas 2004; Woodward and Shaw 2008; Gaivoronski et al. 2012; Chen et al. 2013; Woodward and Tomberlin 2014; A. Xepapadeas and C. Roseta-Palma, 2003 discussion paper University of Crete, Rethymnon, Greece, on instabilities and robust control in fisheries). There have, however, been two important limitations in the application of robust optimization to resource management to date. First, robust optimization methods have usually been applied to highly stylized models with analytical solutions (Woodward and Shaw 2008). While qualitatively informative, such an approach does not easily translate to applied problems such as fishery stock assessment. Second, while the idea of a worst-case scenario is clear in principle, in

practice the question of how bad things could actually become usually has no objective answer. Doole and Kingwell (2010) have provided a numerical application that addresses the first problem, and Woodward and Tomberlin (2014) address both problems in a fashion similar to that shown below but in a highly stylized setting.

In this paper we develop a data-driven approach to precautionary management using methods of robust optimization and apply that approach to an actual stock assessment model for the Chesapeake Bay blue crab *Callinectes sapidus* fishery. Blue crabs support the most valuable commercial fishery in the Chesapeake Bay, with an average dockside value of approximately US$88 million per year during 2010–2016. New target and limit fishing mortality rate reference points were adopted following the 2011 benchmark stock assessment (Miller et al. 2011). The fishery is currently managed with a target exploitation rate for adult females, which, following the recommendations in Restrepo et al. (1998), was arbitrarily set at 75% of the estimated exploitation rate that would achieve the maximum sustainable yield. The management agencies use a suite of regulations to achieve this target, including sex-specific minimum size limits, season limits, daily harvest limits, and other regulations (Huang et al. 2015).

METHODS

Robust optimization for fisheries management.— Traditionally, the formulation of management advice from stock assessments can be characterized as a multistep process (although the process may be condensed into a single modeling framework). First, the parameters of the fisheries biological model are estimated. Using these parameters, the analysts then estimate management reference points and the range of outcomes that might be achieved, often focusing on achieving maximum sustainable yield (MSY). The results often include the fishing mortality rate expected to achieve the MSY (F_{MSY}) or the exploitation rate that achieves that goal (μ_{MSY}), which can be used to set a target or limit total allowable catch (TAC). MSY-based reference points are often used to provide an upper threshold for fishing (Mace 2002), and ad hoc adjustments are often made to develop conservative or precautionary targets given the imperfect understanding of the system and its stochastic nature.

To formally consider the process of including a buffer between the target and the recommended upper fishing threshold, suppose that the population and fishery are described by a model with a vector of parameters, θ. The best estimate of these parameters, θ*, is often found by maximizing the likelihood function L, i.e., given the available data, $\theta^* = \arg\max L(\theta)$. Let $MSY(\theta^*)$ be the maximum sustainable yield given the set of parameters θ^*. This can be formally written as

$$MSY(\theta^*) = \max_C C \quad \text{s.t.} \quad E\dot{x} = f(x, C; \theta^*) \geq 0, \quad (1)$$

where C is a level of harvest from the fishery, $f(x, C; \theta^*)$ is the instantaneous growth rate after harvest, and $E\dot{x}$ refers to the expected rate of change in the fish stock, x, given the parameters θ^*.

Precautionary management is, in effect, an acknowledgement that it may not be appropriate to simply optimize expected benefits based on the single best estimate of θ^*. Robust optimization formally allows the consideration of uncertainty in parameter estimates. Max–min decision rules have a rich empirical and theoretical foundation and are a compelling way to operationalize robust optimization. Experimental studies dating back to Ellsberg (1961) have shown that individuals do not simply maximize expected benefits when they are uncertain about the underlying probability distribution, frequently adopting a max–min decision rule instead. More recently, Kameda et al. (2016) found that agents regularly adopt such a rule when making decisions that affect the welfare of others and in uncertain situations, and both of these factors are prevalent in the choices of fishery managers. Theoretically, Gilboa and Schmeidler (1989) ask what are rational choices under conditions of ambiguity (i.e., when decision makers are uncertain about the underlying probability distribution itself), and they find that a max–min decision rule can be consistent with axioms of rationality. This rule is frequently referred to as robust optimization (Hansen and Sargent 2007). Hence, a max–min decision rule is both consistent with observed human behavior and based on rational choice theory.

In the current context, robust optimization would involve setting the harvest (or harvest rate) target *as if* the decision makers faced parameter values from the set of possible values, Θ, that would give rise to the lowest level of sustainable yield. That is, for a fishery manager seeking to maximize sustainable yield, the robust optimization problem would be

$$MSY^R(\Theta) = \min_{\theta \in \Theta} \max_C C \quad \text{s.t.} \quad Ex = f(x, C; \theta) \geq 0 \; \forall \; \theta \in \Theta,$$
$$(2)$$

or, using equation (1),

$$MSY^R(\Theta) = \min_{\theta \in \Theta} MSY(\theta). \quad (3)$$

If θ^R is the parameter vector that solves (3), then $MSY(\theta^R) \leq MSY(\theta)$ for all $\theta \in \Theta$. Hence, the solution to (3) will satisfy the constraint in (2) requiring that the catch rate be at least sustainable for all $\theta \in \Theta$. The robust MSY, $MSY(\theta^R)$, could then be used to establish a target TAC or be used to calculate a target robust fishing

mortality rate. This policy rule would be appropriate if policy makers were not confident about the exact value of the parameters; they would thus set the TAC so that it would not exceed the MSY for any set of parameter values that fall within the allowable set, Θ.

The size of the set Θ, therefore, becomes a key choice. Nilim and El Ghaoui (2005) point out that the likelihood ratio around the estimated parameters for a system can be used to establish bounds on Θ based on levels of statistical confidence. This is similar to Hansen and Sargent's (2007:16) entropy measure, which seeks to identify a policy that is robust for the set of models that "are difficult to distinguish statistically from the approximating model with the amount of data at hand." For example, decision makers may choose a 90% precaution level under the belief that they cannot reject the hypothesis that the true parameters are anywhere within the 90% confidence interval. In this case, the set of parameter values (Θ) would be those that lie within a 90% confidence interval around θ^*. The precaution level, however, is not a probability statement about the chance that the policy will be robust; it is more conservative than that because it is derived from a max–min decision rule that maximizes the worst possible outcome from the set of parameter values that decision makers want to consider.

To implement this approach, we start with the likelihood ratio statistic for the parameter vector θ:

$$D = -2\ln(L(\theta)/L(\theta^*)), \quad (4)$$

the distribution of which is approximated by the chi-square distribution with one degree of freedom. For a given probability level α, therefore, the set of all admissible values of θ would be those with $D \leq \chi_\alpha^2$. Equivalently, a parameter vector θ lies within the admissible range if $L(\theta)/L(\theta^*) \geq \beta^\alpha$, where $\beta^\alpha = \exp(-\chi_\alpha^2/2)$. For example, θ lies within the 90% confidence interval around the likelihood-maximizing vector if $L(\theta)/L(\theta^*) \geq 0.258$.

Figure 1 shows graphically how robust optimization would work in the case of a model with a single normally distributed parameter or the marginal distribution of a derived quantity, θ. The estimate θ^* associated with maximum likelihood coincides with the peak of the likelihood function. A policy that treats θ^* as known is not precautionary, i.e., a 0% precaution level (PL). In the figure we assume that the left side of the distribution is the pessimistic side, i.e., if $\theta < \theta^*$, the MSY associated with this parameter value will be lower. Hence, the robust-optimal parameters for the 60% and 90% PLs are chosen from that side with $\theta^R(90\%) < \theta^R(60\%) < \theta^*$, and $MSY^R(90\%) < MSY^R(60\%) < MSY(0^*)$. Figure 2 presents the case of a model with two parameters, θ_1 and θ_2. The concentric ellipses show the range of parameters that lie within increasingly larger confidence intervals around the maximum-likelihood values, θ^*. The dotted lines show the
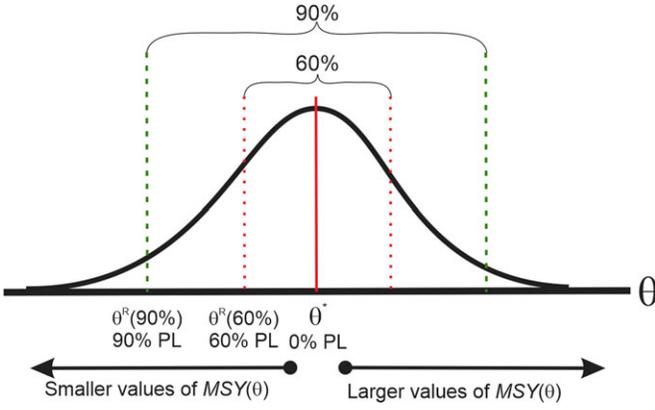
FIGURE 1. Example of robust estimates for the case of a single normally distributed parameter (θ), where θ^* is the maximum-likelihood estimate and $\theta^R(60\%)$ and $\theta^R(90\%)$ indicate the parameter values associated with 60% and 90% precaution levels (PLs), respectively. The brackets at the top of the figure indicate the width of a two-tailed confidence interval with the given percentage. MSY(θ) represents the values of the maximum sustainable yield conditional on θ.
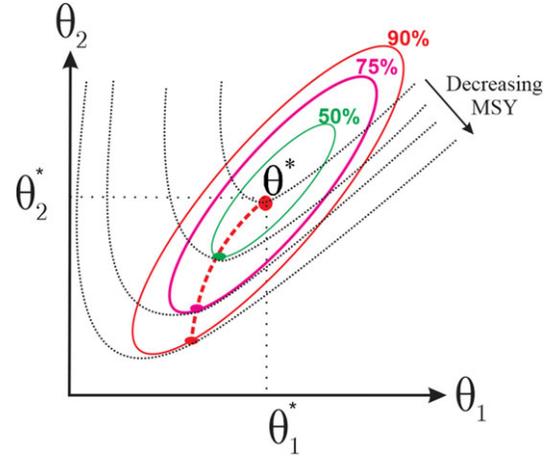

FIGURE 2. Example of robust optimization for the case of two parameters (θ_1 and θ_2), where $\theta = (\theta_1^* \theta_2^*)$ are the maximum-likelihood estimates; the ellipses represent likelihood contours. The dotted lines represent the levels of MSY associated with different parameter values. The dots along the dashed line sloping downward from θ^* indicate the parameter values with the lowest MSY for any set of such values within a given confidence interval around $(\theta_1^* \theta_2^*)$.

MSY values as functions of θ_1 and θ_2. The dots at the tangent points indicate the solutions to the robust optimization problem, indicating the parameter values that give rise to the lowest possible MSY within a given confidence interval.

Using this precaution level criterion for defining the set Θ, the robust optimization problem would be written

$$MSY^R(\Theta) = \min_{\theta} MSY(\theta) \quad \text{s.t.} \quad L(\theta)/L(\theta^*) \geq \beta^{\alpha}.$$

This optimization problem can be solved using the Lagrangian $\mathscr{L}$:

$$\mathscr{L} = MSY(\theta) - \lambda(L(\theta) - \beta^{\alpha} \cdot L(\theta^*)), \qquad (5)$$

where λ is the Lagrange multiplier. For well-behaved optimization problems, λ is positive and increases as the constraint becomes more binding. Hence, there will typically be an inverse and monotonic relationship between the probability level α and λ; as α increases, raising the precaution level, the value of λ decreases.

Holding λ constant at an arbitrary value, the solution to equation (5) can also be found by minimizing over θ the function

$$\mathscr{L}' = \frac{1}{\lambda} MSY(\theta) - L(\theta) - \beta^{\alpha} \cdot L(\theta^*). \qquad (6)$$

Because $\beta^{\alpha} \cdot L(\theta^*)$ is a constant, dropping it from equation (6) will not affect the solution. The robust optimization problem can, therefore, be solved by choosing θ to *maximize* the function

$$\mathscr{L}'' = L(\theta) - \omega MSY(\theta), \qquad (7)$$

where $\omega = \lambda^{-1}$.

This final objective function, equation (7), can be interpreted as a penalized maximum-likelihood function. If $\omega = 0$, the problem reverts to a simple maximum-likelihood problem with the solution θ^*. As ω increases, the parameters that are identified will be pushed away from θ^* in the direction that minimizes $MSY(\theta)$. For a given value of ω, the associated distance away from θ^* in terms of the confidence interval can be recovered using the likelihood ratio (equation 4) and the χ^2 statistic. In essence, this approach provides a numerical solution to estimating confidence intervals using a profile likelihood method. While this approach would not be necessary if we were only considering an estimated parameter, it becomes useful when considering a quantity like MSY that is a function of multiple estimated parameters.

This suggests a three-step process by which to identify a range of robust-optimal policies for increasing levels of precaution:

1. With $\omega = 0$, solve for the maximum-likelihood parameter values θ^* and the associated value of MSY. Store the value of the likelihood function, $L(\theta^*)$.
2. Gradually increasing ω, solve for the parameter values that solve the weighted likelihood function (equation 7). Store the values of the likelihood function $L(\theta^{\omega})$ and the MSY associated with each value of ω.

3. For each of the stored likelihood ratios $L(\theta^\omega)/L(\theta^*)$, use the chi-square statistic to recover the level of precaution associated with each value of ω. The *MSY* values can then be used to infer a robust MSY for each level of precaution.

As we also show, for each MSY value it is possible to calculate the associated fishing mortality rate F, yielding a potential F reference point (either target or limit) as used in most U.S. marine fisheries.

In our application below, we estimate the parameters of the robust stock assessment model for the Chesapeake Bay blue crab fishery with different values of the weight ω. Because the relationship between ω and the levels of precaution are difficult to anticipate, some trial and error was necessary to choose a range of values for ω that would map out precaution intervals up to 98%. In this particular application, we used values between 0 and 0.385 in 0.001 increments.

Assessment model. — We applied the robust optimization approach derived above to the 2011 Chesapeake Bay blue crab stock assessment model (Miller et al. 2011). The Miller et al. (2011) assessment uses a sex-specific catch, multiple-survey analysis (SSCMSA) with sex-specific harvest data and three fishery-independent data sources. The full description of the assessment model is provided in the Appendix, and variable definitions are given in Table 1. Briefly, the model is a statistically fitted population dynamics model that estimates abundance, fishing mortality, and the parameters of the stock–recruitment relationship. The model includes a Ricker stock–recruitment function that allows estimation of MSY and the stock size and fishing mortality rates that achieve MSY. The assessment separates the population into two age-groups: prerecruit (age 0) crabs and fully recruited (age 1+) crabs. Thus, the model tracks the dynamics of four stages of blue crabs: age-0 males, age-0 females, age-1+ males, and age-1+ females. Model parameters are estimated using a penalized maximum-likelihood approach that fits several data time series simultaneously: the harvest, winter dredge survey abundance, Maryland trawl survey catch per unit effort (CPUE), and Virginia Institute of Marine Science trawl survey CPUE.

The SSCMSA includes a sex-specific version of the Ricker stock–recruitment model to estimate age-0 abundance in the beginning of each year (Miller et al. 2011). Productivity at low abundance is a function of female abundance, while density dependence is a function of both male and female abundance:

$$R_{y+1,s} = x_s a SP_{y,f} e^{-b(SP_{y,f}+SP_{y,m})} e^{\delta_y},$$

where $R_{y,s}$ is recruitment in year y of sex s ($s = \{m, f\}$), x_s is the sex ratio of recruits of sex s, a and b are estimated parameters from the stock–recruitment relationship, $SP_{y,s}$ is number of spawners of sex s in year y, and δ_y is a

TABLE 1. Variable and parameter definitions for the Chesapeake Bay blue crab stock assessment model (Miller et al. 2011).

Variable or parameter	Definition
y	Year
s	Sex
i	Index of abundance
f	Female
m	Male
k	Number of observations
x	Sex ratio at recruitment
M	Natural mortality rate
η	Partial recruitment to the fishery
κ	Proportion of mortality before spawning
τ	Proportion of mortality before Maryland trawl survey
Estimated values	
R	Recruitment
N	Abundance
SP	Adult spawner abundance
I_R	Recruitment index of abundance
I_N	Adult index of abundance
Fundamental parameters (estimated)	
N_0	Initial adult abundance
R_0	Median recruitment
δ	Log-scale deviations from median recruitment
F	Instantaneous fishing mortality rate
α, β	Stock–recruitment parameters
q	Catchability
Variance terms	
σ_R	Log-scale SD for recruitment deviations
σ_i	Log-scale SD for observation error in indices of abundance
σ_F	SD for variability in the ratio of male to female fishing mortality during 1968–2006
μ	Mean of the ratio of male to female fishing mortality during 1968–2006
Reference point variables	
YPR	Yield per recruit
N_{YPR}	Abundance per recruit for YPR calculations
SPR	Spawners per recruit
N_{eq}	Equilibrium age-1+ abundance
R_{eq}	Equilibrium age-0 abundance
C_{eq}	Equilibrium catch in numbers

normally distributed process error. Compensatory mortality of age-0 blue crabs is likely driven by cannibalism by age-1+ blue crabs (Hines and Ruiz 1995), which makes the Ricker model well suited for this stock.

Abundance in the age-1+ category of sex s, $N_{y+1,s}$, is estimated as the sum of age-0 recruits and age-1+ adults that survived from the year before,

$$N_{y+1,s} = N_{y,s}e^{-(M+F_{y,s})} + R_{y,s}e^{-(M+\eta F_{y,s})},$$

where M is the instantaneous natural mortality rate (from all nonfishing sources), F is the instantaneous fishing mortality rate, and η is the partial recruitment to the fishery for age-0 crabs. Natural mortality is assumed to be 0.9 per year and is the same for age-0 and age-1+ crabs (Miller et al. 2005; Hewitt et al. 2007). The instantaneous fishing mortality rate is estimated for each year and sex. The partial recruitment for age-0 crabs is specified outside of model fitting and is assumed to be 0.6 based on the growth patterns of juvenile blue crabs (Miller et al. 2011).

The number of spawners is calculated by decrementing the number of age-1+ individuals at the beginning of the year by mortality that occurred before spawning:

$$SP_{y,s} = N_{y,s}e^{-\kappa(M+F_{y,s})},$$

where κ is the proportion of total mortality prior to spawning (0.37 at approximately July 1). The assessment model also assumed that natural and fishing mortality followed the same seasonal patterns. We model catch using a sex-specific Baranov catch equation,

$$C_{y,s} = \frac{F_{y,s}}{F_{y,s} + M}\left(1 - e^{-(M+F_{y,s})}\right)N_{y,s}$$
$$+ \frac{\eta F_{y,s}}{\eta F_{y,s} + M}\left(1 - e^{-(M+\eta F_{y,s})}\right)R_{y,s},$$

where $C_{y,s}$ is the number of individuals of sex s that are caught in year y.

In Miller et al. (2011), the parameters of the stock assessment model were estimated using a penalized maximum-likelihood approach to maximize the fit between the observed and predicted indices of abundance from the three surveys, total catch for 1968–1993, and sex-specific catch for 1994–2009. The same data are used here. The winter dredge survey is assumed to provide an absolute estimate of abundance (i.e., catchability $[q] = 1$) for age-1+ blue crabs (Sharov et al. 2003). For all other survey indices of abundance, catchability is estimated. Catchability is sex-specific for the age-1+ stage but combined for the age-0 stage in all surveys because rapid identification of the sex of small blue crabs in the field is prone to error.

Calculation of MSY.— We calculate maximum sustainable yield (MSY)–based reference points by adapting the methods of Shepherd (1982) for a sex-specific stock–recruitment model. Spawners per recruit (SPR) is calculated as the product of equilibrium age-1+ abundance and survival until spawning:

$$SPR_s = \frac{x_s e^{-((1+\kappa)M+\eta F_s+\kappa F_s)}}{1 - e^{-(M+F_s)}}.$$

Yield per recruit (YPR) is calculated by applying the Baranov catch equation to the equilibrium abundance per recruit of age-1+ and age-0 crabs:

$$N_{YPR,s} = \frac{x_s e^{-(M+\eta F_s)}}{1 - e^{-(M+F_s)}},$$

and

$$YPR_s = \frac{F_s}{M + F_s}\left(1 - e^{-(M+F_s)}\right)N_{YPR,s}$$
$$+ \frac{\eta F_s}{M + \eta F_s}\left(1 - e^{-(M+\eta F_s)}\right)x_s.$$

The equilibrium abundance of age-1+ crabs is calculated by rearranging the Ricker stock–recruitment function and applying the SPR for each sex:

$$N_{eq,s} = \frac{\log_e SPR_f + \log_e \alpha + \sigma_R/2}{\beta} \times \frac{SPR_s}{SPR_f + SPR_m}.$$

Equilibrium recruitment is the quotient of the sex-specific equilibrium abundance of age-1+ individuals and SPR:

$$R_{eq} = \frac{N_{eq,s}}{SPR_s}.$$

Equilibrium catch (i.e., sustainable yield) is the product of equilibrium recruitment and YPR,

$$C_{eq,s} = R_{eq,s}YPR_s,$$

and total equilibrium catch is the sum of equilibrium catch across sexes,

$$C_{eq} = \sum_s R_{eq,s}YPR_s.$$

Estimation of robust reference points.— The blue crab stock assessment model was implemented in AD Model Builder (Fournier et al. 2012). Any solution that failed to converge (based on the largest first partial derivative of the objective function) was excluded from later analysis. For a given set of parameters, MSY was found using a Gauss–Newton search over fishing mortality rates. We used the ratio of male to female fishing mortality from the last year of the model (2010) to estimate MSY, although it is possible to use any other ratio of male to female fishing mortality.

RESULTS

In Figure 3 we present the MSY^R for a wide range of precaution levels, from 0% (i.e., using maximum-

likelihood parameter values) to 98%. While the estimated *MSY* that could be achieved at the MLE for the parameters of the model is nearly 500 million blue crabs per year, the confidence intervals around this estimate are fairly large (coefficient of variation = 31%). As we consider higher levels of precaution, the robust parameter values diverge from the maximum-likelihood values in the direction that leads to the lowest sustainable yield. At the 50% precaution level, the associated MSY^R falls about 20% to 400 million crabs per year, indicating that values within a 50% confidence interval around the maximum-likelihood values are consistent with MSY values of at least 400 million crabs. If policy makers seek a 90% precaution level, the MSY^R value falls by 40% from the base level with no precaution, to nearly 300 million crabs per year. Thus, as the precaution level rises the MSY^R values fall substantially. On the other hand, the decline is bounded for the range of precaution levels presented. Even at the most conservative level presented (98%), the MSY^R value is still more than 50% of the *MSY* associated with the MLE parameters.

It is more common for fisheries managers to impose a constant-fishing-mortality-rate harvest control rule than a constant harvest control rule, so in Figure 3 we also present an alternative reference point, a robust fishing mortality rate (F^R) which is equal to the F (assuming the maximum-likelihood parameter values θ*) that would match the corresponding MSY^R values. The MLE for F_{MSY} was approximately 0.99/year. The target fishing mortality rate from the stock assessment was approximately 0.65/year (exploitation rate = 0.33/year), which corresponds to about 45% precaution. The 90% precaution level for the F_{MSY} was F = 0.46/year. As policy makers seek higher levels of precaution, the fishing mortality rate declines at roughly the same rate as the *MSY*. Our

FIGURE 3. Robust maximum sustainable yield (MSY^R) and robust instantaneous fishing mortality rates (F^R) for different precaution levels for the Chesapeake Bay blue crab stock assessment model.

approach identifies how much lower they need to be to match a given level of precaution.

DISCUSSION

In this paper, we provide an alternative way to develop precautionary reference points for fisheries management based on robust control. One way of thinking about robust control is that it can be used to estimate reference points that attempt to maximize yield while assuming a specific degree of pessimism about the future (i.e., the precaution level). Instead of reflecting an ad hoc adjustment, policy recommendations are expressed in terms similar to standard confidence intervals; for instance, a policy recommendation might be expressed as robust up to a 90% confidence interval, which we call a 90% precaution level. In this way, our approach has much in common with that advocated by Dankel et al. (2016) because the resulting management advice is clear and the role played by uncertainty is transparent.

The robust optimization approach proposed here has several attractive features. First, it is a direct application of the max–min decision rule frequently mentioned in discussions of precautionary management. Second, it is an improvement over previous fisheries applications of robust control in that the range of possible parameter values (the set Θ) is derived from the familiar notion of a statistical confidence interval. Finally, it has the advantage that a standard level of precaution can be chosen by decision makers and then applied to different fisheries with vastly different levels of data and analysis. Although the level of precaution would be consistent, decisions would tend to be less conservative when the natural resource system is better understood. However, our approach relies on being able to estimate MSY within the assessment model because the basis for the reference point is the maximization of sustainable yield using precautionary estimates of stock productivity. A similar approach could be developed for other commonly used fishery management reference points (e.g., the spawning potential ratio), but an objective to maximize is needed.

Our approach is not a replacement for more holistic evaluations of management performance and risk like management strategy evaluation (MSE; Punt et al. 2016). Rather, it is a tool that can be used to provide additional information about precautionary reference points or to develop candidate reference points for more detailed evaluations of potential management performance. Specifically, our application of a robust control approach attempts to find the MSY assuming that the productivity of the stock is less than that at the MLE. Thus, it only attempts to maximize long-term yield and does not explicitly account for other potential fishery objectives. Management strategy evaluations are used to explore the expected
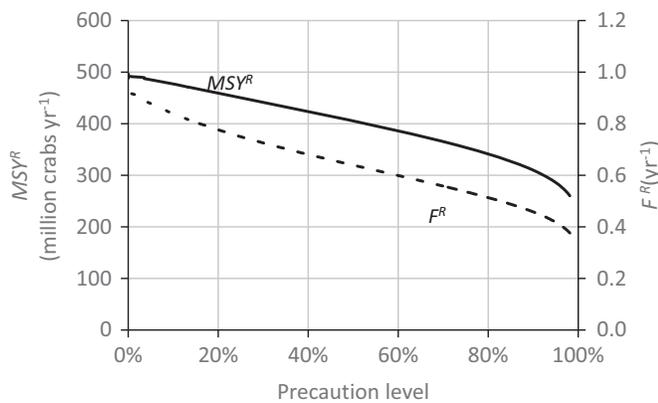
trade-offs among multiple management objectives. In many cases, the goal of an MSE is not to find the optimal solution but to identify management options that provide acceptable trade-offs among competing objectives (Miller and Shelton 2010; Punt et al. 2016).

What precaution level should be used to make management decisions? There is no objective answer to that question, and given the trade-offs inherent in the management choice, policy makers will have differing opinions about how much precaution is warranted. If policy makers want to reduce the probability of a poor outcome, they should choose higher precaution levels (e.g., 95% rather than the 90% in our analysis). In U.S. fisheries, managers have chosen probabilities of overfishing that could be used in the approach we developed. For example, in the Mid-Atlantic region, if the stock is above the estimate of the biomass that would produce MSY for a species with a typical life history, the target probability of $F > F_{MSY}$ is 40% (Mid-Atlantic Fishery Management Council 2011). In the blue crab example, this would correspond to a precaution level of approximately 20%. The approach we propose could be used to evaluate how alternative levels of precaution would affect management choices. For example, Wiedenmann et al. (2017) evaluated several alternative levels of precaution for the Mid-Atlantic Fishery Management Council's harvest control rule and found that the effects of adopting more precaution differed among life history and data quality scenarios. We believe that the precaution levels in our analyses are more intuitive with respect to what they are attempting to achieve than those of other approaches to calculating precautionary reference points. Simulation testing using an MSE approach would be helpful in determining the amount of precaution that most aligns with managers' goals.

As with all stock assessment models, our approach retains many of the limitations of the underlying model. Stock assessment models vary substantially as to which components are assumed to be known and which are estimated. Because of the inability to include all of the uncertainty in the model, the precision of estimates is often thought to reflect a substantial underestimate of the true uncertainty (Ralston et al. 2011; Magnusson et al. 2013). For example, in our blue crab application several of the parameters (including the natural mortality and selectivity of age-0 crabs) were assumed to be known. Therefore, simply using the uncertainty estimated within the assessment model will underestimate the true uncertainty. However, using a max–min criterion to identify management options that will perform as well as possible under poor conditions is a general way to include precaution in management regardless of how the uncertainty is estimated. If the analyst believes that substantial sources of uncertainty are not included in the assessment model, then a direct application of our approach is not advised. For example, if a

substantial retrospective pattern were present in the stock assessment results, the uncertainty within the model would likely be underestimated and our method could produce unrealistically optimistic results (although the likely bias depends on the direction of the retrospective pattern).

We used a profile likelihood approach to estimate confidence intervals for the estimated reference points, but other methods are also available. Magnusson et al. (2013) evaluate three common approaches (Markov chain–Monte Carlo [MCMC], asymptotic standard errors [ASE], and bootstrapping) for incorporating uncertainty into stock assessments and recommend using MCMC or ASE for constructing confidence intervals for age-structured stock assessments. Our use of profile likelihood for implementing the robust optimization approach is similar to using ASE or MCMC for estimating confidence intervals. In additional analyses, we compared the confidence intervals generated from our likelihood profiling with ASEs and found that assuming a lognormal distribution with the ASEs for MSY produced results very similar to the profile likelihood confidence intervals except at the extreme tails of the distribution. The approach we used to estimate profile likelihood confidence intervals worked well for our blue crab assessment model, but the default profile likelihood approach in AD Model Builder failed to converge on a solution. Regardless of the method used to estimate the confidence intervals of the reference points, we feel that our approach has the advantage of a clear normative motivation and appropriately adjusts the management targets to the uncertainty in the parameter values.

Other proposed approaches to precautionary management have similarities to our proposed approach. For example, Shertzer et al. (2010) proposed a method for setting precautionary catch limits, commonly called the P^* approach, that is currently used to inform catch limits for federal fisheries management in several regions of the United States. The P^* approach attempts to estimate a level of catch that achieves a specific probability of overfishing (P^*, i.e., the target probability that F will exceed its upper threshold reference point). The P^* approach requires estimates of the distribution of the catch (called the overfishing limit [OFL]) that would achieve the upper-threshold fishing mortality rate, which is used to define overfishing for federally managed stocks. The result of the P^* approach is a catch limit that is used as an upper limit for the annual catch limits recommended by the fishery management councils. This approach has been implemented in different ways in different regions. For example, the Pacific and Mid-Atlantic Fishery Management Councils use the point estimates of the OFL from the assessments but derive uncertainty estimates from outside analyses because the uncertainty in the stock assessments is thought to be underestimated (e.g., Ralston et al. 2011). In contrast, a procedure that pairs Monte Carlo simulation with a

nonparametric bootstrap (MC bootstrap) is used to estimate uncertainty and apply the *P** control rule in the South Atlantic region.

Our proposed approach was designed to estimate precautionary target reference points for fishery management. However, some fishery management systems may not directly use such a reference point. Current U.S. federal management uses a series of precautionary buffers to develop catch limits, such that the OFL ≥ acceptable biological catch (ABC) ≥ annual catch limit (ACL) (National Standard 1; https://www.ecfr.gov/cgi-bin/retrieveECFR?gp=&SID=3ea20ed553f359cdaf6ce0d768a9b9b6&mc=true&n=sp50.12.600.d&r=SUBPART&ty=HTML#se50.12.600_1310). The OFL is the highest level of catch and provides a technical definition for overfishing. A buffer between the OFL and the ABC is supposed to add precaution by accounting for "scientific" uncertainty, i.e., the uncertainty associated with the estimated reference points and stock biomass. In many regions of the United States, a *P** approach (Shertzer et al. 2010) is used to estimate an ABC that has a specific probability of overfishing. The ACL is supposed to account for "management" or implementation uncertainty. Current guidance also allows for a target at or below the ACL to further account for implementation uncertainty. This approach to adding precaution has some general similarities to our robust control approach in that it is a way to produce a precautionary buffer. However, our approach attempts to maximize sustainable yield under a precautionary estimate of stock productivity, whereas current federal management largely attempts to avoid overfishing a prespecified fraction of the time.

For some U.S. fisheries, 75% of the limit fishing mortality reference point has been adopted as a precautionary target, following Restrepo et al. (1998). Blue crab managers in the Chesapeake Bay have adopted a target exploitation rate that is 75% of the exploitation rate that would achieve MSY (Miller et al. 2011). The robust optimization approach provides decision makers with additional information on how much precaution they are exhibiting when adopting a target. Comparing the target instantaneous fishing mortality rate for blue crabs in the Chesapeake Bay (0.66/year for adult females) with our results, we find that the current target entails a precaution level of about 45%. This level may not align with policy makers' goals for managing the fishery and may need to be revisited. For example, on average blue crab abundance has remained below its target level during 2012–2017 (Chesapeake Bay Stock Assessment Committee 2018), and this may be because managers are not being as precautionary as they expect given the basis of their exploitation rate target.

The use of methods to formally include precaution in the selection of management targets has recently increased. Admittedly, any approach that relies on the estimated uncertainty from a single model is heavily dependent on the assumption that the model provides a good approximation to reality. In our approach, reducing uncertainty leads to increases in target reference points for yield and fishing mortality. Thus, the question of how to reduce uncertainty in stock assessment models is important. Reducing uncertainty is not as easy as simply adding more years of data. Adding more years of data to a common age-structured assessment approach did not reduce the uncertainty in the estimates of terminal year biomass (Wiedenmann et al. 2015). Therefore, if the goal is to reduce uncertainty, the use of new, more informative data sets would likely be needed. In any case, the robust approach presented here will adjust the buffer between the MLE and the precautionary reference point as data and theoretical understanding evolve over time. However, within the constraints of the model or models adopted for analysis, the approach we propose in this study offers a rigorous and theoretically grounded way for policy makers to think about the amount of precaution associated with alternative management reference points. In addition, we recommend simulation testing of potential robust control reference points before implementing them in a real fishery management situation.

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Appendix: Model Details

The stock assessment model and several sensitivity analyses are described in Miller et al. (2011). An update of the Chesapeake Bay blue crab stock assessment is currently under way but not yet complete as of early 2019. Here we provide a synopsis of the mathematical details of the Chesapeake Bay blue crab stock assessment model.

Abundance in the age-1+ category was estimated as the sum of age-0 recruits and age-1+ adults that survived from the year before:

$$N_{y+1,s} = N_{y,s}e^{-(M+F_{y,s})} + R_{y,s}e^{-(M+\eta F_{y,s})}. \quad (A.1)$$

Variable definitions are provided in Table 1 in the text. Natural mortality was assumed to be the same for age-0 and age-1+ crabs, but we also conducted sensitivity runs that evaluated several sex-specific natural mortality rates. We used 0.9 as our assumed natural mortality rate based on the previous stock assessment for Chesapeake Bay blue crabs (Miller et al. 2005; Hewitt et al. 2007).

The instantaneous fishing mortality rate was estimated for each year and sex. The partial recruitment for age-0 blue crabs was specified as 0.6 and was the same for males and females. About 90% of the age-0 blue crabs at the beginning of any year grow large enough to enter the fishery during that year. A partial recruitment of 0.3 was considered a lower bound based on both the amount of time that age-0 crabs are vulnerable to the softshell–peeler fishery and the proportion of the catch from later months (when most crabs that were age 0 at the beginning of the year have grown into the fishery). Abundance during the first year of the model was estimated separately for age-0 and age-1+ crabs and then combined.

The number of spawners was calculated by decrementing the number of age-1+ crabs at the beginning of the year by mortality that occurred before spawning,

$$SP_{y,s} = N_{y,s}e^{-\kappa(M+F_{y,s})}. \quad (A.2)$$

The proportion of mortality that occurred before spawning was set at 0.37 because we assumed a spawning date of July 1 and 37% of the pot effort in Maryland has occurred by July 1 on average. The assessment model also assumed that natural and fishing mortality followed the same seasonal patterns. This approach assumes that the same proportions of annual mortality occurred prior to spawning for both males and females during this period.

We modeled catch using a sex-specific Baranov catch equation with partial recruitment for age-0, namely,

$$C_{y,s} = \frac{F_{y,s}}{F_{y,s} + M}\left(1 - e^{-(M+F_{y,s})}\right)N_{y,s}$$
$$+ \frac{\eta F_{y,s}}{\eta F_{y,s} + M}\left(1 - e^{-(M+\eta F_{y,s})}\right)R_{y,s}. \quad (A.3)$$

The exploitation rate of fully selected blue crabs was calculated as the product of the annual mortality rate and the proportion of total mortality due to fishing:

$$u_{y,s} = \frac{F_{y,s}}{F_{y,s} + M}\left(1 - e^{-(M+F_{y,s})}\right). \quad (A.4)$$

OBSERVATION MODEL

The model was fitted to data from three surveys: the Chesapeake Bay blue crab winter dredge survey (WDS), the Maryland trawl survey (MTS), and the Virginia Institute of Marine Science trawl survey (VTS). The WDS and the VTS surveys are treated as beginning-of-the-year surveys:

$$\hat{I}_{R,y,s} = q_i R_{y,s}, \quad (A.5)$$

$$\hat{I}_{N,y,s} = q_i N_{y,s}, \quad (A.6)$$

where the surveys are assumed to have constant catchability over time. For the MTS, we treated the survey as occurring in the middle of the year, such that age-0 prerecruits from the beginning of the year were recruited to the age-1+ category by the time of the survey,

$$\hat{I}_{N,y,s} = q_i(N_{y,s}e^{-\tau(M+F_{y,s})} + R_{y,s}e^{-\tau(M+\eta F_{y,s})}. \quad (A.7)$$

We assumed that 67% of total mortality ($F + M$) had occurred by the time of the MTS based on a September 1 date for the trawl survey and the cumulative amount of crab pot effort in Maryland before September 1 (Miller et al. 2011). The age-0 portion of the MTS indexes recruitment at the beginning of the next year. We assumed that the WDS provided an absolute estimate of abundance

(i.e., $q = 1$) for age-1+ blue crabs. For all other survey indices of abundance, catchability was estimated using the MLE approach by calculating the average difference (on a log scale) between the observed index of abundance and predicted abundance (Miller et al. 2005):

$$\log_e q_i = \frac{\sum\limits_{y} \log_e I_{R,y} - \log_e R_y}{k_i}, \qquad (A.8)$$

for recruits and

$$\log_e q_i = \frac{\sum\limits_{y} \log_e I_{N,y,s} - \log_e N_{y,s}}{k_i}, \qquad (A.9)$$

for age-1+ crabs. Catchability was sex specific for the age-1+ stage but combined for the age-0 stage.

LIKELIHOOD AND PENALTY FUNCTIONS

We estimated the parameters by minimizing the objective function, which was the sum of the likelihood components for each data source and the penalties for recruitment deviations and deviations from the mean 1994–2006 ratio of male to female fishing mortality. The model was estimated using AD Model Builder (admb-project.org). We assumed lognormal observation errors for the indices of abundance from the MTS and VTS as well as for catch:

$$L_i = k_i \log_e(\sigma_i) + \frac{1}{2\sigma_i^2} \sum_{y \in i} \left(E_{i,y} - O_{i,y}\right)^2, \qquad (A.10)$$

where E and O are the estimated and observed values of the indices of abundance. The variances were assumed for each data source, and constants were ignored to simplify the equations. We assumed that the recreational crab catch, which is not reported, represented 8% of the total commercial catch and was proportionally constant over time. For the winter dredge survey, we assumed normally distributed errors with a constant coefficient of variation (CV) because of the large sample sizes in the survey (approximately 1,500 stations per year),

$$L_i = \sum_{y \in i} \log_e(E_{i,y}\mathrm{CV}_i) + \frac{1}{2\left(E_{i,y}\mathrm{CV}\right)^2} \sum_{y \in i} \left(E_{i,y} - O_{i,y}\right)^2. \qquad (A.11)$$

The log-scale standard deviations of catch were specified at 0.1 to indicate that catch was relatively accurate. The CVs of the WDS were estimated from design-based estimators. The average CV over time for age-1+ males and females was approximately 10%, so we assumed a 10% CV for the winter dredge survey. The log-scale SDs of the trawl surveys were iteratively tuned until the input value was approximately equal to the post hoc value (McAllister and Ianelli 1997). Recruitment deviations followed a lognormal distribution,

$$L_R = k_R \log_e(\sigma_R) + \frac{1}{2\sigma_R^2} \sum_y \delta_y^2. \qquad (A.12)$$

The log-scale standard deviation of recruitment was estimated during model fitting.

A penalty on the relative fishing mortality between males and females was imposed on years before sex-specific catch data were available to constrain the model from having large interannual differences in the relative fishing mortality rates:

$$L_F = k_F \log_e(\sigma_F) + \frac{1}{2\sigma_F^2} \sum_y \left(\frac{F_{y,m}}{F_{y,f}} - \mu\right)^2. \qquad (A.13)$$

The mean and variance for the ratio of male to female fishing mortality were calculated using years during which sex-specific catch data were available but before sex-specific management measures were imposed (1994–2006).