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A Management Strategy for Sedentary Nearshore Species that Uses Marine Protected Areas as a Reference

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Abstract.—Classical approaches to fisheries stock assessment rely on methods that are not conducive to managing data-poor stocks. Moreover, many nearshore rocky reef species exhibit spatial variation in harvest pressure and demographic rates, further limiting traditional stock assessment approaches. Novel management strategies to overcome data limitations and account for spatial variability are needed. With the ever-increasing implementation of no-take marine protected areas (MPAs), there is great potential for improving decision making in management through comparisons of fished populations with populations in MPAs at spatially explicit scales. We developed a management strategy that uses a combination of data-based indicators sampled inside and outside of MPAs as well as model-based reference points for data-poor, sedentary nearshore species. We performed a management strategy evaluation of this MPA-based decision tree model for a hypothetical population of grass rockfish *Sebastes rastrelliger* in California. We introduced process, observation, and model uncertainty in numerous scenarios and compared these scenarios with the precautionary approach currently used to manage data-poor species. Our model consistently improved total catches while maintaining the biomass and spawning potential ratio at levels well within acceptable thresholds of management. We suggest further exploration of this MPA-based management approach, and we outline a collaborative research program in the California Channel Islands that may well be suited for testing an experimental management procedure.

In the United States, fisheries management often relies on quantitatively complex population dynamic models to calculate current and virgin biomass levels, exploitation rates, and sustainable catch levels (Hilborn and Walters 1992). These techniques require substantial amounts of data, make numerous assumptions, require specific expertise, and use model outputs to inform the decision-making process rather than the data itself (Hilborn 2003). Traditional stock assessment frameworks are ill-equipped for use on data-poor species that exhibit spatial variability in demography and harvest. Many marine fisheries, however, target stocks that are characterized by these features (Grafton et al. 2006; Gunderson et al. 2008). To overcome the limitations of traditional stock assessment frameworks, a new paradigm in small-scale fisheries management is emerging that has as its foundation adaptive responses to social, biological, and environmental conditions (Hilborn and Walters 1992); use of simple, data-based indicators of stock performance (Hilborn 2003); incorporation of multiple user groups into the stewardship of the resource (Gunderson et al. 2008); new incentive structures (Hilborn et al. 2005; Hilborn 2007; Costello et al. 2008); use of appropriate spatial scales (Wilen 2004; Prince 2005; Crowder et al. 2006); and ecosystem-based approaches, including the integration of marine protected areas (MPAs; Lubchenco et al. 2003).

Setting appropriate harvest levels for marine fishes is often conducted via estimation of performance indicators, such as the existing biomass (B) of the population or the fishing mortality rate (F). These indicators are compared with biological reference points, such as the biomass that achieves maximum sustainable yield (MSY; B_{MSY}) or the fishing mortality that achieves MSY (F_{MSY}). Control rules, such as the 40–10 rule in U.S. federal fisheries management (Restrepo et al. 1998), are used to adjust the levels

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of harvest and/or exploitation rates based on the relationship between indicators and reference points. Common reference points used today are notoriously difficult to estimate, so a common default is to use proxy indicators, such as $F_{\%}$, the level of F that achieves a desired spawning stock biomass per recruit (SSBR). An extension of SSBR is to relate it to an unfished level, specified as the spawning potential ratio (SPR). For highly resilient stocks, an SPR of 0.4 ($SPR_{0.4}$) is considered risk averse, while less-resilient stocks require SPR levels closer to 0.5–0.6 (Dorn 2002). For data-poor fisheries, in which insufficient data are available for a full assessment, the Food and Agriculture Organization of the United Nations precautionary rule (FAO 1995) is implemented. In these cases, Restrepo (1998) recommended setting harvest at a fraction of historically stable catch levels. Although this approach may be sufficient for stocks in a rebuilding stage or for stocks that do not support high-value fisheries, there is in most cases a need for more adaptive approaches that promote efficiencies in harvest.

Data-based indicators, such as the catch per unit effort (CPUE) and the size structure of the catch, can be used as proxies for SPR and may reflect stock status as effectively as stock assessment outputs (Hilborn 2002; Basson and Dowling 2003; Campbell et al. 2007). They are also relatively simple metrics that generate the greater transparency and user group buy-in necessary for effective decision making and thus contribute to enhanced efficiency in management, especially through collaborative approaches (Campbell et al. 2007). Development of a harvest strategy that uses size-based and catch-based metrics was initiated in Australia for a longline tuna and billfish fishery in the Tasman Sea (Campbell et al. 2007). The process relies on simple algorithms to adjust harvest based on the comparison between empirical data and historical catch records as well as static per-recruit models. The use of static reference points alone, however, may fail to adequately reflect the dynamic state of the resource through space and time (Rosenberg et al. 1996). Moreover, SPR calculations make unreasonable assumptions that (1) the stock is at equilibrium, (2) recruitment is not compensatory, and (3) natural mortality (M) and other life history characteristics are known without error (Mace et al. 1996).

In this article, we develop a decision tree model based on work by Campbell et al. (2007); the decision tree model overcomes the limitations of static reference points by utilizing a combination of SPR models, trends in CPUE over time, and sampling conducted within no-take MPAs. The MPA-based management strategy has four levels of decision making. In level 1, an initial total allowable catch (TAC) is set by adjusting the previous year's TAC based on information derived from the size structure of the catch in relation to the size structure inside MPAs. The subsequent three levels examine trends in CPUE over time and the relationship of the size structure and CPUE to static per-recruit models. Each of these subsequent levels allows for further adjustment of the TAC depending on the relationship between the empirical performance indicators and predetermined reference points.

To demonstrate the potential for implementation of this MPA-based decision tree model, we conducted a management strategy evaluation (MSE; Smith 1993, 1994) for a hypothetical population of grass rockfish *Sebastes rastrelliger*, a commercially and recreationally harvested sedentary, nearshore rocky reef fish on the West Coast of North America. Management strategy evaluation is a simulation procedure that allows for the evaluation of tradeoffs between alternative management strategies under various process and observation uncertainties (Punt 1992; Cooke 1999). We describe the development of the decision tree model and the associated equations for each of the four levels. We then use MSE to test the robustness of the MPA-based decision tree framework to process and observation uncertainty as well as sampling variability. Tradeoffs in biomass and yield between the decision tree and the current management strategy in which harvest is set at a fraction of historically stable levels are detailed. Lastly, we discuss the potential for implementing this method in an experimental test case fishery in the Santa Barbara, California, nearshore live-fish fishery.

Incorporation of MPAs into Fisheries Management

The use of MPAs in a management strategy framework offers distinct advantages over methods that do not incorporate their use. First, nearshore rocky reef species display spatial heterogeneity in life history characteristics (Gunderson et al. 2008), making it difficult to apply optimal harvest strategies over coastwide scales (Hart 2001). Using MPAs as proxies for baseline conditions at spatially appropriate (local) scales may improve our ability to set optimal harvest levels and allow for the inclusion of local knowledge, collaborative research, and co-management structures. Second, nearshore rocky reef populations are influenced by dynamic environmental processes, such as El Niño, anomalous upwelling, and shifts in the Pacific Decadal Oscillation. Static equilibrium models will fail to account for temporal changes in population demography and will thus be ineffective tools by themselves in setting harvest levels during extreme environmental conditions. Third, SPR analyses are sensitive to estimates of M; therefore, the use of MPAs as a reference point reduces the need to estimate natural mortality in all levels of the decision-making process, thus reducing the potential for misrepresenting the true state of the resource. By simultaneously incorporating the use of static models and MPAs into the decision-making framework, we minimize the chance of overestimating or underestimating the appropriate harvest level.

Methods

Model Species

Grass rockfish are shallow-dwelling, sedentary reef fish that range between Oregon, USA, and central Baja California, Mexico. Genetic evidence suggests mean larval dispersal distances of 10 km/generation, indicating that local retention mechanisms may influence early life history and the spatial heterogeneity of population demographics (Buonaccorsi et al. 2004). Grass rockfish are heavily targeted in the multispecies nearshore live-fish fishery of the West Coast, in which distributors pay premium prices for the opportunity to sell live fish to restaurateurs and local markets. Grass rockfish also make up a large component of a recreational shore-based fishery. Both the commercial and recreational fisheries are managed by using the precautionary approach (FAO 1995), in which catches are set at 50% of historically stable levels. No stock assessment has been conducted on grass rockfish, and completion of such an assessment in the near future is unlikely because of the data-poor nature of the fishery.

Decision Tree Model

The MPA-based decision tree management strategy we develop here uses a combination of empirically derived CPUE and size-based metrics inside and outside of MPAs as well as model-based reference points to set sustainable harvest levels. The model also requires basic biological information, such as an age–length relationship (e.g., von Bertalanffy), size or age at reproductive maturity, length–fecundity relationship, and an estimate of M. The basis of the management strategy was developed by Froese (2004), who suggested that sustainable management of fisheries resources may be achieved by assuring adequate representation of three size-classes in the harvest: recruits; prime individuals; and old individuals. Here, the term "recruits" refers to the smallest size bin in the catch, representing individuals that have not yet reproduced and individuals that have been reproductively mature for 1–3 years. The "prime" size bin represents those individuals in the center of the size distribution (around the mode), while the "old" size bin represents the oldest individuals, known as mega-spawners.

The decision tree has four successive levels that each compares data-based performance indicators with predetermined reference points. Adjustments to the previous year's TAC are made based on these comparisons (Figure 1). The following sections provide an overview of each of the four levels of the decision tree and a description of the associated equations used for calculating the necessary adjustment to TAC.

Level 1.—Level 1 of the decision tree sets an initial TAC by using a modified slope-to-target rule. The slope-to-target rule is an algorithm that adjusts a current TAC up or down based on the slope between the present measured CPUE of prime-sized fish ($CPUE_{prime}$) and a desired fraction of $CPUE_{prime}$ observed within an MPA, given an acceptable time frame to achieve the desired level. If the present $CPUE_{prime}$ is below the desired level, then the subsequent setting of TAC will decrease. If the present $CPUE_{prime}$ is above a desired state, then the subsequent TAC will increase.

To account for uncertainty surrounding CPUE estimates, an exponentially weighted 5-year moving average of $CPUE_{prime}$ is used in both the fished area and the MPA population. To calculate the TAC by using the modified slope-to-target rule, we first determined the optimal target reference point for $CPUE_{prime}$ that would achieve $SPR_{0.4}$ while simultaneously maximizing catch. We calculated the value to be 40% of the $CPUE_{prime}$ found inside the MPA (see Decision Tree Parameter Optimization for details). The use of this reference level, however, is not appropriate until the MPA population reaches an approximation of carrying capacity. Therefore, for the phase-in period, we use the following equation to calculate the appropriate slope-to-target value (V_t):

$$V_t = (A_t - \Theta_t B_t)/d, \tag{1}$$

where d is the time frame to return the stock to the desired level, A_t is the $CPUE_{prime}$ observed outside the MPA, B_t is the $CPUE_{prime}$ observed inside the MPA, and Θ_t is a phase-in period multiplier defined as

$$\Theta_{t+1} = \begin{cases} \Theta_t - \dfrac{0.6}{\text{MGT}} & \text{for } t = 2 \text{ to } t_K \\ 0.4 & \text{for } t > t_K, \end{cases} \tag{2}$$

where $\Theta_{t=1}$ is 1 and t_K is the time at which our simulated age-structured population reaches 90% of the carrying capacity under no harvest—roughly equal to the mean generation time (MGT) of this hypothetical population (10 years).

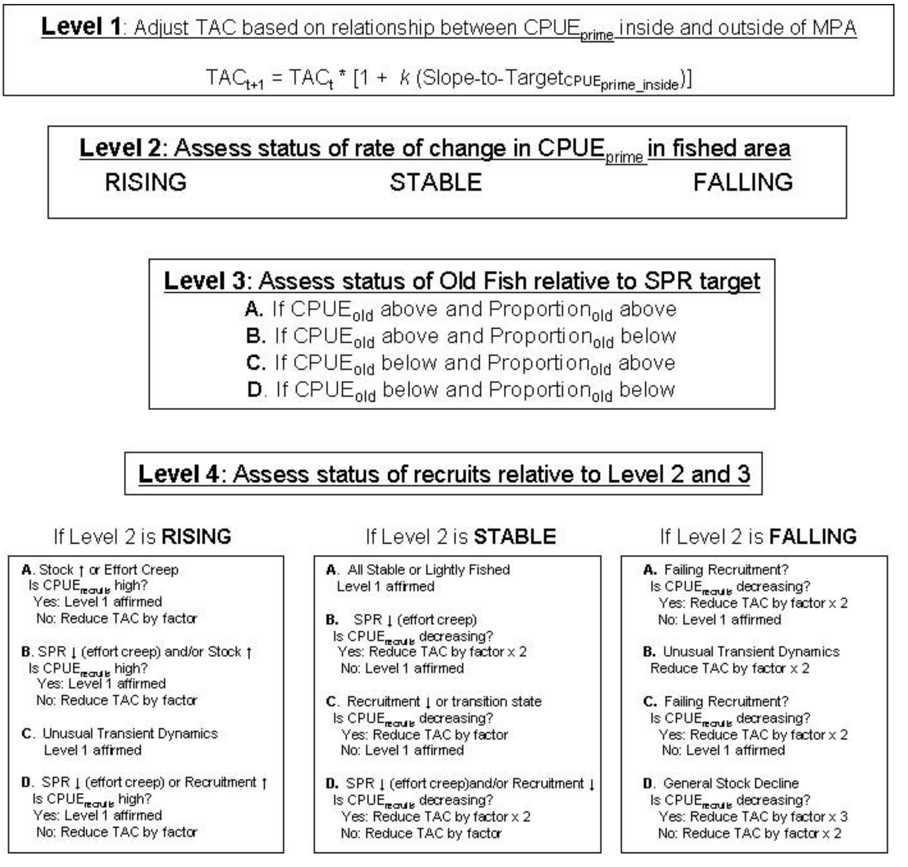

FIGURE 1.—Schematic of the four levels of the marine protected area (MPA)-based decision tree model (TAC = total allowable catch; CPUE = catch per unit effort; $CPUE_{prime}$ = CPUE of prime-sized fish; k = responsiveness factor; proportion_old = proportion of old fish; $CPUE_{old}$ = CPUE of old fish; $CPUE_{recruits}$ = CPUE of recruit-sized fish; factor = TAC reduction factor).

We use the slope-to-target calculation to set the TAC in level 1 with the following equation:

$$TAC_{t+1} = TAC_t \times [1 + k(V_t)], \qquad (3)$$

where k is the responsiveness factor determining how extreme the adjustment of the TAC will be relative to V_t.

When V_t is positive, this indicates that the $CPUE_{prime}$ in the fished population is above the target value and therefore the TAC for the following year will increase. When V_t is negative, $CPUE_{prime}$ in the fished population is below the target value and the TAC will decrease in the following year.

Level 2.—In level 2, the trend in $CPUE_{prime}$ over a 5-year period is used to determine whether catches are increasing, stable, or falling. Time-averaged CPUE is used as an initial estimation of whether the population is increasing or decreasing. An exponentially weighted moving average over 5 years is used again to evaluate whether the change from the previous year to the current year falls outside of the 5-year average. If the annual change is greater than 5% above the average, then the trend is increasing. If the annual change is below 5% of the average, then the trend is decreasing (Table 1); otherwise, it is stable.

Level 3.—In level 3, the relationship between the proportion of old fish (proportion_old) and the CPUE of old fish ($CPUE_{old}$) in the fished population is compared with the $CPUE_{old}$ and proportion_old derived from per-recruit models. Level 3 is intended to inform managers whether catches of old fish are increasing or decreasing and to determine whether the trend results from a change in the selectivity of older size-classes to the gear or is due to recruitment pulses that altered (i.e., reduced) the true proportion of old fish in the population.

In our simulated case study, our objective was to maintain SSBR levels at 40% of unfished conditions

TABLE 1.—Parameters used in the decision tree model at each level of inquiry. Asterisks in the "value" column indicate the four parameters that were optimized by using formal techniques (see text for details). All other parameter values were taken from previous work (Campbell et al. 2007) and discussions with fishery scientists (MPA = marine protected area; $CPUE_{prime}$ = catch per unit effort for prime-sized fish; $CPUE_{old}$ = CPUE of old fish; proportion_old = proportion of old fish; $CPUE_{recruits}$ = CPUE of young fish; TAC = total allowable catch; and SPR = spawning potential ratio).

Decision level	Parameter	Value
Level 1	• Number of years over which the slope of $CPUE_{prime}$ is calculated (slope to target; *d*)	10 years*
	• Target value for $CPUE_{prime}$	0.4 of $CPUE_{prime}$ inside MPA*
	• Feedback gain/responsiveness factor, *k*	0.9*
	• Time until MPA achieves 90% of carrying capacity (t_k)	10 years
Level 2	• Bound on the percentage annual change in $CPUE_{prime}$ to define stability in this indicator (note that change is relative to the mean value of $CPUE_{prime}$ over the previous 5 years)	5% per year
	• Number of years over which mean $CPUE_{prime}$ is calculated	5 years (weighted moving average)
Level 3	• Target value for $CPUE_{old}$	SPR = 0.4
	• Target value for proportion_old	SPR = 0.4
Level 4	• Value of $CPUE_{recruits}$ to define high recruitment	80% $CPUE_0$
	• Decrease in $CPUE_{recruits}$ to define declining recruitment	10% per year
	• Reduction factor on TAC	10%*
	• Number of years over which mean $CPUE_{recruits}$ is calculated	5 years (weighted moving average)

($SPR_{0.4}$). Values for $CPUE_{old}$ and proportion_old that result in $SPR_{0.4}$ conditions were derived from per-recruit modeling, which required basic biological information and an estimate of *M*. The proportions of old fish in the harvested population as well as in the modeled population were calculated relative to the proportion of the other size-classes (recruits and prime) in these respective populations and were therefore scaleless. On the other hand, CPUE is an absolute value, and therefore the data-based estimate of CPUE may not scale with the modeled CPUE value at $SPR_{0.4}$. To reconcile the scaling problem, a number of options are available to managers, including the use of historical fishermen knowledge and data from inside existing MPAs. We assumed that the maximum attainable CPUE in a real population is equivalent to the maximum attainable CPUE in the modeled population. This assumption made it possible to scale the estimate of $CPUE_{old}$ that results in $SPR_{0.4}$ for comparison with the data-based estimates.

Level 4.—Level 4 provides an estimate of whether recruitment overfishing is occurring by assessing whether the CPUE of young fish ($CPUE_{recruit}$) is above or below desired reference levels. Depending on the outcome in levels 2 and 3, the analysis in level 4 compares the $CPUE_{recruit}$ to estimated unfished levels of $CPUE_{recruit}$ calculated through per-recruit modeling or, alternatively, whether the pattern of $CPUE_{recruit}$ over the previous few years has been rising, stable, or falling. In the former scenario, we determine whether $CPUE_{recruit}$ is significantly below unfished conditions by setting a threshold at 80% of unfished levels. In the latter scenario, we determine whether the trend is rising, stable, or falling based on whether the annual change in $CPUE_{recruit}$ was greater or less than 10% of the 5-year moving average.

Management Strategy Evaluation

To conduct the MSE, we first built an age-structured population dynamics model specific to grass rockfish based on published data (Love and Johnson 1999). The population was then "sampled" via a simulated collaborative data collection program, and associated performance indicators were calculated. We used these performance indicators in the decision tree model to calculate the appropriate TAC. The TAC is then harvested from the simulated population in the following year, and the population is updated via a series of dynamic equations (Figure 2; Appendix A). This cycle is repeated for 30 years, and uncertainty is introduced into the model via process, observation, and sampling error by using Monte Carlo simulation (Cooke 1999; Smith et al. 1999). We developed an MSE specific to the decision tree that addresses four objectives of fisheries manage-

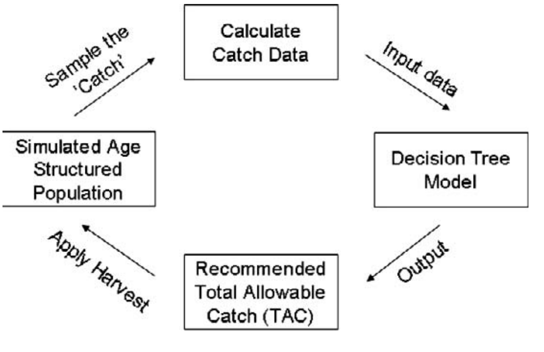

FIGURE 2.—Flow chart of the management strategy evaluation process.

TABLE 2.—Parameter set of the operating model (M = natural mortality; F_{max} = maximum fishing mortality; B–H = Beverton and Holt 1957; CPUE = catch per unit effort).

Parameter	Value	Source	Definition
Number of age-classes	19+	Love and Johnson 1998	19 age-classes and a plus group
s	0.8	A. MacCall, personal communication	1 − M
u (years 1–30)	0.51	—	$3F_{max}$
z	0.75	A. MacCall, personal communication	Steepness of B–H stock–recruit function
L_{∞}	51.3	Love and Johnson 1998	Asymptotic von Bertalanffy length
k	0.11	Love and Johnson 1998	Von Bertalanffy growth parameter
t_0	−2.41	Love and Johnson 1998	Theoretical age at length 0
α_1	0.045	Love and Johnson 1998	Coefficient of the length–weight relationship
β_1	2.77	Love and Johnson 1998	Coefficient of the length–weight relationship
α_2	0.12	Love and Johnson 1998	Coefficient of the length–fecundity ogive
β_2	4.09	Love and Johnson 1998	Coefficient of the length–fecundity ogive
α_3	−0.73	Love and Johnson 1998	Coefficient of the length–maturity relationship
β_3	17.49	Love and Johnson 1998	Coefficient of the length–maturity relationship
Hyperdepletion	0.5	Hilborn and Walters 1992	Nonlinear relationship between CPUE and abundance
Hyperstability	1.5	Hilborn and Walters 1992	Nonlinear relationship between CPUE and abundance

ment. First, we wanted to calculate the probability that the model can maintain biomass and SPR above the limit reference levels of 10% and 20% of virgin levels under multiple sources of uncertainty. Second, we wanted to test whether yield could be increased relative to yield under the present management strategy while maintaining biomass and SPR at acceptable levels of sustainability. Third, we wanted to test whether the model could maintain biomass and SPR and allow increased yield while also reducing year-to-year variability in catch. Finally, we wanted to determine whether the cost of management could be reduced by comparing model outcomes from decision making conducted annually versus once every 3 years.

Operating Model

We built two age-structured population models specific to grass rockfish with 19 age-classes and a plus group (Punt and Hilborn 1997; Appendix A), representing two distinct populations with similar life history characteristics and environmental pressures. The models were parameterized such that they could be subjected to process and observation error. Life history information, such as growth rates, maturity ogives, and fecundity ogives, was based on empirical data (Love and Johnson 1999). The value of M was assumed to be 0.2, typical of most West Coast rockfish stock assessments (A. MacCall, National Marine Fisheries Service, personal communication). Selectivity of fishing gear took on a logistic form with knife-edged selectivity occurring at the minimum size limit, similar to other species in the nearshore finfish complex (Alonzo 2004; Key et al. 2005). Recruitment was modeled by using a Beverton–Holt stock–recruitment function, with a steepness (h) value of 0.75 and subject to year-to-year recruitment variation (σ_r) that was the same for both populations. The representative equations for the population dynamics model are listed in Appendix A, and the associated parameter values are provided in Table 2.

Temporal patterns in the operating models were chosen to reflect the conditions observed in the live-fish fishery at the northern Channel Islands in the Santa Barbara Channel, California, from 1984 to the present day, encapsulating the growth, peak, and decline of the commercial fishery. Significant management measures were incorporated into the model, including a minimum size limit regulation enacted in 1999 and the establishment of a network of MPAs in 2003. For the first 15 years of the simulated fishery, we set harvest pressure equal to $3F_{max}$ in both populations. After this period, we "instituted" a minimum size limit and reduced harvest pressure to 50% of historically stable levels, similar to that which occurred in the nearshore commercial finfish fishery during this time. In 2003, we removed harvest on one population to resemble the initiation of an MPA. At this point, we began making harvest adjustments on the population outside the reserve by using the decision tree model. All other dynamics remained the same with the exception that the harvested population received a maximum of 5% of the available recruiting age-1 individuals from the MPA population via larval spillover.

The equations for catch and CPUE and the resulting size structures from these metrics were assumed to be taken from a standardized catch-and-release sampling regime inside and outside of MPAs in collaboration with commercial fishermen. The selectivity of the gear (and thus the resulting metrics) is similar to that which occurs in the commercial fishery.

Decision Tree Parameter Optimization

We optimized four decision tree parameters that had significant influence on the adjustment of TAC from

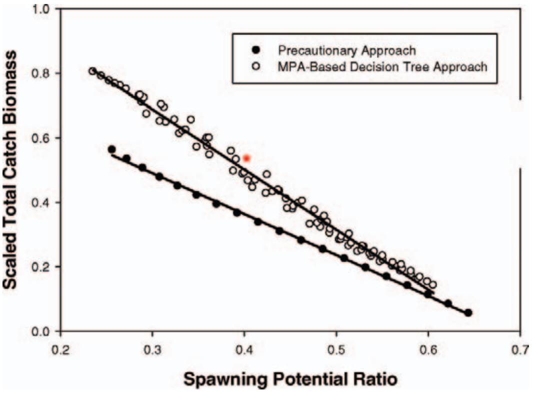

FIGURE 3.—Schematic depicting the tradeoffs between spawning potential ratio and total catch biomass (MPA = marine protected area). The open circles represent the combinations of the four most critical decision tree parameters that we searched over to find the optimal parameterization. The closed circles represent a range of total allowable catch levels between 10% and 100% of historically stable catch levels in our simulated population, reflecting the precautionary approach to management. The red star indicates the chosen combination of parameter values for future management strategy evaluation.

one year to the next. Each of the four decision tree levels was parameterized such that the setting of TAC would result in an SPR of 0.4 under limited uncertainty. These four parameters are identified in Table 1 by asterisks in the "value" column and include the following: the number of years over which the slope of $\mathrm{CPUE}_{\mathrm{prime}}$ is calculated in the level 1 slope-to-target algorithm; the target value for the $\mathrm{CPUE}_{\mathrm{prime}}$ found inside MPAs for level 1; the *k* in level 1; and the reduction factor for level 4 (Table 1). To optimize these parameters, we explored all possible combinations by using 1,000 Monte Carlo simulations, each executed over a 30-year time period with minimal uncertainty. To compare the decision tree model with the status quo precautionary approach in which the TAC is set at a fraction of historically stable catches, we also calculated SPR values and total catch biomass over a wide range of possible fractions of historically stable catches from 10% to 100%. These simulations were also executed over 30-year periods. We used the 5 years of catch before establishment of MPAs for the historically stable period as this stability held true in all iterations. We plotted the Pareto frontier between the realized SPR and total catch biomass from each of these combinations of parameters for the decision tree model and the precautionary approach (Figure 3) at year 30. The combination of parameters that resulted in the desired levels of $\mathrm{SPR}_{0.4}$ while maximizing total catch biomass at year 30 was chosen for future MSE tests (Table 1, denoted by asterisks) with increased uncertainty.

Management Strategy Evaluation Scenarios

We ran six decision tree scenarios incorporating process error, observation error, and sampling variability and compared them with two scenarios in which TACs were set at 50% of historically stable levels to reflect the current management approach. The eight scenarios (Table 3) examined combined the following conditions: year-to-year recruitment variation; observation error surrounding CPUE estimates; hyperstability and hyperdepletion relationships between CPUE and abundance (Appendix B); and situations in which fishermen target juveniles disproportionately to their abundance ("effort creep"; Appendix B).

The uncertainties and error structures covered a broad but not comprehensive range of possible scenarios. The first four scenarios simulated extreme levels of uncertainty for recruitment and CPUE as well as hyperdepleted conditions of the harvested population (Table 3). In scenario 1 (baseline), we allowed sampling from the population and TAC decisions to be made every year. Scenario 2 (10%) had a 10% limit on the annual allowable decrease in TAC levels as well as a 25% maximum annual allowable increase in TAC. In scenario 3 (3 years), we allowed sampling, TAC

TABLE 3.—The eight scenarios modeled in this case study. Columns 2 and 3 represent life history information, columns 4–7 represent various uncertainties in the model, and the final column depicts how decisions were made by using the decision tree (M = natural mortality; σ_R = recruitment variation; σ_{CPUE} = variation in catch per unit effort; effort creep = disproportionate targeting of recruit-sized fish). See the main text for further details.

Scenario	M	Steepness	σ_R	σ_{CPUE}	Effort creep	Hyperstability/hyperdepletion	Decision making
1	0.2	0.75	0.6	0.5	0	Hyperdepletion	Baseline
2	0.2	0.75	0.6	0.5	0	Hyperdepletion	10%
3	0.2	0.75	0.6	0.5	0	Hyperdepletion	3 years
4	0.2	0.75	0.6	0.5	0	Hyperdepletion	No decision
5	0.2	0.75	0.6	0.5	−0.5	Hyperstability	Baseline
6	0.2	0.75	0.6	0.5	−0.5	Hyperstability	10%
7	0.2	0.75	0.6	0.5	−0.5	Hyperstability	3 years
8	0.2	0.75	0.6	0.5	−0.5	Hyperstability	No decision

TABLE 4.—Outputs from the decision tree management strategy evaluation. Percent catch change relates the percentage increase or decrease in catch relative to the baseline precautionary approach (scenarios 4 and 8). Columns 2 and 3 depict the probability that the spawning potential ratio (SPR) will drop below critical thresholds of 0.10 and 0.20 of unfished levels in 1,000 Monte Carlo simulations. Columns 4 and 5 depict the probability that the total biomass will drop below critical thresholds of 0.10 and 0.20 of unfished biomass (B_0) in 1,000 Monte Carlo simulations. Average SPR is the average for the 30-year time period.

Scenario	Catch change (%)	<0.10 SPR	<0.20 SPR	<0.10 B_0	<0.20 B_0	Average SPR
1	+91	1.42	22.84	0.00	1.79	0.32
2	+147	1.82	28.35	0.00	2.42	0.30
3	+100	1.70	25.40	0.00	2.29	0.32
4	0	0.43	10.19	0.00	0.93	0.49
5	+39	0.99	17.09	0.00	1.25	0.43
6	+69	1.85	24.04	0.00	2.42	0.35
7	+32	1.67	22.81	0.00	2.25	0.38
8	0	0.47	11.17	0.00	0.98	0.46

decisions, and adjustments to be made every third year. Scenario 4 was the reference case in which no decisions were made and a constant precautionary TAC was applied, set at 50% of the average catch levels in the 5 years before MPA establishment. Scenarios 5–8 also simulated extreme levels of uncertainty in CPUE and recruitment variability, a hyperstable relationship between CPUE and abundance, and effort creep on recruit-sized fish (Table 3). Effort creep on juvenile fishes is modeled into scenarios by placing a 50% effort increase on recruits while reducing effort by 50% on prime-sized and old fishes (Appendix B). Scenarios 5–7 were subjected to the same sampling conditions and harvest rules as scenarios 1–3. Scenario 8 is the reference case similar to scenario 4.

Performance Measures

Our model was programmed to maintain SPR as close to 0.4 as possible. Maintenance of $SPR_{0.4}$ may be an appropriate risk-averse level for grass rockfish, which appear to be shorter lived and more resilient to overfishing than deeper-dwelling, long-lived West Coast rockfishes (Parker et al. 2000). To test whether the decision tree model is robust to uncertainty in our MSE scenarios, we calculated the probability that SPR and total biomass dropped below the limit reference points of 10% and 20% of virgin levels during a 30-year period. We also calculated the average SPR and the total catch biomass over the same time period. Total catch biomass was represented as a percent change in total catch relative to the reference scenarios in which the precautionary approach was used to set TACs. We chose these metrics because they cover a range of potential user group objectives.

Results

We used the set of parameter combinations (Table 1) that maximized the Pareto efficiency between $SPR_{0.4}$ and total catch biomass at the end of a 30-year time period under minimal uncertainty (Figure 3, denoted by asterisk) for all future MSE tests under various levels of uncertainty. We also examined the tradeoff between $SPR_{0.4}$ and total catch biomass for a range of precautionary harvest levels set between 10% and 100% of historically stable catch levels and applied annually for a 30-year time period. The precautionary approach never yielded higher SPR and catch than the MPA-based decision tree approach (Figure 3). We then compared the decision tree model under multiple uncertainty scenarios, fishermen behaviors, and management options with the precautionary approach in which the TAC for grass rockfish was set at 50% of historically stable catch.

The first three scenarios, consisting of hyperdepletion, recruitment variability, and error in CPUE estimates, resulted in substantially higher total catch biomass after a 30-year period than the precautionary approach. Scenario 1, in which decisions were made annually, resulted in a 91% increase in catch relative to the precautionary method. Scenario 2 resulted in a 147% increase, and catch in scenario 3 increased by 100% (Table 4). All scenarios maintained SPR and total relative biomass (B/B_0; ratio of B to unfished [virgin] biomass, B_0) at levels close to or above the target ($SPR_{0.4}$); the exception was scenario 2, in which harvest was never allowed to increase more than 25% or to decrease more than 10% (Figure 4). In the first three scenarios, biomass did not drop below $0.2B_0$ more than 2.3% of the time. Biomass never dropped below $0.1B_0$ under any scenario, including the precautionary approach (scenario 4).

In scenarios 5–7, we incorporated hyperstability, effort creep on juvenile fish, recruitment variation, and error around CPUE estimates (Table 3). This extreme variability still managed to substantially increase catches while maintaining total biomass and SPR conditions near target reference levels (Figure 4).

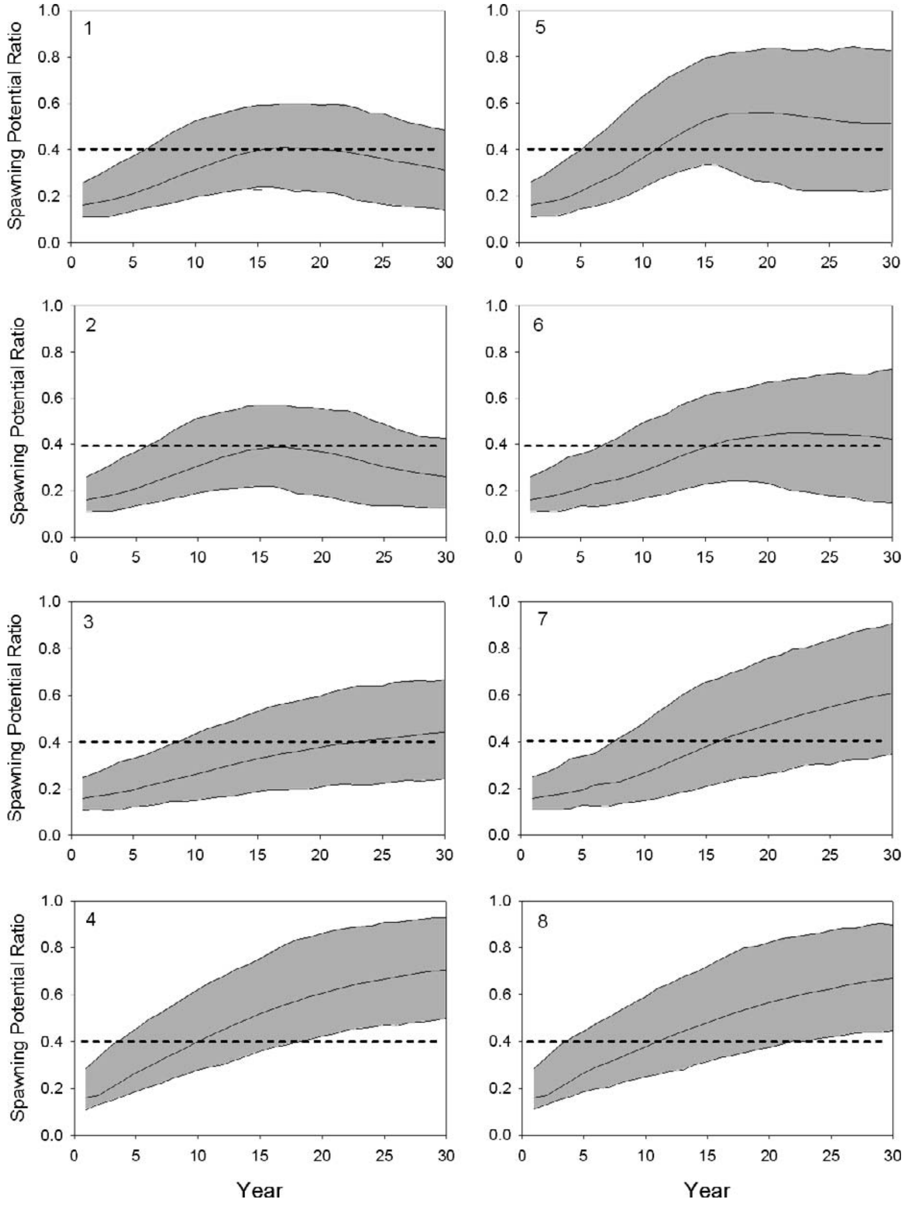

FIGURE 4.—Results of eight scenarios using management strategy evaluation for a 30-year time period. The solid black line depicts the median spawning potential ratio (SPR) over a 30-year time period using the marine protected area-based decision tree. The gray shaded area represents the range of the 10th- to 90$^{\text{th}}$-percentile SPR. The dashed line represents the target SPR value of 0.4. The numbered inset relates to the scenario modeled (1–8). Scenarios 4 and 8 are the precautionary scenarios in which harvest was constant at 50% of historically stable catch levels.

When decisions were made annually (scenario 5), catch increased relative to precautionary levels by 39%. Scenario 6 resulted in a 69% increase, and scenario 7 resulted in a 32% increase. Scenarios 5 and 7 were both conservative, yielding lower catches but high values for SPR and B/B_0. Scenario 6 was right on target at $SPR_{0.4}$ by the end of 30 years. For all of the scenarios, SPR values and B/B_0 never dropped below 10% of virgin levels more than 3% of the time.

Table 4 presents the percent increase in total catch biomass relative to the precautionary approach, the average B/B_0, and the probabilities that SPR and B/B_0

drop below 10% and 20% of virgin levels at any time during the 30-year analysis. All eight scenarios revealed that catch levels increased and SPR and biomass levels remained above threshold values (1) whether decisions were made every year or every 3 years and (2) whether or not a limit on the allowable annual change in TAC was implemented. We plotted the trajectory of SPR over a 30-year time period for all modeled scenarios (Figure 4). As noted above, when hyperstability and effort creep on recruits were modeled into the scenarios, SPR was maintained at high levels and catch decreased. The opposite was true for hyperdepletion, in which catches increased and SPR remained between 0.25 and 0.40.

Discussion

Our results reveal that data-based management strategies incorporating MPAs provide a powerful tool in helping to set sustainable harvest levels for sedentary nearshore marine species. We found that over a 30-year time period, the decision tree model maintained biomass and SPR levels close to target reference levels in nearly all cases, with little probability of dropping below limit reference points. Catch biomass consistently increased relative to the precautionary approach in which suboptimal harvesting occurred. Although the scenarios examined in this article do not cover the entire range of possible forms of uncertainty and stock dynamics that influence spatially structured nearshore stocks, the scenarios we used tested the ability of the model to maintain SPR at sustainable levels while also producing high levels of catch.

Important outcomes of this modeling exercise were the gains in efficiency from scenarios in which (1) analyses were performed every 3 years and (2) TAC levels were constrained to an allowable annual increase of 25% and an allowable decrease of 10%. This is encouraging because the costs of implementing a model such as this will be significantly reduced if sampling and analyses can be undertaken every 3 years. Moreover, if fishermen can reasonably expect to maintain stable annual catches, they may be more inclined to share the costs of management.

Nonlinear relationships between CPUE and abundance posed significant difficulties for maintaining target SPR levels; this was especially true when hyperdepletion was modeled. In these cases, TAC was often set too high. When applied to real-world cases, issues such as nonlinear CPUE estimates should be thoroughly vetted with stakeholders to determine the strength of these interactions. By taking advantage of the well-designed, objective-driven monitoring programs currently conducted for nearshore rocky reef species in California, estimates of CPUE may be approximately linearly related to abundance. The sampling methodology should always be standardized to reduce uncertainty in comparisons. Although we used CPUE as the level 1 metric to compare inside and outside of MPAs, it is perfectly reasonable to test the ability of fisheries-independent sampling, such as diver transect surveys, to set the initial TAC. This may further reduce nonlinearities in CPUE and abundance relationships. In fact, we recommend that a thorough examination of all possible data sources should be subjected to MSE if and when a method such as this is formally accepted for design and use in a fishery.

The use of MPAs in this model contributes significantly to the success of this management strategy, but there are a number of potential concerns with using MPAs as proxies for an unfished population. These include, but are not limited to, the relationship between adult movement and MPA size and the density-dependent changes in growth and survivorship of species within MPAs. Indeed, the use of MPAs in this management strategy is successful for those species that have small home ranges relative to the size of the reserve such that little to no migratory spillover occurs. This assumption may be valid for many of California's nearshore rocky reef species (e.g., sea urchins, abalone, nearshore fishes, crabs, and lobsters). Density-dependent changes in growth and mortality may be more difficult to account for. There is still very little empirical evidence validating changes in these ecological dynamics inside MPAs. We recommend that future use of the decision tree model should incorporate ecological dynamics as a means of learning.

We assumed in our simulation tests that the MPA and the fished area were separate, self-recruiting populations, save for the 5% larval spillover out of the reserve into the fished area. It is clear that increased rates of larval spillover significantly decrease the potential for dropping below threshold values of SPR and B/B_0 while allowing for increased catches. A full examination of larval connectivity scenarios between the reserve and the fished population is beyond the scope of this article but should be considered when determining the appropriate spatial scale at which to apply a method such as this.

We did not include the aggregate contribution of individuals inside the MPA to our calculations of total biomass and SPR. Therefore, our calculations of the probability of dropping below critical values of biomass and SPR are extremely conservative. In real-world applications, the size and spacing of MPAs relative to the harvested area will play a major role in determining the true probability of a population dropping below threshold values. A full examination of MPA size and spacing is beyond the scope of this article. Nevertheless, we recommend that a rigorous evaluation of these issues based on the best available information be conducted by stakeholder groups engaged in designing a decision tree process.

The MSE we performed assumed that life history information, such as growth and M, was known without error in the equilibrium models (levels 3 and 4), thereby biasing our results. This assumption causes the population to stabilize at a level above or below the target reference point indefinitely (Campbell et al. 2007). The propensity of the decision tree model to stabilize population indicators under uncertainty around life history data is superior to traditional stock assessments in which misinformation may result in stock decline or even collapse. Nevertheless, consideration of the potential problems associated with errors around basic life history information is warranted, and basic biological research to gather needed data is advised. If there is valid concern about dropping below $SPR_{0.4}$ due to uncertainty around life history information or other forms of process and observation uncertainty, the best solution would be to set reference SPR levels greater than necessary, thereby increasing precaution.

Our scenarios represent relatively simple cases that do not fully illustrate the flexibility of the decision tree process, especially in its capacity to use various forms of information and to generate different outputs. For example, fisheries-independent estimates of density, such as diver transect surveys, could be used in level 1. Instead of generating a TAC, which may not be the appropriate regulatory metric, effort allocation (number of traps or days) outputs can be generated. Many different adjustments to the model are possible and should be thoroughly considered before full MSE and implementation. As in any management strategy, management objectives should be thoroughly discussed among stakeholders, and when possible, formal evaluation of empirical data should be used in simulation models before proceeding with any strategy. In our case study with grass rockfish, we chose the decision tree parameters that maximized catch while maintaining $SPR_{0.4}$. However, a well-organized stakeholder process should examine these target reference points and objective functions to design a strategy that best suits the needs of the fishery. The decision tree process provides the opportunity for stakeholders to proactively manage the fishery in a transparent procedural framework rather than through a reactionary approach (Campbell et al. 2007).

We suggest that efficient gains in management can be achieved by adopting use of the decision tree in a localized, collaborative framework. The appropriate spatial scale of management units should consider the spatial variability in demographic rates, the geographic placement of MPAs, and the ability to organize stakeholders at ports of landing. This method has potential to fulfill the goals of the California Marine Life Management Act (MLMA 1998) and lead to effective community-based management for a number of reasons: (1) the fisheries-dependent nature of the data inputs required in the model presents a tremendous opportunity to include fishermen in collaborative research and management; (2) the spatial scale with which MPAs are being implemented will allow for socially and biologically appropriate regulations reflecting variability in harvest pressure, demographics, and social organization in local ports; (3) the method is transparent, user friendly, and generally understood by fishermen and community stakeholders at large; and (4) the use of MPAs in this process supports the stated goals of the California Department of Fish and Game, which advocates MPAs as tools in fisheries management (CDFG 2002).

Research programs that foster community involvement in the data collection and management of nearshore finfish and other species (e.g., Calobster Research Organization [www.calobster.org]) provide a foundation to develop and implement collaborative management programs like the decision tree process. We are currently engaged in a research program that fosters community involvement in the data collection and management of nearshore finfish and other species at the northern Channel Islands off the coast of Santa Barbara, California. We are gathering spatially explicit life history information, size structure, and CPUE data on grass rockfish, cabezon *Scorpaenichthys marmoratus*, California sheephead *Semicossyphus pulcher,* and other nearshore finfish harvested in the live-fish fishery in California. There is growing interest among the involved stakeholders to explore management options, including the establishment of an experimental program centered on using the decision tree framework to manage nearshore finfish at the Channel Islands.

Implementing novel assessment techniques for data-poor stocks in California and elsewhere will first require adaptive approaches at local scales. The success of such programs will rely heavily on the involvement of local communities, the flexibility of the management authority, and the scientific rigor of the decision-making strategy. As such, we are continually refining the evaluation process as stakeholder objectives become clear and as more complex issues, such as spatial connectivity of populations and dedicated access agreements, are considered. We encourage further discussion of this approach from the stakeholder communities at large in order to stimulate reform in California's nearshore fisheries management.

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Appendix A

The operating model is a typical female-only, age-structured model and assumes that the population is closed with respect to immigration and emigration. Natural mortality is set at 0.2 and is assumed to be independent of age and time. Selectivity to gear follows a logistic form and is knife-edged at the minimum size limit of 30 cm (Punt and Hilborn 1997).

The starting conditions for the age-groups are as follows:

$$\begin{aligned} N_1 &= R_0 \\ N_{a+1} &= N_a S(1 - uv_a) \qquad \text{for } a > 1, \quad a < N \\ N_n &= N_{n-1}\frac{(1-u_t v_n)S_n}{[1-(1-u_t v_n)S_n]} \qquad \text{for } a = N, \end{aligned} \tag{A.1}$$

where S is the survival from natural mortality, u is the fraction harvested of fully vulnerable individuals, v_a is the vulnerability of age-a fish to the fishery, and R_0 is the recruitment in year 1.

The number of individuals of each age thereafter is defined as

$$N_{a,t} = \begin{cases} R_t & \text{for } a = 1 \\ N_{a-1,t-1}S(1-uv_a) & \text{for } a > 1 \\ (N_{a-1,t} + N_{a,t})S(1-uv_a) & \text{for } a = N, \end{cases} \tag{A.2}$$

where R_t is the recruitment in year t.

Total egg production in year t (E_t) is

$$E_t \sum_a m_a f_a N_{a,t}, \tag{A.3}$$

where m_a is the fraction of the population of age a that are mature females and f_a is the number of eggs per mature female of age a.

The catch in year t (C_t; expressed in biomass) is defined as

$$C_t = \sum_a N_{a,t} w_a v_a u. \tag{A.4}$$

The CPUE is defined as

$$\text{CPUE} = \frac{\sum_a c_t}{e}, \tag{A.5}$$

where e is effort and is defined as C_t/B_v. B_v is the vulnerable biomass defined as

$$B_v = \sum_{a=1}^{a} N_a w_a s_a, \tag{A.6}$$

where w_a is the weight at age and s_a is the selectivity ogive.

Appendix B

Nonlinear relationships in catch per unit effort (CPUE) and abundance are fairly typical of most fisheries, and have been explained most effectively by the terms hyperdepletion and hyperstability (Hilborn and Walters 1992). Under harvest, hyperdepletion occurs when CPUE falls much more rapidly than abundance, while hyperstability occurs when CPUE remains constant in the face of declining abundances. The equation describing hyperdepletion and hyperstability is

$$\text{CPUE} = \text{CPUE}^{b},$$

where a b-value of 0.5 indicates hyperdepletion and a b-value of 1.5 indicates hyperstability.

Effort creep in this case study is defined as increased fishing pressure on the recruit size-class relative to the prime and old size-classes. For scenarios 5–8, we increase effort on recruits by 50% and decrease effort on old fish by 50% through the following calculation:

$$\text{Effort creep on recruits} = u \times \text{ec} + u$$
$$\text{Effort decrease on old fish} = u - u \times \text{ec},$$

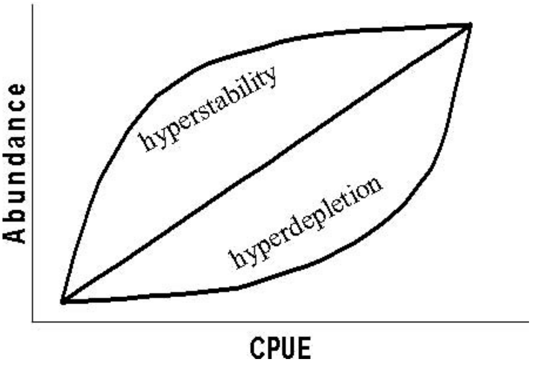

FIGURE A.1—Potential nonlinear relationships between CPUE and abundance in the management strategy evaluation.

where ec = -0.50 and u is the fraction of fishing mortality.