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Pretesting the Likely Efficacy of Suggested Management Approaches to Data-Poor Fisheries

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Abstract.—The thrust of this paper is that decision rules for the management of data-poor fisheries cannot be based on expert judgment alone. Such rules need to specifically link management responses to the values of the indicators available for the fishery and their trends. Prior simulation testing is needed to confirm that the application of any rules suggested is likely to achieve the objectives sought for the fishery. The management procedure (MP) approach (also called management strategy evaluation), which provides a framework for such testing, is summarized briefly. How this approach could be used to develop a decision rule for a fishery for which the only indicator available is the mean length of the catch is presented as an example. The extent to which the ability to meet management objectives could be improved if an unbiased index of relative abundance were available, and an MP based on a fitted population model applied, is illustrated. An MP developed for the fishery for Patagonian toothfish *Dissotichus eleginoides* off the sub-Antarctic Prince Edward Islands is summarized. This illustrates how the MP testing framework can be used in circumstances in which the available indicators conflict, leading to considerable uncertainty about the present resource status. The information content of indicators is closely related to the extent to which they vary about trends in the underlying resource attributes (e.g., catch per unit effort and underlying abundance). The compilation of lists of the statistical properties (such as the coefficients of variation and autocorrelations) of the residuals about detrended time series of the indicators, together with their likely relationships to the underlying attribute, for fisheries worldwide is suggested. This would provide a sound basis for specifying error structure in the simulation tests advocated for both generic and case-specific decision rules for data-poor fisheries.

A typical ideal for a fishery assessment scientist is a resource for which accurate data on total catch are available from the inception of the fishery, together with some reasonably precise fishery-independent index of abundance (e.g., from a research survey or tag recovery program conducted in a comparable manner over a considerable period of time that continues to the present). The addition of reliable annual age data for the catch (and desirably for any of the catches used to develop the abundance index) allows variations in recruitment to be taken into account. From this information, quantitative advice can be developed on the catch or effort (related to fishing mortality) levels appropriate to move resource abundance toward some target considered to correspond to optimal utilization (where this target is frequently related to the estimated abundance to provide the maximum sustainable yield level [MSYL]).

Such ideals are seldom attained in practice. Line fisheries in which recreational fishers are the dominant user group are a ready example. For a start, total

catches are usually very difficult to estimate with confidence. In South Africa, attempts have been made to estimate fishing mortality from length distribution data by means of the analysis of a catch curve obtained with the aid of information on somatic growth; management measures to raise or lower this fishing mortality have then been developed in the light of a comparison of this fishing mortality estimate with some reference point based on a spawner-biomass-per-recruit analysis (Griffiths 1997; Attwood 2003). However, such a comparison can be biased through error in the estimate used for natural mortality (never easy to determine) and the impact of nonequilibrium effects on the catch curve (see Butterworth and Punt 1990 for a fuller discussion)—aside from the frequent difficulty of calibrating the relationship between the desired change in fishing mortality and the magnitude of the management measure needed to achieve it (e.g., the daily bag limit or duration of the fishing season).

The use of fishery indicators (e.g., the mean length of the catch) and their temporal trends as input into decision rules based primarily on expert judgment (perhaps within a “traffic light” framework; Caddy 2002) has at times been suggested in southern Africa and elsewhere as an attractively simple and appropriate approach to management in data-poor (and even some data-rich) situations (O’Boyle 2003; ICES 2007; Potts et al. 2008). Frequently, the direction of change in such

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indicators relates to whether existing management measures need to be made more or less restrictive. However, even in the happy situation in which all such indicators point toward a common direction for a change in management measures, so that the difficult issue of how to weight different sources of information with contradictory implications does not arise, the fundamental question remains as to how to quantify the change required to achieve the objectives for the fishery.

Thus, for example, it might be clear from the trends in an indicator that the total allowable catch or fishing effort needs to be decreased, but by how much? Too little a decrease runs the risk of undue reduction of the resource, thus threatening its future productivity; too great a decrease could cause unnecessary socioeconomic disruption. One also has to consider how much the trends in the resource monitoring data reflect random noise rather than the underlying resource dynamics.

The thrust of this paper is that management decisions cannot be reliably based on qualitative “expert judgment.” Even in data-poor situations, in which the standard stock assessment exercises are not possible, proposed decision rules need to be subjected to prior simulation testing to confirm that they are likely to achieve the objectives sought for the fishery.

The basic framework for such simulation testing (known as the management procedure approach or management strategy evaluation) has already been developed and applied to a number of relatively data-rich fisheries, as summarized in the following section. This paper illustrates how this might be done in a data-poor situation—one in which the mean length of the catch is the only index available—and contrasts its performance with that for the same situation in which there are enough data to take a standard approach. This is followed by a summary of the development of a management procedure for the fishery for Patagonian toothfish *Dissotichus eleginoides* off the sub-Antarctic Prince Edward Islands, for which the data quality is not only poor but two different indicators provide conflicting indications as to the status of the resource. Finally, some suggestions are made as to the areas in which further investigation of this approach is needed.

The Management Procedure Approach

The management procedure approach had its origins in the response of the Scientific Committee of the International Whaling Commission to the commission’s decision to impose zero catch limits (i.e., a moratorium) on commercial whaling in 1982. A major reason for this decision was uncertainty as to the determination of sustainable catch levels, together with the lack of a clear way to incorporate that uncertainty

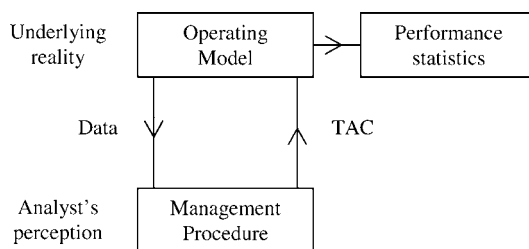


FIGURE 1.—Schematic representation of the simulation testing of a management procedure (MP).

into a “best (stock) assessment” of the resource (Punt and Donovan 2007).

A management procedure (MP) is defined as a set of prespecified methods for collecting and analyzing data on the status of a resource together with a simulation-tested decision rule that furnishes a management recommendation (such as a total allowable catch) based on those data (Butterworth et al. 1997). Simulation testing is required to ensure that the decision rule provides the necessary feedback from the data to adjust management measures so as to achieve the objectives for the fishery. This necessitates that the pseudodata generated in the testing process incorporate the level of error (e.g., the sampling error associated with a survey) that would be anticipated in practice. Furthermore, continued simulation with the decision rule (typically for 10–20 years, though longer if very long-lived species are concerned) must show that it attains the objectives not only when the current best assessment of the resource reflects the true underlying dynamics but also when there are other plausible hypotheses consistent with the data.

Figure 1 illustrates the calculation process. An operating model (OM) is developed to represent the possible underlying dynamics of the resource (the “best assessment” could be used for this purpose). This model generates resource monitoring data (e.g., abundance and catch per unit effort) of the type and with the same error structure that would be available in practice. These data are fed into a formula (the MP) that determines the TAC recommendation. The formula may be complex (e.g., replicating the standard annual assessment plus catch control law basis) or simple (such as making the change in TAC proportional to a recent trend in the catch rate). Importantly, the computer evaluations are structured so that the formula is not based on knowledge of or direct input from the actual underlying dynamics of the resource (the current values of the variables of the OM) except as reflected in the data available for assessment purposes, as would be the case in practice.

The calculated value of the TAC is then input into the OM so that the dynamics can be updated by 1 year, and the loop in Figure 1 is repeated until the end of the projection period. The performance of the MP is then summarized in terms of measures drawn from the underlying reality and the OM (such as the average annual catch achieved over the period) as well as a comparison of the final population abundance with the target level. To take into account the imprecision in current estimates, the random noise in future data generated by the OM, and the variation in future recruitment and perhaps also in selectivity, this whole process is typically repeated 100 times, so that the performance outputs take the form of statistical distributions rather than single values.

The choice of a final formula from among a number of candidate MPs is determined by consideration of the trade-offs among performance statistics (the best formula provides the greatest average annual catch without having a lower percentile for resource abundance that drops below some limit that could pose a threat to future recruitment). The performance statistics considered include not only those for an OM corresponding to the current best assessment; the set of simulations described above are repeated for other OMs—ones that represent different, but still plausible representations of the resource and fishery dynamics. To be acceptable, a candidate MP must demonstrate robust performance for these various OMs. In this way, the concerns of the precautionary approach—taking due account of uncertainties—are addressed (FAO 1995).

There is a growing body of literature detailing the MP approach (or the MSE) and its application to fisheries in many parts of the world (e.g., Butterworth and Punt 1999; Cooke 1999; Smith et al. 1999; Bentley et al. 2003; Kell et al. 2006; Punt 2006; Plagányi et al. 2007; and De Oliveira et al. 2008). Butterworth (2007) summarizes the pros and cons of the MP approach relative to traditional best assessment-based management. Rademeyer et al. (2007) include a glossary of the terminology that has developed in the field, and Butterworth (2008) discusses some implementation issues and experiences.

A Comparative Example

The example that follows contrasts the management of the same fishery in data-rich and data-poor situations by applying an MP approach in both cases. The scenario considered is a common one: a resource has been depleted, certainly to below its MSYL; catches have been reduced, but it is unclear whether this is sufficient to achieve sustainability; and recovery to a target level such as MSYL is desired.

The details of the OM describing the underlying

situation are provided in the appendix. Parameter values have been selected to mimic a species of intermediate size and longevity (natural mortality = 0.3/year) with a typical level of recruitment variability ($\sigma_R = 0.5$). Catches are determined by a selectivity-at-age function (selectivity includes the effects of availability [i.e., different spatial distributions for different age-classes] as well as gear selectivity) that is stochastic, with autocorrelation both with respect to age and over time.

The OM generates annual values for both catch per unit effort (CPUE) and mean catch length. There is an unbiased linear relationship between CPUE and abundance, but there is also variation about this relationship because of fluctuations in selectivity at age and observation error ($\sigma_{\text{CPUE}} = 0.25$; see equation A.14 in the appendix, which is in the vicinity of what might be expected in practice). The variability in selectivity also causes temporal variation in the true mean length of the catch, but again there is observation error ($\sigma_{\text{len}} = 0.25$; see equation A.23). This last value was chosen to ensure a coefficient of variation (CV) in the observed mean length over the last 20 years of about 8% (a value based on those in the fisheries for Atlantic cod *Gadus morhua* in the Gulf of Maine, Patagonian toothfish at the Prince Edward Islands, and South African hake *Merluccius* spp.).

In the reference-case OM, the underlying situation is one in which the depletion of the resource after four decades (B_{40}^{sp}) is 20% of the average preexploitation level (K^{sp}) in terms of spawning biomass, that is, $B_{40}^{\text{sp}}/K^{\text{sp}} = 0.2$, which corresponds to an MSYL of 0.36. Alternative scenarios in which depletion is 10% or 30% are also considered to test the robustness of the model.

The simulation testing considers a subsequent 20-year management period (i.e., years 41–60) under catches prescribed by an MP. Two situations are contrasted, one that is data rich and one that is data poor.

The Data-Rich Case

Annual catches are known since the inception of the fishery and CPUE from year 10. These data are used as input into a population-model-based MP (termed here CPUE based) that each year fits an age-aggregated dynamic production model with a production function of the Schaefer form to provide estimates of current abundance and MSY fishing mortality ($F_{\text{MSY}} = r/2$, where r is the intrinsic growth rate, for this form). After modification by the control parameter λ (see equation A.28), the catch associated with this fishing mortality is used to adjust the recommended TAC in a smooth manner (facilitated by restrictions on the range of values for r and a limit of 15% on the extent to which the TAC can change from one year to the next). By

itself, this formulation does not provide sufficient safeguards against undue resource depletion, so that an additional factor (μ) reduces the TAC further if recent CPUE values drop below a specified level (see equations A.24–A.33).

The Data-Poor Case

For this situation, no direct index of resource abundance is available, only the mean length of the catch l being monitored. The associated “empirical” MP (termed l based) changes the TAC each year in a manner that depends linearly on \bar{l} (see equation A.33 and the accompanying text) under the assumption that in broad terms higher (lower) values of \bar{l} indicate higher (lower) fishing mortality.

The same single realization of past (years 1–40) stochastic components of the reference-case OM is used to test both of these MPs, though for the future (years 41–60) 50 realizations are used; for each of these, however, the stochastic variables have the same values whichever MP is being tested to enhance the reliability of the comparisons of results. For the same reason, the values of the stochastic variable remain unchanged for the two robustness tests, only the value of the preexploitation abundance K^{sp} being varied to provide different values of depletion in year 40. Note that this does not mean, for example, that recruitment in year 45 will be the same for either MP in a particular realization: though the value of ε_{45} in equation (A.16) will be the same, the value of B_{45}^{sp} will differ as a result of the particular preceding catches assigned under each MP. (For a real application, more realizations would be used for both past and future periods; the numbers were kept smaller here in the interests of simplicity for what is intended purely as an illustrative exercise.) Figure 2 shows the single fixed past realizations and three of the future realizations of CPUE and \bar{l} respectively under the corresponding MPs together with the associated time series of TACs.

Results

The values of the control parameters of the CPUE-based MP (λ and the parameters of the factor μ ; see equation A.24) were chosen to secure appropriate performance in these simulation tests of the MPs. Essentially, though the effects of the two interact, λ was set to attain recovery to MSYL in 10 years in median terms (which is broadly compatible, for example, with what might be required under fisheries legislation in the USA; see U.S. Office of the Federal Register 2008) for the reference-case OM (for which depletion is 20% at year 40), and the μ were specified to ensure that extinction was avoided in the robustness test with depletion at 10% in year 40 (see Figure 3A).

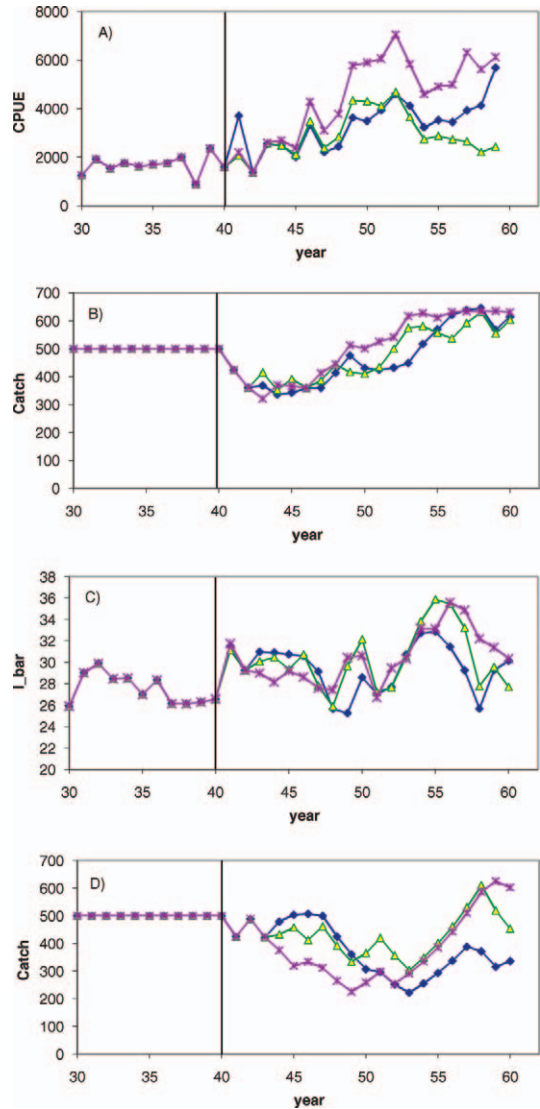


FIGURE 2.—CPUE-based (data-rich) MP trajectories for (A) CPUE and (B) catch and mean-length-based (l) (data-poor) trajectories for (C) l and (D) catch for three simulations of the $B_{40}/K^{sp} = 0.2$ scenario. See text for full details.

The median and 90% probability interval (PI) values for the performance statistics for the CPUE-based MP are given in Table 1 for the reference-case OM and the two robustness tests. Note in particular the value of the lower 5th percentile for final abundance at B_{61}^{sp}/K^{sp} for the reference-case OM (0.236), which characterizes the risk of unintended depletion of the resource under this MP.

To compare the performance of the CPUE-based MP in a data-rich situation with that of an \bar{l} -based MP in a

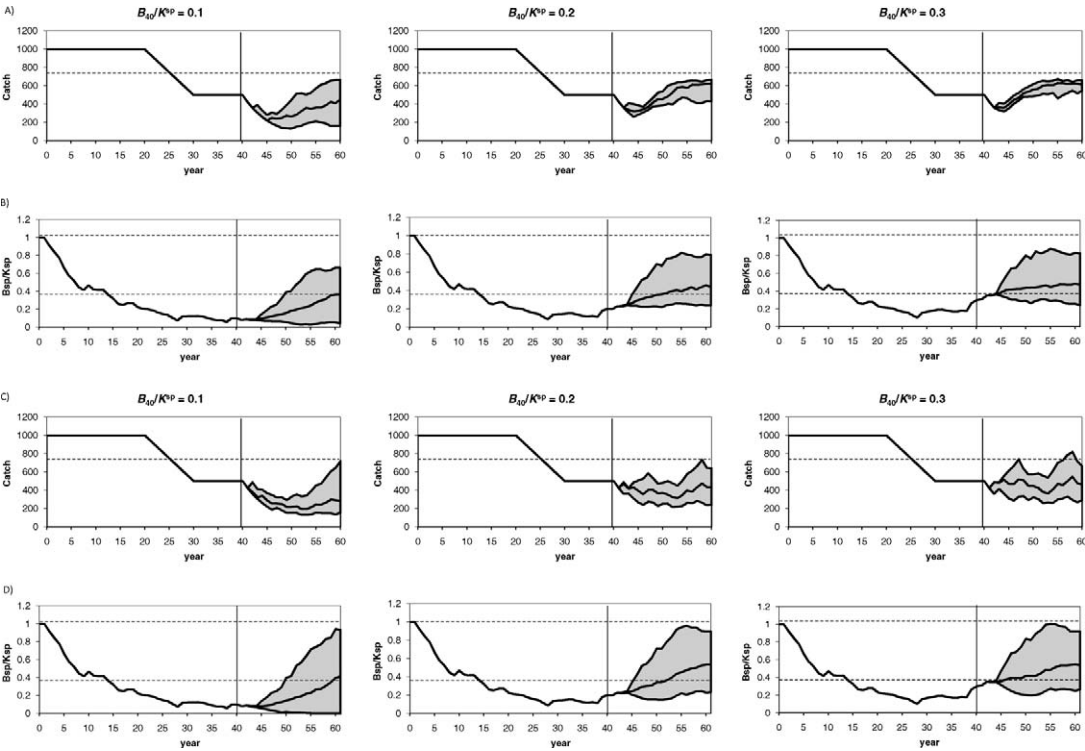


FIGURE 3.—(A)–(B) CPUE-based (data-rich) MP trajectories for catch and B_{61}^{sp}/K^{sp} for three levels of B_{40}^{sp}/K^{sp} . Medians and 90% probability intervals are shown. The dotted lines in panels (A) and (C) indicate the maximum sustainable yield (MSY) values; the lower dotted lines in panels (B) and (D) indicate the values of B^{sp}/K^{sp} at which a deterministic MSY is achieved.

data-poor situation, it is sensible to select the control parameters for the latter to achieve the same performance (in some respect) as in the former. The statistic characterizing risk as set out in the previous paragraph was chosen for this purpose, so that in some sense the MP performances were compared under equivalent levels of resource risk. The \bar{l} -based MP has two control parameters ($\bar{\omega}$ and l_0/l_{past} ; see equation A.33 and the

accompanying text), the values of which can be varied to provide different trade-offs in performance. These values were selected so that the lower 5th percentile for final abundance at B_{61}^{sp}/K^{sp} for the reference-case OM was the same under both the \bar{l} -based and CPUE-based MPs. Satisfying one condition with choices for two parameters still leaves one degree of freedom; as the value of l_0/l_{past} is increased from the 0.9 chosen, the

TABLE 1.—Comparison of summary performance statistics (medians with 90% probability intervals in parentheses) between the CPUE-based and the \bar{l} -based MPs.

Statistic ^a	B_{40}^{sp}/K^{sp}	CPUE-based MP	\bar{l} -based MP
C_{ave} (metric tons)	0.1	327 (246–428)	273 (234–394)
	0.2	477 (434–519)	400 (357–447)
	0.3	525 (485–556)	461 (411–534)
B_{61}^{sp}/K^{sp}	0.1	0.366 (0.045–0.655)	0.414 (0.000–0.930)
	0.2	0.439 (0.236–0.792)	0.533 (0.235–0.898)
	0.3	0.473 (0.241–0.827)	0.540 (0.266–0.922)
AAV	0.1	13.5 (11.7–14.6)	13.5 (12.3–14.6)
	0.2	8.2 (6.5–10.1)	12.3 (10.7–13.6)
	0.3	6.3 (5.00–7.7)	11.7 (9.8–13.5)

^a C_{ave} = the average annual catch over the 20-year projection period; B_{61}^{sp}/K^{sp} = the spawning biomass at the end of the projection period relative to that at the start of the fishery; and AAV = the average interannual variation in catch over the projection period expressed as a percentage.

risk-related statistics for the robustness test with depletion at 10% in year 40 improve slightly, but at the expense of a large drop in average catch. The choice made was considered to reflect a reasonable trade-off between these two aspects of overall performance.

The performance statistics for the \bar{l} -based MP tuned in this way are reported in Table 1 and shown in Figure 3B, which is to be compared with the results for the CPUE-based MP in Figure 3A. It is immediately evident that for the same resource risk, the lesser information content of the mean length data in the data-poor situation leads to a deterioration in performance in terms of other summary statistics: average catch over time decreases by about 15%, the interannual variability in the TAC increases by 50%, and the ranges of both the average catch over the 20-year period simulated and the abundance at the end of this period increase. Furthermore, the \bar{l} -based MP shows less robustness: for the test with depletion in year 40 at 10%, the envelope of the lower 5th percentile of the spawning biomass distribution shows cases of extinction each year after about 15 years, whereas it stabilizes at about 5% of the preexploitation level for the CPUE-based MP.

Management of the Prince Edward Islands Toothfish Fishery

The fishery for Patagonian toothfish off the sub-Antarctic Prince Edward Islands reflects two atypical and important features: particularly substantial illegal, unregulated, and unreported fishing initially, followed by nontrivial levels of cetacean depredation as sperm whales *Physeter macrocephalus* and particularly killer whales *Orcinus orca* developed the ability to take the fish from longlines as they were hauled.

An early assessment (Brandão et al. 2002) estimated the resource to be severely depleted, as one might expect given the large reduction in CPUE that followed the high initial catches (see Figure 4). However, when catch-at-length data from long-lining as well as those from a brief period during which a pot fishery operated were taken into account in subsequent assessments, the situation became less clear (e.g., Brandão and Butterworth 2006). These data (Figure 4) do not show the decrease in mean length that would be expected if fishing had substantially reduced abundance. The estimates of current abundance range from heavily depleted to above MSYL as the weight given to the data shifts from favoring the CPUE data to favoring the catch-at-length data.

The combination of high uncertainty about overall removals, conflicting indications from the available indices, and the lack of a fishery-independent index of

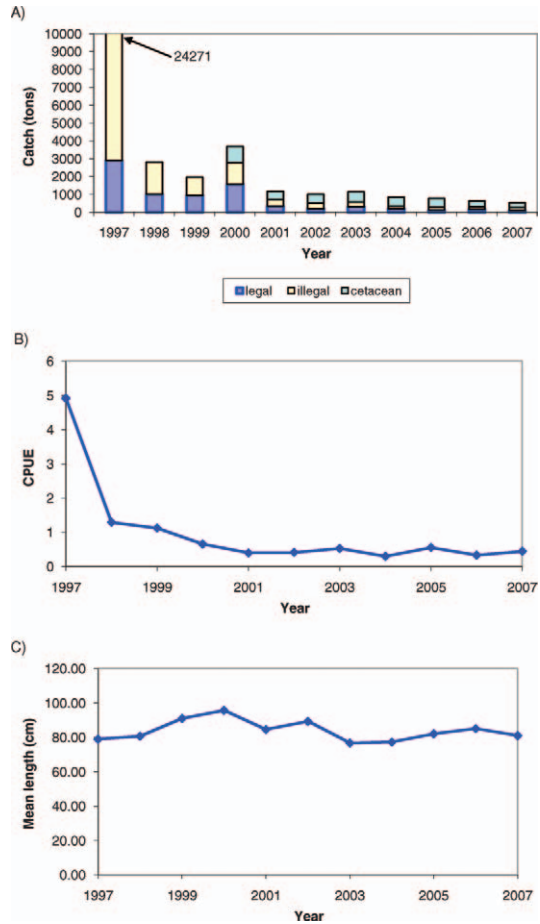


FIGURE 4.—Assessment data available for Patagonian toothfish in the neighborhood of the Prince Edward Islands. Panel (A) shows the annual removal by category (legal, illegal, and due to cetacean depredation; panel (B) shows the generalized-linear-model-standardized CPUE; and panel (C) shows the mean length of the legal longline catch.

abundance effectively make this a data-poor situation. To address (especially) the uncertainty about the current status of the resource arising from the conflicting past trends in these indices, Brandão and Butterworth (2009) developed an empirical MP using longline CPUE and the mean length of longline catches for input. The MP sought robust performance across a wide range for present abundance, aiming to increase current catches if the abundance were high relative to the preexploitation level but to exercise restraint if the stock were heavily depleted. It looked to future trends in the two indices to indicate implicitly which of the two scenarios corresponded to reality as the feedback

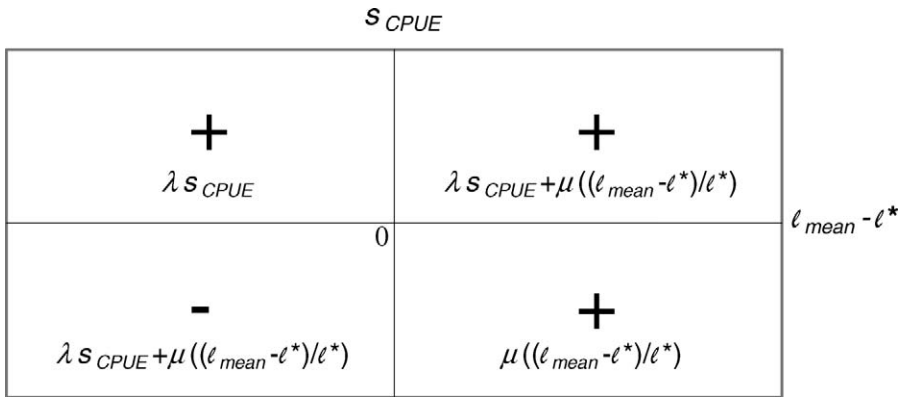


FIGURE 5.—Decision structure in the Patagonian toothfish MP, which takes into account the trend in CPUE (s_{CPUE}) but reaches different decisions as to total allowable catch (TAC) depending on whether biomass is above or below the MSY level (i.e., whether the mean length at capture is greater or less than ℓ^*). The plus and minus signs indicate whether an increase or decrease in catch is required. The catch control rule has the form $TAC_{y+1} = TAC_y(1 + \psi)$, where ψ is given by the formula in the applicable quadrant.

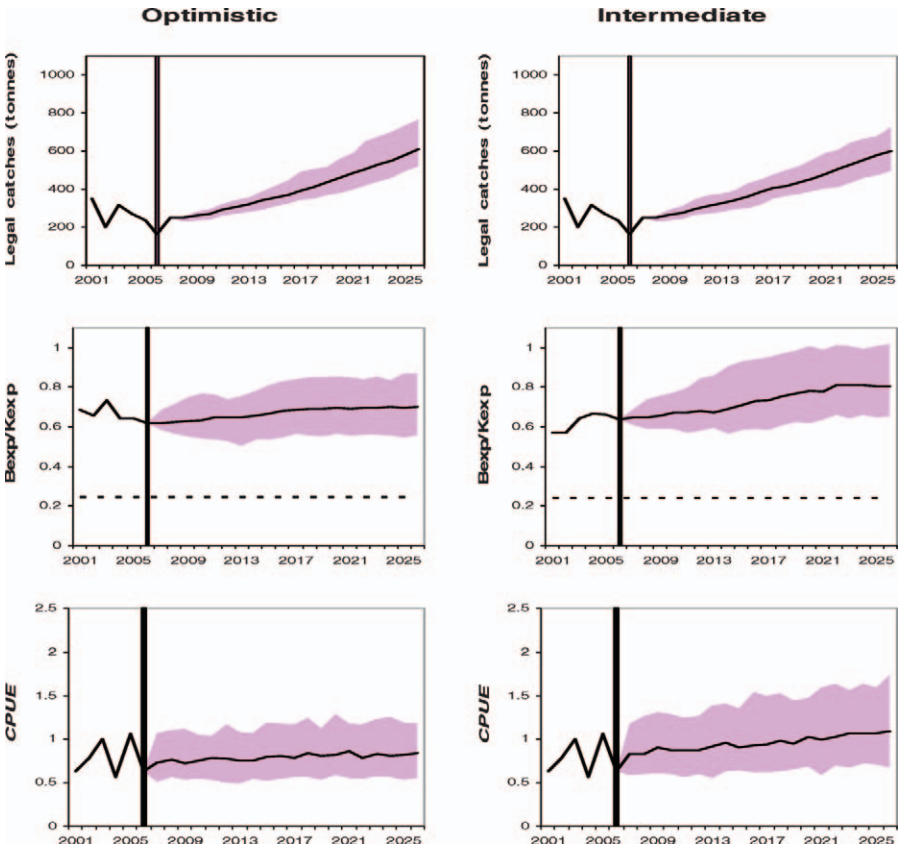


FIGURE 6.—Median trajectories of the legal annual catches of Patagonian toothfish by longliners in metric tons (top row), exploitable biomass depletion (middle row), and CPUE (bottom row) under the MP across four scenarios for current depletion relative to the preexploitation level: 68% (optimistic), 57% (intermediate), 37% (less pessimistic), and 15% (pessimistic). The shaded areas represent 90% probability envelopes. These results assume that illegal catches continue at a constant rate of 150 tons per year and that cetacean depredation remains at the same level as in the immediate past (i.e., equal to the longline catch landed). The dotted lines in the middle row show the value at which MSY is achieved.

features of the MP modified future TACs in an appropriate manner.

An important aspect of the testing process is the manner in which the conflict between the available indices is handled. The approach followed mirrors that adopted by the scientific committee of the International Whaling Commission to test the robustness of an MP for bowhead whales *Balaena mysticetus* (IWC 2001). In generating future (pseudo)data for this testing process, the extent of the variability about the underlying trends is customarily estimated from the fits of OMs to past data. However, this becomes problematic when there are data conflicts (and hence systematic trends in the residuals for such fits), so that the associated variance estimates are inappropriately large for use in generating future observations.

Therefore, different OMs assume the past bias in one or the other of the indices to have been sufficient to eliminate model misspecification (this may be done by simply ignoring different subsets of past data in fitting these OMs). This is not outside the bounds of

plausibility in the Patagonian toothfish case, in which the early high CPUE might reflect the fishing down of some localized high-density aggregations that made little contribution to overall abundance; alternatively, the initial fishing might have focused on areas in which the length distributions of the fish were not representative of those overall. The ability of the MP to implicitly discriminate between the alternative scenarios then relies on the assumption that past biases do not continue into the future, future observations serving as unbiased indices of the underlying resource attributes and manifesting realistic levels of observation error.

An interesting aspect of the Patagonian toothfish case that needed to be factored into the MP design is that the direction of change in one of the key indicators (CPUE) does not unambiguously define the direction of the appropriate management response. For example, if the resource is heavily depleted, a reduction in CPUE suggests that abundance has fallen yet further below the MSYL and that the TAC needs to be reduced;

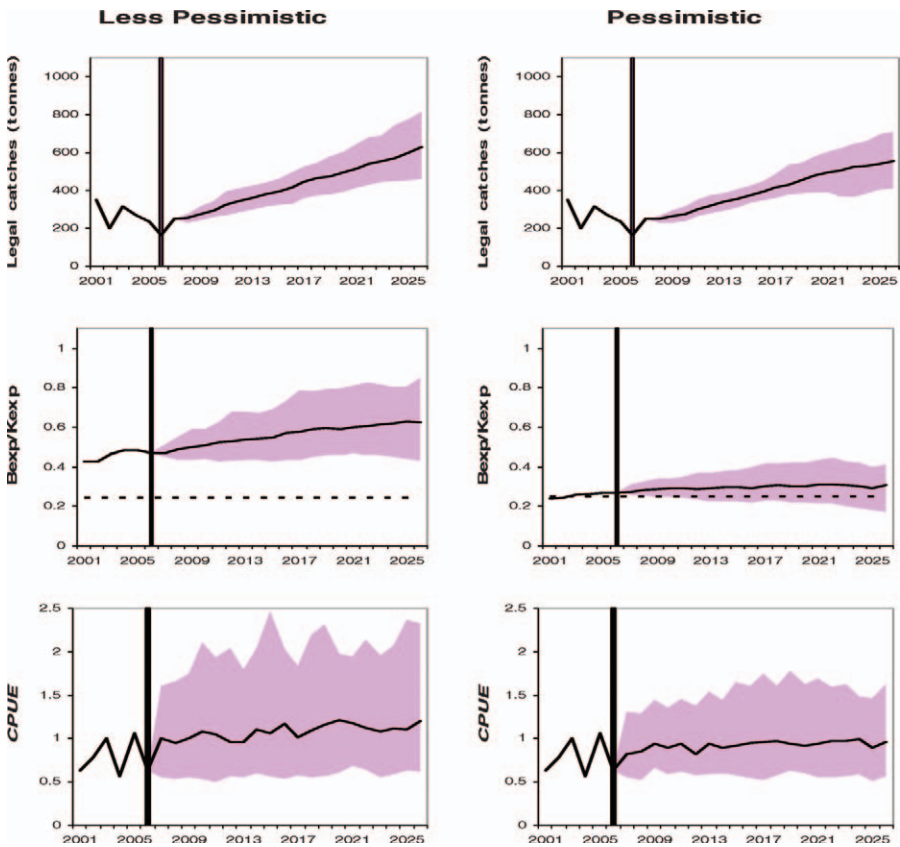


FIGURE 6.—Continued.

however, if the current abundance is above the MSYL, a drop in CPUE is neither necessarily undesirable in terms of resource status nor indicative of the need to reduce the TAC. To allow for this, the MP formulae applied (and which of the two indices they take into account in computing a TAC recommendation) change depending on whether or not CPUE is increasing and whether or not the mean length of the catch is above a specified level (ℓ^*), which serves as a proxy for the MSYL. The details are shown in Figure 5, three control parameters (λ , μ , and ℓ^*) being available to tune the procedure to provide the desired trade-off in performance across the various summary statistics.

Figure 6 shows the anticipated performance for the MP selected across four scenarios for current depletion relative to the preexploitation level: 68% ("optimistic"), 57% ("intermediate"), 37% ("less pessimistic"), and 15% ("pessimistic"). These four scenarios were developed by shifting the relative weightings in the model fitting process from the catch-at-length data toward the CPUE data. In making this selection, the preference of the industry for a low probability that CPUE will drop much below its present level played an important role; this preference arose from the fact that the fishery is economically marginal at present as a consequence both of the recent increase in the price of fuel and of the role of cetaceans in reducing CPUE. Note from the plots in Figure 6 that the probability of a drop in CPUE is anticipated to be low whatever the present resource status but that TACs are nevertheless projected to increase (slightly) faster the less the current depletion of the resource.

Discussion

It needs to be stressed that the comparative example presented in this paper is intended only to illustrate how the MP approach could be applied in data-poor situations. It is *not* intended to constitute an analysis that is definitive in itself or in respect to the likely quantitative benefits from management of a data-rich as distinct from a data-poor fishery. For example, no account is taken of "implementation error," that is, how well actual catches could be regulated and monitored in practice and how closely they would correspond to intended TACs. Such errors would probably be larger in most data-poor situations, thus increasing the benefits from collecting data with greater information content.

While the example does demonstrate that average catches need to be lower in a data-poor situation for the same level of risk to the resource, not too much should be read into the numerical difference (some 15% in this example). No claim is made that the two MPs considered are the best that could be fashioned for

the data available to them. The purpose of the exercise is rather to illustrate how the magnitude of such effects might be evaluated in an actual case and what the key input information would be in terms of its impacts on the results.

Such key information certainly includes the likely statistical properties of the measurements of indicator values as they relate to the underlying resource attribute in question. The information content of indicators is closely related to the extent to which they vary about trends in the corresponding attributes (e.g., CPUE with respect to the underlying abundance). In this case, the CV and autocorrelation of the two indices over the first 10 years of applying an MP averaged 40% and 19% for CPUE and 7.5% and 4% for mean catch at length (\bar{l}). The variability in CPUE stems from the fluctuations in selectivity at age as well as observation error and may be high compared with what would be expected in a well-monitored, data-rich fishery, so that the calculations here probably underestimate the likely advantages of moving to a data-rich situation to some extent.

A further advantage of the data-rich situation is that the biases in the relationships between data and the underlying resource attributes for which they serve as indices would probably be less than for the types of data typically available in data-poor situations. This leads to the requirement for a wider range of robustness tests across which an MP for a data-poor situation would need to demonstrate adequate resource risk-related performance, forcing its control parameter values to be set more conservatively, which would lead to lower catches.

As an aid to future applications of an MP approach to data-poor fisheries, priority should be given to compiling lists of the statistical properties of measurements of indicator values (such as CVs and autocorrelations of residuals about detrended time series) together with the likely relationships of these indicators to underlying resource attributes over a range of resources worldwide. This would be similar to the exercise undertaken in the 1990s by the late Ram Myers and colleagues (e.g., Myers et al. 1995) to develop a database of spawning stock and recruitment estimates for a wide range of fish stocks. Such lists would guide the appropriate specification of OMs for MP testing where the OMs need to relate reasonably closely to reality by providing a sound basis for specifying the error structures in the OMs. This is important not only (and obviously) for the development of generic MPs for data-poor fisheries but also for MPs tailored to particular fisheries; in data-poor situations key information will not be available for the resource concerned, so that values from similar

resources elsewhere will be needed to provide guidance.

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Appendix: The Operating Model

The underlying operating model for the fishery is an age-structured production model (ASPM) in which the dynamics of the population are described by the following equations:

$$N_{y+1,0} = R(B_{y+1}^{\text{sp}}) \quad (\text{A.1})$$

$$N_{y+1,a+1} = (N_{y,a}e^{-M_a/2} - C_{y,a})e^{-M_a/2} \quad 0 \leq a \leq m-2 \quad (\text{A.2})$$

$$N_{y+1,m} = (N_{y,m}e^{-M_m/2} - C_{y,m})e^{-M_m/2} + (N_{y,m-1}e^{-M_{m-1}/2} - C_{y,m-1})e^{-M_{m-1}/2} \quad (\text{A.3})$$

where

- $N_{y,a}$ = the number of fish of age a at the start of year y ;
- $C_{y,a}$ = the total number of fish of age a taken by the fishery in year y ;
- $R(B^{\text{sp}})$ = the recruitment–spawner biomass relationship (see below);
- M_a = the natural mortality rate for fish of age a ;
- m = the largest age considered (and corresponds to a “plus group”).

The approximation of the fishery as a pulse catch in the middle of the season is of sufficient accuracy for the purposes of this paper.

The total number of fish of age a caught each year ($C_{y,a}$) is given by

$$C_{y,a} = S_{y,a}F_yN_{y,a}e^{-M_a/2}, \quad (\text{A.4})$$

where $S_{y,a}$ is the fishing selectivity at age, which varies here from year to year, and F_y is the fishing “mortality”

(i.e., the proportional catch for an age-class for which $S_{y,a} = 1$) in year y .

Thus the total catch by weight for each year (C_y) is

$$C_y = \sum_{a=0}^m w_{(a+1)/2} C_{y,a}, \quad (\text{A.5})$$

where $w_{(a+1)/2}$ denotes the midyear mass of a the fish of age a , which is assumed to be equal to the average of the mass at the beginning of the year (w_a) and that at the end of the year (w_{a+1}).

The fishing selectivity at age in any one year is governed by a deterministic form of S_a modified by lognormally distributed variability that is correlated both from one age to the next and from one year to the next. In symbols,

$$S_{y,a} = S_a e^{\tau_{y,a} - \sigma_\tau^2/2}, \quad (\text{A.6})$$

where

$$\tau_{1,0} \sim N(0, \sigma_\tau^2) \quad (\text{A.7})$$

and

$$\tau_{1,a+1} = \rho_a \tau_{1,a} + \sqrt{1 - \rho_a^2} \chi_{1,a+1} \quad (\text{A.8})$$

with

$$\chi \sim N(0, \sigma_\tau^2). \quad (\text{A.9})$$

It follows that

$$\tau_{y+1,0} = \rho_y \tau_{y,1} + \sqrt{1 - \rho_y^2} \chi_{y+1,1} \quad (\text{A.10})$$

and

$$\tau_{y+1,a+1} = \rho_a \tau_{y+1,a} + \sqrt{1 - \rho_a^2} \chi_{y+1,a+1}. \quad (\text{A.11})$$

The exploitable (“available”) component of abun-

TABLE A.1.—Parameter values selected for the operating model.

Parameter	Value
l_{∞}	54.56 cm
K	0.183/year
t_0	−0.654/year
c	0.0078 gm/cm ³
D	3.0
a_m	3 years
M	0.3/year
m	10
h	0.6
σ_R	0.5
q	1.0
σ_{CPUE}	0.2
σ_{sel}	0.4
p_a	0.5
p_y	0.5
σ_{len}	0.25

dance at midyear is given by

$$B_y = \sum_{a=0}^m w_{a+\frac{1}{2}} S_{y,a} N_{y,a} e^{-M_a/2}. \tag{A.12}$$

The proportion of the exploitable component of the resource harvested each year (F_y) is therefore given by

$$F_y = C_y/B_y. \tag{A.13}$$

Catch per unit effort (CPUE) is related to B_y by

$$\text{CPUE}_y = q B_y e^{\eta_y}, \quad \text{where } \eta_y \sim N(0, \sigma_{\text{CPUE}}^2). \tag{A.14}$$

The spawning biomass in year y is given by

$$B_y^{\text{sp}} = \sum_{a=a_m}^m w_a N_{y,a}, \tag{A.15}$$

where a_m is the age corresponding to 100% sexual maturity (here taken to be described by a knife-edge function of age). The number of recruits at the start of fishing year y is related to the spawner stock size by a stock–recruitment relationship. A Beverton–Holt form is assumed, namely,

$$R(B_y^{\text{sp}}) = \frac{\alpha B_y^{\text{sp}}}{\beta + B_y^{\text{sp}}} e^{\varepsilon_y - \sigma_R^2/2}, \quad \text{where } \varepsilon_y \sim N(0, \sigma_R^2). \tag{A.16}$$

To work with estimable parameters that are more meaningful biologically, the stock–recruit relationship is reparameterized in terms of the preexploitation equilibrium spawning biomass, K^{sp} , and the “steepness” of the relationship, defined as the fraction of pristine recruitment (R_0) that results when the spawning biomass drops to 20% of its pristine level, that is,

$$hR_0 = R(0.2K^{\text{sp}}). \tag{A.17}$$

From this it follows that

$$\alpha = \frac{4hR_0}{5h - 1} \tag{A.18}$$

and

$$\beta = \frac{K^{\text{sp}}(1 - h)}{5h - 1}. \tag{A.19}$$

Given a value for the preexploitation spawning biomass of the fish, together with the assumption of equilibrium age structure at the time ($y = 1$) exploitation commences, the following equation is solved to determine R_0 :

$$K^{\text{sp}} = R_0 \left(\sum_{a=1}^{m-1} f_a w_a e^{-\sum_{a'=0}^{a-1} M_{a'}} + \frac{f_m w_m e^{-\sum_{a'=0}^{m-1} M_{a'}}}{1 - e^{-M_m}} \right), \tag{A.20}$$

where because of the assumption of knife-edge selectivity, f_a is 0 or 1 depending on whether or not a is less than a_m .

Numbers at age for subsequent years are then computed by application of equations (A.1)–(A.20).

The mean length of the catch (\bar{l}_y) each year is given by

$$\bar{l}_y = \sum_{a=0}^m P_{y,a} l_a, \tag{A.21}$$

where $P_{y,a}$ is the proportion by number of the total catch of age- a fish in year y and is given by

$$P_{y,a} = \frac{C_{y,a}}{\sum_{a=0}^m C_{y,a}}, \tag{A.22}$$

and the length at age (l_a) is calculated from the von Bertalanffy growth equation $l_a = l_{\infty}(1 - e^{-\kappa(a-t_0)})$ with associated weight-at-length relationship $w_l = cl^d$.

Parameter Values for the Specific Case Considered

The parameter values specified for the scenario considered (see Tables A.1, A.2) were chosen to reflect a fish of intermediate size and longevity, growth and maturity values as determined (or assumed) for the South African horse mackerel *Trachurus trachurus capensis* being used (M. Kerstan, Department of Environmental Affairs, South Africa, personal communication quoted in Horsten 1999; and R. W. Leslie, personal communication quoted in Butterworth and Clarke 1996).

For this scenario a management procedure (MP) is introduced after 40 years of harvesting, with all past catches known but resource indices (either CPUE or mean length) available for only the last 30 of those years. The historical catch is set to a constant level of

TABLE A.2.—Selectivity (S_a), midyear length at age ($l_{(a+1)/2}$), and beginning year weight at age (w_a) in operating model simulations.

a	S_a	$l_{(a+1)/2}$ (cm)	w_a (g)
0	0.0	10.20	1.81
1	0.2	17.62	22.57
2	0.4	23.80	72.14
3	0.6	28.94	146.88
4	0.8	33.23	238.71
5	1.0	36.79	339.40
6	1.0	39.76	442.17
7	1.0	42.24	542.11
8	1.0	44.30	636.01
9	1.0	46.02	722.00
10+	1.0	47.44	799.27

1,000 metric tons for each of the first 20 years (in reality, the catch would increase over the initial years of the fishery, but this complication is immaterial to the issues under study here); this is reduced linearly to 500 tons by year 30 (a response to broad indications of resource decline) and then kept constant at that level to year 40.

The baseline scenario incorporates one fixed realization of the stochastic components of recruitment and selectivity (equations A.16 and A.6) over the historical period. The reason for this was simplicity: having a single value of K^{sp} rather than a distribution is adequate for an illustrative exercise. The corresponding recruitment series and the selectivity-at-age relationships for the last 4 years (36–39) are shown in Figures A.1 and A.2. The initial value of K^{sp} is then specified so that the depletion of this component of the resource at the start of year 40 is 20%, that is, $B_{40}^{sp}/K^{sp} = 0.2$.

For the historical time series of CPUE and \bar{l} , a single realization of the stochastic components of equations A.6 and A.16 is considered over the years 10–40. If the ASPM (which reflects the true dynamics, in contrast to the Schaefer model's approximation) is fit to these CPUE data with all parameter values and residuals known except for the value of K^{sp} (which is estimated in the fitting process), B_{40}^{sp}/K^{sp} is estimated to be 0.278 (so that the specific CPUE values generated for the scenario are not that misleading as regards the actual

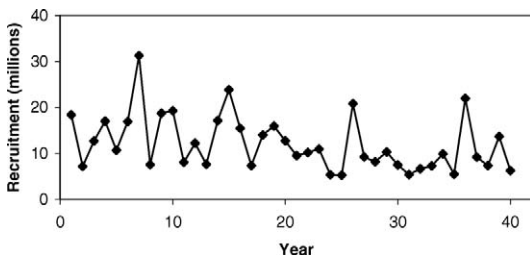


FIGURE A.1.—The recruitment series for years 1–40 used in model simulations.

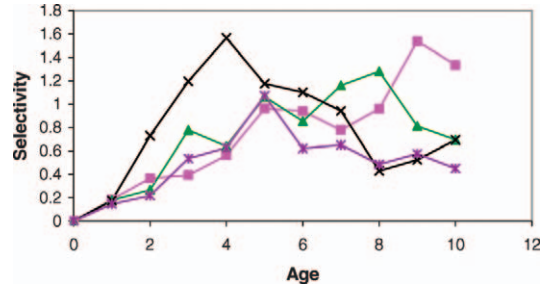


FIGURE A.2.—Selectivity-at-age relationships for years 36–39; Squares = 1936, triangles = 1937, crosses = 1938, and stars = 1939.

status of the resource). Figure A.3A shows the actual B^{sp} trajectory together with that estimated in this manner from the CPUE data and the CPUE data themselves, indicating that the two trajectories do not differ greatly.

The approximate 95% confidence interval on the value of B_{40}^{sp}/K^{sp} estimated as specified above that is provided by ± 2 Hessian-based standard error estimates is 0.213–0.342, so that the status of the resource would not be that clear at the time management commences 40 years after the onset of exploitation. To reflect this uncertainty in broad terms, two alternative scenarios are also considered. In the first, all of the parameters and residuals are the same as those in the baseline scenario except that K^{sp} is adjusted to correspond to current depletions of B_{40}^{sp}/K^{sp} at 10% and 30% instead

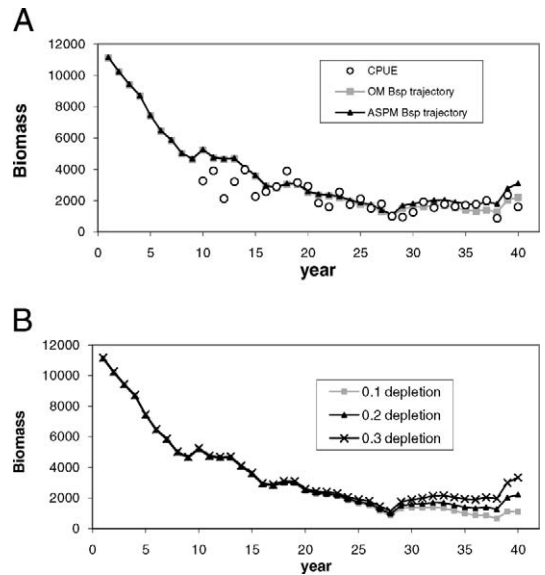


FIGURE A.3.—Panel (A) shows the B_y^{sp} trajectory of the actual operating model together with that estimated by fitting an ASPM to the CPUE data, and the CPUE data themselves. Panel (B) shows the baseline B_y^{sp} trajectory together with those for the two alternative depletion tunings.

of 20%. In the second, the value of catchability (q) is adjusted so that the geometric mean of $\text{CPUE}_y/B_y^{\text{sp}}$ is the same as in the baseline scenario (yielding $q = 1.144$ and 0.878 for the 10% and 30% depletion scenarios, respectively). The baseline and alternative B_y^{sp} trajectories are shown in Figure A.3B.

The Management Procedures

The ASPM operating model is used to project the resource biomass over a period of 20 years. This is effected using the equations above given the catches indicated for each year after year 40 by the MP under consideration. This process is also used to generate the two monitoring indices that would be available for managing the fishery, CPUE and the mean catch length. A total of 50 replicates of the projections over future years 41–60 are generated for each scenario–MP combination considered.

Two MPs are considered: one based on the Schaefer age-aggregated population model using CPUE data and an empirical MP using data for the annual mean length of the catch only. Both MPs impose a constraint of 15% on the extent to which the total allowable catch (TAC) is permitted to change from one year to the next.

In projecting forward, further CPUE and \bar{l} observations need to be generated. For CPUE, equation A.14 above is used; for \bar{l} , observation error is added to the $P_{y,a}$ values generated from equation (A.22) as follows:

$$P_{y,a}^* = P_{y,a} e^{\varphi_{y,a} - \sigma_{\text{len}}^2 / (2P_{y,a})} \quad \text{where } \varphi_{y,a} \sim N(0, \sigma_{\text{len}}^2 / P_{y,a}), \quad (\text{A.23})$$

the form chosen for the variance seeks to mimic the greater variability for ages for which proportions (and hence sample sizes) are smaller.

The $P_{y,a}^*$ values are renormalized so that $\sum_{a=0}^m P_{y,a}^* = 1$.

CPUE-based MP.—This MP first fits the Schaefer model

$$B_{y+1} = B_y + rB_y \left(1 - \frac{B_y}{K}\right) - C_y \quad \text{with } B_1 = K \quad (\text{A.24})$$

to all of the historical catch and CPUE data from year 10 to the immediately previous year to estimate the parameters r and K . This estimation involves minimizing the negative log-likelihood

$$-\log_e L = n \log_e \sigma_c + \sum_{y'=10}^{y-1} [\log_e \text{CPUE}_{y'}^{\text{obs}} - \log_e (qB_{y'})]^2 / 2\sigma_c^2, \quad (\text{A.25})$$

where

$$\sigma_c = \sqrt{\frac{\sum_{y'=10}^{y-1} (\log_e \text{CPUE}_{y'}^{\text{obs}} - \log_e qB_{y'})^2}{y-10}} \quad (\text{A.26})$$

and

$$q = \exp \left(\sum_{y'=10}^{y-1} \frac{\log_e \text{CPUE}_{y'}^{\text{obs}} - \log_e B_{y'}}{y-10} \right)$$

subject to the constraint

$$0 \leq r \leq 0.6.$$

The TAC for year $y+1$ is then given by

$$\text{TAC}_{y+1} = 0.5\text{TAC}_y + 0.5\text{TAC}_y^{\text{Schaefer}}, \quad (\text{A.27})$$

where

$$\text{TAC}_y^{\text{Schaefer}} = \mu_y \lambda \frac{r}{2} B_y. \quad (\text{A.28})$$

Here, λ is set to 0.5 to give the desired performance (securing recovery to the MSY level in 10 years in median terms) and μ_y is based on the ratio of the “recent” CPUE value to the values for years 30–39 as in Figure A.4, with

$$\text{CPUE}_{\text{recent}} = \frac{(\text{CPUE}_{y-1}^{\text{obs}} + \text{CPUE}_{y-2}^{\text{obs}} + \text{CPUE}_{y-3}^{\text{obs}})}{3} \quad (\text{A.29})$$

and

$$\text{CPUE}_{\text{past}} = \frac{\sum_{y=30}^{39} \text{CPUE}_y^{\text{obs}}}{10}. \quad (\text{A.30})$$

The 15% maximum interannual TAC change constraint is imposed as follows:

$$\text{If } \text{TAC}_{y+1} > 1.15\text{TAC}_y \quad \text{then } \text{TAC}_{y+1} = 1.15\text{TAC}_y \quad (\text{A.31})$$

$$\text{If } \text{TAC}_{y+1} < 0.85\text{TAC}_y \quad \text{then } \text{TAC}_{y+1} = 0.85\text{TAC}_y. \quad (\text{A.32})$$

Length-based MP.—The TAC for year $y+1$ is provided by the formula

$$\text{TAC}_{y+1} = 0.5\text{TAC}_y + 0.5\text{TAC}_y^{\bar{l}}, \quad (\text{A.33})$$

where $\text{TAC}_y^{\bar{l}}$ is based on \bar{l}_{y-1} as shown in Figure A.5.

The value 0.9 was chosen for the ratio $\bar{l}_0/\bar{l}_{\text{past}}$ for overall performance; the value 0.6 was selected for $\bar{\omega}$ so that the lower 5th percentile of the $B_{61}^{\text{sp}}/K^{\text{sp}}$ statistic for the $B_{40}^{\text{sp}}/K^{\text{sp}} = 0.2$ depletion scenario was equivalent

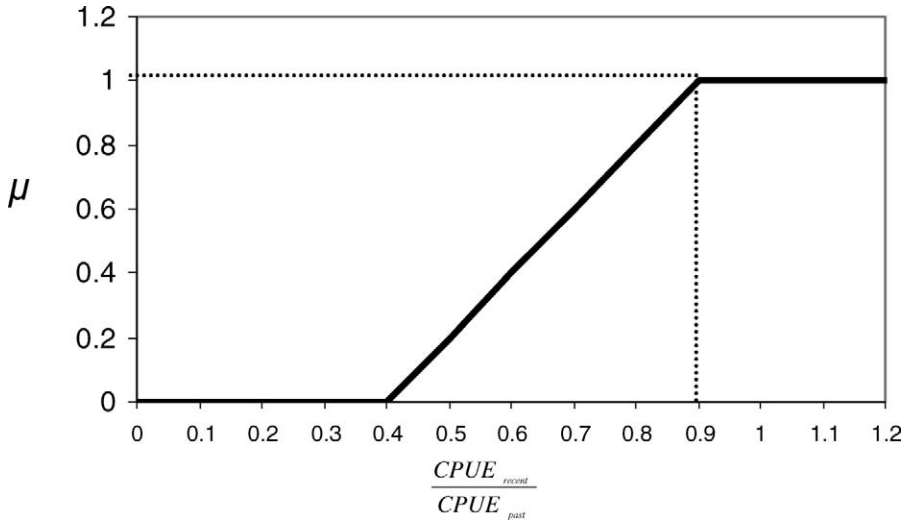


FIGURE A.4.—Relationship between μ and the ratio of $CPUE_{recent}$ to $CPUE_{past}$.

to that for the CPUE-based MP (a value of around 0.236). A 15% maximum interannual TAC change constraint is imposed, as in the CPUE-based MP.

Performance statistics.—Three statistics were used to compare the performance of the two MPs, one related to catch, one to risk, and one to the variability in the TAC. The catch-related statistic was the average annual catch over the 20-year projection period (C_{ave}); the risk-related statistic was the spawning biomass at the end of the projection period relative to that at the

start of the fishery (B_{61}^{sp}/K^{sp}); and the TAC variability-related statistic was the average interannual variation in catch over the projection period expressed as a percentage (AAV).

To test an MP with respect to a particular scenario, 50 replicates were run, so that a distribution was obtained for each of these quantities (usually summarized by its median [i.e., the average of the 25th and 26th values] and 90% probability interval [as evaluated by EXCEL from the ordered list of 50 values]).

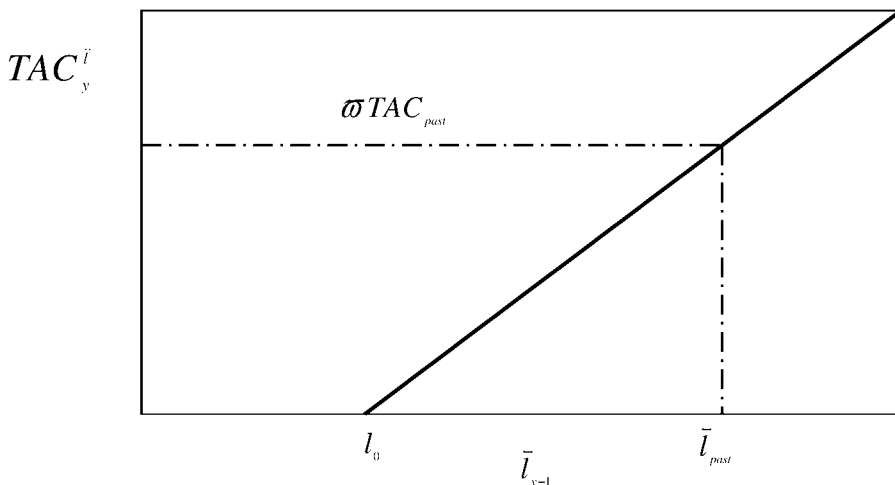


FIGURE A.5.—Relationship between TAC and average length at catch. Symbols are defined as follows: $\bar{\omega}$ = the tuning parameter (here set to 0.6), TAC_{past} = the average TAC value for years 30–39, $l_0 = 0.91\bar{l}_{past}$, and \bar{l}_{past} = the average value of \bar{l}_y for years 30–39.