

# IN SEARCH OF ROBUST HARVEST RULES FOR PACIFIC HALIBUT IN THE FACE OF UNCERTAIN ASSESSMENTS AND DECADAL CHANGES IN PRODUCTIVITY

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## ABSTRACT

In the conventional ‘assessment-based approach’, catch quotas are calculated as some target harvest rate (not necessarily fixed) applied to a ‘best’ estimate of exploitable biomass produced by the stock assessment. In the alternative ‘management-procedure approach’, quotas are computed from a predetermined feedback control rule, usually a simple algorithm for adjusting catches in response to monitoring indices. Uncertainty and instability of stock assessments complicate the implementation of the conventional approach. For example, estimates of Pacific halibut biomass have changed substantially from year to year, mostly in response to changes in methodology and newly available survey data. Although the changes improved the assessments, the use of an assessment-based approach to set quotas led to unnecessary disruptions in the fishery. Simulations using operating models derived from recent halibut assessments suggest that a management procedure based on a simple delay-difference model could provide stable and adequate yields and perform similarly to two harvesting strategies considered suitable for Pacific halibut (fixed exploitation rate and constant spawning-biomass-per-recruit), implemented assuming no assessment errors. An advantage of such an approach is that once a robust rule is in place, quota setting can be decoupled from assessment, at least until the latter indicates that modifications are needed.

A dominant trend in the implementation of the precautionary approach (FAO, 1995) has been to develop conservative harvest rules based on target and threshold reference points for biomass and fishing mortality (Hilborn et al., 2001). These are intended to prevent overfishing by advocating more conservative fishing targets and by triggering corrective management actions when thresholds are approached or exceeded (Restrepo et al., 1998). These harvest rules are normally implemented according to an ‘assessment-based approach’, that is by application of the desired harvest rate to an estimate of current stock biomass produced by an annual stock assessment, typically some form of catch-at-age analysis. For this procedure to work, stock assessments must be reliable and consistent from year to year, and reference points must be well determined. Both conditions are difficult to meet in reality. Stock assessments are often based on insufficient data, which result in substantial assessment uncertainty. Several competing assumptions can usually be made to fill information gaps, so assessment uncertainty tends to be dominated by structural uncertainty. Competing models often result in very different biomass levels, even in different biomass trends, which complicate the implementation of generic harvest rules. In addition, changes in model structure between successive assessments can result in substantial changes in estimates, which may unnecessarily disrupt management if point estimates are carried into catch-quota recommendations.

A second problem is that generic reference points are often related to population parameters, such as unfished biomass and spawning biomass per recruit, and to MSY-related parameters, whose estimation, meaning, and usefulness are often elusive. For example, consider those fisheries based on species of limited mobility (for which spatially explicit strategies may work best), species with complex life histories and mating sys-

tems, mixed stocks, and stocks that show decadal changes in productivity or are affected by regime shifts. Conventional reference points based on unfished biomass would have little value in these situations, whereas other ad hoc approaches may work well. In the specific case of stocks that exhibit persistent trends in productivity, simple decision rules that respond more directly to monitoring signals may be as or more effective at maintaining stocks at reasonably productive levels than more elaborate rules based on uncertain and evolving stock assessments.

In the present paper, I address the problem of managing a nonstationary stock, the Pacific halibut, in the face of structural uncertainties and unstable assessments. I contrast two alternative approaches for developing quota recommendations for that fishery. First, I review the assessment-based approach followed by the International Pacific Halibut Commission (IPHC) and discuss the difficulties my fellow members and I encountered when trying to implement what we considered was a suitable harvesting strategy. Then I examine an alternative approach for setting quotas based on a simpler management procedure (Butterworth and Punt, 1999). I develop 'operating models' (Butterworth and Punt, 1999) for Pacific halibut based on the assessment conducted in 1999, and I use these to test two management procedures based on a delay-difference model fitted to simulated indices of abundance. Simulations are conducted by Markov Chain Monte Carlo (MCMC) methods (Gelman et al., 1995; Parma, in press) to sample parameters from the models' full posterior distributions. I discuss the advantages of such simple decision rules as a way to stabilize the process of quota setting and still provide adequate yields.

#### MANAGEMENT OF PACIFIC HALIBUT: THE LIMITATIONS OF THE ASSESSMENT-BASED APPROACH TO SETTING QUOTAS

Pacific halibut stocks have supported a longline commercial fishery in Canadian and U.S. waters for more than 100 yrs; catches have fluctuated between 20 and 70 million lb. (9.07 and 31.75 million kg). The stocks have shown decadal changes in recruitment and growth, linked to shifts in climatic regime affecting the entire ecosystem in the northeast Pacific (Clark et al., 1999). Since 1923, stocks have been studied and managed by the IPHC (Sullivan and McCaughran, 1995.)

The harvesting strategy followed over the last 15 yrs consists of setting catch quotas as a fixed fraction of the estimated exploitable biomass in each of the IPHC regulatory areas (Fig. 1) and imposing a minimum size limit on the landings to reduce catches of immature fish. The rationale for such a strategy is that fixed exploitation rates have been shown to cope well with the effects of climate change, by allowing the stock to fluctuate in phase with the changes in productivity (Parma, 1990; Walters and Parma, 1996). Harvest rates in the range 0.20–0.30 were recommended on the basis of simulations conducted under different recruitment scenarios consistent with historical experience (Sullivan et al., 1999).

Although the choice of harvesting strategy appeared sensible on paper, its implementation was complicated by poor assessment performance. A separable catch-at-age model (CAGEAN) fitted to commercial catch-per-unit-effort (CPUE) data was used to estimate stock abundance from 1985 to 1995 (Deriso et al., 1985). Assessments produced with this model showed a strong retrospective pattern; stock sizes were initially overestimated in the late 1980s (Parma, 1993) and then underestimated in the 1990s (Clark et al., 1999). The retrospective problem was associated with changes in catchability caused by a dramatic decrease in size at age in the central Gulf of Alaska (Fig. 2), which conflicted

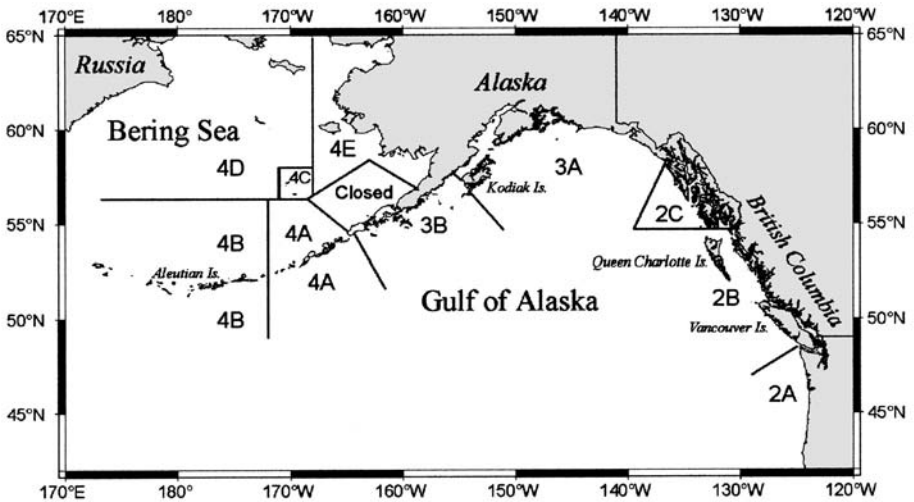


Figure 1. International Pacific Halibut Commission regulatory areas.

with the model assumption of constant selectivity. A size- and age-structured model that accounted for trends in growth and selectivity was implemented in 1997 (Sullivan et al., 1999). In the central Gulf of Alaska (IPHC Area 3A), where trends in size at age have been most severe, the new model resulted in stock size estimates approximately twice the estimates obtained in previous years with CAGEAN (Fig. 3). The retrospective problem was cured by the new models, which provided consistent estimates from year to year

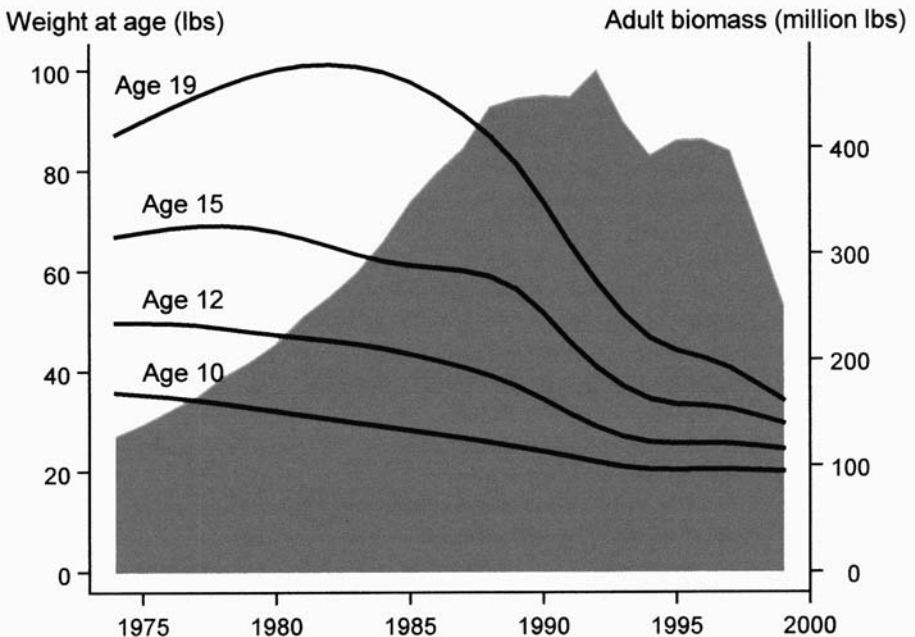


Figure 2. Smoothed trends in weight at age of Pacific halibut in the commercial catch of Area 3A together with estimated age-6+ biomass.

### Exploitable Biomass (million lbs)

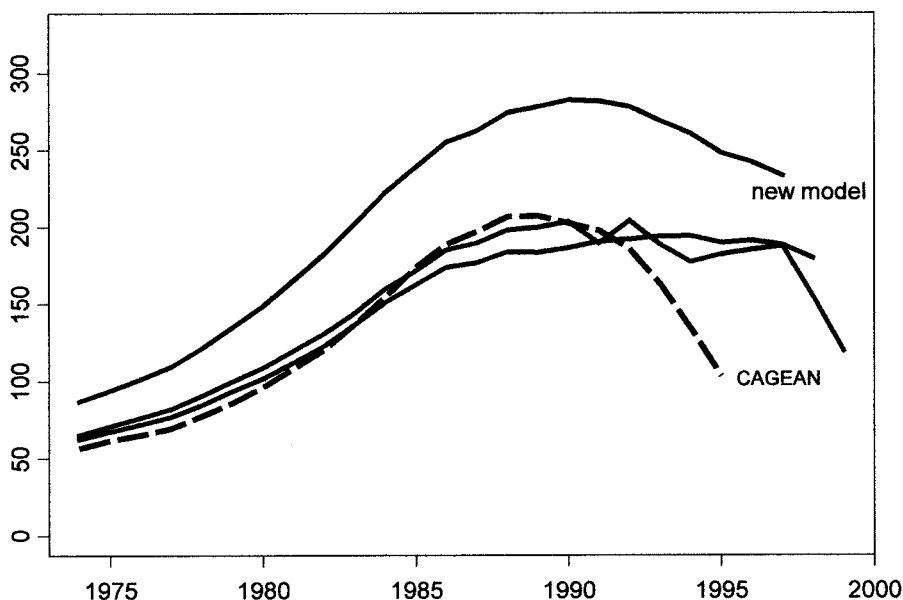


Figure 3. Successive assessments of exploitable biomass of Pacific halibut in the central Gulf of Alaska (IPHC management area 3A). CAGEAN is a separable catch-at-age model used until 1995. Starting in 1997 a new size- and age-structured model was used. Abundance estimates dropped in the assessment of 1998 because a lower value was used for the coefficient of natural mortality.

(Parma, in press), but new analyses by Clark (1999) and reevaluation of age composition data from lightly fished areas prompted a lowering of the working value of natural mortality in 1998 (from 0.20 to 0.15). As a result, a decrease in the absolute estimates of stock sizes countered some of the previous increases caused by the model adjustments. The input data available for the assessments have also evolved, as the program of longline surveys, interrupted in 1986, was resumed and expanded, and sampling of halibut catches from National Marine Fisheries Service trawl surveys was initiated to provide fishery-independent data on growth and abundance. Poor fit of the survey size compositions and inconsistencies between catch rates obtained by the longline and trawl surveys have led to further research and modifications of the assessment models (W. G. Clark, unpubl. data). In summary, although the database and the quality of the assessments have improved over recent years, other factors have converged to produce inconsistent assessments from year to year (Fig. 3).

Because the stock size was well above average when these developments took place, it would have been safe to maintain close-to-status-quo catches while the biomass estimates were raised and lowered. Indeed, changes in the quotas were gradually phased in to reduce impacts on the fishery, but no defensible procedure was in place to accomplish it. The harvesting strategy adopted by IPHC specified that a fixed harvest rate of 20% would be used to set quota recommendations, but it did not specify the procedure for estimating the exploitable biomass. Therefore, changes in the assessments would have led to major

disruptions in the fishery if the strategy had been implemented at face value using 'best' available biomass estimates.

The experience with halibut shows how coupling of the assessment and management processes can be problematic, given their different natures. As a scientific endeavor, assessment approaches are expected to evolve in response to developments in the stock, the fishery, and the monitoring programs. Management, on the other hand, needs fully specified rules to guide decisions, rules selected for their ability to achieve management goals in simulation trials, including minimizing sharp adjustments in the catches.

#### DEVELOPMENT OF AN OPERATING MODEL TO TEST ALTERNATIVE MANAGEMENT PROCEDURES FOR PACIFIC HALIBUT

A management procedure for a quota-based fishery like Pacific halibut must specify the monitoring statistics to be used for management and how they will be translated into quota recommendations. Many kinds of estimators and decision rules can be used to compute quota recommendations, ranging from empirical data-driven approaches (see, e.g., Geromont et al., 1999) to more elaborate model-based algorithms (see, e.g., Kell et al., 1999). Informed choices can be facilitated by testing of alternative candidates against a series of performance indicators that reflect management goals. A critical aspect of the evaluation process is to construct simulation or operating models that adequately represent likely future scenarios for the stock and the fishery and that reflect key uncertainties in the assessments.

Below, I develop operating models for Pacific halibut based on current knowledge about the stock structure and using results from the historical assessments together with further assumptions about future trends in productivity. I use a Bayesian approach to conduct the policy evaluation, which involves the following steps:

1. Use existing data and assessment models to estimate joint posterior distributions of model parameters.
2. Randomly select many sets of parameters from the posterior distributions and use them to simulate a series of underlying 'true' population trajectories that are compatible with the historical data.
3. Use different projection models to extend the population trajectories beyond the historical data. The projection models use the parameter sets from step 2, plus some additional functional and parameter assumptions.
4. Generate the data needed to implement the evaluated management procedures as follows: for the historical time period, use the actual historical data; for future years, generate the data from the underlying population trajectory, together with assumptions about observation error.
5. Implement the candidate feedback procedures or decision rules using the simulated data to determine future catch quotas.
6. Compute a series of statistics to evaluate their performance.

**ASSUMPTIONS ABOUT STOCK STRUCTURE.**—Harvest guidelines for Pacific halibut stocks are derived on the assumption that the stocks in the Gulf of Alaska (Areas 2 and 3, Fig. 1) constitute a single reproductive unit. This assumption is supported by the prolonged pelagic egg and larval stages, during which extensive intermingling of fish spawned in different grounds occurs while larvae drift north and west carried by the prevailing ocean currents (Skud, 1977), and also by preliminary analysis of microsatellite DNA (P. Bentzen,

J. Britt and J. Kwon, unpubl. data). The Bering Sea stock is considered a separate reproductive unit, although the two areas are interrelated through larval transport from the Gulf of Alaska into the Bering Sea (St-Pierre, 1989) and through migration of juveniles from the Bering Sea to the gulf (Skud, 1977). Halibut recruitment in the gulf is therefore affected by by-catch of juveniles in the Bering Sea (Clark and Hare, 1998), so estimates of recruitment derived from the assessments are inflated to account for this prerecruit mortality.

Annual stock assessments are conducted separately for each IPHC regulatory area on the assumption that exchanges of adults among those fishing grounds are negligible. This assumption is supported by tagging data. Tags recovered by the commercial fishery, which takes place primarily during the spring and summer, when halibut are on their feeding grounds, indicate that adults have a high fidelity to their summer grounds, even though they undertake extensive winter spawning migrations (Skud, 1977). An exception may be migration from the western portion of the gulf (Area 3B) into the central and southern areas, which may be significant at least for the youngest ages (Deriso and Quinn, 1983; Hilborn et al., 1995). No analytic assessments are done for Area 3B; instead, biomass in that area is evaluated relative to that in other areas by survey estimates. The analysis here only includes Areas 2 and 3A (Fig. 1).

#### ASSESSMENT MODELS AND ESTIMATED POPULATION TRENDS

The operating models were derived from analysis of historical data on catch at age and CPUE for the commercial fishery (period 1935–1999) and from age compositions and catch rates from the IPHC longline surveys conducted during 1976–1986, with varying frequency in different areas, and more regularly since 1993. (Data used in this analysis are available at <http://www.iphc.washington.edu/halcom>. Sullivan et al., 1999, provide further documentation.) The models are spatially explicit, reflecting current separate assessment and management by IPHC regulatory areas. First a size- and age-structured model, similar to that used for the annual IPHC assessments (as described in Appendix 1), was applied separately to areas 2A+2B, 2C, and 3A (Fig. 1). The assessment model is a standard age-structured population model, except for a few fundamental features:

1. Changes in commercial selectivity at age are driven by underlying trends in size at age in the stock.
2. Commercial selectivity is a time-varying function of size, forced to be zero for fish smaller than the size limit (81 cm).
3. Trends in size at age are modeled as stochastic processes fitted to size-at-age data from commercial and survey catches.
4. Commercial catchability is modeled according to a time-series approach so that strict proportionality between CPUE and population size is not assumed.

Model equations are provided in Table A1 of Appendix 1. The regular assessments cover the period 1974–present to exclude the effects of a change in size limit that took place in 1973. Halibut start recruiting to the commercial fishery at about age 8 to 10 depending on the area and growth rate, and they contribute to the catches up to age 20+. Females mature around age 11, an age that has been remarkably stable over time in spite of the drastic decrease in size at age (Clark et al., 1999).

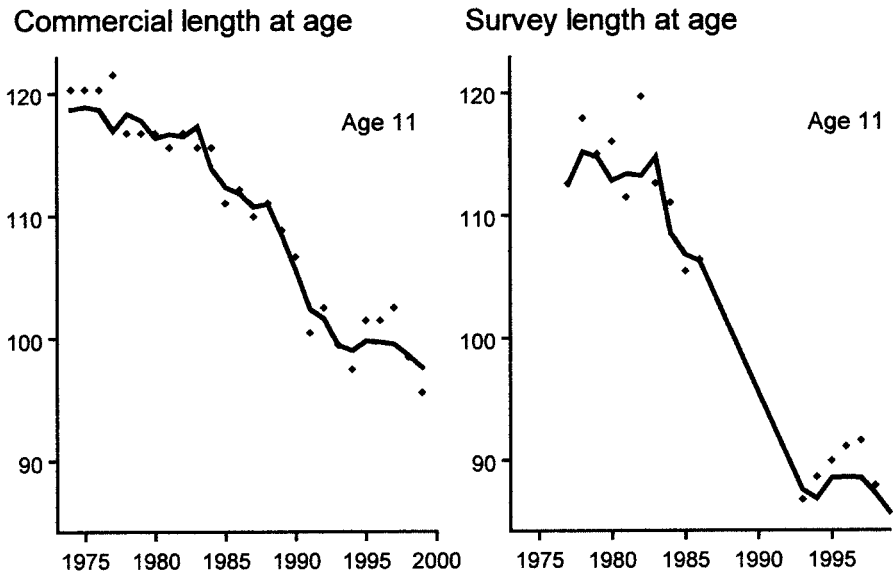


Figure 4. Observed and predicted median length at age 11 in the commercial and survey catches of Pacific halibut in the central Gulf of Alaska.

The operating model was identical to the assessment model, except that some further assumptions were needed for projection of population sizes, mostly for those processes that were allowed to change over time: recruitment, growth, and fishing selectivity. Different models of future recruitment and growth rates were considered, as discussed in the next section. Commercial selectivity was assumed to be constant at size; parameters estimated for the most recent years were used.

Although the model was the same as that used in standard IPHC assessments (Sullivan et al., 1999), the context was different, so a different approach was used to estimate model parameters and their uncertainty. The structure of the likelihood function and prior distributions were identical to those used in the assessment model (see Appendix 1, Tables A2–A4). In standard assessments, however, point estimates of abundance are derived by maximization of a penalized likelihood function (details in Sullivan et al., 1999) and used to compute recommended quotas. Here, instead, the models were used for policy evaluation, so a full Bayesian analysis was performed to approximate the posterior distribution of model parameters, including those representing stochastic variability in the processes (e.g., recruitment and growth). An MCMC method based on the Metropolis-Hastings rule (Gelman et al., 1995) implemented in the AD Model Builder software (Otter Research Ltd., 1999) was used to obtain samples from the posterior distribution to initialize the simulations. The algorithm and methods are described in detail by Parma (in press). One million MCMC draws were done separately for the different model structures used for each regulatory area. A sample ( $n = 1000$ ) from the multivariate posterior distribution from each was stored and used in the policy evaluation.

The assessment results indicate that the declines in size at age, which were most severe in Area 3A (Fig. 4), resulted in substantial reductions in age-specific selectivity. Thus, the poor show of young age classes in the commercial catch during the 1990s was explained

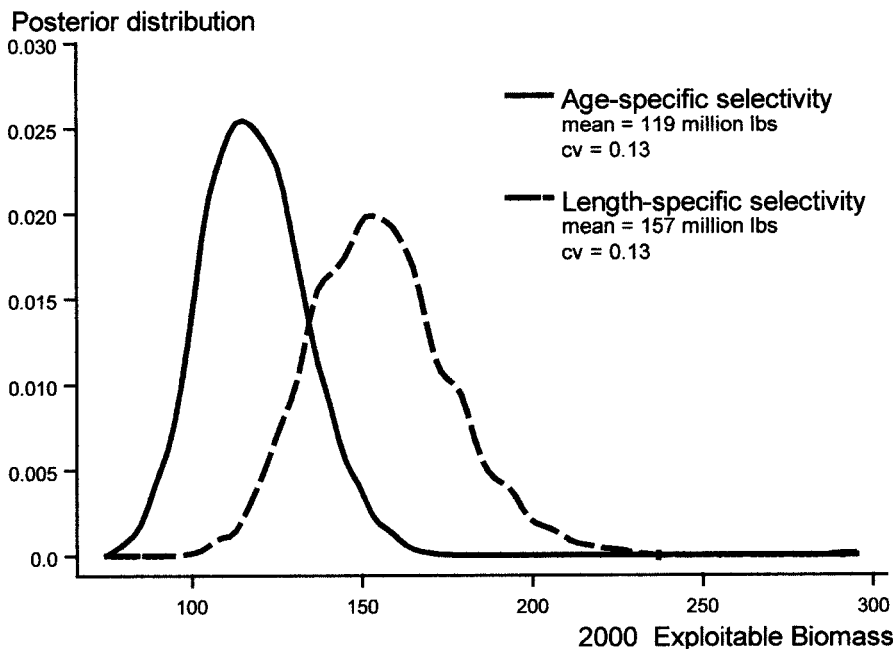


Figure 5. Posterior distributions of predicted exploitable biomass conditioned on two different assumptions about survey selectivity (constant at age or at length), approximated by MCMC.

as decreased selectivity for smaller fish rather than as weak recruitment (Clark et al., 1999). Under the new models, the 1977 and subsequent year classes were very strong, leading to a rapid build up of exploitable biomass coastwide. Estimates of recent year classes, however, are very uncertain because fish are too small to recruit to the commercial fishery. In principle, age composition from the survey catches, which are not affected by the minimum size limit, would permit earlier assessment of the strength of incoming year classes. However, the interpretation of survey catch rates in the face of drastic changes in size at age is uncertain, as it is not clear to what extent survey selectivity is a function of size, age, or both. Two versions of the assessment models have been used since 1997 at IPHC to reflect this uncertainty, one in which survey selectivity at length is constant and the other in which survey selectivity at age is constant (Sullivan et al., 1999).

Predictions from the two models differ, especially in Area 3A, where growth changes have been most severe. Estimated recruitments and exploitable biomass are substantially higher under the size-specific assumption than under age-specific selectivity. Marginal posterior distributions of exploitable biomass approximated by MCMC indicate that uncertainty is dominated by differences between the two model structures (Fig. 5). For precautionary reasons, the more conservative model (age-based selectivity) was used for setting quotas at IPHC. Here, instead, the structural uncertainty was carried into the policy evaluation by use of the posterior distributions corresponding to the two model structures to conduct the simulations. The support given by the data to the alternative models was evaluated by computation of the Bayes factor, as approximated with the harmonic mean estimator (Kass and Raftery, 1995; Parma, in press). Results overwhelmingly favored the age-specific survey selectivity assumption, even though no difference could be appreci-



ated visually in the plots of observed and predicted data. This result is not surprising given the very large number of observations available. An advantage of Bayes factors is that they could be used to integrate policy results across the alternative operating models. I preferred, however, to maintain the identity of the hypotheses in considering the results, as I was particularly interested in evaluating the robustness of the procedures tested with respect to those uncertainties. In addition, it would be premature in this case to rule out some models solely on the basis of Bayes factors, as it is not clear how sensitive these are to minor changes in statistical assumptions (e.g., relative weights given to different data components), addition of new data, etc.

**MODELING FUTURE GROWTH AND RECRUITMENT.**—Two alternative models were used to represent area-specific growth in the simulations. Both are variations of the basic growth model used in the 1999 halibut assessment (Appendix 1, Table A1). Mean log length at age satisfies the equation

$$\exp(\mu_{a+1,t+1}) = \alpha_t + \beta \exp(\mu_{a,t}^+),$$

where  $\mu_{a,t}^+$  is the mean log-length of fish of age  $a$  surviving the fishing season in year  $t$ . Area subscripts have been dropped to simplify the notation. The mean log length at age 6 (first age class in the model),  $\mu_{6,t}$ , is modeled as a time series

$$\mu_{6,t+1} = \mu_{6,t} + \mu \varepsilon_t \quad \mu \varepsilon_t \sim N(0, \mu_6 \sigma^2),$$

and the growth intercepts  $\alpha_t$  are modeled either as density-dependent random processes or as time series.

1. *Density-dependent growth.*—The abrupt drop in growth rates and weight at age observed in Area 3A coincided with the build-up of total biomass in the area (Fig. 2) and coastwide, giving support to a density-dependent hypothesis to explain trends in growth rates. Although the assessment indicates that both the size at recruitment and the growth increment for adult fish decreased over the last 15 yrs, the latter accounted for most of the change in size at age. Density-dependence was therefore incorporated in the growth intercept. For simplicity, a linear effect of the following form was assumed.

$$\alpha_t = \alpha_1 - \alpha_2 \left( \frac{B_t - \bar{B}}{B} \right) + \alpha \varepsilon_t \quad \alpha \varepsilon_t \sim N(0, \alpha \sigma^2),$$

where  $B_t$  is total biomass for ages 6 and older, and  $\bar{B}$  is average biomass over 1974–1999. Parameters  $\alpha_1, \alpha_2, \{\alpha \varepsilon_t\}$ , and  $\sigma^2$  were estimated jointly with the other parameters of the assessment model, as illustrated in Fig. 6.

2. *Time-series (density-independent) trends in growth rates.*—Because many changes took place in the ecosystem at the time when halibut growth rates dropped, trends in growth could also have been driven by environmental factors independent of density. A time-series model was used to represent environmental effects, where

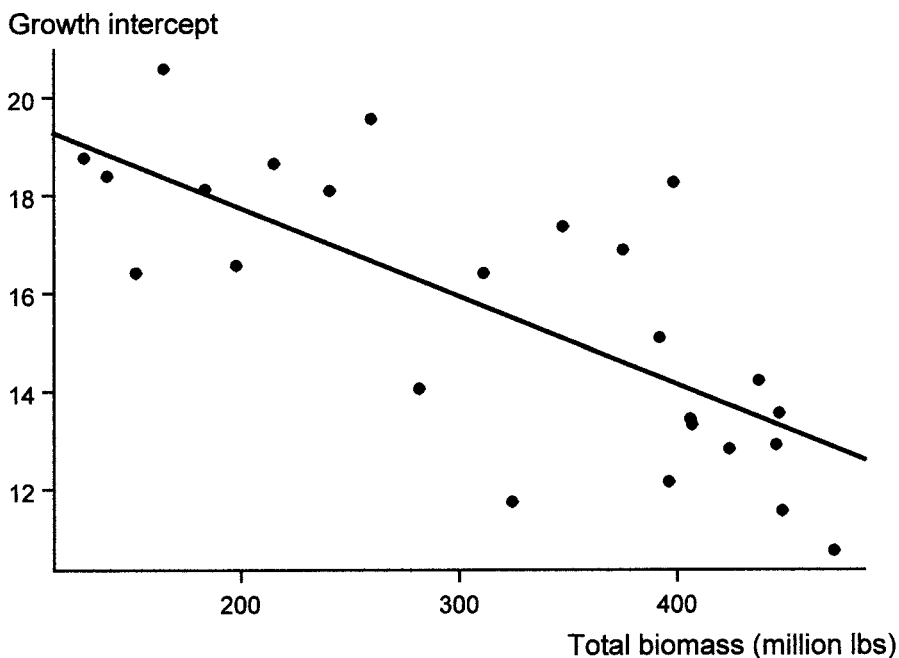


Figure 6. Growth-rate parameter  $\alpha_i$  as a function of total biomass estimated for IPHC Area 3A. Fitted line corresponds to the density-dependence model used to simulate future stock trajectories.

$$\ln(\alpha_{t+1}) = \ln(\alpha_t) + \alpha \varepsilon_t \quad \alpha \varepsilon_t \sim N(0, \alpha \sigma^2).$$

Analysis of stock recruitment required combining estimates from all three areas for the period 1935–1999. Historical abundances prior to 1974 were estimated from commercial catch at age and CPUE according to a flexible age-structured model, but the final abundances were forced to match those estimated by the (age-based and length-based selectivity) assessment models. Details are provided by Sullivan et al. (1999). For the most recent period covered by the assessment (1974–1999), MCMC results were used. One thousand series of spawning biomass and recruitment were computed from each of the stored MCMC sets of parameters for each area and were summed over areas.

The stock recruitment relationship obtained with the most likely parameter values for each area (values at the mode of the posterior distribution) shows long-term trends in recruitment independent of the parental stock size (Fig. 7). Two models were considered to represent this relationship:

1. *Ricker model with autocorrelated environmental effects.*—The number of recruits at age 6

$$R_{t+6} = SB_t e^{a-bSB_t + \varepsilon_t}$$

where  $SB_t$  is reproductive biomass and  $\varepsilon_t$  represent random environmental effects. The latter are modeled as an autoregressive process of order 1,

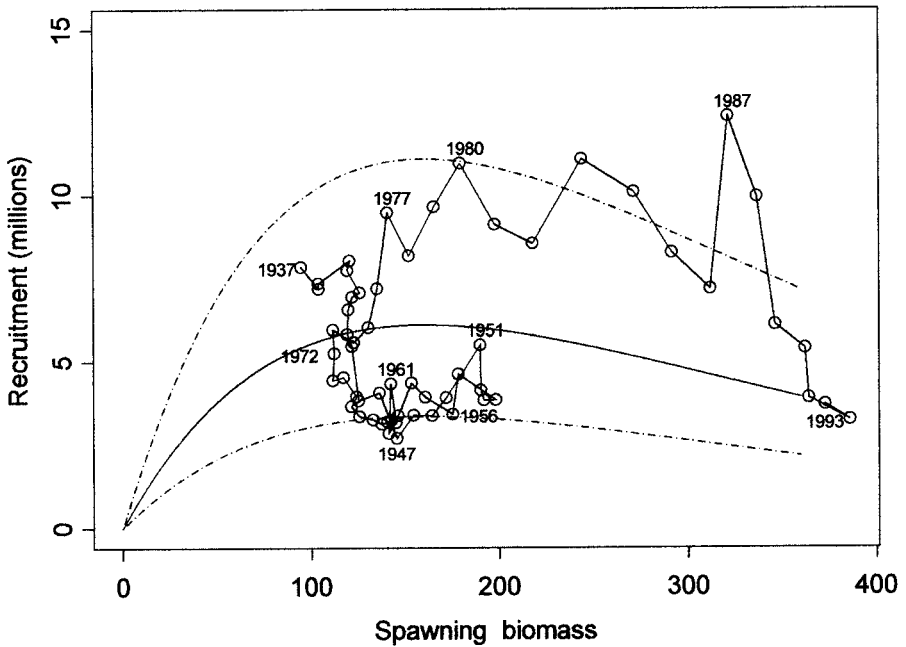


Figure 7. Stock-recruitment relationship of Pacific halibut in the northeast Pacific. Lines correspond to the median, 10th, and 90th percentiles of a Ricker model with autocorrelated environmental effects.

$${}_r\varepsilon_t = \rho_r \varepsilon_{t-1} + e_t,$$

where  $e_t$  is Gaussian with mean 0 and variance  $(1 - \rho_r^2) \sigma^2$ . The parameter  $\sigma^2$  represents the variance of  ${}_r\varepsilon_t$  and  $\rho$  the correlation between  ${}_r\varepsilon_t$  and  ${}_r\varepsilon_{t-1}$ .

2. *Asymptotic model with autocorrelated trends in carrying capacity.*—In this scenario, expected recruitment increases in proportion to reproductive biomass until carrying capacity is reached and is constant thereafter,

$$R_{t+6} = \min(sSB_t, Ke^{r\varepsilon_t}).$$

Carrying capacity is affected by autocorrelated environmental conditions modeled as before. The slope  $s$  was set at the maximum estimated value of  $R_{t+6}/SB_t$ .

I estimated stock-recruitment parameters for each of the stock-recruitment series put together by combining the historical estimates (1935–1973) with the MCMC results for the most recent period. The posterior distribution of stock-recruitment parameters, conditional on each of the MCMC parameter sets, was approximated by estimation of its mode and the variance-covariance of the stock-recruitment parameters at the mode. I simulated stock projections by drawing the MCMC parameter sets for each of the areas, together with the stock-recruitment parameters from their conditional distribution. Therefore, each full set of parameters drawn constituted one realization from the joint posterior distribution of all model parameters (including the stock-recruitment parameters).

Because recruitment estimates used in the analysis were adjusted upward to compensate for prerecruit mortality due to by-catch, the estimated stock-recruitment parameters correspond to recruitment rates in the absence of by-catch. By-catch of sublegal halibut was accounted for in the simulations by a 10% decrease in recruitment (Clark and Hare, 1998).

#### PERFORMANCE OF ALTERNATIVE MANAGEMENT PROCEDURES

**DECISION RULES BASED ON SIMPLE MODELS.**—Management procedures explored in this analysis were based on the use of a simple delay-difference model to determine catch quotas separately for each regulatory area as

$$C_t = H_t \hat{B}_t, \quad \text{Eq. 1}$$

where  $\hat{B}_t$  is the exploitable biomass estimated from the delay-difference model and  $H_t$  is a target harvest rate. In addition, variability in the catches was constrained so that the absolute relative change in catches from year to year did not exceed 10%.

For each projected year, a delay-difference model was fitted to indices of exploitable biomass, total catches, and weight-at-age data. Actual historical data were used for the period 1974–1999; for the projected years, data were simulated from the operating model. The indices used for the historical period correspond to the actual survey CPUE of legal-size fish in weight available sporadically for different years and areas. Trends in catch rates obtained for legal-size fish in the longline surveys have been consistent with catch rates from National Marine Fisheries Service trawl surveys (W. G. Clark, unpubl. data), lending support to the use of these indices to drive the catch-decision rule.

The estimator was based on the following recursive equation:

$$B_{t+1} = \left( \frac{a_t}{\bar{w}_t} - b_t \right) \left( e^{-0.5M} B_t - C_t \right) e^{-0.5M} + R_{t+1}^w \quad \text{Eq. 2}$$

where  $M$  is the coefficient of natural mortality,  $C_t$  is total catch in weight,  $R_t^w$  is annual recruitment biomass (made up of several year classes),  $\bar{w}_t$  is average weight of recruited fish, and  $a_t$  and  $b_t$  are time-varying growth parameters estimated by fitting of the model

$$w_{a,t} = a_t + b_t w_{a-1,t-1}$$

to historical or simulated weight-at-age data in the commercial catch. Average weights  $\bar{w}_t$  and catches were assumed known. Recruitment biomass was assumed to be independent of stock size and serially correlated such that

$$\log(R_{t+1}^w) - \overline{\log(R^w)} = \rho \left( \log(R_t^w) - \overline{\log(R^w)} \right) + R^w \varepsilon_{t+1}, \quad \text{Eq. 3}$$

where  $\overline{\log(R^w)}$  is mean log recruitment biomass,  $\rho$  is the coefficient of autocorrelation of log-recruitment deviations, and  ${}_R \varepsilon_t$  is process error. Initial biomass,  $B_{1974}$ , was set to the 1974 estimate of exploitable biomass obtained from the regular assessments, as the latter is robust to the alternative assumptions made in the assessment model.

Two different procedures were considered for estimation of  $\hat{B}_t$ . In the first, I assumed that a series of indices of exploitable biomass would be available in the future for each regulatory area, such as the CPUE of legal-size fish obtained by the setline surveys currently conducted in the Gulf of Alaska. In a second procedure, I assumed instead that estimates of exploitation rates or absolute abundance would be available from a tagging study. The implementation of such a tagging study has been considered at IPHC to help bound abundance estimates. In both cases, abundance indices proportional to exploitable biomass were generated from the simulated population trajectories as

$$I_t = q \left( \sum w_{a,t} \frac{S_{a,t}}{S_{20,t}} N_{a,t} \right) e^{\varepsilon_t} \quad \text{where } \varepsilon_t \sim N(0, SD^2). \quad \text{Eq. 4}$$

I computed exploitable biomass by aggregating biomasses at age times the age-specific commercial selectivities rescaled to have a maximum of 1. The proportionality coefficient  $q$  was either obtained by fitting of actual historical survey CPUE data for the most recent period (1993–1999) to the series of exploitable biomass estimated by the assessment models or was set to 1 to generate absolute abundance estimates. Observation error was multiplicative and log-normally distributed; the absolute estimates were assumed to be rather imprecise ( $SD = 0.50$ ), whereas relative indices were generated with lower variability ( $SD = 0.20$ ).

In both cases, the delay-difference model was fitted to historical and simulated data on the assumption of both observation error and variability in the recruitment process. Each year, a number ( $n_t$ ) of abundance indices would be available in addition to the complete series of catches, average weights, and growth parameters. The parameters  $\rho$  and  ${}_R \sigma^2$  were fixed. These parameters determine the amount of process error in the estimation and thus control the variability of the catches by controlling how much the estimator smooths the observations. The lower the process variability, the less the estimator is able to respond to new observations and the more stable the quotas. These parameters are robust to the assessment uncertainties, so they were estimated from the times series of recruitments obtained from the size- and age-structured assessments ( $\rho = 0.8$ ,  ${}_R \sigma = 0.25$ ). In this way, the degree of process variability allowed in the estimator was consistent with that of the actual stocks, as estimated in the assessments. Alternatively, the amount of process variability could be used to tune the decision rule to produce the desired balance between stability and ability to respond to monitoring signals.

Estimation procedures differed depending on whether or not  $q$  was assumed known.

FITTING THE DELAY-DIFFERENCE MODEL TO RELATIVE ABUNDANCE INDICES.—The unknown parameters in this case were the recruitment mean and deviations and the catchability,  $q$ . I estimated these by maximizing the penalized log-likelihood function

$$\ln L = -0.5n_t \log \left( \sum_i \left( \log(I_t) - \log(\hat{I}_t) \right)^2 \right) - 0.5 \frac{\sum_t R^w \epsilon_t^2}{R^w \sigma^2}, \quad \text{Eq. 5}$$

with respect to  $q$  and the series  $\{R^w \epsilon_t\}$ . The procedure was computationally intensive, as it involved solving a nonlinear optimization for each area and year  $t$  in the simulations within each MCMC replicate.

**FITTING THE DELAY-DIFFERENCE MODEL TO ABSOLUTE ABUNDANCE INDICES.**—In this case,  $q$  for the simulated indices was assumed known, and a more efficient numerical algorithm based on the Kalman filter was implemented in the simulations. The assessment of historical trends was based on the actual relative CPUE indices as in the previous case. Results for 1999 were used to initialize the Kalman equations. Details are provided in Appendix 2.

In both cases, an equilibrium approximation to the optimal harvest rate,

$$H_{\text{opt}} = 1 - \frac{1}{g_e + \sqrt{A(1-g_e)}} \quad \text{where } g_e \equiv g_t = e^{-M} \left( \frac{a_t}{w_t} - b_t \right)$$

(Walters and Parma, 1996) was used to adjust harvest rates as a function of the changing growth parameters  $a_t$  and  $b_t$ . The parameter  $A$  in the equation above corresponds to the slope at the origin of a Beverton-Holt stock-recruitment function times the average weight of recruits. Its value was fixed so that  $H_1^{\text{opt}} = 0.20$  when current growth parameters estimated from recent weight-at-age data were used in the equation. This procedure forced the harvest rate at the start of the simulations to be equal to the current target used by IPHC, which is on the conservative side of the recommended range (Sullivan et al., 1999).

**ASSESSMENT-BASED PROCEDURES.**—To compare the performance of the decision rules above with more traditional procedures, I examined two assessment-based approaches. The first was a standard fixed-exploitation-rate strategy, as has been used in the past by IPHC. I set quotas as a fixed fraction of the exploitable biomass estimated with the assessment model. This strategy corresponds to a fixed fishing-mortality target only if a consistent definition of exploitable biomass (computed with a fixed selectivity schedule) is used. Estimated selectivities, however, change over time in response to changes in assumptions or actual changes in the stock and the fishery. Furthermore, selectivities differ with region, as fish become vulnerable when they are younger in the southern regions than in the central Gulf of Alaska. Changes in selectivity over time and space complicate the implementation of the fixed-exploitation-rate strategy.

An alternative approach (Sullivan et al., 1999) is to attempt to equalize the reproductive contribution per recruit over space and time (as opposed to the exploitation fraction). The appeal of a constant spawning-biomass-per-recruit strategy is that it may be more robust not only to changes in selectivity but also to changes in weight at age, as the harvest fraction would be automatically adjusted in a compensatory way. To implement this strategy in the simulations, I computed, for each area and year, the harvest rate that would result in a given target spawning biomass per recruit, using year and area-specific commercial selectivities and weights at age in the catch.

As discussed above, the assessment models used for Pacific halibut are too complex to be implemented in the simulations, so ad hoc approximations to simulate implementation errors similar to those used by Parma (in press) would have to be employed. However, because the goal here was just to provide a standard for comparison, I evaluated the performance of the assessment-based strategies under optimal conditions, that is, assuming perfect knowledge of stock status and perfect control of harvest rates.

**PERFORMANCE INDICATORS.**—Short-term performance of the different procedures was examined in terms of average yield, relative change in spawning biomass, and risk that the spawning biomass would drop below the minimum historical record over the first 10 yrs of simulations. Stock sizes reached historical minima in the mid-1930s and again in the mid-1970s, prompting substantial cuts in quotas to rebuild the stocks. Estimates of recruitment for periods of low spawning biomass are above average (Fig. 7), and there is no indication that halibut stocks were ever recruitment-overfished, so the minimum record cannot be equated with an overfishing threshold. Managers and the industry, however, prefer to maintain the stock size within its historical range, a sensible objective given the long history of sustained exploitation of Pacific halibut. I also examined long-term yields by running the simulations for 50 yrs. Results are presented as average indices and box plots for selected combinations of operating models and management procedures.

## RESULTS

Average long-term yield produced under fixed-exploitation-rate strategies was insensitive to the choice of harvest rate within the range 0.20–0.40, irrespective of the stock-recruitment model used, and whether the operating model was derived from the age-based or the size-based survey indices, when growth rates were assumed to be density dependent (Fig. 8, Table 1: operating models 1 and 3). Under a harvest-rate target of 20%,

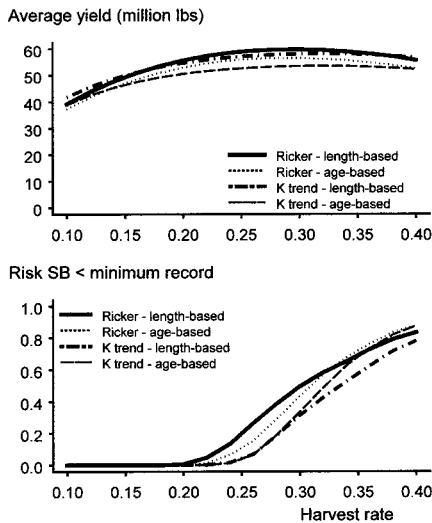


Figure 8. Long-term (50-yr) average yield and probability that the reproductive biomass will drop below the historical minimum over the next 10 yrs for different fixed exploitation rates. Operating models based on age-based or length-based survey selectivity and two different stock-recruitment models: a Ricker model with autocorrelated environmental effects and a broken-stick model with trends in carrying capacity. Individual growth is assumed to be density dependent.

Table 1. Performance of different management procedures implemented on the basis of different operating models for Pacific halibut, based on different stock-recruitment relationships (SRR) and alternative assumptions about growth and survey selectivity. HR is fixed exploitation rate, SBR is constant spawning biomass per recruit (in pounds), and DD rel and DD abs are two procedures based on fitting a delay-difference model to relative and absolute biomass indices, respectively;  $H_{opt}$  is an approximately optimal harvest rate. Performance indicators are the average annual yield over 50 and 10 yrs, the average spawning biomass (SB) in year 2010 relative to year 2000, and the probability that the SB will drop below the historical minimum in the first 10 yrs of the projections.

Operating model	Management procedure	50-yr average yield	10-yr average yield	Change in SB ( $SB_{2010}/SB_{2000}$ )	$P(SB < SB_{min})$
<b>1. SRR:</b>	HR = 0.30	53	59	0.38	0.00
asymptotic.	0.25	52	57	0.52	0.03
<b>Growth:</b>	0.20	51	53	0.60	0.34
density-	SBR = 35	55	58	0.48	0.03
dependent.	40	54	55	0.57	0.00
<b>Selectivity:</b>	DD rel - $H_{opt}$	52	59	0.59	0.01
age-based.	DD abs - $H_{opt}$	53	55	0.82	0.01
<b>2. SRR:</b>	HR = 0.30	45	44	0.36	0.56
asymptotic.	0.25	44	41	0.43	0.24
<b>Growth:</b>	0.20	43	39	0.53	0.02
density-	SBR = 35	46	41	0.46	0.13
independent.	40	46	38	0.55	0.00
<b>Selectivity:</b>	DD rel - $H_{opt}$	48	48	0.45	0.26
age-based.	DD abs - $H_{opt}$	46	50	0.64	0.06
<b>3. SRR:</b>	HR = 0.30	58	69	0.33	0.31
asymptotic.	0.25	57	65	0.41	0.04
<b>Growth:</b>	0.20	55	61	0.53	0.00
density-	SBR = 35	60	66	0.39	0.05
dependent.	40	59	63	0.47	0.00
<b>Selectivity:</b>	DD rel - $H_{opt}$	51	65	0.52	0.01
length-based.	DD abs - $H_{opt}$	58	61	0.75	0.01
<b>4. SRR:</b>	HR = 0.30	48	54	0.47	0.54
asymptotic.	0.25	48	52	0.34	0.25
<b>Growth:</b>	0.20	47	48	0.47	0.01
density-	SBR = 35	50	50	0.37	0.20
independent.	40	50	48	0.44	0.02
<b>Selectivity:</b>	DD rel - $H_{opt}$	50	57	0.40	0.25
length-based.	DD abs - $H_{opt}$	49	56	0.61	0.06



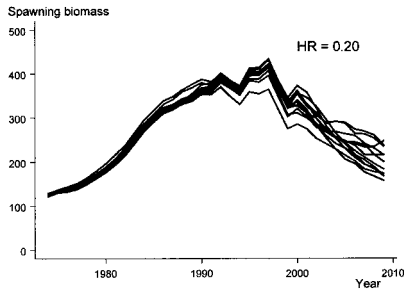


Figure 9. Sample of historical and simulated trends in spawning biomass (million lb.; 453,600,000 kg) under a 20% fixed exploitation rate. Operating model is based on the age-specific selectivity assessment model, density-dependent trends in growth, and an asymptotic stock-recruitment model with trends in carrying capacity.

expected exploitable biomass declined substantially, reflecting poor estimated recruitment over recent years (Fig. 9). The probability that the spawning biomass would drop below minimum records increased rapidly for harvest rates above 0.25. When, instead, growth rates fluctuated independently of stock size, yields were lower and risks were higher (Table 1: operating models 2 and 4). This result arises because of the lower productivity under current depressed growth rates and because growth rates would not necessarily improve as the stock size declines in the coming years as in the alternative, density-dependent growth hypothesis. However, maximum yields were again obtained in the range 0.20–0.30. These results are consistent with previous evaluations of alternative harvest rates, which were conducted on the assumption that weights at age would not change in the future (Sullivan et al., 1999).

The fixed-spawning-biomass-per-recruit harvest strategy led to relatively small increases in long-term yield (5–7% for similar risk levels) compared to the fixed-exploitation-rate strategies (Table 1, Fig. 10). Spawning biomasses per recruit in the range of 25–40 lb.

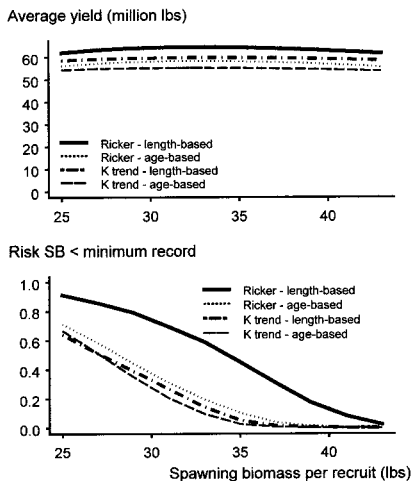
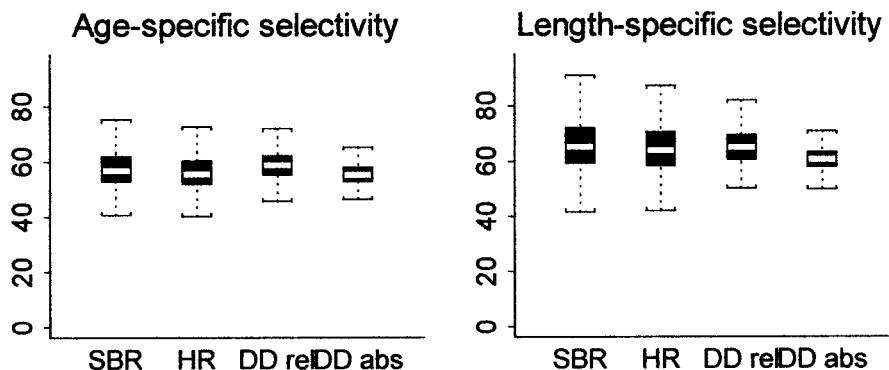
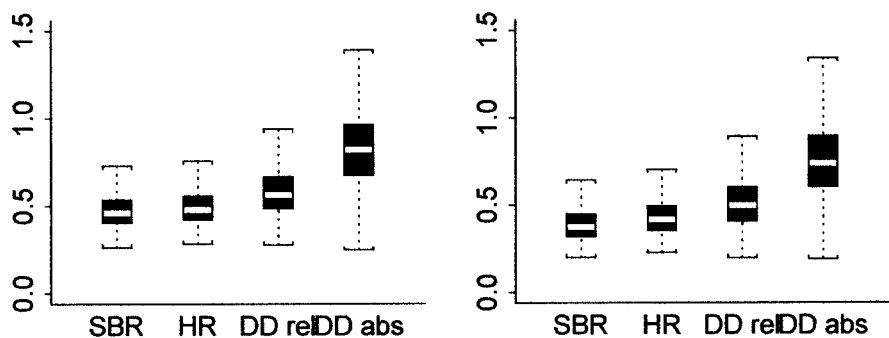


Figure 10. Long-term (50-yr) average yield and probability that the reproductive biomass will drop below the historical minimum over the next 10 yrs for targets of spawning biomass per recruit. Operating models based on age-based or length-based survey selectivity and two different stock-recruitment models: a Ricker model with autocorrelated environmental effects and a broken-stick model with trends in carrying capacity. Individual growth is assumed to be density dependent.

## 10-yr average yield (million lbs)



## SB(2010)/SB(2000)



## 50-yr average yield (million lbs)

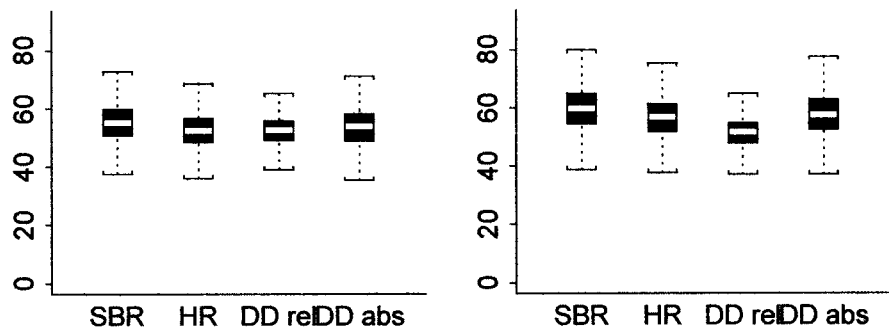
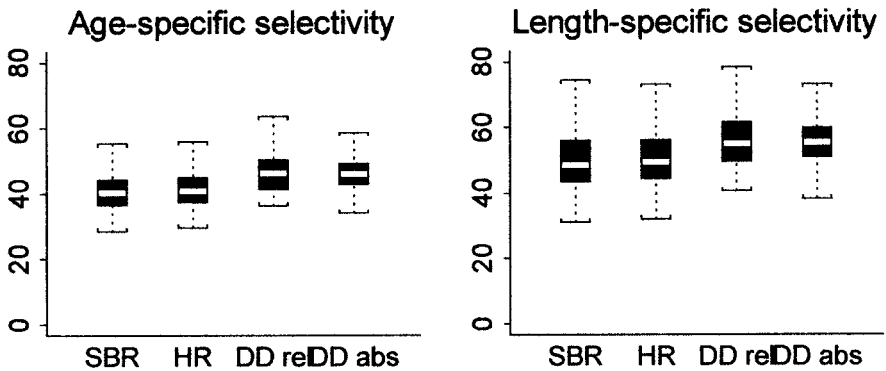
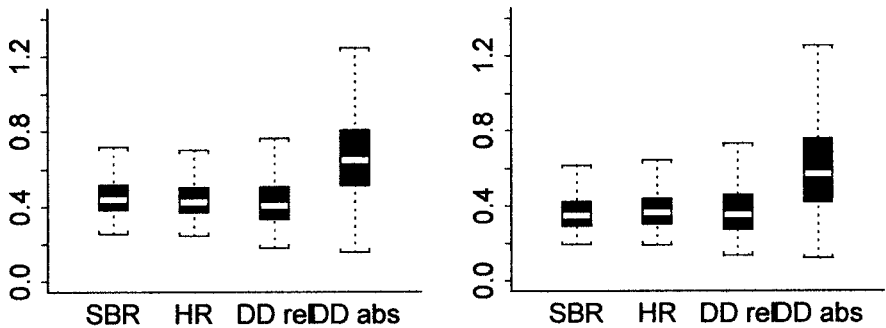


Figure 11. Performance of different management procedures in Monte Carlo simulations assuming density-dependent growth trends. Two management procedures (DD rel and DD abs) are compared to results obtained by implementation of a 0.24 fixed harvest rate (HR) and a target spawning biomass per recruit of 35 lb. (15.88 kg) on the assumption of perfect information. The management procedures involve fitting a delay-difference model to relative (DD rel) or absolute (DD abs) indices of abundance. Operating models are based on age-specific (left-hand panel) or length-specific (right-hand panel) survey selectivity. Recruitment is generated by an asymptotic model with trends in carrying capacity. Performance is indicated by boxplots ( $n = 1000$ ) of average 10-yr and 50-yr yield and change in reproductive biomass after 10 yrs.

## 10-yr average yield (million lbs)



## SB(2010)/SB(2000)



## 50-yr average yield (million lbs)

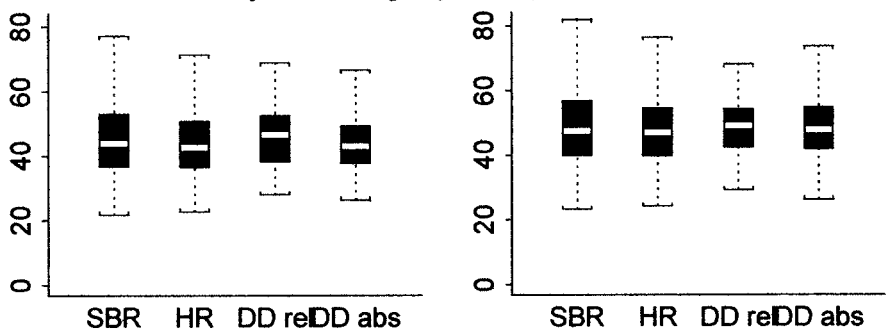


Figure 12. Performance of different management procedures in Monte Carlo simulations assuming density-independent growth trends. Two different management procedures (DD rel and DD abs) are compared to results obtained by implementation of a 0.24 fixed harvest rate (HR) and a target spawning biomass per recruit of 35 lb. (15.88 kg) on the assumption of perfect information. The management procedures involve fitting a delay-difference model fitted to relative (DD rel) or absolute (DD abs) indices of abundance. Operating models are based on age-specific (left-hand panel) or length-specific (right-hand panel) survey selectivity. Recruitment is generated by an asymptotic model with trends in carrying capacity. Performance is indicated by boxplots ( $n = 1000$ ) of average 10-yr and 50-yr yield and change in reproductive biomass after 10 yrs.

(11.34–18.14 kg) resulted in highest yields for all operating models, but risks of being below the minimum spawning-stock biomass increased rapidly at low spawning biomass per recruit (<35 lb. [15.88 kg]).

The two management procedures based on the delay-difference model performed similarly to the two strategies above in terms of long- and short-term yields and risks (Table 1, Figs. 11–12). Average decreases in spawning biomass over the first 10 yrs were generally lowest for the procedure based on fitting absolute abundance, even for comparable 10-yr average yields. This was the case even though the simulated absolute abundance indices had much lower precision ( $CV = 0.50$ ) than did the relative indices ( $CV = 0.20$ ). Apparently the constraints in the process variability assumed in the delay-difference equations in addition to the constraints in the year-to-year changes in the catches were able to smooth out the noise in the data. The delay-difference model used to drive the decision rule was misspecified especially in not being able to account for changes in commercial selectivity at age that accompanied the changes in size at age in the operating model. This problem did not degrade the performance of the procedure, however, as the estimator would still track changes in exploitable biomass, whether those were driven by actual changes in abundance or by changes in selectivity, provided the abundance indices were unbiased.

#### DISCUSSION

Ideally, the performance of alternative harvesting strategies should be evaluated in conjunction with the procedure or assessment method that will be used to implement them (Cooke, 1999). Although this procedure is easy for simple model- or data-driven management procedures, assessment-based procedures may be harder to evaluate if the assessment is too complex. This is the case of the assessment models used for Pacific halibut, so past evaluations of harvesting strategies used different error structures to represent future assessment errors, as a substitute for implementing the actual estimator in the simulation trials. Assessment performance is particularly difficult to anticipate and simulate when structural uncertainty is admitted (Parma, in press). Policy evaluations that use some error distribution to simulate implementation error are incomplete because only one component of the management procedure—the harvesting strategy—is specified; the estimator to be used in the implementation is not.

The advent of powerful computers and efficient optimization packages has led to increased use of complex assessment models in an attempt to increase realism and incorporate different data sources and prior information into an integrated statistical framework. These estimators are particularly hard to evaluate in a management procedure context. Clearly, these complex models allow a more realistic representation of uncertainty by facilitating incorporation of adequate process and observation errors. For example, the use of time-series approaches to model temporal trends in dynamic processes such as catchability, selectivity (see, e.g., Fournier et al., 1998), and growth, as done in the Pacific halibut model, is a good compromise that increases model flexibility without freeing up too many parameters. Whether or not these complex assessment models improve management performance when used as part of the decision rule to set catch quotas is unclear, however (National Research Council, 1998). Their value as assessment and research tools should be best seen in their ability to represent alternative states of nature (hypotheses) to consider in the evaluation of different candidate management procedures.

The development of management procedures has emphasized the identification of decision rules that are robust to major assessment uncertainties and tend to perform well across all scenarios considered in the simulation trials (Butterworth and Punt, 1999; Cooke, 1999). Ideally, alternative hypotheses should each be assigned a probability so that they can be differentially weighted when trade-offs between risks and benefits of different decision rules are evaluated. Otherwise, aiming for robustness may lead to choices that are precautionary even under extreme worst-case scenarios, no matter how unlikely those scenarios may be, at the expense of forgone yield opportunities. When used in combination with Bayesian methods such as MCMC or Sampling Importance Resampling to approximate posterior distributions of parameter values and probabilities of different model structures (Kinas, 1996; McAllister and Ianelli, 1997; Punt and Hilborn, 1997; Patterson, 1999; Parma, in press; McAllister and Kirchner, this issue), complex assessment models are an excellent tool for simulating alternative scenarios for policy evaluation.

An advantage of simple decision rules is that they can be readily evaluated in simulations, so they can be tuned to improve the chances of achieving management goals in the face of uncertain assessments and predictions. Experience with evaluating management procedures has indicated that simple decision rules tend to perform just as well as or better than those based on more complex estimators (Punt, 1993; Butterworth and Punt, 1999). This result is explained by poor performance of point estimators based on complex, overparameterized models such as VPA, which tend to fit noise. In the Pacific halibut analysis, the two simple management procedures explored performed similarly to conventional fixed-exploitation-rate and constant-biomass-per-recruit strategies, even though the latter were implemented on the assumption of no assessment errors. This result may hold also for other stocks with moderate to slow dynamics, like Pacific halibut, especially if the yield-versus-harvest-rate curve is flat.

The incorporation of (constrained) process error and measurement error into the estimation of the delay-difference model may be a good compromise between the stiffness of simple deterministic models used in other management procedures and the use of purely empirical approaches to drive the decision rule. Other variants of decision rules could be tested to improve performance. For example, some design features could be added to reduce the probability of driving the stock size to very low, potentially risky levels. One possibility is to use estimates of annual surplus production to set an upper bound on catch quotas when the stock size is low or decreasing. This option was certainly successful with Pacific halibut when implemented to promote stock rebuilding in the 1980s. Finally, empirical rules that respond directly to the data could be explored, such as those suggested by Hilborn (this issue) and Hilborn et al. (2002). In conclusion, although other alternatives exist that merit further examination, results of the present paper are encouraging, as they suggest that simple feedback rules may stabilize the quotas and still provide adequate yields for the Pacific halibut fishery. In general, an advantage of the management-procedure approach is that, once in place, the decision rules can simplify the process of quota setting, while allowing research and assessments to evolve at their own pace, independent of the annual management cycle.

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## LITERATURE CITED

- Butterworth, D. S. and A. E. Punt. 1999. Experiences in the evaluation and implementation of management procedures. *ICES J. Mar. Sci.* 56: 985–998.
- Clark, W. G. 1999. The effects of an erroneous natural mortality rate on a simple age-structured stock assessment. *Can. J. Fish. Aquat. Sci.* 56: 1721–1731.
- \_\_\_\_\_, and S. R. Hare. 1998. Accounting for bycatch in management of the Pacific halibut fishery. *N. Amer. J. Fish. Manage.* 18: 809–821.
- \_\_\_\_\_, S. R. Hare, A. M. Parma, P. J. Sullivan and R. J. Trumble. 1999. Decadal changes in halibut growth and recruitment. *Can. J. Fish. Aquat. Sci.* 56: 1–11.
- Cooke, J. G. 1999. Improvement of fishery-management advice through simulation testing of harvest algorithms. *ICES J. Mar. Sci.* 56: 797–810.
- Deriso, R. B. and T. J. Quinn II. 1983. The Pacific halibut resource and fishery in Regulatory Area 2. II. Estimates of biomass, surplus production, and reproductive value. Scientific report, Int'l. Pacific Halibut Commission, No. 67. Int'l. Pacific Halibut Commission, Seattle, Washington. 89 p.
- \_\_\_\_\_, \_\_\_\_\_ and P. R. Neal. 1985. Catch-age analysis with auxiliary information. *Can. J. Fish. Aquat. Sci.* 42: 815–824.
- FAO (Food and Agriculture Organization of the United Nations). 1995. Precautionary approach to fisheries. Part 1: Guidelines on the precautionary approach to capture fisheries and species introductions. FAO Fisheries Tech. Pap. no. 350, Part 1. FAO, Rome. 52 p.
- Fournier, D. A., J. Hampton and J. R. Sibert. 1998. MULTIFAN-CL: a length-based, age-structured model for fisheries stock assessment, with application to South Pacific albacore, *Thunnus alalunga*. *Can. J. Fish. Aquat. Sci.* 55: 1–12.
- Gelman, A., J. B. Carlin, H. S. Stern and D. B. Rubin. 1995. Bayesian data analysis. Chapman & Hall, London. 526 p.
- Geromont, H. F., J. A. De Oliveira, S. J. Johnston and C. L. Cunningham. 1999. Development and application of management procedures for fisheries in southern Africa. *ICES J. Mar. Sci.* 56: 952–966.
- Hilborn, R., J.-J. Maguire, A. M. Parma and A. Rosenberg. 2001. The precautionary approach and risk management. Can they increase the probability of successes in fishery management? *Can. J. Fish. Aquat. Sci.* 58: 99–107.
- \_\_\_\_\_, A. M. Parma and M. Maunder. 2002. Exploitation rate reference points for west coast rockfish: are they robust and are there better alternatives? *N. Amer. J. Fish. Manage.* 22: 365–375.
- \_\_\_\_\_, J. Skalski, A. Anganuzzi and A. Hoffman. 1995. Movements of juvenile halibut in IPHC Regulatory Areas 2 and 3. Technical report, Int'l. Pacific Halibut Commission, No. 31. Int'l. Pacific Halibut Commission, Seattle, Washington. 44 p.
- Kass, R. E. and A. E. Raftery. 1995. Bayes factors. *J. Amer. Stat. Assoc.* 90: 773–795.

- Kell, L. T., C. M. O'Brien, M. T. Smith, T. K. Stokes and B. D. Rackham. 1999. An evaluation of management procedures for implementing precautionary approaches in the ICES context for North Sea plaice (*Pleuronectes platessa* L.). *ICES J. Mar. Sci.* 56: 834–845.
- Kimura, D. K., J. W. Balsiger and D. I. Ito. 1996. Kalman filtering the delay-difference equation: practical approaches and simulations. *Fish. Bull., U.S.* 94: 678–691.
- Kinas, P. G. 1996. Bayesian fishery stock assessment and decision making using adaptive importance sampling. *Can. J. Fish. Aquat. Sci.* 53: 414–423.
- McAllister, M. K. and J. N. Ianelli. 1997. Bayesian stock assessments using catch-age data and the Sampling/Importance Resampling algorithm. *Can. J. Fish. Aquat. Sci.* 54: 284–300.
- National Research Council. 1998. Improving fish stock assessments. National Academy Press, Washington D.C. 177 p.
- Otter Research Ltd. 1999. AD Model Builder documentation on line. <http://otter-rsch.com/admodel.htm>.
- Parma, A. M. 1990. Optimal harvesting of fish populations with non-stationary stock-recruitment relationships. *Nat. Resour. Model.* 4: 39–76.
- \_\_\_\_\_. 1993. Retrospective catch-at-age analysis of Pacific halibut: implications on assessment of harvesting policies. Pages 247–265 in G. Kruse, D. M. Eggers, R. J. Marasco, C. Pautzke and T. J. Quinn II, eds. *Proc. Int'l. Symp. Management Strategies for Exploited Fish Populations*. Alaska Sea Grant College Program Report No. AK-SG-93-02. Alaska Sea Grant College Program, Univ. Alaska, Fairbanks, Alaska.
- \_\_\_\_\_. (in press). Bayesian approaches to the analysis of uncertainty in the stock assessment of Pacific halibut. In J. M. Berkson, L. L. Kline and D. J. Orth, eds. *Incorporating uncertainty into fishery models*. Amer. Fish. Soc., Bethesda, Maryland.
- Patterson, K. R. 1999. Evaluating uncertainty in harvest control law catches using Bayesian Markov Chain Monte Carlo virtual population analysis with adaptive rejection sampling and including structural uncertainty. *Can. J. Fish. Aquat. Sci.* 56: 208–221.
- Punt, A. E. 1993. The comparative performance of production model and ad hoc tuned VPA based feedback control management procedures for the stock of Cape hake off west coast of South Africa. Pages 283–299 in J. S. Smith, J., J. Hunt and D. Rivard, eds. *Risk evaluation and biological reference points for fisheries management*. Canadian Special Publication of Fisheries and Aquatic Sciences no. 120. National Research Council of Canada, Ottawa, Canada.
- \_\_\_\_\_ and R. Hilborn. 1997. Fisheries stock assessment and Bayesian analysis: the Bayesian approach. *Rev. Fish Biol. Fish.* 7: 35–63.
- Restrepo, V. R., G. G. Thompson, P. M. Mace, W. L. Gabriel, L. L. Low, A. D. MacCall, R. D. Methot, J. E. Powers, B. L. Taylor, R. R. Wade and J. F. Witzig. 1998. Technical guidance on the use of precautionary approaches to implementing national standard 1 of the Magnuson-Stevens Fishery Conservation and Management Act. NOAA Tech. Memo. NMFS-F/SPO-##.
- Skud, B. E. 1977. Drift, migration, and intermingling of Pacific halibut stocks. Scientific report, Int'l. Pacific Halibut Commission, No. 63. Int'l. Pacific Halibut Commission, Seattle, Washington. 42 p.
- St-Pierre, G. 1989. Recent studies of Pacific halibut postlarvae in the Gulf of Alaska and eastern Bering Sea. Scientific report, Int'l. Pacific Halibut Commission, No. 73. Int'l. Pacific Halibut Commission, Seattle, Washington.
- Sullivan, P. J., and D. A. McCaughran. 1995. Pacific halibut assessment: changing strategies for changing times. Pages 129–144 in G. T. Sakagawa and M. Stocker, eds. *Assessment methodologies and management*. Proc. World Fisheries Congress, Theme 5. Oxford & IBH Publishing Co., New Delhi.

- \_\_\_\_\_, A. M. Parma and W. G. Clark. 1999. The Pacific halibut stock assessment of 1997. Scientific report, Int'l. Pacific Halibut Commission, No. 79. Int'l. Pacific Halibut Commission, Seattle, Washington. 84 p.
- Walters, C. and A. M. Parma. 1996. Fixed exploitation rate strategies for coping with effects of climate change. Can. J. Fish. Aquat. Sci. 53: 148–158.

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## APPENDIX 1

### ASSESSMENT MODELS USED FOR PACIFIC HALIBUT

The assessment methods used for Pacific halibut are described in detail by Sullivan et al. (1999). Only slight modifications have been introduced for this analysis, mostly the use of a more flexible time-series growth model as described by Parma (in press) (Table A1, density-independent growth trends) and the incorporation of density-dependent growth as an alternative hypothesis (Table A1, density-dependent growth trends). I refer the reader to Sullivan et al. (1999) for further discussion of specific model assumptions, input data, and estimation procedures. Tables below summarize the fundamental process equations (Table A1), model predictions (Table A2), parameterization and prior distributions of model parameters (Table A3), and likelihood function (Table A4).



Table A1. Equations describing the age- and size-structured models used for Pacific halibut assessments.

<b>Process</b>	<b>Notation</b>
<b>Abundance dynamics</b>	
$N_{a+1,t+1} = N_{a,t} e^{-M} (1 - {}_b H_{a,t}) (1 - {}_c S_{a,t} (1 - e^{-F_t}))$ $N_{20^+,t+1} = N_{20^+,t} + N_{20^+,t} e^{-M} (1 - {}_b H_{20^+,t}) (1 - {}_c S_{20^+,t} (1 - e^{-F_t}))$	<p><math>a</math>: age 6, ..., 19; plus group <math>a=20^+</math>  <math>t</math>: 1974, ..., 1997  <math>N_{a,t}</math>: abundance at age <math>a</math> and year <math>t</math>  <math>{}_c S_{a,t}</math>: age-specific commercial selectivity  <math>{}_b H_{a,t}</math>: bycatch mortality rate <sup>a</sup>  <math>F_t</math>: fishing mortality  <math>M</math>: natural mortality</p>
<b>Commercial catchability</b>	
$\ln({}_c q_{t+1}) = \ln({}_c q_t) + {}_q \varepsilon_t \text{ where } {}_q \varepsilon_t \sim N(0, {}_q \sigma^2)$	<p><math>{}_c q_t</math>: commercial catchability</p>
<b>Commercial selectivity</b>	
${}_c s_t(X) = \begin{cases} 0 & \text{for } X < \ln(81) \\ e^{-\frac{(X - {}_c X_t^{\text{full}})^2}{2 {}_c v_t}} & \text{for } \ln(81) \leq X \leq {}_c X_t^{\text{full}} \\ 1 & \text{for } X > {}_c X_t^{\text{full}} \end{cases}$ ${}_c X_{t+1}^{\text{full}} = {}_c X_t^{\text{full}} + {}_c X_t^{\text{full}} \varepsilon_t \text{ where } {}_c X_t^{\text{full}} \varepsilon_t \sim N(0, {}_c X_t^{\text{full}} \sigma_t^2)$ $\ln({}_c v_{t+1}) = \ln({}_c v_t) + {}_c v_t \varepsilon_t \text{ where } {}_c v_t \varepsilon_t \sim N(0, {}_c v_t \sigma_t^2)$ ${}_c S_{a,t} = \int_{-\infty}^{\infty} {}_c s_t(X_{a,t}) p(X_{a,t}) dX_{a,t}$	<p><math>X_{a,t}</math>: log-length at age <math>a</math> and year <math>t</math>  <math>{}_c s_t(X)</math>: length-specific commercial selectivity  <math>{}_c X_t^{\text{full}}</math>: log-length at full selectivity  <math>{}_c v_t</math>: variance-like parameter of half-normal selectivity function  <math>p(X)</math>: probability density of <math>X</math></p>

<sup>a</sup> Estimated internally by the model assuming numbers killed by size categories are known without error.

Table A1. continued.

Process	Notation
<b>Growth</b>	$X_{a,t}$ : log-length at age and year
$X_{a,t} \sim N(\mu_{a,t}, \sigma^2)$	$\mu_{a,t}$ : mean log-length at age and year
$\mu_{6,t+1} = \mu_{6,t} + \mu \varepsilon_t$ where $\mu \varepsilon_t \sim N(0, \mu_6 \sigma^2)$	$\mu_{a,t}^+$ : mean log-length at age $a$ after the fishing season in year $t$
$\exp(\mu_{a+1,t+1}) = \alpha_t + \beta \exp(\mu_{a,t}^+)$	$\sigma^2$ : variance of log-length at age
$\mu_{a,t}^+ = \frac{\int_{-\infty}^{\infty} X_{a,t} (1 - c_s s_t(X_{a,t})) (1 - e^{-F_t}) p(X_{a,t}) dX_{a,t}}{\int_{-\infty}^{\infty} (1 - c_s s_t(X_{a,t})) (1 - e^{-F_t}) p(X_{a,t}) dX_{a,t}}$	$p(X_{a,t})$ : Gaussian density with mean $\mu_{a,t}$ and variance $\sigma^2$
(a) Density-independent growth trends:	$B_t$ : total biomass of age six and older in year $t$
$\ln(\alpha_{t+1}) = \ln(\alpha_t) + \alpha \varepsilon_t$ where $\alpha \varepsilon_t \sim N(0, \alpha \sigma^2)$	$\bar{B}$ : average biomass over 1974-1999
(b) Density-dependent growth trends:	
$\alpha_t = \alpha_1 - \alpha_2 \left( \frac{B_t - \bar{B}}{\bar{B}} \right) + \alpha \varepsilon_t \quad \alpha \varepsilon_t \sim N(0, \alpha \sigma^2)$	
<b>Survey selectivity</b>	${}_s s_t(X)$ : survey selectivity at length
${}_s s_t(X) = \begin{cases} e^{-\frac{-(X - X_t^{\text{full}})^2}{2 {}_s v_t}} & \text{for } X \leq {}_s X_t^{\text{full}} \\ 1 & \text{for } X > {}_s X_t^{\text{full}} \end{cases}$	${}_s S_{a,t}$ : survey selectivity at age
${}_s S_{a,t} = \int_{-\infty}^{\infty} {}_s s_t(X_{a,t}) p(X_{a,t}) dX_{a,t}$	${}_s X_t^{\text{full}}$ : log-length at full selectivity
(a) Length - specific :	${}_s v_t$ : variance-like parameter of half-normal selectivity function
${}_s X_t^{\text{full}} = {}_{s_j} X^{\text{full}}$ or ${}_{s_c} X^{\text{full}}$	${}_{s_j} X^{\text{full}}, {}_{s_c} X^{\text{full}}$ : log-length at full selectivity for J- and Circle hooks
${}_s v_t = {}_{s_j} v$ or ${}_{s_j} v$	${}_{s_j} v, {}_{s_c} v$ : variance-like parameters of selectivity functions for J- and Circle hooks
(b) Age - specific :	${}_{s_j} S_a, {}_{s_c} S_a$ : (constant) age-specific selectivity for J- and Circle hooks
${}_s X_{t+1}^{\text{full}} = {}_s X_t^{\text{full}} + {}_{s_j} X^{\text{full}} \varepsilon_t$ where ${}_{s_j} X^{\text{full}} \varepsilon_t \sim N(0,1)$	
$\ln({}_s v_{t+1}) = \ln({}_s v_t) + {}_{s_j} v \varepsilon_t$ where ${}_{s_j} v \varepsilon_t \sim N(0,1)$	
constrained so that ${}_s S_{a,t} = {}_{s_j} S_a$ or ${}_{s_c} S_a$	

Table A2. Equations describing model predictions of observed variables.

<b>Predicted variable</b>	<b>Notation</b>
Commercial catch at age $C_{a,t} = N_{a,t} e^{-\frac{M}{2}} (1 - {}_b H_{a,t}) {}_c S_{a,t} (1 - e^{-F_t})$	$C_{a,t}$ : catch at age $a$ and year $t$
Fishing effort $E_t = \frac{F_t}{{}_c q_t}$	$E_t$ : predicted effort ${}_c q_t$ : commercial catchability in year $t$
Survey CPUE $CPUE_t = {}_{sH} q_t \sum_{a=6}^{20^+} {}_{sH} S_{a,t} N_{a,t}$	${}_{sH} q_t$ : survey catchability for hook type $H$ in year $t$ ${}_{sH} S_{a,t}$ : survey selectivity for hook type $H$ in year $t$
Survey age composition ${}_{sH} P_{a,t} = \frac{{}_{sH} S_{a,t} N_{a,t}}{\sum_{j=6}^{20^+} {}_{sH} S_{j,t} N_{j,t}}$	${}_{sH} P_{a,t}$ : survey age proportions for hook type $H$ in year $t$
Mean and variance of log-length at age ${}_c \mu_{a,t} = \frac{\int_{-\infty}^{\infty} X_{a,t} {}_c S_t(X_{a,t}) p(X_{a,t}) dX_{a,t}}{{}_c S_{a,t}}$ ${}_c \sigma_{a,t}^2 = \frac{\int_{-\infty}^{\infty} X_{a,t}^2 {}_c S_t(X_{a,t}) p(X_{a,t}) dX_{a,t}}{{}_c S_{a,t}} - ({}_c \mu_{a,t})^2$	${}_c \mu_{a,t}$ : mean log-length at age and year in the commercial catch ${}_c \sigma_{a,t}^2$ : variance of log-length at age and year in the commercial catch Note: for survey equations replace subscript $c$ for $s$

Table A3. Estimated parameters and prior distributions.

Process	Estimated parameters	Value or Prior distribution
Natural mortality	$M$	0.15
Fishing mortality	$\theta_1 = \overline{\ln(F_t)}$ $\theta_{2,26} = \ln(F_t) - \overline{\ln(F_t)}, \sum_{t=2}^{26} \theta_t = 0$	$U(-\infty, \infty)$ $U(-5,5)$
Recruitment	$\theta_{27} = \overline{\ln(N_{6,t})}$ $\theta_{28,52} = \ln(N_{6,t}) - \overline{\ln(N_{6,t})}, \sum_{t=28}^{52} \theta_t = 0$	$U(-\infty, \infty)$ $U(-15,15)$
Initial abundance	$\theta_{53} = \overline{\ln(N_{a,1974})}, a = 7, \dots, 20^+$ $\theta_{54,67} = \ln(N_{a,1974}) - \overline{\ln(N_{a,1974})}, \sum_{t=54}^{67} \theta_t = 0$	$U(-\infty, \infty)$ $U(-15,15)$
Commercial selectivity	$\theta_{68} = e^{-\lambda_{1974}^{\text{full}}}$ $\theta_{69,92} = e^{-\lambda_{t,1974}^{\text{full}}} \leq \ln(130), t = 1974 - 1997$ $\theta_{93} = \ln(e_{1974})$ $\theta_{94,117} = e_t, t = 1974 - 1997$	$U(\ln(81), \ln(130))$ $N(0, 0.05^2)$ $U(-5, -2.5)$ $N(0, 0.05^2)$
Commercial catchability	$\theta_{118} = \ln(q_{1974})$ $\theta_{119,142} = q_t, t = 1974 - 1997$	$U(-15, -10)$ $N(0, 0.03^2); q_{t,1994}$ unconstrained <sup>a</sup>
Growth	$\theta_{143} = \alpha_{1974}$ $\theta_{144,165} = \alpha_t, t = 1974, \dots, 1995$ $\theta_{166} = \beta$ $\theta_{167} = \sigma$ $\alpha \sigma^2$	$U(4,20)$ $N(0, \alpha \sigma^2)$ $U(0.6, 1)$ $U(0.05, 1.)$ (a) density-independent trends: variance fixed at $0.10^2$ (b) density-dependent trends: variance estimated with prior $\propto 1/\alpha \sigma^2$
Size at recruitment	$\theta_{168} = \mu_{6,1974}$ $\theta_{169,192} = \mu_t, t = 1974, \dots, 1997$	$U(-\infty, \infty)$ $N(0, cv^2), cv=0.1 \ t < 1996;$ $cv=0.02 \ t \geq 1996$
Initial size at age	$\theta_{193} = \alpha_0$ $\theta_{194} = \beta_0$ $e^{\mu_{a+1,1974}} = \alpha_0 + \beta_0 e^{\mu_{a,1974}}$	$U(-\infty, \infty)$ $U(0.6, 1)$
Survey catchability	$\theta_{195} = \ln(q)$	$U(-10., -15.)$

<sup>a</sup> To allow more variability during transition to individual quotas in the US.

Table A3. continued.

<b>Process</b>	<b>Estimated parameters</b>	<b>Value or Prior distribution</b>
Survey selectivity, hook type H=J or C <sup>b</sup>	(a) length-specific:	
	$\theta_{196:197} = {}_{s_1}X^{\text{fall}}, {}_{s_c}X^{\text{fall}}$	$U(\ln(66), \ln(130))$
	$\theta_{198:199} = \ln({}_{s_1} \nu), \ln({}_{s_c} \nu)$	$U(-\infty, \infty)$
	(b) age-specific: constrained so ${}_{s_H}S_{a,t} = {}_{s_H}S_a$	
	$\theta_{196:197} = {}_{s_1}X^{\text{fall}}_{1977}, {}_{s_c}X^{\text{fall}}_{1984}$	$U(\ln(66), \ln(130))$
	$\theta_{198:199} = \ln({}_{s_1} \nu_{1977}), \ln({}_{s_c} \nu_{1984})$	$U(-\infty, \infty)$
	$\theta_{200:228} = {}_{s_1}X^{\text{fall}} \varepsilon_t$ and $\ln({}_{s_1} \nu \varepsilon_t)$	$N(0,1)$
	$t = 1977 - 1982; 1984 - 1986; 1993 - 1997$	

<sup>b</sup> J-hook used during 1977-1984 and Circle-hook during 1984-1986 and 1993-1998

## APPENDIX 2

## KALMAN FILTER APPROXIMATION TO ESTIMATING PARAMETERS OF THE DELAY-DIFFERENCE MODEL USING ABSOLUTE ESTIMATES OF EXPLOITABLE BIOMASS

A Kalman filter approximation was derived by adjustment of equations in Kimura et al. (1996) to the specific model assumptions in Eqs. 2 and 3. Define the state variables  $B_t$  as the total recruited biomass in the middle of year  $t$ ,  $B_t^{adult}$  as the portion of  $B_t$  that was already recruited in year  $t - 1$ ,  $R_t$  as the recruitment biomass, and  $H_t$  as the harvest rate, such that

$$B_{t+1}^{adult} = G_t(B_t^{adult} + R_t)$$

$$R_{t+1} = \rho(R_t - \bar{R}) + \varepsilon_t$$

where

$$G_t = H_t \left( \frac{a_t}{\bar{w}_t} - b_t \right)$$

and the autocorrelation of recruitment deviations  $\rho$  and the mean recruitment  $\bar{R}$  are assumed known.  $H_t$  is approximated as  $C_t/\hat{B}_t$ , where  $\hat{B}_t$  is the Kalman estimate of  $B_t$ . The random variable  $\varepsilon_t \sim N(0, v)$  corresponds to process error with variance  $v$  assumed known and set to  $v = cv^2 \hat{R}_t^2$ , where  $\hat{R}_t$  is the Kalman estimate of  $R_t$ , and  $\rho$  and  $cv$  are calculated from the series of biomasses at age 10 estimated from the assessments setting

$$cv = SD[(B_{10,t} - \bar{B}_{10}) - \rho(B_{10,t-1} - \bar{B}_{10})] / \bar{B}_{10}.$$

The observation equation is approximated as

$$I_t = B_t + \xi_t,$$

where  $\xi_t \sim N(0, m)$  is measurement error with variance assumed known and set to  $m = SD^2 \hat{B}_t$ , where  $SD = 0.5$  is the standard deviation of the log-normal errors used to generate the indices of absolute abundance (Eq. 4).

The Kalman filter was used to estimate  $\hat{B}_t$  in the decision rule of Eq. 1. Initial conditions for the state variables and their variance-covariance were approximated by fitting of the delay-difference model to historical survey CPUE data. Equation 5 was maximized with respect to  $q$  and the series  $\{R_t \varepsilon_t\}$  and estimated parameters were used to compute adult biomass and recruitment for the final year (1999). These were used as  $\hat{B}_0^{adult}$  and  $\hat{R}_0$  to initialize the Kalman filter; their variance-covariance was derived from the approximated variance-covariance of the estimated model parameters according to the Delta method, as implemented in the software AD Model Builder (Otter Research Ltd., 1999). Estimation of the state variables for subsequent years occurs in two steps:

1. Initial projections based on process equations:

$$\hat{B}_{t+1}^+ = G_t(\hat{B}_t^{adult} + \hat{R}_t)$$

$$\hat{R}_{t+1}^+ = \rho(\hat{R}_t - \bar{R})$$

with variance-covariance matrix

$$\mathbf{V}_{t+1}^+ = \begin{bmatrix} V[\hat{B}_{t+1}^+] & Cov[\hat{B}_{t+1}^+, \hat{R}_{t+1}^+] \\ Cov[\hat{B}_{t+1}^+, \hat{R}_{t+1}^+] & V[\hat{R}_{t+1}^+] \end{bmatrix}$$

projected as

$$V[\hat{B}_{t+1}^+] = G_t^2(V[\hat{B}_t^{adult}] + V[\hat{R}_t] + 2Cov[\hat{B}_t^{adult}, \hat{R}_t])$$

$$V[\hat{R}_{t+1}^+] = \rho^2 V[\hat{R}_t] + v$$

$$Cov[\hat{B}_{t+1}^+, \hat{R}_{t+1}^+] = \rho G_t(V[\hat{R}_t] + Cov[\hat{B}_t^{adult}, \hat{R}_t])$$

2. Kalman updates based on new data  $I_{t+1}$ :

$$\begin{bmatrix} \hat{B}_{t+1}^{adult} \\ \hat{R}_{t+1} \end{bmatrix} = \begin{bmatrix} \hat{B}_{t+1}^+ \\ \hat{R}_{t+1}^+ \end{bmatrix} + \mathbf{K}(I_{t+1} - \hat{I}_{t+1}),$$

where

$$\hat{I}_{t+1} = \hat{B}_{t+1}^+ + \hat{R}_{t+1}^+ \quad \text{with} \quad V[\hat{I}_{t+1}] = V[\hat{B}_{t+1}^+] + V[\hat{R}_{t+1}^+] + 2Cov[\hat{B}_{t+1}^+, \hat{R}_{t+1}^+] + m$$

$$\text{and } \mathbf{K} = \begin{bmatrix} \frac{V[\hat{B}_{t+1}^+] + Cov[\hat{B}_{t+1}^+, \hat{R}_{t+1}^+]}{V[\hat{I}_{t+1}]} \\ \frac{V[\hat{R}_{t+1}^+] + Cov[\hat{B}_{t+1}^+, \hat{R}_{t+1}^+]}{V[\hat{I}_{t+1}]} \end{bmatrix}$$

with variance-covariance matrix updated as

$$\mathbf{V}_{t+1} = \mathbf{V}_{t+1}^+ - \mathbf{K}[V[\hat{B}_{t+1}^+] + Cov[\hat{B}_{t+1}^+, \hat{R}_{t+1}^+]]\hat{R}_{t+1}^+ + Cov[\hat{B}_{t+1}^+, \hat{R}_{t+1}^+].$$