A simple simulation approach to risk and cost analysis, with applications to swordfish and cod fisheries

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Abstract.– Monte Carlo simulation is used to quantify the uncertainty in the results of sequential population analysis and related statistics. Probability density functions describe the measured or perceived uncertainty in the inputs to the assessment model. Monte Carlo simulation is then used to examine the variability in the resulting parameter estimates (stock sizes and fishing mortalities), derived statistics (e.g., $F_{0.1}$), and in the management regulations necessary to achieve various management objectives. We show how relative frequency histograms of the simulation results can be used to describe the risk of not meeting a given management goal as a function of the catch quota selected. We also show how to compute the expected cost, in terms of potential yield foregone, associated with picking a conservative quota. This enables one to balance risks and costs or to allow risk to vary within proscribed limits while keeping the catch quota stable. We illustrate the use of the Monte Carlo approach with examples from two fisheries: North Atlantic swordfish and northern cod.

Manuscript accepted 29 July 1992.
Fishery Bulletin, U.S. 90:736–748 (1992).

Fishery managers recognize the dangers of accepting parameter estimates without consideration of the variability inherent in the estimates of fish stock status and related parameters. Early strategies for dealing with this were quite simple, such as replacing the estimate of the fishing mortality giving the maximum yield (F_{max}) by a more conservative value. Sensitivity analyses, in which the effects of various perturbations of the inputs are observed, have commonly been employed to obtain impressions of the probable bounds on the errors (e.g., Pope 1972, Pope and Garrod 1975). Recently, various authors have used the delta method (see Kendall and Stuart 1977: 246–248) to obtain analytical expressions or numerical solutions for the variances and covariances of outputs from simple sequential population analyses (SPAs) (Saila et al. 1985, Sampson 1987, Prager and MacCall 1988, Kimura 1989). These solutions tend to be complex, only asymptotically valid, and highly model-specific. They have only been worked out for the simplest SPA models and some simple quota-setting procedures (e.g., Pope 1983).

It is possible to measure how well the population estimates correspond to trends in indices of abundance when calibration procedures are applied to sequential population analyses. The variance-covariance matrix of the stock sizes estimated directly in the optimization procedure is calculated from the inverse Hessian or its approximation (Seber and Wild 1989); the variance of any function of these parameters is then approximated by the delta method. But estimates of standard errors of population sizes obtained in this way do not reflect all the variability in the inputs and the uncertainty in the model, because they are conditioned on a number of assumptions such as natural mortality being exactly known. For example, similar trends in population abundance may be obtained when two very different values of natural mortality rate are assumed as inputs; despite the similar trends (and hence correlation with the abundance indices), there may be large differences in the absolute estimates of abundance.

In this paper we use the term "uncertainty" to describe any variability or error that arises during the stock assessment process. Uncertainty can enter into an assessment in various ways. There may be uncertainties in the values of the inputs, e.g., the total catch may be estimated with error. Also, the formulation of the assessment model may be subject to uncertainty, and the analyst may make data-dependent decisions during the analysis which are subject to error. The degree to which these sources of error are incorporated into the analyses will determine the perceived uncertainty in the overall assessment results. If all sources of error are not appropriately accounted for, then estimates of the uncertainty in the assessment results may be too small.

Monte Carlo simulation is a convenient tool for studying a model's outputs given different types and levels of error in the model's inputs (e.g., Restrepo and Fox 1988). In a sensitivity analysis framework, Pope and Gray (1983) and Rivard (1983) used a Monte Carlo approach to study the relative contribution of various inputs to the overall uncertainty in total allowable catch (TAC) estimates obtained from calibrated SPAs. Francis (1991) used Monte Carlo simulation analysis to construct risk curves describing the chances of not meeting management objectives as a function of the catch quota. In this paper, we present a general method, also based on Monte Carlo simulation, to account for uncertainty in assessment results, including the parameters directly estimated from the SPAs as well as derived statistics used to set management targets and allowable catches. We also show how the simulation results can be used to quantify the risk (of not meeting a management goal) associated with the selection of a given TAC, and we describe a measure of the cost of picking a conservative catch quota.

We apply the simulation method to swordfish *Xiphias gladius* in the North Atlantic Ocean and cod *Gadus morhua* off eastern Newfoundland and southeastern Labrador. These fisheries are quite different in nature. Swordfish are highly migratory, managed internationally with fishing mortality controls, and the data set allows for the estimation of only a few parameters in models with many constraints. Northern cod, on the other hand, are demersal, managed by quota, and the availability of age-specific survey indices allows for the estimation of many parameters with a minimum number of assumptions.

Quantifying uncertainty by simulation

Suppose the only uncertainty in the inputs to an assessment model concerns the value of the instantaneous natural mortality rate, M, and that M could be anywhere in the interval 0.15–0.25/yr with equal likelihood. One could compute the assessment model results for a large number of uniformly spaced values of M in this interval (e.g., 100) and make histograms of the results. This would represent the perceived information about the relative likelihood of the estimated output taking on various values. If not all values of M were believed to be equally likely, one could weight the 100 outputs by the probability associated with the corresponding inputs.

The above procedure becomes awkward when there are a number of inputs subject to uncertainty, because the number of combinations of input parameter values becomes very large. An alternative is to use a Monte Carlo approach in which values of the inputs are drawn randomly from probability distributions. A sufficiently large number of plausible input data sets are thus generated and used to compute the assessment model results such that the distributions of the estimated outputs are clearly defined. This may involve hundreds or thousands of runs, depending on the types of data and models used (in our work we found that 500–1000 data sets were necessary to obtain stable results).

A typical assessment of a fish stock using SPA involves three levels of analysis. First, data are prepared for the SPA. This usually involves estimating and ageing the annual catch, and computing indices of abundance for calibration. Second, the SPA itself is carried out (it is also frequently termed "VPA," for Virtual Population Analysis). In many cases, several SPAs are carried out to examine the goodness-of-fits of the input data to alternative model formulations or simply to examine the sensitivity of the results to the alternative formulations. Third, derived statistics are computed. These are commonly biological reference points (F_{max}, $F_{0.1}$; Gulland and Boerema 1973), and forward projections of stock status and catches under alternative management actions.

It is easy to see how the Monte Carlo approach can be used to characterize the uncertainty in the entire analysis process, starting with the raw data collected for the first step in the above procedure. For instance, the total annual catches and their proportions at age can be obtained by resampling the original data that led to the catch estimates, through a non-parametric bootstrap (Efron 1982). These bootstrapped catches would then be used in the SPAs, whose results, in turn, would affect the values of projected future catches.

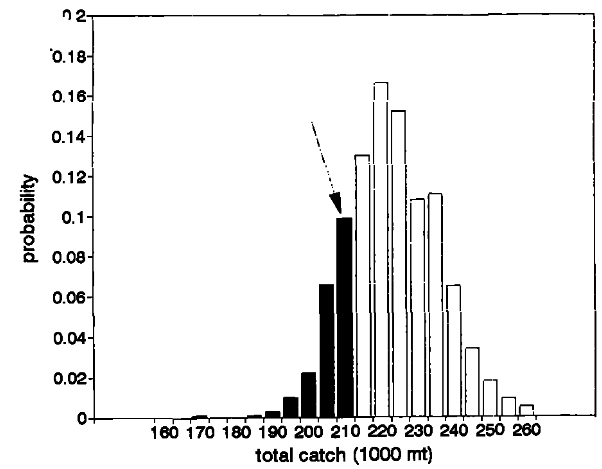

Figure 1
Probability mass distribution (relative frequency) for estimates of total catch of cod *Gadus morhua* necessary to have 1991 fishing mortality equal to that of 1990. Estimates were obtained from 1000 simulated data sets analyzed by the ADAPT approach. If a total catch of 210,000 mt is selected (arrow), the probability that fishing mortality will exceed the status quo is estimated by the sum of histogram bar heights to the left of 210,000 (i.e., the shaded portion).

In practice, however, the time and computer resources required to carry out such a large-scale simulation make it more practical to derive the input uncertainty distributions from parametric statistical analyses of data. This would involve assuming a distribution type for the inputs and estimating their mean and variance. For example, by virtue of the central limit theorem, an estimated mean has an approximately normal distribution if the sample size is sufficiently large.

Often, the distributions determined for some of the inputs will not be based on a rigorous statistical treatment of the data, but rather will represent educated guesses about the likelihood of the inputs taking on particular values (this is probably most true for the natural mortality rate, M, which is usually assumed and not estimated). The outputs would then represent the analyst's personal uncertainty in the assessment results.

The above approach can be generalized to allow for uncertainty in the formulation of the SPA model as well. Suppose one believes that there is a 70% chance that the fishing mortality rate in the last year does not decline with age after a fully recruited age (this is often known as a "flat-topped" partial recruitment curve), and a 30% chance that it does decline ("dome-shaped" partial recruitment). Then one could conduct 70% of the simulations with an SPA that assumes the flat-topped curve and 30% with the dome-shaped curve. The resulting combination of outputs would reflect the intuitive estimate of uncertainty about the SPA model formulation. Similarly, the approach can also account for uncertainty concerning data-dependent decision making. For example, if several abundance indices are available, one might subject each index to a preliminary test to decide whether the index is acceptable for calibrating the SPA, e.g., via analysis of residuals. One can repeat this decision-making process for each of the simulated data sets and thus account for the uncertainty associated with screening indices.

In summary, the Monte Carlo approach to quantifying uncertainty consists of generating a large number of pseudo-data sets, drawn at random from specified distributions, and carrying out *the entire assessment* procedure for each data set. The distributions of the assessment outputs and derived statistics are then summarized, e.g., as histograms. The simulation is thus viewed as a means for translating input and model uncertainties (measured and/or perceived) into output uncertainties.

Analyzing the consequences of management options

Estimating risks

The simulation results can also be used to quantify the uncertainty associated with a future management action. An example is the determination of uncertainty in the catch of the current year that would maintain the fishing mortality at the level of the previous year ($F_{\text{status quo}}$). A point estimate might be computed as follows. An SPA of some sort is used to estimate the population size at the end of the previous year and the fishing mortality during that year. Assuming that recruitment in the current year is equal to the long-term average, the estimated population size in the current year can be computed. Finally, the harvest which causes the population to experience the same fishing mortality rate as that estimated for the previous year can be computed. To quantify the uncertainty in this result, the whole procedure can be repeated 1000 times, each time perturbing each input to the SPA by a random amount (as per the specified uncertainty distributions). This results in 1000 sets of estimates of population size, fishing mortality, and natural mortality rate which, together with a set of randomly-drawn values for recruitment, can be used to generate 1000 estimates of the total allowable catch which will cause the fishing mortality to remain unchanged. These values can be organized into a relative-frequency histogram such as in Figure 1.

From the histogram, it appears that the most likely (modal) value for achieving the management goal

($F_{status\ quo}$) is a quota of 220,000 mt, but the actual value might be anywhere from ~170,000 to 260,000 mt. If the TAC is set at 220,000 mt, then these results suggest there is roughly a 50% chance of the fishing mortality increasing and a 50% chance of it decreasing. Suppose one is risk averse and chooses a TAC of 210,000 mt instead. What would be the perceived risk, or probability of exceeding the target fishing mortality, under this quota?

The risk of exceeding the target fishing mortality ($F_{status\ quo}$) is given by the proportion of the area under the histogram to the left of the TAC chosen (Fig. 1). Thus,

$$\mathrm{Prob}(F_{achieved} > F_{target}) = \sum_{i=1}^{I} p(i)$$

where p(i) is the probability mass (relative frequency of outcomes) associated with the ith bar of the histogram, and I is the number of bars to the left of the chosen TAC. This probability can be computed for any value of the TAC. In practice, the risk would be computed by sorting in ascending order the 1000 catch values obtained from the simulation, and then plotting the cumulative count of outcomes less than any value of the TAC versus that value of the TAC (Fig. 2). One can also derive a family of risk curves. For example, separate curves could be generated for the risk of exceeding $F_{status\ quo}$ by each of several amounts (in absolute or relative numbers). For each of the 1000 simulation runs, one computes the value of $F_{status\ quo}$ and the catch that causes current F to exceed the status quo by the specified amount. The resulting histogram of catches is summed to obtain the risk curve.

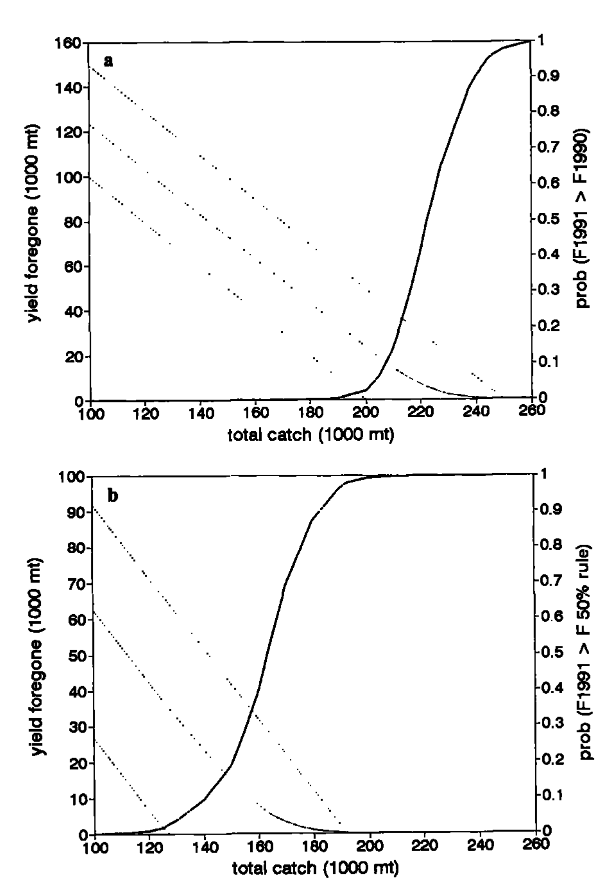

Figure 2

(a) Probability of exceeding the current (1990) cod *Gadus morhua* fishing mortality and expected value of the potential yield foregone (with 95% confidence band determined as the 2.5th and 97.5th percentiles of the distribution resulting from 1000 simulations) as functions of total catch selected for 1991. (b) Probability of the 1991 fishing mortality exceeding the 50% rule fishing mortality, and expected value of the yield foregone (with 95% confidence band), as functions of the total catch selected for 1991.

Estimating cost as yield foregone

If we choose a conservative value for the TAC in order to ensure that risk of exceeding the target fishing mortality will be small, then we are probably passing up some of the yield we could have had in the short term while still meeting our objective (e.g., see Bergh and Butterworth 1987). It is possible to describe this cost in economic or biological terms. Here, we express the cost as the expected value of the potential yield foregone, which we define as follows. For any TAC, x, let

$$\delta(i) = \begin{cases} 0, & \text{yield associated with ith interval of histogram} \leqslant x \\ 1, & \text{yield associated with ith interval of histogram} > x. \end{cases}$$

Then,

$$E(\text{potential yield foregone}) = \sum_{i=1}^{\infty} p(i)\ \delta(i)\ (y(i) - x)$$

where E(| |) denotes the expectation operator, the summation is over all intervals of the histogram (Fig. 1), and y(i) is the yield associated with the ith interval of the histogram. The expected potential yield foregone can be plotted against the corresponding TAC (Fig. 2). Here, y(i) − x is a possible value of the yield foregone provided it is non-negative; negative values are eliminated by the indicator function δ(i); p(i) is the probability that the yield foregone is equal to δ(i) (y(i) − x). In practice, the expected yield foregone would be computed by setting all simulated catches which are less than the TAC equal to zero and then computing the mean of the 1000 values minus the TAC. The results can then be plotted versus the TAC for various choices of TAC (Fig. 2).

It should be noted that this cost relates to the upcoming year only. One can also calculate the fate of the biomass left in the water at the end of the upcoming year. That is, one can ask whether this biomass left in the water will increase or decrease over the year. In general, for a quantity of biomass left in the water, the relative change in its biomass over the year is given by

relative change in unfished biomass =

$$e^{-M} \frac{\sum_a P_a W_{a+1}}{\sum_a P_a W_a} - 1.$$

Here, P_a is the proportion of the stock that is age a; W_a, the average weight of animals at age a; M, the (constant) instantaneous natural mortality rate; and the summations are over all age groups of interest.

Trade-offs in decision making

The manager can now choose how to trade off potential yield and risk. For example, consider the option of a TAC of 210,000 mt as a means of maintaining the fishing mortality at a constant level. From Figure 2a, the perceived risk of the fishing mortality exceeding the target mortality is ~14%. The expected value of the potential yield foregone for this TAC is ~14,000 mt. If, instead, a TAC of 215,000 mt is selected, the risk of exceeding the target fishing mortality becomes 26% and the expected value of the potential yield foregone becomes 10,000 mt. Thus, an increase in the TAC of 5,000 mt would almost double the risk of exceeding $F_{status\ quo}$ while reducing the expected potential yield foregone by 30%.

Another way to present the results of the SPA simulations is to plot percentiles of output distributions versus the TAC selected. For example, for each SPA run on simulated data, one can take the estimated population size and iteratively seek the fishing mortalities that will result in each of several TACs. Then, for any value of TAC one can compute the median and 2.5th and 97.5th percentiles of the distribution of fishing mortalities. Since instantaneous fishing mortality may not be meaningful to some interested parties (such as fishing industry groups), one may wish to look at the distribution of changes in population biomass associated with particular choices of the TAC (Fig. 3).

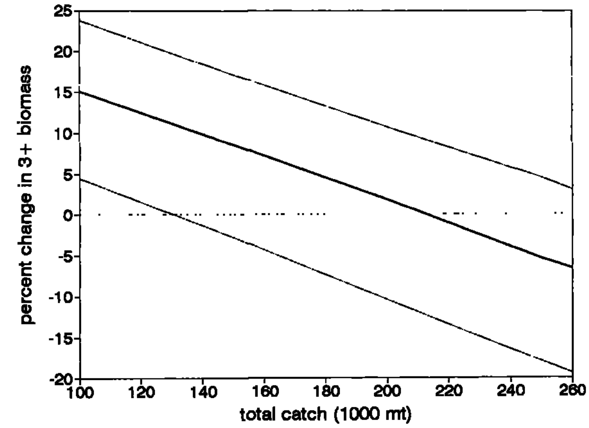

Figure 3

Percentiles of the distribution of relative change (%) in biomass of cod *Gadus morhua* age 3 and above, as a function of the total catch selected for 1991. Dotted lines: (top) 97.5th percentile; (middle) 50th percentile; (bottom) 2.5th percentile.

Thus, we have two approaches which we can summarize as follows. The first approach is to select a goal or objective (such as $F_{status\ quo}$ or $F_{0.1}$) and then quantify the chances of achieving that goal as a function of the TAC or effort restriction selected. The second is to quantify the consequences of choosing different quotas or effort restrictions. Both approaches are useful to managers. A manager might first ask how a specific management objective like $F_{0.1}$ can be met. A graph similar to Figure 2a makes it clear that the trade-off between risks and costs must be balanced. The manager might also want to know the consequences of picking particular quotas or effort restrictions. For example, for economic or political reasons, it may be difficult to stick with a management policy if a large quota reduction is called for. In this case, the consequences to the stock of maintaining the status quo or reducing the quota by various intermediate amounts may be of interest. A graph similar to Figure 3 may be helpful for this.

Managers and industry have a strong interest in maintaining stability in a fishery. Conflicts can easily arise when annual assessments provide only point estimates of the quota required to achieve a specified goal. This is because random error in the estimates implies that annual adjustments in the quota will be proscribed even when no changes are in fact necessary. Instead of letting the quota "float" from year to year, one can stabilize the quota and let the risks float from year to year. Thus, as long as the risks remain within certain limits, there is no need to adjust the quota. (Here, the risks can include potential stock collapse as well as foregone potential yield.)

The sequential population analysis model: ADAPT

The examples presented below use data from two very different fisheries that are assessed with the same SPA approach, known as ADAPT (Gavaris 1988). ADAPT is widely used in the eastern United States and Canada. Here we describe the basic method briefly and direct the interested reader to more details in Parrack (1986), Gavaris (1988), Conser and Powers (1990), and Powers and Restrepo (1992).

The objective in ADAPT is to minimize deviations between observed (age-specific) indices of abundance and those predicted by what is commonly referred to as virtual population analysis (VPA). Let the subscripts t, a, and i denote time, age, and abundance-index sequence number, respectively. The basic equations governing the model are

$$N_{at} = N_{a+1,\,t+1}\, e^{Z_{at}}, \tag{1}$$

$$C_{at} = F_{at}\, N_{a+1,\,t+1}\, (e^{Z_{at}} - 1)/Z_{at}, \text{ and} \tag{2}$$

$$I_{it} = q_i\, N_{at}\, (1 - e^{-Z_{at}})/Z_{at}, \tag{3}$$

where N = stock size in numbers of fish, C = catch in numbers, I = index of relative stock abundance (each index is associated with one or more ages which must be specified), F = instantaneous fishing mortality rate, Z = total instantaneous mortality rate ($Z = F + M$), and q = coefficient of proportionality between relative abundance and absolute abundance. Inputs to the model are the catch, natural mortality, and relative abundance indices. Given that there are T years of data, A ages, and Y indices, a search algorithm, e.g., Marquardt-Levenberg (Seber and Wild 1989), is used to estimate the parameters q_i ($i = 1 \ldots Y$) and $N_{a,\,T+1}$ ($a = 2 \ldots A$) that minimize the weighted residual sum of squares:

$$RSS = \min \sum_i \sum_t \lambda_i\, (I_{it} - \widehat{I_{it}})^2, \tag{4}$$

where the weights, λ_i, may be input or estimated via iteratively-reweighted least squares.

ADAPT, like other VPA calibration procedures, requires model constraints in order to reduce the number of parameters. Hence, the stock sizes for the last age each year are not normally estimated but are instead derived from a specified relationship between F_{At} and $F_{A-1,\,t}$. Additional constraints may be required when the amount of relative-abundance data does not support the estimation of a large number of parameters. Often, as in the swordfish example below, this involves estimating the relative selectivities of the various age-groups in year T in some fashion external to the calibration process. This leads us to add to our explanation the notion that ADAPT is generally thought of as a framework rather than a rigid model. Thus the reader is likely to encounter applications that deviate from the model in equations (1) through (3). For example, for swordfish, A is a "plus" group consisting of ages A and older. For cod in Atlantic Canada, the objective function (4) is modified to allow for lognormal errors. A detailed presentation of some of the most commonly used options in ADAPT can be found in Powers and Restrepo (1992).

Assessment uncertainty: Application to North Atlantic swordfish

Swordfish in the North Atlantic Ocean are assessed by the International Commission for the Conservation of Atlantic Tunas (ICCAT). Interest is centered on the level of fishing mortality relative to reference values (e.g., F_{max}), and on trends in mortality and stock abundance. Potential management options involve restrictions aimed at controlling fishing mortality. The assessment procedure is continually changing as experience is gained. The procedure below was used for the 1989 assessment (ICCAT 1990).

Assessment procedure

Nine age-groups were recognized in the commercial catch, ages 1 to 9+. There were 11 years of catch-at-age data from 1978 to 1988. Fleets from the United States, Japan, and Spain accounted for most of the catch. Eleven abundance indices were available based on fleet-specific catch rates from the longline fisheries (ICCAT 1990).

Details of this assessment of the stock are presented in ICCAT (1990). Briefly, the procedure used was as follows. (1) A separable virtual population analysis, SVPA (Pope and Shepherd 1982), was computed in order to obtain estimates of the age-effects or partial recruitment in the last year for which data were available. Data from 1983 to 1988 were used for this under the assumption that the selectivity pattern remained stable during that period. For that analysis the terminal fishing mortality was set to 0.2/yr and selectivity for the oldest age group was 3.0. (2) The ADAPT approach to sequential population analysis was then used for calibration, with each abundance index used separately. A weighting factor for each index was obtained by setting the weight for the ith index equal to the reciprocal of the mean squared error after calibrating with the index. In performing the calibrations, ages 5 and above were assumed to be fully recruited ($S_a = 1.0$ for $a = 5, 6, \ldots, 9+$) and the partial recruitment for the other ages was as determined from the SVPA (i.e., from step 1). (3) The set of weights computed for the abundance indices were then rescaled so that they summed to unity. (4) The weights were then used in recalibrating the ADAPT SPA using all of the abundance indices at once. In doing so, the following constraints were used: S_1 was taken from the separable virtual population analysis, S_2 through S_5 were directly estimated through calibration, and S_6 through S_{9+} were set equal to the estimated S_5. The objective function used in the calibration was to minimize the weighted sum of the squared deviations from the predicted abundance indices as in equation (4).

After the fishing mortalities and population sizes were computed by the sequential population analysis, the values of F_{max} and $F_{0.1}$ were calculated from yield-per-recruit computations. Data from the terminal year (i.e., the most recent year available) were used to project the catch in the current year and then project the catch for the next year. For this, recruitment in the current year and the following year were assumed by ICCAT to be equal to the long-term mean recruitment obtained in the sequential population analysis. The projections were made for a variety of fishing mortalities, specifically $F_{0.1}$, F_{max}, and $F_{status\ quo}$.

Specification of uncertainty in the inputs

One thousand simulated data sets were analyzed using a version of ADAPT written in FORTRAN 77 (available from the authors). The formulation of the problem was made to mimic the 1989 ICCAT assessment for North Atlantic swordfish. However, we emphasize that the uncertainties in the inputs specified below are our *ad hoc* choices and, although realistic, are intended mainly for illustrative purposes.

Natural mortality Uncertainty in the natural mortality rate (M) was specified as a uniformly-distributed random variable in the interval 0.1–0.3/yr. The value of 0.2 used by ICCAT (1990) is at the center of this range, and the choice of a uniform distribution places equal confidence in all values in the interval.

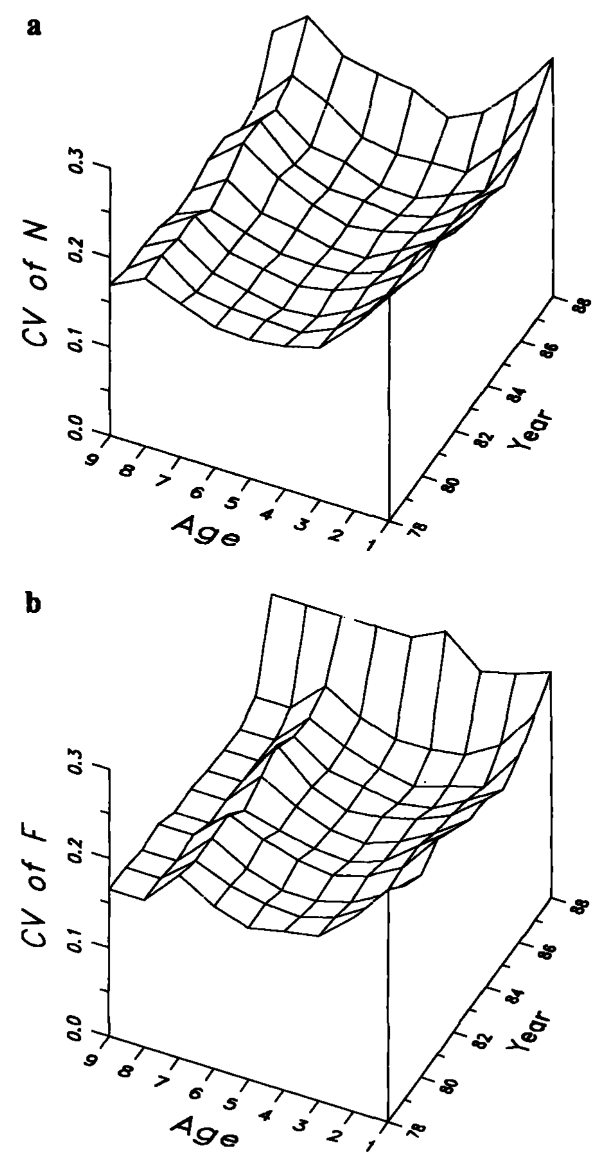

Figure 4
Coefficients of variation of outputs from the sequential population analyses of simulated swordfish *Xiphias gladius* data sets. (a) Age- and year-specific estimates of population numbers; (b) age- and year-specific estimates of instantaneous fishing mortality.

Catch-at-age Total annual catches were represented by lognormally-distributed random variables with coefficients of variation of 10% and expected values equal to those in the assessment. A coefficient of variation of 10% indicates that the catches are known with high precision. The proportions of the total catch in any year that make up each age component were assumed to follow a multinomial distribution with expected values

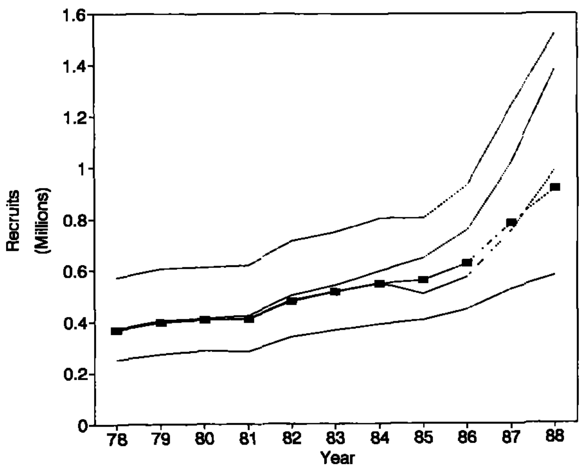

Figure 5
Distribution of swordfish *Xiphias gladius* recruitment estimates, by year, from the sequential population analyses. Outer lines are from the Monte Carlo simulations and show 95% confidence bands (determined as the 2.5th and 97.5th percentiles of the distribution resulting from 1000 simulations). Inner pair of lines shows confidence bands obtained from the information matrix after a single run of the ADAPT program using actual data. Line with symbols gives median estimate for each year from the simulations.

equal to the observed proportions and sample size equal to 1% of the annual catch. This model for the uncertainty was purely heuristic rather than based on measured variances.

Abundance (CPUE) indices The 11 available indices from the longline fisheries were also assumed to be lognormally distributed with a coefficient of variation of 10%. We chose a value of 10% as a rough approximation for all indices in all years. However, there is no reason why each index could not have a different coefficient of variation for each year depending on the amount of data available.

Results of swordfish simulations

The simulations gave rise to 1000 sets of age- and year-specific fishing mortality rates and population sizes. We computed the coefficient of variation of these sets of estimates for each age-year combination (Figs. 4a, b). As expected, the coefficients of variation were highest in the most recent year, 1988. Also, the age groups which form the bulk of the catch (ages 3–5) were the best determined. It is interesting to note that the coefficients of variation of fishing mortality rates for ages 8 and 9 were consistently lower than those for preceding ages. This is due to the manner in which the estimates for ages 8 and 9 were determined: it was assumed that $F_{8t} = F_{9t}$ (subscripts refer to age and year, respectively), and these were computed as a weighted average of fishing mortalities for ages 5–7. Thus, the uncertainty in the estimates of fishing mortality for the last two age-groups is solely a function of the uncertainties in the estimates for ages 5–7. This underscores the fact that the simulation results are conditional not only on the input-uncertainty distributions but on the formulation of the model being fitted as well.

The median recruitment (age 1) from the simulations increased over time (Fig. 5). However, the 95% confidence bands, defined by the 2.5th and 97.5th percentiles of the 1000 estimates, are quite wide. The confidence bands provided by the delta method for a single run with the actual data are much narrower than the ones obtained by the Monte Carlo approach. The former confidence bands indicate there is no uncertainty in the results for the converged part of the SPA in contrast to the simulation results. This is because the delta method results, based on the information matrix of a single run, are conditional on the natural mortality rate, catch at age, etc., being known exactly whereas the simulation accounts for uncertainty in these inputs. For this reason, we believe the simulation results are more reasonable.

Note that there appears to be very little interannual recruitment variability in the time-series (Fig. 5). This is probably due to the fact that fish ages were estimated from lengths deterministically by inverting the Gompertz growth equation, and this tends to blur the age-groups.

The population of fish age 5 and above appears to have declined rather steadily over time while the weighted fishing mortality rate appears to have increased (medians, Figs. 6a, b). Here, weighted fishing mortality is defined as the mean of the fishing mortality estimates for ages 5 through 9+, computed with weights proportional to the estimated population size at age. Again, the confidence bands are very wide.

It should be noted that for each run the estimates of fishing mortality, F_{at}, and population size, N_{at}, are highly correlated not only with each other but also with the value of natural mortality, M, used in the simulation run. For this reason, it is appropriate to examine trends in an estimated quantity one run at a time. We computed the ratio of the weighted fishing mortality in a given year t to the weighted F in the base year (taken to be 1978 in this example) for each simulation run (Fig. 7). The distribution of the fishing mortality ratio in 1979 was centered around 1.0; the ratio in 1986, 1987, and 1988 was >1.0 in 100% of the runs, thus clearly indicating that fishing mortality has increased. This result is not obvious from examination of Figure

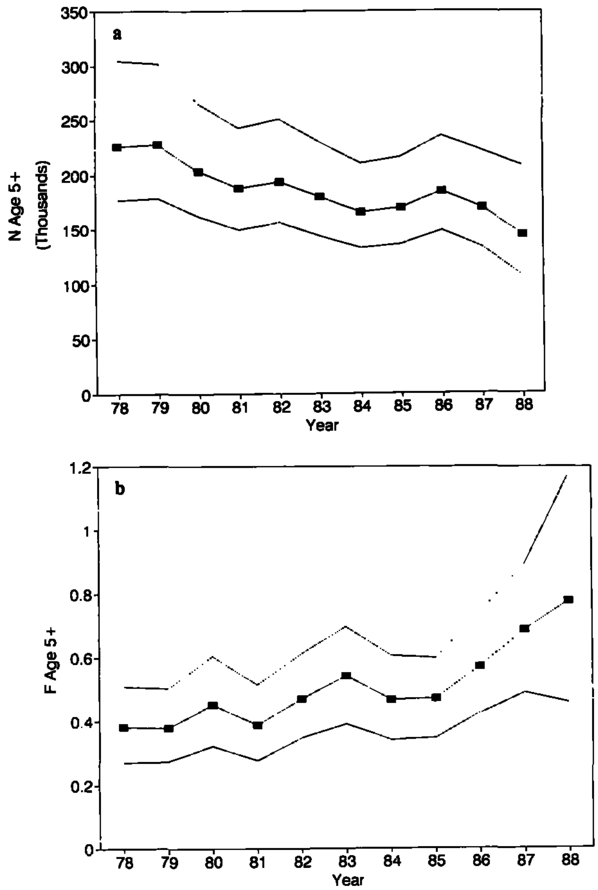

Figure 6
Medians, 2.5th percentiles, and 97.5th percentiles of the output distributions from the Monte Carlo simulations. (a) Distribution of estimates of the population size of swordfish *Xiphias gladius* aged 5 and above; (b) distribution of estimates of fishing mortality for swordfish aged 5 and above.

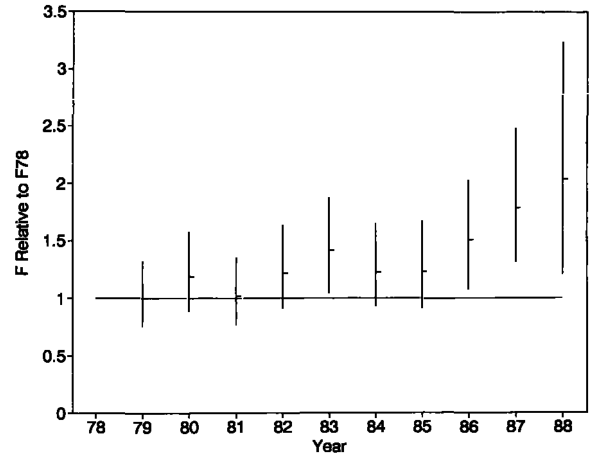

Figure 7
Distribution of the ratio of swordfish *Xiphias gladius* fishing mortality in year y to that in 1978 as a function of the year. Vertical bars indicate 95% confidence intervals based on percentiles; horizontal bars represent the median ratio.

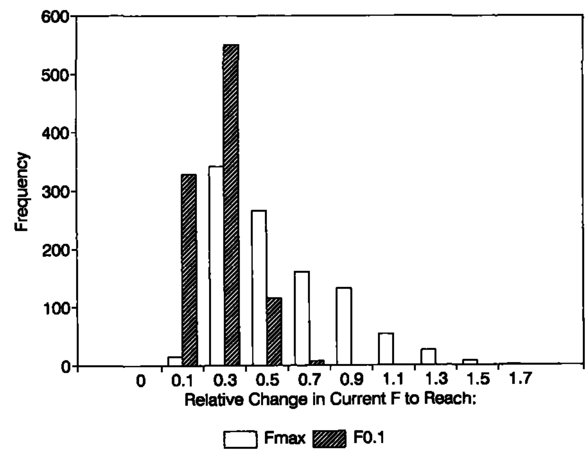

Figure 8
Multipliers necessary to bring the vector of age-specific fishing mortalities in the terminal year to the $F_{0.1}$ and F_{max} levels, for 1000 simulated data sets for swordfish *Xiphias gladius*.

6b and illustrates how very easily the Monte Carlo approach lends itself to hypothesis testing.

Of course, the goals of an assessment are not restricted to estimating population sizes and mortality rates. Interest is often centered on catch projections and quotas, effort regulations, and risk analyses. For swordfish assessments, it is useful to contrast the estimated current level of fishing mortality against reference points such as $F_{0.1}$ and F_{max}. The uncertainty in such comparisons (e.g., the ratio of current F to $F_{0.1}$) can easily be quantified using the Monte Carlo procedure. For each simulation run, we computed the multiplier that would be necessary to bring the estimated vector of age-specific fishing mortalities in the terminal year to the $F_{0.1}$ and F_{max} levels (Fig. 8). For the computations, we used the run-specific natural mortality rate and the weight-at-age relationships used by ICCAT in the 1989 assessment. No uncertainty was specified for weight relationships although this could easily be added if appropriate information were available. From Figure 8 it is evident that, to achieve the $F_{0.1}$ goal, fishing mortality must be cut to ~25% of its current value. With respect to F_{max}, it appears that fishing mortality must be cut by ~50% (Fig. 8). Note, however, that this conclusion is considerably less

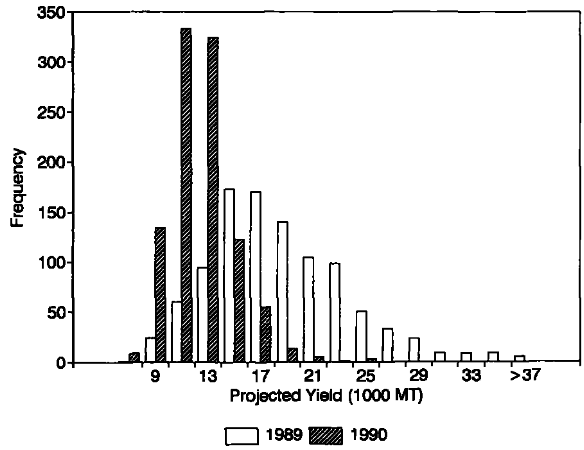

Figure 9
Distribution of 1989 estimated swordfish *Xiphias gladius* catches when fishing mortality is kept the same as in 1988 (open bars), and distribution of 1990 estimated catches when fishing mortality is equal to the midpoint between the 1988 fishing mortality and $F_{0.1}$, assuming 1989 fishing mortality was the same as in 1988 (cross-hatched bars).

certain than that for $F_{0.1}$ as evidenced by the fact that the distribution of multipliers is broader for F_{max} than for $F_{0.1}$. But, as an anonymous reviewer pointed out, it is interesting to note that the mode of both distributions is about one-third of the status quo F.

We also computed 1000 projected catches in weight for 1989 with fishing mortality equal to that in 1988. We then projected the catch for 1990 with fishing mortality set at the midpoint between the fishing mortality in 1988 and $F_{0.1}$ (Fig. 9). This method gradually reduces fishing mortality to minimize the short-term impact of decreased landings on fishermen (see Pelletier and Laurec 1990, for a discussion). Recruitments for 1989 and 1990 were drawn randomly from the empirical distribution of recruitments estimated from 1978–87 on each iteration. If the fishing mortality does not change in 1989 from the level in 1988, catches are likely to be somewhere around the 1988 yield of ~18,000 mt. The 1990 yields are likely to be ~11,000–13,000 mt.

Using the Monte Carlo results, it is equally simple to obtain distributions of catches for fishing at other exploitation levels or to obtain distributions of fishing mortalities for fixed catch quotas. Similarly, the distribution of other projected variables, such as the spawning-potential ratio that results from various catch and fishing mortality options, can be computed. In doing so, it is important to have the values of the inputs used in calibrating the SPAs (e.g., natural mortality) stored in each iteration, so that the projection computations use the same values.

Risks and costs: Application to northern cod

We studied the cod fishery in NAFO Divisions 2J + 3KL and based our simulations on the data and methods described in Baird et al. (1990). Additional data, described below, were obtained from the files at the Northwest Atlantic Fisheries Centre, St. John's, Newfoundland. The simulations reflect our own perceptions and experience about the sources and nature of the uncertainties in the assessment. As with the swordfish example, the selection of management objectives for simulation was made for illustrative purposes.

This cod fishery is managed by quota. The assessment uses trawl-survey data and commercial catch-rate data to calibrate the SPA.

Assessment and simulation procedures

Only a brief description of the assessment procedure is given here since the details are not important for understanding the use of the simulation method. The catch-at-age data for ages 3–13 for each year from 1978 to 1989 were taken from Table 7 of Baird et al. (1990). Coefficients of variation of these catch estimates were computed using the method of Gavaris and Gavaris (1983); these coefficients were available in the files. The coefficients of variation ranged from 2 to 17%. Age- and year-specific catch rates from research-vessel surveys for the period 1978–89 and associated coefficients of variation (Baird et al. 1990, table 23) were used to tune the sequential population analysis. The coefficients of variation were ≤30% in 87% of the cases. Age- and year-specific catch rates from the offshore commercial trawl fishery for ages 5–8 for the period 1983–89 were standardized by the method of Gavaris (1980) for use as an index of abundance for tuning the SPA (Baird et al. 1990, table 39). We developed estimates of the coefficients of variation for the commercial catch-rate indices. In all cases, these were close to 10%. Natural mortality for this stock is believed to be around 0.2/yr.

In the simulations, the point estimates of the inputs were replaced by random variables with the same expected values and coefficients of variation as specified above. Catch at age values were generated as normal random variables, while the research-vessel and the commercial catch rates were generated as lognormal random variables. The value of the natural mortality rate was generated as a uniform random number between 0.15 and 0.25/yr.

The specific formulation of the ADAPT model was as follows. The research-vessel indices were obtained in the fall and were assumed to represent population size at the end of November. The commercial catch-rate indices were assumed to represent population size at the beginning of the year. The fishing mortality F for the oldest age-group (13) was calculated as 50% of the mean F for ages 7–9 weighted by population number at age. The objective function to be minimized differed from equation (4) in that lognormal errors were assumed and the weights, λ_i, were fixed to be 1.0.

Projections for 1990 and 1991 were made using the same procedures used in the most recent annual assessment (Baird et al. 1990). Population and fishing mortality projections for 1990 were made by randomly selecting a value for recruitment from the historical set of estimated recruitments and assuming that (1) the total catch in 1990 is 225,000 mt (the fixed Canadian quota in place when the assessment was done in 1990, plus an additional 25,000 mt in expected foreign catch), and (2) the partial recruitment (selectivity) vector for 1990 is equal to that estimated for 1989 in each simulated SPA.

Catch projections for 1991 were made in two ways. In one, we set the fishing mortality for 1991 equal to that for 1990 and solved for the catch. In the other, we set the fishing mortality for 1991 equal to

$$\min\{(\hat{F}_{0.1}+\hat{F}_{1990})/2,\ 2\ \hat{F}_{0.1}\}.$$

This is the 50% rule formulated by the Canadian Atlantic Fisheries Scientific Advisory Committee (Canada Department of Fisheries and Oceans 1991) for a gradual movement towards $F_{0.1}$. We also computed the fate of yield foregone and the distribution of population changes for various choices of the total catch.

Results of cod simulations

We generated risk curves for two fishing mortality objectives for 1991 (Figs. 2a, b). These curves can be put in perspective by noting that the Canadian total allowable catch for 1990 was 199,262 mt while the total catch (Canadian plus international) may have been as high as 235,000 mt. To have a 50% risk of increasing the fishing mortality in 1991 over the 1990 level, one would set the total catch at 225,500 mt; to have a 50% chance of exceeding the fishing mortality associated with the 50% rule would entail setting the total catch at 163,000 mt. It appears that a cut in the TAC would be necessary to have a reasonable chance of preventing the fishing mortality from exceeding the 1990 value. Substantial cuts in the harvest would be required to ensure a high probability of meeting the 50% rule.

For values of the TAC for which the risk is less than 25%, the expected value of the yield foregone is approximately a linear function of the TAC (Figs. 2a, b). That is, for every change in the TAC of 1000 mt, the expected yield foregone changes by ~1000 mt. The fate of biomass left in the water is to increase by ~13% in a year (mean of 1000 simulations = median = 12.9%; 95% confidence band based on 2.5th and 97.5th percentiles is 7.2% and18.4%). The relative change in biomass of fish aged 3 and above is also a linear function of the TAC (Fig. 3). Note, however, that the relative change in biomass cannot be determined very precisely as evidenced by the wide confidence bands.

We presented results of catch projections for two scenarios. Often, one might like to examine a larger number of options. For example, if current fishing mortality exceeds F_{max}, then one could explore various ways to reduce fishing mortality in gradual steps as well as exploring the consequences of various types of "status quo" options. The simulation approach is versatile enough to handle fixed catch, fishing mortality, and biomass objectives, as well as objectives involving relative change. Thus, one could have any of the following objectives for fishing mortality: achieve F = 0.40/yr, achieve $F = F_{0.1}$, reduce F by 40%, or adjust F so that biomass changes a given fixed or relative amount.

In some fisheries, catch and population projections may be highly dependent on the assumptions made about recruitment. When this is the case, it may be helpful to quantify the uncertainty separately for various segments of the population. For example, we computed the distribution of relative change in age 3+ biomass of cod (from 1989 to 1991) for various choices of the TAC. The wide confidence bands (Fig. 3) reflect the large uncertainty in future recruitment. We could have quantified the relative change in the biomass of age 5+ fish. From the ADAPT run based on 1989 data, we already have an estimate of age-3 biomass in 1989. This biomass can be projected forward to age 5 in 1991; hence, we do not need to generate a random value for recruitment. The uncertainty in the biomass of age 5+ fish should thus be smaller than the uncertainty in age 3+ biomass. Unfortunately, the latter quantity may be of greater interest.

Conclusions

Monte Carlo simulation has long been regarded as a very useful quantitative tool, especially for sensitivity analysis (e.g., Pope and Gray 1983, Rivard 1983). It is also quite useful for studying the properties of specific assessment procedures (e.g., Mohn 1983, Kimura 1989). Here, we follow Francis (1991) and use it to quantify the risks of not meeting the objectives for the fishery as a function of the management measures imposed. The simulation approach we present can be used with assessment models other than ADAPT. For example, one could use Monte Carlo simulation to quantify the effects of uncertainty in input data, assumptions, and model formulation on the outputs from the CAGEAN (Deriso et al. 1985) or stock synthesis (Methot 1990) methods. We believe that this simulation framework is not only a versatile and intuitive method to estimate uncertainty, risks, and costs, but in many cases it may also be the only practical way to incorporate some types of input uncertainty which are not estimated statistically. Because the estimated uncertainties in the model outputs are conditional on what is known and what is assumed about the inputs, failure to acknowledge possible sources of uncertainty in a realistic manner may lead to overly optimistic views of the uncertainties in the model outputs. The Monte Carlo approach forces one to examine the nature and magnitudes of the uncertainties in the inputs and in the model formulation, and it allows one to study how uncertainties are propagated through the assessment and into the projections ultimately used for management recommendations.

It appears feasible to quantify risks and costs for a wide variety of management options when the assessments are accomplished by any of a variety of analytical models. It remains to determine what risks (and costs) should be quantified, how much risk is acceptable, and for how long. For example, we do not know how to quantify the risk of stock collapse due to recruitment failure, but we might wish to quantify the risk of the spawning biomass falling below 20% of the virgin level in three years out of five. If we assume that this represents a dangerous situation (see Beddington and Cooke 1983, Brown 1990, and Goodyear 1990, for thoughtful discussions), then the risk should be kept low. On the other hand, if we consider the risk of exceeding the economically-optimal fishing mortality (however defined), then we might like the risk to be close to 50%, i.e., as likely to be above the optimum as below it. (Of course, we should consider the relative costs of over- and undershooting the target mortality). If F is not close to the economic optimum fishing mortality, then one must also devise a way to determine what is the best trajectory to take for arriving at the long-term goal. It is beyond the scope of this paper to address what are appropriate goals, biological reference points, and trajectories.

Finally, for any stock assessment, the results of a Monte Carlo simulation study are necessarily conditional on what is assumed about the sources of uncertainty, including the model chosen for the assessment. Since decisions about some of the sources of uncertainty are subjective, the results are personal views of uncertainty, risk, cost, etc. If three scientists assess a given stock, they can generate three separate sets of simulation outputs. The combination of their simulations provides a picture of their collective uncertainty about the assessment results. Alternatively, they can agree that a minimal estimate of the uncertainty is provided by the one set of results that are the least uncertain.

A more detailed study of the relative sensitivities of the assessment outputs and risk curves to the choice of input distributions can be carried out via sensitivity analysis (Miller 1974). In this Monte Carlo framework, sensitivity analysis would consist of introducing planned perturbations to the input-uncertainty distributions and then measuring the overall effect on the model's outputs. This should aid in the identification of key inputs so that more effort could be placed on improving their estimates. This is more difficult than it may seem. A given input that is perturbed during the sensitivity analysis (say, catch at age) will cause different degrees of change in the various output distributions: stock sizes, fishing mortalities, $F_{0.1}$, projected catches, etc. Furthermore, this impact may change over time. For instance, assumptions about recruitment become very dominant as the projections are made further ahead in time. Nonetheless, sensitivity analysis can be very useful in identifying trade-offs between the benefits of precision and the cost of obtaining that precision.

Acknowledgments

Partial support for this study was provided through the Cooperative Institute for Marine and Atmospheric Studies by National Oceanic and Atmospheric Administration (NOAA) Cooperative Agreement NA90-RAH-0075 and by the Canadian Government's Atlantic Fisheries Adjustment Program (Northern Cod Science Program). We thank Nicholas Payton for programming assistance and Peter Shelton, Al Pinhorn, Donald Parsons, and two anonymous reviewers for helpful comments.

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