SCRS/1990/028 Rev.

Col.Vol.Sci.Pap. ICCAT, 35 (2) : 355-361 (1991)

INCORPORATING UNCERTAINTY IN VPA RESULTS VIA SIMULATION

V. R. Restrepo, J. E. Powers**, S. C. Turner***

**Coop. Institute for Marine and Atmospheric Studies, University of Miami, 4600 Rickenbacker Causeway, Miami, Florida, U.S.A.*

***NMFS, Southeast Fisheries Center, 75 Virginia Beach Drive, Miami, Florida, U.S.A.*

SUMMARY

Simulation methods are employed to allow incorporation of uncertainty in input parameters to the ADAPT VPA methodology. Empirical probability distributions describing the VPA results are developed using Monte Carlo techniques. The methodology described allows for incorporation of uncertainty parameters that are either internal or external to the ADAPT methodology.

RESUME

Les méthodes de simulation sont employées pour permettre d'introduire les incertitudes dans les paramètres d'entrée de la méthodologie VPA ADAPT. La distribution empirique des probabilités décrivant les résultats de la VPA est élaborée au moyen de techniques Monte-Carlo. La méthodologie décrite permet d'introduire des paramètres d'incertitude qui ne sont ni internes ni externes par rapport à la méthodologie ADAPT.

RESUMEN

Se emplean métodos de simulación que permiten la incorporación de incertidumbre de los parámetros de entrada en la metodología de ADAPT VPA. Por medio de técnicas Montecarlo, se desarrollan distribuciones empíricas de probabilidad que describen los resultados VPA. La metodología descrita permite la incorporación de parámetros de incertidumbre que pueden ser internos o externos a la metodología ADAPT.

INTRODUCTION

Stock assessments are typically carried out with the "best" available information. The best information is usually identified as representing the most likely ("true") values for the parameters that characterize the population under study. When Virtual Population Analysis (VPA) is used, the resulting estimates of fishing mortalities and population sizes are taken to be the best ones, given that the input parameters and other required quantities used to run the VPA are true. In these cases the estimates of F and N are said to be <u>conditional</u> on the inputs being known precisely.

But the inputs used for VPAs and most fishery assessment models are rarely known precisely. Moreover, inputs are known with varying degrees of precision. Historically, the effects of input parameter uncertainty on the results of a model have been considered by simple sensitivity analysis. However, a more complete description of uncertainty in the inputs to the assessments is of obvious value. Restrepo and Fox (1988) demonstrated the usefulness of Monte Carlo simulations as a tool to "translate" the uncertainty about the inputs into uncertainty in the outputs of a simple yield-per-recruit analysis. Turner and Powers (1990) demonstrated the value of this approach in stock projections for swordfish and bluefin tuna. In essence, if some measure of the precision of the inputs can be expressed in simple form as probability density functions, then it is possible to determine how precise model results are.

In this paper we show how input uncertainty can be easily incorporated in VPA results via simulation. To illustrate this, we use the ADAPT methodology for calibrating VPAs (Gavaris 1988, Conser and Powers 1990) with the 1978-1988 data for the North Atlantic swordfish fishery used in the 1989 ICCAT assessment.

DESCRIPTION OF THE METHOD

The Monte Carlo procedure consists of running the VPA a large number of times, each time selecting the input values randomly from specified probability density functions (referred to as uncertainty distributions). The inputs to ADAPT are a catch-at-age matrix, one or more abundance indices used for tuning, and a value of natural mortality (M). In addition, it is necessary to specify an objective function, desired transformations and/or a series of constraints that may be placed on the model.

The key to the simulations is to specify an adequate uncertainty distribution for each input. If an input is originally estimated using a statistical technique that yields lognormally-distributed parameter estimates then the input uncertainty should be lognormal. This is the case with CPUE indices obtained from loglinear models (GLMs). But an input like M is not usually estimated by statistical means and its uncertainty distribution must be determined subjectively. In this case, a uniform distribution would indicate that M is likely to lie between the specified lower and upper limits, with all values within the range having the same probability of being the true M. Alternatively, a triangular distribution for M would indicate that the value at the mode is more likely to be the true parameter than are those values at the extremes.

AN EXAMPLE: NORTH ATLANTIC SWORDFISH

The simulations were run using a version of ADAPT written in FORTRAN 77. The formulation of the problem was made to mimic the 1989 ICCAT assessment for North Atlantic swordfish. However, we emphasize that the choices we made for the uncertainty distributions are *ad hoc* and intended mostly for illustrative purposes. These input distributions were as follows:

Natural mortality:
Uniformly distributed between 0.1 and 0.3 per year. Although a value of 0.2 used by ICCAT is at the center of this range, the choice of a uniform distribution places equal confidence in all values within the interval [0.1, 0.3].

Catch at age:
Total annual catches were assumed to be lognormally distributed with a coefficient of variation of 10% and expected value equal to those in the 1989 assessment. A CV value of 10% indicates that the catches are known with relatively 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 equal to the observed proportions.

CPUE indices:
The 11 available indices from longline data were also assumed to be lognormal with a CV of 10%. We chose a value of 10% as a rough approximation for all indices in all years. Note, however, that each index could be specified to have a different CV each year, as the precision of the estimates varies depending on the amount of annual data used for the regressions.

A total of 1000 simulation runs were performed, in order to estimate 1000 matrices of F and N by age and year. Each run involved the following steps:

1) Generate one set of inputs (M, indices, catch).

2) Run a separable VPA with the 1983-1989 data to get a selectivity-at-age vector to be used in step 3.

3) Tune the VPA with one index at a time, and estimate the Mean Square Error (MSE).

4) Assign weights to each index as MSE^{-1} (from step 3) to be used in the next step. Note that steps 2-4 could be skipped, if weights could be assigned based on *a priori* information.

5) Tune the VPA using all indices weighted, estimate F and N matrices and save the results as well as all the inputs that were generated.

The parameters estimated in steps 2 and 4 above were the same as those in the 1989 assessment. The objective function to be minimized was also the same.

EXAMPLE RESULTS

The simulation provides 1000 estimates of N by age and year corresponding to the 1000 sets of randomly-selected inputs. It is of interest to examine how the uncertainty in the inputs affects the precision of the estimates by age and year. This can be accomplished by computing the coefficient of variation for each age-year combination (Figure 1). As expected, the estimates are more precise in the earlier years and more imprecise in the terminal year. In terms of age, the highest precision is in ages 3 to 5, which are dominant in the catches.

Variability in the estimates of F shows a similar pattern but the estimates seem to be less precise (Figure 2). It is interesting to note that the CV for ages 8 and 9 is consistently lower than that for preceding ages. This is due to the manner in which the F estimates for ages 8 and 9 are obtained in the ADAPT formulation for swordfish: it is assumed that $F_{8y} = F_{9y}$ and they are computed as a pooled average of F for ages 5 to 7. Thus, the uncertainty in the estimates of F for the last two ages is solely a function of the uncertainties of the F estimates for ages 5, 6 and 7. This underscores the fact that the simulation results are conditional not only on the input uncertainty distributions, but on the formulation of the ADAPT problem as well.

The simulation approach is naturally amenable to the analysis of trends in the estimates. The 1000 simulation estimates of a given output can be thought of as providing information about the possible bounds of the "true" output. Figure 3 shows the median of the estimates of N at age 1 by year, and approximate 95% confidence limits, represented by the 2.5^{th} and 97.5^{th} percentiles. The overall trend suggests that recruitment may be increasing, although the approximate confidence bands around the estimates are broad. Figure 4 is a similar plot of the trend in population sizes for ages 5+, indicating a decline but with proportionally narrower confidence bands. Figure 5 shows the trend in full F (defined as the F estimates weighted by estimated N, for ages 5 to 9+). Again, the trend appears to be increasing, but the confidence bands are wide.

It should be noted that the estimates of F and N are highly correlated not only with each other (one follows from the other - once catch is known - from the catch equation), but also with the input value of M that is used. For this reason, it is appropriate to examine trends in an estimated quantity one run at a time. This is illustrated in Figure 6 where we computed the number of times that full F in every year was greater than full F in 1978. That is, F_Y and F_{1978} were compared on an individual iteration basis. Thus, from Figure 6, we can say that in 1979 F was greater than F_{1978} in 47% of the runs, and in 1987 and 1988, F was greater than F_{1978} in all of the runs. Note that this result would not be obvious upon examination of Figure 5.

Examining estimates of N and F by year and age are usually not the ultimate goal of an assessment. More often, interest is centered on results that are useful to generate management advice for the near future. Managers may want to consider catch projections, compute quotas or effort regulations, or conduct risk analyses. In swordfish assessments, it is useful to estimate the current level of F (i.e., in the terminal year) with respect to reference points such as $F_{0.1}$ or F_{max}. The input and output distributions generated by the Monte Carlo procedure can be easily incorporated into yield per recruit analyses to quantify the uncertainty in these F comparisons.

For each simulation run, we computed $F_{0.1}$ and F_{max} as multipliers of the estimated F at age vector in the terminal year, using the value of M that was generated during that run. The necessary weight at age information was the same as that used in the 1989 assessment. Uncertainty in the weight-at-age relationship could also be introduced in the same fashion as in the simulations above, but was not in this example. Figure 7 shows the 1000 pairs of estimates expressed as a ratio with respect to the current F. Thus, a value of 0.6 for F_{max} indicates that an F that leads to maximum yield per recruit is 40% lower than the current F. It is interesting to note that, despite the large uncertainty in the terminal year F eastimate (Figure 5), the apparent relative change in F that is required to reach $F_{0.1}$ is relatively precise: the 1000 computed values cluster around 0.25, suggesting a reduction in F centered around 75%. With respect to F_{max}, the choice is not as clear because the required relative changes are more broadly distributed. Note, however, that most values lie below 1.0, suggesting that maximum yield per recruit is much more likely to be achieved by a reduction in F rather than by an increase in F.

Projections can also be easily accommodated into the simulation framework. We computed 1000 projected catches (in weight) in 1990 at the status quo F, at F_{max} and at $F_{0.1}$, using the terminal year (1988) estimates of F and N and assuming that the F vector in 1989 would be identical to that of 1988. Recruitment for 1989 and 1990 was set equal to the mean of the estimates from 1978 through 1987. Figure 8 shows what these projected 1990 yields could be, relative to the 1988 yields. If the status quo is maintained, catches are likely to decrease to somewhere between 60% and 90% of current ones (conditional on our assumption about projected recruitment). Catches that could result in an F_{max} level would lie somewhere between 20% and 60% of the current ones. Catches for an $F_{0.1}$ level would be even lower (Figure 8). Again, these results indicate that for our swordfish example, management regulations that lead to $F_{0.1}$ levels are characterized by much less uncertainty than are the corresponding ones for F_{max} levels.

DISCUSSION

The flexibility allowed for in specifying various types of distributions for the inputs is one of the main advantages of the Monte Carlo procedure. Methods based on Taylor series expansions (e.g., the delta method, Seber 1982) are an alternative for estimating standard errors of F and N in cohort analysis (Saila et al. 1985, Sampson 1987, Prager and MacCall 1988, Kimura 1989) but these assume that all inputs and outputs are normally distributed.

An additional advantage of the simulation method is that by storing all simulated inputs (catches, M, etc.) and estimated outputs (N, F) it is straightforward to carry out projections that contain very useful information. With this method, it is not necessary to present the likely consequences of a desired regulation as single point estimates. Instead, the recommended actions or possible consequences can be presented as probability distributions which clearly highlight the uncertainties involved, from the scientists' perspectives. Naturally, these probability distributions are conditional on the choices made about the input uncertainty distributions and the VPA formulation being used. The latter condition cannot be dealt with in the simulations, as there are inflexible assumptions in every assessment model (i.e., the general structure of the equations used). But the first condition can be dealt with if the scientists involved in the assessment can reach a consensus regarding the uncertainty associated with each input.

ACKNOWLEDGMENTS

Partial support for this study was provided through the Cooperative Institute for Marine and Atmospheric Studies by National Oceanic and Atmospheric Administration Agreement NA85-WCH-06134.

REFERENCES

Conser, R.J., and J.E. Powers. 1990. Extensions of the ADAPT VPA tuning method designed to facilitate assessment work on tuna and swordfish stocks. ICCAT Coll. Vol. Sci. Pap. 32:461-467.

Gavaris, S. 1988. An adaptive framework for the estimation of population size. Canadian Atlantic Fisheries Scientific Advisory Committee Res. Doc. 88/29.

Kimura, D.K. 1989. Variability, tuning, and simulation for the Doubleday-Deriso catch-at-age model. Can. J. Fish. Aquat. Sci. 46:941-949.

Prager, M.H., and A.D. MacCall. 1988. Sensitivities and variances of virtual population analysis as applied to the mackerel, *Scomber japonicus*. Can. J. Fish. Aquat. Sci. 45:539-547.

Restrepo, V.R., and W.W. Fox, Jr. 1988. Parameter uncertainty and simple yield-per-recruit analysis. Trans. Amer. Fish. Soc. 117:282-289.

Saila, S.B., E. Lorda, and H.A. Walker. 1985. The analysis of parameter error propagation in simple fishery models. Mar. Res. Econ. 1(3):235-246.

Sampson, D.B. 1987. Variance estimators for virtual population analysis. J. Cons. int. Explor. Mer 43:149-158.

Seber, G.A.F. 1982. The Estimation of Animal Abundance and Related Parameters, 2nd edition. Charles Griffin & Company, Ltd., London.

Turner, S.C., and J.E. Powers. 1990. Methods for evaluation of the impact of fisheries management. ICCAT Coll. Vol. Sci. Pap. 32:483-486.

FIGURE 1. Coefficients of variation for age- and year-specific estimates of population size (N, in numbers) for 1000 simulated data sets.

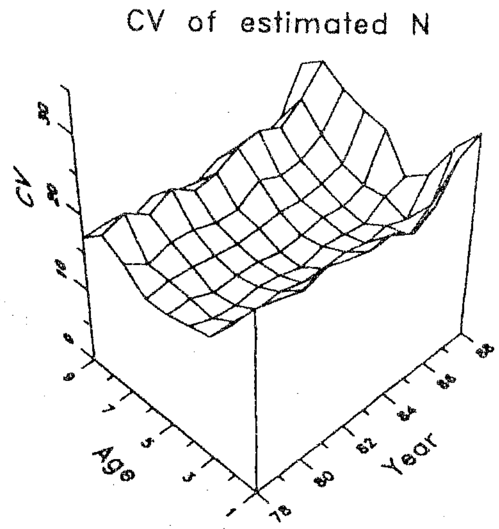

FIGURE 2. Coefficients of variation for age- and year-specific estimates of fishing mortality (F, per year) for 1000 simulated data sets.

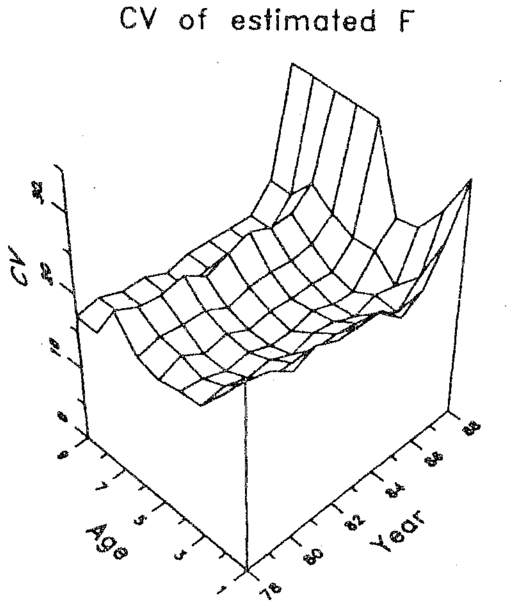

FIGURE 3. Median age 1 population estimates by year along with 2.5th and 97.5th percentiles from 1000 simulated outputs.

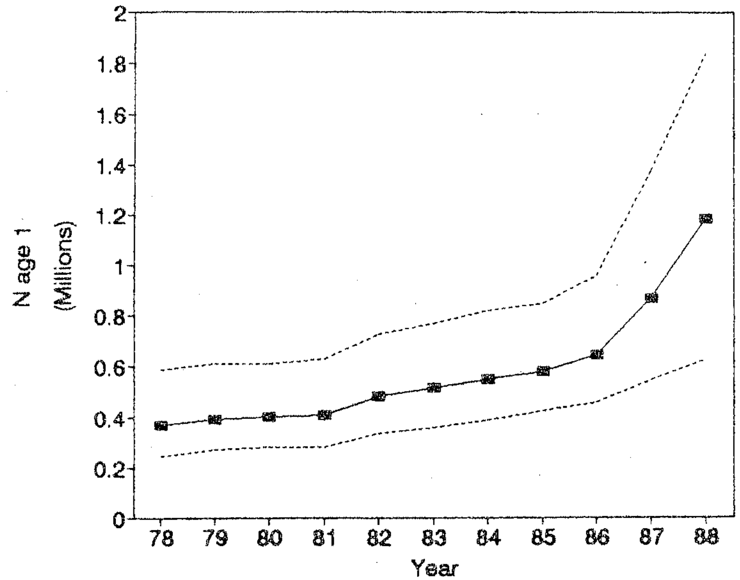

FIGURE 4. Median population size estimates for ages 5 and above by year, along with 2.5th and 97.5 th percentiles from 1000 simulated outputs.

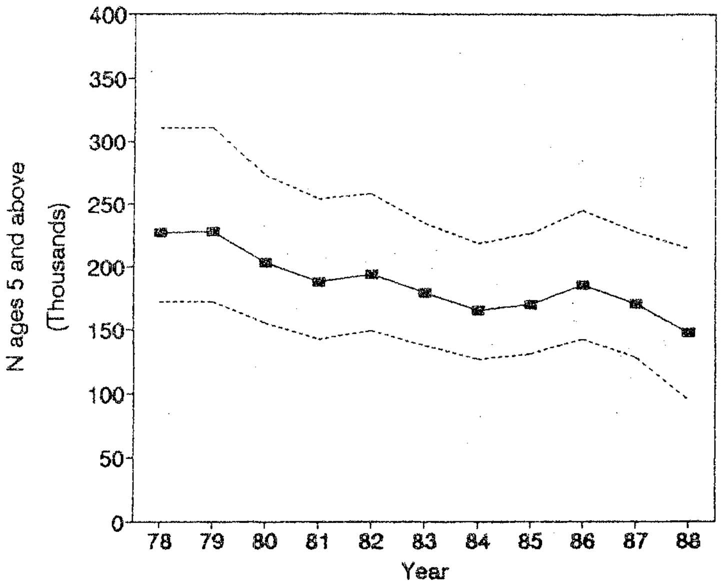

FIGURE 5. Median full F estimates (F for ages 5 to 9+, weighted by N) by year along with 2.5th and 97.5th percentiles from 1000 simulated outputs.

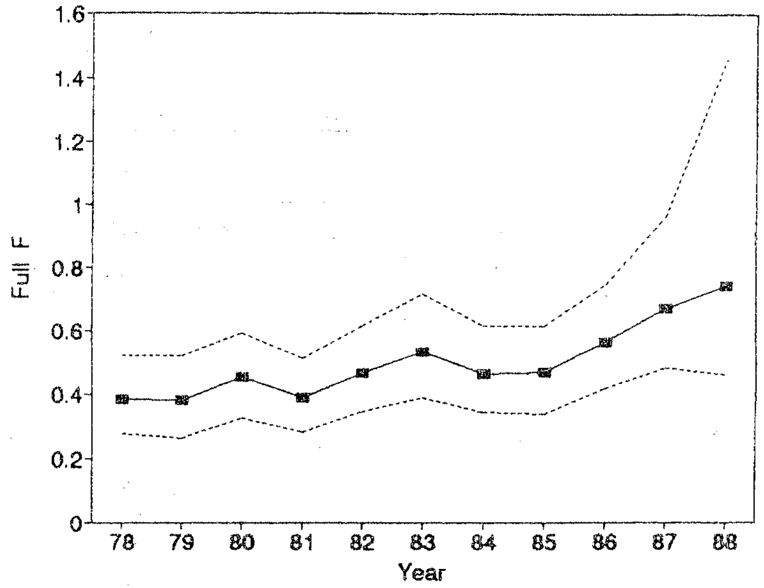

FIGURE 6. Proportion of runs in which the estimated year-specific full F was greater than the estimated full F for 1978.

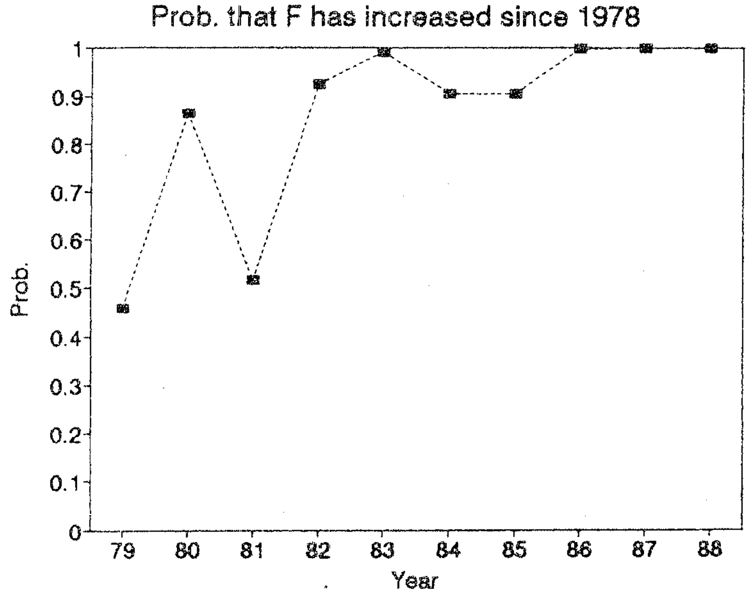

FIGURE 7. Frequency distribution for the relative changes in terminal year F vector required to reach F0.1 and Fmax in 1000 simulated data sets.

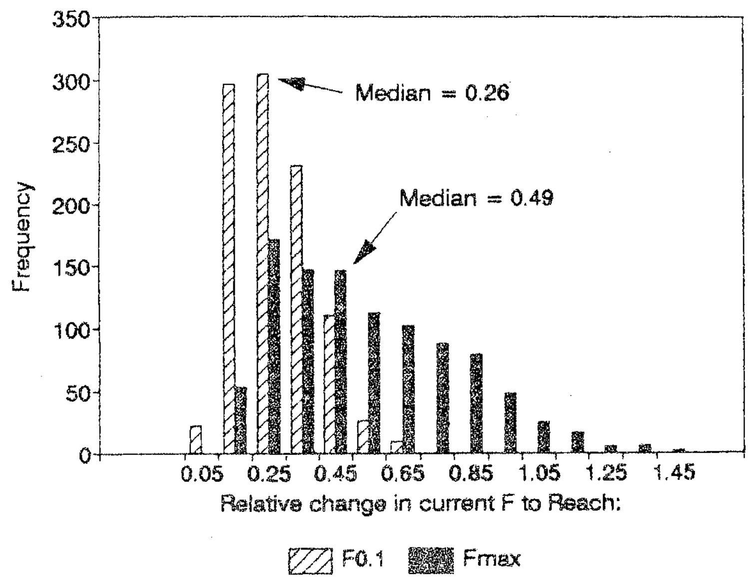

FIGURE 8. Frequency distribution for projected yields in 1990 at 3 levels of fishing mortality, relative to 1988 yields in 1000 simulated data sets.