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Effects of Growth Variability on Estimation of the Biological Reference Point $F_{0.1}$, with Examples from Chesapeake Bay, USA

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Abstract

Von Bertalanffy growth parameter estimates derived from ageing contain errors and imprecisions, as do growth parameter estimates derived from length-based models. These uncertainties propagate into management models and benchmarks based on the estimates. Thus management benchmarks are imprecise, and may be biased even when the original parameter estimates are unbiased (but uncertain).

A Monte Carlo study was conducted to examine propagation of uncertainty from growth parameters into the management measure $F_{0.1}$. Size-at-age data from several anadromous fish species found in Chesapeake Bay (eastern USA) provided examples. While these particular species are not managed by $F_{0.1}$, the simulations are nonetheless illustrative.

Length-at-age data were supplied by colleagues at the Maryland Department of Natural Resources and the Virginia Institute of Marine Sciences. Species studied were American shad (*Alosa sapidissima*), alewife (*Alosa pseudoharengus*), blueback herring (*Alosa aestivalis*), and striped bass (*Morone saxatilis*). Estimates of natural mortality M, age at first capture t_c, and age at recruitment t_r were also supplied. Because growth varied by sex, analyses of the alosid stocks were performed using both pooled data and data separated by sex. The data for shad were collected geographically and they were analyzed by area, but the stock structure was not well known.

The simulation procedure for each data set began with estimation of a reference set of growth parameters and its covariance matrix. Parameter estimates for several data sets did not converge after 150 iterations, but since the parameter estimates at this stage seemed to characterize mean growth well, the analysis was continued. As the absolute magnitude of asymptotic weight (W_∞) was of no importance, W_∞ was estimated from asymptotic length (L_∞) by assuming weight proportional to length and dividing by 200 as a scaling factor. Reference estimates of $F_{0.1}$ and $Y_{0.1}$ (yield at $F_{0.1}$) were then computed from the reference vector of growth parameter estimates.

The analysis continued with simulation of variability in the parameter estimates. For each data set, 1,000 random triplets of growth parameters were generated from a trivariate normal distribution whose mean was the reference vector of growth parameter estimates and whose covariance matrix was their estimated covariance matrix. For numerical reasons, the simulation had to be abandoned for eight example data sets in which the estimated correlation of K and L_∞ was extreme ($r > 0.999$). For the other data sets, $F_{0.1}$ and $Y_{0.1}$ were estimated for each vector of simulated growth parameters. Analyses of variability and bias in $F_{0.1}$ and $Y_{0.1}$ were made; bias was defined as the difference between the mean of simulated values and the reference value. A few duplicate simulations using 5,000 realizations demonstrated the sufficiency of the 1,000 realizations used for this work.

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For evaluation of bias and variability, the relative bias in $F_{0.1}$ or $Y_{0.1}$ were defined as the bias divided by the reference estimate, the result expressed as a percentage. The relative range was defined as the interquartile range (the 75th percentile minus the 25th percentile) divided by the reference estimate, the result expressed as a percentage.

The frequency distributions of simulated values of $F_{0.1}$ and $Y_{0.1}$ included unimodal, bimodal and some highly skewed distributions. In most cases, the shapes of the distributions of $F_{0.1}$ and $Y_{0.1}$ were dissimilar.

The biases resulting from growth variability were small, typically on the order of −0.02/year in the estimate of $F_{0.1}$. The relative bias for all 21 data sets analyzed was negative, and usually smaller than 1%, but had a highly skewed distribution; the mean was −2.6%, and the most sizable bias was −16.9%; this was the only one more than −10%. The examples with unconverged growth parameters had minimal biases, although this is likely to be due to chance.

Compared to the very small biases, the variability in $F_{0.1}$ was larger but usually moderate. The mean relative range was 10.2%. The distribution was highly skewed, with four of the 21 analyses having a relative range over 20%. The largest relative range was 29.1%.

The simulated estimates of $Y_{0.1}$ exhibited more bias and variability than the estimates of $F_{0.1}$. Biases were generally negative, the examples in which growth parameters did not converge had larger relative biases and larger relative ranges.

The alosid stocks examined here, which have a large spawning mortality, are unlikely candidates for management by $F_{0.1}$. The striped bass data probably provide more representative examples. Those examples exhibited very small relative biases in $F_{0.1}$ (magnitude less than 1%) and relatively small relative ranges (less than 20%). However, estimates of yield were biased downwards by as much as 40% (the figures for alosids were worse).

The simulation methods used here certainly underestimate the actual bias and variability that would be expected in using these data for yield-per-recruit modeling: only the variability in the growth data as collected was considered, without considering other sources of error and variability, such as gear selection and other non-random sampling or systematic ageing errors. Although the methods described here could readily be used to examine the effects of systematic errors, only variability was looked at because variability but not error could be estimated from the data at hand. Although it was found that random variability caused only negative biases in $F_{0.1}$, there is no reason to believe that systematic errors cause only negative biases. Negative bias implies a more conservative management scheme; conversely, positive bias in the estimate would suggest less conservative management. Another reason that the detection and correction of systematic errors is particularly important is that the bias caused by systematic errors is not generally reduced by increased sampling intensity.

The simulation approach developed here is flexible and could be modified to investigate the effects of systematic errors, random variability or a combination of the two; the uncertainty could follow any empirical or theoretical distribution. Because the method is not limited to a particular population dynamics model, it could be used to examine other management goals, such as maintaining a particular level of eggs-per-recruit or spawning stock per recruit. $F_{0.1}$ was chosen for this study as a representative measure in common use. However, it might not be appropriate, in for example a species exhibiting large discontinuous mortality. In such a case, a numerical simulation model might be used to incorporate the discontinuous mortality. In short, any model that uses growth parameters could be analyzed by the methods shown here. Where systematic errors in ageing are better understood, such as after age validation studies, these methods could be used to arrive at a better understanding of the uncertainties involved in the application of a growth-based management scheme.