Providing quantitative management advice from stock abundance indices based on research surveys

Thomas E. Helser
Northeast Fisheries Science Center
National Marine Fisheries Service, NOAA
166 Water Street, Woods Hole, MA 02543

Daniel B. Hayes
Northeast Fisheries Science Center
National Marine Fisheries Service, NOAA
166 Water Street, Woods Hole, MA 02543
Present address: Department of Fisheries and Wildlife
13 Natural Resources Building
Michigan State University, East Lansing, MI 48824

Abstract.—Index-based assessments, in which research survey indices serve as the primary source of abundance information, are used for many commercially harvested stocks in the Northeast region. Such assessments generally provide advice only on trends in the relative size of the stock, lack a biological reference point or level, and lack a decision framework for drawing statistical inferences about the state of the resource. We present a stochastic simulation technique for inferring population status relative to an index-based reference point. We applied an integrated moving average model to trawl data on Atlantic wolffish, *Anarhichas lupus*, to derive fitted indices and propose using the lower quartile (25th percentile) of the fitted indices as a reference point. From bootstrapping techniques applied to model residual errors we empirically characterized the variance and shape of the parent distributions of both a fitted abundance index at any point in time and the lower quartile. Treating these distributions as jointly continuous random variates, we generated the cumulative density function for the condition *Pr(index < lower quartile)*. Thus, for any value of the lower quartile, we can determine the probability that the fitted index at any point in time lies below that value of the biological reference point. An examination of the joint cumulative probability satisfying this condition is important because it allows us to ascertain quantitatively the likelihood of correctly deciding whether such a stock is below a prescribed threshold level.

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Standardized multispecies bottom trawl surveys conducted annually in the spring and autumn by the Northeast Fisheries Science Center (NEFSC, 1993) have been integral to the scientific advice for managers of the northwest Atlantic fishery resources. Not only do the surveys provide an efficient means of collecting biological and ecological information on a suite of finfish and invertebrates in the Northwest Atlantic, but they also provide the principal means of monitoring changes in population abundance. The trawl surveys use a stratified random sampling design in which stations are allocated to strata roughly in proportion to stratum area and are randomly assigned to specific locations within strata. Generally, the stratified mean number or weight per tow is used as an index of relative abundance (Grosslein, 1969; Clark, 1979). Such indices of abundance can be quite variable because of heterogenous spatial distributions (Byrne et al., 1981), year to year changes in catchability (Byrne et al., 1981; Collie and Sissenwine, 1983), and natural changes in population abundance. As such, the observed time series of abundance indices reflects two sources of random variation: 1) measurement error arising from within and between year survey sampling variability; and 2) true or "process" error arising from actual changes in population abundance. Measurement error in the survey estimates can be filtered from process variability by using autoregressive-integrated-moving-average (ARIMA) models (Box and Jenkins, 1976). However, the estimation of the parameters of a full ARIMA model for fisheries research surveys is often problematic because of the relative shortness of the time series (Pennington, 1985). Pennington (1985) described an approach based on an a priori specification of an integrated moving average model in which change in population size follows a simple random walk. Pennington (1986) and Fogarty et al. (1986) have applied this approach to a number of northwest Atlantic species or stocks, such as yellowtail flounder, *Pleuronectes ferrugineus*. This approach has become the standard method for deriving "fitted" abundance indices used in the Northeast region (NEFSC, 1993).

While over 400 species of finfish and invertebrates have been caught in NEFSC's bottom trawl survey during 1963–92, 62 species are caught consistently nearly every year (Fig. 1). Roughly half of these 62 species have some economic importance and are therefore assessed by various means (NEFSC, 1993; Fig. 2). For the traditionally important groundfish species, such as Atlantic cod, *Gadus morhua*, haddock, *Melanogrammus aeglefinus*, and yellowtail flounder, adequate data are available to perform a size or age-structured assessment (yield per recruit or Virtual Population Analysis [VPA]). These types of assessments are usually accompanied by biological reference points based on fishing mortality rates, absolute stock abundance levels, or both, as indicators for stock sizes below which long-term yield or productivity may be jeopardized. While survey abundance indices are important to "calibrate" results of analytical models for these species and stocks, they serve as the only source of abundance information to assess the status of the majority of stocks in the Northeast region (Fig. 2). Research survey index-based assessments generally provide only qualitative advice on the relative size of the stock and typically do not generate reference points commonly used by fishery managers.

In this paper, we extend the present procedures of deriving fitted survey abundance indices to inferring population status relative to an index-based reference point in a probabilistic framework through simulation. We use Pennington's (1985) a priori integrated moving average approach to derive fitted survey time series and then characterize trends in population abundance relative to an index-based reference point defined to be the lower quartile (25^{th} percentile) of the fitted time series. Our choice of the lower quartile for a reference point was rather arbitrary. However, the use of an interquartile (such as the 25^{th} percentile) computed from the data series over a range of years with reasonably high (as well as low) population sizes probably provides a reasonable reference point and would serve as such even as the time series lengthens. We then used a bootstrap procedure to characterize the uncertainty in both the fitted index and the reference

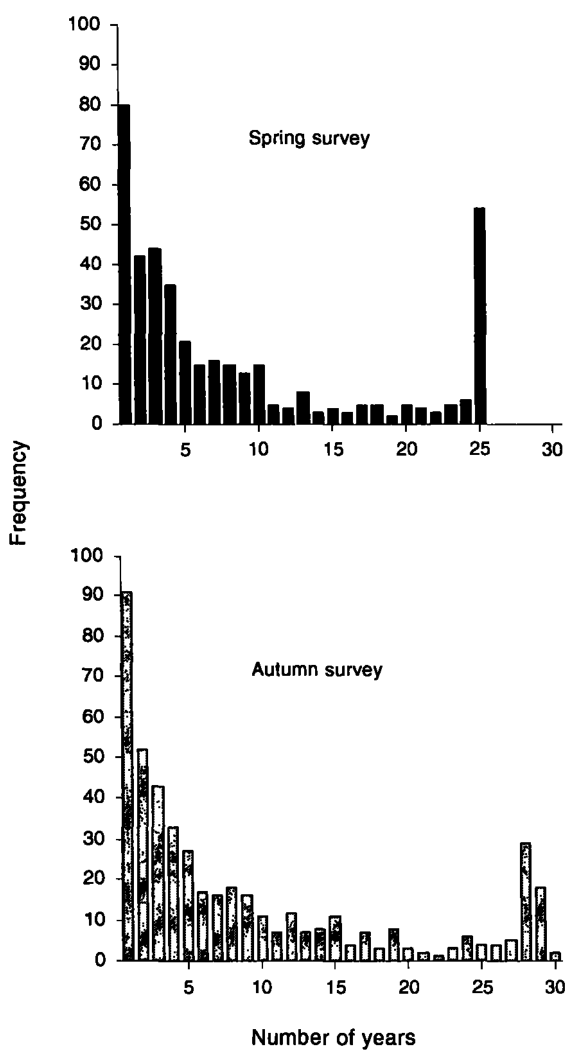

Figure 1
Frequency of the number of years various species (includes over 400 fish and invertebrates) occurring in the Northeast Fisheries Science Center's autumn bottom trawl survey since 1963 and spring bottom trawl survey since 1968. Data included up to 1992.

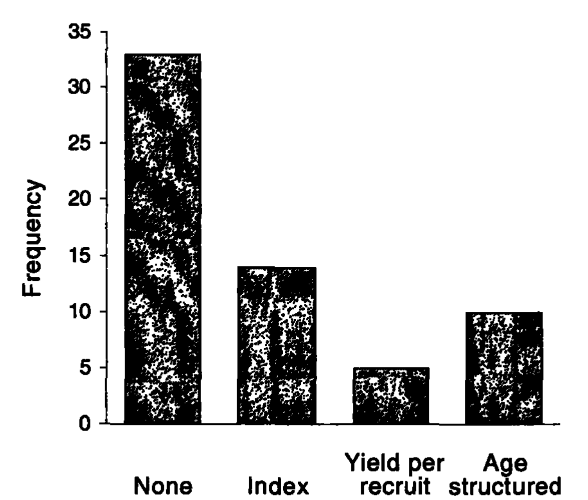

Figure 2
Frequency of assessment types performed on 62 species of fish consistly caught each year in the Northeast Fisheries Science Center's autumn and spring bottom trawl survey.

point and provide a probabilistic framework within which management decisions may be based.

Statistical methods

Estimation of abundance indices

Bottom trawl surveys have been conducted in the autumn since 1963 and in the spring since 1968 by the Northeast Fisheries Science Center. The surveys are based on a stratified random sampling design and are used to develop time series of abundance indices that are not subject to biases inherent in fishery-dependent data. A detailed review of the survey sampling design, methodology, and application has been provided by Grosslein (1969), Clark (1979), and Almeida et al. (1986). Following Cochran (1977), the stratified mean catch per tow is expressed as

$$\bar{y}_t = \sum_{h=1}^{l} \frac{N_h \bar{y}_h}{N}, \tag{1}$$

where N = total area of all strata; N_h = area of stratum h; $\bar{y}_h$ = sample mean in stratum h. The true abundance of a fish stock can be modeled as a population process with a linear stochastic difference equation of the form

$$\begin{aligned} z_t &= \phi_1 z_{t-1} + \phi_2 z_{t-2} \ldots \phi_p z_{t-p} \\ &-\theta_1 a_{t-1} - \theta_2 a_{t-2} \ldots \theta_q a_{t-q}, \end{aligned} \tag{2}$$

where z_t is the population abundance at equally spaced points in time, ϕi and θi are autoregressive and moving average parameters, respectively, and a_t's are independent identically distributed (*iid*) normal random $N(0, \sigma^2)$ errors. The autoregressive component represents "memory," while the moving average component represents past "shocks" or perturbations in the system. A principal objective of time-series analysis is to filter the effects of measurement error in the raw survey abundance indices from "true" or process variability resulting from changing population levels. Box and Jenkins (1976) described a general class of models that estimate the parameters in Equation 2 that represent the autoregressive integrated moving average process. The model can be expressed in more compact form as

$$\phi(B) z_t = \theta(B) a_t, \tag{3}$$

where B is the backward shift operator, and all other parameters are defined as above in Equation 2. If a time series of survey abundance estimates, y_t, are assumed to be directly proportional to the true population size, z_t, and it is further assumed that the survey index is measured with error, that is $y_t = z_t + e_t$ (where the e_t's are *iid* $N(0, \sigma_e^2)$), then the survey time series may be represented by

$$\phi(B) y_t = \eta(B) c_t, \tag{4}$$

where y_t is the survey abundance estimates, B is the backshift operator, and c_t's are *iid* $N(0, \sigma_c^2)$. The autoregressive parameter, ϕ, remains unchanged in Equation 4 while η is the new integrated moving average parameter that reflects error in the survey abundance estimates. Appropriate model specification is determined by examining the autocorrelation and partial autocorrelation functions, by estimating appropriate parameters, and by checking for model adequacy (Box and Jenkins, 1976). However, this formal procedure of specifying and adequately estimating parameters is typically hampered by short time series of data such as those from fishery-independent surveys. Pennington (1985, 1986) has proposed an approach based on a priori specification of the model which addresses: 1) the limitation in the length of the survey time series; and 2) changes in the population availability or catchability. Following Pennington (1986), the true population can be represented as

$$z_t = z_{t-1} e^{a_t} \text{ or } (1-B)\ln z_t = a_t. \tag{5}$$

Here the a_t's represent the process variability or those factors which cause changes in the population from year t–1 to year t (such as recruitment, fishing mortality, migrations, etc.). Pennington (1985) demonstrated that if the model (Eq. 5) and the ratio of variances, σ_e^2/σ_c^2, are known, then z_t and the variance of the estimator can be estimated. If we again assume the survey index, y_t, to be an estimate of the true population abundance, z_t, and that the measurement errors of the index are multiplicative, then

$$\ln y_t = \ln z_t + e_t. \tag{6}$$

Assuming the e_t's are *iid* $N(0, \sigma_e^2)$ and independent of the a_t's, then y_t can be represented by the integrated-moving average model:

$$(1-B)\ln y_t = (1-\theta B) c_t, \tag{7}$$

where the c_t's are *iid* $N(0, \sigma_c^2)$ and represent the residuals generated by fitting the model to the observed data. For the model (Eq. 7)

$$\theta = \frac{\sigma_e^2}{\sigma_c^2} \text{ and } (1-\theta)^2 = \frac{\sigma_a^2}{\sigma_c^2}. \tag{8}$$

Therefore, fitting the model (Eq. 7) to the observed survey abundance indices provides an estimate of θ and from Equation 8, an estimate of σ^2_e/σ^2_c. Pennington (1986) notes that this approach has several advantages over using the raw indices in that: 1) the resulting model variance is more precisely estimated, as survey variance is affected by varying catchability from year to year; and 2) relevant information contained in the other years of the survey is used in estimates for a particular year. Further, the fitted survey series is considered to be more precise than the original series (Pennington, 1985, 1986; Fogarty et al., 1986). At this point the fitted index, with sufficient length of time, may be used to characterize trends in abundance relative to a chosen reference point. An estimate of the forecast variance of the fitted time series can be calculated (Box and Jenkins, 1976), although the reference point (i.e. interquartile) is deterministic. Further, if the time series is short, a correct specification and estimation of the model parameters will be difficult and parametric estimation of the variance uncertain. To overcome these constraints, nonparametric methods with bootstrapping techniques (Efron, 1982) were used to estimate the variances of the fitted index and the reference point as well as to determine the shape of their parent distributions. This approach is particularly useful in making inferences between the observed population level as estimated by the fitted index and the reference point, within a probablistic framework.

Bootstrap procedure

Once a maximum likelihood estimate of the integrated moving average parameter, θ, has been obtained from Equation 7, "fitted" estimates of the survey population abundance, y_t, with known residual errors are available at equally spaced points in time, such that

$$(1-B)\ln \hat{y}_t = (1-\hat{\theta})c_t = a_t, \tag{9}$$

where $Var(a_t) = Var[(1-\theta)c_t] = (1-\theta)^2\sigma_e{}^2 = \sigma_a{}^2$ (see Eq. 8). The variance of $\hat{y}_t$ is given by

$$V(\hat{y}_t) = \sigma_e^2\left(1-\frac{\sigma_e^2}{\sigma_c^2}\right). \tag{10}$$

We applied bootstrapping procedures (Efron, 1982) to the vector of residual errors generated by the integrated moving average model (Eq. 7) applied to log-transformed survey abundance estimates. For the *ith* bootstrap replicate, n values of the model residuals were randomly selected with replacement (redefined as c'_t) and added to the predicted abundance estimates (y_t) to obtain n new pseudo-values $y_t{}^*$. Thus, a particular realization with the same underlying process was generated, where

$$y_t^* = \hat{y}_t + \sqrt{\hat{\theta} C_t^*}. \tag{11}$$

Assuming that Equation 7 provides an adequate representation of the actual population levels of the time series, it can be shown from Equations 8–11 that the bootstrap generated realizations take on the random component because of measurement error, since (from Eq. 8)

$$V\left(\sqrt{\hat{\theta} C_t^*}\right) = \theta\sigma_c^2 = \sigma_e^2. \tag{12}$$

Conceptually, this random resampling of the residuals mimicked a hypothetical resampling of the entire time series of abundance estimates with random variation generated from measurement error superimposed on the underlying process variation (i.e. variation in population levels). Random sampling of residuals and generation of n new time-series pseudo-values were repeated m times (i.e. m bootstrap replicates were performed). For each i^{th} bootstrap replicate, the prespecified integrated moving average model in Equation 7 was again fitted to the n new pseudo-values of the time series by using the same moving average parameter estimate, $\hat{\theta}$. The n new pseudo-values of the times series and the new fitted values for the m bootstrap replicates are given as

$$\left[y_{t_1}^*, y_{t_2}^*, y_{t_3}^*, \ldots, y_{t_m}^*\right], \tag{13}$$

and

$$\left[\hat{y}_{t_1}^*, \hat{y}_{t_2}^*, \hat{y}_{t_3}^*, \ldots, \hat{y}_{t_m}^*\right], \tag{14}$$

respectively. The lower quartile corresponding to each of the n new pseudo-values of the m bootstrap replicated time series as

$$\left[\hat{q}_1^*, \hat{q}_2^*, \hat{q}_3^*, \ldots, \hat{q}_m^*\right]. \tag{15}$$

Rather than obtaining new estimates of θ for the model fitting to each bootstrap replicate, we followed Pennington's (1985) suggestion that, given the large variability inherent in marine trawl surveys, a preliminary estimate of $\hat{\theta}$ between 0.3 and 0.4 appears to be an appropriate value for estimating an abundance index, and we set the value of $\hat{\theta}$ to that originally obtained from Equation 7. Finally, to complete the bootstrap replication procedures we made two final calculations; the mean of the lower quartile obtained from the n-fitted pseudo-values of the m bootstrap replicates, and the mean-fitted survey abundance index for each year. These are given as

$$\bar{\hat{y}}_t = \frac{1}{m}\sum_{i=1}^{m}\hat{y}_t^* \qquad (16)$$

and

$$\bar{\hat{q}} = \frac{1}{m}\sum_{i=1}^{m}\hat{q}^*. \qquad (17)$$

This resampling process is conditioned on the set of residuals from a fitted model to the observed data, and no distributional assumption is made concerning the structure of the error. The sample size of residuals for the example given here (25 to 30) should be adequate to characterize the tails of the underlying error distribution, and bootstrap estimates of the mean and lower quartile should have converged sufficiently as the number of resampled replicates m was performed 1,000 times. As such, the mean and variances generated by these new realizations of the time series for both the fitted index and the reference point, as well as the shape of their parent distributions, provide the necessary information for making inferences about the population. Further, this approach to generating variances and confidence intervals is particularly useful because explicit solutions to the "normal equations" cannot be derived because of the nonlinear nature of the equations representing the underlying population process (Rawlings, 1988).

Making inferences

Decisions made by fishery managers are often based on the state of the resource relative to a chosen management target or reference point. One question that forms the basis of management action is the following: Given the uncertainty in both the index of abundance and the value of the chosen reference point, what is the probability that the index in year t is less than or equal to the reference point? Statements of probability and inferences regarding the state of the resource can be formulated by using the bootstrap generated data in the following manner: Let the fitted index for any particular year ($\hat{y}_t^*$) and the lower quartile ($\hat{q}^*$) generated from m bootstrap replications be random variates Y_1 and Y_2, respectively. In addition, assume that Y_1 and Y_2 are jointly continuous random variates with the density function $f(y_1,y_2)$. In practice, we want to determine the $P(Y_1<Y_2)$, that is, the probability that Y_1, which takes of the value of y_1, is less than Y_2, taking on the value of y_2. This probability is computed as

$$P(Y_1 < Y_2) = \int_{-\infty}^{\infty}\left[\int_{-\infty}^{y_2} f(y_1,y_2)dy_1\right]dy_2. \qquad (18)$$

Further, we may wish to determine the probability of Y_1 being less than Y_2 for each possible value of y_2 in its domain and sum the resulting probabilities giving the cumulative probability distribution function. Thus, for any possible value of the reference point, $\hat{q}^*$, we can determine the probability that the fitted index, $\hat{y}_t^*$, lies below the value of the lower quartile for all possible values. By analogy, this can be extended to consider the joint probability that two consecutive years of the fitted survey abundance indices lie below the reference point. This approach takes into account the uncertainty in both the value of the fitted survey index for any given year (or two consecutive years) and the reference point to which the population level is compared.

An example

The Atlantic wolffish, *Anarhichas lupus,* is a cold water, bottom-dwelling species distributed from the Newfoundland banks to Nantucket (Bigelow and Schroeder, 1953). Little is known about the biology of wolffish in the western Gulf of Maine and Georges Bank region. Catches of wolffish in research surveys are low owing to its rather sedentary behavior and small, localized populations.

In U.S. waters, wolffish are taken primarily as bycatch in a mixed groundfish fishery and in other large mesh otter trawl fisheries. Commercial landings of wolffish in the Gulf of Maine-Georges Bank region averaged only about 220 metric tons (t) before 1970, after which they increased by nearly a factor of six; from 200 t in 1970 to 1,300 t in 1984 (Fig. 3). After peaking in 1984, commercial landings have steadily declined by about 100 to 200 t per year and reached 500 t in 1990, the lowest in nearly a decade. NEFSC spring survey abundance indices have shown a consistent downward trend, particularly since the early 1980's (Fig. 3).

Although no formal definition of overfishing presently exists for wolffish, this resource is presently considered overexploited and depleted on the basis of declining trends in commercial landings and survey indices (NEFSC, 1993). While this may intuitively be the correct conclusion regarding the status of the resource, there is little guidance in terms of its present level relative to its long-term abundance or to an appropriate reference point for fisheries

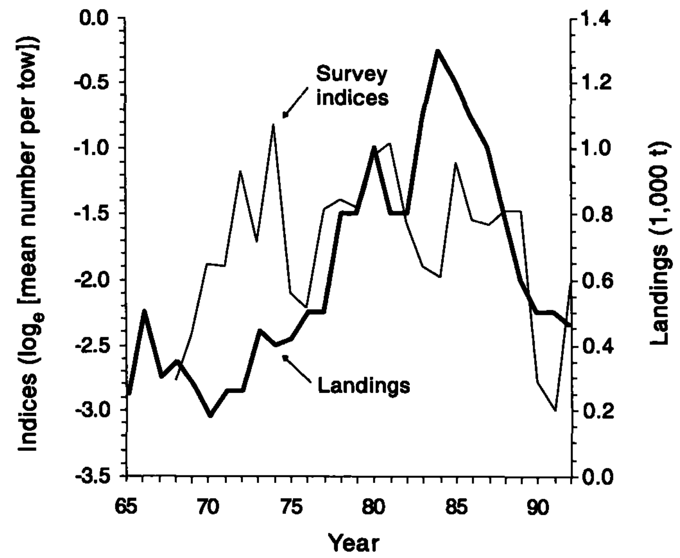

Figure 3

Atlantic wolffish, *Anarhichas lupus*, landings (thousands of metric tons) and spring bottom trawl survey indices ($\log_e$[stratified mean number per tow]) from 1968 to 1992.

management, or both. Given the data limitations for wolffish, what value will serve as a reasonable reference point or proxy for a level of stock abundance below which the stock may be in jeopardy? For our example we chose the lower quartile of the fitted survey abundance indices for wolffish as a reference point. Admittedly the choice of a computed statistic and the period of years of the survey indices used are rather arbitrary; the situation for each species should be carefully considered and a suitable reference point agreed upon by fishery managers. However, no matter which reference point is used, a simple comparison of a survey index in any given year with a survey-based reference point fails to consider the variability in each of these quantities.

Results and discussion

Estimates of the stratified mean number per tow (transformed by natural logarithms) clearly show declining trends in abundance, and the fitted index derived from time-series analysis appeared to provide a good, and less variable, representation of the observed data (Fig. 4). The maximum likelihood estimate of the integrated moving average parameter (θ) was 0.50 [SE(θ)=0.20], although it is probably not reliably estimated as indicated by the relatively flat maximum likelihood surface between 0 and 0.6.

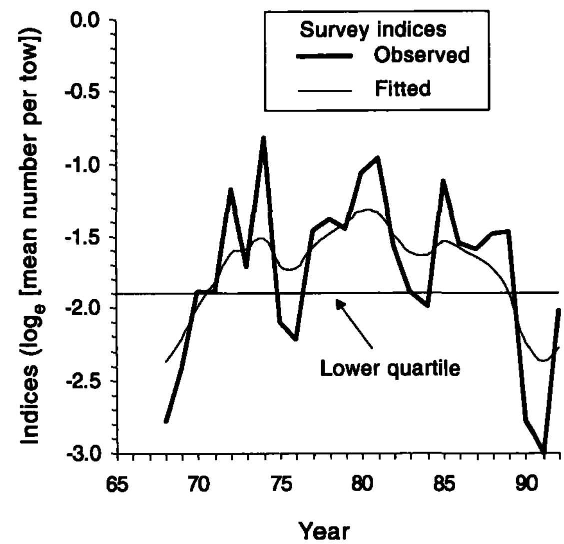

Figure 4

Predicted indices derived from an integrated moving average model fitted to observed Atlantic wolffish, *Anarhichas lupus*, spring bottom trawl survey indices ($\log_e$[stratified mean number per tow]) from 1968 to 1992. Predicted indices are compared to the lower quartile (25th percentile) of 1968–92 fitted indices as an arbitrary chosen reference point.

Pennington (1985, 1986) noted similar problems and concluded that the relative shortness of the time series of trawl data makes reliable estimation of the moving average parameter difficult. Although Pennington suggested using a value ranging from 0.3 to 0.4 appropriate for many stocks, we used the value of 0.50 because an analysis of the residuals from the model indicated that they were normally distributed (P>0.10).

The fitted estimates of abundance over the entire time series produce an index whose variance is considerably less than the variance of the observed series (Pennington, 1986). A comparison of a fitted index to the reference level (i.e. the lower quartile or 25th percentile) derived from the fitted indices should provide a reasonable evaluation of the stock's status because these reflect "true" trends in population abundance from only process variability (the effect of survey variance has been reduced). The fitted indices indicate that wolffish abundance has declined since the early 1980's and that by 1990 the index had fallen below the reference point (lower quartile= –1.90) to –2.2 (Fig. 4). In a hypothetical sense, if managers of this resource considered the lower quartile of the fitted indices a reasonable reference point, the 1990 index might have triggered some action, although it could be argued that the downward trend itself might be cause for concern. However, given the relative closeness of the fitted value of the 1990 index (–2.2) to the reference point (–1.9), as well as the uncertainty in both values, a logical question to ask is: What is the probability that the fitted 1990 index lies below the reference point?

Probability statements addressing this question can be derived from the parent distributions of both the fitted indices and reference points from the 1,000 bootstrap replications (Fig. 5). For the wolffish example, each of these distributions appear log-normally distributed, the 1990 fitted index exhibiting slightly more dispersion about its mean (as would be expected) compared with the reference point (Fig. 5). Both the fitted index and lower quartile means are nearly identical to the expected values (computed from the initial integrated moving average model fit), indicating little or no bias and uncorrelated model residual errors. Thus, for the time series on wolffish, an a priori integrated moving average model specification appears appropriate to describe the underlying population process.

For any value of the lower quartile we can state the probability that the fitted 1990 index lies below that value of the reference point using a discrete approximation of Equation 18. This simply represents the area integrated under the joint density

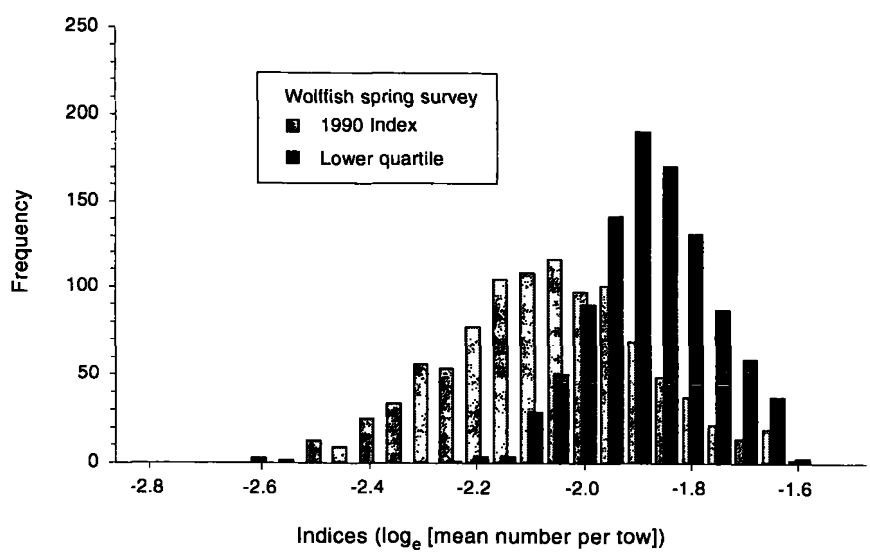

Figure 5

Comparison of empirical distributions of the 1990 spring survey index predicted by an integrated moving average (IMA) model fitted to 1,000 bootstrapped generated realizations of the survey time series 1968–92 and the lower quartile (25th percentile) of those predicted indices. The 1,000 realizations of the time series were generated by sampling with replacement the IMA model residual errors and randomly adding these to the predicted survey indices.

where the value of the fitted index is less than the value of the lower quartile (Fig. 6). The probability that the fitted 1990 index lies below the estimated value of the lower quartile (−1.9) is approximately 60% (Fig. 6). Further, because of the shape of the parent distribution of the lower quartile, the probability that the 1990 index lies below the reference point increases rapidly for higher and higher values of the reference point. For example, the probability that the 1990 index lies below a value of −1.85, which is nearly as likely as the bootstrapped mean (Fig. 5), increases to almost 75% and reaches nearly 85% at a value of −1.8 (Fig. 6). As an alternative to making inferences about the level of the population at only one point in time, fishery managers may wish to consider the likelihood of two (or more) consecutive years jointly falling below the value of the reference point. To address this question, we computed the joint probability of the 1990–91 and the 1990–92 fitted survey indices falling below our chosen reference point. The fitted survey indices over the 1990–92 period were as likely as those over the 1990–91 period to be below the reference point: approximately a 57% probability that the indices jointly fell below the reference point. This indicates that current population levels (as indexed by the fitted abundance indices) are considerably below the prescribed threshold level if the lower quartile of the fitted time series were

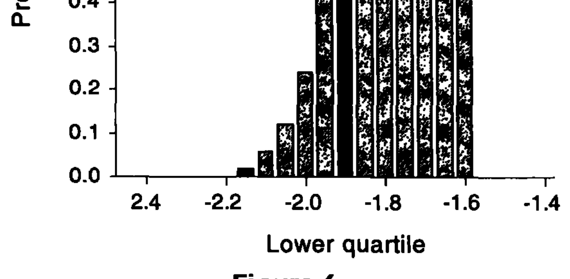

Figure 6

Probability that the value of the 1990 spring survey index predicted by an integrated moving average (IMA) model fitted to 1,000 bootstrapped generated realizations of the survey time series 1968–92 lies below the value of the lower quartile (25th percentile) derived from the predicted bootstrapped indices 1968–92.

adopted as the acceptable reference point. It should be emphasized that an "acceptable" reference point in this example refers more to choice of the range of years used for computation of the reference than to the choice of the interquartile, specified in this case to be the 25th percentile. We advise using a range of years for the abundance index which represents reasonably high population sizes and then using that fixed set of years for computation of the reference point even as the time series lengthens. This would prevent a ratcheting effect where the reference point declines as the abundance index declines, while allowing a characterization of the uncertainty in the reference point.

In conclusion, this technique represents an advancement for index-based assessments in the provision of quantitative advice for the management of fish populations surveyed by research vessels that are otherwise lacking in data sources. This approach provides an examination of the joint cumulative probability for the condition *Pr(index in year t, t+1, ... , t+m* < lower quartile) and is important because it allows the likelihood of correctly deciding whether or not a stock is below a prescribed threshold abundance or reference point to be ascertained quantitatively. We emphasize that the computation of a reference point from the time-series data is arbitrary and should be based on a series of observations representing reasonably high as well as low stock abundances. Finally, we illustrated these procedures with trawl survey data for wolffish in the natural log scale, which when the data are differenced, produces homogeneity of variance and stationarity of the time series (Nelson, 1973). It should be noted that retransformation back to the linear scale is likely to result in some bias. We did not examine the effects of transformation bias in this study but suggest that these effects be investigated in the future.

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