American Fisheries Society Symposium ##:##–##, 2003

Quality and Quantity of Fisheries Information in Stock Assessment

YONG CHEN
School of Marine Sciences, 225 Libby Hall, University of Maine, Orono, Maine 04469
E-mail: ychen@maine.edu

HARSHANA RAJAKARUNA
Department of Biology, Memorial University of Newfoundland
St. John's, Newfoundland, Canada A1C 5R3

Quantitative fisheries assessment models, based on biological theories and empirical observations, are defined by parameters that characterize the population dynamics of the stocks (Megrey 1989; Quinn and Deriso 1999). Reliable estimation of these parameters is a central issue in fisheries stock assessment and management (Chen and Paloheimo 1998; Walters 1998). Typically, parameters are estimated by fitting the models to data collected from the studied fish stock (Hilborn and Walters 1992). The quality of parameter estimation, which determines the quality of stock assessment, can be affected by many factors (NRC 1997, 1999; Chen and Fournier 1999; Quinn and Deriso 1999). Two of the most important factors are quality and quantity of fisheries data.

Quality of fisheries data is related to the precision and accuracy of measurements made on fisheries variables and is influenced by many factors, including data type; nature of fisheries; management regime; and economic, social, or ecological values of fisheries. Measurement errors are often used to determine the quality of fisheries data. Errors originating from different sources have different statistical properties. Errors in directly measuring a fisheries variable or a well-designed sampling program tend to be random in nature and small in magnitude. However, in some cases, errors associated with fisheries data can be nonrandom and biased, a characteristic of low-quality data. One example of this is catch statistics in a quota-managed system. Fishers may try to maximize their profits for a given quota by highgrading, a practice of discarding less valuable or desirable catch (usually small fish) and keeping only the valuable or desirable catch (usually large fish). In this case, only landed catch is included in catch statistics. Thus, the total catch is underestimated and the estimation of size composition is biased. Total catch statistics can also be underestimated by other harvest and management strategies—bycatch, legal size limitation, or trip limits—or by underreporting. In some cases, however, fishers may overreport catches to qualify for government assistance programs (e.g., unemployment insurance, retraining programs, etc). Overall, however, in an output-control fisheries management regime, the total catch is more likely to be underestimated than overestimated. Similar patterns have been observed for other fisheries variables (Hilborn and Walters 1992; NRC 1997).

The quantity of fisheries data describes the amount of information available for stock assessment, which can be grouped into two categories: diversity of data and amount of data. "Diversity of data" refers to either the variety of data that measures different characteristics of fisheries (e.g., total catch and age composition) or the number of sources from which the same type of data is collected (e.g., fisheries-independent and -dependent abundance indices). "Amount of data" refers to the amount of data of the same type from the same source (e.g., number of years in which age compositions are estimated for commercial catch). They may have different impacts on parameter estimation and stock assessment. Insufficient data in either category may lead to large uncertainty or even bias in estimating vital stock parameters and ultimately to mismanagement and overexploitation of stocks (NRC 1997, 1999).

Fisheries data are often collected from comprehensive sampling and reporting schemes for commercial fisheries, such as port and sea sampling programs and logbook systems and fisheries-independent surveys (Hilborn and Walters 1992). Data collected from fisheries often include catch (e.g., commercial landed or reported catch, discarded catch, recreational catch, and bycatch), measures related to fishing effort, length/age composition of catch estimated from subsampling the catch, length- and weight-at-age information, size-specific maturation and fecundity information, and abundance index (Ricker 1975; Hilborn and Walters 1992; Parsons

1993; Chen 1996). For a given fishery, however, the quantity of data collected tends to be positively related to its economic and social values. A valuable fishery tends to have many kinds of data with long time series from different sources (fisheries-independent and -dependent).

Many fisheries models exist in stock assessment (Megrey 1989). These models differ greatly in mathematical structure, assumptions, data requirement, biological and ecological implications, and output (Quinn and Deriso 1999). The choice of a model for a given fishery is commonly decided by the quantity and quality of fisheries data available for stock assessment. An economically or socially important fishery tends to have a large amount of data collected from different sources and with good quality, and it has more reliable information for stock assessment. Stock assessment models used in describing the fishery tend to have a high level of complexity, with fewer assumptions, and try to describe the details of fisheries processes. However, for a less valuable fishery, the quantity of data are small; simple models are less realistic biologically, and more assumptions may have to be used in stock assessment. The quality and quantity of fisheries data are thus critical in determining the type of fisheries models for stock assessment.

In this study, using two fisheries as examples, we evaluate the impacts on stock assessment of biased errors, which affect the quality of fisheries data, and lack of data diversity, which affects the quantity of fisheries data. For the biased error, we evaluate the impact of excluding discarded catch on stock assessment. For the data diversity, we evaluate how the lack of data diversity and dependence on fisheries-dependent data might affect the quality of stock assessment.

Methods and Materials

Data quality affected by biased error

Landed catch and abundance index data estimated from a research survey (Shelton et al. 1996) and discarded catch data (Kulka 1996) were obtained for the northern cod fisheries in Northwest Atlantic Fisheries Organization (NAFO) subdivision 2J3KL for 1980–1994 (Figure 1). Age-groups 2–13 were considered in this study. Landed catch, abundance index, and discarded catch in the selected time period all showed declining trends in recent years (Figure 1). By reversing the order of the data (i.e., catch, abundance index, and discarded catch) by year (i.e., 1994–1980, 1993–1981, etc.), we simulated a fishery with an inclining trend in landed and discarded catch and abundance index.

Pope's (1972) equation, described as follows, is often used in a virtual population analysis (VPA):

$$(1) \qquad N_{i,j} = N_{i+1,\,j+1}e^{m} + C_{i,\,j}e^{\frac{M}{2}},$$

where $C_{i,j}$ is the true catch of fish of age i in year j, $N_{i,j}$ is the number of fish of age i alive at the beginning of the year j, and M is natural mortality. Thus $N_{i,j}$ can be reconstructed if we know the number of fish alive at the beginning of the next year (i.e., $N_{i+1,\,j+1}$), the catch of age i and year j ($C_{i,j}$), and M. Pope's model assumes that the catch is taken in the middle of the year and that natural mortality occurs continuously throughout the year. Natural mortality is considered to be constant among age groups at 0.2 for the cod (Shelton et al. 1996). For each complete cohort—defined as a cohort that has passed through the fishery and no longer makes contributions to the fishery—the number of fish alive at the terminal age is assumed to be 0, and the number of fish alive at the beginning of each year can be back-calculated, beginning from the catch at the terminal age of the cohort (Hilborn and Walters 1992).

For incomplete cohorts—cohorts that still make contributions to the fishery (thus still contribute to current catch)—the number of fish alive at the beginning of each year is estimated by a tuned VPA. The objective function of the tuned VPA commonly used can be written as

$$(2) \qquad SS = \sum_{j}\sum_{i}[\ln(I_{i,j}) - \ln(q_i N_{i,j})]^2,$$

where $I_{i,j}$ is the abundance index of fish at age i in year j, and q_i is an age-specific catchability coefficient. The number of fish alive at the beginning of the most recent year (i.e., current year) for each incomplete cohort and catchability coefficient of each age-class are simultaneously estimated by minimizing this objective function (Gavaris 1988). Fishing mortality $F_{i,j}$ is estimated from the following equation:

$$(3) \qquad F_{i,j} = -\ln \frac{N_{i+1,\,j+1}}{N_{i,j}} - M$$

For each type of fishery, inclining or declining, stock size was estimated using two sets of catch data. The first set included landed catch only, and the second included both landed and discarded catch. The bias in estimating parameter (β) resulting from excluding the discarded catch in the estimates was described using the relative bias (RB) index, defined as

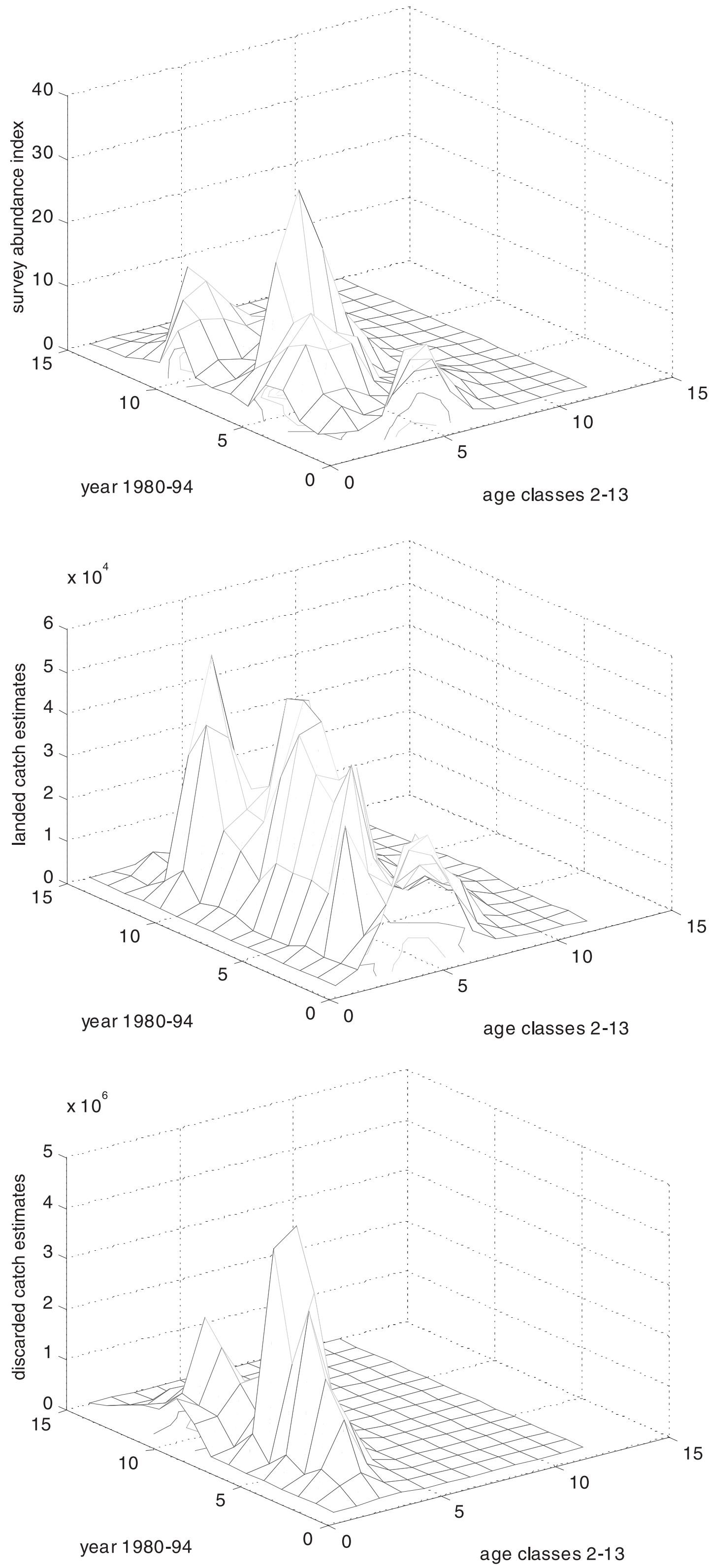


Figure 1. Landed and discarded catches and survey index of cod in NAFO subdivision 2J3KL, 1980–1994.

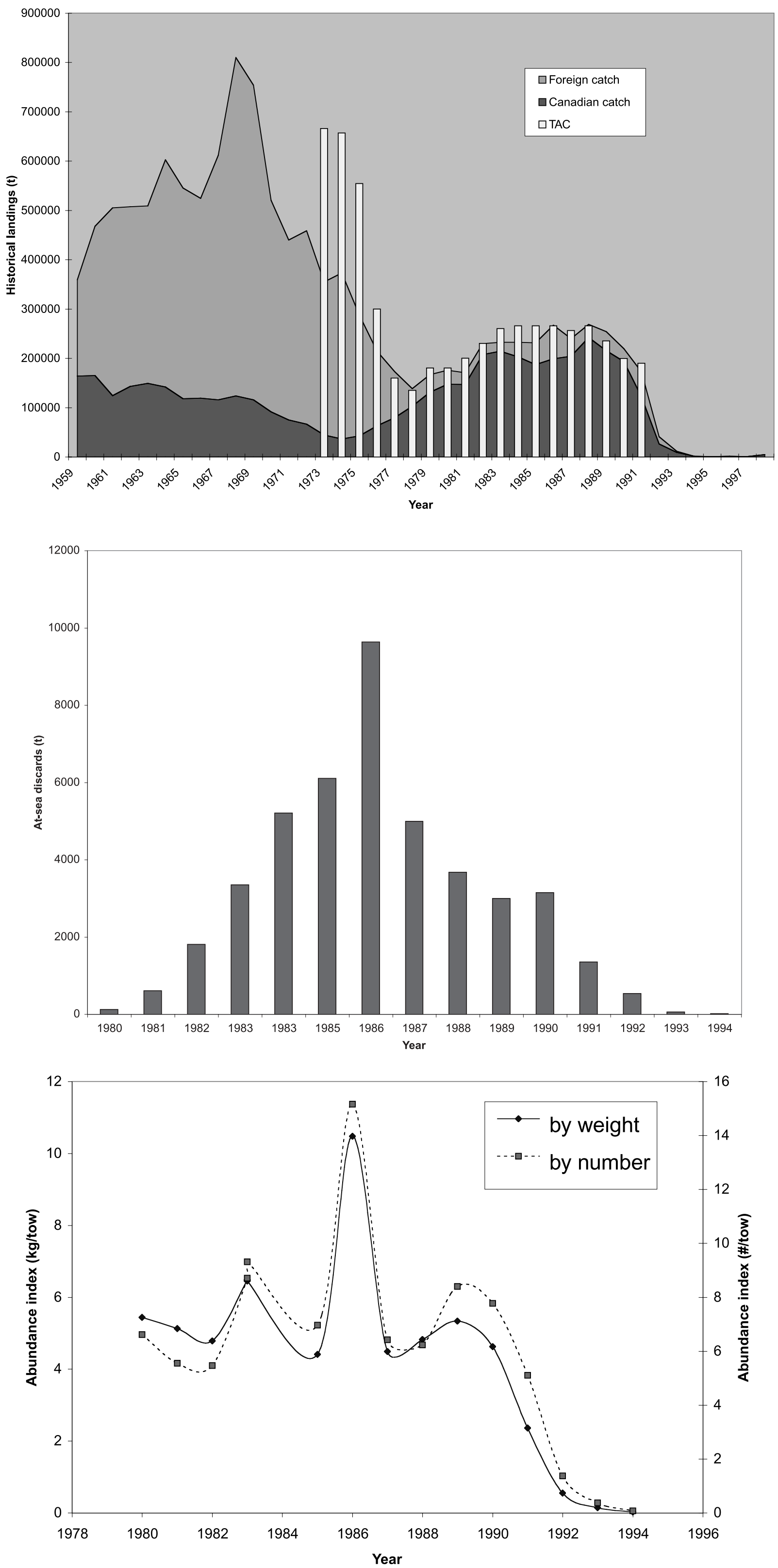


Figure 1. continued

$$(4) \qquad RB\,(\beta_{\text{landed catch only}} = \frac{\hat{\beta}(\text{landed catch only}) - \hat{\beta}(\text{landed and discarded catch})}{\hat{\beta}(\text{landed and discarded catch})} 100\%$$

A positive RB value indicates an overestimation while a negative RB value suggests an underestimation, resulted from biased catch data that fail to include discarded catch in stock assessment.

Because discarded catch data were available only up to age 13 and fish older than age 13 were taken into the same age-group, age 13 was taken as the terminal age for incomplete cohorts. In the calculation of stock size for complete cohorts, catch data up to age 20 were taken for a more accurate assessment.

Data quantity affected by data diversity

The case of the New Zealand abalone *Halitosis iris* (the PAU 5B paua stock) fishery illustrates the consequence of lack of data diversity in stock assessment. This fishery has characteristics typical of many stock assessments, such as multiple data sources and a complex Bayesian assessment model. Since 1986, the PAU 5B abalone stock has been managed with an individual transferable quota system and a minimum legal size of 125-mm shell length. A stochastic length-based observation error time-series model was constructed to represent the dynamics of the PAU 5B stock (Breen et al. 2000). This model consists of four submodels: a Beverton–Holt stock recruitment model, a length-based growth model, a catch-at-size model, and an observation model that describes the relationship between stock abundance and abundance indices observed in the fishery. The shape of the stock recruitment curve is defined by the steepness in stock recruitment parameter (*h*), defined as the proportion of virgin recruitment occurring when the spawning biomass is 20% of the virgin biomass (Francis 1992). Virgin biomass was assumed to exist in 1974, which was considered reasonable because catch before 1974 was small. (Detailed information on the fishery and models can be found in Breen et al. 2000 and Chen et al. 2000.)

Catch information was available from 1974 to 1999 (Figure 2). Standardized catch per unit effort (CPUE) was estimated from effort in the commercial fishery from 1984 to 1998 (Kendrick and Andrew 2000), and relative abundance indices were calculated from diver surveys for 1994–1996 and 1998 (Andrew et al. 2000). Length frequencies were available from diver surveys in 1989, 1994, 1995, and 1998 and from catch sampling for 1992–1999.

Recruited biomass (B) and the two abundance indices were considered related with two observational models:

$$(5) \qquad (\text{CPUE})_t = q_1 B_I e^{\varepsilon_{\text{CPUE},\,I}} \text{ and } I_t = q_2 B_t e^{\varepsilon_{I,\,t}}$$

where q_1 and q_2 are catchability coefficients, and the error terms were assumed to be normally distributed, as $\varepsilon_{\text{CPUE},\,I} \subset N(0, \sigma^2_{\text{CPUE}})$, $\varepsilon_{I,\,t} \subset N(0, \sigma^2_{I})$. After log transformation of Equation 5, the follow-

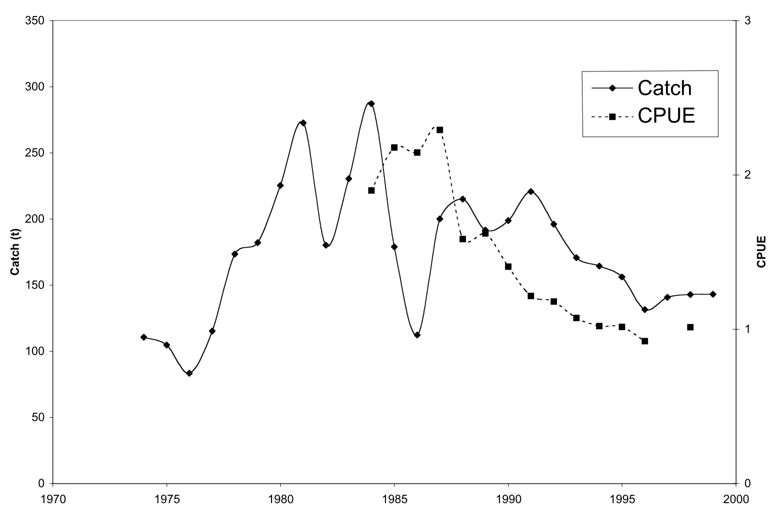


Figure 2. Catch, standardized catch-per-unit effort (CPUE), survey index, and length-frequency data estimated from the fishery and survey for the New Zealand paua fishery (the PAU 5B paua stock).

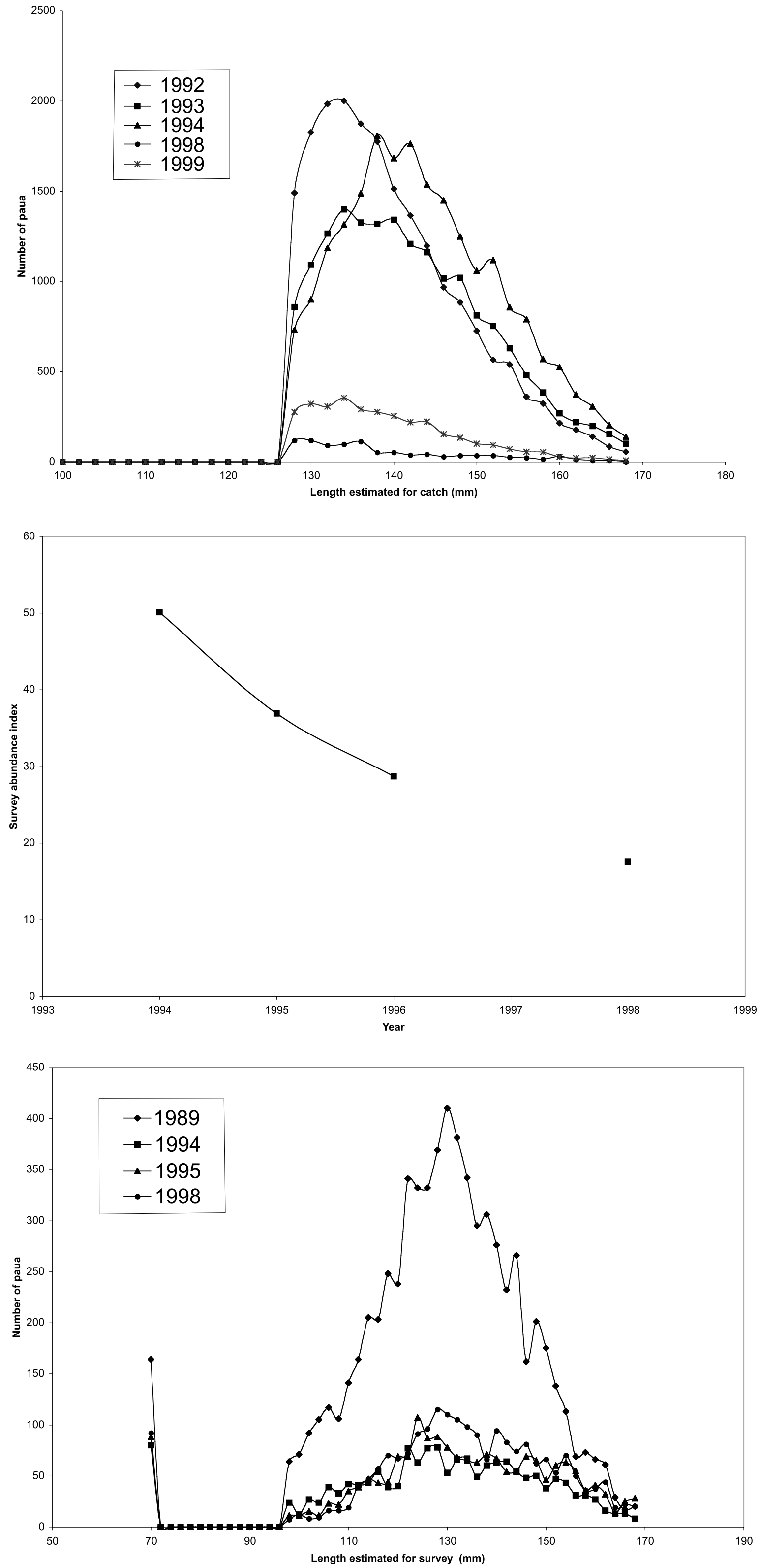


Figure 2. continued

ing likelihood functions were derived for the CPUE and abundance index data:

$$(6a)\quad p(\mathrm{CPUE}_t \mid C_t, \beta) = \prod_t \left[\frac{1}{\sqrt{2\pi}\,\hat{\sigma}_{cpue}} \exp\left(-\frac{[\ln(\mathrm{CPUE}_t) - \ln(q_1 B_t)]^2}{2(\hat{\sigma}_{cpue})^2}+0.01\right)\right]$$

$$(6b)\quad p(I_t \mid C_t, \beta) = \prod_t \left[\frac{1}{\sqrt{2\pi}\,\hat{\sigma}_{I}} \exp\left(-\frac{[\ln(I_t) - \ln(q_2 B_t)]^2}{2(\hat{\sigma}_{I})^2}+0.01\right)\right]$$

where β is a vector of parameters to be estimated (see Chen et al. 2000 for details). $\hat{\sigma}_{cpue}$ and $\hat{\sigma}_{I}$ are the standard deviations estimated using log CPUE and log abundance index data. The observed length frequencies were related to the predicted proportion of fish at length with a model with observation errors following a multinomial distribution. The following likelihood function was used:

$$(7)\quad L(p)=\prod_t\prod_i \frac{1}{\sqrt{2\pi\, p_{i,t}\,(1-p_{i,t})+0.1/\Omega}}\exp\left[\frac{-N_{i,t}\,(p_{i,t}-\hat{p}_{i,t})^2}{2[p_{i,t}\,(1-p_{i,t})+0.1/\Omega]}+0.01)\right]$$

where subscripts t and i indicate year and length class, Ω is the number of length classes (equal to 50 for all years), $p_{i,t}$ is the proportion of fish in length class i in year t, and $N_{i,t}$ is the effective sample size used to determine the proportion of fish in year-class i in year t. The 0.01 term in the second part of the likelihood increases the thickness of tails, making the likelihood less sensitive to outliers. The $0.1/\Omega$ term prevents the variance from approaching 0 as the $p_{i,t}$ value approaches 0 or 1 (Fournier et al. 1990).

All parameters except h and M were assumed to have noninformative priors described by uniform distributions (see Breen et al. 2000; Chen et al. 2000); parameters h and M were assumed to have informative priors. The prior distributions are $h \subset N(0.7, 0.2^2)$, truncated by lower and upper boundaries of 0.4 and 0.975, and $M \subset N(0.1, 0.5^2)$, truncated by lower and upper bounds of 0.01 and 0.5.

Five data sets were simulated (Table 1). The base data set includes data from all sources. The data sets of Tests I–IV include data with either survey data or part of fishery data missing. Thus, the data sets for Tests I–IV reflect scenarios of lack of data diversity.

For each set of data defined in Table 1, posterior distributions of the model parameters were estimated using the Markov Chain Monte Carlo (MCMC) simulation approach. The Hastings–Metro algorithm was used. The simulation was started from the parameters at the mode of the posterior distribution, which was identified by minimizing the total objective function, which includes the negative log-likelihood components and the prior probability contributions. The lag between samples was 200. The model was implemented in AD Model Builder (Fournier 1996). (Detailed descriptions on estimating posterior distributions can be found in Fournier 1996.) Half a million simulations were run for each data set.

Posterior distributions were considered for only seven parameters: M; h; current (1999) stock biomass (B_{cur}); depletion of the stock in 1999 (B_{cur}/B_0); exploitation rate in 1999; projected stock biomass in 2004 (B_{2004}), assuming retention of the then-current total allowable catch of 148 tons for

Table 1. Simulated New Zealand paua data sets used in the study of data quantity.

Data set	Data source			
	Survey		Fishery	
	Index	Length frequency	Index	Length frequency
Base case	Yes	Yes	Yes	Yes
Test I	Yes	Yes	Yes	Yes
Test II	Yes	Yes	Yes	Yes
Test III	Yes	Yes	Yes	Yes
Test IV	Yes	Yes	Yes	Yes

the next 5 years); and change in stock biomass between 1999 and 2004 (B_{2004}/B_{cur}). These parameters are included because of their importance in defining the dynamics of fish stocks and management (Hilborn and Walters 1992; Smith et al. 1993; Walters 1998). To evaluate the impacts of lack of data quantity, posterior distributions derived for the base data set were compared with those derived for each of the four test data sets defined in Table 1.

Results

Impacts of biased error

The stock sizes of early years in the selected time period tended to be underestimated for both inclining and declining fisheries, and the magnitude of the underestimation was rather small (Figure 3). The reasons for this were that the stock of early years mainly consisted of fish from complete cohorts and that the size of a complete cohort was always underestimated when discarded catch was excluded from VPA, irrelevant of the type of the fishery.

For the declining fishery, the relative error had negative values and was small in early years but became larger in recent years. The relative errors for recent years were in the neighborhood of 50%. The negative value of the relative errors suggests that stock sizes were consistently underestimated throughout the time period. The large relative errors for recent years indicated that the underestimation of stock sizes of recent years were more serious than those for early years in the declining fishery.

For the inclining fishery, the values of relative errors were negative in early years but became positive in recent years (Figure 3). The reason is that complete cohorts had more weights in the bias of stock sizes in early years. At some point, the bias approached 0 when the negative biases were nullified by the positive biases for incomplete cohorts. For more recent years, incomplete cohorts had more weights, resulting in positive biases (Figure 3). Thus, stock sizes of more recent years tended to be overestimated for the inclining fishery.

For both types of fisheries considered in this study, the relative bias of stock biomass remained lower than that of stock sizes (Figure 3). Biases were small for the estimated fishing mortality rates for both fisheries considered.

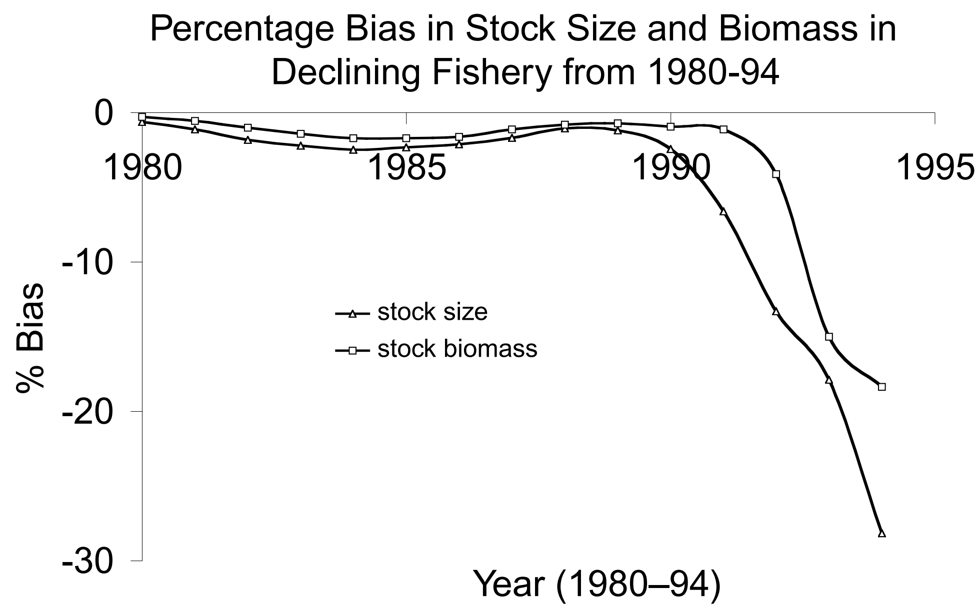
Impacts of the lack of data diversity

The exclusion of a subset of data (i.e., test data sets) in stock assessment tended to result in differences in posterior distributions for stock parameters (Figure 4). However, the magnitude of the difference differed among parameters for a given test data set and among test data sets for a given parameter. Overall, the largest difference occurred for all parameters when no fisheries-independent data were available (i.e., data set for Test III). In this study, the lack of fisheries-independent data led to large increases in natural mortality, current stock biomass, the stock recruitment steepness parameter, depletion level, projected biomass, and changes of biomass in 5 years; it also led to large decreases in virgin biomass and current exploitation rate. Thus, had the fishery-independent data not been available, the fishery would have been described as having a much better status and being able to sustain much higher fishing mortality, and current catch quota level would be too low (Figure 4). Similar patterns could be observed for other test data sets, although the magnitude of the difference was smaller than that when there were no independent data available in stock assessment. All the test data sets with certain information missing (Table 1) tended to lead to a more optimistic estimation about the current status of the fish stock and stock productivity (see current stock biomass and depletion level in Figure 4).

A statistical summary of posterior distributions for the full data set is presented in Table 2. For the four test data sets listed in Table 1, variances of posterior distributions increased for all parameters except exploitation rate compared with those estimated using the full data set (Table 3). Overall, the data set for Test III had the largest increase in variance and the data set for Test IV had the smallest. This suggests that there would be a larger uncertainty in parameter estimation if there were no fisheries-independent data. For fisheries-independent data, survey abundance index and survey length-frequency data had different impacts on uncertainties of parameter estimation. The increase in uncertainty of posterior distributions resulting from the missing of survey abundance index was much larger than that resulting from the missing of survey length-frequency data (Table 3). The absence of catch length-frequency data had the smallest impacts on uncertainties of posterior distributions. Results similar to those observed in Figure 4 could be found when comparing means of posterior distributions between the full data set and test data sets (Table 3).

Discussion

A common problem associated with a tuned VPA in assessing cod stocks in Atlantic Canada is that the



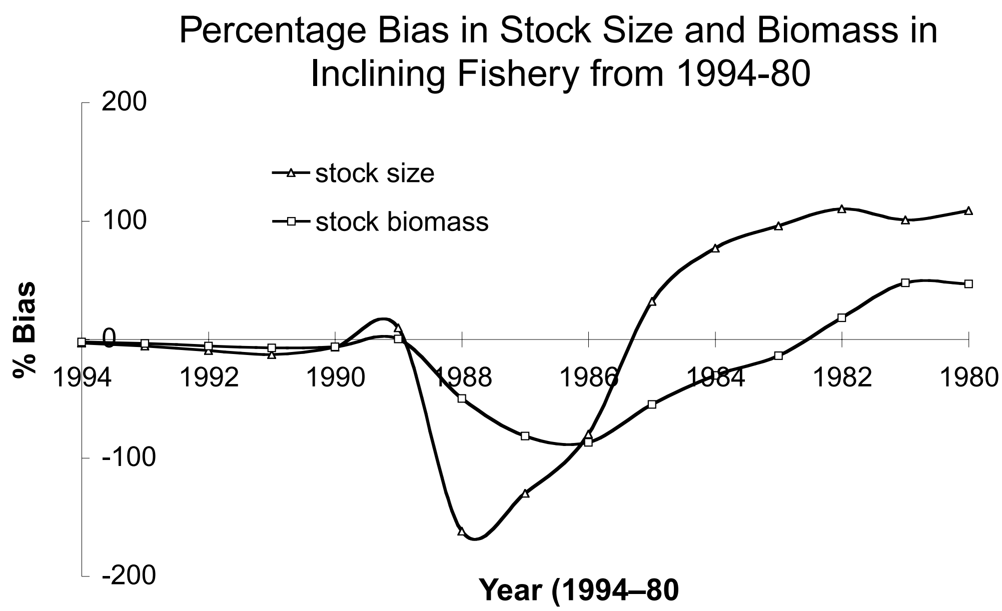
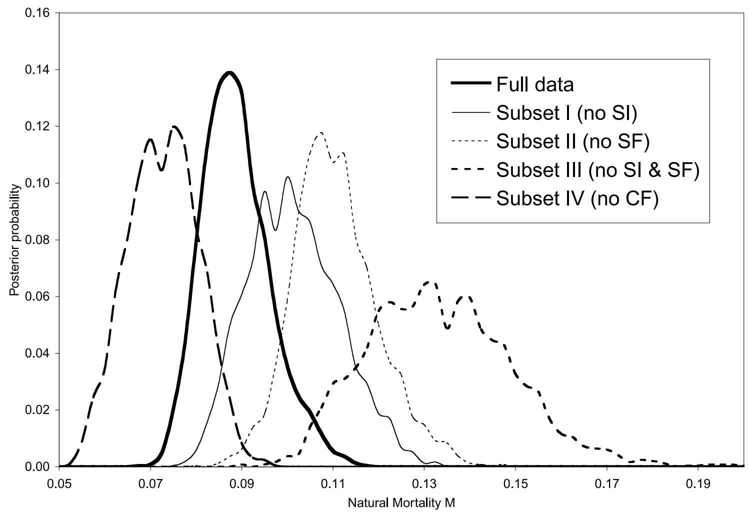
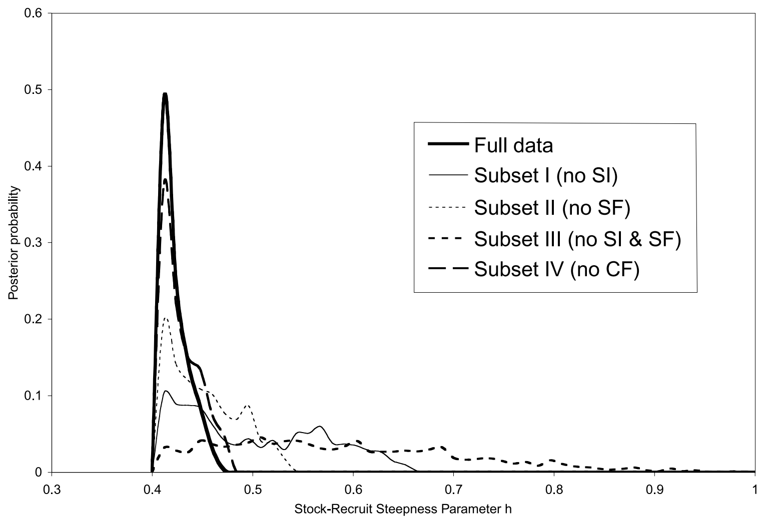


Figure 3. Relative bias calculated using equation 4 for stock size and biomass estimated without including discarded catch in virtual population analysis.

current stock size tends to be higher than the sizes estimated for the same year when more years of data become available (Sinclair et al. 1990). This problem has been referred to as the "retrospective problem." Many hypotheses were developed to explain it, including the exclusion of discarded catch. The focus of the present study, however, was the bias in stock size estimates that resulted from the exclusion of discarded catch in VPA. The retrospective problem exists in VPA for data both with and without discarded catch. Differences in its impacts on stock size estimates between these two sets of catch were expected to be small, and the results derived probably were not affected by this problem.

The results of this study suggest that unaccounted catch in stock assessment using tuned





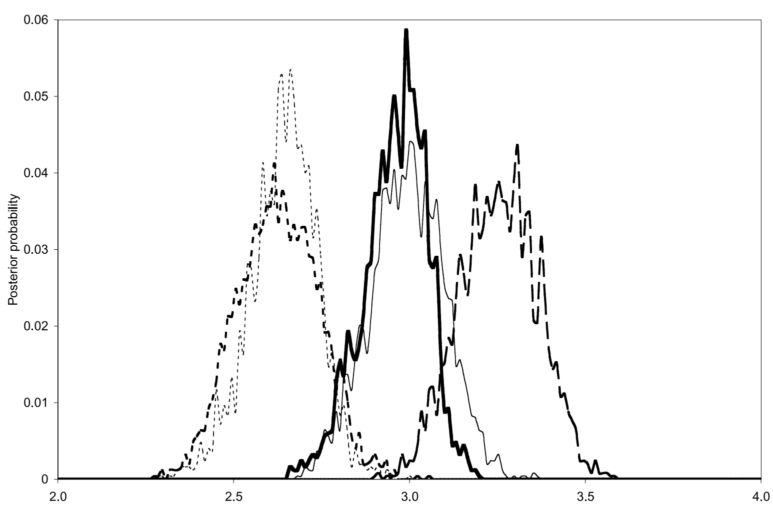


Figure 4. Posterior distributions of eight stock and management parameters estimated using a full data set and four test data sets defined in Table 1.

Table 2. Summary of the posterior distributions for parameters estimated for the New Zealand paua fishery with the full data set defined in Table 1. Erate, exploitation rate; Depl, depletion level.

Parameter	Statistics of posterior distributions				
	Mean	Median	Lower 5%	Upper 5%	SD
M	0.088	0.087	0.077	0.102	0.007
h	0.417	0.412	0.401	0.445	0.014
B0	2,953,748	2,962,570	2,790,987	3,082,556	90,316
Bcur	430,520	425,605	322,937	553,589	69,662
B2004	134,889	107,163	74,434	280,972	67,481
Erate	0.341	0.336	0.258	0.443	0.055
Depl	0.146	0.144	0.110	0.188	0.024
Change	0.301	0.264	0.208	0.502	0.096

Table 3. Summary of the relative differences in mean and standard deviation (SD) of posterior distributions of the key paua fishery stock and management parameters between full data set and test data sets defined in Table 1. Parameters are explained in the text.

Parameter	Difference index of mean (%)				Difference index of STD (%)			
	I	II	III	IV	I	II	III	IV
B0	1.2	–10.7	–11.2	10.0	17.5	6.2	28.0	22.0
M	14.3	24.8	50.7	–18.3	33.9	23.9	112.0	3.3
h	18.9	7.1	40.5	1.5	408.2	148.2	778.5	32.9
Bcur	70.4	–2.0	88.2	19.5	67.8	–0.1	129.0	27.5
B2004	293.9	45.4	453.2	23.0	130.2	32.4	198.4	40.2
Erate	–41.4	2.1	–46.3	–16.1	–42.4	2.8	–38.4	–11.6
Depl	68.3	9.8	111.8	8.5	57.8	14.0	142.9	7.7
Change	135.9	48.4	202.3	1.2	13.9	36.4	0.4	22.5
Average	80.5	18.8	125.5	12.3	96.5	33.0	178.5	21.00

The difference index was calculated as $j[S(\beta)]=([S(\beta)]_j - [S(\beta)]_{full\ data})/[S(\beta)]_{full\ data}$ *100% where $[S(\beta)]_j$ is a statistic of the posterior distribution of parameter β estimated for test data set j (Table 1) and $[S(\beta)]_{full\ data}$ is a statistic of the posterior distribution of parameter β for the full data set (Table 1).

VPA does not always underestimate or overestimate stock sizes. The direction of bias in the estimation might be influenced by the temporal patterns of landed catch, discarded catch, and abundance index data. Stock sizes were more likely to be underestimated for declining fisheries, but overestimated for inclining fisheries by excluding discarded catch from VPA if discarded catch followed the same temporal patterns as landed catch. A similar approach was applied to other fisheries data to test the correlations between temporal trends in catch and abundance index data and the direction of biases, and similar results were obtained. However, further study is needed to identify the mechanisms behind the relationship.

The impacts of excluding discards on fishing mortality estimates were small. Yet others (e.g., Tallman 1991; Myers et al. 1998) suggest that the potential bias in the estimation of fishing mortality could be the most critical factor when discarded catch estimates are excluded. The results of this study show that the bias in estimation of stock size was more important than the bias in the estimation of fishing mortality. A simple reason for this is that a fishing mortality parameter is sensitive only to relative changes in the number of fish between immediate age classes in a given cohort and that the exclusion of discarded catch influences estimation of the number of fish alive for all age-groups.

In a quota-managed fishery, chances are that fishers more likely underreport their catches. The impact on VPA of misreporting in such a fishery may be the same as that of discarding. This analysis may be generalized for the impact of biased error in data on VPA. We have not yet analyzed the impact of patterns of landed and discarded catch on the age axis on the direction of bias. Thus, if misreporting takes the form that differs from that of discarding on the age axis, the impact of misreporting on VPA could be different from that of discarding.

The patterns of bias also shows that the relative bias of stock biomass was greater than that of stock size for the current year. It implies that discarding may introduce larger biases to the estimation of new recruitments than to that of older fish. For declining fisheries, management strategies formulated on the basis of stock assessments without accounting for discarded catch are likely to lead to safer resource management policies (but underutilization of fisheries resources). On the other hand, overestimation of stock for inclining fisheries as a result of excluding discards may result in overexploitation as a result of overestimation of stock sizes.

In this study, only one type of biased error in fisheries data (i.e., underestimation of catch) was considered, and the impact of the error on stock assessment was large. It is clear from this example that we should pay special attention to data quality in stock assessment and should take every effort to reduce the errors in fisheries data. Without high-quality fisheries data, the derivation of a high-quality fisheries stock assessment—which is the basis for formulating an optimal management strategy—is unlikely.

The importance of the quantity of fisheries data in stock assessment has been increasingly realized. The problems associated with using data collected from commercial fisheries as sole input data in stock assessment have been raised (Hilborn and Walters 1992). For many fisheries, more and more effort has been spent to collect data independent of fisheries in the hope that the extra information can improve the accuracy and precision of fisheries stock assessment. Although just a case study, this study shows the importance of including fisheries-independent data in improving the quality of stock assessment and danger of overdependence on fisheries-dependent data. However, it should be realized that such an improvement could be achieved only with the collection of fisheries-independent data, which tend to be unbiased and precise and have good representations of characteristics of the targeted population. If extra data have large errors, then the inclusion of such information may reduce the quality of stock assessment.

The results of this study suggest that the inclusion of extra information reduces uncertainties in parameter estimation (Table 3) because of the consistent temporal patterns between fisheries-dependent and fisheries-independent data (Figure 2). In the case of different data having contradicted information about the targeted fishery, uncertainties in parameter estimation are more likely to increase than decrease with the inclusion of the extra data. Background information on data collection and fisheries is thus needed to determine the relative reliability among data sets. A weighting scheme can then be developed to represent the relative reliability of these data in estimating parameters in stock assessment. Data sets collected from a well-defined fisheries-independent survey, however, tend to be unbiased and representative of the targeted fish stock and are thus more reliable than the data collected from fisheries.

The results of this study also show that data of a different type, even collected from the same source (e.g., survey abundance index and survey length-frequency data in this study) could have different impacts on stock assessment. Although only four observations were obtained from the independent survey (Figure 2), the survey abundance index showed that it had the most significant impact on parameter estimation (Table 3, Figure 4). This suggests that there is a need to determine the relative importance of different kinds of fisheries data with respect to stock assessment in allocating sampling effort to ensure that most critical information is collected.

Acknowledgments

This study was supported by a Natural Sciences and Engineering Research Council of Canada operating grant (to Y. C.) at the Memorial University of Newfoundland, Canada; the visiting scientist program of the New Zealand National Institute of Water and Atmospheric Research; and the Maine Department of Marine Resources.

The authors are grateful that N. L. Andrew and P. Breen at NIWA kindly allowed the inclusion of the New Zealand paua fishery data in this manuscript.

References

Andrew, N. L., J. R. Naylor, P. Gerring, and P. R. Notman. 2000. Fishery independent surveys of paua (*Haliotis iris*) in PAU 5B and 5D. New Zealand Fisheries Assessment Report 2000/3.

Breen, P. A., N. L. Andrew, and T. H. Kendrick. 2000. Stock assessment of PAU 5B for 1998–99. New Zealand Fisheries Assessment Report 2000.

Chen, Y. 1996. A Monte Carlo study on impacts of the size of subsample catch on estimation of fish stock parameters. Fisheries Research 26:207–225.

Chen, Y., P. Breen, and N. Andrew. 2000. Impacts of outliers and mis-specification of priors on Bayesian fisheries-stock assessment. Canadian Journal of Fisheries and Aquatic Science 57:2293–2305.

Chen, Y., and D. Fournier. 1999. Impacts of atypical data on Bayesian inference and robust Bayesian approach in fisheries. Canadian Journal of Fisheries and Aquatic Science 56:1525–1533.

Chen, Y., and J. E. Paloheimo. 1998. Can a more realistic model error structure improve parameter estimation in modelling the dynamics of fish populations? Fishery Research (Amsterdam) 38:9–19.

Fournier, D. A. 1996. AUTODIFF. A C++ array language extension with automatic differentiation for use in nonlinear modeling and statistics. Otter Research Ltd., Nanaimo, British Columbia, Canada.

Fournier, D. A., J. R. Sibert, J. Majkowski, and J. Hampton. 1990. MULTIFAN: a likelihood-based method for estimating growth parameters and age-composition from multiple length frequency data set illustrated using data for southern bluefin tuna (*Thunnus maccoyii*). Canadian Journal of Fisheries and Aquatic Science 47:301–317.

Gavaris, S. 1988. An adaptive framework for the estimation of population size. CAFSAC research document 88/29. Canadian Atlantic Fisheries Scientific Advisory Committee, Department of Fisheries and Oceans, St. Andrews, New Brunswick, Canada.

Francis, R. I. C. C. 1992. Use of risk analysis to assess fishery management strategies: a case study using orange roughy (*Hoplostethus atlanticus*) on the Chatham Rise, New Zealand. Canadian Journal of Fisheries and Aquatic Science 49:922–930.

Hilborn, R., and C. J. Walters. 1992. Quantitative fisheries stock assessment: choice, dynamics, and uncertainty. Chapman and Hall, New York.

Kendrick, T. H., and N. L. Andrew. 2000. Catch and effort statistics for paua (*Haliotis iris*) in PAU 5A, 5B, and 5D, and a summary of standardised CPUE indices. New Zealand Fisheries Assessment Report 2000.

Kulka, D. W. 1996. Discarding of cod (*Gadus morhua*) in the northern cod and northern shrimp directed trawl fisheries, 1980–94. NAFO Scientific Council Studies 29:67–79.

Megrey, B. A. 1989. Review and comparison of age-structured stock assessment models from theoretical and applied points of view. Pages 8–48 *in* E. F. Edwards and B. A. Megrey, editors. Mathematical analysis of fish stock dynamics. American Fisheries Society, Symposium 6, Bethesda, Maryland.

Myers, R. A., J. F. Hutchings, and N. J. Barrowman. 1998. Why do fish stocks collapse? The example of cod in Atlantic Canada. Ecological Applications 7(1):91–106.

NRC (National Research Council). 1997. Improving fish stock assessments. National Academy Press, Washington D.C.

NRC (National Research Council). 1999. Sustaining marine fisheries. National Academy Press, Washington D.C.

Quinn, T. J., II, and R. B. Deriso. 1999. Quantitative fish dynamics. Oxford University Press, New York.

Parsons, L. S. 1993. Management of marine fisheries in Canada. NRC Research Press, Ottawa, Ontario, Canada.

Pope, J. G. 1972. An investigation of the virtual population analysis using cohort analysis. International Commission for the Northwest Atlantic Fisheries Research Bulletin 9:65–74.

Ricker, W. E. 1975. Computation and interpretation of biological statistics of fish populations. Bulletin of the Fisheries Research Board of Canada 191.

Shelton, P. A., D. E. Stansbury, E. F. Murphy, G. R. Lilly, and J. Brattey. 1996. An assessment of the cod stock in NAFO divisions 2J+3KL. DFO Atlantic Fisheries research document 96/80. Department of Fisheries and Oceans, St. John's, Newfoundland, Canada.

Sinclair, A., D. Gascon, R. O'Boyle, D. Rivard, and S. Gavaris. 1990. Consistency of some northwest Atlantic groundfish stock assessments. NAFO SCR document 90/96.

Smith, S. J., J. J. Hunt, and D. Rivard, editors. 1993. Risk evaluation and biological reference points for fisheries management. Canadian Special Publication of Fisheries and Aquatic Science 120.

Tallman, R., 1991. Reduction of uncertainty caused by discarding in the fisheries of the Gulf of St. Lawrence. NAFO Science Council Studies 16:39–48.

Walters, C. J. 1998. Evaluation of quota management policies for developing fisheries. Canadian Journal of Fisheries and Aquatic Science 55:2691–2705.