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# Drawbacks of complex models in frequentist and Bayesian approaches to natural-resource management

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**Abstract.** Previous studies have shown that, for managing harvest of natural resources, overly complex models perform poorly. Decision-analytic approaches treat uncertainty differently from the maximum-likelihood approaches these studies employed. By simulation using a simple fisheries model, I show that decision-analytic approaches to managing harvest also can suffer from using overly complex models. Managers using simpler models can outperform managers using more complex models, even if the more complex models are correct and even if their use allows the incorporation of additional relevant information. Decision-analytic approaches outperformed maximum-likelihood approaches in my simulations, even when Bayesian priors were uninformative.

**Key words:** Bayesian decision analysis; harvest models; maximum likelihood; modeling a semelparous species; natural-resource management; optimal model complexity; Ricker model equations.

## INTRODUCTION

Historically, there have been two opposing principles guiding the amount of complexity incorporated into models used for making environmental management decisions. The first was that acknowledging uncertainty greatly improves decisions (Hilborn and Peterman 1996). Because our understanding of ecosystems and anthropogenic influences on them tends to be poor and our data are limited and noisy, assuming our best model is correct often leads to disaster (Hilborn and Peterman 1996, Walters and Maguire 1996). We are better off admitting our uncertainty and examining the robustness of our decision to phenomena that cannot be definitively proven to exist; for example, an increase in the efficiency of harvesters over time, or the existence of depensatory (Allee) effects that might lead to the collapse of the population if its abundance were reduced too much. Incorporating these effects means adding functional relationships and parameters to our models, or trying alternative values of parameters that are already included.

However, the other principle is that our limited and noisy data are insufficient to allow estimating more than a few parameters reliably (Schnute 1987, Hilborn and Walters 1992). Studies have shown that attempting to fit models more complex than the data will support often results in very poor predictions (Uhler 1979). Management decisions based on such models can be very wrong (Hilborn 1979, Ludwig and Walters 1985). The consensus among natural-resource analysts was that the best decisions could be made using models with an interme-

diate level of complexity (Starfield and Bleloch 1986, Hilborn and Mangel 1997, Walters and Martell 2004). Such models gave better predictions than models not incorporating uncertainty, or than highly detailed models involving a higher degree of biological realism.

The statistical interpretation of these principles, taught in basic courses at every university, is that there is a trade-off between bias and variance (Burnham and Anderson 1998). The more real phenomena (and thus parameters) that are incorporated into a model, the lower the bias but the higher the variance in the parameter estimates. For management purposes, whether to add another parameter to a model depends upon the specific trade-off between increased variance and reduced bias, and how this affects the management objectives. However, it also depends upon the shape of the loss function (Reckhow 1994); i.e., the consequences to yield and stock health resulting from a sub-optimal management decision based upon an incorrect parameter estimate (Fig. 1).

With Bayesian methods, it is no longer obvious that there is a point of diminishing returns to incorporating additional parameters in the model; some Bayesian approaches can incorporate more parameters than data (Clark 2005). This is because Bayesian decision-analysis approaches do not rely solely on a (possibly bad) point estimate of the parameter value, but rather an entire probability distribution of possible values; the best action is chosen based on its probability-weighted outcome ("expected loss") over the range of possible states of nature (Keeney 1982, Berger 1985, Adkison and Peterman 1996, Punt and Hilborn 1997). Incorporating additional parameters has consequences. The results of Bayesian approaches using simple low-dimensional models vs. results obtained using biologically realistic, high-dimensional models may differ substantially (Clark 2005). The recommended management decision, which

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is the object of the analysis, may also change dramatically as complexity is added to the model (Pascual and Hilborn 1995, McAllister and Kirchner 2002).

It is often assumed that the decision-analytic results obtained using more highly parameterized models are better than those based on simpler models. This assumption, if true, would imply that models used in natural-resource management and conservation should become much more complex than they are currently. It would also imply that training of biometricians should increase the emphasis on computer programming and numerical analysis, as the technical aspects of decision analysis with complex models are quite challenging (Walters and Ludwig 1994, McAllister and Ianelli 1997, Punt and Hilborn 1997). However, a rigorous examination of the performance of decision analysis as a function of the complexity of the models used in the analysis has not been done.

I attempted to address the following questions:

1) Given data sets typical to natural resource management questions, can decision-analytic approaches based on biologically more realistic, highly parameterized models perform better than approaches based on simpler but less realistic models?

2) Does the amount and quality of the data available affect the optimal model complexity?

3) How severe are the consequences of using less complex, more tractable models in decision analyses?

I used an operating-model approach, in which the performance of a management approach is investigated in a realistic simulation (Kimura 1990, Butterworth et al. 1997), to address these questions. I simulated a semelparous population subject to human exploitation, controlled by simulated scientists and managers who were using either a maximum-likelihood approach or decision analysis to periodically update a harvest rate (Collie and Walters 1993). I examined how the complexity of the models used by managers affects their performance, measured in terms of both the health of the exploited population and the realized catch (see Plate 1).

## METHODS

### Models used

In this simulated fish-stock management, either of two models may be used by managers. The first is a Ricker stock-recruitment model where two parameters ( $\alpha$ ,  $\beta$ ) are estimated. The second is the Ricker model augmented to include environmental covariates, where additional parameters ( $\gamma$ ) quantifying the influence of the environmental factors are also estimated (Quinn and Deriso 1999). The latter is termed the "correct" model below, as it forms the basis for producing the simulated data.

In all trials, the simulated exploited population's recruitment is in fact governed by the more complex model; that is, the environmental factors affect recruitment. Managers estimate the likelihood of parameter combinations using either the correct, complex model or

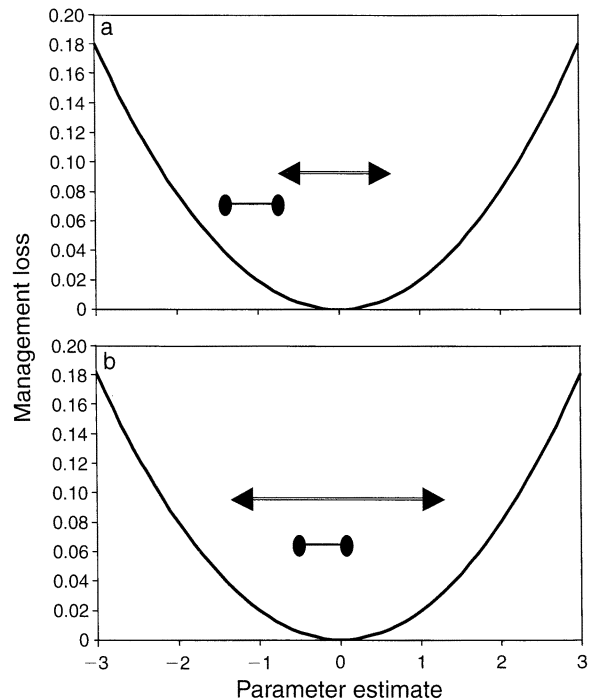


FIG. 1. Two contrasting cases of the trade-off between increased variance and reduced bias. The solid line shows the management loss given a particular estimate of the value for the parameter. The barbell represents the range of probable estimates for a model with few parameters. The arrows represent the range of probable values for a model with more parameters. (a) Adding parameters greatly reduces bias while only slightly increasing variance, thus reducing the statistical expectation of the loss. (b) Adding parameters greatly increases the variance relative to the reduction in bias, thus increasing expected loss.

the simpler two-parameter form that ignores environmental effects. The harvest rate is then chosen based on either the maximum-likelihood estimate of the model's parameters or on a Bayesian decision analysis. Managers choose the harvest rate that is predicted to give the largest expected value of the equilibrium catch.

**Ricker model equations.**—A model of a population of a semelparous species (e.g., a Pacific salmon) subject to harvest was constructed as follows:

$$S_{t+1} = R_t(1 - h) \quad (1)$$

$$R_t = S_t e^{(\alpha - S_t/\beta + \varepsilon_t)} \quad (2)$$

where  $S$  = spawners in year  $t$ ;  $R$  = recruitment from spawners in year  $t$ ;  $h$  = fraction harvested,  $\alpha$ ,  $\beta$  = parameters of Ricker model; and  $\varepsilon_t$  = environmental variation in recruitment in year  $t$ . Environmental variation is modeled as being due to both known and unknown factors, as follows:

$$\varepsilon_t = \left\{ \left[ 1 - \sum_{i=1}^j \text{abs}(\gamma_i) \right] \omega_t + \sum_{i=1}^j \gamma_i E_{i,t} \right\} \frac{\sigma}{k} \quad (3)$$

$$k = \sqrt{\left[1 - \sum_{i=1}^j \text{abs}(\gamma_i)\right]^2 + \sum_{i=1}^j \gamma_i^2} \quad (4)$$

$$\omega_t \sim \mathcal{N}(0, 1) \quad E_{i,t} \sim \mathcal{N}(0, 1)$$

where  $\omega_t$  = the random component of variation in recruitment in year  $t$ ;  $j$  = the number of environmental factors affecting recruitment;  $E_{i,t}$  = the value of the  $i$ th environmental factor in year  $t$ ;  $\gamma_i$  = the effect of the  $i$ th environmental factor on recruitment;  $\text{abs}$  = absolute value;  $\sigma$  = standard deviation (SD) in the logarithm of recruitment; and  $k$  = a scalar to ensure  $\sigma$  is the achieved SD.

The equations specify a standard Ricker curve, except that a fraction ( $\Sigma \gamma$ ) of the SD resulting from environmental variation ( $\varepsilon_t$ ) is due to one or more measured environmental covariates ( $E_t$ ). A scaling factor ( $k$ ) is calculated so that the total environmental variation retains a SD of ( $\sigma$ ), irrespective of the number or relative contribution of the environmental covariates.

In these simulations, the manager fitting a model to describe the dynamics of this stock and to estimate the best harvest rate to apply would face the following scenario: data available = vectors **R**, **S** and matrix **E**; unknown parameters ( $\alpha$ ,  $\beta$ , and, when environmental effects are estimated,  $\gamma$ ); and known parameters ( $\sigma$ ). Given values of the parameters  $\alpha$  and  $\beta$ , for a given harvest rate ( $h$ ) the equilibrium number of spawners ( $S^*$ ) can be shown to be

$$S^* = [\ln(1 - h) + \alpha]/\beta. \quad (5)$$

Likewise, the equilibrium catch is

$$C^* = S^*h/(1 - h) \quad (6)$$

(ignoring the effect of variability, which could be accounted for by multiplying by the constant  $\exp[\sigma^2/2]$ ; Hilborn and Walters 1992).

#### Likelihood and priors

To simplify the calculations involved in each of a great number of simulation trials, I assumed the parameter  $\sigma$  was known to managers employing both approaches. Accordingly, the joint likelihood ( $L$ ) of the parameters was proportional to the sum of squared residuals of the fit to the observed recruitments.

$$-\ln L \sim \sum_{t=1}^T (\ln R_t - \ln \hat{R}_t)^2. \quad (7)$$

In Bayesian applications, uniform priors were assigned to all other parameters over a wide range of biologically plausible values (for details see *Simulations: Simulation scenarios*, below). The priors for some parameters were unrealistically broad to minimize the potential for unintentionally incorporating informative boundaries (Adkison and Peterman 1996); however, the computational method for sampling from the posterior

(see *Simulation scenarios: Details ... Bayesian posterior*, below) would not explore values that greatly diverge from those supported by the data. To facilitate comparison among the maximum-likelihood and Bayesian approaches, in maximum-likelihood trials likelihoods were set to 0 for parameter values outside of the range of the priors, effectively incorporating identical prior information into both approaches.

#### Simulations

The simulations assumed that five years of spawner and recruit data were initially available. Managers then calculated the optimal harvest rate using one of the following approaches: maximum likelihood without environmental variables (ML), maximum likelihood with environmental variables (ML<sub>EV</sub>), decision analysis without environmental variables (DA), and decision analysis with environmental variables (DA<sub>EV</sub>). For computational simplicity, the harvest rates ( $h$ ) managers could select were constrained to increments of 0.01 between values of 0.01 and 0.99. Every five years the data to date would be reanalyzed, and the estimated optimal harvest rate updated. The simulated fishery ran 35 years. Performance was measured as the catch over the last 30 years of the simulation. The abundance of spawners in the last year of the simulation was also recorded.

*Details of maximum-likelihood parameter estimation.*—When employing maximum-likelihood methodologies, every five years the simulated managers used a nonlinear search algorithm to find the maximum-likelihood estimates of the parameters of the model they were employing (i.e., once every five years they would re-do their data analysis using all data to date). Once the parameter estimates were obtained, Eq. 6 was used to calculate the constant harvest rate (to the nearest 0.01) that maximized the equilibrium catch, conditional on these parameter values. This harvest rate ( $h$ ) was applied for the next five years of the simulation.

*Details of calculation of Bayesian posterior.*—When employing a Bayesian approach, every five years the simulated managers used a Metropolis (Markov chain Monte Carlo; MCMC) algorithm to draw sample parameter combinations from the posterior distribution. Each chain was started at the true parameter combination (an unrealistic shortcut used to minimize convergence problems), then run for 6000 iterations of which the first 1000 were discarded. The proposal distribution for the MCMC algorithm was a uniform distribution on a simple hypercube whose width was chosen from preliminary trials to give efficient sampling from the posterior (Gelman et al. 2004).

For each parameter combination drawn, the equilibrium catch was calculated for each possible harvest rate ( $h$ ) between 0.01 and 0.99. The expected catch for each harvest rate was next calculated as the average equilibrium catch (from Eq. 6) across all 5000 parameter combinations. The harvest rate that had the largest



TABLE 1. Average cumulative catch, years 6–35, from either 900 000 iterations (ML and DA) or 100 000 iterations ( $ML_{EV}$  and  $DA_{EV}$ ) of each scenario, based on the number of environmental variables (1, 2, or 5).

No. variables	$\sigma^\dagger$	$\gamma^\ddagger$	ML	$ML_{EV}$	DA	$DA_{EV}$
1	0.10	0.10	9.29	9.26	9.46	<b>9.46</b>
	0.10	0.20	9.29	9.27	9.46	<b>9.46</b>
	0.10	0.50	9.29	<b>9.44</b>	9.46	<b>9.54</b>
	0.60	0.10	8.27	8.10	8.54	8.42
	0.60	0.20	8.27	8.20	8.54	8.40
	0.60	0.50	8.27	<b>8.80</b>	8.54	<b>8.89</b>
	1.10	0.10	8.71	8.44	8.77	8.35
	1.10	0.20	8.71	8.50	8.77	8.49
	1.10	0.50	8.71	<b>9.26</b>	8.77	<b>9.16</b>
2	0.10	0.05	9.29	9.25	9.46	9.45
	0.10	0.10	9.29	9.24	9.46	<b>9.46</b>
	0.10	0.25	9.29	<b>9.35</b>	9.46	<b>9.51</b>
	0.60	0.05	8.27	7.87	8.54	8.44
	0.60	0.10	8.27	7.91	8.54	8.35
	0.60	0.25	8.27	<b>8.40</b>	8.54	<b>8.66</b>
	1.10	0.05	8.71	8.18	8.77	8.37
	1.10	0.10	8.71	8.17	8.77	8.42
	1.10	0.25	8.71	8.64	8.77	8.73
5	0.10	0.02	9.29	9.23	9.46	9.46
	0.10	0.04	9.29	9.22	9.46	9.46
	0.10	0.10	9.29	9.23	9.46	9.46
	0.60	0.02	8.27	7.84	8.54	8.41
	0.60	0.04	8.27	7.84	8.54	8.45
	0.60	0.10	8.27	8.17	8.54	8.53
	1.10	0.02	8.71	7.91	8.77	8.43
	1.10	0.04	8.71	7.94	8.77	8.53
	1.10	0.10	8.71	7.85	8.77	8.63

Notes: Bold numbers signify that a model incorporating environmental variables performed better than a model without these variables. Key to abbreviations: ML, maximum-likelihood model; DA, decision-analytic model; EV, with environmental variables.

$^\dagger$  Standard deviation of the logarithm of recruitment.

$^\ddagger$  Strength effect of each environmental variable.

expected catch was then applied for the next five years of the simulation.

**Simulation scenarios.**—I simulated 27 scenarios, with all possible permutations of the following alternative parameter values:

$$\sigma = 0.1, 0.6, \text{ or } 1.1$$

$$j = \text{number of environmental variables} = 1, 2, \text{ or } 5$$

$$\gamma = 0.1/j, 0.2/j, \text{ or } 0.5/j.$$

In all scenarios,  $\alpha = 1.0$ ,  $h = \alpha/2$  for years 1–5,  $\beta = 1$ ,  $S_1 = \text{the initial, first year spawner abundance}$ ; a random number uniformly distributed between 0 and  $\beta$ . For priors,

$$\alpha = \text{Uniform}(0, 1\ 000\ 000)$$

$$\beta = \text{Uniform}(0, 1\ 000\ 000)$$

$$\gamma = \text{Uniform}(-1/j, 1/j).$$

Based on the variability observed in preliminary trials, each scenario was simulated 100 000 times. Where environmental variables were ignored by analysts, all trials with a particular value of  $\sigma$  could be combined

(i.e., all nine permutations of  $j$  and  $\gamma$ ), for a total of 900 000 trials.

## RESULTS

The differences among management approaches were small (Table 1) relative to the variability among simulation trials; standard deviations of total yield were about 0.7, 3, and 5 for  $\sigma$  of 0.1, 0.6, and 1.1, respectively. Nonetheless, clear differences in the average performance of different approaches were seen. As predicted, in a maximum-likelihood framework using a simpler, incorrect, model was sometimes better than using the correct, but more complex, model. Managers employing the simpler maximum-likelihood (ML) model often achieved higher average yields than managers using the ML model with environmental variables ( $ML_{EV}$ ), even though the  $ML_{EV}$  model was correct (Table 1, Fig. 2). The same result was found for a Bayesian decision-analysis (DA) approach (Table 1, Fig. 3).

Simple, incorrect models gave better management results as the influence of the environmental factor affecting recruitment weakened. The correct model was superior if a single environmental factor explained 50% of the SD ( $\sigma$ ) in recruitment (i.e.,  $\gamma = 0.5$  and number of environmental variables = 1; lines 3, 6 and 9 in Table 1). For managers employing decision analysis, the correct model could also be superior (barely) with two environmental variables, or with a single environmental variable having a weaker effect, as long as the SD was not too large (lines 1, 2, and 11 in Table 1, Fig. 3). However, regardless of the statistical methodology, a model without environmental variables was usually superior if a single environmental variable explained only 10% or 20% of the SD in recruitment, if the environmental effects were due to multiple variables, or if the SD was larger (Table 1, Figs. 2 and 3).

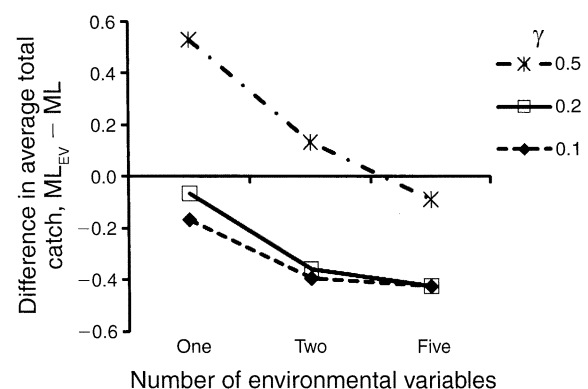


FIG. 2. Average difference in cumulative catch, years 6–35, between a maximum-likelihood approach incorporating environmental variables (100 000 simulations) and a maximum-likelihood approach without these variables (900 000 simulations); i.e.,  $ML_{EV} - ML$ . The x-axis shows the number of environmental variables affecting the Ricker stock–recruitment relationship, in total contributing 0.1 (solid diamond), 0.2 (open square), and 0.5 (asterisk) of the SD in recruitment. The SD ( $\sigma$ ) in these simulations is 0.6.

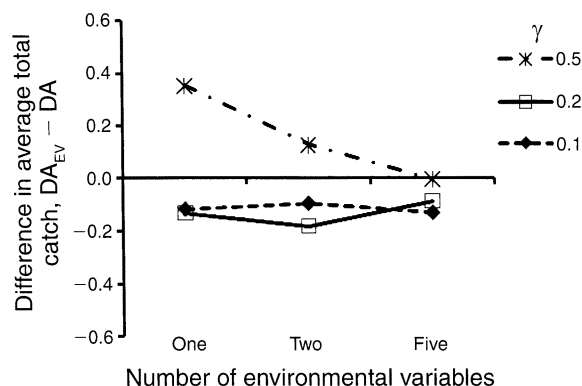


FIG. 3. This figure is the same as Fig. 2 except that it shows the difference in cumulative catch, years 6–35, between a decision-analytic approach incorporating environmental variables (100 000 simulations) and a decision-analytic approach without these variables (900 000 simulations); i.e.,  $DA_{EV} - DA$ .

As the information content of the data increased, the performance of the more complex models improved. Information content increases with the length of the time series available to managers, and decreases with the random variation about the stock–recruitment relationship. With low SDs ( $\sigma = 0.1$  or  $0.6$ ), the simpler model initially gave higher yields, but more complex models outperformed the simpler ones as the managers accumulated more years of data (Fig. 4).

Regardless of which model was used, decision analysis almost always gave a higher average yield than maximum-likelihood approaches (Table 1, Fig. 5). If environmental covariates were not included, this advantage was smallest when the SD of recruitment was large ( $\sigma = 1.1$ ). If environmental covariates were included, the advantage of a decision-analytic approach was smallest

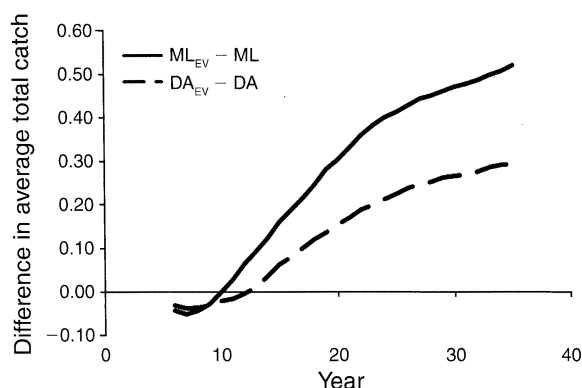


FIG. 4. Time series of the average difference in cumulative catch between managers using a model with environmental variables and those using a model without environmental variables. The solid line represents differences between managers using maximum-likelihood approaches ( $ML_{EV} - ML$ ); the dashed line represents decision-analytic approaches ( $DA_{EV} - DA$ ). Results are shown for years 6–35 of the simulations, where a single environmental variable contributes 0.5 of the SD in recruitment relationship. The SD ( $\sigma$ ) in these simulations is 0.6.

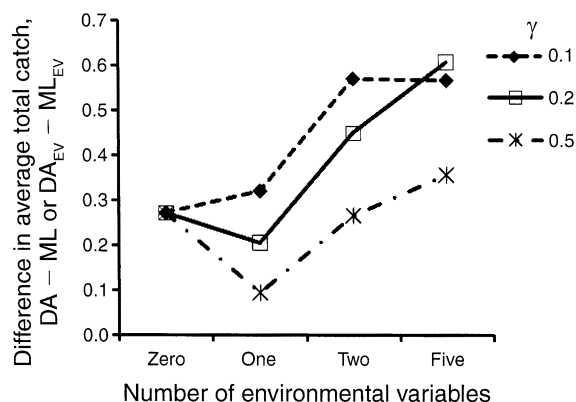


FIG. 5. This figure is the same as Fig. 2 except that it shows the difference in cumulative catch, years 6–35, between a decision-analytic approach and a maximum-likelihood approach using the correct model; i.e., either  $DA - ML$  (900 000 simulations) or  $DA_{EV} - ML_{EV}$  (100 000 simulations).

when environmental covariates had strong effects (Table 1). Decision-analytic approaches suffered smaller declines in yield than maximum-likelihood methods with more parameters in the model, particularly when five parameters were added (Table 1, Figs. 2 and 3).

There was very little difference among scenarios in the final status of the simulated stocks (not shown); across all 27 scenarios, average final stock sizes varied only between 0.36 to 0.43 (the optimal number of spawners was 0.44). (Note that the model abundances are fractions because, since the model dynamics are independent of the scaling parameter beta that controls abundance levels, I chose a beta value of 1.) However, decision-analytic approaches always resulted in average final stock sizes as large as or larger than maximum-likelihood methods, and also in a smaller probability that the spawning stock in year 35 was less than 0.1. The lowest values of final stock size resulted from maximum-likelihood approaches when the SD was high ( $\sigma = 1.1$ ). Highest values of final stock size tended to occur when the SD was lowest ( $\sigma = 0.1$ ), with both maximum-likelihood and decision-analytic approaches.

## DISCUSSION

Adding parameters to a model involves a trade-off; for a given data set, models with few parameters result in precise parameter estimates, while including additional parameters reduces precision but also reduces the bias in these estimates. The benefit of including additional parameters may not be realized, of course, if the equation that incorporates them does not reasonably accurately describe the effect of the factors they are designed to represent. The trade-off from adding parameters to a model is a statistical phenomenon not readily translated into real-world consequences, although management actions based on either highly biased or highly uncertain estimates of stock size and productivity are likely to be far from optimal. Ludwig



PLATE 1. Alaskan salmon seiners and spawning sockeye salmon. Photo credits: M. D. Adkison.

and Walters' (1985) simulation of an exploited fish stock showed that management performance (measured as the similarity between the true optimal harvest level and its model-derived estimate) could degrade as model complexity outstripped the information in the data.

The simulations presented here mirror their results. In many of the simulated scenarios, management scientists using a more complex model achieved lower yields than those using a simpler form. This was true even though the more complex model was correct, in that the environmental factors included did affect the productivity of the managed population. This poorer performance also occurred despite the fact that using the more complex model allowed the incorporation of additional relevant data, i.e., the time series of environmental states.

Maximum-likelihood approaches include a set of tools for limiting model complexity; e.g., tests of statistical significance or model selection tools like the Akaike information criterion (Burnham and Anderson 1998). However, the criteria used to decide whether to include an additional variable are based on statistical considerations that may not be closely related to management objectives, and they may not result in the optimal form for providing management advice (Walters and Martell 2004).

Bayesian decision-analytical approaches to resource management differ from maximum-likelihood approaches in the way that they deal with uncertainty. Alternative parameter combinations (and even model forms) are considered in Bayesian decision analysis, and the management action is chosen taking into account uncertainty about the true state of nature (Hilborn and Peterman 1996). However, accounting for this uncertainty can also have drawbacks. In this study, the increased uncertainty resulting from increasing the complexity of a model sometimes negated the benefit of additional realism, and even of incorporating additional relevant data. However, decision analysis appeared less sensitive than maximum-likelihood methods to the deleterious effects of increasing model complexity.

Very complex, highly parameterized models are sometimes employed by natural-resource scientists (e.g., McAllister and Ianelli 1997, National Research Council 1998, Hanselman et al. 2005). In the not-so-distant past, model complexity in Bayesian management approaches was constrained by computational limitations. Recent developments have made computational issues much less relevant; widely available tools such as WinBugs (Spiegelhalter et al. 2004) and AD Model Builder (Otter Software 1996) now make Bayesian



calculations for complex models widely accessible to management scientists with basic statistical training.

Decision analysis was superior to a maximum-likelihood approach in almost every simulation in this study, both in terms of average catch and average stock size. Decision analysis has two theoretical advantages over maximum-likelihood approaches. The one most often emphasized by advocates of its use for resource management is the ability of Bayesian statistical methods to incorporate additional information in the form of prior distributions (Brodziak and Legault 2005). This additional information might come from a meta-analysis of populations with similar properties (e.g., Myers et al. 1999, Chen and Holtby 2002), or could even be qualitative judgments elicited from experts (McDaniels 1995, Gavaris and Iannelli 2000). However, in the simulations presented here the prior distribution was not responsible for the superior performance of decision analysis. The prior contained no information beyond what was available to the maximum-likelihood approaches; priors were uniform over wide ranges, and in the maximum-likelihood estimation approach, likelihoods were set to 0 outside of these ranges.

Rather, the superior performance of the decision-analytic approaches came from their other theoretical advantage. The maximum-likelihood (ML) approach is to find the policy that gives the best predicted performance for a single (most likely) scenario corresponding to the ML parameter estimates. In contrast, the decision-analytic approach is to find the policy that gives the best expected performance across all scenarios, weighted by the probability that each scenario is true (Keeney 1982). This necessarily results in a policy that is robust to a range of plausible scenarios, rather than optimal for the single most likely one. The greater the uncertainty, the more robust the policy chosen. In a situation where the loss function is symmetric (i.e., where the cost of an overestimate is equal to that of an underestimate of the same magnitude), a maximum-likelihood approach and a decision-analysis approach will give similar recommendations (Reckhow 1994). However, symmetric losses are unlikely in a natural-resource management context where the population dynamics are complex and future population size depends on the current management decisions. As a result of selecting robust policies, not from including extra information, decision-analytic approaches proved superior in this study.

### *Conclusions*

This study suggests that for managing harvests of renewable natural resources, the optimal model structure is not necessarily the most realistic. The optimal model complexity is limited by the information content of the data. At times it can be better to ignore relevant data, as its information content may not be sufficient to justify the additional parameters necessary to incorporate it into the management model. The information

content is most obviously determined by the quantity of the data and the precision with which it is measured; however, other qualities can be just as important (Clark 2005). In Ludwig and Walters' (1985) simulations, information content was primarily determined by the "contrast" in the data, i.e., the range in the intensity of harvest rates and the resultant range of responses of the simulated fish stock available in the data. In the simulations presented here, the information content was primarily determined by the strength of the effect of the environmental variable on recruitment relative to the total variability in recruitment.

In this study, decision-analytic approaches had a performance superior to approaches based on maximum likelihood. In addition to their ability to incorporate additional data in the form of meta-analyses or expert opinion, decision analyses necessarily result in a harvest strategy that is robust to uncertainty, and this quality by itself can produce superior performance. Decision-analytic approaches were also more robust to degradation in performance caused by use of overly complex models. Nonetheless, this study suggests that simpler, incorrect models may still produce better management results than more realistic and complex models even when a decision-analytic approach is used.

How should management scientists decide whether to incorporate additional, model-complicating data into their management analyses? Unfortunately, I suspect a definitive answer requires extensive simulations using an operating model approach tailored to the specifics of the resource in question. However, natural-resource management analyses are most likely to benefit from an additional variable if it has been carefully measured, if there are many observations, if a wide range of values have been observed, and if it has a strong effect on the resource.

### ACKNOWLEDGMENTS

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### LITERATURE CITED

- Adkison, M. D., and R. M. Peterman. 1996. Results of Bayesian methods depend on details of implementation: an example estimating salmon escapement goals. *Fisheries Research* 25:155–170.
- Berger, J. O. 1985. *Statistical decision theory and Bayesian analysis*. Second edition. Springer-Verlag, New York, New York, USA.
- Brodziak, J., and C. M. Legault. 2005. Modeling averaging to estimate rebuilding targets for overfished stocks. *Canadian Journal of Fisheries and Aquatic Sciences* 62:544–562.
- Burnham, K. P., and D. R. Anderson. 1998. *Model selection and inference: a practical information-theoretic approach*. Springer-Verlag, New York, New York, USA.
- Butterworth, D. S., K. L. Cochrane, and J. A. A. DeOliviera. 1997. Management procedures: a better way to manage fisheries? The South African experience. *American Fisheries Society Symposium* 20:83–90.



- Chen, D. G., and L. B. Holtby. 2002. A regional meta-model for stock-recruitment analysis using an empirical Bayesian approach. *Canadian Journal of Fisheries and Aquatic Sciences* 59:1503–1514.
- Clark, J. S. 2005. Why environmental scientists are becoming Bayesians. *Ecology Letters* 8:2–14.
- Collie, J. S., and C. J. Walters. 1993. Models that 'learn' to distinguish among alternative hypotheses. *Fisheries Research* 18:259–275.
- Gavaris, S., and J. N. Ianelli. 2000. Statistical issues in fisheries' stock assessment. *Scandinavian Journal of Statistics* 29:245–267.
- Gelman, A., J. B. Carlin, H. S. Stern, and D. B. Rubin. 2004. *Bayesian data analysis*. Second edition. Chapman and Hall/CRC Press, London, UK.
- Hanselman, D. H., C. R. Lunsford, M. F. Sigler, and J. T. Fujioka. 2005. Alaska sablefish assessment for 2006. Pages 341–428 *in* Stock assessment and fishery evaluation report for the groundfish fisheries of the Gulf of Alaska. North Pacific Fishery Management Council, Anchorage, Alaska, USA.
- Hilborn, R. 1979. Comparison of fisheries control systems that use catch and effort data. *Journal of the Fisheries Research Board Canada* 33:1–5.
- Hilborn, R., and M. Mangel. 1997. *The ecological detective: confronting models with data*. Princeton University Press, Princeton, New Jersey, USA.
- Hilborn, R., and R. M. Peterman. 1996. The development of scientific advice with incomplete information in the context of the precautionary approach. Pages 77–101 *in* Precautionary approach to fisheries. Part 2: Scientific Papers. Fisheries Technical Paper 350/2. United Nations Food and Agriculture Organization, Rome, Italy.
- Hilborn, R., and C. J. Walters. 1992. *Quantitative fisheries stock assessment: choice, dynamics, and uncertainty*. Chapman and Hall, New York, New York, USA.
- Keeney, R. L. 1982. Decision analysis: an overview. *Operations Research* 30:803–838.
- Kimura, D. K. 1990. Approaches to age-structured separable sequential population analysis. *Canadian Journal of Fisheries and Aquatic Sciences* 47:2364–2374.
- Ludwig, D., and C. J. Walters. 1985. Are age-structured models appropriate for catch-effort data? *Canadian Journal of Fisheries and Aquatic Sciences* 42:1066–1072.
- McAllister, M. K., and J. N. Ianelli. 1997. Bayesian stock assessment using catch-age data and the sampling-importance resampling algorithm. *Canadian Journal of Fisheries and Aquatic Sciences* 54:284–300.
- McAllister, M., and C. Kirchner. 2002. Accounting for structural uncertainty to facilitate precautionary fishery management: illustration with Namibian orange roughy. *Bulletin of Marine Science* 70:499–540.
- McDaniels, T. L. 1995. Using judgment in resource management: a multiple objective analysis of a fisheries management decision. *Operations Research* 43:415–426.
- Myers, R., K. G. Bowen, and N. Barrowman. 1999. Maximum reproductive rate of fish at low population sizes. *Canadian Journal of Fisheries and Aquatic Sciences* 56:2404–2419.
- National Research Council. 1998. *Improving fish stock assessments*. Report of the Committee on Fish Stock Assessment Methods. National Academy Press, Washington, D.C., USA.
- Otter Software. 1996. *An introduction to AD model builder*. Available Box 265, Station A, Nanaimo, BC V9R 5K9 Canada.
- Pascual, M. A., and R. Hilborn. 1995. Conservation of harvested populations in fluctuating environments: the case of the Serengeti wildebeest. *Journal of Applied Ecology* 32:468–480.
- Punt, A. E., and R. Hilborn. 1997. Fisheries stock assessment and decision analysis. *Reviews in Fish Biology and Fisheries* 7:35–63.
- Quinn, T. J., II, and R. B. Deriso. 1999. *Quantitative fish dynamics*. Oxford University Press, New York New York, USA.
- Reckhow, K. H. 1994. Importance of scientific uncertainty in decision making. *Environmental Management* 18:161–166.
- Schnute, J. T. 1987. Data uncertainty, model ambiguity, and model identification. *Natural Resource Modeling* 2:159–211.
- Spiegelhalter, D., A. Best, N. Best, and D. Lunn. 2004. *WinBUGS user manual*. MRC Biostatistics Unit, Institute of Public Health, Cambridge, UK.
- Starfield, A. M., and A. L. Bleloch. 1986. *Building models for conservation and wildlife management*. McMillan, New York, New York, USA.
- Uhler, R. 1979. Least squares estimates of the Schaefer production model: some Monte Carlo simulation results. *Canadian Journal of Fisheries and Aquatic Sciences* 37:1284–1294.
- Walters, C. J., and D. Ludwig. 1994. Calculation of Bayesian posterior probability distributions for key population parameters. *Canadian Journal of Fisheries and Aquatic Sciences* 51:713–722.
- Walters, C., and J. Maguire. 1996. Lessons for stock assessment from the northern cod collapse. *Reviews in Fish Biology and Fisheries* 6:125–137.
- Walters, C. J., and S. J. D. Martell. 2004. *Fisheries ecology and management*. Princeton University Press, Princeton, New Jersey, USA.