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**Possible solutions to some challenges facing fisheries scientists and managers**

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## 1. Abstract

The purpose of this paper is to review some recent work on five key challenges in fisheries science and management: (1) dealing with pervasive uncertainties and risks, (2) estimating probabilities of occurrence for uncertain quantities, (3) coping with time-varying parameters, (4) evaluating performance of proposed management actions, (5) and communicating about technical issues. Many of these challenges are exacerbated in fisheries that harvest multiple stocks. Various methods provide partial solutions to these challenges: (1) Risk assessments and decision analyses take uncertainties into account by permitting several alternative hypotheses or assumptions to be considered at once. (2) Hierarchical models applied to multi-stock data sets can improve estimates of probability distributions for model parameters compared with single-stock analyses. (3) Kalman filters can improve tracking of temporally changing productivity of fish stocks resulting from factors such as climatic change. (4) Operating models of complete fishery systems provide comprehensive platforms for testing management procedures. (5) Finally, results from research in other disciplines such as cognitive psychology can facilitate better communication about uncertainties and risks among scientists, managers, and stakeholders.

Key words: Bayesian analysis, decision analysis, hierarchical models, Kalman filter, operating models, risk assessment, risk communication, uncertainty

## 2. Introduction

Fisheries scientists and managers face significant challenges on several fronts. Uncertainties are pervasive due to natural variability in components of aquatic ecosystems, imperfect information about those components, and lack of perfect control over fisheries. It is also difficult to estimate probabilities on the uncertain elements of stock assessments. Furthermore, climatic variability and change are potential sources of large alterations in productivity of fish stocks that must be taken into account when evaluating proposed management actions. Fisheries scientists who provide advice to managers also face the task of taking into account uncertainties and risks in their analyses and then communicating the complex and technical results effectively to decision makers and the public. Some key challenges facing fisheries managers and scientists include (1) dealing with pervasive uncertainties and the resulting risks, (2) estimating probabilities for those uncertain quantities, (3) recognizing and dealing with changes in parameters over time, (4) comprehensively evaluating management options while taking major sources of uncertainty into account, and (5) and communicating the essence of such elaborate analyses to interested parties.

These challenges apply to most fisheries situations, but they are amplified where a single stock is harvested sequentially by different fisheries or where multiple stocks are harvested in one fishery (multi-stock fisheries). Methods for responding to these challenges are widely applicable, and are not restricted to multi-stock situations. In some cases, multi-stock situations can provide opportunities for solutions to certain challenges.

This paper has two purposes. First, it elaborates on the above challenges facing fisheries scientists and managers. Second, the paper describes some potential solutions to each challenge by reviewing some recent research. Although most examples here are from Pacific salmon (*Oncorhynchus* spp.) fisheries, many of the lessons learned are applicable to other species.

## 3. Challenges and some possible solutions

### *3.1 Challenge #1 - Uncertainties and risks are pervasive*

To put the challenges facing fisheries scientists and managers into context, consider a typical fishery system (Figure 1), wherein the natural aquatic system is sampled by scientists and harvesters and the resulting data are used by stock assessment scientists to estimate abundance, productivity, recruitment, and other attributes of a stock. Scientists also estimate how several potential management actions, such as various harvest rates or enhancement activities, might affect indicators of outcomes. Scientists provide stock assessment advice to fisheries managers and interested parties (stakeholders), ideally with some iterative feedback. Managers then consider their management objectives along with input from stock assessment scientists and stakeholders before recommending a particular action such as a harvest rate, which then affects the natural system (Figure 1).

There are numerous sources of uncertainty (ellipses in Figure 1) in such fishery systems; five are: (1) natural variability across space and time in distribution, abundance, and productivity of fish populations, (2) observation error (i.e. imperfect information), which arises from measurement error as well as sampling error (Mace and Sissenwine, 2002), (3) difficulty with communication among scientists, managers, and stakeholders about technical scientific information and its associated uncertainties, (4) unclear management objectives, and (5) implementation error, which is the difference between a management goal and the actual realized state of spawning stock biomass or fishing mortality rate, for instance.

These uncertainties can be large and affect interpretation of data, results of analyses, rank orders of management options, and effectiveness of those options. They are important because they create risks -- biological risks for fish populations, economic losses for those in the fishing industry, and social disruptions for people in fishing-dependent communities. Uncertainties are pervasive; they occur in all fishery systems to varying degrees. Therefore, most decisions in fisheries management should take uncertainties into account. This applies to decisions not only on harvest regulations but also on activities such as ocean ranching and other attempts to increase abundance of fish stocks.

### *3.2 Potential solutions to challenge #1*

#### 3.2.1 Stock assessments can account for uncertainties

The challenge of pervasive uncertainties has been met by increasingly sophisticated technical tools in fish stock assessments. It is no longer widely acceptable to provide scientific advice to managers on possible consequences of management actions based only on best-fit, or point, estimates of current stock biomass and productivity parameters of stocks, for example. Stock assessments in many regions now routinely take several sources of uncertainties into account quantitatively (National Research Council (NRC), 1998; Quinn and Deriso, 1999). This includes the International Council for the Exploration of the Sea (ICES) region, where growing emphasis on conservation concerns and application of the precautionary approach (FAO 1995) has led to many analyses to estimate probabilities that stock indicators will cross reference points (Lassen and Sparholt 2000). Furthermore, the European Commission is actively encouraging policy-oriented research that takes uncertainties into account and applies risk assessment. In addition, various forms of risk assessment and decision analysis have been found particularly useful in certain situations for evaluating a broad range of management options in the context of uncertainties (Francis and Shotton 1997; McAllister et al. 1999).

### 3.2.2 Risk analysis

Risk analysis (i.e. risk assessment) includes four components. (1) At its core is a stochastic model of system processes that considers a wide range of quantified hypotheses about those processes, i.e. different parameter values or structural forms of relationships among variables. (2) Uncertainties are taken into account by weighting these alternative hypotheses by the degree of belief in them or the probability of their occurrence. (3) Indicators of uncertain outcomes are then derived from management objectives. (4) The model then estimates the probability distribution of these indicators for each of the proposed management actions.

Risk assessment methods for ecological systems were derived in the early 1990s from human health risk assessment techniques, which were designed to estimate health risks from toxic chemicals (NRC, 1993). Although there are obvious parallels in these two fields of risk assessment, there is one crucial difference. In assessment of risks to human health, the mortality rate was widely agreed upon as the most important indicator for determining the adequacy of regulatory policies. A standardized set of human health risk assessment procedures emerged (NRC, 1983). In contrast, in resource management, including fisheries, there are many indicators of interest, and some, such as biodiversity, are hard to quantify. Partly for this reason, no standardized risk assessment procedures have been developed for ecological systems, although various general frameworks have been used in several countries (Power and McCarty, 2002). An important point here is that assessment of risks in ecological systems is a relatively new field (NRC, 1993); methods are continually evolving, as can be seen in issues of journals such as *Risk Analysis* and *Human and Ecological Risk Assessment*.

Fisheries scientists, managers, and stakeholders should always carefully state what they mean when using the term "risk" to avoid misunderstandings. "Risk" has different meanings to different people. For example, a frequently used indicator of risk in the ICES region is the probability that a stock's biomass will drop below the biomass limit reference point, $B_{lim}$. Alternatively, members of the fishing industry are often more directly concerned with reductions in their harvest and revenue. Conservation groups might be worried about shifts in community structure as a result of harvesting certain species too heavily. Fisheries managers usually consider all of these indicators and more, while making difficult tradeoff decisions (the risk management step, discussed below). In any case, it is often appropriate to consider both components of risk, the probability of various events occurring, as well as the magnitude of each of those events' outcomes.

### 3.2.3 Decision analysis

Risk analyses should be taken further. It is not sufficient for decision makers to merely see a description and quantification of uncertainties and risks. Decision makers ultimately want to know how the uncertainties and risks affect the ability of each potential management option to meet a particular management objective (which may composed of several component sub-objectives). To provide this information, scientists often conduct decision analyses (Clemen, 1996; Peterman and Anderson, 1999), which add four new components to the four already mentioned for risk assessment: (5) one or more management objectives, (6) a decision tree or decision table to help structure the analysis and communicate its content, (7) a ranking of management options that results from conducting the decision analysis, and (8) extensive sensitivity analyses of effects of changes in various assumptions on that rank order of management options. In this context, risk assessment procedures can be thought of as a subset of the decision analysis approach (Figure 2). One fundamental difference between risk assessment and decision analysis is that the latter method focuses on how uncertainties affect the rank order of management options, given a management objective. Decision makers also benefit from sensitivity analyses that illustrate how that rank order changes for different management objectives.

Before giving a detailed example of decision analysis, I review several benefits of decision analysis over standard approaches to decision making. First, by taking uncertainties into account explicitly, decision analysis often indicates that a management option that will best meet an objective will be different than the one recommended by a simpler analysis based only on point estimates of parameters and state variables, i.e. ignoring uncertainties (Reckhow, 1994; Frederick and Peterman, 1995). For example, Robb and Peterman (1998) found that the abundance estimate for the Nass River (British Columbia, Canada) sockeye salmon (*O. nerka*) population that was optimal for opening an upstream First Nations fishery was 40,000 fish when only the point estimates of model components were used. In contrast, when a decision analysis was conducted that took into account uncertainty in both the structural form of the stock-recruitment relation as well as its parameters, that optimal abundance tripled to 120,000. The main reason for a decision-analysis result being different from the deterministic analysis is that in fisheries systems, losses associated with deviating from an optimal state are usually asymmetric (e.g. loss in long-term value of the catch is higher for a spawning biomass that is 50% below some desired level than for one that is 50% above). Similarly, probability distributions for uncertain quantities are often asymmetric. Given either of these conditions, it usually becomes optimal to choose an action that "hedges" away from the higher potential losses (Reckhow, 1994). When decision makers consider political, economic, and social pressures, the final recommended action may or may not still hedge in this direction.

A second benefit of decision analysis is that it can include various structural forms of models as alternative hypotheses in a single analysis. This is important because mis-specification of a model's components (compared to the real-world situation) may produce inaccurate estimates of outcomes, yet we usually do not know the correct specification of the model. A significant point is that decision analysis does not require scientists, stakeholders, or others to agree on which *single* model should be used in analyses of management options. Instead, several alternative models can be included. Analysts then have the difficult tasks of choosing which alternative models are legitimate and necessary to include, and assigning a probability to each model. These are complex topics beyond the scope of this paper, but Punt and Hilborn (1997) and McAllister and Kirchner (2002) provide excellent advice.

Third, decision analysis has been applied extensively in several fields, including applied ecology (Dorazio and Johnson, 2003) and fisheries management (Punt and Hilborn, 1997). It has provided valuable insights into complex decision problems.

Perhaps the most extensive example of a decision analysis in fisheries management is the recent evaluation of recovery plans for seven depleted spring and summer chinook salmon (*O. tshawytshca*) populations from the Snake River sub-basin of the Columbia River system in the Northwestern United States, which were listed under the U.S. Endangered Species Act (Peters and Marmorek, 2001). Adult and juvenile fish migrate through several reservoirs and dam systems, and also face problems from nearby agricultural lands, harvesting, predation, and changing of ocean conditions. Large uncertainties about the various factors that contributed to the decline in abundance of these stocks over the past several decades led to contentious debates about interpretations of data (Marmorek and Peters, 2001). A decision analysis framework included many of these hypotheses in one analysis along with uncertainties in them (Peters and Marmorek, 2001).

The decision analysis was aimed at identifying acceptable recovery options to be implemented by the U.S. National Marine Fisheries Service. One example of a quantitative management objective (the "recovery" objective) was to find a management action such that 6 out of the 7 Snake River stocks would exceed their respective desired target spawner abundances in at least 50% of the last 8 years of 48-year Monte Carlo simulations (Peters and Marmorek, 2001). Other management objectives considered by participants in this analysis had a similar format. This approach of using the top 6 of 7 stocks was designed to ensure that the best-off stocks met the objective, while recognizing that there is some non-zero probability that the recommended action will not be successful for all stocks. This approach to structuring a multi-stock management objective may be useful elsewhere.

A decision tree reflected many complexities of the Snake River chinook salmon problem (Figure 3). These dealt largely with uncertainties in the data and hypotheses about mechanisms operating during downstream freshwater migration by juveniles, as well as delayed mortality effects in the ocean. These uncertainties and hypotheses were described by stochastic simulation models. A wide range of weightings for alternative hypotheses were evaluated and one of the management options (A3), removing the lower four Snake River dams, was the highest-ranked and most robust option after extensive sensitivity analyses (Peters and Marmorek, 2001). It met the management objective stated above with the highest probability under the widest range of assumptions.

This example of the endangered Snake River chinook salmon also illustrates that decision analysis is a useful framework for focusing efforts of members of a diverse multi-stakeholder team and taking their various hypotheses and uncertainties into account (Marmorek and Peters 2001). Normally, decision analyses can also simultaneously include economic or other indicators to provide information for decision-makers who must make difficult tradeoffs. Unfortunately, for bureaucratic and jurisdictional reasons in this Snake River salmon problem, economic indicators of the effects of various management options were estimated by a separate group and were not part of this formal decision analysis. Even so, evaluations of the effect of uncertainties in biological and physical processes on performance of the management options were more thorough than would have been the case without a decision analysis.

Three recent examples of application of decision analysis illustrate the benefits of this method; the first two apply to problems in the ICES region. Kuikka et al. (1999) explored how environmental uncertainties affect recruitment and growth in Baltic cod and the optimal mesh size for managing that fishery. That decision analysis demonstrated that increased mesh size would reduce the probability of a stock collapse and also meet other management objectives. This decision analysis approach for Baltic cod has been accepted formally within the ICES region as a basis for scientific advice to managers for this stock. Another decision analysis on Baltic cod also showed that a reduced fishing mortality rate is necessary to substantially reduce the probability of stock collapse; this result was robust to various assumptions about the structure of the model (Jonzén et al., 2002). Finally, Punt et al. (2002) successfully used decision analysis to extensively evaluate harvesting options for Australia's multi-stock, multi-species South East Fishery.

Thus, risk assessment and decision analysis are useful tools for dealing systematically with some of the uncertainties and risks facing fisheries scientists and managers. Alternative hypotheses can be incorporated into a single analysis, numerous uncertainties can be taken into account explicitly, and the rank order of management options can be identified under a variety of assumptions through sensitivity analyses. Despite these benefits, annual stock assessments typically consider only some elements of complete risk assessments and decision analyses. It would be impractical to go through complete analyses each year when only small changes in stock status or management options are expected; annual stock assessments already consume considerable time and effort. Instead, comprehensive risk assessments and decision analyses are especially useful when developing pre-agreed-upon general management procedures that are intended to be in place for a considerable period before being re-evaluated (McAllister et al. 1999). This topic is expanded upon below under challenge #4.

### 3.2.4 Risk management

Risk management is the process in which decision makers "manage the risks" by choosing a particular action, or set of actions, after taking into account the scientific advice generated by the risk assessment, decision analysis, and stock assessment, *as well as other factors not considered explicitly in those analyses* (Figure 2). Because of this last point, risk management is not a purely scientific process. Management objectives usually include diverse components that lead to compromises or tradeoffs. For instance, a common three-part objective in fisheries management is to obtain an acceptably low probability that a fish stock will fall below a biomass limit reference point, while maintaining the cumulative harvest above some desired level and minimizing year-to-year variation in catch. Usually, all three indicators cannot be optimized at once, so tradeoffs are required. The relative weighting put on different components of an objective by decision makers is situation-dependent; there is no scientifically "correct" way to weight those components. Scientists can provide crucial advice, though, by indicating how much of one indicator will be lost for a given gain in another under each of a wide variety of possible management options.

Clear communication is critical at the risk management step. To improve the efficiency and effectiveness of decision-making, and to ensure that all the scientific information is understood, there should be an iterative, two-way flow of information among people responsible for the steps of risk analysis, decision analysis, and risk management (Figure 2), as well as the stakeholders. This is not intended to be a linear, single-pass-through procedure (Morgan and Henrion, 1990, p. 40). Furthermore, scientists should provide scientific advice in a format that is readily understandable by others (a topic covered below under challenge #5).

### *3.3 Challenge #2 - Estimating probabilities for uncertain quantities*

Another challenge for fisheries scientists is to estimate uncertainties for components of analyses such as those described in the decision analysis above. We can (1) directly calculate the probability from a lengthy data set, such as annual water levels in a river, (2) use judgments of experts, or (3) use the data available along with Bayesian methods to produce a posterior probability distribution describing the degree of belief in the uncertain components (Ellison, 1996; Punt and Hilborn, 1997). All three approaches face challenges. The first option is not commonly used because lengthy data series for uncertain components are rare in fisheries. The second option, seeking opinions from experts, is used widely. However, such elicitations of expert judgments are well known by cognitive psychologists to be subject to bias and incorrect estimates of precision due to many factors (Morgan and Henrion, 1990, p. 102). For instance, asking a group of experts to provide an estimate of a parameter somewhere within a designated range tends to produce a different distribution than if the question is completely open-ended, without a suggested plausible range. Furthermore, if a question is ambiguous concerning the exact quantity about which an opinion is being sought, each expert in a group might think about a different location, season, life stage, etc. when giving an opinion. This would make the distribution wider than it should be and might also bias it. An unambiguous question will ensure that experts' responses reflect only uncertainty about the parameter's value, rather than uncertainty about which entity the parameter represents (Morgan and Henrion's 1990 "clarity test", p. 50).

The third option for describing uncertainties in stock assessments, namely using the available data in conjunction with Bayesian statistical methods, is increasingly common, but it is far from widespread (NRC, 1998). A prior probability distribution can be combined with the likelihood distribution derived from the data and the resulting posterior probability distribution can quantify the degree of belief in different values of some parameter, for example. Such posterior probabilities can then be used in a risk analysis and decision analysis to weight the various hypotheses about the parameter's value. For complex fish stock assessment models that have numerous uncertain parameters, computationally intensive methods such as Markov Chain Monte Carlo (MCMC) methods (Gelman et al., 1995) or sampling-importance-sampling (SIR) algorithms (Rubin, 1988) can estimate joint and marginal posterior probability distributions.  MCMC methods are becoming easier to implement with new software (e.g. WinBUGS, Spiegelhalter et al., 1999).

One major challenge about this third, or Bayesian, option for describing uncertainties is deriving defensible prior probability distributions. When data are not very informative about a parameter due to too few data points, low contrast, or large natural variability and observation error, for example, the shape of the posterior probability distribution is greatly affected by the choice of the prior probability distribution (Ellison, 1996). This can have important management implications. If the resulting posterior probability distribution is too narrow, for instance, it may underestimate the probability of extreme cases that lead to deleterious conservation outcomes. This general problem is acute for relatively unproductive stocks that are a conservation concern (Rivot et al., 2001); such stocks typically have relatively few data and there is a potentially high cost of incorrectly estimating the probability of decline or recovery of a stock. For this reason, some researchers argue that, given relatively uninformative data, it is most appropriate to use an uninformative prior probability distribution to avoid biasing the posterior (Walters and Ludwig, 1994; Punt and Hilborn, 1997). Others argue to use independent biological information where it is available to create an informative prior (McAllister et al. 1994, 2001).

*3.4 Potential solutions to challenge #2*

Hierarchical models are a quantitative tool that can help deal with this issue and produce defensible informative priors through using large sets of data on multiple populations. Rather than assuming that each population's parameter values are statistically independent from those of other populations, hierarchical models allow for some underlying structure or pattern in parameters. For instance, all stocks of a given species might be assumed to have a maximum reproductive rate that is drawn from the same normal probability distribution, with a single mean and variance (e.g. Myers et al., 1999). Such models are hierarchical in the sense that each population's value of some uncertain parameter, such as the *'a'* parameter of the Ricker stock-recruitment model, represents a sample from a distribution that is described by unknown parameters, which must also be estimated. Hierarchical models include mixed-effects models (fixed and random effects) estimated by classical or Bayesian methods. Such models have proven very useful for combining information across multiple populations of the same or similar species, as well as across species, or across years (Myers et al., 1997, 1999, 2001; Liermann and Hilborn, 1997; Myers, 2001; Su et al., 2001; Adkison and Su, 2001; Chen and Holtby, 2002; Mueter et al., 2002a). These analyses have identified consistent and limited ranges of values for certain parameters across groups of populations, such as maximum annual reproductive rates across species worldwide (Myers et al., 1999) and a narrow range of coefficients reflecting effects of summer sea-surface temperature on survival rates of Pacific salmon populations (Mueter et al., 2002a). In the absence of other information, these types of results are useful either for establishing prior probability distributions for such parameters to be used in Bayesian updating or for specifying directly the posterior probability distributions or weightings to be used in decision analyses.

An example of applying a hierarchical Bayesian model (HBM) to pink salmon (*O. gorbuscha*) in the Northeastern Pacific Ocean demonstrates an additional benefit of this type of analysis: reduced uncertainty in parameter estimates of stock assessment models and improved advice to managers. A frequent challenge in parameter estimation is that natural environmental variation tends to mask underlying patterns in data. To the extent that multiple stocks share common environmental situations, they should show similar responses to environmental variation. Hierarchical models can attribute some of the observed variation to such common responses, thereby permitting better estimates of model parameters. To understand the following application of a hierarchical model to pink salmon, some further background is essential.

In previous work, we found that some of the 43 pink salmon stocks in the Northeastern Pacific Ocean showed positive covariation in their residuals from their stock-specific best-fit Ricker stock-recruitment model ("productivity") (Pyper et al., 2001). Productivity of nearby stocks (i.e. less than ~ 500 kms apart) was more positively correlated than between more distant stocks. This result is consistent with findings in a wide variety of species and locations, including Pacific herring (Ware and McFarlane, 1989); North Sea and North Atlantic fishes

(Shepherd et al., 1984), Baltic salmon (McKinnell and Karlstrom, 1999), Northeast Pacific sockeye and chum salmon (Peterman et al., 1998; Pyper et al., 2002; Mueter et al., 2002b), and numerous other marine and freshwater species (Myers et al., 1997). A consistent finding of most of these studies is that positive covariation in various measures persists for distances up to several hundred km, but as stocks become increasingly separated, the correlation decreases toward zero.

In our hierarchical Bayesian analysis of pink salmon, this positive covariation among stocks permitted us to treat nearby stocks as "statistical replicates" when fitting a model, which tended to average out observation errors across stocks (Su et al., 2003, submitted). We fit a generalized Ricker model:

(1) $$\log_e(R_{it}/S_{it}) = a_i - b_i S_{it} + \gamma_i SST_{it} + \varepsilon_{it},$$

where $S_{it}$ is the spawner abundance for stock $i$ in brood year $t$ and $i$ = 1, ..., 43, $R_{it}$ is the resulting recruitment, $a_i$ and $b_i$ are parameters of the basic Ricker model, $\gamma_i$ is the coefficient reflecting the effect of summer sea-surface temperature ($SST_{it}$) in the region where each stock's juveniles spend their first four months in the ocean, and $\varepsilon_{it}$ is the residual variation. We used spatially correlated prior distributions to reflect possible regional similarity of the stock-specific $a_i$ and $\gamma_i$ parameters (Su et al., 2003, submitted).

We found that our multi-stock hierarchical Bayesian model gave more precise estimates of the $a_i$ and $\gamma_i$ parameters than separate analyses of each stock (Figure 4) (Su et al., 2003, submitted). These narrower posterior probability distributions will lead to improved estimates of biological reference points that are affected by these parameters because some of the environmentally induced variation in productivity has been better accounted for than in single-stock analyses. Such probability distributions are also useful informative prior probability distributions for analyses of other pink salmon stocks, and can also be used to weight different combinations of parameter values in decision analyses.

Thus, although multi-stock situations normally create problems for scientists and managers (e.g. caused by simultaneous harvesting of several stocks with different productivities), in situations where several stocks respond similarly to some variable, hierarchical models can improve stock assessment information. Hierarchical models provide a consistent, rigorous method for estimating informative prior probability distributions that are more precise for certain parameters than if populations were analyzed separately. Furthermore, such methods should lead to improved confidence in the stock assessment process by managers and stakeholders. Despite these benefits, the hierarchical modelling approach is not appropriate for all parameters, because quantities such as a stock's unfished equilibrium are likely to depend on the quality of spawning or juvenile rearing habitat, which can vary dramatically between even nearby stocks due to human- or naturally-induced differences in habitat. In addition, the hierarchical modelling approach will not be useful for improving models of environmental effects on fish populations in cases where the responses to a given environmental variable are uncorrelated among stocks.

### *3.5 Challenge #3 - Time-varying parameters*

Most stock assessments assume that model parameters are constant over time, along with the limit and target reference points calculated from them. However, some parameters, such as body growth rate and productivity, respond to changing environmental conditions. Such parameters should therefore instead be considered variables in models (Walters, 1987). For instance, there was a regime shift to a more productive ocean system in the Northeast Pacific in the mid-1970s, most likely due to changing atmospheric and oceanographic conditions. Productivities of many sockeye salmon stocks increased as a result (Adkison et al., 1996; Peterman et al., 1998). Such changes have important management implications. In periods of low productivity, proportional harvest rates should be reduced, and in periods of high productivity they can be increased. If stock assessment models assume that productivity is constant, then insufficient action may result during unproductive periods to protect stocks from potentially serious overfishing. Unfortunately, only the largest and most rapid changes in parameters are recognizable amid the noise of observation error and natural variation in survival and recruitment. The challenge is thus to build stock assessment models that can reflect temporal changes in important coefficients of model processes.

*3.6 Potential solutions to challenge #3*

The most common approach to dealing with this issue is to make a quantity such as the natural mortality rate, M, a function of one or more variables, such as predator abundance. This approach is used in those few cases where appropriate data are available (e.g. multi-species virtual population analysis in the ICES region, supported by extensive data on stomach samples, e.g. Rice and Gislason, 1996). Where such data do not exist, simple parametric sensitivity analyses can be conducted using low, medium, and high values of the parameter that is considered to be a variable.

The general method of state-space modelling (Chatfield, 1989) is a more comprehensive method for dealing with time-varying parameters though. Many scientists have used this approach to estimate time-varying parameters of fish stock assessment models, most commonly using a Kalman filter (Collie and Sissenwine, 1983; Walters, 1986; Mendelsohnn, 1988; Pella, 1993; Schnute, 1994; Millar and Meyer, 2000).

A simple example illustrates how a Kalman filter model works. Based on previous analyses (Adkison et al., 1996; Peterman et al., 1998), we cast a Ricker (1975) stock-recruitment model for sockeye salmon in the context of a Kalman filter to allow the Ricker *a* parameter to vary over time (Peterman et al., 2000, 2003). A Kalman filter consists of two parts. First is the "observation equation" (Chatfield, 1989), which in our case described the relationship between the two observed quantities, $R_t$ and $S_t$:

(2) $$\log_e(R_t / S_t) = a_t + bS_t + v_t$$

where $S_t$ is abundance of spawners in brood year *t*, $R_t$ is abundance of adult recruits of all ages produced by those spawners, *a* is the mean productivity (in units of $\log_e(R/S)$) at low spawner abundance, and *b* reflects the effects of spawner abundance on productivity. This equation differs from the standard Ricker model in one important way: the *a* parameter is subscripted by brood year, *t*, to reflect changes over time in productivity. Those temporal changes are governed by a second stochastic process, described by the "system" or "state equation" (Chatfield, 1989); we assumed a random walk process:

(3) $$a_t = a_{t-1} + w_t \ .$$

The error terms $v_t$ and $w_t$ in equations (2) and (3) are assumed to be normally distributed and independent, with variances $\sigma_v^2$ and $\sigma_w^2$, respectively. We termed equations (2) and (3) together the "Kalman filter random-walk" model. We used a simple, yet flexible, random walk in equation (3), rather than a particular temporal pattern, because no one knows the temporal changes that have occurred in the true $a_t$. Nevertheless, as shown by the simulations in Peterman et al. (2000), such a Kalman filter random-walk model performs relatively well at tracking a wide variety of true underlying temporal trends in $a_t$, including sinusoidal patterns, step functions, and autoregressive processes (Figure 5).

Because our simulations showed that this Kalman filter random-walk method for estimating the Ricker *a* parameter had the best performance compared to other common parameter estimation methods (Peterman et al., 2000), we used a Kalman filter in a separate empirical analysis to reconstruct the best estimates of Ricker $a_t$ values for the world's most abundant and commercially valuable sockeye salmon stocks, those in Bristol Bay, Alaska (Peterman et al., 2003). Most of these eight major stocks showed considerable temporal variation in reconstructed productivity (likely induced by oceanographic conditions) at both short and long time scales; three examples are given in Figure 6. Productivity of some stocks increased over the 40-year period, others decreased, and yet others showed periods of both large increases and decreases. These temporal changes in productivity have important management implications. The proportional harvest rates that would have maximized the sustainable yield (which was the management goal in Alaska for these stocks) were quite different in some periods from the optimal harvest rate estimated from the standard Ricker model that assumed constant parameters (Figure 7). Analyses of such stocks using a Kalman filter approach may thus improve decision making by providing evidence of changing productivity.

*3.7 Challenge #4 - Evaluating performance of management options*

Even if the challenges described above are met, scientists and managers will still be uncertain about which management option will best meet a given management objective, due to the complex feedbacks among system components.

*3.8 Potential solutions to challenge #4*

Given a clearly stated objective, simulations can be done to evaluate the relative performance of management options before they are put into practice. Although fisheries scientists routinely conduct numerous stochastic simulations, the most comprehensive method to evaluate options is to simulate the workings of the entire feedback system shown in Figure 1 (not just part of it) using an "operating model" (Linhart and Zucchini, 1986). Such models are analogous to flight simulators; the latter include detailed dynamic feedback processes to help pilots determine which decision-making protocols work best to meet a given objective (e.g. reaching the simulated destination) in the presence of a wide range of possible, but uncertain, simulated contingencies. Similarly, operating models of fisheries typically simulate (1) the stochastic dynamics of a "true" (or assumed) natural population, (2) a process of sampling data from that true population, including observation error, (3) a stock assessment step that uses those sampled data to update annual estimates of state variables and parameters, (4) harvest control rules that specify the effect of estimates from the stock assessment step on the choice of management actions by decision-makers who have a given objective, (5) implementation of those actions, and (6) the effect of those realized actions on the "true" population (Punt, 1992; de la Mare, 1996, 1998; Sainsbury, 1998). This process is usually repeated over many simulated decades in thousands of Monte Carlo trials, with indicators calculated to determine how well the management objective is met.

Normally, operating models are used to explore numerous situations and structures for the first four components of the system described in the paragraph above. First, a wide range of alternative hypotheses about scenarios for the "true" population are routinely considered in successive simulations. The specific nature and form of steps 2, 3, and 4 (collectively often called a management procedure, de la Mare, 1996) can be varied across runs of the operating model to determine the best combination of sampling procedure (e.g. sampling methods and times/places to sample), types of models and parameter estimation methods (e.g. constant or time-varying parameters, maximum likelihood or Bayesian updating), and harvest control rules (functional forms and parameter values). The final result of applying an operating model is a relative ranking of management procedures based on those that are most robust to a wide range of conditions. Just as with decision analysis, sensitivity analyses can be done to illustrate how that ranking changes with different management objectives.

The fifth component of an operating model mentioned above, implementation error, is extremely important. Implementation error is the deviation between a desired state and the actual realized outcome (Rosenberg and Brault, 1993; Rice and Richards, 1996). This error arises from a combination of non-compliance with regulations by harvesters, changing catchability, other dynamic processes in the fishing fleet, natural processes such as unusual ocean conditions, or choice of the wrong management action to achieve a target objective. Implementation error can be a large source of uncertainty and variation, yet it is rarely included in the exploration of management options in stock assessments. To rectify this situation, simulations of performance of management actions can include implementation error by using a stochastic harvesting process in an operating model. In certain cases, the magnitude and direction of implementation error can be captured by relatively simple stochastic relationships that reflect the net effect historically of the physical, biological, and human processes that create implementation error, even though the details of those processes are not known (Bocking and Peterman, 1988; Peterman et al., 2000).

Such comprehensive operating models of entire fishery systems provide a strong test of the robustness of management options (Cooke 1999). An excellent and early example of the application of operating models to evaluate management procedures was the International Whaling Commission's (IWC's) development of the Revised Management Procedure (RMP) (IWC, 1994 Annex H; de la Mare, 1996; Kirkwood, 1997). The IWC's analyses explored many shapes of functions for the harvest control rule in the presence of uncertainty in estimates of whale abundance (based on studies of errors in visual sitings). Those analyses also examined model performance under numerous combinations of uncertainty in stock identity (in multi-stock fisheries) and temporal trends in abundance and productivity of whales arising from environmental change and interactions with other species. The harvest control rule that performed best for the whale situation was robust to these sources of uncertainty (de la Mare, 1996). Operating models have also been applied in many other situations (e.g. Smith, 1993; Butterworth and Punt 1999 and the rest of that issue of the ICES Journal of Marine Science; Peterman et al., 2000). The European Commission and ICES scientists are currently actively developing operating models for a wide variety of fisheries in the ICES region to derive robust management procedures (including harvest control rules) for each (e.g., Kell et al. 1999). The general conclusion from past work on this topic is that such comprehensive simulations of sources of uncertainties provide different recommendations to decision makers than if an analysis of only a subset of those uncertainties were conducted.

### *3.9 Challenge #5 - Communication*

Communication among scientists, managers, and stakeholders is another source of uncertainty or error that affects fishery systems (Figure 1). Stock assessment, risk analysis, and decision analysis are highly technical endeavors and it is difficult to effectively convey the assumptions, results, and implications to people who are not actively involved in analyses. Many sources of communication problems are obvious, but some are more subtle. As an example of the latter, cognitive psychologists who do research on how people reason about uncertainties and risks have found that there can be widely different intuitive interpretations of such seemingly straightforward terms as "probability". Teigen (1994) found that people interpret "probability" in six different ways. It can reflect the (1) *chance* of seeing a given outcome for a stochastic process (which most scientists would intend in a stock assessment context); (2) *tendency* or ease with which some event is perceived to occur (if a stock size has been low recently, people may perceive a higher *tendency* probability of its dropping dangerously low, even if a calculated *chance* probability indicates otherwise); (3) *knowledge* or awareness of the range of possible outcomes (if you are aware of only one possible outcome, you will assign it a high *knowledge* probability); (4) *confidence* or degree of subjective belief in some outcome based on one's experience, (5) *control*, with more management influence over the outcome leading to a higher perceived probability of an outcome occurring, or (6) *plausibility* of the scenario (how convincingly the case is presented). Thus, what may seem like a relatively simple concept to fisheries scientists who use "probability" every day may inadvertently lead to misunderstanding because a given style or format of presentation may trigger different probability concepts in listeners.

*3.10 Potential solutions to challenge #5*

There is no simple answer to the problem of communicating technical information. It takes concerted effort by managers, scientists, and stakeholders through ongoing involvement in analyses to improve mutual understanding (e.g. Smith et al. 1999). As well, scientists could use more training in how to communicate technical concepts more effectively to non-technical audiences. For example, after extensive experiments, Gigerenzer and Hoffrage (1995) found that people were more likely to correctly interpret the *chance* probability noted above when results were stated in frequency format rather than as decimal probabilities. Fisheries scientists should exploit this finding when presenting the probability of some outcome occurring under a proposed management regulation (i.e. Teigen's 1994 *chance*). For instance, compare the following statements about the effect of a proposed fishing mortality rate:

- "There is a probability of 0.2 (or a 20% chance) that the stock biomass will drop below its limit reference point within 5 years."
- "Two out of every 10 situations like this will lead to the stock biomass dropping below its limit reference point within 5 years."

Those who work frequently with numbers know these are equivalent statements, but it has been shown that for most people, the second statement is less likely to cause confusion because its frequency format prompts concrete thinking about sets of cases, which can be visualized and counted (Gigerenzer and Hoffrage, 1995). This frequency format is easier, more direct, and less ambiguous than thinking about the decimal probability of the low-abundance situation. Anderson (1998) provides other examples of applying these concepts of frequency format to management of natural resources.

To extend this idea of frequency format for uncertain events to a multi-stock fishery, consider a case in which 5 fish stocks are vulnerable to harvest in a given area and time, but they differ in their limit reference points and current stock biomass relative to those reference points. Say that stock assessment scientists evaluated a particular proposed management regulation via Monte Carlo simulation. If they used the recommended frequency format, they would, for example, report that "In 3 out of 10 situations like this, any 2 of the 5 fish stock biomasses would drop below their limit reference points in the time period considered." According to the studies of Gigerenzer and Hoffrage (1995), fisheries managers and stakeholders would find this statement more understandable (and would act more logically and consistently on the information) than a statement using the more typical probability format, such as "There is a probability of 0.3 that 40% of the stocks would drop below their limit reference points in the time period considered."

This simple idea of using frequency format has another benefit; it may help reduce the confusion over the term "risk" discussed earlier. Mislabeling a probability of an undesirable outcome as a "risk" reflects a failure to understand the dimensions (units) of risk and its components. In the concretely pictured sets produced in peoples' minds by presenting information about uncertainties in a frequency format, the tangled concept of risk and its attendant arithmetic and dimensional errors would scarcely come up. Thinking in frequencies automatically and intuitively separates the two components of risk described earlier into two activities everyone does easily from an early age -- they *visualize* the possible outcomes and their costs as separate cases, and they *count* the cases.

Everyone working in fishery systems should also recognize the special problem that perceptions of risk are often quite different from experts' estimates of risk (Slovic, 1987). Perceptions of risks by stakeholders tend to be higher than estimated risks when, (1) they have less control over uncertain events, (2) they are not actively involved in the decision-making process, (3) the source of risks is completely new, or (4) risks are not being shared equally among stakeholder groups (Slovic, 1987). This again is a well-studied topic in the literature of cognitive psychology and management science. If fisheries scientists and managers are aware of these factors affecting perceptions of risk, they can take steps to reduce errors of interpretation and conflicts. Fisheries scientists and managers would therefore benefit from becoming familiar with research results in this area and from involving cognitive psychologists in projects, such as Gerd Gigerenzer and his colleagues (Gigerenzer et al., 1999; Gigerenzer, 2000).

## 4. Conclusion

There is one last important point to make about uncertainties and risk management. Sometimes decision makers become unjustifiably concerned about the reliability of biological information provided by fish stock assessment scientists because of the numerous uncertain components that are included in analyses, such as alternative structural forms of models and probability distributions of parameter values.  However, managers and stakeholders should keep these detailed descriptions of uncertainties in perspective. They should *not* put low weight on the biological information simply because fisheries scientists have been so explicit about describing major sources of uncertainties. Such uncertainties also exist for economic and social factors; they are just not usually as well described as the uncertainties associated with physical and biological factors. Fisheries managers and stakeholders should therefore set the same standards for accepting information as evidence for economic and social indicators as they do for physical and biological indicators. Of course, the response will be, "We don't have the same extent of data on economic and social indicators." This may be true. Nevertheless, economic factors such as price/tonne of fish show considerable uncertainty, analogous to that of oceanographic factors affecting mortality of fish, for instance. We should therefore encourage more research on economic and social processes, including those in the fishing sector such as movement of vessels and discarding behavior of vessel crews (Hilborn, 1985; Dorn, 2001; Ulrich et al. 2002). Results of such research should aim to incorporate harvesters into models as dynamic, not static, components, and to reflect uncertainties in processes and parameter values.

This review paper has highlighted some major challenges in fisheries science and management. Potential solutions to these challenges are provided by advanced quantitative methods such as decision analysis, Kalman filters, hierarchical models, and operating models. Methods and lessons learned from other disciplines such as cognitive psychology can also help deal with the challenge of improving communication among scientists, managers, and stakeholders. Considerable research is already being conducted on many of these topics by scientists in the ICES region and elsewhere. Despite these advances, there is still substantial work to be done. Not only do the methods such as decision analysis need to be applied in a wider variety of situations, but the underlying assumptions made by each approach to the five challenges discussed here need to be further explored.

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**Figures**

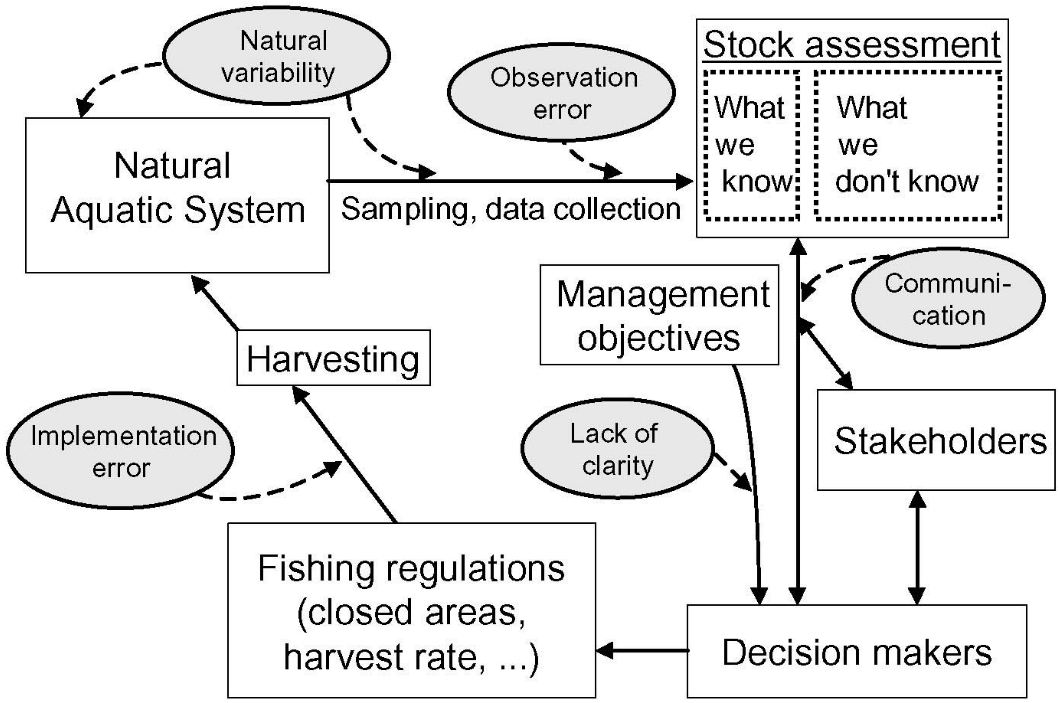


Figure 1. A conceptual diagram of the flow of information and actions in a typical fishery system. Rectangles represent components of the system, solid arrows indicate flows of information and actions between components, and ellipses represent major sources of uncertainty (adapted from C.J. Walters (personal communication); Hilborn and Peterman,1977; and de Young et al., 1999).

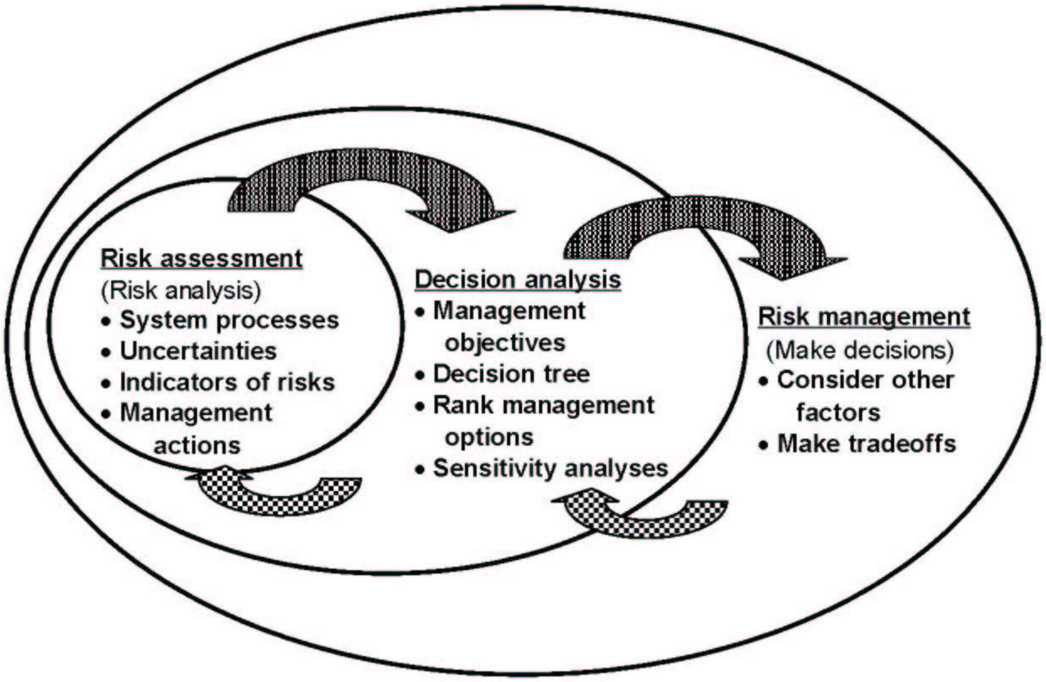


Figure 2. Risk assessment or risk analysis is a component of a decision analysis, which considers those uncertainties and risks when ranking management options in the context of a stated management objective. Results from these analyses provide advice to decision makers (risk managers), who also consider other information. Checkered arrows indicate iterative feedback.

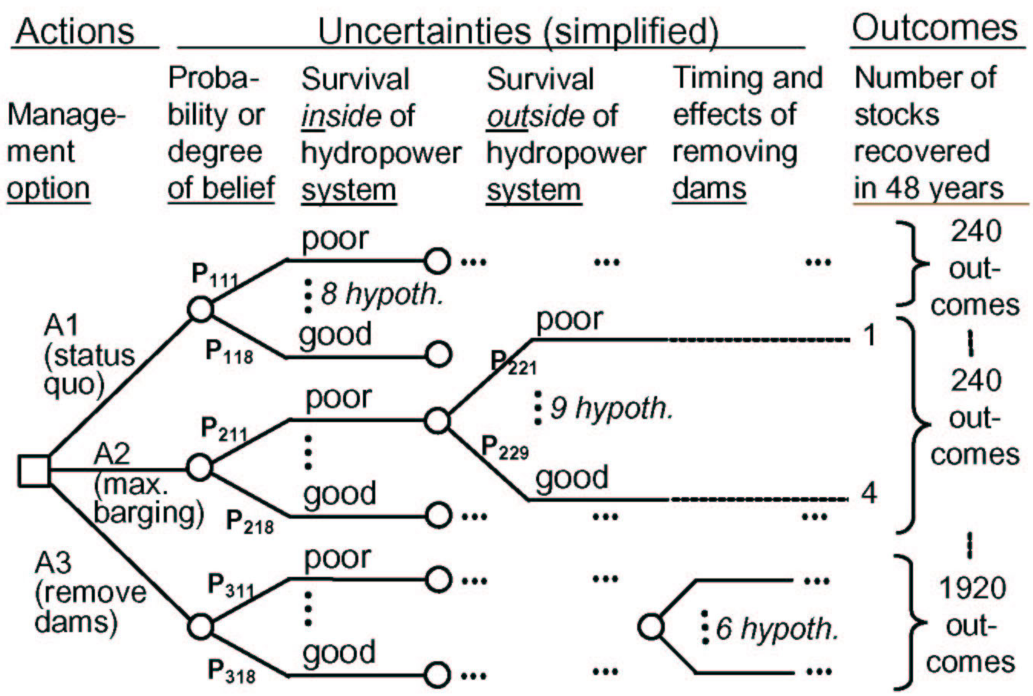


Figure 3. A simplified decision tree representing the main elements of the analysis of management options for meeting a recovery objective for the seven spring and summer chinook salmon populations of the Snake River, western United States (U.S.), that were listed under the U.S. Endangered Species Act. The three main management actions (out of six actually considered) were status quo (A1), maximize barging of juveniles during downstream migration (A2), and remove the four lower Snake River hydroelectric dams (A3). Numerous uncertain hypotheses (only some of which are shown, as reflected by ... symbols) are grouped into three categories, survival rate of juveniles inside the hydroelectric power system, survival rate outside that system, and the timing and physical/biological effects on the river of removing the dams. Each uncertain state of nature had a probability of occurrence ($P_{ijk}$) (varied in later sensitivity analyses). The model calculated an outcome (in terms of the number of chinook stocks recovering) for each combination of management action and uncertain state of nature. Management options were ranked based on the expected (weighted average) outcomes across all possible states of nature (adapted from Peters and Marmorek, 2001).

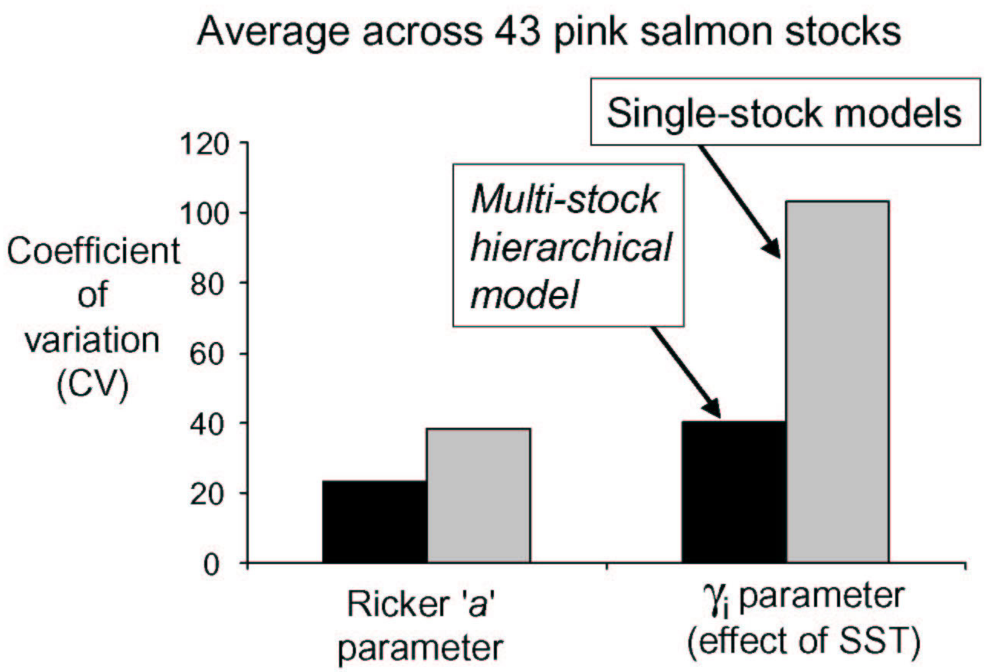


Figure 4. Averages across 43 pink salmon stocks from the Northeastern Pacific (Washington state, U.S.A., through to western Alaska) of coefficients of variation (standard deviation divided by the mean) for estimates of $a_i$ and $\gamma_i$ in equation (1). Hatched bars in each pair are for estimates derived from fitting equation (1) to each stock's data separately; solid bars are for estimates from the multi-stock hierarchical Bayesian model (results adapted from Su et al., 2003, submitted).

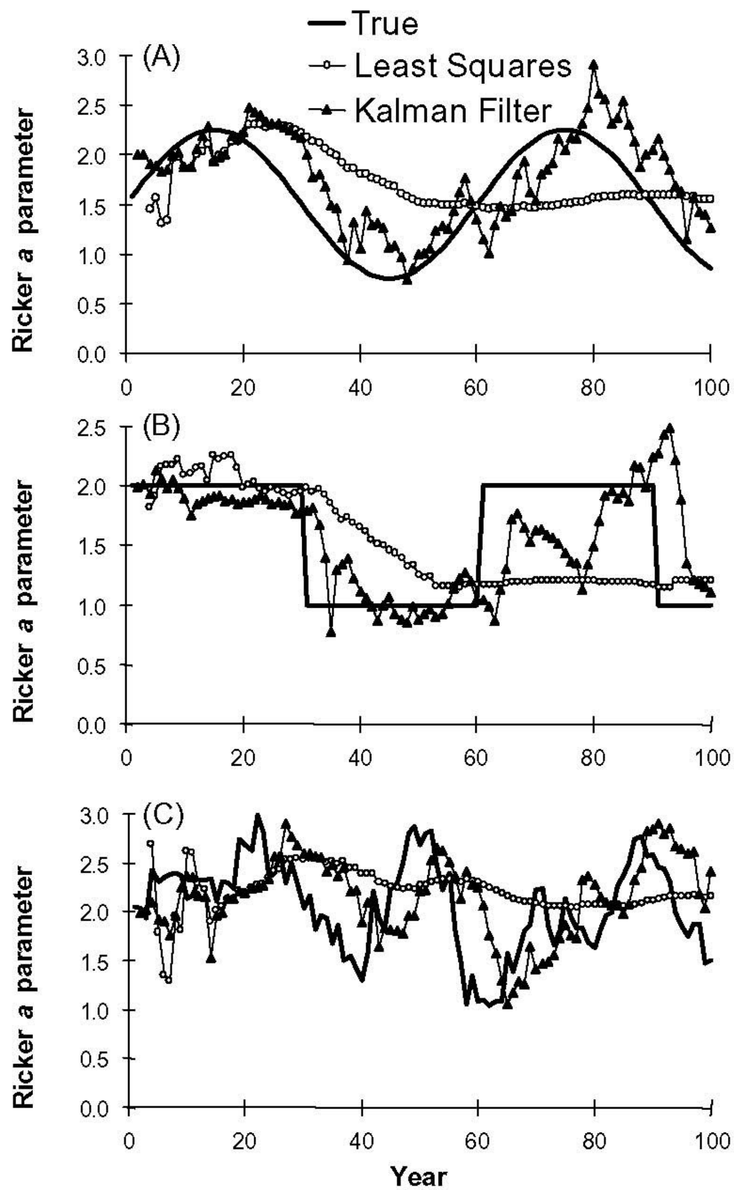


Figure 5. True values (solid lines) of the Ricker *a* parameter for a simulated pink salmon stock and values estimated annually using standard least squares (open circles) or a Kalman filter (solid triangles). Hypothetical scenarios for the true Ricker *a* value are (A) sine wave, (B) step function, and (C) autoregressive (AR(1)) processes (reprinted from Peterman et al., 2000).

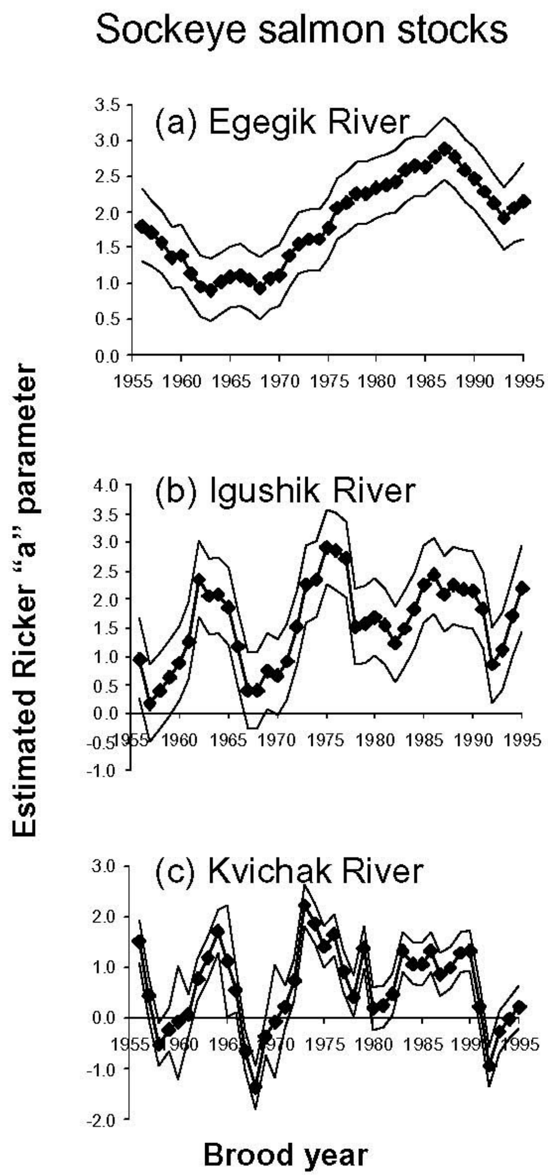


Figure 6. Estimates of the smoothed Ricker *a* parameter (solid diamonds) for three stocks of sockeye salmon from Bristol Bay, Alaska derived using a Kalman filter random-walk model, with 95% confidence limits (thin lines) (adapted from Peterman et al., 2003).

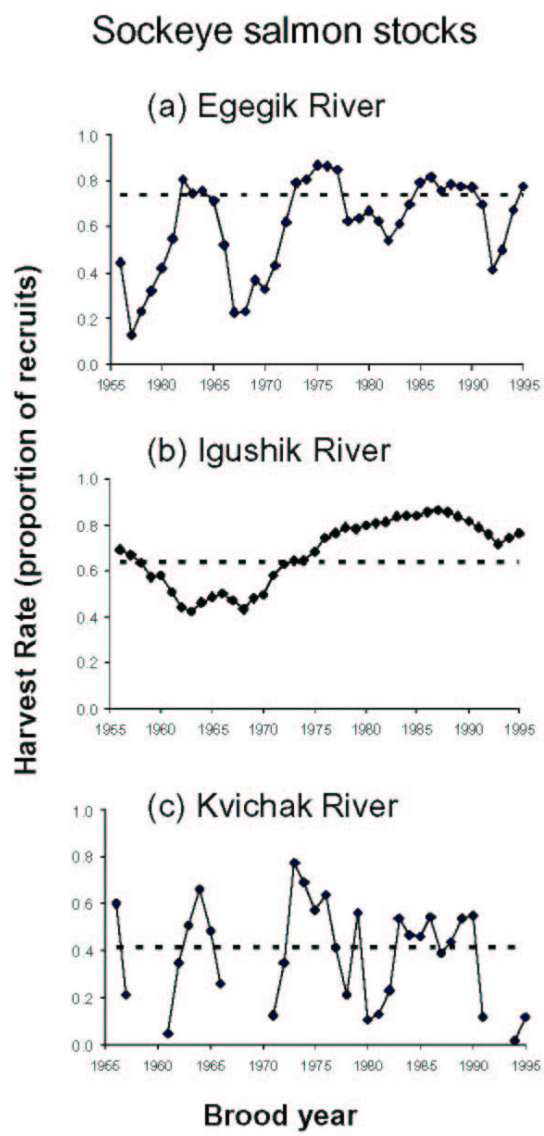


Figure 7. Optimal proportional harvest rates for the same sockeye salmon stocks as in Figure 6, based on parameter estimates from the Kalman filter (solid diamonds) or the standard Ricker model (dashed line) (adapted from Peterman et al., 2003). It is not possible to estimate optimal harvest rates for years in which the estimated Ricker $a_t$ value is negative (see Figure 6).