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Possible solutions to some challenges facing fisheries scientists and managers

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The purpose of this paper is to review recent work on four key challenges in fisheries science and management: (1) dealing with pervasive uncertainties and risks; (2) estimating probabilities for uncertain quantities; (3) evaluating performance of proposed management actions; and (4) communicating technical issues. These challenges are exacerbated in fisheries that harvest multiple stocks, and various methods provide partial solutions to them: (i) risk assessments and decision analyses take uncertainties into account by permitting several alternative hypotheses to be considered at once. (ii) Hierarchical models applied to multi-stock data sets can improve estimates of probability distributions for model parameters compared with those derived through single-stock analyses. (iii) Operating models of complete fishery systems provide comprehensive platforms for testing management procedures. (iv) Finally, results from research in such other disciplines as cognitive psychology can facilitate better communication about uncertainties and risks among scientists, managers, and stakeholders.

Keywords: Bayesian, decision analysis, hierarchical model, Kalman filter, operating model, risk assessment, risk communication, uncertainty.

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Introduction

Fisheries scientists and managers face many significant challenges; here are four.

1. Uncertainties and the risks they create are pervasive owing to natural variability in components of aquatic ecosystems, imperfect information about those components, and lack of perfect control over fisheries.
2. It is difficult to estimate probabilities for the uncertain factors in stock assessments.
3. Fisheries scientists who provide advice to managers must comprehensively take into account uncertainties and risks in their analyses of management options.
4. Scientists must communicate complex and technical results effectively to decision makers and the public.

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 to deal with certain challenges, as will be shown later.

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

Challenges and some possible solutions

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). 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. The resulting model is used to estimate how several potential management actions, such as various harvest rates or enhancement activities, might affect outcomes. Scientists

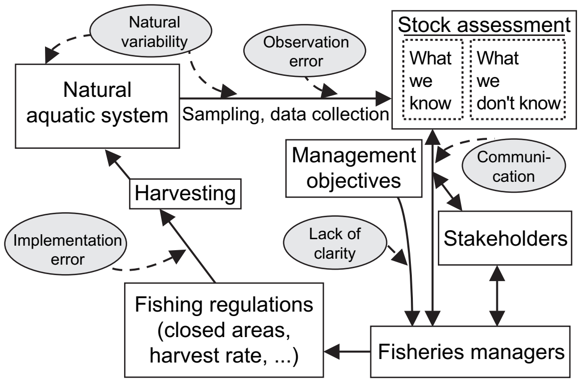

Figure 1. A conceptual diagram of the flow of information and actions in a typical fishery system. Rectangles represent components of the system, solid arrows indicate flows of information and actions between components, and ellipses represent major sources of uncertainty (adapted from C. J. Walters,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

then provide stock assessment advice to fisheries managers and interested parties (stakeholders), ideally with some iterative feedback. Managers 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.

Such fishery systems contain numerous sources of uncertainty (ellipses in Figure 1). Five are:

(i) the natural variability across space and time in distribution, abundance, and productivity of fish populations;
(ii) observation error (i.e. imperfect information), which arises from measurement error as well as sampling error (Mace and Sissenwine, 2002);
(iii) the difficulties associated with communication among scientists, managers, and stakeholders about technical scientific information and its associated uncertainties;
(iv) unclear management objectives;
(v) implementation error, which is the difference between a management goal and the actual realized spawning-stock biomass or fishing mortality rate, for example.

These uncertainties can be large and can affect interpretation of data, the results of analyses, the rank orders of management options, and the effectiveness of those options. Uncertainties are therefore 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 and occur in all fishery systems to varying degrees. Consequently, most decisions in fisheries management should take uncertainties into account. This applies to decisions not only concerning harvest regulations, but also the design of monitoring schemes and activities such as ocean ranching or other attempts to increase abundance of fish stocks.

Potential solutions to Challenge 1

That stock assessments can account for uncertainties is well known; the challenge of pervasive uncertainties has been met by increasingly sophisticated technical tools. For instance, 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. 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 assessments made for the stocks investigated through the International Council for the Exploration of the Sea (ICES), an organization in which growing emphasis on conservation concerns and application of a precautionary approach (FAO, 1995) has led many analysts to estimate probabilities that stock indicators will cross reference points (Lassen and Sparholt, 2000). Further, the European Commission is actively encouraging policy-orientated research that takes uncertainties into account and includes risk assessments. Risk assessments and decision analysis have also been particularly useful for evaluating a broad range of management options in the context of uncertainties (Francis and Shotton, 1997; McAllister and Kirkwood, 1999).

Risk assessment

To avoid misunderstandings, fisheries scientists, managers, and stakeholders should always clearly state what they mean by the term “risk”. Technically, it has two components, the magnitudes of adverse consequences that will arise from events that are uncertain, and the chances (i.e. probabilities) of those events and their consequences occurring. “Risk assessment” (i.e. risk analysis) refers to the general process of estimating both components of risk, not just one or the other.

As yet, there is no standardized risk-assessment procedure for fisheries situations, let alone ecological systems in general, although various broad frameworks for the latter have been developed (Power and McCarty, 2002). This lack of standardized methodology is partly because those that have been developed were mainly derived in the early 1990s from specialized procedures for estimating human health risk from toxic chemicals [National Research Council (NRC), 1993]. Therefore, ecological risk assessment is a relatively new field and methods are continually evolving (and can be found within the pages of such journals as *Risk Analysis* and *Human and Ecological Risk Assessment*).

Generally, a typical risk assessment in fisheries management includes five components. (i) First is a management objective, which often includes factors such as expected catch, variation in catch over time, and probability of the spawning biomass or other variable crossing a limit reference point (a condition to be avoided). Indicators are identified to measure how well a management objective is expected to be met. (ii) Several management options are considered for achieving the objective. (iii) A stochastic risk-assessment model of system processes includes (iv) a wide range of quantified hypotheses about those processes, i.e. different parameter values or structural forms of relationships among variables. (v) Uncertainties are taken into account by weighting these alternative hypotheses and their consequences by the degree of belief in them or their probability of occurrence. The model then estimates the probability distribution of outcomes or other indicators for each proposed management action. Risk assessments are usually linked to further analyses, such as the procedure for decision analysis described next.

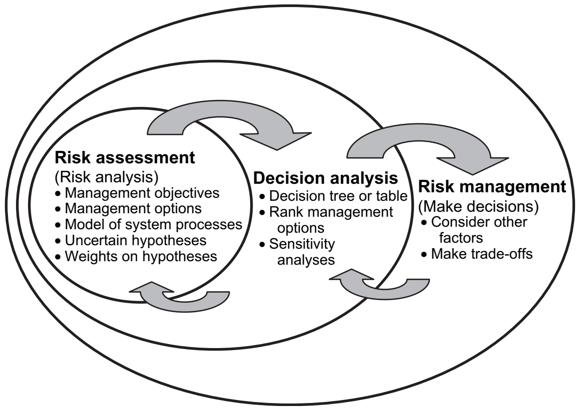

Figure 2. Risk assessment or risk analysis is a component of a decision analysis, which considers uncertainties and risks when ranking management options in the context of a stated management objective. Results from these analyses provide advice to decision makers (risk managers), who also consider other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

Decision analysis

It is not sufficient for decision makers merely to see a description and quantification of uncertainties and risks. They want to know how uncertainties and risks affect the ability of each potential management option to meet particular management objectives. To provide this information, scientists often conduct formal quantitative decision analyses (Walters, 1986; Clemen, 1996; Peterman and Anderson, 1999), which add three new components to the five already mentioned for risk assessment: (vi) a decision tree or decision table to help structure the analysis and communicate its content, (vii) a ranking of management options that results from conducting the decision analysis, and (viii) extensive sensitivity analyses to show decision makers the effects of changing various assumptions on that rank order of management options. In this context, procedures for risk assessment can be thought of as a subset of decision analysis (Figure 2).

Decision analysis has several advantages over standard approaches to decision making. First, by taking uncertainties into account explicitly, decision analysis often indicates that the best management option for meeting an objective will be different from that recommended by a simpler analysis based only on point estimates of parameters and state variables, i.e. an option that ignores uncertainties (Reckhow, 1994; Frederick and Peterman, 1995). For example, Robb and Peterman (1998) found that the adult abundance estimate for returning Nass River (British Columbia, Canada) sockeye salmon (*O. nerka*) that was optimal for opening an upstream First Nations fishery was 40 000 fish when only 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 fish. 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. where loss in long-term value of catch is higher for a spawning biomass that is 50% below some desired level than if it 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 with the real-world situation) may produce inaccurate estimates of outcomes, and yet we usually do not know the model's correct specification. 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.

Such alternatives create two important limitations of decision analysis; analysts must choose not only which alternative models are legitimate and necessary for inclusion, but also they must assign a probability to each model. Such choices may influence the rank order of actions, particularly in cases where data are relatively uninformative about the alternative models (i.e. unable to distinguish among them) and where different models lead to considerably different predictions. As yet, there is no definitive answer to this problem. This is a complex topic beyond the scope of this paper, but Punt and Hilborn (1997) and McAllister and Kirchner (2002) provide useful advice.

Perhaps the most extensive example of a decision analysis in fisheries management is a recent evaluation of recovery plans for seven depleted populations of spring and summer chinook salmon (*O. tshawytshca*) from the Snake River sub-basin of the Columbia River system in the northwestern United States (Peters and Marmorek, 2001). Those stocks were listed under the US Endangered Species Act. Adult and juvenile fish migrate through several reservoirs and dam systems, and also face problems from nearby agricultural lands, harvesting, hatcheries, predation, and changing ocean conditions. Large uncertainties about the various factors that contributed to reduced stock abundance over several decades led to contentious debates about interpretations of data and which salmon population model was most appropriate for evaluating management options designed to achieve their recovery (Marmorek and Peters, 2001)[1]. A decision-analysis framework defused some of the debate by including multiple hypotheses and models in one analysis along with uncertainties in them (Peters and Marmorek, 2001).

The decision analysis was aimed at identifying acceptable actions to be implemented by the US National Marine Fisheries Service. One example of a quantitative management objective (the "recovery" objective) was to find a management action with at least a 50% chance of having six of the seven Snake River stocks exceed their respective desired target spawner abundances during the last 8 of the next 48 years (Peters and Marmorek, 2001). Other management objectives considered had a similar format. This approach (using the top six of seven stocks) assigned priority to the best-off stocks, while recognizing that there was some non-zero probability that the recommended action would not be successful for all stocks. This approach to structuring a multi-stock management objective may be useful in other fisheries.

A decision tree reflects some key elements of the Snake River chinook salmon problem (Figure 3). These elements dealt largely with uncertainties in data and hypotheses about mechanisms operating during downstream freshwater migration by juveniles, as well as delayed mortality effects in the ocean. The uncertainties, hypotheses, and outcomes were incorporated into a stochastic simulation model. A wide range of weightings for alternative hypotheses were evaluated and one of the management options (A3), removing the four lower Snake River dams, was the highest-ranked and most robust option after extensive sensitivity analyses were conducted across a wide range of assumptions (Peters and Marmorek, 2001).

This example for the endangered Snake River chinook salmon stock also illustrates that decision analysis is a useful framework for focusing efforts of members of a diverse multi-stakeholder team, and taking into account their sometimes strongly differing views about hypotheses and uncertainties (Marmorek and Peters, 2001).

[1] Available on line at http://www.consecol.org/vol5/iss2/art8.

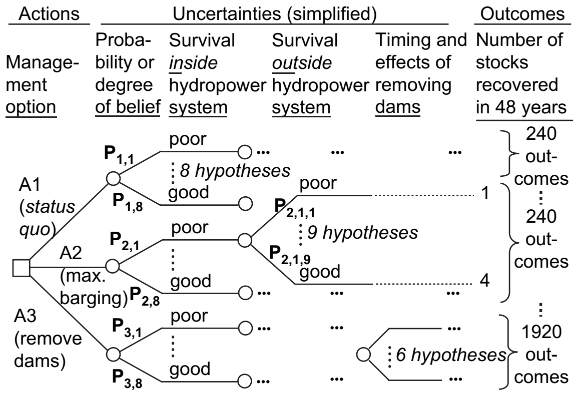

Figure 3. A simplified decision tree representing the main elements of an analysis of management options for meeting a recovery objective for 7 spring and summer chinook salmon populations from the Snake River (western United States) that were listed under the US Endangered Species Act. The three main management actions (out of six actually considered) were *status quo* (A1), maximize barging of juveniles during downstream migration instead of letting them swim through the entire hydroelectric power system (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 (i.e. the sets of dams and reservoirs), survival rate outside that system, and the timing and physical/biological effects on the river of removing the dams. Each hypothesized uncertain state of nature had a probability of occurrence ($P_{i,j,k}$), which was 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; only one example set of stochastic outcomes is shown. Management options were ranked based on the expected (weighted average) outcomes across all possible states of nature (adapted from Peters and Marmorek, 2001).

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

Clearly, risk assessment and decision analysis are useful methods 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. Actions may emerge that are robust to such a range of assumptions.

Despite these benefits, risk assessment and decision analysis cannot resolve all issues related to uncertainties and risks. The methods have serious limitations in addition to the two already mentioned (choosing which alternative models/hypotheses to include, and how to weight them). First, where a management objective includes conflicting components, such as maximizing catch but minimizing the chance of stock collapse, decision analysis cannot indicate the action that makes the best trade-off between those components; managers must make that trade-off. The only exceptions are if those components are expressed in common units such as utility, or if one or more components imposes an absolute constraint. A second limitation arises from deciding on the variables and processes to include in an analysis. Because the omitted processes likely also have associated uncertainties, any risk assessment or decision analysis can lead to overconfidence in the results. This is also true of any other quantitative approach. Third, risk assessments and decision analyses are difficult to describe, especially to non-technical people who use the results. Finally, not only is expertise in these methods limited, so is time. There may not be enough expertise or time to apply advanced methods as part of annual stock assessments, which already consume considerable time and effort. To help deal with time constraints, comprehensive risk assessments and decision analyses could be most useful for developing pre-agreed state-dependent and time-independent management procedures (control rules, management strategies) that are intended to be in place for a considerable period before being re-evaluated (McAllister and Kirkwood, 1999). This topic is expanded upon later under Challenge 3.

Risk management

Risk management is the process in which decision makers "manage the risks" by selecting a particular action, or set of actions. They do so after taking into account scientific advice from a risk assessment, decision analysis, or stock assessment, as well as other factors not considered explicitly in those analyses (Figure 2). Because of these "other factors", risk management is not a purely scientific process; it involves subjective judgements about compromises or trade-offs. There is no scientifically "correct" weighting for catch, year-on-year variation in catch, or probability that a fish stock will fall below a biomass limit reference point. Nevertheless, results from risk assessments can indicate how much of one of these indicators will be lost for a given gain in another, under each management option.

Clear communication is critical to risk management. To improve the efficiency and effectiveness of decision making, and to ensure that all scientific information is understood, there needs to be an iterative, two-way flow of information among people responsible for risk analysis, decision analysis, and risk management, as well as between these people and stakeholders.

Challenge 2: estimating probabilities for uncertain quantities

Another challenge for fisheries scientists is to estimate probabilities, or degrees of belief, for parameters that are considered uncertain. We can

(i) directly calculate probabilities from a lengthy data set, such as annual water levels in a river,
(ii) use expert judgement, or
(iii) use the data available along with Bayesian methods to produce a posterior probability distribution (Ellison, 1996; Punt and Hilborn, 1997).

There are difficulties with all three approaches. The first is not commonly used because lengthy data series for uncertain components are rare in fisheries. Even where such series exist, questions arise about relevance of very old data because underlying processes can change. The second approach, seeking expert opinion, is used widely. However, such elicitations of expert judgements are well known by cognitive psychologists to be subject to bias, and incorrect estimates of precision are attributable to many factors (Morgan and Henrion, 1990, p. 102). For instance, 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 their 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 (the "clarity test" of Morgan and Henrion, 1990, p. 50).

The third approach for describing uncertainties in stock assessments, using available data in conjunction with Bayesian statistical methods, is increasingly used, but it is far from widespread [National Research Council (NRC), 1998]. A prior probability distribution can be combined with a likelihood distribution derived from data, and the resulting posterior probability distribution can quantify the degree of belief in different values of some parameter. Such posterior probabilities can then be used in a risk analysis and decision analysis to weight various hypotheses about the value of the parameter. One major challenge about this third, or Bayesian, approach to describing uncertainties is to find means of deriving defensible prior probability distributions. When data are not too informative about an uncertain parameter owing to data paucity, 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. For example, if the resulting posterior probability distribution is too narrow, 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 non-informative data, it is most appropriate to use a completely non-informative prior probability distribution for a parameter to avoid biasing the posterior (Walters and Ludwig, 1994; Punt and Hilborn, 1997). Others argue for using independent biological information where it is available to create an informative prior (e.g. a narrow normal distribution; McAllister *et al.*, 1994, 2001). In situations with data that are very informative about the uncertain quantity, the nature of the prior is relatively unimportant, because the narrow likelihood will dominate the calculation of the posterior.

Potential solutions to Challenge 2

A hierarchical model is a quantitative tool that can help produce defensible informative priors through use of 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 the parameters. For instance, all stocks of a given species might be assumed to have a maximum reproductive rate that is drawn from a single normal probability distribution that has a 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 parameter a_i of the Ricker (1975) stock-recruitment model [Equation (1) below], 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 species, as well as across species, or across years (Liermann and Hilborn, 1997; Myers *et al.*, 1997, 1999, 2001; Adkison and Su, 2001; Myers, 2001; Su *et al.*, 2001; Chen and Holtby, 2002; Mueter *et al.*, 2002). Those analyses identified generally consistent and limited ranges of values for particular parameters, such as maximum annual reproductive rates across fish species worldwide (Myers *et al.*, 1999), and a narrow range of coefficients reflecting the effects of summer sea surface temperature on survival rates of Pacific salmon populations (Mueter *et al.*, 2002; Su *et al.*, 2004). In the absence of other information, such results are useful either for establishing prior probability distributions for parameters to be used in Bayesian updating, or for directly specifying posterior probability distributions or weightings to be used in decision analyses.

To illustrate the usefulness of hierarchical models, consider the common problem of estimating parameters of fisheries models in the presence of large natural environmental variation, which tends to mask parameter values. To the extent that multiple stocks share common environments, they should show similar responses to environmental variation. Indeed, numerous studies have documented positive covariation among stocks in particular variables across several hundreds of kilometres, and as stocks become increasingly separated, the correlation approaches zero. Such studies cover a variety of species and locations, including Pacific herring (*Clupea pallasaii*; Ware and McFarlane, 1989); North Sea and North Atlantic fish (Shepherd *et al.*, 1984), Baltic salmon (*Salmo salar*; McKinnell and Karlström, 1999), Northeast Pacific sockeye salmon, pink salmon (*O. gorbuscha*), and chum salmon (*O. keta*; Peterman *et al.*, 1998; Pyper *et al.*, 2001, 2002), and numerous other marine and freshwater species (Myers *et al.*, 1997). Hierarchical models take advantage of such situations by attributing some of the observed variation to responses that are shared among stocks (i.e. are common to them), thus permitting more precise estimates of model parameters. Such models therefore "borrow strength or information" from stocks with similar parameter values.

An example for 43 pink salmon stocks in the Northeastern Pacific Ocean demonstrates the benefit of applying a hierarchical Bayesian model (HBM). The pink salmon stocks with ocean entry points for seaward-migrating juveniles that are less than ~500 km apart show positive covariation in residuals from their stock-specific, best-fit Ricker stock-recruitment models (Pyper *et al.*, 2001). In our hierarchical Bayesian analysis of pink salmon, this positive covariation among stocks permitted stocks to be treated as "statistical replicates" when a model was fitted; this tended to average out observation errors across stocks (Su *et al.*, 2004). We used a generalized Ricker model:

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

where S_{it} is the spawner abundance of stock i in brood year t and i = 1, …, 43, R_{it} the resulting recruitment, a_i and b_i parameters of the basic Ricker model, γ_i 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 ε_{it} is the residual variation. We used spatially correlated prior distributions to reflect possible regional similarity of the stock-specific a_i and γ_i parameters (Su *et al.*, 2004).

This multi-stock hierarchical Bayesian model gave more precise estimates of the a_i and γ_i parameters than separate analyses of each stock (Figure 4; Su *et al.*, 2004). These narrower posterior probability distributions permit 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. The probability distributions can also be used to weight different combinations of parameter values in decision analyses.

Therefore, although multi-stock situations normally create problems for scientists and managers (perhaps 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. Such models provide a consistent method for estimating informative prior probability distributions that are more precise for particular parameters than if populations were analysed separately.

Nevertheless, hierarchical models and Bayesian approaches are not panaceas; they have limitations too. A hierarchical model will not be beneficial for estimating parameters unless they are at least somewhat similar across data sets. For instance, quantities such as a salmon stock's unfished equilibrium abundance may differ considerably between even nearby stocks as a consequence of human-induced or natural differences in freshwater habitat. In such a case, the uncertainty about any single stock's unfished equilibrium abundance will be reduced little, if any, by applying a hierarchical model that uses data from other nearby stocks. In addition, the hierarchical modelling approach will not be particularly advantageous when there are only a few data sets on different populations. Also, although estimates of parameters from hierarchical Bayesian models usually have lower mean-squared errors (are statistically "more efficient") than estimates from separate Bayesian analyses of single data sets (Gelman *et al.*, 1995), the performance of such hierarchical estimators needs to be evaluated with "operating models" (see Challenge 3 below) to generate numerous realizations of multiple data sets in order to determine the performance of the Bayesian estimates.

Bayesian methods for estimating probabilities for uncertain quantities also have limitations. Complex fish stock assessment models that contain numerous uncertain parameters require sophisticated and computationally intensive techniques. In such situations, joint and marginal posterior probability distributions can be estimated with sampling-importance-resampling (SIR) algorithms (Rubin, 1988) or Markov Chain Monte Carlo (MCMC) methods (Gelman *et al.*, 1995). The latter can be used by employing relatively new software (e.g. WinBUGS; Spiegelhalter *et al.*, 1999). However, problems can result from the nonlinear nature of most fisheries models, in which estimates of two different parameters may be correlated, for instance. This can cause convergence problems for MCMC methods. In such cases, careful re-parameterization of the model is necessary (e.g. Meyer and Millar, 1999). Care should be taken to choose the appropriate scale for non-informative priors in fisheries models. For example, parameters such as σ in lognormal models should have a flat prior on the $\log(\sigma)$ scale (Gelman *et al.*, 1995; Millar, 2002). It is often difficult to find non-informative priors, especially for variances of random effects in hierarchical models. Therefore, sensitivity analyses must also be conducted with different priors to determine the extent to which they affect the posterior distribution.

Finally, all fisheries models, including hierarchical Bayesian ones, will result in incorrect estimates of parameters and inappropriate management advice if the models assume (as most do) that parameters are constant over time when they in fact vary temporally. For instance, body size and stock productivity can change with climate, so models should reflect these possibilities. State-space models (Chatfield, 1989) can deal with time-varying parameters, and many fisheries scientists have used this approach, most commonly by applying a Kalman filter (Collie and Sissenwine, 1983; Walters, 1986; Mendelsohn, 1988; Pella, 1993; Schnute, 1994; Millar and Meyer, 2000; Peterman *et al.*, 2000, 2003). However, state-space models have been limited to relatively simple fisheries situations.

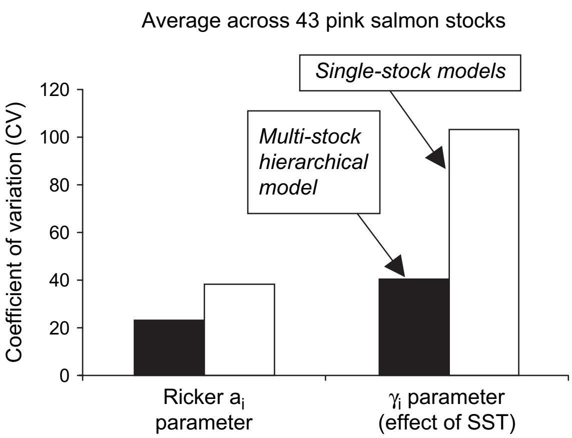

Figure 4. Averages across 43 pink salmon stocks from the Northeastern Pacific (Washington state, USA, through to western Alaska) of coefficients of variation (standard deviation divided by the mean) for estimates of a_i and γ_i in Equation (1). Open bars in each pair are for estimates derived from fitting 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.*, 2004).

Challenge 3: evaluating the performance of management options

Even if the challenges described above are met, scientists and managers will still be uncertain about the management option that will best meet a given management objective or set of objectives, owing to complex interactions and feedbacks among components of fishery systems (Figure 1).

Potential solutions to Challenge 3

Given a clearly stated objective, simulations can be done to evaluate relative performances of proposed management options. Although fisheries scientists routinely conduct stochastic simulations, the most comprehensive method to evaluate options is to simulate 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 are best in the presence of a wide range of possible, but uncertain, simulated contingencies. Similarly, operating models of fisheries typically aim to identify robust decision-making rules by simulating six components:

(i) the stochastic dynamics of a "true" (i.e. assumed) natural population;
(ii) samples of indices of abundance or other data from that "true" population, including observation error;
(iii) where needed, a stock assessment step that uses those sampled data to update annual estimates of state variables and parameters;
(iv) state-dependent harvest control rules that specify the effect of either sampled indices or stock assessment estimates on the choice of management actions;
(v) implementation of those actions, including error; and
(vi) 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 a given management objective is met. Indicators for each of several objectives can be produced.

Normally, operating models are used to explore numerous situations and structures for the first four components above. For example, a wide range of alternative hypotheses about scenarios for the "true" population are considered routinely in successive simulations. The specific nature and form of components (ii), (iii), and (iv) (collectively often called a management procedure or strategy; 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 is usually 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 should also be conducted to indicate how that ranking changes with different management objectives.

The fifth component of an operating model, implementation error, is extremely important. It is the deviation between a desired state and the actual realized outcome (Rosenberg and Brault, 1993; Rice and Richards, 1996). This error typically arises from a combination of non-compliance with regulations by harvesters, changing catchability, and other dynamic processes in the fishing fleet. Implementation error can be a large source of variation, yet it is rarely included in the exploration of management options in stock assessments. Such omission leads to overconfidence in the effectiveness of proposed management actions. To rectify this situation, analysts can include implementation error by employing a stochastic harvesting process in an operating model based on historical data or hypotheses.

Such comprehensive operating models of entire fishery systems provide a strong test of robustness of management options (Cooke, 1999). An excellent and early example of operating models to evaluate management procedures was the International Whaling Commission's (IWCs) development of the Revised Management Procedure (RMP; IWC, 1994; de la Mare, 1996; Kirkwood, 1997). The IWCs analyses explored many shapes of functions for the harvest control rule while taking into account uncertainties in estimates of whale abundance. Those analyses also examined model performance under numerous combinations of uncertainty in stock identity in multi-stock fisheries and temporal trends in abundance of whales resulting from environmental changes or interactions with other species. The harvest control rule that performed best for whales was robust to these sources of uncertainty (de la Mare, 1996). Operating models have also been applied in many other situations [see Smith, 1993; Butterworth and Punt, 1999, and several papers published in Volume 56(6) of the *ICES Journal of Marine Science*; Peterman *et al.*, 2000]. 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; 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 only a subset of those uncertainties were analysed.

Nevertheless, operating models can be formidable to implement. Not only do they require advanced expertise, but more processes must be included than in most standard stock assessment models. These processes include a description of potential sampling errors, which are usually unknown. Intangible or other factors that are not simulated may strongly influence the performance of some control rule when it is applied "in the field", leading to overconfidence in the results of the operating model. Further, time constraints often preclude analyses with operating models.

Challenge 4: communication

Communication among scientists, managers, and stakeholders is another source of uncertainty or error that influences fishery systems (Figure 1). Stock assessment, risk analysis, and decision analysis are highly technical endeavours. It is difficult to convey assumptions, results, and implications effectively to people who are not actively involved in the analyses. Many sources of communication problems are obvious, but some are more subtle. As an example of the latter, cognitive psychologists who conduct research on how people reason about uncertainties and risks have found 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:

(i) the *chance* of seeing a given outcome for a stochastic process (which most fisheries scientists would intend in a stock assessment context);
(ii) the *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 or probability of its dropping dangerously low, even if a calculated chance probability indicates otherwise);
(iii) the *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);
(iv) the *confidence* or degree of subjective belief in some outcome based on one's experience;
(v) *control*, with more management influence over the outcome generally leading to a higher perceived probability of an outcome occurring;
(vi) the *plausibility* of the scenario (how convincingly the case is presented).

Therefore, 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.

Potential solutions to Challenge 4

There is no simple answer to the problem of communicating technical information. It takes concerted effort by managers, scientists, and stakeholders through ongoing involvement and interaction in analyses to improve mutual understanding (Smith *et al.*, 1999). Of course, scientists could be trained better 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 interpret the *chance* probability noted above correctly when results for a wide variety of problems were stated in frequency format rather than as decimal probabilities. Fisheries scientists should exploit this fact when presenting the probability of some outcome occurring (i.e. *chance* as described by Teigen, 1994). For example, compare the following statements about the effect of a proposed fishing mortality rate:

(i) "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";
(ii) "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 a single low-abundance situation. Anderson (1998)[2] provides other examples of applying these concepts of frequency format to management of natural resources.

To extend this idea of frequency format to uncertain events in a multi-stock fishery, consider a case in which five fish stocks are simultaneously vulnerable to harvest, but they differ in their limit reference points and current stock biomasses 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 three out of ten situations like this, any two of the five fish stock biomasses would drop below their limit reference points during the 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 during the period considered."

[2] Available only on line via the Internet at http://www.consecol.org/vol2/iss1/art2.

This simple idea of using frequency format has another benefit; it may help reduce the confusion over the term "risk" discussed earlier. Mislabelling a probability of an undesirable outcome as the only measure of "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 arise. 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* each of the possible outcomes/costs as separate cases, and they *count* the cases.

A special problem of communication is 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:

(i) they have less control over uncertain events;
(ii) they are not actively involved in the decision-making process;
(iii) the sources of risks are completely new;
(iv) the risks are not being shared equally among stakeholder groups (Slovic, 1987).

This is a well-studied topic in the literature of cognitive psychology and management science. If fisheries scientists and managers are aware that such factors affect perceptions of risk, they can take steps to reduce errors of interpretation and conflicts by, for instance, involving knowledgeable stakeholders in risk assessments and giving them more input to the decisions.

Of course, using frequency format and being aware of risk perception issues can only help with a small portion of the challenges related to communicating uncertainties and risks. Good documentation, early and frequent interactions among interested groups, and "gaming" workshops using models can also only go so far in bridging the gap between technical specialists and others. We need many more innovative approaches to facilitating two-way communication.

Conclusion

There is one last important point to make about uncertainties and risk management. Sometimes, decision makers become unjustifiably worried 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 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 described as well as 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 rigorous data on economic and social indicators." This may be true, but economic factors such as discard rate and price per tonne of fish show considerable variation. Clearly, therefore, there should be a united call for more research on economic and social processes, such as movement of vessels and discarding behaviour 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 has hopefully highlighted some of the major challenges in fisheries science and management. Potential solutions to these challenges are partly provided by advanced quantitative methods such as decision analysis, hierarchical models, and operating models. Methods and lessons learned from other disciplines such as cognitive psychology can also help improve communication among scientists, managers, and stakeholders. Considerable research is already being conducted on many of these topics by scientists in the ICES family, and elsewhere. Nevertheless, despite these advances, there is still substantial work to be done to reduce the problems and limitations described above for each potential solution to the challenges presented here.

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