American Fisheries Society Symposium 71:357–372, 2009

Mind the Gap: Uncertainty and Model Communication between Managers and Scientists

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Abstract.—Natural resource management requires difficult decisions, broad societal costs, and sacrifices from private landowners and public agencies. With so many financial, ecological and cultural resources at stake, policy-makers, managers, and citizens need scientific predictions that can help resolve conflicts and balance the often competing needs of ecosystems and communities. Modeled information is essential for meeting this need. The words "model uncertainty" are often misinterpreted as describing a lack of knowledge about model output. In fact, they describe knowledge, not only of the one most likely modeled estimate, but also of all the other possible estimates that the model might have provided, and their likelihood. We present six case studies, from salmon habitat recovery planning, illustrating how scientists can provide more useful products by describing distributions of possible outcomes as formal probability distributions, as confidence intervals, or as descriptions of alternative scenarios. In terms of management effectiveness, the communication and use of model uncertainty can be at least as important as the quality of the original model.

Introduction

Natural resource management demands trade-offs between public resources, private resources, and ecological needs. Excellent examples of challenging natural resource management decisions are found in habitat restoration planning for ESA-listed salmonids, which inhabit streams and rivers over most of Washington, Oregon, Idaho, and California. Restoration and protection actions aim to improve the status of these salmon populations; yet, salmon recovery will require difficult decisions, broad societal costs, and sacrifices from private landowners and public agencies (Lackey et al. 2006). With so many resources at stake, policy-makers, managers, and citizens need and expect science to provide answers and predictions that can help resolve conflicts and identify sets of actions that balance ecological needs against competing societal demands for natural resources. Two of the most important questions for which scientific answers are desired in salmon habitat recovery planning are, "What kind and how many fish will be produced as the result of a particular set of restoration actions?" (Question 1) and "What combinations of recovery actions will be sufficient to recover a particular salmon population or group of salmon populations?" (Question 2). In both cases, the role of science is to inform the decision-making process with the best available data and analyses. Often, empirical data are insufficient, and various sorts of models are employed (Beechie et al. 2003).

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The words "model uncertainty" are often misinterpreted as describing a lack of knowledge about model output. In fact, they describe knowledge, not only of the one most likely modeled estimate (i.e., a point estimate), but also of all the other possible estimates that the model might have provided, and their likelihood. There are five types of uncertainty found in modeled predictions (Table 1). Uncertainty in modeled predictions can stem from the inherent variability of natural systems, measurement errors, imprecisions in parameter estimates, inaccuracies in model structure, and differences between conditions used for model building and conditions to which modeled predictions are applied. Uncertainty in modeled predictions is unavoidable; therefore, embracing and communicating uncertainty is essential to wisely employing models in fisheries and habitat management (Steel et al. 2003). For example, analyses of uncertainty can describe what the worst-case scenario might be or what the odds of undesirable outcomes are, and therefore inform decisions about how much to hedge a bet or how robust a final strategy needs to be. The purpose of this paper is to describe the importance of model uncertainty as an essential management tool. To do this, we sketch a caricature of the relationship between management and science and then describe six case studies. In each case study, we describe how scientists can provide more useful products by reporting distributions of possible outcomes as formal probability distributions, as confidence intervals, or as descriptions of alternative scenarios. While it is rarely possible to identify all possible sources of uncertainty (Table 1) in modeled predictions, each of the following examples tackles at least one source and demonstrates how managers are able to make better decisions with access to complete information about modeled estimates, including uncertainty. Clear descriptions of model uncertainty can fill the gap between science and management by enabling a better understanding of the information that exists and, therefore, better natural resource decisions.

The caricature of scientist-manager communication.—Managers make decisions and scientists provide information on which to base those decisions. Many times both sides are relying on model output and yet they fail to communicate effectively about management needs and science capabilities. Managers often do not define questions that can be answered with existing (or at least feasible) models and they rarely demand that model output include the clear descriptions of biases, uncertainties, and strengths that are necessary for making the most informed use of model output. Scientists hesitate to tackle the tough questions because they can rarely be answered with precision or certainty, and scientists often fail to provide managers with all of the information necessary to make the best use of model output in a management setting. This two-sided simplification of model results leads to overconfidence and poor decisions that rely on point-estimates and leave the salmon resources unnecessarily susceptible to small errors in model inputs or model structure. Such decision-making strategies employ only a fraction of what models can provide.

Case Studies of Model Communication

We present six case examples of how accounting for uncertainty can help in salmon decision-making. Three of the examples address Question 1 and three examples address Question 2.

Question 1: What kind of fish response (number of fish, distribution of fish) will we get for a particular set of restoration actions?

TABLE 1. Types of uncertainty in modeled predictions (modified from Steel et al. 2003). Examples refer to the six examples of model uncertainty communication described in this manuscript.

Class of uncertainty	Brief definition	Habitat example	Methods for quantifying	Possibilities for reducing or managing
Prediction uncertainty	Difference between the modeled response (based on data or models from situation A) and the true response (situation B).	Uncertainty of predicting habitat capacity of a given watershed after instream restoration using estimates of fish density from current conditions.	Leave-one-out estimates of prediction error rates. Simulation studies comparing conditions where model was built to application conditions.	Collect data for conditions in which predictions are required. Do not extrapolate beyond model development conditions. Report and use confidence intervals (Example #2).
Parameter uncertainty	Difference between the true parameter such as an average or a regression (coefficient) and the parameter as estimated from the data.	Uncertainty of parameters describing juvenile survival as a function of water temperature.	Statistical theory for model coefficients derived from data. Sensitivity analysis for model coefficients from other sources (Example #4).	Collect more data or more accurate data. Collect data over a wider variety of conditions.
Model uncertainty	Difference between natural system and the mathematical equation used to describe it. Includes model form and set of predictors.	Uncertainty in the relationship between habitat conditions and fish capacity. Uncertainty in best set of habitat descriptors.	Statistical descriptions of model fit: Akaike's information criteria (AIC), Bayesian information criteria (BIC), likelihood ratios, F-statistics. Monte Carlo simulations (Examples #3 and #4).	Consider wide variety of models (Example #6). Sensitivity analyses (Example #5).

TABLE 1. Continued.

Class of uncertainty	Brief definition	Habitat example	Methods for quantifying	Possibilities for reducing or managing
Measurement uncertainty	Difference between true value and the recorded value.	Uncertainty in measurements of data used to build the predictive model, i.e. fish or redd density under differing habitat conditions.	Test accuracy of measurement technique against standard method or known values.	Improve measurement techniques. Increase replicates. Calibrate biased measurement techniques.
Natural stochastic variation	Inherent random variability.	Natural fluctuations in population size, habitat selection, or habitat conditions.	Variance of observed data. Variance of observed data under alternative conditions (Example #1).	Collect more replicates for conditions of interest. Stratify data collection.

Multiple sources of uncertainty confound the prediction of how many fish a restoration action or suite of actions might produce, making it difficult to identify robust restoration strategies for salmon populations (Beechie et al. 2006). However, identifying and incorporating sources of model uncertainty into such predictions is an essential tool for narrowing the range of potential management options (e.g., Hall et al. 1988; Francis 1992; McAllister et al. 1994, Francis and Shotton 1997).

Example 1: Estimating the effect of wood placements on juvenile coho salmon abundance: Using all the data to make more detailed predictions.—Data are usually reported as means and, where significant differences are found, a point estimate of the difference is reported. In this first example, we look at a sub-sample of data from Roni and Quinn (2001). They sampled 30 streams in western Washington and Oregon to quantify the responses of juvenile salmonid populations to artificial placement of large woody debris. They reported that juvenile coho salmon *Oncorhynchus kisutch* densities were 1.8 and 3.2 times higher in treated reaches compared to reference reaches during summer and winter, respectively (Roni and Quinn 2001).

What if, instead of the customary point estimates, the entire distribution of data were reported (Figure 1)? Quantities of interest to managers could be quickly calculated or estimated from the distribution. For example, managers might be interested in the odds of a negative response to large woody debris placement. This probability can be easily calculated or estimated from the distribution of fish responses across all sites. On average, juvenile coho response to this wood placement was positive. Yet, we can also estimate that there is a 25% chance that juvenile coho density will be reduced after restoration (Figure 1). For some managers or for very small fish populations, the risk of a negative response may be more important than the average positive increase. From the distribution of data, it is also possible to estimate the odds of a dramatic positive fish response (Figure 1) or to identify the range of fish responses that might be expected, say, 50% or 75% of the time, by calculating confidence intervals.

This wood placement example provides clear evidence that knowledge about data or model uncertainty provides increased information for making informed management decisions. As scientists resist the temptation to hide distributions as noise around an all-important point estimate, managers will be able to demand this extra information and incorporate it into their resource management decisions.

Example 2: Prioritizing barrier removals using estimates of model precision.—Steel et al. (2004) predicted winter steelhead (anadromous rainbow trout) *O. mykiss* redd density (redds per kilometer) from geology, land use, and climate variables in the Willamette River basin, Oregon. This model was then used to predict redd density upstream of 111 probable migration barriers as a metric by which to prioritize barriers for removal. The authors combined information on potential redd density and stream length to estimate the total number of redds that might be supported if the barriers were removed. Looking at total km of stream blocked, habitat suitability (predicted redd density) and predicted total number of redds, it was difficult to distinguish between two of the largest existing barriers. Because of assumed imprecisions in the statistical model, a fourth metric was also developed, the bottom of the 95% confidence interval. This metric describes the lowest predicted redd density, given variation in the empirical data on which the statistical model was built. It can be described as an estimate of the worst-case model output and is interpreted as the value above which 97.5% of model predictions fall. Note that model accuracy was not and could not be assessed.

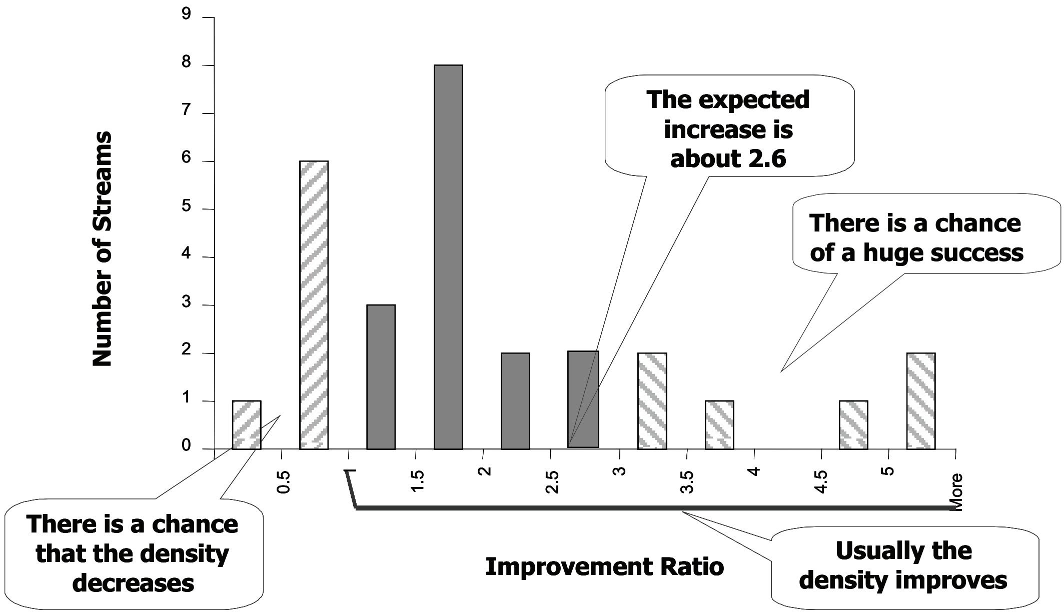

Figure 1. The full distribution of empirical observations provides much more information than a point estimate of the mean response. This annotated histogram describes the post-treatment to pre-treatment ratio of juvenile coho salmon in 28 streams in Oregon and Washington (data reported in Roni and Quinn 2001).

There were differences in this metric that distinguished the two largest barriers. Using the bottom of the 95% confidence interval, the authors were also able to identify three additional high priority barriers that might have been overlooked using only stream length, mean predicted redd density, or mean predicted number of redds (Figure 2) (Steel et al. 2004). These are barriers for which the point estimate of predicted number of redds was not as high as for other barriers. However, when compared to other barriers, one can be much more certain that the blocked habitat will support a large number of fish. A risk-averse manager might be interested in this type of uncertainty-based metric for prioritizing of habitat restoration actions because the metric will identify those actions which may be least likely to fail.

Example 3: Estimating potential Chinook salmon spawning capacity: Ruling out potential actions using uncertainty estimates.—The complexity of the salmon life cycle generates bottlenecks in productivity because particular life stages are limited by some external factor. For example, juvenile coho productivity might be limited by the amount of intermittent stream habitat in Oregon coastal watersheds (Ebersole et al. 2006) or population size in the Skagit River watershed might be limited by estuarine survival (Greene et al. 2005). Predicting the salmon population response to a particular restoration action depends on whether the habitat being considered for restoration is, indeed, limiting productivity. For example, projects aimed at increasing spawner habitat would yield little or no benefit if, in fact, juvenile habitat were limiting.

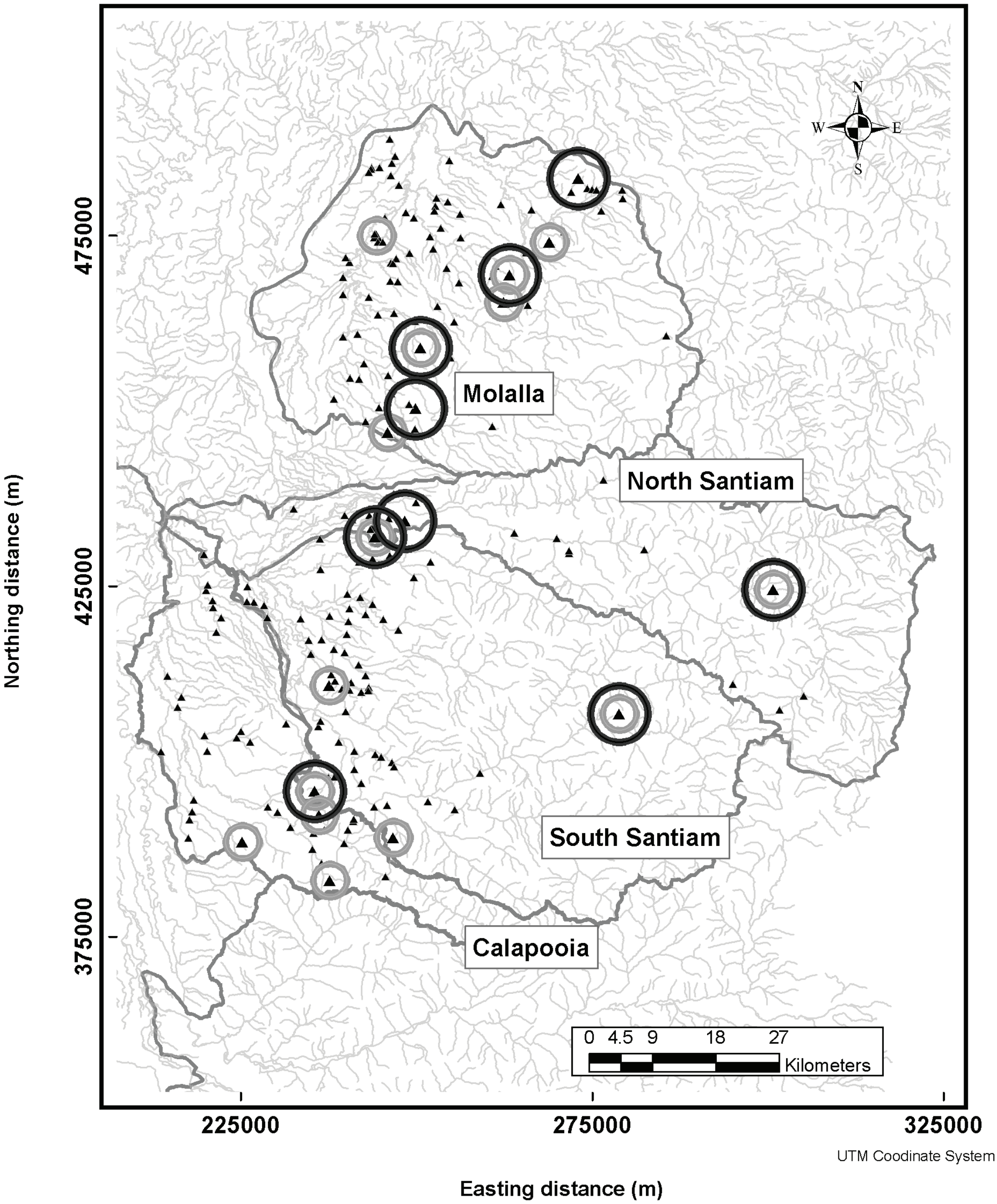

FIGURE 2. Watersheds draining to impassible barriers in four catchments within the Willamette River basin. Small light circles identify barriers blocking the most suitable habitats as measured by stream length, predicted redd density or the largest number of redds. Dark circles identify barriers blocking habitat with the best worst-case prediction of redd density (bottom of the 95% confidence interval). Modified from Steel et al. 2004.

Limiting factor assessments are designed to identify population performance bottlenecks. They compare current population performance at a particular life stage to population performance as predicted by some external factor, for example, quantity of spawning habitat. If the current number of spawners is similar to the maximum number of spawners given available habitat, then quantity of spawning habitat might be limiting. If the current number of spawners is substantially less than the maximum spawners predicted by the quantity of spawning habitat, then managers can assume that some other factor is the primary limiting factor. The difficulty with these types of analyses is that models must necessarily be used to make predictions of current and potential population performance and these models are often imprecise. Here we illustrate how incorporation of uncertainty into limiting factor assessments can rule out management strategies that are unlikely to succeed (Beechie et al. 2006).

In this example, the question being asked is "Will spawning habitat restoration actions increase spawner abundance of six populations of Chinook salmon in the Skagit River, WA?" which stemmed from a prevailing view that spawning habitat availability might limit population size. However, there were no estimates of spawning habitat capacity, and managers could not determine whether spawning habitat was limiting population performance. Beechie et al. (2006) combined empirical predictions of habitat availability (based on digital elevation models, hydrography, and aerial photography) with empirical predictions of potential spawning population sizes (based on redd frequencies, redd sizes, and numbers of spawners per redd) to estimate spawner capacity of watersheds inhabited by six populations of Chinook salmon. Using Monte Carlo simulations, uncertainty around the spawning habitat capacity estimates was also quantified. The resultant confidence intervals were enormous, spanning up to four orders of magnitude. Nevertheless, a comparison between the estimated current number of spawners in each population and the estimated spawner capacity given current habitat conditions found a less than 1% overlap in confidence intervals for five of the six populations (Table 2). Thus, even though uncertainty in estimating spawner capacity is substantial, current population sizes are much smaller than even the lowest predictions of habitat capacity.

Even given uncertainty about the current number of spawners and the potential capacity of the habitat, managers can be quite sure that the amount of spawning habitat is not currently limiting productivity and, therefore, that there is little chance that restoration actions targeting spawning habitat will improve these populations in the near term. The model results suggest that there is already enough habitat of sufficient quality. Quantification of many of the sources of uncertainty in modeled predictions, even though enormous, allowed managers to remove suites of expensive restoration projects from the list of high priority recovery actions. This example illustrates that decision-making can continue in the face of uncertainty.

Question 2: What combinations of recovery actions will be sufficient to recover a particular salmon population or evolutionarily significant unit (ESU)?

Example 4: Sensitivity analyses provide important information about how to incorporate the output from large models in decision-making.—The Ecosystem Diagnosis and Treatment (EDT) model uses habitat and salmon population information to predict the abundance, productivity, and diversity of Pacific salmonids (Mobrand Biometrics 2004). The model has been widely used in Puget Sound and in the Columbia Basin to prioritize restoration and recovery actions, to set recovery goals, and to predict the consequence of

TABLE 2. Adult spawner population estimates compared to median model estimates of spawner capacity obtained from the Monte Carlo simulations, and percent overlap of the population and capacity distributions for six Chinook populations in the Skagit River basin (Modified from Beechie et al. 2006.).

Population	1952–2001 Population Median	Monte Carlo Median	Percent Overlap of distributions
Lower Skagit	2,606	145,442	<0.1%
Upper Skagit	6,845	122,498	0.2%
Cascade	208	8,836	<0.1%
Lower Sauk	658	36,000	0.1%
Upper Sauk	492	18,226	0.1%
Suiattle	559	1,742	51.4%

proposed habitat, harvest, and other actions (e.g., Shared Strategy Development Committee 2007; NWPPC 2005). The model is the primary analytical tool for deciding on actions in many salmon recovery plans; therefore, it is essential to understand and to quantify the level of confidence that decision-makers can have in modeled predictions. When EDT predicts that a proposed action will result in an increase of 317 fish, is it possible that reasonable and small adjustments of input data or internal parameters might have resulted in a modeled estimate of only 15 fish or even of 50 fish or possibly 1,000 fish?

Because of the complexity of this model, estimates of model precision are very difficult to obtain but are essential for appropriate use of modeled results in watershed planning. Using a large number of Monte Carlo simulations, a sensitivity analysis quantified how model outputs vary when the distribution of plausible internal and external parameters are considered (McElhany et al. 2009, this volume). The size of the model output interval describes the precision of the modeled output, given model structure, and quantifies the confidence managers can have that modeled predictions are stable, despite what is unknown about input parameters. These model output intervals will improve regional and local decision-making based on EDT model output by providing answers to many key questions, including: (1) What are the minimum and maximum fish benefits that the model might have predicted? And (2) will more habitat data refine our predictions of current or potential fish population performance?

McElhaney et al.'s (2009) sensitivity analysis has taken tens of thousands of computer hours but even preliminary results are providing useful information. Model output intervals in which most but not all parameters were varied are large enough (e.g., 2,500–6,200 fish) to lead to new or changed decisions regarding, for example, whether to restore passage to blocked habitat or whether to allow harvest of a population. As well, the sensitivity analyses have discovered that the model is more sensitive to internal parameters than to user input parameters (e.g., habitat parameters). This means that reducing the uncertainty in the habitat input parameters may not provide a particularly large reduction in overall model uncertainty. Assessments of model accuracy (e.g., Rawding 2004) are also helping to improve the use of this large model in large-scale watershed planning.

Example 5: Impact of model structure on the choice of a habitat restoration strategy.— In many cases, assumptions that drive model structure, e.g. the presence or absence of density dependence, can have enormous impacts on modeled predictions (Greene and Beechie 2004). In this example, the question addressed is "How might different assumptions of density dependence alter the choice of restoration strategy?" Assumptions about salmon behavior are required to construct a life cycle model, including assumptions about behavior at high densities (Greene and Beechie 2004). There are three options for modeling this behavior: mortality does not change at high densities (density-independent mortality), salmon do not move to avoid competition and suffer higher mortality at high density (density-dependent mortality), or salmon move to other habitats to avoid competition and reduce their mortality (density-dependent movement). Greene and Beechie (2004) compared predictions of population response to habitat restoration using each of the three possible assumptions above and found that predicted equilibrium population size varied by roughly a factor of four. This wide variation indicates that limitations in our knowledge of where density dependence occurs in the salmon life cycle restrict our ability to predict the magnitude of population responses to restoration actions. If we assume density-independence, restoration actions focused on spawning habitat would have the greatest benefit (Figure 3). Under density-dependent mortality, expanding delta capacity would yield the greatest benefit. Under density-dependent movement, expanding spawning, freshwater rearing, and delta rearing capacity would all have roughly equal benefit (Greene and Beechie 2004). In contrast, the model shows that improving survival in the nearshore would benefit salmon populations in all scenarios, although it is not clear that nearshore habitat is degraded or in need of restoration.

In this example, assuming one form of density-dependent behavior and ignoring the others might lead to the wrong conclusions about where to focus restoration efforts. Uncertainty about model structure substantially inhibits our ability to predict which restoration strategy is most likely to improve salmon populations. In this case, model uncertainties cannot be resolved or easily interpreted. Managers might easily conclude that this model alone does not suggest a clear management strategy, and that they should seek a balanced restoration strategy that is robust to assumptions about density dependence.

Example 6: Using multiple models to evaluate alternative future scenarios.—Aquatic habitat restoration and protection actions enacted now will determine future watershed conditions, influence rates of salmon population recovery, and determine the likelihood of eventual recovery of ESA-listed salmonids. Thus, predicting how alternative watershed management strategies will impact future conditions is a key to making the best decisions now. Scenario planning is a decision-making tool that can lead to more robust decisions in the face of uncertain information as well as to increased understanding of key uncertainties in data, theory, and modeled predictions (Peterson et al. 2003). Steel et al. (2008) developed a scenario-based, spatially explicit decision support system for predicting responses to alternative management strategies in the Lewis River watershed, a tributary to the Columbia River located in southwestern Washington State. Using each of six strategies, they identified a suite of restoration actions and predicted the effect of those actions on future landscapes. They then predicted how habitat and fish might respond to those future landscapes. Both habitat and biological response models were used to evaluate the future landscapes because there was more confidence in predictions of habitat response to restoration and protection actions; yet, eventually, it is the biological response that is of greatest interest. The use of multiple models allows the explicit evaluation of trade-offs between

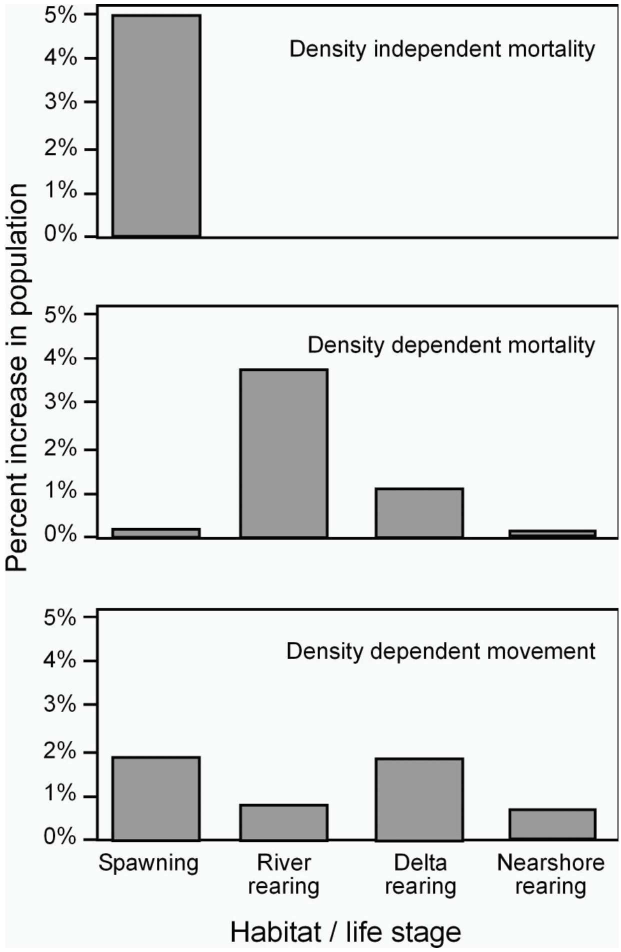

FIGURE 3. Influence of differing model assumptions on predicted increase in spawner population size as a result of increasing each habitat area by 5%. The assumption of density-independent mortality predicts that spawning habitat restoration will be most effective; assuming density-dependent mortality predicts that restoring river rearing habitats will be most effective; and assuming density-dependent movement predicts that a more even distribution of restoration efforts will be most effective. (Modified from Green and Beechie 2004).

using available resources to improve particular watershed attributes such as sediment delivery or quantity of habitat as well as trade offs between allocating resources to different parts of the basin.

Eight habitat and fish models were used to evaluate landscapes predicted to result from each of the six restoration strategies. As expected, the estimated best strategy differed depending on which evaluation model was applied. For example, if one only considered riparian condition, often thought to be a great indicator of watershed health and habitat quality, strategy C, which focused restoration efforts on the lower reaches, appears to provide the best use of funds. However, the use of sediment and hydrology models suggests that the most effective strategies are D and E, in which restoration efforts are focused on forested headwater areas. Metrics from the biological models, such as egg-to-fry survival and spawning capacity, identify strategies A (which focuses restoration effort on removing migration barriers) and C as the best strategies. Instead of identifying one best course of action for all managers, species, or goals, the scenario-based approach allows decision-makers to explicitly incorporate their own priorities and risk tolerances to develop a final strategy that best balances their set of objectives.

Redundant models enabled focused comparisons between two models of unknown accuracy and precision. For example, salmon spawning capacity was estimated using two different models. One model estimated capacity in the range of 25,000 fish and a different and independent model based on remotely sensed habitat quantity and quality estimated capacity in the range of 95,000 fish (Steel et al. in press). Using both models in one basin will allow calibration of either model in other basins. Managers can correct for the over- or under-estimation inherent in the two approaches. While both models aim to measure the same thing, spawning habitat capacity, each model predicted a different "best" strategy, A versus C (Figure 4). The use of both models reduces overconfidence in either model.

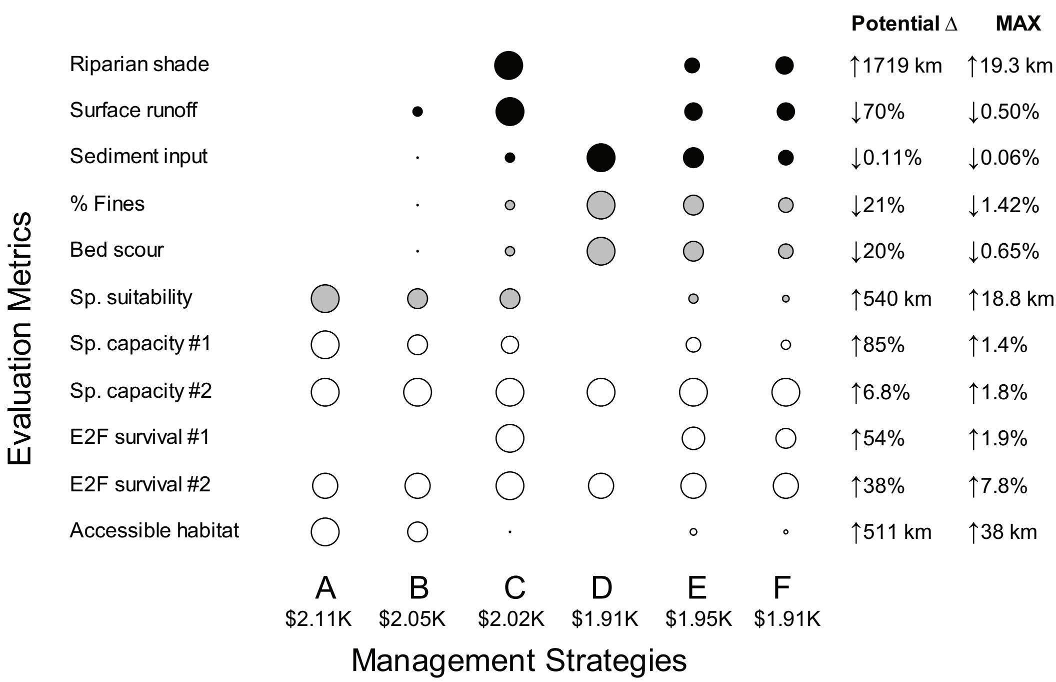

FIGURE 4. Comparison of multiple watershed management strategies (each consisting of a suite of restoration actions) using multiple evaluation metrics. Circles are scaled within a row so that the largest circle represents the maximum value observed for that metric. Black circles represent improvements in watershed processes, gray circles are improvements in habitat conditions, and light gray circles are improvements in fish responses. All circles describe km improved except Sp. Capacity #2 which describes total fish and E2F survival #2 which is unitless. Potential change estimates the difference between current and historical conditions for each metric. MAX describes the maximum improvement across all management strategies for each metric. Abbreviations: Sp. = spawner; E2F = egg-to-fry (Data from http://www.nwfsc.noaa.gov/research/divisions/ec/wpg/documents/lrcs/LewisRiverCaseStudyFinalReport.pdf).

TABLE 3. Selection of a modeled watershed management strategy for on-the-ground actions, given unique management concerns, manager biases, and known model uncertainties (Modified from Steel et al. 2008; final report from NOAA available at http://www.nwfsc.noaa.gov/research/divisions/ec/wpg/documents/lrcs/LewisRiverCaseStudyFinalReport.pdf).

Biological Focus	Manger ideas about model uncertainty	Strategy Selected
Capacity and survival of juvenile salmonids (all species) in lower reaches.	Concerned about imprecision and inacurracy of complicated habitat or biological response models.	Strategy A: Open new habitat (barrier removal).
	Strong faith in a particular model.	Strategy C: Improve quality of existing habitat through riparian restoration, instream improvements, and floodplain reconnection in lower watershed.
Success of reintroducing spring Chinook above impassable hydropower dams.	Strong faith in fine-scale models of sediment transport and routing which have been proven and tested in other basins; reduced confidence in biological models.	Strategy D: Decommission roads and open migration barriers on federal lands in upper watershed.
	Confidence in remotely sensed model of spawning capacity because of ability to estimate model precision.	Balance spending between strategies A, E, and F, which emphasize opening and restoring new habitat above the dams.

Using multiple models also allows managers to incorporate their own knowledge about model biases and limitations into management decisions. Table 3 illustrates how managers can select a watershed management strategy based on both biological consideration and model accuracy and precision. Given a particular concern (e.g., survival of juvenile fishes in the lower reaches), the manager can compare models based both on output and reliability. Formal sensitivity analyses for each model would be ideal and sensitivity analyses for this multi-model decision support tool are underway.

Conclusions

For the foreseeable future, fisheries management is going to rely on incomplete empirical data, expert judgment, anecdotal evidence, qualitative relationships, and models of all types. This situation is not unique to fisheries; it is the nature of both policy-making and endangered species management. In a series of statements by environmental scientists from universities, public agencies, and private companies, the importance of accepting the inevitability of scientific uncertainty, as well as understanding and communicating that uncertainty, was expressed repeatedly. For example, Farland (2005) said that equating "the term sound science with the need for science without uncertainty to support decisions [is] an antithesis to public health protection" and Hushka (2005) agreed "sound science is not the pursuit of certainty before taking action." These scientists agreed that the quantification of uncertainty and the use of that information in decision-making are essential. Small (2005) listed four needs for the development and use of models and this included the examination of model sensitivity and uncertainty of model predictions to suites of reasonable inputs or assumptions. Lackey (2006b) went further and defined an axiom of environmental policy, "if something can be measured accurately and with confidence, it is probably not particularly relevant in decision-making." All modelers are aware of the old axiom, "All models are wrong, some are useful." In fact, one of the most useful things about a model is the description of how it might be wrong. This uncertainty can be quantified to improve environmental decision-making, as exemplified by the six case studies above.

How scientists can improve the use of modeled predictions in decision-making.— The use of modeled information will be improved when scientists and decision-makers begin communications about management needs and scientific possibilities early on, in the project planning stages. Both parties should discuss the source and magnitude of uncertainty in empricial data and in modeled output. Just as importantly, scientists can improve their ability to communicate uncertainty. The term uncertainty can refer to many similar but different concepts: chance or random events, plausibility or credibility, extrapolation from one known situation to a different situation, or confidence in a theory, a model, or model results (Anderson 1998) (Table 1). Clearly identifying the source, the type and the magnitude of uncertainty will increase the appropriate use of that information. One simple change in the way results are worded could quickly improve communication between scientists and policy-makers or managers. To be best understood, probabilities should be stated as long-run odds. For example, if you install 100 restoration projects, 25 are likely to result in decreased juvenile coho densities. Cognitive psychologists have demonstrated that this type of statement is much more easily understood and applied than single-event probability statements that describe the same information as "there is a 25% chance that a particular restoration project will result in reduced juvenile coho densities" (Anderson 1998).

If scientists were in the habit of reporting results as probability distributions, and journal editors rejected every paper that reported a point estimate without a confidence interval (where a confidence interval were possible), a culture of false precision would give way to improved understanding of what we know and a quantification of what we do not know. Clearly, such a change would lead to more complete use of all the information that models can provide and improved natural resource decision-making.

How managers can improve the use of modeled predictions in decision-making.— Mangers need to embrace uncertainty as well. As we have demonstrated, a clear understanding of model uncertainty can provide managers with dramatically increased information on which to base decisions. Just as scientists work to avoid presenting an overconfident point-estimate, managers must resist the temptation to demand it. Denying the uncertainty in our scientific models has lead to dogma, muddling of science and policy, inappropriate reliance on point-estimates, and risky decisions. Often, this has led to misunderstanding and a delay of important decisions until more data are collected.

There is an urge to strip away the scientific uncertainty when managers sell a policy decision to the public; however, decisions can be made in the face of uncertainty, given appropriate communication of results. In the future, improved communication about uncertainty will lead to more robust decisions; decisions that incorporate both the best scientific information and the uncertainty surrounding it. Scientific information can then be used to support the separate process of making policy decisions about acceptable risks and trade-offs between different types of risk. Ideally, collaborations between scientists and managers can enable bet-hedging strategies, diversified restoration programs, comparisons of multiple models, and planning that incorporates all modeled information, both point-estimates and measures of uncertainty.

Acknowledgments

We would like to thank Randall Peterman, Simon Fraser University, and Joel Reynolds, U.S. Fish and Wildlife Service, for comments after the presentation that improved the ideas presented in this manuscript. And we thank Owen Hamel and Chris Jordan, NOAA Fisheries, for reviews of the manuscript.

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