MANAGING UNCERTAINTY IN HABITAT RECOVERY PLANNING

The salmon ecosystem recovery planning approach proposed in this guidance document requires a complex series of decisions about habitat actions despite large amounts of uncertainty in the available information from many sources. This uncertainty can result in risks to habitats and populations from inappropriate management advice (Fogarty et al. 1996). Past failures of management plans to prevent population declines and collapse are due in part to the failure to recognize uncertainty in available information and a lack of procedures for including uncertainty in the decision-making process (Wade 2001). Inevitably, decisions will be based on a tapestry of models, estimates, expert opinions, myths, predictions, and data. By identifying, quantifying, and acknowledging the uncertainty in information used for recovery planning, we can increase the likelihood that recovery plans will be successful. The benefits of explicitly accounting for uncertainty include capturing all the available information regarding uncertain factors, providing the full range of possible outcomes and the probability of observing each, and identifying the key drivers of overall uncertainty in model projections (Mishra 2001). In this section we provide guidance via quantitative and qualitative examples for managing uncertainties inherent in habitat recovery planning.

A brief example illustrates how identifying and quantifying uncertainty can help a resource manager make explicit trade-offs between potential positive outcomes and acceptable risks. In choosing between two possible culverts for restoring fish passage, one might be given information that removal of culvert A is predicted to increase fish capacity by 120 fish while removal of culvert B is predicted to increase fish capacity by 100 fish. With no estimates of uncertainty, the manager would choose culvert A because it has the highest expected increase in fish capacity. However, more complete information might indicate that replacement of culvert A would open habitat that was less certain to be occupied (120 ± 70), while replacement of culvert B would open wetland habitat with a high degree of certainty (100 ± 10) to be quickly colonized. With the additional information, decision makers could then explicitly choose between a higher but less likely increase in fish capacity and a lower but more certain increase in fish capacity. In this example, neither action is likely to cause harm (a negative change in fish capacity). In other situations, actions with a high potential payoff may also contain some risk of being detrimental to fish, for example, when deciding whether to use chemical herbicides to remove nonnative vegetation from riparian areas. Without an estimate of the magnitude of uncertainty in the information on which decisions must be made, decision makers cannot make informed decisions.

The importance of clearly communicating uncertainty has been repeatedly emphasized in the fisheries literature (Francis and Shotton 1997):

- "Understanding the risk or uncertainty associated with choices could help fisheries managers select management strategies, decide which types of risks and uncertainty inhibit the effectiveness of management techniques, and finally, recognize which types of uncertainty must inevitably remain" (Peterson and Smith 1982).
- "Point estimates should be accompanied by variance estimates" (USCTC 1997).
- "The managers' task may be made easier if uncertainty in a fishery assessment were expressed" (Francis 1992).

- "Scientific advice to fishery managers needs to be expressed in probabilistic terms to convey the uncertainty about the consequences of alternative harvesting policies" (McAllister et al. 1994).
- "Clearly, when management decisions are to be based on quantitative estimates from fishery assessment models, it is desirable that the uncertainty be quantified and used to calculate the probability of achieving the desired target and/or risk of incurring undesirable events" (Caddy and Mahon 1995).

Such reporting of uncertainty in data and predictions has become common in harvest management (Rosenberg and Restrepo 1994). However, uncertainty is not often incorporated into salmon habitat recovery planning despite broad consensus that considering uncertainty is important and necessary in the conservation and management of species (Mangel et al. 1996, Flaaten et al. 1998, Akcakaya et al. 2000, Ralls and Taylor 2000, Wade 2001).

In this section, we first describe five types of uncertainty embedded in predictions of habitat capacity. We follow this with two examples of uncertainty in habitat management issues related to recovery planning. In each example, we describe how management decisions might be improved by acknowledging, quantifying, and reducing uncertainty in the decision-making process. The first example describes qualitative strategies for reducing uncertainties regarding chemical contaminants and making structured decisions in the face of limited empirical data. The second example describes the use of decision tables for making decisions that incorporate uncertainty. The final subsection describes strategies for making decisions when empirical data are lacking. Here we distinguish between variability, which is characterized by differences in a variable's value over time, space, or populations, and uncertainty, which is lack of knowledge about a true and constant value of a quantity (Morgan et al. 1990, Cullen and Frey 1999). Our discussion of methods for reducing uncertainty is purposefully simplified throughout, but references are provided for each example so that interested readers can locate more detailed information. By omitting site-specific and mathematical details, we intend to express a general framework for incorporating uncertainty into decisions.

Types of Uncertainty

Precise and accurate predictions are a fundamental goal in the aquatic sciences. Improved management of aquatic resources will result from a predictive science that can forecast the consequences, costs, and benefits of management actions (Pace 2001). A prediction might be a value (e.g., habitat capacity estimate, extinction risk, or survival rate) or a relationship between a habitat action and a biological response (e.g., effects of high flows on egg survival, effects of a particular restoration technique on fish survival, or projected population trajectories under different climate scenarios). Population viability and habitat goals (Phase I recovery planning) as well as prioritized project lists and watershed plans (Phase II recovery planning) must be developed from these types of predicted values and relationships. Informed plans and decisions will be based on both the predictions and the uncertainty surrounding them.

The five types of uncertainty found in predictions of habitat capacity are predictive uncertainty, parameter uncertainty, model uncertainty, measurement uncertainty, and natural stochastic variation (Table 13). Evaluating the relative magnitudes of the five types of

Table 13. Tools and methods for quantifying and reducing uncertainty.

Class of uncertainty	Brief definition	Habitat example	Method for quantifying	Possibility for reducing
Prediction uncertainty	Difference between modeled response and true response.	Uncertainty of predicting habitat capacity of a given watershed after instream restoration.	Leave-one-out estimates of prediction error rates. Simulation studies comparing conditions where model was built to those in which it is being applied.	Collect data for conditions in which predictions are required. Do not extrapolate beyond conditions under which model was developed.
Parameter uncertainty	Difference between true parameter (such as an average or a regression coefficient) and parameter as estimated from the data.	Uncertainty of parameters describing change in capacity as a function of changes in watershed condition.	Statistical theory for model coefficients derived from data. Sensitivity analysis for model coefficients estimated from other sources.	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 relationship between habitat conditions and fish capacity. Uncertainty in which habitat descriptors are best predictors of fish capacity.	Statistical descriptions of model fit: Akaike's information criteria (AIC), Bayesian information criteria (BIC), likelihood ratios, F-statistics.	Consider wide variety of models. Conduct sensitivity analyses.
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 number of replicates. Calibrate biased measurement techniques.
Natural stochastic variation (process uncertainty)	Inherent random variability.	Natural fluctuations in population size, habitat selection, or habitat conditions.	Variance of the observed data. Variance of the observed data for different sets of conditions.	Collect more replicates for conditions of interest. Stratify data collection.

uncertainty embedded in a particular prediction is valuable because it tells us where to be skeptical. More formally, we may pursue value of information (VOI) analysis to establish which additional information is most likely to improve our decision-making position (Raiffa and Schlaifer 1961, Raiffa 1997). VOI techniques seek to identify situations in which the cost of reducing uncertainty is outweighed by the benefit of the reduction. In some cases, the predictive uncertainty turns out prohibitively large and the available empirical data therefore provides little guidance for decision making. In such cases, other decision-making processes that do not require quantitative predictions can be used (see Using Decision Rules When Empirical Data Are Inadequate subsection, page 86).

To a great degree, the five types of uncertainty are nested: prediction uncertainty includes parameter and model uncertainty, which each includes measurement error and natural variability. Here we start with prediction uncertainty, the broadest form of uncertainty, and work down to the underlying natural variation. We provide examples of how each type of uncertainty arises, how it might be quantified, and how it might be reduced (Table 13). We conclude each subsection with a summary of how decision making can be improved by quantifying and acknowledging each class of uncertainty. A series of questions to ask of any prediction is in Table 14.

Prediction Uncertainty

Predictions include uncertainty from natural stochastic variation of the system being modeled, measurement uncertainty of the data used to build the model, uncertainty surrounding the form of the model, and parameter uncertainty (components addressed in the following subsections). In addition, predictions can include uncertainty that results from applying a model to a new situation. For example, a capacity estimate for Watershed X might predict future capacity based on current and past data for the same watershed or an estimate of current capacity for Watershed X might be based on data collected in other watersheds. Both cases involve extrapolating from conditions under which data were collected to new conditions. Uncertainty associated with these or similar extrapolations, say from the laboratory to the field, is difficult or impossible to quantify but must be considered and described.

Prediction uncertainty can be evaluated by ground-truthing (i.e., field measurement of specific attributes), prediction confidence intervals, and cross-validation simulation studies. Ground-truthing will help quantify the accuracy and precision of past predictions about current conditions, but can only suggest how well the model may perform under future conditions. Prediction confidence intervals can be computed in situations for which the manager does not need to extrapolate beyond the original data (Zar 1984). Where there is more than one predictor variable, caution should be used in defining the joint sample space beyond which one is extrapolating. In cross-validation simulations, the model is constructed and parameterized using a subset of the data (Stone 1974). The model is then assessed by how well it predicts that subset of data excluded from model construction. Cross-validation simulations do not include uncertainty associated with extrapolating from measured to unmeasured conditions. To assess how well a model may predict unmeasured conditions requires careful consideration of those model components that may be sensitive to expected differences between measured and unmeasured conditions (i.e., current vs. future conditions). Models can be compared in their

Table 14. Questions to guide the evaluation of predictions.

Prediction uncertainty
How similar are the conditions under which the original information was gathered to those for which the prediction is being made? How sensitive is the model (data, mechanism, and parameter estimates) to site-specific details?
Parameter uncertainty
Is the prediction sensitive to small changes in parameter estimates? If so, how precise are the estimates of those parameters?
Model uncertainty
What are the assumptions on which the prediction is based? How sensitive is the prediction to these assumptions?
Measurement uncertainty
Could any of the information on which the prediction is based be biased? How precise and how accurate are the data?
Natural stochastic variation (process uncertainty)
Can measurements be stratified across conditions to reduce the effects of natural variability?

relative sensitivity to changing conditions. Models that rely on predictors only correlated with the causal factors are particularly likely to have high levels of prediction uncertainty, because in new situations the correlations on which the model is based may no longer be coincident with the causal mechanism.

Parameter Uncertainty

Model parameters are necessarily estimated with uncertainty. A statement of the uncertainty of these parameter estimates is critical for making informed management decisions. Parameters that have biological meaning provide a context for interpreting the associated uncertainty. For example, imagine one had created a regression model to estimate smolt density as a function of the number of pieces of wood in the stream. The model would include a parameter, for example 12.3, that estimated the increase in smolt density for each piece of wood. The conclusion from such a model without parameter uncertainty estimates might be to embark on a widespread wood placement plan. However, if the parameter estimate had been more completely expressed as 12.3 ± 15.1, we might diversify the types of restoration actions used or choose a different restoration action with a smaller but more certain fish response and little or no risk of an adverse affect. For statistical models, parameter estimates are developed from the data and the uncertainty associated with these estimates is relatively easy to compute. For mechanistic models, parameters may be estimated from data, from similar models of other phenomena, or by expert opinion. When parameters are not estimated from data, the uncertainty surrounding them can be difficult or impossible to quantify. If estimates from such models are used, the potential uncertainties should be described; the direction and magnitude of the potential errors can often be estimated qualitatively.

Sensitivity analyses can be used to estimate the effect of parameter uncertainty. Nominal range or local sensitivity analysis computes the effect on model outputs of systematically varying each parameter in the model across its range of plausible values while holding the other inputs at their nominal values. Where small changes in parameter values lead to large changes in model predictions, the uncertainty of those parameters should be carefully evaluated. Models that are extremely sensitive to changes in parameter estimates and have highly uncertain estimates of those parameters will yield predictions with large uncertainty. Even where models produce highly uncertain predictions, they may be useful for quantifying the uncertainty in predictions and determining the type and quality of information that would be required to produce predictions with acceptable levels of certainty. The sensitivity analysis tells the managers that predictions are sensitive to particular conditions and that they will either have to increase precision of parameter estimates or ensure that management plans are robust to expected uncertainty. Increased precision of parameter estimates can be achieved by collecting more data, data over a wider range of values, or better data (data with less measurement uncertainty).

Model Uncertainty

Nearly all estimates and predictions used in management are explicitly or implicitly based on an underlying model. Uncertainty exists about both the model form (e.g., a linear relationship vs. a Ricker curve) and which predictor variables to include. Model uncertainty results from an incomplete understanding and a simplified representation of ecological systems and functions (Fogarty et al. 1996). For example, we might have a model that predicts habitat capacity as a linear function of several habitat parameters: wood density, pool density, gradient, adjacent land use, and water temperature. The default assumption may be to use a simple linear regression model. However, we may be uncertain whether the effects of these five habitat descriptors are additive or have a linear relationship to habitat capacity, and we may also be unsure if these five habitat descriptors are the best set of predictors or if an alternate set might perform just as well. Many statistical tools (adjusted R-squared, Akaike's information criteria or AIC, Bayesian information criteria or BIC, F-tests, likelihood ratio tests, cross-validation metrics) are available for choosing between models (Burnham and Anderson 1998). In general these techniques balance the degree to which the model fits or predicts the data with the complexity of the model, usually expressed as the number of parameters.

Models that fail to describe the ecological process accurately or to include an important predictor can have enormous management implications. Model predictions can be of the wrong magnitude or even the wrong direction. Resource managers and ecologists have often erred significantly by failing to consider model uncertainty. For example, the prevailing model of habitat effects on fish survival once assumed that fish survival decreases with increasing amounts of instream wood, and as a result, large amounts of wood were removed from streams and rivers (Maser et al. 1988). Thus habitat degradation in the Pacific Northwest can in part be attributed to a failure to assess the possibility that this model was incorrect (Beechie et al. 1996).

Model uncertainty is very difficult to quantify because there are an infinite number of possible models; none is exactly correct. Simulation studies generate data using a particular model, then ask questions about the behavior of those data (Morgan et al. 1990). They can quantify the degree to which the structure of the model influences the model's predictions. Averaging predictions from a suite of models can reduce the impact of model uncertainty on management predictions (Burnham and Anderson 1998, Cullen and Frey 1999). Beyond these tools, reducing model uncertainty is extremely difficult. Schnute and Richards (2001) suggest that model uncertainty be managed by keeping an open mind, identifying all assumptions, and testing those assumptions continuously.

Measurement Uncertainty

Measurement uncertainty or observation error is simply the difference between a true value and our recorded observation of it. It results from measurement, sampling, and data processing errors (Francis and Shotton 1997). All observations carry some degree of measurement uncertainty. This uncertainty may be large and problematic or small and of negligible consequence. Some phenomena such as the survival of fish in different habitats are inherently difficult to measure. Consequently, the variables associated with these phenomena have a high degree of measurement uncertainty. Other phenomena such as stream discharge can be measured quite accurately. Uncertainty resulting from sampling error occurs when the measured samples are not representative of the population for which inference is being made. The incorporation of measurement and sampling errors can obscure or create relationships between variables (Ludwig and Walters 1981, Walters and Ludwig 1981). Measurement error as defined here can also occur during data processing and storage.

Measurement uncertainty is directly related to both the accuracy and the precision of the measurement technique. Accuracy in a measurement technique, the inverse of uncertainty, describes the average distance between the measured value and the truth. The precision of a measurement describes the variability around that average. Therefore, a measurement tool can be highly precise (low variance across repeated measurements) and yet inaccurate (the average of repeated measurements is far from the true value). In other words, it is quite possible for a measurement to be characterized by little variability but a large degree of uncertainty. While there have been many attempts to estimate measurement uncertainty in, for example, habitat surveys (Pleus 1995, Roper and Scarnecchia 1995, Poole et al. 1997) or redd surveys (Jones et al. 1998, Dunham et al. 2001), the known uncertainty in these types of data is rarely included in the uncertainty of predictions from models that are based on these types of data.

Measurement uncertainty can result in systematic error or bias. Bias is a directional error that results from measurement using a systematically inaccurate tool. Biased or potentially biased measurements might include subjective assessments or incomplete records. A less visible form of bias occurs when a measurement technique tends to overestimate in certain conditions and underestimate in other conditions. A simple example is helicopter redd surveys. Redds are easier to identify where there are fewer trees; therefore the accuracy or uncertainty of the measurement may depend on whether there are riparian buffers. If the bias is not corrected, the data might erroneously predict increases in redd density with removal of riparian trees.

Measurement uncertainty can be reduced but not eliminated. Replication is the best way to reduce the uncertainty, though it will not remove bias resulting from the use of inaccurate measurement tools. Bias can be corrected using unbiased measurements. Measurement uncertainty in expert opinion or subjective assessments can be very difficult to assess because no actual data exists. Although it may be possible to determine how well experts agree with one another (precision), it is impossible to assess or quantify accuracy when there are no accurately measured data available for comparison. In such cases, sensitivity analyses (as just described in the Parameter Uncertainty subsection) can provide an assessment of the degree to which small amounts of measurement uncertainty or bias in the input data might affect predictions (Morgan et al. 1990). Measurement uncertainty may also be quantified using repeated measurements or by computer-intensive techniques such as resampling or bootstrap methods (Efron and Tibshirani 1991, 1993). By quantifying measurement uncertainty, the value of collecting more data with the same measurement or sampling technique versus a more expensive technique can be weighed.

Natural Stochastic Variation

Natural stochastic variation is the inherent random variability in ecological systems, such as temperature or population fluctuations. It also incorporates the underlying stochastic nature of population dynamics (Rosenberg and Restrepo 1994). It contributes to our inability to make precise predictions. Increased amounts of natural stochastic variation, often called process uncertainty, require increased numbers of observations (either more sites or more replications or both) to make estimates of a given precision (Shea and Mangel 2001). Very high levels of natural variation can mean that estimates of the required precision are simply impossible to obtain (Korman and Higgins 1997).

Identifying and quantifying natural stochastic variation helps us to distinguish between situations in which small amounts of additional data should dramatically increase our ability to make good decisions and situations in which additional data are unlikely to provide significant increases in the accuracy of predictions. This is the heart of VOI analysis discussed earlier. In some cases, stratifying the data or redefining the question can reduce the effects of natural stochastic variation. For example, we might make separate estimates of in-river survival for wet versus dry years. Resource managers would then be able to make more informed decisions about the value of habitat restoration plans that potentially have different effects in wet versus dry years. Because stochastic variation is a natural phenomenon, it cannot be reduced to increase the precision of our predictions. Where it can no longer be reduced by stratification, quantifying and acknowledging stochastic variation is the best way to manage it.

In summary, an informed management decision requires information about the uncertainty of the predictions on which that decision will be based (Pace 2001, Regan et al. 2002). Evaluating the uncertainty in each prediction requires the dissection of that uncertainty into its classes. Each class as well as methods for quantifying and reducing uncertainty are summarized in Table 13. By asking the questions in Table 14, we can identify critical knowledge gaps, improve predictions, and reduce the chances of making poor or uninformed decisions because of poor predictions.

Example 1: Creating a Prioritized List of Restoration Projects

Once we have a series of predictions with their associated uncertainties, we must combine them into an action plan (see Prioritizing Potential Restoration Actions within Watersheds section, page 60). In this example, we demonstrate one method of setting up a decision table for using predictions and their confidence intervals to develop a project list for a habitat recovery plan. Developing a project list is difficult because of uncertainty about how fish may respond to changes in the environment. For instance, we may have a list of potential actions, each of which is expected to increase pool habitat. There are uncertainties in estimating the increase in pool area and about the density of fish that can be supported by a given amount of pool habitat. By explicitly including the uncertainty in a decision table, we can identify the actions with the highest expected final fish density and determine the potential value of reducing the uncertainty. Analogous examples have been worked out in the harvest literature (Hilborn and Walters 1992).

The first task in setting up a decision table is to describe the "alternative states of nature" and ascribe probabilities to these states. In this example, the alternative states of nature are the alternative hypotheses about how many juveniles are supported by a given area of pool habitat. Table 15 presents sample hypotheses and associated probabilities. The probabilities associated with each hypothesis may be generated in a number of ways. One method that can combine multiple types of information is meta-analysis, which pulls together information from multiple sources (Liermann and Hilborn 1997, Myers et al. 2001). Other Bayesian analysis techniques can also be used to combine disparate sources of information. A trademark of Bayesian analysis is the assignment of probabilities to alternative states of nature (Wade 2000). Strengths and weaknesses of the Bayesian approach are described by Dixon and Ellison (1996). If only limited

Table 15. Input information and results of decision analysis for prioritizing restoration actions. Example alternative hypotheses about the states of nature (i.e., density of fish per m^2 of pool habitat) and the relative probability that the hypothesis is true are in the first two rows. All probabilities must sum to one. Expected outcomes for potential habitat actions (total fish) as a function of each hypothesized fish density are displayed below the hypothesis probabilities. Overall expected outcomes (increase in total number of fish) of each potential action, given all potential states of nature, are in last column.

Hypothesized fish density per pool		5	10	15	20	Overall expected outcome
Hypothesis probability		0.1	0.3	0.5	0.1	
Potential action	Remove culvert A	2,744	4,892	5,248	5,786	4,945
	Remove culvert B	2,844	3,400	3,858	6,457	3,879
	Remove riprap	2,012	4,172	4,260	4,340	4,017
	Add wood	1,568	3,410	5,963	6,230	4,784

or ambiguous data are available, expert opinion can be solicited to assign probabilities to the various hypotheses. Numerous texts describe the complexity of selecting a group of experts, combining their disparate judgments, and other challenges of this approach (Morgan et al. 1990, Cooke 1991). As noted earlier in the section, knowing if expert opinion is correct is impossible precisely because we use it in situations for which we have no data. If expert opinion is used to assign probabilities to a set of hypotheses, then the prioritized list that emerges from the decision-analysis process will be a formalization of those opinions.

The next step in setting up a decision table is to associate an outcome with each potential action, assuming each of the alternative hypotheses about the state of nature is true. For example, if the hypothesis that pools can support five juvenile fish per m^2 is true, then the number of fish expected from the removal of culvert A might be 2,744 fish. In this example the outcome is number of fish, but other appropriate outcome units such as fish per dollar may be of interest. This outcome is calculated based on an assessment of the number of pools that would be made available after removal of the culvert. More realistic and detailed decision tables might include additional information such as the number of riffles, types of pools, depths of pools, or quality of expected pool habitat. Table 15 shows potential outcomes in total fish for a number of management actions as a function of fish density in pools.

Finally, we calculate the final expected outcome of each potential action, given the probabilities of the states of nature (Table 15). The expected outcome of each action is calculated by summing the expected outcome for each state of nature multiplied by the probability that the state of nature is true. For example, the expected outcome for removal of culvert A is $(2744 \times 0.1) + (4892 \times 0.3) + (5248 \times 0.5) + (5786 \times 0.1) = 4945$. Table 15 shows the expected outcome for each of the four potential actions. The largest expected increase in total number of fish is associated with removal of culvert A.

This is an extremely simple example. Hypotheses about the states of nature will often involve more than a single dimension (e.g., more than pool density). Many types of information can be included in the analysis, but there will often be only one or two critical uncertainties that drive a decision. Decision tables provide a structured method for including and communicating uncertainties and can easily be constructed for many of the examples in this document. For example, the methods described in the Prioritizing Potential Restoration Actions within Watersheds section, page 60, could be modified to include uncertainty about fish response, restoration costs, or habitat quality by using the decision table methodology described here. Another tool for making decisions is a logic tree, which models the impact of uncertainties in states of nature and in the occurrence of future conditions on possible outcomes (Kessler and McGuire 1999). Logic trees are particularly useful when only subjective probabilities about the states of nature exist.

Example 2: Water Quality and Habitat Recovery Planning

Uncertainty in habitat planning can result from the omission of a key habitat variable, such as water quality. The quantity and quality of salmon habitat are both important determinants of salmon population viability. Stream temperatures, sedimentation, and water pollution are all examples of measures of habitat quality. However, empirical data for the various forms of water pollution are rarely incorporated into habitat models. Consequently, the complex impacts of urbanization, agricultural land uses, and industrial activities on the chemical condition of salmon habitat may lead to large levels of uncertainty in habitat recovery planning. In this example, we suggest ways to improve habitat decision making by incorporating water quality data. We provide nonquantitative solutions to reducing uncertainties that result from the omission of key habitat variables.

Environmental monitoring studies have consistently detected a wide array of metals, pesticides, and other toxic substances in the surface water and sediment of salmon habitats, and also in the tissues of salmon themselves. These contaminants may affect salmon abundance and survival via immediate lethal effects on individual fish. However, such effects are rare compared to the vast array of potential sublethal effects that may reduce individual fitness and population performance and potential indirect effects such as reductions in the abundance of key prey taxa. Despite documented exposure conditions (Wentz et al. 1998, Ebbert and Embrey 2002), the impact of environmental contaminants on salmon health or on the biological integrity of aquatic systems is poorly understood and habitat-based models for salmon recovery rarely capture the biological significance of water and sediment quality. Predictions of salmon population viability are likely to have high levels of model and prediction uncertainty if water and sediment quality are not included in model development.

There are several reasons why the specific determinants of chemical habitat quality are often excluded from habitat models. First, chemical habitat quality can be difficult and expensive to measure. Second, there is a general absence of toxicological data for most of the chemicals that have been detected in salmon habitat. Third, many conventional endpoints or biomarkers of chemical exposure have no clear or consistent relationship to the survival or reproductive success of the exposed animal. Consequently, there is often a disconnect between the biological scale at which toxicological studies are conducted and the data requirements for current habitat recovery models (Hansen and Johnson 1999a, 1999b).

Recovery plans that capture broad spatial and temporal patterns of chemical habitat degradation, despite incomplete empirical data, will minimize uncertainties around predicted outcomes of restoration actions and therefore reduce risks to salmon populations. Contaminants occur in complex mixtures whose composition varies in time and space. Salmon habitat conditions may reflect current land use activities or activities that were restricted or banned many years ago (e.g., persistent chemicals such as DDT). Moreover, water quality at a specific point within a watershed may be determined by land use activities that are far removed from the focus of restoration efforts. Acknowledging the large spatial and temporal scales at which contaminants can affect fish helps identify some of the uncertainty associated with predicting the effects of restoration actions. We can surmise, for example, that the uncertainty of predicted increases in habitat capacity for a given restoration action is likely higher in areas with high levels of past or present on-site or upstream chemical contamination. Likewise, we might expect inaccuracy and prediction uncertainty in survival estimates that are extrapolated from a stock within a pristine watershed to a stock that migrates through a highly contaminated estuary.

In many cases, we do have data on chemical contamination but we do not know how to incorporate it into habitat recovery planning. A limited number of studies have specifically addressed the impacts of environmental contaminants on biological processes in Pacific salmon that are clearly linked to survival, migratory success, or reproductive success (Kruzynski and Birtwell 1994, Arkoosh et al. 1998, Hansen et al. 1999, Heintz et al. 2000, Scholz et al. 2000, Rice et al. 2001, Meador et al. 2002). The challenge in estimating the effects of toxic chemicals on salmon health is to identify which contaminants are known or suspected to occur in particular habitats and pathways of toxicity for these chemicals that have significance for the survival, migratory success, or reproductive success of wild salmon.

Planners or researchers should utilize the primary toxicological literature in the development of recovery plans. Answers to the following questions can often be found in the toxicological literature and will enable more accurate and precise predictions about the effects of specific chemical contaminants on predicted salmon population performance.

1. What is the evidence that a contaminant or class of contaminants is present in salmon habitat?
2. What are the expected environmental concentrations?
3. How long will exposures last?
4. What life history stages of salmon are likely to be affected?
5. What are the primary possibilities for sublethal toxicity in fish?

From this information it may be possible to estimate the chances that the contaminant is currently or may in the future be a significant limiting factor in salmon population viability within the geographic area of concern.

Incorporating toxicological data can improve decisions about the prioritization of water quality improvements versus physical habitat restoration. For example, in watersheds where insecticides occur (primarily in agricultural and urban areas), it should be possible to estimate the potential loss of invertebrate prey, the subsequent reduction in the growth of juvenile fish, and the likelihood that salmon from contaminated habitats will have a lower rate of marine survival. If environmental monitoring data are unavailable, recovery planners might extrapolate potential chemical concentrations from other (monitored) basins with similar agricultural or urban land use. Even simple comparisons between reported environmental concentrations and toxicity thresholds for aquatic invertebrates can reduce the scientific uncertainty surrounding the potential effects of contaminants on salmon population viability. This in turn would improve restoration prioritization and watershed management plans.

For water quality and other habitat characteristics about which less is known, it is clearly better to acknowledge the uncertainties and incorporate the available information, no matter how limited. In the example of water quality, we can estimate and incorporate the direction of the effect even when we are not yet able to quantify the magnitude of that effect. We can also seek empirical data from nontraditional sources. Moreover, identifying key uncertainties will help establish priorities for ongoing and future research.

Using Decision Rules When Empirical Data Are Inadequate

A careful and honest examination of uncertainty in data, predictions, and models will inevitably lead to the identification of situations in which adequate empirical data for making a decision are simply not available. Uncertainty should not lead to inaction. Methods are being developed to allow quantitative analysis of the sensitivity of decisions to uncertainties in the data. For example, sensitivity analyses were used to demonstrate that the best management decision for Hector's dolphin (*Cephalorhynchus hectori*) was robust to model uncertainties, and thereby removed uncertainty in the scientific data as an excuse for inaction (Slooten et al. 2000). In the face of large amounts of uncertainty in empirical relationships, simulation models and decision analysis were used to evaluate management actions for listed salmonids in the Snake River basin (Peters and Marmorek 2001, Peters et al. 2001). Where empirical data are inadequate, we strongly discourage basing decisions on biased or imprecise predictions, prioritization systems for which guesswork must be substituted for data, or information that becomes inaccurate or imprecise at the scale for which the decision must apply. Instead, we suggest that resource managers provide an explicit rationale for the decision that requires minimal data.

The most important characteristics of a decision rule are that it can be documented and is robust. Documentation is important because future managers will need to understand the basis for the decision. This requirement prevents arbitrary decisions in the face of inadequate data. Decision rules that are robust to uncertainties in the information help prevent risky management decisions (Schnute and Richards 2001). Decision rules presented in the literature include the following two examples.

The Precautionary Principle can be stated as, "When an activity raises threats of harm to public health or the environment, precautionary measures should be taken even if some cause and effect relationships are not fully established scientifically" (Raffensperger and Tickner 1999). Because this principle shifts the burden of proof to those who create risks and does not define which risks are most important (Hilborn et al. 2001), it has generated much controversy and confusion about its appropriate implementation. However, there are many examples of national and international policies that have been based on the Precautionary Principle. European environmental law is based on the Precautionary Principle through the 1992 Treaty on European Union, and the Rio Declaration from the United Nations Conference on Environment and Development binds the United States to implement the Precautionary Principle in environmental health protection (Raffensperger and Tickner 1999). While we are not advocating this particular decision making rule, we present it as an example of a relatively simple guiding principle for high-level decisions in the absence of definitive data.

Safe Minimum Standard (SMS) is another decision-making rule that has received considerable attention. The SMS approach is a collective choice process that prescribes protecting a given level of a renewable resource unless the social costs are excessive (Berrens 2001). This approach to making environmental decisions is usually invoked in settings involving considerable uncertainty and potentially irreversible losses. It prioritizes social costs over loss of renewable resources. We present this approach for comparison to emphasize the importance of carefully choosing the decision-making principle and documenting exactly what considerations should be involved. The choice of a guiding principle will dictate management decisions until improved information is available.

The choice of a decision-making rule need not be purely theoretical. The Assessment Approach for Habitat Recovery Planning section, page 5, discusses the importance of defining a habitat strategy that includes gathering additional data and taking interim actions. This habitat strategy is an excellent example of how a guiding principle can be used for decision making until adequate data become available. The Prioritizing Potential Restoration Actions within Watersheds section, page 60, presents guidelines for selecting restoration actions before all of the habitat data are available. Again, this is a simple and effective method for dealing with incomplete information.

Another common approach to formalizing decision making without adequate empirical data or quantitative predictions is a scoring matrix. A scoring matrix can be used to prioritize potential actions, project proposals, potential action sites, or information gathering. The advantage of a scoring matrix is that ranks can be based on weighted priorities, for example, project longevity, proximity to other projects, or land ownership. The decision path can be clearly explained and is easily repeatable. As better information becomes available, the matrix can be adjusted. A disadvantage of the scoring matrix is that the weights assigned to each priority can dramatically alter the outcome and specifying a satisfactory weighting function in advance is often difficult. Examples of scoring matrices in current use include the Snake River Salmon Recovery Region Comprehensive Project Scoring Matrix (SRSRC 2002), the Lower Columbia Fish Recovery Board Interim Habitat Strategy Project Scoring Sheet (LCFRB 2001), and the Skagit System Cooperative methodology for rating individual landscape processes (Appendix C, page 157). The scoring matrix provided by the Lower Columbia Fish Recovery Board dedicates a section to "Certainty of Success," explicitly including some metrics of uncertainty.

In each of the above examples, it is important to consider whether the decision strategy is robust to the types of uncertainties that exist. A strategy that would be beneficial under a scenario that has a 50% chance of representing reality but detrimental the rest of the time is not a robust choice. Strategies should be developed so that the outcome is acceptable given the range of possibilities for which there is uncertainty. Again the Hector's dolphin management plan is an example of a strategy that is explicitly robust to the uncertainties in the data (Slooten et al. 2000).

Using decision-making strategies that require minimal data carries two obligations. First, we must evaluate whether improved information would produce a cost-effective improvement in decision making (VOI analysis). If so, then a strong attempt to reduce uncertainties by gathering more or better information is required. The analyses described in the Types of Uncertainty subsection above can identify critical information uncertainties and reduce their impact. Second, we must set a time frame for reevaluating the decision. In the best possible scenario, decision strategies requiring minimal data serve as interim measures until additional information is available.

In conclusion, we emphasize that estimates of uncertainty—quantitative where possible, qualitative for other situations—should be included with all information being considered in a decision-making framework. A systematic treatment of uncertainty should include:

1) identification of uncertain events, states of nature, relationships, and parameters,
2) determination of the likelihood associated with each potential state or value,
3) use of data or models to evaluate consequences of each potential state or value, and
4) examination of the relationship between uncertain inputs and potential outputs to identify key uncertainties (Mishra 2001).

Even where a formal analysis of uncertainty is not possible, describing sources and magnitudes of uncertainty is important in providing managers with enough information to weigh potential risks and benefits of possible actions (Rosenberg and Restrepo 1994).

A careful examination of the sources and causes of uncertainty will ensure informed decisions and make improvements in both precision and accuracy likely. Quantifications of uncertainty can be formally incorporated into decision making using decision tables. In other situations, simple strategies such as collecting data at multiple scales or incorporating data from other disciplines will provide for more informed decisions. However, a lack of empirical data need not prevent informed decisions from being made in a clear and formal manner. It is possible to implement strategies that require minimal data. Such strategies are preferable to using biased or imprecise predictions, guesswork disguised as data, or information that is inappropriate to the scale of the decision.

As we said earlier in this technical memorandum, our conceptual approach to habitat recovery planning is holistically focused on restoring or preserving watershed and ecosystem processes to provide good quality salmon habitat over the long term. This implies that restoration of ecosystems to support salmon will include a wide range of actions affecting the life cycles of multiple species. We began with a conceptual framework for understanding relationships among land uses, watershed functions, habitat conditions, and biota as a basis for organizing the habitat-related questions that each recovery plan should attempt to answer. We separated recovery planning into two phases—Phase I planning that identifies recovery goals and Phase II planning that identifies causes of habitat loss or degradation and necessary ecosystem restoration actions. Then we showed how results from both assessments can be used to prioritize restoration actions and how incorporating estimates of uncertainty into the decision-making process increases the likelihood of success in salmon habitat recovery planning. Finally, new information gained from assessments and management experiments should be used to update the recovery plan.