16.0 Uncertainty Associated with Performance Measure Application

The Everglades ecosystem is complex and our understanding of its physical and biological processes, organizations and functions is incomplete so uncertainty is common. In general, uncertainty refers to a degree of dissatisfaction of some knowledge and expectations (Breckling and Dong 2000). A subject is uncertain when it is not exactly known or determined, or can not be reliably predicted (Prigogine and Stengers 1984, Lemons 1996). Specific meaning of uncertainty may vary in different situations and is dependent on context. In our performance measures, uncertainty exists in targets, protocols, quantitative models and verbal descriptions. Uncertainty varies among performance measures in terms of types, sources and magnitude. Decision-making in ecosystem restoration always faces uncertainty; therefore, documentation and characterization of uncertainty are important. They provide decision makers a certain level of confidence, while warning against a false sense of accuracy.

A desirable and widely used method of characterizing uncertainty in models is to identify a probability distribution of errors in model output based on field data. Inferential statistics can then be used to define confidence intervals, and a threshold level of risk can be assigned. When possible and appropriate, this method should be used and statistics should be documented. However, this method requires a large quantity of quality data. For restoration of a complex system, such as the Everglades ecosystem, long-term, site-specific data at a large spatial scale are needed. At present, these data are lacking for many performance measures. In this situation, recognizing presence of uncertainties, their sources and trade-offs among them is the first step in characterization and can offer very useful information to decision makers.

16.1 General Classification of Uncertainty

Uncertainty can be classified in various ways. Regan et al. (2002) categorized uncertainty into two main types: epistemic and linguistic uncertainty. These two types are discussed in the following paragraphs.

Epistemic uncertainty is associated with knowledge of the state of a system. It includes uncertainty due to limitations of measurement devices, insufficient data, extrapolations and interpolations, and variability over time or space. A main epistemic uncertainty for CERP pertains to hydrological and ecological history of the Everglades. Epistemic uncertainty includes several types:

- **Measurement error and systematic error –** our mental and physical limitation to observe the physical or biological world accurately
- **Natural variation and inherent randomness** - our ability to predict to a certain range of accuracy and inability to predict to a desired degree of accuracy
- **Subjective judgment** - result of interpretation of data, particularly when data are scarce and error prone. Subjectivity is a major source of

> disagreement, another kind of uncertainty. Subjectivity and disagreement are to be expected when human values are involved.

Linguistic uncertainty includes vagueness, context dependence, ambiguity, indeterminacy of theoretical terms, and under specificity. All of these uncertainties arise in both natural and scientific language. Restoration efforts involve a multidisciplinary approach incorporating many scientific, engineering, sociological, economic and other disciplines. Inconsistency exists among vocabularies of these disciplines. Meaning of words evolves as restoration proceeds and they evolve among people at different rates. While RECOVER works hard to reduce linguistic uncertainty, we recognize that it still exists within the program.

It is important to recognize that tradeoff exists among different types of uncertainties. Because of these tradeoffs, we need complementary targets, protocols and models. Below we briefly discuss target uncertainty and protocol uncertainty. Since models often determine both targets and protocols, model uncertainty also will be briefly discussed. Please note that these uncertainties are all interrelated.

16.2 Target Uncertainty

Two types of targets are common in performance measures: numerical estimates and directional comparisons. Numerical estimates are exact numbers or ranges of numbers. In plan evaluations, quantitative projections are compared against the target number to assist in selecting the best alternative. Directional comparison does not need an exact number. It seeks an increase or decrease.

Plans with these two types of targets may be susceptible to different kinds of uncertainty. Tradeoffs exist. For example, directional comparison often is less susceptible to systematic biases. If biases can be reasonably assumed to be consistent and thus cancelled in comparisons, they would not influence rank of plans during comparisons. On the other hand, if the target is a numerical estimate, bias more likely influences rank of plans during comparison. However, difference in directional comparison may or may not be interpretable, physically or biologically, or in terms of restoration success. Often, directional comparison is not adequate for quantifying restoration success and numerical estimates are needed.

Knowledge of uncertainties is important when both potential benefits and potential damages are key concerns. If target uncertainty is high and if potential damage is costly or difficult to reverse, we may need to set a minimum safe threshold level as a constraint in plan optimization. In other words, uncertainty is a determining factor in deciding whether we need to focus on maximization of benefits or minimization of potential damage or both.

16.3 Protocol Uncertainty

Often, uncertainty is lower if a performance measure is spatially or temporally more aggregated. For example, yearly averages of water elevation or animal abundance are much less uncertain than daily values. On the other hand, high levels of aggregation will miss important information, often leading to homogenization and loss of natural variation. For example, timing of seasonal processes and spatial configuration of biological communities are important components of ecosystem health and integrity. Using yearly average will totally miss seasonal timing, and using seasonal averages cannot help much in restoration of natural timing. A small error in timing can lead to a large rounding error, such as a change in month when monthly average data are used. In the same light, selection of spatial regime also affects uncertainty. Each indicator region, transect and sub-region has its own level of uncertainty. Again, if uncertainty of a performance measure target is high and if potential damage is costly or difficult to reverse, we may need to set a minimum safe threshold level in protocol as a constraint in plan optimization.

16.4 Model Uncertainty

Many performance measures require models to evaluate projections or assess of system response. Models synthesize empirical information, including professional judgments, into a formal organized framework, and generate logical, quantitative projections according to given assumptions. Common assumptions in hydrologic planning include those about climate condition, water control structures and water control operations. Model projections based on these assumptions can be compared quantitatively to evaluate consequences of these assumptions in terms of specific performance measures. Thus, model projections are extremely useful for scenario selection. Models are also used to support monitoring design since models can be used to identify critical components of the system and missing links among components. Because models have formal structures, they also allow people to evaluate and characterize uncertainty explicitly and quantitatively.

Models are simplified, quantitative representations of real systems. Models are usually comprised of state variables and mathematical equations linking state variables. State variables describe state or conditions of system components, which often are issues in decision-making and management. Equations usually have specific functional forms and contain some prefixed numbers. These numbers are parameters. Other explicit and implicit model components include boundary conditions and spatial-temporal domains. For dynamic simulation, state variables have initial conditions. Uncertainties are associated with these model components in various ways.

A model may be used to address different questions and to support different performance measures. Uncertainty varies with questions, because different parts of model output vary in sensitivity to uncertainty sources and different targets and protocols vary in sensitivity to model uncertainty.

Additional discussion of model uncertainty can be found in the *Model Uncertainty Workshop Report* (RECOVER 2002). This report can be found at the following web site: http://www.evergladesplan.org/pm/recover/recover_docs/et/052402_mrt_uncertainty_report.pdf.

Sources of Model Uncertainty

Uncertainty in model output have at least four potential sources: ignorance, errors, stochasticity and inherent unpredictability. These potential sources are discussed in the following paragraphs.

Ignorance can be a consequence of lack of knowledge, or a consequence of a conscious decision, based on technical or non-technical considerations. Many interactions and environmental factors are ignored in models. Usually only variables of primary interest are included. In models, all ignored influences are implicitly represented by parameters and functional forms thus assumed constant. When these influences change, particularly when CERP scenarios alter these influences, this kind of ignorance will bring about biases or errors in model projections.

Errors can occur in estimation of parameters, formulation of models, specification of boundary and initial conditions, and computational procedures caused by epistemic constraints, mismatches of model representations and field observations, and mismatches of spatial and temporal scales. Note that errors and bias from one source could propagate and amplify through model structure, and lead to both qualitative and quantitative uncertainties in modeling outcomes (Gardner et al. 1980). Model parameters for three classes of models - hydrologic, biogeochemical and ecological - vary and each has an associated level of uncertainty. In general, state-based parameters (e.g., water stage, abundance of organisms) perform better than rate-based parameters (e.g., water flow, productivity). Parameter error consequences can be analyzed via a technique called “uncertainty analysis”. Nevertheless, complete, quantitative consequence characterization of all errors and their interactions is difficult.

Many model parameters are inherently stochastic. They can be characterized by a probability distribution but not by one accurate number. Uncertainty due to stochasticity can be reduced by using data with a large sample size.

The system could be intrinsically unstable. Some models contain nonlinear equations and chaos could occur in these models. When chaos occurs, even a high level of accuracy and precision in measuring state variables, parameters and model formation will not improve long-term prediction. Magnitude of uncertainty in prediction approaches the magnitude of the overall variability of the system quickly through time.

Simple versus Complex Models

Different types of models exist. Some are simple and some are complex. Trade-offs exist among different types of models with respect to uncertainty. For example, simple models may involve more ignorance. One common way to reduce uncertainty caused by ignorance is to include additional variables into models, making them more complex. Complex models contain more parameters and other specific details. They represent more specific information, and thus they are more realistic. However, data requirement grow very fast to avoid potential bias in parameter estimation, and potential errors in identification of functional formula and interplay of these errors increase quickly with the level of complexity. Such kinds of errors and biases may bring about a large uncertainty in model outcomes. Gardner et al. (1980) found that complex ecological models usually amplify parameter errors.

Further, with simple models, analytical solutions exist, which provide a convenient base for statistics. Statistics can provide measures of stochasticity. It is very difficult to find analytical solutions for complex models. Thus, it is more difficult to design a general statistical formula for complicated simulation models. This statistical difficulty leaves room for uncertainty about and caused by stochasticity. Complex models usually 'postdict' better but may not necessarily predict better (Gauch 1993). Disagreement exists among modelers in favor of simple versus complex models. Given a specific question, an optimal level of complexity may be reached (Costanza and Sklar 1985, Hilborn and Mangel 1997).

Classes of Models: Hydrologic, Biogeochemical and Ecological

Three classes of models are used to support CERP planning: hydrologic, biogeochemical and ecological models. Each has associated uncertainty. Model uncertainty generally increases when moving from hydrologic models, to biogeochemical models, to ecological models due to increase in both model structural error and parameter uncertainty. Usually, hydrological data are much more abundant than that of biogeochemistry, which are much more abundant than ecological data. Another key factor that leads to this pattern of increasing uncertainty is the relationship between hydrologic models and biogeochemical and ecological models. Hydrologic model output is usually used as an input parameter for both ecological and biogeochemical models. This linkage can lead to error propagation and magnification due to initial error in hydrologic models. Further discussion of specific parameter uncertainty is provided under the detailed model class discussions below.

Hydrologic Models

All CERP projects must be evaluated for hydrologic effects. Hydrologic, hydraulic and hydrodynamic models have been proposed and developed for these projects. They are spatially-explicit, deterministic simulation models. Modeling applications include simulation of surface water system, groundwater system, and interactive surface water-groundwater system. Water elevation is a common, focal-state variable for all of these models. Among them, the South Florida Water Management Model (SFWMM) is most frequently used in regional decision-making.

Compared with biogeochemical and ecological models, hydrologic models generally have lower uncertainty due to abundant data and reliable physical rules. Usually, uncertainty of water elevation is lower than uncertainty of flow in model output.

Uncertainty analyses have been conducted at various degrees in applications of these models, although insufficiently. These analyses quantify responses of model output to errors in parameters and provide very valuable information for decision makers. Uncertainties originating from other sources have rarely been analyzed. A major uncertainty in application of model output is scale mismatch.

Biogeochemical Models (Water Quality Models)

A large number of biogeochemical models, or water quality models, have been planned or developed for South Florida systems. Some are spatially explicit and some are not. Focal-state variables and spatial domains also vary. Some simulate phosphorus, and some simulate other chemicals, including metals. Some models simulate biogeochemical dynamics, using hydrologic model output as input, and some have their own hydrologic engines. Most of these models are still under development or still require peer review. Characterization and documentation of uncertainty associated with output of these models are generally lacking.

Hydrologic projects undoubtedly affect biogeochemical dynamics. One particularly important aspect of uncertainty in CERP decision-making is propagation or bounding of uncertainty originated from hydrologic models. Propagation processes are not understood. Analyses are generally needed to understand and characterize uncertainty of this group of models. In general, biogeochemical models have less uncertainty associated with them than ecological models.

Ecological Models and Tools

A large number of ecological models and tools have been proposed and developed for South Florida systems. This is a very diverse group of tools. They can simulate ecosystem processes, focus on community dynamics, investigate population changes, or present landscape patterns and processes. Some models are deterministic; some stochastic. They are spatially explicit or spatially implicit. Spatial domains vary, as do temporal resolutions and scales. Ecosystems are complex and hierarchical, and ecosystem components respond to environmental changes at different spatial and temporal scales and domains.

Uncertainty associated with these ecological models varies greatly. When used together, these ecological models may complement each other. Common conclusion from a diverse group of models can provide a high level of confidence, which a single model alone would not be able to provide. When different models suggest opposite directions, uncertainty needs to be identified and analyzed.

When each ecological model or tool is evaluated alone, uncertainty level is usually high because of trade-off of various kinds of uncertainty, such as trade-off between simple and complex designs. A universally optimal design of ecological tools is not available, although given a specific question, a specific design can be most useful and can give the maximum level of confidence.

A particular group of ecological tools are hydrologic suitability indices. This group includes habitat suitability indices (HSIs) and spatially-explicit suitability indices (SESI). These tools are extremely simplified presentations of hydrologic-ecologic links. They are so simplified that they do not contain state variables of ecological entities, and therefore do not really simulate ecological interactions. They assume that ecological processes and ecological history are unimportant and thus can be ignored. Often, a hydrologic surrogate is used as an ecological index. Simplicity allows them to be very user-friendly and easy to implement, and the results are easy to communicate. Ignorance of these tools makes them extremely unrealistic and thus difficult to link them with field observations. Often, numbers generated by these index tools are difficult to interpret ecologically.

Simplicity of HSIs allows some uncertainties to be analyzed and characterized without tremendous difficulties. Usually, uncertainty from hydrologic model output will propagate in computation and propagation can be tracked. For example, averaging and aggregation of indices can lead to additional uncertainty. Averaging across a period of time is sensitive to uncertainty generated by ignorance of history leading to underestimation or under representation in indices of chronic effects of ecological disasters and damages. Ecological systems typically experience hysteresis. Hysteresis means that ecological disasters and damages occur in a short time period, and recovery from disasters and damages takes a much longer time. Slow recovery is not considered by indices. When averaged across a time period, infrequent disaster or damage and long-term consequences may not be seen.

Ignorance, unrealistic ecological presentation, and loose link between the indices and field measurements, makes uncertainty evaluation based on field data difficult. Many indices are not scale specific and appear scale independent. This makes them easy to use with models of different scales, but often leads to scale mismatch.

Simulation models are more realistic presentations. They allow key ecological processes to be represented and are extremely useful and can complement simple indices. Some ecological simulations are complex, and ecological data are usually difficult and expensive to collect accurately. Thus, level of uncertainty is high, in terms of errors in parameter estimation, equation identification, natural variability and stochasticity, and nonlinear error propagation. Due to the complexity of model structure and model implementation, a high level of expertise is usually needed when applying these models to support decision-making. Communication of model uncertainty is extremely important and usually difficult. Relatively poor communication between modelers and model users adds another barrier and difficulty to the uncertainty issue. Documentation needs to be clear, complete and easy to read. When simulation output is used in decision making, caveats provided in the documentation need to be considered.

16.5 Dealing with Uncertainty

Factors Increasing Uncertainty

Complex feedback among modeling, planning, operation, management and engineering design may cause uncertainty propagation, particularly in context of an evolving restoration project. Unexpected changes take place all the time. Local, regional, national and global environments change, and these changes are often beyond our control. Goals, objectives and constraints of projects sometimes also change. These changes may bring in more uncertainty to models, because models are forced to perform functions for which they were not originally designed. For example, the SFWMM is now carrying out many jobs that had not been anticipated when the model was conceived. Some projects may change model boundary conditions. Some projects are covering areas outside model spatial domain. Some projects need information in a much bigger spatial resolution. Efforts need to be made to reduce this kind of uncertainty.

Measures Reducing Uncertainty

Standardized procedures and an integrated approach are needed to handle and control uncertainty. Breckling and Dong (2000) suggested the following:

- **Collect available hydrologic and ecological information.** These data, especially data from long-term observations, are necessary to evaluate temporal and spatial variability and to identify inconsistencies in a priori model information.
- **Increase field observations.** Large samples can reduce errors of estimated parameters if stochasticity is the major source of uncertainty. Statistical methods provide a repertoire to estimate this uncertainty aspect. If repeated observations fail to follow presumed statistical distributions, inherent instability or lack of knowledge of important factors may be the reason.
- **Compare related cases.** Comparison of similar cases may reveal a lack of information. Important processes and effects may be obscure in one case but more apparent in another.
- **Combine different approaches.** Different types of models may complement each other in terms of uncertainty. If models prone to different types of uncertainty point to the same direction, decision-making confidence increases.
- **Embrace different predictions.** Divergence of predictions from different types of models or among experts indicates large uncertainty. Different models may give different results trying to simulate the same thing and are a good indicator of uncertainty; therefore having multiple models simulating the same thing is desirable. For example, in hurricane track predictions, multiple models are used to lend

confidence to tracks. Meteorologists spend a lot of time focusing on confidence zones in these simulations when forecasting landfall of a storm.

- **Think nonlinearly.** 1) Pay attention to potential phase transitions and hysteresis effects. In nonlinear dynamical systems, state shift and hysteresis can occur. A small change of only one of the system parameters or a marginal external influence can cause dramatic changes of the whole system's behavior and organization. Dramatic state change and hysteresis can bring about surprises and irreversible, undesirable consequences if ecologists ignore signals of nonlinear processes and structural instability (Carpenter et al. 1999, Dong et al 2002). 2) Consider chaos (predictable unpredictability). Chaos prevents long-term predictions. Chaotic systems inherently increase small uncertainties to a macroscopic level. These systems are predictable only for the short term. With sound knowledge of underlying structure and processes of a system, the usual time span of reliable prediction can be estimated. In ecology, we usually do not deal with pure chaotic systems but with an overlay of ignorance, stochasticity, errors and chaotic dynamics.
- **Be aware of scales, hierarchy and emergent properties.** Observed patterns at lower organizational levels and finer spatial-temporal scales may or may not match with patterns at higher levels or large scales. The whole may be greater than the sum of the parts. Linear scaling up or down may produce biases, and scale mismatch may lead to surprise later. Multi-scale investigation and experimentation may provide further insight and reduce potential bias and uncertainty.

Quantification, Presentation and Documentation of Uncertainty

Decision-making needs to consider uncertainty. Thus, uncertainty needs to be characterized and documented so that caveats can be provided to decision makers and stakeholders when performance measures are used. Complete and accurate quantification of uncertainty are desirable, but often impractical. Nevertheless, some measures of uncertainty can be made and are useful.

Formal uncertainty analysis and sensitivity analysis offer a variety of metrics that characterize uncertainty. Note that uncertainty analysis and sensitivity analysis are two types of techniques that typically characterize outcomes of parameter uncertainty, but not influences of other uncertainties. Comparisons between model output and expert opinions and among outputs of different models are very useful in identifying inconsistencies and gaps for each performance measure. Resulting agreements and disagreements measure uncertainty. Consensus often increases confidence; disagreements indicate uncertainty, and sometimes provide clues of potential surprises. Opinions of independent peer reviews can present the degree of satisfaction and dissatisfaction, thus are a measure of uncertainty. Results of uncertainty and sensitivity analyses, expert technical reviews and independent peer reviews should be documented.

Decision-making and Uncertainty

Decision-making is often difficult in CERP planning, not only because of uncertainty involved in performance measure restoration targets, evaluation protocols and models, but also due to the complexity of the decision-making process itself. Yet decisions have to be made in a timely manner. Not deciding what actions to take and delaying decision-making both are de facto options, which are often very costly and thus bad decisions.

It is desirable to make robust decisions that are error tolerant. Management should always consider potential failures in advance. Considerations should be given to both benefit maximization and minimization of damages. Ecological damage can be very costly and difficult to reverse, including damages that result from taking no action. CERP itself is a result of regret caused by previous hydrological alterations. We need to minimize potential future regret caused by insufficient restoration.

Planners should always consider potential failures in advance, use the Adaptive Management Strategy (RECOVER 2006), and follow precautionary principles. The Adaptive Management Strategy allows performance measures, quantitative tools and project plans to evolve with new information and monitoring feedback. As CERP is implemented, the Everglades ecosystems also will evolve. Monitoring projects will detect newly emerging processes and developments. Concerns of uncertainty are also context dependent, and may vary in different situations. Planning and decision-making will be a continuous optimization process that continuously revises and adjusts project plans and designs, based on new information. Planners particularly need to be sensitive to surprises and unintended ecological consequences.

One robust strategy in ecological restoration is to minimize human intervention and control. Restoration decisions should attempt to minimize interventions, so that enough room will be left for systems to recover from damages caused by human intervention and some safety margins will be kept. Plans with the least human intervention and controls should be chosen if ecological benefits are not significantly different among the alternatives given the uncertainty involved.

Uncertainty should not be overemphasized and should not be used as a main reason to delay decision-making. For example, overemphasis of quantitative uncertainty in ecology would put overdue burden on ecological studies that often require long-term data.

For CERP decision-making, critical uncertainties include quantification of ecological benefits, apparent conflicts among species and ecosystem components, nature-society conflicts, and conflicts among interest groups. It is a great challenge to reduce these kinds of uncertainties.

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