ERDC/EL TR-12-18

Environmental Laboratory

US Army Corps of Engineers®
Engineer Research and Development Center

Environmental Benefits Analysis Program

Ecological Modeling Guide for Ecosystem Restoration and Management

Todd M. Swannack, J. Craig Fischenich, and David J. Tazik

August 2012

ERDC/EL TR-12-18
August 2012

Ecological Modeling Guide for Ecosystem Restoration and Management

Todd M. Swannack, J. Craig Fischenich, and David J. Tazik

Environmental Laboratory
U.S. Army Engineer Research and Development Center
3909 Halls Ferry Rd.
Vicksburg, MS 39180-6199

Final report

Prepared for U.S. Army Corps of Engineers
Washington, DC 20314-1000

Abstract

Ecological models are important tools for planning ecosystem restoration and management activities. Models help to organize thinking, conceptualize understanding of complex systems, and forecast environmental benefits that may result from proposed restoration and management actions. This report provides information to guide environmental planers in selection, development, evaluation, and documentation of ecological models. A number of critical issues are addressed, including specifying objectives and formulating a sound conceptual model, choosing among types of models, deciding when to develop a new model, systematically evaluating the quantitative model, addressing parameter and model uncertainty, developing sections of the model through iteration, analyzing alternatives, and documenting results. Quantitative modeling is shown to be a dynamic process that is best served using an iterative approach. In practice, individual parts of a conceptual model are quantified and evaluated in a stepwise fashion until the entire model is captured quantitatively. This iterative approach creates transparency in model development, which can remove the “black-box” stigma that has been associated with the use of models in the environmental sciences.

Contents

Figures and Tables

Figures

Tables

Preface

The research documented in this report was conducted for and funded by the Environmental Benefits Analysis (EBA) Program. The EBA Program is sponsored by Headquarters, U.S. Army Corps of Engineers and is assigned to the U.S. Army Engineer Research and Development Center (ERDC) under the purview of the Environmental Laboratory (EL), Vicksburg, Mississippi. The EBA Program Manager is Glenn Rhett.

This report was prepared by Dr. Todd M. Swannack of the Wetlands and Coastal Ecology Branch (EE-W), Dr. J. Craig Fischenich of the Ecological Resources Branch (EE-E); Ecosystem Evaluation and Engineering Division (EE); and Dr. David J. Tazik, ERDC-EL. At the time of publication, Patrick S. O'Brien was Chief, CEERD-EE-W; Antisa Webb was Chief of CEERD-EE-E; Dr. Edmond Russo was Chief, CEERD-EE; and Dr. Alfred Cofrancesco was the Technical Director. The Director of ERDC-EL was Dr. Beth Fleming.

COL Kevin J. Wilson was the Commander of ERDC, and Dr. Jeffery P. Holland was the Director.

Unit Conversion Factors

Multiply	By	To Obtain
cubic feet	0.02831685	cubic meters

1 Introduction

Background

Over the last several decades, models have become an important tool in environmental decision making; most modern environmental projects require models. Although quantitative models are often required for projects, there is still considerable apprehension when applying models to environmental problems. Ecosystems are inherently complex, and for any given environmental system, the number of interacting factors is large (e.g., weather, species, hydrology, geomorphology, anthropogenic factors, etc.). Each factor operates at different spatial and temporal scales. Therefore, it is rare to have a complete dataset that encompasses all the different permutations of environmental conditions, yet planning activities must often determine how a system will respond under extreme conditions – i.e., outside the range of available field data. Modeling is an excellent tool for analyzing environmental systems because it helps to fill data gaps and provides a mechanism to systematically compare scenarios across a broad range of conditions that would not be possible in the field.

The process of modeling helps researchers to organize their thoughts and research direction, facilitates communication, and creates a level of transparency that can dispel the myth that models are “black-box” endeavors. However, models do have limitations and should not be viewed as all-inclusive or as a panacea for environmental decision making. Since environmental models are simplified representations of complex systems, they are often built using assumptions regarding the unknown components in the model. The usefulness of a model hinges on understanding whether the data and assumptions used to develop the model are sufficient enough to inform decisions. It is also important to understand that models should inform, not dictate, decision-making processes (Glaser and Bridges 2007). Modeling does not provide all the answers, rather good models should inform management/planning decisions and their results should be incorporated with results from field studies and professional judgment (by subject matter experts) before final decisions are made.

Model types

Several types of models have been used for determining environmental benefits, ranging from simple empirical relations describing the expected habitat preferences of species to complex, dynamic models of material flow (e.g., water, sediment, etc.) to agent-based or spatially explicit models that address large-scale dynamics (e.g., Foran et al. 2011; Guisan and Zimmermann 2000). Some projects use multiple types of models to address their questions. In general, the models used to assess environmental benefits fall into six basic classes (analytical, conceptual, index-based, simulation, statistical, and spatial), each with their strengths and weaknesses. There is significant literature available discussing different types of models, so only a brief description of each model type will be given (for more detail refer to Wissel 1992, Grimm 1994, Grant 1998, Ford 1999, Peck 2000, Jørgensen and Bendoricchio 2001, Grimm and Railsback 2005, Fischenich 2008, Grant and Swannack 2008, Jørgensen and Fath 2011). Table 1 provides a brief summary of model types, general usage, and examples. Regardless of the type of model, all models should be developed using the methodology explained below.

Table 1. Description of model types often used for modeling environmental benefits.

Model	General Use	Example
Analytical	Systems where solution to closed form equations represent system	Population growth, Lotka-Volterra models
Conceptual	Diagramming relationships among components, organizing information, determining data needs	CEMCAT (see Fischenich 2008, for more examples)
Index	Determining habitat quality across a landscape, relates species presence to environmental variables	HSI, HGM
Simulation	Modeling dynamics of complex systems that have multiple factors interacting across scales, often have spatial components	Agent-based models, ADH-CASM, ELAM, ICM, system dynamic models
Statistical	Analysis of datasets to determine distributional properties of the data	ANOVA, goodness-of-fit, regression, t-test,
Spatial	Projects where particular spatial attributes are important can be incorporated into simulation models	GIS, EDYS

Analytical models are models for which a specific mathematical form can be written as an equation or set of equations. These models are solvable in “closed form” – they have a general solution that applies to

situations that the model can represent. Common types of analytical models are represented by differential or difference equations (or a series of those equations).[1] An example of an analytical model is the equation for exponential population growth

$$N = e^{r(t-c)} \tag{1}$$

Using this model, the population size (N) can be calculated for any time-step (t), just knowing the population size and the rate of growth (r), where c represents a constant and e is the base of the natural logarithm.

Conceptual models represent the system of interest qualitatively, usually as a diagram showing the relationships among important variables. A wide variety of approaches are used for developing conceptual models, ranging from simple depictions that show the system's components or connections, to others that imply the first steps towards quantitative model development (Jørgensen and Fath 2011). It is almost impossible to quantitatively model an environmental system without a conceptual model. Conceptual models can serve as templates for quantitative models, allowing researchers to visualize their system and identify important flow paths and feedback loops. However, conceptual models cannot be used to forecast system dynamics or to quantitatively compare scenarios. There has been considerable work describing the different approaches used for developing conceptual models (Ford 1999, Peck 2000, Fischenich 2008, Grant and Swannack 2008, Jørgensen and Fath 2011).

Index models are commonly used for planning and restoration studies. Briefly, an index model is intended to translate quantitatively based measures of individual habitat features or processes into a relative assessment of habitat suitability or ecosystem condition (Tirpak et al. 2009). Two common index-based approaches are habitat suitability index (HSI) models and the hydrogeomorphic (HGM) approach that is used to rapidly assess wetland function. The HGM methodology is thoroughly

[1] Differential and difference equations are different mathematical expressions of the same model. A *differential equation* expresses the relationship between a dependent variable (y) and one or more independent variables (x's) in terms of rates of change (r) – e.g., population size (N) at time "t" is a function of the change in N with respect to time (r=dN/dt). A *difference equation* uses a sequence of numerical differences to compute an output (y) at time "t" based on past and present input of the independent variable (x's) and past outputs of the dependent variable (y) within the time frame of interest – e.g., N at time "t" is a function of N at (t-1) plus the portion of new N added during that interval.

documented and has been broadly applied throughout USACE districts (Brinson 1993, Smith et al. 1995, Smith 2001) and will not be discussed in detail.[1] The HSI approach quantitatively relates potential for species presence to habitat characteristics. Species have complex relationships with their environment and HSI models provide a simple method for characterizing potential for habitat to support target species/communities across a landscape. In general, species-habitat associations are scaled from 0 to 1, with 1 representing a favorable or "ideal" relationship that represents habitat quality at a particular location. Multiple indices can be combined into a composite score or single indices can be used to interpret habitat quality. For example, an oyster HSI relates potential for oyster presence to bottom substrate and mean salinity, among other factors (Cake 1983) to determine habitat suitability in the Gulf of Mexico. The quantitative relationships between species and habitat that are used to develop these models are generally based on literature, field studies, or expert opinion. Understanding the relationships between species and habitat is a complex and evolving field of study. Likewise, HSI models should be viewed as adaptable hypotheses of species-habitat relationships rather than actual cause-effect relationships.[2] Index-based models are valuable because they serve as a foundation for improved decision-making and increased understanding of habitat relationships because the species-habitat relationships represent specific hypotheses that can be tested and improved.

Simulation, or process-based, models are typically computer programs designed to numerically represent the behavior of a system and its characteristic component elements and processes (in environmental simulations, these models describe how environmental conditions change across time and may involve integrating multiple disciplines (e.g., hydrodynamics, population dynamics, climate, etc). These models are developed to capture and mimic real-world systems, that unlike real systems, can be experimented upon at various scales with minimal risk to the real environment (Peck 2004). The opportunity presented by models is capacity to more rapidly test a broader array of alternatives without risk to the environment (or lost investment). Simulation models represent the relevant aspects of a system – e.g., drivers, stressors, and ecological outputs and attributes that may be subject to management influence. Simulation models are often complex, consisting of many interacting variables, but one of their strengths is that they provide a tool with which to understand complex systems.

[1] http://el.erdc.usace.army.mil/wetlands/guidebooks.cfm

[2] Note that a perfect quality index score may not translate to increased species presence/utilization.

Examples of simulation models include *agent-based models* (Grimm and Railsback 2005, Goodwin et al. 2006), *system dynamics models* (Odum 1983, Ford 1999, Grant and Swannack 2008) and *coupled hydrodynamic-ecological models* (Cerco and Noel 2010, Dalyander and Cerco 2010).

Spatial models are any models that incorporate a spatial dimension, which can be represented implicitly or explicitly. In spatially implicit models, the specific locations are not defined and are represented as number or proportion of sites within a given attribute. Spatially explicit models, where specific, geo-referenced locations are considered, are more common in environmental benefits analysis. These models generally include use of a geographic information system (GIS) and can be index-based (e.g., if an HSI model is designed to output habitat suitability maps) or can be included as part of a simulation model. Environmental models often have a spatial component associated with them (i.e., focusing on a specific place) and spatial models are often treated as components of larger models.

Statistical models are data-driven and represent the distributional properties of the data. In general, these types of models identify how well data can be explained by a set of factors or how well variables correlate to each other. These models do not explicitly address causation; rather, they provide tools that explore how well a given set of data can be explained by a suite of factors (e.g., the relationship between water quality or bird species diversity and the width and vegetation density of riparian buffer strips along a stream reach). Common types of statistical models include linear or nonlinear regression, analysis of variance (ANOVA), analysis of covariance (ANCOVA), contingency tables, t-tests, and goodness-of-fit tests, among others.

2 Model Selection

Two major issues must be considered in selecting an appropriate model. First, the project team should align model selection criteria/process with the problems and opportunities to be addressed and associated information demands of the study/project.[1] The team should thoroughly discuss project scope, scale and objectives, ecosystem characteristics, availability of data, and project duration with subject matter experts, stakeholders, and staff/leadership of involved agencies. During these discussions, it is common for people to have or form expectations that may or may not be realistic, seek complexity that may or may not be necessary, and be familiar with a particular type or "brand" of model and request that it be used. However, it is important to recognize that many different types of models can be used to address environmental problems and familiarity with a particular type of model does not indicate its usefulness for a specfic project. The authors recommend adhering to the principle of parsimony when choosing a type of model, that is, given a choice between multiple, appropriate model types, choose the simplest approach that can address the problem sufficiently. For example, when trying to determine where to best place oyster beds for restoration, a large-scale, ecosystem-hydraulic modeling approach might not provide better answers compared to a much simpler HSI type model, which requires less resources (i.e., time, effort and cost) compared to a more complex model. Even when problems, opportunities, and expectations are well-defined prior to model selection (and frequently they are not), choosing the right model for a given problem is not an easy task. Foran et al. (2011) identified some of the issues involved with selecting models for ecological forecasting and used the relationships among prescriptive utility, model type, and effort involved in model development to help narrow down the choices of models for a given project (see Figure 2 in Foran et al. (2011)).

The second issue that project delivery teams will face is whether or not to develop a new model for each project or to use an existing model. Specifically, the issue is the degree to which existing models of the system or of similar systems can be applied to the project to yield applicable information of adequate quality. In an extreme case, a model may not exist that can be

[1] Step 1 of the Corps planning process; see Engineer Regulation 1105-2-100, Planning Guidance Notebook, 22 April 2000, http://www.iwr.usace.army.mil/docs/11052100.pdf

adapted, and a completely new model is necessary. Developing a new model maximizes the likelihood that the model will be capable of addressing the questions for that specific project. However, model development requires labor, funding, and effort that might exceed the resources or life cycle of many projects. Using an existing model might decrease the time it takes to prepare a model for application, but given the uniqueness of each environmental issue, existing models may need to be adapted (in some instances, significantly) to be appropriate for application to different project settings.

A model's existing certification or approval of a model for use[1] is no guarantee that it is (or will be) appropriate for application to all study/project settings. It is paramount to thoroughly understand the intended uses, assumptions, limitations, and data requirements for any model, certified or not, during its consideration for application to a project's specific setting and context. It might also be worthwhile to consider regional demands for a planning model that has broad applicability to comparable ecosystems throughout a given ecological region (e.g., McKay and Pruitt, in preparation). Such demands might suggest there are benefits to be gained via development of a regional model, where costs of development might be distributed among its potential beneficiaries. The Ecosystem Restoration Gateway maintains an online library of planning models that includes basic information about each including their certification status (http://cw-environment.usace.army.mil/model-library.cfm?CoP=Restore&Option=Start). Users can refer to that link or contact the National Ecosystem Planning Center of Expertise (ECO-PCX, http://el.erdc.usace.army.mil/ecocx/index.cfm) to retrieve or offer information about cataloged models or models that could be added to the Ecosystem Restoration Gateway library.

[1] Engineer Circular 1105-2-412, "Assuring the Quality of Planning Models" (USACE 2011), reflects USACE policy requiring use of certified or approved models for all planning activities. It is important to note that this requirement is not to be interpreted as universally excluding from consideration models that have not yet been reviewed and certified/approved for use. Rather the policy reflects a requirement that models used in support of planning decisions are to be reviewed for their capacity to yield reliable information within a specified context/setting prior to arrival at a planning decision.

3 Model Development

This chapter focuses on guiding users through phases of model development. The steps described below generally follow Corps guidelines;[1] however, the terminology used here follows that generally accepted in the field of ecological modeling. Once a specific problem has been identified and both the planning and modeling objectives have been clearly defined, the basic approach is as follows:

- Develop a conceptual model identifying the specific cause-effect relationships among important components of the system of interest.
- Quantify these relationships based on analysis of the best information possible, which can include scientific data or expert opinion.
- Evaluate the information yielded by the model in terms of its ability to yield information that describes or emulates system behavior.
- Apply the model to address questions regarding the effects of particular project alternatives.
- Perform periodic post-audits of model applications to manage confidence in the model and the information it yields (this will be incredibly important as adaptive management practices are implemented).

In practice, model development does not proceed continuously from the conceptual model to model application. Rather, as described in Chapter 7, *Modeling in Practice,*" model development iterates through a series of intermediate developmental phases (each a more mature form of its predecessor, and sometimes halting further development because information needs are found to have been met). However, in general, a model is first conceptualized, then quantified and evaluated as the model becomes fully integrated into a form that can be applied for its intended use (Figure 1). Model documentation should be developed and modified throughout each stage of a model's development, which not only facilitates compiling documentation at the end of the development activity, but also forces the model development team to more thoroughly understand relationships among and between model development steps and model development

[1] Engineer Circular 1105-2-412, "Assuring Quality of Planning Models," USACE 2011 http://140.194.76.129/publications/eng-circulars/EC_1105-2-412_2011Mar/EC_1105-2-412_2011Mar.pdf

objectives, and contributes to the credibility of work products (e.g., studies and projects) that rely on information yielded by the model. The term "model development team," used throughout this document, represents the group of individuals involved in the development of the model. Model development teams should be composed of modelers, project managers, subject matter experts, engaged stakeholders, and other interested parties. Model development should be coordinated with the PCX for any certification requirements as laid out in EC 1105-2-412 (USACE 2011). As explained below, a collaborative and iterative approach to model development is essential for maintaining transparency and scientific defensibility.

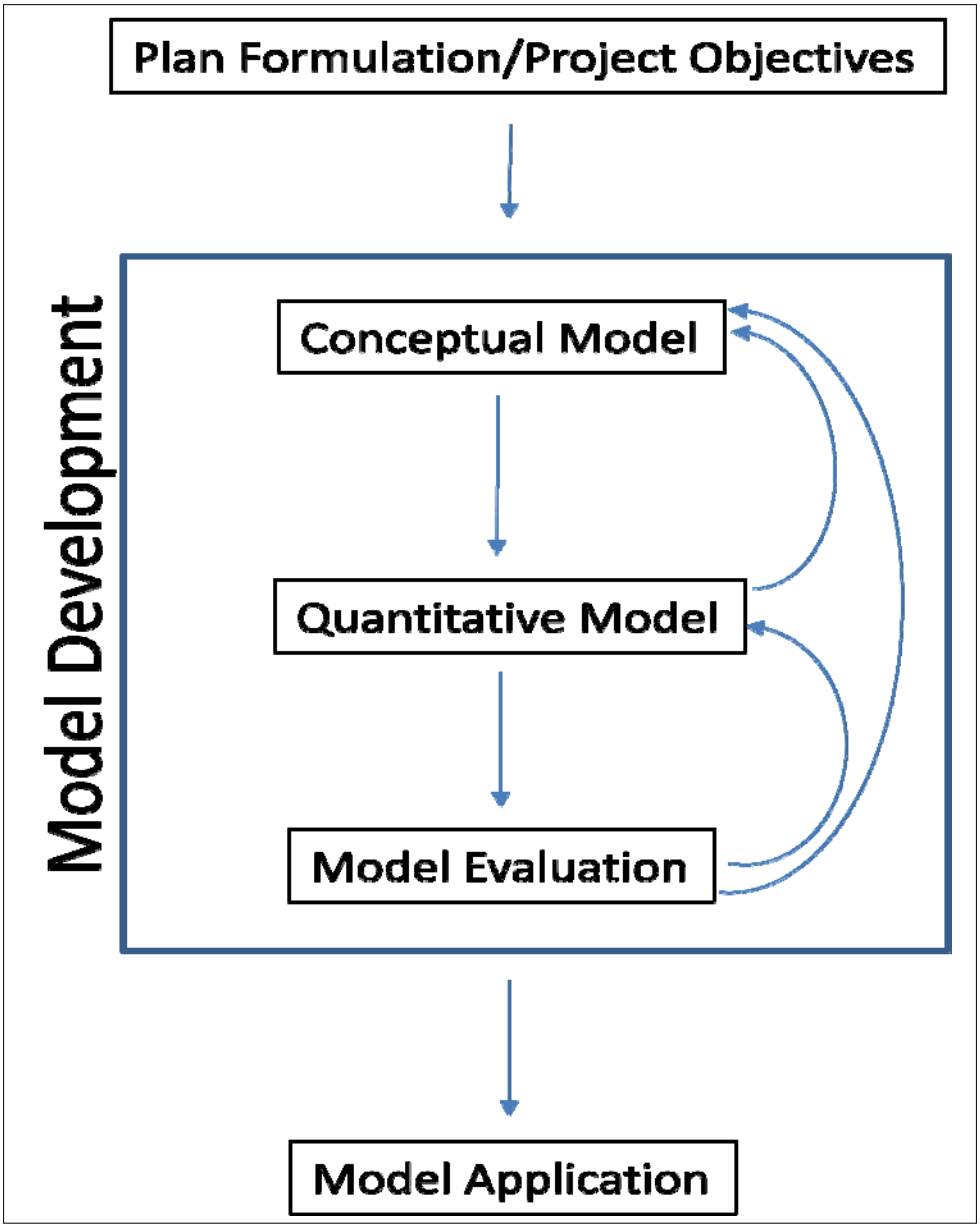


Figure 1. Diagram depicting the modeling process. Straight arrows indicate flow of process, curved arrows represent the iterative nature of modeling.

4 Conceptual Modeling

Conceptual models are qualitative, diagrammatic summaries that describe important components of a system and the interconnectedness among those components. Conceptual models help identify how drivers and stressors will impact system dynamics and are useful blueprints for developing quantitative models that can project those dynamics. Conceptual models are incredibly useful because they force stakeholders to visualize the system in a precise way (Fischenich 2008). Given the complexity of environmental systems and the sheer abundance of factors that can affect natural processes, these models provide a mechanism to organize information and also serve as a heuristic tool that can facilitate discussions across disciplinary boundaries. It is almost impossible to develop a common/collective understanding of the system of interest and develop quantitative models without first conceptualizing the system.

This section focuses on describing a generalized, good-practice approach for developing conceptual models that can then be used as the foundation for developing quantitative models. For more detailed descriptions of the use and application of conceptual models, refer to Fischenich (2008), which describes different types of conceptual models and identifies general good practice guidance for their use in restoration project planning. When developing conceptual models as templates for quantitative models, six general steps should be followed (described in detail below):

1. Precisely define objectives and criteria for evaluation.
2. Bound the system of interest.
3. Represent the conceptual model.
4. Describe the expected patterns of model behavior.
5. Identify data quality and quantity.
6. Identify context for model use.

Precisely define objectives and criteria for evaluation

The initial focus of conceptual model development is to identify and review information needs and expectations of those engaged in a particular (planning) study, and formulate objectives to guide model development efforts and manage expectations. The objectives must be defined as precisely as possible because it is considerably easier to develop a

conceptual model (and later a quantitative model) if the objectives of the model application have been delineated clearly. Solicitation of input from local subject-matter experts at this stage can be beneficial because they can facilitate the integration of expert information into the model design and development.

The criteria that the model must meet should also be specified, for example:

- The model should have a structure that reasonably portrays relationships between the resource(s) of interest and system elements that cause or contribute to changes in their condition and distribution.
- Model results (or conclusions based on the model's application) should correspond well with both real-system behavior and data from the real system.
- The model can, once fully developed, effectively differentiate between project alternatives that differentially affect elements that cause or contribute to changes in the resource(s) of interest.
- Model results should help to guide metric selection to gauge environmental response to management actions.

It is important to formally document these criteria and the process/ participants engaged during their development so that the model development team and others can refer back to them throughout and following model development.

Bound the system of interest

Setting an appropriate assessment area and model boundary conditions can be challenging. Environmental systems are complex and certain components may not be important for a particular project, but only a detailed knowledge of the system can identify those components. Furthermore, every model can be conceptualized in myriad ways and the goal is to identify those components that provide a clear, concise, and informative view of the system, given the objectives of the project.

Bounding the system of interest consists of differentiating between those components that should be included in the model from those that should be excluded. In this case, components refer to any important process or variable that is relevant to the problem. An overly complex model is not desirable, but neither is excluding components that might be critical to the

solution of the problem. Engaging subject matter experts is crucial to identifying these important components. Detailed discussions with the experts will help identify what should be included in the conceptual model, and what might be best accounted for as assumed or boundary conditions (as well as how such assumptions might affect/influence later model application). Careful thought should also be given to how the model is bounded in time and space, including whether a regional, rather than site-specific, model should be developed (e.g., McKay et al. (2011)). If the temporal and spatial scales are too broad, then too much attention may be focused on unnecessary components and processes, which take focus away from critical system processes. The documentation for this step should include the reasoning and logic behind choosing which model components to include.

Represent the conceptual model

Formal representation of conceptual models involves creating a diagram of the system. There are several different ways to represent a conceptual model, ranging from simple depictions of the system to relatively complex representations written in a modeling language. These diagrams play an important role in modeling by providing a “big-picture” point of view and more importantly, facilitating communication among stakeholders. This step defines how those components and variables included in the model are interrelated. One of the most common types of conceptual models is a box-and-arrow diagram, which provides a relatively easy framework for representing complex environmental systems: variables can be represented with boxes or other symbols and those variables that interact with each other can be connected with arrows. Direction and strength of interactions and levels of uncertainty can be represented as well. The exact symbology used for a particular modeling effort is not that important; however, it is paramount to maintain precision and consistency with the symbology used within a given model (that is, make sure all variables of a certain type are drawn the same way), and to clearly define what the symbols represent (that is, font, line, polygon, and image/symbol styles should have consistent meaning). Many different techniques are used to draw and develop conceptual models; however, a detailed description of these techniques is outside the scope of this document. Much has been written on different approaches (Starfield and Bleloch 1986, Fries et al. 1998, Ford 1999, Jørgensen and Bendoricchio 2001, Ogden et al. 2005, Fischenich 2008, Grant and Swannack 2008, Jørgensen and Fath 2011). Programs, such as

CEMCAT[1] (Dalyander and Fischenich 2010) have been developed to facilitate the conceptual modeling process. Documentation at this stage should include not only the conceptual model, but also a detailed description of how the components are related, including rationale and linkages (i.e., explain why the conceptual model was constructed the way it was) (Killgore et al. 2008, Casper et al. 2010). At this point, the model development team should refer to the model design objectives to be sure that model development is progressing in the intended direction (and if not, document the rationale for deviations from those objectives and engage the eventual users of the model to inform them of potential impacts on expectations).

Describe the expected patterns of model behavior

Subject-matter experts and model developers will always have some expectations concerning patterns of model behavior. These expectations should be formally described and thoroughly documented before the model has been quantified for two main reasons: (1) these descriptions can serve as points of reference during model evaluation, and (2) to ensure that the expected patterns of behavior provide the types of projections that will be useful for addressing the objectives once the model is applied. These expectations can be based on, but are not limited to, what can be supported by available data. Expert opinion (and its documentation) is critical during this step because subject matter experts likely know more about relationships among model variables than can be documented in a rigorous way by data alone. Further, for environmental systems, there are always important aspects of system dynamics for which there are no data, but experts may have logical and valid ideas about how those components interact. It is common to formalize these expectations as graphs representing changes in values of important variables over time, but any aspect of system behavior for which there is an expectation should be noted (for example, noting the minimum and maximum values of particular variables, proportional relationships (as variable A increases, B decreases), etc). Projected patterns of response to project alternatives should also be documented thoroughly. Consideration should be given to the cost-effectiveness of the proposed scenarios that the model will address. Expectations of model behavior are frequently left implicit, and therefore imprecise, which can result in the model not being designed appropriately and therefore being incapable of representing important aspects of system behavior that are needed to

[1] http://cw-environment.usace.army.mil/eba/news.cfm?Option=Title&Code=0&Id=821

address the objectives. These expectations should be viewed as reference points on which to evaluate the model, but should be flexible enough to be adapted if the model reveals some aspect of system behavior that the model development team had not thought of.

Identify data quality and quantity

Once the conceptual model has been formulated to a sufficient degree, it is important to describe, in detail, the type of data that are required to parameterize the model, then to determine the availability of those data. Further, any uncertainties associated with those data need to be identified and an explicit plan must be formulated on how to deal with those uncertainties. While data needs are often known before the conceptual model has been developed, the conceptual modeling process may actually reveal previously unknown data requirements. It also helps to focus data acquisition strategies and to identify critical research needs that can address data gaps, which may also provide a basis for targeting data needs for monitoring and adaptive management planning purposes. Once again, the model development team should at this point refer to the model design objectives to be sure that model development is progressing as intended. The model development team might also consider reengaging those who intend to apply the model to discuss any changes in expectations, and/or any changes that might be warranted based on information learned during model development activities completed to date.

Identify context for model use

The context in which the model is to be used must be described and documented precisely, which includes listing all of the restrictive assumptions that must be made for the model to be useful for projecting system dynamics. If the restrictive assumptions under which the model is useful are not thoroughly documented, then the model may be applied inappropriately. It is important to note that an exhaustive list of assumptions is impossible, such as those assumptions that can be left implicit (e.g., the sun will continue to rise). Model development teams should focus on documenting those assumptions that should be stated explicitly (e.g., minimum flow must be X) because they cannot reasonably be assumed to remain true/constant under all foreseeable applications. Documenting the appropriate use of the model is a critical step in model development because it provides the framework for model development, the standards for model formulation and evaluation, the standards for model application, and the context within which the results will be interpreted and upon which its applications will be judged.

5 Quantitative Model

Given that several types of models are used for projecting environmental benefits, as discussed above, this section will not include a detailed description of using particular types of mathematics or statistics for modeling environmental benefits. Rather, this section will specify generalized good practice for developing quantitative models of environmental systems. Quantitative model development follows five steps, which will be discussed in more detail below. A detailed example is provided in Chapter 7, "*Modeling in Practice.*"

1. Linking to the conceptual model.
2. Selecting the general quantitative structure, time unit, and spatial scale for the model.
3. Identifying functional forms of model equations.
4. Estimating the parameters of the model equations.
5. Executing the baseline model.

Linking to the conceptual model

The conceptual model discussed above should be used as the template for the quantitative model. Too often, quantitative models do not have a formalized conceptual component. However, tightly linked conceptual-quantitative models facilitate not only model development and evaluation, but also communication among stakeholders. Each linkage between components in the conceptual model should be represented quantitatively. One helpful technique is to label the conceptual model with symbols that refer to equations used in the quantitative model.

Selecting a general quantitative structure for the model

The choice of a particular mathematical style depends on the background and experience of the modeler, the intended application(s) of the model (e.g., what will the model results be used to demonstrate), and the type of model being developed. For example, index-based models do not require complicated mathematics, whereas large-scale simulation models might use more involved mathematics such as a series of differential equations. Theoretically, the dynamics of the system should be able to be reproduced equally using different mathematical techniques/methods. Developers

should pursue a general strategy of developing a set of equations that determine, at selected points in time, the value of each important variable included in the model.

For environmental models, it is critical to identify a time-step between iterative solutions of model equations. For example, if tree growth is an important variable of interest, then forecasting tree growth every second may not be useful, whereas forecasting tree growth every year would probably provide a more appropriate level of detail. Time units need not be confined to familiar units such as 1 day or 1 year, but they may be defined as any length that allows the model to address the objectives and appropriately represent the temporal dynamics of the system. Choosing a time unit is not trivial – if the time unit is too long, the model may not capture some of the important processes, whereas if it is too short, the risk of reducing interpretability is increased (e.g., there is little point in projecting population dynamics on a daily basis if the dynamics of interest occur on an annual basis and when the important question is population persistence over 50 years). Once the appropriate time unit has been chosen, the time unit and logic used to make the choice need to be included in the documentation[1].

Likewise, it is important to identify the appropriate spatial scale for the model output. Environmental processes have different impacts at different spatial scales, so it is important to consider how those processes should be represented quantitatively. It is important to consider not only direct impacts of a project, but to also consider indirect impact. For example, a stream restoration project will directly impact the habitat surrounding the stream, but may also have impacts further downstream. Once the appropriate spatial scale is chosen, the scale and logic used to make the choice should be documented. The choice of a spatial scale closely coincides with the choice of the temporal scale. Selecting the wrong space or time scales can contribute to erroneously low or high values of important variables, so careful consideration must be given to both.

Identifying functional forms of model equations

The next step in quantitative model development is to determine the functional forms of the model equations--that is, determining if the general forms of the equations representing specific relationships are linear,

[1] Note that the typical Corps planning horizon is 50 years, so that a 5-10 year time-step may be sufficient for applications in feasibility studies.

sigmoidal, exponential, etc. Examples are illustrated in Chapter 7. This is analogous to choosing which type of statistical analysis to perform on a dataset (e.g., linear regression, non-parametric tests, etc.). A model can contain multiple types of functional forms, and the more complex the model, the more likely that it will contain multiple types of functional forms.

Four general types of information can be used, individually or in combination, to determine a functional form for a particular relationship: (1) quantitative data, (2) information based on theoretical or empirical relationships, (3) qualitative information, and (4) information gained from experimenting with the model itself. Empirical data are most useful, particularly if available from within the system of interest. However, there are almost always important relationships for which there are no data or observations. In these cases, the scientific literature or subject matter experts may provide sound theoretical, empirical, or qualitative relationships that can be used in place of hard data. For situations where data and qualitative understanding are lacking, insight can be gained into possible functional forms or a model equation by hypothesizing different functional forms and observing model behavior in response to each. Through such experimentation, the choices of functional forms can be narrowed by excluding those forms that produce unreasonable results. Obviously, the number of equations that can be identified by this technique (within a given model) is small – the more equations specified by trial and error, the higher the likelihood that reasonable results occur only by chance. It is important to use functional relationships that are interpretable within the subject matter of the project (e.g., hydrologically, environmentally, etc). If functional relationships are not documented and interpretable, then the ability to describe overall model behavior is compromised. As a matter of practice and communication with non-modelers, the model development teams should at this point consider revisiting and updating conceptual models to reflect/document the manner in which functional forms were developed.

Determining functional relationships can be difficult, but one rule of thumb is to describe the functional relationships clearly in words before describing them mathematically. Modelers and stakeholders should take a few minutes to describe the model verbally. If areas of the model are difficult to explain verbally, then it is likely that those areas will be difficult to explain mathematically. These are generally the areas that require more thought and research. Another common approach for dealing with functional relationships is to describe them graphically. Graphical

representations provide an intermediate step between verbal and mathematical representations. If functional forms are unknown, it is often useful to assume linear relationships between variables as a first step. Linear functions are useful for ecological models when trying to project trends in long-term dynamics and when the general relationship between two variables is understood (e.g., variable A increases when variable B decreases), but the exact form is not. Once more information is gathered, these functional forms can be changed. Figure 2 provides an example of how to describe a functional relationship verbally, graphically, and mathematically.

Estimate the parameters of the model equations

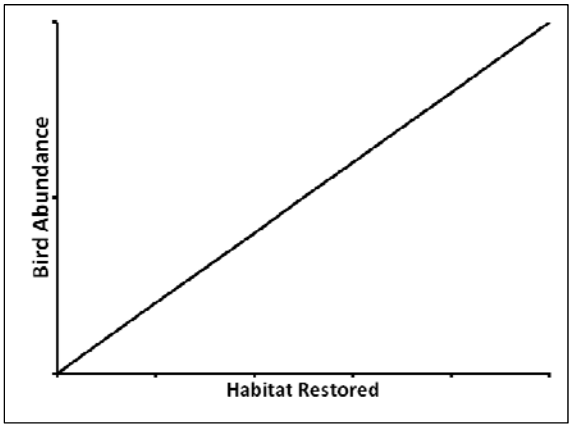
Information on which to base parameterization of model equations comes from the same four sources as choosing the functional forms. In fact, choosing the functional forms and parameterizing model equations are often based on the same information. However, from a modeling standpoint, these should be viewed as distinct events because the former generally has more profound implications concerning environmental interpretations of model structure than the latter. Stated another way, in general, the functional form of an equation controls the pattern of the results, whereas the parameter value controls the magnitude.

The specific methodologies used to estimate parameters of model equations are as diverse as the field of statistics and the appropriate methodology will vary depending on the type of data being analyzed (e.g., hydrologic data and population data require two different approaches). The important point is simply that parameters should be estimated using appropriate statistical techniques. Often equations resulting from these statistical analyses actually become a part of the model. Statistical or data-driven models should be applied with caution when the conditions being modeled are outside the dataset from which the model was derived. For example, a sediment model for a particular stream that was based on discharges ranging from 1000 to 5000 cubic feet per second (cfs) might not be reliable when assessing flows in excess of 20,000 cfs. In the shorebird example above, the relationship was developed based on habitat availability in the range of 3,000 to 6,000 ha and might not hold when one is much outside this range. By highlighting and tracking these sorts of factors/questions, model development teams can help others prepare the model for review and appropriate application, and be ready to offer suggestions for model improvements that might be required to adapt the model for broader application.

A project has been proposed to restore salt marsh habitat along a coastal region to create a more natural habitat and to restore spring shorebird populations along the coast. Anecdotal evidence indicates that shorebird abundance increases if cord grass (*Spartina alterniflora*) is not allowed to spread into the mudflats[1]. However, the team is not quite sure how to model it. They understand that increasing mudflat habitat should increase bird abundance. The verbal or written model in this case would be:

For every hectare of habitat we restore to mudflats, we expect an increase in shorebird abundance

The team realizes that this verbal model does not contain enough information to represent the relationship mathematically, but it can be represented graphically:



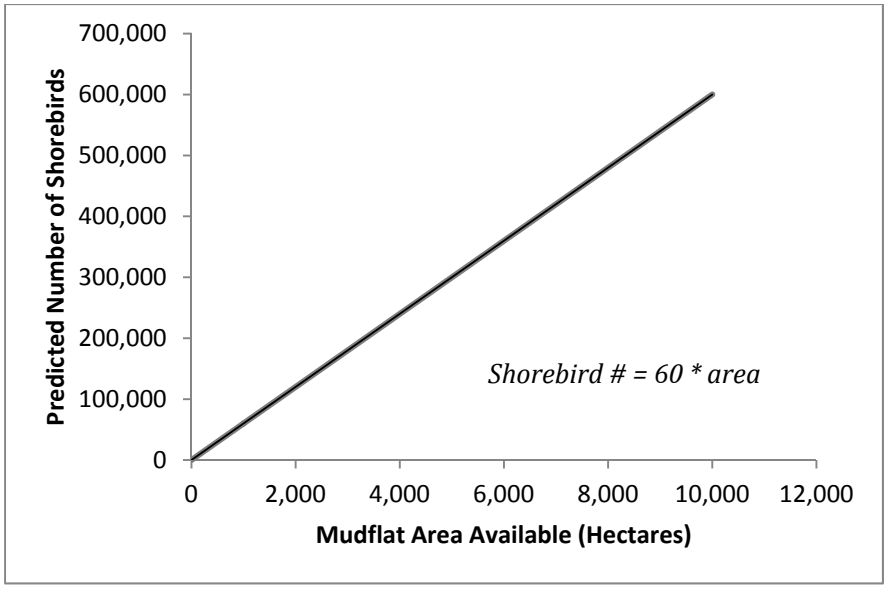
After the team understands the general relationship, they consult subject matter experts and the scientific literature and learn that previous salt marsh restoration projects resulted in an increase of approximately 60 shorebirds in the spring with every hectare of habitat restored. The verbal model would then be:

For every hectare of habitat restored (i.e., mudflat habitat), we expect an increase of $A = \pi r^2 60$ *shorebirds in the the spring.*

The graphical model would then be reformatted to include these numbers.

Figure 2. Simplified example of representing model components verbally, graphically, and mathematically.

[1] This example is based on data presented in Stralberg et al. (2004). However, the numbers used in this example were approximated and should not be considered factual.



In this case, the equation of the line from the reformatted graphical relationship represents the quantitative model:

$$Increase\,in\,spring\,shorebird\,abundance = 60 * \left(hectares\,of\;habitat\,restored\right)$$

This equation could then be used as part of a larger model or incorporated into a benefits algorithm to determine the environmental benefits of the project. This example illustrates how models can be developed using verbal, graphical, or mathematical descriptions. Note that several assumptions are made in this model, two of which are (1) there is an unbounded upper limit, and (2) there are zero birds if there is no mud flat. It is important to document the assumptions so that the model development is transparent and defensible.

Figure 2. (concluded).

In cases where no quantitative data are available, qualitative information from the literature or expert opinion can be used to establish assumptions on which to base estimates of model parameters. This may seem like a much less rigorous process than analyzing data, and indeed most scientists and engineers feel less comfortable quantifying models this way. However, relying solely on quantitative data may result in long and futile searches for data that do not exist. Subject matter experts generally know more about a system than can be confirmed with data. The ultimate goal is to use techniques that allow the model development team to appropriately interpret the available information to quantify important relationships within the system of interest. It is likely that more mistakes (in model

projections) will be made by excluding important system processes from the model because of a lack of data than by quantifying qualitative data for missing components.

Execute the baseline model

The baseline model represents the behavior of the system under a particular set of conditions that are being used as a benchmark or standard against which to compare project alternatives. Note that the model is still in development and is about to be evaluated. At this stage, do not apply the model to the project alternatives. The model should be run and the results used during the model evaluation phase (see Chapter 6). The initial conditions used for the baseline simulation must be defined carefully, since these conditions are often used as a point of reference for both evaluating the model and comparing alternatives.

6 Model Evaluation

The goal of model evaluation is to determine if the model is acceptable for its intended use, i.e., that it is useful for addressing the objectives of the project (Rykiel 1996). At this point, the model should not be considered complete because it has not undergone a rigorous evaluation process. Model evaluation involves evaluating all aspects of the model, including theory, computer code, parameter values, model behavior, and comparisons with data (Glaser and Bridges 2007, Grant and Swannack 2008). The model development team should be intimately involved with the evaluation process. The model evaluation procedures, the model's performance at each stage of the evaluation process, and any actions taken pursuant to evaluation procedures should be thoroughly documented. The importance/significance of good documentation practices (i.e., organized and sufficient documentation of information used to support decisions made during development and/or to demonstrate reliability of model results) cannot be overstated. This documentation will provide model users, as well as outside reviewers, a greater understanding of how and why the model behaves the way it does. Given the wide range of potential types of models that can be used for modeling environmental benefits, each with their own set of appropriate evaluation criteria, this section will focus on describing how to thoroughly examine the characteristics of a model that make it useful.

Given the wide range of disciplines that use models, several terms are used across the disciplines, and have similar, but distinctly different meanings. For example, model evaluation has also been termed model validation (Rykiel 1996) or corroboration (Pascual et al. 2003). For example, validating a hydrodynamics model and an ecological model are different. Hydrodynamic models must meet specific, and accepted, criteria if the model is considered "valid;" however, there are no generally accepted standards for validating ecological and environmental models (Rykiel 1996, Grimm and Railsback 2005) and there has been considerable debate within the scientific community regarding both terminology and technique. In this manuscript, model evaluation refers to the rigorous process of evaluating models and it consists of several steps, one of which is validation. Figure 3 provides a more detailed description of terminology used in evaluating models. This section of the report provides generalized good practice

guidance for evaluating models. The baseline model is evaluated following five steps, each of which will be described in more detail below.[1]

The terms calibration, verification, and validation have different meanings across disciplines. When performing a model evaluation, it is important that the terminology being used is defined precisely by the model development team. For the purposes of this document, the terms calibration, verification, and validation will be defined as below.

Calibration: The process of adjusting model parameters, within physically defensible, and ecologically reasonable, ranges, until the resulting predictions give the best possible fit to the observed data. In some disciplines, calibration is also referred to as "parameter estimation."

Verification: Examination of the algorithms and numerical technique in the model to ascertain that they truly represent the conceptual model and that there are no inherent numerical problems with obtaining a solution. In some disciplines, verification is also referred to as “code testing.”

Validation: The process of confirming a model's applicability, usually conducted by applying a calibrated model to a set of data separate from that used in the calibration process to demonstrate the accuracy of predicted results. In some disciplines, validation is also referred to as “evaluation, skill/fitness testing, or post-auditing.”

Figure 3. Common terms used in model evaluation.

1. Evaluate correspondence between model results and expected patterns of model behavior (e.g., are model computations correct)(model verification)
2. Examine correspondence between model projections and data from real system (e.g., does the model adequately emulate characteristics of the real world)(model validation)
3. Adjust empirical parameters or model coefficients to match a known behavior, expert opinion or reference site data (e.g., modify model parameters so that it adequately emulate characteristics of the real world) (model calibration)
4. Determine levels of uncertainty associated with model forecasts
5. Identify data gaps and research needs that may not have been obvious during conceptual model development

[1] Note that different discplines evaluate models in sequential orders different than presented here. The order itself (particularly steps 1 – 3) are not “set in stone.” Most model evaluation is done iteratively and the steps can be cycled through more than once.

Evaluate correspondence between model results and expected patterns of model behavior (model verification)

Model behavior is always a result of the rules written in mathematics or computer code, but, surprisingly model behavior can result from several things: conceptual, logical, or computing errors or the interactions among model components. Therefore, model behaviors always need to be explained before being accepted. This step involves comparing model results to the a priori expectations identified during the fourth step of conceptual model development (i.e., "describe the expected patterns of model behavior"). In these comparisons, look for obvious impossibilities, such as negative values for variables that must be positive or implausibly high or low values for particular variables. While this may seem trivial, models that show gross inconsistencies with the expectations are common (Figure 4). These inconsistencies may result from fundamental misconceptions about the nature of the relationships within the system. Or, they may result from erroneous expectations, which were illuminated from the model itself. In either case, the model development team is obligated to reconcile differences either through re-conceptualizing/requantifying the model or by adapting the expectations based on the new knowledge gained from the model.

Once a model no longer exhibits obviously implausible behavior, the general dynamics of components should be examined to ensure that the timing of maximum and minimum values, the relative amplitude and periodicity of fluctuations, and relationships with other variables are reasonable. Inadequacies detected as a result of this closer examination may still be caused by fundamental misconceptions about the nature of the relationship within the model (that is, the model could be conceptually flawed), but at this point, it is likely that the inadequacies resulted from erroneous parameter estimates or perhaps by inclusion of incorrect functional forms. Understandably, these inconsistencies can be fixed by adjusting parameter values or functional forms; however, it is important to remember that functional forms need to have environmental/ecological interpretations and should not be adjusted just to match expectations. Refer to the section titled "Adjust empirical paramenters or model coefficients to match a known behavior, expert opinion, or reference site data" for a detailed description of adjusting parameter values. The model development team should thoroughly document the methods they used to address this step.

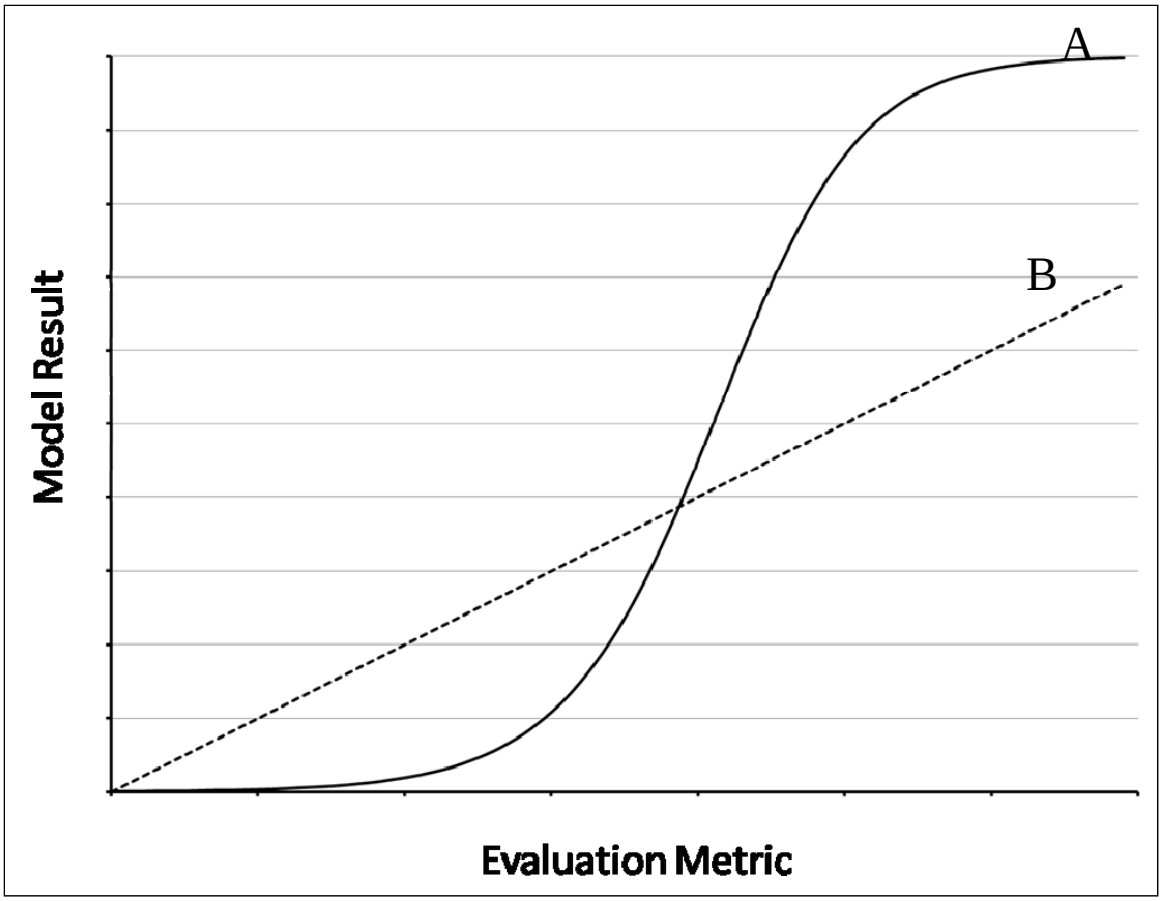


Figure 4. Graphical depiction of comparing (A) model results, to (B) expected patterns of model behavior. In this example, the expected patterns of model behavior do not match the results generated by the model. The functional relationships in the model that were used to generate this behavior must be reevaluated.

Examine correspondence between model projections and data from real system (model validation)

The manner in which model projections are compared to data from the real system depends on the specific objectives of the project, the type of model being used, and the type of data available. During this step, the model is tested against an independent dataset to observe how well the model fits those data (Figure 5). Data from the real system that are used in model evaluation must be independent of data used to develop the model or the model cannot be rejected. The idea behind this exercise is that if the model provides a good representation of the system, then it should be able to represent other systems or conditions equally well (Glaser and Bridges 2007). It is also important to note that this exercise will only confirm the model behavior under the range of conditions exhibited in the independent dataset. For environmental systems, it is often difficult to obtain an

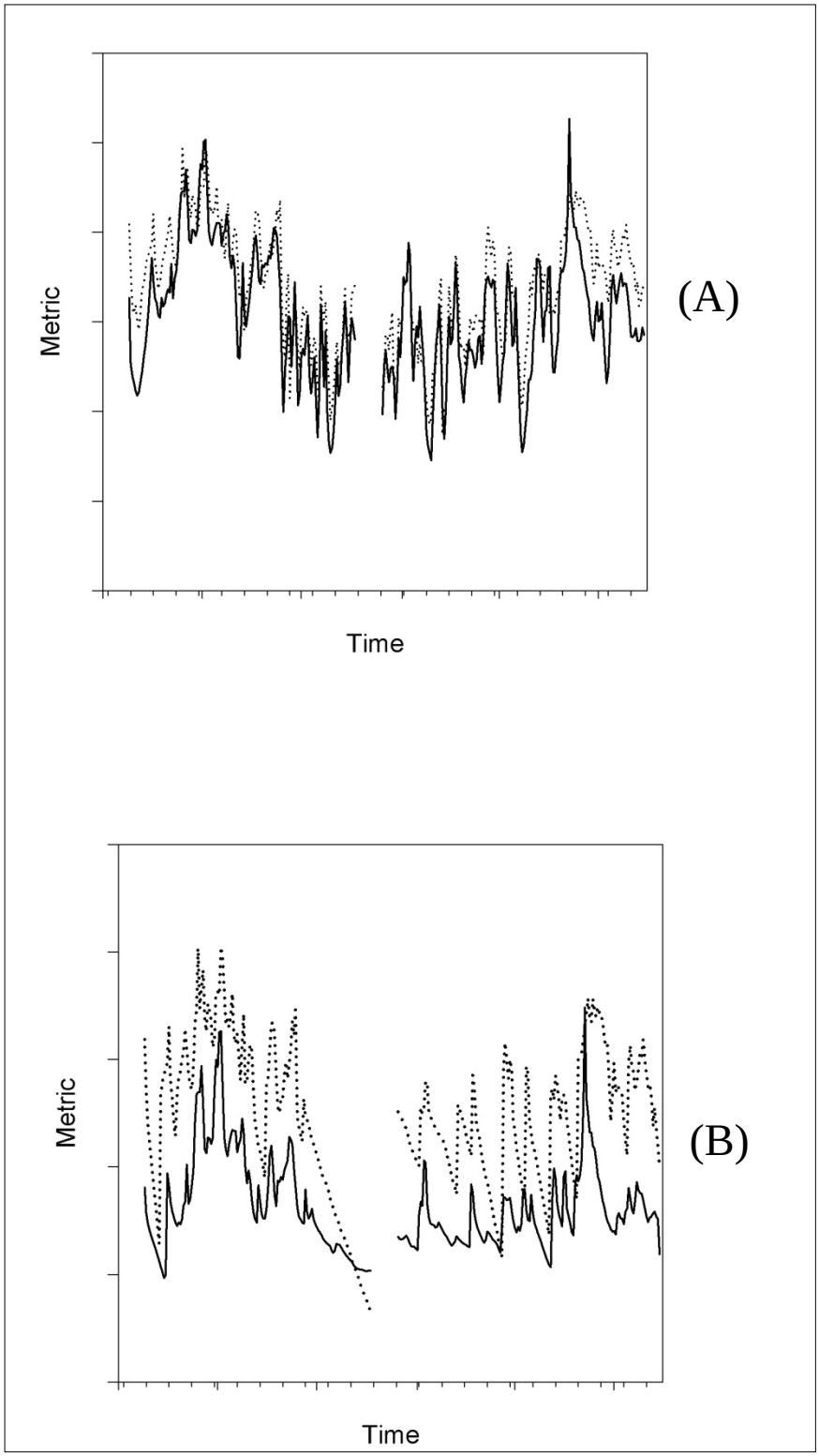


Figure 5. Examples of criteria used for model evaluation. (A) Comparison of model projections (solid line) to real data (dotted line) where the model results and real data compare relatively well. (B) Comparison of model projections (solid line) to real data (dotted line) where the model results and real data do not compare well and parameter values may need to be adjusted in order to generate acceptable patterns.

independent dataset to validate the model. One common approach is to divide the dataset and parameterize the model with some of the data and then validate it with the other.

Validation is always required to understand model reliability and to quantify uncertainty in the model results. It attempts to determine which sources of uncertainty should be considered when developing management strategies. Validation results can be used to determine which model revisions would be needed to reduce the uncertainty. Jørgensen and Fath (2011) identified three pertinent questions that should be asked during validation:

1. What is the uncertainty of the data used to build the model? The uncertainty associated with the data should be thoroughly documented. If there is a high degree of uncertainty, then statements justifying the use of those data should also be included.
2. Do the observations represent a wide range of system dynamics? If not, then additional data collection, under a wider range of conditions, should be considered.
3. Are some important processes or components missing or described wrongly in the model? Part of this question can be answered by evaluating the correspondence between model results and the expected patterns of model behavior, as described earlier in this chapter; however, it is likely that the process of validation will reveal further inadequacies in the model and these can be addressed by reevaluating those components in the same manner as described earlier.

The model development team should thoroughly document the methods used to address this step.

Adjust empirical parameters or model coefficients to match a known behavior, expert opinion or reference site data (*model calibration*).

The goal of this step is to improve parameter estimation by “fine-tuning” parameter values in the model. Parameters in environmental science are rarely known as exact values, and unlike physical systems, these parameters are not constant but change across time, space, and situation. All ecological models are simplifications of the natural world. The most important components and processes may be included, but the model will not account for every detail – the influence of some unimportant components and processes can be accounted for by the calibration. This may give slightly

different parameter values from the real, but unknown, values in nature, but this difference may partly account for the influence from omitted details (refer to Figure 5 for an example of model results where the parameter values might need to be adjusted to achieve a better match between model results and real system behavior).

It is difficult to determine beforehand which parameters will be adjusted for calibration because the choices of parameters that improve model behavior depend on the specific interactions among components within the model. Choosing parameters for calibration should be based on the degree of uncertainty associated with each parameter. Those parameters associated with high levels of uncertainty should be considered for calibration first. Calibration should not be carried out randomly if more than two or three parameters have been selected for calibration. For example, if 10 parameters need to be calibrated and the uncertainties justify testing 10 values of each parameter, then the model needs to be run 10^{10} times, which is intractable (Jørgensen and Fath 2011). A common approach is to vary each parameter using its minimum, maximum, and reported values to determine how the model behaves when the parameter is changed. Parameters should be varied one at a time until the behavior of the model is understood. The model development team should thoroughly document the methods they used to address this step.

Determine levels of uncertainty associated with model forecasts

After verification, validation, and calibration of the model have been completed, uncertainty in model outputs (i.e., forecasts) remains and must be dealt with in the context of environmental decision making. Most ecological systems are so complex that it is completely impractical to gather data on all important aspects of a system. As a result, most environmental models include varying levels and types of uncertainty, ranging from parametric uncertainty (e.g., a particular parameter value may be associated with a large confidence interval and the true value of that parameter is unknown) to structural uncertainty (e.g., having to hypothesize how components are related). Therefore, techniques have been developed to evaluate the levels of uncertainty present within a model. At this stage in model development, most of the structural uncertainty should have been dealt with, but there is often considerable parametric uncertainty in the system. Given the large range of uncertainty associated with environmental parameters, it is important to describe in detail how that uncertainty propagates through the model. The general goal is to determine the degree

of response of model behavior to changes in various model components. By identifying parameters, relationships, or submodels to which the model behavior is the most responsive, uncertainty analysis may provide an indication of the relative accuracy with which each parameter or relationship should ideally be estimated (and help potential users to identify or differentiate between reducible and irreducible forms of uncertainty embedded in the model).

Mathematical models developed to study ecosystems do not reveal "the truth," they merely provide an approximation of the phenomena being modeled based on incomplete knowledge. The reasons for this are many, but are based in part on the fact that understanding of ecosystem processes is limited, and ecosystems themselves are decidedly stochastic. Thus, ecological models are built under uncertainties in the values of the factors (e.g. the growth rate of a specific population), in the parameterization of the system (e.g. the boundary conditions of the dynamics), and in the choice of mutually exclusive scenarios (e.g. the choice of equations that describe dynamics). Identifying and characterizing the uncertainty associated with ecological models is a necessary precursor to decision-making based on the model results (Suedel et al., in preparation). One technique to help understand how these uncertainties might influence/affect model validation and eventual application is a "sensitivity analysis."

Sensitivity analysis aims at establishing the relative importance of the input factors employed in a model, answering questions such as:

- "Which variables have the greatest effect on model results?"
- "Which of the uncertain input factors are more influential in determining the variability affecting the inference?"
- "Which input could be eliminated with the least effect on the variance of the output of interest?"
- "Are there factors whose effect on the output is so low that they can be confidently fixed anywhere in their ranges of variation without affecting the results?"

McKay and Pruitt (in preparation) show how sensitivity analysis can be used to address these questions for a case study involving the Wetlands Value Assessment model.

The steps of a sensitivity analysis are similar to those of the calibration process; however, they are significantly different in interpretation. Calibration refers to the fine-tuning of parameters to determine accurate values. Sensitivity analysis seeks to disclose how perturbations of model elements (inputs, parameters, or even algorithms) affect responses in outputs (and which elements provoke the strongest responses). For example, if a model is highly sensitive to changes in a particular variable (that is, if the results fluctuate dramatically depending on the value of an important parameter), this can (but does not always) translate into a lack of confidence in model projections, particularly if the available input data are of poor quality or accuracy. There are several ways to deal with a lack of confidence in model projections. Multiple parameterizations of the model can be applied to the specific problem, each having a different estimate for the given parameter(s). Another option is to represent the uncertain parameter as a random variable, with the degree of variability reflecting the level of uncertainty in the estimates, and then run several repetitions of the model to generate average system behavior.

The breadth of uncertainties in the model that were discovered during the uncertainty analyses must be thoroughly documented, so that model users can understand the conditions in which the model behaves reasonably. Model projections are less accurate when the variables are parameterized using conditions that exceed the dataset from which the model was derived.

Identify data gaps and research needs that may not have been obvious during conceptual model development

The last step in model evaluation is to identify any data gaps and research needs that arose during model evaluation. One common occurrence during model evaluation is that data gaps that were not obvious during conceptual and quantitative model development reveal themselves. This allows stakeholders to identify future research needs or changes to the present model to accommodate data availability. Further, the process of rigorously evaluating a model causes the model development team to think about the system in a new way, which may result in reconceptualizing or re-quantifying some, or all, of the model. If that is the case, then the subject matter experts should incorporate this new knowledge into the model framework and evaluate it using the same processes described above.

7 Modeling in Practice

Background

In theory, model development proceeds smoothly from conceptual model development through model application; however, this rarely occurs in practice and quantifying models of environmental systems can seem overwhelming. Modeling is an iterative, dynamic process (Odum 1984, Ford 1999, Grant and Swannack 2008) and environmental models are best developed through an iterative approach where a preliminary conceptual model is developed; then a small section of that conceptual model is quantified and evaluated, addressing challenges or incorporating new ideas as they occur; then a new piece of the conceptual model is quantified and evaluated; and so on, until the entire conceptual model is represented quantitatively. Model development is most successful when the model is constructed in this manner collaboratively with modelers, subject matter experts, and the eventual end-users of the model. Unfortunately, this iterative approach to model development is seldom documented, but each of the practical activities can be directly related to the three steps mentioned above (conceptualize, quantify, evaluate). As the model development team quantifies each piece of the conceptual model, they are forced to constantly reevaluate the model, both conceptually and quantitatively. Often the pieces that fit well together conceptually do not make sense after performing a quantitative evaluation of those pieces. However, by quantifying and evaluating small pieces of the model separately, the process becomes significantly easier and this provides greater insight into system dynamics and greatly reduces the likelihood of mathematical or logical errors. This chapter provides good practice guidance on how to proceed through the modeling process. An example is provided in Figure 6 to further illustrate the concepts.

In practice, the first step of modeling is to develop a preliminary conceptual model of the entire system, following the steps discussed in conceptual model formulation. Once the conceptual model has been represented, the next step is to outline and document a “plan-of-attack” for quantifying the model. Then, identify a series of intermediate developmental models (IDM) that will be quantified sequentially until the final model has been completely quantified.

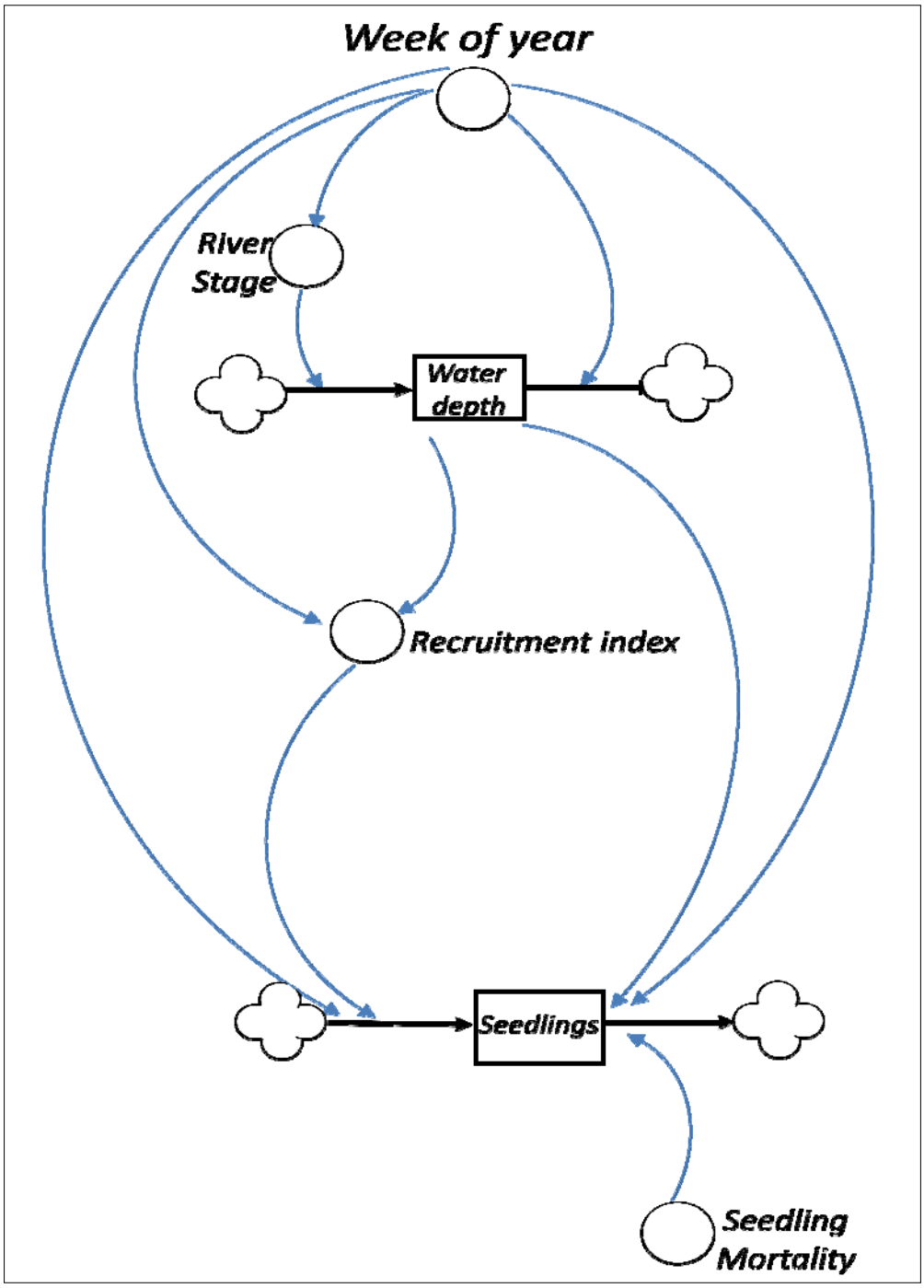


Figure 6. Preliminary conceptual model depicting how inundation affects tree growth.

Once the plan of attack has been outlined, the next step is to begin quantifying and evaluating the series of IDMs (Grant and Swannack 2008). There is not a particular order in which IDMs should be developed – in general, the first IDM should be trivially simple and subsequent IDMs should be increasingly complex. Making each addition to subsequent IDMs as simple as possible facilitates the identification and correction of

errors and also promotes understanding of the relationships within the model. Quantification of each IDM should follow the steps outlined in Chapter 3, "*Model Development*."

As each IDM is built, it should be rigorously evaluated before proceeding to the next, following the steps described in Chapter 6, "*Model Evaluation*." If the IDM does not meet the evaluation criteria, then it should return to an earlier step in model development, either quantitative or conceptual. The most common form of adjustments made during the modeling process are discovering that the conceptual model has too few or too many components or that the functional forms of model equations do not produce reasonable results. This point emphasizes the need for concurrent documentation, evaluation, and review during model development.

Modeling is often viewed as a "black box" activity and there may be several groups of people that do not trust the results of models. The model development team, as well as potential users of the model or its information, should be engaged as early as possible in the modeling process to maintain transparency and foster an environment in which trust (between developers and users) can develop. Thoroughly documenting each IDM is incredibly important because as the IDMs become more complex, the team might want to revisit an earlier version and proper documentation facilitates this process. Further, documentation provides transparency for peer-reviewers, certification reviewers, policy makers, and the interested public, and this is critical when the model is being used for environmental projects.

Example of modeling in practice

The purpose of this example is to briefly illustrate how to both develop a model using the IDM approach and emphasize the iterative nature of model development. Assume that the main task at hand is to develop a simple model of the system and that the model development team working on the project has identified the recruitment of seedlings as an environmental benefit of the restoration project. Note that the model presented here is simple, will not be fully quantified, and is only intended to be a descriptive illustration of the concepts IDM and the iterative nature of modeling in practice.

A bottomland hardwood forest lies in the floodplain of a dam-controlled river. Historically, the forest was inundated in the spring and essentially dry from late summer through winter. During high spring flow, the forest stored water, which mitigated flood damage

downstream. During dry-down events, the trees' seeds germinated and new recruitment occurred. Current operations have prolonged the annual flooding season, preventing new seedlings from establishing themselves. There are plans to alter dam operations to restore the hydrology and habitat to more natural conditions. One of the proposed metrics for assessing the environmental benefits of this project is increasing seedling recruitment, which, over time, would create a "healthier" bottomland hardwood community. The objective of this project is to develop a model to determine if changes in hydrology lead to an increase in the overall number of seedlings in the forest.

Example: Preliminary Conceptual Model

The first step for solving this problem would be to develop a preliminary conceptual model that represents the entire system. This step exactly follows the steps described in *Conceptual Model Development*. For this example, the objective has been identified, so the next step is to bound the system of interest. There are myriad considerations, but as a first step, the model development team decided, after much discussion, that the system could be conceptualized as a box-and-arrow diagram[1] having two major components: the depth of water in the forest during the growing season and the number of seedlings in the forest,[2] represented as rectangles). The depth of water fluctuates seasonally, increasing and decreasing as water enters the floodplain in the spring and leaves in the summer (indicated by arrows). The team decided that it was not interested in where the water came from or where it went after it left the floodplain.[3] Likewise, recruitment is a seasonal process. Quantitative values for average seedling recruitment and historical seedling mortality are available and these variables were represented explicitly. The team has a general idea about how much water depth

[1] In general, boxes represent points of accumulation (or storage spaces) and can be thought of as storage spaces from which material (in this case water or biomass) can be moved in and out (via the darker arrows in the diagrams). Lighter arrows indicate directional influence. For example, the water volume on the floodplain affects tree recruitment, but in this model, tree recruitment does not affect water volume.

[2] The team recognized that there were other components that could be added but decided that other ecological processes were not directly involved with seedling recruitment. Given the complexity of the system, the team decided that the first step should be to create a simple model to explore the overall dynamics of the system, then develop more complex models if needed.

[3] Sources and sinks in this diagram (represented by clouds) represent origination and termination points, respectively. These points represent the boundary of the system and encompass the processes outside the bounds of the system. For example, the team decided that it did not want to model all of the intricacies involved with tree growth (such as photosynthesis, etc.), rather they only wanted to consider how water accumulation affected overall biomass.

changes in the floodplain over the course of an average year and also knows that if water remains on the floodplain during the summer, then new trees are not recruited because the seeds cannot germinate. However, the team is not sure of exactly what the relationship between inundation and recruitment looks like, so they decide that it would be best represented as an index variable (the circle labeled *recruitment index*). Figure 7 depicts the preliminary conceptual model.

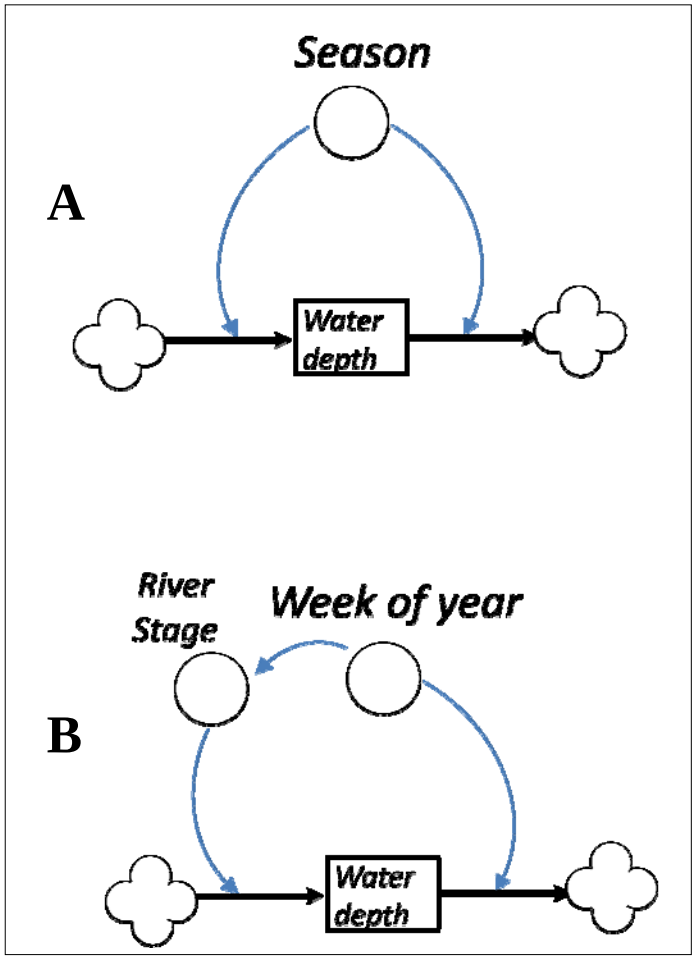


Figure 7. First intermediate developmental model representing the hydrologic component of the system. (A) represents the original conceptualization, and (B) represents the reconceptualization of the model that includes more precise information regarding the relationship between water depth on the floodplain and time of year.

Once the conceptual model has been developed, the model must be documented. At this stage, several assumptions have been built into the model (such as why certain variables were included or omitted and which variables interact with each other). These assumptions must be recorded in the model documentation. As mentioned previously, it is important to

thoroughly document each stage of model development. After conceptual model documentation has been completed, the development team must describe how the model is expected to behave, identify data quality and quantity, and describe its context for use (Chapter 4).

Example: First Intermediate Developmental Model (IDM_1)

The team first chose to quantify the relationship between *Season* and *Water Depth* (Figure 2A). The team decided that they could not appropriately quantify the model without knowing the stage of the river at particular times and based on this knowledge, they realized that stage must be included explicitly, so they reconceptualized their system to include river stage[1] (Figure 2B). The team realized that season was not a precise time unit, so they decided that week of year would work best for both the hydrodynamic and ecological pieces of the model (Figure 2B). The team used gauge data and scientific literature to develop a quantitative hydrodynamic model that captured the processes that inundated the floodplain at the appropriate depth in the spring and was dry in the summer. The team then evaluated the model and documented the equations, following the guidelines in *Quantitative Model Development* and *Model Evaluation*.

Example: Second Intermediate Developmental Model (IDM_2)

Next, the team developed an IDM for the dynamics of the trees (Figure 3A). After some discussion, the team decided that week of year affected both seedling recruitment and normal mortality. Specifically, the team knew the approximate time of year when the seedlings germinated and had some data available that indicated seedling mortality changed seasonally (Figure 3B). The team then quantified this IDM by using scientific literature and available data, evaluating and documenting each step as they went.

There are two important items worth noting for this IDM. First, seedlings are only recruited during a specific time of year, so the model must include a conditional statement that only allows recruitment during the appropriate season.[2] The second is that the team knows that *tree recruitment* depends

[1] Reconceptualizing a model is a common occurrence and should be considered a normal part of the modeling process. As the model development team becomes more familiar with the system, they will likely realize that particular components of the model might be better represented differently. By following the IDM and iterative approach to model development, reconceptualizing the system becomes an integral part of the modeling process.

[2] Generally, conditional statements are written as IF-THEN-ELSE statements, where the model checks to see if a condition is true or not. In this case, the statement could be written as IF it is the growing season, THEN seedlings can germinate, ELSE no seedlings (ELSE can also be interpreted as 'otherwise')

on *water depth;* however, this IDM does not contain *water depth*. In cases like this, it's best to use a surrogate for the variable, run the model to ensure that it is working, and then reparameterize it once the IDMs are linked (see IDM_3 for a better description). These surrogate variables should come from the scientific literature. For example, data might exist from other systems that could be used as a surrogate (for example, recruitment from a similar, but unaffected floodplain). Once IDM_2 was completed, it generated tree recruitment and death seasonally, as was reported in the literature.

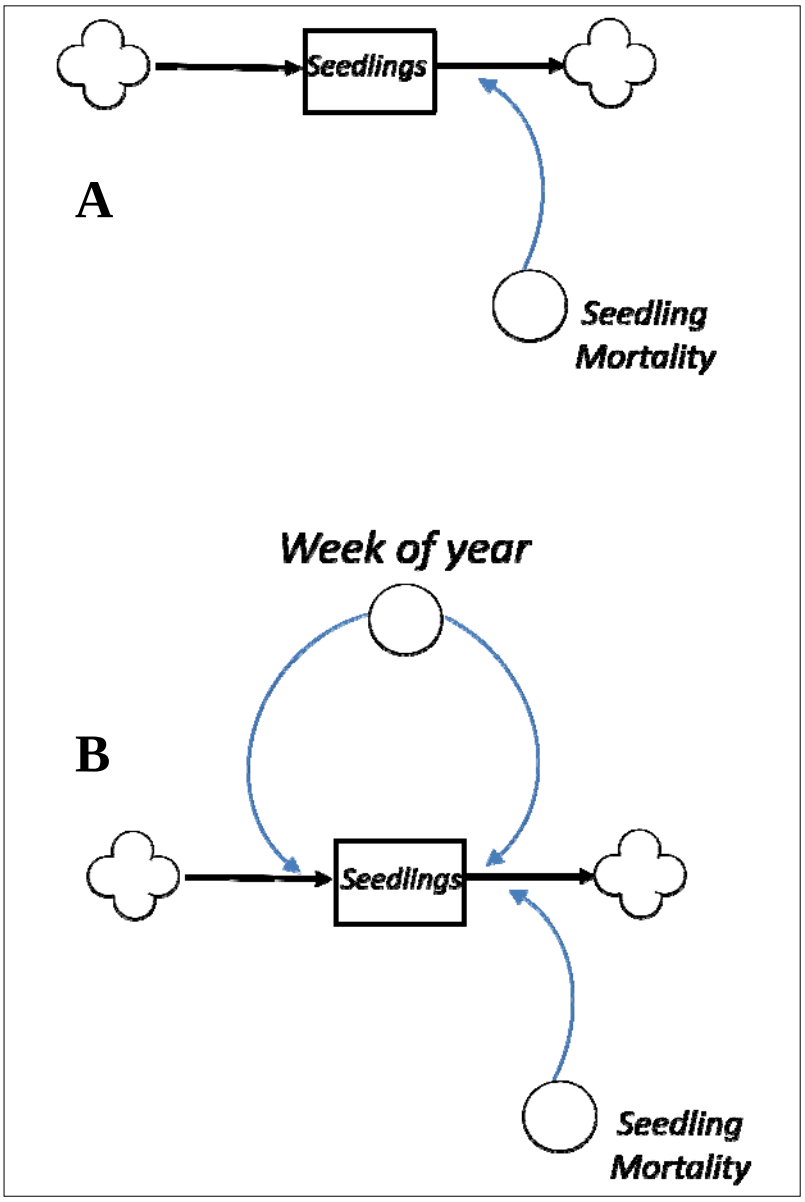


Figure 8. Second intermediate developmental model representing the ecological component of the system. (A) represents the original conceptualization, (B) represents the reconceptualization of the model that includes more precise information regarding the relationship between tree biomass, recruitment, and time of year.

Example: Third Intermediate Developmental Model (IDM_3)

The final IDM represents the system as it has been reconceptualized during the IDM process and now the team needs to link IDM_1 and IDM_2 (Figure 9). As previously mentioned, the team understands the general relationship between tree recruitment and water depth and understands that water depth affects both recruitment and mortality (Figure 9). The relationship between seedling mortality and water depth has been well documented for this particular forest system, so the team can quantify that relationship. Although quantitative data are not available from either field work or the scientific literature to study the relationship between water

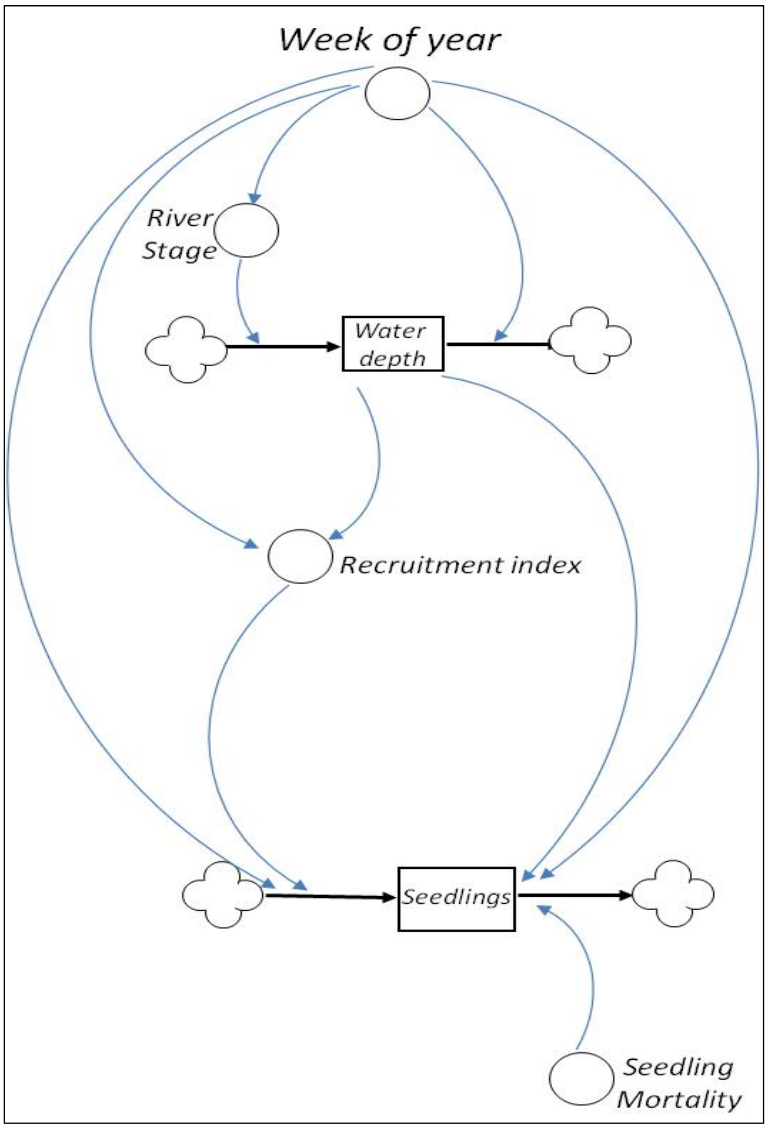


Figure 9. Final intermediate developmental model representing the complete, reconceptualized system, after two intermediate developmental models were completed.

depth and recruitment, the team needs to determine if the proposed project will enhance seedling recruitment. One common technique used to solve this dilemma is to create an index[1] of how water depth affects tree recruitment. The team decided that the *number of weeks the floodplain was inundated* would be a good metric for relating water depth to tree recruitment. In this case, an index-based approach is appropriate because the team knows the general quantitative structure of the relationship; specifically, if there is water on the floodplain during the growing season, then recruitment decreases. The surrogate value for *tree recruitment* should be replaced with an appropriate value before the model is run.

There is some uncertainty regarding exactly how recruitment decreases with increasing inundation (that is, the functional form of the relationship is unknown). The team identified three potential functional relationships that made ecological sense for the variable *recruitment index*: linear, exponent-tial decline, and sigmoid (also called s-shaped or logistic) (Figure 10). However, the team could not decide which of these best represented the relationship among *week of year*, *water depth*, and *tree recruitment*. The most appropriate approach is to thoroughly evaluate the model using each of the three relationships (following each of the steps in Chapter 6, "*Model Evaluation*"). Once each version has been evaluated, the results should be compared against each other to see how much difference there is among model runs. This is a sensitivity analysis (Chapter 6) because the model is determining sensitivity to changes in the functional form of a particular variable. There are four general outcomes from this type of analysis:

1. None of the model runs generated results that make sense.
2. One or more of the runs generated completely unreasonable results, while the others seemed reasonable.
3. All model results seem reasonable, but the results are significantly different.
4. All model results seem reasonable and are very similar.

[1] A detailed description of index-based modeling is outside the scope of this document. Briefly, the index is scaled between 0 and 1, where 1 represents the best possible conditions and 0 represents the worst. This scale is then combined with other variables in a model, using whatever mathematical technique the team decides is best. For this example, 1 would represent the *number of weeks inundated* that created the best situation for *tree recruitment* (represented by a 1). The shapes of the lines (the functional forms) represent how the relationship between *weeks inundated* and *tree recruitment* change as *weeks inundated* changes. Once the floodplain is inundated for a certain period of time, no trees would be recruited (indicated by an index value of 0).

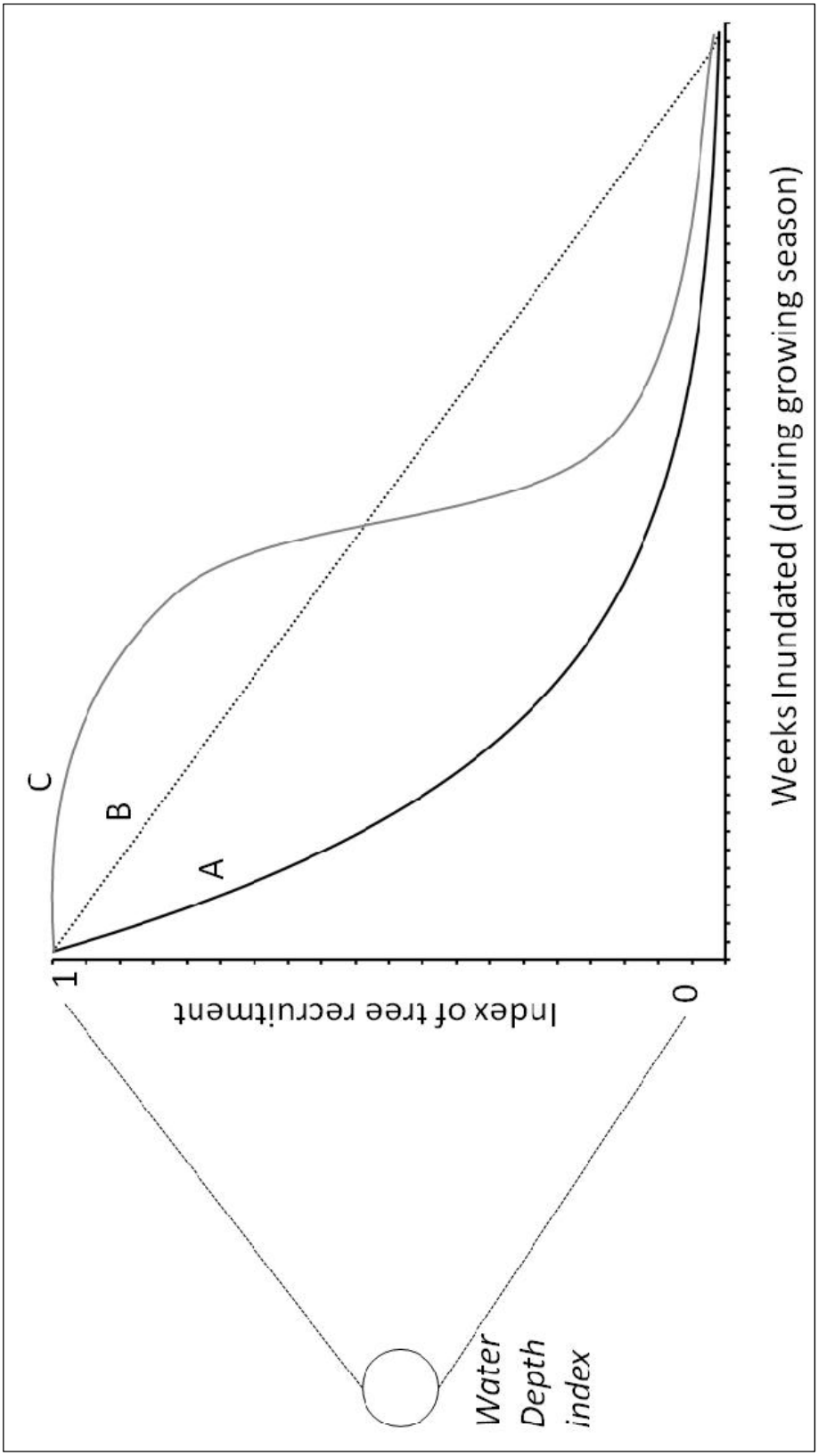


Figure 10. Qualitative diagram of the *Water Depth Index* variable representing three proposed functional forms between weeks inundated and the index of tree recruitment – (A) exponential decline, (B) linear decline, (C) sigmoid. Note that the water depth index depends on how many weeks the floodplain is inundated. This would be calculated inside the *Water Depth Index* variable.

When none of the results make sense (outcome 1), then the functional forms that were chosen likely do not represent the actual relationship in nature, or the model does not include an important variable or process. For the former, the team should identify other functional forms to evaluate. If the latter is the case, then the model should be reconceptualized to include the important processes. When one or more of the model runs seem reasonable, but others do not (outcome 2), then the model development team should discard the functional forms that did not generate reasonable results. If all of the model results seem reasonable, but are significantly different (outcome 3), then the model development team must decide if they want to move forward using more than one version of the model (where each version is a model containing a different functional form for the index variable). This is very common in ecological modeling and it allows the team to capture some of the uncertainty associated with the system (applying multiple versions of the model is discussed in more detail below). Finally, if all of the model runs generated logical and reasonable results, which are not significantly different from each other (outcome 4), then the model development team must decide if using just one functional form will suffice (that is, they can choose one of the relationships and discard the others). This process must be documented extensively because it provides a record of how the team dealt with uncertainty in the system. Once the final IDM has been thoroughly evaluated and documented, the team may proceed to *Model Application*.

Example: Model Application

Once all of the IDMs have been developed and evaluated, the model is ready to be applied to the problem. For this example, the proposed project will be affecting *River stage* and the model will be forecasting how changes in *River stage* affect tree recruitment. The team will need to develop model runs for each of the proposed project alternatives and compare those results to a future without-project scenario. If the team decided to move forward with multiple versions of the model (see outcome 3 in IMD_3), then the model would need to be run for each functional form (Figure 10) for each of the proposed project alternatives and also for the future without project. The team then compares the results, documents the outcomes, and determines which alternative provides the most benefits (refer to Chapter 8, "*Model Application*" and Chapter 9, "*Model Documentation, Quality Assurance, and Communication*" for more details).

Example: Summary

In practice, model development does not proceed fluidly from the conceptual model to model application. Rather, models are developed via a series of intermediate developmental models, each of which has a conceptual diagram that is used as a template for quantification and a thorough evaluation, documenting each step in the process. This process makes it easier to quantify complex models, find conceptual or logical errors, and develop all of the proper documentation. In this example, the model development team started with a simple conceptual model of a system, then through the model development process, realized that the simple model did not quite capture all of the important processes, so the team reconceptualized the system as it developed the model, resulting in a more precise representation of the system (Figure 11). The resulting model was more complex, but the IDM approach facilitated new components being integrated into the model. Recognizing that the modeling is an iterative process, the team was able to quickly adapt its new ideas into model development.

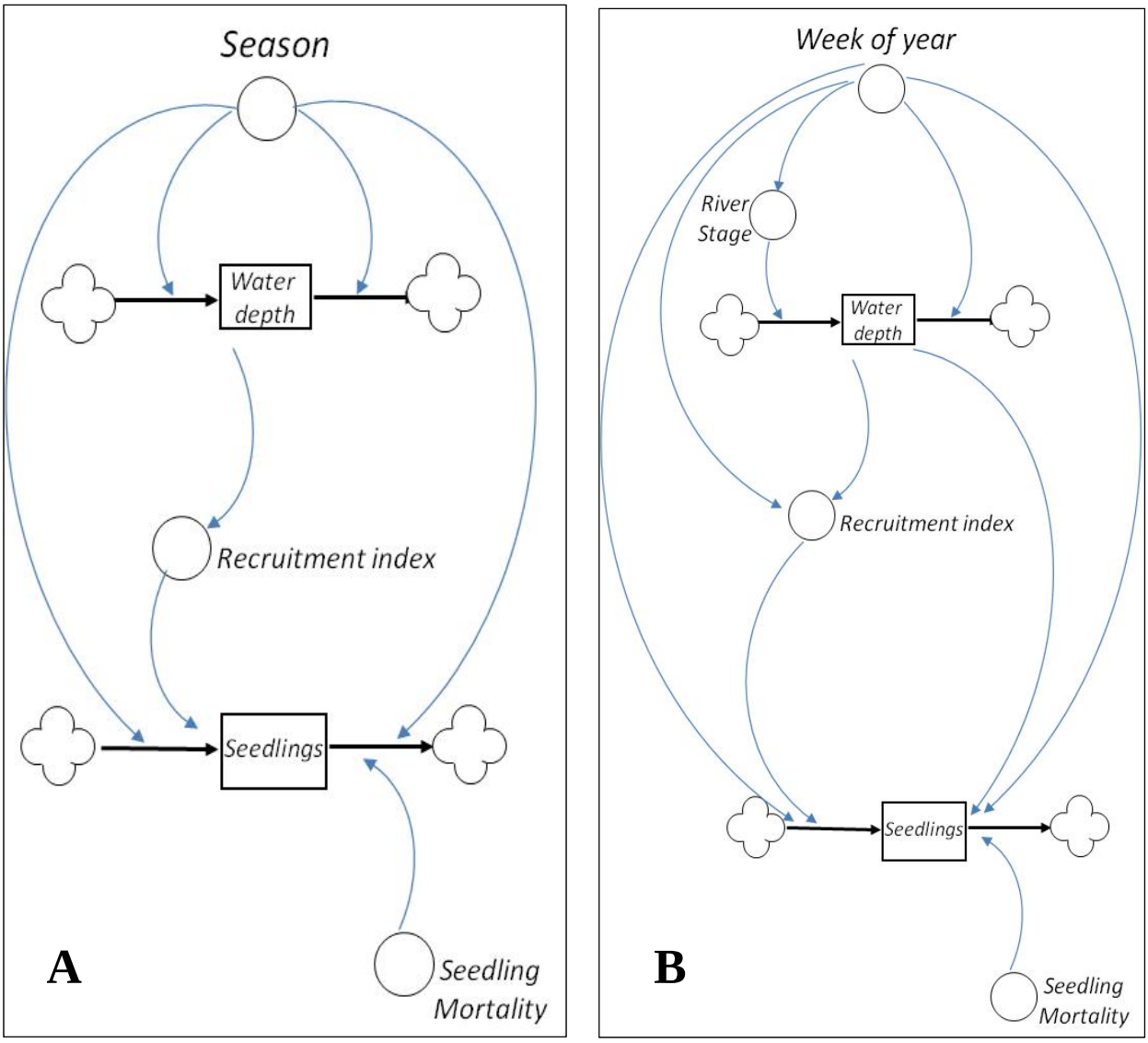


Figure 11. Comparison of (A) the model, as originally conceptualized by the model development team, and (B) the model after the team completed the modeling process.

8 Model Application

The goal of this phase of model development is to apply the model during execution of the planning study or project activities. For environmental benefits analysis, this most often entails using the model to develop information that will be used during evaluation and comparison of various planning alternatives. During an investigation, models can be applied in many ways. In most instances, model application will involve three sequential activities:

1. Define project alternatives.
2. Apply model to alternatives and a future-without-project alternative and to any alternative scenarios.
3. Analyze and interpret results.

Definition of project alternatives

At this stage, the suite of study baselines and preliminary alternatives have largely been defined and documented. The project baselines (future without-project condition, and sometimes the existing condition) and each of the alternatives (or at least an initial array of alternatives) have been developed and characterized to a level of detail sufficient to synthesize/produce data or other information necessary to run the model. The model is applied to each of the study baselines and alternatives by those familiar with or trained in the application of the model in accordance with its prescribed standards for application.[1] Each baseline and alternative typically yields a unique set of data (and in some instances other parameters) that are input into and processed by the model to produce outputs. The outputs produced by the model are used by the study/project team during attempts to characterize conditions that one might expect to result in the absence (i.e., future without-project condition) or presence of (i.e., alternatives) future federal action. The conditions of each alternative are typically compared against the future without-project condition to identify where beneficial and detrimental impacts might be occurring. The resulting observations may inform decisions to proceed with a specific action or to modify/develop

[1] The study team should seek to fully understand assumptions that must be demonstrated "true" throughout the model's application. Likewise, the study team should seek to understand and account for the influence of boundary conditions (or changes in boundary conditions) that might influence the interpretation or credibility of observations that are based on model results.

alternatives in an informed manner based on what was observed during the prior suite of model results. During this iterative process of alternative development/refinement, model application, and results evaluation/comparison, study/project teams should use all the tools at their disposal to understand and document the rationale supporting their conclusions, recommendations, and decisions. For instance, the conceptual model (of the model to be applied) could be used by the study team to anticipate how measures associated with a proposed alternative might affect resources of concern. Other best practices that study teams might consider during development and documentation of model-informed alternative analyses include:

- Performance and consideration of results of uncertainty analysis: if the model has a high degree of uncertainty, it is likely that multiple iterations of each alternative should be run to encompass the uncertainty (refer to the section in Chapter 7 titled "Example of modeling in practice" for example).
- Development and documentation of a decision context(s): It is important to have a clearly defined decision context in mind so that sets of testable model alternatives can be developed in a logical, rather than shotgun approach, which could yield misleading (or meaningless) information.
- Careful design of model runs helps to mitigate the chance that the model is not used under conditions for which it was not designed.
- Careful and organized documentation of modeling activities for later use by reviewers and decision-makers, keeping in mind that documentation of context and rationale may be just as important as documentation of actions and the consequences of actions.

Apply model to all alternatives

Once the model scenarios have been identified, apply the model to all the alternatives, including a future-without-project alternative. Results from model runs should be saved and cataloged so that they are easy to find, and more importantly, easy for someone else to use. One major issue with model results is that the modeler names results files ambiguously, making it impossible for others to find and/or interpret how to use those files. There is not a standard convention for file naming, but the common approach is to include dates and/or times in the filenames, which prevents files from being overwritten. The filename structure should be included in

the documentation so future model users understand how to read and use model output.

Analyze and interpret results

Results from the model application should be analyzed using several techniques and should not be limited to a statistical test determining significance. First results among model runs should be compared to determine if there are any significant differences among model runs. Subject matter experts should carefully scrutinize the results and determine how to interpret them environmentally; that is, are the results environmentally significant? Often results can be mathematically significant, but those differences *detected by statistical techniques* may not affect the system ecologically (Glaser and Bridges 2007). Ecological significance will vary among projects, but it should be defined and documented for each situation. Other factors, such as cost, should be considered as well.[1]

Finally, results should be appropriately interpreted with regards to uncertainty in the system. If the model has proven sensitive to changes in parameter values (from the sensitivity analysis), then the results should be interpreted in terms of its uncertainty. That is, if model results vary over a wide range, then the subject matter experts should determine how those results affect management decisions as the project progresses.

[1] This is done in Step 4 of the planning process – i.e., Evaluation of Alternatives using Cost Effectiveness and Incremental Cost Analysis.

9 Model Documentation, Quality Assurance, and Communication

Throughout the modeling process, model development involves clearly communicating the model and its results to a broad group of interested stakeholders, which can include the scientific community, the appropriate Planning Centers of Expertise, other agencies, policy makers, potential users of the model, the interested public, etc. This is accomplished through two tasks: (a) documenting the model by describing its technical aspects, and (b) explaining how to use and interpret the model and its results to interested parties. Documenting a model and its results is of paramount importance if the model is to be received well among the stakeholders. Documentation should be created during model development and not after the model is completed, which can be accomplished with interim reports or reviews.

The model development team should be documenting the model as it moves through each step of the modeling process and this stage involves compiling the documentation. Model documentation requires thoroughly explaining the conceptual and technical aspects of how the model was built. The problem being addressed, the specific objectives, the information base being drawn upon, the technical method used to analyze the information, and the results and conclusions must be described. There must be an understandable link between the conceptual model and the quantitative model. Data sources and the types of mathematics used should be explained. More importantly, the assumptions that were made regarding the relationships among variables (i.e., functional forms and parameter values) must be explicitly addressed. Models are all based on assumptions and this information must be thoroughly documented for a model to have scientific defensibility. The limitations of the model should be explained clearly and concisely and the appropriate use of the model should be described anytime the model is requested or used. As mentioned throughout this guide, documenting the model as it is built facilitates this step. The ideal documentation results in technically competent people being able to recreate the model from its description. Model documentation should

follow the guidelines established for model certification by Headquarters, USACE.[1]

Transmitting the model to interested parties has always been a difficult task. Model development usually requires many decisions that make sense to the model developers, but when viewed by others after completion of the model, may not make much sense. Confidence in the model is always higher the earlier stakeholders or potential users become involved with the process. In cases where interested parties cannot be involved with model development, a clearly documented model is helpful, but communication is also easier if emphasis is placed on the environmental interpretations and general trends of the results rather than the specific numerical values. General trends usually are more relevant in a management context than numerical output; however, modelers have a tendency to become preoccupied with presenting details at the expense of a clear overview. Clear and concise communication of a model is crucial if it is to be used for making or informing policy.

[1] see http://140.194.76.129/publications/eng-circulars/EC_1105-2-412_2011Mar/EC_1105-2-412_2011Mar.pdf.

10 Summary and Additional Information

This report provides good practice guidance for developing quantitative environmental models to model environmental benefits. Modeling efforts should begin by precisely indentifying objectives for the project. Once the objectives have been identified, a conceptual model should be developed and then used as the template for quantitative model development. Quantitative modeling is a dynamic process and models are best developed through an iterative approach where a preliminary conceptual model is developed, and then small sections of that conceptual model are quantified and evaluated in a piecewise fashion until the entire conceptual model is represented quantitatively. This iterative approach facilitates model development and documentation, as each section of the larger model is conceptualized, quantified, evaluated, and documented as it is built.

Research presented in this technical report was developed under the Environmental Benefits Assessment (EBA) Research Program. The USACE Proponent for the EBA Program is Rennie Sherman. The Technical Director is Dr. Al Cofrancesco, and the Program Manager is Mr. Glenn Rhett of the ERDC Environmental Laboratory. The authors gratefully acknowledge technical reviews and suggestions provided by Nathan Beane, Carl Cerco, Sarah Miller, David Price, Bruce Pruitt, and Antisa Webb (ERDC), Jeff Tripe (Kansas City District), Shawn Komlos (IWR), John Wright and Brook Herman (Chicago District).

References

Brinson, M. M. 1993. *A hydrogeomorphic classification for wetlands*. Technical Report WRP-DE-4. Vicksburg, MS: U.S. Army Engineer Waterway Experiment Station.

Cake, E. W., Jr. 1983. *Habitat suitability index models: Gulf of Mexico American oyster*. FWS/OBS-82/10-57. Washington, DC: Fish and Wildlife Service, U.S. Department of the Interior.

Casper, A. F., R. A. Efroymson, S. A. Davis, G. Steyer, and B. Zettler. 2010. *Improving conceptual model development: Avoiding underperformance due to project uncertainties*. EMRRP Technical Note Collection. ERDC-TN-EMRRP-EBA-5. Vicksburg, MS: U.S. Army Engineer Research and Development Center.

Cerco, C., and M. Noel. 2010. Monitoring, modeling, and management impacts of bivalve filter feeders in the oligohaline and tidal fresh regions of the Chesapeake Bay system, *Ecological Modelling* 221: 1054-1064.

Dalyander, P., and C. Cerco. 2010. Integration of a fish bioenergetics model into a spatially explicit water quality model: Application to menhaden in Chesapeake Bay. *Ecological Modelling* 221: 1922-1933.

Dalyander, P. S., and J. C. Fischenich. 2010. CEMCAT: *Conceptual Ecological Model Construction Assistance Toolbox*. EMRRP Bulletin No. 10-1. Vicksburg, MS: U.S. Army Engineer Research and Development Center.

Fischenich, C. 2008. *The application of conceptual models to ecosystem restoration*. EBA Technical Notes Collection. ERDC TN-EMRRP-EBA-01. Vicksburg, MS: U.S. Army Engineer Research and Development Center.

Foran, C. M., I. Linkov, E. A. Mobert, D. L. Smith, and D. M. Soballe. 2011. *Ecological forecasting tools and planning of ecoystem restoration projects*. EMRRP Technical Notes Collection. ERDC TN-EMRRP-EM-10. Vicksburg, MS: U.S. Army Engineer Research and Development Center.

Ford, A. 1999. Modeling the environment: An introduction to system dynamics modeling of environmental systems. Washington, DC: Island Press.

Fries, C., M. Carisson, B. Dahlin, T. Lamas and O. Sallnas. 1998. A review of conceptual landscape planning models for multiobjective forestry in Sweden. *Canadian Journal of Forest Research* 28:159-167.

Glaser, D., and T. S. Bridges. 2007. Separating the wheat from the chaff: The effective use of mathematical models as decision tools. *Integrated Environmental Assessment and Management* 3:442-449.

Goodwin, R. A., J. M. Nestler, J. J. Anderson, L. J. Weber, and D. P. Loucks. 2006. Forecasting 3-D fish movement behavior using a Eulerian-Lagrangian-agent method (ELAM). *Ecological Modeling* 192: 197-223.

Grant, W. E. 1998. Ecology and natural resource management: Reflections from a systems perspective. *Ecological Modelling* 108:67-76.

Grant, W. E., and T. M. Swannack. 2008. *Ecological modeling: A common-sense approach to theory and practice*. Oxford: Blackwell Publishing.

Grimm, V. 1994. Mathematical models and understanding in ecology. *Ecological Modelling* 75-76:641-651.

Grimm, V., and S. F. Railsback. 2005. *Individual-based modeling and ecology*. Princeton, NJ: Princeton University Press.

Guisan, A., and N. E. Zimmermann. 2000. Predictive habitat distribution models in ecology. *Ecological Modelling* 135:147-186.

Jørgensen, S. E., and B. D. Fath. 2011. *Fundamentals of ecological modelling: Applications in environmental management and research.* 4th ed. Amsterdam: Elsevier.

Jørgensen, S. E., and G. Bendoricchio. 2001. *Fundamentals of ecological modelling.* 3rd ed. Amsterdam: Elsevier.

Killgore, K. J., J. J. Hoover, C. E. Murphy, K. D. Parish, D. R. Johnson, and K. F. Myers. 2008. *Restoration of delta streams: A case history and conceptual model.* EMRRP Technical Notes Collection. ERDC TN-EMRRP-ER-08. Vicksburg, MS: U.S. Army Engineer Research and Development Center.

McKay, S. K., and B. Pruitt. *An approach for developing regional environmental benefits models*, in preparation. Vicksburg, MS: U.S. Army Engineer Research and Development Center.

McKay, S. K., B. A. Pruitt, C. J. Anderson, J. A. Curran, A. D. Ochoa, M. C. Freeman, B. Rashleigh, and E. D. Trawick. 2011. Constructing a conceptual model linking drivers and ecosystem services in Piedmont streams. In *Proceedings of the 2011 Georgia Water Resources Conference, Athens, Georgia*.

Odum, E. 1984. The mesocosm. *BioScience* 34:558-562.

Odum, H. T. 1983. *Systems ecology*. New York: John Wiley & Sons.

Ogden, J. C., S. M. Davis, K. J. Jacobs, T. Barnes, and H. E. Fling. 2005. The use of conceptual ecological models to guide ecosystem restoration in South Florida. *Wetlands* 25:795-809.

Pascual, P., N. Stiber, and E. Sunderland. 2003. *Draft guidance on the development, evaluation and application of regulatory environmental models.* Washington, DC: Council for Regulatory Environmental Modeling.

Peck, S. 2000. A tutorial for understanding ecological modeling papers for the nonmodeler. *American Entomologist* 46:40-49.

Peck, S. L. 2004. Simulation as experiment: A philosophical reassessment for biological modeling. *Trends in Ecology and Evolution* 19:530-534.

Rykiel, E. 1996. Testing ecological models: the meaning of validation. *Ecological Modelling* 90:229-244.

Smith, R. 2001. *Hydrogeomorphic approach to assessing wetland functions: Guidelines for developing regional guidebooks. Chapter 3. Developing a reference wetland system*. ERDC/EL TR-01-29. Vicksburg, MS: U.S. Army Engineer Research and Development Center.

Smith, R. D., A. Ammann, C. Bartoldus, and M. M. Brinson. 1995. *An approach for assessing wetland functions using hydrogeomorphic classification, reference wetlands, and functional indices*. Technical Report WRP-DE-9. Vicksburg, MS: Army Engineer Waterways Experiment Station.

Starfield, A. M., and A. L. Bleloch. 1986. *Building models for conservation and wildlife management*. New York: Macmillan.

Stralberg, D., V. Toniolo, G. Page, and L. Stenzel. 2004. *Potential impacts of non-native Spartina spread on shorebird populations in South San Francisco Bay*. PRBO Report to California Coastal Conservancy (Contract# 02-212). Stinson Beach, CA: PRBO Conservation Science.

Suedel, B.C., J. Valverde, J. Vogel, I. Linkov, J. C. Fischenich, T. S. Bridges, and M. Plumley. *Application of risk management concepts and methods for ecosystem restoration: Principles and best practice*, in preparation. Vicksburg, MS: U.S. Army Engineer Research and Development Center.

Tirpak, J. M., D. Jones Farrand, F. R. Thompson, III, D. J. Twedt, C. K. Baxter, J. A. Fitzgerald, and W. B. Uihlein III. 2009. Assessing ecoregional scale habitat suitability index models for priority landbirds. *The Journal of Wildlife Management* 73:1307-1315.

U.S. Army Corps of Engineers (USACE). 2000. *Planning guidance notebook*. Engineer Regulation 1105-2-100. Washington, DC.

U.S. Army Corps of Engineers (USACE). 2011. *Assuring the quality of planning models*. Engineer Circular 1105-2-412. Washington, DC.

Wissel, C. 1992. Aims and limits of ecological modelling exemplified by island theory. *Ecological Modelling* 63:1-12.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
August 2012

2. REPORT TYPE
Final

3. DATES COVERED *(From - To)*

4. TITLE AND SUBTITLE
Ecological Modeling Guide for Ecosystem Restoration and Management

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Todd M. Swannack, J. Craig Fischenich, and David J. Tazik

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
U.S. Army Engineer Research and Development Center
Environmental Laboratory
3909 Halls Ferry Road
Vicksburg, MS 39180-6199;

8. PERFORMING ORGANIZATION REPORT NUMBER
ERDC/EL TR-12-18

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
U.S. Army Corps of Engineers
Washington, DC 20314-1000

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

Ecological models are important tools for planning ecosystem restoration and management activities. Models help to organize our thinking, conceptualize our understanding of complex systems, and forecast environmental benefits that may result from proposed restoration and management actions. This report provides information to guide environmental planers in selection, development, evaluation and documentation of ecological models. A number of critical issues are addressed, including specifying objectives and formulating a sound conceptual model, choosing among types of models, deciding when to develop a new model, systematically evaluating the quantitative model, addressing parameter and model uncertainty, developing sections of the model through iteration, analyzing alternatives and documenting results. Quantitative modeling is shown to be a dynamic process that is best served using an iterative approach. In practice, individual parts of a conceptual model are quantified and evaluated in a stepwise fashion until the entire model is captured quantitatively. This iterative approach creates transparency in model development, which can remove the "black-box" stigma that has been associated with the use of models in the environmental sciences.

15. SUBJECT TERMS
Conceptual models
Ecological models
Ecosystem restoration and management
Environmental benefits
Quantitative modeling

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			**19b. TELEPHONE NUMBER *(include area code)***
UNCLASSIFIED	UNCLASSIFIED	UNCLASSIFIED		60	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. 239.18