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Ecological Forecasting Tools and Planning of Ecosystem Restoration Projects

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PURPOSE: A wide variety of ecological forecasting tools are used to support the project planning process within the U.S. Army Corps of Engineers (USACE). These tools range from relatively simple empirical relations describing the expected habitat preferences of species (or guilds of species) to complex, dynamic models of water movement, sediment, and other material fluxes to behavior-based models of individual organisms (agent-based models) and spatially-explicit tool(s) that address habitat and landscape mosaics (e.g., Guisan and Zimmermann 2000). Models or tools from across this spectrum have played important roles at various points in the planning process within the USACE, but district level planners have faced major challenges in finding and applying suitable ecological forecasting tools, especially for smaller (e.g., Water Resources Development Act (WRDA) Section 1135) projects which may be funded by less than $100,000 ($5 million maximum) and which are allowed only one or two years for completion (ER-1105-2-100). Thus, the choice of a specific tool in many planning applications has been based on factors (i.e., project size, funding, duration) not directly related to a formal, technical evaluation of tool capability or suitability.

This technical note reviews some of the most commonly used USACE forecasting tools and models in ecological restoration. It outlines an approach for comparing these tools that will help USACE planners and their project stakeholders better identify and select appropriate forecasting models. Although this technical note is not a primer or a selection metatool (i.e., a tool to select tools), it is hoped that this note will contribute to a long-term goal of USACE staff (both planners and researchers) to become better-informed developers and consumers of ecological forecasting tools. Secondarily, this note is intended to give researchers a clearer view of what USACE planners need (but do not have available) with regard to ecological forecasting capabilities.

BACKGROUND: At a recent USACE planning workshop (ERDC 2008b), a need was expressed for improved modeling frameworks and decision support tools that effectively integrate models and knowledge bases into the USACE planning process. Technologies that assist users in selecting ecological models for specific planning projects — including those for which certification and regulatory requirements must be satisfied — were also identified as potentially helpful. Further, it was acknowledged that substantial value would be added if such tools and models could be nested within a user-friendly, decision-support system (DSS), especially if they addressed multi-species and multi-habitat planning issues. Finally, the need for a structured approach in selecting or evaluating the suitability of existing tools was also recognized.

Based on these discussions, it appears that a significant, sustained effort will be required within the research and development community (e.g., U.S. Army Engineer Research and Development Center (ERDC) and researchers outside the USACE) to close major gaps in science and technology. For example, our present ability to forecast the behavior, or future condition, of complex ecological systems in detail is rudimentary and mostly empirical. Although a broad understanding of the important interactions in well-studied ecological systems is assumed, scientists suffer from a general inability to identify a manageable, quantifiable subset of critical interactions or processes that can be expressed (and parameterized) as process-based, numeric formulations that are mathematically tractable and encapsulate the essence of system behavior. Except in the simplest situations (e.g., a single species responding to the physical environment without substantial feedback), our complex, process-based ecological models seldom reflect (or forecast) the ecological responses we actually observe in situations outside the limits of the original calibration data set; at least not with a level of accuracy, reliability, and at a spatial-temporal scale that makes the results of these complex approaches more useful for planners and decision makers than simpler, semi-empirical techniques. The large investment that is often needed to obtain the data for implementing such models, or to verify their performance, is another stumbling block to their use in the USACE process.

For the results of research to be useful to USACE planners, an additional effort is needed to transfer these tools to the planning practitioners. Thus, there is a strong need for educational outreach by the research community, as well as close interaction between the USACE planning and research communities during the development and deployment of forecasting tools.

It is important to recognize that planning involves risk and uncertainty and that the best plans address uncertainty explicitly and in appropriate ways (IWR 1997). Planners therefore need tools that help them minimize this uncertainty, and that can be used under very tight resource constraints. Existing tools generally fall short of addressing this need.

ECOLOGICAL FORECASTING WITHIN THE USACE PLANNING PROCESS: For researchers to better understand what planners need and want, it is essential for them to know how forecasting tools are used within the USACE planning process. It is important to remember that planning is a relatively focused look into the future: it is an attempt to describe very specific aspects of the future if no action or if a specific course of action (e.g., a project) is undertaken. Due to the fact that the future can never be completely known, planning involves — at some level — an element of guesswork. At best, it employs forecasts based on experience, expert opinion, good information, and the most appropriate methods. At its worst, the planning process can be little more than an educated guess. In any case, the possible or probable future cannot be accurately portrayed to decision makers or to the public as precise and certain; therefore, our forecasting tools should provide some indication of uncertainty or risk. Whenever possible, the basis for projections, and the magnitude of uncertainty around these projections, should be clearly indicated.

The general practice of ecological forecasting and the evaluation of alternatives within the USACE ecological restoration process seems to rest on a working assumption that if the critical physical-chemical characteristics of the habitat (which scientists can build or manage) can be established and maintained within some specified design limits, then the complex biology and ecology (mostly beyond scientists' control or understanding) will largely take care of themselves (e.g., "if you build it, they will come"). There are exceptions, of course, where direct biological manipulations (stocking, eradication, and controlled burns) are part of the management measures used in a project, but these are more often left to other resource agencies to develop and deploy. The use of forecasting and evaluation tools tends to follow a parallel pattern: one set of tools or models (ranging from simple to complex) are used to predict the physical-chemical conditions that might be expected with and without the proposed project (often with good accuracy and precision), and another set of tools or models (often more simple and index-based) uses the output from such models to assign and sum the habitat value or quality produced by the management alternatives (including the no-project condition). For this approach to be most effective, the physical-chemical model forecasts and the habitat evaluation tools should be well-coordinated (i.e., the output of the physical-chemical model must be suitable for use by the habitat assessment tool). Additionally, the interaction could be made seamless for the end user if the two modules of software communicated directly, or at least shared a simple data exchange mechanism.

The engineer regulation that pertains to the planning processes (ER-1105-2-100) includes a number of broad mandates with regard to ecological forecasting. For example (section 2-4):

> *"…The future without-project condition constitutes the benchmark against which plans are evaluated. Forecasts of future without-project conditions shall consider all other actions, plans and programs that would be implemented in the future to address the problems and opportunities in the study area in the absence of a Corps project. Forecasts should extend from the base year (the year when the proposed project is expected to be operational) to the end of the period of analysis.*
>
> *… Expected environmental conditions, especially trends in ecosystem change, shall be considered in forecasting with- and without-project conditions. Forecasted environmental conditions can be based on a variety of different sources of information available from Federal, State and other natural resource management agencies and private conservation entities."*

It is a significant challenge for a planner to successfully navigate the six-step, iterative, planning process of the USACE in a timely manner while meeting all its requirements. The approach to forecasting and evaluation that has emerged can be viewed as a practical adaptation to this challenge and to the general state of ecological forecasting. One consequence of this approach is that planners are unlikely to use complex ecological models directly (except in relatively rare instances), but successful planning may nonetheless rely on expert opinion that has been informed by such models.

Ecological forecasting may come into play at several points within the standard USACE planning process (cf. ER 1105-2-100). In smaller projects of short duration, however, there is very little time for the planner to evaluate or implement complex forecasting tools, and therefore, in the earliest phases of planning (i.e., prior to a feasibility study), formal forecasting tools may not be utilized. Some knowledge of these tools (and their limits) may be very important at these earliest stages, nonetheless. For example, during a reconnaissance study (limited to $100,000 and

12 months or less), more detailed tools that would normally be utilized during the feasibility study are reviewed and may be selected (or at least a preference is indicated). Planners must therefore consider, even at these early stages of planning, which forecasting tools should be reviewed as available and applicable for the later stages of their project. An important factor in the tool selection process for the feasibility study may be the degree to which the selected tool draws upon (or incorporates) the work already completed in reconnaissance. Again, it is unlikely that these more complex tools will actually be implemented in the reconnaissance phase because — although there is a requirement for the reconnaissance to include a preliminary screening of alternatives (ER-1105-2-100) — only a rough estimate of probable outcomes is needed at this point. Experience and professional judgment, rather than quantitative tools, usually prove to be more useful.

As planning advances to the feasibility study, ecological forecasting tools are apt to play a more significant role (Figure 1). The feasibility study must identify, in some detail, the underlying problems that a project will address. Objectives of the project must also be determined, and two major forecasts (with and without the project) must be made. In addition, a preferred project alternative must be selected, along with an indication the scientist has anticipated the most likely or most significant ecological outcomes of several alternatives.

In the earliest segments of the feasibility study (i.e., still Step One of the overall planning process), conceptual models and very simple tools may be put to good use. This stage identifies the fundamental nature of the problem in greater detail, and the general feasibility and efficacy of several alternatives receive some initial screening here. A variety of simple and complex tools may be applied for these purposes and to more closely define the requirements (objectives) of a suitable project (solution). In smaller projects (i.e., < $100,000), USACE District staff are more likely to develop these objectives very rapidly in consultation with stakeholders. Simple and rapidly applied tools can be very helpful to the planners at this point in the process, particularly during smaller projects.

In the more detailed development of alternatives that follows (i.e., in Step Two of planning), formal ecological forecasting tools may be used to project the critical physical, chemical, and morphological (i.e., land form) characteristics (habitat) of alternative futures. This prediction may involve such things as detailed hydraulic and water quality modeling or hydrologic and climate analysis (e.g., flood frequency or storm frequency). Later, in Step Four (evaluating alternatives), the projected future conditions are used as input for the ecological models (evaluation tools) that assign quality (value) to the quantity of habitat conditions projected for the various alternatives. Step Four also entails environmental evaluations and impact assessments, which may include analyses of project effects on fish and wildlife habitat, endangered species, ecosystems, and water and air quality. This may require a certain level of ecological forecasting as well; interestingly, the ecological models chosen for this later stage of evaluation are often relatively simple, index-based tools that have known outcomes or are well-recognized and accepted. This reflects scientists' weaker ability to quantify complex ecological processes and interactions.

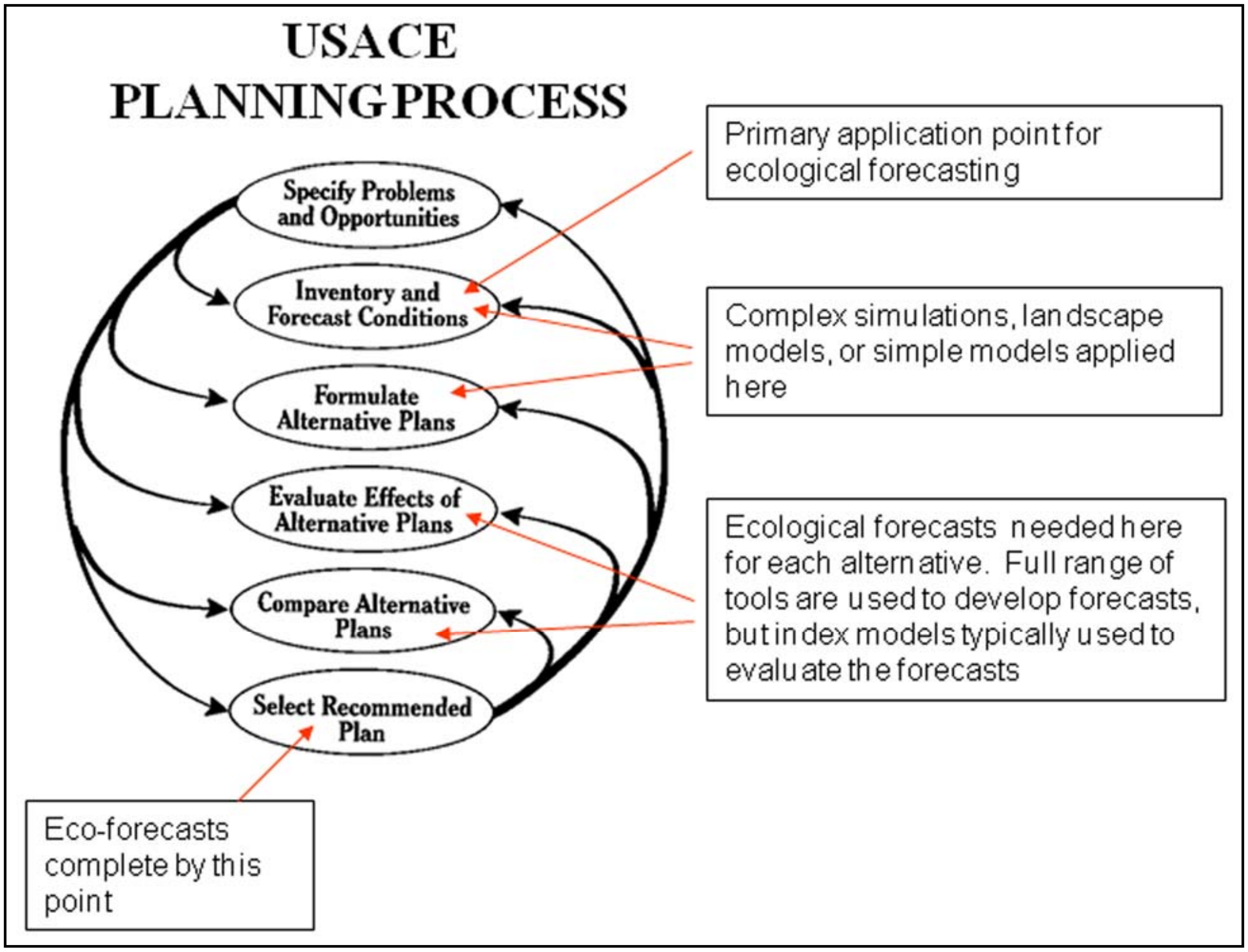

Figure 1. Forecasting tools of various types are applicable at many points in the planning process.

Within the six steps of the formal planning process there are numerous areas where ecological forecasting tools might be applied:

- **Step 1. Identifying Problems and Opportunities.** Should include a determination of "how much is enough," and answer whether the "enough" condition can be attained. This determination may not be considered forecasting in the strictest sense, but does involve predicting or identifying the critical variables that will govern the future condition.

- **Step 2. Inventorying and Forecasting Conditions.** The starting point for ecological forecasting during the planning process. This step requires forecasts and evaluations of the "no-action" or "without project" alternative.

- **Step 3. Formulating Alternative Plans.** Projections of future physical-chemical conditions, or configurations, under alternative plans.

- **Step 4. Evaluating Alternatives.** Ecological evaluation of the conditions (habitats) that result from different project alternatives will require forecasts of the potential ecological conditions that result from each alternative set of management measures (this was possibly accomplished in Step Three) and an evaluation of the ecological benefits expected from the conditions that are produced by the management measures. An evaluation of ecological benefits is often performed with simple (e.g., index-based) tools.

- **Step 5. Comparing Alternative Plans.** Alternative plans that successfully pass the screening in Step Four are compared with one another in Step Five. This step may revisit the forecasts produced in earlier steps, or a need for additional forecasting may emerge here. This step may be informal, and may be merged with Step Four.

- **Step 6 and Beyond: Selecting a Plan.** Plan selection will be based on the forecasting done in previous steps. Although additional ecological forecasting will not be needed in the planning process beyond this point, detailed projections (often based on engineering models) will almost certainly be needed to design specific management measures when the selected plan is implemented. The forecasting tools that are used in the implementation phases of a project will be determined in part by the forecasts used to develop objectives and alternative measures during the planning process. Consequently, for USACE projects to fully realize the benefits of ecological forecasting, knowledge and the selection of appropriate tools must occur very early in the planning process. However, in an adaptive management process, these tools will continue to be used as the ecological response to management actions is developed.

SELECTION OF FORECASTING TOOLS: When a forecasting tool is being selected in the planning process, the user will, if possible, turn first to tools that are familiar and available; next, the user may consult with a knowledgeable and experienced source. During a short-term project, the selection process may not go beyond the software currently available on the user's computer. Therefore, to improve the use of forecasting tools in the USACE planning process, particularly for short-term projects, the first objective must be to increase user familiarity with the available and appropriate tools. Secondly, the users must have immediate access to the tools on their desktop. This technical note emphasizes the first of these two objectives. Detailed guidance on the selection of specific tools or descriptions of the wide assortment of tools available for specific planning purposes goes beyond the scope of this technical note. Although it has been under consideration by ERDC staff for many years, developing such guidance that is at once user-friendly, accessible, and reliable, has presented significant technical and conceptual challenges. Instead, the major categories of ecological forecasting tools that have a history (or potential) of use in the USACE planning process will be introduced. Some of the general strengths and weaknesses of the tools in these categories will be pointed out (using some specific examples) and suggestions on the selection process will be provided. An ordination framework is also posited, and some of the more commonly used tools will be positioned into that framework to give users an initial foothold into the tool selection process.

The Role of Conceptual Models. Conceptual models can play an extremely useful role in the planning process. Conceptual models do not produce forecasts directly, but planners can use them for communication with fellow planners, scientists and engineers, and stakeholders. They can also provide the starting point for models that do make forecasts. A good conceptual model requires the explicit expression of spatial and temporal scales, major relations, assumptions, and information needs. It can, therefore, be very useful in identifying the underlying problem that a project must address, the actions that might produce the desired benefits (problems and opportunities), and it can indicate the most promising approaches and their major limitations (objectives and constraints) that planners need to consider for further forecasting efforts. It can also lead naturally to the selection of appropriate forecasting tools. Scientists and engineers use conceptual models almost instinctively, and thus they may not immediately recognize the value of elaborating such a model, but the process of creating a conceptual model with the participation of stakeholders, even though it may be time-consuming, can be extremely helpful in conveying to stakeholders and decision-makers the essence of a restoration project, its priority information needs, and sources of uncertainty. There is substantial literature to guide users in the development of conceptual models (e.g., Casper et al. 2010) and automation tools are also available to assist in the conceptual modeling process (e.g., http://www.gomrc.org/tools.html), and we will not discuss those further.

Scale Considerations. Perhaps the most important aspect of ecological restoration planning that is also a major consideration in the selection of forecasting tools, are the scales of time and space that will dominate the driving inputs (and major outputs) of the project and its surrounding ecosystem. Ecological forecasts are similar to meteorological forecasts in that both have fundamental scales of time and space to which they are relevant. For example, a global forecast of average temperature rise over the next several centuries would not be particularly useful for planning a Sunday picnic. Likewise, we would not use a 12-hour, local weather forecasting tool to make predictions into the next century.

It is important to recognize that the processes that have overriding, dominant influence on the behavior and survival of an ecosystem can vary dramatically at differing scales and can be characterized very differently — jumping scales is therefore treacherous (also see review by Hains and Soballe 2007). For example, a project that enables a fish to pass a specific obstacle in its migration does not necessarily benefit the long-term survival of the species. The project may have only helped the fish into a net or into the jaws of a waiting predator, or increased competitive pressure on a fish that could pass the obstacle without assistance. The long-term, disastrous effect of releasing large numbers of hatchery-reared fish (to "augment" wild populations), which are genetically ill-suited to survival in the wild, is a good example of failure to recognize scale issues (i.e., short-term, local increases in individual numbers vs. long-term, population survivability). Interestingly, a variation on hatchery rearing (i.e., release of sterile males) has been used for decades to reduce populations of disease-carrying mosquitoes, but the parallels between this control technique and fish hatchery operations was largely unnoticed. Another example is the construction of a few, high-quality "attractor" habitats that causes large numbers of the target species to congregate in small areas. This causes a highly visible — but local — increase in numbers. While at the scale of the population across a broad area, the attractor may only serve to increase the population's vulnerability to predation, fishing pressure, and disease.

It is the responsibility of the planner (ER 1105-100-2; Orth and Yoe 1997) to consider "external" influences on a proposed project from within the same system or region that might result from other projects or anticipated changes (e.g., economic conditions, a sea level rise, climate change, etc.). Obviously then, the difficulties of choosing appropriate time and space scales and the proper tools for developing forecasts cannot be avoided in the planning process. The planner needs to decide how far the significant influence of proposed or existing project(s) in the study region will extend (in both time and space) into (or from) the surrounding ecosystem. Summing or forecasting these combined influences across a complex mosaic of projects and landscapes can seem intractable. Nevertheless, it is not difficult to find documentation for projects the effectiveness of which have been radically altered by the influence of other projects or long-term changes in the larger region surrounding a project.

Unfortunately, there are currently no tools available to help the planner resolve these issues of scale. A common approach has been to skirt the issue by comparing alternatives with the assumption that "all other things remain equal," but that approach cannot be defended when some alternatives are substantially more vulnerable to external influences than others. There is no simple way to deal with these complexities.

Complex and Simplified Approaches: Accuracy without precision. The behavior of complex systems (i.e., ecosystems) is often difficult to predict with precision (i.e., within narrow limits), but accuracy and developing an unbiased estimate is possible, and is often more important than precision in ecological forecasting. It is often unrecognized that accuracy can sometimes be better achieved with simpler approaches. Consider, for example, climatological forecasting of hurricane risk. A relatively simple, statistical model can provide an unbiased estimate of how often a hurricane can be expected to strike a general area (e.g., the coast of Louisiana). Such a model will not predict exactly where, or when — or even if — a particular storm will hit a specific area because it lacks precision. A more complex model, in contrast, may predict the exact path (within a few miles) of a particular storm, in a particular period of time. However, the prediction from the complex model may be consistently wrong (i.e., biased and inaccurate) because of errors in its assumptions, parameters, or input data. Further, such a model may have very little utility until a storm has formed and is approaching a specific segment of the coast. It is not suitable for long-term forecasts.

Parsimony and Uncertainty. Models that attempt to forecast future conditions must contend with at least two major sources of uncertainty: (1) parametric and formulation uncertainty, which can result from the degree to which the formulations and relations within the model itself reflect the actual system, and (2) input uncertainty which results from inaccuracies, uncertainties, or variations in the data that are used as external inputs to the model. A parsimonious model is one with as few parameters as possible for a given quality of a result, and a parsimonious model is generally more desirable in ecological forecasting. Models with a large number of internal parameters and external inputs can be strongly influenced by the interaction of numerous small errors. In this non-parsimonious condition, the model's behavior (and accuracy) may be very site-specific and despite mechanistic internal formulations, is actually empirical (i.e., dependent upon a specific combination of parameter settings that are "fit" (or "tuned") to a specific set of observed data). The accuracy of a complex model is thus very difficult or even impossible to assess. Its performance under conditions not specifically matching the "calibration data" may be difficult to evaluate without additional data or extensive experience with the model in diverse situations. Such verification can be extremely difficult to obtain. Simpler models may also be imprecise because they ignore many detailed processes. Their accuracy and precision likewise needs to be verified with field data, but the data required for verification of simpler tools is apt to be more obtainable. In any case, it should never be assumed that a more complex (i.e., less parsimonious) model or tool will automatically provide better results.

Utility. The selection of an appropriate forecasting tool for planning should depend on several factors. Ideally, it should hinge on the usefulness of the tool for the task at hand; i.e., the ability of the tool to meet established standards of reliability or acceptance and to provide the necessary information in a suitable form within the allowed timeframe and with the available resources.

When evaluating forecasting tools for this technical note, the concept of "prescriptive utility" was employed. This concept is often used in fields such as political science or economics (Luce and Detlof von 1994). Prescriptive utility is a term that describes the usefulness of an explanation or model for either prescriptions of policy or general decision-making. In the present context, this term describes the usefulness of a model or tool to accurately predict future ecological and environmental conditions and, with similar accuracy, to indicate the best course of action. This may or may not be correlated to its accuracy in other realms. For example, it is easy to imagine a model which very accurately assesses (or diagnoses) the present status of an ecosystem (e.g., species diversity or biotic integrity), but which cannot predict the condition of that ecosystem at any point in the future. Such a model has low prescriptive utility. Alternatively, a model may offer little insight as to the present ecosystem condition, but it may be very capable of indicating which, out of a set of alternatives, will be the least deleterious. This type of model would have high prescriptive utility. Furthermore, prescriptive utility captures, to some extent, the generality of the model. For example, some models may be highly accurate for a single lake and be highly prescriptive in that case, but they might be inapplicable to other lakes. Such specificity can decrease the overall prescriptive utility, and this possibility was taken into account in our assignment of prescriptive utilities. This metric is more difficult to conceptualize and more difficult to quantify than, for example, accuracy as represented by a percent error or another less trivial assessment. However, prescriptive utility may better capture the applicability of forecasting models, and it takes into account, for planning purposes, many of their possible shortcomings.

CLASSIFICATION OF FORECASTING TOOLS: Because the number of available ecological forecasting tools span a broad spectrum of complexity and input requirements (Table 1), it can be difficult to make meaningful comparisons among them. To assist in the evaluation and selection of tools for a specific planning application, a classification of tools is proposed, according to the effort required to implement them and the utility of their outputs. In this framework, tools can be compared by viewing their position on a plot of effort vs. utility (Figure 2), and the selection of a specific tool can then be guided, in part, by balancing the resources available against the utility of the output. To illustrate this approach, please see (1) a metric for the effort required by a tool and (2) a metric of utility for the model output. In the classification example presented here, differing model types have been mixed together (e.g., forecasting models and evaluation tools). Consequently, presented results may not be immediately applicable to an actual choice between competing tools, but they do illustrate the concept.

Table 1. Summary of models and tools commonly used for ecosystem restoration planning within USACE.

Name	Description	Uses	Major Limitations/ Comments	Outcome?[a]	Predict from range?[b]	Needed current action?[c]
Habitat Suitability Index (HSI)	Evaluation of physical parameters to determine whether conditions permit specific species to thrive.	Determine potential of habitat conditions to support a specific species.	Non-dynamic, no prescriptive information.	No	Maybe?	No
Wetlands Evaluation Technique (WET)	Probabilistic evaluation of wetland functionality with respect to social significance, effectiveness or opportunity.	Compare habitat types and assess wetland functionality.	Not predictive - "should not guide design." Cannot be used to determine design limits.	No	No	No
Hydrogeomorphic Model (HGM)	Designed to "rapidly assess wetland functions, compute potential project impacts, calculate mitigation requirements, and project future with- and without-project scenarios."	Assess wetland functions; assess project impacts or calculate wetland mitigation using probable index of function.	Needs prior, detailed, regional assessment to facilitate further assessments.	Yes	Yes	No
Shared Vision Model (SVM)	Produces a collective vision from stakeholders about acceptable/optimal outcomes.	Conflicts over water resources.	Based on generic alternatives and group brainstorming.	No	No	No
Incremental Instream Flow Methodology (IFIM)	"Fish passage, spawning, and rearing habitat" are quantified as a function of discharge for selected species.	Physical simulation calculates habitat index from flow parameters.	Like HSI, embedded into a consensus negotiation framework.	No	No	No
Habitat Evaluation Procedure (HEP)	A spatial, temporal application of HSI descriptions. Integration of "suitability" over the aerial extent and time.	Designed to "quantitatively compare… alternative management practices."	Same as HSI.	No	Yes	No
EPA Rapid Bioassessment Procedure (RBP)	"An evaluation of the condition of a waterbody using biological surveys and other direct measurements of the resident biota in surface waters."	Used to assess habitat impairment through biological measurements and surveys.	Require developed indices of biotic integrity (IBI); indices not conductive to identifying source of impairment.	No	Maybe	No
CE-QUAL-W2	2D Model to describe longitudinal-vertical hydrodynamics and water quality for reservoirs/lakes, rivers, and estuaries.	Eutrophication, other TMDL studies, contamination extent and management.	2D, lateral averaging, vert. stratification is based on hydrostatic assumptions.	Yes	Yes	No
CE-QUAL-RIV1	1D Model to describe longitudinal hydrodynamics and water quality for rivers.	Eutrophication, other TMDL studies, contamination extent and management.	Vertical stratification is based in hydrostatic assumptions.	Yes	Yes	No
USGS 3-D Variable-density Groundwater Flow and Transport (SEAWAT)	Simulation of flow of variable-density groundwater as well as heat and solutes.	Saltwater intrusion, brine migration.	Requires technical knowledge and significant data input.	Yes	Yes	No

(Continued)

Table 1. (Concluded)

Name	Description	Uses	Major Limitations/ Comments	Outcome?[a]	Predict from range?[b]	Needed current action?[c]
Environmental Fluid Dynamics Code (EFDC)	Hydrodynamic model to simulate water quality constituent movement in 3D.	Movement of suspended sediments, contaminants, deposition, resuspension and transport.	Long-term data needed for calibration and verification.	Yes	Yes	No
Adaptive Hydraulics & Transport Model (ADH)	"Modular, parallel, adaptive finite-element model for one-, two-, and three-dimensional flow and transport."	Groundwater, overland flow, Navier-Stokes flow and shallow water.	Requires technical knowledge and significant data input	Yes	Yes	No
Everglades Landscape Model (ELM)	"Regional-scale, integrated ecological assessment tool designed to understand and predict the landscape response to different water management scenarios in south Florida, USA"	Landscape responses to water and nutrient management scenarios.	Designed for specific region, limited data availability, intended for use as one of a set of management tools.	Yes	Yes	No

[a] Does the application estimate the probable outcome of actions?
[b] Does the application predict the outcome from a range of alternatives?
[c] Does the application estimate current actions needed for a future condition?

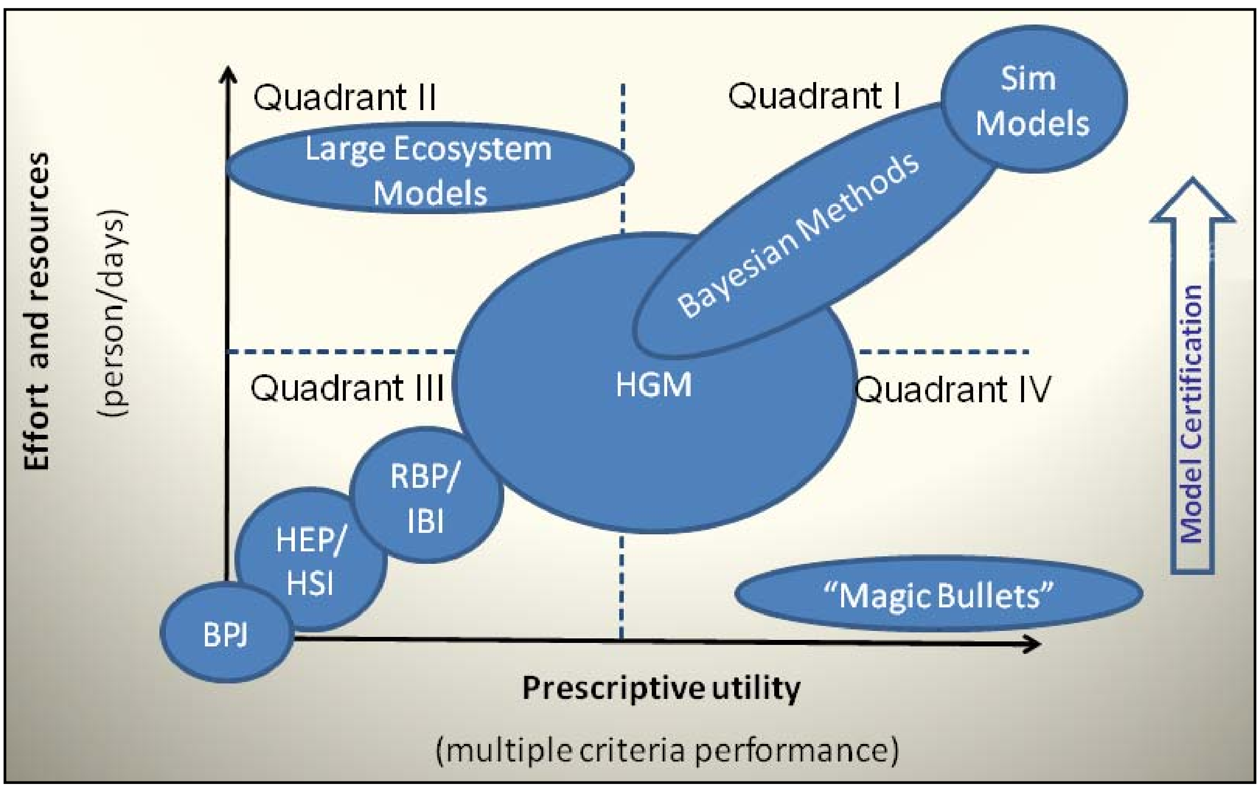

Figure 2. Classification of ecological forecasting tools based on effort and utility.

The metric of effort (person/days) includes the effort for compiling and analyzing the necessary raw data and then setting up and running the tool or model. This simple metric captures the time and the cost of implementation. The total person/days for a tool or model includes the effort for researching and choosing the appropriate method or approach, the collection and input of field data (if required), certification of the model if necessary (USACE 2008), and the actual implementation and interpretation of the tool or model. It is, however, important to note that person/days is a simplification that does not capture all of the necessary information in some situations. For example, the time required to collect data for ecological models may involve sampling across multiple seasons (Hubbard 2009); and in such cases, the total effort may be just a few person/ days, but it may have to be extended over many months or even years. Such a timeframe may be impractical for a specific planning effort, even though the effort required is relatively small, because the time available for planning may be too short. Models that may encounter such limitations are noted; however, within this technical note it is not possible to fully characterize such details.

Prescriptive utility was described earlier as a measure of tool utility. This concept can be quantified by a rigorous methodology such as stochastic multicriteria acceptability analysis (SMAA). Such an intensive, formal quantification effort was outside the scope of this technical note. Instead, utility was assigned by more qualitative methods (including elicitation of expert judgment, general applicability, and predictive outputs) and from the variety of descriptors resulting from the method (e.g., population stability, water quality, diversity, geographic boundaries). In evaluating prescriptive utility, we also used the following criteria for each method: (1) Does the method estimate the probable outcome(s) of a specific event or action? (2) Does the method predict the probable outcome(s) of a range of alternative actions or events? (3) Does the method estimate the present action(s) needed to produce a desired future condition?

The classification approach can be used to group models into "bins" or quadrants such as "high utility, low effort" versus "high utility, high effort" (Tervonen et al. 2009). To demonstrate the usefulness of ranking effort versus utility, we reviewed and evaluated some of the models and tools that are widely used by USACE District planners. This review included a range of methods/tools with differing data and resource requirements (Table 1). We noted the detail and certainty of the model output, and then each model or tool was placed on a semi-quantitative coordinate system describing the relative effort required for implementation and the prescriptive utility of the tool output (Figure 2).

The list of tools that were reviewed (summarized individually below) was extracted from the proceedings of the Chicago 2008 workshop on "Ecosystem Planning Model Requirements: District/Division Needs" (ERDC 2008b) and from conversations with William Hubbard, Chief of the Environmental Resources Branch of the New England District. The following methods and models were included: Best professional judgment (BPJ), Floristic Quality Assessment (FQA), Habitat Evaluation Procedures (HEP, which uses Habitat Suitability Indexes or HSI), Hydro-geomorphic Model (HGM), Rapid Bioassessment Procedures (RBP, which uses the Index of Biotic Integrity or IBI), and Qualitative Habitat Evaluation Index (QHEI) (ERDC 2008; Hubbard 2009). It should also be noted that locally derived and calibrated models are often used, but as they are more numerous and have applicability in very small regions, they fall into a separate category for the purpose of this analysis.

Some of the tools and models reviewed here have no explicit spatial or temporal component, and so it becomes the responsibility of the user to determine if the time and space scales of the project (or question) are properly matched to these "non-dimensional" tools that predict an "average" condition These index tools are generally most useful for valuing and totaling benefits — not for forecasting — and they must be coupled with physical-chemical forecasts of appropriate scale. The appropriate extent (domain) for a tool in space and time is not immediately apparent even if it includes space and time explicitly and often it can be evaluated only by individuals with technical knowledge of both the tool and the relevant ecological processes and setting.

Best Professional Judgment (BPJ). The overall discussion of Best Professional Judgment will be limited, as it is not a quantitative modeling process, but rather an elicitation of an opinion from an expert in the field. Acquisition of applicable data and site analysis may occur; however, the processing of this data and the overall decision are conducted by that expert, often using his experience and intuition as the crucial tools. In general, BPJ is a rather low-effort methodology as extensive analysis is not required. Depending on which expert opinion is used, the complexity of the case, and the traceability of that decision process, the efficacy of this method cannot usually be classified as higher rather than lower prescriptive utility. Even so, BPJ still operates within many other frameworks, especially when model outputs do not fully inform a decision (i.e., results do not point to a specific remediation) or when model outputs are not sufficient (Hubbard 2009). In the context of modeling, BPJ does not have the quantitative or methodological rigor to be classified as a model and should be avoided in such usage whenever possible.

The efficacy of BPJ is classified as low in this context because expert advice — however accurate — is not a quantitative or rigorous forecasting methodology despite its widespread use in various aspects of the restoration process. By definition, the outcome of expert consultation will vary with each expert and each instance for which they are consulted. Further, the use of BPJ is unacceptable in projects requiring centralized review of methods (Hubbard 2009), and therefore should be avoided. While it is not possible or desirous to eliminate expert judgment from all aspects of ecological forecasting, emphasis should be placed on quantitative models which can be informed and analyzed by experts.

Floristic Quality Assessment (FQA). FQA is a method for evaluating wetland floristic quality using the richness of "conservative species," as determined by guides, to native plants for a specific area (Hubbard 2009). Originally, this method was developed for the Chicago area by Swink and Wilhelm (1994). Each species is ranked for its conservatism (e.g., a native, threatened species with high site fidelity earns a high ranking) and an index is created by summing the rankings of conservatism for each identified species. The method requires a seasonal assessment of the species in its habitat. Several states have developed conservatism rankings for plant species.

Although the effort in creating a FQA may be relatively low, seasonal evaluation, as mentioned above, is necessary. The resulting index will have a range of locations within the effort versus a prescriptive utility classification scheme. The outcome does not provide a prescription of action for restoration or management. Therefore, other techniques must be used to determine the best course of action (Hubbard 2009).

Habitat Evaluation Procedures (HEP) and Habitat Suitability Indexes (HSI). Habitat Suitability Indexes are at the core of HEP methods. An HSI exists for a variety of organisms (e.g., beaver and American oysters) and provides a model for the interaction of that species with several parameters of its habitat. The HSI produces an index describing the suitability of a given environment as habitat for that organism (U.S. Geological Survey 2009). The models are developed by researchers, using data from the literature and the field to establish relationships between habitat parameters and the overall quality of the habitat for a given organism; their intended use is for environmental impact assessments and habitat management (Cake 1983). These models were developed in the 1980s and are not intended to be updated; they have been grandfathered into the certified list of models and are widely used (USACE 2008; U.S. Geological Survey 2009).

For data input, the information about the habitat varies per species and corresponds to the parameters which would hypothetically influence the quality of habitat; for example, the Gulf of Mexico oyster HSI requires that a percentage of the bottom be covered with suitable cultch (shell and rock), summer water salinity, a mean abundance of living oysters, historic mean salinity, a mean interval between killing floods, mean substrate firmness, a mean predator abundance, and a mean disease intensity (Figure 3) (Cake 1983). These data clearly require some degree of site information (e.g., percent of the bottom covered with suitable cultch) and some historical data (e.g., the mean interval between killing floods); the actual analysis with these data is very straightforward and requires little specialized skill or complex computation. The performance of the habitat with respect to a given metric (like bottom cultch) then corresponds to a unitless number between 0 and 1 indicating the degree to which it is favorable; the score each metric is given is then combined in a pre-defined formula to give an overall score from 0–1 indicating how well the overall habitat is suited to that species (Cake 1983; Bender, Roloff et al. 1996). A high score (near 1) is considered to be a favorable habitat, while those scores closer to zero are considered unsuitable habitats (Hubbard 2009).

The HSI models are the basis for the HEP methods. HEP is the term used to describe the process of collecting the necessary data and evaluating a habitat with an HSI model. These are the go-to methods for assessing how a project may impact a given habitat (Hubbard 2009). Extensions of this methodology do exist, especially the incorporation of Geographic Information Systems (GIS) to fully map the location of suitable habitats (Daugherty, Sutton et al. 2009).

HSI models, despite widespread usage, have a variable degree of efficacy. HSIs do not explicitly link policy or management prescriptions to outcomes, and BPJ is used within this overall framework to identify the aspects of the habitat that were found to be lacking (Hubbard 2009). Furthermore, the accuracy of results with the HSI varies. A comparison of squirrel habitats found a lack of statistical significance between scores of 0.38 and 0.81 out of a total score of 1.0 (Bender, Roloff et al. 1996). Similarly, a study of the HSI model for beaver habitat found 83 percent of the variation in the population at different locations to be unexplained by the HSI models (Robel, Fox et al. 1993). On the other hand, some studies have found the HSI models to have good predictive power and accurately reflect populations (Brennan 1991; Williams, Hahs et al. 2008; Daugherty, Sutton et al. 2009). Daugherty, Sutton et al. also inferred prescriptions for sturgeon management from their GIS/HSI model, for measures such as removal of barriers to migration versus stocking with fecund adults, based on the habitat scores in different areas for different life stages. The authors also noted, however, that their analysis, while proving accurate for the sturgeon population, ignores inter-species interactions and the effects that actions such as removing migration barriers might have on the dispersion of deleterious invasive species such as Sea Lamprey (Daugherty, Sutton et al. 2009). As such, the HSI models generally fall in the third quadrant (low effort, low utility) of our proposed classification (Figure 1). Their lack of certainty and differentiating ability, as well as the necessity to link prescription with results, limits the prescriptive value of this simple procedure.

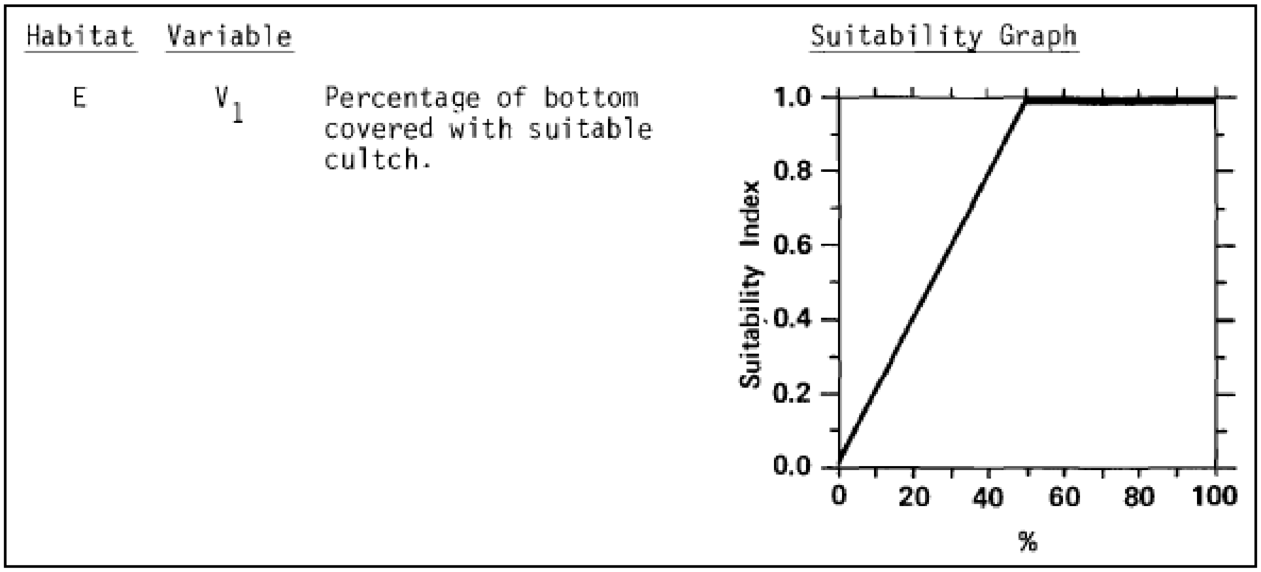

Figure 3. Modified from Cake (1983); An example graph for Gulf of Mexico, American oysters. This graph relates the percentage of the bottom covered with suitable cultch (substrate for oyster attachment) to a suitability index, which later will be used as variable V_1 in the formula to determine the overall habitat index.

Hydrogeomorphic Model (HGM). The HGM approach has been described as a “tool to rapidly assess wetland functions, compute potential project impacts, calculate mitigation requirements, and project future with- and without-project scenarios” by collecting methodologies and making models which use reference values from a close-to-pristine wetland of a similar type (ERDC 2008; Hubbard 2009). The goal of its development was to design an accessible method while maintaining a level of robustness and flexibility to accommodate all wetland types (Brinson 1993). There are essentially two stages: first, development and application; regional guidebooks are developed to establish reference wetlands and link the hydrogeomorphic properties and the wetland functionality. Then the guidebooks are used to explore alternative projects and their impacts (ERDC 2008; Franklin, Kupfer et al. 2009). Consultation with local experts can be used to help calibrate models and to establish the reference wetlands (Weller, Snyder et al. 2007).

The hydrogeomorphic variables used in the models can be broken into categories, usually hydrology, soils, and vegetation. Examples include water table slope, surface water connections, water table fluctuation, over bank flood frequency, water table depth, soil integrity, soil clay content, subsurface water velocity, redoximorphic features, subsurface storage volume, “O’’ horizon biomass, ‘‘A’’ horizon biomass, tree biomass, understory vegetation biomass, ground vegetation biomass, woody debris, tree density, and plant species composition (Franklin, Kupfer et al. 2009). These variables are measured and used to derive the functional capacity indices (FCIs), which capture various wetland functions such as maintenance of characteristic subsurface hydrology, cycling of nutrients, removal and sequestration of elements and compounds, export of organic carbon, and maintenance of characteristic plant community (Franklin, Kupfer et al. 2009); the FCI ranges from 0 (worst) to 1 (optimal), relative to the functionality of the reference (Wardrop, Kentula et al. 2007). To apply the method, each analyzed wetland is categorized into a "class," such as a depression versus lacustrine fringe; then it is categorized into a "subclass," such as an isolate depression versus a headwater complex; then an appropriate model is used corresponding to that subclass, (i.e., an isolated depression and headwater complex model, respectively) (Wardrop, Kentula et al. 2007).

When the necessary guidebooks are already developed, this procedure is very rapid and is lauded as a timesaving method (ERDC 2008). The HGM approach is, in practice, not widely used because the perception exists that it is more time-intensive than other methods (Hubbard 2009).

The HGM model aims to function in the "low effort, high prescriptive utility" quadrant, with an emphasis on speed. ERDC (2008) estimates the procedure can take as little as 4 hours. However, due to the fact that these models are regionalized, the time necessary to complete the procedure increases exponentially if the model has not been previously developed. Development of regional HGM models and guidebooks takes 1-2 years per subclass per region, and assessments of efficacy can easily use multiple years of data (Cole, Brooks et al. 2002). In this situation there are trade-offs, because having a regional model allows the assessment to be accurate and ignore some model variables, thus minimizing measurement effort; however, having regional models does not allow for "trading" of models or data. In a study of the transferability of such models between Pennsylvania and Oregon, it was found that small differences in hydrology — such as the constancy of the surface inundation — could have drastic effects. The wetland processes could be dominated by aerobic versus anaerobic metabolism, for example. The conclusion reached was that while some extrapolation can occur, great caution must be exercised (Cole, Brooks et al. 2002). As with all models, care must be taken that the model is properly calibrated and accurately reflects the dominant processes. As the functionality of the system is not directly measured under this model but rather calculated from other data, errors or misrepresentation of processes can occur. For example, Wardrop et al. found some issues with heavy reliance on a single model variable (Vhydrochar) in applying HGM models in central Pennsylvania (Wardrop, Kentula et al. 2007).

Despite these criticisms, which limit the usefulness of HGM models, the efficacy of these models in distinguishing between wetland types and functions and for prioritizing management has been clearly demonstrated (Wardrop, Kentula et al. 2007; Weller, Snyder et al. 2007; Franklin, Kupfer et al. 2009). As these models are further refined and regional guidebooks are made available or updated to accommodate criticisms (e.g., Franklin, Kupfer et al. 2009), the intended use of these models seems possible. Regional planners have echoed this sentiment in recommending the expanded use of HGM models (Hubbard 2009).

Rapid Bioassessment Procedures (RBP) and Indices of Biotic Integrity (IBI). Rapid Bioassessment Procedure is the methodology that underlies the usage of Indices of Biotic Integrity, which is a model type that was first developed by Karr (1981) (Figure 4). Karr originally conceived of this approach because the reliance on levels of individual water quality variables was not inclusive of all chemical-physical stressors and it ignored the possibility of synergistic effects between these stressors. In addition, the influence of non-chemical factors (e.g., water temperature, flow velocity, water stage) was not taken into account, rendering pronouncements of impairment largely meaningless in an ecological sense (Karr 1981). The concept behind the RBP is that a variety of metrics, which encompass species richness, indicator species, and reproductive success are combined to produce a robust indicator of ecological or biotic integrity of the ecosystem (e.g., Figure 4, U.S. Environmental Protection Agency 2009). Efforts have been made to correlate the value of this index with specific environmental variables to help identify candidate causes for ecological impairment. However, it has generally not been possible to directly manage a specific aspect of the environment and obtain a predicted change in the IBI.

Species Composition and Richness
Number of Species
Presence of Intolerant Species
Species Richness and Composition of Darters
Species Richness and Composition of Suckers
Species Richness and Composition of Sunfish (except Green Sunfish)
Proportion of Green Sunfish
Proportion of Hybrid Individuals
Ecological Factors
Number of Individuals in Sample
Proportion of Omnivores (Individuals)
Proportion of Insectivorous Cyprinids
Proportion of Top Carnivores
Proportion with Disease, Tumors, Fin Damage, and Other Anomalies

Figure 4. A typical list of metrics that are combined to form an index of biological integrity (Karr 1981).

Since Karr's model was developed, many similar IBIs have been produced for differing habitats, and these rely on a different set of metrics. Sampling procedures may also vary, depending on the location of interest (Bonada, Dallas et al. 2006; U.S. Environmental Protection Agency 2009). Whatever the metrics and scoring procedures used, the final output is a single number that represents the quality of the ecosystem; its location within a predefined range indicates the overall assessment — e.g., "good," "excellent," etc. (Karr 1981; U.S. Environmental Protection Agency 2009).

As with other methods, site-specific data are needed, and in this case it consists of a survey of biota. As the name of the procedure implies, this method is relatively quick. These methods are used increasingly within the United States and now almost every state uses some version of them (U.S. Environmental Protection Agency 2009).

The use of RBP/IBI has been relatively successful in assessing ecosystem health and has shown significant correlations with environmental stressors (i.e. positive correlation with highly dissolved oxygen and negative correlation with turbidity) (Qadir and Malik 2009), but the approach has limited application for forecasting and prescriptive measures. The input parameters for RBP and IBI are often not subject to direct management actions (e.g., "the percentage of individuals with deformities") or obvious actions (i.e. causal connections) that might alter these inputs. The implicit agglomeration of all environmental inputs into one index does not reflect how environmental changes impact the biota. Further investigations are needed to establish causal links to the observed degradation, and thus the necessary remediation is not indicated. The language used to describe the uses for IBIs is often centered on "monitoring changes" (Kane, Gordon et al. 2009; Qadir and Malik 2009) or "understanding" a system (Qadir and Malik 2009). The overall applicability is also decreased as temporal variations necessitate either periodic sampling (Kane, Gordon et al. 2009), or temporal calibration/climate variability inputs for modeling (Mazor, Purcell et al. 2009). Furthermore, in terms of translatability of these indices regionally or from ecosystem to ecosystem, sampling procedures make translation difficult as does differences in assemblages between ecosystems (Mazor, Schiff et al. 2009).

RPB/IBI has high utility for monitoring or for evaluating stressor levels based on biotic assemblages. However, the lack of causal connections, specificity in defining the environmental elements to be restored, and absence of predictive power require a very low score for this approach on the prescriptive utility scale. This is a monitoring tool, not a forecasting tool.

Qualitative Habitat Evaluation Index (QHEI). The QHEI method was designed by the Ohio EPA for the evaluation of physical habitat quality in flowing waters (Hubbard 2009). The variables necessary for evaluation under this method include stream substrate, cover, meander pattern, riffle-pool sequences and riparian corridor. The developers have a standard field chart for stream evaluation using a series of checked boxes and a percent estimation of cover. The evaluation produces an overall score which may correlate with the IBI for the area. The effort to apply this method as well as the prescriptive utility, and the associated limitations, mirror those of the IBI discussed above.

Large and Complex Models. The following models are a diverse collection, but we have grouped them together because they are used less frequently for USACE planning purposes; due mainly to their greater complexity, time requirements, specificity of function, etc. However, they represent the state-of-the science in forecasting models and are appropriate for use in some larger, longer-term projects and are an important and emerging segment of the tools that can be used in environmental restoration. Examples of these models include: Bayesian models (e.g., Hierarchical procedures), Risk Analysis based planning, individual-based agent models and simulation models.

Bayesian methods. Bayesian models use an approach that can be particularly useful in situations where data are limited, due to the fact that they incorporate "prior data" either from past experimentation or from expert judgment (Choy, O'Leary et al. 2009). They are also useful for very large, complex datasets from which patterns and process elicitation is desirous, or for datasets which span long time-frames (Illian, Møller et al. 2009; Wang 2009). These models "force the parameterization of null and alternative hypotheses," yielding results with a percent confidence in those results (Ellison 1996). There is a great deal of flexibility and variation in how such models may be used, since the Bayesian approach can be applied to a large variety of other procedures. Hierarchical procedures commonly use Bayesian analysis, because it is one of the few methods that can fit the models (Lele and Dennis 2009).

Because Bayesian methods describe the methodology and analysis of data rather than an explicit model, it is difficult to conduct a detailed analysis of their utility or the effort required to implement them. However, several comments about this approach are warranted. The use of Bayesian methods yields results that include a percent confidence value; this is especially relevant to environmental decision making, as it gives policy makers the quantitative rigor that is often cited as a reason for ignoring ecological reports (Ellison 1996). Recently developed ecological models, such as BTREED (Lamon et al. 2008) (BTREED links nutrient and chlorophyll-a levels) use Bayesian tools. The motivation for the BTREED model was to balance the need for a simplified model with relatively simple inputs against the need for accuracy. It was shown that altering the level of confidence required can accomplish this balance (Freeman, Lamon III et al. 2009).

Another example of a Bayesian method is the use of a Bayesian Belief Network (BBN) to determine the uncertainty associated with inputs that capture logical and causal relationships to predict algal cover in coral reefs. The BBN uses empirical data, statistic associations, mathematical representations of these relationships (Renken and Mumby 2009). However, there is a greater degree of statistical processing required for Bayesian methods and some Bayesian approaches, such as hierarchical models, require specific training on model use (Illian, Møller et al. 2009; Ogle 2009). Over the past decade, the use of Bayesian models has generated considerable interest among both ecologists and statisticians (Ogle 2009), but there has been criticism regarding the scientific and mathematical rigor of Bayesian models, especially with respect to determining priors (i.e. the body of prior knowledge upon which new knowledge is concatenated) (Lele and Dennis 2009).

Risk analysis. For several years, the USACE has used quantitative risk analysis (RA) for Risk-Informed Decision-Making (Harper 2007). At present, all flood damage reduction projects are required to complete an RA that evaluates the uncertainty in "flood discharge, flood stages and flood damage" (Moser 1997). Monte Carlo simulations are used to combine these uncertainties and produce an estimate of structural performance that is then compared to the National Economic Development (NED) criteria of cost and reliability.

RA-based planning requires the use of a model or simulation to predict the frequency and probability of an event or outcome. The simulation, or risk assessment, may require significant historical or predictive data and some quantitative modeling experience. Therefore, like Bayesian methods, the effort required for the RA can be quite variable based on the available data, but the utility of the RA result can be high. The analysis compiles uncertainties associated with several input variables and produces a probability for an event. Also like Bayesian methods, the utility of this method can be increased by having an experienced risk assessor interpret the results of the RA.

Agent-based models. Agent-based modeling is a computational aggregation of many autonomous agents' actions in order to predict emergent group behavior or outcomes (Bousquet and Le Page 2004). These models focus on the rules that govern an agent's behavior and the interactions (or social organization) that it follows. An example of this type of model, the Numerical Fish Surrogate, has been used to predict the response of populations to changes in water quality and hydrodynamics (Goodwin 2006). These models are computationally intensive and require modeling expertise to implement and interpret, and are therefore considered to be high on the resource requirement scale. However, they do provide a forecast probability along with specific assumptions about parameters that can be used for planning purposes in evaluating different scenarios. The output of these models is specific enough to have high prescriptive utility.

Simulation models. Simulation models, such as the Everglades Landscape Model (ELM) and the Adaptive Hydraulics (ADH) model are tools that can be used to visualize the range of possible outcomes based on differing management decisions. These models are generally highly technical and require substantial experience or training to use and evaluate. Hence, they are considered to be "high" on the required resources scale. Moreover, they may require extensive or unavailable data sets as inputs or for validation. The resulting benefit from the increased effort is a detailed analysis of potential future scenarios. The outcomes of these models are sometimes bounded by explicit confidence limits and quantified uncertainty, and when this is included, such models have high prescriptive utility. Many complex simulation models, nevertheless, do not have defined confidence limits, and in some cases they are highly specific to a single ecological setting or focus on one process or factor. For wider application of simulation models, more models will have to be developed and validated and their confidence limits defined.

FUTURE RESEARCH DIRECTIONS: There remain very large gaps in our scientific knowledge relating to ecosystem restoration as well as in our technological ability to deliver existing knowledge to planners and stakeholders. Most of these gaps cannot be adequately addressed without long-term commitment of scientific resources and an involvement of the research community beyond the USACE and federal government. A few of the higher-priority needs are described here.

Researchers need to be aware of their end users and must collaborate with them — to the extent possible — in the development of forecasts and forecasting tools. Possible end users include planners, managers, decision makers, and the general public. Forecasts based solely on scientific objectives have little impact on policy because there is no stakeholder. In contrast, climate change forecasts developed under the Intergovernmental Panel on Climate Change (IPCC) have been influential; in part, because they respond to a request from governments (Clark et al. 2001).

Risk and Uncertainty. The emerging field of ecological forecasting aims to predict "the state of ecosystems, ecosystem services and natural capital, with fully specified uncertainties … contingent on explicit scenarios for climate, land use, human population, technologies and economic activity." (Clark et al. 2001). The tools being used and developed for ecological forecasting seek to limit uncertainty and to allow meaningful forecasts for future ecosystem states. The notion of specified uncertainties is most important, because for a forecasting tool to have much value (i.e., to be something relied upon in the planning process), the users and decision makers must have some grasp of its accuracy, precision, and applicability at the specific space and time scales of the candidate project.

Forecasting methods in common use provide an estimate or prediction of what is considered the most likely condition that will result from defined inputs to specified initial conditions (without confidence intervals). In some rare cases, they quantify the likelihood of a particular future in terms of confidence, risk, or probability (again, with defined inputs to a defined initial condition). In no cases did any of the common tools provide confidence intervals around the initial conditions and inputs that are most likely to produce a desired future condition (with or without a specified probability of success). The Bayesian methods discussed previously come closest to this.

Assessing the uncertainty surrounding typical ecological forecasts is not something apt to be undertaken by the typical end user without assistance from the forecasting tool itself or from the tool developers. Thus, there is a need to expand most of the existing tools to include a sensitivity analysis utility, or for developers to fully explore the sensitivity of their tools with parametric studies or field data and convey the results of such studies to their users in a readily accessible and interpretable (i.e., user-friendly) framework. The context of a scientific journal article is generally not suitable for this type of communication.

Risk is another aspect, or consequence, of uncertainty, and Risk Analysis (RA) attempts to quantify the consequences of an uncertain event. Due to the fact that the outcome of an ecological restoration project may be uncertain, in terms of ecological benefits, there are strong parallels and potential connections between forecasting in ecological restoration and risk analysis. USACE planners use Risk Analysis (RA) in flood reduction studies, but no formal requirement exists to use such approaches in environmental restoration projects. There is software for Flood Damage Reduction Analysis (i.e., HEC-FDA), but nothing comparable in the ecological realm. Can the same principles of risk analysis be applied? Can similar tools be developed?

There are significant hurdles to using the RA approach in ecological forecasting. Traditional RA focuses on estimates of exposure and effects. The likelihood of a specific, low-probability event or condition is estimated, and extended periods of record, either real or simulated, are used to develop these specific probabilities. This is generally not the situation in ecological restoration and forecasting. Extended periods of record are generally not available and those aspects of the system around which we can actually quantify uncertainty may not be the overwhelming drivers of system variability. The approach of risk analysis nonetheless offers important benefits that need to be transported into the arena of ecosystem restoration if possible.

Closely related to Risk Analysis, Net Environmental Benefits Analysis (NEBA) (Efroymson et al. 2003) likewise seems to offer some promise for environmental forecasting in the USACE planning process. Net environmental benefits are the gains in environmental services or other ecological properties attained by actions, minus the environmental injuries caused by those actions. NEBA is a methodology for comparing and ranking the net environmental benefit associated with multiple management alternatives. NEBAs can be conducted for a variety of stressors and management options, including chemical contaminant mitigation and hydropower mitigation (Efroymson et al. 2003).

NEBA can be viewed as an extension of the ecological risk assessment framework of the EPA (USEPA 1998). However, it has significant differences, as the EPA framework does not normally consider benefits, and risk assessors are usually not familiar with assessments that include benefit estimates (Efroymson et al. 2003). One of the potential advantages of NEBA to the planning process is that this framework can help avoid an alternative that provides no net environmental gain relative to the no-project alternative. NEBA is particularly appropriate if any of the alternatives under consideration have significant negative ecological effects or minimal ecological benefits. Finally, NEBA can be used when multiple options offer net ecological gain, but the one with the greatest net gain is not apparent without formal analysis.

Index Approaches. A potentially important step forward in the use of indices for evaluation of alternative ecological management measures is the biodiversity security index (BSI). This is an indicator of benefit based directly on the "value" of restored population units and biologically distinct and scarce species. The value is determined by a public desire to sustain all species as indicated in law and opinion. (Cole 2009).

Cumulative Impacts. Tools are not generally available that allow USACE planners to directly forecast the combined effects of multiple projects or multiple management actions, but such tools are sorely needed. Some derivative of the NEBA approach previously presented may offer promise. The NEBA methodology helps identify and compare net environmental gains of alternative management options (Efroymson et al. 2003).

Emerging Approaches. Recent research in ecological forecasting has been aimed at developing models that limit uncertainty and allowing meaningful forecasts for future ecosystem states despite non-linearity or non-stationarity in several variables. Several approaches have been taken (such as averaging the outputs of several models and "downscaling" large-scale models), but these efforts have required large amounts of data and involve the experimental evaluation of models across spatial and temporal scales that may be inappropriate. For example, large-scale predictions from the Intergovernmental Panel on Climate Change (IPCC) are being "downscaled" for regional or local planning. Such downscaling requires detailed, technical understanding of the large-scale model as well as additional local data, such as local topographic measurements, to generate local predictions that have enough certainty to be useful.

The participants at the Chicago workshop (ERDC 2008b) noted that most restoration activities within the USACE to date have addressed habitat quality in a generally species-specific manner. However, functional attributes, including ecosystem services, need to be considered in future projects. Approaches to ecosystem management must go beyond the management of habitats or patches through the development and application of models that address watershed- or landscape-scale considerations. Ecosystems adapt and evolve to changing conditions, and this requires planning models capable of forecasting alternative future conditions at the ecosystem scale.

DISCUSSION: There has been substantial, recent, scientific activity on the topic of ecological restoration and ecological forecasting (e.g., Hobbs and Suding 2008), but most of the more advanced scientific concepts currently discussed in the context of ecological or ecosystem restoration are not yet suitable for routine application by USACE planners. For example: it is recognized that ecosystems (e.g., shallow lakes) may exhibit or experience alternative stable states that tend to be self-perpetuating and that strongly resist change to another stable condition once established. This is closely linked to the concept of ecological thresholds, in which a system resists change until some threshold is crossed and then a cascade ensues that cannot be reversed. The "incremental" approach to evaluating the benefits of alternatives in the planning process may not readily accommodate these notions, nor would the approach of forecasting physical-chemical conditions and assuming an "incremental" ecological response.

The issue of scale in ecosystem restoration and planning is likewise not being fully addressed, even within scientific circles, and thus important landscape or holistic aspects of restoration are not given adequate consideration. Cumulative impact analysis, as required under NEPA, requires consideration of scale effects, but the approach to meeting these NEPA requirements in project planning is far from "cook book." Technology transfer and educational outreach that communicate the important issues of scale in ecosystem restoration, and specific scale issues in specific projects or types of projects are needed.

Small-scale approaches (i.e., individual, agent-based models) have had significant success in restoration efforts and show substantial promise. Although it is not impossible to apply our "fine scale" knowledge to large-scale systems and problems, this can only be successful when we understand the large-scale driving factors that emerge (and may dominate) at that level, because only then can we see what finer-scale processes have utility for forecasting large-scale events and trends. For example, the molecular processes of photosynthesis are the basis for all plant life and a forest is a collection of individual plants, but a molecular-level model of photosynthesis will probably not have great utility forecasting the future condition of coastal redwood forests over the next several centuries unless that fate is driven primarily by an unusual perturbation in the photosynthetic process (e.g., in response to altered CO_2 levels) or by unusual successes or failures of a few individual trees (e.g., a genetic mutation), rather than substantial changes in large-scale external factors such as land use, fire, flood, or lumber extraction.

As the list of considerations in tool selection expands, the complexity of selecting an optimal tool seems to expand exponentially and it becomes nearly impossible to reduce the selection process to a simple series of steps with quantifiable inputs. An ability to fully recognize the technical merits and limitations of the myriad of forecasting tools available is generally outside the realm of expertise required of USACE planners, and attempts to create an expert system or a "tool selection tool" have collapsed in failure. The process of selecting a forecasting tool thus remains something of an art form, and is a political process, strongly influenced by preferences, experiences, and existing capabilities rather than the utility of the available tools. Better choices can be made, nonetheless, and sound scientific information can inform those choices, even though the final decision may hinge on other considerations.

Risk and uncertainty can reduce the credibility of plans and decisions and the information content of a forecast is inversely proportional to its uncertainty (Clark et al. 2001). Therefore, approaches for reducing and/or quantifying uncertainty throughout the planning process are needed. Forecasting future conditions is not a deterministic process and innovative approaches are required to quantify the uncertainty of forecasts.

SUMMARY: This note presents an approach to quantifying and facilitating the process of selecting ecological forecasting tools and for conveying the technical merit of differing tools to planners and decision-makers. A scoring system, such as the one illustrated here, may help planners and researchers select or recognize appropriate forecasting tools that can have utility within the time and resource constraints of a specific restoration project. A scoring approach such as this can also be helpful in creating realistic expectations as to the resources that a specific forecasting tool will require and what relative utility can be expected of its output.

The general finding of our classification exercise is that those tools which have high prescriptive utility require significant investment of time and resources (i.e., there are no "magic bullets"). Furthermore, few of the planning methods currently in use provide an estimate of the present actions (i.e., management measures) that are needed to create a desired future condition and the evaluation (index) tools that we examined give no indication of uncertainty or confidence.

SPECIFIC FINDINGS.

1. There is a strong need for simpler, less resource-driven forecasting tools. (90 percent of applications are smaller projects (< $100,000) and less than one year duration.)

2. Technology transfer (education) is necessary to properly select and use existing forecasting tools and models.

3. A framework is needed to guide planners in the use of forecasting tools.
   a. A tiered decision approach is recommended: Start with Quadrant I, and only if necessary, invest in Quadrant IV approaches (Figure 2).
   b. More USACE-certified models are needed to increase their utility for planners.
   c. Add project feedback to models in an effort to increase user understanding of the range of outcomes from restoration or engineering activity.

4. Forecasting methods should better address cumulative impacts.
   a. Repeated use of methods that do not adequately consider external influences and interactions may result in large, unexpected changes in ecosystem function (i.e. "death by 1,000 cuts").
   b. Meta-analysis or multiple projects and adaptive management approaches may improve forecasts at larger scales of both time and space.

POINTS OF CONTACT: For additional information on the Ecosystem Management and Restoration Research Program (EMRRP), please consult http://el.erdc.usace.army.mil/emrrp/emrrp.html or the manager of the Ecosystem Management and Restoration Research Program (EMRRP), Glenn Rhett (601-634-3717, Glenn.G.Rhett@usace.army.mil. This technical note should be cited as follows:

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