ERDC/TN EMRRP-EM-11
September 2023

Defining Levels of Effort for Ecological Models

by Aubrey Harris,[1] Nathaniel Richards,[2] and S. Kyle McKay[3]

BACKGROUND: While models are useful tools for decision-making in environmental management, the question arises about the level of effort required to develop an effective model for a given application. In some cases, it is unclear whether more analysis would lead to choosing a better course of action. This technical note (TN) examines the role of ecological model complexity in ecosystem management. First, model complexity is examined through the lens of risk informed planning. Second, a framework is presented for categorizing five different levels of effort that range from conceptual models to detailed predictive tools. This framework is proposed to enhance communication and provide consistency in ecological modeling applications. Third, the level of effort framework is applied to a set of models in the Middle Rio Grande River system to demonstrate the framework's utility and application. Ultimately, this TN seeks to guide planners in determining an appropriate level of effort relative to risks associated with uncertainty and resource availability for a given application.

INTRODUCTION: Ecosystems are complex networks affected by interactions between geomorphology, hydrology, and biology (Castro and Thorne 2019). Ecosystem restoration and management often require tools to understand links between environments, ecosystem processes, and surrounding social systems. Ecological models provide a mechanism for understanding system dynamics, quantifying management outcomes, and informing decisions. These tools can take forms ranging from simple conceptual depictions to complex integrated biophysical models (Swannack et al. 2012). Ecological model specification depends on many factors such as the focal system, desired outputs, driving variables, and necessary spatial or temporal resolution (Jakeman et al. 2006).

Throughout this TN, the term *model* is used in a general sense to include all numerical tools used in US Army Corps of Engineers (USACE) projects, which range in complexity from simple spreadsheets to complex models with thousands of lines of computational code. All models, ecological or otherwise, are limited in level of detail, bound by their assumptions about the system of interest, and constrained by logistical concerns like project schedules and available funding (Schmolke et al. 2010). Identifying an appropriate level of model complexity (Larsen 2016) is a fundamental challenge in model application and development in conservation, restoration, and

[1] US Army Engineer Research and Development Center (ERDC), Environmental Laboratory (EL), Albuquerque, NM, Email: aubrey.e.harris@usace.army.mil
[2] US Army Corps of Engineers (USACE), Headquarters, Email: nathaniel.s.richards@usace.army.mil
[3] ERDC-EL, New York, NY, Email: kyle.mckay@usace.army.mil

management. This includes identifying sources of uncertainty and their likelihood to have negative impact on project success (Game et al. 2013). In some cases, more information will not impact management decisions because feasibility or cost-effectiveness are the limiting factors (Maxwell et al. 2015). Modelers should ensure that salient and credible model parameters are used relative to possible management actions or the ecosystem process in question (Brauman et al. 2022). Robust project management strikes a balance between addressing information gaps that affect project effectiveness while also conforming to pragmatic issues like timely project delivery and limited budgets (McDonald-Madden 2008).

Within the USACE, issues of model complexity manifest in a variety of practical concerns that influence project planning, design, and operations, including the following:

- What model outcomes address critical uncertainties of the project?
- What level of model complexity is needed to inform this decision?
- How does model selection, from simple to complex, affect intended performance, input requirements, and development histories?
- Should more input data be gathered to better reflect the modeled ecosystem?
- Are there sufficient resources (e.g., time, funding, expertise) to increase model complexity?
- What is the risk tolerance of decision-makers?
- What model will provide sufficient information and confidence to make a decision?

This TN examines the issue of model complexity and the appropriate “level of effort” (LoE) required for ecological applications. First, model complexity is addressed relative to critical uncertainties via risk-informed decision making. Second, a framework is proposed for defining levels of effort to aid in consistency and transferability of ecological models. Third, a brief case study is presented to demonstrate the utility of the level of effort framework.

MODEL COMPLEXITY AND RISK-INFORMED PLANNING: Environmental management decisions are affected by many forms of uncertainty (Ascough et al. 2008), and there are many approaches to quantify and manage uncertainty during project decision making (Schultz et al. 2010). The USACE has operationalized these techniques through the process of risk-informed planning, which is defined as “an analytic-deliberative process to efficiently reduce uncertainty by gathering only the evidence needed to make the next planning decision, and to manage the risks that result from doing so without more complete information” (ECB 2019-3). In this paradigm, model complexity is based on aligning the level of analysis with its effects on decision quality. In other words, the level of effort to develop a model should be guided by identifying and resolving uncertainties that may affect a project’s course of action.

The issues of model complexity and decision quality can be further reinforced through a hypothetical example (Figure 1). A general analytical goal of increasing model complexity is often tied to reducing uncertainty and increasing decision quality. However, fiscal and technical resources are required to increase model complexity. Trade-offs are typically encountered in choices to increase model complexity or remain at a current level. Decision quality, uncertainty, and resources may all have non-linear relationships to complexity, and Figure 1 simply presents one example.

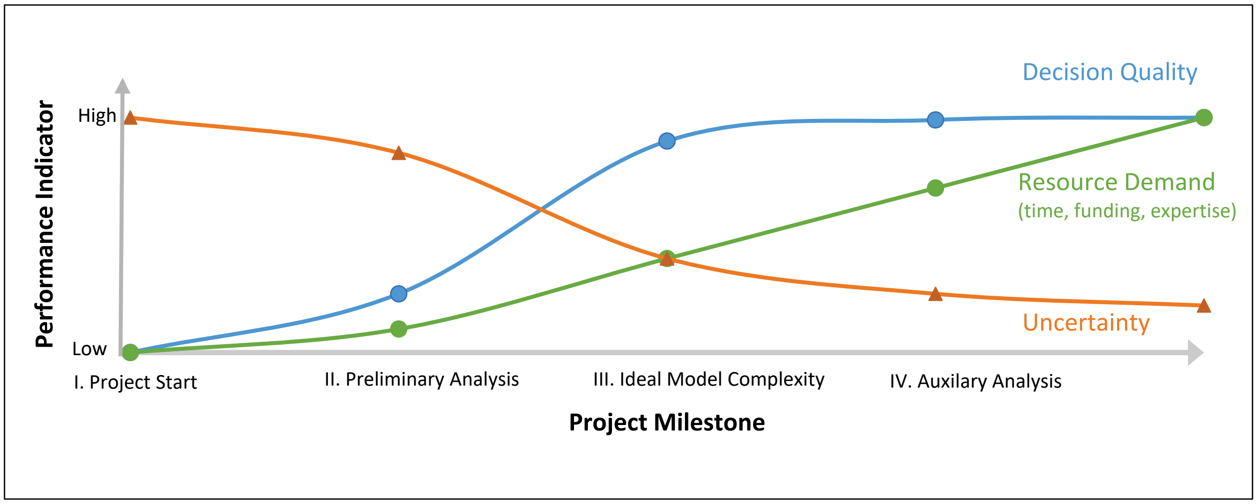

Figure 1. How increasing model complexity affects decision quality and resource demands while also reducing uncertainty.

When is it "worth it" to invest in model complexity? Model complexity does not necessarily ensure that decision quality is improved. Analogous to data collection, one may find that after a threshold level of effort, increasing data collection provides homogenous or redundant information to what is already known. In some cases, new data may be unique, but still not sufficiently different to affect project decisions.

Figure 1 presents four milestones that may occur during model development (I-IV). At the project start (I) uncertainty is at its highest level and decision quality is low. Any model development is progress toward milestone (II), where uncertainties are reduced, and relatively little resources have been expended. The decision of going from milestone (II) to (III) may be rather straightforward in that decision quality is significantly improved at a low investment of resources. However, it is sometimes unclear when the ideal model complexity has been reached, and continual investment of resources leads to milestone (IV), where decision quality is not improving, and the return on resource investment does not greatly reduce uncertainty. The investment of resources to move from (III) to (IV) may still be warranted if a reduction in uncertainty is required to meet risk tolerances for this project.

In risk assessment, there is a natural tension to create a parsimonious model that balances complexity and resource investment. Risks occurring from an insufficiently detailed model include (1) not understanding system dynamics, (2) over- or under-predicting project outcomes, (3) investing in the wrong action, (4) mischaracterizing processes leading to unintended consequences, or (5) miscommunicating outcomes.

Conversely, project risks also occur from excessive model complexity such as (1) budget and schedule overrun, (2) collection of superfluous data not on the critical path, (3) unavailable expertise to execute or interpret models, and (4) reduced transparency and communicability from complex models with many parameters and assumptions.

The issues of model complexity and level of effort arise in every discipline involved in USACE project execution, and many communities of practice have provided techniques for navigating these choices. For instance, cost estimates are defined relative to five classes ranging from extremely high to low risk levels (i.e., Classes 5 to 1, respectively), and a minimum estimation class is identified for common USACE project execution milestones (ER 1110-2-1302). These classes provide a mechanism for consistency in estimates relative to common design thresholds and associated contingency cost ranges.

The hydraulic modeling community has provided technical guidance for practitioners navigating these issues addressing discipline specific choices about input data, treatment of steady versus unsteady flow, and choices of model dimensionality (Brunner et al. 2020). Similarly, Knight (2021) provides technical guidance for hydro-analytic issues with an emphasis on levels of review and software complexity for broad-scale implementation. At present, there is no comparable guidance for levels of complexity and effort for ecological modeling and the following sections seek to fill this gap.

LEVELS OF EFFORT FOR ECOLOGICAL MODELING: As a field of practice, ecological modeling contains a variety of modeling approaches (e.g., conceptual, statistical, systems) that address a diverse suite of ecosystem components (e.g., habitat, population, community). The diversity of tools and applications often complicate project planning and lead to divergence in use of ecological models across USACE. Here, the analytical frameworks of cost engineering and hydrodynamic modeling are used to define classes of ecological models. These LoE attempt to provide a lexicon that aligns ecological model complexity with risk-informed planning. Specifically, the level of effort framework seeks to address three objectives.

- *Enhance communication about ecological models*. Ecological modeling is often perceived as a “black box” process due to a variety of challenges (Herman et al. 2019), many of which stem from model communication and understandability by technical and nontechnical stakeholders. A consistent set of classifications for ecological models would provide a standard lexicon for addressing model complexity in a given application. The framework would also help manage expectations about the resolution of outcomes and predictive goals of a given model or use.

- *Increase consistency in ecological model use across the USACE*. Shared language about model complexity is also likely to increase consistency in model use across diverse studies, regions, and ecosystems. Defining levels of effort could (to a degree) standardize model use and review thresholds for different decision contexts in the agency.

- *Align ecological models with other analytical tools*. Improved communication and consistency would likely lead to more predictability in USACE ecological model uses. This predictability could help align ecological modeling with parallel analytical disciplines, and levels of effort could be used to align ranges of uncertainty from different disciplines in the same analysis (e.g., ensuring cost and benefit levels contain similar levels of uncertainty in cost-effectiveness and incremental cost analyses).

Defining levels of effort. Ecological models are used in varying capacities through project planning, design, and operations. The following classification proposes five LoE in ecological modeling (Table 1), which span a gradient from non-quantitative, conceptual tools (LoE-5; lowest complexity) to well-vetted tools for quantitative prediction in high stakes conditions (LoE-1;

highest complexity). This spectrum carries with it concomitant changes in project risk, resource requirements, and levels of uncertainty. The following sections provide a more detailed description of each LoE. The classes can generally be thought of as addressing qualitative outcomes only (LoE-5), relative prediction between actions (LoE-4 and LoE-3), and pattern recreation (LoE-2 and LoE-1). These LoEs are designed to facilitate communication and do not represent ecological modeling policy and should only be used in this context.

Table 1. Scope of different levels of effort (LoE) for ecological modeling (LoE-5 is lowest level of effort; LoE-1 is highest).

Level of Effort	Predictive Goals	USACE Certification	Integration with Other Models
5	Qualitative comparison	None	None
4	Relative comparison among divergent actions	Possible	Usually standalone or few inputs from other tools
3	Relative comparison among similar actions	Typical	Input data often generated by other models
2	Coarse pattern recreation	Yes	Typically includes coupling with other input streams, but tools remain independent or applied in sequence
1	Refined pattern recreation	Yes	Tightly linked with other data sources and models with interdependent processes (e.g., feedback dynamics)

- *LoE 5 (lowest complexity)*: These models are qualitative conceptualizations of an ecosystem. The models help inform early forms of prediction about an ecosystem (e.g., Action-A could affect variable-B and ultimately outcome-C). The models formalize professional judgement and provide more transparency and replicability than judgement alone, and these models are required of all restoration studies (Fischenich 2008). Conceptual models often undergo informal review (e.g., input from stakeholders) but are not formally reviewed beyond their role in reports and documents.

- *LoE 4*: In this level of effort, models assist users in differentiating the relative effects of different actions. For instance, Site-D is 50% better than Site-E in terms of a potential ecological outcome. These methods are typically semi-quantitative and rapid analyses, which rely on a combination of scoring, binary outcomes, or quick analyses of readily available data. LoE-4 models could also involve more refined tools applied without rigorous data sets (e.g., an existing habitat model parameterized only with estimates of field conditions).

- *LoE 3*: Tools become more quantitative, sensitive, and locally tailored at this LoE. These models still emphasize relative comparison but are also capable of comparing similar alternatives (e.g., “scales” of an alternative). LoE-3 models often use more locally targeted data or outputs from other models (e.g., hydraulic model inputs for depth). These models have often undergone peer review such as USACE certification (EC-1105-2-412) and/or journal publication.

- *LoE 2*: These well-developed quantitative models often represent an increase in depth and breadth of model outcomes over LoE-3. These tools pivot from relative prediction to recreation of patterns that can be verified or validated against empirical data. Models may include dynamic simulation through time, rather than static “snapshots” from LoE-3. This LoE often involves loose coupling and integration with other models, but tools remain applied independently (e.g., a climate model used to parameterize a long-term ecological forecast). LoE-2 models have typically undergone multiple forms of review and verification over a longer development cycle. However, these models can also represent LoE-3 models applied in a novel format to better reflect environmental variability or assess uncertainty.

- *LoE 1 (highest complexity)*: The most refined LoE are tools that are thought to accurately predict patterns and have been validated and calibrated to local conditions over time. LoE-1 models are often tightly integrated with other models to include feedback mechanisms and dynamic simulation through time. These models can be thought of as the “industry standard” or “go-to” model for an application, and they have often been extensively reviewed, agreed upon by regional stakeholders (sometimes after litigation), and vetted through multiple applications. Models at this LoE are somewhat uncommon and are only typically developed to guide long-term, programmatic decision making in high-profile situations (e.g., Columbia River fish passage, Missouri River operations).

Importantly, selecting a modeling approach or software alone does not indicate its LoE. A given software could be applied across multiple levels depending on local parameterization. For instance, a standardized habitat modeling software could be used to “game out” effects of different management actions early in a project (LoE-2). The same software could then be preliminarily applied with national or regional data sets to estimate project outcomes (LoE-3), and then detailed local data could be collected to drive more refined estimates for permitting and compliance (LoE-2). As such, the LoE should be thought of as aligned relative to different “use cases” of models to inform decisions.

Use cases for ecological models. Models cannot be separated from their application context. The LoE needed may depend on how an ecological model will be used to inform project planning, design, operations, or decision making (McKay et al. 2019). Table 2 presents a variety of use cases common to USACE projects and decisions, which is derived from existing cost engineering guidance (ER 1110-2-1302) and augmented by the authors’ experiences in ecological modeling. The level of effort may vary depending on the context in which a model is being applied. For instance, some projects occur at large scales (e.g., in terms of spatial extent, capital investment), represent complex decisions (e.g., nuanced trade-offs between outcomes), or levels of controversy, all of which may affect the level of effort. This alignment of use cases and consequences generally reflects the USACE approaches to project review (ER 1165-2-217) and identification of “mega” studies (USACE 2021). Table 2 also recommends a *minimum* LoE for each use case, although more refined LoEs could be applied (e.g., LoE-2 or LoE-1 in a Chief’s report), if the situation requires. Most restoration applications tend to only require LoE-3, and LoE-2 and LoE-1 are more commonly encountered for compliance issues (e.g., endangered species impacts).

Table 2. Examples of use cases of different ecological modeling LoEs (5 is the lowest level of effort; 1 the highest). Note that the recommended LoE is the *minimum* effort recommended for a given decision type.

Common Use Cases	Project Scale, Decision Complexity, or Level of Controversy	Recommended *Minimum* LoE
Preliminary project planning (Federal Interest Determination, objective setting…)	Any	5
Alternatives Milestone Meeting	Any	4
Civil Emergency Management Program	Low	4
	High	3
Restoration or mitigation site selection	Low	4
	High	3
Initial alternatives comparison (e.g., divergent alternatives at a given site)	Any	4
Feasibility alternatives analysis and mitigation planning	Low	4
	High	3
Federally recommended plan in a Continuing Authorities Program	Low	4
	High	3
Feasibility federally recommended plan in Chief's Report	Low	3
	High	2
Other feasibility scale reports (e.g., General Reevaluation, Limited Reevaluation, Engineering Decision, Post Authorization Change)	Low	3
	High	2
Advancing design levels in Pre-construction Engineering and Design	Any	3
Endangered species management as part of a Biological Opinion	Low	3
	Moderate	2
	High	1

CASE STUDY: A case study in the Middle Rio Grande is used here to discuss how LoEs or complexity are applied in a project setting. The Middle Rio Grande is a nearly 170-mile segment from the New Mexico-Colorado border and Elephant Butte Dam near Truth or Consequences, New Mexico. This reach of river has been a major focus for multiple agencies, restoration projects, and water management actions. Several ecological models with different scopes and goals have been developed for this system to inform these decisions.

- *LoE-5 – Conceptual Ecological Model*: The Middle Rio Grande Endangered Species Collaborative Program is an interagency organization with objectives to coordinate research and adaptive management strategies for endangered species in this river system. Their Science and Adaptive Management Committee developed conceptual models of life cycle requirements for the endangered Rio Grande silvery minnow and two endangered bird species (MRGESCP SAMC 2020). These LoE-5 models aid in communication among agencies and identification of critical uncertainties, which then guides research priorities in the system.

- *LoE-4 – Semi-Quantitative Site Screening and Hydrologic Metrics*: Two LoE-4 tools have been applied to inform management in the Middle Rio Grande. First, the Bosque Community Index (Burks-Copes et al. 2012) was formulated to record ecosystem function in the Middle Rio Grande riparian forest (i.e., bosque) at a community level. This index captures spatially distributed conditions such as vegetative structure, soils, and inundation frequency. The model was applied to rate portions of a large study area as optimal to most degraded conditions, thus supporting project planning for habitat management. This index model leveraged a variety of quantitative and spatial datasets to create a relative assessment of existing habitat quality. However, generalized indices are challenging to validate and often difficult to use in forecasting, which limits their utility and leaves a relatively high level of uncertainty.

  A second example of LoE-4 models in this system uses hydrologic metrics to infer environmental flow outcomes. Critical life cycle processes are correlated with discharge or stage time series metrics (e.g., number of days above a floodplain accessing discharge). For the Middle Rio Grande, a decadal analysis of streamflow and floodplain inundation was used to define Rio Grande silvery minnow refugia habitat and associated discharge levels (Harris 2020; Gronewold 2010). While streamflow is certainly related to floodplain inundation, spatial variability in inundation patterns lead to significant uncertainty in prediction and limit utility for some types of decisions.

- *LoE-3 – Site-scale Riparian Restoration Alternatives Analysis*: Based on the community index model discussed in LoE-4, a USACE certified habitat evaluation procedure was developed for single-time-use in a restoration feasibility study (Burks-Copes et al. 2009). This analysis compared long-term effectiveness of different restoration methods at various scales to each other and the without-project condition. The result not only quantified potential alternatives in economic and ecosystem benefit terms, but also increased the confidence that the selected alternative will be effective at achieving project goals.

- *LoE-2 – Aquatic Habitat Models with Coupled Hydraulics*: This model developed a habitat suitability index for Rio Grande silvery minnow using field measurements of species presence, water depth, and velocity (Harris 2023). The analysis used increasingly complex hydrologic and hydraulic habitat area characterizations of the spring runoff and compared these to species population measurements over the course of several years. Hydraulic-habitat analyses pinpointed seasonal durations and flow magnitudes that correlated with larval fish production. The habitat suitability index was validated with empirical field observations, which confirmed ecosystem processes identified in lower-level qualitative models while also adding quantitative metrics that can be applied for restoration site design and other adaptive management techniques. However, the model specificity increases (i.e., aquatic habitat only rather than riparian and aquatic) as model complexity increases; thus, demonstrating a common trade-off in levels of effort.

- *LoE-1 – Does Not Presently Exist*: In this case study, there are no ecological models that would qualify as a fully endorsed set of tools, agreed upon for species management. Part of the challenge in developing a model for species management in this system is the complexity in geomorphology, hydrology, and species needs and the need to address multiple ecosystem types (i.e., aquatic and riparian). In addition, multiple agencies have different priorities for management of the Middle Rio Grande, presenting conflicting perspectives and priorities.

No single tool meets all the needs for modeling in this system. Acknowledging the different levels of model complexity is helpful in project planning and communication. All levels of effort have roles in developing a body of knowledge regarding ecosystem function. However, increasing model complexity reduces uncertainties when managing these complex systems and therefore allows planners to make decisions with reduced risks associated with uncertainty as projects proceed from concept to execution.

SUMMARY: Models are effective tools in various levels of project planning. In the early stages of project planning, LoE-5 models facilitate communication, while LoE-3 models can provide relative comparisons for decision making. Later, during advanced engineering and design, more refined models (LoE-1 or 2) can provide confidence in project success through pattern recreation.

The LoE necessary is dependent on the context of the ultimate decision needs. While model complexity does not always have a proportional relationship with decision quality, modelers and decision makers need to consider the ultimate decision needs upfront. In turn, this provides critical information to determining the “right” model complexity and level of detail. Greater risk may require greater complexity, rigor, and level of detail. Determining when it is “worth it” to invest in model complexity is a careful consideration of time, resources, and necessary decision quality.

The purpose of this TN is to demonstrate the utility of increasingly complex models, while also identifying thresholds where a LoE may be deemed sufficient relative to perceived risks and model uncertainty. It is expected that increasing the LoE for models does have potential to address knowledge gaps, however the LoE should be gaged against its potential to affect management actions given a set of constraints.

ADDITIONAL INFORMATION: The authors are grateful for thoughtful input from the ERDC integrated ecological modeling team. Specifically, reviews by Dr. Todd Swannack, Dr. Michael D. Porter, and Darixa Hernandez-Abrams significantly improved this TN. The use of products does not represent an endorsement of these products by either the authors or the Department of the Army. The study was conducted with support from the Ecosystem Management and Restoration Research Program (EMRRP). For information on EMRRP, please contact the program manager,

Dr. Brook Herman (Brook.D.Herman@erdc.usace.army.mil) or consult https://emrrp.el.erdc.dren.mil/. This TN should be cited as follows:

> Harris A., N. Richards, and S. K. McKay. 2023. *Defining Levels of Effort for Ecological Models*. ERDC/TN EMRRP-EM-11. Vicksburg, MS: US Army Engineer Research and Development Center. http://el.erdc.usace.army.mil/emrrp/emrrp.html.

REFERENCES

Ascough, J. C., II, H. R. Maier, J. K. Ravalico, and M. W. Strudley. 2008. "Future Research Challenges for Incorporation of Uncertainty in Environmental and Ecological Decision-Making." *Ecological Modelling* 219(3–4): 383–99. https://doi.org/10.1016/j.ecolmodel.2008.07.015.

Brauman, Kate A., Leah L. Bremer, Perrine Hamel, Boris F. Ochoa-Tocachi, Francisco Roman-Dañobeytia, Vivien Bonnesoeur, Edwing Arapa, and Gena Gammie. 2022. Producing Valuable Information from Hydrologic Models of Nature-Based Solutions for Water." *Integrated Environmental Assessment and Management* 18(1): 135–47. https://doi.org/10.1002/ieam.4511.

Brunner, G., G. Savant, and R. E. Heath. 2020. *Modeler Application Guidance for Steady Versus Unsteady, And 1D Versus 2D Versus 3D Hydraulic Modeling*. TD-41. Hydrologic Engineering Center, Institute for Water Resources, US Army Corps of Engineers.

Burks-Copes, K., and A. Webb. 2009. *Middle Rio Grande Bosque Ecosystem Restoration Feasibility Study Habitat Assessment using Habitat Evaluation Procedures*. ERDC/TN EL TR-12-21. Vicksburg, MS: US Army Engineer Research and Development Center.

Burks-Copes, K., and A. Webb. 2012. *A Bosque Riparian Community Index Model for the Middle Rio Grande, Albuquerque, New Mexico*. ERDC/TN EL TR-12-26. Vicksburg, MS: US Army Engineer Research and Development Center.

Castro, Janine M., and Colin R. Thorne. 2019. "The Stream Evolution Triangle: Integrating Geology, Hydrology, and Biology." *River Research and Applications* 35(4): 315–26. https://doi.org/10.1002/rra.3421.

Fischenich, J. C. 2008. *The application of conceptual models to ecosystem restoration*. ERDC/TN EBA -08-1. Vicksburg, MS: U.S. Army Engineer Research and Development Center.

Game, Edward T., James A. Fitzsimons, Geoff Lipsett-Moore, and Eve McDonald-Madden. 2013. "Subjective Risk Assessment for Planning Conservation Projects." *Environmental Research Letters* 8(4): 045027. https://doi.org/10.1088/1748-9326/8/4/045027.

Gronewold, R. 2010. *Historic Inundation Analysis along the Middle Rio Grande for the Period 1990 to 2009. Prepared for the Middle Rio Grande Endangered Species Act Collaborative Program - Population Viability Analysis Work Group*. Albuquerque, NM.

Harris, A. 2020. *Areal Inundation along the Middle Rio Grande for 2010-2018 Based on 2012 Geometry. Prepared for the Middle Rio Grande Endangered Species Act Collaborative Program - Population Viability Analysis Work Group*. Albuquerque, NM.

Harris, A. 2023. *Hydraulic modeling and environmental flows analysis for ecological modeling*. University of New Mexico, Doctoral dissertation.

Herman, Brook D., S. Kyle McKay, Safra Altman, Nathan S. Richards, Molly Reif, Candice D. Piercy, and Todd M. Swannack. 2019. "Unpacking the Black Box: Demystifying Ecological Models through Interactive Workshops and Hands-on Learning." *Frontiers in Environmental Science* 7. https://doi.org/10.3389/fenvs.2019.00122.

Jakeman, A. J., R. A. Letcher, and J. P. Norton. 2006. "Ten Iterative Steps in Development and Evaluation of Environmental Models." *Environmental Modelling & Software: With Environment Data News* 21(5): 602–14. https://doi.org/10.1016/j.envsoft.2006.01.004.

Knight, S. K. 2021. *The case for evaluating hydroanalytic information*. WaterWonks LLC and Department of Homeland Security's Coastal Resilience Center.

Larsen, Laurel G., Maarten B. Eppinga, Paola Passalacqua, Wayne M. Getz, Kenneth A. Rose, and Man Liang. 2016. "Appropriate Complexity Landscape Modeling." *Earth-Science Reviews* 160: 111–30. https://doi.org/10.1016/j.earscirev.2016.06.016.

Maxwell, Sean L., Jonathan R. Rhodes, Michael C. Runge, Hugh P. Possingham, Chooi Fei Ng, and Eve McDonald-Madden. 2015. "How Much Is New Information Worth? Evaluating the Financial Benefit of Resolving Management Uncertainty." *The Journal of Applied Ecology* 52(1): 12–20. https://doi.org/10.1111/1365-2664.12373.

McDonald-Madden, Eve, Peter W. J. Baxter, and Hugh P. Possingham. 2008. "Making Robust Decisions for Conservation with Restricted Money and Knowledge." *The Journal of Applied Ecology* 45(6): 1630–38. https://doi.org/10.1111/j.1365-2664.2008.01553.x.

McKay, S. K., N. Richards, and T. Swannack. 2019. *Aligning ecological model development with restoration project planning*. ERDC/TN EMRRP-SR-89. Vicksburg, MS: US Army Engineer Research and Development Center.

Schmolke, Amelie, Pernille Thorbek, Donald L. DeAngelis, and Volker Grimm. 2010. "Ecological Models Supporting Environmental Decision Making: A Strategy for the Future." *Trends in Ecology & Evolution* 25(8): 479–86. https://doi.org/10.1016/j.tree.2010.05.001.

Swannack, T. M., J. C. Fischenich, and D. J. Tazik. 2012. *Ecological Modeling Guide for Ecosystem Restoration and Management*. ERDC/EL TR-12-18. Vicksburg, MS: US Army Engineer Research and Development Center.

USACE (US Army Corps of Engineers). 2011. *Assuring quality of planning models*. EC-1105-2-412. Washington, DC.

USACE (US Army Corps of Engineers). 2016. *Civil Works Cost Engineering*. ER 1110-2-1302. Washington, DC: Headquarters, US Army Corps of Engineers.

USACE (US Army Corps of Engineers). 2019. *Risk Informed Decision Making for Engineering Work During Planning Studies*. ECB-2019-3. Washington, D.C.

USACE (US Army Corps of Engineers). 2021. *Interim Guidance for Civil Works Mega Studies*. CECW-P, Washington, DC: Headquarters, US Army Corps of Engineers.

USACE (US Army Corps of Engineers). 2021. *Civil Works Review Policy Engineering*. ER 1165-2-217. Washington, DC: Headquarters, US Army Corps of Engineers.