Adaptive Implementation of Water Quality Improvement Plans: Opportunities and Challenges

Adaptive Implementation of Water Quality Improvement Plans: Opportunities and Challenges

L. Shabman, Ph.D.

K. Reckhow, Ph.D.

M.B. Beck, Ph.D.

J. Benaman, Ph.D.

S. Chapra, Ph.D.

P. Freedman, P.E.

M. Nellor, P.E.

J. Rudek, Ph.D.

D. Schwer

T. Stiles

C. Stow, Ph.D.

Nicholas School of the Environment and Earth Sciences

Nicholas Institute

Duke University

September 2007

Acknowledgments

A number of organizations and individuals contributed significantly to this effort. We gratefully acknowledge funding support from the United States Environmental Protection Agency (USEPA) Office of Research and Development, the USEPA Office of Water (OW), the Water Environment Research Foundation, the Federal Water Quality Coalition, the National Association of Clean Water Agencies, the County Sanitation Districts of Los Angeles County, and the Irvine Company. Individuals from these organizations, notably Fred Andes, Margaret Stewart, and Chris Hornback attended committee workshops and offered many useful comments. David Katz was an early enthusiastic supporter of this project and provided helpful advice. Tim Wool from the USEPA was an active participant in the workshops and contributed in many ways to strengthen the report. Francoise Brasier and Mike Haire of the OW were generous of their time so that we could meet and discuss the OW perspective. The Urban Water Research Center at University of California-Irvine hosted one of the three committee workshops, helping us gain a better understanding of TMDL issues in the western United States. Last, but by no means least, QEA (Quantitative Environmental Analysis, LLC), through the efforts of Jennifer Benaman, Leslie Kjellstrand, and Jennifer Marshall provided invaluable editorial assistance that considerably improved the final report.

Table of Contents

Executive Summary

In 2001, at the request of Congress, the National Research Council (NRC) established a committee to examine the scientific basis of the United States Environmental Protection Agency's (USEPA) Total Maximum Daily Load (TMDL) program. The resultant report *Assessing the TMDL Approach to Water Quality Management* was presented to Congress and to the USEPA later that year. The NRC committee concluded that, while the science and data in support of TMDLs were weak in a number of instances, practical reforms were possible that would enhance the effectiveness of the TMDL program. Recommendations made by the NRC committee, including the need to more explicitly consider uncertainty in all steps of water quality improvement planning and the value of adaptive implementation approaches in face of this uncertainty.

One particular concern was that the uncertainty in TMDL forecasts and in the predictions of the efficacy for control actions is often large, with the consequence that implementation actions for water quality improvement might be ineffective and therefore wasteful of limited water quality program resources. The NRC committee believed that this possible consequence of uncertainty was most effectively addressed through a "learning while doing" approach. A water quality implementation plan would be prepared and initial control actions taken. Then there would be an ongoing assessment of the efficacy and costs of the actions, model improvements made based on the new information, and revisions then made to the implementation plan based on new analyses. This was termed *adaptive implementation* (AI) to achieve TMDL reductions and attain water quality standards (WQS). To facilitate this process, the NRC committee recommended more explicit evaluation and reporting of model prediction uncertainty in the development of TMDLs and implementation plans. The NRC report called for AI, but it did not provide vital details concerning how AI could be conducted in the context of the current TMDL program.

In 2004, the Center for the Analysis and Prediction of River Basin Environmental Systems at Duke University convened an expert panel to explore the expanded use of AI in the TMDL program and to produce a report that could be used as a resource

document for the USEPA, the states, and others who develop and implement TMDLs. This report describes approaches for utilizing AI in the face of uncertainty related to data, models, pollutant loads, the impacts of controls, and uses and criteria. The report's scope extends to the applicability of AI for promoting water quality improvement outside of the TMDL program. AI means that once a TMDL estimate and implementation plan is in place, implementation begins, but uncertainty is not forgotten. AI allows a continuing focus on reducing the uncertainty that was recognized in the TMDL and implementation plan, through water body-specific and carefully targeted monitoring, ongoing research, and experimentation. Opportunities to learn while implementing control actions are actively and systematically pursued. The new knowledge focuses on reducing uncertainties in the TMDL, the implementation approaches, and/or the uses and criteria. AI can succeed only if there is a conscious, well directed effort, with sufficient resources to learn, improve decision models, and revisit water quality management implementation plans over time.

The report describes the current water quality management process in order to set the stage for proposing ways to bring AI to water quality management, recognizing that AI is not the appropriate strategy in all water quality management circumstances. As a result, the report makes a distinction between standard (or conventional) implementation of TMDLs and AI, and describes approaches to AI that are executed within the TMDL program and outside the TMDL program as part of a watershed management effort.

Standard implementation (SI) of a TMDL would occur when the level of certainty regarding causes, remedies, and water body condition is high or when the costs of making an error in the face of uncertainty are deemed acceptable. In SI, the only question surrounding the TMDL implementation plan is "when". AI should occur where uncertainty is substantial and the costs of error are deemed significant. The implementation question goes beyond "when" to include "where, what, and how". In cases where

uncertainty extends to the assignment of the WQS (uses and/or criteria), the implementation question also adds "why" or "how much".

What is meant by "error" and the "costs of error"? SI in the face of uncertainty creates the real possibility that strict adherence to the original implementation plan over time will cause resources to be spent on the controls at sources and locations that will not produce desired water quality outcomes. This scenario can be avoided using an AI approach. Another benefit of the adaptive approach is the possibility of continual learning and future implementation flexibility, even while initial controls move forward. This possibility may resolve stakeholder deadlocks, where disputes over defining the "perfect" long-term plan become the enemy of taking any action at all.

AI can take at least three pathways:

- Implementing the TMDL where there is no question about the endpoint to be attained by the TMDL.
- Implementing the TMDL where the applicability of the assigned WQS (designated use and/or water quality criteria) is uncertain.
- Implementing watershed management, where the impairment is the manifestation of stressors lying outside the requirements of the Clean Water Act or TMDL regulations (habitat disturbance, hydrologic modification, and geomorphic alteration).

While there may be crossover among these pathways, the main consideration is the level of uncertainty in the TMDL and/or the efficacy of the implementation plan, with consideration of the costs of error.

AI begins with installation of certain controls to move the watershed in the direction of reducing pollutant loads, while also providing information on their effectiveness in improving water quality at different geographic and time scales. With new knowledge, the original watershed analysis, water quality analyses, and models can be revised to update the estimates of current and future pollutant loads and the resulting water quality in the impaired water body. The new information is used to revise and modify the implementation plan of the original TMDL. If a WQS assessment is added to this mix, then AI expands the concept of "learning while doing" to the assignment of appropriates WQS to the

waterbody. This reassessment of the implementation strategy distinguishes AI from SI.

Outside of the TMDL program, using AI to achieve WQS can be done as part of a watershed management effort. However, TMDL implementation triggers a particular kind of regulatory process linked closely to the National Pollutant Discharge Elimination System (NPDES) permitting program, while watershed management has a broader perspective. Watershed management may be a good fit for impairments that are caused by factors other than regulated pollutants (e.g., man-made alteration of physical, chemical, or biological characteristics of a water body). Therefore, watershed management can implement measures to restore habitat through re-vegetation, combat flow depletion by purchasing water rights, or breach retention dams and re-establish stream functions through geomorphic modifications.

AI is likely to be a more challenging approach to water quality management than SI. The advantages of AI will need to be weighed against these challenges before choosing an AI approach for any watershed. As is noted in this report, impairments dominated by non-point source pollutants represent a particularly appropriate case – but not the only case – for AI. There are specific situations within watersheds where point sources are significant and water quality management would benefit from the AI approach that is described in this report.

Making AI work means addressing several challenges. An organization needs to commit resources to the learning process. More specifically, there needs to be an initial implementation plan, a funding strategy to support the commitment of follow-on monitoring and modeling, and support for continuing stakeholder involvement that will achieve agreement on modifications to the implementation plan over time. When there are point sources of pollutants, attention may need to be paid to possible accommodations for AI in the NPDES permitting process, because AI may result in modification to the TMDL or the wasteload allocation (WLA) over time.

A number of analytic tools are available to assess uncertainty and thus to support the AI process. This report provides a history of uncertainty analysis (primarily in the context of modeling) and presents practitioners with some of the available tools that can aid in uncertainty assessment associated with AI. While these techniques may be unfamiliar to many practitioners, it is important that uncertainty analysis be applied since it

provides key information useful for deciding how to proceed with the assessment for water quality improvement.

More than 20,000 TMDLs have been developed and more will be developed based on current and future impaired water listings.

The current strain on available resources puts a premium on decision making that will direct limited implementation resources toward assuring attainment of WQS. Unless implementation plans incorporate a strategy to reduce the uncertainty underlying many of these TMDLs, states or other organizations may find their ability to attain WQS to be severely tested over the next decade.

Chapter 1: Origins and Purpose

In the 1990s, environmental groups took the USEPA and many states to court to obtain compliance with the 1987 Clean Water Act (CWA) requirement to list impaired waters and develop water pollutant loading limits defined in the CWA as Total Maximum Daily Loads (TMDLs). The courts required immediate listing of impaired waters and set aggressive compliance schedules to develop the necessary TMDLs. In response, the USEPA developed considerable guidance and support for states to perform the required work. However, this was a significant new effort for the states, whose water quality management staff and budget resources were already thin, and where data and models to meet the program requirements were often inadequate. Against this background, Congress asked for an assessment of the scientific basis of the TMDL program. The National Research Council (NRC) convened a committee who completed a fast track study. The overriding theme of the NRC report was that, given reasonable expectations for data availability and the inevitable limits on our conceptual understanding of complex systems:

"…statements about the science behind water quality management programs must be made with acknowledgment of uncertainties (NRC 2001)."

Photo courtesy of Jennifer Benaman.

Perhaps the most widely cited recommendation from the report was that, in the face of uncertainty, states should implement an adaptive approach to achieve the TMDL targets and attain water quality standards (WQS). Adaptive management is a concept that had been developed and advocated for natural resources management decision making under uncertainty for many years (Holling and Chambers 1973; Holling 1978; Walters 1986; Lee 1993). The NRC report indicated that it was necessary to apply the concept of adaptive management to water quality management and the requirements of the CWA. The result was termed *adaptive implementation* (AI) and was described

as an iterative process in which TMDL objectives and the implementation plans to meet those objectives were regularly reassessed during the ongoing implementation of controls.

The central theory of AI is that uncertainty can be reduced over time only by studying and/or modeling watershed and water quality responses to load reductions, implementing controls, and then carefully and methodically assessing the results in order to ***learn while doing***. The learning would be incorporated into improved modeling and/or analysis that would, in turn, lead to more informed decision making. AI was a way to make progress in meeting WQS while also reducing admittedly large uncertainties. The NRC report was clear: the initial TMDL loading restrictions and implementation plans might need to be revised, as new information is obtained. The report also recommended the need to employ various types of uncertainty analyses and expand related guidance.

On a technical level, with respect to the mathematical models representing the natural system, the report called for calculating and representing prediction uncertainty in a rigorous way, while selecting and rejecting model results on the basis of a prediction error criterion. Because relatively few water quality models have undergone thorough uncertainty analysis, it was suggested that the USEPA selectively target post-implementation TMDL compliance monitoring for verification data collection so that model prediction error could be assessed. To carry out that error analysis to support AI, the report suggested using strategies that combine monitoring and modeling to expedite TMDL development, such as Bayesian techniques. Finally, the report called for guidance/software to support uncertainty analysis. Officials who responded to the NRC report indicated that providing technical assistance to the states to allow them to better acknowledge uncertainty and incorporate uncertainty analysis into TMDL-related modeling is a high priority for the USEPA.

Following the NRC report, AI earned many supporters and a great deal of literature was published seeking to explain and expand the concept. Also, questions have arisen concerning how to apply AI, as well as related concepts such as “phased TMDLs”. In a recent memorandum (USEPA 2006; see Appendix B), the USEPA sought to update past recommendations to clarify the concept of phased TMDLs and contrast it with staged and AI. The literature and the 2006 memorandum clearly indicate that it is possible to fit the

general AI concept within the current CWA parameters and regulations governing the USEPA and states' compliance with the Act. However, the need for the 2006 USEPA memorandum illustrated that the NRC report was unclear about how the call for AI meshed with other CWA requirements. For example, while the NRC report was critical of the use of an arbitrary margin of safety (MOS) in setting the TMDL, the report did not explain how uncertainty analysis could be used to meet the CWA requirement that the TMDL achieve WQS. Likewise, an adaptive decision making approach in water quality management is best supported by technical analyses, highlighting key areas of uncertainty that focus on the benefits of learning through implementation, targeted monitoring, experimentation, and literature reviews. However, these analyses can add expense to the planning and implementation process, and states will need to determine when an adaptive approach to implementation is warranted. The NRC report did not provide any guidance for when the AI approach might or might not be warranted.

To address these and other matters, Duke University's Center for the Analysis and Prediction of River Basin Environmental Systems took the initiative to convene an expert panel in 2004:

To organize and conduct a series of expert workshops to write and publish a monograph on the interpretation of, monitoring and analytical requirements for, and execution of an adaptive implementation approach to water quality improvement. The monograph will serve as a resource document to the USEPA as it prepares guidance, in cooperation with the states, on the analytic strategies and collaborative decision making processes for execution of the total maximum daily load (TMDL) program.

The panel (see Appendix A for panel member biographies) was composed to explore the expanded use of adaptive implementation in the TMDL program. They met and corresponded over a two-year period on the concepts and issues. As the panel explored the concepts of AI and adaptive management, it came to realize that the approach also had applicability for promoting water quality improvement outside of the TMDL program. Hence, this report, although initiated and focused on the TMDL program, discusses AI in other contexts as well.

First and foremost, AI is a tool to better develop and implement the TMDLs and thereby promote improvements in water quality for impaired water, despite the inherent uncertainty present in environmental analysis. Second, AI can be used to create watershed management plans for impaired waters that might precede a TMDL and/or supplant the requirement to develop a TMDL. Last, AI can be used as an improved water quality protection tool for non-impaired waters in order to prevent future impairment. It is the belief of the panel that the use of AI in each of these contexts will provide significant progress towards meeting our national goals for water quality restoration and protection.

In the following chapters, we first describe the current water quality management process, setting the stage for better defining AI and then proposing ways to bring AI to water quality management. In Chapter 3, we describe AI and discuss conditions under which states might choose between AI and standard (i.e., non-adaptive) implementation (SI). Chapter 4 follows with suggestions for planning, permitting, funding, and stakeholder involvement approaches that are needed to realize the benefits of adaptive decision making. Finally, in Chapter 5 we describe the technical tools available to support those who choose adaptive decision making approaches.

Chapter 2: Uncertainty in Water Quality Management and the Logic for Adaptive Implementation

This chapter briefly summarizes the process for a watershed-based water quality management program and the place of TMDLs in that program. Then it identifies places where analytical uncertainties can enter and affect the process and inhibit the cost-effective attainment of water quality standards (WQS). The chapter then expands on these basic ideas to explain the case for using AI, setting the stage for the topics of the last three chapters: when to select an AI process for water quality management, the financial and regulatory considerations in making AI work, and the analytical tools available to support AI.

The Water Quality Planning and Implementation Process

In the CWA water quality strategy, states establish WQS for water bodies. The WQS consist of a designated use (such as swimming, protection of aquatic life, drinking, etc.) and criteria that are indicative of the uses (such as bacterial or dissolved oxygen concentration criteria). The criteria are either numeric or narrative. Water quality standards also include an anti-degradation policy. The uses and associated criteria deemed appropriate to specific waters are assigned. Then monitoring data are collected and evaluated to determine if these uses and criteria are being achieved.

If standards cannot be attained by technology-based or more stringent effluent limitations on point sources, the water is listed as impaired and a TMDL must be developed to meet the applicable WQS. In turn, controls on the pollutant are expected to be identified, based on the models and analysis that supported the setting of the TMDL. The TMDL is a calculation of the maximum amount of a pollutant from point and non-point sources that a water body can receive and still meet WQS with a margin of safety (MOS). If the standards assigned to the water body are deemed inappropriate or unattainable, they may be modified if the state conducts a use attainability analysis (UAA) to support such a conclusion. In such cases, a TMDL may not be required or a different TMDL may be applied. In addition, if pollution, for example hydrologic alteration, is the cause of the impairment, a TMDL may not be required.

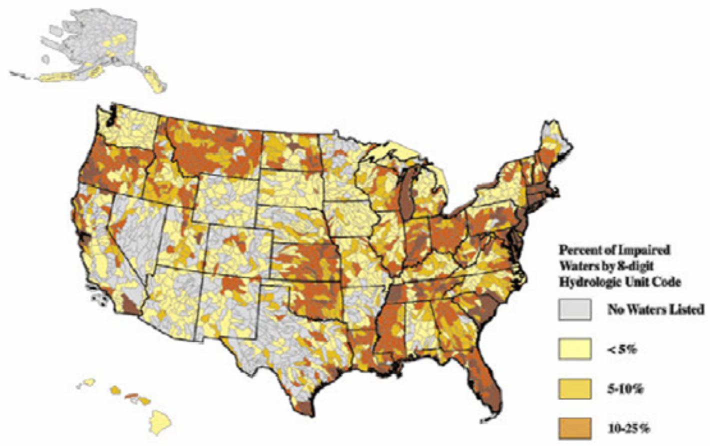
With the TMDL calculated, a plan for controls on pollutants is expected to be

developed (based on the models and analysis that supported the setting of the TMDL). This control plan is expected to be implemented for point sources through limits in their National Pollution Discharge Elimination System (NPDES) permits and for non-point sources through other means. The CWA provides no direct regulatory limits for non-point source runoff. Instead, controls were to be encouraged through various local, state, and federal planning and funding programs.

As implementation proceeds, monitoring data continue to be collected to assess the condition of each water body for which a TMDL was developed and where implementation is underway. Once uses and criteria are attained, the water is no longer listed as impaired, but monitoring continues as a part of the ongoing water quality management process.

Uncertainty Abounds

The CWA water quality strategy appears straight forward, but each step may be accompanied with scientific or policy uncertainty. Thus, the water quality management challenge is how to recognize and accommodate the scientific uncertainty within the CWA. (NRC 2001; Freedman 2001).



Impaired Watersheds.
Image courtesy of USEPA.

Impaired Waters Uncertainty

From time to time, Section 303(d) of the CWA requires a list of waters for which technology-based effluent limitations are not sufficient to meet WQS. A study by the General Accounting Office (GAO 2000) points out that only six states indicated they had enough data to fully assess their waters. Thus, there are (and will always be) data limitations. As a result, there will always be analytical uncertainty in establishing whether water quality criteria are being met and in assessing the effectiveness of implementation in securing WQS. Methods of data assessment that

accommodate the reality of limited data sets and that report the resulting uncertainty for the listing and delisting process must be recognized when assessing progress in achieving water quality standards. The interpretation of these data – the assessment process, – can not only rely on statistical inference procedures, but also may employ water quality models and best professional judgment (BPJ). These same data limitations, with resulting uncertainties, permeate other parts of the water quality management process, as discussed next.

TMDL Load Uncertainty

A TMDL needs to identify the pollutant causing a water quality impairment, identify the sources of that pollutant, and develop load and wasteload allocations that will meet the water body loading capacity. Establishing the target pollutant loadings for the TMDL requires an understanding of how loadings are related to achievement of the WQS, as well as the sources and volumes of existing loadings in the watershed. This analysis requires not only a robust data set, but also an understanding of pollutant origin, fate, and transport processes in the water body.

These understandings are generally represented in models that relate pollutant loadings to resultant water quality criteria, so that needed reductions in existing sources of pollutants can be determined. However, reliable water quality modeling was identified as one of the biggest challenges in the TMDL program both by the USEPA in their 20 Needs Assessment (USEPA 2002) and in the NRC's evaluation of the TMDL program (NRC 2001). Furthermore, in their review of approved TMDLs, the Water Environment Research Foundation (Freedman et al. 2003a) found that only one of six TMDLs actually employed site-specific mathematical modeling, with the rest using generalized models or conceptual relationships.

The central TMDL question, "if loads are reduced by X% will water quality criteria be met?" relies on models. Models are a way to organize knowledge about a water body and then use that knowledge to answer this central TMDL question. Because models are abstractions of reality, the answers to the central TMDL question are accompanied by uncertainty (See Box 2-1). In large water bodies with multiple stressors, site-specific modeling is essential for setting a site-specific TMDL and making fair and

effective allocation of loads to achieve WQS. However, it is in these large, complex water bodies where uncertainty can be especially large.

This uncertainty was anticipated by the CWA, who issued subsequent regulations and guidelines for implementing Section 303(d) of the Act. As a result, the TMDL includes a margin of safety (MOS) to account for lack of knowledge concerning the relationship between effluent limitations and water quality. The USEPA guidance provides that this requirement can be fulfilled by using an explicit MOS such as reserving 10% of the loading capacity or an implicit MOS, which can be included by making conservative assumptions in the modeling process.

In a review of approved TMDLs, Dilks et al. (2004) found that 30% of the TMDLs reviewed did not explicitly consider uncertainty; of the remainder, only one of 120 explicitly calculated the uncertainty and incorporated that assessment into the definition of the MOS.

Box 2-1. Models and Water Quality Management

Models are central to water quality management programs. Models can take many forms (NRC 2001), but whatever the form they all begin with a conceptual representation of the multiple relationships affecting water quality (a conceptual model) and then proceed to mechanistic and/or empirical equations (a mathematical model), followed by measurements and/or scientific judgment to parameterize the mathematical model so that it can be solved for prediction and/or explanation.

Forecasting (prediction) uses models to conduct experiments "on paper" before committing significant private and public resources to an action. For example, models are asked "what will be the effect on the level of dissolved oxygen in an estuary if nutrient loads in an upstream area are reduced by a certain amount?" Another use of models is explanation. For example, if the condition of a water body was monitored (the monitoring would focus on whether the water quality criterion is being met), a model might be used to explain the factors that led to the measured condition or a model could be used to explain why the water quality criterion is not being met in a water body that has multiple stressors.

Box 2-1 (cont'd).

Often the word "model" conjures up an image of a set of linked mathematical equations representing watershed hydrology, geomorphology, ecology, and water chemistry, as well as human behaviors that affect the way that water and waste are handled.

Scientific understanding of watershed processes continues to grow, and the data and computing power to use those data continue to advance, supporting the development of complex models. Nonetheless, complex and comprehensive models may be the exception and not the rule, and may even be inappropriate and unnecessary in many settings. Models will include intuitively held mental constructs, as well as highly complex mathematical representations that are solved by computer algorithms and rely on access to extensive data sets which may not be available. The existing scientific knowledge of the cause and effect relationships; the amount of data, staff and budget resources and time available for conducting analysis; and other considerations will influence the complexity of the analytical model used.

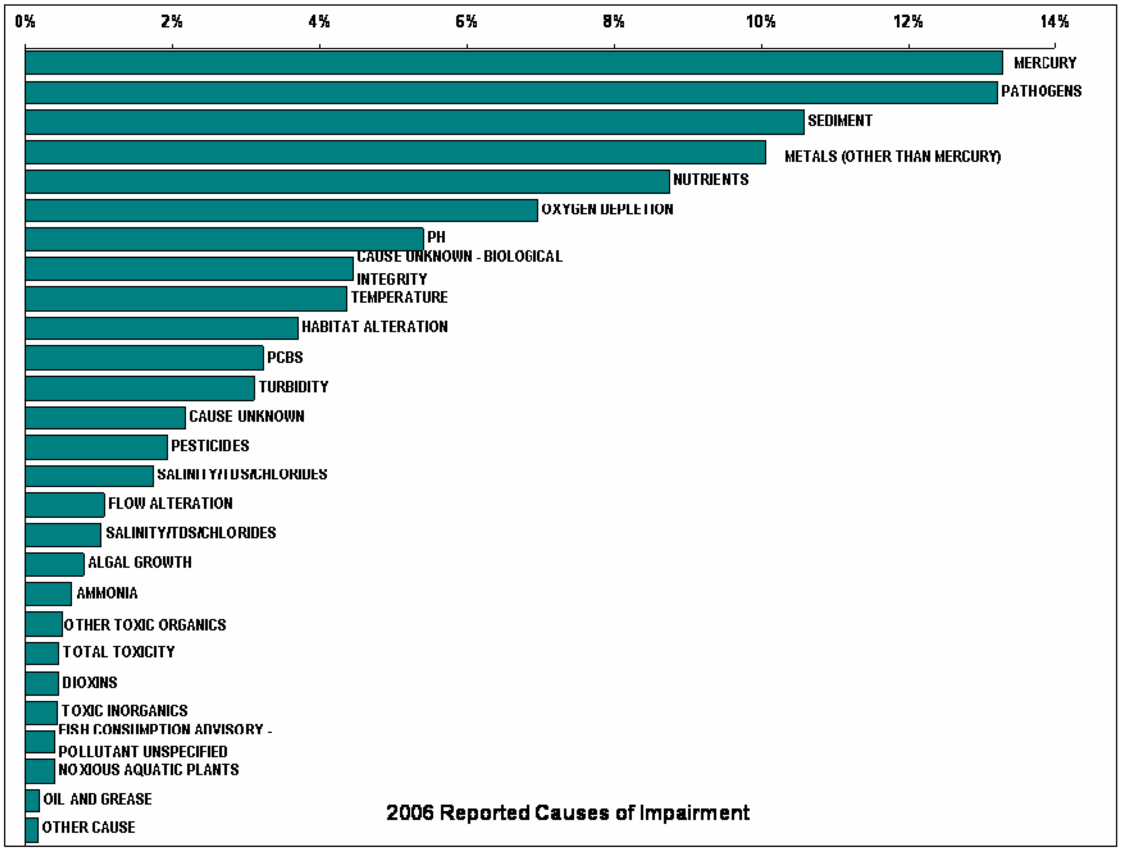
Predictions from simple models may be uncertain, because the models do not reflect the full complexity of a situation. Predictions from complex models also can be uncertain, because data to represent the conceptual ideas in the model are limited or the underlying relationships in the model are not well documented. The reality is that all analysis (predictions and explanations) will be accompanied by uncertainty. This said, models are the central way in which we organize our understanding of complex systems and how they work, and by which we can gain an appreciation for the most significant data and knowledge gaps about how water quality problems arise and may be addressed.

In many cases, a default MOS of 10% to 20% was used as allowed by the USEPA. The NRC report on TMDLs concluded that the level of uncertainty in TMDL evaluations is rarely well defined and often large (NRC 2001). Chapter 5 of this report includes a detailed review of analytical uncertainty and what we know about its causes and consequences for prediction of TMDL load limits and prediction of the effectiveness of controls.

Narrative criteria are another cause of uncertainty in setting a TMDL loading. Many states adopted numeric water quality criteria to support their designated uses without consideration of site-specific conditions or their relationship to actual feasible use. States also adopted narrative criteria that describe certain

characteristics that should or should not be present in a water body. However, such criteria provide no quantitative metric for assessing water bodies or establishing TMDL endpoints (Freedman et al. 2003b). For example, the “no toxic substance in toxic amounts” criterion is often applied in cases where there are fish consumption advisories. Concentrations of a chemical in fish tissue may be used as a TMDL target, even though these criteria are not explicitly listed in the state standards.

Similarly, an “ecologic harm” narrative criterion is often employed for eutrophic conditions to establish nutrient concentration targets. In each case, there is often considerable debate as to the suitability of the parameter and/or numeric concentration. Almost half of the waters listed as impaired are based on narrative criteria on nutrients, algae, sediments and siltation, fish consumption advisories, habitat alterations, and biologic conditions (Freedman et al. 2003b).



Data compiled from http://oaspub.epa.gov/waters/national_rept.control

Implementation Uncertainty

The implementation plan for water quality improvement is based on the TMDL requirement to allocate the allowable loading (the TMDL estimate) between point sources (wasteload allocation [WLA]), non-point sources that could include background levels (load allocation [LA]) and the MOS. That is, the TMDL is the sum of the WLA, the LA, and the MOS. No hard and fast requirements exist for making that assignment, except the general admonition that the TMDL should assure that water quality standards will be attained.

One problem in establishing an implementation plan to secure a TMDL is the large uncertainty in quantifying the contributions of and effectiveness of controls on non-point sources. Comprehensive data are generally available on wastewater loadings of many pollutants of concern through the NPDES permit program, creating an analytical foundation for NPDES and other permitting sources. With approximately 90% of the TMDLs involving non-point sources as the sole or contributing cause of non-attainment, it is critical that expected reductions from controls like best management practices be reliably quantified. However, the USEPA in their *20 Needs Study of the TMDL Program* (2002) identified this as a priority problem. A study by GAO (2000) indicated that only three states felt that they had adequate data to quantify non-point sources loadings or effectiveness. Other research funded by the Water Environment Foundation (WERF; Freedman et al. 2003) found that of more than 200 reviewed TMDLs, 20% had no quantitative estimates of non-point sources and two-thirds of the TMDLs did not quantify individual non-point sources.

Not only does this uncertainty raise questions about the TMDL itself and the necessary MOS, but it also raises questions about the split between the WLA and the LA. Uncertainty about non-point source loadings and only limited understanding of the efficacy of non-point sources controls make it difficult to affirm that the WLA, LA and MOS and the implementation plans that follow will secure WQS. Faced with this uncertainty,

some states have focused their implementation on point sources controls, because those sources are readily measured and regulated. However, such a focus cannot assure attainment in watersheds where non-point sources make a significant contribution to loads.

Use and Criteria Attainability Uncertainty

Section 303(d) of CWA requires states and tribes (or the USEPA, when necessary) to establish WQS for all water bodies. Most states began by adopting the CWA goals of fishable and swimmable uses to be attained statewide, and then identifying criteria that would be indicators of that use (for example, a statewide dissolved oxygen criterion might be a proxy for fishable use). Some states applied the same uniform approach to designating other kinds of uses such as public water supplies, agriculture, non-contact recreation, etc. Because state standards must be reviewed for needed revisions and additions every three years (triennial review process per CWA 303[c]), the state can develop more refined criteria that recognize differences among water bodies even as the use may remain unchanged. For example, a dissolved oxygen criterion for a fishable use might be different between a mountain stream and a low-land black water swamp. As another example, a fecal bacteria criterion may differ depending on whether a recreation use is for water contact or non-water contact. In addition to the triennial review requirement, the CWA's standards setting process includes regulations and guidance that allows for assignment of site-specific standards (uses and criteria) that may deviate from a uniform statewide standard in a particular location. One process that allows for revision/refinement of the assigned designated use is a UAA.

The UAA allows for use changes in response to factors including consideration of natural pollutants, low flow, irreversible man-made changes, hydrologic/hydraulic modifications, and socio-economic hardship. Short-term variances are also allowed based on the same factors and are specific to a particular pollutant and discharger. A study by the GAO (2002) reported that eight of 15 states said they needed to revise their designated uses, and 14 of 15 said their water quality criteria needed modifications. The selection of a TMDL end-point depends on the uses and criteria to be attained, but the uses and criteria appropriate and attainable for a particular water body may be uncertain.

When Does Uncertainty Matter?

When the future costs of a wrong decision are significant, uncertainty takes on relevance when making the initial decision. There is a dilemma of what to do in the presence of uncertainty only when the costs (consequences) of making an error (often a subjective concept as opposed to a calculated number) are significant. However, uncertainty does not need to be taken into account when making an initial decision if the future costs of being wrong are trivial. What future, but less than certain, cost should be avoided and what is an acceptable amount to spend today to avoid that future cost?

In water quality management, costs are realized in many forms. Costs include financial outlays made by governments or private individuals for water quality planning and pollutant control. Costs can also include the adverse consequences to human health or ecological conditions that persist when pollutant control efforts do not lead to attainment of uses or when people rightly or wrongly avoid use of waters that are not suited for their designated use.

Consider this illustration: With some level of confidence, analysts have concluded that there is a water quality violation of a microbial bacteria criterion that was set to support water contact recreational use. However, monitoring data were limited, so there is the possibility that there is no violation. One cost of concluding that the water is impaired is a significant financial outlay for water quality improvement planning and implementation of controls that, in hindsight, may prove to have been unnecessary. Also, once impairment is publicized, there may be public avoidance of the water body and an unnecessary loss of public use values. Considering these costs, it is suggested that more information be collected and analyzed before the impairment determination is made. However, if there was an error in concluding no impairment exists when there is a violation, it could impose another cost: an outbreak of infection with high costs to individuals who come in contact with the water. The possibility of this significant cost may argue for listing the water with less robust data. Now extend this illustration to prediction uncertainty. Prediction uncertainties may result in making expenditures for reductions from the wrong sources or for securing reduction levels that are higher than necessary to meet the criterion. In the presence of prediction uncertainties and in recognition

of control costs versus possible adverse health effects, imposing “conservative assumptions” to accommodate prediction uncertainty may be justified in order to avoid the costs of adverse health effects. While recognition of uncertainty among water quality managers and stakeholders is widespread and not in dispute, differences arise over how to respond to that uncertainty based on different views about the current and future costs of errors that might be made and the acceptability of different costs.

The question that states face is how to develop and when to implement a plan for pollutant control if uncertainty in its many facets is recognized. Some argue that in the face of TMDL uncertainty, more study and evaluation should be done before setting the TMDL limit, making allocations of load, and beginning implementation, especially if control costs are substantial. They might support more explicit risk assessment and beginning implementation if, for example, there is an 80% chance that the control actions to meet the TMDL will result in WQS attainment. This may mean gathering more data in an effort to reduce uncertainty. If control costs are modest, some would choose to move ahead with those controls to meet the TMDL, even in the face of uncertainty, as a logical implementation strategy; others see the decision on what to do under uncertainty differently, because they view the cost consequences differently. By not acting swiftly, a significant and adverse outcome might occur that could have been avoided. That is why some view seeking more certainty for the TMDL as delay and are willing to accept the costs of a wrong decision as being “protective of water quality.”

The Case for Adaptive Decision Making

If an assessment is unambiguous and the water body is impaired, the search for certainty before implementing any controls across sources could be seen by some stakeholders as delay and by others as a necessary step to reduce uncertainty, particularly when significant costs are involved. If something needs to be done, a plan must express what, by what sources, and on what schedule? These are the crucial questions to debate and often spawn dispute among stakeholders. The questions, once a TMDL is prepared, become how the implementation process will unfold over time and what regulatory or incentive instruments will be applied to what sources.

One way to approach implementation we will call ***standard implementation*** (SI). Under SI, uncertainty might be noted, but this uncertainty is not incorporated into a plan of action to be developed after the TMDL is finished. That plan will include control actions, including the writing of NPDES permits, plans for controls on non-point sources, and an implementation schedule for those actions based on existing model predictions of the effect of the identified controls. Actions are defined in the initial time period and then are pursued according to the implementation schedule. The effectiveness of the plan in meeting WQS might be evaluated by whether the implementation schedule for controls is being met, as much as by the water quality outcomes being realized. Such a plan is justified if there is a high degree of confidence in the predictions of the plan's ability to meet WQS. Once implementation of the controls has been completed, the water body is assessed. If WQS are not achieved, new actions are identified and a new TMDL may be required. During this process, monitoring occurs as part of the overall water quality assessment process for the state. If that overall assessment process finds that standards are achieved before implementation is complete, then the adoption of further controls can be cancelled.

Adaptive implementation (AI) means that once a TMDL is in place and implementation begins, uncertainty is recognized. AI requires a conscious, well directed effort, with sufficient resources to learn and revisit all water quality management decisions over time. A continued focus on reducing the uncertainty is recognized in the TMDL and implementation plan, through watershed-specific and carefully targeted monitoring, ongoing research, and experimentation. Opportunities to learn while implementing control actions are actively and systematically pursued, and the new knowledge is brought to bear on reducing uncertainties in the TMDL limit, implementation approaches, and/or the uses and criteria. At any point, as implementation proceeds, any element of overall water quality management might be revisited and revised, including control actions and schedule for their implementation. This ongoing interest in learning how well the plan is working in order to revise the implementation plan and its purposes is what distinguishes adaptive from standard implementation.

Chapter 3: TMDL Implementation Options in the Presence of Uncertainty

Section 303(d)(1)(C) of the CWA mandates that the TMDL "shall be established at a level necessary to implement the applicable water quality standards with seasonal variations and a margin of safety which takes into account any lack of knowledge concerning the relationship between effluent limitations and water quality". The TMDL is developed by the state, with EPA approval (or alternatively developed and issued by the USEPA). It includes an overall pollutant loading capacity, and the load is then distributed as a wasteload allocation (WLA) for CWA-regulated sources or a load allocation (LA) for sources not regulated under the CWA. A MOS accounts for uncertainty about the linkage between the TMDL estimate and the attainment of the standard. In this chapter, we will explain how adaptive implementation (AI) differs from standard implementation (SI), beginning with initial TMDL development that is set to "assure attainment" of the WQS with a MOS. Both include an implementation plan that is predicted to secure WQS.

The requirement to include a MOS makes it clear that TMDLs are to be developed with recognition of uncertainty, but rarely is there consideration of that uncertainty in executing an implementation plan. The uncertainty that is recognized in the analysis leading to the TMDL tends to be put aside, and implementation is proposed and executed as if there was little or no ambiguity about the relationship between the TMDL components and the assurance that the standard will be attained. In the SI approach, the plan is set forth in the initial time period, adhered to over time, and is executed as regulatory and financial resources become available.

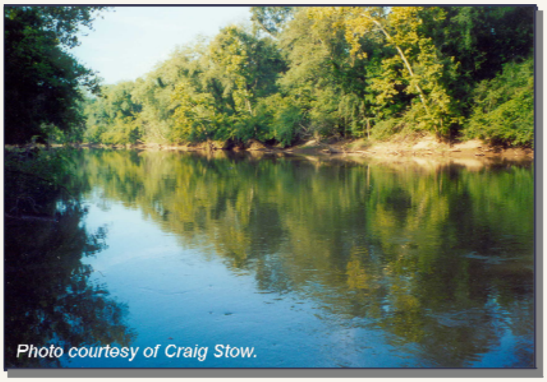


Photo courtesy of Craig Stow.

Adaptive implementation is a conscious effort, supported with sufficient resources, to seek new knowledge as implementation proceeds, with the expressed intent to use that knowledge to continuously revise the initial implementation plan. Adaptive

implementation means that the new knowledge created through studies and monitoring improves our understanding of the water body and advances the models in a continuing decision making process. Adaptive implementation has the dual purpose of reducing pollutant loads and providing new knowledge for improving future water quality management decision making.

Implementation Alternatives: Overview

Regardless of which implementation pathway is chosen, water quality management under the TMDL program follows a five-step process, with steps two, three, and four reviewed by the USEPA as part of a TMDL report (Figure 3-1).

1. Establishment of WQS for the water body being evaluated.
2. Assessment of compliance with standards.
3. Determination of the need for a TMDL.
4. Development of the TMDL.
5. Implementation of controls to restore uses by meeting water quality criteria.

The first step – assigning standards to a water body – is generally viewed as preceding the setting of a TMDL. We will argue that, in some cases, this step can be integrated with the TMDL process to consider the applicability of the assigned WQS. This possibility is shown in the lower right-hand portion of Figure 3-1 and is discussed in detail later in the chapter.

Steps Two, Three, and Four are also shown following the left-hand side of Figure 3-1, as these steps would unfold under SI. The biennial assessment process assembles and interprets monitoring data and other analyses to determine whether the assigned standards are being attained. If they are not attained, then the water may be listed as impaired. A plan is put in place based on the setting of the TMDL and the resulting WLAs and LAs, as well as choosing an MOS. As the plan is implemented, the biennial assessment process is used to evaluate the success of the plan.

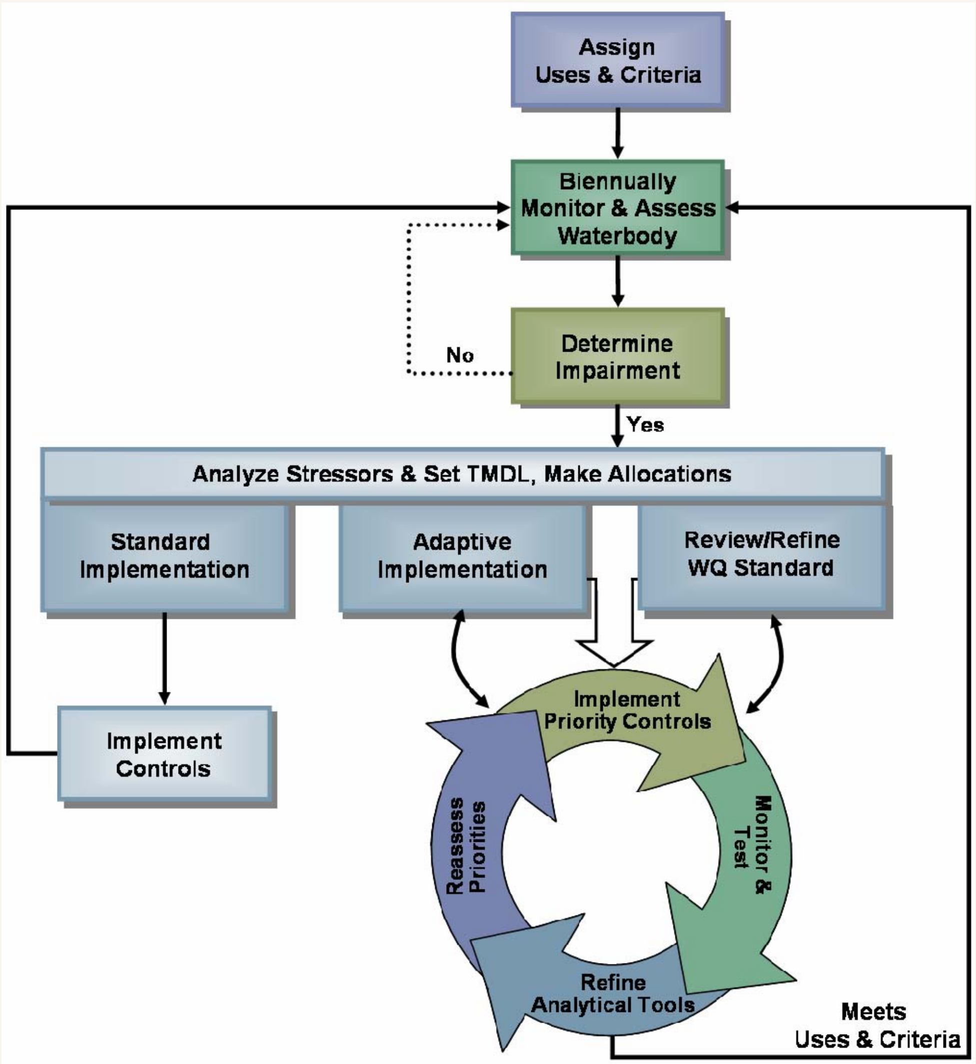


Figure 3-1. Alternative Implementation Processes.

This required biennial monitoring occurs in both standard and adaptive implementation. However, under AI there may be other monitoring activity, as well as other studies and analyses that are consciously dedicated to improving the analytical processes that will be used to make adjustments to future implementation plans depicted in the circular flow in the lower right-hand portion of Figure 3-1. This lower right-hand portion illustrates how adaptive implementation of controls (Step Five) can increase the likelihood that the TMDL will secure the WQS. Using the AI process will require initiative by the states and support from the USEPA, whose support may be found in the 2006 memorandum included in Appendix B (USEPA 2006). It ultimately will fall to the states to choose between SI and AI. In general, SI is most appropriate where the level of certainty regarding causes, remedies, and water body condition is

high and/or the costs of making an error are deemed acceptable. AI is favored where uncertainty is substantial and the costs of error are high.

AI in TMDLs can include implementing the TMDL plan where there is no question about the end point to be attained by the TMDL, as well as implementing the TMDL where the applicability of the original WQS (designated use and/or water quality criteria) is open to review as implementation moves forward. In addition, AI can be used to advance a general watershed management plan, where the impairment is caused in whole or in part by stressors outside the regulatory reach of the TMDL program. These stressors include habitat disturbance, hydrologic modification, and geomorphic alteration. Adaptive implementation means that over time there is an organized and well supported program that uses new knowledge to continually re-evaluate the effectiveness of possible actions to meet the TMDL. Clearly, AI can be resource intensive and, as such, cannot be applied for all waters. AI would be chosen by states only after consideration of site-specific circumstances and the added costs to the decision making process for ongoing planning and evaluation.

Standard Implementation

When a TMDL is followed by SI, there are few concerns with uncertainties about the sources or loads of the pollutants causing the impairment. Similarly, the actions needed to attain the WQS are assumed to be known. The only question in SI is "when". Little or no deviation or modification to the plan is expected to implement the controls that are predicted to meet the TMDL. What is unknown is the availability of resources to implement those remedial controls over time. The TMDL is predicted to be successful in achieving WQS, provided the necessary investments are made to abate pollutant loading to levels prescribed within the plan. Standard implementation can be conducted in stages to spread the costs of controls over time. Post-TMDL monitoring in the biennial assessment process is conducted to determine whether assigned standards are being met. The role of monitoring is to confirm compliance, rather than reduce uncertainty.

As an example, a small stream is listed as impaired for dissolved oxygen. Controls on the amount of organic material creating biochemical oxygen demand (BOD) are predicted to restore dissolved oxygen levels in the stream (nominally at or above 5 mg/l), that will be

secured by controls at a wastewater plant and by preventing cattle from entering the stream. This prediction is made with high confidence. The controls on BOD may be implemented through improved treatment of wastewater. The only uncertainty is how soon funding will be obtained to upgrade the wastewater treatment facility and how quickly land can be fenced by adjacent landowners to restrict access to the stream by cattle. This problem calls for standard implementation.

Standard implementation is appropriate when the causes of impairment are predominantly point sources or clearly defined non-point sources and when the water body tends to be small (to minimize the effect of external factors influencing ambient water quality). Early TMDLs (pre-1995) that centered on point source control lent themselves to standard implementation.

As states develop TMDLs on larger water bodies that are impaired by multiple factors and often involving complex, non-point sources, the logic for SI – the presumption of certainty in all steps of the water quality management process – is less likely to hold. Many water quality management situations across the nation meet this description. More than 40,000 TMDLs remain to be implemented, many of which have no straightforward strategy toward successful attainment of WQS because of these complexities.

Adaptive Implementation

As TMDLs move beyond impairments of simple linear stream segments to a watershed scale, the uncertainty about the complex and dynamic linkages between pollutant sources and water quality results in model prediction uncertainty about the choice and placement of controls. In turn, this increased uncertainty creates the prospect of designing and then executing an ineffective implementation plan. In these places, the implementation question goes beyond “when” to include “where, what, and how”. As these implementation questions become more pronounced and the model predictions that provide answers to the questions are less certain, AI will iteratively employ pollutant reduction measures with the twin goals of reducing loads and reducing uncertainty (through learning) to improve future decision making about needed controls.

Model prediction uncertainty may extend to the estimate of current pollutant loads and the efficacy of control practices in reducing loads. There can be

prediction uncertainty about whether the load reductions, if they are secured, are in the right amounts, in the right locations, and for the right stressors to attain ambient WQS. In situations where non-point sources of pollutants are the primary stressors, there is often a lack of sufficient data and model resolution to represent the spatial and temporal relationships and this leads to these uncertainties. This complicates the selection of possible controls, which may not be fully understood until implementation begins. Further, as the density and land use of a watershed changes, the response and needed controls can change.

Adaptive implementation begins with installation of certain controls; termed “Priority Controls” in Figure 3-1, that move the watershed’s water quality in the direction of reducing pollutant loads, while also providing information on their effectiveness in influencing water quality at different geographic and time scales. With the new knowledge, the original analyses and models can be revised to update the estimates of pollutant loads and resulting water quality. This approach has been expressed as “learning while doing”, and the new information is used to revise and modify the implementation plan of the original TMDL (see the circular flow in Figure 3-1).

This conscious and directed effort at reassessment of the implementation strategy distinguishes AI from SI. Under AI, a premium is placed on the gathering of additional information during implementation to improve future models used to support water quality management decisions. This monitoring investment not only assesses the ongoing status of impairment for the water body (as in the biennial assessment), but also adds information on the effectiveness of controls that have been implemented and those controls being contemplated for future implementation. In addition, AI also can rely on more than just water quality monitoring to reduce uncertainties. Active experimental designs that secure new information on the effectiveness of controls and attention to developments in the professional literature are also a part of AI.

Similar to SI plans, AI initially includes a long-term implementation plan and schedule with milestones. Adaptive implementation also includes a process to collect additional data and develop new information to support updates to modeling for the improved understanding of the water system. A funding strategy

has to be in place to ensure that implementation actions can move forward and that funds are available to support the monitoring, evaluation, and model updating. Stakeholder involvement in decision making, when moving through the AI cycle, will be required as revisions to the implementation plan, the TMDL, or the assigned standards are considered. More on these requirements is provided in Chapter 4.

Starting Implementation: The Initial TMDL

The initial TMDL, including the allocation of the load to the three categories of WLA, LA, and MOS, is based on the models and data available at the time. There are no definitive guidelines on how to make the allocations, except to note that the CWA includes the general expectation that a TMDL will attain standards. In the simplest form, the MOS is a specific percent of the calculated TMDL, based on judgment made by the modeler and the agency on the uncertainty in the TMDL assessment. In some instances, to satisfy the MOS requirement, a series of conservative assumptions are made throughout the model development process that has the effect of reducing the loading left for the WLA and LA. This is called the implicit margin of safety approach. (Box 3-1 includes language taken for the draft Christina River TMDL as an example). If the implicit MOS is used, the sources of uncertainty are made clearer when described in some detail. The discussion of the key areas of uncertainty in the TMDL modeling and how they were addressed is more revealing than an arbitrary percent reduction in the total load. This information can help guide decision making when determining what implementation path – SI or AI – to follow to minimize the likelihood that investments and regulations will fail to achieve the standards. It is even possible that the state could quantify (using the tools described in Chapter 5) the probability that the TMDL as calculated will achieve the standard and use the knowledge of that likelihood to choose either the SI or AI path for implementation. This kind of analysis will allow stakeholders to better understand the certainty in the calculations and comment on the prudence of the SI versus AI approach. Especially important is that this open information on degrees and sources of uncertainty can focus monitoring and other investigations on where the “learning” is needed to reduce the possibility of a failure if an AI approach is chosen.

Box 3-1. USEPA's Christina River TMDL and the Margin of Safety.

MOSs may be implicit, built into the modeling process, or explicit, taken as a percentage of the WLA, load allocation, or TMDL. In consideration of the sheer quality and quantity of data, and the development of the HSPF [Hydrologic Simulation Program – FORTRAN] watershed loading model which will be linked to this EFDC [Environmental Fluid Dynamics Code] model, EPA is utilizing an implicit MOS through the use of conservative assumptions within the model application. An example of a conservative assumption used in this model is the discharge of point sources located on tributaries directly into the model without consideration of attenuation in the tributary water. The effect is conservative in terms of the main stem river segment since modeling directly to the main stem will not consider potential attenuation between the point of discharge into the tributary and confluence with the downstream main stem segment.

This could potentially affect the pollutant allocation scenario. The exact nature of the effect is not known and could be positive or negative. The reverse, however, is not conservative when considering the tributary since negative water quality impacts could be occurring. The ability to model these water quality effects is extremely limited due to lack of resources, time, and data and use of this conservative assumption is valid. Additional factors in the MOS for the TMDLs for the Christina River Basin include:

- *All point sources were set to their maximum permitted loads for the TMDL allocations.*
- *Streamflows were set to critical 7Q10 conditions for the TMDL allocations.*
- *No shading of the stream due to vegetation canopy was incorporated into the model; therefore, full sunlight conditions reach the stream during daylight hours resulting in maximum photosynthetic activity.*
- *Also, no cloud cover was incorporated into the model TMDL allocation runs resulting in maximum solar radiation reaching the stream.*
- *Stream water temperatures were set to critical high values based on historical data at USGS monitoring stations.*
- *Finally, all of the above items occur simultaneously resulting in very conservative conditions for the TMDL allocations.*

Box 3-1 (cont'd).

It should be pointed out that this modeling effort relies on data which could be easily characterized as extensive and high-quality. The number of United States Geological Survey (USGS) stations and water quality stations, period of record, multiple sources of data, site-specific studies, and comprehensive review and analysis of the model application and techniques all contribute to the confidence EPA has in this TMDL analysis.

The EPA argument defending the implicit approach as necessarily conservative can be found within the Christina River TMDL comments and responses (see USEPA 2001).

The initial TMDL will be accompanied by an implementation plan that is predicted, in the initial time period, to secure the WQS. If SI is followed, there is adherence to that plan, and if AI is followed, there is a continuing process to make adjustments to the plan. In either case, the initial TMDL allocations, which are required for an USEPA-approved TMDL, have a direct effect on the design of the implementation plan. The portion of the TMDL included in the WLA is the foundation for issuing or revising of NPDES discharge limits. The portion of the TMDL in the LA defines the scale and scope of strategies that will be required to control loads from sources that are not regulated under the CWA.

If an AI approach is chosen, making this division and knowing that initial control plans later may be revised, the state might focus on control measures in an initial implementation period that are the least costly to implement and easiest to reverse. One approach is to set the overall TMDL with the MOS for model uncertainty and then call for equal percent reductions across all sources that result in the TMDL limit being met. This is a simpler rule that can be applied using output from the existing TMDL models. The result, in a non-point source dominated system, is to put much of the allowable load on the LA side of the equation, and that also is where there is significant model uncertainty about loads, the effects of loads on standards, and the efficacy of load control methods.

A more intentional approach would be to recognize the differences in loading by source and in control costs and to make an allocation that meets the TMDL at the lowest possible total cost. Costs are difficult to calculate precisely, due to cost and control effectiveness uncertainties, but, as a general principle, minimization would be applied to logically exempt sources that have only a small contribution and high control costs. This could lead, for example, to seeking

relatively greater reductions from non-point sources in the initial TMDL, if it appears that those reductions could be accomplished with relatively less capital investment than if the reductions had to be implemented by the point sources. If more information later shows that the non-point reductions cannot be completely accomplished or that greater reductions are needed from the point sources, needed changes can be made in the implementation plan with less concern as to unnecessary control costs or "antibacksliding" restrictions that limit point source permit changes (see Chapter 4 for additional discussion).

Adaptive Implementation with Consideration of Water Quality Standards

This variation to AI incorporates consideration of the appropriateness of the WQS assigned to the specific water body, either as the designated use or as the criteria for that use. In these situations, the questions framing the uncertainty of the impairment include those already addressed through AI, plus the addition of "why" or "how much". "Learning while doing" extends to gaining knowledge and understanding of the attainable uses of the water body and what constitutes actual impairment to those uses. In this case, monitoring serves to reduce the uncertainty between the chemical characteristics of the water and the attainment of assigned uses. In the meantime, certain implementation actions can and should still be initiated to reduce pollutant loads, while the standards assigned to the water body are being re-evaluated. A key distinction of an AI approach that considers WQS is that the gap between current and desired conditions is progressively narrowed, as a better understanding is achieved of loading, water quality response, and an attainable standard that might be set as part of this process.

Designated uses for a water body may be reviewed and revised through a use attainability analysis (UAA), by implementing regulations for the CWA. Changes to the designated uses result in alternative water quality criteria to support the revised use. As an example, an ephemeral stream with a designated use for cold water spawning habitat should undergo a UAA to remove that use because of hydrologic limitations in supporting the use. In other cases, the analysis may show that a use can be refined rather than removed. For example, a generic recreation use might be revised so it applies only to wading (rather than swimming) or to restricting swimming during dangerous high flow

events, if the standards violations are wet weather-related. Or, a use might be geographically limited to the point of application, such as a stream used for a public drinking water supply. In each of these cases, the use would be revised or refined.

In other situations, the uses of the water body, such as aquatic life support or recreation, remain the same, but the criteria might need review to reflect local conditions. An example of impairments where an alternative criterion might be warranted includes salinity issues induced by natural saline intrusion. Often, applicable situations might involve narrative criteria for sediment and nutrients or legacy pollutants. For these, translations of the narrative criteria to attainable numeric criteria may need to be defined or refined if a realistic TMDL is to be written and implemented. These modifications to site-specific criteria are governed by protocols defined by regulation.

In situations where the uses or the applicable criteria need to be re-evaluated, changes are not to be implemented casually; they require thorough examination of the existing conditions, existing uses the relevant science, cost considerations, stakeholder involvement, and application of appropriate regulations or state policies. Detailed discussions of change in uses and criteria are beyond the scope of this report which focuses on adaptive implementation. However, other references and research are available for detailed guidance and regulations (Dupuis et al. 2005; Freedman and Dupuis 2007).

Watershed Management and Adaptive Implementation

Using AI to achieve WQS is not restricted to setting TMDLs and implementing required pollutant reductions to meet the TMDL. Watershed management outside of the TMDL process has been employed for decades to address non-point sources of pollution and implicitly includes an adaptive process, especially when there is ongoing analysis and assessment of the efficacy of the actions being implemented. The watershed management approach is gaining favor with the USEPA, as an alternative to the TMDL process. This is reflected in their guidance on listing decisions, which allows states to put certain waters in Category 4b of the 303(d) list, where water quality is expected to be restored through established watershed management and planning programs in lieu of TMDLs (see Box 3-2).

Box 3-2. An Application of Watershed Management.

An example of an adaptive watershed management approach is the work done by Vermont to reduce phosphorus loadings to Lake Champlain. The initial approach to controlling phosphorus was done through the TMDL process. Vermont made initial allocations of phosphorus loads in 1996 between point and non-point sources. Vermont noted that reductions in phosphorus loading from point source treatment and application of agricultural best management practices (BMPs) were negated by new storm water loadings from developments. Vermont legislation then authorized the development of Watershed Improvement Plans (WIPs) for implementing source controls for storm water. Each WIP is tailored to the conditions of specific watersheds and targets measures in priority areas in phases. For watersheds impaired by storm water, Vermont law requires the state to develop either a TMDL or a state-approved process that includes verification of listed waters, development of storm water management plans, and adaptive management/implementation.

Plan development under the Vermont framework sets targets to balance flow and reduce loads through improving recharge from impervious areas, reducing peak volumes flowing in stream channels, and retaining storm water volumes and associated loads of pollutants via a mix of management measures. The program monitors indicators of each implementation action, changes in primary stressors, and the condition of ecological habitat. This information is used to direct changes in the management strategy, including experimental testing of approaches to improve progress toward meeting WQS. Within Lake Champlain, there is considerable uncertainty surrounding the potential loadings and ambient lake phosphorus concentrations. After each source in Vermont (and New York and Quebec) is addressed, follow-up monitoring determines the goodness of fit for the expected lake response. These post-implementation data also support adjusting TMDL phosphorus concentration targets, the models used to estimate the loads, and resulting trophic state of the lake.

Guidelines for Choosing Adaptive Implementation

Adaptive implementation is more costly and more challenging than standard implementation. Each state will have to weigh the benefits of AI against the added costs (as compared with standard implementation) for each watershed and pursue adaptive implementation in places where there are adequate resources. The following list of considerations will tend to favor adaptive approaches.

Non-Point Dominated Loading Increases Model Prediction Uncertainty

Probably the most significant factor favoring AI is the nature of the pollutant sources, point versus non-point. TMDLs dominated by non-point source pollution represent a particularly appropriate case, but not the only case, for AI. By the nature of the runoff chiefly driving non-point source pollution, the water quality relationship between pollutant sources and the water body is complex and uncertain. The transient and highly variable loading characteristics confound our understanding of precise cause and effect relationships and result in uncertain predictions of responses to current and desired inputs. Further, our knowledge of the precise performance of control measures is weak and highly uncertain. Non-point pollution also typically emanates from runoff over a large watershed area. The same controls in different areas influence water quality to different degrees resulting in more uncertainty. Overall, this situation is ripe for experimentation and adjustments reflecting new knowledge, which is the main tenant of adaptive management.

The institutional context for non-point source controls is also much more accommodating for AI than that for point sources. Load allocations assigned to unregulated non-point sources are typically less explicit. Also, legal constraints on individual non-point sources are minimal under the CWA, and current national policy generally directs that their abatement be conducted via incentive-based programs in a watershed. Hence, without regulatory requirements, implementation land parcel-by-parcel is uncertain, which prompts the important need for monitoring and a review of implementation plans, i.e., adaptive implementation.

Water Body Complexity Increases Model Prediction Uncertainty

Complex water quality management problems have multiple sources of

pollutants, multiple pollutants of concern, multiple pollution stressors, and multiple options for controls. Thus, an estuary of a large river is a more complex system than a small headwater feeder stream to the same river. More complex systems generally pose conceptual or computational modeling challenges and are often "data poor". As a result, model prediction uncertainty for relating the TMDL to the standard and for the setting of the WLA and LA is likely to be greater in complex water bodies. Water body complexity increases the justification for choosing AI.

Narrative Criteria Need Quantitative Refinement

In TMDLs that involve narrative criteria, the exact water quality criteria needed to restore the impaired use is often unclear. As a result, it can be difficult to define the exact level of control needed for point sources and for non-point sources. Ultimate control levels could be more or less and generally can not be defined until more "learning" is achieved following initial implementation. Impairments based on narrative criteria can be potential candidates for AI, even if they involve point sources.

Multiple Stressors Increase Model Prediction Uncertainty

As the multiplicity of stressors increases, there is more uncertainty about the predicted effects of pollutant load reduction actions on attainment of standards. An AI approach is especially important for settings where impairments are caused by pollution as well as pollutants. The USEPA distinguishes pollution as the man-made alteration of the physical, chemical, or biological characteristics of a water body. TMDLs deal with reducing pollutant loads, but are not appropriate for pollution. However, AI, especially in the context of watershed management, can blend federal and state authorities and programs to comprehensively address impairment of waters by pollutants and pollution. Watershed management can encompass measures to restore habitat through re-vegetation, combat flow depletion by purchasing water rights or by breaching retention dams, and re-establish stream functions through geomorphic modifications.

Uncertainty May Lead to a Misallocation of Limited Resources

When high control costs are associated with major capital investments, then adaptive approaches that emphasize facility operational enhancements, BMPs, or small capital

improvements may be the first actions implemented to avoid making expenditures on ineffective controls. Meanwhile, adaptive approaches would be undertaken to better define what is necessary to ultimately secure WQS. Thus, in impaired water bodies with both point and non-point sources, there are situations when the full measure of point source reductions are best deferred and re-evaluated using AI. As noted earlier, an adaptive approach would suggest an initial point source reduction plan that achieved some percentage of reductions whose benefits were more certain.

As an example, while storm water is regulated as a point source because of the CWA requirements for NPDES Phase 2 permits, storm water is non-point in nature in terms of its transient and variable characteristics and uncertain effectiveness of management approaches. NPDES permits for storm water generally require BMPs in urban settings. This condition is perfectly suited for AI wherein you establish goals, experiment with BMPs, and iteratively reduce the uncertainty of water quality response under wet weather conditions, while simultaneously reducing the pollutant loads from developed land.

Situations with legacy sources of pollutants can call for a similar approach to implementation. In some places, the load from point and non-point sources of a pollutant is minor relative to loads from legacy sources (e.g., contaminated sediments) or non-CWA sources (e.g., atmospheric deposition). In these cases, water quality planning and management approaches may favor adaptive approaches because of the high cost and ineffectiveness of achieving significant reductions by controlling current discharges. The legacy and uncontrollable loads would be addressed under another regulatory program or authority. The pollutant control implementation plan would require BMPs or other pollutant minimization actions.

Level of Stakeholder Conflict Impedes Progress

A TMDL implementation plan that ignores uncertainty and the cost of error can often generate stakeholder disagreements and difficulty in moving forward with a TMDL plan. Some, citing uncertainty and possible costs of “overspending” on controls, argue for more study. Others, seeing the same uncertainty and concerned about being “protective of water quality”, argue for an even more stringent MOS (with its

attendant costs). Meanwhile, disputes could arise over the scope of regulatory authorities, the WLA and LA allocation, and the adequacy of the financial resources to implement the plan. The result is often stalemate, legal action, and delay in implementing any water quality improvements. Adaptive decision making approaches are well suited to breaking the deadlock and promoting consensus among disputing parties.

Why Choose Adaptive Implementation?

With SI, there is a real possibility that strict adherence to the original implementation plan will cause resources to be spent on the controls at sources and locations that will not produce desired water quality outcomes. This possible outcome is inconsistent with the CWA; the TMDL is expected to explicitly "assure attainment". The implementation plan that follows the TMDL should deliver on that assurance, but in the face of uncertainty, a plan is at best a naïve promise and at worst a possible waste of public resources that can undermine public support for water quality improvement programs in general. Budget and political pressures are also growing to document actual water quality progress, instead of counting approved TMDL reports and issued NPDES permits. In this setting, SI offers neither the required documentation of performance nor the demonstration that funds are being well spent. Adaptive approaches can offer both.

This being said, the preceding discussion is only a guide to trigger consideration of AI and not a set of rules mandating adaptive over standard implementation. The decision to use adaptive approaches involves a professional judgment, cumulatively considering all of the possible benefits, while recognizing the greater costs and challenges of taking an adaptive approach and stakeholder consensus.

Chapter 4: Organizational, Resources, and Regulatory Challenges for Adaptive Implementation

Implementation plans are usually staged with commitments to move forward as resources and authorities permit, regardless of the implementation approach. A principal difference between standard and adaptive implementation is that AI acknowledges what is unknown and establishes a deliberate, meaningful commitment to learning as implementation progresses, so that future regulatory and investment decisions offer increased assurance that WQS will be met.

AI will succeed only if there is a commitment of resources to the learning process. Previous research has outlined various administrative elements that are necessary to support adaptive decision making approaches, including a plan of progressive implementation, a funding strategy to support the commitment of ongoing monitoring and modeling, and support for continuing stakeholder involvement (Freedman et al. 2004, 2003a). These issues, as well as the need for regulatory flexibility, are discussed in this chapter.

Photo courtesy of Craig Stow.

Implementation Steps

AI begins by taking the steps needed to secure WQS, as identified in the initial TMDL. It is possible that these early steps will be taken in recognition of model uncertainty. The Neuse River implementation process is a case example of AI done outside of the TMDL process (Box 4-1), although in this case, the underlying modeling provided a far richer explication of the uncertainties in the modeling than is true for most TMDLs. An example of a TMDL implementation that comes closer to AI, because there was uncertainty about the uses and criteria, is the implementation plan for the Upper Santa Clara River Chloride TMDL (Box 4-2).

Box 4-1. The Neuse River.

For the Neuse River, the decision by the State of North Carolina with USEPA concurrence was to seek a 30% reduction in delivered nutrient loads to the Neuse estuary from all sources. The decision process was informed by the results from both technical modeling and a formally convened panel of stakeholders. The several models used in developing the initial Neuse River water quality improvement strategy had suggested a wide range of load reductions, and, in some cases, individual modeling efforts calculated and reported errors in the estimates. The WQS that governed the Neuse planning process required that a chlorophyll-a criterion of 40 ug/L be met 90% of the time. One model result suggested that a 30% load reduction might result in a violation of the criterion more than 10% of the time, but the model prediction error was also reported. At the same time and equally important, significant disagreement existed over whether the criterion had sound scientific basis, given the origin of the measured data and uncertainty over whether the criterion was a compelling surrogate for the desired uses. In recognition of: 1) sharply increasing predicted costs in seeking more than a 30% reduction; 2) the uncertainties of the predicted criterion response; and 3) the need for a review of the criterion, a 30% reduction was selected as the first increment. Based on the weight of multiple model results, the general conclusion was that there was a 50-50 chance of meeting the WQS with a more stringent 45% load reduction. Practically, it only was possible to secure agreement on the 30% reduction, but not more. In fact, state officials recognized that failure to reach agreement on an acceptable first increment of load reduction could have resulted in court challenges and delay of any reductions taking place. Instead of delaying water quality improvement actions by seeking an exact and ultimately elusive answer to the correct criterion and long-term strategy, the Neuse River plan is now being implemented with an understanding that the plan will be revisited over time.

The TMDL plan states the following:

It should be acknowledged from the outset that though the predictions and decisions contained in this document are based on the best currently available information, there is substantial uncertainty in them. For this reason, the North Carolina Department of Water Quality (DWQ) intends to follow an adaptive approach to managing the estuary. In other words, DWQ will use the models to guide decision making, but continuing observation of the watershed and estuary, as nitrogen controls are implemented (i.e., Neuse Rules, and other measures such as wetlands restoration and establishment of conservation easements), is expected to be our best approach for determining the appropriate level of management.

Box 4-1 (cont'd).

Point sources have begun implementation of control requirements under an innovative approach to NPDES permitting and the agricultural nutrient reduction strategy in North Carolina, within the Neuse River Basin and Tar Pamlico River Basin Watershed. Management plans serve as an example of control actions as interim goals. In these river basins, county-based local area committees establish a plan using BMPs on farms within their county to achieve a calculated 30% reduction in nitrogen loading from a baseline.

Box 4-2. The Upper Santa Clara River.

For the Upper Santa Clara River, the decision by the State of California, with USEPA concurrence, was to establish a WLA, based on an instantaneous maximum of 100 mg/l of chloride to protect salt-sensitive agricultural uses. This TMDL recognized that there were uncertainties with implementing some of the tasks in the implementation plan for the TMDL, and thus it originally provided a 13-year time frame with re-openers to address changes in the plan and schedule. The TMDL is in the process of being amended/approved to shorten the schedule to 11 years. There was significant disagreement over whether the use and criterion had a sound scientific basis in setting the WLA. Consequently, the implementation plan included special studies at the beginning of the schedule to evaluate what might be an appropriate chloride threshold that could serve as the basis for the development of a site-specific water quality criterion. The implementation plan also included actions to evaluate the effectiveness and reliability of pollutant prevention/source reduction in reducing chloride loadings. This is primarily done through programs aimed at taking residential self-regenerating water softeners out of service, which are a substantial source of chloride. These steps were to be undertaken before requiring point sources to embark on building advanced treatment systems to remove chloride from wastewater at an estimated capital investment of more than $350 million.

After initial actions are taken, there should be a period during which the merits of additional actions are evaluated. The schedule also must include interim water quality goals, based on the model-predicted water quality outcomes for the controls scheduled to be in place at specified times. At those times, an assessment of water quality conditions is made, and reasons for making or missing attainment, including consideration of whether controls have been implemented on schedule, are evaluated and reported to stakeholders. In this way, the time schedule differs

from the implementation schedule commonly associated with SI.

Because learning must occur before subsequent implementation steps, adequate time must be scheduled for new information to be incorporated into updated models. In some cases, the results of well designed experiments may be available in a few years. If larger scale system responses are the basis for learning, then some response lags must be accommodated. It is important to select an appropriate time increment based on the specific situation. One way to truncate the time until there is enough learning to take the next step is to assess progress through models and monitoring. There should be initial consensus in setting up the adaptive decision making program.

Planning, Institutional Organization and Funding for Learning

AI requires monitoring of the whole watershed and of control practices put in place, as well as conscious experimentation, active tracking of scientific literature in multiple disciplines, and application of new data and knowledge to refine the models. At times, less resource-demanding approaches to learning may be appropriate, but there must be some initial commitment to the adaptive process, if AI is to be a true alternative to SI.

Adaptive implementation also requires a commitment of staff and budget, as well as maintenance of the collaborative stakeholder process. The leadership for the models maintenance and improvement function (i.e., use of new knowledge) must be clear and should have an organizational home in a watershed group, a joint implementation powers authority, a state regulatory agency, or other institution formed for the TMDL or that has been formed to oversee water quality in the affected watershed. If a review of WQS and/or multiple stressors on the watershed involves many agency programs, finding a "lead organization" with the ability to coordinate multiple programs for an AI approach should be a priority. In many states, the implementation authorities (regulatory and financial) for point source controls and non-point source controls are fragmented and diffused. As a result, a dedicated organizational form may need to be developed to assure continuity and support for the adaptive decision making process.

The budget costs for such a planning effort (professional staff,

monitoring, etc.) will be significant, and budget requirements will be further increased by the need to support not only technical work, but also the organization and collaborative process. For Lake Champlain, Vermont estimated that coordination in each of the seven direct watersheds feeding into the lake required $75,000 annually. Actual installation of BMPs required annual costs of $2.9 million for agriculture, $300,000 for construction, and $115,000 for back roads in the lake watersheds. Annual monitoring costs were significant; ambient lake and tributary monitoring required $290,000 per year, tracking, and evaluating BMPs cost $282,000 each year, and stream gauging was an annual outlay of $210,000. Additionally, research establishing a linkage of lake and watershed management to lake trophic state was an estimated $200,000 annual cost, while updating land use and land cover databases required $1 to $2 million every five years. However, the budgets available for watershed planning in general and the TMDL program in particular remain limited, illustrating the need for budget commitments over the long term (Box 4-3).

Box 4-3. The Tar Pamlico Case.

The Phase II agreement for the Tar Pamlico Nutrient Trading Program in North Carolina, which ran from 1994 to 2004, included a plan to update the estuarine model at the end of the agreement. Since Phase II was completed and Phase III was initiated, the state decided not to update the model because: 1) funding was prioritized to complete TMDLs in other parts of the state leaving no money for a model update; and 2) the nutrient loading trends in the Tar Pamlico estuary are going in the right direction, and therefore a model update is a low priority. The Phase III agreement signed in 2005 contains a condition that if the standards are not achieved by 2013, then this funding decision will be reassessed and additional load reductions made.

Funding is a challenge facing SI as well as AI. However, the coordination role given to the organization charged with advancing the AI process might provide the added advantage of expediting and targeting funding for implementation. Such an organization need not have its own funds, but could include in its mission leveraging and coordination of funds from other sources. By pooling resources from all levels of government and from the private and non-government organization sectors, activities can be advanced without waiting for assistance from any one revenue source. If adequate funding levels are developed through pooling of resources, various tasks necessary for implementation do not have to compete against one another for funding. It is especially important to keep in mind that many funding sources have rules and conditions that limit their role in supporting certain activities. By leveraging the resources, many of these constraints, such as cost-share provisions and purchase restrictions, can be managed without disruption with the scheduling of tasks. The multiple tasks, both continuing evaluation as well as implementation, that are essential to the success of AI can draw upon many sources of funds for support. Box 4- 4 includes programs that are illustrative of the scope of possibilities and suggests the value in having a coordinating mechanism that can administer and oversee the flow of funds for program execution.

Box 4-4. Sources of Funding for AI.

Modeling, a central feature of AI, can be supported by USEPA funds under Sections 106, 104(b)(3), and 319. Federal support for improved and enhanced monitoring is also available under these programs. The Corps of Engineers' Planning Assistance to states' programs may also support modeling efforts. Watershed planning, coordination, outreach, and development programs are supported by the EPA 319 program and may draw upon the Natural Resources Conservation Service (NRCS) PL-566. Implementation of controls can be advanced through the revolving loan program and through United States Department of Agriculture (USDA) programs such as the NRCS' Environmental Quality Improvement Program, Conservation Security Program, Conservation Reserve Program, and Wetland Reserve Programs. The NRCS can also offer technical advisory services to land owners.

Box 4-4 (cont'd).

Most states have seen their general funding for planning and implementation restricted due to budgetary constraints. In response, many have developed alternate funding mechanisms to supplement water quality management activities. For example, the Kansas State Water Plan Fund charges $.03/1000 gallons of municipal retail water sales to generate $1.5 million annually for implementing BMPs, and the Maryland "flush tax" adds funds for cost sharing programs to reduce nutrient loads to the Chesapeake Bay. Dedicated taxes, such as Missouri's 1/8% sales tax for soil conservation projects and the taxes paid to support the Florida water management districts, are examples of special taxing authorities. In Kansas, $2 million of lottery revenue is annually transferred to the Kansas State Water Plan Fund. Vermont imposes a fee of $30,000 per impervious acre, which can be discounted by installing storm water control practices to improve water quality, recharge, and stream channel protection. Similar programs of storm water fees can be found across the nation.

In kind services that support planning could be integrated into a project for executing an adaptive process. For example, more resources for monitoring could be made available by developing effective, credible citizen monitoring programs. The Volunteer Water Information Network is an example of a good citizen monitoring program (i.e., http://www.unca.edu/eqi/vwin.htm). Citizens are trained by University of North Carolina (Ashville) professors and samples are collected off bridges where distance to stream surface has been calibrated to river flow allowing loads to be estimated. Furthermore, collaboration in their monitoring programs among dischargers to measure not only outfall effluent, but also ambient conditions might be expected. North Carolina was able to monitor nearly 40% more waters with the same level of effort after monitoring was conducted on a more coordinated watershed basis (USEPA 1996).

Regulatory Support to Adaptive Approaches

Adaptive implementation is justified in part by uncertainty over the precise TMDL limit that will secure a WQS. Even though precise numbers may not be available, an example of this uncertainty could be as follows:

If $100 million is spent on controls to reduce loads by 30%, modeling indicates there is an 80% probability that the resulting reduction will achieve the water quality criterion. If $400 million is spent to secure a 40% reduction in load, modeling indicates there is an 85% probability of meeting the water quality criterion.

Furthermore, these probability estimates themselves have a confidence interval of +/-15 %.

In reference to these example numbers, because significant cost increases do not “assure” a significant increase in the probability that the criterion will be achieved; the initial action might be to make a 30% reduction, with an initial WLA and LA to secure that reduction. However, the current TMDL regulations require that the initial calculation of WLAs and LAs must show that the WQS would be met. But, in the face of uncertainty, even major additional expenditures often will not provide the additional assurances that standards will be achieved. The commitment of AI is to determine if additional reductions are warranted. Nonetheless, guidelines and regulatory approaches that accommodate the possibility of AI are necessary for NPDES permitted sources. This accommodation of AI may result in modification to the TMDL or the WLA over time. However, we need to assure that the NPDES permitting process progressively implements NPDES source controls, while not delaying the progress towards WQS.

The obstacles in the current NPDES process to executing meaningful adaptive approaches for point sources can be significant. For example, in the case of AI, a TMDL could be adopted with stringent allocations, but the wasteload allocations that are necessary are uncertain and have a high compliance cost. Later, there is recognition that the WLAs could be relaxed based on newly available scientific information and new modeling of the system that shows either that the TMDL was too low, and/ or that the split between the WLAs and LAs that would secure the TMDL loading capacity was in error. If the NPDES permits for sources under the WLAs are issued before the new information is secured, those permits must contain effluent limits “consistent with” the adopted wasteload allocation, in accordance with federal regulations (see 40 CFR 122.44(d)(1)(vii)). Once that permit is issued with the TMDL-based limits, anti-backsliding requirements could apply. Consequently, even if the TMDL or the resulting WLA and LA split is modified, or a new TMDL is issued to replace the first one, it may not be possible to modify the permit to give dischargers the relaxed limits that are recognized to be appropriate (see CWA Sections 402(o) and 303(d)(4)).

However, there may be some room for flexibility. EPA needs to clarify the application of anti-backsliding concepts

where a source receives a limit based on a TMDL, and the state then revises the TMDL to provide a higher allocation for that source as the result of AI. In some of these circumstances, EPA could craft a flexible approach that would allow the limits to be revised, consistent with the anti-backsliding provisions (see Appendix C for more detail).

Compliance Schedules

Regulatory requirements need to be predictable enough to allow for reasoned investment decision making by the regulated parties who will make investment and management decisions that affect the operation of their facilities. This need for predictability can affect the time schedule for the adaptive program. In most states, a permit compliance schedule would be limited to three years within the term of the permit. In other states, the schedule is limited to five years, the same term as the permit. As a result, the final effluent limits (i.e., water quality-based effluent limits) must be met by the end of the compliance schedule as a permit condition. Because AI involves a process of data collection and reassessment to adjust allocations that generally takes substantially longer than three to five years, final permit limits likely would be set prior to the possibility of modification as the result of AI. One way for EPA to address this situation is to issue guidance to the states, indicating that they can and should issue compliance schedules longer than five years to sources that are receiving limits based on an adaptively implemented TMDL. (EPA has already allowed some states to issue schedules longer than five years in appropriate circumstances.) In order to issue these longer-term schedules, some states may have to amend their rules and/or statutes; otherwise this option would not be available in those states.

If the uses and criteria for a water body selected for AI are reassessed, then the timing implications must be recognized in the adaptive decision making schedule. However, this is not the same process as the triennial review of state WQS and need not adhere to that three-year schedule. In fact, the process of reviewing the assignment of uses and criteria, whether through a UAA or through the development of site-specific criteria, will typically focus on the refinement of uses and criteria for the site-specific circumstances rather than making widespread changes in standards. The decision steps and related analysis of the attainability of uses and criteria through the TMDL process and resultant controls on point and non-point sources

should unfold as part of a clear schedule in the AI process. In some cases, such as the Upper Santa Clara River Chloride TMDL (see Box 4-2), this may occur early in the schedule; in other cases, such consideration should await the learning that is necessary and expected as a part of the AI process. Assurances of the viability of the AI process must be in place. Without such assurances, some stakeholders might feel that their only opportunity to get actions that will secure WQS will be when the initial TMDL is completed and an implementation plan set, even if it is a staged implementation process.

In the absence of clear guidance from EPA, permitting authorities may not be willing to allow revision of permit limits based on the adaptive processes described here. The result would be to restrict subsequent revisions to point source discharge limits developed from a TMDL as the result of an AI process. That would make it very difficult to use adaptive concepts for any TMDL that involves point sources, unless the implementation plan makes it possible to modify point source control requirements through the adaptive processes over time.

Approaches to permitting are needed that can accommodate all stakeholders' concerns and allow flexibility. The USEPA has promoted watershed approaches to permitting and concepts of trading that could help in this regard. These approaches are described further in Appendix C.

Stakeholders and Adaptive Processes

Adaptive decision making is ultimately about making societal decisions based on acceptable costs, willingness to accept risk of making errors, and water quality goals. This means that AI demands a well-supported and continuing collaborative stakeholder process. The volume of literature about the promise and the challenges of collaborative decision making – and collaborative learning – for environmental management has greatly increased. For watershed-based water quality management, the general commitment to stakeholder involvement and collaborative decision making will need to be given a specific form that is not only sensitive to CWA processes, but also pays attention to the economic, legal, chemical, biological, and engineering dimensions of decisions of the adaptive approaches.

The process must be designed to provide stakeholders with incentives to stay with the collaboration over time. If

participants seek other regulatory or legal avenues to advance their individual objectives, the adaptive process will falter. Keeping everyone “at the AI table” over time will require skill and commitment as well as organizational, legislative, and executive branch support for the adaptive process.

There are many specific design questions that are well explained in the collaboration literature, including matters of representation, decision rules, and much more. These design requirements can be addressed and may differ from watershed to watershed, but before any specific process is designed, it would be advantageous to have an advocate for AI as a different way forward. This needs to be more than a local stakeholder advisory committee or watershed group. There needs to be strong support by agency management to move in a direction that is outside of the conventional TMDL procedures. One key challenge will be clarifying the decision-making roles and responsibilities of governmental units in the federal system. The USEPA, the states’ water quality management agencies, and local governments all will have responsibilities. At the same time, the roles and decision authority of regulated parties, citizens, and interest groups such as environmental organizations will need to be recognized. In that regard, the USEPA should issue guidance for the TMDL program that supports AI approaches. The concepts for AI and the technical requirements identified in this report can be the foundation for this USEPA action.

Moving Forward

By its very nature, AI eliminates the tendency to establish – or to pretend to establish – certainty in decision making before acting, but the logic for AI over SI will need to be carefully explained and defended. Adaptive implementation advocates must speak to the public about the uncertainty that exists throughout the water quality management process. The public should not expect that an agency can always declare with confidence that certain actions will (or will not) secure a water quality standard. At the same time water quality managers can be caught up in the search for certainty before taking action, fearing that they may be held responsible if they pursue a water quality strategy that later proves to be wrong. The result can be delay rather than progress as more analysis is called for to resolve uncertainty before acting. Stakeholders who might bear significant costs under standard implementation become allies in the search for certainty

before acting. Pretending there is certainty when there is uncertainty, and proposing SI over AI, can lead to vigorous, and often counterproductive, disputes over what courses of action to follow, resulting in a stalemate and no action. Adaptive implementation advocates should emphasize the opportunity to learn while doing so that the reality of uncertainty does not become the enemy of progress in water quality improvement.

Chapter 5: Uncertainty and its Role in Technical Analysis for TMDL Development and Adaptive Implementation

Why Focus on Uncertainty?

The NRC committee recognized that a major impediment to successful TMDL development was the substantial uncertainty in TMDL modeling (NRC 2001). TMDLs are typically based on a one-time modeling exercise; that is, a model is selected or developed, adjusted to fit the water body of concern and then applied once to evaluate the stressors (pollutants and pollution) causing the impairment and to set the TMDL limits for the pollutants. Based on these models, a WLA and LA decision and an implementation plan must be developed to meet the water quality standards. This approach would be acceptable if water quality models were highly reliable. However, most models have extremely large prediction errors, based on model applications for which prediction error was assessed. Furthermore, simply applying an MOS to address uncertainty will not prevent the possibility of making implementation decisions that fail to secure the standards or that do so at unnecessarily high cost. Recognizing this, the NRC committee argued for "a second chance" to reset the implementation plan if the initial TMDL proved to be inadequate or wrong. It was primarily for that reason that the NRC report identified AI as the path forward (NRC 2001).

Lynn Betts, USDA NRCS.

The greater the cost of uncertainty, the more an adaptive approach to water quality implementation actions is warranted. Specifically, the greater the uncertainty that the forecast load reduction will achieve compliance, the greater the likelihood for unnecessary costs (pollutant control and/or environmental damage), in contrast to situations with relatively little uncertainty. Adaptive implementation reduces uncertainty through the "learning while doing" process. However, data and analytical tools must be available for analysis if the promise of AI is to be realized. Fortunately, these tools are available now and can be put to immediate use.

Why Do We Need Tools to Understand Uncertainty for Adaptive Implementation?

Under current practice, an explicit MOS (e.g., a 10% or 20% reduction in the model required for the TMDL) is often selected in place of conducting a model uncertainty analysis during TMDL development. To facilitate TMDL approval and move expeditiously to implementation, this practice might continue under SI, but there should be a clearer description of the basis for the chosen percentage (e.g., a previous uncertainty analysis), especially if there is a reason to believe that ±10% or ±20% is smaller than the actual uncertainty. Another alternative is to derive the MOS based upon model applications that employ conservative parameters (i.e., an implicit MOS). Here too, it would be expected that there would be reporting of the key sources of uncertainty in the TMDL report.

If AI is chosen and the implementation phase begins, a more formal uncertainty analysis with the TMDL and load allocation models will be useful in the assessment of progress and the rapid determination of any necessary modifications. Of particular importance, the uncertainty analysis at this stage would allow post-implementation monitoring data to be combined with pre-implementation model forecasts; this would yield the most reliable early assessment of the success of the load reduction allocation and allow for using the new data to make model refinements, with the improved model identifying needed modifications in the implementation plan.

In a complex model, in which many constituent hypotheses about the behavior of the given environmental system are assembled, it is possible to argue that all of the model's components are subject to uncertainty. The model's input functions, such as upstream water quality for a given stretch of river and effluent quality from point source discharges, will be subject to uncertainty, especially when looking to the future; as too will be the present conditions of the state variables (such as current in-water body concentrations of pollutants) and the set of model parameters (and the correlation between parameters). Even the assumptions about the structure of the model are uncertain, i.e., the mathematical expressions for the way in which the inputs relate to the state variables, the state variables amongst themselves, and the state variables to the observable output responses of the system (e.g., the water quality criterion).

Many of the system's input functions, such as the concentrations of pollutants in agricultural runoff, will be largely unknown, being subject to a sparse and, therefore, uncertain empirical knowledge base from the past. Policy actions, such as future input functions, cannot be assumed to be known with certainty. There is no guarantee that contemplated upgrades to a wastewater treatment facility will perform as assumed in planning. Because of this reality, formal uncertainty analysis can help to isolate the most critical unknowns that need to be addressed as the implementation proceeds.

The effort expended to quantify uncertainty should be commensurate with the costs or risks of making the wrong decision. Here again, it is hard to discern, *prior to* conducting the analysis of uncertainty, exactly what those costs might be. One early approach might be to enumerate the levels of uncertainty through conservative assumptions on estimated inputs, state variables, and model parameters. That is to say, the first assumptions will be to err on the side of presuming more, as opposed to less, uncertainty should apply. As experience accumulates, quantification of uncertainty can be based on more refined assessments of the available field data and, for example, the accumulating body of estimates quoted in the literature on the range of values expected of the model's parameters. Yet, given parameter uncertainties and correlations, a more sensible approach to model calibration is not to focus on determination of single, point estimates of those parameters, but to estimate parameter sets that meet an acceptable fitting criterion.

The practical determination of the acceptable parameter sets of a given model, the need for developing monitoring plans in the face of uncertainty, the uncertainties in the correlations and relationships between model parameters, and sometimes even uncertainties in model input and output all substantiate the need to not only understand uncertainty, but to have practical tools to apply to situations. These tools can be simple, such as a one-at-a-time sensitivity analysis, or complex, such as a Monte Carlo Simulation (MCS), coupled with model performance criteria. Whether the approach is simple or complex, the need to understand is still dominant.

The History of Analyzing Uncertainty in Practical Applications

During the 1970s when assessing the consequences of model uncertainty, there emerged the familiar tension between using a simple, approximate method (called first-order error analysis) or employing the more complete, but computationally intensive, approach of some form of MCS (Beck 1987). A hybrid compromise was also possible. The behavior of the full, high-order mechanistic [1] model could be approximated by a much simpler, low-order regression-like model, and MCS could then be applied to the latter. Nearly all these early studies focused on the problem of managing lake eutrophication, including the use of a highly complex model for the carbon-, nitrogen-, and phosphorus-cycle dynamics in Lake Ontario (Di Toro and van Straten 1979; van Straten 1983). Results showed that a 10% error on the model parameters, on the initial states assumed for the lake, and on the solar radiation patterns (i.e., inputs to the model) could lead to prediction errors of the trophic state well above 100-200% (as compared with monitoring data) during certain periods of the annual cycle (Argentesi and Olivi 1976). van Straten's (1983) results for the model of Lake Ontario likewise underlined the considerable magnitude of the errors in predictions that might be obtained: of up to 2050% for example, although the parameter errors relevant to this analysis were correspondingly high, with individual values exceeding 1000%. The results of Scavia et al. (1981), working with a version of the same Lake Ontario model adapted for the inner portion of Saginaw Bay, Lake Huron, were similar to those of van Straten (1983). For parameter, initial-state, and input-disturbance error levels ranging between 24% and 202%, maximum prediction errors of between 148% and 772% were obtained. The same sorts of results are reported in Beck and Halfon (1991) in their analysis of another mechanistic model of Lake Ontario. In all of these, some of the highest prediction error levels were associated with state variables representing zooplankton concentrations. Ample evidence from those first few studies suggested that the mechanistic models of water quality available at the time, in particular the larger, higher-order

[1] *A mechanistic, or process, model is one that is claimed by the modeler to adequately represent the scientific theory in the equations of the model. This is in contrast to an empirical, or statistical, model that is a statistical (e.g., regression) fit to data and may not express relationships consistent with scientific understanding.*

models, gave predictions that were highly uncertain with coefficient variations upwards of 700% (if such a statistic has any real meaning). To be able to predict only that all things are more or less equally probable (i.e., there is no difference in predicted outcomes because of uncertainty) is not a useful basis for regulatory and investment decision making.


Sarah Wilson, USDA NRCS

The invaluable outcome of such research is that analyses of the uncertainty attached to the model's predictions should allow one to rank the contributions to that uncertainty arising from the various sources: the assumed future input functions; the current state of the system; the model's parameters; and the uncertainty/error in the model's structure. For example, parameter uncertainty was found to be much more significant than initial-state or input-disturbance uncertainty in the study of Scavia et al. (1981), whereas Somlyody's (1983) analysis of a one-dimensional model for the seiche behavior of Lake Balaton, Hungary, indicated that uncertainty in the wind direction (an input disturbance) would be considerably more important than uncertainty in the model parameters, such as the bottom friction coefficient. Given the inevitably limited budget for further research, the analysis of uncertainty identified better wind-direction observations as the *priority* for future investments in field work. This kind of outcome is precisely why AI is advocated. While actions to control pollutants are being pursued, additional monitoring and experimentation aimed at reducing model uncertainty for future decision making are also undertaken.

In the modeling research community (particularly among hydrologists and water quality modelers), it is becoming increasingly recognized that models – mechanistic models in particular – suffer from what is called "a lack of model identifiability". That is, given a set of historical field data and a candidate model structure with system, states, and parameters, many combinations, or "sets" of values for the parameters can be found to yield more or less equally good fits of the model to the data. This is plausible, in part, because all models are approximations of the actual processes, and because essentially all parameters

are effective (e.g., spatially- and temporally-averaged) values that are unlikely to be adequately represented by a fixed constant. This condition, also called "equifinality", is well-documented in the hydrologic sciences (Beven and Binley 1992; Beven and Freer 2001), but has only rarely been presented in the water quality modeling research literature (e.g., Omlin and Reichert 1999; Benaman 2003).

So, the modeler must confront the question: which of those combinations of model parameters (and structures) should be used for predicting future behavior? If only one such combination is used, it might remain valid under predicted conditions that are radically different from those of the past, not the least as a function of the contemplated actions of management, but, just as likely, it might not remain a valid parameterization of the model for the future. For example, if a model of a river is calibrated to historical data that is representative of a relatively wet period, how certain are we of the predictions of that model to a condition that simulates extended low flows or even droughts? Under this deterministic scenario, with no account being given of the uncertainty surrounding predicted future behavior, the community of stakeholders might be entirely unaware and (mistakenly) supremely confident in pursuing the wrong course of action. If all possible combinations are tried, all outcomes in the future might be rendered equally probable, as the results from the aforementioned 1970s and 1980s research demonstrated [2]. Yet, there would at least be the scope for acknowledging the need to acquire more information before acting, as well as indications of the specific direction in which best to search for this information.

Still, decisions to address WQS violations must be made, regardless of the inadequacies of models (or data). In previous chapters, we argue that an AI process uses uncertainty to determine an initial course of action, rather than ignoring uncertainty and its accompanying costs or be paralyzed by uncertainty. Hence, the technical challenge is to identify practical

[2] *There are certain factors, relating specifically to the possible consequences of identifiability that will tend to counterbalance the generation of such enormous prediction error levels: these are the effects of covariance (correlation) among the estimation errors of the model parameter values. For instance, in van Straten's (1983) case study of Lake Ontario, it was possible to reduce the prediction errors by more than an order of magnitude when correlations among the parameter estimation errors (with correlation coefficients of up to 0.8-0.9) were taken into account.*

approaches for estimating uncertainty to begin that AI process. With this knowledge, the modeler has an obligation to inform decision makers of the prediction uncertainty in the models, so that decision makers can determine when an AI approach to reduce that uncertainty is warranted.

The Use of Sensitivity Analyses to Guide Targeted Monitoring

Sensitivity analysis (see Reckhow [1994] and McMahon et al. [2003] for examples) is a useful technique for determining post-implementation monitoring priorities for a watershed. Using sensitivity analysis, we are able to determine what/where/when monitoring and experimentation would be most useful for reducing TMDL forecast error. This is accomplished by running the model with changes in, for example, one or more uncertain parameters; the level of these changes should reflect the uncertainties in the parameters. The parameters that yielded the largest changes in the model response would then be top candidates for further research or monitoring to reduce prediction uncertainty. Note that sensitivity analysis, which focuses on the effect of errors in one or a few parameters on predictions, is different from uncertainty analysis where the objective is to assess the effect on predictions of *all* error terms in the model.

Assessing Status and Progress

Given the number of TMDLs and the cost of water quality monitoring, it seems likely that the progress of many TMDLs will be assessed with relatively small post-implementation datasets. Yet, if the TMDL is employing AI, even a limited-scope monitoring program can be designed with "learning while doing" as the basis for special post-implementation studies. In some instances, the states may be able to rely also on their 303(d) monitoring to augment the reassessment. This may have some merit because lags in system response and natural variability in water quality can delay definitive (e.g., statistically supported) conclusions concerning compliance with standards. However, assessing compliance using model-estimated concentrations alone is probably less reliable than measurements, because of the uncertainty associated with the model and model parameter estimates. Thus, combining monitoring data from an appropriately designed monitoring program with model predictions should be a prudent strategy for assessing compliance (see the Bayesian approach described in Appendix D).

Because model parameters often are estimated based on historical data, predictions of water quality concentrations can be irrelevant to current or future conditions. For example, when a model is used for TMDL planning, the model's parameters are inevitably estimated, based on pre-TMDL data. Once the TMDL program is implemented, changes in waste generation and delivery processes may require a modified model or modified model parameters. As a result, updating a model's prediction using monitoring data is an essential requirement of an AI approach to the TMDL program. One way this may be done is as follows:

- **Step 1**: Apply a water quality model to define the allowable pollutant load; the forecast from this model provides the initial estimate of how the water body will respond to the required pollutant load reductions. Uncertainty analysis must be part of the overall modeling process, as an estimate of error in the model forecast is needed for the learning step in AI.
- **Step 2**: After the load reductions are implemented (i.e., non-point and point source pollution controls), a properly-designed monitoring program is established; this program can be focused on the results of a sensitivity analysis associated with the assessment of particular pollutant controls and/or on overall water body compliance with standards. In addition, there may be field experiments and, in all cases, careful tracking of the professional literature. All these activities have the intent of improving the decision support model.
- **Step 3**: The pre-implementation model forecast (from Step 1) could be combined with the post-implementation monitoring, perhaps using Bayesian analysis (from Step 2); this provides the best overall estimate of success and provides the basis for any necessary revisions to the TMDL and/or to the model (see Appendix D).

Step 3 is the critical learning step, and what is learned is recorded by making improvements to the initial model. For the specific water quality impairment under consideration, the initial model forecast is revised in light of the monitoring data, with each (model and data) weighted by its uncertainty. In an

iterative manner, as uncertainty is reduced, each revised forecast should lead us closer to attaining the standard.

The concepts expressed in the three steps may be generalized in an informal way when error calculations are not feasible, perhaps due to the complexity of the model coupled with limited data. For example, in Step 1, previous applications of a particular model or perhaps expert judgment (elicited from a water quality modeler familiar with the model being used) can become the substitute basis for the calculated pre-TMDL model forecast error. For the design of the monitoring program in Step 2, sensitivity analyses using the model should reveal critical terms for improved estimation when combined with judgmental or statistical estimates of error. If the model is found to be sensitive to particular parameters or to particular observations (in the calibration step) and these parameters/observations are relatively uncertain, then these parameters or observations become candidates for post-implementation monitoring/ experimentation. More formal and rigorous approaches are identified and briefly described in the Appendix D, with references that provide essential details.

A Final Thought on Uncertainty Analysis

We live in a world in which we constantly encounter uncertainty associated with our proposed future actions, whether it involves financial investments, job selection, or protection of water quality. Given that reality, we learn in many facets of everyday life how to make good decisions in the face of uncertainty. However, many public sector decisions, such as proposed actions to achieve WQS, present a particular challenge due to the complexities of the scientific relationships and interactions. We believe that the AI approach outlined here provides a prudent strategy for addressing the complexities of water quality management. In the long run, we anticipate that this will result in a more efficient TMDL program and better attainment of our nation's WQS.

Appendix A: Committee Members' Biographies

Leonard Shabman, Ph.D. After three decades at Virginia Tech, in 2002 Leonard Shabman joined Resources for the Future as a resident scholar. Shabman's interest is in expanding the contribution of economic analysts to water resource policy formation. His range of policy interests include flood hazard management, wetlands permitting, natural resources damage assessment, reservoir investment and operations, water supply and demand assessment. His present research is focused on development of evaluation protocols for large scale ecosystem restoration projects, permitting under Section 404 of the Clean Water Act. With respect to water quality management his interests extend to incorporating scientific uncertainty in the implementation of water quality improvement programs and design and implementation of market like incentives into water quality management. He currently serves as a member of the National Research Council's Water Science and Technology Board.

Kenneth H. Reckhow, Ph.D. Dr. Reckhow is professor and chair of Environmental Sciences and Policy in the Nicholas School of the Environment and Earth Sciences at Duke University. On the faculty at Duke since 1980, Dr. Reckhow concurrently served as director of The University of North Carolina Water Resources Research Institute and was an adjunct professor in the Department of Civil Engineering at North Carolina State University between 1996 and 2004. He is a past-president of the National Institutes for Water Resources and of the North American Lake Management Society, past-Chair of the North Carolina Sedimentation Control Commission, and has served on the Boards of the American Water Resources Association and the Universities Council on Water Resources. He has published two books and over 100 papers, principally on water quality modeling, monitoring, and pollutant loading analysis. In addition, Dr. Reckhow has taught several short courses on water quality modeling and monitoring design, and he has written eight technical guidance manuals on water quality modeling. He is serving, or has served on the editorial boards of Water Resources Research, Water Resources Bulletin, Lake and Reservoir Management, Journal of Environmental Statistics, Urban Ecosystems, and Risk Analysis. He received a B.S. in engineering physics from Cornell University in 1971 and a Ph.D. from

Harvard University in environmental systems analysis in 1977. In 2001, Dr. Reckhow served as Chair of the National Academy of Sciences Committee to Assess the Scientific Basis for the EPA TMDL Program.

M. Bruce Beck, Ph.D. Dr. Beck is Professor and Eminent Scholar in the Warnell School of Forestry and Natural Resources at the University of Georgia, where he holds the Wheatley-Georgia Research Alliance Endowed Chair of Water Quality and Environmental Systems. He is also Visiting Professor and Senior Research Associate in the Department of Civil and Environmental Engineering at the Imperial College of Science, Technology, and Medicine in London, and currently Institute Scholar at the International Institute for Applied Systems Analysis in Laxenburg, Austria. Professor Beck holds a first degree in Chemical Engineering from the University of Exeter (1970) and a PhD in Control Engineering from King's College, Cambridge (1973). He is editor of the book Environmental Foresight and Models: A Manifesto, published in 2002. Current projects under his leadership include research into nutrient trading schemes for watershed management, handling uncertainty in models at the science-policy interface, and "Grand Challenges of the Future in Environmental Modeling"; a project associated with the National Science Foundation's Environmental Observatory initiatives. Bruce Beck has led the Sustainability Program of the International Water Association (IWA) since its inception in 2001 and has been a member of the National Research Council's Committee on Models in the Regulatory Decision-Making Process (2004-2007).

Jennifer Benaman, Ph.D. Dr. Benaman is Vice President and Senior Managing Engineer at Quantitative Environmental Analysis, LLC; an environmental consulting firm. She holds a Ph.D. in Civil and Environmental Engineering from Cornell University, where she conducted research related to uncertainty of complex environmental models and their impact on the TMDL process. She also received a M.S. from University of Texas at Austin in Civil Engineering, specializing in water quality analyses and modeling, and a B.S. in Civil Engineering from Florida Institute of Technology. She has experience and expertise in water quality and watershed modeling, including data analyses, mathematical models, and sensitivity and uncertainty analyses. She has presented multiple papers and workshops on the

national level related to water quality issues and TMDLs. Her recent work has also focused on educating industry and stakeholders on the TMDL process and how it affects them. This effort has entailed advising industrial and public clients on TMDLs, their impact, and their implementation.

Steve Chapra, Ph.D. Dr. Chapra presently holds the Lewis Berger Chair for Computing and Engineering in the Civil and Environmental Engineering Department at Tufts University. Dr. Chapra received engineering degrees from Manhattan College and the University of Michigan. He has authored seven textbooks including Numerical Methods for Engineers--which has been used at over 150 universities throughout the world. He has also authored the book Surface Water-Quality Modeling, the standard text in that area. Before joining the faculty at Tufts, Dr. Chapra worked for EPA, NOAA, Texas A&M, and the University of Colorado. He has also served as the Associate Director of the Center for Advanced Decision Support in Water and Environmental Systems (CADSWES), and has been a visiting professor at Duke University, the Imperial College of Science, Technology and Medicine (London), the University of Reading and the University of Washington. His general research interests focus on surface water-quality modeling and advanced computer applications in environmental engineering. His research has been used in a number of decision-making contexts including the 1978 Great Lakes Water Quality Agreement. In addition, he was the 1993 recipient of the ASCE's Rudolph Hering Medal for the outstanding paper in the field of environmental engineering. Aside from his activities in environmental engineering, he has written several texts on computing and engineering for which he was awarded the 1987 Meriam-Wiley Distinguished Author Award by the American Society for Engineering Education. He has taught over 60 workshops on water-quality modeling in the United States, Mexico, Europe, and South America. Finally, he has been recognized as the outstanding teacher among the engineering faculties at both Texas A&M (1986 Tenneco Award) and the University of Colorado (1992 Hutchinson Award). He is also the first recipient of the AEESP Wiley Award for Outstanding Contributions to Environmental Engineering and Science Education in the fall of 2000.

Paul Freedman, P.E., Mr. Freedman is co-founder and President, of LimnoTech; a firm specializing in water

quality issues for over 30 years. Mr. Freedman has worked in over 40 states for clients including the U.S. EPA, other Federal agencies, major municipalities coast to coast, Fortune 500 industrial firms, and numerous other public and private entities. Mr. Freedman is a nationally recognized modeling expert who has been instrumental in advancing new innovations, including the development of PC-based models, graphic interfaces, probabilistic analysis, wet weather models, watershed models, and toxic substance modeling. He has taught, presented, and lectured throughout the U.S. on watershed management, wet weather issues including stormwater CSO and SSO, TMDL, permitting, and many other environmental issues including over 200 presentations and papers. Mr. Freedman is also recognized for his contributions to national policy development having served on numerous professional and government task forces, committees, and work groups.

Margaret H. Nellor, P.E. Ms. Nellor has over 28 years of professional experience in the environmental field including water and wastewater quality management, research, regulatory and legislative policy development and analysis, water recycling, groundwater replenishment, source control and pollution prevention. She is also very active in professional activities related to the environmental profession. She currently is the President of Nellor Environmental Associates, Inc., an environmental engineering consulting firm that provides technical services and assistance related to wastewater management, water recycling, regulations, legislation, and policies. She previously was the Assistant Department Head of Technical Services for the County Sanitation Districts of Los Angeles County, which provides for the wastewater and solid waste management needs of over five million people in Los Angeles County, California. In that capacity, she was responsible for the overall administration of the agency's wastewater quality, compliance, water reclamation, and laboratory and research programs. Ms. Nellor has a Masters Degree in Environmental Health Engineering and a Bachelors Degree in Civil Engineering from the University of Texas at Austin and is a member of the University of Texas Civil and Architectural Engineering Academy of Distinguished Alumni. She is a registered civil engineer in California and Texas, and is a Diplomate in the American Academy of Environmental Engineers. She serves on the University of Texas Engineering

Foundation Advisory Council of the College of Engineering. She was the past President of the WateReuse Association and currently serves on the Association's Board of Directors. She also served as the Vice-President of the WateReuse Foundation's Board of Directors and currently serves on the Foundation's Research Advisory Committee. She also serves on the Water Environment Research Foundation's Research Council and the Water Environment Federation's Water Reuse Committee. She served on the Board of Directors for the National Association of Clean Water Agencies (NACWA), and chaired NACWA's Regulatory Policy Committee and Mercury Workgroup. She was the Co-Chair of the Environmental Protection Agency's Effluent Guidelines Task Force, and was the past Chair of Tri-TAC. She is the author and/or co-author of over 20 technical publications, papers, and has also contributed to books and manuals of practice.

Joe Rudek, Ph.D. Dr. Rudek is a Senior Scientist with North Carolina Environmental Defense. Dr. Rudek is involved, both within North Carolina and nationally, on issues associated with nonpoint source pollution, especially intensive livestock production and sediment pollution. He was very active in the Technology Peer Review Panel for evaluating alternative technologies as part of the North Carolina Attorney General's agreement with Smithfield Foods, Inc. and Premium Standard Farms from 2000-2006; and the USDA Agricultural Air Quality Task Force (2002-2006). Dr. Rudek has published articles on the impact of atmospheric deposition of nitrogen to coastal waters and on nutrient cycling in rivers and estuaries and was a selected by the National Research Council (in 2002) to review both the interim and final reports of the Committee on Air Emissions from Animal Feeding Operations. Dr. Rudek was appointed to the NC Sedimentation Control Commission in 2003 and reappointed in 2005. He currently chairs the SCC Technical Advisory Committee. Dr. Rudek received his Ph.D. (in 1992) from the University of North Carolina at Chapel Hill. Since completing his degree he has worked with the USGS and as a private consultant involved with Natural Resource Data Assessments. He has been at Environmental Defense since 1996.

Dick Schwer. Mr. Schwer is a senior consultant in environmental engineering for the DuPont Company in Wilmington Delaware. He received a B.S. in

Chemical Engineering from the University of Wisconsin and a Masters degree in Environmental Engineering from the University of Cincinnati. He has worked for DuPont for over 35 years on wastewater treatment and water quality programs at DuPont manufacturing facilities. He also has been engaged in advocacy on water quality regulations and guidance for DuPont and the American Chemistry Council, especially concerning the TMDL Program. Dick has been a co-chair of the last two national TMDL Conferences sponsored by the Water Environment Federation and has appeared on several stakeholder panels concerning TMDLs as a representative of industry.

Thomas Stiles. Mr. Stiles has managed the Kansas TMDL Program since 1998, completing the state's TMDL Court Decree requirements with the development of over 400 TMDLs over 1999-2006. Previously, he was Assistant Director of the Kansas Water Office overseeing state water policy and implementation of the State Water Plan. He received his B.S. from Colorado State University in Watershed Science and his M.S. from the University of Minnesota in Forest Hydrology. He is a past Chairman of the Interstate Council on Water Policy and has served as Water Quality Committee Chairman for the Western States Water Council.

Craig Stow, Ph.D. Dr. Stow is a research scientist at the NOAA Great Lakes Environmental Research Laboratory in Ann Arbor, MI. He holds a Ph.D. in environmental modeling from Duke University, an M.S. in marine sciences from Louisiana State University, and a B.S. in environmental technology from Cornell University. Before entering research he worked in the LA Department of Environmental Quality, drafting NPDES permits. Craig's research interests include pollutant behavior and effects in aquatic systems, ecological forecasting, probabilistic modeling, and policy-relevant inference using modern quantitative approaches.

Appendix B: EPA Guidance on Adaptive Implementation

USEPA Memorandum dated August 2, 2006 from Benita Best-Wong, Director of Assessment, and Watershed Protection Division to Water Division Directors Regions I-X, entitled *Clarification Regarding 'Phased' Total Maximum Daily Loads*.

Appendix C: A Review of Options to Address Regulatory Challenges

Antibacksliding Restrictions

The antibacksliding provisions of the CWA are contained in Sections 402(o) and 303(d)(4). These provisions generally prohibit an upward revision of water quality-based effluent limitations, once such limits are set. Section 303(d)(4), however, provides exceptions for impaired waters if: 1) the cumulative effect of all revised effluent limitations based on the TMDL will assure attainment of the WQS, or 2) the designated use that is not being attained is removed. In addition, Section 402(o) allows revision of effluent limits when information that was not available at the time of permit issuance would have justified the application of a less stringent limit (Section 402(o)(2)(B)). However, that exception only applies "…*where the cumulative effect of such revised allocations results in a decrease in the amount of pollutants discharged into the concerned waters and such revised allocations are not the result of a discharger eliminating or substantially reducing its discharge of pollutants due to complying with the requirements of this chapter [i.e., the Clean Water Act] or for reasons otherwise unrelated to water quality*."

The USEPA has not issued guidance on how these antibacksliding provisions should be applied, so it is not clear how they would be implemented with respect to TMDL-based NPDES permit limits within an AI approach to water quality improvement. One reading is that because the provisions refer to revised "effluent limitations" and "wasteload allocations", which apply only to point sources, they do not allow backsliding in a situation where a point source is receiving a relaxed limit because non-point sources are receiving increased load allocations. That would mean that if the point sources were issued stringent allocations in an initial TMDL, but the subsequent, revised TMDL concluded that their allocations could be larger (because the non-point sources were larger than initially thought and need to be reduced more), there would be no relaxation of the limits on the point sources. There is another possible reading of the antibacksliding provisions, realizing that it is well-established under the NPDES program, that in determining appropriate permit limits for a point source (under Section 301(b)(1)(C)), one can consider loading reductions being made by other sources on the water body

including non-point sources. If those reductions will lead to attainment of standards, then there is no need to reduce the loadings from the point source at issue. The same rationale could be used regarding Sections 303(d)(4) and 402(o): if the point source limits, when considered in combination with required reductions being made by other sources, will either "*assure the attainment of such water quality standard*" (for 303(d)(4)) or "*result in a decrease in the amount of pollutants discharged*" (for 402(o)), then it would seem that the statutory tests have been met and the point source can "backslide" to the less stringent limit that is consistent with the TMDL.

In another scenario, water quality conditions might improve so that the WQS is attained, but it may be difficult to revise NPDES effluent limits because anti-degradation requirements would apply. In this case, the discharger would have to make a successful anti-degradation demonstration, based on technical and social/economic grounds (see CWA Section 303(d)(4)(B)). Also, based on further evaluation during the adaptive management process, it may be determined that the designated use can be revised, and that the proper use can be achieved with relaxed water quality-based effluent limitations; in some such situations, it may be possible to revise the limits.

Innovative Approaches for Permitting on Impaired Waters

In assessing options for addressing the permitting challenges on impaired waters in an adaptive management context, one model is the process for development of pre-TMDL permits in California. On March 7, 2001, the California State Water Resources Control Board (State Board) adopted Order WQ 2001-06 that addressed “interim permits”, which are permits that regulate pollutant discharges to listed impaired waters prior to TMDL development. The State Board ruled that it was appropriate for an agency to take the following interim permitting approach: 1) to include an interim, performance-based mass limit with a compliance schedule; and 2) to include a statement in the findings section of permits to the effect that final effluent limitations will be based on the wasteload allocations in the TMDL that is eventually developed. In this procedure, the state did not have to put an arbitrary, pre-TMDL water quality-based limit in the permit, for immediate compliance, when appropriate water quality-based limits will eventually be determined in the TMDL itself. This solution would depend on no

final TMDL being set as long as there is an active commitment to the AI process.

There may also be opportunities for flexibility in states where implementation plans are incorporated into their TMDLs. In those situations, a defined implementation period would be set with final wasteload allocations not going into effect until certain adaptive decision making goals have passed. That would give time for loading reductions to take place from other sources, for effectiveness of reductions to be assessed, and for possible changes to the assigned uses or criteria to be made. Those analyses may result in changes to the wasteload allocations before they must be implemented through an NPDES permit limit. This opportunity would not exist in states where implementation plans are not made a part of the TMDL or for TMDLs issued by USEPA, which do not include implementation plans. In those situations, allocations established in the TMDL would need to be implemented without waiting for a triggering event, so the opportunity to apply an adaptive approach to the wasteload allocations would not be readily available.

Another permitting concept may be applicable when the point source discharge is a minimal source of the pollutant, which is often because other stressors or legacy pollutants are the primary causes of the impairment. In this case, non-numeric effluent requirements, such as specifying Best Management Practices (BMPs) or Pollutant Minimization Programs (PMPs) instead of numeric limits, may be applied to the point sources. BMPs and PMPs have already been applied by the USEPA and states in several situations, including storm water discharges and point source discharges of mercury and PCBs. If point sources were required to implement BMP or PMP programs in the initial implementation plan, a subsequent TMDL and plan revision could retain the BMP/PMP approach or switch to the NPDES limit if that is deemed warranted by new information. However, if a BMP or PMP approach is used, the agency would still need to show, through the TMDL process, how those programs contribute (in a quantitative way) toward attainment of the WQS.

Watershed Permitting and Trading Approaches

Under watershed permitting and water quality trading approaches, states could, in some applications, set discharge limits with a recognition that the initial WLA may later prove overly stringent, but reductions required by that

initial WLA would still be secured until information suggests otherwise. Although not specifically done to accommodate a TMDL, one model in application for the Neuse River is the group compliance permit, where the point source nutrient discharges can be adjusted up or down over time within the constraints established by the permit without triggering an NPDES rewrite (Shabman and Stephenson 2004). Another possible approach is through trading, which allows a point source to meet control obligations by supporting pollutant load reductions by other sources. This approach is subject to equity concerns if the point source is likely to sponsor reductions that are in excess of what they might be expected to achieve at their own source. To date, trading has been generally limited to nutrients and sedimentation, but may be applicable for other pollutants. For more information, see: the following websites: http://cfpub.epa.gov/npdes/wqbasedpermitting/wspermitting.cfm or http://www.epa.gov/npdes/pubs/watershedpermitting_finalguidance.pdf

Appendix D: Tools to Understand and Quantify Uncertainty in Modeling

Introduction

There are many practical and well developed approaches to assessing TMDL forecast uncertainty; however, those who conduct the TMDL modeling should view this as an introduction to some of the most useful techniques. The referenced literature (and other relevant sources) may be consulted for further guidance on the application of these techniques.

Approaches to Dealing with Limited Data in TMDLs, Modeling, and Monitoring

The first step in a TMDL analysis is to assess the sources and provide first order or bounding estimates of the pollutant loadings associated with various sources. There will obviously be uncertainty associated with these estimates because of data quantity/quality limitations. However, generating such estimates is a prudent first step in a TMDL analysis.

The second step is the development of a mass balance for the system for which the TMDL is being developed. Based on the load quantification step, the mass balance for the system is attempted to ensure that all loads are considered and there are no ‘missing’ sources that could hamper any eventual remediation. Constructing a mass balance entails comparing the magnitude of the loading estimates from the various pollutant sources (i.e., point discharges plus the relevant diffuse sources described in the previous section) with the observed change in in-stream pollutant loading across the TMDL segment. An example for a river is shown schematically in Figure D-1.

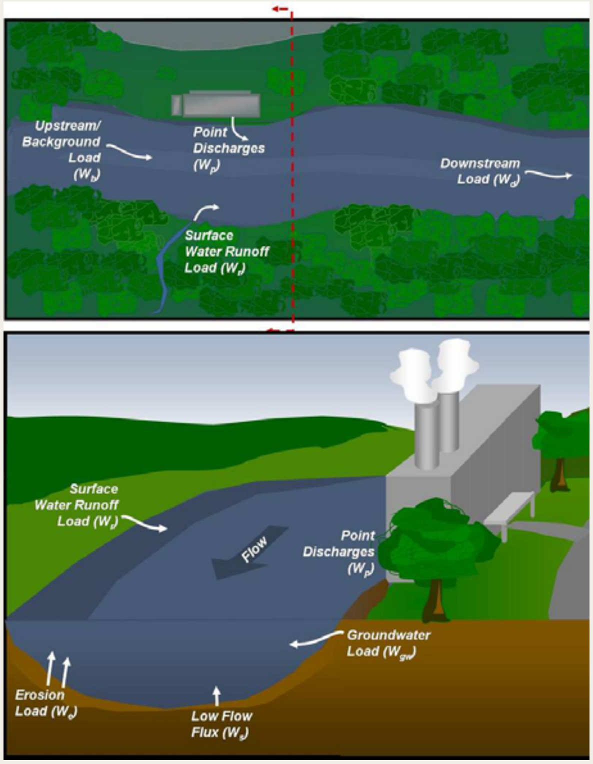


Figure D-1. Schematic of a mass balance for a TMDL segment.

The mass balance comparison for this example is expressed as:

$$W_d - W_b \overset{?}{=} \sum W_p + \sum W_r + \sum W_e + \sum W_s + \sum W_{gw}$$

The loads are presented as sums in the above equation because the calculations for the diffuse sources (e.g., watershed and sediments) can be applied to individual sub-reaches and the loadings summed, where spatially-variable data exist.

Not all of the sources shown in the above equation will be significant at a given site; those that are not can be eliminated from the TMDL analysis. In many cases, without constructing the mass balance to compare these loads, such a determination cannot be made. If the sum of point and non-point pollutant loadings is not consistent with the load increase across the TMDL reach (within the uncertainty limits of both), other 'missing' sources may significantly contribute to the water body, and additional investigation and/or data collection may be warranted.

One consideration that has not been addressed is pollutant loss mechanisms. Depending on the contaminant, the spatial scale of the TMDL assessment and the physical, chemical, and biological processes occurring in the water body, reductions in the mass of the pollutant transported across the area of study may be occurring. Examples of loss processes include:

- settling of particle-bound contaminants;
- volatilization;
- photolysis;
- biodegradation; and
- other chemical transformations (e.g., change in speciation from oxidation/reduction).

Similar to the approaches for load quantification, preliminary estimates of the mass reduction associated with these loss mechanisms can be developed from first principles.

The final step in the approach to TMDL development should entail the creation of a conceptual model of the system. The conceptual model is a verbal description of the fate, transport, and transformations that determine the pollutant's concentrations within the area of interest. The quantitative basis for the conceptual model is the mass balance developed above. By comparing the magnitude of the various sources, internal loading mechanisms (e.g., from sediments), and potential loss mechanisms, it is possible to identify the processes that are most important to water quality excursions in the affected segment or water body.

The conceptual model should be central to the remainder of the TMDL development, including any model application, load allocation, monitoring, and investigation into implementation strategies. The model provides information so that data collection and decision making can be properly focused in the TMDL process. The conceptual model (and the load quantification on which it is based) is intended to be updated throughout the TMDL process as additional information becomes available.

Sensitivity Analysis

A main objective of sensitivity analysis is to identify the important parameters in a water quality model. A sensitivity analysis is defined as a method in which parameter values are perturbed from their default or "base case" value, the model is run, and then the model output is analyzed to determine the impact on the simulation results. However, in multi-parameter models, a sensitivity analysis to narrow down the hundreds of parameters to just a few important ones becomes an overwhelming task. To add to the complexity, many parameters may affect multiple model output variables. For example, a parameter which controls surface water runoff may also affect soil erosion, because erosion is dependent on the magnitude of surface water runoff. It is easy to see how a potential sensitivity analysis could escalate into a difficult and daunting task. Although various global sensitivity methods attempt to approach multi-parameter sensitivity, these methods can require thousands of computer runs, becoming hindered by computational time. For example, Meixner et al. (1999) recently performed a global sensitivity analysis on

a relatively simple watershed model, which required 20,000 model realizations to investigate the sensitivity of 24 parameters. In most cases, modelers want to determine the important parameters with minimal computational effort. Consequently, it is desirable to apply an efficient initial analysis that establishes the important parameters. These parameters could then be further analyzed during model calibration or during a more global uncertainty analysis.

Sensitivity of complex environmental models is not a new area of study. McCuen’s (1973) method is one of the most common approaches to sensitivity analysis: single parameter sensitivity in which parameters are changed “one-at-a-time” and the resulting model response is reviewed. This early research introduced the concept of sensitivity in hydrologic modeling by presenting the mathematical foundations for a basic sensitivity analysis of a simple groundwater model. McCuen (1973) discussed the concept of a sensitivity index which normalizes a model's response to a parameter value perturbation. The sensitivity index concept was quickly adopted by modelers.

Carlson and Fox (1976) used sensitivity indices applied to a watershed snowmelt-flood frequency model in Alaska. Nearing et al. (1990) also adopted the use of sensitivity indices on the United States Department of Agriculture's (USDA) Water Erosion Prediction Project (WEPP) to study sediment erosion parameters. In addition, Fontaine and Jacomino (1997) used sensitivity indices to explore the impact of different hill slope and reach parameters on flow, suspended sediment, and cesium concentration simulated by the Hydrologic Simulation Program FORTRAN (HSPF). Benaman (2003) and Lenhart et al. (2002) used normalized results to analyze the response of an agricultural model, the Soil and Water Assessment Tool (SWAT) to soil parameters. Vandenberghe (2001) investigated the sensitivity of the SWAT model to nutrient-specific parameters related to simulating algae growth, dissolved oxygen, and eutrophication.

The use of an index to analyze the sensitivity of a model has its advantages: the computational burden is typically minimal, and the general concept is easy to convey. However, there are limitations to this approach. A sensitivity index is the response to a change of just one parameter at a time. A more accurate representation of overall model sensitivity could be determined using a global sensitivity method, described later in this

section. The index can still be key to understanding the "most important" parameters in a model, as well as aiding in monitoring plan development.

Monte Carlo Simulation

Monte Carlo simulation (MCS) is a numerical method for generating simulated data using random numbers and assumed probability distributions (Ang and Tang 1990; Morgan and Henrion 1990) that reflect the uncertainty in model inputs, parameters, and the model equations (*if* the MCS is comprehensive). The purpose of MCS is to use multiple sets of simulated, but realistic input values, "run" these values through the model, and assess their impact on model predictions. MCS is the result of multiple "runs" of a model, with numerous random selection of sets of inputs, followed by application of the model once for each input set. This yields a prediction of the distribution of model outputs. The distribution of the model outputs is then analyzed, and an estimate of the overall uncertainty in the model output is obtained.

The number of iterations to perform in each MCS is identified through a stability analysis of the MCS results with particular attention to the output variable(s) of concern. This stability analysis entails repetitive simulations (of X iterations each), followed by a statistical analysis on the distributions of the output variable of concern. If the distributions are insufficiently stable, then another round of simulations (of X*Y iterations each, where Y>1) is run. This procedure is repeated until the results are satisfactorily stable.

A variety of graphical and statistical approaches are used to describe the MCS outputs. These may include tables of Spearman Rank Correlation Coefficients (SRCC, also referred to as Spearman's Rho) and probability plots of key model outputs.

Regionalized Sensitivity Analysis (RSA) and GLUE

Another option is to consider whether lack of identifiability or presence of equifinality should change the perspective of water quality modelers from seeking a single "optimal" value for each model parameter, to seeking a distribution of parameter sets that all meet a pre-defined fitting criterion (or multiple criteria). These acceptable parameter sets may then provide the basis for estimating model prediction error associated with the model parameters.

The development of methods for identifying acceptable parameters sets for large multi-parameter environmental models with limited observational data began with the work of Hornberger and Spear (1981). Their method, called regionalized (or generalized) sensitivity analysis (RSA), is essentially a Monte Carlo sampling approach that can be used to identify parameters to which a model is most/least sensitive. Hornberger and Spear advocated the application of this method as a means to prioritize future sampling and experimentation for model and parameter improvements.

RSA is simple in concept, and is a clever way to use limited information in a Bayesian-like manner to define model parameter distributions. Given a particular model and a system (e.g., water body) being modeled, the modeler first defines the plausible range of certain key model response variables (e.g., chlorophyll-a, total nitrogen) as the "behavior". Outside the range is "not the behavior". The modeler then samples from (often uniform) distributions of each of the model parameters and, using the model, computes the values for the key response variables. Each complete sampling of all model parameters, leading to prediction, results in a "parameter set". All parameter sets that result in predictions of the key model response variables in the "behavior" range are termed "behavior generating" and thus become part of the model parameter distribution. The other parameter sets that do not meet this behavior criterion are termed "non-behavior generating".

Hornberger and Spear (1981) proposed that the cumulative distribution function and the Kolmogorov-Smirnov (KS) statistic be applied to each parameter distribution from these two data sets (behavior generating and non-behavior generating). For a particular parameter, if the behavior generating and non-behavior generating distributions are substantially different (based on the KS statistic), then prediction of the key response variables is sensitive to that parameter. Hence, resources devoted toward model improvement might be preferentially allocated toward improved estimation of that parameter.

In addition, we can consider the distribution of the behavior generating parameter sets as reflecting equifinality. Thus the empirical distribution characterizes the error (variance and covariance) structure in the model parameters, conditional on the model and on the fitting criterion (the defined

plausible range of key response variables).

The Generalized Likelihood Uncertainty Estimation (GLUE) approach is an extension of the original regionalized sensitivity analysis; the binary system of acceptance/rejection of behavioral/non-behavioral simulations is replaced by the use of a likelihood measure that assigns different levels of confidence (weighting) to different parameters sets (Beven and Binley 1992; Zak and Beven 1999; Page et al. 2004). Unlike other techniques (e.g., Bayesian Monte Carlo, Importance Sampling, Markov Chain Monte Carlo), the term "likelihood" has a very broad meaning in the GLUE methodology, and it is specified "as any measure of goodness-of-fit that can be used to compare observed responses and model predictions," as long as it fulfills particular characteristics (Zak et al. 1997). A wide variety of likelihood functions can be found in the GLUE literature, e.g., likelihood measures based on the sum of squared errors (Beven and Binley 1992; Sorooshian and Gupta 1995; Freer et al. 1996; Benaman 2003), fuzzy measures (Franks et al. 1998; Page et al. 2004), or qualitative measures for model evaluation (Beven 2001).

The GLUE procedure requires a large number of Monte Carlo model runs sampled from probability distributions across plausible parameter ranges. Prior knowledge regarding the expected joint parameter distributions can be incorporated by assigning appropriate prior likelihood weights to each of the parameter sets (rather than in the sampling density; see Schulz et al. 1999). The behavioral runs are selected on the basis of a subjectively chosen threshold of the likelihood function and are rescaled so that their cumulative total is 1.0. The weighting assigned to the retained behavioral runs is propagated to the model output and forms a likelihood-weighted cumulative distribution of the predicted variable(s), which is used for estimating the prediction uncertainty ranges (Beven and Binley 1992).

GLUE also has the ability to update likelihood weights (and thus predictive uncertainty) by successive application of Bayes Theorem, as additional monitoring data become available for model-to-data comparison. The refinement of the predictive uncertainty can be assessed each time the likelihood function is updated by the use of appropriate quantitative measures (e.g., the probabilistic Shannon Entropy measure or the U-uncertainty; see the relevant

discussion in Beven and Binley 1992). Unless the combination of a "likelihood" function with a threshold criterion corresponds to a well-defined probability distribution that directly connects the data with model input and output parameters, GLUE does not have a clear Bayesian interpretation (Engeland and Gottschalk 2002). For example, the 95% "uncertainty bounds" resulting from GLUE can have a different statistical interpretation than the 95% credible intervals (Lamb et al. 1998). In addition, the GLUE procedure is mainly based on the parameter-set ability to produce "behavioral" simulations, and, thus it is difficult to extract information regarding the individual parameter effects on the model response (which can also be a problem with RSA). Even though the use of scattergrams (projections of the sampled high dimensional response surface onto single parameter dimensions) can give some insight, they cannot reflect the full complexity of the response surface (Page et al. 2004). Finally, it should also be noted that depending on the likelihood measure and the behavioral/non-behavioral threshold used, GLUE (and RSA) can be particularly inefficient in sampling acceptable runs, e.g., the application of GLUE to the MAGIC model by Page et al. (2004) classified 7,200 out 11 million runs (0.066%) as acceptable.

Random-search Inverse Methodology for Model Evaluation (RIMME)

In a spirit of decision-oriented pragmatism, somewhat more general frameworks for handling uncertainty in environmental decision making, specifically in association with the use of mechanistic models of watershed water quality, have emerged. One encompasses a Random-search Inverse Methodology for Model Evaluation (RIMME) (Osidele and Beck 2003) tailored broadly to deployment in what has been called adaptive community learning (Beck et al. 2002). The "Inverse" element in this particular framework for the analysis of uncertainty signals the intent to try to answer questions posed in the following form: what science — *and* technology *and* policy — might be key to minimizing the risks of having the public's (*not* just the scientist's, *or* the engineer's, *or* the policy analyst's) worst fears come to pass; and what science — *and* technology *and* policy — might be key to maximizing the probability of having their best hopes realized, including regulatory-based, target patterns of behavior?

The Chattahoochee River, as it flows southwest through the city of Atlanta from Buford Dam, with the hydroelectric facility on the outlet from Lake Lanier down to Lake West Point, continues to be a focus for just such great concern in matters of stream and lake water quality management (Cowie and Borrett 2005). When the mechanistic model STAND is employed for simulating hydraulic, sediment, and nutrient (phosphorus) behavior in this segment of the Chattahoochee and subjected to an analysis of uncertainty in the RIMME framework, we find that uncertainties in the operation of Buford Dam, (i.e., uncertainties associated with the system's inputs) are more significant for the "reachability" of target sediment and nutrient characteristics downstream in Lake West Point, than are uncertainties in our understanding of the "science" mobilized within STAND as reflected in the model's parameters (Osidele et al. 2003a). When STAND is coupled with the BASINS-HSPF model for the same stretch of the Chattahoochee, and "relaxed" and "strict" interpretations are made of Georgia's *narrative* standards for downstream suspended sediment concentrations, uncertainties in the temporal pattern of operations at Buford Dam become less critical to achieving designated uses under the relaxed interpretation (Osidele et al. 2003b).

Upstream of Buford Dam, where stakeholders in a Foresight Workshop were invited to imagine their worst fears and greatest hopes for the future of Lake Lanier's long-term well-being[3], a RIMME analysis of a 13-state food-web model for the lake enabled key reservoir attributes for the "feared" end-point to be ranked as follows: (i) nutrient loading; (ii) fish production; (iii) zooplankton production; and (iv) sediment-water-nutrient interactions (Osidele and Beck 2003). For the "desired" end-point, rankings were: (i) nutrient loading; (ii) sediment-water-nutrient interactions; (iii) fish production; and (iv) microbial production. Overall, 94 input factors were analyzed, comprising 57 process parameters, 12 initial conditions, and 25 parameters describing the temporal patterns of the input functions. Under an adaptive implementation strategy – perhaps conditioned by some judgment or enumeration of the likelihoods of either

---

[3] Hopes and fears for the long-term future are self-evidently grossly uncertain features, with elements of heterogeneity deriving from different outlooks on the nature of the man-environment relationship attaching to a healthy democracy of stakeholders not all adhering to the same views (Fath and Beck 2005).

the feared or the desired (distant future) end-point eventually coming to pass – initial actions would be a prudent combination of curbs on nutrient loadings from the watershed and further field work (research) under a limited budget, designed to reduce the scientific uncertainty surrounding solely "fish production," say. Later, armed with the learning obtained, a revised food-web model and adjusted stakeholder foresight regarding longer-term end-points, the cycle of dialog, discussion, learning, and action would all be repeated again (and again, as the future unfolds).

Bayesian Analysis

Information synthesis is usually the motivation for employing Bayesian analysis; thus Bayesian analysis serves as an excellent approach for the analytics of adaptive implementation. The conventional application of a Bayesian approach emphasizes the combination of prior information (in this case, from the TMDL forecast model) and a single set of data (post-implementation monitoring data). However, it is shown in Bayesian statistics texts that sequential updating using the posterior from the previous step as a prior in the subsequent step is equivalent to updating using all of the data together; thus sequential updating provides a means to investigate possible temporal patterns in the data, which is attractive for adaptive implementation.

To provide an example of sequential Bayesian updating for adaptive implementation of a TMDL, a series of computer programs was developed to automate an annual updating process. A TMDL model was initially used to predict 1992 nitrogen concentration in the Neuse Estuary (North Carolina) based on land use and nitrogen loading scenarios. This prediction is the "prior" probability distribution (prior to taking samples) for nitrogen, and it provides the initial TMDL forecast. Next, sample data from 1992 for nitrogen concentration are combined with the prior to yield the "posterior" (posterior, or after, collecting data) prediction for nitrogen; this yields the best 1992 estimate for nitrogen based on all available information. Further, if some TMDL implementation has occurred, this can provide the first assessment of TMDL success. Then in 1993, the 1992-posterior becomes the 1993-prior, and it is combined with 1993 sample information to yield the 1993-posterior. This provides an updated assessment of TMDL success and may serve as a basis for adaptive implementation. This process can continue as long as new data become available.

To demonstrate this process, a Bayesian SPARROW model-predicted 1992 nitrogen concentration distribution for the Neuse River Estuary was used to develop a prior distribution of the mean and variance of log nitrogen concentration, and the sequentially updated posterior predictive distributions for each subsequent year are presented (Figures D-2 and D-3). The same process was repeated for the chlorophyll-a concentration distribution in the Neuse River Estuary (Figure D-4). The prior distribution for chlorophyll-a was developed using an empirical model (Neu-BERN; Borsuk et al. 2004a) and the results from the SPARROW model. Although the prior distribution based on Neu-BERN over-estimated the chlorophyll-a concentration, the sequentially updated posterior predictive distributions (based on post-implementation measurements) quickly converged to a distribution similar to the observed chlorophyll-a concentration data (Figure D-4).

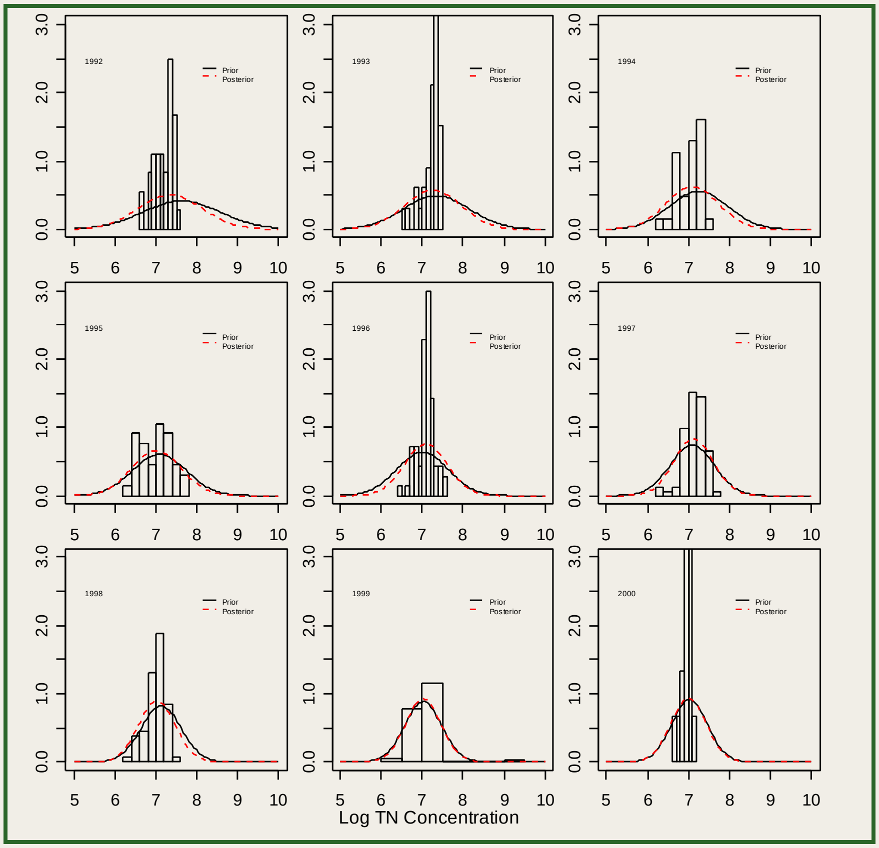


Figure D-2. Sequentially updated predictive distribution of nitrogen concentration in the Neuse River Estuary. *The solid black lines are the prior distribution used for each year; the red dashed lines are the resulting posterior predictive distributions for the same year; and the data are shown in histograms.*

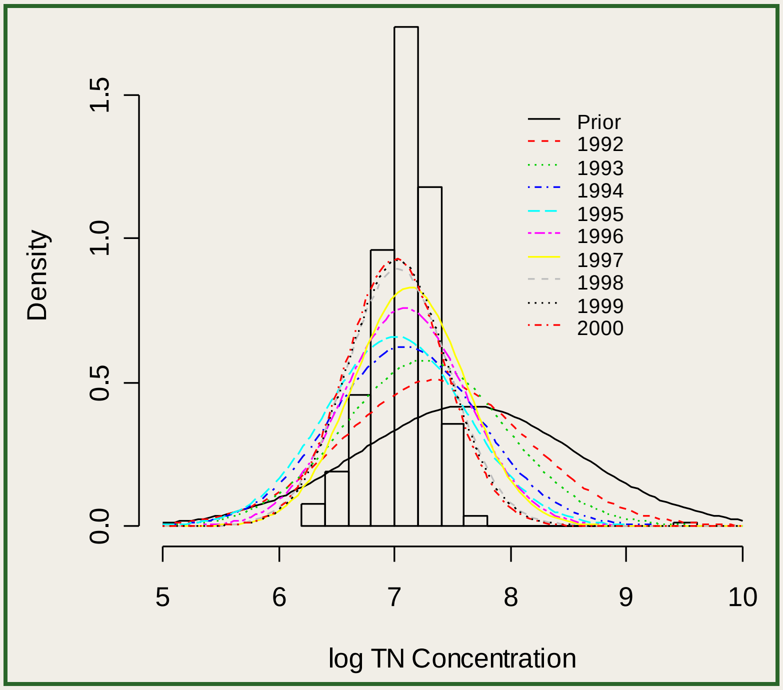


Figure D-3. Sequentially updated posterior predictive distribution of log nitrogen concentrations in the Neuse River Estuary. ***The histogram shows the combined nitrogen monitoring data collected from 1992 to 2000.***

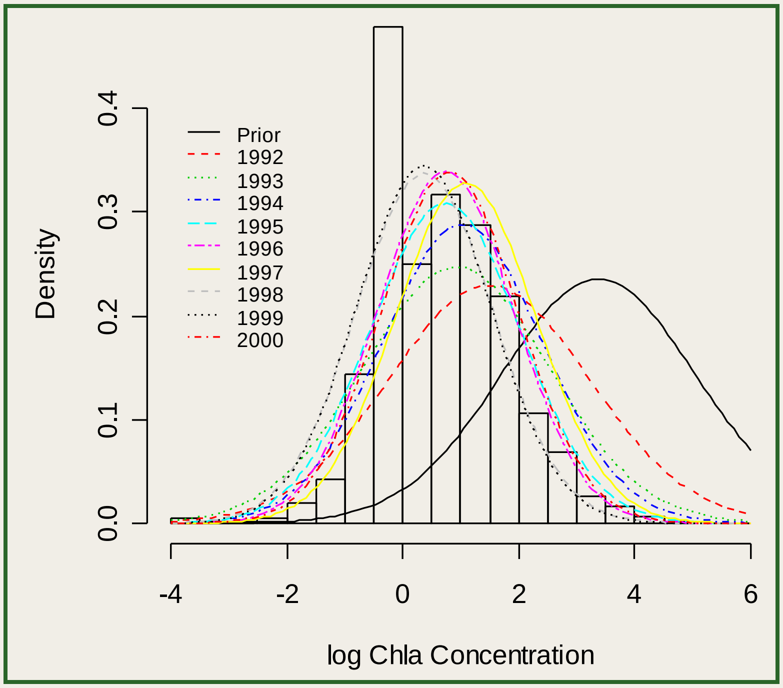


Figure D-4. Sequentially updated posterior predictive distribution of log chlorophyll-a concentrations in the Neuse River Estuary. *The histogram shows the combined chlorophyll-a monitoring data collected from 1992 to 2000.*

Challenges to Applying Uncertainty Tools

Over the years, the technical approaches for undertaking analyses of the uncertainty of predictions from mechanistic models of water quality have become somewhat more available to model users. As early as the mid-1980s, the best-known of all such models, the USEPA's QUAL2E model, was supported with a limited version of standard software for first-order error analysis and Monte Carlo simulation (Brown and Barnwell 1987). In a more general setting, software for the analysis of model uncertainty and sensitivity is reviewed by Saltelli et al. (2000), and we can conclude from the publication in 2004 of the "primer", *Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models* (Saltelli et al. 2004), that indeed such analyses ought to be readily undertaken in practice, as opposed to only in research. The RIMME framework, originally developed for models with 10 to 20 state variables containing up to a 100 parameters (or factors), is currently being implemented in the context of far higher-order models, within the USEPA's Framework for Risk Analysis in Multimedia Environmental Systems - Multimedia, Multipathway, and Multireceptor Risk Assessment (FRAMES-3MRA; Babendreier and Castleton 2005).

Appendix E: Acronyms

AI .... Adaptive Implementation
BASINS .... Better Assessment Science Integrating Point and Non-Point Sources
BMPs .... Best Management Practices
BOD .... Biochemical Oxygen Demand
BPJ .... Best Professional Judgment
CWA .... Clean Water Act
DWQ .... (North Carolina) Department of Water Quality
EPA .... Environmental Protection Agency (see USEPA)
FRAMES .... Framework for Risk Analysis in Multimedia Environmental Systems
GAO .... General Accounting Office
GLUE .... Generalized Likelihood Uncertainty Estimation
HSPF .... Hydrologic Simulation Program-FORTRAN
KS .... Kolmogorov-Smirnov
LA .... Load Allocation
MCA/MCS .... Monte Carlo Analysis/Monte Carlo Simulation
MOS .... Margin of Safety
NGO .... Non-Governmental Organization
NPDES .... National Pollutant Discharge Elimination System
NRC .... National Research Council
PMPs .... Pollutant Minimization Programs
RIMME .... Random-Search Inverse Methodology for Model Evaluation
RSA .... Regionalized Sensitivity Analysis
SI .... Standard Implementation
SRCC .... Spearman Rank Correlation Coefficients (Spearman's Rho)
SWAT .... Soil and Water Assessment Tool
TMDL .... Total Maximum Daily Load
UAA .... Use Attainability Analysis
USDA .... United States Department of Agriculture
USEPA .... United States Environmental Protection Agency
WEPP .... Water Erosion Prediction Project
WERF .... Water Environment Research Federation
WIP .... Watershed Improvement Plans
WLA .... Wasteload Allocation
WQS .... Water Quality Standard(s)

References

Ang, A.H-S., and W.H. Tang, 1990. *Probability Concepts in Engineering Planning and Design, Vol. 2 - Decision, Risk, and Reliability*. New York: John Wiley & Sons.

Argentesi, F. and L. Olivi, 1976. *Statistical Sensitivity Analysis of a Simulation Model for the Biomass-Nutrient Dynamics in Aquatic Ecosystems, in Proceedings of 4th Summer Computer Simulation Conference*. La Jolla, CA: Simulation Councils, 389-393.

Babendreier, J.E. and K.J. Castleton, 2005. Investigating Uncertainty and Sensitivity in Integrated, Multimedia Environmental Models: Tools for FRAMES-3MRA. *Environmental Modeling and Software* 20:1043-1055.

Beck, M.B., 1987. Water Quality Modeling: A review of the Analysis of Uncertainty. *Water Resources Research* 23:1393-1442.

Beck, M.B. and E. Halfon, 1991. Uncertainty, Identifiability and the Propagation of Prediction Errors: a case study of Lake Ontario. *Journal of Forecasting* 10:135-161.

Beck, M.B., D. Butler, and M.R. Schutze, 2002. *Modeling, Simulation and Control of Urban Wastewater Systems*. New York: Springer Verlag. 363 pp.

Benaman, J. 2003. *Uncertainty and Sensitivity Analyses for Watershed Models: Hydrology and Sediment Transport Modeling on the Cannonsville Reservoir System*. Ph.D. Dissertation, Cornell University, Department of Civil and Environmental Engineering.

Beven, K. J., 2001. *Rainfall-Runoff Modeling*. England: John Wiley and Sons Ltd.

Beven, K.J. and A. Binley, 1992. The Future of Distributed Models: Model Calibration and Uncertainty Prediction. *Hydrological Processes* 6:279-298.

Beven, K.J. and J. Freer, 2001. Equifinality, Data Assimilation, and Uncertainty Estimation in Mechanistic Modeling of Complex Environmental Systems Using the GLUE Methodology. *Journal of Hydrology* 249:11-29.

Borsuk, M.E., C.A. Stow, and K.H. Reckhow, 2003. An integrated approach to TMDL development for the Neuse River Estuary using a Bayesian probability network model (Neu-BERN). *Journal of Water Resources Planning and Management* 129:271-282.

Borsuk, M.E., C.A. Stow, and K.H. Reckhow, 2004a. A Bayesian network of eutrophication models for synthesis, prediction, and uncertainty analysis. *Ecological Modeling* 173:219-239.

Borsuk, M.E., C.A. Stow, and K.H. Reckhow, 2004b. The confounding effect of flow on estuarine response to nitrogen loading. *J. Environ. Eng*. 130:605-614.

Brown, L. and T. Barnwell, 1987. *The Enhanced Stream Water Quality Models QUAL2E and QUAL2E-UNCAS: Documentation and User Manual*. Prepared for United States Environmental Protection Agency, Athens, GA.

Carlson, R.F. and P.M. Fox, 1976. A Northern Snowmelt-Flood Frequency Model. *J. Water Resources Research* 12:786-794.

Cowie, G.M. and S.R. Borrett, 2005. Institutional Perspectives on Participation and Information in Water Management. *Environmental Modelling and Software* 20(4):469-483.

Dilks, D.W. and P.L. Freedman, 2004. Improved Consideration of the Margin of Safety in TMDL Development. *Journal of Environmental Engineering ASCE Special TMDL Issue* June 2004.

Di Toro, D.M. and G. van Straten, G., 1979. *Uncertainty in the Parameters and Predictions of Phytoplankton Models.* Working Paper WP-79-27, International Institute for Applied Systems Analysis, Laxenburg, Austria.

Dupuis, T., S. Doran, B. McMillan, L. MacPherson, T. Moore, and L. Terry, 2005. *Collaborative Water Quality Solutions: Exploring Use Attainability Analyses*. National Association of Clean Water Agencies, Washington, DC and Water Environment Research Foundation, Alexandria, VA.

Engeland, K. and L. Gottschalk, 2002. Bayesian estimation of parameters in a regional hydrological model. *Hydrology and Earth System Sciences* 6(5):883-898.

Fath, B.D. and M.B. Beck, 2005. Elucidating Public Perceptions of Environmental Behavior: A Case Study of Lake Lanier. *Environmental Modelling and Software* 20(4):485-498.

Fontaine, T.A. and T.M.F. Jacomino, 1997. Sensitivity Analysis of Simulated Contaminated Sediment Transport. *Journal of the American Water Resources Association* 33:313-326.

Franks, S.W., P. Gineste, K.J. Beven, P. Merot, 1998. On Constraining the Predictions of a Distributed Model: The Incorporation of Fuzzy Estimates of Saturated Areas in the Calibration Process. *Water Resources Research* 34:787-797.

Freedman, P.L., 2001. CWA's New Clothes, A Critical Review of the TMDL Program. *Water Environment and Technology* 13(6):28-32.

Freedman, P. and T. DuPuis, 2007. Factors for Success in Developing Use Attainability Analyses", 2007 in press, Water Environment Research Foundation, Alexandria, VA.

Freedman, P.L., A.D. Nemura, and D.W. Dilks, 2004. Viewing Total Maximum Daily Loads as a Process, not a Singular Value: Adaptive Watershed Management. *J. of Env. Eng*. 130(6):695-702.

Freedman, P.L., W.M. Larson, D.W. Dilks, D. Schecter, A. Nemura, T. Naperala, J.V. DePinto, M.G. Prothro, G.W. Boese, A. Dettlebach, L. Nothman, K. Thornton, D. Ford, P. Massirer, T. Soerens, K.B. Stevens, and J.A.H. Sobrinho, 2003a. *Navigating the TMDL Process: Evaluation and Improvements*. Water Environment Research Foundation. Alexandria, VA.

Freedman, P.L., D.W. Dilks, H. Holmberg, P. Moskus, G. McBride, C. Hickey, D. Smith, and P. Striplin, 2003b. *Navigating the TMDL Process: Method Development for Addressing Narrative Criteria*. Water Environment Research Foundation. Alexandria, VA.

Freer, J., K. Bevin, and B. Ambroise, 1996. Bayesian estimation of uncertainty in runoff prediction and the value of data: An application of the GLUE approach. *Water Resources Research* 32(7):2161-2173.

General Accounting Office (GAO), 2002. *Water Quality Inconsistent State Approaches Complicate Nation's Efforts to Identify Its Most Polluted Waters.* January 2002. GAO-02-186.

General Accounting Office (GAO), 2000. *Water Quality Key EPA and State Decisions Limited by Inconsistent and Incomplete Data*. March 2002. GAO/RCED-00-54.

Holling, C.S., and A.D. Chambers, 1973. Resource Science: the Nurture of an Infant. *BioScience* 23:13-20.

Holling, C.S., 1978. *Adaptive Environmental Assessment and Management. International Institute for Applied Systems Analysis.* Caldwell: Blackburn Press. 377 pp.

Hornberger, G.M. and R.C. Spear, 1981. An Approach to the Preliminary Analysis of Environmental Systems. *Journal of Environmental Management* 12:7-18.

Lamb, R., K. Beven, and S. Myrabo, 1998. Use of spatially distributed water table observations to constrain uncertainty in a rainfall-runoff model. *Advances in Water Resources* 22(4):305-317(13).

Lee, K.N., 1993. *Compass and Gyroscope*. Washington: Island Press. 243 pp.

Lenhart, T., K. Eckhardt, N. Fohrer, H.G. Frede, 2002. Comparison of two different approaches of sensitivity analysis. *Physics and Chemistry of the Earth* 27:645-654.

McMahon, G., R.B. Alexander, and S. Qian, 2003. Support of Total Maximum Daily Load Programs Using Spatially Referenced Regression Models. *Journal of Water Resources Planning and Management* 129:315-329.

McCuen, R. H., 1973. The Role of Sensitivity Analysis in Hydrologic Modeling. *Journal of Hydrology* 18: 37-53.

Meixner T., H.V. Gupta, L.A. Bastidas, and R.C. Bales, 1999. Sensitivity Analysis Using Mass Flux and Concentration. *Hydrological Processes* 13:2233-2244.

Morgan M. G. and M. Henrion, 1990. *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*. Cambridge: Cambridge University Press.

National Research Council, 2001. *Assessing the TMDL Approach to Water Quality Management*. Washington: National Academy Press.

Nearing M.A., L. Deer-Ascough, and J.F. Laflen, 1990. Sensitivity Analysis of the WEPP Hillslope Profile Erosion Model. *Transactions of the American Society of Agricultural Engineers* 33:839-849.

Omlin, M. and P. Reichert, 1999. A Comparison of Techniques for the Estimation of Model Prediction Uncertainty. *Ecological Modelling* 115:45-59.

Osidele, O.O. and M.B. Beck, 2003. An Inverse Approach to the Analysis of Uncertainty in Models of Environmental Systems. *Integrated Assessment* 4:265-282.

Osidele O.O., W. Zeng, and M.B. Beck, 2003a. Coping With Uncertainty: A Case Study in Sediment Transport and Nutrient Load Analysis. *J. Water Resources Planning and Management* 129(4):345-355.

Osidele, O.O., W. Zeng and M.B. Beck, 2003b. *Uncertainty evaluation of sediment loading and transport for the Chattahoochee River at Atlanta, Georgia*. In proceedings TMDL 2003, Water Environment Federation.

Water Environment Federation.Page, T., K.J. Bevin, and D. Whyatt, 2004. Predictive Capability in Estimating Changes in Water Quality: Long-Term Responses to Atmospheric Deposition. *Water, Air, and Soil Pollution* 151:215-244.

Qian, S.S., K.H. Reckhow, J. Zhai, and G. McMahon, 2005. Nonlinear regression modeling of nutrient loads in streams: A Bayesian approach. *Water Resources Research*: July 2005.

Reckhow, K.H., 1994. Water quality simulation modeling and uncertainty analysis for risk assessment and decision making. *Ecological Modelling* 72:1-20.

Saltelli, A., K. Chan, and E.M. Scott, 2000. *Sensitivity Analysis*. Winchester: Wiley. 504 pp.

Saltelli, A., S. Tarantola, F. Campologna, and M. Rocho, 2004. *Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models*. 232 pp.

Scavia, D., R.P. Canale, W.F. Powers, and J.L. Moody, 1981. Variance Estimates for a Dynamic Eutrophication Model of Saginaw Bay, Lake Huron. *Water Resources Res.* 17:1115-1124.

Schultz, K., K. Beven, and B. Huwe, 1999. Equifinality and the Problem of Robust Calibration in Nitrogen Budget Simulations. *Soil Science Society of America Journal* 63:1934-1941.

Somlyody, L., 1983. Input Data Uncertainty and Parameter Sensitivity in a Lake Hydrodynamic Model. In *Uncertainty and Forecasting of Water Quality*, edited by M.B. Beck and G. van Straten. Berlin: Springer.

Sorooshian, S. and V.K. Gupta, 1995. Model Calibration. In *Computer Models of Watershed Hydrology*, edited by V. Singh. Highlands Ranch: Water Resources Publications.

USEPA, 2002. *The Twenty Needs Report: How Research Can Improve the TMDL Program*. EPA841-B-02-002. 43 pp.

USEPA, 2006. *Clarification Regarding 'Phased' Total Maximum Daily Loads*. Memorandum from Benita Best-Wong, Director, Assessment and Watershed Protection Division to Water Division Directors Regions I-X, August 2, 2006.

USEPA, 1996. *Why Watersheds*. EPA Document EPA800-F-96-001 February 1996. http://www.epa.gov/owow/watershed/why.html.

USEPA, 2001. *Comments and Responses on Christina River TMDL*. http://www.epa.gov/reg3wapd/tmdl/de_tmdl/ChristiniaRiver/pdf/Christina_comments.pdf.

Vandenberghe, V., A. Griensven, and W. Bauwens, 2001. Sensitivity Analysis and Calibration of the Parameters of ESWAT: Application to the River Dender. *Water Science and Technology* 43:295-301.

van Straten, G., 1983. Maximum Likelihood Estimation of Parameters and Uncertainty in Phytoplankton Models. In *Uncertainty and Forecasting of Water Quality*, edited by M.B. Beck and G. van Straten. Berlin: Springer.

Walters, C., 1986. *Adaptive Management of Renewable Resources*. New York: Macmillan Publishing.

Zak, S.K. and K.J. Beven, 1999. Equifinality, Sensitivity, and Predictive Uncertainty in the Estimation of Critical Loads. *The Science of the Total Environment* 236:191-214.

Zak, S. K., K.J. Beven, and B. Reynolds, 1997. Uncertainty in the Estimation of Critical Loads: A Practical Methodology. *Water, Air, and Soil Pollution* 98:297-315.