Managing Water Quality in the Face of Uncertainty

A Robust Decision Making Demonstration for EPA's National Water Program

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Preface

The U.S. Environmental Protection Agency (USEPA) Office of Research and Development sponsored a study by the RAND Corporation to explore how Robust Decision Making (RDM) methods could be used to manage climate change and other key uncertainties faced by USEPA's National Water Program. The study began in May 2011 and was completed in March 2014. This final project report provides results from two case studies that apply RDM to water quality decision processes at USEPA's Office of Water and partnering regional and state regulatory agencies. The results are intended to inform USEPA's efforts to better incorporate robustness and adaptivity into current programs when faced with deeply uncertain scientific information about future conditions.

The research reported here was conducted in the RAND Environment, Energy, and Economic Development Program, which addresses topics relating to environmental quality and regulation, water and energy resources and systems, climate, natural hazards and disasters, and economic development, both domestically and internationally. Program research is supported by government agencies, foundations, and the private sector.

This program is part of RAND Justice, Infrastructure, and Environment, a division of the RAND Corporation dedicated to improving policy and decisionmaking in a wide range of policy domains, including civil and criminal justice, infrastructure protection and homeland security, transportation and energy policy, and environmental and natural resource policy.

Questions or comments about this report should be sent to the project leaders, Robert Lempert (lempert@rand.org) or Jordan Fischbach (Jordan_Fischbach@rand.org). For more information about the Environment, Energy, and Economic Development Program, see http://www.rand.org/energy or contact Keith Crane, the director, at eeed@rand.org. Information about the RAND Corporation can be found at www.rand.org.

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Summary

The U.S. Environmental Protection Agency Office of Water (USEPA/OW) is charged with ensuring the health and safety of the nation's water bodies and drinking water supply. To carry out this mission, the Clean Water Act, as amended, gives the Administrator of USEPA the authority to set water quality standards, engage with states and localities developing plans to meet these standards, review and approve such plans, provide financial and other assistance for implementation, and seek legal sanctions and fines for any failure to comply (33 U.S.C. § 1251 et seq., 2002). One key step USEPA and its state, local, and tribal partners take in protecting water quality is the development of implementation plans that specify the actions a community will take to attain total maximum daily load (TMDL) water quality standards.

However, these plans typically do not take climate change or other challenging uncertainties into account and may be vulnerable to future change or surprise. To assist USEPA and its partners, RAND researchers explored how Robust Decision Making (RDM) methods can be used to develop a plan that identifies robust and adaptive near- and long-term strategies and is based on the best available science as well as public engagement. In the course of the study, the researchers examined two pilot case studies—one on the Patuxent River in Maryland and one on the North Farm Creek tributary of the Illinois River—to explore and illustrate how RDM might help to improve USEPA future water quality decisions and uncertainties.

How Uncertainty Threatens Water Quality Implementation Plans

USEPA seeks broad public engagement when working to protect water quality. Its goal is to conduct a decisionmaking process that transparently and predictably uses the best available scientific information. However, much of the relevant information is uncertain, which complicates the pursuit of this goal. USEPA and its partners have often grappled with imperfect data regarding the hydrology, pollution sources, and pollutant flows in the water bodies they seek to protect. This uncertainty has been significantly exacerbated in recent years by factors such as climate change, changing patterns of land

use and other socioeconomic trends, and the pursuit of promising but largely untested approaches, such as green infrastructure, to environmental management.

TMDL implementation planning typically relies on a combination of observed data and computer simulation modeling. Observed data are used to identify the sources of pollution affecting lakes, streams, and rivers, as well as monitor how conditions change over time. Simulation models are used to suggest how pollution levels might change in the future, with or without policy interventions intended to reduce future pollution levels. While historical data provide the foundation for understanding the hydrology and pollution loads in a watershed, simulation models provide the best means available to make systematic inferences about future water quality. Such inferences are necessary to have a forward-looking plan.

Future projections are typically developed using rainfall-runoff simulation models. This study focuses on the use of such models to support TMDL planning processes. Although such models are typically calibrated using observed data, they can sometimes produce implausible or incorrect results due to a lack of sufficient resolution, skill, or overall scientific understanding of the system. In addition, even adequately skilled models can generate erroneous estimates of future water quality due to external drivers that may evolve in unanticipated ways, such as hard-to-predict estimates of future climate, land use patterns, other socioeconomic factors, or policy implementation outcomes. These drivers are sometimes referred to as "deep" uncertainty, because the parties to a decision do not know—or cannot agree on—the best model for relating actions to consequences, nor the likelihood of future events.

When faced with deep uncertainty, the best approach is often to use a process of *iterative risk management*. Such an approach should recognize that some uncertainties are irreducible and help produce water quality implementation plans that are *robust* in the face of this uncertainty. It should also include an *adaptive* process of acting, monitoring, and changing course in response to new information.

Although the analysis currently used to develop water quality implementation plans often uses a risk management framework, to date it has proved difficult to fully exploit the benefits of flexibility and experimentation in TMDL implementation planning. In large part this owes to institutional constraints. But standard analytic approaches do not necessarily facilitate the development of robust and adaptive plans due to a lack of appropriate methods for using uncertain simulation model results as part of forward-looking analysis. Climate change and the opportunities created by new approaches to environmental management have exacerbated this gap and suggest that new analytic approaches are needed to help make water management plans more flexible and robust. Such new approaches may help reconcile the tension between the need for accountable, transparent, and objective governance and the benefits of flexibility and experimentation.

New Approach Can Make Uncertain Science Decision-Relevant

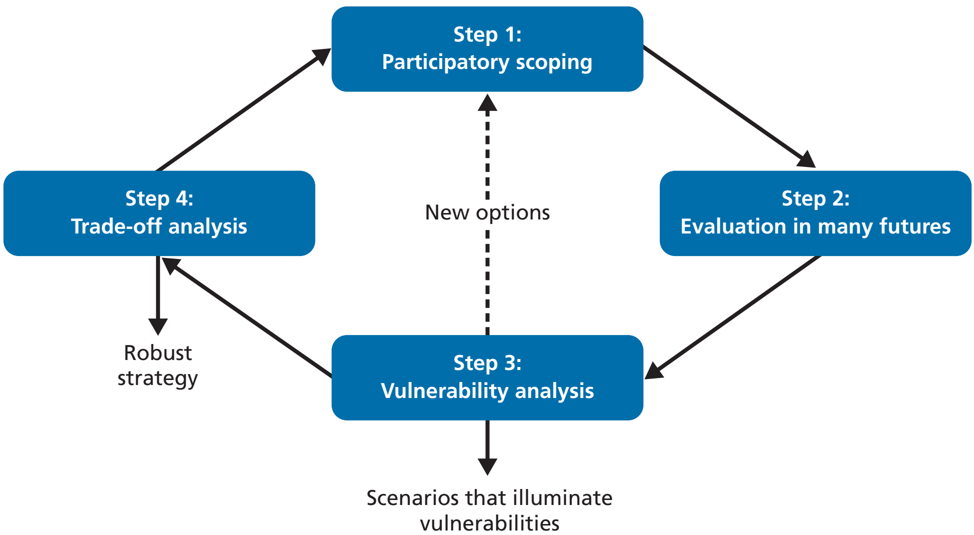
RDM is a new approach that can incorporate uncertain scientific and socioeconomic information into water quality implementation plans. RDM differs from many of the analytic approaches currently used by USEPA in that it employs a "backward" analysis. Rather than beginning with an agreed upon set of assumptions about the future, RDM begins with a proposed plan or plans, uses analytics to stress-test them over many futures, and concisely summarizes the conditions in which each plan will work well or poorly. RDM adopts an "exploratory modeling" approach that uses simulation models not as tools for prediction, but simply as a means to map assumptions onto consequences without necessarily privileging one assumption over another. RDM can significantly enhance the value of simulation models initially designed for predictive analysis by running them over many plausible paths into the future in order to identify vulnerabilities of proposed strategies and potential robust responses.

RDM provides several advantages over traditional methods relevant to water quality implementation planning. First, the approach provides a way to draw decision-relevant information from a wide range of imperfect projections. This includes uncertainty about the future as well as the uncertainty inherent in imperfect hydrologic simulation models. RDM also supports improved plans by providing output in a scenario-based form that helps decisionmakers to agree on which decision to choose without requiring prior agreement on assumptions. This can reduce conflicts among stakeholders as well as facilitate interagency processes.

As shown in Figure S.1, the RDM process starts with a decision structuring exercise in which parties to the decision define the key factors in the analysis (Step 1). Analysts next use simulation models representing these key factors to evaluate a proposed TMDL implementation plan or plans in each of many plausible paths into the future, which generates a large database of simulation model results (Step 2). In the third step, analysts and decisionmakers use visualization and statistical "scenario discovery" algorithms to explore these many paths into the future and identify the key factors that distinguish futures in which TMDL plans meet and miss their goals. In the fourth step, analysts and decisionmakers identify and evaluate ways to improve plans to increase the range of futures over which they succeed.

This overall process aims to facilitate stress-testing of proposed TMDL implementation plans and deliberation among diverse stakeholders on appropriate responses to any vulnerabilities. The approach aims to embed systematic quantitative reasoning about the consequences of, and trade-offs among, alternative decision options within a framework that recognizes the legitimacy of different interests, values, and expectations about the future.

Figure S.1
RDM Process for Deliberative Iterative Risk Management



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Two Case Studies Demonstrate RDM Analysis for Water Quality

This report considers two pilot case studies—one on the Patuxent River in Maryland and one on the North Farm Creek tributary of the Illinois River near Peoria—to explore and illustrate how RDM might help USEPA and its partners to improve TMDL implementation planning in the face of imperfect models, climate change, and other uncertainties. We chose these case studies based on an extensive screening process with USEPA/Office of Research and Development (ORD) and USEPA/OW staff, seeking two regions that (1) face diverse water quality management challenges, (2) already apply hydrologic simulation models, and (3) have relevant TMDL implementation planning activities currently under way for which an RDM analysis might provide useful information.

Patuxent River Case Study

After a series of discussions with Chesapeake Bay Program representatives, RAND and USEPA identified a key tributary of the Chesapeake Bay, the Patuxent River, as a good candidate to test the value of RDM for water quality management decisions. The chosen focus for this pilot is urban stormwater management. The Patuxent River is located between Baltimore and Washington. Its watershed is the largest entirely within Maryland, is highly urbanized, and has a rapidly growing population. The results of this pilot analysis can serve as a template for future planning as the Chesapeake Bay Program incorporates climate change into its future water quality planning for the broader Chesapeake Bay region. Table S.1 summarizes the key factors considered in this pilot.

To perform the quantitative water quality experiments in this case study, we applied the Chesapeake Bay Program's Phase 5.3.2 Watershed Model and the supporting Scenario Builder modeling suite. The study uses three key water quality performance metrics—annual average delivered loads of nitrogen, phosphorus, and sediment from the Patuxent River to the Chesapeake Bay—and focuses on pollutant loads from the urban sources. We also considered the cost of implementing best management practices (BMPs) as a performance metric.

Phase II of Maryland's Watershed Implementation Plan (WIP) sets water quality TMDL targets for the Patuxent River through a combination of historical water quality and hydrology monitoring data and detailed simulation modeling, and specifies a series of BMP investments designed to meet these new standards. We tested the performance of this plan across a range of plausible futures.

Initial results confirmed that, with historical hydrology, current land use, and current population assumed, Maryland's Phase II WIP is able to meet the specified stormwater TMDL targets. However, for the three contaminants of concern—nitrogen, phosphorus, and sediment—the Phase II WIP often did not meet these targets when a nonstationary climate and potential future changes in population or land use development patterns were considered.

Table S.2 summarizes the performance of the two plans by way of example. "Current Management" (no new BMP investment beyond 2010) and "Phase II WIP" (BMP

Table S.1
Key Factors Considered in the Patuxent Case Study

Uncertain Factors (X)	Policy Levers (L)

Hydrology and climate change
• Observed historical hydrology (1984–2005)
• Downscaled climate projections
  • 2035–2045
  • 2055–2065
Land use
• Population growth (2010–2050)
• Infill, sprawl, and forest conservation
BMP effectiveness
Evapotranspiration model parameters
	MDE Phase II Watershed Implementation Plan BMPs, including
	• Stormwater management–filtering practices
	• Stormwater management–infiltration practices
	• Urban stream restoration
	• Urban forest buffers

Systems Model Relationships (R)	**Performance Metrics (M)**
Phase 5.3.2 Chesapeake Bay Watershed Model • Airshed model • Land use change model • Watershed model • Chesapeake Bay model	Metrics • Nitrogen delivered loads • Phosphorus delivered loads • Sediment delivered loads • Implementation costs (extended analysis only) Targets • Phase I WIP TMDLs • Phase II WIP TMDLs (2017 interim; 2025 final)

Table S.2
Futures in Which Phase II Target Is Met, by Strategy and Contaminant

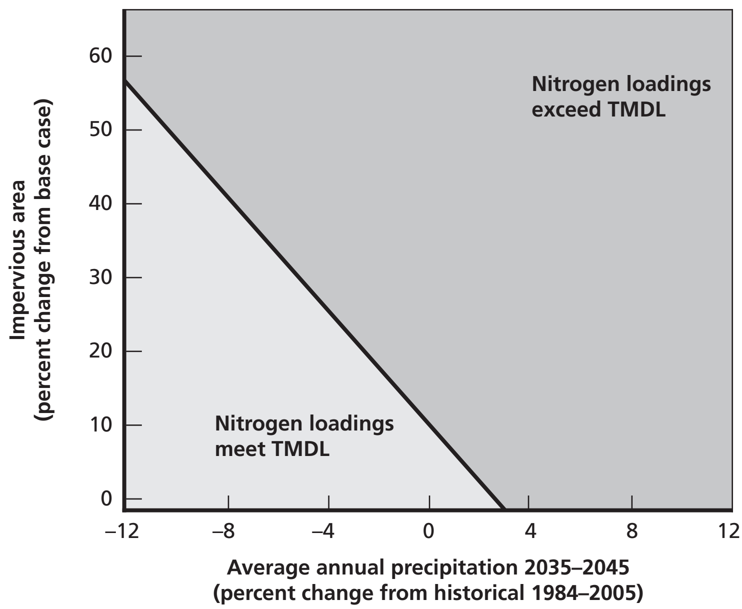
	Number (Percentage) of Futures Meeting the Phase II Target					
	Historical Hydrology 1984–2005		Climate Altered Hydrology 2035–2045		Climate Altered Hydrology 2055–2065	
Performance Metric	Current Management	Phase II WIP	Current Management	Phase II WIP	Current Management	Phase II WIP
Nitrogen target	0 (0)	1 (14)	9 (7)	35 (28)	13 (10)	31 (25)
Phosphorus target	0 (0)	2 (29)	6 (5)	42 (33)	5 (4)	35 (28)
Sediment target	0 (0)	3 (43)	15 (12)	59 (47)	15 (12)	55 (44)
Meets all three targets	0 (0)	1 (14)	6 (5)	30 (24)	5 (4)	29 (23)

investments implemented as specified in Maryland's WIP) were simulated in this study in 259 different futures. Each future represents a single realization of the model reflecting one set of assumptions about future climate-influenced hydrology, population, and land use development patterns. For the three key contaminants considered, the table summarizes the number and percentage of futures in which the TMDL target is met in three hydrology periods: 1984–2005 (historical hydrology, seven futures), 2035–2045 (126 futures), and 2055–2065 (126 futures).

Table S.2 shows that current management rarely leads to attaining the Phase II WIP targets. The Phase II WIP increases the proportion of futures in which the target is met. For instance, with the Phase II WIP the percentage of futures meeting the sediment target increases from 0 percent to 43 percent for the historical climate projection, 12 percent to 47 percent for the 2035–2025 climate projections, and 12 percent to 44 percent for the 2055–2065 climate projections, respectively. However, as previously noted, the Phase II WIP does not meet TMDL targets in a substantial fraction of cases.

Our vulnerability analysis identified two key drivers that best described when these targets were not met: an increase in precipitation due to climate change, or an increase in the amount of impervious area cover in the Patuxent Basin caused primarily by population growth. Either individually or in combination, these uncertain drivers led to pollutant loads from the Patuxent above the recently established long-term targets even when assuming that the substantial Phase II management infrastructure would be in place. For instance, Figure S.2 shows the results of our vulnerability analysis for the nitrogen TMDL. The figure shows regions representing all futures in which the Phase II WIP is implemented. These futures plotted in terms of two key uncertain dimensions: the average annual precipitation change from the historical conditions (x-axis), and change in impervious land area in the Patuxent River watershed (y-axis).

Figure S.2
Futures in Which Phase II WIP Meets and Misses Nitrogen TMDL



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The dark shaded region defines a decision-relevant scenario space described by the average annual precipitation change from historical conditions, and the percentage growth in impervious land area in the Patuxent River watershed. It shows that futures that display either higher precipitation, increased impervious area, or a combination of both lead to increased runoff, which in turn yields larger-than-expected nitrogen loads flowing into the Chesapeake Bay. These results show that average precipitation would need to stay constant or decline *and* impervious area would need to remain at the mid-to-low end of the plausible range to consistently meet the nitrogen TMDL with the Phase II WIP implemented as currently constructed.

A preliminary extension to this analysis, considering how individual BMP types could be used to augment the plan, suggests that additional investment in some BMPs, including green infrastructure options such as wet ponds, wetlands, and urban filtering practices, could help achieve stormwater TMDL targets cost-effectively in some future scenarios of concern. However, in other cases, the scale of infrastructure investment needed would likely exceed the available land area for these BMPs and could be very expensive. Based on this analysis, we conclude that the State of Maryland should consider a broader range of options, such as changes to land use practice, to help reduce or avoid more impervious area growth.

North Farm Creek Case Study

The State of Illinois is beginning the process of implementing pollution control and restoration plans for the Middle Illinois River. RAND and USEPA chose the North Creek Tributary as a second case study because it includes a significant amount of agricultural land and is currently addressing agricultural runoff challenges. Our analysis built on the 2012 load reduction strategy and BMP implementation plan for the North Farm Creek subwatershed, one of two pilot areas selected by the State of Illinois for initial development of load reduction strategies. The North Farm Creek Implementation Plan envisions an adaptive management approach that deploys BMPs in three phases: nonstructural (years 0–3), structural (years 3–10), and monitoring and adaptive management (years 10–20).

The key factors considered in this pilot analysis are shown in Table S.3. In particular, the case study uses climate projections from the North American Regional Climate Change Assessment Program (NARCCAP) and the Soil and Water Assessment Tool (SWAT), a model commonly used by USEPA and many jurisdictions countrywide for TMDL development. The North Farm Creek Implementation Plan includes eight BMPs, four of which could be simulated in the SWAT model available to this study. We refer to this as the Modeled Implementation Plan, and its performance is compared to futures in which no additional BMPs are implemented ("Current Management"; see Table S.4).

We used the simulation model to explore the performance of the Current Management strategy and the Modeled Implementation Plan over 140 futures, comprising seven alternative climate projections and 20 assumptions about the actual effectiveness of the BMPs. This analysis suggests that future climate change could significantly increase pollution loads in North Farm Creek (by 30–60 percent for nitrogen, and 85–200 percent for phosphorus, respectively) under Current Management.

Table S.4 shows that the modeled BMPs could significantly reduce these pollution loadings. In the current climate, these modeled BMPs would meet both the

Table S.3
Factors Considered in the North Farm Creek Case Study

Uncertain Factors (X)	Policy Levers (L)
Effects of climate change on streamflow BMP effectiveness • Intrinsic performance • In response to climate change	Draft Implementation Plan, including structural management options: • Green infrastructure • Grassed waterways • Conservation tillage Adaptive management responses
Systems Model Relationships (R)	**Performance Metrics (M)**
SWAT model of North Farm Creek calibrated to meet current water quality Airshed model	TMDL compliance for: • Nitrogen • Phosphorus • Sediment

Table S.4
Futures in Which TMDL Targets Are Met, by Plan and Pollutant for North Farm Creek

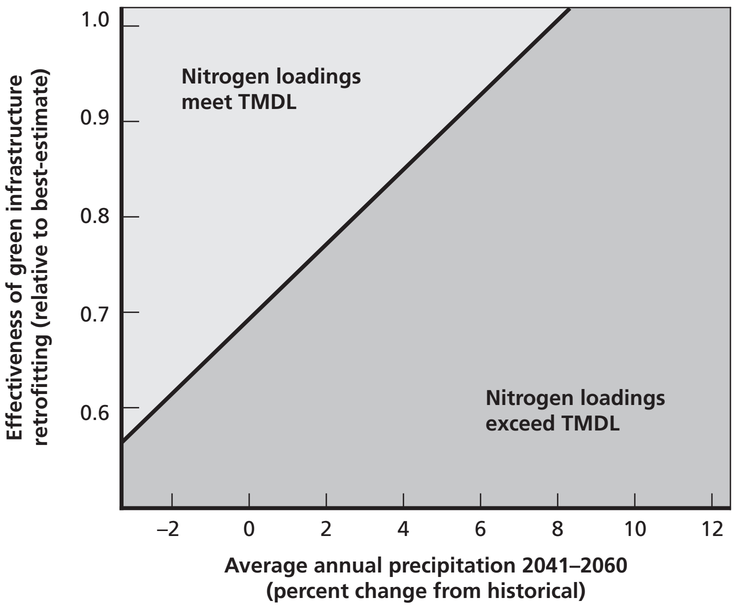
	Number (Percentage) of Futures Meeting the TMDL Target			
	Current Climate		Future Climate (2041–2060)	
Pollutant	Current Management	Modeled Implementation Plan	Current Management	Modeled Implementation Plan
Nitrogen target	0 (0)	20 (100)	0 (0)	52 (43)
Phosphorus target	0 (0)	20 (100)	0 (0)	0 (0)
Sediment target	0 (0)	0 (0)	0 (0)	0 (0)

nitrogen and the phosphorus targets over the full range of assumptions about BMP effectiveness. In future climates, the modeled BMPs would meet the nitrogen target in about 40 percent of the futures considered. The failure of the modeled plan to meet the phosphorus and sediment standards in our analysis results in part from the fact we modeled only some components of the full North Creek Implementation Plan but may also result from aggressive targets for these pollutants.

As shown in Figure S.3, our vulnerability analysis identified two key drivers that best described the conditions in which nitrogen loadings under the modeled BMPs in the Implementation Plan might exceed the TMDL: an increase in the annual precipitation combined with actual effectiveness of green infrastructure retrofitting less than that assumed in the plan. In the figure's upper-left region, the Implementation Plan generally meets the nitrogen TMDL. In the lower right-hand region, the plan generally fails to meet the TMDL due to a combination of too-high precipitation and too-low green infrastructure effectiveness. The horizontal axis spans the full range of the NARCCAP climate projections used in this analysis. The North Farm Creek plan would meet its TMDL goals if green infrastructure were only 70 percent as effective as estimated as long as precipitation stays at historic levels. But if precipitation rises by 8 percent, well within the range of the NARCCAP projections, the modeled plan could fail to meet its goals even if the green infrastructure worked as well as projected.

The information from this vulnerability analysis can help inform the design and implementation of the North Farm Creek adaptive management plan. Monitoring the two factors that define this region—average annual rainfall and BMP effectiveness—and responding, if necessary, with additional investment in enhanced green infrastructure or other BMPs could improve the plan's ability to adapt over time to meet the nitrogen TMDL.

Figure S.3
Futures in Which the Modeled Implementation Plan Meets and Misses TMDL Goals



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Lessons Learned

These two case studies provide three important lessons for the development of TMDL implementation plans under conditions of uncertainty.

- **Climate change could have a significant impact on the success of water quality plans.** In both pilot regions studied, TMDL plans expected to meet water quality standards if future climate resembles the past do not meet these standards over a wide range of plausible future climate conditions. However, climate change is not the only important uncertainty, nor is it necessarily the dominant one. In the Patuxent case study, an increase in the area covered by impervious surfaces such as roads or parking lots would reduce the ability of the watershed implementation plan to meet current TMDL targets. Assumptions about BMP effectiveness are similarly influential on future plan success in the North Farm Creek pilot.
- **Rainfall-runoff simulation models, when used appropriately, can provide useful information for TMDL planning even in the face of deep uncertainty.** Used within an RDM framework, these models can help decisionmakers explore the performance of TMDL plans across many plausible paths into the future. Visualization and statistics on the resulting database of model runs can then help

to identify the types of future conditions in which TMDL plans will meet or miss their water quality goals, suggest how plans can be modified to address these vulnerabilities, and help craft adaptive management plans by suggesting signposts and contingent actions. Statistical and visualization packages to enable these tasks are now readily available.

- **Currently available simulation tools are suitable for such RDM analyses, but much could be done to improve their utility.** For instance, the treatment of BMPs in both models could be improved, in terms of both resolution and skill. In addition, a greater emphasis on process-based representations would facilitate consideration of more types of BMPs and allow exploration over a wider range of assumptions about their effectiveness. The treatment of inputs in both models could also be streamlined to better integrate with simulations of a more complete range of biophysical and socioeconomic processes and to facilitate scanning over many possible futures.

Looking to the Future

To improve and maintain high water quality standards in changing, often difficult-to-predict conditions, USEPA will need to employ iterative risk management and rely increasingly on robust and flexible implementation plans. Such plans should be developed as part of science-based, transparent, accountable, and participatory processes. These case studies describe analytic methods and tools that can be used to support participatory processes, but more work is needed for full-scale implementation. Building on this foundation could significantly enhance USEPA's ability to ensure water quality in the face of climate and other uncertainties.

Future analysis could help make TMDL plans more robust by considering a wider range of potential uncertainties and a richer set of response options. For instance, the current case studies considered uncertainty in either future land use or BMP effectiveness, but not both together. In addition, future work could explore a wider range of socioeconomic factors and, importantly, consider water quality as part of a more integrated multisector water management or land use plan.

The treatment of adaptive TMDL implementation plans could also be considerably expanded beyond that considered here. Future analyses could lay out multistage adaptive plans along the lines of the 2012 North Farm Creek Future Implementation Plan. These plans would include specific sets of near-term actions, signposts to monitor, and contingency actions to take in response to observations of one or more signposts. The analysis could then help compare and evaluate the robustness of proposed adaptive plans and would also allow decisionmakers to consider the benefits of investing in monitoring systems that would improve the information available to them over time.

Improvements to the analytic tools used in this study could significantly improve the effectiveness of the decision support available to water quality planners. In addition to improvements to the underlying simulation models (discussed above), improved planning tools could facilitate the design and comparison of multistage adaptive TMDL management plans. Improved visualization packages could make the results more broadly accessible. Packaging such tools in more user-friendly and potentially web-accessible toolkits could help make these methods widely available to decision-makers at the local, state, and regional levels.

These two case studies also suggest how new decision support methods can facilitate more effective risk management for the nation's overall efforts to improve water quality. RDM and similar analytic decision support methods can expand the range of conditions in which water quality implementation plans will be successful—that is, they can "adjust as planned" as future change unfolds. This makes it less likely that TMDL implementation plans, the organizations tasked to develop them, or the underlying standards would need to be changed. That said, because adaptive management principles are at the core of this approach, RDM also can help empower USEPA, state regulators, and other authorities to revisit and revise plans, the planners, and standards if necessary as new technology emerges or new scientific findings unfold.

The regulations used to protect water quality provide key tools to promote the public interest but must be carefully designed to enhance benefits, reduce adverse consequences, and respond effectively to environmental, socioeconomic, and other types of change. In particular, climate change and the opportunities created by new approaches to environmental management, such as green infrastructure, have created a need for new analytic approaches to help make water management plans more flexible and robust. Such new approaches may help reconcile the tension between the need for accountable, transparent, and objective governance and the benefits of flexibility and experimentation. These methods do so by enabling exploration over a wide range of plausible futures, systematically identifying those future conditions in which proposed water management strategies do or do not meet their goals, helping to identify specific milestones and midcourse corrections that can help strategies adapt over time, and identifying the trade-offs among alternative robust adaptive strategies—all within a process designed to facilitate stakeholder input and deliberation. This report provides only an initial exploration of the possibilities, but such approaches offer the potential to facilitate the development of robust, adaptive water quality management that may be more appropriate under the conditions of deep uncertainty arising from climate change and many other trends in our rapidly changing world.

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This report was the result of an active and productive collaboration with many partners, and their collective contributions, support, and feedback were invaluable. We would first like to thank and acknowledge Susan Julius and Tom Johnson of USEPA's Office of Research and Development, who oversaw the overall effort and were active and engaged partners throughout. Chris Weaver, Deputy Director of the U.S. Global Change Research Program, provided a guiding vision and early support for the project. For the Patuxent River case study, we worked closely with USEPA's Chesapeake Bay Program. Our particular thanks to Lew Linker, Gary Shenk, Gopal Bhatt, Matt Johnston, and Peter Claggett for helping to scope the study, providing the water quality modeling and supporting its use in this setting, and for feeding in a variety of key model inputs for the Robust Decision Making analysis. For the North Farm Creek case study, we are grateful to Jennifer Clarke of the Illinois Environmental Protection Agency and Chris Urban for Region V, USEPA, for their interest and support. Dwight Atkinson of the USEPA Office of Water suggested this case study and provided useful encouragement and support throughout the effort. Jon Butcher and Sam Sarkar of TetraTech calibrated the SWAT model and provided invaluable guidance in its use. RAND's Gary Briggs helped us modify the model for use in the RDM analysis and suggested key innovations that made the analysis possible. Linda Mearns and Seth McGinnis helped us interpret some of the subtle differences among the climate projections. Debra Knopman and Keith Crane helped us sharpen our arguments over the entire report, and Evan Bloom's work on RDM and adaptive strategies provided us valuable guidance in developing our ideas. Finally, we gratefully acknowledge and thank the peer reviewers for this document, Steven Popper (RAND) and an anonymous external reviewer. Comments from both reviewers were insightful and helped us improve the final narrative.

Abbreviations

BASINS	Better Assessment Science Integrating Point and Nonpoint Sources
BCA	benefit-cost analysis
BCSD	bias corrected and spatially downscaled
BMP	best management practice
CAT	Climate Assessment Tool
CBLCM	Chesapeake Bay Land Change Model
CCSM3	Community Climate System Model
CGCCM3	Third Generation Coupled Climate Model
CMIP	Coupled Model Intercomparison Project
GCM	general circulation model
GFDL	Geophysical Fluid Dynamics Laboratory
HADCM3	Hadley Center Coupled Model, version 3
HadRM	Hadley Regional Model
HRU	hydrologic response unit
HSPF	Hydrological Simulation Program–Fortran
ICLUS	Integrated Climate and Land Use Scenarios
IEPA	Illinois Environmental Protection Agency
IPCC	Intergovernmental Panel on Climate Change
LID	low-impact development

LRS	load reduction strategy
MDE	State of Maryland Department of the Environment
MIROC	Model for Interdisciplinary Research on Climate
NARCCAP	North American Regional Climate Change Assessment Program
NPDES	National Pollutant Discharge Elimination System
NRC	National Research Council
ORD	USEPA Office of Research and Development
OW	Office of Water
PCA-PRIM	principal component analysis–patient rule induction method
PRIM	patient rule induction method
RDM	Robust Decision Making
SRES	Special Report on Emissions Scenarios
SSURGO	Soil Survey Geographic database
SWAT	Soil and Water Assessment Tool
TMDL	total maximum daily load
USDA ARS	U.S. Department of Agriculture Agricultural Research Service
USEPA	U.S. Environmental Protection Agency
USGS	U.S. Geological Survey
WIP	watershed implementation plan
WRF	Weather Research and Forecasting model
XLRM	uncertainties, policy levers, relationships, and performance measures

CHAPTER ONE

Water Quality Decisions Are Challenged by Future Uncertainty

> Our regulatory system . . . must be based on the best available science. It must allow for public participation and an open exchange of ideas. It must promote predictability and reduce uncertainty.
>
> Executive Order 13563, January 18, 2011

> Plans are worthless, but planning is everything.
>
> Dwight D. Eisenhower

Introduction

The U.S. Environmental Protection Agency (USEPA) and its Office of Water (OW) are charged with ensuring the health and safety of the nation's water bodies and drinking water supply. To carry out this mission, the Clean Water Act, as amended, gives the USEPA administrator the authority to set water quality standards, engage with states and localities developing plans to meet those standards, review and approve such plans, provide financial and other assistance for implementation, and seek legal sanctions for any failure to comply (33 U.S.C. § 1251 et seq.).

In conducting these activities, USEPA seeks broad public engagement in a process that transparently and predictably uses the best available scientific information. However, much of the relevant information is uncertain, which complicates the pursuit of these aims. USEPA and its partners have often grappled with imperfect data regarding the hydrology and pollution flows in the water bodies they seek to protect. But today, this uncertainty has been significantly exacerbated by factors such as climate change, changing patterns of land use and other socioeconomic trends, and the pursuit of promising but novel approaches to environmental management. This creates a tension between the need for accountable, transparent, and objective governance on the one hand, and the benefits of flexibility and experimentation as a means for managing uncertainty on the other.

This report demonstrates a new approach, called Robust Decision Making (RDM), for incorporating uncertain scientific and socioeconomic information into one key step in protecting water quality—the development of the implementation plans that specify the actions communities will take to attain total maximum daily load (TMDL) water quality standards. Through two case studies, one focused on the Patuxent River in the Chesapeake Bay watershed and the other on the North Farm Creek Tributary of the Illinois River, this study suggests how water quality planners can: (1) test TMDL implementation plans over a wide range of futures; (2) use vulnerability analysis to facilitate the development of flexible and adaptive plans; and (3) identify key trade-offs among alternative improvements intended to make plans more robust. Overall, the report suggests that RDM-based analyses can help USEPA and its partners successfully manage uncertainty by developing flexible and robust plans within a process designed to facilitate stakeholder input and deliberation.

Challenges and Opportunities in the Uncertainties Affecting TMDL Planning

This study focuses on the use of hydrologic rainfall-runoff water quality simulation models in support of TMDL planning processes. Such planning processes generally rely on a combination of observed data and simulation modeling to support decision-making. In particular, these analytic tools are used to (1) identify the sources of pollution affecting particular lakes, streams, and rivers; (2) suggest how pollution levels might change in the future with and without various policy interventions that aim to reduce future pollution levels; and (3) monitor how conditions change over time.

Observational data provide the foundation for understanding the hydrology and pollution loads in a watershed. Rainfall-runoff simulation models, when calibrated to the observed data, can deepen understanding of the past and present state of a hydrologic system. In addition, such simulation models also provide the best means available to make systematic and comprehensive inferences about future water quality. TMDL implementation planning requires such foresight, because the policy measures identified in these plans can take time to implement, may last for decades, and are costly to build, maintain, or improve in future years. For instance, investments in new infrastructure may affect pollution levels for decades. TMDL plans may also impose requirements on businesses, farms, and residences, which can generate public disapproval if these requirements do not reduce pollution as expected. Simulation models provide a convenient and accessible way to compare the potential benefits and costs of alternative TMDL plans before actions are initiated.

However, water quality projections generated by simulation models can sometimes produce implausible or incorrect results. In some cases, the models lack sufficient resolution or skill. Such models' ability to predict pollution levels depends on both the quality and the quantity of observed monitoring data available for model calibration, as well as the extent to which the model adequately represents the physical processes in complicated and variable systems. When water quality models lack sufficient skill, planners can improve them by gathering additional monitoring data and working to improve the representation of the system in the model.

Even adequately skilled models, however, can generate erroneous estimates of future water quality due to external drivers that may evolve in unanticipated ways. Climate change presents one obvious source of uncertainty potentially affecting future water quality and the effectiveness of actions intended to improve it (USEPA, 2010c). Traditionally, water quality planning has assumed that future streamflow, precipitation, and other relevant hydrological processes in a region will remain similar to those in the recent past, enabling an analysis that supports water quality planning to confidently employ historical and current observations as the basis for future simulations. With climate change, however, such stationarity no longer remains a reliable assumption (Milly et al., 2008). While current General Circulation Models (GCMs) offer one of the best available sources of information regarding projections of future climate, they remain imperfect tools for estimating future temperature and precipitation patterns at the requisite spatial and temporal scales. This irreducible uncertainty may not be a temporary situation. There are strong reasons to believe such models will not soon achieve the reliability and precision generally expected of observations of historical and current climate (Weaver et al., 2013). As noted by the National Research Council (2009), climate change is certain to surprise us.

Uncertain socioeconomic drivers can also affect future water quality. Notably, population growth and changing patterns of land use across the country—for instance, continuing urbanization of previously undeveloped areas, or changes in agriculture crop choices and practices—can have substantial effects on water quality, most often negative. Moreover, many promising responses to climate change and these other types of stresses on the nation's lakes, rivers, and streams, such as low-impact development (LID) or nature-based "green" infrastructure, also introduce significant uncertainty into the analysis. While the potential benefits are promising, the effectiveness of these new types of interventions may vary from location to location, and implementation will depend on the skill and commitment of many different actors. More broadly, as the focus of water quality efforts moves from "point" sources that can be directly monitored and regulated, such as factories or power plants, to "nonpoint" or distributed pollution sources, such as agricultural water runoff, confident predictions of the cost and effectiveness of various measures are likely to grow more difficult.

As a result, even without climate change USEPA might consider incorporating new decision support methods for managing uncertainty in TMDL implementation planning. But federal agencies have also recently embarked on a concerted effort to incorporate climate change into their planning processes. Doing so provides a unique opportunity to improve their overall planning processes by exploring new methods designed to more effectively manage many types of significant and irreducible uncertainty.

Robust Decision Making

To address this uncertainty challenge, the USEPA Office of Research and Development (ORD) asked RAND to consider how RDM methods might help USEPA/OW better manage climate and other uncertainties in its National Water Program. RDM (Lempert, Popper, and Bankes, 2003; Lempert et al., 2006; Lempert and Collins, 2007) is an iterative, quantitative methodology designed to support decisionmaking under conditions of deep uncertainty. Deep uncertainty occurs when the parties to a decision do not know—or agree on—the best model for relating actions to consequences or the likelihood of future events (Lempert, Popper, and Bankes, 2003). Deep uncertainty can be associated with key inputs to a planning challenge—such as future temperature or precipitation conditions given a changing climate—but can also describe "model uncertainty" emerging from limited, imperfect, or competing representation of physical systems using present-day computer models.

RDM has seen increasing application and success in areas focused on planning, in particular flood risk (CPRA, 2012; Groves, Sharon, and Knopman, 2012; Fischbach et al., 2012; Lempert et al., 2013) and water management applications (Groves and Lempert, 2007; Groves et al., 2008; Means et al., 2010; U.S. Bureau of Reclamation, 2012). The present study examines the extent to which, given the differing institutional and other contexts, RDM might also contribute to water quality management decisions.

RDM rests on a simple concept. Rather than using models and data to describe a best-estimate future, RDM runs one or more models over hundreds to thousands of different sets of assumptions to describe how plans perform in many plausible futures. The approach then uses statistics and visualizations based on the resulting large database of model runs to help decisionmakers identify those model assumptions and future conditions where their plans will perform well or poorly. This information can help decisionmakers develop plans more robust to a wide range of future conditions.

RDM may prove a promising tool for USEPA because it can help the agency develop more robust and adaptive TMDL plans in a manner that is science-based, transparent, and accountable to the public in the face of imperfect models, climate change, and other uncertainties. In particular, RDM may help USEPA to employ *iterative risk management*, the recommended approach for climate-related decisions (Intergovernmental Panel on Climate Change [IPCC], 2012; National Research Council [NRC], 2010; IPCC, 2014), in situations where the best available scientific information remains imprecise. USEPA already organizes its water quality and TMDL planning processes around such an iterative risk management approach. For instance, when setting drinking water standards, water quality for the nation's water bodies, and standards for TMDLs, the agency follows a recursive process of monitoring, analysis, public input, decision, and review (see Appendix A). RDM and related methods may provide useful information on the design of such adaptive strategies more effectively than other analytic approaches often considered by USEPA.

Patuxent River and North Farm Creek Case Studies

This report considers two pilot case studies—one on the Patuxent River in Maryland and one on the North Farm Creek tributary of the Illinois River—to explore and illustrate how RDM might help USEPA and its partners to improve TMDL implementation planning in the face of imperfect models, climate change, and other uncertainties. We chose these case studies based on an extensive screening process with USEPA/ORD and USEPA/OW staff, seeking two regions that (1) face diverse water quality management challenges, (2) already apply hydrologic simulation models, and (3) have relevant TMDL implementation planning activities currently under way for which an RDM analysis might provide useful information (see Appendix B).

The Patuxent River and North Farm Creek case studies satisfy these criteria. The former is largely urban and faces substantial urban stormwater management challenges, while the latter includes a significant amount of agricultural land and is currently addressing agriculture runoff challenges. In both cases, the requisite models and data were available, for the Patuxent as part of USEPA's Chesapeake Bay Program, and for the Illinois River as part of USEPA's Twenty Watersheds project (USEPA, 2013). In both cases, the models have sufficient skill at reproducing pollution flows under historical and current conditions in order to focus our analysis on uncertainties generated by potential future changes in climate or socioeconomic trends.

In both case studies, we conduct a vulnerability analysis of current TMDL implementation plans: Phase II of Maryland's Watershed Implementation Plan for the Patuxent River, and the 2012 load reduction strategy and best management practice (BMP) implementation plan for the North Farm Creek watershed, respectively. In both cases, our analyses confirm that current plans will meet their TMDL targets if future climate is similar to historic climate and key socioeconomic trends evolve as expected. But both case studies also identify plausible combinations of changes in future trends in which the two current TMDL implementation plans may not prove successful. The analyses then suggest ways that the plans might be modified, now and in the future, to expand the range of futures over which the water quality goals can be met.

Organization of This Report

This study's two case studies demonstrate how RDM can help USEPA and its state, tribal, and local partners to develop robust and flexible TMDL implementation plans in the face of climate change and other hard-to-predict uncertainties. The approach described is designed to support a transparent, objective, and science-based iterative risk management process.

The next chapter of this report provides an overview of our proposed methodological approach for robust adaptive TMDL planning. Chapter Three presents the Patuxent River urban stormwater management case study. Chapter Four presents the North Farm Creek rural runoff case study. Chapter Five draws the case studies together and provides preliminary conclusions.

CHAPTER TWO

Analytic Tools for Robust Adaptive Water Quality Management

Introduction

As theory and practice in many fields make clear, the best response to deeply uncertain conditions is often to pursue strategies that are robust and adaptive (Rosenhead, 1990; Rosenhead, Elton and Gupta, 1972). Robust strategies perform well across a wide range of plausible futures; that is, their outcomes are insensitive to uncertainty. Often strategies achieve robustness through adaptivity, evolving over time in response to new information (Walker, Marchau, and Swanson, 2010; Rosenhead, 2001).

While USEPA's decision processes are designed around concepts of iterative risk management, the current practice does not facilitate the development of TMDL implementation plans designed to be adaptive, nor does it provide the means to ensure they are robust. In part, this is due to the shortcomings of commonly used analytic methods not well suited to examining robustness and informing the design of adaptive strategies. In addition, a variety of institutional, political, and cognitive barriers can make it hard to implement adaptive strategies (Renn, 2008; Lee, 1993) or consider questions of robustness (Lempert, 2013; Lempert, Popper, and Bankes, 2003; Lempert and Light, 2009).

As just one example, Holling (1978) notes that adaptive management[1] necessarily embraces the concept that failure can lead to success. This is because gathering good data requires conducting alternative activities, some of which prove more successful than others. However, organizations and policymakers often fear the consequences of being identified with failure and may resist any systematic monitoring or data col-

[1] Note that the term *adaptive management*, widely used in the ecological and planning literatures, can have two different meanings. The term can refer to situations in which the choice of policy is strongly influenced by a requirement to generate reliable new information (Holling, 1978; Holling, 1996). But the term is also used more generally to refer to policies designed to respond to new information (NRC, 2009). The former, sometimes called *active adaptive management*, might involve forest managers who explicitly pursue alternative management practices on similar plots of land in order to gather scientific data on the most effective practices. The latter, sometimes called *passive adaptive management*, might involve a water management agency that pursues a portfolio of investments in different BMPs, largely to manage risk, but also intending to shift resources among investments in the future depending on which prove most successful. Unless otherwise noted, this study uses the term to mean passive adaptive management.

lection that might make errors easier to identify and trace to a specific source. More broadly, there exists a fundamental tension between, on the one hand, the rationalized legal and administrative procedures designed to ensure that public servants provide accountable, objective, and predictable management for their democratic polities, and on the other, the practice of policy flexibility and experimentation (Kloppenberg, 1986; Weber, 1922).

This study explores how new analytic methods for TMDL planning might help resolve this and similar tensions.

Robust Decision Making

The discussion of how a new approach to TMDL planning might help reconcile the conflicting demands of flexibility and experimentation versus accountability, objectivity, and predictability may be usefully grounded in the broader context of decision support. The NRC (2009) defines decision support as the "set of processes intended to create the conditions for the production and appropriate use of decision-relevant information." A key tenet of decision support is that analytics—the discovery and communication of meaningful patterns in quantitative information—are most effective when closely linked to user needs. In practice, this often means placing the primary focus on decisionmaking processes and understanding how information products can best facilitate these processes.

RDM (Lempert, Popper, and Bankes, 2003; Lempert et al., 2006; Hallegatte et al., 2012) provides one set of analytics in a decision support process that may facilitate TMDL planning under uncertainty. RDM belongs to a set of decision support approaches that begin with specific decisions under consideration and ask questions relevant to the choice among these decisions to organize information about possible future conditions such as those associated with climate or socioeconomic factors. The literature offers several names for such approaches, including "context-first" (Ranger et al., 2010), "decision-scaling" (Brown, 2010), and "assess risk of policy" (Carter et al., 2007; Dessai and Hulme, 2007; Lempert et al., 2004). All share the central idea of (1) beginning with a proposed plan or plans, (2) identifying future conditions where the plan fails to meet its goals and then (3) organizing available information about the future to help policymakers identify potential responses to those vulnerabilities and decide whether and when to adopt these responses.

RDM thus differs from many of the decision processes currently used by USEPA in that it employs a "backward" analysis. Rather than beginning with an agreed upon set of assumptions about the future, RDM begins with a proposed plan or plans, uses analytics to stress-test them over many futures, and concisely summarizes the conditions in which each plan will work well or poorly.

It is important to note that RDM uses simulation models in a way that is fundamentally different from analytic approaches, such as those commonly used by USEPA, that begin with agreement on a set of assumptions about the future. The latter regard models as predictive representations of reality sufficiently accurate to recommend the best response to an uncertain future. In contrast, RDM adopts an "exploratory modeling" approach (Bankes, 1993; Weaver et al., 2013) that regards models as mapping assumptions onto consequences without necessarily privileging some assumptions over others. Frequently, RDM can significantly enhance the value of decisionmakers' current models, generally designed for predictive analyses, by running them over many plausible paths into the future in order to identify vulnerabilities of proposed plans and potential robust responses.

Such "backward" analysis can help decisionmakers balance between two compelling but flawed responses to the challenge of planning under conditions of deep uncertainty. On one hand, decisionmakers may neglect important but uncertain factors. For instance, they may assume climate stationarity rather than attempt to include imperfect projections of future climate change in their analysis. In extremis, decisionmakers may rely solely on observational data to avoid reliance on imperfect simulation models. Such choices can produce narrowly accurate quantitative estimates but inform TMDL implementation plans better suited to past conditions than those of the future.

On the other hand, decisionmakers may choose to treat the full range of uncertainties within the framework of probabilistic decision and risk analysis. This in fact can prove the best approach when reliable probabilistic estimates are available. But when uncertainties are deep, plans based on best-estimate probability distributions can fail if the future unfolds differently than expected. In addition, while adaptive strategies can be represented within probabilistic decision analytic frameworks with approaches such as stochastic dynamic optimization, it can prove very complicated to do so with the detailed simulation models often used for TMDL planning. Finally, analyses that rely on broad agreement on a single joint probability distribution for a wide range of future biophysical and socioeconomic trends may inhibit efforts to generate consensus when the choice of any single distribution is insufficiently supported by the science and when different distributions are correlated with the differing economic interests and ethical values of the parties to the decision.

RDM avoids the first response by providing a means for drawing decision-relevant information from a wide range of imperfect projections. RDM avoids the second response by providing analytic output in a scenario-based form that helps decisionmakers to agree on which decisions to choose without requiring prior agreement on assumptions. This can reduce conflicts among stakeholders as well as facilitate interagency processes.

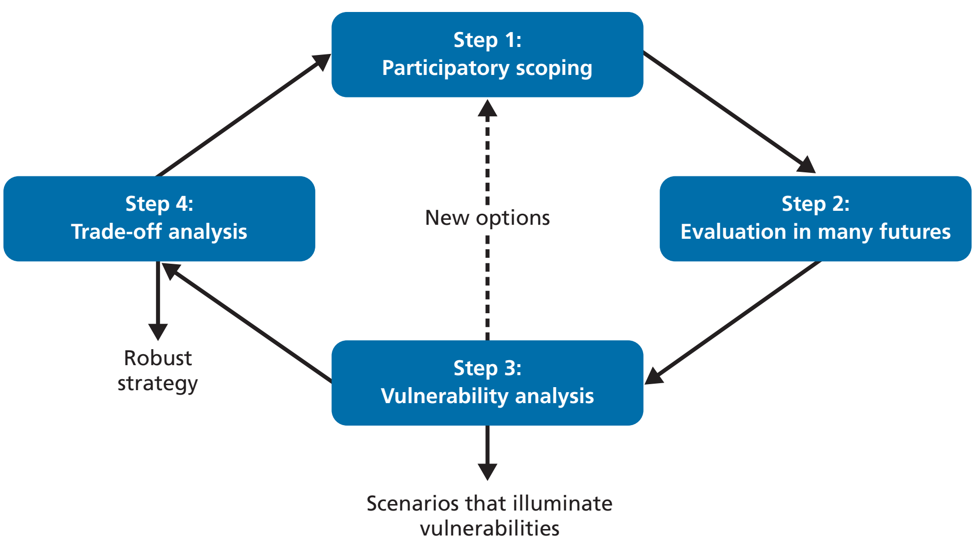
Deliberation with Analysis Process

RDM's process begins with a decision structuring exercise as illustrated in Figure 2.1. In this step decisionmakers define the objectives and metrics of the decision problem, policy options that could be used to meet these objectives, the uncertainties that could affect the success of proposed plans, and the relationships that govern how plans would perform with respect to the metrics (Step 1). This scoping activity often uses a framework called "XLRM," described in Chapter Three, which helps to collect and organize the information needed for the simulation modeling.

In Step 2, analysts use the resulting simulation model to evaluate plans in each of many plausible futures. This generates a large database of simulation model results. In Step 3, analysts and decisionmakers use visualizations and "scenario discovery" to explore the simulation data and identify the key combinations of future conditions in which each candidate plan might not meet decisionmakers' objectives. For example, TMDL implementation plans may fail to meet regulatory goals if climate change is more severe than expected and key BMPs perform less well than estimated. Such a scenario ("severe climate change and ineffective BMPs") may concisely capture the vulnerabilities of the TMDL implementation plan.

Next, using the trade-off analysis (Step 4), decisionmakers may identify a suitable robust strategy. Or, they may decide that none of the alternatives under consideration proves sufficiently robust. In this case they could return to the search for suitable candidates, perhaps through modification of or hybridization among the initial set, this

Figure 2.1
The RDM Approach



RAND *RR720-2.1*

time with deeper insight into the strengths and weaknesses of the alternatives initially considered.[2]

This RDM process explicitly follows a "deliberation with analysis" process of decision support, in which parties to the decision deliberate on their objectives, options, and problem framing; analysts generate decision-relevant information using the system models; and the parties to the decision revisit their objectives, options, and problem framing influenced by this quantitative information (NRC, 2009). RDM adds to this general approach the concepts of running the analysis backward—that is, beginning with a proposed plan—and testing plans against many different plausible futures. The overall process aims to facilitate deliberation among diverse stakeholders by embedding systematic quantitative reasoning about the consequences of, and trade-offs among, alternative decision options within a framework that recognizes the legitimacy of different interests, values, and expectations about the future (Lempert, 2013; Parker et al., 2015).

Scenario Discovery

The third RDM step, identifying vulnerabilities, plays a major role in the case studies discussed in this document. By understanding in detail the conditions under which TMDL plans may fail to meet their goals, planners may better understand how they might adjust these plans either in the present or in the future as conditions evolve.

Figure 2.2 summarizes the scenario discovery analytics that play a key role in this RDM vulnerability analysis. This hypothetical example begins with a large database of model run results in which each such entry represents the performance of one alternative plan in one future framed by an explicit set of assumptions. Some of the values in each entry in the database represent specific assumptions about future climate and other relevant factors; other values represent important performance metrics, such as pollution loadings addressed in a TMDL. The scenario discovery cluster-finding algorithms then seek to parse the database to provide a concise description of those combinations of future conditions that best distinguish the future cases in which the implementation plan does or does not meet its goals.

In Figure 2.2, each axis represents a different uncertain parameter, and each point in the scatterplot shows the outcome from one unique combination of these parameters in the simulation (that is, one plausible future). Open circles show futures in which the plan meets its goals, while the filled circles show "vulnerable futures" in which the minimum performance standard is not met.

The goal in scenario discovery is to describe one or more sets of vulnerable futures as a concise, understandable, and decision-relevant scenario. In this context

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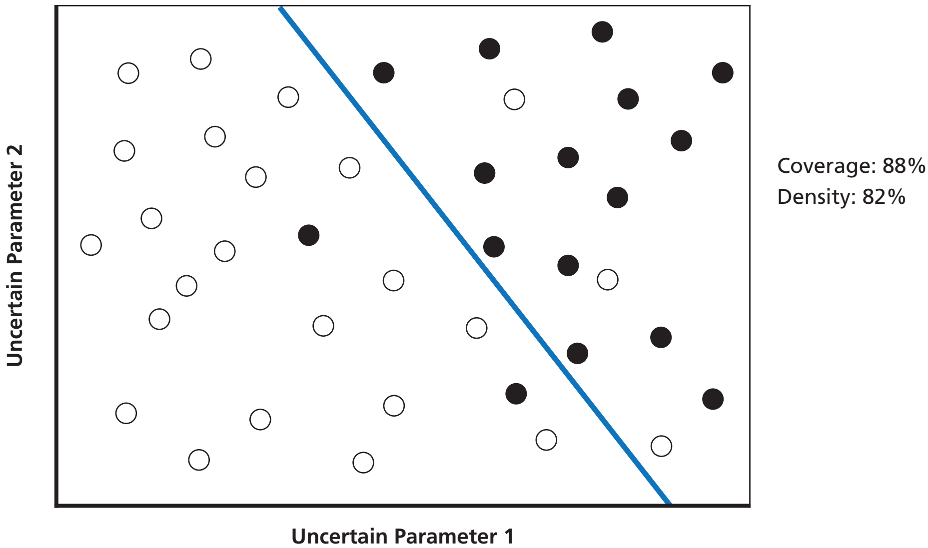
[2] There are also other paths through the RDM process. Information in the database of model results might help identify the initial candidate plan, or information about the vulnerabilities of the candidate plan may lead directly to another scoping exercise to revisit objectives, uncertainties, or plans.

Figure 2.2
Notional Scenario Discovery Analysis



RAND *RR720-2.2*

and throughout the remainder of this report, we use the term *scenario* to describe a set of futures that share one or more decision-relevant attributes. The algorithms used to support this process seek to balance between the competing goals of simplicity and accuracy using three measures of merit: coverage, density, and interpretability. *Coverage*, also known as precision or positive predictive value, is the fraction of the total number of cases representing vulnerable futures that are actually represented by the scenario conditions. The scenario in Figure 2.2 has coverage of 88 percent because the scenario contains 14 of the 16 futures in which the plan fails. *Density*, also known as sensitivity or recall, is the fraction of cases within the scenario that are vulnerable. The scenario in Figure 2.2 has a density of 82 percent, because the plan fails in 14 of the 17 futures it contains.

Interpretability is the ease with which the scenario can be communicated to and understood by plansmakers. It is typically measured heuristically as the number of restrictions used to define the scenario, with a smaller number generally proving to be more easily interpretable. The scenario shown in Figure 2.2 is defined by constraints on only two uncertain parameters. Improving any one of these three measures often comes at the detriment of one or both of the others; any scenario represents a balance between the accuracy and simplicity of its representation of a plan's vulnerabilities. The case studies in this report use a classification algorithm called PRIM (Patient Rule Induction Method) (Friedman and Fisher, 1999) combined with a principal component analysis to generate the scenarios (Bryant and Lempert, 2010; Groves and Lempert, 2007; Dalal et al., 2013).[3]

The scenarios crafted through this process also provide the foundation for adaptive management, that is, developing, evaluating, and comparing potential modifications to the alternative plans that might reduce these vulnerabilities (Step 4). The design of such plans is often not obvious, but by providing detailed understanding of the vulnerabilities of proposed plans, RDM often helps decisionmakers identify and choose more successful adaptive plans (Groves et al., 2014; Bloom, 2015; Lempert and Groves, 2010; Lempert, Popper, and Bankes, 2003). For instance, knowing that a particular TMDL implementation plan may fail to meet goals under a particular set of conditions might help decisionmakers decide to modify that plan with an alternative mix of BMPs. Scenario discovery facilitates this process by identifying the specific conditions to which the plan is vulnerable.

Facilitating Robust Adaptive TMDL Implementation Plans

To understand how RDM and the scenarios it helps to identify might facilitate robust and adaptive TMDL planning, it is useful to differentiate explicitly between three attributes of decisionmaking approaches: metrics, criteria, and processes (Lempert, 2014). Many discussions of decisionmaking approaches often blur the distinction between these very different attributes (Kalra et al., 2014).

Decision metrics represent systematic methodologies used to measure the consequences of alternative decisions. USEPA analyses use several different types of decision metrics, including benefit-cost analysis, cost-effectiveness analysis, and multiobjective frameworks. RDM analyses have used all three types.[4] In this study, the case studies use multiattribute decision metrics based on pollution loadings, the relationship of these loadings to TMDL goals, and the cost of alternative BMPs.

Decision criteria are used to rank alternative decisions according to the decision metrics. Many approaches use optimality criteria, that is, they choose the decision option that gives the best performance contingent on some set of best-estimate assumptions. This is problematic when such performance is dependent on actual future conditions, or if multiple criteria are actually to be considered. In contrast, RDM uses a robustness criterion. The literature has many definitions of robustness, such as: (1) achieving some acceptable level of performance over a wide range of plausible futures and (2) trading some optimal performance for less sensitivity to broken assumptions (Lempert and Collins, 2007). The case studies in this report do not emphasize the

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3 Software packages that help to perform these analyses are available online (Benjamin P. Bryant, 2014).

4 For example, see Lempert (2014).

choice among alternative TMDL plans but do judge existing plans by their ability to satisfice over a wide range of futures.

Lastly, a *decision process* includes several elements. Two that are particularly germane here include: (1) the analytic steps used to compare alternative options, and (2) the associated interactions between analysts and information users through which information is incorporated into decisions. As noted, RDM's "backward" analysis, which begins with a plan for consideration rather than a consensus view on the uncertainties, helps decisionmakers agree on decisions without having to agree on the underlying assumptions about the future.

This distinction, between criteria and measures on one hand and decision processes on the other, becomes particularly useful in illustrating how RDM can facilitate the development of robust, adaptive TMDL implementation plans. In particular, RDM interacts with adaptive planning at two levels: the design of the plans themselves and the processes by which the plans are created and implemented.

Recent years have seen a growing interest in formalizing the concepts, methods, and tools for developing and evaluating adaptive strategies (Haasnoot et al., 2013; Walker and Marchau, 2003; Groves et al., 2013; Lempert and Groves, 2010). Rosenhead (1972), one of the first to explore the connections between robustness and adaptive strategies, defines a decision as a "commitment of resources that transforms some aspect of the decision-making environment." A plan, which foreshadows "a set of decisions which it is currently anticipated will be taken at some time or times in the future," is often adaptive because it often also includes "an identification of an intended future state which necessarily implies a set of future decisions." Walker and colleagues (2001) similarly define adaptive strategies as comprising "sequential combinations of policy options. Some options are implemented right away; others are designed to be implemented at an unspecified time in the future or not at all if conditions are inappropriate."

Essential components of an adaptive plan include a planned sequence of actions, the potential to gain new information that might signal a need to change this planned sequence, and actions that would be taken in response to this new information. The sequential decisions of traditional decision analysis (Morgan and Henrion, 1990), as well as real options approaches (Trigeorgis, 1996), follow this structure. Introducing language used in RDM analyses, Dewar (2002; 1993) describes a planning methodology in which decisionmakers identify the key assumptions underlying a proposed plan. Dewar then defines *shaping actions* as those designed to make key assumptions more likely to resemble actual future conditions; *hedging actions* as decisions to be taken if key assumptions begin to fail; and *signposts* as observed events or thresholds that suggest such an assumption is indeed failing.

Table 2.1 provides a taxonomy of attributes and processes for developing and implementing adaptive strategies. The first column lists seven such attributes. The second column describes the contribution of each attribute. The third column lists how RDM and similar analyses might contribute to supporting that attribute.

Table 2.1
Attributes of Adaptive Decision Strategies

Attribute	Purpose	How RDM Might Contribute
Attributes of plans themselves		
1. Forward looking	Identify longer-term vulnerabilities (including forgone opportunities) of near-term plans and potential responses to those vulnerabilities.	Enable useful consideration of the near-term implications of a large multiplicity of plausible futures.
2. Automatic plan adjustment	Specify signposts that indicate need for plan adjustment and contingent actions to take in response to those signposts.	Identify and evaluate alternative combinations of shaping actions, hedging actions, and signposts.
3. Integrated plans	Combine management of multiple elements of a system in a holistic plan that recognizes linkages among system elements.	Improve ability to consider multiple system elements, which often have differing levels of uncertainty.
Attributes of context in which plans are developed and implemented		
1. Iterative review and continuous learning	Regularly review plans to address emerging issues and trigger important plan adjustments.	Help understand the conditions under which adaptive strategies may succeed or fail.
2. Multistakeholder deliberation	Improve legitimacy, salience, and comprehensiveness of decisions with deliberation among parties to the decision, all recognizing an "open impartiality" that accepts legitimacy and importance of view of others.	Embed analysis in process of deliberation with analysis that recognizes multiple worldviews; demands clear explication of reasoning, logic, and values; and facilitates iterative assessment.
3. Diversity of approaches	Implement a variety of alternative plans to gain knowledge about the most effective approaches.	Can help with experimental design in cases where variation is planned as part of active adaptive management.
4. Decentralized decisionmaking	Improve flexibility and responsiveness by placing decisionmaking authority and responsibility at the lowest effective and accountable level of governance.	Can help jurisdictions at multi-levels develop plans without certainty about the actions of other jurisdictions.

SOURCE: Adapted from Swanson et al. (2006; 2010).

Based on Swanson et. al. (2006; 2010), this taxonomy offers a structure for considering what analytic approaches such as RDM may contribute to TMDL planning. The first three elements refer primarily to attributes of the policies themselves. The third element, in noting that an adaptive strategy should often consist of a portfolio of actions that aim to influence multiple elements of a complex interacting system, draws on key insights from integrated water resource management and the concept of *defense in depth* employed in integrated flood risk management. The final four elements refer primarily to the context in which the plans are developed and implemented, which in general should encourage review and response, encompass a diversity of approaches to promote learning, decentralize decisionmaking, and emerge from a process of multistakeholder deliberation.[5] Note that the earlier elements in the taxonomy, such as *forward looking* and *automatic plan adjustment*, tend to relate to information products that might be delivered by a quantitative analysis. The latter elements in the taxonomy, such as *multistakeholder deliberation* and *decentralized decisionmaking*, tend to relate to decision support processes and the institutions in which they are embedded.

RDM has demonstrated success in supporting the development of plans with the first three attributes listed in Table 2.1. RDM is forward looking, in the sense that it evaluates a proposed plan over many hundreds to thousands of plausible paths into the future. The approach then identifies the key factors distinguishing those futures in which the plan meets its goals from those where it does not. This information can help identify combinations of signposts, hedging actions, and shaping actions within a stakeholder process of deliberation with analysis that can help decisionmakers to craft these elements together into adaptive strategies.

RDM has also demonstrated success in supporting planning processes with the last four attributes listed in Table 2.1. In particular, RDM has been used to facilitate multistakeholder deliberation and develop adaptive plans that pursue a diversity of approaches (Groves et al., 2013; Groves, Sharon, and Knopman, 2012).

Case Studies Illuminate These Themes

The case studies we describe in the next two chapters begin to implement and test these ideas. The Patuxent River case study (Chapter Three) examines the water quality management plans for the basin over hundreds of futures defined by alternative assumptions about future climate and land use. The analysis identifies the sets of future conditions for which an existing implementation plan meets or misses its water quality goals. The analysis concludes by examining the cost-effectiveness of additional investment in options that could reduce the vulnerabilities of the current plan. The second case study (Chapter Four) similarly identifies the vulnerabilities of the current water quality implementation plan for the North Farm Creek tributary of the Illinois River over dozens of futures defined by alternative assumptions about future climate and BMP effectiveness. In contrast to the Patuxent River plan, however, the North Farm Creek plan was laid out as an adaptive management strategy. The second case study therefore begins to describe the types of signposts and response options the region could use to implement this adaptive strategy. The case studies emphasize the first three steps of the

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5 The taxonomy in Table 2.1 largely maps onto Swanson et al.'s (2006) seven tools for adaptive policies. But the Swanson taxonomy focuses on distinguishing between tools useful for anticipated and for unanticipated changes. The taxonomy here focuses more on distinguishing between attributes of the plan and those of the context in which they are developed. In addition, the taxonomy here includes the attribute of integrated plans that has become increasingly important in areas such as integrated water resource management.

RDM process shown in Figure 2.1 and provide only initial explorations of potential new planning options and the trade-offs among them.

Overall, RDM and related analytic approaches may offer the potential for an improved approach to TMDL planning that both provides the information needed for the development of robust adaptive plans and supports the types of deliberative and stakeholder-involved processes such strategies may require. After presenting the two case studies, the final chapter will assess the extent to which the analyses here approach these goals and suggest potential next steps to enhance the ability of USEPA and its partners to ensure the health and safety of the nation's waters in the face of climate change and other uncertainties.

CHAPTER THREE

Managing Storm Water in Maryland's Patuxent River Basin with Climate and Land Use Uncertainty

Introduction

Managing Storm Water in a Densely Developed Urban Watershed

The Chesapeake Bay is the largest coastal estuary in the United States: a complex ecosystem that includes important habitats, food webs, and other coastal resources. The Chesapeake Bay watershed stretches across more than 64,000 square miles, encompassing parts of six states—Delaware, Maryland, New York, Pennsylvania, Virginia, and West Virginia—and includes major metropolitan centers such as Baltimore and Washington, D.C. The Bay and its tributary rivers, wetlands, and forests provide homes, food, and protection for complex groups of animals and plants. Marine species of all types and sizes either live in the Bay and its tributaries or use its waters as they migrate along the East Coast.

The health of the Chesapeake Bay is challenged by the interactions between the Bay's ecosystems and the human communities that depend on its water resources. In particular, pollution from urban stormwater runoff in the form of nitrogen, phosphorus, or dissolved sediment flowing into the Bay can significantly hinder the capacity of bay grasses to grow and reduce oxygen levels that are needed by all aquatic species (Orth and Moore, 1983; Najjar et al., 2010; Chesapeake Bay Program, 2013a). Managing the level of these nutrients in the Bay is a continual challenge, exacerbated by pressures from several different sources. For instance, changes in land use patterns, triggered by urban development, contribute to the transformation of forest and farmland into developed areas with roads, septic systems, and impervious surfaces that reduce natural infiltration into soil and facilitate the transportation of pollutants into the Bay (Lowrance et al., 1997). In addition, climate change is expected to exacerbate these problems. Climate projections for the Chesapeake Bay region include increased precipitation in winter and spring, which can increase the flow of nutrients and sediments to the Bay, and higher air and water temperatures, which can diminish the capacity of bay grasses to grow (Najjar et al., 2010).

After a series of discussions with Chesapeake Bay Program representatives, RAND and USEPA identified one key tributary of the Chesapeake Bay, the Patuxent River, as a good candidate to test the value of RDM for urban stormwater management decisions. The Patuxent River is located between Baltimore and Washington (Figure 3.1). Its watershed is 957 square miles in area (2,479 km^2), highly urbanized, and has a rapidly growing population.

Urban growth in the Patuxent River Basin transforms farmland and forests into developed areas, increasing the land area covered by impervious surfaces such as roads and parking lots. This development process increases urban runoff and, in turn, can increase the amount of pollutants reaching the Patuxent River and flowing into the Chesapeake Bay. Under many circumstances, urban runoff can lead to a higher concentration of nitrogen, phosphorus, or sediment in water bodies (Cheung et al., 2003; Leopold, 1968; Taylor et al., 2005; Van Metre, Mahler, and Furlong, 2000; Wolman and Schick, 1967), which can make maintaining adequate water quality standards a substantial challenge. Urban runoff from the Patuxent River is a key stressor for water quality in the Bay, making this location a good choice for our first case study.

The Patuxent is also the largest and longest river entirely within the State of Maryland; its watershed is the largest in the state. The Chesapeake Bay Program expects that the results of this pilot analysis will serve as a template for future planning as it incorporates climate change into its future water quality planning for the broader Chesapeake Bay region as mandated by Executive Order 13508 (Office of the Press Secretary, The White House, 2009). Note that the Patuxent is also a tidal river and faces future water quality threats (e.g., channel erosion) from sea level rise. The interaction of the river and coastal change when considering future climate impacts is important but could not be incorporated into this initial pilot study.

Meeting Current and Future Water Quality Standards

To improve water quality in the Chesapeake Bay, in 2010 USEPA and the Bay watershed jurisdictions—Maryland, Virginia, Pennsylvania, Delaware, West Virginia, New York, and the District of Columbia—established a TMDL for pollutants that can enter the Bay. The states within the Bay then allocated caps for nutrient and sediment loads across their major basins and developed statewide watershed implemetation plans (WIPs) that set forth a series of actions designed to meet their respective TMDL targets.

Maryland's WIP consists of three planning phases with a final implementation date of 2025. The first planning phase was completed in 2010; Phase II, drafted in 2012, is currently being implemented. The development of Phase III will begin in 2017 and is expected to further refine the implementation plans developed in Phase I and Phase II. Maryland's Phase I WIP set initial limits on the amount of nutrient and sediment contributions from different sources and established guidelines for the plans to be used for reducing the levels of these pollutants entering the Chesapeake Bay. Phase II builds on this initial effort by providing more geographic detail regarding the TMDLs and the plans required to meet these targets. In addition, to develop Phase II the State of Maryland Department of the Environment (MDE) and USEPA placed a

Figure 3.1
Map of the Patuxent River Watershed

SOURCE: Modified from Bachman and Krantz, 2000.
RAND *RR720-3.1*

greater emphasis on collaborating with key local stakeholders and other federal agencies. During the yearlong collaborative effort, for instance, there were nearly 100 outreach events that engaged state staff members, soil conservation managers, local decisionmakers, and other federal partners (MDE, 2012).

Table 3.1 shows the overall WIP targets from Phase II for the Patuxent River from each pollutant source. Compared with Phase I, the Phase II targets are more ambitious in terms of the planned pollutant reduction. Table 3.3, in contrast, compares just the nitrogen, phosphorus, and sediment targets for stormwater across the Phase I and Phase II WIP.

The Phase II Patuxent TMDL targets were set through a combination of historical water quality and hydrological monitoring data, coupled with simulation modeling conducted by USEPA's Chesapeake Bay Program. The plan calls for a substantial long-term investment of $14.4 billion for Maryland's contribution to Bay restoration from 2010 to 2025, $7.4 billion (51 percent) of which would go toward stormwater pollutant reduction BMPs (MDE, 2012).[1] We estimate the Patuxent River share of these stormwater BMP costs at approximately $2.5 billion.[2] Despite the significant

Table 3.1
Maryland's Phase II Watershed Implementation Plan Targets for the Patuxent River

	2025 Final TMDL Target (million pounds/year)		
Source Sector	**Nitrogen**	**Phosphorus**	**Sediment**
Agriculture	0.427	0.064	37.21
Forest	0.472	0.014	13.51
Nontidal atmospheric	0.021	0.002	N/A
Septic	0.038	N/A	N/A
Stormwater	0.936	0.079	43.97
Wastewater	0.948	0.083	8.871

SOURCE: MDE, 2012.

1 USEPA (2014) defines BMPs as "techniques, measures or structural controls used to manage the quantity and improve the quality of stormwater runoff."

2 The cost estimate for the Patuxent alone considers the acreage of BMPs implemented in Phase II WIP described in the input parameters of the Phase 5.3.2 model for the Patuxent (Table 3.5) and the annualized costs of each BMP estimated by King and Hagan (2011) for the period 2010–2025. The BMPs included in this estimate are bioretention, bioswale, dry detention ponds, erosion and sediment control, dry extended detention ponds, urban filtering practices, infiltration practices without sand and vegetation, infiltration practices with sand and vegetation, vegetated open channels, wet ponds and wetlands, and retrofit urban stormwater.

cost and long time frame for implementation, the performance of the WIP has not been tested against a changing climate, alternate future land use patterns, or other key uncertainties.

Best Management Practices to Reduce Stormwater Runoff Pollution

A key goal of this effort was to consider how performance of BMPs to control urban stormwater pollution would be affected over the long term given climate change. Best management practices were first introduced to reduce the peak discharge volume into storm sewers. Dry ponds were built to retain the water and release it gradually into the sewage system. For this reason, such ponds are one of the most common BMPs for controlling urban stormwater pollution in the United States today. Later, environmental concerns led to the idea of LID, which suggests that new projects should impose the least possible changes to the environment, including hydrology (Dietz, 2007). BMPs were needed not only to decrease the peak discharge of stormwater runoff, but also to ensure that the runoff does not carry pollutants. This increased the popularity of "green" BMPs such as bioretentions, bioswales, and infiltration trenches. In addition to reducing runoff volume, these BMPs offer other benefits such as sediment retention, plant uptake of pollutants, and natural filtration as a means to treat stormwater (i.e., the water is filtered when it infiltrates the soil).

Scientific understanding of actual BMP performance when implemented remains limited. Monitoring data are labor-intensive to gather, site- and design-specific, and difficult to generalize broadly (Jones et al., 2004). Existing stormwater BMP data are typically characterized by large uncertainties and allow for only rough or heuristic estimates of potential pollution load reduction from proposed new infrastructure investments (King and Hagan, 2011).

This limitation on scientific knowledge is exacerbated by climate change, which could alter the frequency or intensity of precipitation events in watersheds such as the Patuxent, potentially leading to an increased number of large storm events (IPCC, 2012; National Climate Assessment and Development Advisory Committee [NCADAC], 2013; Wuebbles et al., 2014). Further, there are few existing studies on BMP effectiveness as a function of storm size. To our knowledge, only one study to date has modeled pollutant removal in BMPs (Ackerman and Stein, 2008), while several others focused on the discharge reduction for various storm sizes (Damodaram, 2010; Heitz, Khosrowpanah, and Nelson, 2000). Ackerman and Stein (2008) found that BMP effectiveness suffered during large storms and wet years, with effectiveness most sensitive to infiltration rates. Damodaram (2010) concluded that the infiltration-based LIDs are more successful than storage-based conventional BMPs in reducing peak flow during small storms. But for large storms, the conventional BMPs deliver better results; the authors recommend implementing a combination of LIDs and conventional BMPs. Heitz, Khosrowpanah, and Nelson (2000) used a simulation model to show that a detention pond needs to increase in size relative to its drainage area (a proxy for the amount of runoff reaching the pond) to boost volume capture efficiency. This study did not specify the effect on pollutant removal, but the authors expect it to be nonlinear.

This chapter considers how USEPA and the State of Maryland should plan for stormwater management in the long term given the substantial uncertainties about climate, land use, and the effectiveness of BMPs for contaminant removal.

Approach

Participatory Scoping Using the XLRM Framework

This pilot was a collaborative effort between RAND, USEPA/ORD, and the Chesapeake Bay Program. Stakeholder engagement played an important role in the study. The authors and partnering organizations conducted an in-person kickoff meeting on October 5, 2012, at the Chesapeake Bay Program office in Annapolis, Maryland. At that meeting, participants developed a more detailed scope for the study and identified the key contributors for different elements of the study.

The scoping approach organizes the results from the participatory workshop within the "XLRM" framework originally formulated by Lempert, Popper, and Bankes, 2003. In the XLRM abbreviation, "M" stands for the objectives to be met and the *performance metrics* that are used to quantify these objectives; "L" stands for management plans (or *levers*) that can be used to achieve these objectives; "X" stands for uncertain factors that could affect the ability to achieve decisionmakers' objectives, often related to long-term uncertainty; and "R" stands for physical and economic *relationships* among these elements as reflected in planning models. Each one of these categories was discussed in depth with the study partners, with several subsequent telephone calls and other exchanges to further consolidate and elaborate important elements. We use this framework to organize and describe the study scope.

The study team identified four types of uncertainties for this effort: hydrologic uncertainty related to climate change, future population growth, changes to land use patterns, and BMP effectiveness across different storm types. Against these uncertainties, we tested the range of BMPs specified in Maryland's Phase II WIP for the Chesapeake Bay TMDL, including green infrastructure options such as urban forest buffers, permeable pavement, bioretention, vegetated open channels, and urban infiltration practices.

To perform the quantitative water quality experiments, this case study applies the Chesapeake Bay Program's Phase 5.3.2 Watershed Model and the supporting Scenario Builder modeling suite, which includes a land use change model and an airshed model. The study uses four key performance metrics, including annual average delivered loads of nitrogen, phosphorus, and sediments from the Patuxent basin to the Chesapeake Bay, specifically focusing on pollutant loads from the urban source sectors. We also considered BMP implementation cost as a performance metric for a portion of the analysis.

Table 3.2 shows the final XLRM matrix developed for this effort. Each portion of the scope is described in further detail in the sections following.

Performance Metrics

During the scoping workshops, participants identified three main sources of contaminants relevant for our case study: stormwater, wastewater, and other sources (primarily undeveloped/forested areas and agriculture). Each category contributes roughly one-third of the overall pollutant load into the Chesapeake Bay from the Patuxent River Basin. However, because this case study is intended to focus specifically on stormwater management, we consider only sources of contaminants directly tied to the corresponding urban land uses (Chesapeake Bay Program, 2013b):

- **Construction:** Includes construction land, exposed rocks, and beaches.
- **Extractive:** Includes active and abandoned mines, gravel pits, and other extractive uses that require urban storm sewer systems regulated within urban jurisdictions.
- **Impervious and pervious land uses:** Includes impervious and pervious segments in areas characterized by a high percentage of constructed materials (e.g., asphalt, concrete, buildings, etc.). These land uses include single-family housing units (low-intensity residential), apartment complexes and row houses (high-intensity residential), and commercial, industrial, and infrastructure uses.

Table 3.2
XLRM Scoping Summary for the Patuxent Case Study

Uncertain Factors (X)	Policy Levers (L)

Hydrology and climate change
• Observed historical hydrology (1984–2005)
• Downscaled climate projections
  • 2035–2045
  • 2055–2065
Land use
• Population growth (2010–2050)
• Infill, sprawl, and forest conservation
BMP effectiveness
Evapotranspiration model parameters
	MDE Phase II WIP BMPs, including:
	• Stormwater management–filtering practices
	• Stormwater management–infiltration practices
	• Urban stream restoration
	• Urban forest buffers

Systems Model Relationships (R)	**Performance Metrics (M)**
Phase 5.3.2 Chesapeake Bay Watershed Model • Airshed model • Land use change model • Watershed model • Chesapeake Bay model	Metrics • Nitrogen delivered loads • Phosphorus delivered loads • Sediment delivered loads • Implementation costs (extended analysis only) Targets • Phase I WIP TMDLs • Phase II WIP TMDLs (2017 interim; 2025 final)

Water Quality Metrics

Based on the TMDL and Maryland's Phase II WIP targets and drawing from these land uses, the three contaminant outcome metrics simulated using the Phase 5.3.2 Watershed Model were

- Average annual nitrogen delivered loads to the Bay (millions pounds/year)
- Average annual phosphorus loads to the Bay (millions pounds/year)
- Average annual sediment loads to the Bay (millions pounds/year).

These metrics are crucial for assessing the Patuxent Basin's ecosystem health. Excess nitrogen and phosphorus enhance the growth of dense algal blooms that adversely affect blue crabs, block sunlight needed by bay grasses to grow, and reduce available oxygen needed by bottom-dwelling species (Chesapeake Bay Program, 2013a; Najjar et al., 2010). Excess sediment blocks sunlight needed by plants that grow in the Bay's shallows, which in turn affects young fish and shellfish that use these ecosystems for protection. Sediment can also have acute and chronic effects on aquatic life when combined with chemical contaminants. In addition, excess sediment has a direct economic impact by silting ports and channels, thus reducing navigation (Chesapeake Bay Program, 2013a).

In order to maintain a healthy environment in the Chesapeake Bay and support restoration efforts, the TMDLs set limits on the amount of nutrients and sediment that can enter the Patuxent or subsequently flow into the Chesapeake Bay (Table 3.3, Table 3.4). Our analysis compares the results from future simulations against these established thresholds. We identify as vulnerable those cases that exceed these limits.

Table 3.3
Maryland WIP Stormwater Target Loads for the Patuxent River

	Annual Target (million pounds/year)		
Pollutant Type	**Phase I**	**Phase II 2017 Interim**	**Phase II 2025 Final**
Nitrogen	2.740	1.029	1.029
Phosphorus	0.210	0.078	0.078
Sediment	85	52	55.9

SOURCE: MDE, 2012, adjusted by the pilot study team. Note that these thresholds are adjusted to the calibration runs of the Phase 5.3.2 model and differ somewhat from those listed in the Phase II WIP report and in Table 3.1 of this report. Differences between calibration results and actual Phase II WIP targets can arise because districts and local authorities have room for adjusting the model's estimated targets to their regions.

As part of this analysis, it was necessary to adjust the thresholds stipulated in Maryland's Phase II WIP slightly to better reflect the calibration results from the Phase 5.3.2 model. This adjustment was verified with the Chesapeake Bay Program. Differences between calibration results and the actual Phase II WIP targets can arise because districts and local authorities still have some room for adjusting these models' estimated targets to the context of their regions.

In our simulations, the Patuxent Basin's contribution to the Chesapeake Bay TMDL for each contaminant was calculated using the watershed model, but the policy analysis focused only on the urban stormwater portion of the plan. Other contaminant sources, such as wastewater, agriculture, and forests, were allowed to vary across the uncertain futures considered (e.g., greater sprawl yielding more septic systems), but were not otherwise taken into consideration when comparing between stormwater management plans.

During the scoping workshop, participants agreed that this effort is relevant to planners in several agencies, including USEPA's Office of Water and Chesapeake Bay Program. However, because Maryland's Department of the Environment is ultimately responsible for meeting the stormwater management goals for the Patuxent, this study takes the state's perspective when considering alternate policy approaches—in particular, the MDE WIP for stormwater loads—even though the results address the overall TMDL set by USEPA.

Best Management Practice Costs

We adapted standardized cost estimates for new BMP implementation from Maryland's Department of the Environment for each of the stormwater BMP types discussed below (King and Hagan, 2011). The estimates represent the unit cost associated with the implementation of each BMP per acre of area treated, as shown in Table 3.5.

Policy Levers

For this case study, we considered two different plans for managing the Patuxent's nutrient levels. The first approach, *Current Management*, shows the case in which

Table 3.4
Maryland Phase II WIP Final 2025 Stormwater Target Loads, by Land Use

Land Use Type	Nitrogen	Phosphorus	Sediment
Construction	0.094	0.017	17.814
Extractive	0.013	0.002	1.217
Nonregulated developed	0.198	0.013	3.399
Regulated developed	0.724	0.046	33.470

NOTE: Quantities in millions of pounds per year (MDE, 2012). Adjusted by the pilot study team to match Patuxent calibration results.

Table 3.5
Best Management Practice Unit Costs

BMP Full Name	Average Annual Implementation Cost (dollars per acre-foot treated)
Standard stormwater management (gray infrastructure)	
Dry detention ponds and hydrodynamic structures	3,181
Erosion and sediment control	1,310
Infiltration practices without sand and vegetation	3,789
Infiltration practices with sand and vegetation	4,431
Mechanical street sweeping	754
Nature-based stormwater management (green infrastructure)	
Bioretention	3,875
Bioswales	3,031
Urban forest buffers	2,860
Urban filtering practices	4,156
Retrofit stormwater management	6,429
Vegetated open channels	1,810
Wet ponds and wetlands	1,968
Urban stream restoration	4,116

SOURCE: Modified from King and Hagan (2011). *Retrofit stormwater management* is the average annual cost of *bioretention* (retrofit–highly urban), *dry extended detention ponds* (retrofit), and *wet ponds and wetlands* (retrofit). *Urban filtering practices* is the average annual cost of filtering practices (sand, above ground) and filtering practices (sand, below ground).

no additional actions are taken for managing nutrients in the Bay beyond the BMPs already implemented as of 2012. This no-action case serves as a baseline, against which we compare the approach set forth in the State of Maryland Phase II WIP. In this case, the simulation results reflect the outcomes in which all BMPs identified in the state's plan are implemented in the Patuxent by the year 2025. Table 3.6 shows how the additional BMPs build on existing management. The tabular results reflect that the Phase II WIP includes the implementation of several new green infrastructure BMP types, such as bioretention or bioswales, as well as expanded investment in existing BMPs, such as urban nutrient management or erosion and sediment control.

Uncertain Factors (X)

During the scoping discussion, participants identified four potential key sources of uncertainty to consider in this case study:

Table 3.6
Best Management Practices Included in the Phase II WIP

BMP Name	Unit	2012 Progress	2025 WIP	Change from 2012
Standard stormwater management (gray infrastructure)				
Dry detention ponds and hydrodynamic structures	Acres	4,857	2,885	–1,972
Erosion and sediment control	Acres	1,258	1,848	590
Stormwater management generic BMP	Acres	19,566	7,443	–12,123
Urban nutrient management	Acres	13,544	30,898	17,354
Urban infiltration practices	Acres	1,012	1,511	498
Mechanical street sweeping	lbs/year	–	568,089	568,089
Nature-based stormwater management (green infrastructure)				
Bioretention	Acres	–	2,131	2,131
Bioswales	Acres	–	1,654	1,654
Urban forest buffers	Acres	68	881	813
Urban filtering practices	Acres	1,482	9,480	7,997
Retrofit stormwater management	Acres	3,501	12,660	9,159
Vegetated open channels	Acres	–	595	595
Wet ponds and wetlands	Acres	4,850	7,839	2,989
Urban stream restoration	lbs/year	22,948	11,481,346	11,458,398

SOURCE: Phase 5.3.2 model supporting data.

1. the effects of a changing climate on the future basin hydrology
2. potential changes to future land use in the Patuxent Basin from population growth or new development patterns
3. uncertainty regarding the contaminant removal effectiveness of stormwater BMPs
4. alternative carbon dioxide adjustment scenarios.

Hydrologic Uncertainty

The effects of a changing climate on future water quality in the Patuxent River are the central uncertain drivers to be considered in this analysis. To consider potential changes in hydrology due to a changing climate, we included downscaled air temperature and precipitation sequences from selected climate models and emissions scenarios provided for this purpose and already adapted for the Phase 5.3 model by the Chesapeake Bay Program. Specifically, we used time series inputs derived from IPCC

Fourth Assessment Report (AR4) models, and subsequently downscaled by U.S. Geological Survey (USGS) (Solomon, 2007; Wilby et al., 2004), to develop a series of *climate-altered hydrology* projections designed to represent different plausible hydrology futures. The downscaling yielded hourly time series data at one-eighth degree spatial resolution for use in the model from six GCMs across three IPCC Special Report on Emissions Scenarios (SRES) emissions scenarios (Najjar, Patterson, and Graham, 2009; Pruzinsky and Bhatt, 2012; IPCC, 2000) (Table 3.7).

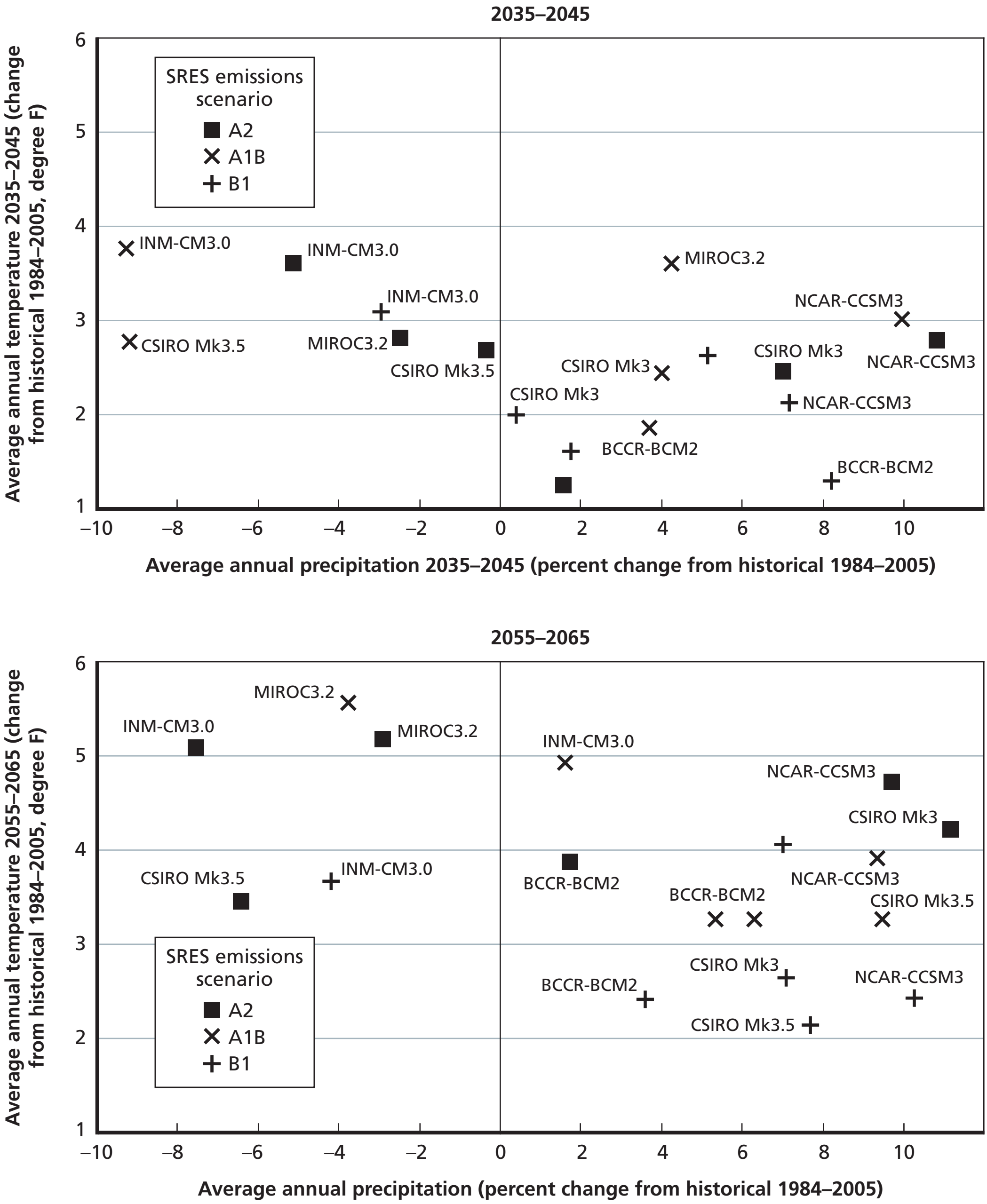
Using results from all models across three emissions scenarios resulted in a total of 18 climate-altered hydrology projections. Based on data availability, we considered two ten-year future time periods from these sequences: 2035–2045 and 2055–2065. For each model and emissions scenario, Figure 3.2 shows how the temperature and precipitation inputs vary over the period 2035–2045 (top pane) and 2055–2065 (bottom pane) in comparison with the *observed historical* climate in the Patuxent. These changes are summarized by the average change in annual precipitation (x-axis, percent change) and average temperature anomaly (y-axis) relative to the 1984–2005 historical baseline.

Temperatures in the set of climate projections used range from an increase of 1.25 to 3.75 degrees Fahrenheit by 2035–2045 up to 5 to 5.5 degrees Fahrenheit by 2055–2065. Examining the 2035–2045 results, we find that the downscaled projections show a wide range of potential changes to future precipitation from different models and emissions scenarios, from an average annual rainfall decline of nearly 10 percent to an increase of over 10 percent. The precipitation projections vary within each emissions scenario, showing no obvious pattern, but some clustering is noted for results from the

Table 3.7
Summary of AR4 Climate Models and Emissions Scenarios Applied in Case Study

GCM Name	Source
BCCR-BCM2	Bjerkenes Centre for Climate Research, Norway
CSIRO Mk3	Commonwealth Scientific and Industrial Research Organization, Australia
CSIRO Mk3.5	Commonwealth Scientific and Industrial Research Organization, Australia
INM-CM3.0	Institute of Numerical Mathematics, Russia
MIROC3.2	Model for Interdisciplinary Research on Climate, National Institute of Environmental Studies, Japan
NCAR-CCSM3	National Center for Atmospheric Research, U.S.A., Community Climate System Model 3
Emissions Scenarios	
SRES A2	
SRES A1B	IPCC Special Report on Emissions Scenarios (IPCC 2000)
SRES B1	

Figure 3.2
Change in Precipitation and Temperature from the Historical 1984–2005 Period for Two Future Time Periods



RAND *RR720-3.2*

same GCM run across emissions scenarios. For example, all three Institute of Numerical Mathematics Coupled Model Version 3.0 (INM-CM3.0) runs tend toward drier future conditions, while the NCAR-CCSM3 runs are clustered near the high end of higher precipitation futures for the Patuxent Basin. The 2035–2045 results in Figure 3.2 confirm that the model uncertainty associated with precipitation is high and could lead to a range of plausible outcomes when translated into runoff and pollutant load.

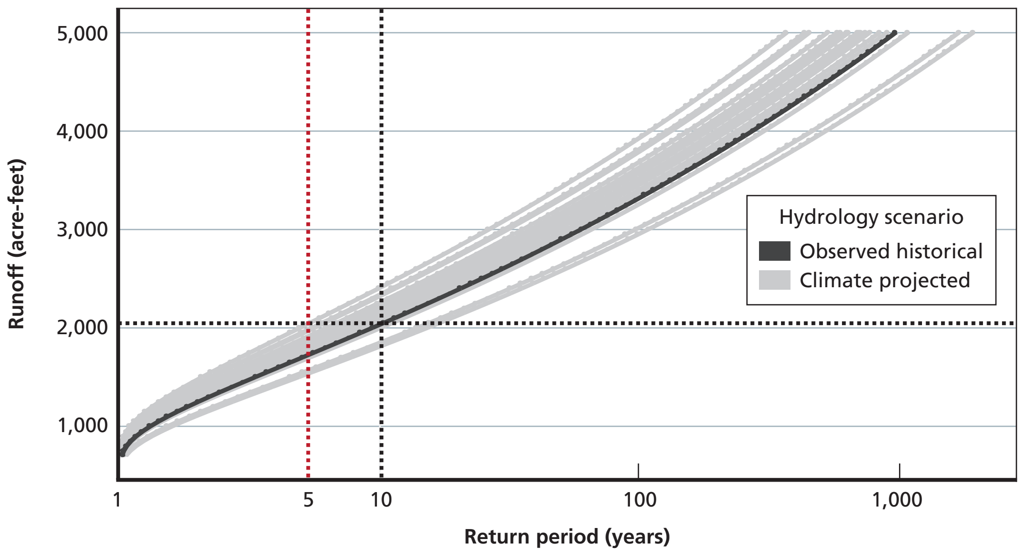
The bottom pane, showing the additional change by 2055–2065, tells a similar story. As expected, the 2055–2065 projections yield warmer conditions than the 2035–2045 climate sequences, though the rate of increase varies by model and emissions scenario. In contrast, the precipitation changes are much more heterogeneous: Some of the 2055–2065 projections are wetter than in 2035–2045, while others are drier. The change over 20 years can be dramatic for a given model and emissions scenario. For example, the CSIRO Mk3.5 model in the A1B scenario goes from one of the "driest" models, on average, in 2035–2045, to one of the "wettest" by 2055–2065. In contrast, the MIROC3.2 model shows wetter futures for the Patuxent in the earlier period, but drier futures 20 years later.

We considered both future time periods in our analysis. However, for the remainder of this chapter, for convenience we describe results from the 2035–2045 period only. This period better overlaps with the time horizon of the Phase II WIP, and the bottom line results are very similar from both future hydrology periods. Appendix C includes analysis results for the 2055–2065 climate sequences.

Another way to represent the climate-altered hydrology projections is by fitting an extreme value distribution to the resulting runoff volumes. Figure 3.3 shows the annual exceedance probability (return period) of daily runoff from the observed historical hydrology data set compared with the 18 climate-altered hydrology projections for 2035–2045, fitted using a Log-Pearson Type III three-parameter distribution commonly applied when considering extreme precipitation or flood events. Here, two log-transformed distribution parameters (standard deviation and skew) are held constant at the values derived from the historical data, while the distribution mean is allowed to vary with the climate-altered hydrology projections.

Results are similar to Figure 3.2 but generally show that most climate-altered hydrology futures show (a) an increase in runoff volume at any given return period, and (b) larger runoff volumes per event becoming more likely by 2035–2045 in most cases. For example, the historical upper bound 10 percent annual chance (10-year) daily runoff volume for the basin is 2,050 acre-feet (black dashed lines). Most climate-altered hydrology projections show this volume becoming more likely by 2035–2045, with the most extreme projection showing this volume doubling in annual likelihood to a 20 percent annual chance (five-year) event.

Figure 3.3
Observed Historical and Climate-Altered Hydrology Daily Runoff Volume Return Periods for the Patuxent River Basin



NOTE: Solid black line shows daily runoff by return period from the observed historical hydrology scenario. Gray shading shows the range of daily runoff projections from the climate projected hydrology scenario. Black dashed lines highlight the 10-year daily runoff, while the red dashed line shows how this volume might occur more frequently in one extreme climate projection.
RAND *RR720-3.3*

Land Use Uncertainty

Twelve land use scenarios were included in this case study. These land use scenarios reflect potential future changes across two key dimensions: population growth and land use patterns. To account for an uncertain and growing population, we considered four population scenarios, accounting for population growth for the period 2010–2050.[3] Several scenarios were adapted from USEPA's Integrated Climate and Land Use Scenarios (ICLUS) by our Chesapeake Bay Program partners for use in this study.[4] The population growth scenarios, in order of increasing population, include

1. **2010 population:** Assumes that the population of the Patuxent Basin will remain constant at 2010 levels (725,000) for the next four decades.

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3 The Patuxent Basin includes portions of the following counties in Maryland: Anne Arundel, Howard, Montgomery, Prince George, Calvert, Charles, and St. Mary.

4 USEPA developed the ICLUS scenarios by adapting U.S. Census population and migration projections to be consistent with the storyline of IPCC's SRES scenarios. Population is projected using two models: (1) a demographic model that generates population projections at the county level, and (2) a geospatial model that estimates population density based on housing units at a 2.47-acre (1-hectare) resolution (USEPA, 2009b).

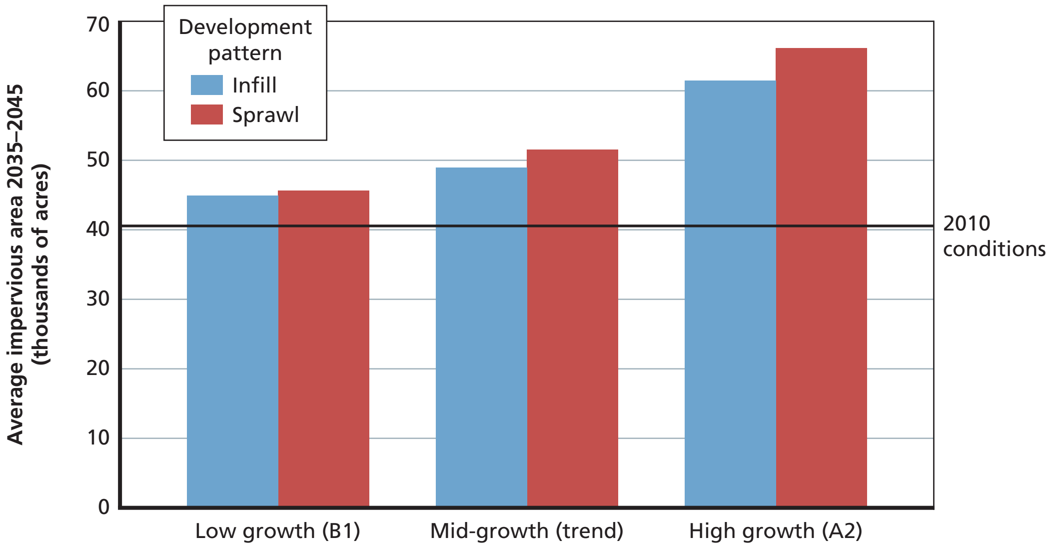
2. **ICLUS B1 scenario:** Land use changes under this scenario result from potential changes in urban growth rates resulting from a rapid demographic transition to low mortality and fertility, consistent with the IPCC SRES B1 scenario. The population would reach 773,000 residents by 2050.
3. **Trend growth:** Under this land use scenario, population growth in the Patuxent Basin will continue on the observed historical trend, increasing the population from 725,000 residents in 2010 to 940,000 residents by 2050.
4. **ICLUS A2 scenario:** Land use changes under this scenario as a result of potential population growth over the coming decades resulting from a slow demographic transition to low mortality and fertility, consistent with the IPCC SRES A2 scenario. Under this scenario, the population would reach 1.31 million residents by 2050.

The second dimension corresponds to future development patterns, reflecting either future infill for already dense areas, or "sprawl" as new residents convert forested or agricultural regions to new urban development areas. Once again, the Chesapeake Bay Program played a key role in developing these scenarios by applying Version 2.0 of the Chesapeake Bay Land Change Model (CBLCM). The CBLCM uses U.S. Census data and a growth allocation model to project future urban area at each watershed segment. Then, for each segment, the proportions of urban growth that affect other land uses (e.g., farmland, forest, sewer, septic) are estimated using a stochastic cellular automata model customized for the Chesapeake Bay that extrapolates historic patterns of urban growth into the future (Goetz and Jantz, 2006; Claggett et al., 2008). CBLCM parameters were adjusted to reflect two plausible future land use patterns:

1. **Infill:** This scenario assumes that the absorption of housing units within the existing built and sewered landscape increases by 50 percent over recent growth patterns.
2. **Sprawl:** This scenario assumes that new growth follows the recent historical pattern, leading to additional urban acreage at lower population density.

A factorial combination of population projections and development patterns produces a total of eight land use scenarios. These scenarios primarily affect both runoff and pollutant loads through the conversion of forest, agriculture, or other pervious land use types to new impervious ground cover. Figure 3.4 shows the increase in impervious land cover across the scenarios with no additional policy efforts undertaken and when compared with land use in the Patuxent Basin in 2010. As shown in the figure, a combination of sprawl and more rapid population growth could lead to an increase of over 63 percent in impervious cover by 2050, whereas more benign futures could see a roughly 10–20 percent increase.

Figure 3.4
Impervious Area Projections for Three Land Use Scenarios



RAND *RR720-3.4*

Additional Uncertainties

We also explored several other sources of uncertainty during the investigation, discussed briefly below. Both uncertain drivers were later removed from the final experimental design after initial testing and were instead replaced with single point estimates to reduce computation time.

Effect of Climate Change on BMP Performance

We initially considered a range of parameters reflecting varying BMP performance with increasingly large storm events. The scenarios varied in terms of how rapidly the BMP's capacity to remove contaminants is reduced as a function of runoff event return frequency, ranging from the case in which BMP performance is not affected by runoff return frequency to a case in which BMP performance degrades rapidly. Initial testing of this uncertain relationship, however, showed little variation in WIP performance when alternate assumptions were considered. For the final experimental design in this analysis, the Chesapeake Bay Program's initial assumptions regarding how BMP contaminant removal declines as storms increase in size were applied across all cases.

BMP performance uncertainty also could include uncertainty related to future operations and maintenance (O&M) of stormwater BMPs. Inadequate maintenance could dramatically affect BMP performance. This uncertainty was not considered in the Patuxent case study but is addressed in the Illinois River case study described in Chapter Four.

Carbon Dioxide Adjustments

The Phase 5.3.2 model uses potential evapotranspiration to evaluate evaporative losses from vegetation. In the context of the Patuxent River, evapotranspiration is a potentially important factor in determining the precipitation that runs off into the Patuxent River. Previous empirical studies suggest that higher levels of carbon dioxide could reduce evapotranspiration losses by around 10 percent, which could lead to higher flows in the Chesapeake Bay (Butcher, 2013; Lockwood, 1999).

Given the potential importance of evapotranspiration in determining water flows in the Patuxent River, it is important to increase the accuracy of these estimations in the Phase 5.3.2 model. Currently, the model does not take into account the effect of changes in carbon dioxide emissions in the plant growth estimations. In order to account for this effect, we used new adjusted plant growth parameters that account for the effect of rising carbon dioxide emissions on increases in plants' water use efficiency. This reduces evapotranspiration and can potentially increase water flows in the Patuxent River (Butcher et al., 2014).

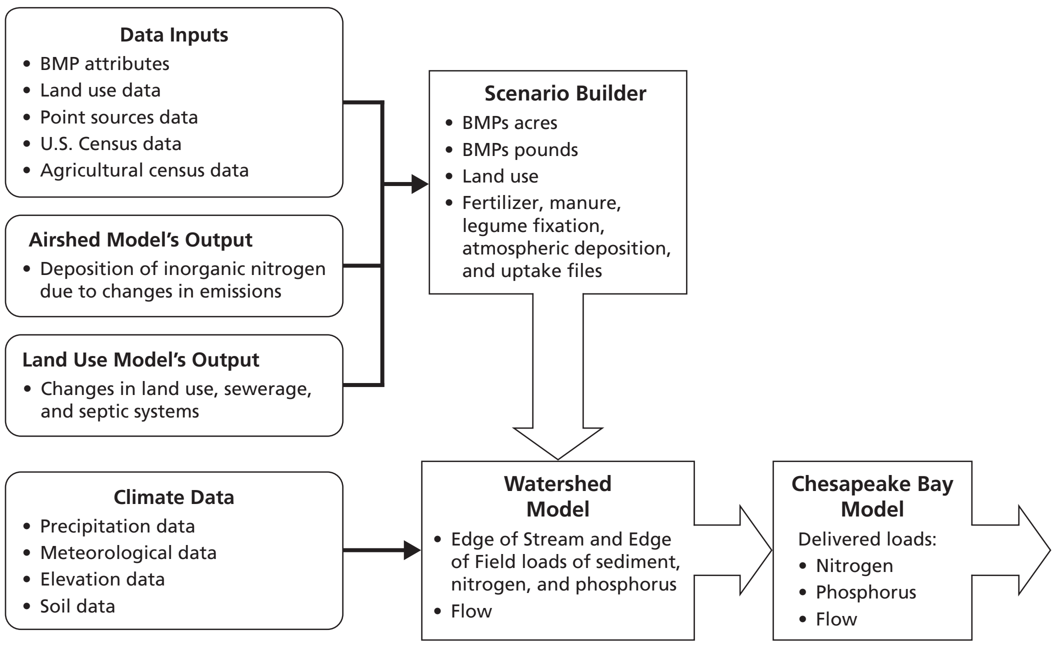
However, simulation tests showed that the parameter adjustments resulted in runoff increases on the order of 1 percent or less. As a result, rather than consider both the original and revised parameter assumptions in the scenario analysis, for simplicity the results presented below are shown only with the carbon dioxide adjustment in place.

Relationships

The Phase 5.3.2 Watershed Model integrates a number of modules that were applied to complete the simulations in this case study. The overall model architecture is summarized in Figure 3.5. The *airshed model* and the *land use change model* generate inputs needed by the watershed model. The airshed model takes into account nitrogen emissions from power plants, vehicles, and other sources to predict the amount and allocation of these pollutants into the Patuxent Basin. The land use model estimates the effects of urban land use and population on sewer and septic systems based on data from the U.S. Census, land cover trends, sewer service areas, population projections, and land conversion trends. The *scenario builder* module combines the inputs from these two models and other data to produce input tables for the watershed model, which describe BMP acreage or direct load reductions (where applicable), total acreage by land use type, and other input data. The *watershed model* uses information provided by scenario builder and climate data to estimate the amount of nutrients and sediments reaching the Patuxent Basin. The Chesapeake Bay model predicts the changes in water quality due to the changes in input loads from the watershed model (USEPA, 2010a).

Appendix C of this document provides additional information about the Phase 5.3.2 simulation model, including results from previous model calibration and validation studies.

Figure 3.5
Chesapeake Bay Phase 5.3.2 Watershed Model Flowchart



SOURCE: Chesapeake Bay Program (2013b).
RAND *RR720-3.5*

Experimental Design and Case Generation

We conducted several simulation experiments using the scope outlined in the previous sections. The experimental design included a full factorial sampling design across the uncertain inputs, including

- 19 hydrology projections (18 climate-altered hydrologies + 1 observed historical)
- two ten-year future hydrology time periods (2035–2045; 2055–2065)
- current (2010) population and three future population trends
- two development patterns.

We considered all possible combinations of these scenario inputs for future conditions, yielding 222 futures. We also tested all hydrologies—the observed historical (1 projection) and all climate-altered hydrology projections across both time periods (18 x 2 = 36 projections)—against the current population and land use, essentially adding a land use scenario in which no net change occurs. This yielded another 37 futures, for a total of 259 futures. Both plans were then tested against this common set of futures, yielding a total of 518 cases considered. Each case was run using the Phase 5.3.2 model in a server environment and took approximately 40 minutes to complete, yielding a total of 345 hours of runtime for the analysis.

Analysis Steps

The primary results from this analysis can be considered a vulnerability assessment (stress-testing) of Maryland's Phase II WIP. Discussion of the analysis proceeds in several steps. We first summarize the range of pollutant loads across the 259 futures, with and without the WIP implemented. We then compare these results to MDE's WIP targets to determine how often the state is or is not meeting its intended goals in different futures.

Using these targets, we next use clustering algorithms to perform "scenario discovery," as described in Chapter Two, with the goal of identifying a small set of input parameters and associated thresholds that best distinguish the conditions in which the plan does meet the TMDL targets from those in which it does not (Bryant and Lempert, 2010; Groves and Lempert, 2007). Scenario discovery algorithms are applied to the 259 cases in which the WIP is implemented to best characterize those conditions leading to vulnerability. In addition, we applied a variation of these methods that combines Principal Component Analysis (PCA) and PRIM (Dalal et al., 2013). This PCA-PRIM approach, discussed later, allowed us to identify latent components that are linear combinations of the input parameters considered in the model and that best describe the most vulnerable cases for each contaminant.

This case study identifies potential vulnerabilities but does not formally consider new BMPs or other augmentations to Maryland's stormwater plan using the same modeling approach. However, the final portion of this analysis takes a first step toward considering such potential augmentations. In this final step, we use the Phase 5.3.2 model to help identify which BMPs provide the most consistent load reduction across different types of hydrology projections, as well as those BMPs that appear to provide cost-effective performance based on a simplified comparison of load reduction and cost. Using the BMP types identified, we then calculate order-of-magnitude costs for potential augments in selected scenarios to show what additional investment may be required to improve the robustness of Maryland's plans.

The analysis was conducted for all contaminants; similar patterns of results were found for nitrogen, phosphorus, and sediment. We describe selected results for the historical climate sequence and for the 2035–2045 climate sequences in the next section. Additional results for all three contaminants, as well as for the 2055–2065 projections, are provided in Appendix C.

Results of the Analysis

Water Quality Results Across Many Futures with the Phase II WIP

Results from the simulation runs generated by the experimental design are shown in Figure 3.6 for two key pollutant load metrics: nitrogen (x-axis) and sediment (y-axis). Results for phosphorus show a similar pattern and are provided in Appendix C. The scatterplots following provide a summary of all cases run in the experimental design with the Phase II WIP implemented. Each point represents one future—one realization of the model with a single climate, population, and land use development projection. We use two symbol types to show whether the case reflects the observed historical hydrology (x) or climate-projected hydrology (o). Colors show the type of land use development assumed, and the symbols are sized according to the population growth projection.

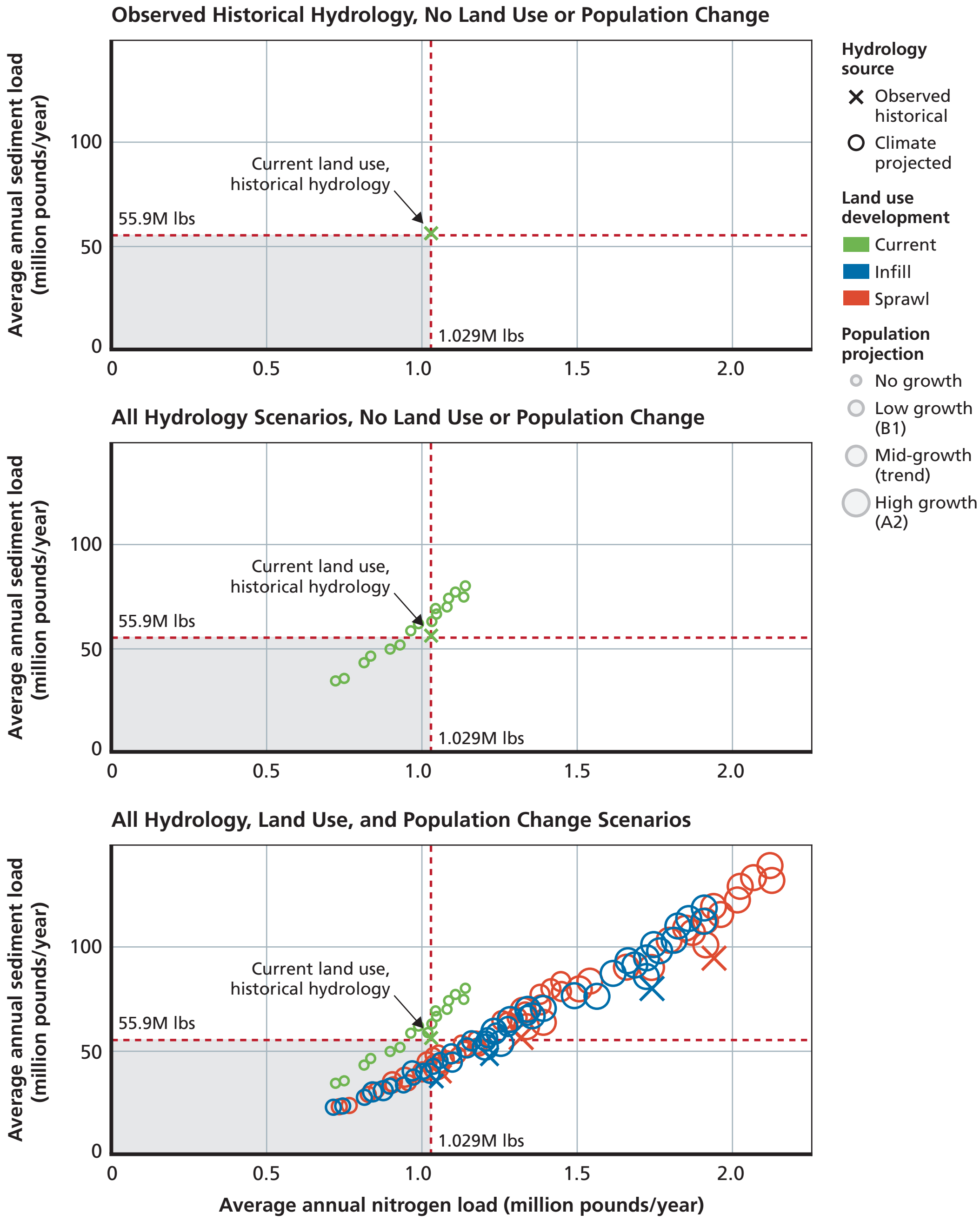
Figure 3.6 also includes lines indicating the final 2025 TMDL targets for these contaminants (red dashed lines). Points that fall in the gray shaded quadrant meet both standards, while those in the upper-right quadrant meet neither standard. Points in the lower-right quadrant meet the sediment load target, but not nitrogen, and the reverse is true in the upper-left region.

The figure includes three panes. In the first pane, a single future is shown, which assumes observed historical hydrology and no change in population or land use. As expected, with these assumptions, the Phase II WIP exactly meets the TMDL targets set for these pollutants. In the second pane, however, results are shown across all hydrology assumptions—including both the observed historical and climate-altered cases—while population and land use are held constant at no net change. In the final pane, all futures in the experimental design are shown, varying both hydrology and land use assumptions.

Figure 3.6 reveals several key results. When the climate-altered hydrologies are included (middle pane), the figure shows futures in which the TMDLs are met, and those in which they are exceeded, in nearly equal numbers. When hydrology, population, and land use all vary together, however (bottom pane), the Phase II WIP does not consistently meet the new targets across most or all plausible futures. Many cases, especially those with higher population projections, show nitrogen and sediment TMDL exceedances upward of 50 to 100 percent beyond the established target. Greater pollutant loads are most clearly correlated with higher population projections (point size). Also of note is how closely results from each contaminant correlate with one another—in this case, they have an R-squared value of 0.97. Similar correlations, with R-squared values above 0.90, are observed with phosphorus (not shown). This suggests that cases stressing for one contaminant are nearly always stressing for all contaminants.

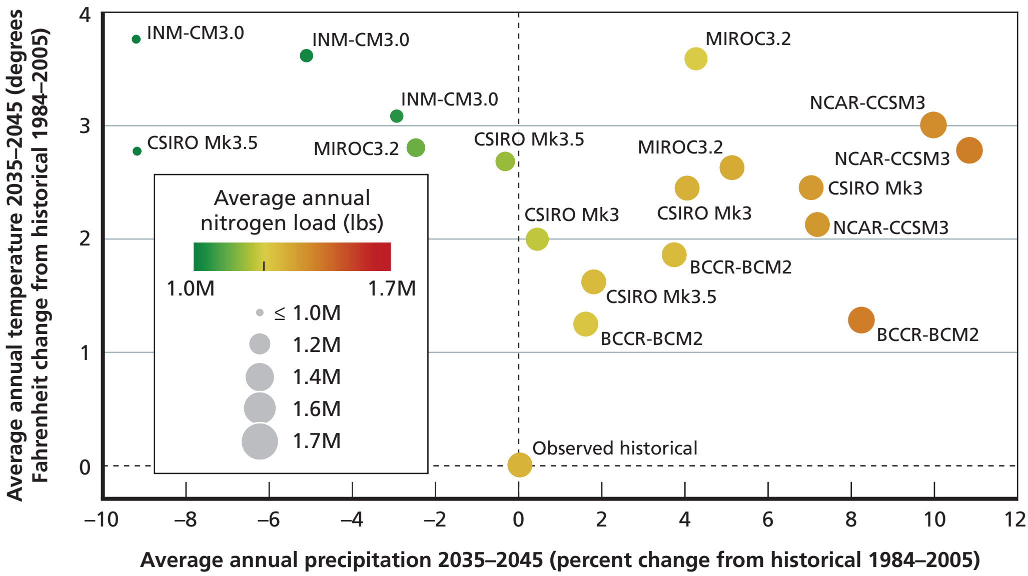
Figure 3.7 shows these results across uncertainties concerning only the observed historical and climate-altered hydrology projections. Here, nitrogen loads are indicated by color and point size and are shown across the same temperature (y-axis) and precipi-

Figure 3.6
Nitrogen and Sediment Loads Across All Futures, Phase II WIP (2035–2045)



RAND *RR720-3.6*

Figure 3.7
Nitrogen Load, by Climate Model, for One Land Use Scenario, Phase II WIP (2035–2045)



RAND *RR720-3.7*

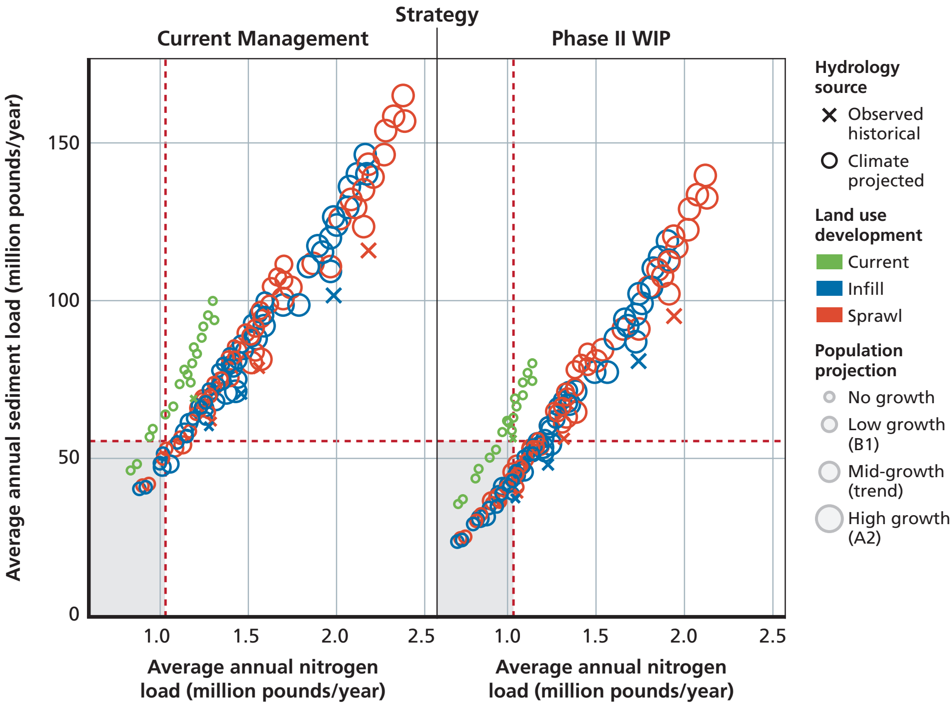
tation (x-axis) dimensions as shown in Figure 3.2. This figure shows one population projection (trend) and development pattern (sprawl; middle red column in Figure 3.8) across all hydrology projections considered, once again focused on the Current Management plan.

Holding population and land use constant, Figure 3.7 shows that nitrogen loads also vary across the climate projections with a clear—and expected—trend toward increasing pollutant loads with increased average annual precipitation. Only the cases that project a substantial reduction in average precipitation of approximately 3 percent or greater result in nitrogen loads close to the TMDL target without additional BMPs implemented. Of note is that, when we consider hydrology variation alone, the observed historical value (origin) falls in the middle of the range rather than representing a more- or most-favorable case. This is because some of the climate-altered hydrology projections display drier conditions than the historical records (left quadrant). In these cases, less precipitation also leads to less urban runoff, which in turn decreases the nitrogen loads reaching the Patuxent River.

Phase II WIP Outcomes Compared with Current Management

We next consider how the Phase II WIP improves upon previous stormwater management. Figure 3.8 shows the same scatterplot as the bottom pane of Figure 3.6, but with two panes included to show both the "Current Management" plan (no new investment beyond 2010, left pane) and a future in which all stormwater BMPs in the Phase II

Figure 3.8
Scatterplot of Nitrogen and Sediment Loads Across All Futures, Both Plans (2035–2045)



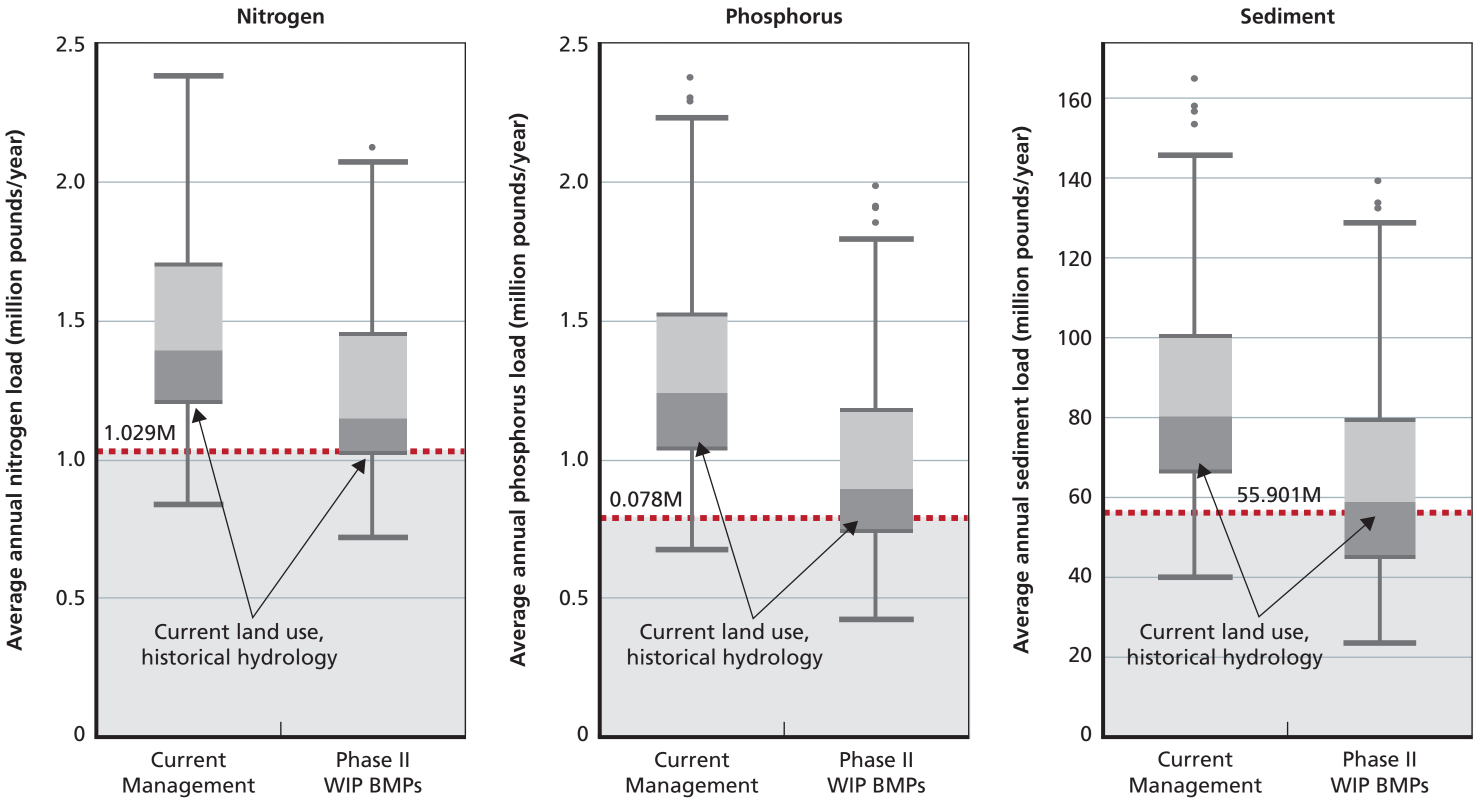
NOTE: Dashed red lines show the TMDL target for each contaminant.
RAND *RR720-3.8*

WIP are implemented (right pane). The same set of uncertain futures is shown for both plans.

Figure 3.8 shows that, under current management, the new TMDL targets are almost never met across the range of uncertain futures. When the WIP is implemented, we observe a consistent reduction in pollutant loads for both metrics shown and across the futures considered (points shift toward the origin). As a result, the Phase II WIP represents a clear improvement over current management and allows the state to meet either one or both of the TMDL targets in additional futures.

Another way to visualize these results is via boxplot summaries of all futures (Figure 3.9). This figure shows all three contaminants of concern, with and without implementing the Phase II WIP, and summarizes the distribution of the range of the futures in each case. Note that this summarizes the distributional pattern of results alone and makes no assumption about the likelihood of any of the futures. The figure also notes where the 2025 Phase II WIP TMDL target is located with respect to the majority of cases (dashed red line), and the plot is annotated to show the point where

Figure 3.9
Boxplot Summary of Pollutant Loads Across All Futures, 2035–2045



NOTE: Dashed red lines show the TMDL target for each contaminant. The boxplots presented do not represent probability distributions, but instead report the results of a set of model runs (futures). Each point summarized represents one mapping of assumptions to consequence, and the points are not assumed to be equally likely. Each individual future shifts downwards when BMPs are applied.
RAND *RR720-3.9*

current population/land use and historical hydrology—the case used initially by the State of Maryland to develop the TMDLs—falls in the distribution.

The boxplot summaries show that, with the Phase II WIP in place, the nitrogen target is exceeded in nearly three-quarters of the simulated futures. Only the lower tail (lowest 25 percent of cases) falls below the target line. Results are somewhat better for phosphorus and sediment, with the sediment target met in nearly half of the futures.

For this analysis, a future is considered to be acceptable (not vulnerable) when the TMDL target is met for a particular pollutant. This suggests four types of cases:

1. futures in which the nitrogen target is met
2. futures in which the phosphorus target is met
3. futures in which the sediment target is met
4. futures in which all three targets are met.

Table 3.8 summarizes the performance of each plan across the 259 futures considered for each type of case for each of the three periods considered in this study: 1984–2005 (seven futures), 2035–2045 (126 futures), and 2055–2065 (126 futures).

As expected, Current Management rarely leads to attaining the Phase II WIP targets across all the specified failure modes. When the Phase II WIP is implemented, it increases the proportion of futures in which the target is met substantially. For instance, with the Phase II WIP the percentage of futures meeting the sediment target increases from 0 percent to 43 percent for the historical hydrology, 12 percent to 47 percent for the 2035–2025 climate projections, and 12 percent to 44 percent for the 2055–2065 climate projections, respectively. However, as previously noted, the Phase II WIP does not meet the TMDL target in a substantial fraction of cases: over two-

Table 3.8
Futures in Which Phase II Target Is Met, by Plan and Contaminant

	Number (Percentage) of Futures Meeting the Phase II Target					
	Historical Hydrology 1984–2005		Climate Altered Hydrology 2035–2045		Climate Altered Hydrology 2055–2065	
Performance Metric	Current Management	Phase II WIP	Current Management	Phase II WIP	Current Management	Phase II WIP
Nitrogen target	0 (0)	1 (14)	9 (7)	35 (28)	13 (10)	31 (25)
Phosphorus target	0 (0)	2 (29)	6 (5)	42 (33)	5 (4)	35 (28)
Sediment target	0 (0)	3 (43)	15 (12)	59 (47)	15 (12)	55 (44)
Meets all three targets	0 (0)	1 (14)	6 (5)	30 (24)	5 (4)	29 (23)

thirds of all futures for phosphorus in all three hydrology periods, for instance, and nearly three-quarters of all futures for nitrogen.

Identifying Decision-Relevant Scenarios

Our next step was to use the scenario discovery methods introduced in Chapter Two (Bryant and Lempert, 2010) to identify those future conditions most frequently associated with vulnerable outcomes for these contaminants. This discussion focuses on results for the nitrogen target only, but similar results emerge for the other two contaminants (see Appendix C). The goal was to characterize these futures as one or more descriptive scenarios—a small representative set, identified analytically—that could later be used to identify or test additional options designed to reduce vulnerability.

This analysis starts by looking across all uncertain inputs considered. We characterized the uncertainties with several different types of statistical summaries to see which could most concisely explain the effects of uncertainty on the success of the Phase II WIP—that is, the highest coverage and density, as explained in detail in Chapter Two. Table 3.9 shows a summary of the value ranges of both hydrology and land use that we used as inputs for the scenario discovery clustering analysis. These parameter ranges include the observed historical hydrology and the 2035–2045 climate projections. Appendix C provides a more detailed tabulation of these parameter inputs, as well as a similar table for the 2055–2065 climate projections.

Table 3.9 shows that each hydrology input is described in terms of average precipitation (annual, summer, and winter), average temperature (annual, summer, and winter), average annual runoff, or the mean of the fitted Log-Pearson Type III distribution (Figure 3.3). The combination of these metrics provides a comprehensive description of each climate projection and allows the clustering algorithms to exploit differences across the hydrology sequences to identify the most relevant vulnerable regions. The table also presents the land use scenario characterizations used as inputs for scenario discovery. The seven land use scenarios are described in terms of the surface area for each land use type. These characterizations allow scenario discovery to identify the land use type and range that best explains futures in which the Phase II WIP does not meet its TMDL targets.

The parameter inputs described in Table 3.9 were used in a scenario discovery analysis using the Patient Rule Induction Method (Friedman and Fisher, 1999). In addition, we augmented the standard scenario discovery clustering approach with a preprocessing step that uses PCA to identify linear combinations of these inputs (i.e., hydrology and land use characterizations) that are closely correlated. This preprocessing step is useful for characterizing policy regions not well described using the traditional "hyper-rectangular" regions provided by the traditional scenario discovery method. PCA transforms the input data into independent linear combinations that are then used as inputs in the PRIM algorithm. These linear combinations can describe latent

Table 3.9
Uncertain Input Value Ranges Used in Scenario Discovery (Observed Historical and 2035–2045 Hydrology)

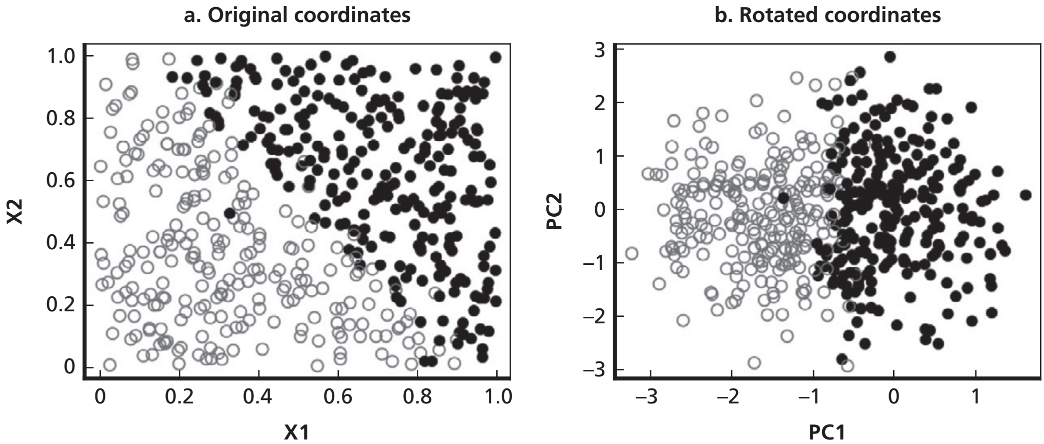
	Range		
Uncertainty Type	**Low**	**High**	**Units**
Hydrology inputs			
Average precipitation			
Annual	40.1	48.9	Inches
Summer	21.0	26.0	Inches
Winter	17.9	23.7	Inches
Average temperature			
Annual	55.9	59.6	Degrees F
Summer	69.1	72.8	Degrees F
Winter	42.6	46.7	Degrees F
Average annual runoff			
All areas	232.8	387.6	Thousands of acre-feet
Impervious areas only	111.9	151.8	Thousands of acre-feet
Annual maximum 24-hour runoff[a]	1.2	1.5	Thousands of acre-feet
Land use inputs			
Impervious	40.5	66.2	Thousands of acres
Pervious	137.3	253.0	Thousands of acres
Construction	1.1	9.0	Thousands of acres
Nonregulated developed	49.0	129.4	Thousands of acres
Regulated developed	128.8	189.8	Thousands of acres

[a] Annual maximum 24-hour runoff is used as a parameter input (mean) for the Log-Pearson Type III distribution. The values shown above are converted for the distribution by first converting to log(runoff), and then taking the mean across the ten-year sequence. The subsequent parameter range used in the distribution estimate is 7.05 to 7.34.

features in the input data and can be used as more suitable descriptions of regions of vulnerable futures with high coverage and high density.

Figure 3.10 shows an illustration of the use of PRIM with and without PCA. The black dots denote cases in which the plan in consideration fails to meet its goals, and open circles cases in which the plan under consideration performs as intended. The left pane shows the results of using PRIM without PCA. In this case two inputs, X1 and X2, describe the vulnerable region. However, the vulnerable region cannot be well

Figure 3.10
PCA-PRIM Example Results



SOURCE: Dalal et al., 2013. Used with permission.
NOTE: The black dots cluster describes the vulnerable region of the experiment: a) in the original coordinate system using PRIM with no PCA and b) in the rotated coordinate system using PRIM with PCA.
RAND *RR720-3.10*

described by a rectangle, as it clearly displays a triangular shape. The right pane shows the results of using PRIM with PCA. In this case, the two principal components PC1 and PC2 are linear combinations of inputs X1 and X2 found by implementing PCA (i.e., $\mathrm{PC1} = \alpha_1 X1 + \beta_1 X2; \mathrm{PC2} = \alpha_2 X1 + \beta_2 X2$). In this rotated coordinated system, the vulnerable region can be well described by a rectangular region (Dalal et al., 2013).

In the following paragraphs we describe the results of using scenario discovery to understand the futures in which the nitrogen TMDL target is not met, using the observed historical and 2035–2045 hydrology inputs. Similar analysis for the phosphorus and sediment TMDL targets is provided in Appendix C.

In the first iteration of this clustering analysis, we found that a single characterization, average annual runoff from impervious areas only, concisely describes futures in which the nitrogen TMDL target is not met with the Phase II WIP. Using this single characterization, 94 percent of all futures that do not meet the nitrogen TMDL (coverage) are described by those cases in which runoff from impervious areas exceeds 114,990 acre-feet. In addition, the nitrogen TMDL is not met in 95 percent of futures in which runoff from impervious areas is above 114,990 acre-feet (density). This initial iteration provides an easily interpretable, one-dimensional threshold that describes a vulnerable region with both high coverage and high density. Of note is how low this threshold falls in the range of total annual runoff from impervious areas (Table 3.9)—that is, it is very close to the lower bound. We refer to this vulnerable, stressing scenario as the "Increased Impervious Runoff" scenario. The nitrogen TMDL is met only in futures in which impervious area runoff is kept at a minimum (best-case) across the scenario range.

Although this one-dimensional threshold provides an easy-to-understand description of the vulnerable region for the nitrogen TMDL, it provides no further information about how specific hydrology and land use changes could affect the performance of the Phase II WIP TMDL plan. As a result, we conducted a second experiment using PCA-PRIM to identify linear combinations of distinct changes in both precipitation and impervious land cover that also describe high coverage and high-density decision-relevant scenario regions.

Table 3.10 shows the results of using PCA across the input parameters considered in this case study (Table 3.9). The columns indicate the three possible combinations (PCs) found using PCA, and rows indicate the parameters included in each combination. The cell values denote the standardized loadings (unit scale) for the input parameters considered by the different components. These standardized loadings indicate the correlation between the components and the corresponding parameter. The final row indicates the proportion of variance explained by each of the proposed components.

The three components described in Table 3.10 were considered in our analysis. PC1 is a linear combination of impervious area and average annual runoff. PC2 is a linear combination of the average annual precipitation, the mean of the adjusted Log-Pearson Type III runoff distribution, and average annual runoff. Finally, PC3 is a function only of the average annual temperature.

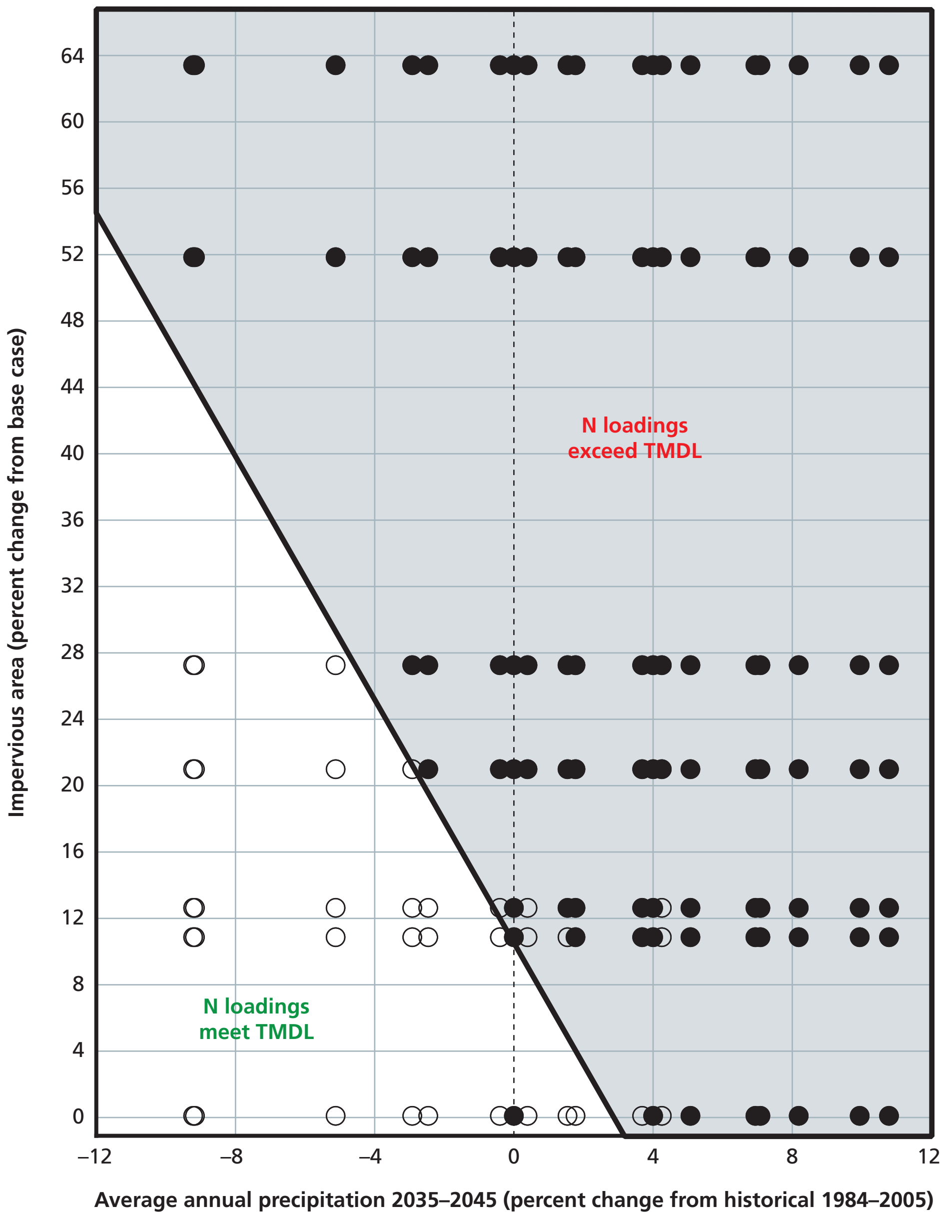
According to these results, PC1 explains the largest share of the variance across the input parameters (Table 3.10, bottom row). That is, using PC1 directly as an input parameter in PRIM provides regions with higher density than the traditional scenario discovery approach, and with higher density and coverage than the components of PC2 or PC3. Therefore, PC1 was selected as the most suitable linear combination of input parameters for the PCA-PRIM analysis.

Figure 3.11 shows the results of this second experiment. The figure shows a scatterplot of all futures. Open circles show nonvulnerable cases, where the nitrogen TMDL

Table 3.10
Standardized Loadings in PCA Analysis

Variable	PC1	PC2	PC3
Average annual temperature	–	–	0.99
Average annual precipitation	–	0.92	–
Annual maximum 24-hour runoff	–	0.32	–
Impervious area	0.99	–	–
Average annual runoff	0.86	0.43	–
Proportion of variance explained	45%	27%	25%

Figure 3.11
Futures in Which Phase II WIP Meets and Misses Nitrogen (N) TMDL



RAND *RR720-3.11*

target is met, and filled circles indicate futures in which the TMDL is exceeded. These are plotted against the two key uncertain dimensions on the axes identified with PCA-PRIM: the average annual precipitation change from the historical conditions (y-axis), and change in impervious land area in the Patuxent River watershed (x-axis). The region highlighted in gray was selected using the PCA-PRIM process to explain most of the vulnerable futures.

The shaded region defines a single decision-relevant scenario described by two factors: the average annual precipitation change from historical conditions, and the percent growth in impervious land area in the Patuxent River watershed. The angled line defines the cutoff for this region as a linear combination of both factors, according to the following functional form:

Impervious Area Change[%] + 5.05 × *Precipitation Change*[%] > 11%.

This linear equation describes the relationship between these two factors that describes the vulnerable region identified with PCA-PRIM. It shows that futures that fall inside this region display higher precipitation, increased impervious area, or a combination of both. Any of these combinations leads to increased runoff, which in turn yields larger-than-expected nitrogen loads flowing into the Chesapeake Bay. This region captures 99 percent of the total of vulnerable cases for nitrogen (coverage). Within this region, 93 percent of the cases are vulnerable (93 percent density).

An increase in precipitation leads to higher runoff directly, and this in turn results in higher nitrogen loads. According to the above equation and Figure 3.11, an increase in average annual precipitation of more than 2 percent over the historical baseline would nearly always lead to exceeding the TMDL irrespective of the size of future impervious areas. Similarly, an increase in impervious area leads to higher urban runoff, which also leads to higher nitrogen loads. If impervious area increases more than 50 percent above the current baseline (consistent with the ICLUS A2 high population projection; see right two bars on Figure 3.4), vulnerability always emerges, irrespective of whether average precipitation increases or declines. In addition, in many other futures in which impervious land cover increases between 0 and 50 percent, the nitrogen TMDL target is not met, even in cases in which average precipitation stays constant or declines. Put another way, average precipitation would need to stay constant or decline *and* impervious area would need to remain at the mid to low end of the plausible range in order to meet the nitrogen TMDL consistently with the Phase II WIP as currently constructed.

The decision-relevant scenario shown in Figure 3.11 can also inform the choice of signposts that might give decisionmakers early warning of emerging conditions in which their TMDL plans might miss their goals. For instance, similar to the discussion in Groves et al., 2014, decisionmakers might use data on building permits and other indicators of construction plans to determine whether impervious cover in the Patuxent region is trending toward the range (gray area) where nitrogen loadings might exceed the TMDL.

We repeated the same set of experiments, using both a standard PRIM and PCA-PRIM approach, for phosphorus, sediment, and a combination of all three contaminants (vulnerable if all three targets are exceeded). Similar results were found for the other contaminants, though construction land cover was also identified as a key driving variable along with impervious area runoff when using the simple PRIM approach to evaluate vulnerability with respect to phosphorus or sediment loading. When using PCA-PRIM, results for phosphorus were very similar to those for nitrogen, but sediment TMDL vulnerability emerged only with larger increases in impervious area, precipitation change, or a combination of both. Results from all experiments for the 2035–2045 climate projections are provided in Table 3.11. More detailed scenario discovery analysis results for all contaminants are also provided in Appendix C.

What Options Could Maryland Consider to Augment Its Existing Plan?

As previously noted, testing plans that build on or augment Maryland's current Phase II WIP could be performed within the same modeling framework, but that was beyond the scope of this effort. However, given the vulnerability that emerges as a result of increased runoff—due to an increase in average precipitation, an increase in impervious land cover, or both—as a next step we used the same modeling toolkit to conduct a preliminary assessment of each BMP type to consider what augments might be most effective to help mitigate this vulnerable scenario. This step illustrates what could be done as part of a fuller treatment. We considered two key factors:

Table 3.11
Scenario Discovery Analysis Summary Results

Metric	Scenario Definition	Coverage (%)	Density (%)
Standard PRIM			
Nitrogen	Impervious area runoff > 114.5 thousand acre-feet	94	95
Phosphorus	Impervious area runoff > 104.6 thousand acre-feet Construction area > 2.1 thousand acres	87	90
Sediment	Impervious area runoff > 103.6 thousand acre-feet Construction area > 3.3 thousand acres	86	88
Combined	Impervious area runoff > 104.6 thousand acre-feet Construction area > 3.3 thousand acres	86	83
PCA-PRIM			
Nitrogen	Impervious area change[%] + 5.1 × Precipitation change [%] > 11%	99	93
Phosphorus	Impervious area change [%] + 4.5 × Precipitation change [%] > 16%	94	87
Sediment	Impervious area change [%] + 1.9 × Precipitation change [%] > 27%	82	89
Combined	Impervious area change [%] + 1.7 × Precipitation change [%] > 27%	88	91

NOTE: Results shown for 2035–2045 climate projections.

1. How effectively does the BMP remove contaminants on a per-unit basis, given a range of potential future precipitation values?
2. Which options could provide additional load reduction cost-effectively using simplified, first-order cost estimates?

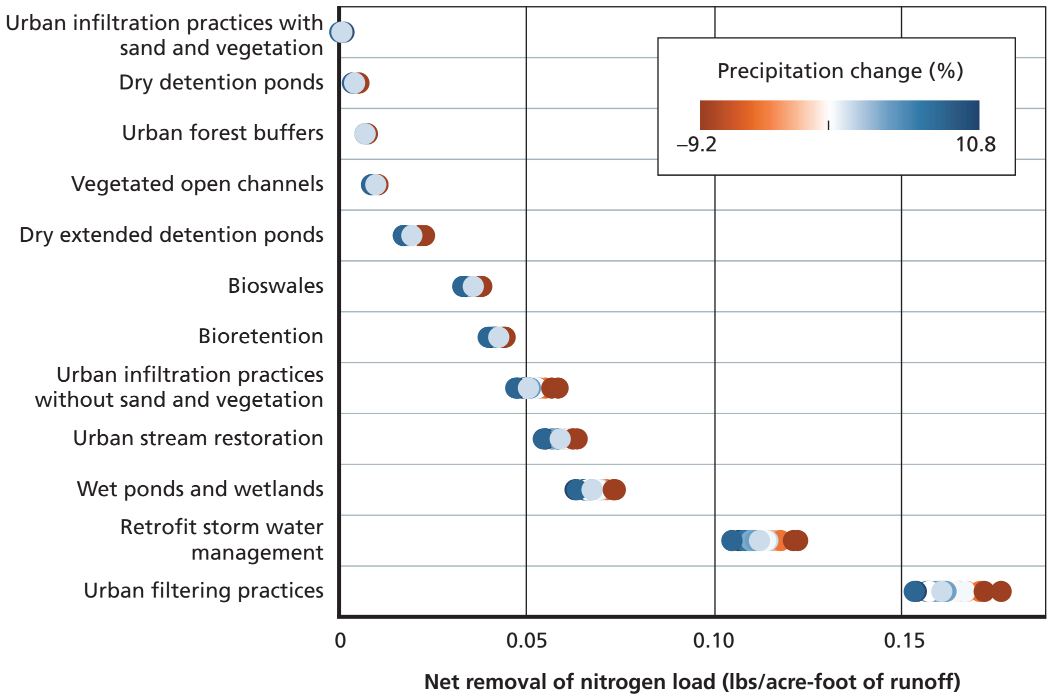
To address the first question, we conducted an additional simulation experiment with the goal of characterizing load reduction for each BMP type normalized as net pounds of nitrogen removal per unit volume of runoff (acre-feet). We considered the performance of each of the 19 BMPs implemented in the Patuxent as part of the Phase II WIP in isolation (Table 3.6), comparing the performance of each individual BMP in turn to a future without additional action in 19 baseline and climate-altered hydrology sequences (18 downscaled climate projections for 2035–2045 plus one observed historical sequence). The experiment was conducted only for the BMPs implemented in the upper part of the Patuxent to conserve computational resources. The experiment totaled 380 simulation runs and took an additional 127 hours of runtime to complete running the Phase 5.3.2 model in a server environment with 16 CPU cores running at 2.4GHz.

Given the particular concern with impervious land cover identified using scenario discovery, in the remainder of this section we focus on BMP performance specifically for impervious land uses only. Results are shown in Figure 3.12 across the range of hydrology uncertainty considered. This figure shows how normalized net removal of nitrogen varies across the climate projections for each BMP. Results are summarized for each projection according to the change in average precipitation relative to the 1984–2005 observed historical average.

Figure 3.12 shows that the BMPs vary widely in terms of net nitrogen load removal. This is driven primarily by assumptions about BMP performance built into the Phase 5.3.2 model that were not tested rigorously nor allowed to vary in this analysis. Performance for each BMP varies, with better performance occurring when average precipitation declines and with steadily worsening load removal in higher precipitation futures. Overall, however, a series of low-impact or green infrastructure BMP types appear to provide good performance. For example, urban filtering practices (sand filtering above and below ground), retrofitting, wet ponds and wetlands, and urban stream restoration show notably better per-acre-foot performance than other BMP types. The variation with precipitation/runoff differs by BMP, but the range of variation seems to scale with net removal in each case.

This rough ranking is retained when comparing BMP cost-effectiveness using order-of-magnitude cost estimates. To make cost-effectiveness comparisons across different BMPs, it is necessary to also estimate the net per-unit removal effectiveness for each BMP. Net effectiveness was estimated by normalizing the removal effectiveness of each BMP per unit of runoff (pounds per acre-foot of water treated).

Figure 3.12
Nitrogen Removal Effectiveness for Impervious Land Use, by BMP Type



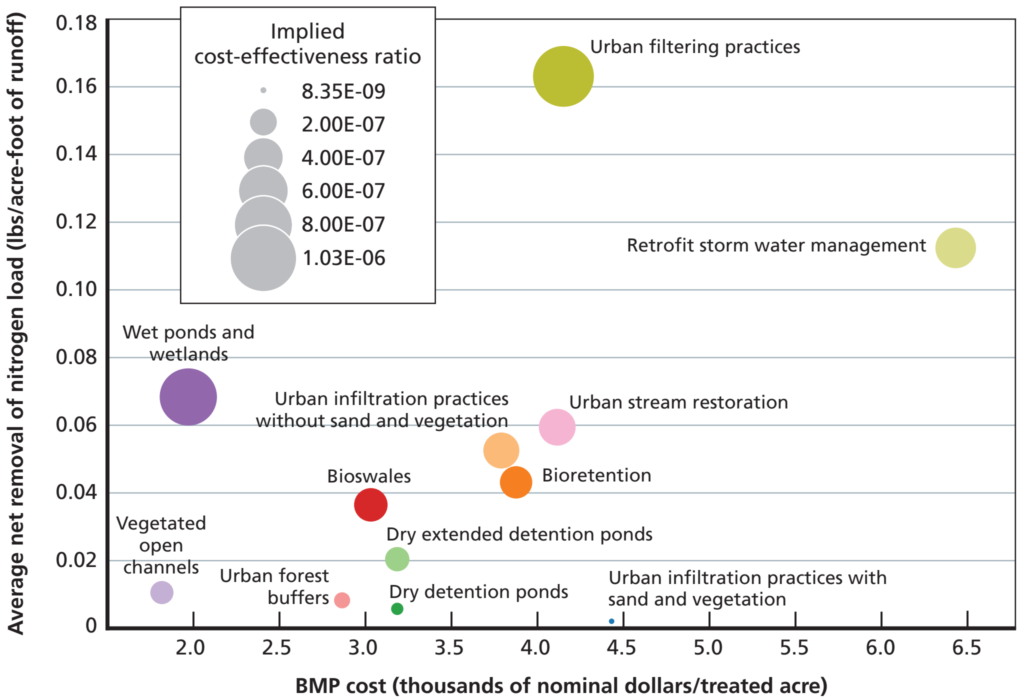
NOTE: In this chart, zero precipitation change is relative to the historical average. BMP types not applied to impervious areas are omitted.
RAND *RR720-3.12*

Figure 3.13 shows a scatterplot of the normalized net nitrogen removal (y-axis)—here showing the average across the range of hydrologic uncertainty—plotted against the assumed cost per acre for each BMP type. The point size is scaled by the implied cost-effectiveness ratio (normalized nitrogen removal divided by per-acre BMP cost).

This simplified cost-effectiveness comparison shows substantial variation in average BMP cost for the subset shown, ranging from below $2,000 to upward of $6,000 per treated acre-foot of water. Given the variation in performance, wet ponds and wetlands appear to provide reasonable net removal at relatively low cost for impervious land uses. The best performer in terms of net removal, urban filtering practices, is also one of the more expensive options on a per-acre-foot of water basis, but nevertheless shows good performance in terms of cost-effectiveness relative to most other BMPs. A series of others, ranging from bioswales to urban stream restoration, also provide reasonable cost effectiveness when compared with other approaches on a per-unit basis.

The results of this analysis can be used to make a preliminary, first-order assessment of the available options to reduce the vulnerability of the Phase II WIP. Figure 3.14 presents two examples to illustrate this point. Each point represents one future.

Figure 3.13
Nitrogen Removal Cost-Effectiveness for Impervious Land Use, by BMP Type



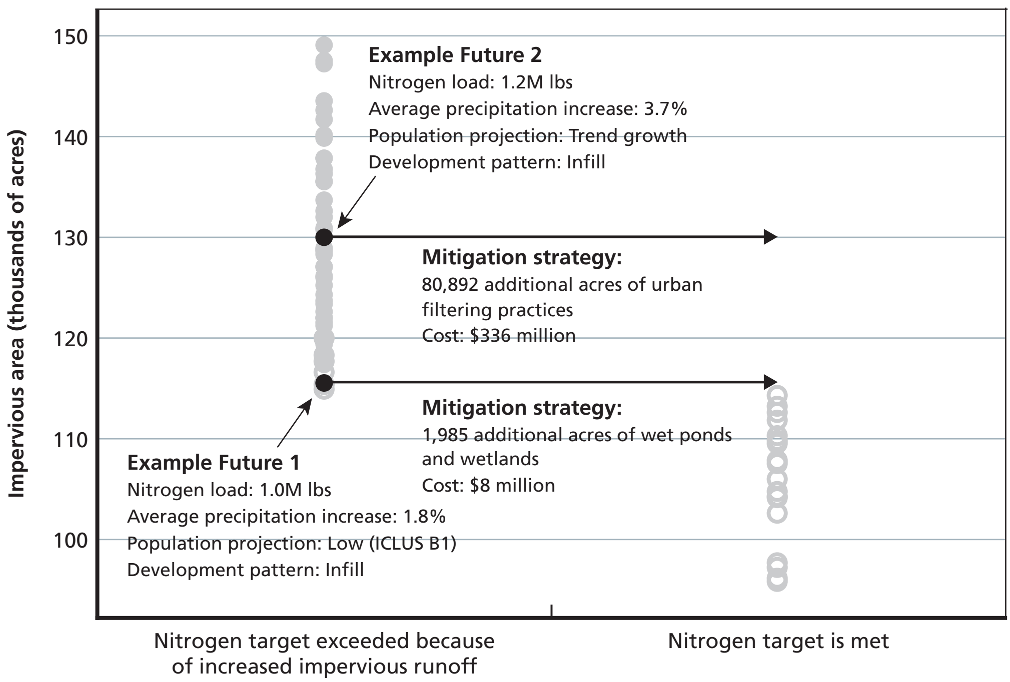
RAND *RR720-3.13*

Open circles show nonvulnerable cases, where the nitrogen TMDL target is met, and filled circles indicate futures in which the nitrogen TMDL is exceeded. The futures are divided into two columns, with those on the left belonging to the "Increased impervious runoff" scenario previously defined using scenario discovery, and those on the right not included in this scenario. The black shaded points denote two example futures from this scenario for which we have estimated the scale and cost of mitigation efforts to reduce the vulnerability. The text annotations describe each of these futures and the corresponding hypothetical mitigation strategy.

In the first example future shown in Figure 3.14, the Patuxent Basin exceeds the nitrogen TMDL by only 3,935 pounds (small exceedance). This future has moderate impervious area growth associated with low population growth and infill growth patterns but shows increased average precipitation compared with historical values. One possible approach to reduce nitrogen loads is to expand the implementation of some BMPs already included in the Phase II WIP.

Based on simplified estimates of net BMP effectiveness, we calculated the additional effort needed to mitigate the vulnerability in this future, here assuming an approach that expands the application of wet ponds and wetlands in the Patuxent Basin. For the hydrology conditions in this future, wet ponds and wetlands remove

Figure 3.14
Example of Mitigation Options for Two Vulnerable Futures for the Nitrogen TMDL



RAND *RR720-3.14*

7,875 pounds of nitrogen (i.e., BMP net effectiveness × impervious runoff) and the Phase II WIP creates 7,839 acres of wet ponds and wetlands in the Patuxent, leading to a ratio of removed nitrogen to implemented acres equal to 1.005 (pounds/implemented acre). In this rough calculation, the basin would need at least an additional 3,917 acres of wet ponds and wetlands investment to reduce nitrogen loads below the TMDL target, at a cost of approximately $8 million.

Using a similar approach with the second example future in Figure 3.14 and applying urban filtering practices as the example BMP, we found that meeting the TMDL would require the implementation of this BMP on an additional 80,892 acres at a cost of $336 million. However, augmentation at this scale is infeasible: The Patuxent Basin simply does not have sufficient additional urban acreage on which these practices could be implemented. This suggests how difficult it might be to mitigate the vulnerability from high impervious runoff futures using existing practices, whether traditional (gray infrastructure) or nature-based (green infrastructure). Instead, additional options—potentially including land use practices designed to avoid creating new impervious cover even with new urban growth—may be needed to meet or maintain water quality objectives in stressing future conditions.

Of course, this final analysis is substantially simplified. BMPs do not function in isolation but rather as a part of a treatment train in conjunction with other upstream and downstream management practices. As a result, the simplified estimates presented in Figure 3.14 are likely to be biased downward in terms of the amount of contaminant reduction provided when compared with more sophisticated or high-resolution BMP treatment designs. In general, this analysis is at a pilot scale and does not provide sufficient information to support additional action. It is suggestive of what options the State of Maryland could consider to augment its WIP for impervious land use areas, but further analysis will be needed to formally consider potential stormwater management augmentation to Maryland's Phase II WIP in light of the vulnerabilities identified in this pilot analysis. Additional analysis is needed to thoroughly test alternate approaches against the range of futures considered in this report, as well as other key uncertainties that could not be addressed in this pilot-scale study.

Summary

In this chapter, we performed a pilot study of urban stormwater management focused on the Patuxent River Basin. We tested the stormwater investments included in the State of Maryland's Phase II Watershed Implementation Plan against a wide range of plausible future hydrology or land use conditions, looking forward approximately 40 to 50 years, using the Chesapeake Bay Program's Phase 5.3.2 model together with scenario inputs developed and provided by Chesapeake Bay Program partners. Our initial vulnerability analysis showed that Maryland's Phase II WIP meets new water quality TMDL targets for nitrogen, phosphorus, and sediment, assuming historical hydrology and current land uses. In addition, when compared with Current Management, the Phase II WIP increases the number of plausible futures in which TMDL targets are met, especially cases where all three targets are exceeded with Current Management.

More often than not, however, the Phase II WIP does not meet TMDL targets when a changing climate and future changes in population or development patterns are considered. Specifically, scenario discovery demonstrates that water quality targets for nitrogen are most often not met when precipitation increases over the historical average (or declines by only a small amount), impervious land cover increases, or both. Similar patterns were observed for phosphorus and sediment targets. To help hedge against these vulnerable outcomes, the state could consider greater investment in BMP types such as wetlands or urban filtering practices that appear to provide cost-effective pollutant load reduction for impervious areas when compared with other approaches.

However, a preliminary analysis suggests that in some plausible stressing futures, none of the BMP types considered could meet existing water quality targets. The high level of vulnerability suggests that it may be difficult to meet the newly established

TMDLs at reasonable cost with existing technology and practice once climate uncertainty and land use changes are considered. In turn, this suggests that:

1. Additional options may be needed for the basin, including changes to land use practice, to help avoid future impervious area growth.
2. Suggested potential signposts that would indicate the need for additional BMP investments or new policy options should be monitored.

These topics are taken up for further discussion in Chapter Five.

CHAPTER FOUR

Evaluating the Impacts of Climate Change on the Water Quality Implementation Plan for the North Farm Creek Tributary of the Illinois River

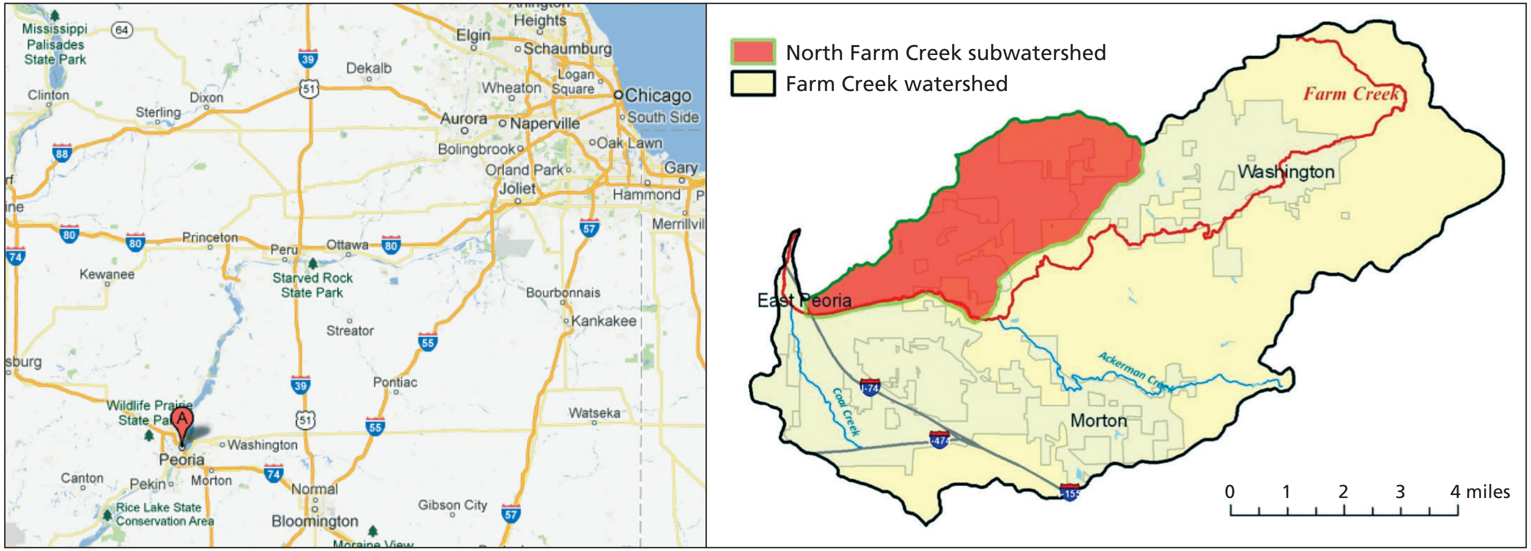
Introduction

The Illinois River, a principal tributary of the Mississippi River Basin, flows for about 270 miles across central Illinois, beginning just south of Chicago and joining the Mississippi near St. Louis. The Illinois River drains approximately 28,000 square miles, an area including 90 percent of the state's population. The river is a major source of waterborne commerce, fishing, and recreation. In the early 1900s, the Illinois River had abundant fisheries and carried extensive commerce. By mid-century, however, the river had been significantly degraded, with sedimentation impeding navigation and its fisheries depleted. The National Research Council (NRC, 1992) identified the Illinois River as one of three large-floodplain river ecosystem restoration priorities in the United States.

In 1997, the State of Illinois adopted an Integrated Management Plan that has since guided restoration and protection of the river (Illinois River Strategy Team, 1997). The Middle Illinois River watershed, surrounding Peoria, ranked high on the state's list of impaired waters. As part of its overall efforts, in 2010 the state targeted this area for developing TMDL standards. The first phase of developing TMDL, recently completed, identified the key contaminants threatening this part of the river. These include phosphorus, dissolved oxygen sedimentation, siltation, total suspended solids (sediment), pH, alteration in streamside vegetation as a potential biological impairment, and fecal coliform bacteria as a potential impairment to human health.

Illinois is now beginning the process of implementing pollution control and restoration plans for the Middle Illinois River. Illinois selected two pilot areas, North Farm Creek (Figure 4.1) and Dry Run Tributary, to demonstrate the development of load reduction implementation plans. The Illinois Environmental Protection Agency (IEPA) and USEPA have provided additional resources in the form of technical assistance to the Peoria and Tri-County Area TMDL partnership to make this planning process more useful to local decisionmakers. In December 2012, the state published a load reduction strategy for the two selected subwatersheds (Tetra Tech, 2012b). The analysis in this report focuses on one of these pilot areas, North Farm Creek, and aims to sup-

Figure 4.1
North Farm Creek Subwatershed on the Peoria Area of the Illinois River



SOURCES: Google Maps (left panel) and Tetra Tech (2012) (right panel).

RAND *RR720-4.1*

port load reduction efforts in the pilot area as well as throughout the Middle Illinois River Watershed.

The Farm Creek case study described in this chapter focuses on managing the effects of climate change and other uncertainties on the North Farm Creek Implementation Plan using the December 2012 load reduction strategy as the starting point. The strategy did not previously consider climate change, and IEPA and USEPA Region 5 officials expressed an interest in such an analysis. A recent USEPA study that conducted watershed modeling in 20 large U.S. drainage basins (Johnson et al., 2012) suggests that climate change could have a significant impact on pollution loads in this region.

North Farm Creek is located upstream of the confluence point of Farm Creek and the Illinois River (Figure 4.1). Developed land constitutes 54 percent of the total watershed area of 6,248 acres. But North Farm Creek also has significant agricultural lands, with 15 percent cultivated cropland and 7 percent pasture (Table 4.1).

The North Farm Creek Subwatershed is an important component of the Middle Illinois River's overall TMDL and load reduction strategy (LRS) because this subwatershed contributes significantly to concentrations of nitrogen, phosphorus, total suspended solids, chloride, and bacteria in the region (Tetra Tech, 2012b). Agriculture makes an important contribution to this water quality impairment as the source of about half of the nitrogen, phosphorus, and suspended solids (Figure 4.2).

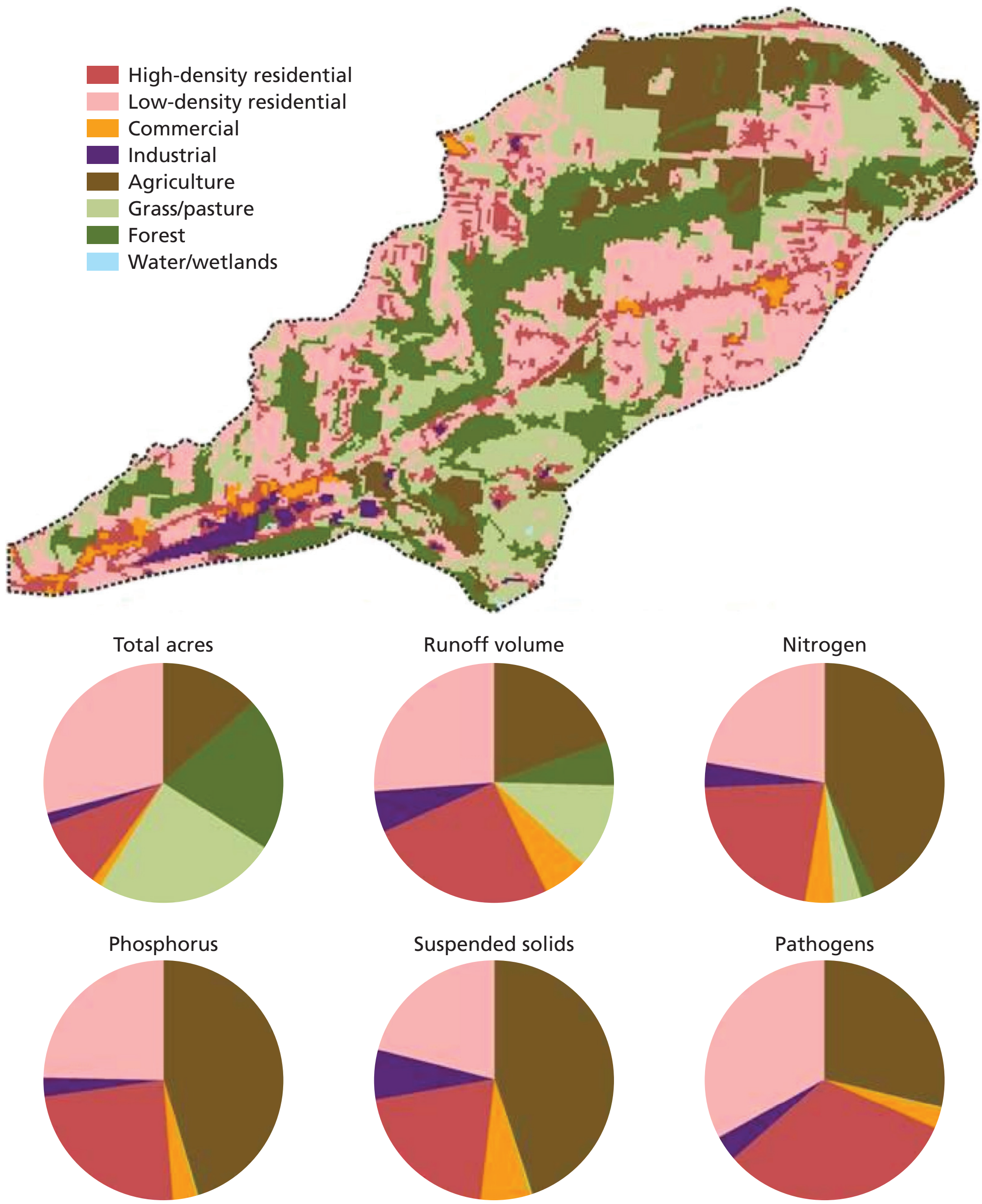
These impairments are due to various physical and anthropogenic factors. Specifically, four main processes have been identified as the largest sources of nutrients and pollutant loads in North Farm Creek: (1) watershed, stream bank, and gully erosion; (2) urban and agricultural stormwater runoff; (3) National Pollutant Discharge Elimination System (NPDES)[1] facilities and sanitary sewer overflows; and (4) deicing agents. The North Farm Creek subwatershed consists of many ravines, and the steep

Table 4.1
Land Use in the North Farm Creek Subwatershed

Land Use	Percentage Area
Developed	54
Deciduous forest	23
Cultivated crops	15
Grassland/pasture	7
Bare rock/sand/clay	1
Water and wetlands	<1

[1] NPDES is a national program established under the Clean Water Act to regulate point-source discharges of pollutants into U.S. waters. Under this program, any facility discharging pollutants must obtain an NPDES permit that governs the types, amounts, and conditions under which pollutants may be discharged to a receiving water body.

Figure 4.2
Pollution Sources in the North Farm Creek Subwatershed



SOURCE: Tetra Tech (2012b).
RAND *RR720-4.2*

topography of the land leads to high levels of erosion and sediment transport. In addition, large quantities of urban stormwater runoff are transported over impervious surfaces. Wastewater discharges from three permitted NPDES facilities in the area further exacerbate the in-stream nutrient and bacterial loadings. At least one sanitary sewer overflow outfall has occurred in the area and discharged 4,500 gallons of untreated wastewater into Farm Creek (Tetra Tech, 2012b).

North Farm Creek provides a useful case study for this report for two reasons. First, in contrast to the Patuxent River watershed, which is largely developed land, the region includes runoff from agricultural lands as a significant source of pollution. Second, this study extends the modeling conducted in USEPA's Twenty Watersheds study (Johnson et al., 2012), which was intended as a national scale assessment of streamflow and water quality sensitivity to climate change in different regions of the nation, to consider potential management responses to this risk. The Twenty Watersheds study employed the SWAT watershed model, version 2005 (Soil and Water Assessment Tool) (Nietsch et al., 2011). This case study provides additional insights into how climate change can be appropriately included in such analyses using SWAT and addresses the extent to which existing tools might need to be augmented to achieve this goal. In addition, this case study provides useful information to decisionmakers in the North Farm Creek region for making their implementation plans more robust to potential climate change.

Approach

This case study was conducted in collaboration with the Illinois Environmental Protection Agency and with USEPA Region 5. The RAND team and representatives of these organizations held several meetings by phone during the course of the effort and met in person in February 2014. As in Chapter Three, this case study employed the "XLRM" framework (Lempert, Popper, and Bankes, 2003) to help guide discussions with USEPA and IEPA as well as model development and data gathering. Table 4.2 summarizes these factors, described in detail in the subsections following.

Relationships

This case study uses a SWAT model originally developed as part of USEPA's 20 Watersheds Study to estimate pollution loads in the North Farm Creek subwatershed under the influence of alternative climate change projections. SWAT was selected for use in that study because it is

- a dynamic simulation with time steps sufficiently short (at least daily) to examine the implications of any changes in the frequency or intensity of extreme events on hydrologic and water quality outcomes
- process-based, so that the simulations respond to changes in meteorological inputs

Table 4.2
Factors Considered in the North Farm Creek Case Study

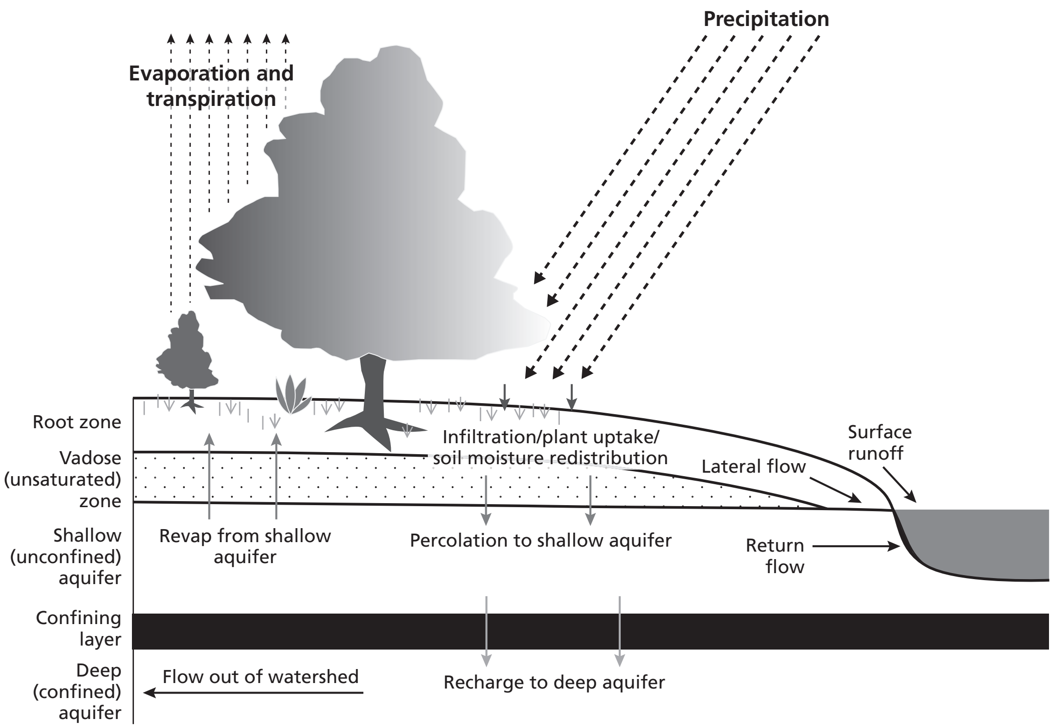
Uncertain Factors (X)	Policy Levers (L)
Effects of climate change on streamflow BMP effectiveness • Intrinsic performance • In response to climate change	Draft Implementation Plan, including structural management options: • Green infrastructure • Grassed waterways • Conservation tillage • Adaptive management responses
Systems Model Relationships (R)	**Performance Metrics (M)**
SWAT model of North Farm Creek calibrated to meet current water quality airshed model	TMDL compliance for: • Nitrogen • Phosphorus • Sediment

- able to explicitly account for the effects of climate change on plant growth (including atmospheric carbon dioxide concentrations), which can have important effects on hydrology and pollutant loads
- able to simulate water quality in North Farm Creek with sufficient skill
- widely used and accepted for hydrologic, water quality, and regulatory applications
- in the public domain (Johnson et al., 2012; USDA-ARS, 2014b).

SWAT is a river basin scale model developed by the U.S. Department of Agriculture Agricultural Research Service (USDA ARS) to quantify the impact of land management practices in large, complex watersheds. SWAT partitions a given watershed into smaller subbasins, each composed of many hydrologic response units (HRUs). Each HRU aims to represent a homogeneous area, with a single soil type, land use, and land slope. As shown in Figure 4.3, SWAT considers the major modes of water transport within HRUs. SWAT requires data on land topography, soil distribution, and temperature and precipitation. Based on these data, SWAT simulates a number of land and in-stream hydrological (water balance and transport) and nutrient (nitrification, eutrophication, and erosion) processes. SWAT has been used extensively in watershed modeling and TMDL development. Several studies review the scientific applications of SWAT in a variety of contexts (for example, see Gassman et al., 2007).

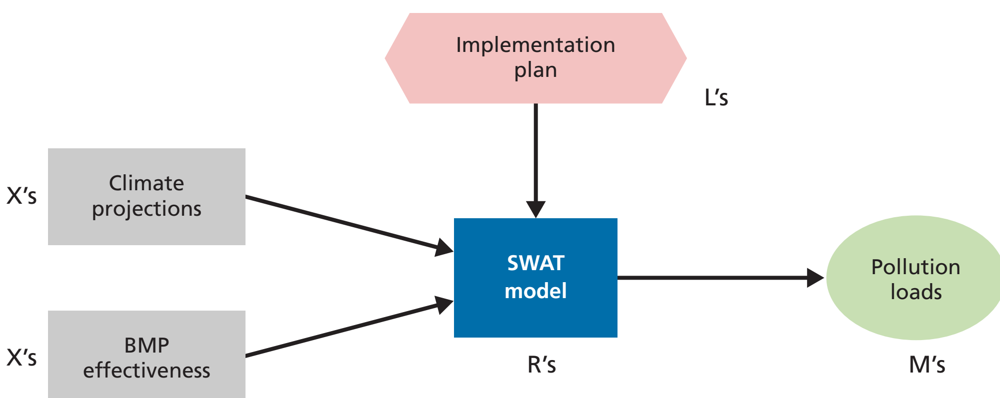
The SWAT model allows us to estimate future pollution loads in North Farm Creek. As shown in Figure 4.4, the model combines a description of various alternative pollution control plans (described below), gathers information on future climate and BMP effectiveness, and calculates the resulting pollution loads. We can represent alternative plans, hydrology in future climates, and assumptions about BMP effectiveness by adjusting appropriate parameters in the SWAT model, as described in detail

Figure 4.3
Processes Considered in the SWAT Model



SOURCE: Nietsch et al. (2011). Used with permission.
RAND *RR720-4.3*

Figure 4.4
Modeling Schematic for North Farm Creek Case Study



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below. These are labeled in Figure 4.4 according to their respective XLRM grouping (Table 4.2).

The SWAT model used in the 20 Watersheds study, calibrated for the Illinois River inclusive of North Farm Creek, was made available to the study team. However, our case study required recalibration of this SWAT model for two reasons: (1) the Illinois River model for the 20 Watersheds study did not cover the full time period of interest for the present analysis, and (2) SWAT is scale dependent, so that output from the larger Illinois River model is not an accurate representation of the loadings in the smaller-scale North Farm Creek subwatershed.

For this recalibration, North Farm Creek was delineated into 33 subbasins, and data from two U.S. Geological Survey (USGS) gauging stations (for hydrology calibration) and one IEPA water quality station (for water quality calibration) were used to calibrate and validate the SWAT model. Other data used in the recalibration included

- 10-meter digital elevation model taken from the National Hydrography Dataset's NHDPlus hydrography database (USEPA, 2010d)
- land use and land cover information incorporated from the 2006 National Land Cover Database (Fry et al., 2011)
- information on the four main types of soil in the watershed from USDA's Soil Survey Geographic database (SSURGO)
- meteorological data, including precipitation and daily temperature minimum and maximum, from Peoria airport station, part of the Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) meteorological data set (USEPA, 2008)
- additional meteorological inputs such as solar radiation and windspeed from SWAT's built-in weather generator (Nietsch et al., 2011).

Overall, the recalibrated SWAT model shows sufficient skill at reproducing pollution flows in North Farm Creek for the purposes of our analysis. Using data from the historical period 2000–2012, we evaluated the model's performance for hydrology using statistical criteria and graphical comparisons to establish goodness-of-fit. Overall, the model skill was rated as good because the model met seven of nine calibration criteria.

For water quality, data on total suspended solids (TSS), total phosphorus (TP), soluble reactive phosphorus (SRP), total nitrogen (TN), total Kjeldahl nitrogen (TKN), and nitrate+nitrite nitrogen (NO_x) were used for calibration (October 2005–August 2010) and validation (October 2000–August 2005). From this analysis, the model skill for sediment and nutrient loads (except phosphorus) was rated very good. Appendix D describes the SWAT model calibration and validation in more detail.

We needed to make several other modifications to SWAT in order to automate multiple runs for use in the RDM analysis. We first obtained the FORTRAN binaries for the model and compiled them so that they could be modified and run on a Unix cluster. This was necessary because out-of-the-box, SWAT is an executable file that cannot be modified. Next, we modified SWAT so as to circumvent the data input process. Typically, a graphical user interface is used to provide HRU-specific input files, which the model then reads and runs. However, even a small-scale watershed such as North Farm Creek contains close to 8,000 HRUs, and manually generating input files for even a few futures would be a cumbersome task. We edited the program routines to provide more flexible treatment of the BMPs such that BMP activation, BMP nutrient removal efficiencies, and BMP effectiveness parameters were directly supplied for the relevant parts of the watershed inside the source code rather than generated individually for each future.

Despite SWAT's considerable capabilities, the model has some limitations relevant for this study. First, SWAT does not model interaction between HRUs for certain watershed processes such as groundwater or base flow (Narasimhan et al., 2013), which can introduce error in the hydrology and nutrient processes of the model if different types of land use need to interact. Second, SWAT allows BMPs to be applied only to HRUs, which have no real geographic meaning.[2] In actuality, the placement of BMPs occurs over a defined area, chosen on the basis of on-the-ground knowledge of the watershed conditions. Such considerations are lacking in the model. Finally, SWAT uses a daily time step, which means that subdaily events affecting flow and nutrient transport are not adequately modeled.

Policy Levers

The Implementation Plan for North Farm Creek (Tetra Tech, 2012b) describes a number of load-reduction measures, divided into structural and nonstructural management options. This plan is the focus of our analysis. In addition to examining the potential impacts of climate change and any vulnerabilities it might create, the study also compared a plan consisting of some of the BMPs in this *Implementation Plan* to a *Current Management* plan, representing the case in which no additional management actions are taken. In addition, the study suggests potential modifications to the Implementation Plan that might reduce its potential vulnerabilities.

The Implementation Plan, as shown in Table 4.3, consists of six nonstructural management options and eight structural management options. Nonstructural management practices, also termed *source control practices*, aim to prevent runoff from a site, whereas structural management practices refer to redevelopment or retrofits of pollutant control and conveyance structures. Some of the former, such as education programs and the development of ordinances, are applied to the entire watershed. But in most cases, management options are applied only to particular land area types. For

2 For example, a single HRU could be spread over two pieces of land that are not contiguous.

instance, green infrastructure retrofitting is applied to impervious surfaces in developed areas, while conservation tillage is appropriate for cultivated agricultural areas.

The Implementation Plan includes qualitative rankings for the level of pollution reduction provided by each BMP (moderate or high) and for the cost (low, moderate, and high). In addition, the plan envisions an adaptive management approach consisting of a three-phased implementation schedule that combines both monitoring and adjustment over time. The plan unfolds according to the following schedule:

Table 4.3
BMPs Considered In Case Study

Activity	Critical Area	Phasing I/II/III	Pollution Removal	Cost
Nonstructural Management Options				
Education and pollution prevention programs	Watershed wide	H/C/C	Moderate	Low
Ordinance development	Watershed wide	H/C/C	Moderate	Moderate
Street and parking lot sweeping	Impervious surfaces	H/C/C	Moderate	Moderate
Pet waste education and outreach campaign	Residential areas	H/C/C	Moderate	Low
Wildlife implementation practices	Riparian areas	H/C/C	Moderate	Low
Salt management plan	Impervious salted areas watershed wide	H/C/C	High	Low
Structural Management Options				
Green infrastructure retrofitting	Impervious areas	M/H/C	High	High
SSO control	East Peoria Oakwood Ave. outfall	H/C/C	High	High
Disinfection of primary sewage plant effluents	Sundale Sewer Corp.-Highland	H/C/C	High	High
Stabilizing erosion of steep slopes	Storm sewer outfalls, steep slopes	H/C/C	High	Moderate-High
Stream bank restoration	Eroding stream banks	L/H/H	High	High
Riparian area management	Riparian areas	H/H/C	High	Moderate
Grassed waterways	Cultivated agricultural areas	H/M/L	High	Low
Conservation tillage	Cultivated agricultural areas	H/M/L	High	Low

NOTE: Shading shows BMPs modeled in this study. Unshaded entries included in North Farm Creek Load Reduction Strategy but not included in this case study. Activity levels in each phase: H = High, C=Continued at prior-phase level, M= Moderate, L = Low. SSO = sanitary sewer overflow.

- Phase I (years 0–3): Implement nonstructural BMPs and begin planning for structural BMPs
- Phase II (years 3–10): Begin implementing structural BMPs
- Phase III (years 10–20): Monitoring and adaptive management.

Each phase has associated milestones and goals designed to measure progress and suggest the need for midcourse corrections in the plan. The milestones refer to the qualitative levels of activity shown in Table 4.3 under the column "phasing." For instance, the emphasis on green infrastructure retrofitting is high in Phase II and is continued into Phase III. The quantitative goals for pollution removal (fourth column) refer to particular levels of pollution load reduction expected at particular points in time. The Implementation Plan uses implementation schedules and qualitative High/Moderate/Low "emphasis" categories (i.e., the extent to which particular BMPs have been implemented) and pollution loadings as its primary evaluation tools. The plan uses these tools to suggest triggers that may indicate a need for modifications over time. For instance, the plan may need to be modified if observed BMP performance does not align with expectations, or if water quality conditions do not improve.

In this case study, we do not consider the entire Implementation Plan. Instead, we model the performance of four structural BMPs: green infrastructure retrofitting, riparian area management, grassed waterways, and conservation tillage. Our analysis is limited to these four BMPs because, as described in detail below, the option to model the other BMPs is either not provided in SWAT or is provided in a way that is not suitable for RDM analysis. Table 4.3 highlights these BMPs with shaded rows. We follow these BMPs through the adaptive management process described in the Implementation Plan, with the aim of providing a quantitative understanding of their ability to achieve pollution load reductions, the uncertainties that affect these reductions, and the types of triggers that may be effective in allowing for adjustments over time.

Table 4.4 summarizes the land use type and removal efficiencies for the BMPs used in this study. Each BMP can in practice be applied to the given land use, but we apply it only to the land use in bold for reasons discussed below. We modeled the effectiveness of these four BMPs using SWAT's built-in "generic conservation practice" module, which enables the user to specify nutrient- and sediment-removal efficiencies and to specify the type of land use or HRU to which the BMP is applied. For the nonurban BMPs considered in this study, we use removal efficiencies as estimated by Waidler et al. (2012). The range of urban BMP removal efficiencies was taken from the Implementation Plan. The range of agricultural BMP removal efficiencies was taken from Dermisis et al. (2010) and Hallock (2007).

To model the phased implementation of the Implementation Plan, we first quantified the different levels of emphasis in the plan (High/Medium/Low) by assuming that these categories refer to the percentage of the relevant HRUs to which the plan can be applied, namely 100 percent (High), 50 percent (Medium), and 25 percent

Table 4.4
Land Use Type and Removal Efficiencies for BMPs Considered in Case Study

Structural BMP	Land Use (HRU)	BMP Removal Efficiency (%)	Uncertainty in Removal Efficiency [Implied Effectiveness]
Green infrastructure retrofitting	Urban	Phosphorus = 47 Nitrogen = 48 Sediment = 52	Phosphorus = [0.76–1.0] Nitrogen = N/A Sediment = [0.39–1.0]
Grassed waterways	Cropland (corn, soy); **pasture**	Phosphorus = 75 Nitrogen = 70 Sediment = 65	Nitrogen = [0.3–1.0] Phosphorus = N/A Sediment = [0.62–1.0]
Riparian area management (filter strips)	Cropland (corn, soy); pasture; **rangeland**	Phosphorus = 75 Nitrogen = 70 Sediment = 65	Phosphorus = N/A Nitrogen = N/A Sediment = [0.53–1.0]
Conservation tillage	**Cropland (corn, soy)**; pasture	Phosphorus = 45 Nitrogen = 55 Sediment = 75	Phosphorus = N/A Nitrogen = N/A Sediment = N/A

(Low).[3] We then randomly assigned BMPs to HRUs of the appropriate land use type for each of the three implementation levels. For instance, for a Medium application of the grassed waterways BMP, we randomly assigned this BMP to half the cropland and pasture HRUs in North Farm Creek. It was necessary to use such random assignments because SWAT does not allow spatially targeted placement of BMPs. The number of HRUs is sufficiently large, however, that our results are insensitive to the details of any particular random assignment.[4]

SWAT has several limitations in its treatment of BMPs that are particularly germane to this analysis and, we expect, for any future attempts to use SWAT for RDM studies. Here we describe some of these limitations. At the close of the chapter we describe how they might be addressed in future work.

This study considered only four types of BMPs. While SWAT has several built-in modules that simulate a variety of BMPs, only the "Generic Conservation Practice" module was suitable for the RDM analysis. The generic module enables user-defined input of removal efficiencies, while management-specific modules allow only user-defined input of structural management parameters, such as the geometry of the grassed waterway or filter strip. However, the information required to relate the structural parameters to removal efficiencies is generally lacking, as is information regarding

3 This assumption is analogous to that made in the analysis (done using the Long-Term Hydrological Impact Analysis [L-THIA] model) for some structural BMPs as part of the North Farm Creek Implementation Plan report (Tetra Tech, 2012b).

4 To check this, we generated an ensemble of runs (n = 5) and noticed that the ensemble standard deviation in yearly loadings was 20.3 lbs/year for nitrogen, 3.4 lbs/year for phosphorus, and 1,550 lbs/year for sediment. These magnitudes are much smaller than the model uncertainty and climate uncertainty described below.

how climate change will affect such relationships. Thus, we restricted ourselves to using the generic module in which we can directly specify (and modify) removal efficiencies.

In particular, using the generic BMP module precluded treatment of two important BMPs: stream bank restoration and slope stabilization. In principle, SWAT could address these two BMPs by modifying the model's physical channel equations. For example, one could simulate both BMPs indirectly by changing the soil erodability factors associated with stream banks and channels that the BMPs are designed to affect. Similarly to the challenge of SWAT's nongeneric BMP modules, such an approach poses problems because the physical relationship between a parameter such as soil erodibility or bank slope and pollutant removal efficiency is not known; the effects of climate change on these relationships are not known; and changing the physical equations SWAT uses to model watershed processes risks introducing model uncertainty and errors. The need to exclude stream bank restoration and slope stabilization BMPs from the analysis affects most significantly the projected sediment and phosphorus loadings and less significantly the nitrogen loadings.

In addition, SWAT can use the generic BMP module only *once* in any one HRU. For example, if we use the SWAT generic BMP module to simulate the effect of implementing porous pavement in urban HRUs, then the generic module cannot also be used to add bioswales to those same HRUs. We thus use the SWAT generic module to simulate all four BMP types by assuming that only one type of BMP is applied in each HRU. In reality, multiple BMPs could be applied in the same HRU. Table 4.4 shows the land types in bold to which we apply each BMP. While this assumption underestimates the true removal capacity of the plan, it still enables us to apply BMPs to the entire region. Moreover, in a practical context, all BMPs cannot necessarily be co-applied all the time.[5]

Overall, however, these limitations suggest that our analysis likely underestimates the possible levels of nutrient and sediment reduction.

Uncertainties

This case study focuses on two important uncertainties—climate change and the effectiveness of various BMPs—that may affect the ability of the Implementation Plan to meet the TMDL goals for the region.

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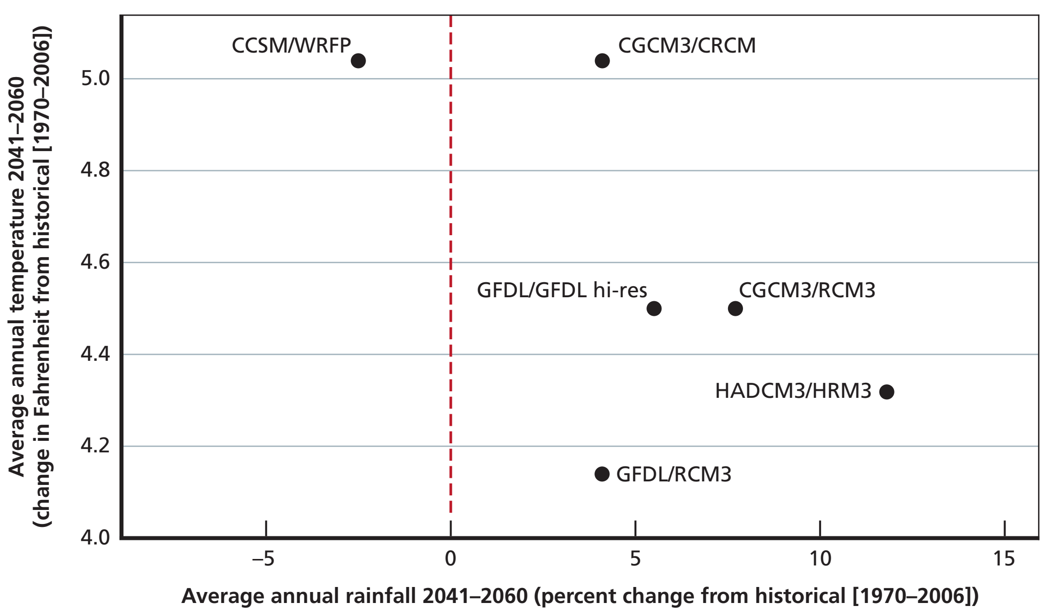
[5] The ability to be co-applied as well as the removal efficiencies of multiple BMPs is dependent upon BMP type, HRU characteristics, weather patterns, and other factors (Srinivasan, 2015). Nevertheless, we can get a sense of the lower and upper bounds through a simple example. Without loss of generality, suppose we apply two BMPs, with efficiencies given by E^1 and E^2, to an area containing two HRUs of equal size. Case 1: each BMP can be applied to only one HRU, so the overall removal capacity will be: $Eff_1 \approx (E^1 + E^2)/2$. Case 2: each BMP can be applied to both HRUs so the overall removal capacity will be: $Eff_2 \approx E^1 + (1\text{-}E^1) \times E^2$. Suppose we're interested in phosphorus removal through conservation tillage ($E^1 = 0.45$) and grassed waterways ($E^2 = 0.75$). As such, for case 1 $Eff_1 = 0.6$, and for case 2 $Eff_2 = 0.86$. Thus, the maximum difference is not large relative to the performance uncertainties we are considering. Moreover, this difference is reduced as the number of BMPs and/or their removal capacities increase.

To represent uncertainty in future climate, this case study uses six mid-21st century (2041–2070) climate change projections from the North American Regional Climate Change Assessment Program (NARCCAP) that were also used in the USEPA 20 Watersheds Study (Mearns et al., 2006). These consist of six pairings of one of the GCMs used in the IPCC Fourth Assessment Report (IPCC, 2007) with a higher-resolution regional climate model.[6] Each pairing provides a 50-square-kilometer grid over North America. This downscaled output is archived for two 30-year periods (1971–2000 and 2041–2070) at a temporal resolution of three hours. Each GCM in the NARCCAP ensemble is driven by the IPCC A2 emissions projection, which is among the highest of the carbon emissions scenarios in the Special Report on Emissions Scenarios (SRES) set (IPCC, 2000).

As shown in Figure 4.5, the six projections show a range of plausible deviations from historic temperature and precipitation patterns in the North Farm Creek area. All six projections are hotter than the historic baseline, with increases in average annual

Figure 4.5
Range of Climate Projections Used in This Study



RAND *RR720-4.5*

[6] The six pairings used in this and the 20 Watersheds study are the: (1) Geophysical Fluid Dynamics Laboratory (GFDL) GCM with the Regional Climate Model (RegCM) RCM (NCAR regional climate model), (2) GFDL GCM with the GFDL RCM, (3) Third Generation Coupled Climate Model (CGCM3) GCM with the RegCM RCM, (4) CGCM3 GCM with the Weather Research and Forecasting Model (WRF) RCM, (5) Hadley Center Coupled Model, version 3 (HADCM3) GCM with the Hadley Regional Model (HadRM) RCM, and (6) Community Climate System Model (CCSM3) GCM with Canadian Regional Climate Model CRCM RCM.

temperatures ranging from about 4.1 to 5.0 degrees Fahrenheit. Five of the six projections are wetter than the historic baseline, with up to a 12 percent increase in average annual rainfall, while the sixth is slightly drier (2 percent decline). This pattern is typical of most ensembles of regional climate projections, which generally show a larger spread in precipitation than temperature and, in particular, often disagree about the sign of future precipitation changes (IPCC, 2013).

Watershed modeling at the scale of the North Farm Creek requires higher spatial resolution than the 50-square-kilometer NARCCAP projections, and detailed efforts also depend on meteorological variables in addition to average annual temperature and precipitation. This information was generated using a "change factor" or "delta" method. An approximately 30-year time series of observed local climate for each National Climatic Data Center weather station used by the Illinois River Basin SWAT model was obtained from the 2006 Metrological Database in USEPA's BASINS system. Historical temperature and precipitation values for each weather station used by the model were then adjusted to represent each of the six NARCCAP scenarios using the BASINS Climate Assessment Tool (CAT) (USEPA, 2013). The analysis used monthly climate change statistics, representing the difference between the 2041–2070 and 1971–2000 time periods in each NARCCAP projection, to perturb these observational data, which were then used as inputs into the SWAT model's weather generator to create realizations of other climate variables based on monthly statistics conditional on the precipitation projections.

As discussed in Chapter Three, climate change is expected to affect the intensity and frequency of extreme precipitation events (IPCC, 2012). More intense precipitation events may have significant impacts on water quality (USEPA, 2009a). To represent changes in event intensity, climate change scenarios calculated separate monthly climate change statistics for daily precipitation within different percentile classes from the NARCCAP model outputs. In particular, the delta method perturbations were applied separately to precipitation events in the greater- and less-than-70th percentile event classes, while maintaining the appropriate mass balance.[7] Most of the climate projections show increases in precipitation volume for larger, more extreme events, with a constant or decreasing volume of precipitation in the smaller events.

It is important to note that the six NARCCAP projections used in this study likely represent an underestimate of the full range of potential future outcomes. The 20 Watersheds study compared the water quality results obtained from the six NARCCAP projections to eight additional projections obtained from applying the delta method directly to the outputs from the four GCMs (without first coupling to the RCMs) and by applying the bias-corrected and spatially downscaled (BCSD) downscaling method

[7] The delta method is a technique to downscale the global results of GCMs to produce regionally specific climate forecasts. An elementary discussion of this technique is available from Scenarios Network for Alaska and Arctic Planning (SNAP) (2015).

to the GCM outputs (USEPA, 2013). The study found in general that projections of flow and water quality in each of the 20 basins were sensitive to the choice of GCM projection and to the downscaling method. In addition, the IPCC has provided an updated ensemble of over 100 new climate projections as part of the recently released Fifth Assessment report (IPCC, 2013). This CMIP5 (Climate Intercomparison Project 5) ensemble, derived from roughly 30 GCMs run with up to four alternative projections of atmospheric greenhouse gas concentrations, spans a much larger range of temperature and, especially, precipitation than those provided by the six NARCCAP projections used in this study. The range of projections considered in this case study thus represents a lower bound on the potential range of future climate changes that might face North Farm Creek.

We represent uncertainty regarding the effectiveness of various BMPs by varying over a wide range their ability to remove pollution. In practice, BMP effectiveness may vary depending on the specific conditions in which the BMP is deployed, how well the BMP is maintained over time, and the effects of climate change. As noted in the discussion surrounding Table 4.3, the literature provides a range of estimates for the performance of each BMP. We choose the high end of the range as 100 percent effectiveness. The lowest removal efficiency estimate in the literature for each of the four BMPs is roughly half of the highest estimate, so we set the low end of the uncertainty range at 50 percent effectiveness.

Metrics

The TMDL and LRS study for the North Farm Creek subwatershed requires reductions in bacteria, total suspended solids, and nutrients to meet water quality goals. Table 4.5 shows the plan's specific reduction goals. Our analysis will focus on total suspended solids, nitrogen, and phosphorus. These contaminants have sufficiently long time series of water quality data available at a fine enough spatial scale to properly calibrate the SWAT model for North Farm Creek.

Table 4.5
North Farm Creek TMDL and LRS Reduction Goals

Pollutant	Reduction Requirement (%)
Sediment	88
Nitrogen	17–63
Phosphorus	21–73

Experimental Design and Case Generation

Using these XLRM factors, we examined the performance of alternative pollution control plans for the North Farm Creek subwatershed over a wide range of futures. Each future consists of one assumption about future climate and one set of assumptions about future BMP effectiveness. The experimental design that defines this range of futures was composed of

- a full factorial sample over seven hydrology sequences (six downscaled climate projections and one projection that repeats the observed historical record)
- 20 sets of BMP effectiveness parameters generated using a Latin hypercube sample over the range 50 percent to 100 percent for each of the four BMPs.[8]

Considering all possible combinations of these scenario inputs yielded 140 different futures. For each of these futures, we ran the model for both the Current Management plan (no additional BMPs) and the modeled BMPs in the Implementation Plan, for a total of 147 cases.[9] Nitrogen, phosphorus, and sediment loads were recorded for each case. We then used the database of run results to understand the potential effectiveness of the plan over a range of future conditions. Each case was run in a server environment and took approximately 20 minutes to complete, yielding about 47 hours of runtime for the full array of results discussed here.

Results

Figure 4.6 first compares the Current Management and the modeled BMPs in the Implementation Plan (hereafter the *Modeled Implementation Plan*) using box-plot summaries of annual nutrient and sediment loadings across all the futures considered in this analysis. Note that for each pollutant, the modeled plan reduces both the load and the variation in load across the plausible futures. For instance, with Current Management, nitrogen loads in North Farm Creek range from 22,000 to 60,000 lbs/yr. With the modeled plan in place, nitrogen loads range from 15,000 to 30,000 lbs/yr.

The Modeled Implementation Plan shows similar improvements for phosphorus and sediment. These calculations also suggest that the Implementation Plan would be significantly more effective at reaching the TMDL standards for North Farm Creek, shown by the red lines (Tetra Tech, 2012a), for nitrogen than for the other two pol-

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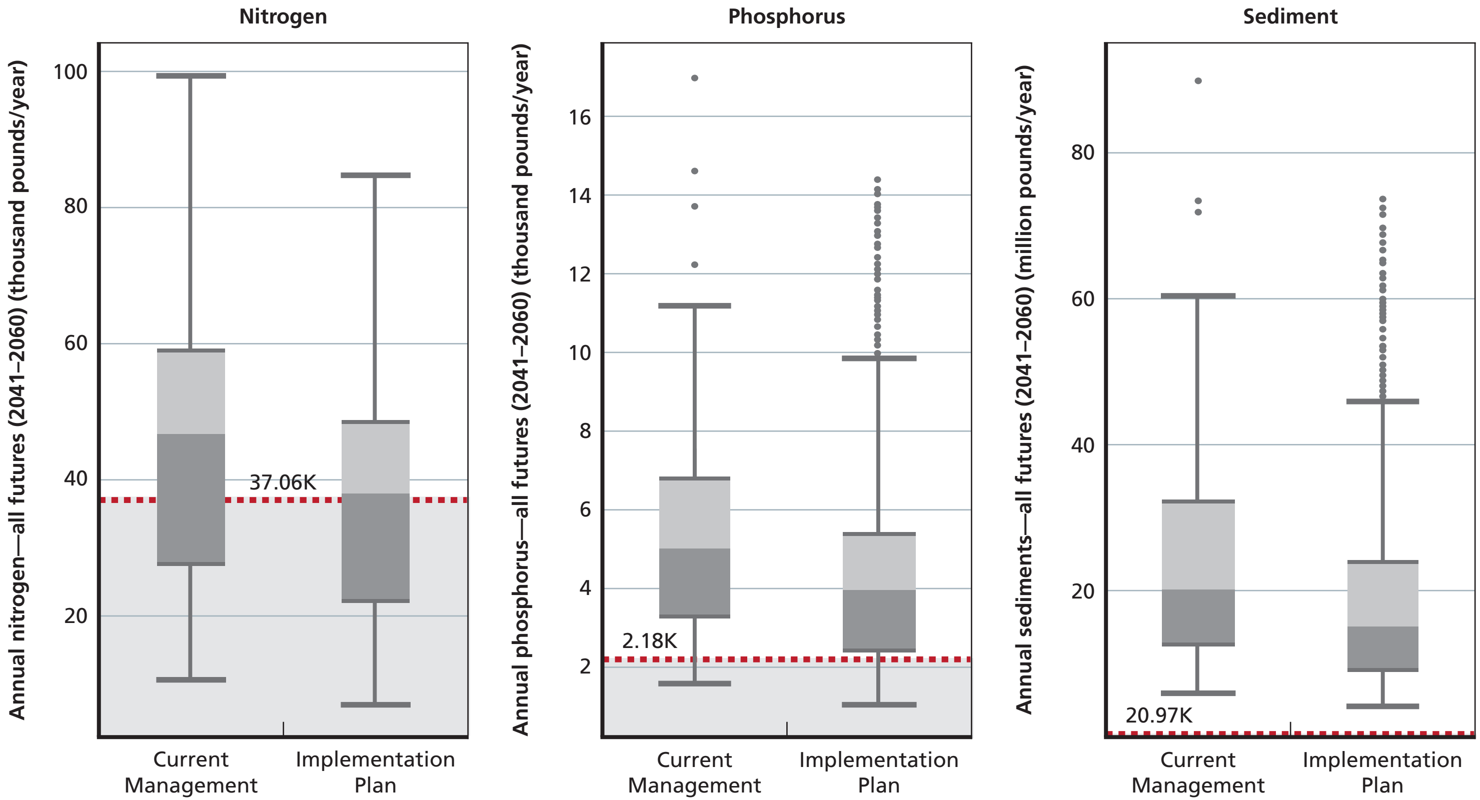
8 Latin hypercube sampling is a method used to obtain simulation parameters from a multidimensional distribution such that each dimension is equally represented. This reduces the number of simulation runs required to produce stable outputs in stochastic simulations.

9 The number of cases is 147 because the BMP effectiveness uncertainties do not affect the Current Management Plan.

Figure 4.6
Annual Nutrient Loads Across All Future Projections (2041–2060) Under Current Management Versus Modeled Implementation Plan



NOTE: The red lines show the TMDL target for each pollutant. The boxplots presented do not represent probability distributions, but instead report the results of a set of model runs (futures). Each point summarized represents one mapping of assumptions to consequence, and the points are not assumed to be equally likely. Each individual future shifts downward when BMPs are applied.

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lutants.[10] For nitrogen, roughly 50 percent of the cases meet or perform better than the TMDL standard, while for phosphorus, a little less than 25 percent of the cases meet or perform better than the TMDL standard. For sediment we find that nutrient loads *always* fail to meet the TMDL standard.

Table 4.6 summarizes the performance of the Modeled Implementation Plan across the futures considered in this analysis. In contrast to the annual loads in Figure 4.7, this table considers the average load for each pollutant over the entire time series in each future. The first column shows, as expected, that in the current climate the Current Management plan does not meet the TMDL for nitrogen, phosphorus, or sediment. The second column shows that if the modeled plan were currently in place, it would meet the nitrogen and phosphorus TMDLs, but not sediment, over the full range of assumptions about BMP effectiveness considered here. The third column shows that the Current Management plan would not meet the TMDLs in any of the six future climates considered in this analysis. The fourth column shows that by mid-century the modeled plan would meet the nitrogen TMDL in nearly 40 percent of the futures but would not meet the phosphorus and sediment TMDLs.

As discussed in more detail later, the failure of the modeled plan to meet the phosphorus and sediment standards in our analysis likely results from a combination of limitations of the current modeling—in particular the fact that we model only half the

Table 4.6
Futures in Which TMDL Targets Are Met, by Plan and Pollutant, for North Farm Creek

	Number (Percent) of Futures Meeting the TMDL Target			
	Current Climate		Future Climate (2041–2060)	
Pollutant	Current Management	Modeled Implementation Plan	Current Management	Modeled Implementation Plan
Nitrogen target	0 (0)	20 (100)	0 (0)	52 (43)
Phosphorus target	0 (0)	20 (100)	0 (0)	0 (0)
Sediment target	0 (0)	0 (0)	0 (0)	0 (0)
Meets all three targets	0 (0)	0 (0)	0 (0)	0 (0)

NOTE: This table shows one future for current management in the current time period; 20 futures for the modeled plan in the current time period, representing a range of assumptions about BMP effectiveness; six futures for current management at midcentury, representing a range of climate projections; and 120 futures for the modeled plan at midcentury, representing a range of climate projections and assumptions about BMP effectiveness.

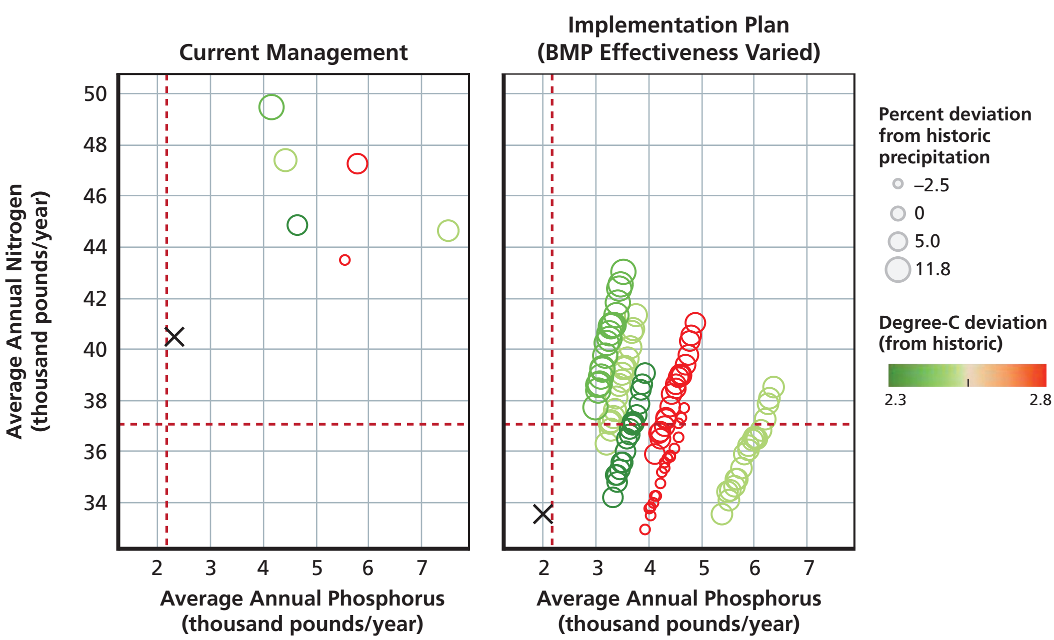
[10] The TMDL targets were derived by multiplying the TMDL values for Farm Creek by two scaling factors. The first scaling factor equates a given nutrient load derived from SWAT to the empirical load reported in the TMDL report. The second scaling factor is the ratio of a given nutrient load in North Farm Creek versus Farm Creek.

structural BMPs and none of the nonstructural management options—and aggressive targets for these pollutants in the North Farm Creek plan.

We can next use the analysis to explore key drivers that explain this variation in performance. Figure 4.7 compares the Current Management and modeled plan using scatterplot summaries of the average nitrogen and phosphorus loads for the 20-year period 2041–2060. Each point represents one of the futures considered in the analysis. The figure shows pollution loading for each future with a point whose color and size indicate the climate variables in each future. A red-shaded point indicates a future climate with larger temperature increases over historical. Similarly, a larger point indicates future climates with greater precipitation than historical. The "x" in each panel indicates the loadings with historic climate. The scatter of similarly colored and sized points in the right panel owes to the range of assumptions regarding BMP effectiveness.

Comparing the right and left panels suggests, similarly to Figure 4.6, that the modeled plan lowers nitrogen loads to meet the TMDL for many futures, but that even with the plan in place phosphorus loads remain above the TMDL standard across all future conditions. Figure 4.7 suggests that differences in precipitation largely explain the difference in the projected nitrogen loading to streams, as indicated by the larger

Figure 4.7
Nitrogen and Phosphorus Loads for Current and Modeled Implementation Plan



NOTE: Figure shows nitrogen and phosphorus loadings for current (left panel) and Modeled Implementation Plan (right panel) for each future considered in the analysis. Dot size shows future precipitation, dot color shows future temperature, and x indicates historic climate. Dashed red lines show TMDLs.

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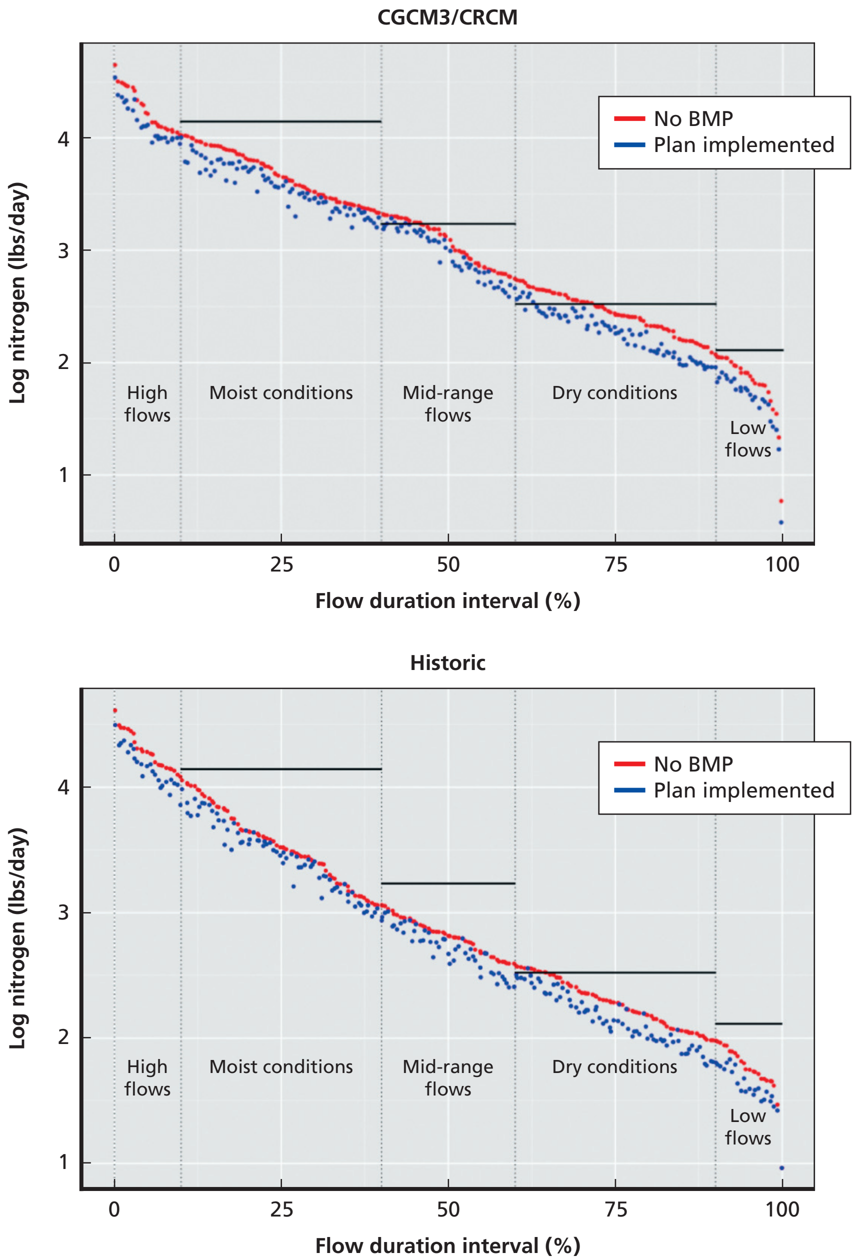
points for higher values of nitrogen loadings. For phosphorus, there is no clear trend in temperature or precipitation among the future climate projections, though the combination increases pollutant loads. Nutrient transport is highly correlated with BMP effectiveness, especially for nitrogen, as shown by the large spread of loadings for each climate projection in the right panel of Figure 4.7.

To further test the effects of these drivers, we reran the SWAT model while holding temperature constant at historic values and varying precipitation according to the alternative climate projections, as well as vice versa. We found that increased precipitation tends to increase sediment and nutrient loadings. However, the form of nitrogen considered in the TMDL (inorganic nitrites and nitrates, or NO_2NO_3) was most sensitive to precipitation changes, while phosphorus and sediment were comparatively less sensitive. In contrast, temperature does not appear to have any directional effect on nutrient and sediment loadings in our analysis. This could owe to competing mechanisms at play: Higher temperature leads to higher evapotranspiration, which in turn reduces surface flow volumes. On the other hand, higher temperatures also lead to increased carbon dioxide, leading to additional plant growth. This in turn increases the net phosphorus and nitrogen in the watershed. This behavior is consistent with earlier studies that find that precipitation (particularly surface runoff), and not temperature, is the driving factor for nutrient and sediment loadings to watersheds, and furthermore NO_2NO_3 is most sensitive to precipitation change when compared with phosphorus and sediment (Ficklin et al., 2010). Our results are consistent with these findings for all futures except CCSM-WRFP, which is about 2.5 percent drier and about 5° C hotter than historic climate, yet it results in higher nutrient and sediment loadings as compared to the historic climate. This could be because while our temperature increases are similar, our precipitation decreases are only a quarter as large as those considered in the (Ficklin et al., 2010) study. This decrease may not be significant enough to drive down sediment and nutrient loadings in the CCSM-WRFP future.

The differential response of nitrogen and phosphorus loadings to future changes in climate variables in our model is consistent with the sensitivities discussed in the literature. In general, previous studies suggest that the influence of precipitation and temperature changes on water quality results from several counterbalancing forces, with the overall result highly sensitive to local geology (Murdoch, Baron, and Miller, 2000). On the one hand, wetter futures dilute the point- and non-point-source pollutants entering streams, thereby improving water quality. However, because water residence times are lower, wetter futures also increase erosion and sediment transport while reducing chemical and biological transformations in the soil (Mulholland et al., 1997). Wetter climates also increase the spatial extent of surface runoff, and consequently increase the pollutant loadings from point- and non-point sources (Lins and Slack, 1999). Phosphorus loading, in particular, goes up due to increased weathering and erosion (Covich et al., 1997).

It also proves useful to consider the dependence of the Modeled Implementation Plan on various flow intensities. For instance, Figure 4.8 compares nitrogen loadings

Figure 4.8
Flow Duration Curves for Nitrogen



NOTE: The solid black lines represent TMDLs for a given flow duration interval.
RAND *RR720-4.8*

in North Farm Creek for the Current Management (red line) and Modeled Implementation Plan (blue points) for the historic (lower panel) and CGCM3-CRCM (upper panel) climate projections. The CGCM3-CRCM climate projection has the highest combination of nitrogen and phosphorus loads. The TMDL targets for each flow duration interval are indicated with solid black lines. The data plotted are at the monthly time step, which seems to offer the optimal accuracy/variation trade-off.[11]

The scatter of points in Figure 4.8 stems from the range of assumptions about BMP effectiveness. This figure suggests that for nitrogen the Modeled Implementation Plan performs adequately under high- and low-flow conditions but performs less well under mid-flow conditions. Water residence times are likely to be highest during mid-flow conditions, enabling bulk transport of nutrients into the stream. During low-flow conditions, there is not enough volume, and during high-flow conditions the water does not have enough time to absorb large amounts of nitrogen.

Overall, the projections for phosphorus loadings for the Modeled Implementation Plan, which always exceed the TMDL, are likely high. First, because of SWAT model limitations the analysis was unable to include stream bank restoration and efforts to stabilize slopes, two of the most important BMPs for controlling phosphorus. Second, the modeling assumptions in SWAT generally lead to elevated levels of phosphorus and sediment for two interrelated reasons: (1) sediment and phosphorus transport are tightly coupled in SWAT, and (2) in watersheds with a mix of developed and undeveloped areas, such as North Farm Creek, SWAT transports all runoff as sheet flow across the *pervious* sections without any piping or channelization, which results in the overestimation of sediment from developed areas. Given that, this analysis may overestimate sediment and phosphorus transport (Tetra Tech, undated). Finally, local IEPA staff report that the phosphorus TMDL for North Farm Creek may have been set at a very stringent level.

Identifying Vulnerabilities and Adaptive Management Responses

We can now use the information in Figure 4.7 to summarize the conditions under which the Modeled Implementation Plan does or does not meet its TMDL goals. We focus on nitrogen because we expect the model results to be most accurate for that pollutant. These conditions, which represent scenarios that illuminate the vulnerabilities of the plan (Lempert, 2013), can then be used to suggest how an adaptive management plan might respond over time to help ensure North Farm Creek meets its water quality goals (Lempert and Groves, 2010).

The scenario discovery analysis finds that the loadings generally exceed the TMDL in 2041–2070 under conditions with high precipitation and relatively low effectiveness

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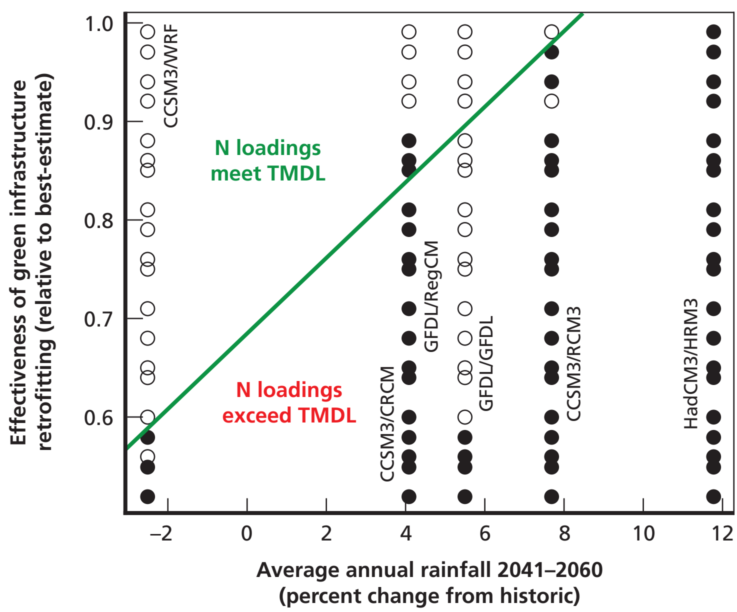
[11] Typically, shorter time steps result in poorer model results compared to longer time steps (Moriasi et al., 2007). On the other hand, plotting longer time step data may obscure the daily variation needed to investigate the flow-dependent performance of these BMPs.

of the green infrastructure refitting BMP. In particular, nitrogen loadings satisfy the TMDL in any future that lies above a line defined by the following two conditions:

1. Green infrastructure retrofitting effectiveness is 100 percent, and precipitation increases less than 8 percent above historic, or
2. Precipitation decreases 2.5 percent below historic, and green infrastructure retrofitting effectiveness is at least 60 percent of the best estimate.[12]

This is not surprising. Increased precipitation increases nitrogen loading. Half of North Farm Creek's area is currently developed, and as discussed in Chapter Three, developed impervious land is a major source of nitrogen. The Modeled Implementation Plan uses green infrastructure retrofitting as its main BMP for controlling runoff from

Figure 4.9
Futures in Which the Modeled Implementation Plan Meets and Misses TMDL Goals



NOTE: Green line shows scenario in which nitrogen loadings under the modeled BMPs in the North Farm Creek Implementation Plan exceed the TMDL. Filled and open circles indicate cases in which nitrogen loadings exceed and fall below the TMDL, respectively. The six climate model projections associated with each data column are also indicated. Note that two projections overlap.

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[12] This cluster has coverage and density of 99 percent and 77 percent, respectively; that is, nitrogen loadings exceed the TMDL in 77 percent of the cases that meet these conditions, and 99 percent of the cases in all the runs in which nitrogen exceeds the TMDL are explained by these conditions.

developed areas. So the effectiveness of such BMPs should significantly affect the plan's ability to control nitrogen.

This scenario can help to inform the milestones and midcourse corrections the North Farm Creek Implementation plan might use to adapt, over time, to new information, to improve its ability to meet the nitrogen TMDL. If at the end of Phase II of the plan, precipitation seems likely to be higher than historic and green infrastructure BMPs are performing as expected, then North Farm Creek might accelerate deployment of these BMPs in Phase III. If the green infrastructure BMPs are not performing as well as expected at the end of Phase II but precipitation is expected to stay close to historic levels, then accelerating deployment of these BMPs might still make sense. If precipitation increases are expected and the green infrastructure BMPs are performing poorly, then North Farm Creek may need to explore other options, including a potential change in the nitrogen TMDL.

The anomalous behavior of the GFDL/GFDL climate projection in Figure 4.9 suggests some of the strengths and weaknesses of this analysis. Note that this projection suggests that the current TMDL plan would meet its goals over a much wider range of precipitation and BMP effectiveness changes than suggested by the other climate projections. In general, the SWAT model suggests that higher temperature and precipitation lead to higher nutrient loadings.

The GFDL/GFDL projection has, however, the largest late summer temperature increase (roughly +5° C) compared to the other five climate futures. This temperature increase occurs around the same time as a fairly large decrease in precipitation (roughly −40 percent). Because SWAT's physical modeling of the impact of temperature and precipitation is nonlinear, both the timing and particular combination of precipitation decrease and temperature increase drive the reduction in contaminant load that eventually ends up in leach and runoff, as our results reflect.[13] In particular, the late-summer increase in temperature does not significantly impact plant growth but does result in higher evaporation, which in turn increases soil storage and infiltration capacity. As a result, additional rain produces lower runoff, which in turn reduces contaminant loads. Moreover, the concurrent decrease in precipitation in the GFDL/GFDL projection occurs during the later stage of crop growth in our model. This affects biomass growth such that plants take up fewer nutrients, runoff is reduced, and thus nutrient loadings to nearby streams are smaller.

This information suggests that: (1) attributes of future climate beyond average annual precipitation may also be important in determining the success of North Farm Creek's TMDL implementation plans, (2) the use of downscaled GCM projections within an RDM decision framework can help suggest these attributes, and (3) an ensemble of only six projections may be too small in number to provide reasonable inference on the most important combinations of attributes.

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[13] Personal communications with Dr. Raghavan Srinivasan, SWAT Developer at Texas A&M.

Observations About Using SWAT for RDM Analyses

This study provides insights into how the SWAT watershed model might be modified to facilitate RDM analyses. Overall, SWAT is a good candidate for such analyses given its reasonable skill at reproducing historic pollution flows, its fast runtime, and its ability to model numerous different types of management practices. However, with a few modifications the model's ability to support RDM analyses could be significantly improved.

First, SWAT could be modified to include functionality such that alternative land-use and management scenarios can be input into the model without having to supply input files for each HRU (or through modifying the core program routines, as we did in this case study). SWAT can already read up to 18 precipitation and temperature files, and while land-use and management inputs are slightly more complex, extending such functionality should not be too complicated.

Second, when simulating BMPs in climate- and land use–change studies, we have information only on the BMP removal efficiencies in alternative futures but do not have information on the precise structural features of the BMP associated with those removal efficiencies. However, SWAT currently asks the user to control BMP effectiveness by adjusting these structural parameters (e.g., the width of a grassed waterway or a filter strip). To facilitate RDM analyses, it would be advantageous if for each BMP type an option were given—similar to the generic conservation practice module—to directly adjust nutrient removal efficiencies without knowledge of its structural parameters. Relatedly, a major drawback of BMP simulations in SWAT is the HRU-based targeting of the BMPs, which has no geographic meaning. In practice, BMPs are applied to specific plots of land in the watershed, and the choice of where to install a BMP is a major consideration in how effective a given plan will be in meeting its goals.

Finally, SWAT's ability to model phosphorus and sediment should be improved. SWAT Rev. 591 was the latest version of the model available when modeling work on this case study began. In recent months, considerable revisions were made to SWAT to fix major issues with sediment yield, channel erosion, and channel transport capacity (i.e., USDA-ARS, 2014a). Similar changes may be necessary for phosphorus transport.

The above observations suggest several criteria upon which to judge whether a given watershed model is suitable for an RDM analysis, as summarized below.

Computational Features

The computational features that make a given watershed model suitable for an RDM analysis are

- fast runtime so many thousands or millions of scenarios can be simulated quickly
- ability to handle multiple climate scenarios as inputs
- automatable handling of model inputs and outputs. For the Farm Creek analysis, we wrote UNIX Shell scripts to iteratively run under alternative scenarios and

supply relevant inputs and handle output. Models that have this capability by default would significantly improve ease of use.

Simulation Features

The simulation features suitable for an RDM analysis are

- physical process-based models. Such models are helpful for RDM because they enable the representation and assessment of alternative management plans by letting the user modify model parameters. For example, many BMPs in the North Farm Creek analysis were represented by directly altering nutrient removal efficiencies in SWAT transport equations. Furthermore, BMPs could be "switched" on or off, which is a more realistic depiction of the watershed management context
- appropriate temporal resolution. SWAT simulates watersheds on a daily time step. Models with daily or even subdaily time steps may be more suitable for RDM because they can capture the variability in climate events that drive water quality metrics. Longer time step models may not adequately capture such variability, although their runtimes are typically much faster. Given the importance of capturing climate change–induced variability in drivers of water quality as well as the increasing rate of computing power, it makes sense to develop higher-resolution models that are potentially slower with current computational speeds, but may be improved over time.

Summary

This chapter describes a pilot study evaluating the vulnerability of the North Farm Creek Implementation Plan over a wide range of futures including future climate change and alternative assumptions regarding the effectiveness of four BMPs. We find that climate change could significantly affect the North Farm Creek Implementation Plan's ability to meet its TMDL targets for nitrogen, phosphorus, and sediment. In particular, we find that the plan's ability to meet the nitrogen TMDL is most sensitive to annual average rainfall and the effectiveness of green infrastructure retrofitting.

We used the SWAT model, version 2005, in this analysis. SWAT offers a promising platform for an RDM approach to water quality management. However, this study identified several modifications to the SWAT model that might significantly enhance its suitability for such purposes.

The North Farm Creek Implementation Plan envisions an adaptive management approach with a phased BMP deployment that combines both monitoring and adjustment over time. The current plan uses implementation schedules and load reduction as its primary evaluation tools. This study suggests monitoring precipitation trends and BMP effectiveness might also provide valuable information on how the Implementation Plan might be adjusted over time.

CHAPTER FIVE

Implications for USEPA Water Quality Management

The USEPA/OW and its state, local, and tribal partners must ensure the health and safety of U.S. water bodies and drinking water supplies. They must do so in the face of deep uncertainty regarding future climate, land use, other drivers of change, as well as the future cost and performance of potential new pollution control approaches such as low-impact development. It is widely understood the future climate, particularly precipitation, is difficult to predict at the spatial and temporal scales relevant for water quality. Nonetheless, EPA's draft *Climate Change Adaptation Plan* (Cross-EPA Work Group on Climate Change Adaptation Planning, 2012) describes a need to "integrate, or mainstream, considerations of climate change into its programs, policies, rules and operations" (p. 7), while OW's *Climate Change Adaptation Implementation Plan* calls specifically for the agency to "identify ways to better integrate climate change considerations into water quality management planning projects and processes" (Office of Water, 2013, p. 11).

These uncertainties create significant challenges for the appropriate use of scientific information. Effective water quality plans should be forward looking, that is, consider the future consequences of today's actions. Such foresight is generally needed because some steps for improving water quality involve investments in long-lived infrastructure, or otherwise require people, businesses, and farms to alter practices and behaviors. Linking current actions to future consequences generally requires projections from hydrologic simulation models, which in turn require model-based projections of future climate, economic activity, land use, and other factors. But uncertainty makes the projections from such models unreliable. As a result, relying on best-estimate forecasts from these models can lead to plans that fail to meet their goals, and may complicate the process of reaching agreement on plans among stakeholders with differing interests and expectations.

This study provides an initial exploration of the extent to which RDM can improve decisionmakers' ability to effectively employ potentially unreliable simulation models for TMDL implementation planning. A primary focus is on uncertainty associated with climate change, but the methods described can address a wide range of socioeconomic uncertainties as well. Importantly, TMDL planning under conditions of uncertainty is not only, or even primarily, an analytic challenge. Such plans must be developed in a manner that the public finds accountable, objective, and predictable. These attributes can conflict with potentially effective approaches to uncertainty management based on flexibility and experimentation.

This chapter reviews how the two case studies address the challenge of TMDL implementation planning under climate and other uncertainties. We then explore how future work might build on these RDM methods to more fully support USEPA and its partners in ensuring water quality.

Summary of Case Study Findings

Though preliminary, the results from our two initial case studies suggest that RDM can usefully support USEPA/OW efforts to incorporate and manage uncertainty from climate change and other drivers in its decisions. Specifically, in these case studies we used RDM to help provide

1. a detailed understanding of where current management plans do or do not meet water quality goals under future conditions
2. a systematic identification of risks, highlighting key scenarios for future planning
3. information to help specify the milestones and midcourse corrections appropriate for adaptive management
4. useful information on trade-offs among alternate approaches for managing these risks.

Patuxent River Case Study Findings

Phase II of Maryland's Watershed Implementation Plan set water quality TMDL targets for the Patuxent River, part of the Chesapeake Bay watershed, through a combination of historical water quality and hydrology monitoring data and detailed simulation modeling. Our analysis suggested that these TMDL targets would be met when we assumed historical hydrology and current land uses. However, for three contaminants of concern in the Chesapeake—nitrogen, phosphorus, and sediment—the Phase II WIP often would not meet these targets under scenarios incorporating climate change or future changes in population or development patterns.

Our vulnerability analysis identified two key drivers that best described when these targets were not met: an increase in precipitation due to climate change or an increase in the amount of impervious area cover in the Patuxent Basin primarily due to population growth. Either individually or in combination, these uncertain drivers led to pollutant loads from the Patuxent above the recently established long-term targets even with the substantial Phase II management infrastructure in place. A preliminary extension to this analysis, considering how individual BMP types already included in the plan could be used to augment the plan further, suggests that additional investment in some BMPs, including green infrastructure options such as wet ponds, wetlands, and urban filtering practices, could help achieve stormwater TMDL targets cost-effectively in some stressing futures. However, in other cases the scale of infrastructure needed would likely exceed the available land area for these BMPs. Based on this analysis, the State of Maryland should consider a broader range of options, such as changes to land use practices to help reduce or avoid more impervious area growth.

North Farm Creek Case Study Findings

The State of Illinois is beginning the process of implementing pollution control and restoration plans for the Middle Illinois River. Our study built on the 2012 load reduction strategy and BMP implementation plan for the North Farm Creek subwatershed, one of two pilot areas selected by the state for the initial development of load reduction strategies. The North Farm Creek Implementation Plan envisions an adaptive management approach that deploys BMPs in three phases: nonstructural (years 0–3); structural (years 3–10); and monitoring and adaptive management (years 10–20). Our analyses found that future climate change could significantly increase pollution loads in North Farm Creek (by 30–60 percent for nitrogen, and 85–200 percent for phosphorus). We also found that implementing plan BMPs can significantly decrease pollution loads even under futures where the climate has changed. We found that the Implementation Plan's ability to meet the nitrogen TMDL targets depends primarily on changes in average annual rainfall and change in the effectiveness of green infrastructure retrofitting. Monitoring these two factors and responding, if necessary, with enhanced green infrastructure deployments or deployments of other BMPs could improve the plan's ability to adapt over time to meet the nitrogen TMDL.

Facilitating Adaptive Water Quality Management

The best responses to deeply uncertain conditions often employ strategies that are robust and adaptive. Robust strategies perform well over a wide range of plausible futures. Adaptive strategies are designed to evolve over time in response to new information. Such robust and adaptive strategies often emerge from an iterative risk management process.

USEPA's current processes for setting water quality standards and TMDL planning do include many attributes of iterative risk management. For instance, with its sequences of state standard setting, public comment, USEPA approval, and periodic review, the process for setting water quality standards (shown in Appendix B, Figure B.1) incorporates at least four attributes of adaptive decision strategies shown in

Chapter Two, Table 2.1, including iterative review, multistakeholder deliberations, diversity of approaches, and decentralized decisionmaking.

But TMDL implementation plans are not generally robust and adaptive. Some are presented as static strategies, without any explicit treatment of uncertainty or flexibility. Even those TMDL plans that do refer to adaptive management, such as the North Farm Creek plan, tend to describe the process qualitatively and do not provide specifics on how the plan might adapt over time or describe the gains that adaptivity might offer. In part, USEPA and its partners have not pursued robust and adaptive TMDL plans because they lack the appropriate analytic methods to do so.

Patuxent and North Farm Creek case studies help to demonstrate the utility of RDM and related methods to support adaptive TMDL planning. It thus proves useful to summarize how they do so and to explore how the underlying RDM methods might in the future be extended to provide analytic support for an entire process of climate-related iterative risk management for water quality.

At the most basic level, the RDM approach demonstrated here provides a framework for articulating the basic components of a forward-looking adaptive decision strategy: near-term actions, signposts, and contingent actions. In each case study, the near-term actions are the BMPs proposed in the current TMDL implementation plans. The vulnerable scenarios for those plans provide information on appropriate signposts. In the Patuxent Basin, for instance, the vulnerable scenario in Figure 3.11 (Chapter Three) suggests that decisionmakers monitor average annual precipitation and changes in impervious area. If observations suggest that conditions are moving into the upper right-hand corner of the figure, decisionmakers could respond with contingent actions—for instance, increasing deployment of those BMPs listed in Figure 3.14 (Chapter Three). In North Farm Creek, the vulnerable scenario in Figure 4.9 suggests that decisionmakers monitor BMP effectiveness and average annual rainfall. If observations suggest that conditions are moving into the lower right-hand corner of the figure, decisionmakers could respond with contingent actions: increasing deployment of those BMPs that were proving most effective in the region.

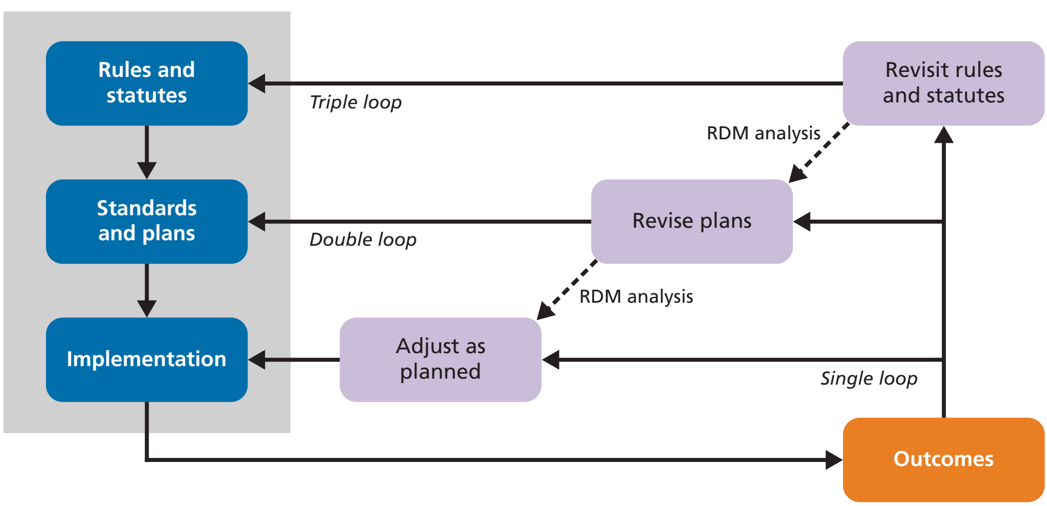
Clearly, these case studies provide only an initial sketch of the types of information decisionmakers require to develop effective adaptive TMDL implementation plans. The speed with which contingent actions can be deployed will dictate the amount of advance warning decisionmakers will need that they are approaching a vulnerable scenario. Similarly, decisionmakers will need to compare the cost of mistakenly deploying a contingent action when it is not needed to the costs of not deploying it when it is to determine how much confidence they need that a relevant signpost has been observed.

Different signposts will also require different monitoring strategies. In the Patuxent region, for instance, observing changes in impervious area might require assembling detailed land use data and using building permits to project the future land use changes. Meteorological observations can provide data on current and past average precipitation, but these trends do not necessarily lead to accurate forecasts of future precipitation. Until the ability to make such climate projections improves, decisionmakers in Maryland may find it useful to rely more heavily on signposts related to future impervious area than on those related to future climate.

Generalizing from the case studies, we can begin to consider how the process of stress-testing plans to identify vulnerable scenarios, which then can be used to identify signposts and contingent actions, might facilitate a broader process of adaptive water quality management. To do so, it is useful to distinguish three tiers of processes that can affect the ability of adaptive strategies to meet their goals in the face of uncertainty. Figure 5.1 draws on the "learning loop" framework (Argyris and Schon, 1978; Hargrove, 2002; Keen, Brown, and Dyball, 2005; Kolb and Fry, 1975; Peschl, 2007), often used in the resilience and climate change adaptation literature, which we have modified here to focus on those processes most relevant to water quality management. In particular, the figure aims to capture some of the rich institutional context in which robust adaptive strategies would be developed and implemented.

The left side of the figure shows three tiers of environmental policymaking. First, Congress enacts statutes such as the Clean Water Act (outer tier). These statutes authorize USEPA to conduct processes such as shown in Figure A.1 (Appendix A) to develop standards, enforce these standards, and create suitable implementation plans (middle tier), which may include investments in infrastructure and control practices, regulatory changes, and nonstructural management options. USEPA, states, and other jurisdictions then carry out these implementation plans (inner tier).

Figure 5.1
Three Tiers of Adaptive Decisionmaking



SOURCE: Adapted from IPCC (2012), Figures 1–3, and from Folke, Chapin, and Olsson (2009).
RAND *RR720-5.1*

Adjustments over time in response to new information can occur at each of these levels. As suggested by our case studies, an adaptive TMDL implementation plan could specify milestones to measure progress toward meeting a regulatory standard, and additional actions to take—for example, increased investment in a specific treatment technology—in response to observations related to those milestones. The "adjust as planned" tier on the right side of Figure 5.1 represents such adjustments, which take place within the context of an existing plan. In other cases, it may prove useful or necessary to revise or recreate the implementation plan, or revisit the standard-setting process itself. This might be necessary if, for example, new information suggests the current implementation plan will likely not meet its intended standard, if the standard itself may be insufficient to address water quality or public health goals, or if the standard proves to be difficult or impossible to achieve. The middle tier in Figure 5.1 represents such a process. Lastly, it may prove necessary to return to Congress to revise the statutes themselves in light of new information, as shown by the figure's upper tier.[1]

Ideally, planned adaptation would be contained within the inner tier, unfolding according to a prenegotiated and predetermined set of observations and responses to those observations. But in practice, it is impossible to develop plans that can encompass all contingencies. Moving to the middle tier, standards can be changed and plans modified or rewritten, but repeatedly revisiting plans and standards can lead to inconsistent, unpredictable, and unenforceable regulations. The outer tier, employing the fundamental decisionmaking institutions of a democratic polity, in principle offers the most flexibility in responding to new conditions. But passing new statutes or revisiting standard-setting processes can be extremely costly in terms of both time and effort.

In principle, RDM and related decision support approaches, such as those demonstrated in these case studies, could improve the ability of USEPA, state regulators, and other authorities to develop and implement adaptive water management plans by expanding the range of contingencies that can be addressed within the inner tiers, thereby reducing the need to move to the outer tiers. As its basic concept, the analyses described in our case studies begin with a plan, stress test it over a wide range of plausible futures, identify the conditions in which the plan performs poorly and well, and use this information to suggest ways in which the plans might be made more robust. The case studies demonstrate this process for implementation plans that lie in the inner "adjust as planned" tier of Figure 5.1. Both case studies suggest that in some futures it may prove useful to increase investment in already-identified BMPs, and suggest signposts that would signal the need to take such additional actions. Plans developed using such methods would be robust to a wider range of contingencies, and thus reduce the range of futures in which a new planning process would be necessary to ensure compliance with TMDLs, as suggested by the dashed lines in Figure 5.1. In essence, such

1 Using the terminology of triple-loop learning, the lowest tier in Figure 5.1 represents single-loop learning, the middle tier double-loop learning, and the highest tier triple-loop learning.

adaptive TMDL plans would regularize a process within Tier 1 that would otherwise require the more difficult process of revisiting plans and standards in Tier 2.[2]

Similarly, such RDM-based decision support might expand the range of conditions addressed within the middle, "revise rules and plans" tier, also suggested by the dashed lines in Figure 5.1. For instance, one might use simulation modeling to stress test the water quality standard setting process over a wide range of plausible futures to understand the range of conditions the process might successfully address, and how changes in that process and the information it uses might significantly expand the range of such conditions. This process could formally incorporate projected (rather than historical) estimates of precipitation or other climate extremes—in a planned cycle of review using the best scientific evidence available—and could lead to different TMDL standards and specific criteria for reviewing and potentially adjusting those standards. In the outermost tier, understanding and expanding the range of conditions addressed within the process of setting water quality standards could guide any statutory revisions needed to establish such processes and reduce the need to make subsequent revisions.

Table 5.1 explores how RDM might help improve water quality management in each of these tiers, the actions that might be taken, and those who might take primary responsibility for such actions. When considering specific infrastructure plans (first column), such as Maryland's Phase II WIP or North Farm Creek's Implementation Plan, RDM can help identify plausible vulnerabilities due to climate and other drivers and additional infrastructure investment options that help hedge against such stressing futures. For instance, Figure 4.9 (Chapter Four) from the North Farm Creek case study suggests the combinations of precipitation change and BMP effectiveness beyond which the Implementation Plan might need to incorporate new types of BMPs. Figure 3.11 (Chapter Three) from the Patuxent case study suggests the combinations of climate change and land use changes beyond which the problem framing might usefully switch from one of water quality regulation to that of land use planning. In the second column, RDM might also usefully inform more systematic state or regional planning that addresses water quality goals in the context of broader, multiobjective water management or land use plans, in which states with enforcement responsibility can seek to meet water quality targets along with other goals via more systematic changes to land use practices. The third column suggests how RDM might inform federal and state actions to modify the standard setting process.

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2 See related discussion for water supply management in Bloom (2015).

Table 5.1
Case Study Results in the Adaptive Decisionmaking Framework

	Adjust as Planned	Revise Plans	Revise Standards
	Improve plans by adjusting them based on the difference between what is expected and what is observed.	Use new information to question basic assumptions and reevaluate plan scope, objectives, and range of options.	Use new information to revise water quality standards or to build adaptation into the standard-setting process.
Patuxent River Case Study			
How well do urban stormwater pollution control BMPs perform over the long term, given uncertainty about climate and land use?			
Analytic findings: • TMDL targets not met in most futures because of growth of impervious land cover and/or changes in precipitation • Cost-effective green infrastructure BMPs plausible for limited coping with uncertainty			
Potential actions	Hedging/ mitigation for future conditions: invest more in cost-effective BMPs to help meet TMDLs (e.g., wetlands, urban filtering)	Consider how to ensure that impervious land cover is kept to a minimum: alter land-use patterns	Revisit TMDL-setting based on historical information and whether water quality standards are achievable: modify policy on how water quality standards are set
Potential actors	State agencies	State agencies	State agencies and USEPA
North Farm Creek Case Study			
How might climate change affect the implementation plan for North Farm Creek subwatershed?			
Analytic findings: • Future climate change could significantly increase pollution loads in North Farm Creek • Implementing plan BMPs can significantly decrease pollution loads under future climate • Useful to consider TMDLs at different flow intensities			
Potential actions	Adjust Phase III BMPs based on monitoring of climate and BMP effectiveness	Expand set of BMPs	Revisit TMDLs, especially phosphorus
Potential actors	State agencies	State agencies	State agencies and USEPA

Looking to the Future

This report's Patuxent and North Farm Creek case studies demonstrate how an RDM-based decision support approach could improve the management of climate and other uncertainty in TMDL implementation planning. But these two case studies present only an initial exploration and suggest many ways in which such analyses might be usefully expanded in the future.

While both case studies identify vulnerable scenarios that combine both projections of future climate and projections of other uncertain factors (impervious surfaces in the Patuxent and a simple proxy for BMP effectiveness for North Farm Creek), future work could consider a much wider range of uncertainties. Due to computational and resource limitations, for instance, the Patuxent case study did not consider uncertainty regarding BMP effectiveness, and the North Farm Creek case study did not consider uncertainty regarding future land use, though these two factors are likely important in both regions. Neither case study explored the full range of socioeconomic factors that might affect pollution flows and BMP effectiveness, and the BMPs considered were drawn solely from existing plans. In addition, both case studies considered water quality in isolation, but not as part of a more integrated, multisector water management or land use plan.

The treatment of adaptive TMDL implementation plans could also be considerably expanded beyond that considered here. Future analyses could explore alternative observations that might be made and the specific triggers that might be established to indicate the need for contingent actions. Such analyses would allow the design and comparison of alternative adaptive plans. In addition, such attention would allow decisionmakers to consider the benefits of investing in observation systems (for both biophysical and socioeconomic systems) that would improve the information available to them over time. Both case studies also suggest how new decision support methods might facilitate adaptive strategies within the middle and outer tiers of water quality management. Both case studies suggest the types of futures in which the local authorities might need to engage with federal officials to reexamine the appropriate TMDL standards. Such analyses might also begin to suggest what investments in observations might be most useful to support the two highest tiers of adaptive decisionmaking, if and when it becomes required.

Future work might also help expand the quantitative toolkit available to analysts and decisionmakers. The North Farm Creek case study suggested some specific augmentations to the SWAT model that would improve its ability to conduct RDM analyses. More broadly, the hydrology simulation models currently used for TMDL planning were generally not designed for the type of multiscenario analysis demonstrated here. There are many ways in which the ability of such models to support such analyses could be improved, from the details of the way they handle inputs and output files, to their ability to interact more easily with models and projections that represent the more complete range of biophysical and socioeconomic factors that affect water quality.

The regulations used to protect water quality provide key tools to promote the public interest but must be carefully designed to enhance benefits, reduce adverse consequences, and respond effectively to environmental, socioeconomic, and other types of change. In particular, climate change and the opportunities created by new approaches to environmental management, such as green infrastructure, have created a need for new forward-looking analytic approaches to help make water management plans more flexible and robust. Such new approaches may help reconcile the tension between the need for accountable, transparent, and objective governance and the benefits of flexibility and experimentation. These methods do so by enabling exploration over a wide range of plausible futures, systematically identifying those future conditions in which proposed water management plans do or do not meet their goals, helping to identify specific milestones and midcourse corrections that can help plans adapt over time, and identifying the trade-offs among alternative robust adaptive plans—all within a process designed to facilitate stakeholder input and deliberation. This report provides only an initial exploration of the possibilities, but such approaches offer the potential to facilitate the development of robust, adaptive water quality management that may be more appropriate under the conditions of deep uncertainty arising from climate change and many other trends in our rapidly changing world.

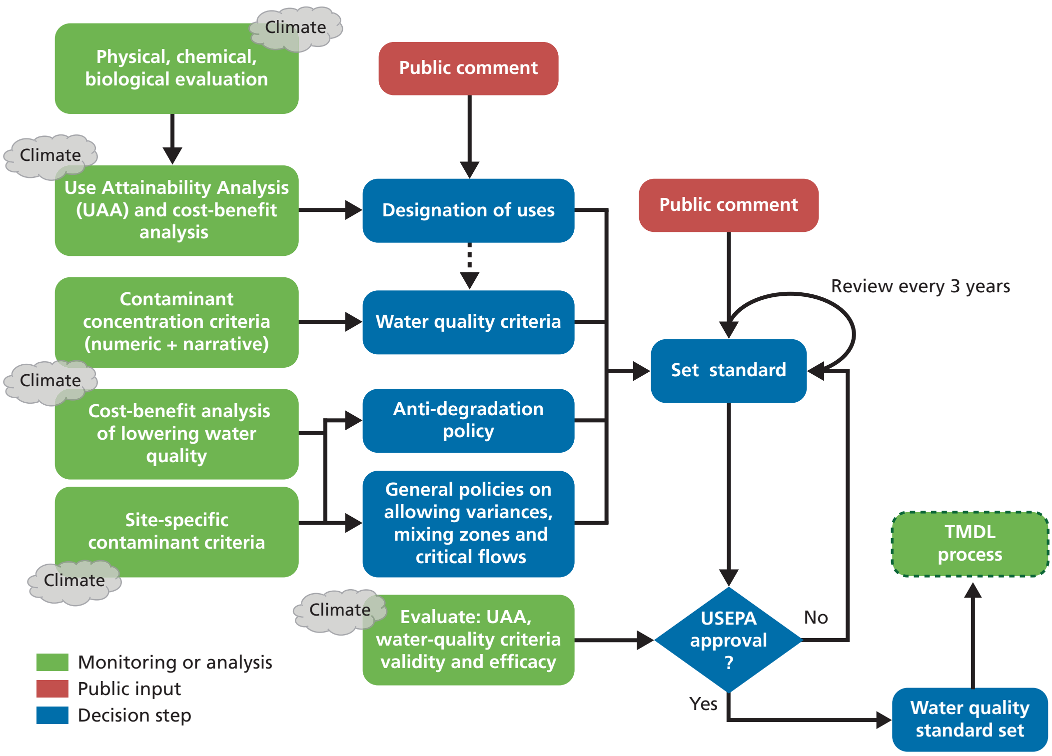
APPENDIX A

Iterative Risk Management Process for Setting Water Quality Standards

This appendix suggests how USEPA's current process for setting water quality standards represents an iterative risk management process potentially affected by climate change. Under the Clean Water Act, states and tribes have primary responsibility for developing water quality standards for each of the water bodies in their jurisdictions. USEPA issues technical guidance for developing criteria and conducts a final review before implementation. These state and tribal processes typically involve gathering scientific evidence, expert judgment, and USEPA guidance; soliciting public comment and review; and drafting of rules, review, and eventual approval by USEPA.

Figure A.1 shows a flowchart developed by the authors to represent USEPA's process for setting water quality standards (USEPA, 1994; USEPA, 1991). The process includes monitoring and analysis (green boxes) and a variety of decision steps (blue boxes). The process follows an iterative risk management process in the sense that it includes provisions for public input on the decisions informed by this analysis (red boxes), and the use of iteration to update and revise plans and standards. On this flowchart, we have highlighted the steps in which climate-related uncertainty could affect the analysis outcomes and thus influence USEPA's eventual decisions.

Figure A.1
USEPA Process for Setting Water Quality Standards



SOURCE: Adapted from USEPA (1994).
RAND *RR720-A.1*

APPENDIX B

Criteria for Choosing Case Studies

We chose the Patuxent River and North Farm Creek case studies based on an extensive screening process with USEPA/ORD and USEPA/OW staff. We reviewed a number of potential regions, seeking two case studies with diverse attributes and the potential for significant RDM analyses. In particular, we sought case studies that could

1. demonstrate how RDM could prove useful to USEPA/OW as a method for climate-related decision support
2. inform judgments about the range and types of USEPA plans for which an RDM analysis might prove valuable
3. provide information addressing current high-priority USEPA/OW water quality planning efforts.

Our previous experience with RDM analyses, coupled with the fact that these efforts were intended to be pilot tests, also suggested we wanted case studies with specific attributes:

1. significant potential climate impacts
2. multiple uncertain factors (climate and land use, for example) that affect USEPA's ability to achieve its goals
3. a range of policy options available to address the intended goals
4. existing models and data relatively easy to adapt for the RDM analysis
5. OW and/or other USEPA personnel able to participate in an RDM case study.

We chose the Patuxent River and North Farm Creek case studies because they both are potentially affected by climate change, had local stakeholders interested in working with us, and provide a useful contrast. The former is largely urban and faces substantial urban stormwater management challenges, while the latter includes large rural areas and is currently addressing agriculture runoff challenges. The necessary modeling and data were also available in both cases, for the Patuxent as part of USEPA's Chesapeake Bay Program, and for the Illinois River as part of USEPA's 20 Watersheds project (USEPA, 2013).

APPENDIX C

Supplemental Information for the Patuxent River Case Study

This appendix presents additional information in support of the analysis described in Chapter Three of this report but not otherwise presented in the main body. The appendix is divided into three main sections. The first section provides additional information about the calibration and validation of the Phase 5.3.2 model conducted by the Chesapeake Bay Program modeling team. The second section shows additional simulation and vulnerability analysis results for the 2035–2045 hydrology period, including both phosphorous load results across many futures and additional scenario discovery. The final section presents a similar set of simulated results for the 2055–2065 hydrology period, across all three contaminants. Note that the scenario discovery analysis was not repeated for the 2055–2065 time period.

Phase 5.3.2 Watershed Model Calibration and Validation

The Phase 5.3.2 model has been the subject of numerous validation and verification exercises, starting with its first application to the Chesapeake Bay watershed (Donigian et al., 1994). In addition, the Scientific and Advisory Committee of the Chesapeake Bay Program provides ongoing technical oversight for the model, discussing both the validity of its application for bay plans and future model development (Band et al., 2008).

Phase 5.3.2 model calibration is an iterative procedure of model development and refinement in which simulated and observed data are compared to ensure that the parameters chosen for representing the physical characteristics of the bay result in coherent results. The validation exercise compares simulated data against observed data that were not used for the calibration process. This provides an independent assessment of the model's capacity for simulating the physical characteristics of the bay, including water flows and nutrient loads.

The Phase 5.3.2 Bay Watershed Model segments are defined in a way that river segments are close to instream flow and water quality monitoring stations. Calibration and validation rely on a comprehensive set of monitoring sites within the Chesapeake Bay watershed. The model uses data collected from a total of 767 stations: 237 sites for flow, 215 for total phosphorus, 200 for suspended sediments, and 115 for total nitrogen (STAC, 2011; USEPA, 2010b). Figure C.1 shows the full set of monitoring stations used for Phase 5.3.2 model calibration.

The calibration process compares model output to monitored streamflow and water quality data for the years 1985–2005 at in-stream monitoring sites. The calibration includes various parameters, such as suspended sediments, total phosphorus, organic phosphorus, particulate phosphorus, phosphate, total nitrogen, nitrate, total ammonia, organic nitrogen concentrations and loads, and temperature (USEPA, 2010b).

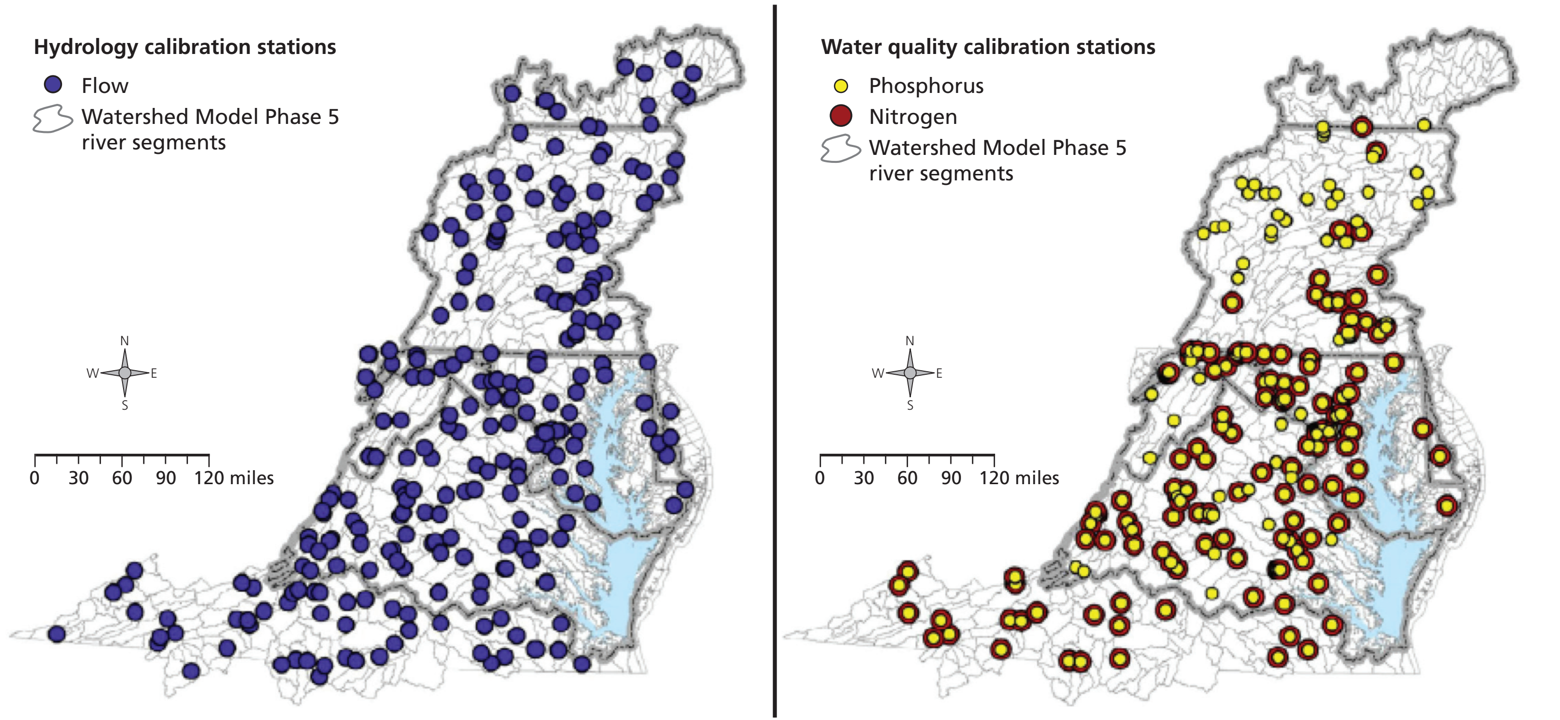
The Chesapeake Bay Program has conducted several studies comparing the results of the model against observed data at different locations within the Chesapeake Bay. These comparisons were made for the Patuxent River using data collected by the USGS at Bowie, Maryland. Figure C.2 compares the results of simulated output by the Phase 5 model and observed flow data. The top panel compares these two data series using daily data time series. The bottom panel presents the cumulative flow estimates for the observed and the simulated data.

The comparison of the flow data shows that the Phase 5 tends to slightly overestimate flow estimates in the river, but is generally in close range with the observed data.

Similarly, Figure C.3 shows the comparison between observed and simulated data for total nitrogen in the Patuxent River. For total nitrogen, the observed and simulated data show the same pattern of behavior across time (top panel), and the differences between simulated and observed results tend to be small (bottom panel).

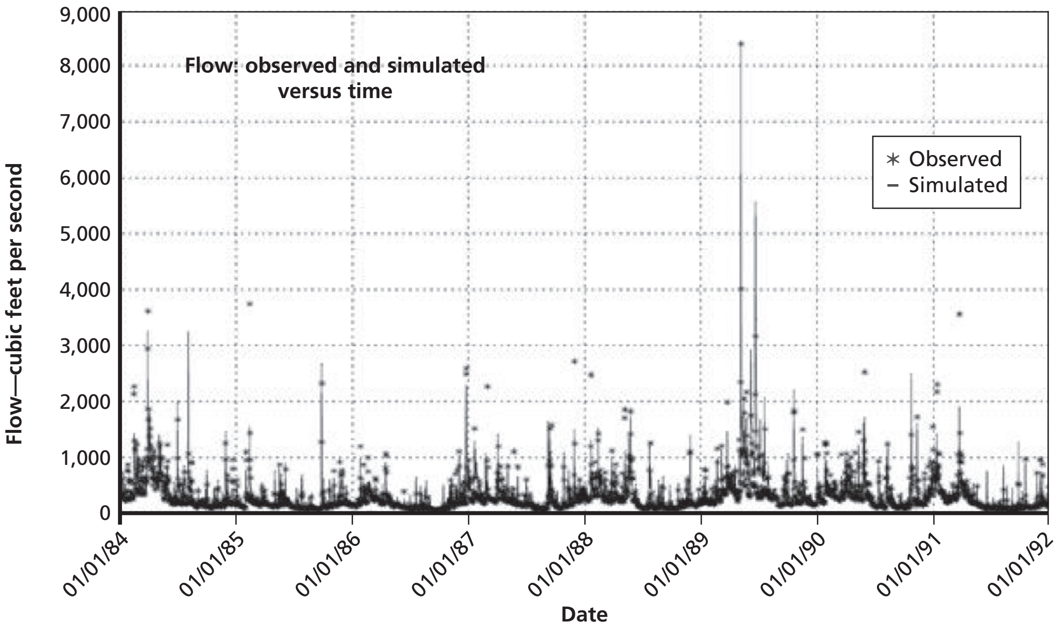
Finally, a separate validation exercise was conducted to compare simulated data against observed data that were not used for the calibration process. This provided an independent assessment of the model's capacity for simulating the physical characteristics of the bay, including water flows and nutrient loads, and is documented separately by the Chesapeake Bay Program (USEPA, 2010b).

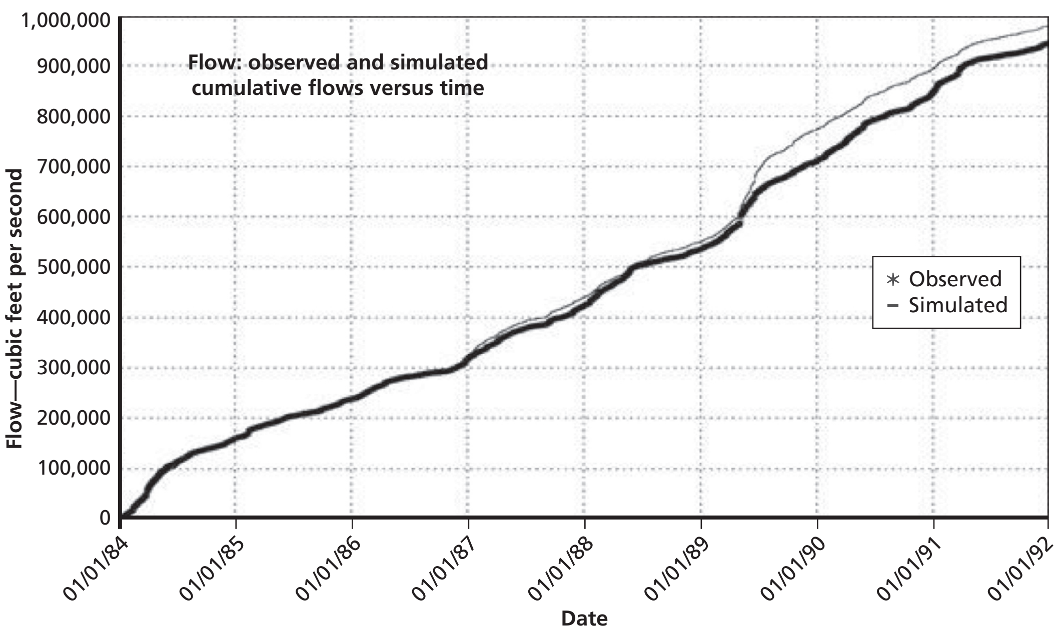
Figure C.1
Phase 5.3 Model Hydrology (Upper Panel) and Water Quality (Lower Panel) Calibration Monitoring Stations



SOURCE: USEPA (2010b). Sampling points are overlaid on the Phase 5.3.2 model river segments.
RAND *RR720-C.1*

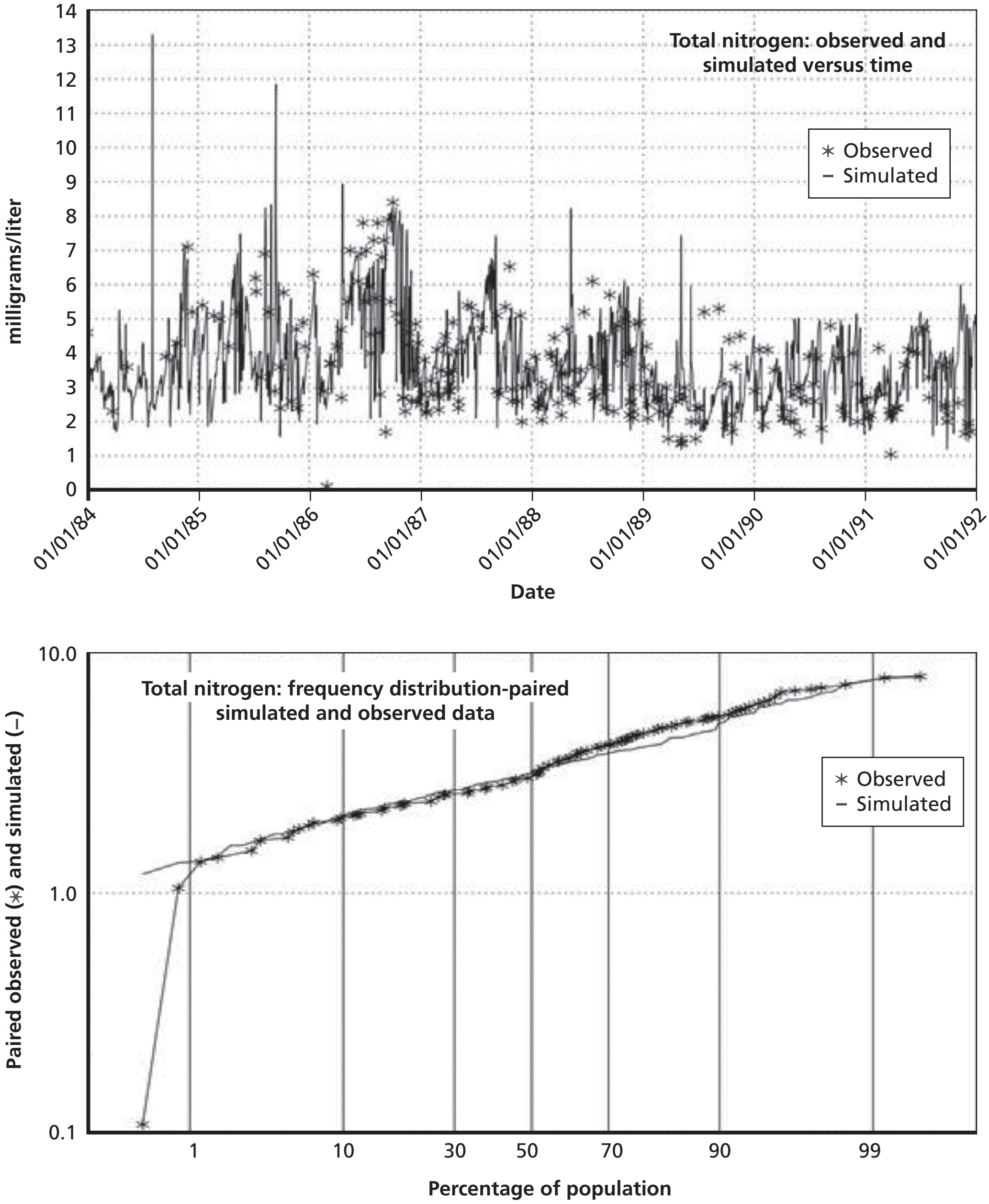
Figure C.2
Patuxent River Simulated and Observed Data for Flow (upper panel) and Cumulative Flow (lower panel) at Bowie, Maryland





SOURCE: Greene and Linker et al. (1998).
RAND *RR720-C.2*

Figure C.3
Patuxent River Simulated and Observed Total Nitrogen Data at Bowie, Maryland

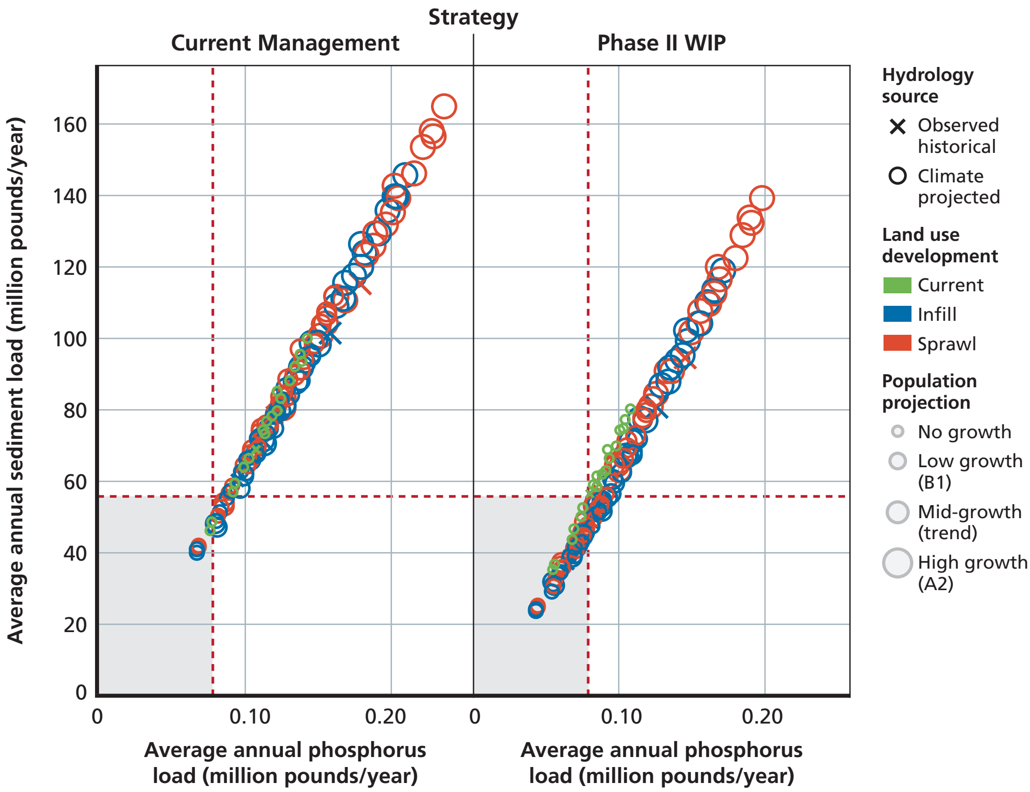


SOURCE: Linker et al. (1998).
RAND *RR720-C.3*

Additional Results for the 2035–2045 Hydrology Period

Water Quality Results Across Many Futures

Figure C.4
Scatterplot of Phosphorous and Sediment Loads, Both Plans (2035–2045)



RAND *RR720-C.4*

Scenario Discovery Results for Phosphorus and Sediment

This section provides additional results from the scenario discovery analysis, including results for phosphorus and sediment. The same approach described in the main body was applied for these additional contaminants.

Tables C.1 and C.2 provide additional detail on the characterization of both the climate and land use uncertainties, respectively, for the scenario discovery analysis.

Table C.1
Climate Scenario Characterizations Used in Scenario Discovery

Climate Scenario	Emissions Scenario	Hydrology Years	Average Precipitation (inches)			Average Temperature (degrees Fahrenheit)			Average Runoff (acre-feet)		Mean Log-Pearson Type III
			Annual	Summer	Winter	Annual	Summer	Winter	All Areas	Impervious Area	
Observed historical	Observed historical	1984–2005	44.1	23.4	20.8	55.9	69.1	42.6	341,079	134,978	7.2
BCCR-BCM2	SRES A1B	2035–2045	45.8	23.3	22.4	57.7	70.5	44.8	343,313	139,305	7.2
	SRES A2	2035–2045	44.8	23.7	21.1	57.1	70.4	43.8	332,390	136,122	7.2
	SRES B1	2035–2045	47.8	24.1	23.7	57.1	69.9	44.3	387,593	149,778	7.3
CSIRO Mk3	SRES A1B	2035–2045	45.9	23.9	22.0	58.3	71.7	44.9	342,574	140,212	7.2
	SRES A2	2035–2045	47.2	23.7	23.6	58.3	71.2	45.4	362,242	145,130	7.3
	SRES B1	2035–2045	44.3	22.7	21.6	57.9	70.6	45.1	315,605	132,211	7.2
CSIRO Mk3.5	SRES A1B	2035–2045	40.1	22.2	17.9	58.6	72.2	45.0	232,800	111,905	7.1
	SRES A2	2035–2045	44.0	21.9	22.1	58.5	72.3	44.7	308,848	131,403	7.2
	SRES B1	2035–2045	44.9	24.6	20.3	57.5	70.8	44.1	325,514	134,969	7.2
INM-CM3.0	SRES A1B	2035–2045	40.1	21.0	19.1	59.6	72.5	46.7	232,927	112,331	7.1
	SRES A2	2035–2045	41.9	21.5	20.3	59.5	72.8	46.1	261,454	119,847	7.1
	SRES B1	2035–2045	42.8	24.0	18.9	59.0	72.5	45.4	273,339	123,769	7.2
MIROC3.2	SRES A1B	2035–2045	46.0	22.9	23.1	59.5	72.4	46.5	327,887	138,062	7.2
	SRES A2	2035–2045	43.0	22.1	20.9	58.7	71.7	45.6	286,299	125,864	7.2
	SRES B1	2035–2045	46.4	24.0	22.4	58.5	71.6	45.3	341,068	140,334	7.3

Table C.1—Continued

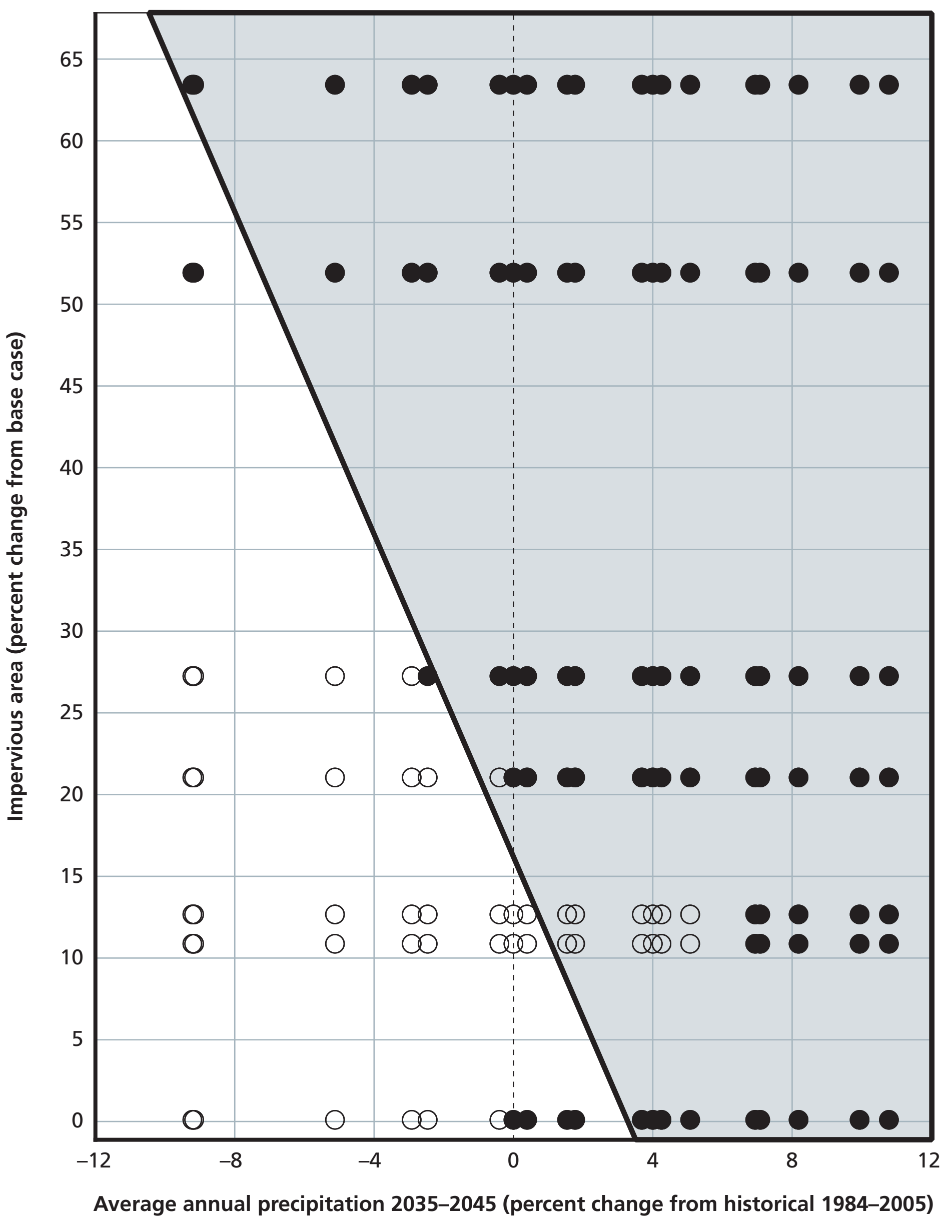
Climate Scenario	Emissions Scenario	Hydrology Years	Average Precipitation (inches)			Average Temperature (degrees Fahrenheit)			Average Runoff (acre-feet)		Mean Log-Pearson Type III
			Annual	Summer	Winter	Annual	Summer	Winter	All Areas	Impervious Area	
NCAR-CCSM3	SRES A1B	2035–2045	48.5	25.7	22.9	58.9	72.3	45.4	373,850	150,088	7.3
	SRES A2	2035–2045	48.9	26.0	22.9	58.6	72.1	45.1	381,998	151,754	7.3
	SRES B1	2035–2045	47.3	24.5	22.7	58.0	71.6	44.3	364,628	146,083	7.3

Table C.2
Land Use Scenario Characterizations Used in Scenario Discovery

		Land Use Type Area (acres)					
Development Pattern	**Urban Growth Projection**	**Extractive**	**Impervious**	**Pervious**	**Construction**	**Nonregulated Developed**	**Regulated Developed**
Current	2010 population (3 million residents)	1,258	40,531	137,259	6,578	48,967	128,822
Infill	ICLUS B1 scenario (3.05 million residents)	1,258	44,922	157,673	1,134	69,806	132,789
	Trend growth (3.9 million residents)	1,258	49,014	178,918	3,053	85,525	142,407
	ICLUS A2 scenario (6.02 million residents)	1,258	61,521	235,603	6,166	124,233	172,890
Sprawl	ICLUS B1 scenario (3.05 million residents)	1,258	45,618	160,064	1,112	70,330	135,352
	Trend growth (3.9 million residents)	1,258	51,554	187,652	3,605	87,666	151,540
	ICLUS A2 scenario (6.02 million residents)	1,258	66,213	253,016	8,962	129,422	189,807

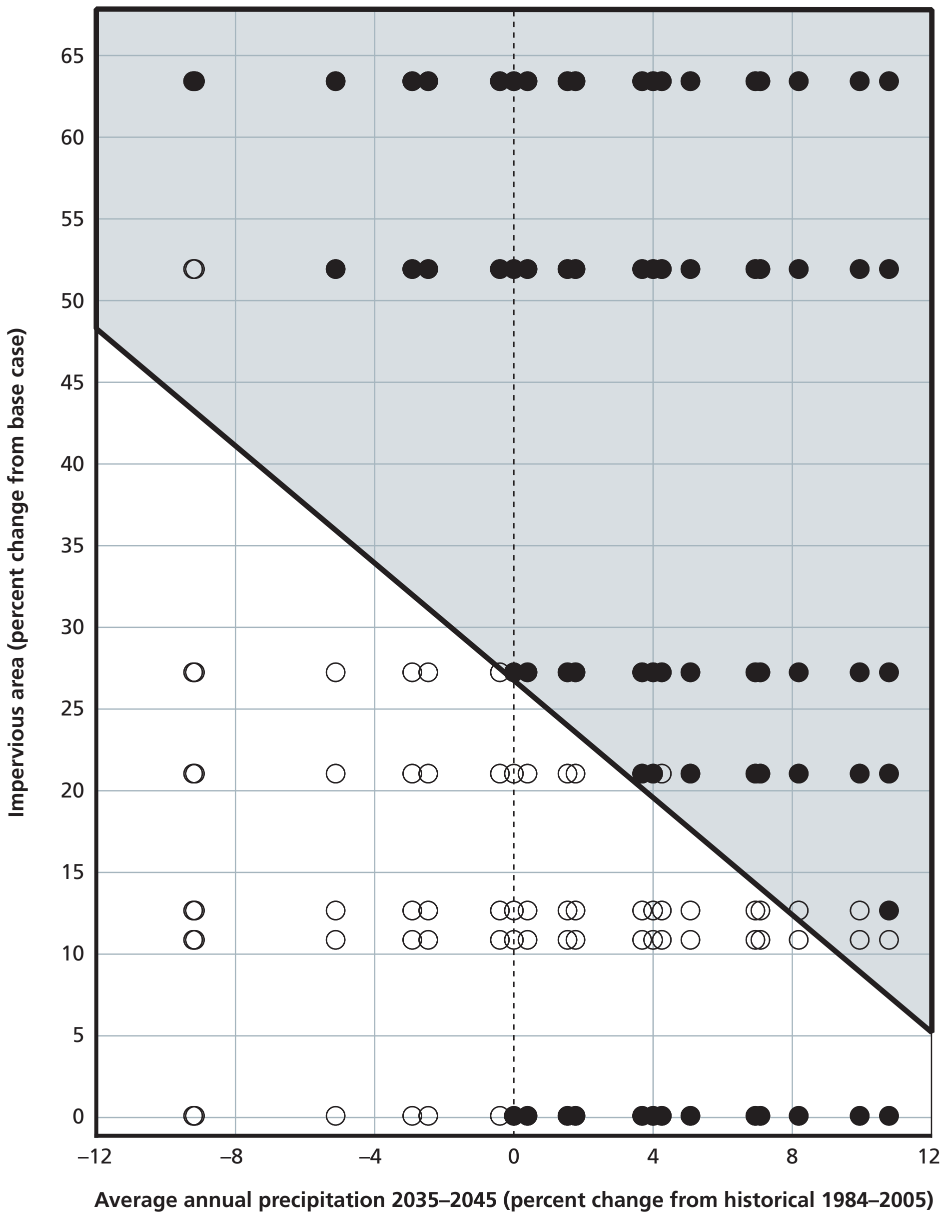
The figures that follow show the vulnerable regions identified in the scenario discovery analysis for phosphorus, sediment, and all contaminants combined, meaning that all three targets are exceeded. All figures are from the 2035–2045 hydrology period.

Figure C.5
Decision-Relevant Scenario Identified for Phosphorus TMDL



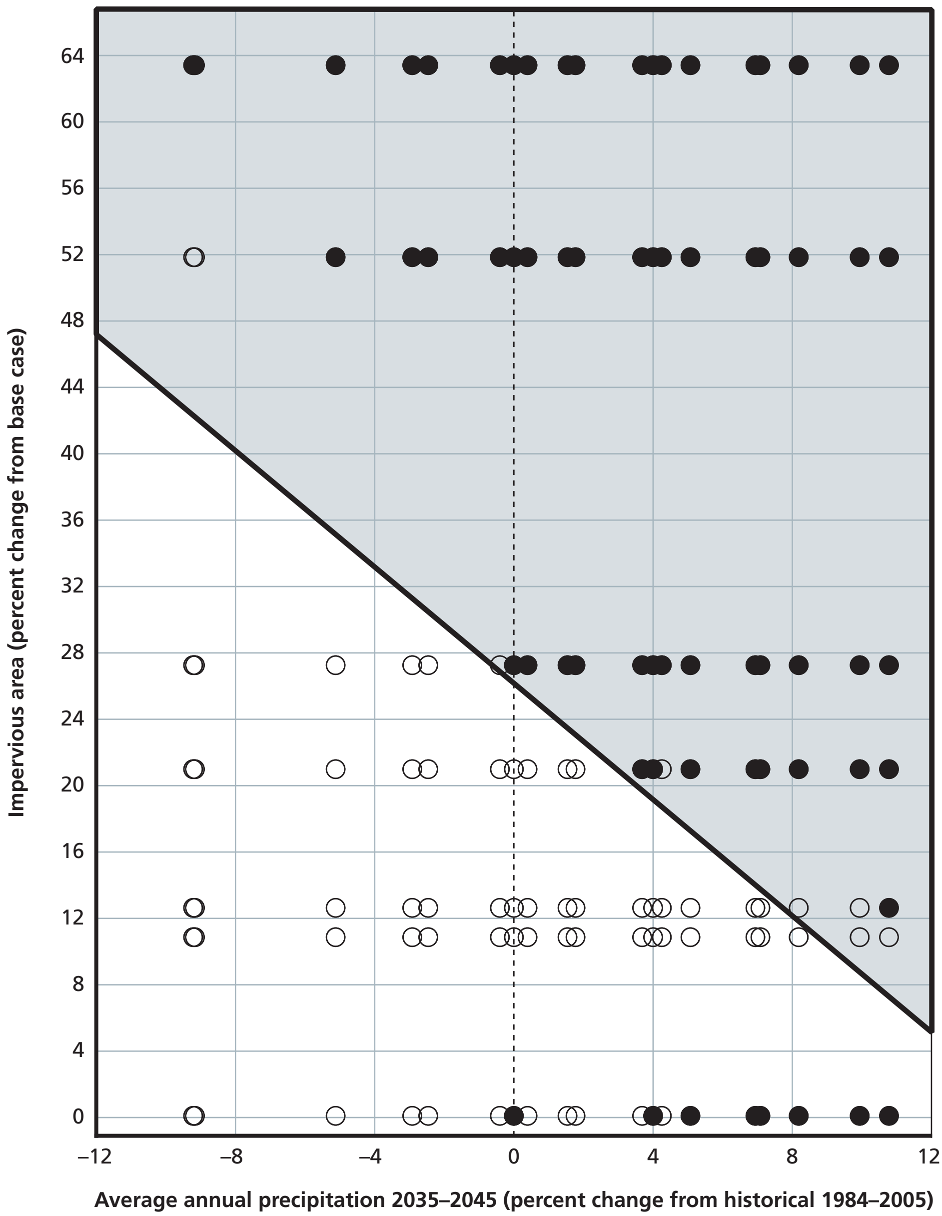
RAND *RR720-C.5*

Figure C.6
Decision-Relevant Scenario Identified for Sediment TMDL



RAND *RR720-C.6*

Figure C.7
Decision-Relevant Scenario Region Identified for All Three Contaminants



RAND *RR720-C.7*

Results for the 2055–2065 Hydrology Period

Water Quality Results Across Many Futures

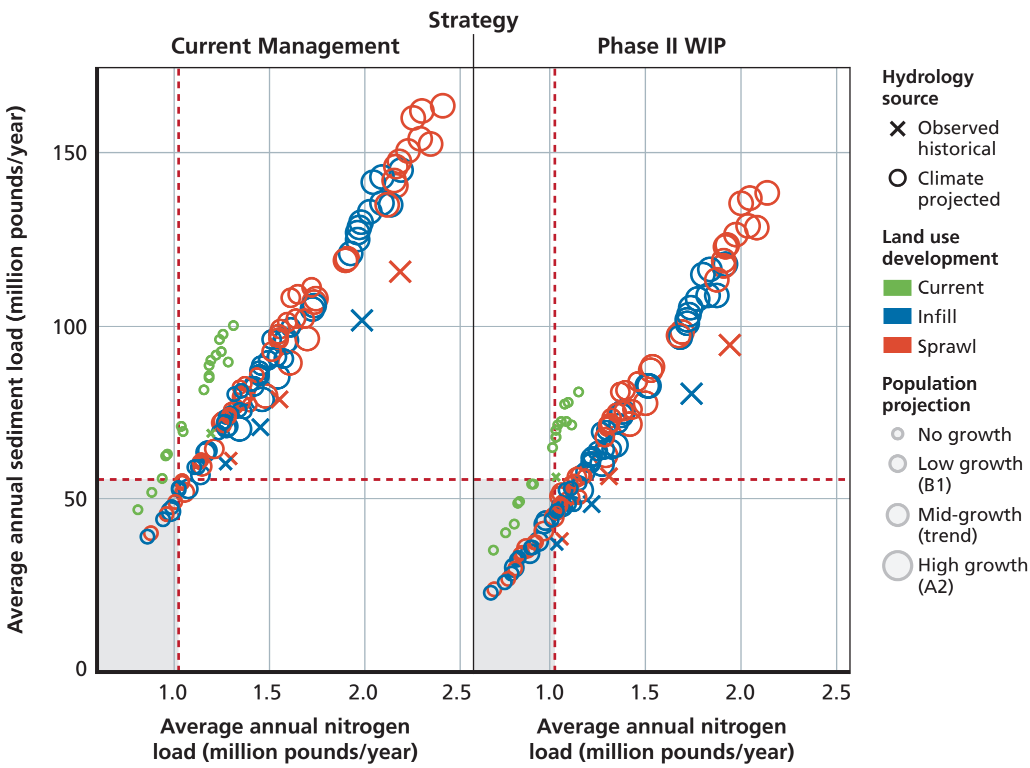
As discussed in Chapter Three, the potential effects of climate change on future water quality in the Patuxent River are a key uncertainty in our analysis. To address this, we considered the effect of 18 downscaled climate sequences for two different time periods: 2035–2045 and 2055–2065. Chapter Three presented results from the 2035–2045 period in detail. In this section, we provide additional information regarding the 2055–2065 simulations.

Table C.3 presents a summary of the hydrological characteristics of the 2055–2065 climate sequences. These ranges include only the 2055–2065 climate projections. The subsequent figures show results from the analysis for this additional time period.

Table C.3
Characterization of Climate Scenarios (2055–2065 Hydrology)

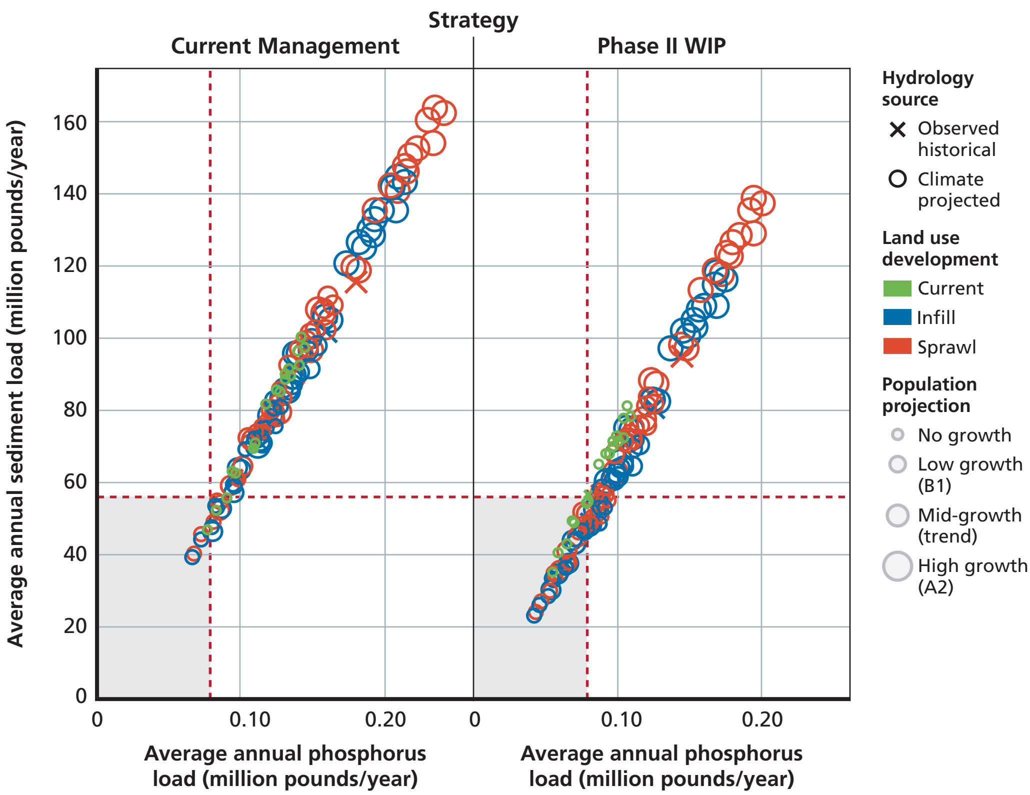
	Range		
Uncertainty Type	**Low**	**High**	**Units**
Hydrology Inputs			
Average precipitation			
Annual	40.8	49.0	Inches
Summer	20.2	26.3	Inches
Winter	18.5	24.7	Inches
Average temperature			
Annual	58.0	61.4	Degrees F
Summer	70.9	74.7	Degrees F
Winter	44.7	48.0	Degrees F
Average annual runoff			
All areas	226.08	386.0	Thousands of acre feet
Impervious areas only	112.44	152.2	Thousands of acre feet

Figure C.8
Scatterplot of Nitrogen and Sediment Loads, Both Plans (2055–2065)



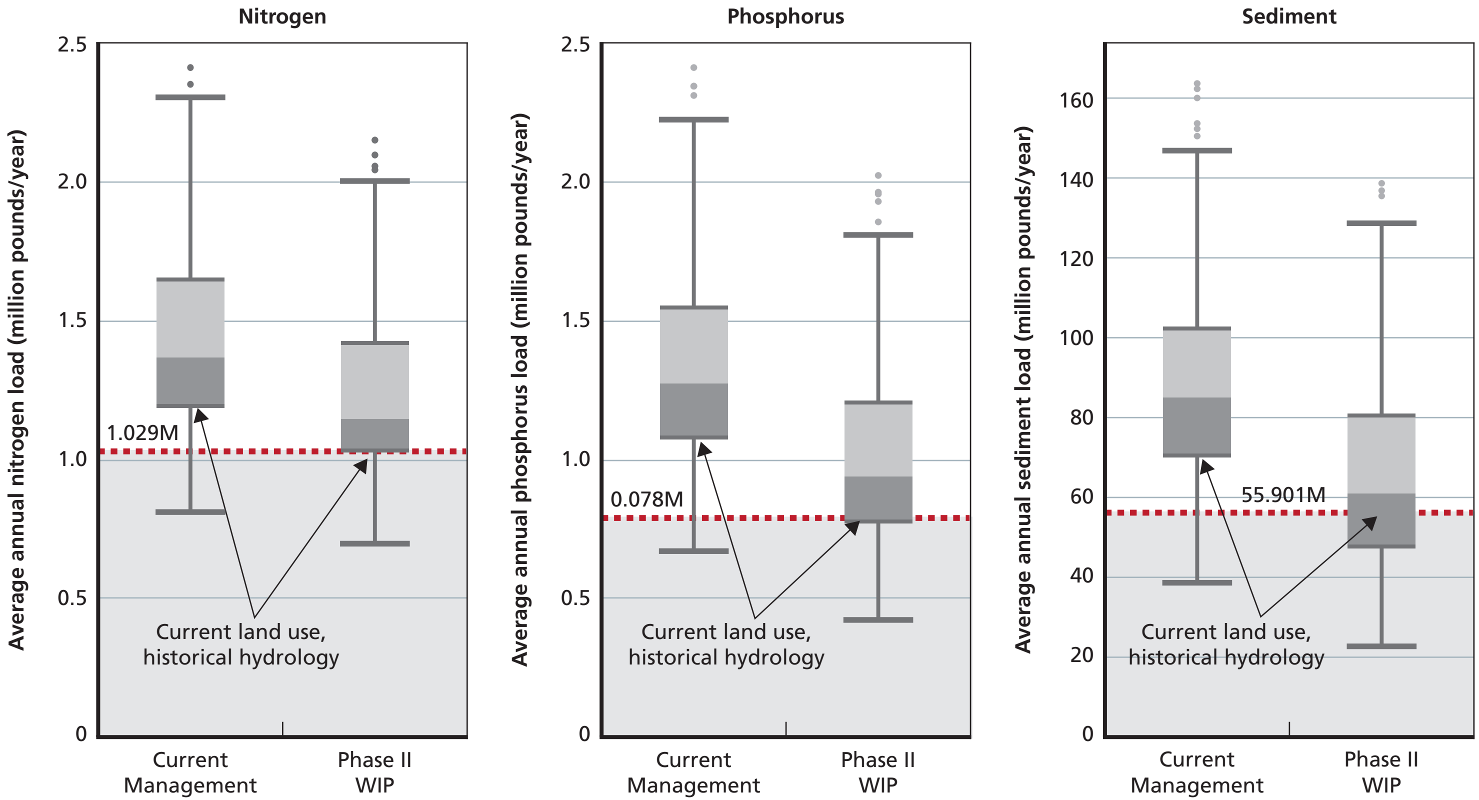
RAND *RR720-C.8*

Figure C.9
Scatterplot of Phosphorus and Sediment Loads, Both Plans (2055–2065)



RAND *RR720-C.9*

Figure C.10
Boxplot Summary of Contaminant Loads Across All Futures (2055–2065)



RAND *RR720-C.10*

APPENDIX D

SWAT Model Calibration and Validation

The hydrologic and water quality modeling for the North Farm Creek case study was done using SWAT Rev. 591, which was calibrated and validated to observed flow using two USGS stations and one water quality station from Illinois Environmental Protection Agency. In this appendix, we provide a summary of the full calibration report (TetraTech, 2014).

The physical characteristics of the watershed—reaches, subbasins, and HRUs—were modeled using the 10-meter digital elevation model (DEM) incorporated into the NHDPlus hydrography database (USEPA, 2010d). Land use and coverage was based on the 2006 National Land Cover Database (Fry et al., 2011). Soil characteristics such as depth, particle size distribution, bulk density, hydraulic connectivity, and available water capacity were derived from the USDA SSURGO.

Daily time series on precipitation and maximum and minimum air temperature through 2006 were obtained from the Peoria Airport station and have been processed, quality checked, and gap-filled as part of the BASINS meteorological dataset (USEPA, 2008). Limited water quality data was available, and as a result only one of the two available USGS stations located upstream of the mouth of the watershed was used for water quality calibration.

Hydrology Calibration and Validation

Model performance for hydrology was evaluated over the period 2000–2012. Goodness-of-fit was assessed through graphical comparisons and the relative error method. The full hydrology calibration criteria are provided in Table D.1, while the summary statistics for the hydrology calibration and validation are shown in Tables D.2 (Fondulac Creek near East Peoria) and D.3 (Farm Creek at Farmdale), respectively.

Table D.1
SWAT Model Hydrology Calibration Criteria

Statistic	Criteria (%)
Error in total volume	≤ 10
Error in 50% lowest flows	≤ 10
Error in 10% highest flows	≤ 15
Seasonal volume error (summer)	≤ 30
Seasonal volume error (fall)	≤ 30
Seasonal volume error (winter)	≤ 30
Seasonal volume error (spring)	≤ 30
Error in storm volumes	≤ 20
Error in summer storm volumes	≤ 50

Table D.2
Hydrology Calibration and Validation Summary Statistics at Fondulac Creek near East Peoria

SWAT Simulated Flow		Observed Flow Gage	
Reach outflow from outlet 5 11.91-year analysis period: 10/1/2000–9/31/2012 Flow volumes are (inches/year) for upstream drainage area		**Fondulac Creek Near East Peoria, Ill.** Manually entered data Drainage area (sq mi): 5.54	
Total simulated in stream flow	8.51	Total observed in stream flow	8.81
Total of simulated highest 10% flows	4.36	Total of observed highest 10% flows	5.45
Total of simulated lowest 50% flows	0.63	Total of observed lowest 50% flows	0.63
Simulated summer flow volume (months 7–9)	1.40	Observed summer flow volume (7–9)	0.96
Simulated fall flow volume (months 10–12)	1.10	Observed fall flow volume (10–12)	1.49
Simulated winter flow volume (months 1–3)	2.11	Observed winter flow volume (1–3)	2.58
Simulated spring flow volume (months 4–6)	3.89	Observed spring flow volume (4–6)	3.78
Total simulated storm volume	4.09	Total observed storm volume	4.83
Simulated summer storm volume (7–9)	0.37	Observed summer storm volume (7–9)	0.46

Table D.2—Continued

Errors (Simulated–Observed)	Error Statistics		Recommended Criteria (%)	
Error in total volume	–3.48		10	
Error in 50% lowest flows	0.40		10	
Error in 10% highest flows	–19.91		15	
Seasonal volume error—summer	45.97		30	
Seasonal volume error—fall	–26.14	>>	30	Clear
Seasonal volume error—winter	–18.27		30	
Seasonal volume error—spring	2.99		30	
Error in storm volumes	–15.31		20	
Error in summer storm volumes	–19.69		50	
Nash-Sutcliffe coefficient of efficiency, E	0.436	Model accuracy increases as E or E’ approaches 1.0		
Baseline adjusted coefficient (Garrick), E’	0.335			
Monthly Nash-Sutcliffe Efficiency	0.814			

Table D.3
Hydrology Calibration and Validation Summary Statistics at Farm Creek at Farmdale

SWAT Simulated Flow		Observed Flow Gage	
Reach outflow from outlet 10 12-year analysis period: 10/1/2000–9/30/2012 Flow volumes are (inches/year) for upstream drainage area		**Farm Creek at Farmdale, Ill.** Manually entered data Drainage area (sq mi): 27.4	
Total simulated in stream flow	9.70	Total observed in stream flow	10.20
Total of simulated highest 10% flows	5.26	Total of observed highest 10% flows	5.57
Total of simulated lowest 50% flows	0.89	Total of observed lowest 50% flows	0.94
Simulated summer flow volume (months 7–9)	1.77	Observed summer flow volume (7–9)	1.28
Simulated fall flow volume (months 10–12)	1.35	Observed fall flow volume (10–12)	1.47
Simulated winter flow volume (months 1–3)	2.57	Observed winter flow volume (1–3)	2.97

Table D.3—Continued

SWAT Simulated Flow		Observed Flow Gage	
Simulated spring flow volume (months 4–6)	4.02	Observed spring flow volume (4–6):	4.49
Total simulated storm volume	3.74	Total observed storm volume:	3.96
Simulated summer storm volume (7–9)	0.83	Observed summer storm volume (7–9):	0.53
Errors (Simulated–Observed)	**Error Statistics**	**Recommended Criteria (%)**	
Error in total volume	–4.88	10	
Error in 50% lowest flows	–4.58	10	
Error in 10% highest flows	–5.47	15	
Seasonal volume error—summer	38.14	30	
Seasonal volume error—fall	–7.79	>> 30	Clear
Seasonal volume error—winter	–13.51	30	
Seasonal volume error—spring	–10.47	30	
Error in storm volumes	–5.61	20	
Error in summer storm volumes	56.53	50	
Nash-Sutcliffe coefficient of efficiency, E	0.491	Model accuracy increases as E or E' approaches 1.0	
Baseline adjusted coefficient (Garrick), E'	0.409		
Monthly Nash-Sutcliffe Efficiency	0.867		

Water Quality Calibration and Validation

Water quality calibration and validation were conducted for monthly simulated and observed loads for total suspended solids (TSS), total phosphorus (TP), soluble reactive phosphorus (SRP), total nitrogen (TN), and nitrogen species—namely, total Kjeldahl nitrogen (TKN) and nitrate+nitrite nitrogen (NO_x). Water quality calibration and validation periods were 2005–2010 and 2000–2005, respectively. Table D.4 provides summary statistics for the water quality calibration and validation.

Table D.4
Water Quality Calibration and Validation Summary Statistics, Camp Street Bridge in East Peoria

	Calibration						Validation					
Statistic	**TSS**	**TKN**	**NOx**	**TN**	**SRP**	**TP**	**TSS**	**TKN**	**Nox**	**TN**	**SRP**	**TP**
Average absolute error (%)	25.90	56.40	60.00	47.30	29.90	35.90	21.20	60.20	62.10	44.20	45.20	37.40
Median absolute error (%)	11.80	36.40	31.10	26.20	28.60	24.60	8.30	39.70	29.10	24.70	40.10	20.90
Relative error (%)	–12.20	11.10	10.70	23.60	26.40	–4.80	–0.20	27.20	–1.60	15.70	42.30	10.00
Nash-Sutcliffe Efficiency	0.891	–0.467	0.342	0.482	0.81	0.551	0.942	–0.682	0.415	0.692	0.604	0.421

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The U.S. Environmental Protection Agency Office of Water (USEPA/OW) is charged with ensuring the health and safety of the nation's water bodies and drinking water supply. To carry out this mission, the Clean Water Act, as amended, gives the Administrator of USEPA the authority to set water quality standards, engage with states and localities developing plans to meet these standards, review and approve such plans, provide financial and other assistance for implementation, and seek legal sanctions and fines for any failure to comply. One key step USEPA and its state, local, and tribal partners take in protecting water quality is the development of implementation plans that specify the actions a community will take to attain total maximum daily load (TMDL) water quality standards. However, these plans typically do not take climate change or other challenging uncertainties into account and may be vulnerable to future change or surprise. To assist USEPA and its partners, RAND researchers explored how robust decision making (RDM) methods can be used to develop a plan that identifies robust and adaptive near- and long-term strategies and is based on the best available science as well as public engagement. In the course of the study, the researchers examined two pilot case studies—one on the Patuxent River in Maryland and one on the North Farm Creek tributary of the Illinois River—to explore and illustrate how RDM might help to improve USEPA future water quality decisions and uncertainties.

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