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# A Vulnerability Framework for Assessing the Risks to Water Supply Systems Under Climate Uncertainty in the Urban Northeastern United States

Sarah Whateley

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**A VULNERABILITY FRAMEWORK FOR ASSESSING  
THE RISKS TO WATER SUPPLY SYSTEMS UNDER  
CLIMATE UNCERTAINTY IN THE URBAN  
NORTHEASTERN UNITED STATES**

A Dissertation Presented

by

SARAH V. WHATELEY

Submitted to the Graduate School of the  
University of Massachusetts Amherst in partial fulfillment  
of the requirements for the degree of

DOCTOR OF PHILOSOPHY

February 2016

Department of Civil and Environmental Engineering

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Richard Palmer, Department Chair  
Department of Civil and Environmental Engineering

## DEDICATION

*“To my family, for their endless love, support, and encouragement.”*

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## ABSTRACT

# A VULNERABILITY FRAMEWORK FOR ASSESSING THE RISKS TO WATER SUPPLY SYSTEMS UNDER CLIMATE UNCERTAINTY IN THE URBAN NORTHEASTERN UNITED STATES

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The northeastern United States is not commonly considered a drought prone region. Yet there are increasing pressures on water utilities throughout the region that constrain their ability to supply reliable water. These include new constraints on water withdrawals and requirements to release additional water for ecological purposes. Finally, there is the emerging concern associated with climate change. The vulnerability of any particular system, however, is not easily assessed, as it is dependent on a variety of factors that go beyond simple changes in precipitation and temperature. These include the size of the watershed, the volume of storage, required releases, and water demand. This dissertation will develop a pragmatic framework that incorporates these factors to allow rapid assessment and comparative analysis of



water utilities vulnerability to climate change. The analysis uses a vulnerability-based assessment, based on stress testing, which identifies the problematic scenarios first and then uses climate information to provide context regarding the risk associated with those scenarios. The approach is demonstrated in an analysis of the major cities of the Northeast U.S., New York City, NY, Boston, MA, Springfield, MA, Hartford, CT, and Providence, RI. Next, a generic version of the framework is implemented in a novel online software tool designed for smaller utilities that may lack the ability to conduct a full vulnerability analysis. Lastly, this work explores the impact of various sources of uncertainty (i.e., internal variability, mean climate change, and future emission scenario) on water supply in the northeastern United States. The dissertation shows pragmatic approaches to climate change vulnerability analysis that water utilities can implement and update to assess and manage their climate change risks for both large and small utilities.

# TABLE OF CONTENTS

	Page
ACKNOWLEDGMENTS .....	v
ABSTRACT .....	vii
LIST OF TABLES .....	xiii
LIST OF FIGURES .....	xiv
CHAPTER	
INTRODUCTION .....	1
<b>1. SELECTING STOCHASTIC CLIMATE REALIZATIONS TO EFFICIENTLY EXPLORE A WIDE RANGE OF CLIMATE RISK TO WATER RESOURCE SYSTEMS .....</b>	<b>13</b>
1.1 Abstract .....	13
1.2 Introduction .....	13
1.3 Methods .....	16
1.3.1 System Description .....	16
1.3.2 Stochastic Climate Scenarios .....	17
1.3.3 Baseline Method: Full Climate Stress Test .....	18
1.3.4 Method 1: Sampling hydrologic realizations using the Sequent Peak Algorithm .....	19
1.3.5 Method 2: Empirically sampling climate realizations .....	20
1.4 Application of Methods .....	22
1.4.1 Method 1: Subset stochastic ensemble based on SPA .....	22
1.4.2 Method 2: Subset stochastic ensemble based on critical climate statistics .....	24
1.4.3 Comparison to a full vulnerability analysis .....	25
1.5 Conclusion .....	26
1.6 Acknowledgments .....	29

<b>2.</b>	<b>CLIMATE STRESS TESTING NORTHEAST WATER SUPPLY: AN ASSESSMENT OF VULNERABILITIES AND CLIMATE RISK EXPOSURE</b>	<b>30</b>
2.1	Abstract	30
2.2	Introduction	31
2.2.1	Study sites	35
2.2.1.1	Massachusetts Water Resources Authority (Boston, MA)	35
2.2.1.2	Springfield Water and Sewer Commission (Springfield, MA)	36
2.2.1.3	Providence Water’s Scituate Reservoir Complex (Providence, RI)	37
2.2.1.4	Metropolitan District Commission’s Water Supply System (Hartford, CT)	37
2.2.1.5	New York City Water Supply System (New York City, NY)	37
2.3	Methods	38
2.3.1	Stress test approach	38
2.3.2	Empirically sampling climate realizations	39
2.3.3	Hydrologic models	40
2.3.4	System simulation models	41
2.3.4.1	Boston	41
2.3.4.2	Springfield	41
2.3.4.3	Providence	42
2.3.4.4	Hartford	42
2.3.4.5	New York City	42
2.3.5	Performance metrics	43
2.4	Results	45
2.4.1	Stochastic climate simulations compared with historic conditions	45
2.4.2	GCM projections	45
2.4.3	Stress test results	46
2.4.4	Climate robustness indices	52
2.5	Discussion	52
2.6	Conclusion	56
2.7	Acknowledgments	57

<b>3. A WEB-BASED SCREENING MODEL FOR CLIMATE RISK TO WATER SUPPLY SYSTEMS IN THE NORTHEASTERN UNITED STATES</b> .....	<b>58</b>
3.1 Abstract .....	58
3.2 Software availability .....	58
3.3 Introduction .....	59
3.4 Climate Risk Assessment Methodologies .....	64
3.4.1 Scenario-Based Climate Risk Assessment .....	64
3.4.2 Decision-Scaling: A Vulnerability-Based Framework .....	65
3.5 ViRTUE: Vulnerability and Risk Assessment Tool For Water Utilities .....	66
3.5.1 Development Approach .....	66
3.5.2 Model Theory .....	68
3.5.3 Tool Workflow .....	70
3.6 Case Study: Springfield Water and Sewer Commission .....	76
3.6.1 Model Application .....	76
3.6.2 Validation .....	81
3.7 User Feedback .....	85
3.8 Discussion .....	86
3.9 Conclusion .....	88
3.10 Acknowledgements .....	89
<b>4. ASSESSING THE RELATIVE EFFECTS OF EMISSIONS, CLIMATE MEANS, AND VARIABILITY ON WATER SUPPLY</b> .....	<b>90</b>
4.1 Abstract .....	90
4.2 Introduction .....	90
4.3 Methods .....	94
4.3.1 Generating natural variability and climate change data .....	95
4.3.2 Assessing sources of uncertainty: hydrologic and systems models .....	96
4.3.3 Analysis of variance method .....	96
4.4 Application of methods .....	98
4.4.1 Reservoir system descriptions .....	98
4.4.2 Hydrologic Model .....	102

4.4.3	Metric for assessing system performance .....	102
4.4.4	Analysis of variance methodology .....	103
4.5	Partitioning uncertainty in reservoir performance .....	103
4.6	Discussion .....	110
4.7	Conclusion .....	112
4.8	Acknowledgements .....	113
<b>CONCLUSION .....</b>		<b>114</b>
<b>APPENDIX: VIRTUE SOFTWARE AVAILABILITY AND LICENSING .....</b>		<b>118</b>
<b>BIBLIOGRAPHY .....</b>		<b>122</b>

## LIST OF TABLES

Table	Page
1.1 Computational times of the full vulnerability analysis, Method 1, and Method 2. ....	28
1.2 Percent difference between quantiles of reliability and vulnerability across the two methods and the full stress test. ....	28
2.1 Summary of system characteristics .....	38
2.2 GCM projection range, perturbation method, and variability approach used in the climate impact studies of Northeast water supply. ....	46
2.3 Average Climate Robustness Index across 9 climate variability realizations under current demand conditions given assumptions of the Multivariate Normal and Uniform distributions over climate change and GCM space. ....	52
2.4 GCM projection range, perturbation method, and variability approach used in this study. ....	54

## LIST OF FIGURES

Figure	Page
1.1 a. Correlation coefficients between required storages and the minimum d-year precipitation value (i.e. minimum 2-year precipitation); b. the ratio of demand to inflow of a water supply system versus the minimum d-year precipitation. ....	21
1.2 Relationship between reservoir performance and required reservoir storage calculated using the sequent peak algorithm (a,c) and minimum 2-year precipitation (b,d). Red dots represent select required storages and minimum 2-year precipitation values from the distribution of all synthetically generated realizations (obtained using Method 1 and Method 2). ....	23
1.3 A distribution of a.) water supply reliability and b.) vulnerability across all natural variability realizations under wet/no change, no change, and dry/hot climate scenarios. Select performance quantiles (horizontal dotted lines) drawn from all realizations using Method 1 and Method 2 are illustrated as red triangles and black squares, respectively. ....	27
2.1 (left) Historic (black line) and simulated (9 grey lines) time series of annual precipitation (mm) from 1949 to 2010, and (right) historic (black bar) and simulated (9 grey bars) maximum drawdown (million gallons) of the Scituate Reservoir System in Providence, RI. ....	45
2.2 Water supply reliability for all systems averaged across 9 realizations of natural variability. ....	47
2.3 Water supply reliability for all systems averaged across 9 realizations of natural variability for the ‘worst case’ realization. ....	48
2.4 Water supply vulnerability as a percentage of average monthly (or weekly for Boston) demands averaged across 9 realizations of natural variability. ....	49

2.5	Water supply vulnerability as a percentage of average monthly (or weekly for Boston) demands for the ‘worst case’ realization. . . . .	50
2.6	Distribution of minimum monthly reservoir storage across 9 realizations under three extreme climate change scenarios: dry conditions- 25% decrease in precipitation, 5 degree C increase in temperature ( <b>top</b> ), hot conditions- no change in precipitation, 5 degree increase in temperature ( <b>middle</b> ), and no change in climate ( <b>bottom</b> ). Results are illustrated for (from left to right) the Scituate Reservoir in Providence, Cobble Mountain Reservoir in Springfield, Barkhamsted and Nepaug Reservoirs in Hartford, Delaware and Catskill Reservoir systems in New York City, and the Quabbin and Wachusett Reservoirs in Boston. . . . .	51
3.1	Schematic diagram of the components and workflow of the ViRTUE application to assess climate risks to water supply systems. . . . .	67
3.2	Screen shot of the ‘Choose Location’ tab of ViRTUE. Climate altered time series of monthly precipitation and monthly temperature are generated in this step by clicking on the map near the reservoir system of interest. Time series of historic average monthly precipitation (left) and temperature (right) appear on the user interface. . . . .	77
3.3	A hydrograph (left) and flow duration curve (right) produced in the ‘Generate streamflow’ tab of ViRTUE. The black lines illustrate historic flows and the red lines illustrate modeled flows. The Nash-Sutcliffe efficiency value of 0.58 quantifies the performance of the abcde hydrologic model calibration. . . . .	78
3.4	System diagnostics of ViRTUE: Period of record water supply reliability (top left), reservoir storage as a percent of capacity (top right), annual storage for a particular month (bottom left), and monthly inflows into the system (bottom right). The left panel illustrates climatic and socioeconomic changes (slider bars) that can be explored to test system performance. Storage capacity, drainage area of the reservoir, a target reliability, and daily water supply demands are the inputs required. . . . .	79
3.5	Distribution of changes in mean precipitation (%) and mean temperature (Celsius) based on an ensemble of GCM projections (RCP emission scenario 4.5 from the World Climate Research Programme’s (WCRP’s) Coupled Model Intercomparison Project Phase 5 (CMIP5) multi-model dataset . . . . .	80



3.6	Climate response surface of water supply reliability for the Springfield water supply system. Regions in blue are considered ‘acceptable’ system performance according to a user-specified reliability threshold level. Regions in red are considered ‘unacceptable’ system performance. Additionally, an ensemble of GCM projections are plotted as points on the climate surface.....	82
3.7	Fraction of climate projections that suggest acceptable/unacceptable system performance .....	83
3.8	Climate response surface for Springfield’s water supply reliability using ViRTUE’s system simulator (left) and a systems model that accounts for Springfield’s reservoir rule curves (right) .....	84
4.1	TxPxE combinations of levels of the three factors. The length of P, T, and E vary based on CMIP3 and CMIP5 climate projections and emission scenarios. ....	99
4.2	Map of case study locations (created on July 22, 2015 using NASA, TerraMetrics Scribble Maps) .....	100
4.3	CMIP3 (left) and CMIP5 (right) GCM ranges for different emission scenario storylines for Springfield (top), Providence (middle), and Hartford (bottom). ....	104
4.4	Normal quantile-quantile plots for (a) Springfield, MA, (b) Providence, RI, and (c) Hartford, CT ANOVA results for mean reservoir storage as a percentage of capacity at each 38 year time period. The results shown here are from the analysis based on CMIP3 climate projections. ....	105
4.5	The residuals versus predicted values for mean reservoir storage as a percentage of capacity ANOVA results for (a) Springfield, MA, (b) Providence, RI, and (c) Hartford, CT. The results shown here are from the analysis based on CMIP3 climate projections. ....	106
4.6	The fraction of total variance (%) (a,c,e) and total variance (b,d,f) of mean reservoir storage for Providence, RI, Springfield, MA, and Hartford, CT over a subset of temperature changes, precipitation changes, and emission scenarios (SRES-A1B, A2, and B1) derived from CMIP3 climate projections. ....	108

4.7 The fraction of total variance (%) (a,c,e) and total variance (b,d,f) of mean reservoir storage for Providence, RI, Springfield, MA, and Hartford, CT over a subset of temperature changes, precipitation changes, and emission scenarios (RCP- 2.5,4.5,6.0, and 8.5) derived from CMIP5 climate projections. ....109

## INTRODUCTION

Water resource managers and decision-makers are faced with many uncertainties when planning and managing water systems: future population, per capita water demands, regulatory requirements, environmental standards, consumer preferences, and climate change among others. These uncertainties impact both short-term operational decisions (e.g. water allocation) and long-term adaptation decisions (e.g. infrastructure investments). Despite the inherent uncertainty in future conditions, water planners must decide how to plan and manage their water systems with the resources available to them.

Developing effective management strategies and adaptation actions that reduce risk to water resources requires an assessment of regional climate hazards on existing system procedures [Mastrandrea *et al.*, 2010b]. Climate risk assessment of water resource systems is a process for identifying and evaluating vulnerabilities that may threaten existing infrastructure and system performance. The process often involves a series of climate/weather models, rainfall-runoff models, and systems models to evaluate the impacts of climate change and variability on system functioning. Yet, this process concentrates on identifying climate impacts of a particular system, limiting our understanding of regional risks and pressures on water availability. Also, for a region such as the Northeast United States, with a large concentration of highly populated cities with significant water demands that are managed by a variety of utilities and companies, an analysis of this type would not illustrate the potential risks and vulnerabilities to systems related to factors such as environmental flow requirements and changes in demand.

An example of new requirements being made of water utilities is the recent push for environmental flow releases. Recent work by biologists and ecologists that has linked deterioration of the aquatic ecology in a basin to flow alteration by dams and reservoirs has prompted policy makers to consider environmental flow regulations [*Olden and Naiman*, 2010; *Richter and Thomas*, 2007; *Richter et al.*, 2011; *Watts et al.*, 2011]. In the Northeast, efforts have gone toward developing a framework for the permitting of water withdrawals under the Water Management Act (WMA) to help establish sustainable management of water resources that balance both anthropogenic and ecological needs. Ongoing pilot studies, guided by the Massachusetts Executive Office of Energy and Environmental Affairs (EEA), test the new Sustainable Water Management Initiative (SWMI), designed to sustain the magnitude and timing of the natural flow regime. However, the risk associated with requiring water utilities to release more water under conditions of climate change is not known.

Previous studies that have explored climate change risks to water supply in the Northeast, most of which focus on the New York City and Boston water supply systems, have found varying results [*Kirshen et al.*, 1995; *Kirshen and Fennessey*, 1995; *Vogel et al.*, 1997b; *Lettenmaier et al.*, 1999; *Matonse et al.*, 2012; *Blake et al.*, 2000; *Horton et al.*, 2011]. For example, *Kirshen and Fennessey* [1995] and *Kirshen et al.* [1995] climate impact studies of municipal water supply in Metropolitan Boston estimated the amount of water that could be reliably supplied from the Quabbin and Wachusett Reservoirs to the Boston area for different climate scenarios derived from the simulations of Global Circulation Models (GCMs). They concluded that Boston's source of water is highly sensitive to the climatic changes explored, suggesting the potential need to develop new sources of water supply and adjust the costs of water to users. Other work by *Vogel et al.* [1997a] used a simple regional hydroclimatologic model of annual streamflow to explore the sensitivity of Boston's water supply system performance to climate, leading roughly to the same results found in the much more

detailed approaches used by *Kirshen et al.* [1995]. However, a later study done by *Lettenmaier et al.* [1999] looked at the impacts of both climatic and non-climatic effects on future system performance for the Boston water supply system and found that the non-climatic effects of future system performance (i.e. demand growth) exceeded the effects of climate change over system planning horizons.

*Matonse et al.* [2012] investigation of the impacts of climate change on New York City's water supply used future climate scenarios projected by different GCMs as inputs to a Generalized Watershed Loading Functions (GWLF) watershed model to simulate inflows required to run a water supply systems model (OASIS). Results from this study suggest the NYC reservoir system will continue to show high resilience and annual reliability, and low vulnerability in the future despite projected changes in seasonal hydrology in the region.

These studies provide snapshots of the effects of specific climate change scenarios from certain GCMs driven by certain emissions scenarios on the systems. However, they lack the ability to identify the specific climate changes that should cause concern for the water managers and larger populace of the Northeast U.S. Given that climate models are continuously being updated, that they share significant biases, and that they are recognized to only explore the 'minimum range of maximum uncertainty,' the utility of information gained from previous studies may be lacking. Only *Vogel et al.* [1997a] sought general relationships between water supply reliability and climate change, albeit using simple analytical approximations to estimate reliability. In addition, previous studies have focused solely on large systems, notably the water supply systems serving New York City and greater Boston. No study in the published literature has focused on smaller supply systems.

This dissertation seeks to efficiently identify the climate change vulnerabilities of water supply systems in the Northeast U.S., and upon doing so, uses the identified problematic climate changes to put available climate change projections into

context. The methodology employed in *Brown et al.* [2012] is used to study the municipal surface water supply systems in Boston, MA, New York City, NY, Hartford, CT, Springfield, MA, and Providence, RI to develop a general understanding of the vulnerabilities to both climate change and natural variability of larger water supply systems in the Northeast U.S. The methods are then generalized in the form of a novel online software tool for use by managers of small water supply systems for climate risk screening assessments. The tool is presented and demonstrated on both large and small systems. The results reveal the differences in vulnerabilities that can be identified by using a consistent vulnerability-based framework across systems, both large and small.

### **Vulnerability-based climate risk assessment**

Traditionally, water supply impact studies evaluate system performance by combining downscaled Coupled Ocean-Atmosphere Global Climate Models (OA/GCM) with rainfall-runoff models and reservoir operations models to predict future climate risk [*Rajagopalan et al.*, 2009a; *Wilby and Dessai*, 2010; *Wiley and Palmer*, 2008]. These ‘top-down’ or scenario-based approaches use projected climate change scenarios to evaluate system performance. Top-down approaches undertaken for the purposes of making adaptation or reservoir operating decisions tend to propagate significant uncertainties, generating large uncertainty ranges in climate impacts and system risk [*Dessai et al.*, 2009]. For example, the inherent uncertainty in GCM projections related to initial condition ensembles [*Deser et al.*, 2012], climate forcings [*Stainforth et al.*, 2005], and model inadequacies due to poorly understood climate physics and computational complexity [*New and Hulme*, 2000] make it difficult to incorporate information from these scenarios into adaptation decisions [*Stainforth et al.*, 2007b]. Hydrologic model error is an additional source of uncertainty, with possible errors associated with the hydrologic model parameters, model structure, and prediction

errors [*Steinschneider et al.*, 2012]. There is also uncertainty in the systems models due to mismatches of operating guidelines, demand forecasts, and changes in the priorities of system operations [*Wood et al.*, 1997b].

Given these concerns, alternative methods of climate risk assessment have emerged that build from the concepts of classic decision theory and scenario planning. In standard decision theory, options are evaluated based on the reward they are expected to deliver given a particular state of nature. The states of nature represent the uncertain future. For each combination of a decision (e.g., selection of an option) and a future state of the nature, there is an outcome, often called the reward. Given this structuring of a decision problem, decision analysis then provides protocols, called decision rules, for selecting the best option. For example, a common decision rule used in water resources is maximizing expected utility, which uses probabilistic information to select among alternatives under uncertainty [*Weaver et al.*, 2012]. While decision theory is a powerful tool for identifying optimal management strategies given the available information, it is highly sensitive to the characterization of uncertainty. For example, if the ‘maximize expected utility’ approach is used, then the optimal decision is very dependent on the probabilities assigned to the future states of the world. If a maximax decision rule is used, then its highly dependent on the judgment of which future is most likely. Finally, if a maximin or minimax regret is used, then it is dependent on the range of states of nature that are considered, and in particular what the ‘worst case’ is selected to be.

Rather than suggest a single, best-guess plan of action, several studies have attempted to incorporate the concept of robustness for water resources planning and design that rely on selecting strategies that perform well across the range of generated scenarios [*Lempert and Collins*, 2007; *Ray et al.*, 2013; *Watkins Jr and McKinney*, 1997]. These methods include Info-Gap Decision Theory [*Ben-Haim*, 2006], Robust Decision Making (RDM) [*Lempert et al.*, 2006; *Lempert and Groves*, 2010], Robust

Optimization [Ray *et al.*, 2013; Watkins Jr and McKinney, 1997], Real Option analysis [Wang *et al.*, 2006], Decision-Scaling [Brown, 2010], and the scenario-neutral approach [Prudhomme *et al.*, 2010]. These bottom-up approaches are designed to identify system vulnerabilities over a range of plausible future conditions to aid in selecting robust adaptation strategies. In all cases, the concept of robustness plays a key role in analysis, where a robust strategy has the capacity to maintain performance amidst uncertainty [Lempert *et al.*, 2001].

Other decision-making methods focus on maintaining flexibility in the face of uncertainty. Forward-thinking decision-makers may try to account for the influence of future conditions on current decisions by designing projects that allow, but do not require, alterations to the use of a system through time. First introduced in the economics and finance literature [Arrow and Fisher, 1974; Myers, 1977], the value of maintaining flexibility in future decisions to avoid unwanted consequences is referred to as an ‘option value.’ The notion of option value has been applied in water resources planning, using ‘real options’ in engineered projects to help hedge against the risk of unexpected future outcomes [Steinschneider and Brown, 2012]. While real-option approaches offer a time dimension in planning, they can be technically complex to apply to real cases because of the need to agree on the value of deeply uncertain future options [Kalra *et al.*, 2014]. That is, while it is useful to consider real options among the decision options, it is not a formal decision making approach and thus follows traditional decision analysis methods with consequent foibles.

A robust decision framework prevalent in the literature is Info-Gap Decision Theory. Info-Gap Decision Theory is based on the idea that there is a ‘gap’ in the availability of information suitable to make complex decisions and this lack of knowledge requires we sample a wider range of uncertainty [Ben-Haim, 2001]. The method seeks to maximize the robustness of a decision based on minimum performance requirements [Matrosov *et al.*, 2013], where thresholds set the minimum level of system



performance that must be achieved. In this case, the region of uncertainty surrounding an estimate defines the robustness of a decision. A robustness function helps decision-makers explore the capacity of management options to meet certain performance thresholds as uncertainty grows, and uses an uncertainty parameter,  $\alpha$ , to define the domain in which an option is robust. Ultimately, the decision-maker is presented with a trade-off between higher performance (or reward) and robustness to uncertainty.

Robust Decision Making (RDM) is an analytic method for characterizing climate uncertainty by assessing the performance of plans over multiple climate futures. The analysis first characterizes a problem, defines a strategy or portfolio of options to address the problem, and then evaluates the strategy by generating future climate scenarios using stochastic simulation, with model parameters estimated from the observed historical record or downscaled climate model projections [*Lempert and Groves, 2010*]. The process is iterative, and if system vulnerabilities are identified through data mining techniques, alternative options can be explored. A regret-based definition of robustness is applied with RDM, where a robust strategy has relatively small regret when compared with the alternatives across a wide range of plausible futures [*Lempert and Groves, 2010*]. Robust Decision Making is designed to identify both the factors that cause system vulnerabilities and the strategies that reduce those vulnerabilities under deep uncertainty.

Decision-Scaling is a methodological framework which inverts GCM-based approaches to climate risk assessment by evaluating system performance over a range of climate futures that are systematically explored in terms of climate change and variability to reveal vulnerabilities independent of any assumed probabilities. The process is generally referred to as a climate stress test. This is similar to the ‘scenario neutral’ approach developed by [*Prudhomme et al., 2010*]. Multiple sources of climate information (i.e., climate projections, paleoclimate reconstructions, and subjective climate

information) can be used to evaluate risks associated with the vulnerabilities identified [Brown, 2010; Brown et al., 2011]. This methodology uses a decision analysis framework to characterize the climate future so that it is both relevant to the decision at hand and enhances the robustness of the decision under uncertainty. Similar to other robustness based approaches, in Decision-Scaling, robust adaptation strategies are defined as those that perform acceptably over a range of future uncertainty and can be compared with maximum performance over a smaller range.

Decision-Scaling has been employed in several studies of water resources management under an uncertain and changing climate regime, including climate impact studies in the Upper Great Lakes [Brown et al., 2011; Moody and Brown, 2013], the Niger River Basin in West Africa [Ghile et al., 2013], the Melbourne bulk water supply system in Melbourne Australia [Turner et al., 2014], several large river basins in the Himalaya region including the Aral Sea basins (Syr Darya and Amu Darya), the Indus Basin, the Ganges Basin, and the Brahmaputra Basin [Yang et al., 2013, 2014], and an urban water supply system in the Northeast US [Brown et al., 2012].

The work presented in this dissertation will use a Decision-Scaling approach to climate risk assessment in the Northeast U.S. In recognizing our limitations in projecting the future, this study uses Decision-Scaling to tailor the analysis to focus on the future climate states that are most vulnerable and estimates probabilities associated with those decision-relevant climate states [Brown et al., 2012]. This reduces the computational time and resources necessary for analysis, and permits rapid identification of vulnerabilities to climate change across multiple water supply systems, both large and small. Using a consistent vulnerability-based framework across systems of varying scale will help develop a general understanding of climate risks in the Northeast United States.

## Application of vulnerability-based approaches in the Northeast

To date, few studies have used bottom-up frameworks to explore climatic or other impacts on water supply utilities in the Northeast. Two noteworthy exceptions are presented in the work of *Brown et al.* [2012] and *Whateley et al.* [2014], in which the Decision-Scaling framework is applied to stylized municipal surface water supply systems in the Northeast U.S. to examine water supply reliability and risks due to climate change. The results from *Brown et al.* [2012] reveal that increases in temperature (resulting in increases in evapotranspiration and decreases in streamflow) and small increases in precipitation (that do not overcome these increases in evapotranspiration to increase streamflow) reduce reliability for the Quabbin-Wachusett reservoir system located in central Massachusetts. In *Whateley et al.* [2014], the decision-scaling framework is used to assess the impact of future climate change and uncertainty on the Springfield Water and Sewer Commission’s (SWSC) water supply system and results illustrate the additional robustness that can be gained through adaptation. These analyses also incorporate climate projections from GCMs to estimate probabilities of future climate states relevant to the decision at hand that may warrant action. The analysis framework in both studies couples a stochastic assessment of risks with potential insights from available climate projections for informed decision-making under climate change uncertainty.

However, most previous Northeast risk assessment studies found throughout the literature do not effectively explore future uncertainties, as they rely on coupled ocean/atmosphere general circulation models (OA/GCMs) to assess climate risks [*Hayhoe et al.*, 2006; *Horton et al.*, 2011; *Kirshen et al.*, 2008; *Zion et al.*, 2011]. For example, *Horton et al.* [2011] introduce a framework for adaptation planning in which New York City stakeholders preselect a climate projection range to assess climate hazards based on their prior experience making long-term decisions under uncertainty. Although this paper focuses on the provision of stakeholder-relevant climate infor-

mation for adaptation planning, it only provides a snapshot of the effects of specific climate change scenarios from certain GCMs driven by certain emission scenarios on New York City systems. In general, the use of GCM projections as the drivers of risk assessment studies in the Northeast precludes the discovery of plausible climate risks and represents a lower bound on the range of climate uncertainty [*Stainforth et al.*, 2007a].

In addition, most of these climate studies focus on decision-making under climate change uncertainty and do not explore other uncertain factors often deemed more important to planning horizons relevant to water resource systems, such as changes in population, land use, weather variability, environmental regulation, and water demand [*Lins and Stakhiv*, 1998]. *Hawkins and Sutton* [2009] and *Hawkins and Sutton* [2010] further emphasize that internal climate variability (i.e. the natural fluctuations in the climate system that arise in the absence of external forcings) is a significant source of climate uncertainty relevant to adaptation planning at regional scales. Designing effective strategies for provision of water-related services in the Northeast U.S. is dependent on the ability to characterize uncertainty and manage the resultant risks to system performance.

### **Accessibility of vulnerability-based climate impact analysis**

A notable gap in climate change studies related to water supply is that small systems are rarely studied. Climate change studies are typically performed for large water resource systems that are capable of investing the time and resources necessary for such analyses. However, small water utilities may be most susceptible to climate change but do not have the means to assess system performance under future uncertainty. This dissertation addresses this gap, using the vulnerability-based framework to develop an online tool that can be used to rapidly assess climate change

and other impacts on smaller utilities (i.e. serving populations of 125,000 or less) in the Northeast U.S.

The need for screening-level, computer-based models and tools to integrate knowledge and provide support in decision-making and management is confirmed by the scientific literature [*Anderson et al.*, 2004; *Borowski and Hare*, 2006; *Chapra*, 1991; *Welp*, 2001]. However, few software packages exist that provide these services to small water utilities and are simple and easy to use. One exception is the U.S. Environmental Protection Agency's (USEPA) Climate Resilience Evaluation and Awareness Tool (CREAT), designed to help the water sector assess regional and local climate-change impacts. This desktop-based tool leads utilities through a self-directed exploration of potential climate change related risks and adaptation options [*Travers*, 2010].

In contrast, a web-based screening-level tool may help narrow the persistent gap between knowledge production and use by removing software dependencies, simplifying scenario testing, and providing a user-friendly interface [*Lemos et al.*, 2012]. Recent advances in web standards, browser performance, and free and open-source software (FOSS) present a promising new avenue for developing planning tools that are more user-friendly and accessible than traditional desktop software. Moreover, these technological Web advances have transformed the implementation, design, and deployment of decision support systems (DSS) [*Bhargava et al.*, 2007].

The use of web applications for environmental modeling is only beginning to appear in the literature [*Sun*, 2013; *Walker and Chapra*, 2014b]. *Walker and Chapra* [2014b] developed an interactive web application with a rapid screening model for investigating potential water quality impairments due to BOD discharges. To the authors' knowledge, there are no web-based tools designed for exploring water supply system performance under climate change. This presents an opportunity to embed the Decision-Scaling framework into a web-based climate risk assessment tool for water supply utilities in the Northeast U.S.

The primary contribution of this dissertation is to present new tools and methodologies for exploring climate risks to water supply systems in the northeastern United States. The following four chapters present a pathway forward in the sustainable management and planning of water resource systems given the irreducible uncertainty in future climate, hydrologic, and socioeconomic states of the world.

## CHAPTER 1

# SELECTING STOCHASTIC CLIMATE REALIZATIONS TO EFFICIENTLY EXPLORE A WIDE RANGE OF CLIMATE RISK TO WATER RESOURCE SYSTEMS

### 1.1 Abstract

There are significant computational requirements for assessing climate change impacts on water resource system reliability and vulnerability, particularly when analyzing a wide range of plausible scenarios. These requirements often deter analysts from exhaustively identifying climate hazards. This technical note investigates two approaches for generating a subset of stochastic climate realizations that efficiently explore a range of risk to water supply systems. In both methods, a large ensemble of stochastic weather time series is generated to simulate the natural variability of the local climate system, and a selected subset of these sequences is used in the impacts assessment. Method 1 selects the subset by first passing the entire ensemble through a rainfall-runoff model and then screening the hydrologic sequences using the sequent peak algorithm. Method 2 selects a subset of climate sequences based on climate statistics alone, prior to hydrological modeling. Both methods provide insight for identifying the climate statistics that best relate to the vulnerability of the water system and can be used to reduce the computational burden of modeling climate variability and change impacts.

### 1.2 Introduction

In recent decades, water resource engineers have considered the implications of climate change on the planning and design of water projects [*Nemec and Schaake*, 1982;

*Johnson and Weaver, 2008; Horton et al., 2011; Brekke et al., 2009; Hamlet, 2011; Mastrandrea et al., 2010a; Wiley and Palmer, 2008; Wood et al., 1997a*]. General circulation models (GCMs) are a popular tool to generate climate scenarios for use in impact assessments but they are limited by their poor ability to simulate climate at fine spatial and temporal scales [*Grotch and MacCracken, 1991; Musau et al., 2014; Stainforth et al., 2007b; Masson and Knutti, 2011*], and their complexity makes it computationally challenging to characterize uncertainty [*Katz, 2002; Murphy et al., 2009; Knutti and Sedláček, 2012*]. A variety of downscaling procedures have been proposed to alleviate some of these issues [*Prudhomme et al., 2010; Lempert and Groves, 2010; Leavesley, 1994*]. One increasingly utilized approach [*Wilby and Dawson, 2012; Jones et al., 2009*] relies on stochastic weather generation to create several time series of weather that reflect climate changes consistent with GCM projections, but also preserve local characteristics of natural variability poorly represented by the climate models.

Researchers have long recognized the advantages of using stochastic techniques for generating synthetic streamflow sequences for assessment of water resource systems [*Fiering, 1997*]. A ‘climate stress test’ represents an expansion of this traditional approach, where the benefits of sampling a wide range of stochastically generated variability are combined with controlled sampling of changes in climate. A key feature of the climate stress test is an exhaustive sensitivity analysis using exploratory modeling techniques to identify plausible climate changes and realizations of natural variability that could negatively impact the water system [*Brown, 2010; Brown et al., 2012*]. A weather generator is typically used as part of the algorithm to develop these plausible scenarios [*Steinschneider et al., 2014a, 2015b; Steinschneider and Brown, 2013*].

Even with modern computing power the exploratory modeling process used in the stress test can be computationally demanding, and both accessibility to high performance computing resources and the perceived time and effort of preparing models and



data for exploratory analysis may limit the number of scenarios explored by analysts. If the climate stress test is to be adopted more widely for climate change impact analyses, methods are needed to overcome the computational challenges associated with large ensembles of stochastically generated climate scenarios. *Steinschneider et al.* [2014a] and *Steinschneider et al.* [2015b] introduce two climate selection techniques that reduce the computational burden of exploring the effects of both climate change and natural variability in a stress test. In both studies, a small subset of stochastic realizations is selected from a larger ensemble of stochastic weather time series, with the selection criteria based on climate statistics thought to be closely associated with system performance, for example, the two year minimum precipitation. However, the degree to which a climate statistic such as two year minimum precipitation related to the vulnerability of the water supply system could only be determined after the full computational modeling chain, with all its resource demands, was completed.

The objective addressed in this technical note is to develop a pre-processing method that allows the identification of the appropriate statistic to use for assessing the degree of challenge that a particular stochastic realization imposes on the water resource system. This allows the selection of a subset of realizations that can be used for stress testing the system, by selecting a set of realizations that span the range of variability a system might face in the future in terms of the challenge to the system (from nonthreatening to very challenging) or by choosing a small number of challenging realizations. The method is also generally useful for identifying the climate statistic that is most indicative of vulnerability of the system, which can then be compared with climate change studies to assess the level of concern that climate change poses for the system.

## 1.3 Methods

It has long been tradition to use a large number of simulations to assess the vulnerability of a system and this trend has only increased with a number of studies in the recent literature that run a huge suite of simulations through runoff and reservoir models [*Lempert and Groves, 2010; Brown et al., 2011, 2012; Stedinger et al., 1985*]. A contributing factor is the advanced methods based on data mining that have emerged for evaluating and interpreting results. It is beneficial under climate change analyses to assess the effects of climate changes and the possible variability that might be faced in the future but attempting to do so results in computational limitations. In addition, methods that rely on heuristic optimization approaches (e.g., genetic algorithms) are often limited in the number of realizations that can be evaluated.

Two options are assessed for pre-processing stochastic realizations to identify climatic hazards to water resource systems. Under the first approach, we drive a hydrologic model with all of the synthetic climate sequences and then employ sampling techniques that eliminate the need to carry all of the simulations through the system simulation model. In the second approach, we develop methods to select stochastic realizations prior to running them through the hydrologic model. We compare the results of these two methods against a full climate stress test using a large ensemble of stochastic realizations to determine the benefits and costs of the increased computational efficiency.

### 1.3.1 System Description

A stylized water supply system in the northeast U.S. is used to demonstrate the proposed methods. The system and its operations are based on the Springfield Water and Sewer Commission's (SWSC) water supply system located in the Westfield River Basin in Central Massachusetts. The system is composed of two primary reservoirs: Cobble Mountain Reservoir ( $8.642 \times 10^7 \text{ m}^3$ ) and Borden Brook Reservoir ( $9.464 \times 10^6$

$m^3$ ). For the purposes of this analysis, Cobble Mountain is modeled as the major storage reservoir and Borden Brook as a run-of-river facility. Reservoir operations in the model are based on a simple hedging policy adapted from the SWSC Drought Management Plan, which reduces releases in times of drought to save water for future use [Camp Dresser and McKee, 2005]. As such, reservoir operations influence whether the system meets the target demand and in turn, effects water supply reliability. The system has a draft ratio (i.e., ratio of target annual demand to mean annual inflow) of 0.64. A version of the ‘abcd’ rainfall-runoff model [Thomas, 1981a], modified to account for snow accumulation and melt, is used to convert climate sequences to streamflow sequences. Details on the hydrologic and system simulation model used in this technical note can be found in Whateley *et al.* [2014]. More information on the system and its operations can be found in Westphal *et al.* [2007] and Camp Dresser and McKee [2005].

### 1.3.2 Stochastic Climate Scenarios

Both methods considered in this technical note require the generation of a large ensemble of plausible climate scenarios that represent realizations of local-scale natural climate variability. A simple first order autoregressive model (AR(1)) was fit to basin-averaged, annual precipitation data [Maurer *et al.*, 2002] and used to generate 10,000, 62-year sequences of annual precipitation. Only stochastic realizations with a mean that deviated from the historic annual precipitation mean by  $\leq 1\%$  were retained, reducing the original 10,000 time series to 3,880. This down selection is used to preserve the historic mean in the generated data, an important step in climate change analyses to ensure each trace has the same baseline mean. Annual average temperature values were simulated using a k-Nearest Neighbor algorithm (k-NN) whereby historical annual temperature means were selected from historical years with similar observed precipitation to the simulated annual precipitation from the AR(1) model.

All annual variables are disaggregated to a monthly time step using the method of fragments [*Srikanthan and McMahon, 2001*].

### 1.3.3 Baseline Method: Full Climate Stress Test

In a traditional climate stress test, the full ensemble of stochastic climate sequences is perturbed with a prescribed climate change, either as a step shift [*Whately et al., 2014*] or transient change [*Steinschneider et al., 2015b*], and used to force a rainfall-runoff model to generate a large ensemble of climate-altered streamflow sequences. These streamflow sequences are then passed through a water resource simulation model to produce an ensemble of performance statistics, such as water supply reliability and vulnerability metrics [*Brown et al., 2012*]. The monthly time-based reliability [*McMahon et al., 2006*] and vulnerability metrics in this analysis are defined as the probability that a system is in a satisfactory state in a given month (i.e., meets the target demand) and the average volumetric severity of a failure (i.e., not meeting the target demand) during a failure month, respectively [*Hashimoto et al., 1982*]. In this study, three transient linear climate change trends were imposed on the 3,880 stochastic sequences in the Baseline method to assess system performance under climate change: wet/no change (125% of historic precipitation and no change in temperature), dry/hot (75% of historic precipitation and 5 degree C increase in temperature), and no change in climate. Transient trends are imposed instead of step changes because they reflect a more realistic depiction of future change, although step changes can be applied with no loss of generality. These three climate changes, coupled with the 3,880 stochastic simulations, produces 11,640 total simulations (3,880x3) to be run through the hydrologic and systems models in the full stress test.

### 1.3.4 Method 1: Sampling hydrologic realizations using the Sequent Peak Algorithm

In the first method, the sequent peak algorithm (SPA) [Thomas and Burden, 1963] is used as a pre-processing step to approximate system performance across the range of all stochastic climate scenarios without running hydrologic simulations through the water resources systems model. Oftentimes, water resource systems models, e.g., WEAP [Stockholm Environment Institute, SEI, 2001] and MODSIM [Labadie, 1995], can take hours to days to run. In this way it provides a shortcut for choosing traces that span the range of variability relevant to the system. The same hydrologic sequences as developed in the Baseline method are used as input into the SPA to calculate the minimum required storage capacity necessary to meet target demands for the synthetic hydrological record without incurring reservoir failure.

$$K_t = \max\{0, K_{t-1} + R_t - Q_t\} \quad (1.1)$$

$$K^* = \max\{K_t\} \text{ over all } t=1,2,\dots,2T \quad (1.2)$$

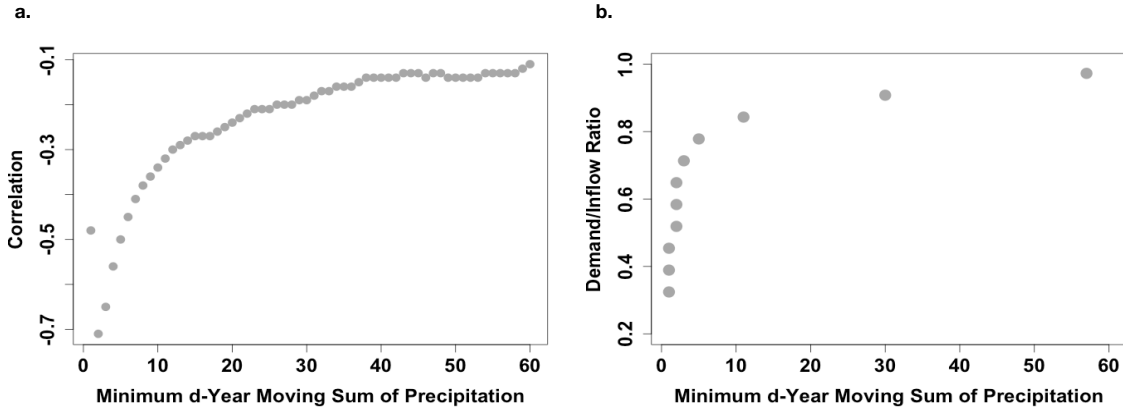
where  $K_t$  is the reservoir storage at a monthly time step  $t$  and  $K_{t-1}$  is the reservoir storage at time step  $t - 1$ .  $R_t$  is the system's water supply demands at time step  $t$  and  $Q_t$  is the inflow into the system at time step  $t$ .  $K^*$ , the maximum of all  $K$  values, represents the minimum total storage requirement necessary to meet water supply demands without failure over two consecutive flow sequences (i.e. twice the period of record). The analysis is carried out over two cycles to account for the possibility that the critical period lies toward the end of an inflow sequence. The minimum total storage requirement ( $K^*$ ) is calculated for all hydrologic sequences. A large minimum storage requirement implies a large maximum yield deficit and hence a challenging realization of natural climate variability.

The analyst then selects a small subset (5-10) of the required reservoir storages associated with empirical quantiles of the distribution of  $K^*$  (e.g., the 10%, 25%, 50%, 75%, 90%). The exact number of subsamples and quantiles can be chosen through dialogue with the stakeholder partner. In some cases, only an extreme realization may be desired. The streamflow realizations associated with these required storages are then traced back to the specific climate realizations (from the original 3,880) used to generate them. Similar to the Baseline method, mean climate changes are imposed on this small subset of climate realizations by applying linear trends of future climate change. In this study, the system model is run over 9 selected realizations of climate variability combined with the 3 different climate trends for a total of 27 simulations, as compared to the 11,640 in the Baseline method.

### 1.3.5 Method 2: Empirically sampling climate realizations

Although Method 1 shortens the amount of time that is typical of a full vulnerability analysis (see Table 1), there can be significant computational requirements for running thousands of climate sequences through hydrologic models. While parsimonious, hydrologic models (like the ‘abcd’ model) often do not add substantially to the computational time of a stress test, the present trend in hydrology is towards more detailed, physically-based models (e.g., DHSVM [Wigmosta *et al.*, 1994] and VIC [Liang *et al.*, 1994]) that can take hours to days to calibrate and run for all stochastic climate sequences.

In the second method, a sampling technique similar to the one presented in *Stein-schneider et al.* [2014a] is introduced to select climate time series prior to running them through any hydrologic or systems models. Here, the SPA method is applied to the weather realizations to estimate a suitable drought statistic to use for reflecting the challenge of each realization to the water resource system. The first step in this procedure requires the analyst to explore the relationship between required storages



**Figure 1.1.** a. Correlation coefficients between required storages and the minimum d-year precipitation value (i.e. minimum 2-year precipitation); b. the ratio of demand to inflow of a water supply system versus the minimum d-year precipitation.

(the SPA metric) and the minimum d-year moving sum of annual precipitation (for all possible d-year drought lengths from  $d=1$  to  $d=62$ ) to identify which climate statistic is most correlated with the SPA metric. The most correlated statistic (i.e., the suitable drought statistic to use for analysis) is then calculated for the entire ensemble of stochastic climate simulations and, similar to Method 1, a subset of the original stochastic climate simulations is selected with drought statistics that span the distribution of drought statistics under the entire stochastic ensemble. These climate realizations are post-processed with different climate trends to produce the climate simulations that are used in the stress test.

Figure 1.1 is provided as a reference for analysts who want guidance on identifying a suitable drought statistic without applying the SPA method to their system. Monte Carlo methods were used to explore the relationship between the draft ratio (ratio of demand to inflow) of a reservoir system and the minimum d-year moving sum of annual precipitation, enabling any user with a similar demand configuration to the test system to determine a suitable value for  $d$  based on the draft ratio of their system. The draft ratios range from 0.32 to 0.97.

This note illustrates a limited consideration of potential drought statistics, focusing on different minimum d-year precipitation totals  $Y_{min}^d$  on an n-year simulation. While the selection of a single drought metric based on running annual totals of precipitation is insufficient to characterize the risk that different climate time series pose to a water supply system, this study tests whether they provide a sufficient approximation to appropriately select a small subset of climate time series to represent the risk of natural variability.

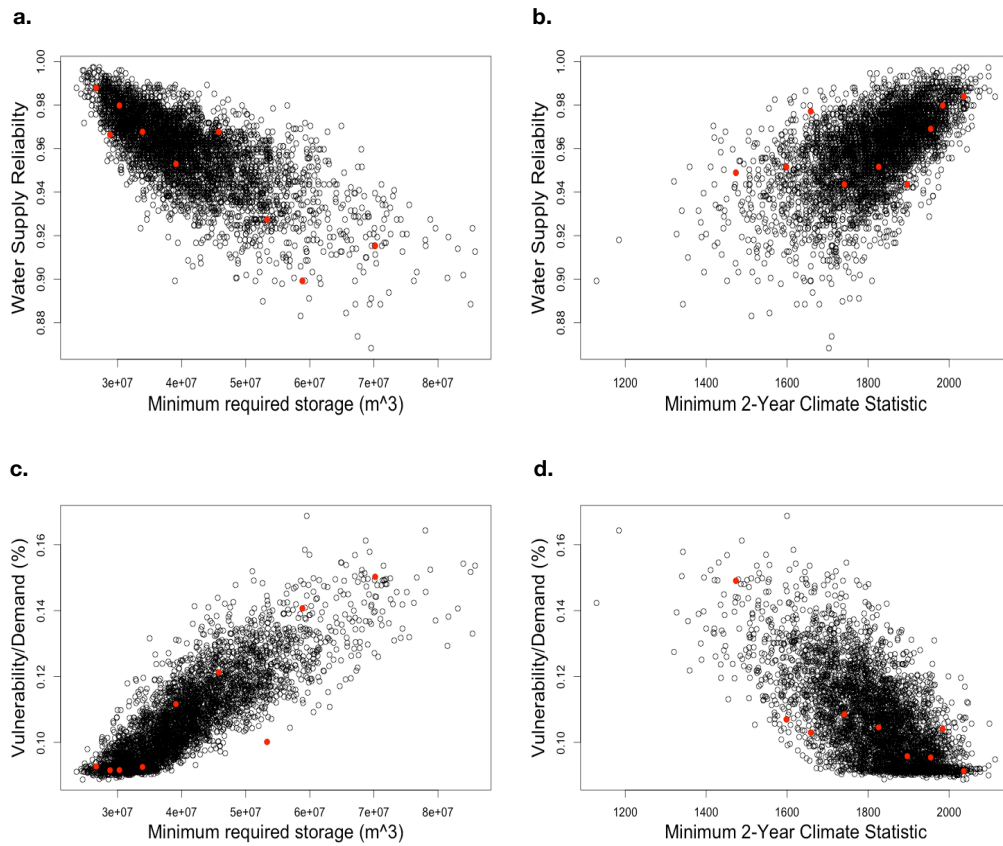
## 1.4 Application of Methods

### 1.4.1 Method 1: Subset stochastic ensemble based on SPA

Figure 1.2a and Figure 1.2c illustrate the relationship between the SPA metric and water supply reliability and vulnerability, respectively, under all stochastic simulations. Data points representing nine selected results from the SPA analysis are highlighted in red. These points correspond to streamflow realizations causing minimum required storage ( $K^*$ ) values at quantiles of 0.01,0.05,0.1,0.25,0.5,0.75,0.9,0.95, and 0.99 across all simulations. Quantiles are selected to ensure a full range of variability (defined in terms of the characteristics of the system) is sampled for a given mean climate state. As such, the selected traces stress the system in such a way that the results can be interpreted in terms of risk related to climate change. However, having generated the subset of traces, analysis can focus on particular quantiles or traces based on the interests of the analyst (i.e., one could place greater emphasis on the driest realizations by focusing on the lower tail of the distribution).

The selection of stochastic simulations in Method 1 will accurately represent the potential impacts of natural climate variability on system performance if there is a close relationship between the SPA and performance metrics. This is because the selected simulations, based on the quantiles of the SPA metric distribution, will also represent similar quantiles in the distribution of performance metrics under natural





**Figure 1.2.** Relationship between reservoir performance and required reservoir storage calculated using the sequent peak algorithm (a,c) and minimum 2-year precipitation (b,d). Red dots represent select required storages and minimum 2-year precipitation values from the distribution of all synthetically generated realizations (obtained using Method 1 and Method 2).

climate variability (as represented by the 3,880 stochastic simulations) if the fits in Figures 1.2a,c are very precise. As seen in Figures 1.2a,c, the relationship between reservoir performance and the SPA metric is clearly linear with some noise (Pearson’s  $r$  value of -0.71 and 0.85 for reliability and vulnerability, respectively). The strong fit suggests that the SPA method can be an effective approach to select a subset of stochastic simulations for the stress test. Given the noise in the relationships, we recognize that the approach is imperfect and does not guarantee that the selected climate sequences will represent the full range of system performance that could arise under natural variability. This is seen by the non-monotonic progression of the selected simulations in Figures 1.2a,c along the reliability and vulnerability axes. However, the benefits of computational efficiency may be substantial and the selected climate sequences still span most of the distribution of system performance across the original stochastic ensemble.

#### **1.4.2 Method 2: Subset stochastic ensemble based on critical climate statistics**

Results for identifying the  $d^{th}$  drought statistic (i.e., the minimum  $d$ -year moving sum of annual precipitation) are presented in Figure 1.1. Figure 1.1a shows the Pearson R correlation coefficient between the SPA metric and the minimum annual, 2-year, 3-year, ...,  $d$ -year moving sums of precipitation. For the system presented in this work, the minimum 2-year moving sum of annual precipitation was most correlated with the SPA metric (correlation of -0.72). Furthermore, results from a Monte Carlo simulation illustrate how a system’s demand to inflow ratio can be used to choose an appropriate  $d^{th}$  drought statistic for any demand configuration of the test system (Figure 1.1b).

Figure 1.2b and Figure 1.2d illustrate the relationship between system performance metrics and the minimum 2-year precipitation values across all stochastic

simulations, with selected quantiles (0.01,0.05,0.1,0.25,0.5,0.75,0.9,0.95,0.99) of the 2-year drought metric highlighted. The relationships in Figures 1.2b,d appear linear within the limits of the tested data, but as expected, they are more noisy than for the SPA metric in Figures 1.2a,c. This is because metrics derived from inflows are bound to predict system performance with greater accuracy than those derived directly from climate data. As such, Method 1 is more likely to choose an appropriate subset of stochastic simulations for the stress test than Method 2. However, Method 2 does still provide some utility in choosing stochastic simulations, as the selected sequences generally span the range of system performance across all stochastic simulations. It also has the considerable advantage of not requiring hydrologic modeling simulations for selection.

### 1.4.3 Comparison to a full vulnerability analysis

Three climate trends were imposed on the 9 selected stochastic weather sequences from Methods 1 and 2 and were used to drive a stress test of the Springfield system. The results (i.e., the range of performance and computational time) are compared against a full stress test that alters all stochastic climate realizations with the three climate trends (Figure 1.3). Table 1 reports the computational times for Methods 1 and 2. It should be noted, however, that run time is highly variable depending on the hydrologic and systems models used in the stress test, and the actual time values here are less important than their relationship to one another across methods.

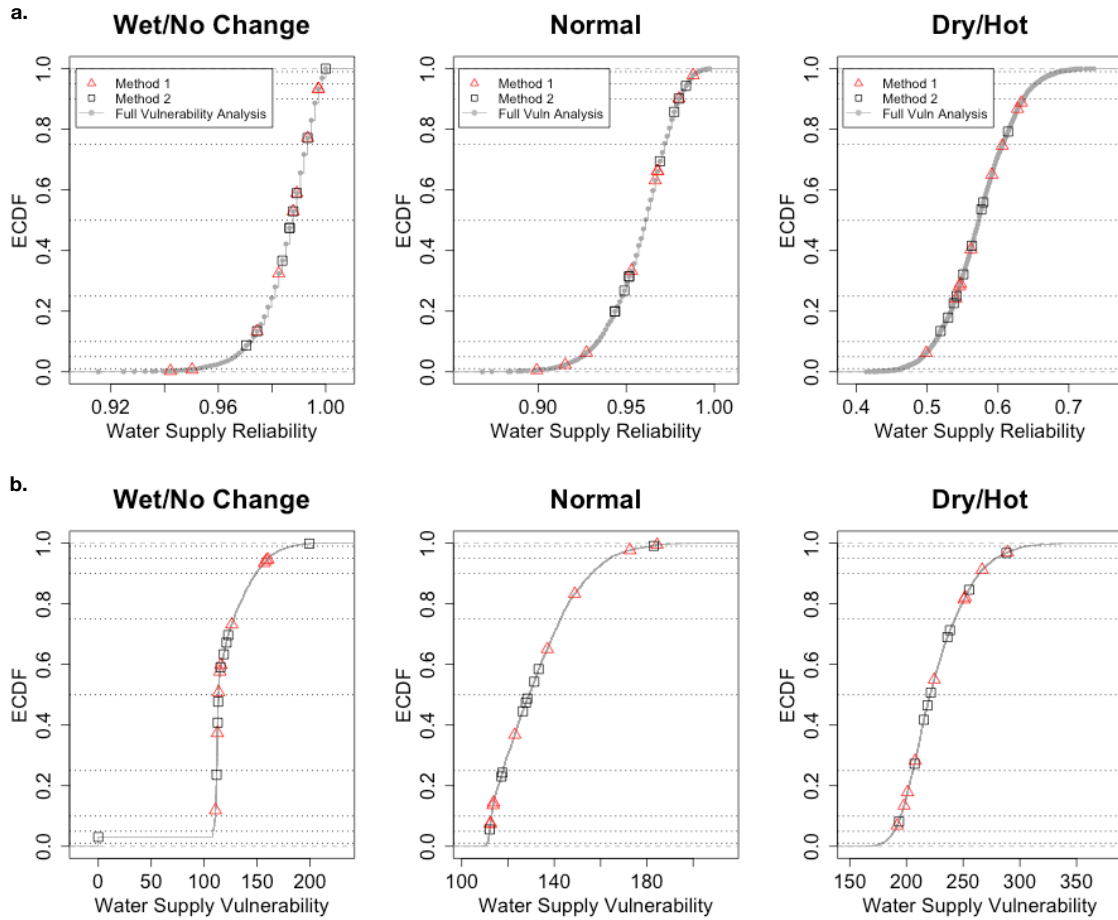
Figure 1.3a(b) illustrates the distribution of water supply reliability (vulnerability) across all stochastic realizations with wet/no change, baseline, and dry/hot climate trends imposed. The red triangles and black squares represent performance results based on select quantiles (horizontal dotted lines) from Methods 1 and 2. Results indicate that the selected climate simulations consistently span the majority (i.e., inter-quartile range) of the distribution of system performance, while Method 1 also

tends to contain sequences nearer to the tails of the full stress test than Method 2. In a few cases (i.e., under the wet/no change and normal reliability scenarios), reliability values overlap and the boxes/triangles appear darker. Table 2 illustrates the percent difference between quantiles of reliability and vulnerability across the two methods and the full stress test.

In general, both methods, but particularly Method 1, effectively capture the full range of variability for a given mean climate state (with percent difference values in Method 1 ranging from 0.41 to 1.24 for reliability and 0.35 to 5.18 for vulnerability), suggesting that these approaches can be used to lighten the computational burden of the stress test. It is important to recognize that these methods are imperfect and can lead to a selection of climate sequences that are unlikely to capture the complete range of natural climate variability that can influence the system. However, given the gains in computational efficiency, this tradeoff may be worthwhile depending on the risk-tolerance and resources of decision-makers. Lastly, while further research is needed to assess whether these methods would work effectively in all systems, previous work linking climate statistics to system performance of complex water supply systems [Turner *et al.*, 2014] suggests the plausible application of these methods to a range of different systems.

## 1.5 Conclusion

This technical note explores the use of two sampling techniques to overcome computational burdens of exhaustively assessing both climate change and variability impacts on water resource systems. The first method employs the sequent peak algorithm to screen climate and hydrologic sequences to drive a manageable number of water resource model simulations while still exhaustively exploring vulnerabilities using a climate stress test approach. Method 2 further reduces the computational burden by selecting climate realizations prior to running them through a hydrologic



**Figure 1.3.** A distribution of a.) water supply reliability and b.) vulnerability across all natural variability realizations under wet/no change, no change, and dry/hot climate scenarios. Select performance quantiles (horizontal dotted lines) drawn from all realizations using Method 1 and Method 2 are illustrated as red triangles and black squares, respectively.

**Table 1.1.** Computational times of the full vulnerability analysis, Method 1, and Method 2.

Method	Full Vulnerability Analysis	Method 1	Method 2
Generate Climate Realizations	80.44	80.44	80.44
Calibrate Hydrologic Model	6.93	6.93	6.93
Extreme Climate Trends	122.42	0.43	2.58
Extreme Streamflow Trends	962.68	56.95	2.37
Reservoir Systems Model	309.81	0.79	0.72
<b>Total Time (s)</b>	<b>1482.28</b>	<b>145.54</b>	<b>93.04</b>

**Table 1.2.** Percent difference between quantiles of reliability and vulnerability across the two methods and the full stress test.

Quantile	Reliability		Vulnerability	
	Method 1	Method 2	Method 1	Method 2
<b>0.01</b>	0.89	3.92	1.22	0.97
<b>0.05</b>	1.17	1.87	0.35	4.46
<b>0.1</b>	0.72	1.57	0.65	4.12
<b>0.25</b>	0.42	0.28	3.56	6.98
<b>0.5</b>	0.56	0.98	4.90	1.06
<b>0.75</b>	0.42	0.28	4.1	10.60
<b>0.9</b>	1.24	0.27	4.79	17.25
<b>0.95</b>	0.55	0.55	5.18	20.67
<b>0.99</b>	0.41	0.82	1.5	0.68

model. Results suggest that both methods, but particularly Method 1, can effectively reduce the computational burden of climate impact assessments for water systems, while still effectively exploring vulnerabilities. A recognized limitation in the evaluation of these methods is that one relatively simple water supply system over a restricted range of climate change scenarios (i.e., only three plausible climate change trends) was explored. Additional analysis is required to characterize the universal applicability of these methods across different systems and system models, and across a wider range of climate change scenarios. However, the present work suggests these approaches are promising for characterizing the effects of climate uncertainty on water resource systems. They are also useful for identifying key climate statistics that are most related to a water resource systems' climate vulnerabilities.

## 1.6 Acknowledgments

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## CHAPTER 2

# CLIMATE STRESS TESTING NORTHEAST WATER SUPPLY: AN ASSESSMENT OF VULNERABILITIES AND CLIMATE RISK EXPOSURE

### 2.1 Abstract

In the northeastern United States water is generally thought to be abundant. Yet, increasing pressures on water utilities throughout the region, including new constraints on water withdrawals, requirements to release additional water for ecological purposes, and the emerging concern associated with climate change, may constrain their ability to supply reliable water. Assessing the vulnerability of any particular system is challenging because a variety of factors that go beyond simple changes in precipitation and temperature must be considered, such as the size of the watershed, the volume of storage, required releases, and water demand. This analysis uses a vulnerability-based framework, based on stress testing, to identify problematic scenarios first and then uses climate information to provide context regarding the risk associated with those scenarios. The approach is demonstrated in an analysis of several of the major cities of the Northeast U.S.: New York City, NY, Boston, MA, Springfield, MA, Hartford, CT, and Providence, RI. Through comparative analysis, this paper demonstrates a comprehensive approach to characterizing climate risks to water supply that synthesizes across the findings of individual studies and in doing so contributes to a deeper understanding of climate risks to water supply as demonstrated in this application to the northeastern United States. Results of the analysis demonstrate how vulnerabilities can be compared for different systems to help prioritize adaptation.



## 2.2 Introduction

The Northeast U.S. has a large concentration of highly populated cities with significant demands for water supplies that are currently being managed through a variety of water utilities and companies. The risks faced by these utilities vary by location and sector, and their vulnerabilities are changing not only as a result of increasing population, changes in demand, urbanization, regulatory constraints, and changes in technology, but also with a variable and changing climate. While previous studies have assessed the impact of particular projections from climate models for water systems in the Northeast US, this paper seeks to identify the specific climate conditions that are problematic. The approach allows easy comparison of several representative systems, five large water supply utilities in the northeastern U.S., New York City, NY, Boston, MA, Springfield, MA, Hartford, CT, and Providence, RI.

Over the last century, the Northeast has experienced a number of short-term droughts due to interannual variability of precipitation that, accompanied with high demands on fresh-water resources, have stressed many of the water supply systems in the region. In the early to mid 1960s, a combination of a low pressure anomaly over the midlatitude North Atlantic Ocean and cold sea surface temperatures (SSTs) on the coast resulted in a multi-year period of decreased precipitation [*Seager et al.*, 2012] that caused problems for many Northeast water supply systems. For example, in 1967 the Quabbin Reservoir experienced a historic low, dropping to 44% of its total capacity. At 38% of capacity the system begins to violate water quality standards, and if a drought of this magnitude occurred regularly, the Boston system would need to consider building a new, expensive treatment plant [*Joyce*, 1994; *Lettenmaier et al.*, 1999]. Similarly, between 1965-1966 the Springfield Water and Sewer Commission's (SWSC) primary storage was drawn down to approximately 30% [*Westphal et al.*, 2007] and the Metropolitan District Commission's (MDC) reservoirs dipped to 42% of capacity [*Woodside*, 2002].

Since the significant drought of the 1960s, a subsequent wet period associated with high pressure anomalies over the North Atlantic Ocean and warm SSTs has favored increased precipitation in the region [Seager *et al.*, 2012]. The combination of a long term wetting trend and large decreases in water demand due to conservation measures and leak detection efforts has resulted in decreased supply worries for most water supply systems in the region. However, with climate change underway there is natural concern that water supply systems may be vulnerable to future changes.

Climate change threatens water supply with rising temperatures [Trombulak, 2004] that may cause increased evaporative demand, decreases in wintertime snowpack, and earlier snowmelt [Hayhoe *et al.*, 2006; Huntington *et al.*, 2004]. Hayhoe *et al.* [2006] suggested a general increase in drought frequency in the future, driven by soil moisture deficits and reduced precipitation. However, a number of previous studies exploring climate change impacts to water supply in the Northeast that model the actual water resource system, focusing primarily on the New York City and Boston water supply systems, have found varied results [Kirshen *et al.*, 1995; Kirshen and Fennessey, 1995; Vogel *et al.*, 1997b; Lettenmaier *et al.*, 1999; Matonse *et al.*, 2012; Blake *et al.*, 2000; Horton *et al.*, 2011].

All studies use a set of statistically downscaled GCM projections to assess the impact of those projections on the water supply system. Kirshen and Fennessey [1995] and Kirshen *et al.* [1995] used 4 mean climate changes from 4 GCMs under a  $CO_2$  doubling scenario covering a range of +3.11 to +8.27 degree Celsius temperature change and -7.6 to +23% precipitation change and a single historical variability trace to assess the Quabbin and Wachusett Reservoirs (operated by the Massachusetts Water Resources Authority (MWRA)). The analysis showed that the climate projections with temperature and precipitation changes of +4.9 degrees Celsius and -7.6% and +3.67 degrees C and -1.6% caused a problematic decrease in streamflow (33% and 16%, respectively) and yield (43% and 23%, respectively), requiring development of

new sources of water supply and other measures to provide reliable water if that particular projection came to be true. Other projections in the same study indicated increases in system safe yield as a result of increases in precipitation, resulting in overall inconclusive results. *Vogel et al.* [1997b] linked a simple regional hydroclimatologic model of annual streamflow (driven by the same GCM projections that were used in *Kirshen and Fennessey* [1995]) with storage-reliability-resilience-yield (SRRY) relations to determine the sensitivity of the Boston metropolitan water supply system to climate change, and with the exception of one of the GCM projections explored, their results agreed with *Kirshen and Fennessey* [1995] in both the direction and magnitude of changes in yield.

*Lettenmaier et al.* [1999] used 5 transient GCM projections and a doubled- $CO_2$  scenario from 3 models which showed temperature increases of 1.2 to 5.9 degrees Celsius and precipitation changes of -6 to 15% between 1990 and 2050, and found that the Boston system was relatively insensitive to these five climate changes, with slight decreases in runoff primarily influenced by changes in precipitation and PET. Demand growth scenarios of 325 mgd (based on pre-conservation average water demand level of 1987) and 285 mgd (based on pre-conservation average water demand level of 1993) were included and led to slight declines in water supply reliability for some GCM scenarios when compounded by decreasing runoff, illustrating greater impacts than the climate effects alone.

*Matonse et al.* [2012] investigation of the impacts of climate change on New York City's water supply used 16 GCM projections of future air temperature and precipitation constructed from 3 models using a delta change method and the historical variability trace. The results suggested that for these projections which ranged from a 2.2 to 3.4 degree increase in temperature and 12.7 to 15.3% increase in precipitation (for all GCM models combined), the NYC reservoir system can provide high resilience and annual reliability.

In sum, the studies imply a range of vulnerabilities for the systems considered and in general indicate the present uncertainty in climate change impacts on water supply in the region. None of the results conclusively describe the climate vulnerabilities of the systems that were studied. Instead, only the effects of the particular GCM projections used were learned. The result is an incomplete assessment of each system with only a small number of scenarios considered and alternative variability largely unexplored. Consequently, the climate conditions that are problematic to these systems remains largely unknown which is remarkable given the size of the systems, populations served and the number of previous studies.

The previous studies all reveal the impacts of specific climate projections on the system of interest, but the results remain dependent on the climate projections that are used and the various pre-processing steps applied to the projections. These include a bias correction step (using multiple linear regression methods [*Lettenmaier et al.*, 1999] and delta-change methods [*Matonse et al.*, 2012]) and treatment of variability (using historical variability [*Matonse et al.*, 2012; *Kirshen and Fennessey*, 1995] and performing multiple steady state analyses by imposing mean monthly climate changes for various decades on the historic period [*Lettenmaier et al.*, 1999]). Thus the fundamental vulnerability of these systems to climate change remains unknown because the results are conditional on these modeling choices. Furthermore, comparison across systems is difficult for the same reasons. *Vogel et al.* [1997b] provides an interesting exception, seeking general relationships between water supply reliability and climate change, albeit using simple analytical approximations to estimate reliability.

In a study of the MWRA system, *Brown et al.* [2012] introduced the Decision-Scaling framework where the vulnerability of the system to a wide range of plausible climate changes is assessed independent of climate projections to reveal the climate conditions that cause concern. GCM projections are then introduced within the context of the fundamental climate vulnerability of the system. The approach has

been subsequently expanded to incorporate a climate stress test [*Steinschneider and Brown, 2013*] to systematically explore climate changes and identify vulnerabilities, to assess adaptation options [*Whateley et al., 2014; Steinschneider et al., 2015b*], include hydrologic modeling uncertainty [*Steinschneider et al., 2014a*], and explore the effects of variability versus mean changes in climate (Whateley et al., submitted; Whateley et al., in prep).

This paper demonstrates the use of the framework to conduct a comparative analysis of multiple systems within a consistent analysis that allows meaningful comparisons and provides fundamental insights regarding the state of water supply systems in the Northeast U.S. The study reveals the climate changes that are problematic to all and the climate changes that affect some but not others. The analysis is applied to the municipal surface water supply systems in Boston, MA, New York City, NY, Hartford, CT, Springfield, MA, and Providence, RI, which collectively supply water to 12.8 million people, approximately 23 percent of the population in this region. The analysis represents the most exhaustive assessment of climate risk to Northeast water supply, systematically exploring plausible climate changes and variability effects. While the results are specific to the region, the assessment framework is general.

The paper proceeds as follows. Section 1 describes the study sites explored in this analysis. Section 2 presents the methods, models, and performance metrics used to compare the multiple systems. Sections 3 and 4 present the results of this study and a discussion of how they compare with earlier climate impact studies in the region. Section 5 concludes the work.

## **2.2.1 Study sites**

### **2.2.1.1 Massachusetts Water Resources Authority (Boston, MA)**

The Massachusetts Water Resources Authority (MWRA) manages the water supply for Boston, MA and the surrounding communities (over 2.5 million people). The

primary water supply reservoirs for the Boston system include the Quabbin Reservoir (412 billion gallons (BG)) and the Wachusett Reservoir (65 BG). MWRA also maintains back-up reservoirs throughout the system, providing an additional 7.7 BG. The Quabbin Reservoir is located eighty miles west of Boston, storing water from the east and west branches of the Swift River. The Wachusett Reservoir is located fifty-five miles west of Boston, and stores water from the Quinepoxet and Stillwater rivers and Quabbin Aqueduct water transfers from the Quabbin Reservoir. Prior to 1992, water demands exceeded the system's safe yield of 300 mgd, however, have since decreased to approximately 200 mgd as a result of aggressive water conservation measures.

#### **2.2.1.2 Springfield Water and Sewer Commission (Springfield, MA)**

The Springfield Water and Sewer Commission's (SWSC) water supply system is located in the Westfield River basin in Central Massachusetts. The system is composed of two major water supply reservoirs: Cobble Mountain Reservoir (22,829 million gallons (MG)) and Border Brook Reservoir (2500 MG). Reliable water supply from the Cobble Mountain Reservoir is of high priority, as it is the second largest water supply in Massachusetts. The SWSC's water supply system is a water source for Agawam, East Longmeadow, Longmeadow, Ludlow, Westfield, and the city of Springfield, serving a total population of around 250,000 people. Following the devastating drought of the 1960s, a pump station was constructed such that water could be transferred from the Littleville Reservoir to the Cobble Mountain Reservoir as a precautionary measure against future droughts of that magnitude. The pump has never needed to be used since its installation. Consequently, the Cobble Mountain Reservoir receives its inflows from surface runoff, direct precipitation, and the Borden Brook Reservoir located upstream. The Cobble Mountain system has a firm yield of 42.70 mgd, with an actual average annual usage of 36.57 mgd [*Levin et al.*, 2011].

### **2.2.1.3 Providence Water’s Scituate Reservoir Complex (Providence, RI)**

The Scituate Reservoir Complex, also managed by MWRA, is located in central Rhode Island. The system consists of six major reservoirs: Scituate, Moswaniscut, Regulating, Barden, Westconnaug, and Ponaganset. The reservoir system is responsible for meeting the water needs of 60% of the state (650,000 people). The safe yield of the system is 92 mgd, which is higher than the average demand supplied to customers over the last 20 years (68 mgd). Water demand projections estimate 69 mgd and 71 mgd by 2015 and 2030, respectively.

### **2.2.1.4 Metropolitan District Commission’s Water Supply System (Hartford, CT)**

The Metropolitan District Commission is responsible for managing the water supply for the greater Hartford area (400,000 people). The system consists of two major water supply reservoirs: Barkhamsted Reservoir (22400 MG) and Nepaug Reservoir (9500 MG). The Barkhamsted Reservoir meets approximately 70% of the total water demand (57 mgd) and the Nepaug Reservoir meets the remaining 30%. Additional reservoirs are available for potential water supply along the East and West Branches of the Farmington River, including the Colebrook Reservoir maintained by the U.S. Army Corps of Engineers, the West Branch Reservoir (6.5 BG of potential drinking water supply), and Lake McDonough (2.9 BG of potential water supply), however, the main purpose of these reservoirs is not for water supply.

### **2.2.1.5 New York City Water Supply System (New York City, NY)**

The New York City Water Supply System (NYCWSS) consists of two surface water reservoir systems: the Croton system located in Westchester County and the Catskill/Delaware system (referred to as the West-of-Hudson (WOH) system) located 125 miles North and West of New York City. The Croton system acts as a transfer station for WOH, except in times of drought, when the Croton system is drawn down

**Table 2.1.** Summary of system characteristics

Location	Storage Capacity	Population Served	Demands	Demand/Inflow	Major Water Supply Reservoirs
New York City, NY	460,900 MG	9 million	1000 mgd	0.67	Delaware System: Cannonsville, Neversink, Pepacton, Rondout Catskill System: Schoharie, Ashokan East and Ashokan West
Boston, MA	412,000 MG (Quabbin); 65,000 MG (Wachusett)	2.5 million	200 mgd	0.87	Quabbin and Wachusett
Providence, RI	39,000 MG	650,000	75 mgd	0.58	Scituate, Moswaniscut, Regulating, Barden, Westconnaug, and Ponaganset
Hartford, CT	31,900 MG	400,000	57 mgd	0.52	Barkhamsted and Nepaug
Springfield, MA	22,829 MG	250,000	42 mgd	0.64	Cobble Mountain and Borden Brook

to meet demand. The Delaware system contains 4 reservoirs: Cannonsville (95700 MG), Neversink (34900 MG), and Pepacton (140200 MG) that operate in parallel with each other and in series with Rondout (49600 MG) to meet 60% of the city’s daily water. The Catskill system contains 2 reservoirs that operate in series to supply 40% of daily water needs: Schoharie (17600 MG) and Ashokan (122900 MG). Water travels from the Delaware and Catskill systems into the Kensico Reservoir before entering the NYC distribution system.

## 2.3 Methods

### 2.3.1 Stress test approach

Decision-Scaling is used to tailor the analysis of these large water supply systems to focus on the future climate states that are most vulnerable and estimate probabilities associated with those decision-relevant climate states [Brown *et al.*, 2012; Ghile *et al.*, 2013; Turner *et al.*, 2014; Hallegatte *et al.*, 2012; Brown *et al.*, 2011; Brown, 2010; Weaver *et al.*, 2012; Whateley *et al.*, 2014; Steinschneider *et al.*, 2015b]. The stress test approach used in Decision-Scaling begins with an ensemble of stochastic climate sequences that are perturbed with a variety of transient linear trends and used to force a rainfall-runoff model to generate an ensemble of climate-altered streamflow sequences. These streamflow sequences are then passed through a water resources simulation model to produce an ensemble of performance statistics. The stress test approach is applied to the large water supply systems in the Northeast to



systematically investigate the impacts of natural variability and climate change on performance.

### **2.3.2 Empirically sampling climate realizations**

There are significant computational requirements for assessing climate impacts on large and complex water resource systems under uncertainty, particularly when analyzing a wide range of climate change and natural variability scenarios. As such, it is beneficial to strategically select stochastic realizations that capture the full range of variability that is possible prior to running them through hydrologic or systems models. Transient linear climate change trends can then be applied to the subset of stochastic variability realizations to produce the climate simulations to be used in the stress test. In this study, a new procedure is applied to the Decision-Scaling framework to select an informed subset of stochastic climate realizations for a particular water supply region that explores a range of climate risk to the water supply system.

The procedure uses Method 2 of Whateley et al., (submitted) to empirically sample a subset of stochastic climate realizations that represent the risk of natural variability to each of the systems. In this method, a drought index (i.e., minimum  $d$ -year moving sum of annual precipitation) is selected for each system that represents the difficulty of a particular realization in terms of its affects on the system being analyzed. Nine climate realizations are selected with drought statistics that span the distribution of the drought index under the entire stochastic ensemble of climate simulations. For example, for a drought index of  $d=2$ , the minimum 2-year moving sum of annual precipitation is calculated for all stochastic simulations, and quantiles (e.g., 0.1,0.25,0.5,0.75,0.9,etc.) of the distribution of the 2-year drought index are selected that correspond to climate realizations. Then, transient climate change trends are imposed on the 9 climate time series to be used in the climate stress test. In this study, 121 transient linear trends were imposed on the 9 stochastic climate sequences

to assess performance for each system: 25% decrease to 25% increase in historic precipitation at 5% increments and 0 to 5 degrees Celsius increase in temperature at 0.5 degree increments. The result is an exhaustive yet efficient exploration of possible climate changes and their impacts that can be used to define the problematic conditions for each system.

### 2.3.3 Hydrologic models

A modified version of the ‘abcd’ rainfall-runoff model [Thomas, 1981b] was used to convert climate sequences to streamflow sequences for New York City, Providence, Hartford, and Springfield. The modified model [Martinez and Gupta, 2010] incorporates an additional snow component (i.e. a snow storage zone) to account for the influence of snow accumulation and melt on hydrologic processes in the northeastern United States, adding an additional parameter ‘e’. The hydrologic model was calibrated to historic streamflows on a monthly time step using the shuffled complex evolutionary algorithm (SCE) [Thyer et al., 1999; Duan et al., 1992] for each reservoir system: USGS 01181000 West Branch Westfield River at Huntington, MA for Springfield, USGS 01188090 Farmington River at Unionville, CT for Hartford, USGS 01115187 Ponaganset River at South Foster, RI for Providence, and using inflows to each of the seven reservoirs of the New York City system (i.e. Cannonsville Reservoir, Neversink Reservoir, Pepacton Reservoir, Rondout Reservoir, Schoharie Reservoir, and the Ashokan East and Ashokan West Reservoirs).

For the Boston system, four independent hydrology models were calibrated at a weekly time step for each of the four basins associated with the MWRA water supply system: the Quabbin Basin (USGS 01174565 West Branch Swift River near Shutesbury, MA), the Wachusett Basin (USGS 01095220 Stillwater River near Sterling, MA), the Ware River Basin (USGS 01173500 Ware River at Gibbs Crossing, MA), and the Connecticut River Basin (USGS 01170500 Connecticut River at Mon-

tagne City, MA). The hydrologic model for Boston is embedded in the Stockholm Environment Institute’s Water Evaluation and Planning tool (WEAP) [*Stockholm Environment Institute, SEI, 2001*]. The WEAP model is described in more detail in the following section.

A Nash Sutcliffe efficiency coefficient [*Nash and Sutcliffe, 1970*], commonly used to assess the predictive performance of hydrologic models, was calculated for each calibration. Nash Sutcliffe coefficients across all systems ranged from 0.33 for the Ashokan East inflows to 0.81 for the Ponaganset River.

### **2.3.4 System simulation models**

#### **2.3.4.1 Boston**

The simulation model of the Boston water supply system was first developed in STELLA [*US Army Corps of Engineers, 1994*] in the early 1990s by researchers at the University of Washington [*Werick and Willeke, 1994*] and was later translated into the Stockholm Environment Institute’s Water Evaluation and Planning tool (WEAP). The WEAP model used for this analysis operates on a weekly time step to calculate reservoir storages and releases based on target storages and water demands that fluctuate throughout the year. Specifically, from October 15 through June 14, Ware River flows in excess of 85 mgd are diverted to the Quabbin Reservoir via the Quabbin Aqueduct. However, flows are only diverted if the Quabbin Reservoir is below its ‘normal’ storage level (i.e. a monthly storage target defined by the MWRA). There are also required minimum releases from the Quabbin Reservoir to the Swift River, which are governed by flows in the Connecticut River (measured at the USGS gaging station in Montague City, MA).

#### **2.3.4.2 Springfield**

The Springfield water supply simulation model was built in R [*Whateley et al., 2014*] based on current operating policies reproduced from the SWSC’s drought man-

agement plan. The model operates on a monthly time step. Additional details on the system simulation model used in this study can be found in *Whateley et al.* [2014] and more information on system operations can be found in *Westphal et al.* [2007] and *Camp Dresser and McKee* [2005].

#### **2.3.4.3 Providence**

The simulation model for Providence operates on a monthly time step. The model was originally constructed in STELLA with the guidance of Providence Water, and was later translated into R for this analysis. Reservoir operations in the model are relatively straightforward. Water is drawn directly from the Scituate Reservoir to meet water supply demands, with an additional minimum downstream release requirement to the Pawtuxet River of 9 mgd. Current operations attempt to refill the reservoir by June 1, and spill water to the Pawtuxet River when levels exceed the 400 foot overflow spillway. The other reservoirs in the system have minimal regulation and mostly act as run-of-river storage facilities.

#### **2.3.4.4 Hartford**

The Hartford water supply simulation model was developed in R on a monthly time step. The two major water supply reservoirs, Barkhamsted Reservoir and Nepaug Reservoir, were treated as run-of-river facilities left to fill and spill. Storages and releases from these two reservoirs were calculated based on inflows and water supply demands (assumed to be constant throughout the year). Other potential water supply was not accounted for in the model.

#### **2.3.4.5 New York City**

The New York City simulation model was developed in R on a monthly time step. The monthly model used in this analysis was adapted from the original daily mass balance model built in the Screening Tool for the Assessment of Turbidity and Supply

(STATS), which is constructed using Vensim software (Rossi et al., 2015). Operations in this model are based on the ‘New York City Rule’ [Lund and Guzman, 1999], which defines releases from reservoirs based on the probability of refill by June 1. The purpose of defining releases in this way is to minimize the probability of spills (i.e. minimize expected shortages). The New York City systems model also incorporates Federal and State regulations. More information on the system’s operations can be found in Rossi et al. (2015).

### 2.3.5 Performance metrics

Common system metrics such as reliability (i.e. percentage of time a system operates without failure)(Equation 2.2), vulnerability (i.e. average magnitude of failures) (Equation 2.3), and robustness (i.e. acceptable performance over a range of future uncertainty) are calculated to evaluate system performance. A shortfall ( $Sh(t)$ ) (Equation 2.1) occurs if monthly (weekly) system demands are not met. Reliability is based on the total number of shortfalls over the period of record, and vulnerability is based on the magnitude of shortfall. A reliability threshold of 95% is used to distinguish acceptable versus unacceptable system performance. The metrics used in this analysis are adapted from *Hashimoto et al.* [1982], *Loucks et al.* [2005], and *Moody and Brown* [2013].

$$Sh(t) = \begin{cases} 0 & demand(t) - release(t) \leq 0 \\ 1 & demand(t) - release(t) > 0 \end{cases} \quad (2.1)$$

$$R = 1 - \frac{\sum_{t=1}^T Sh(t)}{T} \quad (2.2)$$

$$V = \sum_{t=1}^T demand(t) - release(t) > 0 \quad (2.3)$$

A climate robustness index (CRI) is used to quantify and compare the robustness across systems [Moody and Brown, 2013]. The CRI incorporates thresholds of

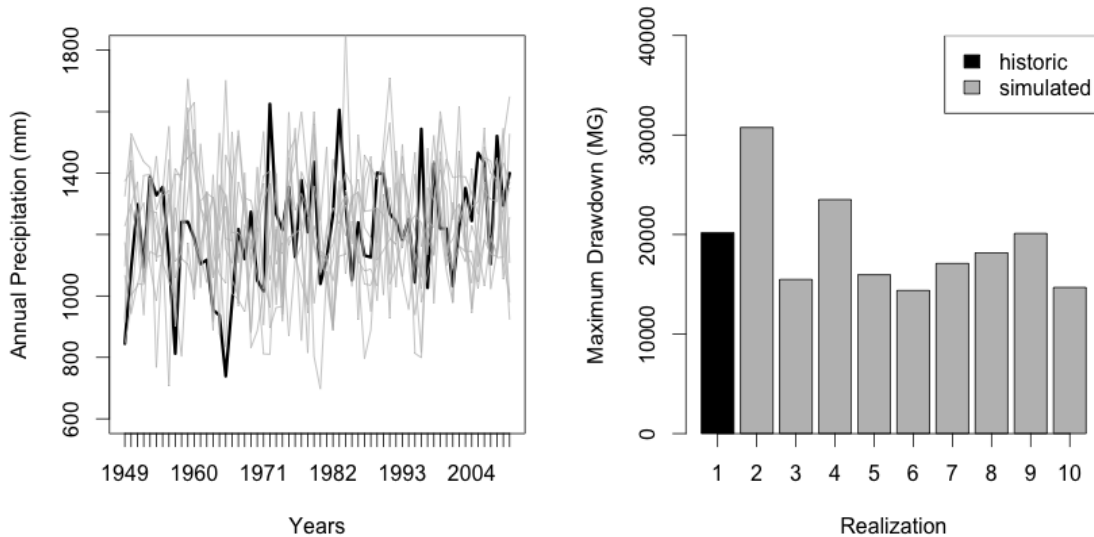
acceptable performance for a system (i.e. 95% reliability) into a binary performance function to characterize vulnerability. Climate projections are then incorporated into the CRI to weight the robustness according to the assumed probability of a given climate change [*Whateley et al.*, 2014].

$$CRI = \int_{\mathbf{x}_0}^{\mathbf{x}_J} \Lambda(\mathbf{x}_j) f(\mathbf{x}_j) dx \quad (2.4)$$

where  $\Lambda(\mathbf{x}_j)$  is a binary performance function that returns a value of 1 (acceptable performance) or 0 (unacceptable performance) for each climate scenario,  $x_j$ , based on a performance threshold and  $f()$  is a probability density function describing the probability distribution of climate changes,  $\mathbf{X}$ .

The climate robustness index is a useful metric for quantifying the ability of a system to provide acceptable performance over a wide range of future climate, without being dependent on assumed probabilities of that future climate. The CRI's in this study were conditioned on three probabilistic assumptions of future climate: 1) a multivariate normal distribution fit to the ensemble of GCM projections described earlier, 2) a uniform probability distribution over all plausible climate states explored in this analysis, and 3) a uniform distribution applied to the GCM space (i.e., the outermost range of the GCM projections).

Lastly, climate response surfaces are created to visually parse the climate space (e.g. changes in mean precipitation and temperature) into regions of acceptable and unacceptable performance based on thresholds of acceptable performance. These provide a clear visual communication of the climate conditions that are problematic for each system.



**Figure 2.1.** (left) Historic (black line) and simulated (9 grey lines) time series of annual precipitation (mm) from 1949 to 2010, and (right) historic (black bar) and simulated (9 grey bars) maximum drawdown (million gallons) of the Scituate Reservoir System in Providence, RI.

## 2.4 Results

### 2.4.1 Stochastic climate simulations compared with historic conditions

Figure 2.1 (left) illustrates the variability and range of the stochastic time series of annual precipitation for Providence, RI over a 62-year time period from 1949-2010 (grey lines), and how they compare with the historic annual precipitation (black line). This 62-year period encompasses the 1960s drought, when annual precipitation reached a historic low for all of the systems explored in this analysis. Figure 2.1 (right) shows the historic (black bar) and simulated (9 grey bars) maximum drawdown (MG) of the Scituate Reservoir System in Providence.

### 2.4.2 GCM projections

An ensemble of GCM projections (RCP emission scenario 4.5) from the World Climate Research Programmes (WCRP's) Coupled Model Intercomparison Project

**Table 2.2.** GCM projection range, perturbation method, and variability approach used in the climate impact studies of Northeast water supply.

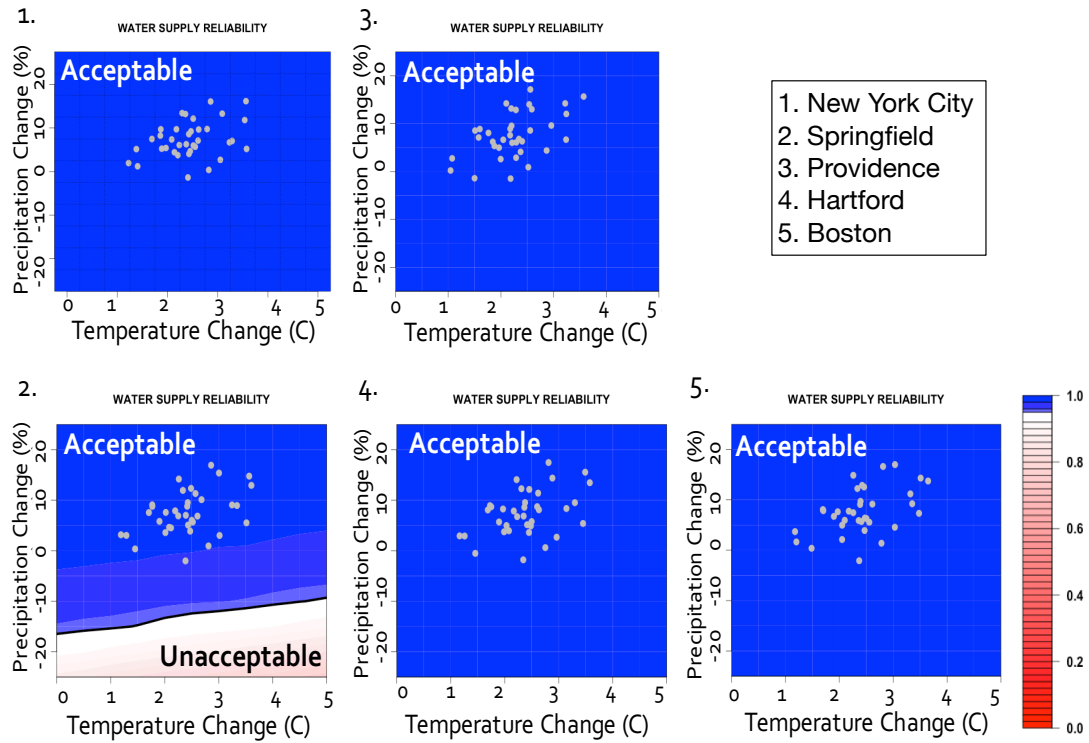
Location	Temperature (C)	Precipitation (%)	Perturbation Method	Treatment of variability
New York	1.2 to 3.6	-1 to 16	Transient linear changes	Stochastic variability traces
Boston	1.2 to 3.7	-2 to 17		
Providence	1 to 3.6	-1.5 to 17		
Hartford	1.2 to 3.6	-2 to 17		
Springfield	1.2 to 3.6	-2 to 17		

Phase 5 (CMIP5) multi-model dataset [Taylor et al., 2012] were used in the analysis to illustrate the direction of GCM-based climate changes relative to the problematic climate changes that were found as a result of the climate stress test. Gridded simulated data over each region where the reservoir system is located was downscaled to a monthly temporal resolution and 0.125 degree spatial resolution based on the bias-correction spatial disaggregation (BCSD) statistical downscaling method [Reclamation, 2013]. Mean monthly precipitation and temperature data were extracted for the time period between 1950 and 2099, and percent and absolute differences between future (50 years centered around 2050) and historic (1950-1999) precipitation and temperature data were calculated, respectively. The range of precipitation and temperature projections for each location is illustrated in Table 2.2. In general, the maximum projected CMIP5 temperature values are smaller than in previous studies (see Table 2.4 for comparison). While the means superimposed on the climate stress test results provide an indication of GCM trends, inter-model correlations and arbitrary sampling of models likely bias the visual image [Steinschneider et al., 2015a].

### 2.4.3 Stress test results

Figure 2.2 illustrates climate response surfaces of water supply reliability averaged across the 9 realizations of climate variability. In Figure 2.2, the black contour line indicates the 95% reliability threshold. The blue region represents acceptable system performance (i.e., above the 95% reliability threshold) and the red region represents unacceptable system performance. The ensemble of CMIP5 GCM projec-

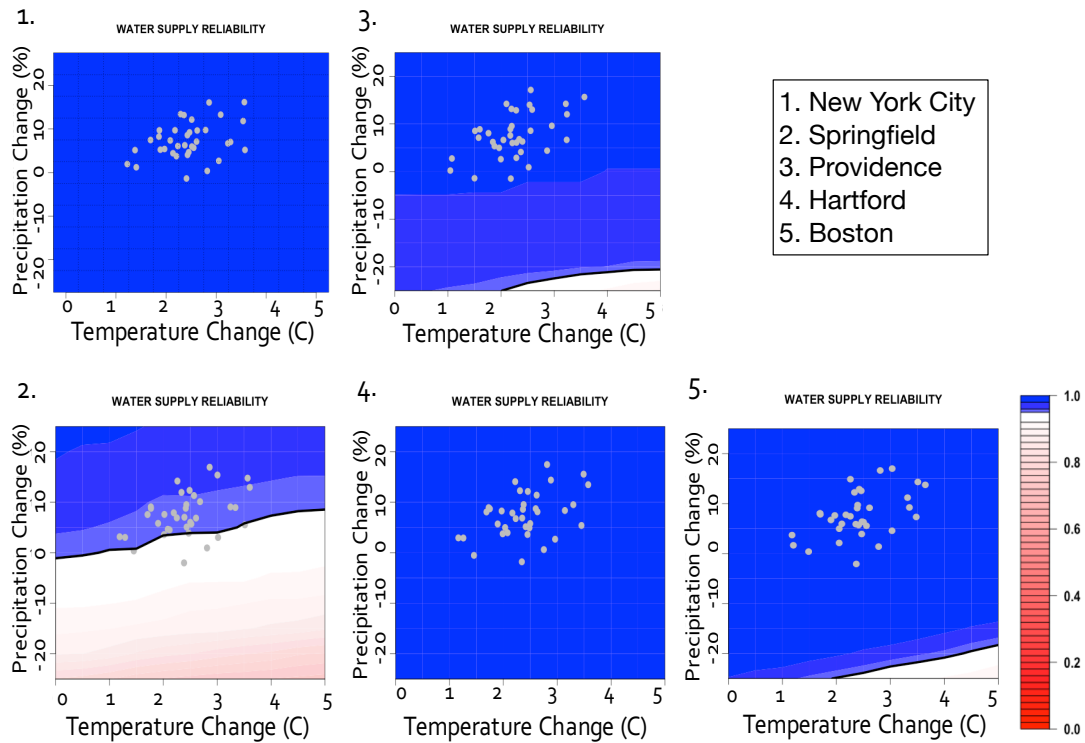




**Figure 2.2.** Water supply reliability for all systems averaged across 9 realizations of natural variability.

tions are superimposed on each response surface, represented as grey points. In all locations except Springfield, water supply reliability was above 95% across climate change space. For Springfield’s water supply system, reliability drops below the 95% threshold when precipitation decreases by approximately 16%.

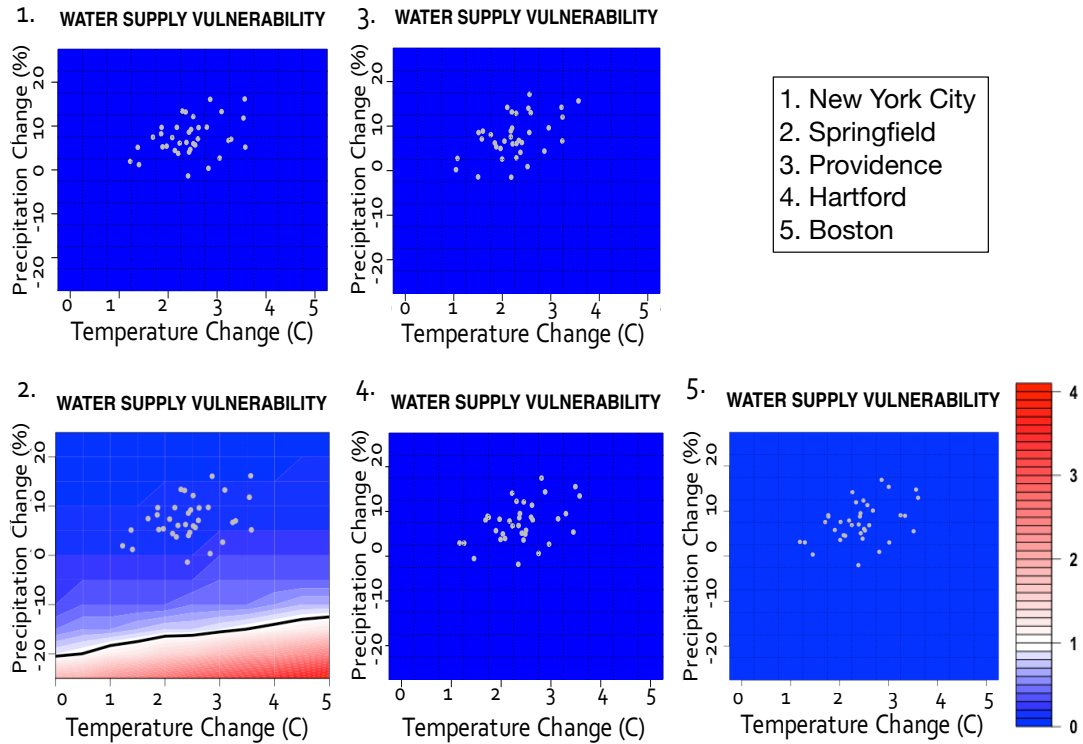
Figure 2.3 illustrates response surfaces of water supply reliability for the ‘worst case’ climate variability realization (i.e., the climate variability realization that has the largest magnitude decrease in reliability across climate change space). In historical climate terms, this stochastic realization would have a cumulative probability of being exceeded of 0.03%, meaning it would be a drought with return period of approximately 3,000 years. For the Boston, Providence, and New York City systems (locations where water supply demand projections are available), water supply demand was increased



**Figure 2.3.** Water supply reliability for all systems averaged across 9 realizations of natural variability for the ‘worst case’ realization.

to 250 mgd (25% increase in demand), 120 mgd (60% increase in demand), and 1600 mgd (60% increase in demand), respectively. For Boston and Providence, these demand increases were the points at which water supply reliability first dropped below the 95% threshold level, however, it is unlikely that these demand scenarios will occur in the future. For New York City, even with a significant increase in demand, the reliability remained above 95%.

Figure 2.4 illustrates vulnerability as a percentage of average monthly/weekly demand averaged across the 9 realizations and Figure 2.5 illustrates vulnerability as a percentage of average demand for the ‘worst case’ climate variability realization. In this case, the vulnerability threshold is defined as a shortfall magnitude that is 1% of the average demand for the system. Water supply demand was increased for the New York City, Boston, and Providence systems, however, the demand increases

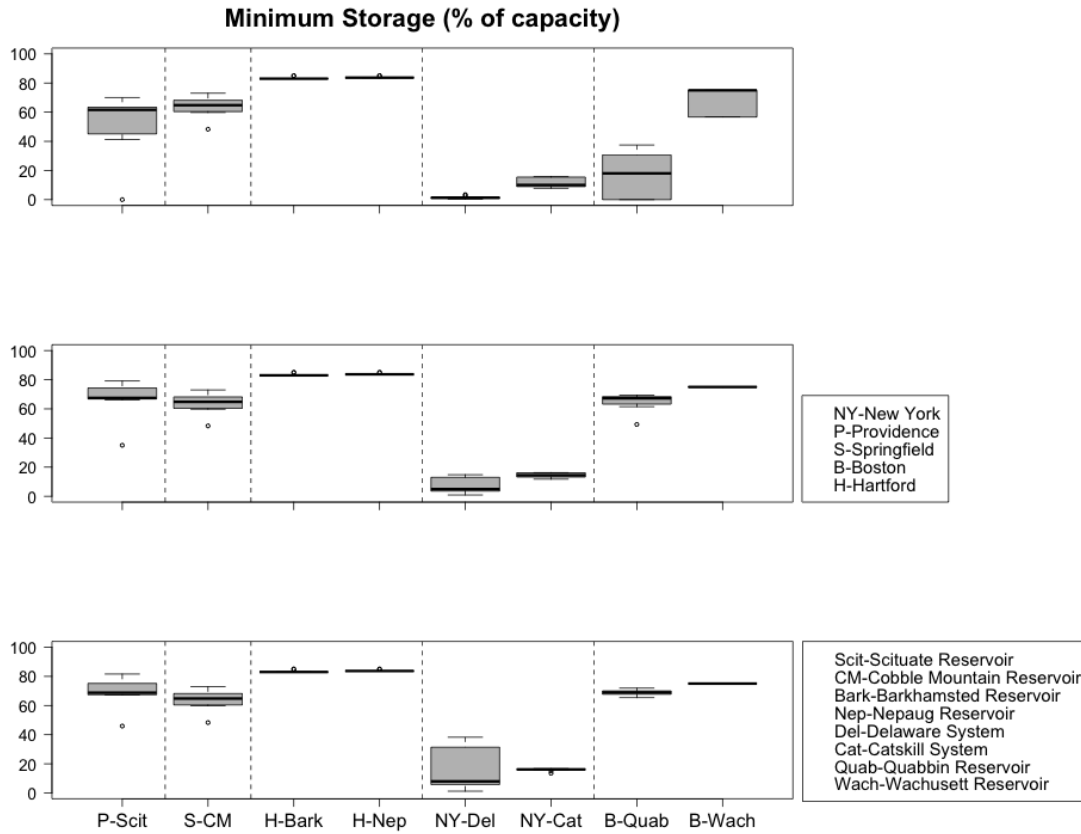


**Figure 2.4.** Water supply vulnerability as a percentage of average monthly (or weekly for Boston) demands averaged across 9 realizations of natural variability.

explored (New York City demand increased to 1600 mgd, Boston demand increased to 400 mgd, and Providence demand increased to 160 mgd) never resulted in a shortfall magnitude that exceeded the threshold level.

Figure 2.6 shows minimum storage as a percent of total capacity for the major reservoirs in each system under dry conditions (top- 25% decrease in precipitation and 5 degree increase in temperature), hot conditions (middle- no change in precipitation and 5 degree increase in temperature) and no change in climate (bottom). For New York City, reservoir capacity is lumped together for the Delaware system and the Catskill system.





**Figure 2.6.** Distribution of minimum monthly reservoir storage across 9 realizations under three extreme climate change scenarios: dry conditions- 25% decrease in precipitation, 5 degree C increase in temperature (**top**), hot conditions- no change in precipitation, 5 degree increase in temperature (**middle**), and no change in climate (**bottom**). Results are illustrated for (from left to right) the Scituate Reservoir in Providence, Cobble Mountain Reservoir in Springfield, Barkhamsted and Nepaug Reservoirs in Hartford, Delaware and Catskill Reservoir systems in New York City, and the Quabbin and Wachusett Reservoirs in Boston.

#### 2.4.4 Climate robustness indices

Table 2.3 shows the average climate robustness indices across the 9 climate variability realizations for each water supply system. Results are shown for three probabilistic assumptions of future climate change. The robustness indices for the Boston and Springfield systems (when conditioned on a uniform probability distribution over all grid cells, and in Springfield’s case, a uniform distribution over grid cells encompassing the GCM space) suggest that adaptation may be necessary in the future to maintain acceptable performance.

**Table 2.3.** Average Climate Robustness Index across 9 climate variability realizations under current demand conditions given assumptions of the Multivariate Normal and Uniform distributions over climate change and GCM space.

	Boston	Springfield	Providence	Hartford	New York City
Uniform	<b>0.99</b>	<b>0.75</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>
Uniform (GCM space)	<b>1.0</b>	<b>0.98</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>
Multivariate Normal	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>

## 2.5 Discussion

The results from this analysis suggest that water supply systems in the Northeast are robust to a wide range of climate changes, including increasing temperature and decreasing precipitation, as well as severe variability. The robustness of these systems across climate change space and averaged across climate variability realizations is illustrated by the response surfaces in Figure 2.2 and Figure 2.4 and climate robustness indices in Table 2.3. Given a reliability threshold of 95%, all systems perform acceptably under current climate conditions (0 degree Celsius change in temperature, 0% change from historic precipitation). The Springfield system is the only system that falls below the reliability threshold across all of climate space, but only when precipitation drops by approximately 16%. This comprehensive assessment updates

previous studies which were dependent on the GCM projections used and resulted in inconclusive results due to choice of projections.

The Springfield, Boston, and Providence systems all fail to meet the reliability threshold at the extremes of climate change space in the ‘worst case’ climate variability/demand realization (Figure 2.3). As noted above, based on historical statistics the return period of such a drought is approximately 3000 years and the precipitation reduction is beyond those indicated by climate projections from GCMs.

The climate robustness index is used to compare the relative robustness of a particular system or system configuration to other systems over a wide range of climate changes. It is an indication of the range of climate change a system can handle. The index can be conditioned on assumptions about the probability of future climate changes. Under the assumption of a multivariate normal distribution fit to the ensemble of GCM projections, the CRI suggests all systems are 100% robust to future climate change (i.e., they maintain a reliability of 95% across climate change space). When the range of climate changes used in the climate stress test is weighted uniformly (uniform distribution) or the range of climate changes indicated by the most extreme GCM projections is weighted uniformly (uniform distribution applied to the range of GCM projections), the Springfield and Boston CRI’s fall slightly below 1 (Table 2.3).

In general, the results from this study are similar to earlier GCM-based climate impact analyses of water supply in the Northeast. For example, *Lettenmaier et al.* [1999] found that the Boston system was relatively insensitive to temperature increases of 1.2 to 5.9 degrees Celsius and precipitation changes of -6 to 15%, but accompanied with demand increases, experienced slight declines in water supply reliability (3 and 39% declines in reliability for returns to 1992 and 1987 levels of demand (285 and 325 mgd, respectively). *Matonse et al.* [2012] also found similar results to this study for the New York City water supply reservoirs, illustrating that changes in climate,

**Table 2.4.** GCM projection range, perturbation method, and variability approach used in this study.

Location	Citation	Temperature	Precipitation (%)	Perturbation Method	Treatment of variability
New York City	Matonse et al. (2011, 2012)	2.2 to 3.4 (all models combined)	12.7 to 15.3% (all models combined)	Mean changes	Historical variability trace
Boston	Kirshen et al. (1995)	3.1 to 8.3	-7.6 to 23%	Mean changes	Historical variability trace
	Vogel et al. (1997)	3.1 to 8.3	-7.6 to 23%	Mean changes	Historical variability trace
	Lettenmaier et al. (1999)	1.2 to 5.9	-6 to 15%	Transient changes	Historical variability trace

as projected by 16 GCMs, will not result in substantial changes in annual reliability in the future. However, several earlier studies were difficult to compare to this study because they used alternative performance measures (i.e., measures other than reliability, vulnerability, and robustness) or other/unknown treatments of variability that were inconsistent with the systematic way that variability was treated here. For example, *Kirshen and Fennessey [1995]* and *Kirshen et al. [1995]* observed a range of potential climate change impacts on reservoir-system safe yield due to the scenarios of 4 GCM models. They found that future temperature increases of 3.67 and 4.9 degrees Celsius with precipitation decreases of 1.6 and 7.6% respectively, resulted in decreases in system yield, whereas temperature increases of 3.11 and 8.27 degrees Celsius with precipitation increases of 13 and 23% resulted in increases in system yield. Table 2.4 summarizes the range of projected temperature and precipitation changes from GCMs, the perturbation method, and treatment of variability used in previous climate impact studies of Northeast water supply.

While climate change and variability do not appear to be major threats to water supply in the Northeast, a combination of these climatic changes with demand growth may pose a problem in the future. Specifically, the Boston and Providence water supply systems perform well under current demands, but increases in demand (25% increase for Boston and 60% increase for Providence) may cause problems in the future if they coincide with 2+ degree Celsius increases in temperature and decreases in precipitation of approximately 20% (due to internal climate variability and climate change). By any measures this is an extreme scenario but provides an indication of the specific conditions that are problematic. This is demonstrated in Figure 2.3. While it



is difficult to predict what future water demands will be as more people move to urban areas from rural communities and temperatures increase over time, water utilities in this region have made great strides in system efficiency. Since the 1960s, many utilities have changed their overall management approach from increasing supply to meet demands to promoting water conservation and managing demand to fall within current supplies. The results in this analysis suggest that the improvements made by many of these systems over the last 50 to 100 years have increased their robustness to future climatic stressors.

The primary factors that seem to contribute to system vulnerabilities and poor system performance include system size and demand requirements. Springfield is the smallest of the five systems explored based on the current population, demand requirements, and reservoir storage availability, and had the greatest number of shortfalls under the more extreme climate change scenarios. Other larger systems explored in this study generally maintained high performance across climate change space. However, the New York City and Boston water supply systems, the two largest water supply systems in this study, suffered from significant storage drawdowns under extreme climate conditions despite their continued ability to meet demands (Figure 2.6). Large decreases in reservoir storage can cause water quality issues, which ultimately may require expensive treatment options. Thus, it is vital to consider reservoir storage levels in addition to performance metrics when assessing the vulnerabilities of water supply systems in this region.

Although many of these large systems have improved management practices, addressed infrastructure weaknesses, and lessened demand requirements since the 1960s drought, they have not yet been tested with another drought event of this severity. The combination of increased population, decreased precipitation due to internal atmospheric variability, and potential increases in temperature in the future may cause difficulties for the water supply systems in the Northeast. The results from this anal-

ysis, however, suggest that most of these utilities have improved over the last 50-100 years and have developed the necessary management and storage requirements to remain robust in the future.

There are some limitations associated with the reservoir operations models (i.e. an incomplete representation of the physical systems and unaccounted for water supply reserves) that are important to consider when analyzing the vulnerabilities to water supply in this region. For example, the systems models in this study do not consider direct reservoir evaporation, and with increased temperatures, this may contribute to water shortages in the future. For example, approximately 9% of the Quabbin Reservoir capacity evaporates each year based on historic temperatures. In addition, interbasin water transfers and backup water sources are not accounted for in this study, which could be tapped into under emergency drought conditions.

## **2.6 Conclusion**

The ability to reliably meet water supply demands in the future is of high priority for water utilities. In general, many of the water utilities in the northeastern United States are not concerned about their ability to meet water supply needs despite future uncertainty. Since the 1960s drought of record, utilities have operated their systems in an anomalously wet period of atmospheric variability and have successfully been able to improve system performance with strict conservation measures and infrastructure developments. This study confirmed the robustness of several of the large water supply systems in the Northeast, and in doing so, presented the most comprehensive analysis of the state of water supply in this region.

The stress test approach used to assess climate risks in this study enabled the exploration of system vulnerabilities to a wide range of potential future mean changes in climate, while simultaneously exploring the impacts of natural climate variability on system performance. The combination produced the most comprehensive assessment

of Northeast U.S. water supply to date and enables conclusions about these systems that are not affected by the uncertainty of climate change projections. In a region with a large concentration of highly populated cities with significant demands for water supply, this study also assessed the impacts of demand increases in the future. The combination of these system stressors is ultimately what will define water supply system performance in the future.

Lastly, the comparative vulnerability-based approach presented in this study uniquely addresses the state of water supply in the Northeast by quantifying the robustness of systems using the climate robustness index. The ability to quantify the robustness of systems helps identify relevant risks independent of any assumed likelihoods of future climate states occurring. Future studies of water supply systems in the Northeast can use this metric to investigate the robustness of alternative system adaptations if the current operational strategies are ever deemed inadequate.

## **2.7 Acknowledgments**

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## CHAPTER 3

# A WEB-BASED SCREENING MODEL FOR CLIMATE RISK TO WATER SUPPLY SYSTEMS IN THE NORTHEASTERN UNITED STATES

### 3.1 Abstract

The aim of this study is to describe the development and application of a web-based decision support tool (ViRTUE) for performing climate risk evaluations of water supply systems. The tool is designed for small-scale water utilities in the northeastern United States that may lack the resources for detailed climate change risk investigations. Development of this tool demonstrates a relatively new approach to web application development using the Shiny framework for the R programming language to create an interactive environment for stakeholders and water managers to explore climate vulnerabilities. Using a decision-scaling framework, the tool allows the user to perform a climate stress test to evaluate the performance and vulnerability to water supply shortfalls of local reservoir systems over a wide range of potential climate change scenarios using a generic systems model. Probabilities of future climate conditions derived from climate projections then help inform utility operators of impending risk.

### 3.2 Software availability

Product Title: Vulnerability and Risk Assessment Tool for Water Utilities (ViRTUE)

Developer: Sarah Whateley

Contact Address: Dept. of Civil and Environmental Engineering,

University of Massachusetts Amherst, 130 Natural  
Resources Rd. Amherst, MA 01003  
Contact Email: [swhatele@umass.edu](mailto:swhatele@umass.edu)  
Available Since: 2013  
Programming Language: R  
Availability: <https://virtue.shinyapps.io/myapp>  
Source Code: <https://github.com/swhatele/ViRTUE>  
Cost: Free

### 3.3 Introduction

Water resource managers and decision-makers are faced with many uncertainties when planning and managing water systems including changes in future population, per capita water demands, regulatory requirements, environmental standards, and climate, among others. These uncertainties impact both short-term operational decisions (e.g. water allocation) and long-term adaptation decisions (e.g. infrastructure investment). Despite the inherent uncertainty in future conditions, water planners must decide how to plan and manage their water systems with the resources available to them. This study addresses these issues through a pragmatic framework for rapid assessment of climate change vulnerability for water utilities. The framework is implemented in a novel web-based tool called Vulnerability and Risk Assessment Tool for Water Utilities (ViRTUE), which is designed for small-scale water utilities that may lack the financial or technical resources to perform more detailed climate change risk investigations.

Developing effective management strategies and adaptation actions that reduce risk to water resources requires an assessment of regional climate hazards on existing system infrastructure and operations [*Mastrandrea et al.*, 2010a]. Climate risk assessment of water resource systems is a process for identifying and evaluating vul-

nerabilities that may threaten existing infrastructure and system performance. The process often involves a series of climate/weather models, rainfall-runoff models, and systems models to evaluate the impacts of climate change and variability on system functioning. Yet, this process can be time and resource intensive, especially for smaller utilities that often lack the ability to conduct a full vulnerability analysis.

In general, the water resources literature focuses primarily on large systems, with relatively few applications for small-scale systems. Climate change studies are typically performed for large water resource systems that are capable of investing the time and resources necessary for such analyses [*Horton et al.*, 2011; *Kirshen et al.*, 2008; *Lettenmaier et al.*, 1999]. However, small water utilities may be most susceptible to climate change but do not have the means to assess system performance under future uncertainty. While potentially less equipped to perform computationally-intensive climate analyses, small systems may have more flexibility, less institutional complexity, and greater adaptive capacity to cope with climate change than larger systems [*Hamlet*, 2011]. The development of an easily accessible (i.e. web-based) climate vulnerability tool, designed for rapid assessment of climate risks to water resources systems, would encourage smaller utilities to identify and prepare for potential vulnerabilities in the future.

The need for screening-level, computer-based models and tools to integrate knowledge and provide support in decision-making and management is supported by the scientific literature [*Anderson et al.*, 2004; *Borowski and Hare*, 2006; *Chapra*, 1991; *Welp*, 2001]. However, few software packages exist that are inexpensive, simple to use, and provide these services to small water utilities. One exception is the U.S. Environmental Protection Agency's (USEPA) Climate Resilience Evaluation and Awareness Tool (CREAT) designed to help the water sector assess regional and local climate-change impacts. This desktop-based tool leads utilities through a self-directed exploration of potential climate change related risks and adaptation options [*Travers*, 2010]. In con-

trast, a simple, web-based tool for assessing climate vulnerabilities of water systems may provide advantages such as ease of use, accessibility, collaboration, instant modifications, and wide availability [Byrne *et al.*, 2010]. A web-based screening-level tool would also help narrow the persistent gap between knowledge production and tool use by removing software dependencies, simplifying scenario testing, and providing a user-friendly interface [Lemos *et al.*, 2012]. Finally, this tool is designed to employ the decision-scaling methodology [Brown, 2010; Brown *et al.*, 2011, 2012; Whateley *et al.*, 2014], a vulnerability-led alternative to the GCM projection-led assessment process employed in CREAT.

Recent advances in web standards, browser performance, and free and open-source software (FOSS) present a promising new avenue for developing web-based tools that are more user-friendly and accessible than traditional desktop software [Swain *et al.*, 2015]. These advances in web technologies have transformed the implementation, design, and deployment of decision support systems (DSS) [Bhargava *et al.*, 2007; Booth *et al.*, 2011; Sun, 2013]. Decision support systems provide users with computer-based tools (i.e. models and data processing capabilities) that help support complex decision-making and encourage interactive problem solving [Salewicz and Nakayama, 2004]. In the last decade, web-based approaches to DSS software have increased the accessibility of decision-making tools to individuals without extensive modeling experience.

The use of web applications for environmental modeling is becoming more common in the literature [Goodall *et al.*, 2011; Walker and Chapra, 2014a]. For example, [Walker and Chapra, 2014a] developed an interactive web application, WIRM, with a rapid screening model for investigating potential water quality impairments due to biochemical oxygen demand (BOD) discharges. The WIRM tool gives users the ability to interactively adjust parameters for rapid evaluation and visualization of the relationships between parameter values and model output. As another ex-

ample, [Goodall *et al.*, 2011] present an application for a service-oriented computing (i.e. where software systems are interconnected to allow for community and multidisciplinary modeling) for modeling water resource systems using web services. Specifically, their study seeks to develop standards and procedures for data gathering, processing, and visualization of hydrologic simulation models on the web with the objective of more robust and effective implementation design. Yet, many modern web technologies such as these require prior knowledge of and experience with standard web languages (HTML, JavaScript, and CSS), making the web development process inaccessible to many researchers and practitioners.

In more recent years, the development of new web frameworks offers an opportunity to create web applications directly from common scientific languages such as R and Python. This further increases the accessibility of scientific research and modeling tools because researchers can create web applications based on programming languages they are already familiar with, and without needing to become experts in web development. This paper presents a web-based tool developed using the Shiny web application framework [RStudio, Inc., 2014] for the R statistical computing language [Team, 2014]. Shiny allows users with no web development skills to create interactive and fully-featured web applications written entirely in the R language. Using Shiny, the application developer can write both the front-end (i.e. client-side) user interface and the back-end (i.e. server-side) computational engine using familiar R functions and syntax. Shiny automatically converts the user interface code into standard web languages (HTML, CSS, and JavaScript) that can be run in any modern web browser. Shiny also handles client-server communications for passing application inputs and outputs between the user and the server, facilitating rapid development of interactive user interfaces.

Recently, publications of Shiny web applications have appeared in a wide range of scientific fields, including a web-based mapping application for precision agricul-



ture [Jahanshiri and Shariff, 2014], the development of a data exploration tool for microbial communities [Beck *et al.*, 2014], an interactive web application to assist in knowledge elicitation about water requirements of floodplain and wetland vegetation [Guillaume and Fu, 2013], and a web server for predicting transcriptional regulatory modules [Liu and Miranda-Saavedra, 2014]. The role of Shiny in all of these applications is to take complex scientific concepts and present them through an intuitive and user-friendly graphical interface. The Shiny web application framework thus offers a promising new method for developing decision support applications in the water resources community. In particular, the server side framework, which offers reactive expressions that automatically regenerate output data and figures when changes are made to the input [Wan and Hudak, 2000], allows developers to create interactive web applications that are well suited for self-directed climate risk assessment of water resource systems.

To the authors' knowledge, there are no web-based tools designed for exploring water supply system performance under climate change. This study addresses this gap by presenting a web-based tool that uses a vulnerability-based framework to rapidly assess climate change and other impacts on small water supply utilities (i.e. serving populations of 250,000 or less). This tool also demonstrates a new approach for enabling researchers and practitioners to create web-based modeling software that can be programmed entirely within the R programming language. Section 2 introduces traditional methods of assessing climate impacts on water supply systems and describes the vulnerability-based framework used in ViRTUE to allow water utilities to interactively evaluate risks to their systems. Section 3 describes the development approach, model theory, and workflow used in ViRTUE. Section 4 illustrates an application of the tool in a case study of a water supply system in the northeastern United States and compares the vulnerabilities identified using ViRTUE with output from an independent simulation model of the case study system. Section 5 describes

outreach and feedback on the application and utility of the tool for small-scale water supply systems in the northeastern United States. Sections 6 and 7 end the paper with a discussion and conclusion of the tool’s contributions to the water resource and environmental modeling communities.

## **3.4 Climate Risk Assessment Methodologies**

### **3.4.1 Scenario-Based Climate Risk Assessment**

Traditionally, water supply impact studies evaluate system performance by combining downscaled Coupled Ocean-Atmosphere Global Climate Models (OA/GCM) with rainfall-runoff models and reservoir operations models to predict future climate risk [Rajagopalan *et al.*, 2009b; Wiley and Palmer, 2008; Wilby and Dessai, 2010]. These top-down or scenario-based approaches use projected climate change scenarios to evaluate system performance.

Top-down approaches undertaken for the purposes of making adaptation or operational decisions tend to propagate significant errors, generating large uncertainty ranges in climate impacts and system risk [Dessai, 2009]. For example, the inherent uncertainty in GCM projections related to initial condition ensembles [Deser *et al.*, 2012], climate forcings [Stainforth *et al.*, 2005], and model inadequacies due to poorly understood climate physics and computational complexity [New and Hulme, 2000] make it difficult to incorporate information from these scenarios into adaptation decisions [Stainforth *et al.*, 2007b].

Given these concerns, alternative methods of climate risk assessment have emerged that build from the concepts of decision theory and scenario planning. Rather than suggest a single, best-guess future, these methods attempt to incorporate the concept of robustness into water resources planning and design, selecting strategies that perform well across a range of generated scenarios [Lempert and Collins, 2007; Ray *et al.*, 2013; Watkins Jr and McKinney, 1997]. These methods include Info-Gap Decision

Theory [*Ben-Haim, 2001*], Robust Decision Making (RDM) [*Lempert et al., 2006; Lempert and Groves, 2010*], Robust Optimization [*Ray et al., 2013; Watkins Jr and McKinney, 1997*], Real Option analysis [*Wang et al., 2006*], Decision-Scaling [*Brown, 2010*], and the scenario-neutral approach [*Prudhomme et al., 2010*]. Such ‘bottom-up’ approaches are designed to identify system vulnerabilities over a range of plausible future conditions to aid in selecting robust adaptation strategies.

### **3.4.2 Decision-Scaling: A Vulnerability-Based Framework**

Decision-scaling is a bottom-up methodological framework which inverts GCM-led approaches to climate risk assessment by evaluating system performance over a range of climate futures independent of any assumed probabilities [*Brown et al., 2011*]. Rather than evaluate vulnerabilities among a small set of future climate projections as generated by the GCMs, the decision-scaling method involves systematically exploring a virtually unlimited number of future scenarios to reveal system vulnerabilities by using a stochastic weather generator. The process is generally referred to as a climate stress test [*Brown and Wilby, 2012*]. Multiple sources of climate information (i.e. GCM projections, paleoclimate reconstructions, and subjective climate information) can be used to evaluate risks associated with the vulnerabilities identified [*Brown, 2010; Brown et al., 2011*]. This methodology uses a decision analysis framework to characterize the future climate so that climate scenarios are derived from the decision at hand. Similar to other robustness-based approaches, decision-scaling defines robust adaptation strategies as those that perform acceptably over a range of future uncertainty [*Steinschneider et al., 2014b; Whateley et al., 2014; Moody and Brown, 2013*].

In this study, the decision-scaling framework is embedded in a web-based tool designed for water utilities in the northeastern United States. In recognition of limitations in projecting the future climate, the tool uses decision-scaling to tailor the

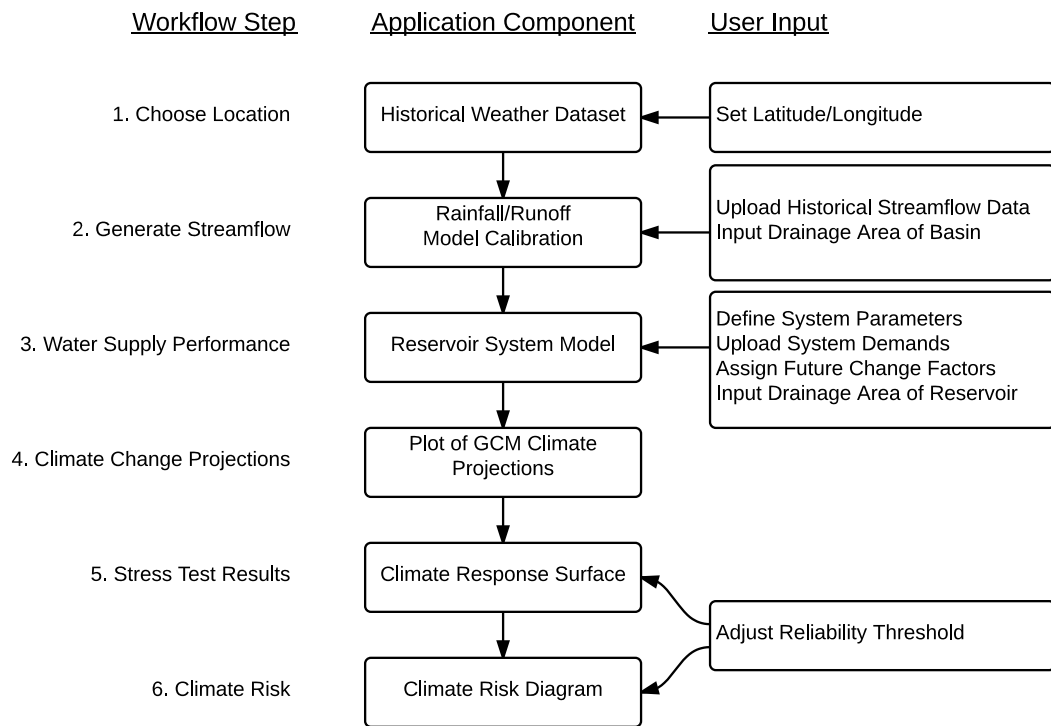
analysis to focus on the future climate states that pose the greatest threat to system performance and estimates probabilities associated with those decision-relevant climate states [Brown and Wilby, 2012]. This reduces the computational time and resources necessary for analysis, and permits rapid identification of vulnerabilities to climate change. It is particularly well suited for small utilities, which comprise small spatial areas and thus are not well served by coarse resolution GCM projections.

### **3.5 ViRTUE: Vulnerability and Risk Assessment Tool For Water Utilities**

The Vulnerability and Risk Assessment Tool for Water Utilities (ViRTUE) is a web application for assessing risks to small-scale water supply systems in the northeastern United States (available at <https://virtue.shinyapps.io/myapp>). While ViRTUE is currently designed for the Northeast U.S. in terms of data availability and vetted hydrologic models, in principle it is fully generalizable to other regions. The tool provides a mechanism to understand and explore individual water utilities climate risk exposure using a stress test, in which the performance of local reservoir systems is tested over a wide range of potential climate and socioeconomic changes. The components and workflow of the application are illustrated in Figure 3.1. This section will describe the development approach, model theory, and interface/workflow of ViRTUE.

#### **3.5.1 Development Approach**

ViRTUE was developed using the Shiny web application framework for the R programming language. R is a free and open source statistical programming language that is becoming increasingly popular among environmental modelers and scientists [Muenchen, 2013]. Traditionally, converting a simulation model or statistical analysis to a web application required substantial knowledge of standard web lan-



**Figure 3.1.** Schematic diagram of the components and workflow of the ViRTUE application to assess climate risks to water supply systems.

guages (HTML, CSS, and JavaScript) in order to construct the user interface. This requirement presents a challenge for scientists and engineers who are not familiar with modern web languages or development practices. The Shiny web development package provides a powerful framework allowing researchers to write web applications using only R functions and syntax. Because Shiny converts the R source code into HTML/JS/CSS automatically, the developer can create an entire interactive web application in R (see Interactive Web Apps with shiny Cheat Sheet for a template of the software architecture<sup>1</sup>). Although knowledge of HTML, CSS, and JavaScript is not required, Shiny also provides the flexibility to incorporate these languages to create more advanced and innovative web features. For example, ViRTUE incorporates an open-source JavaScript library for interactive maps, called leaflet<sup>2</sup>, which enables the user to click on a map to define the location of their reservoir system.

### 3.5.2 Model Theory

The stress test approach used in ViRTUE begins with the generation of monthly time series of precipitation and temperature using a stochastic weather generator. The weather generator is a stochastic model for generating synthetic time series of climate variables. It allows exploration of user defined climate changes, including changes in means and variability that are plausible yet not sampled by GCM projections [*Steinschneider and Brown, 2013; Stainforth et al., 2007b*]. While the use of climate change projections can reveal vulnerabilities to the projections that happen to be used, this approach reveals vulnerabilities to specific climate changes.

The monthly weather generator in ViRTUE couples a wavelet decomposition with an autoregressive model of annual precipitation to account for low frequency climate oscillations in the Northeast [*Steinschneider and Brown, 2013*]. A k-nearest neighbor

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<sup>1</sup><http://shiny.rstudio.com/images/shiny-cheatsheet.pdf>

<sup>2</sup><http://leafletjs.com>, accessed December 15, 2014

resampling approach is then used to disaggregate the stochastically generated annual precipitation time series to a monthly time step, preserving the covariance structure between weather variables. The weather generator is trained using historical data from a gridded observed meteorological dataset covering 1949-2010 (over a 1/8 degree grid cell space) [Maurer *et al.*, 2002]. Multiple climate realizations (i.e. fifty time series of monthly precipitation and temperature) are generated to account for internal climate variability (i.e. the natural fluctuations in the climate system that arise in the absence of external forcings).

Linear trends in temperature and precipitation are applied to each variability realization to simulate transient climate change. This approach allows plausible climate change space to be effectively and exhaustively explored. Currently the changes in climate that can be explored in the tool are limited to percent changes in mean annual precipitation and absolute changes in mean annual temperature from historic values for the region of interest (i.e. the latitude and longitude coordinates of the water supply reservoir). Exploration of variability changes are also possible but have not been incorporated yet.

The monthly weather variable time series, adjusted to represent climate changes, are then used as input to a lumped-parameter hydrologic model to estimate monthly streamflow. This hydrologic model is adapted from the ‘abcd’ model developed by [Thomas, 1981a]. The original ‘abcd’ model was modified to account for the influence of snow accumulation and melt on hydrologic processes in the northeastern United States, which introduces a fifth parameter (e) and is commonly referred to as the ‘abcde’ model [Steinschneider *et al.*, 2012; Martinez and Gupta, 2010]. The abcde model is calibrated to historic streamflows within ViRTUE using the shuffled complex evolutionary algorithm (SCE), a probabilistic global optimization method designed for parameter estimation in conceptual rainfall-runoff models [Thyer *et al.*, 1999; Duan *et al.*, 1992]. This model was chosen for use in ViRTUE because of its parsimonious

nature (i.e. few parameters) and geographic and hydrologic compatibility in the Northeast.

The output of the hydrologic model is then used as input for a simple, reservoir systems model that follows ‘standard’ operating policies (i.e. meet a release target if sufficient water is available, otherwise release all available water in the current time step) so that it is generalizable to any system [Loucks *et al.*, 2005]. The reservoir model is designed for the analysis of a single reservoir system, however, multiple reservoirs can be lumped together for a crude assessment of total system risk. In practice, standard operating policies are used primarily for planning purposes. Alternatively, the user can select a hedging option that imposes pre-specified operating policies that reduce releases in times of drought (i.e. when reservoir levels drop below drought severity thresholds) to explore system performance under operational practice. Most operators adopt hedging policies to save water in the reservoir for future releases in case there is an extended period of low inflows [Loucks *et al.*, 2005]. In ViRTUE, hedging policies are adapted from the Springfield Water and Sewer Commission’s (SWSC) drought severity index curves, which are typical of small systems [Camp Dresser and McKee, 2005; Westphal *et al.*, 2007].

### **3.5.3 Tool Workflow**

The decision-scaling framework embedded in ViRTUE leads a user through a self-guided, six-step process arranged as a series of tabbed panels on the user interface. In the first three steps of the process, the user performs a climate stress test of their system to identify vulnerabilities based on a wide range of potential climate change scenarios (as described above). After performing the stress test, the user is presented with additional information regarding the probabilities of these scenarios based on GCM output in order to assess the risk of not meeting water supply demands. Note that these GCM projections are best viewed as subjective probabilities of future



climate change. Ultimately they categorize the climate change projections in terms of whether they indicate problems for the utility or not. A more formal approach for developing climate change probabilities is in development, although they will necessarily remain subjective probabilities [Steinschneider et al., 2015a].

ViRTUE is designed to be used by stakeholders and water managers without the need for external support from scientists or engineers by providing guiding instructions through each step of the analysis. In addition, users can download the results of each step in the analysis and save key figures for their records and for use in climate reports. The following sub-sections describe each of the six steps of the analysis in detail.

### **Step 1: Choose Location**

In the first step of ViRTUE, the user specifies the location of their reservoir system by clicking on an interactive map. The location information (i.e. latitude/longitude) is used to retrieve historical climate data for that location to create synthetic future climate time series using the weather generator described in Section 3.2. Climate changes are imposed on one of the stochastically generated weather realizations, chosen at random from the fifty total realizations created. As a result, for each iteration of the tool a slightly different result will emerge based on the randomly selected weather realization chosen for that analysis. After all climate change scenarios are created, time series of historic monthly precipitation (mm) and temperature (degrees C) from 1949 to 2010 are presented to the user.

### **Step 2: Generate Streamflow**

In the second step, the user provides historical flow data to calibrate the rainfall-runoff model described in Section 3.2. The historical flow data can be provided as either direct inflows to the reservoir or measured streamflow from a nearby monitoring gage. If flows are taken from a nearby gage station ( $Q_{gaged_t}$ ), the tool uses

a simple drainage area ratio method to scale the volume of water coming into the system [Archfield and Vogel, 2010].

$$Q_{ungaged_t} = \frac{A_u}{A_g} Q_{gaged_t} \quad (3.1)$$

where  $Q_{gaged_t}$  are historic flows at a nearby gage,  $A_u$  is the drainage area of the ungaged site,  $A_g$  is the drainage area of the gaged site (required as input in Tab 2), and  $Q_{ungaged_t}$  are the ungaged flows into the reservoir. The ability to estimate streamflow at an ungaged site ( $Q_{ungaged_t}$ ) is particularly important for small reservoir systems that have short or no historic inflow records.

When the historical flow data are uploaded, the application uses the historical climate data retrieved in step 1 to calibrate the rainfall-runoff model using the SCE algorithm as described in Section 3.2. After this model is calibrated, the user interface displays hydrographs and flow duration curves of the historical and simulated flows for evaluating the calibration. The goodness-of-fit of the model calibration is indicated by the Nash-Sutcliffe efficiency (NSE) coefficient [Nash and Sutcliffe, 1970]. For users unfamiliar with this metric, instructions on how to interpret its value are provided by clicking on the plot.

### **Step 3: Water Supply Performance**

In step 3, the calibrated rainfall-runoff model is coupled to the reservoir systems model described in Section 3.2. The user provides a series of inputs including reservoir capacity, drainage area of the reservoir ( $A_u$ ), daily water supply demands, and the threshold for system reliability (i.e. 95%). The reliability threshold defines what is considered acceptable performance in terms of reliability (i.e. the acceptable number of shortfall months over the period of record) for the system [Hashimoto *et al.*, 1982].

$$R = 1 - \frac{\sum_{t=1}^T Sh(t)}{T} \quad (3.2)$$

where  $R$  is the difference between unity and the ratio of the total number of shortage months that occur and the total number of months in the record ( $T$ ). The shortfall function,  $Sh(t)$ , is a binary variable that is set to one if releases are less than the water supply demand for month  $t$ , and zero otherwise.

After the inputs are specified, the application uses the climate-altered flow realizations generated from the calibrated rainfall-runoff model as input into the generic systems model to simulate system performance. The results are presented as a series of plots including annual reservoir storages as a percent of capacity, monthly storages for a particular month of choice (e.g. April storages from 2014-2075), average monthly inflows into the reservoir, and overall water supply reliability ( $R$ ).

In addition to evaluating system performance based on historical climate conditions, the user can also interactively explore the impact of incremental changes in climate and other variables on system performance using slider bars on the user interface. Adjustments that can be made include changes in mean annual temperature (0 to 5 degree C at 0.5 degree intervals), changes in mean annual precipitation (75 to 125% of the historic mean at 5% intervals), changes in mean annual demand (0 to 200% of the historic mean at 5% intervals), additional storage capacity (0 to 200% at 10% intervals), and additional minimum flow (0 to 300 MGM at 5 MGM intervals). Although most of this paper focuses on climate risks to water systems, the allocation of limited water supplies to meet both human and ecological needs remains a challenge for small utilities. As such, the capability to explore changes in population (demand) and regulatory policies (minimum flow requirements) is included in ViRTUE.

Lastly, there are two simple system alternatives that can be explored. The first alternative is increasing reservoir size by adjusting an additional storage capacity option. This alternative approach requires significant capital investment. The second

alternative strategy is to alter operating policies, which requires much less investment by a utility. Clicking the 'Hedge' checkbox of ViRTUE imposes restrictions on water supply releases during droughts (see section 3.2) beyond what the standard operating rules would predict. Implementing release rules provides a more realistic depiction of system performance since 'standard' operating policies are not often followed in practice.

#### **Step 4: Climate Change Projections**

In step 4, ViRTUE provides information about the distributions of changes in mean precipitation (%) and mean temperature (Celsius) based on an ensemble of GCM projections (RCP emission scenario 4.5) from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project Phase 5 (CMIP5) multi-model dataset. Gridded simulated data was downscaled to a monthly temporal resolution and 0.125 degree spatial resolution based on the bias-correction spatial disaggregation (BCSD) statistical downscaling method [*Reclamation*, 2013]. This tab allows users to visualize the range of climate changes (centered around 2050) projected for the region where their reservoir system is located. The GCM output is specific to the location of the user's system as specified in step 1. The GCM projections allow utilities to better assess the likelihood of climate risks identified through the stress test. The projected changes are displayed as a histogram reflecting the range and frequency of the climate changes represented by the ensemble of climate change projections. The purpose of this step is to illustrate the kinds of climate changes that a representative set of projections indicates for their location.

#### **Step 5: Stress Test Results**

In step 5, an overview of the results from the climate risk assessment is presented to the user. This overview is shown as a climate response surface of water supply reliability. A climate response surface is a representation of system performance (i.e.

contours of system reliability) across climate change space (e.g. changes in annual mean temperature and precipitation). In this display the climate response surface is divided into regions of ‘acceptable’ and ‘unacceptable’ system performance according to a user-specified reliability threshold level. The climate change space encompasses the full range of mean changes in precipitation and temperature that can be explored in step 3.

The user can adjust the reliability threshold, which changes the areas defined as acceptable and unacceptable. Additionally, GCM projections are superimposed on the climate response surface to illustrate the distribution and range of the projections relative to the impacts (in terms of reliability) that such changes would have. In this way the projections are put into the context of their implications for the system. However, rather than simply learning whether projections indicate risks or not, this visualization allows the user to determine which climate changes cause hazards, whether those changes are sampled by the projections or not. For instance, if a water utility only has trouble meeting demands when mean precipitation decreases and the GCM projections show only increases in mean precipitation in the future, they may conclude that their system is at low risk of failure.

### **Step 6: Climate Risk**

In the final step, the overall risk in terms of acceptable/unacceptable system performance is presented. Here risk is defined as the fraction of projections that fall below the reliability threshold level. The results are shown in the form of a bar chart with one bar illustrating the fraction of GCM projections that fall above the threshold of reliability (acceptable) and the other bar showing the fraction of GCM projections that fall below the threshold of reliability (unacceptable).

## 3.6 Case Study: Springfield Water and Sewer Commission

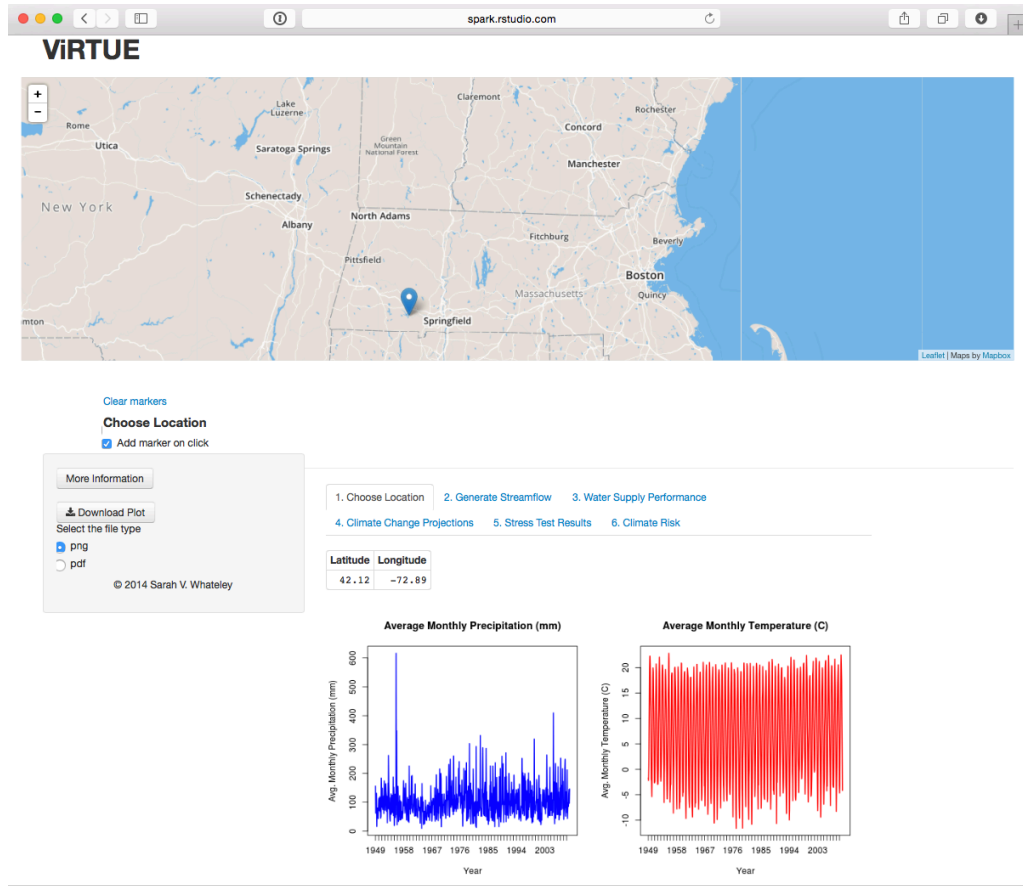
To demonstrate an application of ViRTUE, we present a case study using the Springfield Water and Sewer Commission’s (SWSC) water supply system. The reservoir system, located in the Westfield River Basin in Central Massachusetts, consists of three major reservoirs: Cobble Mountain Reservoir (total storage at max elevation is 22,829 MG), Borden Brook Reservoir (2,500 MG), and Littleville Reservoir (10,560 MG). The SWSC serves a population of approximately 250,000 people in Massachusetts, including the municipalities of Agawam, East Longmeadow, Ludlow, Westfield, and Springfield. For the purposes of this analysis, Cobble Mountain Reservoir was treated as the system’s major storage reservoir, with inflows from surface runoff, direct precipitation, and the Borden Brook Reservoir located upstream. The Borden Brook Reservoir was excluded from the analysis because it has minimal active operation and primarily functions as a run-of-river facility.

### 3.6.1 Model Application

Figure 3.2 shows a screen shot of ViRTUE after the first step of analysis is complete. In this case, the marker is placed at the base of the Cobble Mountain Reservoir and time series of historical average monthly precipitation (mm) and temperature (Celsius) from 1949-2010 are generated and displayed on the user interface.

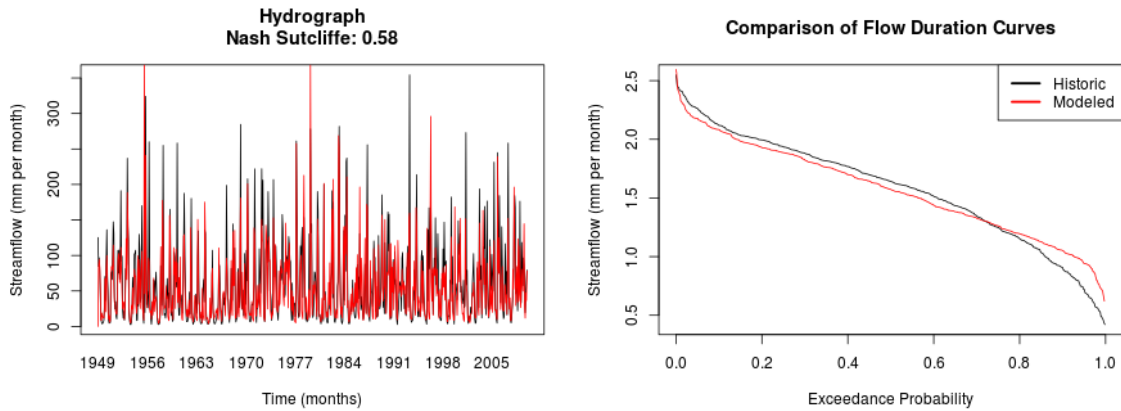
Figure 3.3 illustrates output from the second step of ViRTUE, in which the abcde model is calibrated to historic flows at the West Branch Westfield River station at Huntington, MA (USGS 01181000). Since flows in this case are taken from a nearby gage station ( $Q_{gaged_t}$ ), the tool uses the drainage area ratio method described earlier. Calibration of the model in this case yielded a Nash-Sutcliffe efficiency of 0.58, which is acceptable for a water supply system with no flood risk concerns.

Figure 3.4 shows a screen shot of performance results generated from the tool’s systems model under base case conditions (i.e. no change in mean climate or de-



**Figure 3.2.** Screen shot of the ‘Choose Location’ tab of ViRTUE. Climate altered time series of monthly precipitation and monthly temperature are generated in this step by clicking on the map near the reservoir system of interest. Time series of historic average monthly precipitation (left) and temperature (right) appear on the user interface.

## Calibrated Model Performance

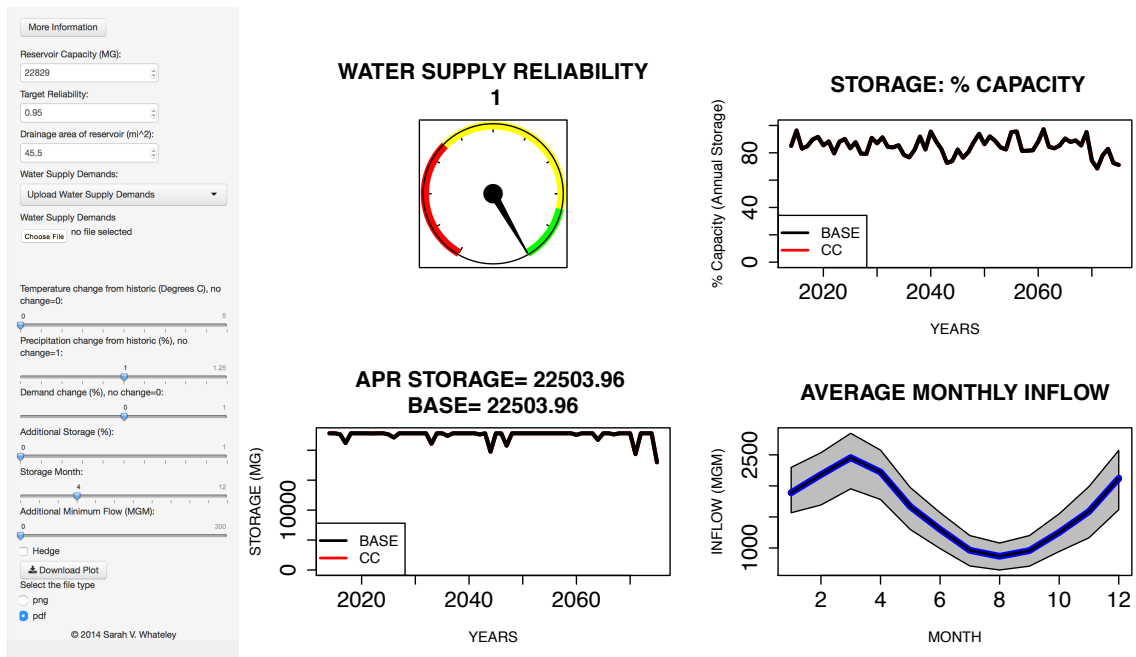


**Figure 3.3.** A hydrograph (left) and flow duration curve (right) produced in the ‘Generate streamflow’ tab of ViRTUE. The black lines illustrate historic flows and the red lines illustrate modeled flows. The Nash-Sutcliffe efficiency value of 0.58 quantifies the performance of the abcde hydrologic model calibration.

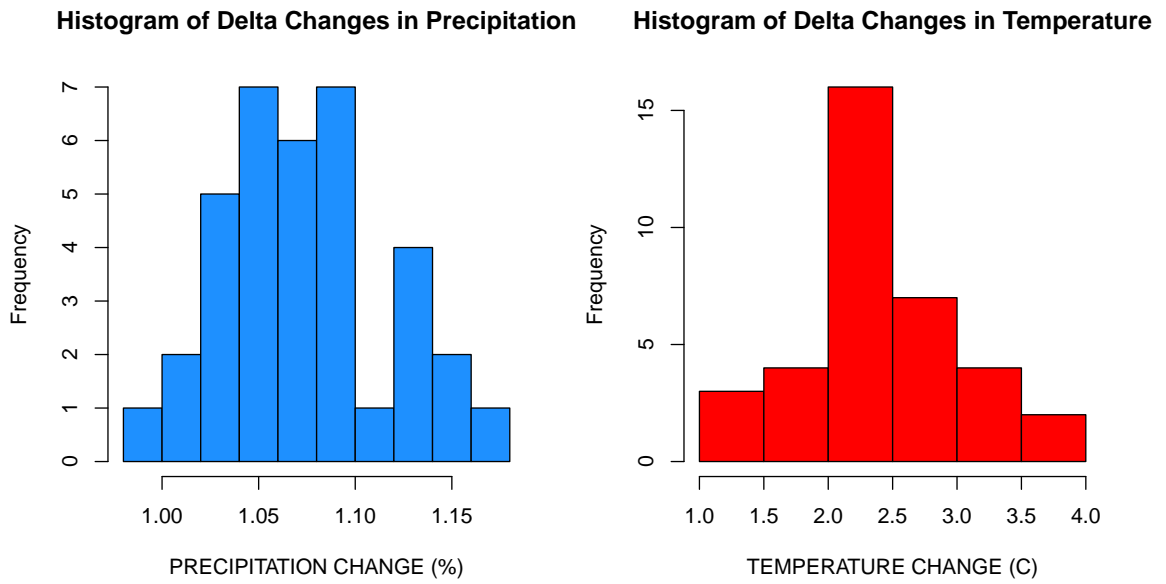
mands). Under base case conditions the water supply reliability over the period of record is 100% (top left plot in Figure 3.4). In addition, the storage as a percent of capacity fluctuates between 80% and 100% (top right), and the April storage remains near capacity for all future years (bottom left). The hydrograph (bottom right) peaks in April for both the base case flows (blue line) and all climate altered flows (grey polygon), which is expected in a region where the wintertime snowpack persists into the late spring. In addition, flows are the lowest in the hot summer months.

Figure 3.5 illustrates the distributions of changes in mean precipitation (%) and mean temperature (Celsius) based on an ensemble of GCM projections from the WCRP’s CMIP5 multi-model dataset. The GCM projections suggest mean temperature increases of 2.4 degrees Celsius and mean precipitation increases of 7.5% by the year 2050.





**Figure 3.4.** System diagnostics of ViRTUE: Period of record water supply reliability (top left), reservoir storage as a percent of capacity (top right), annual storage for a particular month (bottom left), and monthly inflows into the system (bottom right). The left panel illustrates climatic and socioeconomic changes (slider bars) that can be explored to test system performance. Storage capacity, drainage area of the reservoir, a target reliability, and daily water supply demands are the inputs required.



**Figure 3.5.** Distribution of changes in mean precipitation (%) and mean temperature (Celsius) based on an ensemble of GCM projections (RCP emission scenario 4.5 from the World Climate Research Programme’s (WCRP’s) Coupled Model Intercomparison Project Phase 5 (CMIP5) multi-model dataset

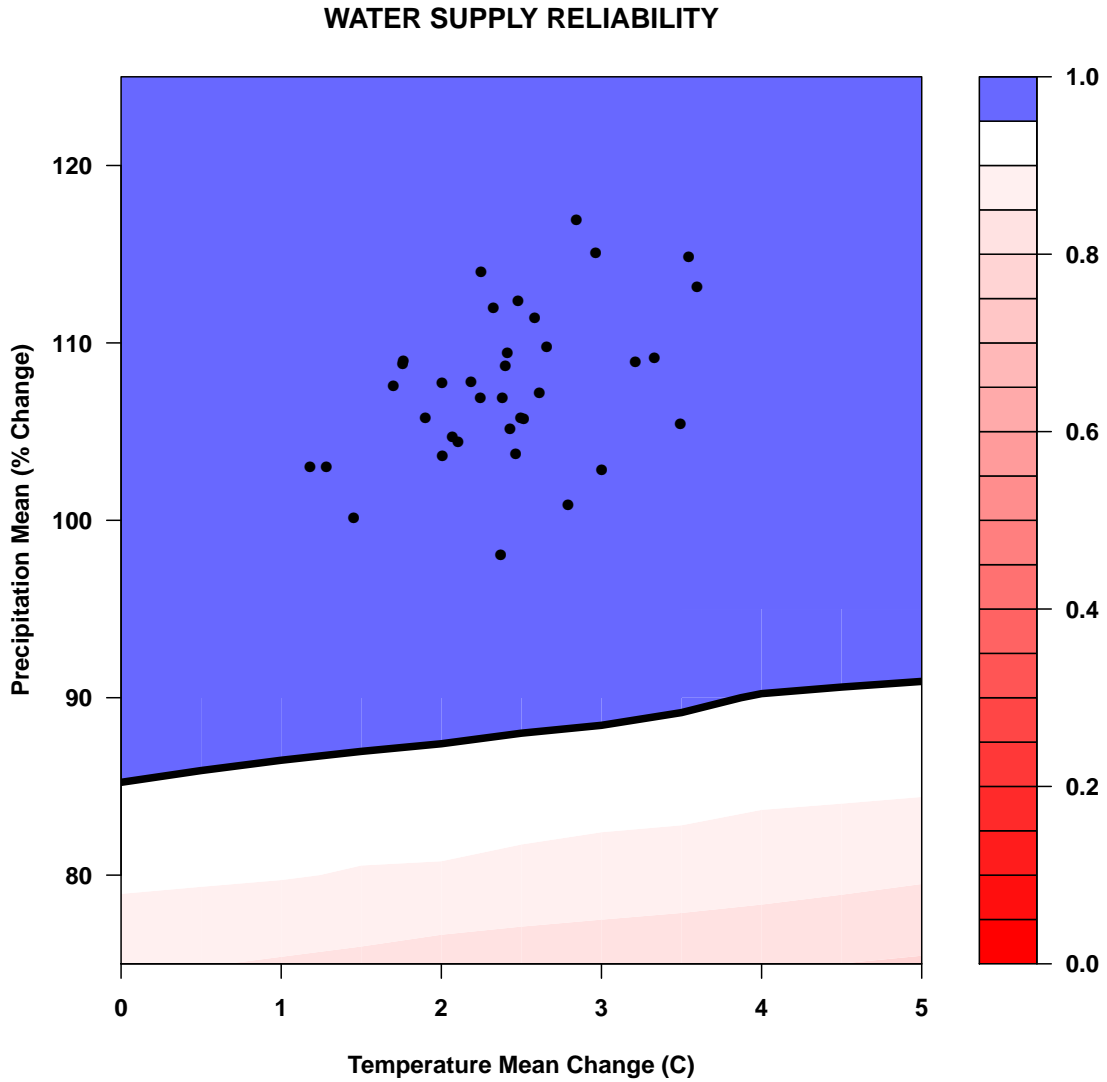
The climate response surface of water supply reliability for the Springfield water supply system is illustrated in Figure 3.6. Regions in blue are considered ‘acceptable’ system performance according to a user-specified reliability threshold level (i.e. the black contour line represents a water supply reliability of 95%). Regions in red are considered ‘unacceptable’ system performance. Additionally, the ensemble of GCM projections are plotted as black points on the climate surface. An analysis done strictly with GCM projections would suggest Springfield’s system will perform acceptably in the future. However, if projections are wrong and mean precipitation decreases (by approximately 15%), water supply reliability would drop below the 95% threshold.

Results from Figure 3.7 illustrate that 100% of the GCM projections in Figure 3.6 fall above the reliability threshold. Therefore, the Springfield system performs adequately across all future climate projections and the fraction of climate projections that suggest acceptable performance is 1 (fraction of climate projections that suggest unacceptable performance is 0).

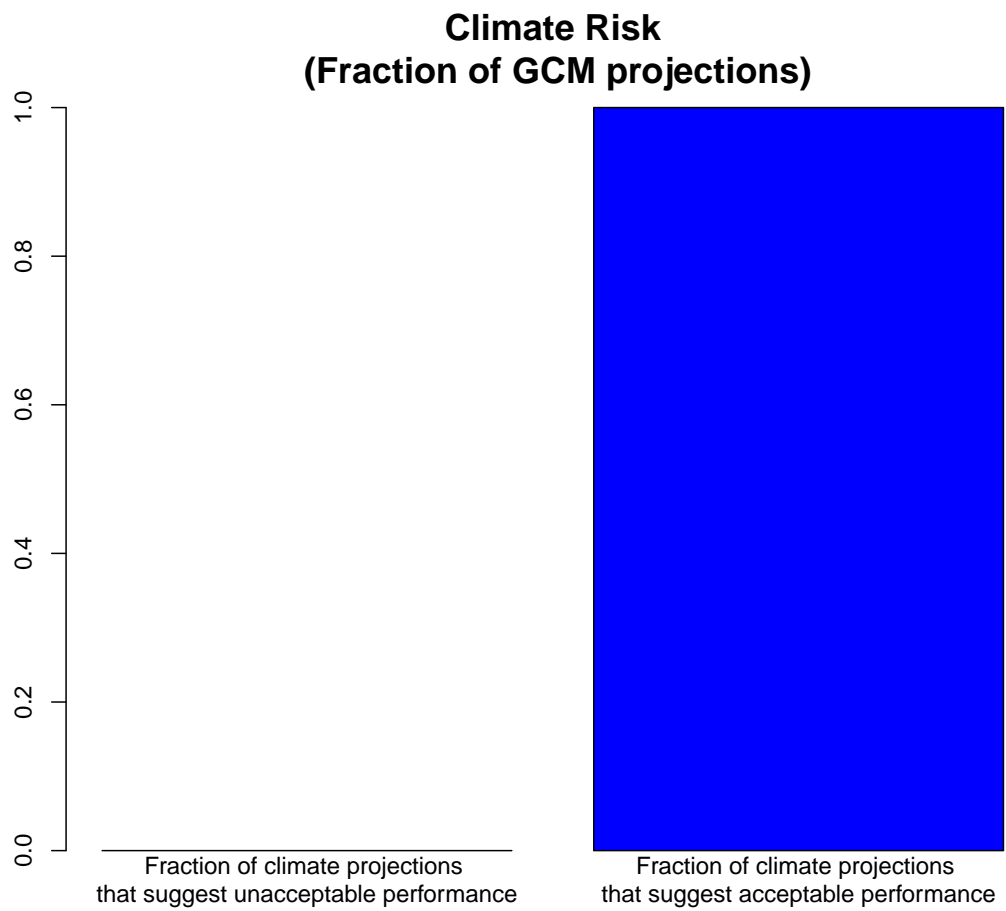
### 3.6.2 Validation

A comparison of the generic system simulator embedded in ViRTUE with a more detailed simulation model of Springfield’s reservoir operating policies (outside of the tool) was conducted.

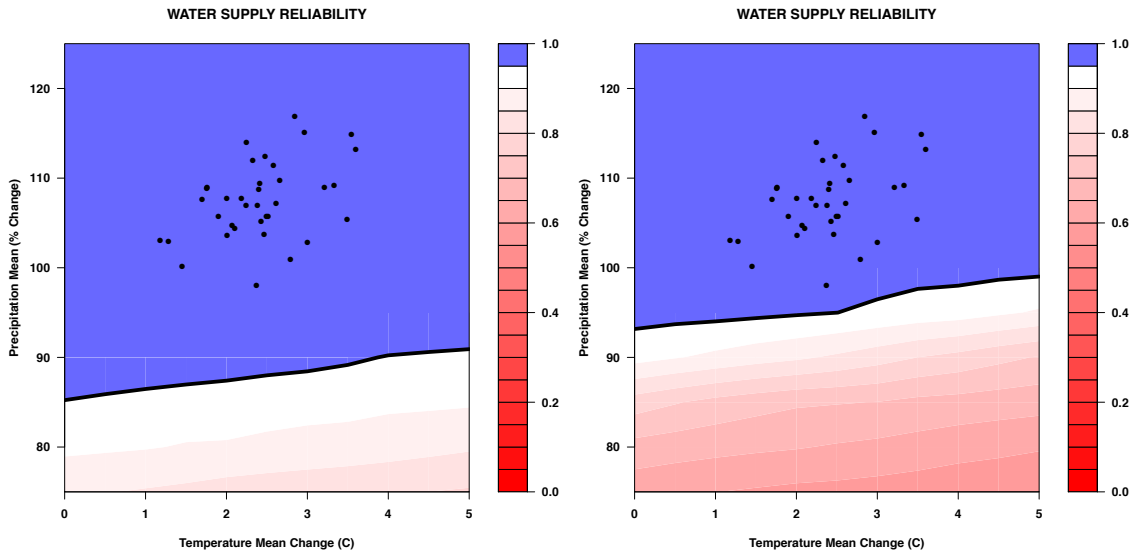
Figure 3.8 compares the climate response surfaces of reliability using output from ViRTUE (left) and a reservoir model of Springfield’s water supply system (right). The Springfield simulation model that incorporates more realistic reservoir-operating policies exhibits modest differences with the ViRTUE results. For example, the system specific model yields unacceptable system performance when mean precipitation is reduced by  $\sim 6\%$  whereas the ViRTUE simulator reports vulnerability beginning at



**Figure 3.6.** Climate response surface of water supply reliability for the Springfield water supply system. Regions in blue are considered ‘acceptable’ system performance according to a user-specified reliability threshold level. Regions in red are considered ‘unacceptable’ system performance. Additionally, an ensemble of GCM projections are plotted as points on the climate surface.



**Figure 3.7.** Fraction of climate projections that suggest acceptable/unacceptable system performance



**Figure 3.8.** Climate response surface for Springfield’s water supply reliability using ViRTUE’s system simulator (left) and a systems model that accounts for Springfield’s reservoir rule curves (right)

a reduction of  $\sim 15\%$ . However, the results are generally consistent and provide the same message regarding climate risk to this system.

Output from the system simulator was also compared with historical data to assess the tool’s ability to capture known risks from the past. For example, during the period between 1964 and 1967, the northeast United States experienced a severe drought and the Cobble Mountain Reservoir dropped down to approximately 30% of capacity. This was the most severe drawdown on record. During this period of time, there was a 20-25% drop in total precipitation for a few years. Validation results demonstrated the tool’s ability to reproduce the Cobble Mountain Reservoir’s drop in storage during this period of time (i.e., reservoir storage dropped to 25% of capacity between 1965 and 1966).

### 3.7 User Feedback

In addition to evaluating the tool by comparing its performance with output from a simulation model specific to the system, the application and utility of the web-based tool to water supply systems in the Northeast was assessed through interviews with water managers and stakeholders. Development of the tool has involved significant outreach efforts throughout the Northeast, including meetings, webinars and phone conversations with several water utilities and companies in the region (e.g. Springfield Water and Sewer Commission, Amherst Public Works, Scituate Water Department, and United Water), attendance at local water conferences (e.g. New Hampshire Department of Environmental Service's (DES's) Annual Drinking Water Source Protection Conference in Concord, NH and NEWWA Spring Conference and Exposition in Worcester, MA), and demonstrations for representatives at regulatory agencies and governmental organizations (e.g. Massachusetts Division of Ecological Restoration, Massachusetts Water Works Association (MWWA), Executive Office of Energy and Environmental Affairs in Boston, MA, and the Environmental Protection Agency (EPA)).

This outreach has helped shape the various components of the tool and the design of its interactive interface. For example, water supply operators at the SWSC requested that monthly storages for a particular month of choice (e.g. April storages across time) appear on the tool's interface, since monthly storage variations impact both reservoir operations and system performance. Other utilities suggested the tool output (i.e., historical climate plots, hydrologic model calibration and reservoir performance plots, etc.) be downloadable for use in annual reports. In addition, several small utilities at the DES's Annual Drinking Water Source Protection Conference in Concord, NH emphasized the importance of being able to use measured flows at a nearby gage station instead of direct inflows to their reservoir because they either had no inflow data or only a short record of streamflow measurements. Lastly, a number

of users of the tool (e.g., Amherst Public Works) indicated a need for a groundwater component, as the tool is currently designed only for surface water utilities. As such, we aim to expand the tool to groundwater-sourced utilities in the future.

### 3.8 Discussion

Two key findings emerge from this analysis. First, a new web-based tool, ViRTUE, was successfully created using the Shiny web framework for small-scale water supply utilities to assess risks to their systems, where ordinarily such analyses would not be feasible. With very few inputs (see Figure 3.1) the simple, screening level vulnerability assessment in ViRTUE yields time series of historic climate, system reliability, storages, and inflows for a range of climatic and demand conditions. In addition, an ensemble of climate projections are provided, with results showing where in climate change space a system is vulnerable and the fraction of climate projections that suggest acceptable/unacceptable system performance according to a threshold of reliability. From these results, a water supply manager may choose to take action to better prepare for potential future changes that pose a risk to system performance, whether those changes include climate change, changes in demand, or additional minimum flow requirements. If their system exhibits significant vulnerabilities, a more in depth analysis of risks may be warranted.

The performance of ViRTUE was evaluated by application to a representative water supply system in the Northeast, the Springfield Water and Sewer Commission's (SWSC) water supply system. The results from the screening-level analysis of ViRTUE provide the same message regarding climate risk to the system as the results found using the system-specific simulation model of the Springfield system (Figure 3.8), and thus demonstrate the value of the tool for a vulnerability assessment of small systems. Future versions of the tool will also illustrate changes in internal variability within the same iteration.



While this study presents an application of ViRTUE to a water supply system in the Northeast, the components of the tool can be adjusted for use in other regions of the world. To do so would require some minor adjustments, i.e., adjusting the parameters of the weather generator to account for low frequency variability in the region, uploading historical climate data for the region to the server, evaluating the performance of the ‘abcd’ hydrologic model to ensure it is a suitable structure for many catchments in the region (if not, it could be replaced with a new hydrologic model), and uploading GCM projections for the specific region of interest to the server. It is important to note, however, that using ViRTUE in regions that are data-sparse may be more difficult because of the need for long annual precipitation time series in estimating parameters in the wavelet decomposition. While the tool is generalizable to other regions, it should be tested on a case-by-case basis.

The second finding is that the Shiny web framework, as demonstrated by ViRTUE, introduces a relatively new approach to web application development that allows modelers to focus less on specific web technologies, and instead focus on converting their existing models and analyses into interactive web applications. As such, it is a valuable resource for individuals with limited web development skills looking to make models and tools more accessible to the water resources community. There is demand for more decision-making tools in water resources, however, they are often difficult to come by because of the divergent skill sets of scientists, engineers, web developers and decision makers. This paper demonstrates the use of the Shiny web framework to bridge that gap, allowing for collaborative development of web tools that can be coded in the widely-used and free R statistical computing language. Web-based tools of this nature offer opportunity for more dynamic and collaborative water resource management.

### 3.9 Conclusion

The study was motivated by the belief that small water utilities may be vulnerable to climate change but lack the resources to assess their risks. A web-based climate risk assessment tool, ViRTUE, was designed to help water utilities, particularly small-scale operators with less time and resources to invest in such studies, to identify vulnerabilities to changes in climate, demand, and environmental flow regulations. ViRTUE provides utilities the opportunity to perform a self-directed vulnerability analysis through an easy-to-use and widely-accessible platform. A web-based platform offers many advantages, such as wide availability, user accessibility, instant modifications, and the removal of software dependencies. There are also some disadvantages of using the web for such analyses including security vulnerabilities (i.e. concern for putting sensitive system specifications online), over simplification of system attributes made to support web-based simulation, and slower analyses than desktop tools due to network traffic and downloading time [Byrne *et al.*, 2010]. Overcoming these potential challenges with web-based simulation is vital for widespread use and acceptance of web-based tools in the water resources community.

The tool presented in this study is designed to assist water managers confronted with the potential challenges of climate impacts through a screening level risk assessment of water supply systems. Ultimately, decision-makers must address water resources management under uncertain future climate and socioeconomic changes. With no financial consequences and minimal time investment, utilities can interactively explore the vulnerabilities of their system and begin to assess the potential investments they may need to make in the future. The application of this tool will be particularly potent in developing countries, where utilities often lack alternative modeling tools. For small-scale water supply systems, a web-based tool may be the only option to assess system vulnerabilities under future uncertainty for their planning and management.

### 3.10 Acknowledgements

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## CHAPTER 4

# ASSESSING THE RELATIVE EFFECTS OF EMISSIONS, CLIMATE MEANS, AND VARIABILITY ON WATER SUPPLY

### 4.1 Abstract

Designing effective strategies for provision of water-related services is dependent on the ability to characterize uncertainty and manage the resultant risks to system performance. This work explores the impact of various uncertainties (i.e. internal variability, mean climate change, and future emission scenarios) on water supply in the northeastern United States. A new framework is implemented to explore the vulnerability of reservoir systems to climate change and attribute vulnerabilities to changes in mean climate, natural variability or greenhouse gas emission scenarios. The analysis of variance (ANOVA) is used to develop a generalized understanding of the contributions of these uncertainties to system performance. A diagnosis of the relative risks to water supply will help water resource engineers better plan and adapt to uncertain future conditions. The results indicate that uncertainty in water supply system performance can be attributed mostly to uncertainty in internal variability over policy-relevant planning horizons and thus adaptation efforts should focus on managing climate variability.

### 4.2 Introduction

The water resources community faces prodigious challenges in planning and managing adaptation to a changing and uncertain climate. Uncertainty in the magnitude

of internal climate variability coupled with the potential for substantial climate change during the next century makes it difficult for decision-makers to identify effective and robust adaptation strategies [Dessai and Hulme, 2007]. Quantifying the influence of different sources of climate uncertainty on water resource system performance may help guide adaptation efforts. For example, while the effects of natural climate variability cannot be reduced in the long term [Knutti, 2012], improvements in seasonal and interannual forecasting may help inform operational decisions. Moreover, vulnerabilities to mean changes in precipitation or temperature would guide one toward tracking the evolution of changes and projections of such changes over time.

In many cases, adaptation planning to climate change is based on highly uncertain projections of future climate derived from global climate models (GCMs). The uncertainty in GCM projections (e.g., temperature and precipitation) is due to inaccuracies in the climate model structure, unknown greenhouse gas emission scenarios and initial conditions, internal variability, and downscaling methods [Yip *et al.*, 2011; Hawkins and Sutton, 2009; Groves *et al.*, 2008]. While there are a large number of projections available based on a range of emission scenarios, adaptation planners are unsure of what future to plan for or how to best characterize the future. A common approach is to use a set of GCM projections for vulnerability analysis to reveal vulnerabilities to the projections used, yet it is still unclear whether to attribute the vulnerability to aspects of the projection (e.g., future emission scenario) or the fundamental vulnerability of the system to changes in climate.

Climate research provides insight into the relative effects of the components of uncertainty in future climate and climate projections. For example, studies have disaggregated the inherent uncertainty in climate model projections from GCMs into components of initial condition uncertainty, model uncertainty, and emission scenario uncertainty to characterize their relative importance in predicting climate variables (i.e., temperature and precipitation) over different spatial and temporal scales [Hawkins

and Sutton, 2010, 2009; Cox and Stephenson, 2007; Yip et al., 2011]. For example, Hawkins and Sutton [2009] estimate the contribution of sources of uncertainty by fitting polynomial functions to temperature predictions from 15 different GCMs, under historical forcings and three future Intergovernmental Panel on Climate Change (IPCC) Emission Scenarios (SRES A1B,A2, and B1). In further work, they investigate the contribution of uncertainty by utilizing precipitation projections [Hawkins and Sutton, 2010]. In general, for time horizons of 3 decades or longer, Hawkins and Sutton [2010] found that scenario uncertainty dominates. However, the dominant sources of uncertainty for policy-relevant spatial (regional) and temporal scales (30 to 50 years) are model uncertainty and initial condition uncertainty (internal variability), with internal variability dominating for the first two decades. Yip et al. [2011] found comparable results using the analysis of variance (ANOVA) to attribute uncertainty from multimodel ensembles into scenario uncertainty, model uncertainty, and internal variability.

While climate research has explored components of uncertainty in future climate and climate projections, no work has gone toward diagnosing the effect of various sources of uncertainty on water supply systems. However, several studies have looked at the effect of different sources of uncertainty on flood frequency [Kay et al., 2008; Reynard et al., 2004], runoff [Arnell, 1999; Dobler et al., 2012; Bosshard et al., 2013; Prudhomme and Davies, 2008a, b; Wilby, 2005], and hydropower production [Finger et al., 2012]. Most of these studies found that GCM structure (e.g., parameterizations) is an important source of uncertainty in climate change impact studies on a regional scale. For example, Kay et al. [2008] explored the uncertainty in future greenhouse gas emissions, GCM structure, downscaling from GCMs, and the internal variability of the climate system (i.e., uncertainty in the initial conditions of GCMs), among other sources of uncertainty on flood frequency impact in England. The results from this study suggest that uncertainty from GCM structure (from 5 GCMs)

is the dominant source of uncertainty in predicting the change in flood magnitude at five return periods (2,5,10,20 and 50 years), but this is mostly driven by the predictions of one of the five GCMs explored. *Prudhomme and Davies* [2008a, b] also found that GCM uncertainty (from 3 GCMs) is the largest source of uncertainty in the impact of climate change on monthly mean flows at four British catchments, with downscaling uncertainty also significant. Using ANOVA techniques, *Bosshard et al.* [2013] quantified the contributions of different uncertainty sources (i.e., uncertainties arising from 8 different climate models, 2 statistical postprocessing techniques, and 2 hydrological models) on seasonal runoff and found that the climate models are the dominant source of uncertainty during summer and autumn, but the other sources of uncertainty dominate during winter and spring, when runoff quantiles are low. In general, results from these studies reveal only a limited estimation of the overall uncertainty, since large ensembles of GCMs are not available due to the associated high computational demand.

In this study we explore the relative effects of various sources of uncertainty (i.e., emission scenario uncertainty, climate change uncertainty, and internal variability) on water supply system performance using analysis of variance methods (ANOVA). Previous GCM-based studies that explore the relative effects of uncertainty in climate variability and uncertainty arising from climate change impacts are limited to only a small number of scenarios and by the fact that natural variability is poorly represented in climate models. Consequently, the results remain dependent on the modeling choices and climate projections that are used in the analysis. Instead, the methodology employed here samples from a wide range of stochastic variability and mean climate change scenarios (*Whateley et al.*, in preparation), controlling for uncertainty in climate change trends versus variability without relying on GCM projections. We illustrate the methodology by applying it to the reservoir system performance of three water supply systems in the northeastern United States. This is the first time

a study has assessed the relative importance of various sources of climate uncertainty on water supply systems. The methodological approach presented in this paper is designed to help water utilities prioritize adaptation decisions under the pressure of both climate change and variability impacts.

The remainder of the paper is organized as follows: section 4.2 sets the stage methodologically, describing the data generation process, variables and set up of the analysis, and the general methodological approach. We then illustrate an application of the ANOVA methodology to three water supply systems and present the results in sections 4.3 and 4.4. We complete the paper with a discussion and conclusion in sections 4.5 and 4.6.

### **4.3 Methods**

Previous research has based their analyses on GCM projections, and in some cases have used ANOVA techniques to attribute different uncertainty sources. Results from these studies, however, are dependent on the models' representation of natural climate variability, which is not well simulated in current global climate model projections. For this reason, a GCM-driven approach does not sufficiently sample climate variability, which is critical in a vulnerability analysis of water supply since water availability is often dependent on seasonal and interannual climate fluctuations. Thus, the approach is altered here. In this study we created a dataset that captures both the the range of changes and corresponding sources of the changes seen. First, we use stochastic weather generation to create time series of weather that preserve local characteristics of natural variability poorly represented by the climate models. Then, we impose transient climate change trends to capture both the joint impacts of long-term climate change and natural climate variations. Finally, we employ analysis of variance methods to explore the relative effects of various sources of uncertainty on system performance. The details are described below.



### 4.3.1 Generating natural variability and climate change data

This study uses a simple, first order autoregressive model fit to basin-averaged, annual precipitation data [Maurer *et al.*, 2002] to generate 10,000 152-year sequences of annual precipitation data. A random sample of thirty of these sequences (all with means less than or equal to 1% of the historic mean to preserve the historic mean in the generated data and ensure each stochastic trace has the same baseline mean) were carried through the analysis (Whateley *et al.*, in review). The thirty sequences were selected from the total to reduce the computational time of the analysis. A k-Nearest Neighbor algorithm (k-NN) was employed to simulate annual temperature values and all annual variables were disaggregated to a monthly time step using the method of fragments [Srikanthan and McMahon, 2001]. At this point, with no climate changes imposed on the generated sequences, the thirty sequences represent a range of internal variability in the climate system.

The process then involves a mapping between the generated data, climate models, emission scenarios, and climate variability. To account for future change, transient linear changes were imposed on each of the thirty realizations (all with a baseline mean that deviated from the historic mean by less than or equal to 1%). The transient changes applied to the realizations were defined based on the outermost range of temperature and precipitation projections from a 19 member ensemble of GCMs from the World Climate Research Programme's (WCRP's) Coupled Model Inter-comparison Project Phase 3 (CMIP3) and Phase 5 (CMIP5) multimodel dataset for different emission scenario storylines. These include the three SRES emission scenarios from CMIP3 ( $E^3$ ): A1B, A2, and B1 (with a scenario denoted by  $k = 1, 2$ , or 3) and the four RCPs from CMIP5 ( $E^5$ ): RCP 2.5, 4.5, 6, and 8.5 ( $k = 1, 2, 3$ , or 4). We obtained monthly gridded simulated data that was downscaled to a 0.125 degree spatial resolution based on the bias-correction spatial disaggregation (BCSD) statistical downscaling method [Reclamation, 2013]. For example, under an A2 emis-

sion scenario storyline, an ensemble of CMIP3 climate projections for a particular location may suggest temperature increases between 1 and 3.5 degrees Celsius (where temperature change is denoted by  $T$ ), and precipitation changes between -10% and 10% (precipitation change denoted by  $P$ ) by the year 2050. In this case, climate trends between 1 and 3.5 degrees C (at 0.5 degree C increments) and -10% and 10% change in precipitation (at 5% increments) would be imposed on the 30 stochastic realizations (with a realization denoted by  $l = 1, 2, \dots, 30$ ), for a total of 30 different climate changes (i.e., 6 temperature changes ( $i = 1, 2, \dots, 6$ ) x 5 precipitation changes ( $j = 1, 2, \dots, 5$ )). This results in 6 temperature observations and 5 precipitation observations for a particular emission scenario across all stochastic realizations (denoted by  $L_{ijk}$ ) for a total of 900 (30x30) total scenarios.

#### **4.3.2 Assessing sources of uncertainty: hydrologic and systems models**

Climate-altered time series of precipitation and temperature were converted to streamflow sequences using a hydrologic model. Streamflow sequences were then used as input into water supply systems models to assess performance over time. The models used in this study are described in detail below. System performance ( $x(i, j, k, l)$ ) was assessed over four consecutive thirty-eight year periods ( $\theta_1=1948$  to 1985,  $\theta_2=1986$  to 2023,  $\theta_3=2024$  to 2061,  $\theta_4=2062$  to 2100). A thirty-eight year period, which divides evenly into the 152-years of simulated data, is long enough to filter out interannual variation or anomalies, but also short enough to be able to show longer climatic trends. Analysis of variance methods were then used to test differences between temperature change, precipitation change, and emission scenario means for each 38 year time period.

#### **4.3.3 Analysis of variance method**

Analysis of variance methods were employed to partition the observed variance in system performance (for a 38 year period of time) into components attributable

to different sources of variation. A three-factor fixed effects ANOVA was used to determine the uncertainty in system response attributable to uncertainty in precipitation change ( $P$ ), temperature change ( $T$ ), and emissions scenario ( $E$ ) and their interactions and uncertainty in system response attributable to internal variability ( $l$ ). The resultant set up is three independent variables (i.e., the three fixed factors are temperature change, precipitation change, and emission scenario) and one dependent variable (i.e., system performance metric for a 38 year time period). The number of levels of these factors is denoted as  $i$ ,  $j$ , and  $k$  respectively, where  $L_{ijk}$  is the number of observations made with factor  $T$  at level  $i$ , factor  $P$  at level  $j$ , and factor  $E$  at level  $k$ . In this study,  $L_{ijk}$  is composed of thirty stochastic realizations.

The ANOVA was performed on the portion of climate change space defined by CMIP3 and CMIP5 GCM projections under different assumptions of future greenhouse gas concentrations as described above. The number of observations made with factors  $T$ ,  $P$ , and  $E$  for levels  $i$ ,  $j$ , and  $k$ , varied based on the range of temperature and precipitation values projected by the CMIP3 and CMIP5 GCMs (Figure 4.3). The fixed effects model for the three-factor ANOVA is in Equation 4.1.

$$x(i, j, k, l) = \mu + \alpha(i) + \beta(j) + \zeta(k) + \gamma(i, j)^{TP} + \gamma(i, k)^{TE} + \gamma(j, k)^{PE} + \gamma(i, j, k)^{TPE} + \epsilon(i, j, k, l) \quad (4.1)$$

where  $x(i, j, k, l)$  is the performance metric for a given level  $ijk$  of the factors  $T, P$ , and  $E$ , and a given realization  $l$ . The total ensemble mean of all simulations is  $\mu$ ;  $\alpha(i)$  is the deviation of mean temperature change from the overall ensemble mean  $\mu$ ;  $\beta(j)$  is the deviation of mean precipitation change from the overall ensemble mean;  $\zeta(k)$  is the emission scenario deviation;  $\gamma(i, j)^{TP}$ ,  $\gamma(i, k)^{TE}$ ,  $\gamma(j, k)^{PE}$  and  $\gamma(i, j, k)^{TPE}$  are the interaction terms between mean temperature change, mean precipitation change, and emission scenario. The error term  $\epsilon(i, j, k, l)$  is assumed to be independent and

identically distributed as  $N(0, \sigma^2)$ . These residuals (i.e., the unexplained variance) calculate the variance across the  $L$  observations, representing the internal climate variability [Yip *et al.*, 2011].

Figure 4.1 illustrates an example of all combinations of the three factors for the case where system performance ( $x_{ijkl}$ ) was calculated for three different temperature changes (factor T,  $i=3$ ) and four different precipitation changes (factor P,  $j=4$ ) for a particular emission scenario (factor E,  $k=1$ );  $L=30$  reservoir storage values were made for each of the  $3 \times 4 \times 1 = 12$  combinations of levels (italicized) of the three factors.

The total sum of squares,  $SS_{total}$ , is used to express the total variation that can be attributed to various factors (i.e.,  $SS_T$ ,  $SS_P$ ,  $SS_E$ ) and is calculated using Equation 4.2. Dividing the magnitude of ANOVA results by the total sum of squares gives a normalized metric of the relative fraction of uncertainty contributed by the individual and joint effects of factors.

$$SS_{total} = SS_T + SS_P + SS_E + SS_{TP} + SS_{TE} + SS_{PE} + SS_{TPE} + SS_\epsilon \quad (4.2)$$

In this case,  $SS_\epsilon$  represents the uncertainty explained by internal climate variability (i.e., the variance across stochastic realizations).

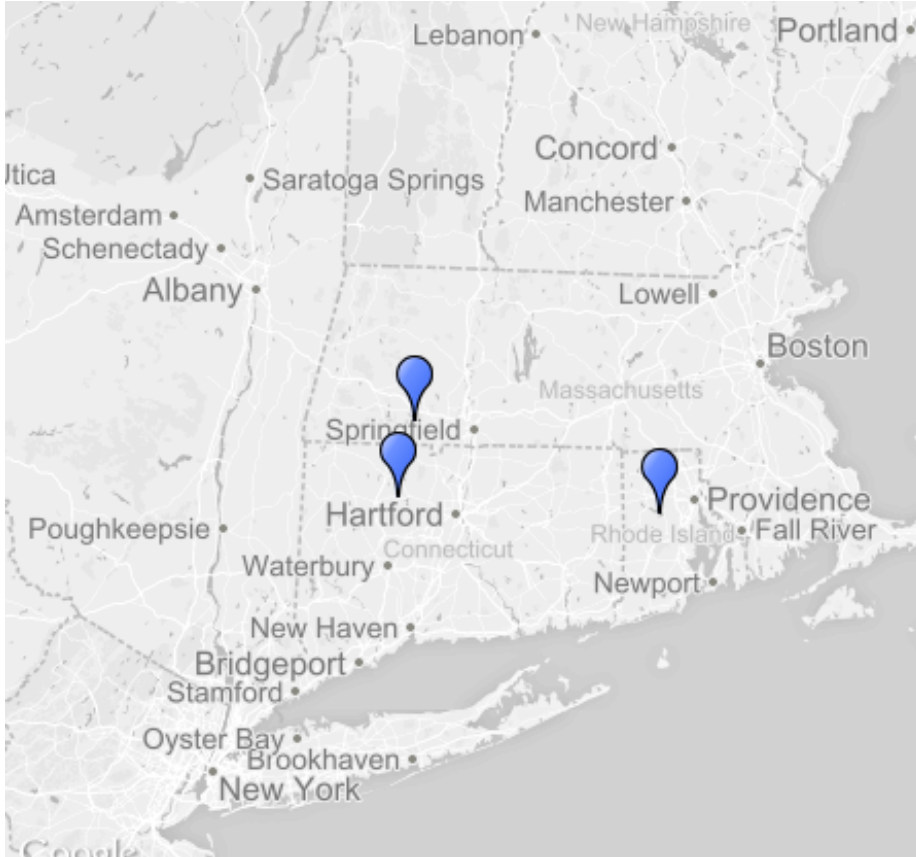
## 4.4 Application of methods

### 4.4.1 Reservoir system descriptions

We demonstrate the ANOVA approach using three stylized water supply systems in the Northeast U.S. located in Springfield, MA, Providence, RI, and Hartford, CT (Figure 4.2). We chose to explore these water supply systems because they represent a variety of system sizes and operational strategies that may benefit from a better

<b>E<sub>1</sub></b>				
	<b>P<sub>1</sub></b>	<b>P<sub>2</sub></b>	<b>P<sub>3</sub></b>	<b>P<sub>4</sub></b>
<b>T<sub>1</sub></b>	X <sub>1111</sub>	X <sub>1211</sub>	X <sub>1311</sub>	X <sub>1411</sub>
	X <sub>1112</sub>	X <sub>1212</sub>	X <sub>1312</sub>	X <sub>1412</sub>
	X <sub>1113</sub>	X <sub>1213</sub>	X <sub>1313</sub>	X <sub>1413</sub>
	.	.	.	.
	.	.	.	.
	X <sub>11130</sub>	X <sub>12130</sub>	X <sub>13130</sub>	X <sub>14130</sub>
<b>T<sub>2</sub></b>	X <sub>2111</sub>	X <sub>2211</sub>	X <sub>2311</sub>	X <sub>2411</sub>
	X <sub>2112</sub>	X <sub>2212</sub>	X <sub>2312</sub>	X <sub>2412</sub>
	X <sub>2113</sub>	X <sub>2213</sub>	X <sub>2313</sub>	X <sub>2413</sub>
	.	.	.	.
	.	.	.	.
	X <sub>21130</sub>	X <sub>22130</sub>	X <sub>23130</sub>	X <sub>24130</sub>
<b>T<sub>3</sub></b>	X <sub>3111</sub>	X <sub>3211</sub>	X <sub>3311</sub>	X <sub>3411</sub>
	X <sub>3112</sub>	X <sub>3212</sub>	X <sub>3312</sub>	X <sub>3412</sub>
	X <sub>3113</sub>	X <sub>3213</sub>	X <sub>3313</sub>	X <sub>3413</sub>
	.	.	.	.
	.	.	.	.
	X <sub>31130</sub>	X <sub>32130</sub>	X <sub>33130</sub>	X <sub>34130</sub>

**Figure 4.1.** TxPxE combinations of levels of the three factors. The length of P, T, and E vary based on CMIP3 and CMIP5 climate projections and emission scenarios.



**Figure 4.2.** Map of case study locations (created on July 22, 2015 using NASA, TerraMetrics Scribble Maps)

understanding of the relative importance of various sources of uncertainty on system performance.

### **Springfield Water Supply System**

The Springfield Water and Sewer Commission (SWSC) operates the Cobble Mountain Reservoir (reservoir storage capacity is 22,829 million gallons (MG)) and Borden Brook Reservoir (2500 MG) located in the Westfield River basin in Central Massachusetts. The Cobble Mountain and Borden Brook Reservoirs are the two major water supply reservoirs used to meet the water needs of Agawam, East Longmeadow, Longmeadow, Ludlow, Westfield, and the city of Springfield (a total population of around 250,000). In this study, system operations were modeled in R (on a monthly

time step) [*Whateley et al.*, 2014] based on the SWSC’s drought management plan. More information on the system and simulation model can be found in *Whateley et al.* [2014] and *Westphal et al.* [2007].

### **Providence Water Supply System**

The Massachusetts Water Resources Authority (MWRA) is responsible for managing the Scituate Reservoir Complex in central Rhode Island (total system capacity is 39,000 MG). The system, composed of six major reservoirs (Scituate, Moswaniscut, Regulating, Barden, Westconnaug, and Ponaganset), is responsible for meeting the water needs of 650,000 people. The simulation model used in this analysis was developed under Providence Water’s guidance, and the operations are relatively straightforward (Whateley et al., in prep). The monthly model was originally constructed using STELLA modeling and simulation software and was later translated into the R programming environment.

### **Hartford Water Supply System**

The Hartford water supply system is managed by the Metropolitan District Commission (MDC) and supplies water to the greater Hartford area (400,000 people). Seventy percent of the total water demand is met by the Barkhamsted Reservoir (22400 MG) and thirty percent of the total water demand is met by the Nepaug Reservoir (9500 MG). Additional reservoirs, such as the Colebrook Reservoir, the West Branch Reservoir, and Lake McDonough on the East and West Branches of the Farmington River, offer additional water supply if needed, but water supply is not their primary function. In this analysis, the Barkhamsted and Nepaug Reservoirs were treated as run-of-river facilities left to fill and spill. The Hartford water supply simulation model was developed in R on a monthly time step.

#### 4.4.2 Hydrologic Model

In this study, climate-altered time series of precipitation and temperature were converted to streamflow sequences using a version of the ‘abcd’ rainfall-runoff model [Thomas, 1981a], modified to account for snow accumulation and melt. The ‘abcd’ hydrologic model was calibrated to historic streamflows on a monthly time step using the shuffled complex evolutionary algorithm (SCE) [Thyer *et al.*, 1999; Duan *et al.*, 1992] for each reservoir system explored. For the Springfield water supply system, the ‘abcd’ hydrologic model was calibrated using historic streamflow from the West Branch Westfield River at Huntington, MA gage (USGS 01181000), which yielded a Nash Sutcliffe efficiency coefficient of 0.61. For the Providence and Hartford water supply systems, ‘abcd’ models were calibrated using historic streamflow from the Ponaganset River at South Foster, RI gage (USGS 01115187) and Farmington River at Unionville, CT gage (USGS 01188090), yielding Nash Sutcliffe efficiency coefficients of 0.81 and 0.63, respectively.

#### 4.4.3 Metric for assessing system performance

The systems models for each case study site were used to simulate mean reservoir storage as a percentage of reservoir capacity for each 38 year time period (i.e., the dependent variable in the analysis of variance). The metric is normalized by reservoir capacity so that the results can be compared across systems. Mean reservoir storage is well suited for this type of analysis because 1) it is correlated with performance metrics such as reliability and resilience [Vogel *et al.*, 1999] that stakeholders often use to assess system behavior, 2) it is a meaningful metric to observe through time, demonstrating periods of water scarcity and abundance, and 3) it directly relates to system functioning such that a better understanding of the relative importance of different components of variation (i.e., climate change and variability) may be useful for improving operations.



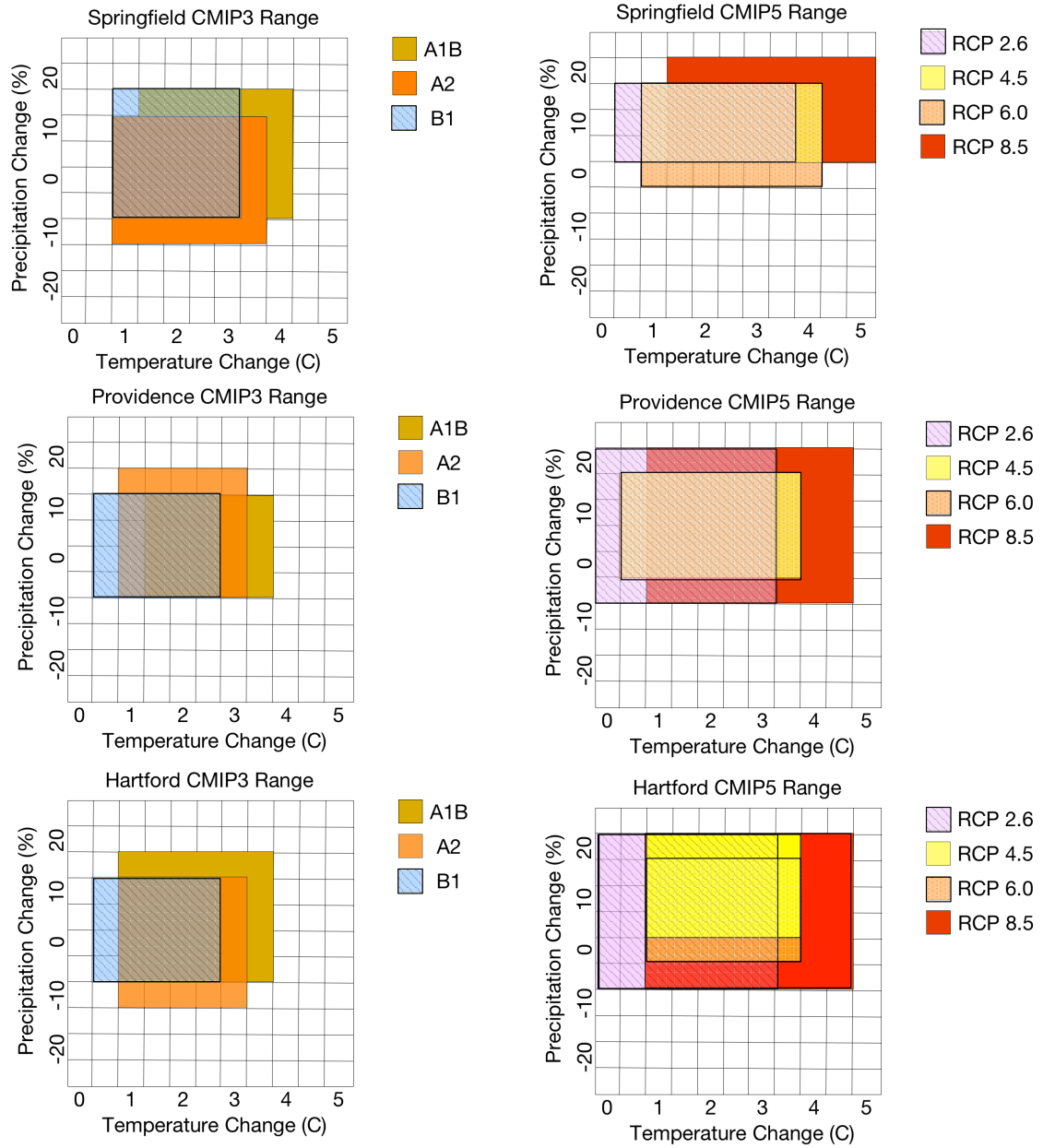
#### 4.4.4 Analysis of variance methodology

The three-way ANOVA was used to quantify the uncertainty in mean reservoir storage as a percentage of capacity over a subset of temperature changes, precipitation changes, and emission scenarios derived from CMIP3 and CMIP5 climate projections. Figure 4.3 illustrates the portion of the climate space over which the ANOVA was performed for each location. Mean monthly temperature and precipitation were extracted from CMIP3 and CMIP5 datasets under different emission scenarios for the time period between 1950 and 2099 and averaged for future (50 years centered around 2050) and historic (1950-1999) climate conditions. The analysis of variance was performed over the space encompassing all emission scenario ranges for the CMIP3 and CMIP5 datasets. In some cases, the ranges of precipitation and temperature changes for different emission scenarios overlap.

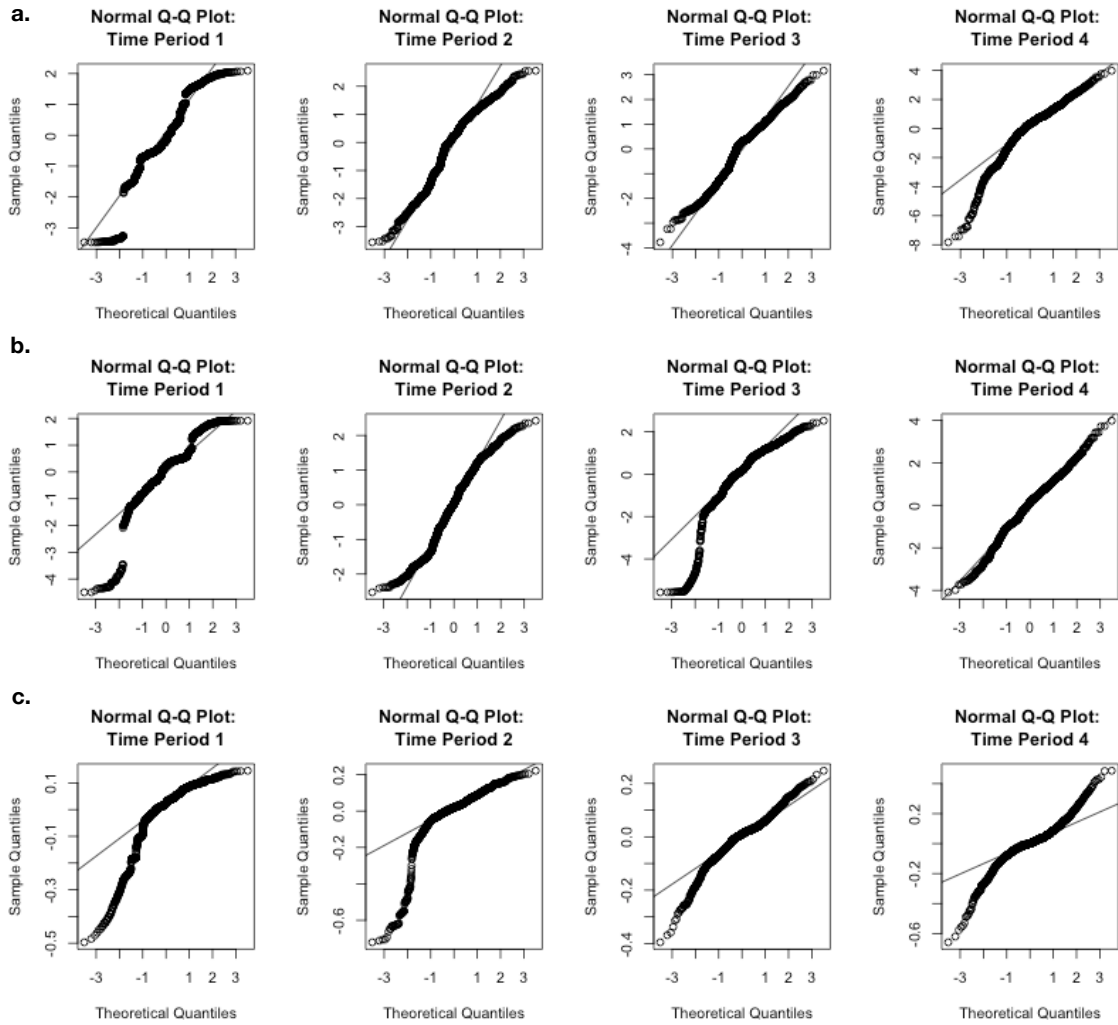
The assumptions of the ANOVA (i.e., normality of residuals and homogeneity of variance) were tested using the Shapiro-Wilk normality test, plotting a histogram and Q-Q plot of the residuals, and plotting the residuals versus predicted values. The Shapiro-Wilk tests indicated that the residuals are not distributed normally (p-value greater than 0.05) and in general, do not exhibit constant variance (except in the first time period). For some time periods and locations, however, the residuals appear normal (e.g., Figure 4.4b time period 4). The heteroskedasticity of the residuals in later time periods is illustrated in Figure 4.5. Violation of the normality and constant variance assumptions affects the significance of the ANOVA results but does not invalidate the overall conclusions of the analysis (Berry and Feldman, 1985; Tabachnick and Fidell, 1996).

### 4.5 Partitioning uncertainty in reservoir performance

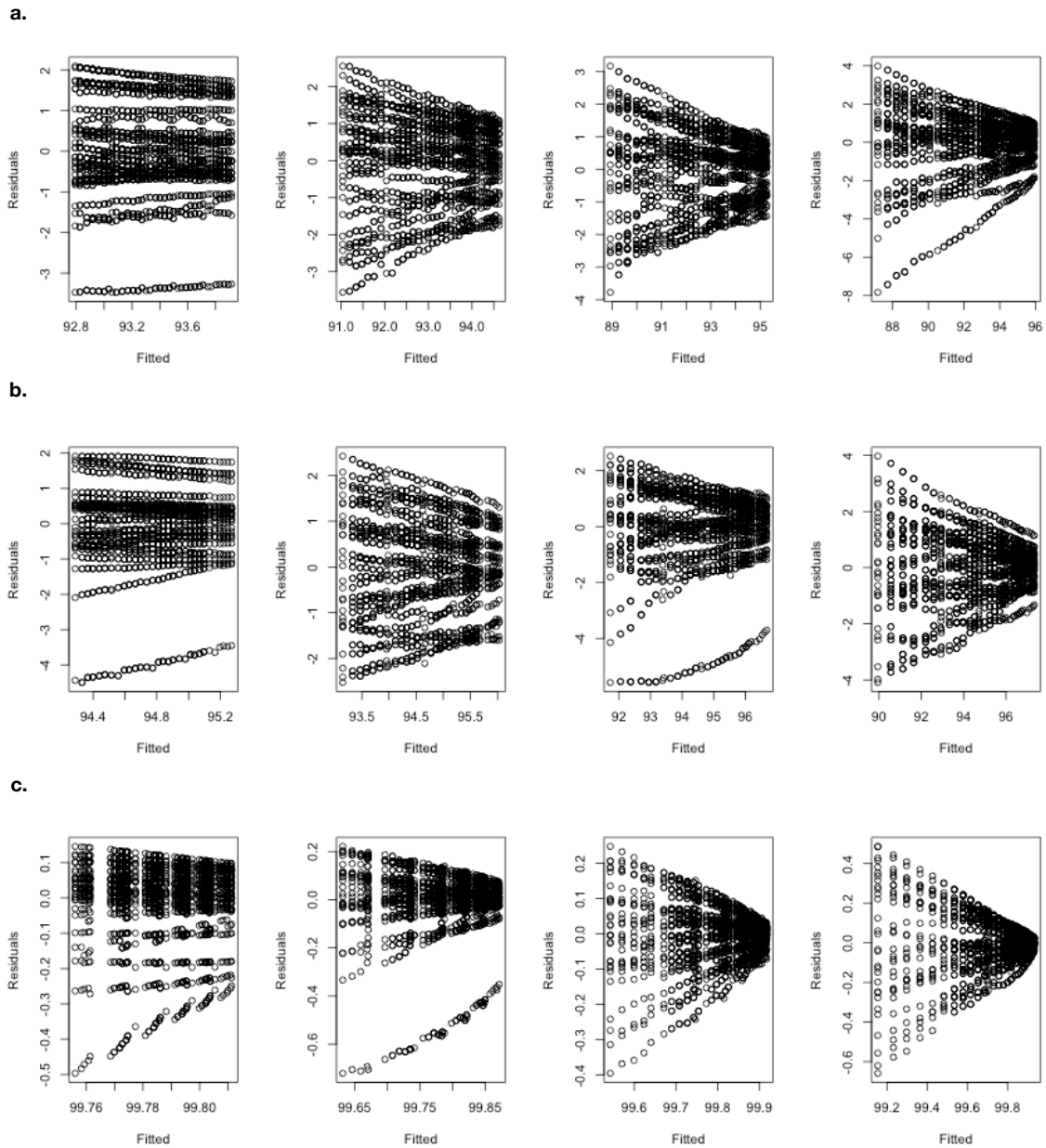
Figures 4.6a,c, and e illustrate the fraction of total variance (%) (i.e., the uncertainty divided by the total sum of squares) of mean reservoir storage for Providence,



**Figure 4.3.** CMIP3 (left) and CMIP5 (right) GCM ranges for different emission scenario storylines for Springfield (top), Providence (middle), and Hartford (bottom).



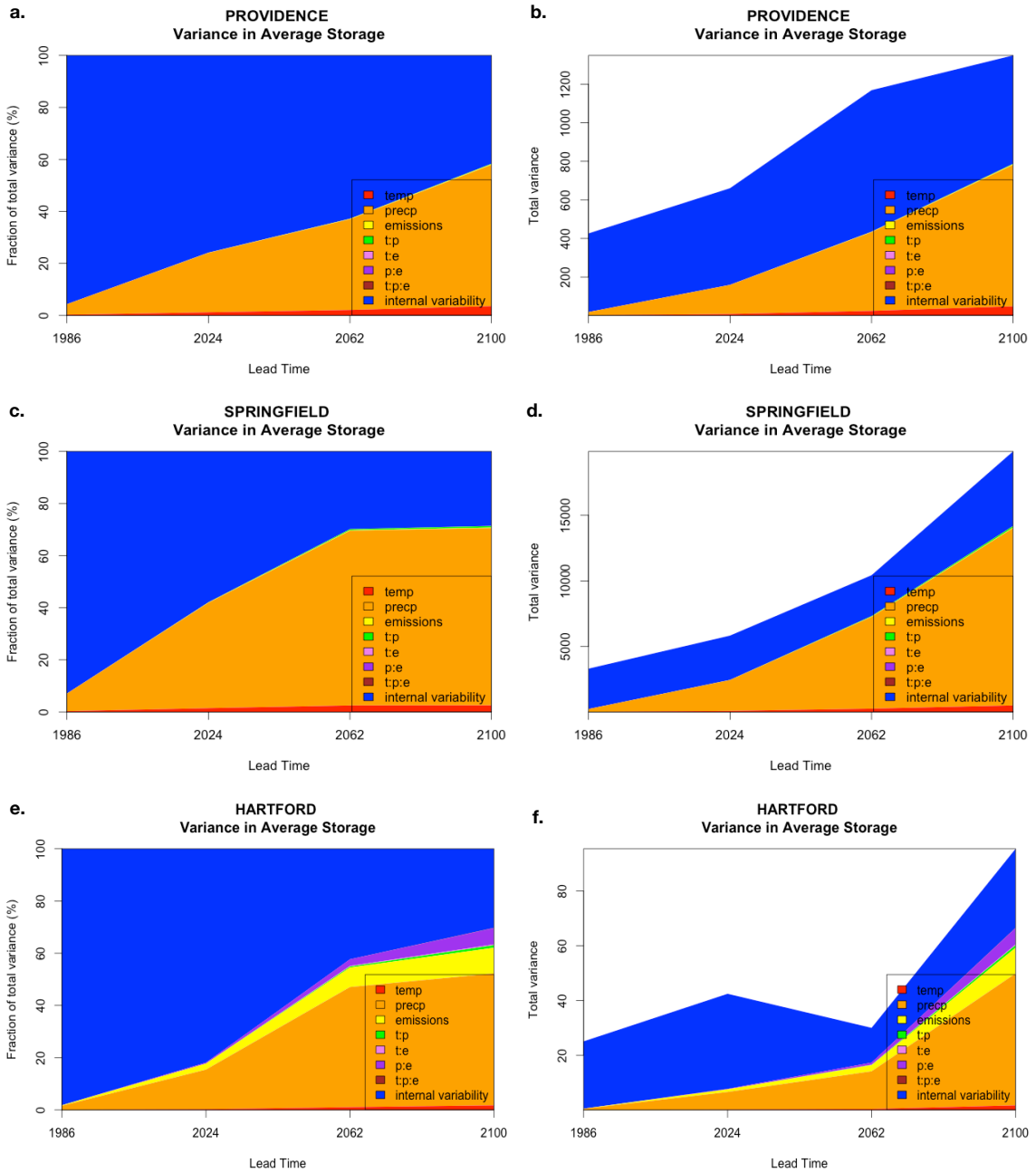
**Figure 4.4.** Normal quantile-quantile plots for (a) Springfield, MA, (b) Providence, RI, and (c) Hartford, CT ANOVA results for mean reservoir storage as a percentage of capacity at each 38 year time period. The results shown here are from the analysis based on CMIP3 climate projections.



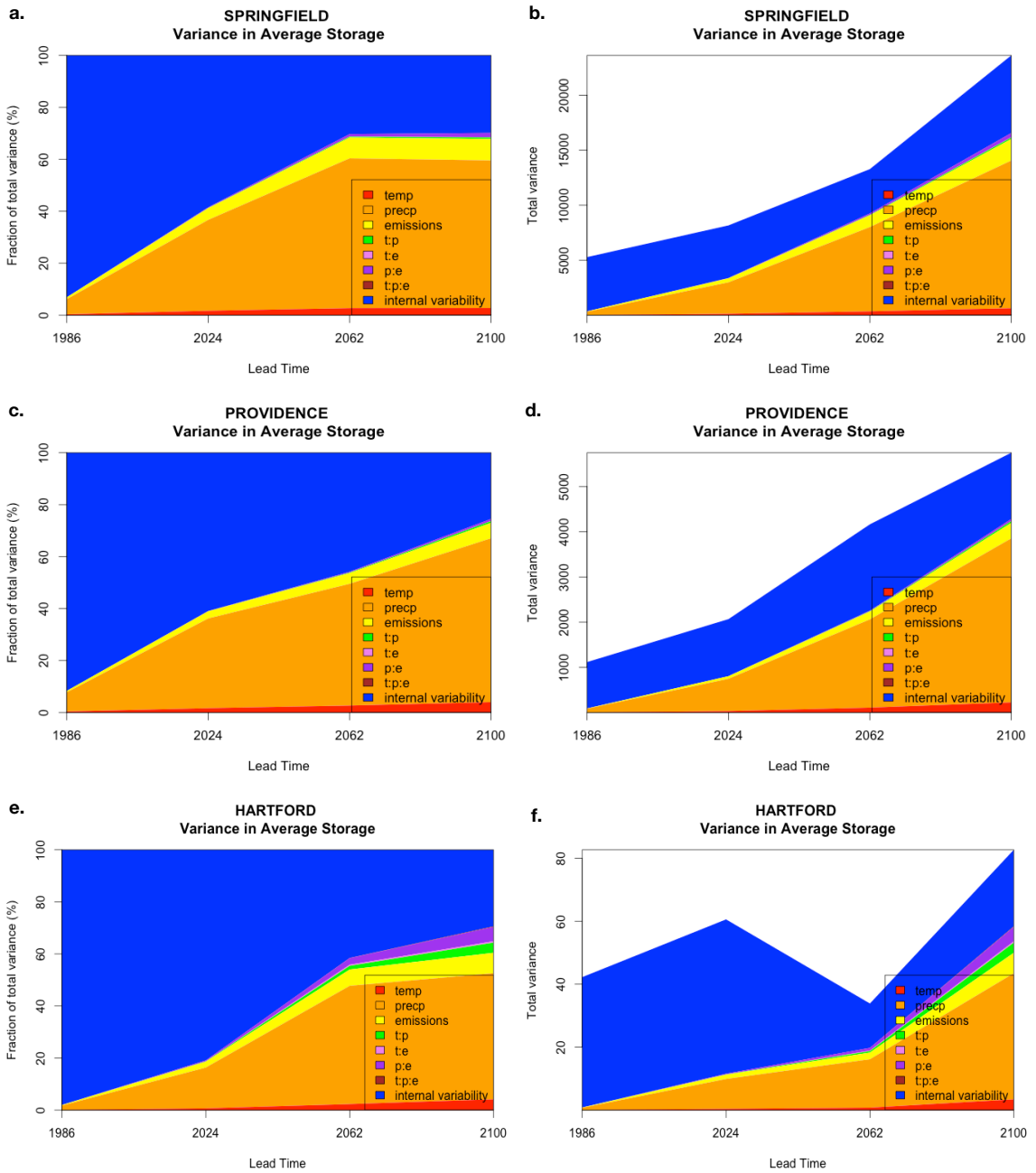
**Figure 4.5.** The residuals versus predicted values for mean reservoir storage as a percentage of capacity ANOVA results for (a) Springfield, MA, (b) Providence, RI, and (c) Hartford, CT. The results shown here are from the analysis based on CMIP3 climate projections.

RI, Springfield, MA, and Hartford, CT, respectively. The total variance in mean reservoir storage for these locations is illustrated in Figures 4.7b,d, and f. Results show that the fraction of variance due to internal variability (blue region) dominates for the first few decades and uncertainty in precipitation change (orange region) dominates in the latter part of the century. Specifically, internal variability contributes between 93% and 98% of the total uncertainty for all locations for mean reservoir storage over the first 38 year time period (1948-1985). Mean precipitation change contributes between 51% and 68% of the total uncertainty for all locations for mean reservoir storage over the last 38 year time period (2062-2100). The fraction of total variance in mean reservoir storage due to temperature change, emission scenario, and all interaction terms is minimal in comparison. These results, based on CMIP3 data, are similar across the three study sites, however, uncertainty in reservoir storage due to emission scenario uncertainty and joint effects of precipitation and emission scenario uncertainty appear in the later part of the century for the Hartford water supply system.

Figure 4.7 shows the fraction of total variance and total variance of mean reservoir storage using data from the CMIP5 dataset. Although the overall message is similar to the results in Figure 4.6, where uncertainty in internal variability dominates in the beginning of the century and uncertainty in precipitation change dominates in the later half of the century, emission scenario uncertainty has some importance in system response at all locations. Emission scenario uncertainty contributes between 7% and 8% of the total uncertainty by the end of the century. This may be due to the wider range in precipitation and temperature projections for CMIP5 than for CMIP3 [Knutti and Sedláček, 2012] and the evolution of emission scenario development in the IPCC's Fifth Assessment Report (focusing more on the significance of the emission scenarios from a climate forcing perspective rather than just a human development perspective) [Moss *et al.*, 2010].



**Figure 4.6.** The fraction of total variance (%) (a,c,e) and total variance (b,d,f) of mean reservoir storage for Providence, RI, Springfield, MA, and Hartford, CT over a subset of temperature changes, precipitation changes, and emission scenarios (SRES-A1B, A2, and B1) derived from CMIP3 climate projections.



**Figure 4.7.** The fraction of total variance (%) (a,c,e) and total variance (b,d,f) of mean reservoir storage for Providence, RI, Springfield, MA, and Hartford, CT over a subset of temperature changes, precipitation changes, and emission scenarios (RCP-2.5,4.5,6.0, and 8.5) derived from CMIP5 climate projections.

## 4.6 Discussion

Three key findings emerge from this analysis. First, the results from this study can be used to help guide adaptation efforts under the competing pressures of climate change and natural variability. The three water supply systems used to exemplify the methodology in this study are most sensitive to uncertainty in internal variability over policy-relevant time horizons. In other words, water availability is dependent on the interannual variability of streamflow, which is common for systems located in snow-dominated basins. These results highlight the importance of appropriately sampling variability in vulnerability analyses, which few other studies have adequately addressed. Second, we note that nothing can be done about internal variability of the climate system from a predictive sense in the long term and thus projections do not help in adaptation efforts. Instead, management efforts can focus on short-term events and concerns over changes in variability. For example, water resource systems may be able to manage variability with seasonal climate forecasts [*Steinschneider and Brown, 2012; Kim and Palmer, 1997; Sankarasubramanian et al., 2009b, a*], drought management plans and operational adjustments [*Westphal et al., 2007*], and flexible adaptation strategies [*Pahl-Wostl, 2007*]. Real options and option-based water transfers are some examples of flexible adaptation strategies that can be used to hedge against the risk associated with unexpected climate outcomes [*Wang et al., 2006*]. Moreover, incorporating information about climate variability into water management may aid adaptation to longer-term climate change impacts.

Lastly, if climate change uncertainty dominates (i.e., uncertainty in mean temperature and precipitation change), which may be the case for very large, complex water supply systems with multi-year reservoir storage capacities, adaptation efforts can prioritize long-term trends instead of variability. For example, improvements in demand efficiency and conservation efforts [*Alcamo et al., 2007*], infrastructure investments (e.g., leak control) (US Global Change Research Program, 2009), and economic



policy (including water pricing) [*Bates et al.*, 2008; *Miller et al.*, 1997; *Brookshire et al.*, 2004] may make systems more robust to future change. These options offer less expensive alternatives to infrastructure expansion.

In general, the systems explored in this study are insensitive to uncertainty in mean climate change for planning horizons of several decades, with uncertainty in system response mostly due to uncertainty in internal variability. Mean runoff relative to demand may drive this distinction. Over the last several decades, significant efforts have gone toward demand management and water supply augmentation activities in the region (e.g., water conservation, leak control, and public education), improving the robustness of many Northeast water systems to future change (e.g., Boston's water supply system was able to reduce demand below the safe yield of the reservoir system [*Kirshen and Fennessey*, 1995]). A limitation of this study may be the lack of consideration of the impacts of demand uncertainty on system performance, as water use is mainly driven by non-climatic factors such as population and economic growth, changes in demand, environmental flow requirements, and so on. However, with demand projections this could be incorporated into the analysis. In addition, the choice and range of economic scenarios (i.e., the SRES scenarios used in CMIP3 projections versus the RCP scenarios used in CMIP5 projections) affects its relative contribution to uncertainty in system response, and the introduction of new emission scenarios would provide more variability.

The water supply performance results (Figures 4.6 and 4.7) are similar to previous local scale climate effects studies that found internal variability to be the dominant source of uncertainty in temperature and precipitation projections [*Hawkins and Sutton*, 2010; *Räisänen*, 2001; *Deser et al.*, 2012], but the effects here are even more pronounced. Also, previous climate effects studies found that the dominant sources of uncertainty were dependent on the climate variable of interest, illustrating that both internal variability and model uncertainty are more important for precipitation

changes than for temperature changes [*Hawkins and Sutton, 2010; Räisänen, 2001; Hawkins and Sutton, 2009*]. In this study, results showed that mean precipitation change was the dominant source of uncertainty in predicting water supply performance (in the later half of the century), and uncertainty in mean temperature change had almost no influence.

## 4.7 Conclusion

It is challenging to plan and manage water resource systems under future climate uncertainty. A methodology was applied in this study to partition various sources of uncertainty (i.e., climate change, internal variability, and emission scenario) in predicting water supply system performance to better understand their relative importance over time. The results provide a fundamental understanding of the source of vulnerabilities to climate change, and the sources of uncertainty that are most important. In addition, this study presents a new approach for prioritizing adaptation efforts in water resources. An analysis of three water supply systems in the Northeast U.S. illustrates that uncertainty in internal climate variability is significant at policy-relevant planning horizons. For these systems, risks associated with climate variability should receive more attention. Uncertainty in mean changes in precipitation and temperature may become more relevant in the mid-term and distant future, but most actions taken to manage climate variability would also help to reduce the risks associated with climate change.

The conclusion from this study is that an improved understanding of the dominant sources of uncertainty in predicting reservoir performance, based on insights gained from the ANOVA method, may help water managers prioritize adaptation. The proposed method allows for a clear understanding of the relative importance of various sources of uncertainty, and does not rely on progress in climate science to help reduce prediction uncertainty from internal variability.

## 4.8 Acknowledgements

This work was funded by the Consortium for Climate Risk in the Urban Northeast (CCRUN)- a NOAA Regional Integrated Sciences and Assessments (RISA) project (Funding Opportunity Number: NOAA-OAR-CPO-2012-2003304). The views expressed in this manuscript represent those of the authors and do not necessarily reflect the views or policies of NOAA.

## CONCLUSION

Investigating the impact of climate change and variability on regional water supply is essential to the sustainable management of water resource systems in the northeastern United States. Changes in the availability of water due to climatic changes coupled with the intensification of anthropogenic disturbances, aging infrastructure, population growth, and new constraints on water withdrawals for ecological purposes challenge both the larger, sophisticated water utilities in populated urban areas, as well as the numerous midsized and smaller cities with limited technical resources. While some effort has gone toward exploring climate risks to large water supply systems in the Northeast, the research on water supply system vulnerabilities is fragmented and small systems are relatively understudied.

This dissertation shows pragmatic approaches to climate change vulnerability analysis that water utilities can implement and update to assess and manage their climate change risks for both large and small utilities. A variety of new methods and tools are presented to assess water supply systems' vulnerabilities to a wide range of potential challenges that go beyond simple mean changes in precipitation and temperature, including changes in water demand, required releases, and natural climate variability. The result is a better understanding of problematic future scenarios for many individual water supply systems in the Northeast that can be used to help guide decision-makers' adaptation planning and infrastructure investments by identifying the systems with the greatest risks.

The stress test approach implemented in the climate impact analyses of Northeast water supply was used to assess climate risks and explore system vulnerabilities

across a wide range of potential changes in mean climate and natural climate variability. Given the computational demands of the exploratory modeling process used in the stress test, a pre-processing method was developed to allow an analyst to select a small number of climate variability realizations that span the full range of variability a system may face in terms of the challenge to the system (Chapter 1). Using this computationally efficient sampling technique, a comprehensive analysis of the climate risks to several large water supply systems in the Northeast (New York City, NY, Boston, MA, Springfield, MA, Providence, RI, and Hartford, CT) illustrated the robustness of large water utilities in this region (Chapter 2). For the smaller utilities, the stress test approach was embedded in an online tool to create an interactive environment for stakeholders and water managers to explore climate vulnerabilities. The web-based platform for climate risk assessment offers many advantages such as user accessibility, wide availability, and instant modifications and feedback (Chapter 3). While identifying climate vulnerabilities with the stress test approach is an important first step toward being able to address problematic conditions through adaptation measures, designing effective adaptation strategies is also dependent on the ability to characterize uncertainty and diagnose risks. Analysis of variance methods were used to gain an improved understanding of the dominant sources of uncertainty (i.e. uncertainty in internal variability, mean climate change, and future emission scenarios) in predicting reservoir performance to help water managers prioritize adaptation (Chapter 4).

The work presented in this dissertation provides the most exhaustive assessment of climate risks to Northeast water supply, and also reveals a number of future research needs that would further increase both the accessibility and scope of climate impact analysis in the region and elsewhere. First, there are several features that can be added to future versions of the web-based tool ViRTUE, such as the presentation of climate risks due to internal variability, the addition of a groundwater component,

and a drag-and-drop simulation model feature that allows users to incorporate multireservoir operations. In addition, it would be valuable to pilot the tool in other locations around the country and world, particularly in developing countries where utilities often lack alternative modeling tools.

Secondly, since uncertainty in internal variability plays a large role in predicting water supply system performance over short-term planning horizons (highlighted in the results of Chapter 4), efforts should go toward developing and improving methods and strategies for managing variability. For example, future research should focus on improving seasonal climate forecasts, drought management plans and operational alternatives, and flexible adaptation strategies. Thirdly, given the influence of non-climatic factors on reservoir performance in the Northeast (i.e., changes in demand, restrictions on water withdrawals, and minimum flow requirements), more work should be done to better understand local demand projections and ecological flow requirements. These factors, compounded with a changing climate regime, may have a significant impact on the availability of water for individual systems. Yet, there is limited data on future water demands and the research on ecological flow requirements in this region is still in its infancy.

Lastly, despite efforts to improve the accessibility and reduce uncertainty in model-derived climate risk assessments, significant time and resources are invested in understanding the impacts of climate change on individual water resource systems. Few studies have tried to generalize the sensitivity of water supply system behavior to future water stresses. It would be beneficial to develop systematic relationships between reservoir system properties and their sensitivities to future uncertainty in the northeastern United States. Specifically, the vulnerability-based decision framework could be coupled with reservoir system properties to derive response surfaces that could be used to estimate system vulnerabilities anywhere in the region. Then, the performance of reservoir systems with different attributes (e.g. system storage, in-

flows, watershed areas) could be tested in a simulation environment using a stress test that explores a wide range of potential future changes in precipitation, temperature, demand, and water withdrawals. Generalized response surfaces characterized by reservoir system properties could be used as screening tools to help identify vulnerabilities to uncertain future conditions and present an alternative to complex direct impact studies.

**APPENDIX**  
**VIRTUE SOFTWARE AVAILABILITY AND LICENSING**



# Vulnerability and Risk Assessment Tool for Water Utilities (ViRTUE)

ViRTUE is an R/Shiny web application for assessing risks to small-scale water supply systems in the northeastern United States. The tool provides a mechanism to understand and explore individual water utilities climate risk exposure using a stress test, in which the performance of local reservoir systems is tested over a wide range of potential climate and socioeconomic changes.

ViRTUE was developed by Sarah Whateley and the [Hydrosystems Research Group](#) at UMass Amherst.

## Features

- Point-and-click map interface for viewing historical climate data for a location
- Perform a stress test of your water supply system to identify climate risks and hazards
- Interactively explore system vulnerabilities to changes in climate, demands, and minimum flow requirements
- Explore adaptation alternatives (e.g., additional reservoir storage and operational adjustments) and instantaneously observe their impact on system performance
- Assess the likelihood of vulnerabilities occurring based on the most up-to-date climate science (CMIP5 Global Climate Model projections)
- Download the results of the tool's climate risk assessment for use in reports and documents
- Step-by-step instructions and 'help' bubbles in each tab of the tool for ease-of-use and self-guided training

## Availability

This repository contains the code and data requirements for the application of ViRTUE.

The live version of this site is available here: <https://virtue.shinyapps.io/myapp>

## Local Installation/Requirements

ViRTUE requires R version 2.15 or later. For best results, use the latest version of R.

To install R and RStudio Desktop go to: <https://www.rstudio.com/products/rstudio/download/>

ViRTUE depends on several R packages. To install them, run the following commands from within R.

```
install.packages(c("shiny", "ncdf", "mnormt", "MASS", "zoo",  
  "maps", "mapproj", "psych", "mnormt", "fields", "plotrix",  
  "chron", "leaflet", "shinyBS", "devtools"))  
devtools::install_github("trestletech/ShinyDash")  
devtools::install_github("rstudio/shinyapps")
```

To obtain the ViRTUE source code, clone this repo using git (`git clone https://github.com/swhatele/ViRTUE.git`), or [download the zip file](#) from the repo homepage on github and extract the files to some directory.

## External Data

ViRTUE relies on one dataset that must be retrieved externally from the application due to its size. This dataset contains monthly historical climate data for the Northeast US extracted from the [Gridded Meteorological Data: 1949-2010](#) dataset by Maurer et al. 2002:

Maurer, E.P., A.W. Wood, J.C. Adam, D.P. Lettenmaier, and B. Nijssen, 2002, A Long-Term Hydrologically-Based Data Set of Land Surface Fluxes and States for the Conterminous United States, *J. Climate* 15, 3237-3251.

This dataset can be downloaded as a zip file from the following URL:  
<https://s3.amazonaws.com/umass-virtue/climate-data.zip>

Simply download this zip file and extract the contents to the `/app` folder. Note that these files must all be located directly within the `app/` folder, and not a subdirectory (e.g. `app/data_39.0625_-74.8125`).

## Running the Application

To start ViRTUE, open a new R session in RStudio and set the working directory to the root folder of this repo (e.g. using `setwd()`).

Then run the following commands:

```
library(shiny)
runApp("./app")
```

## Package Versions

The latest release of the application was tested using the following R environment:

```
> sessionInfo()

R version 3.2.1 (2015-06-18)
Platform: x86_64-apple-darwin14.3.0 (64-bit)
Running under: OS X 10.10.4 (Yosemite)

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
```

```
attached base packages:
[1] stats      graphics  grDevices  utils      datasets  methods   base

other attached packages:
[1] mnormt_1.5-3      maps_2.3-10      ggplot2_1.0.1    shinyapps_0.4.1.4
shinyBS_0.61      ShinyDash_0.0.1  leaflet_1.0.0
[8] shiny_0.12.1

loaded via a namespace (and not attached):
 [1] Rcpp_0.12.0      rstudioapi_0.3.1 magrittr_1.5      MASS_7.3-43
munSELL_0.4.2    colorSpace_1.2-6 xtable_1.7-4      R6_2.1.0
 [9] plyr_1.8.3      stringr_1.0.0    httr_1.0.0       tools_3.2.1      grid_3.2.1
gtable_0.1.2    htmltools_0.2.6  digest_0.6.8
[17] RJSONIO_1.3-0   reshape2_1.4.1  htmlwidgets_0.5  mime_0.3
stringi_0.5-5   scales_0.2.5     XML_3.98-1.3     jsonlite_0.9.16
[25] httpuv_1.3.2    proto_0.3-10
```

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