



University of
Massachusetts
Amherst

Hydrologic Forecasts And Adaptation To Climate Change In The Northeast Water Sector

Item Type	Master Projects
Authors	Whateley, Sarah
DOI	10.7275/HB1E-4993
Download date	2026-04-18 23:51:06
Link to Item	https://hdl.handle.net/20.500.14394/4820

**HYDROLOGIC FORECASTS AND ADAPTATION TO CLIMATE CHANGE IN THE
NORTHEAST WATER SECTOR**

A Master's Project Report Presented by:

Sarah Whateley

Submitted to the Department of Civil and Environmental Engineering of the University of
Massachusetts Amherst in partial fulfillment of the requirements for the degree of

Master of Science in Environmental Engineering

September 2012

Department of Civil and Environmental Engineering

**HYDROLOGIC FORECASTS AND ADAPTATION TO CLIMATE CHANGE IN THE
NORTHEAST WATER SECTOR**

A Master's Project Report Presented by:

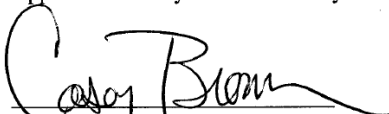
Sarah Whateley

Environmental and Water Resources Engineering Program

Department of Civil and Environmental Engineering

University of Massachusetts Amherst

Approved as to style and content by:


Name, Chairperson


Name, Member

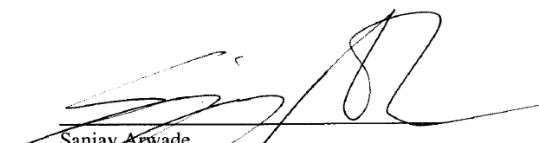

Sanjay Arwade
Graduate Program Director
Civil and Environmental Engineering Department

Table of Contents

List of Figures.....	IV
Acknowledgments	VI
1. Introduction.....	1
2. Seasonal Climate Forecasts as Innovations and the Challenges of Adoption.....	4
2.1 Abstract.....	4
2.2 Introduction.....	4
2.3 Diffusion of Innovations Framework	7
2.4 Methods.....	9
2.5 Application of DOI Framework.....	14
2.5.1 Relative Advantage	14
2.5.2 Compatibility	17
2.5.3 Complexity.....	22
2.5.4 Trialability.....	24
2.5.5 Observability.....	27
2.6 Implications for adaptation to Climate Change.....	29
2.7 Discussion.....	31
2.8 Conclusion	37
2.9 References.....	38
3. A climate change space-based method for estimating robustness for water resources supply.....	42
3.1 Abstract.....	42
3.2 Introduction.....	42
3.3 Methodology	48
3.3.1 Target system vulnerabilities, stakeholder concerns, and performance thresholds	49
3.3.2 Risk Discovery: Identifying sensitivity to climate changes	50
3.3.3 Evaluating Robustness	54
3.4 Application: A Case Study of an urban water supply system.....	56
3.4.1 Target system vulnerabilities, stakeholder concerns, and performance thresholds	56
3.4.2 Risk Discovery: Identifying sensitivity to climate changes	60
Weather Generator	60
Hydrology Model.....	62
Systems Models	64
3.4.3 Evaluating Robustness	68
3.5 Results	71
3.6 Discussion.....	78
3.7 Conclusion	81
3.8 References.....	82
4. Conclusion	87
Appendix A	89
Appendix B	90

List of Figures

Figure 1: Rogers' Categorization of Innovativeness: the bell-curve (blue) illustrates the distribution of individuals who adopt new innovations over time. The cumulative percentage of individuals who adopt is illustrated by the S-curve (red); the instantaneous rate of adoption equals the slope of the S-curve at a given time. (onhealthtech.blogspot.com)	8
Figure 2: Map of the Connecticut River Basin (CRB) and its sub-basins. The blue line represents the main stem of the Connecticut River.....	12
Figure 3: Three-month probabilistic outlook of precipitation across the United States (National Weather Services' Climate Prediction Center (CPC)).....	19
Figure 4: Characteristics of Innovation: understanding the influence of Rogers' five innovation attributes on adoption.....	33
Figure 5: Schematic of the 'bottom-up' decision framework for quantifying robustness	49
Figure 6: Map of the Connecticut River Basin with the Westfield Basin (focus of this study) shaded green.....	57
Figure 7: Springfield Water and Sewer Commission (SWSC) Drought Severity Levels for the Cobble Mountain Reservoir. Storage levels for 'normal' and 'moderate' drought conditions are specified for days of the year.	58
Figure 8: Schematic of the 'abcd' hydrology model used in this study, adapted from Martinez and Gupta, 2010.....	62
Figure 9: Hydrograph (top) and flow duration curve (bottom) of predicted flows from the calibrated hydrology model (red line) and observed flows from the Huntington gage station (black line) located in the Westfield Basin.	63
Figure 10: System representation of the Little Reservoir System (CDM, S. W. (2005). <i>Drought Management Plan</i> . Massachusetts.).....	65
Figure 11: Piecewise linear cost function; increasing cost penalties (\$) are imposed on the system for increasing magnitudes of shortfalls (mgd) to water supply demand.....	67
Figure 12: Histograms of temperature and precipitation changes developed from an ensemble of 39 GCMs (left). Delta changes are calculated by comparing 50 years of future GCM means with 50 years of historic GCM means. The relationship between temperature and precipitation variables (i.e. covariance) is illustrated on the right.	70

Figure 13: Climate response surfaces over climate change space (changes in precipitation and temperature) for normalized shortage costs (\$) (a) under standard and (b) optimal (right) operating policies. 72

Figure 14: Climate response surfaces over climate change space (changes in precipitation and temperature) for water supply reliability (a) under standard and (b) optimal operating policies. 73

Figure 15: Two-dimensional plots of system adequacy in meeting water supply demand given changes in precipitation (left) and temperature (right). Comparisons are made for standard operations (red line) and optimal operations (black line). A PDF along the x-axes is used to demonstrate the most probable future temperature and precipitation changes according to GCM-based projections. 74

Figure 16: Precipitation elasticity, a measure of system responsiveness to changes in rainfall, is illustrated in the top figure. Temperature sensitivity, a measure of system responsiveness to changes in temperature, is illustrated in the bottom figure. Comparisons are made between standard operations (red line) and optimal operations (black line). 75

Figure 17: Climate response surfaces over climate change space (changes in precipitation and temperature) for water supply reliability under standard operations (left) and optimal operations (right). PDFs from climate change projections are superimposed over climate change space to observe likelihoods of future climate changes. 77

Figure 18: Comparisons of 'acceptable' performance metrics are illustrated for assumptions of the multivariate normal distribution and the uniform distribution. Standard (red bar) and optimal (black bar) operations are compared. 78

Acknowledgments

This thesis work was funded by the National Oceanic and Atmospheric Administration's (NOAA) Sectoral Applications Research Program (SARP), award number NA100AR4310182. I would like to thank NOAA for their support in this research.

I would also like to express my sincere gratitude to my thesis advisor, Dr. Casey Brown, for his guidance and support throughout this process. His continued excellence and dedication as an advisor continue to inspire me through my academic endeavors. I would also like to thank my other committee member Dr. Richard Palmer for his encouragement and expertise throughout this process. Both Dr. Brown and Dr. Palmer's efforts and leadership in our Water Resources Research Group have made this educational experience both enjoyable and productive. Likewise, my interactions with the faculty at the University of Massachusetts Amherst through class work and research endeavors have been extremely positive and have cultivated my interests in Environmental Engineering.

I am infinitely thankful for the support and assistance I have received from my peers in the department. In particular, Scott Steinschneider has served as an invaluable role model and friend throughout this process, always willing to provide guidance and encouragement when needed. Also, Dr. Austin Polebitski and Paul Moody were always willing to assist and share their extensive knowledge in the field of water resources.

Lastly, I would like to thank my friends and family for their continued support and encouragement.

1. Introduction

Innovative approaches are needed for improving water resources management and decision-making under hydroclimatic uncertainty. Presently, water resource management and infrastructure design relies on an assumption of stationarity, the notion that ‘natural systems fluctuate within an unchanging envelope of variability’ (Milly et al., 2008). However, the need to reexamine this paradigm has proliferated in recent literature due to alterations in the hydrologic landscape (Pahl-Wostl, 2007; Peel and Bloschl, 2011). Sustainable management of water resource systems is becoming increasingly difficult as a result of intensification of anthropogenic disturbances, channel modifications, land-cover changes, and future uncertainty in climate change and variability. As we transition from a static paradigm towards a more dynamic and uncertain hydrologic landscape, we must develop new methodologies to endure climate uncertainty and variability.

The use of hydrologic forecasts may be an important adaptation to a nonstationary climate in the future, as they can provide valuable insight into weather and climate variability (Pagano et al., 2001; Steinschneider and Brown, 2012). Additionally, seasonal hydrologic forecasts can provide information to water managers about future water availability, which may influence reservoir-operating policies. While seasonal forecasts serve as a potential tool for adaptively managing water systems, it is not clear that water resource systems are receptive to innovations such as the use of forecasts. This thesis presents two studies that evaluate decision-making frameworks under future climate uncertainty. The first study qualitatively evaluates the applicability of the diffusion of innovations framework (DOI) for assessing the adoption of seasonal hydrologic forecasts by water managers in the Connecticut River Basin (CRB). The second study presents a

new decision framework for quantitatively evaluating adaptation alternatives that are robust to a wide range of possible climate changes.

In the second chapter of this thesis a conceptual framework is evaluated for relevance to the analysis of seasonal climate forecast adoption by water managers in the CRB. The diffusion of innovations framework (DOI) provides the context for understanding adoption of forecasts in water management. Methods used in this analysis include the distribution of a survey, interviews, and a literature review. The broad applicability of Rogers' (2003) DOI framework is found to be useful for understanding management decisions and adoption of innovations, and can be leveraged to improve on the production and presentation of forecasts. The principles of DOI described in this analysis provide insight into the current state of forecast use in the CRB and on improvements that can be made in forecast production to better fit the operating and decision-making needs of water managers.

The third chapter of this thesis uses a new decision framework for assessing the impact of future climate change and uncertainty on water supply systems to define and demonstrate a new metric for quantifying robustness. The metric is based on the range of climate change space over which an alternative provides acceptable performance. GCM-based climate projections are used to create a "climate-informed" version of the metric. The method is demonstrated on a water supply system in the Northeast US to evaluate the additional robustness that optimal reservoir operations can provide over stationary reservoir rule curves.

Overall, this thesis attempts to better understand and improve upon traditional decision-making tools for water resources planning and management. The two studies together provide insight into the perceived challenges of water resource management in the Northeast US and present tools for addressing these challenges given future climate uncertainty. Findings from these studies can be used to help reform water resource management, overcoming barriers to innovation that allow for robust system adaptations.

2. Seasonal Climate Forecasts as Innovations and the Challenges of Adoption

2.1 Abstract

Water managers face increasing challenges due to climate change and the rising competition for water services. Technological advances in monitoring and forecasting the earth's climate system offer a potentially useful tool to help the water resources community meet these challenges. In particular, the use of climate information has been identified as potentially beneficial in water management decisions. However, previous research has found that the implementation of new ideas and practices are impeded by a plethora of challenges such as low forecast skill, institutional obstacles, and political disincentives to innovation. To better understand the challenges associated with forecast use at seasonal-to-interannual, decadal or longer time scales, this paper evaluates a diffusion of innovations (DoI) framework to assess the adoption of climate informed forecasts by water managers in the Northeastern United States. Methods used for this analysis include the distribution of a survey, interviews, and a literature review. Results indicated that while much attention has been focused on institutional obstacles, in the Connecticut River Basin (CRB), the obstacles were related to the characteristics of the forecasts themselves. Primary concerns related to relative advantage and compatibility. The results suggest that local, tailored decision support systems may provide the most benefit for engineered forecast use in this region. Most important, evaluation of the DoI framework makes clear that the challenges to forecast use are not unique, but rather consistent with the adoption process of any innovation.

2.2 Introduction

Climate change undermines the basic assumptions by which water systems have been designed and managed historically. Anthropogenic disturbances, channel modifications, land-cover changes, and increased variability imply future hydrologic processes may differ from the past (Milly et al., 2008). The use of long-range ‘climate informed’ forecasts may be an important adaptation to a nonstationary climate in the future, as they can provide valuable insight into hydrologic variability (Pagano et al., 2001; Steinschneider and Brown, 2012). However, water allocation, risk reduction, alteration to water storage levels, and seasonal demand continue to be operational priorities for water managers and stakeholders (Kabat et al., 2003). Adapting current system practices to better deal with a changing climate not only requires the availability of new information, but also assumes the system is able to change based on the new information (Pahl-Wostl, 2007).

Climate informed forecasts provide a useful tool for adapting operational decisions to better deal with climate changes. Numerous studies describe the prospects of seasonal forecast use in water management (Gong et al., 2010; Kim et al., 1997; Pagano, P.C. et al., 2001; Pagano et al., 2002). Predictability of oceanic-atmospheric circulation patterns provides water management agencies the opportunity to incorporate teleconnections into their operations and decision-making (Chiew et al., 1998). For example, prediction of the El-Niño Southern Oscillation phenomenon (ENSO) may provide insight for water resources management around the world because of its significant influence on precipitation at seasonal timescales (Rajagopalan et al., 2000; Kahya and Dracup, 1994). One illustration of this is discussed in Pagano et al. (2002), in which climate informed forecasts during the 1997-1998 El-Niño event were used by Arizona water management agencies to help predict winter precipitation. The use of seasonal hydrologic forecasts in this case helped a

number of agencies mitigate the threat of devastating floods, cyclones, and tropical Pacific hurricanes in the area. Overall, climate teleconnections may offer improved seasonal-to-interannual, decadal, or longer term predictability of streamflow, which can be utilized in operating reservoirs and managing water systems (Hamlet and Lettenmaier, 2000, Steinschneider and Brown, 2012).

However, despite the potential benefits, it is not clear that water resource systems are receptive to innovations such as the use of seasonal hydrologic forecasts in practice. Financial constraints, complexity, individual accountability, flexibility, insufficient skill, and institutional obstacles often limit the adoption of forecast information (Dow et al., 2007; Lemos, 2008; Pagano, P.C. et al., 2001; Pagano et al., 2002; Rayner et al., 2005; Romsdahl, 2011; Yarnal et al., 2006). While the problem is well known, there is no framework for understanding and addressing the challenge.

The diffusion of innovations framework (DoI) provides a context for understanding adoption of forecasts in water management. Some studies have suggested limitations in diffusion research related to its generalizability across principles (Wejnert et al., 2002; Lemos, 2008). Arguing that a simple conceptual model could be applied to the water sector, Lemos (2008) adapted a theoretical framework (Wejnert et al., 2002) based on DoI to existing water resource decision systems in Brazil and the United States that categorically explored the dissemination of information through characteristics of innovations, innovators, and environmental context. More specifically, this study assessed the flexibility of water managers to adopt seasonal climate forecasts (SCF) through an exploration of institutional environments, communication, access to

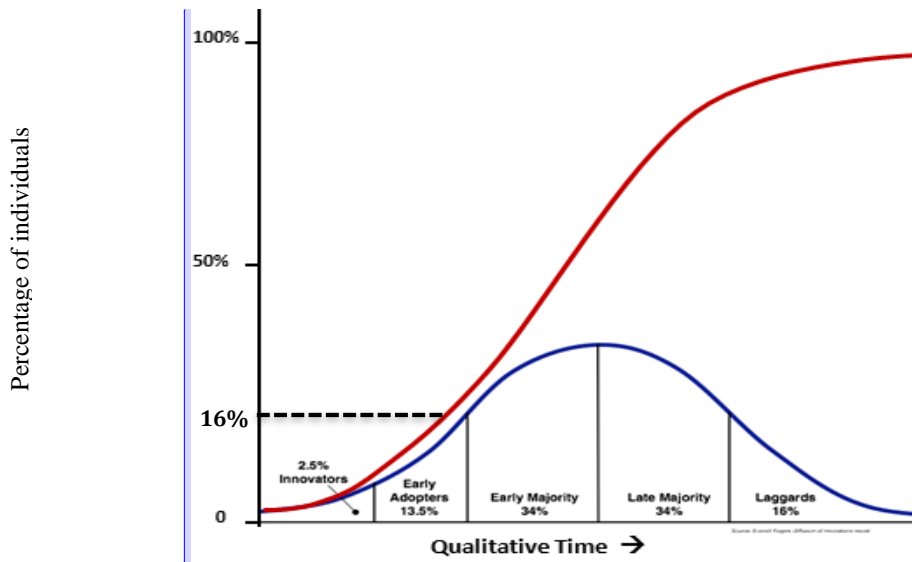
Comment [S1]: Couldn't think of a better word.

knowledge, and perceived ‘fit’ of information with decision-making needs. Results from this study indicated that the design and implementation of new institutional environments in Brazil offered flexibility that encouraged the use of new decision tools, while adoption of innovations in the U.S. was inhibited by fragmented and risk-averse systems. The present paper builds from this start by assessing the DoI framework as a tool to improve our understanding of the effect of the forecast characteristics on adoption. The use of ‘climate informed’ forecasts in water management is explored through a literature review, a survey, and interviews with CRB water managers.

This paper forwards and evaluates the hypothesis that the diffusion of innovations framework, which seeks to explore the spread of new ideas through a social system, is one means of better understanding how, why, and at what rate we would expect water managers to accept the innovations needed for adaptation to climate change, such as seasonal forecast use (Rogers, 2003). The framework is evaluated based on previous studies on seasonal forecast use in the water sector and applied to original work on this subject in the Northeast US.

2.3 Diffusion of Innovations Framework

In this study, the diffusion of innovations framework was evaluated for relevance to the analysis of seasonal climate forecast adoption by water managers in the Northeast US. The evaluation was conducted through a literature review, online survey, and interviews. Survey and interview topics were designed to explore the applicability of the five key characteristics of innovation that influence the rate of adoption described in Roger’s (2003). The DoI framework is probably most well-known for the description of adopters of innovation (Figure 1).



Comment [S2]: Cannot figure out citation listed in tiny written text but listed website...I could probably remake this figure if you think this will be a problem with reviewers...

Figure 1: Rogers' Categorization of Innovativeness: the bell-curve (blue) illustrates the distribution of individuals who adopt new innovations over time. The cumulative percentage of individuals who adopt is illustrated by the S-curve (red); the instantaneous rate of adoption equals the slope of the S-curve at a given time. (onhealthtech.blogspot.com)

According to the theory, DOI describes 'a basic and fundamental explanation of human behavior change,' where the 'rate of adoption of a new idea usually follow(s) an S-shaped curve over time' (Rogers, 2003). Adoption starts off slowly with cautious acceptance of new technologies, rapidly accelerating over time until it reaches a plateau of skepticism. While 'early adopters' tend to be considered pioneers in exploring new technologies, they are often the first to encounter barriers to innovation. At this stage, adopters are vulnerable to the imperfections of new technologies. Numerous studies have cited potential barriers to innovation in water resources management related to the characteristics of the adopters (Dow et al., 2007; Lemos, 2008; Pagano, P.C. et al., 2001; Pagano et al., 2002; Rayner et al., 2005; Romsdahl, 2011; Yarnal et al., 2006).

However, the DoI framework also provides a structure for understanding characteristics of the innovation and the effects of those characteristics on adoption. Rogers (2003) identified characteristics of innovation (i.e. relative advantage, complexity, compatibility, trialability, and observability) that affect the rate of adoption. These terms are:

Relative advantage: The amount of improvement a new innovation contributes to present conditions. Adoption of this innovation is dependent on the enhancement it is able to provide.

Complexity: The extent to which individuals must overcome difficulties in understanding and utilizing a new innovation. Adoption of this innovation is often conditional on the innovator's ability to convey information and remove ambiguity.

Compatibility: The extent to which a new innovation is consistent with past, present, and future conditions. Adoption of this innovation is a function of the degree of effort required to adapt current values to new technologies.

Trialability: The ability to experiment with a new innovation without having to fully commit to its adoption and implementation. Adoption of this innovation requires institutional flexibility and willingness to explore new options with some risk.

Observability: The opportunity to view the impact of a new innovation on an external source, so as to minimize direct consequences of adoption. Adoption of this innovation is often beyond the adopter's control, and thus is only beneficial in certain circumstances.

This paper focuses on how these perceived attributes of innovation impact seasonal hydrologic forecast adoption by water managers.

2.4 Methods

Previous studies have investigated seasonal forecast skill in the Northeast US. Yet, few studies have explored the application and perceptions of seasonal forecasts in water management for this region. The following section describes the geographic and demographic scope of this study and

introduces the approach used for understanding and evaluating seasonal forecast adoption. A brief description of the survey and interview questions is presented.

2.4.1 Setting

In the Northeast United States, studies have demonstrated skill in predicting seasonal climate variability and streamflow based on atmospheric-oceanic circulation patterns and water content measures such as snow and soil moisture (Bradbury, 2001; Bradbury et al., 2002; Hartley and Keables, 1998; Kingston et al., 2007; Steinschneider and Brown, 2011). For example, North Atlantic Oscillation (NAO) indices are positively correlated with monthly and wintertime averaged streamflow, particularly at the inland locations of New Hampshire, Vermont, Massachusetts, and Connecticut (Bradbury, 2001). Similarly, sea-surface temperature anomalies (SSTA) of the North Atlantic Tripole (NAT) off the coast of the eastern United States have been shown to influence climate and hydrology in the Connecticut River Basin (CRB) (Steinschneider and Brown, 2011).

Seasonal hydrologic forecasts can provide information for water managers about future water availability, which may influence reservoir-operating policies. For example, wintertime snow accumulation and melt have a large impact on the hydrology of the CRB during the following spring. Snow accumulation and soil moisture that persist into the late spring can greatly influence the magnitude of streamflow (Morin et al., 2008). The extent of wintertime snowpack that persists into the early spring exerts significant control over inter-annual variability of spring flows, with important implications for basin-wide drought and flood control management. While

precise predictions of streamflow months in advance are difficult in the CRB, they may provide some useful foresight for system operations.

Comment [S3]: Moved this paragraph here from above...I think it fits better here, but may be out of place still...

This study focused on water managers in the Connecticut River Basin, one of the largest basins in the Northeast. The Connecticut River Basin extends over 11,250 square miles, and is the source of water supply for the metropolitan Boston area (Figure 2). Previous studies have shown potential predictability and benefits of forecast use in the basin. The atmospheric-oceanic climate circulation patterns described above may provide the basis for forecasting models and decision support tools for water managers' reservoir operating policies in the CRB. For example, Steinschneider and Brown (2012) show how seasonal forecasts based on climate teleconnections outperform static operations and operations based on GCM projections in adapting to climate change. Understanding how water managers in the CRB perceive the use of seasonal hydrologic forecasts in decision-making may provide insight into potential improvements to enhance the development and use of climate information for operations.

To investigate current use of seasonal climate forecasts in this region, a survey was developed for administration to local water managers in the CRB who were connected to the water systems either through their influence on dam operations, water supply, water quality, ecological flows, aquatic species, flood control, or hydroelectric power production.



Figure 2: Map of the Connecticut River Basin (CRB) and its sub-basins. The blue line represents the main stem of the Connecticut River.

Thirty-nine out of one hundred and nine candidates participated in the survey, yielding a thirty-six percent response rate. Eight of the thirty-nine respondents were categorized as water managers, who were responsible for reservoir operations. These included water managers from the Farmington Basin, which supplies drinking water to the city of Hartford, New Hampshire operators that manage Lake Winnepisakie and over two-hundred other lakes in New Hampshire, the Army Corps of Engineers, who own fourteen flood control dams in the basin, and TransCanada, Inc., a private energy company which supplies six hundred megawatts of power via its thirteen hydroelectric stations on the Connecticut and Deerfield Rivers (Hachey, 2011). Several of these organizations were later contacted for follow-up interviews to attain additional information about their operations and use of forecasts.

Survey questions were specifically designed to address the basis of Rogers' (2003) diffusion of innovations, focusing on the impacts that relative advantage, complexity, compatibility, trialability, and observability have on forecast use. A secondary focus of the survey was to explore adopter-perspectives on innovation, addressing aspects others found important and reported in the literature. These specific topics in the survey aimed to investigate water managers' and stakeholders' preferences, opinions, and perceptions of forecast information. Due to the relatively small sample, results are discussed qualitatively.

The first part of the survey focused on demographic information, allowing for observation of the impact that age, experience, gender, and education have on the adoption of forecasting. Questions regarding managers' reservoir operations such as how their systems are used and physical systems such as size of the system were also incorporated into the survey to compare forecast use based on the nature and focus of their organization. Other sections of the survey focused on acquisition and use of information aimed at determining where weather and forecast information was obtained, what information was collected, and what time scale was most useful for management purposes.

In interviews with managers, survey questions were reiterated for a better understanding of the source and type of climate information used, the resolution of forecasts obtained, and the desired detail of data (see Appendix A for discussion questions). Group interview sessions were held at a Hydroclimate Workshop at the University of Massachusetts, Amherst. Climate information for the basin was presented at the workshop, including the current hydroclimate state of the basin,

seasonal outlooks and discussion of climate change. Water managers' and stakeholders' perceptions of climate change were also investigated in the survey and interview questions.

2.5 Application of DOI Framework

In this section, the DoI framework is applied to seasonal climate forecasts and the likely perception of these traits in the view of water managers. Each of the traits of innovation from the DOI is reviewed in terms of findings from the literature, the survey, and interviews. They are discussed in order of their importance to seasonal forecast adoption based on a review of the literature and results from this study.

2.5.1 Relative Advantage

Relative advantage, defined by Rogers (2003) as “the degree to which an innovation is perceived as being better than the idea it supersedes,” is one of the most influential aspects of adoption found throughout the literature. In the case of seasonal hydrologic forecasts, the concept of relative advantage is the degree to which water managers believe that a forecast provides more information than just assuming that conditions will be similar to previous years. Relative advantage for water managers could be measured by improved reliability of water supply, better ability to manage flood risks, or greater hydropower production. It is closely linked to forecast skill, which can be seen as a prerequisite. However, it is also related to the system and the ability to use seasonal hydrologic forecasts in operations.

The relative advantage of seasonal forecasts is typically measured against climatology and the long-term ‘normals’ for a site. Climate predictors can be used by water managers to dynamically alter operating policies rather than depending on the long-term average inflows, or an

unconditional ensemble of inflows. For example, predicted flood risk can augment reservoir operations by encouraging additional releases and available fill based on future and anticipated inflow (Gong et al., 2010). Hydropower facilities can also benefit from adjusting reservoir operations and improving long-term planning strategies based on seasonal hydrologic forecasts (Callahan et al., 1999; Steinschneider and Brown, 2012).

Although not using the term, most studies of seasonal forecast use in the literature focus on relative advantage, either demonstrating the benefit of using climate informed forecasts (Hamlet and Lettenmaier, 2000) or discussing the effect of forecast skill on adoption (Steinschneider and Brown, 2012). Studies show benefits of seasonal forecast use in hydropower (Kim et al., 1997; Callahan et al., 1999), water supply (Pagano et al., 2001), flood control (Callahan et al., 1999), and drought management (Chiew et al., 1998). However, it is worth noting that all of these studies are modeling studies. While potential relative advantage is demonstrated in many of these studies, there are few studies that demonstrate it in practice.

Despite model-based studies, water managers' perceive relative advantage of forecasts to be low. For example, Rayner et al. (2005) illustrates that organizational decisions rarely incorporate climate information into operations due to perceived low forecast skill. Interviews from their study indicated that "given the current skill level of the forecasts, most of our respondents believe that there is not enough imaginable improvement to rationalize investment in re-tooling their models, decision processes, and plans" (Rayner et al., 2005). Similarly, Pagano et al. (2001) observed water managers' skepticism and uncertainty in forecast skill despite the strong predictive influence of El Nino on Arizona's timing of snowmelt and streamflow magnitude.

The relative advantage of using a forecast is not only dependent on skill, but also on its perceived risk (O'Connor et al., 2005). In the literature, relative advantage is often assessed from a risk neutral perspective, and not from a risk averse perspective. By investigating the theory and empirical evidence for predictability of seasonal climate information in the 20th century, Goddard et al. (2001) hypothesized that the relative advantage of incorporating forecasts into decision-making would reduce managers' risk and costs while improving predictability and profits.

While numerous studies investigate forecast adoption in the Western United States (Hamlet and Lettenmaier, 2000; Callahan et al., 1999; Pulwarty and Redmond, 1997), less research has addressed forecast use in the Northeast. In the Northeastern United States, the use of seasonal-hydrologic forecasts to inform reservoir operating policies has been shown to improve decision-making in water resource management, theoretically providing some relative advantage (Gong et al., 2010; Steinschneider and Brown, 2012). These are again model-based studies. However, while the relative advantage of seasonal forecasts is likely lower than in regions affected by ENSO, links to the Atlantic Ocean variability show promise (Steinschneider and Brown, 2011; Bradbury et al., 2002).

Survey and interview responses from water managers in the CRB suggest that the relative advantage of a forecast is highly dependent on the nature of the system being operated and the objective skill of forecast information. Survey results indicated that water managers' confidence in various time horizons of forecast information varied, with confidence of forecasts decreasing as time scale increased. Overall, managers expressed minimal confidence in forecasts over five

days and none of the managers surveyed were confident in a six month forecast. While water managers recognize the relative advantage of using short-term forecasts in operations, they lack confidence in seasonal and monthly hydrologic forecasts.

In addition to forecast skill, discussions with water managers in the CRB emphasized the impact that specific system operations can have on managers' perceptions of the relative advantage of forecasts. For example, interviews with USACE flood control dam operators revealed that decisions are made based on 'how much precipitation we are going to get in the next few days.' Their operations are event based and not influenced by the probabilities of seasonal values. Consequently, the relative advantage of using a seasonal forecast was not observed by any of the flood control dam operators interviewed. However, water supply operators expressed desire for foresight as to whether a dry spell would extend into a drought. They identified clear relative advantage for a skillful seasonal forecast. Likewise, hydroelectricity operators described trade-offs in operations between releasing water at present to take advantage of high prices balanced against the risk of low inflows in the season ahead. In these cases, as in many reported in the literature, the lack of perceived forecast skill is a major component of perceived lack of relative advantage.

2.5.2 Compatibility

Compatibility with existing values, past experiences, and needs of potential adopters encourages the use of an innovation in decision-making (Rogers, 2003). There is broad evidence in the literature that compatibility is a key aspect of forecast adoption. In water resource management, compatibility can be interpreted to mean, for example, that forecasts are geographically suitable

for application to a particular system, temporally appropriate for operations, or congruent with institutional objectives. It is often the case, however, that seasonal forecast information is not compatible with water resource operations. Issues related to these three compatibility issues, namely spatial scale, temporal scale and institutional compatibility, are frequently cited in the literature as discussed in more detail.

Spatial Scale Compatibility

Spatial scale compatibility plays a large role in willingness to adopt seasonal hydrologic forecasts, since climate information at too coarse a scale may not provide adequate information to water managers trying to operate their local systems (Callahan et al., 1999; Rayner et al., 2005). Spatial scale compatibility is influenced by two main factors: (1) the differences in hydrologic scaling versus weather and climate scales and (2) the lack of scale efficiencies in hydrologic forecasting.

Despite significant progress in the development of hydrologic models and computational power, spatial scales resolved in weather and climate models limit predictive skill in surface hydrologic processes (Gentine et al., 2012). Coarse weather and climate models that produce forecasts for a large region (i.e. the Northeast US) are not necessarily relevant to water resource management, where watershed scale hydrologic processes inform operational decisions. For a hydrologic forecast, distributed data and hydrologic processes are combined via nonlinear processes to produce streamflow at a specific point. Producing ‘point’ forecasts at locations needed for water management can be difficult and time consuming. The issue of spatial scale compatibility poses

as a significant constraint for water managers seeking to use forecast information to better operate their systems. Figure 3 below illustrates an example of information that is too coarse for managers to use to make informed operating decisions. The figure displays the CPC precipitation outlook probabilities across the entire country.

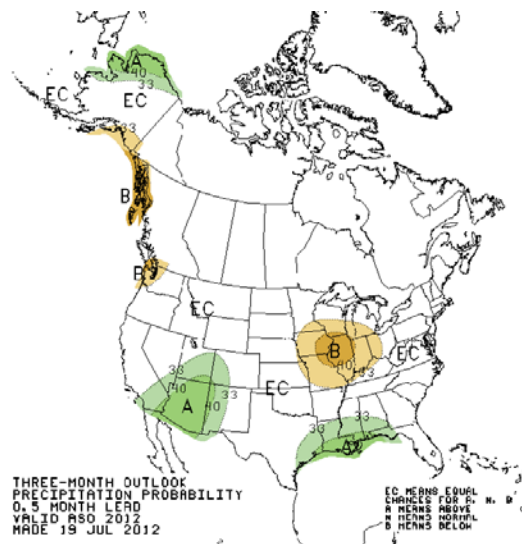


Figure 3: Three-month probabilistic outlook of precipitation across the United States (National Weather Services' Climate Prediction Center (CPC))

Temporal Compatibility

The temporal resolution of forecasts, which can range from a 1-day prediction to a 6-month outlook, impacts its role in water management decision-making. In part due to differences in forecast skill, long-term forecasts are often perceived to be less useful than short-term forecasts.

This may be a function of the way managers' operate their systems (Yarnal et al., 2006), regional

predictability of atmospheric/oceanic patterns (Goddard et al., 2001), or institutional constraints (Rayner et al., 2005), among other possibilities.

The compatibility of the time-scale of forecasts with operations is partially dependent on the type of system being managed (Hamlet and Lettenmaier, 2000). For example, flood control operations may benefit from longer term forecasts that predict winter snow melt contributing to high spring flows, or from short-term forecasts predominantly used for immediate adjustments to reservoir operations and emergency response (Callahan et al., 1999). A water supply utility may see longer-term forecasts as beneficial for managing storage and releases over time, dependent on potential summer drought or spring flooding forecasts. A hydroelectric facility may find long-term forecasts useful for optimizing power marketing, maintenance, or reservoir operations (Callahan et al., 1999). Appropriate temporal resolution of forecast information may provide managers with more dynamic and effective reservoir operating policies, potentially cutting down on operating costs and system failures.

To improve temporal compatibility of forecasts with water resource management practices, additional forecasting production efforts are required. Yet, there are scientific and cost impediments to producing compatible forecasts which continue to serve as barriers to their development. The temporal compatibility of forecast information with water management needs remains a challenge.

Institutional Compatibility

Ideally, water managers are seeking forecast information that contributes to their existing management practices so that minimal expenses, training, and operational changes need to be made (Goddard et al., 2001). Institutional compatibility has a prominent influence on forecast adoption, as demonstrated in an analysis of the institutional arrangements in Brazil and the United States (Lemos, 2008). In Lemos' study, the perceived 'fit' of climate information into current system practices played a significant role in managers' willingness and flexibility to adopt. Similarly, Pagano et al. (2002) describe the impact of institutional factors, such as sensitivity to climate variability, flexibility, and legalities, which discourage the use of forecasts in water management.

Many of the institutional challenges and barriers to seasonal forecast adoption cited throughout the literature are related to compatibility issues. For example, the compatibility of flexible water resource policies that adjust according to forecast information may be constrained by the availability and capability of built systems (i.e. reservoirs and pipelines) (Rayner et al., 2005). Additionally, the conflicting jurisdictions of agencies (e.g. legal water allocation rights, power generation demands, minimum flow requirements, etc.) complicate the development of tailored forecast information (Rayner et al., 2005). Overcoming these barriers can be challenging due to the costs associated with building new infrastructure and difficulties of tailoring seasonal forecasts to competing management and regulatory needs. Without significant institutional reforms, the adoption of seasonal forecasts into operations continues to pose as a challenge.

In the case of the CRB, survey and interview responses from water managers indicated that a lack of compatibility of seasonal hydrologic forecasts with system operations was a significant

barrier to adoption. Survey results were consistent with the literature, indicating that short term forecast information was perceived to be more useful than monthly or seasonal outlooks. Water management in the Northeastern United States is heavily dependent on extreme weather events that occur, and although there are advantages to understanding the state of the basin, a large portion of management decisions are responsive to short term weather events, such as heavy rainfall and flooding. Additionally, although some operators sought out drought forecasts, they indicated that “common droughts don’t impact us very much; with so much volume we can get through a couple of years.”

In follow-up interviews with water utility managers, it was apparent that seasonal forecast information was desired, but unavailable for their preferred locations. While forecast information on the main stem of the Connecticut River is prevalent, site-specific forecasts that are more compatible with system operations in the sub-basins and tributaries of the river are lacking.

2.5.3 Complexity

Complexity is defined as the degree to which an innovation is perceived as difficult to understand and use (Rogers, 2003). Case studies of seasonal forecast use provide evidence that complexity is indeed one of the major factors in adoption and use of forecast information in water resource operations (Rayner et al., 2005; Dow et al., 2007; Lemos, 2008). In this study, we refer to the complexity of the forecast itself, the degree to which it is difficult to understand or interpret, and the difficulty in obtaining it.

A particular challenge identified in the literature is that seasonal forecasts are typically presented in probabilistic terms (Nicholls, 1999). Probabilities assigned to a range of outcomes are more difficult to incorporate with decisions than a simple most likely prediction (i.e., a “best guess”). However, due to the chaotic nature of the atmosphere, it is difficult to accurately predict climatic conditions beyond a few days and probabilities provide a more realistic depiction of uncertainty. Therefore, the representation of forecast information in categorical probabilities, such as the likelihood of being above or below average, is a common method of presenting forecast information that is more consistent with their skill. Additionally, it is often difficult to decipher the forecast itself, either because of insufficient labeling or coarsely displayed predictions. Figure 3 is an example of a probabilistic, categorical forecast that displays a three-month probabilistic outlook of precipitation across the United States, prepared by the National Weather Services’ Climate Prediction Center (CPC). Extracting probabilistic information from this forecast that is useful for decision-making at the river basin-scale may not be intuitive for water managers.

There are numerous examples in the literature that illustrate the effects of complexity in using seasonal probabilistic forecast information in water management (Rayner et al., 2005; Dow et al., 2007; Lemos, 2008; Pagano et al., 2002). Pagano et al. (2002) describe that probabilistic forecast information made available to users by the National Weather Service’s (NWS) Climate Prediction Center (CPC) is often misinterpreted or incorrectly translated due to complexity and unfamiliarity with technical jargon. For example, probability anomalies (shifts in likelihoods) are often confused with expected quantities (e.g. magnitude of precipitation). The inherent complexity of natural systems, built environments, and institutional arrangements complicates the development of probabilistic forecasts, creating a large gap between the knowledge base of

the producers of complex climate information and the users of these products (Rayner et al., 2005).

In the study of water managers in the CRB, the complexity of obtaining information, incorporating it into operations, and technically understanding forecasts were not identified as significant barriers to adoption. Survey responses suggested that water managers in the CRB found forecast information to be easy to locate. Responses did indicate that probabilities were the aspects of forecasts that were most difficult to understand.

Group discussions with water managers indicated that despite the ease of locating forecasts, going to numerous websites and sources to collect the information was tedious and time-consuming. Water managers collect climate information from NOAA's website, weather.gov, and streamflow forecasts from the National Weather Service (NWS) River Forecast Center. They also obtain information from the NWS Climate Prediction Center and daily weather from www.weather.com. One interviewee indicated that they 'track technical river service forecasts twice a day, day-to-day weather, USGS stream gage data, and river center data.' The results indicate that for a particular system, such as a river basin, the presentation of the variety of sources of weather and climate data for a river basin, perhaps through a single portal, may be extremely useful for water managers.

2.5.4 Trialability

The diffusion of innovations framework suggests that the ability to try a new technology and dismiss it with minimal consequence increases its rate of adoption. Rogers (2003) refers to this concept as trialability. As described in Rogers (2003), trialability facilitates the adoption of new

innovations, as it increases confidence and learning while reducing risk and uncertainty in decision-making. In a general sense, there is a positive correlation between the trialability of a new idea and its rate of adoption because ‘a personal trial can dispel uncertainty about a new idea,’ instill user confidence, and provide context for its use under one’s own conditions (Rogers, 1995).

In the case of water resources management, trialability and the lack thereof may be the most important yet most overlooked aspect of seasonal forecast adoption. The ability to test the effectiveness of a forecast in water resource management may often be low, as the consequence of a single ‘missed’ forecast can lead to system failure and public discontent. In addition, seasonal forecasts are made relatively rarely, a small number of forecasts per year, precluding the ability to quickly run many trials and evaluate results. As a result, the lack of trialability presents as an important impediment.

It is well established that water managers tend to be risk averse in practice (Lemos, 2008). This is because an operational error can have large negative consequences. Scrutiny follows any impacts resulting from hydrologic extremes often independent of any culpability on the part of water management operations. Thus, water managers generally choose to ‘avoid damages rather than optimize returns’ (Pagano et al., 2001). Because there is no ability to take a system “off line” for experiments, any trial of a new innovation consequently holds the risk of a major failure and public impacts.

The typical approach to address the trialability problem is through simulation modeling of reservoir operations. Based on this approach numerous studies have shown potential value in the use of forecasts. However, the literature studies often simplify the operational environment in which forecasts would typically be used and decisions made, presenting a challenge to translating study results to practice. Present operating rules generally rely on operating procedures developed through careful and lengthy study. It is not elementary to deviate from such standards and guidelines. For example, the United States Army Corp of Engineers (USACE) spends decades testing various techniques and procedures for incorporating climate forecasts into operations before they encourage full integration into system practices (Rayner et al., 2005).

A second important aspect of seasonal climate forecasts is that the repeat time of a trial is long, possibly requiring a wait time of three months to determine if it turned out correctly or provided any benefit. Therefore, it is difficult to evaluate forecasts numerous times. Modeling again can address this concern particularly through the use of retrospective forecasts but the translation to practice remains.

A third factor affecting trialability of forecasts may be the hierarchical nature of organizations. Individuals' willingness to adopt seasonal forecast information within an organization may be affected by their status or position within that organization. Often, individuals with less power are required to have their decisions evaluated by others within their organization, which may deter them from taking chances, making mistakes, or trying new innovations. Consequently, trialability may be low in these cases.

Overall, trialability had a minimal role in seasonal forecast adoption by water managers in the CRB; however, hierarchical establishments were reported as an impediment to seasonal forecast use. Survey results indicated that position within an organization impacts forecast use. When individuals' decisions were evaluated by others in their organization respondents did not use forecast information. However, when the majority of individuals' decisions bypassed hierarchical review, water managers more frequently used forecast information, indicating a willingness to try new things with less oversight. The necessity to have management decisions evaluated by many people in an organization may delay the ability to affect the system, or add additional pressure to avoid error. Many interview participants indicated that feedback from their supervisors for public safety, performance evaluations, and budgetary responsibilities played a key role in how they were evaluated. This additional pressure decreases the trialability of seasonal hydrologic forecasts.

2.5.5 Observability

Rogers (2003) defines observability as the 'degree to which the results of an innovation are visible to others.' The ability to observe the results of an innovation helps build user confidence, lessens the number of unsuccessful adoptions, and encourages promising innovation. In water resource management, observability would mean the ability to witness similar organizations benefit from the use of seasonal hydrologic forecasts). The ability to observe another organization's use of climate and forecast information provides an opportunity for managers to evaluate the benefits of forecast use without initially disrupting their own system operations. This verification provides increased confidence and acceptance of products. Organizations

currently using forecasts could play an important role in providing insight into their experiences using forecast products in decision-making.

The concept of observability has appeared in the literature although not named as such. For example, Callahan et al. (1999) surmised that documentation of current uses and experiences with forecasts would be a valuable resource to water agencies and would provide insight into forecast effectiveness in water resource operations. Sharing this information among water resource agencies through demonstration projects would improve communication among agencies and help them familiarize with and incorporate products into their systems.

Observability may play a role in the adoption of forecast information in the CRB. There are limited ‘example’ organizations that use seasonal forecasts. Interviews with water managers indicated that communication throughout the CRB was limited, and smaller organizations were often not informed of operations taking place elsewhere in the basin. In interviews, managers specified that their ‘wish list’ would include an ‘information system in which operator responses are communicated on the Connecticut River.’ However, it is often the case in the Northeast that the greatest adopters of seasonal hydrologic forecasts are in private hydroelectricity firms, which tend to keep their operational methods private. Consequently, this is an indication of limited information exchange between operations, which limits any flow of information regarding seasonal forecast use. Although operators did not express it directly, the lack of the ability to observe successful forecast use in the basin hampers the odds of adoption. Observability could facilitate in the spread of climate information and forecast use in the basin, yet it is impeded by an inadequate exchange of information across water management sectors.

2.6 Implications for adaptation to Climate Change

Seasonal hydrologic forecasts may become increasingly valuable to operations in the future as climate change, variability, and human alterations to the watershed landscape undermine the basic assumptions by which water resource systems and infrastructure have been designed and managed historically. If the historic record becomes a less successful predictor of future conditions as a result of nonstationarity, the relative advantage of seasonal climate forecasts may increase. Steinschneider and Brown (2012) demonstrated how forecasts could be used to adapt to changing climate conditions as they evolve. In this section we use the DoI framework to consider the implications for the use of seasonal forecasts as an adaptation to changing future conditions.

At present, it is not clear if expectations of climate change increase or decrease interest in seasonal forecasts. O'Connor et al. (2005) suggest that water managers who believe that climate uncertainty and extreme weather could directly affect their systems and operating policies are encouraged to adopt seasonal climate forecasting. While improvements in climate forecast technology and awareness of climate change promote adaptation and infiltrate decision-making, many challenges still remain (Romsdahl, 2011).

In conversations with water managers in the CRB, some of the major causes for concern in future water management included increases in regulation, costs and/or complexities of water management, legalities, and climate uncertainty. While water managers in the CRB are beginning to think about climate change and its potential impacts on their systems, the use of seasonal forecasts as an adaptation has not yet entered the conversation. At this point “none of

the [climate change concerns] are really in the forefront to the point where its changed operations.” It remains unclear in some circumstances, how managers “would approach [such issues] since everything is done on such a short term basis.” While the ‘climate change conversations have become more prominent in the last 5 years, climate change is still too far in the future to use as a planning tool.’ Despite managers’ concerns for future climate and/or regulatory changes, minimal action has taken place to adapt to these changes.

In the survey of CRB managers, participants’ were asked questions that explored their views on how climate change and uncertainty in the future may affect their operations. The surveyed water managers generally believe that the climate is changing and that individuals’ choices impact climate change. Follow-up interviews with managers suggest that observable differences are already beginning to occur:

“I can’t numerically articulate it, but my gut tells me the game is changing. There is no flood control on the drinking water reservoirs; water is just spilled when floods come through. Over the last decade, more water has been spilled. It seems like large events are occurring more frequently, whereas historically, the 1955 flood and the 1938 hurricane stand out.”

Survey and interview responses from our study indicated that there was widespread agreement that water management would become more difficult in the future. Our results were consistent with O’Connor et al. (1999) study of Pennsylvania’s Susquehanna River Basin indicating that since the vast majority of surveyed managers deal with surface water, their concern for climate change and variability in the future was elevated. O’Connor et al. (1999) suggest that water systems that rely on surface water (as opposed to groundwater) are more vulnerable to conditions

caused by droughts and flooding.

While water managers in the CRB were less inclined to adopt seasonal and monthly forecasts due primarily to issues related to relative advantage and compatibility, they remained interested and concerned about longer-term future climate conditions. Yet, the ability to dynamically update operating policies according to a seasonal forecast may increase the relative advantage in the future as climate change and nonstationarity begin to influence water resource decision-making. Additionally, frequent updates of operating policies in response to predicted climatic events could influence the trialability of seasonal forecasts, as relevance and applicability to current management policies dwindles. Despite their interest in climate change, the current shortcomings, complexities, and incompatibilities of available forecasts preclude their use as an adaptation. Whether their concern for increased future challenges to their systems is a function of regulatory restrictions, legalities, or climate uncertainty, water managers in the CRB are thinking about the future of their systems and the challenges they may encounter. They largely expressed interest in forecast information and innovation in general in response to these challenges.

2.7 Discussion

The diffusion of innovations framework provides a framework for understanding and analyzing forecast use and innovation adoption in general. A literature review of forecast adoption in the United States illustrated that the attributes presented in the DoI framework, such as relative advantage, complexity, compatibility, trialability, and observability, are relevant factors that affect the adoption of seasonal and long-term forecasts. The DOI framework also allows these forms of climate information to be placed within a larger context of innovations and their

adoption. As a result, a fundamental insight emerges, namely that the challenges to the use of seasonal climate forecasts are not unique but rather consistent with any innovation. Perhaps most important, it allows insight as to how to address those challenges and which may be more easily addressed (i.e. compatibility) and which would be more difficult, such as relative advantage.

A conceptual map is introduced to summarize the relative effects of innovation traits on adoption for a particular setting. Figure 4 summarizes the results from this study using a quantitative ranking system of the innovation characteristics and their influence on adoption. The convergence point of the five attributes occurs at 0, where a factor would have no influence in facilitating adoption. As the points of the polygon expand out to the edge of the circle for each characteristic their influence on the adoption process is considered to be more significant. The left image represents the case where each attribute is critical to adoption (adoption should be highly likely since all factors are at their ideal value). The right image illustrates the influence of innovation characteristics on adoption of seasonal forecasts in the CRB, where polygon points are closest to 1 for complexity and trialability. This implies that these characteristics are fairly high relative to what they would need to be for adoption to occur. Conversely, relative advantage and compatibility are relatively low, which is where improvements can be made. This representation can be broadly applied to establish the influence of attributes on adoption (described by Equation 1).

$$Attribute\ Value = \frac{Status\ of\ Attribute}{Status\ With\ No\ Impediment\ to\ Adoption} \quad (1)$$

The equation above can be illustrated with an example based on DoI characteristics in the CRB. Assume the rating system described above is on a scale of 0 to 1, with the 'status with no impediment to adoption' being equal to 1. The attribute value for relative advantage in the CRB would likely be low (e.g. 0.3) indicating that in this basin the relative advantage of seasonal forecasts is perceived to be small relative to what it would need to be for adoption to occur. Once the impact of these characteristics has been recognized, approaches to overcoming these challenges and barriers can be appropriately addressed.

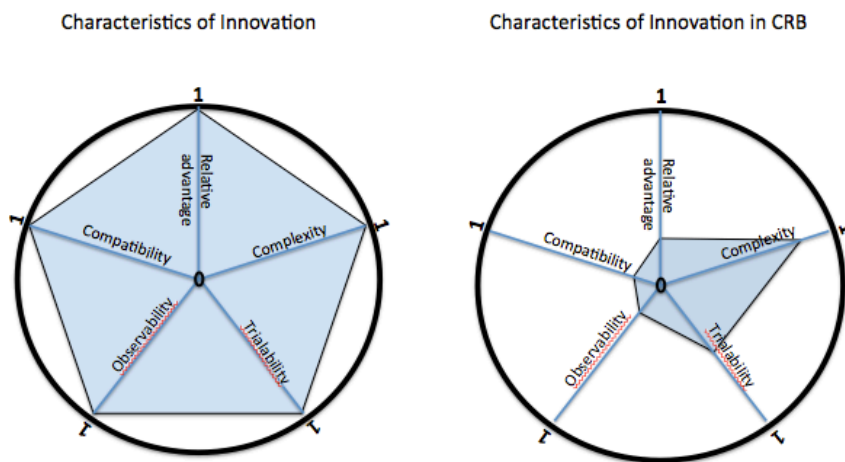


Figure 4: Characteristics of Innovation: understanding the influence of Rogers' five innovation attributes on adoption

Within the CRB and elsewhere, it is clear that relative advantage is the significant factor in seasonal forecast use, (Steinschneider and Brown, 2012; Callahan et al., 1999; Lemos, 2008). Despite technological advances that show promise for improved seasonal climate forecast skill, it remains difficult to achieve (Ishikawa et al., 2011). While many insightful studies have

highlighted the institutional challenges in water management agencies, the need for improved seasonal forecasts cannot be overstated.

The second most important of the traits of innovations for seasonal forecasts is compatibility with current operating policies in water management. Previous studies discuss the importance of compatibility, although stated in different terms (Rayner et al. 2005; Callahan et al., 1999; Lemos, 2008). There is a clear need for the tailoring of seasonal hydrologic forecasts for specific users at specific locations. Modeling studies that demonstrate relative advantage of forecasts always include highly tailored forecasts for the point of use. However, this creates a scale challenge for forecast production. Unlike the production of weather or climate forecasts of precipitation or temperature, hydrologic forecasts require calibration at each point of use. Thus seasonal hydrologic forecasts that are available, such as through the National Weather Service River Forecasting Center, are limited in the points where they can provide forecasts. This gap provides an opening for private providers or consultants and in cases they are providing this service although it will rarely appear in scientific literature.

Similarly to compatibility, complexity of seasonal forecast information can be overcome by tailoring information to water managers' needs. Rayner et al. (2005) make several suggestions for overcoming complexity and encouraging technical advancement in management. For example, they propose that the transparent incorporation of new ideas into existing practices should be encouraged by a clear translation of scientific material through employed staff and organizational networks.

Trialability of seasonal forecasts appears in the literature as a factor that influences adoption. Whether a function of risk aversion (Pagano et al., 2001), organizational hierarchies (O'Connor et al., 2005), or time constraints (Wood and Lettenmair, 2006), the lack of trialability is an important aspect of adoption of seasonal forecasts. To overcome the challenges associated with trialability in system operations, there is a need to reduce the risks associated with forecast use. While there have been many modeling studies that demonstrate forecast value in the risk free modeling environment, there is need for reducing real world risk of use in operations. For example, insurance mechanisms may be used to hedge risk of low probability events and the institutional risk that accompany them (Brown and Carriquiry, 2006; Wilby and Keenan, 2012). In other cases, real options may provide a risk hedge (Steinschneider and Brown (2012). In these ways, the consequences of a 'missed' forecast are reduced through mechanisms or operations that greatly diminish the impact on the system (and downstream political impacts).

The limited observability of forecast use may also be a barrier to adoption. Although the practicality and usefulness of seasonal hydrologic forecasts varies among different water sectors, there is an overall need for improved communication and collaboration among users and producers of climate information in the CRB that may facilitate in overcoming observability barriers to adoption. An overall improvement in communication channels throughout the basin may also increase knowledge of how forecasts can be used for operations. Compiling forecast information for water managers based on where they are located, while still providing a means for basin wide and user/producer communication, may facilitate in the spread of seasonal forecast use in the CRB.

A single river basin knowledge ‘portal’ may be one way to combat issues related to observability, as it would provide a place for water managers to collaborate and accrue useful information. This may be generally described as a decision support system (DSS), in which a computerized tool is used to help support operational decisions. Alemu et al. (2011), in their study of operators of the Washington State Snohomish Public Utility District’s (SnoPUD) Jackson Project, demonstrate that ‘significant operational gains can be achieved with the use of forecast information integrated in a DSS.’ The development of a ‘portal’ for discussion of forecasts and use may encourage adoption. Likewise, creating a knowledge portal for water managers in the CRB would improve communication and facilitate in the exchange of ideas. Social systems such as these allow water managers and stakeholders to express their concerns and relay experiences that could facilitate in the development of operational policies. Additionally, it may advance the spread of technical information and practices that are often lost in communication when transferred between a source and the end users (Rogers, 2003).

In the case of the CRB, relative advantage and compatibility, and to a less extent trialability and observability were the key characteristics of forecasts affecting adoption. Addressing these concerns would require working with specific users who saw potential value in forecast use to develop decision support for their operational decisions. There would also be benefit in providing a venue for the development of a river basin portal for dissemination and discussion of climate information within the water managers of the basin. Such a river basin portal may be deemed an operationalization of the knowledge network concept, which has been advanced as an avenue to promote innovation adoption (Feldman et al., 2009).

Confidence in seasonal hydrologic forecast skill remains low in the basin. While relative advantage influenced seasonal forecast use to varying degrees depending on the type of system being operated, conversations with water managers suggested that confidence in seasonal forecast skill was also partially a reflection of their regional availability and exposure. A river basin portal does not improve relative advantage but perhaps can increase the awareness of whatever advantage there may be. While not much can be done in the immediate future to increase forecast skill, our efforts should focus on achieving the most benefit from existing forecast skill.

2.8 Conclusion

The diffusion of innovations framework presents a general tool for understanding the challenges of seasonal climate forecast adoption by water managers. It makes clear that the challenges associated with seasonal forecast use are common to all innovations. It also points to possible remedies. The relative advantage and compatibility of seasonal hydrologic forecasts appear to be the most significant factors in the CRB. The encouraging finding is that most of these factors can be addressed, although not without significant effort. For example, compatibility and complexity may be ameliorated through the development of local, tailored decision support systems, while trialability and observability may be at least partially addressed through knowledge portals. Relative advantage depends on advances in forecast skill, probably most challenging, but DSS may provide more relative advantage for a given skill level. The findings suggest that there is much that can be done to enhance the adoption of seasonal forecasts and institutional barriers are not a universal impediment.

Acknowledgments: This work is funded under a grant from the Sectoral Applications Research Program (SARP) of the National Oceanic and Atmospheric Administration (NOAA) Climate Program Office (NA10OAR4310182). The views expressed in this report represent those of the authors and do not necessarily reflect the views or policies of NOAA. The authors appreciate the efforts of water managers of the Connecticut River Basin who came to the workshop, completed surveys and spoke with us. An additional thanks to Ed Sarachik who first recommended that co-author Casey Brown read *Diffusion of Innovations*.

2.9 References

- Alemu ET, Palmer RN, Polebitski AS, Meaker B (2010) A decision support system for optimizing reservoir operations using ensemble streamflow predictions. *J Water Resour Plan Manage*. doi:10.1061/(ASCE)WR.1943-5452.0000088
- Araghinejad, S., Burn, D. H., & Karamouz, M. (2006). Long-lead probabilistic forecasting of streamflow using ocean-atmospheric and hydrological predictors. *Water Resources Research*, 42(3). doi:10.1029/2004WR003853
- Bradbury, J. A. (2001). Relation of hydrologic drought in New England to large-scale atmospheric circulation patterns (p. 238).
- Bradbury, J. A., Keim, B. D., & Wake, C. P. (2002). US East Coast trough indices at 500 hPa and New England winter climate variability. *Journal of climate*, 15(23), 3509–3517.
- Broad K, Leiserowitz A, Weinkle J, Steketee M. 2007. Misinterpretations of the “cone of uncertainty” in Florida during the 2004 hurricane season. *Bulletin of American Meteorological Society* 88: 651 – 667.
- Callahan, B., Miles, E., & Fluharty, E. (1999). Policy implications of climate forecasts for water resources management in the Pacific Northwest. *Policy Sciences*, 32(3), 269–293.
- Chiew, F. H. S., Piechota, T. C., Dracup, J. A., & McMahon, T. A. (n.d.). El Nino/Southern Oscillation and Australian rainfall, streamflow and drought: Links and potential for forecasting. *Journal of Hydrology*, 204, 138–149.
- Dow, K., O'Connor, R. E., Yarnal, B., Carbone, G. J., & Jocoy, C. L. (2007). Why worry? Community water system managers' perceptions of climate vulnerability. *Global Environmental Change*, 17(2), 228–237. Elsevier.
- Dracup, J. and Kahya, E. (1994). The relationships between U.S. streamflow and La Nina events. *Water Resources Research* 30(7): doi: 10.1029/94WR00751. issn: 0043-1397.
- Feldman, D.L., Ingram, H.M. (2009). Making Science Useful to Decision Makers: AMS: Climate Forecasts, Water Management, and Knowledge Networks. Weather, Climate and Society.
- Flato, G., & Boer, G. (2001). Warming asymmetry in climate change simulations. *Geophysical Research Letters*, 28(1), 195–198.
- Gentine, P., Troy, T.J., Lintner, B.R., Findell, K.L. (2012). Scaling in Surface Hydrology: Progress and Challenges. *Journal of Contemporary Water Research and Education*, Issue 147: 28-40.

- Gong, G., Wang, L., Condon, L., Shearman, A., & Lall, U. (2010). A Simple Framework for Incorporating Seasonal Streamflow Forecasts into Existing Water Resource Management Practices. *JAWRA Journal of the American Water Resources Association*. doi:10.1111/j.1752-1688.2010.00435.x
- Groisman, P. Y., Knight, R. W., & Karl, T. R. (2001). Heavy precipitation and high streamflow in the contiguous United States: Trends in the twentieth century. *American Meteorological Society*.
- Hachey, 2011. Committee Bill No. 1: An Act Concerning Connecticut's Energy Future. *TransCanada Power Marketing Ltd.*
- Hamlet, A. F., & Lettenmaier, D. P. (2000). Long-range climate forecasting and its use for water management in the Pacific Northwest region of North America. *Journal of Hydroinformatics*, 2(3), 163–182.
- Hartley, S., & Keables, M. J. (1998). Synoptic associations of winter climate and snowfall variability in New England, USA, 1950–1992. *International Journal of Climatology*, 18(3), 281–298. Wiley Online Library.
- Hayhoe, K., Wake, C. P., Huntington, T. G., Luo, L., Schwartz, M. D., Sheffield, J., Wood, E., et al. (2006). Past and future changes in climate and hydrological indicators in the US Northeast. *Climate Dynamics*, 28(4), 381–407. doi:10.1007/s00382-006-0187-8
- Hodgkins, G. A., Dudley, R. W., & Huntington, T. G. (2003). Changes in the timing of high river flows in New England over the 20th Century. *Journal of Hydrology*, 278(1-4), 244–252. doi:10.1016/S0022-1694(03)00155-0
- Houck, M. H.: 1992, 'A systems approach to real-time reservoir operations', in Topping, B. H. V. (ed.), *Optimization and Artificial Intelligence in Civil and Structural Engineering*, Kluwer Academic Publishers, Dordrecht.
- Huntington, T. G., Hodgkins, G. A., Keim, B. D., & Dudley, R. W. (2010). Changes in the proportion of precipitation occurring as snow in New England (1949–2000).
- Ishikawa, T., Barnston, A.G., Kastens, K.A., Louchouart, P. (2011). Understanding, evaluation, and use of climate forecast data by environmental policy students. *The Geological Society of America, Special Paper 474*.
- Kabat P., Schulze R.E., Hellmuth M.E., Veraart J.A. (editors), 2003. Coping with impacts of climate variability and climate change in water management: A scoping paper. DWC-Report no. DWCSSO-01 International Secretariat of the Dialogue on Water and Climate, Wageningen, Netherlands.
- Kalra, A., & Ahmad, S. (2009). Using oceanic-atmospheric oscillations for long lead time streamflow forecasting. *Water Resources Research*, 45(3). doi:10.1029/2008WR006855
- Kim, Y.O., & Palme, R. N. (1997). Value of seasonal flow forecasts in Bayesian stochastic programming. *JOURNAL OF WATER RESOURCES PLANNING AND MANAGEMENT*.
- Kingston, D. G., McGregor, G. R., Hannah, D. M., & Lawler, D. M. (2007). Large-scale climatic controls on New England river flow. *Journal of Hydrometeorology*, 8(3), 367–379.
- Lemos, M. C. (2008). What Influences Innovation Adoption by Water Managers? Climate Information Use in Brazil and the United States¹. *JAWRA Journal of the*

- American Water Resources Association, 44(6), 1388–1396. Wiley Online Library.
- McIntyre, N., H. Lee, H. Wheeler, A. Young, and T. Wagener (2005), Ensemble predictions of runoff in ungauged catchments, *Water Resour. Res.*, 41, W12434, doi:10.1029/2005WR004289.
- Meinke, H., & Stone, R. C. (2004). Seasonal and inter-annual climate forecasting: the new tool for increasing preparedness to climate variability and change in agricultural planning and operations. *Climatic Change*, 1–33.
- Milly, P., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., & Stouffer, R. J. (2008). Stationarity is dead: whither water management *Earth*, 4, 20.
- Morin, J., Block, P., Rajagopalan, B., & Clark, M. (2008). Identification of large scale climate patterns affecting snow variability in the eastern United States. *International Journal of Climatology*, 28(3), 315–328. Wiley Online Library.
- Nicholls N. 1999. Cognitive illusions, heuristics, and climate prediction. *Bulletin of the American Meteorology Society* **80**: 1385–1397.
- O'Connor, R. E., Yarnal, B., Dow, K., Jocoy, C. L., & Carbone, G. J. (2005). Feeling at risk matters: water managers and the decision to use forecasts. *Risk Analysis*, 25(5), 1265–1275. Wiley Online Library.
- O'Connor, R. E., Yarnal, B., Neff, R., Bord, R., Wiefek, N., Reenock, C., Shudak, R., et al. (1999). WEATHER AND CLIMATE EXTREMES, CLIMATE CHANGE, AND PLANNING: Views of Community Water System Managers in Pennsylvania's Susquehanna River Basin. *JAWRA Journal of the American Water Resources Association*, 35(6), 1411–1419. Wiley Online Library.
- Pagano, P.C., Hartmann, H. C., & Sorooshian, S. (2001). USING CLIMATE FORECASTS FOR WATER MANAGEMENT: ARIZONA AND THE 1997–1998 EL NIÑO. *Journal of the American Water Resources Association*, 37, 1139–1153.
- Pagano, T. C., Hartmann, H. C., & Sorooshian, S. (2002). Factors affecting seasonal forecast use in Arizona water management: a case study of the 1997-98 El Niño. *Climate Research*, 21(3), 259–269. INTER-RESEARCH.
- Pahl-Wostl, C. (2007). Transitions towards adaptive management of water facing climate and global change. *Water Resources Management*, 21(1), 49–62. Springer.
- Palmer, R. N., Smith, J. A., Cohon, J. L. and ReVelle, C. S.: 1982, 'Reservoir management in the Potomac River Basin', *J. Water Resources Plann. Manag.* **1(1)**, 47–66.
- Post, D.A., Jones, J.A., Grant, G.E., 1998. An improved methodology for predicting the daily hydrologic response of ungauged catchments through regionalization. *Environ. Model. Software* 13, 395-403.
- Pulwarty, R., & Redmond, K. (1997). Climate and salmon restoration in the Columbia River basin: The role and usability of seasonal forecasts. *Bulletin of the American Meteorological Society*, 78(3), 381–397.
- Rajagopalan, B., Cook, E., Lall, U., & Ray, B. K. (n.d.). Spatiotemporal variability of ENSO and SST teleconnections to summer drought over the United States during the twentieth century. *Journal of climate*, 13, 4244–4255.

- Rayner, S., Lach, D., & Ingram, H. (2005). Weather forecasts are for wimps: why water resource managers do not use climate forecasts. *Climatic Change*, 69(2), 197–227. Springer.
- Romsdahl, R. J. (2011). Decision support for climate change adaptation planning in the US: why it needs a coordinated internet-based practitioners' network. *Climatic Change*, 1–30. Springer.
- Steinschneider, S., & Brown, C. (2011). Influences of North Atlantic climate variability on low-flows in the Connecticut River Basin. *Journal of Hydrology*, 409(1-2), 212–224. Elsevier B.V. doi:10.1016/j.jhydrol.2011.08.038
- Steinschneider, S. and Brown, C. (2012). Dynamic reservoir management with real options risk hedging as a robust adaptation to nonstationary climate. In review.
- Wagener, T., H. S. Wheater, and H. V. Gupta (2004), *Rainfall-Runoff Mod-elling in Gauged and Ungauged Catchments*, Imperial College Press, London.
- Wejnert, B., 2002. Integrating Models of Diffusion of Innovations: A Conceptual Framework. *Annual Review of Sociology* 28:297-326.
- Wilby R., Keenan, R. (2012). Adapting to flood risk under climate change. *Progress in Physical Geography*, 36(3):348-378.
- Wood, A. W., & Lettenmaier, D. P. (2006). A Test Bed for New Seasonal Hydrologic Forecasting Approaches in the Western United States. *Bulletin of the American Meteorological Society*, 87(12), 1699–1712. doi:10.1175/BAMS-87-12-1699
- Yarnal, B., Heasley, A. L., O'Connor, R. E., Dow, K., & Jocoy, C. L. (2006). The potential use of climate forecasts by community water system managers. *Land Use Water Resour. Res.*, 6, 3.1–3.8.
- Yazicigil, H., Houck, M. H. and Toebes, G. H.: 1983, 'Daily operation of a complex reservoir system', *Water Resources Res.* **19(1)**, 1–13.

3. A climate change space-based method for estimating robustness for water resources supply

3.1 Abstract

Many water resources planning and operation decisions are affected by climate uncertainty. Given concerns about the credibility of climate projection-based impact assessments, many water planners seek adaptation alternatives that are robust given a wide range of possible climate futures. However, there is no standardized paradigm for quantifying robustness in the water sector. This study uses a new framework for assessing the impact of future climate change and uncertainty on water supply systems and defines and demonstrates a new metric for quantifying robustness. The metric is based on the range of climate change space over which an alternative provides acceptable performance. GCM-based climate projections are used to create a “climate-informed” version of the metric. The method is demonstrated on a water supply system in the Northeast US to evaluate the additional robustness that optimal reservoir operations can provide over stationary reservoir rule curves.

3.2 Introduction

The effects of climate change and potential non-stationarity in hydrologic variables undermine many assumptions upon which water resources infrastructure has been historically managed and designed. Emerging scientific evidence suggests that anthropogenic activities are altering the water cycle, resulting in changes to the probabilistic behavior of hydrologic variables that were previously assumed stationary in time. Sustainable management of water resources under this pattern of change is becoming increasingly difficult to evaluate, generating a vast need for new

adaptation strategies to cope with shifting climate regimes (Kundzewicz et al., 2008). However, deep uncertainty in future climate projections (Lempert et al., 2006) precludes a precise description of future hydrologic change, requiring adaptation strategies that are robust. Qualitatively, an adaptation strategy is robust if it results in satisfactory performance across a range of potential climate changes. This study proposes a ‘bottom-up’ approach that quantifies water resource system robustness under climate uncertainty. A new climate space-based robustness metric is defined to evaluate the effectiveness of system adaptations over a range of climate change space. The metric can also be informed using a probabilistic weighting inferred by a range of GCM-based projections or other sources of climate information in order to consider the likelihood of different climate changes. The climate space-based metric provides a straightforward way to identify robust adaptation strategies among various alternatives across a wide range of potential futures and immediately makes clear how different assumptions of future climate later adaptation decisions.

Classical decision analysis in water resources engineering has relied on the assumption that the risk of climate outcomes important to infrastructure design and management can be characterized using probability models describing their frequency. With appropriate probability distributions assigned to natural (and unknowable) forcings affecting the performance of a water system, an optimal plan or design can be chosen from among a set of alternatives with respect to chosen performance measures (Loucks, 2005 (Ch.8); Morgan and Henrion, 1990; Lempert et al., 2006). Traditionally, system performance has been evaluated using measures such as reliability, resilience, and vulnerability, describing how likely a system is to fail, how quickly it recovers from failure, and the severity of its failure (Hashimoto et al., 1982). For example, a water supply

system may define failure as the inability to meet water supply demand and may judge performance based on the frequency of, resilience to, and severity of water shortages (Hashimoto et al., 1982a). In water planning applications, mathematical simulation and optimization models are often used to predict the behavior of system designs and policies over time, assuming that climate variables follow time-invariant probability density functions. While this decision framework has proven very powerful in the past (Goodwin and Wright, 2004), the process hinges on an accurate description of the probabilistic behavior of natural conditions (i.e. climate). If probability distributions of key climate variables shift in unforeseeable ways under long-term climate change, traditional decision theory, as currently practiced, may no longer be an appropriate paradigm to guide water resources planning and management.

There have been many attempts to assess the impacts of future climate on water resource systems that do not rely on assumptions of stationarity. These studies often use ‘top-down’ or scenario-based approaches to evaluate system performance by downscaling climate projections from generalized circulation models (GCMs) over a range of greenhouse gas emission scenarios (Manning et al., 2009; Wiley and Palmer, 2008; Christensen and Lettenmaier, 2007; Brekke et al., 2009; Vicuna et al., 2010; Lopez et al., 2009). Downscaled (Wilby et al., 2009) and bias corrected (Murphy, 1999) climate sequences generated from GCMs can then be propagated through hydrologic models and impact models to estimate system performance over time.

While GCM-based scenarios are useful for evaluating potential climate change impacts, due to biases and uncertainties they are less useful for exploring and evaluating risks (Brown and Wilby, 2012). The inherent uncertainty in these projections related to climate forcings, initial condition ensembles, and model inadequacies (i.e. parameterization) (Stainforth et al., 2007)

make it difficult to incorporate information from these scenarios into adaptation decisions. Additionally, with no associated likelihoods or reliable probability estimates, it is not plausible to assess the relative risk of potential adaptation strategies.

Recently, there has been interest in ‘bottom-up’ approaches to climate change impact assessments. In this approach, the objective is to reduce system vulnerabilities to climate variability without relying on climate change projections generated by GCMs (Brown et al., 2012; Dessai et al., 2009; Mastrandrea et al., 2010). Such approaches allow decision-makers to evaluate system impacts over a wide range of futures including those forecasted by GCMs but also those that may lie outside of the range of GCM scenarios. Climate change projections can still be incorporated into later stages of the analysis to estimate relative probabilities of system hazards, moving toward a risk-based adaptation decision-making framework (Brown et al., 2011; 2012; Pittock et al., 2001). This risk-based framework provides opportunity to develop and assess adaptation strategies that are robust over a wide range of climate changes (Lempert et al., 2002; Groves, 2006).

In water resource planning, robustness is qualitatively defined by the ability of a system to adjust its operations or adapt to changes in future design conditions. Numerous studies in the literature have explored robust adaptation to climate change and uncertainty in water management (Lempert, 2010; Wilby and Dessai, 2010; Dessai and Hulme, 2007). For example, Lempert (2010) describes the benefits that a robust decision making approach can provide in addressing climate uncertainty in water resources management by assessing the performance of agency plans over climate futures, using statistical algorithms to understand when plans fail, and

addressing vulnerabilities through an exploration of adaptive plans that reduce present value costs over time. Additionally, Wilby and Dessai (2010) describe a procedure for evaluating adaptation strategies that are robust under climate change without relying on the uncertainty associated with GCM projections. Their framework explores various adaptation options at the system level and selects only those adaptations that reduce system vulnerabilities under the historic climate regime. However, in these frameworks for decision-making with uncertainty, robustness is not quantified.

There is a paucity of research employing quantitative metrics of robustness that integrate well with current water resource systems analysis tools. Hashimoto et al. (1982b) define robustness measures as the probability that the cost for a particular design under some future demand condition is less than or equal to some multiple of the least cost design. This metric is essentially a measure of regret. However, that methodology only allows for an analysis of relative performance with respect to the optimal design rather than a measure of absolute performance of a given design across multiple futures. Watkins and McKinney's (1997) study of robust optimization (RO) for a water supply system defines a robust plan as one that maintains a high (but not maximized) expected value of performance metrics across scenarios while also maintaining a small (but not minimized) variance of performance metrics across those scenarios. The RO model, though innovative, does not easily incorporate stakeholder driven definitions of acceptable system performance integral to its utility in practice.

One novel approach to quantifying robustness in a water system is illustrated in Moody and Brown's (2012) study of the Upper Great Lakes. In this study, quantitative robustness indicators

are used to measure the range of acceptable performance for a given model output variable over future climate states. Acceptable (or satisfactory) performance is defined using a binary performance function driven by a chosen threshold, where metrics above or below this threshold are assigned values of 0 and 1 respectively. The range of acceptable performance is calculated using a climate informed robustness index (CRI), created by taking the product of the binary matrix and an assumed probability distribution and integrating over climate change space. The CRI is conditional on stakeholder driven performance thresholds and on assumptions of probabilities of future climate events occurring. In that study, robustness measures are applied to the regulation of outflows from Lake Superior in the Great Lakes. These quantitative metrics are useful for informing water resource decision-making with stakeholder input and evaluating system performance across regulation plans.

In this study we extend the work of Moody and Brown (2012) by adopting their metrics for quantifying robustness under climate change uncertainty using a new ‘bottom-up’ framework. The methodology begins with an assessment of system vulnerabilities to climate change, weights risks to relevant changes using assumed probability distributions, and evaluates robustness of alternative adaptations over the range of climate change space. A unique aspect of this approach is that it incorporates information from GCMs in the later stages of analysis, providing a ‘climate informed’ version of the robustness metric. This approach follows a three-step process to quantify robustness; 1) target system vulnerabilities and stakeholder concerns to define system performance thresholds, 2) perform a ‘risk discovery’ sensitivity analysis using synthetic time series developed from a weather generator, and 3) quantify robustness based on the climate change space over which there is acceptable performance.

This study demonstrates this approach in evaluating operational changes in water supply as an adaptation to climate change. The process, designed to support decision-making, is evaluated by comparing a reservoir system's standard management strategies with optimal operations over climate change space. Details of the methodology are described in Section 3. An application of the approach to a water supply system in the Northeast United States is presented in Section 4. Results are presented in Section 5, and the paper concludes with a discussion in Section 6.

3.3 Methodology

The methodological approach taken in this paper, referred to as decision-scaling (Brown et al., 2011), inverts the popular scenario-based approach to climate risk assessment by evaluating system performance over a range of climate futures 'unbounded' by GCM projections. This is done through an exploration of 'expected values' of climate informed robustness indices conditioned on different probabilistic assumptions. Climate robustness measures adapted from Moody and Brown (2012) are used to evaluate 'acceptable performance' over a range of climate scenarios. Quantifying robustness of alternative adaptations under climate change is presented in this study as a three-step process, explained below. Figure 1 illustrates a schematic of this 'bottom-up' framework.

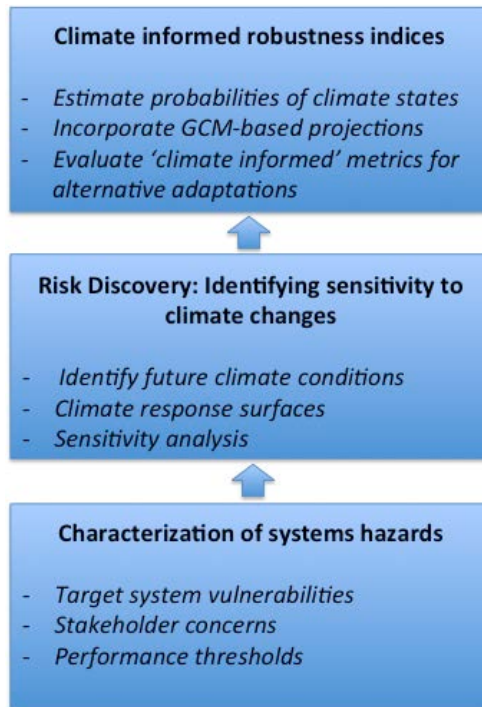


Figure 5: Schematic of the 'bottom-up' decision framework for quantifying robustness

3.3.1 Target system vulnerabilities, stakeholder concerns, and performance thresholds

The first step identifies water manager and stakeholder concerns about future climate conditions and system vulnerabilities. Execution of this step requires communication with managers about their current operating policies, design and planning strategies, and system weaknesses. Additional insight into system operations can be gained by using computer models, where management practices can be simulated under current and future climate conditions to address operational challenges and the impacts of their management systems can be illustrated over a wide range of hydrologic futures. Communication with stakeholders, systems models, and

background research of water resource systems may help target system vulnerabilities and define performance thresholds.

Performance thresholds define a lower limit of acceptable system functioning that does not significantly diminish the integrity of the system over time. In water planning applications, thresholds may be controlled by economics, safety, productivity, or ecological impacts. To effectively address water managers' concerns and evaluate system weaknesses to climate change, performance indicators, $F(X)$, can be calculated for the system conditional on a given climate regime, X . Thresholds can be placed on these performance indicators to define acceptable system performance over climate change space. For a water supply utility motivated to meet demand, reliable allocation of water resources would likely dictate the development of their performance metrics and thresholds. Thus, a threshold (e.g. 98%) could be placed on a reliability performance indicator (as defined by Hashimoto et al., 1982) to distinguish between acceptable and unacceptable system performance. After performance indicators and thresholds have been established, the proposed framework makes use of climate-altered variables, hydrologic models, and impact models to explore the climate change space to reveal where systems are most vulnerable.

3.3.2 Risk Discovery: Identifying sensitivity to climate changes

Having identified system performance thresholds and indicators in the previous step, this analysis transitions to evaluating the system's vulnerability to relevant climate conditions. System vulnerabilities or 'failures' occur in climate change space where performance thresholds are not met. This analysis of system sensitivity to future climate states is referred to as 'risk

discovery’ and consists of three components (Brown et al., 2012); an investigation of future climate conditions, the development of ‘climate response surfaces,’ and a sensitivity analysis of system responsiveness to incremental changes in climate.

Identifying future climate conditions

The generation of realistic climate sequences (X) that represent different climate regimes is useful for understanding potentially problematic conditions in the future. As the foundation for all future steps in the analysis, climate sequences are used to assess system performance and risk estimates through time. Ultimately, scenarios are used to develop ‘climate response surfaces,’ illustrating system sensitivity and vulnerability to future hydrologic changes.

There are a number of ways in which climate change scenarios are generated, including the development of historically based stochastic time series, paleo-climate reconstructions (Ghile et al., 2012), GCM output, and the less explored method of weather generation. Regardless of the methodology used to generate climate sequences for this analysis, it is essential that the time series are sufficiently long to capture inter-annual and decadal variability and long-term trends in climate. These are the factors that complicate decision-making, increase uncertainty, and pose the greatest threat to system infrastructure and design in the future. In this study, use of a weather generator that captures possible changes in climate provides inputs for simulation and optimization models (see section 4.1).

Climate sequences can be developed over any range of potential climate futures. Choosing that range can be done in a number of ways, including assessing conditions from the paleo-record, arbitrarily setting boundaries, or applying a ‘safety factor’ that expands the climate space beyond that explored by GCM projections. In this study, for example, a ‘safety factor’ is established based on the range of future climate changes predicted by GCMs. The final climate change space explored ranges from +/- 25% of historic average precipitation and between 0 and 5 degrees Celsius increases in historic average temperature. The idea is that this ‘space’ is not bounded by GCM projections of future climate, but rather extends over a broad scope of potential futures.

Climate response surfaces

For this part of the analysis, climate sequences (described in the previous section) are used to evaluate changes in performance metrics over climate change space. The application of systems models provides a mechanism for assessing system performance. Systems models are used to explore changes in performance variables and reservoir operations over potential climate futures using climate altered hydrologic sequences as input. Discovery of climate risks through this process allows for the development of climate response surfaces, which display changes in system responses using a ‘gridded map’ of performance indicators. The limits of climate change space represented by these response surfaces are designed to capture a wide range of futures, testing systems over conditions they may never actually encounter. Consequently, climate response surfaces help address future uncertainty and system vulnerabilities without relying on model predictions of climate.

Sensitivity Analysis

The final component of ‘risk discovery’ measures the sensitivity of performance metrics to incremental changes in climate. This is done through a sensitivity analysis, where system responsiveness to changes in climate are quantified using precipitation elasticity (ε) and temperature sensitivity (S) metrics.

In this study, methods for determining these metrics are adapted from Vano et al. (2012), where they suggest a method for understanding P and T impacts on runoff to gain insight into future changes. Precipitation elasticity and temperature sensitivity are calculated using Equations 1 and 2.

$$\varepsilon = \frac{\frac{F(X) + \Delta P\% - F(X)}{F(X)}}{\Delta P\%} \quad (2)$$

$$S = \frac{\frac{F(X) + \Delta T - F(X)}{F(X)}}{\Delta T} \quad (3)$$

In the equations above, F(X) is defined as the system performance indicator variable at some ΔT and ΔP .

For this analysis, the performance variable is chosen to evaluate the system’s ability to meet water supply demand. Municipal water suppliers, described in the conceptual example presented later, put significant emphasis on meeting water demand, and consequently, a degree of change in temperature or a shift in precipitation amounts could drastically impact system operations.

While long-term changes in climate may leave water resource systems vulnerable to supply shortages, failed infrastructure, and economic deficits, gradual changes in climate may still adversely impact operations. A sensitivity analysis can provide insight into how changes in climate influence system performance, facilitating in water resources management and planning.

3.3.3 Evaluating Robustness

The last stage of this methodology incorporates thresholds and performance indicators established in step 1 into the analysis to identify probabilities of achieving ‘acceptable performance’ over climate change space and determine the ‘expected value’ of system robustness over time. ‘Acceptable performance’ is defined using a binary performance function (Moody and Brown, 2012). The binary performance function is illustrated in Equation 3.

$$\begin{aligned}\Lambda(X) &= 1 \text{ if } Y_T \geq Y \\ &= 0 \text{ if } Y_T < Y\end{aligned}\quad (4)$$

The binary performance function, $\Lambda(X)$, is given a value of 1 (acceptable performance) or 0 (unacceptable performance) for each climate state depending on its relation to a predefined threshold. Y is the threshold of acceptable performance, preferably chosen by the water managers and stakeholders of the system, and Y_T is the variable of interest at a particular point in climate space.

Climate robustness indicators (CRI) adapted from Moody and Brown (2012) are used to evaluate system performance over a range of climate scenarios, where climate informed robustness indices are conditioned on different probabilistic assumptions. This robustness indicator can be used to evaluate the probability of ‘acceptable’ performance’ over time by integrating the product of the binary performance function and a chosen probability distribution over climate change space. The CRI is illustrated in Equation 4.

$$CRI = \int_{a2}^{b2} \int_{a1}^{b1} \Lambda(X) P(X) d\Delta T d\Delta P \quad (5)$$

where $\Lambda(X)$ represents the binary performance function at a given climate state, X , and $P(X)$ is the probability of that given climate state. The upper and lower bounds of the integrals are defined as the limits of the climate change space for temperature ($a1, b1$) and precipitation ($a2, b2$).

This step of this analysis addresses the likelihoods, $P(X)$, of climate changes occurring. In reality, there is no way to prescribe reliable probabilities to the future climate. Instead, probability distributions are used as a sensitivity factor to see how assumptions of likelihoods affect risk estimates. The use of different probability distributions may provide alternative implications about future climate and risk. For example, GCM-informed probabilities of climate changes differ from those determined by a uniform distribution with equal likelihoods of future conditions.

An exploration of the ‘expected value’ of the performance indicators can also be done using the CRI by replacing the binary performance function with performance indicators (Equation 5).

$$CRI = \int_{a_2}^{b_2} \int_{a_1}^{b_1} F(X) P(X) d\Delta T d\Delta P \quad (6)$$

where $F(X)$ represents the variable of interest (e.g. water supply reliability) at a given climate state, X , and $\Pr(X)$ is the probability of that given climate state.

3.4 Application: A Case Study of an urban water supply system

This ‘bottom-up’ framework is used to address the impacts of climate change and uncertainty through a risk assessment that evaluates alternative adaptation strategies over a range of climate changes. This is done in an application of a water utility system, in which standard operations are compared to optimal operations to get a sense of potential operational adaptations that could be made in the future. This final step aids decision-making and planning in the future.

3.4.1 Target system vulnerabilities, stakeholder concerns, and performance thresholds

A case study of a municipal water supply system in the Northeast US is used to demonstrate the applicability of the methodology described above. This example will demonstrate how the robustness index is calculated and how it can be used to compare alternative adaptation strategies. In this case, an optimal change in operations is compared with static operations. This

provides an indication for what the ‘upper bound’ of operational adaptations could be if it were possible to have perfect climate information and execution of these policies.

The water system evaluated in this study is the Little River water supply system. The Little River system, located at the base of the Westfield River Basin (Figure 3), consists of three major reservoirs: Cobble Mountain Reservoir (22,829 million gallons (MG)), Borden Brook Reservoir (2,500 MG), and Littleville Reservoir (10,560 MG). The Cobble Mountain Reservoir is the second largest water supply in Massachusetts. It serves multiple purposes including water supply, flood control, and hydroelectric power. Reliable water supply from this conventional reservoir is of high priority, as it is a water source for Agawam, East Longmeadow, Longmeadow, Ludlow, Westfield, and the City of Springfield.

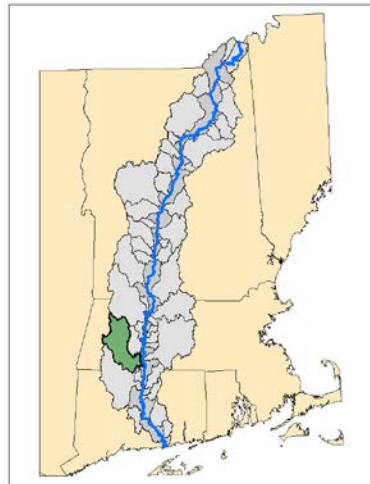


Figure 6: Map of the Connecticut River Basin with the Westfield Basin (focus of this study) shaded green.

Cobble Mountain Reservoir receives its inflows from surface runoff, direct precipitation, and the Borden Brook Reservoir located upstream. Historically, regulations for Borden Brook Reservoir have been minimal, allowing most water to spill into Cobble Mountain. For the purposes of this analysis, Cobble Mountain and Borden Brook are modeled as such.

Following the devastating drought of the 1960s, the Springfield Water and Sewer Commission (SWSC) developed a drought management plan. The plan defined drought severity levels to indicate what actions should be taken given the storage at different times of the year in Cobble Mountain Reservoir (Figure 4). Vigilant management of the system is necessary to ensure the security of the supply of clean and safe water to the City of Springfield.

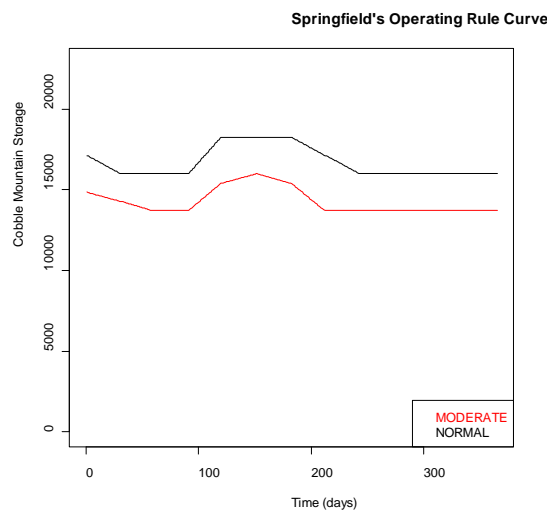


Figure 7: Springfield Water and Sewer Commission (SWSC) Drought Severity Levels for the Cobble Mountain Reservoir. Storage levels for 'normal' and 'moderate' drought conditions are specified for days of the year.

The concern for drought impacts on the system emphasizes the need for evaluating adaptations using a robust decision framework. For this reservoir system, the proposed approach is used to understand the best possible improvements that can be achieved through alternative operations. To assess these potentials this analysis simulates optimal reservoir operations and compares them to standard operations. This represents the upper limit on what operational changes could provide, whereas real gains would be less. The first step in the framework requires an understanding of system operations to produce relevant decision thresholds and performance indicators. For the purposes of this stylized analysis, we arbitrarily chose realistic thresholds of performance to evaluate operational adaptations.

Although any number of statistics could be assessed for this type of analysis, the performance indicators explored in this study include water supply reliability (R) (Loucks, 2005) and normalized shortage costs (C_N) over the 50-year period of record (t) (Equations 6 and 7). Shortfalls (Sh) under standard operating conditions are determined by counting the number of times that Cobble Mountain (CM) storage drops below moderate drought severity levels. Shortfalls under optimal operating conditions are determined by counting the number of times that releases from CM fall short of meeting water supply by more than 10% of the assumed average demand (30 mgd).

$$R = 1 - \frac{\sum_t Sh(t)}{t} \quad (7)$$

$$C_N = \frac{\sum_t C_S(t)}{C_B} \quad (8)$$

The base case shortage costs (C_B) illustrated in the denominator of Equation 7 are defined as the shortage costs (C_S) (obtained from the simulation model) that occur under conditions of no change in historic temperature and precipitation.

The following two sections of this paper (sections 4.2.1 and 4.2.2) describe the development of climate-altered flows using a stochastic weather generator and hydrology model. These sections are followed by descriptions of the simulation and optimization models of the urban water supply system. The simulation model is designed to illustrate impacts of climate change on current reservoir operating policies, while the optimization model assesses the benefits accrued from having perfect foresight of future conditions. Ultimately, the comparison of models can indicate whether there exist alternative adaptation strategies that are robust under a future hydroclimatic regime.

3.4.2 Risk Discovery: Identifying sensitivity to climate changes

Weather Generator

Weather generators are useful for producing long synthetic weather series, when ground-based meteorological data are unavailable, inadequately recorded, or spatially limited (Wilks and Wilby, 1999). These statistical models replicate key properties of the observed meteorological record. Past studies have used weather generators for crop modeling (Richardson and Nicks, 1990), observations of extreme weather events or severe droughts on crop behavior (Mearns et al., 1984), sensitivity studies, climatic variability, ecological models, hydrologic effects on water

bodies (Schimel et al., 1997), climate change sensitivity, and the estimation of missing meteorological data.

Previous studies have explored the use of weather generators in climate impact assessments (Wallis and Griffiths, 1995; Harrison et al., 1995; Semenov and Barrow, 1997; Wilks, 1992). Weather generators are particularly useful for climate change studies focusing on vulnerabilities of water resource systems at regional scales because of their ability to capture climate variability and create limitless sequences of weather data (Harris et al., 2012).

This study uses a newly developed semi-parametric weather generator that combines the techniques discussed in Apipattanavis et al. (2007) with climate change effects (Steinschneider and Brown, in prep). The weather generator parametrically simulates the occurrence of rainfall using a Markov Chain stochastic model that moves between states (i.e. rain or no rain) according to transition probabilities developed from the historical record. Rainfall amounts are determined through a non-parametric weather sampling technique referred to as K-Nearest Neighbor (KNN). Climate alterations are then imposed on the climate sequences, either by adding degrees C temperature values (i.e. 1°C, 2°C, 3°C, etc.) to each day in the period of record, or altering precipitation values using a quantile mapping technique. Advantages of this model come from coupling the benefits of parametric (Jones et al., 1972; Nicks and Harp, 1980; Richardson, 1981) and non-parametric (Wilks and Wilby, 1999) methods of weather generation, allowing for flexibility in generating ‘scenarios consistent with seasonal climate forecasts’ (Apipattanavis et al., 2007). Ultimately, the development of this model enables studies in water resources planning and management.

Hydrology Model

A physically-based hydrologic model is used in this analysis to generate inflows. The hydrologic sequences correspond to climate changes simulated by the weather generator. A form of the 'abcd' model is used, originally formulated by Thomas (1981). This conceptual lumped-parameter model was chosen because of its parsimonious nature (6 parameters) and geographic and hydrologic compatibility with the case study discussed later. While the 'abcdef' model is suitable for this analysis (with the addition of snow and snow melt parameters), it is not the only option for hydrologic modeling in the context of this framework. Details of the model are discussed in Martinez and Gupta (2010), where they observe model performance using the United States HCDN data set (Vogel and Sankarasubramanian, 2005). A depiction of the model is represented in Figure 5.

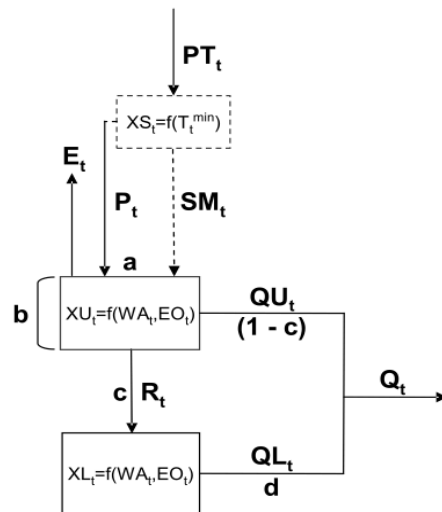


Figure 2. Structure of the *abcd* model, with snow component added (dashed lines).

Figure 8: Schematic of the 'abcd' hydrology model used in this study, adapted from Martinez and Gupta, 2010

The model is manually calibrated to fit historic flows at the Huntington gage station located in the Westfield Basin. Figure 6 illustrates a hydrograph (top) and flow duration curve (bottom) for the predicted (red line) and historic (black line) flows at this site. A Nash-Sutcliffe value of 0.3166 is calculated to evaluate model performance, however, minimal emphasis was placed on model calibration. In terms of water supply, getting the distribution of peak flows correct is less important than accurately modeling monthly flows. However, future work will explore the impact of hydrologic model calibration on system performance.

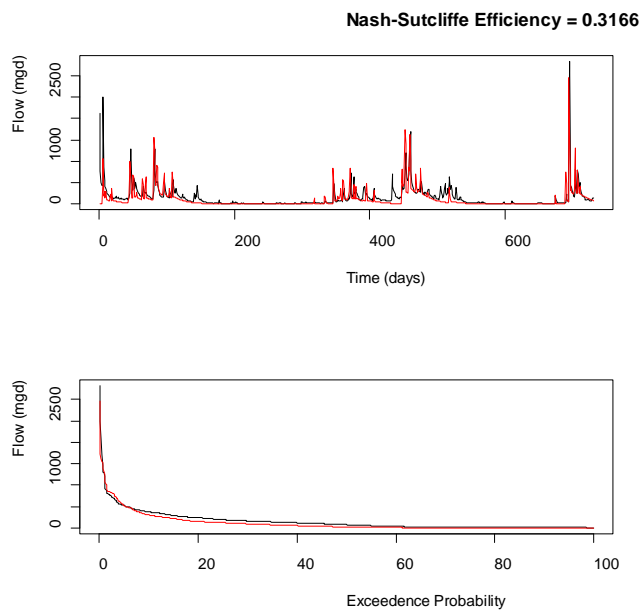


Figure 9: Hydrograph (top) and flow duration curve (bottom) of predicted flows from the calibrated hydrology model (red line) and observed flows from the Huntington gage station (black line) located in the Westfield Basin.

Ultimately, the goal of producing climate-altered weather and streamflow sequences is to create baseline conditions for assessing climate risk at a local scale.

Systems Models

The systems models developed for this study are used to evaluate changes in various performance metrics (i.e. reliability, shortage costs, and water supply adequacy) over climate change space. Fifty years of climate-altered streamflow sequences are input to the systems models to produce ‘climate response surfaces’ of variables across a range of temperature and precipitation values and elasticity/sensitivity over incremental changes in climate.

This study explores changes in performance indicators over temperature (T) increases of 1 degree Celsius to 5 degrees Celsius, with uniform perturbations of 0.5 degrees Celsius. Precipitation (P) changes are observed from 75% of historic to 125% of historic values, with uniform increases of 5%. As mentioned previously, this climate space is determined based on a ‘safety factor,’ calculated for precipitation by increasing the maximum percent change and decreasing the minimum percent change in precipitation from GCM-projections by 20%. The ‘safety factor’ is calculated for temperature by increasing the maximum and decreasing the minimum temperature changes from GCM-projections by 50%.

System Simulation Model

A simulation model of the urban water supply system was designed to test how their current operating policies perform with future climate change. A depiction of the system is represented in Figure 7. The simulation model reproduces long-term daily system operations based on historic reservoir operating policies. It captures the interrelationships, interdependencies, and functions of the system based on seasonal operational needs and concerns.

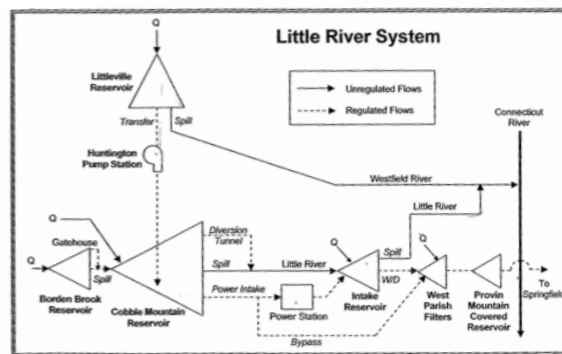


Figure 2-1
Little River Reservoir System

Figure 10: System representation of the Little Reservoir System (CDM, S. W. (2005). *Drought Management Plan*. Massachusetts.)

A cost function (Equation 8) was developed using the drought severity levels described previously (refer to Figure 4 for plot of drought severity levels). Increasing cost penalties are imposed on the model for missing thresholds. The cost function has the following features: when Cobble Mountain storage levels (S) are above the ‘normal’ drought severity threshold ($DSL1$), no costs are incurred. However, if reservoir storage levels enter the ‘mild drought’ zone, the cost of implementing ‘voluntary conservation restrictions,’ which reduce water supply demand by

10%, is \$3179 (C1). This cost was obtained from the SWSC’s drought management plan. Moreover, if storage levels drop below the moderate drought severity level (DSL2) and enter the ‘moderate drought’ zone, ‘mandatory conservation restrictions’ are implemented, with a 20% reduction in water supply. A 20% or greater reduction in water supply demand is counted as a system shortfall. The resulting costs are \$6358 (2*C1 or \$C2). Finally, if ‘mandatory conservation restrictions’ are in place and the system is not able to meet the already reduced water supply demand, a cost penalty of \$15,895 (5*C1 or C3) is applied. Water supply restrictions of 10 and 20% were established based on the assumption that the average water supply demand was 30 million gallons per day (mgd). This is higher than actual demands in the system, but was arbitrarily chosen for the purposes of this study.

$$Cost_t = \begin{cases} 0 & S_{t-1} > DSL1_{t-1} \\ 3C_1 & DSL1_{t-1} > S_{t-1} \geq DSL2_{t-1} \\ 3C_1 + 3C_2 & DSL2_{t-1} > S_{t-1} > 0; S_{t-1} + Inflow_t \geq Demand_t \\ 3C_1 + 3C_2 + C_3(Demand_t - Release_t) & DSL2_{t-1} > S_{t-1} > 0; S_{t-1} + Inflow_t < Demand_t \end{cases} \quad (9)$$

Systems Optimization Model

To compare current reservoir operations to an adaptation strategy based on optimal operations, an optimization model was built using the linear modeling software, LINGO 12.0. The objective function for this model minimizes the cost of having water supply shortfalls (where a shortfall is defined by the difference between water supply demand and releases at time t) by applying a similar cost function to the one described above. However, instead of following drought severity levels used by Springfield’s system, penalties are implemented based on water supply deficiencies, illustrated by the piece-wise linear loss function (Figure 8). For example, if the model, given that it has perfect foresight over the period of record, takes a shortfall of 5 million

gallons on a given day to minimize overall costs, it will apply the lowest cost (C1) to the first 3 mgd, and then apply the second lowest cost (C2) to the remaining 2 mgd.

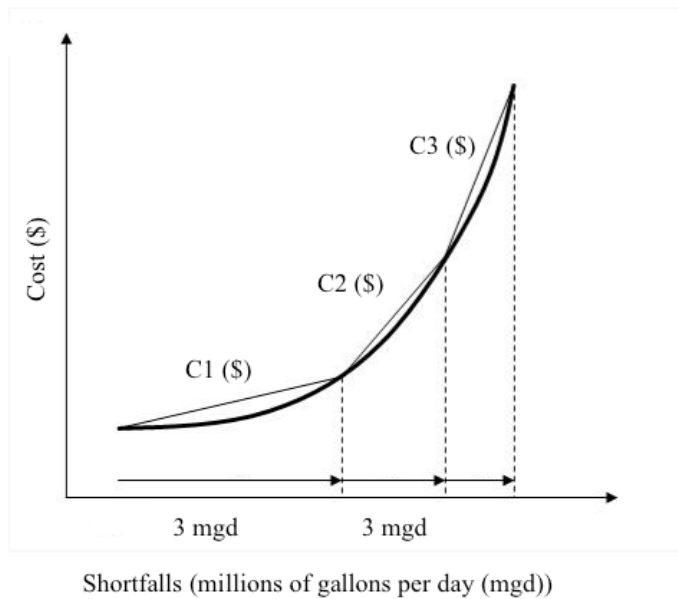


Figure 11: Piecewise linear cost function; increasing cost penalties (\$) are imposed on the system for increasing magnitudes of shortfalls (mgd) to water supply demand

Decision variables and constraints for this model include continuity equations that ensure all mass balance requirements are met, capacity constraints, shortfalls, and water supply releases (mgd) over the 50 years evaluated. Overall, this model determines optimal operations for minimizing the cost of shortfalls given perfect foresight. Given that decision-makers never have perfect foresight, this optimization model only provides an idealistic upper bound for systems operations. Additionally, the model is limited by the chosen constraints, and alterations to these values would impact the results.

Sensitivity Analysis

An analysis of system sensitivity to incremental changes in climate highlighted the points at which temperature and precipitation most impacted operations. The ability to adequately meet water supply demand, referred to here as water supply adequacy (WSA), over these changes in temperature and precipitation is vital for the longevity of Springfield's water utility system. Although potential changes in demand may occur in the future and complicate operations, projections of these changes are not explored in this analysis. However, adequacy in meeting current water supply demand was used as a metric in the sensitivity analysis (Equation 9).

$$WSA = t - Sh \quad (10)$$

where t represents the total number of days in the 50-year simulation record and Sh is the total number of shortfalls over that simulation length.

3.4.3 Evaluating Robustness

Evaluating robustness using the CRI requires an assumption of a probability distribution that describes future climate. In this study we assess two statistical extremes, one very centrally focused, the other evenly distributed and thus heavy on the tails. First, a uniform probability distribution (Equation 10) of climate changes is assumed. The uniform distribution, which applies equal weight across climate change space, can be used when there is significant uncertainty in the probabilities associated with future climate scenarios and their distribution cannot be accurately estimated.

$$\begin{aligned}\Pr(X) &= \frac{1}{b-a} \text{ if } a \leq x \leq b \\ &= 0 \text{ if } x < a \text{ or } x > b\end{aligned}\tag{11}$$

where a and b represent the limits of the climate variables (i.e. precipitation and temperature) explored.

Information from GCM projections can be incorporated into the analysis to assign probability ‘weightings’ of risk. Thus, for comparison, climate inputs are conditioned on an assumed probability distribution developed using information from GCM projections. While there are a number of distributions that could be used to model variability of climate conditions, a simple multivariate normal distribution is assumed. The multivariate normal distribution is described in Equation 11.

$$\Pr(X; \mu, \Sigma) = \frac{1}{(2\pi)^{k/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2} (X - \mu)^T \Sigma^{-1} (X - \mu)\right)\tag{12}$$

with mean vector μ and covariance matrix Σ . This equation models the independent random variables of delta changes in mean future (2025-2074) and historic (1950-1999) temperature and precipitation. Histograms of expected changes in temperature and precipitation

across 39 GCM simulations¹ are illustrated in Figure 2 (left). Also shown is a scatter plot illustrating their relationship (right).

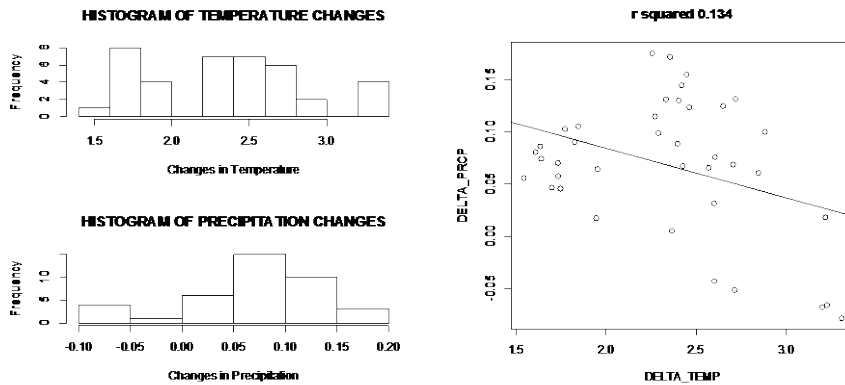


Figure 12: Histograms of temperature and precipitation changes developed from an ensemble of 39 GCMs (left). Delta changes are calculated by comparing 50 years of future GCM means with 50 years of historic GCM means. The relationship between temperature and precipitation variables (i.e. covariance) is illustrated on the right.

The distributions used in this analysis demonstrate the extremes in our understanding of future climate probabilities. Assigning equal likelihoods to future climate events, evenly distributed through space, suggests that we have no knowledge of the future climate. Conversely, assigning likelihoods to future climate according to GCM-based projections provides a limited and centrally focused view of the future. It is not clear what probability distribution is best for describing likelihoods over climate change space.

¹ Only distinct GCM simulations were used for this analysis, eliminating simulations that came from the same model but had varying initial conditions (IC). This was done to avoid redundancy and reduce IC uncertainty. Therefore, the sample of 112 GCM simulations was reduced to 39.

3.5 Results

In this section, ‘risk discovery,’ sensitivity analyses, and robustness indices are presented for two alternative operating strategies, one that follows standard policies and the other that provides an upper bound on operations. An investigation of future climate conditions and development of ‘climate response surfaces’ provides the basis for understanding system vulnerabilities over time. Considering the likelihood of different climate changes using a probabilistic weighting inferred by a range of GCM-based projections allows for a better understanding of future performance. Ultimately, this analysis assesses the value of alternative adaptation strategies for system operations in an uncertain future climate regime.

Risk Discovery

Climate response surfaces were developed for each alternative operating policy to assess system vulnerability over climate change space. Figure 9a shows the response surface for shortage costs under standard operations. Changes in the base case shortage costs (defined in section 3.2) across climate change space are indicated by the contour line labeled with a 1. Under standard operations, significant increases in shortage costs occur as mean temperatures increase and precipitation values decrease. Thus, in order to maintain the present day shortage costs of \$33 million dollars for the period of record, precipitation amounts would have to increase as temperatures increase. This does not include discounting for the time value of money.

Similar results were observed when shortage costs under optimal operations were evaluated over climate change space. However, the normalized 'base case' shortage costs occurred at only 95% of historic precipitation (Figure 9b). While there were minimal differences between the shortage costs accrued under standard and optimal operations over climate change space, marginal improvements were observed for the optimal 'base case' conditions.

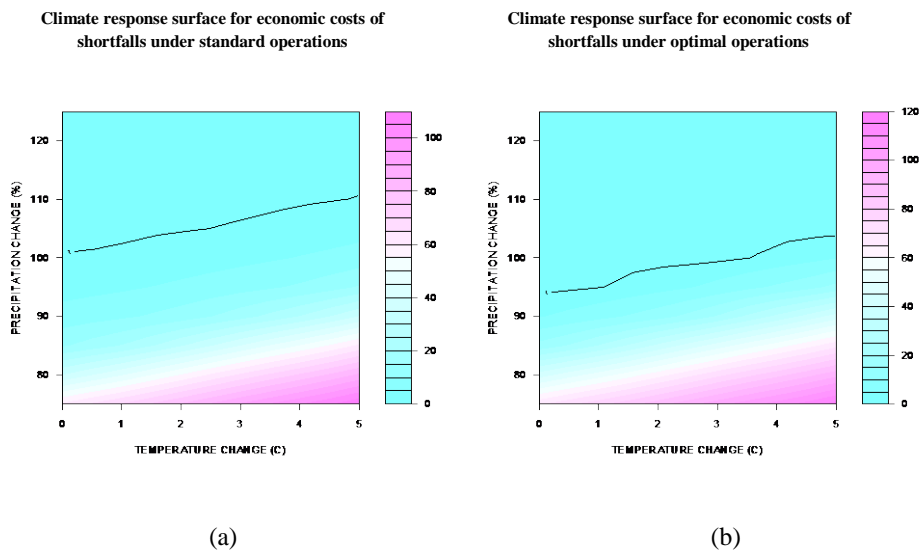
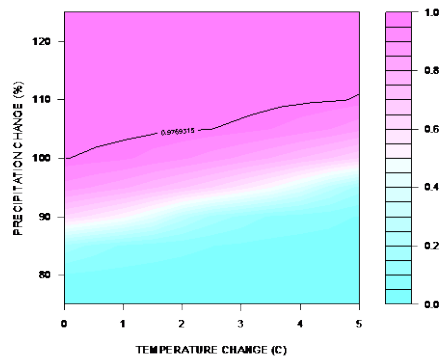


Figure 13: Climate response surfaces over climate change space (changes in precipitation and temperature) for normalized shortage costs (\$) (a) under standard and (b) optimal (right) operating policies.

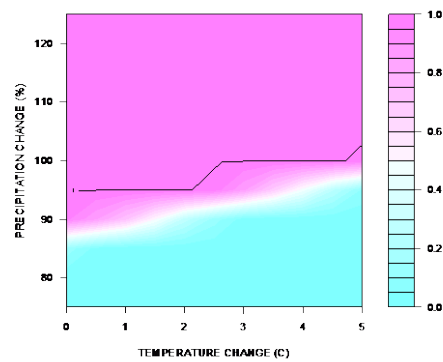
Response maps for water supply reliability followed a similar pattern, but differences between the operational 'plans' were slightly more pronounced (Figure 10). Maintaining a 'base case' reliability of 97% as mean temperatures increase over time requires augmented rainfall amounts.

Climate response surface for water supply reliability under standard operations



(a)

Climate response surface for water supply reliability under optimal operations



(b)

Figure 14: Climate response surfaces over climate change space (changes in precipitation and temperature) for water supply reliability (a) under standard and (b) optimal operating policies.

Sensitivity Analysis

For both standard and optimal operations, decreases in precipitation and increases in temperature indicated reductions in water supply adequacy (Figure 11).

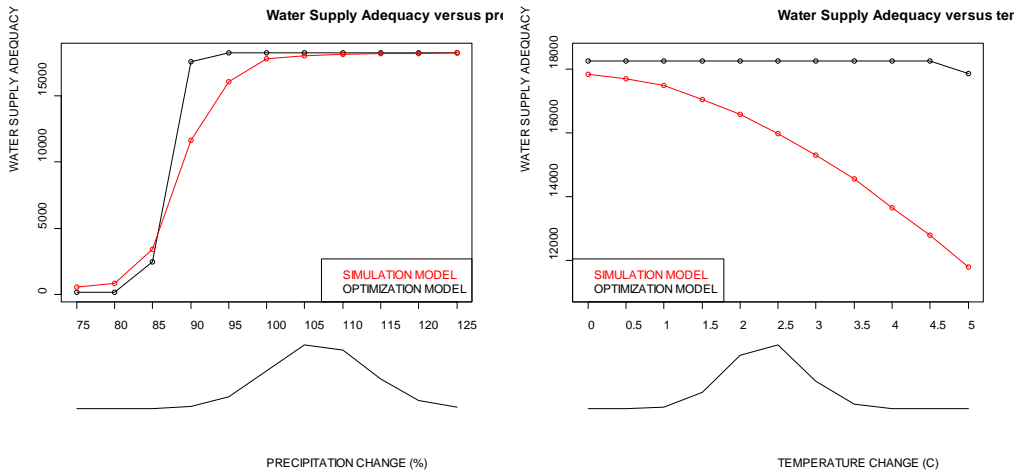


Figure 15: Two-dimensional plots of system adequacy in meeting water supply demand given changes in precipitation (left) and temperature (right). Comparisons are made for standard operations (red line) and optimal operations (black line). A PDF along the x-axes is used to demonstrate the most probable future temperature and precipitation changes according to GCM-based projections.

Differences in performance between the two operational alternatives (standard and optimal) are negligible across changes in precipitation. However, optimal operations are less sensitive to changes in temperature than standard operations. This may be a result of a shift in the hydrograph with changes in climate, altering the timing and magnitude of spring melt. While the optimization model can foresee these changes and alter operations accordingly, the simulation model is vulnerable to potential decreases in the spring peak and increases in winter streamflow. If it were just a matter of less water being available in the system as temperatures increase (i.e. evaporation), both operating policies would be inhibited.

Precipitation elasticity, a measure of how sensitive the system is to being able to meet water demand given changes in rainfall, is illustrated in Figure 12. For both operational alternatives, elasticity spikes at around 80-85% of historic precipitation. The significantly more pronounced spike produced from the optimization model is likely a function of its nature to exploit the additional water available in the system with increased precipitation. Temperature sensitivity, which measures how sensitive the system is to being able to meet water demand given changes in temperature, starts to occur within 0.5 degrees C for standard operations and 4 degrees C for optimal operations (Figure 12). Results from the optimization model appear to be significantly less sensitive to changes in temperature than the simulation model output.

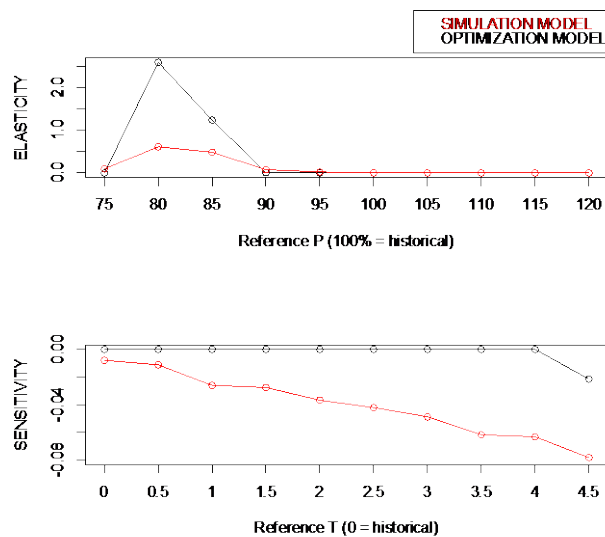


Figure 16: Precipitation elasticity, a measure of system responsiveness to changes in rainfall, is illustrated in the top figure. Temperature sensitivity, a measure of system responsiveness to changes in temperature, is illustrated in the bottom figure. Comparisons are made between standard operations (red line) and optimal operations (black line).

Climate informed robustness indices

Results from this part of the analysis yield expected values of robustness indices conditioned on different probability assumptions. Robustness metrics can then be used as decision tools to evaluate alternative adaptations to climate change.

GCM-based climate projections were incorporated into the analysis to create ‘climate-informed’ robustness metrics. Multiplying GCM informed probabilities of climate changes by water supply reliability and integrating over climate change space gave an ‘expected value’ or robustness index of future reliability. Results from the simulation model yielded a robustness index of 0.87, as compared with the base case reliability of 0.97. The robustness index calculated using optimization results was 0.93, which was a 7% decrease from the base case of 1. Thus, given GCM-based probability assumptions, optimal operations would be preferred over standard operations, indicated by the higher robustness index.

The selection of a performance threshold was used to transform the metrics across climate change space to binary values representing ‘acceptable’ or ‘unacceptable’ performance. In this study, a 95% reliability threshold was used as a lower bound of acceptable performance. CRI’s were then calculated by multiplying assumed probabilities by this new binary performance matrix. Figure 13 illustrates contours of reliability and GCM-based probability density values across climate change space evaluated for both optimal and standard operations. The 95% reliability thresholds are illustrated by the black contour lines and the ‘base case’ reliability values are illustrated by the red contour lines. The black points illustrate the delta changes in

temperature and precipitation obtained from the GCM projections. ‘Acceptable’ performance CRI’s are calculated by integrating the space above the 95% contour lines.

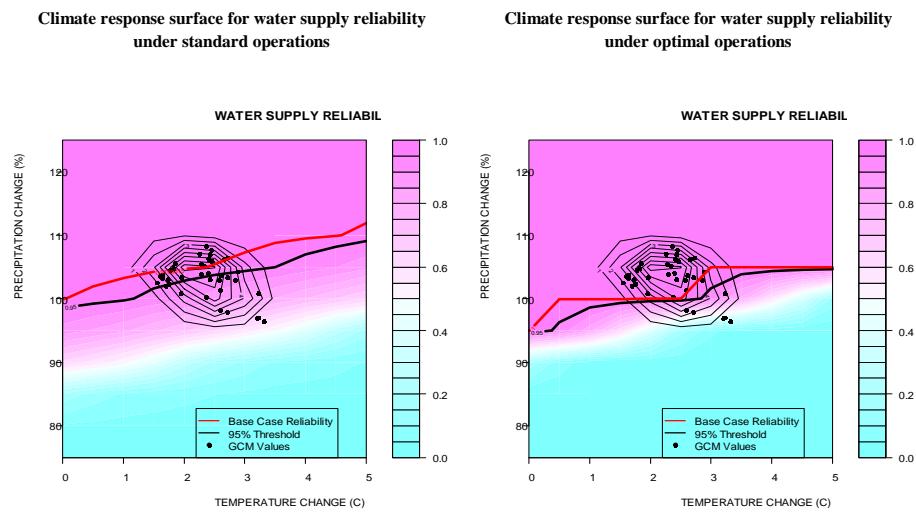


Figure 17: Climate response surfaces over climate change space (changes in precipitation and temperature) for water supply reliability under standard operations (left) and optimal operations (right). PDFs from climate change projections are superimposed over climate change space to observe likelihoods of future climate changes.

For standard operations, the probability of ‘acceptable’ performance given GCM-informed probabilities was found to be 43%. In comparison, optimal operations yielded a probability of ‘acceptable’ performance of 82%. However, the reality is that the future is uncertain and assuming a uniform distribution may be more appropriate. When the uniform probability distribution was assumed, standard operations suggested a probability of ‘acceptable’ performance of 43%, whereas the optimal operation results dropped to 50%, a significantly

smaller margin of error. A summary of these results for the two operational alternatives and distributions is illustrated in Figure 14.

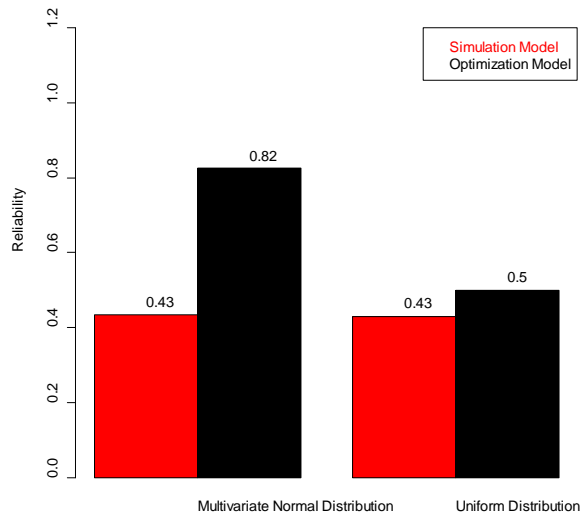


Figure 18: Comparisons of 'acceptable' performance metrics are illustrated for assumptions of the multivariate normal distribution and the uniform distribution. Standard (red bar) and optimal (black bar) operations are compared.

3.6 Discussion

The framework presented in this study is designed to facilitate in decision-making, confronting the potential challenges of climate impacts through risk assessment and robust adaptation. Ultimately, decision-makers must confront water resources management under an uncertain and changing climate regime. While assumptions can be made about the likelihood of future climate states occurring, it is necessary that system adaptations are robust to a wide range of potential conditions that may be encountered.

The approach presented in this paper is useful for quantifying robustness of alternative adaptations. Without relying on GCM projections in the initial stages of analysis, this approach identifies relevant risks and investigates robustness of adaptations over a much wider range of climate futures. While GCM-based projections can still provide ‘climate-informed’ weightings of future conditions in the later stages, the framework is not limited by the deep uncertainty of these scenarios. Rather, scenarios are treated as a lower bound on the range of climate uncertainty.

As demonstrated in this study, this ‘bottom-up’ approach can be used to evaluate the effect of changing operations on system performance. This study focused on the differences between standard and optimal operations for a water utility system. With optimal operations, the assumption is that you have perfect forecasts and perfect operations based on those forecasts, providing an upper bound on performance. The incorporation of hydrologic forecasts may provide more realistic and practical benefits to system operations. Steinschneider and Brown (2012) show that [the implementation of operational forecasts for this system provides significant improvement in reservoir performance under nonstationary hydrology. While forecast skill may degrade under climate change influencing its use as an adaptation strategy, real options such as water transfers or investments in pumps and pipelines connected to alternative water sources, may offer sufficient benefits to hedge against risks.](#)

Results from this study indicate that changes in operating policies would present little benefit to system performance. With similar ‘climate response surfaces’ and closely related ‘water supply adequacies’ over changes in temperature and precipitation, there is no reason to believe that optimal operations would provide significant improvement in performance. Additionally, given the uncertainty in GCM projections and the likely ill-suited use of the multivariate normal distribution in this analysis, we put more confidence in our assumption of the uniform distribution, in which robustness indices for the two operational alternatives are nearly identical. There is, however, sensitivity to the choice of end points when using the uniform distribution. As such, a sufficiently wide range of climate change futures should be assessed in this analysis. Although little benefit was observed for operational alternatives in this study, the use of this framework in other applications may provide more insight into favorable adaptations.

Since optimal operations provide minimal benefit to system performance in the future, uncertainty remains in the most appropriate action to take. In order to address this issue, further efforts are required. For example, there is a need for improved understanding of future changes in interannual variability of temperature and precipitation. In this study, we evaluate the potential impacts of mean climate changes on a water utility system, however, understanding the risk associated with changes in interannual variability (i.e. enhanced and depleted seasonal rainfalls) would be an interesting avenue for future work.

3.7 Conclusion

Exploration of robust adaptation strategies for risk reduction that are able to develop and change with the climate as it evolves into the future requires the development and assessment of water management strategies that are less sensitive to historical statistics and robust under future climate projections. Adaptation will require both flexibility in working under the confines of old infrastructure and reservoir operating tools, and the robust innovation of new management tools.

As we transition from a static paradigm toward a more dynamic and uncertain hydrologic landscape, we must develop new methodologies to endure extreme weather events and climate variability. The ‘bottom-up’ framework presented in this paper aims to develop and forward current management practices under nonstationary assumptions, incorporating robust approaches into dynamic reservoir operations and design.

The effective initiation of new adaptation strategies will require interdisciplinary cooperation among engineers, economists, stakeholders and climate scientists to advance our understanding of how to prepare for future climate uncertainty. With a new methodology for operating under a nonstationary hydrologic environment, we envision robust management strategies to risk that dynamically and flexibly vary with time, avoiding another century of stagnant operating policies and infrastructure design.

3.8 References

- Apipattanavis, S., Podestá, G., Rajagopalan, B., Katz, R. W. (2007). A semiparametric multivariate and multisite weather generator. *Water Resources Research*, 43(11). doi:10.1029/2006WR005714
- Arnell, N, Liu, Chunzhen, Compagnucci, R, Da Cunha, L, Hanaki, K, Howe, C, Mailu, G, Shiklomanov, I, Stakhiv, E, Doell, P (2001). Hydrology and water resources, Climate Change: Impacts, Adaptation, and Vulnerability, 191-234.
- Brekke, L.D., J.D. Anderson, E.P. Maurer, M.D. Dettinger, E.S. Townsley, A.Harrison, and T.Pruitt (2009). Assessing reservoir operations risk under climate change, *Water Resour. Res.*, 45, W04411,doi:10.1029/2008WR006941.
- Brown, C., Werick, W., Leger, W., Fay, D. (2011). A decision-analytic approach to managing climate risks: application to the Upper Great Lakes. *Journal of the American Water Resources Association*, 47(3): 524-534.
- Brown, C., Ghile, Y., Laverty, M., Li, K. (2012). Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector. In review.
- Christensen, N.S. and D.P. Lettenmaier, (2007), A multimodel ensemble approach to assessment of climate change impacts on the hydrology and water resources of the Colorado River basin, *Hydrol. Warth Syst. Sci.*, 11, 1417-1434.
- Dessai, S. and Hulme, M. (2007). Assessing the robustness of adaptation decisions to climate change uncertainties: A case study on water resources management in the East of England. *Global Environmental Change*, 17(1): 59-72.
- Dessai, S., Hulme, M., Lempert, R., Pielke, R., Jr. (2009). Climate prediction: a limit to adaptation? *Adapting to Climate Change Thresholds, Values, Governance*, 1–15.
- Ghile, Y., Moody, P., Brown, C. (2012). Paleo-Reconstructed Net Basin Supply Scenarios the Upper Great Lakes.
- Gleick, P. (2000). The Changing Water Paradigm. *International Water Resources Association*, Look at Twenty-first Century Water Resources Development, 25(1), 127–138.
- Groves, David G. (2006). New Methods for Identifying Robust Long-Term Water Resources Management Strategies for California. Santa Monica, CA: RAND Corporation, http://www.rand.org/pubs/rgs_dissertations/RGSD196.
- Groves, D.G., Yates, D., Tebaldi, C. (2008). Developing and applying uncertain global climate change projections for regional water management planning. *Water Resources Research*, 44: 1-16.
- Goodwin, P. and G. Wright, (2004). Decision Analysis for Management Judgment. Third Edition.
- Harrison PA, Butterfield RE, Downing TE (eds) (1995). Climate change and agriculture in Europe. Assessment of impacts and adaptation. Environmental Change Unit, University of Oxford.

- Harris, C. N. P., Quinn, A. D., Bridgeman, J. (2012). The use of probabilistic weather generator information for climate change adaptation in the UK water sector. *Meteorological Applications*, n/a–n/a. doi:10.1002/met.1335
- Hashimoto T., Stedinger, J.R., Loucks, D.P. (1982a). Reliability, resiliency, and vulnerability criteria for water resource system performance evaluation. *Water Resources Research*, 18: 14-20.
- Hashimoto, T., Loucks, D.P., Stedinger, J.R. (1982b). Robustness of Water Resources Systems. *Water Resources Research*, 18(1): 21-26.
- Hobbs, B.J., P.T. Chao, B.N. Venkatesh, (1997). Using decision analysis to include climate change in water resources decision-making *Climatic Change*, 37:177–202.
- Hodgkins, G. A., Dudley, R. W., Huntington, T. G. (2003). Changes in the timing of high river flows in New England over the 20th Century. *Journal of Hydrology*, 278(1-4), 244–252. doi:10.1016/S0022-1694(03)00155-0
- Huntington, T. G., Hodgkins, G. A., Keim, B. D., Dudley, R. W. (2010). Changes in the proportion of precipitation occurring as snow in New England (1949–2000).
- Johnson T. and Weaver C. (2009). A framework for assessing climate change impacts on water and watershed systems. *Environmental Management*, 43(1): 118-134.
- Jones, W., R. C. Rex, and D. E. Threadgill (1972), A simulated environmental model of temperature, evaporation, rainfall, and soil moisture, *Trans. ASAE*, 15, 366–372.
- Lempert R.J (2002), A new decision sciences for complex systems, *Proceedings of the National Academy of Sciences*, 99(90003): 7309-7313.
- Lempert, R.J., Groves, D.G., Popper, S.W., Bankes, S.C. (2006). A general, analytic method for generating robust strategies and narrative scenarios. *Management Science*, 52(4): 514-528.
- Lempert, R.J. and Collins, M.T. (2007). Managing the Risk of Uncertain Threshold Responses: Comparison of Robust, Optimum, and Precautionary Approaches. *Risk Analysis*, 27(4): 1009-1026.
- Lempert, R.J. (2010). Robust Decision Making Approach to Managing Water Resource Risks. *American Geophysical Union*.
- Lopez, A., Fung, F., New, M., Watts, G., Weston, A. and Wilby, R.L. (2009). From climate model ensembles to climate change impacts: A case study of water resource management in the South West of England. *Water Resources Research*, 45, W08419.
- Loucks, D. P., J. Stedinger, and D. Haith (1981). *Water Resource Systems Planning and Analysis*, ch.8, Prentice Hall, Upper Saddle River, N. J.
- Lund, J. R. (2002). Floodplain planning with risk-based optimization. *J. Water Resour. Plann. Manage.*, 128(3): 202–207.
- Manning, L. J., Hall, J. W., Fowler, H. J., Kilsby, C. G., Tebaldi, C. (2009). Using probabilistic climate change information from a multimodel ensemble for water resources assessment. *Water Resources Research*, 45(11). doi:10.1029/2007WR006674
- Martinez G.F. and H.V. Gupta (2010), Toward improved identification of hydrological

- models: A diagnostic evaluation of the “abcd” monthly water balance model for the conterminous United States, *Water Resour. Research*, 46: 1-21.
- Mastrandrea, M. D., Heller, N. E., Root, T. L., Schneider, S. H. (2010). Bridging the gap: linking climate-impacts research with adaptation planning and management. *Climatic Change*, 100(1), 87–101. doi:10.1007/s10584-010-9827-4
- Means, E., Laugier, M., Daw J., Pirmie, M. (2010). Decision support planning methods: incorporating climate change uncertainties into water planning. Water Utility Climate Alliance (WUCA)
- Mearns, L.O., Katz, R.W., Schneider, S.H. 1984: Extreme high-temperature events: changes in their probabilities with changes in mean temperature. *Journal of Applied Meteorology* 23, 1601–13.
- Milly, P., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., Stouffer, R. J. (2008). Stationarity is dead: whither water management? *Earth*, 4, 20.
- Moody P., C. Brown (2012), Modeling Stakeholder Defined Climate Risk on the Upper Great Lakes.
- M.G. Morgan, M. Henrion, (1990). Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis Cambridge University Press, Cambridge.
- Morgan, M., Henrion, M., Small, M. (1992). Uncertainty: A guide to dealing with uncertainty in quantitative risk and policy analysis. Cambridge University Press.
- Murphy, J. (1999). An evaluation of statistical and dynamical techniques for downscaling local climate. *Climate*, 12: 2265-2284.
- Nicks, A. D., and J. F. Harp (1980). Stochastic generation of temperature and solar radiation data, *J. Hydrol.*, 48, 1–7.
- Pittock, A.B.; Jones, R.N.; Mitchell, C.D. (2001). Probabilities will help us plan for climate change – without estimates, engineers and planners will have to delay decisions or take a gamble, *Nature*, 413 (6853), 249.
- Rajagopalan, B., Nowak, K., Prairie, J., Hoerling, M., Harding, B., Barsugli, J., Ray, A., Udall, B. (2009). Water supply risk on the Colorado River: Can management mitigate? *Water Resources Research*, 45(8). doi:10.1029/2008WR007652
- Richardson, C.W. (1981). Stochastic simulation of daily precipitation, temperature, and solar radiation. *Water Resources Research* 17, 182–90.
- Richardson, C.W. and Nicks, A.D. (1990). Weather generator description. In Sharpley, A.N. and Williams, J.R., editors, *Erosion/productivity impact calculator. 1. Model documentation. Agricultural Research Service Technical Bulletin* 1768, Washington, DC: US Department of Agriculture, 93–104.
- J.S. Risbey (1998). Sensitivities of water supply planning decisions to streamflow and climate scenario uncertainties. *Water Policy*, 1: 321–340
- Semenov, M.A. and Barrow, E.M. (1997). Use of a stochastic weather generator in the development of climate change scenarios. *Climatic Change* 35, 397–414.
- Schimel, D.S., VEMAP Participants and Braswell, B.H. (1997). Spatial variability in ecosystem processes at the continental scale: models, data and the role of disturbance.

Ecological Monographs 67, 251–71.

- Stainforth D.A., Allen, M.R., Tredger, E.R., Smith, L.A. (2007), Issues in the interpretation of climate model ensembles to inform decisions, *Phil.Trans.R.Soc.A*, 365,2163-2177.
- Steinschneider, S. and Brown, C. (2012). Dynamic reservoir management with real options risk hedging as a robust adaptation to nonstationary climate. In review.
- Thomas, H.A. (1981). Improved methods for National Water Assessment, report, contract WR 15249270, U.S. Water Resources Council, Washington, D.C.
- Vano, J. A., Das, T., Lettenmaier, D. P. (2012). Hydrologic sensitivities of Colorado River runoff to changes in precipitation and temperature. *Journal of Hydrometeorology*, 1–53.
- Vicuna, S., J.A. Dracup, J.R. Lund, L.L. Dale, and E.P. Maurer (2010), Basin-scale water system operations with uncertain future climate conditions: Methodology and case studies, *Water Resour. Res.*, 46, W04505, doi:10.1029/2009WR007838.
- Vogel, R. M., Sankarasubramanian, A. (2005). *USGS Hydro-Climatic Data Network (HCDN): Monthly Climate Database, 1951-1990*.
- Wallis, T.W.R. and Griffiths, I.F. (1995). An assessment of the weather generator (WXGEN) used in the erosion/productivity impact calculator (EPIC). *Agric. For. Meteorol.*, 73: 115-133.
- Watkins, D.W., Jr., D.C. McKinney (1995), Robust optimization for incorporating risk and uncertainty in sustainable water resources planning, paper presented at Modeling and Management of Sustainable Basin-scale Water Resource Systems, IAHS, Boulder, CO.
- Wilby, R.L. (2005). Uncertainty in water resource model parameters used for climate change impact assessment. *Hydrological Processes*, 19: 3201–3219.
- Wilby, R. L., Troni, J., Biot, Y., Tedd, L., Hewitson, B. C., Smith, D. M., Sutton, R. T. (2009). A review of climate risk information for adaptation and development planning. *International Journal of Climatology*, 29(9), 1193–1215. doi:10.1002/joc.1839
- Wilby, R. L., Dessai, S. (2010). Robust adaptation to climate change. *Weather*, 65(7), 176–185. doi:10.1002/wea.504
- Wiley, M.W. and R.N. Palmer (2008). Estimating the impacts and uncertainty of climate change on a municipal water supply system, *ASCE Journal of Water Resources Planning and Management*, 134 (3): 239-246.
- Wilks, D.S. 1992: Adapting stochastic weather generation algorithms for climate change studies. *Climatic Change* 22, 67–84.
- 1999a: Interannual variability and extreme- value characteristics of several stochastic daily precipitation models. *Agricultural and Forest Meteorology* 93, 153–69.
- 1999b: Multisite downscaling of daily precipitation with a stochastic weather generator. *Climate Research* 11, 125–36.
- 1999c: Simultaneous stochastic simulation of daily precipitation, temperature, and solar radiation at multiple sites in complex terrain. *Agricultural and Forest Meteorology*,

in press.

Wilks, D., Wilby, R. (1999). The weather generation game: a review of stochastic weather models. *Progress in Physical Geography*, 23(3), 329–357.

4. Conclusion

It is clear from this work that there is a need for innovative approaches to water resource management that are robust under different assumptions of future climate. To address this issue, this thesis explored conceptual and quantitative decision-making frameworks for assessing the impact of future climate change and uncertainty on innovation and adaptation of water supply systems.

In the second chapter of this thesis, the diffusion of innovations framework is presented as a general tool for understanding the challenges of forecast adoption. Results indicated that while much focus has been on institutional obstacles, in the Connecticut River Basin (CRB), the obstacles were related to the characteristics of the forecast itself. Primary concerns related to relative advantage and compatibility. The results suggest that local, tailored decision support systems may provide the most benefit for engineered forecast use in this region. Most important, evaluation of the DOI framework makes clear that the challenges to forecast use are not unique, but rather consistent with the adoption process of any innovation.

The third chapter used a new robust decision-making framework to quantify risk. The approach in this study was demonstrated in an application to evaluate operational changes in water supply as an adaptation to climate change. A novel comparison was done using a new robustness metric that can be informed by GCM information. The methodology was developed to help support decision-makers in operating their systems with uncertain climate information, developing and forwarding current management practices under nonstationary assumptions.

Interactions and communication with stakeholders and water managers provide the foundation for these studies. In the first study, surveys and interviews with managers in the CRB offered a conceptual basis for understanding the adoption of forecast information. In the second study, the importance of communication with stakeholders and water managers was emphasized for determining acceptable performance thresholds and system specific vulnerabilities that govern the success of the framework. Given the importance of communication and collaboration among users and producers of climate information, we sought to compile forecast and climate information for water managers in the CRB (see Hydrosystems Newsletter, Appendix). Still, much can be done to improve basin wide user/producer communication, enhancing the adoption of new innovations and robust management strategies.

References

- Milly, P., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., & Stouffer, R. J. (2008). Stationarity is dead: whither water management? *Earth*, 4, 20.
- Pagano, P.C., Hartmann, H. C., & Sorooshian, S. (2001). Using climate forecasts for water management: Arizona and the 1997-1998 El Nino. *Journal of the American Water Resources Association*, 37, 1139–1153.
- Pahl-Wostl, C. (2007). Transitions towards adaptive management of water facing climate and global change. *Water Resources Management*, 21(1), 49–62. Springer.
- Peel M.C., and Blöschl G. (2011). Hydrologic modeling in a changing world. *Progress in Physical Geography*, 35(2):249-261.
- Rogers, E., 2003. *The Diffusion of Innovations*. Fifth Edition. Free Press, New York NY.
- Steinschneider S. and Brown C. (2012) Dynamic reservoir management with real options risk hedging as a robust adaptation to nonstationary climate. In review.

Appendix A

March 8, 2011

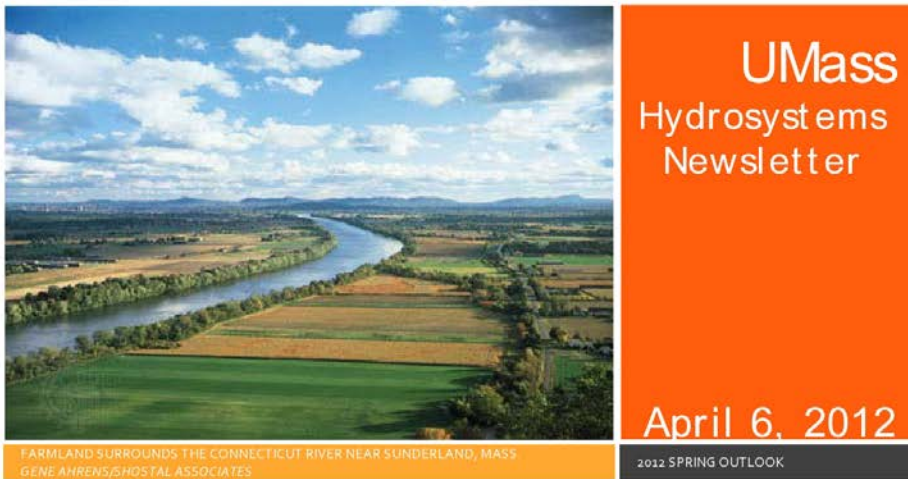
NOAA Workshop Focus Group Script:

1. Good afternoon. I am ____<name>_____. I am a _____<role>_____.
2. I am going to help *moderate* our discussion during our lunch break.
3. The goal of our discussion is going to be for you to provide us with specific information that we can use to create more understandable and useful forecast information.
4. I'd like to go around the table and have you introduce yourselves. Please tell us your name, the name of your organization, and your role within the organization.
5. We are going to discuss four questions today. We have about ____<time> ___ for our discussion, so I am going to try to limit our discussion to about ____<time>_____ per question.
6. Does anyone have questions about the goals of our discussion?
 - a. Answer if any
7. The first question I would like to discuss is
 - a. What sources of weather and climate information do you currently use to make decisions about how you manage your system (for example, www.weather.com or NERFC, water demand, energy prices)?

Follow up questions:

- b. What do you get from that site?
 - c. What do you use it for?
 - d. If you do not use forecasting, what are some of the reasons for this?
8. Thank you for your responses. I'd like to move on to our second question.
 - a. How would you describe the level of detail of forecasting information you currently receive, if any?
 - b. Is this the level of detail you want?
9. Thank you again for your responses. I'd like to move on to our third question.
 - a. What type of weather, climate, or forecast information would be useful for you to have?
-In other words, what is your wish list?
10. Thank you again for your responses. I'd like to move on to our fourth question.
 - a. What performance measures do you currently use to evaluate your effectiveness?
In other words, how do you know when you are doing a good job?
11. We have about 5 minutes left. Does anyone have any last comments they would like to provide us with that you didn't have the time to state during the discussion?
12. Thank you so much for sharing your thoughts with us. I'm going to give each of you a blank sheet of paper that you can use to write down any comments that you think of this afternoon. We'll collect the sheets at the end of the day.

Appendix B



A Climate Outlook for New England

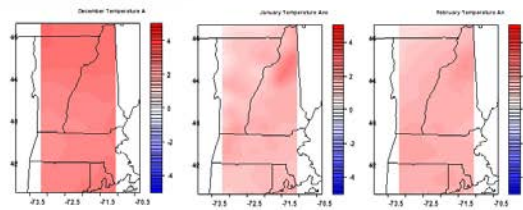
by Sarah Whateley, Scott Steinschneider, and Casey Brown

A year ago the Hydrosystems Research Group at the University of Massachusetts Amherst convened a spring workshop designed to bring water managers together to discuss hydroclimate information, such as:

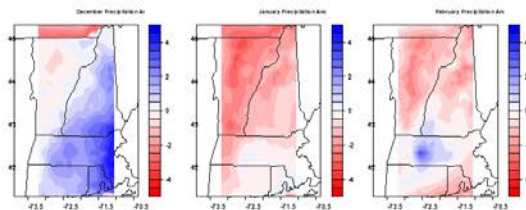
- Latest snow pack information
- Hydrologic outlook
- Seasonal climate outlook
- Current climate trends and change

Based on the input from last year's workshop, a 2012 hydrologic outlook is presented in this newsletter.

To the seasoned New Englander, this past winter has seemed warm and dry. Wintertime temperature and precipitation anomalies confirm this view, with high 2011/2012 average winter temperatures and low average winter precipitation compared with the historic average. These conditions could be cause for concern with regard to expected water availability and flows going into the spring and summer seasons.



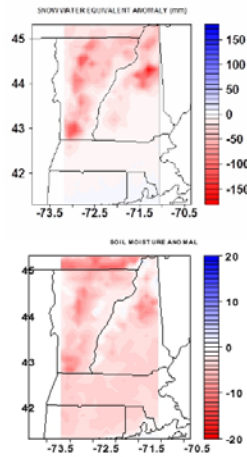
Wintertime temperature (degrees Celsius) anomalies from this past winter



Wintertime precipitation (inches) anomalies from this past winter

Current State of the Basin

Analysis of the water content in the basin provides insight into the magnitude of spring flows we may expect to encounter. This is illustrated by the snow water equivalent (mm) and soil moisture (mm) anomaly images displayed below.



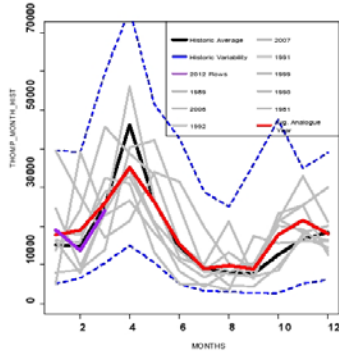
Snow water equivalent and soil moisture anomalies (departures from normal) from February 12, 2012

Wintertime snow accumulation and melt have a large impact on the hydrology of the Connecticut River Basin during the following spring. The extent of wintertime snowpack that persists into the early spring exerts significant control over inter-annual variability of spring flows, with important implications basin-wide. Although less prominent than in the Western United States, studies have shown that the timing and magnitude of discharge from rivers in the Northeast is strongly correlated with snow mass coverage and succeeding melts (Groisman, et al. 2001). Seasonal predictions of spring flows based on antecedent snowpack conditions can inform management decisions.

Based on the current values of these "state variables," an outlook can be estimated by looking at flow values from previous years with similar hydrologic conditions. This process is described below.



Thompsonville gage on the Connecticut River Basin



Analogue forecast: Monthly streamflow at Thompsonville

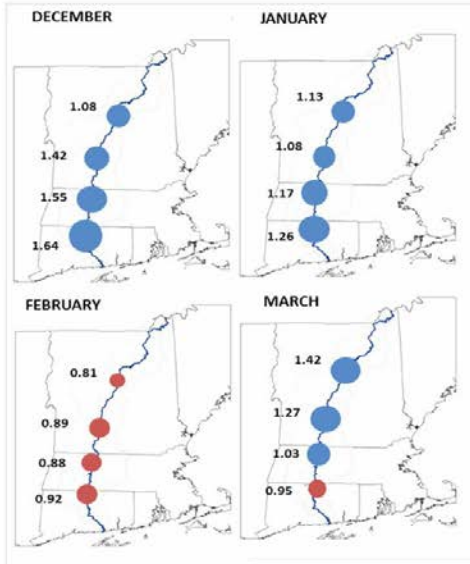
Streamflow Outlook at Thompsonville

The Thompsonville gage was used as a representative point for the basin in terms of spring streamflow. The Thompsonville gage is located at the mouth of the basin on the main stem of the Connecticut River, and subsequently integrates the hydroclimatic effects occurring in the basin. A subset of historical years were selected based on their conditions compared with the state of the basin in mid-February of this year. Since observations indicated a drier basin than average, it would be expected that the analog years would exhibit similar characteristics. These similar years and their average were compared to the average historical streamflow values. The figure to the left displays a hydrograph of monthly streamflow for the analog years and average monthly streamflow across the historical

record at the Thompsonville gage. The blue dotted lines show the maximum and minimum historic monthly flows. The hydrograph shows that most average flows for the analog years (grey lines) in April are lower than the historic average flows in April. In addition, the average of the analog years, as illustrated by the red line in the figure, is lower than the historic April average. The purple line displays current flows to date. Note that beyond April the average of the previous years does not differ from the long term average, indicating that low April flows does not imply low flows throughout the summer. In fact in late summer, the analog years are actually wetter than average.

WINTER STREAMFLOW COMPARISONS

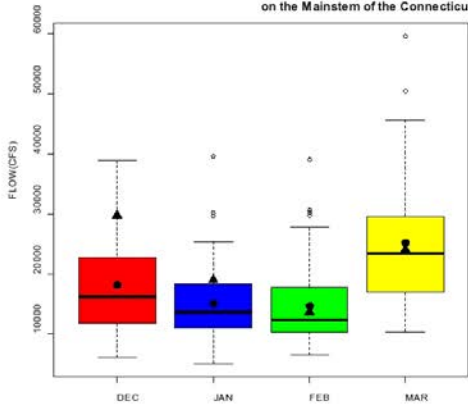
Ratio of Average Winter Streamflow



Streamflow at four gages in the Connecticut River Basin

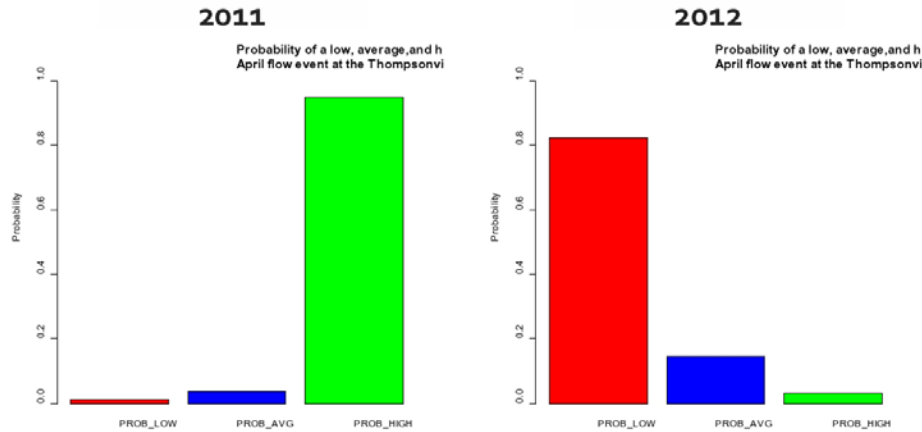
Streamflow within the basin provides a quick summary of the winter hydrologic conditions. The figure on the top left shows the ratio of average winter streamflow for December, January, February, and March, at four different USGS gage stations in the basin. The stations, listed from South to North, are: Connecticut River at Thompsonville, Connecticut River at Montague, Connecticut River at North Walpole, and Connecticut River at Wells. The ratio of average winter streamflow is in comparison to the average monthly streamflow over the historic record (1950-2011). A number greater than 1 illustrates that streamflow magnitudes this past winter were greater than average. December, January, and March ratios were all greater than 1, except for the March Thompsonville ratio. Monthly flows ranged from a 3 to 64% increase in streamflow magnitude. Conversely, February ratios were all less than 1. Recalling the climate anomalies displayed earlier, it appears that the wet and warm conditions in the early winter caused rapid snow melt and early runoff, followed by low February flows which rebounded in March.

Average Monthly Flows at the USGS Gage on the Mainstem of the Connecticut River



The bottom left figure displays the same information illustrated in a different form. Focusing on the Thompsonville gage only, the box plots represent the distribution of flows for December, January, February, and March from 1950-2011, with the black line representing the median flow. The black triangle indicates the 2012 average flow value for each month, and the black circle indicates the average monthly flow for the historic record. Flows in December and January of this year were significantly higher than the historic average, whereas, February and March flows from this year were near normal.

PROBABILISTIC OUTLOOK



Probabilistic Outlook

Precise predictions of streamflow months in advance are difficult in the Connecticut River Basin. Instead, estimates of the probability of being above or below normal are about the best that can be done. Our probabilistic analysis of data for 2011 and 2012 is represented in the figures above, in which the probability of having a low, average, or high mean April flow value at the Thompsonville gage is evaluated. In 2011 (illustrated by the top left figure) there was a 96.8% probability of a high flow event in April at the Thompsonville gage. In 2012, illustrated by the top right figure, there is an 82.3% probability of a low flow event in April at the Thompsonville gage.

What does this probabilistic information mean?

A follow up analysis of flows in April 2011 confirmed that last year's flows were approximately 15% higher than average April flows over the historical record at the Thompsonville gage. Furthermore, the highest peak flow in April of last year was 6% higher than the average maximum peak flow in April over the historical record. Heading into the spring with a fairly wet basin last year resulted in high April flows. The figure to the right demonstrates Thompsonville April average streamflow and where the magnitude of 2011 flows fit into the historical record. The figures earlier in this newsletter have illustrated that this year we are entering the 'peak' flow season with a dry basin. Consequently, April flows are predicted to be lower than the historic average.

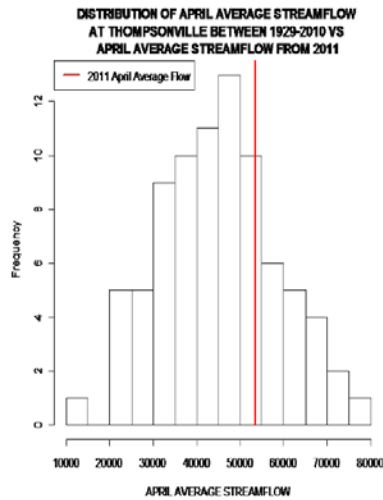


Figure 12: April Average Streamflow From 2011 Compared to April Average Streamflow at Thompsonville Between 1929 and 2010

Climate Teleconnections

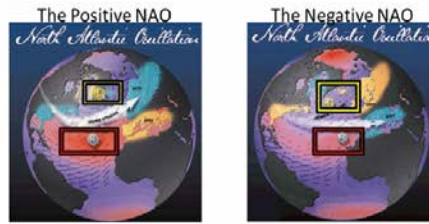
With advances in long-lead forecast skill emerging from improved understanding of oceanic-atmospheric circulation patterns, water management agencies have attempted to incorporate climate teleconnections into their operations and decision-making (Araghinejad, et al., 2006; Kalra and Ahmad, 2009). The most famous teleconnections are associated with the El Niño/Southern Oscillation (ENSO). However, ENSO has little effect here. In the Northeastern United States, some studies have demonstrated skill in predicting seasonal climate variability and streamflow based on the impact of atmospheric-ocean circulation patterns related to the North Atlantic (Bradbury, 2001; Bradbury et al., 2002; Hartley and Keables, 1998; Kingston et al., 2007; Steinschneider and Brown, 2011).

Climate variability in this region is driven mostly by year-to-year fluctuations influenced by atmospheric pressure in the North Atlantic (North Atlantic Oscillation) and patterns of Atlantic sea-surface temperature anomalies (SSTA), otherwise known as the North Atlantic Tripole (NAT). The first two images on the right illustrate the negative and positive phases of the NAO and sea surface temperature anomalies in the Atlantic. Studies have found this large-scale climate phenomena can be used in seasonal hydrologic forecasting with the largest effects on temperature. For example, the phase of the NAO (positive or negative) influences winter precipitation in the Connecticut River Basin, and consequently impacts wintertime streamflow (Bradbury, 2001). Other studies have linked sea-surface temperatures that persist into the summer with low-flow hydrology in the basin (Steinschneider and Brown, 2011).

What do teleconnections tell us this year?

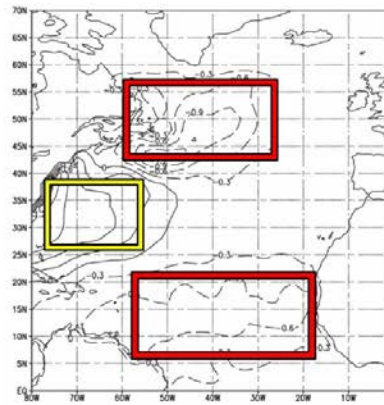
The NAO is currently in its positive phase, which is often associated with above-average temperatures in the eastern United States (see figure to the right). While this fact may explain the warm winter, the atmospheric climate phenomenon can be unpredictable, potentially changing phases on a week-to-week basis. Recently, it was trending negative. The North Atlantic Tripole however, controlled by Atlantic sea surface temperatures, persists for longer time periods due to oceanic 'memory' and is less likely to change phases in a forecasting season. Since July 2010, SST indices have remained negative. Wintertime NAT indices in the negative phase have been shown to be correlated with low ODLFs (one day low flows) at the Thompsonville gage (Steinschneider and Brown, 2011).

NORTH ATLANTIC OSCILLATION

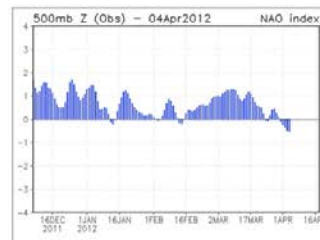


<http://www.ideo.columbia.edu/res/pi/NAO/>

NORTH ATLANTIC TRIPOLE



NAO INDEX: POSITIVE PHASE FOR THE PREVIOUS 120 DAYS OF RECORD



http://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/nao_index.html



University of Massachusetts' Hydrosystems Research Group (from left to right: Austin Polebitski, Caitlin Spence, Sarah Whateley, Jessica Pica, Alec Bernstein, Scott Steinschneider)

Conclusion

In summary, the winter has been warm and dry, resulting in below average water content in the basin. Consequently, we anticipate that flows in April will be below the historic average, raising concern for drought and water shortage issues in the lower part of the basin. However, there is no reason to assume that the drought will persist into the summer based on our analysis. Sea surface temperatures in the North Atlantic bear watching to assess the risk of drought as spring evolves. Our goal for this newsletter is to provide climate and hydrologic information for the benefit of water managers. We welcome your feedback regarding the information presented here and how it may be improved or more general comments about seasonal hydrologic forecasting and water management. Please send any comments to swhateley@engin.umass.edu.

This research was funded by NOAA grant, award number NA100AR4310182. More information about the Hydrosystems Research Group is available on our website: <http://lcee.umass.edu/lcee/hydrosystems>

REFERENCES:

- Clark, R., Deque, M. (2003). Conditional probability seasonal predictions of precipitation. *Journal of the Royal Meteorological Society*, 129(587): 179-193.
- Araghinejad, S., Burn, D. H., & Karamouz, M. (2006). Long-lead probabilistic forecasting of streamflow using ocean-atmospheric and hydrological predictors. *Water Resources Research*, 42(3). doi:10.1029/2004WR003853
- Bradbury, J. A. (2001). Relation of hydrologic drought in New England to large-scale atmospheric circulation patterns (p. 238).
- Bradbury, J. A., Keim, B. D., & Wake, C. P. (2002). US East Coast trough indices at 500 hPa and New England winter climate variability. *Journal of climate*, 15(23), 3509-3517.
- Groisman, P. Y., Knight, R. W., & Karl, T. R. (2001). Heavy precipitation and high streamflow in the contiguous United States: Trends in the twentieth century. *American Meteorological Society*.
- Hartley, S., & Keables, M. J. (1998). Synoptic associations of winter climate and snowfall variability in New England, USA, 1950-1992. *International Journal of Climatology*, 18(3), 281-298. Wiley Online Library.
- Kalra, A., & Ahmad, S. (2009). Using oceanic-atmospheric oscillations for long lead time streamflow forecasting. *Water Resources Research*, 45(3). doi:10.1029/2008WR006855
- Kingston, D. G., McGregor, G. R., Hannah, D. M., & Lawler, D. M. (2007). Large-scale climatic controls on New England river flow. *Journal of Hydrometeorology*, 8(3), 367-379.
- Steinschneider, S., & Brown, C. (2011). Influences of North Atlantic climate variability on low-flows in the Connecticut River Basin. *Journal of Hydrology*, 409(1-2), 212-224. Elsevier B.V. doi:10.1016/j.jhydrol.2011.08.038.

UMass
Hydrosystems
Newsletter

University of Massachusetts
Amherst
Amherst, MA 01003