A hazard-based risk analysis approach to understanding climate change impacts to water resource systems: application to the Upper Great Lakes

Paul Markert Moody
University of Massachusetts - Amherst, pmoody@engin.umass.edu

Follow this and additional works at: http://scholarworks.umass.edu/open_access_dissertations

Recommended Citation
A HAZARD-BASED RISK ANALYSIS APPROACH TO UNDERSTANDING CLIMATE CHANGE IMPACTS TO WATER RESOURCE SYSTEMS: APPLICATION TO THE UPPER GREAT LAKES

A Dissertation Presented

by

PAUL M. MOODY

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

DOCTOR OF PHILOSOPHY

May 2013

Civil and Environmental Engineering
A HAZARD-BASED RISK ANALYSIS APPROACH TO UNDERSTANDING CLIMATE CHANGE IMPACTS TO WATER RESOURCE SYSTEMS: APPLICATION TO THE UPPER GREAT LAKES

A Dissertation Presented

by

Paul M. Moody

Approved as to style and content by:

Casey Brown, Chair

David Ahlfeld, Member

Erin Baker, Member

Richard Palmer, Member

Richard Palmer, Department Head
Department of Civil and Environmental Engineering
DEDICATION

To my patient and loving wife.
ACKNOWLEDGMENTS

I would like to thank my advisor, Casey Brown, for his guidance and support. I would also like to thank the members of my committee: David Ahlfeld, Erin Baker, and Richard Palmer for their helpful comments and suggestions.

I would like to thank the U.S. Army Corps of Engineers and the International Joint Commission who provided funding in support of the research and related travel. Additional thanks to the American Geophysical Union for allowing the use of copyrighted materials in this manuscript.

I wish to thank the U.S. Army for the opportunity to attend graduate school and the follow on opportunity to teach at the U.S. Military Academy at West Point. This has been a rewarding assignment and an opportunity for growth.

I wish to express appreciation for the individuals who participated in the Great Lakes study. Specifically, I wish to thank collaborators at the University including Jesus Morales, Ke Li, Yonas Ghile, and John Sullivan as well as external collaborators including Bill Werick, Bryan Tolson, David Fay, Yin Fan, Wendy Leger, and Masoud Asadzadeh.

Finally, a special thank you to my friends and family who provided support and encouragement throughout the program.
ABSTRACT

A HAZARD-BASED RISK ANALYSIS APPROACH TO UNDERSTANDING CLIMATE CHANGE IMPACTS TO WATER RESOURCE SYSTEMS: APPLICATION TO THE UPPER GREAT LAKES

MAY 2013

PAUL M. MOODY, B.S., MASSACHUSETTS INSTITUTE OF TECHNOLOGY
M.S., MASSACHUSETTS INSTITUTE OF TECHNOLOGY
Ph.D., UNIVERSITY OF MASSACHUSETTS AMHERST

Directed by: Professor Casey Brown

Water resources systems are designed to operate under a wide range of potential climate conditions. Traditionally, systems have been designed using stationarity-based methods. Stationarity is the assumption that the climate varies within an envelope of variability, implying that future variability will be similar to past variability. Due to anthropogenic climate change, the credibility of the stationarity-based assumptions has been reduced. In response, climate change assessments have been developed to quantify the potential impacts due to climatic change. While these methods quantify potential changes, they lack the probabilistic information that is needed for a risk-based approach to decision-analysis. This dissertation seeks to answer two crucial questions. First, what is the best way to evaluate water resource systems given uncertainty due to climate change? Second, what role should climate projections or scenarios play in water resources evaluation? A decision analytic approach is applied that begins by considering system decisions and proceeds to determine the information relevant to decision making. Climate based predictor variables are used to predict system hazards using a climate response function. The function is used with climate probability distributions to determine metrics of system robustness and risk. Climate projections and additional sources of climate information are used to develop conditional probability distributions for future climate conditions. The robustness and risk metrics are used to determine decision sensitivity to
assumptions about future climate conditions. The methodology is applied within the context of
the International Upper Great Lakes Study, which sought to determine a new regulation plan for
the releases from Lake Superior that would perform better than the current regulation plan and
be more robust to potential future climate change. The methodology clarifies the value of
climate related assumptions and the value of GCM projections to the regulation plan decision.
The approach presented in this dissertation represents a significant advancement in accounting
for potential climate change in water resources decision making. The approach evaluates risk
and robustness in a probabilistic context that is familiar to decision makers and evaluates the
relevance of additional climate information to decisions.
TABLE OF CONTENTS

ACKNOWLEDGMENTS............................................................................................................. v

ABSTRACT................................................................................................................................ vi

LIST OF TABLES...................................................................................................................... xi

LIST OF FIGURES.................................................................................................................... xii

LIST OF ABBREVIATIONS ...................................................................................................... xvii

CHAPTER

1 INTRODUCTION.................................................................................................................. 1

1.1 Great Lakes History and Regulation................................................................. 5
1.2 Decision Making Under Uncertainty................................................................. 8
1.3 Water Resource Metrics..................................................................................... 10
1.4 Top-Down Climate Change Impact Assessment ............................................. 12
1.5 Bottom-Up Climate Change Impact Assessment .............................................. 14
1.6 Climate Uncertainty............................................................................................ 14

2 MODELING STAKEHOLDER-DEFINED CLIMATE RISK.............................................. 17

2.1 Introduction ............................................................................................................. 17
2.2 Background ............................................................................................................ 22

2.2.1 Previous Climate Change Assessments of the Great Lakes ....................... 22
2.2.2 Bottom-Up Assessment Methods................................................................. 25

2.3 Method ..................................................................................................................... 27

2.3.1 Stakeholder-Defined Thresholds................................................................. 28
2.3.2 Hazard Discovery ............................................................................................ 31
2.3.3 Climate Response Function .......................................................................... 35

2.3.3.1 Model Output — Coping Zone Occurrences ....................................... 35
2.3.3.2 Model Input — Climate Measurement ............................................... 36
2.3.3.3 Statistical Model Description................................................................... 37
2.3.3.4 Climate Response Function Results for Lake Superior and Lake Michigan-Huron...................................................................................... 41
2.3.3.5 Sensitivity to Initial Water Level......................................................... 45

2.3.4 Climate Response Surfaces........................................................................... 48
3

3.1 Introduction .................................................................................. 55

3.1.1 Water Resource System Performance Indicators ...................... 60
3.1.2 Robustness .............................................................................. 61

3.2 Robustness Index Development .................................................. 63
3.3 Application to the Great Lakes .................................................... 71
3.4 Results ....................................................................................... 74

3.4.1 Hazard Contours and Graphical Robustness Indicators .......... 75
3.4.2 Robustness and Climate Informed Robustness ....................... 80
3.4.3 Climate Informed Robustness with a Shifting Mean ............... 84

3.5 Conclusion .................................................................................. 87

4

4.1 Introduction .................................................................................. 89

4.1.1 Risk Metrics ............................................................................ 91
4.1.2 Multi-Objective Criteria and Risk ............................................ 94

4.2 Application to the Great Lakes .................................................... 96
4.3 Results ....................................................................................... 99

4.3.1 Risk and Uncertainty of Extreme Threshold Exceedance ......... 101
4.3.2 Multi-Objective Risk: by Stakeholder Group ......................... 103
4.3.3 Threshold Sensitivity and Adaptation ....................................... 106
4.3.4 Policy Adaptation and Risk .................................................... 109
4.3.5 Climate Change Based Risk to Stakeholders ......................... 111
4.3.6 Climate Informed Risk with a Shifting Mean ......................... 113

4.4 Conclusion .................................................................................. 116

5

5.1 Introduction .................................................................................. 120
5.2 Climate Information Sources ...................................................... 122

5.2.1 Historic Climate ..................................................................... 126
5.2.2 Paleo-Based Stochastic Climate .............................................. 126
5.2.3 Historic-Based Stochastic Climate ................................................. 127
5.2.4 Statistically Downscaled GCM Projections ........................................ 128
5.2.5 Dynamically Downscaled RCM/GCM Projections ................................. 129
5.2.6 Coupled Hydrosphere-Atmosphere Research Model (CHARM)........... 130
5.2.7 Stochastic GCM Simulation............................................................. 131
5.2.8 Climate Information Source Review .................................................. 131

5.3 Climate Informed System Risk .................................................................. 133

5.3.1 Plausibility of Climate Change ............................................................ 134
5.3.2 Expected Impact Conditioned on Climate Information Source .......... 137
5.3.3 Regulation Plan Selection and Climate Information Source ............... 141

5.4 Conclusion............................................................................................... 143

6 SUMMARY AND KEY FINDINGS .................................................................. 145

REFERENCES.................................................................................................. 149
# LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1: Coastal Coping Zone Definitions for Lakes Superior, Michigan, and Huron</td>
<td>30</td>
</tr>
<tr>
<td>3.1 Regulation plan summary and description for six Lake Superior outflow regulation plans</td>
<td>74</td>
</tr>
<tr>
<td>4.1: Coping zone thresholds defined for Lake Superior and Lake Michigan Huron by stakeholder group. The ecosystem thresholds include a frequency component where exceeding the threshold once in four years is moderate impact and three times in four years is severe impact</td>
<td>98</td>
</tr>
<tr>
<td>5.1: Annual NBS by climate information data source for Lake Superior. The NBS is normalized to a percent change from the average from the historic record</td>
<td>124</td>
</tr>
<tr>
<td>5.2: Annual NBS by climate information data source for Lake Michigan Huron. The NBS is normalized to a percent change from the average from the historic record</td>
<td>124</td>
</tr>
</tbody>
</table>
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1.1: Great Lakes Basin. Note that the Upper Great Lakes includes Lakes Superior, Michigan, Huron, St. Clair and Erie. (Accessed from Michigan Sea Grant: <a href="http://www.miseagrant.umich.edu/explore/about-the-great-lakes/">http://www.miseagrant.umich.edu/explore/about-the-great-lakes/</a> on 2 Oct 2012)</td>
<td>4</td>
</tr>
<tr>
<td>Figure 2.1: Coping zone levels for coastal, water use, recreational boating, commercial navigation and ecosystem sectors for Lake Superior, Michigan-Huron, Saint Clair and Erie. Coping zones correspond to sector impact tolerance. Coping zone A is negligible impact, coping zone B is moderate impact and coping zone C is severe impact.</td>
<td>31</td>
</tr>
<tr>
<td>Figure 2.2: Scatter histogram of 30-year realizations from the stochastic data set, plotted by percent change mean and standard deviation of the annual Net Basin Supply. Each dot represents a 30-year segment from the stochastic data set. The size of the red circles and blue diamonds are proportional to the number of coastal coping zone C (severe impact) occurrences.</td>
<td>34</td>
</tr>
<tr>
<td>Figure 2.3: Comparison of observed and modeled expected value of coastal coping zone fractional occurrences for Lake Superior. Figure includes coping zone C (severe impact) and coping zone B (moderate impact) occurrences as a function of mean NBS.</td>
<td>43</td>
</tr>
<tr>
<td>Figure 2.4: Lake Superior coastal upper zone B (moderate impact). The observed mean NBS and zone fraction values from the stochastic series are plotted with black dots. The modeled expected value curve and probability distribution functions shown for NBS mean percent changes of -15% to 15% are plotted in red.</td>
<td>44</td>
</tr>
<tr>
<td>Figure 2.5: Expected coping zone C (severe impact) occurrence on Lake Superior and Lake Michigan-Huron as a function of percent change mean NBS. The mean NBS is varied while the standard deviation and serial correlation are held constant to show the relationship between mean NBS and coping zone C occurrence.</td>
<td>45</td>
</tr>
</tbody>
</table>
Figure 2.6: Lake Superior 30-year level exceedance curve sensitivity to initial lake-level for four fencepost NBS sequences. The fencepost NBS sequences were selected with ±10% mean and ±20% standard deviation of NBS. The starting levels were the 5%, 50% and 95% exceedance December lake-levels. 47

Figure 2.7: Comparison of three- and four-parameter predictive models on Lake Superior coping zone occurrences. The three-parameter model includes the mean, standard deviation and serial correlation of the annual NBS over a 30-year segment. The four-parameter model adds the starting lake-level to the predictive model. The correlation, p, between the observed and predicted value is given for each model. 48

Figure 2.8: Regulation plan performance on Lake Superior and Michigan-Huron. The top graphs show contours of equal expected number of coastal coping zone C occurrences. Each contour, n, represents n-times the historic zone C occurrence rate. The bottom graphs provide a comparison of ten regulation plans. The graphs compare contour lines at twice the historic coping zone C occurrence rate. 50

Figure 3.1: Lake Superior expected coastal coping zone C occurrences for different changes in the mean and standard deviation of the annual net basin supply. Contour levels are expresses as multiples of the historic occurrence rate by regulation plan. Better performance is indicated by a lower contour level. Subplots show regulation plan (a) 77A, (b) 55MR49, (c) Nat64D, (d) Bal26, (e) 77B, and (f) P129. 77

Figure 3.2: Lakes Michigan-Huron expected coastal coping zone C occurrences for different changes in the mean and standard deviation of the annual net basin supply. Contour levels are expressed as multiples of the historic occurrence rate by regulation plan. Subplots show regulation plan (a) P77A, (b) 55MR49, (c) Nat64D, (d) Bal26, (e) P77B, and (f) P129. 78

Figure 3.3: Graphical robustness indices of width, height, and area with respect to changes in the mean and standard deviation of net basin supply, shown for Lake Superior. The graphical robustness indicators are shown for regulation plan 1977A with a threshold of acceptable performance equal to twice the historic coastal coping zone C occurrence rate. 79

Figure 3.4: Graphical measures of robustness for Lake Superior and Michigan-Huron. Plots of robustness (a) length, (b) height, and (c) area are presented for each regulation plan. 80
Figure 3.5: Tradeoff curve for the Robustness Index (a) and the Climate-Informed Robustness Index (b) calculated for Lake Superior (x-axis) and Lake Michigan-Huron (y-axis) under different regulation plans. The Robustness Index applies a uniform probability distribution over the climate variable space; while the Climate-Informed Robustness Index applies a multivariate normal probability distribution fit to the 55,590-year historic based stochastic data series. Greater values are better for each axis. Each regulation plan is indicated by a label and a circle. .......................................................... 84

Figure 3.6: Sensitivity of the Climate-Informed Robustness Index (CRI) for each regulation plan with respect to changes in the mean net basin supply for both (a) Lake Superior and (b) Lake Michigan-Huron. Here, the mean of the NBS mean, μ_NBS, is varied while the mean of the NBS standard deviation, μ_NBS^2, the mean of the NBS serial correlation, μ_NBS^3, and the covariance matrix, Σ, were held constant.................................................................................................................. 86

Figure 4.1: Risk Matrix Based on Probability of Occurrence (on the x-axis) versus Impact of Occurrence (on the y-axis). Green Represents Low Risk, Amber is Moderate Risk, Orange is High Risk and Red is Very High Risk [Brown et al., 2012b]. Risk matrix format is adapted from Cox [2008] and Ni et al. [2010]. .......... 94

Figure 4.2: Expected value and 90 percent confidence interval for Coping Zone C (extreme lake level). The figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan low extremes and d) Lake Michigan Huron high extremes for the coastal coping zones. The expected value is based on a shifting mean NBS, an annual NBS standard deviation of 0.0 and an annual NBS serial correlation of 0.1. ........................................................................................................... 103

Figure 4.3: Expected value and 90 percent confidence interval extreme level occurrences for coastal, commercial navigation, recreational boating, boat launch, water use, and ecosystem coping zones. The figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan low extremes and d) Lake Michigan Huron high extremes. The expected value is based on a shifting mean NBS, an annual NBS standard deviation of 0.0 and an annual NBS serial correlation of 0.1. ........................................................................................................... 106
Figure 4.4: Expected value and 90 percent confidence interval for extreme water level occurrences showing the sensitivity of increasing or decreasing the coastal coping zone threshold by 5 cm. The figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan low extremes and d) Lake Michigan Huron high extremes. The expected value is based on a shifting mean NBS, an annual NBS standard deviation of 0.0 and an annual NBS serial correlation of 0.1. ......................................................... 109

Figure 4.5: Expected value and 90 percent confidence interval of extreme level occurrence for Lake Superior Regulation Plan 1977A and Plan Natural 64D. The figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan low extremes and d) Lake Michigan Huron high extremes. The expected value is based on a shifting mean NBS, an annual NBS standard deviation of 0.0 and an annual NBS serial correlation of 0.1. ........... 111

Figure 4.6: Extreme water level related risk on Lake Superior for 10,000 stochastically generated climates centered on the historic mean NBS. Figure a) shows the risk of extreme low for -10% mean NBS, b) shows the risk of extreme high for +10% mean NBS, c) shows the risk of extreme low with no NBS change, d) shows the risk of extreme high with no NBS change, e) shows the risk of extreme low with -10% mean NBS, and f) shows the risk of extreme high with -10% mean NBS............................ 116

Figure 4.7: Extreme water level related risk on Lake Michigan Huron for 10,000 stochastically generated climates centered on the historic mean NBS. Figure a) shows the risk of extreme low for -10% mean NBS, b) shows the risk of extreme high for +10% mean NBS, c) shows the risk of extreme low with no NBS change, d) shows the risk of extreme high with no NBS change, e) shows the risk of extreme low with -10% mean NBS, and f) shows the risk of extreme high with -10% mean NBS......................................................... 116

Figure 5.1: Boxplots of mean annual NBS by climate information data source for a) Lake Superior and b) Lake Michigan Huron. The mean annual NBS is normalized to percent change from the historic average NBS. ......................................................... 125
Figure 5.2: Plausibility of 10 percent change in mean annual NBS conditioned on climate information source. Figures include a) -10% non-exceedance probability on Lake Superior, b) +10% exceedance probability on Lake Superior, c) -10% non-exceedance on Lake Michigan Huron and d) +10% exceedance on Lake Michigan Huron. The data information sources included the historic based stochastic data, the paleo based stochastic data, the statistically downscaled GCM data, the dynamically downscaled RCM data, and the stochastic GCM data sets. The exceedance and non-exceedance probabilities are based on an empirical distribution and on a normal distribution for each data set. 136

Figure 5.3: Expected fraction of extreme water level threshold exceedance using conditional empirical and normal probability distributions. Figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan Huron low extremes and d) Lake Michigan Huron high extremes. 140

Figure 5.4: Median values for extreme water level threshold exceedance with error bars at 0.1 and 0.9 cumulative probability and shown for each climate information data source. Figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan Huron low extremes and d) Lake Michigan Huron high extremes. 141

Figure 5.5: Expected fraction of extreme water level threshold exceedance for egulation plan P77A and Natural 64D and for probability distributions based on the historic-based stochastic, the paleo-based stochastic, the statistically downscaled GCM, the RCM, and the GCM-based stochastic data sets. Figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan Huron low extremes and d) Lake Michigan Huron high extremes. 143
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AHPS</td>
<td>Advanced Hydrological Prediction System</td>
</tr>
<tr>
<td>AMG</td>
<td>Adaptive Management Group</td>
</tr>
<tr>
<td>AR</td>
<td>Auto-Regressive</td>
</tr>
<tr>
<td>BWT</td>
<td>Boundary Water Treaty</td>
</tr>
<tr>
<td>CCC</td>
<td>Canadian Climate Centre</td>
</tr>
<tr>
<td>CGCMx</td>
<td>Canadian General Circulation Model, version x</td>
</tr>
<tr>
<td>CHARM</td>
<td>Coupled Hydrosphere-Atmosphere Research Model</td>
</tr>
<tr>
<td>CLRRM</td>
<td>Combined Lake Regulation and Routing Model</td>
</tr>
<tr>
<td>CRF</td>
<td>Climate Response Function</td>
</tr>
<tr>
<td>CRI</td>
<td>Climate-Informed Robustness Index</td>
</tr>
<tr>
<td>CSM</td>
<td>Contemporaneous Shifting Mean</td>
</tr>
<tr>
<td>ET</td>
<td>Evapotranspiration</td>
</tr>
<tr>
<td>FAR</td>
<td>First Assessment Report</td>
</tr>
<tr>
<td>GCM</td>
<td>General Circulation Model, alternatively Global Climate Model</td>
</tr>
<tr>
<td>GFDL</td>
<td>Geophysical Fluid Dynamics Laboratory</td>
</tr>
<tr>
<td>GISS</td>
<td>Goddard Institute for Space Studies</td>
</tr>
<tr>
<td>GLRCM</td>
<td>Great Lakes Regional Climate Model</td>
</tr>
<tr>
<td>HadCMx</td>
<td>Hadley Circulation Model, version x</td>
</tr>
<tr>
<td>IJC</td>
<td>International Joint Commission</td>
</tr>
<tr>
<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
</tr>
<tr>
<td>IUGLS</td>
<td>International Upper Great Lakes Study</td>
</tr>
<tr>
<td>K-NN</td>
<td>K-Nearest Neighbor</td>
</tr>
<tr>
<td>LOSLRS</td>
<td>Lake Ontario and St. Lawrence River Study</td>
</tr>
</tbody>
</table>
MPI  Max Planck Institute
NBS  Net Basin Supply
OSU  Oregon State University
PDSI Palmer Drought Severity Index
PET  Potential Evapotranspiration
PFEG Plan Formulation and Evaluation Group
RAP  Robust Adaptive Planning
RARM Risk Assessment and Risk Management
RCM  Regional Climate Model
RDM  Robust Decision Making
RO  Robust Optimization
SRES Special Report on Emissions Scenarios
TWG  Technical Working Group
UKMO United Kingdom Meteorological Office
USPCC United States Presidential/Congressional Commission
CHAPTER 1

INTRODUCTION

The Great Lakes comprise the largest managed water body in the world, holding approximately 20% of the world’s fresh water [International Joint Commission, 2005]. The lakes have significant economic, environmental and social importance to a large region of the United States and Canada. The lakes are managed by the International Joint Commission (IJC), a joint governmental agency comprised of United States and Canadian personnel with the mission of overseeing the regulation of obstructions and diversion that would impact levels or flows in waters on the international boundary between Canada and the United States. The potential changes to the Great Lakes system due to climate change and other uncertainties are of concern to the IJC and Great Lakes stakeholder groups. The water levels in the Great Lakes and the flow rates in the interconnecting channels result in significant benefits or costs accrued to the stakeholders around the Great Lakes [Levels Reference Study Board, 1993]. Climate change could result in significant changes to the lake water levels or flow rates resulting in major costs or loss of benefits to those who rely on the Great Lakes.

The Upper Great Lakes consist of Lake Superior, Lake Michigan, Lake Huron, Lake St. Clair and Lake Erie, with a diagram of the Great Lakes included in Figure 1.1. The channel connecting Lake Michigan and Lake Huron is deep and wide enough that the two lakes are hydraulically connected and modeled as one lake in most water balance models. Lake Ontario is not included as part of the Upper Great Lakes due to a nearly 100 m head loss between Lake Erie and Lake Ontario, which occurs at Niagara Falls. In contrast, there is only a 10 m head loss between Lake Superior and Lake Erie. This is illustrated in Figure 1.2, which contains a side profile of the elevation changes in the system. The upper lake system has one flow regulation point, at Sault Ste. Marie, located at the outflow from Lake Superior into the St. Marys River.
The Lakes are managed in accordance with agreements between the United States and Canadian governments including the Boundary Waters Treaty of 1909, the Orders of Approval from 1914 and the Supplementary Orders of Approval from 1979. A bi-national board of control has operational control of the system, implementing the IJC-approved regulation plan. Clites and Quinn [2003] describe the history of Great Lake regulation and prior regulation plans that led to the current regulation plan, plan 1977A, which has been in place since 1990.

In 2005, the IJC began the International Upper Great Lakes Study (IUGLS). A primary study goal was to improve Lake Superior outflow regulation. The IUGLS followed the completion of the Lake Ontario and St. Lawrence River Study (LOSLRS) which considered management of the lower Great Lake System. The IUGLS included a review of regulation and operation of control structures, identification of potential improvements to the regulation plan, and a testing of regulation plan performance under variability and climate change scenarios [International Joint Commission, 2005]. The IUGLS board sought to understand risk exposure on the Upper Great Lakes system due to climate change and how regulation plans could be used to potentially mitigate or reduce the residual risk.

Several prominent studies had examined potential impacts of climate change on the Great Lakes using a “top-down” approach. The top-down approach focused on using climate projections from downscaled General Circulation Models (GCMs) to generate potential system impacts. The projections were downscaled to drive hydrologic models which would then drive system models, resulting in point estimates of potential impacts due to climate change. Wilby and Dessai [2010] described the “cascading uncertainty” that is inherent in this approach, where each step adds additional uncertainty, which reduces the accuracy and usefulness of the results. Early studies used small samples of one to four GCM projections for point estimates while later studies considered ensembles of GCMs to provide an envelope of potential changes. While this
approach provides a range of potential impacts due to climate change, it has been unclear how to apply the results to inform water resources related decisions.

The goal of the research in this study is to develop and apply new methods and metrics for analyzing climate change impacts in a way that would be useful to decision makers. The methods and metrics are validated through application within the context of the IUGLS and the recommendation for a replacement Lake Superior outflow regulation plan. The approach used is a “bottom-up” assessment that starts with system hazards as defined by stakeholders. These hazards are used to define thresholds within a water resources system model. A statistical model is developed and parameterized to predict hazard occurrence based on climate related predictor variables. The climate predictor variables can be treated as random variables from a probability distribution that is not stationary in time. Different sources of climate information, such as the historic record, stochastic-based records, paleo-based records, and GCMs, can be used to parameterize this probability distribution. The probability distributions, conditioned on their specific assumptions, can then be used in a decision framework.
Figure 1.1: Great Lakes Basin. Note that the Upper Great Lakes includes Lakes Superior, Michigan, Huron, St. Clair and Erie. (Accessed from Michigan Sea Grant: http://www.miseagrant.umich.edu/explore/about-the-great-lakes/ on 2 Oct 2012)
1.1 Great Lakes History and Regulation

The Great Lakes system is a vital part of the economic, environmental, and social structure for a significant number of Canadians and Americans through water supply, fisheries, recreation, ecological services, commercial navigation, hydropower production and many other benefits. On the other hand, extreme events, such as flooding and drought, can result in severe costs across many of the sectors. The IJC approves the regulation plan, and delegates the plan implementation to a bi-national control board. The current plan, plan 1977A, seeks to balance extreme water levels on Lake Superior with those on Lake Michigan-Huron. The IUGLS sought potential replacement plans that would reduce potential costs and increase potential benefits for stakeholders and that would be robust to uncertainty in water supply due to climate change.
Hartman [1988] and Clites and Quinn [2003] both described the history of development and regulation of the Upper Great Lakes in great detail, while the highlights are covered here. Prior to the late 1800s, Lake Superior outflow was controlled by a submerged rock ledge that acted like a large weir. The piers supporting the International Railroad Bridge were completed in 1888, reducing the channel conveyance significantly. Further development, including diversion canals for hydropower and ship canals were added, increasing the channel conveyance. To help regulate the outflow, the Canadian Lake Superior Power Company constructed “compensating works” or 16 meter wide sluice gates at the head of the St. Marys River rapids in the vicinity of the rock ledge, beginning construction in 1901. The net effect of development at Sault Ste. Marie was to raise Lake Superior’s average level by 0.18 m.

The Boundary Waters Treaty of 1909 between Canada and the United States did three important things. It established the IJC, it provided the IJC with the mission to oversee any obstruction or diversion that would affect levels or flows in both countries, and it established the order of precedence for decisions regarding the international waters. The three named purposes were:

1) Domestic and sanitary use

2) Navigation including servicing canals and locks for navigation

3) Power and irrigation use

The IJC investigated the natural range of Lake Superior levels and estimated the impact of regulation and issued the Order of Approval in 1914 to establish guidelines that the Board of Control would follow. The 1914 Order of Approval stipulated that regulation should maintain Lake Superior within the range of 183.4 m to 183.86 m, IGLD 85. This narrow range (0.46 m) was impractical and was broadened to a 0.75 m range (between 184.0 m and 183.25 m). The IJC maintained a series of regulation plans in accordance with the 1914 Orders of Approval. While
the plans were modestly successful at maintaining Lake Superior within the given range, 
downstream levels on Lake Michigan-Huron were not considered. Extreme low levels on Lake 
Michigan-Huron in 1963-1964 caused public concern that regulation did not consider impacts on 
downstream lakes. This was changed with the issue of the 1979 Supplementary Order of 
Approval. The new order included the principle that the lakes should be maintained at the same 
relative position within their historic range, which introduced the idea of balancing the extreme 
water levels between the Lakes. The result was regulation plan 1977, which was modified in 
1990 to regulation plan 1977A. The modifications included a five month forecast for the lakes, a 
smoother seasonal transition, and provisions to reduce the risk of flooding below the locks. 

Regulation plan 1977A has been in place since 1990. Since that time, the IJC has 
conducted three major studies: the Levels Reference Study, the Lake Ontario-St. Lawrence River 
Study (LOSLRS), and the IUGLS. The Levels Reference Study was a precursor to the other 
studies, taking a comprehensive look at the lake water levels, channel flow rates, and Net Basin 
Supplies (NBS) for the historic record and considering the impacts of regulation. NBS is 
expressed as a flow rate and is the net flux of water into a lake including direct precipitation, 
evaporation, and runoff. NBS does not include inter-lake flows or inter-basin transfers. The 
LOSLRS examined regulation of Lake Ontario and the St. Lawrence River. The LOSLRS identified 
significant tradeoffs and conflict between the stakeholders on Lake Ontario and the 
stakeholders along the St. Lawrence River. As a result, the LOSLRS has been complete since 
2006 yet the recommendations have yet to be implemented. The IUGLS began in 2007 with 
primary goals of identifying channel conveyance changes in the St. Clair River and their impacts 
and identifying a regulation plan that would be potentially more robust to climate variability and 
climate change. This work supports the second objective. The IJC is still required by treaty to 
consider municipal and industrial water use, navigation, and hydropower benefits and costs; it
now also considers other stakeholder interests including ecosystems, recreational boating and tourism, and coastal land uses. New plans must show net improvements in performance across all sectors without any disproportionate losses to any given sector.

1.2 Decision Making Under Uncertainty

Ultimately, the aim of this research is to facilitate a better understanding of climate related uncertainty in water resource systems by decision makers. With that in mind, it is important to understand how decisions are made. Schneller and Spichas [1983] discussed five criteria that can be used for decision making under uncertainty. These are Wald, Savage, Hurwicz, Laplace and Starr criteria. The Wald maxi-min criterion is a conservative approach that selects the decision with the maximum value of the minimum utility across all outcomes. Hurwicz’s coefficient of optimism maximizes a weighted average of the maximum and minimum utility for a given strategy. For a weight of 0, the criterion is the same as the maxi-min criterion; while a weight of 1 yields the optimistic maxi-max criteria. The Savage mini-max regret minimizes the maximum difference between the utility of the best strategy for an outcome and the utility for the selected outcome. The Laplace criterion assigns equal probability to each outcome or end state and selects the strategy with the maximum expected utility. Starr’s domain criterion can be applied to decision making with discrete future states. The probabilities of each end state are plotted in a Euclidean probability space. The available decisions are evaluated in the probability space to determine which decisions are best in which region of the climate state. The decision with the largest domain is selected.

The commonly used Von Neumann – Morganstern decision analysis framework seeks to maximize a decision maker’s expected utility [Von Neumann and Morganstern, 1947]. In this construct, the utility of each decision is evaluated for every outcome and a probability weighted
outcome or expected utility is determined. *Howard* [1988] describes procedures for formulating, eliciting, evaluating, and appraising a decision problem using tools such as strategy-generation tables, decision trees, and influence diagrams.

The primary difference between decision making under risk and decision making under uncertainty is the degree to which the probability distribution of the future states is known or can be estimated. In cases where the probability distribution of future states cannot be estimated, robustness can be used as a decision criterion. In these cases, satisficing solutions that allow for adequate performance over a wide range of future states are preferred over solutions that are optimal over a narrow range of future states.

In the case of many water resources decisions, one could argue that there is future climate information available that can be used to develop probability distributions for key uncertain variables and parameters. In this case, one moves from decision making under uncertainty towards decision making under risk. *Brown et al.* [2012a] argued that the proper way to frame this type of decision is in a Bayesian decision model of decision making with imperfect information. The Bayesian decision model tailors climate change analysis to provide the information most useful for decision making. The posterior probabilities of uncertain parameters and variables are conditioned on the data available. For climate change, the available data includes GCM projections. Unlike weather forecast projections that can be evaluated to determine their skill at predicting the weather tomorrow, next week, or even next season, GCM projections and downscaling techniques cannot be evaluated for their skill in any meaningful way.
1.3 Water Resource Metrics

Water resource managers consider metrics of system performance in the context of the decision criteria discussed in the previous section. These metrics can be used to evaluate system performance under different conditions or with different options. There are several traditional measures of water resource system performance evaluation that support system analysis and decision making in a multi-objective framework. System performance is frequently expressed in terms related to system failure such as reliability and vulnerability or in monetary terms such as in benefit-cost analysis.

Three common statistical summaries of performance are reliability, resiliency, and vulnerability. These are described by Hashimoto et al. [1982b], by Loucks et al. [2005], by Mays [2005], and various additional sources. Reliability is the probability of the system being in a satisfactory or non-failure state, resilience is the probability of recovery from a failure or non-satisfactory state, and vulnerability is a measure of the severity of the failure [Loucks et al., 2005]. These measures can be used to summarize or compare performance over a time series, such as in a stochastic simulation used to evaluated competing courses of action for a decision. The use of these criteria may help illustrate how a project may perform in the uncertain future and characterize any periods of unsatisfactory performance [Hashimoto et al., 1982b]. These criteria can be used as screening criteria to eliminate poorly performing options or as evaluation criteria to assess remaining options.

The traditional water resource design parameters have contributed to the successful design and implementation of countless water resource projects. While anthropogenic climate change and land use changes have eroded the underlying assumption of stationarity, this paradigm is still dominant. For projects with a short design life and a relatively small scale, the traditional indicators used for water resources system design may be adequate. Based on their
scope, the consequences of failure in these cases will be relatively limited. For projects or systems with longer design lives, greater uncertainty, greater complexity, and significant consequences of failure, these traditional indicators may be insufficient [Dessai and Van Der Sluijs, 2007; Lempert et al., 2006; Stakhiv, 2011]. In these cases, system robustness is an additional and important performance measure.

A robust system, regulation plan, or design is one that performs adequately over a wide range of inputs. Robustness supports a satisficing approach which emphasizes satisfactory performance under a wide range of inputs or states rather than optimal performance under a narrow range of inputs. Simon [1956] initially described satisficing in the context of decision making. Stakhiv [2011] applied satisficing in a water resources context and described it as “producing robust solutions that may not meet strict economic efficiency tests, but are still risk cost-effective.”

The concept of robustness has been gaining increasing prominence in water resources analysis, especially when considering systems with significant and irreducible uncertainty, as associated with climate change. The idea of robustness applied to water resource systems is not new, but the applications continue to evolve and mature. Hashimoto et al. [1982a] described robustness as the flexibility to adapt to a wide range of demand conditions at little additional cost. By defining robustness in terms of economic performance, these measures can complement other economic measures such as benefit cost analysis.

Several researchers have proposed schemes or processes to identify robust decisions and policy. Many of these are based on system performance over a range of scenarios. Watkins and McKinney [1995, 1997] developed a framework of Robust Optimization (RO) to support decision making. Their work relies on generation and evaluation of many scenarios to identify the options that are optimal or near optimal for all scenarios. Lempert et al. [2002] introduced
Robust Adaptive Planning (RAP) to reduce vulnerability to surprise events. RAP is designed to explore scenarios that cause system failure to better understand low probability and high impact events. Later, Lempert and Collins [2007] compared system performance under robust, optimum and precautionary approaches. Lempert and Collins [2007] asserted that the best framework is largely dependent on the characterization of uncertainty and on the requirements to communicate decision related information. Groves et al. [2006] and Lempert et al. [2003] developed Robust Decision Making (RDM) to explore policy options over many plausible states. RDM avoids assigning probabilities to future states, which Lempert et al. [2004] argued make it applicable in cases of deeply uncertain future conditions. It uses a regret based measurement combined with hedging or adaptive policies to reduce regret. In this case, regret is the difference between the best outcome for a given state and the outcome associated with the decision under consideration.

1.4 Top-Down Climate Change Impact Assessment

There have been many studies of climate change assessment using the top-down, or climate-science-centric, assessment paradigm. This paradigm can use a single GCM projection or an ensemble of GCM climate projections. Here, top-down refers to a process that starts at the GCM model and proceeds through inter-coupled models to develop estimates of potential system impact due to uncertainties, including potential climate change. The GCM projections are typically downscaled to local, hydrologically relevant variables or coupled with Regional Climate Models (RCMs), which then are used as input for a hydrologic model and a systems model. The process output is an estimate of system performance as a result of the given GCM. Critics, such as Wilby and Dessai [2010], argued that the cascading uncertainty, or uncertainty and error added at each step in the process, make such top-down approaches inappropriate for
use in decision making. Additionally, GCMs may capture mean behavior adequately, but may not have adequate skill to capture the variability and extremes, which are important to water resources decision making [Hirsh, 2011]. Stainforth et al. [2007] argue that the GCMs may only provide a lower bound on the range of uncertainty for future climate variability.

Top-down studies of climate change impact on the Great Lakes include those by Bruce [1984], Cohen [1986], Sanderson [1987], Croley [1990], Hartmann [1990], Chao [1999], de Loë and Kreutzwiser [2000], Mortsch et al. [2000], and Lofgren et al. [2002]. These studies all used from one to six GCM model projections to estimate potential climate change impact. These studies do not address how likely (or unlikely) a given climate projection is or provide the probabilistic information that may make the information more useful from a decision makers point of view.

Several studies have considered ensembles of GCM projections to assess potential climate change impact on the Great Lakes [Räisänen and Palmer, 2001; Tebaldi and Knutti, 2007; and Angel and Kunkel, 2010]. The most extensive ensemble study on the Great Lakes was by Angel and Kunkel [2010]. Their study supported the IUCLS and used an ensemble of 565 GCM model projections from 23 modeling centers, including 160 projections for an A2 (moderately high), 211 projections for an A1B (intermediate), and 194 projections for the B1 (low) SRES emissions scenarios. Angel and Kunkel [2010] assumed that each model outcome had an equal but unknown probability of occurrence because there is no accepted methodology to determine relative model skill. They used 30-year projections centered on 2020, 2050 and 2080. The ensemble results showed a wide range of average modeled lake levels with the mean average lake levels for the ensemble below the historic mean levels, but the model ensemble provided support for both increasing and decreasing mean water levels. Wilby and Deassai [2010] recommend against a probabilistic interpretation of model ensemble results, because the
resultant distributions are highly dependent on the experimental design. Additionally, Knutti et al. [2010] discussed model evaluation, stating that it is impossible to calibrate and evaluate climate model predictions of climate change because they relate to a state never observed before.

1.5 Bottom-Up Climate Change Impact Assessment

While the majority of the climate change assessment studies on the Great Lakes have been within a top-down paradigm, there is a growing body of research on bottom-up assessment techniques. Dessai [2009] argued that the development of successful adaptation strategy in the face of deep uncertainty (related to climate change) can be accomplished by avoiding the analysis approach that places climate prediction at its heart. He argues for an exploratory modeling approach that systematically explores the implications of a wide range of assumptions and policy options to determine policies with acceptable performance despite irreducible uncertainties. Several studies have recommended using bottom-up strategies to assess climate change impact [Dessai and Hulme, 2010; Brown et al., 2011; Wilby and Dessai, 2010]. While bottom-up strategies differ, the approaches begin with understanding system sensitivity to uncertainty rather than with climate projections from GCMs or RCMs. While bottom up climate assessment techniques have been applied to water supplies including in England [Dessai and Hulme, 2007] and the Boston Water Supply [Brown et al., 2012a], the approach has not been applied to the Great Lakes system.

1.6 Climate Uncertainty

The risk associated with actual and potential climate change and climate variability will continue to challenge hydrologists, engineers, planners and decision makers [Stedinger and
Griffis, 2011]. The statistical framework of stationarity has contributed to the understanding of past climate variability but there remains debate about how to use the past climate variability with other climate information such as GCM projections and paleo based information to consider how climate variability may evolve into the future. Milly et al. [2008] suggested a temporal evolution of nonstationary hydrologic variables and their probability distributions. Stedinger and Griffis [2011] applied this concept to models of flood risk by using time-dependent parameters in the log-Pearson type III distribution. Stakhiv [2011] argued that the standard practices based on stationarity can be extended to accommodate aspects of future climate uncertainty, but did not specify how.

The question remains about how to account for the uncertainty associated with present and future climate conditions. Dessai and Hulme [2004] made the argument that the water resources community needs to develop climate probability estimates to support climate adaptation policy and decision making. One approach to developing probability distributions involves application of the Bayesian framework to fit and forecast parameters. Reis and Stedinger [2005] applied a Bayesian framework to model flood frequency analysis. Sang et al. [2010] applied this framework to a hydrologic frequency analysis and use this model to consider peak discharge values and to rainfall design values.

Hobbs [1997], Tebaldi et al. [2005], and Smith et al. [2009] combine the concept of using a Bayesian framework to determine climate parameters with analysis of multi-model ensembles of GCM projections. As Hobbs [1997] stated, Bayesian analysis is a practical and appropriate tool for making inferences about climate change and making decisions based on those inferences. Hobbs [1997] lists four main advantages of using a Bayesian analysis, including: making inferences on parameters including expected value and credible intervals, both for the historic record and projected into the future (in contrast with frequentist methods which cannot
project future parameter values); identification of optimal strategies and good decisions; estimation of the value of additional information that may be used to alter decisions and improve expected system performance; and determination of robustness, defined here as sensitivity of results to the assumptions made in the analysis. Tebaldi et al. [2005] used a Bayesian framework to develop future climate variable probability distributions, noting that the framework facilitates inferences and decision making. The Bayesian framework requires explicit assumptions; therefore the resulting posterior distributions for the variables and parameters of interest are conditioned on the assumptions made. Smith et al. [2008] applied the Bayesian analysis to combine an ensemble of climate information from nine GCMs with historic data to estimate future climate probability distributions.

The chapters of this dissertation describe the proposed methods for analyzing climate change uncertainty for water resource systems and how these methods can be used to improve information available for decision making. Throughout the dissertation, the methods are applied to the Upper Great Lakes within the context of the IUGLS. Chapter 2 describes the development and application of the Climate Response Function (CRF) that relates climate statistics to system performance based on stakeholder-determined threshold exceedance. Chapter 3 presents methods of defining system robustness to climate change using the CRF. Chapter 4 describes threshold exceedance risk and examines how the risk varies by climate condition, stakeholder group, threshold definition, and decision. Chapter 5 considers multiple sources of climate information available to the IUGLS to develop conditional probability distributions for potential climate conditions and for potential future hazards due to those conditions. Chapter 6 concludes the dissertation with a summary of the key findings and a discussion of potential future research.
CHAPTER 2

MODELING STAKEHOLDER-DEFINED CLIMATE RISK

Climate change is believed to pose potential risks to the stakeholders of the Great Lakes due to changes in lake-levels. This paper presents a model of stakeholder defined risk as a function of climate change. It describes the development of a statistical model that links water resources system performance and climate changes developed for the Great Lakes of North America. The function is used in a process that links bottom-up water system vulnerability assessment to top down climate change information. Vulnerabilities are defined based on input from stakeholders and resource experts and are used to determine system performance thresholds. These thresholds are used to measure performance over a wide range of climate changes mined from a large (55,590-year) stochastic data set. The performance and climate conditions are used to create a climate response function, a statistical model to predict lake performance based on climate statistics. This function facilitates exploration and analysis of performance over a wide range of climate conditions. It can also be used to estimate risk associated with change in climate mean and variability resulting from climate change. Problematic changes in climate can be identified and the probability of those conditions estimated using climate projections or other sources of climate information. The function can also be used to evaluate the robustness of a regulation plan and to compare performance of alternate plans. This paper demonstrates the utility of the climate response function as applied within the context of the International Upper Great Lakes Study.

2.1 Introduction

The International Upper Great Lakes Study (IUGLS) was launched in 2005 to assess the performance of the operations plan that regulates outflows from Lake Superior, which
represents the only hydraulic control on levels in the Great Lakes above Niagara Falls (thus levels on Lakes Superior, Michigan, Huron and Erie). An important question in this assessment is the potential impact of climate change on the Upper Great Lakes system. The Great Lakes hold approximately 20% of the world’s fresh water and are significant economically, environmentally, and socially to a large region of the United States and Canada. Considered as a system, the Great Lakes system represents the largest managed water resources system in the world. The IUGLS capitalized on the best available hydroclimatological science to inform the assessment of climate change impacts. However, a methodology for linking the science, and particularly the uncertain projections of future climate from a variety of sources, with decisions that were based on stakeholder concerns was lacking. Dessai and Hulme [2004] contrasted top-down and bottom-up approaches to inform climate adaptation policy, suggesting that methods that utilize both approaches may be needed. Brown et al. [2011] described a “bottom up meets top down” approach to climate risk assessment and outlined how this approach could be applied to the analysis of Lake Superior outflow regulation alternatives. This study presents the model used to estimate stakeholder-defined impacts as a function of possible changes in climate. A parametric statistical method is used to assess climate change related impact in terms relevant to stakeholders. The process involves correlating climate to hazards and identifying the climate conditions that lead to adverse system impacts. A related study considers the probabilities of climate conditions and how different sources of climate information such as historical climate, paleo reconstructed climate, General Circulation Model (GCM) climate projections, and expert opinion can be used to estimate climate probabilities and climate related risk.

Previous studies of the impact of climate change on the Great Lakes have used scenario based approaches to assess potential climate change impact by predicting the system response to specific climate conditions [Angel and Kunkel, 2010; Bruce, 1984; Chao, 1999; Cohen, 1986;
These top down methods used projections of future conditions and impacts, to provide estimates of potential climate change induced impacts from downscaled GCM projections. These early studies developed methodologies for generating climate change scenarios and impact assessments.

There are a number of limitations to such top-down approaches. Top down analysis uses GCM projections with high uncertainty and unknown accuracy to project system response and behavior. As Lempert et al. [2010] stated, the “predict-then-act” top-down approach can run into problems in the analysis and development of long term policy due to conditions of deep uncertainty. Increasing spatial and temporal precision of GCM output can easily be misunderstood for increasing accuracy, resulting in overconfidence in the understanding of the future and an underestimation of the irreducible uncertainty [Dessai et al., 2009]. Unlike a deterministic forecast, the skill of a climate projection cannot be tested in comparison to observations. Wilby and Dessai [2010] noted the cascading uncertainty inherent in using GCM projections to support adaptation decisions. To overcome the issue of uncertain model accuracy, studies by Räisänen and Palmer [2001], Tebaldi and Knutti [2007], Angel and Kunkel [2007], and others have considered ensembles of GCM projections. Yet there is no accepted methodology for evaluating relative quality of GCMs in terms of predictive skill or credibility [Angel and Kunkel, 2010]. Even GCM ensembles that include extreme predictions may not capture the true range of climate uncertainty [Stainforth et al., 2007]. Additionally, as Hirsh [2011] points out, the GCM projections may not be answering the questions relevant to water resources decision making. While GCMs may provide credible information about average annual changes, their ability to estimate variability, seasonality, and major storms, and other factors more relevant to water systems is much less reliable. Barsugli et al. [2009] assessed
aspects of GCM projections and rated estimates of hydrologic variability as low to moderate. 

Or, as Hirsh [2011] states, “we have the most confidence in statements about the least important aspects of hydrology (the central tendency), and the least confidence in the most important aspects (extreme events)”. 

An alternative approach, presented here, starts with the physical system and determines the system conditions that constitute hazards or failure as defined from stakeholder input. The process then identifies the climate conditions that cause those hazards. The hydrological system is modeled with the Combined Lake Regulation and Routing Model (CLRRM) as described by Clites and Quinn [2003]. The CLRRM uses monthly Net Basin Supply (NBS) values and applies water conservation, routing, and regulation release rules to determine Great Lakes water-levels and flow rates in the interconnecting channels. The NBS for each lake is the net water flux due to direct precipitation, runoff, and evaporation. NBS does not include interlake transfers or diversions, which are typically modeled separately. The uncertainties associated with the CLRRM and estimates of monthly NBS values have been discussed in the context of the IUGLS [Neff et al., 2005]. The CLRRM has been calibrated, evaluated, and tested with historic data and synthetically generated data to obtain a coherent understanding of system response to a variety of inputs. This understanding of the system response can be combined with input from stakeholder groups that identify the conditions that concern the stakeholders the most. This “hazard discovery” process identifies the climate conditions that result in the most problematic system states. The climate conditions and hazards are linked using a “climate response function”, a model based on the statistical relationship between the climate conditions and hazards. Using this process, one obtains an understanding of which climate conditions pose the most severe hazards in terms relevant to the concerned stakeholder
groups. The process is termed “decision-scaling” [Brown et al., 2011]. Prudhomme et al. [2010] described a related “scenario neutral approach.”

With an understanding of climate related hazards, one can use the climate response function, driven by various types of climate data, to estimate probabilities of problematic climate conditions based on the climate information source. This allows one to examine system risk by using climate probability conditional on the source of climate information. Starting with climate probabilities based on historic observations, one can establish a climate risk baseline. Then one may use other sources such as paleo reconstructed climate or GCM projected climate to determine how the alternate source of climate information alters estimated climate risk. The historic record provides an estimate of the distribution of key predictive climate variables; GCM output, expert judgment, and other sources of climate information can then be used to generate new estimates of climate variable distributions representing possible future conditions.

The novel contribution of this paper is the development of a model of stakeholder-defined risk, termed a climate response function, which links these risks on the Upper Great Lakes to climate conditions as part of a bottom up meets top down climate risk assessment process. The model has a number of potential applications, including identification of climate hazards, estimation of climate risks and evaluation of lake regulation plans. Climate response surfaces developed from the climate response function clearly show the impact of climate on performance and facilitate understanding of the performance of system options such as regulation plans under different climate regimes. The paper proceeds with a review of regulation of the Great Lakes and previous climate change analyses, the description of the model and results for the upper Lakes, followed by a discussion of findings and implications.
2.2 Background

The International Joint Commission (IJC) was established as a result of the Boundary Waters Treaty of 1909 to oversee the regulation of obstructions and diversions that would impact levels or flows in waters on the international boundary waters between Canada and the United States. The IJC complies with the agreements found in the Boundary Waters Treaty, the Orders of Approval from 1914 and the Supplementary Orders of Approval from 1979. The Treaty and the Orders establish the guidelines for lake regulation allowing the IJC latitude to determine and follow a regulation plan that follows the letter and intent of these documents. Clites and Quinn [2003] describe the history of Great Lake regulation and the prior regulation plans that led to the current regulation plan, plan 1977A, which has been in use since 1990. Plan 1977A essentially seeks to keep Lake Superior and Lake Michigan-Huron at the same relative position with respect to their long term mean water-level.

The IJC completed the Lake Ontario-St. Lawrence River Study (LOSLRS) in 2005 to review regulation of levels and flows in the Lake Ontario – St. Lawrence River system while considering the impact of regulation on all affected interests and then launched the International Upper Great Lakes Study (IUGLS) in 2005. Prior to the IUGLS, previous studies have looked at climate change impacts on the Great Lakes, but the IUGLS has provided the opportunity for a comprehensive review of lake-level impacts, regulation plans, and climate related risk.

2.2.1 Previous Climate Change Assessments of the Great Lakes

As the scientific community began to recognize rising levels of CO$_2$ and other greenhouse gases, scientists and researchers began to model and explore the potential impacts on climate. Prior to the Intergovernmental Panel on Climate Change (IPCC) First Assessment Report (FAR) in 1990, several researchers began to look at the potential impacts of climate
change on the Great Lakes system. Early investigations into the impact of climate change have used a top-down approach to estimate changes [Cohen, 1986; Sanderson, 1987; Hartmann, 1990; Mortsch and Quinn, 1996; Crolely, 1990; Chao, 1999; Mortsch et al., 2000; Lofgren et al., 2002, and Lofgren et al., 2011]. These studies and their findings are discussed below. These studies used a single or limited number of GCM outputs to estimate the impact on NBS, lake-levels, economic interests, and environmental interests. Later studies incorporated increasing numbers of GCM simulations, up to large ensembles of model runs.

The following studies considered the hydrologic impact resulting from one or more downscaled GCM projection. Cohen [1986] used steady state double CO$_2$ scenarios from the GISS and GFDL models to estimate NBS components and extrapolate a 10-30% reduction in NBS over the Great Lakes. Water level changes were not reported. Sanderson [1987] used a steady state double CO$_2$ scenario and the GISS model to estimate mean lake-level reductions of 0.3 to 0.8 m over the Great Lakes, mean flow reductions up to 20%, a higher incidence of low lake-levels, and significant increased costs or losses to commercial shipping and hydropower.

Sanderson [1987] did not report changes in NBS. Hartmann [1990] used three doubled CO$_2$ scenarios from the GISS, GFDL, and OSU model centers and a GISS transient case for 1980 to 2060. The steady state models predicted an NBS reduction of 16 mm to 479 mm on Lake Superior and 210 mm to 399 mm on Lake Michigan-Huron (expressed as a depth over the lake) and lake water level reductions of 0.46 m to 0.47 m on Lake Superior and 0.99 m to 2.48 m on Lake Michigan-Huron. For the GISS transient case, Lake Superior had an increased NBS of 17 mm per decade and a decreased water level by 13 mm per decade while Lake Michigan-Huron had a decreased NBS of 34 mm per decade and a decreased water level by 59 mm per decade. Additionally, the climate model caused the lake regulation plan to fail on Lake Ontario for each scenario and on Lake Superior for the GFDL scenario. Crolely [1990] considered three steady
state double CO2 cases with the GISS, GFDL, and OSU models and one transient case from 1980-
2060 using the GISS model. *Crole y* [1990] reported decreases in NBS of 23% to 51% for steady
state scenarios and 27 to 75 mm per decade for the transient cast. *Crole y* [1990] did not report
lake levels. *Chao* [1999] conducted climate change analysis using eight transient scenarios (two
each from GFDL, UKMO-Hadley, MPI, and CCC) and two doubled CO2 scenarios (from GFDL and
CCC). *Chao* [1999] did not report NBS changes, but did project water level decreases of 0.2 m to
0.9 m on Lake Superior and decreases of 0.3 m to 1.8 m on Lake Michigan-Huron. *Mortsch and
Quinn* [1996] used four double CO2 scenarios from the CCC, GISS, GFDL and OSU centers. They
did not report changes in NBS but did project lake level reduction ranges of 0.75 m to 11.3 m on
Lake Superior and 0.01 m to 0.31 m on Lake Michigan-Huron. *Mortsch et al.* [2000] used the
CGCM1 and HadCM2 models with doubled CO2 levels and with transient CO2 increases in the
2021-2040 and 2041-2060 timeframes. While NBS was not reported, lake level reductions of
0.23 m to 0.47 m on Lake Superior and 0.99 m to 2.48 m on Lake Michigan-Huron were
reported. *Lofgren et al.* [2002] used the CGCM1 and HadCM2 models with doubled CO2
scenarios and twenty-year transient scenarios centered on 2030, 2050, and 2070. *Lofgren et al.*
[2002] reported decreased Lake Superior levels by 0.01 m to 0.8 m and a change -2.48 m to
+0.35 m on Lake Michigan-Huron. *Lofgren et al.* [2011] examined how evapotranspiration (ET) is
modeled from GCM projections, a key step in using GCM projections to determine NBS. They
found that the standard method, based on an air temperature proxy, overestimated ET,
resulting in lower NBS and lake levels. By applying an energy budget approach that satisfies
conservation of energy, *Lofgren et al.* [2011] found more conservative changes in NBS and water
levels than previous climate change assessments, in some cases reversing water level
predictions from a decrease of 0.19 m to an increase of 0.13 m on Lake Superior or from a
decrease of 0.44 m to an increase of 0.41 m on Lake Michigan-Huron.
Angel and Kunkel [2010] considered an ensemble of 565 model runs from three greenhouse gas emission scenarios and 23 GCMs. While many previous studies indicated a reduction in lake-levels due to climate change, this broad ensemble revealed projections implying both higher and lower mean water levels. The range and uncertainty inherent in their findings was wide, with projections of precipitation ranging from an increase of 20 cm to a decrease of 5 cm annually. They found that the total range of mean lake-level change was −3.0 m to +1.5 m, which is a large range compared to the range between the historic maximum and minimum lake-level of 1.12 m on Lake Superior and 2.07 m on Lake Michigan-Huron.

While the vast majority of previous climate change impact assessments used a top-down approach that started with GCM output, a few have taken alternate approaches. Notably, McBean and Motiei [2008] eschewed GCM data and conducted statistical trends in meteorological and hydrological data and identified statistically significant increasing trends in many variables, including rising flow rates in all connecting channels. No previous study has attempted to define climate risks in stakeholder terms.

2.2.2 Bottom-Up Assessment Methods

In contrast to the “top-down” approaches described above, a risk-based, or “bottom-up”, approach may be more useful for supporting decision making under climate uncertainty [Brown et al., 2011; Lempert et al., 2004]. In general, these approaches consider the system and hazards to the system based on interactions with stakeholders.

Jones [2001] described a risk-based approach that used GCMs as the scenario generator to identify and manage risks. Johnson and Weaver [2009] described a similar approach to identify climate based risk. However, these approaches still use GCM projections to identify climate hazards and thus have similar limitations as other scenario-based methods. These
approaches may be well suited to consider system performance under potential future
scenarios to estimate a range of potential future impacts, but may not be as well suited to
support decision making under uncertainty due to potential climate change.

Recent studies provide examples of rethinking along this direction of analysis.

Prudhomme et al. [2010] presented a scenario-neutral approach to identify hazards and the
climate conditions that contribute to those hazards. This was used to develop a climate impact
model that used climate conditions to predict fluvial flooding. Wilby and Dessai [2010] followed
a similar approach to use a system vulnerability analysis to create adaptation options, and then
used climate change scenario information to determine no-regrets or low-regrets adaptation
options. Brown et al. [2012a] used a surrogate system performance function that predicts water
system reliability from climate in the metropolitan Boston water supply system to support
decision making under uncertainty.

Brown, et al.[2011] described a decision-analytic-based approach for estimating climate
risk on the Upper Great Lakes called decision-scaling that links a bottom-up process with
available top-down projections that can be applied in cases of where climate information is
uncertain but may be informative. The assessment considers the system of interest and its
vulnerability to climate impacts. The vulnerability assessment uses input from concerned
stakeholders to identify key impacts or system states with unacceptable performance. The
hazard identification process identifies climate conditions that lead to poor system performance
and is conducted without consideration of the probability of those climate conditions occurring.
The relationship between hazards and climate conditions is quantified in a climate response
function. This model is the quantitative link between impacts and climate and can be used with
projections of climate from a variety of sources to estimate climate-informed risks (conditional
on the source of climate information). Combining the hazards associated with climate with estimates of climate probability allows the assessment of climate-informed risks. This chapter describes the development of the climate response function as applied to the Upper Great Lakes. The development of estimates of future potential climate probability is discussed in Chapter 5. Dessai and Hulme [2004] present arguments for and against assigning probability density functions to future climate conditions. Despite being subjective and conditional, probability density functions for future conditions are relevant for climate decision-making [Dessai and Hulme, 2004]. Brown et al. [2011] discussed considerations on how to incorporate different sources of climate information such as GCM projections, Regional Climate Models (RCMs), paleo climate based models, and even expert opinion, to develop conditional probabilities for future climate states.

2.3 Method

The methodology described in this paper leads to the creation of a climate response function that relates climate statistics to stakeholder-defined risk. The process starts with understanding what is important to stakeholders in terms of risk and impact. This involves interacting with stakeholder groups and translating their priorities and concerns into model variables, resulting in sector specific variables and thresholds that can be used to evaluate system performance in terms relevant to the stakeholders. The next step is a hazard discovery process involving data mining to identify periods of poor system performance (as defined by the stakeholders) and relevant climate variables that influence system performance. This study utilized a 55,590-year stochastic data set based on historic data for this purpose. This data set provides a wide range of climate conditions to create and assess the statistical relationship between model variables and system performance. After the data mining process, statistical
models are proposed and evaluated to select a model that is consistent with the data and can effectively explain or replicate the important relationships within the system. The result is the development of the climate response function to predict Upper Great Lake system performance relevant to stakeholders and that uses measures of climate change as function inputs. The function and how it can be used to understand a complex system and inform decisions is described in more detail below.

2.3.1 Stakeholder-Defined Thresholds

The IUGLS established six Technical Working Groups (TWGs) to address six primary areas of stakeholder concern on the Upper Great Lakes. The 1909 Boundary Waters Treaty and the 1914 Orders of Approval governing the regulation of the Great Lakes specify that water use, commercial navigation, and hydropower are protected interests [Clites and Quinn, 2003]. The Treaty requires the IJC to consider impacts in the three specified areas and encourages the IJC to consider impact on other interests. These additional interests include ecosystems, coastal, recreational boating and tourism. As part of this analysis, the IUGLS commissioned the six TWGs to determine which changes to the Great Lakes were of greatest concern. In all sectors, lake-levels were determined to be the most important measure of sector performance. The hydropower, commercial navigation and ecosystem TWGs also found that flow rates in the interconnecting channels were relevant indicators of system performance. A similar model can be created to consider exceedance of threshold flow rates, where channel flow rates are relevant to stakeholders.

Each TWG conducted extensive surveying, working groups, public information sessions, and analysis to determine how lake-levels related to sector performance. The TWGs used this stakeholder input to develop coping zone thresholds as a state-based method to quantify sector
performance. While the TWGs each provided a single set of thresholds per Lake, there is some
underlying uncertainty in their definition. Coping zone thresholds inherently reflect sensitivity
to extreme lake-levels, so the threshold values vary over spatially within a sector. Also, the
thresholds are not fixed in time; they will change with better understanding of the relationship
between water-levels and performance and with response to adaptation measures that affect
this sensitivity. More details about the process each TWG used to determine coping zone
thresholds are on the IUGLS technical report site\(^1\). Coping zone A is the preferred or acceptable
zone where there is little to no environmental or economic negative impact due to lake-levels.
Coping zone B is the range above and below zone A where there is a temporary, reversible, and
non-severe negative impact due to the lake-levels. Coping zone C is the range above and below
zone B where the negative environmental or economic impact is acute, irreversible, or
potentially long lasting. The coping zone levels are included in Figure 2.1 for all lakes and
sectors. The method described in this article has been applied to each of the TWG-defined
coping zones and on each of the Upper Great Lakes. While each coping zone threshold is
represented by a single water-surface elevation level, there is remaining uncertainty associated
with the threshold values. The TWGs amassed data from across their respective stakeholder
groups to determine a single lake-wide value. Extrapolating the site-specific impact thresholds
over an entire Great Lake does not capture the uncertainty and variability in sensitivity to
changing water levels within each sector. This source of uncertainty and variability is not
included in this analysis. Coping zones are similar to the impact thresholds described by Jones
[2001]. Jones [2001] stated that stakeholder-defined thresholds clearly communicate uncertain
outcomes in terms that are relevant to stakeholders and decision makers.

\(^{1}\) Available at: www.iugls.org/sup-tech-reports.aspx
This analysis focuses on the Coastal TWG coping zone definitions for Lake Superior and Lake Michigan-Huron in the interest of brevity. While the model and analysis for each stakeholder coping zone and for each Great Lake were provided to the IUGLS, only the model and analysis for the coping coastal coping zone on Lakes Superior and Michigan-Huron are presented here, while Chapter 4 includes discussion about the other coping zones. As seen in Figure 2.1, the coastal coping zone thresholds are relatively close to the historic average water-levels compared to other coping zones. This is an indication that the coastal interests are relatively sensitive to water level extremes. Unlike the LOSLRS where gains by one stakeholder group were offset by losses from another group, stakeholder impacts based on coping zone threshold exceedance did not exhibit tradeoffs between stakeholder groups. There are tradeoffs between impacts on Lake Superior versus Lake Michigan-Huron, which will be discussed further. Additionally, the IUGLS examination of the regulation of Lake Superior outflow focused on the impacts on Lakes Superior and Michigan-Huron. A summary of average coastal coping zone levels for Superior and Michigan Huron is included in Table 2.1. The coastal coping zones were defined based on the historic lake-levels from 1918 through 2010. With these thresholds established, the risks associated with climate change could be estimated.

<table>
<thead>
<tr>
<th>Lake</th>
<th>Zone</th>
<th>Elevation (m)</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Superior</td>
<td>High C</td>
<td>183.70</td>
<td>Average (by month) of 1985-86 water level</td>
</tr>
<tr>
<td></td>
<td>High B</td>
<td>183.61</td>
<td>10% exceedance levels (by month) from 1918-2010</td>
</tr>
<tr>
<td></td>
<td>Low B</td>
<td>183.22</td>
<td>90% exceedance levels (by month) from 1918-2010</td>
</tr>
<tr>
<td></td>
<td>Low C</td>
<td>182.89</td>
<td>Record low water levels (by month) from 1918-2010</td>
</tr>
<tr>
<td>Michigan-Huron</td>
<td>High C</td>
<td>177.21</td>
<td>Average (by month) of 1985-86 water level</td>
</tr>
<tr>
<td></td>
<td>High B</td>
<td>176.94</td>
<td>10% exceedance levels (by month) from 1918-2010</td>
</tr>
<tr>
<td></td>
<td>Low B</td>
<td>176.04</td>
<td>80% exceedance levels (by month) from 1918-2010</td>
</tr>
<tr>
<td></td>
<td>Low C</td>
<td>175.76</td>
<td>Average (by month) of July 1963 – June 1965 water levels</td>
</tr>
</tbody>
</table>
2.3.2 Hazard Discovery

The hazard discovery process was described by Brown et al. [2011] and by Lempert et al. [2010] as a method of exploring the system robustness under a wide range of plausible states without determining the probability of the conditions. Plausible climate states are states that are possible and reasonable through studies of sources of climate data, including but not limited to historical climate records, stochastically generated climate sequences, GCM and RCM projections, and expert opinion. Climate states that are inferred from one or more sources of climate information cannot be entirely ruled out. This avoids the modeling pitfall of avoiding certain extreme conditions based on the prejudice that the
conditions are unlikely, so they should not be considered. This process facilitates system or policy risk assessment by identifying the conditions under which failure or poor performance occurs. It also allows comparison of the range of successful plan performance in climate space. This analysis may identify “satisficing” alternatives that are robust or have acceptable performance over a wide range of inputs rather than options that are optimal for a small range of inputs. Loucks et al. [2005] described a satisficing approach that establishes minimum performance values for each objective and selects alternatives that meet these criteria over the range of scenarios considered.

In this application, a large database of synthetically generated climate conditions was created using an existing stochastic data set. This study made use of the historic-based, stochastically developed NBS series developed originally for the LOSLRS by Fagherazzi et al. [2005]. This data series provides 55,590 years of monthly NBS values for each of the Great Lakes. The IJGLS study board recommended use of the NBS series developed for the LOSLRS for evaluation of regulation plans and lake performance [International Joint Commission, 2005]. The climate conditions represented in the data series span a greater range of plausible climate than the historic record, which allows testing the Great Lakes system and regulation plans over a broader range of climate than would be possible just using the historic record. The Coordinated Great Lakes Regulation and Routing Model (CGLRRM), described by Crites and Quinn [2003], was used to relate the stochastic NBS series to the corresponding monthly lake-levels and lake outflows.

The stochastic data set contains ample data to explore the relationship between climate and impact as defined by the coping zones. To determine this relationship, the data were parsed into segments that would capture the prevailing climate and resultant impact. This allowed comparison of system performance and climate statistics from each segment. Several
data segment lengths were considered and explored. Thirty year analysis segments were selected for two reasons. First, the available GCM projections for this study were provided in 30 year segments, which is a typical time span used in climate change analysis. Thus the selection of a 30 year segment for the development of a climate response function would facilitate the link to GCM projections. In addition, 30 years is a World Meteorological Organization standard time period to specify climate conditions [Arguez and Vose, 2011].

Once the data set was parsed into 30 year segments, coping zone occurrences and climate statistics were calculated for each segment. Analysis showed that three predictor variables explained a majority of the variation in the coping zone B and C occurrences. The three variables were the mean, standard deviation and serial correlation of the annual NBS. The mean and standard deviation were normalized to a percent change from the historic mean and standard deviation. Figure 2.2 shows the coastal coping zone C occurrences on Lake Superior as a function of the percent change mean annual NBS and the percent change annual NBS standard deviation. In this figure, upper zone C occurrences are shown as red circles and lower zone C occurrences are blue diamonds with the size of the circle or diamond proportional to the number of occurrences.

Figure 2.2 provides important information regarding the relationship between prevailing climate conditions and the impacts as defined by stakeholders. These figures demonstrate the increase in upper zone C occurrence when the system is wetter and more variable, or when the percent change mean NBS and the percent change annual NBS standard deviation increase. Increases in mean NBS imply that there is more water in the system and a greater chance of upper zone C occurrence. The lower zone C occurrences increase as the percent change mean NBS decreases and the percent change annual NBS standard deviation increases. These results
are intuitively consistent with the physical system and demonstrate where significant impacts begin to accumulate.

The hazard discovery process highlighted important features of the Great Lakes response to climate changes. While increases or decreases in the mean NBS increased the prevalence of upper and lower coping zone C occurrences respectively, Lake Michigan-Huron was much more sensitive to change, especially with regard to reduced NBS. Note that this sensitivity is also partially a function of the regulation of flows between Superior and Michigan-Huron according to the current regulation plan 77A.

![Figure 2.2: Scatterhistogram of 30-year realizations from the stochastic data set, plotted by percent change mean and standard deviation of the annual Net Basin Supply. Each dot represents a 30-year segment from the stochastic data set. The size of the red circles and blue diamonds are proportional to the number of coastal coping zone C (severe impact) occurrences.](image-url)
2.3.3 Climate Response Function

The hazard discovery process identified climate variables that were most strongly related to impacts as measured by zone occurrences. The next step in the process is the formalizing of this relationship in the form of a climate response function, a statistical model that links climate with system performance. Many models were proposed and assessed before the current model was selected. The objective was a parsimonious model that was computationally efficient to enable the use of a variety of climate information sources to estimate risk. To evaluate alternatives to the current regulation plan, the model had to be parameterized for each regulation plan. This section will describe model output, input, the deterministic and stochastic model components, and model parameterization. The climate response function uses three model inputs. Section 2.3.3.5 includes a brief section that analyzes adding a fourth model input. The alternate models that were rejected during the modeling process are not described.

2.3.3.1 Model Output – Coping Zone Occurrences

The climate response function determines the expected fraction of months in each coping zone for a given set of climate inputs. This means that the model outputs are fractional values between 0 and 1, inclusive, and are not independent since the five coping zone occurrence fractions must sum to 1. The format of the predictand limits the type of stochastic model components that can be used. For instance, a normal stochastic model component is not appropriate because the normal distribution is supported over an infinite domain while the predictands are not. The model can be used to provide an estimate of the expected value of coping zone occurrence or can be used to estimate a probability distribution for each coping zone.
2.3.3.2 Model Input – Climate Measurement

The parametric statistical model uses three climate statistics as predictors; the mean, standard deviation and the serial correlation of the annual NBS. The mean and the standard deviation of the annual NBS were normalized based on the historic NBS series mean and standard deviation. The percent change mean and standard deviation are centered on or near 0 and effectively unbounded. The serial correlation is bounded between -1 and 1. The three predictors used in the model are defined below:

\[
\overline{NBS} = \frac{1}{m} \sum_{i=1}^{m} NBS_i \tag{2.1}
\]

\[
X_1 = \overline{NBS}^* = \frac{\overline{NBS} - \overline{NBS}_{hist}}{\overline{NBS}_{hist}} \cdot 100\% \tag{2.2}
\]

\[
S_{NBS} = \left( \frac{1}{m} \sum_{i=1}^{m} (NBS_i - \overline{NBS})^2 \right)^{1/2} \tag{2.3}
\]

\[
X_2 = S_{NBS}^* = \frac{S_{NBS} - S_{NBS,hist}}{S_{NBS,hist}} \cdot 100\% \tag{2.4}
\]

\[
X_3 = r = \frac{1}{m-1} \sum_{i=1}^{m-1} \left( \frac{NBS_i - \overline{NBS}}{S_{NBS}} \right) \left( \frac{NBS_{i+1} - \overline{NBS}}{S_{NBS}} \right) \tag{2.5}
\]

where $NBS_i$ is the average annual NBS for the $i$th year, $m$ is 30 years in each analysis segment, the bar indicates an average value, $X_1$ is the percent change mean annual NBS from the
historical mean, the *, or star, superscript indicates percent change in the variable, the “hist” subscript indicates the historical value based on an NBS record from 1900 to 2006, \( S_{\text{NBS}} \) is the standard deviation of annual NBS values, \( X_2 \) is the percent change in standard deviation of NBS from the historical standard deviation, and \( X_3 \) is the serial or auto correlation within the annual NBS values with a one-year lag. In Section 2.3.3.5 the inclusion of a fourth input parameter, the starting water level for the time segment under analysis, is discussed.

2.3.3.3 Statistical Model Description

At the core of the statistical model is the idea that changes in climate will shift and stretch the shape and range of the level exceedance curves for each lake, impacting the probability of exceeding a given threshold value within a given month. A level exceedance curve plots the cumulative non-exceedance probability versus the lake-level. Wetter conditions will shift the curve upwards, increasing the probability of exceeding upper zone C thresholds and decreasing the probability of exceeding lower zone C thresholds. Increased variability will tend to vertically stretch the exceedance curve resulting in increases for both upper and lower zone C coping zone probability. The model uses climate statistics to estimate the probability of being above or below a lake-level threshold, which then can be translated into an expected number of months or fraction of time in a given coping zone. The statistical model is composed of a generalized linear model with a logit transformation and a binomial distribution. This is used to predict the number of months above or below a level threshold out of the 30-year analysis window. The binomial distribution is governed by two parameters: \( n \), the total number of time steps (in this case 360 months in the analysis window) and \( \pi_p \), the probability of not exceeding a given lake-level for a given month. The subscript \( j \) refers to each of the four coping zone thresholds. The inverse logit transformation maps the linear combination of predictor variables
from the real number range of $[-\infty : \infty]$ to the probability range of $[0 : 1]$. An input vector $X$ is multiplied by a vector of regression coefficients, $\beta$, as shown in Equations 2.6 through 2.8.

$$X = [1, X_1, X_2, X_3]$$

(2.6)

$$\beta = [\beta_0, \beta_1, \beta_2, \beta_3]$$

(2.7)

$$X \cdot \beta = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$$

(2.8)

The logit transformation is shown in Equation 2.9 and the inverse logit transformation is shown in Equation 2.10, with $a$ and $b$ serving as dummy variables.

$$\text{logit}(a) = \log \left( \frac{1}{1-a} \right)$$

(2.9)

$$\text{ilogit}(b) = \frac{1}{1 + \exp(-b)}$$

(2.10)

Using the inverse logit transformation, the probability of non-exceedance is calculated using Equation 2.11. The non-exceedance probability is $\pi_j$, where $j$ indicates the coping zone threshold being modeled. It is used in the binomial distribution in Equation 2.12, where $n$ is 360 or the number of months in the 30-year analysis window and $Y_j$ is the number of months with the water level below the $j$th coping zone threshold.

$$\pi_j = \text{ilogit}(X \cdot \beta)$$

(2.11)
\[ P(Y_j = y) = \binom{n}{y} \pi_j^y (1 - \pi_j)^{n-y} \] (2.12)

The binomial distribution has a mean or expected value equal to \( n\pi \), and the probability of the lake-level, \( z \), being less than or equal to a threshold \( Z_j \) in a given month is \( \pi_j \). This model effectively treats the outcome for each month as independent. An area of future work is to consider models that do not treat the individual monthly outcomes as independent, but maintains persistence. The current model is adequate to describe the reliability of a given system which is calculated as the fraction of time not in a failure condition, but would be insufficient to predict system resilience as defined by Loucks et al. [2005], which is the conditional probability that if the system is currently in an unsatisfactory state, it will transition to a satisfactory state in the next time step.

The model parameters were determined using a generalized linear regression by minimizing the residual sum of squares to estimate the parameter vector, \( \beta \). The climate statistics and threshold occurrences for each 30-year window comprised the data to fit the parameters.

The estimated non-exceedance probabilities from each 30-year analysis window are calculated using Equations 2.13 through 2.16, where \( \hat{\pi}_j \) is the fraction of months that do not exceed the \( j \) zone threshold for each coping zone threshold (\( LC \) for lower C, \( LB \) for lower B, \( UB \) for upper B, and \( UC \) for upper C) and \( N_j \) is the number of months out of \( n \) total months in coping zone \( j \).

\[ \hat{\pi}_{LC} = \frac{N_{LC}}{n+1} \] (2.13)
\[ \hat{\pi}_{LC} = 1 - \frac{N_{UC}}{n+1} \]  
(2.14)

\[ \hat{\pi}_{LB} = \frac{N_{LC} + N_{UB}}{n+1} \]  
(2.15)

\[ \hat{\pi}_{UB} = 1 - \frac{N_{UC} + N_{UB}}{n+1} \]  
(2.16)

The generalized linear regression is repeated for each coping zone threshold producing a parameter vector, \( \beta \), for each. Since this analysis is based on the non-exceedance probability, it is fairly straightforward to calculate the proportion or probability of a lower C or an upper C zone. The probability of the lake being in lower C, or \( P(LC) \), is shown in Equation 2.17 and for being in upper C in Equation 2.18.

\[ P(LC) = P(z \leq Z_{LC}) = \pi_{LC} \]  
(2.17)

\[ P(UC) = P(z > Z_{UC}) = 1 - P(z \leq Z_{UC}) = 1 - \pi_{UC} \]  
(2.18)

To be in lower zone B, the lake-level, \( z \), has to be below \( Z_{LB} \) and above \( Z_{LC} \). Hence the probability of lower zone B is given by Equation 2.19 and by similarity, the probability of upper zone B is given by Equation 2.20.

\[ P(LB) = P(z \leq Z_{LB}) \cap P(z > Z_{LC}) = \pi_{LB} - \pi_{LC} \]  
(2.19)
\[ P(UB) = P(z < Z_{UC}) \cap P(z \geq Z_{UB}) = \pi_{UC} - \pi_{UB} \quad (2.20) \]

### 2.3.3.4 Climate Response Function Results for Lake Superior and Lake Michigan-Huron

This section presents the climate response function results for Lake Superior using the coastal coping zones and regulation plan 77A. For brevity, model evaluation results are shown for Lake Superior only; the results for Lake Michigan Huron are similar. Figure 2.3 shows the relationship between the actual zone fraction, in black, and the predicted zone fraction, in blue, for upper C, upper B, lower B and lower C zones on Lake Superior. These graphs show one predictor variable, percent change mean NBS, so the predictand variability based on the NBS standard deviation and serial correlation is not accounted for in the figures.

Figure 2.4 provides a perspective on the model fit for Lake Superior by showing the percent change mean NBS on the x-axis, the zone occurrence fraction on the y-axis, and the probability density function value plotted on the z-axis. The black dots represent the data points from the historic based stochastic series while the red curves represent the zone occurrence expected value and the zone occurrence probability density functions. This figure allows the visual comparison of measured and predicted lake performance for upper coping zone B, or moderate impact from high water levels. The figures for lower B, lower C and upper B coping zones and for Lake Michigan-Huron are similar but not included. The modeled expected value captures the data trends, increasing zone occurrences corresponding with increasing percent change mean NBS for Upper C and Upper B zones and with decreasing percent change mean NBS for Lower B and Lower C zones.

The binomial stochastic model component captures two key components of the data distribution. First, the distribution is appropriate for predictand in that it supports the range
from 0 and 1. Additionally, the binomial distribution accounts for the heteroscedasticity of the data, as shown by the increased variance or dispersion of the data with increasing mean value.

For the binomial distribution, the mean or expected value is $np$ and the standard deviation is $n\pi(1-\pi)$. When the probability is near zero or one, the distribution resembles an exponential distribution with a sharp peak near the domain boundary and a skewed tail. As the probability increases from zero, the peak decreases, the spread increases and the distribution appears more like a normal probability distribution. In this way, the binomial probability density function correctly models the increasing spread and decreasing skewness with increasing probability that characterizes the observed data set.

The climate response function shows the lake-level sensitivity to changes in climate. On Lake Superior, a 10% decrease in mean NBS causes no change in the expected coping zone C occurrence rate, while a 10% increase in mean NBS causes a 5% increase in coping zone C occurrence. In contrast, on Lake Michigan-Huron, a reduction of 10% in mean NBS causes a 27% increase in coping zone C occurrence while a 10% increase in mean NBS does not increase the coping zone C occurrence rate. This is shown graphically in Figure 2.5, which clearly shows that Lake Michigan Huron is more sensitive to changes in NBS. Note that the results shown are for regulation plan 1977A. Regulation plan impact on sensitivity is greater on Lake Superior than on Lake Michigan Huron, as discussed in Section 2.4.
Figure 2.3: Comparison of observed and modeled expected value of coastal coping zone fractional occurrences for Lake Superior. Figure includes coping zone C (severe impact) and coping zone B (moderate impact) occurrences as a function of mean NBS.
Figure 2.4: Lake Superior coastal upper zone B (moderate impact). The observed mean NBS and zone fraction values from the stochastic series are plotted with black dots. The modeled expected value curve and probability distribution functions shown for NBS mean percent changes of -15% to 15% are plotted in red.
2.3.3.5 Sensitivity to Initial Water Level

An additional logical predictor of zone occurrences is the water level of the lakes at the beginning of each 30 year period. For example, if a lake is at a relatively high water level at the beginning of a 30-year segment, it will likely have a greater fraction of months that exceed a high level threshold than a 30-year segment starting at the median water level. The Upper Great Lakes have long residence times, Lake Superior’s is 190 years and Lake Michigan-Huron’s is 100 years, which contributes to the persistent impact of starting water level. The magnitude of the lake sensitivity to starting lake water level was determined in two ways. First, the CLRRM was evaluated with four fencepost 30-year NBS sequences and the starting water level at the
5%, median, and 95% exceedance level. The fencepost plans included a change in the mean annual NBS of ±10% and a change in the annual NBS standard deviation of ±20%. Figure 2.6 shows the impact that starting levels have on the level exceedance curve for these simulations. Note that in each quadrant, the same 30-year NBS sequence was used for each lake level starting value. Figure 2.6 shows that the upper zone occurrences were more sensitive to initial starting conditions at high percent change annual NBS standard deviations (plus 20%, shown in the two left plots) and that lower zone occurrences were more sensitive to initial conditions at low percent annual NBS standard deviations (minus 20%, shown in the two right plots). The initial condition sensitivity did not appear to be impacted by the percent change mean NBS.

Secondly, the starting lake level was added as a fourth predictor variable in the climate response function to evaluate model improvement. Model improvement was measured using correlation, a measure of explained variance. Adding the initial lake-level to the predictive model improves the model fit, as shown in Figure 2.7. However, the inclusion of the additional predictor variable is not justified on two counts. First, the model fit is not significantly improved by the inclusion of the added parameter. The correlation between the observed and predicted coping zone occurrences, \( p \), can be interpreted as the percent of variation explained. The inclusion of the fourth parameter only improves the percent of variation explained by 1-3%.

Second, the starting level at some future time period is unknown. The initial lake-level for any future time period is uncertain and thus could not be included in estimations of future climate risk.
Figure 2.6: Lake Superior 30-year level exceedance curve sensitivity to initial lake-level for four fencepost NBS sequences. The fencepost NBS sequences were selected with ±10% mean and ±20% standard deviation of NBS. The starting levels were the 5%, 50% and 95% exceedance December lake-levels.
Figure 2.7: Comparison of three- and four-parameter predictive models on Lake Superior coping zone occurrences. The three-parameter model includes the mean, standard deviation and serial correlation of the annual NBS over a 30-year segment. The four-parameter model adds the starting lake-level to the predictive model. The correlation, ρ, between the observed and predicted value is given for each model.

2.3.4 Climate Response Surfaces

The climate response function allows development of powerful new tools to analyze the interaction of climate with a water resources system, resulting in a better understanding of the implications of climate change. One of these powerful, new tools is the climate response surface, which graphically illustrates system performance over a range of conditions in climate space which is shown in the upper quadrants of

Figure 2.8. The hazard discovery process clearly identified climate conditions that lead to adverse lake conditions. The climate response function can be used to predict the impact associated with a given climate condition. The upper quadrants of

Figure 2.8 show the contour lines of equal expected number or frequency of coping zone C occurrences. The number of coping zone occurrences has been normalized by the historic rate
of coping zone occurrences. The second contour line is located where the expected value of coping zone occurrences is at double the historic rate of coping zone C occurrence. The shaded areas between the contours get progressively darker with increased frequency of coping zone C occurrences. This figure clearly shows that the most problematic climate conditions occur in the top right and top left of the graph, corresponding to an increasing standard deviation and an increasing or decreasing mean NBS. The figures show that Lake Superior is more vulnerable to increases in NBS while Lake Michigan-Huron is more vulnerable to decreases in NBS for the coastal coping zones. Also, Lake Michigan-Huron is more sensitive to climate changes as shown by higher increases in unacceptable performance over a similar range of climate change. These findings are consistent with the regions identified in the hazard discovery process and shown in Figure 2.2.

The contours shown in the upper quadrants of Figure 2.8 are for plan 1977A for the regulation of Lake Superior outflow. The climate response function can be re-parameterized based on the coping zone occurrences from alternative regulation plans under consideration during the IUELS and new hazard contour plots can be developed. To visualize the impact of regulation plans on lake hazards, the contour corresponding to twice the historic coping zone C occurrence has been isolated for ten different regulation plans and is shown in the lower quadrants of Figure 2.8 for Lake Superior and Lake Michigan-Huron. These figures can be used to identify the plans that perform best over the widest range of climate conditions and identify specific regions of climate space where certain plans are superior to others. These figures also highlight the inherent tradeoffs associated with many water resources problems. Plan 55MR49 offers the best performance on Lake Superior and the worst on Lake Michigan-Huron, while plan P129 has the best performance on Lake Michigan-Huron and the worst on Lake Superior. To gain acceptance with the IUELS study board and the International Joint Commission, a plan
would have to improve performance on one or more lakes without degrading performance on the other lakes. In Chapter 3, the results displayed in Figure 2.8 are used to develop robustness indices to assist in regulation plan evaluation and selection.

Figure 2.8: Regulation plan performance on Lake Superior and Michigan-Huron. The top graphs show contours of equal expected number of coastal coping zone C occurrences. Each contour, $n$, represents $n$-times the historic zone C occurrence rate. The bottom graphs provide a comparison of ten regulation plans. The graphs compare contour lines at twice the historic coping zone C occurrence rate.

### 2.4 Results and Discussion

This analysis discusses how climate conditions can be used to predict risk associated with lake-levels on Lake Superior and Lake Michigan-Huron. While the discussion focuses on the coastal coping zones, the same statistical model fitting has been conducted for all coping zones.
including ecology, commercial navigation, water use, recreational boating, and boat launch coping zones. The model has also been extended to Lake St. Clair and Lake Erie and has been used for ten alternate lake regulation plans. For brevity, the results for the additional zones and lakes are not included in this paper.

The IUGLS goals include assessment of the risk to the Lakes associated with climate change and selection of a new regulation plan. Since the results shown in Figure 2.8 identify climate conditions that increase zone C occurrences beyond an acceptable level, there are several questions that ensue. First, how likely are these climate conditions given the current and potential future climate? Second, are there any plans that perform better overall, in climate conditions that Plan 77A does not, or over a wider range of climate conditions? The first question about the likelihood of climate conditions is an area of ongoing research and will be addressed in a future paper. The implications of this question are essential to the understanding of risk associated with climate changes. Conditions with severe consequences but negligible likelihood are low risk. Climate change may alter the distribution of the climate parameters, which may increase the likelihood, and therefore the risk, associated with specific problematic climate conditions.

However, even without the use of climate information to estimate relative probabilities of the identified hazards, much insight is gained from the climate response function. For example, based on the definition of risk prescribed by the coastal TWG stakeholders, it is shown that Lake Michigan-Huron is much more sensitive to small changes in climate. A five percent decrease in the mean NBS yields a doubling of the historical occurrences of problematic lower lake-levels. These hazards occur much more frequently on the low side; it takes a mean NBS increase of 15 percent to double the historic hazard occurrences. These changes to the mean
NBS are not only within the range of the historic based stochastic data set, they are within the range of projected NBS values based on GCM projections.

The approach described above is sensitive to the choice of the threshold level. The thresholds represent the lake-levels where stakeholder impact increases. These levels are not uniform or static. Dessai and Hulme [2004] discuss adaptation measures and classify them as policy actions taken by governments through legislation, regulation and other means and actions taken by private decision makers through autonomous, responsive, or instantaneous adaptation actions. Through these private decisions to employ individual adaptation measures, stakeholders and stakeholder groups can widen their coping zone thresholds which would reduce their risk exposure under historic climate variability and potential future climate variability. The climate response function has helped identify the climate conditions that cause the most concern. This work highlights the areas of increasing risk, which can be used to support decision analysis for adaptation measures.

A major advantage of the climate response function is that it allows the use of climate inputs from alternate sources of climate information, such as downscaled GCM projections or paleo analysis. This allows the tailored use of climate information by taking climate statistics for use as predictors in the climate response function. This model can be used with a single climate change projection to generate a point estimate of expected system performance or over a range of climate to generate performance estimates for the entire range. Even more insight may be gained by assigning a probability distribution for each climate variable and allowing the sources of climate information to influence the variable probability distributions. With estimates of climate probability and climate impacts, one can integrate over the range of each climate variable to determine an overall expected value of impact. This expected value of impact will then be a function of the source of climate information through the probability distribution.
function and a function of the regulation plan through the parameterization of the climate
response function. This result can be used to examine how the system performance is related
to the source of climate information and the regulation plan. Importantly, when new climate
projections become available, the climate response function can be used to quickly estimate the
impacts resulting from the climates simulated by those projections.

2.5 Conclusion

Climate change is an issue of grave concern on the Great Lakes. Stakeholders are
sensitive to relatively small changes in lake-levels. Previous studies of climate change using
projections of future climate have shown a wide range of possibilities. In this study the
objective was to develop a model of stakeholder-defined risk that could be used to put such
climate projections into context. Development of this climate response function is a key
component in the “bottom up meets top down” process called decision scaling, by linking
system performance as defined by stakeholders to climate conditions. The function facilitates
the assessment of the vulnerability domain, the region of climate space which results in
unsatisfactory system conditions. Using the climate response model, three statistics from a 30
year climate series of Net Basin Supply explains over half of the performance variability in Great
Lakes coping zone occurrences. Adding additional inputs, such as initial lake-level, could
increase the model accuracy, but would reduce the model utility.

The analysis reveals the effect that changes in key climate statistics has on the
occurrence of problematic lake-levels in the Upper Great Lakes. In doing so, the climate
conditions that are problematic are identified. Climate information, including GCM projections
or paleo data, can be used to inform decision makers of the possible probabilities associated
with these conditions. The climate response function can be used to develop climate response
surfaces that show system performance as a function of climate to provide a visual and quantifiable measure of performance and robustness. It can also be used to evaluate alternative regulation plans by assessing the range of climate conditions over which each can provide acceptable performance as measured by lake-levels. These applications are being pursued in current work. The model described in this paper was a vital input to the decision making process on lake regulation in the IUGLS.
CHAPTER 3

ROBUSTNESS INDICATORS FOR EVALUATION UNDER CLIMATE CHANGE

Given the range of future uncertainty, there is increasing interest in developing and evaluating water management strategies that are robust to an uncertain future. As part of a process termed “decision scaling”, a climate response function was developed to isolate the impact of climate change on a water system in terms of hazards identified by stakeholders. The climate response function was then used to evaluate system performance over a wide range of climate conditions and to define robustness indicators. The robustness indicators, which measure system performance as a function of climate state, are conditioned on explicit assumptions about climate variable probability distributions. To illustrate this process, it is applied to the Upper Great Lakes to evaluate system robustness related to water management decisions and assess the impact of climate probability assumptions. The robustness indicators were used to identify decisions that outperformed other courses of action regardless of assumptions of future climate probabilities.

3.1 Introduction

The field of water resources has the challenge of designing and analyzing systems under uncertainty. This is not a new challenge, as natural hydroclimate variation provides ample uncertainty. Classical analysis metrics, such as expected value, were developed with the underlying assumption of stationarity [Hirsch, 2011], where stationarity is “the idea that natural systems fluctuate within an unchanging envelope of variability” [Milly et al., 2008]. Lins and Cohn [2011] observed that the water resources planning community has used the concept of stationarity as a planning tool but has never been ignorant of the limitations associated with this assumption. To compensate for uncertainty, water resource engineers include redundancy and
safety factors in their designs; which help systems to function adequately over a wider range of conditions than they were designed for [Stakhiv, 2011].

Climate change, resulting from anthropogenic changes to the atmospheric chemistry, may increase the uncertainty related to predicting future climate and its effect on engineered water resource systems. Climate change “includes the very real possibility that there will be even greater variability – that is, floods and droughts will become more frequent and of greater magnitude and longer duration” [Stakhiv, 2011]. Designing and evaluating water resources systems that will continue to perform adequately with the increased uncertainty due to climate change presents a significant and ongoing challenge.

As the body of research into the potential impact of climate change grew, many asked if we needed to look beyond stationarity based design and analysis tools [Brown, 2010; Milly et al., 2008; Waage and Kaatz, 2011]. Since the concern issued by Milly et al. [2008] there has been a significant body of research on incorporating uncertainty related to climate change into design, analysis, and decision making. A fundamental issue is how best to use uncertain climate information from varied and uncertain sources such as climate projections from General Circulation Models (GCMs). Many climate change assessment studies have used a top-down approach that starts with GCM projections, continues with a downscaling technique such as statistical or dynamic downscaling, which then drives hydrology models and systems models to estimate potential impact. Top down studies of potential climate change impacts include Vicuna et al. [2007] in the California Central Valley, Angel and Kunkel [2010] in the Great Lakes basin, VanRheenen et al. [2011] in the Portland, Oregon water supply and California Central Valley, Johnson and Sharma [2011] in the Sydney, Australia water supply, Chen et al. [2011] in a Quebec, Canada basin, and Harding et al. [2012] in the Colorado River Basin. There are many
more top-down, GCM driven, climate change impact studies that could be cited here, these are just a few.

While this process yields point estimates of impacts when using a small number of GCM projections or a range of estimates when using an ensemble of projections, the process does not yield probabilistic information about future water supply and impact that is useful in a decision context. Also, there are additional sources of climate information such as paleo data and expert opinion which can be combined with the measured data record and GCM projections to better understand the potential future climate. While GCMs and other uncertain sources of climate information may be illustrative of potential impacts, it remains unclear how they can be used in a decision or design framework.

As the discussion continues, several salient points emerge. First, the community cannot abandon classical stationarity-based methods. Štaňhiv [2011] argued that it is “imperative to adapt and extend existing conventional methods and evaluation criteria” because “GCMs (General Circulation Models) cannot provide an adequate foundation for the design of hydraulic infrastructure.”

While these top-down, or climate-science centric, approaches provided quantitative estimates of potential impacts, they did not provide the probabilistic information needed to support decision making. As Stainforth et al. [2007] discussed, the climate information from climate ensembles merely provides a lower bound on the maximum range of uncertainty rather than providing forecasts or bounds on uncertainty. Dessai and Hulme [2004] described how decisions are made in a risk assessment framework, which considers impacts and probabilities of those impacts. They presented cases for and against developing probabilities for future climate and concluded that the usefulness of climate probabilities is “highly context dependent” [Dessai and Hulme, 2004].
Secondly, decision making under uncertainty is not new [Raiffa 1968, Morgan and Hendrion, 1990]. There is a continuum of uncertainty, from the uncertainty inherent in a stationary climate to the deep uncertainty as a result of future climate change. Lempert et al. [2004] defined deep uncertainty in the context of Bayesian decision theory as “the condition where the decision maker does not know, or multiple decision makers cannot agree on, the system model, the prior probabilities for the uncertain parameters of the system model and/or the value function.” The selection of appropriate tools used for decision making under uncertainty is dependent on the characterization of the uncertainty. Stationarity-based techniques can be applied when the uncertainty is well bounded within the historic variability while Lempert et al. [2006] argued that techniques such as Robust Decision Making (RDM) can be applied in cases of deep uncertainty. Assuming that the uncertainty is well bounded can lead decision makers to optimal but non-robust solutions that leave systems vulnerable to high-impact surprise events. RDM advocates shifting the emphasis from making optimal decisions that maximize economic efficiency to satisficing decisions that provide adequate performance over a wide range of outcomes. In cases where temporal uncertainty exists, but the conditions of deep uncertainty may not, methods that apply probability distribution with non-constant parameters have been used [Stedinger and Griffis, 2011]. The work presented here proposes an approach to frame future climate uncertainty in terms of decisions to examine the effects that assumptions regarding climate futures will have on decision making.

This chapter applies the decision analytic framework first proposed by Brown et al. [2011] to explore robustness under uncertainty in the Upper Great Lake system. The analysis considers existing and proposed indicators of robustness. The climate response function that relates climate statistics to hazards identified by stakeholders was developed to explore system vulnerability to climate change. While this function was developed in the context of the Great
Lakes, the approach can be generally applied to identify the key climate related variables that
can be used to predict system performance. By determining conditional probability
distributions for these climate variables, one can determine the sensitivity of system
performance and decisions to climate changes and assumptions related to climate probability
distributions.

The function assesses system performance over a wide range of climate conditions and
alternative operational choices. This paper describes how the function can be used to quantify
system robustness and evaluate climate information value with respect to decision making. In
contrast to robustness measures that consider performance over a large discrete set of time
series scenarios, this approach considers performance over a continuous range of climate input
variables. Robustness is quantified in a generalizable climate informed robustness index that
allows explicit consideration of future climate probabilities. Available climate information,
including projections from GCMs and RCMs as well as paleo based climate data, can be used to
inform potential ranges of climate change or to develop conditional probability distributions for
climate data. This allows the inclusion of available climate information and the evaluation of its
potential impact on water resource system management decisions.

The approach is designed to be generally applicable for use in planning and decision
making under climate change uncertainty. This paper presents a review of water resource
performance indicators, including other methods used to assess system robustness. Then, new
measures of robustness are defined and applied in the context of analysis of outflow regulation
plans on the Upper Great Lakes. The paper then summarizes the findings and potential future
application of the new methods.
3.1.1 Water Resource System Performance Indicators

There are several traditional measures of water resource system performance evaluation that support system analysis and decision making in a multi-objective framework. System performance is frequently expressed in monetary terms such as in benefit-cost analysis or in terms related to system failure such as reliability and vulnerability.

For benefit-cost analysis, the project life costs are compared with the net benefits, in terms of net present value. To assess net benefits, benefits and damages are related to one or more hydrologic model variables. For instance, stage-damage curves relate the estimated monetary damages to a river or lake water level. When a probability distribution is applied to the hydrologic variable, then one can integrate the product of the benefit or damage curve times the probability density function over the range of the hydrologic variable. The best course of action is the one that optimizes the net present value. While this is often a routine process, there are two special circumstances that can cause difficulty. The first is if the damage function related to extreme events rises at a rate faster than the probability distribution approaches zero. Weitzman [2011] referred to these cases as fat-tailed distributions due to the probability density in the extreme events. This case of damages increasing faster than probability decreases results in an improper integral that does not converge. The second circumstance is the deep uncertainty described above where the probability distribution is unknown and cannot be estimated with confidence. In these cases, optimizing the expected net present value is not appropriate. Instead, strategies that consider adequate system performance over a wide range of plausible conditions or scenarios are used.

Additional measures of performance are considered in multi-objective decision frameworks. Three common statistical summaries of performance for water supply are reliability, resiliency, and vulnerability. These are described by Hashimoto et al. [1982b], by
by Mays [2005], and various additional sources. Reliability is the probability of the system being in a satisfactory or non-failure state, resilience is the probability of recovery from a failure or non-satisfactory state, and vulnerability is a measure of the severity of the failure [Loucks et al., 2005]. Additional measures may be appropriate for non-water supply systems by comparing water levels or flow rates to system specific thresholds. These metrics capture dimensions of system performance for a given time series and system model. These measures can be used to summarize or compare performance over a time series and evaluated for competing courses of action for a decision. The time series used could be the historic data record or a synthetic data record generated stochastically, from a weather generator, or from downscaled GCM projections. In this way, these measures can be used to evaluate performance over any potential future scenario. As a result, each of these measures is implicitly conditional on the probabilities associated with each scenario or sequence. The use of these criteria may help illustrate how a project may perform in the uncertain future and characterize any periods of unsatisfactory performance [Hashimoto et al., 1982b]. These criteria can be used as screening criteria to eliminate poorly performing options or as evaluation criteria to assess remaining options.

3.1.2 Robustness

A robust system, regulation plan, or design is one that performs adequately over a wide range of inputs. Robustness supports a satisficing approach which emphasizes satisfactory performance under a wide range of inputs or states rather than optimal performance under a narrow range of inputs. Simon [1956] defined satisficing as a decision-making approach that attempts to meet an acceptable standard. When this concept is applied in a water system analysis and decision making framework, it results in robust solutions with acceptable
performance for a wide range of end states or scenarios. This section explores how robustness has been used previously while the next section discusses the development of new measures.

The concept of robustness has been gaining increasing prominence in water resources analysis, especially when considering systems with significant and irreducible uncertainty, as associated with climate change. The idea of robustness applied to water resource systems is not new, but the applications continue to evolve and mature. Hashimoto et al. [1982a] described robustness as the flexibility to adapt to a wide range of demand conditions at little additional cost. By defining robustness in terms of economic performance, these measures can complement other economic measures such as benefit cost analysis.

Several researchers have proposed schemes or processes to identify robust decisions and policy. Many of these are based on system performance over a range of scenarios. Watkins and McKinney [1995, 1997] developed a framework of Robust Optimization (RO) to support decision making. Their work relies on generation and evaluation of many scenarios to identify the options that are optimal or near optimal for all scenarios. This approach to robustness focuses on minimizing change in the optimal solution which is different than assessing the range over which a system provides acceptable performance.

Lempert et al. [2002] introduced Robust Adaptive Planning (RAP) to reduce vulnerability to surprise events. RAP is designed to explore scenarios that cause system failure to better understand low probability and high impact events. Later, Lempert and Collins [2007] compared system performance under robust, optimum and precautionary approaches. Lempert and Collins [2007] asserted that the best framework is largely dependent on the characterization of uncertainty and on the requirements to communicate decision related information.

Lempert et al. [2003], Groves and Lempert [2007], and Lempert and Groves [2010] developed Robust Decision Making (RDM) to explore policy options over many plausible states.
RDM has been widely applied in support of water resources planning [Dessai and van der Sluijs 2007, Groves et al. 2008a 2008b 2008c 2008d, and Joyce et al. 2010]. RDM avoids assigning any single probability to future states, which make it applicable in cases of deeply uncertain future conditions. It uses a regret based measurement combined with hedging or adaptive policies to reduce regret. In this case, regret is the difference between the best outcome for a given state and the outcome associated with the decision under consideration.

The literature includes several robustness metrics. RDM includes counts or fractions of scenarios with acceptable performance [Groves and Lempert, 2007]. Wong and Rosenhead [2000] proposed Robust Analysis and introduced a robustness score, as the ratio of desirable configurations attainable from a commitment set (an initial decision or set of decisions) to the total number of desirable configurations. The desirable configurations were defined by a range of acceptable performance for a single uncertain variable or a vector of uncertain variables. In these cases, there are implicit assumptions about future climate states related to how scenarios are generated and selected that may be obscured from the decision maker. The work presented here seeks to develop robustness as a function of potential future climate states rather than as a function of specific time series or scenarios. Additionally, the assumptions concerning future climate states are included to make the linkage between climate probability assumptions and predicted system performance more transparent to decision makers.

3.2 Robustness Index Development

In this analysis, several measures of robustness are developed in this section and then applied in the context of water resource management decisions on the Upper Great Lake system. The specifics of the case study will be discussed in Section 3.3, followed by the results in Section 3.4. Here, robustness is a measure of satisfactory system performance over a range
of inputs, conditioned on an assumed probability distribution or plausible range of probability distributions for those inputs. Scenario-based approaches that consider robustness across a set of plausible scenarios typically use an implicit assumption that each scenario is equally likely.

Because the approach used here uses a climate response function that uses climate variables to predict system performance rather than time series or scenarios, the results are not dependent on a specific set of scenarios used in the approach. Thus, the robustness index is independent of climate scenarios, which allows the evaluation of the impacts of specific assumptions about climate variable distributions. Performance is calculated as a function of climate variables using a “climate response function”, and robustness is calculated based on the range of the climate variables resulting in acceptable performance. From a decision maker’s perspective, this approach may help illustrate the connection between potential future climate conditions and robustness by identifying the climate conditions that cause poor performance. Lempert et al. [2006] used a similar process to identify scenarios that lead to poor performance, referring to these scenarios as vulnerabilities. A potential improvement in the proposed approach is that available climate information can be used to develop and apply probability distributions to the potential future climate states to test decision sensitivity.

This method, like other robustness based approaches, is concerned with satisfactory system performance. Satisfactory performance is defined by a range of acceptable performance of a model output variable or vector of variables. Performance thresholds are used to evaluate system performance. The appropriate thresholds vary by system, and can be related to system reliability, critical water levels or other measures relevant to the system.

Generically, satisfactory system performance can be evaluated in Equation 3.1 using a binary performance function. In this equation, \( \Lambda(d, X) \) is the binary performance function, \( d \) is the decision, \( X \) is a vector of climate variables representing a future climate state, \( Y(d, X) \) is
the value of the performance metric and a function of the decision and the climate state, and
$Y_T$ is the acceptable threshold for the performance metric.

$$
\Lambda(d, X) =
\begin{cases}
1 & \text{if } Y(d, X) \leq Y_T \\
0 & \text{if } Y(d, X) > Y_T
\end{cases}
$$  \hspace{1cm} (3.1)

Based on this definition, the binary performance function will compute to 1 for acceptable performance and 0 for unacceptable performance. The binary performance function can be evaluated across the multi-dimensional climate response variable space represented by the vector of climate state variables, which will determine the region in climate space that leads to expected satisfactory performance for a given decision.

The result can be displayed graphically by considering performance as a function of two predictor variables by considering a planar cross-section within the multi-dimensional climate space. The graphical depiction of performance as a function of climate factors is similar to the risk response surface in climate space developed by Jones [2001] and the flood response surfaces developed by Prudhomme et al. [2010].

While the application here is developed in climate variable space, it is similar to Starr’s Domain Criteria which considers decisions in future state probability space, as described by Schneller and Sphicas [1983]. Starr’s Domain Criteria was developed to support decision making under uncertainty. Potential future states were split into an exhaustive and mutually exclusive set of discrete states. Then the decision with the optimal expected utility can be found for any specified distribution across the discrete future states, resulting in strategic domains in probability space where a given decision has the greatest expected utility. This allows
evaluating decision sensitivity to assumptions about the probabilities of future states and allows consideration of the decision maker’s prior belief about the probabilities.

This process can be repeated for alternate decisions or courses of action, resulting in graphical comparisons of decision performance. The graphical comparisons identify plans that perform adequately over the largest regions of climate space, or are more robust. This robustness can be quantified in several ways, including calculating the Euclidean distance, area, or volume in climate space with acceptable performance for a given decision. In these cases, the relative magnitude of these measurements provides an indication of relative robustness with respect to the climate variable or variables used.

The binary performance function in Equation 3.1 can be considered over a wide range of plausible climate conditions or states within a climate sampling space to calculate a robustness index. The robustness index is described in Equation 3.2 and is the integral of the binary performance function divided by the integral of the climate space considered, resulting in a fraction between 0, or never meeting the criteria, and 1, or acceptable performance over the entire range considered. In this case, three climate variables are shown, but this can be generalized to the appropriate number of climate variables required for a specific application.

\[
\text{RI}(d) = \frac{\iiint A(d, \mathbf{X}) \, dx_1 \, dx_2 \, dx_3}{\iiint dx_1 \, dx_2 \, dx_3}
\]

(3.2)

The value of the Robustness Index will vary based on the climate response variable domain that is used to evaluate Equation 3.2. To evaluate alternate decisions, one must use consistent limits of integration.
The method described here is not reliant on the evaluation of a large discrete set of scenarios. In contrast, methods described by Wong and Rosenhead [2000] and Groves and Lempert [2007] considered the ratio of successful outcomes from an ensemble of potential future scenarios with uniform weighting to each outcome. In these cases the potential futures are generated with a scenario generator and treated as equally likely. Groves et al. [2008b] expanded this method by using uniform weighting as an initial screening for alternatives, then applying assumed probability distributions to the results.

A count of scenarios says nothing about the range over which those scenarios were generated. Thus, the result is dependent on the assumptions related to the distribution used to generate the scenarios. Unfortunately, this dependency would be transparent to decision makers and potentially provide a false sense of robustness. That is, the assumptions would be implicit in the calculation of the count, and it would not be clear to what extent the scenario generation affected the count, and unclear to decision makers how robust a plan truly was. Scenario count is meaningless without understanding the ranges over which the scenarios were generated and is also dependent on the sampling of that range. The index presented in this paper calculates robustness over a climate variable range. This has at least two important attributes that are an improvement over count based robustness approaches. The first is that it allows the explicit recognition and consideration of the result on the assumed climate future and the ability to make the results conditional on, and estimable on, any probability distribution of the future climate space that one may want to explore. Second, and perhaps more important, the approach allows the identification of the specific climate conditions that cause problems, which has the additional benefits of: facilitating adaptive responses, focusing climate research to better provide insight regarding these conditions, and allowing assessment of credibility of information sources for future climate in regard to these specific conditions.
The robustness index has an implicit uniform probability distribution assumption that provides uniform weight to the entire range of climate states considered, including potentially unlikely extreme climate states and climate states near the historic conditions. The uniform probability may be appropriate in cases of deep uncertainty, where the probability distribution of each climate state is unknown and cannot be estimated, but may be less appropriate when there is climate information available that can be used to develop conditional probability distributions. When information is available to provide estimates of climate parameter probability density functions, then a climate informed robustness index that includes an assumed probability distribution can be developed. Thus, climate informed robustness is conditional on an assumed probability distribution. If the probability of a given climate state, $X$ can be expressed in general terms as $\Pr(X)$, then the climate-informed robustness index, $\text{CRI}(d)$, can be expressed as:

$$\text{CRI}(d) = \iiint \Lambda(d, X) \Pr(X)dx_1dx_2dx_3$$  \hspace{1cm} (3.3)

By inspection, the robustness index calculated in Equation 3.2 is simply a special case of the climate informed robustness index with a uniform climate probability distribution. The climate informed robustness index can be used to explore decisions and their sensitivity to climate probability distributions and their underlying assumptions. One of the major challenges in planning with uncertainty is that the appropriate probability distribution is not clear. In their case for developing probability distributions for future climate, Dessai and Hulme [2004] discussed how probabilities of climate change would be useful in a risk assessment framework. They stated, “Such a framework would not yield predictions because we are dealing with conditional and subjective probabilities, but would manage uncertainties (Jones, 2000b)[sic],
leading to more informed decision making” [Dessai and Hulme, 2004; Jones, 2000]. However, the generation of an a priori probability distribution of future climate may in fact be a needless exercise. In fact, it may be a particularly painful exercise if the hope is to achieve a consensus view of future probabilities. One is quickly faced with aspects of climate change adaptation that some have argued make it a “wicked problem.”

This approach can used to assess decision related implications of alternate assumptions about potential future climate states. Specifically, one can use different sources of climate potential climate information or combine different climate information sources using different weights. Using historic climate information to derive the probability distribution leads to an estimate of the robustness based on the historic variability, which is analogous to reliability. Then the probability distribution can be adjusted based on information from sources ranging from paleo derived data, from future climate projections and expert opinion. In this way, one can determine if and how the decision is sensitive to the climate variable probability distribution and to the underlying assumptions.

Dessai and Hulme [2004] discussed that climate change uncertainty results from both epistemic and stochastic uncertainty. In this context, the stochastic uncertainty is inherent in the probability distribution model for individual climate outcomes or realizations. The probability distribution that describes variability in the past and current climate may likely describe future variability. The epistemic uncertainty is represented by the unknown, and unknowable, parameterization of the climate state probability distribution. The approach presented here can be used to explore decision sensitivity to both types of uncertainty.

There are many probability distributions available to model the distribution of the climate variables used in the climate response function. One of the most general models is the
multivariate normal distribution, which is parameterized by a vector of mean values, \( \mu \), and a matrix of covariances, \( \Sigma \). The multivariate normal distribution is provided in Equation 3.4.

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

where \( X \) and \( \mu \) are \( k \)-length vectors of climate variables and climate variable means and \( \Sigma \) is the symmetric, positive definite \( k \times k \) covariance matrix. This form of climate probability distribution can be fit to a climate record and used to evaluate climate informed robustness. Then the mean and covariance parameters could be either refit to a different climate data series or adjusted based on assumptions about climate change to reevaluate climate informed robustness.

The use of the multivariate normal distribution does not contradict the robustness based approach presented in this paper. The methodology allows the decision maker to assess the implications of a particular assumptions regarding future climate change. This chapter explores two possible assumptions: a uniform distribution applied to a broad range of climate futures and a normal distribution which covers an even wider range but assigns more probability to the central tendencies rather than the extreme values. Because the distributions are extreme in their assignment of probabilities to the center versus the tails, they present a useful comparison for eliciting the effect of this assumption. A key aspect of the deep uncertainty was that decision makers disagree on the probabilities of future climate [Lempert et al., 2004]. The methodology presented here allows one to explore the effect of such disagreements, without the assumption that the probability distribution is correct.

One can fit probability distributions based on the historic record, the historic-based stochastic series or other sources of climate information, such as paleo climate reconstructions.
(Y. Ghile, P. Moody, and C. Brown, Paleo-Reconstructed Net Basin Supply Scenarios for the Upper Great Lakes, submitted to *Climactic Change, 2012*) or General Circulation Model (GCM) output [Angel and Kunkel, 2010]. Hobbs [1997] discussed techniques for using Bayesian methods to estimate climate probability distribution functions from other sources of climate information. This framing of the problem changes the focus from attempting to predict future climate and selecting the best decision for that climate to a focus on determining if a potential climate probability distribution that favors one decision is more or less likely than one that favors a different decision.

Yet another way to use the climate informed robustness index is to examine how the CRI varies as a function of the climate probability density function. For instance, the stochastic based 30-year mean NBS can be fit to the multivariate normal distribution discussed above. One can explore how the CRI varies over a shifting climate. This can be achieved by varying the mean, \( \mu_n \), for the \( n \)th climate predictor variable while holding the other mean values and the covariance matrix fixed. This process identifies the sensitivity of competing decisions to shifts in the climate mean. The process can be extended to other types of climate shifts, such as changes in variability or persistence.

### 3.3 Application to the Great Lakes

The Upper Great Lake system is vastly complex with many factors determining the lake levels and interconnecting channel flows. The IJC, which oversees issues related to the boundary waters between Canada and the United States, commissioned the IUGLS to identify a regulation plan for the outflow from Lake Superior that would be more robust to potential climate change. Chapter 2 and [Moody and Brown, 2012] described the development of a climate response function model that was created to isolate the effect of long term persistent
climate on the Lake system. The climate response function is a statistical relationship between lake performance and climate statistics from a 30-year climate record. In this case, the statistics of the mean, standard deviation, and one-year serial correlation from 30-year Net Basin Supply (NBS) were selected as the climate response function inputs based on model deviance and explained variance. While these specific inputs are consistent with those used by Vogel and Bolognese [1995], who used similar climate statistics to predict reservoir reliability, they may not be the most appropriate predictor variables for all systems. In the Great Lakes system context, NBS is the net flux due to direct precipitation, runoff and evaporation. Fluxes due to inter-lake flows and diversions are modeled separately. The mean and standard deviation are normalized by the historic NBS mean and standard deviation to yield a percent change. In this way the change in the mean measures whether the system is wetter or drier, the change in the standard deviation is a measure of variability and the serial correlation measures the persistence.

Lake performance is determined by lake coping zones which are discrete lake level zones based on input from key stakeholder groups. In the context of the IUGLS, six stakeholder groups including municipal and industrial water use; commercial navigation; hydropower; ecosystem; coastal interests; and recreational boating provided information about hazardous conditions specific for their group. These groups provided lake level and connecting channel flow rate performance thresholds which established five state-based coping zones per stakeholder group. Coping zone A is the preferred condition in the middle of the range of levels or flow rates, coping zone B is outside coping zone A where there is moderate economic or environmental damage, and coping zone C is outside coping zone B and characterized by severe or acute economic or environmental damage. While the thresholds for the coping zone transitions vary by stakeholder group, the remainder of this paper will focus on the coastal
coping zone thresholds, which tend to be the most restrictive. Jones [2001] used a similar stakeholder defined impact thresholds and found them useful for analysis and communication of impact and risk.

*Moody and Brown* [2012] described the climate response function in greater detail. It uses a generalized linear model with a logit transformation and a binomial distribution to predict coping zone occurrences based on three climate variable inputs: the mean, standard deviation and serial correlation of the annual NBS over a 30 year analysis window. The generalized linear model parameters were fit using the 55,590-year stochastic data set developed by *Fagherazzi et al.* [2005] for the LOSLRS and with the associated lake levels using the CGLRRM as described by *Clites and Quinn* [2003]. Using correlation as a measure of explained variance, the generalized linear model captures over half of the explained variance of the predicted coping zone occurrences.

One of the fundamental questions that the IUGLS sought to answer was whether Lake Superior outflow regulation plan 1977A could be improved to better meet needs and interests within the basin [*International Joint Commission*, 2005]. More specifically, the study sought to review Lake Superior outflow regulation and its impacts on lake levels and inter-lake flows in the system within the context of historical climate conditions and under potential future conditions as a result of natural variability and potential climate change. This study directly informs this question by assessing plan performance in terms of robustness in the context of climate variability and climate change.

The IUGLS considered many historic and proposed regulation plans for the outflow of Lake Superior. This study summarizes the findings for six different plans. The plans are described in Table 3.1. The current plan, plan 1977A (P77A), has been in place since 1991 and seeks to balance the water levels between Lake Superior and Lake Michigan-Huron. The other
plans include historic plans such as Plan 1955 modified rule of 1949 (55MR49) which focused on controlling Lake Superior within a narrow range of water levels, and four alternate proposed plans, named Natural 64 D (Nat46D), Plan 129 (P129), Balance 26 (Bal26), and Plan 1977B (P77B). The history of Lake Superior outflow regulation is covered extensively by Clites and Quinn [2003]. Each plan was evaluated with the same stochastic NBS series using the CGLRRM. The NBS series and the resulting lake levels were used to parameterize the climate response function for each regulation plan. These separate parameterizations were the basis of comparison for the robustness.

<table>
<thead>
<tr>
<th>Regulation Plan</th>
<th>Short Plan Title</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1955 Modified Rule of 1949</td>
<td>55MR49</td>
<td>A historic plan that was used from 1955 to 1973. The plan minimizes extremes on Lake Superior, resulting in increased extremes on Lake Michigan-Huron. Induced for comparison purposes.</td>
</tr>
<tr>
<td>Natural 64D</td>
<td>Nat64D</td>
<td>A proposed plan that seeks to release a flow similar to an unregulated flow.</td>
</tr>
<tr>
<td>Balance 26</td>
<td>Bal26</td>
<td>A proposed balancing plan similar to plan 1977A but with simpler operational rules.</td>
</tr>
<tr>
<td>Plan 1977B</td>
<td>P77B</td>
<td>A proposed plan based on plan 1977A. The plan decreases gate changes to benefit the fishery in the St. Marys River rapid.</td>
</tr>
<tr>
<td>Plan 129</td>
<td>P129</td>
<td>A proposed plan that seeks to minimize extremes on Lake Michigan-Huron, resulting in increased extremes on Lake Superior. A &quot;fencepost &quot; plan to determine the limits of regulation.</td>
</tr>
</tbody>
</table>

3.4 Results

In this section, the graphical robustness indices, the robustness index, and the climate informed robustness index are calculated and compared for six Lake Superior outflow regulation...
plans. The results presented here are a subset of the analysis provided directly to two working groups within the IUGLS: the Plan Formulation and Evaluation Group (PFEG) and the Adaptive Management Group (AMG). The results complemented a scenario-based analysis by providing an understanding of how the Upper Great Lakes system performance varies as a function of regulation plans under different conditional climate variable probability distributions. In contrast, the scenario based approach was deterministic and compared regulation plan performance over a subset of ten different centuries of NBS sequences. Ultimately, these results contributed to the IUGLS board’s recommendation to the IJC to adopt plan Natural 64D as the recommended replacement plan for Plan 1977A.

3.4.1 Hazard Contours and Graphical Robustness Indicators

When the climate response function is used as a predictive tool for each regulation plan and over a range of climate inputs, one can estimate the climate conditions with acceptable system performance for each plan and which plans are more robust. Figure 3.1 and Figure 3.2 show contours of constant expected value of coping zone C (acute impact) occurrence for each regulation plan, listed in Table 3.1, as a function of annual NBS mean and standard deviation on Lake Superior and Lake Michigan-Huron respectively. The coping zone occurrence rate is normalized by the historic coping zone C occurrence rate. In each graph, the x-axis is the mean annual NBS percent change, the y-axis is the annual NBS standard deviation percent change, and the NBS serial correlation is held constant. The $n$ contour line is located where the expected value of zone C occurrences is $n$ times the historic zone C occurrence rate. For instance, the second contour is the line where the expected number of zone C occurrences is twice the historic rate. Regulation plans with greater areas in white, or with lower relative occurrence rates, are more robust. Relatively shallow contour slopes indicate that the regulation plan
effectively compresses the lake range resulting in fewer zone C occurrences. In these figures, Plan 55MR49 appears to perform best on Lake Superior while plan P129 performs best on Lake Michigan-Huron. These plans are included in the comparison because they demonstrate the limits of lake outflow regulation. Plan 55MR49 minimizes extreme fluctuations on Lake Superior at the expense of levels on Lake Michigan-Huron while P129 minimizes extreme fluctuations on Lake Michigan-Huron at the expense of levels on Lake Superior. Quantifying the robustness for a given regulation plan and the tradeoffs between plan performance is explored further in the next section.

By selecting and isolating a zone C occurrence contour, one can generate graphical or Euclidean based robustness indices. Three Euclidean based robustness indices are defined graphically in Figure 3.3, for Lake Superior and plan P77A at twice the historic coping zone C occurrence rate. The shaded area is the region of a planar projection in climate space with acceptable performance, or where the binary performance function evaluates to one. Three robustness indices include: a robustness length along the mean NBS, a robustness height along the NBS standard deviation, and a robustness area, which combines measures along the NBS mean and standard deviation. The robustness length is the length along the mean NBS axis with acceptable performance and is a function of a regulation plan’s robustness to changes in the mean NBS. It is measured in percent change mean NBS. The robustness height is the maximum NBS standard deviation with acceptable performance. It is a function of a regulation plan’s robustness to changes in NBS variability and is measured in standard deviation percent change. The robustness area is the region of acceptable performance bounded by the mean NBS axis. It is a function of a regulation plan’s robustness over changes in both the NBS mean and standard deviation. The area units are in NBS mean and standard deviation. Figure 3.4 displays the length, height and area for each plan on Lake Superior and Lake Michigan-Huron. In each
measure, a higher number is an indicator of greater robustness. The tradeoffs between robustness on Lake Superior and Lake Michigan-Huron are clearly evident in all three measures. Plans P77A and Nat64D demonstrate relatively high graphical robustness measures for Lake Superior and acceptable measures for Lake Michigan-Huron.

Figure 3.1: Lake Superior expected coastal coping zone C occurrences for different changes in the mean and standard deviation of the annual net basin supply. Contour levels are expresses as multiples of the historic occurrence rate by regulation plan. Better performance is indicated by a lower contour level. Subplots show regulation plan (a) 77A, (b) 55MR49, (c) Nat64D, (d) Bal26, (e) 77B, and (f) P129.
Figure 3.2: Lakes Michigan-Huron expected coastal coping zone C occurrences for different changes in the mean and standard deviation of the annual net basin supply. Contour levels are expressed as multiples of the historic occurrence rate by regulation plan. Subplots show regulation plan (a) P77A, (b) 55MR49, (c) Nat64D, (d) Bal26, (e) P77B, and (f) P129.
Figure 3.3: Graphical robustness indices of width, height, and area with respect to changes in the mean and standard deviation of net basin supply, shown for Lake Superior. The graphical robustness indicators are shown for regulation plan 1977A with a threshold of acceptable performance equal to twice the historic coastal coping zone C occurrence rate.
Figure 3.4: Graphical measures of robustness for Lake Superior and Michigan-Huron. Plots of robustness (a) length, (b) height, and (c) area are presented for each regulation plan.

3.4.2 Robustness and Climate Informed Robustness

The robustness index, as defined in Equation 3.2, is shown in the top half of Figure 3.5 for Lake Superior and Lake Michigan-Huron. On Lake Superior, the most robust plans are 55MR49, P77A, and Nat64D, while plan P129 is the least robust. Plans 55MR49 and P77A are relatively robust on Lake Superior because the plans successfully reduce the extreme variations on the lake. By releasing more water at the high end and less water on the lower end, the plans keep Lake Superior closer to the historic mean better than the other plans. The effect is seen downstream on Lakes Michigan-Huron where plan 55MR49 has the lowest robustness indicator.
value and P129 has the highest value. Additionally, there is less variation across the plans on Lakes Michigan Huron because regulation has a greater impact on Lake Superior levels than it does on water levels downstream. The symmetric nature of the values for robustness for the same plan on the two lakes is a result of the inherent tradeoff that results from balancing any excess or shortage of water across the system. Under the uniform probability distribution assumption implicit in the robustness index, plan P77A is superior to the other plans under consideration. Switching to a different plan would either cause a drop in robustness for both Lakes or would cause a significant drop in robustness on Lake Superior with a modest improvement on Lake Michigan-Huron.

The results are a bit different when climate informed robustness is considered. The bottom half of Figure 3.5 shows climate informed robustness, as defined in Equation 3.3, for the six regulation plans on Lake Superior and Lake Michigan-Huron based on a multivariate normal climate variable probability distribution fit from the 50k-year stochastic-based data series. Conditional probability distributions of future climate can be used to determine the sensitivity of decisions to climate probability distributions. As a starting point, the distribution was fit using the climate statistics from 30-year segments from the 50k-year stochastic data series. Later in the analysis, the probability distribution is shifted to consider the potential impact from changes to the probability distribution. The multivariate normal distribution is parameterized with a vector of mean values, $\mu$, and a covariance matrix, $\Sigma$, calculated by Equations 3.5 and 3.6, for three variables

$$\mu = [E[x_1], E[x_2], E[x_3]]$$

(3.5)

$$\Sigma = [\text{Cov}[x_i, x_j]]_{i=1,2,3; j=1,2,3}$$

(3.6a)
\[ \Sigma = \begin{pmatrix} s_{x_1}^2 & \rho_{12} s_{x_1} s_{x_2} & \rho_{13} s_{x_1} s_{x_3} \\ \rho_{12} s_{x_1} s_{x_2} & s_{x_2}^2 & \rho_{23} s_{x_2} s_{x_3} \\ \rho_{13} s_{x_1} s_{x_3} & \rho_{23} s_{x_2} s_{x_3} & s_{x_3}^2 \end{pmatrix} \]  

(3.6b)

where \( E[x_i] \) is the expected value or mean of the \( i \)th variable, \( s_{x_i}^2 \) is the variance of the \( i \)th variable, \( s_{x_i} \) is the standard deviation of the \( i \)th variable, and \( \rho_{ij} \) is the correlation coefficient between the \( i \)th and \( j \)th variables. As before, \( x_1 \) refers to the mean annual NBS, \( x_2 \) refers to the annual NBS standard deviation and \( x_3 \) refers to the annual NBS serial correlation. The climate informed robustness values are similar to the robustness index values, except higher. The uniform distribution used in the robustness index provides a relatively high weight to the extreme climate outcomes that cause the system to fail, which causes the robustness index values to be lower. While the greater relative weight on the extremes may not be realistic in all circumstances, it can be used to show relative performance under extreme conditions.

The climate informed robustness tradeoffs are shown in the bottom half of Figure 3.5. The climate probability distribution is an approximation of the stationary climate distribution. The resulting graph shows that plans P77A, Nat 64D, P129, and 55MR49 are on the tradeoff frontier. Plans P129 and 55MR49 have unacceptable performance on Lake Superior and Lake Michigan-Huron respectively. Plan Nat 64D provides an increase in Lake Michigan-Huron robustness with a relatively small reduction in Lake Superior robustness.

Additionally, one can consider how climate informed robustness varies with different assumptions about climate variable probability distributions. The climate informed robustness shown in the bottom half of Figure 3.5 uses a probability distribution function fit from the historic-based stochastic data set, thus they are estimates of system robustness with the assumption of a stationary climate. A consideration that arises from this analysis is how risk and
robustness evolve with changing assumptions about future climate conditions. This is considered in a naïve sense in the next section, by examining the impact of a shifting mean climate. Future work will examine this issue further through the application of a Bayesian analysis framework which can be used to develop conditional probabilities of future conditions. Frequentist, or classical, statistical methods can be applied to measured data from the historic record but cannot use subjective information such as expert opinion or forecast information such as projections from GCMs. Bayesian analysis can use all of these sources of information in a meta-analysis to determine conditional probabilities of future states.
Figure 3.5: Tradeoff curve for the Robustness Index (a) and the Climate-Informed Robustness Index (b) calculated for Lake Superior (x-axis) and Lake Michigan-Huron (y-axis) under different regulation plans. The Robustness Index applies a uniform probability distribution over the climate variable space; while the Climate-Informed Robustness Index applies a multivariate normal probability distribution fit to the 55,590-year historic based stochastic data series. Greater values are better for each axis. Each regulation plan is indicated by a label and a circle.

3.4.3 Climate Informed Robustness with a Shifting Mean

The climate state probability density function and the climate response function allow one to explore the impact of changes in climate statistic probability distributions. This is used to estimate how the climate informed robustness will change with the climate statistic probability distributions. *Stedinger and Griffis* [2011] discussed using temporally variant parameters in a log Pearson type III distribution of flood peak flow rates. They discussed three models for a
temporally evolving distribution, by allowing the mean to vary over time, the mean and
standard deviation to vary over time, and the mean, standard deviation and skewness
coefficient to vary over time. In a similar manner, one can model a shifting mean in the
distribution of the mean annual NBS and test system performance and decision criteria as a
function of the shifting mean. This can be modeled by holding the covariance matrix, \( \Sigma \), as well
as the mean of the standard deviation, \( \mu_2 \), and the mean of the serial correlation, \( \mu_3 \), constant
while varying the mean of the mean annual NBS, \( \mu_1 \). In this case, the covariance matrix, \( \Sigma \), and
the mean vector, \( \mu \), were fit with the 55,590-year historic-based stochastic data set, but the
mean of the NBS mean, \( \mu_1 \), was varied between -15% and +15%, which covers a credible range
of climate shift based on an ensemble of GCM projections [Angel and Kunzel, 2010]. This range
was chosen by the authors to illustrate the resulting system impact from shifting the climate
predictor variable multivariate distribution within a credible range of mean values. This does
not imply that a greater shift is unlikely, merely that the impact was not assessed. The climate
informed robustness index was calculated using the binary performance function times the
probability density over climate space. This process yielded the climate informed robustness as
a function of a shifting mean climate and a decision, as shown in Equation 3.7.

\[
\text{CRI}(\mu_t, d) = \int \Lambda(d, X) \Pr(X; \mu, \Sigma) dx_1 dx_2 dx_3
\]  

(3.7)

Figure 3.6 shows the climate informed robustness for a shifting mean, \( \mu_t \), on Lake Superior and
on Lake Michigan-Huron. The results highlight the vulnerabilities on each lake to shifting
climate. Lake Michigan-Huron is vulnerable to dryer conditions regardless of plan. While some
regulation plans, such as P129, perform slightly better over the entire range and plan 55MR49
performs worse, all plans exhibit similar vulnerability to decreases in mean climate. The results
on Lake Superior show that 55MR49 performs well on Lake Superior over the entire climate range considered. For relatively modest reductions in the mean NBS, plans P129 and Bal26 show a sharp decline in performance. Plan Nat64D outperforms plan P77A in the case of decreasing mean NBS.

![Graph](image)

Figure 3.6: Sensitivity of the Climate-Informed Robustness Index (CRI) for each regulation plan with respect to changes in the mean net basin supply for both (a) Lake Superior and (b) Lake Michigan-Huron. Here, the mean of the NBS mean, $\mu_{b}$, is varied while the mean of the NBS standard deviation, $\mu_{d}$, the mean of the NBS serial correlation, $\mu_{s}$, and the covariance matrix, $\Sigma$, were held constant.
3.5 Conclusion

This chapter establishes the relevance of several new and emerging measures of robustness of water resource systems. Robustness will not likely replace more traditional measures of performance, but instead will be used as a complementary measure to ensure systems are more robust to climate uncertainty and other factors. The climate informed robustness index allows explicit consideration of the probabilities of future climates with associated uncertainties and the incorporation of credible climate information. As a result, it is seen as particularly useful for climate change impact analysis where there are often multiple possible sources of probabilities for future climate.

The analysis above showed how robustness measures can be applied in the case of the Upper Great Lakes to consider alternatives to regulation of Lake Superior outflow. This case study highlights some important features. First, there are inherent tradeoffs within the system. Large improvements on Lake Superior come at a cost on Lake Michigan-Huron. Regulation plan P77A sought to balance the highs and lows on both lakes, and as a result it was difficult to design a plan that would improve overall performance. Second, these tools are helpful in identifying system vulnerabilities to help identify decisions that could mitigate residual risk due to adverse impacts. In some cases, such as reduced NBS on Lake Michigan-Huron, there are no decisions that offer significant improvement. In these cases, adaptation to lower water levels may be the appropriate solution. Third, additional work needs to be done to consider how climate probability distributions will change as a result of climate change. A Bayesian framework that uses climate information in a meta-analysis to develop conditional probability distributions will add significantly to this approach. This approach can potentially provide an effective way to use available climate information from GCM and RCM projections to support water resources decision making.
The results show that regulation plan P77A performs well on both lakes and under a wide range of conditions. There are marginal improvements that can be made using plan Nat64D, especially considering shifts to drier conditions. This finding were shared with the IUGLS and contributed to Nat64D being recommended by the IUGLS board to the International Joint Commission as the replacement plan to plan P77A [International Upper Great Lakes Study Board, 2012].

The techniques presented in this paper allow the comparison of competing regulation plans in a context appropriate for use with GCM projections, rather than in a deterministic context. The method is based on the use of a climate response function to evaluate predicted impact over a wide range of climate inputs. Decisions are evaluated over a wide range of climate inputs using robustness indicators, conditioned on assumptions about the probability distributions for the climate inputs.
CHAPTER 4

CLIMATE RISK ASSESSMENT WITH STAKEHOLDER DEFINED THRESHOLDS

Risk is commonly used to inform the decision making process for managed water resource systems. While there are different methods to quantify risk, generally the methods focus on determining impacts and probabilities related to potential future conditions or states. When the impacts and probabilities are well defined, this is a straightforward process. When there is significant or irreducible uncertainty, different strategies must be employed to account for this uncertainty. Decision scaling has been applied as a bottom-up method to analyze impacts of the uncertainties related to climate change. Decision scaling uses a “climate response function” that links estimates of critical threshold exceedance based on climate predictor variables to estimate impacts and risk. This can be determined for a multiple interest groups to compare risk exposure and reveal potential risk tradeoffs between different interests. Climate change probability distributions can be developed and analyzed to determine their sensitivity on system impact and risk. This process is applied to the Upper Great Lakes in the context of the International Upper Great Lakes Study (IUGLS) to quantify stakeholder based risk. The coastal, commercial navigation, recreational boating, ecological, and municipal water use sectors are presented.

4.1 Introduction

Assessing the potential impact on water systems from climate change is a crucial step in understanding and addressing water supply issues now and into the future. There are many tools available for assessing water resource system performance under the assumption of a stationary climate, but there is not a consensus in the water resources community on evaluating system performance under non-stationarity. Until recently, the focus has been on climate
assessment tools and top-down approaches that use General Circulation Model (GCM) projections for a given emissions scenario and timeframe, downscale the GCM output to create input for a hydrologic model to develop a water supply series for a basin of interest, use the water supply in a system model and then evaluate system performance under the future conditions.

This top-down approach has been criticized for an “explosion of uncertainty” [Henderson-Sellers, 1993] or “cascading uncertainty” [Wilby and Dessai, 2010], due to the uncertainties that are introduced at each level of the modeling process. The uncertainty and the related potential error and bias propagate through the modeling process, resulting in low confidence in estimates of impact.

While this approach provides point estimates and ranges of potential system impacts, the approach does not provide results that are directly applicable to water resources decision making. Pittock and Jones [2000] discussed the need to shift from developing predictions and ranges of impacts, to developing risk assessments that quantity risk in a decision framework. Decision making under uncertainty is frequently made using risk analysis and mitigation. Jones [2001] described how water resources decision makers use risk assessment and management techniques to manage uncertainty in water systems. Brekke et al. [2009] also applied a risk assessment framework to evaluate reservoir operation under climate uncertainty. Incorporation of risk to multiple stakeholders allows analysts and decision makers to find more sustainable solutions to “wicked” problems in water resource planning and management [Kasprzyk et al., 2013; Rittel and Webber, 1973]. While conducting multiple component analysis adds complexity to interpretation of the results, it avoids pitfalls associated with aggregation of results into a single measurement of performance [Kasprzyk et al., 2013; Maass et al. 1962].
These include focusing solely on objectives that can be easily monetized or the dominance of a factor in the performance measure.

This chapter considers risk related to critical threshold exceedance, with thresholds determined by stakeholder groups. This allows comparison of risk exposure between groups, potentially revealing differential risk and risk tradeoffs. Additionally, risk sensitivity to changing climate conditions is explored.

4.1.1 Risk Metrics

Water system performance metrics were developed within a stationary framework. Stationarity is the assumption that climate realizations occur as a result of random processes, but are realizations from a constant probability distribution. One strategy for addressing non-stationarity in the context of climate change and other causes is to adapt these familiar metrics for a non-stationary framework. Risk is one of the commonly used metric to evaluate water resource systems performance. There are many ways to quantify risk, several prominent ways are discussed below.

The method of describing risk used in this chapter is taken from the engineering economics description of risk. It is the expected value of an adverse impact, or the probability weighted performance. The approach is used by the United States Presidential/Congressional Commission on Risk Assessment and Risk Management [1997] and in Bayesian Decision Analysis [Hobbs et al., 1997] which evaluates decisions for the maximum expected value or the minimum expected loss. The expected value is generated by integrating the product of the impact of a given state times the probability density value of that state over the range of plausible state values. Considering a climate state vector $X$, with an impact or hazard function of the climate
state $I(X)$ and a probability density function $Pr(X)$. The expected value of the hazard, $E(I)$, can be calculated with Equation 4.1.

$$E(I) = \int I(X)Pr(X) \, dX$$

(4.1)

This approach is effective in cases where the impacts and probabilities for the potential climate states are well characterized. In cases where the climate state probability distribution is not well characterized, the approach can still be used but the result is then conditioned on the assumptions about climate probabilities. Jones [2001] discussed the use of conditional climate probability distributions to estimate conditional probabilities of exceedance for specific impact thresholds.

The expected value approach can present difficulty in the case of so called “fat-tailed distributions” where the severity of the impact increases faster towards infinity than the probability approaches zero, resulting in an unbounded integral. The expected value approach produces a finite expected value only when the probability approaches zero faster than the impact approaches infinity [Nordhaus, 2011; Weitzman, 2011].

Another method of describing risk is the probability of a failure in a system, where the failure is considered unsatisfactory system performance [Hashimoto et al., 1982a]. This state based definition does not require specification of how unsatisfactory the performance or condition is, just that a system parameter exceeds its allowable threshold. From this definition, Hashimoto et al. [1982a] proceed to develop additional performance measures including reliability which describes the probability that the system will be in a satisfactory state, resiliency which describes how long it takes for a system to return to a satisfactory state and vulnerability which describes the severity of the consequences of the unsatisfactory
performance. Estimates for system failure probabilities are typically estimated using long hydrologic data series which are then run through a hydrologic model. The model outputs are evaluated against the thresholds to determine the increments that resulted in unsatisfactory performance. This approach is well suited for scenario based approaches that use historic, synthetic, or projected water supply sequences to generate estimates of risk.

Under the assumption of a stationary climate, one can use the historic record or a synthetic data series based on the historic record in conjunction with a hydrologic model to estimate risk. Through stochastic simulation, one can generate a wide range of credible water supply series to test the water system performance. This approach is scenario based in that one generates climate scenarios and evaluates performance under each scenario. Each scenario is normally considered to be equally as likely as other scenarios. Using a large set of plausible scenarios provides a wide range of climate inputs which can allow for the evaluation of additional performance measures such as robustness.

Brekke et al. [2009] applied a similar approach to the evaluation of reservoir operations under uncertainty due to climate change. In this case, they selected performance thresholds and determined the climate conditions that led to unsatisfactory performance related to their performance threshold. These conditions are similar to the vulnerabilities discussed by Kasprzyk et al. [2013] and Lempert et al. [2010]. Brekke et al. [2009] then applied a conditional probability distribution to the climate conditions and integrated the probability distribution in the region with unsatisfactory performance. In this framework, risk was the change in hazard probability relative to the baseline (stationary) hazard probability. This approach helps frame risk in terms relevant to decision makers and stakeholders.

Barker and Haines [2009] discussed using risk based decision making to avoid extreme or disastrous outcomes, rather than using it to identify the best or optimal strategy. They also
discuss difficulties related to the uncertainty inherent in modeling the probability of extreme events.

Another method of assessing and managing risk is through the use of risk matrices that are used to plot damage or impact versus probability of occurrence, and are shown in Figure 4.1. Events that are low probability and low impact are low risk, while events that are high probability and high impact exhibit very high risk. Risk reduction and mitigation strategies include measures that reduce the impact of an event or by reduce the likelihood of an event. Management and adaptation options can be used to reduce water resources related risks. While climate changes may increase the likelihood of certain impacts, strategies to mitigate these risks can be developed. Significant climate change shifts may necessitate adaptation measures to increase the tolerance to higher or lower water levels, as discussed in Section 4.3.3.

![Risk Matrix](image)

**Figure 4.1:** Risk Matrix Based on Probability of Occurrence (on the x-axis) versus Impact of Occurrence (on the y-axis). Green Represents Low Risk, Amber is Moderate Risk, Orange is High Risk and Red is Very High Risk [Brown et al., 2012b]. Risk matrix format is adapted from Cox [2008] and Ni et al. [2010].

### 4.1.2 Multi-Objective Criteria and Risk

The use of multi-objective criteria in water resource analysis dates back to the Harvard Water Program and is discussed by Maass et al. [1962]. Since that time, there have been significant advancements in methods to identify solutions from multi-objective problems, some
of which are discussed below. There have not been cases in the water resources literature
where multi-objective approaches have been applied to reduce risks due to uncertainty
specifically.

*Haines and Hall* [1974] discussed using multi-objective analysis in cases where there
were significant non-commensurable objectives. In these cases, non-inferior solutions were
developed and the decision maker’s preferences, or value, was used to decide among the non-
inferior solutions.

*Hämäläinen et al.* [2001] applied a multi-objective framework to a regulated lake-river
system in Finland. Through the evaluation of performance measures over a full range of
decision variables, they determined the efficient set of outcomes. This efficient set is similar to
the Pareto efficiency curve where improvements in a performance measure can only be made
by degrading one or more of the other performance measures. The best solution from this
efficient set was selected after eliciting valuation of the competing objectives from the decision
maker.

*Kasprzyk et al.* [2013] adapted Robust Decision Making (RDM), which considers single
objectives, to consider multiple objectives. They stated that “aggregating multiple performance
measures into single value can yield negative decision biases that result because different
aspects of performance are rewarded and penalized in way that cannot be predicted *a priori*
*Kasprzyk et al.,* 2013.” Typically approaches that use a single value consider monetary
benefits, which may result in inadequate consideration of non-monetary benefits such as
ecosystem services.

The multi-objective analysis process reveals which objectives are in potential conflict.
Within a bottom-up climate risk analysis, it can also potentially reveal which objectives have the
most residual risk and under which potential climate conditions. This approach is used to
consider stakeholder risk for six different stakeholder groups on the Upper Great Lakes.

4.2 Application to the Great Lakes

The IUGLS sought to identify a Lake Superior outflow regulation plan that would
outperform Plan 1977A over the historic record as well as potential future climate conditions
that may result from climate change. Chapter 2 described the development and application of a
climate response function to predict impact as a result of climate statistics. Chapter 3 applied
the climate response function to evaluate the Great Lakes system robustness to climate change
and evaluate potential regulation plans for Lake Superior regulation. This section develops risk
based metrics to consider risk by stakeholder groups and also estimates remaining uncertainty
in impact determination.

The IUGLS established Technical Working Groups (TWGs) to evaluate the impacts of lake
levels and channel flows within specific interest group sectors. The Boundary Water Treaty
(BWT) of 1909 between Canada and the United States established precedence for the
commercial navigation, hydropower, and water use special interests. Since then, additional
special interests including coastal landowners, recreational boating and tourism, and ecological
interests have been recognized as legitimate special interests on the Great Lakes.

During the IUGLS, impact within each sector has been quantified in several ways. The
development of the climate response function, discussed in Chapter 2, focused on a state-based
approach in which each stakeholder group defined impact thresholds, called coping zones.
Coping zones are defined based on the level of impact related to lake water levels or channel
flow rates and relate to perceived impact from the stakeholder group. The coping zones
describe three levels of impact and help describe a stakeholder group’s sensitivity to extreme
water levels and water level variability. Coping zone A is characterized by little to no economic or environmental impact and is normally in the middle of the range. Coping zone B is the range above or below coping zone A where there is a moderate economic or environmental impact. Levels in the coping zone B range may lead to temporary or moderate financial losses within a sector, but should not result in significant losses. Coping zone B may result in fishery or habitat degradation. Coping zone C is the range above or below coping zone B. Levels in the coping zone C range result in acute or severe economic or environmental impact. These impacts can include significant damage to infrastructure, severe economic losses resulting in foreclosures or bankruptcy, or an acute loss of critical habitat. The coping zone thresholds vary by stakeholder group and, for some groups, also vary by season. The threshold levels are included in Table 4.1, which includes the annual mean value for a stakeholder group, though the process allows thresholds to be defined by levels, duration, frequency and rate of change as well. The use of coping zones allows the development of probabilistic tools to evaluate climate change impacts within the system.
Table 4.1: Coping zone thresholds defined for Lake Superior and Lake Michigan Huron by stakeholder group. The ecosystem thresholds include a frequency component where exceeding the threshold once in four years is moderate impact and three times in four years is severe impact.

<table>
<thead>
<tr>
<th>Lake Superior</th>
<th>Coping Zone Threshold (m above m.s.l.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stakeholder</td>
<td>Severe Low</td>
</tr>
<tr>
<td>Coastal</td>
<td>183.70</td>
</tr>
<tr>
<td>Water Use</td>
<td>184.91</td>
</tr>
<tr>
<td>Recreational Boating</td>
<td>184.60</td>
</tr>
<tr>
<td>Boat Launch</td>
<td>183.79</td>
</tr>
<tr>
<td>Commercial Navigation</td>
<td>184.70</td>
</tr>
<tr>
<td>Ecosystem</td>
<td>184.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lake Michigan Huron</th>
<th>Coping Zone Threshold (m above m.s.l.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stakeholder</td>
<td>Severe Low</td>
</tr>
<tr>
<td>Coastal</td>
<td>177.21</td>
</tr>
<tr>
<td>Water Use</td>
<td>178.60</td>
</tr>
<tr>
<td>Recreational Boating</td>
<td>177.60</td>
</tr>
<tr>
<td>Boat Launch</td>
<td>177.39</td>
</tr>
<tr>
<td>Commercial Navigation</td>
<td>177.50</td>
</tr>
<tr>
<td>Ecosystem</td>
<td>177.65</td>
</tr>
</tbody>
</table>

The use of threshold or state based impacts is not new. *Pittock and Jones* [2000] defined impact thresholds as “any degree of change that can link the onset of a given critical bio-physical or socio-economic impact to a particular climate state or states.” *Jones* [2001] applied impact thresholds to climate change to determine conditional exceedance probabilities which were used to assess adaptation and mitigation decisions.

The other primary method to quantify impacts is to monetize the benefits and losses from each sector. This allows the evaluation of the net economic benefit for a given decision or regulation plan for a given hydrologic scenario. While this approach can be applied with any hydrologic sequence, results are often presented for a small set of sequences. In the case of the IUGLS, this was done for 13 scenarios [*International Upper Great Lakes Study Board*, 2012]. The main advantage of this approach is that benefits and costs expressed in aggregate and by
stakeholder group are directly calculated. One of the 13 scenarios was the historic record, which is a familiar reference for the decision makers and stakeholders. The other 12 scenarios included seven sequences from the stochastic data set representing extreme climate sequences from the stochastic data record, two dynamically downscaled RCM simulations, two stochastically generated sequences from a GCM-based stochastic data set, and one sequence that applied a linear trend to NBS trends based on the data record from 1,960-2,009. While this approach allowed a precise estimate of benefits or damages associated with each combination of decision and NBS sequence, the approach does not attempt to determine the relative likelihood of any of the sequences; each sequence is seen as plausible and effectively treated as equally likely. Additionally, while the aggregate cost-benefit can determine which decision or plan is overall best for a given NBS sequence, this approach has a few additional issues to consider. First, for each stakeholder group, the value of an additional dollar’s cost or benefit may not be seen as equal. Additionally the total benefits or costs for a small number of stakeholders can dominate the results, resulting in the interests of those stakeholders dominating the analysis results. Finally, there are the issues related to quantifying the noneconomic value, especially for ecological and aesthetic related costs and benefits. The threshold based approach used here avoids some of these issues by using state based interpretation of water levels. It allows direct comparison of the risk of the water levels that cause severe impacts between stakeholder groups.

4.3 Results

The analysis presented here will focus on the most severe impact, the coping zone C (severe impact) occurrences. This section considers model sensitivity to several important
factors. The first source of uncertainty is the variability or noise remaining after applying the climate response function. The deterministic component of the climate response function captures how climate influences coping zone occurrence. The stochastic model component captures the variation or uncertainty from all other factors that influence lake water levels and water level threshold exceedance. The next sections explore threshold exceedance sensitivity based on three main factors. First, each stakeholder group has a different set of coping zone thresholds. More restrictive thresholds increase the likelihood of exceeding the thresholds resulting in a greater fraction of high impact coping zones. Second, each set of coping zone thresholds is used to represent an entire stakeholder group on a given lake. Each stakeholder group actually has a range of sensitivity to lake water levels. While the range of threshold values is not available, Section 4.3.3 considers how shifting coping zone thresholds by 5 cm higher or lower could impact predicted coping zone occurrences. Then in Section 4.3.4, the impact of Lake Superior outflow regulation is examined. Two regulation plans are considered, Plan 1977A which is the current plan and Plan Natural 64D which is the new proposed regulation plan from the IUGLS final study report.

Finally, Sections 4.3.5 and 4.3.6 explore how the assumptions about how climate meta-parameters relate to stakeholder risk. This is accomplished by fitting a multivariate normal probability model for the predictor climate variables, stochastically sampling many climate variable vectors from the probability distribution, applying the climate response model, and generating coping zone occurrences for each climate realization. This process results in risk curves that show the likelihood (based on the fraction of climate realizations) versus the impact (measured as fraction of high impact coping zone occurrence). This is method is applied to a climate distribution centered on the historic climate and then repeated for a ten percent
increase or decrease in the mean of the mean climate meta-parameter to illustrate how risk changes by sector with a changing climate.

4.3.1 Risk and Uncertainty of Extreme Threshold Exceedance

The climate response function provides a probabilistic model that predicts coping zone occurrences with a generalized linear model based on three climate-related statistics. The deterministic model component accounts for the variability due to the mean, variability and serial correlation of the NBS sequence, while the stochastic component accounts for the variability not captured by this model. In this study related to the Upper Great Lakes, the stochastic component is a binomial function with two parameters: \( n \), or the number of months in the analysis window which is 360, and \( \pi \), the probability of non-exceedance for a given threshold. The binomial distribution has an expected value of \( n\pi \) and it has a variance of \( n\pi(1-\pi) \). For probabilities close to 0 or 1, the variance is small and the distribution is skewed. As probabilities approach 0.5, the variance increases, the distribution is less skewed and the distribution appears more Gaussian. For a binomial distribution with parameters \( n \) and \( \pi \), it is easy to estimate exceedance probability values with standard statistical software.

In Figure 4.2, the coping zone C occurrences are shown for Lake Superior and Lake Michigan-Huron for the coastal coping zone. The figures are created using a mean NBS that varies from -20 to +20 percent change mean NBS, and no change in the NBS standard deviation or serial correlation to isolate the effect of the mean NBS on the coping zone occurrence distribution. The range of -20 to +20 percent was chosen based on the range of mean NBS values from downscaled GCM projections in the Angel and Kunkel [2010] GCM ensemble for an A2 SRES scenario and a thirty year window centered on the year 2,050. The selection of this range does not carry any implications about the likelihood of climate change exceeding this
range, merely that changes beyond this range were not included in the analysis. Conditional probabilities for specific changes in mean NBS are discussed in Chapter 5. The figure includes the expected value of occurrence along with the 0.05 and 0.95 exceedance values, so the range covers 90 percent of the predicted coping zone occurrences.
Figure 4.2: Expected value and 90 percent confidence interval for Coping Zone C (extreme lake level). The figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan low extremes and d) Lake Michigan Huron high extremes for the coastal coping zones. The expected value is based on a shifting mean NBS, an annual NBS standard deviation of 0.0 and an annual NBS serial correlation of 0.1.

4.3.2 Multi-Objective Risk: by Stakeholder Group

The coping zone thresholds are one way to show tolerance to extreme water levels within a stakeholder group. This tolerance is not static in time and is not uniform across the sector or even geographically across a lake. It is a representative threshold beyond which stakeholders expect to see rising economic or environmental costs due to extreme water levels. Table 4.1 shows the coping zones by lake and by stakeholder groups. Chapter 2 focused on the
coastal coping zone thresholds because they tended to be more restrictive than the coping zones for the other stakeholder groups. Figure 4.3 shows the climate response model coping zone occurrences for Lake Superior and Lake Michigan Huron for the commercial navigation, water use, coastal, recreational boating, boat launch and ecosystem sectors. In each case, the expected value of impact, measured as fraction of months exceeding the extreme water level threshold, is shown as a function of mean NBS.

The climate response function model essentially predicts the exceedance probability for a given threshold level. For sectors such as water use, the coping zone C thresholds are never reached in the historic record and even in the 55,590 year stochastic time series developed for the Great Lakes by Fagherazzi et al. [2005]. Since the model parameters are fit based on performance in the 55,590 year stochastic data series, if the coping zone thresholds are not exceeded within that extensive set, the model parameters become less certain and the model does not predict coping zone C occurrences. As a result of the relatively wide thresholds for the water use, recreational boating, commercial navigation, and ecosystem sectors, the system is robust in these areas to response to changes in climate conditions, based on the thresholds reported within each sector. As the thresholds become more restrictive, the model predicts an increasing fraction of coping zone C occurrences. This is shown in the increasing coping zone occurrences for coastal and boat launch coping zones in particular. These areas show a significant increase in predicted coping zone C occurrence as the mean NBS departs from the historical mean.

On Lake Superior, only the coastal and boat launch stakeholder groups have a significant number of occurrences. For mean NBS decreases of 10 percent or more, the model predicts over 10 percent of the months will be in lower coping zone C. For mean NBS decreases over 20 percent, 5 percent of the months could be in the lower coastal coping zone C. For increases in
mean NBS, the model predicts 5 percent coping zone C occurrence for the coastal coping zone at an NBS increase of 10 percent and for the boat launch coping zone at an NBS increase of 15 percent.

On Lake Michigan Huron, the model predicts significant increases in coping zone occurrences if the mean NBS decreases. NBS decreases in the range of 10 to 20 percent result in coping zone C occurrences that approach 50 for recreational boating and exceed 50 percent for coastal, ecosystem, and boat launch coping zones. This highlights the sensitivity to low water conditions identified for Lake Michigan Huron. In terms of sensitivity on the high end, there is a similar increase in terms of coastal and boat launch coping zone occurrences with increasing mean NBS on Lake Michigan Huron as is seen on Lake Superior.
Figure 4.3: Expected value and 90 percent confidence interval extreme level occurrences for coastal, commercial navigation, recreational boating, boat launch, water use, and ecosystem coping zones. The figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan low extremes and d) Lake Michigan Huron high extremes. The expected value is based on a shifting mean NBS, an annual NBS standard deviation of 0.0 and an annual NBS serial correlation of 0.1.

4.3.3 Threshold Sensitivity and Adaptation

The variation in modeled coping zone occurrences by stakeholder group is a result of the sensitivity each stakeholder group has to water level extremes, as expressed through coping zone thresholds. Another way to consider this sensitivity is to look at how coping zone occurrences can be affected by small increases or decreases in the coping zone thresholds for a
given stakeholder group. To explore coping zone threshold sensitivity, the coastal coping zones were used as a baseline because the coastal coping zones showed a significant number of occurrences over the range of the stochastic climate. To determine the model output sensitivity to threshold levels, the coping zone thresholds were adjusted by 5 cm lower and higher. This adjustment was selected arbitrarily to determine predicted occurrence sensitivity to hazard thresholds. Then, the climate response function parameters were refit to the new thresholds. These parameters were then used to develop expected value and 90 percent confidence intervals on coping zone occurrences over a range of changing climate conditions. The results are shown in Figure 4.4 for Lake Superior and Lake Michigan Huron. The results were consistent with expectations in that higher thresholds meant fewer upper coping zone C occurrences and a greater fraction of lower coping zone C occurrences and lower thresholds had the opposite effect. Of note, for NBS values near the historic mean, there is minimal change as a result of changing the coping zones thresholds. As the mean climate moves further from the historic mean, the threshold sensitivity is exacerbated.

The upper quadrants of Figure 4.4, for Lake Superior, show that a 5 cm threshold shift can change the coping zone C occurrence rate by a factor of 2 either up or down. For instance, on the lower coping zone C figure, at a mean NBS percent change of -15%, the occurrence rate varies from 0.015 for minus 5 cm, 0.03 for no change, to 0.06 for plus 5 cm. The trend is similar for upper zone C coping zones. The results for Lake Michigan Huron show a similar trend, but with less sensitivity than on Lake Superior. This is also seen by the significant overlap of the 90 percent confidence intervals over the mean NBS values considered.

An important conclusion that can be drawn from this analysis is that any adaptation by individual stakeholders or groups of stakeholders to increase their tolerance to extreme water levels, as manifested by a changing coping zone threshold, is a way to reduce risk exposure.
These adaptations are referred to as individual adaptations by Dessai and Hulme [2004] or as autonomous adaptations by Jones [2001]. Physical changes that result in changing coping zone thresholds by as little as 5 cm can effectively halve the risk of the high impact coping zone C occurrences on Lake Superior. Given the historic monthly lake level standard deviation of 15 cm, this is a small change to have a significant impact on risk. The risk reduction on Lake Michigan Huron is smaller but still significant. Studies within each stakeholder group can look at the costs and feasibility of these measures to develop benefit-cost estimates for alternatives.
Figure 4.4: Expected value and 90 percent confidence interval for extreme water level occurrences showing the sensitivity of increasing or decreasing the coastal coping zone threshold by 5 cm. The figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan low extremes and d) Lake Michigan Huron high extremes. The expected value is based on a shifting mean NBS, an annual NBS standard deviation of 0.0 and an annual NBS serial correlation of 0.1.

4.3.4 Policy Adaptation and Risk

The previous section considered physical adaptation measures that could expand the coping zones and reduce risk of coping zone C occurrences. This section considers policy level adaptation actions taken at the International Joint Commission (IJC) level. Dessai and Hulme [2004] classified actions taken by governments and government agencies through legislation or
regulation as policy adaptation, while Jones [2001] refers to these actions as planned adaptation. A major component of the IUGLS was a study to determine potentially better regulation plans for the outflow from Lake Superior. The study confirmed that the current control structure at Sault St. Marie can influence lake levels on Lake Superior, but the impact is smaller on Lake Michigan Huron and continues to dissipate further downstream. Additionally, regulation is a balancing act between impacts on the lakes and on the St. Marys River. Small improvements in one component tend to degrade the other components. The IUGLS considered “fencepost” plans to determine the feasible range of control by regulation but focused on “balancing” plans that used various rules to balance water deficits and surpluses across the lakes. Ultimately, the study board recommended adopting regulation plan Natural 64D, renaming it as plan 2012. Chapter 3 discussed regulation plan performance in terms of robustness, comparing six different plans and their impacts on Lake Superior and Lake Michigan Huron.

In Figure 4.5, the impact of regulation on coping zone C occurrences is considered, comparing performance of Plan 1977A and Plan Natural 64D on Lake Superior and Lake Michigan Huron. As noted in Chapter 3, Plan Natural 64D performs better on Lake Superior under drier conditions, or has fewer lower coping zone C occurrences as the mean NBS decreases. This is offset by an increase in upper coping zone C occurrences as the mean increases. The Lake Superior graphs show significant overlap of the 90 percent confidence intervals for the upper and lower coping zones. This shows that the performance difference predicted by the climate response function parameterization could be lost in a noisy signal. On Lake Michigan Huron, the performance is nearly identical for the two regulation plans.
Figure 4.5: Expected value and 90 percent confidence interval of extreme level occurrence for Lake Superior Regulation Plan 1977A and Plan Natural 64D. The figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan low extremes and d) Lake Michigan Huron high extremes. The expected value is based on a shifting mean NBS, an annual NBS standard deviation of 0.0 and an annual NBS serial correlation of 0.1.

4.3.5 Climate Change Based Risk to Stakeholders

The preceding analysis has considered the variability in predicted coping zone occurrences as a function of a single climate outcome or series of climate outcomes. A climate outcome, in this context, is a vector of the climate response function inputs, namely the mean, standard deviation, and serial correlation of the annual NBS over a 30-year timeframe. In the previous analysis, the climate response function was evaluated at a regular interval along the
mean NBS variable axis while the standard deviation and serial correlation were held constant at their historical value. This procedure allows one to model the coping zone occurrence variability with a shifting mean climate condition from a drier overall climate to a wetter overall climate. While one can evaluate the climate response function for a given climate outcome, that climate outcome is just one of many possible climate outcomes. By generating a probability distribution model of climate conditions, one can stochastically sample climate outcomes from a climate statistical model and sample from the probability density function generated by the climate response function. This process allows one to model performance as a function of the assumptions in the climate probability density function model. This section discusses the development of a climate probability density function appropriate for the mean, standard deviation and serial correlation of the annual NBS, followed by the stochastic application of that model to estimate system performance.

The climate response function was developed through data mining from 55,590 years of stochastically generated NBS series and the associated water levels. The stochastic data series was developed by Fagherazzi et al. [2005] and is seen as representing a plausible range of climate variability for a stationary climate. The range of climate conditions in this rich data set encompasses the range of climate conditions in the ensemble of Global Circulation Model (GCM) projections [Angel and Kunkel, 2010]. In this analysis, the stochastic data set is assumed to represent a series of climate realizations from the potential range of climate. The range of climate is modeled by fitting a multivariate normal distribution to the NBS climate statistics from this stochastic data set.

The multivariate normal distribution is discussed in more detail in Chapter 3. The parameterization of the multivariate normal distribution provides an estimate of the statistical variability associated with a NBS climate modeled by the historic-based stochastic climate.
Using this NBS climate model combined with the climate response function, one can stochastically sample NBS mean, standard deviation and serial correlation values from the multivariate normal distribution and then use these values to generate coping zone occurrences. By repeating this process many times over, one can generate an estimate of the threshold exceedance probability distribution based on the assumptions about the climate probability distribution and the assumptions in the model parameterization. The climate probability distribution that is based on the stochastic NBS series and that represents the stationary climate will be used in this section. The next section will model a changing climate by changing the climate model parameters. To evaluate performance, the stochastic sampling is repeated to generate many realizations of climate and coping zone occurrences. One can then look at the fraction of the samples that exceed performance criteria to estimate the risk of exceeding certain performance thresholds.

4.3.6 Climate Informed Risk with a Shifting Mean

The climate state probability density function and the climate response function allow one to explore the impact of changes in climate statistic probability distributions. This is used to estimate how the climate informed robustness will change with the climate statistic probability distributions. One of the simplest assumptions one can make about a changing climate is a shift in the mean climate value. This method of modeling a non-stationary process is similar to the method discussed by Steding & Griffis [2011]. They used a log Pearson type III distribution to model flood risk. Alternate non-stationarity models were considered by considering a time variant mean, a time variant mean and standard deviation, and a time variant mean, standard deviation, and skewness. In a similar way, a non-stationary climate can be modeled by holding the mean of the standard deviation, \( \mu_\sigma \), the mean of the serial correlation, \( \mu_\rho \), and covariance
matrix, Σ, constant while varying the mean of the mean annual NBS, μ₁. Figure 4.6 and Figure 4.7 show the results from this process for Lake Superior and Lake Michigan Huron, respectively, for each of the stakeholder groups. Both figures show six graphs considering the low and high extreme value exceedance in the left and right columns and showing a ten percent increase in μ₁, no change to μ₁ and a ten percent decrease in μ₁ for the top, middle and bottom rows. As expected, increasing the mean NBS meta-parameter by ten percent results in significant increases in the risk of upper zone C acute impact occurrences and decreases the risk of lower zone C acute impact occurrences, while decreasing the mean NBS meta-parameter has the opposite effect. The figures also show the increased risk sensitivity on Lake Michigan Huron for decreases in mean NBS, though this sensitivity would be reduced if the lower coping zone C thresholds were reduced through adaptation and other measures.
Figure 4.6: Extreme water level related risk on Lake Superior for 10,000 stochastically generated climates centered on the historic mean NBS. Figure a) shows the risk of extreme low for -10% mean NBS, b) shows the risk of extreme high for +10% mean NBS, c) shows the risk of extreme low with no NBS change, d) shows the risk of extreme high with no NBS change, e) shows the risk of extreme low with -10% mean NBS, and f) shows the risk of extreme high with -10% mean NBS.
Figure 4.7: Extreme water level related risk on Lake Michigan Huron for 10,000 stochastically generated climates centered on the historic mean NBS. Figure a) shows the risk of extreme low for -10% mean NBS, b) shows the risk of extreme high for +10% mean NBS, c) shows the risk of extreme low with no NBS change, d) shows the risk of extreme high with no NBS change, e) shows the risk of extreme low with -10% mean NBS, and f) shows the risk of extreme high with -10% mean NBS.

4.4 Conclusion

The threshold based risk assessment process presented in this chapter is a valuable tool for understanding risk associated with uncertainty due to climate change, applied to multiple stakeholder groups. Rather than focusing on the bottom line, this application focuses on hazard impact thresholds determined by stakeholder groups that classify results by impact: low,
moderate, or severe. This measure allows the direct comparison of impacts across sectors. The climate response function developed in Chapter 2 offers a probability distribution of hazard occurrence as a function of climate factors, including mean climate. This allows confidence intervals for climate change impact for each stakeholder group. This shows which groups are most sensitive to climate change impacts.

Adaptation actions are assessed in two important ways. First, individual adaptation actions are considered. These are actions that private individuals take to reduce their risk exposure. While the specific risk reduction measures are too numerous to discuss, actions that shift stakeholder impact thresholds by as little as 5 cm are shown to dramatically increase or decrease risk exposure. Second, policy or government level adaptation action is considered by examining the impact Lake Superior outflow regulation has on risk. In the case of the IUGLS, there is negligible policy adaptation impact on Lake Michigan Huron and minor impacts on Lake Superior. This is largely because Lake Superior outflow regulation has a larger impact on Lake Superior water levels and because the current regulation plan is a generally good plan that does not have significant room for improvement.

From this analysis, it is clear that significant shifts in mean climate conditions would cause significant increases in stakeholder risk on Lake Superior and Lake Michigan Huron. The risk is not evenly distributed among the stakeholders; it is a function of the critical threshold water levels. Policy or government level adaptation would not be sufficient to reduce overall risk or risk to individual stakeholder groups. Autonomous adaptation measures taken individually or by stakeholder groups would be required to expand the tolerable range of water levels. While this chapter focuses on the probability of hazardous impact by stakeholder group for a given change in mean climate, it does not answer the question about how likely a given change in mean climate is. This is discussed in Chapter 5, where conditional probabilities of
specific changes in mean climate are developed. These probabilities are conditioned on the sources of climate information and assumptions used to develop them.
CHAPTER 5

ASSESSING CLIMATE RISK ON THE UPPER GREAT LAKES USING MULTIPLE SOURCES OF CLIMATE INFORMATION

Water resource managers have to design and assess systems to perform adequately into the future. Current practice is based on stationarity, or the assumption that the future climate conditions will be statistically similar to the past. Due to anthropomorphic climate change, this design and analysis assumption is seen as increasingly reasonable. There is a need for methodologies to develop decision-relevant information from available climate information and projections. Many climate change impact assessments have used downscaled GCM projections to estimate potential future impacts while others reject these projections based on questions about accuracy and bias. The debate raises the question about the roles that GCM projections and other sources of climate information should play in informing future climate uncertainty. Bottom-up or decision-centric approaches allow the use of GCMs as a potential information source to inform the analysis of future climate conditions and how their distribution may influence water resources decisions. Since the future climate cannot be sampled, diverse sources of climate information such as GCM projections, stochastically generated data, paleo-based data, and expert opinion can serve as surrogates for data measurements and can be analyzed to develop conditional and subjective climate probability distributions. These probability distributions can be used to evaluate system performance and water resource decisions for sensitivity to assumptions related to climate change uncertainty. In this chapter, various sources of climate information developed during the IUGLS are compared and their implications to threshold based risk are discussed.
5.1 Introduction

Water resource managers need information to support analysis of and decisions concerning water resource systems. Under the stationarity assumption, this information is based on the climatic data record. Milly et al. [2008] defined stationarity as “the idea that natural systems fluctuate within an unchanging envelope of variability.” Under this assumption, the future climate will have the same statistical distribution as the data record. The changing climate, due to anthropomorphic atmospheric changes of greenhouse gas concentrations, makes this assumption less useful for the analysis of how water resource systems may perform in the future.

Jones [2001] applied a risk management based framework to climate change impact assessment. In this framework, conditional probability distributions are developed for key climatic variables. These climatic variables are linked with threshold exceedance impacts developed by researchers and stakeholders. While the true probability distribution of the climatic variables remains unknown, the conditional probabilities allow a risk management based assessment. Jones [2001] completed the analysis by showing how a combination of adaptation and mitigation actions could reduce the risk of exceeding critical thresholds.

Dessai and Hulme [2004] argued that probability distributions for future climate conditions were needed to support decision making. As Hobbs [1997] stated, the classical statistical techniques that can be used with data from the historic record cannot be used with climate projections to infer future climate probability distributions. Hobbs [1997] argued that Bayesian methods can be used with different sources of climate information to develop conditional and subjective probability distributions that can be used in a decision context. There are many sources of information that can be used to make inferences about potential future
climate, with each source having its own assumptions, limitations, uncertainty, potential bias, and credibility.

The IUGLS sponsored by the IJC, the bi-national group responsible for the management and allocation of the boundary waters between Canada and the United States, included many studies about the potential future climate that may affect the Great Lakes region. These studies about climate variability include stochastically generated data, paleo-based data, GCM projections, RCM projections, and even subjective sources such as expert opinion. When used in a bottom up, or decision centric framework, the climate information can be used to support analysis to determine the system performance sensitivity with respect to assumptions made about future climate conditions. Since the probability distributions are conditional, the performance estimates will be too.

This chapter examines a set of the climate information sources developed in support of the IUGLS. These sources are used to develop conditional probability distributions for future climate conditions. Finally, these probability distributions are applied to Climate Response Function (CRF) developed in Chapter 2. The CRF predicts water level threshold based hazards from long term (30-year) climate statistics. When the CRF is used with climate probability distribution functions, it can predict potential climate informed system risk by information source and that determines risk sensitivity to assumptions about future climate. In this case, a Bayesian decision analysis, similar to what Hobbs et al. [1997] described, is applied to determine conditional expected utility for a given decision and a given climate information source. The Great Lakes Study is used to illustrate the example, but the process can be generally applied to analyze and evaluate water resource systems risk under uncertainty.

It is notable how little the lake dynamics are understood on inter-annual and decadal timescales. On decadal timescales, there is clear evidence of temporal structure, such as years
of high levels followed by years of low levels, that are currently unexplained [Brown, 2011].
Lake levels are generally unpredictable more than a month ahead, except for a moderate prediction skill in predicting spring levels from the preceding fall in years not affected by ENSO [Brown, 2011]. There is paleo-based evidence that the lake level range has been greater than the relatively narrow range they currently exhibit. By analysis of each of the sources of climate information, one can assess performance over a wide range of conditions beyond the conditions in the historic record to determine how the system and decisions about the system are sensitive to climate.

5.2 Climate Information Sources

One of the IUGLS objectives was to determine how vulnerable the Upper Great Lakes were to potential climate change. Prior to the IUGLS, there had been many top-down or climate science centric studies that used downscaled GCM projections to estimate future impacts on the Great Lakes. These studies ranged from small samples of one or two projections up to a 565 member GCM projection ensemble [Angel and Kunkel, 2010]. Dessai et al. [2009] argued that climate prediction is limited by irreducible uncertainties. Additionally, Stainforth et al. [2007] stated that the GCM ensemble approach may only provide the lower bound on the maximum range of future climate uncertainty, meaning that the true range of uncertainty may be larger than the range provided by the GCM ensemble. Additionally, GCM ensembles do not contain the probabilistic information needed to inform system related decisions. Wilby and Dessai [2010] stated that it is dangerous to perceive ensembles of climate projections as actual probabilities of change since the model results are highly dependent on experimental design.

As an alternative to assembling larger ensembles of downscaled GCM projections, other groups have pursued creating models with finer temporal and spatial resolution. These regional
climate models (RCMs) at a high-resolution may be driven by or connected to lower resolution GCMs. Wilby and Dessai [2010] cautioned against misconstruing high-resolution with high-accuracy. While RCMs may result in finer resolution projections, the projections are still dependent on the underlying model assumptions and model for future conditions cannot be evaluated in a meaningful way, that is, in a way relevant to decision making in the near future.

Climate projections are just one of many sources of climate information available; this section outlines sources developed for and relevant to the Great Lakes Study. In order to compare each of the sources of climate information, each data source is converted into a monthly Net Basin Supply (NBS), which is the net flux into a lake from precipitation, evaporation and runoff, expressed as an average flow rate in cubic meters per second (cms). Inter-lake flow and inter-basin transfers are not included in NBS, they are considered separately in the Great Lakes routing model. The data available from each data source is summarized by taking the mean annual NBS values over a 30-year analysis window and then normalizing this mean NBS by the historic mean NBS, resulting in a percent change from the historic observed NBS. This is done for several reasons. First, as observed by Hirsch [2011], climate models are believed to be better at predicting mean behavior, rather the variability and the extreme behavior. Second, the Great Lakes system exhibits long term persistence, resulting in decadal scale fluctuations in water supply. By averaging climate model results and the historic record over a longer time period, these fluctuations will be averaged out. This reduces the noise from normal fluctuations that may be out of synch versus signals that the climate model is predicting for a changing climate. Finally, this work uses the CRF discussed in Chapter 2 that relates long term climate statistics to stakeholder based impacts. The CRF uses the 30-year mean, standard deviation and one-year lag auto correlation to predict water levels that exceed extreme water level thresholds, as defined by stakeholders within the basin.
The information sources are briefly described below and summarized in Table 5.1 for Lake Superior, Table 5.2 for Lake Michigan Huron and as boxplots for both lakes in Figure 5.1. All data sets referred to in the text are available from the IUGLS web site\(^2\). Section 5.3 will use the results from this section with the CRF to estimate stakeholder risk conditioned on the different data sources. While the studies cited here are relevant to the Great Lakes system in particular, the same process of creating a meta-data set of all relevant climate information to evaluate system sensitivity to climate assumptions and information sources can be applied generally.

**Table 5.1: Annual NBS by climate information data source for Lake Superior.** The NBS is normalized to a percent change from the average from the historic record.

<table>
<thead>
<tr>
<th>Information Source</th>
<th>30 year sequences</th>
<th>Min NBS</th>
<th>Median NBS</th>
<th>Max NBS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Historic Record</td>
<td>3</td>
<td>-5.87%</td>
<td>2.93%</td>
<td>6.64%</td>
</tr>
<tr>
<td>Historic-Based Stochastic</td>
<td>1853</td>
<td>-17.59%</td>
<td>-0.28%</td>
<td>16.63%</td>
</tr>
<tr>
<td>Paleo-Based Stochastic</td>
<td>1666</td>
<td>-25.81%</td>
<td>2.24%</td>
<td>23.41%</td>
</tr>
<tr>
<td>Statistically Downscaled GCM</td>
<td>162</td>
<td>-17.50%</td>
<td>9.12%</td>
<td>34.39%</td>
</tr>
<tr>
<td>Dynamically Downscaled RCM/GCM</td>
<td>8</td>
<td>-12.94%</td>
<td>2.39%</td>
<td>15.25%</td>
</tr>
<tr>
<td>CHARM</td>
<td>1</td>
<td></td>
<td>6.25%</td>
<td></td>
</tr>
<tr>
<td>Stochastic GCM Simulation (A2)</td>
<td>500</td>
<td>-27.09%</td>
<td>-25.46%</td>
<td>-23.78%</td>
</tr>
<tr>
<td>Stochastic GCM Simulation (A1B)</td>
<td>500</td>
<td>-26.94%</td>
<td>-25.41%</td>
<td>-23.73%</td>
</tr>
</tbody>
</table>

**Table 5.2: Annual NBS by climate information data source for Lake Michigan Huron.** The NBS is normalized to a percent change from the average from the historic record.

<table>
<thead>
<tr>
<th>Information Source</th>
<th>30 year sequences</th>
<th>Min NBS</th>
<th>Median NBS</th>
<th>Max NBS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Historic Record</td>
<td>3</td>
<td>-8.31%</td>
<td>-0.36%</td>
<td>12.63%</td>
</tr>
<tr>
<td>Historic-Based Stochastic</td>
<td>1853</td>
<td>-19.37%</td>
<td>1.32%</td>
<td>18.71%</td>
</tr>
<tr>
<td>Paleo-Based Stochastic</td>
<td>1666</td>
<td>-22.35%</td>
<td>-2.92%</td>
<td>22.58%</td>
</tr>
<tr>
<td>Statistically Downscaled GCM</td>
<td>162</td>
<td>-18.54%</td>
<td>7.12%</td>
<td>38.71%</td>
</tr>
<tr>
<td>Dynamically Downscaled RCM/GCM</td>
<td>8</td>
<td>-2.13%</td>
<td>4.46%</td>
<td>6.11%</td>
</tr>
<tr>
<td>CHARM</td>
<td>1</td>
<td></td>
<td>24.99%</td>
<td></td>
</tr>
<tr>
<td>Stochastic GCM Simulation (A2)</td>
<td>500</td>
<td>-3.81%</td>
<td>-2.16%</td>
<td>-0.52%</td>
</tr>
<tr>
<td>Stochastic GCM Simulation (A1B)</td>
<td>500</td>
<td>-3.30%</td>
<td>-1.78%</td>
<td>-0.20%</td>
</tr>
</tbody>
</table>

---

\(^2\) Data sets are available at http://www.iugls.org/Datasets
Figure 5.1: Boxplots of mean annual NBS by climate information data source for a) Lake Superior and b) Lake Michigan Huron. The mean annual NBS is normalized to percent change from the historic average NBS.
5.2.1 Historic Climate

The historic NBS data is available from the IJGLS website for the years 1900 to 2008. The historic NBS data is not measured directly, but is imputed from other measurements using one of two methods. The data set uses the residual method, which is a mass balance on the change in storage, inflows, outflows, and diversions. Alternatively, the component method is the summation of estimates of precipitation on the lake, evaporation off of the lake and direct runoff from tributaries. Both methods produce estimates of the true value and are subject to uncertainty [International Joint Commission, 2005].

The primary advantage of the historic record is that it contains values based on measurements. This means that the historic NBS data set is a credible data set that has happened in the past and that a similar NBS could happen in the future. The measurements from the historic record are the primary data source for stationarity based methods. The primary disadvantages of the historic data set are that it is a relatively short data set, with only 109 years of data. Considering that the techniques applied here look at average values over 30-year analysis windows, that results in only three independent data points or a moving window average. Additionally, the historic data record does not provide information about potential future climate values, other than trends that are highly sensitive to the data window analyzed.

5.2.2 Paleo-Based Stochastic Climate

An additional way of considering what may occur in the future is to consider what has occurred in the past. While one cannot directly extend the historic record beyond the historic data record, methods exist to use paleo-based analogs to recreate the past climate. This approach was applied to generate a paleo-based stochastic NBS series (Ghile et al. Paleo-Reconstructed Net Basin Supply Scenarios for the Upper Great Lakes, submitted to Climatic
The methodology was adapted from *Prairie et al.* [2008] and used a non-homogenous Markov chain model to simulate the hydrologic state using Palmer Drought Severity Index (PDSI) reconstructed data and k-nearest neighbor (K-NN) to resample observed NBS magnitudes and create a 50,000-year, paleo-based stochastic data set. The PDSI data series was based on tree ring data available from the National Climatic Data Center for Paleoclimatology, which has good coverage in the Upper Great Lakes region dating back over 1,000 years. This study used the tree record for the years from 1,004 – 2,003. While tree ring data does correlate well with precipitation magnitude, it is effective in predicting overall wet or dry conditions. Extended wet or dry conditions can lead to extreme high or low lake levels. This approach can be effective at developing extended wet or dry NBS series and the related extreme high or low water levels beyond what was experienced during the historic record. Because this data set was developed from resampling the historic record, no new monthly or annual NBS values were developed. This means that it is not an appropriate data set to analyze annual or monthly variability. However, because the sampling of wet and dry years is based on the tree-ring evidence, the data set contains spells with longer persistence of wet or dry conditions, making it useful and relevant to a study of long term climate trends such as the 30-year analysis windows used in the development of the CRF.

### 5.2.3 Historic-Based Stochastic Climate

Prior to the IUGLS, the IJC conducted the LOSLRS to examine regulation of flow rates at Cornwall, Ontario on the St. Lawrence River. As part of the LOSLR Study, *Fagherazzi et al.* [2005] developed a stochastic NBS data set for each of the Great Lakes. They used a autoregressive model, AR(2), to model Lake Superior NBS and used a contemporaneous shifting mean model, CSM, for Lake Michigan-Huron. The stochastic model generated 55,590 years of
monthly NBS values for the lakes that preserved the fundamental characteristics of the historic NBS record, including statistics such as mean, variance, skew, temporal autocorrelation and spatial cross correlation.

The primary advantage of the historic-based stochastic data set is that it provides a much broader sampling range of NBS values than the historic data set does. As seen in Table 5.1 and Table 5.2, the range in mean NBS is significantly greater than the range seen over the historic data set. This increased range can be used with the Combined Great Lakes Routing and Regulation Model (CGLRRM) to predict lake water levels. The greater range results in extreme values of high and low water levels beyond what is seen in the historical record. The range of NBS sequences provides a rich set of plausible NBS sequences to evaluate performance and robustness. One disadvantage is that the historic-based stochastic data set is based on the assumption of stationarity and there is no information about potential climate change inherent to the data or the underlying assumptions.

5.2.4 Statistically Downscaled GCM Projections

Angel and Kunkel [2010] developed a 565 member ensemble of GCM projections from the A2, B1 and the A1B SRES scenarios. They statistically downscaled the GCM projections using the Advanced Hydrological Prediction System (AHPS) to calculate NBS sequences for the current climate, or 1970-1999, and for three future time periods (2005-2034, 2035-2064, and 2065-2094). Since the projections for the current climate showed bias, they used a bias correction based on the actual 1970-1999 NBS values and applied the bias correction to the future projections.

Seglenieks and MacKay [2011] analyzed the Angel and Kunkel [2010] ensemble and focused on the 162 projections from 18 different climate models. The subset of projections are
all from the A2 SRES scenario, on the higher end of emissions scenarios but not the highest, and on the years 2035-2064. In this timeframe, the choice of SRES scenario had little impact on the Great Lakes system [Seglenieks and MacKay, 2011].

This paper focuses on the subset of 162 downscaled GCM projections used by Seglenieks and MacKay [2011]. The projections are based on atmospheric-oceanic coupled models with increasing greenhouse gas concentrations, so the projections represent a potential future climate. While it is possible to examine a given model’s ability to replicate past conditions and estimate its accuracy and bias, one cannot simply project the same accuracy and bias forward into the future. Since there is no widely accepted way to evaluate projections for accuracy and bias, the application of a probability distribution to the results and to use the results in a decision framework is problematic. If the ensemble members are unweighted, then GCMs with many projections have a higher influence then models with few projections.

5.2.5 Dynamically Downscaled RCM/GCM Projections

Lofgren [2010], a proponent of Regional Climate Models, stated that the “delta method” for downscaling coarse-grid GCM projections cannot accurately account for the local hydrologic components. Rather than downscaling GCM projections directly, Lofgren [2010] advocates using a coupled RCM-GCM that has the benefits of capturing the global trends driven by the atmospheric and oceanic interactions from the GCM with a regional model that captures the effects of the large local features including the topography and the Great Lakes. The Great Lakes Regional Climate Model (GLRCM) is driven by the Canadian GCM CGCM3.1 v2 [Scinocca et al., 2008] using the observed 20th century emissions to drive the current climate and an SRES A2 emissions scenario for the future climate.
While the GLCRM results have greater spatial resolution and retain the effects from key topological and hydrologic features, they still require bias correction to match model results to historic measurements. The bias correction method used by MacKay and Seglenieks [2010] is similar to the delta method used to correct downscaled GCM projections. The bias correction varies spatially for each of the Great Lakes basins. The bias correction used for the historic time period (years 1,961 – 2,000) is applied to the future time period (years 2,041 – 2,070) although it is unclear if using the same bias for the future period is an appropriate assumption. Due to the computational cost of running the coupled GCM-RCM model, the available data set only includes eight projections. After bias correction, the model average predicts an increase in Lake Superior NBS by nearly 2.4% and a decrease in Lake Michigan-Huron NBS by 2.2%. Since these changes are within the bias correction and uncertainty, there is not a significant signal from the RCMs for a change in NBS for either lake in the future time period.

5.2.6 Coupled Hydrosphere-Atmosphere Research Model (CHARM)

Lofgren [2010] criticized the delta method’s potential evapotranspiration (PET) calculation and developed a variation of the delta method. In the new method, PET is calculated by using an energy budget approach rather than merely using temperature. As temperatures rise, the temperature method tends to overestimate PET, resulting in lower NBS estimates. The revised CHARM model corrects this relationship, resulting in a model that is reported to better capture historic results and generates presumably better estimates future results. The one CHARM projection available on the IUGLS data set site showed a 6% increase in mean NBS for Lake Superior and a 25% increase in mean NBS for Lake Michigan Huron for the period from 2043 through 2070. With only one data point from the CHARM model, it is difficult to interpret the results in a probabilistic context.
5.2.7 Stochastic GCM Simulation

Seidou et al. [2011] used GCM projections to stochastically generate 500 sequences of 100-year net basin supplies for the time period 2,001 – 2,100 using both the SRES A1B and A2 scenarios. The model was bias corrected based on a contemporary calibration period from 1957 through 1988 and a validation period from 1989 through 2009. To compare the stochastic GCM results to Angel and Kunkei's [2010] GCM ensemble, the 30-year segment from 2041 through 2070 was analyzed. As seen in Table 5.1, Table 5.2 and Figure 5.1, the stochastic GCM sequences did not produce the same variability in terms of projected mean NBS values. The projections were within a relatively narrow range considering the large sample size. Additionally, the projections indicate a significant drop in the mean NBS on Lake Superior (a range from -27% to -24% for the A2 scenario), which is lower than any of the other sources of climate information. While the projections on Lake Michigan Huron were closer to the historic mean (a range from -4% to -0.5%), the range was still much smaller than the other stochastic sets or the GCM ensemble. Seidou et al. [2011] have a stated goal of developing sequences with significant variability with extreme values beyond the historic range. In terms of long term (30-year) mean values, Seidou et al. [2011]'s data set is relatively uniform.

5.2.8 Climate Information Source Review

The meta-data set of NBS time series discussed in the previous sections provides a subset of the climate information available for describing past, current and future climate. While each data set by itself may have benefits or drawbacks to their individual use, the meta-data set can be useful when combined with a bottom-up or decision centric approach to climate change analysis. If the bottom-up approach identifies climate conditions that cause unacceptable behavior but those dangerous climate conditions are not represented by the
meta-data set, the likelihood or plausibility of their occurrence is less likely than dangerous climate conditions that are seen in multiple members of the meta-data set. The ranges and median values from each data set are included in Table 5.1 and Table 5.2, expressed as mean annual NBS over a 30-year window and normalized to a percent change from the historic mean annual NBS. Additionally, the data set ranges are compared as boxplots in Figure 5.1.

The historic record is the baseline that all other data sources are compared with to characterize the nature of the climate variation implied by the different information sources. The historic-based and paleo-based stochastic data sets provide a wider range of mean NBS values than the historic range. This allows testing the routing and regulation system model with sequences beyond the conditions experienced during the data record. The CRF was fit using the historic-based stochastic NBS data set and the associated water levels. The statistically downscaled GCM ensemble has a greater spread of 30-year mean annual NBS values than either the historic- or paleo-based stochastic data sets. This creates the issue that using the CRF with the full range of mean NBS values in the GCM ensemble involves extrapolation of the statistical relationship between climate and impact. As a result, the impacts related to the extreme high or low average NBS values are subject to greater uncertainty than the values near the center of the NBS range.

The range of the eight dynamically downscaled RCM projections is within the range of the historic-based stochastic distribution for both lakes. The single CHARM projection available falls within the interquartile range of the historic record and the paleo-based data set for Lake Superior, but is significantly higher on Lake Michigan Huron. Similarly, the stochastic GCM projections are within the historic interquartile range for Lake Michigan Huron but significantly lower on Lake Superior. It is unclear if these results are a result of a model bias or an underlying signal.
The next section discusses the implications on climate-based risk using each of the data sets and the climate response function developed in Chapter 2 and in Moody and Brown [2012]. This analysis facilitates and understanding of how climate based risk can vary with the source of climate information considered and the assumptions made in the analysis. Ultimately, this information supports a decision making framework complete with decision makers and stakeholders who have their own set of beliefs about the credibility of each data set and its relevance to the analysis of future climate.

5.3 Climate Informed System Risk

This section discusses some of the potential impacts related to a climate based on the CRF and conditioned on the different sources of climate information. In this section, the impacts related to each data set are considered separately rather than grouped into a single meta-data ensemble. Since there is some subjectivity in how data sets could or should be weighed by credibility, accuracy and potential bias, the information sources are not pooled. This allows the results to be compared by data set. This section addresses what each data source says about the likelihood of a ten percent or greater shift in the NBS, the expected extreme water level threshold exceedance rate, and the risk related to doubling the extreme water level threshold occurrences, all based on the source of climate information.

In this analysis, the probability distributions considered include a non-parametric probability distribution and a normal distribution fitted to each data set. Since there is only one data point from the CHARM model, it will be used as a point estimate without a distribution. Additionally, since the two stochastic GCM simulation data sets have significant overlap they have been combined and fit with a single distribution.
5.3.1 Plausibility of Climate Change

One way to consider the potential climate change is to examine what the different sources of climate information may imply about the plausibility of potential change. Jones [2001] used conditional probabilities of exceeding certain thresholds for specific climate parameters. This approach is adopted here to consider the relative likelihood of decreasing or increasing the mean NBS by ten percent or more, conditioned on each data source. In this context, the probability distribution for the stationary climate is approximated by the historic-based stochastic data set. In a similar fashion, the paleo-based stochastic data set is used to approximate the probability distribution for the climate over the past millennium. These are used as a comparison for the statistically downscaled GCM ensemble, the eight member RCM ensemble and the GCM based stochastic data series.

The historic record has included significant wetter and drier periods with respect to the long term average. Table 5.1 and Table 5.2 indicate that the maximum 30 year NBS annual average was 6.6% higher and 12.6% higher than the long term average for Lakes Superior and Michigan Huron respectively. The minimum 30 year NBS annual average was -5.9% and -8.3% for Lakes Superior and Michigan Huron. These ranges show the extreme of what has been measured and experienced, but are not the extreme of what is possible. This section considers the plausibility of extreme climate conditioned on the different sources of climate information. While ten percent is a bit arbitrary, it is more extreme than all but the maximum 30-year NBS on Lake Michigan Huron.

Figure 5.2 shows the likelihood of realizing a 30-year average annual NBS greater than ten percent from the historic average for each of the climate information sources discussed above. The historic-based and paleo-based data sets indicate a similar likelihood of extreme values with an approximately 0.05 conditional probability of non-exceedance for a ten percent
decrease in NBS on Lake Superior. The conditional exceedance probability for a ten percent increase on Lake Superior is approximately 0.1, or roughly double the probability conditioned on the historic-based data series. On Lake Michigan Huron, the exceedance probabilities based on the paleo-based series are both approximately double the probabilities based on the stochastic data series. This may be an indication that the variability and range of long term mean NBS over the past millennium was higher than it has been over the last hundred years.

The statistically downscaled GCM ensemble shows a similar range as the historic- and paleo-based stochastic data sets, as shown in the boxplots in Figure 5.1. The higher mean and greater standard deviation of the ensemble members result in a significantly higher exceedance probability of an average NBS increase greater than ten percent. The conditional probability of exceeding +10% is 0.45 on Lake Superior and 0.40 on Lake Michigan Huron. The eight member RCM ensemble indicates a potential increase in the variability of the average NBS with an approximate 0.2 probability of a shift in the Lake Superior NBS by -10% and an approximate 0.15 probability of a shift by +10%. On Lake Michigan Huron, the RCM ensemble members show less variability resulting in a reduction in the probability of a 10% increase or decrease.

The stochastic GCM data series has a significantly lower average NBS on Lake Superior, resulting in a 1.00 conditional probability of an average NBS reduction greater than -10%. It is unclear whether this maybe a signal from the Canadian General Circulation Model version 3 (CGCM3), a bias from the downscaling process or another explanation. The ensemble results for Lake Michigan Huron are much closer to the long term average NBS and also show a relatively small variability, resulting in a 0.0 conditional probability of exceeding a 10% increase or decrease in average NBS.
Figure 5.2: Plausibility of 10 percent change in mean annual NBS conditioned on climate information source. Figures include a) -10% non-exceedance probability on Lake Superior, b) +10% exceedance probability on Lake Superior, c) -10% non-exceedance on Lake Michigan Huron and d) +10% exceedance on Lake Michigan Huron. The data information sources included the historic based stochastic data, the paleo based stochastic data, the statistically downscaled GCM data, the dynamically downscaled RCM data, and the stochastic GCM data sets. The exceedance and non-exceedance probabilities are based on an empirical distribution and on a normal distribution for each data set.
5.3.2 Expected Impact Conditioned on Climate Information Source

The US Presidential/Congressional Commission on Risk Assessment and Risk Management define risk as “the probability that a substance or situation will produce harm under specified conditions. Risk is a combination of two factors: the probability that an event will occur, and the consequences of the adverse event [USPCC RARM, 1997].” This definition is applied to a standard measure of risk in water resource systems: expected value of an adverse impact. It is calculated by evaluating the impact related to an outcome times the probability density function of that outcome and integrated over the range of the outcome. The CRF developed in Chapter 2 is used to predict impact as a function of climate outcomes. The CRF can then be used with conditional probability distributions of future climate outcomes to develop estimates of risk.

GCMs and RCMs are thought to be more reliable in predictions of mean behavior than in predictions of extremes or of higher order statistics [Hirsch, 2011]. The CRF is evaluated using the mean annual NBS values from each climate information data source. The empirical and normal probability distributions discussed and presented in Section 5.2 are used for the average NBS. The expected value of impact is then calculated in Equation 5.1, where impact, \( I \), is a function of mean NBS, \( X \); probability is a function of mean NBS; and the integral is evaluated over the range of mean NBS.

\[
E[I] = \int I(X)P(X)dX
\]

(5.1)

This process is similar to the risk response surface analysis used by Jones [2001], where the response is determined by the CRF and the climate outcome probability is conditional on the data source and assumptions used.
Under the assumption of stationarity, one can use the probability distribution based on
the historic record to determine the expected value. Under non-stationarity, any probability
distribution will be conditional and may be subjective, resulting in a range of estimates for
expected impact. When used in a decision context, this process helps decision makers
understand decision sensitivity to climate probability distribution assumptions. Figure 5.3
includes the expected value of the fraction of months that are expected to have an extreme low
or extreme high water level. The thresholds were determined by stakeholder groups in the
IUGLS, in this case the coastal property thresholds are used because they are the most
restrictive. The impact for a given mean NBS is determined by the CRF as described in Chapter 2
and by Moody and Brown [2012]. The probability of a given change in mean NBS is determined
by an empirical distribution and by a normal distribution fit to the climate information data
sources described in Section 5.2.

The results in Figure 5.3 show Lake Superior and Lake Michigan Huron hazard sensitivity
to climate information source. On Lake Superior, the historic-based stochastic distribution, the
paleo-based stochastic distribution, the statistically downscaled GCM ensemble and the RCM
ensemble all show low risk for low water level extremes. The stochastic GCM data set based on
the CGCM3 projections all have a significant reduction in mean NBS during the 2041-2070
timeframe, resulting in a significant increase in low water level risk. The statistically downscaled
GCM ensemble-based probability distribution results in an elevated risk of extreme high water
levels. On Lake Michigan Huron, the paleo-based probability distribution shows an increased
risk for extreme low levels and the statistically downscaled GCM ensemble based probability
distribution indicates an increased risk of extreme high water levels.

While expected values in Figure 5.3 show the expected average over many theoretical
potential climates, they do not capture the range of potential extreme water level threshold
exceedance rates that each climate information source may indicate. Figure 5.4 shows similar results with a plot of the median extreme water level occurrence rate with error bars indicating the 0.1 and 0.9 exceedance probability values. The median, 0.1 and 0.9 exceedance probability values are based on a normal probability distribution fit to each data series.

The results shown in Figure 5.4 indicate that while the expected value of extreme high lake level occurrence under the distribution fit to the downscaled GCM data is close to 0.1, the 0.1 exceedance value is much higher, at 0.28 for Lake Superior and 0.32 for Lake Michigan Huron. For the low extreme levels, the probability distribution from the paleo-based data set shows a 0.1 exceedance of 0.42, which may be a signal that there was a greater incidence of lower lake levels due to lower NBS over past millennium.
Figure 5.3: Expected fraction of extreme water level threshold exceedance using conditional empirical and normal probability distributions. Figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan Huron low extremes and d) Lake Michigan Huron high extremes.
Figure 5.4: Median values for extreme water level threshold exceedance with error bars at 0.1 and 0.9 cumulative probability and shown for each climate information data source. Figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan Huron low extremes and d) Lake Michigan Huron high extremes.

5.3.3 Regulation Plan Selection and Climate Information Source

The impact of climate information source and climate probability distributions on the decisions can be assessed by evaluating the expected system performance by regulation plan and by climate data source. This is shown below, in Figure 5.5, for Lake Superior and Michigan Huron for regulation plans P77A and Natural 64D. The other four regulation plans discussed in Chapter 4 were ruled out as non-acceptable so they are not considered here.
The results are consistent with the findings in Chapter 4. The two regulations plans are both balancing plans in that they balance the extremes above and below Sault Ste. Marie and thus their performance is similar. Considering low extreme water levels, plan Natural 64D performs marginally better on both Lake Superior and on Lake Michigan Huron. In the case of the GCM-based stochastic data set, which has relatively uniform and very large reduction of mean NBS (-25%), the difference in the fraction of coping zone C occurrences is approximately 0.04 (4%), otherwise the difference is small. This result indicates a potential overall system improvement with plan Natural 64D for reductions in mean NBS.

Considering the performance on the high extreme water levels, plan Natural 64D performs slightly better than plan P77A on Lake Michigan Huron but worse on Lake Superior. The largest performance difference is approximately 0.03 (3%) fewer coping zone C occurrences on Lake Superior for the statistically downscaled data set. These results reflect the tradeoff between high water levels on Lake Superior and Lake Michigan Huron that cannot be mitigated with the choice of regulation plan.

Overall, the performance changes between plans as a function of the climate information data source and assumptions are small. As a comparison, the changes are smaller than changes in system performance estimates due to individual adaptation measures by adjusting stakeholder thresholds by plus or minus 5 cm. While the risk levels change as a result of the climate information source, the decision is not sensitive to the choice of data source or assumptions.

The finding that the decision is not sensitive to the choice of data source is important. Better climate science and approximations of potential future impacts may be informative of the magnitude of impact, but would not alter the decision recommendation. In cases where the
decision was sensitive to the climate information source and assumptions, then there may be additional decision value from better future climate information.

![Graphs showing expected fractions of extreme water levels](image)

Figure 5.5: Expected fraction of extreme water level threshold exceedance for regulation plan P77A and Natural 64D and for probability distributions based on the historic-based stochastic, the paleo-based stochastic, the statistically downscaled GCM, the RCM, and the GCM-based stochastic data sets. Figure includes a) Lake Superior low extremes, b) Lake Superior high extremes, c) Lake Michigan Huron low extremes and d) Lake Michigan Huron high extremes.

5.4 Conclusion

Much of the focus for climate change has been on trying to predict the future climate and reduce future climate uncertainty. While climate science will continue to focus on these
questions, it is time for the water resources community to develop and apply appropriate
decision making methodologies that can assimilate climate information from diverse sources.
While inferences based on climate projections from GCMs or based on paleo-based data may
not be as strong or easily applied as inferences based on stationarity and a long historic record,
the process allows users to extend risk assessment and management based techniques to the
uncertain climate future. By using conditional and subjective probability distributions, one can
test system performance and decision sensitivity to the assumptions and data used to develop
those probability distributions.
CHAPTER 6

SUMMARY AND KEY FINDINGS

The challenges relating to decision making under risk and uncertainty are certainly not new challenges to the water resources community. Uncertainty in supply, demand, and other significant factors is a driver for designing systems that are robust and resilient. Climate change is a prominent source of uncertainty that has direct impact on water supplies and demands.

Stationarity based design and analysis has been used to account for climate and water supply variability, but cannot be applied directly when stationarity cannot be assumed. There currently is no widely accepted method for accounting for climate change uncertainty. Several methods that have been proposed are discussed throughout the dissertation, including discussion on their relative advantages and disadvantages.

The field of climate science has expanded rapidly, with climate modeling centers producing more climate projections with increasing precision and resolution, but with an unknown change in accuracy. The water resources community has been using these projections in a top-down process with a variety of downscaling techniques to drive hydrologic models and system models in order to generate point estimates and ranges of potential system impacts. Despite continued improvement in climate science and modeling, climate projections and downscaled hydrologic projections cannot be evaluated for accuracy or skill in a meaningful way. In contrast, forecasts can be assessed for their skill in predicting climate, weather or hydrology by determining their hit rate or frequency of getting the forecast right.

In this dissertation I have argued that the top-down approach to using GCM climate projections to drive water resource system analysis or design may not produce the information that is most relevant to water resources decision making. I have applied a decision centric approach that focuses on the water system first. The approach determines the climate
vulnerabilities, or climate conditions that the system and decisions relating to the system are sensitive to, then uses available climate information to determine the credibility or plausibility of the climate vulnerabilities.

The top down approach attempts to determine what the climate conditions will be like (and hence the hydrology and system will be like) at some future date. Alternatively, the decision-centric approach assess the system vulnerabilities to determine which range of climate conditions favor one decision over another decision and use available climate information to estimate which climate range is more likely.

The climate response function, described in Chapter 2, uses long-term average climate statistics to predict system impact. This choice was deliberate based on the available climate information and the quality of the information. Hirsch [2011] discussed the relative accuracy or predictive skill of GCM projections and found that estimates of mean behavior tend to be more accurate than estimates of variability and higher order statistics. Hence the CRF is designed to use the GCM based information that is more likely to have an accurate signal.

This approach to climate change vulnerability and system robustness is novel and allows the description of system performance and risk in a probabilistic manner that is familiar to decision makers. While probability distributions can be estimated from the measured historical record using classical or frequentist techniques, the probability distributions developed from other sources of climate information, such as the paleo record or GCM projections, are conditional and or subjective. As a result, the inferences about the system developed from these probability distributions are conditional and or subjective as well.

Proponents of RDM and other scenario based techniques argue that the future climate uncertainty is such that probability distributions should not be used. By not assigning probability distributions to future climate scenarios, they have implicitly assigned uniform
probability distributions to the scenarios. This implicit assumption is often transparent to the
decision maker, potentially resulting in a false sense of robustness. The methods presented
here allow the systematic analysis using multiple sets of assumptions and climate information
sources which each result in conditional probability distributions of climate and impacts. This
has the additional benefit of clearly showing system and decision sensitivity to assumptions
about the range and probability distribution for potential future climate. This greater
understanding of system and climate sensitivity can then be used to inform data collection and
analysis plans and to inform adaptive management processes.

*Milly et al.* [2008], *Brown* [2010], *Stakhiv* [2011], and others advocated the development
and implementation of new techniques to incorporate climate change uncertainty into water
resources planning and analysis. *Stakhiv* [2011], in particular, advocated developing techniques
that adapt classical (*i.e.* stationarity) based methods to deal with climate change. The approach
to robustness presented in Chapter 3 and to risk presented in Chapters 4 and 5 adapt traditional
applications of risk and robustness to incorporate uncertainty due to climate change. The
resulting climate informed robustness and climate informed risk allow the calculation of familiar
metrics within the context of climate change.

This approach was developed and applied within the context of the IUGLS which sought
to determine the best Lake Superior outflow regulation plan in terms of performance over an
uncertain future. The work presented in this dissertation was instrumental in showing that the
existing plan (Plan 1977A) effectively balances risk and impact above and below Sault Ste. Marie,
but plan Natural 24D (also referred to as Plan 2012 by *International Upper Great Lakes Study
Board* [2012]) is more robust, especially when considering decreases in water supply to the
basin. The approach developed and presented here is complementary to a relatively traditional
scenario based approach that evaluated plan performance over a small number of hand
selected water supplies. This approach was able to incorporate probabilistic estimates of future climate in a way that cannot be done with scenario based techniques.

The climate response function and the climate informed risk and robustness metrics highlighted several key insights into long term water resource planning. First, it required the development of the explicit relationship between climate and system impact, allowing the identification of climate conditions that resulted in system vulnerabilities and conditions that favored one decision over another. Second, it allowed the modification of existing metrics that are familiar to decision makers and stakeholders to incorporate climate change uncertainty. Third, it allows the systematic evaluation of the impact and sensitivity of different sources of climate information and the probability density functions generated from them on system performance and on potential decisions. While no approach will successfully predict what will occur in the future, the approach described here provides a way to explore how climate changes and assumptions impact system performance and decisions. While developed specifically for the Great Lakes system, the approach is broadly applicable to other water resource systems.
REFERENCES


Dessai, S., M. Hulme, R. Lempert, and R. Pielke (2009), Do We Need Better Predictions to Adapt to a Changing Climate? *Eos Trans. AGU, 90*(13), 111.


King, G. W., Union of Concerned Scientists, and Ecological Society of America. (2003), *Confronting climate change in the Great Lakes region: impacts on our communities and ecosystems*, Union of Concerned Scientists; Ecological Society of America, Cambridge, MA.


Lam, D. C. L. and W. M. Schertzer (1999), *Potential climate change effects on Great Lakes hydrodynamics and water quality*, American Society of Civil Engineers, Reston, VA.


Lempert, R., S. Popper, and S. Bankes (2003), *Shaping the next one hundred years: new methods for quantitative, long-term policy analysis*, Rand Corp, Santa Monica, CA.


Raiffa, H. (1968), Decision analysis: introductory lectures on choices under uncertainty, Addison-Wesley, Reading, MA.


