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METHODS FOR INCORPORATING ECOLOGICAL IMPACTS WITH
CLIMATE UNCERTAINTY TO SUPPORT ROBUST FLOOD MANAGEMENT
DECISION-MAKING

A Dissertation Presented

by

CAITLIN MARIE SPENCE

Submitted to the Graduate School of the
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CLIMATE UNCERTAINTY TO SUPPORT ROBUST FLOOD MANAGEMENT
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                                      Environmental Engineering

DEDICATION

To my parents Lynn McCarty and Clay Spence, who made this work possible in so many ways.

ACKNOWLEDGMENTS

ABSTRACT

METHODS FOR INCORPORATING ECOLOGICAL IMPACTS WITH
CLIMATE UNCERTAINTY TO SUPPORT ROBUST FLOOD MANAGEMENT
DECISION-MAKING

FEBRUARY 2017

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Modern and historic flood risk management involves accommodating multiple
sources of sources of uncertainty and potential impacts across a broad range of
interrelated sectors. Sources of uncertainty that affect planning include internal
climate variability, anthropogenic changes such as land use and system performance
expectations, and more recently changes in climatology that affect the resources
supporting the system. Flood management systems potentially impact human
settlements within and beyond the systems' scope of planning, local weather patterns,
and associated ecological systems. Federal guidelines across nations have called for
greater consideration of uncertainty and impacts of water resources planning projects,
but methods for meeting these needs remain poorly established. At the same time,
there is increased attention to the ecological impacts of water resources systems and
growing expectations that negative impacts be mitigated. The confluence of climate
change and increasing demand for environmental quality presents a challenging flood
management decision context. This work presents several alternative methods for
incorporating ecological impacts into flood risk management and evaluation
procedures alongside climate uncertainty, which are illustrated through application to
a flood management system on the Iowa River. First, to integrate climate change and

uncertainty information into these decision models, the dissertation presents a decision-centric trend detection test in which the threshold for accepting or rejecting a trend in observed data is determined by the expected cost of drawing a false conclusion. Next, the dissertation presents a decision model to choose a portfolio of adaptation options based on portfolios' expected economic and monetized ecological performance under uncertain future flood hazard. The dissertation also develops a robust optimization model with an alternate treatment of ecological performance to maximize the range of future conditions over which performance is acceptable in both economic and ecological impact sectors. Lastly, the dissertation presents a method for deriving a posterior distribution of changes in climate parameters based on a combination of a prior constructed based on climate model projections and likelihood based on the historic record. The goals of this work are to develop enhanced decision support tools that accommodate the unique context of flood risk management decisions and to improve the set of methods available to characterize future flood hazard and its associated uncertainty.

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LIST OF SYMBOLS AND ABBREVIATIONS

Abbreviations

FRM: Flood Risk Management

WRM: Water Resources Management

CMIP3: Coupled Model Intercomparison Project Phase 3

CMIP5: Coupled Model Intercomparison Project, phase 5

USACE: United States Army Corps of Engineers

US: United States

EAC: Expected Annual Cost

EAF: Expected Annual Floodplain

RO: Robust Optimization

DS: Decision Support/Decision Scaling (Brown et al., 2012)

RDM: Robust Decision Making (Lempert and Popper, 2003)

MORDM: Multi-Objective Robust Decision Making (Kasprzyk et al., 2013)

NDM: Nonstationary Decision Model

VIC: Variable Infiltration Capacity rainfall-runoff model (Xiang et al., 1994).

OLS: Ordinary Least Squares

GCM: General Circulation Model

RCM: Regional Climate Model

POT: Peaks-Over-Threshold

MCMC: Monte Carlo Markov Chain

GPD: Generalized Pareto Distribution

cfs: Cubic feet per second, a measure of discharge or volumetric flow rate.

HCDN: Hydro-Climatic Data Network.

AMJ: April-May-June.

Symbols

H_o: Null hypothesis.

H_A: Alternative hypothesis.

α : Statistical significance, or probability that the null hypothesis of no effect is rejected when an effect in fact exists (Chapter 3); weight on a term within a larger optimization objective function (Chapter 5); or the location parameter of a Gamma probability distribution (Chapter 6).

β: Probability of failing to identify an extent trend or effect as statistically significant, and thus reject the null hypothesis of no effect (Chapter 3), or the scale parameter of a Gamma probability distribution (Chapter 6).

Q: Discharge or volumetric flow.

$\widehat{\beta_1}$: An estimate of a trend parameter.

$\widehat{\sigma_{\widehat{\beta_1}}}$: Estimated standard error of an estimated trend parameter.

$\alpha_{\widehat{\beta_1}}$: Statistical significance of estimated trend $\widehat{\beta_1}$ in the data.

$\beta_{\widehat{\beta_1}}$: Probability of correctly rejecting the null hypothesis of no trend when the estimated trend is $\widehat{\beta_1}$.

α_o: A risk-based statistical significance threshold.

μ_x: The mean or expectation of a series in year x.

$\Delta\mu$: Change in the expectation of a series between two points in time.

p: An indication of an effect's level of statistical significance.

γ: An arbitrary proportionality constant used to relate change in the expectation of a flow probability distribution to change in the flood risk and damage to cost relationship (Chapter 3); or weight on a term within the objective function in an optimization problem (Chapter 4).

x_I: Infrastructure-based FRM adaptation decision variable in optimization problem.

$x_I{}^*$: Optimal value of infrastructure-based FRM decision variable.

x_O: Options-based FRM adaptation decision variable in optimization problem.

$x_O{}^*$: Optimal level of options-based FRM adaptation decision variable.

Z: Objective function value.

R: Regret, or the difference in outcome between the outcome under the optimal set of actions and the set of actions actually taken under a given state of the world (Chapter 4; Chapter 5), or the number of climate models used in an analysis (Chapter 6).

s: Annual flood peak (log-cfs).

t: Year since beginning of planning period, or t-statistic.

β_μ: Trend in the mean of annual flood peak probability distribution.

σ: Standard deviation, or the scale parameter of a POT probability distribution (Chapter 6).

μ_o: Mean in beginning of the planning period.

$\widehat{\mu_{proj}}$: Mean of a variable of interest estimated from climate model projections.

$\widehat{\mu_{hist}}$: Mean of a variable of interest estimated from historic observations of the variable.

$\vec{x}$: A vector set of decision variables which represent adaptive FRM actions and the levels of each.

$\vec{\Delta}$: A set of climate variables.

A_t: Maximum expected inundated area during year t.

D: Flood damage.

C: Cost of managing flood risk.

r: Discount rate (Chapter 4, Chapter 5) or one of a number of climate models used in a climate impacts assessment (Chapter 6).

P: Annual average precipitation.

T: Annual average temperature.

$\vec{\theta}$: The set of parameters of an extreme flow probability distribution.

q: Peak flow.

x: The value of a climate index.

k: The number of flow exceedences per year in a POT probability distribution.

v: The rate parameter of a POT probability distribution, or the precision parameter of a normal distribution.

τ: An alternate representation of the precision parameter of a normal probability distribution.

ξ: The shape parameter of a POT probability distribution.

δ: A measure of bias.

CHAPTER 1

THE NEED FOR DECISION FRAMEWORKS WHICH ACCOMMODATE

UNCERTAINTY AND ECOLOGICAL IMPACTS IN FLOOD RISK

MANAGEMENT

Floods are a type of natural disaster that cause severe costly damage around the world and within the United States. In addition to economic damage, floods disrupt the social infrastructure that makes up our society, affecting different segments of the population disproportionately. The physical causes of flooding stem from factors as diverse as extreme precipitation, infrastructure failure, break-up of natural dams, tidal forces, and placement of vulnerable development in areas prone to inundation. Flooding is therefore a complex and interdisciplinary phenomenon that damages physical and social infrastructure while impacting ecosystems in both positive and negative ways through multiple functional levers. This dissertation focuses on storm-driven riverine flooding, which is common in the United States and throughout the world. Riverine flooding is common because rivers deliver a unique confluence of multiple benefits to society, which include transportation, drinking water, irrigation, power supply, food supply, cultural and recreational benefits, and others. These benefits incentivize development of areas near rivers even though these areas are occasionally inundated during bank overflow events.

A number of structural and non-structural mitigation strategies may mitigate the risk of damage to floodplain development. These strategies largely fall into two categories: First, strategies that reduce the probability of vulnerable areas becoming inundated; and second, strategies that reduce the vulnerability of frequently inundated areas. Each strategic approach reduces one part of the components of flood risk, which is the

product of the risk of inundation and the consequences of inundation. Strategies that reduce the probability of inundation typically take a structural approach, using either built or natural infrastructure to mitigate peak flows. Examples of built infrastructure that reduce the likelihood of inundation include flood control reservoirs, which hold back a portion of high flows to reduce flood peaks, and levees, which physically block high river flows from inundating vulnerable land. Natural infrastructure such as detention ponds or land cover may be used to slow the transmission of precipitation into the river by increasing surface roughness, infiltration capacity, transpiration, or other hydrologic characteristics of the basin that attenuate flood peaks. Strategies which reduce the vulnerability of development in flood-prone areas are built into the development itself and include construction techniques which are resistant to water damage, drainage infrastructure to allow the swift retreat of floodwaters, zoning flood-prone areas for low-value land or flood-tolerant uses, or physical elevation of structures above flood levels. A combination of these risk management strategies is typically employed to maximize the benefits derived from using the floodplain with a minimum risk of damage.

Optimal combination of inundation reduction and vulnerability reduction techniques would be easily achieved if each developed floodplain were planned as a whole at one point in time, constructed, and thereafter remained forever static. However, it is more realistic for development in floodplains to grow incrementally over time, increasing in vulnerability the while, until the floodplain becomes economically and socially important enough to necessitate a formal flood risk management system. This development pattern makes it difficult to efficiently coordinate flood-resistant land use patterns and construction techniques in the entirety of the floodplain's development and incentivizes inundation-reduction infrastructure such as dams and

levees. These large-scale infrastructure products are commonly funded jointly by local and state or national governments with the main purpose of maximizing economic development. Depending on the magnitude of the system, flood infrastructure may either be designed to convey/mitigate flow with a certain known exceedance probability (e.g. the hundred-year flood) with the least cost or to avoid the greatest amount of damage with the least amount of cost, measured by the cost:benefit ratio. The expected damage associated with a river's flow regime may be calculated by combining the relationship between flow and damage caused by those flows with the probability of peak flows' occurrence. Flood management projects' economic efficiency may be assessed by imposing changes on the probability of peak flow resulting from implementing the project, imposing changes in vulnerability resulting from the project on the flow/damage relationship, re-calculating expected damage, and adding project implementation costs. Comparing expected net cost with the project in place to expected net cost without the project reveals whether the proposed flood management project is economically justified. These criteria may be evaluated for a single piece of flood control infrastructure, such as a culvert or a reservoir, or for a larger flood control system made up of a combination of infrastructure, land use management/zoning policies, insurance contracts, etc.

A common thread in the suite of techniques used to assess or compare the performance of potential flood risk management projects is the reliance on a known probability distribution of the frequency and/or magnitude of peak flows, which is estimated from flow records. The assumption that underpins this practice is that floods in the future will be distributed identically to floods observed in the past. However, there are a number of reasons this may not be true, and flood management projects based on this assumption may be subject to either over-design or under-

design. These include changes to the basins' hydrologic properties caused by erosion, structural, or land use/land cover changes, low-frequency variability in precipitation and temperature, or long-term climate change caused by greenhouse gas emissions into the atmosphere.

Climate nonstationarity has been broadly accepted by the water sector as a new paradigm for design and planning (Milly et al., 2008), but methods for incorporating nonstationarity into flood risk management are not well established. Traditional metrics used to measure the performance of water resources systems such as reliability or expected costs have been estimated based on an assumption of stationary hydrology, so updates to these metrics which accommodate nonstationarity are needed (Brown, 2010). This is been a subject of significant attention in the water sector, which has proposed several updated methods for calculating metrics such as reliability or benefit-cost ratio assuming nonstationary hydrology. A number of methods have been developed which represent the parameters of the probability distribution of extreme events as nonstationary, with relationships to time or to synoptic covariates (Griffis and Stedinger, 2007). The nonstationary probability distribution is a key component in a number of decision models based on water systems' expected performance under nonstationary conditions (e.g. Zhu et al, 2007; Rosner et al., 2014; Woodward et al., 2013), but requires an estimate of the parameters' relationship to time. The aforementioned nonstationary design metrics and decision models share a common basis in a single projected climate or land use trajectory, when in reality the trajectory is uncertain and influenced by multiple interacting factors (Lempert, 2003; Stainforth et al., 2007b). Climate uncertainty is compounded by additional sources of uncertainty such as land use change and

vegetation change in frequency analysis of extreme hydrologic events such as floods and droughts.

Estimates of the future peak flow probability distribution are typically derived from either extrapolation of trends observed in the historic record or from physical modelling of the climate and/or land use system. The benefit of extrapolating trend estimated from peak flow observations is that the trend may be identified even if the factor(s) causing the trend are not well understood. Modelling studies, on the other hand, may connect changes in climate or land cover which have occurred recently or which are expected to occur with their likely hydrologic consequences that are not yet evident in observations. However, the particular contextual circumstances of flooding challenge both trend extrapolation from historic records and modelling studies of future flood characteristics. Floods' rarity makes data on their past occurrence sparse, and therefore trend detection in records of extreme flows is inherently difficult (Hirsch, 2011; Easterling et al., 1999). Bowling et al. (2000)'s study of minimum detectable trends in flow in western Washington, United States indicate that most river flow records may not be long enough to identify trends at standard significance thresholds if they do exist. Ziegler et al. (2005)'s study of trends in river flow as predicted by climate model output in the largest river basin in the United States, the Mississippi River Basin, finds that flow trends at the magnitude predicted by climate models would require records of between 87 and 143 years to identify the GCM-predicted trends at 5% significance. Chapter 3 presents a trend detection framework that specifies statistical significance threshold of flood peak trend as that which equalizes expected over- and under-preparation costs, increasing the economic efficiency of flood adaptation decisions.

Due to the challenges associated with predicting future hydrologic behaviour based on flow records, climate model simulations of common inputs to hydrologic models such as precipitation, temperature, or solar radiation may be used to estimate future flood hazard. While long-term average precipitation and temperature are not without influence on such influential factors as the presence or magnitude of snowpack, seasonal melt timing, or soil moisture patterns, it is intense precipitation on the timescale of hours to days which has the most direct influence on riverine flood occurrence. Intense precipitation is not represented in global climate models, which simulate the physics of the ocean, land surface, and atmosphere at too coarse a spatial resolution to capture the fine-scale moisture transport that creates hurricanes, tropical cyclones, tropical moisture exports, atmospheric rivers, or convective or orographic precipitation events which are associated with intense precipitation and flooding throughout the world (Barsugli et al., 2009; Merz et al., 2012, Hirsch, 2011; Flato et al., 2012). Climate model output may be bias-corrected, downscaled, or translated through a weather generating function to more realistically resemble the characteristic weather at an area of interest, but these techniques are based on no signal in the most direct meteorological causes of flooding so therefore provide only limited information on future flood hazard that is subject to a high degree of uncertainty. In summary, uncertainty in future peak flow probability that is estimated based on flow records, climate projections, and traditional hypothesis testing frameworks limits the practical use of existing nonstationary flood management design tools on a known trend in the probability distribution of floods (e.g. Stedinger and Griffis, 2007; Rootzen and Katz, 2013; Salas and Obeysekara, 2014).

The lack of credible information sources on which to base future flood frequency estimates issues two parallel scientific challenges to the water sector. First is the

challenge of adapting existing flood management design criteria and decision frameworks to uncertainty or deep uncertainty in the peak flow probability distribution. The second challenge is to develop superior estimates of future peak flow which realistically quantify uncertainty. The following sections review the state of the science in each area.

Numerous decision making frameworks have been developed to incorporate uncertain estimates of future climate into decision making. These delimit the scope of uncertain conditions under which a system must perform through a number of techniques, and assess performance across the range of uncertain conditions differently as well. Risk-based decision making assesses a system's expected performance across a range of scenarios, each with a known probability (e.g. USACE, 1996; Lund, 2002). This framework may therefore be applied to stationary or nonstationary flood risk management, but relies on a known probabilistic description of either peak flows or trend in peak flows. The previous section has established the lack of credible techniques for quantifying the uncertainty in such an estimate. A number of decision support techniques address the issue of decision making under the circumstance of a lack of probabilistic description of uncertainty, which is described in this dissertation as "deep uncertainty" and also sometimes described as "severe uncertainty." Robust decision making (RDM) (e.g. Lempert & Groves, 2008) has been applied to a wide variety of decision contexts within and beyond water resources management (e.g. Regan et al., 2005; Lempert et al., 2012). RDM couches a system simulation model within algorithms which search for scenarios that lead to poor system performance over a wide set of possible future conditions, altering the system to seek adaptive alternatives that increase robustness. Robustness is measured through satisficing, or through another metric deemed suitable for the specific application. The framework

avoids relying on probabilistic descriptions of uncertainty, instead simulating performance under many alternative scenarios. An alternative robust decision framework based on RDM is Multi-Objective Robust Decision Making (MORDM), which is designed to seek decisions that are robust in terms of multiple objectives. Like RDM, MORDM is based around a high-dimensional search, but seeks Pareto non-dominated solutions to present stakeholders with a range of robust decision choices (Kasprzyk et al., 2013). Similarly, Info-Gap Decision Theory selects robust management strategies based on their performance across varying levels of uncertainty in a radius of acceptable performance (Korteling et al., 2013). Applications of both RDM and Info-Gap to decision support for managing climate-sensitive systems have relied on climate models to delimit the range of future climate conditions (e.g. Matrosov et al., 2013), though climate scenarios outside the bounds of those projected by current models are difficult to dismiss (Stainforth et al., 2007a,b). The Decision Scaling framework for climate risk assessment and adaptation seeks to avoid the possibility of failing to recognize high-impact scenarios outside the bounds of climate projections by focusing the climate adaptation process on a bottom-up vulnerability assessment which is not based on climate model projections (Brown et al., 2012). Projections and/or probabilistic representations of future climate are addressed after system vulnerabilities have been identified under incrementally varied scenarios which extend to the borders of the plausible. Based on the map of the system's response to all plausible scenarios combined with estimates of future conditions, decision makers may decide whether adaptation is necessary based on their own credence in the estimates of future conditions. Chapter 4 of this dissertation demonstrates how the decision scaling framework may be applied to flood risk

management adaptation decisions without relying exclusively on average precipitation and temperature change as decision drivers.

These decision support tools provide a number of examples of how to characterize uncertainty, frame the scenarios across which robustness is measured, assess performance robustness across scenarios, incorporate climate information, and accommodate multiple decision objectives. While these robust decision support tools each seek to guide stakeholders toward robust actions, the decision maker's risk attitude is another important decision driver that is not reflected in previous applications of the decision frameworks. Risk attitude influences the definition of robustness that best matches decision-makers' own preference. The definition of robustness, then, is an important factor affecting FRM decisions that must be explored fully to lead to an actionable decision process (Castelletti et al., 2016). This dissertation demonstrates an approach to robust optimization based on Eco-Engineering Decision Scaling (Poff et al., 2015), which leads to more consistently low-regret optimal and near-optimal solutions than both single-scenario optimization frameworks and past robust optimization framings in water resources management, in a multi-objective flood risk management adaptation decision in Chapter 4.

The second scientific challenge of flood management decision making under uncertainty is improving projections of future flood hazard and finding a credible characterization of flood hazard uncertainty. Common methods for assessing flood nonstationarity range from the purely statistical, in which observed trends are extrapolated into the future, to the physically-based, in which suites of models representing physical exchanges between the atmosphere, land surface, and subsurface are modelled to predict the theoretical impact of land use and climate changes on peak flow events. Purely statistical approaches to modelling future flood

hazard may be as simple as fitting a linear model to the logarithm of annual maximum streamflow, or conditioning probability distribution parameters on climate covariates. Physically-based flood hazard projections typically impose changes in temperature and precipitation indicated by downscaled and bias-corrected climate model projections on a weather time series which forces a hydrologic model, generating modelled river discharge time series from which future flood characteristics may be inferred. The failings of climate model projections of precipitation and temperature to represent the factors that strongly influence flood hazard are documented in the previous section. Purely statistical approaches are subject to high uncertainty in trend estimates and risk missing trends that exist at standard significance thresholds. Statistical flood hazard projection also may fail to herald changes that will occur in the future, whether this is an abrupt change in the probability distribution or a change in the probability distribution parameters' covariates. If land use is a covariate of the parameters, projections of land use change may be used to predict changes in flood hazard based on physical models of land surface processes. Climate covariates such as the phase of a synoptic atmospheric index (e.g. El Nino Southern Oscillation) may also serve as covariates of a flood hazard probability distribution and flood risk management plans may be developed for each phase of the index, but methods for projecting climate indices' frequency and severity into the future are unclear. The inclusion of parameter covariates in peak flow probability distributions provides the strongest platform for connection between statistical models of peak flow and physically-based justification of expected changes. However, to be useful for future planning there must be a credible method of forecasting the covariates' future variability. Chapter 6 of this dissertation presents a statistical framework for combining observed peak flow information and relationship to climate covariates with

model projections of the climate covariates into a probabilistic representation of future flood hazard that is useful for adaptation planning.

In addition to the disruption of traditional planning tools stemming from uncertain climate change, the water sector has also broadly acknowledged the potential negative impacts of water resources development on ecological systems. The ecological impacts of flood risk management vary highly according to the strategies employed to manage flood risk. Flood risk management measures employ two categories of actions: actions that reduce vulnerability to floods and actions that reduce the probability of high flow and inundation events. Economic pressures to develop floodplains often lead the latter category to dominate, typically in the form of flood control reservoirs, levees, dikes, polders, and drainage systems or detention storage. Flood control reservoirs operate by temporarily storing a portion of potential damaging flows, reducing the probability of high-magnitude floods and increasing the probability of low flows. The alteration to the flow regime caused by flood control reservoirs' operations may eliminate ecologically relevant fluctuations in river discharge (Webb et al., 2013). Levees physically block high-value land from floodwaters and do not alter river discharge, but may alter channel hydraulics and thus the discharge/stage relationship downstream, reducing the availability of floodplain habitat (Mays, 2011).

The former category of flood risk reduction strategy, reducing vulnerability to floods, includes such measures as improving flood forecasting, preparation, and evacuation; permanently moving development out of the floodplain through zoning restrictions, or increasing the resilience of structures in the floodplain to flood damage.

Nonstructural flood risk reduction measures have been promoted as generally less ecologically disruptive than structural measures (U.S. Water Resources Council,

2013). Because the first category of actions does not act on the river but on the contents of the floodplain, it is potentially less likely to divert lateral connectivity (e.g. bank overflow events, which could provide riparian species with life-cycle habitat) or upstream/downstream connectivity (which allows migratory species to access varying habitat types suited to various life cycle stages). Ecological impacts of federally funded flood risk management projects are assessed under the "Environmental Quality" account in the 1983 Principles and Guidelines for federal investment in water resources, but outside of meeting environmental regulations, ecological impacts do not play a part in determining project feasibility and are dominated by economic performance when comparing alternate designs. The monetization of ecosystem services is one method proposed to bring projects' ecological and economic impacts onto equal footing, but the monetary value of non-market ecosystem services is highly contentious and thus subject to low credibility among decision makers in practice (Guswa et al., 2014). Chapter 4 of this dissertation presents one framework for incorporating the monetary value of environmental flows' ecosystem services alongside climate uncertainty as an uncertain decision driver in FRM adaptation, facilitating compromise among stakeholders who hold disparate opinions regarding the importance of natural flows.

Recent updates to federal guidelines in the United States and other countries seek to address the weakness in past planning documents by requiring more rigorous consideration of water resources designs' potential ecological impacts, more holistic analysis of floodplain impacts of water resources projects, and more amelioration of those impacts than past requirements (U.S. Water Resources Council, 1983; U.S. Water Resources Council, 2013). The updated Principles and Requirements seek to further the union of economic development and ecological resilience as goals of equal

importance within water resources planning, but do not recommend specific procedures for doing so (U.S. Water Resources Council, 2013).

At the same time as the need for better representation of ecological impacts in water resources engineering grows, the ecological community is faced with the challenge of how to conserve and enhance ecological resilience under uncertain future climate. Past ecological management paradigms, which called to minimize deviation from ecological reference states (Poff et al., 1997), have been subsumed by the arguably irreversible changes in global climatology that are expected to take place in the future. Instead of artificially preserving historic ecosystem characteristics despite shifting regional climatology, ecological conservation moves toward a paradigm of managing ecosystems to maximize their adaptive capacity to shifting conditions. Management actions that support ecological adaptive capacity include enhancing connectivity, which allows species threatened by climate change or other sources of nonstationarity to move to habitats that better support them; and heterogeneity, which provides replacement habitat for displaced species within short distances (Folke et al., 2004). Achieving and sustaining these environmental characteristics is often hampered by the infrastructure we use to manage our water resources and support economic development (Postel and Richter, 2003; Richter et al., 2003). The function of freshwater and riparian ecological systems is intimately entangled with the strategies we choose to manage water resources for economic development.

Many methods for incorporating ecological impacts in water resources planning have been suggested (see Farber et al., 2002; Poff et al., 2015; Ramos et al., 2016), but the updated federal Principles and Requirements for Water Resources Investments in the U.S. has recommended none, only specified that monetizing ecosystem services alone is not sufficient and that official methods are yet to be established (U.S. Water

Resources Council, 2013). In order to effectively support ecological adaptation to changing conditions, the new methods for incorporating ecological impacts in water resources planning must account for the shifting climatological baseline and uncertainty in future climatology in addition to projects' ecological impacts under stationary conditions. Chapter 5 presents a decision framework that incorporates ecological impacts of FRM alongside FRM's economic impacts to meet both performance goals under climate uncertainty.

There is a need to manage for preservation of society's economic function and the function of ecological systems in the face of large-scale, uncertain change in regional climatology that challenges both systems. New decision-making frameworks and evaluation criteria are needed to successfully integrate management of water resources and ecological systems. The paired challenges of designing water resources systems for an uncertain climatic future and for better support of ecological systems presents the water sector with an opportunity to develop new planning frameworks that successfully integrate both goals. This dissertation presents several ways to adapt the decision scaling framework for application to optimization-based decision models that select ecologically resilient flood risk management strategies, which are introduced below and described in more detail in the following sections. Proposed decision frameworks and statistical frameworks are illustrated through application to the Iowa River flood management problem. The Iowa River and Iowa City flood adaptation context is described in more detail in Chapter 2 of this dissertation.

The first chapter of the dissertation expands on the question of how to integrate trend estimation and detection with water resources decision analysis. Adaptation decisions in water resources planning may be triggered by the detection of trends in hydrologic variables that affect system performance. A trend or shift in water-related statistics

may require a response to maintain adequate performance. However, trends in hydrologic variables are often difficult to identify at common significance thresholds (e.g. 5%) due to internal variability, low-frequency variability, long-term persistence, and the focus on events that are inherently rare such as floods or droughts. Statistical significance of a trend detection test represents the probability of rejecting the null hypothesis of no trend when a trend really exists. Statistical power of a trend test, which is often given much less consideration than statistical significance, represents the probability of rejecting the null hypothesis of no trend when a trend does exist. In the context of flood frequency analysis and decision-making, statistical significance is the probability of over preparing; statistical power is the probability of preparing appropriately, and the statistical power subtracted from one is the probability of under-preparing. In the context of decision-making, all outcomes are important. Rather than relying on standard, one-size-fits-all significance thresholds, we derive and present expressions for significance and power thresholds that reflect the expected value of acting based on the identification of a trend (rejecting the null hypothesis) and of failing to reject the null hypothesis. We then present, for a reference set of unaltered stream gages across the contiguous United States, the ratio of expected flood damage to prevention cost at which the expected costs of accepting and rejecting a trend in streamflow are equal. The significance and power thresholds adapt trend detection hypothesis testing so that it is useful in making decisions about flood risk management.

The second chapter of the dissertation expands on the first chapter by considering a wide range of possible trend magnitude in flood peaks through a risk-based flood risk management decision model designed to select infrastructure and options-based flood risk reduction measures with monetized ecological impacts alongside flood damages

and flood management costs within a regret-based decision framework. The adapted model allows managers to select flood management portfolios that perform best over a wide range of possible trends in peak flows and to identify the threshold value of ecosystem services provided by the fluvial flow regime that changes the flood risk measures included in the best portfolio. The framework facilitates compromise among stakeholders and decision makers who hold disparate opinions regarding the importance of ecological objectives.

The third dissertation chapter will explore robust optimization methods that select portfolios of flood risk management alternatives that perform well both economically and ecologically across a wide variety of potential climate changes. The robust optimization analysis is based on a decision scaling-based framing of robust optimization, but is performed under a representative selection of assumptions regarding the range of uncertain decision drivers and robustness definition to represent stakeholders' full range of values, beliefs, and risk preferences. The decision scaling-based robust robust optimization method illustrated in the chapter will avoid monetizing ecological impacts of the management alternatives, instead evaluating ecological performance according to a metric representing an ecologically relevant aspect of the flow regime. Mutual economic and ecologic performance of management plans may be measured using satisficing criteria, expected performance based on probabilistic representations of climate change as derived in the third chapter, or through other methods. Optimal and near-optimal FRM strategies found under each approach are compared *ex post* through regret in a climate stress test. This framework is intended to fill the need for robust flood risk management decision support tools that search directly for robust strategies rather than evaluate the performance of high-performing strategies *ex post*, incorporate stakeholders' diversity of values and risk

preferences in the tools that support the decision-making process, and demonstrate a more rigorous approach to the use of climate information in robust optimization.

When change in flood peaks is expected or suspected but evidence of change is lacking in the historic record, projections of hydroclimatological variables derived from climate models or expert judgment are often used to inform adaptation decisions. However, the methods for doing so in other water systems adaptation applications are not appropriate for developing projections of extreme streamflow and do not adequately quantify uncertainty in the resulting hydrologic projection. The fourth chapter of the dissertation presents a framework to develop probabilistic projections of flood trend based on atmospheric processes associated with extreme precipitation. The framework formally incorporates historic records of flood-correlated atmospheric indices with modelled projections of the indices using Bayes' Theorem in a way that reflects the level of uncertainty in the estimates of atmospheric index in each information source. The goal is to combine these complementary sources of climate information to generate a probabilistic representation of regional climate change that takes into account the degree of uncertainty in each information source. The resulting probabilistic projection of flood trend is derived from flood-producing meteorological processes and suitable for incorporation in decision frameworks which accommodate not only nonstationarity in peak flows, but also uncertainty in the trend in flood peaks.

The work presented in these four chapters seeks to provide examples of how to incorporate ecological impacts in flood risk management and planning, how to make flood adaptation decisions for multiple objectives under uncertainty in future flows, and how best to exploit currently available information sources to inform flood management decision frameworks.

CHAPTER 2

FLOOD RISK MANAGEMENT IN IOWA CITY

The flood frequency analysis techniques and decision frameworks presented in three out of four technical chapters are illustrated through applications to the Iowa City flood management system. Iowa City is located on the Iowa River, which is a tributary of the Mississippi River in the upper Midwestern United States. The Iowa River basin is located entirely in Iowa, which is characterized by a humid continental climate with annual average precipitation of 33.6 inches and snowfall common on an annual basis. Annual average temperature is between 45 and 50 degrees Fahrenheit throughout the basin.

Credibility of average temperature and precipitation in climate model projections and as drivers of flood hazard

Kunkel et al. [1994] and Coleman and Budikova [2010] found that the severe high flow events in 1993 and 2008 were caused by multi-day periods of high precipitation. Furthermore, operators have found Coralville Lake's flood control performance to be sensitive to 15-day flow and precipitation extremes. Short-term precipitation extremes such as the 15-day precipitation extreme are a likely important driver of flood hazard. We compare bias-corrected climate model hindcast simulations [Maurer et al., 2010] of 1- and 15-day precipitation extremes and annual average temperature with the same properties of observed precipitation and temperature [Slack et al., 1994] in the Iowa River basin (Figure 2.1) to assess credibility of simulation.
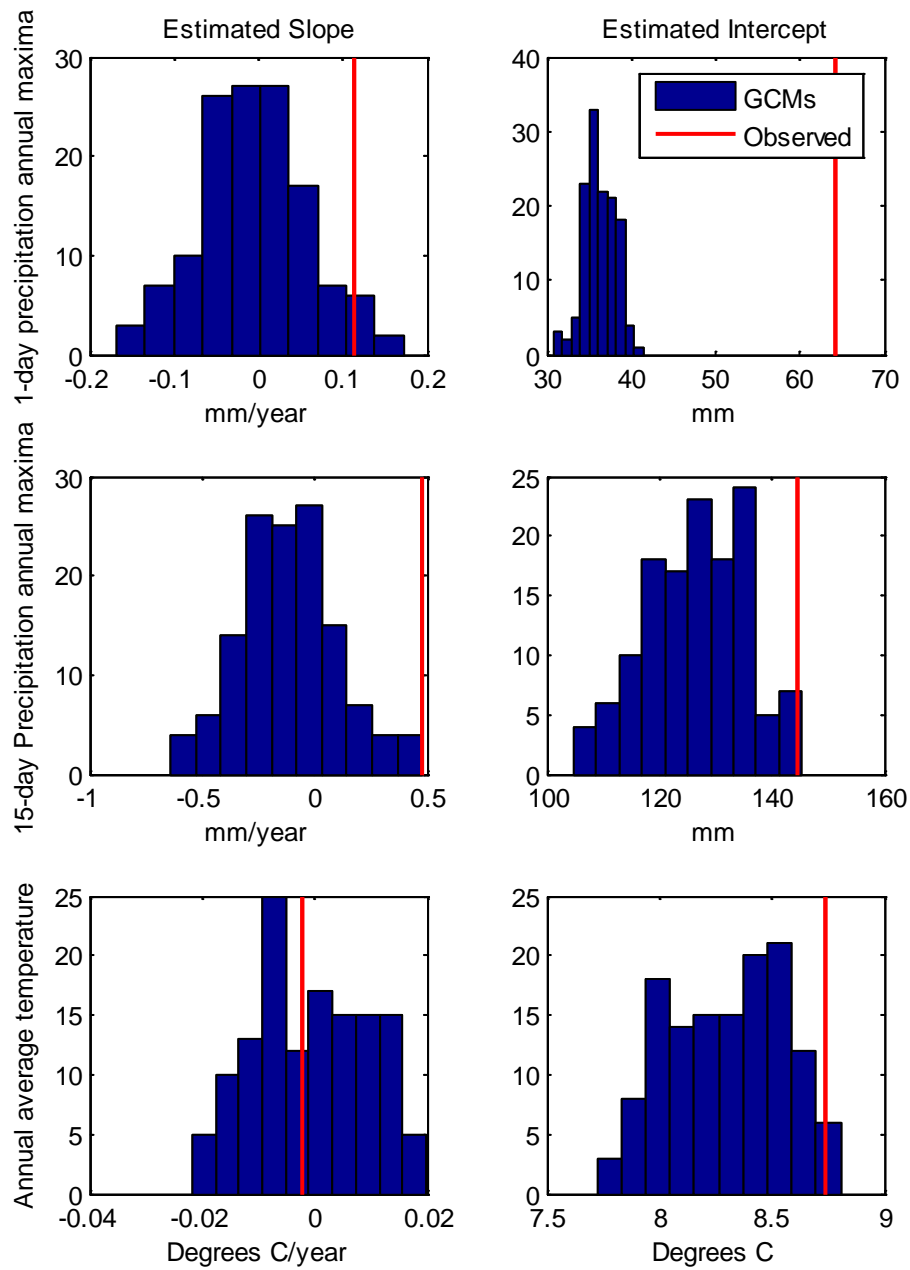
Figure 2.1: Climate model hindcast simulations' (histogram) and recorded (vertical red line) slope of linear trend (column 1) and 1950 intercept of linear trend (column 2) in one-day annual peak precipitation (row 1); annual peak 15-day precipitation sums (row 2); and annual average temperature (row 3).

We find that climate projections almost uniformly underestimate both trend and value of one-day and fifteen-day precipitation sums. This is consistent with climate models' well-documented "drizzle effect," in which simulated precipitation is erroneously frequent and low-intensity [Boberg et al., 2007]. Recorded annual average temperature is higher than modeled annual average temperature (Figure 2.1).

Basin hydrologic characteristics and flood history

The drainage area of the Iowa River below Coralville Dam, the location most relevant to Iowa City, is 3,115 square miles. The region outside Iowa City is dominated by agricultural production, primarily of corn used for livestock feed and ethanol production. The most severely damaging floods in Iowa City and Iowa River in general typically arise after multiple consecutive days of sustained, high-intensity rainfall in late spring or early summer (Kunkel et al. 1994, Coleman and Budikova, 2010, Robertson et al. 2011), with less severe flood occurring as a result of rain-on-snow events in early spring (Hydrosystems, 2013).
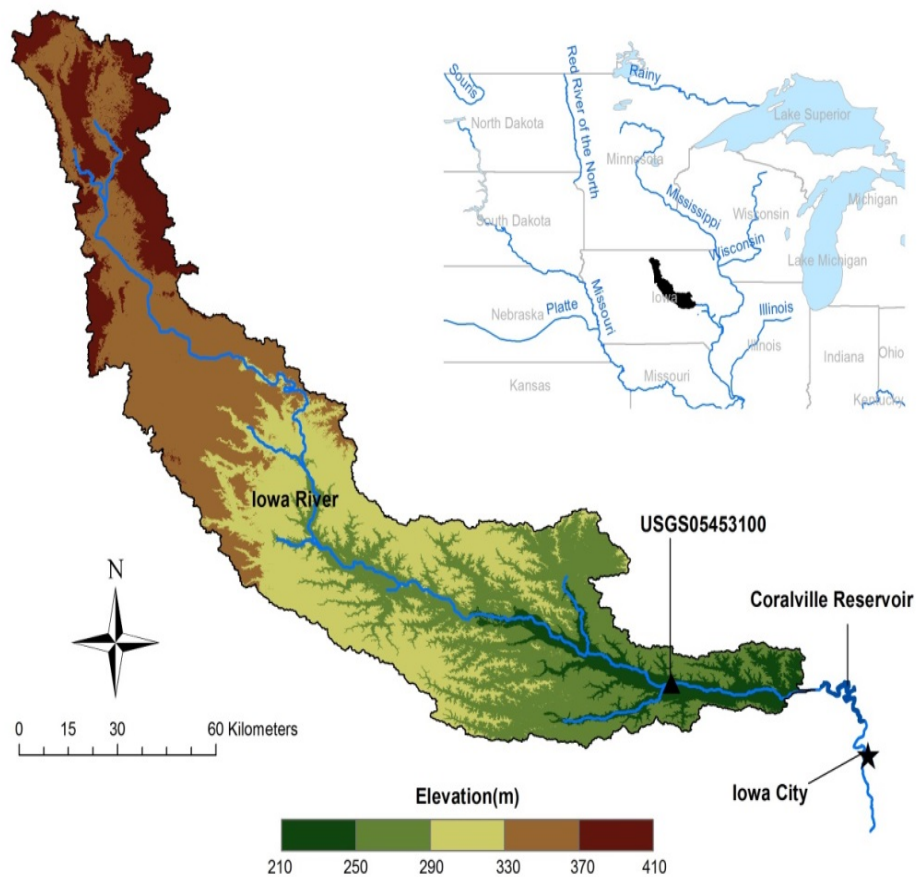
Figure 2.2: Iowa River basin, location within upper Midwestern United States, and major features of flood control system.

Flood management system

Parts of Iowa City are protected from floods by roughly 3000 linear feet of levees at 647 feet elevation, or three feet above the estimated 100-yr flood elevation. In some areas the levees are poorly maintained (McCollough, 2013). Levees were constructed primarily in the 1960s through 1970s, and many are privately owned and maintained. Coralville Reservoir, upstream of Iowa City on the Iowa River, was authorized by the Flood Control Act of 1938 and began regulating flow on the Iowa River in 1958. The reservoir is managed by the U.S. Army Corps of Engineers for flood control and recreation. Coralville Lake is kept at a low storage capacity so that it is able to

attenuate flood peaks on the Iowa River. Currently, the maximum permitted daily release from Coralville Lake is 10,000 cubic feet per second (cfs) during the winter, and 6,000 cfs during the growing season, to protect crops (largely corn) growing on fields downstream of Iowa City (USACE). The reservoir has come near spilling in June 2013, June 2014, and filled to the point of using the emergency spillway in June 2008 and 1993, causing substantial flood damage downstream. Peak flow during the 1993 Iowa River flood, which was part of widespread flooding in the upper Midwestern United States, was estimated at 35,600 cfs. The 2008 flood, also part of widespread Midwestern flooding distributed across multiple river basins, was estimated at 48,200 cfs peak discharge at the inflow to Coralville Reservoir (USGS gage 05453100- Iowa River at Marengo). The recent frequency of high flows raises questions about the presence of a trend, whether due to shifting climatology or other alterations to the basin's hydrological characteristics.

Aquatic and riparian ecosystem and biota

Iowa River's riparian zone is host to tree species such as cottonwoods (*Populus*), silver maple (*Acer saccharinum*), and oaks (*Quercus*), which are characteristic of frequently inundated floodplains (Littin and McVay, 2009). The presence of Coralville Lake inhibits longitudinal connectivity in the river network, while the presence of levees and flood-attenuating influence of Coralville lake's operations reduce the horizontal connectivity between the river and the floodplain by reducing the occurrence of peak flows, physically blocking flow from the floodplain during high flow events in areas protected by levees, and reducing floodplain inundation downstream of levees through hydraulic effects (Parrett et al., 1993; Mays, 2011). Despite the negative influence of disrupting longitudinal connectivity, Coralville Dam is regarded as a barrier structure in preventing the spread of prominent invasive Asian

Carp species (genus *Hypophthalmichthys*). Lake habitat created by the dam also promotes the spread of invasive zebra mussels, *Dreissena polymorpha*, by creating favorable habitat conditions for zebra mussels to outcompete native mussel species (Stoeckel et al., 2004).

Systems modeling framework

The flood frequency analysis and decision frameworks presented in this dissertation are based on a set of modelling tools which emulate the weather in the Iowa River basin, hydrologic response of the Iowa River basin, operations of Coralville Reservoir, hydraulics of the floodplain, and damage caused by flooding to Iowa City and the downstream agricultural fields. This set of modeling tools combines to form a system model which can be used to simulate the performance of the Iowa City flood management system under different adaptation actions and different climate scenarios. A stochastic weather generator (Steinschneider and Brown, 2014) creates ten 60-year stochastic time series of daily temperature and precipitation. Each of these series was adjusted statistically to reflect climate-changed average precipitation (ranging between a 30% decrease and a 30% increase at 10% intervals) and temperature (ranging between a 1 degree decrease and 5 degree increase at one degree intervals), resulting in a total of 49 combinations of temperature and precipitation changes for each of the ten stochastic series for a total of 490 time series. The ten stochastic runs are included to represent the effects of climate internal variability. Each of these stochastic, climate-altered time series is used to force a daily VIC model of the Iowa River to generate synthetic inflows to Coralville Reservoir (Xiang et al., 1994; Hydrosystems, 2013). A model constructed in MATLAB ® based on the Coralville Lake ResSim® U.S. Army Corps of Engineers operations model (Kipsch and Hurst, 2007) translates inflows to the reservoir into releases from the reservoir. A validation

plot for historical inflows to the reservoir between 1992 and 2010 is shown below in Figure 2.3 (Nash-Sutcliffe 0.71).
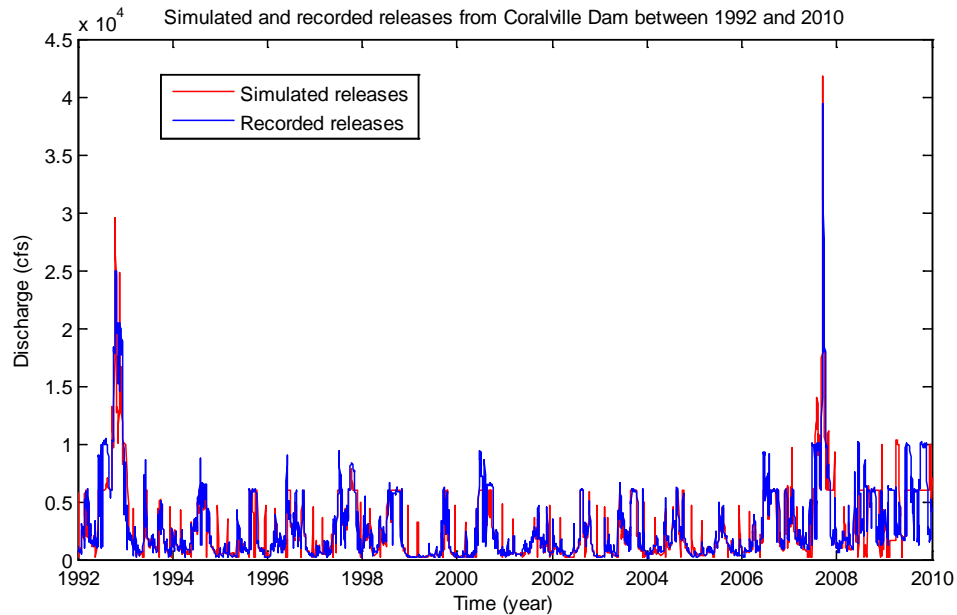
Figure 2.3: Validation for Coralville Reservoir operations model. Simulated releases based on recorded inflows between October 1, 1992 and September 30, 2010 are compared to recorded releases from the same period.

A hydraulic model of the floodplain developed in HEC-RAS by the US. Army Corps of Engineers translates releases from Coralville Lake into downstream floodplain area between Coralville Lake and river mile 46 (46 miles upstream of Iowa River's confluence with the Mississippi River). The HEC-RAS River Analysis System (Brunner, 2001) model was used to derive an empirical relationship between discharge and floodplain area downstream of Iowa City (Appendix A), which is an important proxy of the flood management system's ecological impact. The USACE Rock Island District also provided a table relating discharge, river stage, and damage to Iowa City and the downstream agricultural fields (Hydrosystems, 2013; U.S. Army

Corps of Engineers). Figure 2.4 shows the conceptual linkage between sub-models that form the larger system model.
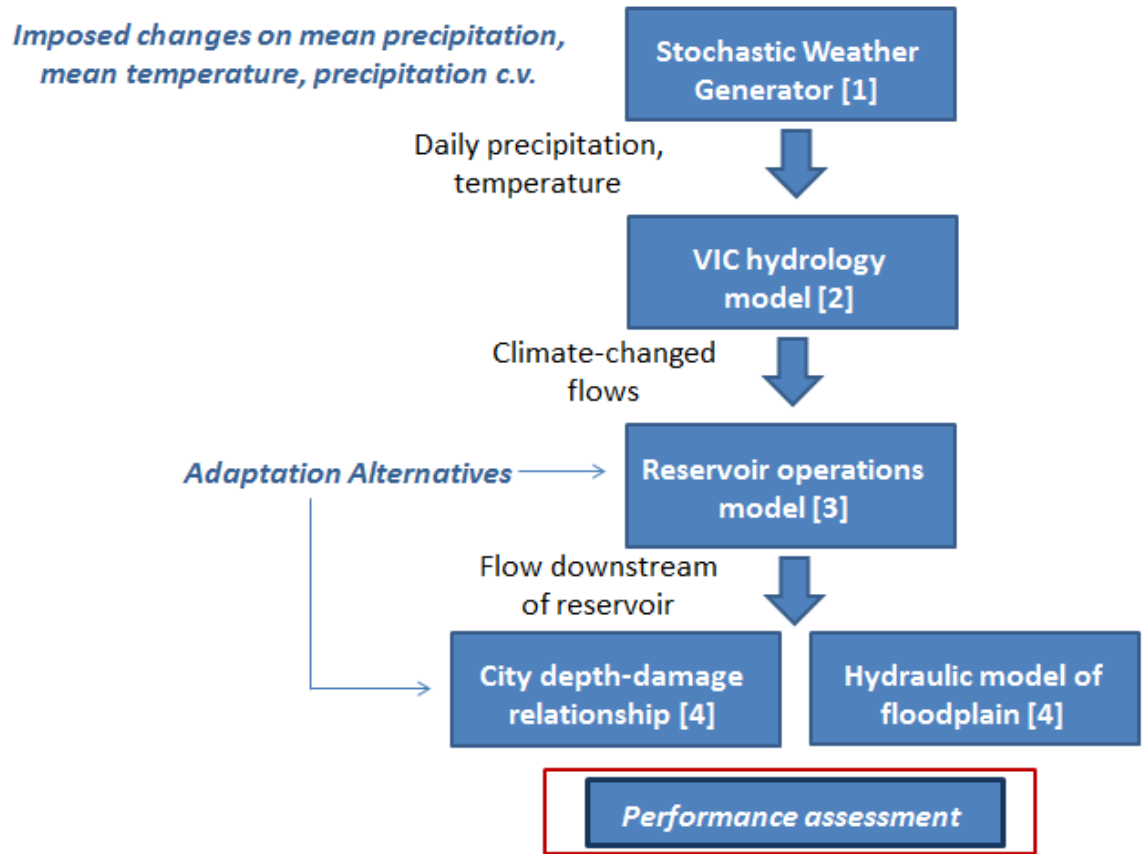
Figure 2.4: Iowa River flood management simulation model, with linkages shown between sub-models.

Economic impact of flood damages, particularly under nonstationary climate, and freshwater and riparian ecological resilience are among the greatest concerns regarding the performance of the Iowa River flood management system (USACE Report ER-1105-2-101). Priorities for the future include protecting against potentially increasing floods and reducing the impacts of hydraulic infrastructure on the river ecosystem to facilitate adaptation to potential changes in climate.

CHAPTER 3

A RISK-BASED STATISTICAL SIGNIFICANCE THRESHOLD FOR FLOOD HAZARD TREND DETECTION

Abstract

Statistically significant trends in hydrological variables motivate adaptation in water resources planning because future conditions are not expected to match the system's design conditions. However, trends in hydrologic variables are often difficult to identify with confidence at common significance thresholds (e.g. 5%) due to low-frequency variability, persistence and the rare nature of extreme events. Trend analysis of flood records increasingly evaluates the likelihood of both type I and type II errors. However, arbitrary significance thresholds ignore the consequences associated with either missing a real trend or accepting as real a nonexistent trend. Here we derive risk-based expressions for significance and power thresholds that reflect the expected value of adapting to a trend (based on rejecting the null hypothesis) and of taking no adaptive action (based on failing to reject the null hypothesis). Using a risk-based significance threshold in trend tests ensures the lower-risk course of action, enabling risk-based flood management decision making. We determine decision-specific significance thresholds for stylized flood adaptation decisions across the contiguous United States, and compare decisions based on the decision-specific significance threshold to decisions based on a standard significance threshold. Results show that typical uniformly applied statistical significance thresholds are likely to increase the risk of being under-prepared for possible trend in flood hazard while risk-based significance thresholds lead to a higher rate of rejecting the "no trend" null hypothesis. In addition, normalized damage:cost ratios are derived

that serve as thresholds on expected over-and under-preparation across the contiguous US.

Introduction

In flood risk assessment, trend detection hypothesis testing is often used to decide whether there is sufficient evidence of increasing flood risk to take adaptive action. The hypothesis test assumes a null hypothesis H_0 of "no trend", and then compares statistical evidence of that hypothesis to statistical evidence in favour of the alternative hypothesis H_A that there is a positive trend. The probability that no trend in fact exists based on the data must be sufficiently low to reject the null hypothesis. A one-sided hypothesis test, which assesses only the possibility that trend is greater than zero, is appropriate in the context of flood management decisions because decreasing flood peaks do not generally cause the same type of negative economic impacts as increasing flood peaks. The choice between whether to reject the null hypothesis is determined based on whether the trend's statistical significance, or likelihood of being observed by chance when there is in fact no trend, is below a certain threshold. Common values of the significance threshold which dictates whether the null hypothesis is rejected are 0.10 (10% chance of falsely rejecting the null hypothesis), 0.05, or 0.01 (e.g. Slater et al., 2015; Wobus et al., 2013).

Hypothesis testing is framed exclusively around trends' statistical significance to prevent mistaken claims that an effect exists when it does not exist, which is called "type I error." For example, Lettenmaier et al. (1994) assess streamflow trends across the continental US and display only areas which have statistically significant trends at the $p < 0.02$ level. Villarini et al. (2009) find inconclusive evidence of trends, change points, and long-term persistence in annual maxima based on a $p < 0.05$ in long stream gage records in the United States, but acknowledge that even these records

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may not be long enough to identify nonstationarity conclusively under standard significance criteria. Similarly, Robson (2002) concludes there is "no statistical evidence" of flood trend in UK flow records based on a 5% significance threshold applied to a number of trend models, but acknowledges the possibility that a trend exists but is not identified by the tests. This type of error is called a "type II error", while the error of rejecting the null hypothesis when no trend exists is called "type I error." While the focus on avoiding type I errors is a sensible philosophy in some contexts, it does not incorporate the consequences of failing to reject the null hypothesis of no trend when a trend actually exists, which may be severe in the context of flood frequency analysis and adaptation (Vogel et al., 2013).

Here we define risk as the expected loss due to an event. Flood frequency analysis tools and design standards can be updated to accommodate nonstationarity in flood hazard and hence minimize risk over time (e.g. Stedinger and Griffis, 2007; Rootzen and Katz, 2013; Salas and Obeysekara, 2014), but these innovations are not used if statistical analysis of the hydrologic time series fails to identify trend. Flood risk management planning presents a special challenge within water resources planning with respect to accounting for nonstationarity. Floods' rarity and variability makes detecting trends in extreme flows records through standard methods inherently difficult (Hirsch, 2011; Easterling et al., 1999). For example, Bowling et al. (2000)'s study of minimum detectable flow trends in western Washington, United States indicates that most river flow records may not be long enough to identify realistically-valued trends with typical statistical significance thresholds. Adaptation decisions based on the outcome of standard hypothesis tests may therefore leave society exposed to unanticipated risk.

To address the vulnerability of standard hypothesis tests to missing a trend, Rosner et al. (2014) apply a decision analytic framework to connect hypothesis testing with the contextual circumstances of water resources decisions by reframing the trend detection hypothesis test in terms of the expected consequences of both over- and under-preparing for a trend in flood peaks. The resulting expected regret decision rule uses statistical power and significance pragmatically in the context of an adaptation decision to maximize economic efficiency and minimize risk (Rosner et al., 2014).

We build on the Rosner et al. (2014) framework to develop an analytical expression of a significance threshold for trend detection equalizes the risk associated with over- and under-preparing. The threshold represents a point of indifference to taking action or not, where the expected value of the decision to take action is equal to the expected value of not acting to reduce flood risk. An adaptation choice that is based on the risk-based trend test will therefore be the least-risk choice out of the choices to adapt or not to adapt.

We compare the implications of both the standard and the proposed risk-based flood trend hypothesis testing framework for adaptation decisions across 1,702 continuous stream gage records located throughout the coterminous United States (Slack et al., 1992; Lins, 2012; Falcone et al., 2010). Specifically, we compare a hypothesis test that is based on a standard $p < 0.05$ significance threshold versus a hypothesis test based on a risk-based significance threshold, using a stylized relationship between trend, damage, and adaptation cost to calculate the risk-based significance threshold. Comparison is made in terms of the rate of rejecting the null hypothesis of no trend and the probability of type II errors. Because location-specific flood damage and adaptation cost data are not available for each gage across the US, we also show the theoretical ratio between flood trend damages and adaptation costs that must be

exceeded at each gage to provoke economically efficient adaptation based on a risk-based significance threshold. The findings show that the use of the risk-based significance threshold to support adaptation decisions leads to a lower likelihood of type II error at many gages and a higher rate of rejecting the "no trend" null hypothesis than the $p < 0.05$ significance threshold. Similarly, the value of the risk-based significance threshold varies widely among the gaged locations, as does the theoretical ratio between flood trend damage and adaptation cost necessary to provoke adaptive action.

Hypothesis testing and flood management decisions

Hypothesis tests for flood trend analysis are framed around the statistical significance of the trend in the peak flow record, α, which represents the probability that the trend is actually zero. However, hypothesis tests do not include the probability of making a type II error or missing a trend that actually does exist, which is is deemed β. The probability that the trend will be correctly identified, $(1 - \beta)$ is called the "power" of the test. Table 3.1 shows the different possible outcomes and the associated probability of each based on the results of a hypothesis test in flood frequency analysis and adaptation decision making.

Table 3.1: Hypothesis testing outcomes in the context of flood frequency analysis and flood risk management with associated probabilities (Rosner et al., 2014).

	H_o: No trend in floods	H_A: Positive trend in floods
Don't adapt	$1 - \alpha$	β
Adapt	α	$1 - \beta$

The possible errors resulting from decisions that are based on the outcome of hypothesis tests include (1) over-expenditure on adaptive measures if there is actually no trend (type 1 error) or (2) insufficient preparation for the increase in peak flows (type 2 error). Possible desirable outcomes include (1) correctly identifying and preparing for a trend that exists and (2) correctly avoiding unnecessary adaptation expenditure if there is no trend (Figure 3.1). Assuming preparatory costs prevent any damages, both branches of the decision tree where the correct preparatory action is taken have net zero consequences. Only branches with incorrect actions have negative consequences. If the decision context is known, the tester or decision maker may calculate the expected consequences of making each type of error using α, β, the cost of preparing for a flood trend C, and the damage D that would be caused by the flood trend without preparatory action (Rosner et al., 2014).
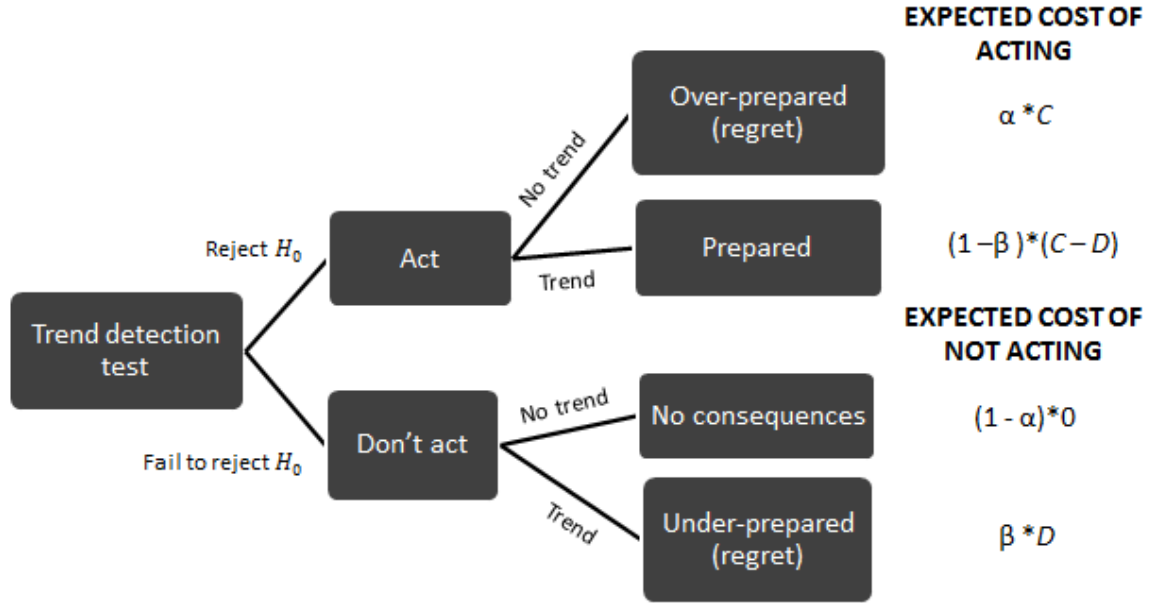
Figure 3.1: Decision tree for adaptation to trend in flood hazard (Rosner et al., 2014)

The choice between adapting and not adapting that maximizes economic efficiency depends on whether the expected cost of under-preparation, βD, is greater or lower than the expected cost of over-preparation, αC (Figure 1). We show how to determine the significance threshold that represents a point of indifference between over- and under-preparation and hence promotes the lower-risk choice.

Deriving a risk-based trend detection significance threshold

For a linear trend estimated in annual peak flows using ordinary least squares (OLS), we find the decision-specific significance threshold α_o that makes the expected cost of adaptation to the OLS trend equal to the expected damage without adaptation, and thus the decision maker indifferent. Vogel et al. (2011) found the log-normal distribution suitable to approximate annual peak flow at river gages across the contiguous US, Q, as log-normally distributed (Equation 3.1), and fit a linear trend in log-peak flows y through Ordinary Least Squares (OLS) (Equation 3.2). The variable

x represents the year in which a peak flow occurs. The OLS trend is estimated using n years of recorded peak flow.

$$\log(Q(x)) = y(x) \sim N(\beta_o + \beta_1 x, \sigma)$$

Equation 3.1

$$y_x = \beta_o + \beta_1 x + \varepsilon_x, \varepsilon \sim N(0, \sigma)$$

Equation 3.2

In null-hypothesis significance testing, the null hypothesis is that trend (β_1) is zero. The alternative hypothesis of a one-sided test is that trend is greater than zero. We choose a one-sided test because we are most concerned with increasing trend in the context of flood risk management. The significance of the estimated trend $\widehat{\beta_1}$, $\alpha_{\widehat{\beta_1}}$, represents the probability that β_1 is zero. In the context of traditional hypothesis testing, we reject the null hypothesis if $\alpha_{\widehat{\beta_1}}$ is sufficiently low, typically below some pre-designated threshold such as $\alpha < 0.05$.

Statistical power, β, depends on the significance threshold α, the variance of the OLS estimate $\widehat{\beta_1}$, $\widehat{\sigma_{\widehat{\beta_1}}}$, and the number of degrees of freedom in the OLS estimate of the linear model, which in this case is $n - 2$. We distinguish between the significance of the estimated trend in the data, $\alpha_{\widehat{\beta_1}}$, and the significance threshold set to decide whether to reject the null hypothesis of no trend, α. The significance $\alpha_{\widehat{\beta_1}}$ of the trend in the data depends on the Student's t parameter (Equation 3.3).

$$\alpha_{\widehat{\beta_1}} = 1 - F(t)$$

Equation 3.3

The student's t parameter can be estimated as the ratio between the estimated trend parameter and its' standard error (Equation 3.4).

$$t = \widehat{\beta_1}/\widehat{\sigma_{\widehat{\beta_1}}}$$

Equation 3.4

The failure to correctly reject the null hypothesis probability, $\beta_{\widehat{\beta_1}}$, depends on the trend's significance, $\alpha_{\widehat{\beta_1}}$, the data's variance, and the degrees of freedom in the model fit (Equation 3.5).

$$\beta_{\widehat{\beta_1}} = F\left(t_{(1-\alpha),(n-2)-}\ \widehat{\beta_1}/\widehat{\sigma_{\widehat{\beta_1}}}\right)$$

Equation 3.5

We designate the t statistic used to calculate $\beta_{\widehat{\beta_1}}$ as $t' = t_{(1-\alpha),(n-2)-}\ \widehat{\beta_1}/\widehat{\sigma_{\widehat{\beta_1}}}$. We seek a risk-based significance threshold $\alpha = \alpha_o$, so that the expected cost of falsely accepting the presence of a trend $C * \alpha_{\widehat{\beta_1}}$ is equal to the expected cost of falsely failing to identify a trend $* \beta_{\widehat{\beta_1}}|n, \alpha_o$. By using the risk-based significance threshold α_o as the decision criterion, the risk of over- and risk of under-preparing are equal (Equation 3.6).

$$C * \alpha_{\widehat{\beta_1}} = D * \beta_{\widehat{\beta_1}}|n, \alpha_o$$

Equation 3.6

By expressing the probability of a false positive $\alpha_{\widehat{\beta_1}}$ and probability of false negative $\beta_{\widehat{\beta_1}}|n, \alpha_o$ in terms of the trend estimate $\widehat{\beta_1}$, its standard error $\widehat{\sigma_{\widehat{\beta_1}}}$, the desired significance threshold α, and the degrees of freedom $n - 2$, Equation 3.6 becomes Equation 3.7.

$$C * (1 - F(\widehat{\beta_1}/\widehat{\sigma_{\widehat{\beta_1}}})) = D * F(t_{(1-\alpha),(n-2)-} \widehat{\beta_1}/\widehat{\sigma_{\widehat{\beta_1}}})$$

Equation 3.7

Solving Equation 3.7 for the risk-based significance threshold α_o yields the following expression (Equation 3.8):

$$\alpha_o = 1 - F\left[F'\left(\frac{C * [1 - F(\widehat{\beta_1}/\widehat{\sigma_{\widehat{\beta_1}}})]}{D}\right) + \frac{\widehat{\beta_1}}{\widehat{\sigma_{\widehat{\beta_1}}}}\right]$$

Equation 3.8

Equation 3.8 may be used to calculate a risk-based significance threshold for trend testing in any flood management decision, provided a record of peak flows exists, the cost of preparing for a trend is known, and the damages associated to fail to prepare for a trend can be estimated. If the significance $\alpha_{\widehat{\beta_1}}$ of the trend in the data is greater than α_o, no action should be taken to prepare for a trend. If significance is less than α_o, adaptation is the optimal decision.

Peak flow trends across the contiguous United States

Using the HCDN Gages II dataset of peak flow records across the United States (Slack et al., 1992; Lins, 2012), we estimate trend in expected annual peak flow using the linear models described by Equations 3.1 and 3.2. If the mean expected peak flow in year x is 10^{μ_x}, the fractional change in flow is $\Delta\mu = (10^{\mu_{2015}} - 10^{\mu_{1950}})/$

$10^{\mu_{1950}}$. Figure 3.2 shows the estimated change in expected peak flow, measured in cubic feet per second (cfs), between 1950 and 2015.
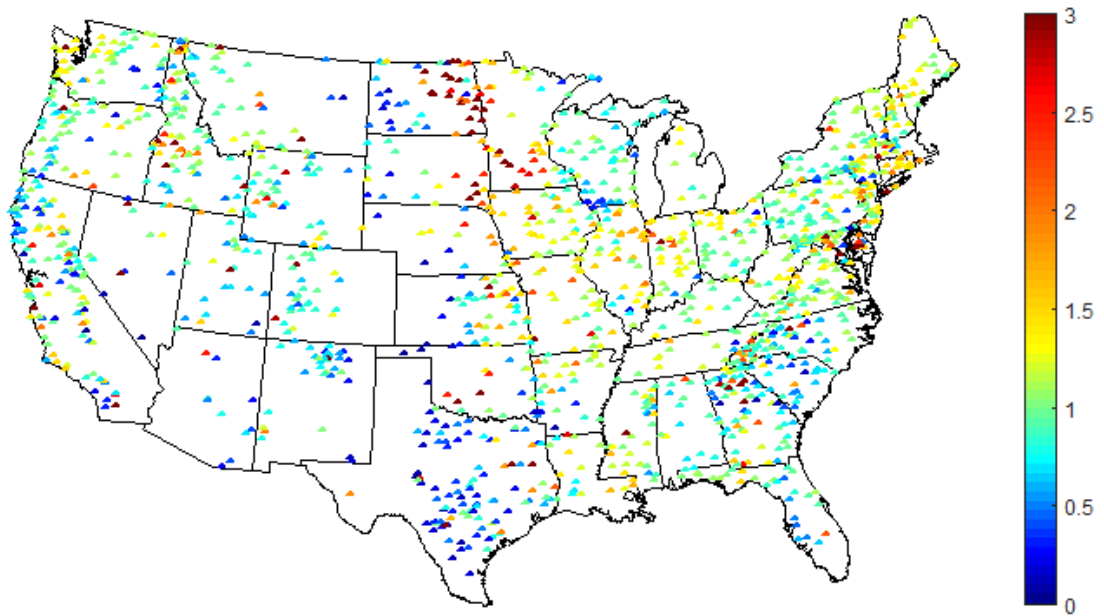
Figure 3.2: Expected change in expected annual peak flow between 1950 and 2015 (fraction). A change of "1" represents no change, a change of "2" represents a doubling in expected annual peak flow, and a change of "0.5" indicates average annual peak flow will become half of its current value by 2050 if the trend were to continue.

OLS estimates of trend, assuming flood peaks are log-normally distributed, indicates increases in annual peak flow across much of the northeast, eastern Midwest, and inland southeast of the United States. Decreases in annual peak flow are also expected across the north and south central United States, southeast, southwest, and some locations on the west coast. These spatial patterns are in agreement with the

analysis of flow magnification factors conducted by Vogel et al. (2011) for regulated, unregulated, and HCDN stream gages (Slack et al., 1993) across the continental US, and with Villarini et al. (2009)'s analysis of trends and change points in HCDN stream gages.

The probability of type I error at each gage and rate of rejecting the "no trend" null hypothesis in a hypothesis test based on a uniform $p < 0.05$ significance threshold are shown in Figure 3.3.
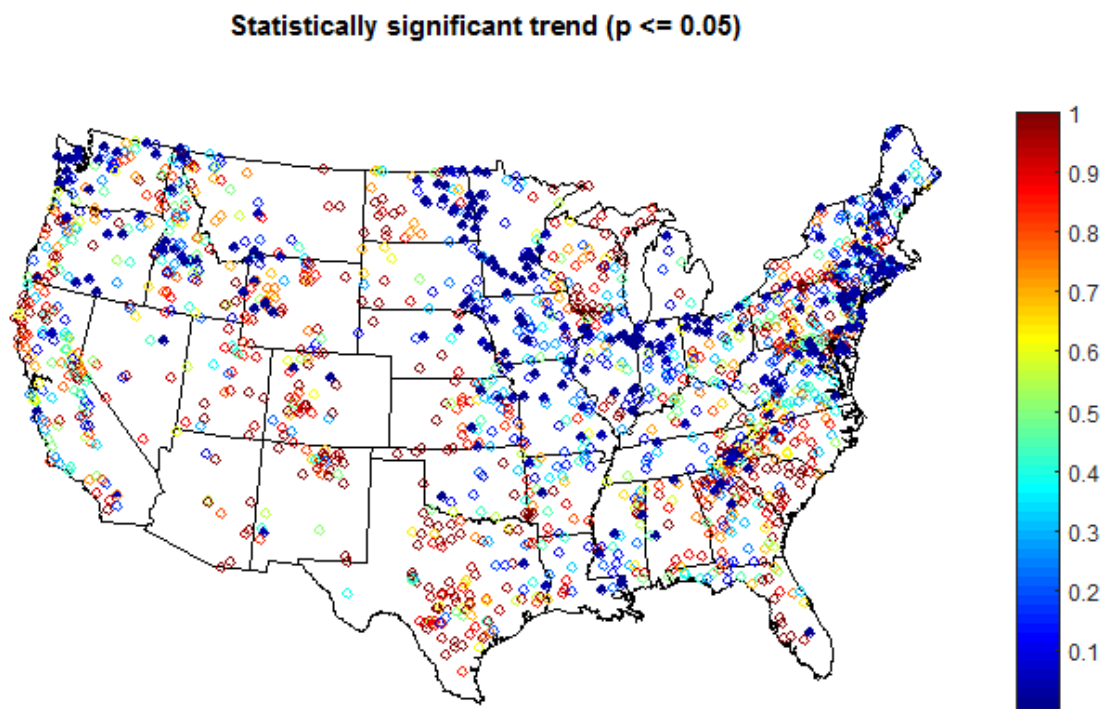
Figure 3.3: Probability of type I error at gages located across the contiguous US (color scale). Statistically significant trend in annual peaks ($p \leq 0.05$) indicated by filled blue markers.

While there is a high probability of type I error at many locations throughout the US, only 16% of gages' trends are statistically significant using the uniform $p < 0.05$ threshold, particularly at locations in the Pacific Northwest, Mississippi River basin, Northeast, and Appalachian Mountains. Few statistically significant trends exist in the Southwest, south central United States, or Southeast (Figure 3). This mimics the spatial pattern in annual peak flow change indicated by OLS trend fitting as shown in Figure 2. Areas with a high rate of statistically significant trend in Figure 3 correspond to areas with strongly positive trend in Figure 2 and with the analysis of flow magnification factors in the same stream gage data set by Vogel et al. (2011).

Statistical power (Equation 3.5) of trendsacross the United States is low when using a 5% significance threshold, leading to a high likelihood of under-preparation for trends that exist, except in parts of the Northwest and Great Lakes region (Figure 3.4).
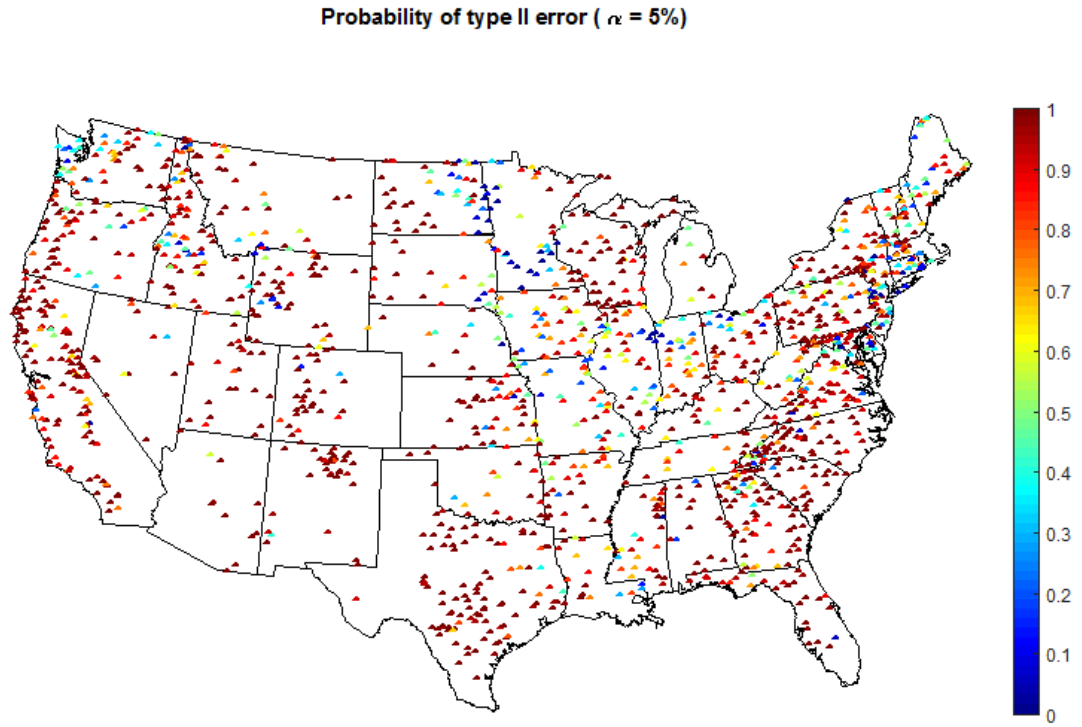
Figure 3.4: Probability of missing a trend in peak flows using a 5% statistical significance threshold (color scale).

In summary, few trends are found to be statistically significant using the typical 5% significance threshold and the likelihood of missing positive trends in peak flows is high at gages across the contiguous United States.

Risk-based trend detection across the contiguous United States

Finding the risk-based significance threshold α_o depends on the cost of adapting to a trend in peak flows and the damage that the increasing peak flows would cost without adaptation action. We approximate a representative ratio between adaptation cost and flood damage without adaptation based on the fractional expected increase in flood peaks between 1950 and 2015 based on the change in annual expected peak flows, $\Delta\mu = (10^{\mu_{2015}} - 10^{\mu_{1950}})/10^{\mu_{1950}}$ based on the OLS estimate of trend (Equation

3.9), in which the damage to cost ratio $D:C$ is proportional to the change in average annual peak flow across the planning period, $\Delta\mu$, multiplied by the proportionality constant γ. The formulation shown in Equation 3.9 assumes damage:cost ratio to be 1 when $\Delta\mu = 0$ (and there is no trend), but increase proportional to $\Delta\mu$ as the change in expected annual peak flow increases over time.

$$\frac{D}{C} = \frac{1 + \gamma * \Delta\mu}{1}$$

Equation 3.9

The stylized trend-dependent damage/cost relationship framed in Equation 3.9 assumes the damage caused by floods will be less than the cost of adaptation if flood peaks are actually decreasing, and damage caused by floods without adaptation will be greater than the cost of adapting under increasing flood peaks. This ratio assumes a fixed cost of adaptation, reflecting a single pre-specified adaptation plan regardless of trend magnitude, but that damages associated with trend are directly proportional to trend magnitude. This simplification is necessary to illustrate the generalized impacts of a risk-based statistical significance threshold, but does not reflect the highly individual relationship between flooding and damage in each adaptation decision. Implicit in this formula is the assumption that adaptation will prevent flood damages regardless of the strength of the trend. We do not consider the case in which flood trend is so strong that adaptation efforts are ineffective. Adaptation expenditures in the case of a correctly identified trend are assumed to completely prevent increased damage costs due to flood trend (see Figure 3.1). The change in expected annual peak flow $\Delta\mu$ is unitless as it is expressed in terms of relative change, so the proportionality constant γ is unitless. This approximation of damage to cost ratio is shown for the contiguous US in Figure 3.5 using a proportionality constant of $\gamma = 3$, so that the

expected damages caused by the flood change by 3% relative to the costs of adaptation for every 1% change in mean annual peak flow between 1950 and 2015 (Equation 3.9).
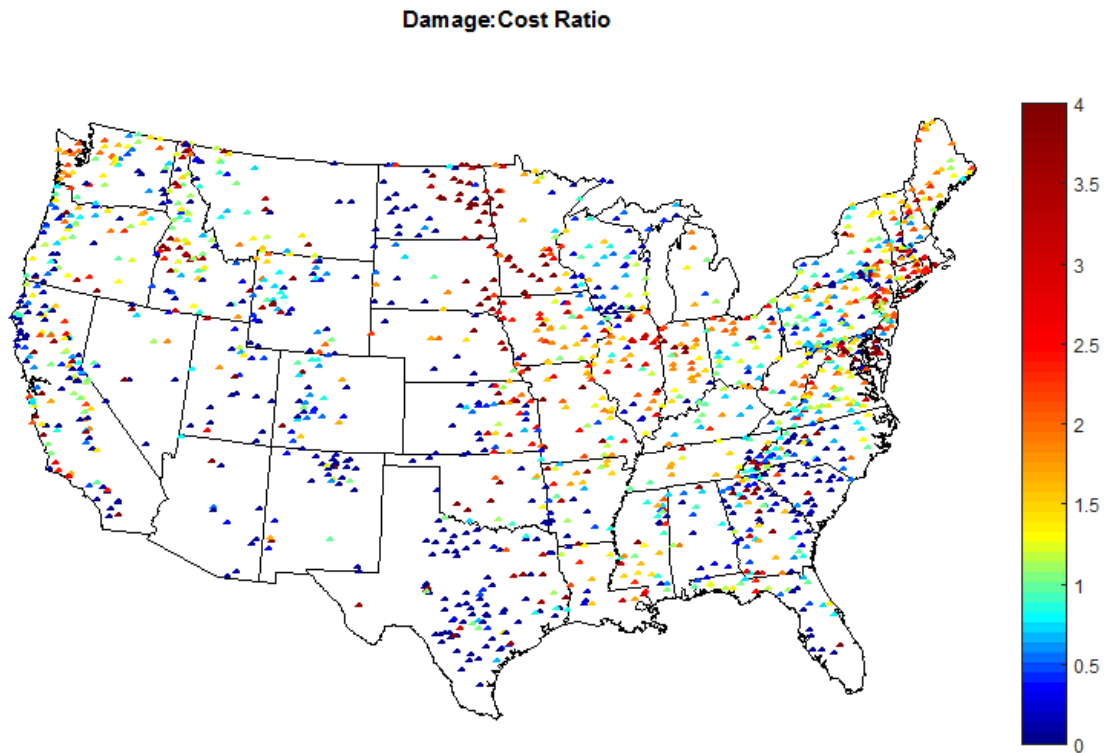
Damage:Cost Ratio

Figure 3.5: Stylized ratio between damages expected if no adaptation measures are taken and cost of preparing for the OLS trend if no trend materializes.

Damage to cost ratio as shown here, in essence, is a benefit:cost ratio because, in the case of a trend in flood peaks, costs spent on adaptation are assumed to completely eliminate damage cost. In the case of correctly identifying and adapting to a trend, the damages that would have occurred without adaptation expenditure become avoided costs, which can also be described as benefits. The ratio is stylized and does not represent actual potential damages of flood trends across the US; estimating damages caused by a trend at each gage and designing adaptation projects for each trend would

be impractical. Furthermore, many gages may measure points on a river where changes in peak flow are unlikely to affect any population.

Figure 3.3 shows the significance of OLS trend in peak flow across the US. Stylized damage:cost ratios (Equation 3.9) complete the information necessary to determine decision-specific significance thresholds across the contiguous US. Figure 3.6 shows the risk-based significance threshold (Equation 3.8) based on the stylized damage:cost ratios (Equation 3.9) calculated from OLS trend at each gage.

Risk-based p-value threshold
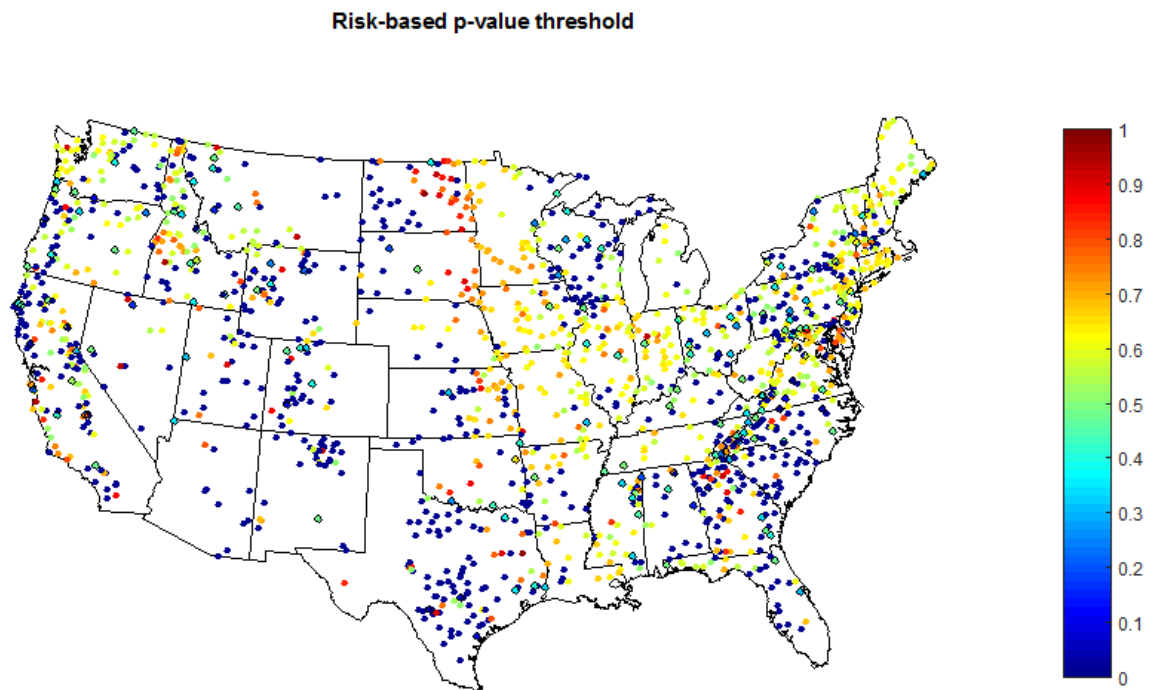
Figure 3.6: Decision-specific significance threshold to equalize expected under- and over-preparation regret for potential trend in flood peaks. Stations that do not exhibit statistically significant trend according to the risk-based threshold highlighted with black circle.

The decision-specific significance threshold is higher than typical standard values (e.g. 0.10, 0.05) at a majority of gages across the United States. Allowing a higher

probability of less strict significance threshold is recommended at gages where the estimated trend slope is strong, such as the Great Lakes region (see Figure 3.1). This reduces the probability of failing to recognize and prepare for a potentially damaging trend (Figure 3.7).

Probability of type II error (risk-based alpha)
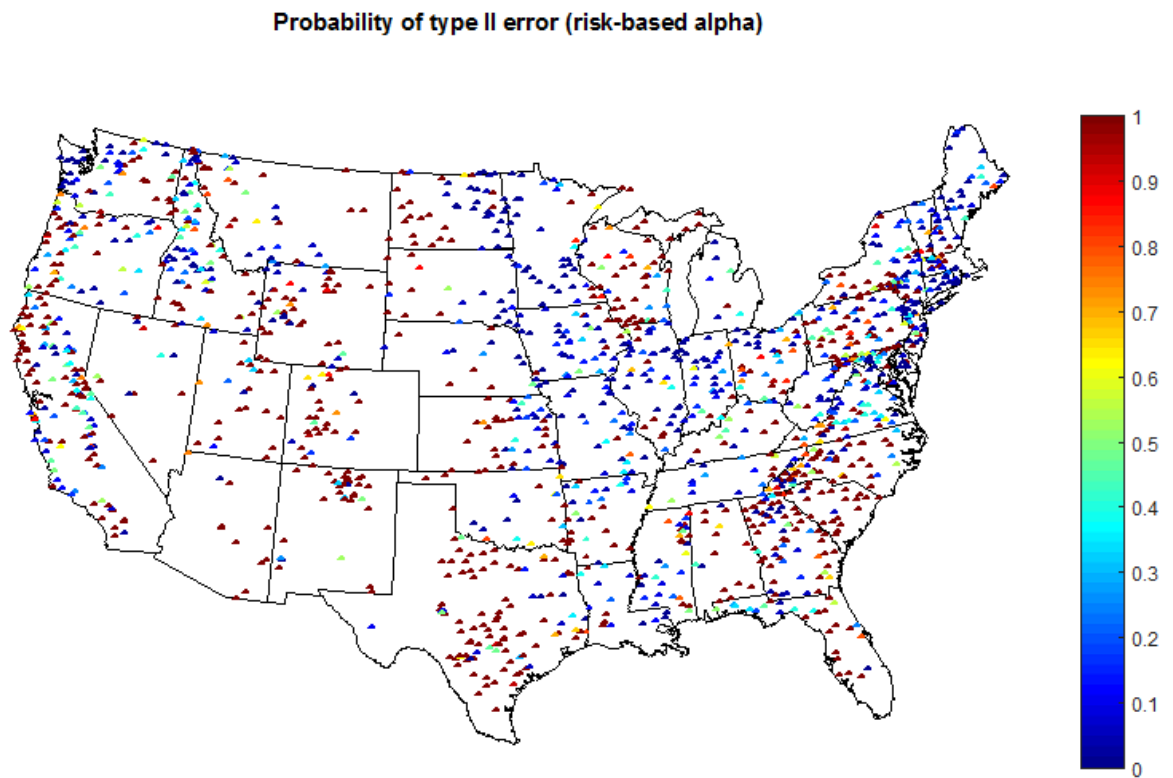
Figure 3.7: Probability of missing a true trend using risk-based significance threshold and stylized damage:cost ratio.

The probability of missing a trend in flood peaks using the risk-based significance threshold in the hypothesis test is low at many gages with increasing trend, but high in regions where floods' estimated trend is negative, such as the Great Plains and Texas region and a corridor down the Appalachian Mountains. The probability of missing a trend using the equal-risk significance threshold is generally much lower than the probability of missing the trend using the 5% significance threshold (Figure 3.5).

Lastly, 85% of gages' peak flows are accepted to be trending using the equal-risk significance threshold (Figure 3.8) as opposed to 16% of gages using the 5% significance threshold (Figure 3.3).

Statistically significant trend (risk-based threshold)
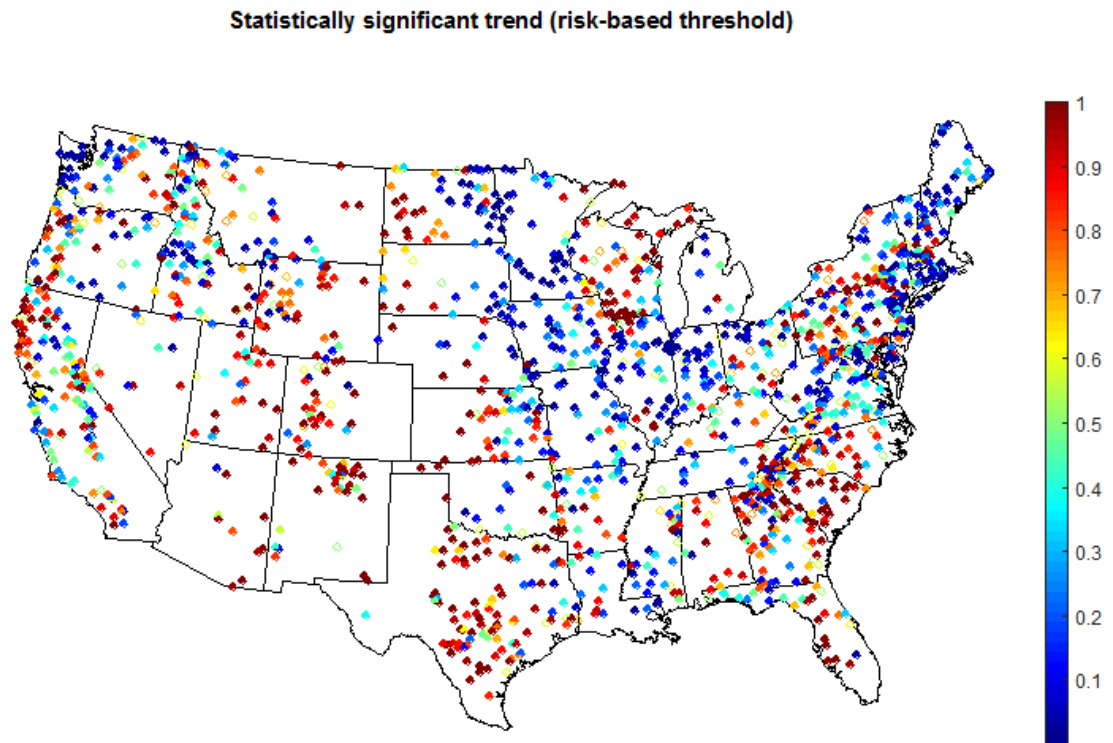
Figure 3.8: Probability of type I error at gages located across the contiguous US based on the risk-based significance threshold (color scale). Statistically significant trend in annual peaks (risk-based significance threshold) indicated by filled markers.

While comparing Figure 3.8 with Figure 3.3 demonstrates conceptually the difference in recommended action taken using a risk-based significance threshold rather than a uniform standard statistical significance threshold, the damage to cost ratios used to determine the significance thresholds are not based on real damage and cost data because adaptation projects and flood vulnerability are not known for each gage used

in this analysis. These data would be available in the context of actually planning an adaptation project. However, to the degree the ratios are realistic, Figure 3.8 suggests that relying on standard statistical significance for trend detection may leave society exposed to more trend related risk than is warranted.

An alternative way to communicate the implications of a decision-specific significance threshold across the contiguous US is to show the hypothetical damage:cost ratio that would equalize the expected costs of over- and under-preparation, given the actual significance of the OLS trend in each gage's record and the probability of type II error using the actual trend significance as the decision threshold (Figure 3.9).

Damage:Cost Ratio to equalize expected cost of over- and under-preparation
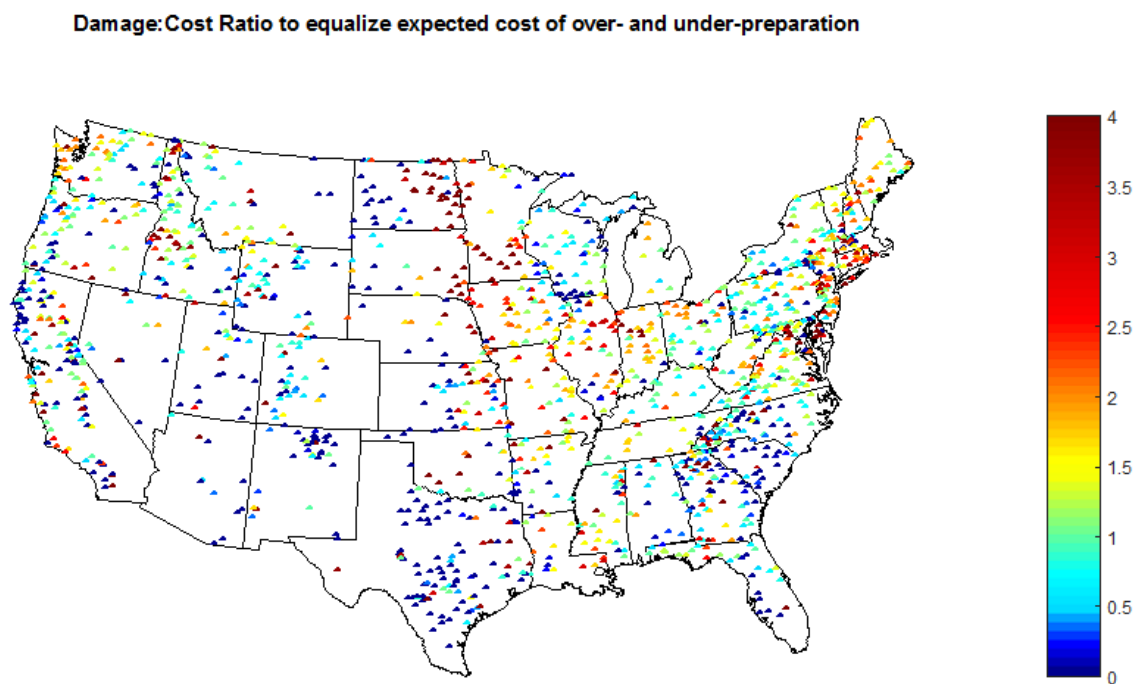
Figure 3.9: Damage:Cost ratio that equalizes expected over- and under-preparing costs calculated using the actual statistical significance of the OLS trend in the gage record as the decision threshold.

Figure 3.9 demonstrates that, for adaptation to be economically justified, expected damage associated with a trend in flood peaks must be only slightly higher than adaptation cost in the central region of the US, more than double adaptation cost in parts of the upper Midwest, less than double at a number of gages throughout the Appalachian Mountains, and mixed along the west coast. This corresponds to damages that are far greater than adaptation costs when the trend significance is low, and damage only slightly greater than adaptation costs when trend significance is high. Most importantly, the difference between damage caused by a trend and cost of adapting to that trend at which adaptation becomes economically justified varies widely by gage, from only a slight difference in cost between damage and adaptation cost to damage multiple times higher than adaptation cost. Decisions based on a uniform significance threshold can therefore be inferred to result in many instances of over- or under-preparation.

Conclusions

As demonstrated by Rosner et al. (2014), flood risk management decisions based on comparing the likelihood and impacts of under- and over-prepared scenarios support higher economic efficiency than decisions based on arbitrary standardized significance thresholds. Using records of unimpacted streamflow throughout the contiguous United States, we use stylized flood trend adaptation decisions to support a comparison between the results of trend detection hypothesis tests based on uniform versus risk-based significance thresholds. The risk-based significance thresholds lead to a higher rate of rejecting the null hypothesis of no trend, and increase the likelihood the hypothesis test will reject the null hypothesis in the case that a trend exists at many stations. Based on the statistical significance of trends in un-impacted stream gages distributed across the continental US, the ratio between damage caused by the

trend and cost of adaptation varies widely across stream gages. This demonstrates the inefficiency of a uniform significance threshold and the benefits of adopting a risk-based significance threshold to support flood nonstationarity adaptation decisions.

The risk-based significance threshold presented in this paper is designed for a simplified decision context that includes only two adaptation scenarios: take no action (assuming no trend) and implementing a single adaptation portfolio (designed to mitigate the OLS trend). Trend scenarios other than the best-fit OLS trend are possible and their consequences should be evaluated in a more complete decision context. The risk-based significance threshold is also designed under the simplifying assumption of log-normally distributed annual peak flows with a temporal trend, and illustrated through a network of stream gages that were selected for minimum anthropogenic influence. In practice, it is rare to develop an flood management project in an area without anthropogenic influence; furthermore, peak flows may also follow a distribution other than log-normal such as Log-Pearson type III; increases in the frequency of high flow events such as would be represented in a partial duration series modelling technique should also be considered. Trends other than a linear temporal trend in expected annual peak flow should be evaluated in practice; for example, change points related to land cover change, regulation, or other causes; low-frequency variability related to continental-scale atmospheric indices; or other non-linear trends. Alternative derivations of the equal expected-cost significance threshold would be useful in the case of these other probability distributions of peak flow. Future changes in local climatology may also cause flood peaks to change in ways not predicted by the data. A method to include other forecasts of future flood behaviour in the analysis would expand the applicability of the analysis.

The simplified risk-based hypothesis-testing framework presented in this paper provides an example of how uncertainty in flood frequency analysis may be integrated with decision support tools. The result is improved economic efficiency of adaptation decisions. A standard significance threshold of $p < 0.05$ is economically sub-optimal and should be higher in many cases.

CHAPTER 4

A DECISION ANALYTIC MODEL FOR FLOOD RISK MANAGEMENT

WITH UNCERTAIN FLOOD HAZARD TREND

Abstract

Decision frameworks and design standards for flood risk management systems may be updated to accommodate nonstationarity through a time-dependent peak flow probability distribution, but operationalizing such a nonstationary FRM framework is hampered by high uncertainty in the relationship between peak flows and time. Likewise, the ecological impacts of flood management are frequently rendered externalities in economic FRM impact assessments because quantifying the monetary value of ecosystem services is challenging and controversial. To address these challenges for ecologically sustainable FRM under climate uncertainty, we modify the decision scaling framework for climate risk assessment to accommodate uncertainty in the nonstationary probability distribution of peak flows and a range of potential values of ecosystem services which would be impacted by both FRM actions and climate change. The proposed nonstationary decision model (NDM) is illustrated through an example application on the Iowa River, which demonstrates that the decision scaling based NDM elicits more economically and ecologically risk-averse FRM strategies than standard established decision frameworks.

Introduction

Lack of stationarity in long-term climate statistics is a growing concern in floodplain management and planning, challenging past design paradigms that assume stationary hydrology. Even under the stationarity assumption, low-frequency design flows are difficult to estimate with confidence because of their rarity in the record (Stedinger,

1983). The potential lack of stationarity therefore further confounds flood management designs and decisions (Kiem et al., 2003; Armstrong et al., 2012; Brown, 2010; Obeysekara and Salas, 2014). Flood risk management frameworks that accommodate nonstationary hydrology must also accommodate uncertainty in future flood behavior.

In practice, flood management systems are designed to withstand a flow a specific recurrence interval (e.g. the 100-year flood) that has a known probability of exceedance (Benson, 1968; U.S. Army Corps of Engineers, 1995; Dawdy et al., 2012). After designs' compliance with regulations is established, designs which provide the prescribed degree of protection are assessed according to their economic efficiency (Water Resources Council, 1983). This approach neglects the impacts of floods more severe than the design flow and risks diminishing reliability under hydroclimatic change (Brown 2011; Gersonius, 2013). Proposed methods to support nonstationary design floods such as reliability "expiration dates" or flow "magnification factors" (Vogel et al., 2011) rely on a known future evolution of flood probability which is difficult to determine for rare or extreme events due to the limited number of events from which the probability distribution can be estimated and the high variability in the events' magnitude.

To address nonstationarity, FRM design frameworks may adopt nonstationary flood probabilities derived analytically or through stochastic simulation (e.g. Zhu et al., 2007; Woodward et al., 2014; Hasnoot et al., 2013; Borgomeo et al., 2015). Stedinger & Griffis (2011) propose a general framework for addressing trends in flood hazard by treating the flood frequency probability distribution's parameters as functions of time, which fits neatly into a risk-based assessment framework. Implementing the

method, however, relies on determining what trend or function of time is appropriate in each flood management context. The question of how to estimate trends in flood hazard is crucial to maintaining protection standards under either the design flow or risk-based flood management paradigm.

Flood hazard trend may be characterized in one of several ways. First, flood hazard may be assumed to be stationary. This approach best resembles the current default practice in floodplain planning. Second, a trend model estimates the relationship between recorded flood peaks and time (e.g. Robson et al., 1998; Lins and Slack, 1999; O'Brien and Burn, 2014; Rosner et al., 2014). Lastly, climate projections from global or regional models may be used to forecast flood hazard changes over the planning horizon (e.g. Zhu et al., 2007; Madsen et al., 2014; Smith et al., 2013).

The first method of assuming stationary flood hazard is no longer considered sufficient without exploring other possibilities (Milly et al., 2008). In current practice, the possibility of a non-zero trend in flood hazard is explored before reverting to the stationarity assumption if no statistically significant trend is found (US Water Resources Council, 1983). Trend detection typically relies on the second method: estimating trend from observed flow records. Trend detection in flood records is hampered by low-frequency variability (Lettenmaier and Burges, 1978; Cohn and Lins, 2005; Armstrong et al., 2013), the inherently rare and variable nature of extreme events, and the possibility that a change in flood behavior has occurred too recently to detect or may change without warning (Reeves et al., 2007; Obeysekera & Salas, 2013). The work of Wilby (2006) and Morin (2011) indicates that trends in extreme events such as high river discharge or heavy precipitation must either be very strong or be maintained longer than many existing flow records to be detected at common

statistical significance thresholds (e.g. p < 0.05). In summary, most trends in flood peaks are likely to be missed by common trend detection methods. Whether a statistically significant trend is detected or not, the trend estimate is uncertain and the decision maker should understand the consequences of a range of possible trends under alternative flood management plans before selecting a plan for implementation.

The last method of estimating flood trend from climate projections may provide insight into future flood behavior that is not foreshadowed by the historic record. Flood trend estimates using this method rely on either a single climate model projection (e.g. Zhu et al., 2007) or an ensemble of projections (e.g. Cloke et al., 2013; Borgomeo et al., 2014), which may be combined into a probabilistic projection using one of the many methods for combining ensembles of projected climate changes, such as Knutti et al. (2002), Tebaldi & Knutti (2007), Sexton et al. (2011), and others. Climate models provide projections of meteorological variables, but do not provide discharge projections at the scale of flood management and planning. To estimate flow trend from climate projections, the analyst must translate climate variables of interest projected by the model(s) (e.g. monthly precipitation, mean temperature) into river discharge using a hydrologic model. Climate models are not skillful in simulating the mechanisms which cause short-term, high-intensity precipitation, the primary driver of floods: Global Climate Models (GCMs) are too spatially coarse to represent the relative processes, while Regional Climate Models (RCMs) have been shown to exhibit significant biases in short-term precipitation (Lenderink & van Meijgaard, 2008; Allan & Soden, 2008; Smith et al., 2014). Neither GCMs nor RCMs are skillful in reproducing precipitation trend (Krakauer & Frekete, 2014), and GCMs in particular are modeled on too coarse a spatial scale to represent the very processes which create intense precipitation (Stainforth et al. 2007a,b). Flood trend estimated

from climate model projections does not present decision makers with the full range of possible future conditions due to model interdependence (Sunyer et al., 2014), uncertainty in model inputs (e.g. emissions pathways), and uncertainty derived from model structure (Lopez et al., 2006; Ylhaisi et al., 2013). Furthermore, it is difficult to prescribe a trend to flood peaks in a given area based on climate projections alone because, though climate change due to increased atmospheric greenhouse gas concentration is often cited as a cause of increasingly severe floods, it is not always clear whether climate change or other shifts such as land use change lead to a trend or shift in floods at a particular location (Hirsch & Ryberg, 2012; Vogel et al., 2011). Regional land use development paths and a variety of social, economic, and environmental drivers may affect flood characteristics (Lambin et al., 2000, Lonigro & Polemio, 2015; Owrangi et al., 2014). In summary, each method of estimating trend in flood hazard yields significant uncertainty and high possibility of bias or missing an extant trend. With no reliable method of estimating flood trend, flood management decision frameworks must be altered to accommodate uncertainty in future hydrologic behavior.

In light of uncertain future hydrologic conditions, investment in infrastructure-based flood risk interventions is increasingly viewed with skepticism in favor of more flexible interventions (Woodward et al., 2014; US Water Resources Council, 2013). When it is not clear whether floods will become more frequent or severe in the future, a costly infrastructure-based intervention such as a large flood control dam or system of levees may be proposed to maximize the degree of protection. If floods then become less rather than more frequent or severe, the cost of infrastructure cannot be recovered, and the flood control structure remains as a permanent feature of the landscape that continually inhibits the lateral and/or longitudinal connectivity of the

riparian network, affects sediment dynamics and reshapes or eliminates riparian habitat (Poff et al., 1997; Bunn et al., 2002). Current stationary or nonstationary flood management frameworks that do not explicitly incorporate flood trend uncertainty risk regret when evaluating infrastructure-based flood control designs. Options-based interventions provide an alternative to irreversible infrastructure investments by enhancing the flexibility of flood management systems, allowing them to quickly react to potential hydrological change. Options-based flood management interventions require an initial investment of time and funds to secure the option of taking and paying for an action later if that action becomes necessary. Examples of options-based flood management interventions might include purchasing land on which one may later decide to build levees, establishing an agreement with landowners to pay to store flood water on low-value land in emergencies, or investing in sand bags and sand bag storage facilities for use in flood emergencies. This type of flexible strategy may postpone infrastructure projects until it is clear that new infrastructure is truly necessary, avoid infrastructure-based flood management interventions entirely, or increase the efficiency of emergency response. Using an options-based strategy to reduce flood risk avoids the irreversible lump-sum payment that is characteristic of infrastructure interventions. Instead, payments are made in smaller installments, once at the beginning of the planning period and afterwards in response to major flow events. This avoids financial regret and may also avoid regret in terms of degraded riparian habitat. The most appropriate balance of permanent and options-based flood management interventions in any given case depends on the vulnerability of the region to changes in flood hazard, the long-term forecast of changes in flood hazard in that area, and the degree of confidence in the aforementioned forecast.

The issue of flood management interventions' potential regret under different flood hazard scenarios elicits another question, namely how to combine interventions' economic consequences with the environmental consequences that make up another important type of regret. Current decision analysis frameworks are primarily driven by economic impacts of floods and flood management, leaving social or ecological impacts as secondary when evaluating alternative plans (e.g. Water Resources Council, 1983). As a result, flood management decisions often affect ecosystems' resilience, or ability to return to a stable state after disruption (Gunderson, 2000). Estimating ecological impacts' monetary value is one way among many alternatives to address environmental impacts in the planning stages by moving impacts to the same units as the primary decision metric of cost (e.g. Gergel et al., 2002; Webb et al., 2013; de Groot et al., 2002), but it is difficult to execute, subject to controversy (Gómez-Baggethun & Ruiz-Pérez, 2011), and not well established in water resources engineering (Chan et al., 2012). Despite these challenges, flood management decision models must reflect and include riparian ecosystems' value to generate acceptable decisions and avoid regret. We have already established that effective flood management decision frameworks must accommodate hydroclimatic uncertainty; they must also first consider impacts on the riparian ecosystem and second accommodate uncertainty in the value of the riparian ecosystem.

In this paper we propose a robust decision model based on the conceptual foundation of decision scaling (Brown et al., 2012) for evaluating flood risk reduction strategies under uncertainty according to their net cost in terms of flood damage, management costs, and impacts on the riparian ecosystem. Decision scaling is a bottom up decision support tool developed for water resources planning that explores the vulnerability of water resources systems to a broad variety of potential climate changes, bringing in *ex*

post long-range forecasts of change to inform the decision. Decision scaling has been applied to decisions concerning lake level management (Moody & Brown, 2012) and other water resources applications (e.g. Brown et al., 2012; Whateley et al., 2014; Steinschneider et al., 2015), and a similar approach (Prudhomme et al., 2010) has been applied to flood risk management decisions. The robust flood management decision model uses optimization to select the minimum-cost strategy under each of a range of flood trend values and values of the riparian ecosystem. Based on the optimal strategies, the decision model selects a robust management strategy that is found optimal under the broadest range of trends or under the trends considered most likely to occur based on external trend estimates, adapting to the decision maker's degree of credibility in these estimates. If more than one strategy is optimal over an equivalent range of trend or considered comparably likely to occur, each competing strategy's regret across the full range of trend may be used to select a flood management strategy. The paper develops the decision model in mathematical terms and then illustrates its application to a stylized example flood risk management decision on the Iowa River.

Decision Model Structure

To develop a robust decision model that reflects uncertainty in the evolution of flood hazard, we expand Lund's (2002) risk-based decision model for selecting plans composed of permanent and/or options-based flood management interventions by (1) adding time-dependence to the probability distribution of annual peak flow, (2) defining a decision rule to select a flood management strategy from among candidate strategies that are each least-cost under some assumed trend in flood hazard, and (3) including a term representing ecological benefits in the cost calculation. Table 1 describes the symbology and parameters used throughout the analysis.

Linear programming optimization model

We define net cost as the combination of flood damage, fixed cost of managing flood risk, and flood-responsive cost of managing flood risk (Equation 4.1). Linear programming optimization minimizes expected net cost by combining permanent and options-based flood management interventions (x_I, x_O), which are the problem's decision variables (Table 4.1).

Table 4.1: List and description of mathematical terms and symbols in nonstationary flood risk management decision model

Symbol	Type	Description
x_I	Decision variable	Infrastructure-based flood intervention
x_O	Decision variable	Options-based flood intervention
s	Parameter	Annual flood peak (log-cfs)
t	Parameter	Year after beginning of planning period
β_μ	Parameter	Trend in mean of annual flood distribution
$D(s|x_I, x_O)$	Function	Damages associated with flood *s*
$P(s|t, \beta_\mu)$	Probability distribution function	Probability distribution of annual peak 1-day flow
$P(\beta_\mu)$	Probability distribution function	Probability distribution of trend in the mean of *P(s)*

$C_f(x_I)$	Function	Cost of implementing decision variable x_I
$C_o(x_O|s)$	Function	Cost of implementing decision variable x_O
$B_{eco}(x_I, x_O)$	Function	Ecological benefit function of the decision variables

Both flood damage and management costs are based on the relationship between peak flow magnitude and either damage caused by flooding or cost incurred at the time of flooding to manage peak flow. Management actions x_I, x_O affect the flow/damage relationship by changing the damage that corresponds to certain levels of peak flow. We refer to flood damages, infrastructure cost, and emergency flood management cost together as "net cost" (Equation 1). The expected annual cost is calculated using a probability-weighted average of flow-damage and flow-responsive management costs based on the probability distribution of annual flood peaks, *P(s)*. The cost of infrastructure-based actions does not depend on the probability distribution of peak flows, but the expected damages and the expected cost of implementing options-based flood management are functions of peak flow magnitudes and their corresponding probabilities. The decision model outlined in Lund (2002) minimizes net cost across a stationary probability distribution of annual peak flow, $P(s)$ (Equation 4.1).

$$Z = \left(D(s|x_I, x_O) * P(s) + C_f(x_I) + C_o(x_O|s) * P(s) \right) \forall s$$

Equation 4.1

It is simple to adapt Lund (2002)'s decision model, which minimizes net cost for a stationary flood hazard, to account for nonstationary flood hazard by treating the

parameters of *P(s)* as functions of time as suggested by Stedinger and Griffis (2011).

Equation 4.2 shows an example of the Stedinger and Griffis (2011) framework for the

log-normal distribution of annual peak flow with a nonstationary mean parameter.

$$P(s) \sim LN(\mu(t), \sigma)$$

Equation 4.2

The relationship between the mean of the distribution of time may take many possible

forms, but we assume a linear trend for simplicity (Equation 4.3).

$$\mu(t) = \mu_o + \beta_\mu t$$

Equation 4.3

With a linearly trending mean parameter of the probability distribution of peak log-

flows, the net cost calculation outlined in Equation 1 becomes as follows (Equation

4.4). The probability of peak log-flow *s* depends on time and the magnitude of trend,

β_μ, and the optimal combination of management interventions x_I^*, x_O^* depends on

the value of β_μ.

$$Z_{\beta_\mu} = \left[\left(D(s|x_I, x_O) * P(s|t, \beta_\mu) + C_f(x_I) + C_o(x_O|s) * P(s|t, \beta_\mu) \right) \right] \forall s, \forall t$$

Equation 4.4

Incorporating ecological impacts in the cost calculation

To incorporate ecological impacts into the risk-based problem formulation, we

monetize deviation from the natural flow regime so that it can be included in the

economic valuation of the decision's net cost (Vogel et al., 2007). This requires an

assessment of the current flood management system's effect on the natural flow

regime, $C_{eco}(status\ quo)$, as well as predicting new management strategies' effect on the natural flow regime $C_{eco}(x_I,\ x_O)$. Ecological benefits of a new management strategy $B_{eco}(x_I,\ x_O)$ are calculated as the deviation between the ecological impact of a proposed new flood management plan and the status quo management plan (Equation 4.5).

$$B_{eco}(x_O) = C_{eco}(x_I,\ x_O) - C_{eco}(status\ quo).$$

Equation 4.5

The value of management strategies' ecological impacts is interpreted into the decision model as a second term. The parameter γ_2, which represents the value of the natural flow regime, is varied to test the sensitivity of the decision to this parameter. The coefficients γ_1 and γ_2 represent the weights on monetized values (management costs and flood damage) and ecological goods and services respectively. When flood damage and management cost are monetized, γ_1 should assume a value of $1 while γ_2 represents the base value of the natural flow regime. Management plans' ecological benefits for the hydrologic and hydraulic characteristics of the floodplain is calculated as an index C_{eco} between 0 and 1, representing the extent of alterations. C_{eco} is the sum of $P_{s,inflow} - P_{s,downstream}$ $\forall s$ under the management plan, determined by the decision variables x_I and x_O.

The nonstationary decision model based on Equation 4 therefore becomes Equation 4.6.

$$Z = \left[\gamma_1 \left(D(s|x_I, x_O) * P(s|t, \beta_\mu) + C_f(x_I) + C_o(x_O|s) * P(s|t, \beta_\mu) \right) - \right.$$

$$\left. \gamma_2 \left(B_{eco}(x_I, x_O) \right) \right] \; \forall s, \forall t,.$$

Equation 4.6

Decision scaling framework and decision rules

Because existing trend estimation methods yield uncertain estimates of β_μ and the value of the flow regime γ_2 may be unclear, we repeat the optimization analysis using Equation 6 as the objective function over a wide range of possible values for β_μ and γ_2. This yields a set of candidate strategies $[x_{I,\beta_\mu,\gamma_2}{}^*, x_{O,\beta_\mu,\gamma_2}{}^*]$, each of which is optimal under some combination of β_μ and γ_2. The decision rule recommends the most robust management strategy according to its range of optimality and/or potential regret. Regret is the difference in outcome between the best possible decision for the state of the world (here, the value of β_μ) and the decision that was actually made. In the context of this decision model, the regret associated with a candidate solution $x_I{}^*, x_O{}^*$ selected under any β_μ under a specific flood trend β_μ is calculated in Equation 4.7. If $x_I{}^*, x_O{}^*$ was selected under the value of β_μ that occurs, regret is zero.

$$R(x_I, x_O | \beta_\mu, \gamma_2) = Z_{\beta_\mu,}(x_I{}^*, x_O{}^*) - Z^*_{\beta_\mu,}$$

Equation 4.7

The decision-maker chooses the set of interventions $[x_I{}^{**} \quad x_O{}^{**}]$ with the lowest maximum regret R_{min} when compared over all possible states of the world (Equation 4.8).

$$R_{min}(x_I**, x_O**) = min\big[max\big[R(x_I, x_O|\beta_\mu, \gamma_2)\big]\,\forall\beta_\mu, \forall\gamma_2\big]$$

Equation 4.8

The rule used to select a decision depends on the decision maker's degree of confidence in the value of γ_2 and the value of β_μ.

To a decision maker fairly confident in the value of the natural flow regime, or at least confident that the value of the natural flow regime lies in some range of values narrow enough to ignore most values of γ_2 used in the analysis, we recommend one of these candidate strategies based on the range of β_μ over which each candidate strategy is optimal. The strategy that is optimal over the broadest range of β_μ in the neighborhood of the decision maker's estimate of γ_2 should be implemented. In cases where long-range climate forecasts are available to provide some estimate of β_μ, the decision maker may choose to prioritize the management strategy that is optimal in the region where β_μ is projected to be according to their confidence in the estimate(s) of β_μ. If no single strategy is optimal over a broad range of β_μ or the projected range of β_μ, the competing management strategies' potential regret should be compared across the full range of β_μ values considered in the analysis. The strategy with the least maximum regret across β_μ should be implemented.

Lastly, the decision maker may be certain of neither γ_2 or β_μ. In this case, the strategy with least maximum regret across all values of γ_2 and β_μ should be implemented (Equation 4.8).

Iowa *City Flood Protection Example*

The decision model is applied to a stylized example based on flood risk management on the Iowa River at Iowa City, IA (Figure 4.1). Existing flood control structures in the area include levees protecting the city and Coralville Lake, a flood control reservoir operated by the United States Army Corps of Engineers (USACE). Recent severe flood events on the Iowa River have challenged the existing flood management system's ability to reduce damage. The floods have raised concerns about whether the hydrologic regime has changed and new management interventions are needed to maintain the previous standard of protection or the floods are merely a product of climate internal variability and do not imply a long-term trend in flood peaks. The decision model is used to select a flood management strategy that minimizes expected net cost under an uncertain change in flood peak behaviour. The strategy includes combinations of levee expansion, an infrastructure-based management intervention, with reservoir re-operation, an options-based flood risk management intervention.
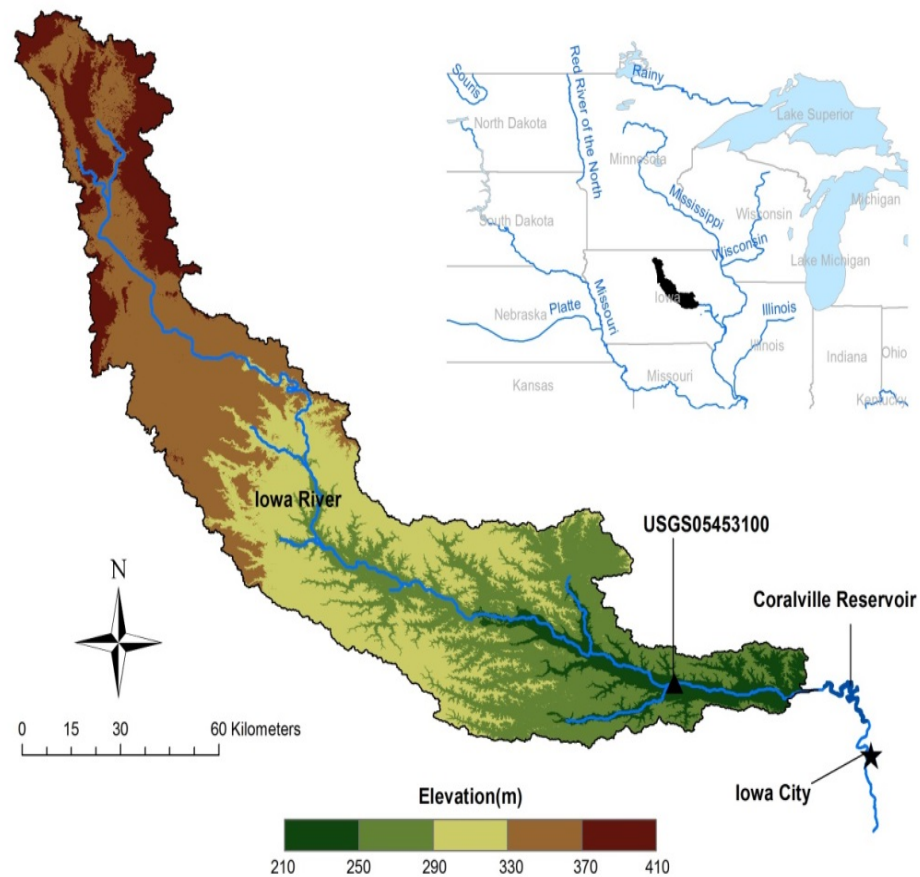
Figure 4.1: Iowa River watershed schematic with Coralville Reservoir and Iowa City.

Sungwook Wi, 2013

Alternative flood management actions

The decision includes two decision variables: 1) increasing the allowable reservoir releases during the growing season, which would increase flood detention storage in the reservoir but also inundate some downstream farmers and 2) raising existing levees by some height between 0 and 6 feet. The first management intervention represents a flexible approach with little principle cost that would mitigate flood damage to a limited degree would be inadequate if there were a long-term increase in flood peaks. Reservoir re-operation represents an option because an initial agreement is needed between the affected farmers, the reservoir operators, and the Iowa City

administration to secure the option of making higher releases; but the high releases are only made if high inflows are anticipated and the reservoir must empty quickly to clear space in the reservoir for an incoming flood. This operations change would allow Coralville Lake to release more water during normal operations and preserve a larger empty storage volume to attenuate flood peaks. Farmers affected by the high releases would also be compensated for crop loss resulting from the new operations. Changing reservoir operations would not require building any new infrastructure, but would require negotiation and planning.

The second management intervention represents a permanent structural measure that would result in regret if there were no upward trend in flood peaks and the recent flooding were due to natural variability. Raising existing levees or installing new levees would be expensive, difficult to reverse, and potentially unnecessary should flood peaks not increase in the future. However, expanding the levee system protecting Iowa City and the other towns downstream of Coralville Lake would reduce damage to the downtown area associated with higher releases from the reservoir during emergency flood operations. If properly maintained, expanded levees would reduce flood risk in currently vulnerable areas. While levees do not alter downstream discharge, they do alter the stage/discharge relationship, so that river flows in contact with the levee flow faster and higher through the levee, and lower and slower over the downstream floodplain (Mays, 2011). In this stylized example, levee presence was assumed for simplicity to lower affected downstream stages by 10% without investigating the relationship through a hydraulic model. For each levee height increase, change in probability of being in each stage category (identical to discharge categories for flood events) was used to determine that levee change's ecological impact. Unlike the addition of agricultural risk sharing, raising levees

removes the downstream stage probability distribution further from a natural flow regime.

Iowa River decision model formulation

A simulation model of the Coralville Lake operating policy and information about the current downstream stage/damage relationship (U. S. Army Corps of Engineers; Table 1) were used to determine the effects of each management action on expected downstream damages and flow regime (Table 2). Ecological benefits associated with increasing levee height are calculated using the downstream stage probability distribution rather than the discharge probability distribution.

The model was parameterized as a linear programming problem which was solved in MATLAB ® using the interior point algorithm. A simulation model of Coralville Reservoir operations was used in conjunction with a 56-year time series of daily inflows to the reservoir from the USGS gage 05453100 at Marengo and discharge-stage stage-damage relationships developed by the U.S. Army Corps of Engineers to estimate the expected reduction in damages due to altering reservoir operations for each 10% relaxation in the growing season limit on maximum release. Changes in flow probability resulting from re-operation were translated to reductions in damages by linearly regressing expected annual damage on relaxation in growing season maximum release. Due to the nonlinear effects of raising levees on damage and the flow regime, levee height was piecewise-linearized into six separate decision variables.

Translating climate projections into flood trend estimates

We estimate projected flood trend β_μ using downscaled CMIP3 and CMIP5 climate model projections of mean precipitation and temperature (Maurer et al., 2007) over

the Iowa River watershed for the twenty years centered on 2050, the end of the planning period. Projected changes in temperature and precipitation translated through a weather generator (Steinschneider and Brown, 2014) and a Variable Infiltration Capacity (VIC) hydrologic model (Xiang et al., 1994) of the Iowa River basin (Hydrosystems, 2013) provide realizations of climate-altered river flows. Trend parameter $\beta_{\mu,proj}$ for each realization is estimated by assuming the historic stationary peak flow probability distribution transitions linearly from the historic mean $\widehat{\mu_{hist}}$ to the projected mean $\widehat{\mu_{proj}}$ between the midpoint of the historic record, $\frac{t_o - t_{current}}{2}$, and the end of the planning period, t_{end} (Equation 4.9).

$$\beta_{\mu,proj} = \frac{\widehat{\mu_{proj}} - \widehat{\mu_{hist}}}{t_{end} - (\frac{t_o - t_{current}}{2})}$$

Equation 4.9

The set of $\beta_{\mu,proj}$ estimated from projected changes in mean temperature and precipitation are used alongside a regression-based estimate of trend from peak flow observations to inform the choice of flood management strategy.

Given the uncertainty in future flooding, the decision model described above is used to understand which combinations of the management interventions are optimal for alternate future states defined by the flood trend parameter. As the value of the flood trend parameter is not known, we find what strategy is optimal under each of a range of possible values of the flood trend parameter. Optimization is repeated using $0, $1,000,000, $2,500,000, $5,000,000, $7,500,000, and $10,000,000 as γ_2 and using values ranging between -0.04 log-cfs/year and 0.04 log-cfs/year as β_μ.

Scenario-Optimal Iowa River Flood Management Strategies

The least-cost decision chosen across a variety of values of the natural flow regime and trends β_μ are displayed in Figure 4.2a. Under increasing trend scenarios, the optimal set of actions includes raising levees. Because of the mutual economic and ecological benefits of raising the growing season maximum release limit from Coralville Reservoir, this is part of the optimal FRM strategy under all scenarios except the lowest values of the natural flow regime and strongest decreasing trend scenarios (Figure 4.2a)
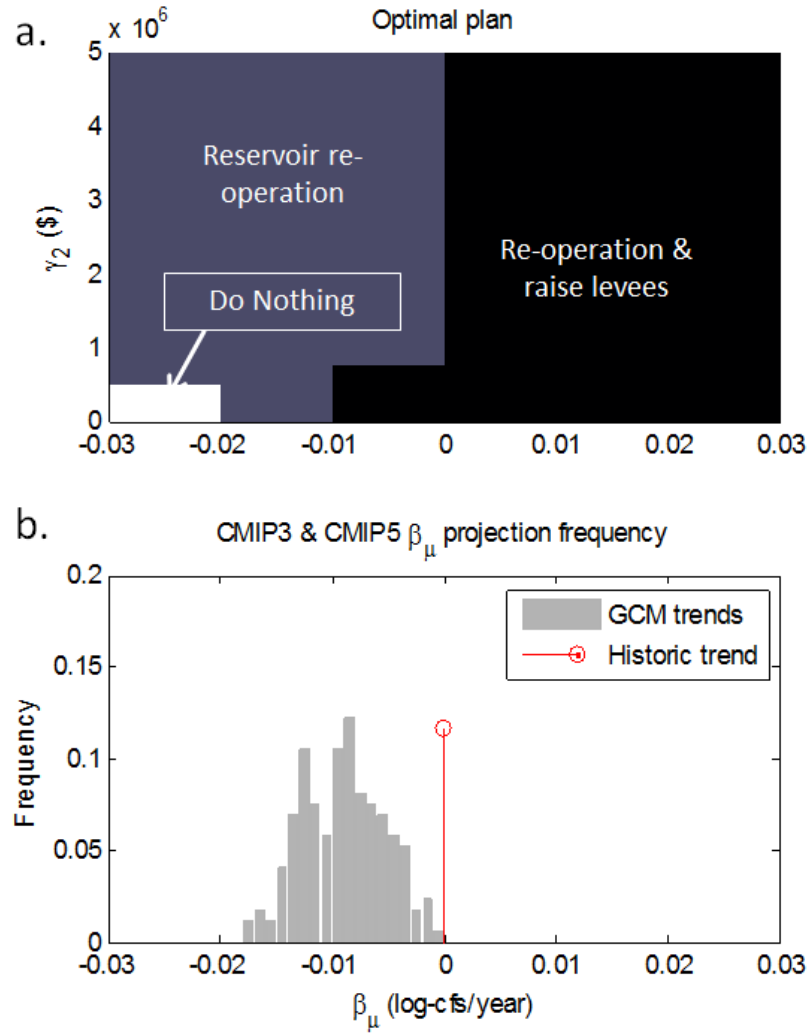
Figure 4.2: (above) Optimal flood management actions under different trends (β_μ) and values of the natural flow regime (γ_2). (below) CMIP3 and CMIP5 projections of β_μ with historic estimate of β_μ (red line).

Estimates of β_μ from CMIP3 and CMIP5 climate projections of changes in mean temperature and precipitation in the region cluster around a median of -0.01 log-cfs/year and range between -0.02 and 0.00 log-cfs/year. The value of β_μ estimated from the historic record is 0.00. None of the trend values estimated from projections or observations are positive (Figure 4.2b).

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Recommended Iowa River Flood Management Strategies

Figure 4.4. shows the regret associated with each of the three candidate scenario-optimal FRM strategies under two representative values of the natural flow regime, $50,000/year and $5 million/year. If Iowa River's natural flow regime is assumed to be $50,000/year, trend-optimal FRM strategies include doing nothing, changing reservoir operations, and combining reservoir re-operation with raising levees. If Iowa River's natural flow regime is assumed to be $50,000/year, trend-optimal FRM strategies include only reservoir re-operation alone under neutral and decreasing trend scenarios and combining re-operation with raising levees under increasing trend scenarios. Figure 4.4 compares each scenario-optimal strategy under both representative values of the natural flow regime, in addition to raising levees alone as, like the three scenario-optimal FRM strategies, raising levees represents the fourth extremal combination of decision variables.
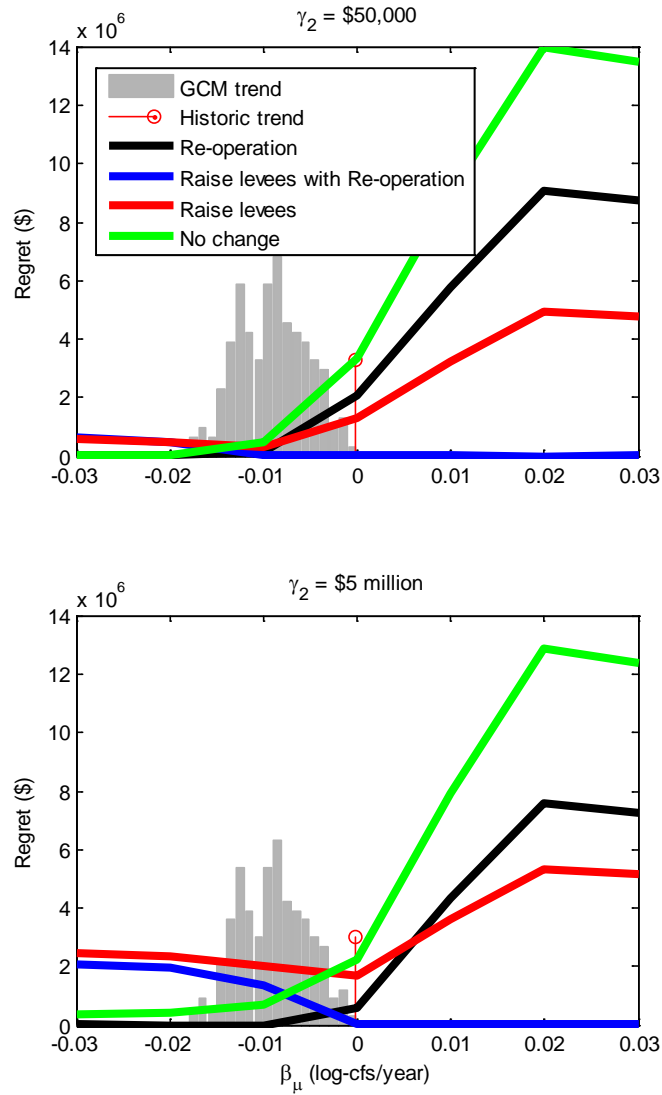
Figure 4.3: Regret ($) associated with three candidate flood management strategies under representative values of the natural flow regime as a function of flood trend, represented as percent change in the hundred-year flood thirty years from present (horizontal axis) and natural flow regime value (vertical axis). Grey histogram represents relative density of climate projections associated with each trend value while red stem represents trend estimate based on flow record. Top: Regret associated with raising levees (red), raising levees alongside reservoir re-operation (blue), changing reservoir operations alone (black), and making no change (green) under a

$50,000/year value of the natural flow regime. Bottom: Regret associated with raising levees (red), raising levees alongside reservoir re-operation (blue), changing reservoir operations alone (black), and making no change (green) under a $5 million/year value of the natural flow regime.

Figure 4.3 provides the decision maker with a means of comparing competitive flood management strategies, assuming the decision maker has a good idea of at least the order of magnitude of the natural flow regime's value. Under both flow regime values, though raising levees combined with reservoir operation is higher-regret than other FRM strategies under decreasing flood trend values values, it is least-regret under increasing flood trend scenarios under which other strategies are associated with severe regret.

If the decision maker(s) have no belief regarding the flow regime value's order of magnitude, the decision maker may prefer to compare all four candidate choices across not only values of β_μ but also the full spectrum of values of the natural flow regime. Figure 4.4 shows regret associated with each value of β_μ, value of the natural flow regime, and each candidate management strategy.
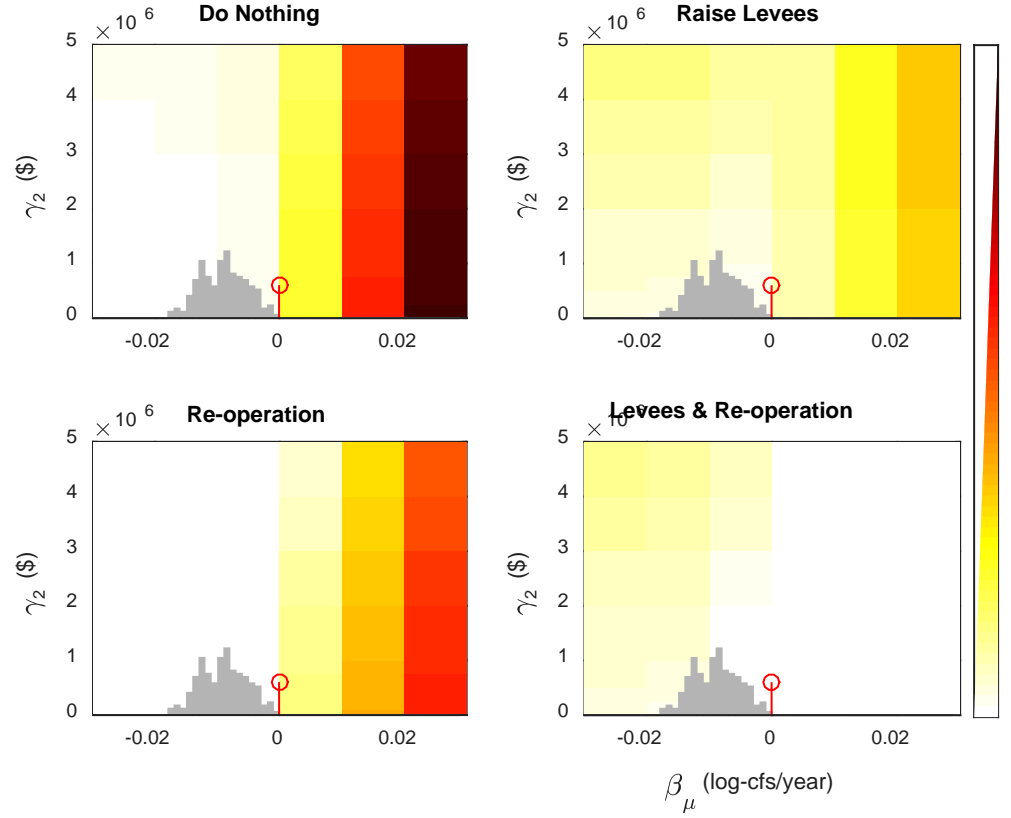
Figure 4.4: Regret associated with each candidate management strategy ($, colorscale) under each combination of β_μ (horizontal axis) and γ_2 (vertical axis). Grey histogram represents relative density of climate projections associated with each trend value while red stem represents trend estimate based on flow record. (a) Do nothing; (b) Raise levees; (c) Reservoir re-operation; and (d) Raise levees and change reservoir operations.

The decision maker willing to consider the full range of values of the natural flow regime and all four choices at once could use a mini-max regret decision rule to compare flood management strategies. Combining raising levees with reservoir re-operation is least-regret flood management strategy out of the four candidate strategies selected by the optimization model. Regret associated with raising levees and changing reservoir operations is highest when expected peak flow is decreasing

by an average of 0.04 log-cfs/year and the natural flow regime is valued at $5 million/year.

The inclusion of raising levees as part of the recommended low-regret FRM adaptation strategy for Iowa City in this decision model is interesting as raising levees is irreversible and results in negative ecological impacts and sunk cost regardless of how flood peaks evolve in the future. It is clear that, though reservoir re-operation is *a priori* regarded as the "low regret" strategy, employing this adaptation alternative alone results in high regret under increasing trend scenarios because it does not provide a sufficient degree of flood protection. However, in combination with raising levees, which does provide sufficient flood protection, reservoir re-operation mitigates negative ecological consequences and leads to a low-regret plan in the case of moderate and highly valued ecosystem services. The scenarios of increasingly high annual peak flows is not indicated by climate model simulations of average precipitation and temperature, but difficult to dismiss as plausible given assessments of intense precipitation in the watershed (See Chapter 2). It is therefore likely that a decision analytical approach sans climate stress test would miss these potential severe consequences and advocate a strategy for adaptation sans levee augmentation, risking severe damage.

Conclusions and Broader Implications of the Decision Model

This analysis presents a decision model based on decision scaling that selects flood risk management strategies assuming flood trend hazard is unknown. The model compares strategies' expected damage costs, management costs, and monetized ecological impacts under a broad range of potential flood trend and values of the natural flow regime. In stylized Iowa River flood management example, floodplain

management decisions based on expected net cost alone are sensitive to the estimate of trend in flood peaks and that the value stakeholders place on flood management's ecological impacts. The decision model may be used to select a flood management strategy assuming the decision maker is confident in the flow regime value but not the trend in flood peaks, or that the decision maker is confident of neither. In the Iowa River example, the decision model recommends combining infrastructural adaptation with nonstructural adaptation measures regardless of what factors the decision maker is informed of unless the natural flow regime is accorded very little value and flood peaks are expected to decrease substantially.

This decision model confers advantages over decision models that utilize a single trend estimate because the inherent uncertainty in flood hazard trend estimates makes decisions based on a single estimate of flood trend particularly vulnerable to poor performance. This decision model first determines what strategy is optimal over each of many systematically varied trend scenarios, then selects a strategy that is least-cost over the broadest or most likely set of trend scenarios. When no one strategy dominates the space, the decision model compares the regret associated with each competitive strategy to recommend the decision with least maximum regret. Using this rule, it is possible that the decision model might recommend a strategy that would have been selected using a single-trend decision model. However, the decision model may also select a different strategy than the strategy that would have been selected by a single-trend decision model with little sacrifice in performance at the point trend estimate in exchange for increased robustness over a range of trend values.

Eliciting trend in extreme flow from climate projections is an active area of research with no well-established method at present. Though mean precipitation and

temperature changes projected by climate models indicate only negative shifts in flood hazard in the Iowa River example, we consider projections of mean temperature and precipitation to be unreliable flood trend predictors because they are not the primary mechanisms that cause flooding. The climate-informed risk assessment of flood drivers in the Iowa River basin in Chapter 2 shows that climate model projections may not reflect important drivers of flood hazard, and thus should not dictate the bounds of the decision space. The consequences of increasingly severe floods in the Iowa City example lead to a preference for infrastructure-based adaptation. Failure to explore the potential consequences of positive trend in flood peaks in the Iowa River example despite the lack of climate projections indicating positive trend would lead to implementing a non-structural adaptation strategy alone that would expose the Iowa City region to unwarranted risk.

We present this decision model and example application to demonstrate the necessity of incorporating uncertain future flood hazard in decision-making frameworks while illustrating the mutual strengths of options-based flood management methods in satisfying the challenges posed by both future uncertainty and maximizing water systems' ecological benefits. The example application's results highlight the need for improved methods of estimating and projecting trends in flood peaks and characterizing ecological impacts of flood management.

CHAPTER 5

DECISION SCALING-BASED ROBUST OPTIMIZATION FOR MANAGING ECONOMIC AND ECOLOGICAL FLOOD RISK

Abstract

Climate nonstationarity and uncertainty raise important issues related to design and planning within the water sector. In addition, the water sector has acknowledged the need for improved methods of incorporating impacts of water resources development on ecosystems into project evaluation. This chapter presents a decision analytic approach to search for and evaluate flood management portfolios that maximize robustness to climate change with respect to both economic and ecological objectives. The model is applied to choose combinations of infrastructural and non-structural, options-based flood management interventions on the Iowa River, which are implemented in stages at decision points that are distributed across the planning period. High-performing FRM adaptation sequences selected through a satisficing-robustness metric based on the decision scaling approach are compared to FRM strategies selected for performance under stationary climate, the central tendency of an ensemble of climate projections, and an alternative robust optimization framing based on expected performance across climate model projections. Results demonstrate that the adaptation sequences selected through the decision scaling-based robustness metric, which evaluates performance across the broadest plausible range of climatic change, tend to exhibit lower potential regret than FRM adaptation sequences selected based on their performance under the stationarity assumption or scenarios based on climate model projections.

Introduction

Hydroclimatic nonstationarity challenges conventional frameworks for flood risk management (FRM) design and decision making, which rely on an assumed probability distribution of peak flows' frequency and magnitude to estimate damage reduction and economic efficiency (e.g. U.S. Water Resources Council, 1983; U.S. Army Corps of Engineers, 2009). The challenge of nonstationarity is that standard frameworks for the design of flood management systems rely on probability distributions of peak flow which are estimated from past flow records and are assumed constant through time. Under nonstationary flood hazard, flood management systems designed through these frameworks leave the contents and economic systems associated with the floodplain exposed to unanticipated risk if the probability distribution of peak flows changes.

Treating the parameters of the peak flow probability distribution as functions of time or functions of time-varying covariates (e.g. Stedinger & Griffis, 2011) is one way to update common FRM design standards and decision criteria to accommodate nonstationary hydrology (e.g. Salas and Obeysekara, 2014). This type of nonstationary peak flow probability distribution has been used to estimate the optimal combination of flood risk management adaptation alternatives that best mitigate risk across a planning period (e.g. Zhu et al., 2007; Woodward et al., 2014, Yazdi & Salehi Neyshabouri, 2012, Olsen et al., 2000), extending previous risk-based optimization analyses which find the FRM strategy that minimizes expected cost across a stationary probability distribution (e.g. Lund et al., 2002). However, the success of FRM designs based on a nonstationary probability distribution of peak flow relies on an assumed relationship between time and the parameters of the probability distribution to estimate future flood hazard. This relationship between the

probability distribution parameters and time is typically derived by extrapolating trend observed in the historic record (e.g. Cunderlik and Burn, 2003; Begueria et al., 2010; Mudersbach and Jensen, 2010; Rosner et al., 2014) or by simulating the effect of projected future temperature and precipitation changes on local hydrology (e.g. Prudhomme et al., 2003; Hanel et al., 2009; Gilroy and McCuen, 2012; Seidou et al., 2012). However, high levels of uncertainty in trend estimates resulting from either estimation technique lead to poor confidence in the resulting designs' optimality.

Deficiencies of these trend projection methods include high uncertainty in trend estimates based on historic data (Fowler & Wilby, 2010; Stedinger, 1983; Vogel et al., 2011), lack of guarantee that observed trends (or lack thereof) will continue into the future (Hirsch, 2011; Vogel et al., 2011), and lack of representation of many meteorological processes that drive floods in climate models (Stakhiv et al., 2007a,b). As a result, estimates of the nonstationary probability distributions of peak flow based on either extrapolation of observed trends or climate model simulations are subject to high levels of uncertainty and thus results in unanticipated flood risk. Substantial volumes of research are devoted to improving techniques for statistically or mechanistically estimating and forecasting trend in flood hazard (e.g. Khaliq et al., 2006; Madsen et al., 2014). The uncertainty in the underlying probability distribution of peak flows limits the benefits of risk-based optimization for FRM that is based on a single assumed peak flow probability distribution, and is one example of a number of challenges that limit the benefits of optimization in the broader field of water resources engineering (see Rogers and Fiering, 1986).

An alternative approach to FRM under nonstationary hydrology adapts existing optimization frameworks to seek robust FRM strategies, that is, FRM strategies whose performance remains favourable across a wide range of possibilities, often

sacrificing the maximum optimal result in doing so (Hall & Solomatine, 2008; Mens et al., 2011; Lempert et al., 2013). While conventional risk-based flood management plans can be said to seek robustness to a range of flood magnitudes, the flood magnitudes are assumed drawn from a single stationary probability distribution or a single climate change scenario rather than a changing and/or unknown probability distribution of future climate state as would be the case under hydroclimatic nonstationarity. Incorporating measures of robustness into optimization-based FRM decision support tools is one way to reconcile optimization with the contextual circumstances of flood risk management decisions.

Two main groups of decision support frameworks incorporate optimization into robust planning approaches for water resources management: First, those that search directly for robust solutions, specifying the robustness definition *ex ante*, which are generally known as "robust optimization"; Second, those which use optimization to search for a variety of high-performing solutions and evaluate the robustness of those solutions *ex posteriori*. The Multi-Objective Robust Decision Making (MORDM), which is based on the Robust Decision Making (RDM) decision support framework (Lempert & Popper, 2003), searches for Pareto-approximate solutions through multi-objective optimization (Kasprzyk et al., 2013). Both RDM and MORDM measure robustness *ex posteriori* according to the uncertainty domain across which they meet (or satisfice) performance objectives (Herman et al., 2015). The Decision Scaling (Brown et al., 2012) based Nonstationary Decision Model (NDM) for FRM (Spence & Brown, in revision), like RDM and MORDM, searches for candidate strategies using optimization under individual isolated scenarios. However, the decision-scaling based NDM analysis searches for the candidate solutions in a "scenario neutral" way via application of a climate stress test, whereby solutions are found across a

systematically generated set of future scenarios that exhaustively explores plausible climate (and other) changes. Unlike RDM or MORDM, the candidate strategies' robustness is evaluated *ex post* across the full systematically sampled range of plausible scenarios rather than the expected value scenario. However, the set of candidate strategies discovered through single-scenario optimization may not include the FRM strategy that is most robust as measured across the full range of uncertain factors.

Robust optimization techniques, which search directly for robust solutions rather than evaluating candidate solutions' robustness *ex post*, provide another method of addressing the issue of brittle optimal solutions. Robust optimization can be distinguished from purely stochastic optimization (such as risk-based optimization) by its accommodation of poorly characterized uncertainty (Mulvey et al., 1995). Rather than optimize for a single scenario, parameter probability distribution, or trajectory of flood hazard, robust and stochastic optimization techniques seek to find the design that ensures the most favourable performance across a number of scenarios according to a pre-specified robustness metric or combination of robustness measures which are summarized in a single objective function. In previous applications, robustness has been summarized in a single objective function by balancing expected performance (essentially a stochastic optimization objective function) against a term representing risk-aversion by measuring the stability of performance across states of the world through deviations from expected performance in each scenario (e.g. Mulvey et al., 1995; Watkins and McKinney, 1997) or a summary of performance threshold violations (e.g. Ray et al, 2014). Past applications of robust optimization in water resources have been restricted to applications outside of flood risk management, and have relied on a single robustness definition (Watkins & McKinney, 1995; Watkins

and McKinney, 1997), advocated a multi-objective approach to represent the various preferences of multiple stakeholders (Hamarat et al., 2014), and defined future scenario assumptions based on climate model output (e.g. Ray et al., 2014).

To avoid missing the consequences of future states of the world not represented by climate model projections, scenario-neutral approaches such as Decision Scaling (Brown et al., 2012) and others (e.g. Prudhomme et al., 2010) assess performance of water systems across the full plausible range of future states of the world, which are systematically and incrementally sampled. Estimates of future states of the world based on climate model projections or other sources, when appropriate, are incorporated *ex posteriori* and do not dictate the range of future climate states which are evaluated. By testing FRM systems' performance across a broad range of future states of the world, erring on the side of implausibility, vulnerability-based approaches such as Decision Scaling (Brown et al., 2012) couch decisions within a complete understanding of the full range of their decisions' potential consequences, working to avoid surprise. The Decision Scaling framework has previously been applied to climate risk assessments of water resources systems through simulation- (Brown et al., 2012, Steinschneider et al., 2015) and optimization- (Spence & Brown, *under revision, WRR*) based systems analysis tools.

Here, the decision scaling-based NDM decision framework is extended to include robust optimization within the search algorithm. The robust optimization framing is based on Eco-Engineering Decision Scaling, which elicits performance thresholds from stakeholders in the water systems community and the relevant ecological management community that must be met in order for the system's performance to be deemed acceptable by either community (Poff et al., 2015). The resulting decision

framework presented here combines decision scaling with robust optimization for multiple FRM objectives, including ecological and economic objectives.

This chapter presents the decision scaling-based robust optimization approach in comparison to several single-scenario, risk-based, and robust optimization-based planning approaches which span representative climate assumptions, ways of aggregating multiple objectives, and risk preferences. The chapter proceeds as follows. First, the chapter presents an example flood management decision based on the Iowa River system, where changes in flood characteristics are a concern to both flood and ecosystem managers and existing flood control infrastructure has already impacted the riparian ecosystem. The proposed decision scaling-based robust optimization approach and other representative planning approaches will be illustrated through the Iowa River example application. Second, each optimization-based planning approach is outlined and described mathematically. Last, optimization analysis is used in conjunction with each planning approach to find a selection of top-performing FRM strategies for the Iowa City/Iowa River flood management system found under each multi-objective and/or robust objective function. The candidate scenario- and robustness-optimal FRM strategies are compared in terms of regret across a broad range of future states of the world in a climate stress test.

Results highlight present actions that lead to strong performance in isolated scenarios as well as robustness across multiple scopes of climate uncertainty. Though multiple planning approaches lead to the same or similar FRM strategy(ies), this indicates the potential to find resolution among stakeholders with disparate values and beliefs for FRM climate adaptation.

Case Study

Iowa City Flood Risk Management

Coralville Reservoir and several sections of levees protect Iowa City from flooding (Figure 5.1). Recent high flow episodes have exceeded the capacity of existing infrastructure in several damaging flood events and raised concerns that the existing FRM system does not supply an adequate degree of protection. The potential hydrologic regime shift caused by climate and/or land use change provokes an adaptation decision, while hydrologic alteration introduced by reservoir operations may have increased the vulnerability of Iowa River's aquatic and riparian ecosystems to further disruption (Nilsson & Berggren, 2000).
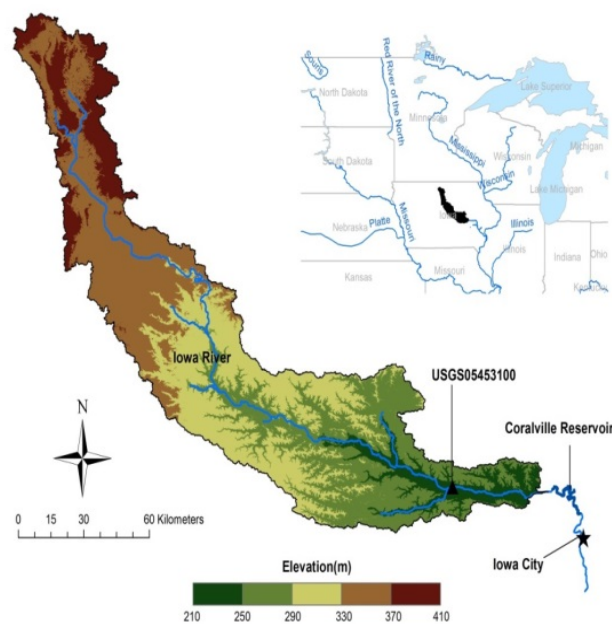
Figure 5.1: Iowa River watershed upstream of Coralville Reservoir.

Flood management goals

The goals for FRM in the Iowa City system are to maximize the economic efficiency of the flood management system, including the costs of managing floods as well as

damage caused by flooding, and to increase the resilience and adaptive capacity of Iowa River's riparian and aquatic ecosystems. The flood management system should maintain acceptable performance with respect to these goals throughout a forty-year planning period that begins in 2010 and ends in 2050 regardless of potential climate changes.

Flood management effectiveness of the proposed set of adaptive actions $\vec{x}$ is quantified through Expected Annual Cost (EAC) under climate change scenario $\vec{\Delta}$, which in the Iowa River example is a combination of change in annual average precipitation and annual average temperature. EAC is a composite of flood damage D and management costs C from only the year t's peak flow $Q_{\max t}$ (Equation 5.1). Damage associated with $Q_{\max t}$ may be affected by the adaptation actions $\vec{x}$. Damage and cost in year t is adjusted to present value using discount rate r.

$$EAC|\vec{x},\ \vec{\Delta}= \frac{1}{T}\sum_{t=1}^{T}\frac{D\big(Q_{\max t}|\vec{x},\ \vec{\Delta}\big)+C\big(Q_{\max t}|\vec{x},\ \vec{\Delta}\big)}{(1+r)^t}$$

Equation 5.1

Cost of flood damage is estimated from Tables provided by the USACE and adjusted for inflation support estimates of damage caused by annual peak flow to Iowa City and the downstream agricultural fields. The value of crop losses caused by peak flows that occur during the growing season is assumed to be \$849/inundated acre based on prices for corn production (Duffy, 2014). The cost of building levees is modeled as a point cost during the time period in which levees are raised.

The system's ecological resilience under a given climate scenario and adaptation plan is quantified through the proxy of Expected Annual Floodplain (EAF) (Poff et al. 2015), which represents the typical floodplain area A inundated by flooding in a given year t, A_t (Equation 5.2).

$$EAF = \frac{1}{T} \sum_{t=1}^{T} A_t | [Q_{\max t}, \vec{x}, \vec{\Delta}]$$

Equation 5.2

To qualify as an ecologically meaningful inundation event, bank overflow must be sustained for a period of at least seven days. If flow falls below the discharge threshold for two days or fewer during the inundation period, the inundation on both sides of the low-water period is considered one event. If flow falls below the discharge threshold for more than two days in a row, the inundation events are considered separate.

Performance thresholds in EAC and EAF separate acceptable performance from unacceptable performance. EAC may increase by up to 75% before performance is deemed unacceptable because EAC includes the cost of new adaptation in addition to flood damage, while the reference EAC of the current system under the no-change scenario does not include adaptation cost. Any EAF less than the reference EAF under the historic climate and management regime is unacceptable and require EAF.

Adaptation alternatives

Two possible adaptation alternatives are available to mitigate flood risk and enhance the Iowa River's ecologically meaningful inundation. These include raising the currently extant levees to protect against higher discharge rates and adjusting the non-

emergency release limit from Coralville Lake during the growing season. The adaptation alternatives are implemented at varying times throughout the planning period of 2010-2050..

Raising levees would reliably protect Iowa City against higher flows to a higher degree than changing reservoir operations, but will alter the hydraulic relationship between river discharge and flow stage (Mays, 2011), reducing downstream floodplain inundation at peak flows. Furthermore, building higher levees will result in sunk cost if flooding does not increase in the future and the higher degree of protection is not needed.

Damage to crops occurs at a lower release discharge from Coralville reservoir (6000 cfs) than damage to Iowa City (10,000 cfs). For this reason, releases from Coralville Reservoir are limited to 6,000 cfs and below during the growing season outside of emergency situations (USACE Report ER-1105-2-101). Outside of the growing season, non-emergency releases from Coralville Reservoir are not permitted to exceed 10,000 cfs. While the lower growing season release limit protects crops from flood damage, it prevents the reservoir from emptying quickly in preparation of expected high flows. This is particularly noteworthy during the growing season because most severe high flow events on the Iowa River occur in the growing season in June and late May after multiple consecutive days of high precipitation (Kunkel et al. 1994, Coleman and Budikova, 2010, Robertson et al. 2011). Furthermore, reducing the release limit during the growing season reduces the frequency of ecologically functional bank overflow events during this time period. Raising the release limit some amount between its current value of 6,000 cfs to the maximum permitted discharge of 10,000 cfs may restore ecologically functional inundation events and

allow the reservoir to more effectively mitigate severely high flows, but would require operating authorities and local government to reimburse farmers for any crop losses resulting from the change.

System model

The flood management and ecohydrological performance of the altered system is evaluated using a system model that simulates the performance of the Iowa City flood management system under different adaptation actions and different climate scenarios. Figure 5.2 illustrates the conceptual linkage between sub-models which form the larger system model.
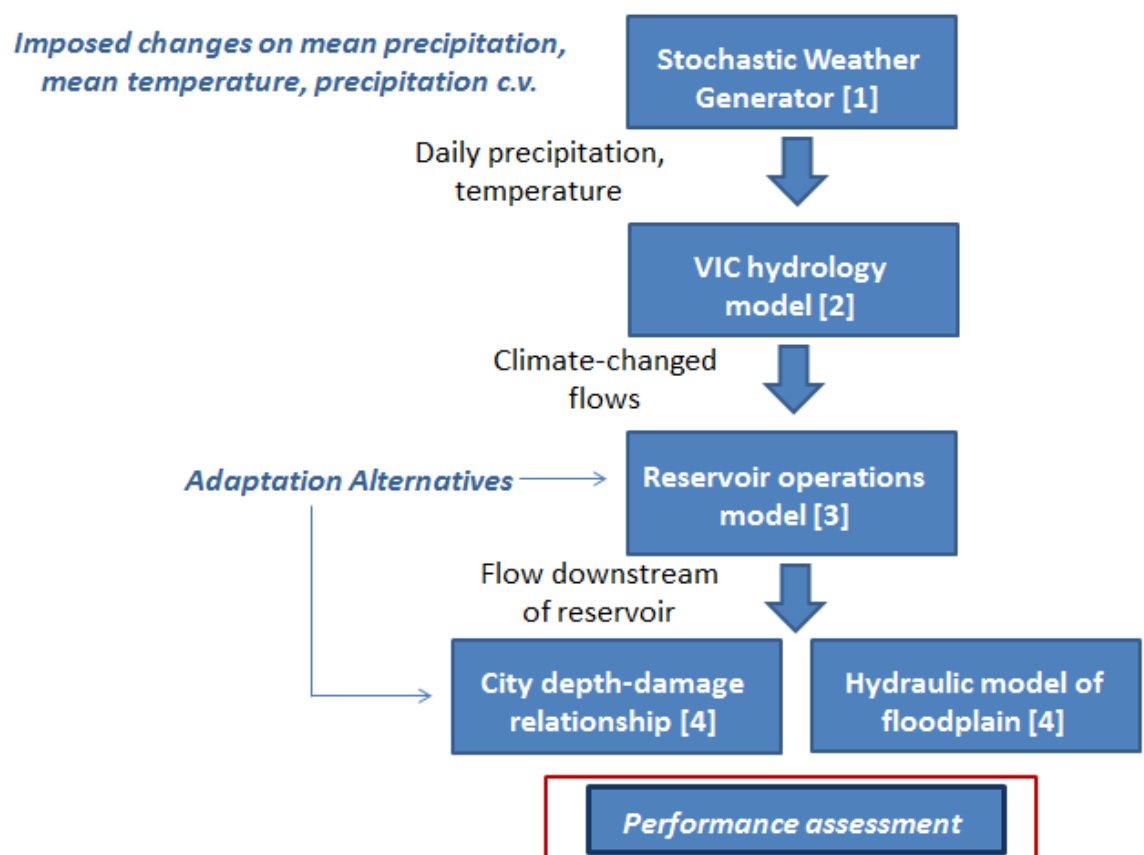
Figure 5.2: Linkages between components of the flood risk and riparian ecosystem system model.

A stochastic weather generator (Steinschneider and Brown, 2014) generates realistic time series of synthetic daily weather which may be statistically altered to reflect climate change scenarios. The stochastically generated, climate-altered time series force a daily VIC model of the Iowa River to generate synthetic inflows to Coralville Reservoir (Xiang et al., 1994; Hydrosystems, 2013). A model constructed in MATLAB ® based on the Coralville Lake ResSim® U.S. Army Corps of Engineers operations model (Kipsch and Hurst, 2007) translates inflows to the reservoir into releases from the reservoir. A validation plot for historical inflows to the reservoir between 1992 and 2010 is shown below in Figure 5.3 (Nash-Sutcliffe 0.71).
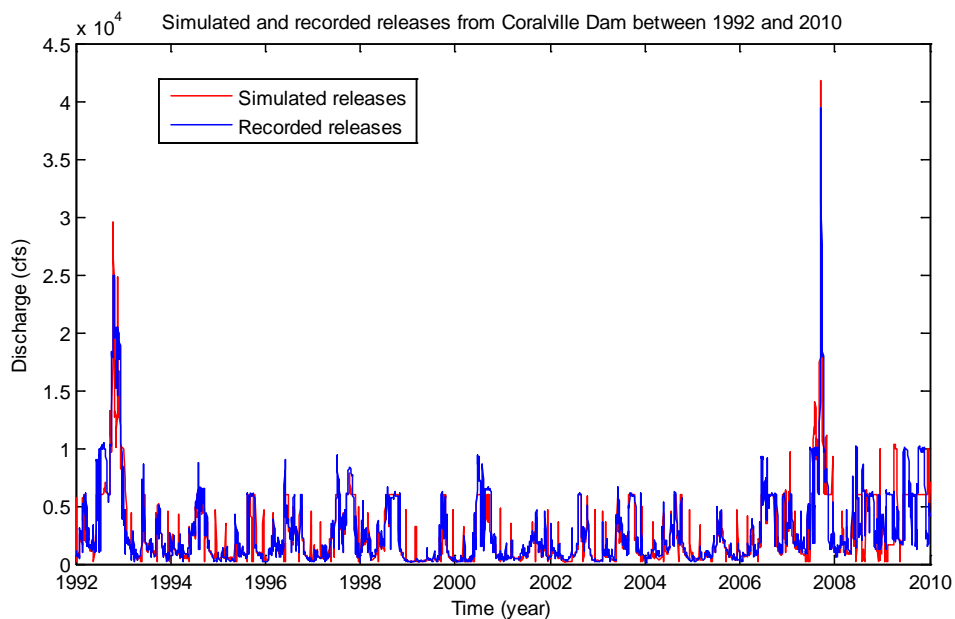
Figure 5.3: Validation for Coralville Reservoir operations model. Simulated releases based on recorded inflows between October 1, 1992 and September 30, 2010 are compared to recorded releases from the same period.

A hydraulic model of the floodplain developed in HEC-RAS by the US. Army Corps of Engineers translates releases from Coralville Lake into downstream floodplain area between Coralville Lake and river mile 46 (46 miles upstream of Iowa River's

confluence with the Mississippi River). The HEC-RAS River Analysis System (Brunner, 2001) model was used to derive an empirical relationship between discharge and floodplain area downstream of Iowa City (Appendix A), which informs the calculation of the ecological objective. The USACE Rock Island District also provided a table relating discharge, river stage, and damage to Iowa City and the downstream agricultural fields (Hydrosystems, 2013.

<u>Methodology</u>

This section presents the framing and mathematical detail of a decision analytic framework for economic and ecological FRM based on a decision scaling approach to robust optimization. A flood management case study on the Iowa River illustrates the decision-scaling based satisficing RO framework. For comparison, several other optimization-based planning approaches are used to search for FRM adaptation sequences for the Iowa River. The planning approaches are based on a number of climate assumptions and methods of summarizing performance across objectives and across possible future states of the world (Table 5.1).

Climate assumptions comprise the range and value of climate parameters across which performance is evaluated. In the case of the Iowa River example application, the sampled climate parameters include annual average precipitation and annual average temperature. In other applications, climate parameters beyond average temperature and precipitation or even non-climatic parameters that are relevant to the decision could be included. The climate assumptions regarding the range and value of the climate parameters include (1) a set of future states of the world based on the decision scaling approach to climate risk assessment, which employs broad range of incrementally sampled combinations of climate parameter values; (2) A set of future states of the world based on low, medium, and high projections of the climate

parameters, which is an approach taken in previously published studies on robust optimization for water resources management and planning; (3) A single combination of precipitation of precipitation and temperature change which represents the central tendency of an ensemble of precipitation and temperature projections; and (4) a single combination of climate parameter values which represent zero change to both precipitation and temperature, representing the stationarity assumption which is commonly used in FRM design and planning. The multiple performance objectives, which in the Iowa River case include an economic and an ecological objective, are aggregated as a single metric that expresses their performance under each climate scenario in two alternative ways: (1) A binary satisficing metric, which takes a value of 1 if performance thresholds are met in both objectives and 0 otherwise; and (2) A weighted sum of normalized performance in each objective. Table 5.1 summarizes the combinations of climate assumptions, methods of combining performance in each objective, and assessing performance across climate scenario taken in each planning approach.

Table 5.1: Names of each representative FRM planning approach and outline of underlying climate assumptions, method of aggregating multiple objectives, and method of summarizing performance across climate scenarios.

Planning approach	Climate assumptions	Aggregating multiple objectives	Summarizing performance across climate scenarios
Satisficing RO	Average precipitation 70%, 80%, 90%, 100%,	Mutual satisficing (performance	Fraction of scenarios with

	110%, 120%, or 130% of historic annual average precipitation; Annual average temperature 1 degree Celsius less, same, 1, 2, 3, 4, or 5 degrees Celsius more than observed.	thresholds must be met in both objectives to achieve acceptable performance in each climate scenario)	acceptable performance
Risk-based satisficing RO	Average precipitation 70%, 80%, 90%, 100%, 110%, 120%, or 130% of historic annual average precipitation; Annual average temperature 1 degree Celsius less, same, 1, 2, 3, 4, or 5 degrees Celsius more than observed.	Mutual satisficing (performance thresholds must be met in both objectives to achieve acceptable performance in each climate scenario)	Weighted fraction of acceptable performance with weights assigned according to estimate of climate scenario probability
GCM-based RO	Combinations of low, medium, and high precipitation and temperature scenarios based on CMIP3 and	Weighted sum of performance with respect to each objective.	Increase of 0.7, 2.7, and 5 degrees Celsius; 84%, 105%, and 122% of historic

	CMIP5 climate model projections		precipitation
Multi-Objective Optimization under GCM climate	Temperature 3 degrees Celsius warmer; 10% more annual precipitation.	Weighted sum of performance with respect to each objective.	None; only one climate scenario included
Multi-objective optimization under stationary climate	Future climate identical to historical climate (37.64" annual precipitation, 11.17 degrees Celsius average temperature).	Weighted sum of performance with respect to each objective.	None; only one climate scenario included

Each planning approach summarized in Table 5.1 combines a set of climate assumptions, technique of combining multiple performance objectives, and method of summarizing performance across a range of assumed possible climate scenarios into an objective function that is used in optimization analysis to find the combination and sequencing of FRM adaptive actions that maximize that objective function in the Iowa River flood risk management example application.

Each choice that contributes to the planning approaches outlined in Table 5.1 represents a type of climate belief, relative prioritization of economic and ecological goals, and risk preference that could realistically be held by the stakeholders in this decision. Some believe that the observed climate is the best guide to future flood hazard, while others believe maximizing performance under the average climate projection is the best way to manage flood risk, and others advocate for robust approaches despite their potential performance sacrifice under baseline climate estimates. Similarly, the satisficing method of combining performance in multiple objectives avoids crossing tipping points in either, while the method used in the multi-objective optimization and GCM-based robust planning approaches trades off economic and ecological performance, allowing good performance in one objective to compensate for poor performance in the other. Lastly, comparing the robust planning approaches' methods of summarizing performance across scenarios represents three different risk attitudes: Risk-based satisficing, assuming the probability distribution of climate changes is an accurate estimate, is a robustness metric best used for decisions that are expected to be repeated at many different locations. It discounts severe consequences under low-probability climate scenarios, which makes sense if decisions using the same metric will be repeated many times by a single entity: the impacts should average out over many repeated decisions. The GCM-based robust optimization planning approach incentivizes performance stability across climate states, seeking to avoid poor performance under even isolated states of the world, indicating more risk aversion. Similarly, the decision scaling-based RO planning approach does not discount the impacts of states of the world not indicated by climate projections, indicating a more risk-averse stakeholder. Each of the latter two planning

approaches might represent the risk attitude (if not the climate beliefs) of a stakeholder who is directly affected by the outcome of the decision.

The singular climate change projection used in the multi-objective optimization of GCM climate is based on the central tendency of an ensemble of CMIP5 model runs' projections of precipitation and temperature change across all RCP scenarios (Taylor et al., 2012), which is reflective of the impetus to plan for the "most likely" future climate predicted by the model deemed most trustworthy or the average of multiple models' runs. Likewise, the weights assigned to the incrementa climate scenarios in the risk-based satisficing planning approach are based on a multivariate normal probability density function of precipitation and temperature change at the end of the planning period. The multivariate normal probability distribution's parameters are estimated using an ensemble of downscaled CMIP3 and CMIP5 climate projections for 2040-2050 over the Iowa River basin (Maurer et al., 2002; Maurer et al., 2007; Taylor et al., 2012). This is the same ensemble of climate model projections used to parameterize the GCM-based robust optimization planning approach and the planning approach based on multi-objective optimization under the GCM climate (Table 5.1). The analysis is based on projections from each model run under each representative SRES scenario (CMIP3) and RCP scenario (CMIP5) used in International Panel on Climate Change (IPCC) reports (IPCC, 2007; IPCC, 2012). Each model is assigned equal weight. The parameters of the multivariate normal probability distribution are calculated according to the mean of average precipitation change between 2040 and 2060 across all models, the mean of average temperature change between 2040 and 2060 across all models, and the covariance between average precipitation change and average temperature change as represented in the model projections.

The following sub-sections outline the mathematical and computational structure of the Iowa City optimization analysis and the robust decision analysis framework which synthesizes the results of optimization based on each planning approach into decision-relevant information.

Objective functions

The Iowa City flood management system's performance metrics are evaluated under multiple stochastic realizations of each systematically sampled and incrementally varied scenario of change in average precipitation and temperature, though any climate- or non-climate drivers of flood risk could be sampled. Five objective functions are used to assess adaptation strategies' performance, reflecting different attitudes regarding the range of climate across which FRM should perform, how the competing objectives should be balanced, and how robustness should be measured. The following sections list the objective functions in the order of most basic to most sophisticated.

Multi-objective optimization: Stationary climate

The first objective function maximizes EAF while minimizing EAC under stationary climate, assuming past precipitation and temperature characteristics P_0 , T_0 will continue throughout the planning period. The economic and ecological objective are weighted by $\gamma_{EAC}, \gamma_{EAF}$ respectively. The weight on the economic objective, γ_{EAC}, is negative so that the composite optimization problem is a maximization problem. The economic and ecological objectives are combined in a weighted average (Equation 5.3).

$$Max\ Z_m|P_*, T_* =\ \gamma_{EAC}Z_{EAC}|P_0, T_0 +\ \gamma_{EAF}Z_{EAF}|P_0, T_0$$

Equation 5.3

Multi-objective optimization: Projected climate

The second objective function used to find FRM strategies for Iowa River prescribes the trajectory of flood hazard according to GCM projections of average precipitation and temperature change over the planning period. The objective function based on maximizing composite economic-ecological performance is given in Equation 5.4.

$$Max\ Z_m|P_*,T_* = \gamma_{EAC}Z_{EAC}|P_*,T_* + \gamma_{EAF}Z_{EAF}|P_*,T_*$$

Equation 5.4

In the Iowa River region, this scenario comprises a 10% precipitation increase and a 3 degree Celsius temperature increase by the 2040-2060 period. These represent the approximate central tendency of the ensemble of GCM projections, specifically the nearest 10% increment of precipitation change to the median precipitation change and the nearest 1 degree Celsius increment of temperature change to the ensemble median (see Table 5.1).

GCM-based robust optimization

We frame the multi-objective function $Z_m|P,T$ in a robust optimization formulation based on Ray et al. (2014) to find an adaptation strategy with superior and stable performance across all climate scenarios. The mean composite performance across climate scenarios and the average positive deviation from mean performance across scenarios comprise the robust objective function Z_R (Equation 5.5).

$$Min\ Z_R = \alpha_1 \left[\frac{1}{nm} \sum_{j=1}^{n} \sum_{k=1}^{m} Z_{m\ j,k} \right] +$$

$$\alpha_2 \left[\begin{matrix} mean \left\{ Z_{m\ j,k} > \left(\frac{1}{nm} \sum_{j=1}^{n} \sum_{k=1}^{m} Z_{m\ j,k} \right) \right\} - \\ \left\{ \frac{1}{nm} \sum_{j=1}^{n} \sum_{k=1}^{m} Z_{m\ j,k} \right\} \end{matrix} \right]$$

Equation 5.5: Multi-objective function for GCM-based robust optimization.

Precipitation scenarios $j \ni J$ and temperature change scenarios $k \in K$ are modeled on past robust optimization formulations for climate adaptation, which are defined by an ensemble of climate model projections.

Decision scaling-based satisficing robust optimization

The satisficing-robust objective function and planning approach is based on concepts introduced by Eco-Engineering Decision Scaling (EEDS), which is a framework for climate risk assessment and decision support that is based on the satisficing of ecological and engineering performance thresholds (Poff et al., 2015). We set minimum performance thresholds for the Iowa River flood management system's economic and ecological performance to translate performance into a binary satisficing criterion of either acceptable or unacceptable performance. The performance threshold is based on comparing performance under a new adaptation plan or climate scenario to performance of the current flood management system without adaptation under the "no change" climate scenario. We denote the economic objective Z_{EAC} and its threshold $Z_{EAC\ O}$. Likewise, we denote the ecological objective Z_{EAF} and its threshold $Z_{EAF\ O}$. The satisficing-robust objective function is therefore denoted by Z_S (Equation 5.6).

$$Max\ Z_S = \sum_{j=1}^{n}\left[\sum_{k=1}^{m}\left[\left(Z_{EAC}(x)_{j,k} < Z_{EAC_O}\right) \& \left(Z_{EAF}(x)_j > Z_{EAF_O}\right)\right]\right]$$

Equation 5.6: Satisficing-robust objective function for multi-objective optimization.

This objective function requires that performance goals in economic and ecological performance be met simultaneously under a given climate scenario. In Equation 5.6, states j correspond to changes in annual precipitation and states k correspond to changes in mean temperature. The representative changes in precipitation and temperature are systematically and incrementally varied across a wide range of values

beyond what is indicated by model projections (Table 5.1). This scoping technique is based on the decision scaling framework, and its goal is to encompass all plausible future precipitation and temperature characteristics.

Risk-based satisficing-robust optimization

Risk-based satisficing robust optimization builds on satisficing robust optimization by assigning probabilities $P(j,k)$ to each climate change scenario j, k based on a probability density function estimated from climate model projections over the river basin. The risk-based satisficing-robust objective function Z_P is shown in Equation 5.7.

$$Max\ Z_P\ = \sum_{j=1}^{n}\left[\sum_{k=1}^{m}P(j,k)\left[\left(Z_{EAC}(x)_{j,k} < Z_{EAC_O}\right)\&\left(Z_{EAC}(x)_j > Z_{EAC_O}\right)\right]\right]$$

Equation 5.7: Risk-based satisficing-robust objective function for multi-objective optimization.

The probabilistic component is included to motivate the optimization algorithm to find a solution that meets economic and ecological performance goals specifically under the types of climate changes that are considered likely to occur, assigning less priority to satisficing climate changes that may be unlikely. The probabilistic framing introduces and explicit stochastic component to the optimization analysis.

Decision variables

The decision variables in the optimization problem represent adaptive actions which may be implemented at different stages throughout a planning period to mitigate flood risk and support ecological resilience on the Iowa River. The specific adaptive actions considered in this analysis include raising existing levees which protect Iowa City some amount between zero and ten feet, and changing a reservoir operation rule that

limits releases from Coralville Reservoir during the growing season to protect downstream crop production. The height by which to raise levees and the new growing season release cap are two design factors. Decisions are implemented in six stages that are distributed at equal intervals across the forty-year planning period, so that changes to the system can be made every seven years. The problem therefore contains a total of twelve decision variables, which are the levees' height at each of the six decision stages and the reservoir release limit at each decision stage.

Constraints

Levees are raised between 0 and 10 feet, and are permitted to increase from time period to time period but cannot be lowered. The maximum non-emergency release limit from Coralville Reservoir may take any value between 6,000 cfs and 10,000 cfs. The release limit may increase, decrease, or stay the same between any two time periods.

Optimization algorithm

A simple continuous genetic algorithm with tournament selection is used to find the solution under each type of robust optimization (Miller & Goldberg, 1995). The genetic algorithm breeds 250 generations of a 150-member population is initiated with random combinations of decision variables with a 20% mutation rate and 90% chance of the fitter chromosome chosen for reproduction during tournament selection, with five elite individuals passed on unchanged from generation to generation. The population is initialized with representative combinations of the two decision variables to ensure evaluation of the extreme values of the decision variables and allow the population to evolve for a maximum of 200 generations, passing on the five best-performing individuals unchanged at the end of each generation. The five best-

performing individuals (or decision sequences) are returned at the end of the evolution process.

Due to the high computational expense of evaluating one iteration of the objective function using this simulation model, which requires 490 separate 60-year daily simulations of reservoir operations and additional post-processing, as well as the smooth response of economic and ecological performance as a function of decision variables, we use response surface methodology under each climate scenario to empirically estimate the performance of any combination of decision variables under each climate scenario without evaluating the full simulation model. The surrogate model response surfaces were developed using full factorial design (Box and Wilson, 1951). Performance of optimal and high-performing FRM strategies found through optimization using the response surface methodology is validated through the simulation model *ex post*.

Synthesizing results to support FRM adaptation decisions

Each of the five aforementioned planning approaches (including the decision scaling-based RO objective function) are optimized to discover a small number of high-performing strategies. These high-performing FRM strategies become candidate FRM strategies for among which stakeholders may choose based on preferences that could not be represented by the objective functions and *ex post* performance evaluation of each high performing strategy.

The performance of each candidate FRM strategy is evaluated across the full range of plausible future states of the world in a climate stress test. Each candidate FRM strategy is also evaluated under all other objective functions to highlight potential solutions which perform well under all objective functions vs. solutions that only

excel with regard to one definition of performance, set of climate scenarios, or risk attitude and perform poorly under others. Because optimal FRM strategies are presented in the form of a sequence of adaptive actions, results highlight both the consequences and advantages of postponing actions which may become necessary under a subset of eventualities, or the costs associated with making irreversible actions too early, risking potential negative outcomes.

Results & Discussion

Optimization of the Iowa River flood management system under different climate assumptions, robustness measures, and methods of aggregating multiple objectives yield a set of high-performance candidate strategies shown in Figure 5.4, which displays the five highest-performing FRM sequences found under each objective function. The high-performing strategies presented by Figure 5.4 show that it is optimal or near-optimal to raise levees by the end of the planning period even under assumed stationary climate, but under robust planning approaches, the expanding range of plausible climate states at each planning stage makes raising levees earlier in the planning period more advantageous. Figure 5.4 also shows that FRM sequences selected under a single assumed climate scenario (stationary climate and the 3 degree Celsius increase with 10% increased precipitation scenario) lead to a less diverse set of candidate adaptation sequences than either decision scaling-based RO formulation or the RO formulation based exclusively on climate model projections. The best candidate FRM strategies selected for their performance under single assumed climate scenarios rely on increasing the reservoir release limit, leaving levees unchanged either entirely or toward the end of the planning period, with each successive high-performing solution raising levees earlier in the planning period. In contrast, FRM adaptation sequences selected through robust formulations took a range of approaches

to achieving robust ecological and economic outcomes, including raising levees at the beginning of the planning period or not at all, and maximizing the reservoir release limit throughout the planning period or allowing it to fluctuate, reducing agricultural costs while enhancing ecological flows.
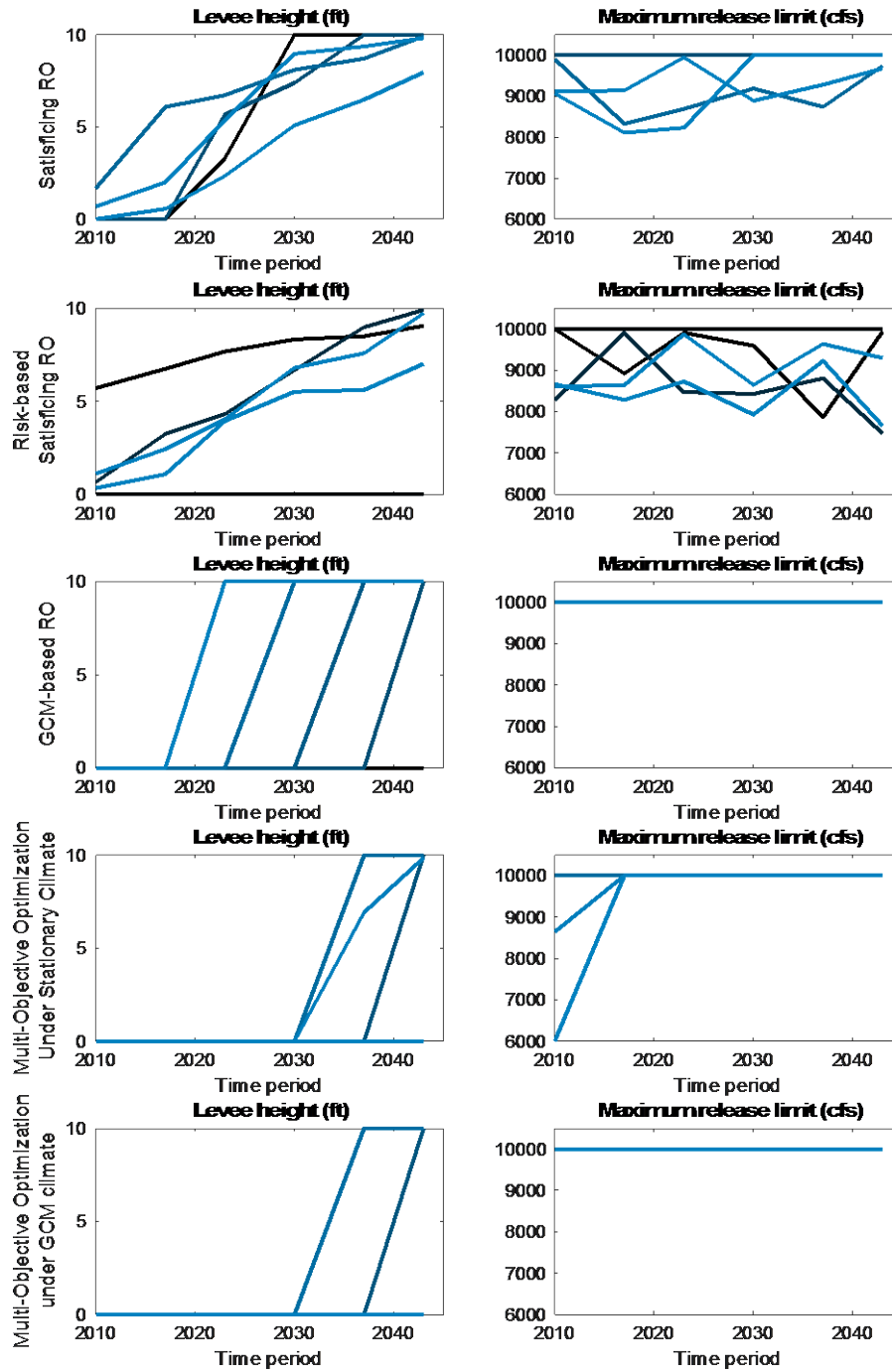
Figure 5.4: Best-performing adaptation strategies as measured by five representative objective functions (rows). Color scale represents performance under each row's objective function with darker colour indicating superior performance and lighter colour indicating less desirable performance.

The comparison among the economic performance of three representative high-performing FRM adaptation sequences in Figure 5.5 illustrates the benefits of raising levees, which lead to more consistency of achieving acceptable economic performance across potential future climates. These selected adaptation sequences correspond to the second highest-performing adaptation sequence selected through risk-based satisficing RO, and both the third and fifth highest-performing adaptation sequence discovered through the GCM-based RO formulation based on Ray et al. (2014). They include (1) Raising the non-emergency release from Coralville Reservoir to a fluctuating, medium level during the growing season throughout the planning period, while gradually raising levees higher at each decision period; (2) Raising levees from their present level to the maximum permitted level at the third decision period, where the horizon of uncertainty has expanded from its current range, while raising the reservoir release limit to the maximum throughout; and (3) leaving levees unchanged until the last period, when it is raised to the maximum, while setting the reservoir release limit to the maximum throughout the planning period (Figure 5.5).
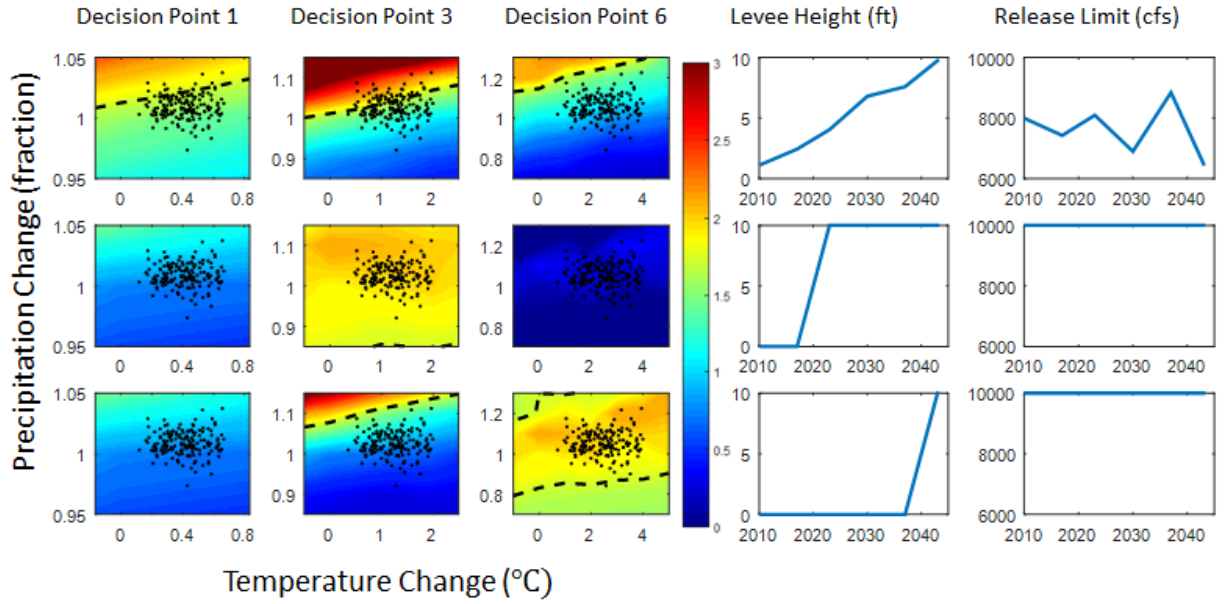
Figure 5.5: (left) Response surfaces of three representative adaptation sequences' (rows) economic performance (color scale) in response to changes in average precipitation (vertical axis) and average temperature (horizontal axis) during the first, third, and sixth (final) planning period (columns). (right) Illustration of selected adaptation sequences (rows) in terms of levee height (left column) and maximum permitted release from Coralville Lake (right column) as a function of time (horizontal axis).

The period in which levees are raised is subject to a uniform increase in net cost across all climate states because the cost stems from construction rather than flood damage. However, in subsequent periods the robustness to economic damages is increased substantially, as shown in the example adaptation sequence in the second row. The investment in raising levees, however, is not necessary to meet economic performance goals under either the assumed stationary climate or the increased precipitation and temperature scenario.

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Raising the growing season release limit from Coralville Reservoir is common to all candidate strategies, though not all raise the release limit to the maximum permitted value or maintain it at the maximum permitted value through the entire planning period (Figure 5.4). This adaptive action is necessary to meet the ecological performance goal of increasing expected inundation downstream of Iowa City under most climates which do not include large increases in precipitation, including the "stationary" climate and the deterministic GCM projection, as the ecological metric response surfaces demonstrate. This is particularly evident in the comparison between the adaptation strategy evaluated in the first row, which does not raise the release limit to the maximum, with the remaining two adaption sequences which do raise the release limit to the maximum throughout the planning period (Figure 5.6). The first adaptation sequence fails to meet the floodplain inundation objective over a wider range of climate space at the end of the planning period than either of the other two example adaptation sequences.
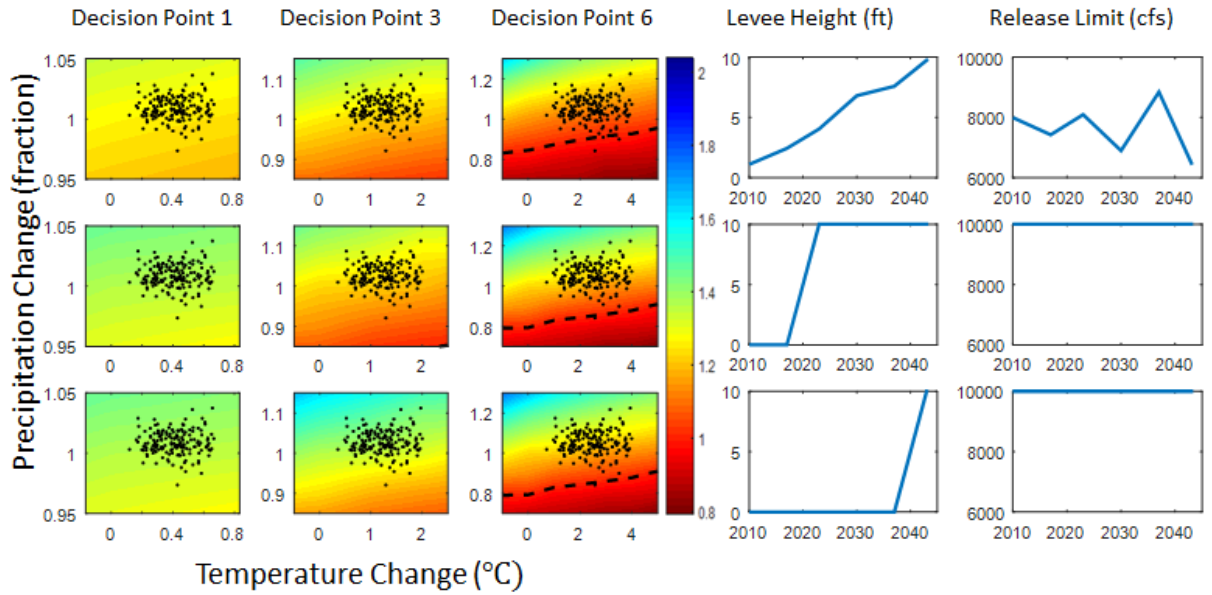
Figure 5.6: (left) Response surfaces of three representative adaptation sequences' (rows) ecological performance (color scale) in response to changes in average precipitation (vertical axis) and average temperature (horizontal axis) during the first, third, and sixth (final) planning period (columns). (right) Illustration of selected adaptation sequences (rows) in terms of levee height (left column) and maximum permitted release from Coralville Lake (right column) as a function of time (horizontal axis).

Figure 5.7 synthesizes the information displayed in Figures 5.5 and 5.6 to highlight the three example high-performing FRM sequences' satisficing behavior throughout the planning period and across future climate states. The second and third example adaptation sequences show how the cost of raising levees from their present elevation by ten feet in a single planning period increases expected cost in that planning period, leading to unacceptably high costs in that planning period. It also demonstrates the benefits of an increased reservoir release limit in improving the frequency of ecologically beneficial floodplain inundation. The gradual increase in levee height exemplified by the first adaptation sequence avoids the impact of sudden levee

increase, but ultimately provides increased economic protection in the last decision period, during which the breadth of climate states considered plausible is currently widest. However, the combination of levees raised by ten feet and reservoir release limit increased to the maximum amount in the last period best mitigates the economic impacts of floods resulting from increased precipitation, as shown in the second adaptation sequence. The first adaptation sequence, which was selected through the decision scaling-based satisficing approach to RO, exemplifies consistently strong satisficing performance throughout the planning period while the other example FRM adaptation sequences exhibit poor satisficing behavior in some parts of the planning period (Figure 5.7).
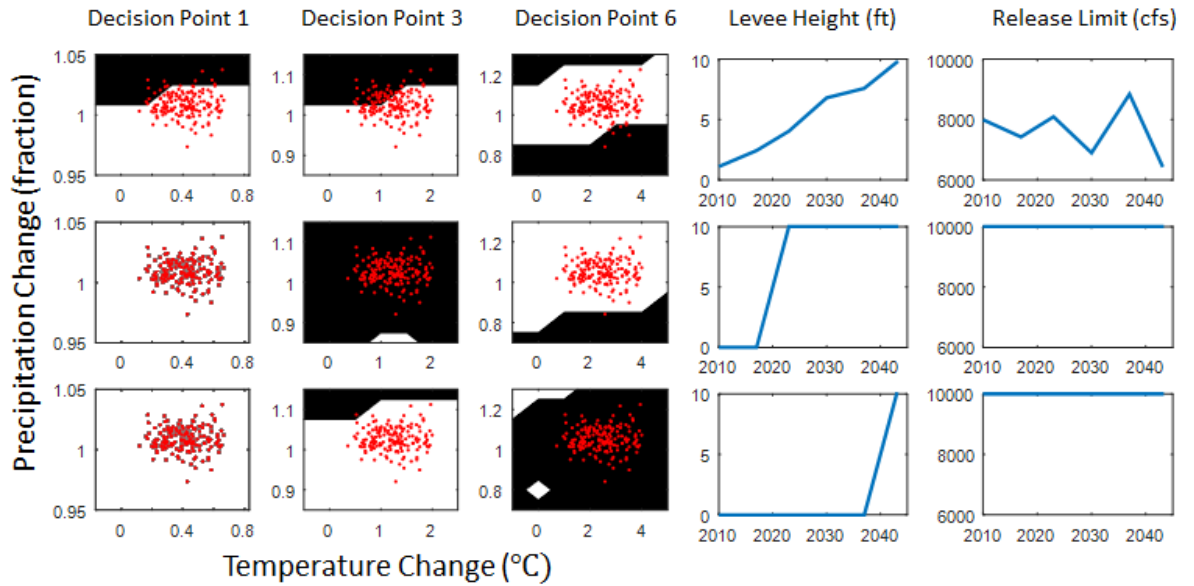
Figure 5.7: (left) Response surfaces of three representative adaptation sequences' (rows) satisficing behavior (black = unacceptable performance, white = acceptable performance) in response to changes in average precipitation (vertical axis) and average temperature (horizontal axis) during the first, third, and sixth (final) planning period (columns). (right) Illustration of selected adaptation sequences (rows) in terms of levee height (left column) and maximum release limit (right column) as a function of time (horizontal axis).

The maximum regret for each representative adaptation sequence is shown in Figure 5.8 as a function of time. Regret is defined as the difference in performance between the FRM strategy implemented and the optimum FRM strategy specific to a single climate scenario and driving objectives of economic performance and ecological performance. Because regret is calculated by comparing "robustness-optimal" FRM strategies to objective- and scenario-optimal FRM strategies, regret provides an exogeneous measure of candidate FRM strategies' robustness for *ex post* inter-comparison.
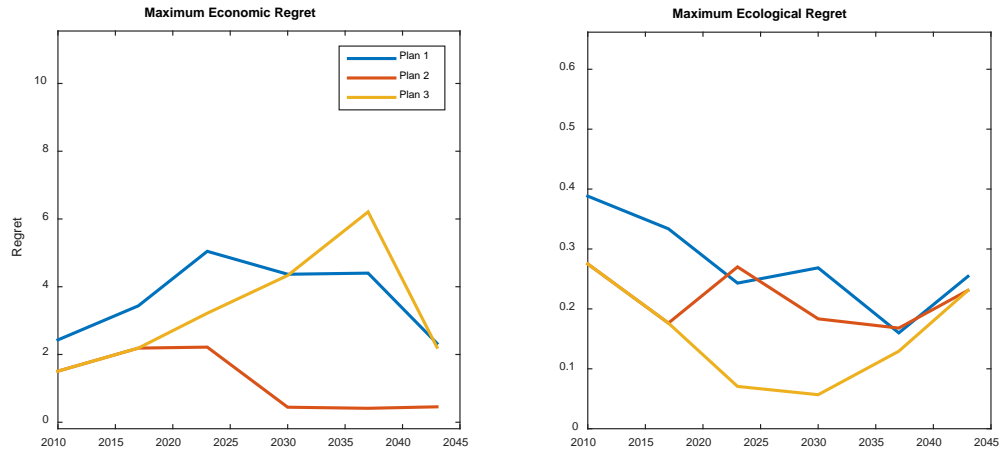
Figure 5.8: Maximum regret across climate space (vertical axis) associated with three representative high-performing solutions (color scale) at each planning stage (horizontal axis).

Economic regret is high in the second to final planning stage under the third plan, just prior to raising levees. This is because a more severe precipitation increase introduces high flow episodes that are not yet mitigated by augmented levees. Similarly, ecological regret is high under example Plan 1, which does not raise the reservoir re-operation alternative to the maximum allowable amount, while maximum ecological regret is low during the intermediate stages under Plan 3 because, while the growing season release limit has been raised to the maximum allowable level, levees have not yet been altered. This is the best strategy to improve the ecological objective and ensure adequate inundation, even under decreased precipitation which reduces the number of bank overflow events.

Comparing high-performing FRM adaptation sequences selected under the five objective functions leads to key insights on the characteristics of solutions found through each objective function. Figure 5.8 compares the robustness of high-performing solutions through the maximum regret across climate space associated

with each high-performing solution, which are separated according to the objective function under which they were selected, as a function of time. In addition to the regret characteristics of the three illustrative adaptation sequences, Figure 5.9 compares the differences in maximum ecological and economic regret under the high-performing FRM strategies among the five planning approaches.
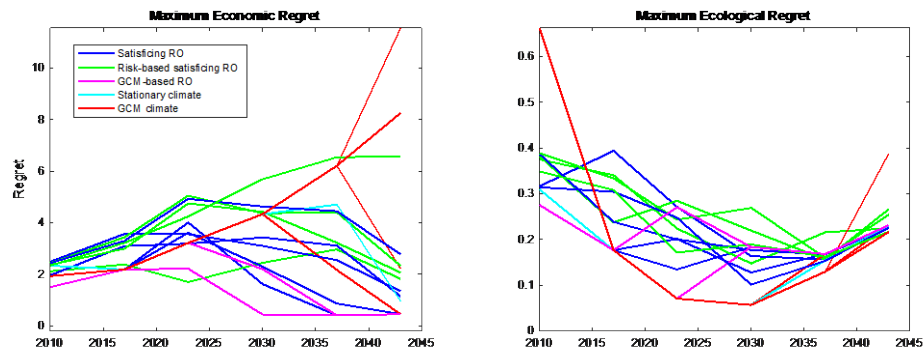
Figure 5.9: Maximum regret across climate space (vertical axis) associated with top five best-performing solutions selected under each objective function (color scale) at each planning stage (horizontal axis).

While multiple FRM sequences selected under each objective function exhibit comparable regret characteristics across time and climate space, FRM strategies selected for high performance in the GCM climate or risk-based satisficing exhibit particularly high economic regret at the end of the planning period and ecological regret at the beginning of the planning period. This is because these strategies discount the most extreme climate assumptions, for example particularly wet climates where levees are necessary to mitigate damage or dry climates where, without re-operation, reservoir operations could threaten aquatic ecosystems, even though these hypothetical climate states cannot be dismissed as implausible. While strategies

selected through the satisficing-based objective function exhibit comparable levels of regret to strategies selected through other objective functions at the middle of the planning period, solutions selected through satisficing RO lead to consistently low economic and ecological regret at latter planning stages under which the widest variety of climate states is assumed possible (Figure 5.8).

Table 5.2 compares high-performing FRM strategies selected under each planning approach in terms of their robustness, as measured by the satisficing metric (Equation 5.6) and performance under the stationary climate. The satisficing-based robustness metric measures the fraction of a incrementally varied and combined climate scenarios in which acceptable performance is achieved in both economic and ecological performance metrics. The satisficed fraction robustness metric is a complement to the maximum regret robustness metric presented in Figure 5.9. Comparing strategies' performance in terms of robustness and performance under the stationary climate elucidates the tradeoff between increasing the consistency with which acceptable performance is achieved and maximizing performance under a single state of the world. Table 5.2 reveals that FRM sequences selected through decision scaling-based satisficing and even risk-based satisficing RO are consistently more robust that strategies selected through GCM-based RO or single-scenario optimization (Table 5.2).

Table 5.2: Comparison of high-performing FRM adaptation sequences' performance under decision scaling-based satisficing objective function (Equation 5.6) and stationary climate objective function (Equation 5.3).

Objective function	Performance rank	Satisficing Performance (fraction of climate scenarios)	Stationary Climate Performance (dimensionless)
Stationary climate	1	0.49	1.92
Stationary climate	2	0.1	1.86
Stationary climate	3	0.04	1.85
Stationary climate	4	0.12	1.83
Stationary climate	5	0.41	1.83
10% more precipitation, 3 ℃ warmer	1	0.49	1.92
10% more precipitation, 3 ℃ warmer	2	0.1	1.86
10% more precipitation, 3 ℃ warmer	3	0.04	1.85

10% more precipitation, 3 ℃ warmer	4	0.41	1.83
10% more precipitation, 3 ℃ warmer	5	0.41	1.83
GCM-based RO	1	0.49	1.92
GCM-based RO	2	0.1	1.86
GCM-based RO	3	0.04	1.85
GCM-based RO	4	0.08	1.83
GCM-based RO	5	0.04	1.81
Risk-based satisficing	1	0.61	1.74
Risk-based satisficing	2	0.49	1.93
Risk-based satisficing	3	0.51	1.66
Risk-based satisficing	4	0.45	1.62
Risk-based	5	0.41	1.7

satisficing			
Satisficing	1	0.67	1.82
Satisficing	2	0.61	1.82
Satisficing	3	0.59	1.71
Satisficing	4	0.57	1.71
Satisficing 5th	5	0.57	1.74

The top-ranking FRM adaptation sequence selected under each objective function that is not based on a satisficing metric satisfices 49% of scenarios. While 49% is only 18% less climate space than the top-ranking FRM sequence selected through satisficing-based RO, which achieves acceptable performance for both objectives under 67% of climate scenarios, satisficing performance of FRM strategies selected through single-scenario optimization or GCM-based RO quickly degrades in the subsequent lower-ranked high-performing adaptation sequences. The high performing strategies selected under the stationary climate, GCM climate, and GCM-based RO planning approaches each include a strategy that satisfices only 4% of the climate space. This is equivalent to 6% of the satisficed space achieved under the best satisficing-based candidate strategy, which satisfices 67% of the precipitation and temperature change scenarios. In comparison, the fifth-best performing FRM sequence selected through satisficing performs only 15% worse than the top-performing FRM sequence selected through satisficing RO. This indicates it is possible to improve the robustness of the FRM system with little sacrifice in performance under the default planning assumption that future climate will resemble

historically observed climate. In contrast, some strategies with highly ranked performance under an assumed stationary climate are highly sensitive to climate variation and change.

The outcome of this example analysis yields several key results accompanied by caveats for application. First, a common archetype of adaptation strategy in which the release limit from Coralville Reservoir is maximized throughout the planning period and levees are raised in stages part way through the planning period performs well with respect to all objective functions in the Iowa River case, which span a representative selection of climate scoping methods and risk attitudes. This presents stakeholders who hold different climate beliefs and risk preferences with a demonstration of how well the decision performs with respect to their own priorities, facilitating compromise and supporting consensus. The optimization analyses also demonstrate that most objective functions, as is common in water resources engineering applications, are flat in the region of the optimum. A number of sometimes diverse alternative FRM strategies lead to the same level or a very similar level of performance under each objective function (Figure 5.4, Table 5.2). While this quality of water resources applications has limited the past application of optimization to dictate real-world management decisions, the multiplicity of high-performing FRM strategies enhances the utility of optimization as a tool in seeking compromise rather than decision dictator.

While a FRM climate adaptation analysis would be incomplete without exploring the consequences of the full range of plausible future climate states, a comparison among FRM strategies developed through robustness frameworks such as decision scaling-based RO and scenario-specific planning frameworks or impact assessment based solely on climate model output can be useful in facilitating compromise among

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stakeholders who hold different climate assumptions and/or risk preferences. Figures such as Figure 5.5-5.5.7 that present visual evidence of the candidate FRM strategies' performance across scenarios and objectives as well as the formal cross-examination of candidate strategies' performance with respect to all objective functions facilitate this discussion by quantifying each stakeholder's individual regret associated with selecting a FRM strategy that does not maximize their preferred objective function. In the case that a consensus cannot be reached, additional adaptation options may need to be considered so that all stakeholders can be satisfied. This reflects the iterative nature of both engineering design and climate adaptation.

Conclusions

This dissertation chapter demonstrates the benefits of a decision scaling-based approach to robust optimization, which leads to more consistently robust adaptation alternatives across optimal and near-optimal FRM strategies. The comparison between decision-scaling based robust optimization, a risk-based variant on the decision-scaling based optimization, conventionally framed GCM-based robust optimization, and single-scenario optimization demonstrates the benefits of decision support tools which accommodate not only uncertainty in the conditions under which a FRM system must perform, but also compare the results of multiple planning approaches. The sequencing of decisions in time enhances adaptive flexibility and furthers compromise, as the framework illustrates where it is possible to postpone actions that are presently controversial until they are more clearly needed. The set of Iowa River optimization analyses presented above compare the strategies that maximize performance under differing climate assumptions, ultimately showing that increased performance can be secured in climate states not indicated by climate model projections through small changes to FRM strategies that maximize performance

under more conventional climate assumptions based on stationary frameworks or climate model output. The decision scaling-based approach to robust optimization innovates on previous RO frameworks through application to FRM, accommodation of multiple objectives, and enhancing the set of climate assumptions used to evaluate potential FRM strategies, leading to the consideration of more robust FRM adaptation strategies than previous RO formulations for managing water resources under climate uncertainty.

CHAPTER 6

**COMBINING HISTORIC AND PROJECTED TREND IN A BAYESIAN
FRAMEWORK FOR FLOOD RISK MANAGEMENT DECISION MAKING
UNDER UNCERTAINTY**

<u>Abstract</u>

The prevalence of robust approaches to FRM decision making under nonstationary climate is driven by weaknesses in established methods of estimating future flood hazard and controversy in the appropriate method of uncertainty quantification. Trends extrapolated from the historic record may have little bearing on future flood hazard, while climate model simulations occur at too coarse a spatial scale to represent flood-producing meteorological features and replicate the temporal characteristics of precipitation poorly. This chapter proposes a Bayesian framework for estimating and quantifying uncertainty in future flood hazard by exploiting the observed connections between continental-scale atmospheric patterns, which are often simulated more skillfully by climate models than localized precipitation, with local-scale flooding. The uncertainty quantification framework estimates the relationship between climate index and a peak flow probability distribution. The posterior distribution of future -correlated climate index is estimated as a Bayesian combination of likelihood sourced from observations or re-analysis of the climate index with a prior synthesized from climate model projections of the climate index in a future period. The prior is synthesized from bias-corrected values of the simulated climate index, whose relative contribution to the prior parameters is proportional to each model's bias in hindcast simulations. The prior is also synthesized in such a way that the prior is more vague in the case that climate models' hindcast simulations exhibit

significant bias, and less vague in the case that climate models' hindcast simulations exhibit low bias. In this way, the posterior distribution of the flood-correlated index draws more heavily from past observations and is more highly uncertain if climate models are uninformative, and is influenced more strongly by climate model simulations if climate models are skilled. The resulting nonstationary peak flow probability distribution may be used to inform risk-based FRM adaptation decisions.

<u>Introduction</u>

Decision making frameworks which accommodate multiple sources of uncertainty are essential to effective flood risk management given the high degree of uncertainty associated with characterizing extreme streamflow. Chapter 2 established that trend detection based on the historic record is likely to miss extant trends given the emphasis on avoiding type I error at the cost of high rate of type 2 error, limited record length, high peak flow variability, and the possible presence of low-frequency variability. The nature of a flood trend, if it exists, is another confounding influence on forecasting flood hazard into the future. If a trend is detected in the record, is it caused by climate or land use change, and will the probability distribution of extreme flow continue to change into the future, halt at a new distribution, or revert to a previous state? If no trend is observed in peak flows, does that necessarily imply no change in flood characteristics will occur over a product's design life? The possibility of regime shifts from one state to another limits the value of statistical analysis of past flows to inform future design standards because observed flood frequency characteristics are not guaranteed to persist and may change abruptly, leading to over- or under- design. This lack of certainty favors robust design. It also, however, emphasizes the need for process-based projections of flood hazard. The future context of flooding is likely to include novel land use and climate characteristics and the past

has only limited ability to predict the future. Statistical analysis of a streamflow record alone provides little justification for forecasting future change as the drivers of observed or suspected trends are not explored. Analyzing changes in land use within the basin or frequency and severity of flood producing storm types in addition, however, may provide insight into whether a trend will continue. Process-based insights are critical to operationalizing the results of statistical analysis in an engineering design context.

The hydrologic and meteorological drivers of flood hazard

The established approach to incorporating climate projections in water resources adaptation planning projects changes in average precipitation and temperature, sometimes alongside shifts in seasonality, onto a hydrosystems model and evaluates the effects of this change. In the case of flood risk management, changes in average precipitation and temperature have a limited relationship to the mechanisms which cause floods (Horton, 1933). The strongest relationship between average precipitation and temperature changes and flooding occurs through the influence of average temperature and precipitation on antecedent conditions, which affect basins' hydrologic response: under higher average precipitation, soil moisture may be higher, leading to faster saturation and more runoff (Horton, 1933; Nied et al., 2014). Higher temperature, however, could lead to increased evapotranspiration and offset the effects of increased precipitation on soil moisture. In combination, changes in average precipitation and temperature could also herald changes to snowpack, which can be a major determinant of flood magnitude through the presence or absence of rain-on-snow events. Nonetheless, changes in average precipitation and temperature do not necessarily correspond to changes in temporally and spatially localized intense precipitation events that are the most crucial ingredient in many, though not all,

instances of flood occurrence (see Hoyt and Langbein, 1939; Goodrich, 1938; Rabot, 1905; Alpert et al., 2002). For example, convective storms such as thunderstorms cause downpours and flooding (Doswell et al., 1996), tropical cyclonic storms, hurricanes, or typhoons are associated with extreme flooding in a number of locations worldwide (Easterling et al., 2000). Flood-producing meteorological processes (for example hurricanes, tropical cyclones, convective and orographic storms, and tropical moisture exports) occur on too fine a spatial scale to be represented by general circulation models (Stainforth et al., 2007a, b; Flato et al., 2013) and exhibit significant biases in regional climate models, output of which is also of limited availability. Projections of precipitation produced by these models are therefore of limited utility to flood risk managers. The association between flooding or extreme precipitation and systematically categorized storm types, however, is well established (e.g. Prudhomme et al., 2002; Cheng et al., 2010), and exploring potential changes in the frequency of flood-correlated meteorological events is a promising avenue toward estimates of future flood hazard. For example, Faiers et al. (1994) develop a synoptic classification of extreme precipitation events of varying duration in Louisiana with the intent of informing storm probability information for the region. However, the literature connecting the occurrence of specific storm types directly to the probability distribution of peak flow is sparse.

Flood-producing storm types are often associated with large synoptic-scale atmospheric or sea surface temperature patterns that shift on a variety of temporal scales, including daily or weekly (e.g. vorticity, wind fields, fluctuations in atmospheric temperature, or geopotential height), seasonal to annual (e.g. the El Nino Southern Oscillation (ENSO)), and inter-annual or decadal (e.g. the Pacific Decadal Oscillation (PDO)). These circulation patterns may be classified through spatial

dimension reduction algorithms such as Empirical Orthogonal Functions and other clustering algorithms and in terms of seasonal timing (e.g. Davis & Rogers, 1992; Kahana et al., 2002). The literature linking sea surface temperature (SST) and atmospheric patterns to extreme precipitation is substantial and established (e.g. Dao, 1958; Goree and Younkin, 1966; Muller, 1977; Barry et al., 1981; Harrison, 1984; Dorling and Davies, 1995; Bellone et al., 2000; Alpert et al., 2004; Alexander, 2016). Precipitation and streamflow anomalies have been correlated with the phase of the El Nino Southern Oscillation (ENSO) (e.g. Chiew and McMahon, 2002; Chandimala and Zubair, 2007), Pacific Decadal Oscillation (PDO) (e.g. Goodrich, 2007), North Atlantic Oscillation (NAO) (e.g. Labudova et al., 2013), and other global-scale patterns (e.g. Xu et al. 2006; Xiao et al., 2014) which fluctuate across time scales that range between daily, monthly, annual, and multi-year or decadal. It also includes the potential for using synoptic-scale atmospheric pressure and circulation-based predictors such as geopotential height for downscaling global gridded model output to local-scale precipitation (Cavazos and Hewitson, 2005). A parallel literature linking circulation-based predictors to streamflow is also established (e.g. Salathé, 2003; Ward et al., 2014; Córdoba-Machado et al., 2016), but includes the development of peak flow probability distributions whose parameters are conditioned on circulation-based climate indices that vary on a monthly to interannual time scale (e.g. Villarini et al., 2013; Stedinger & Griffis, 2011). Unlike localized precipitation or streamflow, circulation-based indices take place across a very broad spatial scale that incorporates a sufficient number of climate model grid cells (presently 1-2 degrees) to constitute the skillful spatial scale of general circulation models (Wilby, 1998; Xu, 1999; Flato et al., 2013). Indeed, one reason general circulation models were originally developed is to aid in understanding large-scale climate dynamics throughout the whole of the

earth's history (Smagorinsky et al., 1965; Holland and Lin, 1975), and the study of synoptic climatology through general circulation models is a robust area of research (Sheridan and Lee, 2010). Climate model projections of synoptic-scale climate indices, therefore, may be more useful to flood risk managers than localized precipitation projections.

The use of general circulation model simulations of synoptic-scale spatial pattern in atmospheric variables to infer changes in local climate variables (especially precipitation), alone or as a downscaling technique, is called "weather typing" (Fowler et al., 2007), and is distinct from other statistical downscaling techniques in that weather typing does not translate gridded model output of a climate variable of interest to the same variable of interest at a local scale. A common criticism of statistical downscaling and bias correction techniques that are based on a transfer function between model output and local climate variable(s) is that they rely on an assumed stationary transfer function, though the stationarity of the transfer function is not guaranteed (Wilby, 1998; Fowler et al., 2007). Downscaling techniques based on weather typing share this weakness in that the relationship between circulation-based predictors and local climate variables is not guaranteed stationary because of a number of reasons, including the failure of pattern scaling schemes to identify and represent interactions among all relevant climate variables and the potential for novel future weather types (see Prudhomme et al., 2002; and Fowler et al., 2007). However, the basis of weather typing on a physical mechanism that connects general circulation to local weather indicates the potential for greater predictive skill than downscaling techniques which do not address the atmospheric mechanism connecting a climate variable at a coarse spatial scale to that same climate variable at a local scale.

This chapter addresses the need for process-based insights into flood hazard evolution by exploiting the climatic mechanisms associated with flood-inducing precipitation to develop probabilistic projections of flood hazard. This chapter applies a process for developing probabilistic, nonstationary flood hazard projections for the Iowa River based on categorizing flood-producing weather events in an area of interest, documenting the synoptic-scale climate indices associated with those event types (e.g. Kahana et al., 2002; Nakamura et al., 2012), quantifying trends in the synoptic-scale climate index, and projecting future variability in the synoptic index inferred from climate model projections and historic observations of the index. The projected variability in climate index informs an index-conditioned peak flow probability distribution, which is used in design. We demonstrate the approach through an application to an adaptation decision in the Iowa City flood management system, which has experienced recent unprecedented damaging flood events, calling into question the existing system's adequacy.

<u>Methodology</u>

The process of developing process-driven probabilistic flood hazard projections for an area of interest consists of several key steps which include systematically exploring and connecting the causes of flooding to outcomes in terms of how flooding will be expected to change in the future. This chapter demonstrates this process in an analysis of flooding on the Iowa River.

Chapter 2 provides a full description of the Iowa City flood management context, so this section gives only a brief overview. To better capture information content in peak flows, the inflows to Coralville Lake as measured at Marengo, USGS gage 05453100, as peaks-over-threshold using a generalized Pareto distribution to represent the magnitude of flow exceedances and a Poisson distribution to model the number of

exceedances per year. The partial duration series technique may include more than one peak flow per year which is not possible using the annual maximum approach. The exceedance threshold is 12,000 cfs, which is the level of discharge at which damages to Iowa City occur.
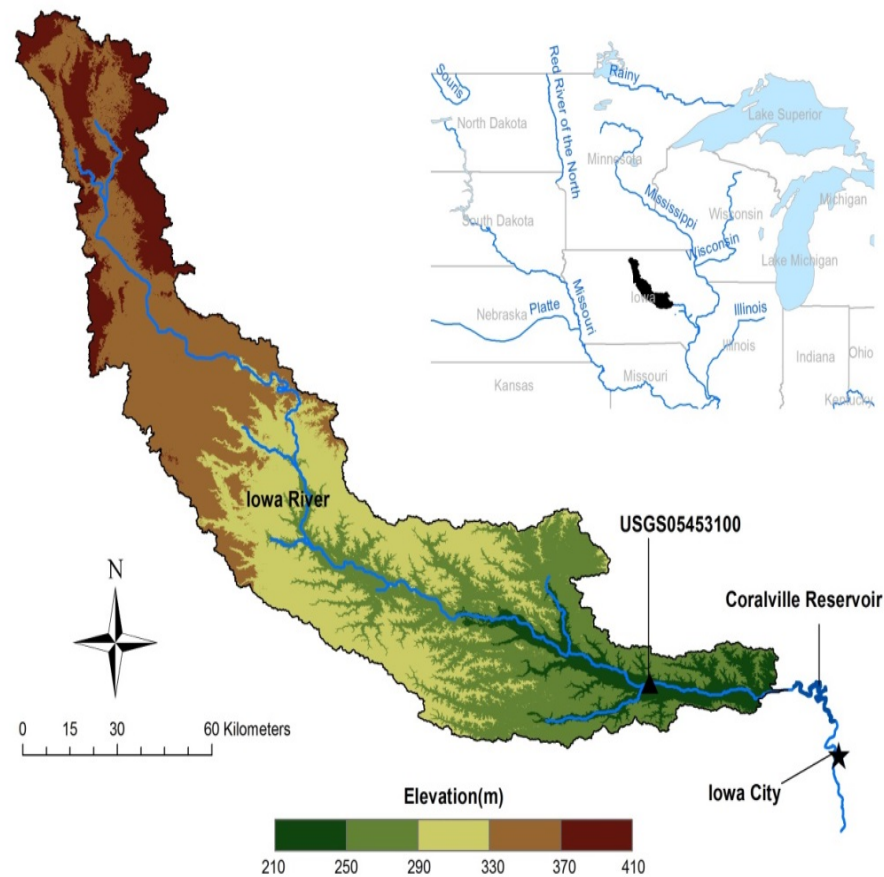
Figure 6.1: Iowa River watershed with Coralville Lake, Iowa City, and detail showing location within the upper Midwest of the United States.

The process begins by exploring and categorizing storm types associated with flood occurrence in the region meteorologically, through spatial classification algorithms . Steinschneider & Lall (2015) quantify the relationship between tropical moisture exports (TMEs) and extreme precipitation. Precipitation extremes in upper Midwest location such as the Iowa River Basin have been linked to tropical moisture exports

(TMEs) from the Gulf of Mexico (Dirmeyer et al., 2010; Knippertz, 2013; Robertson et al., 2015).

It is common for the occurrence of flood-related storms and meteorological events to be correlated with global-scale atmospheric or sea surface temperature patterns. The TME's associated with upper Midwest precipitation extremes have been linked to an atmospheric pressure dipole across the east coast of the US between a maximum in 700-hPa geopotential height surface to the east of the Upper Midwest and minimum to the west of the Upper Midwest region (Nakamura et al., 2013). We calculate the value of this dipole index from the maximum 700-hPa in the box defined by the indices 70W-57.5W, 35N – 45 N and minimum defined in the box defined by the indices 90W to 77.5 W, 35N to 45N in geopotential height gridded re-analysis of station observations provided by the NCEP/NCAR re-analysis project (Kalnay et al., 1996) through time (Figure 6.2).
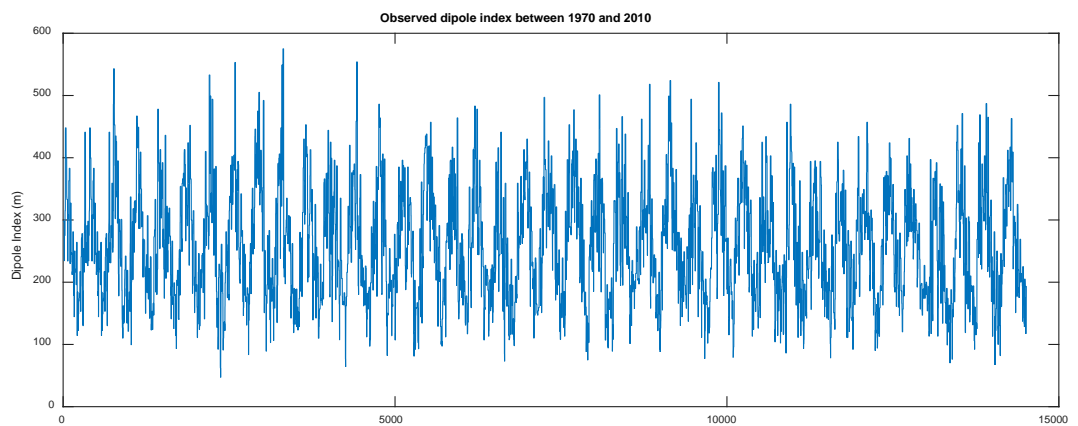
Figure 6.2: Daily values of dipole index from 1970 to 2010.

The dipole index is correlated with extreme discharge events on the Iowa River, including the 2008 flooding that occurred across the upper Midwest (Figure 6.3). An elevated dipole index precedes multiple peaks of the 2008 flood episodes.

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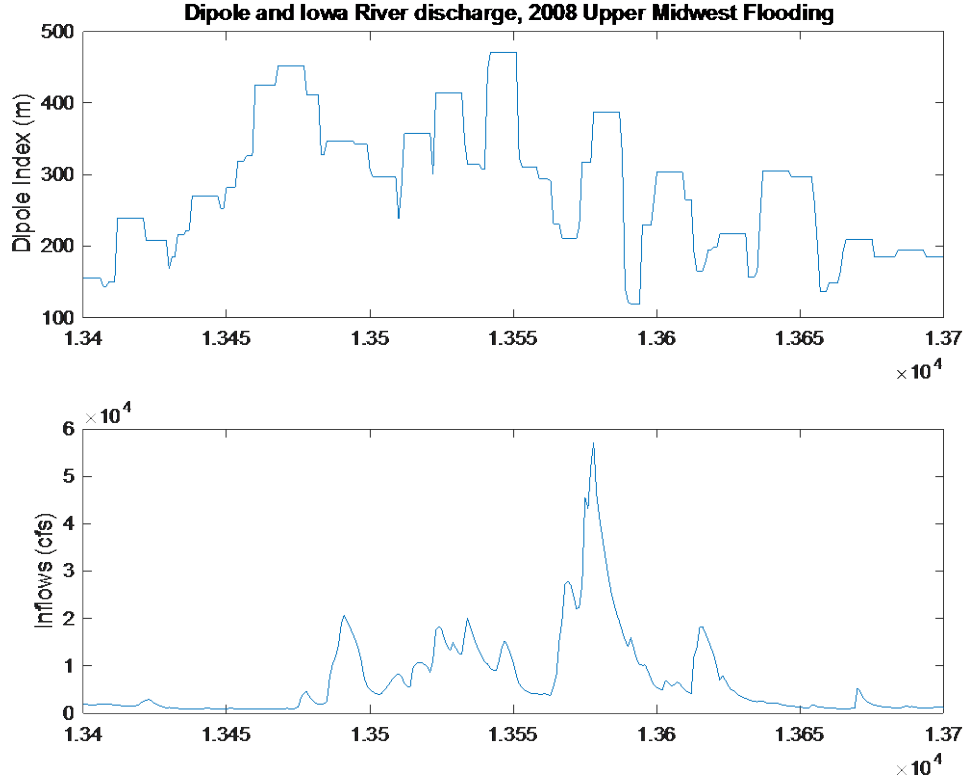
Figure 6.3: 10-day maximum dipole index (m) and inflow to Coralville Reservoir (cfs) during 2008 Upper Midwest floods.

The correlation between frequency and magnitude of extreme streamflow and the value of the dipole index in the preceding ten days prior to a peak flow event is explored by treating the parameters of a Pareto-Poisson peaks-over-threshold probability distribution (Equation 6.1) as functions of the dipole index value x at time t. The rate parameter of the Poisson distribution, v, represents the number of flow threshold exceedences in the given time period. The Generalized Pareto Distribution represents the magnitude of threshold exceedences, and is parameterized through σ, the scale parameter, and ξ, the shape parameter.

$$P(y, k|t) \sim Poisson(v|x_t)GPD(\sigma|x_t, \xi)$$

Equation 6.1

The parameters of the POT model are linear functions of the value of the dipole index so that the number of floods per time period *k* and the typical magnitude of the flow exceedances *y* are conditional on the maximum value of the dipole index observed over a sliding 10 day window (Equation 6.2; Equation 6.3).

$$k \sim Poisson(v_0 + v_1 x_t)$$

Equation 6.2

$$y \sim GPD(\sigma_0 + \sigma_1 x_t, \xi)$$

Equation 6.3

The addition of the dipole index to the POT model improves the model's skill when compared to the dipole-independent model significantly, particularly when the model is restricted to the months in which most flooding occurs, which are April, May, and June (Table 6.1). The parameters of the conditional extreme flow probability distribution are estimated through maximum likelihood estimation (Mendez et al., 2006). The likelihood ratio test quantifies confidence in the improvement in skill introduced by the dipole-conditioned parameters by comparing the goodness-of-fit, as measured by the models' likelihood function, of the dipole-conditioned POT model and the likelihood function of the dipole-independent POT model as a ratio to determine whether the extra parameters add a statistically significant improvement in the goodness-of-fit (Wilks, 1938).

Table 6.1: Peaks over threshold parameters and confidence in skill improvement evoked by incorporating linear relationship to dipole index.

Model	Stationary	Dipole	Stationary-AMJ	Dipole-AMJ
ξ	0.0000	0.0056	0.0000	0.0159
ν_0	1.4737	0.1946	0.7895	3.2648
ν_1	--	0.5050	-	-0.1041
σ_0	8.1684	7.2519	8.3329	7.9586
σ_1	--	0.3729	-	0.1288
Likelihood ratio significance	--	$p < 0.05$	-	$p < 0.001$

An estimate of the future probability distribution of dipole index fully defines the dipole-conditioned peak flow probability distribution so that it may be used in flood management decisions and design choices.

Bayesian analysis of future dipole index

With a strongly statistically significant relationship established between damaging peak flows and the value of the dipole index (Table 6.1), we seek to estimate the value of the dipole index at the end of the planning period, which is 2045, and estimated from climate model projections of dipole index between 2030 and 2059. A posterior distribution of dipole index is estimated by combining a likelihood parameterized through the dipole index estimated from gridded re-analysis of n days of station pressure observations (Equation 6.4) and prior distribution of dipole index formed based on n_r days of simulated geopotential height fields of hindcast and future climate model simulations through Bayes' Theorem.

$$\mathcal{L}(x|\tau,\mu) \propto \prod_{i=1}^{n} \tau^{\frac{1}{2}} \exp\left[\frac{-\tau}{2}(x_i - \mu)^2\right]$$

Equation 6.4

We model the dipole index in the flood season (April-May-June or AMJ) as normally distributed. A Kolmogorov-Smirnov test determines that the daily observations of the dipole index between 1970 and 2010 are normally distributed at 95% confidence levels.

Both the mean and variance of the future dipole index are assumed unknown. Modelling the future dipole index through a normal distribution with unknown mean μ and unknown precision τ (variance raised to the -1 power), a Normal-Gamma distribution is conjugate to the unknown mean and precision of the posterior distribution of dipole index (DeGroot, 1970) (Equation 6.4).

$$NG(\mu,\tau|\mu_o,v_0,\alpha_0,\beta_0) \equiv N(\mu|\mu_o,(v_0\tau)^{-1})Ga(\tau|\alpha_0,\beta_0)$$

Equation 6.4

The prior parameters are denoted μ_0, v_0, α_0, and β_0, while the posterior parameters are denoted μ_n, v_n, α_n, and β_n. The expectation of the Normal-Gamma distribution is given as $E[X] = \mu$ while $E[\tau] = \frac{\alpha}{\beta}$. The variance of the Normal-Gamma distribution is given by $var[X] = \frac{\beta}{v(\alpha-1)}$ and $var[\tau] = \frac{\alpha}{\beta^2}$.

Synthesis of prior parameters from climate model simulations

The prior is constructed out of simulated daily dipole index sourced from several climate models (Table 6.2) simulations of the 2030 to 2060 period, weighted by the models' hindcast simulation skill between 1970 and 2005. The runs of three climate

models, all of which participated in the NARCCAP experiments (Mearns et al., 2012), are included in the analysis. Three runs are included from the Hadley Center Climate Model 3 (HadCM3) and three from the Geophysical Fluid Dynamics Laboratory climate model (GFDL), and one run from the Community Climate System Model 4, which was the only published model run containing daily geopotential height fields from this climate model.

Table 6.2: Characteristics of dipole index simulated by three climate models and multiple stochastic runs of different climate models.

Model	Run	Hindcast mean	Future mean	Hindcast Variance	Future Standard Deviation	Bias (δ_r)
CCSM4	r6	262	223.9	101.7	72.3	0.91
HadCM3	r1	243.4	225.5	77.5	73.4	0.53
HadCM3	r5	241.5	228.1	77.9	72.7	0.53
HadCM3	r9	242.2	223.7	76.9	67.78	0.53
GFDL	r1	260	231	84.4	74.6	0.95
GFDL	r3	259.9	226.3	84.5	69.3	0.88
GFDL	r5	263.4	221.1	85.4	67	0.94

The selected climate models replicate the magnitude, variability, and seasonal cycle of the dipole index with various degrees of skill in the hindcast simulations (Figure 6.4; Figure 6.5).
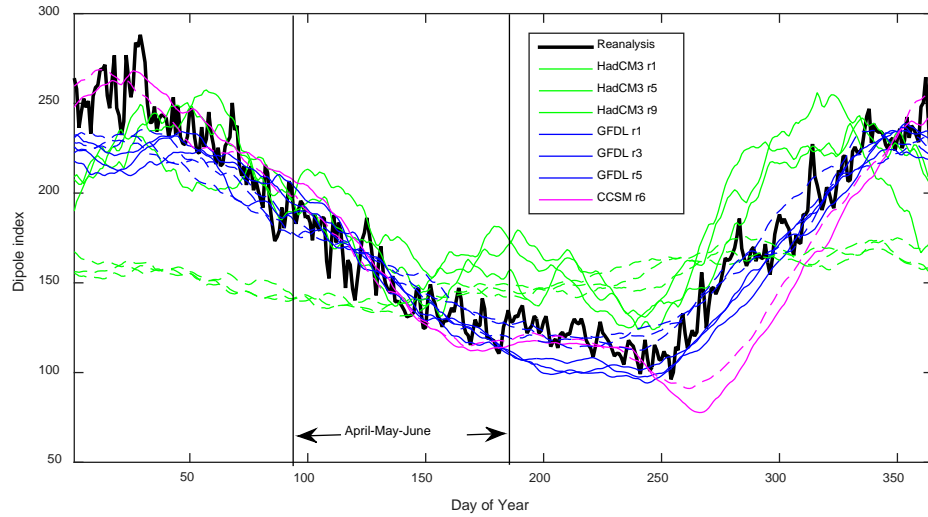
Figure 6.4: Average value of dipole index on each day of the year in hindcast (dashed lines) and future (solid lines) climate model simulations (colored lines) compared with dipole index estimated from re-analysis (black line).

The HadCM3 model simulates a substantially different seasonal pattern in the hindcast simulations from the future simulations (Figure 6.4). A comparison of the distribution of dipole index in future and hindcast climate model runs indicates a trend toward a slight downward shift in dipole index with possible changes in variability (Figure 6.4).
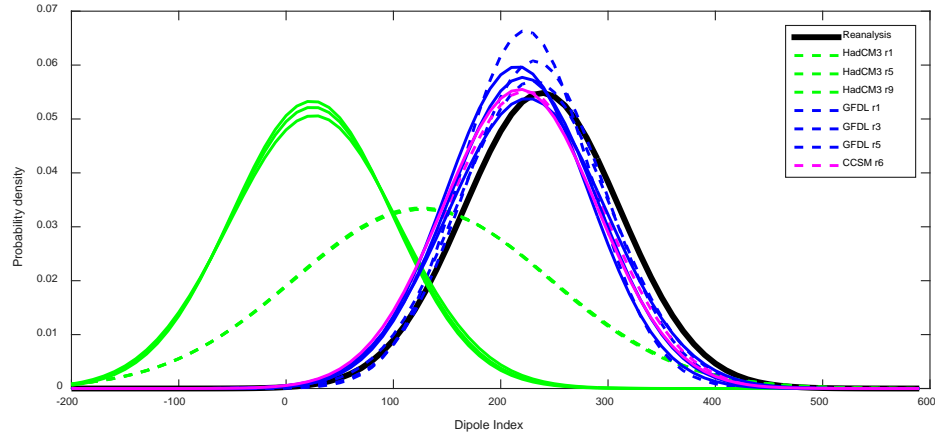
Figure 6.5. Histograms of dipole index as reproduced by hindcast simulation (dashed lines; 1970-2005) and simulation of the future period (solid lines; 2036-2056).

This chapter proposes a method for parameterizing the prior so that the prior's location characteristics are influenced most heavily by models which reproduce the dipole index with least bias, and its shape is more flat if the models exhibit high bias in the hindcast period. The most important feature of the proposed parameterization method is to blend the features of an informative prior, which is typically based on data, and a vague prior, which represents a total lack of knowledge and is conventionally flat with virtually equal probabilities assigned to each parameter value. The degree of vagueness of the prior is ascribed according to the confidence in the change signal suggested by climate model simulations according to model bias in the hindcast period. Using a vague or uninformative prior, the likelihood dominates the posterior distribution. Stronger, informative priors have more influence on the posterior distribution.

The standard Bayesian interpretation of the prior parameters as being estimated from imaginary "pseudo-observations", which is a common term used in Bayesian analysis to conceptualize the formation of a prior probability distribution, provides a basis for

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synthesizing multiple model projections into a single prior that reflects both each models' relative skill and the level of credence in the model-based estimate as a whole. In this chapter, the term "pseudo-observation(s)" will be replaced with the term "simulated output" to reflect the prior's basis on climate model simulations of the 2030-2060 future period. The parameters of a Normal-Gamma model are interpreted such that μ_0 is the sample mean of ν_0 days of simulated output, while the precision τ is estimated from $2\alpha_o$ days of simulated output with sum of squared deviations $2\beta_0$.

The prior mean μ_0 is a weighted average of each model r's mean dipole index μ_r according to each model r's relative skill, $w(\delta_r)$, during the hindcast simulation as measured by the models' bias, δ_r. Relative skill is adjusted to the fraction of the total skill of all models, so that $w(\delta_r) = \frac{\delta_r}{\sum_{r \in R} \delta_r}$. This means that models which exhibit lower bias in the hindcast simulation contribute more weight to the prior mean μ_0 (Equation 6.5).

$$\mu_0 = \frac{1}{R} \sum_{r=1}^{R} w(\delta_r)\mu_r$$

Equation 6.5

"Bias" is the quantitative measure of model skill in reproducing the dipole. In this chapter, bias associated with climate model r out of R total climate models is quantified as the integrated difference between the probability density functions of observed dipole index [$P(x)$] and hindcast simulations [$P(x_r)$]. Because the total probability density under two non-overlapping probability density functions and hence the maximum possible value of this metric is two, the metric is normalized

through multiplication by ½ and subtracted from 1 so that it lies between 0 and 1 with 0 representing least skill and 1 representing perfect skill (Equation 6.6).

$$\delta_r = 1 - \frac{1}{2}\int_{-\infty}^{\infty}(P(x_r) - P(x))dx$$

Equation 6.6

Bias provides a measure of the confidence in the dipole index change signal elicited from comparing the hindcast simulation of dipole index between 1970 and 2005 to the future model output between 2030 and 2060. Thereafter, the prior is constructed based on pre-processed model output of simulated dipole index between 2030 and 2060 that is bias-corrected through quantile mapping (see Wood et al., 2004 for a more complete description of this technique) based on the relationship between observed dipole index between 1970 and 2010 and hindcast simulated dipole index in each model between 1970 and 2005. The transfer function is based on empirically estimated quantiles, with a normal distribution used to extrapolate to quantiles beyond those that occur in the hindcast simulation.

The interpretation of the prior parameters v_o and α_o relates to the number of "pseudo-observations", namely, days of simulated output used to estimate the quantity of interest's mean and precision, respectively. This is apt as it relates to this chapter's application because the prior is synthesized out of modelled values. However, the prior is synthesized from multiple stochastic realizations of multiple models' climate simulations. As the models and model runs each replicate the same dates, the number of days of simulated output on which v_o and α_o are based should not be larger than the number of modelling time steps between the beginning and end of the future simulation. This chapter proposes that v_o may be constructed as a weighted average

of the length of each future simulation v_r, with each simulation length weighted according to that model's bias in the hindcast simulation (Equations 6.7 & 6.8).

$$v_0 = \frac{1}{R} \sum_{r=1}^{R} w(\delta_r) v_r$$

Equation 6.7

$$\alpha_0 = \frac{1}{R} \sum_{r=1}^{R} w(\delta_r) \alpha_r$$

Equation 6.8

The prior parameter β_0 represents the simulated output's sum of squared deviations from the mean. This parameter directly affects the variance of the Normal-Gamma prior distribution (Equation 6.9).

$$var[X]_R = \frac{\beta_0}{v_0(\alpha_0 - 1)}$$

Equation 6.9

While β_o could be constructed, like the other parameters, as a bias-weighted average of the sum of squared deviations from the mean estimated from each climate model, this would allow the variance of simulated climate to directly inform the prior's level of influence on the posterior distribution. For example, a prior distribution based on the simulations of one climate model or a set of climate models that have simulated a given climate index with substantially lower variability than the observed climate index would strongly influence the posterior distribution, even though the low variability in fact should be interpreted as lack of skill and therefore hold little influence over the form of the posterior distribution. For this reason, we specify β_o in

such a way that the variance of the Normal-Gamma distribution is exaggerated proportional to the climate models' bias. It is desirable that the prior variance should be identical to the weighted average of the climate index's variance in future simulations only if the simulations exhibit very low bias. It is possible to choose a β_r for each climate model to achieve the desired variance by adding multiplying the variance in Equation 6.17 and solving for β_r (Equation 6.10).

$$\beta_r = \frac{v_r(\alpha_r - 1)}{\delta_r^n} var[X_r]$$

Equation 6.10

Because δ_r is close to zero when climate model r exhibits very low skill in the hindcast simulation and close to one when climate model r reproduces the climate index skilfully in hindcast simulations, variance is inflated for climate models with low skill and near the simulated variance for climate models which exhibit high skill levels. This chapter proposes that the resulting β_r may then be blended in a weighted average according to each models' bias, as the other prior parameters are synthesized (Equation 6.11).

$$\beta_0 = \frac{1}{R} \sum_{r=1}^{R} w(\delta_r)\beta_r$$

Equation 6.11

The prior parameters, synthesized from R climate model paired hindcast and future simulations of the climate index, blend with the likelihood sourced from observations of the climate index to result in a posterior distribution of the climate index's future value.

Posterior parameters of dipole index probability distribution

Because the Normal-Gamma distribution is conjugate to the unknown mean and precision, the parameters have closed-form analytically derived solutions (Equations 6.12-6.15) and do not require algorithmic techniques such as Monte Carlo Markov Chain (MCMC) for estimation (Bernardo and Smith, 1993). In other applications in which a conjugate prior is not available or appropriate, other estimation techniques of estimating the posterior parameters would be necessary.

$$\mu_n = \frac{\mu_0 v_0 + n\bar{X}}{v_0 + n}$$

Equation 6.12

$$v_n = v_0 + n$$

Equation 6.13

$$\alpha_n = \alpha_0 + \frac{n}{2}$$

Equation 6.14

$$\beta_n = \beta_0 + \frac{1}{2}\sum_{i=1}^{n}(X_i - \bar{X})^2 + \frac{v_0 n(\bar{X} - \mu_0)^2}{2(v_0 + n)}$$

Equation 6.15

The posterior parameters blend the prior and likelihood (Equation 6.4), assigning more weight to the prior if the prior has high precision. The probability distribution representing the likelihood function in Figure 6.5 is a normal distribution whose parameters maximize the likelihood function given in Equation 6.4. The posterior

parameters, estimated using the above described methods, indicate a slight decrease in dipole index and increase in dipole variability (Figure 6.6, Table 6.3)
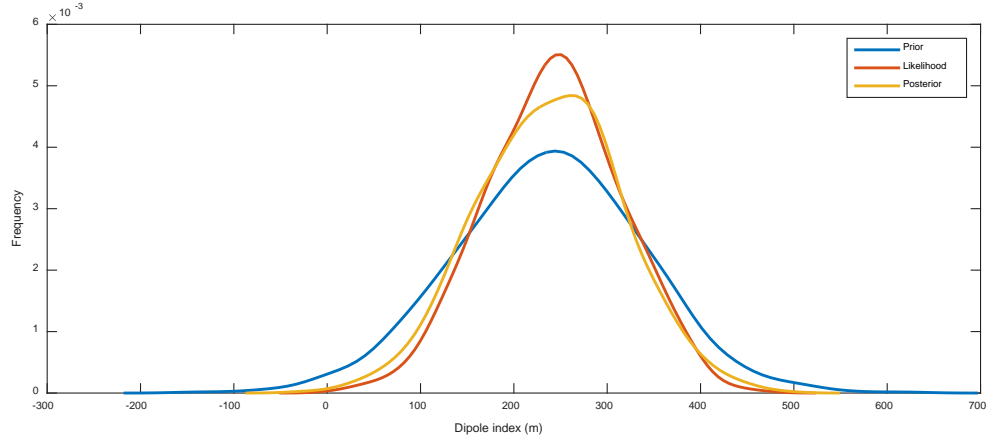
Figure 6.6: Prior, likelihood, and posterior distribution of dipole index.

Table 6.3: Mean and standard deviation of observed dipole index, prior, and posterior distributions of dipole index.

Property	Observed	Prior	Posterior
Mean (m)	243.4	240.1	240.9
Standard deviation (m)	72.7	99.2	74.6

Figure 6.6 shows the probability distribution of the dipole index during the future period of 2030-2060, but a nonstationary probability distribution which transitions between the current distribution of dipole index and the posterior distribution of dipole index. To achieve a nonstationary probability distribution, the parameters of dipole index distribution are modelled as linear functions of time which transition between the maximum likelihood estimate of climate index based on observations, $X \sim N(\mu_0, \sigma_0)$ and the posterior probability distribution of the climate index based on

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both past observations of the dipole index and simulations of its future state (Equation 6.16).

$$\gamma_t \sim N(\mu_0 + (\mu_1|\mu_n, v_n, \alpha_n, \beta_n) t, \sigma_o + (\sigma_1|\alpha_n, \beta_n)t)$$

Equation 6.16

The trend parameters μ_1 and σ_1 are calculated by dividing the difference between μ_n (σ_n) and μ_0 (σ_0) by the time between the historic record of the climate index and the future simulation of the climate index and are shown in Table 6.4.

Table 6.4: Trend parameters in moments of dipole index' probability distribution.

Parameter	Value	Standard error
μ_1	-0.043 m/year	0.019 m/year
σ_1	0.033 m/year	0.019 m/year

Based on the posterior distribution of dipole index, the frequency and magnitude of peak flows on the Iowa River at Marengo, the inlet to Coralville Reservoir, is expected to change with a higher incidence of severe flows and a slight change in the magnitude of severe flows (Figure 6.7).
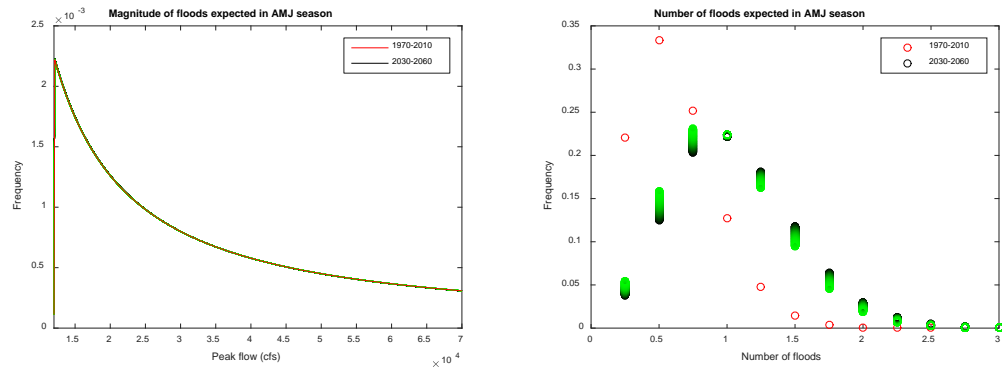
Figure 6.7: Comparison between expected frequency and magnitude of peak flows on the Iowa River during the 1970-2010 period and the 2030-2050 period, based on the posterior distribution of dipole index for the future period and the dipole-conditioned POT model of peak flows. Color scale represents the relative likelihood of different probability distributions of peak flow event frequency and event magnitude, based on the probability of the associated dipole index value (Table 6.1).

As indicated by the parameters of the dipole-conditioned POT model described in Table 6.1, the decreased expected dipole index in the posterior distribution (Table 6.4) leads to an increased number of expected floods but a very slightly decreased expected magnitude of those floods. The analysis indicates the change in probability of floods of different magnitudes will vary little relative to the change in number of floods expected in the AMJ season (Figure 6.7). The projected change in flood hazard to a higher number severe flow events with a similar distribution of magnitudes to those observed in the past favors an initial set of FRM adaptation alternatives that does not necessarily expand storage capacity, but rather allows flood waters to pass more efficiently, clearing Coralville Reservoir's flood storage quickly in preparation for future high flows.

Conclusions

This dissertation chapter presents a novel way to conduct flood frequency analysis by exploiting the connection between continental-scale climate indices and local-scale extreme streamflow. Historic measurements or re-analysis of flood-correlated climate indices are combined with a probability distribution calibrated to reflect bias-adjusted properties of the climate index/indices simulated by general circulation models through Bayes' theorem, resulting in a posterior probability distribution of the climate index of interest in a future period. This chapter demonstrates this framework in application to a case study in Iowa, finding that high flow events may be more frequent in the future but change little in magnitude. The climate models employed in the example application replicate the climate index with varying levels of skill, but generally superior skill to climate models' hindcast simulations of short-term precipitation fields.

This chapter utilizes the statistically modeled relationship between flooding in Iowa and a pressure dipole index that has been correlated with Tropical Moisture Exports, a meteorological mechanism that is associated with heavy and sustained precipitation events in the upper midwest (Nakamura et al., 2012) to develop a probabilistic estimate of future flood hazard. While climate models are generally recognized to simulate circulation patterns such as the pressure dipole with superior skill to localized extreme precipitation, which occurs through sub-grid scale meteorological processes (Flato et al., 2012), the pressure dipole is only one circulation feature associated with a single type of heavy precipitation and high streamflow in the Iowa River basin. A more thorough probabilistic estimate of flood hazard would include a more systematic exploration of meteorological flood drivers and interactions among them, a larger number of climate models' simulations of circulation patterns, and

consideration of the hydrologic impacts of land use change on flood probability. The analysis presented in this chapter focuses on a common type of flood that occurs between April and June, the season associated with the area's most sever and damaging historic floods. Further analysis could profitably explore the potential for novel meteorological flood drivers in this area introduced by unprecedented future climate states, and the effect of seasonal shifts in the occurrence of flood-producing storms on Iowa City flood hazard.

CHAPTER 7

CONCLUSIONS

This dissertation presents several statistical and decision support tools for managing the economic and ecological implications of extreme flows under uncertain future change. Examining the state of the science in flood frequency analysis, nonstationary flood hazard projection, and decision support tools for flood risk management yields several key insights and open research questions. These include the discrepancy between standard statistical techniques used for flood trend detection and the context of adaptation decisions which are based on the flood frequency analysis, the lack of decision support tools for flood risk management decisions under uncertain trend in peak flows, the need for robust FRM decision support tools which include ecological impacts of flood change on an equal basis with economic impacts, and lack of credible, mechanistically-grounded ways to quantify flood trend uncertainty. The flood frequency analysis techniques and decision support tools presented in this dissertation begin to answer these open research questions and point toward further work that would strengthen the practice of flood risk management.

Key findings stemming from the dissertation yield important critiques for the state and practice of FRM adaptation planning. Chapter 3 demonstrates that standard statistical significance for flood trend detection are frequently an inappropriate basis for FRM adaptation decisions, but the use of an alternative approach could result in wide-spread savings. Chapter 4 demonstrates a decision scaling framework for FRM decision-making under uncertainty encourages low-regret investment and facilitates compromise among decision makers who hold disparate values. Chapter 5 extends the approach presented in Chapter 4 to search directly for robust solutions rather than

evaluate the robustness of scenario-optimal solutions ex post, and demonstrates how searching for FRM strategies which satisfy multiple climate assumptions transform a typical criticism of optimization in water resources decisions into an advantage that enables consensus. Chapter 6 demonstrates that climate model output can be incorporated in FRM adaptation decisions in a way that exploits previously established statistical techniques for nonstationary flood frequency analysis and draws on climate models' skillful scale. Chapters 4 and 5 also demonstrate several ways ecological objectives can be incorporated into FRM adaptation planning *ex ante* rather than *ex post*.

These insights demonstrate the utility of robust and multi-objective optimization techniques as tools within wider decision support frameworks for FRM. The insights also imply that flood frequency analysis techniques on which adaptation decisions are based can be improved by revising the statistical frameworks to reflect the context of the resulting decision. Furthermore, frameworks for decision making under uncertainty that are widely applied require special considerations when tailored to flood management decisions. For example, the climate drivers typically used by decision scaling and other decision frameworks that have previously been more widely applied to water supply systems must be altered to account for the meteorological drivers that are most influential to floods but less important for other water resources applications. This dissertation demonstrates several ways to incorporate climate drivers in flood management decisions, showing how varying changes in the probability distribution of extreme flows results in a range of flood probability scenarios far beyond what changes in average precipitation and temperature would indicate, suggesting that standard methods would underestimate the range of possible flood frequency shifts that could occur under climatic

nonstationarity. Changes in flood frequency and severity stem not only from changes in average precipitation and temperature, which are easily derived from pre-processed climate model simulations, but more directly from changes in storm occurrence that connect to large-scale atmospheric patterns. The use of synoptic-scale atmospheric patterns has previously been limited to understanding past flood variability and developing phase-dependent reservoir operations which perform well under low-frequency variability. This dissertation shows that projections of synoptic-scale atmospheric pattern variability under future climate states, an emerging area of research in climate science, can be used in practice to inform nonstationary flood risk adaptation planning.

The importance of these findings hinges on their implications for improving FRM adaptation decisions in terms of the information such decisions are based on, how the supporting information is synthesized, how interrelated objectives are weighed against each other, and how the decision process engages with stakeholders' individual beliefs. Findings indicate a promising avenue for improving federal adaptation projects' economic efficiency and integrating ecological objectives as core goals of FRM adaptation decisions, which is currently known to be needed but no method is officially established. The research also provides an avenue toward quantifying the uncertainty in future flood hazard based on the available evidence, enabling physically-justified risk-based adaptation decisions which consider multiple trend scenarios. Accommodating diverse risk preferences of multiple FRM stakeholders as Chapter 5 demonstrates is not explicitly addressed by existing decision frameworks, but clarifies the tradeoffs stakeholders make during the decision process and enables better-informed adaptation decisions.

While the work presented in the dissertation provides examples of how several open research questions in FRM may be addressed, further work is needed to bring these methods to a form suitable for practice. The dissertation demonstrates the utility of exploiting large-scale climate patterns as a basis for flood hazard projections, but climate model output from which these patterns may be derived are not readily accessible to the non-climate scientist. This points toward the benefits of both deeper integration between the climate science academy and the water sector and toward the utility of web-based tools that support the streamlined analysis of large-scale climate patterns across multiple climate models, similar to those that exist for climate variables that are more commonly used in water resources impact assessment such as precipitation and temperature. This dissertation also includes several tools which are framed around nonstationary probability distributions of peak flow and methods of modelling nonstationary probability distribution parameters. Work that explores methods for estimating various forms of nonstationarity in probability distribution parameters, as well as nonstationarity in different forms of peak flow probability distribution, would improve the general applicability of the frameworks presented by this dissertation. Particularly relevant to the work presented in this dissertation are methods for developing projections and statistical models of how climate processes which exhibit low-frequency variability are likely to change in the future, based on historic and/or paleo records of phase shifts in atmospheric patterns and simulations of synoptic-scale atmospheric patterns' evolution into the future.

In summary, this dissertation confronts two main challenges that inhibit effective adaptation of FRM systems to nonstationary climate, which are the challenge of quantifying uncertainty in future flood hazard and the challenge of developing decision support frameworks which accommodate stakeholders' diverse values,

climate beliefs, and risk preferences while guiding them to a scientifically-justified FRM adaptation plan that supports the welfare of all. The work presented by this dissertation builds on past work in water resources engineering, operations research, climate science, and ecology to lay foundations for addressing both of these challenges. As in the decision scaling framework, this dissertation unites vulnerability-based decision support tools with estimates of future conditions based on the best available information, and the best use of that information, to enable informed adaptation decisions in which the stakeholders' beliefs and objectives play a key role. The key innovations in this dissertation include tailoring the decision scaling framework toward the particular parameters of FRM decisions, enhancing the rigor of statistical tools for FFA in the context of adaptation decisions, introducing the separate objective of ecological adaptation alongside FRM adaptation, and providing a template of how optimization may be included in a vulnerability-based decision framework to better communicate with (and support better communication among) a diverse group of stakeholders. The intention of this dissertation is to present foundational examples of how to advance the practice of integrated, cross-sector flood risk management under uncertain, nonstationary hydrology.

APPENDIX: IOWA CITY FLOW-DAMAGE RELATIONSHIP

Table I. Simplified estimates of flow/damage relationship without new mitigation actions.

Flow category (cfs)	Expected City Damage ($)
< 10,000	0
10000 - 15000	0
15000 - 20000	3,348,033
20000-25000	14,233,400
25000-30000	23,897,867
30000-35000	35,796,000
35000-40000	49,152,000
> 40000	62,508,000

Table II. Damage reduction per unit implementation of flood mitigation strategy.

Flow category (cfs)	Reoperation & reimbursement damage reduction ($/100%)
< 10,000	0
10000 - 15000	-20,354.83
15000 - 20000	-84,766.47
20000-25000	-28,770.36
25000-30000	15,883.54
30000-35000	16,658.22
35000-40000	14,010.82

> 40000	14,698.47

II. Iowa River discharge-inundation relationship

Relationship between flow and floodplain area between Coralville Dam and river mile 46 (between Iowa City and Lone Tree gages)
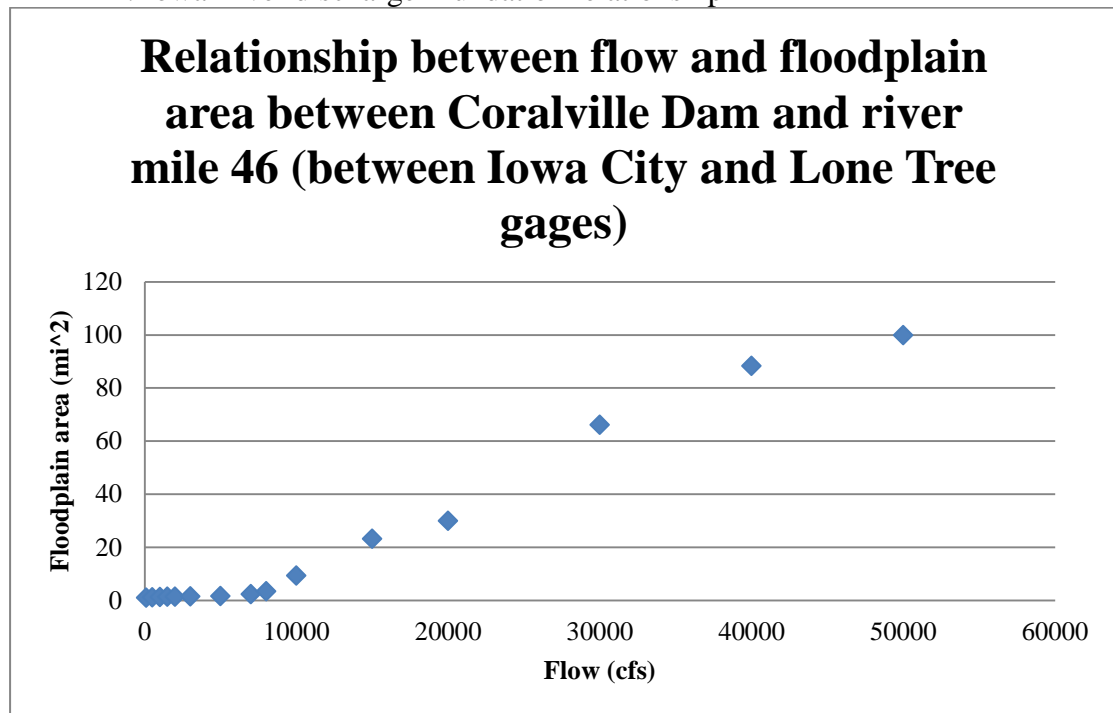
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