FLOOD RISK ASSESSMENT, MANAGEMENT AND PERCEPTIONS IN A CHANGING WORLD

A Dissertation Presented

by

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

DOCTOR OF PHILOSOPHY

May 2018

Civil and Environmental Engineering Department

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DEDICATION

in honor of my Grandad

and for the glory of my Lord and Savior Jesus Christ

because life cannot be bought
… flood victim in Ouagadougou, Burkina Faso

ACKNOWLEDGEMENTS

I would like to express my gratitude to my advisor, Casey Brown, as well as the other members of my committee – Richard Palmer, Krista Gile, and Andrew Robertson – for the many ways they have supported and encouraged my professional growth.

I am grateful to the many current and past members of the Hydrosystems Research Group who have generously contributed their time and knowledge, in particular, Scott Steinschneider, Yi-Chen Yang, Patrick Ray, Baptiste François, and Jacob Kravits. Thank you also to all those with whom I have shared the graduate school journey within the Environmental Water Resources and Engineering program.

I am indebted to the International Institute for Water and Environmental Engineering (2iE) and the United States Embassy in Burkina Faso for their in-country support. In particular, I thank Harouna Karambiri and Lionnel Kaboré, as well as Rosemonde Zongo, Emeline Somda, and David Yameogo. A special thank you to all the participants who gave of their time and their memories.

I am grateful to the National Science Foundation Graduate Research Fellowship Program, the Department of Defense's Strategic Environmental Research and Development Program, and the Fulbright United States Student Program for funding my graduate career and research. The viewpoints expressed herein are mine only.

Finally, thank you to my faithful friends and loving family, especially my dad Doug, mom Danielle, sister Grace, brother Elliott, grandmothers Julia and Jacqueline, parents-in-law Chuck and Joyce, and my husband Scott, for their consistent support and encouragement. I am deeply grateful.

ABSTRACT

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MAY 2018

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Floods are a global challenge that is increasing due to changes in climate and human populations. Using an interdisciplinary approach, this work contributes novel methodologies and knowledge to three key challenges associated with floods. The first chapter builds upon the atmospheric and statistical sciences to provide a general methodology for climate informed approaches to projecting long-term flood events based on large-scale ocean-atmospheric processes. The second chapter builds upon the engineering, decision analysis, and economics disciplines to integrate climate-informed projections with decision-scaling, a decision-making under uncertainty framework, to further flood risk management. The third chapter builds upon the social sciences to provide new knowledge on flood risk perception and mitigation in West Africa. The outcomes of this work contribute important advancements to addressing the clear and urgent need for solutions to floods around the world.

TABLE OF CONTENTS

Page

LIST OF TABLES

Table Page

LIST OF FIGURES

Figure Page

INTRODUCTION

The pressing need for solutions to floods is evident in the increase in flood events over the 20th century, the common recurrence of devastating floods around the world, and the likelihood of continued increases in flood events under projected changes in climate and human populations (Adikari & Yoshitani, 2009; Hallegatte et al., 2013; Milly et al., 2002; Winsemius et al., 2016). However, proposed solutions are determined in part by how floods are defined, which varies across disciplines (Cardona, 2003; Pielke & Downton, 2000; White, 1945; White et al., 2001). According to the natural sciences, floods occur when streamflow greatly exceeds average values due to unavoidable and natural hydro-climatic phenomena. In contrast, the social sciences define floods as a purely socially constructed event that occurs when water causes damages to human life and property. The applied sciences bridge this divide by claiming floods have both natural and anthropogenic causes that result in damages being associated with a natural phenomenon. As the variety of definitions across major scientific disciplines clearly illustrates, flood events are multidimensional.

The multidimensional nature of flood events necessitates interdisciplinary approaches and solutions (B. Merz et al., 2014; Schelfaut et al., 2011). By overlooking social and cultural context, common engineering solutions such as levees and reservoir re-operations may not sufficiently limit risk. For example, levees may actually contribute to increased flood damages due to decreasing perceptions of risk, the so-called "levee-effect" (Di Baldassarre et al., 2013). Many United States (U.S.) counties frequently experience floods (FEMA, 2014), despite being located within a highly developed country that presumably has the necessary economic resources and institutional structure to implement successful flood mitigation and adaption. In contrast, there are many instances of relatively successful approaches and solutions arising from other disciplines besides engineering (Lund, 2015). For example, concepts from economics are used to provide quantitative valuation of flood damages and develop flood insurance policies (B. Merz, Kreibich, et al., 2010; Michel-Kerjan & Kunreuther, 2011). Social science methods are used in post-flood investigations, in understanding how decision-makers use scientific information for flood management, and in understanding how perceptions of floods affect mitigation actions (Bubeck et al., 2012; Morss et al., 2005; Ruin et al., 2014). Methods from the field of decision analysis have been used to develop flood risk management strategies under non-stationarity (Spence & Brown, 2016) and methods and knowledge from the atmospheric and statistical sciences have been used to develop projections of flood events (Arnell & Gosling, 2016; Delgado et al., 2014). Despite these and other advancements, the common recurrence of devastating floods around the world indicates there are still many remaining challenges.

The purpose of this dissertation is to contribute novel methodologies and knowledge, using an interdisciplinary approach, to three key challenges. The first challenge is projecting long-term hydrologic floods events, where long-term refers to planning horizons on the order of 50 to 100 years. Projections are not needed if we assume that the future will resemble the past; however, the possibility of non-stationarity in streamflow from anthropogenic and climatic change makes this assumption untenable (Milly et al., 2008, 2015; Vogel et al., 2011). Skillful projections provide information about the future probability associated with streamflow of a given frequency and magnitude that can be used to evaluate potential flood impacts and the necessity of flood management options.

The first chapter of this dissertation builds upon the atmospheric and statistical sciences to provide a general methodology for climate informed approaches (Delgado et al., 2014; Kwon et al., 2008) to long-term projection of hydrologic flood events. The Ohio River Basin in the U.S. Midwest is used as a case study.

The second challenge is flood risk management. Although a common method of addressing uncertainty in design flood estimates is the use of safety factors, risk-based methods that aim to optimize a metric of interest, such as expected total cost, have become widely advocated (Lund, 2002; B. Merz, Hall, et al., 2010). If the source of uncertainty is non-stationarity in flood events, there are further challenges; typical methods for defining design floods are no longer valid and the non-stationarity must be quantified and projected (Salas & Obeysekera, 2014). The second chapter of this dissertation builds upon the engineering, decision analysis, and economics disciplines to develop a flood risk management method that integrates climate-informed projections with decision-scaling (Brown et al., 2012), a decision-making under uncertainty framework, and compares the results to the traditional model chain method. The flood-prone city of Louisville, Kentucky, located within the Ohio River Basin, is used as a case study.

The third challenge is characterizing the relationship between perceptions of flood risk and associated mitigation actions. Characterizing the relationship between perception and mitigation using qualitative approaches such as questionnaires and interviews (e.g., Tschakert et al., 2010) can provide clues to the potential effectiveness of flood management options from a social and cultural perspective (Bubeck et al., 2013; Fuchs et al., 2017; Slovic et al., 1982). The third chapter of this dissertation builds on the social sciences to provide new knowledge of perceptions and mitigation in Burkina Faso, and a comparative meta-analysis to evaluate and improve flood mitigation recommendations across West Africa. The dissertation concludes by looking towards the future of flood risk assessment, management, and perceptions.

CHAPTER 1

A GENERAL METHODOLOGY FOR CLIMATE INFORMED APPROACHES TO LONG-TERM FLOOD PROJECTION – APPLICATION TO THE OHIO RIVER BASIN

Estimating future hydrologic floods under non-stationary climate is a key challenge for the design of long-term water resources infrastructure and flood management. Climate informed approaches to long-term flood projection are an appealing alternative to traditional modeling chains which are based on downscaled general circulation model (GCM) simulations. The primary purpose of this work is to formalize climate informed approaches into a general methodology consisting of four steps: (1) selection of predictand representing the extreme events, (2) identification of credible large-scale predictors which mechanistically control the occurrence and magnitude of the predictand in the region of interest, (3) formulation, calibration, and validation of a statistical model relating the predictors to the predictand, and (4) projection of the predictand by forcing the model with projections of the predictors. These four steps are based on a review of the current literature, which to-date has primarily focused on model formulation for single gage locations. The four-step methodology is demonstrated using the Ohio River Basin in the U.S. Midwest as a case study. Floods are defined as annual maximum series events during the months of January through April from daily streamflow records at multiple gages in the northwest region of the basin and dimension reduction is performed using principal component analysis. Guided by a literature review, large-scale predictors are identified using correlation maps between the first two principal components of flood events and gridded observations of sea surface temperature, 500 mbar geopotential height, and soil moisture. A Bayesian model is developed based on regression of the principal components on a winter 500 mbar geopotential height pattern similar to the Pacific North American teleconnection pattern as well as concurrent soil moistures in the basin and to the west of the basin over the lower Mississippi River valley. Flood projections are estimated by forcing the model with projections of the predictors from GCM simulations combined using Bayesian model averaging. We demonstrate how climate informed approaches have the potential to be more broadly applicable across the U.S. and conclude with a discussion of benefits and limitations.

1.1 Introduction

Estimating future hydrologic flood events is beneficial to efficient design of water resources infrastructure and management policies. However, standard methods for determining flood risk, such as those recommended in U.S. Geological Survey (USGS) guidelines (England et al., 2015; IACWD, 1982), may no longer be valid given the possibility of non-stationarity in time-series of flood events due to anthropogenic forcing of land and atmospheric processes (Milly et al., 2008, 2015; Vogel et al., 2011). In response, multiple methods of flood risk projection that attempt to account for non-stationarity have been developed (Salas et al., 2012). A simple method is to condition an extreme value distribution on time-dependent parameters to extrapolate an observed trend. However, because the past does not necessarily represent the future (e.g., for a location with a limited record, low-frequency variability may appear to be a long-term trend), such methods may produce misleading results and may in fact be less skillful than a simple assumption of stationarity (Bloschl & Montanari, 2010; Jain & Lall, 2001; Luke et al., 2017).

Another common method of estimating future flood risk is a chain of models, also often known as the top-down or scenario-led approach. This method consists of using bias corrected and downscaled general circulation model (GCM) projections of climate variables (typically precipitation and temperature) to calculate streamflow using transfer functions, numerical hydrologic models or a combination of both. This method has been employed at a variety of spatial scales and locations including globally (Arnell & Gosling, 2016; Dankers et al., 2014; Hirabayashi et al., 2008, 2013; Milly et al., 2002; Winsemius et al., 2016), in China (Leng et al., 2016), throughout Europe (Alfieri et al., 2015; Madsen et al., 2014; Roudier et al., 2016), and in Canada (Seidou et al., 2012). A major concern with this method is that it is driven by GCM simulation of rainfall, which is known to be associated with multiple shortcomings, particularly in regards to extremes (Dai, 2006; Rocheta et al., 2014). Even in the newest generation of GCMs, at the global scale, most GCMs "overestimate precipitation over regions of complex topography (e.g., western North and South America and southern Africa and Asia), while underestimating it over arid regions" and the bias is greater at "high quantiles of precipitation" (Mehran et al., 2014). Over the African continent, Cretat et al. (2014) found that models "greatly overestimate the frequency of intense events, particularly in the tropics, generally fail at simulating the observed intensity, and systematically overestimate their spatial coverage". Over the contiguous U.S., GCMs reproduce large-scale precipitation features but exhibit large variations at the regional scale, with overestimation in humid and cool regions and underestimation in dry regions (Sheffield et al., 2013). In particular, the observed historical increase in extreme precipitation is underestimated and varies widely among models (Wuebbles et al., 2014).

An appealing alternative to the model chain method are climate informed approaches (Kwon et al., 2008), in which a statistical model represents the relationship between large-scale climate patterns which exert physical controls on the frequency and intensity of flood events in the region of interest. Flood projections are then developed by forcing the model with GCM projections of the large-scale climate patterns. Compared to the model chain method, one important advantage of climate informed approaches is that they rely on projections of large-scale ocean-atmospheric patterns, which are more skillfully simulated by GCMs than localized temperature and precipitation (Fuentes-Franco et al., 2016; Ning & Bradley, 2016; Sheffield et al., 2013). Another important advantage of climate informed approaches is that the relative simplicity of a statistical model allows the driving factor behind future change to be easily identified, which facilitates assessment of credibility.

The primary purpose of this work is to formalize climate informed approaches into a general methodology. To date, most applications of climate informed approaches in the literature have focused on developing the relationship between floods and large-scale ocean-atmospheric patterns in the historical record (i.e., identifying teleconnections) (Jain & Lall, 2001; López & Francés, 2013; Ouarda & El-Adlouni, 2011; Renard & Lall, 2014; Zhang et al., 2015). Climate informed approaches have also been used for short-term flood frequency forecasting (Kwon et al., 2008) and a flood early warning system (Lima et al., 2015). However, to the authors' knowledge, the only studies which use climate informed approaches to make long term flood projections are Delgado et al. (2014) for a gage in the Mekong River in China and Tramblay et al. (2014) for a gage in the Mono River in West Africa. Both studies are strongly focused on the case study, only apply the approach to one gage, and provide limited guidance for a more general methodology. Thus, this chapter develops a generalized methodology based on the current literature and demonstrates its application to multiple gages in the Ohio River Basin in the U.S. Midwest as a case study. This chapter concludes with a way forward to broader application across the U.S. and a discussion of its advantages and limitations.

1.2 Generalized Methodology for Climate Informed Approaches

Previous literature has applied climate informed approaches to streamflow extremes in the Mekong River and the East River Basin in China (Delgado et al., 2014; Zhang et al., 2015), Spain and France in Europe (López & Francés, 2013; Renard & Lall, 2014), Iowa, Montana, and Washington in the U.S. (Jain & Lall, 2001; Kwon et al., 2008; Sankarasubramanian & Lall, 2003; Villarini et al., 2013), the Mono River in West Africa (Tramblay et al., 2014) and the Negro River in Brazil (Lima et al., 2015). These approaches have also been applied to precipitation extremes in California in the U.S. (Ouarda & El-Adlouni, 2011; Shang et al., 2011; Steinschneider & Lall, 2015) and Southern Queensland in Australia (Sun et al., 2014). Based on a review of this literature, we have formalized the variety of climate informed approaches into a four-step general methodology (Table 1). Each step and accompanying methods are described below.

*Table 1: The four-step methodology and associated methods. Note that the references are not intended to be exhaustive. * indicates that the reference is not specifically a climate informed approach, but the method is relevant.*

Step	**Key Idea**	**Primary Methods and Selected References**
1. Select predictand	The predictand should be useful to stakeholders and enable identification of predictors	- Annual maximum series (López & Francés, 2013) - Peaks over threshold (Renard & Lall, 2014)
2. Identify credible large-scale predictors	The predictors should (a) mechanistically control the occurrence and magnitude of predictand, (b) be robust under climate change, and (c) be well-simulated in GCMs	- Literature review (Delgado et al., 2014) - Time series correlation (Kwon et al., 2008) - Composite analysis (Jain & Lall, 2001) - Weather typing (Robertson et al., 2015)* - Simulation experiments (Cook, 1999)* - Bayesian identification (Renard & Lall, 2014)
3. Formulate, calibrate, and validate statistical model	The model should represent the link between the predictand and the predictors	- Simple linear regression (Lima et al., 2015) - GAMLSS (Zhang et al., 2015) - Quantile regression (Sankarasubramanian & Lall, 2003) - Bayesian model (Renard & Lall, 2014)
4. Project predictand into future	Force the model with projections of the predictors	- Variety of methods exist to combine projections - Assume stationarity within a window to calculate flood frequency analysis

1.2.1 Step 1: Select Predictand

The first step is to select the predictand. While a common and necessary step to any flood frequency analysis, here the key idea is to define extreme events in such a way that is both useful to stakeholders and for which a relationship to large-scale predictors either exists or can be identified. Thus, streamflow data is preferentially from unimpaired stations, although López & Francés (2013) show how the impact of reservoirs at impaired sites can be accounted for using an index based on catchment area, reservoir capacity, and mean annual runoff. While some studies analyze only one gage (e.g., Delgado et al., 2014) or fit an unique model to each gage within a region (e.g., López & Francés, 2013), a regional analysis allows for better identification of climate effects (Sun et al., 2014) and is more informative for emergency preparedness given that extremes are often not isolated events (Shang et al., 2011). Regionalization requires identification of a hydro-climatologically homogeneous region (Sun et al., 2014) and can be accomplished using techniques such as Bayesian modeling (Renard & Lall, 2014; Steinschneider & Lall, 2015), copulas (Sun et al., 2014), and max-stable processes (Shang et al., 2011). Once the data is acquired, extreme events are often defined as the annual maximum series (AMS) events (e.g., López & Francés, 2013). In some cases, extreme events are restricted to a particular season to enable identification of a clear link to large-scale ocean-atmospheric patterns (e.g., the summer season in Sun et al., 2014). Alternatively, peaks over threshold (POT) methods have been used to capture both number of occurrences and magnitude (e.g., Renard & Lall, 2014; Steinschneider & Lall, 2015). The choice of AMS or POT will be influenced by what information is useful for decision-making (e.g., POT allows frequency to be modeled separately from magnitude) and whether predictors can be identified (e.g., Renard & Lall (2014) and Villarini et al. (2013) apply a climate informed approach to the frequency of flood events from POT, but do not model magnitude).

1.2.2 Step 2: Identify Credible Large-Scale Predictors

The second step is to identify credible large-scale predictors. The key idea is that the identified predictors (a) mechanistically control the occurrence and magnitude of extreme events in the region of interest, (b) are robust under climate change, and (c) are relatively well-simulated by GCMs. At the catchment scale, the causative mechanisms of floods can be divided into five categories: long-rain floods, short-rain floods, flash floods, rain-on-snow floods, and snowmelt floods (R. Merz & Blöschl, 2003). These proximate mechanisms are ultimately generated by ocean-atmospheric patterns, such as extratropical cyclones and sea surface temperature anomalies, operating at much larger spatiotemporal scales, as classically described by Hirschboeck (1988).

In climate informed approaches, ultimate mechanisms to be used as predictors are often identified through review of the hydro-climatology literature or historic reports of flooding (e.g., Delgado et al., 2014; López & Francés, 2013; Shang et al., 2011; Steinschneider & Lall, 2015; Sun et al., 2014; Zhang et al., 2015). For example, Delgado et al. (2014) rely on previous work by Delgado et al. (2012) which uses a wavelet transform to identify the relationship between monsoon season flows in the Mekong River and the Western Pacific monsoon. Relationships in the literature can then be tested by comparing the performance of models with different subsets of predictors, as in Villarini et al. (2013). In addition to literature review, a simple and often-used method of identifying predictors is correlation of time series of the extreme events to time series of pre-defined indices or gridded fields. For example, Kwon et al. (2008) use correlation maps between flood events and seasonal gridded sea surface temperatures to identify regions of high correlation for use as predictors. Another method of identification is composite analysis, which compares the climate patterns associated with the highest events to climatology. For example, Jain & Lall (2001) determine the Nino3 and Pacific Decadal Oscillation anomalies associated with the highest and lowest recorded floods. A similar approach is weather typing, in which the atmospheric circulation patterns associated with extreme events are clustered into types that can then be related to large-scale patterns. For example, Robertson et al. (2015) relate daily circulation types associated with flood events to the El Nino Southern Oscillation (ENSO) and the

Madden-Julian Oscillation. Another technique often used in the climate sciences literature is that of simulation experiments. For example, Cook (1999) perform GCM simulation experiments which show that soil moisture gradients are necessary to generate the African Easterly Jet, a primary driver of the West African Monsoon. Finally, Renard & Lall (2014) provide a unique approach to identification of predictors; they formulate a Bayesian model that uses maximum likelihood estimation to identify spatial patterns in gridded fields (e.g., geopotential heights) which are probabilistically related to flood events.

Once ultimate mechanisms associated with the predictand are identified for use as predictors in the model, they should be further evaluated for robustness under climate change and how well they are simulated by GCMs. Robustness under climate change is important because the predictors are often based on climate variability, but, since the goal is long-term projection, are also intended to be appropriate under changes in mean climate. However, evaluation of robustness is difficult due to the lack of a good reference; GCM projections lack credibility because they do not preserve teleconnections over historic periods (Lee & Black, 2013; Polade et al., 2013; Sheffield et al., 2013) while climate changes in the observed record are much smaller in magnitude than projections. For example, change in global annual average land-surface air temperature has increased approximately 1^{o}C over the 20th century but could increase as much as approximately 4^{o}C over the 21st century if more extreme scenarios of greenhouse gas emission occur (IPCC, 2013).

A simple beginning point is to roughly estimate the expected climate change impacts on floods from first principles. Specifically, the Clausius-Clapeyron equation indicates that increased temperature leads to increased moisture holding capacity of the atmosphere, which will cause precipitation extremes, and thus greater floods for regions where the causative mechanism is primarily rainfall. Similarly, increased temperature will cause more precipitation to fall as rain rather than snow, and will thus alter the timing and the causative mechanism for regions where floods are currently generated by rain-on-snow or snowmelt events. Obviously, however, there are a multitude of both thermodynamics and dynamic feedback mechanisms that may accentuate or dampen these simple first principle effects (Collins et al., 2013; Held & Soden, 2000; O'Gorman & Schneider, 2009); consequently, robustness under climate change can be expected to improve when predictors account for both thermodynamic and dynamic processes (e.g., as used in the downscaling study of Greene et al., 2011). Thus, the Western North Pacific monsoon index used by Delgado et al. (2014) only accounts for changes in dynamics, whereas the soil moisture predictor used in Tramblay et al. (2014) accounts for both dynamics and thermodynamics.

Relatively good simulation by GCMs is important because a central motivation for climate informed approaches is that GCMs poorly simulate extreme precipitation used to force hydrologic models in the more traditional model chain method. Obviously the challenge is determining what "relatively well simulated" means. Qualitatively, it is expected that first-order variables, such as temperature, are more skillfully simulated than derived or second order variables, such as precipitation. Similarly, GCM performance can be expected to increase, to a certain extent, with increasing spatiotemporal scale (e.g., daily data for a grid cell compared to annual data for a region). Quantitatively, many studies have assessed GCM simulation of larger scale patterns (e.g., Bellenger et al., 2014; Fuentes-Franco et al., 2016; Lee & Black, 2013; Ning & Bradley, 2016; Polade et al., 2013; Sheffield et al., 2013; Taschetto et al., 2014; Yim et al., 2015). Such literature may be sufficient to consider the identified predictors as relatively well simulated, especially if the predictors correspond to well-recognized patterns (e.g., ENSO) or highly studied regions. In the absence of literature on the identified predictors, performance metrics can be calculated directly (e.g., spatial and temporal correlation to observations).

1.2.3 Step 3: Formulate, Calibrate, and Validate Statistical Model

The third step is to formulate, calibrate, and validate a statistical model. The key idea is that the model is representative of the link between the identified predictors and the extreme events. The form of the model is often as simple as linear regression of the location and/or scale parameter of the extreme value distribution on the predictor(s) (Delgado et al., 2014; Kwon et al., 2008; Lima et al., 2015; Tramblay et al., 2014). More complex model formulations include using the generalized additive models for location, scale, and shape (GAMLSS) developed by Villarini et al. (2009) (López & Francés, 2013; Zhang et al., 2015), quantile regression techniques (Sankarasubramanian & Lall, 2003), and Bayesian modeling (Renard & Lall, 2014). While the identifying climate indices are often used directly as predictors in a model, López & Francés (2013) reduce the dimensionality by using the first two principal components of an empirical orthogonal function of the identified predictors. Models are calibrated through optimization of likelihood functions using techniques such as the shuffled complex evolutionary algorithm (as used by Delgado et al. 2014), or in a Bayesian context, Monte Carlo sampling methods (as used in Steinschneider & Lall, 2015). Model performance can be evaluated in a variety of ways; those employed in climate informed approaches include but are not limited to deviance statistics (Delgado et al., 2014), the Bayesian and Akaike Information Criterions (Lima et al., 2015; Zhang et al., 2015), assessment of residuals using worm plots and quantile-quantile plots (López & Francés, 2013; Zhang et al., 2015), and leave-one-out cross validation (Lima et al., 2015; Renard & Lall, 2014; Sankarasubramanian & Lall, 2003).

1.2.4 Step 4: Project Predictand into Future

The fourth step is to project the predictand into the future by forcing the statistical model with projections of the predictors. The projections can be stochastically generated time series or short-term forecasts (e.g., Kwon et al., 2008; Lima et al., 2015), but here the focus is on long-term projection using GCM simulations. Surprisingly, except for Delgado et al. (2014) and Tramblay et al. (2014), studies using a climate informed approach have not developed long-term flood projections. However, there are several significant challenges associated with this step. One challenge is obtaining, assessing the performance of, and combining various GCM projections. Both Tramblay et al. (2014) and Delgado et al. (2014) calculate projections of their climate predictors from GCM output. Delgado et al. (2014) then select certain GCMs for inclusion in a multi-model mean based on a non-parametric test of variance equality. As a method to combine projections from different GCMs, the multi-model mean is often used in the climate literature, and performs better than individual models on average, but lack of independence between models leads to small sample sizes (Edwards, 2011; Knutti et al., 2010; Weigel et al., 2010). Alternatively, models may be weighted based on performance metrics following methods such as the climate prediction index (Murphy et al., 2004), reliability ensemble averaging (Giorgi & Mearns, 2002), a variable convergence score

(Johnson & Sharma, 2009) and error metrics (Gleckler et al., 2008; Pierce et al., 2009), but no commonly accepted weighting scheme exists (Stocker et al., 2010). Another option for model combination is Bayesian model averaging (Hoeting et al., 1999), which has been applied to ensemble forecasts (e.g., Raftery et al., 2005).

A second challenge is calculation of a return period from the projections for design purposes. While statistical techniques have been developed for calculation of return periods under non-stationarity (Cooley, 2013; Salas & Obeysekera, 2014), they require summations to infinity, which is possible when extrapolating a trend, but impossible for climate informed approaches (and even the model chain method) when forced with GCM simulations, which extend to 2100 or 2300 at most. When the statistical model is a distribution with parameters dependent on predictors, then the flood magnitude associated with a given return period can be calculated from the distribution quantiles in each time step, as seen in Delgado et al. (2014). However, the calculated flood magnitude and return period are only valid for that time step. The challenge is further compounded if the model is not a distribution, but simply outputs an estimate of the flood event in each time step, which is the case for the model chain method. Regardless of model formulation, current best practice is to assume stationarity within a given window of time and perform flood frequency analysis following traditional techniques such as those given in England et al. (2015).

1.3 Application of Methodology to Case Study

The Ohio River Basin in the Midwest U.S. periodically experiences devastating floods; the most recent occurred in 2015, but records of floods and extreme river stages date back to 1773 (Horton & Jackson, 1913; NWS, 2017a). Here, the Ohio River Basin is used as a case study to illustrate the application of the four-step general methodology to climate informed flood projection.

1.3.1 Select Predictand in the Ohio River Basin

Daily streamflow data for the basin was obtained from the Hydro-Climatic Data Network (HCDN) (Landwehr & Slack, 1992). HCDN Gages are designated as unimpaired or reference gages based on analysis of data up to 1988. A total of 62 gages were identified that have a basin area greater than approximately 500 km^2 (200 square miles) and have less than 0.1% data missing between 1950 and 2015, the chosen analysis period (Figure 1a-b). Through exploratory diagnostics, including correlation (Figure 1c) and empirical orthogonal functions (not shown), we found that maximum flood events in January through April (JFMA) for the 26 gages in the northwest region of the basin are strongly related. As expected from historic records (Appendix A), JFMA maximum flood events capture between 50% - 71% of annual maximum series floods across the 26 gages (Figure 1d). Additionally, JFMA maximum flood events for the 26 gages are likely to be related to the winter teleconnections identified in the literature (see subsequent section). For these reasons, all subsequent analysis was performed on JFMA maximum flood events for the 26 northwest region gages. Based on the Mann-Kendall test, 3 of the 26 gages show a significant positive trend in JFMA maximum flood events; the remaining 23 gages have no significant trend. We note that here, and elsewhere in this chapter, significance is reported at the 95% level unless noted otherwise. To make the analysis regional rather than individual to each gage, a principal component analysis was performed on standardized JFMA maximum event time series for the 26 gages. The first and second principal components, which comprise 66% and 11% of the total variance, respectively, were retained for further analysis and are used to reconstruct the time series of JFMA AMS for each gage. Across all gages, the correlation between the reconstructed and observed time series is significant, ranging from approximately 0.77 to 0.95. Based on the Shapiro-Wilk test for normality, the residuals of the reconstructed time series relative to the observed fail to reject the null hypothesis of a normal distribution for all but four gages.

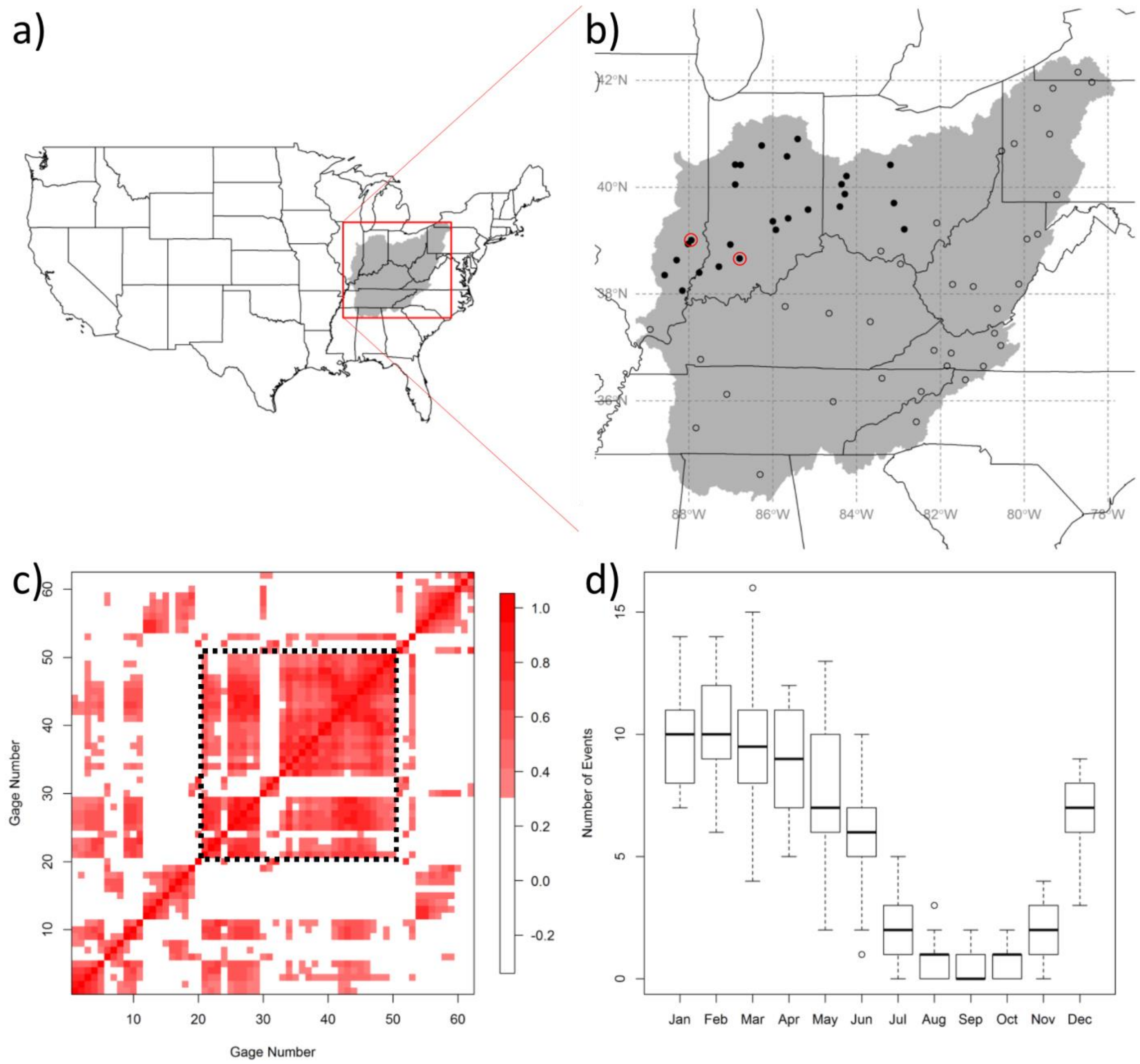

Figure 1: Diagnostic information about flood events. (a) The Ohio River Basin (U.S. Geological Survey hydrologic units 5 and 6) within the U.S.; (b) the Ohio River Basin with the HCDN gages plotted as dots (filled dots indicate gages in the northwest region and the encircled dots are the example gages used subsequently); (c) correlations between the JFMA maximum event of each gage to the other gages, where the dashed box indicates high correlations associated with the northwest region; (d) the number of annual maximum series events in each month for gages in the northwest region.

1.3.2 Identify Credible Large-Scale Predictors in the Ohio River Basin

We begin our identification process with a literature review. At the local scale, Berghuijs et al. (2016) found that AMS flood events in the region are primarily caused by rainfall in excess of soil moisture storage capacity. Historic reports also note the importance of antecedent soil moisture (see Appendix A). At the daily synoptic scale, Schwarz (1961) identifies two typical atmospheric flow patterns, a quasi-stationary front and an occluding low, that can cause heavy winter or spring rains in the region. Both patterns are characterized by a low-pressure trough to the west and a high pressure ridge to the east, which draws warm moist sub-tropical air into the region. This pressure configuration has been explicitly linked to extreme floods in the region by composite analysis and weather typing (Nakamura et al., 2013; Robertson et al., 2015) and is related to the negative phase of the Pacific/North American (PNA) teleconnection pattern (Roller et al., 2016). Its converse, which is related to the positive phase of the PNA, causes cyclonic circulation that inhibits tropical moisture transport and results in drier conditions during the winter season (Ning & Bradley, 2014). The PNA is an intrinsic mode of intra-seasonal atmospheric variability which is strongly impacted, through Rossby wave propagation, by inter-annual tropical climate variability, particularly ENSO (Horel & Wallace, 1981; Wallace & Gutzler, 1981). The PNA can also be impacted by inter-decadal variability associated with the Pacific Decadal Oscillation (PDO) (Yu & Zwiers, 2007). These mechanisms explain the significant correlations observed between winter rainfall or streamflow in the region and PNA (Coleman & Rogers, 2003), ENSO (Gershunov & Barnett, 1998a, 1998b; Higgins et al., 2007; Montroy, 1997; J. Rogers & Coleman, 2003) and PDO (Higgins et al., 2007; Mantua & Hare, 2002).

The relationships identified in the literature were tested using correlation maps. Gridded data was obtained for global monthly sea surface temperatures (Rayner, 2003), global monthly geopotential heights at the 500 mbar pressure level (Kalnay et al., 1996) which is the pressure level used to calculate PNA, and U.S. monthly soil moisture (Fan & van den Dool, 2004). Each grid cell of each data set was converted from a monthly to annual time series by taking the maximum value within either the concurrent months of JFMA for soil moisture, or the preceding months of December through February (DJF) for sea surface temperatures and geopotential heights at the 500 mbar pressure level. The correlation value between the first and second principal components of flood events and the 1950 through 2015 time series at every grid cell for every data set was calculated.

Maps of the correlation values reveal significant relationships that corroborate what is expected from the literature (Figure 2). The first principal component (PC1) is significantly and negatively correlated to the winter Nino3 region and has significant correlation to a winter geopotential height pattern similar to the PNA with pronounced centers over central Canada and the North Pacific. This is expected because the positive phases of winter ENSO and PNA are associated with drier conditions due to cyclonic circulation inhibiting moisture in the Gulf of Mexico from reaching the basin (Ning & Bradley, 2014). PC1 is also significantly correlated to concurrent soil moistures over the northwest region of the basin, reflecting the importance of soil moisture noted by historic reports (see Appendix A) and Berghuijs et al. (2016). The second principal component (PC2) is not significantly correlated with winter sea surface temperatures, but is positively correlated to geopotential heights over the eastern Atlantic, which corresponds to the eastern component of the pressure pattern identified by Nakamura et al. (2013). The second principal component is also positively correlated to soil moistures over the Mississippi River Valley to the west, reflecting the importance of moisture transport from the Gulf of Mexico as discussed in Schwarz (1961).

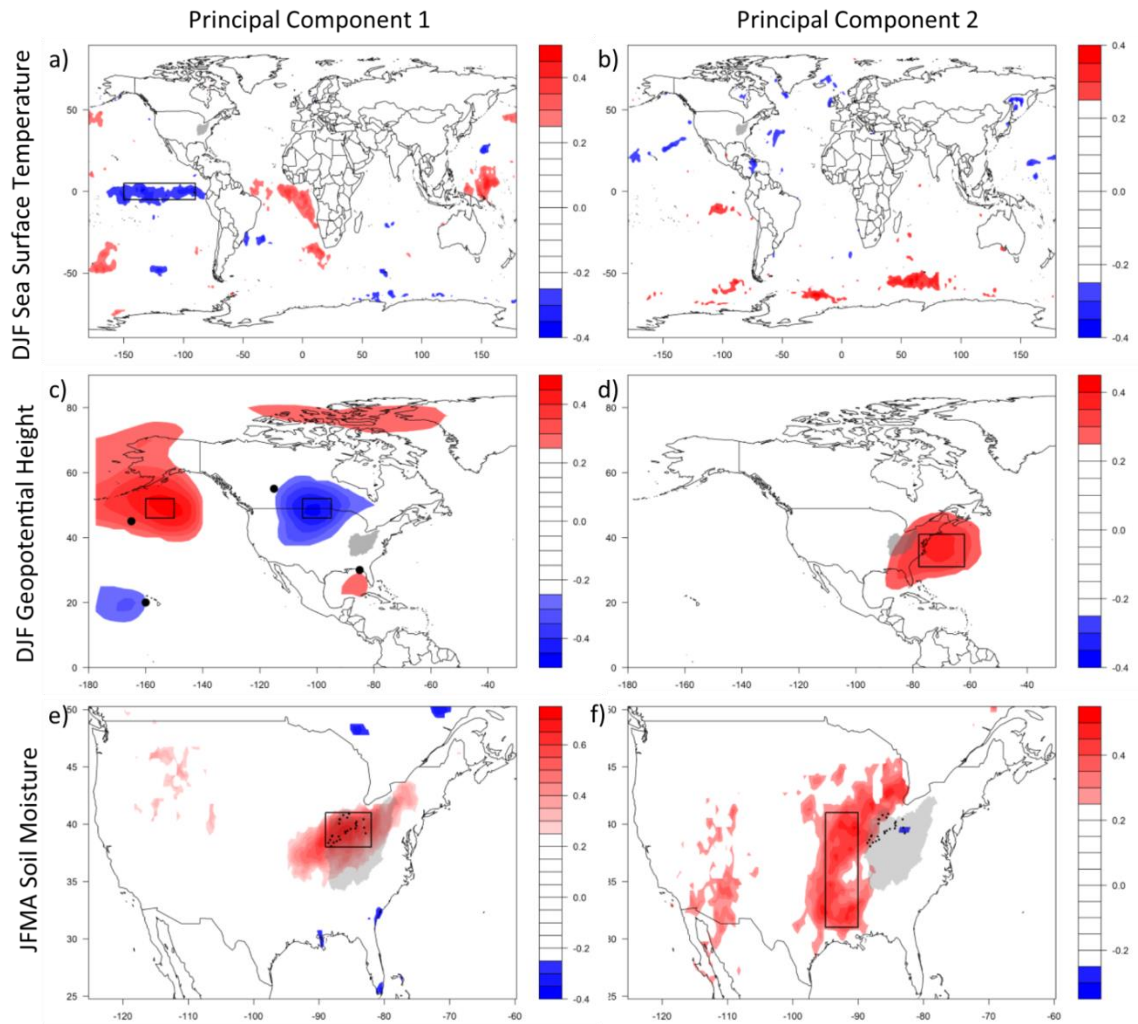

Figure 2: Correlation maps to climate variables. (a) $PC1$ to DJF sea surface temperature (the Nino3 region is outlined by a rectangle); (b) $PC2$ to DJF sea surface temperature; (c) $PC1$ to DJF geopotential heights at the 500 mbar level (the four centers of the PNA are marked by dots and the central Canada and the North Pacific regions are outlined by rectangles); (d) $PC2$ to DJF geopotential heights at the 500 mbar level (the North Atlantic region is outlined by a rectangle); (e) $PC1$ to JFMA soil moistures (the region over the basin is outlined by a rectangle); (f) $PC2$ to JFMA soil moistures (the region over to the west of the basin is outlined by a rectangle). The scale indicates the magnitude of the correlation (white areas are not significant). The basin is in grey and in (e-f) gages in the northwest region are represented as black dots. The x- and y-axis labels are longitude and latitude (degrees), respectively.

From the correlation maps, the following predictors were developed: sst_{Nino3}^{DJF} is the DJF sea surface temperatures averaged over the Nino3 region (5S – 5N, 150W – 90W), hgt_{CC-NP}^{DJF} is the difference in DJF geopotential heights at the 500 mbar level averaged over central Canada (46N – 52N, 160W – 150W) and averaged over the North Pacific (46N – 52N, 160W – 150W), $soil_{basin}^{JFMA}$ is the JFMA soil moisture averaged over the northwest region of the basin (38N – 41N, 89W – 81W), hgt_{EA}^{DJF} is the DJF geopotential heights at the 500 mbar level averaged over the eastern Atlantic (31N – 41N, 78W – 62W), and $soil_{west}^{JFMA}$ is JFMA soil moisture averaged over the Mississippi River Valley to the west of the basin (31N – 41N, 95W – 90W). The predictors were standardized and the resulting correlations are given in Table 2.

Table 2: The correlations between the standardized predictors and the principal components. NA indicates the correlation is not significant.

	sst_{Nino3}^{DJF}	hgt_{CC-NP}^{DJF}	$soil_{basin}^{JFMA}$	hgt_{EA}^{DJF}	$soil_{west}^{JFMA}$
$PC1$	-0.289	-0.530	0.706	NA	0.285
$PC2$	NA	NA	NA	0.375	0.505
sst_{Nino3}^{DJF}	1	0.549	NA	NA	0.289
hgt_{CC-NP}^{DJF}		1	-0.379	NA	NA
$soil_{basin}^{JFMA}$			1	0.337	0.573
hgt_{EA}^{DJF}				1	0.424

1.3.3 Formulate, Calibrate, and Validate Statistical Model for the Ohio River Basin

From among the possible model formulations, Bayesian modeling was chosen for its ability to clearly represent parameter uncertainty. Given the multiple predictors identified, multiple models for each principal component were developed (Table 3). The models were fit over the time period 1950 through 2015 by JAGS in R (Plummer, 2016; Yu-Sung & Yajima, 2015) using three model chains each having 2000 samples with 1000 samples discarded as burn-in. Sufficiently vague priors were placed on the variances (a uniform distribution from zero to 10) and on the coefficients (a normal distribution with mean zero and variance 25). For all models, both the potential scale reduction factor, also known as Gelman's R, and the effective sample size were well within accepted rules of thumb (less than 1.1 and greater than 300, respectively). Predictors are deemed to be significant if the 95% credible interval of the coefficient does not include zero. Model performance is judged by two statistics. The first is the coefficient of determination, R^2, between the simulated and observed principal components; higher is better. The second is the deviance information criterion (DIC) which accounts for parameter uncertainty and is appropriate even when the prior is non-informative or improper; lower is better (Spiegelhalter et al., 2002; Sun et al., 2014).

Table 3: Model form and associated parameters and performance. $N()$ indicates the normal distribution. Values are given as the mean (standard deviation).

Model	**Model Equation**	$\boldsymbol{\alpha_1}$	$\boldsymbol{\alpha_2}$	$\boldsymbol{\alpha_3}$	$\boldsymbol{\alpha_4}$	$\boldsymbol{\alpha_5}$	$\boldsymbol{\beta}$	$\boldsymbol{\sigma}$	$\boldsymbol{R^2}$	**DIC**
PC1sst	$PC1 \sim N\left(\alpha_1 sst^{DJF}_{Nino3} + \beta, \sigma^2\right)$	-1.19 (0.5)	-	-	-	-	-0.01 (0.5)	4.07 (0.37)	0.02 (0.03)	374
PC1hgt	$PC1 \sim N\left(\alpha_2 hgt^{DJF}_{CC-NP} + \beta, \sigma^2\right)$	-	-2.18 (0.45)	-	-	-	-0.01 (0.44)	3.61 (0.33)	0.09 (0.06)	358
PC1soil	$PC1 \sim N\left(\alpha_3 soil^{JFMA}_{basin} + \beta, \sigma^2\right)$	-	-	2.91 (0.38)	-	-	-0.01 (0.38)	3.01 (0.27)	0.25 (0.08)	335
PC1all3	$PC1 \sim N\left(\alpha_1 sst^{DJF}_{Nino3} + \alpha_2 hgt^{DJF}_{CC-NP} + \alpha_3 soil^{JFMA}_{basin} + \beta, \sigma^2\right)$	-0.15 (0.42)	-1.18 (0.45)	2.43 (0.37)	-	-	-0.01 (0.35)	2.79 (0.26)	0.32 (0.08)	328
PC1hgtsl	$PC1 \sim N\left(\alpha_2 hgt^{DJF}_{CC-NP} + \alpha_3 soil^{JFMA}_{basin} + \beta, \sigma^2\right)$	-	-1.27 (0.37)	2.44 (0.38)	-	-	0.00 (0.35)	2.78 (0.25)	0.33 (0.08)	325
PC2hgt	$PC2 \sim N\left(\alpha_4 hgt^{DJF}_{EA} + \beta, \sigma^2\right)$	-	-	-	0.62 (0.21)	-	-0.01 (0.21)	1.66 (0.15)	0.03 (0.04)	256
PC2soil	$PC2 \sim N\left(\alpha_5 soil^{JFMA}_{west} + \beta, \sigma^2\right)$	-	-	-	-	0.87 (0.19)	0.00 (0.19)	1.53 (0.15)	0.08 (0.06)	245
PC2all2	$PC2 \sim N\left(\alpha_4 hgt^{DJF}_{EA} + \alpha_5 soil^{JFMA}_{west} + \beta, \sigma^2\right)$	-	-	-	0.30 (0.20)	0.75 (0.21)	0.00 (0.19)	1.52 (0.14)	0.08 (0.06)	245

The sign of coefficients of the fitted models match what is expected from the correlation maps and the literature; the coefficients for $\mathrm{sst}_{\mathrm{Nino3}}^{\mathrm{DJF}}$ and $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$ are negative, while the remaining coefficients are positive. The intercept, β, is essentially zero for all models, which is expected given that the mean of the principal components is zero. As evaluations of model performance, R^2 and DIC agree; high R^2 implies low DIC, and vice versa. Additionally, as model performance improves, the variance decreases. For models of both PC1 and PC2 with only one predictor, model performance improves as the proximity of the predictor to flood events increases; for example, models based on soil are better than models based on geopotential height. In the models that use all available predictors (PC1all3 and PC2all2), the 95% credible interval of the coefficient on the least proximate predictor ($\mathrm{sst}_{\mathrm{Nino3}}^{\mathrm{DJF}}$ and $\mathrm{hgt}_{\mathrm{EA}}^{\mathrm{DJF}}$, respectively) contains zero, indicating that the predictor is not significant. Based on this result, an alternate model for PC1 (PC1hgtsl) and the soil-based model for PC2 (PC2soil) were chosen as the best models and used in all subsequent analysis. Based on the Shapiro-Wilk test for normality, the residuals of the PC1hgtsl and PC2soil models are normal for more than 96% and 93%, respectively, of the 3000 model runs.

Simulated data for each gage based on observed climate can be obtained by (1) sampling from the best models to stochastically generate the principal components, (2) back-transforming the new principal components using the loadings, (3) de-standardizing, and (4) taking the exponent. To find a quantile of interest for a given gage, l-moments are used to fit the simulated data to a log-Pearson Type 3 distribution, chosen based on an l-moments diagram (not shown). Model performance can be further assessed by visual comparison (Figure 3) and through statistical tests comparing the empirical cumulative distribution function of the observed data to the data simulated from the model when forced with observed climate. Across all gages, the p-value of the Kolmogorov-Smirnov (K-S) and Anderson-Darling (A-D) tests for distribution similarity between the observed data and the median of the stochastic data ranges from 0.57 to 1.0 and from 0.41 to 1.0 respectively, indicating failure to reject the null hypothesis that the distributions are the same. Across all gages, the percent of observed data points which fall outside the 95% credible interval of the simulated data (i.e., a "miss" rate) ranges from 0% to 17%. For the 100 year flood in particular (the 99th percentile), the observed magnitude falls within the simulated 95% credible interval for all except three gages (Figure 3b). Gage 23 has two anomalously high peaks that the model cannot capture, and gages 39 and 40, which are in close spatial proximity, each have an anomalously low peak and no high peaks, which skew the distribution. Finally, the sensitivity of the model to the predictors was tested by setting the predictors to zero. The results exhibited degraded performance, both visually (not shown) and quantitatively. The p-value of the K-S and A-D tests ranges from 0.1 to 0.95 and 0.03 to 0.52 respectively, and the miss rate ranges from 3% to 58%. Overall, based on the tests of model performance described above, the model was deemed satisfactory.

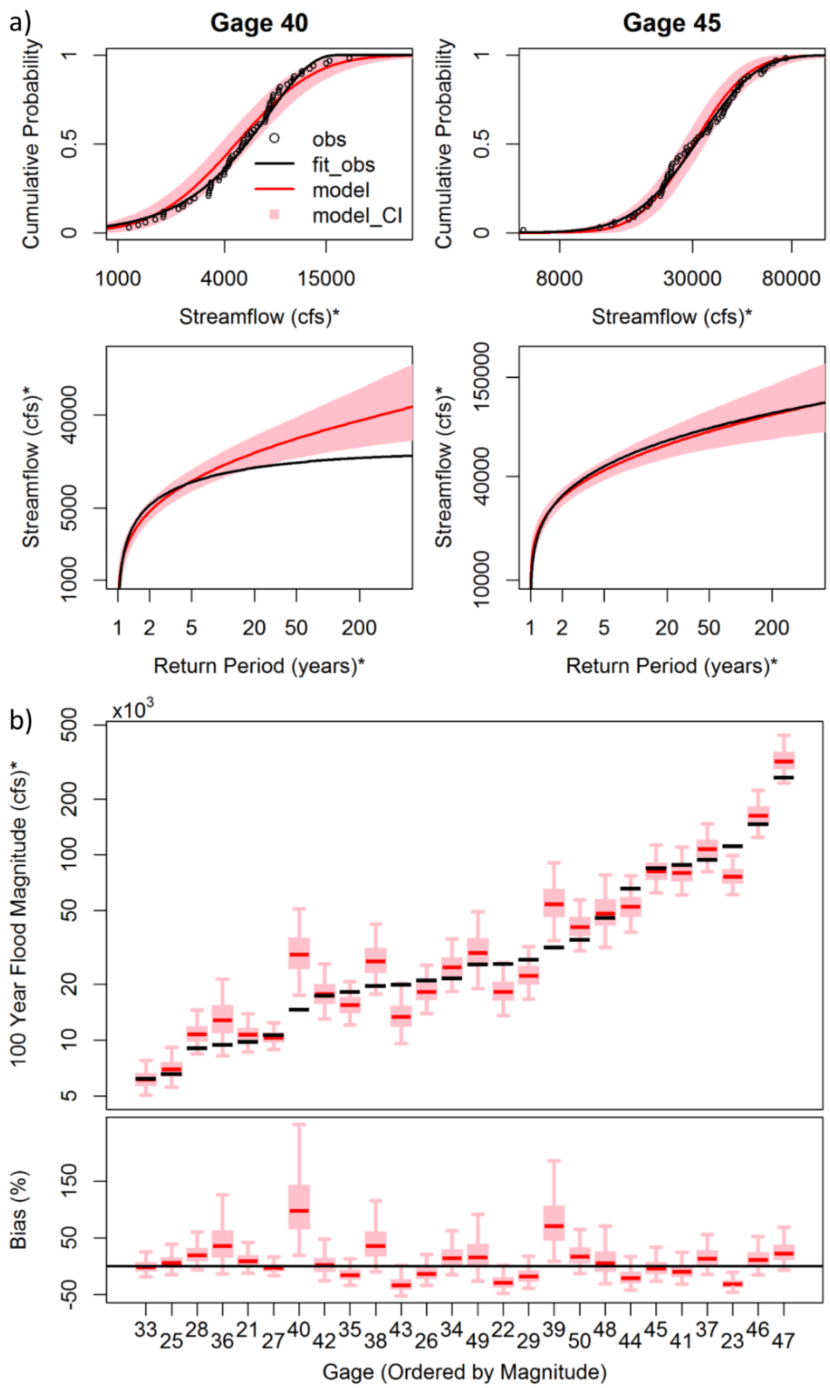

*Figure 3: Performance of statistical model. (a) two example gages illustrating poor and satisfactory performance, the empirical cumulative distribution function based on the Weibull plotting position of the observed data (obs) and the log Pearson type 3 distribution fit to the observed data (fit_obs) and to the model forced with observed climate (model) with associated credible intervals (model_CI); (b) the magnitude and bias of the 100 year flood calculated from the log-Pearson Type 3 distribution for the observed and simulated data. * indicates the axis is on a log-scale.*

1.3.4 Project Predictand into the Future for the Ohio River Basin

To create projections of future flood events, projections of the predictors were obtained from GCM simulations. Specifically, monthly gridded historical runs from 1950 through 2005 and projections from 2006 through 2100 of geopotential heights and soil moisture were obtained from the fifth generation of GCM experiments (CMIP5) directed by the Intergovernmental Panel on Climate Change (Taylor et al., 2012; Van Vuuren et al., 2011). The CMIP5 experiments are based on four scenarios of global warming specified by representative concentration pathways (RCPs) of 2.6, 4.5, 6.0, and 8.5 W/m^2 radiative forcing by the end of the twenty-first century; the experiments also tested various initialization conditions. For simplicity, this study used simulations from 10 GCMs associated with the historical and RCP 8.5 scenarios with initialization condition r1i1p1. The 10 GCMs are CanESM2, CCSM4, CNRM-CM5, CSIRO-Mk3.6.0, GFDL-CM3, GISS-E2-H, HadGEM2-AO, IPSL-CM5A-MR, MPI-ESM-LR, and NorESM1-M. The predictors were calculated in the same manner as described for observed data, where GCM historical data was used to standardize GCM projections.

GCM performance was assessed by reviewing the literature and by performing a variety of statistical analyses on the predictors. According to the literature, while CMIP5 GCMs generally replicate the spatial pattern and magnitude of PNA, the slight errors have a large influence on storm track variability (Lee & Black, 2013; Ning & Bradley, 2016). CMIP5 GCM performance in simulating seasonal persistence of soil moisture over North America is poor, likely due to biases in precipitation (Sheffield et al., 2013). In the warm season in particular, CMIP5 GCMs can capture the seasonal variability, but show biases in magnitude which vary by region and by model (Yuan & Quiring, 2017). For the predictors used in this study, as expected, the GCM historical time series have little to no relationship to the observed time series, that is, correlation to observations are insignificant or very low, because GCMs are not temporally aligned with historic climate except as relates to external forcing such as volcanos and long-term trends in greenhouse gas emissions. More concerning is the fact that the GCMs do not necessarily correctly simulate the co-fluctuations between the predictors. GCMs underestimate the relationship between $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$ and $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$ (the observed correlation from Table 2 is -0.379, but the historical correlations range from -0.27 to 0.33, with only two out of ten significant). Conversely, the GCMs overestimate the relationship between $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$ and $\mathrm{soil}_{\mathrm{west}}^{\mathrm{JFMA}}$ (the observed correlation is 0.573, but the historical correlations range from 0.54 to 0.81). Finally, GCMs seem to correctly simulate the lack of relationship between $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$ and $\mathrm{soil}_{\mathrm{west}}^{\mathrm{JFMA}}$ (none are significant). However, when the temporal aspect is removed, the empirical quantiles of the historical runs generally match observations, with the largest deviances observed in the distribution tails (Figure 4). Specifically, GCM simulation of $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$ uniformly underestimates the lowest quantiles, while overestimating the highest quantiles. GCM simulation of $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$ and $\mathrm{soil}_{\mathrm{west}}^{\mathrm{JFMA}}$ exhibits both positive and negative bias at the lowest quantiles, but uniformly underestimates the highest quantiles. As a comparison, and to provide justification of earlier discussion of GCM bias in extreme precipitation, daily gridded 1/16$^{\mathrm{th}}$ degree GCM simulation of extreme precipitation downscaled using the localized constructed analog method (Bracken, 2016; Pierce et al., 2014, 2015) is also shown relative to observed daily gridded 1/16$^{\mathrm{th}}$ degree extreme precipitation (Livneh et al., 2013); both GCM and observed data are averaged over the spatial domain (89.0625 – 81.9375W, 37.9375 – 41.4375N) before assessing extreme precipitation, defined as precipitation above the 98th percentile of the daily observed data.

Cognizant of the limitations associated with GCM performance in historical runs, we now turn to the projections. According to the literature, CMIP5 GCMs show that future intensification of ENSO and PDO will likely increase PNA variability (Fuentes-Franco et al., 2016), but the spatial patterns and amplitude are highly uncertain (Ning and Bradley, 2016). CMIP5 GCMs also show a general consensus of decreasing soil moisture but that there will be increased land-atmospheric coupling driven by soil moisture variations (Dirmeyer et al., 2013). For the predictors used in this study, the projections exhibit greater inter-model spread than the historical runs (Figure 4); this is to be expected because uncertainty increases further in the future. For $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$, the projections generally indicate an increase, which is accentuated at higher quantiles. Given the negative correlation between floods and $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$, this would indicate a decrease in flood magnitude. For $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$, which is the most significant predictor, there is relatively little change at the extremes, while projections of average values exhibit both increases and decreases. The one exception is GFDL-CM3, which projects a dramatic increase in soil moisture. Although floods and $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$ are positively correlated, the direction of the projections are not clear, excepting GFDL-CM3, and so the impact on floods is not clear. The projections for $\mathrm{soil}_{\mathrm{west}}^{\mathrm{JFMA}}$ exhibit similar tendencies as those for $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$, with the exception that IPSL-CM5A-MR projects a dramatic decrease in soil moisture. While floods and $\mathrm{soil}_{\mathrm{west}}^{\mathrm{JFMA}}$ are positively correlated, since the coefficient on $\mathrm{soil}_{\mathrm{west}}^{\mathrm{JFMA}}$ is relatively small and PC2 only explains 11% of the variance, the impact on floods may be minimal. Projections of the co-fluctuations between the predictors exhibit the same characteristics as in the historical runs; the relationship between $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$ and $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$ is underestimated, the relationship between $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$ and $\mathrm{soil}_{\mathrm{west}}^{\mathrm{JFMA}}$ is overestimated, while the relationship between $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$ and $\mathrm{soil}_{\mathrm{west}}^{\mathrm{JFMA}}$ is approximately correct. GCM projected extreme precipitation shows a dramatic increase for all but CSIRO-Mk3.6.0.

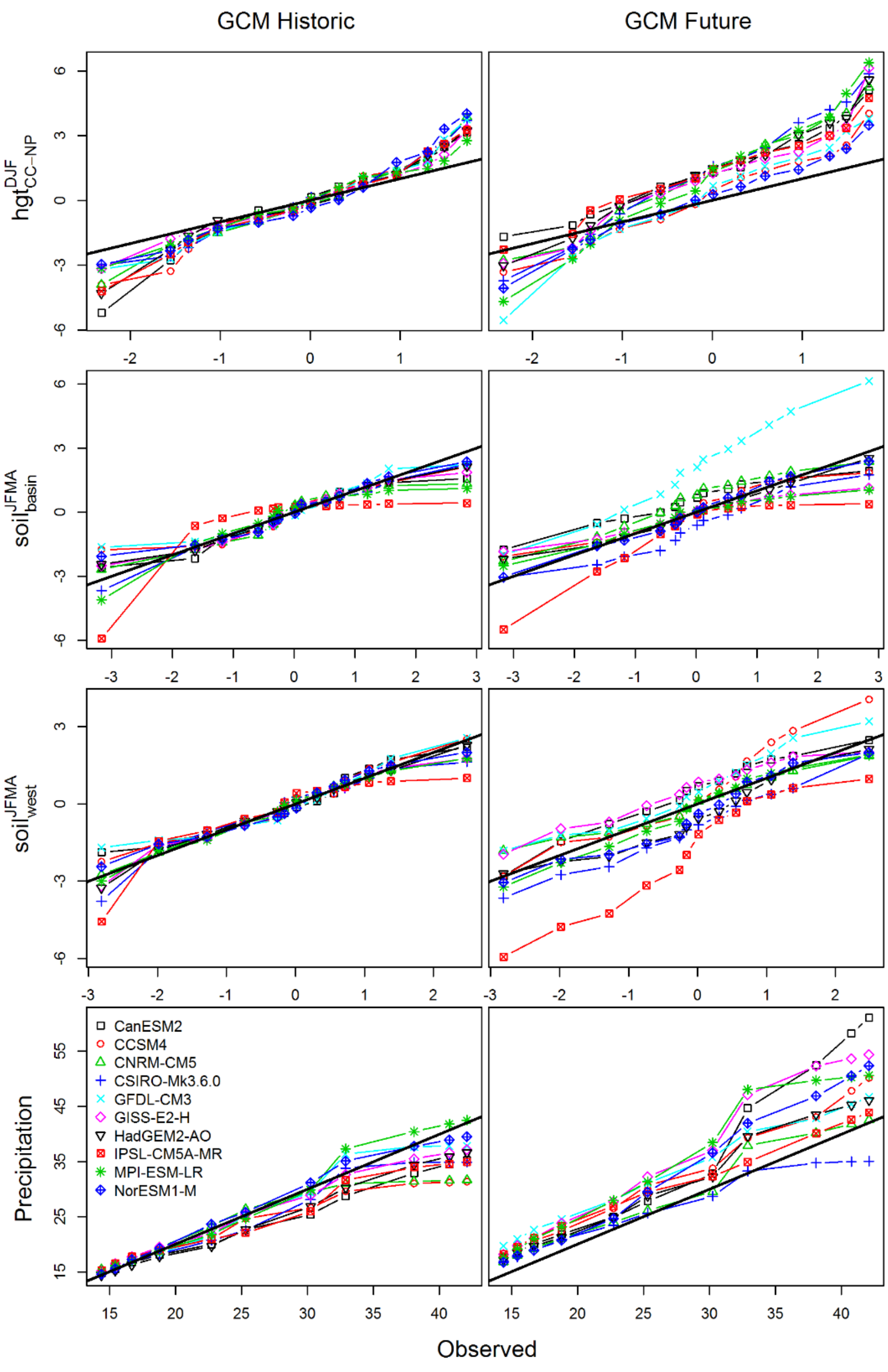

Figure 4: GCM climate variable data. Selected quantiles of the observed data (1950 through 2015) plotted against the same quantiles of the GCM historic (1950 through 2005) and future (2006 through 2100 for all but precipitation which is through 2099). The axes are unit-less because the values are standardized for all but precipitation, which has units of mm. The precipitation quantiles are from JFMA data above the 98th percentile.

The statistical model can be forced by the GCMs by replacing the observed predictors with GCM simulated data. When the model is forced with GCM historical runs, there is generally good model performance based on visual inspection of plots similar to Figure 3a. When the model is forced with GCM projections, quantiles of interest are obtained by assuming stationarity within a given time period and using l-moments to fit the log-Pearson Type 3 distribution as was done with the observed data. The time period is set using a 61 year moving window ending on every decade from 2010 through 2100; the first moving window, covering 1950 through 2010, is representative of the historical period, although 2006 through 2010 are technically projected by GCMs. The GCMs are combined using Bayesian model averaging (Hoeting et al., 1999), as described in Raftery et al. (2005). Because there is no temporal relation between GCMs and observations, the calculation of the weights and the resulting JFMA AMS projections are based solely on the forecasts of PC1, which were sorted within each moving window to create an empirical distribution function. The mean of the weights across the 3000 samples for each GCM range from 0.091 to 0.103, with the lowest weight assigned to IPSL-CM5A-MR, likely as a result of its poor performance in $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$. Overall, the relative proximity of the weights to an equal weighting of 0.1 indicates that no one model significantly under- or out-performs the others.

1.4 Results for the Ohio River Basin

The results show two key outcomes of the general methodology for climate informed approaches as applied to the Ohio River Basin. The first is the change in the flood event distribution between past and future time periods and the second is the attribution of change to various predictors.

1.4.1 Change in Flood Event Distribution

Figure 5 shows JFMA AMS streamflow as a function of return period for three representative GCMs and the Bayesian model average for two example gages. The three representative GCMs were chosen to illustrate no change (NorESM1-M), a decrease (CSIRO-Mk3.6.0), and an increase (GFDL-CM3) in flooding. For a given GCM, there is consistency across gages regarding the direction of change (e.g., NorESM1-M projects no change for both gages), likely due to the high correlations observed between the gages and the regional form of the model. The performance of GCMs in the historic period relative to the observed data largely follows the model performance when forced with observed predictors; gage 40 is poorly represented, while gage 45 is skillfully represented. However, there is some variation among GCMs; NorESM1-M is more skillful than CSIRO-Mk3.6.0 is more skillful than GFDL-CM3. The Bayesian model average has smaller credible intervals than those associated with individual GCMs, likely due to the averaging over GCMs, the linear regression, and the absence of PC2, which all contribute to reducing variability. The Bayesian model average projects a small decrease, which is consistent with the fact that only GFDL-CM3 projects a clear increase, while the remaining GCMs project either no change or a decrease in flood magnitude.

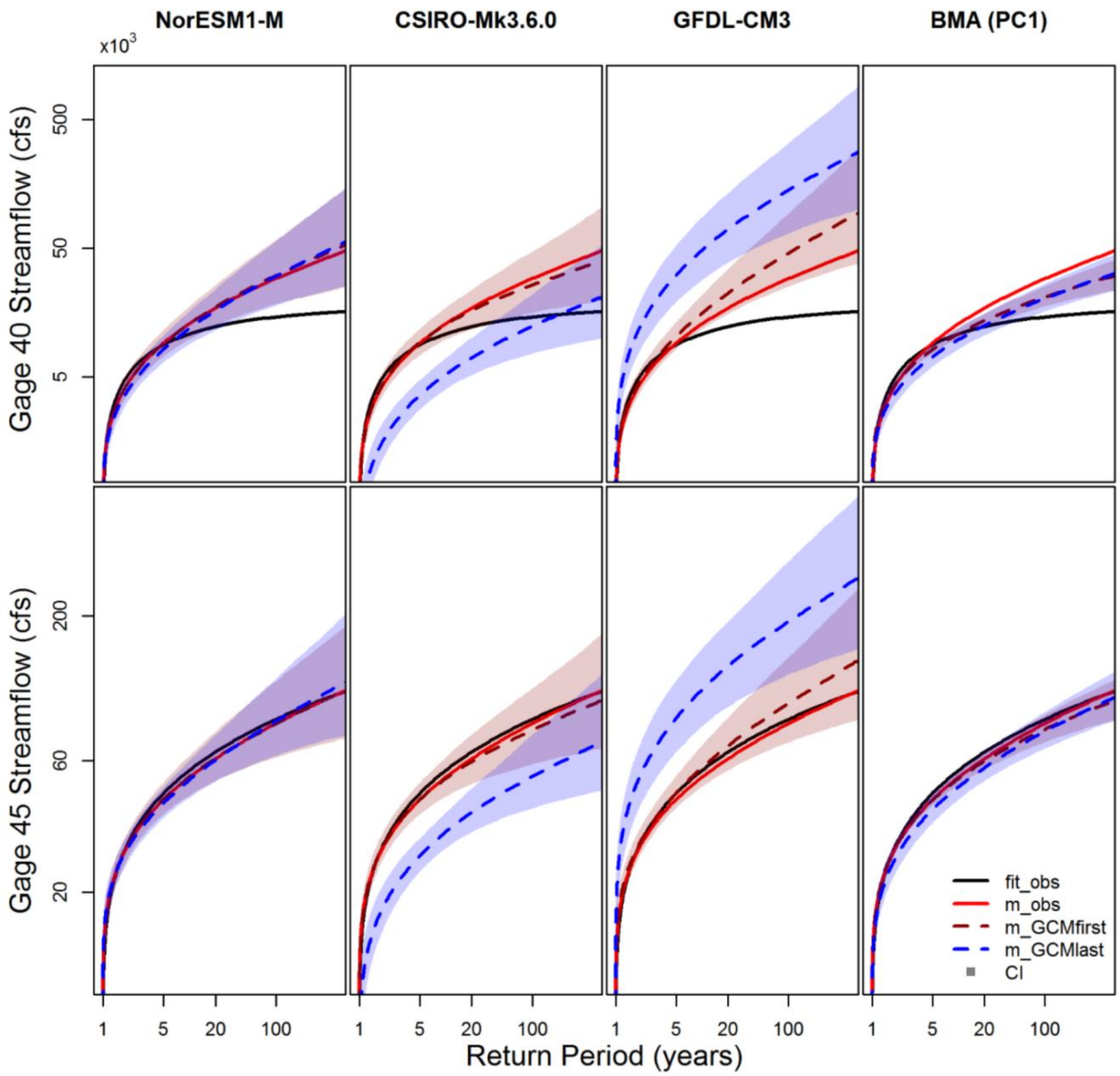

Figure 5: JFMA AMS streamflow as a function of return period for the two example gages from three representative GCMs (NorESM1-M, CSIRO-Mk3.6.0, GFDL-CM3) and the Bayesian model average (BMA (PC1)). The values are obtained from quantiles of the log-Pearson type 3 distribution fit to observed data (fit_obs), to the model output when forced with observed predictors (m_obs), to the model output when forced with GCM predictors from the first moving window from 1950 through 2010 (m_GCMfirst), and to the model output when forced with GCM predictors from the last moving window which is 2040 through 2100 (m_GCMlast). CI is the credible intervals (not shown for m_obs for ease of visualization). All axes are on a log scale.

Figure 6 shows the projected percent change between the last and first moving window (2040 through 2100 and 1950 through 2010, respectively) for the median across all samples of selected flood return periods (20, 100, 200, and 500 years) for all gages as calculated from the Bayesian model average. The homogeneity of the gage response across the northwest region of the basin is clearly seen; for a given flood return period, all gages tend towards the same direction and relative magnitude of change. This behavior is expected given the use of principal components in the statistical model, which was informed by the flood event diagnostics. As the flood return period increases, the percent change increases; the projections indicate relatively large decreases in the 20 year flood, slight decreases in the 100 year flood, essentially no change in the 200 year flood, and slight increases in the 500 year flood. The range of percent change across all four return periods is approximately -8% to 3%. Based on Student's t-test of the difference in means across all samples, the projected changes are significant for all gages for the 20, 100, and 500 year return periods; the projected changes for the 200 year return period are not significant.

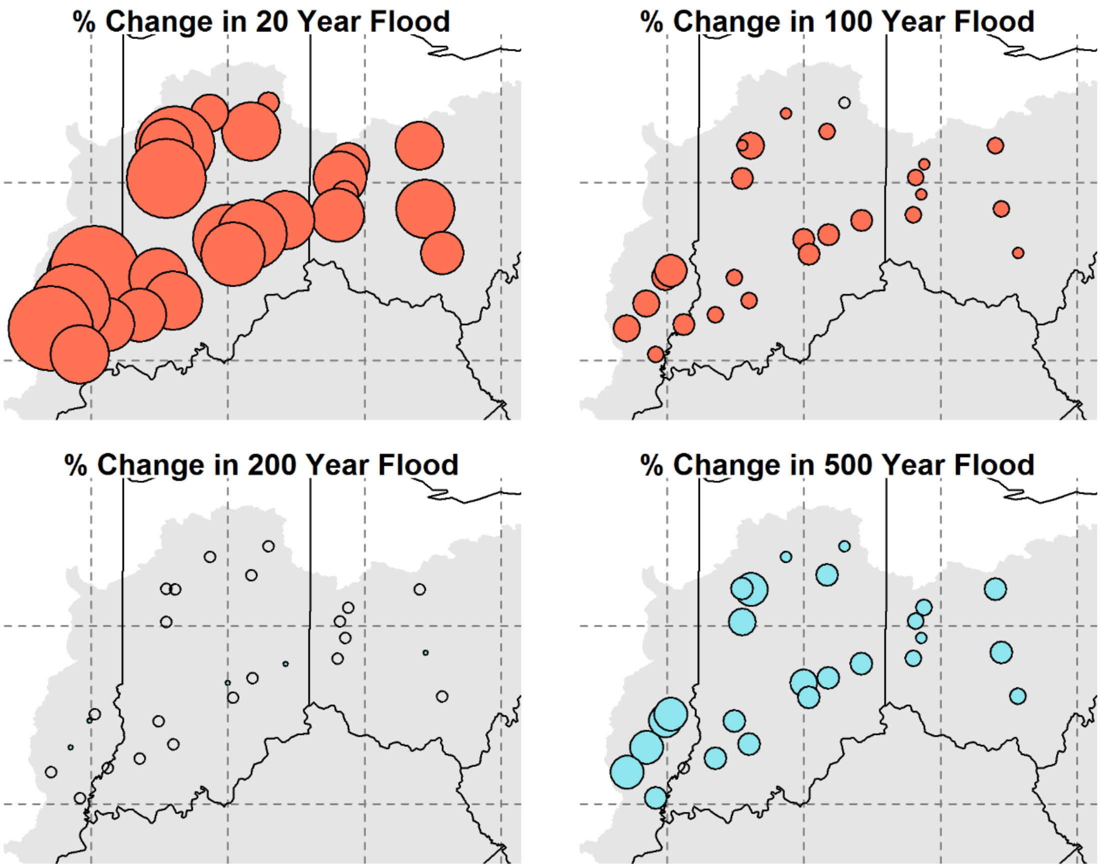

Figure 6: Projected percent change of selected flood return periods for all gages. The color indicates the direction of change (blue is increase, red is decrease, no color is zero change) and the size of the circle indicates the magnitude. The percent change is calculated between the last (2040 through 2100) and first (1950 through 2010) moving window for the median of the Bayesian model average.

How do the results obtained with the climate informed approach compare to those from the model chain method? To the authors' knowledge, there are currently no published studies which specifically analyze model chain flood projections in the Ohio River Basin (although some work on this is done in Chapter 2). However, a general albeit imprecise estimate can be formed from projections of precipitation and from global flood projection studies. The CMIP5 GCMs consistently project an increase in normal and extreme precipitation in the region (Maloney et al., 2014; Wuebbles et al., 2014), which would likely contribute to an increase in flood events. In a relatively simple study with one

GCM and an assumption of idealized carbon dioxide quadrupling, Milly et al. (2002) show that the frequency of the 100 year flood would increase in the Ohio River Basin. Hirabayashi et al. (2013) also show that the multi-model median of 11 GCMs forced by RCP 8.5 project an increase in the frequency of the 100 year flood by 2100 in the region. However, other studies show that for CMIP5 and previous GCM experiments, the sign of change is highly dependent on the GCM (Arnell & Gosling, 2016; Dankers et al., 2014) and ranges from highly positive to highly negative.

1.4.2 Attribution of Projected Change to Predictors

What is driving the projected change in floods for each GCM? Based on Figure 4b, the increase associated with the GFDL-CM3 projections seems to likely be driven by the increase in $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$, but the cause of the decrease in CSIRO-Mk3.6.0 projections is less clear. To better answer this question, the effect of individual predictors or subsets of predictors on the projection results was isolated by subtracting the 31 year moving average from all remaining predictors, thus removing any trend, and forcing the statistical model with the modified time series. For illustrative purposes, results are only shown for the 100 year flood for gage 45 (Figure 7).

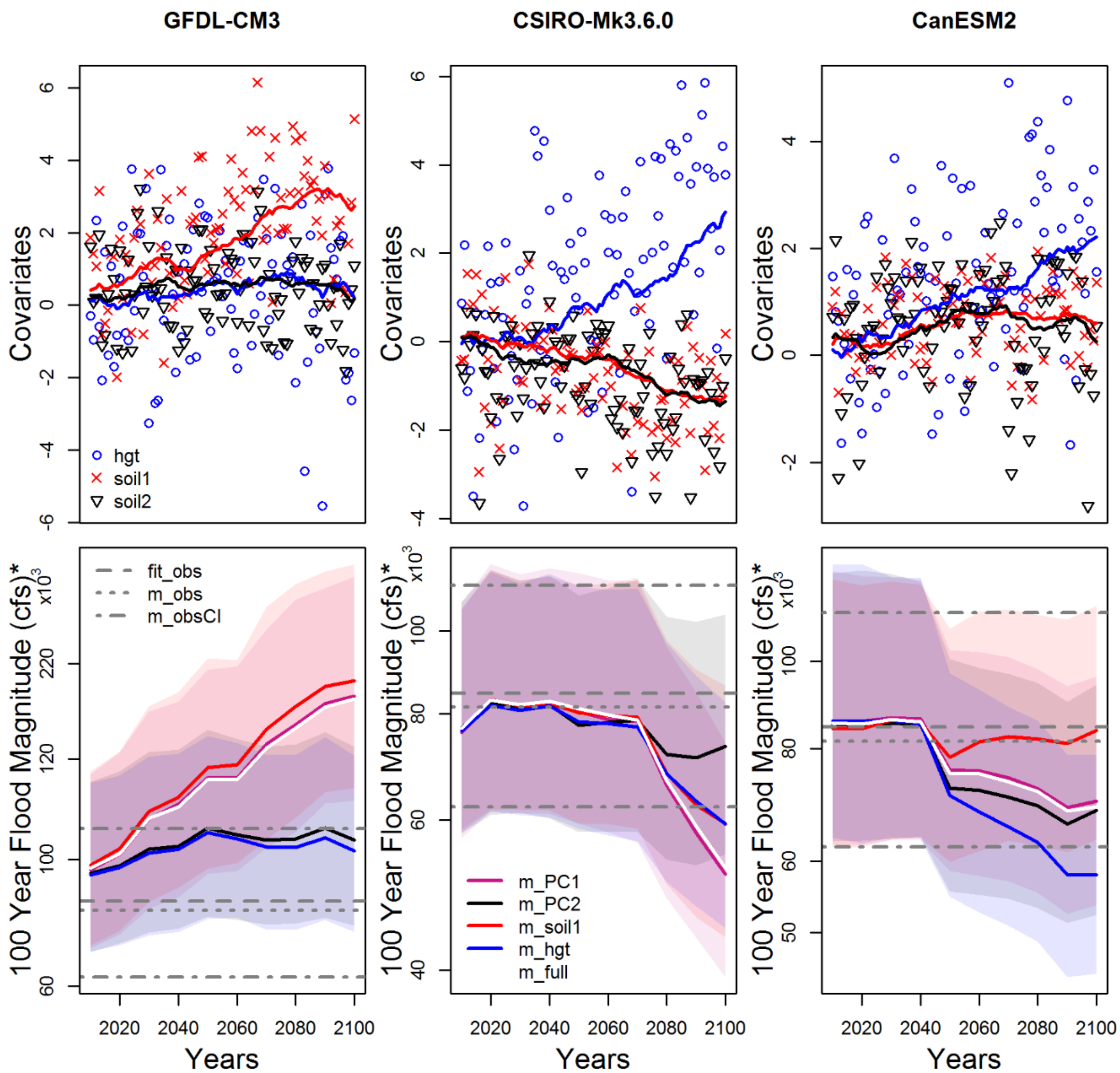

Figure 7: Projections of the predictors and the 100 year flood magnitude for gage 45 from three representative GCMs (GFDL-CM3, CSIRO-Mk3.6.0, and CanESM2). For the predictors, "hgt", "soil1", and "soil2", indicate hgt_{CC-NP}^{DJF}, $soil_{basin}^{JFMA}$, *and* $soil_{west}^{JFMA}$ *, respectively, the lines indicate the 31 year moving average and the y-axis is unit-less because the predictors are standardized. For the 100 year flood, "fit_obs" is the log Pearson Type 3 distribution fit to the observed data, "m_obs" is the model forced with observed predictors and "m_obsCI" is the associated credible intervals, "m_hgt", "m_soil1", and "m_PC2" are the models forced with GCM predictors where only the trend on the indicated predictor (*hgt_{CC-NP}^{DJF}, $soil_{basin}^{JFMA}$, *and* $soil_{west}^{JFMA}$ *, respectively) has been preserved, and similarly, "m_PC1" and "m_full" are the models forced with GCM predictors where the trend on* hgt_{CC-NP}^{DJF} *and* $soil_{basin}^{JFMA}$ *and where the trend on all predictors is preserved, respectively. The shaded areas indicate the credible intervals, and * indicates the axis is on a log scale.*

For GFDL-CM3, the results from the model which preserves the positive trend in $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$ shows the greatest increase in the 100 year flood over time, while the models which only include the relatively negligible trends in either $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$ or $\mathrm{soil}_{\mathrm{west}}^{\mathrm{JFMA}}$ show a correspondingly negligible trend in the 100 year flood. The models which preserve trends in the PC1 predictors and in all predictors follow the same general trend as the model where only trend in $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$ is preserved, although the magnitude is smaller, reflecting the influence of $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$ and $\mathrm{soil}_{\mathrm{west}}^{\mathrm{JFMA}}$. Thus, as expected, the increase in flood magnitude projected by GFDL-CM3 is largely driven by the increase in $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$.

For CSIRO-Mk3.6.0, while the increase in $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$ is nearly two times the absolute magnitude of the decrease in $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$, they cause an approximately similar decrease in flood magnitude. Additionally, while the decrease in $\mathrm{soil}_{\mathrm{west}}^{\mathrm{JFMA}}$ is the same as that of $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$, the resulting decrease in flood magnitude is much smaller. When the opposing trends of $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$ and $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$ are both represented in PC1, they cause an even greater decrease in flood magnitude, which is nearly matched by the full model. These results confirm what is expected from the magnitude and sign of the fitted statistical model coefficients: while all predictors have some effect on flood magnitude, $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$ is the most significant, followed by $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$ followed by $\mathrm{soil}_{\mathrm{west}}^{\mathrm{JFMA}}$.

For CanESM2, the increase in $\mathrm{hgt}_{\mathrm{CC-NP}}^{\mathrm{DJF}}$ causes a large decrease in flood magnitude, similar to CSIRO-Mk3.6.0. In contrast to CSIRO-Mk3.6.0, even though the moving average of $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$ closely follows that of $\mathrm{soil}_{\mathrm{west}}^{\mathrm{JFMA}}$, the model which preserves only the $\mathrm{soil}_{\mathrm{basin}}^{\mathrm{JFMA}}$ trend causes a much smaller decrease in flood magnitude than the model which preserves only the $\text{soil}_{\text{west}}^{\text{JFMA}}$ trend. Initially, this seems counterintuitive, given that $\text{soil}_{\text{basin}}^{\text{JFMA}}$ is a more significant predictor than $\text{soil}_{\text{west}}^{\text{JFMA}}$. However, the variability of $\text{soil}_{\text{west}}^{\text{JFMA}}$ is much higher than $\text{soil}_{\text{basin}}^{\text{JFMA}}$, and in particular, $\text{soil}_{\text{west}}^{\text{JFMA}}$ includes some highly negative outliers, which modify the lower tail of the flood distribution. Thus, the models which preserve trends in the PC1 predictors and in all predictors are similar to the model with only trend preserved in $\text{soil}_{\text{west}}^{\text{JFMA}}$, which lies between the models with only trend preserved in either $\text{soil}_{\text{basin}}^{\text{JFMA}}$ or$\text{hgt}_{\text{CC-NP}}^{\text{DJF}}$. These results illustrate that the projected sign of change may be driven by very different mechanisms depending on the GCM and illustrate the importance of outliers in addition to the mean change.

1.5 Generalization to the United States

We have demonstrated the general methodology for the climate informed approach in the Ohio River Basin. A remaining challenge for this and all previous literature on the climate informed approach is to demonstrate broad applicability across hydro-climatologically diverse basins. As a preliminary attempt to answer this challenge, we assess the potential applicability of ENSO and PNA as predictors for JFMA floods across the contiguous U.S. Streamgages from the Hydro-Climatic Data Network with less than 0.1% data missing between 1950 and 2015 and with catchment area greater than 500 km^2 (200 square miles) were identified, resulting in 422 gages. For each gage, the time series of JFMA maximum flood events was calculated. Only gages with more than 50% of AMS events occurring in JFMA were retained for further analysis, resulting in 255 gages. Monthly Nino3 and PNA indices were obtained from NOAA (2012, 2017) and processed into annual indices by taking the maximum value within DJF. This process closely follows the approach used for the Ohio River Basin case study. Additionally, gridded monthly soil data was obtained from Fan & van den Dool (2004). For every gage, the four closest soil moisture grid points were averaged and then processed into an annual index by taking the maximum value in JFMA.

The correlation between the soil moisture index and JFMA AMS flood events is significantly and positively correlated for all but 2% of gages; however, no clear spatial pattern of the magnitude exists (not shown). The results of correlating the DJF Nino3 and DJF PNA indices to the JFMA flood events are shown in Figure 8. Most gages in the Midwest and Southeast were not included in the analysis because less than 50% of annual maximum events occur in JFMA. Of the gages included in the analysis, gages in the northwest region of the Ohio River Basin are correlated to both PNA and Nino3, which corroborates the diagnostic analysis of the case study. Most gages in the northeastern Midwest (North Dakota, Minnesota, Wisconsin, and northern Illinois) are significantly negatively correlated to PNA, while on the eastern side of the Appalachians, most gages in the Southern Atlantic (Virginia, North Carolina, South Carolina, and eastern Georgia) are significantly positively correlated to Nino3. These results generally align with the literature on relationships between extreme precipitation and ENSO across the contiguous U.S. (Gershunov & Barnett, 1998a, 1998b; Higgins et al., 2007; Zhang et al., 2010). Gages in major mountain ranges, specifically the Sierra Nevada and Cascades on the west coast and the Appalachians on the East coast, are not significantly correlated to either climate indices or appear to have site-specific correlations that are not generalizable across a region (e.g., Oregon). Similarly, most gages in the Northeast are not significantly correlated to either climate index. These results for both the major mountain ranges and the Northeast are likely due to orthographic and snow effects as well as the confounding influence of multiple climate patterns. For example, in the Northeast, snow is a dominant flood generating mechanism (Berghuijs et al., 2016) and the influence of PNA and PDO on precipitation is modulated by the phase of ENSO (Ning & Bradley, 2014). While more work is needed to extend the climate informed method to the whole U.S. and for all seasons of the year, this simple diagnostic analysis shows the potential to apply the climate informed approach for JFMA AMS events in the northeastern Midwest and Southern Atlantic.

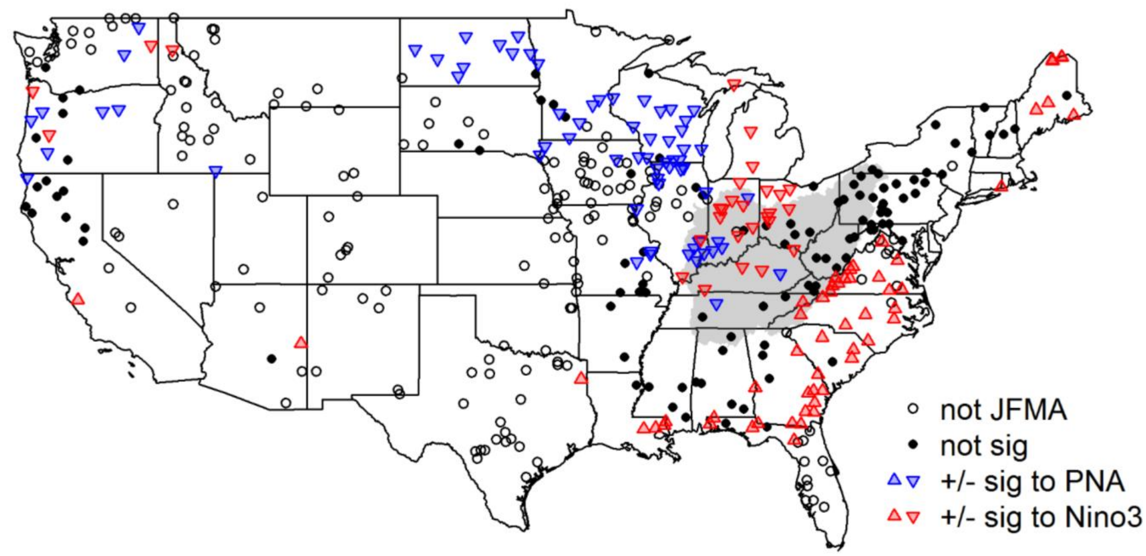

Figure 8: Visual representation of correlation between JFMA maximum event time series and PNA and Nino3. "not JFMA" indicates that less than 50% of the annual maximum events occur in JFMA, "not sig" indicates no significant correlation to either index, and "+/- sig to PNA" or "+/- sig to Nino3" indicates positive/negative significant correlation (if a location is significantly correlated to both indices, the stronger correlation is plotted). The Ohio River Basin is shaded grey.

1.6 Conclusion

The primary contributions of this work are threefold: (1) formalizing climate informed approaches into a general methodology, whereas previous literature has focused primarily on model formulation, (2) applying the methodology in entirety to multiple gages in the Ohio River Basin as a case study, whereas the few existing studies which use a climate informed approach to generate projections were only applicable to one gage, and (3) providing an initial path forward to generalization across the U.S., whereas previous studies are highly region-specific. The initial motivation for using a climate informed approach rather than the model chain method for long-term flood projection is that GCMs more skillfully simulate large-scale ocean-atmospheric patterns in comparison to local temperature and precipitation fields. However, another primary advantage of climate informed approaches, highlighted by the results of the case study, is that the simplicity and transparency of the statistical model allows the driving factor behind projected changes in flood events to be easily identified. This direct causation is obscured when streamflow estimates are the result of a hydrologic model forced by spatially downscaled and bias corrected GCM projections of temperature and precipitation, as is the case in the model chain method.

However, the simplicity of the climate informed approach is also one of its primary limitations. In particular, the statistical model is unlikely to fully explain the variance in flood events; assuming that an important predictor has not be excluded due to modeler error, it is still possible that complex and localized mechanisms causing floods cannot be easily linked to large-scale predictors. Additionally, the identified statistical relationship is assumed to remain stationary into the future, which highlights the importance of identifying predictors that are robust under climate change. Using the Ohio River Basin as an example, a shift in the location and type of ENSO, such as that discussed in Yeh et al. (2009), while uncertain (Taschetto et al., 2014), would have a downstream effect on teleconnections such as the PNA, conceivably causing moisture transport from the Gulf of Mexico to be less frequently directed over the Ohio River Basin. Such a shift is not represented in the current form of the statistical model, yet would have important implications for flood events in the region.

What are the primary remaining challenges associated with implementing the four step methodology more broadly? For step one, methods to select a predictand are generally well-accepted and well-known; the challenge is when suitable predictors are not readily apparent and the predictand must be modified. For example, the case study herein was restricted to a sub-region of the basin and the JFMA season in which the relationships to large-scale predictors was the strongest.

For step two, identification of credible large-scale predictors, there is an extensive climate sciences literature on teleconnections. However, not only are such studies usually written for a climate science readership rather than hydrologists or engineers, such studies often focus on precipitation rather than floods (e.g., in this study, the majority of the cited articles on teleconnections relevant to the Ohio River Basin focus on extreme precipitation). As a result, the conclusions do not necessarily translate to floods, especially when the proximate mechanism is not rainfall (e.g., in this study, attempts to replicate the precipitation relationship described in the literature for flood events was not always successful). Furthermore, predictors used for one region are unlikely to be generalizable to other regions. The simple correlation exercise performed in this study between PNA or Nino3 to JFMA AMS data for stream gages across the U.S. indicates that those climate variables are possibly suitable predictors for only certain regions. Until knowledge about flood teleconnections is better synthesized, step two will likely require lengthy investigation in the climate literature and an in-depth knowledge of climate processes to ensure the credibility of the chosen predictors.

For step three, while methods of formulation, calibration and validation of statistical models are well-known, the challenge lies in correctly representing the relationship between the predictand and predictors. For example, Renard & Lall (2014) note that correlation-based relationships such as that used in this study are common, but may obscure relationships that are non-linear or based on phases, and may be difficult to identify in regions where the coupling between climate and hydrology is particularly complex (e.g., at the intersection of two regions influenced by different major teleconnections). Currently, there is no one well-accepted model format in the climate informed literature; the multi-site Bayesian linear regression model presented here may be easily generalizable by changing the predictors but its general applicability would need to be tested across a hydro-climatologically diverse set of basins.

For step four, while making projections would initially appear to be the easiest step, only two previous studies have done so (Delgado et al., 2014; Tramblay et al., 2014) and this study is the first to do so for multiple gages. As a result, the associated challenges of assessing projection credibility and creating outputs that are useful for decision-making have been only cursorily investigated. Here, the claim for projection credibility is based on the predictor characteristics (demonstrated mechanistic control of flood events, reliability under climate change, and relatively well simulated by GCMs) and the goodness-of-fit statistics for the model. Here too, the projections from multiple GCMs are combined through Bayesian model averaging and return periods are calculated by assuming stationarity within a window. The uncertainty in the projections, caused in part by the different scenarios, initialization conditions, and model structure of the GCMs (Kundzewicz et al., 2017), highlights the need for analyses of uncertainty attribution and reduction, which can borrow from the global sensitivity analysis literature (Razavi & Gupta, 2015; Song et al., 2015), as well as the need to integrate climate informed projections into decision-making under uncertainty paradigms, especially those that take risk- or robustness-based approaches (e.g., Spence & Brown, 2016).

Despite these remaining challenges, climate informed approaches, now formalized into a four step methodology, are a promising and useful alternative to traditional model chain methods for long-term flood projection.

CHAPTER 2

INTEGRATING CLIMATE INFORMED PROJECTIONS AND DECISION SCALING FOR NONSTATIONARY FLOOD RISK MANAGEMENT

Risk-based flood management approaches are challenged by the possibility of non-stationarity in flow magnitudes due to, among other factors, climate change. The key contribution of this work is to advance the field of risk-based flood management by demonstrating how to integrate climate informed projections of flood magnitudes into the decision scaling framework, which can be used to determine optimal design values under uncertainty. Furthermore, this work compares the results of the climate informed method and the decision scaling framework to results from traditional risk analysis based on model chains. This is accomplished for the flood-prone city of Louisville, Kentucky, located on the Ohio River in the Midwest U.S. In the case study, the key decision is the return period of the design flood for the concrete floodwall and earthen levee along the Ohio River channel through the heart of the city. The best design is determined by minimizing the expected total costs, which is the sum of the expected flood damages and the cost of the levee. The results indicate that the best design varies both by the approach, whether traditional or decision-scaling, and by the GCM used to force the models. The conclusion discusses some of the benefits and limitations of both risk-based flood management approaches and highlights areas of future research.

2.1 Introduction

Design of flood infrastructure is determined by the flow magnitude associated with a particular return period, often 100 years (FEMA, 2011; NRC, 2000). However, estimates of flow magnitude are subject to a variety of uncertainties, including measurement error in observations, sample selection and length, choice of distribution, and assumption about the underlying process (i.e., nonstationary vs. stationary) (B. Merz & Thieken, 2005). To address this uncertainty, a common and simple, although sometimes arbitrary, approach used throughout engineering is to apply a safety factor to the design; examples include adding freeboard to levee height or applying multiplicative factors to flood quantiles (EA, 2016; NAP, 2013). A well-accepted alternative approach is to choose the design by optimizing a risk-based metric, which has the advantage of incorporating evaluation of damages and costs, in addition to probability, into design (Lund, 2002; B. Merz, Hall, et al., 2010).

Within the risk-based flood management literature, accounting for non-stationarity in flood magnitude due to climate change has proven to be a significant and on-going challenge. To date, the relatively limited work on this topic includes studies on protection against sea level rise in Mystic Connecticut (Rosner et al., 2014) and in the Thames estuary in London, England (Woodward et al., 2014), and on protection against riverine flooding in Iowa City, Iowa (Poff et al., 2015; Spence & Brown, 2016; Steinschneider et al., 2015), in the American River floodplain, which includes Sacramento California (Zhu et al., 2007), in the Songhuajiang and Biliu river basins in China (Qi, 2017; Qi & Liu, 2018), in West Garforth, England (Berry Gersonius et al., 2013), and for stylized examples (Hino & Hall, 2017; Rehan & Hall, 2016). Within this literature, two issues of primary importance emerge. The first is whether the basic methodology of risk-based flood management needs to be modified given non-stationarity in flood events, and if so, how. The second is how to model or represent non-stationary flood events. Noting that these two issues are coupled (i.e., the methodology influences the representation), we examine the current approaches to these two issues below.

Although some studies have applied the basic methodology of risk-based flood management without modification (Qi, 2017; Qi & Liu, 2018; Rehan & Hall, 2016; Zhu et al., 2007), others have incorporated optimization of a risk-based metric into decision-making under uncertainty frameworks. Rosner et al. (2014), noting that the traditional implementation often addresses the possibility of over-preparation (i.e., concluding a trend exists when it does not) while overlooking the possibility of under-preparation (i.e., rejecting a trend when it exists), combine classical decision-tree analysis with trend tests of historic data. Gersonius et al. (2013), Woodward et al. (2014), and Hino & Hall (2017), noting that the uncertainty associated with non-stationarity requires adaptable and flexible systems, use real options analysis to choose both the timing and type of infrastructure development and modification. Finally, Poff et al. (2015), Spence & Brown (2016), and Steinschneider et al. (2015), noting that traditional risk-based flood management is caught between the need for nonstationary flood projection and the accompanying inherent uncertainty, use decision-scaling, which is a methodology that determines system response to forcing, assesses probable future performance based on projections, and selects the best design based on robustness (i.e., the ability to perform well over a wide range of possible futures).

The methods used to model and represent non-stationarity in risk-based flood management can be classified into two general categories. The first is time-dependent modification of a statistical model of flood events. The magnitude and direction of the modification may be based on observed trends in the historic record; for example, Rosner et al. (2014) detect the historical trend in sea level anomalies and Zhu et al. (2007) impose linear trends determined from the historical record on the mean and standard deviation of the 3 day annual maximum flood. Alternatively, the magnitude and direction of the modification may be arbitrarily or stochastically generated; for example, Spence & Brown (2016) apply a set of systematically chosen linear trends to the mean of the annual maximum flow distribution, Rehan & Hall (2016), Qi (2017), and Qi & Liu (2018) apply a time-dependent linear trend to the location (and scale) parameter of the generalized extreme value distribution for flood events, and Gersonius et al. (2013) assume that the change in rainfall intensity follows geometric Brownian motion. The second method is the "model chain", in which general circulation model (GCM) projections drive the analysis; for example, Woodward et al. (2014) use GCM projections of sea level while Zhu et al. (2007), in addition to using the linear trends described above, use streamflow values derived from a hydrologic model forced by downscaled GCM projections of temperature and precipitation.

To date, to the authors' knowledge, there are not yet any studies which integrate the climate informed method of non-stationary flood projection, which was discussed extensively in Chapter 1, into risk-based flood management. Thus, the key contribution of this work is to advance the field of risk-based flood management by demonstrating how to integrate climate informed projections into the decision scaling framework. As a case study, this work evaluates the total expected costs associated with various levee heights along the Ohio River in Louisville, Kentucky. Importantly, this work improves upon previous nonstationary risk-based flood management studies by calculating damages using HAZUS, a GIS-based tool developed by FEMA, rather than simple damage functions. Additionally, this work compares the decision scaling results to those obtained from following a traditional approach forced by GCM projections of temperature and precipitation and discusses the associated implications on design.

2.2 Case Study Description

Louisville, Kentucky, which is located on the Ohio River and has a population of over 600,000 as of 2016 (US Census Bureau, 2018), has experienced a number of devastating floods. The largest recorded flood occurred in 1937, causing damages estimated at approximately 250 million USD (over 4 billion USD in 2016 dollars) (National Weather Service, 2018b). The 1937 flood, and a subsequent major flood in 1945, motivated investment in flood risk management infrastructure (Louisville/Jefferson County Metropolitan Sewer District, 2018a, 2018b). Despite this investment, floods continue to occur; for example, a flood in 1997 caused 200 million USD (nearly 300 million USD in 2016 dollars) in damages to the city, and a flood in 2009 caused 45 million USD (over 50 million USD in 2016 dollars) in damages to the state (National Weather Service, 2018a, 2018b).

The city's flood risk management infrastructure consists of a major concrete floodwall and earthen levee along the Ohio River main channel as well as pumping stations and smaller levees throughout the city (Louisville/Jefferson County Metropolitan Sewer District, 2018a, 2018b). The main levee system is nearly 26 miles long and was built to withstand a flood crest three feet higher than that observed in 1937 (Louisville/Jefferson County Metropolitan Sewer District, 2018a, 2018b); as recorded in the National Levee Database, it was built to the 500 year flood with three feet of freeboard (USACE, 2018) (based on fitting the log Pearson type 3 distribution using l-moments to the annual maximum series streamflow at the Louisville USGS gage for the full record from 1928 to 2017, the 1937 flood crest of 111,000 cfs has a return period of just under 300 years). However, like much of the infrastructure across the U.S., it is aging; the most recent inspection labeled it as “minimally acceptable” (USACE, 2018). Thus, the Louisville levee system is facing many of the same investment questions that are being asked for flood risk management structures across the U.S.

2.3 Methods

The methodology consists of two main components: developing nonstationary flood projections and performing risk-based analyses. Nonstationary flood projections are developed following the traditional model chain method and following the climate informed method. As extensively discussed in Chapter 1, the climate informed method capitalizes on the fact that GCMs more skillfully simulate large-scale climate patterns compared to local-scale precipitation and uses a statistical model rather than a hydrologic model to estimate future flood magnitude and frequency of occurrence. Projections following the traditional model chain method were developed by performing flood frequency analysis on the output of a calibrated hydrologic model forced with downscaled projections of precipitation and temperature from GCMs. Projections following the climate informed method are based heavily on the process described in Chapter 1, where flood frequency analysis is performed on the output of a statistical model forced by projections of large-scale ocean-atmospheric patterns from GCMs. For each method, the same GCMs were used to facilitate comparisons and the projections were combined using Bayesian model averaging.

Risk-based analysis was performed following traditional methods and following the decision scaling methodology. Unlike traditional methods, which are limited by the scenarios chosen to force the analysis, decision scaling calculates system response to a wide array of stressors, identifies ex-post scenarios, and only then uses projections to assess probability of occurrence (Brown et al., 2012). Risk is quantified as expected total cost, defined as the sum of the levee cost (calculated as a function of levee height) and expected damages (calculated as the integral of flood probability and modeled damages). The traditional risk-based analysis was implemented using the flood probabilities obtained from the model chain method. The decision scaling analysis was implemented using flood probabilities obtained by forcing the climate informed statistical model with stochastic realizations of the large-scale patterns altered by systematically applied linear trends.

2.3.1 Observed Flood Events

Observed daily streamflow data was obtained from USGS gage 03294500, which is located on the Ohio River at Louisville. The gage has a drainage area of 91,170 square miles, has elevation 373.18 feet above NGVD29, and is located at latitude 38^{o}16’49” and longitude 85^{o}47’57”. The gage is considered impaired according to the Hydro-Climatic Data Network (Landwehr & Slack, 1992), due to a system of locks and dams upstream. The impact of impairment on flood peaks was investigated by comparison to naturalized data, aggregated from an hourly to daily time step, obtained from the U.S. Army Corps of Engineers (USACE) over the period 2004 through 2015. Surprisingly, annual maximum series (AMS) flood events in the USACE data were higher than those in the USGS gage data for only five out of the 11 years, and the highest flow over the whole time period is recorded by the USGS gage data. As another indication of relative impairment, a reservoir index was calculated following López & Francés (2013). Accounting for all man-made water bodies on the Ohio River main-stem above Louisville, the maximum reservoir index is 0.034, which is much smaller than the threshold value of 0.25 cited by López & Francés (2013) as indicating significant impairment, likely because the capacities of the man-made water bodies are much smaller than the mean annual flow of the river. Both the comparison to the USACE naturalized flow and the calculation of the reservoir index indicate a lack of significant impairment, especially in regards to flood peaks, and thus the USGS data was used without adjustment.

The work on flood events in the northwest region of the Ohio River Basin described in Chapter 1, which is bordered by Louisville, has shown that January through April (JFMA) AMS flood events are mechanistically linked to winter large-scale climate processes. For this reason, the remainder of this work will focus on JFMA AMS flood events. As with AMS flood events, the JFMA AMS flood events are only minimally impacted by upstream impairment. Furthermore, there is no significant trend in JFMA AMS flood events based on the Mann-Kendall trend test. Here and throughout the remainder of the chapter, significance is reported at the 95% level unless noted otherwise.

Realizing that the full AMS is more useful for management decisions than JFMA AMS, we note that nearly 80% of AMS flood events occur in JFMA. Furthermore, a preliminary analysis (not shown), indicates that the model developed for climate informed projections of JMFA AMS (discussed below) is still statistically significant (although less strongly so) when applied to the full AMS. This likely occurs due to the high percentage of AMS events in JFMA. Furthermore, for those AMS events which occur outside JFMA, more than 80% occur during either December or May and are thus likely to be somewhat influenced by winter climate patterns. The caveat is that the climate informed model derives its credibility from the demonstrated mechanistic link between winter flood events and winter climate processes; applying the model without modification to the full AMS reduces the strength of this credibility.

2.3.2 Traditional Model Chain Flood Projections

The model chain method was implemented by forcing a hydrologic model with GCM projections of precipitation and temperature. The hydrologic model is a distributed version of the Soil Moisture Accounting model (SAC-SMA) coupled with a river routing model as described in Brown et al. (2016). The model was implemented on a daily time step at 1/8th degree grid resolution, with three hydrologic response units (i.e., within each hydrologic response unit, the parameter values are the same for each grid cell). Observed daily gridded 1/16th degree precipitation and average temperature were obtained and aggregated to 1/8th degree (Livneh et al., 2013). Model parameters were calibrated using a genetic algorithm over the period 1970 through 1995 inclusive of a five year warm-up period by maximizing the Nash-Sutcliffe Efficiency (Nash & Sutcliffe, 1970), which yielded 0.88. Model performance in the full time period from 1950 through 2010 is also good although the model over-estimates the upper quantiles; the NSE is 0.86 and the JFMA AMS streamflow as a function of return period is shown in Figure 9.

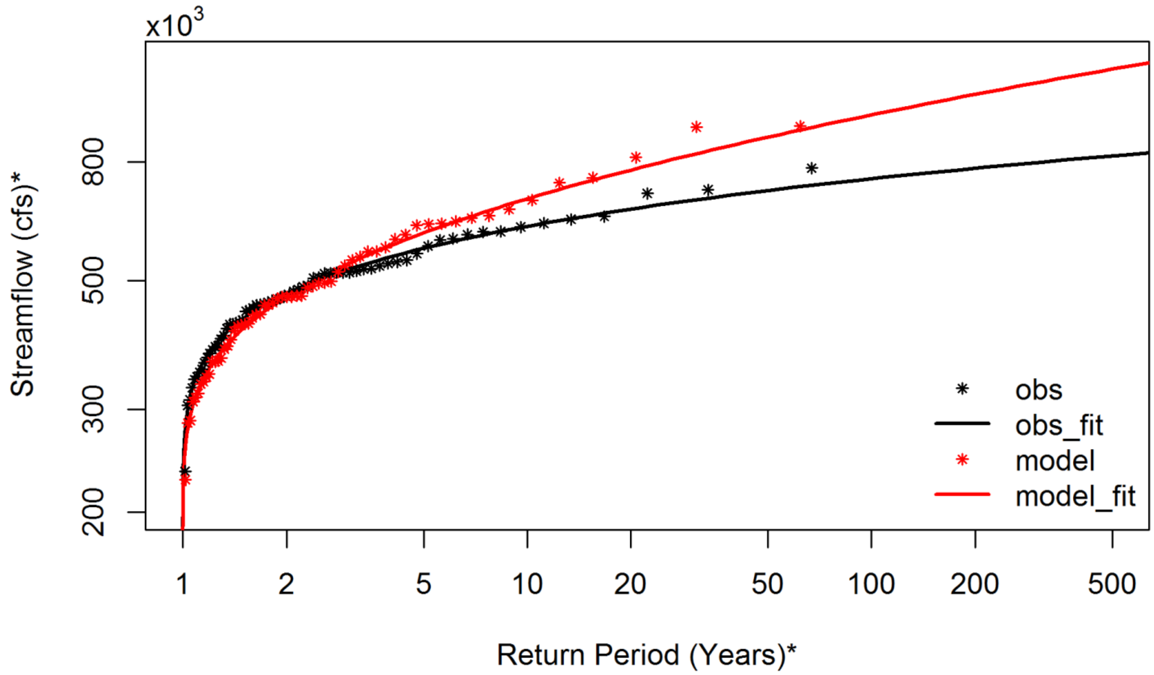

*Figure 9: Performance of the hydrologic model (model) relative to observations (obs). "fit" refers to the log Pearson type 3 (LP3) distribution fit to the data. * indicates the axis is on log-scale.*

To create streamflow projections, historical (1950 through 2005) and projected (2006 through 2099) spatially downscaled and bias corrected data from 10 GCMs in the fifth generation of GCM experiments (CMIP5) directed by the Intergovernmental Panel on Climate Change (Van Vuuren et al., 2011) for two representative concentration pathways (RCPs) (4.5 and 8.5) was obtained (Bracken, 2016; Pierce et al., 2014, 2015); the method used for downscaling and bias correction is the localized constructed analog method. The 10 GCMs are CanESM2, CCSM4, CNRM-CM5, CSIRO-Mk3.6.0, GFDL-CM3, GISS-E2-H, HadGEM2-AO, IPSL-CM5A-MR, MPI-ESM-LR, and NorESM1-M. The GCMs were chosen based on availability of the predictor variables used in both the model chain method and the climate informed method. The ensemble member is r1i1p1, except for CCSM4, which uses r6i1p1, and GISS-E2-H, which uses a combination of r6i1p1, r6i1p3, and r2i1p1, due to data availability constraints (Bracken, 2016). The GCM historical and projected data was then used to force the calibrated hydrologic model. Flood events were estimated by fitting the log Pearson type 3 (LP3) distribution to the JFMA AMS of modeled streamflow in 61 year increments ending on every decade from 2010 through 2099 (because 2100 is not available, the last increment has only 60 years). Confidence intervals for the fitted distribution were obtained by sampling with replacement from the time series to create 3000 alternative time series and fitting the LP3 to each. The flood projections from the multiple GCMs were combined using Bayesian model averaging (Hoeting et al., 1999), as described in Raftery et al. (2005). Briefly, Bayesian model averaging is a method for calculating a probabilistic weighted average of multiple models. The weights reflect model performance, which is assessed by linearly regressing observations onto projections of the variable of interest. Here, the observations (projections) are the flood events calculated from the hydrologic model forced with observed (GCM historical) climate. Furthermore, because GCM and observed climate variability are not temporally aligned, the flood events are sorted before linear regression is performed. Thus, the performance of each GCM is assessed by comparing the empirical distribution function of the model output when forced with observed climate to that of the model output when forced with GCM historical climate. The weights ranged from 0.04 to 0.22, with the lowest assigned to CanESM2 and the highest assigned to MPI-ESM-LR.

2.3.3 Climate Informed Flood Projections

The climate informed flood projections are closely based on the methods and results described in Chapter 1. Gridded monthly climate data (sea surface temperatures – Rayner, 2003; geopotential heights at the 500 mbar pressure level – Kalnay et al., 1996;

soil moisture – Fan & van den Dool, 2004) was converted to annual time series by taking the maximum value within December through February (DJF) or within JFMA. Correlation maps between the annual climate data and JFMA AMS flood events show significant relationships to DJF sea surface temperatures in the eastern tropical Pacific, DJF geopotential heights at the 500 mbar level over central Canada and the North Pacific, and JFMA soil moisture over the basin (Figure 10). From the correlation maps, the following predictors were developed: sst_{ETP}^{DJF} is the DJF sea surface temperatures averaged over the eastern tropical Pacific region (15S – 5S, 145W – 85W), hgt_{CC-NP}^{DJF} is the difference in DJF geopotential heights at the 500 mbar level averaged over central Canada (38N – 46N, 97W – 90W) and averaged over the North Pacific (46N – 52N, 150W – 140W), and $soil_{basin}^{JFMA}$ is the JFMA soil moisture averaged over the center of the basin (37N – 40N, 86W – 81W). The predictors are standardized and the resulting correlations are given in Table 4.

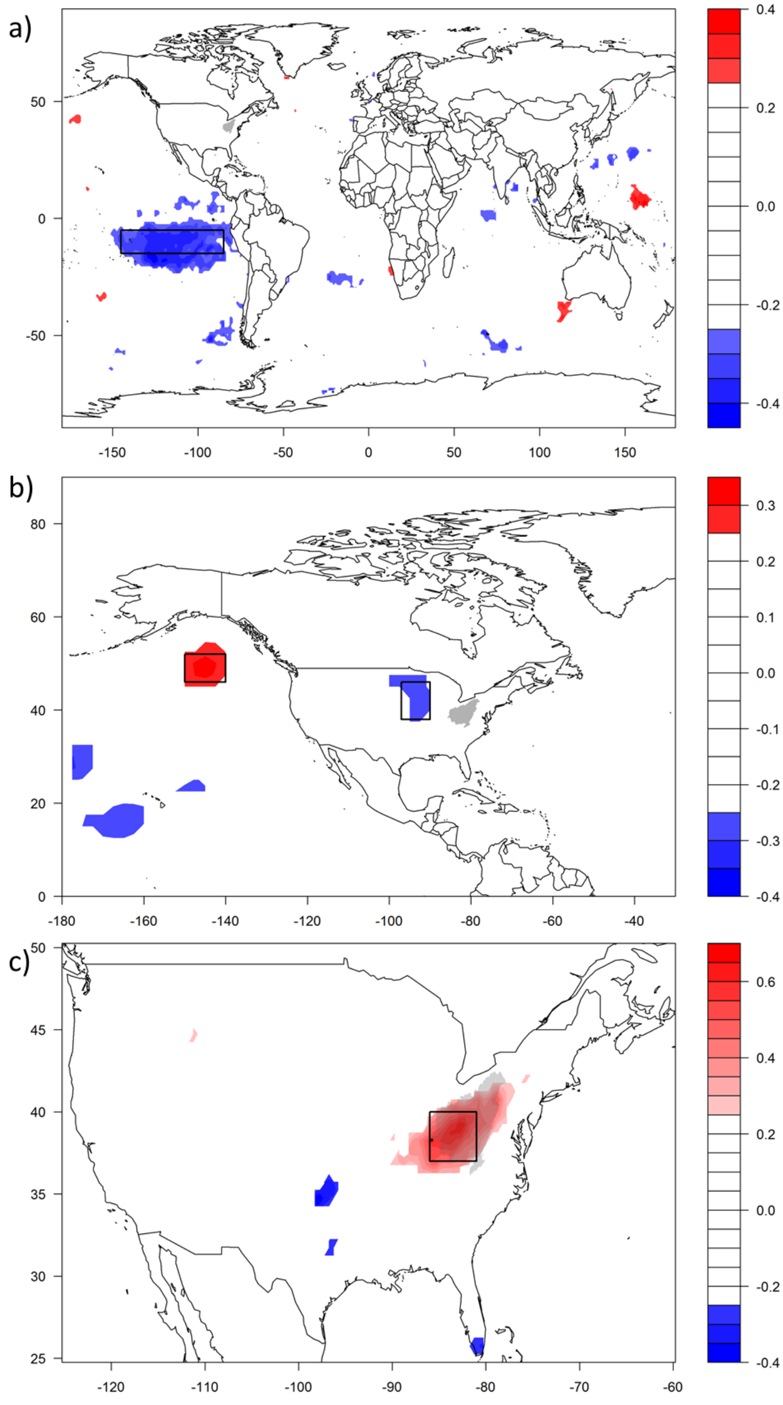

Figure 10: Correlation maps of the standardized logarithm of flood events to climate variables. (a) DJF sea surface temperatures (the region in the eastern tropical Pacific is outlined by a rectangle), (b) DJF geopotential heights at the 500 mbar level (the central Canada and the North Pacific regions are outlined by rectangles), (c) JFMA soil moistures (the region over the basin is outlined by a rectangle and the Louisville gage is represented by a point. The scale indicates the magnitude of the correlation (white areas are not significant), the basin is shaded grey, and the x- and y-axis labels are longitude and latitude, respectively.

*Table 4: Correlations between the standardized predictors and the standardized log of JFMA AMS, denoted X. *, **, and *** indicates that the p-value lies between 0.05 and 0.01, between 0.01 and 0.001, and is less than 0.001, respectively.*

	sst_{ETP}^{DJF}	hgt_{CC-NP}^{DJF}	$soil_{basin}^{JFMA}$
X	-0.378**	-0.376**	0.611***
sst_{ETP}^{DJF}	1	0.403***	-0.270*
hgt_{CC-NP}^{DJF}		1	-0.349**

Given the multiple predictors identified, multiple models were developed (Table 5). The models were fit over the time period 1950 through 2015 by JAGS in R (Plummer, 2016; Yu-Sung & Yajima, 2015) using three model chains each having 2000 samples with 1000 samples discarded as burn-in. Sufficiently vague priors were placed on the variances (a uniform distribution from zero to 10) and on the coefficients (a normal distribution with mean zero and variance 25). For all models, both the potential scale reduction factor, also known as Gelman's R, and the effective sample size were well within accepted rules of thumb (less than 1.1 and greater than 300, respectively). Predictors are deemed to be significant if the 95% credible interval of the coefficient does not include zero. Model performance is judged by two statistics. The first is the coefficient of determination, R^2, between the simulated and observed; higher is better. The second is the deviance information criterion (DIC) which accounts for parameter uncertainty and is appropriate even when the prior is non-informative or improper; lower is better (Spiegelhalter et al., 2002; Sun et al., 2014).

Table 5: Model form and associated parameters and performance. $N()$ indicates the normal distribution. Values are given as the mean (standard deviation).

Model	**Model Equation**	$\boldsymbol{\alpha_1}$	$\boldsymbol{\alpha_2}$	$\boldsymbol{\alpha_3}$	$\boldsymbol{\beta}$	$\boldsymbol{\sigma}$	$\boldsymbol{R^2}$	**DIC**
all3	$Q_{AMS}^{JFMA} \sim N\big(\alpha_1 sst_{ETP}^{DJF} + \alpha_2 hgt_{CC-NP}^{DJF} + \alpha_3 soil_{basin}^{JFMA} + \beta, \sigma^2\big)$	-0.19 (0.11)	-0.12 (0.11)	0.52 (0.10)	0.00 (0.10)	0.79 (0.07)	0.18 (0.08)	159
soil&hgt	$Q_{AMS}^{JFMA} \sim N\big(\alpha_2 hgt_{CC-NP}^{DJF} + \alpha_3 soil_{basin}^{JFMA} + \beta, \sigma^2\big)$	-	-0.19 (0.10)	0.55 (0.11)	0.00 (0.10)	0.80 (0.07)	0.16 (0.08)	160.5
soil&sst	$Q_{AMS}^{JFMA} \sim N\big(\alpha_1 sst_{ETP}^{DJF} + \alpha_3 soil_{basin}^{JFMA} + \beta, \sigma^2\big)$	-0.23 (0.10)	-	0.55 (0.10)	0.00 (0.10)	0.79 (0.07)	0.18 (0.08)	158.5
soil	$Q_{AMS}^{JFMA} \sim N\big(\alpha_3 soil_{basin}^{JFMA} + \beta, \sigma^2\big)$	-	-	0.61 (0.10)	0.00 (0.10)	0.82 (0.08)	0.14 (0.07)	161.9

As in Chapter 1, the sign of coefficients of the fitted models match what is expected from the correlation maps and the literature and the intercept is essentially zero for all models, as expected. R^2 and DIC are inversely related, and the variance decreases as model performance improves. Following logic similar to that in Chapter 1, the model with sst_{ETP}^{DJF} and $soil_{basin}^{JFMA}$ as predictors (soil&sst) is the best and is used in all subsequent analysis. Based on the Shapiro-Wilk test for normality, the residuals of the soil&sst model are normal for more than 95% of the 3000 model runs. Simulated data can be obtained by sampling from the model to stochastically generate a time series, de-standardizing, and taking the exponent. Quantiles of interested are developed by using l-moments to fit the simulated data to a LP3 distribution. When compared to observations, the model does a good job of fitting the data (Figure 11).

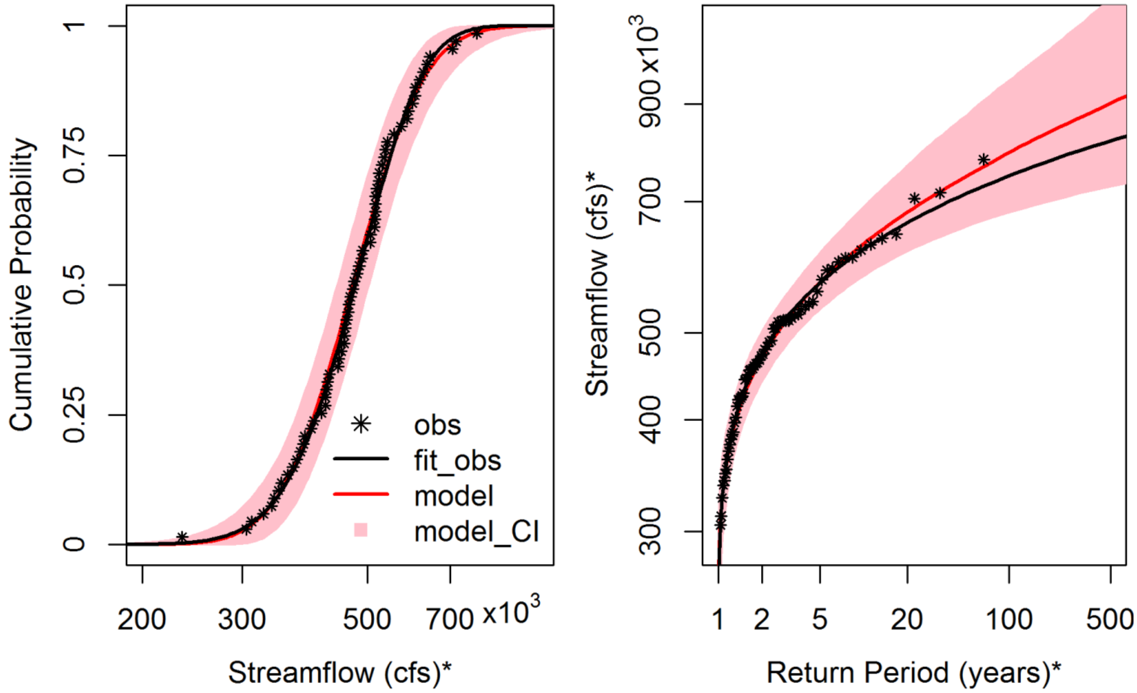

*Figure 11: The performance of the climate informed model. The empirical cumulative distribution function based on the Weibull plotting position of the observed data (obs) and the LP3 fit to the observed data (fit_obs) and to the model forced with observed climate (model) with associated credible intervals (model_CI). * indicates the axis is log-scale.*

Unlike the model in Chapter 1 which includes predictors based on geopotential height, this model includes a predictor based on sea surface temperature. From a climate science perspective, sea surface temperature is a largely thermodynamic variable and can be expected to increase under global warming. Consequently, flood events, which are negatively correlated to sea surface temperatures, can be expected to decrease absent other regulating mechanisms. In the model, soil moisture does provide some regulation, however, a revised model was tested that would better account for both the dynamics and thermodynamics of climate change by replacing the sst_{ETP}^{DJF} predictor with the Southern Oscillation Index (SOI), which is another measure of the ENSO phenomenon and is based on sea-level pressure anomalies in the tropical Pacific. The SOI data, obtained from NCAR (2018), was processed in the same manner as sst_{ETP}^{DJF} to obtain a SOI^{DJF} predictor. However, despite the highly significant correlation between sst_{ETP}^{DJF} and SOI^{DJF}, the revised model had poor performance and was not used for subsequent analysis.

To make projections of future flood events, projections of the predictors are obtained from GCM simulations and used to force the statistical model. Specifically, monthly gridded historical runs from 1950 through 2005 and projections from 2006 through 2100 of sea surface temperature and soil moisture are obtained from the same 10 CMIP5 GCMs used for the model chain projections for RCP 4.5 and 8.5 and the r1i1p1 ensemble member (except that GFDL-CM3 did not have data available for RCP 4.5). Flood events are estimated by fitting the LP3 in 61 year increments ending on every decade from 2010 through 2100. Simulations from each GCM are combined using Bayesian model averaging following the same procedure as described for the model chain method. The weights ranged from 0.094 to 0.103 with the lowest assigned to IPSL-CM5A-MR and the highest assigned to NorESM1-M.

2.3.4 Traditional Risk-Based Analysis

Traditional risk-based analysis consists of optimizing a risk-based metric across a range of probable scenarios. Here, we chose to minimize the expected total cost (similar to Qi, 2017; Qi & Liu, 2018; Rehan & Hall, 2016) , T_k, associated with a levee built to withstand a flood of return period k,

$$T_k = C_k + ED_k \qquad \text{Eq. 1}$$

where C_k is the cost of the levee and ED_k is the expected damages,

$$ED_k = \int_0^\infty P(q)D_k(q)dq \qquad \text{Eq. 2}$$

where $P(q)$ is the probability and $D_k(q)$ is the damages associated with a flood of magnitude q. The flood probability is given by the traditional model chain projections described previously, while calculation of flood damages and levee cost is described below. The calculation of ED_k was accomplished by numerical integration for the first and last moving window of the projections (1950 through 2010 and 2040 through 2099, respectively).

Flood damages were determined from a HAZUS model. HAZUS is a program developed by the Federal Emergency Management Agency and has been applied to a variety of questions concerning flood damage estimation; some examples include the cities of Atlanta, Georgia (Ferguson & Ashley, 2017) Cairo, Illinois (Luke et al., 2015), and Cedar Rapids, Iowa (Tate et al., 2016), the regions of the Middle Mississippi River (Remo et al., 2012) and the Sacramento – San Joaquin Delta in California (Burton & Cutter, 2008), the states of Illinois (Remo et al., 2016) and Pennsylvania (State of Pennsylvania, 2013) and the country of Canada (Nastev & Todorov, 2013). In brief, given a flow volume, HAZUS simulates flooded area elevation and extent using a digital elevation model and flow routing, links that data to census data regarding the type and location of infrastructure, and calculates building loss damages from elevation-cost functions specific to each infrastructure type. HAZUS also estimates indirect damages; that is, “dislocations in economic sectors no sustaining direct damage” (Scawthorn et al., 2006b). However, indirect damages are not reported in this study due to the high uncertainty associated with their estimation. Flood risk management options (e.g., levees/floodwalls, dams, and early warning systems) can also be incorporated into a HAZUS model. HAZUS has different levels of simulation complexity; here, a level 1 analysis (the simplest) was used due to the increased data requirements associated with levels 2 and 3. For a full description of flood damage simulation in HAZUS, see Scawthorn et al., (2006a, 2006b).

Despite the relative simplicity of a level 1 analysis compared to levels 2 and 3, there is still a number of modeling choices required to successfully define and run a HAZUS model. The study region was chosen to be Jefferson County, Kentucky, which includes the city of Louisville, with an area of 900 km^2 (350 square miles). Topographic data was obtained from the USGS's National Elevation Database. The Manning's roughness coefficient was set to the default value of 0.160. Based on a sensitivity analysis, the drainage threshold was chosen to be 225 square miles, corresponding to the smallest area (rounded up to the nearest 5 square miles) for which only the Ohio River is delineated. This choice of drainage area excludes direct modeling of flooding on small tributaries; however, this simplification was deemed appropriate given that only the levee along the main channel is analyzed and not the system of pumps and smaller levees spread throughout the city. The magnitudes of the 2, 5, 10, 25, 50, 100, 200, and 500 year floods used to define the flood event distribution in HAZUS were calculated from the quantiles of the LP3 fitted by maximum likelihood estimation to the JFMA AMS data at the Louisville gage from 1950 through 2015 (the fitted values are 14.4, 0.036, and 37.6 for the location, shape, and scale parameters respectively). The location of the current levee in Louisville was added to the model using data obtained from the USACE's National Levee Database. In HAZUS, the protection level provided by a levee is not specified by its height, but rather by choosing the flood return period for which it protects (within an allowable range of 5 to 500 years). For this analysis, the return periods for the levee protection level were chosen to be 5, 10, 25, 50, 100, and 500; the case of no levee was also modeled.

A continuous damage function is needed for calculation of ED_k, but is computationally expensive. Instead, we assumed that the case of no levee represents an upper limit to possible damages (Figure 12 and Table 6). We note that the high damages caused by the two year flood in the absence of a levee likely occur because the city has experienced significant development after the completion of the levee which relies on the levee's protection. To determine the functional form of damages in the presence of a levee, we performed a preliminary analysis using the levee built for the 100 year flood (Figure 12). The preliminary analysis showed that the damages are linear up to the 100 year flood. Immediately after the 100 year flood, the damages jump up and follow the magnitude of the damages associated with no levee. Intuitively this makes sense; once the flood is greater than 100 years, all the formerly protected areas are now inundated. Based on these results, strategic combinations of levee return period and flood volumes were chosen to minimize computational expense while still fully characterizing the system (Table 6). For any levee, damages from floods below its protection level are assumed to follow the lowest simulated value, while damages from floods above its protection level are assumed to follow the case of no levee. A continuous function is created by assuming a linear piece-wise regression as a function of streamflow between points. For the lower tail of the distribution, damages are assumed to go to zero at the flood with return period 1.01 years, and for the upper tail of the distribution, damages are assumed to increase to 17 billion USD at the flood with return period 3000 years. Damages remain capped at 17 billion USD for all greater floods. Since the return period associated with no levee cannot be calculated, the expected total cost for the levee with return period 1.01 was calculated by linear interpolation between the expected total cost of the case of no levee and the two year levee.

The levee cost, C_k, was estimated using a function modified from Al-Futaisi & Stedinger (1999)

$$C_k = a{h_k}^b \qquad \text{Eq. 3}$$

where h_k is the average height of the levee, a is a scaling parameter, and the exponent b ranges from 2 to 3.5 (here, values of 2.65, 2.75, and 2.85 were used). Because levees in HAZUS are specified by return period rather than height, the average height associated with each levee was determined by running the model without the levee, averaging the modeled height of the water at 40 randomly picked locations along the levee, and adding three feet to represent freeboard. The value of a was estimated using the following approximations, given a lack of more precise data on levee cost. Recalling that the current Louisville levee was designed to the 500 year flood plus three feet of freeboard (USACE, 2018), then its height in HAZUS is approximately 22.7 feet, which is the average height associated with a 500 year protection level including three feet of freeboard. The cost of the 26 mile long levee (USACE, 2018) is approximated to range between 100 to 120 million USD per mile (in increments of 10 million USD); this ratio is roughly estimated from the 14.5 billion USD used to repair and upgrade New Orleans flood protection infrastructure, which includes 133 miles of levees encircling the city, after hurricane Katrina (Llanos, 2015). The nine different possible cost parameter combinations (three values of b by three values of cost per mile) were used in all future analysis.

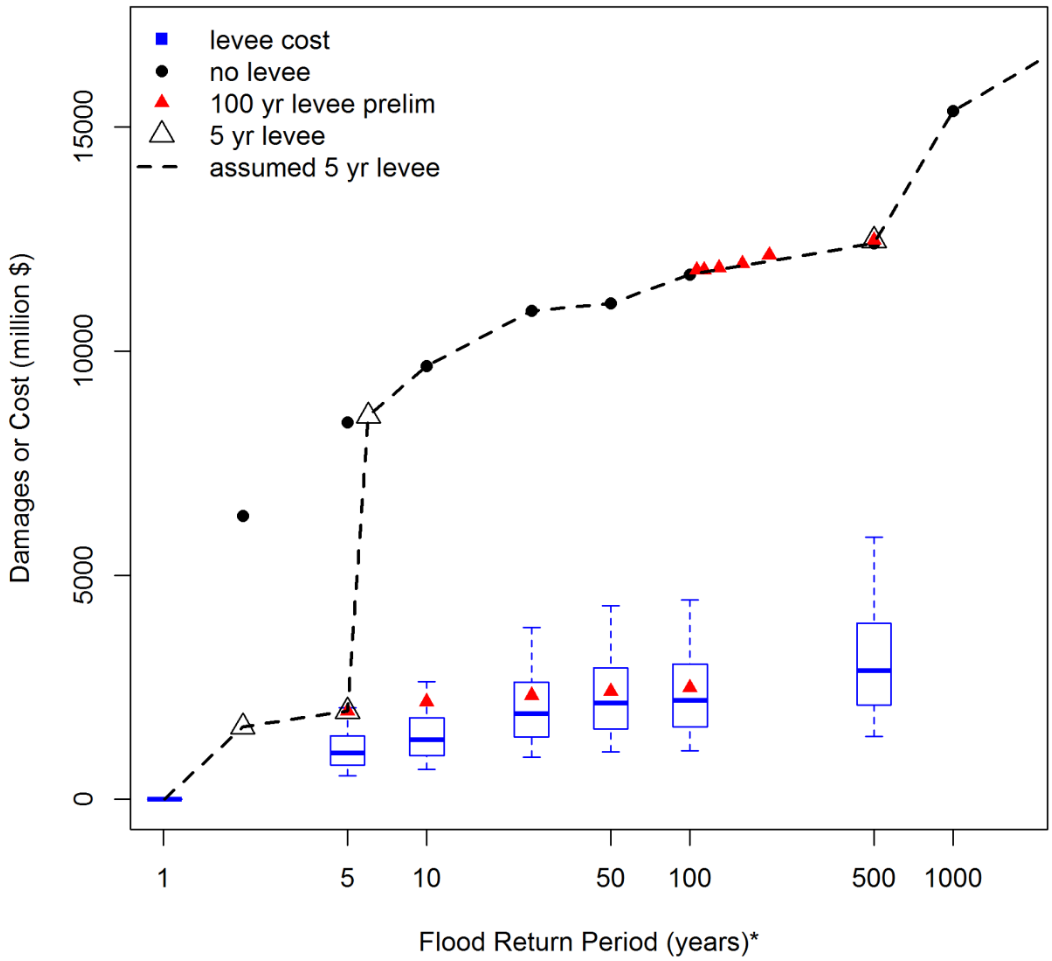

Figure 12: Damages and costs associated with levees. The levee cost ("levee cost") as well as damages with no levee ("no levee"), for the preliminary analysis with the 100 year levee ("100 yr levee prelim"), the 5 year levee ("5 yr levee"), and the assumed damage function for the 5 year levee ("assumed 5 yr levee"). The shape of the assumed damage function is similar across all levee protection levels but is not shown for clarity.

*Table 6: HAZUS data inputs and outputs. The units are as follows: flood return period (FRP) and protection level (PL) (years), flood volume (FV) (1000 cfs), damages (million USD), average height including freeboard (AH) (feet). Grey indicates the value is assumed. *The 1000 year flood magnitude is not a HAZUS input.*

FRP		2	5	6	10	11	25	27	50	55	100	110	500	1000
FV		475	568	583	620	625	676	681	714	719	748	753	819	846*
PL	AH	Damages												
0	0	6,325	8,411		9,673		10,906		11,063		11,703		12,414	15,366
5	15.7	1,617	1,965	8,552	9,673		10,906		11,063		11,703		12,472	15,366
10	17.2	1,617	1,965		2,173	9,730	10,906		11,063		11,703		12,472	15,366
25	19.6	1,617	1,966		2,173		2,315	10,990	11,063		11,703		12,472	15,366
50	20.4	1,617	1,966		2,173		2,315		2,405	11,090	11,703		12,472	15,366
100	20.7	1,617	1,965		2,173		2,315		2,405		2,488	11,807	12,472	15,366
500	22.7	1,617	1964		2,173		2,315		2,405		2,488		2,488	15,366

2.3.5 Decision Scaling Risk-Based Analysis

Like traditional risk-based analysis, decision scaling risk-based analysis also seeks to minimize a risk-based metric and often, though not investigated here, to apply robustness-based approaches (e.g., Spence and Brown, 2016); the key difference compared to traditional analyses is that decision scaling centers around a system vulnerability analysis. Thus, while cost and damages are assessed in the same way using the functions described previously, the flood probabilities do not come from the traditional model chain flood projections, but are systematically and stochastically generated. Only after the system vulnerability analysis is complete are projections superimposed on the results.

Previous decision scaling studies of floods have demonstrated two approaches to generating floods. Poff et al. (2015) and Steinschneider et al. (2015) obtain time series of temperature and precipitation from a stochastic weather generator, apply systematic additive or multiplicative changes to those time series, force a hydrologic model with the perturbed stochastic time series, and then calculated floods from the hydrologic model output. Alternatively, Spence and Brown (2016) apply systematically chosen linear trends to the location parameter of the log-normal distribution. With the climate informed model, there is now a third option in which new flood probabilities are generated from perturbations in the predictors.

Here, perturbations in the predictors are accomplished by bootstrap sampling of the historic record of sst_{ETP}^{DJF} and $soil_{basin}^{JFMA}$ based on sequences from a lag 1 Markov chain built to reproduce the states of sst_{ETP}^{DJF}. The Markov chain operates on an annual time step and has three discrete states, representing El Nino, Neutral, and La Nina conditions. The Markov chain is specified by

$$\pi_j^{t+1} = \sum_{i=1}^{S} p_{ij}\pi_i^t \quad \forall\, j = 1 \ldots S \qquad \text{Eq. 4}$$

where $\mathrm{p_{ij}}$ is the probability of transitioning from state i to j, $\pi_\mathrm{i}^\mathrm{t}$ is the unconditional probability of state i in time period t, and S is the total number of states. The chain is constrained such that the sum of the unconditional probabilities equals one ($\sum_{\mathrm{i}=1}^{\mathrm{S}} \pi_\mathrm{i} = 1$) and the sum of the transition probabilities from a given state to any other state equals one ($\sum_{\mathrm{j}=1}^{\mathrm{S}} \mathrm{p_{ij}} = 1\ \forall\ \mathrm{i} = 1 \ldots \mathrm{S}$).

To calculate the unconditional and transition probabilities, monthly sea surface temperatures averaged over the sst_{ETP}^{DJF} region were obtained from Rayner (2003) for the years 1870 through 2015. Monthly anomalies were calculated using a 31 year moving window ending on the year of interest. For example, the February 1900 monthly anomaly is the February 1900 monthly value minus the mean of all February values from 1870 through 1900. The monthly anomalies were smoothed using a three month moving average, resulting in a dataset from February 1990 to November 2015. A monthly state time series was developed by identifying El Nino (La Nina) months as those for which the smoothed anomaly is ≥ 0.3°C (≤ -0.3°C) for at least six consecutive months; all other months were designated as Neutral. Subsequently, an annual state time series, based on a July to June year, was developed from the monthly time series by identifying as El Nino (La Nina) those years for which as least five months were designated El Nino (La Nina); all other years were designated as Neutral. This process is similar in form to that used by the National Weather Service's Climate Prediction Center (NOAA, 2015). From the annual state time series, the unconditional probabilities are calculated as the number of years in a given state divided by the total number of years and the transition probabilities are calculated as the number of times in which a given initial state is followed by another given state divided by the number of years in the initial state (Table 7). The resulting unconditional probabilities are similar to those reported by Trenberth (1997), in which ENSO state is calculated with slightly different thresholds using the Nino3.4 region.

Table 7: Unconditional and transition probabilities of the Markov chain. The transition probabilities are from the state in the row to the state in the column. EL is El Nino, NU is Neutral, and LA is La Nina.

	Unconditional		Transition	EL	NU	LA
EL		0.27		0.32	0.42	0.26
NU		0.45		0.215	0.57	0.215
LA		0.28		0.28	0.31	0.41

Stochastic realizations of annual states are generated by sampling the state of the first year according to the unconditional probabilities, and then iteratively sampling the state of each successive year according to the transition probabilities associated with the current state. The realizations are 150 years long to match the length of the model chain results from GCM historical runs and projections. In total, 500 realizations are generated; to reduce computational expense, only the 10 whose unconditional probabilities are closest to observed are retained for subsequent analysis. The realizations are then used to perform bootstrap sampling of years in the historic record with replacement (e.g., if the ENSO state is El Nino for a given year, then one of the years designated as El Nino is randomly sampled). Time series of sst_{ETP}^{DJF} and $soil_{basin}^{JFMA}$ are created by drawing the data associated with each bootstrapped year.

To create the stress test, systematic linear trends are added to the stochastic realizations of sst_{ETP}^{DJF} and $soil_{basin}^{JFMA}$. The trends are created such that the total change over the length of the realization ranges from zero to six in increments of two for sst_{ETP}^{DJF} and from -1 to one in increments of one for $soil_{basin}^{JFMA}$. These ranges nearly encompass the range of change projected by the GCMs (Figure 13a). In total, there are four sst_{ETP}^{DJF} scenarios by four $soil_{basin}^{JFMA}$ scenarios by 10 realizations for a total of 160 scenarios used to force the climate informed model. The climate informed model generates 3000 samples, which, when combined with 7 possible levee return periods and 9 possible cost function parameter sets, is highly computationally expensive, especially for numerical integration. Thus, 51 of the 3000 samples which span the sample space are retained for subsequent analysis (Figure 13b). The expected damages and expected total cost are calculated for the last 60 years of the time series, which matches the last moving window used for the traditional risk analysis. Finally, the expected value of the expected total cost over the GCM projections for each levee design is calculated by bilinear numerical integration of a bicubic approximation of T_k and a bivariate normal distribution fitted to the GCM projections for both RCP 4.5 and 8.5.

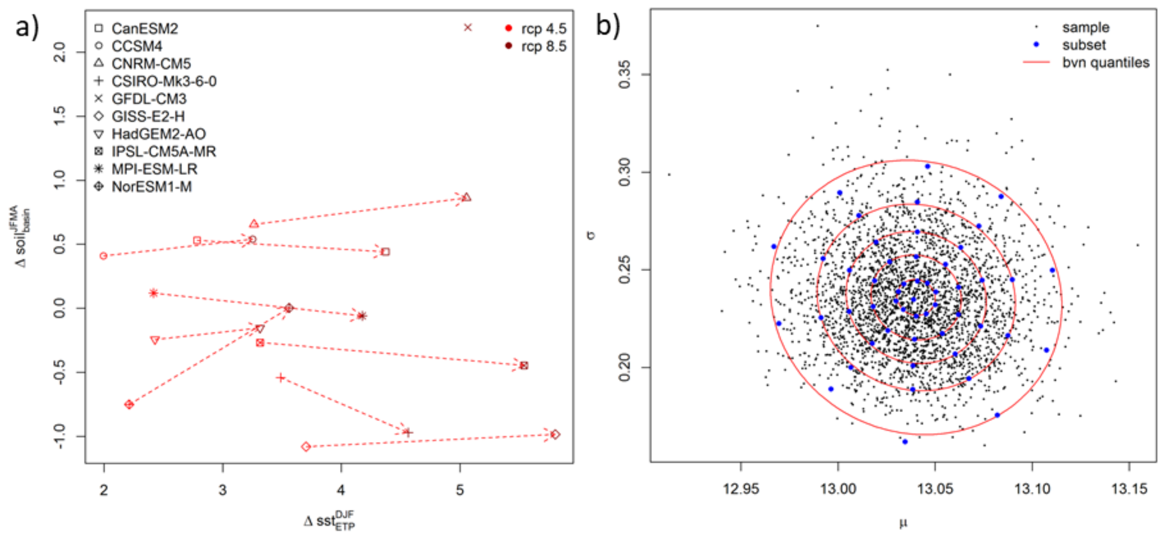

Figure 13: System vulnerability analysis information. (a) Changes in the climate predictors projected by the GCMs (the arrows indicate the change from RCP 4.5 to RCP 8.5 and the axes are unit-less because the values are standardized). (b) Subsets of the samples based on quantiles of a bivariate normal distribution (bvn) fitted to the mean and standard deviation of the fitted LP3 for each sample.

2.4 Results

The results are comprised of two parts. The first is the GCM projections of all climate variables used as drivers for the models (precipitation, temperature, sst_{ETP}^{DJF} , and $soil_{basin}^{JFMA}$) and the resulting flood projections from both the model chain and climate informed approach. The second is the expected total cost results from traditional risk analysis and decision scaling and a comparison of the decision-relevant information from both methods.

2.4.1 Projections

Projections of the climate variables are shown in Figure 14. GCM simulation of sst_{ETP}^{DJF} performs well over the historic period except for underestimation of the high extremes. Future sst_{ETP}^{DJF} is projected to increase, which is expected because temperature-based variables are increasing due to global warming; the greatest increase is associated with

RCP 8.5, which is the more extreme scenario. GCM simulation of $soil_{basin}^{JFMA}$ also performs relatively well over the historic period except for under- (over-) estimation of the high (low) extremes and the unusual behavior of IPSL-CM5A-MR. Future $soil_{basin}^{JFMA}$ may increase or decrease depending on the GCM, with no consistent difference in magnitude of change between RCP 4.5 and 8.5. Notably, GFDL-CM3 projects an exceptionally high increase under RCP 8.5. GCM simulation of extreme precipitation, defined as any daily JFMA data above the 98th percentile, exhibits nearly consistent overestimation over the historic period except HadGEM-AO which consistently underestimates. Future extreme precipitation is projected to increase, with no consistent difference in magnitude of change between RCP 4.5 and 8.5. GCM simulation of temperature exhibits very little bias over the historic period, although the comparison to the other predictors is not direct because the temperature quantiles are calculated from the full daily data. As expected with global warming, temperatures are projected to increase, with the greatest increase associated with RCP 8.5.

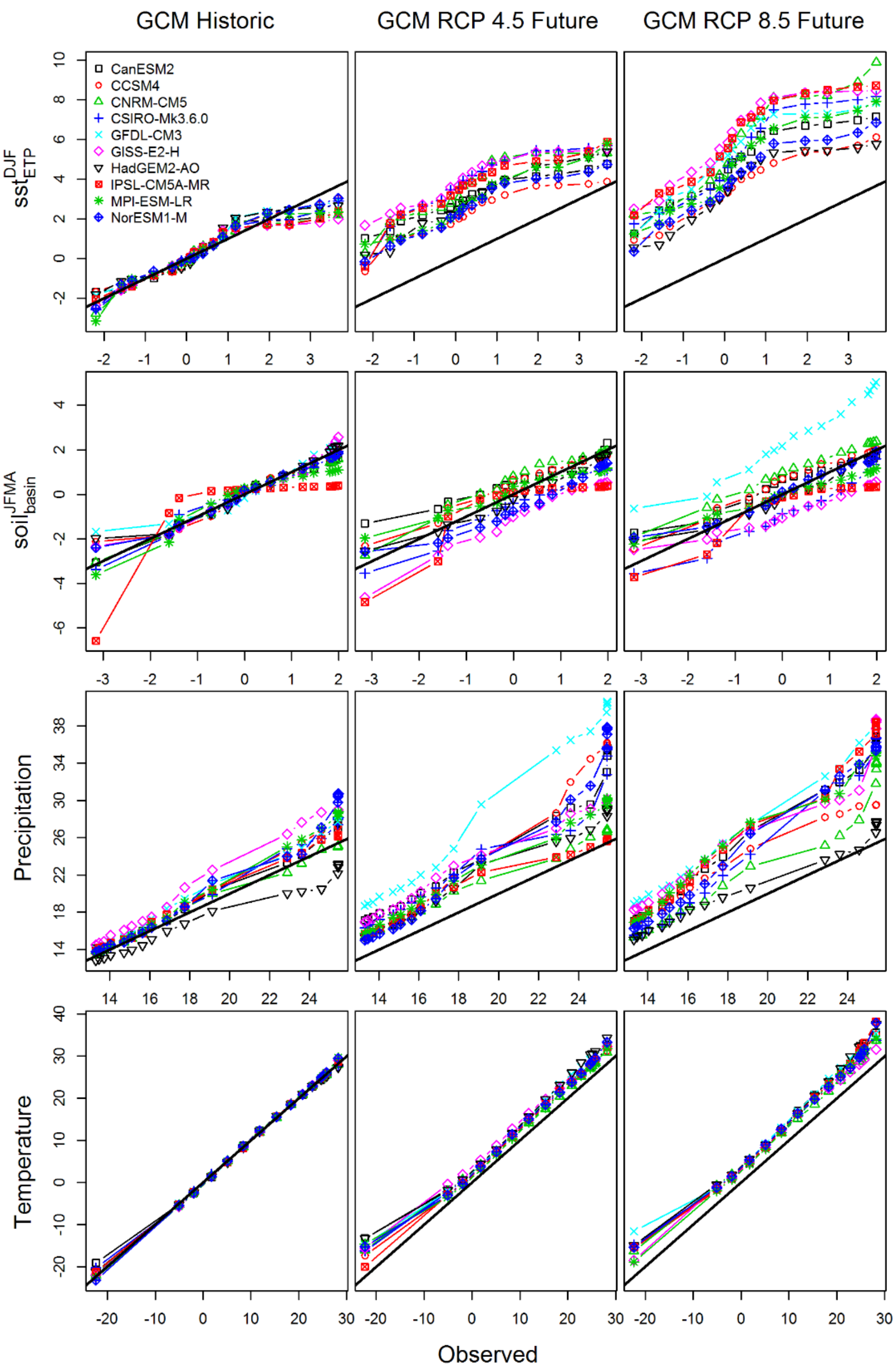

Figure 14: GCM performance and projections of climate variables. Selected quantiles of the standardized annual sst_{ETP}^{DJF} and $soil_{basin}^{JFMA}$ (unit-less) and daily precipitation (mm) and temperature (°C) of observations (1950 through 2010) versus GCM historic (1950 through 2005) and future (2040 through 2100 for sst_{ETP}^{DJF}, and $soil_{basin}^{JFMA}$ and through 2099 for precipitation and temperature) values for both RCP 4.5 and RCP 8.5. The precipitation quantiles are from JFMA data above the 98th percentile.

Flood projections from both the model chain and climate informed methods for select GCMs and the Bayesian model average are shown in Figure 15. GCM performance can be assessed by comparing the model forced with observed climate, hereafter the "observed model", to the model forced with GCM historic climate, hereafter the "GCM historic model". All GCMs perform satisfactorily using the climate informed method (i.e., the GCM historic model closely follows the observed). However, GCM performance varies widely using the model chain method; while the NorESM1-M historic model closely follows the observed model, both the GISS-E2-H and GFDL-CM3 historic models greatly underestimate the upper return periods. Even though this underestimation results in a closer alignment to the observed data, this does not indicate improved performance, but rather that the GCMs are introducing additional error on top of that contributed by the hydrologic model. For both the model chain and climate informed method, the Bayesian model average of the GCM historic models slightly underestimates the observed model.

The direction and magnitude of change projected by the GCMs can be assessed by comparing the GCM historic model to the model forced with GCM future climate from RCP 4.5 and 8.5. Furthermore, the likely causes of the projected changes can be determined from the projected changes in the predictors shown in Figure 14. For the model chain method, flood events are projected to increase in the future by both individual GCMs and the Bayesian model average, likely due to the projected increase in extreme precipitation. Furthermore, the magnitude of the increase is greater for RCP 8.5, the more extreme scenario, than for RCP 4.5; GFDL-CM3 is an exception likely because the projected increase in extreme precipitation is greater for RCP 4.5 than for RCP 8.5.

For the climate informed method, flood events are projected to decrease in the future by both individual GCMs and the Bayesian model average, likely because the large projected increases in sea surface temperature are either not completely offset by projected increases in soil moisture, or for some GCMs, are even accentuated by projected decreases in soil moisture. Here again the exception is GFDL-CM3, where the exceptionally large projected increase in soil moisture offsets the projected increase in sea surface temperature.

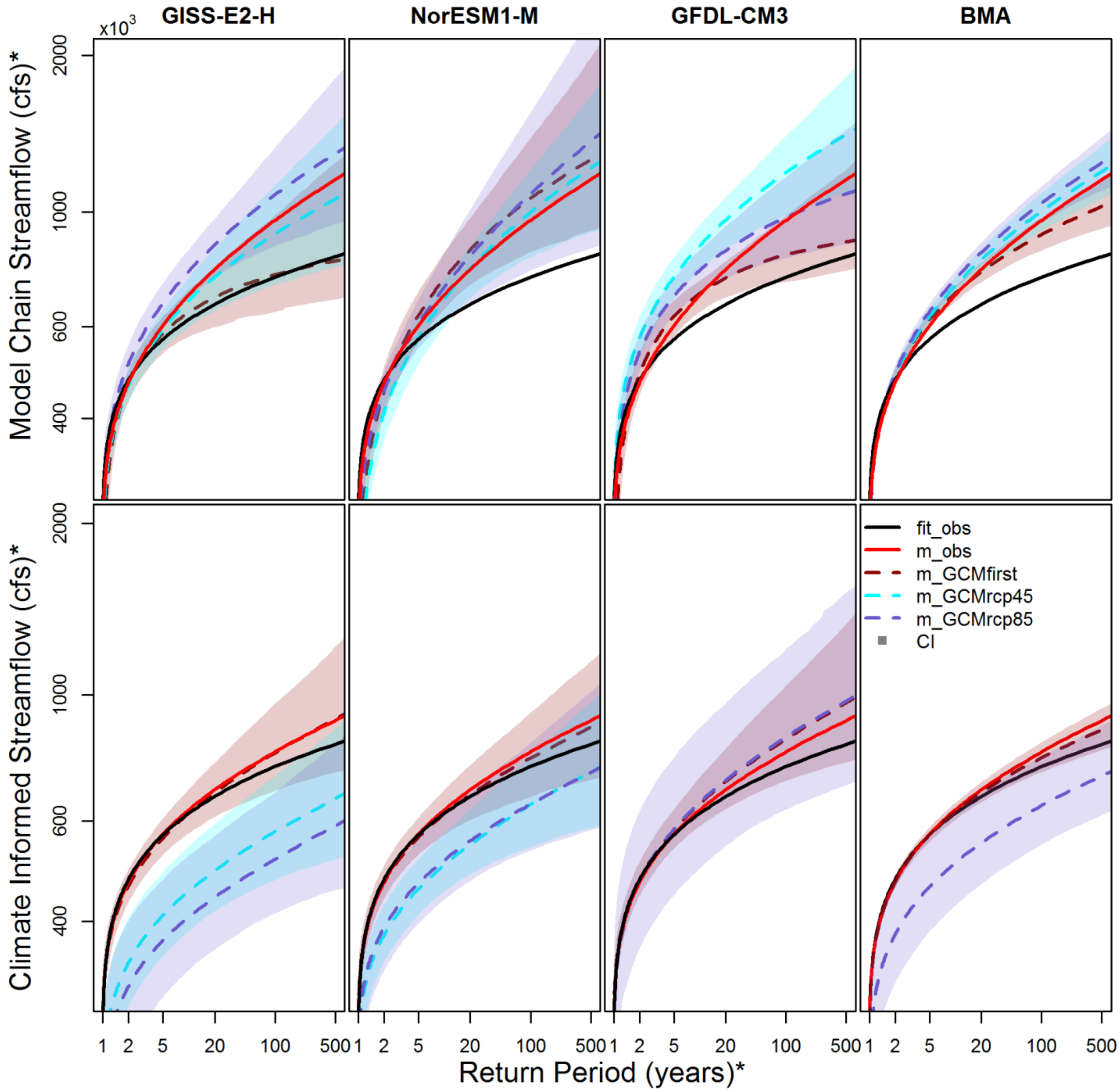

Figure 15: Flood projections from both the model chain and climate informed methods for select GCMs (GISS-E2-H, NorESM1-M, and GFDL-CM3) and the Bayesian model average (BMA). "fit_obs" is the LP3 fit to the observed data, "CI" is the confidence or credible intervals (where the colors correspond to the model), and "m_obs", "m_GCMfirst", "m_GCMrcp45", and "m_GCMrcp85" are median of the LP3 fit to the outputs of the model forced with observed, the model forced with the historic time period from GCMs, and the model forced with the future time period from GCMs for RCP 4.5 and RCP 8.5, respectively. The time periods are the same as those in Figure 14.

2.4.2 Traditional Risk Analysis and Decision Scaling

Expected total cost calculated using the observed flood event probability is shown in

Figure 16. The full confidence interval has been partitioned into the confidence interval

arising from the 9 possible cost function parameter sets (associated with the LP3 fit to observed) and the 3000 samples of possible LP3 fits (associated with the mean cost function). The medians largely overlap and are relatively flat between the 10 year and 100 year levees, although the 100 year levee does minimize expected total cost and would thus be declared the best design. The partitioned confidence intervals indicate that levee cost primarily drives uncertainty at higher return periods. This likely occurs because the upper tail of the flood distribution contributes little probability mass and the uncertainty in the levee cost function is more pronounced at higher return periods compared to lower return periods. Sampling uncertainty only contributes at lower return periods, likely because the bulk of the flood distribution is at lower return periods. The confidence intervals displayed in all subsequent results show both uncertainties.

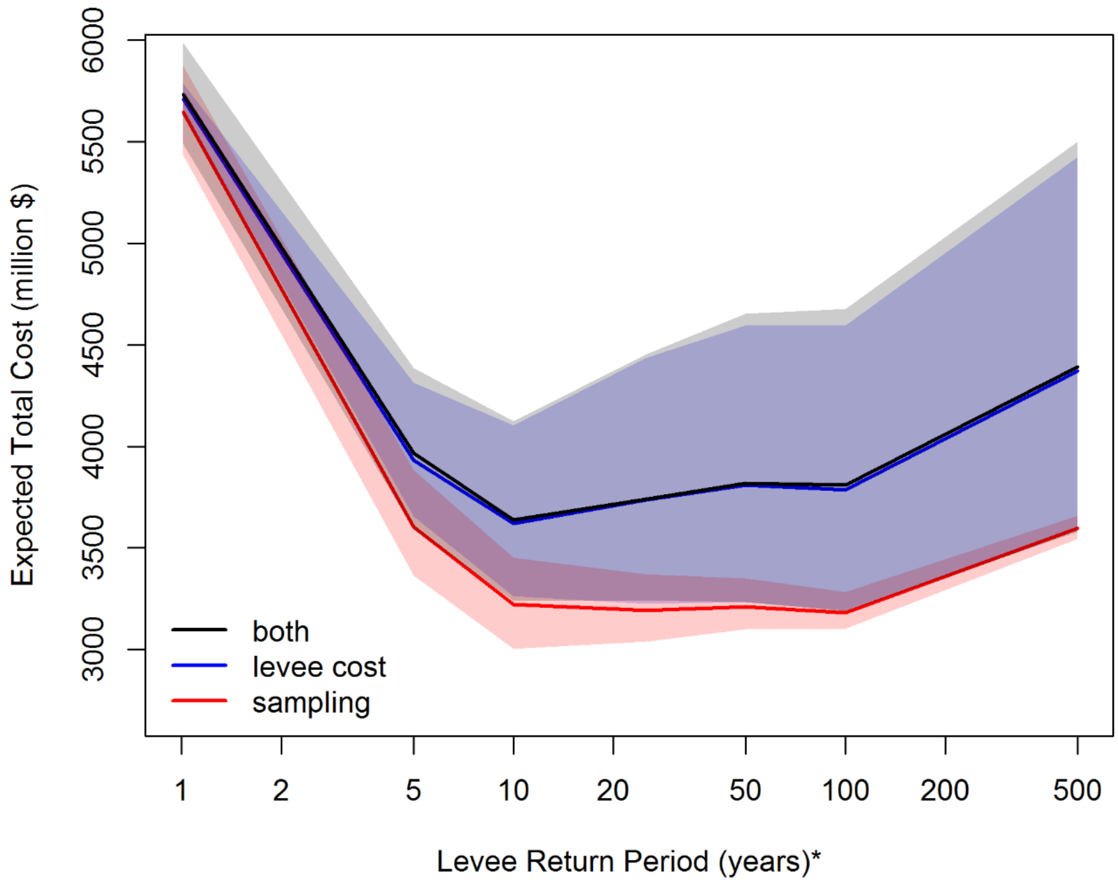

*Figure 16: Expected total cost using the observed data, divided into uncertainty arising from levee cost, sampling, and both. The solid lines indicate the median, the shaded areas indicate the range between the 25th and 75th quantiles. * indicates the axis is log-scale. The x-axis return period is based on the historic record.*

The expected total cost from traditional risk analysis using the model chain results is shown in Figure 17 for the same GCMs as Figure 15 (the Bayesian model average is discussed below). The model forced with observed precipitation and temperature is different from the observed data due to the hydrologic model error discussed previously. As with the flood projections, the expected total cost and the best return period for design varies widely among GCMs. The expected total cost associated with GISS-E2-H aligns with expectations based on the flood projections shown in Figure 15. There is a clear increase from the GCM historic to GCM RCP 4.5 and then GCM RCP 8.5 in both the flood projections and the total expected cost. As the flood distribution increases, the expected total cost associated with levees built for lower return periods increases, such that the best design increases from a return period of 100 years to 500 years in GCM RCP 8.5. Additionally, the alignment seen in the flood projections is maintained in the expected total cost; GCM historic aligns with observations and GCM RCP 4.5 aligns with the model forced by observations. However, for NorESM1-M, the small but apparent projected increases in flood magnitude do not translate to increases, but rather decreases, in total expected cost. Furthermore, the alignment between GCM RCP 4.5 and the model forced with observations seen in the flood projections is not maintained in the expected total cost. This can be explained by the very low bias in the lower flood quantiles, particularly observed in GCM RCP 4.5, which translates to a lower expected total cost even though the upper flood quantiles are high. The results associated with GFDL-CM3 exhibit a mix of the characteristics of GISS-E2-H and NorESM1-M.

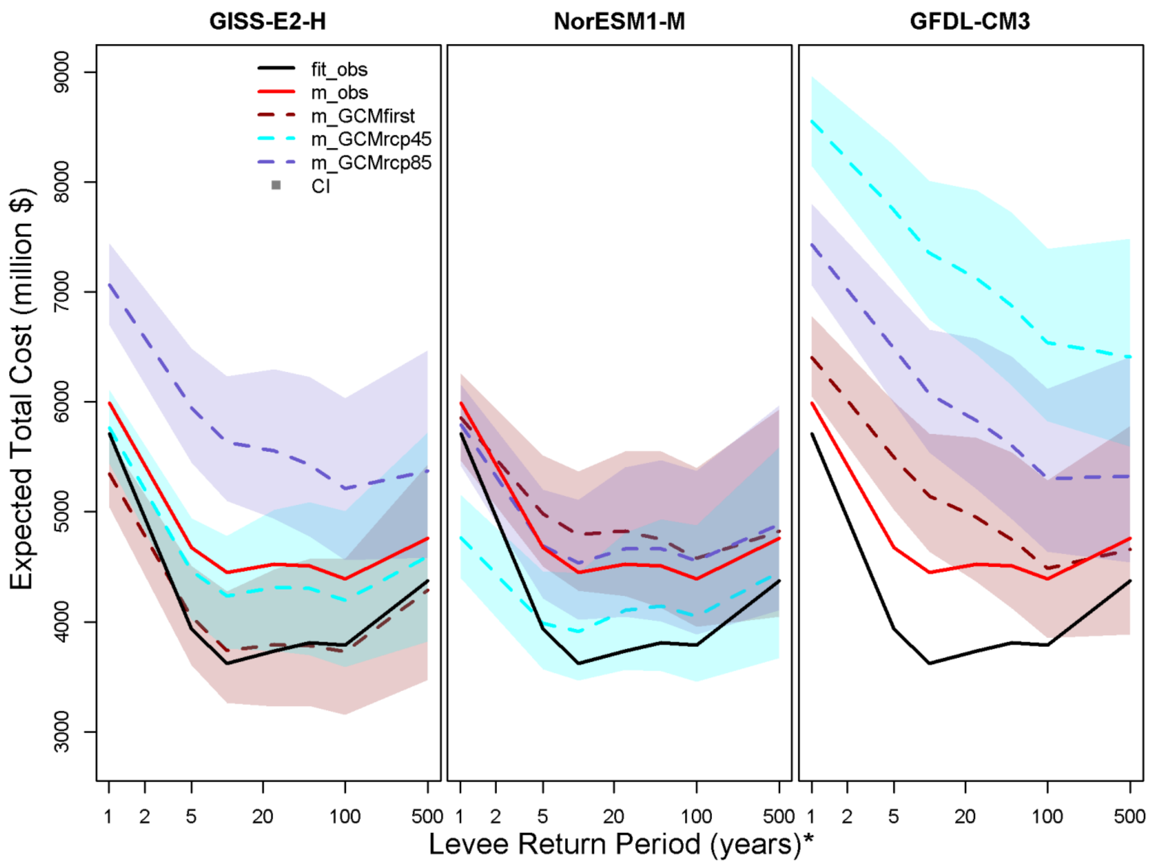

*Figure 17: Expected total cost from traditional risk analysis using the model chain. * indicates the axis is log-scale. The x-axis return period is based on the historic record. The meaning of the legend is the same as Figure 16.*

The expected total cost results from decision-scaling (Figure 18) take a much different form that those from the traditional risk analysis using the model chain. This is primarily due to the vulnerability analysis, which introduces more variables (in particular, four sst_{ETP}^{DJF} scenarios by four $soil_{basin}^{JFMA}$ scenarios by 10 realizations) and only includes GCM projections (which are sst_{ETP}^{DJF} and $soil_{basin}^{JFMA}$, not precipitation and temperature) after the vulnerability analysis is complete. The vulnerability analysis results are shown for the 100 year levee in Figure 18. The relationship of expected total cost to the predictors matches the correlations between flood events and the predictors; expected total cost increases with decreasing sst_{ETP}^{DJF} and increasing $soil_{basin}^{JFMA}$. The diagonal angle of the contours, rather than horizontal or vertical alignment, indicates that neither predictor dominates, but both affect expected total cost. The GCM projections fall below the contour line of expected total cost associated with the no-change scenario, indicating expected total cost may decrease in the future. The exception is soil moisture associated with GFDL-CM3 for RCP 8.5, which results in an elongated bivariate normal distribution for RCP 8.5. The standard deviation of expected total cost across the 10 realizations and the 51 samples is relatively small compared to the magnitude of the median (ranging from 50 to 250 million USD) and is positively correlated to the median values (i.e., the contours follow the same pattern) (not shown).

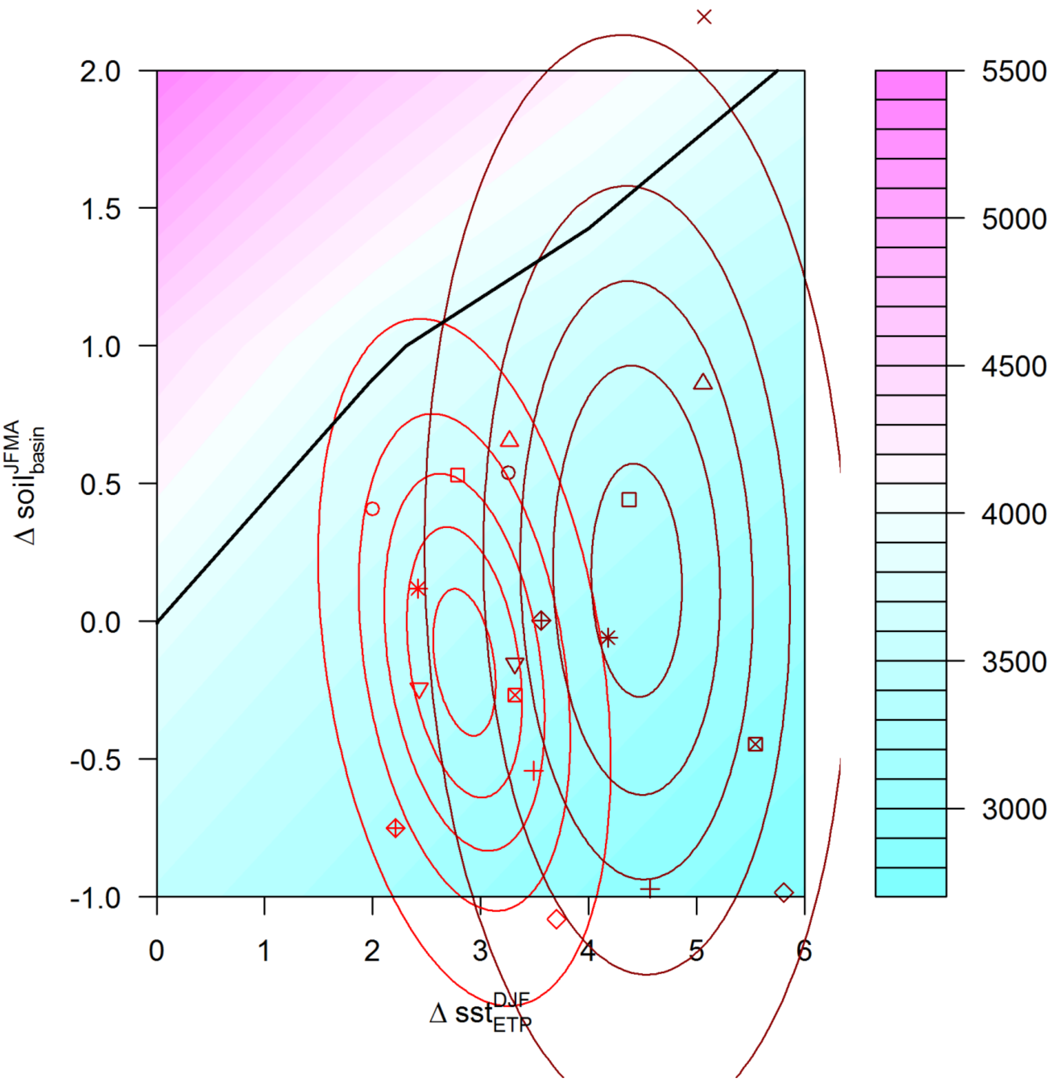

Figure 18: The median vulnerability analysis results for the 100 year levee across the 10 realizations and the 51 samples. The color scale indicates the expected total cost in million USD, the x- and y-axis are the change in the indicated predictor, the solid line is the contour of expected total cost associated with the no-change scenario, the points indicate GCM projections of the predictors (symbols have same meaning as in Figure 13a), and the two ellipses are bivariate normal distributions fit to the GCM 4.5 and 8.5 projections at the 10%, 30%, 50%, 70% and 90% quantiles.

Figure 19 shows a comparison between the decision relevant results of the traditional risk analysis and those of decision scaling for RCP 4.5. The traditional risk analysis results are the Bayesian model average of expected total cost across the 10 GCMs while the decision scaling results are the integral of the distribution of GCM projections with the response surface of expected total cost for each levee size. The results show that the biases in model performance observed in the flood distributions propagate into the decision relevant results. Specifically, the small (large) overestimation of the climate informed model when forced with observations (hydrologic model when forced with GCM historic data) results in a small (large) overestimation of expected total cost. Consequently, the optimal levee design size, defined as the design size which minimizes the median expected total cost, is the 10 year flood when calculated based on the observations and the climate informed model forced with observations, but is the 100 year flood for the traditional risk analysis using GCM historic data.

The direction of projected change in flood distributions also propagates into the decision relevant results. Specifically, the model chain method projection of an increase in the flood distribution due to increases in extreme precipitation causes a corresponding increase in the expected total cost, but not enough to shift the optimal levee size to a higher return period. Conversely, because the GCMs generally project warmer sea surface temperatures but decreasing soil moisture, which causes a decrease in flood events, the expected total cost from decision scaling over the region of likely changes as indicated by the GCMs is lower than the expected total cost of the climate informed model when forced with observations. As a result, the optimal levee design size decreases from the 10 to 5 year flood.

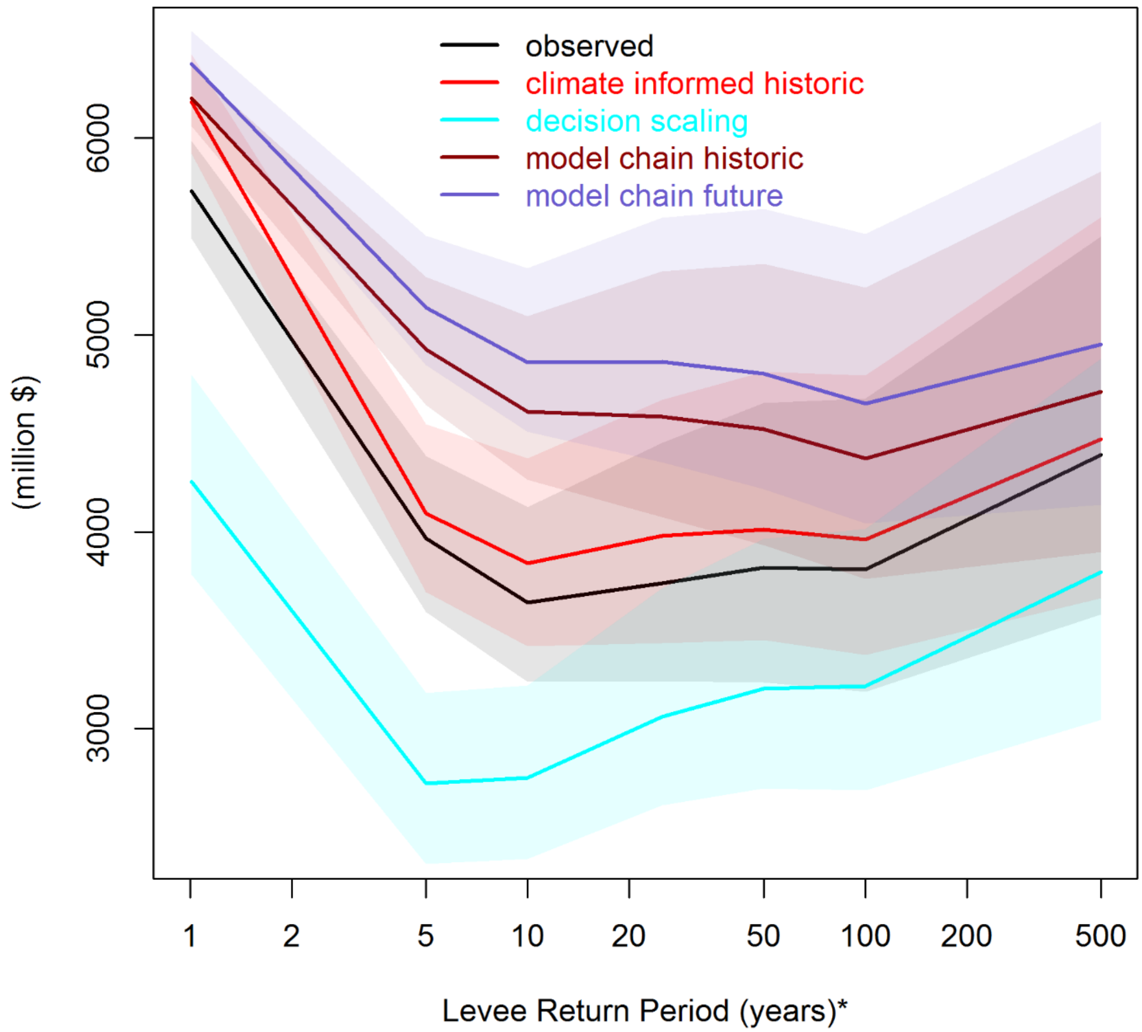

*Figure 19: A comparison of the traditional risk analysis and decision scaling results. "Observed" is the expected total cost from the observed data, "climate informed historic" is the expected total cost of the climate informed model forced with observed climate data, "decision scaling" is the result obtained by numerical integration of the response surface of expected total cost for each levee size with the bivariate normal distribution fit to the GCM RCP 4.5 projections and "model chain historic/future" is the Bayesian model average of the model chain results forced with historic and RCP 4.5 future data from the 10 GCMs. The shaded areas indicate the range between the 25th and 75th quantiles, * indicates the axis is log-scale, and the x-axis return period is based on the historic record.*

2.5 Discussion and Conclusion

This study created flood projections using both the traditional model chain method and the climate informed method for Louisville, Kentucky. It subsequently compared the results of risk-based analyses of the design flood for a levee using both a traditional analysis forced by the model chain scenarios and a decision scaling analysis forced by imposed systematic variations in stochastic realizations of the large-scale climate variables. Thus the contributions of this work are two-fold: the integration of climate informed flood projections into decision scaling and a direct comparison of the model chain approach to the climate informed method and to decision scaling.

The analysis showed that the decision relevant results of the traditional risk analysis, in which the flood distribution and total expected costs increase between the historic and future period, are very different from those of decision scaling, which shows a decrease. This difference can be traced to the projected changes in predictors, since the levee cost and damage functions are the same for both methods. Given that the predictors in both methods come from the same GCMs, one possible explanation for the difference is the inability of GCMs to maintain teleconnections between large-scale ocean-atmospheric patterns and localized precipitation and temperature (Lee & Black, 2013; Polade et al., 2013; Sheffield et al., 2013). Another possible explanation is that the climate informed model, which captures the thermodynamic response of sea surface temperatures to global warming, is missing a feedback mechanism, such as the atmospheric response as represented in geopotential heights, which would capture the dynamics of climate change. An illustration of the importance of accounting for both dynamic and thermodynamic impacts of climate change, in a downscaling application, is given in Greene et al. (2011).

Choosing between the two methods should be based on considerations of both methodology and model credibility. In terms of methodology, as has been convincingly argued elsewhere (e.g., Brown et al., 2012; Spence & Brown, 2016), in comparison to the traditional method which is scenario-led, one strength of decision scaling is its exploration of system response which facilitates evaluation of the robustness of design options. Knowing the system response is valuable information apart from any projection of future changes (e.g., if system performance is satisfactory across all plausible changes in driving forces, then projections and an assessment of their credibility is not necessary). In terms of model credibility, that is, the ability of the model to accurately and precisely represent the important physical processes, Chapter 1 argued that the climate informed approach to flood projection is expected to be more credible than a model chain approach because GCM simulation of large-scale ocean-atmospheric patterns on a seasonal basis is less biased than simulation of daily localized extreme precipitation. Thus, apart from specific case study results, abstract consideration of methodology and model credibility results in a preference for choosing climate informed decision scaling over the model chain.

Specifically for the case study of Louisville, while some bias is observed in the climate informed model predictors as simulated by GCMs over the historic period, large biases are observed in GCM simulation of extreme precipitation over the historic period. The inability of GCMs to reproduce teleconnections for the model chain method and the possibility of a missing feedback mechanism in the climate informed method has already been discussed. Additionally, the hydrologic model was found to be more biased than the climate informed model. When the models are forced by GCM historical climate, performance varied more widely for the model chain method than for the climate informed method. However, it should be noted that the climate informed model explains only a small portion of the variance in flood events (even less than the model in Chapter 1), likely because the contributing area for Louisville includes portions of the Ohio River Basin where tropical Pacific sea surface temperatures and geopotential height patterns similar to the Pacific North American pattern are not strong explanatory variables (Figure 8). Thus, for the specific case study results, consideration of model credibility still indicates a preference for climate informed decision scaling but is tempered by some caveats regarding the credibility of the climate informed model.

There are several avenues of future research which build off this study. The first is improvement of the climate informed model by including more predictors based on a better understanding of the processes driving flood events in the Louisville catchment. One starting point would be to investigate the influence of snow (see Appendix A) or look for large-scale factors which contribute to precipitation in excess of soil moisture holding capacity (Berghuijs et al., 2016). Another starting point would be a detailed analysis into the GCM processes to identify whether teleconnections are maintained, and if not, where biases are introduced. Such an analysis would help explain the observed projections (e.g., why for some GCMs daily extreme precipitation is projected to increase while seasonal soil moisture is projected to decrease), will yield further insight into model credibility, and may also provide increased insight into the driving mechanisms of floods in the region, which could be used to improve the climate informed model. A second avenue of future research is an exploration of uncertainty. In particular, does the elimination of a hydrologic model reduce the uncertainty in the climate informed approach compared to the model chain approach? Additionally, the levee cost function was found to contribute a large portion of uncertainty due to lack of data; better data would reduce this uncertainty. Furthermore, HAZUS is known to have large uncertainties (Tate et al., 2015) which were not accounted for in this analysis. As in Schlef et al. (2018), an analysis of variance could be used for uncertainty attribution. Finally, a third avenue of future research is increasing the accessibility of these methods both in terms of the scientific knowledge required to develop the models (e.g., a study like Berghuijs et al. (2016) which catalogs major large-scale driving forces of floods across the U.S. based on literature review and correlation analysis, as is indicated in Chapter 1) and software platforms that facilitate model development and result visualization (e.g., a web-based application similar to Whateley et al. (2015) tailored to flood events). Increased accessibility of these methods would allow them to be more widely used by decision makers for flood risk management.

CHAPTER 3

RELATING PERCEPTIONS OF FLOOD RISK AND COPING ABILITY TO MITIGATION BEHAVIOR IN WEST AFRICA: CASE STUDY OF BURKINA FASO

The recent increase of devastating floods in West Africa implies an urgent need for effective flood risk management. A key element of such management is understanding how perceptions affect the implementation of mitigation measures. This paper uses the technique of framework analysis in conjunction with the conceptual framework of protection motivation theory to interpret flood perceptions and mitigation actions of flood victims and public officials in Ouagadougou, Burkina Faso as conveyed through in-depth semi-structured interviews. The results show that, despite the experience of a devastating flood in 2009 and clear understandings of flood causes, mitigation actions in Ouagadougou after the 2009 flood varied widely. This occurred due to adverse perceptions that mitigation actions are costly and that personal ability and responsibility to effect change is limited. These adverse perceptions offset neutral or positive perceptions that mitigation measures, if correctly implemented, are effective, and that the risk of flooding is high. The paper concludes with a comparative meta-analysis of West Africa flood perception and mitigation literature that reveals the need for actionable studies on the implementation of specific measures for flood risk management.

3.1 Introduction

West Africa has experienced an increase in flood risk since the great drought of 1968 to 1985 due to increasing urbanization in flood prone regions, extreme rainfall events, and soil degradation (Di Baldassarre et al., 2010; Nka et al., 2015; Sighomnou et al., 2013); from the period 2007 to 2017 there were 130 flood occurrences affecting in total nearly

15.6 million people (EM-DAT, 2017). Furthermore, future flood risk is likely to be further exacerbated by climate change, continued urbanization and land use practices, and societal and political obstacles (Arnell & Gosling, 2016; Winsemius et al., 2016), indicating an urgent need for effective flood risk management.

A key element of effective flood risk management is understanding how perceptions of flood risk and capacity for mitigation affect the implementation of mitigation measures (Bubeck et al., 2013; Fuchs et al., 2017; Slovic et al., 1982). The focus here is on mitigation (i.e., measures to reduce risk, such as maintaining clean storm water systems or relocation to higher ground); the concept of adaptation, while often recommended in conjunction with mitigation for dealing with slowly developing risks such as climate change (Nyong et al., 2007), is less clear in the context of short-duration events such as floods (Birkholz et al., 2014). The first objective of this study is to elucidate the flood perceptions and mitigation actions of flood victims and public officials in Ouagadougou, Burkina Faso. The second objective of this study is to combine the results from Ouagadougou into a comparative meta-analysis of other West African studies on flood perception and mitigation to provide concrete recommendations for risk management. The chapter first reviews West African flood perception and mitigation literature, then describes the study region and describes data collection, subsequently describes the analytical method underlying data synthesis and interpretation, then provides the results and discusses the comparative meta-analysis, and finally concludes with recommendations to reduce flood risk.

3.2 Literature Review

Understanding the relationship between perceptions and mitigation is a key element of effective flood risk management (Bubeck et al., 2013; Fuchs et al., 2017; Slovic et al., 1982), especially given that high perceptions of risk do not always translate to mitigation actions (Bubeck et al., 2012). In West Africa, studies on this topic have become more prevalent in the literature and can be placed into three broad categories: (1) perception of disasters in general, (2) perception and mitigation of changes in hydro-climatology compared to observed hydro-meteorological data, and (3) perception and mitigation of floods exclusively. Related to the third category, but not discussed here, are studies on quantitative flood vulnerability analysis, such as those performed in regions of Ghana (Antwi et al., 2015; Codjoe & Afuduo, 2015; Yankson et al., 2017) and studies solely on flood mitigation strategies, such as those performed in regions of Nigeria and Ghana (Adelekan, 2016; Danso & Addo, 2017; Lolig et al., 2014).

In the first category, studies have been performed in northern Ghana (Antwi-Agyei et al., 2017) and the littoral of Benin (Teka & Vogt, 2010); in the Ghana study, floods are perceived as relatively unimportant compared to various climatic and non-climatic stressors, while in the Benin study, perceptions of flood risk vary among ethnic groups according to primary economic activity (i.e., flooding promotes fishing but damages crops). In the second category, studies have been performed in the northern regions of Togo and Burkina Faso (Badjana et al., 2012; A. Ouedraogo et al., 2017), in Accra and the north-west region of Ghana (Codjoe et al., 2014; Dayour et al., 2014), across the three climatic zones of Benin (Gnanglè et al., 2011), and in regions of Benin, Nigeria, and Mali within the Niger River basin (Oyerinde et al., 2015; Zare et al., 2013). The common findings across these studies are a recent increase in frequency and severity of flood events, generally negative consequences associated with floods (e.g., destruction of crops and homes), and a variety of mitigation strategies or recommendations (e.g., structural flood control, relocation of farmland or goods, and diversification of economic activities).

In the third category (summarized in Table 8 and locations shown in Appendix B), the primary focus has been on the anglophone countries of Nigeria and Ghana; consequently, knowledge of flood perception and mitigation in the many West African francophone countries is limited to a study of newspaper accounts in Niger (Tarhule, 2005), and participant-based studies in Benin and Burkina Faso (Ahouangan et al., 2014; Lassailly-Jacob, 2015). Because many of the studies are based on large-sample survey questionnaires of at-risk populations, little is known regarding the perspectives of local officials or decision-makers apart from the studies of Adelekan (2010), Amoako & Boamah (2015), and Lassailly-Jacob (2015). Finally, because only half of the studies use a theoretical framework to guide the methodological design or interpret the results, the absence of empirical testing of theoretically justified hypotheses makes it difficult to develop generalizable conclusions that can be compared across studies (Kellens et al., 2013). Of those that do use a theoretical framework, most are based on the concept of vulnerability; the exceptions are Adelekan & Asiyanbi (2016) and Odemerho (2014) who use frameworks of risk perception and resilience, respectively. However, deeper understanding could be gained by use of the many other available frameworks described in Birkholz et al. (2014) for exploring the relationship between flood perception and mitigation. In this context, this study seeks to fill some of the identified knowledge gaps by analyzing the perspectives of both flood victims and public officials in a francophone country and by employing a theoretical framework (perception motivation theory) that has been widely used for flood studies (Birkholz et al., 2014; Bubeck et al., 2012) but has not yet been applied to West Africa.

*Table 8: Summary of studies on flood risk perception and adaptation or mitigation in West Africa. [YEAR] indicates focus on flood event of that year. Results are that coming from the study methodology and do not include study recommendations, discussion or conclusion. A * indicates French, all else are English.*

Reference	**Location (characteristics)**	**Data**	**Framework**	**Results**
Adelekan (2010)	Lagos, Nigeria (urban, coastal)	Semi-structured questionnaire to 486 randomly sampled households in four poor urban communities, interviews with key informants, group discussions with community members	“integrated vulnerability framework” (Dolan & Walker, 2006)	Statistics of urban development, wetland loss and rainfall; causes of floods; vulnerability of surveyed households; perception of flood causes, frequency and impacts; adaption/mitigation measures at the individual, household and community level
Adelekan (2011)	Abeokuta, Nigeria (urban, inland)	Questionnaire to 248 residents in 14 flood-affected areas of the town	Vulnerability (based on a combination of existing literature)	[2007] indicators of vulnerability (socio-economic, susceptibility, exposure, and recovery)
Adelekan & Asiyanbi (2016)	Lagos, Nigeria (urban, coastal)	Semi-structured questionnaire to 1000 respondents in 40 flood affected districts	Risk perception, in particular the psychometric risk paradigm of Kraus & Slovic (1988)	[2011, 2012] socio-economic data; flood experience and awareness; concern about floods relative to other problems; concern about flood impacts;

				perceptions of flood vulnerability and risk
Ahouangan et al. (2014)*	Zagnanado, Benin (rural, inland)	Observational visits, semi-structured interviews with key informants, questionnaire to 60 randomly chosen heads of households	Goal is to assess perception of vulnerability (no reference to existing literature)	[2010] perception of risk and flood magnitude; flood disaster management, impact, migratory response and post-event adaptation strategies
Ajibade et al. (2013)	Lagos, Nigeria (urban, coastal)	36 in-depth interviews pre-disaster, 453 questionnaires immediate with the disaster, and six focus group discussions post-disaster of women in three sections of the city	Social vulnerability (Cutter et al., 2003) and feminist political ecology (Rocheleau et al., 1996)	[2011] normal gender-roles and well-being; women's perceptions of floods and gender; differential flood impacts on and coping strategies of women
Amoako & Boamah (2015)	Accra, Ghana (urban, coastal)	38 unstructured questionnaires and in-depth interviews with officials, review of policy documents, workshops/interviews with flood victims and communities	Integrated flood risk management developed by authors (no reference to existing literature)	Perceived and reported causes of floods
Ayoade & Akintola (1980)	Lagos and Ibadan, Nigeria (urban, coastal and inland)	Questionnaire to 266 and 246 randomly chosen households within zones in Lagos and Ibadan, respectively	Goal is to assess perception of flood hazard (no reference to existing literature)	Perceived flood impacts, causes and solutions; mitigation/adaptation strategies
Bempah &	Two	60 interviews,	Authors	[2009, 2010]

Øyhus (2017)	communities in the Northern region (capital Tamale), Ghana (rural, inland)	participant observation, four focus group discussions	created framework to connect beliefs, perceptions, and experience with disaster risk reduction (unclear how referenced literature is used in framework)	perceptions of flood causes and of the national disaster management agency
Douglas et al. (2008)	Lagos, Nigeria and Accra, Ghana (urban, coastal)	Focus group discussions	Participatory vulnerability analysis (Smit & Wandel, 2006)	Perceptions of flooding and its causes and solutions; adaptation strategies
Lassailly-Jacob (2015)*	Kaya, Ouagadougou, and Tougouri, Burkina Faso (urban and rural, inland)	36 semi-directed interviews with officials and flood victims	Goal is to assess perceptions, disaster response, and adaptation (no reference to existing literature)	[2009, 2010] perceptions of causes and characteristics of floods; disaster response; migratory adaptation strategies
Odemerho (2014)	Warri, Nigeria (urban, coastal)	Questionnaire to 129 residents in nine sections of the city	Flood risk resilience (B Gersonius, 2012)	Perceived types and causes of flooding; potential impacts of urban development on flood risk; possible adaptation strategies at government, community and household level
Ologunorisa & Adeyemo (2005)	Baleysa and Rivers states (capitols are Yenagoa and	Questionnaire to 500 landowners chosen by systematic	Goal is to assess perception of flood hazard	Socio-economic data; experience of floods; perceived

	Port Harcourt, respectively), Nigeria (rural, coastal)	random sampling in 15 settlements across three ecological zones	and coping strategies (no reference to existing literature)	characteristics, causes, damages, and solutions associated with floods; short- and long-term adaptation strategies
Oriola (1994)	Ondo, Nigeria (urban, inland)	Questionnaire to 120 landlords using systematic sampling, field measurements	Goal is to assess behaviors that may cause floods and perceptions of flood risk (no reference to existing literature)	Socio-economic data and property characteristics; flood-inducing socio-cultural activities; flood perception and experience
Oruonye (2013)	Jalingo, Nigeria (urban, inland)	Questionnaire to 252 randomly selected respondents in three affected regions in the city	Risk perception (Slovic, 1987) (referenced literature has minimal influence on study design and results)	Experience of flooding; perceived causes and frequency of flooding; duration of evacuation from home; disaster response
Tarhule (2005)	Niger (urban and rural, inland)	1970-2000 archives of the daily state-owned national newspaper	Goal is to assess occurrence, impacts, and perceptions of floods (no reference to existing literature)	Flood occurrence and impacts; perceived causes of floods
Tschakert et al. (2010)	Afram Plains, Bawku (east), and Wenchi regions in Ghana (rural, inland)	Historical matrices mapping in 10 communities, interviews with 72 households selected by stratified random	Vulnerability framework (Perch-Nielsen et al., 2008)	Experience with flood events; flood impacts; household and community response strategies

		sampling in six communities, group discussions in two communities		

3.3 Study Region

Burkina Faso is a landlocked country located in the Savanna and Sahel zones of West Africa. The country gained independence from France in 1960 and has maintained a relatively democratic government despite terrorist attacks and periods of political unrest, including a recent popular revolution and an attempted military coup. However, the country ranks very low on the United Nations Human Development Index (UNDP, 2015), there are high levels of illiteracy, and the economy is primarily based on agriculture (specifically cotton) and gold mining (WB, 2017). There are approximately 18.6 million inhabitants, and the annual average growth rate between 2010 and 2015 was 2.9% for the general population and 5.9% for the urban population (UN, 2017b). The capital, Ouagadougou, is located in the center of the country and is the largest city with approximately 2.7 million inhabitants (UN, 2017b). The second largest city, Bobo-Dioulasso, is located in the southwest of the country and had approximately 0.49 million residents in 2006 (M. Ouedraogo & Ripama, 2009).

The country experiences a variety of natural hazards, of which the most prominent are droughts, floods, and famines (GBF et al., 2014). Flooding is most frequently reported in provinces with large population centers (Ouagadougou and Bobo-Dioulasso are in Kadiogo and Houet, respectively), in the north region, which is closest to the Sahel and suffers from soil degradation by livestock husbandry (Niang, 2006), and in the southwest, where there is higher annual precipitation (MAHRH, 2004) (see Appendix B). Flooding is primarily triggered by heavy rainfall, but is exacerbated by the lack of storm water management systems, inadequate dam maintenance, disrespect of planning regulations, occupation of at-risk zones and poor land use management practices (GBF et al., 2014; Mathon et al., 2002). The whole country, and Ouagadougou in particular, was affected by a devastating flood on September 1st 2009 (GBF et al., 2010), which was triggered by an extreme one-day rainfall total of 261.3 mm (Galvin, 2010; GBF et al., 2010; Karambiri, 2009) (see Appendix B). The severity of the September 1st 2009 flood made it a focal point of this study.

3.4 Study Data

Data collection was accomplished through in-depth semi-structured interviews conducted between January and May 2015 with inhabitants of Ouagadougou who had been victims of the 2009 flood ("flood victims") and with public officials whose roles relate to flood preparation and response ("public officials"). Authorization for human subjects research was obtained from the Institutional Review Board at the University of Massachusetts Amherst and authorization for research in Burkina Faso was obtained from the Burkina Faso Ministère de la Recherche Scientifique et de l'Innovation. The participants were identified using purposeful and snowball sampling. Since this is an in-depth study, the goal of sampling was to reach data saturation (Guest, 2006) as opposed to gathering a large survey sample for statistical analysis. Purposeful sampling was used to identify persons who fit within the two categories of flood victims and public officials as described above, while snowball sampling was used because finding willing participants was highly based on connections. The interviews were conducted in French (the national language) although other languages were used occasionally when initiated by the participant. During the interview, data was collected through audio-taping and note-taking. The audio was transcribed in a denaturalized style by a team of five transcribers following a transcription guide. Translation from French to English was done as necessary.

The interview guides (see Appendix C) queried demographic and flood-related information. The flood victim interview guide asked participants to identify for each remembered flood the date, duration, causes, general impacts in Ouagadougou, personal impacts (specifically to health, home, private goods, and work), and the worst impact. The public official interview guide asked participants to describe the link between their agency and floods, and how their agency plans for, responds to, and evaluates floods. Both flood victims and public officials were also asked to identify what could be changed to limit damages from future floods and how floods compare to other natural disasters. Because the interviews were semi-structured, the researchers asked follow-up questions as necessary. The interview guides did not directly ask about mitigation measures implemented after the 2009 flood, nor directly assess all aspects of coping appraisal (described below). Thus, discussion of these topics was brought up spontaneously by the participants, potentially causing a downward bias in the types and frequency of the reported results but also ensuring that positive answers are authentic.

A total of 33 participants were interviewed: 13 flood victims and 20 public officials. The flood victims comprised nine men and four women, and represented nine different families, seven different city sectors (Figure 20) and a variety of ages and professions: students, housewives, employees of varying economic status, and one retired at the time of the flood. The severity of the flood victims' experience with flooding (either in 2009 or previously) ranged from some water damage in the home, to major water damage and temporary evacuation, to complete loss of home and livelihood. This sample is limited by size and the potential lack of independence between participants from the same family (in one case, two members from the same family were interviewed at the same time). Furthermore, this sample does not include any persons who had taken refuge in a government shelter or any persons who were relocated by the government. The public officials comprised 18 men and two women, and represented administrative, environmental, health, infrastructure, and non-governmental sectors (Table 9). This sample is limited in that it was not possible to arrange an interview with some organizations and the majority of the participants were men; women are underrepresented in public official roles (Helmfrid, 2004). Most participants admitted to not knowing or not remembering information, and in some cases, gave incorrect information (often incorrect flood dates). This is an indication, as would be expected, that the gap in time between the 2009 flood and the interviews in early 2015 affects the memory of participants and thus the reliability of the provided information. However, the gap in time also would cause participants to discuss memories that are most significant, without the urgency of a post-disaster situation, and allows for identification of flood mitigation measures which were implemented over multiple years. Participants also commented on perceived cultural, economic, and educational differences between themselves and the researchers.

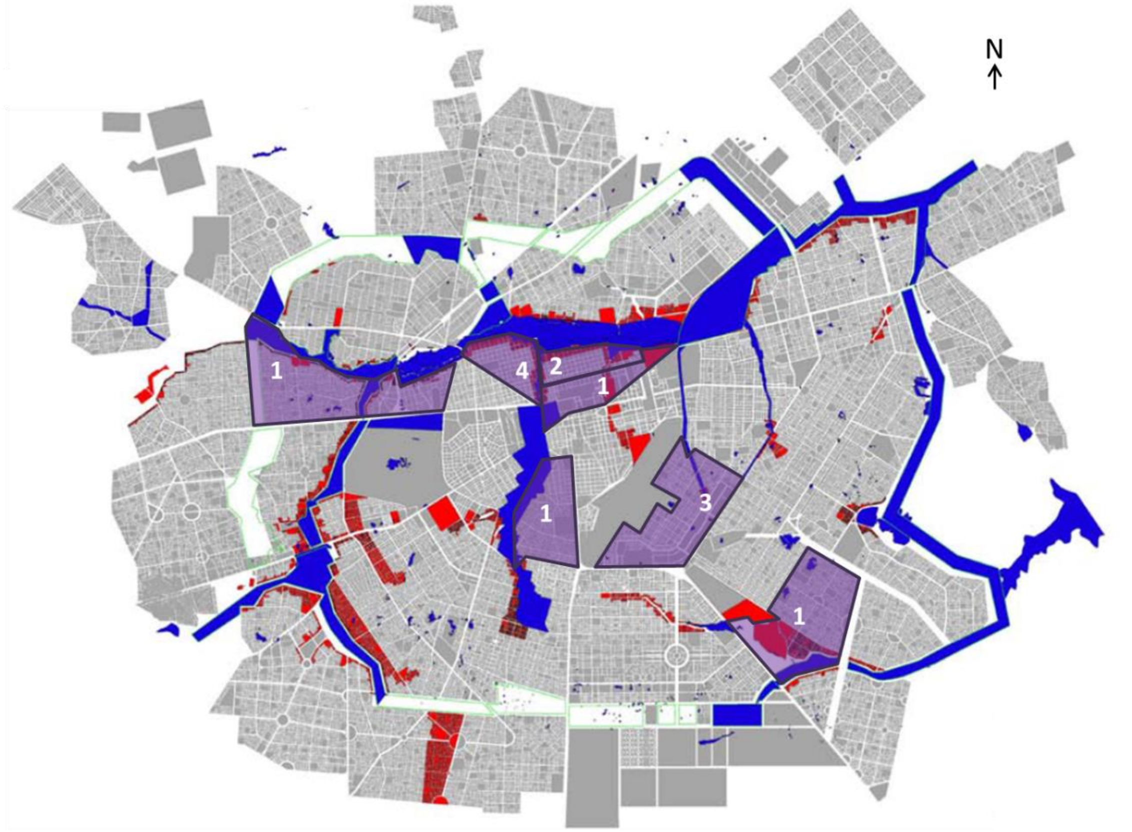

Figure 20: A map of Ouagadougou indicating the areas of flooding (blue) and victims (red) in 2009. Flood victims interviewed in study lived at the time of the flood in the sectors indicated by purple (the numbers indicate the number interviewed). The map is modified from GBF et al. (2010).

Table 9: Agencies represented by the public officials according to the perspective presented during the interview. # indicates the number within each sector.

Sector	#	Agency Name (French)	Abbreviation	Description
Administrative	5	Conseil National de Secours d'Urgence et de Réhabilitation	CONASUR	Disaster response and reconstruction
		Direction Générale de la Protection Civile	DGPC	Civil protection (police, firefighters, military)
		Conseil de Gestion	--	Emergency flood council
		Mairie de Ouagadougou	--	Mayor's office
Environment	3	Direction Générale de la Météorologie	DGM	Meteorology
		Direction Générale des Ressources en Eau	DGRE	Water resources
		Institut de l'Environnement et de Recherches Agricoles	INERA	Environment and agricultural research
Health	6	Centre Hospitalier Universitaire Pédiatrique de Ouagadougou	CHUP-CDG	Pediatric hospital
		Centre Hospitalier Universitaire Yalgado Ouédraogo	CHU-YO	National hospital
Infrastructure	4	Ministère de l'Habitat et Urbanisme	MHU	Housing and urban planning
		Office National de l'Eau et de l'Assainissement	ONEA	Water and wastewater treatment
		Ministère d'Infrastructure, du Désenclavement et des Transports	MIDT	Infrastructure, roadways, transportation
		Société National d'Electricité du Burkina	SONABEL	Power company
Non-governmental	2	Alliance Chrétienne pour la Coopération Economique et le Développement Social	ACCEDES	Aid and relief organization
		Croix Rouge Burkinabé	--	Red Cross

3.5 Analytical Method

The analytical method is summarized in Figure 21.

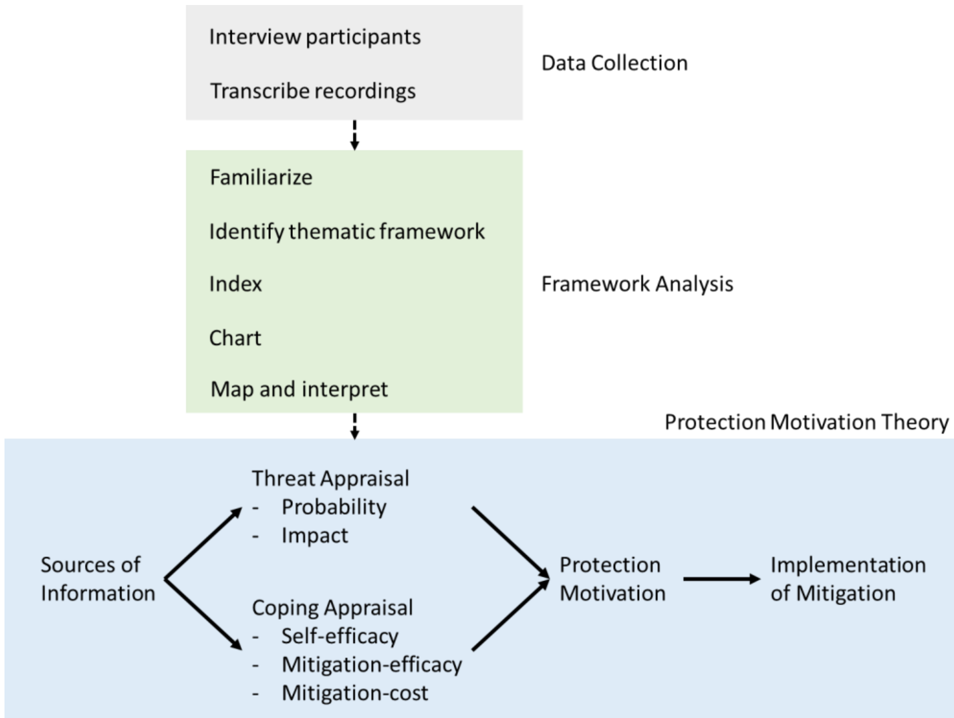

Figure 21: Schematic showing the methodology of this study.

The data were synthesized using the technique of framework analysis (Ritchie & Spencer, 2002) and using the software HyperRESEARCH ("HyperRESEARCH," 2015) as an organizational tool. Framework analysis was originally developed for use in policy-oriented studies, but has since been used to assess health and social impacts of flooding in northwest England (Carroll et al., 2010). Framework analysis is comprised of five steps, which were implemented iteratively as necessary: familiarization, identifying a thematic framework, indexing (also known as coding), charting, and mapping and interpretation. For detailed descriptions of each step, see Ritchie & Spencer (2002). In the mapping and interpretation step, the interview data were complemented by official and academic reports of the flood (GBF et al., 2010; IFRC, 2009, 2010, 2011; Kemking, 2010; OCHA-

ROWA, 2009). The flood victim and public official results were interpreted in tandem due to the limited sample sizes and, in some cases, the overlap in roles; some public officials were personally affected by the flood and some flood victims had leadership roles in the aftermath of the 2009 flood. However, where relevant, clear differences in the perspectives of the two groups, due to differences in the interview guides and in role, are reported. In some cases, the perspective of the public official is considered representative for his or her institution.

The data were interpreted according to the theoretical framework of protection motivation theory (PMT). Of the widely accepted conceptual frameworks to describe the relationship between flood perception and mitigation (Birkholz et al., 2014), PMT uniquely incorporates perceptions of coping ability into the framework (Schwarzer & Fuchs, 1996). As a result, PMT has been used to explain unexpectedly weak relationships in studies which primarily focus on perceptions of risk (Bubeck et al., 2012). PMT was originally developed in the health sciences (R. Rogers, 1975) but was first applied in the context of floods by Grothmann & Reusswig (2006) to predict adaptation actions of at-risk residents in Germany. PMT and variants have since been applied to many flood studies; however, with the exception of studies in Vietnam (Bubeck et al., 2013; Reynaud et al., 2013), most applications have been in developed countries: the Netherlands (Zaalberg et al., 2009), France (Poussin et al., 2014), Australia (Franklin et al., 2014), Austria (Babcicky & Seebauer, 2016), and Germany and Denmark (Bubeck et al., 2013; Koerth et al., 2013).

PMT posits that sources of information feed into a cognitive mediating process which determines a coping response (Maddux & Rogers, 1983; R. Rogers, 1975; R. Rogers &

Prentice-Dunn, 1997) (Figure 21). Coping response, as used by PMT, has approximately the same meaning as mitigation; to avoid confusion with response also implying disaster relief, we subsequently substitute mitigation. The cognitive mediating process is composed of an appraisal of the threat and an appraisal of the ability to cope with the threat. The combination of the two appraisals determines the level of "protection motivation" (i.e., the motivation of an individual to implement some measure of protection). Threat appraisal, more widely known as risk perception, is defined as the perceived probability and perceived consequences of a threat (Bubeck et al., 2012; Grothmann & Reusswig, 2006). Coping appraisal is the assessment of mitigation-efficacy (defined as the extent of belief in the effectiveness of a mitigation measure to reduce risk), mitigation-cost (defined as the estimated costs of implementing a mitigation measure), and self-efficacy (defined as the extent of belief in personal ability to implement the mitigation measure) (Bubeck et al., 2012). Sufficiently high levels of threat appraisal can trigger coping appraisal (Schwarzer & Fuchs, 1996), which, if favorable (i.e., high mitigation-efficacy and self-efficacy and low mitigation-cost), leads to higher levels of protection motivation and increases the likelihood of mitigation measures being implemented (R. Rogers, 1975).

To provide credibility to the results (Auerbach & Silverstein, 2003), the justifiability of the interpretations was maintained by ensuring agreement among the researchers on the interpretation, by reporting only those general themes or ideas which were discussed by multiple participants (generally at least three, some exceptions are noted), by taking into account counter-examples, and by corroborating the results with official and academic reports when possible. The transferability of the theoretical constructs was maintained by using a synthesis technique (framework analysis) and a conceptual framework (PMT) that have been successfully applied to similar studies and by comparing the results to similar studies in West Africa. Quotes from the participants used in support of the results are noted as superscripts and are provided in Appendix C.

3.6 Results

In the results, we first establish the devastating impacts of the 2009 flood as perceived by the participants and confirmed by official reports. We then show that both the participants and official reports exhibit a clear understanding of natural and anthropogenic causes of floods. We subsequently examine flood mitigation implemented after 2009 and recommended solutions as described by the participants. We find that, despite the experience of a devastating flood and clear understandings of flood causes, mitigation actions vary widely. To explain this apparent paradox, we examine the levels of threat appraisal and coping appraisal conveyed by the participants.

3.6.1 Impacts of the 2009 Flood

The September 1st 2009 flood affected 11 out of the 13 regions in Burkina Faso, but the majority of the impacts were concentrated in Ouagadougou. The flood caused as many as 46 deaths and nearly 120,000 victims and the economic impact is estimated at 201 M USD in damages, 33 M USD in losses and 266 M USD in reconstruction needs (GBF et al., 2010). Nearly all aspects of society were impacted: lodging, health, education, agriculture, industry, and infrastructure (GBF et al., 2010; IFRC, 2009, 2010, 2011; Kemking, 2010; OCHA-ROWA, 2009). The impacts described by the participants correspond to four main categories as described in Table 10.

Table 10: Impacts described by the participants in four categories and the number of flood victims (FV) and public officials (PO) who mentioned each impact. Of course, not every participant was affected by every category; for example, some reported no change in work or ability to reach work[16] or no health issues[17].

Category and Impacts	**FV**	**PO**
Public Institutions	-	-
The national hospital was flooded[1]	4	5
School buildings were damaged[2] and were occupied by displaced victims[3]	5	2
Infrastructure	-	-
Lack of potable water due to flooding of a key treatment plant[4]	0	1
Lack of electricity due to flooded transfer stations[5]	2	2
Impassible roads[6]	3	3
Private Goods	-	-
Damage to and destruction of houses and personal property (e.g., clothing, documents, food, and household items)[6]	13	4
Individuals	-	-
Displacement from homes[8]	10	2
Work and study (e.g., increased work for first responders or key officials[9] and inability to attend school or work[10])	9	4
Physical health (e.g., severe malaria[11])	9	2
Mental health (e.g., fear[12], a sense of lost control[13], and adversarial growth (Linley and Joseph, 2004) in the face of challenge[14])	12	7
Loss of life[15]	7	2

The 2009 flood created a lasting and strongly negative impression on the participants; they described the flood as *"catastrophic"*[18] and *"big"*[19] and one public official called floods "*bitter experiences"*[20] while a flood victim said *"what we lived through, we have no desire to experience again"*[21]. The flood victims and some public officials also shared their personal stories, revealing the unquantifiable and sometimes long-lasting effects of experiencing a devastating flood that is not captured in official reports; *"We left the house … it overflowed … I didn't know how to swim, so they dragged me along … even now when it rains at night I can't sleep – I'm afraid! And I'm not the only one."*[8,22]

Overall, both flood victims and public officials discussed impacts to institutions and infrastructure, yet very few public officials discussed impacts to either private goods or individuals, with the noticeable exception of comments by public officials on impacts to mental health. Similarly, the personal stories related by flood victims focused on individual losses, while those related by public officials generally focused on involvement in disaster response. This difference in perspective was likely strongly influenced by the content of the interview guide, in which flood victims, but not public officials, were specifically questioned about general and specific impacts.

3.6.2 Causes of Flooding

Urban floods in Burkina Faso have both natural and anthropogenic causes; causes articulated by the participants are summarized in Table 11 and discussed below.

Table 11: Causes of flooding as articulated by the flood victims (FV) and public officials (PO).

Cause	**FV**	**PO**
Extreme rain	7	3
Storm water management	-	-
Inadequate	9	7
Filled with garbage	5	5
Inadequate/unmaintained dams	6	3
Disrespect of urban planning regulations	-	-
Key infrastructure in at-risk zones	0	6
Mudbrick homes	7	1
Homes in low-lying/un-zoned areas	10	3
Lack of a flood early warning system	1	2
Lack of disaster response plans/coordination	0	11

The primary natural cause of flooding is heavy rainfall (GBF et al., 2014; Mathon et al., 2002), a fact which the participants treated as obvious. For example, in addition to simply stating that rain caused floods, the flood victims sometimes described the duration of flooding by reporting the duration of rainfall. In the prevalent local language of Mooré, the concept of flooding had no specific word but was traditionally described as a "big rain". In particular, the September 1st 2009 one-day rainfall total of 261.3 mm that triggered the flood was *"heavy"*[23], *"extreme"*[24], *"enormous"*[25], and *"exceptional"*[26] (Galvin, 2010); it represents nearly one third of the total rainfall received during the monsoon season (GBF et al., 2010) and it has a return period of more than 10,000 years according to a preliminary statistical analysis (Karambiri, 2009). However, two public officials noted that less extreme rains also cause floods[27], which is corroborated by a statistical study (Hangnon et al., 2015) and which, in an urban environment like Ouagadougou, indirectly confirms the existence of anthropogenic causes.

A major anthropogenic cause of floods is the lack of storm water management systems and inadequate maintenance of dams (GBF et al., 2014). Bayoko et al. (2015) surveyed a major drainage canal in Ouagadougou and documented lack of maintenance of the canal structure and piles of garbage within the canal (the last documented cleaning of the canal occurred between 2006 and 2007). According to participants, the storm water management system in Ouagadougou is inadequate[28], those canals and retaining basins that do exist are often filled with garbage[29], and dams are not maintained[30]. The three in-series dams (barrage n°1, n°2 and n°3) in the heart of Ouagadougou are the outlet of many major drainage canals (GBF et al., 2010) and partially supply water for the city[31].

Another anthropogenic cause of floods is disrespect of urban planning regulations by both the population and the government and occupation of at-risk zones due to population growth and lack of oversight (GBF et al., 2014). For example, Bayoko et al. (2015) documented human occupation of land along the edges of the major canal in

Ouagadougou. Public officials noted that key infrastructure is located in at-risk zones; for example, the national hospital is located adjacent to the third and furthest downstream dam in Ouagadougou[32]. Many flood victims also stated that many people build homes in low-lying or un-zoned areas[33] and many houses, regardless of location but especially in un-zoned areas, are built of mudbrick[34]. As a result, 99% of the houses destroyed in the 2009 flood were constructed out of mudbrick (GBF et al., 2010).

The participants also discussed two factors that accentuate the impacts of floods. The first factor is the lack of a flood early warning system[35]. While the ministry of meteorology is supposed to provide early warning information, the 2009 flood revealed that first, there is a lack of the equipment and technology needed to make sophisticated forecasts, and second, the lines of communication and institutional roles are unclear (GBF et al., 2010). The second factor, discussed by public officials, is lack of disaster response plans[36], which caused a lack of coordination and planning between first responders[37]. Furthermore, those plans that do exist are more theoretical than practical[38] and are often not tested in simulation exercises[39]. Interestingly, IFRC (2011) came to a different conclusion, stating that, for the 2009 flood, “relatively good preparedness was translated into early response” and that there was “good coordination between health and watsan [water and sanitation] departments”. This discrepancy may be due to differences in scope and perspective (e.g., general response across the city versus specific institutional response) or perhaps what occurred on the ground is different from what was filtered up to higher administrative levels.

3.6.3 Mitigation Measures and Recommended Solutions

Given the devastating impacts of the 2009 flood and the clear awareness of the causes of flooding, was there an increase in flood mitigation measures? At the national level, immediate change appears to have been limited; Burkina Faso experienced major flooding in 2010 that did not affect the capital, and hence did not receive nearly as much media attention, but caused almost as many victims as the 2009 flood (GBF et al., 2014)[40]. As described by the participants, mitigation measures in response to the 2009 flood varied widely and involved different levels of societal organization (individuals, communities, and institutions and government) (Table 12). Those at the individual and community level were primarily discussed by flood victims, while those at the institutional or governmental level were primarily discussed by public officials.

Table 12: Mitigation or lack thereof after the 2009 flood as described by the flood victims (FV) and public officials (PO).

Level	Mitigation	Lack of Mitigation
Individual	Voluntary relocation[41] (2 FV) Rebuilt on high point of property and/or with concrete[42,43] (3 FV)	Waiting for government to provide relocation[44] (1 FV) Return to original site after relocation[45] (1 PO)
Community	Build and maintain local canals and earth mounds[46] (2 FV)	
Institution/ Government	Government enforced relocation[45] (2 PO) Provision of cement[43] (1 FV) Improved storm water management[47,48] (5 PO) Completed urban planning study[49] (1 PO) Completed flood zone ordinances[50] (1 FV, 1 PO) Increased outflow rate from dam[51] (1 PO) Creation of the Organisation des Secours (ORSEC) plan for organization of relief efforts[52] (1 PO) Completed construction of a second site with less flood risk[53] (1 PO) Staff training on risks and risk-mapping for institution[54] (1 PO)	No sanctions for those who returned to original site after relocation[45] (1 PO) No flood risk plan[55], even if intended[56] (5 PO) Plan to move assets in flood risk zones to higher ground never achieved[57] (1 PO)

In some cases, mitigation measures implemented at one level of societal organization were ineffective or thwarted at another level. For example, the government relocated people in flood zones to a site (Yagma) on the outskirts of Ouagadougou; however, some returned to their original sites of habitation and rebuilt without incurring any government sanctions[45]. One institution meticulously clears the storm water drainage system on the grounds; however, the internal drainage system discharges to a city-owned drainage system that is not maintained and is full of garbage[47] (Figure 22). One flood victim had enough government-provided cement to rebuild the foundation and less than one meter of the house walls, but then resorted to mudbrick to finish the house[43]. In other cases, flood mitigation was significantly delayed. For example, one flood victim did not finish rebuilding until 2014[42] and one institution was hoping to complete a secondary site by the end of 2015[53]. That same institution took until 2013 to improve storm water management[48] and until 2014 and 2015 to begin to train personnel and map the risks to the institution[54]. Yet delayed action is perhaps better than the lack of action exhibited by some individuals and institutions.

Figure 22: Evidence of mitigation and lack thereof in Ouagadougou. (a) cleared drainage channel that discharges to (b) a filled drainage channel that discharges to (c) a filled collecting basin; (d) another nearly unrecognizable drainage channel that discharges to (c). All except (a) are located on city property. The color-coordinated arrows (dots) indicate the direction of flow (the approximate location of discharge).

The participants also made recommendations for solutions to flooding, many of which overlap with the mitigation measures: a flood early warning system[35] (1 FV, 2 PO), improved storm water management and delimitation of zones at-risk of flooding[58,59] (11 FV, 3 PO), enforcement of zoning laws[60] (4 FV, 2 PO), building houses with concrete[61] (2 FV), and risk management plans[62] (3 PO). Additionally, participants indicated the need for education about flood risks (4 FV, 5 PO) and one public official mentioned the need for direct involvement of the population in flood risk management[63]. The primary solutions recommended by GBF et al. (2010) can be summarized as better finances for risk reduction, investment in the necessary human resources, and development and implementation of an early warning system.

3.6.4 Threat and Coping Appraisal

Assuming that implementation of mitigation measures can be used as a proxy for protection motivation after the 2009 flood, the lack of consistent and immediate mitigation actions within and across all levels of society indicates that protection motivation was not uniformly high. To explain this, we examine levels of threat and coping appraisal as conveyed by the participants. We find that increased levels of flood risk perception after the 2009 flood and relatively high levels of perceived mitigation efficacy were offset by unclear prioritization of floods relative to other disasters, high perceived mitigation costs, and generally low perceived self-efficacy (summarized in Table 13 and discussed below).

Table 13: The elements of PMT discussed by the flood victims (FV) and public officials (PO).

Elements of PMT	**FV**	**PO**
Threat appraisal	-	-
Increased awareness/surprise	7	13
Flood prioritization	-	-
Floods are highly important	0	4
Other disasters are more important than floods	0	2
Difficulty comparing	8	12
Coping appraisal	-	-
Perceived mitigation efficacy	2	2
Perceived mitigation cost	5	11
Perceived self-efficacy	-	-
Philosophy	-	-
Fatalism	3	6
Possible to limit damages	4	11
Responsibility	-	-
Government	8	4
Individual	1	1

3.6.4.1 Threat Appraisal

The 2009 flood generated a distinct increase in flood risk perception in Burkina Faso. The prevailing yet implicit cultural assumption that floods do not occur in Sahel regions[64] was shattered by the unexpected devastation of the 2009 flood[65]. As noted by one flood victim, *"at the risk of being a bit cynical, there is a positive consequence of [the 2009 flood] … it's the awakening of conscience, it attracted attention to the problem"*[66]. According to a government report, "the 2009 flood regenerated interest in the problem of preparation and management of risks and disasters in Burkina" (GBF et al., 2010). There was a change in the prevalent local language of Mooré in which, as mentioned previously, flooding was traditionally described as a "big rain". However, after 2009, a Mooré speaker would easily understand the meaning of the French word "inondation" (meaning flood or flooding), indicating that the 2009 event was significant enough to warrant the appropriation of a unique word from the national language to describe the concept. Further confirmation of the indelible impression made by the 2009 flood occurred during interviews; while the interview guides were structured such that a specific flood was not implied, nearly all participants mentioned the 2009 flood while the researchers were still introducing the study purpose (i.e., before the interview officially began). Furthermore, mention of the 2009 flood to casual acquaintances nearly always elicited strong reactions and personal stories.

Despite the lack of awareness prior to 2009, and the fact that the rainfall of September 1st 2009 was undoubtedly exceptional (Karambiri, 2009), flooding was and is common in Burkina Faso. Records of periodic floods date back to 1988 in government documents and back to 1977 in international databases (see Appendix B). Furthermore, the country had just experienced flooding in 2007 that resulted in nearly as many victims as in 2009 (GBF et al., 2014). However, the impact to awareness of the 2007 flood, similar to subsequent floods in 2010 and 2012, was not as high as the 2009 flood, likely because the physical impacts were more localized and did not severely threaten the functionality of the capital city[40.67]. Relative to other disasters that affect the country, the official ranking of floods (highest consequences and nearly highest probability of occurrence) was the same before and after the 2009 flood (GBF et al., 2008, 2014). For the participants however, the relative priority of floods varied widely. Some public officials were clear that floods are catastrophic[68] while others identified other disasters (e.g., inter-community conflict, which causes more deaths than floods in Burkina Faso but overall affects less people (GBF et al., 2014), and fires) as causing the most concern[69]. Far more participants had difficulty assigning priority. This likely occurred because of a poorly worded interview question, which asked for a comparison of floods with other natural disasters, which is difficult if not impossible due to lack of a uniform scale[70]. Additionally, apart from floods and their counterparts, droughts, there are few perceived natural disasters in the country[71]. Thus, most participants responded by listing disasters that do not occur (e.g., volcanos, earthquakes, tsunamis)[72] or resorted to discussing anthropogenic disasters to make a comparison[69].

3.6.4.2 Coping Appraisal

Perceived mitigation-efficacy was relatively high among the participants considering the readiness with which they offered solutions to flooding, but the exact extent to which those measures would be sufficient was less often discussed. One flood victim expressed that education would completely change perspectives[73] while another victim noted that a house with only the foundation and lower walls made of cement would still be washed away in a high enough flood[43]. One official noted that flood risk is now less than that of other disasters given the mitigation measures implemented after the 2009 flood[69]; however, another official admitted that the implemented measures are not sufficient[74].

Perceived mitigation-cost was uniformly high among the participants and in official reports. For individuals, building homes out of mudbrick, which has no structural stability during a flood, is less expensive than using concrete (GBF et al., 2010) [75]. Un-zoned areas are also inexpensive, but are prone to flooding and people living there usually build with mudbrick because they do not have legal property ownership (GBF et al., 2010)[76]. At the institutional or governmental level, it is costly to build and maintain storm water drainage systems (Bayoko et al., 2015; GBF et al., 2010)[77], enforce zoning laws[78], purchase and maintain hydro-meteorological monitoring equipment[79], and study and implement institutional-level mitigation measures[74]. Furthermore, external funding agencies perpetrate perceptions of high costs by emphasizing disaster relief over resilience[80] and even planning for disaster response is based on finances rather than projected need[81].

The participants discussed two prevalent philosophies regarding the fundamental nature of floods which affect perceived self-efficacy. The first philosophy is that of fatalism, which conveys a sense of hopelessness in the face of flooding and hence a complete lack of perceived self-efficacy[82]. The fatalistic perspective is likely influenced by the sense that flooding is rapid and unpredictable (e.g., it can occur even in drought years), especially with the threat of climate change[71,83]. This perspective is likely further amplified by the cultural lack of long-term planning[84]; as a counter-example to the lack of planning, one participant described the annual planning for health epidemics[85]. The second philosophy is that while rainfall cannot be prevented, the damages can be limited[86], or that, in the most extreme case, floods are a completely anthropogenic catastrophe[87]. The anthropogenic perspective is likely influenced by the fact that floods sometimes occur after small amounts of rainfall, as discussed previously. Furthermore, the anthropogenic perspective clearly implicates humans as at least partially responsible for floods and hence gives humans self-efficacy in mitigation against floods.

Despite the responsibility for floods implied in the anthropogenic perspective, and the clear awareness of the anthropogenic causes of floods discussed previously, the participants' acknowledgement of responsibility, and hence perceived self-efficacy, was very low. Responsibility was often attributed to the government[88], especially by flood victims, in regards to building and maintaining storm water management systems, determining and enforcing flood zone regulations, and educating the population about high risk zones[89]. On the other hand, the official government report, which lists many anthropogenic causes of floods engendered by both the government and the public, still labels flooding as a natural disaster (GBF et al., 2014). Some participants expressed disapproval towards those who live illegally in un-zoned areas or litter garbage[90], but such behavior was blamed on ignorance and lack of education[91]. Only two participants directly acknowledge the role of individuals by speaking in first person; *"the minimal canal system that exists is filled by us, our garbage"* [92] and *"we refused to build on high ground, we refused to build using concrete, we refused to build canals"* [93].

3.7 Discussion

The results of this study show that, despite the experience of a devastating flood and clear understandings of flood causes, mitigation actions in Ouagadougou after the 2009 flood varied widely due to adverse appraisals of mitigation-cost and self-efficacy that offset positive or neutral appraisals of mitigation efficacy and threat. A key question that arises is whether the observations of this study are unique to Ouagadougou, Burkina Faso, or can be generalized to the region. To answer this question, we perform a comparative meta-analysis of these results with those listed in Table 8.

As expected, reported flood impacts are similar across all studies listed in Table 8: public institutions are affected, infrastructure is destroyed or inoperable, there is loss of private property (i.e., homes, goods and food), and individuals' lives, economic livelihoods and health are affected. In studies of rural populations, loss of crops and animals also figure prominently in reported impacts (e.g., Ahouangan et al., 2014; Tarhule, 2005; Tschakert et al., 2010). With very few exceptions (e.g., population groups that rely on fishing as their primary economic activity), floods are overwhelmingly seen as a negative event (Adelekan, 2010a; Tschakert et al., 2010). Similarly, perceived causes of floods are also similar across all studies: heavy rainfall, inadequate and blocked drainage canals, and poor urban development caused by lack of planning. In coastal regions, storm surge and rising tides levels are also attributed to causing floods (Adelekan, 2010a; Adelekan & Asiyanbi, 2016; Douglas et al., 2008). In most cases, as observed in this study, solutions proposed by participants mirror the causes, although some studies report that a portion of the participants provided no solutions.

Reported participant actions to combat flooding are diverse and numerous across the studies in Table 8; among them, particularly extensive and detailed lists are provided by Adelekan (2010), in which actions are categorized by societal level of implementation (i.e., community, household, and individual), by Ajibade et al. (2013), in which actions specific to women are highlighted, and by Tschakert et al. (2010), in which the participants rate the effectiveness of different actions. There are also studies that focus solely on mitigation actions: Adelekan (2016) describes the structural and non-structural measures implemented by public agents and the actions of households, communities, and real estate developers in Lagos, Nigeria (an urban and coastal location), Danso & Addo (2017) describe community institutional actions in Sekondi-Takoradi, Ghana (an urban and coastal location), and Lolig et al. (2014) describe household actions in northern Ghana (a rural and inland location). Thus, the mitigation actions described in this study are only a small representation of possible actions. However, lack of mitigation, as observed in this study, is not directly addressed in any study, but is clearly implied by the repetition of damaging floods and the recommendations for improved flood management included in the discussion and conclusion sections of every study.

Reported threat appraisal also varies across the studies in Table 8 depending on the participant population and the date the study was performed. For example, Adelekan & Asiyanbi (2016) claim an increase in flood awareness in Lagos relative to the study of Ayoade & Akintola (1980), yet experience with flooding may not necessarily translate to high awareness (Ologunorisa & Adeyemo, 2005; Oruonye, 2013). In this study, threat appraisal was found to increase dramatically after the 2009 flood, which shattered the implicit cultural assumption that floods do not occur in Sahel regions; this assumption was, until recently, also shared by the international scientific community (Lassailly-Jacob, 2015; Tarhule, 2005; Tschakert et al., 2010). However, this study also found that other threats may be given higher priority than floods. Similarly, Adelekan & Asiyanbi (2016) found that concern over crime and armed robbery is higher than concern over floods.

In this study, participants perceived mitigation-efficacy to be generally high, while acknowledging some limitations. However, Tschakert et al. (2010) show generally low levels of perceived mitigation-efficacy based on participants' quantitative rating of the effectiveness of specific mitigation strategies. Uniformly high perceptions of mitigation-cost observed in this study are echoed in observations by Adelekan (2010) and Ologunorisa & Adeyemo (2005) that people continue to live in flood-prone regions for economic reasons despite awareness of the risk. Bempah & Øyhus (2017) and Tschakert et al. (2010) note that government and external funding agencies emphasize disaster relief over prevention; similar observations in this study were interpreted to contribute to high perceptions of mitigation-cost. In this study, self-efficacy was found to be limited by a fatalistic philosophy and shifting responsibility to the government; these issues are commonly referenced in the studies in Table 8. The fatalistic philosophy is expressly discussed by Tschakert et al. (2010), perceptions of the lack of ability to control or do something about floods are reported by Adelekan & Asiyanbi (2016) and Douglas et al. (2008), and many studies report at least a small percentage of participants that attribute floods to an act of God (Adelekan, 2010a, 2011, 2016; Bempah & Øyhus, 2017; Lassailly-Jacob, 2015; Ologunorisa & Adeyemo, 2005). Some studies also document perceptions of climate variability and the uncertainty of floods in the region (Tarhule, 2005; Tschakert et al., 2010). A fatalistic conception of flood events may be influenced by the natural sciences definition of floods as a purely natural phenomena (Cardona, 2003) and by technical experts' tendency to neglect cultural, social and political contexts. In contrast, in favor of the possibility of limiting flood impacts also observed in this study, Tarhule (2005) expressly state that floods are portrayed as anthropogenic in newspaper accounts. Finally, lack of responsibility as observed in this study was also noted by Adelekan (2010), Bempah & Øyhus (2017), and Douglas et al. (2008).

3.8 Conclusion

As evidenced by previous studies and the results of this study, the problem of flooding in West Africa is systemic. Furthermore, the resulting devastation is a clear call for improved flood risk management. Studies on perception and mitigation can inform flood risk management from a societal and cultural perspective. Thus, previous studies have also provided a variety of recommended actions, which can be broadly summarized into the following categories:

- Enforcement and improvement of urban planning and building laws, especially as relates to flood zones
- Better drainage systems, which includes improved solid waste management and/or rainwater storage facilities and increased permeability
- Education of risk and mitigation options for at-risk populations
- Improved flood risk management and preparedness across and integrative of all levels of society
- Flood early warning systems
- Improved scientific data and understanding of current and future flood risk
- Flood insurance

Interestingly, relocation of those in at-risk zones does not directly appear in lists of recommendations although enforcement of planning laws implies relocation to varying degrees depending on the context. While voluntary relocation may occur, as observed in this study and others, forced relocation by the authorities is met with mixed reactions, and in some cases a return to the original place of habitation despite the risk (Ahouangan et al., 2014; Ayoade & Akintola, 1980; Lassailly-Jacob, 2015; Ologunorisa & Adeyemo, 2005; Oruonye, 2013; Tarhule, 2005; Tschakert et al., 2010). Many studies appear to recommend risk awareness education with the implicit hope that it will cause voluntary relocation, but, as shown in this study and others, simply raising awareness is not sufficient to motivate action.

Many, if not all, of these recommendations are also appropriate for Ouagadougou, Burkina Faso. Furthermore, through the comparative meta-analysis of previous studies and the use of PMT in this study, these recommendations can be made specific. For example, in Ouagadougou, education of at-risk populations does not need to address flood awareness, which is already high, but should address affordable adaptation measures to reduce perceptions of high mitigation-cost and should address personal responsibility to increase perceptions of low self-efficacy. Similarly, aid agencies could decrease perceptions of high mitigation-costs by expanding efforts beyond disaster relief. Major reductions in flood risk could be gained by improving drainage systems and maintaining a comprehensive solid waste management program; this responsibility falls on both the government and on individuals. Similarly, a flood early warning system, which is largely the government's responsibility, would reduce loss of life and property damages by enabling those in at-risk zones to temporarily re-locate and would improve disaster response by allowing first responders to be prepared.

While recommendations are useful, the similarities across flood perception and mitigation studies in West Africa indicate that saturation has been reached; for change to actually occur, the need now is for action based on studies that address implementation of a specific recommendation. For example, flood early warning systems, even in very simple forms, can increase disaster preparedness and reduce damages (Braman et al., 2013; Tall et al., 2012). In this regard, some work is in progress; for example, the United Nations Development Programme is currently funding a project on “Strengthening Climate Information and Early Warning Systems in Burkina Faso”, which has a flood component (UNDP, 2017). Studies that leverage the increase in research capacity in the region (Hughes et al., 2015) in combination with emerging sources of data such as satellite and microwave tower data (Casse et al., 2016; De Coning, 2013; Hoedjes et al., 2014) can be used to inform and implement effective flood forecasting even in traditionally data-poor regions. Other possibilities include studies on the potential transferability of educational programs (e.g., Ashley et al., 2012) or of economic incentives to decrease dumping of solid wastes into canals systems.

Finally, while there are many challenges to effective flood risk management in West Africa, they are not insurmountable. Flooding is a global problem (Adikari & Yoshitani, 2009) and many of the challenges discussed in this study are not unique to West Africa; for example, inconsistent mitigation has been observed in many flood perception studies (Bubeck et al., 2012) and, as noted by one participant, balancing the need for adequate mitigation with budget constraints is common practice[94]. Thus, there is ample opportunity for the international community to work concertedly towards improved flood risk management. Furthermore, the participants of this study demonstrated that often, change requires a dedicated person or community who understands the problem and has the authority and ability to react. For example, the meticulous cleaning of the storm water drainage system within one institution[47] is led by an individual who received a bachelor degree in water and sanitation[95]. Similarly, a non-governmental organization primarily provided disaster relief until one leader took a course in disaster management and realized the need for mitigation and preparedness[96] and one neighborhood self-organizes each year to build and maintain local channels and protective earth mounds[97]. The examples of these individuals are an encouragement that desperately needed flood risk management can become a reality in West Africa.

CONCLUSION

I am haunted by the story one flood victim in Ouagadougou, Burkina Faso told me about the 2009 flood.

> *We got out and walked how much?*
> *Only 10 steps and the house fell down ...*
> *if someone hadn't woken us up,*
> *we would have been dead in our sleep.*

This person's story is not isolated. To the contrary, it is continually being repeated nearly ten years later. In 2017 alone, there were major floods on every inhabited continent, from the devastation of hurricanes Harvey, Irma, and Maria on the Gulf coast (Fritz, 2018) and cyclone Debbie in New Zealand and Australia (Roy, 2017), to catastrophic monsoon flooding in Bangladesh, India and Nepal (Gettleman, 2017), to freezing cold winter flooding on Germany's Baltic coast ("German Baltic coast hit by storm surge flooding," 2017), to fatal flooding-induced mudslides in Sierra Leone ("Sierra Leone floods kill hundreds as mudslides bury houses," 2017) and in Peru, Ecuador and Colombia (Casey & Zarate, 2017). The sheer scale of destruction, economic impact, and number of people affected is impossible to grasp and more than sufficient motivation to effect change. The key question is: what should be changed and how can that change be effective? In response to this question, this dissertation contributes novel knowledge and methodology to three significant challenges associated with floods. Chapters 1 and 2 address the projection and management of future flooding under non-stationarity due to climate change and Chapter 3 addresses how flood perceptions influence mitigation actions.

Chapter 1 uses climate science and statistics to develop a formal methodology for climate informed approaches to long-term flood projection under climate change. The formal four step methodology, which prescribes how to develop a statistical model based on credible large-scale predictors of flood events and then use the model to make projections, is demonstrated in the Ohio River Basin. An additional preliminary analysis indicates possible application to other regions within the U.S. However, there are still a variety of remaining challenges associated with the method, given its relative novelty, including demonstration of general applicability across a hydro-climatologically diverse set of basins and integration into decision-making frameworks.

Chapter 2 builds on Chapter 1 by comparing climate informed flood projections to projections obtained using a more traditional model chain approach for Louisville, Kentucky. Subsequently, Chapter 2 employs concepts from the economics and engineering disciplines to address flood risk management. In particular, Chapter 2 integrates climate informed projections into decision-scaling, a bottom-up risk-based decision framework, to determine optimal levee design size, and compares the results to those obtained using a traditional (or top-down) risk-based analysis. The disparity in the results obtained from the two methods is traced to differences in the projections and motivates a consideration of the methodological and model credibility of each method.

Finally, Chapter 3 uses social science to provide new knowledge of flood perception and mitigation actions in West Africa. Protection motivation theory is used to analyze interviews with flood victims and public officials in Ouagadougou, Burkina Faso, with particular focus on the devastating 2009 flood. A lack of consistent and systemic mitigation actions after the 2009 flood, despite the increased awareness and clear understanding of causes, is explained by perceptions of high mitigation costs and that personal ability and responsibility to effect change is limited. Similar results are observed in other studies on perceptions in West Africa, indicating the need for actionable studies on the implementation of specific measures for flood risk management.

What synergistic insights can be gained from the diverse set of interdisciplinary approaches and case studies examined in this dissertation? Chapter 1 and Chapter 2 are highly intertwined, given that flood projections are an input to flood risk management frameworks. The uncertainty in projections evidenced in Chapter 1 provides a compelling argument for the risk-based decision-scaling approach employed in Chapter 2, while the comparison of the traditional and decision-scaling approaches in Chapter 2 indicates the importance of projection credibility as discussed in Chapter 1. For Chapter 1, the flood projections are developed for the purpose of informing decision-making. Although simply developing the projections may seem sufficient from a purely climatic or hydrologic perspective, Chapter 3 is a strong reminder that perceptions affect actions. Studies of practitioner acceptance and use of new scientific information (e.g., Cash et al., 2003; Hansen et al., 2011; Morss, 2010) provide valuable insight into how considering credibility and also salience and legitimacy can improve the likelihood that climate informed projections are accepted. Similarly for Chapter 2, the insights in Chapter 3 are a reminder that human actions motivated by perception of protection from a levee in Louisville will actually affect flood risk, the so-called levee effect, which has been studied elsewhere (Di Baldassarre et al., 2013). For Chapter 3, the insights from Chapters 1 and 2 are relevant to Burkina Faso and West Africa more generally. In particular, a seasonal flood warning system for Burkina Faso could use the climate informed methodology (e.g., Lima et al., 2015), using soil moisture and the West African Monsoon Index (Janicot et al., 1998; Tramblay et al., 2014). Furthermore, while Louisville and many other cities in the U.S. are facing the challenge of planning for climate change while dealing with aging infrastructure, Ouagadougou and other developing cities have the opportunity to plan for climate change while developing their infrastructure. Such an opportunity also underscores the necessity of using risk-based (or even robustness-based) methods for decision-making that fully explore system vulnerability, as presented in Chapter 2. Finally, there is a strange comfort in recognizing that, despite the many cultural and economic differences between Louisville in the Midwest U.S. and Ouagadougou in the heart of West Africa, flooding is a common concern with common challenges, such as resource constraints and human perceptions. These commonalities are an opportunity for fruitful research and collaboration that is not only interdisciplinary, but also international.

Clearly, this dissertation is by no means a holistic view of the challenges of flooding. Despite the advancements discussed herein, there are still many areas of research needed. In addition to the topics addressed in this work, there are many others: flood early warning systems, disaster response, the geotechnical and structural design of infrastructure such as levees and dams, operation of infrastructure as part of a larger water resources system, the economics and politics of flood risk management, etc. The list seems endless and when viewed from this perspective, the challenges seem overwhelming. But I contend that we must not allow the challenges to be overwhelming to the point of becoming paralyzing. Perhaps the most significant lesson I personally gleaned from the interviews in Ouagadougou is the importance of the actions and leadership shown by one person or small community to effect change. Similarly, this dissertation is an attempt, through small, to effect change by critically examining and improving our best methods for flood projection and risk management without overlooking the role of human perceptions and actions. We cannot allow the challenge of flooding to go unanswered because, as one flood victim said, “life cannot be bought”.

APPENDIX A

HISTORIC REPORTS OF FLOOD EVENTS IN THE OHIO RIVER BASIN

*Table 14: Summary and citations for the historic reports of flooding in the Ohio River Basin. Date indicates the duration of rainfall (the * indicates an exception where the date of the river cresting is reported because rainfall data is not available). While flood durations are often available, they are usually reported as the dates for which given rivers are above flood stages, which is difficult to standardize across multiple events. Thus, the flood dates may extend beyond the date of rainfall. The greyed rows in the date column indicate that the event occurred within the months of January through April.*

Date	Location	Causes	Notes	Citation
28 Feb – 7 Mar 1867	TN	heavy rain, snowmelt	wet month of February	(Congress, 1939)
25 Jul – 3 Aug 1875	OH	heavy rain	rain was caused by “wave action and resulting convergence along a quasi-stationary frontal zone oriented generally west-to-east”	(Schwarz, 1961)
3 – 14 Feb 1884	OH	heavy rain, snowmelt	wet month of January, large amount of accumulated snow melted by warm temperatures and warm rain, relatively impervious ground from antecedent cold temperatures caused quick runoff	(Horton & Jackson, 1913)
2 – 7 Feb 1883	OH	heavy rain	“major trough aloft, over western portion of the country”	(Schwarz, 1961)
24 – 26 Mar 1904	OH	heavy rain	“intense low pressure disturbance in the central portion of the United States”, “strong inflow of moist unstable air”, “large temperature contrast” in connection with a cold front	(Schwarz, 1961)
4 – 14 Mar 1907	OH	heavy rain, snowmelt	“quasi-stationary frontal type” (see Schwarz, 1961 Figure 1-1) “soil had been saturated by a flood in January” (that event, which is discussed in Schwarz (1961), is smaller than the March event)	(Horton & Jackson, 1913; Schwarz, 1961)
3 – 6 Oct 1910	OH	heavy rain	“intense high over New England” and “north-south trough of low pressure in the Plains States” allowed a “pronounced flow of moist tropical air from the Gulf of Mexico”	(Schwarz, 1961)
23 – 27 Mar 1913	OH	heavy rain	Combination of the “quasi-stationary frontal type” and the “occluding low type (see Schwarz, 1961 Figure 1), ground “practically saturated by previous rains”	(Horton & Jackson, 1913; Schwarz, 1961)
5 – 6, 14 Jul 1916	NC, TN, SC	heavy rain	two tropical cyclones (the latter added to the already saturated soil and full streams)	(Osment, 2008)
7 Mar	TN	heavy		(Moore,

1917*		rain, snowmelt		2016)
7 – 11 Jan 1930	OH	heavy rain	“strong Bermuda High” and “cold High extending into the Northern Plains” resulting in a “southwest-to-northeast front”, “significant trough aloft over the western portion of the country”, “active flow of moist air northward into the frontal zone”, “an isobaric configuration which favors pronounced convergence”	(Schwarz, 1961)
16 – 18 Mar 1936	OH	heavy rain	“occluding low type” (see Schwarz, 1961 Figure 1-2)	(Schwarz, 1961)
5 – 25 Jan 1937	IL, IN, KY, OH, PA	heavy rain	Lack of “cold dry air over the Gulf of Mexico” allowed for a readily available “warm moist current”, “typical quasi-stationary frontal zone” (see Schwarz, 1961 Figure 1-1), snow was not a factor	(NWS, 2017b; Schwarz, 1961; Swenson, 1937)
2 – 7 Oct 1941	OH	heavy rain	“ridge of high pressure over the southeastern states and deep trough aloft over the western portion of the United States” allowing for a “continuing supply of moist tropical air”	(Schwarz, 1961)
20 Feb – 6 Mar 1945	KY, OH	heavy rain	“snowmelt had very little impact”, “rain came in four main waves” over period	(NWS, 2017a)
3 – 7 Jan 1950	IN, KY, OH, TN, WV	heavy rain	“deep trough over the western United States and a ridge over the Eastern States” and moisture from the Gulf of Mexico	(Lott & Myers, 1956; Schwarz, 1961)
27 Jan – 2 Feb 1957	KY, TN, VA, WV	heavy rain	“streams at near-median levels and the ground was saturated”	(USGS, 1964)
18 Nov 1957	TN	heavy rain	Heavy rainfall was associated “with a deepening low pressure system moving north-eastward”, preceding rainfall caused near soil saturation	(TVA, 1961)
20 – 21 Jan 1959	IN, OH	heavy rain	“ground was saturated by a [previous] storm … and was frozen with some snow cover”, “persistent high-pressure area was located off the South Atlantic Coast … an area of low pressure over the Great Plains … the combined circulation … transported a large mass of warm, moist air from the Gulf of Mexico”	(Cross & Brooks, 1959; USGS, 1961)
4 – 19 Mar 1963	KY, NC, OH, TN, VA, WV	heavy rain	“succession of three storms associated with low pressure systems”, in Ohio rain “fell on snow-covered ground”	(Rostvedt, 1968)
2 – 10 Mar 1964	IN, KY, OH,	heavy rain	“floods were caused by two storms”, “melted snow in western Pennsylvania added” to the runoff, “prior to March … soil moisture was seriously deficient” in OH,	(Beaber & Rostvedt, 1965)

	PA, WV		KY, and IN and rainfall had been below normal since the preceding summer	
24 – 29 Mar 1965	KY, TN	heavy rain	“two storms … passed over the area … the first … cause little or no flooding, but it establish antecedent conditions for the second storm”	(Rostvedt, 1970a)
13 Feb 1966	TN	heavy rain, snowmelt	“heavy rain fell on ground that was saturated by the melting of about 10 inches of snow”	(Rostvedt, 1970b)
30 Apr – 15 May 1967	KY, TN	heavy rain	“below average precipitation in preceding months” in Kentucky and rain “came in three storm periods”	(Rostvedt, 1972)
14 – 18 Mar 1973	KY, NC, TN	heavy rain	the flood-causing weather system ”originated as a weak low-pressure system over the intermountain region of the Western United States”, there was a trough extending southward from British Columbia and a ridge over the Eastern United States “that extended northward from the Gulf of Mexico”, moisture came from the Gulf through the Mississippi Valley, a quasi-stationary surface front prolonged the rainfall	(Edelen & Miller, 1976)
10 – 20 Mar 1982	IN, OH	moderate rain, snowmelt	Extensive snowpack melted rapidly with the passage of several warm fronts and the moderate rainfall contributed to the flooding	(Glatfelter & Chin, 1988)
1 – 3 Mar 1997	IN, KY	heavy rain	“upper level ridge was positioned over the east coast with a longwave trough located just east of the Rocky Mountains”, there was a “persistent influx of Gulf moisture northward”, no melting snow but antecedent rainfall had been high	(Austin et al., 1998; NWS, 2017)
1 – 2 May 2010	KY, TN	heavy rain	“drier than normal” antecedent conditions, an upper level trough over the Western United States allowed southerly moist flow into the region that interacted with a northeast-southwest stationary front across the Mississippi Valley	(Service Assessment Team, 2010)
early Mar 2015	KY, OH, PA, WV	heavy rain, snowmelt		(Breslin, 2015; EO, 2017)

APPENDIX B

BURKINA FASO FLOOD PERCEPTION LITERATURE AND FLOODS

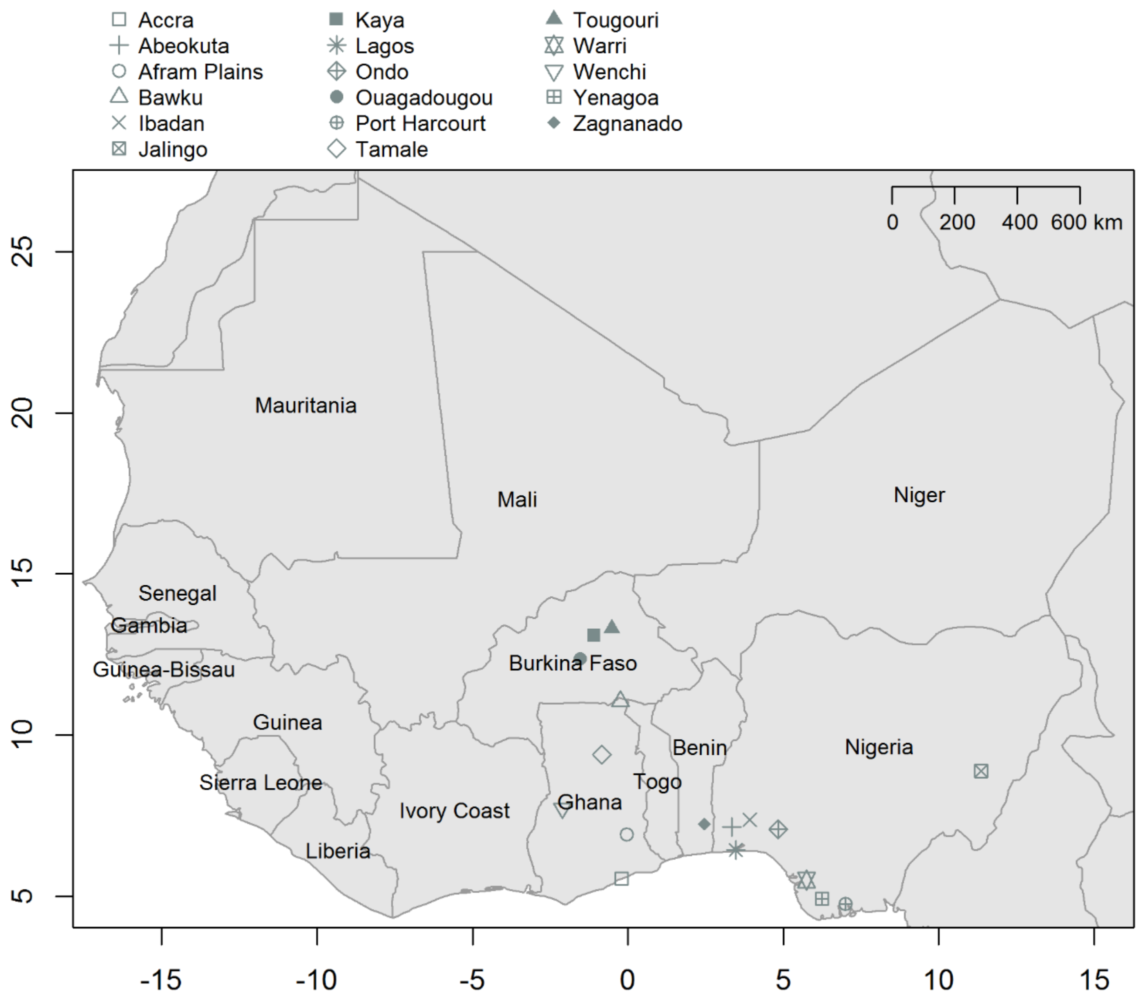

Figure 23: Map of West Africa. The labeled countries are those within the region except the islands of Cabo Verde and Saint Helena (UN, 2017a). Points show the locations of the studies described in Table 8 (with the exception of Tarhule (2005) where the study area was all of Niger). The x- and y-axis numbers are longitude and latitude (degrees) respectively.

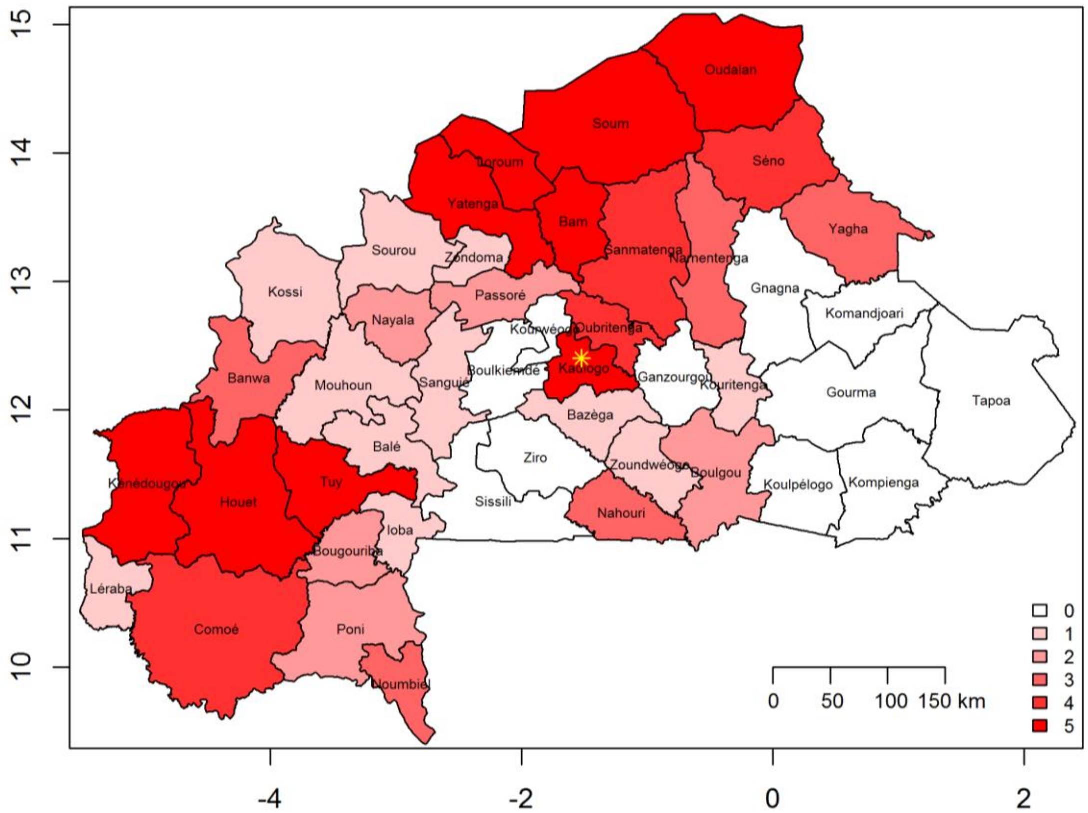

Figure 24: Number of recorded damaging floods by province in Burkina Faso from 1977-2017. The counts are based on data aggregated from Brakenridge (2017), GBF et al. (2014), and EM-DAT (2017). These counts are approximate, given that the data is missing information and that, as necessary, town and region level data was aggregated and disaggregated, respectively, to the province level. The location of Ouagadougou is marked with a yellow star and the x- and y-axis numbers are longitude and latitude (degrees) respectively.

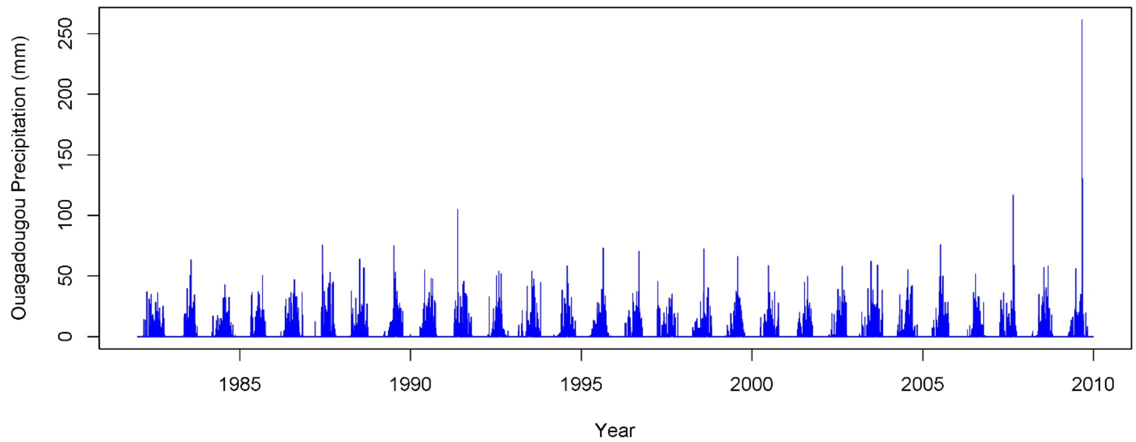

Figure 25: Precipitation (mm) record from the station located at the Ouagadougou Airport (in the center of the city). The annual monsoon and the extremity of the 2009 rainfall event are clearly evident.

Burkina Faso flood events were compiled from the Dartmouth Flood Observatory (Brakenridge, 2017), an official report by the government of Burkina Faso (GBF et al., 2014), and the International Disaster Database (EM-DAT, 2017). The discrepancies among the sources are likely due to the difficulty of accurate reporting in a disaster and the different purposes of the sources. The Dartmouth Flood Observatory does not disaggregate flood events by individual countries. Consequently, data from the Dartmouth Flood Observatory was only included when specifically applicable to Burkina Faso (except the dates of floods, which may refer to flooding in the region). The official report, which is current to 2014, only provides the flood year and only occasionally provides the location. The International Disaster Database includes many floods not listed by the other two sources. To distinguish between the different data sources, superscripts are used to indicate the Dartmouth Flood Observatory[1], the official report[2], and the International Disaster Database[3]. All locations are provinces except when indicated by a superscript to be a town[T] or region[R]. Multiple flood events within one year are noted separately when there is adequate data.

Table 15: Compiled list of floods in Burkina Faso.

Year	**Dates**	**Locations(s)**	**Summary**
1977[3]	September[3]		**People Affected:** 900[3] victims
1984[3]	October[3]	[T]Gorom-Gorom[3]	**People Affected:** 1,500[3] victims
1985[3]	November 6[3]	[T]Banfora[3]	**People Affected:** 572[3] victims
1988[1,2,3]	August 21 – September 2[1] August[3]	Bam, Comoe, Houet, Kadiogo, Kenedougou, Namentenga, Oubritenga, Oudalan,	**Cause:** Heavy rain[1] **Intervention Needed:** Estimated US$ 150,000[2]

		Seno, Soum, Yatenga[1,3] Bazega[1] 16 provinces[2]	**People Affected:** 6,000[1] (14,900[2]) (33,324[3]) victims 11[1] (16[3]) dead **Other Affected:** 975 homes destroyed[2] Granaries and fields destroyed[2] Cattle, poultry and material goods swept away[2]
1992[1,2]	August 1 – September 15[1]	[T]Kongoussi, [T]Ziniare, [T]Tenkodogo[1] 9 provinces[2]	**Cause:** Heavy rain[1] **Damages:** Estimated US$ 2,497,600[2] **People Affected:** 21,400[2] victims **Other Affected:** 3,400 homes destroyed[2] 17 dams or reservoirs damaged or destroyed[2] 3,000 ha of land destroyed[2] Cattle and poultry lost[2]
1994[1,2,3]	September 16 – September 20[1]	20 provinces[2]	**Cause:** Heavy Rain[1] **Damages:** Estimated US$ 1,142,570[2] **People Affected:** 4,000[1] (68,000[2]) (66,500[3]) victims 4[1] (22[3]) dead **Other Affected:** 22 dams or reservoirs damaged[2] 106,560 ha of land destroyed[2]
1999[3]	August[3]	Loroum, Oubritenga, Oudalan, Sanguie, Tuy[3]	**People Affected:** 1,560[3] victims 6[3] dead
2003[1,3]	August 10 – October 19[1,3]	Bam, Bazega, Boulgou, Comoe, Kadiogo, Kenedougou, Loroum, Nahouri, Nayala, Noumbiel, Sanmatenga, Seno, Yatenga, [T]Sebba[3] [T]Dori, [T]Djibo[1]	**Cause:** Heavy Rain[1] **People Affected:** 12,120 victims[3]
2006[1,2,3]	August 3 – October 11[1,3]	Kossi, Oudalan, [T]Gorom-Gorom[1,3]	**Cause:** Heavy Rain[1] **People Affected:** 20,000[1] (15,610[3]) victims **Other Affected:** 6000[1] homes destroyed

			Touro dam collapses[1]
	September 12[3]	Banwa, Loroum, Oudalan, Soum[3]	**People Affected:** 10,000[3] victims
		[R]Boucle du Mouhoun, [R]Centre Nord, [R]Centre Sud, [R]Hauts Bassins, [R]Nord, [R]Sahel, [R]Sud-Ouest[2]	**People Affected:** 11,464[2] victims
2007[1,2,3]	July 28 – August 1[1]	[T]Bama	**Cause:** Heavy Rain[1] **People Affected:** 2,000[1] victims
	July 26 – October 10[1,3]	Bam, Houet, Kouritenga, Kadiogo, Loroum, Nahouri, Namentenga, Oubritenga, Passore, Sanmatenga, Yatenga, Zandoma, Zoundwego[1,3] Banwa, [T]Po, [T]Tiebele, [T]Solenzo, [T]Sanaba, [T]Ouagadougou, [T]Bama, [T]Banh[1] [R]Sahel[3]	**Cause:** Heavy Rain[1] **People Affected:** 95,000[1] (121,043[3]) victims 52[1,3] dead **Other Affected:** 9,000[1] homes destroyed
		13 regions[2]	**People Affected:** 146,202[2] victims 83[2] dead **Other Affected:** 26,833[2] homes destroyed More than 2072 granaries destroyed[2] Cattle, poultry destroyed[2]
2008[2,3]	July[3]		**People Affected:** 560[3] victims
	August – September[3]	[T]Batie[3]	**People Affected:** 4,310[3] victims 6[3] dead
		14 provinces[2]	**People Affected:** 24,676[2] victims 54[2] wounded 5[2] dead
2009[1,2,3] *	June – July[3]		**People Affected:** 500[3] victims
	September 1[3]	[T]Ouagadougou[3]	**People Affected:** 151,000[3] victims 9[3] dead

	August 10 – September 2[1]		**Cause:** Heavy Rain[1]
		[T]Ouagadougou[2]	**People Affected:** 180,386[2] victims 62[2] wounded 41[2] dead **Other Affected:** 33,172 homes destroyed[2]
2010[1,3]	July 21 - July 25[1]		**Cause:** Heavy Rain[1] **People Affected:** 20,000[1] victims 14[1] dead
	August 1 – August 11[1]		**Cause:** Torrential Rain[1]
	July 21 – September[3]	Banwa, Bougouriba, Ganzourgou, Gnaga, Houet, Namantenga, Oudalan, Poni, Sanmatenga, Seno, Soum, Tuy, Yagha, Yatenga[3]	**Damages:** Estimated US$ 176,000[3] **People Affected:** 133,362[3] victims 16[3] dead
			People Affected: 173,276[2] victims
2011[2]			**People Affected:** 8851[2] victims
2012[3]	June 15 – September 5[3]		**People Affected:** 21,000[3] victims 18[3] dead
			People Affected: 73,722[2] victims
2013[3]	August 15 – 17[3]	[R]Hauts-Bassins[3]	**People Affected:** 11,396[3] victims 2[3] dead
2015[1,3]	July 25 – August 19[1]		**Cause:** Heavy Rain[1]
	August 4 – 7[3]	[T]Bobo-Dioulasso, [T]Ouagadougou, Kadiogo, Kenedougou, Tuy, [R]Cascades,[R]Centre[3]	**Damages:** Estimated US$ 31,000,000[3] **People Affected:** 28871[3] victims 54[3] wounded 8[3] dead
2016	June 15 – August 26[1]		**Cause:** Heavy Rain[1] **People Affected:** 34893[3] victims

			35[3] wounded 15[3] dead
2017			**People Affected:** 882[3] victims 2[3] dead

*Note that the data for the September 1st 2009 flood is different than that cited in the main text because the source used in the main text is GBF et al. (2010).

APPENDIX C

INTERVIEW GUIDES AND PARTICIPANT QUOTES

Table 16: Interview guide for public officials.

French	English
Caractéristiques	**Characteristics**
En quoi consiste votre travail ?	What is your job?
Depuis combien de temps occupez-vous ce poste ?	How long have you had this job?
Inondations	**Floods**
Quel est le lien entre votre travail ou votre employeur et les inondations au Burkina Faso, spécifiquement les inondations à Ouagadougou ?	What is the link between your work or your employer and floods in Burkina Faso, specifically floods in Ouagadougou?
Avez-vous déjà eu affaire à des inondations à Ouagadougou ?	Have you already had experience with flooding in Ouagadougou?
Planification	**Planning**
Est-ce que vous incorporez les risques d’inondation dans votre planification ?	Do you incorporate flooding risks in your planning?
Comment est-ce que vous incorporez ces risques ?	How do you incorporate these risks?
Pourquoi est-ce que vous avez choisi cette façon de gérer le risque ?	Why have you chosen this manner of managing the risk?
Est-ce que vous pensez que c’est suffisant ?	Do you think it is sufficient?
Réponse	**Response**
Quand il y a une inondation, quelles sont vos responsabilités ou les responsabilités de votre employeur?	When there is a flood, what are your or your employer’s responsibilities?
Pouvez-vous m’expliquer un cas pratique de responsabilité lors d’une inondation?	Can you give me a practical example of that responsibility regarding a flood?
Quelles sont les difficultés liées dans l’accomplissement de ces responsabilités ?	What are the difficulties associated with accomplishing these responsibilities?
Comment est-ce que vous avez déterminé les meilleures solutions ?	How have you determined the best solutions?
Est-ce vous pensez que c’est suffisant ?	Do you think it is sufficient?
Analyse	**Analysis**
Après une inondation, est-ce que vous ou votre employeur faite des collectes ou des analyses de données ?	After a flood, do you or your employer collect or analyze data?
Quels sont les données que vous avez colletés et quels sont les analyses que vous avez faites ?	What is the data that you have collected and what analyses have you done?
Comment est-ce que les analyses et les	How are the analyses and data used?
	Are there other analyses or other data that

données sont utilisées ? Est-ce qu'il y a d'autres analyses et d'autres données qui vous seront utiles ? Est-ce que vous avez des analyses ou des données que vous pouvez partager avec moi ? [Garder cette question à l'esprit pour les situations approprié].	would be useful for you? Do you have analysis or data that you can share with me? [Only ask this question if it seems appropriate].
Changements Qu'est-ce on pourrait faire pour limiter les dégâts qui seront créés lors des prochaines inondations ?	**Changes** What can be done to limit the damages that will be created by future floods?
Crises Naturelles Comment compareriez-vous les inondations avec les autres crises naturelles ?	**Natural Disasters** How would you compare floods with other natural disasters?

Table 17: Interview guide for flood victims.

French	English
Caractéristiques Vous habitez dans quel secteur de Ouagadougou ? Depuis combien de temps habitez-vous ici ? Quel est votre métier ? Combien des personnes avez-vous en charge ?	**Characteristics** What sector do you live in? How long have you lived here? What is your job? How many people do you take care of?
Inondations Vous vous rappelez de quelles inondations dans Ouagadougou ?	**Floods** What floods do you remember in Ouagadougou?
Date Quel est la date d'inondation ?	**Date** What was the date of the flood?
Durée L'inondation a durée combien de temps ?	**Duration** The flood lasted for how long?
Raisons Quelles sont les raisons de cette inondation ?	**Reasons** What are the reasons for this flood?
Impacts à Ouaga Quels sont les impacts de l'inondation dans Ouagadougou ?	**Impacts in Ouaga** What are the impacts of the flood in Ouagadougou?
Impacts sur Sujet Quels sont les impacts de l'inondation sur vous et votre ménage ?	**Impacts on Subject** What are the impacts of the flood on you and your household?
Santé Est-ce que l'inondation a causé des problèmes de santé pour vous et votre	**Health** Did the flood cause health problems for you and your household? If yes: What types? That lasted for how long? If no: Why not?

ménage ? Si oui : Quels types ? Ça dure pour combien du temps ? Si non : Pourquoi pas ? **Maison** Est-ce que l'inondation a affecté votre maison ? Si oui : Comment ? Pourquoi ? Qu'est-ce que vous avez fait ? Si non : Pourquoi pas ? **Autres Biens Matériels** Est-ce que vous avez perdu les autres biens matériels à cause de l'inondation ? Si oui : De quoi s'agissait-il ? **Travail** Est-ce que l'inondation a affecté votre travail ? Si oui : Comment ? Qu'est-ce que vous avez fait pour y remédier? Si non : Pourquoi pas ? **Autres Impacts** Il y a-t-il d'autres impacts sur vous et votre ménage dont nous n'avons pas parlé ? Si oui : Ils consistaient de quoi ? **Importance** Selon votre estimation, quel est le pire impact ? Pourquoi ? **Changements** Qu'est-ce on pourrait faire pour limiter les dégâts qui seront créé lors des prochaines inondations ? **Crises Naturelles** Comment comparerez-vous les inondations avec les autres crises naturelles ?	**House** Did the flood affect your house? If yes: How? Why? What did you do? If no: Why not? **Other Material Goods** Did you lose other material goods because of the flood? If yes: What were those? **Work** Did the flood affect your work? If yes: How? What did you do to solve this? If no: Why not? **Other Impacts** Were there other impacts on you and your household we have not talked about? If yes: What were those? **Importance** From your perspective, what is the worst impact? Why? **Changes** What can be done to limit the damages that will be created by future floods? **Natural Disasters** How would you compare floods with other natural disasters?

A selection of transcribed and translated quotes from the study participants which support the analyses in the main text are provided below. Different participants are identified by labels indicating flood victim or public official ("FV" or "PO", respectively) and a number. As described in the methodology, audio recording of the interviews was transcribed in a denaturalized style by a team of five transcribers (two of whom are the first two authors) following a transcription guide created by the first two authors. Transcriptions were translated from French to English by the first author. Because the transcription in is a denaturalized style, while some aspects of the conversation have been preserved (e.g., inclusion of pauses, sentence fragments, and selected speech disfluencies), grammatical correctness was also emphasized. Identifying information has been removed to protect the identity of the participants. In some cases, information, denoted by "[]", has been added to clarify the context. In all cases, care has been taken to ensure that the original meaning conveyed by the participant has been preserved.

Table 18: Selected participant quotes. The number indicates the superscript in the main text.

1	PO18 « parce que euh .. tous les bâtiments était inondés eh .. Mais ce qui a un peu compliqué la situation, eh .. Yalgado étant inondé » "all the buildings were flooded [at the pediatric hospital] … but because Yalgado [the national hospital] was flooded"
2	FV07 « Vous allez voir des des des infrastructures d'éducation comme des établissements les murs tombés des.. des bâtiments écroulés » "you would see schools with fallen walls and buildings"
3	FV13 « les classes sont fermées, puisque tout est occupé par des sinistrés » "classes were closed because everything was occupied by displaced victims"
4	PO08 « Quand y a eu l'inondation du 1er septembre 2009 … toute la station de Ouaga qui représente 30% de la production a été touchée … la station est restée à l'arrêt du 1er septembre 2009 au 10 septembre 2009 » "the whole Ouaga station, which accounts for 30% of [drinking water] production, was stopped completely from September 1 2009 to September 10 2009"
5	PO20 « y a des postes de transformations en cabine qui ont été totalement submergés par l'eau … une centrale à Paspanga qui a été totalement inondée aussi et qui a été à l'arrêt pendant deux semaines » , "there were [electrical] transfer stations completely submerged by water … and a central station at Paspanga that was completely flooded and dysfunctional for two weeks"
6	FV06 « dans tous les axes là sur les voies on peut pas circuler. En étant même sur le goudron même tu as l'eau à la poitrine » "the roads were all impassible; standing on the blacktop you had water up to your chest"
7	FV07 « beaucoup de maisons qui se sont écroulées.. et quand la maison s'écroule.. on on perd tout ce qui est dans la maison » "many houses fell down… and when the house falls … you lose all that is in the house" FV03 « tout était… gâté.. mouillé.. tout tout tout tout » "[even though the house was still standing] all was ruined … soaked … all all all"
8	FV07 « quand on est sorti on a marché combien ? 10-10 pas seulement et puis la maison-là est tombée. … si on nous avait pas réveillé là ah.. Ça allait être du sommeil à la mort seulement » "We got out and walked how much? Only 10 steps and the house fell down ... if someone hadn't woken us up, we would have been dead in our sleep." FV11 « on n'était obligé de quitter les maisons … ça débordait … moi qui ne savait pas nager surtout, moi on me tirait … Jusqu'à présent, quand il pleut la nuit je n'arrive pas à dormir. J'ai peur ! Ah ! Je ne suis pas la seule » "We left the house … it overflowed … I didn't know how to swim, so they dragged me along … even now when it rains at night I can't sleep – I'm afraid! And I'm not the only one." PO11 « moi si je raconte les inondations du 1er septembre … je ne pouvais pas rentrer chez moi … Y'avait l'eau partout … vous voyez ? … vous … comprenez ? comment … se trouve les risques ? … Pour une première fois dans ma vie je ne dors pas chez moi. » "If I were to talk about the flood of September 1st … I couldn't go back to my home, there was water everywhere … you see? You understand … the risks? For the first time in my life I didn't sleep in my own home."
9	PO08 « travaillé de jour comme de nuit sans repos pour pouvoir démarrer la station en 10 jours. » "worked night and day without rest to get the station running again in 10 days" PO19 « donc on a travaillé du matin jusqu'à 21 heures, pour pouvoir soigner les malades qui étaient là déjà. » "worked from the morning to 9pm to treat patients who were already there"
10	FV13 « il faut du temps quand on est touché. Bon on ne peut plus aller travailler. Hum .. il faut d'abord chercher des logements. » "it takes time when you are affected [by a flood]; you cannot go to work anymore, you have to first search for housing" FV06 « économiquement euh.. puisque beaucoup de gens n'arrivaient pas, la plupart des.. de la population est.. est commerçante, c'est des gens qui font des activités de commerce » "most of the population are merchants, they could not [recover]" FV07 « je ne pouvais pas aller à l'école parce que la pluie allait mouiller tous mes cahiers,

	mouiller tous » ("I couldn't go to school because the rain soaked all my notebooks"
11	FV06 « après les inondations je crois que j'ai été hospitalisé à- dans une clinique. 4 jours de palu, palu grave » "after the flood I was hospitalized at a clinic, four days of severe malaria"
12	PO15 « Donc la crainte était généralisée. » "fear was everywhere"
13	FV02 « au niveau… psychologique… ça a chauffé parce que tu te rends compte que rien n'est acquis hein ? » "psychologically … things got heated because you realize nothing is for sure"
14	FV07 « l'impact a été positif… c'est une épreuve très difficile, mais … ça m'a enseigné beaucoup de choses et ça m'a fait grandir. ... psychologiquement… parce que j'ai vu la solidarité » "the impact was positive … it was a very difficult trial, but … it taught me many things and made me mature psychologically because I saw the solidarity"
15	FV06 « le plus grave en tout cas.. c'est la vie humaine, parce que la vie ne s'achète pas » "the worst [impact] in any case is human life, because life cannot be bought"
16	FV06 « Ça n'a pas affecté mon travail. » "[the flood] did not affect my work"
17	PO19 « on n'a pas eu d'épidémie de de choléra » "no general cholera epidemic" FV09 « Chez la santé non » "regarding health, no [there were no impacts]"
18	FV13 « en 2009-là vraiment c'était catastrophique » "in 2009 there, truly it was catastrophic"
19	PO05 « 2009 et 2010 et 2012 aussi vraiment des années où on a connu de de grandes inondations » "in 2009 and 2010 and 2012 also, those were years when we experienced big floods"
20	PO06 « des expériences amères de l'inondation » "the bitter experiences of the flood"
21	FV02 « ce qu'on a vécu là... On n'a pas envie de revivre ça » "what we lived through, we have no desire to experience again"
22	FV06 « c'est à l'arrivée là-bas que j'ai constaté que non, au faite cette pluie là… elle n'est pas ordinaire. Donc c'est ça maintenant j'ai commencé à appeler, bon je n'arrivais pas à joindre madame, son téléphone était noyé…. Tu écoutes les radios en parlent ah y a l'inondation y a des gens qui ont été emportés y a des maisons qui sont tombées, bon ! Naturellement comme je suis en maison en banco je sais qu'elle n'est pas aussi dure donc … j'ai eu des inquiétudes. J'ai même demande la permission pour pouvoir venir, on m'a dit que c'est pas possible… je risque d'être victime même … Donc j'étais obligé de rester. Bon avec un cœur vraiment pa- pas dans la joie. » "Arriving [at work] I realized that the rain was not ordinary. So at that time I tried to call my wife, but I couldn't reach her, her cellphone was in the water … you heard on the radio that there was flooding, people swept away, houses falling down. Since my house is mudbrick, I knew it wasn't strong, so naturally I was anxious … I even asked for permission to return home, but they said it wasn't possible… I could have become a victim myself. So I had to stay, but my heart had no joy." FV08 « En tout cas jusqu'à présent là je n'arrive même pas à me rattraper … Moi mon problème… puisque mes enfants là même, même à l'école là je n'arrive même pas à payer » "I still can't catch up [financially] even now [five years later]… my problem is … I can't even pay for school for my children." PO08 « Je n'ai pas pu arriver à la station parce que tout était bloqué… finalement.. disons que j'ai pris des risques … je suis passé avec la voiture dans l'eau.. Je suis arrivé…. on a travaillé de jour comme de nuit sans repos pour pouvoir démarrer la station en 10 jours » "I couldn't get to the station because everything was blocked. Finally, let's just say I took some risks… I took the car through water … finally I arrived … we worked day and night without rest to get the station running again in 10 days." PO19 « Y a beaucoup d'agents de santé qui ne sont pas venus … puisque y avait beaucoup de pluies. Donc nous on est venu quand même parce qu'il fallait voir les malades, mais on n'était deux seulement … on a travaillé du matin jusqu'à 21 heures … donc c'était très compliqué. » "Many of the health providers didn't come… because there was lots of rain. We came anyways because someone had to care for the patients, but there was only two of us… we worked from the morning until 9pm… it was very difficult."
23	FV02 « il y a des fortes pluies comme ça » "there are heavy rainfalls like that"
24	FV10 « y a eu euh une pluie, une pluie extrême » " it was an extreme rainfall"

25	FV05 « en tout cas c'est une, une énorme pluie » "in any case it's an enormous rainfall"
26	PO14 « c'est vrai que ça été une pluviométrie exceptionnelle » "it's true that was an exceptional rainfall"
27	PO04 « petite pluie seulement c'est inondation » "just a small rain and there's a flood" PO12 « ce n'est pas parce que il est tombé 205, 200mm, 250mm forcément que euh .. ça va, ça va euh .. faire des inondations. Il peut tomber 60 mm qui va, qui crée, qui crée des inondations. » "it doesn't necessarily flood because there was 250 mm of rainfall – there could be 60 mm of rain and there would be flooding"
28	PO11 « sur les 6000km de rues, les voies on a environ 500km de caniveau. On a moins de 10%. … c'est faible … y a des bassins versants, ya des grands canaux qui n'ont pas- qui ne sont pas réalisés » "6000 km of roads and about 500 km of canals, less than 10%, it's inadequate, there are retaining basins and large canals that were never built"
29	FV11 « c'est des lieux où on jette des ordures, alors l'eau n'arrive pas à passer » "garbage is thrown there, so water can't flow through"
30	PO14 « la plupart de nos barrages, de nos retenues d'eaux sont ensablés » "most of our dams are filled with sand" FV02 « ils n'ont pas endigué le barrage là. Donc ça fait que quand il y a des fortes pluies comme ça forcement nous … on est inondé. » "they didn't dike up the dam, so of course we are flooded when there are heavy rains"
31	PO08 « pour couvrir la ville de Ouagadougou, Loumbila, Ziniaré … [il y a] deux grandes stations … Paspanga, qui est à Ouagadougou et qui est alimente par les barrages de Ouaga et de Loumbila et … Ziga qui se trouve à 50 km ici, qui est alimente par le barrage de Ziga » "To cover the cities of Ouagadougou, Loumbila, Ziniaré, there are two main [water treatment] stations: Paspanga, which is in Ouagadougou and is supplied by the dams in Ouaga and Loumbia, and Ziga, which is supplied by the dam of Ziga"
32	PO06 « Il ya des bâtiments qui sont construits sur des zones à inondation. » "there are buildings constructed in flood zones"
33	PO09 « le plus durement touché était des occupants des zones d'habitat spontanés, les zones non loties; les occupations des abords des barrages, ils y sont dans une trame plus ou moins euh régulière mais ils sont dans l'illégalité » "those most severely affected lived in non-loti zones, lived on the edges of the dams – they are there more or less permanently but illegally"
34	FV07 « comme c'est pas encore distribué, les gens ne bâtissent pas avec.. avec des maisons en en en en brique dure, c'est avec du banco. Alors que le banco.. en 5 minutes le banco s'en vas hein, lorsque tout est encerclé par l'eau, en 5 minutes, la fondation s'effondre et puis tout s'écroule » "since it [the zone] is not yet distributed, people don't use concrete, they use banco – but banco disintegrates in 5 minutes when surrounded by water"
35	FV01 « si peut-être la météo ou les responsables chargés de des … des climats nous prévenaient qu'attention il y aura des fortes pluies, on peut se préparer » "if meteorologists warned us there would be heavy rain, we could prepare" PO05 « systèmes d'alerte précoce au niveau communautaire ... ça manque pour le moment » "community level early warning systems are missing at the moment" PO03 commentaires: ils ne peuvent pas déterminer la quantité d'eau qui va tomber, par manque de matériel sophistiqué (radar pour scanner les nuages). Notes: the [meterologists] cannot determine the amount of rain that will fall due a lack of sophisticated technology (radar for scanning the clouds).
36	PO13 « normalement, on doit avoir ces dispositifs là sur papier, poser, et puis même interpeller les .. les personnes concernées, en cas de crise … si non c'est de façon spontanée qu'on a essayé de mettre par rapport à la situation du moment, qu'on a essayé de mettre ces dispositifs là en place. Pour pouvoir gérer les inond- l'inondation. Les inondations du 1er septembre. » "normally, for disasters there should be measures in place and all the responders involved – but in the case of the September 1 [2009] flood, it was impromptu, the way we tried to put response measures in place to address the situation"
37	PO13 « mais les premières heures y a eu beaucoup d'acteurs qui se sont mêlés quoi, pour réagir.

	Même ceux qui ne sont pas des professionnels » "in the first hours [after the 2009 flood] there were many responders who were involved – even those who weren't professionals" PO04 « la coordination n'est pas satisfaisante en mon sens du fait que nous avons plusieurs structures qui interviennent dans la gestion des catastrophes, mais ces structures, chaque structure est dans son ministère type. Nous sommes des partenaires mais pour les mobiliser on a des difficultés » "I don't think the coordination is satisfactory because we have many disaster relief agencies, but each is in its own department – we are partners but to mobilize everyone is difficult"
38	PO15 « par rapport aux .. aux inondations de de 2009. C'est bien vrai que souvent on lit les plans, c'est .. en tout cas c'est de la théorie. C'est de la théorie, c'est quelque chose qu'on a péché sur papier eh .. on on s'est rendu compte que sur le terrain c'était autre chose parce que eh .. les acteurs même qui étaient en fait des points focaux récepteurs eh .. les- les chefs de fil sectoriel n'étaient pas vraiment très bien formés » "regarding the 2009 flood – often when you read those plans, it's theory, it's something put on paper – but on the ground we realized it's something entirely different, even the key actors were not well trained"
39	PO18 « théoriquement les plans blancs existent mais rarement on ne fait des simulations » "theoretically plans exist, but we rarely do simulations"
40	PO05 « les exemples les plus … frappant c'est le … cas du 1er septembre 2009, mais aussi les inondations de … 2010 et aussi 2012. Alor le 1er septembre comme vous savez la de … son ampleur au niveau de la ville de Ouagadougou ca été beaucoup plus médiatisé. Mais si on veut voir en terme … de dégâts aussi ce qu'on a vécu en 2010 c'est pratiquement la même chose à la différence que … ça touche beaucoup plus de régions et … une grande ville comme Ouagadougou n'a pas été touchée donc ... ça a été moins médiatisé. » "The most striking examples are September 1st 2009 but also the floods in 2010 and also in 2012. With the September 1st, you know the magnitude in Ouagadougou, it was given much more media coverage. But in regards to damages, what we lived through in 2010 was almost the same the difference being that it primarily affected the provinces and a big city like Ouagadougou was not affected, so it received less media coverage."
41	FV10 « y a aussi le déménagement par peur que ça, ça se répète » "there was the move for fear that it would repeat" FV05 « si vous demandez aux voisins ... les gens qui habitent là-bas sont des.. locataires.. Quand il y'a des inondations comme ça là.. après ça ils s'en vont, ils sortent » "if you asked the neighbors … they are renters … when there's floods like that, they leave"
42	FV06 « il a fallu que moi … je trouve le moyen pour quitter dans la maison en banco pour rentrer un peu en dur … ((indique du doigt deux maisons en ciment dans sa cour)) voilà, c'est deux là j'ai construit. Ca c'est 2014 que je viens de- d'ajouter, c'était en urgence … puisque comme … ici c'est élevé ((indique le fond de la cour)) » "I had to find a way to leave the mudbrick house for a cement house [the participant pointed to two cement houses at the back of the courtyard] so I built those two. I added them in 2014, it was a quick as I could… because there is raised up [the participant indicated the back of the courtyard]"
43	FV08 notes: the participant insisted afterwards on taking us … to see the house – the one the participant reconstructed (painstakingly) after the flood took away the house – the concrete that the government gave was enough for the participant to lay down a floor (that is already cracked and pitted) for the two old people the participant takes care of, and build up about 2 ft of a foundation for the family's house (where the floor is just dirt) and the rest is banco – the participant told us that if water comes up high enough to above the 2 ft – reaching the banco level, then the house will fall again. FV08 « trente sacs de ciment, vingt tôles, cinquante mille, qu'est-ce que ça peut faire? … cinquante mille francs peut prendre maçon ? … peut payer du sable ? ça peut faire des briques ? » "30 sacks of cement, twenty sheets of metal, 50,000 [cfa], what can that do ? 50,000 [cfa] can pay a bricklayer? Can pay for sand? Can make bricks?"
44	FV02 « il n'a qu'à nous déménager correctement, seulement. Nous on était prêts » "[the government] just had to correctly move us, that's all. We were ready"

45	PO13 « ils étaient dans des zones inondables, ils ne doivent plus repo- partir sur leur site d'origine … On les a placé à Yagma. Déménager totalement. » "they were in flood zones. They shouldn't go back to their land … they were installed at Yagma, completely relocated" PO04 « On est parti donner des parcelles aux gens, on a amené à Yagma, ils ont vendus, ils ont fait de ça un fond de commerce, ils ont vendus et ils sont venus s'asseoir encore dans la même chose....comme la police ne passe plus, il a fait de ça une maison maintenant. » "land parcels were given to people, they were taken to Yagma, they sold [the land], used the money to start some commerce, and came and sat down in the same place … since the police don't pass by anymore, there's a house now"
46	FV05 « C'est nous même qui cotisons chaque année ... terre pour entasser sur la route, pour essayer de combler les trous … nous-même on.. nous on fait des.. nous nous nous nous on fait un caniveau » "each year we [the neighborhood] contribute to … put mounds of earth in front of the houses, to fill the potholes … we ourselves made a canal"
47	PO17 « pour éviter les inondations [chaque samedi] on cure tout ce qui est caniveaux … souvent on fait appel à-.. service de la propriété de la mairie qui viennent curer .. les caniveaux extérieurs » "to avoid floods each Saturday we clean all the canals… we often call the cleaning service at the city hall to clean the exterior canals" Notes: they take meticulous care of the canals inside (clearing them out every Saturday) and they have grills on the exits to outside, but from the inside looking out, we can see trash just outside. It's even worse when you go outside, the canal that encircles the [institution], to drain to a small basin, is at least halfway filled with trash, and in some places, the grills on top are so filled with dirt, you can't even tell there is a canal below. Furthermore, the basin is filled, with trash, and growing grass.
48	PO06 « juste apres l'inondation donc en 2014 on a entrepris ca » "just after the flood, that is in 2014 we took on that [clean and construct drainage systems]"
49	PO11 « on avait entamé la réalisation d'une grande étude.. Projet d'assainissement des quartiers de Ouaga … L'inondation du 1er septembre à impli- à amplifier à 200 300% la réussite du projet » "we had begun to implement a big study… waste management for the sectors of Ouaga … the September 1st flood amplified to 200 300% the success of the project"
50	PO09 « un aspect de la période post inondation 2009 … cellule technique de mis en œuvre de décret sur les zones inondables et submersibles dans la ville de Ouagadougou » "after the 2009 flood… [there was a] technical group that put into place ordinance concerning flood risk zones in Ouagadougou"
51	PO08 « pour pouvoir permettre l'évacuation beaucoup plus de l'eau au niveau du déversoir du barrage ... nous avons essayé d'augmenter le débit d'évacuation .. des eaux de barrage N°3 » "to allow much more water to spill from the dam, we tried to increase the outflow rate from dam number 3"
52	PO04 « l'a motivation pour créer ce plan c'est le débordement … de 2009 » "the motivation for creating the [ORSEC] plan was the 2009 flood"
53	PO02 « un autre site pour … on va euh délocaliser certains services sur le site là et laisser d'autres services ici ... c'est pratiquement même terminé ... on espère que d'ici fin 2015 on va aménager » "another site [for the institution] … we will move certain services to the site there and leave others here … it's almost complete … we hope by the end of 2015 to move"
54	PO02 « c'est en décembre que j'ai essayé de former et sensibiliser le personnel au control interne ; et nous avons décidé en 2015 là de faire ce qu'on appelle la cartographie des risques » "In December I tried to train the internal personnel, and we decided in 2015 to map the risks [to the institution]"
55	PO01 « après la la réponse immédiate euh.. il y a pas eu euh il y a pas eu de de grand-chose » "after the immediate response, there wasn't really anything" PO20 « on n'a pas un plan établis, euh ..de .. avec des directives qui doivent dire que en cas d'inondation voilà ce qu'il faut faire » "we do not have a plan that states what to do in case of a flood"
56	PO16 « le plan blanc, après 2009, honnêtement nous avons prévue dans nos activités d'élaborer le plan blanc … Mais à ce jour, nous sommes toujours là-dessus » "the flood risk plan, after

	2009, honestly we planned to create the flood risk plan [for the institution], but we're still at that stage"
57	PO20 « les postes qui étaient dans des zones marécageuses, nous avons pu les .. les identifier et puis faire un budget pour.. le déplacement...Mais je vais dire que euh ils ne sont pas effectivement déplacés à ce jour » "we identified the posts in swampy zones and made a budget for their displacement, but to this day, they are not yet moved"
58	FV06 « la seule solution c'est.. en tout cas eh.. faire des aménagements au niveau.. des des voiries, faire des canalisations ... il doit avoir une équipe à la mairie » "the only solution is to make improvements to roads, build canals … there should be a crew from the city [for cleaning the canals]" FV03 « faire une digue autour du barrage ... et peut-être quant 'on on racle un un barrage » "build a dike around the dam … dredge the dam"
59	FV02 « dans les années à venir peut-être dans les lotissements ils vont faire ils n'ont qu'à mieux étudier tout ça, tous ces risques-là » "for the zoning they'll do in future years, they should do better study of the [flood] risks" PO09 « Euh en fait, la délimitation en elle-même n'est pas la solution euh finale pour limiter les effets. Euh mais elle a au moins le mérite d'alerter. » "the [flood zone] delimitation itself is the not the final solution for limiting impacts, but at least it is an alert"
60	FV13 « si il y a des gens qui veulent s'installer, au moins qu'on puisse les déguerpir. Bon pour pouvoir les placer dans des zones où peut-être avec des euh .. fortes pluies qu'ils ne soient pas touchés. » "for those who try to live [in low areas], at least we could get them out, place them in zones where they won't be affected by heavy rain" PO04 « il faut sanctionner..Il faut taper. Il faut faire la phase supérieure maintenant de la sensibilisation » "you have to sanction, you have to give them a beating, you have to go to the next level of education"
61	FV05 « Faut construire en dure seulement, sinon les maisons tombent » "houses should only be built of concrete, otherwise they fall down"
62	PO11 « on doit réaliser le schéma directeur de l'assainissement pluvial de Ouaga .On doit réaliser le schéma directeur de la gestion des déchets de Ouaga » "we need to develop the planning document for stormwater management in Ouagadougou. We need to develop the planning document for waste management in Ouagadougou"
63	FV11 « il faut euh conseiller les gens à ne plus construire dans les zones inondables ... encourager même si ça coûte cher que les maisons soient surtout construites en ciment ... Eduquer la population à ne plus jeter les ordures dans les caniveaux » "people should be advised to stop building houses in flood zones … should be encouraged to always build with concrete even if it's expensive … should be educated to stop throwing trash in the canals" PO11 « il faut impliquer aussi les populations parce que … on le fait pour eux … Il faut qu'on développe les initiatives pour les populations même peuvent participer à la réalisation des caniveaux. » "the people have to be involved because it's done for them … we have to develop initiatives so that the people are even helping in building canals"
64	FV01 « dans un pays Sahélien, l'eau ne devrait pas être un problème. … Inondation, c'est les choses qu'on qu- qu'on pensait que ça devrait être en Inde, en Guinée où il y a la pluie tout le temps » "in a Sahel country, [too much] water shouldn't be a problem, we assumed floods would happen in India, Guinea, where it rains all the time"
65	PO08 « puisqu'on a été surpris par toute .. cette inondation » "we were surprised by all the flooding [in 2009]" FV11 « Il y a eu d'au- d'autres inondations il ya des années passées, mais pas comme ça. C'est la première fois que..on a vu cette inondation. 2009 là c'était pire que les autres… » "there have been other floods in past years, but not like that – it's the first time we've seen such a flood, 2009 was worse than the others" PO09 « il faut dire que 2009 ça a surpris tout le monde … On parle de l'improvisation mais j'allais dire c'était une réponse spontanée aussi. » "I should note that 2009 surprised everyone… we talk about improvisation, but I'd say it was also a spontaneous response"

66	FV01 « au risques d'être peut-être cynique, il y une conséquence positif de tout ça, c'est l'éveille de conscience, c'est l'attraction c'est à dire attirer l'attention sur le problème » "at the risk of being a bit cynical, there is a positive consequence of [the 2009 flood] … it's the awakening of conscience, it attracted attention to the problem"
67	FV01 « l'impact était localisé. …. Donc du coup, ça n'attirait pas l'attention du tout le monde sur le problème. » "the impact was localized … naturally it didn't draw everyone's attention to the problem"
68	PO11 « euh pour des catastrophes urbaines bon … euh l'inondation c'est la catastrophe la plus grave hein ? » "[in Ouagadougou] flooding is the worst urban catastrophe"
69	PO02 « je pense que après les mesures que nous avons prises là euh, le risque d'inondation ... serait mineur par apport à d'autres risques euh ... un autre risque qui nous ... tient à cœur c'est.. au.. au cas où surviendrait un incendie » "I think that with the measures we implemented then [after the 2009 flood], flood risk would be minor compared to the other risk which keeps us awake at night - a fire" PO15 « en terme .. de .. d'impact … les tensions intercommunautaires impactes plus, même si en fait la survenue, la fréquence est très faible, ça impact plus. ... En dehors de ça, c'est les inondations ... Oh euh pour terminer, y a .. l'insécurité alimentaire » "in terms of impact … inter-community conflict has the greatest impact though it occurs rarely … besides that, it's floods … and after that, food insecurity"
70	FV09 « Donc comparer ces deux phénomènes là c'est vraiment un casse tète » "for me to compare those two phenomenon [droughts and floods] that's really baffling"
71	PO16 « Donc je n'ai pas tellement d'exemples autres que les inondations qui puissent me permettre de faire des comparaisons. » "I don't have other examples besides floods that would allow me to make comparisons" PO07 "On the same year, sometime ... at the beginning of the ... rainy season you have no rains. Crops dies, and by the end ... October, its start raining and you have flood that destroy everything on the same year! How can you explain that?" [participant spoke in English] PO08 « on a pas d'autres grands crises, hormis ces inondations, quand y a pas d'inondation, c'est le contraire, c'est la sècheresse » "We don't have other catastrophes besides these floods. When there's not a flood, it's the opposite, it's droughts"
72	FV10 « ya pas de cyclone ici … ya pas d'eruption volcanique, ya pas de tremblement de terre » "there are no hurricanes here, there are no volcanic eruptions, there are no earthquakes"
73	FV01 « nous ne sommes pas éduqués à ça. C'est une question d'éducation. Pour moi jeter un sachet ce n'est rien, mais si je connais les conséquences pas sur l'un seulement mais sur toute la nation sur tous que ça doit porter je crois ça peut changer totalement ma vue » "we aren't educated … for me, littering a [plastic water] sachet is a non-issue, but if I knew the consequences not only to myself but to the whole nation … I think that could totally change my perspective"
74	PO08 « naturellement, c'est pas c'est pas suffisant. On sait, on a pensé à des choses, mais ça demande quand même des .. des moyens financiers énormes » "naturally, it's not sufficient, we know, we've thought of things, but that needs enormous financial means"
75	FV13 « nous sommes ici en Afrique bon les moyens sont limités, les maisons sont construites en banco. » "we are in Africa, means are limited, houses are built with mudbrick"
76	FV07 « comme c'est pas encore distribué, les gens ne bâtissent pas avec.. avec des maisons en en en en brique dure, c'est avec du banco. » "since [the zone] is not yet distributed, people don't build houses with concrete, they use mudbrick"
77	FV06 « c'est.. le budget qui.. qui n'était pas aussi ça bon. En tout cas mais ce qui est sure, sans caniveaux eh.. on n'est pas à l'abri » "it's the budget which isn't good enough – but without canals, we are without protection" PO11 « les populations veulent les caniveaux mais il faut avoir l'argent » "the people want canals but you have to have money"
78	PO09 « il ne faut pas laisser … euh les populations euh en saillir les espaces à leur gré et euh pour cela une fois que vous avez mis les outils pour organiser l'occupation de l'espace, il faut

	faire accompagner des moyens de contrôle… C'est surtout là il existe … mais on n'a pas suffisamment les moyens pour le faire » "you can't just let the population take the land as they want … once the land is zoned, there has to be some regulation … [regulation] exists, but there isn't enough means to implement it"
79	PO14 « non seulement les moyens sont insuffisants et ..également ... la gestion budgétaire même cause problème … y a le le personnel aussi qui n'est pas suffisant, ah-personnel et .. en terme d'équipement c'est-à-dire nous ne disposons pas euh .. d'un système d'alerte euh .. automatisé, pour pouvoir nous donner les données-fournir les données en temps réel. » "not only are there insufficient means, but how the budget is managed also causes problems… there are insufficient personnel and we don't have an automatic alert system to give us real-time data"
80	PO15 « une fois que euh .. nous dépassons un peu la situation d'urgence, euh .. les partenaires, les acteurs qui .. qui nous accompagnent ne sont plus tellement motivés » "once the disaster has passed, the partners who accompany us are no longer that motivated [to help]"
81	PO05 « En fonction de ce que nous avons comme ressource nous acqui- nous faisons l'acquisition de de matériel et des vivres et nous stockons. » "according to the resources we have, we acquire and stock materials and dry foods [for disaster relief]"
82	PO07 "when you see that there is a problem in your house, and it's raining go out! … but some people will say … "this is my destiny, if God wants me to die in this house I will stay there … les inondations chez nous ici ça se présent comme une fatalité [here floods are seen as a fatality] … we strongly believe sometimes that there is nothing we can do against that." [participant spoke English and in French]
83	PO10 « les difficultés de la gestion de euh.. des inondations parce que là c'était- tout est urgent, c'est urgent et et prioritaire en même temps » "it's difficult to manage floods because everything is urgent and a priority at the same time" PO11 « Nous sommes dans une incertitude avec ces changements climatiques donc on ne sait pas quel est la quantité d'eau qui va tomber » "we are in an uncertain state with climate change, so we don't know the quantity of rain that will fall"
84	PO05 « tout ce qui est aspect préventif là, ce n'est peut-être pas trop dans nos mœurs » "the whole preventive aspect, it's not really part of our culture" PO18 « Vous savez en Afrique, on n'a pas la notion de la prevision » "you know on Africa, there isn't the idea of planning ahead"
85	PO16 « par exemple le cas des maladies .. qui s- à potentiel épidémique, tel que la méningite, … ou bien le cholera généralement, … on élabore un plan de préparation et de réponse a l'épidémie chaque année » "for example the case of diseases which could reach epidemics, like meningitis or cholera, generally there is a plan of preparation and response to epidemics created each year"
86	FV01 « C'est une catastrophe naturelle, ça veut dit qu'on ne peut pas empêcher.. que la pluie vienne. Mais on peut limiter les dégâts. » "it's a natural catastrophe, which means you can't stop the rain from coming, but you can limit the damages"
87	PO04 « Les gens mettent lala les les inondations dans catastrophes naturelles … pour moi c'est catastrophe hum humanthro … Puisque ce n'est pas l'eau qui … ce sont ces dégâts-là qui qui constituent la catastrophe » "people categorize floods as natural catastrophes … but for me it's an anthropogenic catastrophe … because it's not the rainfall … it's the damages that are the catastrophe"
88	FV01 « Les raisons- et pire ! il faut ajouter la négligence ... un pays qui se respecte doit avoir un programme de management des risques » "reasons [for flooding] … you have to add negligence … a self-respecting country should have a risk management program" PO16 « chez l'africain … la prévoyance la, n'est pas trop … dans notre euh.. façon de .. de faire » « là-bas les politiciens ils sont beaucoup plus sensibles aux évènements qui reviennent un peu et qui ont un impact sur la société » "Africans… planning ahead isn't really what we do" "politicians there [in the west] are much more aware of infrequent events that impact society"
89	FV01 « Ils doivent vraiment être responsable, dirent qu'ils ont un rôle majeur à jouer, créer des systèmes de canalisation, éduquer la population à entretenir ce- ce- ces systèmes de

	canalisation. » “they [the authorities] should be responsible, recognize that they have a major role to play, create canal systems, and educate the population to maintain the canals” FV07 « le gouvernement doit les les utiliser.. utiliser leurs connaissances pour voir quels sont les coins dangereux… Mais il faut faire une loi, il faut les sensibiliser d’abord, les expliquer.. ahaa. Et maintenant les aider à évacuer cette endroit-là parce que c’est pas, c’est pas propice … Mais, les autorités au Burkina s’en foutent de cela.. ils s’en foutent, les gens ne prioru- ça ce n’est pas les leur prio- p- priorité » “they [the authorities] should be responsible, recognize that they have a major role to play, create canal systems, and educate the population to maintain the canals”
90	PO09 « les zones non loties. Mais c’est des occupants illégaux ! » “the non-loti zones … the occupants are illegal!” PO04 « quand je vois ça je suis malade … Ils jettent n’importe, vous faites les caniveaux ils vont remplir ça en même temps » “when I see that I’m sick… they toss it [garbage] anywhere, you make the canals and they’ll fill it at the same time”
91	FV07 « nous on a bâti notre maison là-bas on ne savait pas.. c’est l’ignorance. » “we built our house there [in the river bed], we didn’t know – it’s ignorance” FV01 « nous ne sommes pas éduqués à ça. … Pour moi jeter un sachet ce n’y a rien » “we aren’t educated about that … for me littering a [plastic water] sachet is a non-issue”
92	FV01 « le peu du système de canalisation qui existe est bouché par nous-mêmes nos ordures »
93	PO04 « C’est nous qui avons refusé de faire les les caniveaux, c’est nous qui avons refusé de construire dans les hauteurs … c’est nous qui avons refusé de construire avec du dur »
94	PO01 « Donc il faut faire avec ce que le bailleur nous a donné. Donc il faut dimensionner en fonction. … même dans dans les pays euh.. où ils ont beaucoup d’argent, lorsqu’on fait un ouvrage on y a toujours un calcul économique. » “you have to work with what the funder provides, so you have to design accordingly … but even in countries with a lot of money, when you build a project there is always an economic calculation”
95	PO17 « j’ai une licence en eaux assainissement … il y a le système d’évacuation des eaux pluviales … donc ça c’est un lien directement avec euh les inondations » “I have a bachelor degree in water and sanitation … [in that] there is stormwater management, so there is a direct link to floods”
96	PO07 « et notre intervenu- intervention au début on a tout simplement ahh fait le relief, le secours d’urgence. Mais à un certain moment, on a changé complètement la stratégie, parce qu’on se dit que euh moi j’ai une j’ai une formation assez poussée en en en disaster management … vous avez la catastrophe, après vous avez le secours, mais il faut reconstruire … il faut le- ce que vous appelez en anglais le mitigation » “our intervention at first was simply relief, urgent help. But at one point, we completely changed our strategy because I took a particularly convincing course on disaster management … there is the catastrophe and then the relief, but you have to help reconstruct … you have to have what you call in English mitigation”
97	FV05 « C’est nous même qui cotisons chaque année ... terre pour entasser sur la route, pour essayer de combler les trous … nous-même on.. nous on fait des.. nous nous nous nous on fait un caniveau » “each year we [the neighborhood] contribute to … put mounds of earth in front of the houses, to fill the potholes … we ourselves made a canal“

BIBLIOGRAPHY

Adelekan, I. O. (2010a). Vulnerability of poor urban coastal communities to flooding in Lagos, Nigeria. *Environment and Urbanization*, *22*(2), 433–450. https://doi.org/10.1177/0956247810380141

Adelekan, I. O. (2010b). Vulnerability of poor urban coastal communities to flooding in Lagos, Nigeria. *Environment and Urbanization*, *22*(2), 433–450. https://doi.org/10.1177/0956247810380141

Adelekan, I. O. (2011). Vulnerability assessment of an urban flood in Nigeria: Abeokuta flood 2007. *Natural Hazards*, *56*(1), 215–231. https://doi.org/10.1007/s11069-010-9564-z

Adelekan, I. O. (2016). Flood risk management in the coastal city of Lagos, Nigeria. *Journal of Flood Risk Management*, *9*(3), 255–264. https://doi.org/10.1111/jfr3.12179

Adelekan, I. O., & Asiyanbi, A. P. (2016). Flood risk perception in flood-affected communities in Lagos, Nigeria. *Natural Hazards*, *80*(1), 445–469. https://doi.org/10.1007/s11069-015-1977-2

Adikari, Y., & Yoshitani, J. (2009). *Global Trends in Water-Related Disasters : an insight for policymakers*. UNESCO.

Ahouangan, M., Djaby, B., Ozer, P., Hountondji, Y.-C., Thiry, A., & de Longueville, F. (2014). Adaptation et résilience des populations rurales face aux catastrophes naturelles en Afrique subsaharienne. Cas des inondations de 2010 dans la commune de Zagnanado, Bénin. *Eau, Milieux, Aménagement. Une Recherce Au Service Des Territoires*, 265–278.

Ajibade, I., McBean, G., & Bezner-Kerr, R. (2013). Urban flooding in Lagos, Nigeria: Patterns of vulnerability and resilience among women. *Global Environmental Change*, *23*(6), 1714–1725. https://doi.org/10.1016/j.gloenvcha.2013.08.009

Al-Futaisi, A., & Stedinger, J. (1999). Hydrologic and Economic Uncertainties and Flood-Risk Project Design. *Journal of Water Resources Planning and Management*, *125*(6), 314–324.

Alfieri, L., Burek, P., Feyen, L., & Forzieri, G. (2015). Global warming increases the frequency of river floods in Europe. *Hydrology and Earth System Sciences*, *19*(5), 2247–2260. https://doi.org/10.5194/hess-19-2247-2015

Amoako, C., & Boamah, E. F. (2015). The three-dimensional causes of flooding in Accra, Ghana. *International Journal of Urban Sustainable Development*, *7*(1), 109–129. https://doi.org/10.1080/19463138.2014.984720

Antwi-Agyei, P., Quinn, C. H., Adiku, S. G. K., Codjoe, S. N. A., Dougill, A. J., Lamboll, R., & Dovie, D. B. K. (2017). Perceived stressors of climate vulnerability across scales in the Savannah zone of Ghana: a participatory approach. *Regional Environmental Change*, *17*(1), 213–227. https://doi.org/10.1007/s10113-016-0993-4

Antwi, E. K., Boakye-Danquah, J., Barima Owusu, A., Loh, S. K., Mensah, R., Boafo, Y. A., & Apronti, P. T. (2015). Community vulnerability assessment index for flood prone savannah agro-ecological zone: A case study of Wa West District, Ghana. *Weather and Climate Extremes*, *10*, 56–69. https://doi.org/10.1016/j.wace.2015.10.008

Arnell, N. W., & Gosling, S. N. (2016). The impacts of climate change on river flood risk at the global scale. *Climatic Change*, *134*(3), 387–401. https://doi.org/10.1007/s10584-014-1084-5

Ashley, R., Blanskby, J., Newman, R., Gersonius, B., Poole, A., Lindley, G., … Nowell, R. (2012). Learning and Action Alliances to build capacity for flood resilience. *Journal of Flood Risk Management*, *5*(1), 14–22. https://doi.org/10.1111/j.1753-318X.2011.01108.x

Auerbach, C., & Silverstein, L. B. (2003). *Qualitative data; An introduction to coding and analysis*. NYU Press.

Austin, G., Rizzo, K., Matte, A., & Finnerty, B. (1998). *Ohio River Valley Flood of March 1997*. National Weather Service Assessment.

Ayoade, J. O., & Akintola, F. O. (1980). Public Perception of Flood Hazard in Two Nigerian Cities. *Environment International*, *4*, 277–280.

Babcicky, P., & Seebauer, S. (2016). The Two Faces of Social Capital in Private Flood Mitigation: Opposing Effects on Risk Perception, Self-Efficacy and Coping Capacity. *Journal of Risk Research*. https://doi.org/10.1080/13669877.2016.1147489

Badjana, H. M., Batawila, K., Wala, K., & Akpagana, K. (2012). Evolution Des Paramètres Climatiques Dans La Plaine De L'oti (Nord-Togo) : Analyse Statistique, Perceptions Locales Et Mesures Endogenes D'adaptation. *African Sociological Review*, *15*(2), 77–95.

Di Baldassarre, G., Montanari, A., Lins, H., Koutsoyiannis, D., Brandimarte, L., & Blöschl, G. (2010). Flood fatalities in Africa: From diagnosis to mitigation. *Geophysical Research Letters*, *37*(22), n/a-n/a. https://doi.org/10.1029/2010GL045467

Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Salinas, J. L., & Blöschl, G. (2013). Socio-hydrology: Conceptualising human-flood interactions. *Hydrology and Earth System Sciences*, *17*(8), 3295–3303. https://doi.org/10.5194/hess-17-3295-2013

Bayoko, A., Botny-Capel, A.-E., Djekpe, E. M. K., Ousmane Adamou, P., & Andrianisa, H. (2015). *Etude diagnostique des quatre principaux reseaux de drainage de Ouagadougou : cas du canal de Zogona*. Ouagadougou, Burkina Faso: 2iE.

Beaber, H., & Rostvedt, J. (1965). *Floods of March 1964 Along the Ohio River*. Geological Survey Water-Supply Paper 1840-A.

Bellenger, H., Guilyardi, E., Leloup, J., Lengaigne, M., & Vialard, J. (2014). ENSO representation in climate models: From CMIP3 to CMIP5. *Climate Dynamics*, *42*(7–8), 1999–2018. https://doi.org/10.1007/s00382-013-1783-z

Bempah, S., & Øyhus, A. (2017). The role of social perception in disaster risk reduction: Beliefs, perception, and attitudes regarding flood disasters in communities along the Volta River, Ghana. *International Journal of Disaster Risk Reduction*, *23*(April), 104–108. https://doi.org/10.1016/j.ijdrr.2017.04.009

Berghuijs, W. R., Woods, R. A., Hutton, C. J., & Sivapalan, M. (2016). Dominant flood generating mechanisms across the United States. *Geophysical Research Letters*, *43*(9), 4382–4390. https://doi.org/10.1002/2016GL068070

Birkholz, S., Muro, M., Jeffrey, P., & Smith, H. M. (2014). Rethinking the relationship between flood risk perception and flood management. *Science of the Total Environment*, *478*, 12–20. https://doi.org/10.1016/j.scitotenv.2014.01.061

Bloschl, G., & Montanari, A. (2010). Climate change impacts - throwing the dice? *Hydrological Processes*, *24*, 374–381.

Bracken, C. (2016). *Downscaled CMIP3 and CMIP5 Climate Projections - Addendum: Release of Downscaled CMIP5 Clmate Projections (LOCA) and Comparison with Preceding Information*.

Brakenridge, G. R. (2017). Global Active Archive of Large Flood Events. Retrieved from http://floodobservatory.colorado.edu/Archives/index.html

Braman, L. M., van Aalst, M. K., Mason, S. J., Suarez, P., Ait-Chellouche, Y., & Tall, A. (2013). Climate forecasts in disaster management: Red Cross flood operations in West Africa, 2008. *Disasters*, *37*(1), 144–164. https://doi.org/10.1111/j.1467-7717.2012.01297.x

Breslin, S. (2015). Flooding in the Ohio River Valley: Louisville Man Missing after being swept away by floodwaters. The Weather Channel. Retrieved from https://weather.com/news/news/flooding-midwest-south-latest-news

Brown, C., Ghile, Y., Laverty, M., & Li, K. (2012). Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector. *Water Resources Research*, *48*, W09537. https://doi.org/doi:10.1029/2011WR011212

Brown, C., Weatherly, J., & Mearns, L. (2016). *Decision-Scaling : A Decision Framework for DoD Climate Risk Assessment and Adaptation Planning*.

Bubeck, P., Botzen, W. J. W., & Aerts, J. C. J. H. (2012). A Review of Risk Perceptions and Other Factors that Influence Flood Mitigation Behavior. *Risk Analysis*, *32*(9), 1481–1495. https://doi.org/10.1111/j.1539-6924.2011.01783.x

Bubeck, P., Botzen, W. J. W., Kreibich, H., & Aerts, J. C. J. H. (2013). Detailed insights into the influence of flood-coping appraisals on mitigation behaviour. *Global Environmental Change*, *23*(5), 1327–1338. https://doi.org/10.1016/j.gloenvcha.2013.05.009

Burton, C., & Cutter, S. L. (2008). Levee Failures and Social Vulnerability in the Sacramento-San Joaquin Delta Area, California. *Natural Hazards Review*, *9*(3), 136–149. https://doi.org/10.1061/(ASCE)1527-6988(2008)9:3(136)

Cardona, O. D. (2003). The Need for Rethinking the Concepts of Vulnerability and Risk from a Holistic Perspective : A Necessary Review and Criticism for Effective Risk Management. *Mapping Vulnerability: Disasters, Development and People*, *Chapter 3*, 37–51. https://doi.org/10.4324/9781849771924

Carroll, B., Balogh, R., Morbey, H., & Araoz, G. (2010). Health and social impacts of a flood disaster: responding to needs and implications for practice. *Disasters*, *34*(4), 1045–1063. https://doi.org/10.1111/j.1467-7717.2010.01182.x

Casey, N., & Zarate, A. (2017). Mud Erased a Village in Peru, a Sign of Larger Perils in South America. Retrieved from https://www.nytimes.com/2017/04/06/world/americas/peru-floods-mudslides-south-america.html

Cash, D. W., Clark, W. C., Alcock, F., Dickson, N. M., Eckley, N., Guston, D. H., … Mitchell, R. B. (2003). Knowledge systems for sustainable development. *Proceedings of the National Academy of Sciences of the United States of America*, *100*(14), 8086–8091. https://doi.org/10.1073/pnas.1231332100

Casse, C., Gosset, M., Vischel, T., Quantin, G., & Tanimoun, B. A. (2016). Model-based study of the role of rainfall and land use-land cover in the changes in the occurrence and intensity of Niger red floods in Niamey between 1953 and 2012. *Hydrology and Earth System Sciences*, *20*(7), 2841–2859. https://doi.org/10.5194/hess-20-2841-2016

Codjoe, S. N. A., & Afuduo, S. (2015). Geophysical, socio-demographic characteristics and perception of flood vulnerability in Accra, Ghana. *Natural Hazards*, 787–804. https://doi.org/10.1007/s11069-015-1624-y

Codjoe, S. N. A., Owusu, G., & Burkett, V. (2014). Perception, experience, and indigenous knowledge of climate change and variability: The case of Accra, a sub-Saharan African city. *Regional Environmental Change*, *14*(1), 369–383. https://doi.org/10.1007/s10113-013-0500-0

Coleman, J., & Rogers, J. (2003). Ohio River Valley Winter Moisture Conditions Associated with the Pacific – North American Teleconnection Pattern. *Journal of Climate*, *16*, 969–981.

Collins, M., Knutti, R., Arblaster, J., Dufresne, J.-L., Fichefet, T., Friedlingstein, P., … Wehner, M. (2013). Long-term Climate Change: Projections, Commitments and Irreversibility. In T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, … P. Midgley (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1029–1136). Cambridge, UK: Cambridge University Press. https://doi.org/10.1017/CBO9781107415324.024

Congress. (1939). The Chattanooga Flood Problem. (76th Congress, 1st Session, House Document No. 91). Retrieved from http://docplayer.net/4690177-The-east-tennessee-flood-of-1867.html

De Coning, E. (2013). Optimizing satellite-based precipitation estimation for nowcasting of rainfall and flash flood events over the South African domain. *Remote Sensing*, *5*(11), 5702–5724. https://doi.org/10.3390/rs5115702

Cook, K. H. (1999). Generation of the African easterly jet and its role in determining West African precipitation. *Journal of Climate*, *12*(5), 1165–1184. https://doi.org/10.1175/1520-0442(1999)012<1165:GOTAEJ>2.0.CO;2

Cooley, D. (2013). Extremes in a Changing Climate, *65*. https://doi.org/10.1007/978-94-007-4479-0

Cretat, J., Vizy, E. K., & Cook, K. H. (2014). How well are daily intense rainfall events captured by current climate models over Africa? *Climate Dynamics*, *42*(9–10), 2691–2711. https://doi.org/10.1007/s00382-013-1796-7

Cross, W., & Brooks, H. (1959). *Floods of January-February 1959 in Ohio*. Geological Survey Circular 418.

Cutter, S. L., Boruff, B. J., Shirley, W. L., Cutter, S. L., & Carolina, S. (2003). Social Vulnerability to Environmental Hazards Social Vulnerability to Environmental, *84*(2), 242–261.

Dai, A. (2006). Precipitation characteristics in eighteen coupled climate models. *Journal of Climate*, *19*(18), 4605–4630. https://doi.org/10.1175/JCLI3884.1

Dankers, R., Arnell, N. W., Clark, D. B., Falloon, P. D., Fekete, B. M., Gosling, S. N., … Wisser, D. (2014). First look at changes in flood hazard in the Inter-Sectoral Impact Model Intercomparison Project ensemble. *Proceedings of the National Academy of Sciences*, *111*(9), 3257–3261. https://doi.org/10.1073/pnas.1302078110

Danso, S. Y., & Addo, I. Y. (2017). Coping strategies of households affected by flooding: A case study of Sekondi-Takoradi Metropolis in Ghana. *Urban Water Journal*, *14*(5), 539–545. https://doi.org/10.1080/1573062X.2016.1176223

Dayour, F., Yendaw, E., & Jasaw, G. S. (2014). Local residents ’ perception and adaptation / coping strategies to climate- induced disasters in Bankpama , Wa West District , Ghana. *International Journal of Development and Sustainability*, *3*(12), 2186–2205.

Delgado, J. M., Merz, B., & Apel, H. (2012). A climate-flood link for the lower Mekong River. *Hydrology and Earth System Sciences*, *16*(5), 1533–1541. https://doi.org/10.5194/hess-16-1533-2012

Delgado, J. M., Merz, B., & Apel, H. (2014). Projecting flood hazard under climate change: An alternative approach to model chains. *Natural Hazards and Earth System Sciences*, *14*(6), 1579–1589. https://doi.org/10.5194/nhess-14-1579-2014

Dirmeyer, P. A., Jin, Y., Singh, B., & Yan, X. (2013). Trends in Land–Atmosphere Interactions from CMIP5 Simulations. *Journal of Hydrometeorology*, *14*(3), 829–849. https://doi.org/10.1175/JHM-D-12-0107.1

Dolan, A. H., & Walker, I. J. (2006). Understanding Vulnerability of Coastal Communities to Climate Change Related Risks Linked references are available on JSTOR for this article : Understanding Vulnerability of Coastal Communities to Climate Change Related Risks. *Journal of Coastal Research, Proceedings of the 8th International Coastal Symposium (ICS 2004)*, *III*(39), 1316–1323.

Douglas, I., Alam, K., Maghenda, M., Mcdonnell, Y., Mclean, L., & Campbell, J. (2008). Unjust waters: climate change, flooding and the urban poor in Africa. *Environment and Urbanization*, *20*(1), 187–205. https://doi.org/10.1177/0956247808089156

EA. (2016). *Adapting to Climate Change: Advice for Flood and Coastal Erosion Risk Management Authorities*. Bristol, UK.

Edelen, G., & Miller, J. (1976). *Floods of March-April 1973 in Southeastern United States*. U.S. Geological Survey Professional Paper 998.

Edwards, P. N. (2011). History of climate modeling. *Wiley Interdisciplinary Reviews: Climate Change*, *2*(1), 128–139. https://doi.org/10.1002/wcc.95

EM-DAT. (2017). EM-DAT: The OFDA/CRED International Disaster Database. Retrieved from http://www.cred.be/projects/EM-DAT

England, J. J. F., Cohn, T. A., Faber, B. A., Stedinger, J. R., Thomas Jr., W. O., Veilleux, A. G., … Mason, R. R. (2015). *Guidelines for Determining Flood Flow Frequency - Bulletin 17C*.

EO. (2017). Flooding Along the Ohio River. Retrieved from https://earthobservatory.nasa.gov/IOTD/view.php?id=85539

Fan, Y., & van den Dool, H. (2004). Climate Prediction Center global monthly soil moisture data set at 0.5° resolution for 1948 to present. *Journal of Geophysical Research D: Atmospheres*, *109*(10), 1–8. https://doi.org/10.1029/2003JD004345

FEMA. (2011). Answers to Questions About the NFIP, (March), 70.

FEMA. (2014). Flood. Retrieved March 8, 2018, from https://community.fema.gov/hazard/flood-en_us/

Ferguson, A. P., & Ashley, W. S. (2017). Spatiotemporal analysis of residential flood exposure in the Atlanta, Georgia metropolitan area. *Natural Hazards*, *87*(2), 989–1016. https://doi.org/10.1007/s11069-017-2806-6

Franklin, R. C., King, J. C., Aitken, P. J., & Leggat, P. A. (2014). "Washed away"-assessing community perceptions of flooding and prevention strategies: A North Queensland example. *Natural Hazards*, *73*(3), 1977–1998. https://doi.org/10.1007/s11069-014-1180-x

Fritz, A. (2018). Harvey, Irma and Maria now in the top 5 costliest hurricanes on record, NOAA says. Retrieved from https://www.washingtonpost.com/news/capital-weather-gang/wp/2018/01/30/harvey-irma-and-maria-now-in-the-top-5-costliest-hurricanes-on-record-noaa-says/?utm_term=.b33f2b36e2d7

Fuchs, S., Karagiorgos, K., Kitikidou, K., Maris, F., Paparrizos, S., & Thaler, T. (2017). Flood risk perception and adaptation capacity: A contribution to the socio-hydrology debate. *Hydrology and Earth System Sciences*, *21*(6), 3183–3198. https://doi.org/10.5194/hess-21-3183-2017

Fuentes-Franco, R., Giorgi, F., Coppola, E., & Kucharski, F. (2016). The role of ENSO and PDO in variability of winter precipitation over North America from twenty first century CMIP5 projections. *Climate Dynamics*, *46*(9–10), 3259–3277. https://doi.org/10.1007/s00382-015-2767-y

Galvin, J. F. P. (2010). Two easterly waves in West Africa in summer 2009. *Weather*, *65*(8), 219–227. https://doi.org/10.1002/wea.605

GBF, WB, & UN. (2010). *Inondations du 1er Septembre 2009 au Burkina Faso: Evaluation des dommages, pertes et besoins de construction, de reconstruction et de relevement* (Vol. 56803–BF). Government of Burkina Faso, World Bank, United Nations.

GBF, UNDP, & WB. (2008). *Plan National Multi Risques de Preparation et de Reponse aux Catastrophes: Preparation, Interventions de Premiers Secours, Rehabilitation et Reconstruction*.

GBF, UNDP, & WB. (2014). *Plan National Multi Risques de Préparation et de Réponse aux Catastrophes: Preparation, Interventions de Premiers Secours, Rehabilitation et Reconstruction*. Ouagadougou, Burkina Faso.

German Baltic coast hit by storm surge flooding. (2017). Retrieved from http://www.bbc.com/news/world-europe-38516687

Gershunov, A., & Barnett, T. P. (1998a). ENSO influence on intraseasonal extreme rainfall and temperature frequencies in the contiguous United States: Implications for Long-Range Predictability. *Journal of Climate*, *11*, 3192–3203. https://doi.org/10.1175/1520-0442(1998)011<1575:eioier>2.0.co;2

Gershunov, A., & Barnett, T. P. (1998b). ENSO influence on intraseasonal extreme rainfall and temperature frequencies in the contiguous United States: Observations and model results. *Journal of Climate*, *11*, 3062–3065. https://doi.org/10.1175/1520-0442(1998)011<1575:eioier>2.0.co;2

Gersonius, B. (2012). *The resilience approach to climate adaptation applied for flood risk*. Delft University of Technology and UNESCO-IHE Institute for Water Education.

Gersonius, B., Ashley, R., Pathirana, A., & Zevenbergen, C. (2013). Climate change uncertainty: building flexibility into water and flood risk infrastructure. *Climatic Change*, *116*, 411–423. https://doi.org/10.1007/s10584-012-0494-5

Gettleman, J. (2017). More Than 1,000 Died in South Asia Floods This Summer. Retrieved from https://www.nytimes.com/2017/08/29/world/asia/floods-south-asia-india-bangladesh-nepal-houston.html

Giorgi, F., & Mearns, L. (2002). Calculation of Average, Uncertainty Range, and Reliability of Regional Climate Changes from AOGCM Simulations via the "'Reliability Ensemble Averaging'" (REA) Method. *Journal of Climate*, *15*, 1141–1158. https://doi.org/10.1175/1520-0442(2002)015<1141

Glatfelter, D., & Chin, E. (1988). *Floods of March 1982 in Indiana, Ohio, Michigan, and Illinois*. U.S. Geologcal Survey Professional Paper 1467.

Gleckler, P. J., Taylor, K. E., & Doutriaux, C. (2008). Performance metrics for climate models. *Journal of Geophysical Research Atmospheres*, *113*(6), 1–20. https://doi.org/10.1029/2007JD008972

Gnanglè, C. P., Kakaï, R. G., Assogbadjo, A. E., Vodounnon, S., Afouda, J., & Sokpon, N. (2011). Tendances Climatiques Passees , Modelisation , *8*, 26–41.

Greene, A. M., Robertson, A. W., Smyth, P., & Triglia, S. (2011). Downscaling projections of Indian monsoon rainfall using a non-homogeneous hidden Markov model. *Quarterly Journal of the Royal Meteorological Society*, *137*(655), 347–359. https://doi.org/10.1002/qj.788

Grothmann, T., & Reusswig, F. (2006). People at risk of flooding: Why some residents take precautionary action while others do not. *Natural Hazards*, *38*(1–2), 101–120. https://doi.org/10.1007/s11069-005-8604-6

Guest, G. (2006). How Many Interviews Are Enough?: An Experiment with Data Saturation and Variability. *Field Methods*, *18*(1), 59–82. https://doi.org/10.1177/1525822X05279903

Hallegatte, S., Green, C., Nicholls, R. J., & Corfee-Morlot, J. (2013). Future flood losses in major coastal cities. *Nature Climate Change*, *3*(9), 802–806. https://doi.org/10.1038/nclimate1979

Hangnon, H., de Longueville, F., & Ozer, P. (2015). Précipitations Extrêmes Et Inondations À Ouagadougou : Quand Le Développement Urbain Est Mal Maîtrisé …. In *XXVIIIe Colloque de l'Association Internationale de Climatologie*. Liege.

Hansen, J. W., Mason, S. J., Sun, L., & Tall, A. (2011). Review of seasonal climate forecasting for agriculture in sub-Saharan Africa. *Experimental Agriculture*, *47*(2), 205–240. https://doi.org/10.1017/S0014479710000876

Held, I. M., & Soden, B. J. (2000). Water Vapor Feedback and Global Warming. *Annual Review of Energy and the Environment*, *25*, 441–475.

Helmfrid, S. (2004). *A Profile on Gender Relations: Towards Gender Equality in Burkina Faso*.

Higgins, R. W., Silva, V. B. S., Shi, W., & Larson, J. (2007). Relationships between climate variability and fluctuations in daily precipitation over the United States. *Journal of Climate*, *20*(14), 3561–3579. https://doi.org/10.1175/JCLI4196.1

Hino, M., & Hall, J. W. (2017). Real Options Analysis of Adaptation to Changing Flood Risk: Structural and Nonstructural Measures, *3*(3), 1–12. https://doi.org/10.1061/AJRUA6.0000905.

Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., … Kanae, S. (2013). Global flood risk under climate change. *Nature Climate Change*, *3*(9), 816–821. https://doi.org/10.1038/nclimate1911

Hirabayashi, Y., Kanae, S., Emori, S., Oki, T., & Kimoto, M. (2008). Global projections of changing risks of floods and droughts in a changing climate. *Hydrological Sciences Journal*, *53*(4), 754–772. https://doi.org/10.1623/hysj.53.4.754

Hirschboeck, K. K. (1988). Flood hydroclimatology. *Flood Geomorphology*, 27–49.

Hoedjes, J., Kooiman, A., Maathuis, B., Said, M., Becht, R., Limo, A., … Su, B. (2014). A Conceptual Flash Flood Early Warning System for Africa, Based on Terrestrial Microwave Links and Flash Flood Guidance. *ISPRS International Journal of Geo-Information*, *3*(2), 584–598. https://doi.org/10.3390/ijgi3020584

Hoeting, J. A., Madigan, D., Raftery, A. E., & Volinsky, C. T. (1999). Bayesian Model Averaging: A Tutorial. *Statistical Science, 14*(4), 382–417. https://doi.org/10.2307/2676803

Horel, J. D., & Wallace, J. M. (1981). Planetary-scale phenomena associated with the Southern Oscillation. *Mon. Wea. Rev.* https://doi.org/10.1175/1520-0493(1981)109<0813:PSAPAW>2.0.CO;2

Horton, A., & Jackson, H. (1913). *The Ohio Valley Flood of March-April, 1913*.

Hughes, D. A., Jewitt, G., Mahé, G., Mazvimavi, D., & Stisen, S. (2015). A review of aspects of hydrological sciences research in Africa over the past decade. *Hydrological Sciences Journal*, *60*(11), 1–15. https://doi.org/10.1080/02626667.2015.1072276

HyperRESEARCH. (2015). Researchware, Inc. Retrieved from http://www.researchware.com

IACWD. (1982). *Guidelines for Determining Flod Flow Frequency: Bulletin 17B (revised and corrected)*. Washington D.C.

IFRC. (2009). Emergency Appeal No MDRBF008. International Federation of Red Cross and Red Crescent Societies.

IFRC. (2010). *Emergency Appeal No MDRBF008*. International Federation of Red Cross and Red Crescent Societies.

IFRC. (2011). *Emergency Appeal No MDRBF008*. International Federation of Red Cross and Red Crescent Societies.

IPCC. (2013). Summary for Policymakers. In T. Stocker, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, … P. Midgley (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK: Cambridge University Press. https://doi.org/10.1017/CBO9781107415324.004

Jain, S., & Lall, U. (2001). Floods in a changing climate: Does the past represent the future? *Water Resources Research*, *37*(12), 3193–3205. https://doi.org/10.1029/2001WR000495

Janicot, S., Harzallah, A., Fontaine, B., & Moron, V. (1998). West African Monsoon Dynamics and Eastern Equatorial Atlantic and Pacific SST Anomalies (1970--88). *Journal of Climate*, *11*(8), 1874–1882.

Johnson, F., & Sharma, A. (2009). Measurement of GCM skill in predicting variables relevant for hydroclimatological assessments. *Journal of Climate*, *22*(16), 4373–4382. https://doi.org/10.1175/2009JCLI2681.1

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., … Woollen, J. (1996). The NCEP/NCAR 40-year reanalysis project. *Bulletin of the American Meteorological Society*, *77*(3), 437–471.

Karambiri, H. (2009). *Breve analyse frequentielle de la pluie du 1er septembre 2009 a Ouagadougou (Burkina Faso)*. Ouagadougou: 2iE.

Kellens, W., Terpstra, T., & De Maeyer, P. (2013). Perception and Communication of Flood Risks: A Systematic Review of Empirical Research. *Risk Analysis*, *33*(1), 24–49. https://doi.org/10.1111/j.1539-6924.2012.01844.x

Kemking, C. (2010). *Evaluation des strategies de reponses contre les risques naturels lies aux changements climatiques: Cas de l'inondation de Ouagadougou en septembre 2009 au Burkina Faso*. Institut International d'Ingenierie de l'Eau et de l'Environnement.

Knutti, R., Furrer, R., Tebaldi, C., Cermak, J., & Meehl, G. A. (2010). Challenges in combining projections from multiple climate models. *Journal of Climate*, *23*(10), 2739–2758. https://doi.org/10.1175/2009JCLI3361.1

Koerth, J., Jones, N., Vafeidis, A. T., Dimitrakopoulos, P. G., Melliou, A., Chatzidimitriou, E., & Koukoulas, S. (2013). Household adaptation and intention to adapt to coastal flooding in the Axios - Loudias - Aliakmonas National Park, Greece. *Ocean and Coastal Management*, *82*, 43–50. https://doi.org/10.1016/j.ocecoaman.2013.05.008

Kraus, N. N., & Slovic, P. (1988). Taxonomic Analysis of Perceived Risk: Modeling Individual and Group Perceptions Within Homogeneous Hazard Domains. *Risk Analysis*, *8*, 435–455. https://doi.org/10.1111/j.1539-6924.1988.tb00508.x

Kundzewicz, Z. W., Krysanova, V., Dankers, R., Hirabayashi, Y., Kanae, S., Hattermann, F. F., … Schellnhuber, H. J. (2017). Differences in flood hazard projections in Europe–their causes and consequences for decision making. *Hydrological Sciences Journal*, *62*(1), 1–14. https://doi.org/10.1080/02626667.2016.1241398

Kwon, H.-H., Brown, C., & Lall, U. (2008). Climate informed flood frequency analysis and prediction in Montana using hierarchical Bayesian modeling. *Geophysical Research Letters*, *35*(5), L05404. https://doi.org/10.1029/2007GL032220

Landwehr, J. M., & Slack, J. R. (1992). *Hydro-Climatic Data Network: A U.S. Geological Survey streamflow data set for the United States for the study of climate variations, 1874-1988*. Retrieved from https://pubs.usgs.gov/wri/wri934076/1st_page.html

Lassailly-Jacob, V. (2015). Inondations de 2009 et 2010 au Burkina Faso Gestion, perception et mobilites induites. *Mobilite Humaine et Environnement: Du Global Au Local*, 225–244.

Lee, Y. Y., & Black, R. X. (2013). Boreal winter low-frequency variability in CMIP5 models. *Journal of Geophysical Research Atmospheres*, *118*(13), 6891–6904. https://doi.org/10.1002/jgrd.50493

Leng, G., Tang, Q., Huang, S., Zhang, X., & Cao, J. (2016). Assessments of joint hydrological extreme risks in a warming climate in China. *International Journal of Climatology*, *36*(4), 1632–1642. https://doi.org/10.1002/joc.4447

Lima, C., Lall, U., Troy, T. J., & Devineni, N. (2015). A climate informed model for nonstationary flood risk prediction: Application to Negro River at Manaus, Amazonia. *Journal of Hydrology*, *522*, 594–602. https://doi.org/10.1016/j.jhydrol.2015.01.009

Livneh, B., Rosenberg, E. A., Lin, C., Nijssen, B., Mishra, V., Andreadis, K. M., … Lettenmaier, D. P. (2013). A long-term hydrologically based dataset of land surface fluxes and states for the conterminous United States: Update and extensions. *Journal of Climate*, *26*(23), 9384–9392. https://doi.org/10.1175/JCLI-D-12-00508.1

Llanos, M. (2015, August 26). Will New Orleans' $14.5 Billion Walls Stand Up to the Next Big Storm? Retrieved from https://www.nbcnews.com/storyline/hurricane-katrina-anniversary/new-orleans-14-5-billion-walls-n415816

Lolig, V., Donkoh, S., Obeng, F., Isaac, A., Kodwo, G., Jasaw, G., … Kranjac-berisavljevic, G. (2014). Households' Coping Strategies in Drought and Flood Prone Communi ties in Northern Ghana, *9*(4), 1–11.

López, J., & Francés, F. (2013). Non-stationary flood frequency analysis in continental Spanish rivers, using climate and reservoir indices as external covariates. *Hydrology and Earth System Sciences*, *17*(8), 3189–3203. https://doi.org/10.5194/hess-17-3189-2013

Lott, G., & Myers, V. (1956). *Meteorology of Flood-Producing Storms in the Mississippi River Basin*. Hydrometeorological Report No. 34.

Louisville/Jefferson County Metropolitan Sewer District. (2018a). Flood Protection. Retrieved January 1, 2018, from http://www.louisvillemsd.org/what-we-do/flood-protection

Louisville/Jefferson County Metropolitan Sewer District. (2018b). Upgrade Ohio River Flood Protection. Retrieved January 1, 2018, from http://www.louisvillemsd.org/upgrade-ohio-river-flood-protection

Luke, A., Kaplan, B., Neal, J., Lant, J., Sanders, B., Bates, P., & Alsdorf, D. (2015). Hydraulic modeling of the 2011 New Madrid Floodway activation: a case study on floodway activation controls. *Natural Hazards*, *77*(3), 1863–1887. https://doi.org/10.1007/s11069-015-1680-3

Luke, A., Vrugt, J. A., & Sanders, B. F. (2017). Water Resources Research, 5469–5494. https://doi.org/10.1002/2016WR019676.Received

Lund, J. R. (2002). Floodplain Planning with Risk-Based Optimization. *Journal of Water Resources Planning and Management*, *128*(3), 202–207.

Lund, J. R. (2015). Integrating social and physical sciences in water management. *Water Resources Research*, *51*, 5905–5918. https://doi.org/10.1016/0022-1694(68)90080-2

Maddux, J., & Rogers, R. (1983). Protection motivation and self-efficacy: A revised theory of fear appeals and attitude change. *Journal of Experimental Social Psychology*, *19*, 469–479.

Madsen, H., Lawrence, D., Lang, M., Martinkova, M., & Kjeldsen, T. R. (2014). Review of trend analysis and climate change projections of extreme precipitation and floods in Europe. *Journal of Hydrology*, *519*, 3634–3650.

MAHRH. (2004). Le glissement des isohyetes. Ministere de l'Agriculture de l'Hydraulique et des Ressources Halieutiques.

Maloney, E. D., Camargo, S. J., Chang, E., Colle, B., Fu, R., Geil, K. L., … Zhao, M. (2014). North American climate in CMIP5 experiments: Part III: Assessment of twenty-first-century projections. *Journal of Climate*, *27*(6), 2230–2270. https://doi.org/10.1175/JCLI-D-13-00273.1

Mantua, N., & Hare, S. (2002). The Pacific Decadal Oscillation. *Journal of Oceanography*, *58*, 35–44.

Mathon, V., Laurent, H., & Lebel, T. (2002). Mesoscale Convective System Rainfall in the Sahel. *Journal of Applied Meteorology*, *41*(11), 1081–1092. https://doi.org/10.1175/1520-0450(2002)041<1081:MCSRIT>2.0.CO;2

Mehran, A., Aghakouchack, A., & Phillips, T. J. (2014). Evaluation of CMIP5 continental precipitation simulations relative ot satellite-based gauge-adjusted observations. *Journal of Geophysical Research Atmospheres*, *119*, 1695–1707. https://doi.org/10.1002/2013JD021152

Merz, B., Aerts, J., Arnbjerg-Nielsen, K., Baldi, M., Becker, A., Bichet, A., … Nied, M. (2014). Floods and climate: Emerging perspectives for flood risk assessment and management. *Natural Hazards and Earth System Sciences*, *14*(7), 1921–1942. https://doi.org/10.5194/nhess-14-1921-2014

Merz, B., Hall, J., Disse, M., & Schumann, A. (2010). Fluvial flood risk management in a changing world. *Natural Hazards and Earth System Sciences*, *10*, 509–527.

Merz, B., Kreibich, H., Schwarze, R., & Thieken, A. (2010). Review article "assessment of economic flood damage." *Natural Hazards and Earth System Science*, *10*(8), 1697–1724. https://doi.org/10.5194/nhess-10-1697-2010

Merz, B., & Thieken, A. H. (2005). Separating natural and epistemic uncertainty in flood frequency analysis. *Journal of Hydrology*, *309*(1–4), 114–132. https://doi.org/10.1016/j.jhydrol.2004.11.015

Merz, R., & Blöschl, G. (2003). A process typology of regional floods. *Water Resources Research*, *39*(12), 1–20. https://doi.org/10.1029/2002WR001952

Michel-Kerjan, E., & Kunreuther, H. (2011). Redesigning Flood Insurance. *Science*, *333*. Retrieved from http://doi.wiley.com/10.1111/j.1539-6924.2011.01671.x

Milly, P. C. D., Wetherald, R. T., Dunne, K. A., & Delworth, T. L. (2002). Increasing risk of great floods in a changing climate. *Nature*, *415*(6871), 514–517.

Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., … Krysanova, V. (2015). On Critiques of "Stationarity is Dead: Whither Water Management?" *Water Resources Research*, *51*, 7785–7789. https://doi.org/10.1002/2015WR017408

Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., & Stouffer, R. J. (2008). Stationarity is dead: whither water management? *Science*, *319*(5863), 573–574. https://doi.org/10.1126/science.1151915

Montroy, D. (1997). Linear Relation of Central and Eastern North American Precipitation to Tropical Pacific Sea Surface Temperature Anomalies *. *Journal of Climate*, *10*, 541–558.

Moore, G. (2016). The flood of 1917. Times Free Press. Retrieved from http://www.timesfreepress.com/news/opinion/columns/story/2016/jan/24/moore-flood-1917/345947/

Morss, R. E. (2010). Interactions among Flood Predictions, Decisions, and Outcomes: Synthesis of Three Cases. *Natural Hazards Review*, *11*(AUGUST), 83–96. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000011

Morss, R. E., Wilhelmi, O. V., Downton, M. W., & Gruntfest, E. (2005). Flood Risk, Uncertainty, and Scientific Information for Decision Making: Lessons from an Interdisciplinary Project. *Bulletin of the American Meteorological Society*, *86*(11), 1593–1601. https://doi.org/10.1175/BAMS-86-11-1593

Murphy, J. M., Sexton, D. M. H., Barnett, D. N., Jones, G. S., Webb, M. J., Collins, M., & Stainforth, D. A. (2004). Quantification of modelling uncertainties in a large ensemble of climate change simulations. *Nature*, *430*(7001), 768–772. https://doi.org/10.1038/nature02771

Nakamura, J., Lall, U., Kushnir, Y., Robertson, A. W., & Seager, R. (2013). Dynamical Structure of Extreme Floods in the U.S. Midwest and the United Kingdom. *Journal of Hydrometeorology*, *14*(2), 485–504. https://doi.org/10.1175/JHM-D-12-059.1

NAP. (2013). *Levees and the National Flood Insurance Program: Improving Policies and Practices*. Washington D.C.

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part 1 - a discussion of principles. *Journal of Hydrology*, *10*, 282–290.

Nastev, M., & Todorov, N. (2013). Hazus: A standardized methodology for flood risk assessment in Canada. *Canadian Water Resources Journal*, *38*(3), 223–231.

National Weather Service. (2018a). Hydrologic Information Center - NWS Annual Flood Loss Summary Reports To U.S. Army Corps of Engineers. Retrieved January 1, 2018, from http://www.nws.noaa.gov/hic/summaries/index.shtml

National Weather Service. (2018b). Top Ten Flood Events. Retrieved January 1, 2018, from https://www.weather.gov/lmk/toptenfloodevents

NCAR. (2018). CGD's Climate Analysis Section: Southern Oscillation Index (SOI). Retrieved March 4, 2018, from http://www.cgd.ucar.edu/cas/catalog/climind/soi.html

Niang, D. (2006). *Fonctionnement hydrique de differents placages sableux dans le Sahel Burkinabe*. Ecole Polytechnique Federale de Lausanne.

Ning, L., & Bradley, R. (2014). Winter precipitation variability and corresponding teleconnections over the northeastern United States. *Journal of Geophysical Research: …*, *119*, 7931–7945. https://doi.org/10.1002/2014JD021591.Received

Ning, L., & Bradley, R. S. (2016). NAO and PNA influences on winter temperature and precipitation over the eastern United States in CMIP5 GCMs. *Climate Dynamics*, *46*(3–4), 1257–1276. https://doi.org/10.1007/s00382-015-2643-9

Nka, B. N., Oudin, L., Karambiri, H., Paturel, J. E., & Ribstein, P. (2015). Trends in floods in West Africa: Analysis based on 11 catchments in the region. *Hydrology and Earth System Sciences*, *19*(11), 4707–4719. https://doi.org/10.5194/hess-19-4707-2015

NOAA. (2012). Pacific/North American (PNA). NOAA National Weather Service Climate Prediction Center. Retrieved from http://www.cpc.ncep.noaa.gov/data/teledoc/pna.shtml

NOAA. (2015). Cold & Warm Episodes by Season. NOAA Climate Prediction Center. Retrieved from http://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php

NOAA. (2017). Nino3. NOAA Climate Prediction Center. Retrieved from https://www.esrl.noaa.gov/psd/data/correlation/nina3.data

NRC. (2000). *Risk analysis and uncertainty in flood damage reduction studies*. National Academies Press.

NWS. (2017). Flooding in Kentucky. Retrieved from http://www.floodsafety.noaa.gov/states/ky-flood.shtml

NWS. (2017). The Flood of March 1997. Louisville KY Weather Forecast Office The National Weather Service. Retrieved from http://www.weather.gov/lmk/flood97

NWS. (2017). The Great Flood of 1937. Louisville KY Weather Forecast Office The National Weather Service. Retrieved from http://www.weather.gov/lmk/flood_37

Nyong, A., Adesina, F., & Osman Elasha, B. (2007). The value of indigenous knowledge in climate change mitigation and adaptation strategies in the African Sahel. *Mitigation and Adaptation Strategies for Global Change*, *12*(5), 787–797. https://doi.org/10.1007/s11027-007-9099-0

O'Gorman, P. A., & Schneider, T. (2009). The physical basis for increases in precipitation extremes in simulations of 21st-century climate change. *Proceedings of the National Academy of Sciences*, *106*(35), 14773–14777. https://doi.org/10.1073/pnas.0907610106

OCHA-ROWA. (2009). *Burkina Faso 2009 Flood* (Vol. 1–11). United Nation Office for the Coordination of Humanitarian Affairs.

Odemerho, F. O. (2014). Building climate change resilience through bottom-up adaptation to flood risk in Warri, Nigeria. *Environment and Urbanization*, *27*(1), 139–160. https://doi.org/10.1177/0956247814558194

Ologunorisa, T. E., & Adeyemo, A. (2005). Public perception of flood hazard in the Niger Delta, Nigeria. *The Environmentalist*, *25*(1991), 39–45. https://doi.org/10.1007/s10669-005-3095-2

Oriola, E. O. (1994). Strategies for combating urban flooding in a developing nation: A case study from Ondo, Nigeria. *Environmentalist*, *14*(1), 57–62.

Oruonye, E. D. (2013). An Assessment of Flood Risk Perception and Response in Jalingo Metropolis, Taraba State, Nigeria. *Hydrology for Disaster Management*, *3*(4), 113–117.

Osment, T. (2008). Floods of 1916 and 1940. The Digital Heritage Project. Retrieved from https://digitalheritage.org/2010/08/floods-of-1916-and-1940/

Ouarda, T. B. M. J., & El-Adlouni, S. (2011). Bayesian nonstationary frequency analysis of hydrological variables. *Journal of the American Water Resources Association*, *47*(3), 496–505. https://doi.org/10.1111/j.1752-1688.2011.00544.x

Ouedraogo, A., Constant, E., Da, D., & Ouoba, P. (2017). Perception locale de l ’ évolution du milieu à Oula au Nord du Burkina Faso Local perception of the evolution of the environment in Oula in the north of Burkina Faso, *11*(February), 144–156.

Ouedraogo, M., & Ripama, T. (2009). Recensement General de la Population et de l’habitation (RGPH) de 2006, 1–180.

Oyerinde, G. T., Hountondji, F. C. C., Wisser, D., Diekkrüger, B., Lawin, A. E., Odofin, A. J., & Afouda, A. (2015). Hydro-climatic changes in the Niger basin and consistency of local perceptions. *Regional Environmental Change*, *15*(8), 1627–1637. https://doi.org/10.1007/s10113-014-0716-7

Perch-Nielsen, S. L., Bättig, M. B., & Imboden, D. (2008). Exploring the link between climate change and migration. *Climatic Change*, *91*(3–4), 375–393. https://doi.org/10.1007/s10584-008-9416-y

Pielke, R. A. J., & Downton, M. W. (2000). Precipitation and damaging floods: Trends in the United States, 1932-97. *Journal of Climate*, *13*(20), 3625–3637.

Pierce, D. W., Barnett, T. P., Santer, B. D., & Gleckler, P. J. (2009). Selecting global climate models for regional climate change studies. *Proceedings of the National Academy of Sciences*, *106*(21), 8441–8446. https://doi.org/10.1073/pnas.0900094106

Pierce, D. W., Cayan, D. R., Maurer, E. P., Abatzoglou, J. T., & Hegewisch, K. C. (2015). Improved Bias Correction Techniques for Hydrological Simulations of Climate Change*. *Journal of Hydrometeorology*, *16*(6), 2421–2442. https://doi.org/10.1175/JHM-D-14-0236.1

Pierce, D. W., Cayan, D. R., & Thrasher, B. L. (2014). Statistical Downscaling Using Localized Constructed Analogs (LOCA)*. *Journal of Hydrometeorology*, *15*(6), 2558–2585. https://doi.org/10.1175/JHM-D-14-0082.1

Plummer, M. (2016). rjags: Bayesian Graphical Models using MCMC. R package version 4-6. Retrieved from https://cran.r-project.org/package=rjags

Poff, N. L., Brown, C., Grantham, T. E., Matthews, J. H., Palmer, M. A., Spence, C. M., … Baeza, A. (2015). Sustainable water management under future uncertainty with eco-engineering decision scaling. *Nature Climate Change*, (September). https://doi.org/10.1038/nclimate2765

Polade, S. D., Gershunov, A., Cayan, D. R., Dettinger, M. D., & Pierce, D. W. (2013). Natural climate variability and teleconnections to precipitation over the Pacific-North American region in CMIP3 and CMIP5 models. *Geophysical Research Letters*, *40*(10), 2296–2301. https://doi.org/10.1002/grl.50491

Poussin, J. K., Botzen, W. J. W., & Aerts, J. C. J. H. (2014). Factors of influence on flood damage mitigation behaviour by households. *Environmental Science and Policy*, *40*, 69–77. https://doi.org/10.1016/j.envsci.2014.01.013

Qi, W. (2017). A non-stationary cost-benefit analysis approach for extreme flood estimation to explore the nexus of “Risk, Cost and Non-stationarity.” *Journal of Hydrology*, *554*, 128–136. https://doi.org/10.1016/j.jhydrol.2017.09.009

Qi, W., & Liu, J. (2018). A non-stationary cost-benefit based bivariate extreme flood estimation approach. *Journal of Hydrology*, *557*, 589–599. https://doi.org/10.1016/j.jhydrol.2017.12.045

Raftery, A., Gneiting, T., Balabdaoi, F., & Polakowski, M. (2005). Using Bayesian Model Averaging to Calibrate Forecast Ensembles. *Monthly Weather Review*, 1155–1174.

Rayner, N. A. (2003). Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *Journal of Geophysical Research*, *108*(D14), 4407. https://doi.org/10.1029/2002JD002670

Razavi, S., & Gupta, H. V. (2015). What do we mean by sensitivity analysis? The need for comprehensive characterization of “‘global’” sensitivity in Earth and Environmental systems models. *Water Resources Research*, *51*(5), 3070–3092. https://doi.org/10.1002/2014WR016527.Received

Rehan, B. M., & Hall, J. W. (2016). Uncertainty and sensitivity analysis of flood risk management decisions based on stationary and nonstationary model choices, *20003*. https://doi.org/10.1051/e3sconf/20160720003

Remo, J. W. F., Pinter, N., & Mahgoub, M. (2016). Assessing Illinois’s flood vulnerability using Hazus-MH. *Natural Hazards*, *81*(1), 265–287. https://doi.org/10.1007/s11069-015-2077-z

Remo, J. W. F., Carlson, M., & Pinter, N. (2012). Hydraulic and flood-loss modeling of levee, floodplain, and river management strategies, Middle Mississippi River, USA. *Natural Hazards*, *61*(2), 551–575. https://doi.org/10.1007/s11069-011-9938-x

Renard, B., & Lall, U. (2014). Regional frequency analysis conditioned on large-scale atmospheric or oceanic fields. *Water Resources Research*, *50*, 9536–9554. https://doi.org/10.1002/ 2014WR016277

Reynaud, A., Aubert, C., & Nguyen, M.-H. (2013). Living with Floods: Protective Behaviours and Risk Perception of Vietnamese Households. *The Geneva Papers on Risk and Insurance Issues and Practice*, *38*(3), 547–579. https://doi.org/10.1057/gpp.2013.16

Ritchie, J., & Spencer, L. (2002). Qualitative Data Analysis for Applied Policy Research. In *The qualitative researcher’s companion* (pp. 305–329).

Robertson, A. W., Kushnir, Y., Lall, U., & Nakamura, J. (2015). Weather and Climatic Drivers of Extreme Flooding Events over the Midwest of the United States. *Extreme Events: Observations, Modeling, and Economics*, 113–124. https://doi.org/10.1002/9781119157052.ch9

Rocheleau, D., Thomas-Slayer, B., & Wangari, E. (1996). *Feminist Political Econlogy: Global Issues and Local Experiences*. New York, NY: Routledge.

Rocheta, E., Sugiyanto, M., Johnson, F., Evans, J., & Sharma, A. (2014). How well do GCMs represent low-frequency rainfall variability? *Water Resources Research*, 2–31. https://doi.org/10.1002/acr.22212

Rogers, J., & Coleman, J. (2003). Interactions between the Atlantic Multidecadal Oscillation, El Niño/La Niña, and the PNA in winter Mississippi Valley stream flow. *Geophysical Research Letters*, *30*(10), n/a-n/a. https://doi.org/10.1029/2003GL017216

Rogers, R. (1975). A protection motivation theory of fear appeals and attitude change. *The Journal of Psychology*, *91*, 93–114.

Rogers, R., & Prentice-Dunn, S. (1997). Protection Motivation Theory. In D. Gochman (Ed.), *Handbook of health behavior research* (pp. 113–132). New York: Plenum Press.

Roller, C. D., Qian, J. H., Agel, L., Barlow, M., & Moron, V. (2016). Winter weather regimes in the northeast United States. *Journal of Climate*, *29*(8), 2963–2980. https://doi.org/10.1175/JCLI-D-15-0274.1

Rosner, A., Vogel, R., & Kirshen, P. (2014). A risk-based approach to flood management decisions in a nonstationary world. *Water Resources Research*, 1–15. https://doi.org/10.1002/2013WR014561.Received

Rostvedt, J. O. (1968). *Summary of Floods in the United States During 1963*. Geological Survey Water-Supply Paper 1830-B.

Rostvedt, J. O. (1970a). *Summary of Floods in the United States During 1965*. Geological Survey Water-Supply Paper 1850-E.

Rostvedt, J. O. (1970b). *Summary of Floods in the United States During 1966*. Geological Survey Water-Supply Paper 1870-D.

Rostvedt, J. O. (1972). *Summary of Floods in the United States During 1967*. Geological Survey Water-Supply Paper 1880-C.

Roudier, P., Andersson, J. C. M., Donnelly, C., Feyen, L., Greuell, W., & Ludwig, F. (2016). Projections of future floods and hydrological droughts in Europe under a +2°C global warming. *Climatic Change*, *135*(2), 341–355. https://doi.org/10.1007/s10584-015-1570-4

Roy, E. (2017). New Zealand towns hit by “once in 500-year flood” as storm system sweeps in. Retrieved from https://www.theguardian.com/world/2017/apr/06/new-zealand-storm-ex-cyclone-debbie-towns-hit-once-in-500-year-flood

Ruin, I., Lutoff, C., Boudevillain, B., Creutin, J.-D., Anquetin, S., Rojo, M. B., … Vannier, O. (2014). Social and Hydrological Responses to Extreme Precipitations: An Interdisciplinary Strategy for Postflood Investigation. *Weather, Climate, and Society*, *6*(1), 135–153. https://doi.org/10.1175/WCAS-D-13-00009.1

Salas, J., Rajagopalan, B., Saito, L., & Brown, C. (2012). Special Section on Climate Change and Water Resources: Climate Nonstationarity and Water Resources Management. *Journal of Water Resources Planning and Management*, *138*(5), 385–388. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000279

Salas, J., & Obeysekera, J. (2014). Revisiting the Concepts of Return Period and Risk for Nonstationary Hydrologic Extreme Events. *Journal of Hydrologic Engineering*, *19*(3), 554–568.

Sankarasubramanian, A., & Lall, U. (2003). Flood quantiles in a changing climate: Seasonal forecasts and causal relations. *Water Resources Research*, *39*(5), 1–12. https://doi.org/10.1029/2002WR001593

Scawthorn, C., Flores, P., Blais, N., Seligson, H., Tate, E., Chang, S., … Lawrence, M. (2006a). HAZUS-MH Flood Loss Estimation Methodology. I: Overview and Flood Hazard Characterization. *Natural Hazards Review*, *7*(2), 72–81. https://doi.org/10.1061/(ASCE)1527-6988(2006)7:2(72)

Scawthorn, C., Flores, P., Blais, N., Seligson, H., Tate, E., Chang, S., … Lawrence, M. (2006b). HAZUS-MH Flood Loss Estimation Methodology. II. Damage and Loss Assessment. *Natural Hazards Review*, *7*(2), 72–81. https://doi.org/10.1061/(ASCE)1527-6988(2006)7:2(72)

Schelfaut, K., Pannemans, B., van der Craats, I., Krywkow, J., Mysiak, J., & Cools, J. (2011). Bringing flood resilience into practice: The FREEMAN project. *Environmental Science and Policy*, *14*(7), 825–833. https://doi.org/10.1016/j.envsci.2011.02.009

Schlef, K. E., Steinschneider, S., & Brown, C. M. (2018). Spatiotemporal Impacts of Climate and Demand on Water Supply in the Apalachicola-Chattahoochee-Flint Basin. *Journal of Water Resources Planning and Management*, *144*(2010), 1–12. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000865.

Schwarz, F. (1961). *Meteorology of flood-producing storms in the Ohio River Basin (No. 38)*. US Department of Commerce, Weather Bureau.

Schwarzer, R., & Fuchs, R. (1996). Self-efficacy and health behaviours. In M. Conner & P. Norman (Eds.), *Predicting health behaviour: Research and practice with social cognition models* (pp. 163–196). Buckingham: Open University Press.

Seidou, O., Ramsay, A., & Nistor, I. (2012). Climate change impacts on extreme floods I: Combining imperfect deterministic simulations and non-stationary frequency analysis. *Natural Hazards*, *61*(2), 647–659. https://doi.org/10.1007/s11069-011-0052-x

Service Assessment Team. (2010). *Record Floods of Greater Nashville: Including Flooding in Middle Tennessee and Western Kentucky, May 1-4, 2010*.

Shang, H., Yan, J., & Zhang, X. (2011). El Nino-Southern Oscillation influence on winter maximum daily precipitation in California in a spatial model. *Water Resources Research*, *47*(11), 1–9. https://doi.org/10.1029/2011WR010415

Sheffield, J., Barrett, A. P., Colle, B., Fernando, D. N., Fu, R., Geil, K. L., … Yin, L. (2013). North American Climate in CMIP5 experiments. Part I: Evaluation of historical simulations of continental and regional climatology. *Journal of Climate*, *26*(23), 9209–9245. https://doi.org/10.1175/JCLI-D-12-00592.1

Sierra Leone floods kill hundreds as mudslides bury houses. (2017). Retrieved from http://www.bbc.com/news/world-africa-40926187

Sighomnou, D., Descroix, L., Genthon, P., Mahé, G., Moussa, I. B., Gautier, E., … Coulibaly, B. (2013). La crue de 2012 à Niamey: un paroxysme du paradoxe du Sahel? *Science et Changements planétaires/Sécheresse*, *24*(1), 3–13.

Slovic, P. (1987). Perception of risk. *Science*, *236*(4799), 280–285. https://doi.org/10.1126/science.3563507

Slovic, P., Fischoff, B., & Lichtenstein, S. (1982). Why Study Risk Perception? *Risk Analysis*, *2*(2), 83–94.

Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global Environmental Change*, *16*(3), 282–292. https://doi.org/10.1016/j.gloenvcha.2006.03.008

Song, X., Zhang, J., Zhan, C., Xuan, Y., Ye, M., & Xu, C. (2015). Global sensitivity analysis in hydrological modeling: Review of concepts, methods, theoretical framework, and applications. *Journal of Hydrology*, *523*(225), 739–757. https://doi.org/10.1016/j.jhydrol.2015.02.013

Spence, C. M., & Brown, C. M. (2016). Nonstationary decision model for flood risk decision scaling. *Water Resources Research*, *52*(11), 8650–8667. https://doi.org/10.1002/2016WR018981

Spiegelhalter, D. J., Best, N., Carlin, B. P., & Linde, A. (2002). Bayesian Measures of Model Complexity and Fit. *Journal of the Royal Statistical Society. Series B*, *64*(4), 583–639.

State of Pennsylvania. (2013). *Pennsylvania 2013 Standard State All-Hazard Mitigation Plan*.

Steinschneider, S., McCrary, R., Wi, S., Mulligan, K., Mearns, L. O., & Brown, C. (2015). Expanded Decision-Scaling Framework to Select Robust Long-Term Water-System Plans under Hydroclimatic Uncertainties. *Journal of Water Resources Planning and Management*, *141*(11). https://doi.org/10.1061/(ASCE)WR.1943-5452.0000536.

Steinschneider, S., & Lall, U. (2015). A hierarchical Bayesian regional model for nonstationary precipitation extremes in Northern California conditioned on tropical moisture exports. *Water Resources Research*, *51*, 9127–9140. https://doi.org/10.1002/2014WR016259

Stocker, T., Dahe, Q., Plattner, G.-K., Tignor, M., & Midgley, P. (2010). *IPCC Expert Meeting on Assessing and Combining Multi Model Climate Projections - Meeting Report*. *National Center for …*. Retrieved from https://www.ipcc-wg1.unibe.ch/publications/supportingmaterial/IPCC_EM_MultiModelEvaluation_MeetingReport.pdf

Sun, X., Thyer, M., Renard, B., & Lang, M. (2014). A general regional frequency analysis framework for quantifying local-scale climate effects: A case study of ENSO effects on Southeast Queensland rainfall. *Journal of Hydrology*, *512*, 53–68. https://doi.org/10.1016/j.jhydrol.2014.02.025

Swenson, B. (1937). Rivers and floods. *Monthly Weather Review*, 71–77.

Tall, A., Mason, S. J., van Aalst, M., Suarez, P., Ait-Chellouche, Y., Diallo, A. A., & Braman, L. (2012). Using seasonal climate forecasts to guide disaster management: the red cross experience during the 2008 West Africa floods. *International Journal of Geophysics*, *2012*.

Tarhule, A. (2005). Damaging rainfall and flooding: The other Sahel hazards. *Climatic Change*, *72*(3), 355–377. https://doi.org/10.1007/s10584-005-6792-4

Taschetto, A. S., Gupta, A. Sen, Jourdain, N. C., Santoso, A., Ummenhofer, C. C., & England, M. H. (2014). Cold tongue and warm pool ENSO Events in CMIP5: Mean state and future projections. *Journal of Climate*, *27*(8), 2861–2885. https://doi.org/10.1175/JCLI-D-13-00437.1

Tate, E., Muñoz, C., & Suchan, J. (2015). Uncertainty and Sensitivity Analysis of the HAZUS-MH Flood Model. *Natural Hazards Review*, *16*(3), 4014030. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000167

Tate, E., Strong, A., Kraus, T., & Xiong, H. (2016). Flood recovery and property acquisition in Cedar Rapids, Iowa. *Natural Hazards*, *80*(3), 2055–2079. https://doi.org/10.1007/s11069-015-2060-8

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, *93*(4), 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1

Teka, O., & Vogt, J. (2010). Social perception of natural risks by local residents in developing countries-The example of the coastal area of Benin. *Social Science Journal*, *47*(1), 215–224. https://doi.org/10.1016/j.soscij.2009.07.005

Tramblay, Y., Amoussou, E., Dorigo, W., & Mahé, G. (2014). Flood risk under future climate in West Africa : linking extreme value models and flood generating processes, *16*, 5736.

Trenberth, K. E. (1997). The Definition of El Nino. *Bulletin of the American Meteorological Society*, *78*(12), 2771–2777. https://doi.org/10.1175/1520-0477(1997)078<2771:TDOENO>2.0.CO;2

Tschakert, P., Sagoe, R., Ofori-Darko, G., & Codjoe, S. N. (2010). Floods in the Sahel: An analysis of anomalies, memory, and anticipatory learning. *Climatic Change*, *103*(3), 471–502. https://doi.org/10.1007/s10584-009-9776-y

TVA. (1961). Flood on Piney River, November 18-19, 1957, in vicinity of Spring City, Tennessee. Tennessee Valley Authority, Division of Water Control Planning. Retrieved from https://hdl.handle.net/2027/coo.31924005012921

UN. (2017a). Methodology: Standard country or area codes for statistical use (M49). Retrieved January 1, 2017, from https://unstats.un.org/unsd/methodology/m49/

UN. (2017b). UNdata: Burkina Faso. Retrieved January 1, 2017, from http://data.un.org/CountryProfile.aspx?crName=burkina faso

UNDP. (2015). *Human Development Report 2015: Work for Human Development*. UNDP.

UNDP. (2017). Strengthening Climate Information and Early Warning Systems in Burkina Faso. Retrieved January 1, 2017, from http://adaptation-undp.org/projects/ldcf-ews-burkina-faso

USACE. (2018). National Levee Database. Retrieved from http://nld.usace.army.mil/egis/f?p=471:1:0::NO

US Census Bureau. (2018). QuickFacts Louisville/Jefferson County (balance), Kentucky. Retrieved January 1, 2018, from https://www.census.gov/quickfacts/fact/table/louisvillejeffersoncountybalancekentucky/PST045216

USGS. (1961). *Floods on the Kokosing River, Dry Creek and Center Run, at Mount Vernon, Ohio in 1959,1961*. USGS Hydrologic Atlas 40.

USGS. (1964). *Floods of January-February 1957 in Southeastern Kentucky and Adjacent Areas*. US Geological Survey Water-Supply Paper 1652-A.

Villarini, G., Smith, J. A., Serinaldi, F., Bales, J., Bates, P. D., & Krajewski, W. F. (2009). Flood frequency analysis for nonstationary annual peak records in an urban drainage basin. *Advances in Water Resources*, *32*(8), 1255–1266. https://doi.org/10.1016/j.advwatres.2009.05.003

Villarini, G., Smith, J. A., Vitolo, R., & Stephenson, D. B. (2013). On the temporal clustering of US floods and its relationship to climate teleconnection patterns. *International Journal of Climatology*, *33*(3), 629–640. https://doi.org/10.1002/joc.3458

Vogel, R. M., Yaindl, C., & Walter, M. (2011). Nonstationarity: Flood magnification and recurrence reduction factors in the united states. *Journal of the American Water Resources Association*, *47*(3), 464–474. https://doi.org/10.1111/j.1752-1688.2011.00541.x

Van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., … Lamarque, J.-F. (2011). The representative concentration pathways: an overview. *Climatic Change*, *109*, 5–31.

Wallace, J. M., & Gutzler, D. S. (1981). Teleconnections in the Geopotential Height Field during the Northern Hemisphere Winter. *Monthly Weather Review*, *109*(4), 784–812.

WB. (2017). Burkina Faso Overview. Retrieved January 1, 2017, from http://www.worldbank.org/en/country/burkinafaso/overview

Weigel, A. P., Knutti, R., Liniger, M. A., & Appenzeller, C. (2010). Risks of model weighting in multimodel climate projections. *Journal of Climate*, *23*(15), 4175–4191. https://doi.org/10.1175/2010JCLI3594.1

Whateley, S., Walker, J. D., & Brown, C. (2015). A web-based screening model for climate risk to water supply systems in the northeastern United States. *Environmental Modelling & Software*, *73*(November), 64–75. https://doi.org/10.1016/j.envsoft.2015.08.001

White, G. F. (1945). Human Adjustment to Floods: A Geographical Approach to the Flood Problem in the United States. Retrieved from http://www.boulderfloodplain.com/Human_Adj_Floods-GeorgeWhite.pdf

White, G. F., Kates, R. W., & Burton, I. (2001). Knowing better and losing even more: The use of knowledge in hazards management. *Environmental Hazards*, *3*(3–4), 81–92. https://doi.org/10.1016/S1464-2867(01)00021-3

Winsemius, H. C., Aerts, J. C. J. H., van Beek, L. P. H., Bierkens, M. F. P., Bouwman, A., Jongman, B., … Ward, P. J. (2016). Global drivers of future river flood risk. *Nature Climate Change*, *6*(4), 381–385. https://doi.org/10.1038/nclimate2893

Woodward, M., Kapelan, Z., & Gouldby, B. (2014). Adaptive Flood Risk Management Under Climate Change Uncertainty Using Real Options and Optimization. *Risk Analysis*, *34*(1), 75–92. https://doi.org/10.1111/risa.12088

Wuebbles, D., Meehl, G., Hayhoe, K., Karl, T. R., Kunkel, K., Santer, B., … Sun, L. (2014). CMIP5 climate model analyses: Climate extremes in the United States. *Bulletin of the American Meteorological Society*, *95*(4), 571–583. https://doi.org/10.1175/BAMS-D-12-00172.1

Yankson, W. K. P., Owusu, A. B., Owusu, G., Boakye-Danquah, J., & Tetteh, J. D. (2017). Assessment of coastal communities' vulnerability to floods using indicator-based approach: a case study of Greater Accra Metropolitan Area, Ghana. *Natural Hazards*, 1–29. https://doi.org/10.1007/s11069-017-2985-1

Yeh, S.-W., Kug, J.-S., Dewitte, B., Kwon, M.-H., Kirtman, B. P., & Jin, F.-F. (2009). El Niño in a changing climate. *Nature*, *461*(7263), 511–514. https://doi.org/10.1038/nature08316

Yim, B. Y., Kwon, M. H., Min, H. S., & Kug, J. S. (2015). Pacific Decadal Oscillation and its relation to the extratropical atmospheric variation in CMIP5. *Climate Dynamics*, *44*(5–6), 1521–1540. https://doi.org/10.1007/s00382-014-2349-4

Yu-Sung, S., & Yajima, M. (2015). R2jags: Using R to Run "JAGS". R package version 0.5-7. Retrieved from https://cran.r-project.org/packages=R2jags

Yu, B., & Zwiers, F. W. (2007). The impact of combined ENSO and PDO on the PNA climate: A 1,000-year climate modeling study. *Climate Dynamics*, *29*(7–8), 837–851. https://doi.org/10.1007/s00382-007-0267-4

Yuan, S., & Quiring, S. M. (2017). Evaluation of soil moisture in CMIP5 simulations over the contiguous United States using in situ and satellite observations. *Hydrology and Earth System Sciences*, *21*(4), 2203–2218. https://doi.org/10.5194/hess-21-2203-2017

Zaalberg, R., Midden, C., Meijnders, A., & McCalley, T. (2009). Prevention, adaptation, and threat denial: Flooding experiences in the Netherlands. *Risk Analysis*, *29*(12), 1759–1778. https://doi.org/10.1111/j.1539-6924.2009.01316.x

Zare, A., Illou, M., Fossi, S., Bio, T. M., Mahe, G. I. L., Paturel, J., & Barbier, B. (2013). Perception of hydrological changes and adaptation strategies in the Inner Niger Delta in Mali. *Proceedings of HP1, IAHS-IAPSO-IASPEI Assembly*, *358*(July), 129–130.

Zhang, Q., Gu, X., Singh, V. P., Xiao, M., & Chen, X. (2015). Evaluation of flood frequency under non-stationarity resulting from climate indices and reservoir indices in the East River basin, China. *Journal of Hydrology*, *527*(August), 565–575. https://doi.org/10.1016/j.jhydrol.2015.05.029

Zhang, X., Wang, J., Zwiers, F. W., & Groisman, P. Y. (2010). The influence of large-scale climate variability on winter maximum daily precipitation over North America. *Journal of Climate*, *23*(11), 2902–2915. https://doi.org/10.1175/2010JCLI3249.1

Zhu, T., Lund, J. R., Jenkins, M. W., Marques, G. F., & Ritzema, R. S. (2007). Climate change, urbanization, and optimal long-term floodplain protection. *Water Resources Research*, *43*(2), 1–11. https://doi.org/10.1029/2004WR003516