THE RISING RISK OF RISING WATER: EXAMINING RISK PERCEPTION AND OTHER PREDICTORS OF FLOOD MITIGATION BEHAVIOR

By

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ABSTRACT

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As a result of heat-trapping pollution from human activities, rising sea levels and increasing precipitation could within three decades push chronic floods on land currently home to more than 300 million people. Water levels in the Great Lakes, heavy rainfall, and flooding have all substantially increased in Michigan, causing erosion, water quality decline, and negative impacts on society. Taking action to mitigate flooding at all scales is essential to ensure social and economic sustainability. This study explores predictor variables of flood mitigation behaviors among Michigan residents in a proposed theoretical framework that synthesizes three behavioral theories: Theory of Planned Behavior, Values-Beliefs-Norms, and Protection Motivation Theory. This study also includes empirically measured actual flood risk in the theoretical framework, which is often left out in behavioral studies. Actual flood risk alone was found to weakly align with perceived flood risk and was a significant predictor of flood mitigation behavior during regression. However, when other variables were included, actual flood risk became an insignificant part of the model. Instead, subjective norms, perceived flood risk, self-efficacy, education level, having a flood-related home inspection, and having a basement emerged as significant predictors of flood mitigation behaviors. These findings lay the groundwork for future research and have implications for planning around flood mitigation and policy within and beyond the Midwest region.

To my family, my friends, and my advisor Dr. Julie Libarkin.

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This work would not have been made possible without the support of multiple people, including members of my thesis committee, the Geocognition Research Lab (GRL), the Graduate Student Organization (GSO), the MSU Outdoors Club, and my family.

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My gratitude goes to my other two thesis committee members. I am a better scholar because of them. Dr. Adam Zwickle guides me in critically thinking about my results and their meaning; his passion for risk perception and communication influences my appreciation for human dimensions of natural hazards. Dr. Robert Drost never fails to enlighten me about natural hazards and provide advice on my research planning and collaboration, as well as sharing potential career options and ideas with me.

This thesis would not exist without the support of and collaboration with my colleagues and external members of the GRL. The GRL has been a safe place and second home for me to not only work, but to share experiences with fellow colleagues and in turn, grow as a scholar and a human-being. I would like to specifically mention Cailtin Kirby and Paty Jaimes - two Ph.D. students in the GRL - for making the GRL a welcoming and safe place for me to enter into and learn by their example. Both have taught me how to be an effective and empathetic leader who enriches the community and does what is right above all else. They have also taught me to be a thoughtful, equitable, and inclusive researcher. Other graduate and undergraduate students, professors, and postdocs from other labs and departments have enriched the GRL further by being involved in our weekly lab meetings, making it a multi-disciplinary space. Julie, Caitlin, and Paty made this safe and interdisciplinary lab space possible and I deeply appreciate the eye-opening discussions about research and life that the GRL has facilitated. In addition, I would like to thank Dr. Kelly Lazar – a professor at Clemson University – who has acted as a second mentor to me and has provided me with research guidance and support throughout my master's program.

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and love. I look to them for inspiration and am so thankful that they raised me to be a strong and inquisitive woman with a healthy work ethic and passion for learning. I hope to continue making them proud.

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Abstract

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Introduction

Increasing global populations, urbanization, and resource consumption have put immense strain on environmental systems and, in turn, have significantly increased natural hazards exposure, vulnerability, and economic losses (Parker 2000; Klein et al. 2003; Wisner et al. 2004;

Harvatt et al. 2011). Ninety percent of natural hazards in the U.S. involve flooding, making flooding the most common and costliest natural hazard (Kousky et al. 2016). Floods have brought destruction to every state and nearly every county, claiming hundreds of lives annually, inflicting financial losses on households and businesses, and straining the government agencies that provide flood response and relief (Ashley et al. 2008; McShane et al. 2019).

From 2016 to 2019, the annual average number of billion-dollar natural hazards was more than double the long-term average. During this period, damages from severe storms and flooding amounted to more than $300 billion in costs to the public and government (Smith 2020). In 2019, historic flooding in the Midwest caused $10.8 billion worth of damages across millions of acres of land, documented as one of the costliest inland U.S. flooding events on record (Smith 2020). Damages are compounded even further as populations increase and invest more economic growth in infrastructure that can be damaged by flooding (Masson-Delmotte et al. 2018).

Anthropogenic climate change coupled with human activities has altered the hydrological cycle and substantially increased flood risk (Trenberth 2018; Masson-Delmotte et al. 2018). Human activities such as land-use changes, modifications in river morphology, construction of hydropower plants, dikes and weirs, wetland drainage, and agricultural practices have decreased the capacity of watershed systems to mitigate flooding impacts (Masson-Delmotte et al. 2018). Climate change driven sea level rise and heavy rainfall associated with tropical cyclones are putting more strain on watershed systems and exacerbating coastal and fluvial floods (Masson-Delmotte et al. 2018). Coastal flooding is a major concern in the U.S. given that more than 8.6 million Americans live in vulnerable areas along coasts (Vitousek et al. 2017). Florida's sea level is rising at a rate of one inch every three years and this rate is increasing, while hurricanes in the North Atlantic are projected to rise in frequency, intensity, and rainfall (Kekeh et al. 2020).

Other types of flooding, such as fluvial and flash flooding, could affect more than 41 million Americans who live in high-risk areas. Additionally, fluvial and flash floods flush out both pollutants and soil into rivers and streams, contaminating freshwater resources and threatening water security (Solek et al. 2018).

Differences in flood risks among regions reflect a balance between the severity of potential floods, the regional population and vulnerabilities, and the capacity to cope with flood risks, all of which depend on socio-economic conditions as well as topography and hydro-climatic conditions (Tanoue et al. 2016, Masson-Delmotte et al. 2018). For more vulnerable populations (i.e. low-income communities, the elderly, and/or ethnic minority groups), the exposure to flood risk could be an order of magnitude greater than that of communities under sustainable socioeconomic development (Masson-Delmotte et al. 2018). Vulnerable populations are least likely to have flood insurance, access to transportation during an evacuation, or the ability to relocate (Rufat et al. 2015; Adelekan 2010). Flooding also has lasting effects that disrupt the economy, livelihoods, infrastructure, and ecosystems - especially in vulnerable populations (Dewan 2015). Future economic losses and social disruption caused by flooding is projected to occur gradually, although these are likely to be greater in total than the losses experienced during the Great Recession in 2008 (Kunreuther et al. 2019).

Flood losses are not covered by standard homeowners and commercial property insurance policies. Therefore, the Federal Emergency Management Agency (FEMA) administers the National Flood Insurance Program (NFIP) to provide vital coverage to properties in communities that comply with minimum standards for floodplain management (Brown 2016). The Federal Government provides flood insurance to communities located in a Special Flood Hazard Area (SFHA), an area with at least a one-percent chance a flood occurring annually (a 100-year flood), when the community agrees to adopt a floodplain management ordinance to reduce future flood risks (Brown 2016). Although many communities in SFHAs participate in the NFIP, only 15% of people across those communities invest in a flood insurance policy (Kriesel et al. 2004). Due to expanding floodplains, the number of SFHAs identified by FEMA is estimated to increase by an average 45% nationally and 55% in coastal areas by the end of the 21st century (Kunreuther et al. 2019).

Given the expected growing influence of flooding on individual and community well-being, there is an urgent need to understand the ways in which people can adopt adaptive strategies and prepare for flooding across spatial and temporal scales. Flood hazard management requires both individual and community participation and action, as well as national guidance (Burton et al. 1993, 163). However, Americans generally do not perceive flooding as a risk and less than half of people living in flood prone areas engage in some form of flood mitigation behavior (FEMA 2013). Understanding perceived flood risk and drivers of individual engagement in flood mitigation behavior then becomes vital for building effective strategies to reduce actual flood risk. Flood mitigation behavior includes, but is not limited to, creating an evacuation plan, elevating valuables, sealing basements, and supporting flood mitigation policies (Bubeck et al. 2012, FEMA 2013, Masson-Delmotte et al. 2018). If the majority of individuals in a community engage in flood mitigation behaviors, the community will enhance its resiliency and help shape preventative flood policies. Therefore, it is imperative that current individual engagement in flood mitigation behaviors are measured to inform natural hazard management and policy to promote flood mitigation behaviors and reduce destructive impacts of inescapable future floods (Bubeck et al. 2012).

Predicting behavior is a challenge that extends across disciplines. Numerous behavioral theories have been tested, modified, and used in environmental and natural hazard risk studies (Rahman et al. 2016; Oreg et al. 2006; Terpstra et al. 2013; Bockarjova et al. 2014). Behavioral theories that are often used to measure protective behaviors against health risks and environmental impacts include: Theory of Planned Behavior (TPB), Values-Beliefs-Norms Theory (VBN), and Protection Motivation Theory (PMT). The TPB was proposed by Ajzen and suggests that behavior is shaped by an individual's attitude towards the behavior, normative beliefs, and perceived behavioral control (Ajzen 1991). Stern et al. (1999) proposed the VBN theory, which suggests that environmental protective behaviors are more likely to occur when personal values, beliefs and norms are present. PMT was formulated and revised by Rogers (1975; 1983) and suggests that preventive behavior is shaped by perceived severity of a threat, perceived vulnerability to that threat, and the efficacy of the preventive behavior. Unlike TPB and VBN, PMT has been specifically used in the context of actual flood risk (Poussin et al. 2014; Bubeck et al. 2012; Grothmann et al. 2006). Previous studies have also found that people are more likely to engage in flood mitigation behavior if they have been previously impacted by a flood and/or are knowledgeable of flooding and flood safety (FEMA 2013, Spence et al. 2011; Whitmarsh 2008; Poussin et al. 2014, Grothmann et al. 2006). Also, the frequently observed discrepancy between actual flood risks – as measured by physical environmental variables – and perceived flood risks is a cause for concern for natural hazard management (Lechowska 2018). Interestingly, actual flood risk is rarely included in studies of flood mitigation behavior assessments (Brody et al. 2010, Bubeck et al. 2012) and is not typically incorporated into theoretical models.

The current study synthesizes these three theories together and incorporates physical flood risk as measured by the NFIP and personal flood experience. Collectively, this produces a well-rounded theoretical framework for measuring flood mitigation behaviors. This study seeks to identify variables within the synthesized theoretical framework that most influence flood mitigation behavior. Ultimately, this work will help policy makers to develop sustainable solutions that incorporate peoples' perceptions and behaviors into decision making processes. Hence, this study explores the following research questions:

Research Question 1: What is the relationship between perceived and actual flood risk?

Research Question 2: How effective is the proposed theoretical framework in predicting flood mitigation behavior?

Methodology

This research received ethics approval from the Michigan State University Institutional Review Board.

Study Area

The Northern Plains and Upper Midwest regions are at a high risk for flooding caused by snowmelt, intense downpours, and rising lake levels (Pryor et al. 2014). In 2020, the water levels in the Great Lakes reached a record high and are forecasted to continue rising in the future (Kelly 2020). These changes are a response to the combinations of extreme lake evaporation, persistent increases in the magnitude and intensity of precipitation events, and intermittent outbursts of cold arctic air (Fujisaki-Manome et al. 2020). Michigan is surrounded by the Great Lakes, which hold 20% of the world's fresh water, and has more square miles of river per state acreage than many other states (Dahl et al. 1982; EPA 2019). Michigan has been negatively impacted by these unprecedented lake levels and flood risks extend to communities along rivers and other channels connecting the Great Lakes. Flooding across the state affects agriculture, transportation, infrastructure, and water quality (Wheater et al. 2009). Washed out roads, underwater docks, damaged shoreline properties and parks, and extensive flooding are forcing shoreline residents to move inland or invest in flood barriers to protect the shoreline and their homes (Fujisaki-Manome et al. 2020).

Michigan is home to over 40 million people who depend on the preservation of water quality in the Great Lakes, food security, and infrastructure for economic, societal, and personal vitality (Troutman et al. 2020). Additionally, infrastructure such as dams, culverts, bridges, and storm drains were not designed and built based on projections of rising flood risks (Kelly 2020). Consequently, Michigan has experienced several significant and damaging floods in the past fifty years and especially in more recent years (Villarini et al. 2011). In 2013, flood walls along the Grand River in Grand Rapids, Michigan failed as waters rose to record stages, causing over 1,200 homes and 300 roads to flood and causing an estimated $450 million in damages to downtown Grand Rapids (Nordman et al. 2018). In 2020, Mideastern Michigan experienced two dam failures on the Tittabawassee River causing a 500-year (0.2 percent chance of occurring annually) flash flood event (Freedman et al. 2020). This event forced the evacuation of around 10,000 people and caused more than $200 million in damages (Freedman et al. 2020). Given the rising need for effective individual action, attention to flood mitigation behaviors in this region is essential for shaping effective flood mitigation management and policies to reduce the impacts of flooding.

Variables

The proposed theoretical framework (Figure 1) that guides this study synthesizes variables from Protection Motivation Theory (PMT), Theory of Planned Behavior (TPB), Values-Beliefs-

Norms Theory (VBN), and prior research to identify predictors of flood mitigation behaviors. *Flood mitigation behavior* is the phenomenon this theoretical framework aims to understand and predict. It is defined as individual actions that consciously seek to (indirectly or directly) mitigate the impacts of flooding (Bubeck et al. 2012). Specific variables from each theory were therefore chosen based on their observed influence on behavior in previous studies (Libarkin et al. 2018; Gao et al. 2017; Fornara et al. 2020).

Variables drawn from the original PMT include *perceived consequences, perceived vulnerability, fear, self-efficacy, and response efficacy.* Revised PMT additionally adds *flood experience* and *flood knowledge* (Spence et al. 2011; Rogers 1983). Perceived consequences are defined as the range of harmful impacts a flood would have on an individual or an individual's valuables if a flood were to occur (Rogers 1983). Perceived vulnerability is the expected probability of being exposed and susceptible to a flood (Babcicky et al. 2019). Together, perceived consequences and perceived vulnerability define *perceived flood risk* (also termed "risk perception"; Wilson et al. 2019; Sjöberg et al. 2004). Therefore, *perceived flood risk* was calculated by multiplying averaged perceived vulnerability and perceived consequences values together for each survey respondent. *Fear* is concern of being affected by a flood (Poussin et al. 2014; Rogers 1983) and is similar to attitude, which is a variable used in TPB. *Self-efficacy* is the perceived ability to carry out protective actions to prepare for a flood (Rogers 1983) and is the same as perceived behavioral control, a variable used in TPB. *Response efficacy* is the belief that protective actions will in fact be effective to protect oneself or others from being harmed by a flood (Rogers 1983). *Flood experience* is defined as previous experience (direct or indirect) with a flood. *Flood knowledge* is information that has been learned through other means than flood experience (Kellens et al. 2012).

Other variables were drawn from TPB and VBN. *Subjective norms* was drawn from both TPB and VBN and can be defined as perceived social pressure to engage in flood mitigation behaviors (Ajzen 1991). This study uses three types of *values* derived from VBN: *biospheric*, *egoistic*, and *altruistic values*. *Biospheric values* are personal values towards the environment. *Egoistic values* regard oneself as important and the reason for engaging in flood mitigation behaviors. *Altruistic values* are personal values of others and community (Stern et al. 1999).

Two variables - *general risk* (Wilson et al. 2019) and *actual flood risk* (Kick et al. 2011) - were included in the theoretical framework based on previous studies. *General risk* is defined as something that is perceived as risky or hazardous. *Actual flood risk* is defined by FEMA as the probability and magnitude (e.g. depth, velocity, discharge) of flooding. It is important to note that the probability and magnitude defining actual flood risk parallels the perceived consequences and vulnerability that define perceived flood risk.

Finally, a suite of demographic and home environment variables were measured base on their importance in prior studies (FEMA 2013; Osberghaus et al. 2015; Thistlethwaite et al. 2018) and/or their recognized importance in increasing actual flood risk within the home.

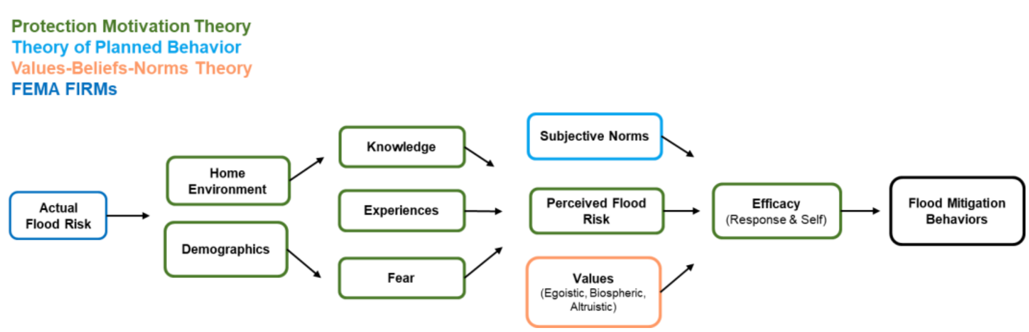

Figure 1 The proposed theoretical framework synthesizes variables from Protection Motivation Theory, Theory of Planned Behavior, Values-Beliefs-Norms, Theory and FEMA FIRMs together to measure flood mitigation behaviors.

Survey Design

A survey probing adult Michigan residents' flood mitigation behaviors was developed to include: 1) Likert-type 4-point scale (i.e. strongly disagree, disagree, agree, strongly agree) questions measuring the variables in the proposed theoretical framework (Figure 1), 2) questions pertaining to the makeup and physical characteristics of the participants' home, and 3) demographic questions in both multiple choice and written response form. Likert-type questions taken from previous literature were modified for this study and used to measure each variable (Grothmann et al. 2006; Spence et al. 2011; Poussin et al. 2014; Slimak et al. 2006; Stern et al. 1999). Home environment questions related to household income, home ownership, home inspections, and home structure were derived from Grothmann et al. (2006). Demographic questions targeted standard age, gender, ethnicity, disability, and education level; these variables have been documented as important in modeling hazard-related behaviors (e.g., Spence et al. 2011). Survey respondents were also asked to provide the closest cross streets to their home address and corresponding zip code as a precise, yet anonymous, location. A prompt was provided at the start of the survey: "The following set of questions ask about flooding in your neighborhood and household. Rate your agreement with each of the following statements." An attention check question was also included to allow for identification and removal of potentially problematic surveys (e.g. Libarkin et al. 2018). All survey items are presented in the Online Supplement.

Survey Procedures and Participants

The survey was administered online via Mechanical Turk (MTurk) from November to January 2020 (N=351) and took on average 7.5 ± 8.8 minutes to complete. Mturk samples are representatively similar to traditional subject pools in terms of race, gender, age, and education (Paolacci et al. 2010). Survey respondents were recruited based on MTurk documentation of reliable performance completing other MTurk tasks and were prescreened to ensure that only those with good performance records participated in this study. Respondents were compensated at a far wage for their labor (~$8/hour). The survey instrument was designed and written in

English and reviewed by research scientists in the Geocognition Research Laboratory at Michigan State University. Survey data was collected over a three-month period across Michigan to achieve a large enough sample and to ensure data collection both during times of flooding and times of non-flooding.

Respondents (n=332) were all geographically located in Michigan and ranged in age from 21 to 77, with an average age of 39.9±11.6 years. More than half of the respondents identified as female, 62%. About 87% of the sample identified as Caucasian, 7% as African American, 3% as Asian, 2% as Latinx, 1% Native American, and 5 participants chose not to respond. Participants represented the entire range of education levels, with 35% having a high school degree, 50% having a bachelor's or associates degree, and 15% having a higher degree (e.g. M.S., M.D., Ph.D., etc.).

Participants were asked a few questions pertaining to their home environment, such as "What is your household annual income?". Participants with a household annual income of less than $35,000 made up 32% of the sample; between $35,000-$75,000 made up 42%; and greater than $75,000 made up 26%. Participants were asked if they owned a home, with 71% saying yes, and 29% saying no. Those that said no were renting a home or apartment. Following this question, participants were asked, "If you own a home, has your home been inspected for flood-related damages?"; 39% responded with yes. A "wet" or flooded basement are a common consequence of heavy rainfall; therefore, participants were asked, "Do you have a basement in your apartment or house?"; 74% of participants said yes. Lastly, 6% of participants indicated that they had experienced evacuation of their home due to flooding (Table 1).

Table 1 Descriptive statistics of sample.

Demographics	
Sample size	N = 351 (Original), N = 332 (Quality Control)
Duration of Study	November to January
Location	Michigan, U.S.
Age	21-77 years
Gender	38% Men, 61%, Women, 1% Other
Ethnicity	87% Caucasian, 16% Other
Education Level	35% GED; 50% B.S or A.S.; 15% Higher Degree
Homeowners	71% Yes
Household Annual Income	32% < $35,000; 26% >$75,000, 42% in between
Home Inspection	39% Yes
Home has a Basement	74% Yes
Evacuation due to Flooding	6% Yes

Actual Flood Risk Analysis

Actual flood risk is measured empirically in the environment. Actual flood risk was calculated using FEMA flood hazard data collected from Flood Insurance Rate Maps (FIRMs) and coupled with survey respondent location in a Geographic Information System (GIS). Based on hydrologic data and topographic surveys, FIRMs identify three levels of flood risk: 1. Level one are those areas of minimal flood risk with a less than 0.2% chance of flooding annually; 2. Level two are areas with intermediate flood risk with 0.2-1% change of annual floods; and 3. Level three are areas with a 1% or greater chance of flooding each year. Level three areas are designated Special Flood Hazard Areas (SFHA) for access to the National Flood Insurance Program. Each participant location was assigned a corresponding FIRM risk level. These FIRM levels were gathered from digital FIRM maps, when available, or read off PDFs of older paper FIRM maps.

To visualize differences in actual and perceived flood risk, differences between actual and perceived flood risk were mapped. To interpolate differences in actual and perceived flood risk in areas with no data, inverse distance weighting (IDW) was used. IDW is one of the most common interpolation methods. It is used to predict the values for any unmeasured location (Childs 2004) and is primarily based on two assumptions: first, unknown values are related to close known values. Second, the amount of influence known value has on an unknown value is directly proportional to the inverse of the distance between points. The value given to an unknown point can be mathematically represented (Bartier et al. 1996; Huang et al. 2011).

$$Z_p = \frac{\sum_{i=1}^{n} w_i Z_i}{w_i} = \frac{\sum_{i=1}^{n}\left(\frac{Z_i}{D_i^p}\right)}{\sum_{i=1}^{n}\left(\frac{1}{D_i^p}\right)} \text{ .... Equation (1),}$$

Where Z refers to the interpolated value of an unknown point, w_i is the weighting function that controls the significance of Z_i, and Z_i is a measured value at a known point. This represents the nearest neighborhood of a produced interpolated point and ranges between -3.13 to 4.98. n is the nearest neighborhood of known points that is required. D_i^p refers to the distance between a known and unknown point, p is a weighting exponent equal to 1 (Guan and Wu, 2008).

Analysis

Multiple methods were used to analyze the survey and actual risk data. First, descriptive statistics of the survey data provided an overview of the sample and informed the analytical approach. This included computing Spearman's rank-order correlations to explore the bivariate relationship between each variable and flood mitigation behaviors. Second, a confirmatory factor analysis (CFA) was conducted on the survey data to ensure validity and reliability of the survey instrument. Third, a Spearman's rank-order correlation was run against perceived and actual flood risk to examine their relationship, couples with the visualization of the relationship through generating a map of perceived minus actual risk in GIS. Fifth, a hierarchical regression was conducted to identify predictors of flood mitigation behavior. Spatial analyses were conducted in ArcGIS, while all statistical analyses were performed using SPSS Statistics 25 and SPSS AMOS 25.

Results

Survey responses from nineteen participants who failed the attention question were removed, leaving n=332 participants.

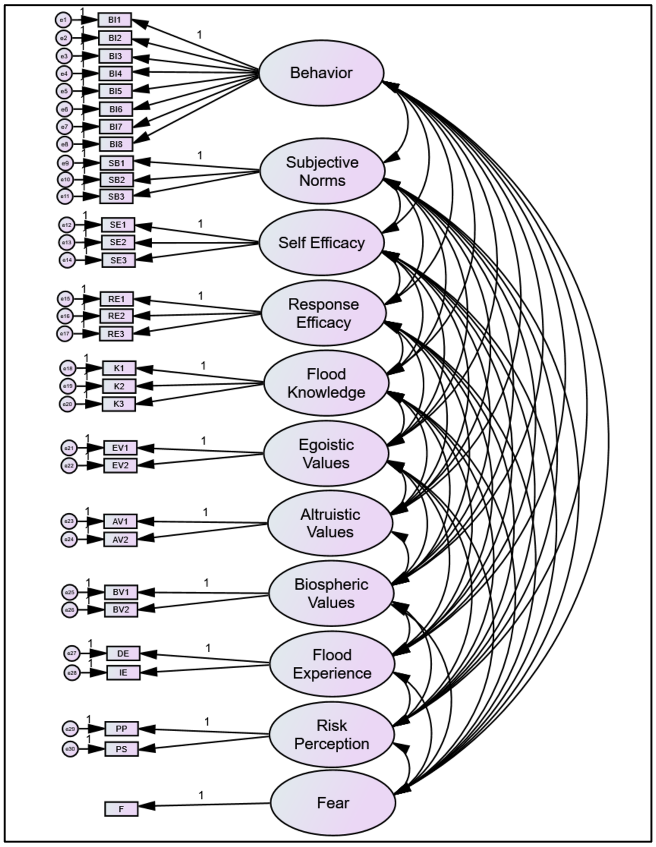

Figure 2 Confirmatory factor analysis with eleven latent variables.

Validity and Reliability

A confirmatory factor analysis (CFA) was run on all Likert items to test the fit of the theoretical framework using robust maximum likelihood estimation (Figure 2). All variables loaded significantly on the latent factors. The comparative fit index (CFI) was 0.787 and the Tucker-Lewis fit index (TLI) was 0.746. We expect CFI and TLI to be less than the ideal values because of the number of uncorrelated items in the model. Point estimates for the RMSEA were adequate at 0.08. In addition, Cronbach's α > 0.6 for all scales with three or more items. Each of the standardized factor loadings and Cronbach's α for Likert scales are displayed in Table 2. Although the CFI and TLI values are lower than the minimum recommended of 0.90, the adequate RMSEA and factor loading suggest a strong model. Cronbach's α is also a measure of internal consistency often reported to support factor analytical results; Cronbach’s is strong for most scales, with expected reduction as the number of items per scales is reduced.

Table 2 Confirmatory Factor Analysis and Cronbach’s Alpha results.

Variables	**Factor Loadings**								
Behavior	0.793								
Behavior	0.734								
Behavior	0.521								
Behavior	0.737								
Behavior	0.602								
Behavior	0.619								
Behavior	0.465								
Behavior	0.406								
Subjective Norms		0.762							
Subjective Norms		0.670							
Subjective Norms		0.689							
Self-Efficacy			0.816						
Self-Efficacy			0.553						
Self-Efficacy			0.522						
Response Efficacy				0.573					
Response Efficacy				0.765					
Response Efficacy				0.493					
Egoistic Values					0.466				
Egoistic Values					0.733				
Altruistic Values						0.505			
Altruistic Values						0.825			
Biospheric Values							0.513		
Biospheric Values							0.668		
Flood Experience								0.777	
Flood Experience								0.838	

Table 2 (cont'd)

Perceived flood risk									**0.852**
Perceived flood risk									0.739
Cronbach's Alpha	0.828	0.746	0.679	0.624	0.509	0.589	0.510	0.789	0.767

Descriptive Statistics

Participants had an intermediate level of understanding of floods and flood safety, with 40% of participants responding correctly to all knowledge items. Participants' opinions on whether they have already or are going to engage in flood mitigation behaviors were fairly distributed. 15% of participants strongly disagreed, 34% disagreed, 33% agreed, and 18% strongly agreed to currently or planning on engaging in flood mitigation behaviors. Measured variables (1 is low and to 4 is high) indicate variation within the population, with individual scores covering the full range of each scale. Flood experience scores were high, averaging 2.7±1.0. Value scores were also high with Egoistic Values averaging 3.0±0.8, Altruistic Values averaging 2.8±0.8, and Biospheric Values averaging 3.2±0.8. Subjective Norm scores averaged 2.5±0.6, Self-efficacy averaging 3.1±0.6 and Response Efficacy averaging 2.9±0.5. Perceived flood risk and general risk scores were moderate to low, 2.1±0.78 and 2.6±1.1, respectively. Lastly, fear scores were also moderate, averaging 2.7±0.9 (Table 3).

Correlations

Spearman's rank-order correlation coefficients between the dependent variable of flood mitigation behavior and the independent variables laid out in the theoretical framework are shown in Table 3. All independent variables demonstrated significant correlations to flood mitigation behavior except for flood knowledge, general risk, education level, household annual income, age, homeowning, and actual flood risk. The strongest correlation to flood mitigation behavior was subjective norms, with similarly strong correlations to self-efficacy and perceived flood risk. In fact, most correlations were high; the smallest correlation observed was with response efficacy, biospheric values, gender, and basement.

Table 3 Spearman's rank-order correlation with flood mitigation behavior.

Variables	Mean	Standard Deviation	Correlation Coefficient
Flood Mitigation Behavior	2.55	0.59	---
Fear	2.73	0.90	.407**
Flood Experience	2.71	0.88	.439**
Subjective Norms	2.47	0.62	.603**
Self-Efficacy	3.08	0.57	.421**
Perceived Flood Risk	2.08	3.03	.513**
General Risk	2.60	1.06	.023
Response Efficacy	2.96	0.51	.326**
Egoistic Values	2.94	0.66	.387**
Altruistic Values	2.83	0.67	.386**
Biospheric Values	3.14	0.62	.343**
Flood Knowledge	2.76	0.49	.083
Education Level	4.23	1.30	.059
Household Annual Income	3.45	1.61	.030
Age	39.4	11.7	-.025
Gender	2.61	0.51	.194**
Homeowner	1.31	0.49	.102
Home Inspection	1.61	0.65	.246**
Basement	1.25	0.43	.163**
Evacuation	1.94	0.24	-.208**
Actual Flood Risk	1.35	0.73	.092

Perceived vs. Actual Flood Risk

According to the Spearman's rank-order correlation, perceived flood risk is significantly, although weakly, correlated with flood risk, $r (332) = 0.13$, $p < 0.05$. This correlation can be observed on the map shown in Figure 3, displaying spatial differences between perceived and actual flood risk (Research Question 1). Interpolation using IDW was achieved for the prediction of differences between actual and perceived flood risk values in areas that were not measured in Michigan. According to IDW, differences between actual and perceived flood risk were classified into ten classes using a defined interval of 0.83. These classes display the spatial distribution of differences in actual and perceived flood risk across the state of Michigan and range from -3.13 to 4.98. Light tan classes represent areas where people hold a perceived flood risk that is the same as their actual flood risk and are close to zero. Classes that are shades of purple indicate people who have a higher perceived flood risk than actual flood risk and range from 1.66 to 4.98. Purple areas are concentrated along the Great Lakes shoreline, although not everyone who lives along the Great Lakes shoreline fits in this category. Classes that are shades of orange indicate people who have a higher actual flood risk than perceived flood risk and range from -0.83 to -3.13. These orange areas primarily occur in the lower peninsula of Michigan. There are two relationship between water bodies and orange areas worth noting. First, in the northern part of the lower peninsula, people living along Lake Michigan-Huron shoreline have a higher actual flood risk than perceived. Second, mid- and southern Michigan host a belt of orange areas that is closely aligned with geographic locations of rivers (Figure 4).

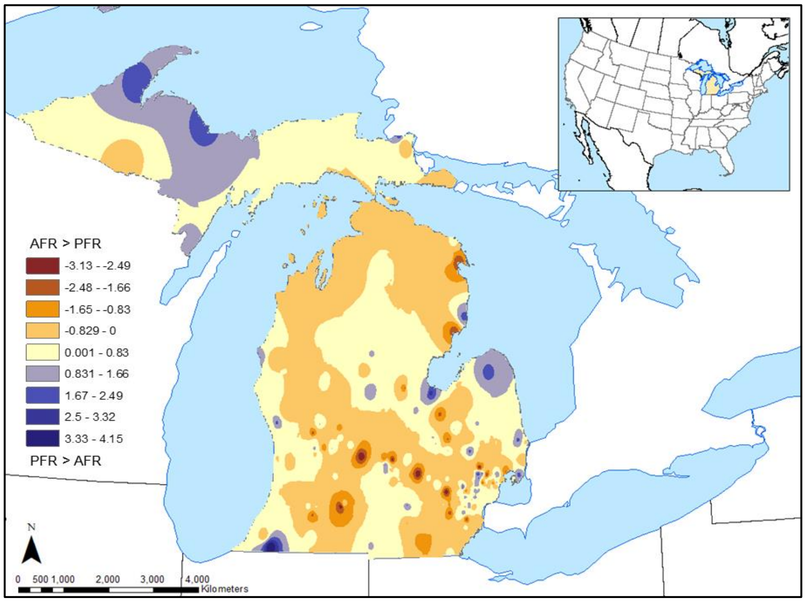

Figure 3 Spatial variation among perceived and actual flood risk through Michigan. Orange areas are where individuals have a higher actual flood risk (AFR) than perceived flood risk (PFR), and therefore values are negative. Purple areas are where individuals have a higher perceived flood risk than actual flood risk and therefore values are positive. Tan areas represent where individuals have similar perceived and actual flood risk and therefore values are close to zero. Raster cell size (0.1, 0.1).

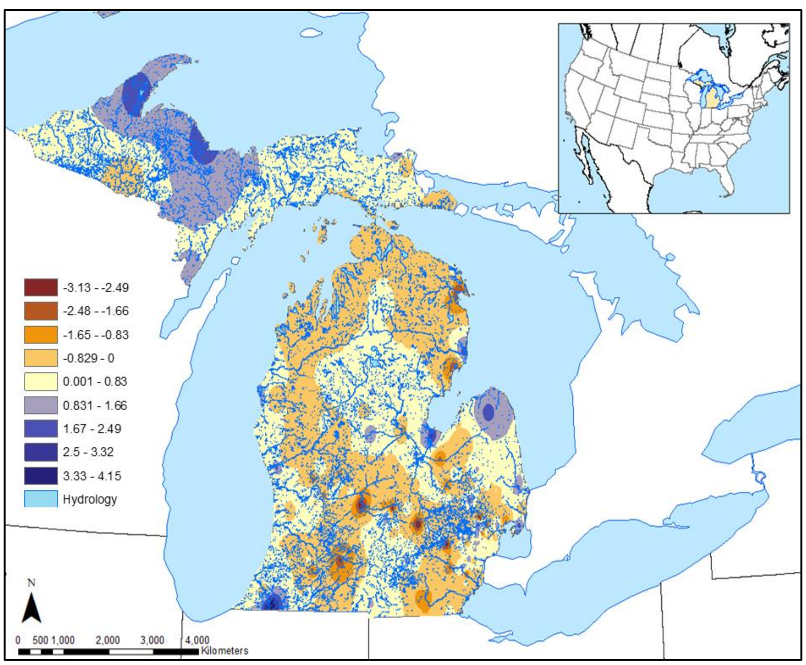

Figure 4 Map shown in Figure 3 with overlaying Michigan hydrology.

Hierarchical Regression

A hierarchical regression was conducted to evaluate the importance of each variable in predicting flood mitigation behavior. Due to the strong correlation between most variables and behavior, all variables were included in the regression. The Durbin-Watson was 1.898 indicating no issue with multicollinearity, and therefore only main effects were considered. The results of the regression analysis are presented in Table 4. The first step included actual flood risk alone ($R^2 = 0.012$, $F = 4.146$, $p < 0.05$). Actual flood risk explained 1% of the variance in flood mitigation behavior. The second step included demographic variables, and these explained 15% of the model variance ($R^2 = 0.164$, $F = 7.282$, $p < 0.001$). Demographic variables of most importance included gender, home inspection, basement, actual flood risk, and flood evacuation. The third step included fear of flooding and flood experience, which explained 18% of the model variance ($R^2 = 0.348$, $F = 45.164$, $p < 0.001$). Variables of most importance in the third step were fear, flood experience, gender, home inspection, basement, and education level. The fourth step consisted of subjective norms, perceived flood risk, egoistic values, altruistic values, and biospheric values, which explained 21% of the model variance ($R^2 = 0.564$, $F = 31.260$, $p < 0.001$). The variables of most importance in the fourth step were subjective norms, perceived flood risk, biospheric values, gender, home inspection, basement, and education level. The fifth and final step included self-efficacy and response efficacy and explained 2% of the model variance ($R^2 = 0.582$, $F= 6.661$, $p< 0.001$). Self-efficacy along with subjective norms, perceived flood risk, home inspection, basement, and education level were the variables of most importance in step five.

Table 4 Hierarchical Regression Results.

	1				2				3				4				5			
Variable	B	SE B	b	t	B	SE B	b	t	B	SE B	b	t	B	SE B	b	t	B	SE B	b	t
Flood Risk	0.12	0.06	0.12	1.99*	0.11	0.06	0.11	2.02*	0.07	0.05	0.07	1.36	0.03	0.04	0.03	0.65	0.02	0.04	0.02	0.40
Gender					0.19	0.06	0.20	3.47**	0.13	0.05	0.14	2.69*	0.08	0.04	0.08	1.97*	0.07	0.04	0.07	1.57
Ethnicity					0.04	0.06	0.04	0.64	0.05	0.05	0.05	0.91	0.01	0.04	0.01	0.28	0.01	0.04	0.01	0.21
Disability					0.06	0.06	0.06	1.01	0.04	0.05	0.04	0.75	0.00	0.04	0.00	0.01	-0.01	0.04	-0.01	-0.26
Education Level					0.15	0.06	0.15	2.45	0.12	0.05	0.12	2.24*	0.11	0.05	0.11	2.49*	0.12	0.04	0.12	2.72*
Home Inspection					-0.15	0.06	-0.16	-2.68**	-0.15	0.05	-0.15	-2.87**	-0.11	0.04	-0.11	-2.47*	-0.10	0.04	-0.10	-2.27*
Home as a Basement					-0.14	0.06	-0.15	-2.55*	-0.10	0.05	-0.10	-1.95*	-0.10	0.04	-0.10	-2.47*	-0.12	0.04	-0.12	-2.83**
Evacuated due to Flooding					-0.19	0.06	-0.19	-3.35**	-0.09	0.05	-0.09	-1.66	-0.04	0.04	-0.04	-0.97	-0.04	0.04	-0.04	-0.88
Household Annual Income					-0.07	0.06	-0.07	-1.18	0.00	0.06	0.00	0.04	0.02	0.05	0.02	0.46	0.01	0.05	0.01	0.32

Table 4 (cont'd)

Fear									**0.25**	**0.06**	**0.26**	4.55 **	**0.06**	**0.05**	**0.06**	**1.13**	**0.03**	**0.05**	**0.03**	**0.63**
Flood Experience									0.27	0.06	0.27	**4.72 ****	-0.02	0.06	-0.02	-0.26	0.01	0.06	0.01	0.18
Flood Knowledge									-0.06	0.05	-0.06	-1.27	-0.06	0.04	-0.06	-1.36	-0.06	0.04	-0.06	-1.47
Subjective Norms													0.41	0.05	0.42	**7.86 ***	0.36	0.05	0.37	**6.67 ****
Perceived flood risk													0.20	0.06	0.21	**3.29 ***	0.20	0.06	0.20	**3.32 ****
Egoistic Values													0.09	0.06	0.09	1.54	0.06	0.06	0.06	1.02
Altruistic Values													-0.01	0.06	-0.01	-0.15	-0.01	0.06	-0.01	-0.10
Biospheric Values													0.12	0.05	0.12	**2.28 ***	0.06	0.05	0.06	1.10
Self-Efficacy																	0.16	0.05	0.16	**3.06 ****
Response Efficacy																	0.05	0.05	0.05	1.06
Adjusted R^2	0.01				0.16				0.34				0.55				0.57			
F change in R^2	3.87 *				6.85 **				25.4 **				24.8 **				6.01 **			

Discussion

The aim of this study was to examine perceived flood risk and other predictors of flood mitigation behavior through answering two questions: (1) What is the relationship between perceived and actual flood risk?; and (2) How effective is the proposed theoretical framework (Figure 1) in predicting flood mitigation behavior? This context of this study was the state of Michigan, an area with overall high flood risk.

First, the relationship between perceived and actual flood risk was considered (Research Question1). Spearman's rank-order correlation results suggested a significant yet weak relationship between the two. Differences between the actual and perceived flood risk were mapped and interpolated using IDW (Figure 3). People living along the Great Lakes shoreline in Michigan generally either over or underestimate their flood risk. Two possible reasons may exist for this. First, lack of nuance in flood risk communication and heterogeneity in elevation of shoreline homes may contribute to this discrepancy between actual and perceived flood risk. Second, several counties in Michigan were missing spatial flood hazard data. Therefore, older, non-digitized FIRMs were used to manually assign actual flood risk scores to survey participants from those counties. This manual assignment could result in incorrect approximation of actual flood risk scores for participants located within these counties. One of Michigan's most populated cities is Grand Rapids, which is in Kent county and lies along the Grand River, Michigan's largest river. Kent county is one of the counties with missing spatial flood hazard data. Due to this discrepancy, actual risk calculation for the western shoreline of the lower peninsula could be erroneous.

People who live in mid and southern Michigan tend to underestimate their flood risk, as shown in the flood risk maps in Figure 3. This phenomenon appears to align with high concentrations of rivers and small lakes in Michigan (Figure 4). It is noted that high flood risk is defined by FEMA as a greater than 1% chance of experiencing an annual flood. This indicates that not all individuals living along rivers and/or lakes have experienced flooding. Lack of flood experience might explain why people living in these areas have a lower perceived than actual flood risk. Additionally, prior research has shown that people who have experienced flooding but without flood damages continue to underestimate their flood risk (Spence et al. 2011; Whitmarsh 2008). Lastly, studies have shown that people tend to be overall not good at perceiving flood risk (Działek et al. 2013; Ceobanu et al. 2009; Heijmans 2001). Therefore, in high risk areas we would expect to see an underestimation of flood risk.

Furthermore, areas where people tend to have a higher perceived flood risk than actual flood risk are primarily located along the Great Lakes shoreline and are especially prevalent in the upper peninsula along Lake Superior. Lake Superior is the largest of the Great Lakes and has experienced dramatic rise in water levels and consequential erosion and flooding along its shoreline (Motiee et al. 2009). Most upper peninsula residents live on or near Lake Superior, increasing their exposure to flooding both individually and as communities. This high prevalence of flooding and could explain why we see higher perceived than actual flood risk for individuals living in this region.

Actual flood risk was not significant in predicting behavior after the second step in the regression. This finding implies that perceived flood risk is an important variable for flood risk managers and policymakers to measure; actual flood risk is not as powerful in predicting behavior and could result in unproductive efforts if measured alone. The interpolated map of perceived and actual risk differences could be the beginnings of a robust tool for risk managers and policymakers to utilize when identifying areas where training for flood mitigation behavior might be most needed.

Second, predictors of flood mitigation behaviors were identified (Research Question 2). A hierarchical regression indicated that individuals having a home with a basement, higher education level, previous home inspection, high subjective norms, high perceived flood risk, and high self-efficacy are more likely to engage in more flood mitigation behaviors. We consider below potential reasons for these observed relationships.

The higher an individual's education level the more likely the individual was to engage in flood mitigation behavior, in alignment with previous behavioral study findings. With a higher education, individuals tend to have better access to informational resources that are useful for engaging in flood mitigation behavior before, during, and after a flood. This might explain why actual flood risk and flood-related evacuation fell out of the model as education level emerged as significant. Individuals who have a high education level and experienced flooding can be expected to seek out information on flood mitigation measures.

Basements in Michigan are well-known to be wet or prone to seepage during rainstorms. In fact, a flooded basement is a form of flood experience, which might explain why it consistently was a significant predictor whereas flood experience emerged as a significant predictor only in the third step of the regression. Similarly, having a previous home inspection for flood damages was a significant predictor of behavior across regression steps. Such a home inspection is an indicator that someone (e.g. homeowner, insurance company, realtor) recognized that the home was prone to flooding. This suggests that at some level the homeowner was primed for learning about flood impacts and potential flood mitigation measures.

Subjective norms, self-efficacy and perceived flood risk were also important predictors of risk behavior. These results are consistent with previous research suggesting that subjective norms and self-efficacy play significant roles in shaping behavior (Tikir et al. 2011; Keshavarz et al. 2015; Bubeck et al. 2018). Certainly, subjective norms are an integral part of a community's culture (Bubeck et al. 2018). People are more likely to behave in similar ways to the people around them due to a perceived social pressure (Minton et al. 2018). Current study findings align with that phenomenon; people are more likely to engage in flood mitigation behavior if they believe other people in their neighborhood or community are also engaging in these behaviors. Self-efficacy, the perceived ability to carry out protective actions against flooding, emerged as a significant predictor of flood mitigation behavior in the fifth and final step in the regression. This is consistent with previous research that has used PMT in studies observing behaviors around flooding (Poussin et al. 2014). Additionally, self-efficacy is the same as perceived behavioral control, a variable used in TPB, which has also often shown to be a predictor variable of behavior among previous research that used TPB (Hamilton et al. 2016; Allred et al. 2019). This finding suggests that if an individual perceives themselves as capable of engaging in flood mitigation behaviors, they are more likely to do so. In this context, being capable to engage in such behaviors can refer to physical and financial capability. Perceived flood risk emerged as a strong predictor of flood mitigation behaviors. Perceived flood risk is a complex phenomenon that is a major focus among risk analysts and has often been measured and associated with behavior. This current study aligns with this association and confirms that there is a significant connection between perceived flood risk and flood mitigation behavior. Also, perceived flood risk has been shown to be strongly driven by emotion, among other variables (Wilson et al. 2019; Xie et al. 2019; Lechowska 2018). This could explain why fear emerged as a significant predictor in the third step but became insignificant in the fourth step when perceived flood risk was added to the regression.

Interestingly, while previous research suggests values are a significant predictor of behavior, values were not significant predictors of flood mitigation behavior. Biospheric values emerged as minimally significant in the fourth step and became insignificant in the fifth and final step of the regression. Previous studies have found biospheric values to have a strong influence on climate change risk perception and pro-environmental behaviors (Libarkin et al. 2018; Kirby et al. 2017). These studies use VBN theory in a much larger context, whereas this study uses VBN theory in a smaller context for a very specific type of behaviors. This suggests two possibilities: (1) the public does not associate flooding and climate change, which aligns with previous studies (Crona et al. 2013); and (2) VBN theory is a better framework for predicting behavior at larger scales and values may not be as important for predicting specific behaviors as previously thought. Future research considering the conditions under which values are important for behavior change is warranted.

Lastly, actual flood risk was significant in the first and second step of the regression but became insignificant thereafter. This indicates that actual flood risk is important if it is the only predictor variable being investigated, which previous studies investigating physical variables have found (Berndtsson et al. 2019; Plate 2002; Schanze 2006). Overall, results suggest that demographic and social variables are much strong predictors of flood mitigation behavior than actual flood risk. Collecting more survey data – to allow full state coverage – and using updated FIRMs could improve the quality and predictive power of the proposed framework as well as provide more insight into the relationship between actual risk and behavior. This study is one of the few to combine actual flood risk, demographic, and social variables in a framework to measure flood mitigation behaviors. Risk management strategies rarely take this approach, which could pose a large disadvantage and create inefficient strategies for harm reduction.

Limitations and Future Work

Although the proposed theoretical framework for predicting flood mitigation behavior shows overall strong explanatory power and has a good model fit, more data collection in the future is needed to uncover nuances that were not captured in this study. One limitation of this study was that the explanatory power of the proposed theoretical framework was just below recommended standards, suggesting that there may be a number of other variables influencing flood mitigation behaviors or that the survey instrument was insufficient at measuring predictor variables of behavior. Exploring flood mitigation behaviors is still an emerging research field with much to improve upon and learn about predictor variables. This study also synthesized empirically measure flood risk and perceived flood risk, which has rarely been done and therefore has no standards based in research. Additionally, some counties lacked spatial flood risk data and therefore less efficient ways of identifying actual flood risk were used, which could pose limitations on the influence of actual flood risk on flood mitigation behaviors, as well as the relationship between actual and perceived flood risk.

This research lays the groundwork for future work in measuring flood mitigation and other protective behaviors. This is important now, more than ever, given the changing climate and increasing exposure and vulnerability to natural hazards. Socio-economic growth has an even larger effect on actual flood risk compared to changes in climate (Winsemius et al. 2016). Vulnerable communities with low-income families, the elderly, and ethnically minoritized groups are at a magnitude greater risk of flooding and harm than other communities (Masson-

Delmotte et al. 2018; Winsemius et al. 2016). The framework presented in this study not only includes social variables to measure flood mitigation behavior, but also includes actual flood risk, socioeconomic, and demographic variables. Incorporating all these variables into models is necessary for informing decision-making around flood mitigation and adaptation planning and policy in areas within and beyond Michigan.

Conclusion

The theoretical framework proposed in this study holds promise for predicting flood mitigation behavior. Using online survey responses from 332 Michigan residents, this study showed that having a home with a basement, high education level, having a home inspection, high subjective norms, high perceived flood risk, and high self-efficacy all had a significant influence on flood mitigation behaviors. In addition, this research empirically demonstrated the significant, however weak, relationship between perceived and actual flood risk. In addition, a map that highlights spatial differences among perceived and actual flood risk was created and shows parallels to the geography and hydrology of Michigan. These findings are timely, given that Michigan is experiencing increased flooding associated with record high water levels in the Great Lakes and heavier rainfall. This study helps provide the foundation for decision-makers to improve planning and policy around flood mitigation and adaptation in the Midwest and beyond.

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