

Why People Adopt Climate Change Adaptation and Disaster Risk Reduction Behaviors

Integrated Model of Risk Communication and Results from Hurricanes, Floods, and Wildfires

JungKyu Rhys Lim

ABSTRACT: With climate change, weather and climate disaster risks are increasing. At-risk individuals can take climate adaptation and disaster risk reduction behaviors to mitigate and prepare for disaster risks, reduce costs from damage, and save their lives. However, previous fragmented studies have not provided an integrated model to directly compare the factors and identify factors that are most influential in at-risk community members' behaviors. I present the Integrated Model of Risk Communication by consolidating major theories. This study uses structural equation modeling of quantitative surveys to simultaneously test the impacts of 15 factors on 15 adaptation behaviors for the two most common federally declared disasters (wildfires and hurricanes with floods) in three disaster-prone U.S. states (California, Florida, and Texas) ($N = 3,468$). Specifically, this study examines 15 behaviors including preparedness, nonstructural mitigation, structural mitigation, insurance purchase, and adaptation policy support. Social norms perceptions, self-efficacy, response efficacy, and resource constraints strongly affect behaviors. Response efficacy strongly affects policy support. Risk perception, knowledge, and climate change perception—commonly argued to be key drivers—are insignificant or weak. The models explain 55%–86% of the variance in adaptation behaviors. Results suggest that the focus of adaptation efforts may need to shift from risk perception and climate change perception to efficacy and social norms.

KEYWORDS: Social science; North America; Adaptation; Communications/decision making; Extreme events; Emergency preparedness

<https://doi.org/10.1175/BAMS-D-21-0087.1>

Corresponding author: JungKyu Rhys Lim, jk.rhys.lim@gmail.com

Supplemental material: <https://doi.org/10.1175/BAMS-D-21-0087.2>

In final form 21 March 2022

©2022 American Meteorological Society

For information regarding reuse of this content and general copyright information, consult the [AMS Copyright Policy](#).

Weather and climate disasters, or extreme weather events, are increasing every year (NOAA 2022; UNDRR 2022). Climate change has increased so-called natural disaster risks, such as wildfires, droughts, floods, and hurricanes (Abatzoglou and Williams 2016; IPCC 2022; Marsooli et al. 2019). Thus, individuals need to engage in behaviors for climate change adaptation, or “the process of adjustment to actual or expected climate and its effects to moderate or avoid harm” (IPCC 2014, p. 76) and reduce disaster risks (Multihazard Mitigation Council 2017; Shreve and Kelman 2014). Governments are now communicating the behaviors that at-risk individuals can take, such as preparedness, nonstructural mitigation, structural mitigation, insurance purchase, and policy support (see Table 1). Still, for at-risk individuals, recognizing their disaster risks and taking behaviors remains a challenge (Kunreuther and Michel-Kerjan 2011).

Governments’ risk communication is most effective when they tap into key drivers of behaviors (Michie et al. 2018; Sheeran et al. 2017). Therefore, identifying those drivers is a priority. However, fragmented research using limited sets of variables, such as social norms perceptions, resource constraints, perceived responsibility, and response efficacy, makes it difficult to determine the most impactful factors when combined (Bubeck et al. 2012; Kellens et al. 2013; Solberg et al. 2010; van Valkengoed and Steg 2019) (see Table 2). Researchers have called for conceptually integrated models that simultaneously compare the impacts of factors that motivate adaptation behaviors (Bamberg et al. 2017; van Valkengoed and Steg 2019; Wilson et al. 2020).

This paper presents an Integrated Model of Risk Communication by consolidating existing theories (see Fig. 1). Through a large-scale survey and structural equation modeling (SEM)

Table 1. Climate adaptation and disaster risk reduction behaviors.

Types	Wildfires	Hurricanes with floods
Nonstructural adaptation	Clear plants, trees, and any ignitable materials within 5 ft (~1.5 m) around the house Clear dead branches, leaves, pine needles from your roof, yard, and gutters	Move valuable furniture and important documents to a higher floor or a safe place
Structural mitigation	Install mesh metal screening over roof vents and windows Put a fire-resistant roof on your home	Purchase flood protection devices, such as protection flaps and water barriers Install a roof covering and/or galvanized metal hurricane straps that can withstand high winds
Insurance purchase	Purchase fire insurance against fire damage	Purchase flood and/or windstorm insurance against hurricane damage
Preparedness	Have a list of items and valuable documents that you will bring in emergency with their locations	
Policy support	Enhancing building codes Changing land use and enforcing restrictions for existing buildings in wildfire-/flood-prone zones to reduce potential damage Providing tax incentives for those who take preventative measures Providing long-term mitigation loans tied to mortgages for those who take preventative measures	

Table 2. Overlapping factors specified by major theories.

Cluster	Theories/ models	Protective motivation theory (PMT)	Extended parallel process model (EPPM)	Protective action decision model (PADM)	Theory of planned behavior (TPB)	Risk Information Seeking and Processing (RISP) model	Person- relative- to-event (PrE) theory
	Primary outcome variables	Disaster risk protection behaviors	Protection motivation	Protective response, information search	Behavioral intentions, behaviors	Information seeking and processing	Disaster risk behaviors
Risk perception	Perceived risk likelihood	×	×	×	×	×	×
	Perceived risk impact	×	×	×	×	×	×
	Risk knowledge					×	
	Negative emotions		×	×		×	
Coping appraisals	Self-efficacy	×	×	×	×	×	×
	Controllability				×		
	Response efficacy	×	×	×			
	Resource constraints	×		×			
	Response knowledge			×		×	
Social norms perceptions		×			×	×	
Perceived protection responsibility				×			×

analysis, the study identifies key drivers of adaptation behaviors by simultaneously examining the impacts of 15 factors on 15 adaptation behaviors for the two most common federally declared disasters (wildfires and hurricanes with floods) in three large disaster-prone U.S. states (California, Florida, and Texas) (FEMA 2021a). Identifying such key drivers will help governments develop effective interventions.

This study extends meta-analyses (Bamberg et al. 2017; Koksall et al. 2019; van Valkengoed and Steg 2019) and reviews (Bubeck et al. 2012; McCaffrey 2015; Wilson et al. 2020) on the factors that motivate adaptation behaviors. The consolidated theories are the psychometric paradigm (Slovic 2000), the protection motivation theory (PMT) (Floyd et al. 2000; Rogers 1975, 1983), the protective action decision model (PADM) (Lindell and Perry 2012; Terpstra and Lindell 2013), the theory of planned behavior (TPB) (Ajzen 2002, 2011), the extended parallel process model (EPPM) (So 2013; Witte 1992), the risk information seeking and processing (RISP) model (Griffin et al. 1999; Yang et al. 2014), and the person-relative-to-event (PrE) theory (Mulilis and Duval 1997, 2003).

Factors motivating climate adaptation and disaster risk reduction behaviors

Psychological factors that can motivate climate adaptation and disaster risk reduction behaviors include risk perception, coping appraisals, social norms perceptions, perceived responsibility, and climate change perception (Bamberg et al. 2017; van Valkengoed and Steg 2019; Wilson et al. 2020).

Risk perception. Risk perception, or threat appraisals, generally refers to how individuals cognitively and emotionally evaluate risks and their vulnerability (Grothmann and Reusswig 2006; Lindell and Perry 2012; van Valkengoed and Steg 2019).

PERCEIVED RISK LIKELIHOOD AND IMPACT. Risk perception is generally considered to be the perceived likelihood (or vulnerability) and impact (or severity) of experiencing negative outcomes

Integrated Model of Risk Communication

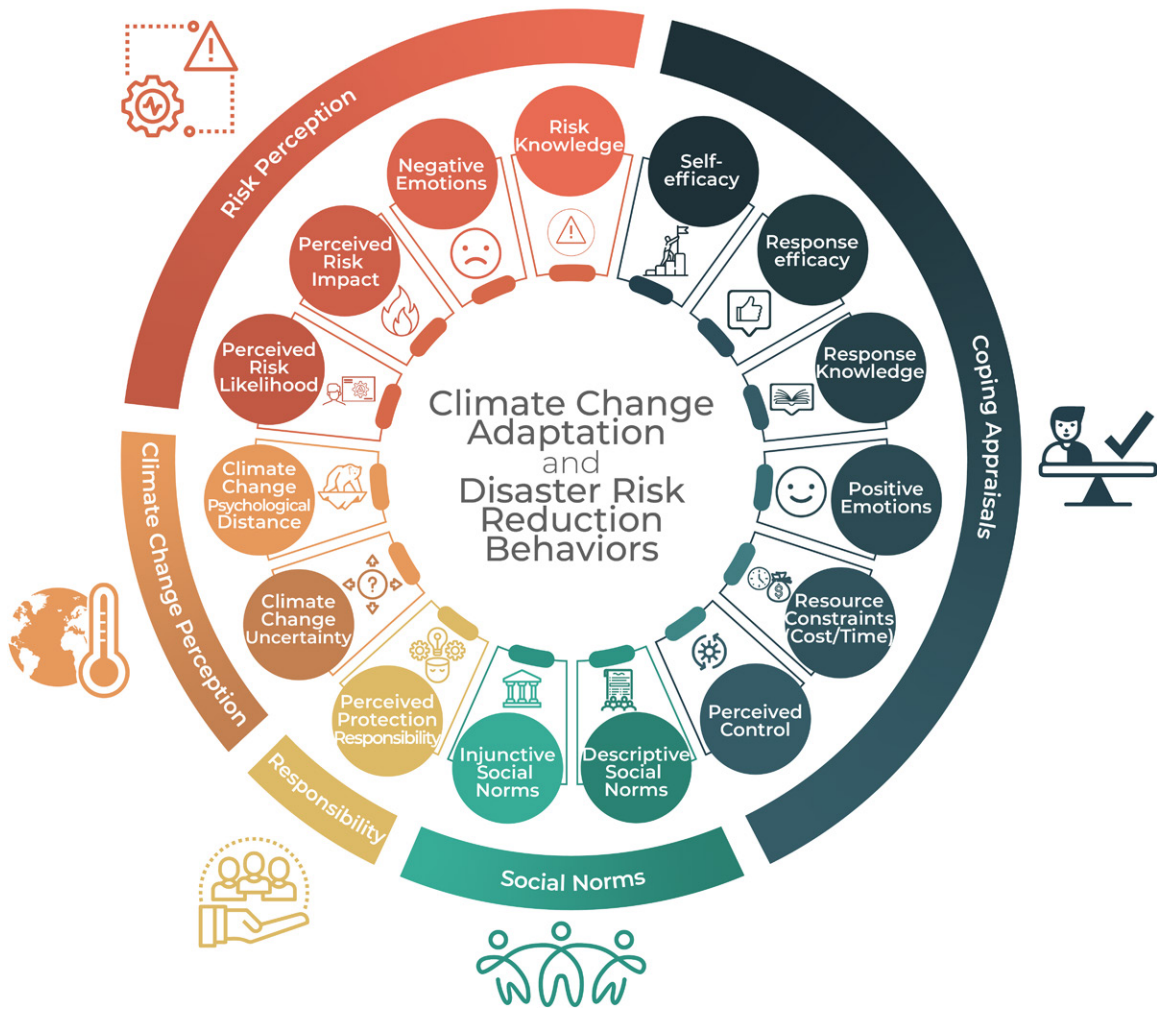


Fig. 1. Integrated model of risk communication.

(Grothmann and Reusswig 2006; Lindell and Perry 2012; Sheeran et al. 2014; Siegrist and Árvai 2020). Research so far has found only small, but significant effects of risk perceptions on mitigation behaviors (McCaffrey 2015; Ripberger et al. 2018; Slotter et al. 2020; van Valkengoed and Steg 2019). A meta-analysis on PMT in a flood prevention context found that threat appraisals are significantly related to flood prevention intentions and behaviors (Bamberg et al. 2017). Another meta-analysis on factors motivating climate change adaptation behavior found that risk perception had small effects on adaptive behaviors (van Valkengoed and Steg 2019). Based on prior research, this paper poses the following hypothesis:

H1: At-risk publics' perceived risk likelihood (H1a) and impact (H1b) positively predict their behavioral intentions. In other words, when at-risk publics feel higher risk likelihood (H1a) and impact (H1b), they would be more likely to engage in climate adaptation and disaster risk reduction behaviors.

NEGATIVE EMOTIONS. Research showed that negative emotions, such as fear, anxiety, dread, and worry, can be generated by and go with risk perception (Balog-Way et al. 2020; Dillard et al. 2017; Myrick and Nabi 2017; So 2013; Terpstra et al. 2014). The integrated crisis mapping (ICM) model found that anxiety is a default emotion in crises and that people experience fright in weather and climate disasters (Jin et al. 2012; Lim et al. 2019b). EPPM research also found that fear and anxiety motivate responses to risks (So 2013;

Witte 1992). Researchers consider negative emotions to be an independent predictor for risk behaviors that are distinct from perceived risk likelihood and impact (Altarawneh et al. 2018; Slovic et al. 2004; Tapsell et al. 2002). Negative emotions were one of the strongest factors motivating disaster preparedness behaviors with large effect sizes (Bamberg et al. 2017; van Valkengoed and Steg 2019). Based on prior research, this paper poses the following hypothesis:

H2: At-risk publics' negative emotions positively predict their behavioral intentions.

Coping appraisals. Coping appraisals are the process through which people evaluate possible actions, their ability to perform those actions, and the cost of proceeding to reduce or address risks (Bubeck et al. 2012; Floyd et al. 2000; Slotter et al. 2020). Some scholars have argued that individuals' coping appraisals influence whether they decide to take protective measures (Grothmann and Reusswig 2006; Milne et al. 2000). Coping appraisals include self-efficacy, response efficacy, positive emotions, and resource constraints (Bubeck et al. 2012; Lindell and Perry 2012).

SELF-EFFICACY, CONTROLLABILITY, AND RESPONSE EFFICACY. Self-efficacy refers to whether people believe they are capable of taking a recommended action (Bandura 2001; Nabi and Myrick 2019; Tannenbaum et al. 2015). Response efficacy is whether people believe performing a recommended action can help reduce the risks and result in desirable consequences (Tannenbaum et al. 2015; Terpstra and Lindell 2013). A meta-analysis found that self-efficacy and response efficacy strongly motivate climate change adaptation behaviors (van Valkengoed and Steg 2019).

Conversely, the Theory of Planned Behavior (TPB) identified controllability, which involves "people's beliefs that they have control over the behavior, and that performance or non-performance of the behavior is up to them" (Ajzen 2002, p. 676). Behavioral control significantly predicted the behavior to keep tree limbs pruned for wildfires (Nox and Myles 2017), protecting the environment against wildfires, and protecting homes against wildfires (Bates et al. 2009). Similarly, Bright and Burtz (2006) also used TPB and controllability when predicting intentions to wildfire mitigation behaviors.

Further, a meta-analysis on protection motivation theory in different risk contexts found that coping appraisals are strongly correlated with behaviors and behavioral intentions (Bamberg et al. 2017; Floyd et al. 2000; Milne et al. 2000). For example, efficacy explained about 32%–41% in behavioral intentions related to flood preparedness in the Netherlands (Terpstra 2010). Based on prior research, this paper poses the following hypotheses:

H3: At-risk individuals' self-efficacy (H3a), controllability (H3b), and response efficacy (H3c) positively predict their behavioral intentions.

POSITIVE EMOTIONS. Positive emotions, such as hope, can help the impacted to cope with disaster risks. Hope was defined as a feeling of "wishing and yearning for relief from a negative situation" and "realization of a positive outcome when the odds do not greatly favor it" (Lazarus 1991, p. 282). The limited studies available explored the impacts of hope on behaviors (Chadwick 2015; Feldman and Hart 2018; Nabi and Myrick 2019; Lim et al. 2019b). Hope also positively triggers individuals to seek and process disaster risk mitigation information (Yang et al. 2010, 2011) and take protective actions during disasters (Lim et al. 2019b). Based on prior research, this paper poses the following hypothesis:

H4: At-risk individuals' positive emotions positively predict their behavioral intentions.

KNOWLEDGE ABOUT RISKS AND RESPONSES. One major reason why people with high risk perception may not take preparedness actions is that they may not know what the appropriate actions are (Wachinger et al. 2013). Risk knowledge can impact risk perception, whereas response knowledge can impact self-efficacy and response efficacy because self-efficacy and response efficacy can stem from having the knowledge required to reduce risks (Lindell and Whitney 2000). Still, van Valkengoed and Steg (2019) found only small, positive effects of knowledge on climate adaptation behaviors, yet there was no distinction between risk knowledge and response knowledge. Conversely, survey studies have shown mixed findings in how risk knowledge may impact preparedness and mitigation behaviors (Botzen et al. 2009; Miceli et al. 2008; Siegrist and Gutscher 2006; Terpstra and Lindell 2013). The meta-analysis also found that objective factual measurement of knowledge has effect sizes similar to subjective self-assessed knowledge (van Valkengoed and Steg 2019). Based on prior research, this paper poses the following hypotheses:

H5: At-risk individuals' risk knowledge (H5a) and response knowledge (H5b) positively predicts their behavioral intentions.

RESOURCE CONSTRAINTS. Resource constraints are the estimated costs and time for individuals to perform a particular behavior (Bubeck et al. 2012; Rogers 1983; Lindell and Perry 2012). Studies have found that cost and time are major impediments to disaster mitigation and preparedness efforts (Martin et al. 2010; Siegrist and Gutscher 2008; Sisante 2018). For example, in multiple studies, the perceived time needed to implement mitigation measures was related to not taking those measures (Grothmann and Reusswig 2006; Kreibich et al. 2011; Siegrist and Gutscher 2008; Poussin et al. 2014). Perceived costs impeded individuals from taking flood damage mitigation behaviors, such as using a water-resistant floor or installing a pump (Poussin et al. 2014; Slotter et al. 2020), and purchasing flood insurance (Terpstra and Lindell 2013). Based on prior research, this paper poses the following hypothesis:

H6: At-risk individuals' resource constraints negatively predict their behavioral intentions.

Social norms perceptions. Social norms are “a common behavior or practice” (Miller and Prentice 2016, p. 340), which can influence how individuals perceive social expectations and behaviors (Ajzen 2011; Cialdini 2012). There are two types of social norms: descriptive and injunctive social norms.

DESCRIPTIVE NORMS PERCEPTIONS. Descriptive norms refer to how prevalent behaviors are among group members and provide a cognitive shortcut to help decision-making (Goldstein et al. 2007; Nolan et al. 2008). The meta-analysis on climate change adaptation behavior found that descriptive norms have a significant effect on adaptive behaviors (van Valkengoed and Steg 2019). Studies have found that descriptive norms significantly predict preparedness behaviors (Bubeck et al. 2013, 2018; Slotter et al. 2020; Vinnell et al. 2019). Yet, one choice experiment study in a wildfire revealed that having neighbors with sparse vegetation rather made individuals less likely to engage in wildfire mitigation behaviors (Dickinson et al. 2020). Based on prior research, this paper poses the following hypothesis:

H7: At-risk individuals' descriptive norms perceptions positively predict their behavioral intentions.

INJUNCTIVE NORMS PERCEPTIONS. Injunctive norms, or norms of “ought,” provide information about whether a social group approves or disapproves of a behavior and help individuals gain and maintain social approval (Cialdini et al. 2006). Van Valkengoed and Steg (2019) found that injunctive norms have a small effect on adaptive behaviors. Survey studies have found that individuals in flood-, wildfire-, and earthquake-prone areas are more likely to prepare for these disasters, if they believe that their friends, neighbors, and family members are prepared (Bubeck et al. 2018; Lo 2013; Nox and Myles 2017). Based on prior research, this paper poses the following hypothesis:

H8: At-risk individuals’ injunctive norms perceptions positively predict their behavioral intentions.

Perceived protection responsibility. Perceived protection responsibility is the perceived responsibility for adopting preventive measures to ensure safety during a hazard event; adopting these measures can be the responsibility of an individual or an outside actor (e.g., government agency) (Lindell and Perry 2012; Mulilis and Duval 1997, 2003). PADM and the PrE theory saw personal responsibility as a core condition to take preparedness action (Mulilis and Duval 1997, 2003; Mulilis et al. 2001). A qualitative study in seismic risk-prone areas in New Zealand found that when protection responsibility was perceived to be low, individuals believed it was not their responsibility to prepare (Becker et al. 2013). The meta-analysis on factors that motivate climate change adaptation behavior found a small effect size of perceived responsibility on adaptive behaviors (van Valkengoed and Steg 2019). Additional studies have indicated that perceived protection responsibility is a core factor influencing preparedness behaviors (Lindell and Whitney 2000; Mulilis and Duval 1997, 2003). Based on prior research, this paper poses the following hypothesis:

H9: At-risk individuals’ perceived responsibility positively predicts their behavioral intentions.

Climate change perception (uncertainty and psychological distance). Climate change perception is believed to be closely related to and influence adaptation and disaster preparedness behaviors (Bouwer 2011; Lavell et al. 2012; Spence et al. 2012; Jones et al. 2017). Individuals often believe that climate change’s impacts are uncertain and distant geographically, temporally, and socially (Bar-Anan et al. 2006; Leiserowitz 2005; Roeser 2012; Spence et al. 2012; Jones et al. 2017). For example, individuals often believe that “most scientists do not agree about climate change impact” and “the science about climate change is far from settled” (Jones et al. 2017, p. 335). Individuals may also think “climate change more likely to impact countries far away” (geographic), “future generations more likely to feel effects of climate change” (temporal), and “climate change will be experienced by people not like me” (social) (Jones et al. 2017, p. 335).

Research has found that climate change psychological distance and uncertainty are significantly related to preparedness to reduce energy use (Spence et al. 2012) and climate change mitigation intentions (Jones et al. 2017). Van Valkengoed and Steg (2019) found a small effect size of perceived responsibility on climate change adaptive behaviors. Based on prior research, this paper poses the following hypotheses:

H10: At-risk individuals’ climate change uncertainty (H10a) and psychological distances (10b) negatively predict their behavioral intentions.

Developing an integrated model of risk communication. Researchers have called for conceptually integrated models that simultaneously compare the impacts of the factors that

motivate adaptation behaviors (Bamberg et al. 2017; Kellens et al. 2013; van Valkengoed and Steg 2019; Wilson et al. 2020). It is not clear which factors strongly motivate climate change adaptive behaviors, as previous studies did not compare all factors in one model (van Valkengoed and Steg 2019; Wilson et al. 2020). Additionally, different theories use different concepts, measurements, and outcomes. For example, a review paper found only one study (Grothmann and Reusswig 2006) that used a combined measurement of perceived probability and consequences for risk perception (Bubeck et al. 2012).

This study consolidates existing theories on the factors that influence adaptation behaviors and develops an Integrated Model of Risk Communication (see Fig. 1). There are five clusters: risk perception, coping appraisals, social norms perceptions, responsibility, and climate change perception. These factors work together to motivate individuals to adopt behaviors.

This list of variables may not be fully exhaustive. Other relevant variables exist, such as trust, experience, homeownership, and place attachment. The selected factors were prioritized based on the academic and practical importance so that future researchers and professionals can try to enact change through interventions. For example, although homeownership and disaster experience are strong factors in motivating adaptation behaviors, policymakers would not enact interventions such as providing homeownership or forcing someone to experience a disaster.

Methods

This study uses large-scale surveys and SEM analysis to simultaneously test the impacts of 15 factors on 15 adaptation behaviors for the two most common federally declared disasters (wildfires, hurricanes with floods) in three disaster-prone U.S. states (California, Florida, and Texas) ($N = 3,468$).

Procedure. Quantitative surveys were used to test the proposed model and to identify key motivating factors for climate adaptation and disaster risk reduction behaviors. At-risk publics in three states participated in a Qualtrics-hosted between July and November 2019, using Amazon Mechanical Turk (MTurk). A university Institutional Review Board (IRB) reviewed and approved this study. Participants were compensated for their time per IRB guidelines, in compliance with the American Psychological Association (APA) ethical standards in the treatment of samples. The recruitment advertisement transparently disclosed the compensation and estimated duration ranges upfront, while studies have found that compensation rates do not influence data quality (Bohannon 2011; Buhrmester et al. 2018).

Once participants provided their consent, participants were asked to provide self-reported responses for five clusters of independent variables for each target behavior. Then, participants were asked to indicate their intention for each target behavior. Finally, participants were asked to provide their socio-demographics (i.e., gender, age). To compare the impact of each factor on behaviors, participants responded to psychological factors for each behavior. The order of all questions was randomized to mitigate order effects.

Disaster types and states. The locations and the types of weather and climate disasters were based on the number of Federal Emergency Management Agency (FEMA) disaster declarations at the state level: hurricanes (Florida, Texas) and wildfires (California, Texas). Since 1953, federally declared disasters in the United States have included hurricanes ($N = 1,264$), wildfires ($N = 1,054$), floods ($N = 786$), tornadoes ($N = 164$), and earthquakes ($N = 29$) (FEMA 2021a). The states that experience the largest number of disasters are California, Texas, Oklahoma, Washington, and Florida (FEMA 2021a). California, Texas, and Florida were selected because they have populations of more than 20,000,000 residents

(U.S. Census 2021; WorldAtlas 2019). The most common federally declared disasters in each state—wildfires for California and Texas and hurricanes for Florida and Texas—were identified.

Recruitment. Participants were recruited through Amazon’s MTurk crowdsourcing platform. To ensure data quality, participants were restricted to people in the United States, who have MTurk reputations of 95% or higher and have completed at least 100 Human Intelligence Tasks (HITs) (i.e., completed 100 tasks on MTurk and did not have more than 5% of their tasks rejected) (Cunningham et al. 2017; Peer et al. 2014).

Participants. In total, the study recorded 3,486 responses from U.S. adult participants: California wildfire risk ($n = 1,031$), Florida hurricane risk ($n = 1,010$), Texas wildfire risk ($n = 725$), and Texas hurricane risk ($n = 720$). The median time to complete the survey was 41.4 min for hurricanes in Florida, 37.4 min for wildfires in California, 37.3 min for wildfires in Texas, and 39.0 min for hurricanes in Texas. Overall, participants’ demographics mirrored the demographics of each state’s residents (see Table 3).

Measures. All items were measured on a seven-point Likert type or semantic differential scale, except perceived risk knowledge and perceived response knowledge, which were measured on a 0–100 scale. See the online supplemental material for more information, including all measures.

TARGET BEHAVIORS. Inspired by previous research (Koksal et al. 2019; Osberghaus 2017; Wolters et al. 2017) and climate adaption and disaster risk reduction materials (NOAA 2019; FloodSmart.gov 2019; NFPA 2019; FEMA 2021b), select adaptation behaviors included nonstructural adaptation behaviors, structural adaptation behaviors, purchasing insurance,

Table 3. Participants demographics.

		Study participants								U.S. population		
		Hurricane and flood risks				Wildfire risks				State		
		Florida		Texas		California		Texas		California	Florida	Texas
Participants (n)		1,010		720		1,031		725				
Median time to complete (minutes)		41.43		39.07		37.41		37.33				
Age	Range	18–79		18–99		18–82		18–76				
	Mean	37.14		35.19		35.18		35.41				
	Standard deviation	20.38		11.53		11.93		11.90				
	Median	34		32		32		32		37	42.5	35
		n	%	n	%	n	%	n	%			
Gender	Male	379	37.5	274	38.1	461	44.7	276	38.1	49.7%	48.9%	49.7%
	Female	622	61.6	437	60.7	555	53.8	440	60.7	50.3%	51.1%	50.3%
	Other, prefer not to say	9	0.9	9	1.3	15	1.5	9	1.2			
Race	Caucasian	679	67.2	409	56.8	556	53.9	423	58.3	36.5%	53.2%	41.2%
	African-American	114	11.3	93	12.9	48	4.7	73	10.1	6.5%	16.9%	12.9%
	Hispanic	126	12.5	130	18.1	176	17.1	130	18	39.4%	26.4%	39.7%
	Asian	38	3.8	50	6.9	166	16.1	50	6.9	15.5%	3%	5.2%
	Native American	15	1.5	8	1.1	15	1.5	18	2.5	1.6%	0.5%	1.0%
	Other	38	3.8	8	1.1	70	6.8	31	4.3	4.5%	2.3%	2.2%
Homeownership	No owner	442	43.8	326	45.3	571	55.4	320	44.1	45.2%	34.6%	38%
	Owner	568	56.2	394	54.7	460	44.6	405	55.9	54.8%	65.4%	62%

Source: U.S. Census (2021).

and preparedness behavior (see Table 1). Additionally, inspired by previous research (Done et al. 2018; Ripberger et al. 2018; Simmons and Kovacs 2018; Vinnell et al. 2019), four adaptation policies were included. These target behaviors were used as dependent variables (endogenous factors).

BEHAVIORAL INTENTIONS. Adopted from prior research (Nabi and Myrick 2019; Terpstra and Lindell 2013; Wilson et al. 2019), behavioral intentions were measured for each behavior by asking three questions. Adapted from Ripberger et al. (2018), Vinnell et al. (2019), and Yang et al. (2014), support for each adaptation policy was measured by asking three questions.

RISK PERCEPTION.

Perceived likelihood (susceptibility or probability). Using a multidimensional measure of risk perception developed from Wilson et al. (2019) and adopted from Witte et al. (1996) and Nabi and Myrick (2019), perceived susceptibility was assessed by rating five statements.

Perceived impact (severity or consequences). Perceived severity was assessed by rating five statements inspired by prior research (Demuth 2018; Nabi and Myrick 2019; Trumbo et al. 2016; Wilson et al. 2019; Witte et al. 1996).

Negative emotions. Affective risks were measured by rating six statements inspired by prior research (Demuth 2018; Dillard et al. 2017; Nabi and Myrick 2019; Trumbo et al. 2016; Wilson et al. 2019; Yang et al. 2014).

Perceived risk knowledge. Adopted from tests of the RISP model (Griffin et al. 2004, 2008, 2013; ter Huurne et al. 2009; Yang et al. 2014), perceived risk knowledge was measured by asking four questions.

COPING APPRAISALS.

Perceived response knowledge. Adopted from tests of the RISP model (Griffin et al. 2004, 2008, 2013; ter Huurne et al. 2009; Yang et al. 2014), perceived response knowledge was measured by asking four questions.

Self-efficacy and response efficacy. Adopted from Bubeck et al. (2018), Witte et al. (1996), Dillard et al. (2017), Terpstra and Lindell (2013), and Nabi and Myrick (2019), self-efficacy was assessed by rating four statements, and response efficacy was assessed by rating four statements.

Positive emotions. Modified from Chadwick (2015) and Nabi and Myrick (2019), positive emotions were measured by rating five statements.

Resource constraints. Adopted from Bubeck et al. (2018), Martin et al. (2010), and Poussin et al. (2014), resource constraints were measured with two statements and three questions.

Perceived controllability. Adopted from Ajzen (2002, 2006), perceived controllability was measured with three statements and questions.

SOCIAL NORMS PERCEPTIONS.

Descriptive and injunctive social norms. Adopted from Bubeck et al. (2013) and Vinnell et al. (2019), descriptive social norms were assessed with four questions/statements, and injunctive social norms were assessed with four questions.

Perceived responsibility. Adopted from Terpstra (2010), Mulilis et al. (2001), Mulilis and Duval (2003), and Becker et al. (2013), perceived responsibility was measured with five statements and questions.

Climate change perception (uncertainty and psychological distance). Adopted from Jones et al. (2017) and Spence et al. (2012), climate change (geographical, social, temporal) psychological distance and uncertainty were assessed using ratings on 13 statements.

Analysis. Structural equation modeling and latent variable path analysis were conducted using Mplus 8.4 (Muthén and Muthén 2017). Structural equation modeling helps researchers reduce measurement errors, which are common in social science research for the latent constructs, and systematically examine effects (Raykov and Marcoulides 2000; Kline 2015).

In total, 38 models with each target behavior (e.g., purchasing flood insurance) as an endogenous factor (dependent variable) were constructed to test the hypothesized models and compare the impact of each factor on behaviors.

Maximum likelihood (ML) assumes data are continuous and multivariates are normally distributed. Violations of these assumptions cause high type I error, biased standard errors, chi-square values, and approximate fit index values (Bandalos and Finney 2019; Mueller and Hancock 2019). Thus, all models were formed using Satorra–Bentler adjustment, which accounts for the nonnormality of the data when estimating standard errors of parameter estimates and goodness of fit indices.

A two-phase modeling process was used to validate the measurement model, because variables are used as latent variables in the model (Anderson and Gerbing 1988). The two-phase modeling process includes the first measurement phase and the following structural phase.

MEASUREMENT MODEL. In the first measurement phase, the model is temporarily respecified so that all latent variables are allowed to covary freely to see if the model achieves an acceptable fit. The model was respecified based on theoretical considerations, Lagrange multiplier tests, and/or relatively large residuals (Mueller and Hancock 2019). In total, 14 pairs of indicators were allowed to correlate, as most of them have similar wordings and sentence structure (see respecification of the measurement model in the online supplemental material).

Correlations between factors were reviewed to examine discriminant validity. All factor correlations were below 0.80 (64% shared variance) except for correlations between 1) injunctive and descriptive norms, 2) self-efficacy and controllability, and 3) climate change temporal and social psychological distance. Additional factor analyses were conducted for each pair of these six factors, and they indicated one factor across all models. Thus, based on prior research (e.g., Ajzen 2002; Cialdini 2012; Rhodes and Courneya 2003; Miller and Prentice 2016), high correlations, and single-factor loading, each pair of these factors were treated as a single factor in the models, despite conceptual differences.

The overall measurement model indicated a great fit [e.g., chi-square, degrees of freedom (df), *p* value, comparative fit index (CFI), root-mean square error of approximation (RMSEA), standardized root-mean squared residual (SRMR)], indicating that the items sufficiently and reliably measured the latent constructs. The fit for structural equation models was evaluated with Hu and Bentler's (1999) criteria: RMSEA 0.06 or lower, SRMR 0.08 or lower, CFI 0.95 or higher. Construct reliability or replicability estimates of the measures (i.e., coefficients *H*) were over or about .70, thus reliable (see the online supplemental material for the SEM model

fit and coefficients H). As the data satisfactorily fit the measurement model, the author moved to the second phase.

STRUCTURAL MODEL. In total, 38 models with each target behavior as an endogenous (dependent) factor were constructed to test the hypothesized models. The originally hypothesized structural relations were formed among the factors, while preserving measurement model modifications made during the first phase. The model fit did not change from the measurement models. All reported coefficients are standardized coefficients.

Factors Motivating Wildfire Risk Reduction and Climate Adaptation Behaviors (Standardized SEM Coefficients)

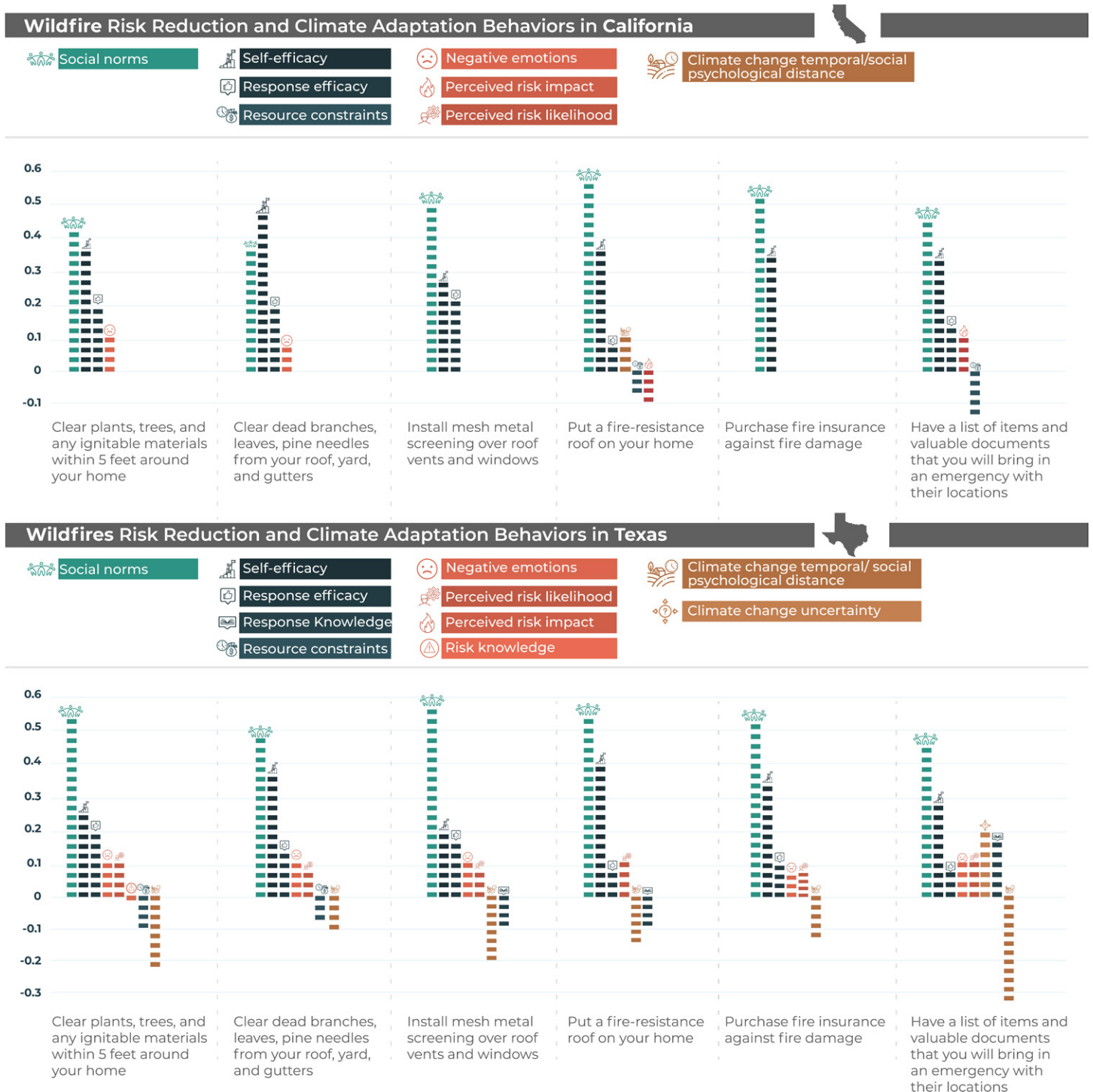


Fig. 2. Factors motivating wildfire risk reduction and climate adaptation behaviors (standardized SEM coefficients).

Factors Motivating Hurricane and Flood Risk Reduction and Climate Adaptation Behaviors (Standardized SEM Coefficients)



Fig. 3. Factors motivating hurricane and flood risk reduction and climate adaptation behaviors (standardized SEM coefficients).

Table 4. Factors motivating wildfire, hurricane, flood preparedness and insurance purchase behaviors. The *p* values are indicated as follows: *, *p* < 0.05; **, *p* < 0.01; *, *p* < 0.001. Standardized SEM path coefficients are reported. Wildfire risks (California, *n* = 1,031; Texas, *n* = 725); hurricane risks (Florida, *n* = 1,010; Texas, *n* = 720).**

Model	Preparedness				Insurance Purchase			
	Have a list of items and valuable documents that you will bring in emergency with their locations				Purchase fire/flood and/or windstorm insurance against fire/hurricane damage			
	01	02	03	04	19	20	21	22
	Wildfires CA	Wildfires TX	Hurricanes FL	Hurricanes TX	Wildfires CA	Wildfires TX	Hurricanes FL	Hurricanes TX
Endogenous factors								
Risk perception								
Perceived risk likelihood	0.006	0.081*	0.01	0.018	0.039	0.061*	−0.036	0.039
Perceived risk impact	0.078*	0.002	−0.004	0.024	0.012	−0.049	−0.003	0.02
Negative emotions	0.038	0.082*	0.116***	0.071	0.024	0.059*	0.12***	0.045
Risk knowledge	0.022	0.001	0.064	−0.08	0.009	−0.019	−0.014	−0.066*
Coping appraisals								
Self-efficacy	0.306***	0.264***	0.278**	0.161	0.391***	0.321***	0.236***	0.397***
Response efficacy	0.13**	0.063	0.074	0.067	0.105***	0.091*	0.163***	0.086*
Resource constraints	−0.112*	−0.326***	−0.141*	−0.267***	−0.013	−0.11*	−0.144***	−0.078
Response knowledge	0.034	0.035	−0.033	0.021	−0.013	−0.035	0.007	0.026
Positive emotions	0.008	0.018	−0.029	0.03	0.024	0.038	0.001	−0.036
Social norms perceptions	0.431***	0.443***	0.493***	0.534***	0.504***	0.503***	0.504***	0.53***
Perceived protection responsibility	−0.003	0.031	−0.02	0.023	0.03	0.055	0.037	−0.089*
Climate change perception								
Geological psychological distance	−0.017	−0.027	0.101*	−0.002	0.003	−0.008	0.08*	−0.03
Temporal and social psychological distance	−0.081	0.181*	−0.023	0.133	0.015	0.052	−0.018	−0.071
Uncertainty	0.036	0.185*	0.014	0.169	−0.061	0.071	0.01	−0.024
<i>R</i> ²	0.702***	0.661***	0.658***	0.617***	0.842***	0.834***	0.751***	0.807***

Findings

The findings are presented with standardized SEM path coefficients and the number of significance to compare the impacts of psychological factors on each behavior (see Tables 4–8). For example, we can interpret the standardized path coefficient of 0.6 that a one-standard-deviation increase in a driving factor is estimated to directly cause a 0.6-standard-deviation increase in the adaptation behavior, holding all else constant, assuming that the model is correct. In other words, the psychological factor with a higher standardized path coefficient has a greater impact on the behavior than others.

Figures 2–5 visualize the impacts of each factor through standardized SEM coefficients. The turquoise bars indicate social norms, while the navy blue bars indicate coping appraisals (e.g., self-efficacy, response efficacy, and resource constraints).

Risk perception.

PERCEIVED RISK LIKELIHOOD (H1A). Perceived risk likelihood is significant in 10 models. Its standardized path coefficients range from −0.103 to 0.128. For wildfire risks, it positively affects intentions to clear dead branches and leaves (TX/Fire: $\beta = 0.078$, $p = 0.008$, M06), to clear plants and any ignitable materials (TX/Fire: $\beta = 0.099$, $p < 0.001$, M08), to install mesh metal screening (TX/Fire: $\beta = 0.082$, $p = 0.001$, M12), to install a fire-resistant roof (TX/Fire: $\beta = 0.087$, $p = 0.001$, M14), to purchase fire insurance (TX/Fire: $\beta = 0.061$,

Table 5. Factors motivating structural and nonstructural wildfire risk mitigation and adaptation behaviors. The p values are indicated as follows: *, $p < 0.05$; **, $p < 0.01$; *, $p < 0.001$. Standardized SEM path coefficients are reported. Wildfire risks (California, $n = 1,031$; Texas, $n = 725$).**

Wildfire risks	Nonstructural risk mitigation				Structural risk mitigation			
	Clear dead branches, leaves, pine needles from your roof, yard, and gutters		Clear plants, trees, and any ignitable materials within 5 ft around your home		Install mesh metal screening over roof vents and windows		Put a fire-resistant roof on your home	
	Model	05	06	07	08	11	12	13
Endogenous factors	Wildfires CA	Wildfires TX	Wildfires CA	Wildfires TX	Wildfires CA	Wildfires TX	Wildfires CA	Wildfires TX
Risk perception								
Perceived risk likelihood	0.02	0.078**	0.021	0.099***	−0.009	0.082**	−0.016	0.087**
Perceived risk impact	0.021	−0.015	0.008	−0.011	0.019	0.01	0.025	0.005
Negative emotions	0.072**	0.097***	0.082**	0.099***	0.043	0.089**	0.041	0.033
Risk knowledge	0.03	−0.075*	0.018	−0.093**	0.002	0.007	−0.018	0.017
Coping appraisals								
Self-efficacy	0.456***	0.343***	0.366***	0.244***	0.28***	0.189***	0.341***	0.36***
Response efficacy	0.192***	0.11*	0.189***	0.182***	0.21***	0.163***	0.078**	0.061*
Resource constraints	0.019	−0.095*	−0.052	−0.199***	−0.065*	−0.2***	−0.068*	−0.125***
Response knowledge	0.011	0.007	0.034	0.031	0.057	−0.087*	0.024	−0.089**
Positive emotions	0.018	0.021	0.007	0.038	0.007	0.041	−0.011	−0.007
Social norms perceptions	0.356***	0.467***	0.406***	0.516***	0.493***	0.541***	0.547***	0.515***
Perceived protection responsibility	−0.027	0.054	−0.029	−0.033	−0.008	0.032	0.031	0.022
Climate change perception								
Geological psychological distance	−0.001	0.029	−0.045	−0.003	0.016	−0.038	−0.012	−0.022
Temporal and social psychological distance	0.022	0.048	−0.06	0.04	−0.029	0.034	−0.084*	0.008
Uncertainty	−0.044	0.042	0.069	0.029	0.018	0.065	0.047	0.028
R ²	0.757***	0.760***	0.764***	0.793***	0.788***	0.825***	0.818***	0.825***

$p = 0.021$, M20), and to support providing tax incentives for wildfire precautions (TX/Fire: $\beta = 0.058$, $p = 0.029$, M31).

For hurricane risks, perceived risk likelihood positively affects intention to purchase flood protection devices (TX/Hurricane: $\beta = 0.065$, $p = 0.013$, M16) and to support providing tax incentives for hurricane precautions (FL/Hurricane: $\beta = 0.128$, $p = 0.001$, M33; TX/Hurricane: $\beta = 0.072$, $p = 0.038$, M34). Conversely, perceived risk likelihood negatively affects policy support intention to change land use for wildfire risks (TX/Fire: $\beta = -0.103$, $p = 0.001$, M28).

PERCEIVED RISK IMPACT (H1b). Perceived risk impact is significant in six models. Its standardized path coefficients range between 0.078 and 0.141. For wildfire risks, it positively affects intentions to have a list for emergency (CA/Fire: $\beta = 0.078$, $p = 0.049$, M01), to support stricter building codes (CA/Fire: $\beta = 0.111$, $p = 0.005$, M23), to support changing land use (TX/Fire: $\beta = 0.086$, $p = 0.018$, M28), to support providing tax incentives for wildfire precautions (CA/Fire: $\beta = 0.141$, $p < 0.001$, M31; TX/Fire: $\beta = 0.122$, $p = 0.001$, M32), and to support providing long-term mitigation loans (CA/Fire: $\beta = 0.139$, $p < 0.001$, M35).

Table 6. Factors motivating structural and nonstructural hurricane and flood risk mitigation and adaptation behaviors. The *p* values are indicated as follows: *, *p* < 0.05; **, *p* < 0.01; ***, *p* < 0.001. Standardized SEM path coefficients are reported. Hurricane risks (Florida, *n* = 1,010; Texas, *n* = 720).

Hurricane and flood risks	Nonstructural risk mitigation		Structural risk mitigation			
	Move valuable furniture and important documents to a higher floor or a safe place		Purchase flood protection devices, such as protection flaps and water barriers		Install a roof covering and/or galvanized metal hurricane straps that can withstand high winds	
Model	09	10	15	16	17	18
Endogenous factors	Hurricanes FL	Hurricanes TX	Hurricanes FL	Hurricanes TX	Hurricanes FL	Hurricanes TX
Risk perception						
Perceived risk likelihood	0.004	0.055	−0.002	0.065*	−0.054	0.032
Perceived risk impact	−0.007	0.044	0.023	0.018	0.038	0.039
Negative emotions	0.056*	0.003	0.059*	0.02	0.069**	0.021
Risk knowledge	−0.003	−0.074*	−0.065	−0.06	−0.018	−0.034
Coping appraisals						
Self-efficacy	0.16**	0.347***	0.272***	0.426***	0.28***	0.341***
Response efficacy	0.245***	0.163**	0.056	0.157***	0.084*	0.123**
Resource constraints	−0.045	0.002	−0.076*	−0.016	−0.086**	−0.049
Response knowledge	−0.025	−0.025	0.036	0.008	0.002	−0.031
Positive emotions	−0.021	−0.058*	0.019	−0.029	0.022	−0.008
Social norms perceptions	0.579***	0.58***	0.603***	0.533***	0.554***	0.62***
Perceived protection responsibility	−0.002	−0.062	−0.035	−0.11***	0.023	−0.058
Climate change perception						
Geological psychological distance	0.061	−0.031	0.051	−0.016	0.018	−0.045
Temporal and social psychological distance	0.021	−0.142**	−0.047	−0.095*	−0.041	−0.101*
Uncertainty	−0.059	−0.077	0.02	−0.064	0.049	−0.086
<i>R</i> ²	0.809***	0.798***	0.784***	0.854***	0.778***	0.862***

NEGATIVE EMOTIONS (H2). Negative emotions are significant in 16 models. Their standardized path coefficient ranged between −0.098 and 0.12. They positively affect intentions to have a list for an emergency (TX/Fire: $\beta = 0.082$, $p = 0.012$, M02; FL/Hrcn: $\beta = 0.116$, $p < 0.001$, M03), to purchase insurance (TX/Fire: $\beta = 0.059$, $p = 0.011$, M20; FL/Hrcn: $\beta = 0.12$, $p < 0.001$, M21), and to support stricter building codes (TX/Fire: $\beta = 0.072$, $p = 0.01$, M24; FL/Hrcn: $\beta = 0.062$, $p = 0.034$, M25) for both hurricane and wildfire risks.

For wildfire risks, negative emotions positively affect intentions to clear dead branches and leaves (CA/Fire: $\beta = 0.072$, $p = 0.005$, M05; TX/Fire: $\beta = 0.097$, $p < 0.001$, M06); to clear plants and any ignitable materials (CA/Fire: $\beta = 0.082$, $p = 0.001$, M07; TX/Fire: $\beta = 0.09$, $p < 0.001$, M08); to install mesh metal screening (TX/Fire: $\beta = 0.089$, $p = 0.001$, M12); and to support changing land use (TX/Fire: $\beta = 0.074$, $p = 0.007$, M28). Conversely, they negatively affect intentions to support providing tax incentives for wildfire precautions (CA/Fire: $\beta = -0.098$, $p < 0.001$, M31).

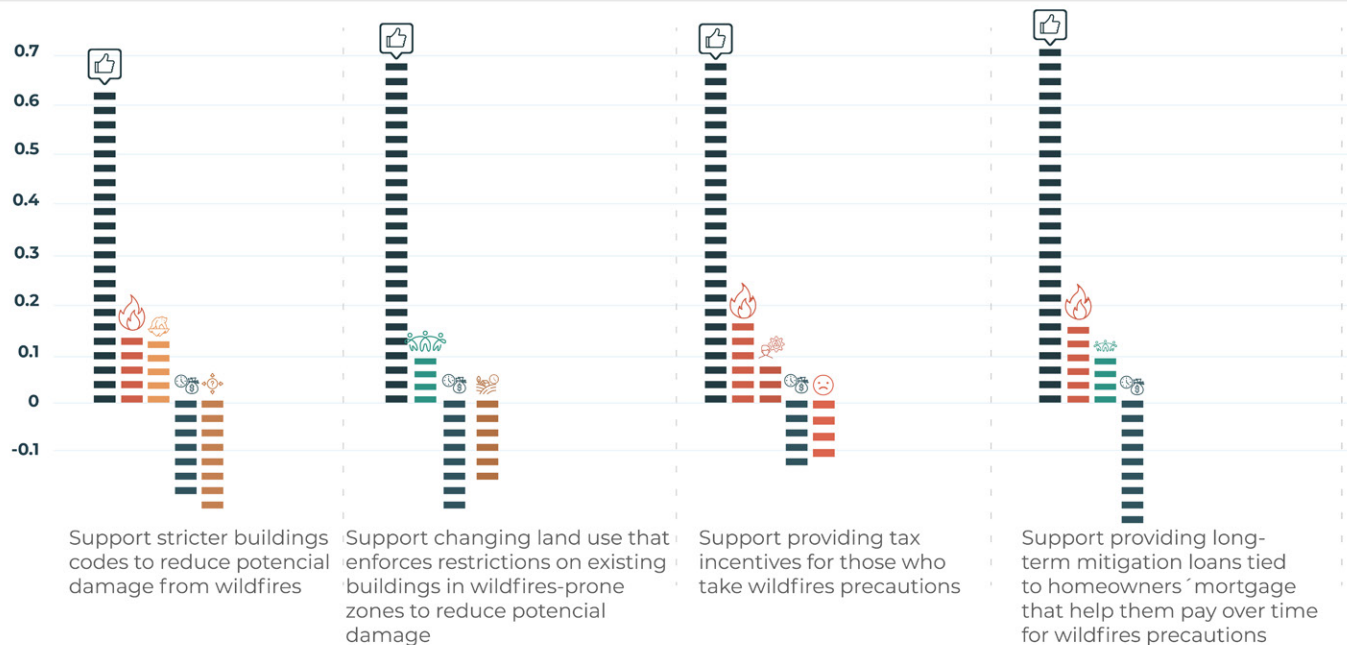
For hurricane risks, negative emotions positively affect intentions to move valuable furniture (FL/Hrcn: $\beta = 0.056$, $p = 0.032$, M09), to purchase flood protection devices (FL/Hrcn: $\beta = 0.059$, $p = 0.014$, M15), and to install a roof covering and/or galvanized metal hurricane straps (FL/Hrcn: $\beta = 0.069$, $p = 0.003$, M17).

KNOWLEDGE ABOUT RISKS (H5A). Risk knowledge is significant in five models. Its standardized path coefficients range between −0.093 and 0.091. For wildfire risks, it negatively affects behavioral intentions to clear dead branches and leaves (TX/Fire: $\beta = -0.075$, $p = 0.028$, M06)

Factors Motivating Wildfire Risk Reduction and Climate Adaptation Policy Support (Standardized SEM Coefficients)



Wildfire Risk Reduction and Climate Adaptation Policy Support in California



Wildfires Risk Reduction and Climate Adaptation Policy Support in Texas

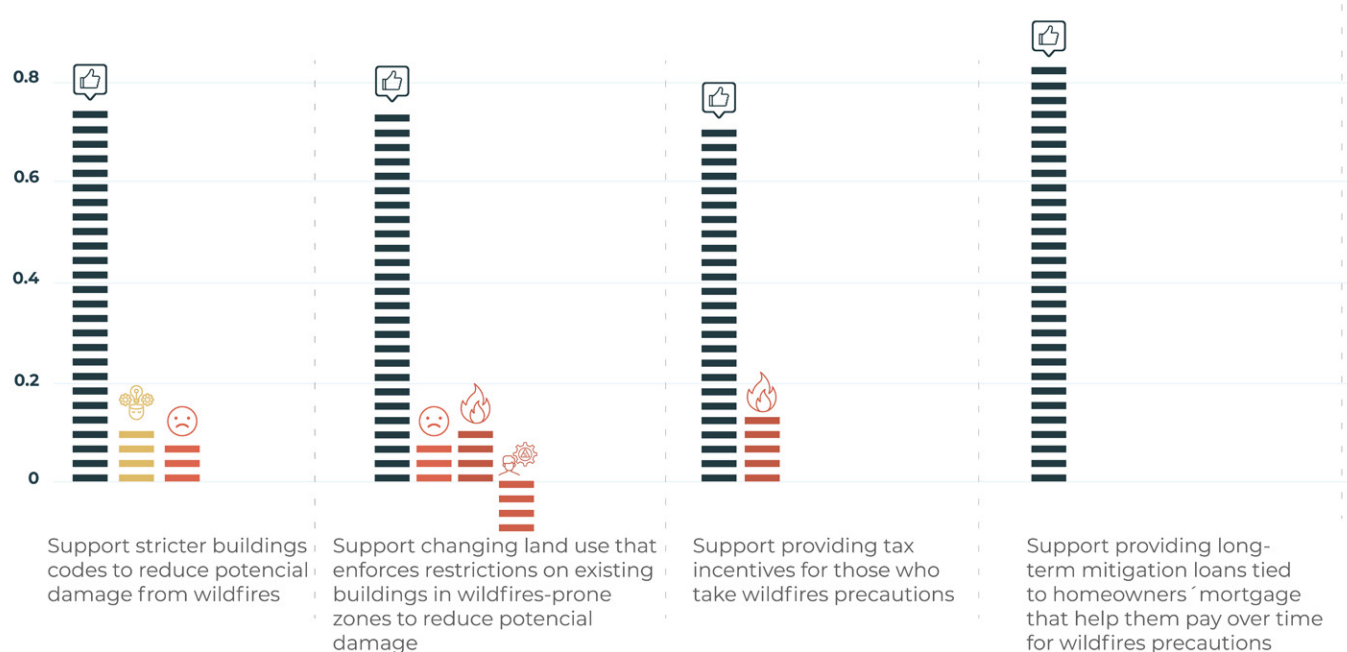


Fig. 4. Factors motivating wildfire risk reduction and climate adaptation policies (standardized SEM coefficients).

Factors Motivating Hurricane and Flood Risk Reduction and Climate Adaptation Policy Support (Standardized SEM Coefficients)



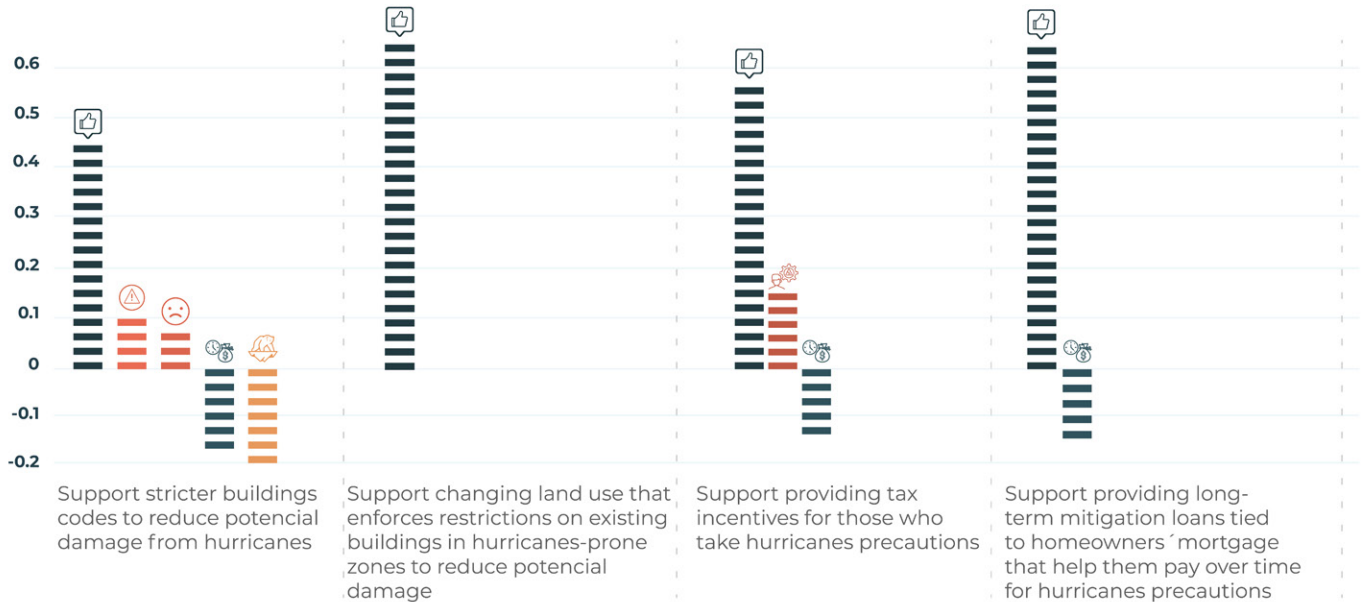
Hurricane and Flood Risk Reduction and Adaptation Policy Support in Florida



Response efficacy
Resource constraints

Risk knowledge
Negative emotions
Perceived risk likelihood

Climate change geological psychological distance



Hurricane and Flood Risk Reduction and Adaptation Policy Support in Texas



Response efficacy
Self-efficacy
Positive emotions

Perceived risk likelihood

Climate change geological psychological distance

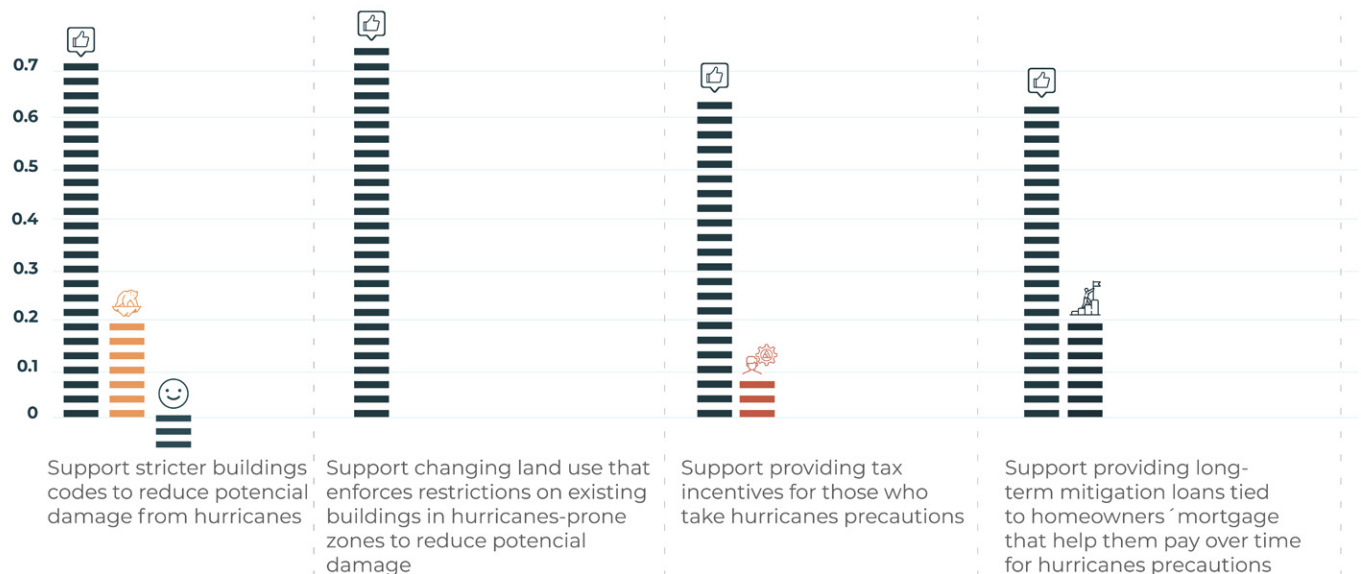


Fig. 5. Factors motivating hurricane and flood risk reduction and climate adaptation policies (standardized SEM coefficients).

Table 7. Factors motivating wildfire risk reduction and adaptation policy support. The *p* values are indicated as follows: *, *p* < 0.05; **, *p* < 0.01; ***, *p* < 0.001. Standardized SEM path coefficients are reported. Wildfire risks (California, *n* = 1,031; Texas, *n* = 725).

Model	Policy support							
	Support stricter building codes to reduce potential damage from wildfires/hurricanes		Support changing land use that enforces restrictions on existing buildings in wildfire/hurricane-prone zones to reduce potential damage		Support providing tax incentives for those who take wildfire/hurricane precautions		Support providing long-term mitigation loans tied to homeowners' mortgage that help them pay over time for wildfire/hurricane precautions	
	23	24	27	28	31	32	35	36
Endogenous factors	Wildfires CA	Wildfires TX	Wildfires CA	Wildfires TX	Wildfires CA	Wildfires TX	Wildfires CA	Wildfires TX
Risk perception								
Perceived risk likelihood	0.035	−0.042	0.006	−0.103**	0.058*	0.001	0.012	−0.062
Perceived risk impact	0.111**	0.039	0.06	0.086*	0.141***	0.122**	0.139***	0.056
Negative emotions	−0.004	0.072*	0.023	0.074**	−0.098***	0.04	−0.029	0.043
Risk knowledge	−0.01	−0.011	−0.017	−0.031	0.023	−0.008	0.001	−0.031
Coping appraisals								
Self-efficacy	−0.038	0.029	−0.094	0.017	−0.046	0.016	−0.078	−0.018
Response efficacy	0.612***	0.741***	0.693***	0.735***	0.694***	0.703***	0.707***	0.811***
Resource constraints	−0.149**	−0.048	−0.168**	−0.043	−0.122*	−0.084	−0.165**	−0.068
Response knowledge	−0.03	0.015	−0.053	−0.006	−0.06	−0.047	−0.044	0.033
Positive emotions	0.004	−0.015	0.025	−0.017	−0.01	0.034	0.018	0.013
Social norms perceptions	0.051	−0.054	0.085*	0.004	0.034	0.013	0.09*	−0.036
Perceived protection responsibility	0.012	0.081**	−0.022	0.055	0.003	0.009	−0.023	0.058
Climate change perception								
Geological psychological distance	0.105**	−0.047	0.041	−0.012	0.016	0.001	0.052	−0.049
Temporal and social psychological distance	−0.083	0.09	−0.132*	0.058	−0.023	−0.053	−0.082	0.02
Uncertainty	−0.167**	−0.086	−0.044	−0.076	−0.006	−0.142	0.012	−0.083
<i>R</i> ²	0.693***	0.741***	0.693***	0.742***	0.598***	0.670***	0.654***	0.720***

and to clear plants and any ignitable materials (TX/Fire: $\beta = -0.093$, $p = 0.004$, M08). For hurricane risks, it negatively affects behavioral intentions to move valuable furniture (TX/Hrcn: $\beta = -0.074$, $p = 0.041$, M10) and to purchase flood and/or windstorm insurance (TX/Hrcn: $\beta = -0.066$, $p = 0.037$, M22). Risk knowledge positively affects behavioral intention to support stricter building codes for hurricane risks (FL/Hrcn: $\beta = 0.091$, $p = 0.042$, M25).

Coping appraisals.

SELF-EFFICACY AND CONTROLLABILITY (H3A, H3B). In our study, factor analysis results indicate a one-factor solution for self-efficacy and controllability, indicating that participants do not distinguish these two concepts, although previous research differentiated them in other contexts (Ajzen 2002).

Self-efficacy is the main driver for adaptation behaviors, except policy support. Self-efficacy is significant in all models except preparedness for hurricanes in Texas and policy support models. Its standardized path coefficients range between 0.16 and 0.456.

For both hurricane and wildfire risks, self-efficacy positively affects intentions to have a list for an emergency (CA/Fire: $\beta = 0.306$, $p < 0.001$, M01; TX/Fire: $\beta = 0.264$, $p < 0.001$, M02; FL/Hrcn: $\beta = 0.278$, $p = 0.001$, M03) and to purchase insurance (CA/Fire: $\beta = 0.391$,

Table 8. Factors motivating hurricane and flood risk reduction and adaptation policy support. The p values are indicated as follows: *, $p < 0.05$; **, $p < 0.01$; *, $p < 0.001$. Standardized SEM path coefficients are reported. Hurricane risks (Florida, $n = 1,010$; Texas, $n = 720$).**

Model	Policy support							
	Support stricter building codes to reduce potential damage from wildfires/hurricanes		Support changing land use that enforces restrictions on existing buildings in wildfire/hurricane-prone zones to reduce potential damage		Support providing tax incentives for those who take wildfire/hurricane precautions		Support providing long-term mitigation loans tied to homeowners' mortgage that help them pay over time for wildfire/hurricane precautions	
	25	26	29	30	33	34	37	38
Endogenous factors	Hurricanes FL	Hurricanes TX	Hurricanes FL	Hurricanes TX	Hurricanes FL	Hurricanes TX	Hurricanes FL	Hurricanes TX
Risk perception								
Perceived risk likelihood	0.054	0.054	0.043	0.022	0.128**	0.072*	0.002	0.019
Perceived risk impact	0.062	0.031	0.025	0.009	−0.017	0.024	0.007	0.036
Negative emotions	0.062*	0	0.015	−0.031	0.041	−0.027	0.022	−0.036
Risk knowledge	0.091*	−0.013	0.012	0.002	0.011	0.016	0.031	−0.016
Coping appraisals								
Self-efficacy	0.09	0.004	0.052	0.046	0.111	0.041	0.106	0.176**
Response efficacy	0.438***	0.641***	0.642***	0.711***	0.544***	0.625***	0.628***	0.62***
Resource constraints	−0.174***	−0.054	−0.066	0.006	−0.11*	−0.086	−0.117*	−0.03
Response knowledge	−0.072	−0.002	0	−0.004	−0.004	−0.036	0.003	0.003
Positive emotions	0.002	−0.073*	−0.017	−0.037	0.001	−0.049	−0.017	−0.037
Social norms perceptions								
Perceived protection responsibility	0.042	0.055	0.059	0.026	0.05	0.06	0.049	0.051
Climate change perception								
Geological psychological distance	0.046	0.047	0.042	0.053	−0.039	0.056	−0.004	0.015
Temporal and social psychological distance	−0.188**	0.175*	−0.074	0.122	−0.093	0.073	−0.052	0.024
Uncertainty	−0.014	0.035	−0.072	0.004	0.044	0.013	−0.029	−0.051
R^2	0.554***	0.648***	0.621***	0.670***	0.561***	0.567***	0.625***	0.625***

$p < 0.001$, M19; TX/Fire: $\beta = 0.321$, $p < 0.001$, M20; FL/Hrcn: $\beta = 0.236$, $p < 0.001$, M21; TX/Hrcn: $\beta = 0.397$, $p < 0.001$, M22).

For wildfire risks, self-efficacy positively affects intentions to clear dead branches and leaves (CA/Fire: $\beta = 0.456$, $p < 0.001$, M05; TX/Fire: $\beta = 0.343$, $p < 0.001$, M06), to clear plants and any ignitable materials (CA/Fire: $\beta = 0.366$, $p < 0.001$, M07; TX/Fire: $\beta = 0.244$, $p < 0.001$, M08), to install mesh metal screening (CA/Fire: $\beta = 0.28$, $p < 0.001$, M11; TX/Fire: $\beta = 0.189$, $p < 0.001$, M12), and to install a fire-resistant roof (CA/Fire: $\beta = 0.341$, $p < 0.001$, M13; TX/Fire: $\beta = 0.36$, $p < 0.001$, M14).

For hurricane risks, self-efficacy positively affects intentions to move valuable furniture (FL/Hrcn: $\beta = 0.16$, $p = 0.001$, M09; TX/Hrcn: $\beta = 0.347$, $p < 0.001$, M10), to purchase flood protection devices (FL/Hrcn: $\beta = 0.272$, $p < 0.001$, M15; TX/Hrcn: $\beta = 0.426$, $p < 0.001$, M16), and to install a roof covering and/or galvanized metal hurricane straps (FL/Hrcn: $\beta = 0.28$, $p < 0.001$, M17; TX/Hrcn: $\beta = 0.341$, $p < 0.001$, M18). It also positively affects policy support intentions to support providing long-term mitigation loan (TX/Hrcn: $\beta = 0.176$, $p = 0.005$, M38).

RESPONSE EFFICACY (H3c). Response efficacy is a main driver for policy support. Only response efficacy is significant across all policy support models, and its standardized path coefficients range between 0.438 and 0.811. For both hurricane and wildfire risks, it positively affects policy support intentions to support stricter building codes (CA/Fire: $\beta = 0.612$, $p < 0.001$, M23; TX/Fire: $\beta = 0.741$, $p < 0.001$, M24; FL/Hrcn: $\beta = 0.438$, $p < 0.001$, M25; TX/Hrcn: $\beta = 0.641$, $p < 0.001$, M26), to support changing land use (CA/Fire: $\beta = 0.693$, $p < 0.001$, M27; TX/Fire: $\beta = 0.735$, $p < 0.001$, M28; FL/Hrcn: $\beta = 0.642$, $p < 0.001$, M29; TX/Hrcn: $\beta = 0.711$, $p < 0.001$, M30), to support providing tax incentives for disaster precautions (CA/Fire: $\beta = 0.694$, $p < 0.001$, M31; TX/Fire: $\beta = 0.703$, $p < 0.001$, M32; FL/Hrcn: $\beta = 0.544$, $p < 0.001$, M33; TX/Hrcn: $\beta = 0.625$, $p < 0.001$, M34), and to support providing long-term mitigation loan (CA/Fire: $\beta = 0.707$, $p < 0.001$, M35; TX/Fire: $\beta = 0.811$, $p < 0.001$, M36; FL/Hrcn: $\beta = 0.628$, $p < 0.001$, M37; TX/Hrcn: $\beta = 0.62$, $p < 0.001$, M38).

Moreover, response efficacy is a main driver for adaptation behaviors. Response efficacy is significant across 18 models among 22 behavior models. Its standardized path coefficients range between 0.061 and 0.245. For both hurricane and wildfire risks, it positively affects behavioral intention to purchase insurance (CA/Fire: $\beta = 0.105$, $p < 0.001$, M19; TX/Fire: $\beta = 0.091$, $p = 0.014$, M20; FL/Hrcn: $\beta = 0.163$, $p < 0.001$, M21; TX/Hrcn: $\beta = 0.086$, $p = 0.048$, M22).

For wildfire risks, response efficacy positively affects behavioral intentions to have a list for an emergency (CA/Fire: $\beta = 0.13$, $p = 0.001$, M01), to clear dead branches and leaves (CA/Fire: $\beta = 0.192$, $p < 0.001$, M05; TX/Fire: $\beta = 0.11$, $p = 0.012$, M06), to clear plants and any ignitable materials (CA/Fire: $\beta = 0.189$, $p < 0.001$, M07; TX/Fire: $\beta = 0.182$, $p < 0.001$, M08), to install mesh metal screening (CA/Fire: $\beta = 0.21$, $p < 0.001$, M11; TX/Fire: $\beta = 0.163$, $p < 0.001$, M12), and to install a fire-resistant roof (CA/Fire: $\beta = 0.078$, $p = 0.004$, M13; TX/Fire: $\beta = 0.061$, $p = 0.021$, M14).

For hurricane risks, response efficacy positively affects behavioral intentions to move valuable furniture (FL/Hrcn: $\beta = 0.245$, $p < 0.001$, M09; TX/Hrcn: $\beta = 0.163$, $p = 0.007$, M10), to purchase flood protection devices (TX/Hrcn: $\beta = 0.157$, $p < 0.001$, M16), and to install a roof covering and/or galvanized metal hurricane straps (FL/Hrcn: $\beta = 0.084$, $p = 0.01$, M17; TX/Hrcn: $\beta = 0.123$, $p = 0.001$, M18).

POSITIVE EMOTIONS (H4). Positive emotions, such as hope, are significant in two models, and their standard path coefficients range between -0.073 and -0.058 . They negatively affect behavioral intention to move valuable furniture for hurricane risks (TX/Hrcn: $\beta = -0.058$, $p = 0.037$, M10) and to support stricter building codes for hurricane risks (TX/Hrcn: $\beta = -0.073$, $p = 0.026$, M26).

KNOWLEDGE ABOUT RESPONSES (H5b). Response knowledge is significant in two models. Its standardized path coefficients range between -0.087 and -0.089 . For wildfire risks, it negatively affects behavioral intentions to install mesh metal screening (TX/Fire: $\beta = -0.087$, $p = 0.015$, M12) and to install a fire-resistant roof (TX/Fire: $\beta = -0.089$, $p = 0.006$, M14).

RESOURCE CONSTRAINTS (H6). Resource constraints are a key barrier to adaptation behaviors. They are significant in 14 models among 22 behavior models. Their standardized path coefficients range between -0.326 and -0.065 .

For both wildfire and hurricane risks, resource constraints negatively affect behavioral intentions to have a list for an emergency (CA/Fire: $\beta = -0.112$, $p = 0.021$, M01; TX/Fire: $\beta = -0.326$, $p < 0.001$, M02; TX/Hrcn: $\beta = -0.141$, $p = 0.024$, M03; TX/Hrcn: $\beta = -0.267$, $p < 0.001$, M04) and to purchase insurance (TX/Fire: $\beta = -0.11$, $p = 0.016$, M20; FL/Hrcn: $\beta = -0.144$, $p < 0.001$, M21).

For wildfire risks, resource constraints negatively affect behavioral intentions to clear dead branches and leaves (TX/Fire: $\beta = -0.095$, $p = 0.027$, M06), to clear plants and any ignitable materials (TX/Fire: $\beta = -0.199$, $p < 0.001$, M08), to install mesh metal screening (CA/Fire: $\beta = -0.065$, $p = 0.022$, M11; TX/Fire: $\beta = -0.2$, $p < 0.001$, M12), and to install a fire-resistant roof (CA/Fire: $\beta = -0.068$, $p = 0.02$, M13; TX/Fire: $\beta = -0.125$, $p < 0.001$, M14).

For hurricane risks, resource constraints negatively affect behavioral intentions to purchase flood protection devices (FL/Hrcn: $\beta = -0.076$, $p = 0.021$, M15) and to install a roof covering and/or galvanized metal hurricane straps (FL/Hrcn: $\beta = -0.086$, $p = 0.005$, M17).

Resource constraints are also a barrier for adaptation policy support. Resource constraints are significant in seven models among 16 policy support models. Their standardized path coefficients range between -0.174 and -0.11 . For wildfire and hurricane risks, they negatively affect policy support intentions to support stricter building codes (CA/Fire: $\beta = -0.149$, $p = 0.002$, M23; FL/Hrcn: $\beta = -0.174$, $p < 0.001$, M25), to support changing land use (CA/Fire: $\beta = -0.168$, $p = 0.001$, M27), to support providing tax incentives for disaster precautions (CA/Fire: $\beta = -0.122$, $p = 0.022$, M31; FL/Hrcn: $\beta = -0.11$, $p = 0.038$, M33), and to support providing long-term mitigation loan (CA/Fire: $\beta = -0.165$, $p = 0.001$, M35; FL/Hrcn: $\beta = -0.117$, $p = 0.017$, M37).

Social norms (H7, H8). Social norms perceptions, including descriptive and injunctive social norms, are the main driver for all adaptation behaviors, except policy support. In this study, factor analysis results showed a one-factor solution for social norms, indicating that participants do not differentiate between descriptive and injunctive norms perceptions. Only social norms perceptions are significant across all behaviors. Their standardized path coefficients range between 0.356 and 0.62 .

For both wildfire and hurricane risks, social norms perceptions positively affect behavioral intentions to have an emergency list (CA/Fire: $\beta = 0.431$, $p < 0.001$, M01; TX/Fire: $\beta = 0.443$, $p < 0.001$, M02; FL/Hrcn: $\beta = 0.493$, $p < 0.001$, M03; TX/Hrcn: $\beta = 0.534$, $p < 0.001$, M04) and to purchase insurance (CA/Fire: $\beta = 0.504$, $p < 0.001$, M19; TX/Fire: $\beta = 0.503$, $p < 0.001$, M20; FL/Hrcn: $\beta = 0.504$, $p < 0.001$, M21; TX/Hrcn: $\beta = 0.53$, $p < 0.001$, M22).

For wildfire risks, social norms perceptions positively affect behavioral intentions to clear dead branches and leaves (CA/Fire: $\beta = 0.356$, $p < 0.001$, M05; TX/Fire: $\beta = 0.467$, $p < 0.001$, M06), to clear plants and any ignitable materials (CA/Fire: $\beta = 0.402$, $p < 0.001$, M07; TX/Fire: $\beta = 0.516$, $p < 0.001$, M08), to install mesh metal screening (CA/Fire: $\beta = 0.493$, $p < 0.001$, M11; TX/Fire: $\beta = 0.541$, $p < 0.001$, M12), and to install a fire-resistant roof (CA/Fire: $\beta = 0.547$, $p < 0.001$, M13; TX/Fire: $\beta = 0.515$, $p < 0.001$, M14). They also positively affect policy support intentions to support providing long-term mitigation loan (CA/Fire: $\beta = 0.09$, $p = 0.042$, M35) and to support changing land use (CA/Fire: $\beta = 0.085$, $p = 0.036$, M27).

For hurricane risks, social norms perceptions positively affect behavioral intentions to move valuable furniture (FL/Hrcn: $\beta = 0.579$, $p < 0.001$, M09; TX/Hrcn: $\beta = 0.58$, $p < 0.001$, M10), to purchase flood protection devices (FL/Hrcn: $\beta = 0.603$, $p < 0.001$, M15; TX/Hrcn: $\beta = 0.533$, $p < 0.001$, M16), and to install a roof covering and/or galvanized metal hurricane straps (FL/Hrcn: $\beta = 0.554$, $p < 0.001$, M17; TX/Hrcn: $\beta = 0.62$, $p < 0.001$, M18).

Perceived responsibility (H9). Perceived responsibility is significant in three models. Its standard path coefficients range between -0.11 and 0.081 . For hurricane risks, it negatively affects behavioral intentions to purchase flood protection devices (TX/Hrcn: $\beta = -0.11$, $p < 0.001$, M16) and to purchase flood and/or windstorm insurance (TX/Hrcn: $\beta = -0.089$, $p = 0.013$, M22). For wildfire risks, it positively affects behavioral intention to support stricter building codes (TX/Fire: $\beta = 0.081$, $p = 0.007$, M24).

Climate change perception.

CLIMATE CHANGE UNCERTAINTY (H10A). Climate change uncertainty is significant in two models. Its path coefficients range from -0.0167 to 0.185 . For wildfire risks, it negatively affects policy support intention for stricter building codes in California (CA/Fire: $\beta = -0.167$, $p = 0.005$, M23) while it positively affects behavioral intentions to have a list for emergencies (TX/Fire: $\beta = 0.185$, $p = 0.024$, M02).

CLIMATE CHANGE PSYCHOLOGICAL DISTANCE (H10B). Climate change temporal and social psychological distance is significant in seven models. Its standardized path coefficients range between -0.142 and 0.181 . It positively affects behavioral intentions to have a list for an emergency for wildfire risks (TX/Fire: $\beta = 0.181$, $p = 0.01$, M02) and to support stricter building codes for hurricane risks (TX/Hrcn: $\beta = 0.175$, $p = 0.01$, M26). Conversely, for hurricane risks, it negatively affects behavioral intentions to move valuable furniture (TX/Hrcn: $\beta = -0.142$, $p = 0.004$, M10), to purchase flood protection devices (TX/Hrcn: $\beta = -0.095$, $p = 0.035$, M16), and to install a roof covering and/or galvanized metal hurricane straps (TX/Hrcn: $\beta = -0.101$, $p = 0.039$, M18). For wildfire risks, it negatively affects behavioral intentions to install a fire-resistant roof (CA/Fire: $\beta = -0.084$, $p = 0.022$, M13) and to support changing land use (CA/Fire: $\beta = -0.132$, $p = 0.021$, M27).

Climate change geological psychological distance is significant in three models. Its standardized path coefficients range between 0.08 and 0.105 . For hurricane risks, it positively affects behavioral intentions to have a list for an emergency (FL/Hrcn: $\beta = 0.101$, $p = 0.016$, M03), to purchase flood and/or windstorm insurance (FL/Hrcn: $\beta = 0.08$, $p = 0.022$, M21), and to support stricter building codes (FL/Hrcn: $\beta = 0.105$, $p = 0.004$, M23).

Discussion

Overall, these results suggest that research and practice on climate adaptation and disaster risk reduction may need to shift their focus from risk perception and climate change perception to efficacy and social norms. The results reveal that social norms perceptions, self-efficacy, and response efficacy significantly and positively predicted adaptation behaviors (see Fig. 6). In particular, results show that social norms perceptions are a key driver for all climate adaptation and disaster risk reduction behaviors (see Table 9), which parallels prior research on wildfire (Bright and Burtz 2006; Nox and Myles 2017) and flood (Bubeck et al. 2013, 2018; Lo 2013)

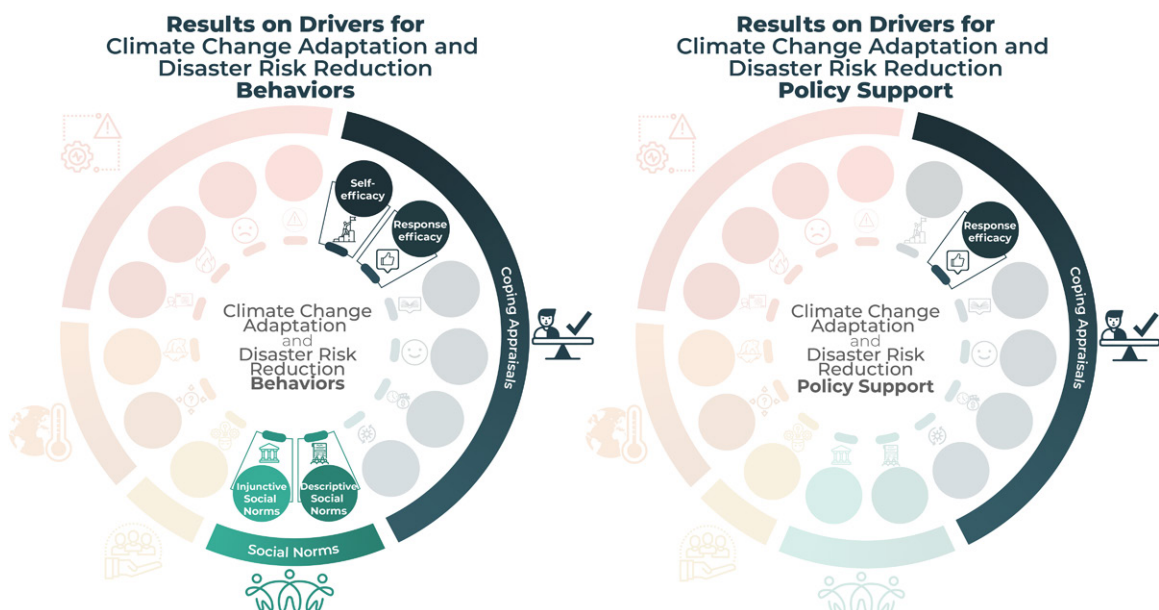


Fig. 6. Integrated model of risk communication and results.

Table 9. Results for drivers of climate adaptation behaviors and policy support.

Hypotheses		Adaptation behaviors			Policy support		
		Standardized SEM coefficients	No. of significance (<i>n</i> = 22)	Results	Standardized SEM coefficients	No. of significance (<i>n</i> = 16)	Results
Risk perception							
H1a	Perceived likelihood	+	[0.06, 0.09]	7	Partially supported	[−0.10, 0.12]	4
H1b	Perceived impact	+	0.07	1		[0.08, 0.14]	5
H5a	Perceived risk knowledge	+	[−0.09, −0.06]	4		0.09	1
H2	Negative emotions	+	[0.05, 0.12]	12		[−0.09, 0.07]	4
Coping appraisal							
H3a	Self-efficacy	+	[0.16, 0.45]	21	Mostly supported	0.17	1
H3b	Perceived controllability						
H3c	Response efficacy	+	[0.06, 0.24]	18	Mostly supported	[0.43, 0.81]	16
H4	Positive emotions (hope)	+	−0.05	1	Partially supported	−0.073	1
H5b	Perceived response knowledge	+	[−0.089, −0.087]	2		–	0
H6	Resource constraints	–	[−0.32, −0.06]	14	Partially supported	[−0.17, −0.11]	7
Social norms perceptions							
H7	Descriptive social norms	+	[0.35, 0.62]	22	Fully supported	[0.08, 0.09]	2
H8	Injunctive social norms						
Protection responsibility							
H9	Perceived protection responsibility	+	[−0.08, −0.11]	2	Partially supported	0.08	1
Climate change perception							
H10a	Perceived climate change uncertainty	–	0.18	1	Partially supported	−0.16	1
H10b	Perceived climate change geographical psychological distance	–	[0.08, 0.10]	2		0.10	1
	Perceived climate change temporal, and social psychological distance	–	[−0.14, 0.18]	5		[−0.18, 0.17]	3

risks, and other contexts, such as smoking (Record et al. 2017), and water preservation (Liang et al. 2018). To motivate the at-risk public to adopt adaptation behaviors, the results suggest that it would be effective to communicate that other people who are important to them, such as neighbors, have already taken adaptation behaviors (i.e., descriptive social norms), that others think that they should adopt the adaptation behaviors (i.e., injunctive social norms), and that they can easily perform adaptation behaviors (i.e., self-efficacy).

Conversely, for adaptation policy support, only response efficacy positively predicts policy support across all policies studied (see Fig. 6 and Table 9). To motivate at-risk publics to support adaptation policies, it would be effective to explain that the policies will effectively help reduce risks and result in desirable consequences (i.e., response efficacy). The results are aligned with prior research that demonstrating evidence of policy effectiveness and benefits can increase policy support (Mantzari et al. 2022). The results show that generating policy support requires different motivators from generating adaptation behaviors.

However, risk perception, protection responsibility, knowledge, and climate change perception, which are commonly argued as key drivers, are not significant or are very weak. SEM

results revealed that only a few factors significantly predicted disaster preparedness behaviors and policy support (see Table 9). These results confirm meta-analysis findings that social norms perceptions, self-efficacy, and response efficacy significantly predict adaptation behaviors (Bamberg et al. 2017; van Valkengoed and Steg 2019). In contrast, the current results do not support prior meta-analysis results that risk perception, perceived responsibility, and climate change perception significantly predict adaptation behaviors (Bamberg et al. 2017; Koksall et al. 2019; van Valkengoed and Steg 2019; Wilson et al. 2020).

These varying results may be because prior studies did not simultaneously compare the entire set of factors on different adaptation behaviors. In particular, prior research relatively understudied social norms perceptions, self-efficacy, and behaviors in wildfire and hurricane contexts (Bamberg et al. 2017; van Valkengoed and Steg 2019). Meta-analyses can highlight the areas where evidence is insufficient, yet they cannot overcome such deficiencies in the original studies (Gurevitch et al. 2018). Future research can replicate this study in different populations or with different disaster types to see if they hold. Additionally, direct effects in SEM can reveal different results from correlation results of meta-analyses; the presence or absence of correlations does not imply the presence or absence of structural causation in SEM (Hancock and Mueller 2013; Kline 2015).

The current results indicate that it is important to simultaneously examine the full set of factors in one model to identify key drivers for developing effective interventions. For example, only TPB (Ajzen 2002, 2011) and RISP (Griffin et al. 2008, 2013; Yang et al. 2014) include social norms perceptions, while only PMT (Rogers 1983) and PADM (Lindell and Perry 2012; Terpstra and Lindell 2013) include resource constraints. This study answers researchers' call for conceptual integration (Bamberg et al. 2017; van Valkengoed and Steg 2019) by proposing the Integrated Model of Risk Communication. Policymakers can use this integrated model to identify key drivers for adaptation behaviors for other risks and regions. Future research can use, test, develop, and extend the model in various risk contexts, by adding interpersonal and societal factors and other adaptation behaviors (Wilson et al. 2020).

Finally, there is still limited understanding regarding how to effectively encourage people's self-efficacy, response efficacy, and social norms perceptions through risk communication and behavioral interventions in climate adaptation contexts. Most studies focused on identifying factors that influence risk perception and adaptation behaviors based on surveys and correlations (Bamberg et al. 2017; Kellens et al. 2013; van Valkengoed and Steg 2019). However, researchers have understudied what interventions or messages can encourage such psychological factors and target behaviors using experiments (Bamberg et al. 2017; van Valkengoed and Steg 2019). Future research needs to examine how to effectively encourage disaster risk reduction adaptation behaviors by increasing self-efficacy, response efficacy, and social norms perceptions (e.g., Dickinson et al. 2020; Kranzler et al. 2020; Lim et al. 2022) and by reducing resource constraints (O'Keefe 2003).

Limitations

Like all research, this study has limitations. This study examined only two types of disasters in three U.S. states using Amazon MTurk. The results cannot be generalizable to other locations and risks. Future research needs to examine different types of disasters in different regions using different sampling methods. Participants may experience disasters relatively often, and their responses may differ from those who experience less frequent disasters. MTurk can have common potential concerns, such as cheaters, speeders, professional survey-takers, or self-selection bias, like most online data collection using convenience sampling, including professional panels and student participants (Kees et al. 2017). This study used self-reported behaviors, which may be biased (Fischhoff et al. 2005; Lim et al. 2019a). Participants may have experienced fatigue and have not paid attention (i.e., satisficing) because of the length

of the survey, although all questions were randomized to minimize order effects. To ensure participants' attention, participants were asked to respond to multiple attention check items across surveys, and only participants who correctly answered them could remain and complete the survey.

Last, the model may look complex and lack parsimony, as this study attempted to compare the impacts of five clusters of psychological factors that multiple theories have identified. However, to reduce these factors, all these factors need to be compared in one model, like this study. By identifying the most impactful factors and demonstrating how to identify them, this paper helps researchers reflect and focus on the most impactful psychological factors that are likely to change community members' behaviors and develop parsimonious theories.

Conclusions

Improving risk communication and decision-making processes is essential to adapt to climate change and mitigate and prepare for disaster risks. Disaster-prone states have regularly experienced severe weather and climate disasters (FEMA 2021a). Thanks to engineering advancements, it is now clear what adaptation behaviors at-risk individuals should take (FEMA 2013; Quarles and Pohl 2018; Rajkovich et al. 2018; Urban Green Council 2013). Still, similar progress has not been made in developing interventions to encourage at-risk individuals to adopt these behaviors (e.g., Buntain and Lim 2018; Lee et al. 2022; Liu et al. 2022; Meyer and Kunreuther 2017). Given that different outcomes require different drivers, it is essential to test all sets of factors when developing interventions (Lim 2021). The next step is to develop effective interventions by focusing on the key drivers identified in the study (e.g., Howe et al. 2018; Lim et al. 2022; Mol et al. 2022) while testing the model for other risks and disaster-prone regions (e.g., Llopis et al. 2020). When the weather enterprise works together on climate change adaptation and disaster risk reduction, we can save more lives.

Acknowledgments. My sincere gratitude goes to Drs. Brooke Fisher Liu, Anita Atwell Seate, Gregory Hancock, Elizabeth Toth, and Erich Sommerfeldt for their guidance and feedback. I would also like to thank Mr. Juan Sebastián Fonseca for his contributions to the data visualization and design. This paper is based on the author's dissertation (Lim 2021). This project was funded by the University of Maryland (UMD) Ann G. Wylie Semester Dissertation Fellowship, the Graduate School Summer Research Fellowship, the University of Colorado Natural Hazards Center's Mitigation Matters research program. The Mitigation Matters program is based on work supported by the National Science Foundation (NSF) (Award 1635593) through supplemental funding from the Federal Emergency Management Agency (FEMA). The findings, conclusions, and recommendations expressed in this article are those of the authors and do not necessarily reflect the views of NSF, FEMA, UMD, or the Natural Hazards Center.

References

- Abatzoglou, J. T., and A. P. Williams, 2016: Impact of anthropogenic climate change on wildfire across western US forests. *Proc. Natl. Acad. Sci. USA*, **113**, 11 770–11 775, <https://doi.org/10.1073/pnas.1607171113>.
- Ajzen, I., 2002: Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior 1. *J. Appl. Soc. Psychol.*, **32**, 665–683, <https://doi.org/10.1111/j.1559-1816.2002.tb00236.x>.
- , 2006: Constructing a theory of planned behavior questionnaire. 7 pp., <http://people.umass.edu/~ajzen/pdf/tpb.measurement.pdf>.
- , 2011: The theory of planned behaviour: Reactions and reflections. *Psychol. Health*, **26**, 1113–1127, <https://doi.org/10.1080/08870446.2011.613995>.
- Altarawneh, L., J. Mackee, and T. Gajendran, 2018: The influence of cognitive and affective risk perceptions on flood preparedness intentions: A dual-process approach. *Procedia Eng.*, **212**, 1203–1210, <https://doi.org/10.1016/j.proeng.2018.01.155>.
- Anderson, J. C., and D. W. Gerbing, 1988: Structural equation modeling in practice: A review and recommended two-step approach. *Psychol. Bull.*, **103**, 411–423, <https://doi.org/10.1037/0033-2909.103.3.411>.
- Balog-Way, D., K. McComas, and J. Besley, 2020: The evolving field of risk communication. *Risk Anal.*, **40**, 2240–2262, <https://doi.org/10.1111/risa.13615>.
- Bamberg, S., T. Masson, K. Brewitt, and N. Nemetschek, 2017: Threat, coping and flood prevention—A meta-analysis. *J. Environ. Psychol.*, **54**, 116–126, <https://doi.org/10.1016/j.jenvp.2017.08.001>.
- Bandalos, D. L., and S. J. Finney, 2019: Factor analysis. *The Reviewer's Guide to Quantitative Methods in the Social Sciences*, 2nd ed. G. R. Hancock, L. M. Stapleton, and R. O. Mueller, Eds., Routledge, 514 pp.
- Bandura, A., 2001: Social cognitive theory: An agentic perspective. *Annu. Rev. Psychol.*, **52**, 1–26, <https://doi.org/10.1146/annurev.psych.52.1.1>.
- Bar-Anan, Y., N. Liberman, and Y. Trope, 2006: The association between psychological distance and construal level: Evidence from an implicit association test. *J. Exp. Psychol. Gen.*, **135**, 609–622, <https://doi.org/10.1037/0096-3445.135.4.609>.
- Bates, B. R., B. L. Quick, and A. A. Kloss, 2009: Antecedents of intention to help mitigate wildfire: Implications for campaigns promoting wildfire mitigation to the general public in the wildland–urban interface. *Saf. Sci.*, **47**, 374–381, <https://doi.org/10.1016/j.ssci.2008.06.002>.
- Becker, J. S., D. Paton, D. M. Johnston, and K. R. Ronan, 2013: Salient beliefs about earthquake hazards and household preparedness. *Risk Anal.*, **33**, 1710–1727, <https://doi.org/10.1111/risa.12014>.
- Bohannon, J., 2011: Social science for pennies. *Science*, **334**, 307, <https://doi.org/10.1126/science.334.6054.307>.
- Botzen, W. J., J. C. Aerts, and J. C. van den Bergh, 2009: Willingness of homeowners to mitigate climate risk through insurance. *Ecol. Econ.*, **68**, 2265–2277, <https://doi.org/10.1016/j.ecolecon.2009.02.019>.
- Bouwer, L. M., 2011: Have disaster losses increased due to anthropogenic climate change? *Bull. Amer. Meteor. Soc.*, **92**, 39–46, <https://doi.org/10.1175/2010BAMS3092.1>.
- Bright, A. D., and R. T. Burtz, 2006: Creating defensible space in the wildland–urban interface: The influence of values on perceptions and behavior. *Environ. Manage.*, **37**, 170–185, <https://doi.org/10.1007/s00267-004-0342-0>.
- Bubeck, P., W. J. Botzen, and J. C. Aerts, 2012: A review of risk perceptions and other factors that influence flood mitigation behavior. *Risk Anal.*, **32**, 1481–1495, <https://doi.org/10.1111/j.1539-6924.2011.01783.x>.
- , ———, H. Kreibich, and J. C. Aerts, 2013: Detailed insights into the influence of flood-coping appraisals on mitigation behaviour. *Global Environ. Change*, **23**, 1327–1338, <https://doi.org/10.1016/j.gloenvcha.2013.05.009>.
- , ———, J. Laudan, J. C. Aerts, and A. H. Thielen, 2018: Insights into flood-coping appraisals of protection motivation theory: Empirical evidence from Germany and France. *Risk Anal.*, **38**, 1239–1257, <https://doi.org/10.1111/risa.12938>.
- Buhrmester, M. D., S. Talaifar, and S. D. Gosling, 2018: An evaluation of Amazon's Mechanical Turk, its rapid rise, and its effective use. *Perspect. Psychol. Sci.*, **13**, 149–154, <https://doi.org/10.1177/1745691617706516>.
- Buntain, C., and J. R. Lim, 2018: #pray4victims: Consistencies in response to disaster on Twitter. *Proc. ACM HUM*, **2**, 1–18, <https://doi.org/10.1145/3274294>.
- Chadwick, A. E., 2015: Toward a theory of persuasive hope: Effects of cognitive appraisals, hope appeals, and hope in the context of climate change. *Health Commun.*, **30**, 598–611, <https://doi.org/10.1080/10410236.2014.916777>.
- Cialdini, R. B., 2012: The focus theory of normative conduct. *Handbook of Theories of Social Psychology*, P. A. M. Van Lange, A. W. Kruglanski, and E. T. Higgins, Eds., Sage, 295–312.
- , L. J. Demaine, B. J. Sagarin, D. W. Barrett, K. Rhoads, and P. L. Winter, 2006: Managing social norms for persuasive impact. *Soc. Influence*, **1**, 3–15, <https://doi.org/10.1080/15534510500181459>.
- Cunningham, J. A., A. Godinho, and V. Kushnir, 2017: Using Mechanical Turk to recruit participants for internet intervention research: Experience from recruitment for four trials targeting hazardous alcohol consumption. *BMC Med. Res. Methodol.*, **17**, 156, <https://doi.org/10.1186/s12874-017-0440-3>.
- Demuth, J. L., 2018: Explicating experience: Development of a valid scale of past hazard experience for tornadoes. *Risk Anal.*, **38**, 1921–1943, <https://doi.org/10.1111/risa.12983>.
- Dickinson, K. L., H. Brenkert-Smith, G. Madonia, and N. E. Flores, 2020: Risk interdependency, social norms, and wildfire mitigation: A choice experiment. *Nat. Hazards*, **103**, 1327–1354, <https://doi.org/10.1007/s11069-020-04037-1>.
- Dillard, J. P., R. Li, E. Mieczkowski, C. Yang, and L. Shen, 2017: Fear responses to threat appeals: Functional form, methodological considerations, and correspondence between static and dynamic data. *Commun. Res.*, **44**, 997–1018, <https://doi.org/10.1177/0093650216631097>.
- Done, J. M., K. M. Simmons, and J. Czajkowski, 2018: Relationship between residential losses and hurricane winds: Role of the Florida building code. *ASCE-ASME J. Risk Uncertainty Eng. Syst.*, **A4**, 04018001, <https://doi.org/10.1061/AJRU6.0000947>.
- Feldman, L., and P. S. Hart, 2018: Is there any hope? How climate change news imagery and text influence audience emotions and support for climate mitigation policies. *Risk Anal.*, **38**, 585–602, <https://doi.org/10.1111/risa.12868>.
- FEMA, 2013: Mitigation ideas: A resource for reducing risk to natural hazards. 88 pp., www.fema.gov/sites/default/files/2020-06/fema-mitigation-ideas_02-13-2013.pdf.
- , 2021a: Data visualization: Summary of disaster declarations and grants. www.fema.gov/data-visualization-summary-disaster-declarations-and-grants.
- , 2021b: Preparedness research. www.fema.gov/emergency-managers/individuals-communities/preparedness-activities-webinars/research.
- Fischhoff, B., R. M. Gonzalez, J. S. Lerner, and D. A. Small, 2005: Evolving judgments of terror risks: Foresight, hindsight, and emotion. *J. Exp. Psychol. Appl.*, **11**, 124–139, <https://doi.org/10.1037/1076-898X.11.2.124>.
- FloodSmart.gov, 2019: Before and after a flood: First, prepare for flooding. FEMA and National Flood Insurance Program, www.floodsmart.gov/first-prepare-flooding.
- Floyd, D. L., S. Prentice-Dunn, and R. W. Rogers, 2000: A meta-analysis of research on protection motivation theory. *J. Appl. Soc. Psychol.*, **30**, 407–429, <https://doi.org/10.1111/j.1559-1816.2000.tb02323.x>.
- Goldstein, N. J., V. Griskevicius, and R. B. Cialdini, 2007: Invoking social norms: A social psychology perspective on improving hotels' linen-reuse programs. *Cornell Hospitality Quart.*, **48**, 145–150, <https://doi.org/10.1177/0010880407299542>.
- Griffin, R. J., S. Dunwoody, and K. Neuwirth, 1999: Proposed model of the relationship of risk information seeking and processing to the development of preventive behaviors. *Environ. Res.*, **80**, S230–S245, <https://doi.org/10.1006/enrs.1998.3940>.
- , K. Neuwirth, S. Dunwoody, and J. Giese, 2004: Information sufficiency and risk communication. *Media Psychol.*, **6**, 23–61, https://doi.org/10.1207/s1532785xmep0601_2.

- , Z. Yang, E. Ter Huurne, F. Boerner, S. Ortiz, and S. Dunwoody, 2008: After the flood: Anger, attribution, and the seeking of information. *Sci. Commun.*, **29**, 285–315, <https://doi.org/10.1177/1075547007312309>.
- , S. Dunwoody, and Z. J. Yang, 2013: Linking risk messages to information seeking and processing. *Ann. Int. Commun. Assoc.*, **36**, 323–362, <https://doi.org/10.1080/23808985.2013.11679138>.
- Grothmann, T., and F. Reusswig, 2006: People at risk of flooding: Why some residents take precautionary action while others do not. *Nat. Hazards*, **38**, 101–120, <https://doi.org/10.1007/s11069-005-8604-6>.
- Gurevitch, J., J. Koricheva, S. Nakagawa, and G. Stewart, 2018: Meta-analysis and the science of research synthesis. *Nature*, **555**, 175–182, <https://doi.org/10.1038/nature25753>.
- Hancock, G. R., and R. O. Mueller, Eds., 2013: Structural Equation Modeling: A Second Course. 2nd ed. Information Age Publishing, 673 pp.
- Howe, P. D. L., J. Boldero, I. M. McNeil, A. Vargas-Saenz, and J. Handmer, 2018: Increasing preparedness for wildfires by informing residents of their community's social norms. *Nat. Hazards Rev.*, **19**, 279, [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000279](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000279).
- Hu, L. T., and P. M. Bentler, 1999: Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct. Equation Model.*, **6**, 1–55, <https://doi.org/10.1080/10705519909540118>.
- IPCC, 2014: *Climate Change 2014: Synthesis Report*. IPCC, 151 pp., www.ipcc.ch/report/ar5/syrl.
- , 2022: *Climate Change 2022: Impacts, Adaptation and Vulnerability*. Cambridge University Press, 3068 pp., https://www.ipcc.ch/report/ar6/wg2/downloads/report/IPCC_AR6_WGII_FullReport.pdf.
- Jin, Y., A. Pang, and G. T. Cameron, 2012: Toward a publics-driven, emotion-based conceptualization in crisis communication: Unearthing dominant emotions in multi-staged testing of the Integrated Crisis Mapping (ICM) model. *J. Public Relat. Res.*, **24**, 266–298, <https://doi.org/10.1080/1062726X.2012.676747>.
- Jones, C., D. W. Hine, and A. D. Marks, 2017: The future is now: Reducing psychological distance to increase public engagement with climate change. *Risk Anal.*, **37**, 331–341, <https://doi.org/10.1111/risa.12601>.
- Kees, J., C. Berry, S. Burton, and K. Sheehan, 2017: Reply to "Amazon's Mechanical Turk: A comment." *J. Advert.*, **46**, 159–162, <https://doi.org/10.1080/00913367.2017.1281781>.
- Kellens, W., T. Terpstra, and P. De Maeyer, 2013: Perception and communication of flood risks: A systematic review of empirical research. *Risk Anal.*, **33**, 24–49, <https://doi.org/10.1111/j.1539-6924.2012.01844.x>.
- Kline, R. B., 2015: *Principles and Practice of Structural Equation Modeling*. 4th ed. Guilford, 534 pp.
- Koksal, K., J. McLennan, D. Every, and C. Bearman, 2019: Australian wildland-urban interface householders' wildfire safety preparations: 'Everyday life' project priorities and perceptions of wildfire risk. *Int. J. Disaster Risk Reduct.*, **33**, 142–154, <https://doi.org/10.1016/j.ijdrr.2018.09.017>.
- Kranzler, E. C., J. Czajkowski, and L. J. Chen, 2020: Identifying promising messages to increase hurricane mitigation among coastal homeowners in the United States. *Risk Anal.*, **40**, 2313–2328, <https://doi.org/10.1111/risa.13560>.
- Kreibich, H., I. Seifert, A. H. Thieken, E. Lindquist, K. Wagner, and B. Merz, 2011: Recent changes in flood preparedness of private households and businesses in Germany. *Reg. Environ. Change*, **11**, 59–71, <https://doi.org/10.1007/s10113-010-0119-3>.
- Kunreuther, H. C., and E. O. Michel-Kerjan, 2011: *At War with the Weather: Managing Large-Scale Risks in a New Era of Catastrophes*. MIT Press, 464 pp.
- Lavell, A., and Coauthors, 2012: Climate change: New dimensions in disaster risk, exposure, vulnerability, and resilience. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*, C. B. Field et al., Eds., Cambridge University Press, 25–64, <https://doi.org/10.1017/CBO9781139177245.004>.
- Lazarus, R. S., 1991: *Emotion and Adaptation*. Oxford University Press, 557 pp.
- Lee, S. Y., J. R. Lim, and D. Shi, 2022: Visually framing disasters: Humanitarian aid organizations' use of visuals on social media *Journalism Mass Comm. Quart.*, <https://doi.org/10.1177/10776990221081046>, in press.
- Leiserowitz, A. A., 2005: American risk perceptions: Is climate change dangerous? *Risk Anal.*, **25**, 1433–1442, <https://doi.org/10.1111/j.1540-6261.2005.00690.x>.
- Liang, Y., K. F. Kee, and L. K. Henderson, 2018: Towards an integrated model of strategic environmental communication: Advancing theories of reactance and planned behavior in a water conservation context. *J. Appl. Commun. Res.*, **46**, 135–154, <https://doi.org/10.1080/00909882.2018.1437924>.
- Lim, J. R., 2021: Developing effective communication for climate change adaptation and disaster risk mitigation. Ph.D. dissertation, University of Maryland, 368 pp., <https://doi.org/10.13016/koey-arbr>.
- , B. F. Liu, and M. Egnoto, 2019a: Cry wolf effect? Evaluating the impact of false alarms on public responses to tornado alerts in the southeastern United States. *Wea. Climate Soc.*, **11**, 549–563, <https://doi.org/10.1175/WCAS-D-18-0080.1>.
- , —, —, and H. A. Roberts, 2019b: Individuals' religiosity and emotional coping in response to disasters. *J. Contingencies Crisis Manage.*, **27**, 331–345, <https://doi.org/10.1111/1468-5973.12263>.
- , —, and A. Atwell Seate, 2022: Are you prepared for the next storm? Developing social norms messages to motivate community members to perform disaster risk mitigation behaviors. *Risk Anal.*, <https://doi.org/10.1111/risa.13957>, in press.
- Lindell, M. K., and D. J. Whitney, 2000: Correlates of household seismic hazard adjustment adoption. *Risk Anal.*, **20**, 13–26, <https://doi.org/10.1111/0272-4332.00002>.
- , and R. W. Perry, 2012: The protective action decision model: Theoretical modifications and additional evidence. *Risk Anal.*, **32**, 616–632, <https://doi.org/10.1111/j.1539-6924.2011.01647.x>.
- Liu, B. F., A. A. Seate, J. Y. Kim, D. Hawblitzel, S. Lee, and X. Ma, 2022: Relationships are built on sunny days: Uncovering quiet weather communication strategies. *Wea. Climate Soc.*, **14**, 223–236, <https://doi.org/10.1175/WCAS-D-21-0096.1>.
- Llopis, J., E. B. Perge, Z. Afif, C. R. Soto, L. M. Padilla, and J. Hsu, 2020: Using behavioral insights to improve disaster preparedness, early warning and response mechanisms in Haiti. World Bank Group Rep., 48 pp., <http://documents.worldbank.org/curated/en/465051578683565433/Using-Behavioral-Insights-to-Improve-Disaster-Preparedness-Early-Warning-and-Response-Mechanisms-in-Haiti>.
- Lo, A. Y., 2013: The role of social norms in climate adaptation: Mediating risk perception and flood insurance purchase. *Global Environ. Change*, **23**, 1249–1257, <https://doi.org/10.1016/j.gloenvcha.2013.07.019>.
- Mantzari, E., J. P. Reynolds, S. A. Jebb, G. J. Hollands, M. A. Pilling, and T. M. Marteau, 2022: Public support for policies to improve population and planetary health: A population-based online experiment assessing impact of communicating evidence of multiple versus single benefits. *Soc. Sci. Med.*, **296**, 114726, <https://doi.org/10.1016/j.socscimed.2022.114726>.
- Marsooli, R., N. Lin, K. Emanuel, and K. Feng, 2019: Climate change exacerbates hurricane flood hazards along US Atlantic and Gulf Coasts in spatially varying patterns. *Nat. Commun.*, **10**, 3785, <https://doi.org/10.1038/s41467-019-11755-z>.
- Martin, I. M., H. W. Bender, and C. Raish, 2010: Making the decision to mitigate risk. *Wildfire Risk*, W. E. Martin, C. Raish, and B. Kent, Eds., Routledge, 131–155.
- McCaffrey, S., 2015: Community wildfire preparedness: A global state-of-the-knowledge summary of social science research. *Curr. For. Rep.*, **1**, 81–90, <https://doi.org/10.1007/s40725-015-0015-7>.
- Meyer, R., and H. Kunreuther, 2017: *The Ostrich Paradox: Why We Underprepare for Disasters*. Wharton Digital Press, 132 pp.
- Miceli, R., I. Sotgiu, and M. Settanni, 2008: Disaster preparedness and perception of flood risk: A study in an alpine valley in Italy. *J. Environ. Psychol.*, **28**, 164–173, <https://doi.org/10.1016/j.jenvp.2007.10.006>.
- Michie, S., R. N. Carey, M. Johnston, A. J. Rothman, M. De Bruin, M. P. Kelly, and L. E. Connell, 2018: From theory-inspired to theory-based interventions: A protocol for developing and testing a methodology for linking behaviour

- change techniques to theoretical mechanisms of action. *Ann. Behav. Med.*, **52**, 501–512, <https://doi.org/10.1007/s12160-016-9816-6>.
- Miller, D. T., and D. A. Prentice, 2016: Changing norms to change behavior. *Annu. Rev. Psychol.*, **67**, 339–361, <https://doi.org/10.1146/annurev-psych-010814-015013>.
- Milne, S., P. Sheeran, and S. Orbell, 2000: Prediction and intervention in health-related behavior: A meta-analytic review of protection motivation theory. *J. Appl. Soc. Psychol.*, **30**, 106–143, <https://doi.org/10.1111/j.1559-1816.2000.tb02308.x>.
- Mol, J. M., W. W. Botzen, J. E. Blasch, E. C. Kranzler, and H. C. Kunreuther, 2022: All by myself? Testing descriptive social norm-nudges to increase flood preparedness among homeowners. *Behav. Public Policy*, <https://doi.org/10.1017/bpp.2021.17>, in press.
- Mueller, R. O., and G. R. Hancock, 2019: Structural equation modeling. *The Reviewer's Guide to Quantitative Methods in the Social Sciences*, 2nd ed. G. R. Hancock, L. M. Stapleton, and R. O. Mueller, Eds., Routledge, 514 pp.
- Mulilis, J. P., and T. S. Duval, 1997: The PrE model of coping and tornado preparedness: Moderating effects of responsibility. *J. Appl. Soc. Psychol.*, **27**, 1750–1766, <https://doi.org/10.1111/j.1559-1816.1997.tb01623.x>.
- , and ———, 2003: Activating effects of resources relative to threat and responsibility in Person-relative-to-Event theory of coping with threat: An educational application. *J. Appl. Soc. Psychol.*, **33**, 1437–1456, <https://doi.org/10.1111/j.1559-1816.2003.tb01957.x>.
- , and D. Rombach, 2001: Personal responsibility for tornado preparedness: Commitment or choice? *J. Appl. Soc. Psychol.*, **31**, 1659–1688, <https://doi.org/10.1111/j.1559-1816.2001.tb02745.x>.
- Multihazard Mitigation Council, 2017: Natural hazard mitigation saves: 2017 interim report. National Institute of Building Sciences, 16 pp., www.fema.gov/sites/default/files/2020-07/fema_ms2_interim_report_2017.pdf.
- Muthén, L. K., and B. O. Muthén, 2017: *Mplus User's Guide*. 8th ed. Muthén & Muthén, 944 pp.
- Myrick, J. G., and R. L. Nabi, 2017: Fear arousal and health and risk messaging. *Oxford Research Encyclopedia of Communication*, Oxford University Press, <https://doi.org/10.1093/acrefore/9780190228613.013.266>.
- Nabi, R. L., and J. G. Myrick, 2019: Uplifting fear appeals: Considering the role of hope in fear-based persuasive messages. *Health Commun.*, **34**, 463–474, <https://doi.org/10.1080/10410236.2017.1422847>.
- NFPA, 2019: Understanding the wildfire threat to homes. National Fire Protection Association, www.nfpa.org/Public-Education/Fire-causes-and-risks/Wildfire/Firewise-USA/Online-learning-opportunities/Understanding-the-Wildfire-Threat-to-Homes.
- NOAA, 2019: Hurricane safety tips and resources. National Weather Service, www.weather.gov/safety/hurricane.
- , 2022: U.S. billion-dollar weather and climate disasters, 1980–present. National Centers for Environmental Information, accessed 15 October 2022, <https://doi.org/10.25921/stkw-7w73>.
- Nolan, J. M., P. W. Schultz, R. B. Cialdini, N. J. Goldstein, and V. Griskevicius, 2008: Normative social influence is underdetected. *Pers. Soc. Psychol. Bull.*, **34**, 913–923, <https://doi.org/10.1177/0146167208316691>.
- Nox, R., and C. C. Myles, 2017: Wildfire mitigation behavior on single family residential properties near Balcones Canyonlands Preserve wildlands in Austin, Texas. *Appl. Geogr.*, **87**, 222–233, <https://doi.org/10.1016/j.apgeog.2017.08.010>.
- O'Keefe, D. J., 2003: Message properties, mediating states, and manipulation checks: Claims, evidence, and data analysis in experimental persuasive message effects research. *Commun. Theory*, **13**, 251–274, <https://doi.org/10.1111/j.1468-2885.2003.tb00292.x>.
- Osberghaus, D., 2017: The effect of flood experience on household mitigation—Evidence from longitudinal and insurance data. *Global Environ. Change*, **43**, 126–136, <https://doi.org/10.1016/j.gloenvcha.2017.02.003>.
- Peer, E., J. Vosgerau, and A. Acquisti, 2014: Reputation as a sufficient condition for data quality on Amazon Mechanical Turk. *Behav. Res. Methods*, **46**, 1023–1031, <https://doi.org/10.3758/s13428-013-0434-y>.
- Poussin, J. K., W. W. Botzen, and J. C. Aerts, 2014: Factors of influence on flood damage mitigation behaviour by households. *Environ. Sci. Policy*, **40**, 69–77, <https://doi.org/10.1016/j.envsci.2014.01.013>.
- Quarles, S. L., and K. Pohl, 2018: Building a wildfire-resistant home: Codes and costs. *Headwaters Economics*, <https://headwaterseconomics.org/wildfire/homes-risk/building-costs-codes/>.
- Rajkovich, N. B., M. E. Tuzzo, N. Heckman, K. Macy, E. Gilman, M. Bohm, and H.-R. Tanner, 2018: Climate resilience strategies for buildings in New York State. Rep. 18-11, New York State Energy Research and Development Authority, 157 pp., <http://ap.buffalo.edu/content/dam/ap/PDFs/NYSERDA/Climate-Resilience-Strategies-for-Buildings.pdf>.
- Raykov, T., and G. A. Marcoulides, 2000: A method for comparing completely standardized solutions in multiple groups. *Struct. Equation Model.*, **7**, 292–308, https://doi.org/10.1207/S15328007SEM0702_9.
- Record, R. A., D. Helme, M. W. Savage, and N. G. Harrington, 2017: Let's clear the air: A campaign that effectively increased compliance with a university's tobacco-free policy. *J. Appl. Commun. Res.*, **45**, 79–95, <https://doi.org/10.1080/00909882.2016.1248471>.
- Rhodes, R. E., and K. S. Courneya, 2003: Self-efficacy, controllability and intention in the theory of planned behavior: Measurement redundancy or causal independence? *Psychol. Health*, **18**, 79–91, <https://doi.org/10.1080/0887044031000080665>.
- Ripberger, J. T., H. C. Jenkins-Smith, C. L. Silva, J. Czajkowski, H. Kunreuther, and K. M. Simmons, 2018: Tornado damage mitigation: Homeowner support for enhanced building codes in Oklahoma. *Risk Anal.*, **38**, 2300–2317, <https://doi.org/10.1111/risa.13131>.
- Roeser, S., 2012: Risk communication, public engagement, and climate change: A role for emotions. *Risk Anal.*, **32**, 1033–1040, <https://doi.org/10.1111/j.1539-6924.2012.01812.x>.
- Rogers, R. W., 1975: A protection motivation theory of fear appeals and attitude change. *J. Psychol.*, **91**, 93–114, <https://doi.org/10.1080/00223980.1975.915803>.
- , 1983: Cognitive and physiological processes in fear appeals and attitude change: A revised theory of protection motivation. *Social Psychophysiology*, J. Cacioppo and R. Petty, Eds., Guilford Press, 153–176.
- Sheeran, P., P. R. Harris, and T. Epton, 2014: Does heightening risk appraisals change people's intentions and behavior? A meta-analysis of experimental studies. *Psychol. Bull.*, **140**, 511–543, <https://doi.org/10.1037/a0033065>.
- , W. M. Klein, and A. J. Rothman, 2017: Health behavior change: Moving from observation to intervention. *Annu. Rev. Psychol.*, **68**, 573–600, <https://doi.org/10.1146/annurev-psych-010416-044007>.
- Shreve, C. M., and I. Kelman, 2014: Does mitigation save? Reviewing cost-benefit analyses of disaster risk reduction. *Int. J. Disaster Risk Reduct.*, **10**, 213–235, <https://doi.org/10.1016/j.ijdrr.2014.08.004>.
- Siegrist, M., and H. Gutscher, 2006: Flooding risks: A comparison of lay people's perceptions and expert's assessments in Switzerland. *Risk Anal.*, **26**, 971–979, <https://doi.org/10.1111/j.1539-6924.2006.00792.x>.
- , and ———, 2008: Natural hazards and motivation for mitigation behavior: People cannot predict the affect evoked by a severe flood. *Risk Anal.*, **28**, 771–778, <https://doi.org/10.1111/j.1539-6924.2008.01049.x>.
- , and J. Árvai, 2020: Risk perception: Reflections on 40 years of research. *Risk Anal.*, **40**, 2191–2206, <https://doi.org/10.1111/risa.13599>.
- Simmons, K. M., and P. Kovacs, 2018: Real estate market response to enhanced building codes in Moore, OK. *Int. J. Disaster Risk Reduct.*, **27**, 85–93, <https://doi.org/10.1016/j.ijdrr.2017.09.040>.
- Sisante, A., 2018: Money to burn? Risk attitudes and private investment to mitigate wildfire risk. Master's thesis, University of Nevada, Reno, 84 pp., <https://scholarworks.unr.edu/handle/11714/3459>.
- Slotter, R., J. Trainor, R. Davidson, J. Kruse, and L. Nozick, 2020: Homeowner mitigation decision-making: Exploring the theory of planned behaviour approach. *J. Flood Risk Manage.*, **13**, e12667, <https://doi.org/10.1111/jfr3.12667>.
- Slovic, P., 2000: *The Perception of Risk (Risk, Society, and Policy)*. Earthscan, 473 pp.

- , M. L. Finucane, E. Peters, and D. G. MacGregor, 2004: Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality. *Risk Anal.*, **24**, 311–322, <https://doi.org/10.1111/j.0272-4332.2004.00433.x>.
- So, J., 2013: A further Extension of the Extended Parallel Process Model (E-EPPM): Implications of cognitive appraisal theory of emotion and dispositional coping style. *Health Commun.*, **28**, 72–83, <https://doi.org/10.1080/10410236.2012.708633>.
- Solberg, C., T. Rossetto, and H. Joffe, 2010: The social psychology of seismic hazard adjustment: Re-evaluating the international literature. *Nat. Hazards Earth Syst. Sci.*, **10**, 1663–1677, <https://doi.org/10.5194/nhess-10-1663-2010>.
- Spence, A., W. Poortinga, and N. Pidgeon, 2012: The psychological distance of climate change. *Risk Anal.*, **32**, 957–972, <https://doi.org/10.1111/j.1539-6924.2011.01695.x>.
- Tannenbaum, M. B., J. Hepler, R. S. Zimmerman, L. Saul, S. Jacobs, K. Wilson, and D. Albarracín, 2015: Appealing to fear: A meta-analysis of fear appeal effectiveness and theories. *Psychol. Bull.*, **141**, 1178–1204, <https://doi.org/10.1037/a0039729>.
- Tapsell, S. M., E. C. Penning-Rowsell, S. M. Tunstall, and T. L. Wilson, 2002: Vulnerability to flooding: Health and social dimensions. *Philos. Trans. Roy. Soc.*, **A360**, 1511–1525, <https://doi.org/10.1098/rsta.2002.1013>.
- ter Huurne, E. F., R. J. Griffin, and J. M. Gutteling, 2009: Risk information seeking among U.S. and Dutch residents: An application of the model of risk information seeking and processing. *Sci. Commun.*, **31**, 215–237, <https://doi.org/10.1177/1075547009332653>.
- Terpstra, T., 2010: Flood preparedness: Thoughts, feelings and intentions of the Dutch public. Doctoral dissertation, University of Twente, 163 pp., <https://doi.org/10.3990/1.9789036529549>.
- , and M. K. Lindell, 2013: Citizens' perceptions of flood hazard adjustments: An application of the protective action decision model. *Environ. Behav.*, **45**, 993–1018, <https://doi.org/10.1177/0013916512452427>.
- , R. Zaalberg, J. De Boer, and W. J. W. Botzen, 2014: You have been framed! How antecedents of information need mediate the effects of risk communication messages. *Risk Anal.*, **34**, 1506–1520, <https://doi.org/10.1111/risa.12181>.
- Trumbo, C. W., L. Peek, M. A. Meyer, H. L. Marlatt, E. Grunfest, B. D. McNoldy, and W. H. Schubert, 2016: A cognitive-affective scale for hurricane risk perception. *Risk Anal.*, **36**, 2233–2246, <https://doi.org/10.1111/risa.12575>.
- UNDRR, 2022: Global assessment report on disaster risk reduction. UNDRR, www.undrr.org/gar2022-our-world-risk.
- Urban Green Council, 2013: NYC Building Resiliency Task Force. Rep. to Mayor Michael R. Bloomberg and Speaker Christine C. Quinn, U.S. Green Building Council, 37 pp., www.urbangreencouncil.org/sites/default/files/2013_brtf_summaryreport_0.pdf.
- U.S. Census, 2021: American fact finder. United States Census Bureau, <https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml>.
- van Valkengoed, A. M., and L. Steg, 2019: Meta-analyses of factors motivating climate change adaptation behaviour. *Nat. Climate Change*, **9**, 158–163, <https://doi.org/10.1038/s41558-018-0371-y>.
- Vinnell, L. J., T. L. Milfont, and J. McClure, 2019: Do social norms affect support for earthquake-strengthening legislation? Comparing the effects of descriptive and injunctive norms. *Environ. Behav.*, **51**, 376–400, <https://doi.org/10.1177/0013916517752435>.
- Wachinger, G., O. Renn, C. Begg, and C. Kuhlicke, 2013: The risk perception paradox—Implications for governance and communication of natural hazards. *Risk Anal.*, **33**, 1049–1065, <https://doi.org/10.1111/j.1539-6924.2012.01942.x>.
- Wilson, R. S., A. Zwickle, and H. Walpole, 2019: Developing a broadly applicable measure of risk perception. *Risk Anal.*, **39**, 777–791, <https://doi.org/10.1111/risa.13207>.
- , A. Herziger, M. Hamilton, and J. S. Brooks, 2020: From incremental to transformative adaptation in individual responses to climate-exacerbated hazards. *Nat. Climate Change*, **10**, 200–208, <https://doi.org/10.1038/s41558-020-0691-6>.
- Witte, K., 1992: Putting the fear back into fear appeals: The extended parallel process model. *Commun. Monogr.*, **59**, 329–349, <https://doi.org/10.1080/03637759209376276>.
- , K. A. Cameron, J. K. McKeon, and J. M. Berkowitz, 1996: Predicting risk behaviors: Development and validation of a diagnostic scale. *J. Health Commun.*, **1**, 317–342, <https://doi.org/10.1080/108107396127988>.
- Wolters, E. A., B. S. Steel, D. Weston, and M. Brunson, 2017: Determinants of residential Firewise behaviors in Central Oregon. *Soc. Sci. J.*, **54**, 168–178, <https://doi.org/10.1016/j.soscij.2016.12.004>.
- WorldAtlas, 2019: U.S. states by size. www.worldatlas.com/aatlas/infopage/usabysiz.htm.
- Yang, Z. J., K. McComas, G. Gay, J. P. Leonard, A. J. Dannenberg, and H. Dillon, 2010: From information processing to behavioral intentions: Exploring cancer patients' motivations for clinical trial enrollment. *Patient Educ. Couns.*, **79**, 231–238, <https://doi.org/10.1016/j.pec.2009.08.010>.
- , —, —, —, —, and —, 2011: Information seeking related to clinical trial enrollment. *Commun. Res.*, **38**, 856–882, <https://doi.org/10.1177/0093650210380411>.
- , A. M. Aloe, and T. H. Feeley, 2014: Risk information seeking and processing model: A meta-analysis. *J. Commun.*, **64**, 20–41, <https://doi.org/10.1111/jcom.12071>.