Chapter 1 Manuscript*

true

January 30, 2021

Abstract

"A concise and factual abstract is required. The abstract should state briefly the purpose of the research, the principal results and major conclusions. An abstract is often presented separately from the article, so it must be able to stand alone. For this reason, References should be avoided, but if essential, then cite the author(s) and year(s). Also, non-standard or uncommon abbreviations should be avoided, but if essential they must be defined at their first mention in the abstract itself."

HIGHLIGHTS

Come back and edit this when results and discussion are finished 1. There is between state variation of lidar use between Idaho and Washington. 2. Data suggests a more variable environment lends to flood risk manager's making more risk-prone decisions. 3. Social learning plays a critical role in shortfall minimization and lidar adoption.

1 INTRODUCTION (~500 to 1000 words)

"State the objectives of the work and provide an adequate background, avoiding a detailed literature survey or a summary of the results."

Flood events cost approximately $230 billion in expenses in United States since 1980 (Information (NCEI) and Information (NCEI), n.d.). Since the National Centers for Environmental Information (NCEI) began tracking natural disaster events in 1980, there has been an increase in flood events in the U.S., some of those with unprecedented amounts of rainfall. This is because as temperatures rise there is an increase in the amount of water vapor in the atmosphere, which increases the potential for extreme rainfall events. In addition to increased flood risk from climate change, there is an increasing rate of population growth and urbanization in coastal and infland floodplains (Pralle, 2019; Qiang, 2019; Schanze, 2006). In 2015, 21.8 million (6.87%) of the U.S. population was identified as being exposed to a

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100-year flood; meaning they lived within the floodplain of a 1% chance flood event. It has become well-established that absolute flood protection is not realistic due to th expense and uncertainities associated with floods, therefore flood risk management has become a more popular term to refer to floodplain management (Schanze, 2006). Communities understand their flood risk typically by using Federal Emergency Management Agency (FEMA) floodplain maps that estimate the extents of flood hazards through hydrologic and hydraulic models. These analyses require topography, rainfall and run-off frequency distributions, and man-made flood control structures (e.g. diversion dams, levees, bridges). In order to adapt to changes in flood risk, many communities have adopted new technology and management practices that have become avaiable in recent years that provide more information and accuracy than flood risk managers have been privy to before.

One of those practices is using higher-resoultion topographic data that is able to model detailed features of the bare earth. Previous research has found that high-resolution topographic data is critical for an accurate floodplain map (Ali et al., 2015; Cook and Merwade, 2009). Accurate floodplain maps are essential for communicating flood risk to vulnerable populations, helping mitigate and adapt to floods, and the functioning of insurance programs, such as the the FEMA's National Flood Insurance Program (Pralle, 2019). In the past, flood risk managers typically used 10-meter or 30-meter resolution Digital Elevation Models from National Elevation Dataset (NED). However, technology for capturing high-resolution topographic data has vastly changed in recent years opening opportunities for communities to gain access to more data. Light Detection and Ranging (lidar) is an example of a technology that vastly changed and is changing the landscape of flood mapping. Lidar is a laser-based remote sensing technology that uses the refleciton of light to measure elevation and features on the ground such as vegetation and structures. Raw lidar data points form a three-dimensial point cloud that can be used in a wide-array of applications. For example, lidar data point clouds can be used to calculate fuel loads and number of vulnerable structures for Wildland-Urban Inferface wildfire risk. In addition, lidar-derived products such as a Digital Elevation Models (DEM) are extensively used as a tool for high-resolution bare earth data (Muhadi et al., 2020).

In an effort to increase the availablility of publically-accessible lidar, several government agencies initiated lidar acquisition projects. Foremost, the United State Geological Survey (USGS) established the 3D Elevation Program (3DEP) in 2010 as the first nationally-coordinated lidar acquisition program with a goal of flying the complete U.S. by 2023 with lidar data. This would be the first ever national baseline of consistent, high-resolution topographic elevation data, including bare earth and 3D point clouds. In addition, FEMA established the Risk Mapping and Planning (RiskMAP) program as part of the Biggert-Waters Flood Insurance Reform Act of 2012. This act charged FEMA with reforming the flood insurance process, while also improving the accuracy and reliability of it's floodplain maps (USGS, 2017). As a result, both 3DEP and RiskMAP programs are used to fund lidar acquistion projects across the U.S. In addition, several other U.S. agencies including the National Oceanic and Atmospheric Administratin (NOAA), the U.S. Department of Agriculture (USDA), the U.S. Army Corps of Engineers (USACE), and U.S. Forest Service (USFS) also participate in idar acquisition. Figure XX displays the footpring of topographic and bathymetric lidar across the continguous, lower 48 states. From this image, there is a clear decrease in the availability of publically-accesible lidar in the western U.S. including

Washington, Idaho, Montana, Oregon, Nevada, Utah, California, Arizona, and New Mexico. As lidar becomes more available and increasingly popular, it is important to understand the factors that influence a flood risk manager's decision to adopt this new technology into their practice of long-term risk mitigation.

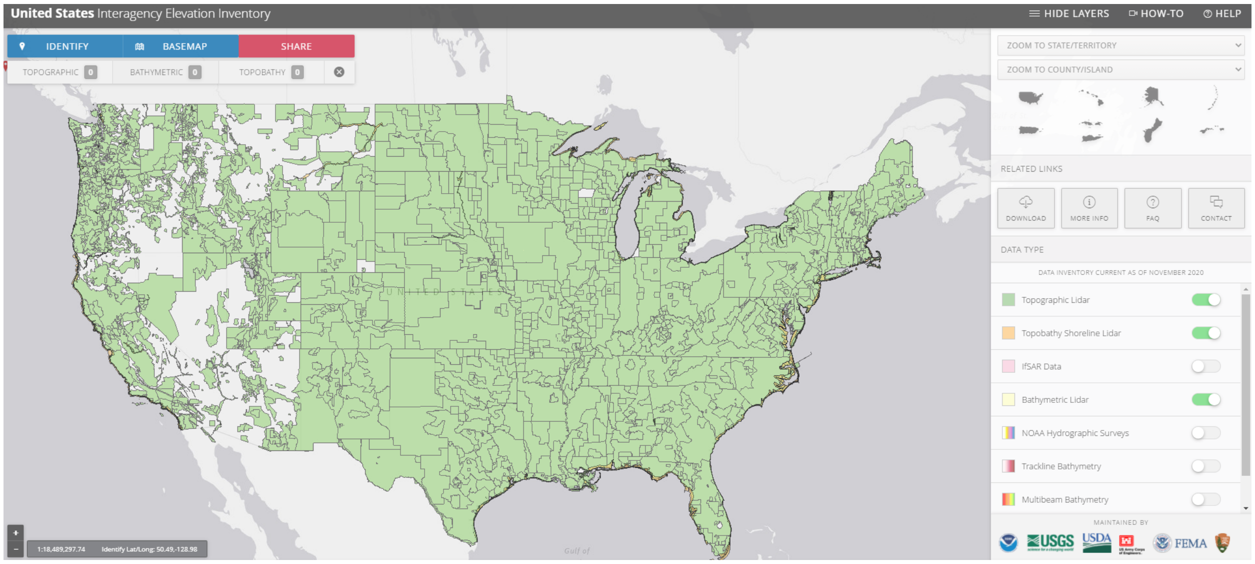


Figure 1: "The U.S. Interagency Elevation Inventory displays all publically-available lidar data and lidar-derived products for the contiguous, lower 48 states.https://coast.noaa.gov/inventory/"

The adoption of a new technology is an inherently risky process due to the variable time to and extent of the reward, in this case accurate floodplain maps (Barham et al., 2014). Risk has a variety of definitions based on the disciplinary domain in which the concept is being examined. In an everyday sense, risk can be considered the chance of a negative outcome occurring (Mishra, 2014). While from an ecologist's perspective risk is an unpredictable variation in the outcome of a behavior, with consequences for an organism's fitness or utility (Winterhalder et al., 1999). However, risk is inherently interdisciplinary and therefore needs to span both social and environmental contexts. For the purposes of this study, risk refers to the quantifiable consequence of a decision given the known, context-specific social and environmental factors. Furthermore, the risk of new technology to manage long-term risk adds an additional layer of affect in decision-making processes. When the saliency of long-term risk mitigation reward exceeds the risk of new technology adoption, we expect to see the adoption of lidar for flood risk management. This study examines the landscape of factors that catalyze the decision to use lidar for flood risk management.

Previous research has examined the role of risk perception in the context of decisions about hazardous activities (Slovic, 1987). Risk perception is a fundamental way to characterize how a person's intuitive risk judgement and allows for the identification, characterization, and quantification of risk. Past findings suggests individuals who perceive that natural hazards pose a greater risk also behave more cautiously (Vinh Hung et al., 2007). Interestingly, studies found the opposite in that individuals who perceive a greater risk engage in fewer mitigating behaviors (Bubeck et al., 2012; Wachinger et al., 2013). This paradoxical behavior suggests that risk perception is more nuanced and moderated by socio-cultural factors (Baerenklau, 2005; Birkholz et al., 2014; Bubeck et al., 2012; Kahan et al., 2007; van Valkengoed and Steg, 2019).This unexpected relationship between risk and mitigating behavior potentially explains the variation in lidar adoption that the western U.S. has seen thus far.

In order to explore the factors that moderate the relationship of risk perception and technology adoption, this study draws upon risk-sensitivity and behavioral ecology theory to quantify the saliency of flood versus technology risk. Lidar use in flood risk management provides an interesting case study because it has proven to be an effective technology for predicting flood risk with higher accuracy than previous topographic data. However, the technology requires investment of resources that can result in delayed to time to reward (e.g. accurate floodplain mapping) and variation of reward based on implementation of technology (e.g. quality level of lidar, correct processing, and education for use of lidar with relevant software).

Kellens et al. reviewed 57 empirically based peer-reviewed articles on flood risk perception and communication to assess overall trends in flood risk research (2013). The authors found that majority of studies were exploratory and did not apply a theoretical framework to examine risk perception (Kellens et al., 2013). Of the studies that employed a theoretical framework, protection motivation theory (PMT) was the most common. PMT The results of this review suggest future research that emphasizes a theoretical framework that caputures physical exposure and hazard experience to assess risk perception. PMT explains individual decisions about preparing for risk as a function of threat appraisal (e.g. likelihood of exposure to a flood, severity of expsoure, and fear) and coping appraisal (e.g. self-efficiacy, outcome efficacy, and outcome costs). If there is low threat appraisal, then adaptive behavior is unlikely to occur. However, if there is a high threat appraisl and high coping appraisal then it is likely an adaptive response will occur. Kuhlicke et al., summarizes additional individual behavior theories that have been used in flood risk management prior, including person-relative-to-event theory, theory of planned behavior, and protection action decision model (Kuhlicke et al., 2020). Additionally, Kuhlicke et al. highlights the use of the social identity model of collective action and social identity model of pro-environmental action as theories that explore the role of collective behavior on group adaptive behavior-related strategies (Kuhlicke et al., 2020).There are several limitations with the application of these theories so far. Firstly, there is limited predictive power of the theories applied so far (Kellens et al., 2013). Secondly, there is limited focus on the role of collective action in flood risk management research and therefore it is suggested that future research apply collective factors more rigourously (Kuhlicke et al., 2020). In addition, recent research suggests the importance of context, local power relations, and constraints/opportunities that affect the complex relationship between risk perception and risk mitigating beahvior; this work calls for a more critical perspective on underlying assumptions of risk perception and a focus on coordination of theories, methods, and variables. (Rufat et al., 2020).

need a theory for prediction & collective behavior

In response, our study employs a behavioral ecology lens, which is the study of adaptive behavior in relation to social and environmental circumstances, as a theoretical framework to classify the underlying context and collective factors that influence risk-migiation behavior (Bird and O'Connell, 2006). Futhermore, we will use risk-sensitivity theory to address the need for more rigorous application of context and collective factors on flood risk mitigaiton behavior.

Research thus far has found that risk-sensitivity theory accounts for a significant amount of variance in decision-making under risk (Mishra, 2014). Specifically, this theory addresses this because it considers risk management at the group-level, where previous theories have not. In addition, risk-sensitivity theory provides a strong predictive model for understanding adapative beahvior under risk (CITE). In the future, we hope that our theoretically-backed framework can standardize the approach for additional flood risk adapative behavior studies to allow for future meta-analyses.

In the next section we review behavioral ecology theory and risk-sensitivity theory. Next, we apply this theoretical framework to our case study of lidar adoption for flood risk management. This is followed by a methods section that explains our survey instrument and statistical analysis approach. The results from our analysis and a discussion about significant trends will follow. Finally, we discuss the implications of these results and need for further reserach (expand)

2 THEORY

"A Theory section should extend, not repeat, the background to the article already dealt with in the Introduction and lay the foundation for further work. In contrast, a Calculation section represents a practical development from a theoretical basis."

2.1 Decision-making under flood risk

Almost all human decisions are made while considering risk, which is different than uncertainty. With uncertainty, the outcome probability is unknown due to lack of knowledge, however this can be overcome with acquiring information about the environment (Henrich and McElreath, 2002). With this information, an individual is now able to discern and quantify varying levels of risk. This is an important distinction to make because uncertainty can alter how an individual makes decisions under risk and therefore, can potentially be a confounding factor in data analyses (Winterhalder et al., 1999). Risk has a variety of definitions based on the disciplinary domain in which the concept is being examined. In an everyday sense, risk can be considered the chance of a negative outcome occurring (Mishra, 2014). While from an ecologist's perspective risk is an unpredictable variation in the outcome of a behavior, with consequences for an organism's fitness or utility (Winterhalder et al., 1999). However, risk is inherently interdisciplinary and therefore needs to span both social and environmental contexts. For the purposes of this study, risk refers to the quantifiable consequence of a decision given the known, context-specific social and environmental factors.

Previous work has disporportionately focused on the effect of risk perception on risk adapating behavior. Risk perception is a basic way to characterize a person's intuitive risk judgement and allows for the identification, characterization, and quantification of risk. For that reason, risk perception has been well studied in the past especially in terms of its role in decision-making under risk due to hazardous activities and technologies (Hung et al., 2003; Slovic, 1987). Interestingly, there has been research that identified an unexpected relationship between risk perception and lack of risk mitigating behavior named the "Risk Perception

Paradox" (Bubeck et al., 2012; Wachinger et al., 2013). This study examines why this phenomena may occur and proposes alternative predictors that may affect an individual's risk mitigation behavior such as social and environmental factors that moderate risk perception's effect size on decision-making and behavior (van Valkengoed and Steg, 2019; Wachinger et al., 2013).

2.2 Theoretical background

Several theories have developed to understand decision-making under risk such as expected utility theory, prospect theory, and hueristic approaches. However, the only theory to account for the influence of evolutionary processes on decision-making under risk is risk-sensitivity theory. While this theory is well-established and can describe patterns of decision-making in variety of contexts, it has been underapplied (Mishra, 2014). Research thus far has found that risk-sensitivity theory accounts for a significant amount of variance in decision-making under risk (Mishra, 2014). This study applies risk-sensitivity theory to decision-making under flood risk to understand the variance in lidar use between Washington and Idaho.

Risk-sensitivity theory is a normative theory traditionally used by behavioral ecologists to explain food acquisition decisions and overall foraging behavior. This theory has been widely-applied in studies of nonhuman animals (Mishra, 2014; Winterhalder et al., 1999). Researchers have found that the energy state of an individual significantly influences their risk preference. Therefore, risk-sensitivity theory predicts that the decision-maker will shift from risk-averse to risk-prone behavior in situations of need where there is a discrepancy between an individual's present state and desired state (Mishra, 2014). Furthermore, previous research has examined risk-sensitivity theory with respect to the human decision-making model. For example, it has been shown that animals do not follow the predicted risk-sensitivity theory pattern when there is reward variance (Mishra, 2014). This could be due to heuristics that an individual uses to perceive their environment.

In addition, it is important to consider the impact of heuristics and biases on decision-making processes for they are a part of the human cognition system and affect how an individual interprets useful knowledge, practices, beliefs, and behaviors (**henrichEvolutionCulturalEvolution2003?**). Within this, there are content and context biases. Content biases are direct, exploitive cues of information resulting in imitation of, typically, fitness-enhancing behavior. Context biases, on the other hand, exploit potential alternative behaviors or strategies. Context biases are of particular interest because they have the ability to lead to evolution and natural selection of information within a population (**henrichEvolutionCulturalEvolution2003?**). In addition, heuristics allows humans to make quick decisions and can be understood as the result of adaptive evolutionary processes to solve recurrent problems (Mishra, 2014). Sometimes these quick decisions are made with incomplete information, which is often true when making decisions under risk, making these decisions bounded by limited information (Mishra, 2014). Therefore, it is important to consider descriptive rationale when understanding the consequential decisions of risk.

2.2.1 Applying risk-sensitivity theory

Risk-sensitivity theory can be applied if the value of interest (e.g. utility, fitness) is nonlinear and one or more of the behavioral alternatives is characterized by unpredictable outcomes (Winterhalder et al., 1999).

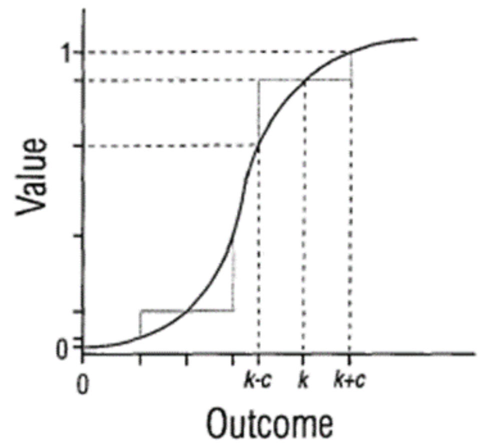


Figure 2: "This graph displays a sigmoid value function to represent the basic logic of risk sensitivity. The concave portion represents decreasing marginal returns. A constant outcome, denoted by k, represents the point where constant equals the probabilities of variable outcome (k+c, k-c). The convex portion represents increasing marginal returns (Winterhalder et al., 1999)."

As seen in Figure 1, when the resource of interest is scarce, value rises at an accelerating rate, convex, until it hits an inflection point where the resource is abundant there is a decelerating rate of value, concave. There are essentially two options for the individual to choose: a fixed reward, k, or an unpredictable reward with equal probability of being either k-c or k+c. An individual who chooses the fixed reward is typically risk averse, whereas the individual who is in poor condition will likely choose the variable reward making them risk prone. This is because the individual is making decisions based on decreasing marginal utility. If they are risk averse, they will remain on the concave shape of the utility function because it is more conservative. If they are risk-neutral, they would have a straight line utility curve at value k. If they are risk-prone, they would remain on the convex portion of the utility curve where they would prefer options with more variation (Henrich and McElreath, 2002). In addition, the risk decision depends on time frame, urgency, and consequence of the decision as discussed previously. Research has found that animals are commonly risk averse when quantity is variable, however they are risk prone when the time to reward is variable (Winterhalder et al., 1999).

Considering these theoretical predictions, we expect to see flood risk managers who are located in variable floodings environments to be more risk prone and therefore choose riskier risk-mitigation behavior. Furthermore, there are additional social and environmental factors that moderate the effect size of risk sensitivity on management decisions.

2.2.2. Risk mitigation behavior

Research has found that individuals, human and nonhuman, make decisions to minimize their chances of falling below subsistence minimum known as shortfall minimization (Henrich and McElreath, 2002). Most of the previous work in this field has been with empirical observations of nonhuman animals in an experimental or laboratory setting. The findings from these studies have shown consistent risk-sensitive behavior. Risk prone resource selection, variable reward versus constant reward with same overall reward value, is more common under negative energy balance for solitary species (Winterhalder et al., 1999). However for larger animals, where there are alternative behavioral tactics to minimize shortfalls, risk-prone behavior is more rare because our their ability for cooperation. Two examples of this risk-minimizing behavior is resource pooling and social learning.

Resource pooling opens up opportunities for trying new technology and techniques that one individual may not have been able to afford or know how to do on their own. For example, farming cooperatives in France have become popular because it allows individuals to pool wealth, tools, and knowledge. Consequently, these farmers see greater returns on investment due to economies of scale from pooled resources (Agarwal and Dorin, 2019). In addition, resource pooling can instill social capital in a community over a united purpose. This is because social capital can create trust, norms of reciprocity, and social networks that can be instrumental in successful group collaboration and cooperation (**wagnerDoesCommunityBasedCollaborative2008?**).

Additionally, social learning is an important component of risk minimization. Social learning is an individual's ability to transmit information to another person. Culture forms as a result of this process, creating a shared set of beliefs and norms among a group of individuals. Culture evolves through the process of natural selection, creating between-group variation of adaptive behavior and cooperation (Richerson et al., 2016). Consequently, some groups evolve to have more successful risk mitigation behavior than others. Institutions are an example of a group that has formed due to collective decision-making. Often times, there is competition between institutions in a similar market. The institution that wins typically has been able to suit the needs of their environment better than their competition (Richerson et al., 2016). This is true for risk mitigation behavior as well and therefore social learning makes working as a group advantageous for minimizing risk. Considering these tactics, we expect to find that flood risk manager's decisions to be affected by these risk miminization tactics.

2.3 Case study

CASE STUDY justification: This is true for the western United States where we can expect to see an increase in precipitation and higher temperatures earlier in the year (Clark, 2010; Division, 2020; Emergency Management, 2018; Ralph et al., 2014).

Technology adoption in flood risk management provides an interesting case study to examine patterns of decision-making under flood risk due to the variation in use and reward of the interested technology. This study examines the adoption of lidar in communities throughout Washington and Idaho. Lidar provides highly detailed and accurate topographic data that flood risk managers use to model floodplains and assess their flood risk. The technology is expensive (~ \$125/km2), requires a lot of storage, and can be slow. In addition, it takes additional training to learn how to process the raw lidar data and integrate the data points into programs such as ArcGIS to create useful products for flood risk management.

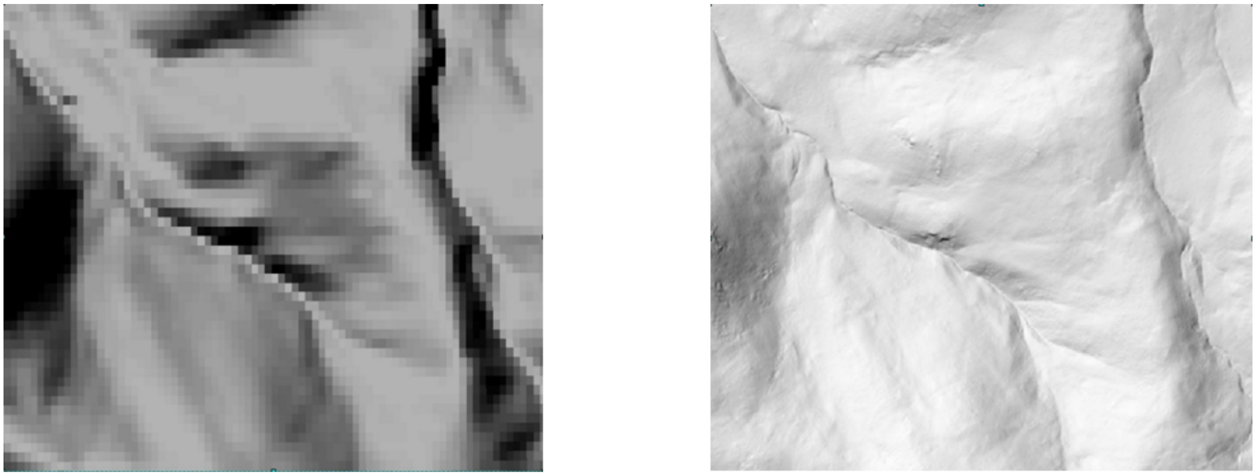


Figure 3: The image on the left is a traditional 30-meter digital elevation model and the image on the right is a 1-meter digital elevation model derived from lidar data.

The United State Geological Survey 3D Elevation Program (3DEP) was created to coordinate nationwide acquisition of lidar by 2023. While this technology has been backed by federal agencies, it has had variable adoption rates across the U.S. One reason for this could be due to local governments having variable risk sensitivity to flooding and consequently varying action in adopting lidar. The two states of comparison in this example are Washington and Idaho. Flooding in Washington typically occurs on a seasonal basis due to rainfall from atmospheric rivers, rainfall on snow, flash foods from storms, and winter storms causing storm surges and high tide (Division, 2020). Idaho is prone to flooding from rivers, flash floods, ice/debris jams, sheet or areal flooding, and mudflows (Emergency Management, 2018). Overall, the two states see different amounts of damage and risk as shown in **??** .

Table 1: Summary information about environmental and social differences between Idaho and Washington.

	Portion of land in 100-year floodplain	Portion of population in 100-year floodplain	Cumulative property loss
Idaho	1.8%	3.7%	\$180 million (1950-2017)
Washington	5.0%	8.8%	\$2 billion (1960-2016)
Difference	3.2%	5.1%	\$1.2 billion

2.3.1 Examining predictors of lidar adoption in further detail

Risk-sensitivity theory suggests that decision-makers should prefer high-risk options in situations of high need, when lower risk options are unlikely to meet those needs (Mishra et al., 2012). In this study, the value represents the adoption of lidar and the outcome is flood risk mitigation. Given this, as well as previously described information about the effects of variable reward and delay, I expect to see an adoption pattern similar to that suggested by the value function in Figure 1. Flood risk managers in negative energy space due to high flood risk, the convex portion of the value function, should act more risk prone in order to try and mitigate negative impacts of floods. Whereas, flood risk managers who are in the positive energy space, the concave portion of the value function, should act more risk averse and may remain status quo. I hypothesize that flood risk managers in Washington are more likely to risk adopting a new technology because of their higher need to address floods.

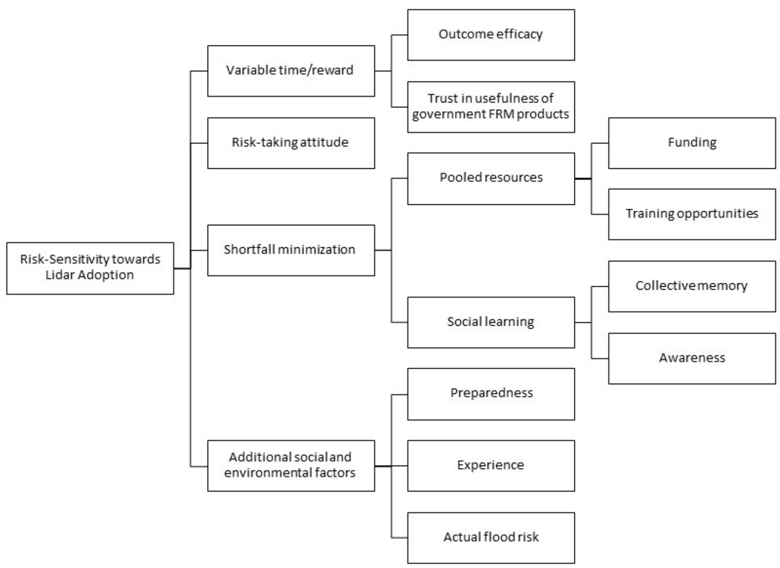


Figure 4: “Flow chart of factors influencing risk-sensitivity towards lidar adoption”

Figure 3 displays the breakdown of factors that may influence a flood risk managers risk sensitivity and consequential decision-making process in adopting lidar. The first component is the variable time and reward of this decision. There is an inherent risk with adopting a new technology because it requires an investment of time and money in order to be adopted. One of way measuring the effect of this variation on adoption is by measuring the outcome efficacy of products produced from using this technology. In this case study, we measured a flood risk manager's trust in the accuracy of scientific products for FRM, as well as their trust in the government to produce useful FRM products.

Risk-taking attitude, also known as risk preferences, has been studied previously as an important predictor of risk mitigation behavior. However, it is distinct from risk sensitivity because... (need to flush out this idea more). Several studies have looked at what factors influence an individual's risk-taking attitude. For example, economists have thought that wealth and demographic variables, such as age and sex, would be highly correlated with risk prone behavior, however the results have not supported this (Henrich and McElreath, 2002). Rather, it has been found that risk preferences can be driven by emotional reactions to a risky situation, individual versus group consideration, and the instability of the environment in which an individual is making a decision (Eckel et al., 2009; Liu, 2012; Nolin and Ziker, 2016; Shupp and Williams, 2008). Therefore, risk-taking attitude, similar to risk sensitivity, is the product of social and environmental cues and has important implications for risk mitigating behavior.

Shortfall minimization is a critical component of decision-making under risk. As discussed previously, risk can be minimized by resource pooling and social learning. Since lidar is an expensive investment, funding opportunities and collaborations can help minimize and share the risk of investing in lidar. For example, the Washington Geological Survey was granted funding from 2015-2021 for the collection and distribution of lidar data and lidar-derived products. Therefore, individuals who adopt this technology in Washington have the potential to minimize their risk of investment by pooling resources. Due to this resource pooling, we expect Washington to see an increase in lidar adoption. In addition, social learning can influence the norms and beliefs that a flood risk manager holds about appropriate adaptive behavior. Research has shown that collective memory provides context and is an important indicator of a community's flood risk culture (Viglione et al., 2014; Wachinger et al., 2013). Collective memory represents a community's ability to keep awareness of previous events that shape their decisions for the future. Often times, flood risk managers develop their collective memory based on information they learn from their peers and experience within their community. This awareness influences an individual to take action based on a collective idea of risk, rather than from individual belief. - add section about awareness

There are additional social and environmental factors that could moderate decision-making under flood risk. These include community preparedness, experiences, and actual flood risk. Community preparedness is the product of the environment the flood risk manager is making decisions in. Community preparedness provides an idea of how a flood risk manager view's their commuinty ability to handle future floods. Futhermore, their past experiences with flooding (e.g. floodign outside designated floodzone or flooding damage) may influence how their decision-making under risk process. Lastly, this study also considered the objective flood risk of Washington and Idaho as summarised in Table 1.

This next section discusses how we measured each of these contributing factors and our methods for survey analysis.

3 METHODS (~ 1,000 words)

"Provide sufficient details to allow the work to be reproduced by an independent researcher. Methods that are already published should be summarized, and indicated by a reference. If quoting directly from a previously published method, use quotation marks and also cite the source. Any modifications to existing methods should also be described."

Survey design

Talk about the specific survey questions that I end up analyzing here...

This survey covered several topics to measure predictors that could affect lidar adoption. This includes the following: awareness, preparedness, risk-taking attitude, collective memory, trust, and outcome efficacy. See Appendix A for a copy of each survey.

Survey procedures and participants

The survey's target respondent was the floodplain manager or administrator from participating and non-participating National Flood Insurance Program (NFIP) communities in Idaho and Washington in the Western United States. This also included individuals that may use lidar for flood risk management applications in conjunction such as Geographic Information System (GIS). Lidar, in this context, means either raw lidar data (e.g. LAS or point clouds) or lidar-derived data (e.g. digital elevation model (DEM)).The majority of sample respondents were municipal, state, and federal employees, as well as some private industry employees. In order to acheive our target population, the sample frame included several sources of contacts including NFIP coordinators, Assocation of State Floodplain Managers (ASFPM) recognized Certified Floodplain Mangers (CFM), county-level GIS administrators, the five largest cities and tribal GIS admnistratators if present, county and tribal emergency managers, the Federal Geospatial Data Coordination Contacts by State, and additional, relevant contacts for the 2019 Northwest Regional Floodplain Managers Assocation (NORFMA) Conference contact list.

In addition, this survey data was collected through a structured, online survey distributed through Qualtrics to email addresses in our sample frame. The survey was sent to Idaho and Washington between May and July 2020. The survey took on average xx minutes. There were four to six email correspondence messages with potential survey participants over the course of four weeks. There was a total of 385 potential survey respondents in Idaho and 356 potential survey respondents in Washington.

Table 2: Survey demographics for Idaho and Washington.

	Idaho	Washington
Sample Size	96	58
Gender	61% male, 39% female	52% male, 41% female
Education	69%	71%
Average Flood Risk Experience (years)	10.6	13.8

Additionally, a non-response analysis (how do I do this?) was run due to the low survey response rate of 24.94% in Idaho, 'r or.rr'% in Oregon, and 11.66% in Washington. However, there were no significant distortions of representativeness found for age, gender, geographical area, or level of education (Need to check this). It is important to note, our data collection was completed during COVID-19 pandemic which required extra time and energy from emergency managers, our target population for this survey. For this reason, we expected a lower survey response than typical (unnecessary to say?).

Survey analysis

A Hierarchical Bayesian approach with a Generalized Logistic Regression meets the model criteria for understanding risk because it is able to characterize non-linear, unpredictable outcomes. Furthermore, a logistic regression was used because the response variable, lidar use, is binary. Therefore, this analysis did not need account for ordered categorical response. This analysis uses a Markov Chain Monte Carlo alogrithm to predict posterior distributions of each parameter's effect on lidar use.

insert bayes theorem

This model has two-levels of analysis. The first level of actors is represented by individual respondents and the second level is the cluster represented by each state. Furthermore, this model follows a binomial distribution curve, where the distribution of lidar use, y_{ij}, can be modeled as follows (https://idiom.ucsd.edu/~rlevy/pmsl_textbook/chapters/pmsl_8.pdf):

$$b_i \approx N(0, \sigma_b)$$

$$\eta_i = \mu_\alpha + \beta x_{ij} + ... + \beta_k x_{ij} + b_i$$

$$\pi_i = \frac{e_i^\eta}{1 + e_i^\eta}$$

$$y_{ij} \approx Binom(1, \pi_i)$$

(1)

where x_{ij}, predictors, are the ith rows of the known design matrices x, and β is a vector of regression parameters. The Bayesian approach allows for adjustment of uncertainity associated with each parameter on the final outcome (lidar use). In order to do this, each parameter has to be assigned a prior belief of that parameter value. The values for these parameters are fit by sampling from these distributions to maxmize the likelihood under this model(Kwon et al., 2008). The regression parameters, β, are normally distributed,

$$\beta_k \approx N(\eta_{\beta k}, \sigma_k)$$

. Additionally, the parameters of this distribution, $\eta_{\beta k}$ and σ_k, also have prior distrubtions assigned to them that are constrained by 0 and a positive value (should I be more specific?).

The primary model included all predictors of interest with a varying intercept due to location. Subsequent models were run, isolaing each predictor and lidar use with vary intercept and slope. In addition, we ran a model comparison and assessed the overall preformance through Leave-One-Out Cross-Validation (LOOCV). This process provides an absolute metric for the model's predictive ability. Lastly, because this model had categorical predictors, we plotted the predicted probablity against the observed proportion for some binning of the data (Levy, 2012) [this text has a great example of how to plot this]

4 RESULTS + DISCUSSION (~2,000)

"This should explore the significance of the results of the work, not repeat them. A combined Results and Discussion section is often appropriate. Avoid extensive citations and discussion of published literature."

64.81% of survey respondents from Washington and 'r or.lidaruse'% survey respondents from Oregon used lidar, where 50% survey respondents from Idaho used lidar. The rest of this analysis explores why this difference may exist. The model for this analysis was estimated to evalute the impacts of various predictors on the use of lidar for flood risk management. The programming language R and program Rstudio for were used to run this analysis. Furthermore, this analysis used MCMC technique with four chains with 1,000 iterations for warmup and an additional 1,000 iterations for the model. Additionally, convergence was checked by visually inspecting the MCMC trace plots of the model parameters. The results of this analysis suggest that awareness and collective memory have significant impact on lidar adoption. Experirence, risk attitude, and outcome efficacy have small to moderate impact on lidar use. Preparedness and government trust did not have a significant impact on lidar use.

displays the results from a varying intercept model that considers the effect of all these factors on lidar use, while using partial pooling for location. This is helpful for drawing out the impact of various predictors, however we invesigated these further to determine state-level differences in predictors and lidar use.

Predictors showing significant effect on lidar use

Network Lidar Use

Social learning plays an important role in technology adoption... our results support that this is the most influential factor of lidar adoption. In Idaho, there is a slope of 4.9, 'r b.or' for Oregon, and 3.5 for Washington. Awareness was measured by asking the survey respondent about the perception of the average severity of flood damage in their community decreasing, staying the same, or increasing. Overall, there was a positive correlation between awareness of future risk and lidar use. Furthermore, Washington had a stronger correlation. This could be due to Washington having seen signifcantly more damage and portion of population at risk to floods shown in .

Awareness

Awareness has a significant effect on lidar use in both Idaho and Washington. In Idaho, there is a slope of 0.6 and in Washington it is 1.2. Awareness was measured by asking the survey respondent about the perception of the average severity of flood damage in their community decreasing, staying the same, or increasing. Overall, there was a positive correlation between awareness of future risk and lidar use. Furthermore, Washington had a stronger correlation. This could be due to Washington having seen signifcantly more damage and portion of population at risk to floods shown in .

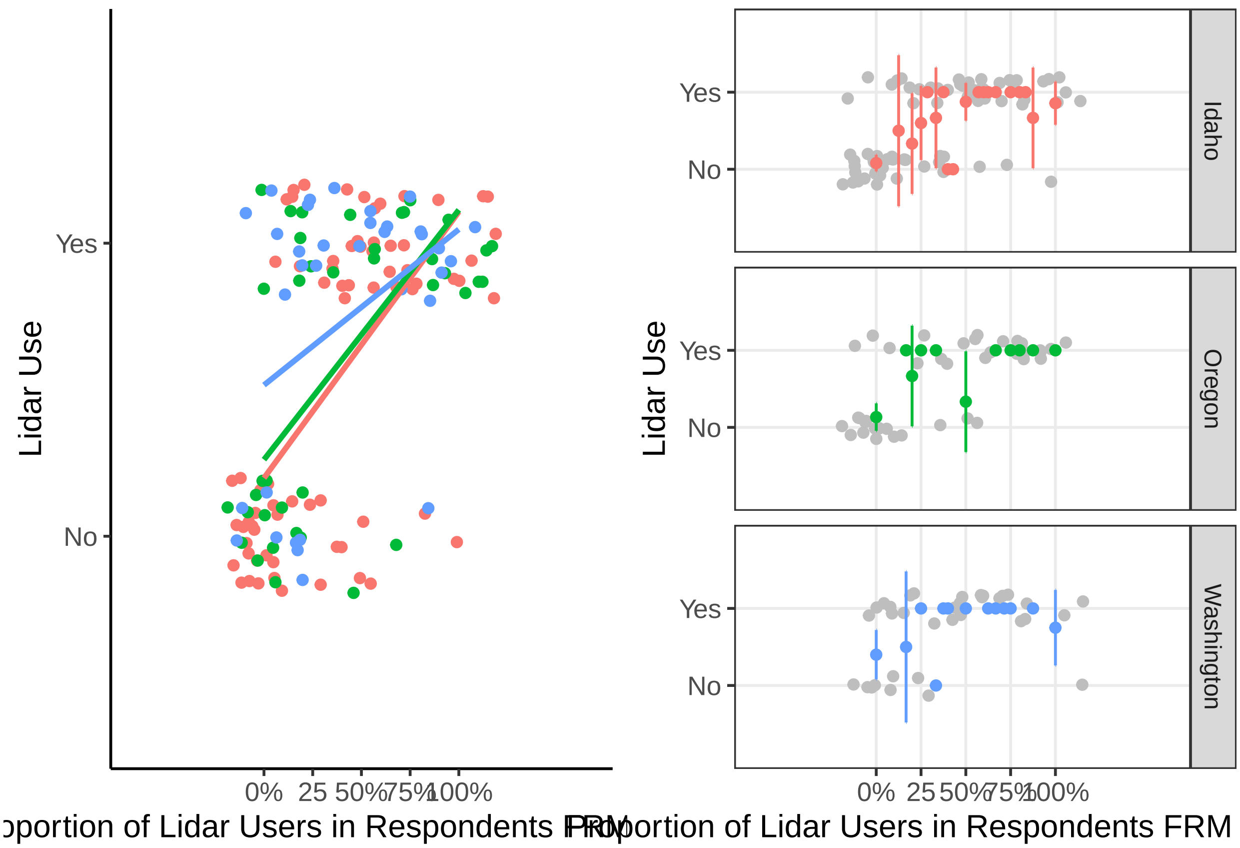


Figure 5: awarnessplot

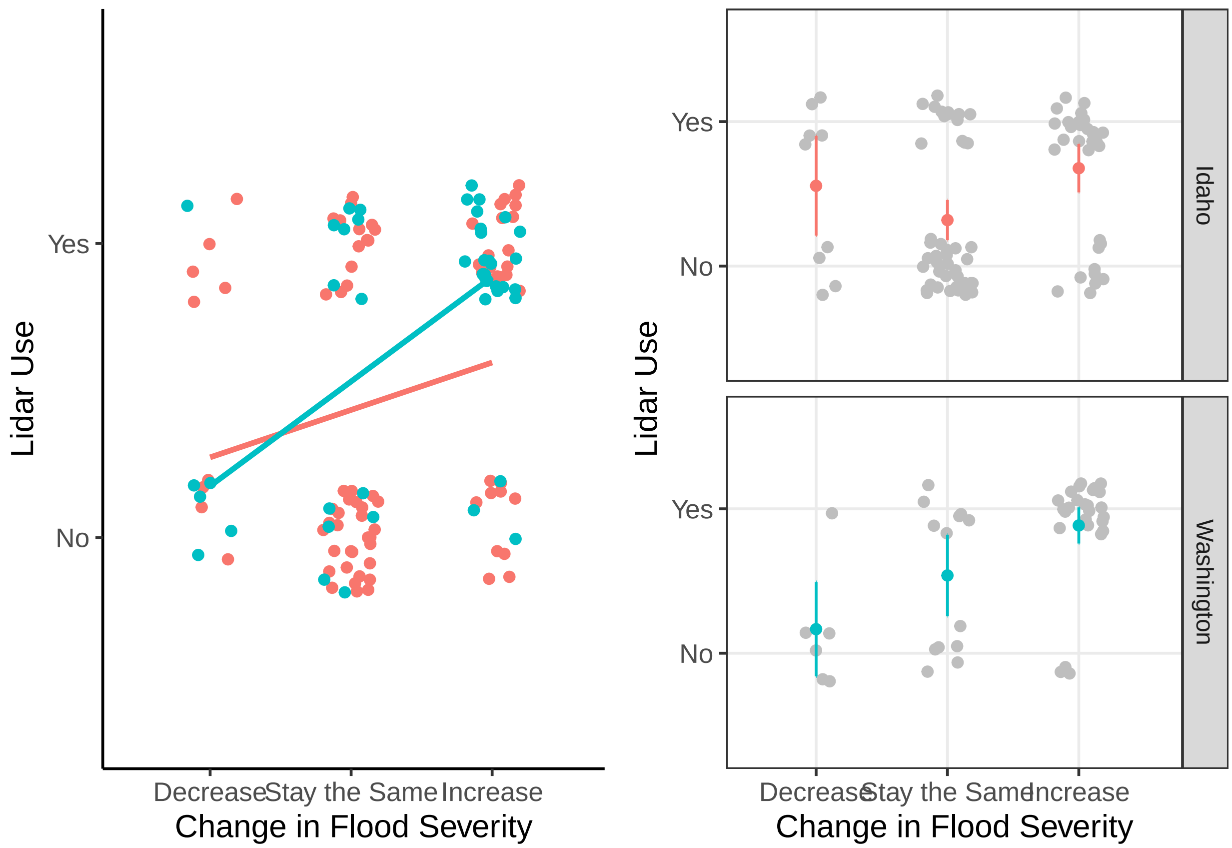
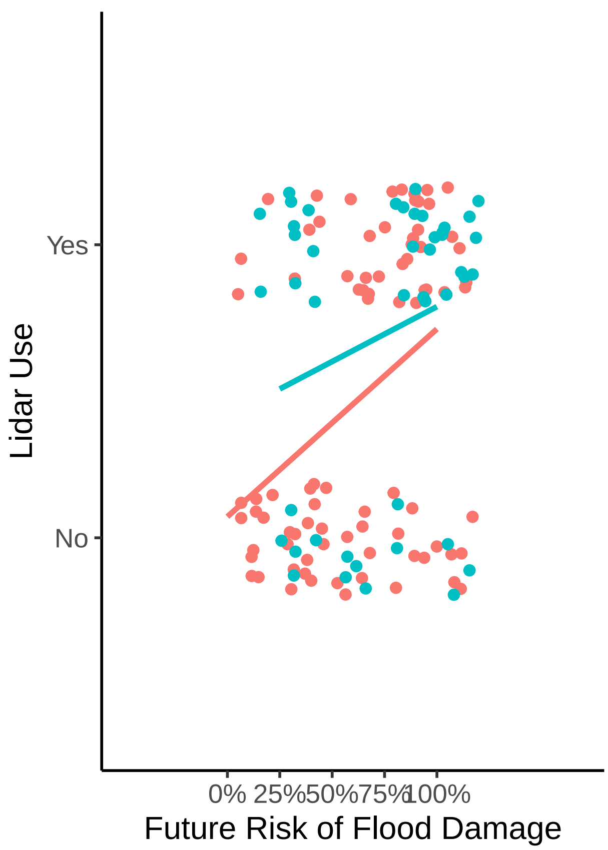
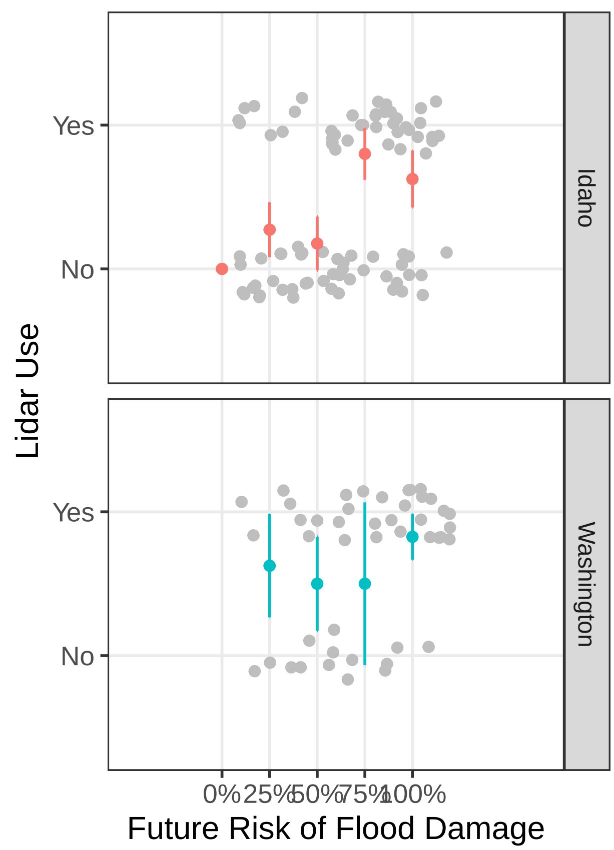


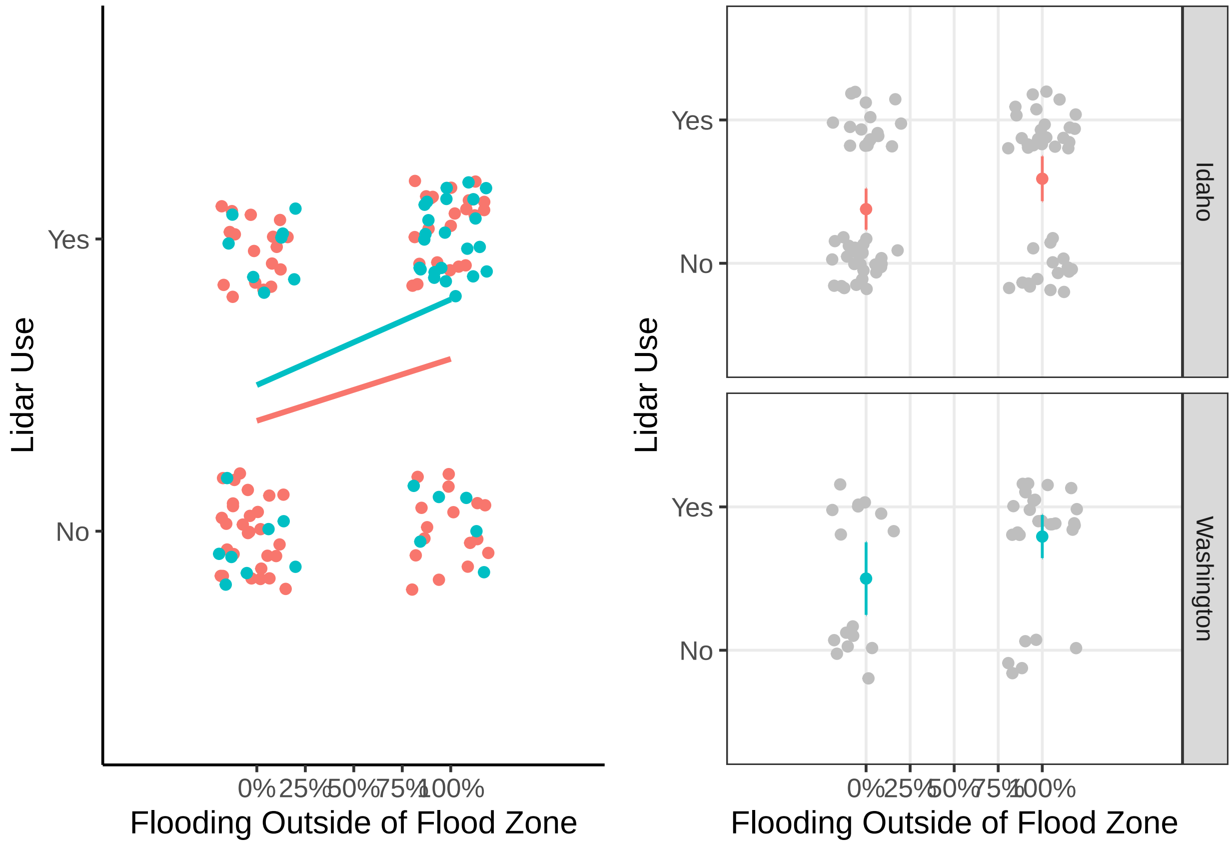
Figure 6: awarnessplot

COllective Memory

Building off the first predictor, awareness, it is important for a community keep awarness high for it often has influence on how people respond to risk. This analysis also investigated collective memory, essentially timeless awareness, to understand its effect on lidar use. Both beliefs on future experiences and reflection on past experiences can make up an individual's collective memory. Furthermore, this memory is a collection of experiences of others through social learning about flood risk management. This survey measured collective memory in two ways. The first question asked the respondent how likely they think damage to property in their community will happen in the next 30 years. The second question asked the repondent if they were aware of floods happening outside of the designated flood zone on their community flood maps. Idaho had a slope of 2 and 0.6 for the relationship between lidar use and future flood risk and past flooding, respectively. Washington had a slope of 1.5 and 0.9 for the relationship between lidar use and future flood risk and past flooding, respectively. Therefore collective memory had, on average, a similar, significant effect on lidar use for both Idaho and Washington.







Predictors showing small to moderate effect on lidar use

Experience

Direct experience has been studied extensively in the past as a singificant predictor of risk perception and behavior. Our survey asked respondents to report if they had experienced damage in their community, with yes or no responses. Our results found a moderate effect of experience on lidar use. Specifically, Idaho had a slope of 0.3 and Washington had a slope of 0.6. Previous research has found variable effects of experience on behavior and suggest that measuring the intensity of the event experience could provide a more informative measure.

Risk Attitude

As discussed eariler, there is a risk inherent with adopting a new technology such as lidar due to variable time delay and reward. In this analysis, risk-taking attitude had no effect in Idaho with a slope of 0 and minor effect in Washington with a slope of ‘r b3.wa. This contradcits the expected result based on risk sensitivity theory. This could be because in fact risk minimization tactics like resource pooling and social learning are not as salient as previously thought in lidar adoption.(??)

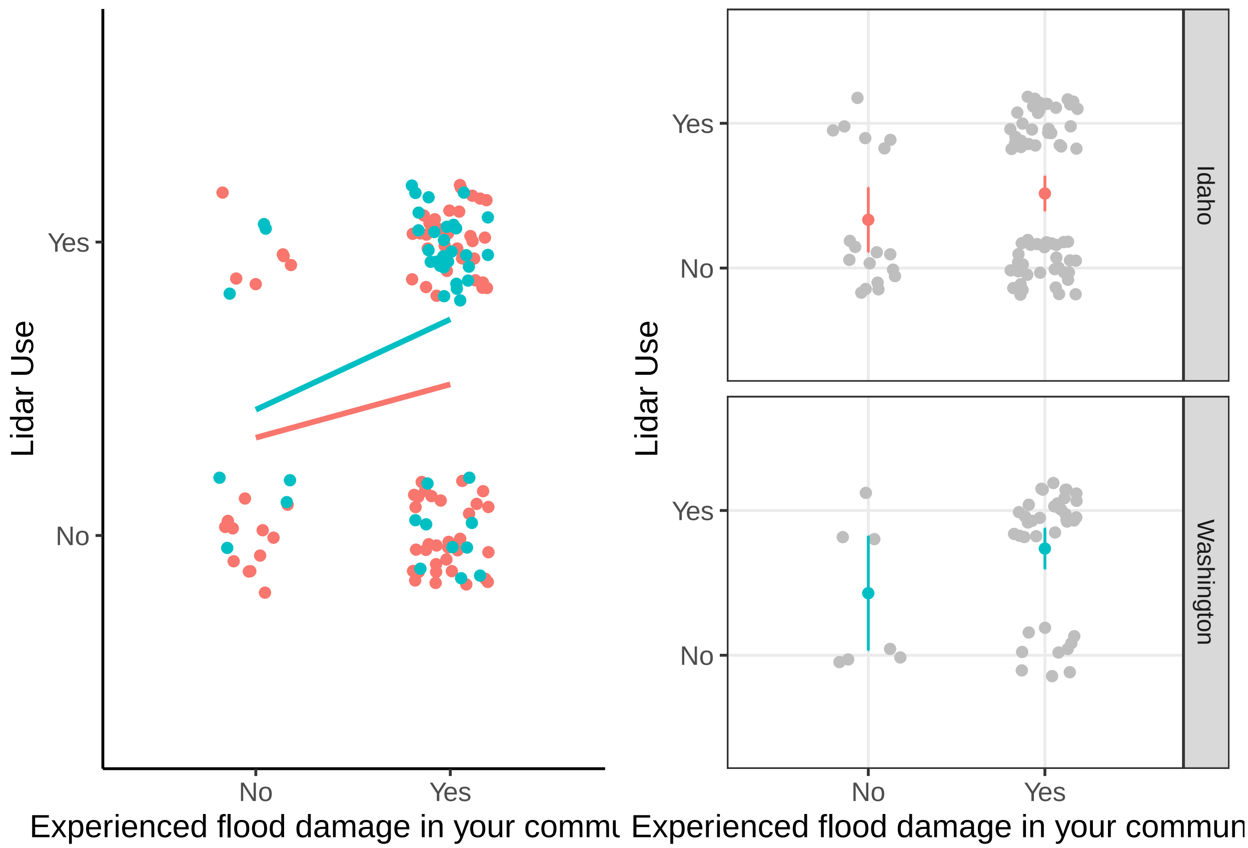


Figure 7: expplot

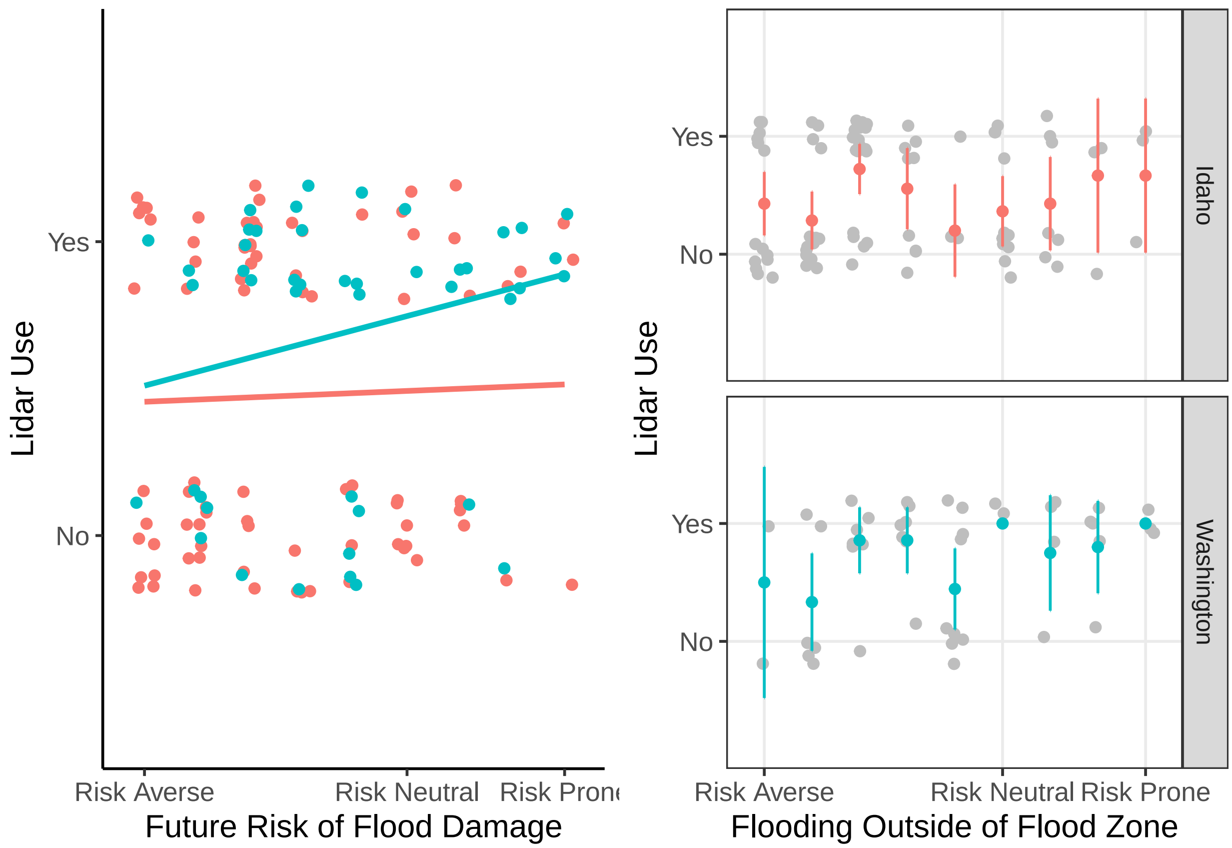


Figure 8: soepplot

Outcome efficacy

The outcome efficacy of the risk being taken can play a significant role in the adoption of the adapative behavior. These results are quite opposing for Idaho and Washington. Idaho has a negative correlation between trust in science and lidar use, whereas Washington has a positive correlation between trust in science and lidar use. This is really interesting… it could be why Idaho continues to use old maps, because they think they are sufficient?

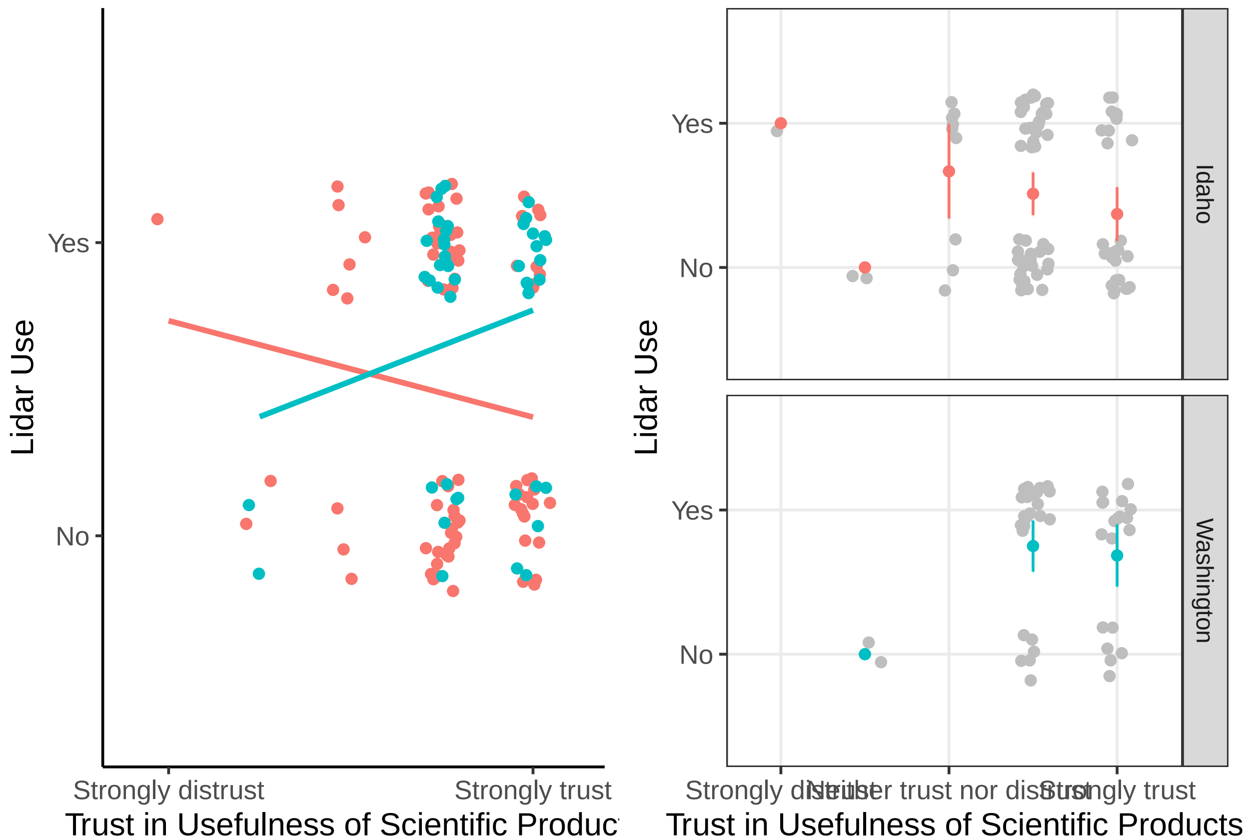


Figure 9: outeffplot

Predictors showing minimal effect on lidar use

Prepared

Still not sure if I should include this one.

Trust in the Government

Often times trust in the government has been measured in relation to ability to adapt. Although, most research has been conducted in terms of the trust the public has for government officials to protect them from floods. This survey asked flood risk managers how much they

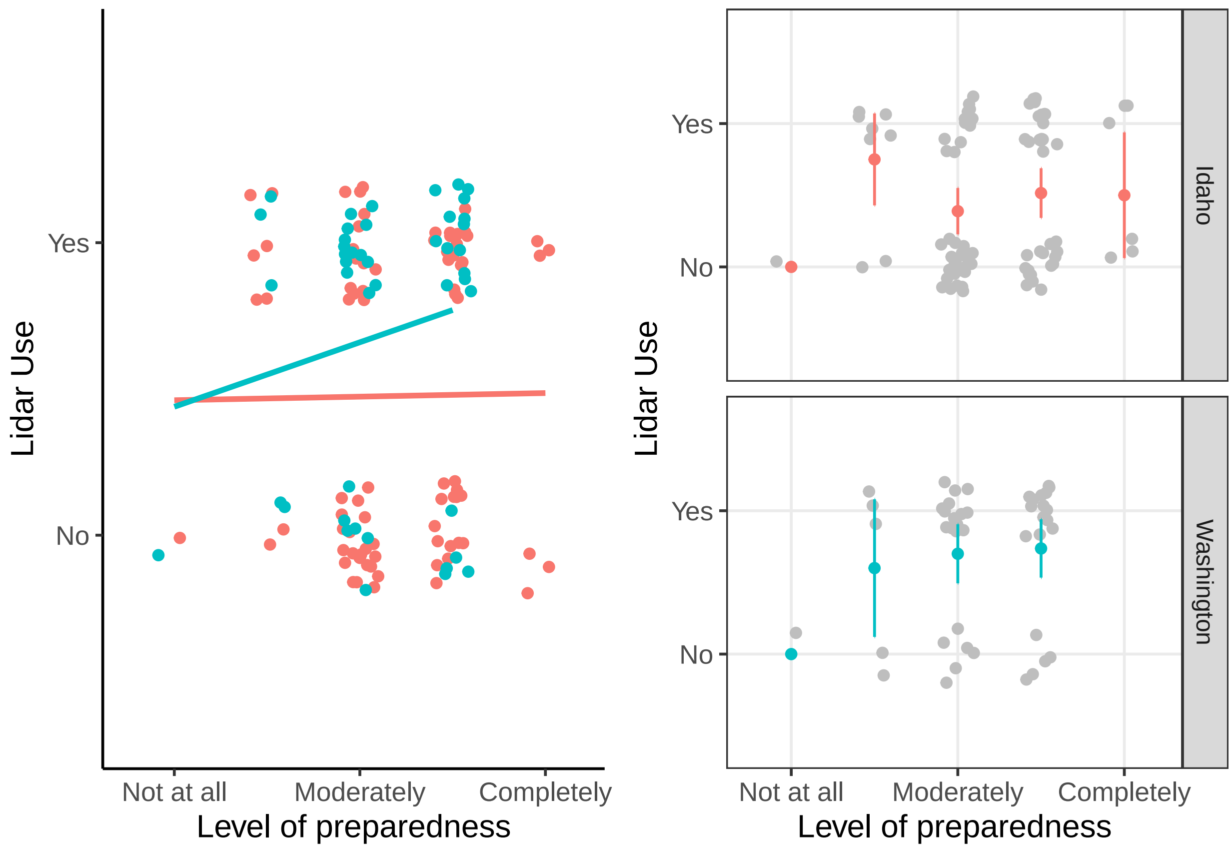
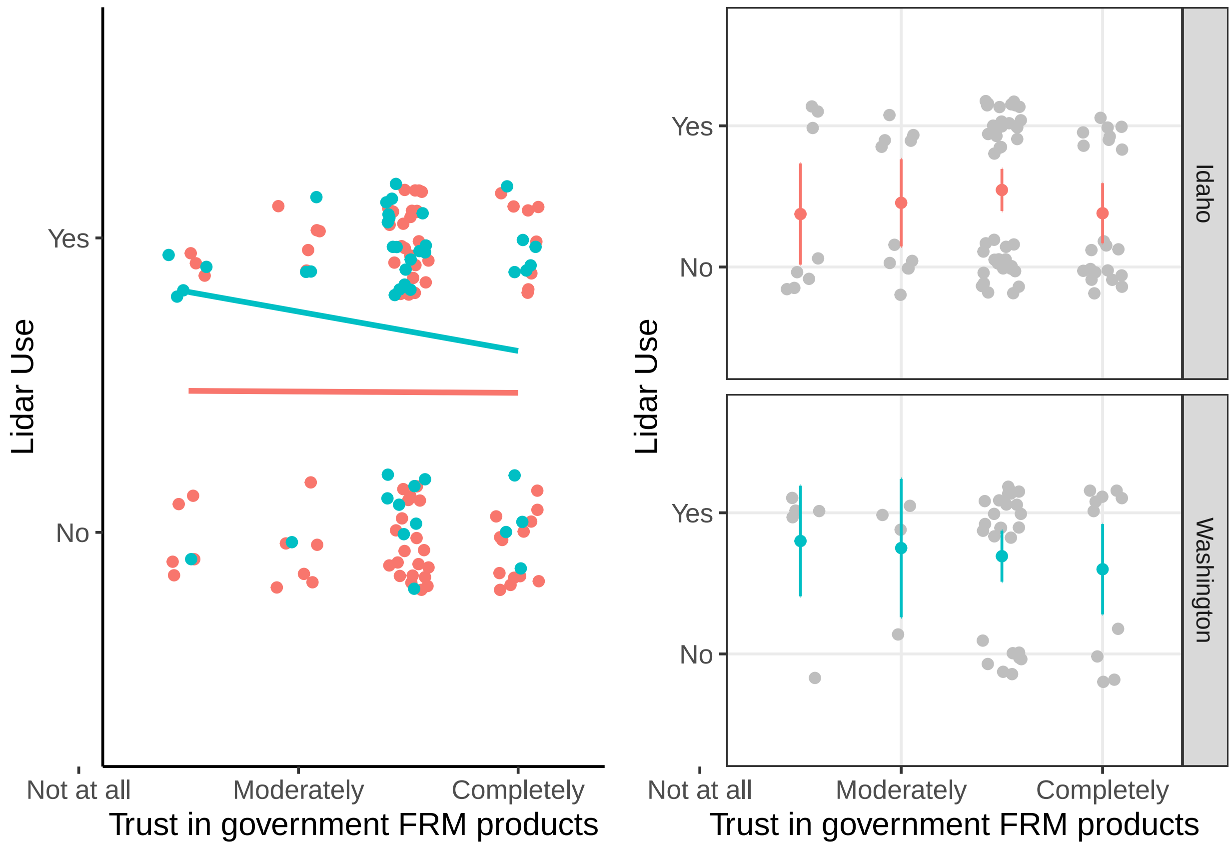


Figure 10: prepplot

trust the usefulness of the products the federal government develops for FRM. Idaho had a slope of -0.1 and Washington a slope of 0. Overall, there was a not a significant relationship between trust in government products and lidar use. Moreover, Washington actually saw a decrease in lidar use with increased trust in federal government FRM products. This could be because flood risk managers in Washington feel that these products are sufficient and they do not need additional data from lidar.



The following are parts of the analysis that I am not sure if I should include or not:

Barriers to lidar use

Part of the survey asked respondents to report on barriers to lidar use. These responses solely came from individuals that did not currently use lidar.

5 CONCLUSION (~500)

"The main conclusions of the study may be presented in a short Conclusions section, which may stand alone or form a subsection of a Discussion or Results and Discussion section."

While this theoretical model has never been applied to understanding risk in hazard management, I think that it could provide improved insight into significant predictors of long-term risk mitigation. This paper examines alternative predictors to risk perception in an effort to address why risk perception may not align with long-term risk mitigation behavior, also called the "Risk Perception Paradox." From a behavioral ecology perspective, these predictors could be cultural and contextual factors that moderate risk perception's effect size on decision-making and behavior. This paper investigates how these predictors may affect lidar adoption in flood risk management in Idaho and Washington. This makes an interesting and effective case study because the benefits of this technology have a variable reward and time delay, two key factors that can feel risky in adopting this technology. Furthermore, the findings from this research could have important implications for the risk field of research and advance our understanding of the driving factors of an individual's long-term risk mitigation behavior.

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