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Social networks impact flood risk mitigation behavior: A case study of lidar adoption in the Pacific Northwest, US

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ABSTRACT

Flood risk and damage are expected to increase in the Pacific Northwest due to climate change. Light Detection and Ranging (lidar) is a remote sensing technology that generates high-resolution topographic data and can therefore produce higher accuracy floodplain maps, an important tool that communities use to assess their flood risk. Despite the promise of lidar for flood risk mitigation, both the availability of lidar data and the use of that data when available varies across the U.S. What factors drive the adoption of technology, such as lidar, for flood risk management? How can we better promote the use of technologies when available? Previous research has identified the importance of various factors in flood risk management, such as risk perception, direct experience, and knowledge of future risk. However, relatively little attention has been paid to how peer influence impacts an individual's choices about how to manage risk. In this study, we examine the adoption of lidar by flood risk managers for risk mitigation, as a function of several factors including risk perception, direct experience, and social networks. We conducted semi-structured interviews with flood risk managers in Idaho to inform the development of an online survey for flood risk managers in Idaho, Oregon, and Washington. Using this survey, we found that flood risk managers who share information with others using lidar are also more likely to use lidar themselves. Furthermore, the more frequently these flood managers communicate, the stronger this peer influence is. This research demonstrates the potential for harnessing social networks to help communities more effectively adapt to changing flood risk hazards.

1. Introduction

Floods are one of the most frequent and destructive natural disasters in the United States (Federal Emergency Management Agency, 2017). Flood events disrupt ecological, cultural, and economic landscapes causing incalculable expenses to our society, often disproportionately impacting vulnerable groups, and putting them at even greater risk in the future (Howell and Elliott, 2019). It is expected that flood events, and their resulting impacts, will increase in the future due to climate change and urbanization patterns (e.g., Pralle, 2019; Schanze, 2006). Ngenyam Bang and Church Burton (2021) recommend several ways flood risk mitigation could be improved including better allocation of resources, updated policy and insurance premiums, education on flood risk preparedness, and informed adaptation and mitigation measures such as the development of tools or techniques for modeling flood risk. Our study focuses on the latter approach of using new tools for modeling flood risk. Lidar (Light Detection and Ranging), a remote sensing technology

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that provides high-resolution topographic data and point cloud data, can be used by flood risk managers to better understand flood risk in their community. Yet, there has been variable adoption of this technology by flood risk managers. Our study explores why this variation exists.

Often, flood risk managers rely on flood hazard maps that were developed for FEMA's National Flood Insurance Program. However these maps provide limited information, and are most relevant for specific aspects of flood risk management such as insurance (Luke et al., 2018). Additionally, they can be influenced by local politics (Pralle, 2019) and have differing quality levels and coverage gaps (Tate et al., 2021). Several studies find that the use of fine-resolution and 3-D flood depth maps, instead of or in addition to FEMA flood hazard maps, are more useful for depicting risk and enhancing flood risk perception and awareness (e.g., Costabile et al., 2021; Luke et al., 2018; Macchione et al., 2019). Fine-resolution and 3-D products related to flood risk management can be derived from lidar data. Examples include high-resolution lidar-derived digital elevation models that provide topographic boundary information for 2-D hydraulic models (e.g., Shen et al., 2015) and changes in floodplain topography over time or due to a flood event (e.g., Izumida et al., 2017). In addition to mapping floodplain topography, lidar data can capture buildings and infrastructure that may affect urban flood risk (e.g., Trepekli et al., 2022; Xing et al., 2019), and can provide flood risk information for locations previously unmapped (e.g., Tate et al., 2021). Results from these high-resolution flood modeling, such as 2-D hydraulic simulation results, can be integrated into a 3-D virtual or augmented reality environment for risk communication (Costabile et al., 2021; Macchione et al., 2019). Given these known applications and benefits of lidar and lidar-derived products, our paper asks what factors influence a flood risk manager to use lidar for flood risk management.

Studies of risk mitigation decision making historically focused on flood risk perception as a main driving factor of mitigation behavior (Bubeck et al., 2012), but this focus has omitted other important social and cultural factors that influence decision making (Rufat et al., 2020). Preliminary findings suggest that social networks can be useful in identifying underlying, contextual social and cultural factors of technology adoption (Peng and Dey, 2013). For example, Azad and Pritchard (2023) find that social capital, which can be thought of as accessible resources in an individual's social network, increased adaptive capacity of village response and recovery to flooding in rural Bangladesh (Azad & Pritchard, 2023). The influence of social networks is still a developing area of study in the case of flood risk mitigation behavior (Bojovic and Giupponi, 2020; Kuhlicke et al., 2020; Lechowska, 2021). Given this knowledge gap, our study specifically focuses on the impact of social networks through peer influence on lidar adoption in flood risk managers at the local government level.

We answer our research question through an empirical study that uses data from eight semi-structured interview responses to develop a survey for which we received 206 survey responses. The survey includes a section that prompted flood risk managers to identify their collaborators, their collaborator's lidar usage and expertise, as well as their communication frequency. We find that peer influence does have a significant effect on their lidar adoption. In the following sections, we describe the context for our case study, methodology for identifying relevant survey participants, distribution of the survey, and details of what the survey measured. We then present our results and discuss the implications of our findings for flood risk mitigation.

2. Case study: Lidar availability in the Pacific Northwest

The increase in lidar availability over the last decade in the U.S. is largely due to the U.S. Geological Survey's (USGS) 3D Elevation Program (3DEP). 3DEP was established in 2010 as the first nationally-coordinated lidar acquisition program. The main goal of 3DEP is to have complete lidar coverage of the U.S. by 2023, given adequate funding (Sugarbaker et al., 2014). However, this project only provides seed funding and depends on additional funds and partnerships in order to acquire lidar. Therefore, each state governs their own lidar coordination and acquisition process.

We conducted our study in three states in the Pacific Northwest of the U.S.: Idaho, Oregon, and Washington. Each of the three states in our study provides a uniquely run and funded program for lidar. The Idaho Lidar Consortium was formed to coordinate state-level lidar acquisition and adoption with state, Tribal, federal, private, and academic members of the lidar community in Idaho. Lidar in Idaho is predominately used for riverine ecosystem management, geologic assessment, as well as natural resource and hazard management (e.g., Mapping for Resilience). The Idaho Lidar Consortium coordinates lidar availability for the state, operates independently of the state government, and relies on grant funding. In contrast, both Oregon and Washington have state-level lidar acquisition and coordination efforts that are housed within state departments. The State of Oregon Department of Geology and Mineral Industries leads the Oregon Lidar Consortium which started with seed funding of $2 million from the Oregon legislature (Oregon Department of Geology and Mineral Industries, 2020). There is now a full-time position within the state department to lead the lidar program. Oregon predominately uses lidar for managing the state's natural hazards and resources, urban infrastructure, and agriculture (Oregon Department of Geology and Mineral Industries, 2020). The Washington Geological Survey was granted funding from 2015 to 2021 for the collection and distribution of lidar data and lidar-derived products; the state predominantly uses lidar for geological applications (e.g., landslides, faults, glacial change), however it is also used for graphics, land-use planning, and agriculture among other uses (Gleason & Markert, 2020). Established in the Department of Natural Resources, the funding came from the Washington State General Fund and also provided funding for two permanent lidar positions, a lidar manager and a lidar specialist. In addition, Washington disseminates interactive information on lidar to educate the public and advocate for sustained lidar investment at the state-level.

The amount of publicly-available lidar is currently increasing across each location (Clark, 2010; Idaho Office of Emergency Management, 2018; Ralph et al., 2014; Washington Emergency Management Division, 2020; Slater and Villarini, 2016). In addition to an increase in lidar availability, high resolution and publicly-available flood risk models are also available now. According to the first publicly-available flood risk model for the lower 48 states created by First Street Foundation (FSF), a research-based non-profit, nearly 70% of properties have more substantial flood risk than previously predicted by FEMA's floodplain maps (First Street Foundation,

Table 1
Summary of individual-level factors, hypotheses, survey questions, and response options. Predictors of lidar adoption, specific hypotheses identifying the predicted directional effect on adoption, and the actual survey questions used to operationalize the predictor.

Factor	Hypotheses	Survey question	Response options
Experience	H1. Flood risk managers with direct flood experience are more likely to adopt lidar.	Have you ever experienced a flood that caused damage to property in your community?	Yes/No
Risk perception	H2. Flood risk managers with higher perceived risk are more likely to adopt lidar.	Thinking about your community in the next 30 years, how likely is it that a flood will cause damage to property in your community?	0% chance, 25% chance, 50% chance, 75% chance, 100% chance
Knowledge	H3. Flood risk managers with knowledge of increased flood severity are more likely to adopt lidar.	In the future, do you think the average severity of flood damage in your community will increase, decrease, or stay the same?	Increase, decrease, stay the same
Risk-taking attitude	H4. Flood risk managers who are more risk-tolerant are more likely to adopt lidar.	Do you generally prefer to take risks or to avoid risks?	0 (I generally prefer to avoid risks) to 10 (I generally prefer to take risks)
Trust	H5. Flood risk managers who trust flood risk management scientific products are more likely to adopt lidar.	How much do you trust the accuracy of scientific products for flood risk management (e.g., topographic data, floodplain mapping, floodplain modeling)?	Strongly trust, somewhat trust, neither trust nor distrust, somewhat distrust, strongly distrust

2020). Part of this discrepancy is because FSF used a model that can predict future flood risk at the property level by mapping flooding at a 3-meter resolution, finer than many current floodplain maps which range in quality up to a 30-meter resolution. In 2020, FEMA estimated that about 4.1%, 6.3%, and 5.6% of properties in Idaho, Oregon, and Washington respectively were at risk of damage to a 100-year flood, whereas FFS estimated that roughly 17.6%, 17.3%, and 16.4% of properties in Idaho, Oregon, and Washington respectively were at risk. All three states (Idaho, Oregon, and Washington) are estimated to be in the top 12 states with the largest difference in projections of flood risk between FSF and FEMA. The discrepancy of properties at risk to flooding underscores the need and usefulness of flood risk managers in these regions to adopt technology such as lidar to better understand their flood risk.

3. Data and methods

3.1. Individual hypotheses

Flood risk management research has identified a suite of factors that influence the uptake of mitigation strategies. Due to the limited literature solely focused on flood risk manager behavior, we review literature that examines behavior across private households, as well as flood risk managers. Table 1 summarizes the factors we chose to represent individual characteristics of flood risk managers, associated hypotheses, as well as the survey questions and response type.

Previous research found direct experience positively influences adoption of flood risk mitigation behavior (e.g., Bubeck et al., 2012; Kellens et al., 2013; Poussin et al., 2014; van Valkengoed and Steg, 2019). We operationalize direct experience as an individual witnessing a hazard and/or an individual who gathered information (e.g., social media, newspaper) from others who had a direct experience with flooding.

Flood risk perception, the perceived probability of a hazard and the impacts of a hazard, has long been considered an important factor in decision making (Birkholz et al., 2014; Lechowska, 2018). Previous research found mostly positive influence of risk perception on risk mitigation behavior, but the practical application of this factor has been contested (e.g., Bubeck et al., 2012; Kellens et al., 2013; Lo, 2013; Birkholz et al., 2014; Poussin et al., 2014; van Valkengoed and Steg, 2019). Thus, we still included risk perception as a factor because there is evidence that is important. We operationalize flood risk perception as an individual's perception that flood damage will impact their community in the next 30 years.

Knowledge, an individual's awareness of climate change and climate-related hazards, can positively influence the uptake of risk mitigation behavior (e.g., Bubeck et al., 2012; Kellens et al., 2013; van Valkengoed and Steg, 2019). We operationalize knowledge as an individual's perception of how average flood damage severity in their community will change.

Previous research found contradictory results for the influence of risk-taking attitude on risk mitigation behavior (e.g., Viglione et al., 2014; Roberts and Wernstedt, 2019; Poussin et al., 2014). However, other research has found that risk-taking attitude can play an important role in the uptake of technology (Liu, 2012). There are two main types of methods to elicit risk-taking attitude, either through an incentivized game or a self-reported questionnaire. Incentivized methods involve a pay-out depending on the amount of risk a participant is willing to take, such as Eckel and Grossman's (2008) method which asks the participant to select one out of five ordered lotteries and the participant is paid out based on the results of the lottery. Dohmen et al. (2011) find that a questionnaire can also be used to deliver a behaviorally-valid measure of risk attitude and that a general risk question is the best all-around explanatory variable as opposed to several context-specific risk questions. Due to our concern of incentivized risk elicitation methods causing mental fatigue and unneeded complication to our survey instrument we chose the questionnaire method. The German Socio-Economic Panel (SOEP) method of self-reported answering represents a valid, low-cost substitute for incentivized lottery schemes (Crosetto and Filippin, 2016). We operationalized the SOEP method with a straightforward question about how risky a person sees themselves generally.

Trust, the extent to which individuals feel like they can rely on others, has varying influence on risk mitigation behavior (e.g., Kellens et al., 2013; Viglione et al., 2014; van Valkengoed and Steg, 2019). We operationalize trust as a flood risk managers' perceived accuracy of scientific products for flood risk management. Due to lidar directly informing scientific products for flood risk management, such as a lidar-derived digital elevation model, we expect that an increase in trust in scientific products would lead to an increase in lidar adoption.

3.2. Social network hypotheses

Our exploration of social networks in this study draws from social learning theory, which posits peer influence as an important predictor of risk mitigation behavior. Peer influence suggests that people learn from each other, and that information, ideas, and beliefs spread among individuals via social learning and imitation (Kuhlicke et al., 2020). The impact of social learning on decision-making is well-established (Creanza et al., 2017) and has clear implications for technology adoption in flood risk mitigation but is relatively understudied in that domain.

Social learning theory is derived from cultural evolutionary theory, which explains cultural variation at the collective-level by examining the ways in which individuals learn from each other. Culture, which is made up of beliefs, knowledge, skills, and attitudes, results from the social transmission of cultural information among individuals via processes of social learning such as imitation and teaching (Boyd & Richerson, 1985). Analogous to genetic evolution, human culture evolves through the process of natural selection involving variation in a population of cultural ideas, the heritable transmission of those ideas via social learning, and differential fitness of those ideas because some ideas are more likely to spread than others (Bandura, 1971; Henrich and McElreath, 2002; Richerson et al., 2016). Cultural evolution is therefore a secondary from of inheritance in humans. In this way, human behavior can be thought of as the co-evolutionary product of change in both the biophysical and social environment.

We can examine how differences in lidar use among risk managers (variation) influence peers through communication (heritable transmission) because of differences in how successfully lidar users and non-users manage flood risk (differential fitness). For example, if highly-influential flood risk manager starts to use lidar to successfully predicts their community's floodplain behavior, then subsequent flood risk managers may also want to follow suit given lidar is available and the individual has the expertise to use the technology. In this example, the individual of influence displayed a different method for floodplain management (variation), where they transmitted a belief to others (heritable transmission), and now this flood risk manager's colleagues want to use lidar for flood risk management as well (differential fitness).

In order to measure the impact of peer influence, we used an ego network research design. This approach is helpful for understanding how local social structures unique to the individual of interest impact their behavior (Hanneman and Riddle, 2005). The ego network approach asks each survey respondent to identify a number of individuals they have a relationship with and subsequently asks them to answer a number of questions about each individual. Fig. 1 displays a hypothetical ego network collected by our survey. We asked respondents to identify up to eight other individuals with whom they share information about flood risk management, whether those other individuals use lidar, how much they communicate with that individual, and their expertise as flood risk managers.

The idea of a "complex contagion" suggests that with repeated reinforcement of an idea, such as lidar use, it can induce adoption (Centola and Macy, 2007). These multiple reinforcements can create credibility and legitimacy in the eyes of the potential adopter because they affirm a developing belief in an individual. Additionally, previous research demonstrates the importance of bridging and bonding social capital in an individual's social network (e.g., Adger, 2010; Azad and Pritchard, 2023). Bridging social capital develops from more distant relationships in an individual's network, where bonding social capital comes from repeated interactions with those who are proximal in an individual's network; bridging can lead to the adoption of new information whereas bonding typically builds trust and reciprocity between individuals (Berardo and Lubell, 2016). Additionally, cultural evolutionary theory suggests that targeting peers with high levels of expertise is an effective shortcut to acquire adaptive information; one example of this is prestige-biased social learning which is a learning strategy where individuals are disproportionately likely to copy the behavior of other successful individuals (Brand et al., 2020). While prestige-biased learning has been identified as important in many other domains, our study identifies it as a driver of technology adoption for flood risk management.

Table 2 summarizes the factors we chose to represent each flood risk managers' social network characteristics, associated hypotheses, as well as the survey questions and response type. Given the importance of different types of relationships, we measured the proportion of lidar users, as well as relative communication frequency and expertise between lidar and non-lidar users, in an individual's network. Specifically, we calculated network lidar usage as the proportion of the respondent's peers that used lidar relative to total peers named. We calculated relative lidar communication frequency as the net difference between the respondent's average communication with lidar users and their average communication with non-lidar users in their network. Similarly, we calculated relative peer lidar expertise as the net difference between the respondent's average expertise with lidar users and their average expertise with non-lidar users in their network.

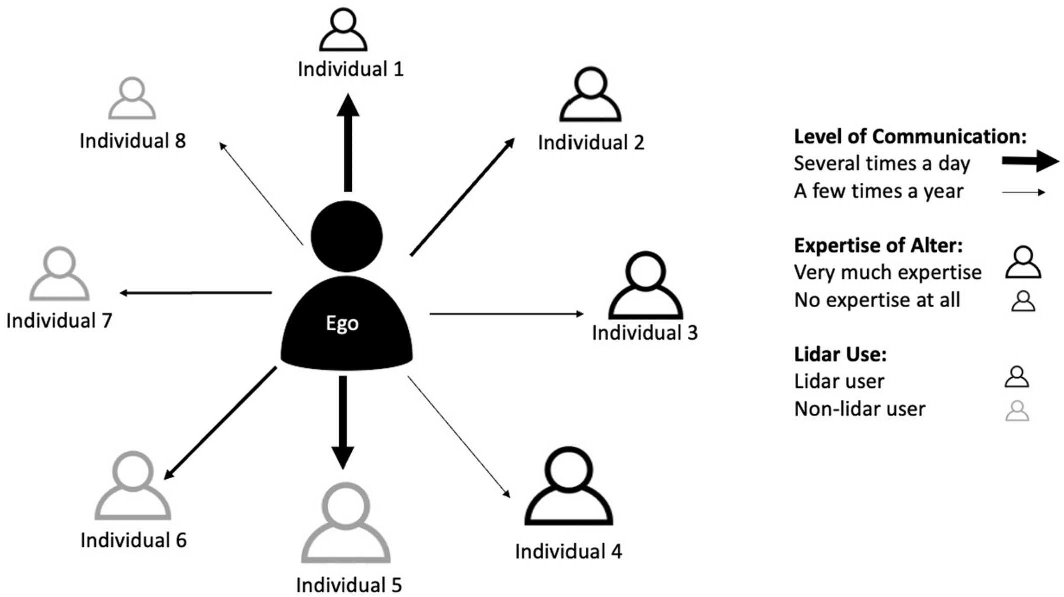

Fig. 1. Visual representation of an ego network structure. This is a hypothetical instance of the data we collected about each individual in our study's ego network analysis. The individual is marked in black if they use lidar and grey if they do not use lidar. The strength of communication between the ego and individual positively correlates with arrow weight. The expertise of the individual positively correlates with the size of the individual symbol. For example, Individual 1 represents an individual that the survey respondent reports as using lidar, communicating with several times a day, and exhibiting some expertise. Whereas Individual 8 represents an individual that the survey respondent reports as not using lidar, communicating with only a few times a year, and exhibiting some expertise.

Table 2
Summary of factors, hypotheses, survey questions, and response options for social network factors. Predictors of lidar adoption, specific hypotheses identifying the predicted directional effect on adoption, and the actual survey questions used to operationalize the predictor.

Factor	Hypotheses	Survey question	Response options
Peer lidar usage	H6. Flood risk managers with higher proportion of lidar users in their network are more likely to adopt lidar.	Looking back over the last 12 months, who are the people with whom you discussed significant matters regarding flood risk management? Please list up to eight people, naming only their initials in order to keep them anonymous. To your knowledge, does [individual X] use lidar?	Open response up to eight individuals
Communication frequency	H7. Flood risk managers who communicate more frequently with lidar users in their network are more likely to adopt lidar.	How often do you communicate (e.g., in-person, online, over the phone) with [individual X]?	A few times a year, once a month, 2–3 times a month, once a week, several times a week, several times a day
Peer lidar expertise	H8. Flood risk managers with high expertise alters that use lidar are more likely to adopt lidar.	On a scale from 0 to 10, how would you rate the expertise of [individual X] in the field of flood risk management?	0 (no expertise at all) to 10 (very much expertise)

3.3. Interview and survey design

We conducted eight informational, semi-structured interviews in the fall of 2019 with stakeholders including flood risk managers, government officials, industry professionals, and academics across Idaho. The interviews lasted about an hour and were recorded when possible. We did not take a formalized coding approach for analyzing these interviews due to the limited number of interviews that were recorded and transcribed. Rather, we pulled out themes we thought were important in our detailed interview notes and interview transcriptions. We then used these themes, in tandem with our literature review findings, to guide the development of our survey questions and make sure they were relevant. Given the challenges associated with drawing strong conclusions from a relatively small number of interviews with different transcription methods, we focus here on using the interview data to bolster what we found in our literature review as important factors for management strategies, but do not draw any concrete conclusions about the study system.

The survey consisted of four main parts. The first part focused on gathering information about the respondent's experience and beliefs about their flood risk management community. The second section was centered on the respondent's relationship with lidar for flood risk management. This section asked if they used lidar, how they used lidar, and if they would like to take part in lidar workshops. The third part gathered information about the respondent's flood risk management information-sharing network. The final part of the survey asked the respondent about their personal beliefs in risk-taking, trust, and included demographic questions such as education and gender. Once we created our survey instrument, we conducted an expert review with eight university students and staff to give feedback about the appropriateness of the survey (e.g., length, difficulty, and readability), question fit to research questions, and survey structure (e.g., question order, section transitions, survey logic). Then the survey went through a pre-testing process with a flood risk manager, an industry professional, and a lidar academic to provide additional feedback from the perspective of a potential, target respondent. This study was approved by the Boise State University's Social and Behavioral Institutional Review Board (090-SB19-212).

3.4. Data collection

Our target population included floodplain managers and administrators in Idaho, Oregon, Washington, and Alaska. We constructed our sample frame using several publicly available lists of managers including National Flood Insurance Program coordinators, Association of State Floodplain Managers recognized Certified Floodplain Managers, county-level GIS administrators, the five largest cities and tribal GIS administrators in our states of interest and if present, county and tribal emergency managers, the Federal Geospatial Data Coordination Contacts by state, and any other additional relevant contacts from the 2019 Northwest Regional Floodplain Managers Association Conference contact list.

We delivered the survey online using Qualtrics to 1,285 email addresses in our sample frame between May and July 2020 (Table 3). The survey took an average of 10 to 15 min to complete. We initially sent an introductory email that stated what was being asked of

Table 3
Summary of survey responses. Number of potential respondents, number of survey responses, response rate (number of responses/potential respondents), number of responses used in descriptive analysis (e.g., respondents passed screening question and answered lidar use question), and number of responses used in inferential analysis (e.g., respondent answered network questions) for each state.

State	Potential Respondents	Number of Responses (Total)	Response Rate	Number of Responses (Descriptive Analysis)	Number of Responses (Inferential Analysis)
Idaho	463	159	34.3%	96	73
Oregon	369	90	24.3%	58	41
Washington	398	81	20.4%	54	35
Alaska	55	8	14.5%	6	0

respondents, why they were selected, and included information about the intent, purpose, and outcomes of the survey (Dillman et al., 2014). We sent three to five follow-up email reminders over the course of the following four weeks.

Our response rates are within the typical bounds for online surveys of 15–34% (Sauermann and Roach, 2013). We did not include Alaska in our final statistical analysis because of an insufficient number of responses. Due to item non-response, which was particularly pronounced for the network section, we excluded almost 25% of the responses in order to conduct our statistical modeling, which requires complete data for analysis. Dropping responses for analysis may result in effect size underestimation (Langkamp et al., 2010).

Around 45% of respondents were over 50 years of age and majority were male and had a university education. On average, respondents worked for 11.5 years as a flood risk manager, with some respondents only working half year and others working as much as 43 years in this field. Respondents reported using lidar mostly for flood risk assessment and floodplain map development, however some respondents reported using lidar for hydrologic and/or hydraulic analysis, hazard mitigation, and educational materials as well. Lidar data was most commonly accessed from county websites, state-specific lidar consortiums, and state websites and least commonly from city websites.

3.5. Data analysis

Bayesian statistics, a popular method in social and behavioral sciences and ecology, provides a way to include prior information about the study system with a likelihood function, based on the observed data, to produce a posterior probability distribution, as opposed to a single point estimate, for each model parameter (van de Schoot et al., 2021). We can then sample from the posterior probability distribution to quantify the effect of specific predictors on our response variable.

We used a Bayesian logistic regression to estimate the relationship between our predictors of interest and our response, lidar adoption. Our statistical model specified the distribution of lidar use, y_i, as binomially distributed with parameters 1 and pi:

$$\mathrm{logit}(p_i) = X_i\beta$$

$$y_i \sim Binomial(1, p_i)$$

where X_i, the predictors, β, the regression parameters, define the linear predictor (Gelman et al., 2020a). This Bayesian approach allowed for adjustment of uncertainty associated with each parameter on lidar adoption. In order to do this, each parameter had to be assigned a prior belief of that parameter value. We used a weakly informative prior distribution to provide modest regularization, reduce the chance of a Type I error, and improve the out-of-sample prediction for regression models (McElreath, 2020). Specifically, we used a Cauchy distribution with a mean of 0 and standard deviation of 2.5 for our model parameters as recommended for logistic regression models with a low sample size (Lemoine, 2019; Gelman et al., 2008). Additionally, we used a Cauchy distribution with a mean of 0 and a standard deviation of 10 for our intercept.

We used four Monte Carlo Markov Chains (MCMC) with 2,000 iterations for warmup and an additional 2,000 iterations for the model. We assessed effective sample size and checked model convergence, indicated by R-hat statistics close to 1 and stable, well-mixed chains (Gelman et al., 2020b).

We assessed the overall model performance through Leave-One-Out Cross-Validation (LOOCV) which was 161.4 with a standard error of 17.5. We used Bayesian R-squared to measure our overall model accuracy. The Bayesian R-squared value for our model was 0.43, which represents a moderate effect size in social science data (Ferguson, 2009). Finally, we used *tidybayes,* a R package (Kay, 2023), to sample from posterior predictive distribution and show the relationship between specific predictors and our response variable, lidar adoption.

4. Results

4.1. Interview findings

We found that rural regions with smaller populations typically place a lower priority on revised mapping and that lidar is often expensive or perceived to be expensive. Therefore, not all communities have adequate funding for acquiring or using lidar. We also found that distrust in scientific products or the federal government can potentially constrain the use of lidar for flood risk management. Some hesitancy was expressed towards making lidar data for private land available to the public due to concern of additional government knowledge and involvement, such as potential for floodplain map revision. At the same time, many interviewees noted the opportunity that high-resolution data from lidar presents in understanding flood risk. Interviewees reported that peers can be influential in the uptake of lidar. In several interviews, we heard that lidar is useful across institutions and organizations for a variety of applications and often the acquisition of lidar requires coordination among stakeholders.

4.2. Descriptive survey results

We asked respondents about the different types of negative outcomes they have personally experienced with flooding in their communities. Over 70% of respondents in each state reported having directly experienced flood damage in their community in the past. We also asked respondents to identify the different types of flood damage they have experienced. Over 75% of respondents reported having experienced damage to property in their community while only about 10% of respondents reported damage to their own home. An intermediate number of respondents reported experiencing injuries or deaths in their community or disruption to basic services (Fig. 2).

We also asked respondents to report the likelihood of various flooding impacts in the next 30 years. Over 90% of respondents were concerned with future flood damage in their community (Fig. 3). Consistent with the findings about experiences with previous floods, respondents reported highest likelihoods for property damage in their community and lowest likelihoods for deaths or injuries to immediate family members. Despite no survey respondents reporting experiencing a death or injury to an immediate family member in the past, over 30% of respondents thought there was at least a 25% chance that this would occur in the next 30 years.

While almost all respondents expect damage to property in their community in the future, nearly 46% think the average severity of flood damage in their community will increase. Respondents' risk-taking attitude ranged from 2 to 10, where 0 means "I generally prefer to avoid risk" and 10 means "I generally prefer to take risks." The most common preference was 2 and average preference was 3.16. About 85% of respondents reported trusting scientific products for flood risk management and less than 4% of responses reported some distrust in scientific products.

The social network section of the survey asked each respondent to name up to eight individuals with whom they discussed significant matters regarding flood risk management over the previous year. Respondents typically reported five peers in their network, although responses ranged from one to eight individuals. Table 4 presents the summary statistics for the social network factors in our study. Lidar usage represents the proportion of lidar users in a respondent's social network. For most respondents, a third of their network was made up of lidar users. Communication frequency was a relative measure from 1 (few times a year) to 6 (several times a day); a positive value means relatively more communication with a lidar user, whereas a negative value means relatively less communication with a lidar user. On average, we found that respondents' spoke more with non-lidar users, −0.31, than lidar users in their peer networks. Lastly, we measured relative lidar expertise on a scale from 0 (no expertise at all) to 10 (very much expertise); a positive value means more expertise in a respondent's network is from lidar users, and a negative value means less expertise in a respondent's network is from lidar users. We found that the average expertise in respondent's peer networks was 0.64 meaning that respondents' rated their peers who use lidar as having more expertise relative to those who do not use lidar.

4.3. Estimation results

Our statistical model allowed us to explore the effect of a multitude of predictors on lidar use in Idaho, Oregon, and Washington. We examined the posterior predictive distribution for each predictor (Fig. 4). Predictors with posteriors that have central tendencies further from zero reflect a stronger relationship with the outcome variable and predictors with posterior distributions with narrower ranges have less uncertainty associated with their estimate.

Direct experience (H1), knowledge (H3), risk-taking attitude (H4), and trust (H5) appear to have central tendencies close to zero and therefore suggest a smaller effect, or no discernible effect, on lidar adoption. Therefore, we did not find support for the direct experience, knowledge, risk-taking attitude, or trust hypotheses. We find support for the risk perception hypothesis (H2) and all three peer influence hypotheses (H6, H7, H8). Peer lidar expertise and communication frequency are estimated with a high degree of certainty and are positively related to lidar adoption, whereas risk perception and peer lidar usage have a lower degree of certainty but exhibit some evidence for a positive effect on lidar adoption. Given these results and the focus of our paper to explore the role of peer

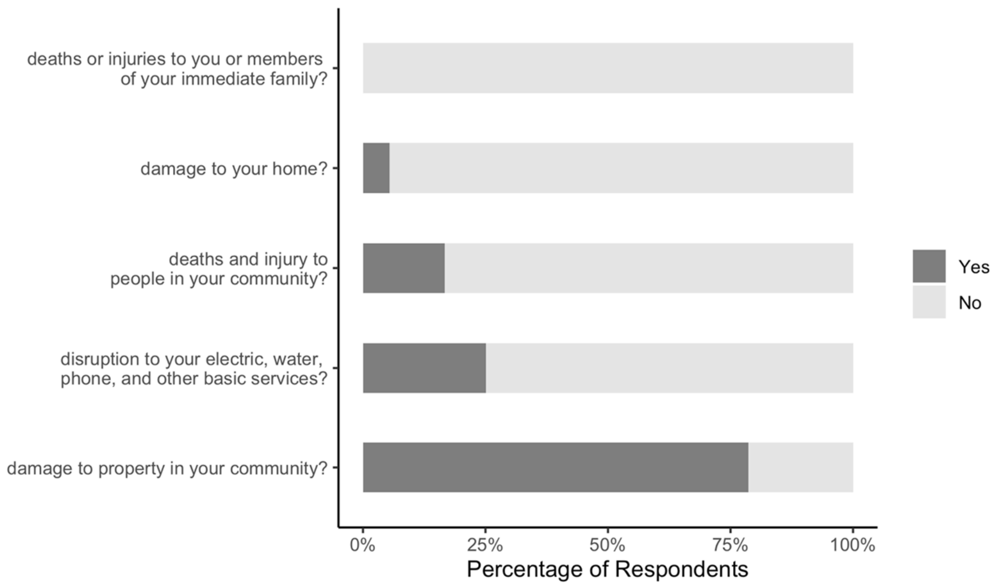

Fig. 2. Summary of survey responses of flood risk managers' direct experiences with flood impacts.

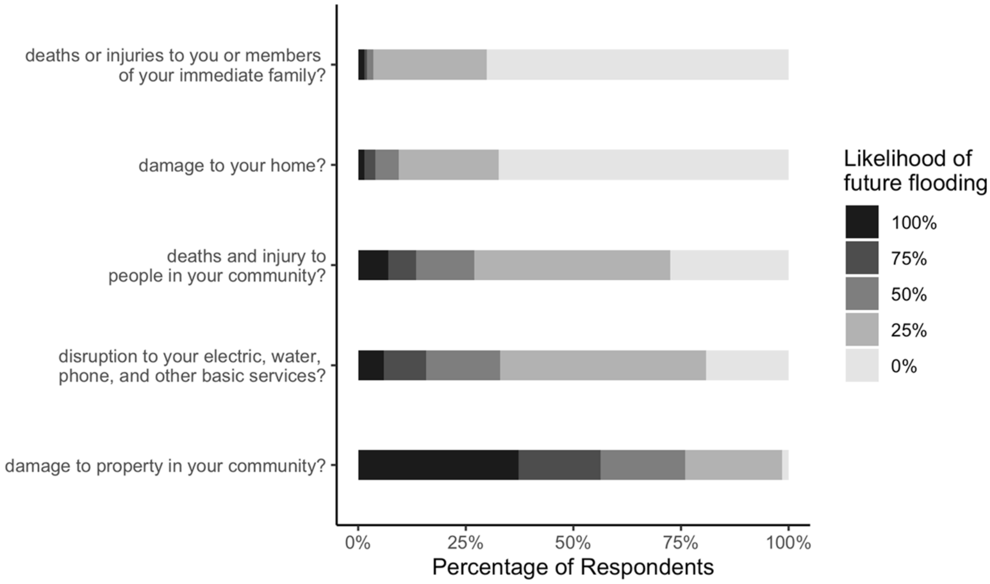

Fig. 3. Summary of survey responses of flood risk managers' perceived flood risk in the future. The survey question asked about the perceived likelihood of future flooding to impact the participant in the next 30 years.

Table 4
Summary of social network factors used in the model.

Factor	Response
Lidar usage: proportion of lidar users in network	Mean = 0.38 Median = 0.33 Range = [0,1]
Communication frequency: level of communication with lidar users	Mean = -0.31 Median = -0.50 Range = [-6,6]
Lidar expertise: expertise of peers who use lidar	Mean = 0.64 Median = 0.95 Range = [-10, 10]

influence on technology adoption, we explored the individual influence of peer lidar usage, communication frequency, and peer lidar expertise on lidar adoption further.

Fig. 5 displays the expected value of our response variable when setting a given predictor to specified levels and holding all other predictors at their median for the state of Idaho (the baseline location category for our model) on our response variable of lidar use. Respondents who reported having more lidar users in their social network also were more likely to report using lidar themselves. For respondents who reported having no lidar users in their network, our statistical model predicts a 52% probability that they use lidar themselves. In contrast, for respondents who report eight lidar users in their network (the maximum possible), our model predicts an 80% probability that they use lidar themselves (Fig. 5a).

Respondents who communicate more with lidar users in their social network also were more likely to report using lidar themselves (Fig. 5b). For respondents who reported no communication with lidar users in their network, our statistical model predicts a 13% probability that they use lidar themselves. In contrast, for respondents who communicate with only lidar users in their network, our model predicts 97% probability that they use lidar; therefore, respondents who communicate regularly with lidar users are more than 7 times more likely use lidar.

Respondents who viewed lidar users in their social network as having expertise were more likely to report using lidar themselves as well (Fig. 5c). For respondents who reported having little expertise among lidar users in their network, our statistical model predicts a 35% probability that they use lidar. In contrast, for respondents who report high expertise among lidar users in our network, our model predicts an 81% probability that they use lidar; therefore, respondents who report higher expertise among lidar users in their network are more than twice as likely use lidar.

5. Discussion

We identified several predictors that contribute to our existing understanding of technology adoption for risk mitigation. Specifically, we investigate the influence of a respondent's peers through measurement of lidar users in their social network, communication

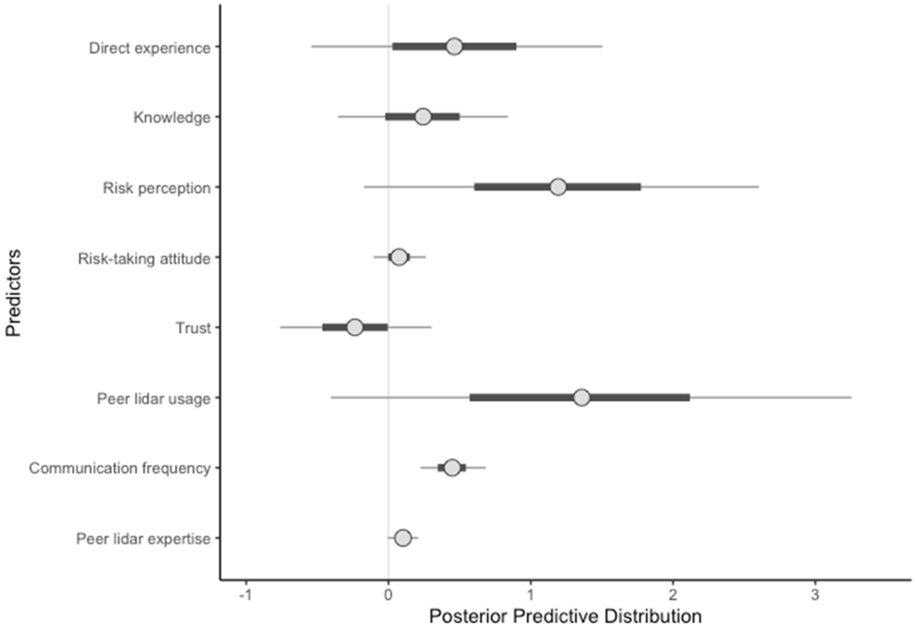

Fig. 4. Model results. Posterior predictive distribution displays the mean parameter estimate with a 50% (thick, dark line) and 89% (thin, light grey line) credible intervals.

frequency with other lidar users, and expertise of those other lidar users. We find that peer influence provided evidence for increasing the likelihood of a flood risk manager adopting lidar adoption (Fig. 5). While previous literature suggested the importance of peer influence more broadly, our findings provide novel support for the role that peer influence plays in technology adoption in a flood risk management context (e.g., Lo, 2013; Poussin et al., 2014; Viglione et al., 2014).

Communication frequency among peers had the biggest change in predicted probability on lidar adoption. Our finding that more frequent communication is associated positively with adoption is consistent with the idea of that repeated exposure with lidar could have legitimized its use for understanding flood risk. We also found that risk managers who communicate with other lidar users with perceived lidar expertise are more likely to adopt lidar themselves. This finding is consistent with our understanding of how people target their social learning in other domains.

The importance of communication also came up during our interviews. One interviewee, a floodplain manager from Idaho at a regional floodplain management conference, mentioned:

"I feel like we should do a lot more networking in the state of Idaho, but oftentimes I have to reach out to people in Washington for help or at the national level for help. And so that's why coming to these conferences is really helpful for me because I meet peers outside of just our immediate, that have similar programs." (Interview #2, personal communication, September 19, 2019).

This point highlights that there are some opportunities for networking at the moment, however the level of networking needs to increase. Another interviewee, a floodplain manager from a less-populated county in Idaho, stated:

"we're all in the same kind of communities, which is helpful sometimes, but it also is a little bit of a silo thing… we are all stuck in the same point of view." (Interview #7, personal communication, November 21, 2019).

These results reiterate what Interview #2 shared; namely, a desire for communication and collaboration among flood risk managers outside their already existing networks. We did not conduct interviews in Oregon or Washington; however, it is possible that a similar sentiment could exist in those states as well. While our quantitative analysis did not explicitly address this idea of diversity in network connections, beyond the extent that silos of lidar users and non-lidar users exist, our findings do support the notion that broadening risk managers' social networks will lead to greater adoption of lidar.

In addition to the importance of peer influence, our findings also showed that risk perception about future flood risk was positively correlated with lidar adoption. As we touched on earlier, some critics of risk perception research argue that it ignores other important social and cultural contextual factors, making it hard to apply findings about perceptions to specific management challenges (e.g., Kellens et al., 2013; Wachinger et al., 2013). However, one way risk perception can be helpful to policy making is by highlighting discrepancies in perceived risk and actual risk of flooding (Bubeck et al., 2012). For example, if a property owner is unaware that they are in a flood zone, then they likely will not buy flood insurance because they do not think they are at risk. Given that 36% of flood claims are from properties outside of the FEMA-designated flood zone (Frank, 2021), the homeowner may be unknowingly at risk to flooding. County or city-level policies that support the use of fine-resolution flood maps to communicate detailed flood risk in addition to flood insurance maps could provide a more accurate depiction of the property owner's physical risk and potentially lead them to take preparedness actions.

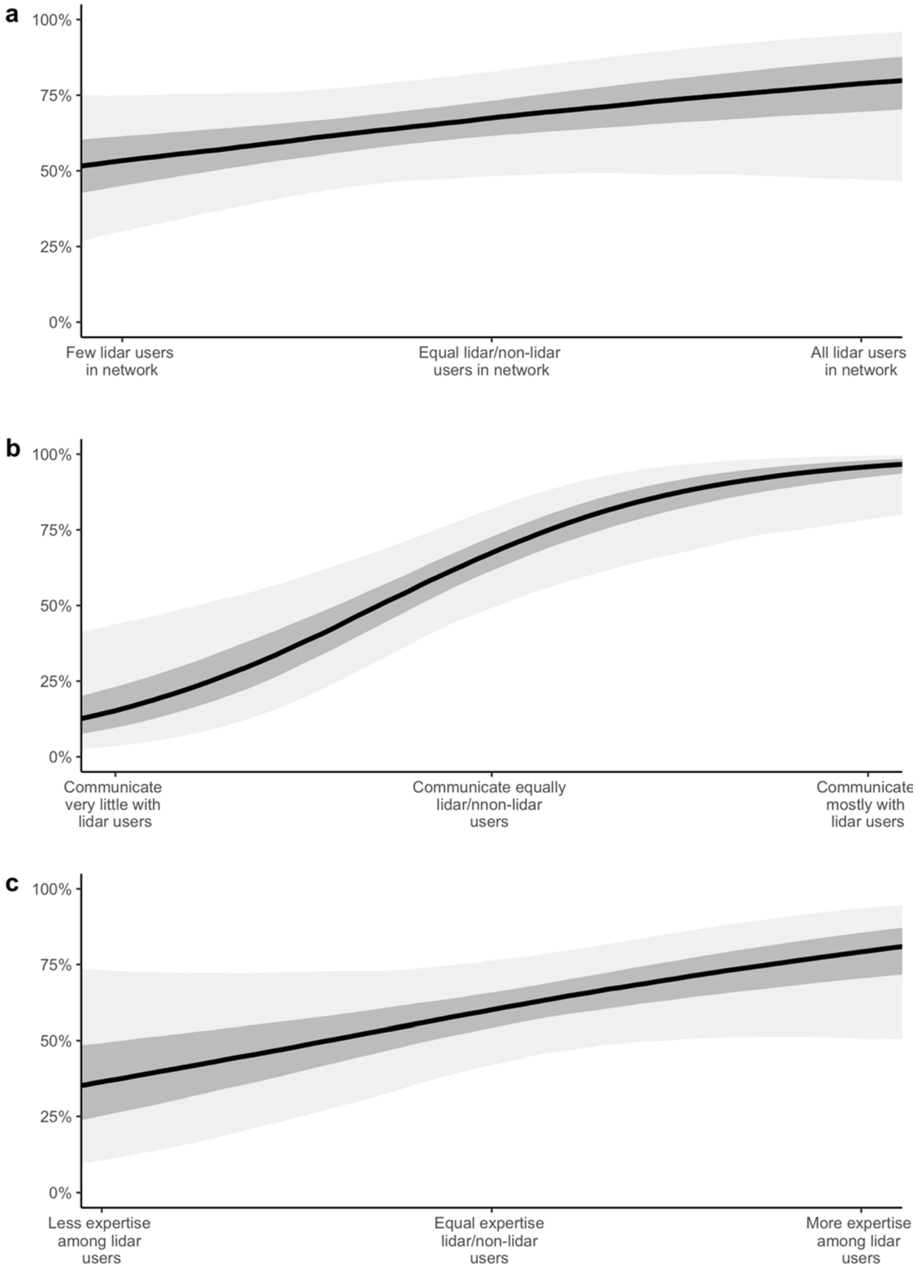

Fig. 5. Effect of peer influences on lidar adoption. The y-axis displays the predicted probability of lidar use as a function of (a) the proportion of respondent's social network using lidar, or peer influence, and predicted lidar adoption, (b) net average frequency of communication with lidar and non-lidar users, or network strength, in flood risk manager's network, and (c) net average expertise of lidar and non-lidar users, or network expertise, in flood risk manager's network. The dark grey and light grey shaded regions represent the 50% and 95% confidence intervals, respectively. These plots reflect the predicted lidar adoption of the predictor of interest while holding all other predictors in the model at their median.

Our results for direct experience were positively correlated with lidar adoption, as supported by previous research on risk mitigation behavior (e.g. Poussin et al., 2014; van Valkengoed and Steg, 2019). It is important to note that the results from this question do not consider the intensity or impact of the event which could be a more informative measure since experiences vary greatly. Surprisingly, risk-taking attitude was not an important driver of lidar adoption. This is perhaps because of the duality of risk that comes with technology adoption and floodplain management. There is an inherent risk in adopting a technology that an individual may not know how to use, but a pay off in managing the flood risk. Conversely, there may be others who are more willing to take the risk of potential flooding in order to minimize the risk of adopting a new technology. This inconclusive finding suggests that we need to look into risk salience further to understand the layering of factors (e.g., technological risk, societal risk) in decision-making. For example, peer influence might reduce the risk of adopting a new technology; that is, if a trusted peer uses lidar, lidar could feel less risky. On the other hand, direct experience with flooding might enhance a person's perceived environmental risk in a way that makes them overcome the risk of adopting a new technology. Furthermore, our inconclusive results regarding trust suggest that a more nuanced measure for specifically measuring trust in various scientific products could have elicited clearer results, since trust likely varies across individuals experiences with and knowledge of specific products.

6. Conclusion

Lidar provides flood risk managers with the technology needed to understand their community's flood risk in a changing environment. The variable adoption of this technology in flood risk managers creates an interesting case study of factors driving long-term risk mitigation behavior. Communication frequency among peers who use lidar increased the likelihood an individual would also use lidar. Because our study involves cross-sectional, observational data, our analysis is limited with respect to making causal inferences about lidar adoption. In addition, our peer influence results were limited by an ego network analysis that only provides one degree of peer connections. Future research could use a full network analysis to identify key stakeholders in the flood risk management community to target information dissemination and risk mitigation behavior changes in the flood risk management community. Additionally, our study does not include the impact and efficacy of lidar use; rather, we operate under the assumption that lidar is useful to flood risk managers as stated in multiple stakeholder interviews and in the literature. The USGS has broken down the benefit-cost ratio for each state to help state-level decision makers plan and manage lidar acquisition in their communities; however, it would be helpful to directly link this work with lidar adoption (United States Geological Survey, 2018). Lastly, given respondent and item non-response, we cannot be certain that our survey sample represented the full range of flood risk manager opinions in Idaho, Oregon, and Washington. Since our survey was distributed during COVID-19, it is possible that flood risk managers may have been occupied by other responsibilities regarding the pandemic and therefore were unable to take our survey limiting our sample size and scope.

Additionally, our study does not provide conclusive causal evidence for peer influence in lidar adoption across different institutional arrangements. We recommend conducting a longitudinal network study to understand the change in lidar use before and after a state implements state-level lidar programming. For example, we find that Washington had the highest peer lidar usage, communication frequency with lidar users, and lidar expertise in their peer networks. Washington also has permanent funding and institutes management of lidar through the state government. Conversely, we saw the lowest lidar usage in Idaho (50%), where the state relies on the Idaho Lidar Consortium, an organization independent of the state government and reliant on grant funding, to coordinate lidar acquisition and adoption.

As flood risk continues to increase due to climate change and urbanization patterns, it is imperative that flood risk managers adopt new methods for understanding and communicating flood risk. Lidar data can be used to provide critical fine-resolution and 3-D products to inform flood risk mitigation decision making. Investment in network building can be a powerful way to increase the uptake of new technology such as a lidar. Future research could examine the impact of education programs and collaborative forums on social network building among flood risk managers. And while this study focuses on lidar adoption in flood risk management specifically, it provides a novel approach for and evidence of the importance of studying social networks and peer influence in flood risk mitigation. Future research could apply our methods to understand other aspects of flood risk management, such as policy diffusion or collaboration among flood risk managers, that lead to more accurate and effective solutions to future flood risk.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data DOI is in the paper. Here is the link to where the data is located: https://www.designsafe-ci.org/data/browser/public/designsafe.storage.published/PRJ-3198

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Appendix. Technology adoption in flood risk management survey

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Technology Adoption in Flood Risk Management Survey

Start of Block: Consent Form

Welcome to the Technology Adoption in Flood Risk Management Survey!

The purpose of this survey is to better understand how managers make decisions about flood risk management. You have been identified as a knowledgeable member of the industry who could provide information for our study. This survey will ask about you, the community you work in, and your use of lidar (Light Detection and Ranging) in flood risk management. Your response will contribute to our understanding of the role lidar plays in flood risk management and help us identify barriers that may exist in its implementation. This survey should take less than 15 minutes to complete.

By selecting “I want to participate”, you are providing your consent to take part in this study.

This survey is completely anonymous. No personally identifiable information will be associated with your responses in any reports resulting from this survey. Your participation is voluntary. If there are any items that you would prefer to skip, please leave the answer blank. You must be at least 18 years old to participate.

For any questions, please contact the principal investigator: Tara Pozzi at tarapozzi@boisestate.edu or Dr. Vicken Hillis at vickenhillis@boisestate.edu.

○ I want to participate. (1)

○ I do not want to participate. (2)

End of Block: Consent Form

Start of Block: Screening Question

This survey is intended for people who are involved in flood risk management in their professional work. Does this description fit your role?

○ Yes

○ No

End of Block: Screening Question

Start of Block: Section 1: Background Information

How many years have you been working in flood risk management: ________________________________

End of Block: Section 1: Background Information

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Start of Block: Section 3: Local Floodplain Information

Idaho respondents: **This next series of questions is about the community where you primarily work in flood risk management. For example, you could name a watershed (e.g. Boise River), a county (e.g. Teton County), or a city (e.g. McCall).**

Oregon respondents: **This next series of questions is about the community where you primarily work in flood risk management. For example, you could name a watershed (e.g. Hood River), a county (e.g. Tillamook County), or a city (e.g. Eugene).**

Washington respondents: **This next series of questions is about the community where you primarily work in flood risk management. For example, you could name a watershed (e.g. Duwamish River), a county (e.g. Columbia County), or a city (e.g. Bellingham).**

Alaska respondents: **This next series of questions is about the community where you primarily work in flood risk management. For example, you could name a watershed (e.g. Eagle River), a borough (e.g. Kenai Peninsula), or a city (e.g. Fairbanks).**

If you work in several communities, please answer the questions considering the one community where you work the most.

What is the name of the community where you work in flood risk management? This can be a city, county, and/or watershed depending on what is most relevant to your work: ________________________________

The National Flood Insurance Program (NFIP) is an agreement between local communities and the federal government to help communities adopt and enforce a floodplain management ordinance to reduce future flood risks.

Is your community currently enrolled in the NFIP?

○ Yes

○ No

○ I am not sure

If no, why is your community not enrolled in the NFIP: ____

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Have you ever experienced a flood that caused...

	Yes	No
damage to property in your community?	○	○
deaths and injury to people in your community?	○	○
damage to your home?	○	○
deaths or injuries to you or members of your immediate family?	○	○
disruption to your electric, water, phone, and other basic services?	○	○

Thinking about your community in the next 30 years, how likely is it that a flood will cause...

	0% chance	25% chance	50% chance	75% chance	100% chance
damage to property in your community?	○	○	○	○	○
deaths and injury to people in your community?	○	○	○	○	○
damage to your home?	○	○	○	○	○
deaths or injuries to you or members of your immediate family?	○	○	○	○	○
disruption to your electric, water, phone, and other basic services?	○	○	○	○	○

End of Block: Section 3: Local Floodplain Information

Start of Block: Section 4: Current Mapping Data

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This next series of questions is about the floodplain maps in the community where you work.

Do you think your community's floodplain maps accurately reflect flood risk?

- ○ Completely accurate
- ○ Mostly accurate
- ○ Moderately accurate
- ○ Slightly accurate
- ○ Not at all accurate

To your knowledge, are there any areas in your community that have flooded in the past, but are not designated in a flood zone on your current flood maps?

- ○ Yes
- ○ No

If you had to say, is your community prepared for a significant flood event?

- ○ Completely prepared
- ○ Mostly prepared
- ○ Moderately prepared
- ○ Slightly prepared
- ○ Not at all prepared

End of Block: Section 4: Current Mapping Data

Start of Block: Section 5: Changing environment

This next section will ask you several questions about whether your community's flood risk is changing.

Please answer the following questions about the same area you reported on before.

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In the future, do you think the average *number of flood events* in your community will increase, decrease, or stay the same?

◯ Increase

◯ Decrease

◯ Stay the same

In the future, do you think the average *severity of flood damage* in your community will increase, decrease, or stay the same?

◯ Increase

◯ Decrease

◯ Stay the Same

End of Block: Section 5: Changing environment

Start of Block: Section 2: Lidar Use

Light Detection and Ranging (lidar) is a laser-based technology that provides a detailed map of the ground (bare earth), vegetation (canopy), and other models of the earth's surface.

Do you currently use lidar?

◯ Yes

◯ No, but I have heard of it

◯ No, I have not heard of it

End of Block: Section 2: Lidar Use

Start of Block: Section 2.3: I have not heard of lidar

Would you and/or your organization be interested in learning more about lidar?

◯ Yes

◯ No

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End of Block: Section 2.3: I have not heard of lidar

Start of Block: Section 2.2: No to lidar use

To what extent do you agree with each of the following statements? (Please check one response for each statement.)

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly agree
Lidar is too expensive for my community to afford	○	○	○	○	○
There is not enough expertise in my community to use lidar	○	○	○	○	○
My community does not use lidar because it is sparsely populated	○	○	○	○	○
My community does not use lidar because it has a low rate of economic development	○	○	○	○	○
We do not use lidar in my community because there is little risk of flooding	○	○	○	○	○
There is not enough political support in my community to make lidar use feasible	○	○	○	○	○
Other:	○	○	○	○	○

How useful do you think lidar could be for the community where you work?

○ Extremely useful

○ Very useful

○ Moderately useful

○ Slightly useful

○ Not useful at all

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There are a number of lidar training tools available both online and in-person. All of them are free and take 1-2 hours to complete. Which of the following training sessions would you personally find to be the most helpful?

- ○ A training session which focuses on the fundamentals of lidar (e.g., how it works; general use).
- ○ A training session which focuses on how to use and integrate lidar technology in conjunction with ArcGIS.
- ○ A training session on how to acquire lidar for your area
- ○ All of the above
- ○ Other: ____

End of Block: Section 2.2: No to lidar use

Start of Block: Section 2.1: Yes to lidar

Where do you access your lidar data? (Check all that apply.)

- ▢ Federal website
- ▢ State website
- ▢ County website
- ▢ City website
- ▢ Idaho Lidar Consortium/Oregon Lidar Consortium/Pugent Sound Lidar Consortium
- ▢ Private source
- ▢ Other:____

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What do you use lidar for? (Check all that apply.)

- ▢ Floodplain map development
- ▢ Hydrologic and/or hydraulic analysis
- ▢ Hazard mitigation
- ▢ Flood risk assessment
- ▢ Educational materials
- ▢ Other: ____

There are a number of lidar training tools available both online and in-person. All of them are free and take 1-2 hours to complete. Which of the following training sessions would you personally find to be the most helpful?

- ◯ A training session which focuses on the fundamentals of lidar (e.g., how it works; general use).
- ◯ A training session which focuses on how to use and integrate lidar technology in conjunction with ArcGIS.
- ◯ A training session on how to acquire lidar for your area
- ◯ All of the above
- ◯ Other:____

End of Block: Section 2.1: Yes to lidar

Start of Block: Section 6: Network

This next section is going to ask you about significant relationships you have in the flood risk management community. Please note that these relationships may be professional or personal in nature, positive or negative.

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Looking back over the last 12 months, who are the people with whom you discussed significant matters regarding flood risk management? Please list up to eight people, naming only their initials in order to keep them anonymous.

- ☐ Person's initials (1):____
- ☐ Person's initials (2):____
- ☐ Person's initials (3):____
- ☐ Person's initials (4):____
- ☐ Person's initials (5): ____
- ☐ Person's initials (6): ____
- ☐ Person's initials (7): ____
- ☐ Person's initials (8):____

End of Block: Section 6: Network

Start of Block: Section 6.1: Individual Network Questions

How often do you communicate (e.g. in-person, online, over the phone) with individual one?

- ○ A few times a year
- ○ Once a month
- ○ 2-3 times a month
- ○ Once a week
- ○ Several times a week
- ○ Several times a day

To your knowledge, does individual one use lidar?

◯ Yes

◯ No

◯ I do not know

On a scale from 0 to 10, how would you rate the expertise of individual one in the field of flood risk management?

	No expertise at all	Very much expertise
	0 1 2 3 4 5 6 7 8 9 10	
()		

Block will repeat up to eight times, depending on number of individuals the survey respondent reported in their peer network.

End of Block: Section 6.1: Alter one

Start of Block: Risk Preference- SOEP

Do you generally prefer to take risks or to avoid risks?

	I generally prefer to take risks	I generally prefer to avoid risks
	0 1 2 3 4 5 6 7 8 9 10	
1 ()		

End of Block: Risk Preference- SOEP

Start of Block: Section 8: Demographic Questions

What gender do you identify with?

◯ Male

◯ Female

◯ Prefer to self-describe:____

What is your age?

- ◯ Less than 20 years
- ◯ 20-29 years
- ◯ 30-39 years
- ◯ 40-49 years
- ◯ 50+ years

What is the highest level of education you have completed?

- ◯ Some high school
- ◯ High school diploma
- ◯ College education, did not graduate
- ◯ College education, Associates degree
- ◯ College education, Bachelor's degree
- ◯ Advanced degree (MA, JD, MBA, PhD)

If you went to college, what was your degree?

- ◯ Engineering
- ◯ Planning
- ◯ Business
- ◯ Public Administration
- ◯ Geography
- ◯ Emergency Management
- ◯ Other:____

How much do you trust the accuracy of scientific products for flood risk management (i.e. topographic data, floodplain mapping, floodplain modeling)?

- Strongly trust
- Somewhat trust
- Neither trust nor distrust
- Somewhat distrust
- Strongly distrust

How much do you trust or distrust the usefulness of the products the federal government develops with respect to flood risk management (i.e. data collection, accurate mapping, floodplain modeling, flood insurance)?

- Strongly trust
- Somewhat trust
- Neither trust nor distrust
- Somewhat distrust
- Strongly distrust

How involved do you think the federal government should be with flood risk management in your community (i.e. data collection, floodplain mapping, floodplain modeling, flood insurance)?

- Completely involved
- Mostly involved
- Moderately involved
- Somewhat involved
- Not at all involved

End of Block: Section 8: Demographic Questions

Start of Block: End of Survey

Thank you for taking the time to fill out this survey!

We plan to share the results of the research with the study participants, other community members, and the larger community of flood risk professionals through peer reviewed publications as well as using an online, interactive format.

Please feel reach to reach out with any questions and/or concerns to the Principal Investigator, Tara Pozzi at 831-225-6419 or tarapozzi@boisestate.edu or the Co- Principal Investigator, Dr. Vicken Hillis at 415-812-6846 or vickenhillis@boisestate.edu.

End of Block: End of Survey-- custom

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