UNDERSTANDING THE BARRIERS AND FACILITATORS OF LIDAR ADOPTION FOR FLOOD RISK MANAGEMENT IN THE PACIFIC NORTHWEST, U.S.

by

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DEDICATION

This work is dedicated to all those who may come across it, whether it's out of interest in lidar being super cool or because you are future graduate student writing your thesis.

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With an endless amount of gratitude, I want to thank my graduate advisor Dr. Vicken Hillis for giving me an opportunity to learn from him and guide me along this process. A big thank you to all of the faculty in Human-Environment Systems research group who have never ceased to inspire and challenge me. In addition, I would like to thank all the professors who I have learned from over the last couple years including Dr. Amy Ulappa, Dr. Kathryn Demps, and Dr. Alison Simler-Williamson and my committee members Dr. Jesse Barber, Dr. Marie-Anne de Graaff, and Dr. Brittany Brand. And a huge hug to my extremely supportive lab mates and colleagues at BSU for helping foster balance and friendship in my life these last two years. Last but not least, I wouldn't be where I am today without the hard work and inspiration of my Dad and the warm heart of my Mom.

ABSTRACT

The understanding of factors that influence technology adoption in emergency planners is foundational for ensuring resilient communities to hazards in the future. We explore these factors through an interdisciplinary, social-ecological science lens. In this thesis, we use cultural evolutionary theory to understand the facilitators and barriers of Light Detection and Ranging (lidar) adoption in flood risk management, as a case study of technology adoption for long-term risk mitigation. We then disseminate our findings through three educational outlets: a webinar, a white paper (Appendix A), and a Story Map. This thesis contributes to our intellectual understanding of technology adoption, as well as provides information to minimize barriers to lidar uptake in Idaho.

In the first chapter of the thesis, we used a mixed-methods empirical study to measure the facilitators of lidar adoption as a risk mitigation tactic in Idaho, Oregon, and Washington. Previous studies disproportionately focused on individual predictors of risk mitigation behavior such as risk perception, without identifying the contextual and collective drivers of risk mitigation behavior. We address this gap by examining both the individual (e.g., direct experience, risk-taking attitude, risk perception) and collective predictors (e.g., peer influence, network expertise) of lidar adoption regionally. We found that peer influence, or the proportion of lidar users in a respondent's social network, network strength, network expertise, and risk perception significantly increase the likelihood of an individual to adopt lidar. The findings of this chapter contribute to

understanding the role of collective predictors in long-term risk mitigation behavior and provide a foundational basis for future disaster research.

In the second chapter of the thesis, we developed three educational outreach products with varying audience and intention in mind. These products addressed barriers identified in our semi-structured interviews and survey instrument from our mixed-methods empirical study discussed in Chapter One. The first product was a webinar that was attended by 65 flood risk managers and included a panel of cross-sector participants. The second product was a white paper, intended for the Idaho Geospatial Council-Executive Committee and Elevation Technical Working Group. With input from these groups, the product will eventually be used to ask for a lidar liaison position and lidar acquisition budget for Idaho. The Story Map accompanies the white paper and provides detailed account of various lidar applications throughout Idaho. The Story Map showcases content from 10 different lidar stakeholders. Both the white paper and Story Map exist in digital formats that are easily shareable and are considered living documents that can be updated as needed.

The overarching goal of this thesis was to understand the facilitators and barriers of lidar adoption and increase uptake of lidar adoption in Idaho. Chapter One focuses on intellectual scholarship and is formatted as a manuscript for publication in the Climate Risk Management journal. Chapter Two focuses on applied scholarship with the greater lidar community. Appendix A is the white paper, Appendix B is a copy of the semi-structured interview instrument, and Appendix C is a copy of the survey instrument. Reference sections follow each chapter individually. This project was funded by the U.S. Department of Homeland Security Grant No. EMS-2019-CA-00030.

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CHAPTER ONE: MANUSCRIPT DRAFT – QUANTIFYING SOCIAL INFLUENCES OF TECHNOLOGY ADOPTION FOR LONG-TERM FLOOD RISK MANAGEMENT IN THE PACIFIC NORTHWEST, U.S.

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 provides high-resolution topographic data and can therefore produce higher accuracy floodplain maps, an important tool that communities use to assess their flood risk spatially. While availability of lidar data varies across the U.S., uptake also varies even when lidar is available. For example, we found, from our survey, that only 50% of flood risk managers in Idaho are using the technology. Previous research investigates important factors in the role of technology adoption in reducing long-term environmental risk. However, the current literature infrequently examines the social processes that impact an individual's choices about how to manage risk. We used a mixed-methods approach to examine the adoption of lidar by flood managers for risk mitigation, as a function of individual (e.g., risk perception, direct experience) and collective predictors (e.g., peer influence, network expertise). We conducted 8 semi-structured interviews with flood risk managers in Idaho and gathered 206 survey responses from flood risk managers in Idaho, Oregon, and Washington. We found that flood managers who share information with other flood managers using lidar are also more likely to use lidar themselves. Furthermore, the more frequently these flood managers communicate, the more likely a

manager is to use lidar. This work provides a foundation for how to incorporate collective factors in mitigation behavior research and reveals potential for increased lidar uptake through collaboration in the flood risk manager community.

Introduction

Floods are one of the most frequent and destructive natural disasters in the United States (FEMA, 2020a; Pralle, 2019). Flood events disrupt ecological, cultural, and economic landscapes causing incalculable expenses to our society, often resulting with vulnerable groups at higher risk in the future (Howell and Elliott, 2019). Flood events in the U.S. are increasing, some of those with unprecedented amounts of rainfall, since the National Centers for Environmental Information (NCEI) began tracking natural disaster events in 1980 (NCEI, 2021). There are largely two factors driving this increase: climate change and population growth and urbanization. As temperatures rise, the amount of water vapor in the atmosphere increases, which exacerbates the potential for extreme rainfall events. In addition to growing flood risk from climate change, population growth rate and urbanization in coastal and inland floodplains is rising (Pralle, 2019; Schanze, 2006). In 2015, 21.8 million (6.87%) of the U.S. population were exposed to the chance of a 100-year flood; meaning they lived in a location that could be inundated by a flood event with 1 in 100 chance of happening each year (Qiang, 2019). Considering these challenges, understanding how to manage changing flood risk is critical.

Flood risk is inherently transdisciplinary and needs to encapsulate the full context of the topic for which it is being applied. Therefore, we understand flood risk to be the quantifiable chance of a flood event given the known contextual (e.g., social, environmental, political) factors. Communities understand their flood risk typically by using Federal Emergency Management Agency (FEMA) floodplain maps, which estimate the extent of flood hazards through hydrologic and hydraulic models. These analyses require topography, rainfall and run-off frequency distributions, and flood control structures (e.g., diversion dams, levees, bridges). Floodplain maps also communicate flood risk to vulnerable populations, help communities mitigate and adapt to floods, and inform flood insurance programs such as FEMA's National Flood Insurance Program (Pralle, 2019). However, in the past decade, 36% of flood claims were for properties outside of the FEMA-designated 100-year flood zone, which increased from the 1990s, where 24% of flood claims were from outside the 100-year flood zone (Ludy and Kondolf, 2012; Frank, 2021). The discrepancy between actual flooding and predicted flooding from flood maps are largely impacted by outdated and inaccurate topographic data inputs, use of historical rainfall patterns, and local politics (Pralle, 2019). For example, 100-year flood events are based on historical rainfall patterns; however, this probability can change based on local land use, river impoundments, the number of impervious surfaces, and long-term climate patterns (USGS, 2018).

Previous research confirms that high-resolution topographic data is critical for an accurate floodplain map (Ali et al., 2015; Cook and Merwade, 2009). In the past, flood risk managers typically used 10-meter or 30-meter resolution terrain models. Now, higher-resolution terrain models (e.g., 1-meter or smaller) are available from technology such as Light Detection and Ranging (lidar). Lidar is a laser-based remote sensing technology that uses the reflection of light to measure elevation and features on the ground such as vegetation and structures. Lidar-derived products are now widely used in flood risk management to model different flooding scenarios with increased accuracy (Muhadi et al., 2020).

Despite the clear efficacy of lidar for flood risk management, topographic and bathymetric lidar are variably available for use across the contiguous, lower 48 states. Most states have greater than 95% coverage, except for eight states situated in the Western U.S, including Washington, Idaho, Montana, Oregon, Nevada, Utah, California, and Arizona. 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 flood risk management. In this chapter, we investigate the factors of technology adoption to understand the driving forces that cause an individual to adopt lidar.

In order to do this, we conducted a mixed-methods study, combining interviews and a survey, with flood risk managers in the Pacific Northwest. We collected data for both individual and collective predictors that could influence an individual to adopt. Historically-studied individual predictors in flood risk management include risk perception, direct experience, knowledge, coping appraisal, trust, risk-taking attitude, and demographics (e.g. (Birkholz et al., 2014; Bubeck et al., 2012; Kellens et al., 2013; Poussin et al., 2014)). Collective predictors represent measurable outcomes of an individual's beliefs and willingness to be part of group (Kuhlicke et al., 2020). Collective predictors can be drawn from a social network analysis and include factors such as peer influence, network strength, and network expertise. While there is limited research in the collective predictors of flood risk management, we chose to look at social processes because of their potential to illuminate behavioral and decision-making influences on flood risk managers.

There are two main objectives with our study: (1) advance our scientific understanding of the processes that affect technology adoption as a form of long-term risk mitigation and (2) quantify facilitators of lidar adoption in flood risk management using a mixed-method approach. We draw from an interdisciplinary, social-ecological science background to meet these objectives. Specifically, we use cultural evolutionary theory, the selection and transmission of culture over time, to inform our selection of individual and collective predictors. In addition, this study is an example of convergence research, which integrates knowledge across disciplines and organizational boundaries to reduce disaster losses and promote collective well-being (Peek at al., 2020). Our study is an example of convergence work because it uses interdisciplinary theory and methodology to engage study participants from diverse, organizational backgrounds including government officials, industry professionals, and academics. By determining the most influential individual and collective predictors of lidar adoption, we can inform concerted efforts of lidar uptake, improve flood risk awareness and knowledge, and form more resilient communities to future flood risk.

Background

Individual and collective predictors of risk-mitigation behavior

Previous research identified the importance of several individual factors as a function of risk mitigation behavior; however, research is limited in the role of collective action (Kuhlicke et al., 2020). Therefore, it is important to look at the combined effects of both individual and collective predictors in predicting risk mitigation behavior so that we can understand the relative contribution of each predictor (van Valkengoed and Steg, 2019). The following section examines previous research into predictors of risk mitigation behavior and then explores how cultural evolutionary theory can help illuminate collective predictors of influence.

Topical Review

Previous flood risk management research focused on flood risk perception as a critical factor of developing effective flood risk management strategies (Birkholz et al., 2014). However, recent research re-examined the role of risk perception in behavior and decision-making because of the difficulty connecting risk perception with management and the challenge of parsing out the connection of risk perception with underlying contextual factors (Rufat et al., 2020). For example, a study by Bubeck et al. (2012) found risk perception to be a weak predictor of precautionary behavior and suggests shifting focus towards flood-coping appraisal for explaining flood risk management behavior. In addition, Kellens et al. (2013) reviewed 57 empirically based peer-reviewed articles on flood risk perception and communication to assess overall trends in flood risk research. The authors found that most 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 explains individual decisions about preparing for risk as a function of threat appraisal (e.g., likelihood of exposure to a flood, severity of exposure, and fear) and coping appraisal (e.g., self-efficacy, outcome efficacy, and outcome costs). The results of this review suggest future research should have more theoretical support and methodological openness; specifically, the use of a theoretical framework that emphasizes the effects of physical exposure and hazard experience (Kellens et al., 2013).

Collective factors of risk mitigation behavior are limited in the existing flood risk management literature; however, initial evidence found the influence of social networks on risk mitigation behavior as important (Bojovic and Giupponi, 2020; Kuhlicke et al., 2020; Lechowska, 2021). Social networks are of particular interest for our study because they are a way of measuring peer influence, the diffusion of ideas, practices, or technologies through network ties from social interactions (Muter et al., 2013). Peer influence is a helpful tool for behavior prediction based on an individual's position in a social network (Daraganova and Robins, 2012; Levin, 1992). Furthermore, the technology adoption literature applied network analysis to measure information exchange and diffusion through network relations (Peng and Dey, 2013). The application of social networks to flood risk management decision-making is still in its infancy; however, the findings from previous research with respect to social networks and technology adoption provide a compelling baseline for using it to understand peer influence in our study.

Additionally, recent research suggests the importance of context, local power relations, constraints, and opportunities that affect risk mitigating behavior calling for convergence research to understand the underlying assumptions of decision-making (Rufat et al., 2020). Given the current gaps of understanding in flood risk management research and the push for convergence research, we employ cultural evolutionary theory to employ a comprehensive theoretical baseline for flood risk mitigation behavior research that can be used across disciplines and scales.

Secondly, the current literature is pre-dominantly focused on the public's flood risk behavior, rather than flood risk managers themselves (Brody et al., 2010; Roberts and Wernstedt, 2019). Our study is solely focused on addressing individual and collective predictors of risk mitigation behavior at the decision-maker level.

Culture and Risk

Culture is information acquired by individuals through social learning, which forms a group of shared beliefs and norms over time (Henrich and McElreath, 2002). Social learning is the observing, modeling, and imitating of behaviors, attitudes, and emotional reactions of others (Bandura, 1971). Social learning differs from individual learning, which is learned from the environment and non-social stimulus, but is not mutually exclusive (Perreault et al., 2012). Several researchers believe social learning improved human adaptability so much that we can inhabit such a wide range of habitats, unlike other animal species (Creanza et al., 2017).

Behavioral adaptations display the variation of culture as a result of the evolutionary dynamics of cultural systems. Cultural evolutionary theory describes this process as the selection and transmission of culture over time. The selection process leads to variation of culture across temporal, spatial, and institutional scales and the transmission leads to adaptation (e.g., adoption of new technology). Reminiscent of genetic evolution, human culture evolves through the process of natural selection. This evolution results in between-group variation of adaptive behavior and cooperation and can lead to increased fitness or utility (Henrich and McElreath, 2002; Richerson et al., 2016). Unlike genetic transmission, it is important to note cultural transmission can occur over a short time scale, within a generation, through social learning (Richerson et al., 2016). Cultural evolutionary theory and social learning are increasingly popular theories used to explain a wide range of phenomena in applications such as natural resource management, sports strategy, and institutional variation (Brooks et al., 2018; Mesoudi, 2019; e.g., Reed et al., 2010; Richerson et al., 2016).

In a similar vein, the cultural theory of risk is the transmission of risk information among a network of individuals through social learning (Douglas and Wildavsky, 1983). Previous flood risk management research suggested the use of cultural theory of risk to contextualize the relationship of risk perception as a function of cultural adherence and social learning (Birkholz et al., 2014). This theory has been employed in a couple empirical flood risk management studies so far and provides an intriguing underpinning of risk perception research (Shen, 2009). Cultural evolutionary theory is like cultural theory of risk; however, it more broadly offers a way to understand the complex dynamics of cultural change through interactions between individuals and populations, such as is needed for flood risk management (Brooks et al., 2018).

Predictor Literature Review

In order to select relevant individual and collective predictors of flood risk mitigation behavior *a priori*, we conducted a literature review of previous work that looked at the effect of the constructs outlined in Table 1.1 on flood risk mitigation.

Table 1.1 Individual and collective constructs studied in flood risk management research. Definition of each individual and collective construct included from our literature review. The listed effect on behavior indicates the direction of the association between the listed construct and the outcome variable, risk mitigation. N.S. signals a non-significant effect direction. Supporting literature includes a non-exhaustive list of articles discussing the importance and effect of each construct on risk mitigation.

	Construct	Definition	Effect on Behavior	Supporting Literature
Individual	Risk perception	Subjective construct that reflects an individual’s perceived vulnerability to and consequence of a hazard.	+/-	Bubeck et al. 2012; Kellens et al., 2012; Lo, 2013; Birkholz et al. 2014; Poussin et al., 2014; van Valkengoed & Steg, 2019
	Experience (direct or indirect)	Represented by an individual witnessing a hazard and/or an individual who gathered information (e.g., social media, newspaper) from others who had direct experience.	+	Bubeck et al. 2012; Kellens et al., 2012; Poussin et al., 2014; Valkengoed & Steg, 2019
	Knowledge	An individual’s awareness of climate change and climate-related hazards.	+	Bubeck et al. 2012; Kellens et al., 2012; Valkengoed & Steg, 2019
	Coping Appraisal	Total response efficacy and self-efficacy considering costs of adopting response.	+/N.S.	Bubeck et al. 2012; Poussin et al., 2014
	Trust	Risk judgement by an individual regarding the ability for others (e.g., science, government) to effectively cope with a hazard	+/-	Kellens et al., 2012; Viglione et al. 2014; Valkengoed & Steg, 2019
	Risk-taking attitude	An individual’s general propensity to engage in risky behaviors.	+/-	Viglione et al. 2014; Roberts & Wernstedt, 2018; Poussin et al., 2014

	Age	An individual's total years of life.	+	Bubeck et al. 2012; Poussin et al., 2014
	Gender	An individual's self-described gender affiliation.	N.S.	Bubeck et al. 2012
	Education	Amount of formal education an individual experienced.	N.S.	Bubeck et al. 2012; Poussin et al., 2014
Collective	Peer influence	Impact of an individual's social network on an individual's ideas, beliefs, and practices.	+	Lo, 2013; Viglione et al. 2014; Poussin et al., 2014; Birkholz et al. 2014; Roberts & Wernstedt, 2018; Bojovic & Giupponi, 2020
	Network Strength	Amount of communication an individual has with their network ties.	+	Lo, 2013; Haer et al., 2016; Bojovic & Giupponi, 2020
	Network Expertise	Individual perception of expert skills or knowledge of their network ties in their field of work.	+/N.S.	Bracken et al., 2016; Roberts & Wernstedt, 2018

Methods

Case study description

We examine the adoption of lidar in communities throughout Idaho, Oregon, and Washington. All three states expect to see an increase in precipitation and higher temperatures earlier in the year. In addition, these three states are similar in that they are currently increasing the amount of publicly-available lidar (Clark, 2010; Division, 2020; Emergency Management, 2018; Ralph et al., 2014; Slater and Villarini, 2016). While Idaho, Oregon, and Washington all reside in the same geographic region, each state's flood risk challenges vary depending on the differing types of landscapes, levels of population growth and urbanization, and resource availability (e.g., funding for flood risk management, educational opportunities for flood risk managers). In addition, each state employs their own lidar coordination and acquisition program, which contributes differential levels of lidar availability as seen in Figure 1.1.

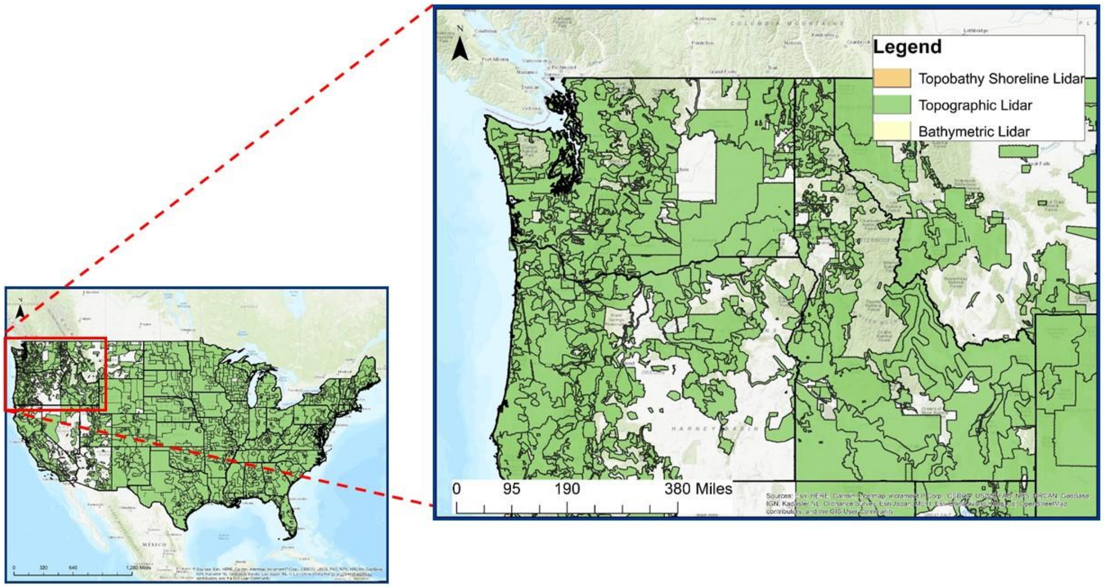

Figure 1.1. U.S. Interagency Elevation Inventory Map of the Pacific Northwest. Publicly-available lidar in our case study extents of Idaho, Oregon, and Washington.

Idaho

In 2019, Idaho was home to 1.79 million people across 82,643 square miles: 21.7 people per square mile (Bureau, 2020a). It is a land-locked state and can be broken down into three main areas: the panhandle in the north is filled with coniferous forests and lakes, the central section is filled with vast mountain ranges and alpine lakes, and the southern section, known as the Snake River Plain, is filled with sagebrush steppe and high desert environment. There is influence from the Pacific Ocean in the north and west side of Idaho, resulting in cloudy, humid, and wet winters, whereas the east is the opposite with wet summers and dry winters. Average annual rainfall ranges from 10" in the arid southwest regions to 50" at higher elevations in certain river basins (FEMA, 2020b). In addition, Idaho sees abundant amounts of snowfall in the mountains.

While most of the population is concentrated in the southern part of the state, there is flooding across the entire state that impacts people and structures. Idaho is prone to riverine flooding, ice/debris jam flooding, levee/dam/canal breaks, stormwater, sheet or areal flooding, and mudflows (Emergency Management, 2018). In 2021, Idaho had 145 NFIP participating communities across 44 counties (FEMA, 2020b).

Lidar acquisition is coordinated by Boise State University's Idaho Lidar Consortium in conjunction with Idaho State University's GIS Research and Training Center, which stores lidar data for public use. There is no state-approved funding set aside for lidar acquisition; therefore, communities rely on local funding and apply for external funding from USGS and/or FEMA. By the end of 2021, Idaho will have 73% of the state covered with publicly-available lidar.

Oregon

In 2019, Oregon had over 4.2 million residents across 95,988 square miles; 43.8 people per square mile (Bureau, 2020b). Oregon can be broken down into six main areas: the Coast Range, the Willamette Lowland, the Cascade Mountains, the Klamath Mountains, the Columbia Plateau, and the Basin and Range Region. There is a maritime influence across the entire state due to the Pacific Ocean. The Coast range is predominantly evergreen forests with many small coastal lakes. The mountain regions are typically several thousand feet above sea-level and have a range of dense forests and lakes. Eastern Oregon contains high desert environment with few steep mountains.

Oregon's population is concentrated in the coastal region of the state. Oregon has an extensive history of multiple types of flooding including riverine flooding, flash floods, ice/debris jam flooding, coastal flooding, shallow area flooding, urban flooding, and playa flooding (Layton et al., 2015). In 2021, Oregon had 228 NFIP participating communities across 36 counties (FEMA, 2020b).

Lidar acquisition is coordinated by the State of Oregon Department of Geology and Mineral Industries' Oregon Lidar Consortium. By the end of 2020, Oregon had 98% of Oregon's populated areas were covered with publicly-available lidar, although eastern Oregon has much sparser coverage of lidar (Geology and Mineral Industries, 2020).

Washington

In 2019, Washington had over 7.6 million residents across 66,455 square miles; 114 people per square mile (Bureau, 2020c). Washington can be broken down into six main areas: the Olympic Mountains, Coast Range, Puget Sound Lowlands, Cascade Mountains, Columbia Plateau, and Rocky Mountains. Most of the areas in the western and northern parts of Washington are predominately evergreen forests, where the eastern and southern parts of Washington are semiarid with grasses, sagebrush, and scattered shrubs. Annual precipitation on the Pacific side of the Olympic Peninsula exceeds 150 inches, but places on the northwest of the peninsula receive less than 20 inches a year and on the eastern side receive less than 8 inches (Augustyn, 2021).

More than three-fourths of the population lives in Puget Sound Lowlands (Augustyn, 2021). 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). It is estimated that in 2021, Washington had 277 NFIP participating communities across 39 counties (FEMA, 2020b).

Lidar acquisition is coordinated by the Washington State Department of Natural Resources and receives funding from the Washington State Legislature to acquire and upkeep lidar data for the state. Over 50% of the state is flown with lidar data (Gleason and Markert, 2020).

Physical flood risk

Since flooding is becoming an increasingly damaging and costly issue, there has been a rise in interest from non-governmental groups to predict flood risk at the property level for households and property owners to be aware of their physical flood risk. First Street Foundation (First Street), a non-profit organization of modelers, researchers, and data scientists, created the first publicly-available flood risk model for the lower 48 states. According to First Street, nearly 70% of properties have more substantial flood risk than previously predicted by FEMA floodplain maps (First Street Foundation, 2020). This discrepancy is due to First Street model's ability to predict property-level, future flood risk. In addition, First Street was able to map flooding at 3-meter resolution, which is higher than many current floodplain maps which can range in quality up to 30-meter resolution. First Street's model also increases visibility of areas whose flood risk remains unexamined by FEMA. To understand the nature of physical flood risk in our case study extent, we compare the FEMA projections to the First Street projections as seen in Table 1.2. It is important to note that FEMA reports Idaho as having the least amount of flood risk relative to Oregon and Washington; however, First Street reports Idaho as having the highest risk. This difference could be because there are still many locations in Idaho that are not mapped by FEMA; therefore, urbanization in floodplain areas could be more likely.

Table 1.2. First Street Foundation and FEMA flood risk predictions. Summary information about environmental and social differences between Idaho, Oregon, and Washington.

	Idaho	Oregon	Washington
Total FEMA Properties at Risk (2020)	38,047	97,918	121,528
Percent FEMA Properties at Risk (2020)	4.1	6.3	5.6
Total FS Properties at Risk (2020)	148,427	268,020	362,612
Percent FS Properties at Risk (2020)	17.6	17.3	16.4

Relevant predictors of lidar adoption

Given the previous literature and summary of our case study extent, we narrowed down our study to focus on eight constructs. Table 1.3 displays the five individual predictors that we selected for our study. We chose these factors because they aligned with repeated themes in our semi-structured interviews, in addition to each factor providing important information to help increase uptake of lidar adoption.

In addition, we selected three collective factors reflected in Table 1.4.

Table 1.3. Individual predictors of lidar adoption. This tables summarizes our hypothesis, survey question, response options, and data structure for each predictor.

Construct	Hypothesis	Survey Question	Response Options	Data Type
Experience	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	Binary
Risk Perception	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%/25%/50%/ 75%/100%	Ordinal categorical (5)
Knowledge	Flood risk managers with knowledge of increase 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	Ordinal categorical (3)
Risk-taking attitude	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 (risk-tolerant) to 10 (risk-averse)	Integer
Trust	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 distrust/Somewhat distrust/Neither trust nor distrust/Somewhat trust/ Strongly trust	Ordinal categorical (5)

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Table 1.4. Collective predictors of lidar adoption. This tables summarizes our hypothesis, survey question, response options, and data structure for each predictor.

Construct	Hypothesis	Survey Question	Response Options	Data Type
Peer influence	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 AlterX use lidar?	Yes/No/I don’t know	Ordinal categorical (3)
Network strength	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 AlterX?	A few times a year/Once a month/2-3 times a month/Once a week/Several times a week/Several times a day	Ordinal categorical (6)
Network expertise	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 AlterX in the field of flood risk management?	0 (no expertise at all) to 10 (very much expertise)	Integer

Several studies implement social network analysis to examine the influence of social ties on communication in disaster management; however, the effect of social networks on other topics in disaster management are minimally explored (Bojovic and Giupponi, 2020). Bojovic and Giupponi (2020) conducted a full network analysis on the diffusion of innovation and technologies for risk management, which was the first study of this topic in disaster management. The study focused on the identification of key actors to effect information dissemination.

Our study uses an ego network analysis, which is helpful for understanding the variation of behavior of individuals through identification of local social structures unique to the individual of interest (e.g., flood risk manager) (Hanneman and Riddle, 2005). We used an open ego network and calculated the predictors of peer influence, network strength, and network expertise from data collected in the survey questions in Table 1.4. Figure 1.2 displays a range of possible network connection situations with varying lidar use, communication, and expertise values that flood risk managers could report about their network connections. For example, Alter 1 represents an individual that the ego, or in this case survey respondent, reports as using lidar, communicates with several times a day, and views with a lot of expertise. Whereas Alter 8 represents an individual that the ego reports as not using lidar, communicates with only a few times a year, and views with no expertise. Respondents could report up to eight peers.

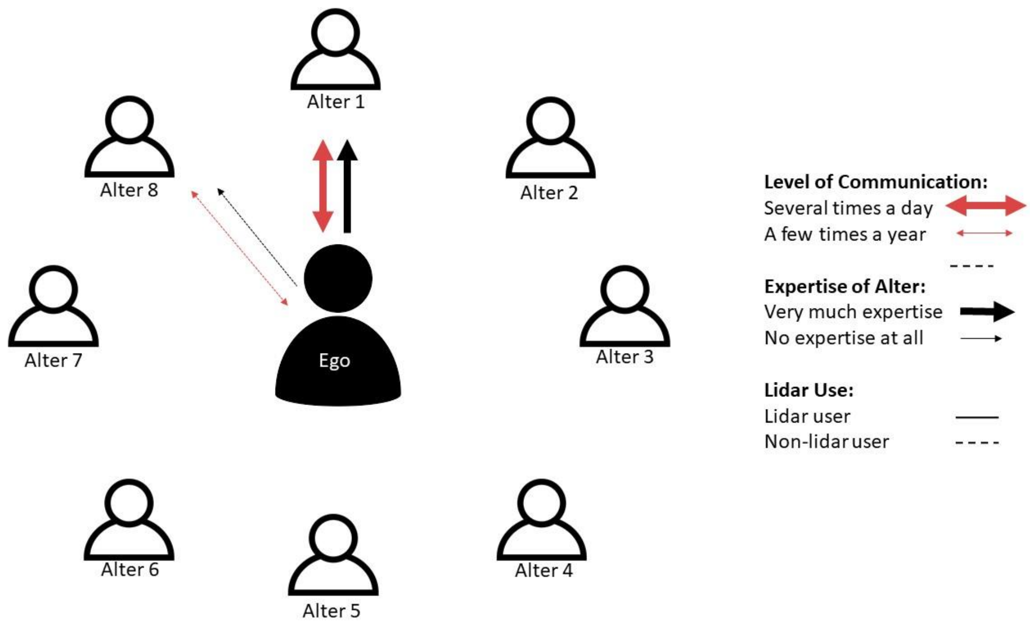

Figure 1.2. Ego network structure. We used an open ego network analysis structure where the ego represents the survey respondent and the lines represent the ties between the ego and their peers, which are labeled as alters.

Peer influence was calculated as the proportion of the ego's alters that used lidar. Network strength was calculated as the ego's net average communication with lidar users minus average communication with non-lidar users in an ego's network. Network expertise was calculated as the ego's net average expertise with lidar users minus average expertise with non-lidar users in an ego's network.

Survey design

Prior to finalizing our survey instrument, we conducted eight, semi-structured interviews with stakeholders including flood risk managers, government officials, industry professionals, and academics. The interviews lasted about an hour and were occasionally recorded. These interviews were used to identify common themes, ensure that our survey questions were relevant, and confirm that we were adequately identifying facilitators and barriers to lidar adoption.

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 was tested as a pilot survey with a flood risk manager, an industry professional, and a lidar academic to provide additional feedback from the perspective of a potential, target respondent.

The finalized survey consisted of four main parts (see Appendix B). 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 including if they used lidar, how they use lidar, and if they would like to take part in lidar workshops. The third part of the survey gathered information about the respondent's flood risk management network. The final part of the survey asked the respondent about their personal beliefs in risk-taking, trust, and demographic questions such as education and gender.

Data collection

Initially, our target population included floodplain managers and administrators in Idaho, Oregon, Washington, and Alaska. Respondents also included individuals that may use lidar for flood risk management applications in conjunction with software applications such as Geographic Information System (GIS). Most sample respondents were municipal, state, and federal employees, as well as some private industry employees. We constructed our sample frame using several publicly available lists of managers including NFIP coordinators, Association of State Floodplain Managers

(ASFPM) recognized Certified Floodplain Mangers (CFM), county-level GIS administrators, the five largest cities and tribal GIS administrators 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 Association Conference contact list.

We delivered the survey online using Qualtrics to 1,257 email addresses in our sample frame between May and July 2020. The survey took an average of 10 to 15 minutes to complete. We used Dillman et al. (2014) guidelines for web and mobile survey implementation. We initially set an introductory email that stated what was being asked of respondents, why they were selected, and information about the intent, purpose, and outcomes of the survey (Dillman et al., 2014). We sent three to five follow-up email correspondence messages over the course of four weeks to help increase our response rate. In addition, we stated the survey was anonymous and participant's information would be kept confidential. Table 1.5 summarizes the potential respondents, number of survey responses, and response rate for each state.

Table 1.5. Comparative survey distribution and collection. Summary of potential respondents, number of survey responses, and response rate for each state.

	Potential Respondents	Number of Responses	Response Rate
Idaho	385	96	24.9
Oregon	356	58	16.3
Washington	463	54	11.7
Alaska	53	6	11.3

We did not include Alaska in our final statistical analysis because of an insufficient number of responses. In addition, both Oregon and Washington had lower response rates than Idaho. Our response rates are within the typical bounds for online surveys of 10-25% (Sauermann and Roach, 2013).

Data Analysis

We used a Bayesian Generalized Logistic Regression (GLR) to estimate the relationship between our predictors of interest and our response, lidar use, because it is binary. The results of this model allowed us to explore the effect of a multitude of predictors on lidar use in Idaho, Oregon, and Washington. We hypothesized that the model would be helpful for understanding the level of predictor influence; however, we expected the predictive capacity of our model to be limited considering the large number of predictors and small sample size of our study.

The model followed a binomial distribution curve, where the distribution of lidar use, y_{ij}, was modeled as follows:

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

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

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

where x_{ij}, predictors, are the ith rows of the known design matrices x, and β is a vector of regression parameters. This Bayesian approach allowed for adjustment of uncertainty associated with each parameter on the outcome, lidar use. In order to do this, each parameter had to be assigned a prior belief of that parameter value. The values for these parameters are fit by sampling from these distributions to maximize 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 distributions assigned to them that are constrained by 0 and a positive value. We used four Monte Carol 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., 2020).

Priors

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, 2015). This study uses a Cauchy distribution as recommended for logistic regression models with a low sample size (Lemoine, 2019; Gelman, 2008).

Validation

We assessed the overall model performance through Leave-One-Out Cross-Validation (LOOCV). This process provides an absolute metric for the model's predictive ability. In addition, we plotted the predicted probability against the observed proportion using counterfactual plots to evaluate the effect of each predictor of interest on lidar adoption (Levy, 2012).

Error

We specified our model to compute 4,000 lidar use predictions based on our predictors. We interpreted the median of these results as the projected lidar use. In addition, we calculated the 50% and 95% uncertainty intervals around the median. We used Bayesian R-squared to measure our overall model accuracy. However, this can be unreliable for small sample sizes, so we also calculated the mean absolute error and root mean square error of our model.

Results

Our interview findings revealed several common barriers and opportunities that informed our predictor selection in Table 1.3 and Table 1.4. Table 1.6 summarizes these findings.

Table 1.6. Interview themes. Summary table of repeated barriers and opportunities that came up during our semi-structured interviews (n=8).

Barriers	Opportunities
- Rural regions with smaller populations typically have lower priority for revised mapping - Lidar is seen as expensive and not all communities / regions have adequate funding - There is potential distrust in scientific products and/or the federal government - Hesitancy towards publicly-accessible lidar from private landowners	- Lidar is useful and desirable to work with - Elected officials have authority in lidar acquisition - Community relationships can be influential in lidar adoption - Lidar acquisition is facilitated by collaboration across multiple institutions and stakeholders

We received the greatest number of survey responses from Idaho (Table 1.7). The results show slight differences in demographic factors. Washington had the highest percentage of female respondents, second highest percentage of respondents with a bachelor’s degree or higher, and longest average length of flood risk manager experience.

Table 1.7. Summary survey demographics. Comparative descriptive statistics for survey demographics across Idaho, Oregon, and Washington.

	Idaho	Oregon	Washington
Sample Size	96	58	54
Female	39%	34%	44%
University Education	69%	81%	76%
Age (50+ years)	50%	43%	43%
Average Flood Risk Experience (years)	10.6	11.2	13.8

Descriptive Results

We found that over 70% of flood risk managers, in all three states, had direct experience with flood damage in their communities (Table 1.8).

Table 1.8. Descriptive statistics of predictors evaluated in our model (n=206).

Construct/ Predictor	Description	Idaho	Oregon	Washington
Direct Experience	Direct experience with flood damage in community (%)	79.20	72.40	85.20
Risk Perception	Perceive future flood damage in the community (%)	97.90	96.60	98.10
Knowledge	Perceived Increase in Flood Severity over time (%)	38.50	41.40	57.40
Risk-Taking Attitude	Average risk-taking attitude (0 to 10 with 10 being risk-tolerant)	2.80	3.30	3.70
Trust	Trust in accuracy of flood risk management scientific products (%)	82.30	81.00	90.70
Peer Influence	Proportion of lidar users in flood risk management network (%)	35.00	40.00	42.00
Network Strength	Net average communication in respondent's network	-0.60	-0.04	-0.02
Network Expertise	Net average expertise in respondent's network (0 to 10 with 10 being of highest expertise)	0.70	0.20	1.00
Lidar Use	Use lidar for flood risk management (%)	50.00	62.10	64.80

Figure 1.3 describes, in finer detail, the types of experiences flood risk managers have had with flooding in their communities. Survey respondents reported experiences that ranged from damage in their communities to damage of their personal homes, deaths and injury to people in their community, and disruption of their utilities.

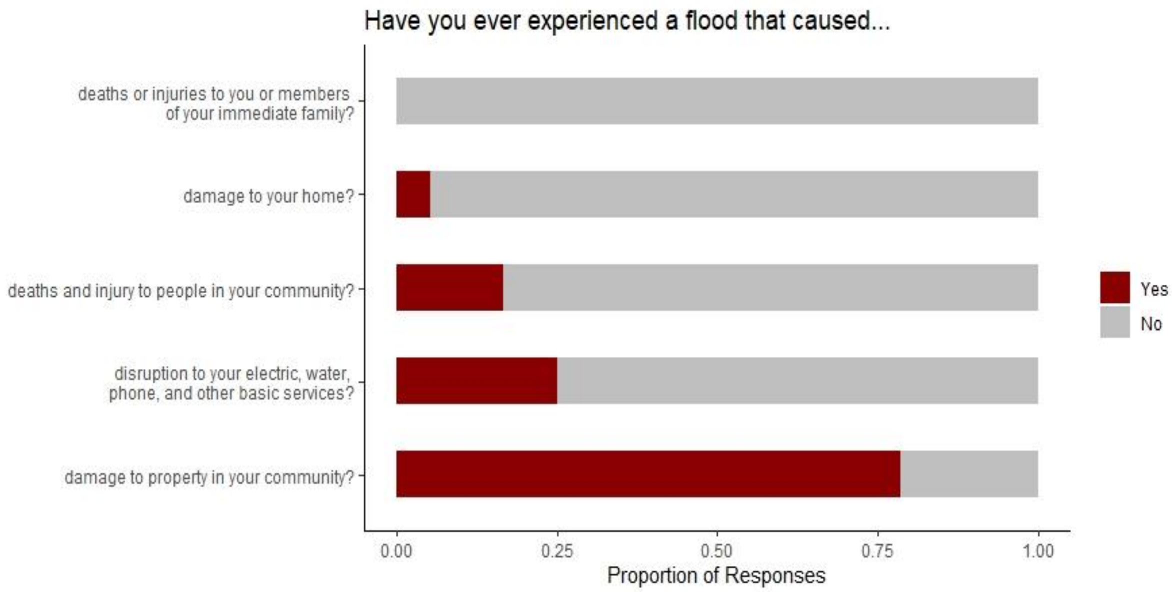

Figure 1.3. Summary of survey responses (n=206) of flood risk managers' direct experiences with floods. This details varying levels of closeness of the experience.

We also asked respondents to report the likelihood of one of those experiences occurring in the next 30 years in their community. Over 90% of respondents were concerned with future flood damage in their community (Figure 1.4).

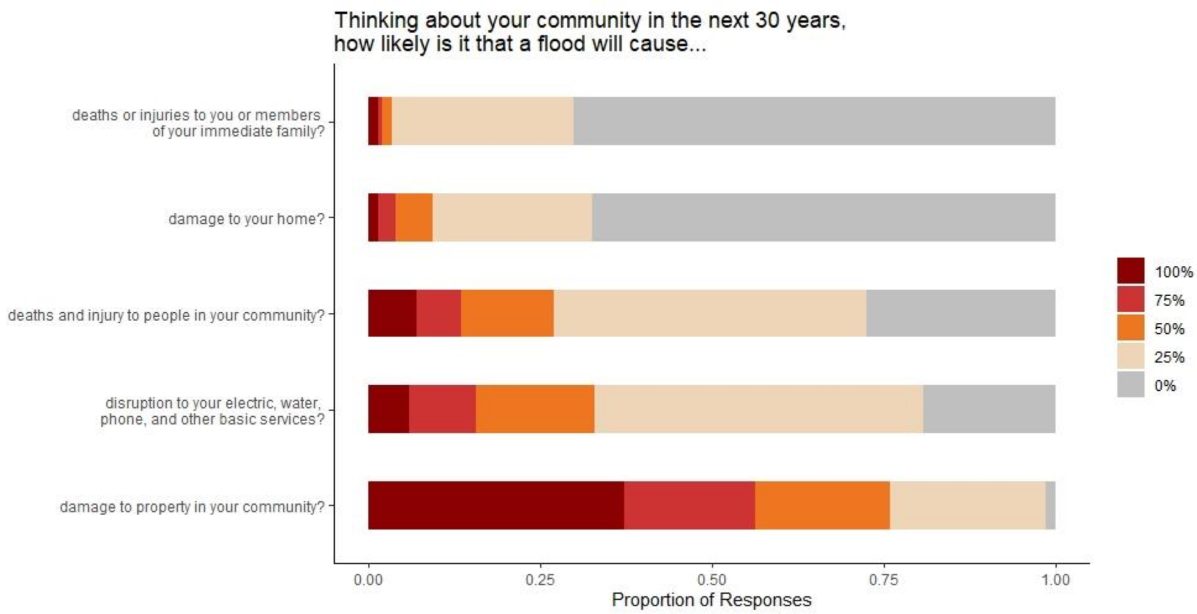

Figure 1.4. Summary of survey responses (n=206) of flood risk managers' perceived flood risk in the future. This details varying levels of closeness of the experience.

In addition, between 38.5% - 57.4% of respondent's expected an increase in flood severity. Flood risk managers in Washington tend to be less risk-averse than managers in Oregon and Idaho. All three states reported a high trust in the accuracy of flood risk management scientific products (e.g., topographic data, floodplain mapping, floodplain modeling), with Washington reporting the highest percentage of trust.

For the collective predictors, about 76% of respondents completed the network analysis section of the survey. Respondents reported one to eight peers in their flood risk management network, with five peers as the median number reported. There were some regional differences. Washington flood risk managers' peer networks, on average, were made up of 42% lidar users, which was higher than Idaho which reported 35%. These findings reflect a similar pattern in that Idaho had the least amount of communication, on average, in their flood risk managers' networks, whereas Washington had the most. In all three states, respondents had slightly more communication with non-lidar users.

Interestingly, all three states reported on average, more expertise with lidar users in their network.

Washington reported the highest amount of lidar use in flood risk management with almost 65% of respondent's using lidar. Idaho reported the lowest amount of lidar users, 50%.

Estimation Results

Our GLR model allowed us to explore the effect of a multitude of predictors on lidar use in Idaho, Oregon, and Washington. We had item-nonresponse in the survey, for the network section, and we dropped incomplete responses to conduct our statistical modeling. Of the 206 usable responses we received, 50 of them did not fill out the network section. Since our model considers both individual and collective predictors and needs equal size data lengths for each predictor in order to run the model, we dropped almost 25% of our data responses, which may result in effect size underestimation (Langkamp et al., 2010).

Table 1.9 displays the results from our GLR model that considers the effect of individual and collective predictors on lidar use.

Table 1.9. Estimation results from the model.

	Mean (log odds)	S.D.	5%	95%
Intercept	-0.9	1.7	-3.7	1.9
Direct Experience	0.4	0.7	-0.6	1.5
Risk Perception	1.2	0.8	-0.2	2.6
Knowledge	0.2	0.4	-0.3	0.9
Risk-Taking Attitude	0.1	0.1	-0.1	0.3
Trust	-0.2	0.3	-0.8	0.3
Peer Influence	1.4	1.1	-0.4	3.3
Network Strength	0.4	0.1	0.2	0.7
Network Expertise	0.1	0.1	0.0	0.2

From our analysis, we examined the Posterior Predictive Distribution for each predictor and the intercept (Figure 1.5). We considered predictors that had parameter estimates whose 90% credible interval did not overlap with zero to be important. These results suggest peer influence, network strength, network expertise, and risk perception effect on lidar use. That is, some attributes had a positive effect on lidar use, and some a negative effect.

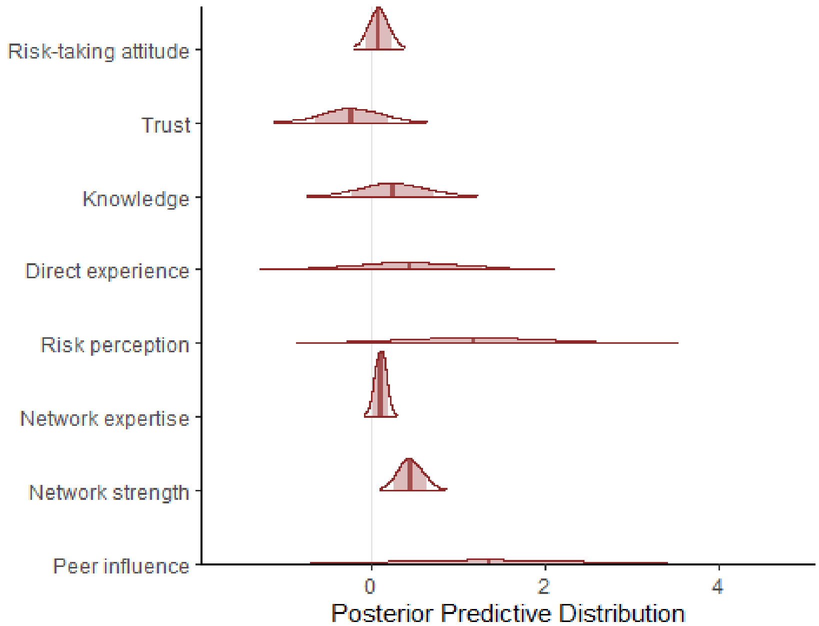

Figure 1.5. Posterior Predictive Distribution for each predictor variable.

Figure 1.6 displays the effect, when holding all other variables at their minimum, of peer influence, which is the proportion of lidar users in a respondent's network on lidar use by region. When every alter in a respondent's network used lidar, 64.4% of flood risk managers were predicted to adopt lidar. Alternatively, when the proportion of lidar user in respondent's network decreased to 0, 32.4% were predicted to adopt lidar.

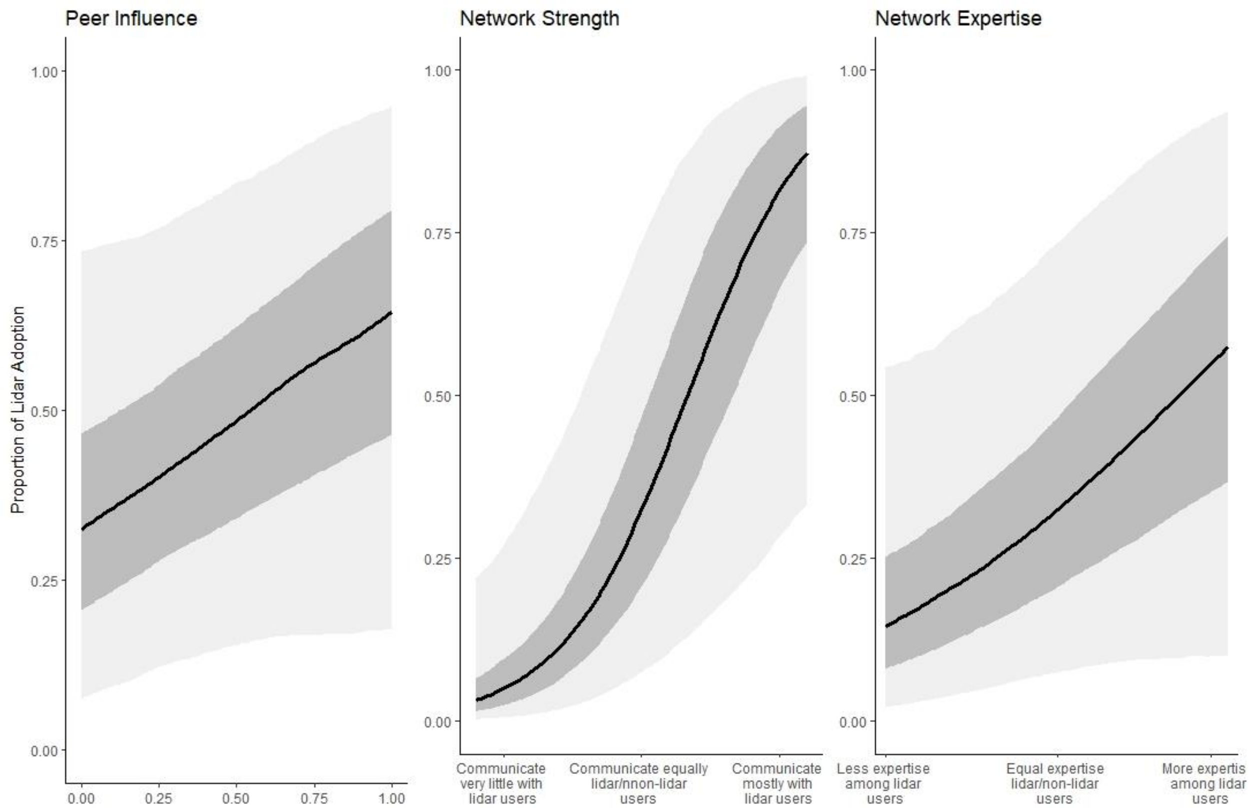

Figure 1.6. Counterfactual plots show the effect of a) the proportion of respondent's social network using lidar, or peer influence, and predicted lidar adoption, b) net average frequency of communication with lidar and non-lidar users, or network strength, in flood risk manager's network, and c) net average expertise of lidar and non-lidar users, or network expertise, in flood risk manager's network. The dark grey and light grey represent the 50% and 95% confidence intervals, respectively.

Both network strength and network expertise had positive correlations with lidar adoption. Network strength resulted in the largest increase in lidar adoption ranging from 3.3% for those who spoke only with non-lidar users to 87.2% for flood risk managers who spoke with only lidar users. Network expertise also had a positive effect, although small. When a flood risk manager's network was made up of expertise from non-lidar users, 14.7% were predicted to adopt as opposed to 57.5% when a flood risk manager's network was comprised of expertise from lidar users.

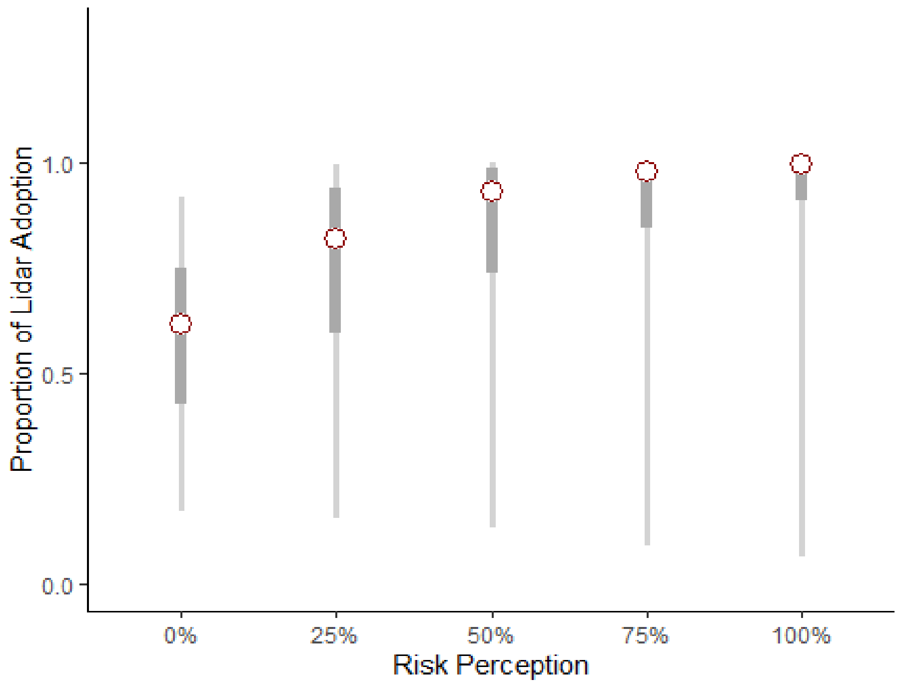

Figure 1.7. Counterfactual plot of risk perception and predicted lidar adoption. The dark grey and light grey represent the 50% and 95% uncertainty intervals, respectively.

Our model also suggests that risk perception was an important predictor of lidar adoption. Figure 1.7 displays the effect, when holding all other variables at their minimum, of risk perception on lidar adoption. We found that when flood risk managers expect 0% chance of future flood risk in their community, 59.9% of flood risk managers are predicted to adopt lidar, whereas flood risk managers who expect 100% chance of future flood risk in their community, 99.3% of flood risk managers are predicted to adopt lidar.

Furthermore, we examined the out-of-sample predictive performance of our model. The Loo Information Criterion was 161.4 with standard error of 17.5. The predictive power of the model was assessed by using a Posterior Predictive Checking from the bayesplot package in R (Figure 1.8).

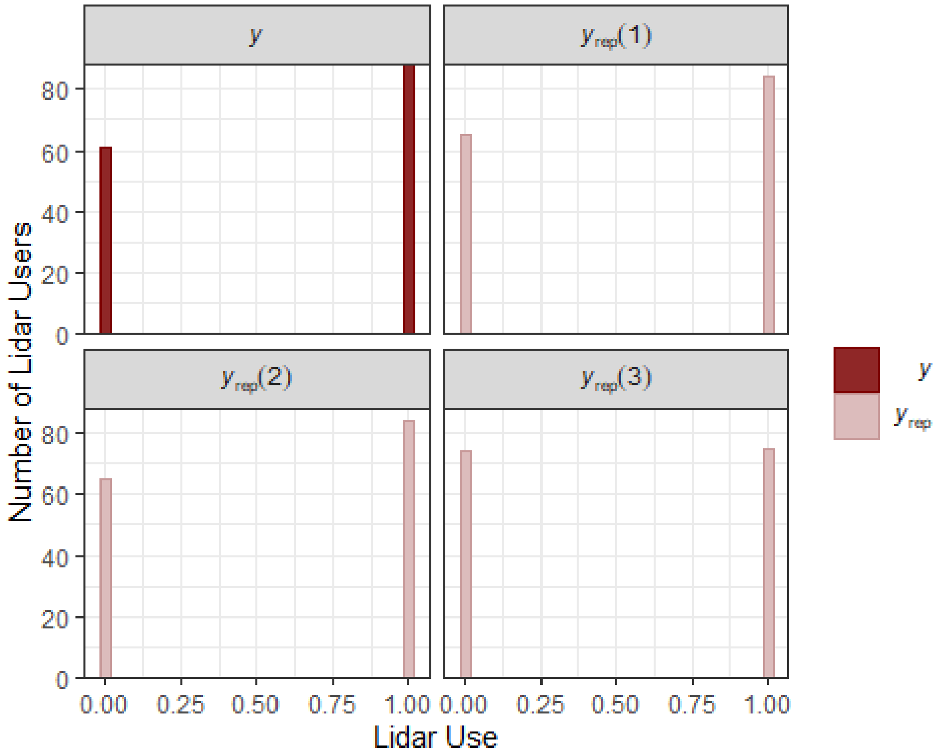

Figure 1.8. Displays a histogram, using the PPC function that represents the number of individuals that do not use lidar (0) in the left column and use lidar (1) in the right column. The y histogram represents the actual data and the yrep represents the data generated from the posterior predictive distribution. Overall, the yrep is representative of the y, meaning our model has an accurate predictive ability.

The Mean Absolute Error of our model was 1.45 and Root Mean Square Error was 1.75; therefore, our model had minimal variance in individual errors in our sample. Lastly, the Bayesian R-squared value for our model was 0.43, which represents a moderate effect size in social science data (Ferguson, 2009).

Discussion

Flooding is one of the most common and destructive of natural disasters. High-resolution topographic data are critical for management of increasing flood risks from climate change and population growth and urbanization. However, the variable uptake of lidar illuminates an interesting discrepancy of knowledge of flood risk and mitigation behavior. Our study examines the individual and collective predictors that could drive a flood risk manager to adopt lidar. By conducting a mixed-methods study, we identified several predictors that contribute our existing understanding of technology adoption for long-term risk mitigation. There are four main findings.

First, our findings show mixed support for individual predictors of lidar use (Figure 1.5), as we predicted from our hypotheses in Table 1.3. Our results show that risk perception positively effects lidar adoption, increasing likelihood of adoption almost 40%. There were minimal regional differences between Idaho, Oregon, and Washington who all reported over 96% chance of future flood damage in their communities. While risk perception positively correlates with lidar adoption, there are limitations in the implementation of this finding for improving flood risk management or for deciphering important underlying, contextual factors that drive the connection between risk perception and lidar adoption (Rufat et al., 2020). Despite the just criticism of risk perception in the flood risk management literature (e.g. Kellens et al., 2013; Wachinger et al., 2013), it can be helpful in policy making practices (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 have a low perception of risk. Considering 36% of flood claims are from properties outside of the FEMA-designated flood zone, there is a clear gap in risk perception and actual risk (Frank, 2021). A spatial comparison of where individuals perceive their risk compared to current floodplain maps can highlight important discrepancies to guide policy makers to focus targeted efforts. For our study, we use the results from the remaining individual and collective factors to provide contextual, correlative factors of lidar adoption.

The second significant finding of our study is that the remaining individual predictors resulted in mixed effects on lidar adoption (Figure 1.5). Direct experience positively correlated with lidar adoption and there were small regional differences with flood risk managers. For example, flood risk managers in Oregon directly experienced almost 13% and 5% less floods than Washington and Idaho, respectively. This finding supports previous research that found positive effect of direct experience on behavior (e.g. Poussin et al., 2014; van Valkengoed & Steg, 2019). It is possible that measuring the intensity or impact of the event experience could be a more informative measure though, since experiences vary greatly. Interestingly, knowledge, risk-taking attitude, and trust effected lidar adoption minimally. While knowledge may be important, our results show it does not seem to play as significant of a role in lidar adoption as other factors (e.g., risk perception). There were regional differences in knowledge, with nearly 20% and 16% more flood risk managers in Washington perceiving an increase in flood severity than in Idaho and Oregon, respectively. In addition, our results were inconclusive on the effect of risk-taking attitude (risk tolerant vs risk averse) on lidar adoption, which is similar to previous flood risk management studies (e.g. Roberts & Wernstedt, 2019; Viglione et al., 2014). 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 investigate risk salience further to understand the layering of factors (e.g., technological risk, societal risk) in decision-making. For example, social 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. Lastly, trust in the accuracy of science minimally correlated with decreasing lidar adoption. This could be because the more an individual trusts the current floodplain maps, the more likely they are to accept them as is instead of trying to update the maps based on new data. Overall, the correlation of trust and technology adoption resulted in mixed effects such as previous studies found (e.g. Kellens et al., 2013; Viglione et al., 2014), and therefore needs to be examined in greater detail to determine significance of its effect on technology adoption for flood risk management.

Third, our findings show that collective predictors (peer influence, network strength, and network experience) most significantly facilitate the adoption of lidar (Figure 1.5). As expected, the respondents with 100% lidar users in their social network were 32% more likely to adopt lidar than those with 0% lidar users in their network. Our finding aligns with existing literature, which also found peer influence to be a facilitator of technology adoption (e.g., Lo, 2013; Poussin et al., 2014; Viglione et al., 2014). Network strength had the largest effect on lidar adoption, increasing the likelihood of lidar adoption almost 84% from flood risk managers who communicate mostly with non-lidar users to those who communicate with mostly lidar users. While network expertise did not have as large of an effect, it increased the likelihood of lidar adoption by almost 43% for respondents who had more expertise from lidar users in their network. These findings support the idea that peers can be highly influential when it comes to adopting new practices, as hypothesized by social learning and cultural evolutionary theory (e.g., Brooks et al., 2018; Mesoudi, 2019; e.g., Reed et al., 2010; Richerson et al., 2016). Furthermore, there was slight regional differences in social network characteristics where, overall, Washington reported the highest lidar peer influence, network strength, and network expertise. Interestingly, Washington also reported the highest percentage of lidar users (64.8%). These findings reiterate the correlation between social processes and lidar adoption, which we also found evidence for during our interviews (Table 1.6). One interview we conducted, with a floodplain manager from Idaho at a regional 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 helpful for me because I meet peers outside of just our immediate, that have similar programs." This is an intriguing point that highlights Washington as the source of lidar information for a flood risk manager in Idaho. Moreover, another interviewee 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." These results show a clear need for increased communication and collaboration for the exchange of critical information that could potentially improve flood risk management practices and lower flood damage in the future.

Fourth, our findings support the behavioral shift in flood risk management to focus on collective action. Rufat et al. (2020) calls for flood risk governance to include collaborative and participatory approaches, which is line with the United Nations Disaster Risk Reduction recommendations and policy goals and opposes historical flood risk governance which is based off false assumptions of individual responsibility for action. Furthermore, current flood risk management literature lacks coordinated and integrated theoretical approach to understanding the drivers of flood risk manager behavior and decision-making ((Kellens et al., 2013; Kuhlicke et al., 2020; Rufat et al., 2020). Our study exemplifies an interdisciplinary and integrated framework that could be replicated to understand the role and effect of collective predictors, alongside individual factors, on other risk mitigation behaviors.

Implications

Our first suggestion is a more targeted focus on increasing collaboration across flood risk manager communities within states and between states. The need for more established networks was found in both our interviews and survey analysis. Federal, state, and local level authorities capitalize on the importance of peer influence and communication, not only for lidar adoption, but for general information dissemination of effective flood risk mitigation behavior and sustained best practices for flood risk management. For example, states could provide targeted networking events for the lidar community to gather and communicate about lidar.

Secondly, we found that Washington had 1.3 times more lidar users than Idaho. In addition to our survey findings, this variation could also be driven by the lidar acquisition and coordination program in Washington. The Washington Geological Survey was granted funding from 2015-2021 for the collection and distribution of lidar data and lidar-derived products. Established in the Department of Natural Resources, the funding came from the Washington State General Fund and provided funding for two permanent lidar positions, a lidar manager and a lidar specialist. In addition, Washington focused on disseminating interactive (e.g. Washington Story Map) information on lidar to educate the public and advocate for sustained lidar investment at the state-level. Oregon and Idaho also have established lidar acquisition and coordination efforts; however, they do not have a permanently funded position to manage lidar. In summary, the lidar model in Washington, which includes two full time positions and sustained state funding, could be one of the reasons we see a higher lidar adoption rate in Washington. Following the model of Washington might promote increased use of lidar in the other states. This would require both policy and funding-level changes in Oregon and Idaho.

Limitations

While we can identify correlative trends, our analysis is limited in understanding the causal inference of these collective predictors on lidar adoption due to the cross-sectional nature of our study. Causal inference could be found by conducting a longitudinal study to see how lidar adoption changes over time, especially with target barrier reduction and increased channels for peer influence and resource sharing. In addition, our social processes results were limited by an ego network analysis that only provides one degree of peer connections. We suggest a full network analysis in the future, which could 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. 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 (Sugarbaker et al., 2014). Lastly, we were unable to confirm if our survey sample demographics represented the full flood risk manager populations in Idaho, Oregon, and Washington. Since our survey was distributed during COVID-19, it is possible that flood risk managers may have been consumed by other responsibilities regarding the pandemic and therefore were unable to take our survey limiting our sample size and scope.

Conclusion

Lidar provides flood risk managers with the technology needed to understand their communities flood risk in a changing environment. The variable adoption of this technology lends to an interesting case study of facilitators to technology adoption for long-term risk mitigation. We used a mixed-method empirical study to understand the individual and collective predictors of lidar use. Overall, peer influence, network strength, network and risk perception were positively correlated with lidar adoption. Whereas knowledge, risk-taking attitude, and trust did strongly correlate with lidar adoption. In addition, our interview findings were congruent with trends from our quantitative analysis. Specifically, there is a desire and need for increased communication and collaboration of flood risk managers within and between states. In the future, we suggest a longitudinal study to understand the change in lidar use over time in order to understand the causality of social processes and lidar adoption. We hope the findings of this study can be used to bolster flood risk management collaboration networks to facilitate targeted risk mitigation behaviors in the future. In addition, we hope that our framework, that uses cultural evolutionary theory and social learning theory, can be used in disaster and hazard management studies to quantify the impacts of collective factors on long-term risk mitigation behavior.

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CHAPTER TWO: PUBLIC SCHOLARSHIP—KNOWING MORE, LOSING LESS THROUGH INVESTMENT IN HIGH-QUALITY ELEVATION DATA IN IDAHO

Abstract

Both natural hazards and urbanization alter the landscape in which they occur. Local and state planners, managers, and officials need access to accurate data regarding the earth's topography, vegetation, and structures in order to respond to these landscape-level changes. Light Detection and Ranging (lidar) is a remote sensing technology that provides high-quality topographic data. However, there has been a slow uptake of raw lidar and lidar-derived products in Idaho. Using the Idaho-specific survey data collected in Chapter One, we quantified the barriers flood risk managers face with lidar adoption in Idaho. We found that lack of funding, expertise, and political support were the top barriers flood risk managers faced. In response, we created three educational outreach products to address these barriers: a webinar, a white paper, and a Story Map. In addition, we expanded our findings from the survey to any application that could benefit lidar in Idaho because we expect to find similar barriers to uptake in those fields. The varied forms of information dissemination will increase knowledge about lidar and in turn, will hopefully increase uptake.

Introduction

In recent years, Idaho has seen an increase in the number of dangerous heat days, drought threat, and number of large fires in conjunction with snowpack trending downward and precipitation increasing. These climate changes pose increased natural hazards threat. In addition, Idaho had the largest single-year population increase of the entire U.S. with a 2.1% increase from 2019-2020 (Press, 2020). The Treasure Valley alone is expected to grow by almost 53%, surpassing 1 million residents by 2040 (COMPASS, 2012). The culmination of hazards and growth over the last year, and projected growth, amplifies vulnerability and requires active, dynamic planning in order to ensure a resilient future for Idahoans. Both human-caused and natural hazards, alongside urbanization, alter the landscape. Planners, managers, and officials need access to accurate data regarding topography, vegetation, and structures in order to respond to these landscape-level changes.

Light and Detection Ranging (lidar) is a remote sensing technology that provides high-quality elevation data. Light can penetrate small openings in canopy cover allowing for measurements of ground features below the canopy, and other topographic features. The data can be processed into Digital Elevation Models (DEM), which show the bare earth and Digital Surface Models (DSM) which show structures such as trees or buildings, on the surface. In addition to raster-layer products, the raw and processed lidar point clouds provide flexibility for a variety of applications. For example, the point clouds can be used in their native 3-D point cloud format or reprocessed into rasters that are tailored to assessing vegetation health. Raw lidar data and lidar-derived products are widely-used across the United States for hazards, resource management, and urban planning, among other applications (e.g., Andersen et al., 2005; Chang et al., 2014; Clifton et al., 2018; Ellett et al., 2019; Muhadi et al., 2020).

In 2010, the U.S. Geological Survey (USGS) established the 3D Elevation Program (3DEP) 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. In 2013, the Idaho Lidar Consortium (ILC) was founded to provide a repository for publicly-available lidar, as well as provide a resource for state-level lidar acquisition and coordination in Idaho. In 2018, the Idaho Lidar Statewide Acquisition Plan (Plan) was created to establish an approach to acquire and recommend quality level standards of publicly-available statewide lidar data and lidar-derived products by 2026 (Elevation Technical Working Group, 2018). The ILC and the Plan have been instrumental in increasing lidar coverage from 18% in 2018 to 73% by the end of 2021. While the founding of ILC has been paramount for the initiation and upkeep of continued lidar data acquisition, there has been varying interest from potential users, in addition to varying resources to acquire lidar, resulting in a fragmented and incomplete lidar coverage of the state (Figure 2.1).

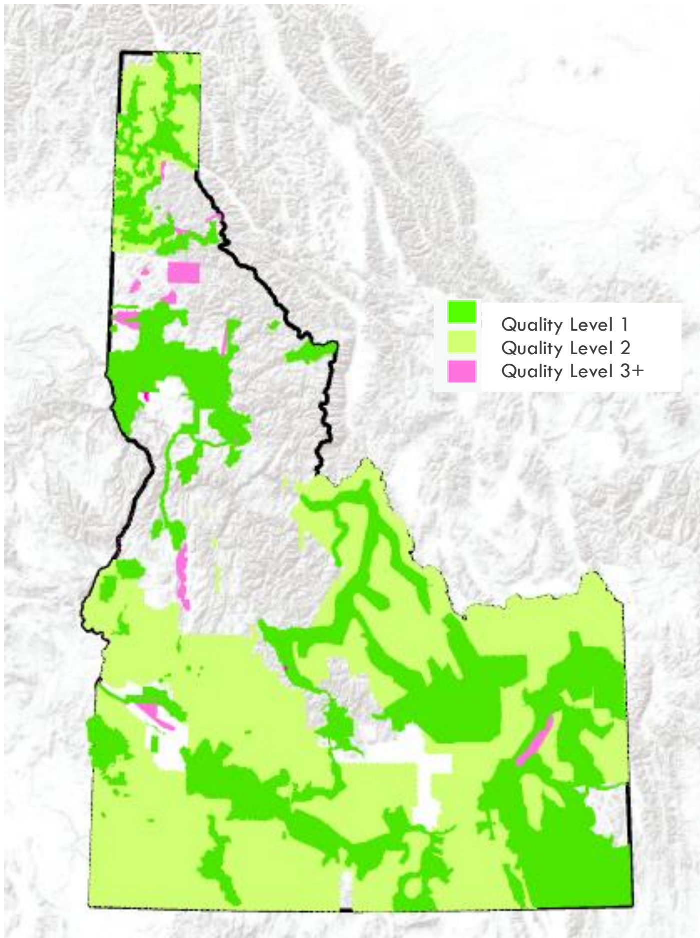

Figure 2.1. Project 2021 lidar coverage. QL represents quality level of lidar flown, where QL1 is the highest quality.

Applied Research

This chapter uses data gathered from Chapter One. Moreover, we specifically look at the data retrieved from Idaho-based survey respondents. In addition, we scale up adoption barriers from flood risk management to address adoption barriers across sectors (e.g. riverine ecosystem management, wildlife and habitat management, forest resource management) and scales (e.g. city, county, state). This approach is informed by innovation adoption theory, which postulates that one way to elicit change in adoption is by identifying the facilitators and barriers correlated with adoption (Wisdom et al., 2014). Some of the common barriers that prevent individuals from adopting are lack of awareness, familiarity, time, autonomy, and ability to access research (Wisdom et al., 2014).

Objectives

There were two main objectives: (1) to understand the current barriers to lidar adoption with flood risk managers in Idaho (2) create and disseminate three educational outreach products tailored to a specific audience and purpose across a wide-scope of lidar applications in Idaho. In order to do this, I worked closely with Dr. Nancy Glenn and Josh Enterkine from ILC to design and carry out an applied research project that aligned with the organization's short-term and long-term goals for lidar adoption in Idaho.

Methods

Case Study Methodology

We used the results from the survey instrument we created for Chapter One of my thesis. Specifically, we focused on solely survey responses from Idaho (n=96). One section of the survey asked respondents about barriers to lidar adoption in flood risk management (Figure 2.2).

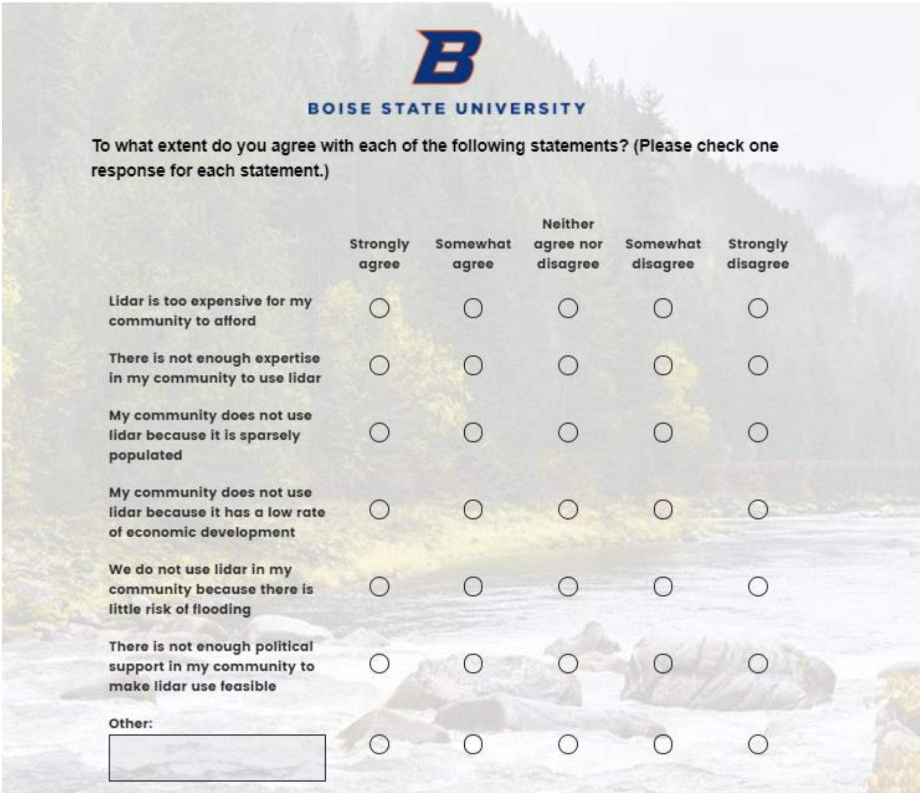

Figure 2.2. Survey question regarding barriers to lidar adoption. This question addressed six potential barriers flood risk managers may face and responses were collected on a likert scale.

In addition, we asked respondents about specific areas they would like training sessions regarding lidar to inform our educational outreach portion of this study (Figure 2.3).

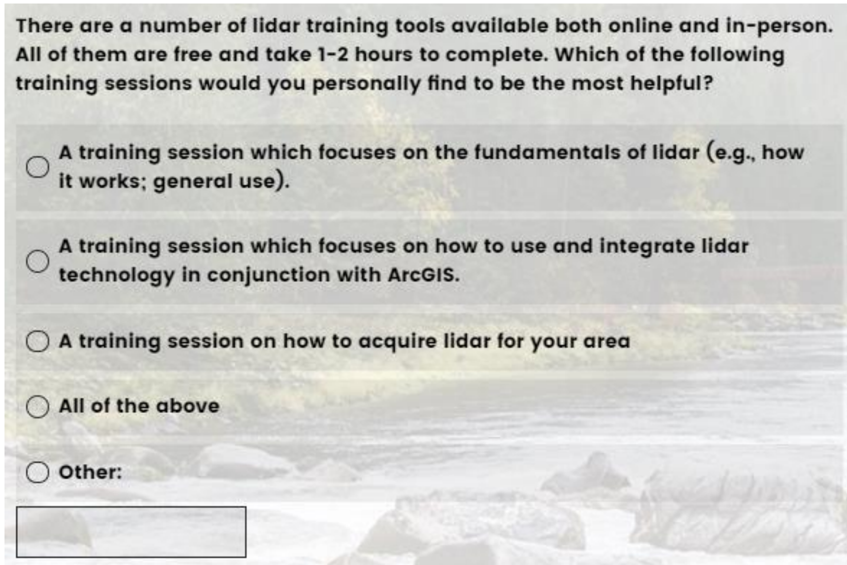

Figure 2.3. Survey question regarding educational workshops of interest to respondents. Survey respondents had four pre-specified answer choices and an open response option.

Communicating Results to Stakeholders

Based on our research findings from Figure 2.2 and Figure 2.3, we created three forms of sharing our results to community stakeholders. Each method of information dissemination was created with a specific audience, intention, and publishing format in mind. The three ways we did this were (1) a webinar summarizing our survey findings specifically for flood risk managers in Idaho, (2) a white paper for the Idaho Geospatial Council – Executive Committee and Elevation Technical Working Group, and (3) a Story Map for a broad audience of potential and current lidar users in Idaho.

The webinar titled, “Current State of Lidar in Idaho for Flood Risk Management”, was part of a series of webinars to engage the broader flood risk management community on lidar use. The intention of this webinar was to share our survey findings from both thesis chapters and discuss the implications of these findings for community stakeholders. This webinar was designed to incorporate best practices for engagement and learning including tailored message for target audience, guest speakers from varied backgrounds, "mini-lectures," audience engagement (e.g., introduction over chat, live discussion), and contact information of speakers for follow-up questions (Bedford, 2016).

The white paper, titled "Knowing More, Losing Less through Investment in High-Quality Elevation Data in Idaho," was written for a very specific audience, the Idaho Geospatial Council – Executive Committee and Elevation Technical Working Group. The intention behind this document was to discuss the current state of lidar acquisition in Idaho, as well as a call to action to ensure the completion of the goals set forth by the USGS 3DEP and the Idaho Lidar Statewide Acquisition Plan. The white paper format provided a way to quickly identify the problem and provide a solution to the problem in a concise, engaging format and inform governmental policy (Stelzner, 2007).

The third form of educational outreach we conducted was through the Environmental Systems Research Institute Story Map (Story Map) application. Research has found that Story Maps are an effective teaching tool for STEM subjects (Groshans et al., 2019). Another study found that Story Maps increase accessibility and enhanced participation in sustainability-related activities (Austin, 2018). In addition, Story Maps provide an integrative approach to science communication by combining concise text with engaging visuals. Considering these advantages, we created a Story Map, titled "Mapping for Resilience." It was written for a broad audience of potential and current lidar users. The intention behind this document was to educate the viewer about how lidar can be used to address a wide range of challenges posed by landscape change due to natural hazards and urbanization. This format provided an engaging and dynamic platform to display the versatility of lidar and complimented the goals of our white paper.

Results

<u>Case Study Results</u>

Around 50% of the survey respondents used lidar for flood risk management in Idaho (Table 1.8). When we examined this at a more granular level, we found that only 32% and 41% of flood risk managers at the City and County level, respectively, used lidar compared to 80% and 86% of flood risk managers at the Industry and State-level, respectively. This shows a clear discrepancy about who is using lidar. For the flood risk managers who did not use lidar, the survey asked about barriers that inhibited them. The top three barriers were lack of adequate funding, expertise, and political support with nearly 50% or more respondents selecting these barriers (Figure 2.4).

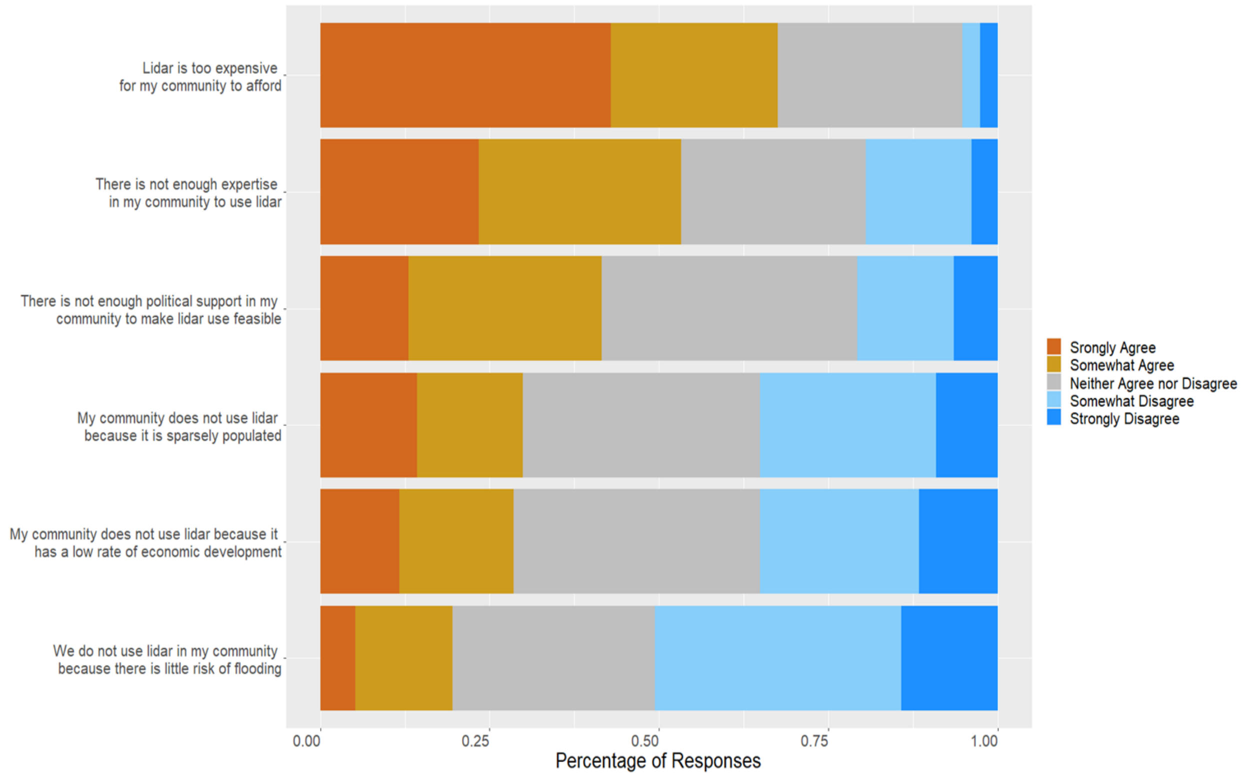

Figure 2.4. Descriptive summary of barriers to lidar adoption for flood risk managers.

In addition, we asked all survey respondents to answer the type of lidar training sessions they would like to attend in the future. 58% of respondents selected they would like to attend sessions about lidar fundamentals, lidar with ArcGIS, and lidar acquisition (Figure 2.5).

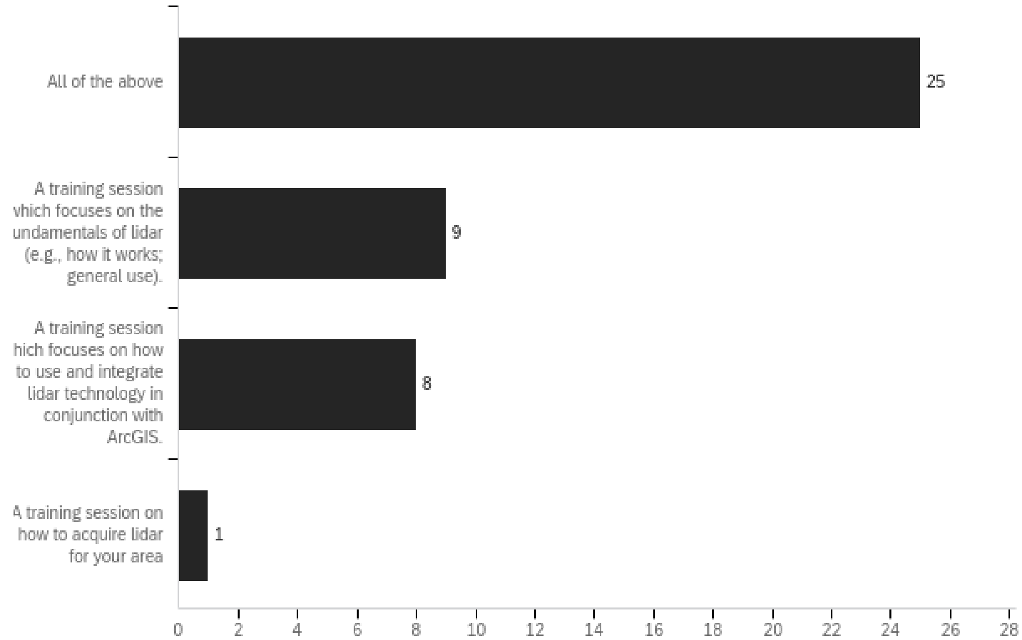

Figure 2.5. Descriptive summary of lidar training sessions of interest to survey respondents. Majority of respondents showed interest in all three trainings.

Communicating Results to Stakeholders Results

The webinar shared the Idaho-specific survey results in October 2020 over Zoom. We sent out the invitation to the webinar though multiple channels including the ILC website, the Idaho GIS listserv, and the Hazards and Climate Resiliency Institute contact list. There were over 65 individuals in attendance and included flood risk management stakeholders such as government officials, industry professionals, and academics. The first part of the webinar was a presentation about the history of lidar coverage in Idaho, the findings from the project, and two guest speakers, Linda Davis, the GIS Manager at the Idaho Department of Water Resources, and Kristine Hilt, the Blaine County Floodplain Manager. The second part of the webinar was a panel discussion facilitated by Dr. Nancy Glenn and prompted by questions from the audience.

The white paper and Story Map were based on the survey results regarding the top three barriers of lidar adoption, which were lack of adequate funding, expertise, and political support. The white paper (Appendix A) primarily focused on formulating an argument for a state-level lidar liaison position that could help facilitate funding opportunities and provide a source of support for the community interested in lidar. The Story Map was created to speak to each of the lidar training session subjects that in turn could minimize the expertise barrier felt by over 50% of the respondents. The story begins with background information about lidar and how it works. Then it describes several primary Business Uses of lidar in Idaho including flood risk management, wildfire management, wildlife and habitat management, riverine ecosystem management, and forest management, among others (Dewberry, 2012). Finally, the story ends with a section about how to acquire lidar and additional resources to build community. These documents will be distributed June 2021 through the ILC website and the Hazards and Climate Resiliency Institute at Boise State University. In addition, it will be distributed with lidar training courses through Idaho State University's GIS Training and Research Center.

Discussion

The three forms of educational outreach distribution played a key role in reaching a wide audience with tailored messaging to that audience. The first form, a webinar, was helpful for disseminating information specifically to flood risk managers, the focus of our case study. The live panel format allowed for an engaging discussion to occur and the online format over Zoom allowed for attendance of flood risk managers across the state. The white paper and Story Map were created for a broader lidar use audience, informed by the findings of our case study, since lidar is a technology that can be beneficial to multiple sectors and types of organizations. Furthermore, the online format of these products makes the broadcasting of these materials easier.

The past year in Idaho was greatly affected by the COVID-19 pandemic and likely lowered the number of survey responses we received. Specifically, we had a survey response rate of 25% in Idaho (Table 1.5); therefore, we did not hear from most of the potential survey respondents. While this survey response rate is typical of an online survey, it is possible this number was lower this year because of flood risk manager's involvement with emergency management in their communities (Sauermann & Roach, 2013). In addition, we were unable to hold in-person interviews and workshops because of COVID-19. While we were still able to complete the important components of the project, I feel as if I did not experience some of the benefits of in-person work such as growing a closer connection with the lidar community in Idaho. Richer connections in the flood risk manager community could have led to increased education for me and community members.

In the future, we suggest sending out the survey again to see if lidar adoption rates increased after this project's educational materials were instituted as a way of assessing product efficacy. This could lead to a longitudinal study, which would better inform how we understand technology adoption. We recommend expanding the survey beyond flood risk managers to all individuals and organizations that may use lidar. This would result in a greater understanding of the landscape of barriers that lidar adopters face. Finally, we recommend that the educational outreach products, specifically the white paper and Story Map, remain as live, dynamic documents that can be updated to reflect the current needs of lidar acquisition and coordination in Idaho.

Future Work

The white paper and Story Map will first be distributed to the Idaho Geospatial Council – Executive Committee and Elevation Technical Working Group on June 3rd. I plan to do this through a presentation and electronic dissemination of materials to relevant individuals. Once the committee has given feedback, we hope to submit the white paper and Story Map to state elected officials to get funded. In addition, the Story Map is a living document that we would like to keep up-to-date as lidar use increases throughout the State.

Conclusion

Using the Idaho-specific survey data from Chapter One, we found that flood risk managers in Idaho experience several barriers to lidar adoption resulting in only 50% of managers using lidar. The top three barriers we found were lack of funding, lack of expertise, and lack of political support. In addition, we found that flood risk managers would like workshops in lidar fundamentals, lidar use with ArcGIS, and lidar acquisition. Considering these findings, we created three forms of educational outreach to create materials tailored for a specific audience and purpose. We held a webinar to share our survey results with flood risk managers in Idaho, wrote a white paper to advocate for a lidar liaison and permanent budget for lidar acquisition and coordination with support from state-level organizations, and created a Story Map to educate current and potential lidar users about lidar fundamentals, applications, and acquisition. We found this work to be received well by the lidar community in Idaho and are hopeful that these educational materials will increase lidar uptake in Idaho.

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APPENDIX A

Knowing More, Losing Less through Investment in High-Quality Elevation Data in Idaho White Paper

Knowing more, Losing Less through Investment in High-Quality Mapping in Idaho

BOISE STATE UNIVERSITY

May 2021

Written by:

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Dr. Nancy Glenn

Josh Enterkine

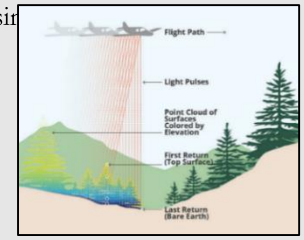
Introduction

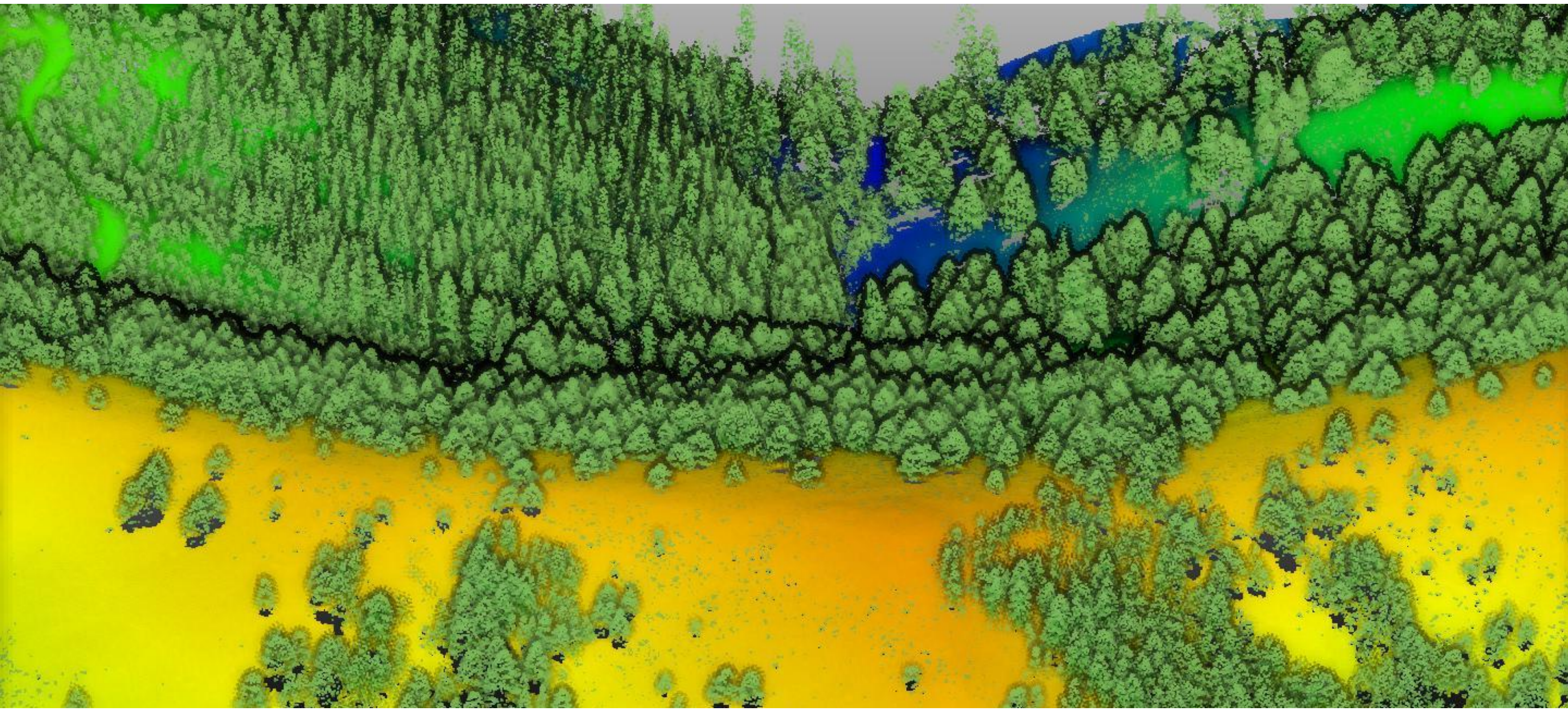
In recent years, Idaho has seen an increase in the number of dangerous heat days, drought threat, and number of large fires in conjunction with snowpack trending downward and precipitation increasing. In addition, Idaho had the largest single-year population increase of the entire U.S. with a 2.1% increase from 2019-2020 (Idaho Business Review, 2020). Furthermore, the Treasure Valley, alone, is expected to grow by almost 53%, amounting to over 1 million residents, by 2040 (COMPASS, 2012). Natural hazards, as well as urbanization alter the landscape in which they occur and therefore planners, managers, and officials need access to accurate data regarding Idaho's topography and vegetation. Light and Detection Ranging (lidar) is a remote sensing technology that provides high-quality topographic data for hazard mitigation. Raw lidar data and lidar-derived products have become widely-used across the United States for hazards, resource management, and urban planning, among other applications, because it creates high-resolution, accurate maps. In response to this growing need for high-quality data, several states have created permanent, state-level positions to manage and coordinate lidar data acquisition efforts (Appendix B). In Idaho, the Idaho Lidar Consortium (ILC) currently manages state-level lidar data coordination efforts. The ILC helped coordinated lidar acquisition across the state, leading to 73% coverage by the end of 2021. While the amount of publicly-available lidar is increasing it is critical that Idaho invests in a plan that ensures continued lidar data collection and implementation to increase the resiliency of Idaho in the future.

This white paper discusses the lidar acquisition process in Idaho and calls for action to ensure the completion of the goals set forth by the USGS 3D Elevation Program (3DEP) and the [Idaho Lidar Statewide Acquisition Plan.]

Lidar Processing

For large areas, lidar data is most commonly collected using airplanes and helicopters. Light is able to penetrate small openings in canopy cover allowing for measurements of ground features below the canopy as well as other topographic features. The data can be processed into Digital Elevation Models (DEM) which show bare earth and Digital Surface Models which show structures (see image below), such as trees or buildings, on the surface. In addition to raster-layer products, the raw and processed lidar point clouds provide flexibility for a variety of applications. For example, the point clouds can be used in their native 3-D point cloud format or reprocessed into rasters that are tailored to assessi





History of Elevation Data in Idaho

2021

- An additional 56% (47,000 sq. miles) of the state will be mapped (some remapped) amounting to 73% (60,783 sq. miles) of the state covered with lidar.

2020

- 25% (24,000 sq. miles) of the state is covered with lidar data.

2018

- Idaho Lidar Statewide Acquisition Plan was created to establish an approach to acquire publically-available statewide lidar data and lidar-derived products for Idaho by 2026 and set reommended standards for lidar data.

2013

- Idaho Lidar Consortium (ILC) is founded to provide a repository for publically-available lidar, as well as a resource for state-level lidar coordination and acquisition in Idaho.

2010

- USGS establishes 3D Elevation Program (3DEP), the first nationally-coordinated lidar acquisition program with a goal of having the complete lidar coverage of the US by 2023 given adequate funding. This would be the first-ever national baseline of consistent high resolution topographic elevation data, including bare earth and 3D point clouds.

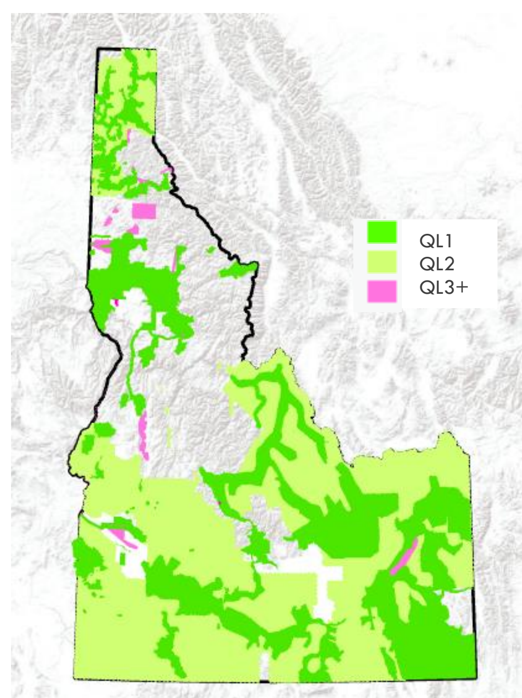
2000

- USGS National Elevation Dataset (NED) provides publically-accessible 10-meter and 30-meter topographic data in Idaho.

Idaho Lidar Coverage

Historically, publicly-available lidar data has been acquired in Idaho through various interested parties such as county officials (e.g., Nez Perce County) and public agencies such as the US Forest Service (USFS), Federal Emergency Management Agency (FEMA), and United States Geological Survey (USGS). While these data are important, this approach to data acquisition has resulted in fragmented and incomplete lidar data coverage in the state. The founding of the ILC has been paramount for the initiation and upkeep of continued lidar data acquisition throughout the state of Idaho. For example, the ILC is currently working to create an official lidar-derived topographic layer for the state of Idaho. This layer will provide a 1-meter resolution DEM that can be used for a wide range of applications. In addition to this product, the ILC aims for continuous up-to-date raw lidar data available across the entire state.

Figure 1. Lidar coverage in 2021. Quality Level 1 (QL1) represents the highest lidar quality level in Idaho. See Appendix C for specifications.



Who is using lidar data in Idaho?

Lidar is currently being used by a range of individuals and agencies including GIS technicians, planners, engineers, academics, among others. Since lidar is used by a vast range of individuals, we spent the last year and a half focused on one specific group of lidar users to learn more about why an individual would or would not adopt the technology; that group was flood risk managers in Idaho. It became evident, through my research, that City and County officials were using lidar at a much lower rate than industry and State-level officials and that several barriers existed in the uptake of lidar including lack of adequate funding and expertise. While these findings are based in flood risk manager's experience, they can also be used to bolster our strategic plan for lidar acquisition and coordination for Idaho, overall, through incorporating measures to reduce uptake barriers and increase accessibility to lidar data and lidar-derived products in Idaho in the future.

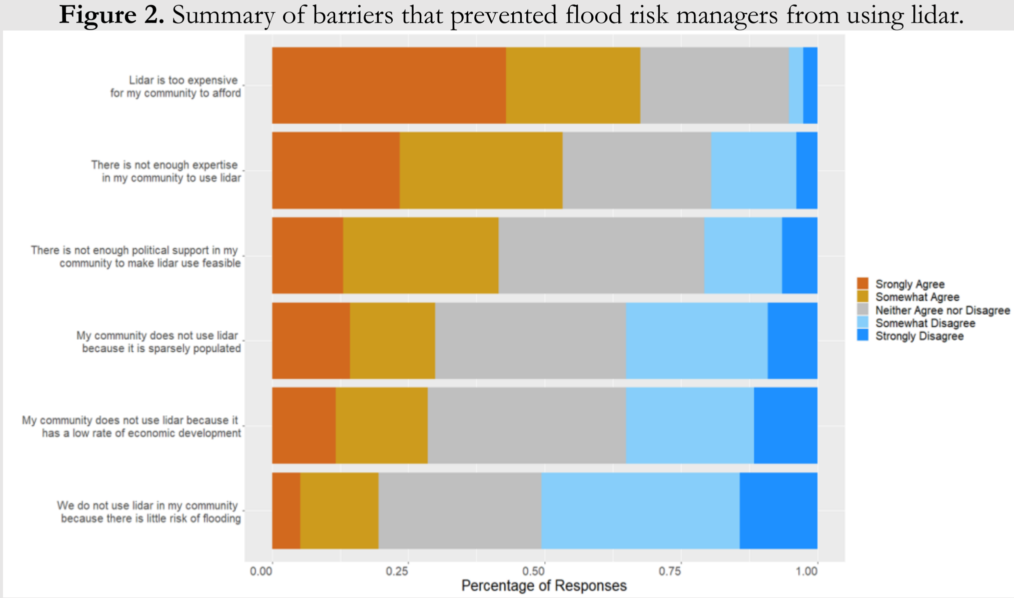
Case study: Lidar Use in Flood Risk Management

This past year we conducted several interviews with flood risk managers to understand the landscape of lidar use in flood risk management in Idaho. Several common themes arose from these conversations:

Barriers	Opportunities
- Rural regions with smaller populations typically have **lower priority** for revised mapping - Lidar is seen as **expensive** and not all communities / regions have adequate funding - There is **potential distrust** in scientific products and/or the federal government - **Hesitancy** towards publicly-accessible lidar from private landowners	- Lidar is useful and **desirable** to work with - Elected officials have **authority in lidar acquisition** - **Community relationships** can be influential in lidar adoption - Lidar acquisition is **facilitated by collaboration** across multiple institutions and stakeholders

These results informed a survey that we sent out from June to August 2020. From this survey, we found that half the respondents used lidar. When we examined this at a more granular level, I found that only 32% and 41% of flood risk managers at the City and County level, respectively, used lidar compared to 80% and 86% of flood risk managers at the Industry and State-level, respectively. This showed a clear discrepancy about "who" is using lidar. Figure 2, below, reports our findings from the survey on the barriers experienced by flood risk managers.

Figure 2. Summary of barriers that prevented flood risk managers from using lidar.



Examples of lidar applications

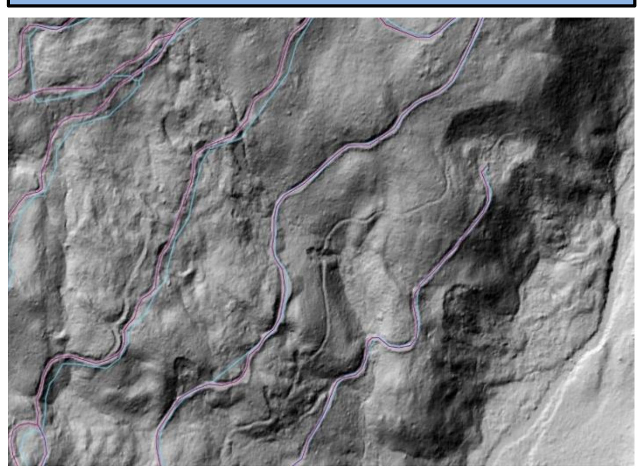
Given the influx of lidar data in Idaho, it has already been used in a wide-array of applications, which the USGS has categorized into specific, measurable Business Uses (BU). There are currently 13 BUs that have been identified for Idaho, which are summarized in Appendix A. Here are two examples of successful applications of lidar within these BUs. To learn about additional lidar applications and how they are making Idaho a more resilient state to climate change and population growth, visit this Storymap about lidar in Idaho called "Mapping for Resilience".

Flood Risk Management: flood risk modeling and mapping of riverine areas
More than 50% of the counties that are using floodplain maps in Idaho are using maps from before 2002 (IOEM, 2018). There is a need to update flood hazard maps to reflect accurate risk based on high-quality topographic data.

In 2017, there were over 100 days of flooding along the Boise River. However, this flooding occurred at much a lower flow rate than officials expected. This event, along with increased urbanization and population, motivated the acquisition of lidar along the Boise River so that flood risk managers could accurately assess the flood potential of the Boise River in the future. This includes modeling flow rates representative of climate change, which is expected to change the timing of peak flows along the river. In addition, lidar can be used to develop a 2-dimensional hydraulic routing model that can provide estimates of physical parameters (e.g., depth and velocity) that can be key components for identifying the spatial distribution of conditions that are critical to account for in water quality models and studies. These studies can illuminate critical habitat, pollutant transport, sediment deposition and scour, and channel migration.

Around three million acres of the Payette National Forest were flown with Quality Level 1 lidar. It is used for many applications including fire planning, timber harvesting, and transportation planning. The detailed nature of lidar data helps planners efficiently improve databases by correcting road alignments, updating inventory, and digitizing roads not already identified. The image to the right shows pre-2017 National Forest Road alignments based on aerial imagery in blue. The realigned National Forest System Roads based on higher-quality lidar data are in magenta. Numerous other routes can be seen in the area which have been inventoried for future analysis. Planners also use lidar to identify channels and define horizontal buffer zones to map channel proximity to road systems. One way lidar is especially helpful is that it can display channel migration, which can help planners understand the history of a channel. The image on Page 6 shows an example of channel migration in Payette River.

Forest Resources Management: plan, monitor, and protect forest resources
Forests are a valuable renewable resource for Idaho. Forests provide a significant asset for the state, as well as for wildlife, recreation, and the climate among other uses.



Considerations to increase lidar coverage and uptake

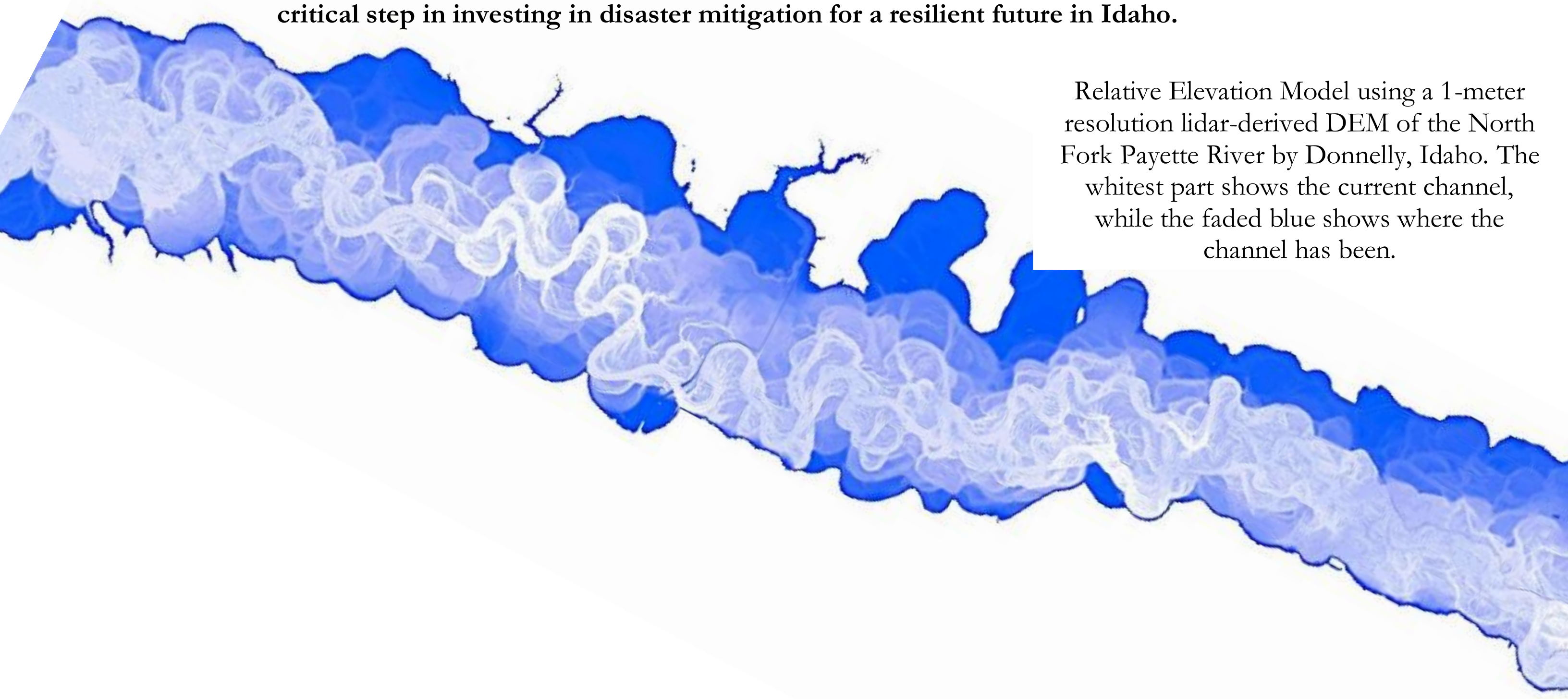
Publicly-accessible lidar data and lidar-derived products have increased in Idaho over the last decade. However, we think a commitment to continuing investment is needed in order to sustain lidar acquisition in the future. One way we could move lidar forward is by engaging in a broader discussion with the state's Elevation Technical Working Group and the Idaho Geospatial Council – Executive Committee. We recommend the following items be considered, discussed, and potentially incorporated into the "Idaho GIS Strategic Plan":

1. A permanent job role at the state-level specifically for coordinating and managing lidar acquisition for Idaho. The ILC acts as a state-level coordinator currently, however this position is dependent on support from universities and external, non-permanent grant funds.
2. A one-time budget approved at the state-level to execute lidar acquisition for the remaining areas of the state that do not currently have lidar and replacement of existing lidar coverage that is 10 years or older.
3. A recurring budget approved for continual lidar acquisition in the future to keep in-line with the Update Frequency outlined in Appendix A.
4. Recurring budget for lidar workshops to educate individuals on how to use lidar with the relevant software needed to complete the BU's outlined in Appendix A.

Benefits of a permanent, state-level investment in lidar include:

1. Systematic, coordinated, and standardized data collection for the entire state.
2. Lidar data and lidar-derived products will be publicly-available across the entire state.
3. Economies of scale provides the potential for lower costs per square mile of data collected due to potential for larger swaths of data collection at a time.
4. There is potential for a greater amount of higher quality lidar data. The USGS 3DEP program provides funding for lidar acquisition projects of Quality Level 2. State-level coordination with local agencies and academic institutions is critical for leveraging lidar acquisition efforts that fund data collection with a minimum of Quality Level 1, which is required for heavily forested and complex terrain.

The Idaho Office of Emergency Management estimates that for every $1 spent on mitigation, there will be $6 in disaster savings. **Budgeting for permanent lidar acquisition and coordination is a critical step in investing in disaster mitigation for a resilient future in Idaho.**



Relative Elevation Model using a 1-meter resolution lidar-derived DEM of the North Fork Payette River by Donnelly, Idaho. The whitest part shows the current channel, while the faded blue shows where the channel has been.

Appendix A

Table 1. There have been 13 primary Business Uses (BU) across seven agencies with specific Mission Critical Activities (MCA) identified for Idaho. These were identified from a survey conducted in 2018 when less than 20% of Idaho has publicly-available lidar (Dewberry & USGS, 2021).

MCA Description				Requirements			Future Operational Benefits	Future Customer Service Benefits	Future Societal Benefits		
Primary Business Use	Agency/ Organization Name	MCA No.	Mission Critical Activity	Data Type	QL/Order	Update Frequency	Total Estimated Annual Operational Benefits	Total Estimated Annual Customer Service Benefits	Education or Outreach	Environ-mental	Public Safety
BU 01 – Water Supply and Quality	Idaho Department of Environmental Quality	21640	Environmental Protection	Inland Topo	QL1	2-3 years	$36,180	Unable to quantify	None	Moderate	Minor
				Inland Bathy	Cross sections and/or transects meet needs	4-5 years	Unable to quantify	Unable to quantify	Moderate	Major	Moderate
BU 02 – Riverine Ecosystem Management	State of Idaho	60130	Riverine Ecosystem Management	Inland Topo	QL1 HD	6-10 years	$127,912	$12,776	Major	Major	Major
				Inland Bathy	QL0B	4-5 years	$68,092	$4,801	Major	Major	Major
BU 04 – Forest Resource Management	State of Idaho	60131	Forest Resources Management	Inland Topo	QL1	2-3 years	$330,414	$478,974	Major	Major	Major
BU 06 – Natural Resource Management	Nez Perce Tribe	21639	Nez Perce Tribe Homeland Asset Management	Inland Topo	QL0	4-5 years	$210,407	$31,150	Moderate	Major	Major
				Inland Bathy	QL1B	4-5 years	$52,683	$20,000	Major	Major	Major
BU 07 – Wildlife and Habitat Management	State of Idaho	60132	Wildlife and Habitat Management	Inland Topo	QL2	4-5 years	$19,906	$57,495	Moderate	Major	Moderate
BU 10 – Geologic Assessment	Idaho Department of Water Resources	1305	Recharge Projects Located Within the Eastern Snake Plain Aquifer Groundwater Model Area	Inland Topo	QL1	4-5 years	$56,030	Unable to quantify	Major	Major	Major
BU 10 – Geologic Assessment	Idaho Geological Survey	21557	Geologic Mapping and Analysis	Inland Topo	QL1	6-10 years	$17,640,510	$309,679	Major	Major	Major
				Inland Bathy	QL2B	>10 years	Unable to quantify	Unable to quantify	I don't know	I don't know	I don't know

BU 12 – Renewable Energy Resources	State of Idaho	60133	Renewable Energy Resources	Inland Topo	QL2	6-10 years	Unable to quantify	Unable to quantify	Minor	Minor	None
BU 15 – Flood Risk Management	State of Idaho	60134	Flood Risk Management	Inland Topo	QL2	4-5 years	$11,733,536	$2,053,001	Major	Moderate	Major
BU 17 – Wildfire Management	Idaho State University	1403	Wildfire Management	Inland Topo	QL1	6-10 years	$449,002	Unable to quantify	Moderate	I don't know	Minor
BU 19 – Land Navigation	Idaho Transportation Department, Division of Highways, District 5	22502	Highway Design, Construction, and Related Activities	Inland Topo	QL2	4-5 years	Unable to quantify	Unable to quantify	Moderate	Major	Moderate
				Inland Bathy	Cross sections and/or transects meet needs	4-5 years	Unable to quantify	Unable to quantify	Minor	Moderate	Minor
BU 20 – Marine and Riverine Navigation	State of Idaho	60135	Marine and Riverine Navigation and Safety	Inland Bathy	QL0B	2-3 years	$1,524,362	$200,623	Moderate	Moderate	Moderate
BU 21 – Aviation Navigation	State of Idaho	60136	Aviation Navigation and Safety	Inland Topo	QL1 HD	Annually	$282,507	$351,854	Minor	Moderate	Moderate

Appendix B

Table 2. Examples of lidar programs in other states.

State	Lidar Delegation	Number of Positions and Titles	Historical Funding Sources*, **	Percent of State Covered in Lidar***	More Information:
California	California Natural Resources Agency, California Department of Conservation	One position (GIS Coordinator)	Federal: USGS, USFS, FEMA, NPS, USACE, NOAA State: Potentially California General Fund Local: County (e.g., Santa Clara, Santa Cruz)	Over 50%	No lidar website No plan Lidar storymap Lidar budget proposal
Washington	Department of Natural Resources	Two positions (lidar manager, lidar specialist)	Federal: USGS, FEMA, USACE, NOAA, NPS, USFS State: State General Fund Local: County (e.g., Pierce, King)	Over 75%	Lidar website Lidar acquisition plan
Illinois	Illinois State Geological Survey	One position (lidar liaison)	Federal: USACE, USGS, NRCS, FEMA State: IDNR, ISGS, IDOT Local: County (e.g., Cook, Kane)	100%	Lidar website Lidar acquisition plan
Florida	Florida Division of Emergency Management	One position (GIS administrator)	Federal: USACE, USGS, NOAA, NPS, FEMA State: State General Fund Local: County (e.g., Leon, Osceola)	Almost 100%	Lidar website Lidar acquisition plan
Kansas	Data Access and Support Center	Working group (TAC Elevation Data Committee)	Federal: USACE, USGS, NRCS, FEMA State: none Local: County (e.g., Adair, Mayes), City (e.g., Ardmore, Grand Lake)	100%	Lidar website No plan Lidar timeline presentation

*Information gathered from the U.S. Interagency Elevation Inventory; however, it is likely there are additional funding sources not captured here.

** Acronyms: USGS (United States Geological Survey), USFS (United States Forest Service), FEMA (Federal Emergency Management Agency), NPS (National Park Service), USACE (United States Army Corps of Engineers), NOAA (National Oceanic and Atmospheric Association), NRCS (Natural Resource Conservation Service), IDNR (Illinois Department of Natural Resources), ISGS (Illinois State Geological Survey), IDOT (Illinois Department of Transportation)

**This includes all data Quality Level 3 or better since lidar acquisition began in each state. See Appendix C for Quality Level Specifications.

Appendix C

Table 3. Lidar Quality Levels based on USGS standards.

Quality Level (QL)	Aggregate nominal pulse spacing (m)	Aggregate nominal pulse density (pulse/m^2)	Smooth surface repeatability, RMSD (m)	Swatch overlap difference, RMSD (m)
QL0	≤0.35	≥8.0	≤0.03	≤0.04
QL1	≤0.35	≥8.0	≤0.06	≤0.08
QL2	≤0.71	≥2.0	≤0.06	≤0.08
QL3	≤1.41	≥0.5	≤0.12	≤0.16

References and Credits

Photos:

Introduction: 3D Point Cloud by Josh Enterkine & Lidar Flight Image by Vermont Center of Geographic Information

Elevation Data Timeline: 2021 Idaho Lidar Coverage Map by Josh Enterkine

Example of lidar applications: Boise River Flooding by the Idaho Statesman and Road Alignment by Jason Wright

Considerations: 3D Point Cloud by Tara Pozzi

References:

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APPENDIX B

Interview Instrument

Study Title: Promoting the use of lidar for flood risk preparedness, planning, and adoption in municipalities across the western US

Interview Script

Principal Investigator: Tara Pozzi

Collaborating Groups/Individuals: Dr. Vicken Hillis, Boise State University

Researcher: *Collect consent forms.* “Thank you for agreeing to speak with me today. The purpose of this study is to better understand how floodplain management currently works, identify gaps and barriers to the implementation of lidar use, and provide opportunities for knowledge and information sharing across the region. You are being asked to participate because you have a stake in flood risk management for your region. If you agree to a semi-structured interview you will be asked to participate in a 1-hour interview and answer questions regarding your role in flood risk management. This may include a short-written questionnaire, audio recording and/or note taking with your permission.

Basic metadata questionnaire Interview Number______(completed by researcher)

Today’s date
Age
Gender
Ethnicity

What is the highest level of education you completed?
1) Some high school
2) High school diploma
3) College education, did not graduate
4) College education, Associates degree
5) College education, Bachelor’s degree
6) Post College, no degree
7) Advanced degree (MA, JD, MBA)

What was your degree?
1) Engineering
2) Planning
3) Business
4) Geography
5) Public Administration
6) Political Science
7) Geology
8) Other

Percent of your time spent on floodplain management.

1) 0-10%
2) 11-20%
3) 21-30%
4) 31-40%
5) 41-50%
6) More than 50%

Floodplain manager experience

1) < 5 years: how many?______
2) 6-10 years
3) 11-15 years
4) 16-20 years
5) > 21 years

What is your approximate yearly household gross income, including all ranch and off ranch income (circle one)?

1) Less than $24,999
2) $25,000 to $34,999
3) $35,000 to $44,999
4) $45,000 to $54,999
5) $55,000 to $64,999
6) $65,000 to $74,999
7) More than $75,000

Are you a Certified Floodplain Manager (CFM)?

1) Yes
2) No

Semi-Structured Questions

Section 1: Interviewee background information

What is your background with flood risk management?

What is your current job title?

What responsibilities do you have in your current role? How much time do you dedicate to each of your responsibilities?

Are you solely responsible for floodplain management or do you have other responsibilities?

Where do you do most of your work? From an office, house, the field?

What professional organizations are you apart of? Do you partake in any continued education courses, and if so what type?

Section 2: Local floodplain management practices

How many floodplain management staff are there? What are the combined years of staff experience in floodplain management?

At a general level, what factors control or significantly influence your work? Policy makers, community welfare, funding, etc.

How does funding work for your region? What are your typical revenue sources? i.e., grants, loans, taxes, technical assistance programs, etc.

What stakeholders (organizations, agencies, people, etc.) do you regularly work with?

Do you follow the minimum floodplain management practices set forth by NFIP? If so, are any of those stricter than NFIP's requirements? Do you feel like you know best management practices for your region?

How well do you think all vested interests in this industry collaborate, coordinate, and communicate with one another? Including other floodplain managers, engineers, developers, homeowners, farmers, etc.

How has recent development affected your floodplain management practices?

Section 3: Flood risk perception in your region

What level of flooding risk do you associate with the area you are responsible for? What is the typical frequency, size, or timing of flooding events? When was the last significant flood event?

How is the flood risk management process conducted in terms of identification, assessment, planning and implementation of projects?

What resources do you use to obtain information about precipitation, climate patterns, etc. that influence your understanding of flood risk?

What are your beliefs on changing climate patterns? Does this affect how you see risk your region?

Does urbanization provide additional risk your region?

What is the extent of public engagement regarding flood risk management and how do you go about engaging the community in these topics?

Section 4: Lidar use in floodplain management

What is your current mapping system? How accurate do you think your current mapping system is in identifying areas of vulnerability in your region?

Are there parts of your region that are unmapped and if so, where? And how do manage flood vulnerabilities in those areas?

Do you personally work with lidar? What other technology do you most often use for flood management?

How do members of the industry use lidar for floodplain management? What is their opinion on this technology?

Section 5: Changes and barriers to change in the industry

What do you see as barriers or issues in floodplain management today? And why do you think they exist? (e.g., where are current gaps or resources you wish you had?)

Based on your previous answer, are there specific areas that our research could assist with flood risk management? If so, where could we be most helpful in filling those gaps?

What do you see as the most effective way to increase lidar uptake in your region?

APPENDIX C

Survey Instrument

Technology Adoption in Flood Risk Management

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 are being asked to participate in this survey because you are 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 answers will be used to contribute to understanding the role lidar plays in flood risk management, as well as help us identify challenges and barriers that may exist to its implementation.

We anticipate the survey will take less than 15 minutes.

Please note:
You must be at least 18 years old to participate. Your participation is voluntary, and your responses will remain confidential. No personally identifiable information will be associated with your responses in any reports of the data. If there are any items that you would prefer to skip, please leave the answer blank.
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.

○ I do not want to participate.

End of Block: Consent Form

Start of Block: Screening Question

This survey is intended for people with primary decision responsibility in flood risk management. 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

Start of Block: Section 3: Local Floodplain Information

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

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 applicable to you.

____

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

What is the reason your community is not enrolled in the NFIP?

____

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 future, how likely is it, if at all, 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

This next series of questions is about the current topographic data and floodplain maps in the community you work with in flood risk management.

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.

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

- ◯ 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 as the current average?

- ◯ 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

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

Start of Block: Section 2.2: No to lidar use

Which of the following reasons prevents you from using lidar (check all that apply)?

	Definitely yes	Probably yes	Might or might not	Probably not	Definitely not
Lack of funding	○	○	○	○	○
Lack of knowledge on how to use lidar	○	○	○	○	○
Sparse population in your flood risk area	○	○	○	○	○
Low development rate and/or urbanization in your flood risk area	○	○	○	○	○
Feel that your area does not have a significant flood risk and therefore does not need new mapping data	○	○	○	○	○
Lack of political support	○	○	○	○	○
Other:	○	○	○	○	○

How useful or useless do you think lidar could be for your flood risk area?

- ○ Extremely useful
- ○ Very useful
- ○ Moderately useful
- ○ Slightly useful
- ○ Not useful at all

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 from (check all that apply)?

- ☐ Federal website
- ☐ State website
- ☐ County website
- ☐ City website
- ☐ Idaho lidar Consortium
- ☐ Private source
- ☐ Other: ____

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.

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: Alter one

How often do you communicate (e.g. in-person, online, over the phone) with ${alter_names/ChoiceTextEntryValue/1}?

- ○ 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 ${alter_names/ChoiceTextEntryValue/1} use lidar?

- Yes
- No
- I do not know.

On a scale from 1 to 10, do you think of ${alter_names/ChoiceTextEntryValue/1} as having or lacking expertise 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

End of Block: Section 6.1: Alter one

Start of Block: Section 6.2: Alter two

How often do you communicate (e.g. in-person, online, over the phone) with ${alter_names/ChoiceTextEntryValue/2}?

- 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 ${alter_names/ChoiceTextEntryValue/2} use lidar?

○ Yes

○ No

○ I do not know.

On a scale from 1 to 10, do you think of ${alter_names/ChoiceTextEntryValue/2} as having or lacking expertise 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

End of Block: Section 6.2: Alter two

Start of Block: Section 6.3: Alter three

How often do you communicate (e.g. in-person, online, over the phone) with ${alter_names/ChoiceTextEntryValue/3}?

○ 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 ${alter_names/ChoiceTextEntryValue/3} use lidar?

◯ Yes

◯ No

◯ I do not know.

On a scale from 1 to 10, do you think of ${alter_names/ChoiceTextEntryValue/3} as having or lacking expertise 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

End of Block: Section 6.3: Alter three

Start of Block: Section 6.4: Alter four

How often do you communicate (e.g. in-person, online, over the phone) with ${alter_names/ChoiceTextEntryValue/4}?

◯ 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 ${alter_names/ChoiceTextEntryValue/4} use lidar?

◯ Yes

◯ No

◯ I do not know.

On a scale from 1 to 10, do you think of ${alter_names/ChoiceTextEntryValue/4} as having or lacking expertise 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

End of Block: Section 6.4: Alter four

Start of Block: Section 6.5: Alter five

How often do you communicate (e.g. in-person, online, over the phone) with ${alter_names/ChoiceTextEntryValue/5}?

◯ 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 ${alter_names/ChoiceTextEntryValue/5} use lidar?

◯ Yes

◯ No

◯ I do not know.

On a scale from 1 to 10, do you think of ${alter_names/ChoiceTextEntryValue/5} as having or lacking expertise 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	

End of Block: Section 6.5: Alter five

Start of Block: Section 6.6: Alter six

How often do you communicate (e.g. in-person, online, over the phone) with ${alter_names/ChoiceTextEntryValue/6}?

◯ 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 ${alter_names/ChoiceTextEntryValue/6} use lidar?

- ◯ Yes
- ◯ No
- ◯ I do not know.

On a scale from 1 to 10, do you think of ${alter_names/ChoiceTextEntryValue/6} as having or lacking expertise 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

End of Block: Section 6.6: Alter six

Start of Block: Section 6.7: Alter seven

How often do you communicate (e.g. in-person, online, over the phone) with ${alter_names/ChoiceTextEntryValue/7}?

- ◯ 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 ${alter_names/ChoiceTextEntryValue/7} use lidar?

- Yes
- No
- I do not know.

On a scale from 1 to 10, do you think of ${alter_names/ChoiceTextEntryValue/7} as having or lacking expertise 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

End of Block: Section 6.7: Alter seven

Start of Block: Section 6.8: Alter eight

How often do you communicate (e.g. in-person, online, over the phone) with ${alter_names/ChoiceTextEntryValue/8}?

- 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 ${alter_names/ChoiceTextEntryValue/8} use lidar?

○ Yes

○ No

○ I do not know.

On a scale from 1 to 10, do you think of ${alter_names/ChoiceTextEntryValue/8} as having or lacking expertise 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	

End of Block: Section 6.8: Alter eight

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)

What was your degree?

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

How much do you trust or distrust the accuracy of scientific products the federal government develops with respect to 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 (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-- custom

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.

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