9-2-2023

Race and Income as Predictors of Trust in Flood Mitigation Strategies

Wendy Nathaly Sangucho Loachamin
Portland State University

Race and Income as Predictors of Trust in Flood Mitigation Strategies

by

Wendy Nathaly Sangucho Loachamin

A thesis submitted in partial fulfillment of the
requirements for the degree of

Master of Science
in
Environmental Science and Management

Thesis Committee:
Melissa Haeffner, Chair
Sahan Dissanayake
Forrest Williams

Portland State University
2023

Abstract

Trust plays a central role in coastal flooding management because the support or opposition to costly mitigation strategies depends, in part, on how much stakeholders trust in the effectiveness of these strategies. Despite the importance of trust in the approval of flood mitigation strategies, trust is rarely measured. Furthermore, Environmental Justice (EJ) studies have consistently shown that BIPOC (Black, Indigenous and People of Color) and low-income communities are more vulnerable to environmental hazards. Therefore, if these communities are more exposed to flooding, we hypothesize they will have less trust in flood mitigation strategies to protect them; yet trust is understudied in EJ research. We test this hypothesis using three commonly tested measures of trust in the risk perception literature: integrity (quality of providing equal or equitable protection), competence (quality of being successful or efficient) and dependability (quality of performing consistently well). Because coastal flood mitigation strategies are varied, we test if trust depends on type: gray (human-made structures using hard building materials), green (solutions that mimic nature by absorbing, diverting, or storing water), or nonstructural (government actions such as flood insurance, land use planning, etc.). We use a randomly and non-randomly sampled survey in Oregon Coast communities that experience chronic coastal flooding. Our findings suggest that race and income can predict trust to a moderate extent, and that respondents trust green strategies more than they trust gray strategies, and do not trust nonstructural strategies. This study contributes to the EJ literature by analyzing race and income as predictors of trust in flood mitigation strategies in coastal areas at risk of flooding. It also contributes to the

risk perception literature by analyzing risk perception factors, specifically, trust factors. The results will provide important information about how different communities perceive flood mitigation strategies, which can be used by flood management and governmental institutions to better communicate potential solutions to diverse groups.

Acknowledgements

Thanks to:

Dr. Melissa Haeffner

Dr. Sahan Dissanayake and Dr. Forrest Williams

The NOAA-funded grant 227221: Trust and community acceptance of coastal flood mitigation

PSU's Environmental Science & Management professors

Surveying volunteers

Sangucho Loachamin Family

Jenn and Tyler Bufford

Chip Dugger

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

Floods are a growing hazard around the world, threatening people's lives and causing physical damage (Linnerooth-Bayer & Amendola, 2003; Jonkman, 2005). Currently, more than 40 million people in the United States live in floodplains; predictions suggest the number will increase to 70 million people by 2050, increasing flood damage by $750 million (Wing et al., 2018; EPA, 2023). Flooding was the third most frequent event in the US between 1980 and 2022 causing $177.9 billion in damage (Smith, 2023). Floods are caused by severe rains, storms, overflowing rivers, dams and other water systems, snowmelt, and weather events such as hurricanes and cyclones (FEMA, 2018). State, federal, and local governments, as well as communities and individuals play an important role in flood management and flood mitigation strategies implementation (e.g., levee building, river dredging, housing elevation, etc.) (Remo et al., 2012).

Flood recovery is hindered by structural economic barriers (Enarson & Fordham, 2000). Communities that currently struggle with environmental injustice are especially vulnerable to flooding due to restricted mitigation options. Low-income communities cannot afford to relocate away from flood-prone areas and have fewer resources to cope with flooding. Flood insurance provides some comfort in evacuation situations, but it is not affordable for everyone. Policyholders, for example, might use insurance funds to cover housing costs rather than staying at rest centers or low-quality accommodations (Lin et al., 2008).

In addition, distinguishing characteristics of areas with high flood exposure and high social vulnerability include high percentages of Black, Native American, and Hispanic populations, low income, low level of education, high presence of mobile homes, and limited english proficiency (Tate et al., 2021). Because flooding information is frequently translated during and after a flooding event, Spanish-speaking residents face "a wall of English" at flood relief facilities. Latin women are the primary users of post-flooding relief systems (e.g., standing in line for emergency services and information, filling out paperwork for recovery, contacting agencies for counseling and health services), and they are more likely to experience racial bias than Latin men and White women. (Enarson & Fordham, 2000).

Trust is a key factor in flood mitigation (Terpstra, 2011) because people's level of trust influences whether they support or oppose the implementation of flood mitigation strategies (Witte & Allen, 2000). Lack of community support can lead to conflicts between stakeholders and prevent government and non-government organizations from successfully implementing flood management measures. Understanding the extent to which people trust mitigation strategies can give insight into what types of programs are most likely to be supported. Other factors that influence the adoption of mitigation strategies include technical and economic implications, risk uncertainty, strategy effectiveness, and social and political points of view (Viglione et al., 2014; Samaddar et al., 2012; Kerstholt et al., 2017). Traditionally, flood management has focused on the adoption of structural or gray strategies while not promoting alongside green and nonstructural strategies, resulting in limited risk reduction and flood preparedness

(Samaddar et al., 2012). Furthermore, the rising vulnerability of coastal communities to flooding has increased the need for effective flood management, which requires collaboration across government institutions as well as community support.

Trust is essential to build and maintain relationships for flood management. People living in flood-prone areas expect that mitigation strategies will protect them from flooding, and low levels of trust may be associated with the perception that flood programs are imposed rather than collaboratively created, and that strategies are inefficient, unreliable, and do not provide expected protection. Low levels of trust are barriers to public support and compliance with flood prevention efforts, especially among underrepresented groups. Because resources are limited and the flood threat is constant, it is increasingly important for people to trust in flood mitigation programs. Delays in implementation or failure of flood mitigation efforts waste time and resources, increasing the vulnerability to flooding.

The recurring problems of public opposition due to low levels of trust and high flooding vulnerability of minorities (e.g., black, Native American, Hispanic populations, low-income communities) highlight the gap in our understanding of how race and income affect trust and what types of strategies are more likely to be supported. In this study I analyze the extent to which race and income can predict trust in flood mitigation strategies. I hypothesize that lower levels of trust in flood mitigations strategies are more likely to occur in nonwhite respondents. I also hypothesize that lower levels of trust in flood mitigations strategies are more likely to occur in respondents with lower income. This study seeks to provide insights into the types of strategies respondents are likely to trust, analyze race and income as predictors of trust, and contribute to the literature on disaster planning and risk perception.

I conducted an online survey in the Oregon Coast to evaluate trust in gray, green and nonstructural strategies using three trust dimensions: integrity, competence, and dependability. The survey also included questions about respondents' income, race, ethnicity and general information. The survey was revised with input from the advisory board composed of eight members active in different institutions managing flooding in the Oregon Coast and approved by the Portland State University Institutional Review Board (IRB). A respondents' profile was done using race, income, as well as other predictors such as education, age, gender, housing status, primary language, disability, time living in the area, flood prediction, flood experience, and flood insurance. The trust dimensions were used to compute a trust index for each kind of strategy, and levels of trust were compared between race and income groups. The relationship between trust in flood mitigation strategies and race and income was evaluated using cross tabulation and correlation. The statistical analysis of race, income, and other predictors included the relationship evaluation using cross tabulation and correlation, principal component analysis (PCA) and Multiple linear regression.

By analyzing trust in gray, green and nonstructural strategies we can identify what kind of strategies respondents are more likely to support. By comparing levels of trust across race and income groups we can identify what group trusts in the strategies, and trust trends among groups. By evaluating the relationship between trust and race and income we can determine if the relationship is statistically significant, and negative or positive.

Statistical analysis can provide more information about the factors that can increase or decrease respondents' trust, and what predictors have the statistical power to model trust in flood mitigation strategies.

Chapter 1 provides information regarding the problems around flooding, research questions and hypotheses. Chapter 2 presents relevant literature in order to situate the concepts evaluated in this study within the theoretical frameworks of environmental justice and risk perception. Chapter 3 provides an explanation and justification of the methodology used, describing the study area, and explaining the data collection and analysis process. Chapter 4 presents the research findings, including respondents’ profile, trust analysis and statistical analysis, followed by a discussion of the findings in Chapter 5. Chapter 6 provides the study's conclusion and limitations, as well as future research.

Chapter 2

Literature Review

2.1 Trust

Trust plays a central role in coastal flooding management because the support or opposition to costly mitigation strategies depends, in part, on how much stakeholders trust in the effectiveness of these strategies. Trust is a firm belief in the reliability, ability, or strength of someone or something (Compston, 2017). It involves the voluntary transfer of resources or authority to another person with the expectation of future reciprocity, but without a guarantee (Ben-Ner & Halldorsson, 2010). Trust is multidimensional and dynamic. It is influenced by community norms, values, and beliefs, as well as cognitive, emotional, and behavioral factors, and it goes through stages of building, destabilization, dissolution, and rebuilding (Paine, 2013; Vanderlinden et al., 2017). Trust dimensions include: 1) integrity, 2) competence, 3) dependability, 4) transparency, 5) objectivity, 6) honesty, 7) empathy, 8) commitment, 9) accountability, and 10) expertise. These dimensions reflect how individuals perceive trust, and are used in disaster communication as well as to build, sustain, and rebuild trust (Liu & Mehta, 2021).

Trust influences people's perception around motive, competence, concerns, and the reliability of institutions (Siegrist & Cvetkovich, 2000). Trust in experts, decision makers, authorities, and information is essential in risk perception of natural hazards (e.g., floods, droughts, wildfires, tornadoes, etc.), natural disaster preparedness, flood management and vulnerability reduction (Bertoldo et al., 2020; Bronfman et al., 2016;

Munoz-Duque et al., 2021; Terpstra, 2011; Wachinger et al., 2010; Wachinger et al., 2013).

People are more likely to adopt mitigation programs and self-protection measures if they trust the information and decisions about the risk (Eiser et al., 2012). For instance, if a flood warning is issued but people do not trust it, they perceive the flooding risk as low and will not take any protective measures. On the contrary, if people trust it, they will perceive the flooding risk as high and will take precautions (e.g., listen to broadcast media for the latest information, sign up for your community's warning system, plan for sheltering in case of evacuation, etc.). On the contrary, mistrust can hinder people's intentions of adopting mitigation programs (Zinda et al., 2021; Rodera et al., 2019). Residents of Troy, NY, for example, complained that different parts of the city were not treated equally because the downtown seawall (gray strategy) could cause flooding in South and North Troy. They also expressed concerns about the inadequate disaster planning, high cost, limited coverage and difficult claims processes of flood insurance, as well as their overall distrust in flood insurance institutions.

Communities that are frequently affected by flooding suffer structural and financial losses, as well as detrimental effects on their physical and mental health, raising concerns about the effectiveness of flood mitigation programs and the capability of flood management institutions (Bertoldo et al., 2020). As a result, trust levels decrease, causing short- and long-term effects. Short-term effects include a longer and more difficult recovery process, feelings of overwhelm and impotence, and lower flood preparedness. Long-term effects include negative perception of decision-making processes and democratic standards (procedural justice), perception of exclusion and discrimination against specific areas of the city and socioeconomic group (distribution justice), slack of social cohesion, and conflict between stakeholders (Ahmad & Younas, 2021; Bronfman et al., 2016; Munoz-Duque et al., 2021).

People can estimate the flooding probability based on trust (Terpstra, 2011). Characteristics such as magnitude, height, condition, being physically tangible (e.g., people walking on dikes and dams in the Netherlands), and perceived efficacy can increase trust (Kievik & Gutteling, 2011; Terpstra & Gutteling, 2008; Väisänen et al., 2016). It is important to note that an excessive level of trust might result in "the levee effect" (Viglione et al., 2014), which explains that the construction of higher dikes reduces flood frequency, resulting in a sense of safety (high trust in dikes) and more intense economic development in flood-prone areas. Consequently, these areas experience less frequent floods with greater damages (Di Baldassarre et al., 2013).

Trust develops when people connect on multiple levels and communicate effectively. Examples of effective communication include giving accurate information, explaining decisions, and acting honestly and appropriately (Paine, 2013). Furthermore, trust is essential for decision-making under uncertain conditions, willingness to pay for projects whose efficiency is sometimes uncertain, long-term success of mitigation programs, acceptance of early warning, and the development of a more resilient and informed society that is better prepared to cope with potential disasters (Haeffner & Hellman, 2020; Kerstholt et al., 2017; Bronfman et al., 2016; Samaddar et al., 2012).

2.2 Environmental Justice and flooding

Environmental justice (EJ) is the equitable protection from environmental risks, fair sharing of environmental benefits and costs, and the meaningful participation of all people regardless of race, color, country of origin, or income (EPA, 2022). EJ has three pillars: 1) Distributive justice, 2) Procedural justice, and 3) Recognition justice.

Distributive justice addresses inequality in access to environmental benefits and burdens. It means having access to environmental goods and having a fair share of environmental bads. Procedural justice addresses the inequity of participation and power in decision-making. It means having a voice and vote in the decision-making giving all communities equal opportunity to defend their interests, and concerns. Recognition justice addresses the lack of respect for different identities and cultural differences. It means to acknowledge all people`s interests, livelihood priorities, values, and knowledge.

EJ communities (communities that are already suffering from environmental injustices) are particularly vulnerable to the impacts of flooding due to their limited flood mitigation options (Douglas et al., 2012). For instance, many disaster relief programs are geared towards homeowners, making them inaccessible for low-income households that do not own a home (Enarson & Fordham, 2000). The resources to implement flood mitigation strategies are not accessible to socially vulnerable individuals (Lin et al., 2008), and migrant families face a more hostile environment than usual as flood relief is restricted to residents (e.g., 1997 flooding in North Dakota and Minnesota) (Enarson & Fordham, 2000). EJ provides a framework for analyzing flood mitigation outcomes and processes, as well as identifying flood mitigation beneficiaries and non-beneficiaries, in order address issues about justice and equality (Eakin et al., 2021).

According to hazard research, flood vulnerability is a social construct. Certain communities are more vulnerable to floods due to land development regulations, infrastructural decisions, and limited criteria for risk management (Eakin et al., 2021). Social status, access to knowledge, insurance, early, and warning systems, gender, property ownership, political power, and health status are all factors that make a difference in similarly exposed communities to flooding (Wachinger et al., 2010). These factors contribute to distributive and procedural justice issues because the limited access to resources and power prevents a meaningful participation in the decision making around flood management, whereas recognition justice concerns include whose knowledge is recognized, who has the power to recognize that knowledge, and the repercussions of mitigation strategies (Eriksen et al., 2015). Furthermore, rising sea levels and higher storm surge may increase the risk of flooding in EJ coastal areas (Perez & Egan, 2016).

Complex gender, racial, ethnic, class stratification and segregation patterns influence residents' relative vulnerability to natural disasters like floods, their capability to recover after floods, and their ability to participate in community reconstruction (Enarson & Fordham, 2000), therefore racial/ethnic minorities and low-income communities experience environmental harm differently than other groups (Perez & Egan, 2016). For instance, Latin women are the main users of post-flooding relief systems (e.g., standing in line for emergency services and information, filling out paperwork for recovery, contacting agencies for counseling and health services), and are more susceptible to racial bias than either Latin men or white women (Enarson & Fordham, 2000).

Race and ethnicity can be a constraint in informal communication during the flood relief process. For instance, despite the presence of bilingual staff at relief facilities, language is a significant obstacle for Spanish-speaking people facing "a wall of English" (Enarson & Fordham, 2000). In addition, the translation effort is often done after the flooding, in difficult circumstances and is not done as part of emergency planning to serve diverse populations (Enarson & Fordham, 2000).

Despite the risk of flooding, less socially vulnerable people prefer to live in coastal areas due to water-related amenities (e.g., proximity to beaches, ocean views, recreational activities), whereas racial and ethnic minorities and low-income populations tend to be relegated to flood-prone areas without water-related amenities (Montgomery & Chakraborty, 2015). Even when both less and more socially vulnerable people live in floodplains, their motivations to do so are different.

Maldonado et al., (2016) found that Hispanic immigrants in Houston face a much higher flood risk than White people. White people in Miami, on the other hand, experienced much higher flood risk than Hispanic immigrants. At the same time, Hispanic immigrants are at a higher risk of flooding than Hispanic and Black people born in the United States; nevertheless, these findings were not statistically significant (Maldonado et al., 2016). Flooding extent, socioeconomic vulnerability, and the percentages of Black and Hispanic populations have a spatial relationship; thus, race, ethnicity and socioeconomic status have an explanatory role in the spatial distribution of flooding extent (Chakraborty et al., 2019).

Infrastructure and urban development decisions affect the distribution of social vulnerability and frequently worsen it by limiting access to essential urban infrastructure and services for minority, low income, and immigrant populations (Wachinger et al., 2010). Taxpayer interests are prioritized over vulnerable communities, and nonstructural solutions rarely address structural inequities, exacerbating issues of injustice (Eakin et al., 2021) (procedural and recognition justice). Adger et al., (2005) stated that, when evaluating mitigation programs, the contribution to social equity should be addressed in addition to effectiveness and efficiency.

The nature of floodings (i.e., natural disasters with unpredictable and uneven frequency) makes an even distribution of flood risk impossible; however, there are ways to ensure that risk management resources, such as government funding, are fairly distributed (Begg, 2018). Therefore, this can be read as an example of distributive justice. A community that is exposed to floods but has adequate resources to prepare, respond, and recover is less likely to exhibit high vulnerability to flooding; conversely, a community that is exposed to flooding but has insufficient resources is more likely to present high vulnerability.

2.3 Flood mitigation strategies

Flood risk management consists of four phases: mitigation, preparedness, response, and recovery (Thieken et al., 2007). Mitigation focuses on reducing flood frequency, flood damage and long-term risk to flood hazards[1] (FEMA, 2013). Preparedness, response, and recovery aim to reduce flood vulnerability[2]. Flood mitigation strategies are infrastructures, projects, programs, or any actions to reduce flood frequency, damage, and risk. Some strategies are widely applied while others are limited by economic, geographic, or technological constraints, and social and political viewpoints (Viglione et al., 2014; WWF, 2017). These strategies can be classified into three major categories: 1) Gray, 2) Green, and 3) Nonstructural.

Gray strategies are human-made structures using hard building materials (Szönyi & Svensson, 2019). They involve physical changes to natural features and are also known as hard or structural strategies (WWF, 2017). Examples include tide gates, dikes, levees, etc. Green strategies are solutions that mimic nature by absorbing, diverting, or storing water. They use vegetation, soil, and natural processes to manage flooding, and provide ecosystem services such as green spaces, habitat for plants, animals and fish, cleaner air, and water (EPA, 2014). Green strategies are also known as natural and nature-based or soft strategies (WWF, 2017). Examples include stream bank restoration, buffers, natural drainage restoration, etc. Nonstructural strategies are actions that do not involve physical interventions (engineering or ecological). They can be categorized into two groups, depending on the nature of the interventions: (1) governance changes, including modification or introduction of laws, regulations or organizational procedures, land use planning, flood monitoring, etc. (WWF, 2017), and (2) community and household

[1] Hazard is something that could potentially cause harm (e.g., flood hazard, fire hazard) while risk is the probability that a hazard occurs (e.g., high risk, low risk) (Wachinger et al., 2010).
[2] Vulnerability is the inability to predict, respond to, and recover from a hazard (Lewis & Kelman, 2010).

practices that aim to promote prevention, mitigation, or adaptation to floods in the community and households (WWF, 2017). They include flood insurance, home relocation, flood proofing, community flood awareness and preparedness, etc. (Reed, 2015).

Chapter 3

Study area description

The Oregon Coast is composed of Clatsop, Coos, Curry, Douglas (zip codes: 97441 97467), Lane (zip codes: 97439 and 97493), Lincoln, and Tillamook counties (Figure 1), and has a population of approximately 701,944 people.

Figure 1. Oregon Coast

The most populous county after Douglas and Lane is Coos County. Over 80% of the population in each county identifies as White, between 0.3% and 1.2% identifies as Black, between 1.8% and 5.1% identifies as Hispanic, between 1.3% and 3.8% identifies as Native American, between 0.9% and 2.5% identifies as Asian, and between 8.4% and 10.1% identifies as Two or more races, as shown in Table 1.

Table 1. Oregon Coast demographics by county and race and ethnicity.

County	Population	White	Black or African American	Hispanic or Latino	Native American	Asian	Two or more races
Clatsop	41,072	84.1%	0.6%	3.8%	1.3%	1.4%	8.8%
Coos	64,929	84.6%	0.4%	2.4%	2.5%	1.2%	8.9%
Curry	23,446	85.0%	0.4%	2.0%	2.4%	0.9%	9.0%
Douglas*	111,201	86.4%	0.4%	1.8%	1.9%	1.1%	8.4%
Lane*	382,971	80.7%	1.2%	4.0%	1.5%	2.5%	10.1%
Lincoln	50,935	80.6%	0.4%	4.2%	3.8%	1.3%	9.7%
Tillamook	27,390	82.6%	0.3%	5.1%	1.4%	1.0%	9.6%

*Total county population
Source: United States Census Bureau, 2021

In general, 82.4% of the population in the Oregon Coast identify as White, 9.6% as two or more races, 3.5% as Hispanic or Latino, 1.8% as Native American, 1.9% as Asian, and 0.8% as Black or African American, as shown in Figure 2.

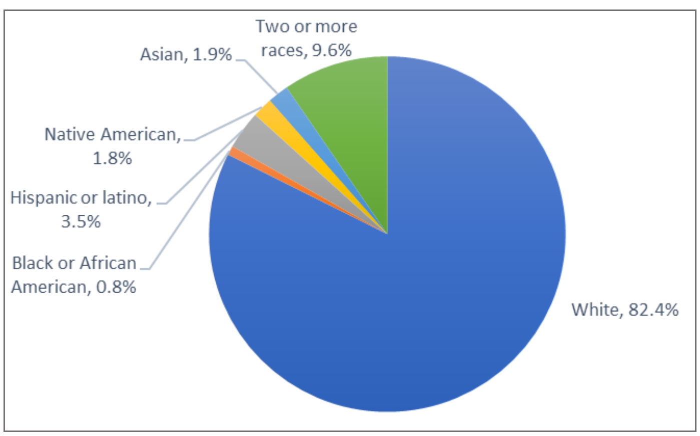
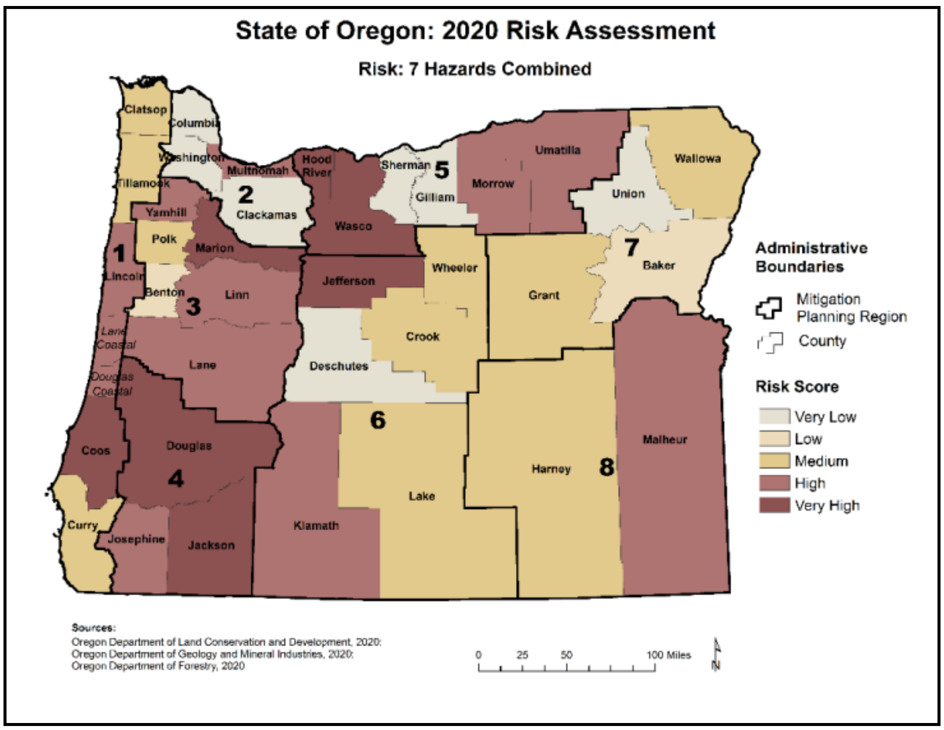


Figure 2. Oregon Coast demographics by race and ethnicity.

Oregon manages natural hazards by region, and the Oregon Coast corresponds to region 1, as shown in Figure 3, which is the only region affected by coastal hazards and tsunamis. Oregon has a long history of flooding, including riverine flooding, flash flooding, coastal flooding, shallow area flooding, urban flooding, playa flooding, and floods induced by ice jams and dam failure. Between 1964 and 2020, 269 disasters have been recorded in Oregon, 219 events included flooding (tsunamis, El Niño, winter storms, flash floods), and 83 took place on the coast (OEM, 2020).



Source: OEM, 2020
Figure 3. Flood Hazards Risk by County in Oregon

The Oregon coast is known for its extreme waves, or "king tides," which have a height of up to 15 meters. The strongest storms and highest storm-generated waves occur during the winter months (October through March) (Komar & Allan, 2000). The wave heights in the Pacific Northwest coast have increased about one meter in the last 25 years (Komar et al., 2013), which might be a factor in the observed increase of coastal flooding in Oregon (OEM, 2020), and can lead to the erosion of coastal dunes and sea cliffs, placing buildings at risk (Komar & Allan, 2000).

Beach sand levels in Oregon typically undergo a yearly cycle of erosion during the winter months and restoration throughout the summer (OEM, 2020). The multi-decadal increases in storm intensities and higher waves have hindered the recovery of sand levels, intensifying the coast erosion (Komar et al., 2013). Human activities such as jetty construction, dredging, planting beach grass, vegetation removal, and residential and commercial development affect the stability of the shoreline, and the ability of beaches, tidal marshes, and dunes to adapt to changing environmental conditions (OEM, 2020).

Distant and local tsunamis pose a hazard to the entire Oregon coast, threatening an estimated $248 million in state buildings and critical facilities. Local tsunamis are created by Cascadia Subduction Zone (CSZ) events, which occur much less frequently but cause more damage, whereas distant tsunamis are caused by Pacific Rim earthquakes. The last CSZ event occurred 300 years ago. Clatsop and Tillamook are the counties most vulnerable to tsunamis (Komar et al. 2013; OEM, 2020).

The Oregon coast has medium to very high flood risk (Figure 3), which is projected to worsen due to climate change, extreme rainfall, insufficient drainage capacity, dams' failure, sea level rise (SLR) and other factors. Oregon has both an emergent and a submergent coast. The emergent coast corresponds to the area south of Coos Bay since it has a tectonic uplift of 2.4 mm/year while the SLR is 1.7 mm/year. The submergent coast corresponds to the area north of Coos Bay since it has a tectonic uplift of 1 mm/year while the SLR is 1.7 mm/year. The increased frequency and magnitude of flooding will exacerbate the damage to property and infrastructure, as well as the vulnerability of areas that already experience flooding frequently. According to the Oregon Department of Geology and Mineral Industries (DOGAMI), flooding threatens 632 state properties worth $900 million and 683 critical facilities worth $1.6 billion (OEM, 2020).

Frequent flooding on the Oregon Coast has raised people's discontent, since federal agencies make flood mitigation decisions without involving the local population (Allen, 2020). As a result, conflicts, lack of cooperation, and opposition to flood mitigation programs have become more common (Haeffner & Hellman, 2020). Dealing with floods can be challenging since economic development and environmental protection must be considered. For instance, proposed modifications to the National Flood Insurance Program, NFIP, restrict development in the 100-year floodplain, upsetting residents. These updates are the result of a lawsuit filed in 2009 by the Audubon Society, which claimed that the NFIP has encouraged development in areas where coho salmon were endangered. FEMA has been working on changes to comply with federal endangered species laws and to achieve zero net loss in flood storage, water quality, and riparian vegetation. Tillamook County has led the way in bridge repairs, riparian rehabilitation projects, flood gate removal, and habitat maintenance for coho salmon and other salmonids for the past thirty years, and the new modifications are perceived as a sign that Tillamook's efforts are not being recognized (Chapell, 2023).

Resources to keep flooding control infrastructures working are limited and even when cities can apply for grants, it is not a guarantee that they will be able to access the funds.

For instance, Coos Bay applied for a FEMA grant to cover the cost of design and construction for the upkeep of Englewood Dike (160-year-old dike), and a $125,000 grant was authorized, but Englewood Diking District members couldn't afford the cost of a 20% match for the grant. A breach of this dike would result in considerable flooding damage to nearby residences, city infrastructure, and a main sanitary sewer. Due to limited resources, the levee district relies on volunteers; if there are no volunteers, the budget is spent on tasks that volunteers usually do (engineer for permit application, grant writer), resulting in insufficient funds for levee restoration. For the past ten years, the district has spent all its funds ($2,800 per year) trying to maintain a small section of the dike, leaving the remaining three-quarters of a mile in need of repair (Harrell, 2018).

The US Army Corps of Engineers has identified eight levees in Clatsop County that are at risk of failure in a major flood. Ten levees have been removed from the federal program because their structures have deteriorated to the point where they could no longer guarantee any level of protection and the levee district has not taken corrective actions. The poor conditions of the levees have been evident in inspections over the last 20 years, and if levees do not provide effective flood control, flood insurance prices will increase (The Astorian, 2018). On a positive note, Tillamook was an example of collaborative decision-making in the Southern Flow Corridor project. It took two years and $11 million for farmers, scientists, and politicians to reach an agreement on flood prevention, demonstrating that it takes time, effort, and resources to repair decades of harm and mistrust among stakeholders (Allen, 2020).

Chapter 4
Methodology

The methodology was divided into two sections: 1) data collection, and 2) data analysis, as shown in Figure 4. The data collection section describes the survey elaboration and distribution. The data analysis section describes how the respondents' profile, trust analysis and statistical analysis were done.

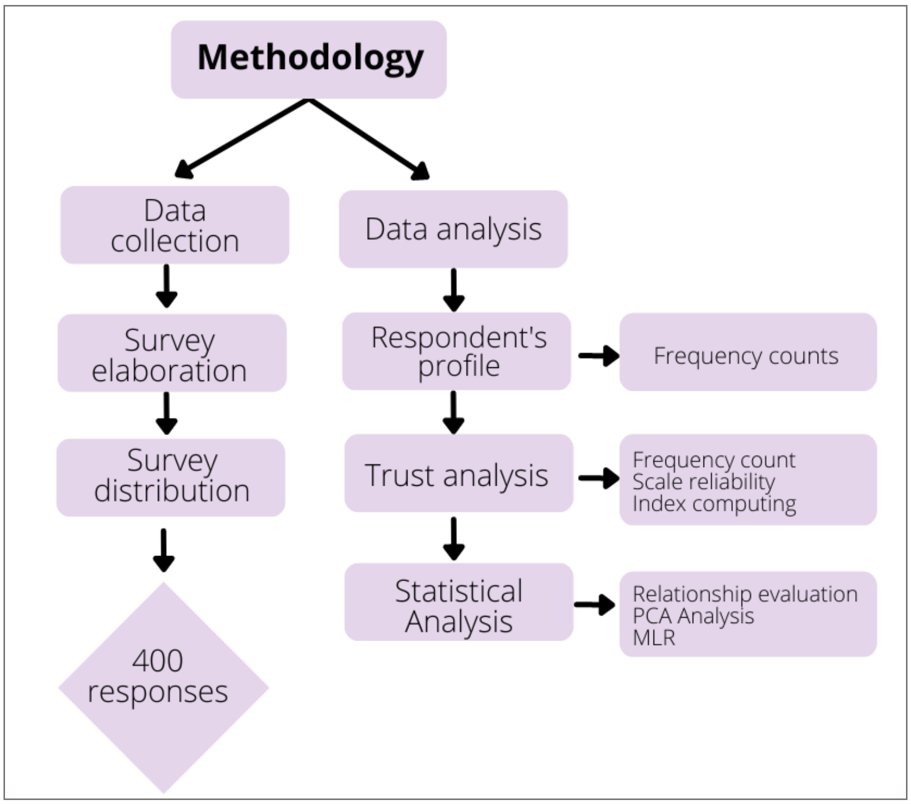


Figure 4. Methodology flow chart

4.1 Data collection

An advisory board was constituted to ensure that the survey language was appropriate and to facilitate the outreach of coastal communities. The advisory board was composed of eight members active in different institutions managing flooding, including Tillamook Estuaries Partners, South Slough Reserve, FEMA, Tillamook Bay Flood Improvement District, Confederated Tribes of Coos, Lower Umpqua, and Siuslaw, and Oregon Department of Land Conservation & Development.

4.1.1 Survey elaboration

The survey evaluated trust in three kinds of mitigation strategies: 1) gray, 2) green and 3) nonstructural. Trust was measured using three trust dimensions that have been used to measure trust in previous studies, according to the literature review: 1) integrity, 2) competence and 3) dependability, and each dimension had one statement (Childers & Grunig, 1999; Bronfman et al., 2016, Kerstholt et al., 2017).

Table 2**.** Evaluation of trust in flood mitigation strategies

I feel they provide equal protection for all.					
	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Gray strategies					
Green strategies					
Nonstructural strategies					
I believe they will keep me safe.					
	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Gray strategies					
Green strategies					
Nonstructural strategies					
I think they are reliable.					
	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Gray strategies					
Green strategies					
Nonstructural strategies					

Integrity is the quality of providing equal or equitable protection. To measure this concept, we used the statement: “I feel they provide equal protection for all”. Competence is the quality of being successful or efficient. To measure this concept, we used the statement: “I believe they will keep me safe”. Dependability is the quality of performing consistently well. To measure this concept, we used the statement: “I think they are reliable”. Respondents were asked to evaluate how much they agree or disagree with the statement for each kind of mitigation strategy using a scale of 1 to 5, being 1=strongly disagree, 2= disagree, 3=neither agree or disagree, 4=agree and 5=strongly agree, as shown in Table 2.

The survey also included questions about race (Which of the following most closely represents the race(s) you identify with?), ethnicity (Are you of Hispanic, Latino, or Spanish origin?), income (Which category describes your 2022 household pre-tax income?), and general information. The advisory board's feedback was used to create the final version of the online survey which was subsequently approved by the Portland State University Institutional Review Board (IRB) and translated to Spanish.

The research team met with the advisory board to present the research objectives, and methods met with the advisory board, which contributed to identifying community interests as well as opportunities to improve our approach to community outreach and participant recruitment. The initial survey draft was developed using the information gathered during the advisory board meeting. We sent the first survey draft to the advisory board and received input on the survey's content, context, narrative, and language. The advisory board reviewed the final version of the survey to ensure that the language was clear, easy to read, and acceptable to assure that respondents could easily reply to the survey.

The advisory board was essential in developing a list of community contacts, recruiting participants for the study, and connecting the research team with diverse demographic groups. The Advisory Board was crucial in building environmental justice through our research by incorporating community needs, values, and concerns into our research, ensuring the survey was culturally sensitive and appropriate, and engaging community organizations and residents of the Oregon coast.

4.1.2 Survey distribution

A postcard with a link and QR code to the online survey was sent to approximately 1,500 addresses randomly selected in Tillamook and Coos Counties on February 16th, 2023. Community members were asked to spread survey flyers to raise awareness, and because the response rate was lower than expected, a door-to-door survey was conducted in Coos County using randomly selected addresses, visiting around 230 homes. A link and QR code to a non-random online survey was created and distributed initially in Tillamook and Coos Counties, eventually reaching the whole Oregon Coast. The company Centiment collected an additional 243 responses. In total 400 survey responses were collected between February and May 2023.

4.2 Data analysis

4.2.1 Respondents' profile

Four hundred survey responses were coded according to the codebook for respondents' profile (Appendix A). The respondent profile was done through frequency counts using the descriptive statistics tools from the IBM SPSS Statistics software.

4.2.2 Trust analysis

Frequency counts analysis was conducted for integrity, competence, and dependability for each kind of strategy (gray, green and nonstructural), and the mean score for each dimension was calculated using the descriptive statistics tools from the IBM SPSS Statistics software, SPSS. Next, a scale reliability analysis was conducted to evaluate how consistently integrity, competence and dependability are measuring trust in gray, green and nonstructural mitigation strategies with an alpha score of 0.808. An alpha score of 0.70 or higher indicates reasonably good reliability (Sweet & Grace-Martin, 2012). Trust indices[3] were computed for gray, green and nonstructural strategies using integrity competence and dependability. A frequency counts analysis was conducted for the trust indices and the mean value for each one was calculated.

4.2.3 Statistical Analysis

The dataset used for the statistical analysis was composed of fourteen variables: trust in gray, green and nonstructural strategies, race, income, flood prediction, flood insurance,

[3] An index is a single score that summarizes two or more variables (Sweet & Grace-Martin, 2012)

flood experience, housing status, education, time living in the area, age, gender and disability. Race was recoded from its six original categories (Appendix B) into a dummy variable, because there were few respondents identified as nonwhite, being 1=white and 0=nonwhite. Flood insurance (Flood_insurance), flood experience (Flood_exp), gender (Gender) and disability (Disability) were also coded as dummy variables and for all variables, the "prefer not to answer" category was considered missing data (more details in Appendix B). The total number of responses (N) in each analysis varies since some of the variables have missing data.

Relationship evaluation

Cross tabulation was used as a significance test to determine that the likelihood of the relationship between race and income and trust in flood mitigation strategies is not the result of chance (null hypothesis) and that the relationship is real (alternative hypothesis). A significance level of 0.05 or less supports the alternative hypothesis (Sweet & Grace-Martin, 2012). In addition, correlation analysis was conducted to learn more about the relationship between variables. Pearson correlation coefficients between 0-0.19 indicate a very low correlation, 0.2-0.39 indicate low correlation, 0.4-0.59 indicate moderate correlation, 0.6-0.79 indicates high correlation, and 0.8-1.0 indicate very high correlation (Selvanathan et al., 2020), and negative coefficients indicate that the correlation is negative. These analyses were done using the cross tabulation and correlation tool from SPSS.

Principal Component Analysis

Principal Component Analysis, PCA, is a method for reducing data dimensions that allows the visualization of more than two variables in two dimensions represented by principal components (PCs) (Jaadi & Whitfield, 2023). PCA analysis was done using the R Project for Statistical Computing Software, R. This analysis was divided in two stages, the first one using trust variables (Trus_green, Trus_ gray and Trus_nons), race and income as predictor, and the second one using trust variables, race, income and nine other predictors (Flood_prediction, Flood_insurance, Flood_exp, Housing_status, Education, Time_living, Age, Gender, and Disability).

Multiple linear regression

Multiple linear regressions were conducted to model trust in gray, green and nonstructural mitigation strategies independently in R. A full multiple linear regression model was fitted, including all the predictors (Race, Income,Flood_prediction, Flood_insurance, Flood_exp, Housing_status, Education, Time_living, Age, Gender, and Disability). Variable selection was made by stepwise selection to get a final model, excluding predictors that did not have a statistically significant relationship with trust. An ANOVA test was performed to determine if the final model was statistically different from the full model. In addition, the Akaike information criterion (AIC) was observed because it evaluates how well the model fits the data, lower values of AIC indicate a better fit. Finally, model diagnostics were run on the final model to analyze the residuals, including a Shapiro-Wilk normality test to analyze the distribution of the residuals, an F test to analyze equal variance, and the variance of inflation factor (VIF) to check for multicollinearity among predictors.

Chapter 5

Results

5.1 Respondents' profile

Most of the respondents live, work, or own a home in Coos county (41.8%) (Figure 5), have a 2022 household pre-tax income between $30,000-$59,999 (31%), and identify as white (72.5%) (Figure 6). In addition, respondents' mean 2022 household pre-tax income is $57,774, which is lower than the mean income at the state level ($70,084).

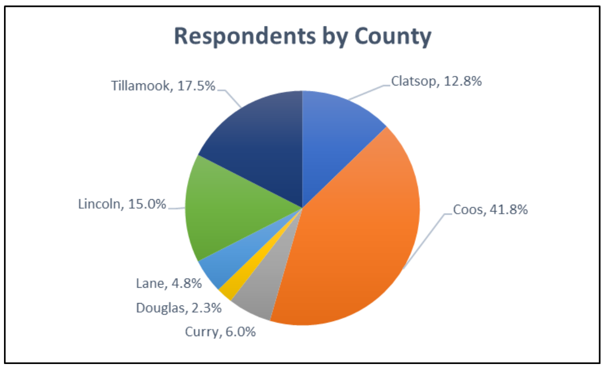
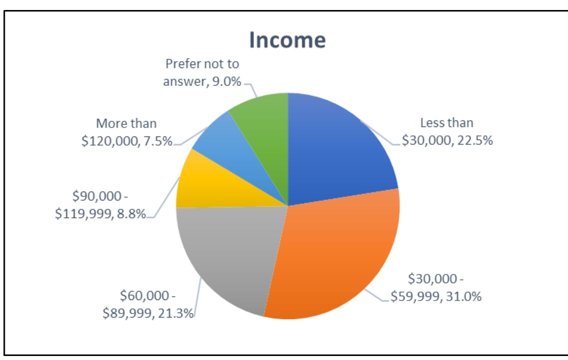


Figure 5. Respondents by county with percentage (N=400)



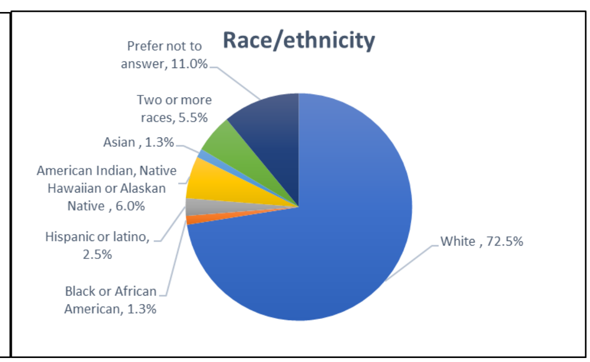


Figure 6. Respondents' income, and race/ethnicity with percentage (N=400).

The mean age is 50 years old and most of the participants are 51-70 years old. Most of the respondents are female (55.0%), have an associate's degree, vocational school, or some college (31.3%), own a home (53.8%), their primary language is English (89.0%) and do not have a disability (61.5%) (Figure 7).

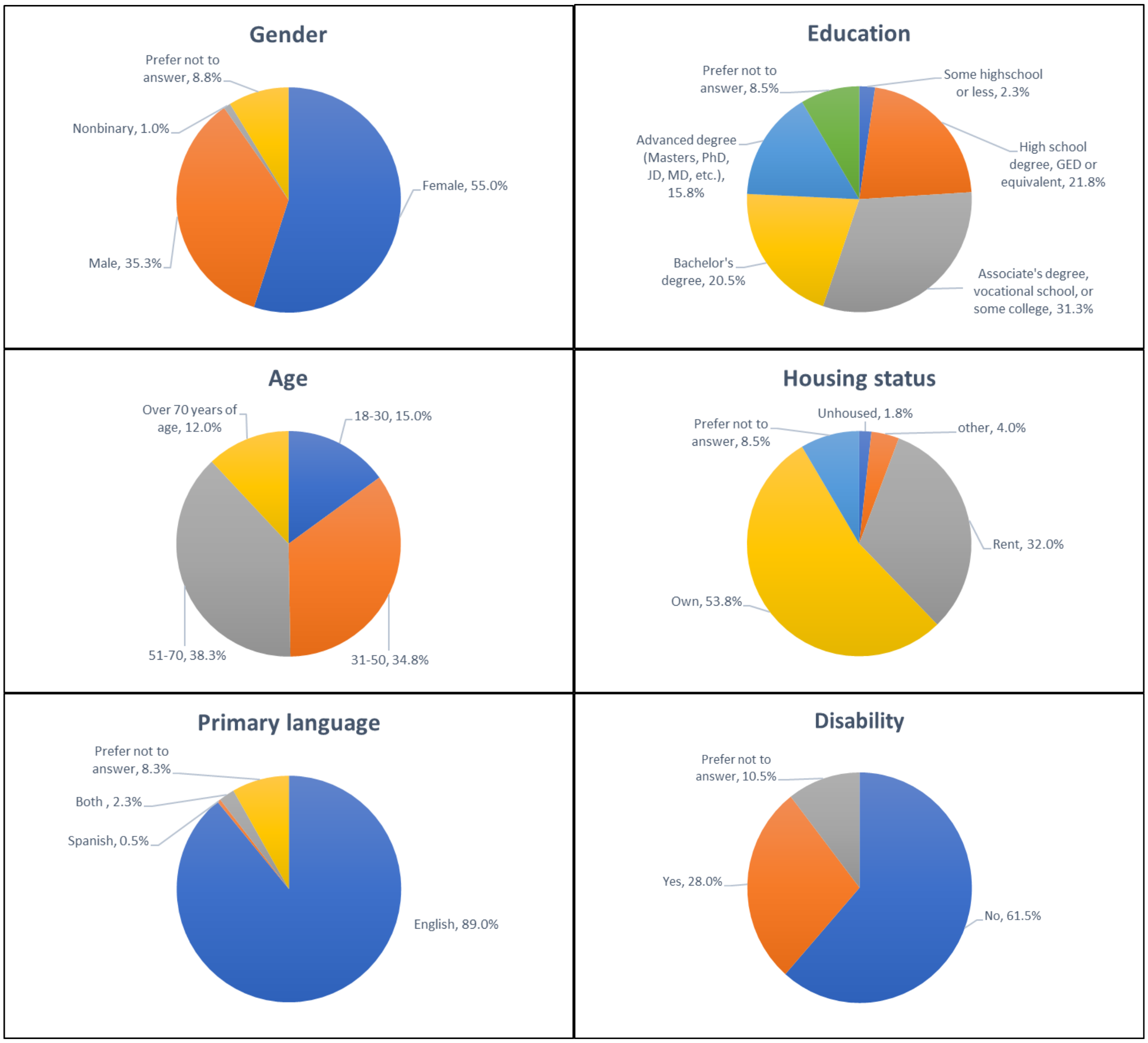


Figure 7. Respondents' gender, education, age, housing status, primary language, and disability with percentage (N=400).

Respondents have lived in or owned a home or a business in the area 12 years on average and most of them have lived in the area more than 15 years (42.0%). Most of the respondents think that flooding is going to increase in the Oregon Coast (63.3%), and do not have flood insurance (59.5%). In addition, 33.8% of the respondents have experienced flooding (Figure 8).

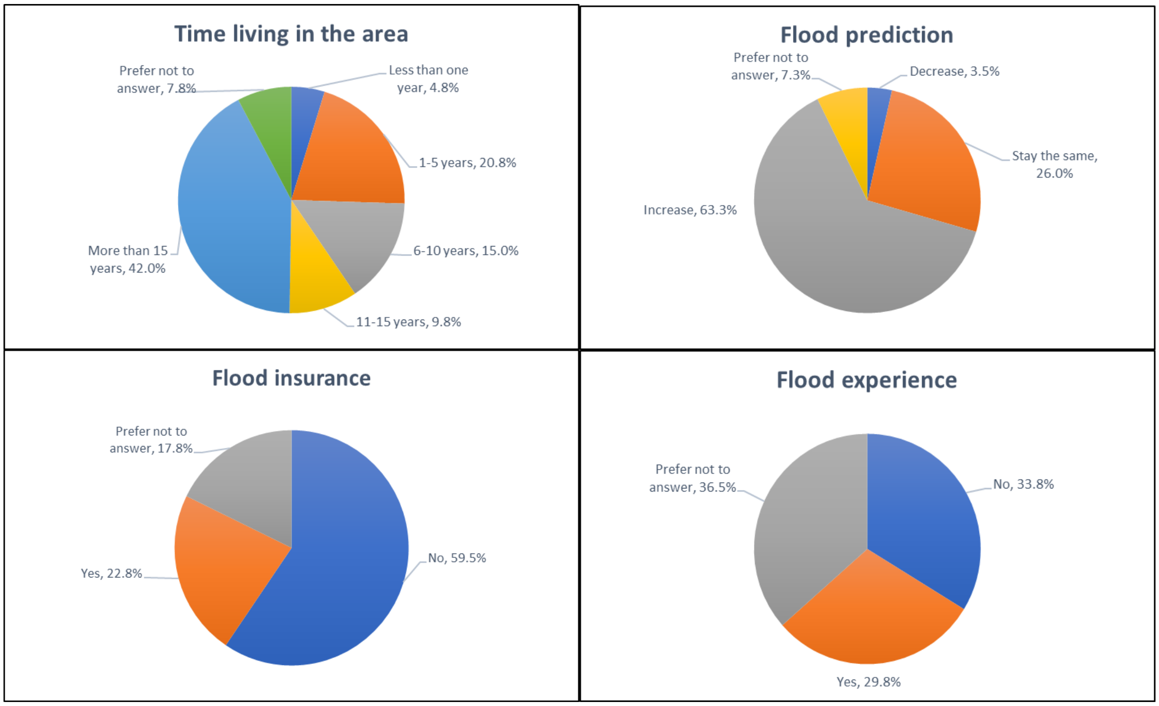


Figure 8. Respondents' time living in the area, flood prediction, flood insurance and flood experience with percentage (N=400).

The respondents' demographics without considering the "prefer not to answer" category are as follows (N=354): 81.4% White, 1.4% Black or African American, 2.8% Hispanic or Latino, 6.8% Native American, 1.4% Asian and 6.2% two or more races. While the Oregon Coast demographics are as follows: 82.4% White, 0.8% Black or African American, 3.5% Hispanic or Latino, 1.8% Native American, 1.9% Asian and 9.6% two or more races, as shown in Figure 9. Both the state and response sample are predominantly white. The percentages of Blacks and Native Americans are higher in the response sample than at the state level.

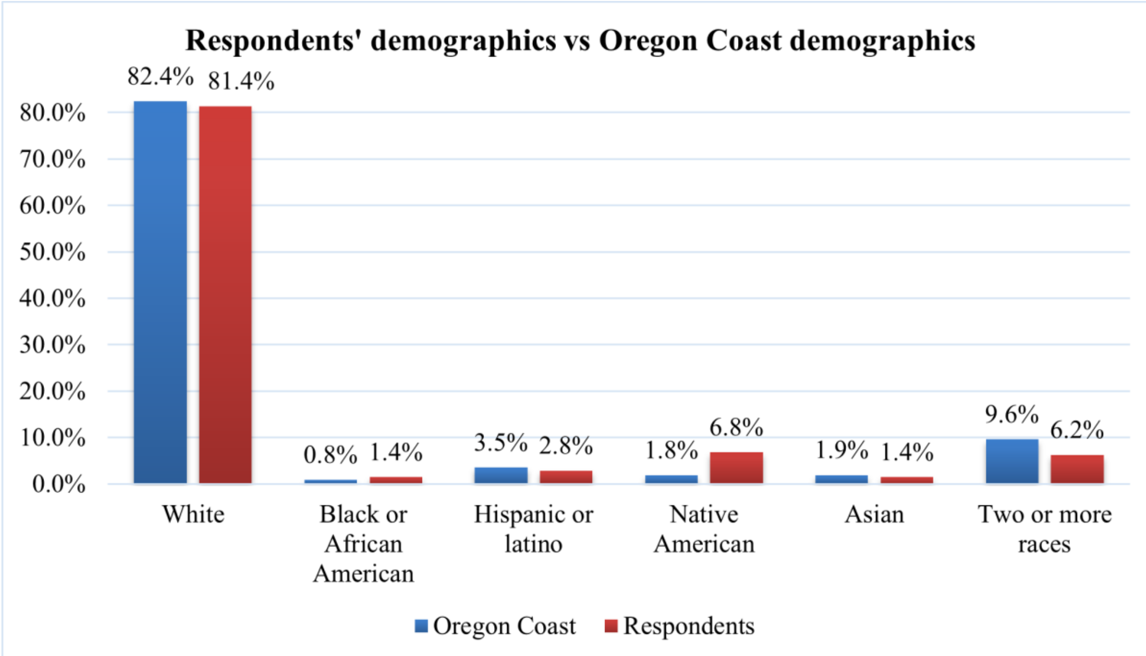


Figure 9. Respondents' demographic vs Oregon Coast demographics.

5.2 Trust analysis

5.2.1 Trust dimensions

About the integrity statement "I feel they provide equal protection for all", for gray strategies (N=399), most of the respondents neither agree nor disagree (35.3%), for green strategies (N=400), most of the respondents agree (34.5%), and for nonstructural strategies (N=398), most of the respondents neither agree nor disagree (33.2%). When looking at the "strongly disagree" category, the higher percentage (12.1%) corresponds to nonstructural strategies. When looking at the "strongly agree" category, the higher percentage corresponds to green strategies (15.3%), as shown in Figure 10. In addition, 31.6% of the respondents strongly disagree and disagree, and 33.1% of the respondents agree and strongly agree with the integrity statement for gray strategies; 21.5% of the respondents strongly disagree and disagree, and 49.8% of the respondents agree and strongly agree with the integrity statement for green strategies; and 42.0% of the respondents strongly disagree and disagree, and 24.9% of the respondents agree and strongly agree with the integrity statement for nonstructural strategies.

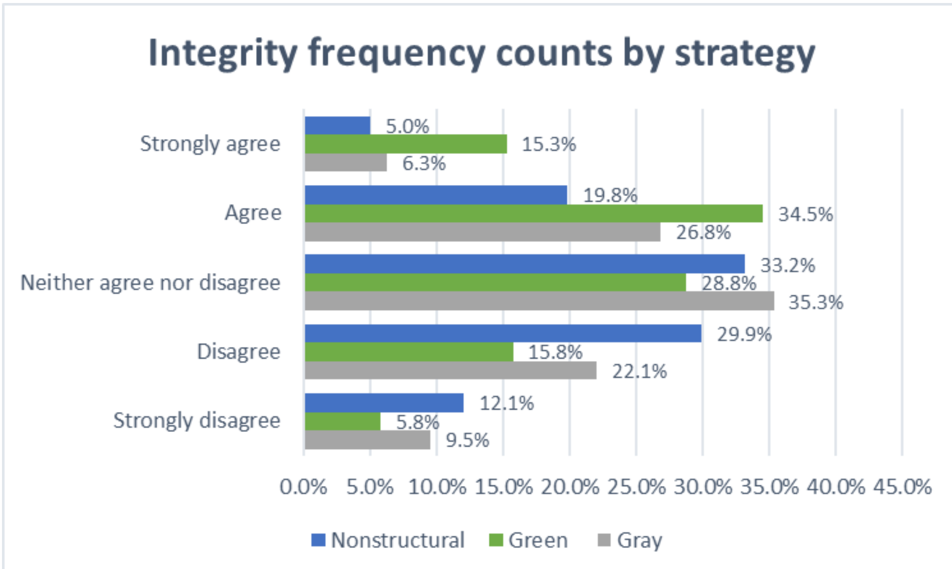


Figure 10. Integrity frequency counts by strategy in response to “I feel they provide equal protection for all” (N=400).

About the competence statement “I believe they will keep me safe”, for gray strategies (N=399), most of the respondents agree (33.3%), for green strategies (N=397), most of the respondents agree (37.5%), and for nonstructural strategies (N=397), most of the respondents neither agree nor disagree (38.0%). When looking at the “strongly disagree” category, the higher percentage (11.1%) corresponds to nonstructural strategies. When looking at the “strongly agree” category, the higher percentage corresponds to green strategies (11.8%), as shown in Figure 11. In addition, 29.1% of the respondents strongly disagree and disagree, and 38.3% of the respondents agree and strongly agree with the competence statement for gray strategies; 21.7% of the respondents strongly disagree and disagree, and 49.4% of the respondents agree and strongly agree with the competence statement for green strategies; and 36.0% of the respondents strongly disagree and disagree, and 25.9% of the respondents agree and strongly agree with the competence statement for nonstructural strategies.

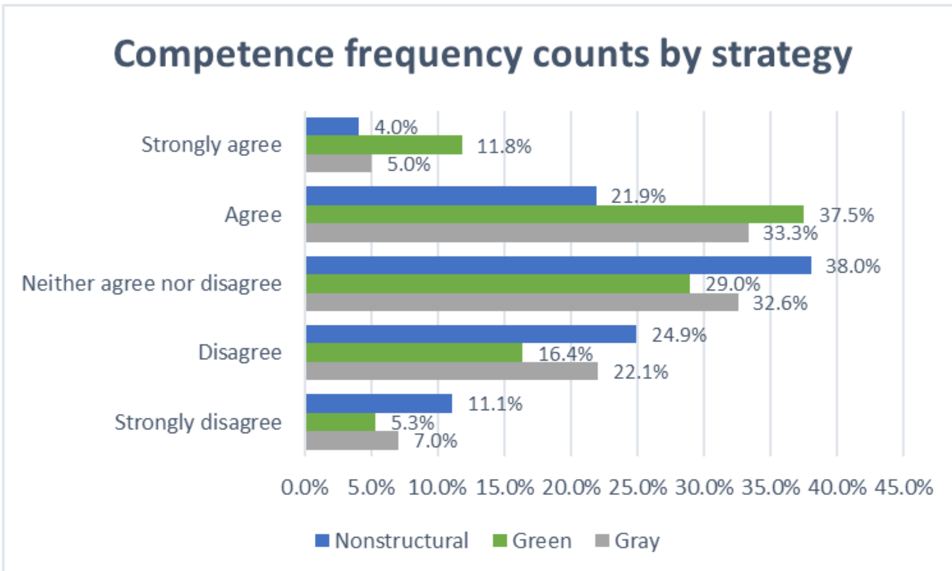


Figure 11. Competence frequency counts by strategy in response to I believe they will keep me safe (N=400).

About the dependability statement “I think they are reliable”, for gray strategies (N=398), most of the respondents neither agree nor disagree (34.2%), for green strategies (N=397), most of the respondents agree (39.6%), and for nonstructural strategies (N=397), most of the respondents neither agree nor disagree (38.5%). When looking at the “strongly disagree” category, the higher percentage (11.3%) corresponds to nonstructural strategies. When looking at the “strongly agree” category, the higher percentage corresponds to green strategies (10.8%), as shown in Figure 12. In addition, 29.6% of the respondents strongly disagree and disagree, and 36.2% of the respondents agree and strongly agree with the dependability statement for gray strategies; 19.8% of the respondents strongly disagree and disagree, and 50.4% of the respondents agree and strongly agree with the dependability statement for green strategies; and 37.0% of the respondents strongly disagree and disagree, and 24.4% of the respondents agree and strongly agree with the dependability statement for nonstructural strategies.

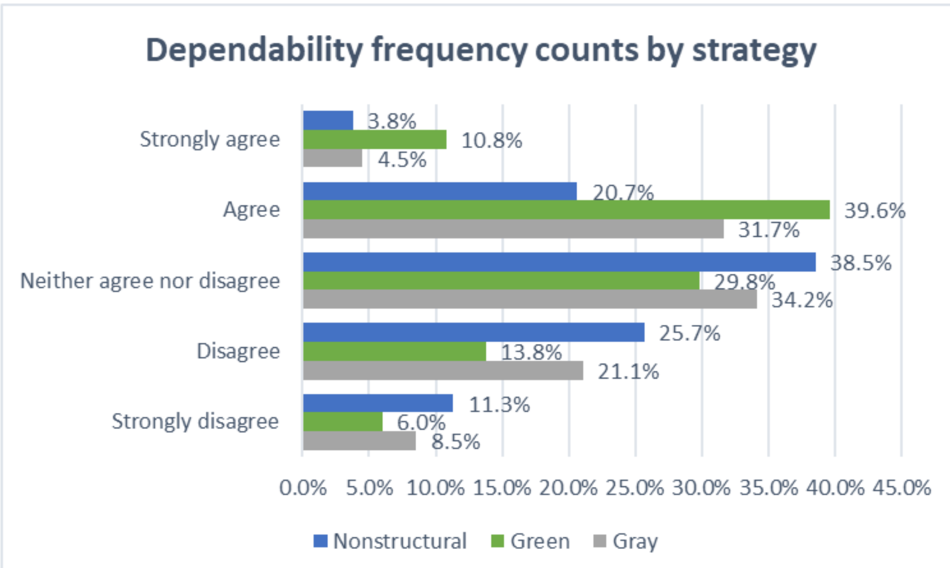


Figure 12. Dependability frequency counts by strategy in response to "I think they are reliable" (N=400)

The mean integrity value for gray strategies is 2.98, for green strategies is 3.38 and for nonstructural strategies is 2.76. The mean competence value for gray strategies is 3.07, for green strategies is 3.34 and for nonstructural strategies is 2.83. The mean dependability value for gray strategies is 3.03, for green strategies is 3.35 and for nonstructural strategies is 2.80, as shown in Figure 13. Values below and equal to 3.00 indicate that respondents perceive that the strategies do not comply with the trust dimension; values above 3.00 indicate that respondents perceive that the strategies comply with the trust dimension. Therefore, respondents believe that green strategies comply with all three dimensions, gray strategies comply with competence and dependability, and nonstructural strategies do not comply with any dimension. In addition, green strategies have the highest integrity, competence and dependability scores compared with gray and nonstructural strategies.

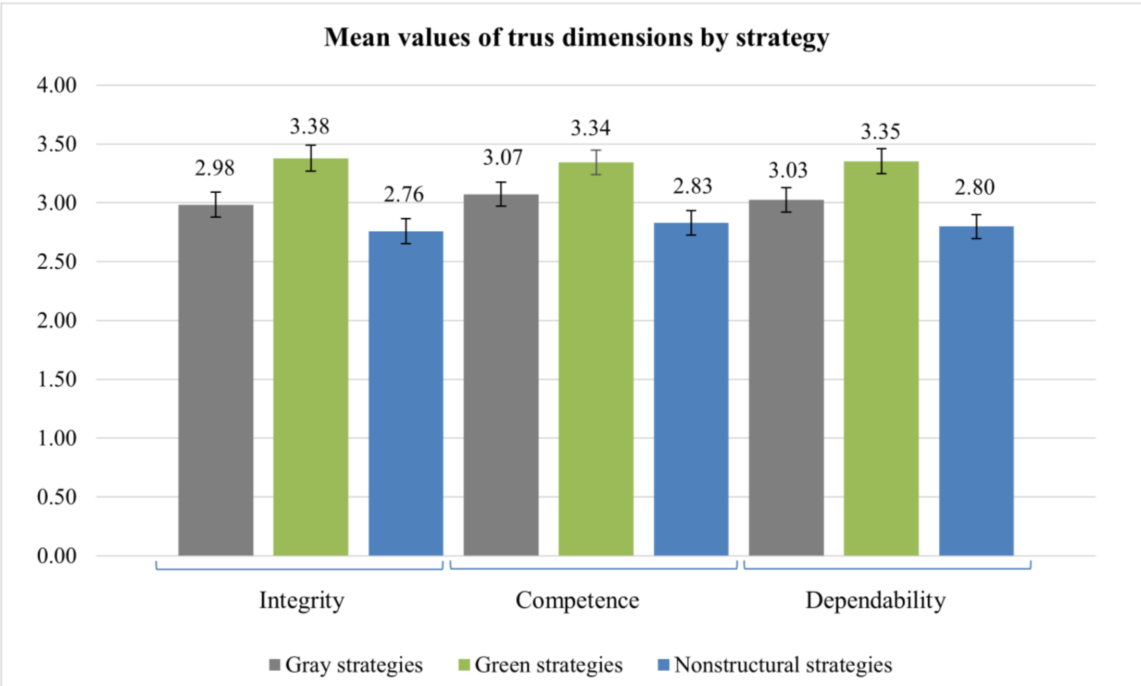


Figure 13. Mean values of trust dimensions by strategy. Values above 3.00 mean that respondents perceive that the strategies comply with the trust dimension. Error bars indicate 95% confidence interval.

5.2.2 Trust indices

The scale reliability analysis produced an Alpha Coefficient of 0.808 for trust index in gray strategies (N=397), 0.836 for trust index in green strategies (N=397), and 0.820 in trust index in nonstructural (N=385) strategies. Therefore, all three indexes have reasonably good reliability. A scale of reliability analysis was run using the trust in gray, green and nonstructural strategies indices in order to determine if a general trust in mitigation strategies index was pertinent, getting an Alpha Coefficient of 0.678 meaning that this index does not have a reasonably good reliability. Furthermore, a scale of reliability analysis was run using the trust in gray and green strategies indices in order to determine if a gray-green index was pertinent, getting an Alpha Coefficient of 0.645 meaning that this index does not have a reasonably good reliability.

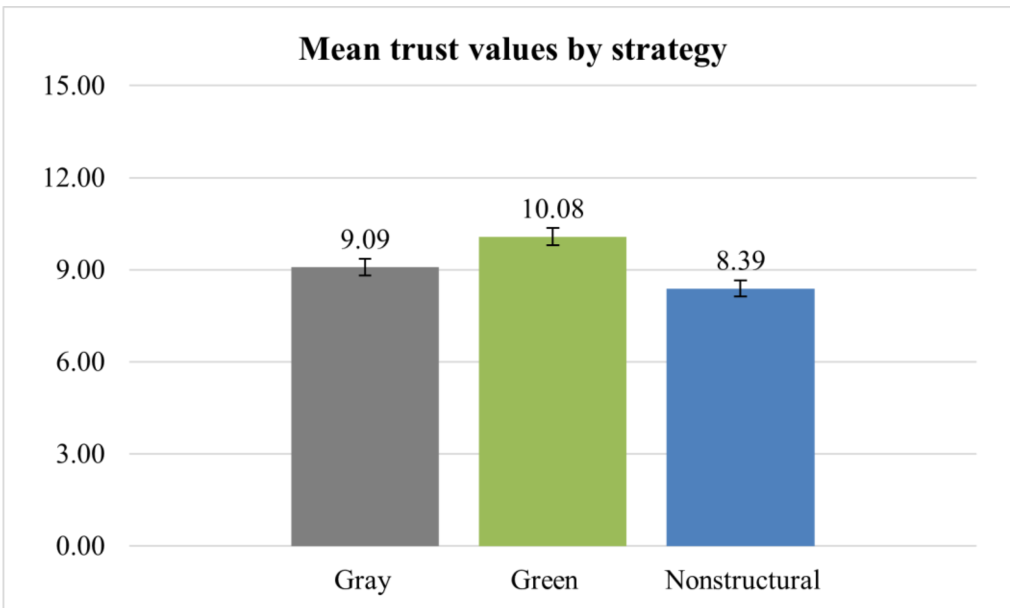


Figure 14. Mean trust values by mitigation strategy. Values above 9.00 mean that respondents trust the strategy. Error bars indicate 95% confidence interval.

The trust indices range from 3 to 15 (more details in Appendix C). Values below and equal to 9.00 indicate that respondents do not trust the mitigation strategies; values above 9.00 indicate that respondents trust the mitigation strategies[4]. Trust in gray, green and nonstructural strategies have a mean value of 9.09 (N=397), 10.08 (N=397), and 8.39

[4] Based on the OECD Guidelines on measuring trust (OECD, 2017).

(N=395) respectively, as shown in Figure 14. Therefore, respondents trust in gray and green strategies, and do not trust nonstructural strategies. In addition, people trust the most in green strategies compared with gray strategies.

The mean values for trust in gray strategies by race and ethnicity do not differ much between White (9.09), Hispanic (9.40), Native American (8.88), Asian (9.60), and two or more race (9.32) respondents. Native American respondents (8.88) have the lowest level of trust in gray strategies and Black respondents (12.00) have the highest. The mean values for trust in green strategies by race and ethnicity do not differ that much between White (10.26), Black (10.60), Hispanic (10.30), Native American (9.79), and two or more race (10.05) respondents. Native American respondents (9.79) have the lowest level of trust in green strategies and Asian respondents (11.80) have the highest. The mean values for trust in nonstructural strategies by race and ethnicity do not differ that much between Hispanic (9.80) and Asian (9.60) respondents, and between White (8.35), Native American (8.65), and two or more race respondents (8.32). Respondents identified as two or more races (8.32) have the lowest level of trust in nonstructural strategies and Black respondents (10.60) have the highest, as shown in Figure 15. Overall, there is no difference in trust levels between White and nonwhite respondents, and both groups trust gray and green strategies but not nonstructural strategies, as shown in Figure 16. It is important to mention that these results might be influenced by the number of respondents for each race and ethnicity.

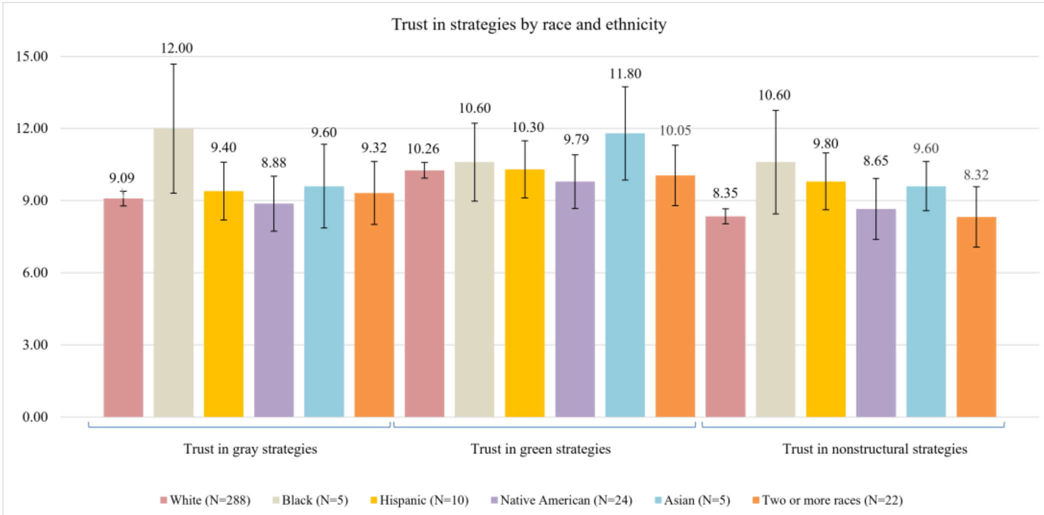


Figure 15. Trust in flood mitigation strategies by race and ethnicity (N=354). Values above 9.00 mean that respondents trust the strategy. Error bars indicate 95% confidence interval.

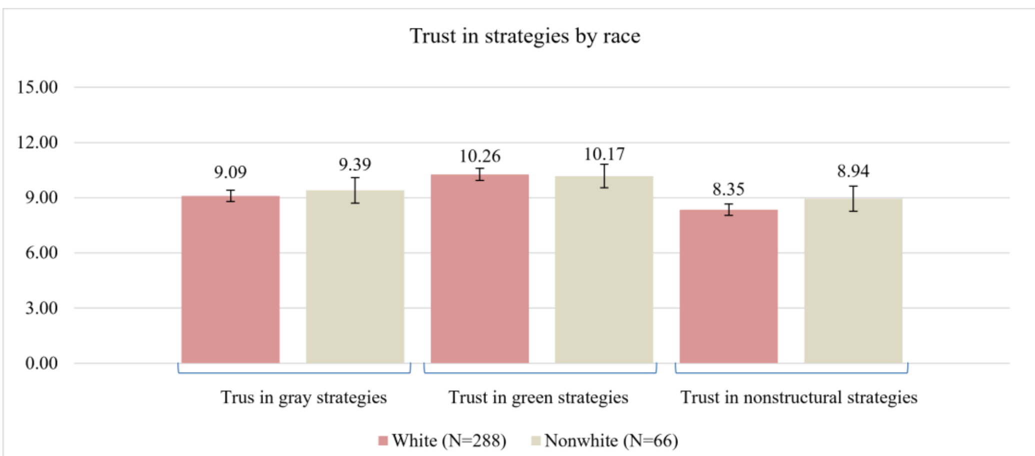


Figure 16. Trust in flood mitigation strategies by race (N=354). Values above 9.00 mean that respondents trust the strategy. Error bars indicate 95% confidence interval.

The mean values for trust in gray strategies by income do not differ much between groups, however, respondents with the highest income (8.63) have the lowest level of trust in gray strategies and respondents with the lowest income (9.30) have the highest. The mean values for trust in green strategies by income shows that all income groups trust these strategies, and respondents with the highest income have the highest level of trust (10.87). The mean values for trust in nonstructural strategies by income do not differ much between groups, however, respondents with an income of $90,000-$119,999 (8.26) have the lowest level of trust in nonstructural strategies and respondents with an income of $60,000-$89,999 (9.30) have the highest, as shown in Figure 17.

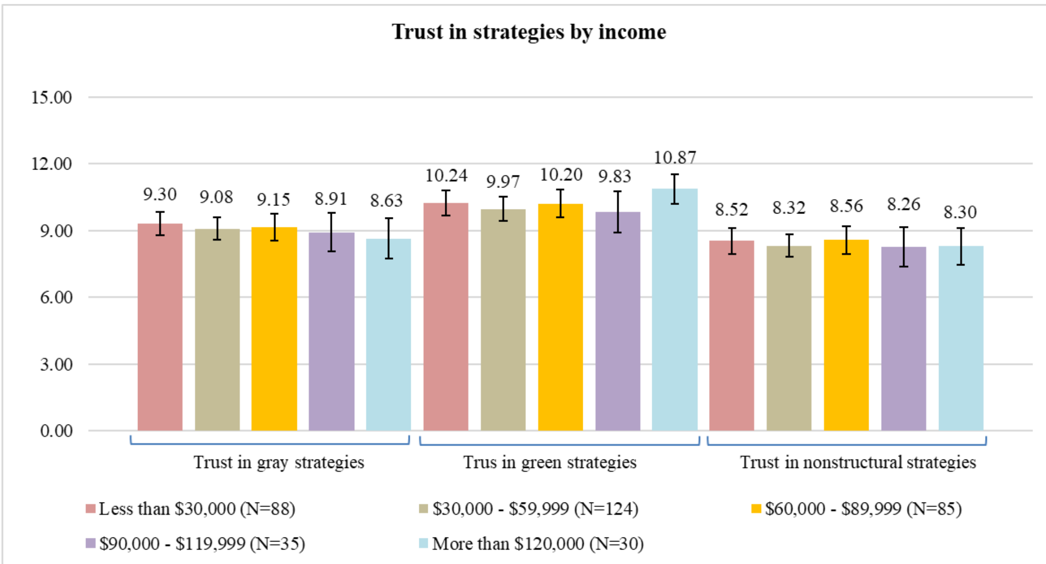


Figure 17. Trust in flood mitigation strategies by income (N=362). Values above 9.00 mean that respondents trust the strategy. Error bars indicate 95% confidence interval.

5.3 Statistical Analysis

The statistical analysis required recoding of race (Race, 1=white and 0=nonwhite), flood insurance (Flood_insurance), flood experience (Flood_exp), gender (Gender) and disability (Disability) were also coded as dummy variables and for all variables, the “prefer not to answer” category was considered missing data. The total number of responses (N) in each analysis varies since some of the variables have missing data.

5.3.1 Relationship evaluation

The Pearson Chi-square coefficient shows that trust in nonstructural strategies and race (0.049), and trust in gray strategies and race (0.050) have a statistically significant relationship. The Pearson correlation coefficient shows that trust in gray strategies has a negative and very low correlation with race (-0.045) and income (-0.059), meaning that white respondents and respondents with higher income tend to have low levels of trust in gray strategies. Trust in green strategies has a positive and very low correlation with race (0.013) and income (0.032), meaning that white respondents and respondents with higher income tend to have higher levels of trust in green strategies. Trust in nonstructural strategies has a negative and very low correlation with race (-0.085) and income (-0.016), meaning that white respondents and respondents with higher income tend to have lower levels of trust in nonstructural strategies, as shown in Table 3.

Table 3. Relationship evaluation between race, income, and trust in mitigation strategies.

	Cross tabulation (Pearson Chi-square coefficient)	**Correlation (Pearson correlation coefficient)**
Trust in gray and race (N=354)	0.050	-0.045
Trust in gray and income (N=362)	0.861	-0.059
Trust in green and race (N=354)	0.259	0.013
Trust in green and income (N=362)	0.746	0.032
Trust in nonstructural and race (N=352)	0.049	-0.085
Trust in nonstructural and income (N=360)	0.091	-0.016

A linear model was run using trust in gray strategies and race since they have a statistically significant relationship, and the following model was obtained: Trust_gray = 9.394 - 0.304(Race). The *p* value for the full model is 0.398, meaning that the model is not characterizing well the relationship between trust in gray strategies and race. In addition, R-squared is 0.002, meaning that 0.2% of the variation in trust in gray strategies is explained by race. A linear model was run using trust in nonstructural strategies and race since they have a statistically significant relationship, and the following model was obtained: Trust_nons = 8.938 - 0.590(Race). The *p* value for the full model is 0.112, meaning that the model is not characterizing well the relationship between trust in nonstructural strategies and race. In addition, R-squared is 0.007, meaning that 0.7% of the variation in trust in nonstructural strategies is explained by race. These findings led to an analysis of the relationship between trust and multiple predictors at the same time, rather than one predictor at a time.

5.3.2 Principal Component Analysis

Gray strategies

A PCA was conducted with trust in gray strategies (Trust_gray), income (Income) and race (Race). The PCA plot in Figure 18 shows that the horizontal axis represents trust in gray mitigation strategies, the vertical axis represents income (top) and race (bottom) in. The arrows show that trust in gray strategies and race are negatively correlated. In addition, respondents with higher income are more likely to show lower levels of trust in gray mitigation strategies than respondents with lower income. White respondents are more likely to show lower levels of trust in gray mitigations strategies than nonwhite respondents.

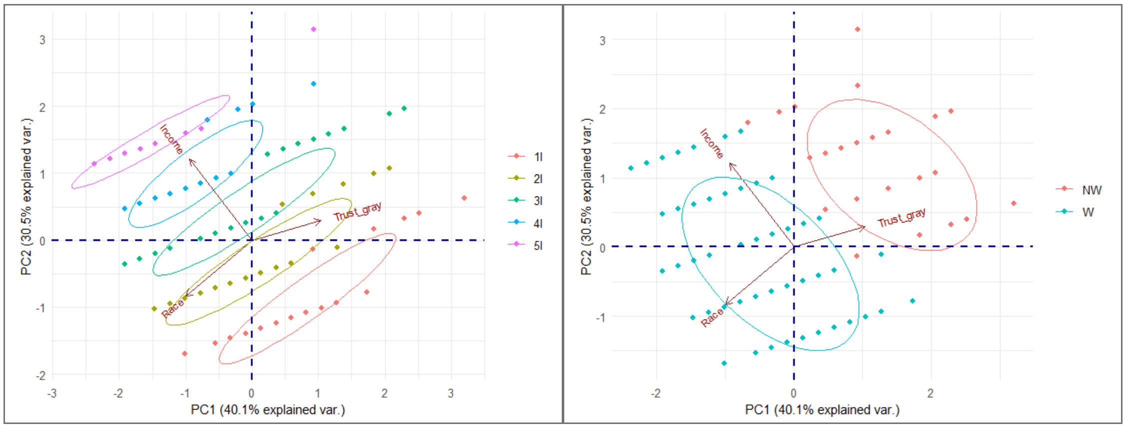


Figure 18. PCA plot of trust in gray strategies (Trust_gray), income and race (N=209). The arrow direction indicates the direction that the variable increases its values, and the arrow length is proportional to its variance. The dots represent the respondents' responses.

A PCA was conducted with trust in gray strategies, income, race and nine other variables (Flood_prediction, Flood_insurance, Flood_exp, Housing_status, Education, Time_living, Age, Gender, and Disability). The PC plot in Figure 19 shows that lower levels of trust in gray strategies are more likely to occur when 1) respondents are older and have been living longer in the area, and 2) respondents are White, own a home, have experienced flooding, and have higher education and income. Higher levels of trust are associated with respondents believing that flooding will increase in the next 15 years.

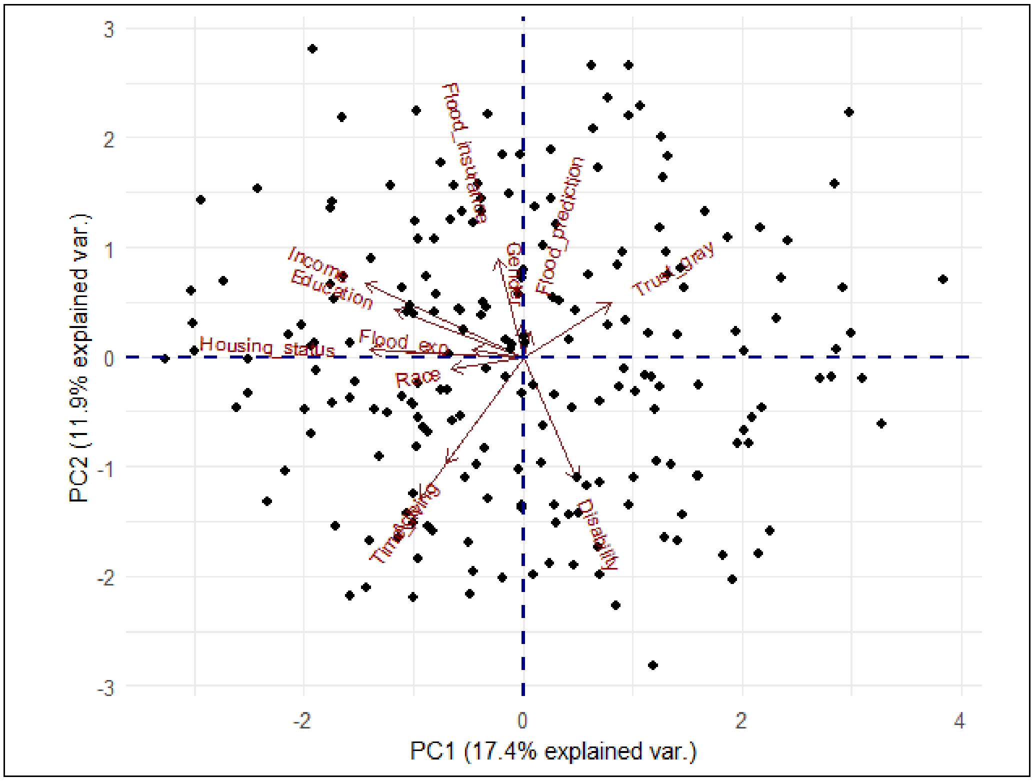


Figure 19. PCA plot of trust in gray strategies and other variables (N=209). The arrow direction indicates the direction that the variable increases its values, and the arrow length is proportional to its variance. The black points represent the respondents' responses.

Green strategies

A PCA was conducted with trust in green strategies (Trust_green), income and race. The PC plot in Figure 20 shows that the horizontal axis represents income and race, and the vertical axis represents trust in green strategies. The arrows show that race and income are positively correlated. It is not clear if trust in green strategies is affected by respondents' income. In addition, nonwhite respondents are slightly more likely to show higher levels of trust in green mitigations strategies than White respondents.

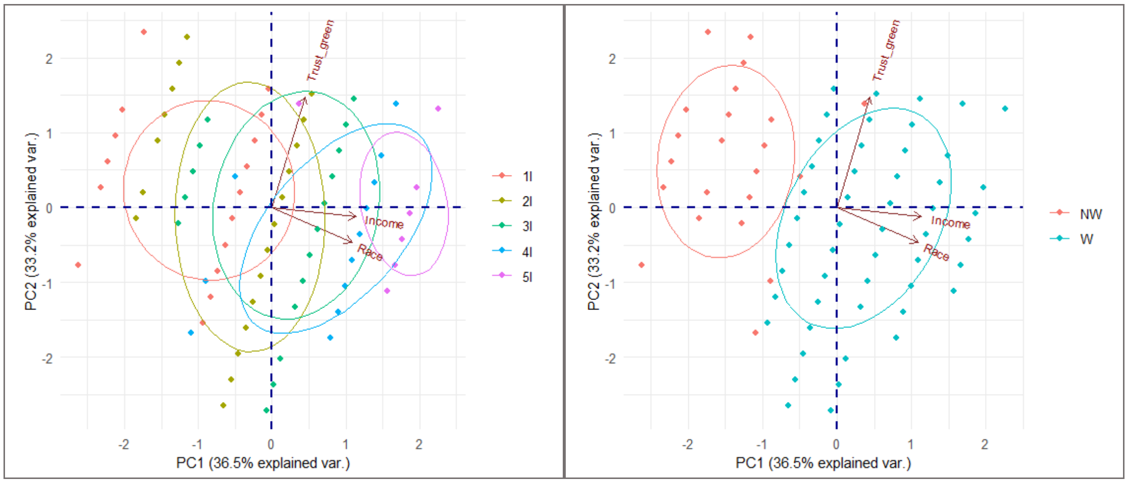


Figure 20. PCA plot of trust in green strategies (Trust_green), income and race (N=209). The arrow direction indicates the direction that the variable increases its values, and the arrow length is proportional to its variance. The dots represent the respondents' responses.

A PCA was conducted with trust in green strategies, income, race and nine other variables (Flood_prediction, Flood_insurance, Flood_exp, Housing_status, Education, Time_living, Age, Gender, and Disability). The PC plot in Figure 21 shows that lower levels of trust in green strategies are more likely to occur when 1) respondents are older and have been living longer in the area, and 2) respondents are White, own a home, have experienced flooding, have flood insurance, and have higher education and income. Higher levels of trust are associated with respondents believing that flooding will increase in the next 15 years and female respondents.

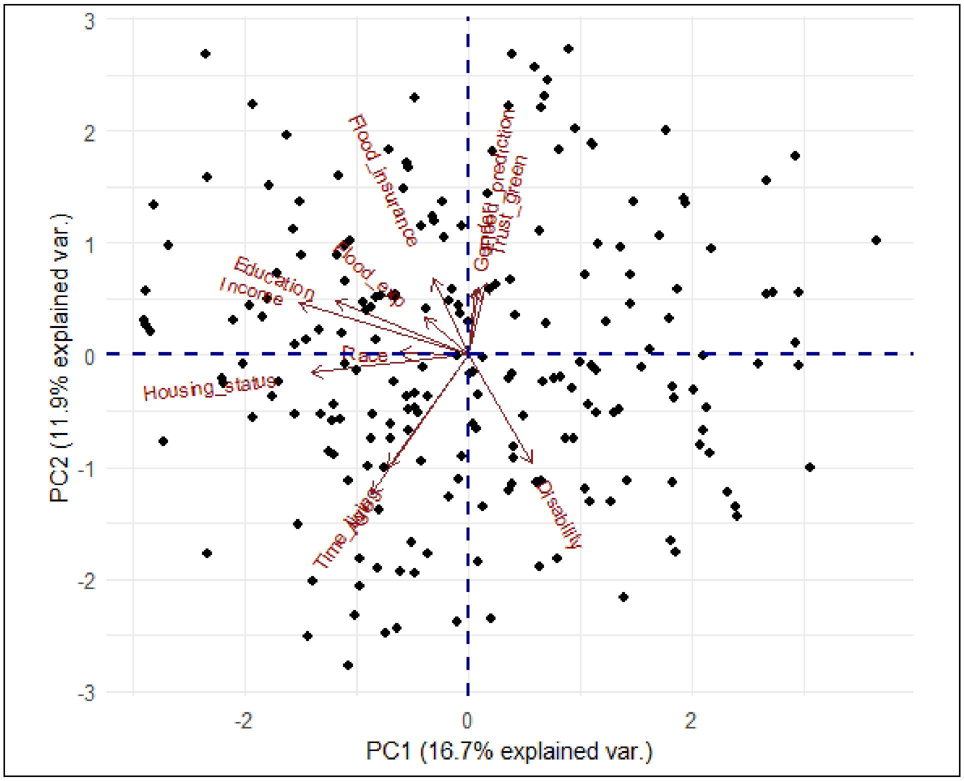


Figure 21. PCA plot of trust in green strategies and other variables (N=209). The arrow direction indicates the direction that the variable increases its values, and the arrow length is proportional to its variance. The black points represent the respondents' responses.

Nonstructural strategies

A PCA was conducted with trust in nonstructural strategies (Trust_nons), income and race. The PC plot in Figure 22 shows that the horizontal axis represents race and income, and the vertical axis represents trust in nonstructural strategies. The arrows show that race and income are positively correlated. It is not clear if trust in nonstructural strategies is affected by respondents' income. In addition, White respondents are slightly more likely to show higher levels of trust in nonstructural mitigations strategies than nonwhite respondents.

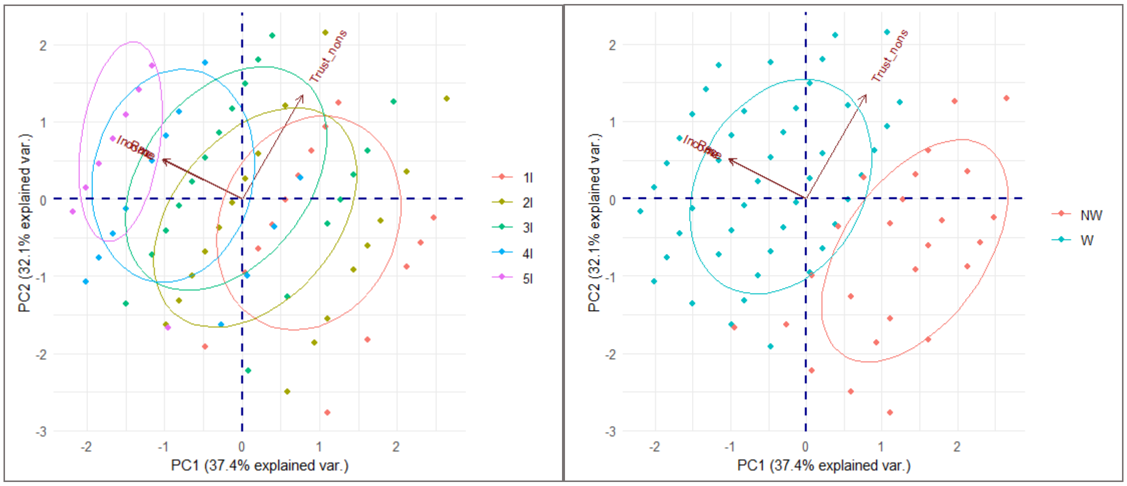


Figure 22. PCA plot of trust in nonstructural strategies (Trust_nons), income and race (N=209). The arrow direction indicates the direction that the variable increases its values, and the arrow length is proportional to its variance. The dots represent the respondents' responses. 23A shows a general PCA. 23B shows the responses by income. 23C shows the responses by race.

A PCA was conducted with trust in nonstructural strategies, income, race and nine other variables (Flood_prediction, Flood_insurance, Flood_exp, Housing_status, Education, Time_living, Age, Gender, and Disability). The PC plot in Figure 23 shows that lower levels of trust in nonstructural strategies are more likely to occur when 1) respondents are older and have been living longer in the area, 2) respondents are white, own a home and have experienced flooding, and 3) respondents have higher income and education. There are no factors that are associated with higher levels of trust in nonstructural strategies.

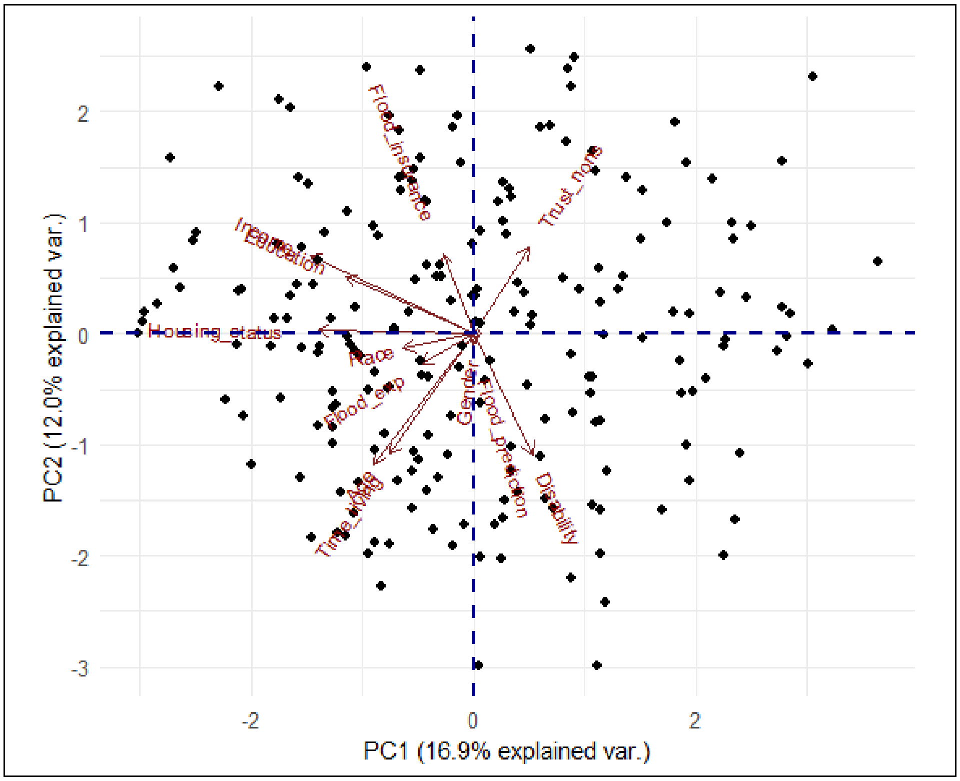


Figure 23. PCA plot of trust in nonstructural strategies and other variables (N=209). The arrow direction indicates the direction that the variable increases its values, and the arrow length is proportional to its variance. The black points represent the respondents' responses.

5.3.3 Multiple linear regression

Multiple linear regressions were conducted to model trust in gray, green and nonstructural mitigation strategies independently in R. Reduced models were obtained by variable stepwise selection, excluding predictors that did not have a statistically significant relationship with trust. An ANOVA test was performed to determine if the final models were statistically different from the full models.

Models with a p value below 0.05 indicate that the model is characterizing the relationship between predictors well, therefore, the full model for trust in green strategies is not characterizing the relationship between trust and the predictors well, as shown in Table 4. The full models for trust in gray, green and nonstructural strategies can explain 7.5%, 3.5% and 4.3% of the variance in trust, respectively. The final models for trust in gray, green and nonstructural strategies can explain 8.8%, 5.0% and 6.4% of the variance found in trust, respectively. The ANOVA analysis showed that the full models and the final models are not statistically different for trust in gray ($p = 0.774$), green ($p = 0.7928$), and nonstructural ($p = 0.958$) strategies, and the AIC values showed that the reduced models have a better fit, therefore the final models were kept.

Housing status is statistically significant for trust in all three kinds of strategies, meaning that respondents that own a home are more likely to have lower levels of trust in all three kinds of strategies. Flood experience and age are statistically significant for trust in gray and nonstructural strategies, meaning that respondents that have experienced flooding and are older are more likely to have lower levels of trust in gray and nonstructural strategies. Education is statistically significant for trust in green and nonstructural strategies, meaning that respondents with higher education are more likely to have higher levels of trust in green and nonstructural strategies. Time living in the area is statistically significant only for gray strategies, meaning that respondents that have lived longer in the area are more likely to have higher levels of trust in these strategies.

Table 4. Full and reduced models for trust in gray, green and nonstructural strategies (****p*<0.01, ***p*<0.05, **p*<0.1)

	Full models			Final models		
	Trust_nons	Trust_green	Trust_gray	Trust_nons	Trust_green	Trust_gray
Constant	11.736 ***	10.639 ***	12.525 ***	11.668 ***	10.487 ***	13.019 ***
Housing_status	-0.678 *	-0.869 ***	-0.729 **	-0.647 **	-0.885 ***	-0.707 **
Flood_exp	-0.994 **	0.087	-1.002 ***	-0.957 **		-0.965 ***
Age	-0.467 *	-0.438 *	-0.649 ***	-0.491 **		-0.726 ***
Time_living	0.065	0.085	0.249 *			0.234 *
Education	0.344 *	0.389 *	0.012	0.303 *	0.408 **	
Flood_prediction	-0.084	0.663 *	0.379		0.602 *	
Gender	-0.633	-0.215	-0.396	-0.589		
Income	-0.084	0.166	-0.023			
Race	-0.047	0.263	-0.57			
Flood_insurance	0.475	-0.401	0.326			
Disability	-0.025	0.269	-0.146			
***p*-value**	0.049	0.081	0.005	0.002	0.003	0.0001
R-squared	0.043	0.035	0.075	0.064	0.05	0.088
AIC	430.3	425.13	400.73	419.89	414	390.97

Flood prediction is statistically significant only for green strategies, meaning that respondents that believe that flooding is going to increase in the next 15 years are more likely to have higher levels of trust in these strategies. Gender is present in the final model of trust in nonstructural strategies; however, it does not have a statistically significant relationship with trust.

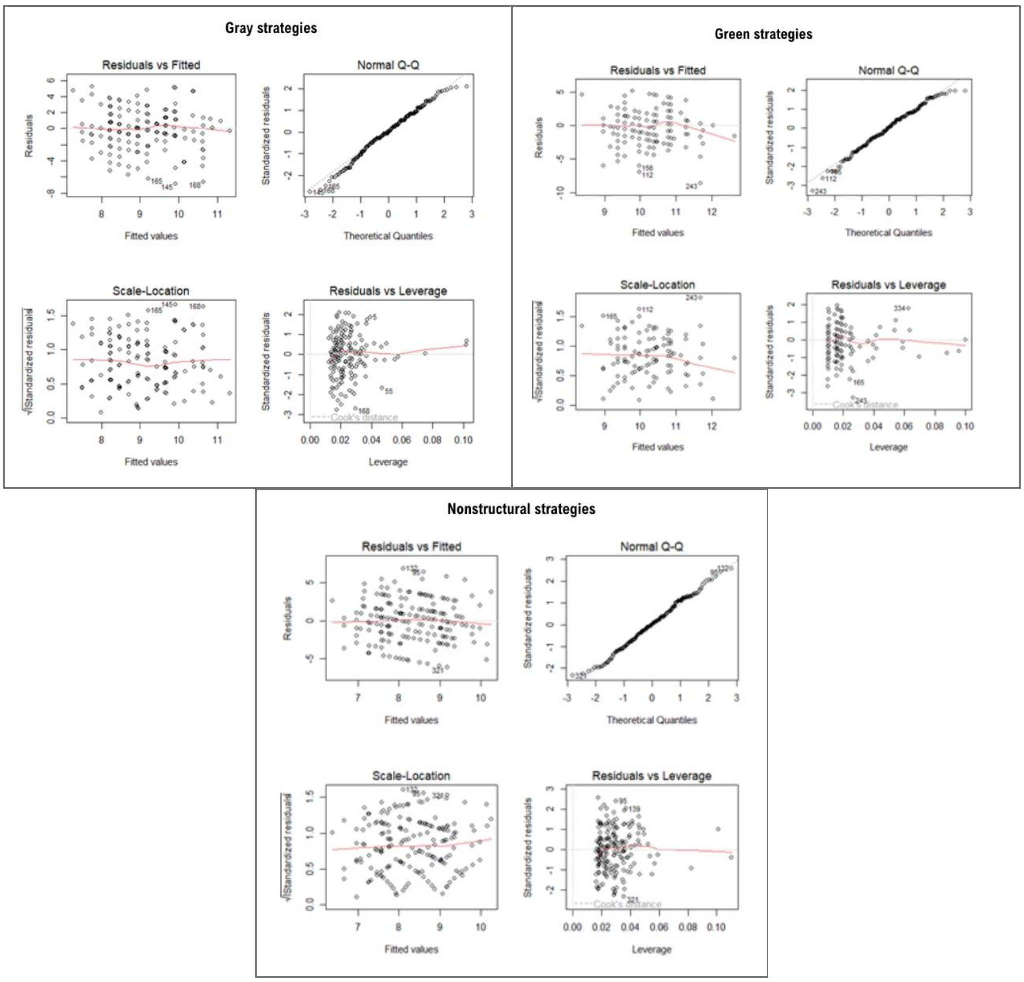


Figure 24. Residuals diagnostic plot for final models. Labels of charts from left to right, top to bottom: Residuals vs fitted: used to analyze if a linear model is appropriate for the relationship in the dataset; Normal Q-Q: visual representation to see if residuals are normally distributed: Scale-location: used to test equal variance; and Residuals vs Leverage: used to identify potentially influential outliers.

Based on the diagnostic plots in Figure 25, the residuals follow a normal distribution for all three final models. In addition, a Shapiro-Wilks test of normality for trust in gray (p = 0.094), green (p = 0.059) and nonstructural (p = 0.5129) strategies showed that the residuals were in the normal range and a F-test for equal variance showed that the residuals are equally distributed for trust in gray (p = 0.657, ratio of variance = 0.915), green (p = 0.1264, ratio of variance = 0.724) and nonstructural (p = 0.91, ratio of variance = 0.9778) strategies. The VIF values showed that some multicollinearity exists between the predictors for trust in gray (VIF ranged from 1.066-1.146), green (VIF ranged from 1.0004-1.0452) and nonstructural (VIF ranged from 1.016-1.091) strategies.

The VIF values showed that some multicollinearity exists between the predictors, therefore, a correlation analysis was performed, as shown in Table 5. Pearson correlation coefficients between 0-0.19 indicate a very low correlation, 0.2-0.39 indicate low correlation, 0.4-0.59 indicate moderate correlation, 0.6-0.79 indicates high correlation, and 0.8-1.0 indicate very high correlation (Selvanathan et al., 2020). Income has low and moderate correlation with housing status and education, respectively, meaning that respondents with higher income tend to have higher education and own a home. Race has very low positive and negative correlation with age and disability respectively, meaning that White respondents tend to be older and do not have a disability. Flood prediction has very low correlation with race and gender, meaning that female and white respondents tend to believe that flooding will increase in the next 15 years. Flood insurance has very low correlation with income, housing status and age (negative), meaning that younger respondents that own a home and have higher income tend to have flood insurance.

Table 5. Pearson Correlation Coefficients between predictors (N=209)

	Disability	**Gender**	**Age**	**Time living**	**Education**	**Housing status**	**Flood experience**	**Flood insurance**	**Flood prediction**	**Race**	**Income**
Income	-0.25	-0.09	0.11	0.1	0.43	0.39	0.13	0.14	-0.11	0.09	1
Race	-0.17	0.09	0.18	0.05	0.05	0.15	-0.09	-0.04	0.13	1	0.09
Flood prediction	-0.03	0.16	0	-0.08	0.01	0.02	0.07	0	1	0.13	-0.11
Flood insurance	-0.01	0.12	-0.16	0.02	0.02	0.14	0.06	1	0	-0.04	0.14
Flood experienc	0.01	0.12	-0.05	0.22	0.12	0.01	1	0.06	0.07	-0.09	0.13
Housing status	-0.12	-0.02	0.23	0.18	0.21	1	0.01	0.14	0.02	0.15	0.39
Education	-0.09	0.02	0.17	-0.01	1	0.21	0.12	0.02	0.01	0.05	0.43
Time living	0.1	-0.02	0.28	1	-0.01	0.18	0.22	0.02	-0.08	0.05	0.1
Age	0.13	-0.03	1	0.28	0.17	0.23	-0.05	-0.16	0	0.18	0.11
Gender	-0.01	1	-0.03	-0.02	0.02	-0.02	0.12	0.12	0.16	0.09	-0.09
Disability	1	-0.01	0.13	0.1	-0.09	-0.12	0.01	-0.01	-0.03	-0.17	-0.25

Flood experience has very low and low correlation with income and time living in the area respectively, meaning that respondents that have been living in the area and have higher income tend to have experienced flooding. Housing status has a low correlation with age, meaning that older respondents tend to own a home. Education has low and moderate correlation with housing status and income respectively, meaning that respondents that have higher income and own a home tend to have higher education. Time living in the area has low correlation with age, meaning that respondents that are older tend to have been living longer in the area. Gender has very low correlation with flood insurance and flood experience, meaning that respondents that have flood insurance and experience flooding tend to be female. Disability has a low negative correlation with income, meaning that respondents with higher income tend to not have a disability.

Chapter 6

Discussion

6.1 Respondents ‘profile

The response sample is mostly composed of educated, English-speaking, old-age adults who have lived in the area for an average of 12 years and own a home. Respondents have a mean 2022 household pre-tax income ($57,774) lower than the mean income at the state level ($70,084). Both the Oregon coast and response sample are predominantly White (82.4% and 81.4%, respectively). The percentages of Black people (1.4% vs 0.8%) and Native American people (6.8% vs 1.8%) are higher in the response sample than at the Oregon Coast level, which could be an indicator that BIPOC communities indeed are more likely to live in flood-prone areas. Similarly, Tate et al. (2021) found that higher percentages of Black, Native American, and Latino populations, and low-income households are distinguishing characteristics of areas with high flood exposure and high social vulnerability. In addition, characteristics such as housing status, income, and demographics can influence how communities cope with flooding, and provide insights into distributive justice issues, such as low resilience due to unequal access to resources before and after floods.

6.2 Trust analysis

Respondents trust gray and green strategies because these strategies comply with the trust dimensions of integrity, competence, and dependability, meaning that they believe that these strategies provide equal protection for all, will keep them safe and are reliable.

Similarly, Deely & Hynes (2020) found that residents of Carlingford Lough in Ireland prefer green strategies over gray strategies, and when both flood protection and ecosystem services are considered, green methods are more cost-effective than gray infrastructure (Wu, 2016; Yang & Zhang, 2021). In contrast, Terpstra and Gutteling (2008) found that people in the Netherlands prefer gray strategies, and Krieger (2013) found that gray strategies are widely used in Germany because people believe they provide the same degree of protection to all residents and allow funds to be allocated in a way that ensures the greatest benefits to all. Furthermore, Yang and Zhang (2021) found that gray strategies outperform green strategies in flood mitigation, and that combined gray-green strategies outperformed strategies applied separately. Our results indicate that respondents trust both types of strategies, but they trust green strategies more; however, we did not examine the extent to which respondents would trust a gray-green approach over a one-type strategy approach.

Resources to maintain gray infrastructure are limited, and without maintenance, some structures have deteriorated to the point where they no longer provide the same level of protection (Harrell, 2018; The Astorian, 2018). Gray strategies have limitations in providing equal, efficient, and dependable flood protection, and are sometimes perceived as exclusionary (Muñoz-Duque et al., 2021; Zinda et al., 2021), which may encourage people to trust green strategies more. In fact, our findings indicate that green strategies are perceived to have better integrity, competence and dependability than gray strategies.

Respondents do not trust nonstructural strategies because these strategies do not comply with any of the trust dimensions, meaning that they believe that these strategies do not provide equal protection for all, will not keep them safe and are not reliable. Nonstructural strategies may be perceived as incompatible with community needs and values, difficult to access, and inappropriate or exaggerated (Bertoldo et al., 2020), resulting in low levels of trust in this kind of strategy. People are concerned about inadequate planning for future disasters, high insurance costs, limited coverage, and difficult claims processes, and their intentions to get flood insurance decrease because they have low trust in flood insurance institutions (Zinda et al., 2021; Rodera et al., 2019).

Communities enrolled in the NFIP (nonstructural strategy) must adhere to rules designed to reduce damage and risk of future flooding in order to receive assistance rebuilding after floods. Environmental groups believe that the NFIP has encouraged development in sensitive floodplain areas without considering the harmful impact on endangered species' habitat. Other groups, on the other hand, are concerned that the program's proposed changes to comply with the Endangered Species Act will negatively impact economic growth (Smith, 2016). Concerns about the flood insurance program have been an ongoing issue, for example, in 2017, the city of Coos Bay sued the National Marine Fisheries Service over restrictive floodplain regulations, and at start of 2023, Tillamook residents strongly criticized FEMA changes to the flood insurance program (Chappell, 2023). People become concerned about EJ when they perceive they have no say in program planning and implementation (an example of procedural justice issue), that changing conditions do not provide a sense of security, and that one group's interests take precedence over those of other groups (an example of recognition justice issue).

Concerns regarding who has the power to decide whose interests are taken into account can result in conflicts between stakeholders and a loss of trust in nonstructural strategies. Furthermore, Eakin et al. (2021) discuss that nonstructural strategy policies rarely address structural inequalities that exacerbate injustice, therefore the contribution of mitigation programs to social equity should be assessed (Adger et al., 2005).

The analysis of trust in mitigation strategies by race and income groups was expected to indicate that White and higher income respondents have higher levels of trust in all strategies than nonwhite and lower income respondents; however, this trend was not observed. It is important to mention that Native Americans had the lowest levels of trust in the gray and green strategies, while respondents of two or more races had the lowest levels of trust in nonstructural strategies. This can be attributed to distributive justice issues reflected in the spatial relationship between flood extent, socioeconomic vulnerability, and percentages of racial minorities in flood-prone areas (Chakraborty et al., 2019). In other words, a disproportionate proportion of racial minorities live in flood-prone locations with inadequate resources to recover and/or relocate. White respondents had the highest level of trust in green strategies compared to nonwhite respondents. This might be attributed to White respondents having a better understanding of how green strategies work through access to higher education, as income and education have a positive correlation. It may also be attributed to White respondents having greater access to this type of program, since racial and ethnic minorities, as well as low-income populations, tend to be relegated to flood-prone areas without water-related amenities or green spaces (Montgomery & Chakraborty, 2015). Furthermore, racial minorities are vulnerable to racial bias (Enarson & Fordham, 2000) and experience environmental damage differently than other groups (Perez & Egan, 2016), which can lead to low levels of trust in mitigation strategies.

6.3 Statistical Analysis

The correlation analysis and PCA results indicate that trust in gray strategies has a negative correlation with race and income, meaning that White respondents and respondents with higher income are more likely to have lower levels of trust in gray strategies than nonwhite respondents with lower income. In addition, trust in gray strategies and race have a statistically significant relationship, however, race can only explain 0.2% of the variance in trust in gray strategies.

The correlation analysis indicates that trust in green strategies has a positive correlation with race and income, meaning that White respondents and respondents with higher income are more likely to have higher levels of trust in green strategies than nonwhite respondents with lower income but these results were not statistically significant. However, based on the PCA plots it is not clear if trust in green strategies is affected by income, nonwhite respondents are more likely to show higher levels of trust in green strategies than nonwhite respondents, and race and income are positively correlated.

The correlation analysis indicates that trust in nonstructural strategies have a negative correlation with race and income, meaning that White respondents and respondents with higher income are more likely to have lower levels of trust in nonstructural strategies than nonwhite respondents with lower income. However, based on the PCA plots it is not clear if trust in nonstructural strategies is affected by income, white respondents are more likely to show higher levels of trust in nonstructural strategies than nonwhite respondents, and race and income are positively correlated. In addition, trust in nonstructural strategies and race have a statistically significant relationship, however, race can only explain 0.7% of the variance in trust in nonstructural strategies. These findings led to an analysis of the relationship between trust and multiple predictors at the same time.

The PCA with trust in gray strategies and other predictors showed that White older respondents that have been living longer in the area, own a home, have experienced flooding, and have higher education and income are more likely to show lower levels of trust in gray strategies. In addition, higher levels of trust in gray strategies are associated with respondents believing that flooding will increase in the next 15 years. However, the MLR indicates that only housing status, flood experience, age, and time living in the area are statistically significant in a model that explains 8.8% of the variance in trust in gray strategies.

The PCA with trust in green strategies and other predictors showed that White older respondents that have been living longer in the area, own a home, have experienced flooding, have flood insurance, and have higher education and income are more likely to show lower levels of trust in gray strategies. In addition, higher levels of trust in gray strategies are associated with respondents believing that flooding will increase in the next 15 years and female respondents. However, the MLR indicates that only housing status, education, and flood prediction are statistically significant in a model that explains 5.0% of the variance in trust in green strategies.

The PCA with trust in nonstructural strategies and other predictors showed that White older respondents that have been living longer in the area, own a home, have experienced flooding, and have higher education and income are more likely to show lower levels of trust in nonstructural strategies. However, the MLR indicates that only housing status, flood experience, age, and education are statistically significant in a model that explains 6.4% of the variance in trust in nonstructural strategies.

Complex gender, racial, ethnic, class stratification and segregation patterns influence residents' vulnerability and resilience (Enarson & Fordham, 2000), similarly, complex housing status, flood experience, age, time living in the area, education, and flood prediction influence people's trust in flood mitigation strategies. Furthermore, risk perception is influenced by sociodemographic factors, trust factors, psychological and cognitive factors, and risk related factors (Mumbi & Watanabe, 2020), and these factors also affect trust in flood mitigation strategies. As a result, a feedback effect or loop between factors/predictors occurs, making trust modeling complex, as evidenced in our trust models, which could only explain 8.8%, 5.0% and 6.4% of the variance in trust in gray, green and nonstructural strategies, respectively.

Social status, access to knowledge, insurance, early, and warning systems, gender, property ownership, political power, and health status are all factors that make a difference in similarly exposed communities to flooding (Wachinger et al., 2010). These factors contribute to distributive and procedural justice issues because the limited access to resources and power prevents a meaningful participation in the decision making around flood management, whereas recognition justice concerns include whose knowledge is recognized, who has the power to recognize that knowledge, and the repercussions of mitigation strategies (Eriksen et al., 2015). Furthermore, rising sea levels and higher storm surge may increase the risk of flooding in EJ coastal areas (Perez & Egan, 2016).

Owning a home tends to decrease levels of trust in all three kinds of strategies. Flooding experience and older ages tend to decrease levels of trust in gray and nonstructural strategies. Higher education tends to increase levels of trust in green and nonstructural strategies. Longer time living in the area tends to increase levels of trust in gray strategies. Believing that flooding is going to increase in the next 15 years tends to increase levels of trust in green strategies. Being female tends to decrease levels of trust in nonstructural strategies, but this was not statistically significant.

Social status, education, insurance, gender, and property ownership are all factors that make a difference in similarly exposed communities to flooding (Wachinger et al., 2010), and our findings suggest that it can also influence people's trust in flood mitigation strategies. Communities that have lived in the same area for generations share a common understanding of that territory, and develop a sense of belonging and attachment, which influence collective behavior and their perception of risk (Bertoldo et al., 2020; Panman et al., 2018). Over time, people develop a form of local knowledge that is often not included in flood management, leading to a loss of trust in mitigation strategies, which can explain why older respondents tend to have lower levels of trust in gray and nonstructural strategies. Furthermore, Terpstra (2011) found that people who have experienced flooding are less likely to trust flood mitigation strategies, and our findings also suggest that respondents that have experienced flooding have lower levels of trust in gray and nonstructural strategies. Moreover, socioeconomic inequality, lack of political power and affordable housing, and job insecurity limit the alternatives for vulnerable groups to leave flood-prone areas (Tate et al., 2021; Panman et al., 2018).

The predictors exhibited low and moderate correlation, indicating that they are interconnected. For example, flood experience correlates with time living in the area, but time living in the area correlates with age; thus, flood experience and age are connected through time living in the area. The predictors also reinforce each other when the correlation is positive, for instance, education and income, which suggests that respondents with higher education tend to have higher income. Finally, the predictors attenuate each other when the correlation is negative, for example, gender and income, which suggests that female respondents tend to have lower income than male respondents. In general, income, housing status and age appeared to be the most correlated with other predictors.

Chapter 7

Conclusion

Race and income can predict trust to a moderate extent but housing status, flood experience, age, time living in the area, education, and flood prediction can predict trust better. Race had a statistically significant relationship with trust in gray and nonstructural strategies, however, race by itself cannot predict trust properly. I hypothesized that lower levels of trust in flood mitigation strategies are more likely to occur in nonwhite respondents, but the results indicated that this is true only for green strategies, while for gray and nonstructural strategies, lower levels of trust occurred in white respondents. I also hypothesized that lower levels of trust in flood mitigation strategies are more likely to occur in respondents with lower income, but the results indicated that this is true only for green strategies, while for gray and nonstructural strategies, lower levels of trust occurred in respondents with higher income. Predictors that were statistically significant when modeling trust in gray strategies include housing status, flood experience, age, time living in the area, education, and flood prediction. Furthermore, respondents trust green strategies more than they trust gray strategies, and do not trust nonstructural strategies. Green strategies may be preferred over gray strategies because they provide ecological services such as pollution control, recreation, and species habitat.

EJ was encouraged by incorporating community opinions and concerns about flood mitigation throughout the research process. Furthermore, the input from the advisory board guaranteed that our survey was culturally sensitive and suitable; community being part of research supports the recognition of the local knowledge value, and encourages meaningful participation. Giving communities a voice in strategy design, implementation, and maintenance can help to build trust (procedural justice). Citizen organizations can provide feedback, but it is only implemented if it is in the best interests of the local government (Begg, 2018), revealing a lack of meaningful participation in flood management. People's experience is valuable in flood management (recognition justice); therefore, a bottom-up approach seems to be more appropriate to build trust.

Government agencies and engineering companies have traditionally selected gray strategies, whereas citizen groups and research institutes have supported green strategies (Yang & Zhang, 2021). Flood impact assessments generally focus on damage to physical assets, but little is known about who is at risk of flooding (Tate et al., 2021). Understanding the social dimensions of flooding can help to determine people's priorities and limitations, as well as develop flood adaptation and risk management programs that are more likely to be supported (Haeffner & Hellman, 2020).

Limitations of this study include the demographics of the study area, as most respondents were White, therefore the number of responses from racial minorities was limited. Future research could replicate the methodology followed in this study in areas more racially diverse and for other natural hazards (e.g., floods, droughts, wildfires, tornadoes, etc.), explore to what extent trust in mitigation strategies is affected by trust in flood management institutions, the extent to which respondents would trust a gray-green approach over a one-type strategy approach, and the contribution to social equity of flood mitigation strategies.

References

Adger, N., Arnell, N., & Tompkins, E. (2005). Successful adaptation to climate change across scales. *Global Environmental Change*, 77-86. DOI: https://doi.org/10.1016/j.gloenvcha.2004.12.005.

Ahmad, N., & Younas, M. (2021). A blessing in disguise?: Assessing the impact of 2010–2011 floods on trust in Pakistan. *Environmental Science and Pollution Research*, 25419–25431. DOI: https://doi.org/10.1007/s11356-020-12332-4.

Allen, S. (2020, August 24). *PSU study explores how opposing groups came together to stop flooding in Tillamook.* From Tillamook Headlight Herald: https://www.tillamookheadlightherald.com/news_paid/psu-study-explores-how-opposing-groups-came-together-to-stop-flooding-in-tillamook/article_9e3fe45a-e1a6-11ea-91c4-cf04d700b46b.html

Begg, C. (2018). Power, responsibility and justice: a review of local stakeholder participation in European flood risk management. *Local Environment*, 383-397, DOI: 10.1080/13549839.2017.1422119.

Ben-Ner, A., & Halldorsson, F. (2010). Trusting and trustworthiness: What are they, how to measure them, and what affects them. *Journal of Economic Psychology*, 64-79. DOI: https://doi.org/10.1016/j.joep.2009.10.001.

Bertoldo, R., Tanga, R., Dias, P., Guignard, S., & Schleyer-Lindenmann, A. (2020). Calculative and relational trust in the management of coastal floods and earthquakes: a comparative study (Confianza calculativa y relacional en la gestión de inundaciones costeras y terremotos: un estudio comparativo). *PsyEcology*, 193-213. DOI: https://doi.org/10.1080/21711976.2020.1734398.

Bronfman, N., Cisternas, P., Lòpez-Vàquez, E., & Cifuentes, L. (2016). Trust and risk perception of natural hazards: implications for risk preparedness in Chile. *Natural Hazards, 81*, 307-327. DOI: https://doi.org/10.1007/s11069-015-2080-4.

Chakraborty, J., Collins, T., & Grineski, S. (2019). Exploring the environmental justice implications of Hurricane Harvey flooding in Greater Houston, Texas. *American journal of public health*, 244-250. DOI: 10.2105/AJPH.2018.304846.

Chappell, W. (2023, April 17). *Flood Insurance: Proposed FEMA changes met with harsh criticism.* From The News Guard, Lincoln City. Oregon: https://www.thenewsguard.com/news/flood-insurance-proposed-fema-changes-met-with-harsh-criticism/article_9889c9c6-d7b3-11ed-925b-9b05b79da6e6.html

Childers, L., & Grunig, J. (1999, November). *Guidelines for Measuring Relationships in Public Relations.* From Institute for Public Relations: https://www.instituteforpr.org/wp-content/uploads/Guidelines_Measuring_Relationships.pdf

Cisternas, P. C., Cifuentes, L. A., Bronfman, N. c., & Repetto, P. B. (2023). The influence of risk awareness and government trust on risk perception and preparedness for natural hazards. *Risk Analysis*, DOI: https://doi.org/10.1111/risa.14151.

Compston, C. (2017, February 1). *It's all about trust*. From https://ndxcc.medium.com/trust-775f27faeecb

Darker, C. (2013). Risk Perception. *Encyclopedia of Behavioral Medicine. Springer, New York, NY*, DOI: https://doi.org/10.1007/978-1-4419-1005-9_866.

Deely, J., & Hynes, S. (2020). Blue-green or grey, how much is the public willing to pay? *Landscape and Urban Planning*, 1-9. DOI: https://doi.org/10.1016/j.landurbplan.2020.103909.

Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Salinas, J., & Bloschl, G. (2013). Socio-hydrology: conceptualizing human-flood interactions. *Hydrology and Earth System Sciences*, 3295–3303. DOI: https://doi.org/10.5194/hess-17-3295-2013.

Douglas, E. M., Kirshen, P. H., Paolisso, M., Watson, C., Wiggin, J., Enrici, A., & Ruth, M. (2012). Coastal flooding, climate change and environmental justice: identifying obstacles and incentives for adaptation in two metropolitan Boston Massachusetts communities. *Mitigation and Adaptation Strategies for Global Change*, 537–562. DOI: https://doi.org/10.1007/s11027-011-9340-8.

Eakin, H., Parajuli, J., Hernández Aguilar, B., & Yogya, Y. (2021). Attending the social–political dimensions of urban flooding in decision-support research: A synthesis of contemporary empirical cases. *Wires Climate Change*, 1-21. DOI: https://doi.org/10.1002/wcc.743.

Eiser, J., Bostrom, A., Burton, I., Johnston, D., McClure, J., Paton, D., & White, M. (2012). Risk interpretation and action: A conceptual framework for responses to natural hazards. *International Journal of Disaster Risk Reduction*, 5-16. DOI: https://doi.org/10.1016/j.ijdrr.2012.05.002.

Enarson, E., & Fordham, M. (2000). Lines That Divide, Ties That Bind: Race, Class, and Gender in Women's Flood Recovery in the US and UK. *Australian Journal of Emergency Management*, 43-52. ISSN:1324-1540.

EPA. (2014, December). *Using Green Infrastructure to Mitigate Flooding in La Crosse, WI*. From United States Environmental Protection Agency, EPA: https://www.epa.gov/sites/default/files/2015-10/documents/lacrosse_tech_assistance.pdf

EPA. (2022, September 6). *Environmental Justice.* From Environmental Protection Agency, EPA: https://www.epa.gov/environmentaljustice/learn-about-environmental-justice

EPA. (2023, June 15). *Manage Flood Risk*. From Environmental Protection Agency, EPA: https://www.epa.gov/green-infrastructure/manage-flood-risk

Eriksen, S., Nightingale, A., & Eakin, H. (2015). Reframing adaptation: The political nature of climate change adaptation. *Global Environmental Change*, 523–533. https://doi.org/10.1016/j.gloenvcha.2015.09.014.

FEMA. (2013, January). *Mitigation Ideas: A Resource for Reducing Risk to Natural Hazards.* From https://www.fema.gov/sites/default/files/2020-06/fema-mitigation-ideas_02-13-2013.pdf

FEMA. (2018, March). *Be prepared for a flood.* From FEMA Preparedness Community: https://community.fema.gov/ProtectiveActions/s/article/Flood

Haefner, M., & Hellman, D. (2020). The social geometry of collaborative food risk management: a hydrosocial case study of Tillamook County, Oregon. *Natural Hazards 103*, 3303–3325. DOI: https://doi.org/10.1007/s11069-020-04131-4.

Harrell, S. (2018, September 29). *Englewood dike close to failing.* From The World: https://theworldlink.com/news/local/englewood-dike-close-to-failing/article_9ab1cb9e-b05f-5fba-b904-f5aaa6aad2e3.html

Jaadi, Z., & Whitfield, B. (2023, March 29). *A Step-by-Step Explanation of Principal Component Analysis (PCA)*. From Built In: https://builtin.com/data-science/step-step-explanation-principal-component-analysis

Jonkman, S. (2005). Global Perspectives on Loss of Human Life Caused by Floods. *Natural Hazards*, 151–175. DOI: https://doi.org/10.1007/s11069-004-8891-3.

Kerstholt, J., Duijnhoven, H., & Paton, D. (2017). Flooding in The Netherlands: How people's interpretation of personal, social and institutional resources influence flooding preparedness. *International Journal of Disaster Risk Reduction*, 52-57. DOI: https://doi.org/10.1016/j.ijdrr.2017.05.013.

Komar, P., & Allan, J. (2000). *Analysis of extreme waves and water levels on the Pacific Northwest Coast.* Corvallis, OR: College of Oceanic & Atmospheric Sciences, Oregon State University.

Komar, P., Allan, J., & Ruggiero, P. (2013). U.S. Pacific Northwest Coastal Hazards: Tectonic and Climate Controls. *Coastal Hazards, Coastal Research Library*, 587-674. DOI 10.1007/978-94-007-5234-4_21.

Krieger, K. (2013). The limits and variety of risk-based governance: The case of flood management in Germany and England. *Regulation & Governance*, 2013) 7, 236–257. DOI: 10.1111/rego.12009.

Lewis, J., & Kelman, I. (2010). Places, people and perpetuity: Community capacities in ecologies of catastrophe. *ACME: An International E-Journal for Critical Geographies*, 191-220.

Lin, S., Shaw, D., & Ho, M. (2008). Why are flood and landslide victims less willing to take mitigation measures than the public? *Natural Hazards*, 305–314. DOI: https://doi.org/10.1007/s11069-007-9136-z.

Linnerooth-Bayer, J., & Amendola, A. (2003). Introduction to Special Issue on Flood Risks in Europe. *Risk Analysis*, 537-543. DOI: https://doi.org/10.1111/1539-6924.00334.

Maldonado, A., Collins, T., Grineski, S., & Chakraborty, J. (2016). Exposure to flood hazards in Miami and houston: Are Hispanic immigrants at greater risk than other social groups? . *International Journal of Environmental Research and Public Health*, 1-20. DOI: 10.3390/ijerph13080775.

Montgomery, M., & Chakraborty, J. (2015). Assessing the environmental justice consequences of flood risk: a case study in Miami, Florida. *Environmental Research Letters*, 1-11. DOI: 10.1088/1748-9326/10/9/095010.

Mumbi, A. W., & Watanabe, T. (2020). Differences in Risk Perception of Water Quality and Its Influencing Factors between Lay People and Factory Workers for Water Management in River Sosiani, Eldoret Municipality Kenya. *Water 12, no.*, 1:25. DOI: https://doi.org/10.3390/w12082248.

Muñoz-Duque, L. A., Navarro, O., Restrepo-Ochoa, D., & Fleury-Bahi, G. (2021). Risk perception and trust management in inhabitants exposed to coastal flooding: The case of Cartagena, Colombia. *International Journal of Disaster Risk Reduction*, DOI: https://doi.org/10.1016/j.ijdrr.2021.102261.

OEM. (2020, September). *Oregon Natural Hazards Mitigation Plan*. From Oregon Office of Emergency Management, OEM: https://www.oregon.gov/lcd/NH/Pages/Mitigation-Planning.aspx

Paine, K. D. (2013, April). *Guidelines for Measuring Trust in Organizations. Institute for Public Relations.* From Institute for Public Relations: https://instituteforpr.org/?s=Guidelines+for+Measuring+Trust+in+Organizations

Panman, A., Madison, I., & Falisse, J.-B. (2018, December 14). *Why do people live in flood-prone areas? Reflections from Dar es Salaam*. From World Bank Blogs: https://blogs.worldbank.org/nasikiliza/why-do-people-live-in-flood-prone-areas-reflections-from-dar-es-salaam

Perez, V., & Egan, J. (2016). Knowledge and Concern for Sea-Level Rise in an Urban Environmental Justice Community. *Sociological Forum*, 885-907. DOI: https://doi.org/10.1111/socf.12278.

Reed, M. (2015, May 6). *Mitigation: Structural and Non-structural*. From PennState Public Health Preparedness: https://sites.psu.edu/workworthdoing/2015/05/06/mitigation-structural-and-non-structural/

Remo, J., Carlson, M., & Pinter, N. (2012). Hydraulic and flood-loss modeling of levee, floodplain, and river management strategies, Middle Mississippi River, USA. *Natural Hazards*, 551–575. DOI: https://doi.org/10.1007/s11069-011-9938-x.

Rodera, G., Hudson, P., & Tarolli, P. (2019). Flood risk perceptions and the willingness to pay for flood insurance in the Veneto Region. *International Journal of Disaster Risk Reduction*, DOI: https://doi.org/10.1016/j.ijdrr.2019.101172.

Samaddar, S., Misra, B., & Tatano, H. (2012). Flood Risk Awareness and Preparedness : The Role of Trust in Information Sources. *IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 3099-3104. DOI: 10.1109/ICSMC.2012.6378267.

Selvanathan, M., Jayabalan, N., Saini, G., Supramaniam, M., & Hussin, N. (2020). Employee Productivity in Malaysian Private Higher Educational Institutions. *PalArch's Journal of Archaeology of Egypt/Egyptology*, 66-79. DOI: 10.48080/jae.v17i3.50.

Siegrist, M., & Cvetkovich, G. (2000). Perception of hazards: The role of social trust and knowledge. *Risk analysis*, 713-720. DOI: https://doi.org/10.1111/0272-4332.205064.

Smith, A. (2016, July 27). *New restrictions on Oregon floodplain development*. From High Country News: https://www.hcn.org/articles/New-restrictions-for-Oregon-floodplain-development-fema-endangered-species-act-lawsuite-national-flood-insurance-program

Smith, A. (2023, January 10). *2022 U.S. Billion-dollar weather and climate disasters in historical context*. From NOAA Climate.gov: https://www.climate.gov/news-features/blogs/2022-us-billion-dollar-weather-and-climate-disasters-historical-context

Sweet, S., & Grace-Martin, K. (2012). *Data Analysis with SPSS: A first course in applied statistics.* Boston: Allyn and Bacon.

Szönyi, M., & Svensson, A. (2019, November 26). *From Grey to Green infrastructure: a paradigm shift needed to deliver on climate action*. From Flood Resilience Portal: https://floodresilience.net/blogs/from-grey-to-green-infrastructure-a-paradigm-shift-needed-to-deliver-on-climate-action/#:~:text=Unlike%20grey%20infrastructure%20green%20or,also%20useful%20in%20binding%20CO2.

Tate, E., Rahman, M., Emrich, C., & Sampson, C. (2021). Flood exposure and social vulnerability in the United States. *Natural Hazards*, 435-457. DOI: https://doi.org/10.1007/s11069-020-04470-2.

Terpstra, T. (2011). Emotions, Trust, and Perceived Risk: Affective and Cognitive Routes to Flood Preparedness Behavior. *Risk Analysis*, 1658-1675. DOI: 10.1111/j.1539-6924.2011.01616.x.

Terpstra, T., & Gutteling, J. M. (2008). Households' Perceived Responsibilities in Flood Risk Management in The Netherlands. *International Journal of Water Resources Development*, *24*, 555-565. DOI: 10.1080/07900620801923385.

The Astorian. (2018, December 6). *Clatsop levees among those in Oregon causing consternation.* From The Astorian: https://www.dailyastorian.com/news/clatsop-levees-among-those-in-oregon-causing-consternation/article_f377bde7-ed8f-531a-bddd-25748e69b1ea.html

The MathWorks. (2007, March). *Curve Fitting Toolbox 1: User's Guide.* From The MathWorks, Inc.: http://cda.psych.uiuc.edu/matlab_class_material/curvefit.pdf

Thieken, A., Kreibich, H., & Mülle, M. (2007). Coping with floods: preparedness, response and recovery of flood-affected residents in Germany in 2002. *Hydrological Sciences Journal*, 1016-1037. DOI: 10.1623/hysj.52.5.1016.

Väisänen, S., Lehtoranta, V., Parjanne, A., Rytkönen, A., & Aaltonen, J. (2016). Willingness of residents to invest in flood mitigation measures and to purchase flood insurance. *E3S Web Conferences*, DOI: https://doi.org/10.1051/e3sconf/20160722001.

Vanderlinden, J., Baztan, J., Touili, N., Kane, I., Rulleau, B., Diaz, S., & Zagonari, F. (2017). Coastal Flooding, Uncertainty and Climate Change: Science as a Solution to (mis) Perceptions? A Qualitative Enquiry in Three Coastal European Settings. *Journal of Coastal Research, Coastal Education and Research*, 127-133. DOI: 10.2112/SI77-013.1.

Venkataramanan, V., Lopez, D., McCuskey, D., Kiefus, D., McDonald , R., Miller, W., . . . Young, S. (2020). Knowledge, attitudes, intentions, and behavior related to green infrastructure for flood management: A systematic literature review. *Science of the Total Environment, 720*, DOI: https://doi.org/10.1016/j.scitotenv.2020.137606.

Viglione, A., Di Baldassarre, G., Brandimarte, L., Kuil, L., Carr, G., Salinas, J., & Blöschl, G. (2014). Insights from socio-hydrology modeling on dealing with flood risk – Roles of collective memory, risk-taking attitude and trust. *Journal of Hydrology*, 518, 71-82. DOI: https://doi.org/10.1016/j.jhydrol.2014.01.018.

Wachinger, G., Renn, O., Begg, C., & Kuhlicke, C. (2013). The risk perception paradox-implications for governance and communication of natural hazards. *Risk Analysis*, 1049-1065. DOI: 10.1111/j.1539-6924.2012.01942.x.

Wachinger, G., Renn, O., Bianchizza, C., Coates, T., De Marchi, B., Domenech, L., . . . Whittle, R. (2010). Risk perception and natural hazards. *CapHaz-Net WP3 Report, DIALOGIK Non-Profit Institute for Communication and Cooperative Research, Stuttgart*, 1-111. http://caphaz-net.org/outcomes-results/CapHaz-Net_WP3_Risk-Perception.pdf.

Wing, O., Bates, P., Smith, A., Sampson, C., Johnson, K., Fargione, J., & Morefield, P. (2018). Estimates of present and future flood risk in the conterminous United States. *Environmental Research Letters*, DOI: https://doi.org/10.1088/1748-9326/aaac65.

Witte, K., & Allen, M. (2000). A meta-analysis of fear appeals: implications for effective public health campaigns. *Health Education & Behavior*, 591-615. DOI: https://doi.org/10.1177/109019810002700506.

Wu, A. (2016, September 1). *Green versus gray infrastructure: The economics of flood adaptation in Fiji*. From Yale Environment Review (YER): https://environment-review.yale.edu/green-versus-gray-infrastructure-economics-flood-adaptation-fiji-0

WWF. (2017, May 24). *Natural and Nature-Based Flood Management: A Green Guide. World Wildlife Fund*. From World Wildlife Fund, WWF: https://www.worldwildlife.org/publications/natural-and-nature-based-flood-management-a-green-guide

Yang, W., & Zhang, J. (2021). Assessing the performance of gray and green strategies for sustainable urban drainage system development: A multi-criteria decision making analysis. *Journal of Cleaner Production*, DOI: https://doi.org/10.1016/j.jclepro.2021.126191.

Zinda, J. A., Williams, L. B., Kay, D. L., & Alexander, S. M. (2021). Flood risk perception and responses among urban residents in the northeastern United States. *International Journal of Disaster Risk Reduction*, DOI: https://doi.org/10.1016/j.ijdrr.2021.1.

Appendix A. Codebook for respondents' profile.

Variable	Code	Description
County	1	Clatsop
	2	Coos
	3	Curry
	4	Douglas
	5	Lane
	6	Lincoln
	7	Tillamook
Race/ethnicity	1	White
	2	Black or African American
	3	Hispanic or latino
	4	American Indian, Native Hawaiian or Alaskan Native
	5	Asian
	6	Two or more races
	7	Prefer not to answer
Income	1	Less than $30,000
	2	$30,000 - $59,999
	3	$60,000 - $89,999
	4	$90,000 - $119,999
	5	More than $120,000
	6	Prefer not to answer
Age	1	18-30
	2	31-50
	3	51-70
	4	Over 70 years of age
Time living	1	Less than one year
	2	1-5 years
	3	6-10 years
	4	11-15 years
	5	More than 15 years
	6	Prefer not to answer
Gender	1	Female
	2	Male
	3	Nonbinary
	4	Prefer not to answer
Education	1	Some highschool or less
	2	High school degree, GED or equivalent
	3	Associate's degree, vocational school, or some college
	4	Bachelor's degree

	5	Advanced degree (Masters, PhD, JD, MD, etc.)
	6	Prefer not to answer
Flood prediction	1	Decrease
	2	Stay the same
	3	Increase
	4	Prefer not to answer
Housing status	1	Unhoused
	2	Other
	3	Rent
	4	Own
	5	Prefer not to answer
Primary language	1	English
	2	Spanish
	3	Both
	4	Prefer not to answer
Disability	1	No
	2	Yes
	3	Prefer not to answer
Insurance	1	No
	2	Yes
	3	Prefer not to answer
Flood experience	1	No
	2	Yes
	3	Prefer not to answer

Appendix B. Variables description.

Variable number	Name	Description
1	County	1=Clatsop, 2= Coos, 3= Curry, 4= Douglas, 5= Lane, 6= Lincoln, 7= Tillamook
2	Integrity_gray	1=Strongly disagree, 2=Disagree, 3=Neither agree or disagree, 4=Agree, 5=Strongly agree
3	Integrity_green	
4	Integrity_nons	
5	Competence_gray	
6	Competence_green	
7	Competence_nons	
8	Dependability_gray	
9	Dependability_green	
10	Dependability_nons	
11	Trust_gray	3=Do not trust at all, 3≤6= Do not trust, greater than 6≤9=Neutral, 9≤12 =Trust, 12≤15=Trust a lot
12	Trust_green	
13	Trust_nons	
14	Income	1= Less than $30,000, 2= $30,000 - $59,999, 3= $60,000 - $89,999, 4= $90,000 - $119,999, 5= More than $120,000
15	Race	0= nonwhite, 1=white
16	Flood_prediction	1= decrease, 2= stay the same, 3= increase
17	Flood_insurance	0= no, 1= yes
18	Flood_exp	0= no, 1= yes
19	Housing_status	1= unhoused, 2= other, 3= rent, 4= own
20	Education	1= Some high school or less, 2= Highschool degree, GED or equivalent, 3= Associate's degree, vocational school, or some college, 4= Bachelor's degree, 5= Advanced degree (Masters, PhD, JD, MD, etc.)
21	Time_living	1= Less than one year, 2= 1-5 years, 3= 6-10 years 4= 11-15 years, 5= More than 15 years
22	Age	1= 18-30, 2= 31-50, 3= 51-70, 4= Over 70 years of age
23	Gender	0= nonfemale, 1= female
24	Disability	0= no, 1= yes

Appendix C. Description of the trust index.

Integrity	**Competence**	**Dependability**	**Trust index value**	**Description**
1	1	1	3	Do not trust at all
2	2	2	6	Do not trust
3	3	3	9	Neutral
4	4	4	12	Trust
5	5	5	15	Trust at a lot

Based on the OECD Guidelines on measuring trust