Community Engagement in Northeast Houston, Texas

Geospatial Results from a Household Survey on the Disaster Experiences of Northeast Houston

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Prepared for the Committee on Community Engagement in Southeast Texas: Pilot Project to Enhance Community Capacity and Resilience to Floods

Gulf Research Program

Resilient America Program
Policy and Global Affairs

National Academies of Sciences, Engineering, and Medicine

COMMITTEE ON COMMUNITY ENGAGEMENT IN SOUTHEAST TEXAS: PILOT PROJECT TO ENHANCE COMMUNITY CAPACITY AND RESILIENCE TO FLOODS

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Preface

Community members possess a vast repository of knowledge of their environment and the risks and threats that they face on a regular basis. They also have a deeper understanding of the social and cultural environment and the factors that make their communities resilient in the face of diverse risks and threats. Despite the value of local knowledge, researchers often fail to bring residents and local stakeholders into the scientific process. When local knowledge is not tapped and used to help interpret scientific data about the very communities from which data are drawn, the likelihood of successful implementation of plans and policies based upon these data is reduced. Building on a definition provided by Cooke and colleagues (2020), Karcher and colleagues (2021, p. 214)[1] define successful projects at the interface of environmental science and policy as

> respectfully conducted, partner-relevant research that is accessible, understandable, shared, and used, enabled by good knowledge exchange products, processes, and social outcomes (e.g., creating networks, mutual understanding, social learning, and trust building), with the potential to contribute to changes in policy and demonstrable societal impact. (Italics in original removed).

In 2022, the National Academies of Sciences, Engineering, and Medicine's Gulf Research Program commissioned a household survey on the disaster experiences of residents and families in Northeast Houston, Texas. This paper summarizes the results of that survey and serves as a background document for discussions between local knowledge experts and technical knowledge experts in the workshop Bridging Diverse Knowledge Systems to Address Flood Risk in Northeast Houston Communities, to be held in Houston on April 26–27, 2023. This workshop convenes researchers and a range of community stakeholders from Northeast Houston to provide feedback on

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[1] Karcher, D.B., C. Cvitanovic, R.M. Colvin, I.E. van Putten, and M.S. Reed. 2021. Is this what success looks like? Mismatches between the aims, claims, and evidence used to demonstrate impact from knowledge exchange processes at the interface of environmental science and policy. *Environmental Science & Policy* 125:202-218. Cooke, S., T. Rytwinski, J. Taylor, E. Nyboer, V. Nguyen, J. Bennett, N. Young, S. Aitken, G. Auld, J-F. Lane, et al. 2020. On "success" in applied environmental research—What is it, how can it be achieved, and how does one know when it has been achieved? *Environmental Reviews*. https://doi.org/10.1139/er-2020-0045

the results of the household survey and discuss how these data can inform future community resilience planning efforts.

This paper and the survey results contained herein represent one dataset for workshop participants to consider as they work together to develop a more comprehensive understanding of the local impacts of flooding in Northeast Houston. Over the course of the workshop, speakers from a range of backgrounds will present other types of data on different topics related to flood risk in Northeast Houston. Through a series of moderated conversations, workshop participants will consider how the household survey data and other datasets can help them:

- develop a more comprehensive picture of the challenges faced by community members across multiple disasters (e.g., pandemic, flooding, environmental hazards),
- identify and consider potential solutions for addressing these challenges, and
- explore potential follow-on activities.

By bringing community members, scientists, and decision makers together, this workshop actively seeks to foster knowledge exchange across diverse knowledge systems and identify opportunities for future collaborations and partnerships to codevelop and advance the work of communities in Northeast Houston.

Scott A. Hemmerling
Chair, Committee on Community Engagement in Southeast Texas: Pilot Project to Enhance Community Capacity and Resilience to Floods

Acknowledgments

We want to thank our partners on this project for their help and support. This project was made possible by partnerships between the National Academies of Sciences, Engineering, and Medicine’s Gulf Research Program (GRP) and Resilient America Program, and West Street Recovery (WSR). We would like to give special thanks to Ben Hirsch and Doris Brown of WSR. In addition, we thank GRP staff Charlene Milliken and Juan Sandoval for their support on this project. We would also like to thank researchers from Texas A&M University at Galveston for their insight and feedback on the survey development. We thank Amber Goff and Scott Goff from Research 4 Progress for programming the survey tool using Qualtrics© XM, performing the survey deployment, and conducting preliminary statistical analyses (e.g., descriptive statistics, cross-tabulations) of the survey data. Finally, we would like to thank the National Academies Community Engagement in Southeast Texas Planning Committee for the support and guidance they provided over the course of this project.

WEST STREET RECOVERY

WSR is a horizontally organized grassroots organization that aims to use Hurricane Harvey recovery to build community power. Its driving principle is to work together with community members, not for them or on their behalf. WSR’s work is rooted in an understanding that Harvey disproportionately impacted specific communities because they lack access to resources and influence and that the same actors and forces that produced these inequities cannot adequately support communities in recovery. Its members believe that the communities most harmed by Harvey are the people who best understand what can protect them in the future. As an interclass, interracial organization, WSR is uniquely positioned to create these connections and help residents improve their neighborhoods in ways they see fit. Its vision is that the community it is helping recover today can organize and become more resilient before the next disaster hits. Therefore, WSR has sought to have the community its direct the work, and has helped form two grassroots organizations: the Northeast Action Collective and the Harvey Forgotten Survivors Caucus.

GULF RESEARCH PROGRAM

The GRP is a division of the National Academies of Sciences, Engineering, and Medicine — a private, nonprofit organization with a 150-year history as an independent advisor to the nation. The GRP was established in 2013 as part of criminal settlements with the companies involved in the 2010 Deepwater Horizon oil spill disaster and received a $500 million endowment to carry out studies, projects, and other activities in research and development, education and training, and monitoring and synthesis. The GRP was charged to "establish a program focused on human health and environmental protection, including issues relating to offshore drilling and hydrocarbon production and transportation in the Gulf of Mexico and on the United States' outer continental shelf." The GRP is the sponsor of this project.

In supporting a safer, more resilient, and sustainable future for the Gulf of Mexico region and all those who call the region home, the GRP uses science, engineering, and medical knowledge to enhance offshore energy safety, environmental protection and stewardship, and health and community resilience. It focuses its work on the Gulf of Mexico and other outer continental shelves of the United States where there is hydrocarbon production, and on their coastal zones. The GRP's work may extend farther inland or into adjacent seas where appropriate.

RESILIENT AMERICA PROGRAM

The National Academies' Resilient America Program was established in 2014 to implement recommendations from the National Academies' 2012 report *Disaster Resilience: A National Imperative*[1] to understand and strengthen community resilience and adaptation. Resilient America brings together experts from the public, private, nonprofit, and academic sectors through meetings, workshops, and other activities, to promote innovative research and evidence-based foundations to inform whole-community strategies for resilience and adaptation; incubate ideas and projects; and conduct education, outreach, and community exchange that advance resilient systems and adaptive capacities in communities, the nation, and around the globe. Resilient America's objective is to harness the power of science, information, and community experience and knowledge for an

[1] National Academies of Sciences, Engineering, and Medicine. 2012. *Disaster resilience: A national imperative.* The National Academies Press.

adaptive and resilient nation to reduce damage and suffering and enable robust recovery from current and future threats and disruptions.

Reviewers

This individually authored paper was reviewed in draft form by individuals chosen for their diverse perspectives and technical expertise. The purpose of this independent review is to provide candid and critical comments that will ensure the quality of the paper and make it as sound as possible. The review comments and draft manuscript remain confidential to protect the integrity of the process.

We thank the following individuals for their review of this paper:

CLARE CANNON, University of California, Davis
TIMOTHY COLLINS, University of Utah
WANYON SHAO, University of Alabama
KEVIN SMILEY, Louisiana State University
KAHLER STONE, Middle Tennessee State University

Although the reviewers listed above provided many constructive comments and suggestions, they were not asked to endorse the content of the paper, nor did they see the final draft before its release. The review of this individually authored paper was overseen by Marilyn Baker, National Academies of Sciences, Engineering, and Medicine. She was responsible for making certain that an independent examination of the paper was carried out in accordance with the standards of the National Academies and that all review comments were carefully considered. Responsibility for the final content rests entirely with the authors.

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BOXES

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Acronyms and Abbreviations

ACS	American Community Survey
AICc	Corrected Akaike information criterion
EBK	empirical Bayesian kriging
ERCOT	Electric Reliability Council of Texas
FEMA	Federal Emergency Management Agency
FIRM	Flood Insurance Rate Map
FRS	Flood Risk Score
GIS	geographic information system
GRP	Gulf Research Program
IDW	inverse distance weighting
LM	Lagrange Multiplier
NFIP	National Flood Insurance Plan
NWS	National Weather Service
OLS	ordinary least squares
PADM	Protective Action Decision Model
QA	quality assurance
QAQC	quality assurance and quality control
QC	quality control
RAP	Resilient America Program
SAR	simultaneous autoregressive (model)
TAMUG	Texas A&M University at Galveston
TDSHS	Texas Department of State Health Services
VIT	Vested Interest Theory
WSR	West Street Recovery

Summary

Building on the lessons learned through previous community engagement efforts in southeast Texas around flood risks, this project engages communities in Northeast Houston to explore (1) how compounding events—specifically, flooding, the COVID-19 pandemic, and Texas Winter Storms (2021)—increase vulnerability and risk to communities; (2) how to effectively communicate these risks to community members; and (3) how to better prepare for and mitigate these risks.

In partnership with West Street Recovery (WSR),[1] Texas A&M University at Galveston (TAMUG), and Research 4 Progress,[2] the Gulf Research Program (GRP) and Resilient America Program (RAP) at the National Academies of Sciences, Engineering, and Medicine designed a household survey to investigate the flood-related experiences of residents from Northeast Houston using quantitative methods and probabilistic sampling. The survey, administered December 2021–January 2022, also asked about residents' experiences with the COVID-19 pandemic and Texas Winter Storms including Winter Storm Uri to capture information about the compounding impacts of the pandemic and winter storm on existing flood disaster preparedness, response, and recovery.

Consultants from Research 4 Progress programmed the survey tool using Qualtrics© XM,[3] performed the survey deployment, and conducted preliminary descriptive statistical analyses (e.g., descriptive statistics, cross-tabulations) of the survey data. The authors then conducted an advanced statistical and geospatial analysis of the survey data. Analyses include descriptive statistics, geocoding response using ArcGIS Pro[4]; comparing "real" risk with perceived flood risk using a Flood Risk Score created using inverse distance weighting and empirical Bayesian kriging; determining the influence of flood risk perception on protective action with classical and spatial regression models; and identifying risk communication preferences and types of services sought after

[1] https://www.weststreetrecovery.org/
[2] https://research4progress.com/
[3] https://www.qualtrics.com/
[4] https://pro.arcgis.com/en/pro-app/latest/get-started/get-started.htm

varying types of disasters (i.e., flooding, the COVID-19 pandemic, and winter storms) with Wilcoxon tests and contingency tables.

This paper will be shared with community partners and used as background material for participants at the workshop Bridging Diverse Knowledge Systems to Address Flood Risk in Northeast Houston Communities, to be held in Houston, Texas, April 26–27, 2023.

1
Project Overview

Building on lessons learned through previous community engagement efforts in southeast Texas focused on flood risks, this project engaged communities in Northeast Houston to explore how compounding events—specifically, flooding, the COVID-19 pandemic, and Texas Winter Storms (2021)—increase vulnerability[5] and risk to communities, how to effectively communicate these risks to community members, and how to better prepare for and mitigate these risks. To better understand the impacts of compounding disasters on communities, the project team conducted a household survey to identify the following:

1. opportunities for communities to better prepare for and mitigate flood risks, both as a stand-alone risk and in the context of compounding disasters (e.g., the COVID-19 pandemic, winter storms);
2. how to better communicate flood risks to the public, including opportunities, mechanisms, and messages for communication in the context of compounding disasters; and
3. how data and science could inform community decision making regarding flood risks directly and as a compounding event.

PROJECT PURPOSE

The purpose of this descriptive project is two-fold: to better understand (1) the flooding experiences of socially vulnerable households located in neighborhoods with a history of repetitive

[5] For this project, *vulnerability* is defined as "the propensity or predisposition to be adversely affected and encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt" (Pörtner et al., 2022, p. 5).

flooding (herein referred to as the study population) and (2) how a chronic stressor (COVID-19 pandemic) and an acute shock (winter storms including Winter Storm Uri) compounded the effects of flooding experiences on the study population.

This paper explores the following questions:

Flood Experience and Risk Perception

1. What are residents' general experiences with flooding events regarding frequency and severity?
2. Do people's perceived location in a floodplain match their "real" risk (are their homes located in Federal Emergency Management Agency [FEMA]–designated floodplains)?

Flood Risk Perception and Protective Actions

3. Are residents with higher perceived flood risk perception more likely to take action (i.e., flood mitigation, evacuation, etc.)?

Flood Risk Communication

4. What are residents' flood risk communication preferences (e.g., trusted sources, popular modes)?
5. Do flood risk communication preferences vary by demographics (e.g., age or gender)?

Compounding Impacts and Recovery

6. How do experiences with accessing post-disaster recovery services compare across residents for general flooding, the COVID-19 pandemic, and Winter Storm Uri?
7. What barriers did the study population experience when seeking post-disaster assistance and services due to flooding, the COVID-19 pandemic, and Texas Winter Storms?
8. Do barriers vary by demographics?

This paper will be shared with community partners and used as background material for participants at the workshop Bridging Diverse Knowledge Systems to Address Flood Risk in Northeast Houston Communities, to be held in Houston, Texas, April 26–27.

Paper Format

The purpose of this paper is to discuss the results from the household survey. *Interpreting* the results was beyond the scope of this paper. More in-depth discussions of the results in the broader context of the flood disasters in Northeast Houston, Texas, will be conducted at the workshop held April 26–27, 2023.

As such, the paper format is organized to reflect only the analysis results. Chapter 1 discusses the project purpose, study area, and sample population. Chapter 2 discusses detailed results of the survey analyses. Finally, Chapter 3 provides a summary of project results. Detailed methodologies for the household survey analyses are not included in Chapters 1–3.

Appendix A provides a more in-depth context of disasters in Houston, Texas. Appendix B provides the detailed methodology used to analyze the household survey. Appendix C provides methodological details for creating the Flood Risk Score variable. Appendix D provides a copy of the household survey on which the analysis is based. Finally, Appendixes E and F provide biographies for the paper authors and the project committee members, respectively.

STUDY AREA

The study area we refer to as Northeast Houston includes the following neighborhoods in zip codes 77016, 77020, 77026, 77028, and 77078: Denver Harbor, East Houston, East Little York, Fontaine, Frenchtown, Greater Fifth Ward, Homestead, Kashmere Gardens, Lakewood Park, Liberty Gardens, Port Houston, Rosewood, Scenic Woods, Settegast, and Trinity Gardens (Figure 1-1).

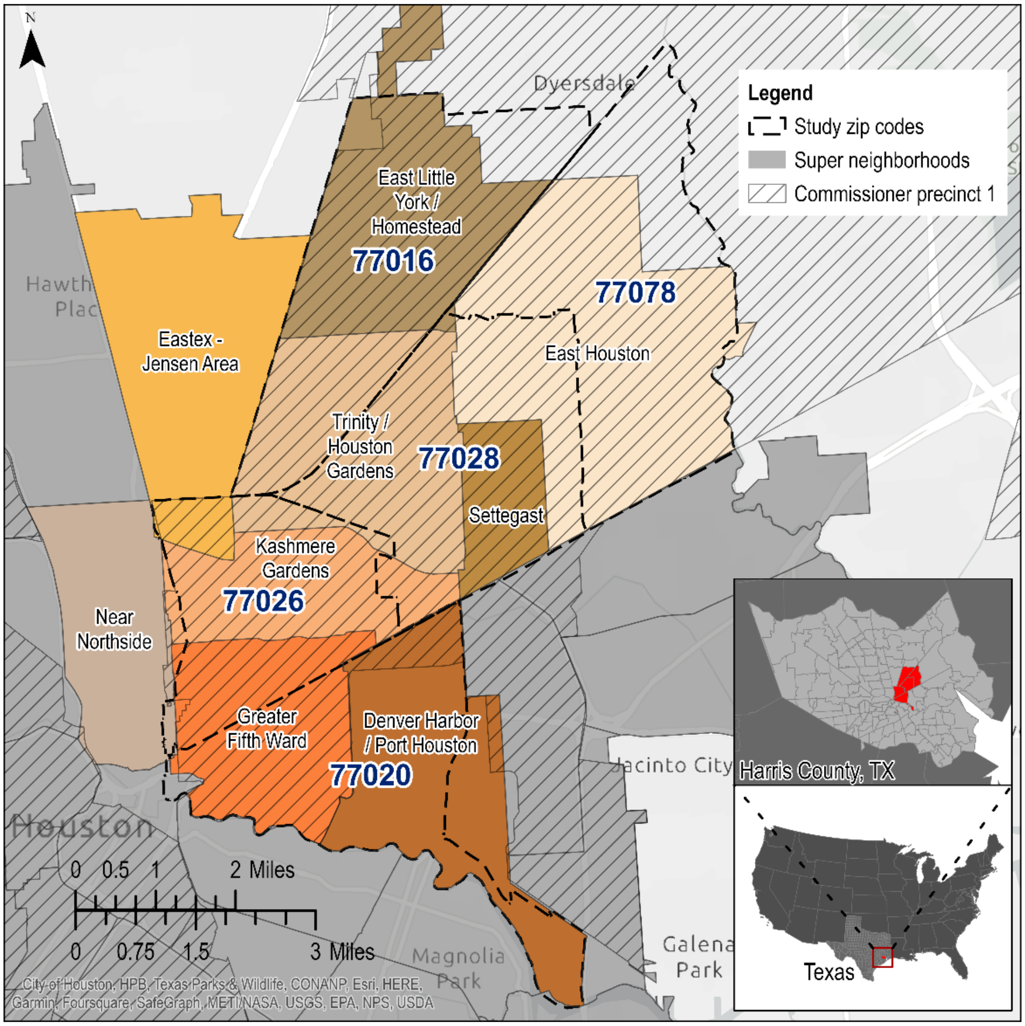

FIGURE 1-1 Project zip codes and Houston super neighborhoods.

Known locally as Northeast Houston, these neighborhoods fall primarily under Harris County Precinct One jurisdiction, with a large section of Denver Harbor/Port Houston falling in Precinct Two.

Flooding and Flood-Related Events in Northeast Houston, Texas

Northeast Houston, Texas, is vulnerable to flooding and hurricane risks, especially during the Atlantic hurricane season (June 1–November 30). The area has been impacted by several major disaster events in the last 10 years, including the Houston Memorial Day Floods (2015), Hurricane Harvey (2017), and Tropical Storm Imelda (FEMA, 2021). The most significant flood-related event to affect Houston was Hurricane Harvey in August 2017, which caused extensive damage in

Northeast Houston. In zip codes 77078, which is included in this study, many drowning deaths occurred, although the area is outside of FEMA-designated 100- and 500-year floodplains (Lee et al., 2021; Pralle, 2019).

Flooding and Flood-related Challenges in Northeast Houston, Texas

Northeast Houston is at risk for flooding because of its topography, the built environment, and regional flooding events that occur multiple times a year. Much of the flooding infrastructure in the study area is open drain ditches, which West Street Recovery and local residents have stated exacerbate flooding impacts, as they get clogged with trash, overgrowth, and debris (FEMA, 2021; Lee and Li, 2021). Weakened infrastructure leads to more frequent flooding during smaller storm events, as the water has nowhere to drain. This can lead to mobility issues for residents who are forced to wade through stagnant flood waters to reach public transit or make it impossible for those with physical mobility issues to leave flooded areas (WSR, 2021). Open ditch drainage systems are more likely to impact low-income communities of color, with 80 percent of Houston's open drain ditches located in such neighborhoods across Houston (Hirsch et al., 2021).

Houston Public Works provides maintenance for cleaning and degrading the ditches, but does so too infrequently to mitigate flooding effectively, leading residents to take responsibility for keeping the ditches clear (City of Houston, 2018). However, many residents lack the resources or physical ability to clean ditches (Wilson and Luo, 2022).

STUDY POPULATION

According to demographic data from the American Community Survey 2015–2019 (US Census Bureau, 2020), residents from the study area are more racially diverse, less educated, more impoverished, and have higher unemployment and a lower median income than the average Houstonian (Table 1-1).

TABLE 1-1 Community Demographics for Northeast Houston Study Zip Codes and the City of Houston, Texas

	Zip Code 77016	Zip Code 77020	Zip Code 77026	Zip Code 77028	Zip Code 77078	Houston, Texas
Population Total Population	30,741	26,357	21,300	17,425	15,663	2,300,000

Households Total Number of Households	9,679	8,670	7,960	5,847	4,640	858,374
Race % Population, One Race Alone	W: 32.7% B: 63.1%	W: 46.2% B: 22.4%	W: 37.4% B: 50.5%	W: 27.5% B: 66.8%	W: 40.1% B: 54.0%	W: 57.0% B: 22.6%
Ethnicity % Population Hispanic/Latino	35.5%	73.6%	45.8%	30.2%	40.9%	45.0%
Education % Population 25+ High School Education	68.6%	63.8%	64.4%	70.2%	70.6%	78.9%
Employment % Population 16+ Employed	48.0%	51.8%	48.6%	48.3%	52.0%	63.3%
Income Household Median Income	$36,335	$32,207	$28,678	$29,014	$40,298	$52,338
Poverty % Population Living in Poverty	26.6%	32.0%	33.9%	29.2%	18.5%	20.1%
Housing % Occupied by Renters	40.5%	55.3%	59.7%	44.1%	39.3%	57.7%

NOTES**:** B = Black or African American alone; W = White alone, population. Statistics for only White alone and Black alone are provided in the table for brevity, as these are the top two predominant racial groups in the study zip codes. The Houston, Texas, column includes all the previous columns (zip codes) and the rest of the Houston population.
SOURCES**:** WSR (2021) and U.S. Census Bureau (2020).

The sampling criteria for the household survey included an adult person aged 18 years or older per household who has resided in a home located within the study area since June 1, 2020. While many residents were likely impacted by (and potentially still recovering from) Hurricane Harvey, this survey was focused on capturing flooding experiences and impacts during the 2020 and 2021 hurricane seasons. As such, June 1, 2020, was chosen as a sampling criterion because it serves as the start of the 2020 hurricane season and is the first hurricane season in which COVID-19 could potentially be a confounding factor for risk reduction behavior. Furthermore, the survey, deployed in 2022, can also capture experiences from two full hurricane seasons (2020 and 2021), potentially compounding factors from COVID-19 and winter storms.

2
Project Results

CHARACTERISTICS OF SURVEY RESPONDENTS

The survey was completed by 555 adults residing in 5 different zip codes in Northeast Houston, Texas, with a response rate of 15.09 percent (4,000 addresses were sampled from 36,796 total households).[6] We conducted quality assurance and quality control (QAQC) (see Box 2-1) to ensure that only responses that were at least 90 percent completed[7] and with all demographic questions answered were used in the analysis.

After QAQC, 537 survey responses were considered viable for descriptive statistical analysis (respondents answered at least 90 percent[8] of all questions and met the survey criteria (Appendix B). While the sample has 54 fewer respondents than the original sample target of 591, the resulting sample still retained a 95 percent confidence level, tolerating a 4 percent margin of error.

BOX 2-1Why Is QAQC Important?

Quality assurance (QA) focuses on ensuring data quality requirements are met before data collection occurs to prevent data from being unusable (e.g., ensuring the survey has well-written questions that address the project's goals) (Mitra, 2016).

Quality control (QC) refers to inspecting collected data to determine whether any observations do not meet data quality (e.g., identifying survey responses that are mostly complete and all fields necessary for statistical analysis are completed) (Mitra, 2016). Responses that do not meet data quality requirements are removed from the analysis.

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[6] The sampling methodology and sample stratification are discussed in further detail in Appendix B.
[7] The survey allowed people to choose to skip some questions or survey "skip logic" did not show them certain questions based on previous responses.
[8] Because of the diverse topics explored in this study, 90 percent was chosen as the survey response cutoff to ensure responses from participants who did not answer some portions of the survey were not excluded from analyses.

Compared with the 2015–2019 American Community Survey data for the study area, this project's household survey data similarly reflect census populations (Tables 2-1 and 2-2). The survey sample comprises 61.6 percent female and 36.9 percent male respondents. Most respondents identify as Black or African American (61.6 percent), and most respondents were 45 years and older (72 percent). Most respondents reported annual incomes of less than $50,000 (73.2 percent) and education levels of high school diploma or equivalent achievements or less (58.1 percent). Regarding residency, 45 percent of respondents reported having lived in their homes for more than 20 years.

TABLE 2-1 Survey Sample Population Compared with 2015–2019 American Community Survey (ACS) Populations for the Five Zip Codes That Comprise the Study Area in Northeast Houston, by Gender, Race, Ethnicity, and Length of Residency

	Survey Sample		2015–2019 ACS	
Gender	**N**	**%**	**N**	**%**
Female/Woman	331	61.6%	43,860	54.0%
Male/Man	199	36.9%	37,311	46.0%
Non-binary	1	0.2%	-	-
I prefer not to answer or blank	7	1.1%	-	-
Race	**N**	**%**	**N**	**%**
American Indian/Alaska Native	2	0.4%	332	0.4%
Asian	1	0.2%	493	0.6%
Black or African American	331	61.6%	42,778	52.7%
White	20	3.7%	2,470	3.0%
Native Hawaiian or other Pacific Islander	0	0.0%	41	0.05%
Other (please specify)	7	1.3%	10,273[a]	12.7%
Don't Know or Refuse	7	1.3%	3,568[b]	4.4%
Ethnicity	**N**	**%**	**N**	**%**
Hispanic or Latino	178	33.1%	21,281	26.2%
Length of residency	**N**	**%**	-	-
Up to 1.5 years	8	1.49%	-	-
1.5 to 5 years	124	23.09%	-	-
5 to 10 years	88	16.39%	-	-
10 to 20 years	107	19.93%	-	-
20 to 30 years	79	14.71%	-	-
More than 30 years	131	24.39%	-	-

[a] Some other race

[b] Two or more races

NOTES**:** The table includes length of residency, but this information is not compared with ACS data as those are unavailable. For gender, while *female* and *male* refer to biological sex, the survey question asks, "What gender are you?" and includes *non-binary* as an answer option. Therefore, the variable is referred to as gender throughout the report. The response options have been adjusted to Female/Woman, Non-binary, and Male/Man.

TABLE 2-2 Survey Sample Population Compared with 2015–2019 American Community Survey (ACS) Populations, by Age, Education, Income, and Tenure

	Survey Sample		2015–2019 ACS	
Age	**N**	**%**	**N**	**%**
18 to 24 years	20	3.7%	10,925	13.5%
25 to 44 years	117	21.8%	27,080	33.4%
45 to 64 years	207	38.5%	27,852	34.3%
65 +	180	33.5%	15,314	18.9%
Prefer not to answer or blank	13	2.4%	–	–
Education	**N**	**%**	**N**	**%**
Less than a high school diploma	113	21%	22,706	32.3%
High school diploma or equivalency	199	37.1%	24,742	35.2%
Some college but no degree	116	21.6%	12,641	18.0%
Associate degree in college (2-year)	44	8.2%	3,025	4.3%
Bachelor’s degree in college (4-year)	31	5.8%	5,068	7.2%
Graduate degree	22	4.1%	2,064	2.9%
Prefer not to answer or blank	13	2.2%	–	–
Income	**N**	**%**	**N**	**%**
Less than $20,000	199	37.1%	11,121	30.0%
$20,000 to $34,999	140	26.1%	7,745	20. 9%
$35,000 to $49,999	54	10.1%	6,484	17.5%
$50,000 to $74,999	46	8.6%	5,400	14.6%
$75,000 to $99,999	13	2.4%	3,219	8.7%
$100,000 to $149,000	5	0.9%	2,088	5.6%
$150,000 or above	0	0.0%	1,013	2.7%
Prefer not to answer	80	14.9%	–	–
Rent/Own	**N**	**%**	**N**	**%**
Rent	358	66.7%	17,630	47.6%
Own	177	33%	19,440	52.4%
Prefer not to answer	2	0.4%	–	–

The survey sample is similar to the total population, with some exceptions. For example, a higher-than-average number of respondents identify as Hispanic/Latino (33.1 percent) compared with the five zip codes’ population (26.2 percent), indicating an overrepresentation of Hispanic/Latino respondents in the survey sample. The sample also overrepresents females/women, residents aged over 65, and renters. In contrast, it underrepresents residents aged 18–24 years and those with median household incomes greater than $75,000.

Because the sample does differ from the population for specific demographic characteristics, such as gender, education, age, and renter/owner status, the authors considered using poststratification weighting to ensure the sample is representative of the population. This process would entail examining how representative the sample is *per zip code*, not simply the 5 zip code areas as a whole.

However, poststratification was not conducted on the sample for two main reasons: First, not every respondent provided zip code data (n = 486 compared with n = 537). Some respondents chose not to share their addresses, and the field survey team did not record this information automatically. Second, poststratification can be a fairly complex process that, if done improperly or without the correct contextualization, can further bias results. Given the incomplete zip code information, the complexity of other analyses in the report, and the intended audience (local community and community partners), the analysis did not use poststratification weighting.

FLOODING EXPERIENCES

Several statistical analyses were used to understand respondents' experiences with flooding, how frequent or severe flooding impacts were, and whether the frequency and severity of flooding events mainly occurred in areas near flood zones, as designated by the Federal Emergency Management Agency (FEMA)–designated flood zones in the Harris County 2019 Flood Insurance Rate Maps (FIRMs).

Descriptive Statistics

Descriptive statistics of the household surveys show that 66 percent of the survey population has experienced flood impacts, and 89.1 percent of all residents at least know of someone who has (Table 2-3).

TABLE 2-3 Results from the Survey Flood Experience and Impacts Questions (Q6–Q8)

Survey Question	Yes	No	Total
Q6 - Have you ever personally experienced the impacts of flooding?	65%	35%	-
Q7.1 - Has a friend, relative, neighbor, or coworker that you know personally…			
had their property damaged in a flood?	89.1%	66%	81%
been injured or lost their life in a flood?	13.5%	4.3%	10.2%

Q7.2 - Have you or someone close to you, such as an immediate family member…			
been injured in a flood?	9.5%	2.1%	6.9%
lost their life in a flood?	2.3%	0.5%	2%
Q7.3 - Due to flooding, have you experienced disruption to…			
your job that prevented/prevents you from working?	69.9%	---	
your shopping and other daily activities?	84.5%		
Q8 - Have any of your previous homes been damaged by flooding?	38.1%	---	

The majority of residents feel that flooding has become more frequent (86.8 percent) and severe (86.2 percent) and that places that have never flooded before are now flooding (84 percent).

Regarding whom is responsible for helping residents prepare for floods, residents believe government agencies (at the local, state, and federal levels) hold the most responsibility; however, most residents are also unsatisfied with the agencies' flood preparation efforts (Table 2-4). Figure 2-1 shows the location of geocoded responses across the five zip codes in the study area, compared with FEMA-designated floodplains.

TABLE 2-4 Responses to Questions "Do you believe ___ is responsible for helping you and your household prepare for floods?" and "If [YES], are you satisfied with their efforts?"

Do you believe __ is responsible for helping you and your household prepare for floods?

	Local Government	State Government	Federal Government	Nonprofits	School District	Place of Employment
YES	**84.50%**	**82.50%**	**77.10%**	**39.70%**	**29.80%**	**20.10%**
	↓	↓	↓	↓	↓	↓
	IF [YES], ARE YOU SATISFIED WITH THEIR EFFORTS?					
YES	39%	31.40%	39.60%	**75.10%**	**63.80%**	**57.40%**
NO	**51.10%**	**56.20%**	**47.10%**	16.90%	28.10%	25.90%
NEUTRAL	9.30%	12%	12.30%	7%	7.50%	13.90%

NOTES**:** Light purple indicates government entities; light blue indicates nongovernmental entities or organizations.

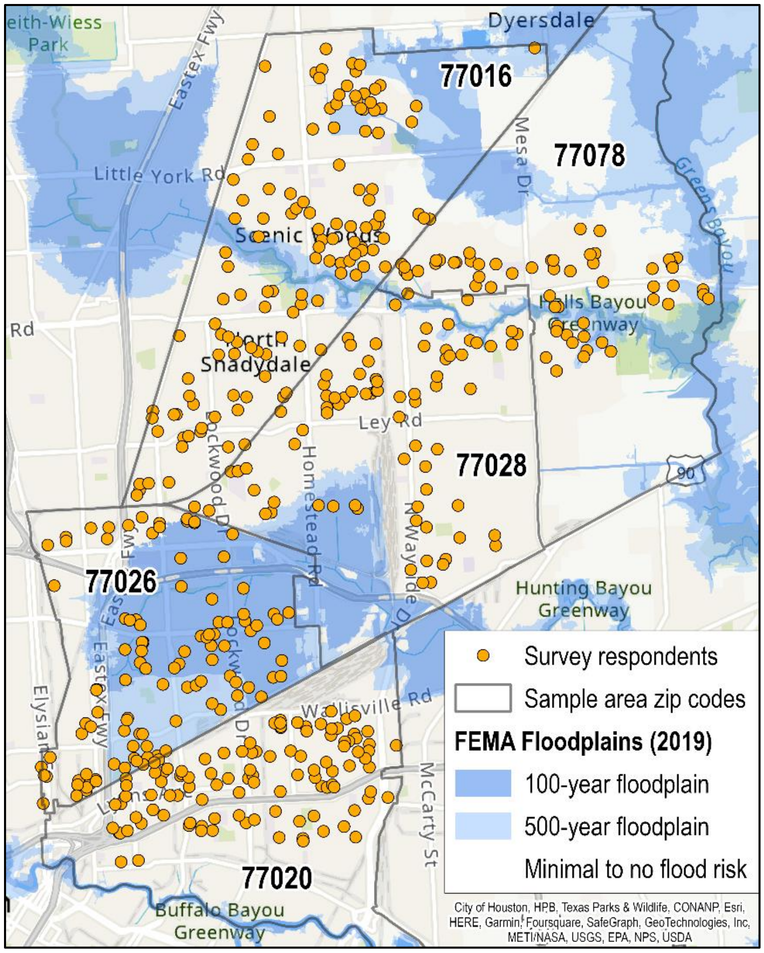

FIGURE 2-1 Geocoded responses from those who provided an address and their location relative to Federal Emergency Management Agency (FEMA)–designated floodplains (n = 486).

Frequency of Flooding Versus Severity of Flooding

The results from mapping the frequency and severity of flooding experiences illustrate several relationships between "real" risks, as designated by the FEMA flood zones in the Harris County 2019 FIRMs (see Box 2-2) and reported flooding experiences from the survey responses.

BOX 2-2

What Are FEMA 100- and 500-Year Floodplains and How Are They Used in Disaster Management?

The Federal Emergency Management Agency's (FEMA's) Flood Insurance Rate Maps (FIRMs) maps define a 100-year floodplain as an area with a 1.0 percent chance *each year* that residents might experience a flood like the one delineated on the FEMA FIRM maps. For respondents who live in a 500-year floodplain, there is a 0.2 percent that they might experience a flood like the one shown on the FEMA flood maps. As such, some areas within these zones may experience multiple 100-year or 500-year floods over multiple years (Watkins, 2022).

Floodplain designations do not suggest that areas outside the floodplain are unlikely to flood, especially if flooding comes from a source other than riverine flooding (which FIRMs are based on) (Rogalski, 2022). However, according to FEMA, "flood maps show how likely it is for an area to flood. Any place with a 1% chance or higher chance of experiencing a flood each year is considered to have a high risk. Those areas have at least a one-in-four chance of flooding during a 30-year mortgage" (FEMA, 2021).

FEMA FIRMS and Flood Risk Management

Communities use FIRMs as regulatory products for making disaster mitigation decisions (Adepoju and Ojinnaka, 2021; Grineski et al., 2022; Wilson and Luo, 2022). Therefore, while FIRMs may not accurately describe all forms of flood risk beyond riverine flooding (Flores et al., 2022; Gelman and Hill, 2007), they are still used for flood risk mitigation and management decision making, which is equally critical for understanding how communities perceive and experience flood risk (Knox et al., 2022).

While FEMA FIRMS are often used as regulatory products for flood risk management, they are not without issues. Several studies have shown that FEMA FIRMs predict flood risks poorly, particularly in southeast Texas (Bates et al., 2021; Flores et al., 2022). This project could have considered using other, more accurate flood risk datasets to gauge "real" flood risk (e.g., the Fathom Global/First Street Foundation flood model [Bates et al., 2021]), but they were not used to represent real risk for one particular reason. These datasets are *not* used currently as regulatory flood risk products in Houston, Texas, nor are they well known to community members. As such, FEMA floodplain maps represent real flood risk that is being compared with reported flooding experiences in this project. In addition, FEMA floodplains include areas of minimal flood risk, so flooding experiences are being compared with all levels of flood risk, not just areas of high flood risk.

Comparing Real Risk with Flooding Experience

As part of the analysis, reported experiences with frequent and severe flooding events were compared with FIRM maps, which are used as sources of real risk in this study. Box 2-3 explains the definition and representation of *real flood risk* as used in this study.

BOX 2-3

Defining Real Risk

Real risk is defined as risk that has been measured or assessed using substantiated methods, such as modeling (Covello et al., 2012; Thompson and Dezzani, 2020). Other terms used to describe real risk include *actual risk* or *objective risk*. Several datasets could be used to describe real flood risk, such as the Fathom U.S. Flood Map (Bates et al., 2021), the AIR Inland Flood Model (Dodov and Weiner, 2013), or other academic models of flood risk (Qiang et al., 2017; Woznicki et al., 2019).

Using the term *real risk* does not suggest that this measure describes risk more accurately than other sources, such as information from individuals or communities with lived flood experiences. Rather, FEMA FIRMS serve as the real flood risk dataset that is being compared with reported flooding experiences to identify how perceived risk compares with regulatory flood risk.

Regarding flooding frequency, 46.7 percent of respondents who personally experienced the impacts of flooding (n = 310)[9] reported their property had flooded twice or more since living in their current home (Figure 2-2).

[9] This n value is lower than the whole sample because only 310 respondents answered that they personally experienced flood impacts.

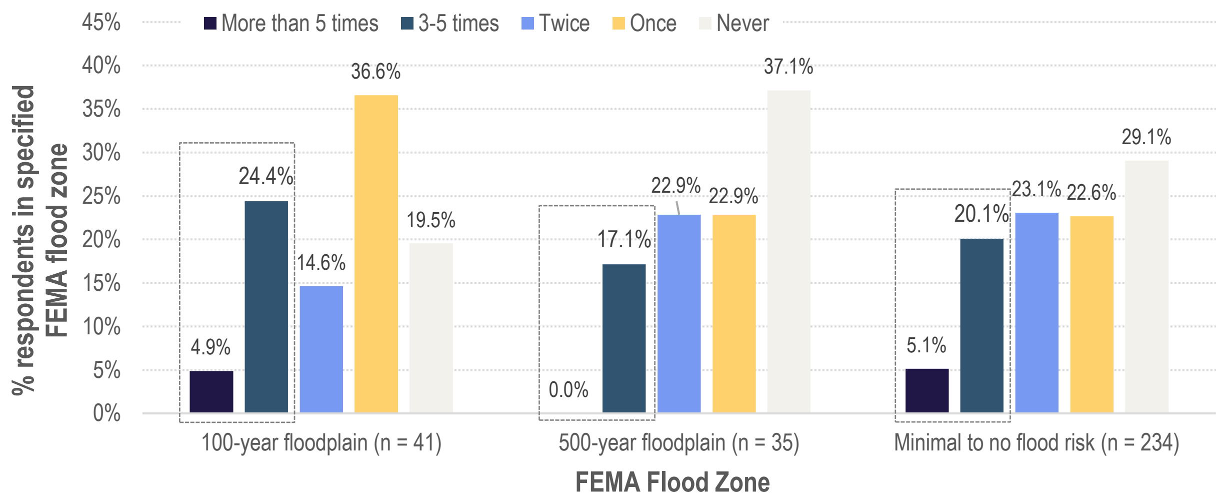

FIGURE 2-2 Percent (%) of respondents within each Federal Emergency Management Agency (FEMA)–designated flood zone type based on the number of times they have experienced flooding events.
NOTE: Columns representing respondents who have experienced flooding 3 or more times since living in their current home are shown in gray dashed boxes.

However, this percentage varies depending on whether a respondent lives within a specific FEMA floodplain designation. Please note that each FEMA floodplain category has a different number of residents who live in that risk category. For example, 41 respondents' homes are located within a 100-year floodplain (see Figure 2-2). Therefore, percentages reflected in the charts are based on the total number of respondents who live in that floodplain category. For example, 29.3 percent of the 41 people who live in a 100-year floodplain have experienced flooding three or more times since living in their current home (Figure 2-2, two columns in dashed boxes).

Similarly, 17.1 percent of the 35 residents who live in a 500-year floodplain have also experienced flooding three or more times since living in their current home. However, 25.2 percent of the 234 respondents whose homes are located in an area of minimal risk to flooding have experienced flooding three or more times.

Regarding flooding severity, 45.5 percent of respondents who personally experienced the impacts of flooding (n = 310)[10] reported that their property was severely damaged twice or more

[10] This n value is lower because only 310 respondents answered that they personally experienced flood impacts.

since living in their current home. These percentages vary depending on whether a respondent lives within a specific FIRM floodplain designation (Figure 2-3).

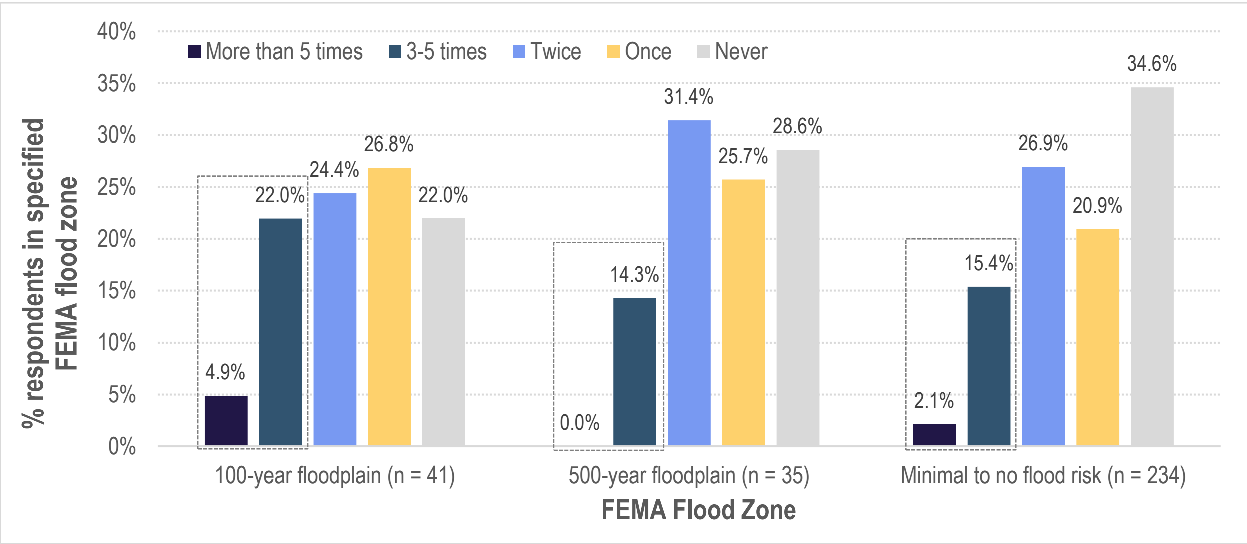

FIGURE 2-3 Percent (%) of respondents within each Federal Emergency Management Agency (FEMA)–designated flood zone type based on the number of times they have experienced severe flooding events.
NOTE: Columns representing respondents who have experienced severe damage from flooding three or more times since living in their current home are shown in gray dashed boxes.

For example, 26.8 percent and 14.3 percent of those living in a 100- and 500-year floodplain, respectively, have experienced severe damage from flooding three or more times since living in their current home. However, 17.5 percent of respondents whose home is located in an area of minimal risk to flooding have also experienced severe damage from flooding three or more times. 'Severe damage was not formally defined in the survey, rather it was left up to the respondent to define what it meant to them.

When comparing these results to the number of people who have experienced flooding or severe damage three or more times since living in their homes, the results suggest that FEMA floodplains do not accurately represent the flooding experiences of respondents.

Comparing Flooding Frequency and Severity Experiences Spatially

The geocoded responses (n = 486)[11] were mapped to demonstrate where respondents experienced flooding frequency and severity compared with FEMA-designated floodplains. In Figure 2-4, the left map shows respondents' reported frequency of flooding. The map on the right of Figure 2-4 shows respondents' reported severity of flooding. Note the representation of respondents who are geolocated outside 100- or 500-year floodplains who reported experiencing flooding three or more times or whose property was severely damaged twice or more since living in their current home.

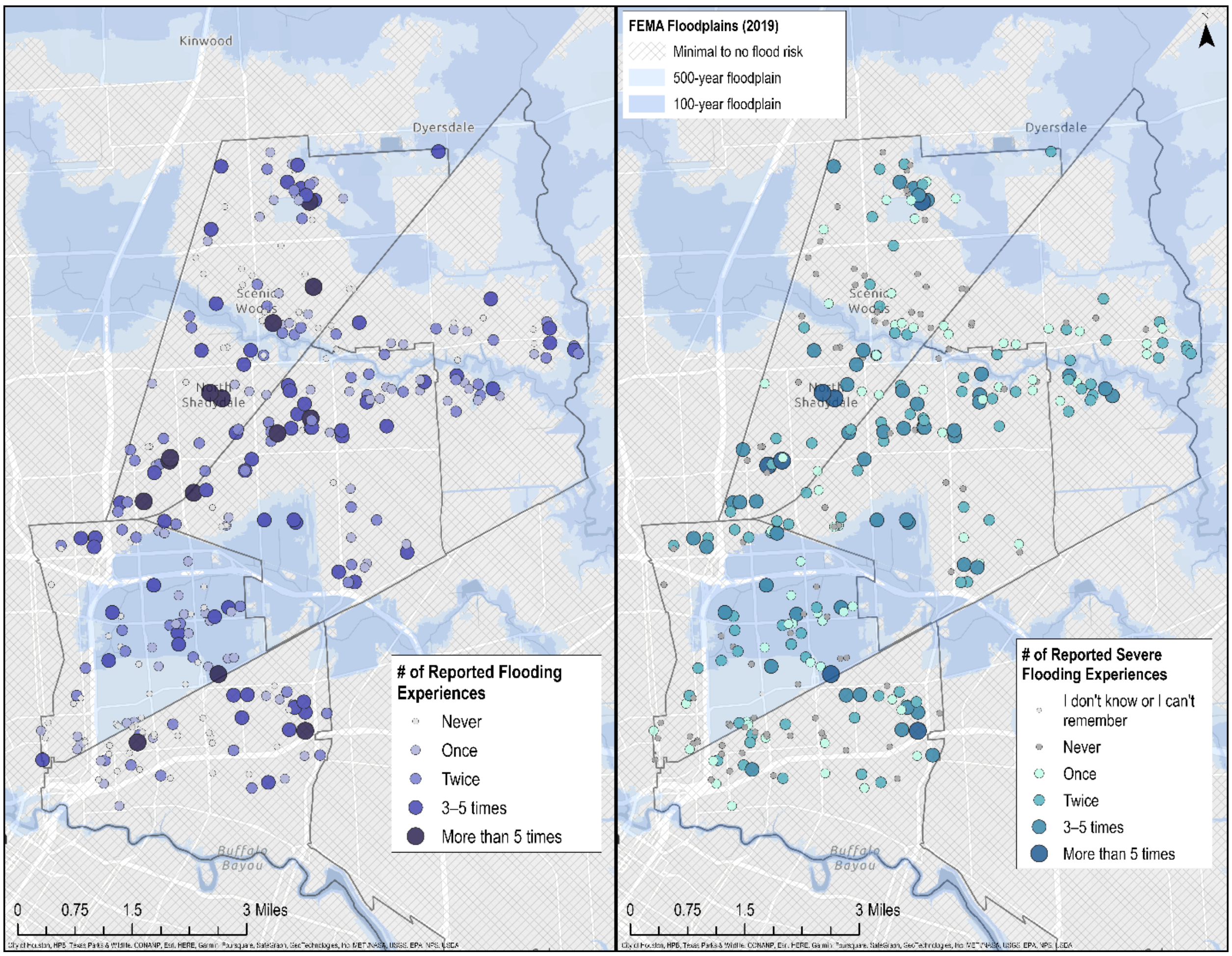

FIGURE 2-4 Mapped locations of respondents in relationship to the Federal Emergency Management Agency (FEMA)–designated floodplains. Geocoded symbols represent the responses to the survey questions "SINCE living in your current home, how many times has your property (e.g., land, home, car) flooded?" (left) or "SINCE living in your current home, how many times was your

[11] This sample size (n) is less than the original 537, as only 486 respondents provided full addresses that could be mapped.

property (e.g., land, home, car) severely damaged?" (right).
SOURCES: City of Houston (2023) and FEMA (2023).

Figures 2-5 through 2-8 show how the frequency and severity of flooding experiences vary based on proximity to other types of infrastructure. For example, most brownfield and Superfund sites are located in the southwestern part of the study area (Figure 2-5).

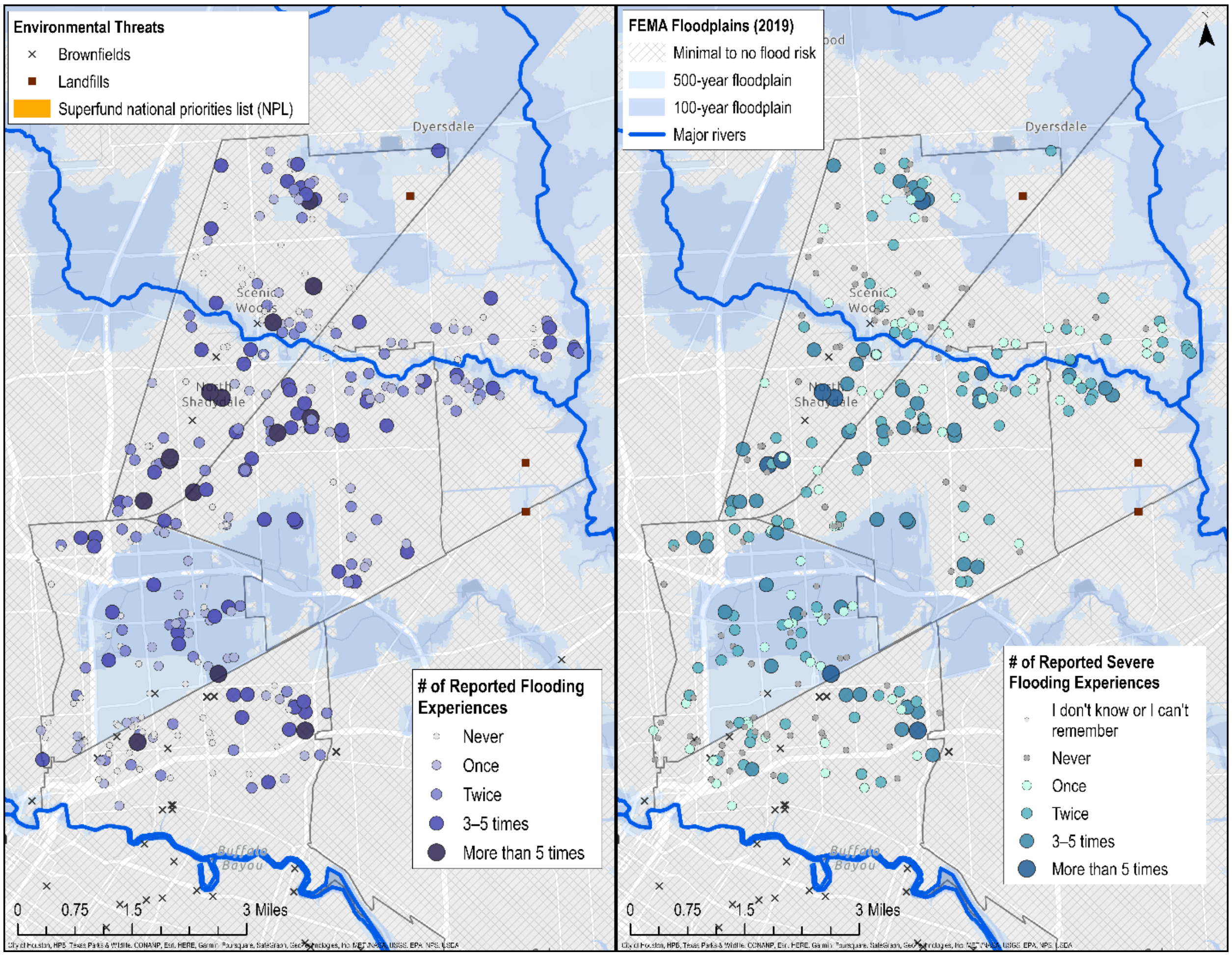

FIGURE 2-5 Comparison of the number of times a household has experienced flooding events (left) or severe flood damage to their home (right) and their proximity to environmental threats such as Superfund sites, brownfields, or landfills.
SOURCES: City of Houston (2023), FEMA (2023), and EPA (2023)

Superfund and brownfield locations often contain health hazardous substances (Summers et al., 2021). Extreme weather events such as flooding increase the likelihood of movement and release of Superfund and brownfield toxic substances to nearby communities (Newman et al., 2022).

Exposure to hazardous chemical and toxicants can impact a community's health (NASEM, 2022; Sansom et al., 2017).

Respondents in the northern part of the study area who experience more frequent and severe flooding are located near several oil and natural gas wells (Figure 2-6).

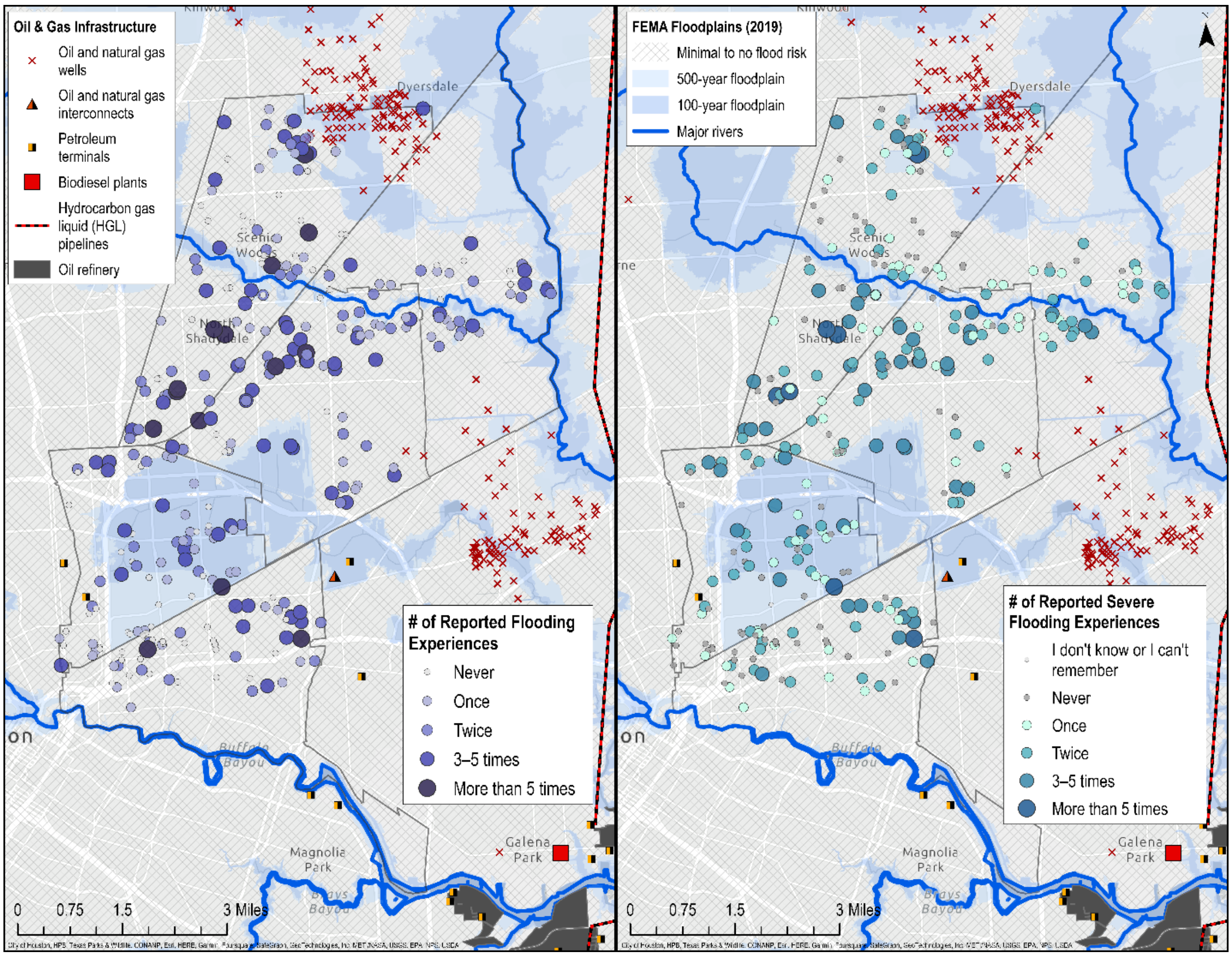

FIGURE 2-6 Comparison of the number of times a household has experienced flooding events (left) or severe flood damage to their home (right) and their proximity to oil and gas infrastructures. SOURCES: City of Houston (2023), FEMA (2023), DHS (2023), and HGAC (2023).

When flooding occurs in areas around oil and gas infrastructure, water can damage the storage tanks and other containers, which can lead to leaking of hazardous or contaminant material to nearby area and communities (Dong et al., 2022; Misuri et al., 2021).

Respondents in the southcentral part of the study area who experience more frequent and severe flooding are also located in areas with high amounts of stormwater infrastructure (Figure 2-7).

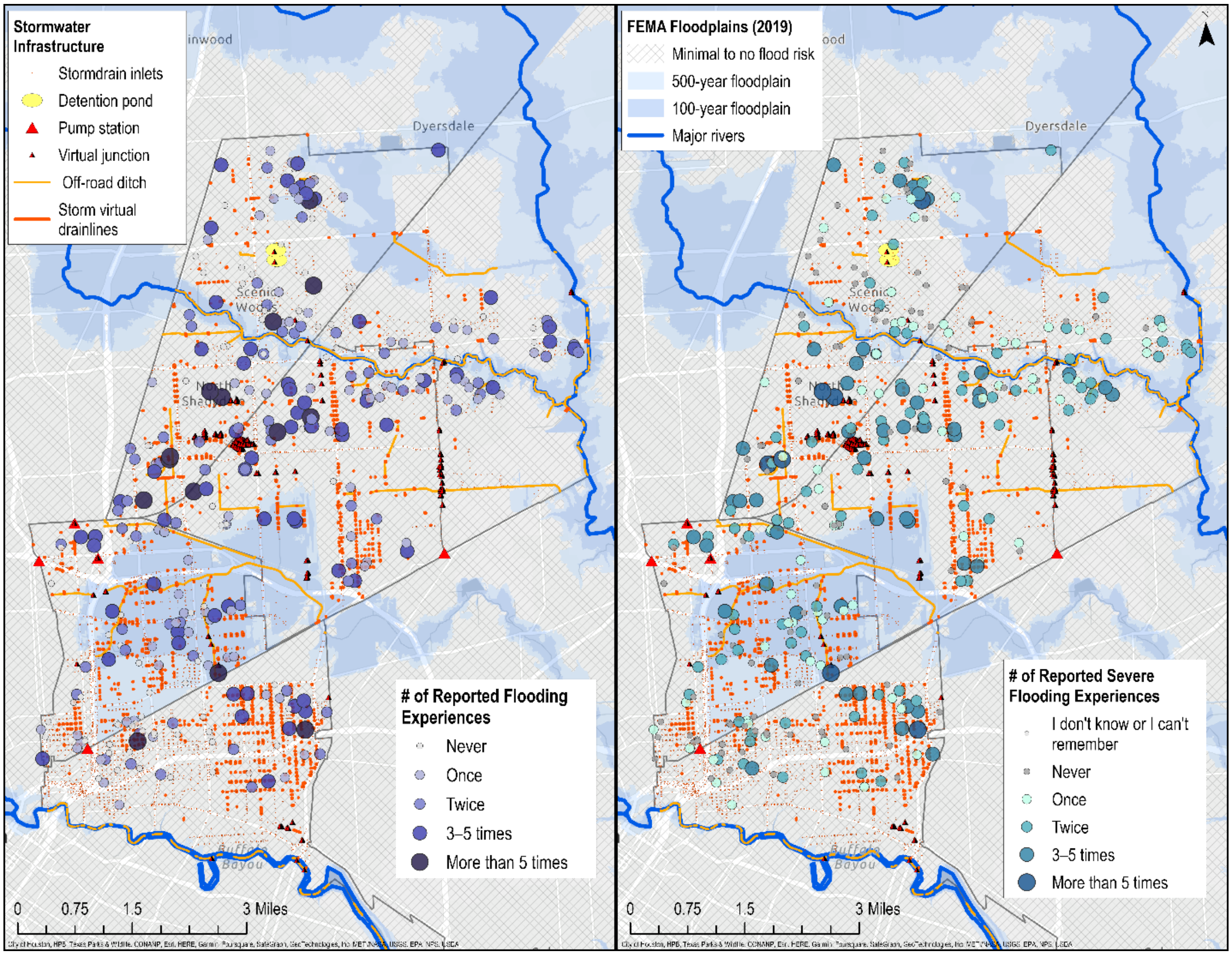

FIGURE 2-7 Comparison of the number of times a household has experienced flooding events (left) or severe flood damage to their home (right) and their proximity to stormwater drainage infrastructure.
SOURCES: City of Houston (2023), FEMA (2023), HGAC (2023), and Houston Public Works Department (2023).

Stormwater infrastructure includes storm drain inlets, detention ponds, pump stations, off-road ditches, and drain lines, all of which function to move and drain water to reduce risk of flooding. However, when stormwater drainage infrastructure fails, water is not able move, leading to flooding in low-lying areas, further exacerbating flood impacts (Gharaibeh et al., 2023; Hendricks and Van Zandt, 2021).

Finally, few greenspaces are located within the study zip codes (Figure 2-8).

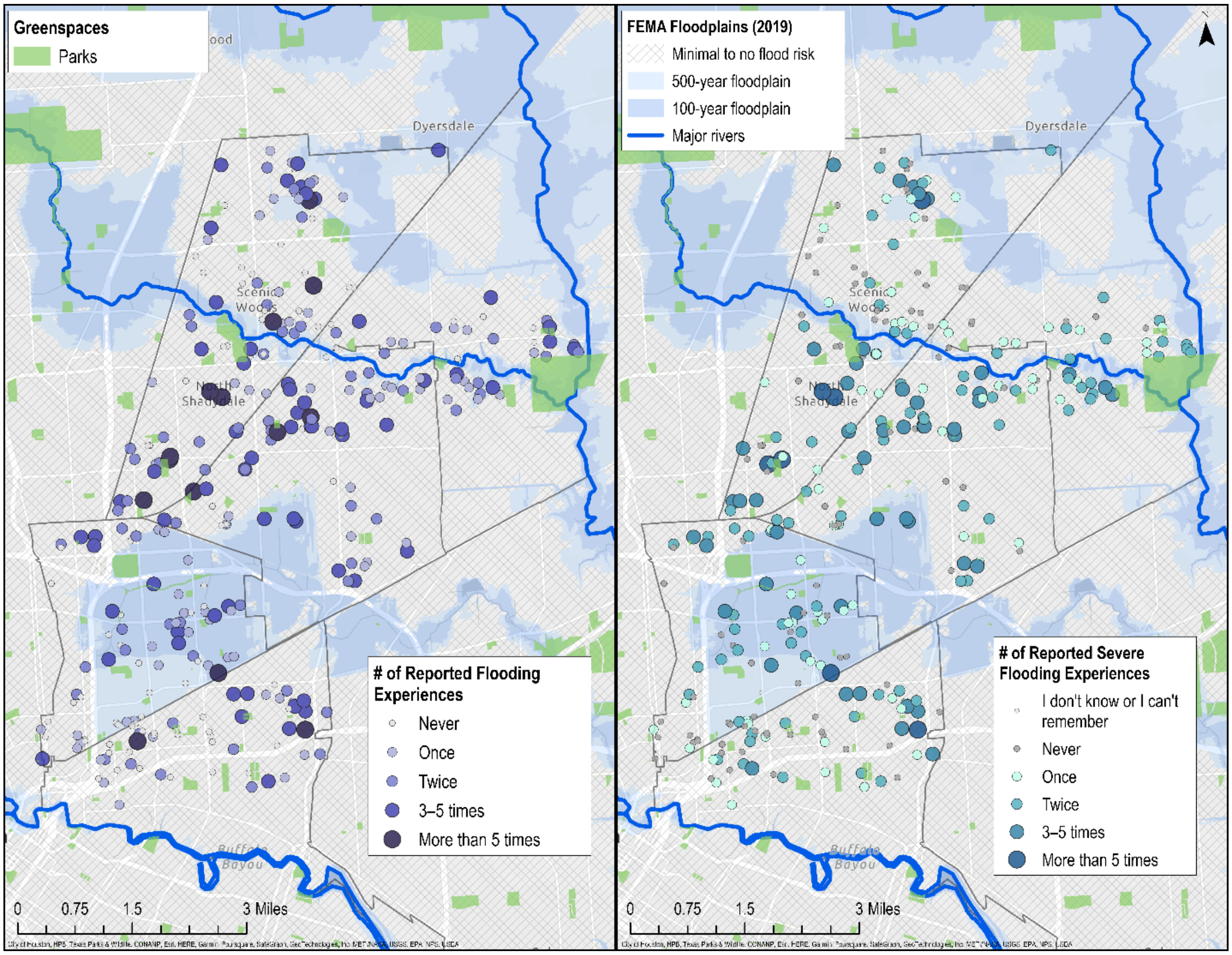

FIGURE 2-8 Comparison of the number of times a household has experienced flooding events (left) or severe flood damage to their home (right) and their proximity to parks/greenspaces.
NOTE: Greenspaces are based on designated green space from the City of Houston.
SOURCES: City of Houston (2023) and FEMA (2023).

Greenspaces can serve a multitude of purposes within a neighborhood. A greenspace can be an area for recreation, provide spaces for exercise and social interactions, minimize pollution, offset greenhouse gas emissions, and reduce urban heat effects (Lee et al., 2015; Miller, 2020). Greenspaces can also act as flood mitigation strategies, as they reduce stormwater runoff (Newman et al., 2019; Roy et al., 2012).

Perceived Risk and Flood Insurance Purchases

Descriptive statistics identified the percentage of people who thought they lived within different floodplain designations and the number of people whose homes are geolocated within a FEMA-designated 100- or 500-year floodplain (Figure 2-9).

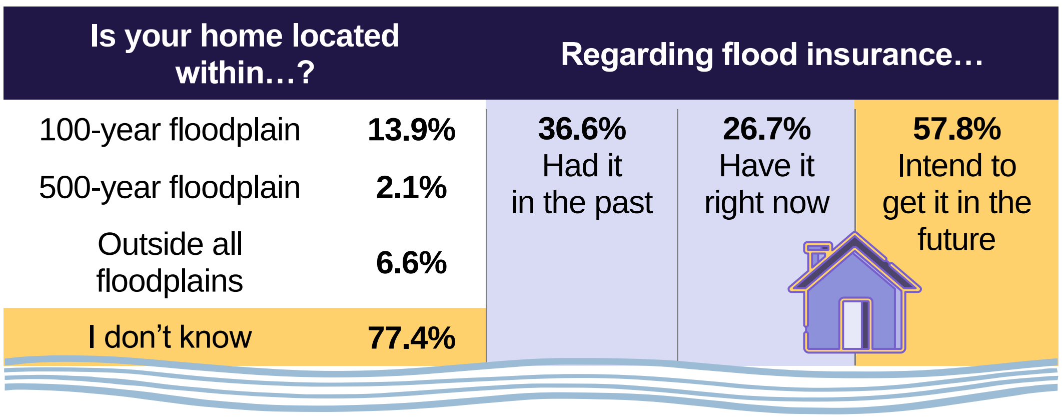

FIGURE 2-9 Percentage of people who think they live in a specific Federal Emergency Management Agency–designated floodplain and percentage of people who have purchased or intend to purchase flood insurance.

Most respondents did not know if they lived in a FEMA-designated floodplain (77.4 percent). The results also show that less than half of residents have had previously or currently have flood insurance (36.6 percent and 26.7 percent, respectively). However, over half of the respondents reported plans to purchase a flood insurance policy in the future (57.8 percent). When comparing this to the number of people who have experienced flooding or severe damage three or more times since living in their homes, the results suggest that FEMA floodplains do not accurately represent the flooding experience of respondents.

Likelihood to Carry Flood Insurance: Renters Versus Owners

The analyses also identified a significant difference between whether homeowners or renters have flood insurance policies. More homeowners live in FEMA-designated 100- or 500-year floodplains than do renters (19 percent versus 9.6 percent), but more renters reported having flood insurance (34.9 percent) than homeowners (10.2 percent). The length of residency in the study area was also associated with whether respondents had flood insurance. More respondents who lived in their homes for over 15 years had flood insurance than shorter-term residents. However, in general, most respondents reported not having flood insurance (65.9 percent) at the time of the survey.

Real Risk

In this study, real risk is determined by geocoding respondents' home addresses and identifying what FEMA floodplain designation it is in using Harris County's 2019 FEMA floodplain maps (see Box 2-4).

Most survey respondents live within a FEMA-designated minimal to no flood risk zone (77.4 percent). Only 22.6 percent of respondents' homes are geolocated in a FEMA-designated 100- or 500-year floodplain. These percentages are based on any geocoded respondent (n = 486) and therefore include the six survey responses that did not answer the survey question "Is your home located within…?."

BOX 2-4

Perceived Risk

Perceived risk describes beliefs, attitudes, judgments, and feelings people have about risks, which can be for different types of risk (Rother, 2019; Siegrist, 2000; Slovic, 2016).

Understanding perceived risk is essential for understanding how people plan for, respond to, and recover from disaster. According to Shrader-Frechette (1990, p. 353), "there is no distinction between perceived risks and actual risks because there are no risks except perceived risks."

Comparing Perceived Risk with Real Risk

When comparing respondents' perceived risk with real risk,[12] only 4 percent of respondents' geolocated in a specific FEMA-designated flood zone (100-year, 500-year, or area of minimal risk)

[12] The comparison of real risk with perceived risk in this study only includes respondents whose home was geocoded and who answered the question "Is your home located within…?" (n = 480), not the total number of geocoded addresses (n = 486). Real risk is represented by the 2019 Harris County FEMA floodplain maps.

also stated that they lived in the same FEMA-designated flood zone. For example, a respondent meeting this criterion would be geolocated in the FEMA 100-year floodplain and also have stated that they live in a 100-year floodplain.

Figure 2-10 further examines how respondents' risk perceptions vary compared with their real risk (the 2019 Harris County FEMA FIRMS).

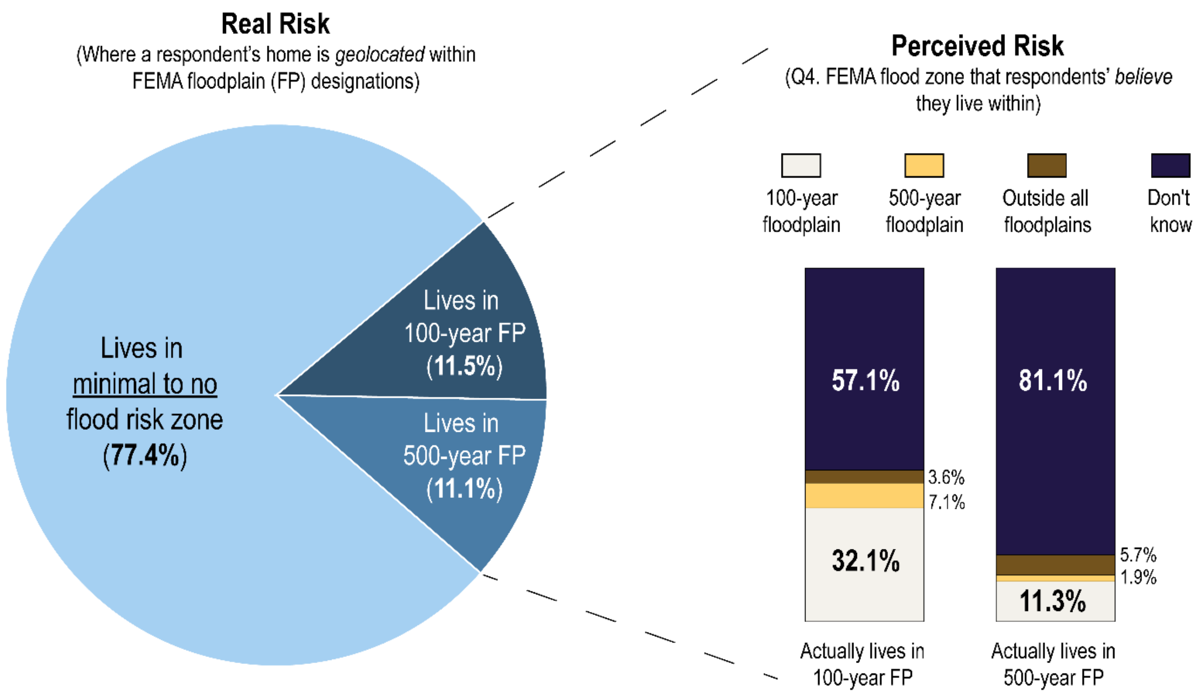

FIGURE 2-10 Percentage of respondents whose home is located in a 100- or 500-year Federal Emergency Management Agency (FEMA)–designated floodplain, compared with their awareness of their flood risk.
NOTES: The figure above is created using only respondents whose home was geocoded, *and* they answered the question "Is your home located within…?" (n = 480). Therefore, the percentages vary slightly from reported real risk percentages.

As shown in Figure 2-10, of the respondents who are geolocated in a 100-year FEMA-designated floodplain (56 respondents), only 32.1 percent also know that they live in a 100-year floodplain. Similarly, only 1.9 percent of respondents who are geolocated in a 500-year FEMA-designated floodplain (53 respondents) also know that they live in a 500-year floodplain, and an additional 11.3% of respondent think they live in a 100-year floodplain. In addition, most residents whose home is geolocated in a 100- or 500-year FEMA-designated floodplain reported that they "don't know" whether they live in that specific flood zone (57.1 percent and 81.1 percent, respectively).

Comparing Real Risk with Perceived Risk Using the Flood Risk Score

To represent flood risk over space, the Flood Risk Scores were interpolated into flood risk surfaces based on perceived and real risk (represented by the 2019 FEMA floodplain maps for Harris County). The Flood Risk Score is calculated based on the following equation:

FLOOD RISK = Hazard (Frequency x Severity of Consequences) x Exposure x Vulnerability

In the equation, *Hazard* describes the probability of a flood event occurring, *Exposure* describes the potential damage to assets and people from flooding, and *Vulnerability* describes the capacity of an individual or household to cope with and adapt to the flood event. How each component is defined and derived from different survey questions is detailed in Appendix C.

The exception is the *Exposure* component. When calculating the real flood risk surface, the calculation uses the geocoded location of a respondent's home in relation to the FEMA floodplains. In contrast, the perceived flood risk surface uses the survey question, "Is your home located within…?".

Once flood risk values were calculated for each respondent, interpolation was used to create flood risk surfaces. Interpolation is the process of creating a value surface by estimating unknown values between sample points (e.g., estimating risk scores in areas between survey respondent scores). While several interpolation methods exist, this study employs and compares two specific interpolation methods: inverse distance weighting (IDW) and empirical Bayesian kriging (EBK).[13]

IDW interpolation estimates unknown values between sample points (the geocoded responses) using the surrounding sample values to calculate an average estimate. However, this estimate is weighted by distance, as IDW assumes that sample points close to one another are more alike than those farther apart. The assumption that nearer sample points are more closely related, and therefore more influential, than farther ones is explicitly tied to the concept of spatial autocorrelation (see Box 2-5).

[13] The reasoning for using IDW and EBK for this study is further discussed in the methodology section (Appendix B).

BOX 2-5

Spatial Autocorrelation

Spatial autocorrelation is based on Waldo Tobler's First Law of Geography (Tobler, 1970, p. 236): "Everything is related to everything else, but near things are more related than distant things." Spatial autocorrelation describes the tendency for observations that are close to one another to have similar values, which can violate **classical statistical** assumptions.

EBK interpolation estimates unknown values between sample points while automatically correcting for spatial autocorrelation in the sample estimation dataset. More detailed information on these interpolation processes can be found in Appendix C. The major difference in calculating the Flood Risk Score lies in the *Exposure* component, depending on whether exposure is based on perceived and real risks. See Figure 2-11 for flood risk surfaces calculated using IDW and EBK.

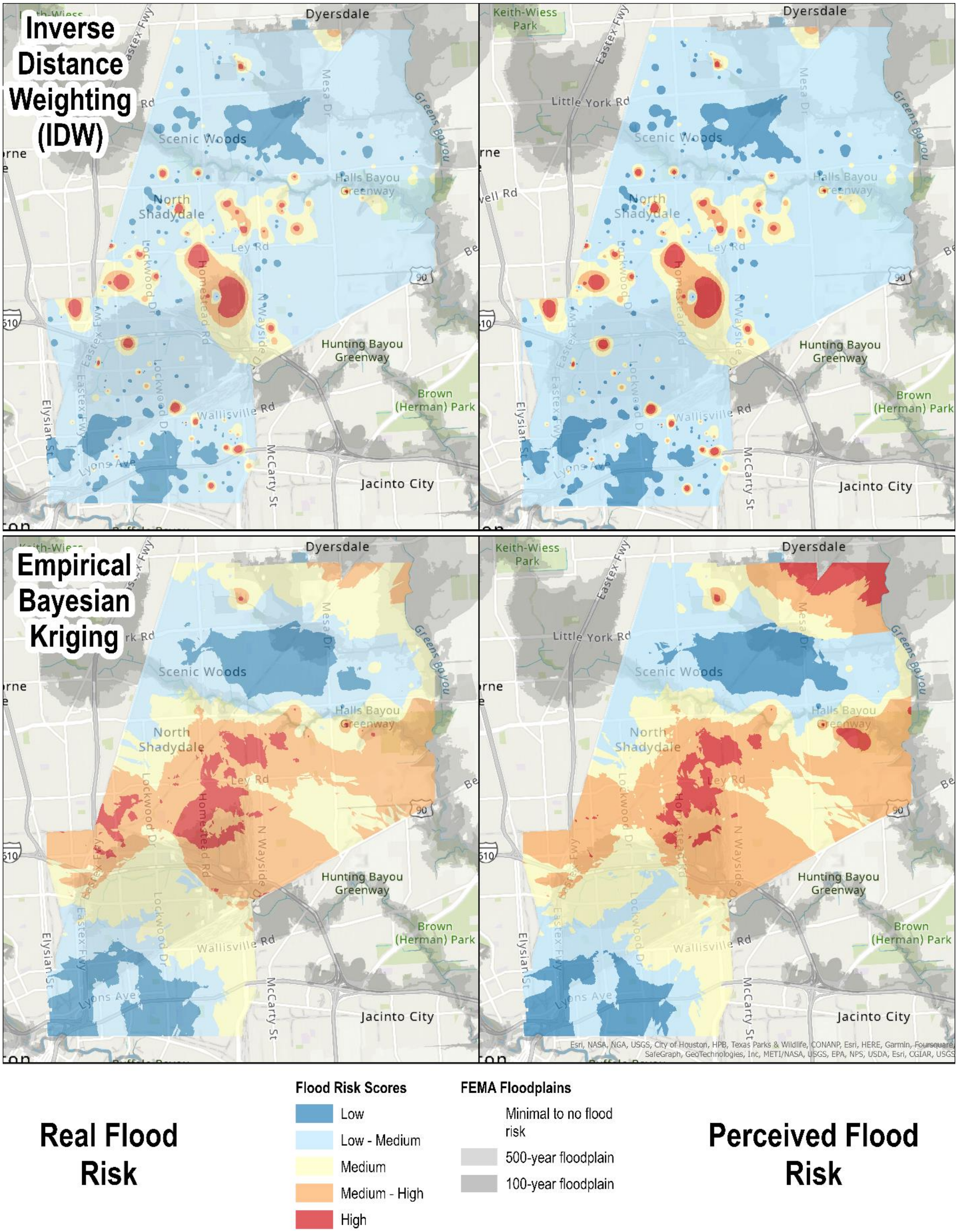

FIGURE 2-11 Comparison of perceived versus real flood risk scores using inverse distance weighting (IDW) and empirical Bayesian kriging (EBK).

The flood risk surfaces show minimal variation between perceived and real risk within each interpolation method. However, differences are more apparent when comparing the interpolation methods.

The IDW flood risk surfaces (top two maps in Figure 2-11) show hot spots of medium to high Flood Risk Scores within the central area of the study site, with several hot spots occurring outside a FEMA-designated floodplain. This pattern occurs in the real (Figure 2-11, top left map) and perceived (Figure 2-11, top right map) flood risk maps, indicating that exposure to flooding itself is not the only factor or most significant factor influencing flood risk.

The EBK flood risk surfaces are similar to the IDW flood risk surfaces in that most medium to high flood risk areas are in the study area's center. However, there is another medium to high flood risk area in both the real risk surface (Figure 2-11, bottom left map) and the perceived risk surface (Figure 2-11, bottom right map), shown in the northeast part of the study zip codes near Dyersdale. The EBK flood risk surfaces also show high flood risk in the perceived flood risk map than in the EBK real risk map.

The interpolation method used to create the flood risk surfaces can result in significantly different outputs. For example, Figure 2-11 shows that a few areas in the IDW flood risk surfaces are considered medium, medium-high, or high flood risk between sample points. In contrast, the EBK surfaces (Figure 2-11, bottom two maps) have significantly more medium, medium-high, or high flood-risk areas. This risk distribution difference is visible in the center of the study area. Several regions estimated to have medium or medium-high flood risk in the EBK surfaces now have overlaps with FEMA-designated floodplains that do not exist in the IDW surfaces.

The EBK maps better represent areas where respondents report high frequency and severity of flood experiences not within the FEMA floodplains as higher risk compared with the IDW maps. These surfaces also identify more areas within a floodplain as higher risk than the IDW maps. Given these results, EBK interpolation is likely more effective for estimating flood risk throughout the study area. EBK better accounts for both calculated, real risk delineated by FEMA floodplains and better represents lived flooding experiences within the study area. EBK is also a better interpolation method because spatial autocorrelation exists in the data. The sociodemographic variables that comprise the *Vulnerability* component (described in Appendix C) and the perceived and real variables that comprise the *Exposure* component in the flood risk equation[14] all exhibit positive spatial autocorrelation (clustering).

FLOOD RISK PERCEPTION AND PROTECTIVE ACTIONS

Ordinary least squares (OLS) and spatial regression models (Box 2-6) were used to determine how flood risk perception influences protective actions taken to mitigate flood risks. The results for the OLS and spatial regression models are shown in Table 2-5.

[14] The interpolation method used to create the flood risk surfaces can result in significantly different outputs (see Appendix B, Box B-4, for an explanation of interpolation).

BOX 2-6

Interpreting Regression Model Results

Regression modeling is a statistical analysis method that uses independent variable(s) to predict the value of a dependent variable and determines the strength of the relationship between them (Gelman and Hill, 2007). Spatial regression modeling takes into account the effects of spatial autocorrelation, as this can cause classical regression models to be less accurate (Burt et al., 2009).

Three main components are used to interpret regression model results:

88. **Coefficients** describe the relationship between the dependent and independent variables. The larger the coefficient value, the stronger the relationship (Gelman and Hill, 2007).
    - ***Positive coefficients*** suggest that as the value of the independent variable increases the mean of the dependent variable increases.
    - ***Negative coefficients*** suggest that as the independent variable increases the dependent variable decreases.
    - For example, if Years in Residence has a positive coefficient of 0.15, that suggests that perceived risk increases as length of residency increases.
89. **P-values** describe whether an independent variable has a significant association with the dependent variable (the relationship likely doesn't exist by random chance). If a p-value is less than 0.05, that variable is considered significant (Gelman and Hill, 2007).
    - For example, if Years in Residence has a coefficient of 0.15 but a p-value of 0.12, then perceived risk increases as length of residency increases, but the relationship could simply exist by random chance.
90. **Model fit** describes how well the independent variables explain variation in the dependent variable together. Common measures of model fit are the adjusted R^2 (ordinary least squares) and the Akaike information criterion (AIC) (spatial regression) (Burt et al., 2009; Gelman and Hill, 2007).
    - For example, the higher the adjusted R^2, the better the model fit. The lower the AICc, the better the model fit.

TABLE 2-5 Results of the Ordinary Least Squares (OLS) and Spatial Regression Modeling for the Relationship Between Real and Perceived Flood Risk, Protective Actions, and Demographic Characteristics

Variable	OLS—Perceived Flood Risk		OLS—Real Flood Risk		Spatial Lag—Real Flood Risk	
	Coefficient	*p-value*	*Coefficient*	*p-value*	*Coefficient*	*p-value*
Weights Variables	–	–	–	–	0.985	0.000
CONSTANT	0.383	**0.046**	0.517	**0.006**	−0.775	**0.000**
Years in Residence	0.001	0.665	0.001	0.675	0.002	0.375
Renter or Owner	−0.048	0.567	0.161	**0.050**	0.102	*0.078*
Housing structure/type	0.200	0.491	0.390	0.174	0.165	0.412
Regarding flood insurance, have you had flood insurance for your home in the past or present?	0.051	0.459	0.075	0.268	0.107	**0.024**
Is your household aware of the City of Houston Disaster Preparedness Guide to better prepare you and your family for a flooding event?	0.133	*0.051*	0.030	0.654	0.007	0.885
How many of the following resources do you have in your home: a battery-powered radio with spare batteries or a hand crank radio, at least 4 gallons of water in plastic containers, at least a 4-day supply of dehydrated or canned food, a household flood emergency plan, and/or a gas-powered or electric generator?	0.023	0.284	0.015	0.474	0.021	0.147
Did you or anyone in your household implement any type of structural mitigation (e.g., elevate your home, dry- or wet-proof your home, install earthen berms, etc.)?	0.032	0.584	−0.023	0.686	-0.050	0.211
Did you or anyone in your household implement any type of non-structural mitigation (e.g., ask the Red Cross about flood risk, purchase flood insurance, ask the landlord about the property's flood risk, etc.?	0.101	**0.015**	0.053	0.192	0.035	0.220
Age of Respondent	0.005	**0.035**	0.003	0.253	0.003	0.148
Number of people in household aged less than 5	−0.029	0.610	−0.036	0.525	0.015	0.707
Number of people in household aged 5 – 17	−0.004	0.894	0.004	0.885	0.018	0.366
Number of people in household aged 18 to 65	0.010	0.727	0.006	0.835	0.000	1.000
Number of people in household aged older than 65	0.104	0.056	0.036	0.507	0.028	0.459
Veteran Status	0.100	0.340	0.106	0.303	0.109	0.133
Gender	−0.114	*0.097*	-0.008	0.910	0.014	0.767
Educational Attainment	−0.118	**0.013**	0.021	0.648	0.017	0.598
Race	0.242	**0.048**	0.096	0.427	0.047	0.577
Hispanic/Latino	0.269	**0.041**	0.037	0.772	0.025	0.783

Household Income	0.036	**0.032**	0.014	0.415	0.013	0.270
How prepared do you think your household is to handle a major flood event?	0.026	0.603	0.065	0.186	0.078	**0.023**
Model Fit Summary						
R^2	13.9%		6.6%		51.6%	
Adjusted R^2	10.3%		2.6%		–	
AICc	1054.54		1039.5		737.667	

NOTES: A common practice in regression modeling is to remove insignificant variables from the model and rerun it. However, insignificant variables are still important, as they help (1) identify which variables are more important for this specific model and (2) make sure the results reflect relationships that theory might expect. Model results (significant or not) should still make sense; therefore, insignificant variables should not be removed without good reason. AICc = Akaike information criterion; R^2 = R squared. Gray cells indicate significant variables for different models. Significant p-values ($\alpha \leq 0.05$) are bolded. Italicized p-values are those that are above 0.05, but have $\alpha \leq 0.1$.

The results from the regression models identify two outcomes of interest. First, the regression model for *perceived flood risk* is significantly associated with residents who take more nonstructural protective actions, older residents, residents with higher education levels, residents who identify as people of color and/or Hispanic or Latino, and lower household incomes. However, the model's explanatory power is relatively low, with an adjusted R^2 of 13.9 percent. Low explanatory power from surveys is not unusual, given that surveys are limited in what they can explain based on the questions they ask. The statistical tests for dependence also found no evidence of spatial dependence within the perceived risk model, indicating that a spatial regression model would likely not improve model fit.

Second, the OLS regression model for *real flood risk* is only significantly associated with renters. However, diagnostic tests found evidence of spatial dependence within the model. Because the Lagrange Multiplier (LM) (lag) and Robust LM (lag) were both significant (Table 2-6), with an $\alpha \leq 0.000$, the diagnostics identified the spatial lag model as the most appropriate spatial regression model for this dataset.

TABLE 2-6 Diagnostic Test Results for Spatial Dependence for Real and Perceived Flood Risk Ordinary Least Squares (OLS) Model

	OLS—Perceived Flood Risk	**OLS—Real Flood Risk**
Diagnostic Test for Spatial Dependence	**Test (p-value)**	**Test (p-value)**
Moran's I (error)	0.7429 (0.45753)	47 (0.000)
Lagrange Multipler (LM) (lag)	0.2748 (0.60015)	1951.3 (0.000)
Robust LM (lag)	0.5011 (0.47901)	61.1 (0.000)
LM (error)	0.1062 (0.74453)	1895 (0.000)

Robust LM (error)	0.3325 (0.56417)	4.8 (0.02806)

Given that floodplains are typically clustered in specific areas throughout the study zip codes, the influence of spatial autocorrelation on the model makes sense. In addition, the results of the spatial real flood risk model show that *real flood risk* is significantly associated with people who have had flood insurance for their homes in the past or present and feel they are more prepared to handle a major flood event. Likewise, the spatial lag model results demonstrate a significant increase in model explanatory power (R2 increased from 6.6 percent to 51.6 percent), which suggests that those who live in FEMA-designated floodplains are more likely to have (or have had) flood insurance and feel more prepared to handle a flood event.

FLOOD RISK COMMUNICATION PREFERENCES

Preferred sources of risk communication were identified based on respondents' answers to Question 22, "To what extent do you seek information about flood preparedness in your area from…?," and Question 23, "From which one of the following would you and your household prefer to receive flood preparedness information?" Most respondents prefer to receive flood preparedness information from their local news meteorologist (73.2 percent), their local city or county emergency management office (55.6 percent), the office of the mayor or city manager (54.5 percent), the National Weather Service (50 percent), and friends or family (21.2 percent). Less than 20 percent of respondents prefer to receive flood preparedness information from other local government agencies (15.1 percent), places of worship (10.4 percent), local school districts (9.1 percent), other sources (5 percent), or employers/coworkers (4.6 percent).

Regarding where respondents prefer to seek flood preparedness information, most use the television, friends, relatives, neighbors, coworkers, and their personal experiences and observations (Figure 2-12). However, the Wilcoxon and contingency table results[15] demonstrate that these preferences significantly vary across some demographic groups. Discussions on how to interpret the Wilcoxon and contingency table results are provided in Box 2-7.

[15] Due to the number of Wilcoxon signed rank tests and Contingency tables conducted for each categorical variable pairing, these results only provide a single example for each test per demographic group. The descriptions of the results will therefore *generally* discuss tables/results not shown in the report.

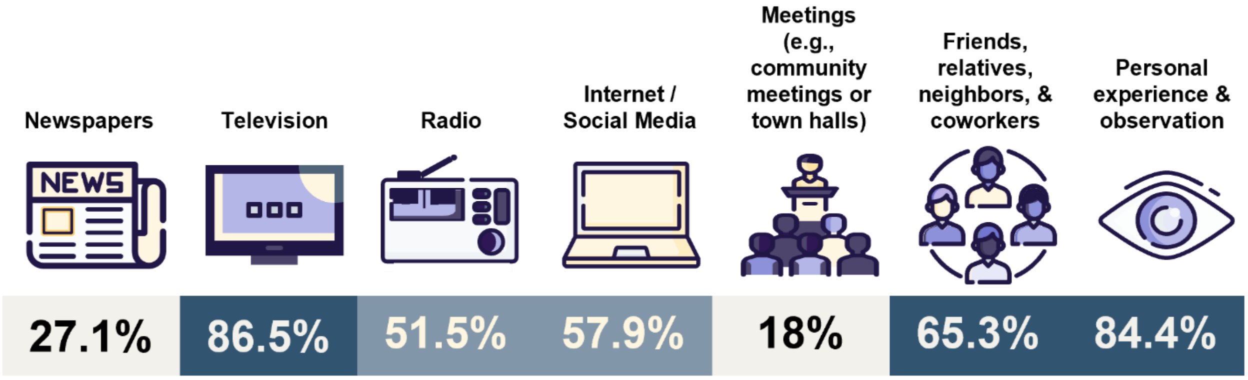

FIGURE 2-12 Percentage of respondents who ranked preferred sources of risk communication as “moderate,” “great,” or “very great” when answering Question 22: “To what extent do you seek information about flood preparedness in your area from…?.”

BOX 2-7

Interpreting Wilcoxon Tests and Contingency Tables

Wilcoxon tests determine whether two or more sets of variable pairs are significantly different from one another. The column “Score Mean” indicates the rank mean of the categorical variable pairing, and the column “Significance” indicates whether the relationship between the two variables is significant when $p < 0.05$. Higher rank sums indicate greater association between two categorial variables.

Contingency tables test the strength of relationships between two categorical variables. In general, the larger the cell deviation value (difference between the observed and expected values) of specific category pairings, the greater the cell Chi^2 value (Agresti, 2013). If the deviation value is positive, more than the expected number respondents chose a particular response, whereas a negative deviation value indicates fewer than the expected number respondents chose a particular response (Agresti, 2013; Kateri, 2014). Therefore, variable category pairings with large deviation and Chi^2 values indicate stronger interdependence between two variables.

Age

Overall, age is significantly associated with preferred sources of flood preparedness information. For example, respondents age 45 and older were more likely to prefer flood preparedness information from television and news (e.g., the score means for both variables are higher in Table 2-7), radio, and the office of the mayor or city manager.

TABLE 2-7 Wilcoxon Signed Rank Test Comparing Age and Extent to Which Respondents Seek Flood Preparedness Information from Television and News Preferences

Category	Count	Score Mean
	Television and News	
18–24 Years	23	231.196
24–44 Years	118	230.462
45–64 Years	207	275.715
65+ Years	180	278.172
Chi^2 = 10.4966	p-value	0.0148*

* $\alpha \leq 0.05$

In contrast, respondents aged 18–44 were more likely to seek flood preparedness information from friends and/or family and the internet/social media. For example, the deviation values shown in Table 2-8 for age groups 18–24 years (8.87) and 25–44 years (20.83) were high positive values, with equally high cell Chi^2 values (15.33 and 21.51, respectively). A greater-than-expected number of respondents in these age groups were more likely to seek flood preparedness information from the internet/social media to a *very great extent* than other age groups. In contrast, a greater-than-expected number of respondents aged 65 and over were more likely to seek flood preparedness information from the internet/social media to a *moderate extent* (cell deviation = 39.50 and Chi^2 = 27.61), whereas all other categories had negative cell deviations (Table 2-8).

TABLE 2-8 Contingency Table Comparing Age Categories and the Extent to Which Respondents Seek Flood Preparedness Information from Internet/Social Media

Count *Deviation* *Cell Chi^2*	**Not at All**	**Small Extent**	**Moderate Extent**	**Great Extent**	**Very Great Extent**	**Total**
18–24 Years	7	4	3	1	14	29
	0.25	−0.91	−6.26	−1.96	8.87	5.58%
	0.01	0.17	4.23	1.29	15.33	62.07%
25–44 Years	33	18	13	9	41	114
	6.47	−1.29	−23.39	−2.62	20.83	21.92%

	1.58	0.09	15.04	0.59	21.51	55.26%
45–64 Years	50 3.46 0.26	40 6.15 1.12	54 −9.85 1.52	27 6.62 2.15	29 −6.38 1.15	200 38.46% 55.00%
65+ Years	31 −10.19 2.52	26 −3.95 0.52	96 39.50 27.61	16 −2.04 0.23	8 −23.32 17.36	177 34.04% 67.80%
Total	121 23.27%	88 16.92%	166 31.92%	53 10.19%	92 17.69%	520
Table Test	**Chi²**	**Chi² Probability**				
Likelihood Ratio	113.98	<.0001*				
Pearson	114.27 2	<.0001*				

* α ≤ 0.05

NOTES: Fisher's exact tests and odds ratios were not run for tables with more than two response categories. Light gray cells show variable pairings with large cell deviation and Chi^2 values. Dark gray cells represent the percent of the population in that age bracket (row) that seeks information about flood preparedness from the internet/social media to a "moderate," "great," or "very great" extent.

Education

A significant association was present between education levels and information sources. Respondents with some college or above were more likely to prefer television and news (Table 2-9) and internet/social media. In contrast, respondents with less than a high school diploma were more likely to prefer friends and/or family, local news, and television and news (Table 2-10). No significant associations were found when analyzing contingency tables comparing education and radio as a source of risk communication.

TABLE 2-9 Wilcoxon Test Tables Comparing Education and Extent to which Respondents Seek Flood Preparedness Information from Television and News

Category	Count	Score Mean
	Television and News	
Less than High School Diploma	113	301.20
High School Diploma or Equivalent	199	274.86
Some College or Above	222	243.75
Chi^2 = 12.2133	p-value	0.0022*

* α ≤ 0.05.

Count *Deviation* *Cell Chi²*	**Not at all**	**Small Extent**	**Moderate Extent**	**Great Extent**	**Very Great Extent**	**Total**
	Flood Preparedness Information from					
Less than High School Diploma	4	7	19	25	58	113
	−2.56	−1.68	−0.47	−10.55	15.25	21.16%
	1.00	0.32	0.01	3.13	5.44	90.27%
High School Diploma or Equivalent	10	16	30	64	79	199
	−1.55	0.72	−4.28	1.39	3.72	37.27%
	0.21	0.03	0.54	0.03	0.18	86.93%
Some College or Above	17	18	43	79	65	222
	4.11	0.96	4.75	9.16	−18.98	41.57%
	1.31	0.05	0.59	1.20	4.29	84.23%
Total	31	41	92	168	202	534
	5.81%	7.68%	17.23%	31.46%	37.83%	
Table Test	**Chi²**	**Chi² Probability**				
Likelihood Ratio	18.55	0.0175*				
Pearson	18.348	0.0188*				

* $\alpha \leq 0.05$.
NOTES: Fisher's exact tests and odds ratios were not run for tables with more than two response categories. Light gray cells show variable pairings with large cell deviation and Chi² values. Dark gray cells represent the percent of the population in that education bracket (row) that seek information about flood preparedness from television and news to a "moderate," "great," or "very great" extent.

Gender

None of the Wilcoxon or contingency table pairings between gender and preferred sources to seek flood preparedness information were considered significant ($\alpha \leq 0.05$). However, pairings between gender and local news had the lowest p-values in the Wilcoxon pairings ($p = 0.198$) (Table 2-11), indicating that the relationship, while not significant, is still relevant potentially.

TABLE 2-11 Wilcoxon Test Tables Comparing Gender and Whether Respondents Prefer to Receive Flood Preparedness Information from Local News

Category	Count	Score Mean
	Television and News	
Male/Man & Prefer Not to Answer	205	274.18
Female/Woman & Nonbinary	332	260.61

Chi2 = 1.656	p-value	0.198

NOTES: Pairing is not significant at the α ≤ 0.05 level. Nonbinary is grouped with Female/Woman because they are considered historically marginalized populations and there were few respondents that identified as such. Prefer not to answer is groups with Male/Man because it is impossible to assume that those respondents are considered historically marginalized populations.

A contingency table was then conducted for the pairing with the lowest p-value, that of gender and local news information sources. While not significant, the results show greater-than-expected numbers of female/women and nonbinary respondents who preferred to seek flood preparedness information from local news when compared with males/men or those who preferred not to answer (Table 2-12). No significant associations were found when analyzing contingency tables comparing gender, television, and news as a source of risk communication.

TABLE 2-12 Contingency Table Comparing Gender Categories and Whether Respondents Prefer to Receive Flood Preparedness Information from Local News

Count *Deviation* *Cell Chi^2*	**Not Preferred**	**Preferred**	**Total**
Male/Man (215) & Prefer not to answer (2)	61	144	217
	6.41	−6.41	40.41%
	0.75	0.27	**26.82%**
Female/Woman & Nonbinary	82	250	338
	−6.41	6.41	62.94%
	0.46	0.17	**46.55%**
Total	143 26.63%	394 73.37%	537
Table Test	**Chi^2**	**Chi^2 Probability**	
Likelihood Ratio	1.65	0.1996	
Pearson	1.66	0.1977	

NOTES: Pairing is not significant at the α ≤ 0.05 level. Fisher's exact test was not run due to significance level being above 0.05. Nonbinary is grouped with Female/Woman because they are considered historically marginalized populations and there were few respondents that identified as such. Prefer not to answer is groups with Male/Man because it is impossible to assume that those respondents are considered historically marginalized populations.

Income

Among household income groups, individuals earning less than $50,000 preferred to receive flood preparedness information from television and news and friends and/or family. Respondents earning between $50,000 and $75,000 were more likely to seek flood preparedness information from social media/internet, county or city emergency management (Table 2-13). Respondents earning between $20,000 and $49,000 were least likely to prefer the National Weather Service (Table 2-14), as shown the by negative cell deviation values.

TABLE 2-13 Wilcoxon Test Tables Comparing Household Income and City or County Emergency Management Preferences

Category	Count	Score Mean
County or City Emergency Management		
$100,000 or more (5) OR Preferred Not to Answer (98)	80	274.28
$75,000 to $99,999	13	284.73
$50,000 to $74,999	46	323.79
$35,000 to $49,999	54	263.69
$20,000 to $34,999	140	286.35
Less than $20,000	199	242.28
Chi^2 = 20.216	p-value	0.0024*

* α ≤ 0.05

TABLE 2-14 Contingency Table Comparing Household Income Categories and Whether or Not Respondents Prefer to Receive Flood Preparedness Information from the National Weather Service

Count *Deviation* *Cell Chi^2*	**Not Preferred**	**Preferred**	**Total**
$100,000 or more (5) OR Preferred Not to Answer (98)	56	47	103
	2.92	−2.92	18.56%
	0.16	0.17	**45.63%**
$75,000 to $99,999	3	10	13
	−3.70	3.70	2.34%
	2.04	2.17	**76.92%**
$50,000 to $74,999	28	18	46
	4.30	−4.30	8.29%
	0.78	0.83	**39.13%**
$35,000 - $49,999	34	20	54
	6.17	−6.17	9.73%
	1.37	1.46	**37.04%**
$20,000 to $34,999	73	67	140
	0.86	−0.86	25.23%
	0.01	0.01	**47.86%**
Less than $20,000	92	107	199
	−10.55	10.55	35.86%
	1.08	1.15	**53.77%**
Total	286	269	5537

	51.53%	48.47%	
Table Tests	**Chi²**	**Chi² Probability**	
Likelihood Ratio	12.181	0.0324*	
Pearson	11.912	0.0360*	

* $\alpha \leq 0.05$.
NOTES: Fisher's exact tests and odds ratios were not run for tables with more than two response categories.

Race/Ethnicity

The only significant association between preferred sources to seek flood preparedness information and race was found between race and the National Weather Service (Table 2-15).

TABLE 2-15 Wilcoxon Test Tables Comparing Race and Whether or Not Respondents Prefer to Receive Flood Preparedness Information from the National Weather Service

Category	Count	Score Mean
	Television and News	
People of Color and/or Hispanic/Latino	506	271.934
White or Prefer Not Answer	31	221.113
$Chi^2 = 4.1782$	p-value	0.0409*

* $\alpha \leq 0.05$

People of color and/or Hispanic or Latino respondents were significantly more likely to seek information from the National Weather Service (Table 2-16) compared with White respondents.

TABLE 2-16 Contingency Table Comparing Race and Whether or Not Respondents Prefer to Receive Flood Preparedness Information from Office of the Mayor or City Manager

Count *Deviation* *Cell Chi²*	**Not Preferred**	**Preferred**	**Total**
People of color and/or Hispanic/Latino	247 −5.53 0.12	259 5.53 0.12	506 94.23% 51.19%
White (Not Hispanic/Latino) or Prefer Not Answer	21 5.53 1.98	10 −5.53 1.97	31 5.77% 32.26%
Total	268 49.91%	269 50.09%	537
Table Tests	**Chi²**	**Chi² Probability**	

Likelihood Ratio	4.272	0.0387*
Pearson	4.186	0.0408*

* α ≤ 0.05.
NOTES: Fisher's exact left-tailed test (p = 0.0306) probability (National Weather Service is Preferred) is greater for people of color and/or Hispanic/Latino respondents than White (not Hispanic/Latino) respondents and those who chose not to answer. Odds ratio is = 0.45.

People of color and/or Hispanic or Latino respondents were significantly more likely to seek information from the National Weather Service (Table 2-16) compared with White respondents. No other significant associations were found between race and other risk communication sources.

When examining only ethnicity, non-Hispanic or Latino respondents were significantly more likely to seek flood preparedness information from the mayor's or city manager's office. In contrast, Hispanic or Latino respondents were significantly more likely to seek flood preparedness information from schools (Table 2-17). This relationship is further demonstrated in the contingency table results (2-18).

TABLE 2-17 Wilcoxon Test Tables Comparing Ethnicity and Office of the Mayor or City Manager and School Preferences

Category	Count	Score Mean
Office of the Mayor or City Manager		
Hispanic or Latino	178	238.649
Not Hispanic or Latino	359	284.049
Chi^2=13.6975	***p-value***	**0.0002***
Schools		
Hispanic or Latino	178	282.211
Not Hispanic or Latino	359	262.45
Chi^2 = 7.7586	***p-value***	**0.0053***

* α ≤ 0.05

TABLE 2-18 Contingency Table Comparing Ethnicity and Whether Respondents Prefer to Receive Flood Preparedness Information from the Office of the Mayor or City Manager (a) Versus School District (b)

(a)

Count *Deviation* *Cell Chi^2*	**Office of the Mayor** **Not Preferred**	**Preferred**	**Total**
Hispanic or Latino	101 20.12	77 −20.12	178 33.15 %

(b)

Count *Deviation* *Cell Chi^2*	**School Districts** **Not Preferred**	**Preferred**	**Total**
Hispanic or Latino	153 −8.76	25 8.76	178 33.15 %

	5.01	4.17	43.26 %
	143	216	359
Not Hispanic or Latino	−20.12	20.12	66.85 %
	2.48	2.07	60.17 %
Total	244 45.44%	293 54.56%	537
Table Tests	**Chi^2**	**Chi^2 Probability**	
Likelihood Ratio	13.717	0.0002*	
Pearson	13.723	0.0002*	

	0.47	4.72	14.04 %
	335	24	359
Not Hispanic or Latino	8.76	−8.76	66.85 %
	0.24	2.34	6.69%
Total	488 90.88%	49 9.12%	537
Table Tests	**Chi^2**	**Chi^2 Probability**	
Likelihood Ratio	7.347	0.0067*	
Pearson	7.773	0.0053*	

* $\alpha \leq 0.05$

NOTES**:** Cells in medium-gray shading indicate deviation and cell Chi^2 values mentioned in the text. Fisher's exact right-tailed tests (p = 0.0002*) probability (Office of the Mayor is Preferred) is greater for not Hispanic or Latino than Hispanic or Latino. Fisher's exact left-tailed tests (p = 0.0068*) probability (Schools is Preferred) is greater for Hispanic or Latino respondents compared to Not Hispanic or Latino respondents. Odds ratios: Office of the Mayor = 1.98; Schools = 0.44.

While more respondents overall prefer flood preparedness information from the office of the mayor (54.56 percent) compared with school districts (9.12 percent), negative deviation values for Hispanic or Latino populations and the office of the mayor pairings (−20.12) suggest fewer Hispanic or Latino respondents than expected prefer that information source (Table 2-18[a]). The Fisher's exact right-tailed test (p = 0.0002*) also shows that respondents who are not Hispanic or Latino are significantly more likely to seek flood preparedness information from the office of the mayor than Hispanic or Latino respondents. In contrast, the deviation value for Hispanic or Latino populations and schools was positive (8.76) (Table 2-18[b]), with the highest cell Chi^2 value in the table (4.72). This information in combination with the Fisher's exact left-tailed tests (p = 0.0068*) suggests that Hispanic or Latino respondents are more likely to seek flood preparedness information from schools than respondents who are not Hispanic or Latino.

Veteran Status

None of the Wilcoxon or contingency table pairings between veteran status and preferred sources to seek flood preparedness information were considered significant ($\alpha \leq 0.05$). However, when contingency tables were conducted on the Wilcoxon pairing with the lowest p-value (county or city emergency management) (Table 2-19), the pairing was significant (Table 2-20).

TABLE 2-19 Wilcoxon Test Tables Comparing Veteran Status and Whether Respondents Prefer to Receive Flood Preparedness Information from County or City Emergency Management

Category	Count	Score Mean
County or City Emergency Management		
Nonveteran	485	265.653
Veteran	52	300.221
Chi^2 = 4.1782	p-value	0.0760

NOTE**:** Pairing is not significant at the $\alpha \leq 0.05$ level.

TABLE 2-20 Contingency Table Comparing Veteran Status Categories and Whether Respondents Prefer to Receive Flood Preparedness Information from Church/Place of Worship

Count *Deviation* *Cell Chi^2*	**Not Preferred**	**Preferred**	**Total**
Nonveteran	430 −4.42 0.05	55 4.42 0.39	485 90.32% 11.34%
Veteran	51 4.42 0.42	1 −4.42 3.61	52 9.68% 1.92%
Total	481 89.57%	56 10.43%	537
Table Tests	**Chi^2**	**Chi^2 Probability**	
Likelihood Ratio	6.293	0.0121*	
Pearson	4.459	0.0347*	

* $\alpha \leq 0.05$

NOTES: Cells in medium-gray shading indicate deviation and cell Chi^2 values mentioned in the text. Fisher's exact left-tailed tests (p = 0.0186*) probability (church/place of worship is preferred) is greater for nonveterans than veterans. Odds ratio = 0.15.

Veteran respondents were more likely than nonveteran respondents to prefer receiving flood preparedness information from county or city emergency management (Table 2-19). Veterans were significantly less likely than nonveterans to seek flood preparedness information from church/place of worship (deviation = −4.25 and cell Chi^2 =3.44) (Table 2-20).

Seeking Flood Preparedness Information from Friends and Family Compared with Proximity to Floodplain

To determine if respondents who preferred to receive flood preparedness information from friends or family were spatially clustered together throughout the study area, we used the geocoded locations of respondents (n = 485) who checked "Yes" for Question 23, "From which of the following entities would you and your household prefer to receive flood preparedness information? Answer choice – 'Friends and/or family?'" (Figure 2-13).

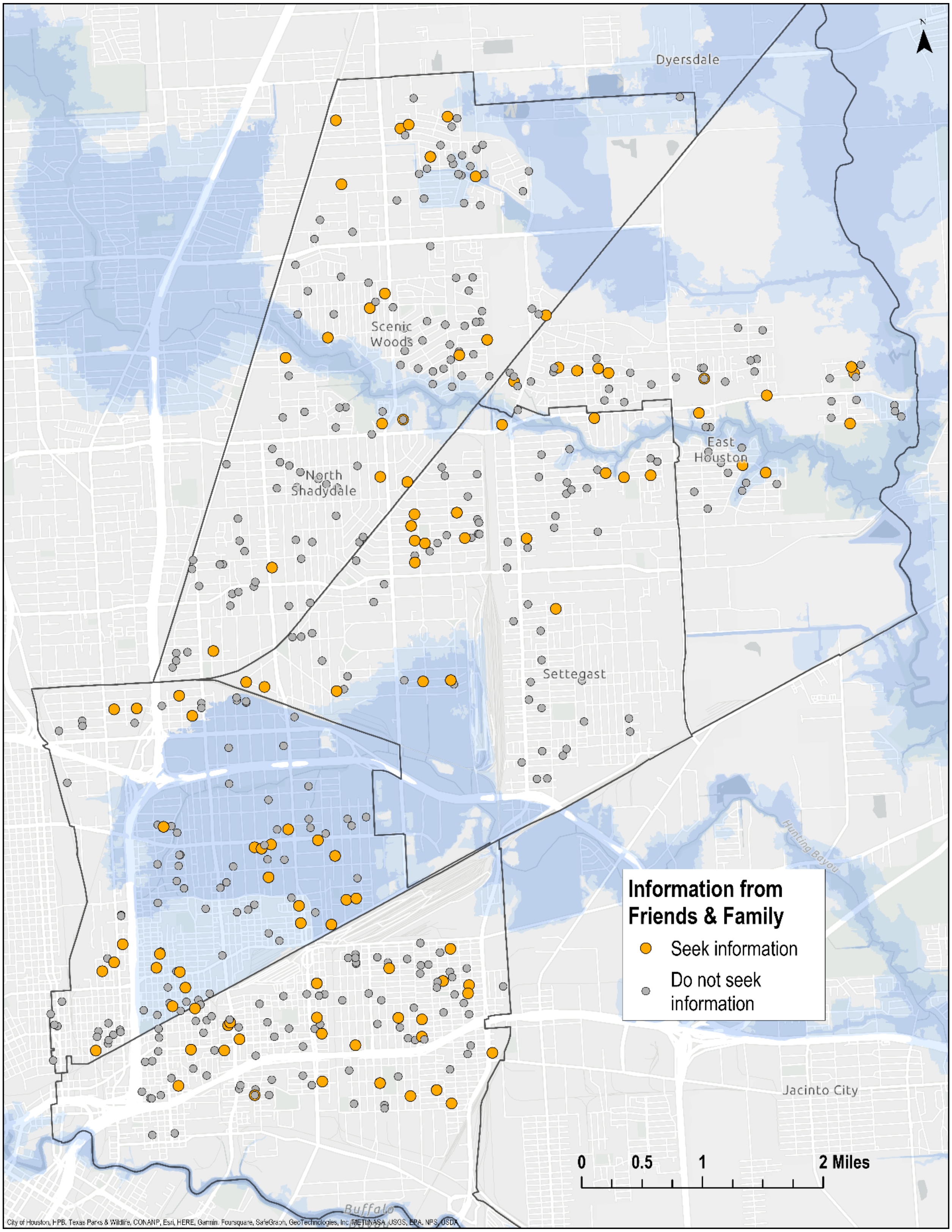

FIGURE 2-13 Locations of residents who seek information from friends and family compared with those who do not.

A cluster analysis was conducted in a geographic information system to determine significant clustering of respondents who prefer to receive flood preparedness information from friends and/or family in the study area. However, no significant clusters were identified. Furthermore, there is no significant difference between the percentage of people within each zip code who prefer to receive flood preparedness information from friends and/or family (Table 2-21).

TABLE 2-21 Kruskal-Wallis Test Number and Percentage of People Who Prefer to Receive Flood Preparedness Information from Friends and/or Family by Zip Code

Zip Code	Number of Respondents	Percentage of Respondents	Expected Score	Score Mean
77020	28	25.50%	31104	225.891
77078	14	24.10%	26730	249.727
77026	28	26.40%	25758	252.057
77028	20	24.10%	20169	246.434
77016	20	15.60%	14094	246.534
Chi^2 = 5.1138		**p-value =** 0.2758*		

* $\alpha \leq 0.05$

POST-DISASTER RECOVERY: FLOODING, COVID-19, AND WINTER STORMS

Impact of COVID-19 Pandemic on Flood-Protective Actions

Respondents reported that the COVID-19 pandemic impacted their ability to stockpile food and water (24.7 percent) and save $500 in emergency savings (37 percent) to a “great extent” and a “very great extent” (Table 2-22).

TABLE 2-22 Percentages of to What Extent COVID-19 Has Impacted Survey Respondents’ Ability to Prepare for an Emergency or Disaster (Question 27)

Question 27	Not at All		Small Extent		Moderate Extent		Great Extent		Very Great Extent		Total
Stockpile Food & Water	191	**36.0%**	103	**19.4%**	106	**20.0%**	77	**14.5%**	54	**10.2%**	531

Put Together a First-Aid Kit	329	**62.0 %**	76	**14.3 %**	63	**11.9 %**	42	**7.9%**	21	**4.0%**	531
Ensure a 4-day Supply of Necessary Medications	311	**58.7 %**	54	**10.2 %**	60	**11.3 %**	66	**12.5%**	39	**7.4%**	530
Save $500 in Emergency Savings	215	**40.6 %**	58	**10.9 %**	61	**11.5 %**	92	**17.4%**	104	**19.6 %**	530

In contrast, over half of the respondents reported that their ability to assemble a first-aid kit (62 percent) and ensure a 4-day supply of necessary medications (58.7 percent) was "not at all" impacted. The results suggest that COVID-19 had a greater impact on respondents' ability to stockpile food and water and save $500 in emergency savings than on their ability to assemble a first-aid kit and ensure they had a 4-day supply of necessary medications.

Of the 535 respondents who answered evacuation questions, 80.6 percent of respondents did not evacuate during Tropical Storm Beta (2020) or Hurricane Laura (2020).[16] Only 8.8 percent and 9.9 percent of respondents evacuated during Tropical Storm Beta (2020) and Hurricane Laura (2020), respectively. Of those who did not evacuate (431 respondents), 27.8 percent (for Tropical Storm Beta) and 26.0 percent (Hurricane Laura) did not evacuate or decided to stay home specifically because of concerns related to the COVID-19 pandemic.

Recovery Services

For flooding, COVID-19, and Texas Winter Storms (2021) , 34.1 percent, 37.8 percent, and 28.1 percent of respondents, respectively, sought different types of services, including physical health, mental health, utility or energy assistance, financial assistance, food assistance, home repairs, employment services, or help from a neighbor (Table 2-23). Over half of respondents (52 percent) sought recovery services for flooding, COVID-19, and winter storms (Table 2-24).

TABLE 2-23 Number (n) and Percentage of Respondents Who Sought Recovery Services for Flooding, COVID-19, and Winter Storms, by Type

[16] No table provided for this section, as the results could clearly be explained in the text.

Recovery Service Sought	Flooding (n)	(%)	COVID-19 (n)	(%)	Winter Storms (n)	(%)
Physical health	25	4.7%	70	13.1%	15	2.8%
Mental health	21	3.9%	36	6.8%	21	3.9%
Utility or energy	76	14.3%	60	11.3%	57	10.7%
Financial	182	34.1%	86	16.1%	50	9.4%
Food	199	37.3%	172	32.3%	103	19.3%
Home Repairs	157	29.5%	–	–	82	15.4%
Employment services	40	7.5%	72	13.5%	–	–
Help from a neighbor	66	12.4%	65	12.2%	71	13.3%
Total Services	***812***	***34.1%***	***902***	***37.8%***	***670***	***28.1%***

TABLE 2-24 Percentage of Respondents Who Sought Recovery Services, by the Disasters for Which They Were Requested

Requested Services For	Number of Respondents	Percentage of Respondents
All disasters (Flooding, COVID-19, and Winter Storms)	**277**	**52.0%**
Single Disasters ONLY		
Flooding Only	7	1.3%
COVID-19 Only	30	5.6%
Winter Storms Only	2	0.4%
Two Disasters		
Flooding and COVID-19	39	7.3%
Flooding and Winter Storms	9	1.7%
COVID-19 and Winter Storms	166	31.1%
Never Requested Services	**3**	**0.6%**

Approximately one-third (31.1 percent) of respondents shared that they sought services for COVID-19 and winter storms, while less than 2 percent sought services for flooding and winter storms. More respondents requested services for two disasters (40.1 percent) than respondents who requested services for a single disaster only (7.3 percent) or never requested services (0.6 percent).

Compounding Barriers to Accessing Services During Floods, COVID-19, and Winter Storms

When seeking these services, 26.8 percent of respondents reported facing barriers to receiving services for flooding recovery. In contrast, only 18.8 percent and 17.1 percent faced barriers to COVID-19 and winter storms services, respectively.[16] Figure 2-14 provides examples of barriers residents faced, specifically when seeking services for flooding recovery.

FIGURE 2-14 Examples of barriers experienced by respondents seeking or applying for services for flooding recovery.

Types of barriers people faced after flooding events generally relate to (1) long wait times to receive services, (2) difficulty in applying for services (e.g., extensive paperwork, some residents' required documents destroyed by the flood, agencies did not follow up on submitted requests, etc.), (3) language barriers to apply for services, (4) ineligibility to receive services, (5) lack of knowledge or information about where to request services, and (6) recovery service providers running out of funds.

Contingency tables showed significant relationships between different types of services sought by respondents by type of disaster (flooding, the COVID-19 pandemic, or winter storms). Specifically, survey questions asked respondents whether they sought financial aid, food assistance, mental health services, help from neighbors, or utility/energy assistance services.

[16] No table is provided for this section, as the results could clearly be explained in the text.

Overall, more respondents encountered barriers to services for flooding disasters than during COVID-19 and winter storms. More respondents than expected experienced barriers to COVID-19 pandemic and flooding, and from winter storms and flooding (deviations = 33.99 and 26.56, respectively, and Chi^2 = 42.77 and 28.86, respectively), compared with respondents who did not experience barriers in these sets of events (Table 2-25).

TABLE 2-25 Contingency Table Comparing Respondents Who Experienced Barriers to Assistance or Receiving Services for Different Disasters

COVID-19 and Flooding			
Count *Deviation* *Cell Chi^2*	Due to flooding, **did not** experience barriers to assistance or receiving services.	Due to flooding, **did** experience barriers to assistance or receiving services.	Total
Due to COVID-19, **did** not experience barriers to assistance or receiving services	342 33.99 3.75	80 −33.99 10.13	422 80.8% **15.3%**
Due to COVID-19, **did** experience barriers to assistance or receiving services	39 −33.99 15.83	61 33.99 42.77	100 19.2% **11.7%**
Total	381 73.0%	141 27.0%	522
Table Tests	**Chi^2**	**Chi^2 Probability**	**Odds Ratio**
Likelihood Ratio	65.442	<0.0001*	6.69
Pearson	72.480	<0.0001*	
Winter Storms and Flooding			
Due to winter storms , **did not** experience barriers to assistance or receiving services	344 26.56 2.22	90 −26.56 6.05	434 82.7% **17.1%**
Due to winter storms, **did** experience barriers to assistance or receiving services	40 −26.56 10.60	51 26.56 28.86	91 17.3% **9.7%**
Total	384 73.1%	141 26.9%	525
Table Tests	**Chi^2**	**Chi^2 Probability**	**Odds Ratio**
Likelihood Ratio	43.029	<0.0001*	4.87
Pearson	47.737	<0.0001*	

* $\alpha \leq 0.05$

NOTES**:** Blue cells = column and row total percentages; light-yellow cells = percentage of respondents who did experience barriers to accessing services during flooding but did not during winter storms or COVID-19; light-brown cells = percentage of respondents that did experience barriers to accessing services during flooding and winter storms or COVID-19. The Fisher's exact right-tailed tests probability (Experienced Barriers for Floods) (p = <0.0001*) is greater for those who also experienced barriers to services during COVID-19. The Fisher's exact right-tailed tests probability (experienced barriers for floods) (p = <0.0001*) is also greater for those who also experienced barriers to services during winter storms.

The results suggest that more respondents experience barriers due to flooding than due to winter storms or COVID-19 (Table 2-25). For example, 15.3 percent of individuals experienced barriers due to flooding but not COVID-19, while 11.7 percent of respondents experienced barriers to flooding and COVID-19. The Fisher's exact tests also suggest that those who experienced barriers to assistance or receiving services during floods were also more likely to experience barriers to services during both COVID-19 and winter storms. In addition, more respondents experienced barriers to flooding, but not winter storms (17.1 percent) compared with those who experienced barriers to services in both events (9.7 percent). No significant relationships resulted when comparing respondents who sought physical health services to different disasters.

Financial Assistance

More respondents sought financial assistance for flooding disasters (34.2 percent) than compared with COVID-19 (16.4 percent) or winter storms (9.4 percent) (Table 2-26).

TABLE 2-26 Contingency Table Comparing Respondents Who Sought Financial Assistance Due to Different Disasters

COVID-19 and Flooding			
Count *Deviation* *Cell Chi²*	Due to flooding, **did not** seek financial assistance	Due to flooding, **did** seek financial assistance	Total
Due to COVID-19, **did not** seek financial assistance	307	140	447
	12.63	−12.63	83.9%
	0.54	1.05	**26.3%**
Due to COVID-19, **did** seek financial assistance	44	42	86
	−12.63	12.63	16.1%
	2.82	5.44	**7.9%**
Total	351	182	533
	65.9%	34.2%	
Table Tests	**Chi²**	**Chi² Probability**	**Odds Ratio**

Likelihood Ratio	9.456	0.0021*	2.09
Pearson	9.842	0.0017*	
Winter Storms and Flooding			
Due to winter storms, **did not** seek financial assistance	331	152	483
	12.93	−12.93	90.6%
	0.53	1.01	**28.5%**
Due to winter storms **did** seek financial assistance	20	30	50
	−12.93	12.93	9.4%
	5.08	9.79	**5.6%**
Total	351	182	533
	65.9%	34.2%	
Table Tests	**Chi^2**	**Chi^2 Probability**	**Odds Ratio**
Likelihood Ratio	15.438	<0.0001*	3.27
Pearson	16.401	<0.0001*	

* $\alpha \leq 0.05$

NOTES**:** Blue cells = column and row total percentages; light-yellow cells = percentage of respondents that did seek financial assistance during flooding but did not during winter storms or COVID-19; light-brown cells = percentage of respondents that did seek financial assistance during flooding *and* winter storms or COVID-19. The Fisher's exact right-tailed tests probability (sought financial services for floods) (p = <0.0001*) is greater for those who also experienced barriers to services during COVID-19. The Fisher's exact right-tailed tests probability (sought financial services for floods) (p = <0.0001*) is also greater for those who also experienced barriers to services during winter storms.

More respondents sought financial services for COVID-19 and flooding (7.9 percent) than for winter storms and flooding (5.6 percent). However, the cell Chi^2 values also indicate that significantly more respondents than expected sought financial assistance for winter storms or the COVID-19 pandemic *and* flooding (deviations = 12.63 and 12.93, respectively, and Chi^2 = 5.44 and 9.79, respectively), compared with those respondents who did not seek assistance for any disaster or *only* for flooding. This is further validated by the Fisher's exact right-tailed tests, which suggest that respondents who sought financial assistance during floods were also more likely to seek financial assistance during both COVID-19 and winter storms.

Food Assistance

Compared with winter storms (19.3 percent) and COVID-19 (32.3 percent), more respondents sought food assistance in response to a flooding disaster (37.3 percent) (Table 2-27).

TABLE 2-27 Contingency Table Comparing Respondents Who Sought Food Assistance to Different Disasters

COVID-19 and Flooding			
Count			

Deviation *Cell Chi²*	Due to flooding, **did not** seek food assistance	Due to flooding, **did** seek food assistance	Total
Due to COVID-19, **did not** seek food assistance	271	90	361
	44.78	−44.78	67.7%
	8.87	14.88	**16.9%**
Due to COVID-19, **did** seek food assistance	63	109	172
	−44.78	44.78	32.3%
	18.61	31.23	**20.5%**
Total	334	199	533
	62.7%	37.3%	
Table Tests	**Chi²**	**Chi² Probability**	**Odds Ratio**
Likelihood Ratio	72.881	<0.0001*	5.20
Pearson	73.580	<0.0001*	
Winter Storms and Flooding			
Due to winter storms, **did not** have difficulty accessing food	304	126	430
	34.54	−34.54	80.7%
	4.43	7.43	**23.6%**
Due to winter storms, **did** have difficulty accessing food	30	73	103
	−34.54	34.54	19.3%
	18.49	31.03	**13.7%**
Total	334	199	533
	62.7%	37.3%	
Table Tests	**Chi²**	**Chi² Probability**	**Odds Ratio**
Likelihood Ratio	59.892	<0.0001*	5.87
Pearson	61.380	<0.0001*	

* $\alpha \leq 0.05$

NOTES: Blue cells = column and row total percentages; light-yellow cells = percentage of respondents that *d id* seek food assistance during flooding but did not during winter storms or COVID-19; light-brown cells = percentage of respondents that did seek food assistance during flooding and winter storms or COVID-19. The Fisher's exact right-tailed tests probability (sought food assistance for floods) (p = <0.0001*) is greater for those who also experienced barriers to services during COVID-19. The Fisher's exact right-tailed tests probability(sought food assistance for floods) (p = <0.0001*) is also greater for those who also experienced barriers to services during winter storms.

Significantly more respondents than expected reported seeking food assistance because of COVID-19 or winter storms and flooding (deviations = 44.78 and 34.54, respectively, and Chi^2 = 31.23 and 31.03, respectively). For COVID-19 and flooding, 20.5 percent of respondents sought food assistance, compared with the 13.7 percent of respondents who sought food assistance because of flooding and winter storms. Respondents who sought services for flooding but not COVID-19 or winter storms also show negative cell deviations (−44.78 and −34.54, respectively), suggesting that fewer respondents than expected sought only food assistance during flood events alone. The Fisher's exact right-tailed tests also suggest that respondents who sought food assistance during floods were more likely to seek food assistance during both COVID-19 and winter storms.

Mental Health Services

More respondents sought mental health services for COVID-19 (6.9 percent) than during flooding disasters (~4 percent) and winter storms (~4 percent) (Table 2-28).

TABLE 2-28 Contingency Table Comparing Respondents Who Sought Mental Health Services During Different Disasters

COVID-19 and Flooding			
Count *Deviation* *Cell Chi^2*	Due to flooding, **did not** seek mental health services	Due to flooding, **did** seek mental health services	Total
Due to COVID-19, **did not** seek mental health services	488 10.58 0.23	9 −10.58 5.72	497 93.3% **1.7%**
Due to COVID-19, **did** seek mental health services	24 −10.58 3.24	12 10.58 78.94	36 6.89% **2.3%**
Total	512 96.1%	21 3.9%	533
Table Tests	**Chi^2**	**Chi^2 Probability**	**Odds Ratio**
Likelihood Ratio	41.120	<0.0001*	27.11
Pearson	88.133	<0.0001*	
Winter Storms and Flooding			
Due to winter storms, **did not** seek mental health services	497 5.17 0.05	15 −5.17 1.33	512 96.06% **2.8%**
Due to winter storms, **did** seek mental health services	15 −5.17 1.33	6 5.17 32.34	21 4.0% **1.1%**
Total	512 96.1%	21 3.9%	533
Table Tests	**Chi^2**	**Chi^2 Probability**	**Odds Ratio**
Likelihood Ratio	16.398	<0.0001*	13.25
Pearson	35.045	<0.0001*	

* $\alpha \leq 0.05$

NOTES: Blue cells = column and row total percentages; light-yellow cells = percentage of respondents that did experience barriers to accessing services during flooding but did not during winter storms or COVID-19; light-brown cells = percentage of respondents that did seek mental health services during flooding and winter storms or COVID-19. The Fisher's exact right-tailed tests probability (sought mental health services for floods) (p = <0.0001*) is greater for those who also experienced barriers to services during COVID-19. The Fisher's exact right-tailed tests probability (sought mental health services for floods) (p = <0.0001*) is also greater for those who also experienced barriers to services during winter storms.

The number of respondents who sought mental health services for COVID-19 and flooding (2.3 percent) was greater than those who sought services for winter storms and flooding (1.1 percent). More respondents than expected sought mental health services during flooding and COVID-19 or winter storms (deviations = 10.58 and 5.17, respectively, and Chi^2 = 78.94 and 32.34, respectively). The Fisher's exact right-tailed tests also suggest that respondents who sought mental health assistance during floods were more likely to seek mental health assistance during both COVID-19 and winter storms. However, most respondents (>93 percent) did not seek mental health services for any disaster event.

Help from Neighbors

More respondents sought help from a neighbor for winter storms (13.3 percent) than during COVID-19 (12.2 percent) and flooding disasters (12.4 percent) (Table 2-29).

TABLE 2-29 Contingency Table Comparing Respondents Who Sought Help from a Neighbor for Different Disasters

COVID-19 and Flooding			
Count *Deviation* *Cell Chi^2*	Due to flooding, **did not** seek help from a neighbor	Due to flooding, **did** seek help from a neighbor	Total
Due to COVID-19, **did not** seek help from a neighbor	428 17.95 0.79	40 −17.95 5.56	468 87.8% **7.5%**
Due to COVID-19, **did** seek help from a neighbor	39 −17.95 5.66	26 17.95 40.04	65 12.2% **4.9%**
Total	467 87.6%	66 12.4%	533
Table Tests	**Chi^2**	**Chi^2 Probability**	**Odds Ratio**
Likelihood Ratio	38.460	<0.0001*	7.13
Pearson	52.041	<0.0001*	
Winter Storms and Flooding			
Due to winter storms, **did not** seek help from a neighbor	418 13.21 0.43	44 −13.21 3.05	462 86.7% **8.3%**

Due to winter storms, **did** seek help from a neighbor	49	22	71
	−13.21	13.21	13.3%
	2.80	19.84	**4.1%**
Total	467	66	533
	87.6%	12.4%	
Table Tests	**Chi²**	**Chi² Probability**	**Odds Ratio**
Likelihood Ratio	20.711	<0.0001*	4.27
Pearson	26.128	<0.0001*	

* $\alpha \leq 0.05$

NOTES: Blue cells = column and row total percentages; light-yellow cells = percentage of respondents that did seek help from a neighbor during flooding but did not during winter storms or COVID-19; light-brown cells = percentage of respondents that did seek help from a neighbor during flooding and winter storms or COVID-19. The Fisher's exact right-tailed tests probability (sought help from neighbors during floods = 1) (p = <0.0001*) is greater for those who also experienced barriers to services during COVID-19. The Fisher's exact right-tailed tests probability (sought help from neighbors during floods = 1) (p = <0.0001*) is also greater for those who also experienced barriers to services during winter storms.

In contrast, 12.4 percent of respondents sought help from a neighbor because of flooding but not because of COVID-19 or winter storms (Table 2-29). For both events, the deviations and Chi² values suggest that more respondents than expected who sought help for COVID-19 or winter storms also sought help for flood events (deviations = 17.95 and 13.21, respectively, and Chi² = 40.04 and 19.84, respectively), compared with those who did not seek help from a neighbor for any disaster event. The Fisher's exact right-tailed tests also suggest that respondents who sought help from a neighbor during floods were more likely to seek help from a neighbor during both COVID-19 and winter storms.

Utility or Energy Assistance

Overall, more respondents sought utility or energy assistance for flooding disasters (14.3 percent) than they did during COVID-19 (11.3 percent) and winter storms (10.7 percent) (Table 2-30).

TABLE 2-30 Contingency Table Comparing Respondents Who Sought Utility or Energy Assistance During Different Disasters

COVID-19 and Flooding			
Count *Deviation* *Cell Chi^2*	Due to flooding, **did not** seek utility or energy assistance	Due to flooding, **did** seek utility or energy assistance	Total
Due to COVID-19,	428	45	473

did not seek utility or energy assistance	22.44	−22.44	88.7%
	1.24	7.47	**8.4%**
Due to COVID-19, **did** seek utility or energy assistance	29	31	60
	−22.44	22.44	11.3%
	9.79	58.88	**5.8%**
Total	457	76	533
	85.7%	14.3%	
Table Tests	**Chi^2**	**Chi^2 Probability**	**Odds Ratio**
Likelihood Ratio	56.266	<0.0001*	10.17
Pearson	77.387	<0.0001*	
Winter Storms and Flooding			
Due to winter storms, **did not** seek utility or energy assistance	425	51	476
	16.87	−16.87	89.3%
	0.70	4.19	**9.6%**
Due to winter storms, **did** seek utility or energy assistance	32	25	57
	−16.87	16.87	10.7%
	5.82	35.03	**4.7%**
Total	457	76	533
	85.7%	14.3%	
Table Tests	**Chi^2**	**Chi^2 Probability**	**Odds Ratio**
Likelihood Ratio	34.359	<0.0001*	6.51
Pearson	45.743	<0.0001*	

* $\alpha \leq 0.05$

NOTES**:** Blue cells = column and row total percentages; light-yellow cells = percentage of respondents that did seek utility or energy assistance during flooding but did not during winter storms or COVID-19; light-brown cells = percentage of respondents that did seek utility or energy assistance during flooding and winter storms or COVID-19. The Fisher's exact right-tailed tests probability (sought utility services for floods = 1) (p = <0.0001*) is greater for those who also experienced barriers to services during COVID-19. The Fisher's exact right-tailed tests probability (sought utility services for floods = 1) (p = <0.0001*) is also greater for those who also experienced barriers to services during winter storms.

However, the percentage of respondents who sought utility or energy assistance for COVID-19 and flooding (5.8 percent) was slightly greater than those who sought utility or energy assistance for both winter storms and flooding (4.7 percent). In addition, more respondents than expected also sought utility services because of COVID-19 or winter storms and flooding (deviations = 22.44 and 16.87, respectively, and Chi^2 = 58.88 and 35.03, respectively) than those who sought utility services for only one event or the other. Finally, the Fisher's exact right-tailed tests show that respondents who sought utility or energy assistance during floods were also more likely to seek utility or energy assistance during both COVID-19 and winter storms.

3
Summary of Project Results

The results from this project reveal several results related to flood experiences, how real and perceived risk differ, how risk perceptions may influence flood-protective actions, preferred flood risk communication sources, and ways in which COVID-19 and winter storms affected (or compounded) the impacts of other flooding events on preparedness and recovery in Northeast Houston, Texas.

FLOODING EXPERIENCES

The results show that flooding events highly impacted the study area. Of all respondents, 89.1 percent have experienced flood impacts or know someone who has, and 65 percent have directly experienced flood impacts themselves. Furthermore, flooding is an impactful and disruptive event for most residents in this area, even though only 22.6 percent of residents are geolocated within a 100- or 500-year Federal Emergency Management Agency (FEMA)–designated flood zone.

The results also identified an imbalance in entities people feel are responsible for helping residents prepare for floods and whether they feel those entities' efforts to help residents are satisfactory. For example, most residents feel that government agencies (at any jurisdictional level) are responsible for helping residents prepare for floods, but more than half of residents do not feel their efforts to help are satisfactory. In contrast, residents place less responsibility for helping residents prepare for flooding on nonprofits, school districts, and places of employment, but also report greater satisfaction in the efforts of these entities to help prepare residents for floods.

FREQUENCY VERSUS SEVERITY OF FLOODING

Several patterns emerge when comparing residents' experiences with the frequency and severity of flooding compared with the 2019 Harris County FEMA Flood Insurance Rate Maps (FIRMs). First, 45.5 percent of residents living in areas of minimal flood risk (based on FEMA floodplain definitions) experienced flooding two or more times and/or reported that their property was severely damaged while living in their current home.

Furthermore, of the residents who live in an area of minimal risk, 19 percent have experienced flooding three or more times, and 17.4 percent have experienced severe damage from flooding three or more times. When comparing these results with the number of people who have experienced flooding or severe damage three or more times since living in their homes, the results suggest that FEMA floodplains do not accurately represent the flooding experience of respondents.

Several respondents affected by frequent and severe flooding outside the 100- and 500-year floodplains are also visibly clustered (e.g., North Shadydale). Respondents living near off-road ditches and higher stormwater infrastructure density also report more frequent and severe flooding. Furthermore, few greenspaces or detention ponds are located in the study area to help absorb floodwaters.

FLOOD RISK PERCEPTIONS: PERCEIVED VERSUS REAL RISK

When considering residents' knowledge of whether they live in a FEMA-designated flood zone according to their geocoded address, several key results emerge. First, 77.4 percent of residents do not know whether or not they live in a floodplain. Furthermore, of the respondents residing within a FEMA-designated 100- or 500-year floodplain, only 32.1 percent know they live in a FEMA-designated flood zone. The results also found that less than half of respondents have or have purchased flood insurance in the past, and 57.8 percent of respondents plan to buy flood insurance in the future. This trend may be in response to their perceptions that the frequency and severity of flooding are increasing.

When calculating the Flood Risk Scores (FRS) and comparing how they differ when accounting for real versus perceived risk, a key finding is that, in addition to exposure (perceived or real), perceived flood risk is influenced by sociodemographic characteristics and the frequency and severity of flood hazards. The method of interpolation used to create flood risk surfaces is also important to consider, as using different methods produced different distributions of flood risk. Of the two approaches used, empirical Bayesian kriging (EBK) better accounts for calculated, real risk delineated by FEMA floodplains. More important, EBK interpolation better represents areas where respondents who are geolocated outside FEMA floodplains report high frequency and severity of flood experiences than the inverse distance weighting maps.

FLOOD PERCEPTIONS AND PROTECTIVE ACTIONS

The classical and spatial regression modeling results found that residents who take more nonstructural protective actions, older residents, residents with higher education levels, residents who identify as people of color and/or Hispanic or Latino, and lower household incomes are significantly associated with higher perceived risk, as opposed to real risk. The results also demonstrate that residents with higher perceived risk are significantly more likely to engage in nonstructural (e.g., ask the Red Cross about flood risk, purchase flood insurance, ask the landlord about the property's flood risk) than *structural* (e.g., elevate your home, dry- or wet-proof your home, install earthen berms) protective actions.

FLOOD RISK COMMUNICATION PREFERENCES

The statistical analyses examining the different forms of preferred and utilized risk communication sources also produced several insights. First, local news is a widely preferred mode of receiving information. Residents across demographic groups prefer to seek flood preparedness information from television and newspapers. On the other hand, most residents do not rely on information about risks from friends and family. In addition to local news programs, residents are more likely to seek or receive flood preparedness information from the internet, government agencies, or community organization sources than from friends or family.

There is also a connection between which entities respondents feel are responsible for preparing households for flood risks, their satisfaction with those efforts, and from which sources respondents are more likely to seek or receive flood preparedness information. For example, while most residents feel that the local government is responsible for helping residents prepare for floods, 51.1% do not feel that their local government's efforts to help are satisfactory. Furthermore, the contingency tables for ethnicity and flood preparedness information sources show that Hispanic and Latino populations were less likely to seek information from the mayor's office but more likely to seek information from schools or their employer. This could indicate a relationship between individuals' satisfaction with different organizations' efforts to prepare households for floods and preferences for flood risk information sources—a relationship that is not explicitly explored in this project but may be helpful to examine further in the future.

POST-DISASTER RECOVERY: FLOODING, COVID-19, WINTER STORMS

Finally, the results provide several insights into how COVID-19 and Texas Winter Storms may have influenced flooding recovery and protective actions. Related to the influence of COVID-19 on flood-protective actions, 27.8 percent and 26.0 percent of respondents did not evacuate during Tropical Storm Beta (2020) or Hurricane Laura (2020), respectively, because of concerns related to the COVID-19 pandemic.

The analyses examining how different services were accessed or used during flooding events, COVID-19, and winter storms also provide insight into (1) what barriers to accessing those services were present and (2) what services were most commonly used for different disasters. For flood recovery services, specific barriers that respondents experienced when seeking or applying for flood recovery services included inconsistent application processes, unreasonable eligibility standards, lack of communication, and (if approved) minimal service received. The types of services sought by respondents also varied by disaster type. For example, the results show that respondents were most likely to experience barriers to services because of a flood compared with other events. In addition, respondents were more likely to seek financial, food, or utility assistance for flooding impacts than COVID-19 and winter storms when seeking recovery services. Respondents who sought assistance for flooding also were more likely to seek assistance for both COVID-19 and winter storms. Finally, fewer respondents (less than 10 percent) sought mental health services after any disaster type.

STUDY LIMITATIONS

As with any project, some limitations should be noted when reviewing these study results. One limitation of the survey is that the number of times a respondent experienced flooding and/or a severe flooding event by the length of time they had lived in their home could not be normalized. However, according to FEMA, “any place with a 1% chance or higher chance of experiencing a flood each year is considered to have a high risk. Those areas have at least a one-in-four chance of flooding during a 30-year mortgage” (FEMA, 2021). Therefore, while the flooding recurrence interval for a specific respondent based on the frequency of flooding by the number of years in residency could not be calculated, the results still provide useful estimations of how many residents experience flooding on a more regular basis outside of FEMA-delineated high-flood-risk areas.

Finally, it should be noted that, at the time of the analysis, the existing FEMA FIRMs for Harris County were effective November 15, 2019 (FEMA, 2019). However, the Harris County Flood Control District and FEMA are currently in the process of releasing an overhaul of FEMA floodplain maps in 2023 for Harris County (HCFCD, 2023; Rice, 2023). These will be the first FEMA maps created based on the risk of river flooding and urban flooding. In addition, hydrologic modeling will also use updated rainfall estimates that better reflect more recent storms (HCFCD, 2023), which has not been done since the 1960s (Rice, 2023). As a result, while some areas will see floodplain delineations shrink, floodplain coverage is expected to increase across most of the county (Rice, 2023).

Furthermore, as stated in Chapter 2, more accurate representations of flood risk (e.g., the Fathom Global/First Street Foundation flood model (Bates et al., 2021) exist, even if they are not currently used as regulatory products. As such, future research should consider comparing the household survey responses with the 2023 updated floodplain information from Harris County and/or other, more accurate flood datasets to determine how much the data used to describe real flood risk affects (and potentially over or underestimates) the results presented here.

NEXT STEPS

These survey results will be provided to community partners as a resource for local decision-making regarding flood risk. In addition, this paper will be shared with community partners and used as background material for participants at the workshop Bridging Diverse Knowledge Systems to Address Flood Risk in Northeast Houston Communities, to be held in Houston, Texas, April 26–27, 2023.

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Appendix A
Disaster Background and Context of Houston, Texas

During Hurricane Harvey (2017), residents from Northeast Houston, Texas, organized to perform rescues, distribute food and water, and meet post-disaster recovery needs. Formalizing their work, residents established the community-based organization West Street Recovery (WSR) to fill continuing gaps in post-disaster recovery (e.g., rebuilding homes) for households who were denied or otherwise unable to access government and nonprofit assistance programs. Since Hurricane Harvey, WSR has led community-engaged research on the flood-related experiences of fellow residents using qualitative methods and/or nonprobabilistic sampling (Texas Comptroller of Public Accounts, 2021).

In partnership with WSR, the Gulf Research Program and Resilient America Program designed a household survey to investigate the flood-related experiences of residents from Northeast Houston using quantitative methods and probabilistic sampling. During the development of this survey, Houston experienced two major disruptive events—the COVID-19 pandemic (2020 to present) and Texas Winter Storms (2021)—that may have affected Northeast Houston residents' abilities to prepare for and/or recover from flooding during the study period. In order to capture information about the impact of the pandemic and winter storm, the project partners added questions to the household survey about residents' experiences with these disasters.

FLOODING AND FLOOD-RELATED EVENTS IN HOUSTON, TEXAS

Flooding has been consistently identified as one of the top-ranked hazard risks for Houston, Texas (Adepoju et al., 2021). According to the City of Houston Hazard Mitigation Action Plan (2018–2023), flooding is highly likely to occur in the near future. Its potential severity is assessed as substantial, characterized by multiple deaths, the complete shutdown of facilities for 30 days or more, and more than 50 percent of properties destroyed or with major damage (Dargin et al., 2021).

In the last 20 years alone, the City of Houston has been impacted by several major flood events arising from Hurricane Ike (2008), the Memorial Day (2015) and Tax Day (2016) floods, Hurricane Harvey (2017), Tropical Storm Imelda (2019), Tropical Storm Beta (2020), and Winter Storm Uri (2021) (Knox et al., 2022; Shultz et al., 2022). Additionally, multiple unnamed storms have caused significant flood damage in areas prone to flooding. Some areas of Houston, such as Northeast Houston, have been historically marginalized from receiving resources and benefiting from flood mitigation efforts, even though they are among the most vulnerable to flooding (Adepoju et al., 2021; Clark-Ginsberg et al., 2021; Dargin et al., 2021; ERCOT, 2021).

DISRUPTIVE EVENTS

Chronic Stressor: COVID-19 Pandemic

On February 26, 2020, the Centers for Disease Control and Prevention confirmed that an individual infected with the novel coronavirus could be the first case of community-based transmission in the United States. Soon after, officials in Santa Clara County, California, identified two individuals who lost their lives to COVID-19 on February 6 and 17, pushing the first-known death from the virus in the United States (February 29) to earlier than previously thought.
On March 4, 2020, the Texas Department of State Health Services (TDSHS) reported the state's first case of COVID-19. The following week, Dr. John W. Hellerstedt, commissioner of TDSHS, declared a state of public health disaster for Texas because of the COVID-19 pandemic. One year later, on March 2, 2021, Texas Governor Greg Abbott issued an executive order that lifted all COVID-19 mitigation measures and "opened the state to 100 percent." Since then, more than 2.5 million confirmed COVID-19 cases and more than 50,000 COVID-19 fatalities in Texas have been recorded (DSHS, 2023). Several subsequent studies have shown disparities in confirmed cases and fatalities that disproportionately burden communities of color in Texas (ERCOT, 2021; Grineski et al., 2022; Treisman, 2021b).

Acute Shock: Texas Severe Winter Storms 2021

In February 2021, a series of winter storms swept through Texas, significantly impacting millions of residents statewide. On February 10, 2021, the National Weather Service (NWS) began tracking an arctic cold front from northwest United States as it entered the panhandle of Texas. On February 12, 2021, Governor Greg Abbott declared a state of emergency for all 254 counties in Texas, certifying that "the severe winter weather poses an imminent threat of widespread and severe property damage, injury, and loss of life due to prolonged freezing temperatures, heavy snow, and freezing rain statewide" (Cardinal et al., 2022). The following day, the NWS issued a winter storm warning for southeast Texas, including Harris and Galveston counties.

As forecasted, the cold front passed through the region on February 14, 2021, resulting in thundersnow, ice, and historically low temperatures. Two days later, another winter storm hit southeast Texas, adding more snow, freezing rain, and ice to the previous hazardous conditions. After almost 9 days, on Saturday, February 20, 2021, the last weather advisory for this event expired. Almost 250 people died during the winter storm (Grineski et al., 2022), 69 percent of Texans lost electricity (for an average of 42 hours), 49 percent lost access to running water (for an average of 2 days), and one-third experienced water damage in their homes (Li et al., 2022).

COMPOUNDING EVENTS AND CASCADING IMPACTS

COVID-19 Pandemic

The impacts of the COVID-19 pandemic have been significant, both directly in terms of human health and mortality and because of cascading effects on community functions (e.g., economy, transportation, governance, education, service-oriented businesses) and well-being (unemployment, social distancing, access to health care, ability to participate in social and cultural activities) (Treisman and Neuman, 2021). For example, social distancing and quarantine measures—critical tools in efforts to reduce and slow the spread of the virus—are restructuring how people and businesses carry out their work. In addition, the timeframe for the closure of schools and service-oriented businesses was uncertain, further exacerbating the impacts of COVID-19 on communities. The impacts and uncertainty of the COVID-19 pandemic have tested the resilience of communities in unprecedented ways.

The COVID-19 pandemic does not change communities' existing risks from natural hazards and other disasters. Instead, the pandemic has exacerbated the impacts of a disaster by increasing community vulnerability, and complicating and limiting the available actions for preparedness, response, recovery, and mitigation (King and Schneider, 2021; Li et al., 2022; Romo, 2021). For example, studies have shown that people have forgone evacuation and sheltering from a natural hazard event out of fear that they might contract COVID-19 or facilitate the virus' spread (Schneider, 2021). In addition, the economic challenges communities have experienced because of this pandemic (e.g., loss of revenue, lack of income due to layoffs and unemployment, understaffing) have limited the resources available for disaster recovery. The pandemic has also exacerbated financial impacts on individuals and families, businesses, and governments affected by new disasters that have occurred during this pandemic (Diaz, 2021; Li et al., 2022).

Texas Severe Winter Storms 2021

The Texas Severe Winter Storms 2021 led to several cascading effects. Extreme weather conditions and peak demand for electricity prompted the Electric Reliability Council of Texas (ERCOT) to initiate rolling outages shortly after midnight on February 15, 2021 (Treisman, 2021a). This action taken by ERCOT was in effect for more than 26 million Texas customers, who represent 90 percent of the state's electric load (Worsham et al., 2022). Power outages affected many nursing homes, clinics, hospitals, and county health departments, jeopardizing the care of hundreds of patients and the integrity of thousands of COVID-19 vaccines (Heidari et al., 2020). In addition, COVID-19 testing and vaccination sites had to close, which delayed local strategies for controlling and preventing the pandemic. Finally, as with other successive climate disasters, Winter Storm Uri disproportionately impacted communities of color in Texas (Treisman, 2021a; Wilson and Luo, 2022; Wise, 2021).

According to the Texas Commission on Environmental Quality, subzero temperatures caused water lines to burst and, subsequently, water pressure to drop in more than 1,000 water systems, affecting more than 14 million Texans (WSR, 2021). In addition, failures in the power grid impaired several water treatment plants, triggering boil-water notices for more than 7 million residents, in 110 counties across the state (Hirsch et al., 2021). As power was restored, residents reported household infrastructure failings (e.g., faulty pipes and toilets) that led to flooding in their homes (Hirsch et al., 2021; Wilson and Luo, 2022). Additionally, power and water outages caused disruptions in the supply chain, leading to food and bottled water shortages (Adger, 2022; Watkins, 2022). In some areas of Texas, the price of scarce goods, such as bottled water, rose to 2–3 times the normal amount (Watkins, 2022).

TDSHS recorded a surge in carbon monoxide poisonings during the week of the winter storms (Foxhall, 2022; Shrader-Frechette, 1990). Between February 11 and 18, 2021, a total of 450 carbon monoxide–related calls were made to the Texas Poison Center Network, and at least 300 carbon monoxide–poisoning cases (two of which were fatalities) were reported in Harris County alone. TDSHS attributed these outcomes to residents' attempts to stay warm using improper indoor heating sources (Foxhall, 2022), a consequence that Harris County Judge Lina Hidalgo referred to as "a disaster within a disaster" (Churchill et al., 2021).

On February 20, 2021, President Biden approved a major disaster declaration to make federal aid available for Texas's immediate and long-term recovery efforts (Rother, 2019). Federal funding was provided to residents in 77 counties for home repairs, temporary housing, and low-cost home loans to cover uninsured property losses; federal funding was also made available to local governments in all 254 counties for infrastructure repairs. In addition, President Biden asked the Department of Health and Human Services, Housing and Urban Development, the Department of Agriculture, and the Department of Defense to identify resources that could further facilitate recovery in Texas (Wise, 2021).

Appendix B
Methodology

SURVEY DESIGN

Sample Size

According to the U.S. Census Bureau American Community Survey 2015–2019, a total of 36,796 households are located in the study area (Table B-1).

TABLE B-1 Number of Households in the Study Area by Zip Code

Zip Code	Number of Households	Percent of Total Number of Households
77016	9,679	26.3%
77020	8,670	23.6%
77026	7,960	21.6%
77028	5,847	15.9%
77078	4,640	12.6%
TOTAL	**36,796**	**100.0%**

SOURCES: U.S. Census Bureau American Community Survey 2015–2019. Sampling frame data assembled by Research 4 Progress (https://research4progress.com/).

Based on a total population of 36,796 households, a sample size of 591 households was sought to obtain a sample with a 95 percent confidence level, tolerating a 4 percent margin of error.

Sampling Frame and Strategy

The sampling frame required a minimum of 3,940 addresses (rounded to 4,000) to obtain the desired sample size of 591 households and a projected recruitment rate of 15 percent. To maintain geographic representation, a simple random sample of 5,000 addresses was selected, proportional to the population of each zip code. The list of addresses was obtained from Database USA.[18]

All addresses were stratified by zip code, and a sampling fraction (i.e., the percent of the total number of addresses) was calculated for each. Then, the sampling fraction was compared with the percent of the total number of households for each zip code (Table B-2).

TABLE B-2 Number of Addresses Stratified by Zip Code

Zip Code	Number of Addresses	Percent of Total Number of Addresses
77016	14,241	28.4%
77020	10,760	21.4%
77026	10,446	20.8%
77028	8,507	17.0%
77078	6,234	12.4%
TOTAL	**50,188**	**100.0%**

SOURCE: Sampling frame data assembled by Research 4 Progress (https://research4progress.com/).

All addresses were randomly sorted into two separate lists. The primary list included 4,000 addresses to be used for the initial round of canvassing, which would verify the eligibility of each address. The secondary list included 1,000 addresses in case the primary 4,000 addresses included an excessive number of ineligible addresses. For example, ineligibility could occur if an address was commercial, vacant, abandoned, or did not exist (Table B-3).

TABLE B-3 All Addresses in Study Area Zip Codes and Subsequent Sampling Counts

Zip Code	Exact Number of Addresses	Exact Percent of Total Number of Addresses	Rounded Number of Addresses	Rounded Percent of Total Number of Addresses	Sampling Frame	Primary List	Secondary List
77016	14,241	28.4%	14,000	28.0%	1,400	1,111	289
77020	10,760	21.4%	10,750	21.5%	1,075	878	197
77026	10,446	20.8%	10,500	21.0%	1,050	819	231
77028	8,507	17.0%	8,500	17.0%	850	682	168
77078	6,234	12.4%	6,250	12.5%	625	510	115
TOTAL	**50,188**	**100.0%**	**50,000**	**100.0%**	**5,000**	**4,000**	**1,000**

SOURCE: Sampling frame data assembled by Research 4 Progress (https://research4progress.com/).

[18] https://databaseusa.com/

Questionnaire

The survey questionnaire was based on formative research conducted throughout 2019 and was developed in consultation with each study partner and Harris County Precinct One from January 2020 to December 2021.

Formative Research

From January to April 2021, the Gulf Research Program and West Street Recovery conducted a series of focus group discussions with a smaller, nonprobabilistic sample of the study population. The discussions aimed to better understand the disaster experiences (threats) and the protective actions taken (responses) by Northeast Houston residents. The results of the focus group discussions were used to identify strategies and inform a policy agenda that could improve disaster preparedness and resilience at the individual, household, and community levels. Additionally, the results suggest that future research should explore elements that motivate residents to take protective actions and the barriers that prevent them from doing so.

Development

This questionnaire uses elements from the protection motivation theory (Rogers, 1975; Rogers and Prentice–Dunn, 1997), protective action decision model (PADM) (Ge et al., 2011; Lindell and Perry, 2003, 2012), and vested interest theory (VIT) (Miller et al., 2013) to better understand the protective actions taken by and barriers to taking protection actions for the study population before, during, and after disasters. According to these theoretical frameworks, an individual will be motivated to take protective actions against a threat (e.g., flooding) if the following is true:

- they perceive it is likely (and/or imminent) that they will be exposed to a threat (susceptibility);
- they perceive the consequences of being exposed to the threat to be severe (severity);
- they believe they have a stake in relevant outcomes (self-interest of potential gains/losses);
- they believe that a protective action is effective at mitigating the threat (response efficacy);

- they believe in their own ability to implement the response (self-efficacy); and
- they perceive factors that could reduce response efficacy and/or self-efficacy to be low (response barriers).

In assessing the threat (susceptibility and severity) and response (response efficacy, self-efficacy, and response barriers), an individual draws from their knowledge and experiences, both of which are influenced by personal and environmental factors. The PADM expands on personal and environmental factors to include environmental cues, social cues, and elements of risk communication, including information sources, channel access and preference, and receiver characteristics. In addition, the model describes how these cues and elements of risk communication influence an individual's decision making on taking protective actions. VIT further expands on knowledge and experience factors to include a person's stake in the outcomes of the disaster, salience (how prominent a person's risk attitudes are toward a risk), perceived certainty, severity and immediacy of consequences, and self-efficacy (Miller et al., 2013).

Taking these elements into account, study partners drafted the original questionnaire with a focus on flooding (e.g., experiences with flood events), flood risk (e.g., knowledge of floodplain), flood risk communication (e.g., trusted sources, channel preferences), and flood-related protective actions (and barriers) throughout the stages of the disaster cycle: preparedness (e.g., household evacuation plan), response (e.g., evacuating to a shelter), recovery (e.g., seeking home repair services), and mitigation (e.g., purchasing flood insurance).

By the second quarter of 2020, study partners became concerned that the COVID-19 pandemic could influence the ability of the study population to prepare for, respond to, and/or recover from flood-related events during the upcoming hurricane season (June 1, 2020, to November 30, 2020). As such, questions regarding COVID-19 were added to the questionnaire's preparedness, response, and recovery sections. Following the Texas Winter Storms (February 2021), study partners became concerned that the impacts of the recent storms could compound those of the COVID-19 pandemic to further influence the ability of the study population to prepare for, respond to, and/or recover from flood-related events during the upcoming hurricane season (June 1, 2021, to November 30, 2021).

To better understand the compounding effects of the COVID-19 pandemic (a chronic stressor) and the Texas Winter Storms (an acute shock) on the flooding experiences of the study population, comparative questions regarding experiences and recovery from both disruptive events were added to the questionnaire.

Final Questionnaire

The survey questionnaire was finalized in the second quarter of 2021 and received approval from the National Academies Institutional Review Board in October 2021. The final survey questionnaire (Appendix D) consists of 51 multiple-choice and open-ended questions organized into eight sections:

1. The **Background** section collects information on the respondent's home (e.g., housing type, floodplain location, flood insurance, etc.), flood experiences (e.g., damage, injuries, disruption to daily activities), and beliefs about flooding (e.g., [I believe that] flooding has become more severe).
2. The **Flood Preparedness** section collects information on the respondent's beliefs on flood preparedness (e.g., household preparedness to handle a major flood event), flood risk communication preferences (e.g., preferred sources of information on flood preparedness), and short-term actions that the respondent has taken to prepare for flooding (e.g., developed a household flood emergency plan). In addition, one set of questions collects information on the extent to which the COVID-19 pandemic influenced the respondent's ability to prepare for flooding (e.g., stockpile food and water).
3. The **Flood Response** section collects information on evacuation experiences from Hurricane Laura (August 2020) and Tropical Storm Beta (September 2020); Hurricane Harvey (August 2017), which was identified during formative research as the most recent benchmark storm, was used as a reference. In addition, one set of questions collects information on reasons for not evacuating, including lack of awareness (e.g., not aware there was a voluntary evacuation), knowledge (e.g., did not know what to do), fear (e.g., unsafe shelters, fear of looting, etc.), means (e.g., no transportation, not enough money to go anywhere else), and concerns related to the COVID-19 pandemic.
4. The **Flood Recovery** section collects information on different types of assistance (e.g., financial assistance, assistance with home repairs) and/or services (e.g., employment

services, mental health services) sought by the respondent or anyone in the respondent's household, as well as any barriers they faced in seeking assistance and/or services. Formative research with the study population revealed a need to further explore the barriers that might complicate or prevent seeking assistance and/or services following a disaster. Therefore, the question on barriers was designed with an open-ended format to maximize the opportunity for descriptive responses written in the respondents' voices.

5. The **Flood Mitigation** section collects information on the respondent's long-term actions to prepare for flooding in general instead of a specific, upcoming event. The survey questionnaire has one set of questions for renters (e.g., asking their landlord about the property's flood risk) and another for homeowners (e.g., elevating their home) since the latter has more agency than the former to make changes to the physical structure of the home. Questions that collect mitigation information from both renters and homeowners include relocation and seeking flood hazard information.

6. Modified from the Flood Recovery section, the **COVID-19** section collects information on experiences related to the pandemic (e.g., missed work or school, decrease in income or reduction in work hours, lost employment, more stress than usual), different types of assistance (e.g., financial assistance, food assistance) and/or services (e.g., employment services, mental health services) sought, and barriers in seeking assistance and/or services.

7. Modified from the Flood Recovery section, the **Winter Storms** section collects information on experiences related to the Texas Winter Storms (e.g., loss of electrical power, loss of heat), different types of assistance (e.g., financial assistance, utility or energy assistance) and/or services (e.g., physical health services, mental health services) sought, and barriers in seeking assistance and/or services.

8. The **Demographics** section collects information on age, family composition, military status, gender, race and ethnicity, educational attainment, and annual household income.

DATA COLLECTION

This section describes the methods used for collecting survey and spatial data.

Survey Data

Recruitment

Multimodal recruitment was carried out over four 2-week phases. In Phase 1, an introductory letter with information on the study was mailed to each of the 4,000 addresses on the primary list. During Phase 2, potential participants were recruited through phone calls and texts, as well as emails, with information on how to schedule a survey via phone, videoconference, or in person (with COVID-19 precautions). In Phase 3, a letter with the final canvassing dates was mailed to all remaining addresses. Lastly, during Phase 4, potential participants were recruited through door-to-door knocking at varying times and days of the week, including weekends. A notification was left at each door knocked with no answer. All addresses that received three door knocks with no answer were retired.

Survey Deployment and Data Collection

For deployment, the survey was programmed into the survey tool using Qualtrics© XM by Research 4 Progress staff. Research 4 Progress staff also programmed the survey in English and Spanish and translated all associated study materials into Spanish. Research 4 Progress also performed the survey data collection[19] and data entry.

Compensation

Survey participants were compensated with a $25 debit card for their participation.

Spatial Data

Several spatial datasets were used for this project to conduct spatial analysis and visual comparisons using geographic information systems (GIS). First, real flood risk data were collected to compare with respondents' risk perceptions (see Box 2-3 in Chapter 2 for this report's definition of *real flood risk*). To represent real flood risk in this project, data were gathered from the National Flood Hazard Layer, which contains flood hazard map data developed by the Federal Emergency Management Agency (FEMA). FEMA Flood Insurance Rate Maps (FIRMs) delineate moderate- to

[19] The survey contained skip logic questions, so respondents may not have been asked certain follow-up questions depending on specific response choices for a particular question. Some questions also allowed respondents to skip questions. Therefore, some surveys were considered complete even when not all questions were answered.

high-risk flood areas through flood zones.[17] FIRMs were initially developed as regulatory products for the National Flood Insurance Program (NFIP) to make or enforce official actions and as nonregulatory products used to understand flood risk from a more user-friendly perspective (see Box B-1).

BOX B-1

History of Flood Insurance Rate Maps (FIRMs) in Flood Risk Management

As stated by Andrew Martin, FEMA Region 2 risk analysis branch chief, "[FIRMS] do one very specific thing: they are flood insurance rate maps, so they decide who has to buy flood insurance and who doesn't" (Pralle, 2019, p. 11).

FIRMs are modeled based on riverine flooding, and therefore do not necessarily identify all possible floodplains, especially in small drainage areas (<1 square mile), nor do they address urban flooding behavior or the potential impacts of climate change (FEMA, 2023). This should be considered when using FEMA FIRMs for flood risk delineation, as places that are not within the 100-year and 500-year floodplains may still flood frequently (FEMA, 2023). However, FIRMs are often used as regulatory products for disaster mitigation and adaptation planning across the United States, particularly in areas where other flood risk products are unavailable (Foxhall, 2022). FEMA has additional products through the Flood Risk Database, such as Flood Risk Products, but these are not available for all jurisdictions (Foxhall, 2022). For example, a database exists for Harris County from 2017, but not for any super neighborhoods (FEMA, 2021). In such instances, more recent FIRMs become the datasets through which flood risk management is guided at the city/county level.

FIRMs parallel FEMA's Flood Risk Database, which provides a wealth of data that may be used to analyze, communicate, and visualize flood risk. Communities are encouraged to use this database to support mitigation efforts and raise awareness (FEMA, 2023).

These maps also serve as regulatory planning products beyond the NFIP. According to

[17] FEMA Glossary, Flood Zones, https://www.fema.gov/glossary/flood-zones.

FEMA, a "FIRM . . . is the official map of a community that defines both the special flood hazard areas and the flood zones applicable to the community" (FEMA, ___, p. ___). Therefore, these maps serve two regulatory purposes: (1) use by the NFIP for floodplain management, mitigation, and insurance purposes, and (2) as the official source of delineating flood risk within a community.

Problems Associated with FEMA FIRMS

It should be noted that while FEMA FIRMS are often used as regulatory products for flood risk management, they are not without issues. Several studies have shown that FEMA FIRMs poorly predict flood risks, particularly in southeast Texas (Bates et al., 2021; Flores et al., 2022). For example, Flores and colleagues' (2022) comparison of population distributions within 100- and 500-year floodplains as delineated by FEMA FIRMs and the Fathom Global/First Street Foundation flood model (Bates et al., 2021) found that almost 1 million people in the greater Houston, Texas, area lived in 100-year flood zones delineated by the Fathom Global/First Street Foundation model but outside of FEMA 100-year flood zones.

Justification for the Use of FEMA FIRMS as Source of Real Risk

While this analysis could have considered using other, more accurate flood risk datasets to gauge real flood risk, such as the Fathom Global/First Street Foundation flood model (Bates et al., 2021), such datasets have not been created for one particular purpose; they are not currently used as regulatory flood risk products in Houston, Texas; and they are not well known to community members. The purpose of this project is not to suggest that FEMA flood zones are more "real" than someone's experience of residential flooding multiple times (see Box 2-3 in Chapter 2). Instead, this project seeks to compare how closely reported flooding experiences align with regulatory products delineating flood risk in the study area.

FEMA Flood Zones

Flood zones of interest for this study are classified as high-risk areas that make up the FEMA-designated 100- and 500-year floodplains and are designated as such in the spatial datasets provided by FEMA under the *In_100* and *In_500* attribute fields. Other GIS data were collected from the City of Houston Geographic Information System Data Portal,[18] Harris County GIS Open Data

[18] https://cohgis-mycity.opendata.arcgis.com/

Portal[19] and the Houston-Galveston Area Council's Regional Data Hub[20] for visual comparisons, including locations of Superfund and brownfield sites, oil and gas infrastructure, parks and green spaces, stormwater infrastructure, and administrative boundaries.

DATA MANAGEMENT AND DESCRIPTIVE STATISTICS

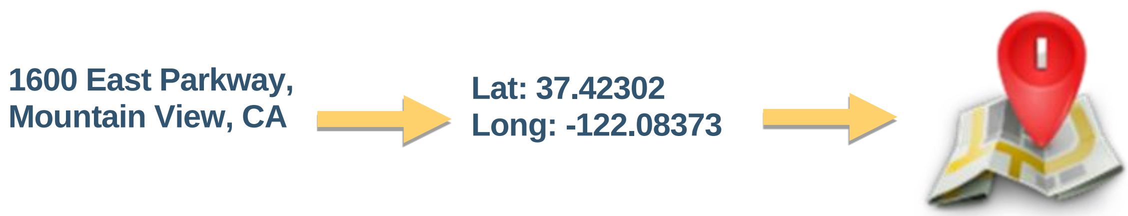
Data Management

After survey data collection was completed, the data were downloaded from Qualtrics© XM and imported into Excel. Finally, the data were cleaned to ensure that only respondents who completed the survey were used for statistical analyses and that all had viable answers to all questions. Any responses with a recorded address were also geocoded (Box B-2) so that they could be mapped and compared with other spatial data, such as FEMA floodplains.

BOX B-2

What is Geocoding?

"Geocoding is the process of converting addresses into geographic coordinates (like latitude and), which you can use to place markers on a map, or position the map" (, p. ___).



DATA ANALYSES

General Flood Experiences

Research 4 Progress conducted preliminary statistical analyses (e.g., descriptive statistics, cross-tabulations) of the survey data (available upon request).

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[19] https://geo-harriscounty.opendata.arcgis.com/
[20] https://gishub-h-gac.hub.arcgis.com/

Perceived Versus Real Risk Analyses

Several statistical methods, including descriptive statistics and regression analyses, were used to answer the question, "Does the study populations' perceived risk match 'real' risk?." First, responses to the survey question "Is your home located within the: 100-year floodplain, 500-year floodplain, outside of all floodplains, or Don't know" were compared with whether or not their geocoded address was located in a FEMA-designated flood zone. Only responses by respondents for whom there was a complete address were used to spatially compare real risk with perceived risk. The spatial statistics and analyses use only 486 of the 533 responses. Descriptive statistics were used to identify how many residents' perceived risk matched their FEMA flood zone risk.

Calculating Flood Risk

After reviewing descriptive statistics for each variable, a flood risk variable was developed to model how different socioeconomic and risk perception factors influence flood risk. *Flood risk* can be defined as a function of hazard (function of the frequency and severity of consequences), exposure (assets and people exposed to flooding), and vulnerability (capacity to deal with the flood event) (Lavell et al., 2012; Santos et al., 2020).

Calculating the Flood Risk Score Variable

A Flood Risk Score (FRS) variable was calculated using the survey responses and FEMA flood zones. The following equation was used to calculate a composite FRS for each home:

$$\textbf{FLOOD RISK} = \textbf{Hazard}_{\text{(Frequency x Severity of Consequences)}} \textbf{ x Exposure x Vulnerability}$$

Two versions of the flood risk variables were created: Real and Perceived Risk. Both surfaces were created to demonstrate how differences in perception can change flood risk across space. The full methodology for creating the FRS variable is found in Appendix C.

Creating Flood Risk Surfaces

To create flood risk surfaces based on the FRS variable for perceived and real risk, National Academies staff geocoded homes with the calculated FRS were used in a spatial statistical method called interpolation (see Box B-3). While many forms of interpolation exist, no one interpolation method is consistently better than others. The estimation performance of interpolation methods is highly variable and dependent on the input dataset, the phenomena being estimated, and their differing assumptions (e.g., local or global perspective, deterministic or stochastic) for the interpolation method to be applicable (Fischer et al., 2021; Luo et al., 2008; Yang and Xing, 2021).

BOX B-3

Interpolation

Interpolation describes creating a spatial “continuous surface” that is estimated from a set of sample points.

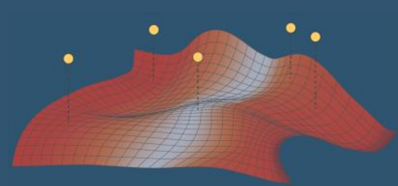

FIGURE B-1 Sample points over interpolated surface.

There are two main types of interpolation:

Deterministic—the surface is created by estimating prediction locations based strictly on the sample points’ measured values.

Example: inverse distance weighting; spline

Probabilistic—created using the statistical properties of the sample points (not measured values) to create surfaces. These methods also account for spatial autocorrelation within the sample points around the prediction location.

Example: ordinary kriging; empirical Bayesian kriging

For this project, a flood risk surface for perceived and real flood risks was interpolated using two types of interpolation in ArcGIS Pro: inverse distance weighting (IDW) and empirical Bayesian kriging (EBK). These methods were chosen because of their prolific use in previous environmental science studies (Li and Heap, 2011; Wu et al., 2019), including precipitation distribution (Yang and Xing, 2021), wind speed (Luo et al., 2008), and flood risk studies (Gao et al., 2014).

IDW is a deterministic interpolation method used widely because of its ease of calculation, easy-to-understand outputs, explicitly addressed spatial autocorrelation (Emmendorfer and Dimuro, 2020; Wu and Hung, 2016). IDW assumes that sample points nearer to the estimated unknown location are more influential than farther sample points (Yang and Xing, 2021). For example, while this project uses IDW to estimate flood risk values at unknown points between the respondents' geocoded homes, the influence of each sample point on that estimate declines with distance. Therefore, when calculating FRS, flood risk values of homes farther from the estimation area are not as influential as closer homes. Like other deterministic interpolation methods, IDW uses mathematical formulas to estimate unknown points, which often leads to a degree of smoothing in the outputs (e.g., outputs are easy to understand).

EBK, in contrast, is a probabilistic interpolation method, meaning the predictors of unknown locations use statistical theory to identify the potential uncertainty associated with the resulting interpolated values (Krivoruchko and Gribov, 2019). Kriging generally describes statistical interpolation methods that assume spatial autocorrelation exists between each sample point. Spatial autocorrelation is identified using a semivariogram,[21] which can then be used to fit an optimal interpolation model between sample points that minimizes prediction errors (Krivoruchko, 2012a). EBK is a form of kriging that corrects for spatial autocorrelation and nonstationarity[22] present in sample estimation datasets, violating classical statistical methodologies. However, EBK uses local, not global,[23] models (each with its own local semivariogram) to estimate a local mean and variance at each interpolation point, as these may vary across a study area (Krivoruchko, 2012b; Krivoruchko and Gribov, 2019). This process helps account for sampling bias, which can occur because of spatial autocorrelation present in a dataset, by estimating the local mean and variance at each estimation point.

EBK was used to create flood risk surfaces because the data points (respondents) exhibit spatial autocorrelation and nonstationarity, which IDW interpolation does not take into account. The

[21] A *semivariogram* is "a function of the distance and direction separating two locations" (Krivoruchko, 2012a, p. 6).
[22] *Spatial nonstationarity* describes how the mean, variance, and autocorrelation structure within a dataset can change across space (Brunsdon et al., 1996).
[23] Global interpolation uses *all* sample points in the estimation process, whereas local interpolation methods estimate each unknown location using a subset of the sample points to estimate the unknown value.

EBK tool in ArcGIS Pro automates more complicated aspects of building a valid kriging surface.[24]

Flood Risk Perception and Protective Actions

Regression Modeling

Multiple linear regression (see Box B-4) was used to determine whether a relationship exists between a respondent's perception that they lived in a 100-year or 500-year floodplain and the likelihood that a respondent would take protective actions against flood risks.

BOX B-4

What Is Regression Modeling?

Regression modeling is a type of statistical analysis that determines the type and strength of a relationship between independent and dependent variables. An *independent variable* (X) is expected to influence a dependent variable. A *dependent* variable (Y) describes what happens as a result of the influence from independent variables; it is what is being tested in an experiment.

Multiple regression uses multiple explanatory variables to help predict the value of Y_i, the dependent variable (Burt et al., 2009).

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \ldots \beta_k X_k + \varepsilon_i$$

Multiple regression is used in cases where one explanatory variable is insufficient to predict the value of a dependent variable. For example, carbon dioxide is not the only cause of global warming and climate change. Several other factors, such as the amount of volatile organic compounds and ozone-destroying chemicals in the atmosphere, may also affect the global climate. Therefore, multiple linear regression with three explanatory variables is needed to determine the combined influence of all three factors on climate change (Burt et al., 2009).

[24] For more information about how kriging and EBK are calculated in ArcGIS Pro, see https://pro.arcgis.com/en/pro-app/latest/help/analysis/geostatistical-analyst/what-are-the-different-kriging-models-.htm.

Two different regression models were conducted with the following dependent variables (Table B-4): (1) a respondent's perceived flood risk (survey question) and (2) a respondent's real risk (geocoded location).

TABLE B-4 Definitions of the Dependent Variables Used in Multiple Regression by their Variable Name and Description

Variable Name	Variable Definition/ Description
Perceived Flood Risk	Responses to survey question "Is your home located within the: 100-year floodplain, 500-year floodplain, outside of all floodplains, or Don't know?"
'Real' Flood Risk	Flood risk score based on the geocoded respondent address and its location in FEMA-designated flood zones

NOTE: FEMA = Federal Emergency Management Agency.

Risk perception has been used in the past as both dependent (Botzen et al., 2009; Shao et al., 2014; Ullah et al., 2020) or independent variables (Scovell et al., 2022; Shao et al., 2017; Terpstra and Lindell, 2013) to predict whether respondents will engage in flood risk reduction behaviors, such as purchasing flood insurance or implementing nonstructural/structural mitigation.

This project uses perceived and real flood risk as *dependent* variables for two reasons. First, while flood risk perception comprises multiple factors, this project focuses on the relationship between a respondent's perception of whether they live within a 100- or 500-year floodplain and the likelihood that they would take protective actions against flood risks.

Second, this project seeks to directly compare the difference between perceived versus real risk in predicting the likelihood of residents taking protective actions. This can only be done by directly comparing the responses to the survey question "Is your home located within the: 100-year floodplain, 500-year floodplain, outside of all floodplains, or Don't know?" to a respondent's geolocation within a FEMA-designated flood risk area.

Independent variables for all three models included types of protective actions respondents had taken for flood risks and demographic characteristics (Table B-5).

TABLE B-5 Definitions of the Independent Variables Used in Multiple Regression by Their Variable Name and Description**.**

Variable Name	Variable Definition/Description

FinsPaPr	Regarding flood insurance, have you had flood insurance for your home in the past or present? (Yes = 1; No = 0)
SE_PreMjrFld	How prepared do you think your household is to handle a major flood event? (Scale 1 to 5)
KW_DisasterGuideN	Is your household aware of the City of Houston Disaster Preparedness Guide to better prepare you and your family for a flooding event?
PrepRes	How many of the following resources do you have in your home: a battery-powered radio with spare batteries or a hand crank radio, at least 4 gallons of water in plastic containers, at least a 4-day supply of dehydrated or canned food, a household flood emergency plan, and/or a gas-powered or electric generator? (Number of resources, out of 5)
ProcStruc	Did you or anyone in your household implement <u>any type of structural mitigation</u> (e.g., elevate your home, dry- or wet-proof your home, install earthen berms, etc.)? (Yes = 1; No = 0)
ProcNonStruc	Did you or anyone in your household implement <u>any type of non-structural mitigation</u> (e.g., ask the Red Cross about flood risk, purchase flood insurance, ask the landlord about the property's flood risk, etc.)? (Yes = 1; No = 0)
NumAge5	Number of people in household Aged less than 5
NumAge5_17	Number of people in household aged 5 – 17
NumAge18_65	Number of people in household aged 18 to 65
Num65Plus	Number of people in household aged older than 65
Veteran	Veteran Status (Yes = 2; No = 1; I prefer not to answer = 1)
Gender	Gender (Female = 2; Male = 1; Gender Binary = 2; I prefer not to answer = 1)
Education	Education Attainment (Less than high school diploma = 3; High school diploma or equivalency = 2; All other values (Some college or above =1)
Race	Race (White = 1; people of color = 2; Prefer not to answer = 1)
Hispanic/Latino	Ethnicity (Not Hispanic/Latino = 1; Hispanic/Latino = 2; Prefer not to answer = 1)
Income	Household Income (Less than \$20,000 = 7; \$20,000 to \$34,999 = 6; \$35,000 to \$49,999 = 5; \$50,000 to \$74,999 = 4; \$75,000 to \$99,999 = 3; \$100,000 to \$149,999 = 2; \$150,000 or more = 1)
RentOwn	Rent or Own (Own = 1, Rent = 2)
Residency	Years in Residence (Number of years)
HousingStruc	Please select the housing type that best describes your home. – Selected Choice: (Single-family home =1; Duplex/Townhouse = 1; Apartment/Condominium = 1; Manufactured or mobile home =2)

NOTES: FinsPaPr = flood insurance past/present; HousingStruc = type of housing/dwelling structure; KW_DisasterGuideN = knowledge of Disaster Guide; Num65Plus = number of people in household aged older than 65; NumAge18_65 = number of people in household aged 18–65; NumAge5 = number of people in household aged less than 5; NumAge5_17 = number of people in household aged 5–17; PrepRes = preparedness resources; ProcNonStruc = nonstructural protective actions; ProcStruc = structural protective actions; RentOwn = renter or owner; SE_PreMjrFld = self-efficacy—prepared for major flood.

Each regression model (equation) and its associated variables are shown in Table B-6.

TABLE B-6 Regression Model Equations for Each Dependent Variable

Dependent Variable (Y_i)	=	Independent variables ($\beta_n X_n$)
Model 1		

$PerFldRisk_i$	=	$\beta_0 + \beta_{FinsPaPr}X_1 + \beta_{SE\_PreMjrFld}X_2 + \beta_{KW\_DisasterGuideN}X_3 + \beta_{PrepRes}X_4 + \beta_{ProcStruc}X_5 + \beta P_{rocNonStruc}X_6 + \beta_{NumAge5}X_7 + \beta_{NumAge5\_17}X_8 + \beta_{NumAge18\_65}X_9 + \beta_{Num65Plus}X_{10} + \beta_{Vet}X_{11} + \beta_{Gender}X_{12} + \beta_{Education}X_{13} + \beta_{Race}X_{14} + \beta_{Hispanic/Latino}X_{16} + \beta_{Income}X_{17} + \beta_{RentOwn}X_{18} + \beta_{Residency}X_{19} + \beta_{HousingStruc}X_{20}\,\varepsilon_i$
Model 2		
$ActFldRisk_i$	=	$\beta_0 + \beta_{FinsPaPr}X_1 + \beta_{SE\_PreMjrFld}X_2 + \beta_{KW\_DisasterGuideN}X_3 + \beta_{PrepRes}X_4 + \beta_{ProcStruc}X_5 + \beta P_{rocNonStruc}X_6 + \beta_{NumAge5}X_7 + \beta_{NumAge5\_17}X_8 + \beta_{NumAge18\_65}X_9 + \beta_{Num65Plus}X_{10} + \beta_{Vet}X_{11} + \beta_{Gender}X_{12} + \beta_{Education}X_{13} + \beta_{Race}X_{14} + \beta_{Hispanic/Latino}X_{16} + \beta_{Income}X_{17} + \beta_{RentOwn}X_{18} + \beta_{Residency}X_{19} + \beta_{HousingStruc}X_{20}\,\varepsilon_i$

NOTES: PerFldRisk = perceived flood risk; ActFldRisk = real flood risk; FinsPaPr = flood insurance past/present; HousingStruc = type of housing/dwelling structure; KW_DisasterGuideN = knowledge of Disaster Guide; Num65Plus = number of people in household aged older than 65; NumAge18_65 = number of people in household aged 18–65; NumAge5 = number of people in household aged less than 5; NumAge5_17 = number of people in household aged 5–17; PrepRes = preparedness resources; ProcNonStruc = nonstructural protective actions; ProcStruc = structural protective actions; RentOwn = renter or owner; SE_PreMjrFld = self-efficacy—prepared for major flood risk.

Spatial Regression Modeling

After conducting multiple linear regression for the flood protective actions, the results were checked to determine whether the data contained any spatial effects or spatial autocorrelation that might influence the results (Chevalier et al., 2021).

The ordinary least squares regression models were run through a program called GeoDa using a spatial weights file to determine if a spatial regression model would be more representative of the data. A spatial weights file calculates “neighborhood” structures for each location—essentially, spatial weights represent possible ways each data point interacts with other data points in space. Because the input dataset is point data, the weights file was created based on IDW. GeoDa then uses six tests to determine spatial dependence in the model. These tests help determine whether additional spatial modeling was required for any of the classical regression models (see Box B-5).

BOX B-5

Classical Versus Spatial Regression

Simultaneous autoregressive (SAR) models account for spatial effects, which can provide more reliable results than classical regression can. While many SAR models exist, we discuss two used for this project (Anselin et al., 2008; Burt et al., 2009).

Spatial Error Model

The spatial error model (eq. 2) is often used to correct for bias from autocorrelation found in spatial data.

$$y=X\beta+\varepsilon$$

$$\varepsilon=\lambda W\varepsilon+u$$

where W is the spatial weights matrix, X is the matrix of observations on the explanatory variables, ε is the vector of spatially autocorrelated error terms, u is the vector of i.i.d. errors, and λ and β are parameters.

The spatial error model is used when ordinary least squares assumptions of uncorrelated error terms are violated.

Spatial Lag Model

The spatial lag model is used when the assumption that “no spatial autocorrelation exists in the dataset” is untrue (eq.3). This model is used when there are substantive spatial dependence and interaction in a dataset.

$$Y=\rho WY+\varepsilon$$

where ε is the error term vector, WY is the spatially lagged dependent variable for the weights matrix, and ρ is the spatial coefficient.

The first is the Moran’s I, which tests for spatial dependence in the model error residuals. If there is spatial dependence, the other tests can be used to determine which spatial model (a spatial error or spatial lag model) is the best representative of the data structure. The other five tests are variations of Lagrange Multiplier (LM) tests, which test for spatial dependence in the linear regression models. The first two tests are the LM (error) and LM (lag) tests, which identify whether a model has spatial dependence and provide information about which spatial model is better for examining the data. If the LM (error) is significant, and the LM (lag) is not, then the spatial error model is the better fit (and vice versa). If both tests are significant, the Robust LM (error) and Robust LM (lag) tests determine which model is more appropriate. If the Robust LM (error) test is more significant (the p-value is smaller), then it should be used as the model of choice for that regression model (and vice versa) (Anselin, 1996, 1999; Anselin et al., 2008).

Based on the GeoDa results, only the real flood risk model (Model 2) exhibited spatial dependence. As a result, the model was rerun using the spatial lag model (the Robust LM [lag] test was the most significant).

Risk Communication Analyses

Descriptive statistics were used to get a general understanding of where residents prefer to receive flood preparedness information. Gulf Research Program staff then conducted several Wilcoxon tests and contingency table analyses to examine how those preferences vary by demographic characteristics.

While regression modeling is commonly used by researchers to control for the effects of all the other relevant demographic characteristics on preferred sources of flood preparedness information, the survey data are categorical, and converting those responses to continuous data could influence data integrity. Regression modeling can also highlight one demographic group over the other (as seen in the protective actions regression), which can mask how specific demographic populations prefer to seek or receive flood preparedness information. It is critical to understand how different populations perceive an information source in order to develop and provide tailored risk communication messaging to a diverse population.

Wilcoxon Tests

Demographic variables (i.e., age, education, race, gender, household income, and veteran status) were compared with responses to Question 22, "To what extent do you seek information about flood preparedness in your area from…?," and Question 23, "From which of the following entities would you and your household prefer to receive flood preparedness information? Check your top 3 from the options below," to determine whether different groups preferred to seek or receive flood preparedness information from different entities. Wilcoxon tests, which are not categorical data analyses methods, were used to determine which demographic and risk communication source variable pairings exhibited significant differences to determine which pairings should be further examined using contingency table analysis (Higgins, 2004).

The survey responses are not normally distributed, so parametric tests such as t-tests and analysis of variance (ANOVA) could not be employed. Parametric statistics are based on assumptions about the distribution of the sample population. Nonparametric statistics, in contrast, are not based on assumptions, so input data can be collected from a sample that does not have a normal distribution.

As such, we used Wilcoxon tests, which are nonparametric. Significant differences in risk communication source preferences are measured using the Chi^2 Approximation tests in JMP®. P-values where $p < 0.05$ indicate whether different demographic populations prefer risk communication methods or sources (Higgins, 2004).

Contingency Tables

Wilcoxon tests that showed significant differences between compared variables were analyzed using contingency tables (i.e., cross-tabulation) to identify whether interdependence between those variable pairings exists (Agresti and Kateri, 2011). Using JMP®, two-way contingency tables were conducted for significant variables pairing combinations between (1) demographics and modes of risk communication variables and (2) demographics and the likelihood of using different sources of risk communication.

Comparing percentages between response combinations provides information about how different demographic groups (i.e., different age groups) will have variable preferences for receiving or seeking flood preparedness information. Significant dependence between two variables is measured using both the Pearson Chi^2 and Likelihood-ratio Chi^2 tests in JMP® (Agresti and Kateri, 2011; Kateri, 2014).

Significant contingency tables ($\alpha < 0.05$) were then examined to identify specific relationships between demographic groups and risk communication modes and sources (e.g., is one age group more likely to prefer flood risk information from social media over other sources?).

Fisher’s exact tests were also run for significant tables to determine whether significant association between two variables existed, as they provide both one- and two-tailed hypothesis testing. Chi^2 tests only examine two-tailed null hypotheses, which do not test an alternate hypothesis in a specific direction (e.g., a variable could be more or less than the null hypothesis claims (Schlotzhauer, 2007). The Fisher's exact test, therefore, tests if a response variable is likely to be more or less than the null hypothesis (no difference) (Kateri, 2014). Odds ratios were only calculated for pairings between preferred modes and sources of risk communication vary by gender, race/ethnicity, and veteran status, as odds ratios are only calculated on tables where each variable only has two response categories in JMP®.

Mapping People Who Prefer Information from Friends or Family

To determine whether specific super neighborhoods were more likely to have people who preferred to receive flood preparedness information from friends or family than others, we mapped respondents based on their preferences, specifically looking at respondents who checked "Yes" for Question 23, "From which of the following entities would you and your household prefer to receive flood preparedness information? – Friends and/or family?." Descriptive statistics and a Kruskal–Wallis test (a nonparametric test use to identify significant differences exist between more than two groups of an independent variable on a continuous or ordinal dependent variable [Schlotzhauer, 2007]) were also conducted to see if this varied between zip codes. Cluster analysis was conducted to determine whether significant clustering of respondents was present.

Compounding Disasters and Recovery Services

To understand how successive disasters might affect access to recovery services, survey responses were used to determine (1) how COVID-19 influenced flooding preparedness and evacuation behavior, (2) whether the number of recovery services sought during a disaster varied between flooding, COVID-19, and Texas Winter Storms, (3) whether specific demographic groups were more likely to request recovery services during different disaster events, and (4) whether specific demographic groups were more likely to experience barriers to services.

Influence of COVID-19 on Other Disaster Protective Actions

Descriptive statistics for two survey questions were examined to determine how COVID-19 influenced flood-protective actions.

1. Question 27, “To what extent has the COVID-19 pandemic impacted your ability to a) stockpile food and water, b) put together a first-aid kit, c) ensure you have a 4-day supply of necessary medications, and d) save $500 in emergency savings?”
2. Question 33, “If you or anyone in your household did not evacuate or decided to stay at home – Concerns related to the COVID-19 pandemic?”

Compounding Disasters and Recovery Services

We then conducted statistical analyses to understand (1) how recovery services sought during a disaster varied based on the disaster type and (2) whether specific demographic groups were more likely to request recovery services during different disaster events or experience barriers to services.

Contingency Tables

Two-way contingency tables were conducted for significant variables, pairing combinations between (1) different services sought during flooding compared to services sought during COVID-19 and winter storms and (2) the rate at which people did or did not experience barriers to assistance or receiving services.

Comparing percentages between these pairings can help determine whether services were more commonly sought during flood events, COVID-19 and winter storms (or vice versa), or by different demographic groups. In addition, this information can help decision makers better understand how many people experience successive barriers to those services during other disasters.

Wilcoxon Tests

To determine whether the number of recovery services sought during a disaster varies between flooding, COVID-19, and winter storms, a three-way Wilcoxon test was conducted based on the possible total services received (Table B-7). Note that these are not separated by the type of service requested but by the total number of services requested.

TABLE B-7 Survey Questions About Different Recovery Services, by Disaster

Service Assistance	**Disaster**		
	Flooding	**COVID-19**	**Winter Storms**

Due to [DISASTER], have you or anyone in your household sought or applied for **financial assistance**?	X	X	X
Due to [DISASTER], have you or anyone in your household sought or applied for **utility or energy assistance**?	X	X	X
Due to [DISASTER], have you or anyone in your household sought or applied for **food assistance**?	X	X	X
Due to [DISASTER], have you or anyone in your household sought or applied for **assistance with home repairs**?	X	X	X
Due to [DISASTER], have you or anyone in your household sought or applied for **employment services**?	X	X	X
Due to [DISASTER], have you or anyone in your household sought or applied for **help from a neighbor**?	X	–	X
Due to [DISASTER], have you or anyone in your household sought or applied **for mental health services**?	X	X	–
Due to [Disaster], have you or anyone in your household sought or applied for **physical health services**?	X	X	X
Due to the WINTER STORMS, have you or anyone in your household sought or obtained any of the following? – **Alternative accommodations (e.g., hotel, shelter, friend or family's home)**	–	–	X
Due to the WINTER STORMS, have you or anyone in your household sought or obtained any of the following? – **Warming centers**	–	–	X
What were the barriers, if any, to getting assistance or receiving services?	X	X	X

Appendix C
Calculating the Flood Risk Variable

According to a special report of the Intergovernmental Panel on Climate Change by Murray and Ebi (2012, p. 43) and Santos and colleagues (2020, p. 4), *flood risk* can be defined as a function of hazard (function of the frequency and severity of consequences), exposure (assets and people exposed to flooding), and vulnerability (capacity to deal with the flood event). As such, a Flood Risk Score (FRS) can be calculated using the equation below:

$$\textbf{FLOOD RISK} = \textbf{Hazard}_{\textbf{(Frequency x Severity of Consequences)}} \textbf{ x Exposure x Vulnerability}$$

Modifying these variables to suit the household level, we create two versions of the flood risk variables: Real (Actual) versus Perceived Risk.

CALCULATING FLOOD RISK:

1. **Hazard (probability of flood event) (A x B)**
   - **(A)** Question 9 response options (severity of damage) (Table C-1)
   - **(B)** Question 10 (frequency of damage) (Table C-1)

TABLE C-1 Survey Response Options for Questions 9 and 10, with Their Respective Value Coding

Q9 – Response Options	Values	Q10 – Response Options	Values
Never	1	Never	1
Once	2	Once	2
Twice	3	Twice	3
3–5 times	4	3–5 times	4
More than 5 times	5	More than 5 times	5

2. **Exposure ($C_{a/b}$ + D, potential damage to assets and people from flooding)**
   - **(C)** Actual & Perceived Risk—Location of the respondent within the floodplains, real or perceived (house location/survey response) (Table C-2)

C(a): 'Real' Risk (Use geocoded location of respondent within FEMA floodplains [house location])		**C(b): Perceived Risk** (Use responses from Q4 [Is your home located within the . . .?])	
Response Options	**Values**	**Response Options**	**Values**
Area of minimal risk of flooding	1	Outside all floodplains	1
Within 500-year floodplain	2	Within 500-year floodplain	2
Within 100-year floodplain	3	Within 100-year floodplain	3
–	–	Don't Know	1

NOTE: FEMA = Federal Emergency Management Agency.

(D) Use responses from Question 6 (personal experience with flooding), where No = 0 and Yes = 1. Calculate value based on Question 6 response choice (Table C-3).

D(a): If No, use Q11
(indirect flood experiences)

Response Options	**Values**		
	Yes	**No**	
a	1	0	
b	1	0	
c	1	0	
d	1	0	
Total (T)	T_{Yes}	T_{No}	$T_{Yes} + T_{No} = T_{Q11}$

D(b): If Yes, use Q7
(direct and indirect flood experiences)

Response Options	**Values**		
	Yes	**No**	
a	1	0	
b	1	0	
c	1	0	
d	1	0	
e	1	0	
f	1	0	
Total (T)	T_{Yes}	T_{No}	$T_{Yes} + T_{No} = T_{Q7}$

3. Vulnerability (capacity of a household to deal with the flood event) (E + F + G + H + I + J +

K)

The most commonly used variables to determine social vulnerability are wealth (annual income), age (number of children/elders per household), and ethnicity (non-European immigrants) (Cutter et al., 2003). For this project, *vulnerability* is defined as “the propensity or predisposition to be adversely affected and encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt” (Pörtner et al., 2022, p. 5).

(E) Use responses from Question 3 (type of housing) (Table C-4).

TABLE C-4 Survey Response Options for the Type of Housing Variable, with Respective Value Coding

Response Options	Values
Single-family home	1
Duplex/Townhouse	1
Apartment/Condominium	1
Manufactured or mobile home	2

(F) Use responses from Question 2 (Do you rent or own your home where you are currently living?) (Table C-5).

TABLE C-5 Survey Response Options for the Renter or Owner Variable, with Respective Value Coding

Response Options	Values
Own	1
Rent	2

(G) Use responses from Question 46 (Vulnerable Populations by Age) (Table C-6).

TABLE C-6 Survey Response Options for the Number of People within a Household by Age Category, with Respective Value Coding

Response Options	Values		
	Yes	No	Count
a. Less than 5 years old	3	0	#
b. 5–17 years old	2	0	#

c. 18–65 years	1	0	#
d. Over 65 years	3	0	#
Total (T)	T_{Yes}	T_{No}	$T_{Yes(a)*Count} + T_{Yes(b)*Count} + T_{Yes(c)*Count} + T_{Yes(d)*Count} = T_{Q46}$

(H) Use responses from Question 48 (Gender) (Table C-7).

TABLE C-7 Survey Response Options for Gender Variable, with Respective Value Coding

Response Options	Values
Female	2
Male	1
Nonbinary	2
I prefer not to answer	1

(I) Use responses from Question 49 (Education) (Table C-8).

TABLE C-8 Survey Response Options for Education Variable, with Respective Value Coding

Response Options	Values
Less than high school diploma	3
High school diploma or equivalency	2
Some college but no degree	1
Associate degree in college (2-year)	1
Bachelor's degree in college (4-year)	1
Graduate degree	1
Prefer not to answer	1

(J) Use responses from Question 50 (Race and Ethnicity) (Table C-9).

TABLE C-9 Survey Response Options for Race and Ethnicity Variable, with Respective Value Coding

Response Options	Values
White (Not Hispanic or Latino)	1
People of color and/or Hispanic or Latino	2

I prefer not to answer	1

(K) Use responses from Question 51 (annual household income) (Table C-10).

TABLE C-10 Survey Response Options for Household Income Variable, with Respective Value Coding

Response Options	Values
Less than $20,000	7
$20,000 to $34,999	6
$35,000 to $49,999	5
$50,000 to $74,999	4
$75,000 to $99,999	3
$100,000 to $149,999	2
$150,000 or more	1

CALCULATING THE FLOOD RISK SCORE

1. Use the formula below to calculate each respondent's FRS (Tables C-11 and C-12).

TABLE C-11 FRS Component Calculation Formulas

Component	Component Variables
Hazard	(A x B)
Exposure	$(C_{(Actual/Perceived)} + D_{(TQ7)})$ *OR* $(C_{(Actual/Perceived)} + D_{(TQ11)})$
Vulnerability	(E + F + G + H + I + J +K)

TABLE C-12 Flood Risk Score (FRS) Calculation Formulas for Real and Perceived Risk and Direct or Indirect Flood Experience

FRS	Description	Formula
ActDirect	Real risk & direct impacts	$(A \times B) * (C_{(Actual)} + D_{(TQ7)}) * (E + F + G + H + I + J + K)$
ActDandI	Real risk & direct + indirect impacts	$(A \times B) * (C_{(Actual)} + D_{(TQ11)}) * (E + F + G + H + I + J + K)$
PerDirect	Perceived risk & direct impacts	$(A \times B) * (C_{(Perceived)} + D_{(TQ7)}) * (E + F + G + H + I + J + K)$

PerDandI	Perceived risk & direct + indirect impacts	$(A \times B) * (C_{(Perceived)} + D_{(TQ11)}) * (E + F + G + H + I + J + K)$

2. After calculating FRS, recode each cell by the below values (Table C-13).

TABLE C-13 Recoded Relative Flood Risk Scores (FRS) Based on Standard Deviation

RELATIVE FRS	STDV	Recode Value
Low	< −1.5 STDV	1
Low to Medium	−0.5–1.5 STDV	2
Medium	−0.5–0.5 STDV	3
Medium to High	0.5–1.5 STDV	4
High	>1.5 STDV	5

Appendix D
Survey: Engaging Communities in Southeast Texas on Flood Preparedness Project

1. **Can we begin the survey?**
    a. Yes
    b. No

For this survey, I will be reading the questions as they are written. The interviewing staff, and that includes me, are instructed to always follow the same questionnaire structure during every interview. Even though some of the questions may seem obvious to you, or may not seem to apply to you, please understand that we ask everyone the same questions in the same order to be consistent. Remember that you do not need to answer any questions that make you uncomfortable.

2. *[If 1 is no]* **is there a better time to meet with you?**

3. **Can you confirm your address please?** *(Does the address match what is listed next to the HID?*
    a. Yes (Match)
    b. No (Does not match)

4. **Are you at least 18 years old?**
    a. Yes
    b. No

5. **Have you lived at this address since June 1, 2020?**
    a. Yes
    b. No

BACKGROUND

Before we talk about flooding, I would like to ask you some questions about your home.

Q1. **How many years have you lived in the home where you now live?**
Response is open-ended. Round down to the nearest integer (whole number).
    a. One and a half years or more. Specify number of years.
    ____
    b. Less than one and a half years

Q2. **Do you rent or own your home where you are currently living?**

a. Rent
b. Own

Q3. **Please select the housing type that best describes your home.**

a. Single-family home
b. Duplex/Townhouse
c. Apartment/Condominium
d. Manufactured or mobile home
e. Other ____

Q4. **Is your home located within the:**

a. **100 year floodplain** *(The 100-year floodplain is defined as the area flooded by an event that has a 1% chance of occurring or being exceeded in any given year.)*
b. **500 year floodplain** *(The 500-year floodplain is defined as the area flooded by an event that has a 0.2% chance of occurring or being exceeded in any given year.)*
c. **Outside of all floodplains**
d. Don't know

Q5. **Regarding flood insurance,**

	No	Yes	Don't Know
have you had flood insurance for your home in the past?	○	○	○
do you have flood insurance for your home right now?	○	○	○
do you intend to get flood insurance for your home in the future?	○	○	○

Flooding Impacts

Flooding can occur in a variety of ways, for example, from hurricanes or heavy rains. The next set of questions focus on your flooding experiences.

Q6. **Have you <u>EVER</u> personally experienced the impacts of flooding?**

a. Yes
b. No

Q7. Are any of the following statements true about ANY of your experiences with floods?

Q7.1 A friend, relative, neighbor, or coworker that you know personally…

	No	Yes	Don't Know
has had their property damaged in a flood	○	○	○
was injured or lost their life in a flood	○	○	○

Q7.2 You or someone close to you, such as an immediate family member…

	No	Yes	Don't Know
has been injured in a flood	○	○	○
has lost their life in a flood	○	○	○

Q7.3 You have experienced disruption to…

	No	Yes	Don't Know
your job that prevented/prevents you from working	○	○	○
your shopping and other daily activities	○	○	○

Q8. **<u>BEFORE living in your current home</u>, have any of your previous homes been damaged by flooding?**

a. Yes
b. No

Q9. **<u>SINCE living in your current home</u>, how many times was your property (e.g., land, home, car) *severely* damaged?**

a. Never
b. Once
c. Twice
d. 3 - 5 times
e. More than 5 times
f. I don't know or I can't remember

Q10. **<u>SINCE living in your current home</u>, how many times has your property (e.g., land, home, car) flooded?**

a. Never
b. Once
c. Twice
d. 3 - 5 times
e. More than 5 times
f. I don't know or I can't remember

Q11. **Are any of the following statements true?**

Q11.1 A friend, relative, neighbor, or coworker that you know personally…

	No	Yes	Don't Know
has had their property damaged in a flood	○	○	○
was injured or lost their life in a flood	○	○	○

Q11.2 Someone close to you, such as an immediate family member…

	No	Yes	Don't Know
has been injured in a flood	○	○	○

has lost their life in a flood	○	○	○

I am going to read you a list of statements about flooding in Houston. For each one, please tell me whether you believe the statement to be TRUE or FALSE. If you are unsure, you can say "I don't know".

	True	False	Don't Know
Q12. Flooding has become more frequent.	○	○	○
Q13. Flooding has become more severe.	○	○	○
Q14. Places that had never flooded before are now flooding.	○	○	○

I am going to read you a list of people, organizations, institutions, and levels of government that may play a role in providing services to residents of Houston. For each one, please tell me --- with a YES or NO --- whether you believe they are responsible for helping you and your household prepare for floods. If you respond with YES, please tell me if you are satisfied with their efforts.

Q15. **Do you believe the federal government is responsible for helping you and your household prepare for floods?**

a. Not Applicable
b. No
c. Yes

Are you satisfied with the efforts of the federal government?

a. No
b. Neutral/no opinion
c. Yes

Q16. **Do you believe the state government is responsible for helping you and your household prepare for floods?**

a. Not Applicable
b. No
c. Yes

Are you satisfied with the efforts of the state government?

a. No
b. Neutral/no opinion
c. Yes

Q17. **Do you believe the local government is responsible for helping you and your household prepare for floods?**

a. Not Applicable
b. No
c. Yes

Are you satisfied with the efforts of the local government?

a. No
b. Neutral/no opinion
c. Yes

Q18. **Do you believe your place of employment is responsible for helping you and your household prepare for floods?**

a. Not Applicable
b. No
c. Yes

Are you satisfied with the efforts of your place of employment?

a. No
b. Neutral/no opinion
c. Yes

Q19. **Do you believe nonprofits (e.g., church, Salvation Army, neighborhood association) are responsible for helping you and your household prepare for floods?**

a. Not Applicable
b. No
c. Yes

Are you satisfied with the efforts of nonprofits?

a. No
b. Neutral/no opinion
c. Yes

Q20. **Do you believe school districts are responsible for helping you and your household prepare for floods?**

a. Not Applicable
b. No
c. Yes

Are you satisfied with the efforts of school districts?

a. No
b. Neutral/no opinion
c. Yes

Q21. **How prepared do you think your household is to handle a major flood event?**

a. Well-prepared
b. Somewhat prepared
c. Not prepared at all

FLOOD PREPAREDNESS

The next set of questions focus on communication and flood preparedness.

Q22. **To what extent do you seek information about flood preparedness in your area from…**

	Not at all	Small extent	Moderate extent	Great extent	Very great extent
Newspapers	○	○	○	○	○
Television	○	○	○	○	○
Radio	○	○	○	○	○
Internet / Social Media	○	○	○	○	○
Meetings, for example community meetings or town halls	○	○	○	○	○
Friends, relatives, neighbors, and coworkers	○	○	○	○	○
Personal experience and observation	○	○	○	○	○

Q23. **From which of the following entities would you and your household prefer to receive flood preparedness information?**

Check your top 3 from the options below

a. Office of the Mayor or City Manager
b. City or County Emergency Management
c. Other local government agency
d. National Weather Service
e. Local news/meteorologist
f. Local school district
g. Church/place of worship
h. Employer or co-workers
i. Friends and/or family
j. Any other entity that I may not have mentioned?______________________________

Q24. **Is your household aware of The City of Houston Disaster Preparedness Guide to better prepare you and your family for a flooding event?**

a. Yes
b. No
c. Don't Know
d. Refuse

Q25. **How helpful has the information from The City of Houston Disaster Preparedness Guide been? Would you say ...**

a. Not Helpful
b. Slightly Helpful
c. Moderately Helpful
d. Helpful
e. Very Helpful
f. Don't Know
g. Refuse

h. N/A, I have not reviewed the information yet

Now, I am going to ask you some questions about preparing for flooding events.

Q26. **Do you have any of the following in your home?**

	No	Yes
a battery powered radio with spare batteries or a hand crank radio	○	○
at least 4 gallons of water in plastic containers	○	○
at least a 4 day supply of dehydrated or canned food	○	○
a first-aid kit	○	○
a household flood emergency plan	○	○
a gas powered or electric generator	○	○

Q27. **To what extent has the COVID-19 pandemic impacted your ability to….**

	Not at all	Small extent	Moderate extent	Great extent	Very great extent
…stockpile food and water	○	○	○	○	○
…put together a first-aid kit	○	○	○	○	○
…ensure you have 4-day supply of necessary medications	○	○	○	○	○
…save $500 in emergency savings	○	○	○	○	○

FLOOD RESPONSE

The next set of questions focus on ways that you and your household responded to flooding events during Hurricane Season 2020 in comparison to Hurricane Harvey (2017).

On Wednesday, August 26, 2020, in preparation for Hurricane Laura, Harris County Judge Lina Hidalgo issued voluntary evacuations for people who live in Zones A and B in Harris County. The next day, Laura turned east, away from Houston, and was downgraded to a tropical storm. Had the storm not turned, "[Laura] would have been an absolutely catastrophic event for us in Houston," said meteorologist Jeff Linder from the Harris County Flood Control District. (On Thursday, August 27, 2020, Hurricane Laura made landfall in southwest Louisiana as a Category 4 hurricane and devastated places like Lake Charles and Cameron, LA.)

On September 20, 2020, in preparation for Tropical Storm Beta, the National Weather Service issued a flash flood watch, storm surge warning, and tropical storm warning for different areas of Harris County. The next day, Beta made landfall near the southern end of the Matagorda Peninsula, TX. Although downgraded to a tropical depression, Beta brought over a foot of rain to some areas of Houston, leaving dozens of city streets flooded and closed, including parts of Interstate 69 and 45 and State Highways 288 and 290.

Think back to the days leading up to Hurricane Laura and Tropical Storm Beta…

Q28. **Did you or anyone in your household evacuate for…**

	Yes	No
Tropical Storm Beta (September 20, 2020)	○	○
Hurricane Laura (August 26, 2020)	○	○
Hurricane Harvey (August 17, 2017)	○	○

Q29. **What date did you / you all evacuate?**

Enter a valid date of the form: mm/dd/yyyy

a. **Tropical Storm Beta** (September 20, 2020) ____________________________
b. **Hurricane Laura** (August 26, 2020) ____________________________
c. **Hurricane Harvey** (August 17, 2017) ____________________________

Q30. **Around what time did you evacuate?**

	Morning	Afternoon	Evening	Middle of the night
Tropical Storm Beta (September 20, 2020)	○	○	○	○
Hurricane Laura (August 26, 2020)	○	○	○	○
Hurricane Harvey (August 17, 2017)	○	○	○	○

Q31. **Where did you / you all go?**

	Community shelter	Friend or relative's home	Hotel/motel or AirBnb	Other (*enter information on next screen*)
Tropical Storm Beta (September 20, 2020)	○	○	○	○
Hurricane Laura (August 26, 2020)	○	○	○	○
Hurricane Harvey	○	○	○	○

(August 17, 2017)

If 'other' is selected on "Where did you / you all go?" enter text here.

a. **Tropical Storm Beta** (September 20, 2020) ____________________________
b. **Hurricane Laura** (August 26, 2020) ____________________________
c. **Hurricane Harvey** (August 17, 2017) ____________________________

Q32. **Did you or anyone from your household stay at home?**

	Yes	No
Tropical Storm Beta (September 20, 2020)	○	○
Hurricane Laura (August 26, 2020)	○	○
Hurricane Harvey (August 17, 2017)	○	○

Q33. **If you or anyone in your household did not evacuate or decided to stay at home, why?** *Check all options below that apply.*

	Beta (September 20, 2020)	**Laura** (August 26, 2020)	**Harvey** (August 17, 2017)
Felt like home was safe	☐	☐	☐
Didn't know what to do	☐	☐	☐
No time to leave	☐	☐	☐
Was not aware there was a voluntary evacuation	☐	☐	☐
There wasn't a mandatory evacuation issued	☐	☐	☐
Job responsibilities	☐	☐	☐
Someone in household was disabled/unable to leave	☐	☐	☐
Did not want to leave pets	☐	☐	☐
No transportation	☐	☐	☐
No place to go/didn't know where to go	☐	☐	☐
Not enough money to go anywhere else	☐	☐	☐
Fear of looting	☐	☐	☐
Problems with shelter (e.g., unsafe)	☐	☐	☐
Concerns related to the COVID-19 pandemic	☐	☐	☐
Afraid authorities would restrict people from returning home	☐	☐	☐

Any other reason that I may not have mentioned?	☐	☐	☐

FLOOD RECOVERY

Now, I am going to ask you some questions about recovering from flooding events. I am going to read a list of experiences that people might go through as a consequence of a flooding event. For each experience, please tell me --- with a YES or NO --- whether you or anyone in your household have ever experienced it. If you respond with a YES, please tell me if it occurred during or before Hurricane Season 2020. If you are unsure, you can say "I don't know".

Q34.

a. **Due to flooding, have you or anyone in your household sought or applied for financial assistance?**
   a. No
   b. Yes

   Was financial assistance sought or applied for ...
   a. In 2020
   b. Before 2020
   c. Don't Know
   d. Refuse

a. **Due to flooding, have you or anyone in your household sought or applied for utility or energy assistance?**
   a. No
   b. Yes

   Was utility or energy assistance sought or applied for ...
   a. In 2020
   b. Before 2020
   c. Don't Know
   d. Refuse

c. **Due to flooding, have you or anyone in your household sought or applied for food assistance?**
   a. No
   b. Yes

   Was food assistance sought or applied for ...
   a. In 2020
   b. Before 2020
   c. Don't Know
   d. Refuse

d. **Due to flooding, have you or anyone in your household sought or applied for assistance with home repairs?**
   a. No
   b. Yes

   Was assistance with home repairs sought or applied for ...
   a. In 2020
   b. Before 2020
   c. Don't Know
   d. Refuse

e. **Due to flooding, have you or anyone in your household sought or applied for employment services?**
   a. No
   b. Yes

   Were employment services sought or applied for ...
   a. In 2020
   b. Before 2020
   c. Don't Know
   d. Refuse

f. **Due to flooding, have you or anyone in your household sought or applied for help from a neighbor?**
   a. No
   b. Yes

   Was help from a neighbor sought for ...
   a. In 2020
   b. Before 2020
   c. Don't Know
   d. Refuse

g. **Due to flooding, have you or anyone in your household sought or applied for mental health services?**
   a. No
   b. Yes

   Were mental health services sought or applied for ...
   a. In 2020
   b. Before 2020
   c. Don't Know
   d. Refuse

h. **Due to flooding, have you or anyone in your household sought or applied for physical health services?**

a. No
b. Yes

Were physical health services sought or applied for ...

a. In 2020
b. Before 2020
c. Don't Know
d. Refuse

Q35. **What were the barriers, if any, to getting this assistance or receiving services?**

Response is open-ended. If there were no barriers, if the respondent doesn't know, or if the respondent refuses to answer, check the appropriate box.

a. Barriers: (enter below)
   ____
b. No barriers
c. Don't Know
d. Refuse

FLOOD MITIGATION

The next set of questions focus on actions that people might take either before or after a flooding event.

Q36.

a. **Due to flooding, have you or anyone in your household moved to a new location?**
   a. No
   b. Yes

   Did you or anyone in your household move to a new location ...
   a. In 2020
   b. Before 2020
   c. Don't Know

b. **Due to flooding, have you or anyone in your household purchased flood insurance?**
   a. No
   b. Yes

   Did you or anyone in your household purchase flood insurance ...
   a. In 2020
   b. Before 2020
   c. Don't Know

c. **Due to flooding, have you or anyone in your household asked the landlord about**

the property's flood risk?

a. No
b. Yes

Did you or anyone in your household ask the landlord about the property's flood risk ...

a. In 2020
b. Before 2020
c. Don't Know

d. **Due to flooding, have you or anyone in your household contacted the Red Cross or government agencies for information about flood hazards in your area?**

a. No
b. Yes

Did you or anyone in your household contact the Red Cross or government agencies for information about flood hazards in your area ...

a. In 2020
b. Before 2020
c. Don't Know

Q37.

a. **Due to flooding, have you or anyone in your household moved to a new location?**

a. No
b. Yes

Did you or anyone in your household move to a new location ...

a. In 2020
b. Before 2020
c. Don't Know

b. **Due to flooding, have you or anyone in your household elevated your entire home out of the 100-year floodplain*?**
**The 100-year floodplain is defined as the area that has a 1-percent chance of being inundated by flood waters in any given year*

a. No
b. Yes

Did you or anyone in your household elevate your entire home out of the 100-year floodplain ...

a. In 2020
b. Before 2020
c. Don't Know

c. **Due to flooding, have you or anyone in your household installed earthen berms around your entire home to the 100-year flood elevation?**
   a. No
   b. Yes

   Did you or anyone in your household install earthen berms ...
   a. In 2020
   b. Before 2020
   c. Don't Know

d. **Due to flooding, have you or anyone in your household dry flood-proofed** your entire home so water cannot get in?**

   *** A dry flood-proofed building is sealed against floodwaters. All areas below the flood protection level are made watertight. For example, walls can be coated with waterproofing compounds or plastic sheeting. Openings like door windows, sewer lines and vents are closed with removable shields or with sandbags.*
   a. No
   b. Yes

   Did you or anyone in your household dry flood-proof your entire home ...
   a. In 2020
   b. Before 2020
   c. Don't Know

e. **Due to flooding, have you or anyone in your household wet flood-proofed*** your entire home so equipment such as the furnace, washer, and dryer is moved to a higher location or protected by a floodwall?**

   ****A wet flood-proofed building intentionally allows flood waters into the building to minimize water pressure on the structure. As a result, the loads imposed on the house during a flood, and therefore the likelihood of structural damage, may be greatly reduced. This method also involves moving valuables and service equipment to a higher location.*
   a. No
   b. Yes

   Did you or anyone in your household wet flood-proof your entire home ...
   a. In 2020
   b. Before 2020
   c. Don't Know

f. **Due to flooding, have you or anyone in your household stored valuable items on the second floor or a higher location of your home?**
   a. No
   b. Yes

Did you or anyone in your household store valuable items on the second floor or a higher location of your home ...

a. In 2020
b. Before 2020
c. Don't Know

g. **Due to flooding, have you or anyone in your household purchased flood insurance?**
   a. No
   b. Yes

Did you or anyone in your household purchase flood insurance ...

a. In 2020
b. Before 2020
c. Don't Know

h. **Due to flooding, have you or anyone in your household contacted the Red Cross or government agencies for information about flood hazards in your area?**
   a. No
   b. Yes

Did you or anyone in your household contact the Red Cross or government agencies for information about flood hazards in your area ...

a. In 2020
b. Before 2020
c. Don't Know

Q38. **Which of the following would incentivize you to protect your home or household from flooding?**

Check all that apply

a. A government grant (such as funds to elevate or flood-proof your house)
b. Loan (to elevate/flood-proof your house)
c. Voluntary buyout (government purchase of your house)
d. Discount on your flood insurance
e. Building permit fee waiver
f. Property tax break
g. Low-impact development/stormwater management (e.g., rain gardens, permeable pavement)
h. Anything else that I may not have mentioned?
   ____
i. None of the above

COVID-19

Now, I'd like to shift our focus from flooding to the current coronavirus (COVID-19) pandemic.

Q39. **Due to the COVID-19 pandemic, did you or anyone in your household experience any of**

the following?
Check all that apply.

a. Have a child at home because their school/childcare/college was closed
b. Miss work or school
c. Lost employment
d. Had to change jobs
e. Had a decrease in income or reduced work hours
f. Cut size of or skipped meals because of cost
g. More stress than usual
h. None of the above
i. Don't Know
j. Refuse

Q40. **Due to the COVID-19 pandemic, have you or anyone in your household sought or obtained any of the following?**
Check all that apply.

a. Physical health services
b. Mental health services
c. Utility or energy assistance
d. Financial help
e. Food assistance
f. Employment services
g. Help from a neighbor
h. None
i. Refuse

Q41. **What were the barriers, if any, to getting this assistance or receiving services?**
Response is open-ended. If there were no barriers, if the respondent doesn't know, or if the respondent refuses to answer, check the appropriate box. (provide examples if requested: didn't know where or how to obtain the service, couldn't afford it, didn't have the transportation to get there)

a. Barriers: ____
b. No barriers
c. Don't Know
d. Refuse

WINTER STORM URI

In February 2021, a series of winter storms lead to a week of challenges that included below-zero temperatures, record-breaking electrical demand, rolling blackouts and power failures, and a number of other challenges, such as burst pipes and flooding in homes.

Q42. **Due to the winter storms, did you or anyone in your household experience any of the following?**
Check all that apply

a. Loss of electrical power

b. Loss of heat
c. Had pipes burst in the home
d. Had flooding in the home
e. Had difficulty accessing water
f. Had difficulty accessing food
g. Had a decrease in income or reduced work hours
h. Moved/considered moving
i. More stress
j. None of the above
k. Don't Know
l. Refuse

Q43. **Due to the winter storms, have you or anyone in your household sought or obtained any of the following?**
Check all that apply

a. Physical health services
b. Mental health services
c. Utility or energy assistance
d. Financial help
e. Food assistance
f. Assistance with home repairs
g. Alternative accommodations (e.g., hotel, shelter, friend or family's home)
h. Warming centers
i. Help from a neighbor
j. None
k. Refuse

Q44. **What were the barriers, if any, to getting this assistance or receiving services?**
Response is open-ended. If there were no barriers, if the respondent doesn't know, or if the respondent refuses to answer, check the appropriate box. (Provide examples if requested: didn't know where or how to obtain the service, couldn't afford it, didn't have the transportation to get there)

a. Barriers: ______________________________
b. No barriers
c. Don't Know
d. Refuse

DEMOGRAPHICS

Q45. **How old are you?**
Enter in years, leave blank if participant prefers not to answer

____

Q46. **How many people in your household are…**
Leave blank if participant prefers not to answer

a. Less than 5 years old ______________________________

b. 5-17 years old ____
c. 18-65 years ____
d. Over 65 years ____

Q47. **Is anyone in your household active military or a veteran of the US armed forces?**

a. Yes
b. No
c. Prefer not to answer

Q48. **What gender are you?**

Check all that apply

a. Female
b. Male
c. Non-binary
d. I prefer not to answer

Q49. **What is your highest level of educational attainment?**

a. Less than high school diploma
b. High school diploma or equivalency
c. Some college but no degree
d. Associate degree in college (2-year)
e. Bachelor's degree in college (4-year)
f. Graduate degree
g. Prefer not to answer

Q50. **What race and ethnicity does your household identify with?**

Check all that apply

a. American Indian/Alaska Native
b. Asian
c. Black or African American
d. White
e. Native Hawaiian or other Pacific Islander
f. Hispanic or Latino
g. Any other race or ethnicity I may not have mentioned? (*please specify*)____
h. Don't Know
i. Refuse

Q51. **In which range is your annual household income?**

a. Less than $20,000
b. $20,000 to $34,999
c. $35,000 to $49,999
d. $50,000 to $74,999
e. $75,000 to $99,999
f. $100,000 to $149,000
g. $150,000 or above

h. Prefer not to answer

Appendix E
Author Biographies

Courtney Thompson is an associate program officer in the Gulf Research Program's Health and Resilience Board. Dr. Thompson comes to the National Academy of Sciences from College Station, Texas, where she worked for 5 years as an assistant professor in geography at Texas A&M University. Her expertise is in human-environment geography, focusing on understanding relationships between social systems and disaster impacts using mixed methods, including geographic information systems (GIS), interviews, survey analysis, and spatial statistics. Her research portfolio includes quantifying how social structuration and multiscalar factors influence the vulnerability and resilience of coastal communities, measuring how populations' exposure to compounding disasters affects vulnerability, perceptions of risk, and risk reduction behaviors over time and space, and understanding inequities in environmental justice communities in Texas. Dr. Thompson received her Ph.D. in geography from the University of Idaho. She also holds an M.S. in geography from the University of Idaho and a B.S. in geography, as well as minors in GIS and geology from New Mexico State University.

Francisca Flores is a program officer in the Gulf Research Program's (GRP's) Health and Resilience Board. Prior to joining the GRP, she worked in the Policy and Global Affairs division with the Resilient America Program, where she engaged diverse stakeholders from communities in Georgia, Maryland, Mississippi, Texas, and Virginia to explore aspects of community resilience to flood-related disasters in order to better understand risk perception, risk communication, and risk behaviors throughout the disaster cycle—before, during, and after flooding events. Before joining the National Academies, Dr. Flores was a consultant for the World Health Organization (WHO), where she was involved in pioneering human security as a novel strategy for the public health efforts of WHO member states in Central America and the Dominican Republic. Specifically, she focused on developing a methodology for enhancing health and human security through the building of community resilience. Dr. Flores received her M.P.H. and Ph.D. in behavioral and community health sciences and completed certificate programs in community-based participatory research and global health from the University of Pittsburgh Graduate School of Public Health. Her dissertation research engaged a diverse group of stakeholders in exploring community resilience against gang violence and its harmful effects on adolescents, their families, and the community as a whole.

Laila Reimanis is a research associate in the Gulf Research Program's Health and Resilience Board. Prior to the National Academies, Ms. Reimanis worked with the Earth Law Center as a communication and outreach associate focusing on ocean rights in Puget Sound. She has also lived and worked in Thailand as an English teacher. Ms. Reimanis received a B.S. in environmental and ecosystem sciences and a B.A. in philosophy from Washington State University, and a master of health sciences in environmental health from the Johns Hopkins University Bloomberg School of Public Health with certificates in risk sciences and public policy, and climate and health.

Appendix F
Committee Biographies

Dr. Scott Hemmerling (Chair) is a senior research scientist at the Water Institute of the Gulf. A cultural geographer with more than 20 years of experience investigating the impacts of environmental change on coastal communities, Dr. Hemmerling's recent work is focused on developing approaches to incorporate local knowledge into assessments of community resilience and quantifying the social value of ecosystem restoration projects. He is principal investigator on the Louisiana Coastal Atlas project, a geographical study examining the effects of historical social, economic, and environmental stresses on community resilience. Dr. Hemmerling is also working on several projects to develop methodological approaches for measuring socioeconomic change in coastal communities, including a social impact assessment methodology for coastal restoration projects and a human-systems monitoring plan as part of Louisiana's System-Wide Assessment and Monitoring Program (SWAMP). Most recently, he has developed approaches for incorporating local knowledge into assessments of community resilience and quantifying the social value of ecosystem restoration projects. Dr. Hemmerling earned his doctoral degree from the Department of Geography and Anthropology at Louisiana State University, a master of science in urban studies with a concentration in applied urban anthropology from the University of New Orleans, and a bachelor of science in environmental studies with a minor in physical geography from the State University of New York at Buffalo.

Dr. Philip Berke is a research professor of land use and environmental planning at the University of North Carolina at Chapel Hill. His work focuses on the relationship between community resilience and urban planning, specifically methods, theory, and metrics of local planning and outcomes. He is lead coauthor of an internationally recognized book, *Urban Land Use Planning* (University of Illinois Press, 5th edition, 2006), which focuses on integrating principles of sustainable communities into urban form; he is also coauthor of a book, *Natural Hazard Mitigation: Recasting Disaster Policy and Planning*, which was selected as one of the 100 Essential Books in Planning of the 20th Century by the American Planning Association Centennial Great Books. Dr. Berke's current research focuses on developing the Plan Integration for Resilience Scorecard. The aim is to better understand interactions among networks of policy institutions, networks of land use and development plans produced by such institutions, and social and physical vulnerability to hazards and climate change. Application of the Scorecard is currently funded by the U.S. Department of Homeland Security and the National Science Foundation to assist cities in the United States and the Netherlands to improve urban resilience planning. Dr. Berke currently serves on multiple advisory boards, including the Urban Institute's Global Evaluation of the Rockefeller Foundation Global 100 Resilient Cities, the National Science Foundation's Social Science Extreme Events Reconnaissance Platform, and the Planet Texas 2050 Technical Advisory Board of UT-Austin.

Dr. Patrick Jones is the executive director of the Institute for Public Policy & Economic Analysis at Eastern Washington University. His past and present professional and volunteer work includes serving as executive director of the Biotechnology Association of the Spokane Region, chair of the St. Luke's Rehabilitation Institute community advisory board, member of the Spokane Economic Development Council, chair of the Spokane Entertainment Arts & Convention Advisory Board, member of the board of the Association of University Business & Economic Research Bureaus, and board member of the Spokane Convention and Visitors Bureau. He is currently chair of the City of Spokane Mayor's Advisory Council on Economic Vitality and was recently inducted into the Spokane Hall of Fame. Dr. Jones has a Ph.D. in applied and agricultural economics from the University of Wisconsin–Madison.

Dr. Brooke Lui is an associate dean for academic standards and policies and ADVANCE professor in the College of Information Studies at the University of Maryland. Her qualitative and quantitative research investigates how government messages, media, and interpersonal communication can motivate people to respond successfully to and recover from hazards. Much of her recent research focuses on tornado risk communication, crisis narratives, and other message strategies. Dr. Liu's research has been funded by government agencies such as the Defense Advanced Research Projects Agency, the Department of Homeland Security, the National Science Foundation, and the National Oceanic and Atmospheric Administration. She has published more than 60 journal articles and book chapters. Additionally, Dr. Liu is cofounder and editor of the first journal dedicated to crisis and risk communication research: the *Journal of International Crisis and Risk Communication Research*.

Dr. Michelle Meyer is the director of the Hazard Reduction and Recovery Center, assistant professor of landscape architecture and urban planning, and community resilience lead for the Institute for Sustainable Communities at Texas A&M University. Her research interests include disaster resilience and mitigation, climate change displacement, environmental sociology, community sustainability, and the interplay between environmental conditions and social vulnerability. Dr. Meyer has worked on various research projects, including disaster risk perception, social capital in disaster resilience, organizational energy conservation, volunteer training program evaluation, evaluation of disaster response plans for individuals with disabilities, social media use among vulnerable populations, how to increase protective action knowledge in Haiti, citizen science protocols for measuring stormwater condition equity, and environmental attitudes and behaviors. She collaborates regularly with nonprofit organizations on applied research, including t.e.j.a.s. (Texas Environmental Justice Advocacy Service), GeoHazards International, local long-term recovery organizations, and the Louisiana Environmental Action Network, as well as with high school students. She implements mechanisms for undergraduate and graduate student involvement in research that supports their education and helps communities become more resilient. Dr. Meyer received her Ph.D. and master's from the Department of Sociology at Colorado State University and her B.A. from Murray State University.

Dr. Diana Mitsova is an associate professor in the School Urban and Regional Planning and director of the Visual Planning Technology Lab at Florida Atlantic University. She joined the School of Urban and Regional Planning in August 2008. Dr. Mitsova's research focuses on using geographic information systems and spatial and statistical analysis to conduct interdisciplinary research to understand the interactions between ecosystems and urban environments and inform sustainable urban planning and environmental practices. Her collaborations include projects with the U.S. Geological Survey, the National Park Service, The Nature Conservancy, and the Harbor Branch Oceanographic Institute. Her recent publications focus on the impact of sea level rise on coastal communities and the implementation of planning approaches related to enhancing shoreline stabilization and coastal resilience. Dr. Mitsova also has a long-standing interest in understanding the impact of urban development on ecosystems and other environmentally sensitive areas. Her work focuses on identifying the functional boundaries of such areas and methods of incorporating them in land use planning in order to minimize the formation of stormwater runoff and protect water resources against sedimentation, nutrient enrichment, and contamination. She received a Democratic Institutions Research Fellowship from the North American Treaty Organization; worked as a research assistant at the Center for Urban Policy and the Environment in Indianapolis, Indiana; and was program director I/ research analyst with the State of Indiana. Dr. Mitsova holds a Ph.D. in regional development planning from the University of Cincinnati, and a master's from the School of Public and Environmental Affairs at Indiana University-Purdue University Indianapolis.

Dr. Hal Needham is the founder and president of Marine Weather and Climate, a company that works with communities to improve resiliency from coastal hazards. In addition, he serves as director for the U-Surge Project (www.u-surge.net), an initiative to provide the first data-driven storm surge and sea level rise analyses for coastal communities. Dr. Needham has worked extensively along the Gulf Coast over the past decade and has provided insights into flood risk during disasters such as Hurricane Harvey. He developed an interest in flood impacts on historic preservation during his tenure as director of the Center for Coastal Heritage and Resiliency at Galveston Historical Foundation. Dr. Needham has an M.S. and Ph.D. from Louisiana State University and a B.S. from The Pennsylvania State University.

Dr. Monica Schoch-Spana is a senior scholar with the Johns Hopkins Center for Health Security and senior scientist in the Department of Environmental Health & Engineering at the Johns Hopkins University Bloomberg School of Public Health. She also holds faculty positions at the Department of Anthropology at Texas State University and the National Consortium for the Study of Terrorism and Responses to Terrorism. Dr. Schoch-Spana's areas of expertise include community resilience to disaster, public engagement in policy making, crisis and risk communication, and public health emergency preparedness. She has led research, education, and advocacy efforts to encourage authorities to enlist the public's contributions in epidemic and disaster management. Her studies have been influential in debunking myths about mass behaviors in the context of bioterrorism, reframing the management of catastrophic health events to include social and ethical-moral dimensions, and persuading leaders to share governance dilemmas with the public, including how to allocate scarce medical resources in a disaster. Dr. Schoch-Spana received her Ph.D. in cultural anthropology from Johns Hopkins University (1998) and a B.A. from Bryn Mawr College (1986).

Dr. Larry Weber is the Edwin B. Green chair, hydraulics and executive associate dean in the College of Engineering at the University of Iowa. His research interests broadly focus on fish passage facilities, physical modeling, river hydraulics, hydropower, computational hydraulics, and ice mechanics. Specifically, he focuses on the design of fish passage facilities by combining hydrodynamic data and biological data on fish response. Dr. Weber and his team apply computational fluids dynamics codes to natural river reaches and hydraulic structures to develop detailed fish passage facilities design. From 2004 to 2017, he was director of the Iowa Institute of Hydraulic Research—Hydroscience & Engineering at the University of Iowa, a world-renowned research institute focusing on education, research, and public service in hydraulic engineering and fluid mechanics. In 2009, he became one of the cofounders of the Iowa Flood Center. Dr. Weber serves the State of Iowa as a member of the Water Resources Coordinating Council and numerous other state and federal agency committees related to water resources planning. In addition, he frequently presents to community groups on water resources–related topics.