Investigating Social Vulnerability in Flood Prone Areas

By
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Abstract

Flooding is a deadly and expensive natural disaster. In the United States, the Federal Emergency Management Agency's (FEMA) National Flood Insurance Program (NFIP) provides federal flood insurance, on a property-by-property basis, to residents to reduce the burden of addressing damage and property losses after a flood event. Despite this mission, in many regions of the country flood risk mapping is sparse, outdated, or undercounts the number of properties exposed to the 100-year floodplain. In addition, housing type and other sociodemographic factors can impact the ability to prepare for and adapt to natural hazard events. This study uses a high-resolution flood risk data set, FEMA undercounts and bivariate Local Indicators of Spatial Association (LISA) models, to identify areas where high flood risk and a high proportion of properties are unaccounted for by FEMA. Then regression modeling is used within four high flood risk subregions (the Pacific Northwest, Central Appalachia, the Gulf Coast, and the Southeast Atlantic Coast), to identify socially vulnerable communities in flood-prone areas. The results illustrate that undercounted regions by FEMA coincide with high flood risk and that in large swaths of the four regions socially vulnerable communities will face unprecedented challenges. In all four regions, some housing types, especially mobile homes and multifamily units correlate with high flood risk. In Appalachia, a region where FEMA systematically undercounts properties, poverty and lack of vehicle access correlate with high flood risk. These findings align with previous flood vulnerability studies yet provide a more detailed analysis of regional differences in communities vulnerable to flooding. We also identify pathways in these subregions to reduce the procedural injustice associated with the NFIP.

Acknowledgements

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1. Introduction

Over the last three decades, flooding events have caused the second-highest number of weather-related fatalities in the United States (Smith, 2022). Apart from the detrimental loss of human life, these events can result in severe and costly destruction to society by damaging infrastructure, residential property, and agriculture. Between 1980 and 2021, for example, the National Center for Environmental Information (NCEI) reported that non-tropical cyclone-related inland flooding has resulted in 624 fatalities and over $164.2 billion in damages (Smith, 2022). These ravages suggest that climate adaptation strategies should consider not only the historic frequency and destruction of flooding but how these trends are shifting across the United States. Moreover, future climate scenarios predict an increase in inland flooding along with an increased intensity of hurricanes and heavy downpours in the United States that, in turn, are expected to escalate potential damage (Lall et al., 2018; Mudd et al., 2014; Wobus et al., 2017).

The Federal Emergency Management Agency's (FEMA) National Flood Insurance Program (NFIP) is the current flood protection program set in place by the US federal government to provide insurance and encourage the development and adoption of flood risk mitigation projects in US communities (Federal Emergency Management Agency, 2020). A key aspect of FEMA's NFIP is the development of flood insurance rate maps (FIRM) which outline flood risk zones in a community, such as the Special Flood Hazard Area (SFHA). The SFHA indicates areas with a 1-percent annual chance of flooding, also known as the 100-year floodplain. For communities participating in the NFIP, all properties backed by a federal mortgage must acquire flood insurance (Federal Emergency Management Agency, 2020). Furthermore, homeowners and renters in communities with an NFIP also have the option of acquiring federal flood insurance.

Despite the FEMA NFIP serving as a mechanism to minimize financial losses due to flood damage, the quality and accuracy of FEMA FIRM maps are inconsistent across the US, particularly in non-coastal regions and within "lower-order" stream networks (Bates et al., 2021; Woznicki et al., 2019). In response to the limitations of the NFIP and other national-level flood risk maps, a recent flood risk data set was created by the non-profit research and technology group First Street Foundation which incorporates fluvial, pluvial, and coastal flood risk into property-level flood risk assessment (First Street Foundation, 2020b). Previous studies have found that ~11 million people live within the FEMA 100-year floodplain (Huang & Wang, 2020) and First Street's improved modeling has found that nearly 6 million at-risk households are unaccounted for in FEMA's estimated bounds (First Street Foundation, 2020a). While Huang & Wang, (2020) identified no racial bias in FEMA's 100-year floodplain and found that other open-source floodplain models tend to underestimate the exposure of Black residents and overestimate the exposure of white residents, none of these models incorporate information about the depth of flooding a property may experience (Huang & Wang, 2020). To remedy this, our analysis focuses on the risk of experiencing at least 15 cm of flooding in order to identify areas that may experience more damage due to deeper flood waters entering their homes. According to the National Flood Services, 2.5 cm of flooding can potentially result in $26,807 of combined damages to the home and personal property but 15 cm of flooding can potentially result in $52,037 of combined damages (Federal Emergency Management Agency, 2019). This is particularly pressing since 15 cm of flooding is expected to affect socially vulnerable populations across the country who will bear a disproportionately heavier cost and have limited capacity to rebound.

Social vulnerability to flooding, and natural hazards more generally, is defined as "the sensitivity of a population to natural hazards and its ability to respond to and recover from the impacts of hazards" (Cutter & Finch, 2008). While the application of the word "vulnerability" to communities based merely on demographic metrics can be contentious (Haalbloom & Natcher, 2012), we find that this term allows us to consider the varying components that may contribute to a community's risk. Understanding the social vulnerability of US residents to flooding can inform how well we can prepare for and adapt to the current and future risk of flooding. Given the potential financial and mental health impacts of flood events (Lowe et al., 2013), several studies have focused on understanding the vulnerability of US residents to flooding. Researchers have leveraged FEMA's existing FIRM maps (Qiang, 2019; Remo et al., 2016), alternative 100-year floodplain products (Huang & Wang, 2020), and others have used more advanced, higher resolution models that encapsulate the different components of flood risk in the United States (Tate et al., 2021). In these efforts, it was found that a higher prevalence of mobile homes, Black residents, and Native American residents were correlated with high flood risk in socially vulnerable areas in the United States (Tate et al., 2021). Furthermore, it has also been found that in the future, the risk of flooding will remain concentrated along the Atlantic and Pacific Coasts but will increase in areas where Black communities currently live (Wing et al., 2022). This is expected since mounting research has shown that low-income and minority residents are more likely to move into high-risk zones (Bakkensen & Ma, 2020). Due to this, there is a great need to pinpoint the places in the US where the greatest flooding is likely to occur. Continued efforts to do so can help ensure that mitigation and adaptation efforts meet the specific needs of current and future flood zone inhabitants.

Despite the general relationship between social vulnerability and resilience to natural hazards, this relationship is not experienced in the same way in all regions of the US (Bergstrand et al., 2015). It is therefore essential to leverage the power of big data and spatial analyses to examine important relationships and to map and quantify climate-related risks for vulnerable populations. In this study, we will answer two research questions:

1. Where do areas of high flood risk and high FEMA underestimation co-occur?
2. Are there socially vulnerable populations in these high-risk regions and how do the characteristics of communities in these regions vary geographically?

We use flood risk data on approximately 142 million buildings across the contiguous United States (CONUS) to estimate flood risk at the census tract-level as well as the proportion of properties in each county unaccounted for in FEMA's SFHA. We also identify hotspots of FEMA undercount and flood risk using spatial clustering models. With this information, we select two major hotspots and combine it with two coastal areas of high flooding risk. We then use a suite of sociodemographic variables and regression modeling to examine the spatial correlation of risk and social vulnerability and to understand the specific sociodemographic factors that impact the risk of exposure to flooding following Tate et al (2020).

Our models indicate that housing type correlates with flood risk in all four regions. In addition, we find that vulnerable communities will face unprecedented challenges due to flooding and FEMA omissions. We highlight where exactly segments of the population face elevated risks and their specific attributes that need attention. Such an analysis is expected to guide policymakers and emergency planners to respond to the unique needs and cultures of vulnerable communities. While our findings coincide with existing studies, we anticipate that using data at a higher spatial resolution, would augment neighborhood-level vulnerability assessment and provide a more nuanced understanding of vulnerability to flooding across the US.

2. Data & Methods

2.1 Flood risk data

This study utilizes flood risk data produced by the First Street Foundation. The First Street Foundation Flood Model estimates the probability of flooding from fluvial, pluvial, coastal, and storm surge flood risk for ~142 million properties across the contiguous 48 states (First Street Foundation, 2020a). Using 1980-2010 as a baseline, the model analyzes multiple environmental possibilities under greenhouse gas emission scenarios with high, medium, and low uncertainty bounds. The output stems from an ensemble of 21 Global Circulation Models (GCM) to account for uncertainty. Where possible, this dataset also accounts for the increased stormwater infiltration rates caused by the implementation of both grey and green infrastructure projects (First Street Foundation, 2020b). This helps supplement the hydraulic characteristics derived from natural streamflow alone and better depicts local adaptation strategies. First Street Foundation's flood risk dataset has been leveraged in recent flood risk assessments (Rhubart & Sun, 2021; Wing et al., 2022) and has been found to have greater coverage than the FEMA FIRM model (Bates et al., 2021)

We downloaded the flood risk data through First Street Foundation's Probability API (version 1.2.0) using Python. This dataset provides the likelihood of flooding at the property level for every five years between 2020 and 2050, at three different thresholds, and under three different emissions scenarios. For this study, we did not look at future risks and focused on the 2020 estimates. Due to our interest in regions currently exposed to high flood risk, we focused specifically on flood risk at or below the 15-centimeter threshold in 2020 under the "mid" scenario of the RCP 4.5 emissions curve.

After downloading the data we then geocoded the location of each property using the coordinate pairs listed for each record and projected the derived point layers into a common projected coordinate system (WGS 84/Pseudo-Mercator). This projection was selected to align with the sociodemographic data used in this analysis. Since area calculations were not utilized in this assessment, the results were not distorted as would be expected by using the Pseudo-Mercator projection on the national scale. To convert the data into a continuous surface across the study area, we used the Multilevel B-spline algorithm (Lee et al. 1997) to spatially interpolate the flood risk values. This resulted in 100-meter spatial resolution raster surfaces for every state in the CONUS. We then merged the raster surfaces (n = 49) into a continuous raster surface covering the entire CONUS. Finally, we calculated the average 2020 flood risk at the census-tract (n = 72,338) and county (n = 3,170) levels across the study area, using zonal statistics (Figure 1).

To identify discrepancies between the FEMA Special Flood Hazard Area and the 100-year floodplain, based on the First Street Flood Factor model, we utilized a publicly available dataset from First Street Foundation's Zenodo data repository. This dataset provides summary statistics for First Street's Flood Factor Model (version 1.3), such as counts of the number of properties within a given flood zone and aggregates the data to several jurisdictional levels for comparison with FEMA's SFHA (First Street Foundation, 2021).

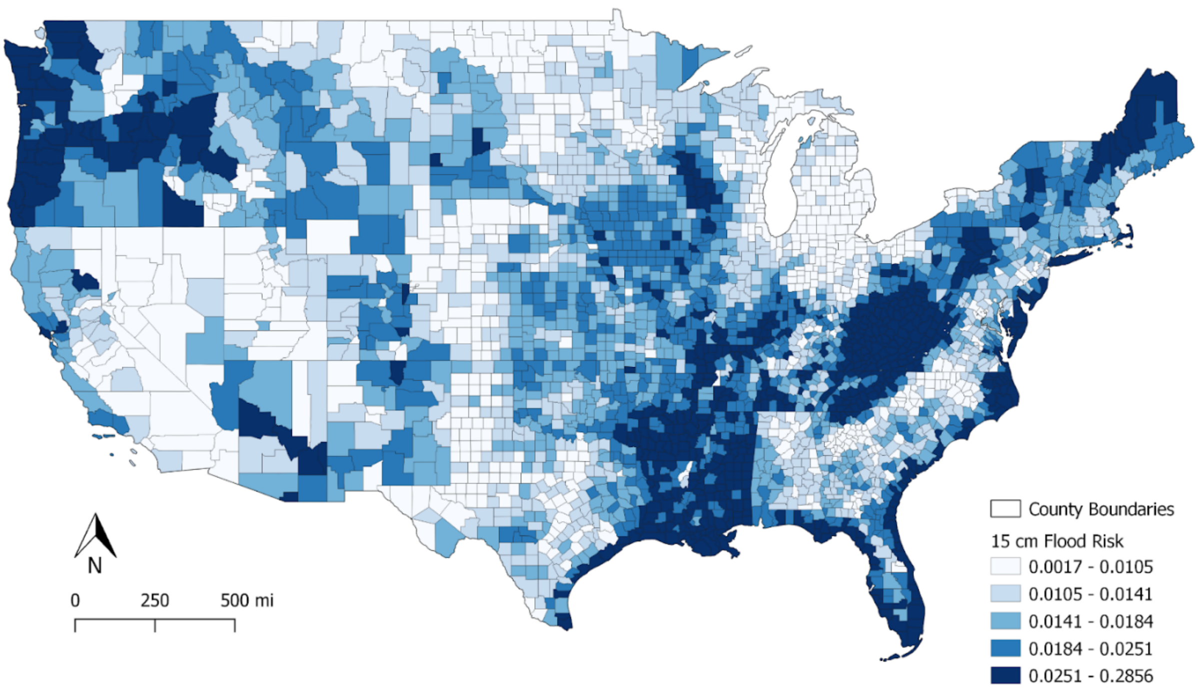

Figure 1. Estimated 15-centimeter flood risk for CONUS in 2020 under the medium emissions trajectory of the RCP4.5 curve. Highest flood risk is noticeable along the coasts, as well as hotspots in the Pacific Northwest, Appalachia, and the southern portion of the Mississippi River Basin.

2.2 Socio-demographic data

In the natural hazard vulnerability literature, multi-level socioeconomic data, gathered by the U.S. Census Bureau serve as a comprehensive and authoritative dataset on understanding sensitivity across the United States. As such, the census tract-level socioeconomic variables selected for this study were primarily selected due to their use in the Center for Disease Control's Social Vulnerability Index (CDC SVI) and the Social Vulnerability Index (SoVI) created by Cutter et al. (2003). SoVI incorporates a variety of socioeconomic variables that reflect the ability of communities to prepare for and respond to a natural hazard event. Rufat et al. (Rufat et al., 2015) have noted that these common socioeconomic variables, such as age or vehicle ownership, may contribute differently to sensitivity at different phases of a flood event. To be more comprehensive, we also included two variables used in the Census Bureau's 2019 Community Resilience Estimates, access to broadband internet and access to health insurance. These variables are included in our model as they contribute more information about how well a community can endure and rebound from a disaster event, however, we merely analyze these variables at the census tract-level rather than using small area estimation techniques (Small Area Estimates Program, U.S. Census Bureau, 2021).

All variables used in this study were selected from the 2014-2018 American Community Survey (ACS) 5-Year Estimates (Table 1 in SI). Given that census tracts across the country are not equal in terms of the total population, a simple calculation of ratios would cause bias to our estimates. To adjust the socio-demographic data, originally expressed in population counts, into a common scale, we first divided the total population of each census tract by 1,000. We then divided each variable by the normalized total population (Tascón-González et al., 2020). This process resulted in normalized rates per census tract for each variable.

2.3 Spatial analysis

Our first research question focused on identifying clusters of counties with high flood risk in 2020 that also had a high proportion of properties that FEMA did not include in the SFHA. These properties that were not included in FEMA's SFHA but were identified by the First Street Foundation as being within the 100-year floodplain will be referred to hereafter as "undercounted properties". To locate significant clusters of high risk and undercounted properties by FEMA, we used the Local Indicators of Spatial Association (LISA) modeling with neighbors weighted based on the first-order Queen's rule of adjacency (Anselin, 1995). For the analysis, we used a 0.005 significance level, and the queen contingency was set to 5. The model identified the significant bivariate clustering of counties based on the 2020 flood risk and the proportion of properties that were undercounted by FEMA.

2.4 Selecting subregions

Our overarching objective was to identify spatial clusters of FEMA underestimation and high flood risk and to examine whether those clusters, and other high flood risk areas in the CONUS, are home to socially vulnerable populations. To do so, first, we calculated the 80th

percentile of county-level flood risk across CONUS. From there, we selected all counties in the study area with a flood risk at or above the 80th percentile (n=622). Through the LISA analysis, we identified two "hotspot" clusters of high property undercount and high flood risk in the Pacific Northwest and Appalachia. We also selected two high flood risk regions along the Gulf and Atlantic coasts for comparison. Parts of these coastal regions were also found to be among the most flood-exposed habitable areas in the CONUS (Tate et al., 2021). Ultimately, we identified four distinct groupings of high-risk counties across the study area: the Pacific Northwest (n=45), Central Appalachia (n=162), the Gulf Coast (n=45), and the Southeast Atlantic Coast (n=28) (Figure 2).

The Pacific Northwest was selected as it was found to have a high proportion of properties undercounted by FEMA. It also contained a mixture of coastal and rural, inland counties. These more rural, inland counties may have more socially vulnerable populations such as individuals living in mobile homes, than urban areas. Central Appalachia was also included in this study due to the high proportion of properties undercounted by FEMA and the prevalence of socially vulnerable communities throughout the region. Including regions with high FEMA undercount and away from coasts will provide a comparison of how well FEMA accounts for non-coastal flooding impacts.

Two coastal regions, the Gulf and Southeast Atlantic coasts, were included in the model because they are at high risk of sea-level rise and tropical cyclone-induced coastal flooding which both exacerbate local flood risk (Marsooli et al., 2019; Wing et al., 2022). Unlike the Pacific Northwest and Central Appalachia, the high flood risk properties in the Gulf Coast and Southeast Atlantic Coast were found to be well accounted for by FEMA. Their inclusion in this analysis allows us to compare the make-up of the populations living in the most flood prone areas of the CONUS. By studying these four regions, we can assess if there is a difference in the populations living in high flood risk areas where FEMA undercounts and accurately accounts for property-level risk. For instance, both coastal regions have a greater proportion of racial minorities than the Pacific Northwest (24% of residents identify as a racial minority) and Central Appalachia (7% of residents identify as a racial minority). In the Gulf Coast, 50% of residents identify as a racial minority while in the Southeast Atlantic counties nearly 42% of residents identify as a racial minority. Given this racial diversity, examining these regions can provide insights into the relationship of race, flood risk, and FEMA undercounting.

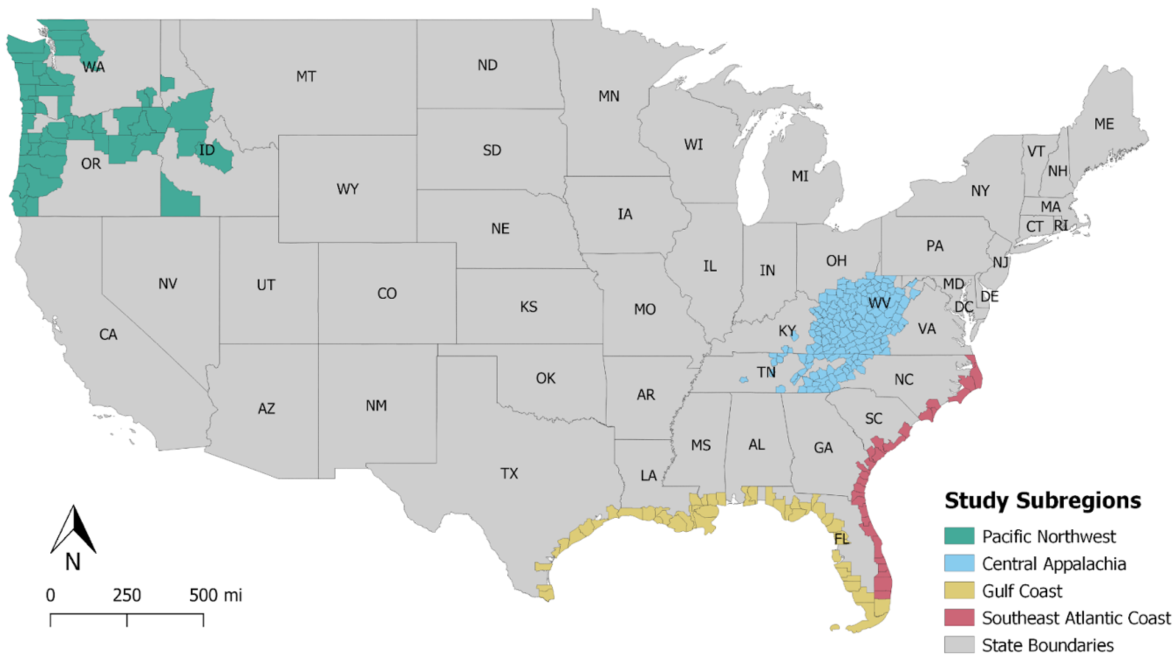

Figure 2. Counties of the four regions analyzed in this study: the Pacific Northwest, Central Appalachia, Gulf Coast, and the Southeast Atlantic Coast.

2.5 Regression models of sociodemographic variables

We ran multinomial regression models to determine which sociodemographic variables were significant predictors of flood risk in each of the four high-risk subregions. We conducted the analysis at the census tract-level for each of the four regions. To minimize skewness we opted to use the weighted least squares regression model using the normalized population as universal weights. To fine-tune the models we started with 17 sociodemographic and resilience variables and manually selected the model with the best fit, reducing the covariates to 11. The Variance Inflation Factor (VIF) was calculated for each model using the *regclass* (v1.6, Petrie, 2020) package in R, to assess multicollinearity between the variables (Thompson et al., 2017). All the factors used in the model have a VIF score less than 5.

3. Results

3.1 Spatial Association of FEMA Undercount and Flood Risk

Figure 3 shows the areas where high FEMA undercounts spatially coincide with the top 20% flood risk according to the First Street models. Our analysis identified two major spatial clusters, the Pacific Northwest and Appalachia as distinct locations with a significant co-occurrence of a high 2020 flood risk and a high percentage of properties excluded from the FEMA SFHA. This finding aligns with previous studies that utilized the high-resolution First Street flood data (Bates et al., 2021; Rhubart & Sun, 2021; Wing et al., 2022). There was not a clear pattern of spatial association between undercounted properties by FEMA and flood risk along the Gulf Coast and the Southeast Atlantic Coast. Most counties in these two subregions have high flood risk but low undercounting by FEMA.

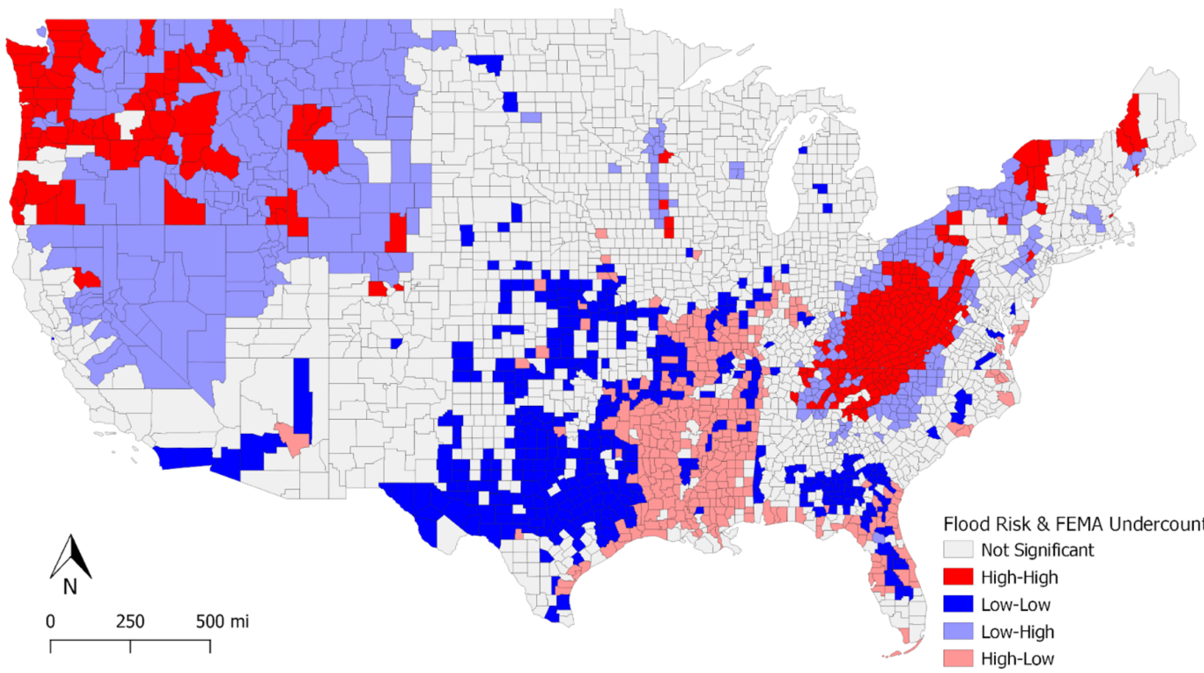

Figure 3. County-level spatial clustering analysis of flood risk and FEMA undercounted properties. High-High denotes high flooding risk coinciding with high FEMA undercounts; Low-Low denotes low flooding risk coinciding with low FEMA undercounts; Low-High denotes low flooding risk coinciding with high FEMA undercounts; High-Low denotes high flooding risk coinciding with low FEMA undercounts.

3.2 Relationship of flood risk and social vulnerability

Applying the regression model to the four subregions, we identified key dynamics between socio-demographics and exposure to flooding. We identified varying inequalities due to housing type in all four regions (Table 2 in SI). Within areas with the highest FEMA undercount, we found tracts within Appalachia with more individuals experiencing poverty who were also more exposed to flood risk, but this was not observed in the Pacific Northwest. On the contrary, we found that higher-income areas were more likely to experience flooding in the two coastal regions. Despite the diversity of significant sociodemographic indicators across the regions, housing type, either whether one lived in a mobile home or multiunit housing, was found to have a significant relationship to flood risk in each of the four regions. The following sections describe the different characteristics of the communities most likely to be affected by flooding in each subregion.

3.2.1 Central Appalachia

Central Appalachia was the only region where educational attainment and poverty are significantly related to residential flood risk and are undercounted by FEMA (Table 1). Specifically our models show that areas with more people without a high school diploma and living below the poverty line will also face higher probabilities of flooding. These hotspots of flood risk and poverty were found in eastern Kentucky, southwestern West Virginia, and a small portion of southwestern Virginia (Fig 4a). Moreover, we found that areas with more people having disabilities live in high risk of flooding. In terms of housing and transportation, we found that areas where more households do not have access to a vehicle are more likely to experience flooding. These areas are found in eastern Kentucky and western West Virginia (Fig 4b). Interestingly, areas with more households lacking broadband internet access are less likely to experience flooding, despite nearly 43% of households in the region not having access to broadband internet (US Census Bureau, 2019). Similarly, areas with more individuals without health insurance, who would be considered “less resilient,” are less at risk of flooding.

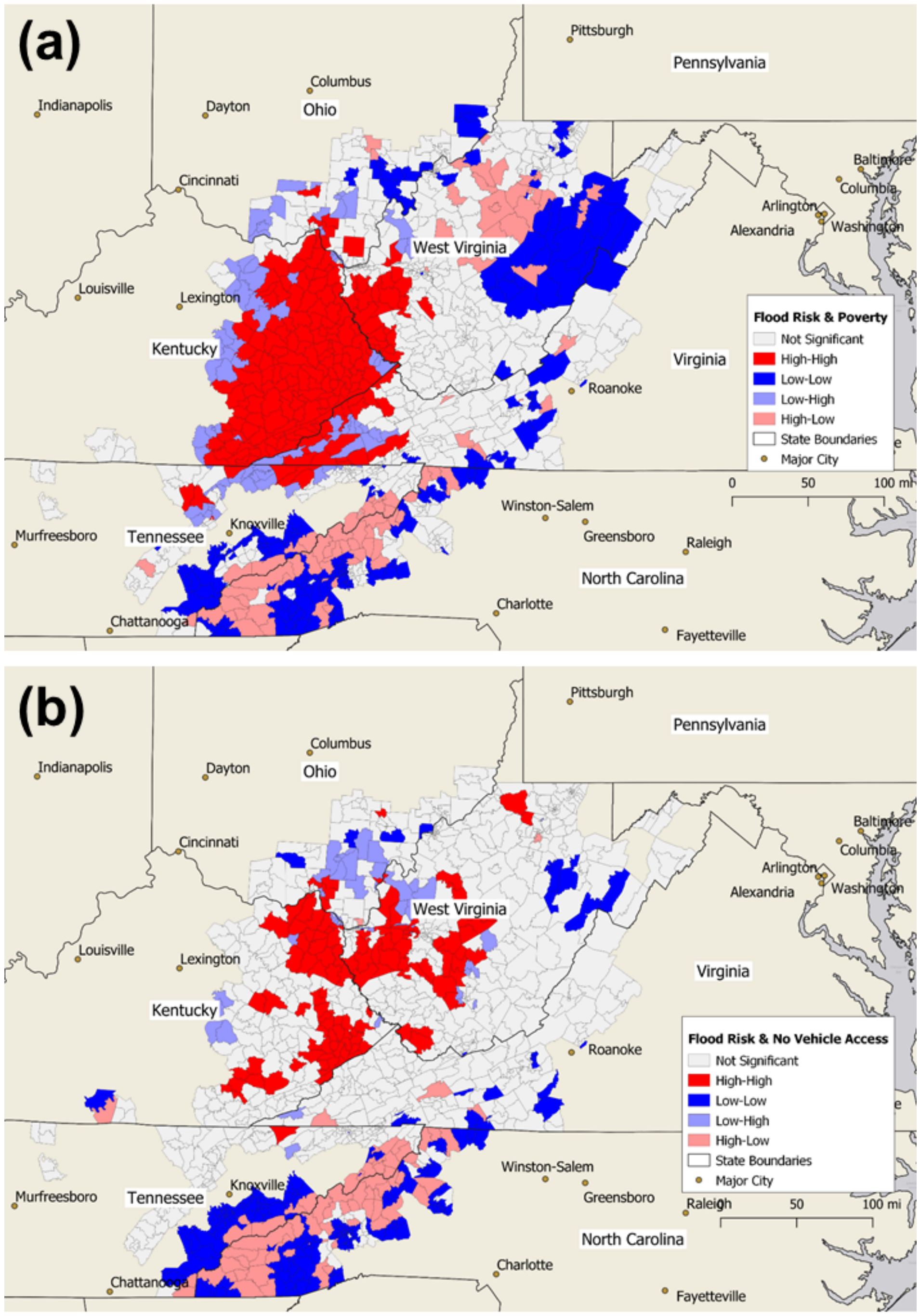

Figure 4. Cluster map of flood risk and vulnerability factors in Central Appalachia. (a) Census tract clusters of flood risk and poverty prevalence. High-High denotes high flooding risk coinciding with high proportion of residents in poverty; Low-Low denotes low flooding risk coinciding with low proportion of residents in poverty; Low-High denotes low flooding risk coinciding with high proportion of residents in poverty, High-Low denotes high flooding risk coinciding with low proportion of residents in poverty. (b) Census tract clusters of flood risk and household vehicle access. High-High denotes high flooding risk coinciding with high vehicle access; Low-Low denotes low flooding risk coinciding with low vehicle access; Low-High denotes low flooding risk coinciding with high vehicle access, High-Low denotes high flooding risk coinciding with low vehicle access.

3.2.2 Pacific Northwest

Our results showed that in the Pacific Northwest, areas where more people identified as minorities are less exposed to high flood risk. In this region, however, only 24.2% of residents identify as racial minorities (US Census Bureau, 2019). Nevertheless, there are still clusters of high flood risk and a high proportion of minority residents in central Washington (Fig 5a). In terms of housing, we found that areas with more mobile homes are also more exposed to flood risk. Clusters of high flood risk and a high proportion of households living in mobile homes were identified in southwest and northeastern Oregon, along Washington’s Pacific Coast, and in central Idaho (Figure 5b). On the contrary, areas with fewer multiunit housing structures are more likely to experience flooding (Table 1). Furthermore, we found that areas where more households did not have broadband internet are more likely to reside in higher flood risk areas.

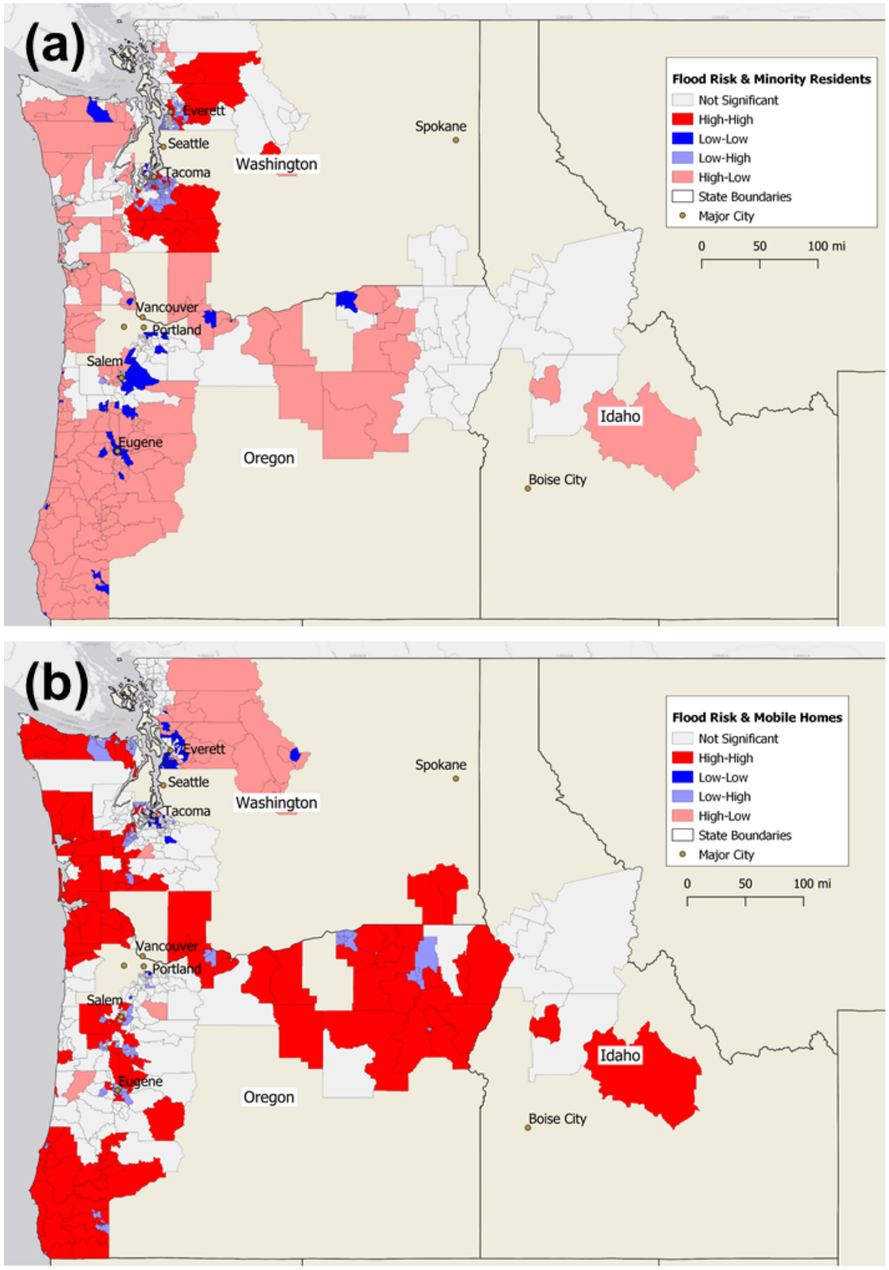

Figure 5. Cluster map of flood risk and vulnerability factors in the Pacific Northwest. (a) Census tract clusters of flood risk and minority residents. High-High denotes high flooding risk coinciding with high proportion of minority residents; Low-Low denotes low flooding risk coinciding with low proportion of minority residents; Low-High denotes low flooding risk coinciding with high proportion of minority residents; High-Low denotes high flooding risk coinciding with low proportion of minority residents. (b) Census tract clusters of flood risk and mobile homes. High-High denotes high flooding risk coinciding with high prevalence of mobile homes; Low-Low denotes low flooding risk coinciding with low prevalence of mobile homes; Low-High denotes low flooding risk coinciding with high prevalence of mobile homes; High-Low denotes high flooding risk coinciding with low prevalence of mobile homes.

3.2.3 Gulf Coast

Within the Gulf Coast region, we found that in areas where individuals earn a higher per capita income there is higher flood risk. This may be due to larger homes being located around scenic water bodies. These areas are found in tracts around Lake Borgne in southeastern Louisiana and southwestern Mississippi, in Vermillion Parish, LA, and the Florida Keys (Fig 6a). The model also revealed that minorities are significantly less likely to experience flooding. This is surprising, as 50% of Gulf Coast residents are minorities, nearly 3.5 times higher than the national average (US Census Bureau, 2019). Interestingly, our models show that areas with more multiunit housing structures are more exposed to flood risk. These areas include Biscone Bay in Miami and in Gulf and Franklin counties along Florida's Forgotten Coast. Like the Pacific Northwest and Central Appalachia, areas with more mobile homes are also more likely to experience flooding (Table 1). Looking at the resiliency factors, access to health insurance is not a significant predictor of flood risk for this region. However, areas where more households do not have a broadband internet connection are more likely to be in flood-prone areas.

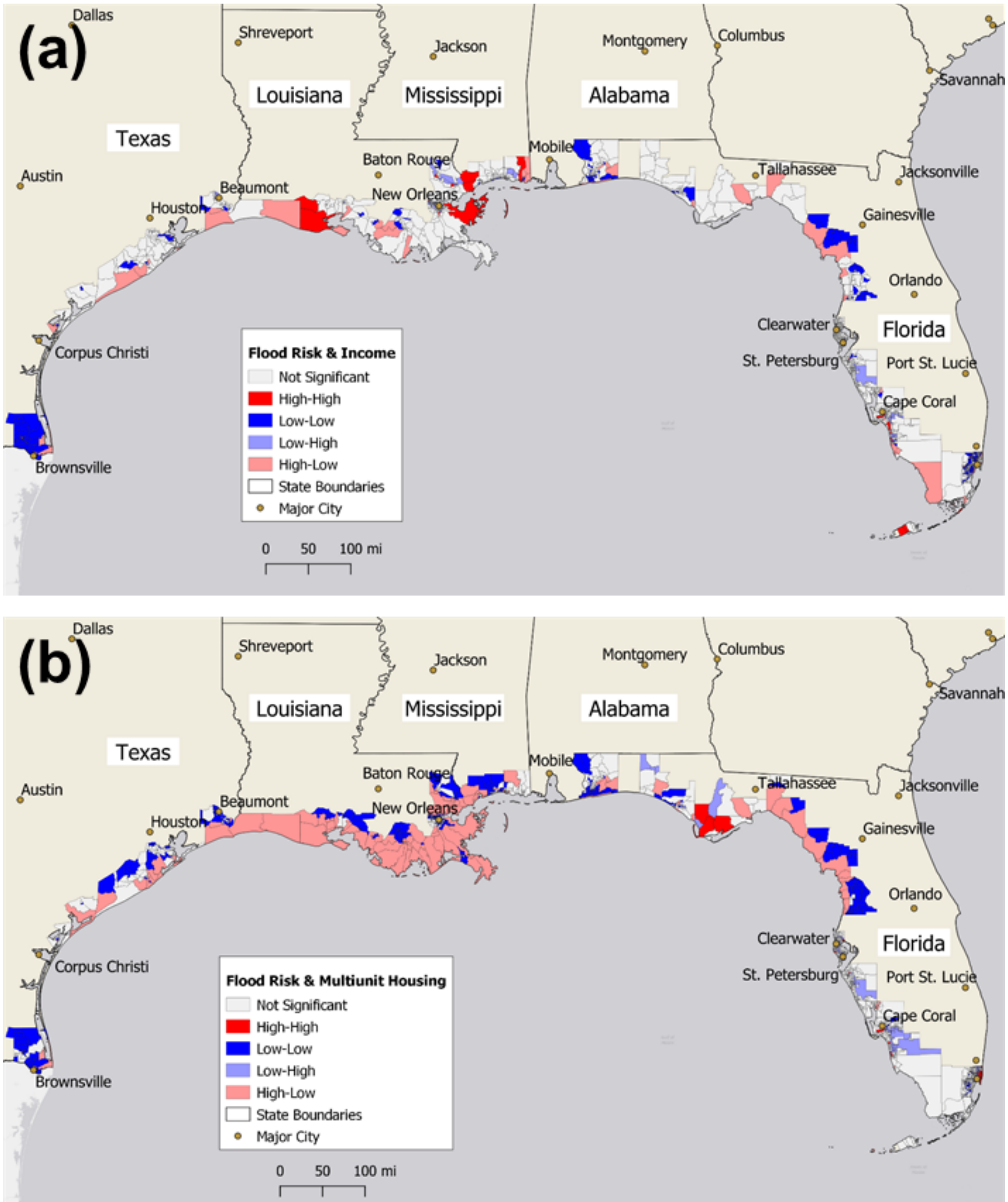

Figure 6. Cluster map of flood risk and vulnerability factors along the Gulf Coast. (a) Census tract clusters of flood risk and per capita income. High-High denotes high flooding risk coinciding with high per capita income; Low-Low denotes low flooding risk coinciding with low per capita income; Low-High denotes low flooding risk coinciding with high per capita income; High-Low denotes high flooding risk coinciding with low per capita income. (b) Census tract clusters of flood risk and multi-unit housing structures. High-High denotes high flooding risk coinciding with high prevalence of multi-unit housing; Low-Low denotes low flooding risk coinciding with low prevalence of multi-unit housing; Low-High denotes low flooding risk coinciding with high prevalence of multi-unit housing; High-Low denotes high flooding risk coinciding with low prevalence of multi-unit housing.

3.2.4 Southeast Atlantic Coast

Similarly to the Gulf coast, along the southeast Atlantic coast, our model shows that higher income residents are at a higher risk of experiencing flooding. This includes communities along North Carolina's southeast coast and in Georgetown County, SC. However, our bivariate model shows that there are also clusters of areas along the southeast Atlantic coast where lower income people experience higher risk (Figure 7a). Areas in the region where more people have a disability are at a lower risk of their homes being flooded. Unlike the three other regions, the prevalence of mobile homes does not give any insight into the likelihood of flooding an area would experience. However, Southeast Atlantic census tracts with more multiunit housing structures are in more flood-prone areas (Figure 7b). One hotspot in Florida was identified in Broward and Palm Beach counties. Lastly, households without broadband internet are also more likely to be exposed to flooding.

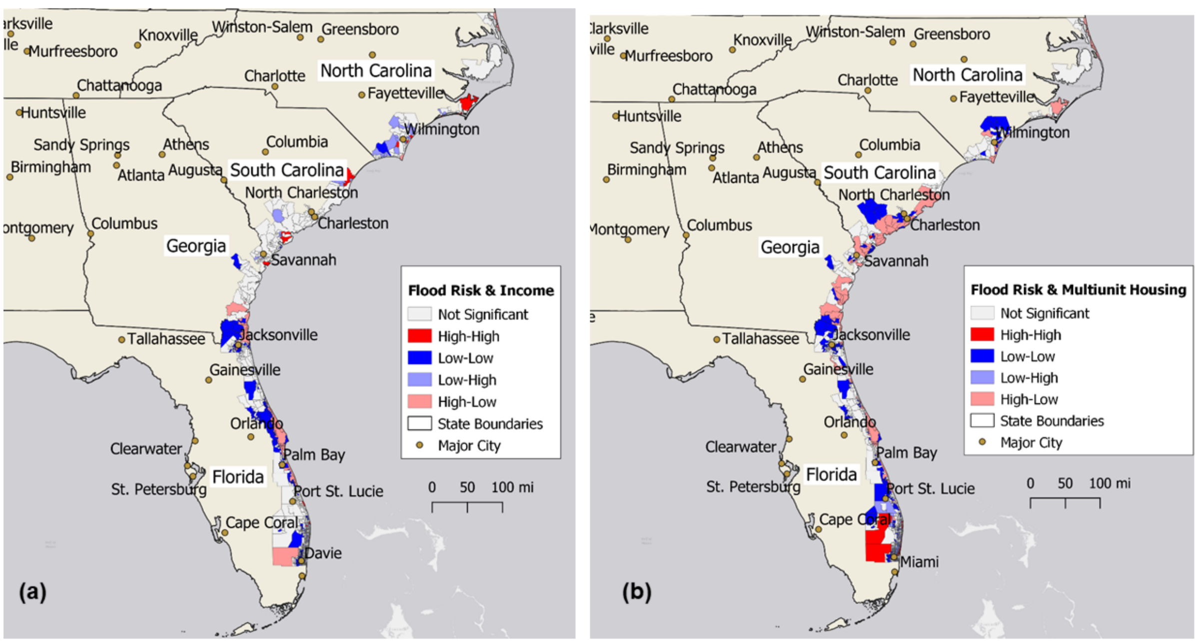

Figure 7. Cluster map of flood risk and vulnerability factors along the Southeast Atlantic Coast. (a) Census tract clusters of flood risk and income. High-High denotes high flooding risk coinciding with high per capita income; Low-Low denotes low flooding risk coinciding with low per capita income; Low-High denotes low flooding risk coinciding with high per capita income; High-Low denotes high flooding risk coinciding with low per capita income. (b) Census tract clusters of flood risk and multi-unit housing structures. High-High denotes high flooding risk coinciding with high prevalence of multi-unit housing; Low-Low denotes low flooding risk coinciding with low prevalence of multi-unit housing; Low-High denotes low flooding risk coinciding with high prevalence of multi-unit housing; High-Low denotes high flooding risk coinciding with low prevalence of multi-unit housing.

Table 1. Multinomial regression model results for the four subregions. The weighted least squares model was used with data at the census tract-level. The total population of the census tract was used as weight. Asterisks indicate significance at: ***p ≤ 0.001, **p ≤ 0.01, *p ≤ 0.05.

		Central Appalachia	Gulf Coast	Southeast Atlantic Coast	Pacific Northwest
Socioeconomics	Below Poverty	0.002961***	0.0003677	0.002495	0.00156
	Unemployed	0.002595	-0.002018	0.01116	-0.001337
	No HS Diploma	0.004657**	-0.001483	-0.002984	0.0001101
	Per Capita Income	0.00002572	0.0000637***	0.00009585***	0.0000121
Household Composition	With Disability	0.005522***	-0.01503***	-0.008851**	0.001652
Minority & Language	Minority (Non-White, Non-Hispanic)	-0.0006623	-0.003894***	-0.006272***	-0.002392***
Housing Type & Transportation	No Vehicle	0.01644***	-0.001738	-0.008683	0.004244
	Mobile Homes	0.01449***	0.009115***	-0.003024	0.004165*
	Multiunit Housing	-0.005481***	0.01248***	0.005279***	-0.004543***
Community Resilience	No Household Broadband Internet	-0.008684***	0.009100*	0.01297***	0.006163***
	No Health Insurance	-0.009624***	0.001783	0.002352	-0.001491
	Intercept	2.064***	4.740***	3.457***	0.87854***
	Adjusted R^2	0.2979	0.1729	0.1955	0.1661

'***' p ≤ 0.001, '**' p ≤ 0.01, '*' p ≤ 0.05

4. Discussion

In our investigation of the first research question, we found that the Pacific Northwest and Appalachia are two hotspots of high flood risk and a large proportion of SFHA excluded properties. Identifying these two areas as having high flood risk aligns with previous studies (Rhubart & Sun, 2021; Wing et al., 2022) that utilized First Street's flood risk data. Beyond being a region with a high proportion of residences excluded from the SFHA, there are 14 communities in high-high clusters in the Pacific Northwest that *are* included in hazard areas but do not participate in the program (Federal Emergency Management Agency, 2022; List B in SI) In Appalachia, there are 48 communities in counties in high-high clusters that do not participate in the NFIP. Not only is the NFIP undercounting at-risk communities in these areas, but many communities that it has identified in the 100-year floodplain are not active participants in the program. This finding poses an opportunity for FEMA to leverage its connections with state, local, and tribal authorities to increase these communities' participation in the program. These non-participating communities are missing out on federal and state investments and may have a lower barrier to entry since they are already identified as at-risk by the agency. It is important to recognize that tools like the Rural Capacity Index have found that communities in these areas of the CONUS may be under-resourced when it comes to the professional staff needed for climate adaptation planning and implementation (Headwaters Economics, 2022). Grants that support not only the project implementation phase but also the planning and discovery phase will be essential for assessing and addressing flood risk needs in these areas. While we did not explore why these communities do not participate in the program, further research into why communities, especially those at risk, choose not to participate will help provide those at risk with the necessary coverage.

In addition to identifying hotspots of high flood risk and high property-level SFHA exclusion, our analysis focused on identifying whether socially vulnerable communities live in flood prone areas. Using the same model to assess the relationship between different sociodemographic variables and flood risk in the CONUS highlighted the difference in the makeup of these communities. Our findings speak to the reality that a "one-size-fits-all" solution to mitigating flood risk is not practical for the entire country. For instance, along the Gulf Coast and along the Southeast Atlantic Coasts, communities with higher incomes were more at risk of flooding yet in Appalachia, higher poverty rates correlated with higher flood risk. On the one hand, the findings in Appalachia align with previous national-level findings that identified high poverty rates as a distinguishing factor high flood risk and high social vulnerability (Tate et al., 2021). However, the notion that wealth is not a valid proxy for flood risk (Kinzer et al., 2021) better describes our findings since we see higher income per capita correlated with flood risk along the coasts. As Kinzer et al. (2021) point out, political "mental maps", or general presumptions held by the public about who lives in floodplains, have guided the policy surrounding the enforcement and reform of the NFIP. Our regression analysis chips away at potential bias in the NFIP by providing additional evidence that both higher-income communities and communities living in poverty are both susceptible to the damages of flooding. This is further supported by the LISA analysis which pinpoints clusters of communities experiencing high flood risk but being at different ends of the sensitivity spectrum (high-high vs. high-low clusters). In 2019, it was found that the average annual flood insurance premium cost was $700 (Federal Emergency Management Agency, 2021). To provide more equitable insurance premiums for policyholders, the NFIP's Risk Rating 2.0 program was phased in during October of 2021 (*Risk Rating 2.0*, 2022). However, 77% of policyholders saw an increase in their premiums (*Options for Making the National Flood Insurance Program More Affordable*, 2021). The federal program focused on "equity in action" does not incorporate a resident's ability to pay for flood insurance into its new metrics. As calls for a means-testing affordability program continue (*Options for Making the National Flood Insurance Program More Affordable*, 2021) and if FEMA strives to address procedural inequalities in the NFIP, this analysis highlights where residents with the highest flood risk and highest financial barriers reside.

The results of our study align with previous findings indicating that the prevalence of mobile homes coincides with high flood risk further indicating the value of tailoring flood mitigation efforts to meet the needs of mobile home residents. Additionally, the prevalence of mobile homes was the only factor with a significant, positive relationship with flood risk in the majority of our study subregions. Past analyses have also found that the prevalence of mobile homes has been linked to flooding vulnerability (Lim & Skidmore, 2019; Rumbach et al., 2020) and assert that it may be driven by the tendency for mobile homes to be sited on lands within floodplains (Rumbach et al., 2020). While there are existing federal flood insurance protections for mobile homes (*Protecting Manufactured Homes from Floods and Other Hazards, A Multi-Hazard Foundation and Installation Guide*, 2009), this finding emphasizes the need for state and county-level mitigation efforts to support the needs of individuals who live in this unique housing structure. For example, a case study of post-disaster recovery from a 2013 flood in Colorado found that a state-run, federally funded program offered to buyout homeowners based on the pre-flood value of their property while mobile home park residents were only offered buyouts based on the post-flood value of their property (Rumbach et al., 2020). As FEMA flood mitigation programs, like the Swift Current, are established with the specific goal of assisting disadvantaged communities who frequently experience flood loss (*Flood Mitigation Assistance Swift Current for Fiscal Year 2022*, 2022) tracking how these funds are allocated within vulnerable communities can limit the perpetuation of procedural injustices.

Furthermore, we found that areas where greater proportions of the population have disabilities in Central Appalachia were more likely to experience flooding. In the American Communities Survey, one may identify as disabled due to hearing, vision, cognitive, ambulatory, self-care, or independent living difficulties (US Census Bureau, 2021). Given this, the ability of individuals to adapt during a flood may vary depending on the nature of one's disability (Alexander, 2015). Disasters can also disrupt access to medical care for individuals with disabilities or impact their ability to evacuate pre-disaster. We cannot disentangle which disabilities individuals in the area may be experiencing based on the ACS. This is primarily due to the level of data aggregation and potential privacy concerns. This hurdle, paired with our findings, highlights a need for emergency management professionals in this region to work with residents and local health care institutions in the area to incorporate flooding adaptation and mitigation strategies focused on residents with disabilities into emergency response plans. Doing so may help meet the unique needs of people with disabilities in Central Appalachia.

Limited by the scope of our flood risk data, we did not assess the intersection of vulnerability and flood exposure in Hawai'i, Alaska, or any United States territories. As our study has shown, the characteristics of the most at-risk communities in the contiguous United States vary spatially. Based on these findings, it is appropriate to assume that similar patterns exist within these outlying states and territories. Future efforts to expand flood vulnerability analyses within these regions provide an additional opportunity to better work with communities in these areas to reduce flooding vulnerability. This is of particular importance as many of these regions are exposed to flooding due to storm surge and sea level rise.

5. Conclusion

This study used high-resolution, flood risk data to identify where residents are excluded from the National Flood Insurance Program's 100-year flood plain. Using bivariate cluster mapping and regressions, we found that the characteristics of the communities in the highest flood risk areas of the contiguous United States vary. Poor communities are more likely to be exposed to flooding in Central Appalachian communities, while wealthier communities are more likely to be exposed to flooding along the coasts. In Central Appalachia, the Gulf Coast, and the Pacific Northwest, mobile homes were positively correlated with flood risk. By considering flood risk as it relates to fluvial, pluvial, and coastal flooding, we uncover a more nuanced, regional understanding of flood vulnerability. Rebuilding connections with at-risk communities and customizing disaster preparedness policies and practices that are inclusive of vulnerable communities will be necessary to reduce the community-level impacts of flooding.

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Supplemental Information

Table 1. Variables used in multinomial linear regression

	Socio-demographic factor	Spatial Resolution	Year	Source
Socioeconomics	Below Poverty Level	Census Tract	2018	CDC Social Vulnerability Index (CDC SVI)
	Unemployed	Census Tract	2018	CDC SVI
	No High School Diploma	Census Tract	2018	CDC SVI
	Per Capita Income	Census Tract	2018	CDC SVI
Household Composition	With Disability	Census Tract	2018	CDC SVI
Minority & Language	Minority	Census Tract	2018	CDC SVI
Housing Type & Transportation	No Vehicle	Census Tract	2018	CDC SVI
	Mobile Homes	Census Tract	2018	CDC SVI
	Multiunit Housing	Census Tract	2018	CDC SVI
Community Resilience	No Household Broadband Internet	Census Tract	2014-2018	American Community Survey (ACS)
	No Health Insurance	Census Tract	2014-2018	ACS

List A. Counties in study subregions

<u>Pacific Northwest</u>

Idaho: Custer, Idaho, Latah, Owyhee, Valley
Oregon: Baker, Benton, Clackamas, Clatsop, Columbia, Coos, Curry, Douglas, Gilliam, Grant, Hood River, Josephine, Lane, Lincoln, Linn, Marion, Polk, Sherman, Tillamook, Umatilla, Union, Wallowa, Wasco, Wheeler
Washington: Chelan, Clallam, Columbia, Garfield, Grays Harbor, Jefferson, Lewis, mason, Pacific, Pierce, Skagit, Skamania, Snohomish, Thurston, Wahkiakum, Whatcom

<u>Central Appalachia</u>

Kentucky: Bath, Bell, Boyd, Breathitt, Carter, Casey, Clay, Clinton, Cumberland, Elliott, Estill, Fleming, Floyd, Greenup, Harlan, Jackson, Johnson, Knott, Knox, Lawrence, Lee, Leslie, Letcher, Lewis, Magoffin, Martin, Menifee, Morgan, Nicholas, Owsley, Perry, Pike, Powell, Rowan, Whitley, Wolfe
North Carolina: Alleghany, Ashe, Avery, Buncombe, Caldwell, Cherokee, Clay, Graham, Haywood, Jackson, Macon, Madison, McDowell, Mitchell, Swain, Transylvania, Watauga, Yancey
Ohio: Adams, Athens, Gallia, Hocking, Jackson, Lawrence, Meigs, Monroe, Pike, Scioto, Vinton, Washington
Tennessee: Anderson, Blount, Campbell, Cannon, Carter, Claiborne, Clay, Cocke, Hancock, Hawkins, Jackson, Johnson, Lewis, Macon, Marion, Meigs, Monroe, Polk, Rhea, Roane, Scott, Sevier, Smith, Sullivan, Unicoi
Virginia: Alleghany, Bath, Bland, Botetourt, Buchanan, Buena Vista, Carroll, Craig, Dickenson, Floyd, Giles, Grayson, Highland, Lee, Montgomery, Norton, Patrick, Pulaski, Rockbridge, Russell, Scott, Smyth, Tazewell, Washington, Wise, Wythe
West Virginia: Barbour, Boone, Braxton, Cabell, Calhoun, Clay, Doddridge, Fayette, Gilmer, Greenbrier, Hardy, Harrison, Jackson, Kanawha, Lewis, Lincoln, Logan, Marion, Mason, McDowell, Mercer, Mineral, Mingo, Monongalia, Monroe, Nicholas, Pendleton, Pleasants, Pocahontas, Putnam, Raleigh, Randolph, Ritchie, Roane, Summers, Taylor, Tucker, Tyler, Upshur, Wayne, Webster, Wetzel, Wirt, Wood, Wyoming

<u>Gulf Coast</u>

Florida: Bay, Charlotte, Citrus, Collier, Dixie, Escambia, Franklin, Gulf, Hernando, Jefferson, Lee, Levy, Liberty, Manatee, Miami-Dade, Monroe, Pinellas, Santa Rosa, Sarasota, Taylor, Wakulla, Walton
Louisiana: Cameron, Iberia, Jefferson, Lafourche, Orleans, Plaquemines, St. Bernard, St. Mary, St. Tammany, Terrebonne, Vermillion
Mississippi: Hancock, Harrison, Jackson
Texas: Aransas, Brazoria, Calhoun, Cameron, Galveston, Jefferson, Kleberg, Matagorda, Willacy

<u>Southeast Atlantic Coast</u>

Florida: Brevard, Broward, Duval, Flagler, Indian River, Martin, Nassau, Palm Beach, St. Johns, St. Lucie, Volusia
Georgia: Camden, Chatham, Glynn, Liberty, McIntosh
North Carolina: Brunswick, Carteret, Currituck, Dare, Hyde, New Hanover, Pender
South Carolina: Beaufort, Charleston, Colleton, Georgetown, Jasper

List B. Communities in high flood risk, high FEMA undercount clusters not participating in NFIP (as of 3/29/2022)

Source: FEMA Community Status Book Report, 3/29/2022

Pacific Northwest

Idaho: City of Plummer, City of Crouch, City of Placerville, City of Franklin, Idaho County, City of Grand View

Montana: Town of Thompson Falls

Oregon: City of Adair Village

Washington: Hoh Indian Tribe, City of Dupont, City of Ruston, Town of Woodway, Town of Northport, City of Tenino

Appalachia

Georgia: Town of Tiger

Kentucky: City of Owingsville, Casey County, Cumberland County, City of Sandy Hook, City of Bellefonte, City of Pippa Pass, City of Blaine, City of Concord, City of Campton, Wolfe County

North Carolina: Town of Mills River

Ohio: Village of West Union, Village of Chauncey, Village of Coolville, Village of Leesville, Village of Conesville, Village of Nellie, Village of Plainfield, Village of Freeport, Village of Batesville, Village of Dexter City, Village of South Salem, Village of Otway, Village of Bolivar, Village of McArthur

Pennsylvania: Borough of Atwood, Township of Burrell, Borough of Elderton, Borough of Ford Cliff, Borough of West Kittanning, Borough of Carmichaels, Township of Lincoln, Borough of Bear Lake, Borough of Cokeburg, Borough of Green Hills, Borough of Long Branch, Township of North Bethlehem

South Carolina: Town of Salem, Town of West Union

Tennessee: Town of Normandy

Virginia: Town of Clintwood, Town of Troutdale

West Virginia: Town of Thurmond, Town of White Hall, Town of Carpendale, Town of Brandonville, Town of North Hills