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Using Disaster Outcomes to Validate Components of Social Vulnerability to Floods: Flood Deaths and Property Damage across the USA

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Abstract: Social vulnerability indicators seek to identify populations susceptible to hazards based on aggregated sociodemographic data. Vulnerability indices are rarely validated with disaster outcome data at broad spatial scales, making it difficult to develop effective national scale strategies to mitigate loss for vulnerable populations. This paper validates social vulnerability indicators using two flood outcomes: death and damage. Regression models identify sociodemographic factors associated with variation in outcomes from 11,629 non-coastal flood events in the USA (2008–2012), controlling for flood intensity using stream gauge data. We compare models with (i) socioeconomic variables, (ii) the composite social vulnerability index (SoVI), and (iii) flood intensity variables only. The SoVI explains a larger portion of the variance in death (AIC = 2829) and damage (R^2 = 0.125) than flood intensity alone (death—AIC = 2894; damage—R^2 = 0.089), and models with individual sociodemographic factors perform best (death—AIC = 2696; damage—R^2 = 0.229). Socioeconomic variables correlated with death (rural counties with a high proportion of elderly and young) differ from those related to property damage (rural counties with high percentage of Black, Hispanic and Native American populations below the poverty line). Results confirm that social vulnerability influences death and damage from floods in the USA. Model results indicate that social vulnerability models related to specific hazards and outcomes perform better than generic social vulnerability indices (e.g., SoVI) in predicting non-coastal flood death and damage. Hazard- and outcome-specific indices could be used to better direct efforts to ameliorate flood death and damage towards the people and places that need it most. Future validation studies should examine other flood outcomes, such as evacuation, migration and health, across scales.

Keywords: social vulnerability; flooding; validation; USA; property damage; death

1. Introduction

1.1. From Risk to Vulnerability

Social vulnerability research has its contemporary origins in risk–hazard research focused on the exposure of people or places to environmental threats [1], demonstrating how various types of environmental or "natural" hazards differentially affect populations based on their underlying susceptibility to harm. The National Flood Insurance Program in the United States reflects the policy impacts of this research [2]. This significance notwithstanding, inadequate attention to the socio-economic conditions that predispose specific populations to greater exposure and consequences has led to various critiques of the risk–hazard approach [3]. New frameworks emerged that focused on societal vulnerability to hazards and captured the root causes of exposure, sensitivity and coping capacity in relation to hazards [4,5]. These frameworks were ultimately enlarged to include the vulnerability of the environment or ecosystem in question and its impacts on exposed populations [6]. A simple definition emerging from this research is that vulnerability is the propensity for loss of lives, livelihood or property when exposed to a hazard [6,7].

Scientists studying the impacts, vulnerability and adaptation associated with climate change grew beyond the risk–hazards framework and began to focus on quantifying and understanding the relationships between hazards, exposure, sensitivity and coping capacity [8–15]. Place-based assessments of vulnerability provided insights into these relationships [16–25] but limited the ability to generalize an understanding of vulnerability across wider geographies. Thus, efforts were made to quantify the social factors that predict the people and locations with a high propensity for loss of life, livelihood and property from a hazard [26] in order to guide disaster management and climate change adaptation policy [11,12]. Indices such as the Social Vulnerability Index (SoVI) are widely used in the literature [25,27,28] and have been formally adopted by government agencies [29], and in vulnerability maps used for adaptation planning [30]. Yet until recently there has been insufficient attention paid to validation [31–35]. The predictive ability of social vulnerability indices remains largely untested, since few studies have examined how vulnerability indices relate to loss and damages, or which socio-demographic factors are most predictive of harm [28,32]. This limits the ability of policy makers to target adaptation strategies that could reduce harm to populations most at risk, because the indices available may be inadequate for predicting loss in a hazard. Validation of widely used indices aids understanding of how factors of social vulnerability may remain constant or change over spatial, temporal and socio-political scales, as well as across different types of hazards [31]. Quantitative social vulnerability assessment requires more attention to internal validity through sensitivity and uncertainty analysis (e.g., Tate et al. [32]) and external validity through the comparison of disaster outcomes with vulnerability metrics (e.g., [34]). As climate-related hazards become more severe, it is important to assess the validity of vulnerability indicators and maps increasingly used to target adaptation resources [35].

Vulnerability assessments increasingly analyze coping capacity, the ability of an individual or population to mobilize assets, or entitlements to cope with loss or mitigate future harm from hazards [36–44]. Coping capacity is markedly difficult to measure over large geographic scales, and among diverse populations, because of data gaps and difficulties in quantifying the complexity of interactions among social structures, institutions and human agency. Metrics tend to capture this complexity inadequately, although a positive relationship between coping capacity and higher levels of education and investment in health has been proposed [10,39,45]. Research on resilience (sometimes defined as the ability to bounce back after a shock) has attempted to construct indices and quantitative assessments that include coping capacity [46–48]. These efforts, however, also lack empirical validation at large geographic scales. Overall, surprisingly few quantitative assessments of the specific factors leading to loss from hazards—or resilience to hazards—based on disaster outcomes exist [34]. Here we add to existing social vulnerability external validation studies of flooding [34,49] by assessing two outcome measures—fatality and property damage—across the continental United States from 2008 to 2012 at the county scale, adopting the above definition of vulnerability. This study represents a larger geospatial extent than previous studies, identifying social factors that transcend local place context that are related to loss and damage across the USA. We focus on riverine flooding and control for flood magnitude, with stream gauge data to examine social factors leading to additional death and damage. The many other potential outcomes related to flooding, such as health effects or long-term economic loss, remain a subject for future research.

1.2. Measuring and Validating Social Vulnerability to Flood Hazards

Flood events affect more people globally than any other type of environmental hazard, and are expected to increase in severity and frequency because of climate and demographic changes [50–53]. Flood vulnerability research has typically focused on hazard (the flood event) and exposure (population and livelihoods that could be impacted by the event). Exposure analyses, as explored in the environmental sciences and engineering, commonly rely on physically-based hydrologic and hydraulic modeling to estimate the extent, depth or frequency of flooding for a given storm event, and calculate the assets and population affected [54–56]. Both qualitative case studies [57,58] and indicator approaches (e.g., the SoVI or similar indices) [21,22,24,59–62] explore the differential impacts of floods on vulnerable people and places.

SoVI was developed by Cutter et al. [26] using a principal component analysis (PCA) on over 30 socio-demographic variables selected through a literature review, which are primarily derived from US census data. PCA is a data reduction technique that uses an orthogonal transformation to convert a set of correlated variables into a new reduced set of uncorrelated variables, or components. The new components that represent a large proportion of variance in the data form the indicators for an additive social vulnerability index.

Social vulnerability is multi-faceted, and no one hazard outcome can serve as a comprehensive proxy for vulnerability validation. Social factors associated with flood vulnerability differ depending on whether the focus is on ex ante mitigation, immediate response, or longer-term recovery from flood events [58]. Therefore, comprehensive validation of social vulnerability to floods requires assessing multiple outcomes, and the social conditions related to each, across the three aforementioned phases of the disaster cycle. Death and property damage, the focus of this analysis, spans the mitigation and immediate aftermath phases of the disaster cycle. Death and property damage were chosen as the outcomes for analysis because of data availability for every county, allowing us to examine salient social vulnerability factors generalizable to the continental US. Outcomes of flood events related to social vulnerability not covered in this paper include agricultural damage, ability to invest in future agricultural adaptation [63], out-migration, rate of return, ability to rebuild [64,65], property buyouts, health impacts not related to morality [15], and psychological impacts (see Rufat et al. [58] for a review of these and other outcomes). We focus our review more on empirical US case studies, the study area for this paper.

1.2.1. Flood Fatality

Social factors leading to fatalities from floods during the event (e.g., from drowning) and morbidity after the event (e.g., health complications; see [66]) differ between high–medium income and low-income countries [58,67]. In lower income countries, females and those who are poor are at a higher risk of flood fatality, often related to increased exposure by residing in the floodplain [67–69]. For example, more women than men drowned in the 1991 cyclone in Bangladesh, potentially due to women being homebound looking after children and valuables, traditional dress that restricts movements, or lower literacy rates [70]. In higher income countries, such as the USA, most fatalities during flood events are due to males drowning in vehicles [71–73]. Fatalities are more common in flash flood events, and in particular regions of the USA on the East Coast along Interstate 95, the Ohio River valley, and south-central Texas [71]. In the US, men exhibit riskier behavior than women in flood events, leading to high fatalities, in contrast to other hazard events in which women are generally more sensitive [72].

Common to all countries is the increased risk of flood-related death among the very young and very old [67,73–75]. The elderly are at risk of death because they may have difficulty evacuating or accessing medical services to treat heat, dehydration, stokes or heart attacks [72]. Furthermore, common to all countries is the higher risk of injury, death and damage from floods and hurricanes for ethnic minorities or communities of color (as well as other disasters, see [76]). Hurricane Katrina, for example, disproportionately affected African-American communities in terms of flood fatality [77]. In Hurricane Katrina, mortality rates were up to four times higher for Blacks than Whites, particularly among elderly populations, suggesting an interaction between race and age [78]. Economic disadvantages, residential choices and difficulty evacuating are all factors, related to systemic and institutional racism, that lead to higher fatality rates among minority populations [79]. Preparedness and mitigation investment by governments may also be systematically lower in communities of color, especially African-American communities [80], increasing their exposure and subsequent flood impacts.

Factors that *reduce* flood fatality include flood mitigation infrastructure [79,81], being in an urban area, and institutional investment in adaptation. Adaptation investments related to preparedness, early warning systems and evacuation plans have effectively lowered property damage and death rates [81]. In all regions of the world (except Sub-Saharan Africa [82]), flood fatality rates have declined since 1980, especially for countries with the largest GDP growth who are hypothesized to be investing in additional adaptation and mitigation [83]. However, early warning systems are less common in rural areas and emergency services more dispersed, compared to urban areas [84,85]. Other studies have found rural areas of the US to be more vulnerable to flood fatalities [86]. Differences may exist among urban areas. For example, rapidly urbanizing areas with less road connectivity were found to be more vulnerable in the Amazon [62] compared to other cities, and social vulnerability hotspots are located both in the urban center and periphery in Shanghai [27].

1.2.2. Property Damage

Property damage represents one component of total economic loss in flood hazard events. Other longer-term economic losses include job loss, crop damage, lost sales or closure of business [87,88], costs of relocation or return, migration, and difficulty finding new work if displaced. Previous research identifying social factors that lead to a higher propensity for property damages have included renter status, income, race and poverty in said factors [89]. Research on property damage at the household level indicates that lower socioeconomic status (e.g., poverty) is correlated with high damage rates because of lower building material quality and reduced ability to withstand flood damage [90]. In the US, for example, unreinforced masonry buildings, which are more susceptible to flood damage [91], are a more common housing type among minority populations in the US [76]. Other studies indicate African-American populations are more likely to experience disproportionate flood damage due to their location in floodplains where homes are cheaper, their reduced access to investments in home protection infrastructure, and receiving less protections from government-built flood mitigation infrastructure [76,80,92,93]. Race may interact with poverty to affect economic damage. For example, in Hurricane Katrina, only low income African-American populations had lower rates of returning and rebuilding, but not African-American populations in general [94]. Studies on tornado damage have found that US census blocks become significantly less poor and more White post-disaster, suggesting poor and minoritized populations may not be able to recover in place, and so migrate [64].

Research indicates that locations with higher rental rates experience a higher propensity for property damage. One exception may be for mobile homeowners: 40% of all tornado deaths occur in mobile homes, but the relationship for floods has, to our knowledge, not been tested [89]. Homeowners have higher rates of purchasing insurance and investing in flood mitigation [58,95], and therefore experience less damage [73,96]. Government programs for disaster assistance in the US, for example, privilege homeowners by design [97]. The relationship between purchasing insurance and race is unclear. One study in Georgia finds African-American populations over the age 45 are more likely to purchase insurance [98], while other studies point to lower rates of insurance purchase by minorities [99]. A recent study in South Carolina after the 2015 floods there, however, showed that National Flood Insurance payouts, loans for small business and Community Development Block Grants for disaster recovery were not reaching all socially vulnerable populations—especially Black populations [65].

Finally, rural areas are hypothesized to be more vulnerable to property loss as a share of total assets (e.g., normalized by total property value). Flood insurance for property owners is twice as common in urban as opposed to rural areas, for example [86]. Rural areas appear to have less flood-protective infrastructure (e.g., dams and levees) per capita compared to densely populated areas with high property values (the National Dam Database, which contains this information, is not available for public download. However, derivative reports using the data from Texas and New Mexico describe more flood protection levees in urban areas. The visual maps appear to favor flood control structure in urban areas.) [100–102]. In this regard, it is noteworthy that the US Federal Emergency Management Agency map modernization project, which updated and produced new flood maps for the US from 2003 to 2008 (immediately prior to this study), focused on highly populated and urban areas [103]. Finally, in the US, development in floodplains has increased in rural areas, but decreased in urban areas from 1980 to 2016, implying increased flood exposure in rural areas of the country [104].

1.3. Validating Social Vulnerability Based on Disaster Outcomes

Several quantitative flood vulnerability analyses combine exposure and sensitivity, and include both biophysical and social variables [15,21,25,59,72,79,105]. Most quantitative assessments use social vulnerability indicators, such as the SoVI, that are generalized for all types of natural hazards [26], and which do not choose sociodemographic variables specific to flood hazards. Different weighting of variables and scales of analysis can lead to unstable results that predict different communities being at risk when small changes in the weights of specific variables are made [31–33]. Even more problematic is the fact that often, social vulnerability indicators are not derived from empirical data on disaster loss specific to flood hazards [58].

We summarize relevant social vulnerability validation studies that use flood disaster outcomes in a regression in the USA (Table 1). We include the studies reviewed for social vulnerability validation by Rufat et al. [34], and an additional study that they exclude [79]. We exclude from this table studies that analyze all hazards, those using Pearson correlation, or qualitative validation. Regression analyses, rather than two variable Pearson correlations, importantly estimate the magnitude and direction of multiple effects while controlling for variation. To validate social vulnerability from flood hazard events, it is essential to control for event magnitude so as to assess the additional variance explained by social factors above and beyond hazard size. We report the geographic extent, temporal extent, scale of analysis, sample size, flood hazard control variable and main finding (statistically significant, with a + for positive correlation and—for negative) of the previous validation studies (Table 1).

Table 1. Summary of quantitative validation for social vulnerability to flood outcomes using correlation or OLS (Ordinary Least Squares) regression. + denotes variables significantly positively correlated with the outcome, and—for variables significantly negatively correlated with outcomes. Note SoVI (The Social Vulnerability Index) is normalized on a z-score, and depending on the studies, positive SoVI scores may represent high or low social vulnerability. For simplification in this table we refer to positive SoVI scores as higher social vulnerability regardless of the numeric transformation employed in the paper. SVI = The Social Vulnerability Index from Flanagan et al. [106]; SoVI = The Social Vulnerability Index [107]; CDRI = Community Disaster Resilience Index [108] RCI = Resilience Capacity Index [109]. FEMA = Federal Emergency Management Authority.

Study	Geographic Extent	Temporal Extent	Scale	N	Hazard Control	Flood Outcome Variable	Main Sociodemographic Variables
Rufat et al. 2019	New York and New Jersey affected Sandy area	one hazard (Sandy 2012)	census track	3947	Flood depth	FEMA Individual Assistance	+SoVI
						% property loss	+socioeconomic status
Zahran et al. 2008	Texas	1997–2001	county	832	precipitation	Fatality	+ social vulnerability (defined as high minority and lower economic status)
Finch et al. 2010	New Orleans	one hazard (Katrina 2005)	census tract	181	Flood Depth	Rate of return to home	-SoVI
Bakkensen et al. 2017 *	10 states (Southeastern USA)	2000–2012	county	41,916	NCDC (National Climate Data Center) magnitude	Fatality	+SVI -CDRI, -RCI
						Damage	+SoVI, +SVI, -CDRI, -RCI
Fekete et al. 2009	3 regions (River Elbe, Mulde, and Danube, Germany)	one hazard in 2002	house-hold	1697	none	Displacement	+urban, +homeowner, +rooms
						Shelter	+age, +homeowner

* includes flash flood, hail, wind, strong wind, thunderstorm, tornadoes.

Most previous attempts to validate the components of social vulnerability based on hazard outcomes have been general to all hazards [19], based on one flood disaster or place [34,60,61], use Pearson correlation [66,110], or are qualitative [23,111]. A few notable exceptions exist. Zahran et al. [79] analyzed over 800 flood events in Texas. Using precipitation and property damage data to control for flood magnitudes, they found two county-level demographic variables correlated to fatalities: high proportions of minorities and lower incomes. In other work, Finch et al. [61] found that high social vulnerability, when controlling for flood depth, predicts lower rate of residents returning home post-Katrina. Other single event flood studies [34,60] validate social vulnerability metrics and other social factors in relation to a variety of flood outcomes, including displacement rate, shelter, property loss and FEMA assistance. The largest spatial and temporal validation study (across the southeastern USA, and the highest sample size, from Bakkensen et al. [49]) included five hazard types (including floods). They found that the social vulnerability indices correlated with higher rates of property damage, but only one social vulnerability index (SVI; see [106]) was positively correlated with fatality rates.

Quantitative validations of social vulnerability to hazards, and to flooding in particular, at large spatial scales remain elusive. One of the challenges is selecting outcome variables that link to one or more of the components of vulnerability [112]. Possible outcome variables range from the immediate, such as fatalities and injuries, to the long-term, such as economic recovery [56]. Various outcome metrics, such as psychological wellbeing, are lacking in availability or are difficult to derive from extant sources, such as demographic data. Data-poor areas of the world are even more challenging to assess, and prevent broad-scale regional or global comparisons.

Despite these challenges, it is imperative to develop methods based on extant data to test the hypothesis that certain social dimensions increase vulnerability to hazards, such as floods [113]. Many researchers who develop social vulnerability indicators do so with the goal of drawing attention to the differential risks faced by those who are most disadvantaged [114,115]. Yet, without rigorous validation efforts, the development and use of such indicators risks being discredited owing to claims that they are unable to predict future harm [35,116]. The ability to understand and predict future risks is particularly important as discourse around loss and damage rises in the UN Framework Convention on Climate Change [117]. Recent social vulnerability validation studies call for more research in order to identify which social vulnerability models and factors consistently explain disaster outcomes, across hazards, outcomes and spatial and temporal scales [58]. This paper contributes to this research by providing the broadest spatial scale validation of social vulnerability to flood hazards to date. We estimate the socio-economic dimensions of vulnerability to death and damage in floods over a large number of events (n = 11,938, all major flood events from 2008 to 2012) in the contiguous United States, controlling for hazard magnitude. Generalized linear regression models address four primary research questions at the US county scale:

1. Which demographic variables predict fatalities directly attributed to floods?
2. Which demographic variables are associated with higher relative flood property damages?
3. Does a composite index of social vulnerability (SoVI) correlate with flood death and damage when accounting for hazard intensity?
4. Which populations and their locations are most likely to experience death and damage in a large (500-year) future flood event?

2. Materials and Methods

Our general approach to social vulnerability validation for floods was to regress flood outcome variables for which data across the contiguous USA were available, and the relative hazard magnitude could be controlled. Property damage and fatalities are two outcomes that fit these criteria, and have been used in other vulnerability validation studies as dependent variables in regression [34,49,79]. Stream gauges can control for riverine and flash flood (but not coastal floods), and we focus on these two flood types for validation. Data analysis and methodological details are provided below.

2.1. Data

2.1.1. Property and Fatality Data

Model response variables—fatality and property damage—are available through SHELDUS [118] version 14.1, downloaded in July 2016 (more recent versions of these data are now available through the Center for Emergency Management and Homeland Security at Arizona State University: https://cemhs.asu.edu/node/7). All flood outcome data were limited to flood events in the contiguous US from 2008 to 2012, excluding coastal floods (n = 11,938). The years 2008–2012 were chosen because they represented the two years precluding and following the 2010 Census, and we assume social dynamics to be stationary for approximately the 5 years of this analysis. We used stream gauge data to control for hazard magnitude, effective for riverine and flash flooding, the flood types included in this analysis. We excluded coastal floods from our analysis as these would have required windspeed or storm surge to control for hazard magnitude, and storm surge data across the US is unavailable. Flood fatalities and damage are the only consistent flood event outcomes in SHELDUS, and were the only ones available across the contiguous US at the time of this study.

Flood fatality data in SHELDUS are from the Storm Data publication provided by the US National Centers for Environmental Information (NCEI, formerly the National Climatic Data Center). Storm Data preparers from the National Weather Service report fatality information in total numbers per event (and usually per county). When the NCEI data report fatalities across several counties, SHELDUS splits the fatality data into each location reported. It is unclear how many fatalities are "direct" (e.g., drowning in water) vs. "indirect" (e.g., medical supplies at a home ran out due to the flood preventing gathering supplies), but these descriptions are sometimes included the event narrative. A total of 247 non-coastal flood fatality events (an event for which at least one death occurred), and a total of 335 deaths, occurred between 2008 and 2012, 238 of which had event descriptions. The quality of these data are subject to National Weather Service reporting, but it is considered the best officially verified and highest quality dataset for significant weather phenomena in the United States (https://www.ncdc.noaa.gov/stormevents/faq.jsp). Undercounts of fatalities or missing records from small events could result in biases in this dataset due to resource constraints in reporting.

For cross validation and for interpretation of the regression models, we text-mined the 238 flood fatality events for select causes and variables based on the limited descriptions. After reading event narratives, we mined the text for trends in age, gender and cause of death. For the gender of the fatalities, the words "woman", "girl", "mother" or "lady" were used to determine if there was a female involved in the fatality; "man", "boy", "son", and "father" were used to determine if a male was involved; "child", "baby", "daughter", "son", "boy", and "girl" were used to determine if there was a young person involved; "elderly" or "senior" were used to determine if there was an elderly person involved; "mobile" and "RV" were used to search to mobile home deaths; "truck", "car", and "vehicle" were used to determine if a car was involved; and "drown*" (to cover "drown", "drowned", and "drowning") were used to search for drowning fatalities. Note that not all event narratives have words that indicate gender, age or cause of death, so this represents patterns in types and causes of death, and not a comprehensive characterization. The number of cases with the presence or absence of each word was added and used to calculate the percentage of cases where these words appeared, in order to gain a sense of the demographic factors in the fatality descriptions.

We analyzed property damage data from SHELDUS, reported at the county scale (n = 11,245 events with damage data). A total of USD 24 billion in losses was recorded, with a mean of USD 2.06 million in damage per event per county, and a median of USD 200,000. Unlike fatality data, where the NCEI data report deaths across several counties, SHELDUS splits the damage data equally across each county affected. These data have a large uncertainty and are characterized as "guesstimates" in the SHELDUS metadata. Property damage data had values greater than 0 for almost all flood events; only 408 had a value of "0". Storm data preparers reporting to the government might use the US Army Corps of Engineers, newspapers, utility companies, insurance adjuster data or other information to estimate monetary damage. Damage includes both private property and public infrastructure. Crop damage amounts are reported separately and are not used in this analysis. Property damage data have been used in vulnerability validation assessments [49]. Other analyses have shown inaccuracies in these data, however, particularly concerning the fact that small or moderate damage is often underreported, and counties vary in what they count as "damage", leading to inaccuracies of up to 40% in estimates [119]. These issues notwithstanding, they remain the best publicly available property damage estimate datasets at a country scale. Recent studies have obtained insurance adjustment data from FEMA, which likely provides improved private household loss estimates, but those data are not publicly available at the time of this study [120]. We considered using the FEMA Public Assistance data [121] federally declared disaster events (n = 351). These property damage estimates are considered to be of higher quality, and have been used in other vulnerability validation studies [34]. However, due to its much smaller sample size, it was not used in this analysis. We normalized property damages by the estimated total housing value in each county in the 2010 US Census. Our normalization approach is similar to studies which have used the ratio of property losses to total value [34] or added a capital stock variable (multiplying income times population) as a control in regression [49]. We recognize the limits of using property data to validate the economic outcomes of flood hazards, because they only represent direct loss and not long-term business and employment loss.

2.1.2. Flood Hazard Magnitude and Built Environment Data

We accounted for riverine and flash flood hazard intensity by using USGS (United States Geologic Service) stream gauge data [122] to calculate the flood return period of each storm event. The NCEI dataset reports a latitude and longitude location of each event, either by the Storm Data preparer entering in the latitude and longitude directly, or by NCEI calculations from a reported location, distance and 16-point compass direction (e.g., 5 miles east-southeast of Atlanta). It was difficult to know which stream gauge best represented the hazard intensity, especially given uncertainty in event coordinates. Our strategy for connecting events to relevant stream gauges was to match event coordinates to the USGS Watershed Boundary Dataset using HUC (Hydrologic Unit Maps) levels 4, 6, 8, 10 and 12. Each HUC level is a different-sized watershed at nested levels of spatial aggregation; level 12 watersheds are small subwatersheds (the smallest size we used), 10 digit are watersheds, 8 digit are subbasin, 6 digit are basins and 4 digit are subregions (the largest size we used). We then selected all stream gauges in all HUCs that overlapped the storm event point, and gathered all stream gauge readings in between the start and end of the flood event as reported by SHELDUS. We selected the maximum instantaneous discharge reading across all HUC levels and days during the event. We assume the maximum discharge represents peak hazard intensity and would provide the best control for the regression. In order to compare hazard intensity for different events, discharge was converted into flood return times using USGS Stream Stats [123]. This method interpolates discharge data using a log-linear model to develop a continuous curve. We matched the flood event discharge data to its location on the Stream Stats curve to estimate the flood return period of the storm event.

We included data on impervious surface, which has been found to increase property damage associated with flood events [124]. We controlled for built environment by including percent of developed impervious surface by county from the National Land Cover Dataset for 2011 [125].

2.1.3. Social Vulnerability Data

Predictor variables are available through the US Decennial Census (2010) and the American Community Survey (ACS). We used all 29 individual predictor variables used in the 2006–2010 version of the Social Vulnerability Index (SOVI) (Cutter et al. 2003), plus two additional variables consistent with the literature that increased propensity for fatalities or damages during a flood event (percent rural [86] and interactions of race and class [94]) (Table 2). The SoVI indicator was purchased from the University of South Carolina (2006–2010 version), at the county scale [118]. The spatial unit of analysis is the county or county-equivalent. Broad-scale geographic effects were controlled for by including US Census regional and division designations as dummy variables for models. All continuous variables, including property damage, social factors, impervious surface and hazard intensity data were converted to Z-scores with a mean of zero and standard deviation of one.

Table 2. Social variables used in the analysis, description, rationale (from Cutter et al. 2003, unless otherwise specified with *), hypothesized relationship (+F for increase in fatalities, -F for decrease in fatalities, +D for increase in damage, -D for decrease in damage), and the data source (DC = decennial census).

Variable	Description	Rationale	Hypothesized Relationship	Source	Census Group or Table
totalPopulation	Total population	To offset fatality models (control for highly populated areas) *	+F	2010 DC	P3
%Black	Percent of population Black	Residential locations in high hazard areas	+F, +D	2010 DC	P2
%NativeAmerican	Percent of population Native American		+F, +D	2010 DC	P3
%Asian	Percent of population Asian		+F, +D	2010 DC	P3
%Hispanic	Percent of population Hispanic		+F, +D	2010 DC	P4
%Female	Percent of population female	Lower wages, family care responsibilities can increase vulnerability, but men more likely to die in floods	-F	2010 DC	P12
%FemaleCivilianWorkforce	Percent of women who are working		+D	2010 5-year ACS	B23001
%FemaleHeadOfHouse	Percent households headed by females		+F, +D	2010 DC	P18
%Under5yo	Percent population under 5	Higher potential for fatalities- drowning	+F	2010 DC	P12
%Over65yo	Percent population over 65	Difficulty evacuating due to mobility constraints	+F	2010 DC	P12
%NursingHome	Percent population in nursing home		+F	2010 DC	P42
%NoEnglish	Percent of population with household has a limited English-speaking status	Difficulty communicating for evacuation *	+F	2010 5-year ACS	B16002
perCapitaIncome	Per capital income in past 12 months	Lower incomes indicate poverty	+D	2010 5-year ACS	B19301
%RenterOcc	Percent population in rental homes	Less invested in flood mitigation to prevent damage	+D	2010 DC	H4
%Unoccupied	Percent of houses unoccupied	Value, quality, of housing stock may indicate “economic health” of a community, overcrowded and vacant housing may be likely to experience more damage	+D	2010 DC	H3
medianHouseValue	Median value of owner-occupied housing (USD)		-D	2010 5-year ACS	B25077
medianRent	Median value of renter occupied housing (USD)		-D	2010 5-year ACS	B25064
%MobileHomes	Percent of population living in mobile homes		+D, +F	2010 5-year ACS	B25024
peoplePerUnit	Number of people per room		+D	2010 5-year ACS	B25014
totalHouseValue	Calculated by summing number of homes in each value category, and adding total value	Used to normalize property damage data *	+D	2010 5-year ACS	B25075
%NoCar	Percent of homes with no vehicle	Could be easier to evacuate, also an indicator of relative less poverty	+F	2010 5-year ACS	B25044
%UnderPoverty	Percent of population living in poverty, defined threshold varies by age, household and number of children	Related to ability to absorb losses and invest in resilience to hazard impacts, access insurance and other programs	+D	2010 5-year ACS	C17002
%Households200k	Percent of households making at least USD 200,000 in joint income in past year		-D	2010 5-year ACS	B19001
%LessThan12yearsEducation	Percent of population who have not completed 12th grade (high school)	Low education constrains ability to understanding warning information	+F	2010 5-year ACS	B15002
%NoHealthInsurance	Percent of population with no health insurance	Hospitals, and ability to access care due to mobility constraints and health insurance, could affect disaster impacts	+F	2010 5-year ACS	B27001
%AmbulatoryDifficulty	Percent of population with mobility constraints		+F	2013 5-year ACS	B18105
HOSTPTC	Per capita number of community hospitals		+F	SOVI variables	
%SocialSecurity	Percent population with social security income	Social dependence indicates economic marginalization requiring extra support	+long term D (not property)	2010 5-year ACS	B19055

Table 2. *Cont.*

Variable	Description	Rationale	Hypothesized Relationship	Source	Census Group or Table
%EmployedInServices	Percent population employed in services including healthcare support, fire-fighting, policing, food preparing and maintenance	Occupations that could be affected by hazard event (e.g., jobs that may not return post-disaster)	+long term D (not property)	2010 5-year ACS	C24010
%EmployedInExtractive	Percent population employed in mining, quarrying, gas extraction or forestry		+long term D (not property)	2010 5-year ACS	C24030
%CivilianUnemployed	Percent population unemployed in labor force	Less economic capacity to invest in resilience	+D	2010 5-year ACS	B23001
%Family	Percent of families where both parents are present	Potential for dual incomes or house labor may increase ability to invest in flood mitigation	-D	2010 DC	P19
%Rural	Rural population/total population per country	Ruralness related to flood fatalities due to access issues, less flood mitigation investment *	+D, +F	2010 DC	(P002001/P002005) in P2
SoVI	2006–2010 Social Vulnerability Index	Hypothesized link to propensity for loss in hazards	+D, +F	University South Carolina	NA
Race-poverty	Multiplying %Black, Hispanic, Asian and Native American with poverty	Intersectional race and poverty lead to outsized hazard impacts, not race alone (Elliot and Pais 2006)	+D	2010 DC and 2010 ACS	P2,3,4 and C170002

2.2. Regression Models

We used regressions on fatality and property damage to test which individual socioeconomic factors, SoVI index values, and biophysical factors (flood intensity and impervious surface) significantly influenced each outcome. We treated fatalities per flood event per county as count data. We use a zero-inflated model (Equation (1)) to relate socio-demographic data to flood fatalities, because there may be one process predicting if any flood fatalities occur (e.g., flood hazard intensity above a certain threshold) and a second process that predicts the number of fatalities (*j*), if a fatality does occur (e.g., social vulnerability factors). Zero-inflated models were implemented with R package 'pscl' [126]. We controlled for fatality exposure (in this case, larger populations that would increase the likelihood one person would die) with an offset (logged population of each county). Count data are often modeled with the Poisson distribution, unless there is over dispersion (variance of fatality count is much higher than the mean of counts). We used the Pearson Chi-squared dispersion test and found over dispersion using a Poisson distribution (using the msme package; [127]). We thus used the negative binomial distribution, recommended for zero-inflated models with overdispersed count data.

$$Pr(y_{it} = j) = \begin{cases} \pi_i + (1-\pi_i)g(y_{it} = 0)\ if\ j = 0 \\ (1-\pi_i)g(y_{it})\ if\ j > 0 \end{cases} \tag{1}$$

y_i = the dependent variable (fatalities) per spatial unit (*i*), counties for each event *(t)*
π_i = logistic link function, $\frac{\lambda_i}{1+\lambda_i}$
g = the negative binomial distribution
$\lambda_i = exp\ (\beta' x_i + \beta' x_t)$
$\beta' x_i$ = coefficients for the time invariant independent variables for each county, *i*
$\beta' x_t$ = coefficients for the time varying independent variables for each event, *t*, such as hazard intensity or presence of a flash flood.

For property models we used an ordinary least squared (OLS) regression as specified in Equation (2).

$$Y_i = \alpha + B_1 x_t + B_1 x_i \ldots\ B_n x_i \ldots + \varepsilon_{it} \tag{2}$$

α is the intercept.

$B_n x_i$ is the coefficient for each independent variable for each county *i*.

$B_n x_t$ are the coefficients for time-varying independent variables for each event, *t*, such as hazard intensity or presence of a flash flood.

ε_{it} is the error term for each event (t) per county (i).

AIC is used to compare model fits [128] for fatality models. AIC (−2(log likelihood) + 2K, where K = number of model parameters) is the Akaike Information Criterion [129], which is used in non-linear models (e.g., when maximum likelihood estimation is used for model fits, which is used for the zero-inflated models in this study) to compare relative model fits. Lower AIC indicates lower out of sample prediction error and a better relative model. AIC numeric values have no range and cannot be interpreted on their own, as the AIC calculation includes constants related to sample size. AIC values for models with the same outcome variable and sample size can be compared relative to each other. Absolute differences between models if AIC > 10 indicate that the two models offer substantially different evidence, and models with lower AIC have better fits. We used percent deviance explained (nulldeviance–modeldeviance)/nulldeviance where deviance = −2(loglikelihood)) [130] to compare the a priori or null model. In this case, the null hypothesis and model is that social vulnerability does not explain any variance in flood outcomes; models 1 and 2 in Table 3, which was compared to models that include sociodemographic or social vulnerability indices. The relative contribution of social factors predicting death above and beyond biophysical factors was quantified via deviance explained.

Table 3. Fatality and Property damage validation models.

Model #	Rationale	Independent Variables	Dependent Variables
1	Null Model	1	Fatality, Damage
2	Biophysical Variables	floodReturnTime + %Impervious+ flashflood **	
3	SoVI index, controlling for hazard intensity	US_SOVI+ floodReturnTime+ %impervious+ flashFlood	
4a	Social factors identified in literature	floodReturnTime + flashFlood + %Rural + %MobileHomes + %UnderPoverty + %Under5yo + %Over65yo + %NoEnglish + %AmbulatoryDifficulty+ %NoHealthInsurance+ HOSPTPC +%LessThan12yearsEducation+ %NoCar	
4b	Social factors identified in the literature + regional variation	floodReturnTime + flashFlood + %Rural + %MobileHomes + %UnderPoverty + %Under5yo + %Over65yo + %NoEnglish + %AmbulatoryDifficulty + %NoHealthInsurance+ %LessThan12yearsEducation + HOSPTPC + %NoCar + regions	
4c	Social factors identified in the literature + divisional variation	floodReturnTime + flashFlood + %Rural + %MobileHomes + %UnderPoverty + %Under5yo + %Over65yo + %NoEnglish + %AmbulatoryDifficulty +%NoHealthInsurance+ %LessThan12yearsEducation + HOSPTPC + %NoCar +divisions	
5a	Social factors identified via machine learning	floodReturnTime + flashFlood + %Rural + %NoEnglish + %Asian	
5b		floodReturnTime + flashFlood + %MobileHomes + %Unoccupied + perCapitaIncome * + %Rural + peoplePerUnit + medianRent + %NoCar + %Hispanic + %NursingHome	Fatality as binary (any deaths >1 set to 1)
5c		floodReturnTime + %Rural+ %Black ***+ %Asian+%Civilianunemployed+HOSPTPC+%NoCar+%Under5yo+%Unoccupied+ medianHouseValue	Property Damage (as ratio of housing value)
6a	Social factors identified in the literature	floodReturnTime + medianHouseValue + %Black +%Asian+ %Hispanic + %Native American+peopleperunit+%unoccupied+ %renters + %Rural + %MobileHomes + %UnderPoverty	
6b	Social factors identified in the literature + regional variation	floodReturnTime + medianHouseValue + %Black +%Asian+ %Hispanic + %Native American+peopleperunit+%unoccupied+ %renters + %Rural + %MobileHomes + %UnderPoverty + regions	
6c	Social factors identified in the literature + divisional variation	floodReturnTime + medianHouseValue + %Black +%Asian+ %Hispanic + %Native American+peopleperunit+%unoccupied+ %renters + %Rural + %MobileHomes + %UnderPoverty + divisions	
6d	Social factors identified in the literature with race–poverty interaction + divisional variation	floodReturnTime + medianHouseValue + %Black * %UnderPoverty +%Asian *%UnderPoverty + %Hispanic * %UnderPoverty + %Native American*%UnderPoverty +peopleperunit+%unoccupied+ %renters + %Rural + %MobileHomes + divisions	

* correlated with households earning over USD 200,000, excluded from model; ** flash flood only included in fatality models (tied to death in the literature, but not property loss); *** correlated with %FemaleHeadofHouse.

R^2 (coefficient of determination) was used to compare model fit for property models, and varies between 0 and 1, with higher values explaining a higher proportion of variance (and a better model). Unlike AIC numeric values, R^2 values can be interpreted as a ratio of variation that the independent variables explain with respect to the dependent variable. The contribution of social factors predicting damage above and beyond biophysical factors was quantified by directly comparing R^2 values. Regressions using observations from spatial data, such as US counties, can be influenced by spatial autocorrelation, meaning the county observations are not independent observations. If the model residuals from a regression are spatially clustered beyond random chance, it indicates a lack of independence and violates the regression assumptions. Standard regression estimates cannot be trusted when spatial autocorrelation is present, because some variables could have inflated the coefficient values, invalidating the tests of significance. We tested for spatial autocorrelation for neighboring counties using queen contiguity (for both the mean and maximum residuals per county, since there are multiple observations for many counties) for both property and damage models using Moran's I. Moran's I is a measure of spatial clustering, assessing the difference between a mean value in a sample, and the relative difference in values of a given observation in the sample with its spatial neighbors from the spdep package (version 1.1-3, [131]). If the spatial clustering of regression residuals is greater than random chance, spatial autocorrelation could inflate model coefficients and significance tests. If the p value for the Moran's I is significant, it indicates spatial autocorrelation is present, the model residuals are clustered beyond random chance, and the correlation coefficients could be artificially inflated.

2.3. Variable Selection and Model Construction

Our approach differs from previous flood studies, which regress disaster outcomes on constructed social vulnerability indices or the combined components of socioeconomic data (e.g., expert weighting, principal component analysis or other statistical transformations termed "vulnerability profiles"). Social vulnerability indices are very sensitive to weighting or combination schemes [132]. Therefore, we take a different approach, and examine individual socioeconomic components of vulnerability to identify which significantly predict hazard outcomes. The aim of our model's strategy was to identify social factors that systematically increase property damage or fatalities across the USA. We compare models constructed using theory (e.g., including variables identified from the literature, discussed above) versus data mining (e.g., machine learning) to identify factors increasing death and damage. We used a machine learning-generalized boosted regression (Gbm) [133] algorithm to estimate the relative importance of the social variables from Table 2 to death and damage events, respectively. We added dummy variables at both regional and division census levels to control for geographic differences in fatality and flood outcomes. We ensured no models included variables that were significantly correlated (>0.55) to prevent multicollinearity, and also calculated variable inflation coefficients to ensure none were greater than 5 [134]. Variable inflation coefficients indicate multi-collinearity in a model, e.g., when the possibility any single variable could be false is inflated by a correlated relationship with another variable in the model. Significance tests (for p values) are unreliable in models with high variable inflation coefficients, and cannot be used for hypothesis testing.

We constructed six types of models to answer our research questions (Table 3). Model 1 is the null model of fatality and property damage. Model 2 contains only the biophysical variables of flood return time, impervious surface and flash floods, while model 3 adds the SoVI index, and both are regressed against both flood fatalities and property damage. Models 4a, 4b and 4c were theoretically informed models for predicting fatalities, controlling for hazard intensity (4a), regional effects (4b) and division effects (4c). Social factors theoretically predicting death include gender, percent Black, percent rural, age (% < 5 years and % > 65 years), mobile homes, poverty, owning a car, factors that could make heeding early warning difficult (difficulty understanding English, ambulatory difficulty, low education) and health (hospitals, health insurance). Social factors theoretically predicting damage include minoritized populations (%Black, %Native American, %Hispanic, %Asian), housing stock and ownership, mobile homes, renters, people per unit, vacancies and and poverty (correlated with per capital income, which was discarded). Median house value was correlated with households making over USD 200,000, median rent and per capital income, variables which we excluded. Female heads of house theoretically are vulnerable to more flood damage, but this variable was correlated with %Black, so it was not included. Percent impervious is also not included in social models, as it is significantly correlated with percent rural (Pearson Correlation = −0.54, $p < 0.001$). Models 6a,6b, 6c and 6d were theoretically informed models to estimate property damage, controlling for hazard intensity (6a), regional effects (6b), division effects (6c), and interacting race and class (6d). Models 5a, 5b and 5c include variables identified through machine learning associated with fatalities as count data (5a), fatalities as binary (5b), and property damage.

2.4. Predictive Maps

Our final research question aims to identify which counties are most vulnerable to riverine flood fatalities and relative property damage for a large event. We use the best fitting models (based on AIC or R^2) to predict the number of fatalities and property damage ratio for an infrequent and large flood event. To make predictions, we set the population in each county to 100,000, so the predicted death count can be interpreted as a fatality rate per 100,000 people. We assume a flood return time of 500 years, which is the largest flood time we can estimate using the Stream Stats model. Property damage is predicted as the ratio of damage. The top 10 counties for predicted fatalities and property damage are listed in Table 7, together with their percentile in the SoVI index (higher percentile = higher social vulnerability, ranging from 0 to 1). A bivariate choropleth map visualizes the predictions from the zero-inflated fatality model and the property damage model. This map uses Fishers' classification to define breaks in the data that display optimal variation in a choropleth map with three classes for each variable, for a total of nine classes. We use Spearmen's rank correlation to compare how the counties most at risk of flood death and property damage compare to high social vulnerability counties identified by the 2006–2010 SoVI index.

3. Results

3.1. Fatalities

Results from textual analysis of the Storm Events Database indicate that the typical flood fatality involves a drowning incident in a car, commonly a man alone, but sometimes involving mothers and children, while crossing a river in a rural area of the country. While not all narratives contained information on gender and age of the people who died, more than 50% of the cases involve men drowning in cars (Figure 1).

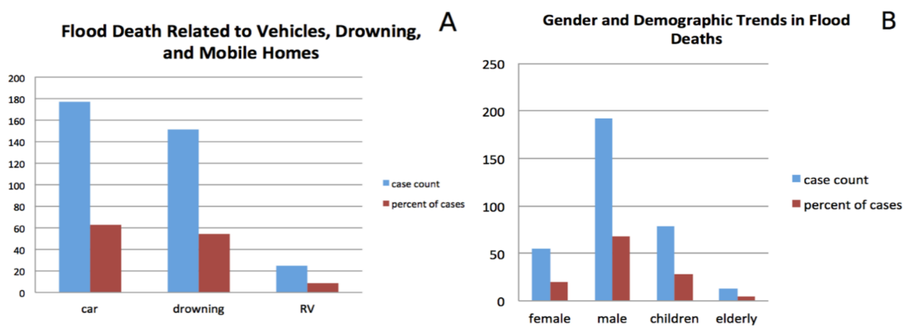

Figure 1. Results of text mining for event narratives from flood fatalities data (n = 283). (**A**) Demographic trends (age and gender) in flood fatalities cases; (**B**) cause of death involving cars, drowning or RVs/mobile homes.

Machine learning using fatality counts, as the response revealed that three county-level variables had a relative importance greater than zero (in order of importance): percent rural (85.9%), percent of that population speaking no English (9.67%), and percent Asian (4.44%). These three variables form model 5a (Table 3). Using a binary variable for fatalities (e.g., presence or absence of a death in a flood event) as the response, the machine learning identified 10 variables with a relative importance greater than zero (Table 4). These 10 variables form model 5b (Table 3).

Table 4. Social variables with non-zero relative importance from machine learning for fatalities and >1% importance for property damage ratios.

Variable	Relative Influence—Fatalities as Counts	Relative Influence—Fatalities as Binary	Relative Influence—ln Property Damage Ratio
%MobileHomes		37.99	0.19
%Unoccupied		16.79	1.12
perCapitaIncome		14.76	1.25
%Rural	85.89	14.01	49.28
%Households200k		5.90	3.06
peoplePerUnit		4.09	0
medianRent		3.87	11.93
%NoCar		1.41	1.31
%Hispanic		0.76	0.54
%NursingHome		0.44	0.91
%No English	9.67		0.48
%Asian	4.44		3.51
%Hospital			7.76
%Black			1.93
%Unemployed			1.81
%FemaleHeadHouse			1.77
%under5			1.56
%perCapitaIncome			1.25
%Unoccupied			

Other variables predicting property damage ratios with relative importance >0 but <1 include %Native American, %noInsurance, %EmployedinServices, %Underpoverty, %Female, %Femaleworkforce, %Socialsecurity and %employedinextractive.

The regression analysis of fatalities indicates that model fit is lowest for models that only include biophysical variables (Model 2, AIC = 2894, Table 5). Model fit increases when SoVI is added (Model 3, AIC = 2829), but performs better when adding the individual social components identified in the literature (Model 4a, AIC = 2732) and geographic controls (Model4c, AIC = 2696). Models constructed with the social factors identified in machine learning do not perform as well as models constructed with theory (Model 5a and Model 5b AIC = 2728 and 2744, respectively). Higher flood magnitude is consistently a significant predictor for increased death counts across all models ($p < 0.01$), while flash floods in particular were not found to be associated with increased death counts. Residuals were significantly spatially autocorrelated for death model residuals (Moran's I = 0.282, $p < 0.001$). However, methods for implementing spatial weights for zero-inflated regression with a negative binomial distribution were not available at the time this paper was written (for a zero-inflated geographically weighted regression with a Poisson distribution, see the lctools package from [135]). Spatial autocorrelation urges caution in model interpretation, as the model fit and coefficient estimates could be overestimated. We only interpret variables as significant that are $p < 0.05$, and not those that are $0.5 < p < 0.1$, due to the potential inflation of coefficient estimates, induced by spatial autocorrelation.

Three social variables have significant and positive coefficients across all model formulations: percent rural, percent of the population under 5 years old, and percent of the population over 65 years old. These three characteristics were also found in the text mining analysis (Figure 1), providing additional validation. Rural percent of the county population is the strongest predictor of death count across all models ($p < 0.01$). Two of the eight regional division variables, both in the southern US (west south central and east south central), have a significant effect in increasing death counts (model 4c: $p < 0.01$, $p < 0.01$, respectively). Counties with higher proportions of younger (<5 years) and elderly populations are correlated with higher flood death counts ($p < 0.01$). Other variables are inconsistent across models. For example, counties with a lower percentage of health insurance coverage for the population are positively correlated with death counts in models 4a ($p < 0.05$) and 4b ($p < 0.1$), but when geographic division controls are added, this significant effect disappears.

Table 5. Zero-inflated fatality model results. ML = machine learning model. Lit indicates models formed from the literature. Table 3 links model descriptions to model numbers in this table.

	Zero Inflated Fatality Models **Dependent Variable:** **Death Count**						
	Biophysical (2)	SoVI (3)	Social (Lit) (4a)	Social (Lit)+reg (4b)	Social (Lit)+div (4c)	Social-ML (count) (5a)	Social-ML (binary) (5b)
floodReturnTime	0.199 *** (0.074)	0.215 *** (0.070)	0.212 *** (0.056)	0.206 *** (0.055)	0.108 ** (0.047)	0.114 ** (0.049)	0.201 *** (0.055)
flashFlood	0.109 (0.197)	0.041 (0.184)	−0.093 (0.164)	−0.137 (0.164)	−0.049 (0.165)	0.115 (0.165)	−0.103 (0.164)
%Impervious	−0.541 *** (0.080)	−0.407 *** (0.075)					
US_SOVI		0.331 *** (0.041)					
%Black			−0.077 (0.104)	−0.191 * (0.114)	−0.161 (0.117)		
%Female			−0.039 (0.149)	−0.126 (0.150)	−0.083 (0.155)		
%NoHealthInsurance			0.326 ** (0.135)	0.258 * (0.140)	0.199 (0.146)		
%Asian						−0.149 * (0.080)	
%NursingHome							0.296 ** (0.118)
%Rural			0.793 *** (0.127)	0.784 *** (0.133)	0.761 *** (0.128)	1.102 *** (0.093)	0.678 *** (0.147)
peoplePerUnit							0.177 (0.153)
%Unoccupied							0.311 *** (0.117)
%MobileHomes			0.070 (0.145)	0.032 (0.153)	0.082 (0.149)		0.413 *** (0.125)
%UnderPoverty			−0.261 (0.207)	−0.204 (0.207)	−0.139 (0.212)		
%Under5yo			0.429 *** (0.133)	0.497 *** (0.142)	0.448 *** (0.137)		
%Over65yo			0.452 *** (0.139)	0.555 *** (0.145)	0.510 *** (0.144)		
%NoEnglish			−0.644 (0.498)	−0.776 (0.511)	−0.992 * (0.518)	0.207 (0.383)	
perCapitaIncome							0.287 (0.177)
%Hispanic							0.087 (0.174)
%NoCar			0.145 (0.147)	0.225 (0.159)	0.235 (0.166)		0.038 (0.117)
%AmbulatoryDifficulty			0.276 ** (0.140)	0.150 (0.149)	0.109 (0.151)		
NE_region				0.123 (0.399)			
S_region				0.597 * (0.306)			
MW_region				0.015 (0.332)			
NE_MA_division					0.357 (0.314)		
S_SA_division					0.290 (0.313)		
S_ESC_division					0.838 *** (0.301)		
S_WSC_division					0.915 *** (0.259)		
medianRent							−0.340 * (0.174)
Constant	−14.521 *** (0.158)	−14.379 *** (0.146)	−14.507 *** (0.159)	−14.777 *** (0.298)	−14.329 *** (0.235)	−13.829 *** (0.200)	−14.313 *** (0.135)
Observations	11,629	11,629	11,629	11,629	11,629	11,629	11,629
Log Likelihood	−1440.462	−1406.797	−1349.118	−1345.736	−1327.129	−1355.418	−1357.420
Akaike Inf. Crit.	2894.924	2829.594	2732.235	2731.472	2696.258	2728.836	2744.839

Note: * p ** p *** $p < 0.01$.

3.2. *Property Damage*

Property damage models reveal trends similar to fatality models (Table 6). Models using only biophysical variables are correlated with a small amount of variation in property damage ratios (Model 2, $R^2 = 0.09$). Variation explained increases with models adding SoVI, which is significantly correlated with damage ratios (Model 3: $R^2 = 0.13$, $p < 0.01$). Models with social factors selected from both the literature and machine learning explained more variation compared to SoVI only models (Models 4a, 4b, and 5c: $R^2 = 0.20$ for each). The best performing model includes race and poverty interactions and geographic divisions (Model 5d: $R^2 = 0.23$). Flood magnitude is significantly and positive correlated, and larger floods increase damage across all models ($p < 0.01$). We did not find spatial autocorrelation in residuals for property damage models (Moran's I = 0.0007, $p = 0.28$)

Table 6. OLS Property damage ratio model results. ML = machine learning model. Lit indicates models formed from literature. Table 3 links model descriptions to model numbers in this table.

OLS Property Models Dependent Variable: Property Damage as Ratio of Total Housing Value							
	Biophysical (2)	SoVI (3)	Social (Lit) (6a)	Social (Lit)+reg (6b)	Social (Lit)+div (6c)	Social+div+ race-class(6d)	Social-ML (5c)
floodReturnTime	0.354 *** (0.029)	0.359 *** (0.028)	0.392 *** (0.027)	0.387 *** (0.027)	0.401 *** (0.027)	0.403 *** (0.027)	0.397 *** (0.027)
%Impervious	−1.013 *** (0.033)	−0.827 *** (0.033)					
US_SOVI		0.283 *** (0.013)					
medianHouseValue			−0.450 *** (0.048)	−0.427 *** (0.052)	−0.287 *** (0.057)	−0.398 *** (0.059)	−0.555 *** (0.045)
%Asian			−0.207 *** (0.048)	−0.211 *** (0.049)	−0.277 *** (0.048)	−0.400 *** (0.063)	−0.229 *** (0.047)
%Hispanic			−0.058 (0.067)	−0.002 (0.072)	−0.209 *** (0.073)	−0.243 *** (0.078)	
%NativeAmerican			0.087 ** (0.037)	0.086 ** (0.039)	0.037 (0.039)	−0.027 (0.066)	
%Black			−0.032 (0.036)	0.015 (0.039)	0.038 (0.038)	−0.193 *** (0.050)	0.112 *** (0.035)
peoplePerUnit			−0.227 *** (0.057)	−0.221 *** (0.057)	−0.267 *** (0.059)	−0.274 *** (0.060)	
%CivilianUnemployed							−0.100 ** (0.045)
%NoCar							−0.132 ** (0.059)
%Under5yo							−0.072 ** (0.035)
%Unoccupied			0.088 ** (0.043)	0.072 (0.045)	0.073 (0.045)	0.104 ** (0.045)	0.116 *** (0.042)
%RenterOcc			−0.086 * (0.048)	−0.084 * (0.049)	−0.190 *** (0.049)	−0.031 (0.053)	
HOSPTPC							0.231 *** (0.030)
%Rural			0.923 *** (0.049)	0.917 *** (0.049)	0.721 *** (0.050)	0.680 *** (0.051)	0.853 *** (0.040)
%MobileHomes			−0.195 *** (0.044)	−0.112 ** (0.050)	0.045 (0.050)	0.091 * (0.051)	
%UnderPoverty			0.329 *** (0.066)	0.346 *** (0.067)	0.481 *** (0.067)	0.315 *** (0.070)	
NE_region				0.383 *** (0.146)			
S_region				−0.019 (0.128)			
MW_region				0.242 * (0.141)			
W_P_division					0.782 *** (0.203)	0.989 *** (0.206)	
NE_NE_division					0.798 *** (0.189)	0.707 *** (0.193)	
NE_MA_division					0.442 *** (0.165)	0.389 ** (0.169)	
MW_ENC_division					−0.343 ** (0.152)	−0.354 ** (0.155)	
MW_WNC_division					1.057 *** (0.151)	0.970 *** (0.153)	
S_SA_division					−0.577 *** (0.148)	−0.392 ** (0.155)	
S_ESC_division					−0.172 (0.159)	−0.071 (0.163)	
S_WSC_division					0.729 *** (0.143)	0.816 *** (0.148)	
%Asian:%UnderPoverty						−0.253 *** (0.059)	
%tUnderPoverty: %Hispanic						0.158 *** (0.053)	
%UnderPoverty: %NativeAmerican						0.057 * (0.032)	
%UnderPoverty:%Black						0.231 *** (0.033)	
Constant	−11.446 *** (0.029)	−11.334 *** (0.029)	−11.337 *** (0.031)	−11.445 *** (0.110)	−11.651 *** (0.118)	−11.842 *** (0.122)	−11.355 *** (0.029)
Observations	11,629	11,629	11,629	11,629	11,629	11,629	11,629
Adjusted R^2	0.089	0.125	0.196	0.197	0.224	0.229	0.198
F Statistic	568.158 *** (df = 2; 11,626)	553.060 *** (df = 3; 11,625)	237.754 *** (df = 12; 11,616)	191.508 *** (df = 15; 11,613)	168.896 *** (df = 20; 11,608)	145.003 *** (df = 24; 11,604)	288.230 *** (df = 10; 11,618)

Note: * p ** p *** $p < 0.01$.

Five social factors significantly increase property damage ratios across all models. Damage is higher in rural counties, and in counties with lower median house values, lower housing density (people per home), higher percentages of population below the poverty line, and in counties with lower percentages of Asian populations across all models ($p < 0.01$). Counties with higher Native American populations experience higher property damage ratios across two models (6a and 6b: $p < 0.05$). An interaction between the percent of Native Americans and people below the poverty line is also significant (model 6d: $p < 0.001$). In the best-performing model (6d), race and class interactions reveal that property damage increases particularly in locations with more poor Black, Hispanic and Native American populations, but decreases in counties with more Asian populations below the poverty line ($p < 0.01$ for all interactions). These results suggest that high damage ratios are concentrated in counties with populations with higher poverty rates and minoritized populations. Geographic location is a significant predictor of property damage in seven of the eight census divisions tested. Damage is significantly higher for the west south central ($p < 0.01$), middle Atlantic ($p < 0.05$) and New England ($p < 0.01$), western Pacific ($p < 0.01$) and western central Midwest ($p < 0.05$), and lower for the eastern central Midwest and south Atlantic division ($p < 0.05$ for both).

3.3. Social versus Biophysical Influence Explaining Variation in Death and Damage

Social factors increase model performance and add significant predictability to flood death (Figure 2A) and damage in the US. Deviance explained from death count models is smaller in models with only biophysical variables (model 2, 0.014), and deviance explained increases when adding SoVI (model 3, 0.037), individual social factors identified in machine learning (model 5a, 0.072), social variables identified in the literature (model 4a, 0.076 and model 4c, 0.091). Variance explained in property damaged increased from just 9% in a biophysical model (model 2) to over 23% when social and geographic factors were added to the model (model 6d) (Figure 2B).

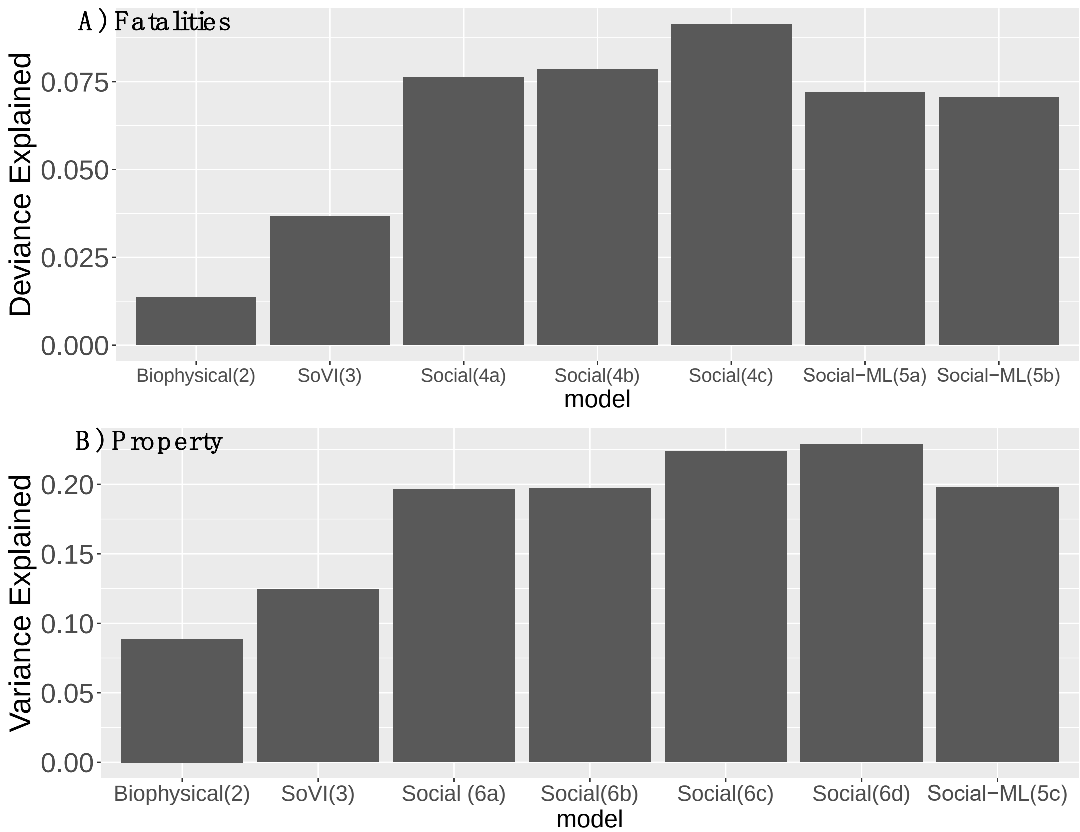

Figure 2. Deviance explained for (**A**) fatality models (difference between each model and a null model in predicting death counts) and R^2 values for (**B**) property models.

3.4. Predicted Spatial Distribution of Death and Damage in a 500-Year Flood Event

The best-performing models for flood fatalities (Model 4c, social vulnerability variables selected from the literature including geographic controls) and damage (Model 6d, social vulnerability variables selected from the literature including geographic control) were used to predict death and damage across the USA for a hypothetical 500-year flood (Figure 3). Results show that in a large flood event, property damages occur across a wide portion of the USA, and are highest across the south east, southwest, Midwest, and in the northern portion of New England. Deaths are highest in the Appalachian region, and in the south-central portions of the US and Plains states, and coincide with high property damage ratios. Only in portions of Utah are there regions with predicted higher deaths but not property damage. Counties with predicted higher death and damage are significantly correlated (Spearman's Rank Correlation = 0.79, $p < 0.001$). Counties with higher predicted damage are more correlated with counties with high SoVI (Spearman's Rank Correlation = 0.63, $p < 0.001$) than counties with predicted fatalities (Spearman's Rank Correlation = 0.42, $p < 0.001$). This suggests SoVI is more predictive of the spatial distribution of counties with higher flood damage relative to local property values than the spatial distribution of flood fatality. The top 10 counties for predicted death and damage do not share any counties (Table 7), but the top three counties for predicted damage also coincide with some of the high SoVI counties (Todd and Shannon, SD and Sioux, ND).

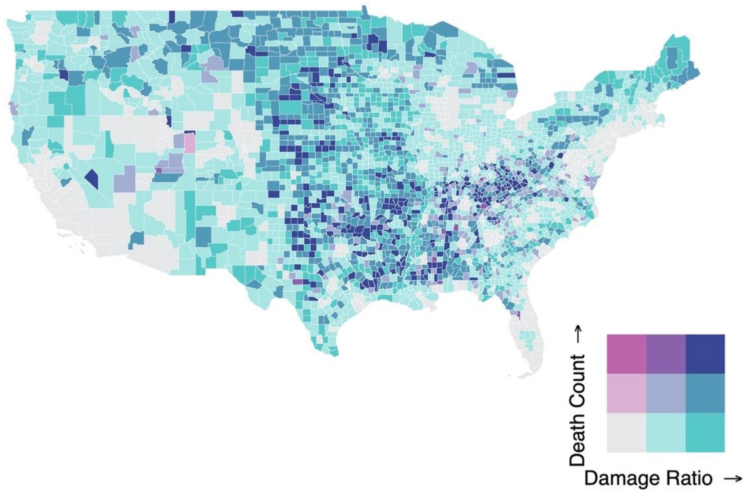

Figure 3. Bivariate choropleth map showing predicted fatality rates (per 100,000 people) and property damage ratios (normalized by housing value across each county) for a 500-year riverine flood event universally affecting the entire contiguous US.

Table 7. Top 10 US counties with highest predicted fatality rates (per 100,000 people) and property damage ratios for a 500-year riverine flood using the 2010 census. SoVI scores (from The Hazards and Vulnerability Institute, 2006–2010 version) reported in percentiles. Higher SoVI percentiles (ranging from 0 to 1) indicates higher social vulnerability.

County	Deaths	SoVI	County	Property Damage	County	SoVI
Baylor, TX	4	0.90	Holmes, MS	0.258	Buffalo, SD	0.87
Stone, AR	4	0.88	Jefferson, MS	0.181	Daniels, MT	0.93
McIntosh, OK	4	0.94	Hudspeth, TX	0.144	Sioux, ND	0.97
Letcher, KY	4	0.79	Shannon, SD	0.099	Brooks, TX	1
Motley, TX	4	0.94	Todd, SD	0.098	Bronx, NY	1
Sabine, LA	4	0.85	Wilcox, AL	0.091	Todd, SD	0.88
McPherson, NE	3	0.56	Buffalo, IL	0.080	Shannon, SD	1
Hickman, KY	3	0.83	Issaquena, MS	0.064	Menominee, WI	0.99
Menard, TX	3	0.99	Allendale, SC	0.062	La Salle, TX	0.90
Montgomery, AR	3	0.96	Sioux, ND	0.059	Clay, GA	1

4. Discussion

Results provide strong support that social vulnerability is correlated with higher death and damage in non-coastal flood events in the US. In general, we found that models including social factors explain about twice as much variation in flood outcomes for death and damage as models including only flood magnitude, flood type and impervious surface. The main variable associated with outsized death and property damage as a proportion of total property value is rurality, which is related to other factors of high social vulnerability. The models of damage and death count both improved significantly in variation or deviance explained when they included SoVI, a composite indicator of social vulnerability. This finding is consistent with previous validation studies, which find that SoVI is correlated with property damage [34,49]. Our study is the first validation of SoVI in relation to flood events across the US. However, the explained variance and deviance of both death and damage continued to increase when specific demographic variables, selected via machine learning or literature review, were added to the models (Figure 2, Table 5). Previous research on Hurricane Sandy likewise found that models constructed with specific components of social vulnerability (termed vulnerability profiles, Rufat et al. [34]) offered higher predictability for distinct flood outcomes than a general index like the SoVI. We found that in addition to general social vulnerability (from the SoVI), rural counties and counties in the central southwestern US have a higher propensity for losses of both lives and property. However, other specific components of vulnerability are related to distinct death versus property loss outcomes.

4.1. Flood Fatalities

Consistent with the previous literature, the model results indicate that counties with more elderly and young populations, as well as rural locations, are related to higher flood fatalities. Quantitative and qualitative studies have found that very old and very young populations are more likely to die in a flood event either from drowning or complications related to medical access post-event [67,72–75]. Rural locations also have an older age distribution in the USA [136], although when including rurality and percent elderly in a county, the same model did not cause multi-collinearity (based on variable inflation coefficient tests). While rurality and age are likely related to higher levels of flood deaths, causation cannot be ascribed from the correlative results presented here.

We found SoVI was positively and significantly associated with flood death counts, contrary to a previous study which did not find SoVI to be a significant factor of flood death across multiple hazards across southeastern States [49]. Bakkensen et al. [49] did not use a direct measure of flood magnitude to control for hazards. Contrary to previous work (e.g., Zahran et al. [79]), we found neither race nor poverty to be significantly correlated with flood deaths. Our sample size, however, did not include significant events such as Hurricane Katrina (2005) and Hurricane Audrey (1957), which indicated that Black populations had higher propensities for flood death [77,78]. Our nation-wide study found regional patterns of flood death in Appalachia, the Ohio River Valley, and in South Central Texas, consistent with previous studies [71,79]. Our models include riverine and flash flood events only, and should not be generalized to coastal flood events. Flood fatalities (for flash floods in particular) could occur in hillslope regions with extreme rainfall patterns, and could be related to other factors not controlled for in this study. Efforts to reduce flood deaths in these locations could include better early warning and near real-time warning systems, especially to indicate evacuation routes on safe roads, since most deaths involved driving in a car. Installing sensors on road crossings where flash floods tend to occur, or where flood deaths have occurred in the past, to alert drivers of dangerous crossings could also be effective.

4.2. Property Damage

Consistent with previous studies, we found SoVI and poverty to be significantly correlated with flood damage [34,49]. Other studies, such as that of Yoon et al. [19], using absolute property damage across multiple hazard types in coastal areas from 1990 to 2010, found urban areas and high ratios of female population to be correlated with property loss. Their results could contradict ours due to differences in spatial extent, temporal extent, and most likely normalization of the dependent variables (our regressions are on property damage ratios, theirs are absolute loss estimates, which one would expect to be very high in urban areas). The significant social factors in the best-performing model indicate that rural areas, and the interaction of race and poverty, have the largest influence on property damage. The most striking result from our models was the significant role of some races (Black, Native American and Hispanic) and poverty in predicting property damage ratios. Previous qualitative research has found, for example, that it is not Black communities generally that suffered greatest property losses in Hurricane Katrina, but low-income Black communities specifically [94]. We found the interaction of poverty and Asian populations to be negative, suggesting regions with poor Asian communities experience less property loss in riverine floods than other populations.

Our results indicate that the influences of poverty–race interactions associated with greater property losses extend beyond Hurricane Katrina, and could be a generalizable phenomenon across the contiguous US, validated by empirical data for over 11,000 riverine events. Other studies of quantitative hazard outcomes have also found significant race interactions; populations census blocks with tornado events in the US from 1980 to 2010 across 25 states became more White and had lower rates of poverty post-hazard, suggesting out-migration by poor and non-White populations [64]. The high propensity for flood-related property loss in poor communities of color could be due to increased flood exposure (due to limited housing choices and more accessible housing in floodplains), poor housing quality, structural racism (e.g., systematic underinvestment in flood mitigation structures such as levees), or institutional racism and bias (e.g., low flood insurance coverage (7%) in Native American communities, because FEMA was not mapping them, a prerequisite for the National Flood Insurance Program [103]). While flood insurance can create moral hazards and increase vulnerability [137], other studies find that payouts from insurance are less likely to reach socially vulnerability communities [65]. Investments in flood mitigation infrastructure, improved zoning, opportunities for buyout and relocation [138], disaster recovery from public programs [65], and financial support for risk transfer mechanisms such as insurance should be targeted towards poor communities of color—Black, Hispanic and Native American specifically—to address this gap.

4.3. Spatial Distribution of Death and Damage and Model Limitations

Our model results indicate significant geographic variation in riverine flood death and damage. Figure 3 suggests specific regions are susceptible to riverine flood outcomes, and the interaction of death and damage. Previous flood research has found that flood exposure trends also exhibit geographic hotspots over the contiguous US [104]. Some of the hotspots of increasing flood exposure due to urbanization in floodplains found in previous studies, for example in Appalachia and along the Ohio River, are the same regions where our model finds coincident high propensities for death and damage in a predicted 500-year riverine flood event (Figure 3). Spatial autocorrelation in flood death models suggests the results presented here may not provide a robust validation of social vulnerability to riverine flood deaths. Developing geographically weighted zero-inflated regression models with negative binomial distributions will be required to provide robust validation of social vulnerability and specific socio-demographic factors for flood death in the US. Subsequent research could extend this study by developing geographically weighted models to explore how social factors at different scales significantly predict death and damage, or vary across the country. We only assessed non-coastal flood events from 2008 to 2012, two years before and after the 2010 census. Efforts to integrate flood events near the 2000 census, and the upcoming 2020 census, could both increase the sample and permit the examination of potential changes in social vulnerability to floods over time.

We only assess aggregate property damage at the county level in this study for non-coastal floods from 2008 to 2012. Future work could compare flood damage directly from FEMA public assistance data or insurance claims, to examine if factors identified in this study prediction flood damage ratios differ in homeowner loss-specific datasets. Vulnerability and resilience to hazards in the US may also change over time [28], and we encourage future studies to empirically validate vulnerability across time to test this hypothesis. Social vulnerability is also likely to change in the future, which can be modeled to improve the understanding of how climate hazards such as sea-level rise may disproportionally expose vulnerable communities [139].

The hazard controls related to flood magnitude from stream gauges are an improvement over past studies, which used precipitation [79] or NCEI intensity scores [49]. Stream gauges represent one point on a river and are an imperfect measure of flood hazard across the county-watershed units used here. Direct measures of spatially explicit flood extent or depth per hazard (as used by Rufat et al. [34]) for each flood hazard in the Storm Events database would be the preferred control variables, but these were unavailable at the time of this study. We exclude all coastal flood events, which likely represent an even larger number of flood deaths and flood damages. Future flood social vulnerability validation studies should seek to integrate and compare differences across riverine, flash and coastal flood events.

An important qualification of our results is that social factors were aggregated at the county level, and variations in flood outcomes at the household level are excluded at this unit of analysis. This means that the relationships described in this study here apply at broad geographic scales, but different relationships may apply at more local scales or at the individual level. A county level analysis of flood fatalities, for example, does not completely control for the excess flood exposure in counties where populations are more concentrated along a river or on floodplains. Other modeling techniques, such as hierarchical or spatio-temporal Bayesian analysis, are increasingly common in epidemiology [140] and natural sciences [141], but to our knowledge these are not yet used in social vulnerability analysis (but there is an example of a resilience assessment based on a Bayesian network [142]). Bayesian methods should be used to test the hypotheses examined here, and will allow for uncertainty analysis in order to better understand the strength of relationships between sociodemographic variables and hazard outcomes. Other important components of social vulnerability, including social cohesion, social capital and risk perception [23] identified in place-based and qualitative studies, are difficult to meaningfully measure at county scales, but their validation across large geospatial scales remains important.

4.4. Further Research Needs

This study adds to a small but growing number of social vulnerability validation studies, further identifying specific social factors that lead to higher propensities for loss in hazard events. While we found indices like SoVI to be correlated with flood death and damage outcomes at the county scale, digging deeper into specific social factors revealed that some, but not all, SoVI components are significant predictors of riverine flood death and damage. Recent studies [34] have suggested validating constructed vulnerability profiles of related social factors as a way forward. We confirm their recommendation that more social vulnerability validation is needed across a wider array of spatial and temporal scales, since the scale and accuracy of both the flood hazard and social vulnerability variables critically affect findings [143]. Socioeconomic and demographic factors at the household, community and larger scales need to be tested in additional multi-scale validation studies, in order to understand how gender, for example, may increase risk of death in a non-coastal flood at a household but not at county scales. Social vulnerability validation across hazards is necessary in order to direct policy interventions to address floods, heat waves and tornados to the populations and places that need them most. Knowing, for example, that people above the age of 65 are more at risk of death from a non-coastal flood may enable policy makers to identify those populations in advance, for early evacuation before floods occur, or to reinforce riverine flood protections near long term care facilities. SoVI scores may serve as a general guide of vulnerability, but hazard-specific models are likely to yield more specific and useful policy recommendations. Finally, social vulnerability validation across phases of the disaster cycle is needed. For example, while populations with young age distributions may have greater propensities for flood death in a hazard event, they might also have higher rates of recovery if children are more psychologically resilient to hazards in the recovery phase [75].

5. Conclusions

Overall, the methods explored in this study indicate that the hazards-of-place model [5], which has inspired decades of research into the social conditions that influence the vulnerability of people-in-place to specific hazards, can be extended by building empirically validated social vulnerability models of hazard-specific disaster outcomes. In this case, sensitivities to non-coastal flood events regarding mortality and economic damage are validated for the 48 contiguous United States using the 2010 census. The results support some of the vulnerability factors identified in past research, including county-level measures of racial/ethnic composition, poverty, the elderly and young population, and rural location. Other factors identified in past research were not related to flood impacts in our analysis, including gender and mobile home prevalence.

The data-driven validation method presented here to assess vulnerability could also be used to validate commonly used indicators of resilience or coping capacity, which also suffer from inadequate validation. Validation not only identifies factors to which disaster mitigation policies should pay attention, but also allows for a more systematic study of changes in social vulnerability over space and time. A place-based yet broad-scale understanding of validated factors leading to social vulnerability is crucial, as urbanization and climate change influence and change the rate, intensity and location of hazards across the globe.

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Data Availability: Data from 500-year return period model prediction for death counts and relative damage form regression models are available at: https://github.com/cloudtostreet/socialvulnerability. Contact the lead author for copies of r code, models or additional data which is available upon request.

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