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Measuring social equity in flood recovery funding

Christopher T. Emrich a, Eric Tate b, Sarah E. Larson c and Yao Zhou a

School of Public Administration, National Center for Integrated Coastal Hazards, and Sustainable Coastal Systems Cluster, University of Central Florida, Orlando, FL, USA; Department of Geographical & Sustainability Sciences, University of Iowa, Iowa City, IA, USA; School of Public Administration, University of Central Florida, Orlando, FL, USA

ABSTRACT

Deconstructing causal linkages between place attributes and disaster outcomes at coarse scales like zip codes and counties is difficult because heterogeneous socio-economic characteristics operating at finer scales are masked. However, capturing detailed disaster outcomes about individuals and households for large areas can be equally complicated. This dichotomy highlights the need for a more nuanced and empirically-driven approach to understanding financial disaster recovery support. This study assessed how social characteristics influenced federal disaster recovery support following the 2015 South Carolina floods. Ordinary linear and spatial regression models provided a mechanism for pinpointing statistically significant links between individual/compound vulnerabilities and resource distribution from four federal disaster response and recovery programmes. The study makes two unique contributions. First, exploration of how social characteristics influence recovery support is a critical, yet understudied path toward fair and equitable disaster recovery. Second, finer scale inquiry across a large impact area is rare in quantitative case studies of US disasters. While we found flood recovery assistance to be strongly associated with physical damage overall the relationship was more tenuous in places with higher social vulnerability. Results indicate that future disaster recovery programs focusing on both physical damage and social vulnerable would lead to a more equitable disaster recoveries. Findings provide new understanding of equity at the intersection of social vulnerability, impacts, and disaster recovery and showcase both best-practices and areas for programme improvements for future disasters.

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KEYWORDS
Flood recovery; disaster assistance; social vulnerability; social equity; distributive equity

1. Introduction

Vaulted into the US national consciousness by the disparate population impacts of Hurricane Katrina (Gabe, Falk, & McCarty, 2005), there has been growing recognition that...
understanding and managing flood disasters requires more than simply characterising hydrological processes and built environment damage. Social inequities are also now understood to be significant drivers of flood exposure, adverse impacts, and recovery trajectories (Burton & Cutter, 2008; Hale, Flint, Jackson-Smith, & Endter-Wada, 2018; Koks, Jongman, Husby, & Botzen, 2015). These drivers are conceptually and empirically investigated in social vulnerability research, which examines how systemic social, economic, institutional, and political processes lead some population groups to face pervasive barriers accessing post-disaster resources. Links between social vulnerability and flood recovery for various disaster types suggest that social characteristics might play an increasingly important role in flood risk management (Burton, 2010; Cutter, Schumann, & Emrich, 2014; Dunning & Durden, 2007). Integrating understanding of social vulnerability with knowledge of environmental and economic processes offers a pathway toward more sustainable futures in the aftermath of disaster (Smith & Wenger, 2007). Disaster management under this paradigm implies a mindset rooted in social equity that emphasises vulnerable populations in the distribution of recovery resources.

Social equity in disaster recovery means that all people have full and equal access in resource distribution and opportunities that enable them to meet their needs. Yet, social vulnerability scholarship is replete with examples of barriers that preclude the realisation of social equity in planning, response, and recovery (Thomas, Phillips, Lovekamp, & Fothergill, 2013). For flood hazards, equity has received growing focus in examining the social dimensions of resilience (Comes, Meesters, & Torjesen, 2019; Doorn, 2017; Doorn, Gardoni, & Murphy, 2019), vulnerability (Collins, Grineski, & Chakraborty, 2018; Rufat, Tate, Burton, & Maroof, 2015), risk management (O’Hare & White, 2018; Thaler, Fuchs, Priest, & Doorn, 2018; Thaler & Hartmann, 2016), and justice (Kaufmann, Priest, & Leroy, 2018; Siders, 2019; Walker & Burningham, 2011). Media and government reports often describe disaster assistance in terms of total amounts authorised or allocated. A complimentary, but often overlooked dimension is distributive equity in disaster programmes: the logic underlying the relative distribution of post-disaster assistance and the associated implications for meeting people’s needs during flood recovery (Muñoz & Tate, 2016; Vinik, 2018). However, social equity is not a principal factor in the distribution of US federal recovery dollars.

Four national programmes dominate the outlay of disaster recovery funds to households in the US: Individual Assistance (IA), the National Flood Insurance Program (NFIP), Small Business Administration (SBA) disaster loans, and the Community Development Block Grant-Disaster Recovery (CDBG-DR). Each differs in eligibility criteria, assistance types, and assistance timing. NFIP pays flood claims based on pre-disaster insurance coverage. IA grants and SBA loan availability require a Presidential Disaster Declaration, while CDBG-DR allocations require a special congressional authorisation after a disaster with large unmet needs remaining after resource allocation from other recovery programmes. Collectively, the four federal programmes form an umbrella of financial resources available to households following major flood disasters. These programmes allocate billions of dollars annually toward disaster recovery, but how equitable is the distribution?

Flood recovery is increasingly recognised as an important part of flood risk management yet one that remains understudied (O’Neill, 2018; Schanze, 2006). Focusing on disaster programmes for housing recovery, this study investigates two research questions: (1) What is the social equity of US post-disaster assistance?; and (2) How does this equity vary by federal programme? To empirically evaluate these questions, we use a
case study of the 2015 South Carolina floods to determine the relationship between social vulnerability indicators and disbursements from four disaster recovery programmes. The remainder of this paper proceeds as follows. The next section explains connections between social equity and social vulnerability, and describes the major US programmes that distribute disaster recovery funds. Sections 3 and 4 describe outcome measures from the South Carolina floods and detail the methods we applied to determine the statistical relationship between social vulnerability indicators and recovery resource outlays. We present the results of the analysis in Section 5, and discuss the major findings and conclusions in Section 6.

2. Background

2.1 Social equity and social vulnerability

Environmental justice scholarship provides useful guidance for conceptualising social equity. The field has long organised research around forms of justice, which include distributive, procedural, social, corrective, and retributive types (Kuehn, 2000). Distributive justice is the right to equal treatment across demographic groups, and associated analyses typically quantify how environmental hazards vary across populations. With its emphasis on the notion that no population group should disproportionately benefit or be burdened by the distribution of environmental harms or resources, social equity strongly aligns with the distributive justice (Ikeme, 2003). Based on social equity principles, the distribution of disaster recovery resources should be based on fulfilling the needs of the affected. But who has the greatest needs after disaster?

For each of the major programmes for disaster recovery, households with the greatest need are largely identified based on physical damage. The identification generally occurs through field assessment of post-disaster damage and estimation of associated repair costs. Under this paradigm, households with damage to highly valued assets are prioritized in the distribution of recovery resources. But this design is unlikely to satisfy the post-disaster needs of socially vulnerable populations. These groups tend to experience greater proportionate losses (Fothergill & Peek, 2004), have less bridging and linking social capital, and face greater delays in receiving recovery dollars (Muñoz & Tate, 2016). To achieve social equity, criteria for defining post-disaster needs should expand beyond physical vulnerability to also include social vulnerability.

Social vulnerability is the heightened propensity of marginalised populations to suffer adverse disaster impacts. Such marginalisation is rooted in socially-stratified economic, social, and political power structures, which manifest as geographic and demographic disparities in wealth, education, and legal rights. Vulnerability researchers have long linked these disparities with differential capacity to prepare for, cope with, and recover from disasters (Wisner, Blaikie, Cannon, & Davis, 2004), with results dispelling the notion that disaster recovery occurs uniformly across all members of affected communities (Smith & Wenger, 2007; Tierney & Oliver-Smith, 2012). To quantitatively model processes of disparity, social vulnerability researchers have used empirical understanding about what makes people and places vulnerable, extracting associated socio-demographic variables and assembling them into indicators of social vulnerability. If tailored to flood recovery, social vulnerability indicators hold promise as measures of social equity.
Social vulnerability manifests differently across the landscape and may compound from underlying demographic characteristics (Emrich & Cutter, 2011; Morrow, 1999). Where one person or place might be vulnerable because of age or racial discrimination, a neighbouring person or place might be vulnerable (or not) due to different characteristics or circumstances (e.g. poverty, renter, residing in a mobile home). Previous studies have found that intersections of vulnerability characteristics are linked to adverse outcomes beyond those associated with individual constituent drivers. For example, Elliott and Pais (2006) in their study of Hurricane Katrina found that low-income Black populations experienced greater post-disaster job loss than low income populations or Black populations alone. Yet despite conceptual and empirical understanding of social vulnerability as compounding, most quantitative studies treat social vulnerability drivers as discrete (Ryder, 2017). Few have explored the interactions between compounded social vulnerabilities and disaster outcomes (Rufat, Tate, Emrich, & Antolini, 2019).

2.2 Disaster recovery programs for housing

FEMA’s National Disaster Recovery Framework clarifies the roles and responsibilities for stakeholders in recovery, recognising first that recovery is a continuum (FEMA, 2016a). Because disasters impact some segments of the population more than others, the ability of an individual or community to accelerate the recovery process is highly dependent on resources (insurance, savings, federal recovery support, non-profit assistance) in every disaster phase. Delivery of the right post-disaster resources to populations in need can significantly reduce recovery time and cost. The distribution of these resources can occur over short time frames after the disaster (days to months) through IA housing grants, NFIP insurance payments, and SBA home loans, as well as in delayed fashion (months to years) through CDBG-DR rebuilding grants (Figure 1).

IA is a grant programme intended to address immediate needs of uninsured and underinsured disaster survivors. IA accounted for 14% of federal disaster spending from fiscal

![Figure 1. Recovery continuum and federal recovery programmes (adapted from FEMA 2016b).](image-url)
years 2007–2016 under the Stafford Act (Reese, 2018), and 4.7 million people applied to the programme in 2017 (GAO, 2018). Among the six IA subprograms, the Individuals & Housing Program is the largest and provides funds for housing repair, short-term lodging reimbursement, personal property replacement, medical care, moving & storage, and transportation costs (FEMA, 2016b). Funding maximums are indexed to inflation, and in 2018 were $33,000 for households and $8,500 for individuals (Reese, 2018), although average payouts are typically much lower. Disaster survivors have up to 60 days after a disaster declaration to apply (Figure 1), and to be eligible must be US citizens or qualified residents, have expenses and needs caused the disaster, and document that other sources of disaster assistance are insufficient to meet needs (Lindsay & Reese, 2018). IA eligibility is also subject to income screening, as families with incomes above 1.25 times the federal poverty level (1.5 times for individuals) are instead referred to the SBA disaster loan programme (Lindsay & Reese, 2018). Recent studies examining the relationship between IA and demographic characteristics found social vulnerability indicators to be significant predictors of the number of applicants, physical damage, and aid granted (Grube, Fike, & Storr, 2018; Rufat et al., 2019). Based on IA’s focus on uninsured and poorer households, we expect moderate overlap between IA grantees and socially vulnerable populations.

The SBA disaster loan programme provides resources to uninsured and underinsured households and businesses. Although managed by the Small Business Administration, 80% of the loan funds are allocated to households (Kreiser, Mullins, & Nagel, 2018). Homeowners can borrow up to $200,000 to repair or restore primary residences to pre-disaster condition, while both renters and homeowners can borrow up to $40,000 to replace damaged personal property (e.g. cars, clothing, furniture). Eligibility requires verification of disaster-related losses, satisfactory credit, and ability to repay the loan (Lindsay & Reese, 2018). The availability of SBA loans for households is triggered by a disaster declaration that includes IA. Because SBA loan recipients incurred underinsured losses yet also have sufficient resources to be deemed credit worthy, we expect a weak positive relationship with socially vulnerable populations.

NFIP provides subsidised flood insurance to property owners in participating communities that map high risk areas and regulate floodplain development. The NFIP coverage ceiling is $250,000 for residential properties, and approximately 90% of residential policies cover single family dwellings (FEMA, 2018). Thus, NFIP is a potentially large source of disaster resources to flood-impacted households. However, property owners in non-participating communities are ineligible to purchase flood insurance. A recent comparison of household income and NFIP found that those without NFIP coverage had a median income of $40,000 (University of Maryland, Center for Disaster Resilience, and Texas A&M University, Galveston Campus, Center for Texas Beaches and Shores, 2018) compared to the national median income of $61,372 (Fontenot, Semega, & Kollar, 2018). This is important because low-income households comprise 51% of households in high risk areas (FEMA, 2018). Meanwhile, a study of Hurricane Harvey found that Black and Hispanic flood victims carried flood insurance at lower rates than whites (Hamel, Wu, Brodie, Sim, & Marks, 2017). We therefore expect NFIP payouts to be lower for socially vulnerable areas due to the predominance among the underinsured of renters, minorities, and low-income residents.
CDBG-DR provides funds for short-term and long-term disaster recovery. Because disbursement of CDBG-DR funds requires a special congressional authorisation, it is often several months post-disaster before programme funds reach affected communities. As such, the programme helps fill gaps in resident needs that remain unmet after NFIP, IA, SBA assistance (SCDRO, 2017). CDBG rules allow for a wider array of permissible expenditures than IA and SBA, so communities have flexibility to tailor spending based on local needs. Receiving states and communities must allocate at least 70% of funds to activities that principally benefit low-to-moderate income households, although waivers have at times relaxed this requirement to 50% for disaster recovery (Boyd & Gonzales, 2011). Low-to-moderate income is defined by CDBG as households below 80% of the median income for their area. Given the explicit programme emphasis on low-income households, we expect CDBG-DR to have a moderate positive relationship with socially vulnerable populations.

Social vulnerability indicators are routinely mapped to describe geographic patterns of social vulnerability and are increasingly applied statistically to analyse disaster outcomes. A far less employed application of social vulnerability indicators is as tools for evaluating disaster programmes. Given that socially vulnerable populations are disproportionately impacted by disasters, does resource distribution through the leading federal disaster programmes accrue to socially vulnerable groups? As such, this article focuses on the following two research questions: (1) What is the social equity of US post-disaster assistance? and (2) How does this equity vary by federal programme?

3. The 2015 South Carolina flooding and severe storms disaster

In October 2015, South Carolina experienced unprecedented flooding as a result of heavy rainfall across the State resulting from Hurricane Joaquin (NWS, 2016). Abundant rainfall in September left saturated soils with little absorptive capacity. Runoff from Joaquin caused rivers to rise quickly and fill water behind a large number of the state’s 2500 dams. An estimated 47 dams statewide breached, flooding downstream residents and businesses (Sasanakul et al., 2017), while more than 500 roads were closed, with some collapsing under the weight of saturated soils. The flooding caused loss of life and extensive damage to dams, bridges, roads, homes, and businesses. The rapid onset resulted in many residents requiring swiftwater rescue, and the damage impacted utilities, wastewater treatment systems, and drinking water treatment and collection systems. The severe storms and flooding prompted a Major Presidential Disaster Declaration opening the flow of federal disaster recovery resources (IA and SBA) to 25 counties across the state (Figure 2).

More than 101,000 applicants filed for IA for the South Carolina’s 2015 flooding disaster (Figure 3(A)). More than 76% are homeowners and about 24% were renters residing mainly in single family homes, duplex units, and mobile homes (SCDRO, 2017). According to the Vulnerability Mapping and Analysis Platform (VMAP, 2019), only about 28% of the IA applicants received disaster recovery resources, a denial rate among the top ten in recent similar disasters. Less than half as many flood victims applied for SBA disaster loans during the weeks following the floods (Figure 3(B)), but only 9.6% of SBA applicants ultimately received loans. NFIP provided payouts to 84% of the 5504 flood victims who filed flood insurance claims (84%) (NFIP, 2016). A CDBG-DR programme for the disaster was
implemented in Spring 2016, and has provided resources to approximately 25% of more than 8000 applicants (25%) to date (Figure 3(D)) (SCDRO, 2019).

4. Methods and data

We compiled recovery programme information from the 2015 South Carolina floods, and demographic variables from the US census. The objective was to statistically explore linkages among univariate and compound social vulnerability, disaster losses, and recovery resources. To do so, we constructed multivariate regression models that use program-specific funding totals as dependent variables and social vulnerability indicators as predictors while controlling for loss.

4.1 Flood outcome measures

Outcome variables for the analyses include loss indicators and programme support indicators for real property (building) and personal property (contents) (Table 1). We calculated loss and support indicators separately by recovery programme because each programme accounts for losses differently.

We computed the dependent and control variables for each programme as sums of multiple damage/loss and support measures (Figure 4). Loss and payouts (grants, insurance, or
loans) to property owners dominate the totals in comparison to losses and payouts for personal property (contents). As such, property losses and payouts appear to be the most useful variable for understanding the driving forces behind disaster equity across the study area. We calculated the program-specific measures of disaster loss as follows:

*Figure 3.* Disaster survivors by recovery support programme – IA (A); SBA (B); NFIP (C); CDBG-DR (D); Combined programmes (E).
Table 1. Disaster outcome variables.

<table>
<thead>
<tr>
<th>Programme</th>
<th>Type</th>
<th>Variable</th>
<th>Description (US dollars)</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>IA</td>
<td></td>
<td>Housing Assistance (HA)</td>
<td>HA building repair/ replacement grant</td>
<td>FEMA (2016c)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Other Needs Assistance (ONA)</td>
<td>ONA contents replacement grant</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>FEMA Full Verified Loss for Real Property</td>
<td>Building damage</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>FEMA Full Verified Loss for Personal Property</td>
<td>Contents damage</td>
<td></td>
</tr>
<tr>
<td>SBA</td>
<td></td>
<td>Current Real Property Loan Amount</td>
<td>Current loan amount for building recovery</td>
<td>SBA (2019)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Current Contents Loan Amount</td>
<td>Current loan amount for contents replacement</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>SBA Verified Real Property Loss</td>
<td>Sum of building damage (manufactured, repair/</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>replace, reconstruction, relocation)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>SBA Verified Contents Loss</td>
<td>Contents damage</td>
<td></td>
</tr>
<tr>
<td>NFIP</td>
<td></td>
<td>Building Payments</td>
<td>Insurance payouts for building repair,</td>
<td>NFIP (2016)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Contents Payments</td>
<td>replacement</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Building Loss</td>
<td>Building damage</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Contents Loss</td>
<td>Contents damage</td>
<td></td>
</tr>
<tr>
<td>CDBG-DR</td>
<td></td>
<td>Final Amount</td>
<td>CDBG-DR funds spent on repair/replacement</td>
<td>SCDRO (2019)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Estimated Rebuilding Amount</td>
<td>Estimated building damage</td>
<td></td>
</tr>
</tbody>
</table>

†Measure of loss. ‡Measure of support.

Figure 4. Loss and support variables by federal disaster recovery programme.
IA loss = sum of FEMA verified loss for personal and real property
SBA loss = sum of SBA verified loss to property (repair and replacement), contents damage, relocation expenses, damage to other structures, manufactured home damage and debris removal
NFIP loss = sum of the building and contents damage as reported by NFIP claims adjusters
CDBG-DR loss = final rebuilding cost or estimated rebuild cost (when the final amount was not available)

### 4.2 Social equity indicators

We selected seven social vulnerability variables (Table 2) at the census tract level using data from the 2011–2015 American Community Survey of the US Census Bureau. The census tract scale is the smallest geographic unit for which demographic variables are considered to be statistically reliable (Spielman, Folch, & Nagle, 2014). The variable selection was guided by findings from previous empirical studies that examined links between social vulnerability characteristics and flood recovery. We used a smaller than typical (VMAP, 2018) subset of vulnerability indicators for two purposes: First, the variables align with the stated goals, event type, and distribution methods of each recovery programme. Second, the small indicator set maintains statistical power in the analysis, enabling exploration of interaction effects as a proxy for compound vulnerabilities.

<table>
<thead>
<tr>
<th>Driver</th>
<th>Indicator</th>
<th>Rationale for Inclusion</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Housing tenure</td>
<td>% Renter Households</td>
<td>Less access to post-disaster housing programmes; lower post-flood return rate; difficulty exiting rental agreements in damaged homes</td>
<td>Finch, Emrich, and Cutter (2010), Kamel (2012), NASEM (2019)</td>
</tr>
<tr>
<td>Financial capital</td>
<td>Per Capita Income</td>
<td>Limited recovery resources and options for post-flood housing; higher post-flood health impacts; disproportionately reside in flood-prone areas; less likely to carry flood insurance</td>
<td>Green, Bates, and Smyth (2007), Masozer, Bailey, and Kerchner (2007), NASEM (2019)</td>
</tr>
<tr>
<td>Race</td>
<td>% Black Population</td>
<td>Higher death and injury rates; negative post-flood health outcomes; less likely to carry flood insurance; lower trust in authority for post-flood assistance; higher employment loss</td>
<td>Elliott and Pais (2006), Li, Aireiss, Chen, Leong, and Keith (2010), Hamel et al. (2017)</td>
</tr>
<tr>
<td>Language proficiency</td>
<td>% Speak English as a Second Language: Not Well or Not At All</td>
<td>Difficulty accessing recovery assistance from governmental and nongovernmental sources; fewer adverse post-flood health outcomes</td>
<td>Collins, Jimenez, and Grineski (2013), NASEM (2019)</td>
</tr>
<tr>
<td>Housing quality</td>
<td>% Mobile Homes</td>
<td>Added repair difficulties; focus of the SC CDBG-DR implementation. Negative post-flood health outcomes; lower recovery rates</td>
<td>SCDRO (2017)</td>
</tr>
<tr>
<td>Age</td>
<td>Age Under 5 and Over 65</td>
<td>Negative post-flood health outcomes; lower recovery rates</td>
<td>Collins et al. (2013), Muñoz and Tate (2016), NASEM (2019)</td>
</tr>
<tr>
<td>Employment</td>
<td>Service Sector Employment</td>
<td>Sector specific employment (service industry) is particularly vulnerable to disasters. Lack of disposable income following disasters decreases the need for often low-paid service sector jobs.</td>
<td>Hewitt (1997), Puente (1999), Heinz Center (2000)</td>
</tr>
</tbody>
</table>
The Pearson correlation coefficients of the social vulnerability indicators range in absolute value from 0.0013 to 0.5257, suggesting they represent distinct dimensions of social vulnerability (Table 3). We examined compounding vulnerability by analysing first-order interactions among programme-specific loss indicators (control variables) and three of the social vulnerability predictors: renters, wealth, and race. We selected only these predictors due to their empirical importance and to retain statistical power across models. The remaining four social vulnerability variables were included in the regression models as individual predictors, but not interacted with the loss indicator.

4.3 Multivariate regression models

We constructed five multivariate regression models to assess social equity in the allocation of flood recovery resources. Each model used programme support as the outcome variable, social vulnerability indicators as predictors, and a loss measure as control. The regression models are a combination of ordinary least squares (OLS) and spatial auto-regressive (SAR) models. To determine if a given OLS model contains residual spatial autocorrelation, we computed the Moran’s I statistic on the OLS residuals. When significant, we applied the Lagrange Multiplier test to determine the dominant form of spatial effects (heterogeneity or dependence), and then applied the appropriate spatial regression model (Spatial Error or SAR). For both the Moran’s I statistic and the spatial regression modelling, we generated the weights matrix based on a K-nearest neighbour schema (K = 10).

The outcome indicators were collected by the federal agencies at the household scale, but we aggregated them to the census tract scale to match the scale of the census demographic variables. The aggregation means that the statistical linkages between social vulnerability variables and outcomes apply to the dominant demographic characteristics of the containing census tracts rather than those of the recipient households. Were the federal programmes to collect detailed demographic data during future distribution of recovery resources, associated equity analysis could produce finer-grained results.

Table 4 provides descriptive statistics for the outcome and predictor variables, including the number of census tracts for which each variable was available. Variations in

---

**Table 3. Pearson correlations of social vulnerability indicators.**

<table>
<thead>
<tr>
<th>% Renters</th>
<th>Per Capita Income</th>
<th>%Black</th>
<th>%ESL</th>
<th>%Mobile Homes</th>
<th>%Population under 5 or over 65</th>
<th>%Service Industry Employment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.00</td>
<td>−0.2767***</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Black</td>
<td>0.3456***</td>
<td>−0.5257***</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% ESL</td>
<td>0.0968***</td>
<td>−0.2163***</td>
<td>0.0430</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Mobile Homes</td>
<td>−0.3391***</td>
<td>−0.3678***</td>
<td>0.0935***</td>
<td>0.1437***</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>% Population under 5 or over 65</td>
<td>−0.3433***</td>
<td>0.2122***</td>
<td>−0.0719**</td>
<td>0.0013</td>
<td>0.0459</td>
<td>1.00</td>
</tr>
<tr>
<td>% Service Industry Employment</td>
<td>0.3795***</td>
<td>−0.4851***</td>
<td>0.4102***</td>
<td>0.4105***</td>
<td>0.0033</td>
<td>−0.0569</td>
</tr>
</tbody>
</table>

***p < 0.01, **p < 0.05.
programme-specific enrolment (e.g. some programmes did not have applicants in some census tracts) resulted in a different set of census tracts for each regression model. Among the programmes, CDBG-DR funds were distributed in the lowest number of tracts, but had the highest average allocation. By contrast, IA resources were distributed to the greatest number of tracts, but had by far the lowest average allocation. Lower average and median percentages across the study area for most of the social vulnerability variables stands in stark contrast to a few instances (% Black, % ESL, and % mobile home) where the maximum percentage in at least one census tract is nearing 100%.

Model 1 is an SAR model with IA support as the dependent variable and equity variables as predictors. Positive spatial autocorrelation between outcome and predictor variables warranted use of a SAR lag model with maximum likelihood. The SAR model tested relationships between average IA grants and the seven social vulnerability predictor variables, both independently and with interactions among the three selected social vulnerability indicators, while controlling for IA losses.

Model 2 analyses the distribution of recovery dollars through the SBA loan programme. We used OLS regression after finding no spatial collinearity between the dependent and independent variables. Average SBA loan amounts were regressed against the seven independent measures of social vulnerability, three of which were also interacted to identify compound vulnerability influences on SBA support controlling for SBA’s measure of loss.

Models 3 and 4 examine NFIP and CDBG-DR data, respectively. SAR modelling was not possible for either programme due to substantial spatial disconnectivity between tracts where funds were allocated (Figure 3). Consequently, we used OLS regression in the analysis for these two programmes. For each, the average support was tested against the seven independent measures of social vulnerability, three of which were selected for interaction among themselves and with the remaining four independent variables, and one control variable of average programme specific damage.

Model 5 is a combined analysis to explore the aggregate ‘federal disaster recovery safety net,’ in which we calculated a measure of total household support as the sum of average support from each of the four programmes. Unfortunately, linking specific assistance recipients across federal programmes is not possible because common identifiers are

### Table 4. Descriptive statistics for disaster recovery programmes.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Median</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Disaster Outcomes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IA Support</td>
<td>764</td>
<td>$600</td>
<td>$650</td>
<td>0</td>
<td>$454</td>
<td>$5584</td>
</tr>
<tr>
<td>IA Loss</td>
<td>764</td>
<td>$634</td>
<td>$810</td>
<td>0</td>
<td>$454</td>
<td>$10,687</td>
</tr>
<tr>
<td>SBA Support</td>
<td>586</td>
<td>$19,256</td>
<td>$15,895</td>
<td>0</td>
<td>$17,628</td>
<td>$190,900</td>
</tr>
<tr>
<td>SBA Loss</td>
<td>586</td>
<td>$30,422</td>
<td>$22,401</td>
<td>0</td>
<td>$25,127</td>
<td>$215,871</td>
</tr>
<tr>
<td>NFIP Support</td>
<td>437</td>
<td>$17,908</td>
<td>$32,319</td>
<td>0</td>
<td>$10,188</td>
<td>$500,000</td>
</tr>
<tr>
<td>NFIP Loss</td>
<td>437</td>
<td>$19,342</td>
<td>$38,495</td>
<td>0</td>
<td>$10,718</td>
<td>$654,401</td>
</tr>
<tr>
<td>CDBG Support</td>
<td>230</td>
<td>$46,167</td>
<td>$18,588</td>
<td>$3185</td>
<td>$45,680</td>
<td>$121,288</td>
</tr>
<tr>
<td>CDBG Loss</td>
<td>230</td>
<td>$45,097</td>
<td>$17,969</td>
<td>$3,185</td>
<td>$44,035</td>
<td>$121,288</td>
</tr>
<tr>
<td>Total Support</td>
<td>582</td>
<td>$52,079</td>
<td>$45,508</td>
<td>$0.00</td>
<td>$39,673</td>
<td>$576,144</td>
</tr>
<tr>
<td><strong>Social Vulnerability</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Renters</td>
<td>764</td>
<td>29.15%</td>
<td>16.95%</td>
<td>0%</td>
<td>25.42%</td>
<td>100%</td>
</tr>
<tr>
<td>Per Capita Income</td>
<td>764</td>
<td>$24,491</td>
<td>$11,424</td>
<td>$0.00</td>
<td>$21,865</td>
<td>$127,428</td>
</tr>
<tr>
<td>% Black</td>
<td>764</td>
<td>30.65%</td>
<td>24.57%</td>
<td>0%</td>
<td>23.81%</td>
<td>97.69%</td>
</tr>
<tr>
<td>% ESL</td>
<td>764</td>
<td>20.38%</td>
<td>21.15%</td>
<td>0%</td>
<td>14.69%</td>
<td>100%</td>
</tr>
<tr>
<td>% Mobile Homes</td>
<td>764</td>
<td>16.18%</td>
<td>17.57%</td>
<td>0%</td>
<td>8.64%</td>
<td>81.75%</td>
</tr>
<tr>
<td>% Population under 5 or over 65</td>
<td>764</td>
<td>21.22%</td>
<td>6.29%</td>
<td>0%</td>
<td>20.73%</td>
<td>57.80%</td>
</tr>
<tr>
<td>% Service Industry Employment</td>
<td>764</td>
<td>19.29%</td>
<td>7.66%</td>
<td>0%</td>
<td>18.00%</td>
<td>55.56%</td>
</tr>
</tbody>
</table>
not collected by each recovery programme. As such, the total safety net model reflects aggregate resources disbursed to places rather than specific households in places. Were common identifiers available, it would allow for an improved measure of household recovery outcomes. Model 5 analysed the same set of predictor variables as in Models 1–4. We identified spatial autocorrelation in the model data and therefore selected SAR over OLS.

Selecting an appropriate loss measure as the control variable emerged as an important methodological decision, because combining losses from each programme would likely result in double counting. A greater understanding of each programme’s loss measure is imperative for making an informed decision in this regard. NFIP only measures losses for individuals with insurance who filed a claim ($N = 5254$), which excludes uninsured populations. CDBG-DR measures loss as a function of rebuilding costs for those in the programme ($N = 8023$), suggesting the possibility of missing damage costs. IA only evaluates losses to essential living spaces, excluding extra bedrooms or living areas inside a home from damage estimates (FEMA, 2019). So although IA includes the highest number of applicants and census tracts across the study area, it underestimates total loss. Because SBA measures all losses to real property and personal property and includes more applicants and census tracts than NFIP or CDBG-DR, we judged the SBA loss measure to be the best suited for the combined analysis. As a result, Model 5 only includes census tracts where SBA was allocated.

5. Results

Pearson correlations between each individual programme’s measure of recovery support and loss (Table 5) show high coefficients for NFIP and CDBG-DR. This strong positive relationship is expected because both programmes focus on repairing or replacing based on total loss. Furthermore, because NFIP is an insurance programme, the average insurance support at the tract level received should be extremely similar to the measure of loss of the claims adjuster. Like NFIP, the nature of CDBG-DR as a single-family repair/replace programme suggests that losses and support will be extremely similar. There are also strong associations between loss and support within the IA programme. The lower correlation value for the SBA programme may be related to ineligibility of applicants or unwillingness to take on a recovery loan.

Table 6 presents the results of the multivariate regression for all five models. Non-significant findings, represented by the empty cells (Table 6) as well as all the variables (Table 2) that had no influence in any model and are not included in results. For each of the programme-specific models, the loss measure is statistically significant in predicting the various forms of support. This suggests that the loss variable is appropriately controlling

<table>
<thead>
<tr>
<th>Loss</th>
<th>CDBG</th>
<th>NFIP</th>
<th>SBA</th>
<th>IA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Support</td>
<td>CDBG</td>
<td>0.9842***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>NFIP</td>
<td></td>
<td>0.9867***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SBA</td>
<td></td>
<td></td>
<td>0.5585***</td>
</tr>
<tr>
<td></td>
<td>IA</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

***p < 0.01, **p < 0.05.
Table 6. Significant regression results for each recovery programme and the composite Federal disaster safety net†.

<table>
<thead>
<tr>
<th>Influence on Program Specific Federal Disaster Recovery Support</th>
<th>FEMA IA Grants</th>
<th>SBA Loans</th>
<th>NFIP Payouts</th>
<th>CDBG-DR Grants</th>
<th>Federal Disaster Safety Net</th>
</tr>
</thead>
<tbody>
<tr>
<td>Program Specific Loss† Per Capita</td>
<td>1.04*** (0.08)</td>
<td>-0.29*** (0.11)</td>
<td>0.96*** (0.05)</td>
<td>1.07*** (0.07)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Income</td>
<td>0.02*** (0.00)</td>
<td>0.74*** (0.34)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Renters</td>
<td>-20,486.9** (9975.40)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Black</td>
<td>-61,082.98*** (20,907.17)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Service Sector Employment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>82,196.59*** (24,141.02)</td>
</tr>
<tr>
<td>Compound (Multi-Variate Drivers of Disaster Losses and Funding)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Programme Specific Loss† and Per Capita Income</td>
<td>-0.00*** (0.00)</td>
<td>0.00*** (0.00)</td>
<td>-0.00** (0.00)</td>
<td>0.00** (0.00)</td>
<td></td>
</tr>
<tr>
<td>Programme Specific Loss† and % Renters</td>
<td>-0.38*** (0.04)</td>
<td>0.22** (0.09)</td>
<td>0.32** (0.12)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Programme Specific Loss† and % Black</td>
<td>1.04*** (0.15)</td>
<td>0.23** (0.04)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per Capita Income and % Under 5 or over 65</td>
<td>-0.03** (0.01)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Renters and % Under 5 or over 65</td>
<td>2054.70** (1024.9)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Speaking English Not Well or Not at All and % Renters</td>
<td>15,307.17** (7541.10)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Speaking English Not Well or Not at All and % Black</td>
<td>-10,385.07** (5051.74)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Speaking English Not Well or Not at All and % Black</td>
<td>-51,146.43*** (19,237.80)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per Capita Income and % Renters</td>
<td>-1.02** (0.51)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Black and % Mobile Homes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>26,318.00*** (12,712.00)</td>
</tr>
<tr>
<td>Constant</td>
<td>-566.95** (268.15)</td>
<td>51,057.08*** (12,988.78)</td>
<td>4324.52 (4634.83)</td>
<td>-18,780.85 (11,339.62)</td>
<td>7833.40 (9554.00)</td>
</tr>
<tr>
<td>Observations</td>
<td>764</td>
<td>586</td>
<td>437</td>
<td>230</td>
<td>582</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-5500.93</td>
<td>-6340.23</td>
<td>-4226.94</td>
<td>-2161.00</td>
<td>-6134.07</td>
</tr>
<tr>
<td>Adjusted $R^2 / (p)$</td>
<td>(0.147****)</td>
<td>0.393</td>
<td>0.985</td>
<td>0.972</td>
<td>(0.439****)</td>
</tr>
</tbody>
</table>

***p < 0.01, **p < 0.05, †SBA losses used for safety net loss models.
variations in loss that would explain the variation in average support received. The OLS and SAR models were structured such that positive beta coefficients in regression results indicated higher amounts of recovery support and larger beta coefficients indicate larger changes in amount received in relation to each single unit change in the predictor variable. Specific model results are discussed below.

5.1 Equity in IA grants

Univariate interactions between predictor variables and IA outcome measures indicated that average loss per applicant per census tract statistically and significantly explained IA support. Here, as losses increased, support also increased. Given this is a control variable, we expected this relationship to be statistically significant. Among the three social vulnerability indicators of greatest interest (% renter, % Black, and per capita income) only income was independently statistically significant in explaining average IA support received per census tract. As income increased, average IA support increased, signifying that census tracts with higher per capita income received higher IA funding. None of the four other indicators of social vulnerability were independently statistically significant (Table 6).

We analysed compound vulnerabilities through variable interactions among the social vulnerability indicators. Two joint interactions are statistically significant for IA: (1) the interaction between age and per capita income and (2) the interaction between age and renters. These findings suggest that in census tracts with higher than average percentage population under 5 and over 65 and higher than average income levels, a lower amount of IA support was provided than in census tracts with below average levels of percentage population under 5 and over 65 and below average income. This suggests that age is an important indicator of social vulnerability and could adversely impact IA support even in cases with higher income levels. For the interaction of age and renters, census tracts with higher than average populations under 5 or over 65 and higher than average renters, a larger amount of IA support was provided than to those census tracts with below average levels of both variables. This suggests IA is reaching socially vulnerable populations in this specific joint interaction.

5.2 Equity in SBA disaster loans

Assessing univariate drivers of SBA support yielded several significant results. Similar to IA, the loss variable is statistically significant (Table 6). However, the directionality of the sign is opposite what we would expect, suggesting that places with higher overall losses received fewer SBA loans. This negative relationship might be because SBA provides loans that must be repaid rather than grants. In these places with higher losses, disaster victims might be either exhibiting higher rates of ineligibility or lower willingness to accept loans as recovery support. Among the social vulnerability indicators, income was negatively correlated with average SBA support, suggesting that as average income increased, the amount of SBA average support decreased. Conversely, as the Black population increased, average SBA support decreased, signifying that census tracts with higher percentage of Black populations were adversely aided by this
programme. No other univariate indicators of social vulnerability were statistically significant.

Interactions among independent variables as predictors of SBA support produced several results. Average loss per applicant per census block was statistically significant when interacted with two of the three of the social vulnerability indicators of greatest interest (per capita income and % Black). In places where losses were higher than average and the Black population or income was higher than average, SBA support was also higher than average. These findings suggest that SBA is reaching non-white populations in census tracts with higher losses and is also serving places where losses and income are generally higher. Among the other measures of social vulnerability, no joint interactions are statistically significant.

5.3 Equity in NFIP insurance payouts

Similar to the findings with the IA programme, the control variable was statistically significant. It is thus acting as an appropriate control for the variation in loss that would explain the variation in average support received at the census tract level (Table 6). Among the univariate social drivers of NFIP support, only renters produced a statistically significant relationship. The high negative coefficient suggests that places with a higher percentage of renters received less NFIP support. This finding makes logical sense, as NFIP is designed for homeowners. No other social vulnerability indicators were individually statistically significant.

Three compounded (multivariate) relationships were revealed through the OLS related to losses and social vulnerability. Losses interacted with income producing a negative influence on NFIP support. This result suggests that where income and loss were higher than average, NFIP support was lower. Similarly, in places where average loss and renters are higher than average, NFIP support was lower. Conversely, in places where the Black population and loss were higher than average, NFIP support was higher.

Two joint interactions of only social vulnerability predictors were statistically significant in understanding NFIP support: (1) the interaction of language proficiency and percentage Black and (2) the interaction between language proficiency and renters. In places with higher than average language proficiency and higher than average Black population, NFIP support was lower than tracts with below average levels of each group. This finding suggests that NFIP is not reaching census tracts with this joint measure of social vulnerability. Conversely, places with both higher than average language proficiency and higher renters received higher NFIP support. This finding is interesting as NFIP building reconstruction loans are only available to homeowners, indicating that these places may also have high numbers of owner-occupied housing.

5.4 Equity in CDBG-DR rebuilding grants

The statistical significance of CDBG-DR loss in predicting support indicates the loss variable is an appropriate control for the variation in loss that would explain the variation in average support received. Interestingly, only one of the social vulnerability indicators (% service sector employment) was significantly explained average CDBG-DR support. As
the percentage of individuals employed within the service sector increased, the average support also increased.

Compounding vulnerabilities produced three significant results in relation to CDBG-DR support. First, places with higher than average programme specific losses and higher than average renters received higher levels of CDBG-DR support. Second, census tracts with higher than average Black populations and higher than average language proficiency received less CDBG-DR support. Finally, tracts with both higher than average renters and income received less CDBG-DR support.

5.5 Equity in composite program support

The composite model combined support from all four programmes, and represents our attempt to model the federal safety net for flood recovery. Unlike the programme-specific models, no beta coefficients were statistically significant for any of the independent or control variables. However, several multivariate interactions produced significant influence on total disaster recovery support. Among these, average applicant loss was statistically significant in interaction with income and renters. These findings suggest that in cases where income and loss were higher than normal, total support was higher. In addition, in census tracts where renters and loss were higher, total average support was higher. The interaction term for mobile homes and percentage Black was also statistically significant. Census tracts with higher than average mobile homes and higher than average percentage Black received higher overall support, signifying the combined social safety net is reaching this joint interaction of social vulnerability.

6. Discussion and conclusions

Vulnerability manifests itself differently across landscapes. The intersection (or compounding) of univariate vulnerability measures (e.g. poverty, race, employment) creates unique situations for every place. These differences should be considered when analysing disaster outcomes. Specifically, considering compounding vulnerabilities in disparity and equity analysis aligns more with conceptual understanding of social vulnerability processes than using only univariate indications of vulnerable populations or indices. Analysis of the compound effects of vulnerability on impacts and outcomes enables understanding of the multivariate nature of social vulnerability drivers. This analytic approach produced findings for each recovery programme and the aggregate federal disaster safety net. Included in these noteworthy findings are non-significant results, significant equitable results, significant inequitable results, and significant results that are neither equitable nor inequitable. The model results did not always support our hypotheses, but did point toward both success and challenges for equitable disaster recovery planning and implementation.

Disaster outcomes are often difficult to predict in the ways that vulnerability literature conceptualised and theorises.1 Disaster losses, in this case, are not always easily explained by univariate social measures or compound vulnerability indicators. The key variables drawn from the literature did not always perform in expected ways when assessing disaster specific outcomes. No programme is 100% equitable or 100% inequitable. Our analysis
identified a balance between equitable outcomes and opportunities for improvement in serving the most vulnerable populations. Although the “balance” between equitable and inequitable outcomes is clear across all programs, one should understand that these do not cancel each other out. Even one instance of inequitable recovery fund distribution should be considered problematic and corrected by respective programs or funding entities in future disaster recoveries.

The IA programme is balanced in that both equitable and inequitable distribution of funds was related to impacts and outcomes. As expected, places with higher damage levels received more IA funding. When accounting for compound vulnerabilities, we find that places with higher losses and higher income levels received less IA recovery support, a finding in line with a general consensus that these populations can likely recover without additional government assistance. Furthermore, and perhaps contrary to expectation, compound vulnerability analysis shows that places with higher average losses and higher % renters received higher amounts of IA recovery support. IA support was not systematically linked with higher or lower social vulnerability in the South Carolina case. In this regard, our hypothesis of a strong overlap between IA funding and socially vulnerable populations was not fully supported.

The SBA loan programme is largely equitable across the impact area with at least three indications of positive equity and only one indication of negative equity. The negative coefficient on SBA fund receipt in relation to SBA average loss indicates that factors associated with SBA loan receipt are more influential than SBA losses alone. Unfortunately, this inequitable outcome points to a potentially troubling finding: places with higher percentages of Black populations received significantly less SBA home loan support than places with lower percentages. Overall, the links between SBA support and social vulnerability align with our hypothesis of a weak relationship. We expected a positive association between vulnerable populations and SBA, but found a mixture of positive and negative outcomes.

NFIP was also balanced in its distribution of funds between equitable and inequitable. Here, places with higher percentage renter populations were less likely to receive funds. This finding expected because NFIP is designed for single family homeowners. When assessing compound vulnerabilities, we find that places with both higher than average NFIP losses and higher renter populations received lower amounts of NFIP payouts. Our hypothesis of a negative relationship between NFIP and social vulnerability is largely supported by our models with only one significant exception. However, we find that a combination of race and low English language proficiency result in lower NFIP payouts.

CDBG-DR provided more recovery support to places with higher per applicant losses than places with lower losses. The state-run programme also provided some support in ways that were not specifically outlined in their programme developments. Supporting our hypothesis of moderate associations between CDBG-DR support and socially vulnerable populations, the single-family home rebuilding programme provided significantly higher levels of funding to places with higher percentages of service sector employees over places with lower percentages. Furthermore, places with higher losses and higher percentages of renters received more funding. These positive unintended consequences of the programme support a broader conceptualisation of social vulnerability beyond individual (rich/poor) indicators. However, places with higher percentages of service sector employees and
Black populations received significantly less CDBG-DR support than places with both lower service industry employment and lower percentages of Black people.

This paper contributes significantly to disaster recovery literature by:

(1) Undertaking analysis of multiple programmes and compound vulnerability at a finer (than county) scale of analysis. Many similar and more detailed individual level analysis must be undertaken if we are to truly understand how these programmes function from the equity perspective. Federal programmes can support this need by collecting applicant level information on vulnerability indicators including race, tenure, employment status, and other information enabling point level analysis of these critical pathways to equitable disaster recovery.

(2) Providing statistical analysis of the interactions (compounding) of flood specific vulnerabilities. This level of complex analysis requires multidisciplinary approach to analyse and address shortcomings in programmes affecting the most vulnerable populations. This type of work cannot be done by statistical analysis alone. Rather, a strong understanding of recovery programmes and associate policies, social science, geography, and demography is required when attempting such analyse at finer scales of geography.

Our results parallel those of other national and international flood recovery studies (Medd et al., 2015; Thrush, Burningham, & Fielding, 2005; Werritty, Houston, Ball, Tavendale, & Black, 2007) in identifying specific recovery challenges for different social groups, housing tenure situations, and age groups. The links between overall damage and disaster recovery funds identified here is undeniable and points towards programs that generally operate as intended. Although we found flood recovery assistance to be strongly associated with physical damage the relationships were more tenuous in places with higher social vulnerability. There are at least two potential confounding reasons for this: 1. Disaster recovery programs are not benefiting vulnerable populations, 2. Analyzing support data collected at the household level and demographic data collected at the tract level creates opportunity for ecological fallacy. Both of these challenges require more research aimed at identifying and understanding these relationships. However, the relationships between disaster outcomes and social vulnerability identified here provide unique opportunities for both better understanding how equity manifests in disaster and for developing more just recoveries in the future. More studies focused on the intersection of disaster, place, and people are needed if we (as a society) want to truly understand and influence future disaster outcomes in a positive manner.

Note

1. Full statistical results for this paper along with additional maps, charts, and graphs related to this work can be found at www.vulnerabilitymap.org.

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Disclosure statement

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ORCID

Christopher T. Emrich  http://orcid.org/0000-0002-6773-7387
Eric Tate  http://orcid.org/0000-0002-9587-3028
Sarah E. Larson  http://orcid.org/0000-0002-9644-2019
Yao Zhou  http://orcid.org/0000-0001-6422-7528

Data availability statement

The data that support the findings of this study are available from the corresponding author, Christopher T. Emrich, upon reasonable request.

References


University of Maryland, Center for Disaster Resilience, and Texas A&M University, Galveston Campus, Center for Texas Beaches and Shores. (2018). *The growing threat of urban flooding: A national challenge*. College Park: A. James Clark School of Engineering.


