Annals of the American Association of Geographers

ISSN: 2469-4452 (Print) 2469-4460 (Online) Journal homepage: https://www.tandfonline.com/loi/raag21

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To cite this article: Samuel Rufat, Eric Tate, Christopher T. Emrich & Federico Antolini (2019): How Valid Are Social Vulnerability Models?, Annals of the American Association of Geographers, DOI: 10.1080/24694452.2018.1535887

To link to this article: https://doi.org/10.1080/24694452.2018.1535887

Published online: 01 Mar 2019.

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How Valid Are Social Vulnerability Models?

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Social vulnerability models are becoming increasingly important for hazard mitigation and recovery planning, but it remains unclear how well they explain disaster outcomes. Most studies using indicators and indexes employ them to either describe vulnerability patterns or compare newly devised measures to existing ones. The focus of this article is construct validation, in which we investigate the empirical validity of a range of models of social vulnerability using outcomes from Hurricane Sandy. Using spatial regression, relative measures of assistance applicants, affected renters, housing damage, and property loss were regressed on four social vulnerability models and their constituent pillars while controlling for flood exposure. The indexes best explained housing assistance applicants, whereas they poorly explained property loss. At the pillar level, themes related to access and functional needs, age, transportation, and housing were the most explanatory. Overall, social vulnerability models with weighted and profile configurations demonstrated higher construct validity than the prevailing social vulnerability indexes. The findings highlight the need to expand the number and breadth of empirical validation studies to better understand relationships among social vulnerability models and disaster outcomes. *Key Words: index, hazards, spatial regression, social vulnerability, validation.*

社会脆弱性模型对灾害缓解和復原计画而言日益重要，但这些模型能够解释灾害后果的程度却仍不甚清楚。使用指标与索引的研究，多半用其来描述脆弱性模式，抑或比较最新设计与既有的测量方法。本文聚焦建构效度，我们于其中探讨一系列运用珊蒂飓风后果的社会脆弱性模型之经验效度。运用空间迴归，协助申请者、受影响的出租者、房屋损害与财产损失的相关测量，在四大社会脆弱性模型及其构成支柱上进行迴归，同时控制洪泛曝险。这些索引在解释住房协助申请者方面表现最佳，但在解释财产损失上表现最差。在支柱方面，与管道和功能需求、年龄、交通和住房相关的主题最具解释力。总体而言，具有加权与概况结构的社会脆弱性模型较盛行的脆弱性索引而言，展现较高的建构效度。该发现强调扩展经验效度研究的数据与幅度之必要，以更佳地理解社会脆弱性模型与灾难后果之间的关系。 *关键词：索引，灾害，空间迴归，社会脆弱性，效度。*

Los modelos de vulnerabilidad social se están volviendo cada vez más importantes para la mitigación de amenazas y para planear la recuperación, aunque sigue siendo confuso qué tan bien pueden ellos explicar las consecuencias de los desastres. La mayoría de los estudios que usan indicadores e índices los emplean, bien para describir los patrones de vulnerabilidad, o para comparar nuevas medidas diseñadas con las existentes. El interés central de este artículo es construir validación, trabajo en el cual investigamos la validez empírica de una gama de modelos de vulnerabilidad social usando los efectos del Huracán Sandy. Usando regresión espacial, las medidas relativas de ayuda de aspirantes, arrendatarios afectados, daños a las viviendas y pérdida de la propiedad, fueron sometidos a regresión en cuatro modelos de vulnerabilidad social y sus pilares constituyentes mientras se hacía control por exposición a la inundación. Los índices explicaron bien lo concerniente a los solicitantes de ayuda en vivienda, en tanto que ellos explicaron muy pobremente la pérdida de propiedad. A nivel de pilar, los temas relacionados con el acceso y las necesidades funcionales, edad, transporte y vivienda fueron los más explicativos. En general, los modelos de vulnerabilidad social con configuraciones ponderadas y de perfil demostraron una validez de constructo más alta que los índices de vulnerabilidad social prevalentes. Los hallazgos destacan la necesidad de extender el número y amplitud de los estudios de validación empírica para entender mejor las relaciones entre los modelos de vulnerabilidad social y las consecuencias de los desastres. *Palabras clave: amenazas, índices, regresión espacial, validación, vulnerabilidad social.*

Disaster scholarship has long described processes that translate social, political, and economic marginalization into adverse human impacts (Blaikie et al. 1994; Fothergill, Maestas, and Darlington 1999; Laska and Morrow 2006). Geospatial modelers have quantified these

Annals of the American Association of Geographers, 0(0), 2019, pp. 1–23 © 2019 by American Association of Geographers
Initial submission, April 2018; revised submissions, June and September 2018; final acceptance, September 2018
Published by Taylor & Francis, LLC.

relationships, using proxy demographic variables to construct indexes of social vulnerability to natural hazards. Foundational studies (Clark et al. 1998; Cutter, Mitchell, and Scott 2000; Tapsell et al. 2002; Cutter, Boruff, and Shirley 2003) established methodologies that spawned a plethora of research that quantifies and analyzes spatial patterns of social vulnerability. The benefit of indexes in reflecting multidimensionality, reducing complexity, and visualizing results is reflected in their growing promotion and use by government for hazard planning, setting priorities, and resource allocation (BRACE 2017; South Carolina Disaster Recovery Office [SCDRO] 2017; West Virginia Department of Commerce [WVDC] 2017; Federal Emergency Management Agency [FEMA] 2018). Yet it remains unknown whether pre-event descriptive patterns reflected in social vulnerability indexes correspond with empirical postdisaster outcomes. Social vulnerability models are descriptive, but to what extent are they explanatory?

Descriptive modeling is advantageous for summarizing and visualizing social vulnerability, but determining their explanatory power requires observational data to test causal hypotheses (Shmueli 2010). Most index studies continue to emphasize describing social vulnerability patterns (Saldajeno et al. 2012; Hou et al. 2016; Colavito, Bjarnadottir, and Li 2017), reproducing index construction methods in varying geographic settings (Chen et al. 2013; Lawal and Arokoyu 2015; Roncancio and Nardocci 2016), and geospatial integration with physical hazard (Santos, del Rio, and Benavente 2013; Frigerio et al. 2016; Remo, Pinter, and Mahgoub 2016; Fischer and Frazier 2018). Despite the proliferation of social vulnerability indexes, there remains limited statistical support for how effectively they actually measure social vulnerability.

Index validation requires modelers to make parameter choices regarding both the index configuration and the disaster outcome measure. The configuration of most social vulnerability indexes is inductive, using factor analysis to identify latent statistical variables (Cutter, Boruff, and Shirley 2003; Rygel, O'Sullivan, and Yarnal 2006). Other configurations include hierarchical models that employ pillars to thematically organize indicators (Chakraborty, Tobin, and Montz 2005; Mustafa et al. 2011) and deductive models that apply a linear combination of indicators (Cutter, Mitchell, and Scott 2000; Wu, Yarnal, and Fisher 2002). The choice of configuration is important, because the statistical robustness has been found to vary with index structure (Tate 2012). For outcome measures, previous studies have evaluated physical damage, economic loss, mortality, migration, and rate of resident return. When selecting an outcome variable for a validation study, conceptually the analyst should be able to complete this statement: "If you are more vulnerable, then … [insert disaster outcome here]." Unfortunately, hypothesized causal linkages between social vulnerability and selected outcome variables are often not explained. Collectively, both index configurations and outcome variables vary widely across previous validation studies, making it difficult to draw generalizable conclusions about the validity of social vulnerability indexes.

The objective of this article is to assess the empirical validity of a range of social vulnerability models that are based on different approaches and assumptions. The first section describes index validation and findings from previous studies. Subsequent sections profile our analysis data: disaster outcome measures from Hurricane Sandy and social vulnerability models. The Methods section describes our application of spatial multivariate regression. We report on the explanatory power of social vulnerability models and their constituent pillars in the results section, before concluding with a discussion of major findings and future research needs.

Model Validation

Model validity is the degree to which a model adequately represents its underlying construct. For the construct of social vulnerability, to what extent do indexes reflect its multidimensionality, interactivity, and causal processes? Previous validation studies for social vulnerability indexes have been focused on convergence, robustness, and construct.

Convergent validation assesses the level of agreement among alternative models measuring the same construct (O'Leary-Kelly and Vokurka 1998; Adcock 2001). Social vulnerability studies have applied statistical and geospatial methods to demonstrate similarity between a new and a widely accepted model (Cutter et al. 2013; Holand and Lujala 2013; Hile and Cova 2015). The prevailing models in the United States are the Social Vulnerability Index (SoVI®) created at the University of South

Carolina (Cutter, Boruff, and Shirley 2003) and the identically named Social Vulnerability Index (SVI) developed at the U.S. Centers for Disease Control (Flanagan et al. 2011). Although the use of an accepted index as a benchmark can demonstrate similarity in the operationalization of social vulnerability, convergent analysis alone is insufficient to demonstrate model validity. This is because two highly convergent models could also both poorly represent social vulnerability.

Robustness validation evaluates the degree to which a model is analytically and statistically sound. Index robustness is often assessed using uncertainty and sensitivity analyses. Uncertainty analysis quantifies the variability in model outputs given changes in model inputs and has been used to measure the stability of social vulnerability index scores and ranks (Jones and Andrey 2007; Tate 2013; Reckien 2018). Sensitivity analysis apportions total uncertainty among input parameters and has been used to identify the most influential stages of index construction (Schmidtlein et al. 2008; Tate 2012; Yoon 2012; Zhang and Huang 2013). Together, uncertainty and sensitivity analyses help measure the internal reliability of an index. Reliability alone is an insufficient indicator of model validity, however, because a statistically robust index could also poorly represent social vulnerability.

Construct or empirical validation examines whether hypothesized processes underlying a measure are borne out with empirical data. Previous empirical studies have collected postdisaster data and assessed index performance using statistical correlation analysis and ordinary least squares (OLS) regression. Decades of disaster case studies have documented how socially vulnerable populations disproportionately experience adverse impacts. Indicator selection for social vulnerability indexes is intended to reflect such outcomes, but to what degree do the index values correspond with empirical disaster data?

> Is the model correct? In this case, the correctness is not so much a matter of its mathematical correctness but rather whether or not the algorithms represent what we intended to model in the real world. In other words, does the model provide a reasonable representation of the processes and spatial interactions of the real-world phenomena being examined? (DeMers 2002, 177)

To assess the state of knowledge of the empirical validity of social vulnerability indexes to natural hazards, we conducted a Web of Science search in August 2017. The search covered the years 2008 to 2017, using the following terms:

- "social vulnerability index" [topic] OR "social vulnerability indicator" [topic]
- AND "hazard" OR "disaster" [topic]
- NOT "climate change" [topic]
- NOT "risk" OR "resilience" [title]

We excluded titles with the terms *risk* and *resilience* to focus on the construct of social vulnerability and excluded the topic of *climate change* to pinpoint papers based on specific hazard events and disasters as opposed to general climatic conditions. We read the abstracts of the 116 articles returned by the search. We removed articles that were purely descriptive, based on anthropogenic hazards (e.g., smoking), or conducted solely convergent or robustness validation. The remaining eleven empirical validation studies are summarized in Table 1. The body of work on empirical validation demonstrates that social vulnerability indicators have statistically explained a range of disaster outcomes, including physical damage, property loss, displacement, and migration. It is difficult to make generalizable conclusions, however, due to the low number of studies and significant variation in methods. Moreover, the outcome variables were rarely described in terms of their conceptual or causal relationship with social vulnerability. Statistical analyses in only half of the studies controlled for hazard exposure or intensity, and only one study accounted for spatial dependence.

The knowledge gaps regarding the quantitative relationship between social vulnerability measures and disaster outcomes are suggestive of a research area that is still emerging. Given the increasing use of social vulnerability metrics in planning and decision making, there is a critical need to better characterize the ability of social vulnerability models to explain disaster outcomes. To do so, we constructed alternative models of prestorm social vulnerability and statistically compared them with postdisaster FEMA data for Hurricane Sandy.

Sandy Disaster Outcomes

Superstorm Sandy was the deadliest and most destructive hurricane of the 2012 season (Blake et al. 2013). At least 233 people were killed along the path of the storm, and the estimated loss total of

Table 1. External validation studies for social vulnerability indexes

Study	Hazard	Social vulnerability predictor	Analysis scale	Outcome measure(s)	Method	Hazard confounder	Statistically significant findings
Abbas and Routray (2014)	River flood	Hierarchical index	Household	Health vulnerability	Correlation	None	Positive association† ($\chi^2 = 0.07$)
Bakkensen et al. (2017)	Severe weather	Deductive and inductive indexes	County	Property loss, mortality, disaster declarations	OLS regression	Exposed elements, event magnitude, disaster frequency	Property loss: SVI,** SoVI;** declarations: SoVI**
Burton (2010)	Hurricane wind and storm surge	Inductive factors	Census tract, block group	Damaged residential structures	OLS regression in catastrophic damage areas	Wind speed, % area inundated	Tract: age and class,*** Asian and agriculture workers,*** black and poor,** rural,** Hispanic**; Block group: urban,*** Black and poor,*** Asian and agriculture workers***
Fekete (2009)	River flood	Inductive variables	Household	Displacement, shelter use	OLS regression	None	Displacement: urban,*** homeownership,** number of rooms**; shelter: age,** homeownership**
Finch, Emrich, and Cutter (2010)	Hurricane storm surge	Inductive index	Census tract	Flood depth, return rate, homeowner assistance	Correlation, OLS regression	Flood depth	Rate of return: negative association*** ($r = -0.3$); SoVI***
Khunwishit and McEntire (2012)	Hurricane	Deductive index	Household	Perceived disaster impact	OLS regression	None	Social vulnerability***
Liu and Li (2016)	River flood	Deductive index	Household	Mortality	Correlation	Only flood-affected homes surveyed	Positive association ($r = 0.75$)*
Myers, Slack, and Singelmann (2008)	Hurricane	Inductive factors	County	Migration	OLS and spatial regression	Damage	Race and socioeconomic factor*
Schmidtlein et al. (2011)	Earthquake	Inductive index	Census tract	Modeled economic loss and debris	OLS regression	Ground motion, distance	Loss: total,*** income normalized,*** area normalized,*** income and area normalized***; debris:

							total,*** area normalized***
Tate et al. (2016)	River flood	Hierarchical index	Census block group	Property buyouts	Correlation	None	Positive association ($r = 0.66$)***
Yoon (2012)	Multihazard	Hierarchical pillars, inductive factors	County	Property loss	OLS regression	None	Hierarchical: ascribed and achieved pillars**; inductive: poverty*

Note: OLS = ordinary least squares; SVI = Social Vulnerability Index; SoVI = Social Vulnerability Index.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.
†p Value not specified.

$79 billion was surpassed only by Hurricane Katrina (FEMA 2013). In the United States, Hurricane Sandy affected twenty-four states, with particularly severe damage in New York and New Jersey. On 29 October, the New York City borough of Manhattan flooded due to a storm surge of 14 feet (4.27 m; Figure 1). Approximately 100,000 homes on Long Island were severely damaged. Across the state of New York, fifty-three Sandy-related deaths were reported, with economic losses estimated at $42 billion ("Hurricane Sandy's Rising Costs" 2012). Meanwhile, thirty-seven Sandy-related deaths were reported in New Jersey (Respaut et al. 2012), with an estimated loss total of $37 billion. Impacted areas reaching predetermined damage thresholds (Salkowe and Chakraborty 2009) can be declared federal disaster areas, enabling the flow of disaster recovery resources through FEMA's Individual Assistance (IA) Program.

Housing units represent nearly 70 percent of all built environment structures across the United States (Comerio 1998; Phillips 2009). Damage to residential units and contents is therefore a suitable and frequently applied indicator of overall disaster impact. There could be substantial variation in the effect of that damage within an impact area due to population characteristics, however. Socially vulnerable areas are often associated with higher concentrations of mobile homes, more rental properties, lower educational attainment, and other factors rooted in social processes, resulting in attenuated capacity to prepare for and respond to disaster events. Because homes in these places generally have lower property values, total economic loss in these places is likely to be lower compared to areas with more valuable homes. Accordingly, the use of relative impact measures might be more appropriate than absolute measures for social vulnerability analysis.

FEMA Outcome Data

The Presidential Disaster Declarations for Hurricane Sandy in New York and New Jersey (FEMA 2012a, 2012b) generated an array of flood hazard and impact data. The hazard data include 3-m geographic information system (GIS) grids of maximum water depth on 31 October 2012 (FEMA 2015). Within FEMA's IA Program, the Individuals and Housing Program (IHP) provides financial assistance and repairs for residents with housing or

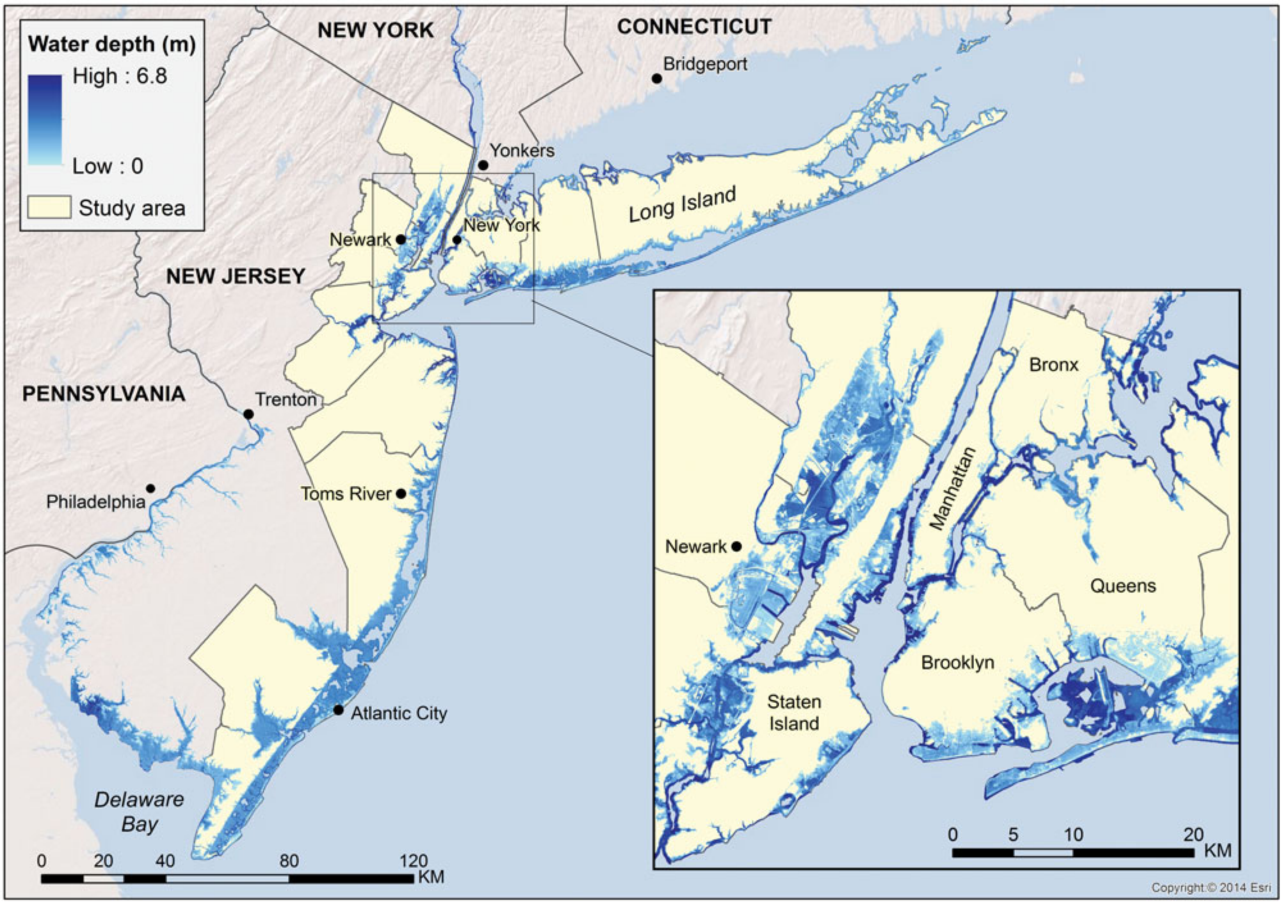

Figure 1. Flood depths in the Hurricane Sandy study area. *Source:* Data from the Federal Emergency Management Agency (2015). (Color figure available online.)

Table 2. Sandy outcome measures

FEMA variable (tract level)	Normalization	Outcome variable
IA applicants	Total population per tract	% Applicants
Renter applicants with personal property damages	Total renter households per tract	% Affected renters
Applicants with housing flood damage	Total nonseasonal housing units housing units per tract	% Damaged housing units
FEMA verified property losses	Median house value	% Property loss
Maximum water depth	None	Maximum flood depth

Note: FEMA = Federal Emergency Mangement Agency; IA = Individual Assistance Program. *Source:* FEMA (2015); Housing and Urban Development (2013).

contents damaged by declared federal disasters (Edgeley and Paveglio 2017). The IHP collects household-level information including number of occupants, age, income, access and functional needs (AFN), and damage to building and contents, among many other data points. There are two IHP subprograms: Housing Assistance (HA), providing repair and replacement funding for real property (building) damage, and Other Needs Assistance (ONA), providing funds for personal property (contents) replacement, medical and dental expenses, and other approved disaster-related household expenses. IHP funds are available to residents who have been denied disaster loans due to affordability and meet other criteria set forth by the Stafford Act. Both HA and ONA target urgent unmet needs, in particular focusing on impacts not covered by insurance.

The FEMA data represent the most comprehensive and consistent data across the study area on impact, relief, and recovery. As such, they are the best available data to validate social vulnerability models in relation to this disaster. Outcome data from the IA program included the number of applicants, number of affected renters, damaged housing units, and building economic loss (Table 2) at the census tract level. We considered each outcome to be an indicator of short-term vulnerability as opposed to long-term recovery. We aggregated the water depth to the census tract level and normalized the IA data using variables from the American Community Survey (ACS) for 2008 to 2012, a time frame representing prestorm conditions. We normalized the IA variables to express them in relative as opposed to absolute terms. We expected each of the normalized Sandy outcomes to be positively related to social vulnerability.

The first two outcome measures in Table 2 describe impacts to people and their belongings. IA applicants can apply via phone, online, or in person at FEMA recovery centers opened across the affected area. We normalized the total number of applicants by the total population in each tract. This measure represents the initial "hand-raising" and assistance-seeking activities undertaken by individuals who were adversely affected. For home repair, HA is available to homeowners but not renters. Both homeowners and renters are eligible for ONA through which they can be compensated for uninsured personal property (contents) loss. We used data for the number of rental units sustaining personal property loss and normalized it by the number of renter households in each census tract.

The second two outcome measures describe relative impacts to residential housing. Property damage data are generated by FEMA when a household applies for IA and is deemed eligible based on ownership and evidence of storm-specific damage. We developed a relative measure of housing damage by normalizing total damaged houses by the total number of housing units in each census tract. FEMA inspection teams visit each eligible home and estimate economic loss to real property (building) and personal property (contents), producing two variables known as FEMA-verified losses. We produced a relative measure of economic property losses by normalizing total real property (building) verified losses by the median house value in each census tract.

Analysis Scope and Scale

The spatially varying nature of floods and the high spatial resolution of the FEMA depth grids (3 m) suggested use of small spatial units. Error in ACS demographic estimates generally increases as aggregation level decreases, however (Spielman, Folch, and Nagle 2014), suggesting the use of large spatial units. Meanwhile, the FEMA outcome data were provided at the census tract level. In the end we selected the tract scale for the analysis to balance tension among availability and error in the input data.

The ideal analysis scope would align with the geographical extent of the disaster, but how is this extent best defined? Plausible choices include an extent based on the physical hazard, disaster outcomes, or affected administrative units. Scope selection based on administrative grounds might align with decision making but can muddle statistical analyses if there is a spatial mismatch between decision-making units and the disaster effects. This occurred for Sandy flooding, as 73 percent of the census tracts in the disaster-declared counties had no flooding. Accordingly, we set analysis scope to encompass the set of tracts that both intersected the Sandy floodplain and had nonzero FEMA outcomes. Table 3 provides descriptive statistics for the outcomes based on this scope at the census tract scale. The skewness and spatial autocorrelation of impact data further confirm that the damages from Hurricane Sandy are spatially concentrated.

Table 3. Descriptive statistics for Sandy outcome measures

Indicator	Tract count	Minimum	Maximum	M	Median	Moran's *I*
IA applicants	1,084	1	2,851	219	41	0.64
Affected renters	608	1	2,601	115.7	3.35	0.48
Damaged nonseasonal housing units	625	14	5,938	479	229	0.56
Real property FEMA-verified losses	1,006	$209	$34,939,476	$1,614,341	$95,283	0.43
Maximum flood depth	1,188	0.001	5.8	3.14	3.17	0.65

Note: IA = Individual Assistance Program; FEMA = Federal Emergency Mangement Agency. *Source:* Data from FEMA (2015) and the American Community Survey (2008–2012).

Table 4. Input variables for the social vulnerability models

Variable	Description	SoVI	Weighted	SVI	SVP
AGE	% Age dependent (under 5 and over 65)	✓			
AGE05	% Age 5 years and under		✓		✓
AGE17	% Age 17 years and under			✓	
AGE65	% Age 65 years and over		✓	✓	✓
ASIAN	% Asian population	✓	✓		
BLACK	% African American population	✓	✓		
CROWDING	% Households with more people than rooms			✓	
DISAB	% Older than 5 years with a disability			✓	
EDU12LES	% Adult educational attainment less than Grade 12	✓	✓	✓	✓
ESLANG	% English as a second language	✓	✓	✓	✓
EXTRACT	% Extractive-sector employment	✓	✓		
FAMMARR*	Married families	✓			
FEMALE	% Female population	✓	✓		
FEMLBR	% Female employment	✓	✓		
FHHOLDS	% Female-headed households	✓	✓		✓
GQ	% Population living in group quarters			✓	
HISP	% Hispanic population	✓	✓		
MDGRENT*	Median rent	✓	✓		✓
MEDAGE	Median age	✓			
MHSEVAL*	Median home value	✓	✓		✓
MOHOME	% Mobile homes	✓	✓	✓	✓
MUTIUNIT	% Housing in multiunit structures			✓	
NATAM	% Native American population	✓	✓		
NOAUTO	% Households with no vehicle	✓	✓	✓	✓
NURSRES	% Nursing home residents	✓	✓		✓
NWHITE	% Ethnic and race minorities			✓	✓
PERCAP*	Per capita income	✓	✓	✓	
PERPUNIT	People per housing unit	✓	✓		✓
POPDENS	Population density				✓
POVTY	% Households in poverty	✓	✓	✓	✓
RENTERS	% Renters	✓	✓		✓
RICH200K*	% Annual income >$200,000	✓	✓		
SERVICE	% Service-sector employment	✓	✓		
SINGHOLDS	% Single-parent households			✓	
SSBEN	% Social Security income	✓	✓		✓
UNEMPLOY	% Unemployed	✓	✓	✓	✓
VACANT	% Vacant housing	✓	✓		✓
Variable count		27	26	15	18

Note: SoVI = Social Vulnerability Index; SVI = Social Vulnerability Index; SVP = Social Vulnerability Profiles.
*Variables with values that increase as social vulnerability decreases were multiplied by −1 to reverse their directionality.

Social Vulnerability Models

To explore the relationship between social vulnerability and Sandy outcomes, we applied four social vulnerability models: an inductive model based on factor analysis (SoVI), a hierarchical weighted model based on expert knowledge, a deductive model composed of thematic pillars (SVI), and a profile approach based on clusters (Social Vulnerability Profile, SVP). Collectively, these models employ the configurations used in the majority of social vulnerability models. All of our models use demographic data from the 2008 to 2012 ACS at the census tract scale. The input variables used for each model are provided in Table 4. Variables with values that increase as social vulnerability decreases were multiplied by –1 to reverse their directionality and are denoted by an asterisk in Table 4. The models were constructed for all New York and New Jersey census tracts in the affected counties ($N = 3{,}947$).

Table 5. Social Vulnerability Index components

Component	% Variance explained	High loading variables
(1) Socioeconomic status	27.8	Per capita income (0.89) Educational attainment (0.83) Poverty (0.67) Unemployment (0.64)
(2) Gender and race (black)	11.2	Female employment (0.88) Females (0.76) African Americans (0.65)
(3) Vehicle access and renters	8.0	No automobile (0.87) Renters (0.81)
(4) Age	6.8	Age dependency (0.89) Social Security beneficiaries (0.83)
(5) Vacant housing	5.2	Vacant housing (0.69)
(6) Access and functional needs	4.0	Nursing home residents (0.90)
(7) Race and ethnicity	3.9	Native Americans (0.92)
(8) Rental housing cost	3.7	Median rent (0.91)

Social Vulnerability Index

Inductive index approaches apply factor analysis based on principal components analysis (PCA) to reduce an initial indicator set into a smaller number of latent factors. Inductive modeling for social vulnerability was popularized by the SoVI, originally constructed at the county scale for the United States (Cutter, Boruff, and Shirley 2003). The SoVI algorithm has since been widely used for description of vulnerability patterns in different countries (Solangaarachchi, Griffin, and Doherty 2012; Siagian et al. 2014; Guillard-Goncalves et al. 2015; Roncancio and Nardocci 2016) and for decision making in disaster recovery (City of Cedar Rapids 2010; SCDRO 2017; WVDC 2017). At the census tract scale, SoVI uses twenty-seven demographic variables from the ACS (Table 4). The current SoVI (Hazards & Vulnerability Research Institute 2015) method and variable lists can be found at www.sovius.org.

We standardized the input variables into *z* scores and entered them into a PCA. A varimax rotation

Table 6. Weighted hierarchical index configuration

Pillar	Variable	Description	Weight %[a]
Socioeconomic status	PERCAP	Per capita income	15.9
	POVTY	% Poverty	14.9
	MHSEVAL	Median value of owner-occupied housing	8.8
	UNEMPLOY	% Unemployed	5.5
	RICH200K	% Families earning >$200,000	3.6
	SERVICE	% Service-sector employment	1.7
	EXTRACT	% Extractive-sector employment	1.5
	EDU12LES	% Adult educational attainment less than Grade 12	1.4
	MDGRENT	Median gross rent	1.9
Population structure	AGE65	% Age under over 65 years	7.9
	AGE05	% Age under 5 years	5.9
	PERPUNIT	People per housing unit	2.4
	FHHOLDS	% Female-headed households	1.9
	FEMLBR	% Female employment	0.8
	FEMALE	% Female population	0.8
Race and ethnicity	BLACK	% African American population	5.2
	HISP	% Hispanic population	2.9
	NATAM	% Native American population	1.5
	QASIAN	% Asian	0.9
Access and functional needs	NURSRES	% Nursing home residents	3.9
	SSBEN	% Social Security income	3.7
	ESLANG	% English as a second language	1.9
	NOAUTO	% No automobile	0.9
Housing structure	RENTERS	% Renter-occupied units	3.2
	VACANT	% Vacant housing	0.5
	MOHOME	% Mobile homes	0.5

Note: [a]Weights derived from Emrich (2005).

was applied to increase the interpretability of the component loadings. Using the Kaiser criterion (eigenvalues greater than 1.0), eight principal components were extracted, which accounted for 71 percent of variance in the original variable set. Based on the high loading variables, we interpreted the components to describe the social vulnerability factor represented by each component. The index was then computed by summing the factor scores in each census tract. Table 5 profiles the components, their explained variance, and correlations with their highest loading variables (greater than 0.6).

Weighted Model

Hierarchical configurations aggregate indicators into pillars that share an underlying dimension of social vulnerability (e.g., socioeconomic status, health). The pillars are then aggregated to create the index. Such indexes require a greater level of theoretical organization than more data-driven inductive models. We constructed a hierarchical model consisting of twenty-six variables organized into five pillars (Table 6). Vulnerability mapping and index design often rely on participatory approaches or expert knowledge for the selection and weighting of variables (Bankoff, Frerks, and Hilhorst 2004). We applied findings from a study that created weights for SoVI variables using subject matter experts in a modified Delphi method (Emrich 2005). Using these weights, we computed weighted indicators as the product of the variable weights and normalized indicator values (min–max scaling). The weighted indicators were then summed within each pillar to create pillar scores, and the pillar scores were averaged to create the index.

Social Vulnerability Index

The SVI, designed at the U.S. Centers for Disease Control, is composed of fifteen indicators (Table 4), which are normalized and summed to create the index. The SVI has elements of both deductive and hierarchical design. In appearance the index is hierarchical because the indicators are conceptually organized into the four themes of socioeconomic status, household composition and disability, minority status and language, and housing and transportation. The SVI is functionally a deductive index, however, because the four themes are mathematically ignored in the aggregation of individual indicators to create the index. The SVI is intended for use by emergency planners and public health officials to identify places and populations susceptible to environmental hazards (Flanagan et al. 2011; Agency for Toxic Substances and Disease Registry [ATSDR] 2017; BRACE 2017).

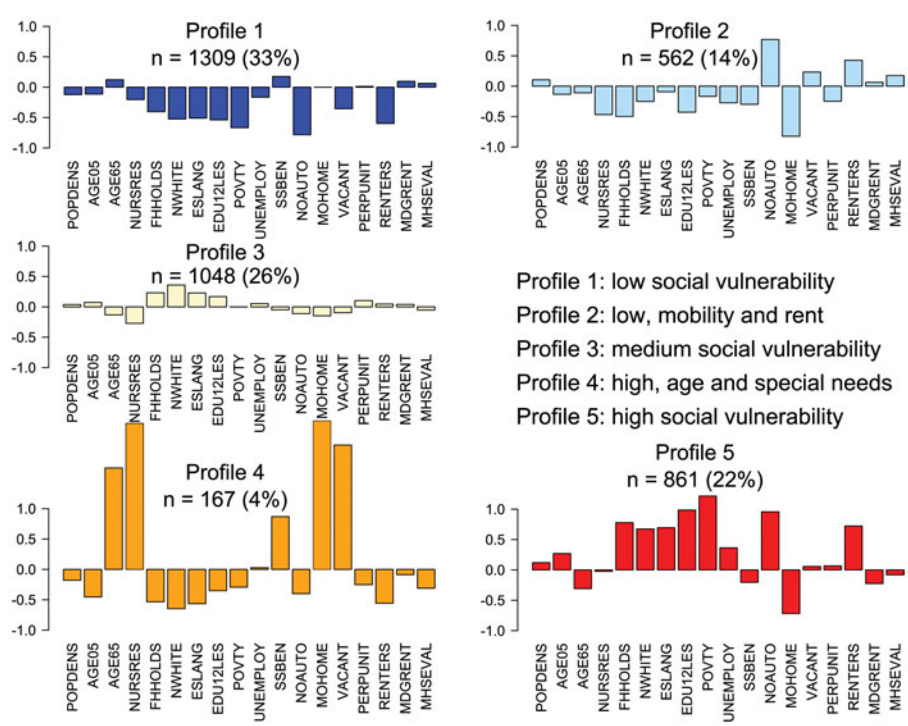

Figure 2. Social Vulnerability Profiles. (Color figure available online.)

Social Vulnerability Profiles

An alternative approach to indexes that quantify social vulnerability magnitude is to produce spatially varying typologies of social vulnerability, or SVPs. Following the methodology described in Rufat (2013), we constructed a set of vulnerability profiles

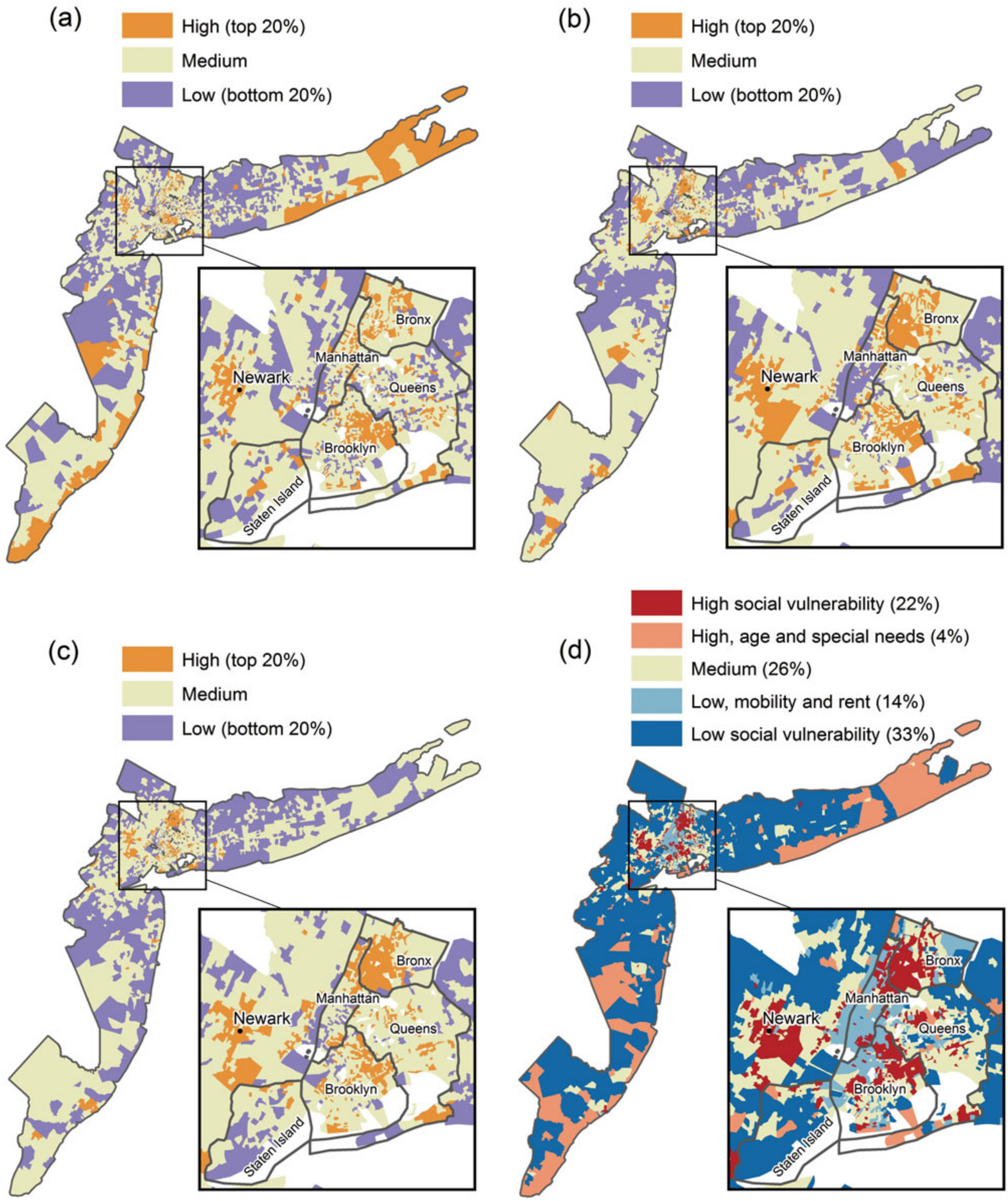

Figure 3. Social vulnerability indexes based on (A) Social Vulnerability Index (SoVI), (B) weighted model, (C) Social Vulnerability Index (SVI), and (D) Social Vulnerability Profile. (Color figure available online.)

using the same data set (Table 4). The correlation analysis was used to reduce the number of variables. This process limited collinearity, prevented implicit weighting, strengthened statistical power, and preserved a balance between the different dimensions of vulnerability to around five demographic, five socioeconomic, and five cultural or institutional variables (Rufat 2013). For example, the share of female-headed households was used to represent all of the gender variables due to the strong correlation among them, and the share of non-white as a surrogate for all population identifying with ethnic and race minorities, resulting in the selection of only eighteen variables (Table 4).

The SVP combines factor analysis and clustering to produce spatially compact vulnerability profiles instead of a single aggregated value like an index. The input variables were entered into a PCA, and five components (70 percent of the total variance) were extracted based on the Kaiser criterion. The factor scores were then used as a distance matrix for hierarchical clustering using Ward's method. The larger threshold in Ward's level index pointed to five as the ideal number of clusters. For each cluster, the eighteen variables were standardized using mean and standard deviation. Each profile is interpreted according to the underrepresentation or overrepresentation of each variable, their association or mutual exclusion, and the resulting impacts on the strengthening (or reduction) of vulnerability (Figure 2). For example, whereas Profile 4 is associating the elderly and nursing home residents, vacant housing, mobile homes, and, to a lesser extent, people dependent on Social Security and was interpreted as the "high social vulnerability, age dependency and special needs," Profile 5 was overrepresenting all other vulnerability indicators and was labeled "high social vulnerability" based on those important interactions across all vulnerability dimensions.

Figure 4. Correlation heat map of social vulnerability and Sandy outcomes. (Color figure available online.)

Model Comparison

Figure 3 displays the spatial distribution of the four models. For the SoVI (Figure 3A), weighted (Figure 3B), and SVI (Figure 3C) models, we classified high values of social vulnerability as the top 20 percent of index scores and low social vulnerability as the bottom 20 percent. The five SVP are mapped in Figure 3D.

The four models are consistent in the places they identify as the most and least socially vulnerable. Otherwise, the Bronx, Brooklyn, and Newark have high modeled social vulnerability across all models. These places are identified by SVP Profile 5 and are associated with higher rates of poverty, renters, and female-headed households and lower rates of educational attainment, English proficiency, and vehicle access. On the other hand, the center of Long Island falls within the low vulnerability category for all of the models, and Manhattan and the New Jersey coast are also classified as low by most models. The spatial distribution of social vulnerability is the most concentrated for the weighted and SVP models and more diffuse for SoVI. Overall, visual inspection of the maps suggests a convergence in the social vulnerability models.

Figure 4 illustrates a Pearson correlation matrix of the social vulnerability indexes and Sandy outcomes, with statistically significant correlations ($p < 0.01$) highlighted in blue for positive correlations and in orange for negative correlations. The three indexes are positively related, with coefficients ranging from 0.35 to 0.75. The weighted model and SVI are the most convergent, in agreement with pattern similarity between Figures 3B and 3C. The indexes have no significant correlation with the Sandy outcomes, however, except for an unexpected negative relationship between SVI and the share of affected renters. Overall, despite differences in model structure, input indicators, weighting, and aggregation schemes, correlation analysis indicates that the three indexes exhibit convergent validity.

Previous convergence validation studies have employed visual map inspection to compare results of a new and established social vulnerability index, as well as methods including difference mapping, statistical correlation, PCA diagnostics, and radar charts (Cutter et al. 2013; Holand and Lujala 2013; Hile and Cova 2015). Although useful, visual assessment and statistical association are inadequate measures of the alignment of social vulnerability indexes models with disaster outcomes. Figure 4 suggests that using correlations might be a misleading approach to validation, as convergence is stronger among the indexes than with the Sandy outcomes. As such, we focused on multivariate regression to evaluate the empirical validity of social vulnerability models.

Construct Validation

For empirical validation, we created a set of OLS regression models, using the normalized Sandy outcomes (Table 2) as dependent variables and social vulnerability measures as independent variables. We controlled for hazard severity using the maximum water depth during Sandy and applied a natural log transform to all outcomes variables to reduce skewness. Regression analyses were then performed at the index and the subindex levels.

At the index level, we constructed twelve multivariate OLS regression models to test the explanatory power of the three indexes with each of the four Sandy outcomes. We constructed another sixteen regression models at the pillar level: four social vulnerability models by four outcome variables. The pillar models used the SoVI components, weighted pillars, SVI themes, and SVP profiles as explanatory variables. The SVP is a more disaggregated measure; to compare it to the three indexes at the index level, a linear parametric one-way analysis of variance (ANOVA) and a Kruskal–Wallis nonparametric test were used on the residuals of a regression between each Sandy outcome and maximum water depth to measure whether the mean and median of each outcome significantly differ from one vulnerability profile to another while controlling for hazard severity.

As regression diagnostics, we applied the multicollinearity condition number to evaluate multicollinearity and the Breusch–Pagan test to assess heteroscedasticity in the residuals. If the Moran's *I* statistic on the OLS residuals indicated spatial dependence, spatial regression was conducted using a weights matrix based on queen contiguity. The Lagrange multipliers, robust and nonrobust accordingly, were used to test for the form of spatial dependence, guiding a decision to perform a spatial lag or spatial error regression. To assess model fit, adjusted R^2 (OLS) and pseudo-R^2 (spatial regression) statistics were reported. Because these two measures are not directly comparable, the Akaike's information criterion (AIC) was computed. A reduction in AIC from OLS to spatial regression indicates improvement in model fit.

Among the social vulnerability models and outcome measures, we performed more than 100 independent statistical tests. As the number of statistical tests increases, so does the likelihood of finding a significant relationship just by chance. Such inflation of Type I error in multiple testing can be countered using a Bonferroni correction, in which the significance level for hypothesis testing is divided by the total number statistical tests performed (Bland and Altman 1995). Bonferroni correction in this study would entail dividing significance levels by 100; that is, considering p values of 0.0001 to be the threshold to maintain a significance level of 0.01 across all tests. Bonferroni critics have argued that the approach inflates Type II error (Morgan 2007), lacks guidelines for what constitutes a family of statistical tests (Cabin and Mitchell 2000), should only be applied to the universal hypothesis of a study (Armstrong 2014), and might not be required for exploratory analyses (Bender and Lange 2001). As a result, we report variable significance across a wide range of values to enable readers to choose whether to apply a Bonferroni correction (i.e., discarding 0.01 or 0.001 p values) according to preferred balance between Type I and Type II errors.

Results

Model-Level Validation

Table 7 summarizes the results at the index level, based on regression models using the indexes and water depth as independent variables and the Sandy outcomes as dependent variables. We considered an index to explain a disaster outcome if it is both statistically significant and has a positive coefficient. For all twelve regression models, the OLS residuals were significantly spatially autocorrelated, so we applied

Table 7. Social vulnerability indexes and Sandy outcomes

Index	Statistic	Ln %Applicants		Ln %Affected renters		Ln %Damaged homes		Ln %Property loss	
		OLS	Spatial	OLS	Spatial	OLS	Spatial	OLS	Spatial
SoVI	Depth	–0.007	0.02	–0.008	0.03*	0.03*	0.04***	0.12**	0.11***
	Index	0.26**	0.14** (error)	0.12	0.04 (lag)	0.18*	0.11* (lag)	0.26	0.14 (lag)
	Adjusted/pseudo-R^2	0.02	0.69	0.005	0.43	0.03	0.44	0.03	0.32
	AIC	4,760	3,747	2,484	2,230	1963	1,704	5,064	3,796
Hierarchical	Depth	–0.007	0.01	–0.03	0.02	0.02*	0.05****	0.11***	0.14****
	Index	0.21*	0.04** (lag)	0.56***	0.39*** (lag)	0.01*	0.03* (error)	–0.05	0.02 (error)
	Adjusted/pseudo-R^2	0.008	0.59	0.06	0.46	0.003	0.47	0.02	0.33
	AIC	4,770	3,764	2,451	2,200	2,038	1,749	5,072	3,497
SVI	Depth	–0.009	0.01	–0.01	0.03*	0.02*	0.06****	0.11****	0.13****
	Index	0.11**	0.03 (lag)	–0.33***	–0.22*** (lag)	–0.06*	–0.04** (error)	–0.16***	–0.14** (error)
	Adjusted/pseudo-R^2	0.01	0.59	0.14	0.48	0.02	0.47	0.04	0.33
	AIC	4,764	3,762	2,394	2,160	2,031	1,746	5,058	3,788
	N	1,084	1,084	608	608	625	625	1,006	1,006

Note: OLS = ordinary least squares; SoVI = Social Vulnerability Index; AIC = Akaike's information criterion; SVI = Social Vulnerability Index.
*$p < 0.01$.
**$p < 0.001$.
***$p < 0.0001$.
****$p < 0.00001$.

spatial regression. The AIC statistic decreased in each instance, indicating an improvement in model fit over OLS. Moving from OLS to a spatial regression model tended to reduce the magnitude of the index beta coefficients or reduce the level of statistical significance. The opposite occurred for the water depth variable.

The Table 7 results indicate substantial variation in the explanatory power of the social vulnerability indexes. This contrasts with the model convergence indicated by Figures 3 and 4, revealing the insufficiency of correlation and convergence studies for validating indexes. IA applicants had significant and positive relationships with the SoVI and weighted model. Based on the pseudo-R^2 values, applicants also had the best model fit for each index. Housing damage was positively and significantly associated with the SoVI and weighted models, suggesting that irrespective of flood hazard, socially vulnerable populations incur a greater proportion of physical housing damage. The relationship between housing damage and the SVI was significant but negative, however. Property loss has the weakest relationship with modeled social vulnerability, as a negative association with the SVI was the only significant relationship.

The weighted index was positively and significantly related to all outcomes except property loss, demonstrating flexibility in explaining a variety of Sandy outcomes. SoVI was positively and significantly related to applicants and housing unit damage. The SVI had negative relationships with housing damage, property loss, and renters, contrary to our hypotheses. The SVI had the weakest explanatory power of the social vulnerability assessments. At the other end, the SVP is the only model with significant positive relationships with all of the Sandy outcomes, even in the case of a Bonferroni correction. The ANOVA and the Kruskal–Wallis tests reveal that each one of the outcomes vary significantly among the five vulnerability profiles when controlling for exposure with p values below 0.0001 in all cases. If applying a Bonferroni correction, the weighted index has more significant relationships with the Sandy outcomes than the SoVI model and percent age of affected renters is the outcome best explained by the indexes.

Pillar-Level Validation

Empirical validation at the pillar level enables examination of which subdimensions of social vulnerability models align with disaster outcomes. We use the term *pillar* to broadly refer to the SoVI components, SVI themes, weighted model pillars, and SVP profiles, all of which are indicator aggregations

Table 8. Social Vulnerability Index components and Sandy outcomes

	Ln %Applicants		Ln %Affected renters		Ln %Damaged homes		Ln %Property loss	
	OLS	Lag	OLS	Lag	OLS	Lag	OLS	Lag
Water depth	–0.009	0.01	0.02	0.05*	0.04**	0.04***	0.12***	0.10****
(1) Socioeconomic status	0.11	0.06	–0.47***	–0.33***	0.02	–0.02	–0.32**	–0.22*
(2) Gender, race	0.52***	0.19**	0.10	0.06	0.10	0.05	0.35*	0.16
(3) No auto, renters	0.42***	0.15***	–0.81***	–0.52***	–0.17**	–0.11*	–0.28**	–0.18
(4) Age	0.14*	0.04*	0.49***	0.28***	0.21**	0.10**	0.28*	0.15
(5) Vacant housing	–0.08	0.07	0.16**	0.12*	0.06	0.06	0.43**	0.29*
(6) Access and functional needs	0.13	–0.02	0.16	0.06	0.15*	0.08	–0.007	–0.06
(7) Native American	0.13	0.06	–0.01	0.04	0.04	0.07	0.17	0.12
(8) Median rent	0.13	0.009	0.06	0.09	–0.01	–0.01	0.09	0.04
Adjusted/pseudo-R^2	0.10	0.70	0.26	0.51	0.07	0.46	0.09	0.34
AIC	4678	3740	2,311	2,128	1,956	1,701	5,016	4,771
Moran's I	0.67****		0.45****		0.50****		0.40****	
Breusch–Pagan	16.5	17.6	4.5	5.7	6.1	13.9	18.9	19.4
Condition number	5.6	5.6	7.2	7.2	7.2	7.2	5.8	5.8
N	1,084	1,084	608	608	625	625	1,006	1,006

Note: OLS = ordinary least squares; AIC = Akaike's information criterion.
*$p < 0.01$.
**$p < 0.001$.
***$p < 0.0001$.
****$p < 0.00001$.

below the index level. As with the index-level regressions, we used the four Sandy outcomes as dependent variables and controlled for hazard severity using water depth. The Moran's *I* statistic for OLS residuals was significant for all OLS models, so spatial regression models were created. The AIC statistic decreased in each case, indicating improved model fit. Similar to the index-level findings, accounting for spatial dependence in the regression tended to reduce beta coefficient magnitude or statistical significance for the pillars, while increasing them for water depth.

Table 8 presents the multivariate regression results for the SoVI components. Overall, flood depth was highly significantly related to the housing outcomes variables but had much weaker relationships with human-centric outcomes. IA applicants and renters had significant relationships with some of the SoVI components, and the models for these outcomes also had the highest pseudo-R^2. The model fit for the applicants variable (pseudo-$R^2 = 0.7$) was much higher than for the other Sandy outcomes. The applicants were disproportionately female and black, renters and lacking car access, and children or elderly. Affected renters were explained by four of the SoVI components, but the relationship was negative with two of them (renters and vehicle and socioeconomic status).

When the renters and vehicle factor is mapped, it becomes clear that it is pinpointing Manhattan. Here, high numbers of renters and people without cars is an indicator of a densely developed and expensive downtown area with high reliance on public transportation as opposed to suggestive of high social vulnerability. This result highlights the importance of context specificity in social vulnerability drivers and disaster phase (Rufat et al. 2015) when interpreting social vulnerability indexes and selecting validation outcome measures.

The factors of gender and race, age, and vacant housing had positive relationships with each Sandy outcome that they significantly explained. Socioeconomic status had negative relationships with property loss and affected renters. As previously described, all input indicators were preprocessed prior to index construction to ensure directionality with social vulnerability. As a result, the negative beta coefficients for socioeconomic status mean that as socioeconomic status increased, so did the percentage of property loss and the percentage of affected renters. The eight SoVI factors have seven significant positive relationships with the outcomes (only two after a Bonferroni correction) and four significant negative associations (two accordingly). Only the first five components of SOVI have explanatory power, though, demonstrating a decline in factor significance with the variance explained by the PCA.

Table 9 reports the multivariate regression results for the pillars of the weighted model. Flood depth was a highly significant predictor of all Sandy outcomes. Property loss had the most significant

Table 9. Weighted model and Sandy outcomes

	Ln %Applicants		Ln %Affected renters		Ln %Damaged homes		Ln %Property loss	
	OLS	Lag	OLS	Error	OLS	Error	OLS	Error
Water depth	–0.0005	0.02**	0.04*	0.08****	0.04**	0.08****	0.15****	0.18****
Socioeconomic status	–0.001***	–0.0004**	–0.0002	–0.0002	–0.0001	0.0001	0.002****	0.003****
Population structure	–0.0001	0.002	0.005**	0.002	0.002	0.001	0.01***	0.007**
Race and ethnicity	0.002**	0.001	–0.0004	–0.0006	0.0005	0.0002	–0.004***	–0.004***
Access and functional needs	0.01***	0.001***	0.002**	0.002**	0.001	0.001**	–0.01**	–0.01***
Housing	0.002	0.001	–0.01****	–0.01****	0.001***	–0.002**	–0.007**	–0.008***
Adjusted/pseudo-R^2	0.07	0.57	0.32	0.46	0.07	0.29	0.14	0.32
AIC	4,412	3,767	2,315	2,205	1,995	1,870	5,120	4,928
Moran's *I*	0.54****		0.29****		0.31****		0.29****	
Breusch–Pagan	8.3	9.0	7.9	10.5	7.5	8.7	9.6	12.3
Condition number	14.3	14.3	14.7	14.7	17.2	17.2	18.1	18.1
N	1,084	1,084	608	608	625	625	1,006	1,006

Note: OLS = ordinary least squares; AIC = Akaike's information criterion.
*$p < 0.01$.
**$p < 0.001$.
***$p < 0.0001$.
****$p < 0.00001$.

Table 10. Social Vulnerability Index themes and Sandy outcome measures

	Ln %Applicants		Ln %Affected renters		Ln %Damaged homes		Ln %Property loss	
	OLS	Lag	OLS	Lag	OLS	Error	OLS	Lag
Water depth	–0.02	0.01	0.02	0.05*	0.03*	0.06****	0.13****	0.11****
Socioeconomic status	0.36	0.16	–0.23	–0.28	–0.18	–0.44	2.03**	1.21
Household composition and disability	0.29	0.24	0.85*	0.39	0.30	0.01	0.39	0.22
Minority and language	–0.51	–0.30	–1.97***	–0.88**	–0.43	–0.41	–3.86****	–2.19***
Housing and transportation	1.05*	0.25	–1.58***	–1.33***	–0.62**	–0.58**	–0.02	–0.24
Adjusted/pseudo-R^2	0.02	0.70	0.24	0.51	0.04	0.48	0.09	0.34
AIC	4,761	3,763	2,323	2,128	2,020	1,740	5,003	4,768
Moran's *I*	0.72****		0.45****		0.53****		0.38****	
Breusch–Pagan	2.9	9.3	6.3	6.4	2.5	11.8	6.2	14.1
Condition number	9.5	9.5	9.3	9.3	10.8	10.8	10.4	10.4
N	1,084	1,084	608	608	625	625	1,006	1,006

Note: OLS = ordinary least squares; AIC = Akaike's information criterion.
*$p < 0.01$.
**$p < 0.001$.
***$p < 0.0001$.
****$p < 0.00001$.

Table 11. Social Vulnerability Profiles and Sandy outcome measures

	Ln %Applicants		Ln %Affected renters		Ln %Damaged homes		Ln %Property loss	
	OLS	Lag	OLS	Lag	OLS	Error	OLS	Error
Water depth	0.02	0.01	0.004	0.04	0.02*	0.06****	0.11****	0.14****
Profile 1 Low vulnerability	–0.71***	–0.21***	–1.29****	–0.73****	–0.13*	–0.05	–0.30*	–0.006
Profile 2 Low, mobility, and rent	–0.17**	–0.03*	–0.35*	–0.14*	–0.41**	–0.19**	–0.08	–0.41
Profile 4: High, age, and special needs	0.81***	0.48**	1.96****	1.37****	0.40**	0.44***	1.55****	0.85***
Profile 5: High vulnerability	0.08*	0.05	0.42*	0.21	0.16	0.10	0.59*	0.69*
Adjusted/pseudo-R^2	0.32	0.71	0.21	0.48	0.05	0.49	0.15	0.43
AIC	3,748	2,763	2,256	2,057	1,923	1,661	4,448	4,189
Moran's *I*	0.71****		0.46****		0.53****		0.42****	
Breusch–Pagan test	6.9	10.8	5.1	5.9	8.5	14.6	9.7	13.9
Multicollinearity condition number	6.4	6.4	7.2	7.2	7.3	7.3	6.4	6.4
N	1,084	1,084	608	608	625	625	1,006	1,006

Note: OLS = ordinary least squares; AIC = Akaike's information criterion.
*$p < 0.01$.
**$p < 0.001$.
***$p < 0.0001$.
****$p < 0.00001$.

relationships across the pillars, but only the relationships with socioeconomic status and population structure were positive. This contrasts with the index-level finding that property loss was the only nonsignificant model for the weighted index. The low model fit (pseudo-$R^2 = 0.32$) indicates that other factors have a strong effect on relative property loss. By contrast, applicants had the best model fit (pseudo-$R^2 = 0.57$) of the outcome measures. As the percentage of IA applicants increased, the only positively and significantly related pillar was access and functional needs. Meanwhile, the housing damage and affected renter outcomes were not predicted by any of the pillars in the hypothesized direction.

The pillars of the weighted model have five significant positive relationships with the Sandy outcomes (only two after a Bonferroni correction) and six significant negative associations (four accordingly). Across the pillars, access and functional needs had a significant relationship with all four outcomes and in a positive direction with all but property loss. The housing and race and ethnicity pillars were the weakest predictors, as all relationships were either nonsignificant or negative.

Table 10 summarizes the regression results for the SVI themes. Overall, the SVI themes have poor explanatory power, as no outcome measure had a positive and significant relationship with any theme. This finding aligns with the results at the index level. The housing and transportation theme includes housing in structures with ten or more units and households with no vehicle. Similar to the results for SoVI factor of renters and vehicle access, the SVI housing and transportation theme is identifying Manhattan. Because the theme also includes the variables of households with more people than rooms and persons in institutionalized group quarters, however, this SVI theme is also identifying other places, complicating interpretation of the negative beta coefficient.

Table 11 presents the regression results at the profile level of the SVP, with four of the five vulnerability profiles entered into the regression as dummy variables. We discarded the medium profile (Profile 3) to avoid multicollinearity issues, resulting in evaluation of the two low and two high vulnerability profiles. Similar to Table 9, the Sandy housing-related outcomes of damage and property loss were highly significantly related to flood depth. IA applicants had the best model fit (pseudo-$R^2 = 0.71$), and overall the SVP has a better model fit with the outcomes (slightly higher pseudo-R^2 and lower AIC) than the pillars of the SoVI, SVI, and weighted indexes.

Contrary to the previous models, the SVP performs as expected. The sign of the profile coefficients consistently aligns with the direction of hypothesized relationships between social vulnerability and disaster outcomes. The high vulnerability profiles (4 and 5) have only positive significant relationships with the Sandy outcomes and the low vulnerability profiles (1 and 2) have only negative significant associations. Yet, the only significant relationship with the high vulnerability profile (Profile 5) is with property loss, a finding that might not be deemed significant after a Bonferroni correction. The "high vulnerability, age and special needs" profile (Profile 4), however, has robust positive links with all the outcomes, indicating a high level of construct validity.

Discussion

The study objective was to assess the empirical validity of a wide range of social vulnerability models using FEMA impact data from Hurricane Sandy. Our comprehensive study design included multiple configurations of social vulnerability, multiple normalized outcome measures, statistical control for hazard severity, and justification for hypothesized relationships between vulnerability and outcomes. Still, attributing the cause of nonsignificant or negative statistical relationships is challenging, because they can occur for at least three reasons:

1. Social vulnerability models or pillars that are weak proxies for social vulnerability processes.
2. Outcome measures that inadequately represent social impacts.
3. Flawed conceptual relationships between social vulnerability and disaster outcomes.

We found that explanatory power varied substantially across social vulnerability models for a given disaster outcome and across outcomes for a given model. The variation across models demonstrates that the configuration of a social vulnerability index has a strong influence on its empirical validity. The variation across outcome variables demonstrates that disaster outcome measures differ in their efficacy as indicators of human impact. Given the multidimensional nature of models and the current weak state of theorized relationships between social vulnerability and specific disaster outcomes, a search for the ideal unidimensional validation measure might prove elusive. There is a need for greater theoretical understanding to aid the construction of social vulnerability models and the selection of validation measures.

Model Validity

Previous empirical validation studies found SoVI to be a significant predictor of property loss, resident rate of return, and earthquake debris at the tract scale (Finch, Emrich, and Cutter 2010; Schmidtlein et al. 2011) and for property loss at the county scale (Bakkensen et al. 2017). We found SoVI to be significantly related to the IA applicants and housing damage but not property loss or affected renters. At the component level, previous studies found socioeconomic status to have significant relationships in the expected direction with property loss (Yoon 2012) and migration (Myers, Slack, and Singelmann 2008) at the county scale and with housing damage at the tract scale (Burton 2010). In our case, we found that socioeconomic status failed to explain housing damage; it did for property loss but not in the expected direction. In short, there is little consistency across studies in social vulnerability dimensions and disaster outcome types (human, housing) found to be empirically valid.

We featured SoVI and SVI in the study design because they are the most prominent social vulnerability configurations, in both recognition and application. Analysis of Sandy data raises questions about the construct validity of each approach. For SoVI, there were notable differences in the explanatory power of the index and its constituent factors. The three components that explain the least amount of variance were not significantly related to any of the Sandy outcomes. One reason could be the reliance on the Kaiser criterion in the SoVI algorithm for determining the number of PCA components to retain. A leading critique of the Kaiser criterion is that it leads to overextraction of components (Costello and Osborne 2005; Ledesma and Valero-Mora 2007). Although a higher factor count might be useful for descriptive purposes, including noninfluential factors in the SoVI aggregation or assigning them equal weights could decrease both parsimony and explanatory power. More research is needed on this topic.

The explanatory power of the SVI was decidedly poor. The only significant relationships between the SVI and the Sandy outcomes were negative. This also occurred at the subindex level, as most of the SVI themes had either nonsignificant or negative relationships with the disaster outcomes. The SVI is being promoted for use by public health officials and planners to identify socially vulnerable areas and populations (ATSDR 2018). Based on the analysis of Sandy outcomes, however, the construct validity of the SVI is weak.

Our study also evaluated alternatives to SoVI and SVI. Compared to these more established models, the weighted index based on expert knowledge had higher validity, explaining both human and housing-related impacts. Previous work, however, found the rankings of hierarchical indexes to be highly sensitive to the choice of weighting scheme (Tate 2012).

Although the SVP is not an aggregated measure, it had the highest explanatory power, significantly explaining all of the Sandy outcomes in the expected direction. These findings indicate a very strong alignment of construct and measure. SVP provides both quantification and qualification of social vulnerability, not only indicating whether each profile has a high or low vulnerability but also explaining why, thus unraveling the spatial distribution of the dominant vulnerability drivers. It directs attention to the locally convergent characteristics giving rise to social vulnerability, the intersectionality of social vulnerability drivers, and clusters of different vulnerability profiles, addressing why some places might be more vulnerable than others (Rufat 2013).

Statistical Model Specification

Our review of previous validation studies (Table 1) found that only half controlled for hazard severity, and only one accounted for spatial dependence. Our study analyzed twenty-eight multivariate regression models that included both. Water depth was statistically significant in most of these models, and spatial dependence was detected in every single one. If hazard influence and spatial dependence existed in the previous studies but were not examined, the results might overinflate the strength of the relationships between social vulnerability and disaster outcomes.

Given the expanding use of social vulnerability measures, there is a broad need for further empirical validation, exploring other input variables, disaster outcomes, disaster stage, and hazard types.

Conclusion

There is a mismatch between the rising application of social vulnerability models and understanding of their empirical validity. The current focus on descriptive and convergent studies is poorly suited to advance knowledge on this front. SoVI and the SVI are the most prominent social vulnerability configurations and are being promoted for use by public health officials and planners to identify socially vulnerable places and populations. Our empirical analysis from Hurricane Sandy, however, raises questions about their construct validity. The weighted model based on expert knowledge performed slightly better. The profile approach (SVP) had the highest empirical validity.

Overall, there is a need for additional studies focused on the construct validity of social vulnerability models and measures. The number of such studies is surprisingly low, particularly given the rising profile of social vulnerability indexes in all phases of hazard planning and decision making. We advise caution when using social vulnerability indexes for high-stakes decision making until there is a more complete understanding of their construct validity. Specifically troublesome is the lack of validation surrounding the freely available Centers for Disease Control SVI model when compared to the more robust profiles approach.

Models can achieve validity through both empiricism and acceptance. The latter is currently the dominant mode. The failure to thoroughly validate the leading models against empirical disaster outcomes introduces a potentially serious problem: Internal validity and convergent validity based on an accepted index are illusory if the model is empirically weak. Ideally model development should proceed by first producing internally robust and empirically valid models, and only then proceed to use the best performers as the baseline for convergence studies. The main research need is thus to identify which social vulnerability models consistently explain disaster outcomes across studies. This will require empirical studies in different places, with variation among models and indicators, outcome measures, hazards, and temporal and analysis scale.

Funding

This research was partially supported by funds from the U.S. National Science Foundation (1333190 and 1707947), under the Humans, Disasters, and the Built Environment program.

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