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Social Vulnerability: Conceptual Foundations and Geospatial Modeling

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Abstract: There is a continuing need for disaster risk reduction strategies to shift emphasis from assessing hazard events toward reducing vulnerabilities within social systems. Conceptualizing and measuring social vulnerability is an important stage along this path. Our current understanding of vulnerability is guided by theories, methodologies, and measurement standards derived from different schools of thought. This chapter provides a summary of core concepts on vulnerability, and its measurement from a social perspective (i.e., social vulnerability). The chapter has three main sections that delve into (1) conceptual frameworks for hazards vulnerability, 2) approaches for measuring social vulnerability, and 3) a case study analysis of social vulnerability in Hurricane Sandy.

Key words: Social vulnerability, vulnerability frameworks, measurement, indicators

1.0 Introduction

Extreme climatic and geophysical events exert enormous negative consequences on people around the world. Faced with ever increasing societal impacts from natural hazards, a wealth of research and analysis has focused on understanding causal processes and impacts. Historically, these efforts centered on characterizing hazard dynamics and using physical structures such as levees to mitigate damage. The result has been a proliferation of technocratic approaches, while financial and human losses from natural hazards continued to escalate. Over time, this gave rise to an alternative explanation that mounting losses are related less to natural event dynamics, and more to the vulnerability of exposed human populations. There is a continuing need for disaster risk reduction strategies to shift emphasis from assessing hazard events toward reducing vulnerabilities within social systems (Briceño 2015). Conceptualizing and measuring social vulnerability is an important stage along this path.

Broadly defined, vulnerability is the potential to suffer loss or harm. This can include structural vulnerability of buildings and lifelines, biophysical vulnerability (physical exposure) of people and places to natural events, and social vulnerability describing differential susceptibility based on social, economic and political factors (O'Keefe et al. 1976; Cutter 2001). As applied in social science research, the term vulnerability generally describes a state of people and populations rather than physical structures, economies, or regions of the earth (Wisner et al. 2004). Vulnerability can vary significantly across both social and geographic space (Liverman 1990; Bohle et al. 1994b; Cutter 1996). Social space refers to who is vulnerable, and is defined by the political, economic, and institutional capabilities of people at a specific time and place (Bohle et al. 1994b; Wisner et al. 2004). By contrast, geographic space describes the location and scale at which people and places are vulnerable (Cutter 1996).

Our current understanding of vulnerability is guided by theories, methodologies, and measurement standards derived from different schools of thought. This chapter provides a summary of core concepts on vulnerability, and its measurement from a social perspective (i.e., social vulnerability). The chapter has three main sections that delve into (1)

conceptual frameworks for hazards vulnerability, 2) approaches for measuring social vulnerability, and 3) a case study analysis of social vulnerability in Hurricane Sandy.

2. Conceptual Frameworks

Many definitions of vulnerability to hazards appear in the literature, with most including components of exposure, susceptibility, and adaptive capacity (Table 1). Exposure is the degree to which people and built environment elements intersect the spatial extent of hazard event. Susceptibility (also expressed as sensitivity or fragility) is the predisposition of exposed people and places to suffer adverse effects from a hazard. Adaptive capacity and coping capacity refer to the ability of people, communities, and systems to adjust to adverse hazard impacts.

Table 1. Selected Vulnerability Definitions

Source	Definition	Tradition
(Mileti 1999)	Measure of the capacity to weather, resist, or recover from the impacts of a hazard in the long term as well as the short term.	Risk-hazard
(Alexander 2002)	Susceptibility of people and things to losses attributable to a given level of danger, a given probability that a hazard will manifest itself at a particular time, in a particular place, in a particular way, and with a particular magnitude.	Risk-hazard
(Bohle et al. 1994b)	Aggregate measure of human welfare that integrates environmental, social, economic, and political exposure to a range of harmful perturbations.	Political economy
(Wisner et al. 2004)	Characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard.	Political ecology
(Turner et al. 2003)	Degree to which a system, subsystem, or system component is likely to experience harm due to exposure or hazard, either a perturbation or stress/stressor.	Social-ecological systems
(Adger 2006)	State of susceptibility to harm from exposure to stresses associated with environmental and social change, and from the absence of capacity to adapt.	Social-ecological systems

Few definitions have been widely agreed upon, in large part because the study of hazards vulnerability has proceeded under at least three distinct conceptual framings. These

include risk-hazard, political ecology, and social-ecological systems frameworks (Eakin and Luers 2006), although other typologies have been suggested (Liverman 1990; Cutter 1996; Turner et al. 2003; Adger 2006). Each is situated within a larger human-ecological modeling framework in which hazards and disasters stem from complex interactions between environment and society. However, the frameworks differ in their conceptualization of the dominant components, processes, and relationships that define human-environmental interactions. Conceptual framing is important because it drives the types of questions that are posed, the analytical methods used to answer them, and the solutions that are implemented. Over time, conceptual frameworks of vulnerability evolved from an initial focus on physical and managerial aspects to more explicit inclusion of social drivers and differential impacts. The following sections describe the evolution of prominent conceptual frameworks that have shaped social vulnerability analyses.

2.1 Risk-Hazard

Vulnerability in risk-hazard is generally defined as the potential for loss or other adverse impacts, or the capacity to suffer harm. Expressed mathematically, risk equals hazard multiplied by vulnerability. Risk is a function of biophysical, social, and economic factors, but in risk-hazard analyses, the hazard assumes the central role. Many studies have highlighted characterization of the spatial distribution of biophysical risk, with the most vulnerable populations considered to coincide with areas of biophysical exposure (Liverman 1990). Due to the assumed dependence on exposure, risk-hazard approaches often favor solutions that seek to modify physical exposure through such actions as monitoring, forecasting, engineering, and land use planning (Hewitt 1983).

Within the risk-hazard tradition, geographers Gilbert White, Ian Burton, and Robert Kates pioneered the study of hazards and human adjustments taken in response to them. Following a series of major floods along the Mississippi River, the US Flood Control Act of 1936 was passed (Congress 1936). The statute granted authority to the US Army Corps of Engineers to build and maintain large-scale flood control structures, such as dams, dikes, floodwalls, and levees. This structural mitigation approach was indicative of the dominant mentality of the day: the root cause of disasters is extreme physical events, and societies

can master flooding through technology. For Gilbert White, there was an alternative range of adjustments to flood hazards, including evacuation, building codes, zoning, public relief, and insurance (White 1945). These were nonstructural approaches that recognized the role of both nature and society in creating hazards.

Social science research in the risk-hazard domain has delved into questions of why people inhabit hazardous areas, what factors influence the adoption of human adaptations to hazards, and how risk perception influences behavior (White 1973). As such, the elements that define risk should expand from a dominance of external natural processes to also include societal dimensions of perception, policies, and management (Cardona 2005). The basic idea is that people exacerbate hazards through behaviors such as developing in floodplains and translating risk perception into action. The focus on societal behavior led this perspective to also be referred to as the behavioral paradigm. In the risk-hazard domain, risk and vulnerability assessments generally proceed through a sequential analysis that progresses from event characterization to exposure to fragility to impacts to potential adjustments (Hewitt 1983; Eakin and Luers 2006). Vulnerability reduction in turn is achieved through decision-making processes that consider natural event characteristics, risk perception, and cost.

The Human Adjustment to Natural Hazards model is indicative of the risk-hazard perspective (Figure 1). It defines a hazard as the intersection of systems of natural events and human activity, governed by a process of human adjustment to both. This interplay of systems produces hazard effects, such as impacts to people, their belongings, economic activity, and social systems. The model is continuous and reflexive in that it assumes feedback effects of human adjustments to future states of natural events and human systems.

aggregate of adjustments implemented and avoided at different scales determines the severity of natural hazards.

Overall, the risk-hazard approach has tended to underemphasize the contribution of human use systems to hazards. Critics have argued that risk-hazard approaches poorly describe how people exacerbate or attenuate hazard effects, and fail to consider the role of political economy in shaping differential exposure and impacts (Turner et al. 2003). In particular, it poorly addresses the societal context in which hazards take place. For example, the range of hazard impacts and available adjustments to a natural event may be influenced by factors exogenous to the system, such as public and private agendas and concurrent economic downturn. However, analysis at the system level may overlook differential hazard exposure and impacts among population subgroups within the system.

Hewitt issued perhaps the strongest condemnation of risk-hazard (including some of his own work), arguing the approach is far too predicated on the causality of environmental determinism (Hewitt 1983), with hazards considered to be exceptional phenomena that occur outside the domain of human-environment interactions. This perspective leads to over-reliance on technocratic solutions that are incapable of addressing important contributing factors such as societal economic, social, and political structure and values. Over time, critiques of the risk-hazard paradigm helped lead to a shift in perspective from natural events toward human vulnerability as the root cause of disasters (O'Keefe et al. 1976; Liverman 1990; Kaspersen et al. 2001; Wisner et al. 2004).

2.2 Political Economy and Ecology

A focus on the social determinants of vulnerability helps explain why people with similar levels of exposure may experience very different levels of adverse impact. The social vulnerability perspective has its roots in the domains of political economy and political ecology. Political economy researchers generally focus on how political, economic, social, historical, and institutional factors (Table 2) produce differential exposure and susceptibility, with particular attention paid to cross-scalar interactions. Political ecologists extend the analysis by examining how these structural determinants generate,

exacerbate, and attenuate environmental hazards (Collins 2008). From both perspectives, disasters result from failures of political and economic systems, producing inequality, marginality, and differential constraints on individual action.

Table 2. Political Economy Determinants of Social Vulnerability

Determinant	Components
Political	Strength of democratic system, human rights, legitimacy of government action, corruption, citizen participation in decision making, linkages to local governments and civil organizations
Economic	Income, wealth, debt, credit access, economic reserves, trade policy
Social	Class, gender, ethnicity, age, religion, immigration status, literacy, education, health
Institutions	Rules, regulations, practices, programs, decision making procedures (e.g., property rights, water rights)

Central research questions related to social vulnerability focus on who is vulnerable, why they are vulnerable, how they are vulnerable, and how institutions contribute to vulnerability (Eakin and Luers 2006). The elevation of sociopolitical and economic factors is illustrated in the Causal Structure of Vulnerability conceptual model (Bohle et al. 1994a), which posits vulnerability as a social space bounded by components of risk exposure, coping capacity, and recovery potential. These components are governed by a place- and time-specific causal structure dependent on human ecology, expanded entitlements, and political economy. Trailblazing researchers in the political economy/ecology tradition include Piers Blaikie, Hans Bohle, Ken Hewitt, Amartya Sen, Michael Watts, and Ben Wisner.

Within the political economy domain, vulnerability is often conceptualized as a lack of entitlements in livelihoods. Entitlements refer to the set of commodities or resources that a person can legally command, obtained through personal labor, production of owned resources, trade, or transfer (Sen 1981). Ownership of these entitlements results from a combination of historical, institutional, and economic factors. Command over entitlements allows for the diversification of livelihoods in the face of a hazard or other stressor, increasing coping ability (Eriksen et al. 2005). Lack of entitlements translates through

social factors, resulting in vulnerability via unequal exposure to hazards (Watts and Bohle 1993).

Context is another factor explicitly considered in political economy/ecology analyses. Societal issues such as policy agendas, resource management, land use patterns, wealth distribution, and economic development may overlap with natural events, combining with place and time to make individual hazards unique (Mitchell et al. 1989; Tobin and Montz 1997). There is also the potential for multiple stressors to occur simultaneously. For example, the occurrence of an extreme natural event concurrent with economic marginality can result in double exposure (O'Brien et al. 2004). Therefore, in order to truly understand hazards, stressors cannot be considered in isolation (Tobin and Montz 1997).

While the Human Adjustment Model evaluates vulnerability largely as function of natural events and managerial decisions, a structural perspective on political economy posits vulnerability as an intrinsic property of human systems. Vulnerability is thus an underlying condition revealed by, rather than resulting from stresses to the system, of which natural events are only one type. Other stresses may originate from unequal access to resources, economic structure, policy agendas, resource management, and violent conflict. For example, the occurrence of an extreme natural event concurrent with economic downturn can result in double exposure to hazards (O'Brien et al. 2004). Accordingly, vulnerability analysis should consider how macro-economic, political, and institutional factors amplify and attenuate vulnerability to hazards. Emblematic of the political ecology viewpoint, the disaster Pressure and Release Model (PAR) highlights a sequence of societal conditions that determine disaster vulnerability (Blaikie et al. 1994). The components and relationships of the PAR are shown in Figure 2.

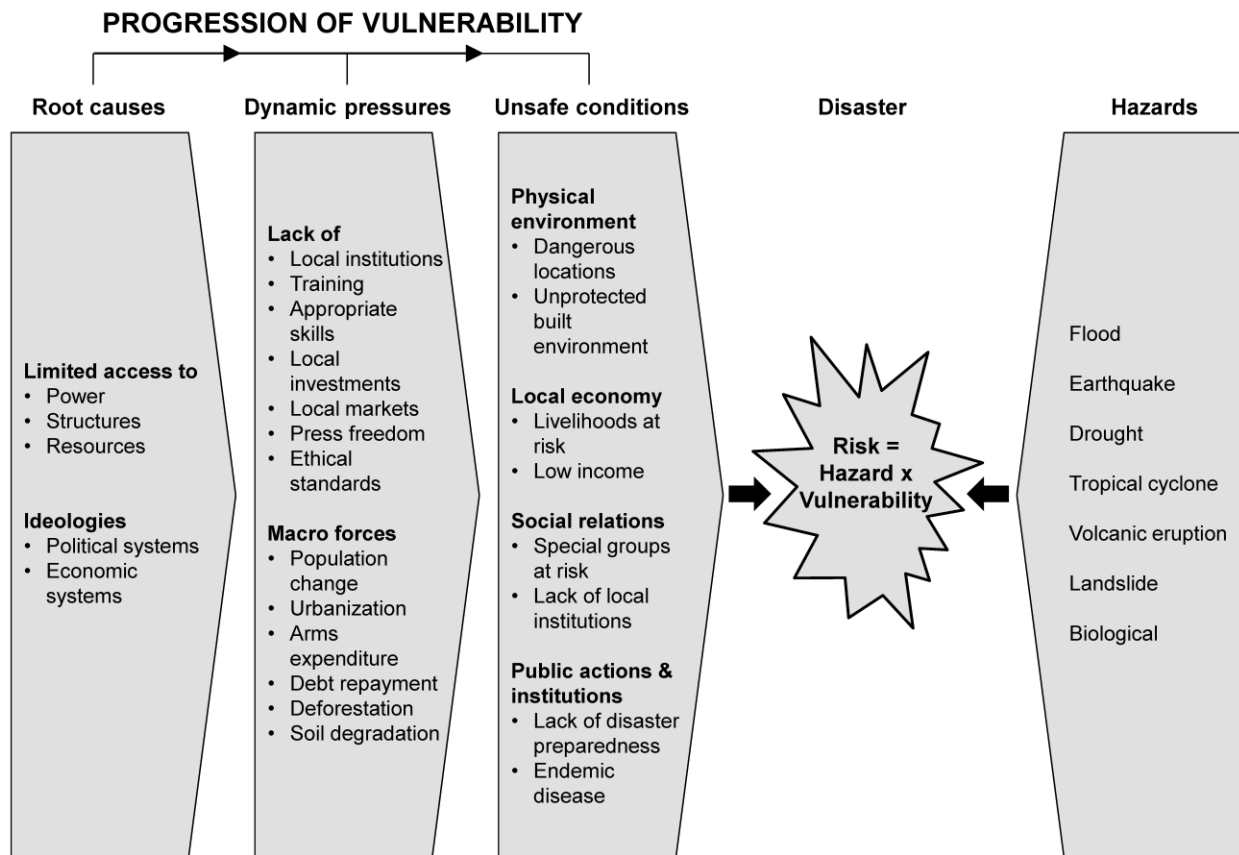


Figure 2. Disaster Pressure and Release Model (adapted from Blaikie et al. 1994)

In the PAR, human vulnerability and physical hazards are opposing and additive pressures that combine to produce disasters. Social vulnerability arises as the result of a progression that proceeds from root causes through dynamic pressures to unsafe conditions. Root causes are societal scale and interrelated political, economic, and demographic structures that establish and sustain power relationships, and govern the allocation of resources. These driving forces are often spatially and temporally distant from the hazard event. Dynamic pressures are institutional, social, and environmental processes that channel generalized root causes into environmental degradation (Kasperson et al. 1995) and specific unsafe conditions. Unsafe conditions are the physical, economic, social and managerial factors that determine differential exposure to hazards at the local scale. The progression of vulnerability combines with hazard severity to exert pressure on people

through disaster impacts and constraints on coping capacity. Only by reducing vulnerability can the pressure of disaster risk be released.

With a focus on the social construction of vulnerability, the PAR is well suited to analyze chronic, slow onset, and spatially diffuse hazards (e.g., drought, climate change) that are more difficult to address with adjustments to the natural events system. Within political economy research, is often equated with extreme natural events themselves. This is a departure from the risk-hazard conceptualization as the intersection of natural and human systems. The strength of the structural perspective of political economy lies in its focus on underlying political, social, economic, and institutional factors that lead to vulnerability, inclusion of scale, and consideration of concurrent stressors other than natural events that may compound vulnerability. However, it has been criticized for downplaying physical aspects of natural-human systems interactions and underemphasizing system feedbacks common in human adjustment models (Turner et al. 2003). Other critics argue that the PAR is well suited for descriptive analysis, but less amenable to quantification.

2.3 Hazards of Place

The Human Adjustment Model and PAR share a focus on system-level interactions between people and environment as the source of vulnerability. But questions remained about the vulnerability of what, and the vulnerability of whom? Vulnerability is frequently described in the academic literature as a dynamic phenomenon that can vary significantly across time and space. Analysis at the system level can provide a good understanding of physical and social causal processes, but not necessarily how they vary spatially and manifest at local scales. To fully understand hazard effects and associated human adjustments, the analysis should expand from a focus on single hazards to all hazards that affect a place (Hewitt and Burton 1971).

The Hazards of Place Model (Cutter 1996) addresses this concern, combining vulnerability from biophysical and social systems to produce vulnerability specific to a particular place and time (Figure 3). In the model, risk (defined as hazard sources, probability, consequences) and hazard mitigation (defined as planning, structural and technological

improvements) interact to determine the initial hazard potential for a place. This is roughly analogous to the ideas of natural system characteristics and human use system adjustment in the Human Adjustment Model. Biophysical vulnerability is generated by the translation of hazard potential through physical characteristics, such as elevation, location, and threat proximity, which comprise the geographic context. Likewise, social vulnerability is produced via the filtering of the hazard potential through social characteristics, such as socioeconomic conditions, risk perception, and coping capacity, which collectively constitute the social fabric of a place. The social fabric is then distilled into place-specific characteristics of marginalized populations (Wisner 1998) and used to measure social vulnerability. Biophysical and social vulnerability dynamically interact to create the vulnerability of a place, which feeds back to influence future states of risk and mitigation.

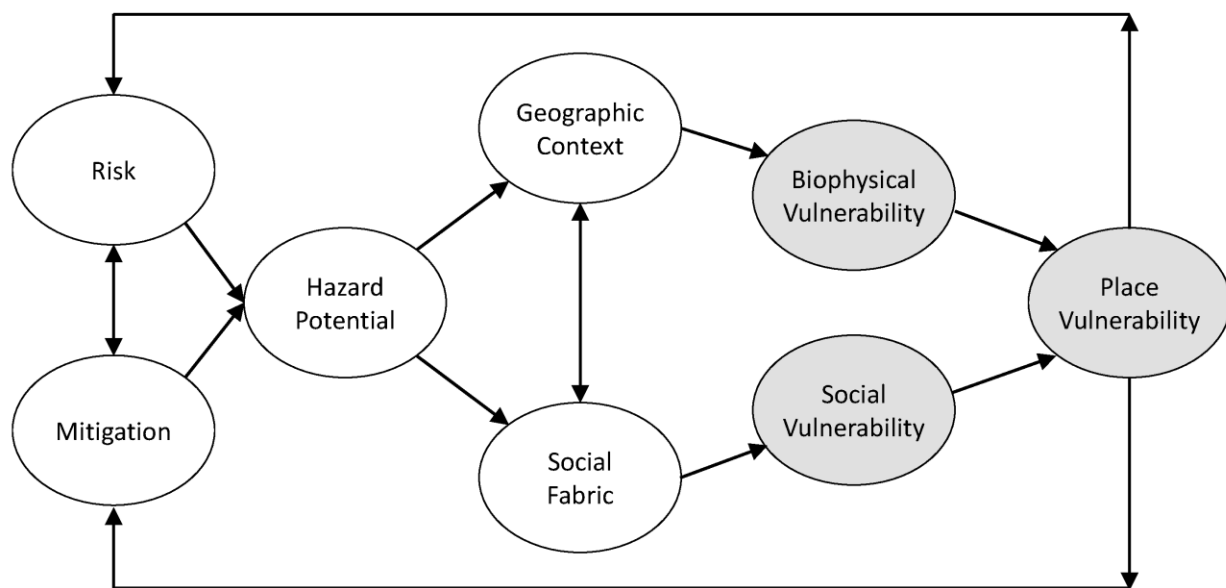


Figure 3. Hazards of Place Model (adapted from Cutter 1996)

‘Place’ in the Hazards of Place Model is not tied to a particular scale, but is intended for application at the community level. Such analysis allows for the comparison of hazard vulnerability of different locales, while revealing how factors contributing to vulnerability combine in different ways depending on geography and scale. The Hazards of Place Model

has typically been implemented in a Geographic Information System (GIS), by spatially integrating biophysical and social vulnerability. This produces results that are explicitly spatial, but doing so can omit vulnerability characteristics and interactions that are difficult to quantify (e.g., social capital) or have limited spatial variation (e.g., governance).

One of the first implementations of the Hazards of Place model was a case study of Georgetown County, South Carolina (Cutter et al. 2000), which mapped indicators of social and natural hazard characteristics. The investigators spatially aggregated frequencies of historical hazard events to create a composite map of biophysical vulnerability. Then they developed a composite index of social vulnerability at the sub-county scale using census demographic data. The social and biophysical maps were combined, and the values summed to produce a composite map representing overall place vulnerability. This place-based approach using geospatial analysis has been since applied in numerous studies of integrated vulnerability (Chakraborty et al. 2005; Collins et al. 2009; Koks et al. 2015).

2.4 Other Vulnerability Frameworks

The evolution in conceptual frameworks has helped shape understanding the social dimensions of vulnerability to natural hazards. However, other frameworks have also been influential. The Social Amplification of Risk model describes how psychological, social, and cultural processes interact with hazard events in ways that amplify or attenuate public perception of risk (Kasperson et al. 1988). Risk perception can modulate the level of social and economic impacts from hazards, potentially limiting response even when capacity exists (Adger 2006).

The social-ecological systems perspective posits natural and human systems as a highly dynamic, tightly coupled system in which people and the biophysical environment are constantly interacting and co-evolving (Turner et al. 2003). Central research questions involve who and what are vulnerable to environmental change, how to identify thresholds that signal change, how changes are attenuated or amplified by human and environmental conditions, and the degree to which resilience is a useful concept for developing proactive strategies for vulnerability reduction.

The Bogardi/Birkmann/Cardona (BBC) conceptual framework adopts a sustainability structure, situating exposure, susceptibility, and coping capacity among environmental, economic, and social dimensions (Birkmann 2014). Through temporal feedbacks, the model highlights emergency management interventions for reducing impacts, and it is intended to be applied to specific hazards. The Methods for the Improvement of Vulnerability Assessment in Europe (MOVE) framework extends the BBC, adding cultural and institutional dimensions of vulnerability to the analysis (Birkmann et al. 2013). Under MOVE, interactions between natural hazards and society produce risk, which is amplified or ameliorated over the long term by risk governance and adaptation.

How vulnerability is defined has a major effect on how it is addressed. This is why conceptual frameworks matter. Frameworks describe the most influential causal factors and the relationships among them. Most vulnerability frameworks share the human ecology underpinnings of the Human Adjustment Model: hazard impacts are a result of human-environmental interactions. Over time, conceptual frameworks of vulnerability evolved toward greater detail and complexity, inclusion of cross-scalar effects and temporal feedbacks, and links to resilience, sustainability, and adaptation. However, even as conceptual understanding of vulnerability processes increases, challenges remain in operationalizing conceptual frameworks into vulnerability assessments.

3.0 Assessment and Measurement

In transitioning from conceptual framing to assessment, much more effort and resources have been invested in understanding physical processes underlying hazards vulnerability than the array of social determinants. Focusing on social vulnerability, measurement is often a precursor to developing strategies to reduce hazard risk. Measurement first requires the ability to identify characteristics that determine a population's risk, as well as an understanding of what enhances or reduces the ability of people to respond to and recover from environmental threats. Translating this understanding of the social fabric of communities into quantitative metrics of social vulnerability is the embodiment of a central aspect of the Hazards of Place model.

Social vulnerability is highly multidimensional and constituted by both tangible and intangible characteristics. This multidimensionality makes it difficult or impossible to represent the concept with a single equation or universal set of metrics across scales and hazards (Birkmann 2014). As a result, there are few consensus guidelines for measuring social vulnerability. There is agreement, however, that quantitative measurement of the concept involves a number of stages, including the selection or compilation of relevant data, data standardization, and aggregation of data to derive a final value (Tate 2012). Due to difficulty with direct measurement, proxy measures are selected to convey the overall capacity of populations to prepare for, respond to, and recover from damaging events. There is a rich tradition of research focused on the factors that increase or decrease the social vulnerability of populations.

This section provides insights into techniques used to understand, measure, and communicate the social vulnerability of populations to hazards and disasters. It is not intended to be an exhaustive review of the literature related to measuring social vulnerability. Rather, we selected methodologies most relevant to the development of composite indicators associated with social vulnerability frameworks discussed in the preceding section. An indicator is a quantitative or qualitative measure derived from observed facts that can simplify and explain a complex reality (Freudenberg 2003). A composite indicator (index), is a mathematical aggregation of individual indicators or thematic sets of indicators that represent different dimensions of the concept being measured.

3.1 Deductive Models

A leading characteristic distinguishing composite indicators of social vulnerability is the structural design, which include deductive, inductive, and hierarchical arrangements (Tate 2012). Deductive approaches are top-down, and they heavily emphasize the theoretical frameworks upon which their variables are selected. The most important dimensions of social vulnerability are identified *a priori*, with typically ten or fewer variables that are standardized and aggregated into an index (Figure 4).

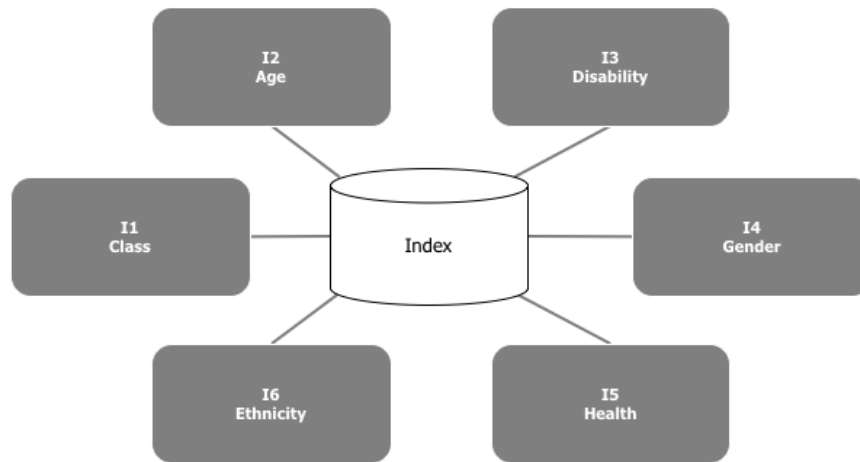


Figure 4. Deductive approach for social vulnerability assessment (Tate 2012)

3.2 Inductive Models

Inductive approaches begin with a larger indicator set (typically 20 or more) that is reduced to a smaller set of values that help to explain the social vulnerability across a given area. This is accomplished using a Principal Components Analysis (PCA) and/or a Factor Analysis (FA) to decompose a large dataset into a smaller number of uncorrelated factors that explain the variance within the data. The resultant factors are aggregated by to build an index (Figure 5).

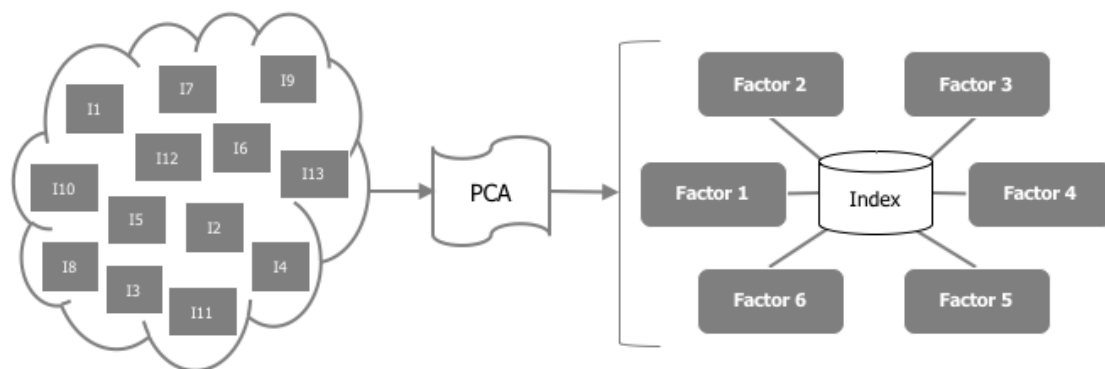


Figure 5. Inductive approach for social vulnerability assessment (Tate 2012)

Inductive approaches for modeling social vulnerability were popularized by the Social Vulnerability Index (SoVI) (Cutter et al. 2003). The SoVI is largely based on social dimensions identified in the PAR and Hazards-of-Place models. The original configuration of SoVI utilized between 29 to 42 variables, depending on the analysis scale. The variables are input into a Factor Analysis that estimates the variability that the original input data has in common due to its intercorrelations, and decomposes this data into factors that explain the social vulnerability of a study area. To ensure that the sign of the factor loadings corresponded with their known influences on social vulnerability, factor scores are scaled by making slight adjustments to their directionality. A positive directionality is assigned to all factors known to increase social vulnerability (race and poverty for example), and a negative directionality is assigned to factors known to decrease vulnerability (indicators such as wealth). This is accomplished by multiplying the loadings by -1 since replacing a component with its inverse subtracts from the overall index. All components are then summed and mapped as standard deviations from the mean allowing for a quantified and visual representation of how social vulnerability varies across space.

Since its inception, the inductive approach for social vulnerability assessment has been expanded to address questions regarding scale (Schmidtlein et al. 2008; Fekete et al. 2010) temporal change (Cutter and Finch 2008), specific hazards (Rygel et al. 2006; Schmidtlein et al. 2011), and integration social vulnerability with physical vulnerability (Burton and Cutter 2008; Finch et al. 2010). Despite its usefulness in reducing data to factors that are potentially explaining the social vulnerability of an area, however, the inductive approaches rely on subjective decision-making at critical stages which could lead to uncertainties within the model outputs (Tate 2013).

3.3 Hierarchical Models

Hierarchical models typically employ 10 to 20 indicators, aggregated into pillars that share the same underlying dimension (e.g. special needs populations, economy, institutional factors). The pillars are then aggregated to create the index (Figure 6). Hierarchical models thus require a greater level of theoretical organization than purely deductive models. Hierarchical models may rely on participatory approaches and/or expert

knowledge both for the selection of variables and for weighting them (Bankoff et al. 2004). Participatory approaches require more time and resources than the deductive or inductive methods, but the increased use of stakeholder-selected indicators and expert-derived weights may result in an index with greater transparency, acceptability, and incorporation of local context.

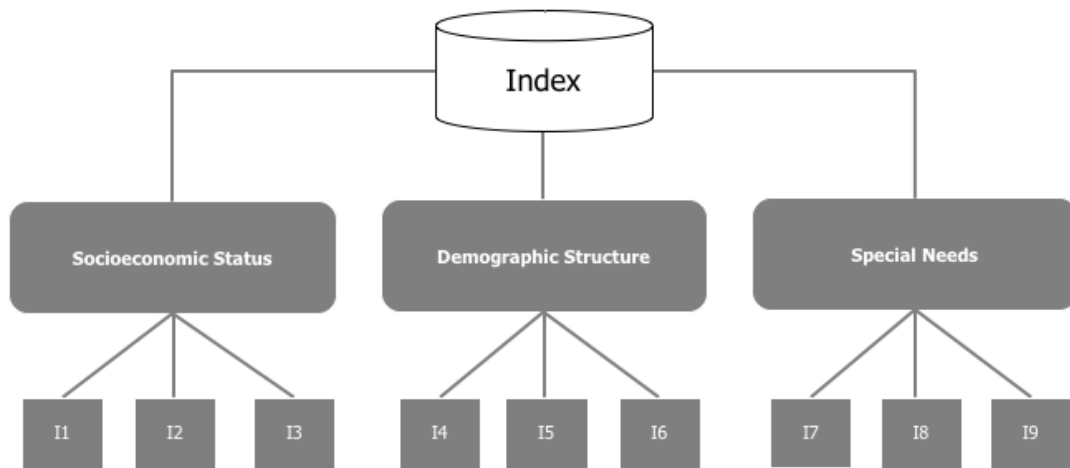


Figure 6. Hierarchical approach for social vulnerability assessment (adapted from Tate 2012)

3.4 Social Vulnerability Profiling

The models described thus far share a design goal of aggregating indicators to measure the spatial variation in the magnitude (e.g. high, medium, low) of social vulnerability. A different approach is to model the spatial variation of the dominant vulnerability drivers. The result is spatially-varying typologies or profiles of social vulnerability (Tuccillo and Battenfield 2016). Emblematic of this approach is the Spectroscopy of Vulnerability (Rufat 2013), which directs attention to interactions among indicators (rather than indicator aggregation) to identify social vulnerability profiles.

The aim of profiling is to identify (1) locally convergent characteristics that give rise to social vulnerability, 2) the intersectionality of characteristics that generate adverse impacts, 3) clusters of different vulnerability profiles, and 4) why some places might be more vulnerable than others. The outputs are well suited to inform the implementation of

targeted mitigation policies. The profiling approach begins by extracting the most relevant vulnerability drivers for a given case study according to the interactions described by the PAR and Hazards-of-Place frameworks. It then reduces the selected variables to around 15 to 20 based on statistical correlations, seeking balance in the count of vulnerability dimensions (i.e. around 5 demographic, 5 socioeconomic and 5 cultural or institutional variables).

Vulnerability profiles are generated through a factor analysis (PCA) on the input demographic data, followed by application of a hierarchical clustering (HAC) method. The factor coordinates of spatial units in the first components extracted from the PCA (i.e., components explaining around 75% of the combined variance) are used as a distance matrix for the Classification (HAC). The HAC is a non-spatial hierarchical clustering algorithm according to Ward's method, without the use of weights. The optimal partitioning is determined without *a priori* expectations. The larger thresholds in Ward's level indexes point to the ideal number of clusters. The combination of factorial analysis and clustering makes it possible to eliminate random fluctuations and to obtain more stable partitioning and compact groups of vulnerability profiles. The output is 3 to 7 relative vulnerability profiles that are mapped alongside a visual representation of the interactions specific to each profile.

Vulnerability profiling requires interpretation of the interactions of each relative vulnerability profile. It also requires explaining why some places might be more vulnerable than others, making it a more holistic approach than the inductive and deductive methods. In that sense, the social vulnerability profiles provide scientists and practitioners a tool to associate natural hazard risk with social vulnerability factors as they diverge across space.

3.4 Qualitative Case Study Approaches

There is considerable diversity of approaches for social vulnerability analysis (Fekete 2012). The models described thus far include only top-down, quantitative approaches. However, qualitative methods can also be employed to assess social vulnerability in case

studies that are in-depth and bottom-up. They encompass a set of context-oriented methods that typically include structured interviews and focus groups. Pre- and post-disaster case studies attempt to uncover drivers of social vulnerability. These driving factors are often described in terms of the real-world processes from which vulnerable conditions are derived. Here, research is aimed at better understanding the complexity of the social system being evaluated. Because of the time-consuming nature of a structured interview, these types of qualitative studies typically occur at the community or household scale, making the findings highly context dependent. Qualitative methods allow for:

- Collecting risk information from experts or community members;
- Communicating risk and social vulnerability with local stakeholders;
- Applying tools to facilitate local use of social vulnerability information to understand the risk of their communities, identify existing strengths and weaknesses, and establish resilience goals corresponding to the needs and capacities of communities;
- Assisting local stakeholders to strengthen existing vulnerability reduction strategies.

4.0 Case Study – Measuring Social Vulnerability for Hurricane Sandy

To illustrate the process of measuring social vulnerability, this section presents a case study based on Hurricane Sandy. The input data were collected from the U.S. Census Bureau and the U.S. Federal Emergency Management Agency (FEMA) to evaluate predictions from a social vulnerability model with a real-world disaster outcome. The analysis adopts multiple assessment's approaches to model pre-storm characteristics of affected populations and to examine interactions among vulnerability drivers. We then compare the results against observed outcome data from Hurricane Sandy.

4.1 Hurricane Sandy

"Superstorm Sandy" was the deadliest and most destructive event of the 2012 Atlantic hurricane season. At least 233 people were killed along the storm path, and direct economic losses were estimated at \$75 billion, a figure surpassed in the U.S. only by

Hurricane Katrina in 2005. Hurricane Sandy affected twenty-four U.S. states, with severe damage in New Jersey and New York. The storm surge hit New York City, flooding streets, tunnels, subways, and cutting power around the city. The East River overflowed its banks, flooding Lower Manhattan with a water depth ranging from 2 to 6 meters (Figure 7). The storm severely damaged or destroyed approximately 100,000 homes on Long Island with more than 2,000 homes deemed uninhabitable there. There were 71 Hurricane Sandy-related deaths in the state of New York. Damage in the state was estimated at \$42 billion. At the peak of the storm, 3 million residents were without power. There were 43 Sandy-related deaths in New Jersey, with direct economic loss estimated at \$37 billion.

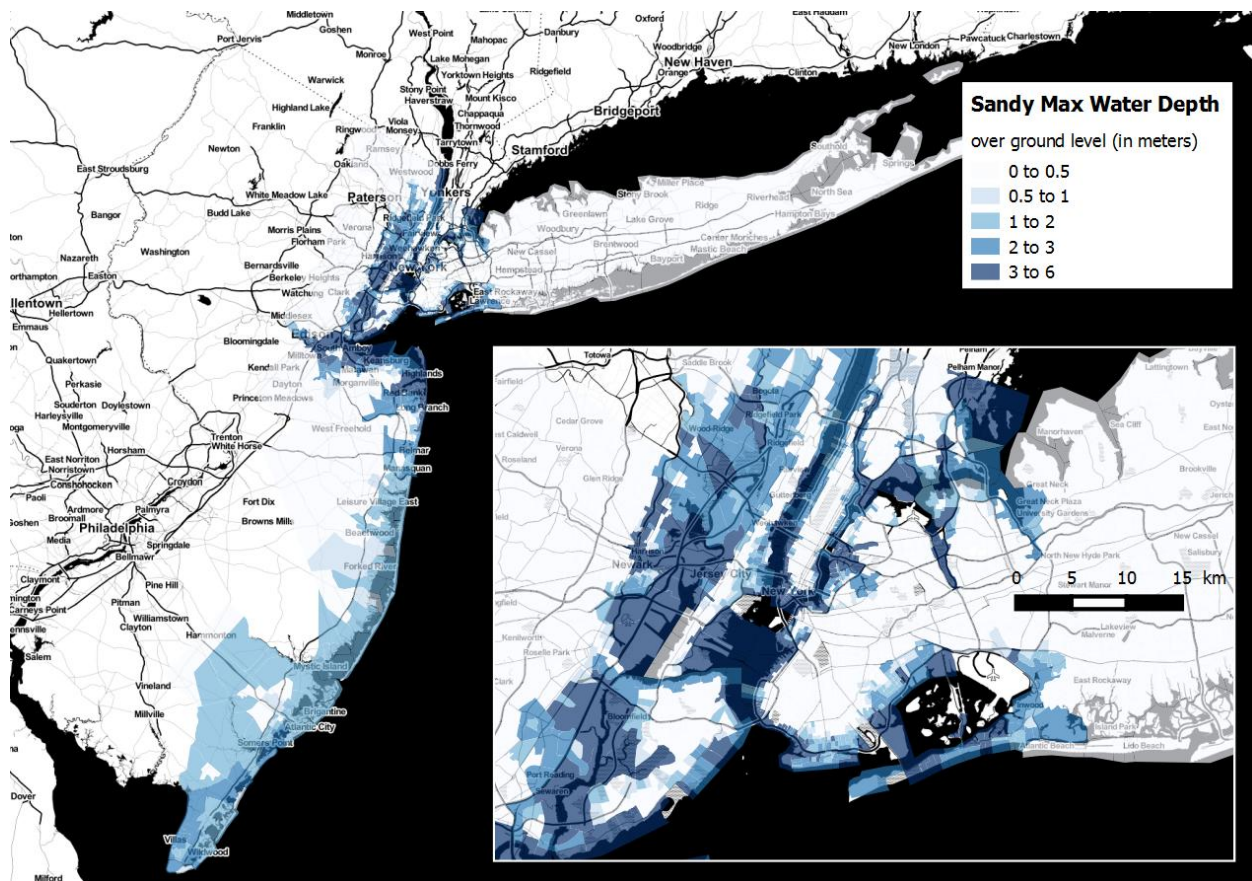


Figure 7. Hurricane Sandy flood depths in New York and New Jersey (FEMA, 2012)

Exposure and outcome data for New York and New Jersey were obtained from FEMA. The exposure data includes water depth over ground on October 31, 2012, as well as calculations of mean of water depth and inundated area during the storm. Sandy outcome

data were used to develop a proxy impact measure at the Census Tract scale of geography, and include loss estimates based on FEMA Verified Loss (HUD 2015), total FEMA-approved applicants for flood compensations (Individual Assistance), total affected uninsured renters, and the number of affected non-seasonal housing units (Table 3). These variables were normalized using sociodemographic data from the 2008-2012 American Community Survey (ACS) from the Census (Table 3). The normalized data were used as outcome measures (dependent variables) to compare social vulnerability indicators with the real-world impact outcomes.

Table 3. Sandy Outcome Indicators (HUD 2015)

Empirical Outcome	Normalization Variable	Outcome Variable
FEMA Verified Loss	Median house value	Relative loss
Applicants approved to FEMA Individual Assistance	Total population	Percent affected people
Non-seasonal housing affected	Total rental housing units	Percent affected non-seasonal housing
Uninsured renters affected	Total rental housing units	Percent affected uninsured renters

4.2 Statistical methods

We assessed social vulnerability using three different approaches for empirical measurement: a) the SoVI, b) a hierarchical model with variable selection and weighting based on expert knowledge, and c) vulnerability profiling. For comparison, the same variable set was applied to each social vulnerability model. The social vulnerability indicators were constructed for all affected census tracts in New York and New Jersey (n=3,950) (Table 4).

Table 4. ACS (2008-2012) SoVI variables

Variable Name	Description
1. POPDENS	Population density
2. AGE	% Age dependency (under 5 + over 65)
3. NURSRES	% Nursing home residents
4. FEMALE	% Female population
5. FHHOLDS	% Female-headed households
6. FEMLBR	% Female employment
7. FAMMARR	% Children in married families
8. BLACK	% African-American population
9. NATAM	% Native American population
10. ASIAN	% Asian population
11. HISP	% Hispanic population
12. ESLANG	% English as a second language
13. EDU12LES	% Adult educational attainment less than Grade 12
14. PERCAP	Per-capita income
15. RICH200K	% Annual Income >\$200K
16. POVTY	% Poverty
17. UNEMPLOY	% Unemployed
18. SSBEN	% Social security income
19. EXTRACT	% Extractive sector employment
20. SERVICE	% Service sector employment
21. NOAUTO	% No automobile
22. MOHOME	% Mobile homes
23. VACANT	% Vacant housing
24. PERPUNIT	People per housing unit
25. RENTERS	% Renters
26. MDGRENT	Median rent
27. MHSEVAL	Median home value

Two inductive models were created for flooded areas in New York and New Jersey. The first applies equal weights and the second was constructed with a weighting scheme derived from using weights derived from the PCA (OECD 2008). Variables whose values increase as social vulnerability decreases (FAMMARR, PERCAP, RICH200K, MDGRENT, MHSEVAL) were multiplied by -1 to change their directionality. The data were then standardized and entered into a PCA. The first 8 components represented 70% of variance. The remaining components with eigenvalues less than 1.0 were omitted. The first seven components corresponded to increasing social vulnerability within an index; whereas the

contribution of the 8th component (representing high median rents) was reversed due to a negative association with the concept. The first seven factor scores for the equally weighted model were therefore aggregated by summation and the eighth component was normalized (subtraction by the mean and division by the standard deviation) and subtracted from the overall index to form the SoVI. The results were mapped in Figure 8 to highlight the outliers, with the highest vulnerability in red and least in blue.

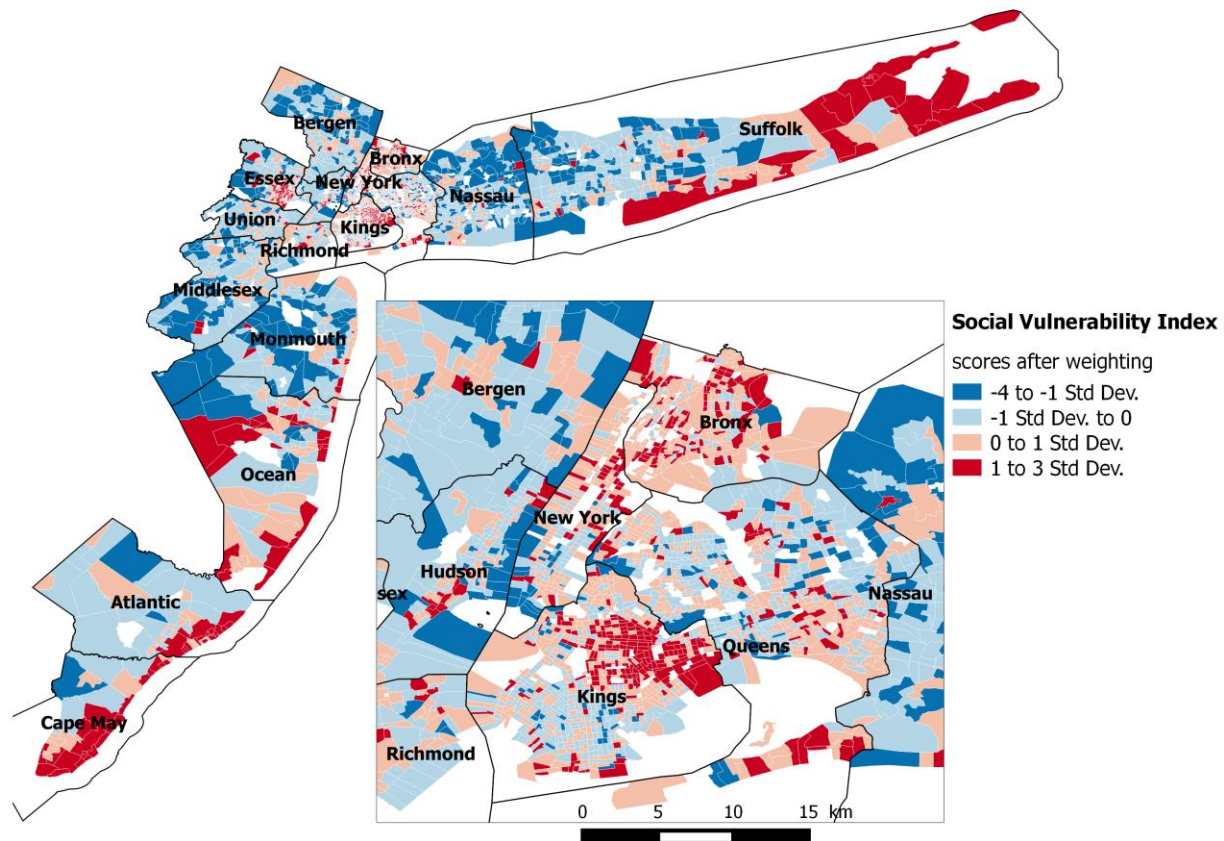


Figure 8. Equally weighted SoVI scores

The second inductive model uses weights defined by the PCA. Here, weights were applied to each factor score based on the initial variance explained by each component, as represented by their eigenvalue. Seven of the eight components resulting from the PCA were weighted and summed to produce the final weighted SoVI score. The eighth component (Median Rent) was weighted and subtracted from the overall index due to its potentially negative contribution to the social vulnerability concept. The resulting score was normalized and mapped following the same method for comparison (Figure 9).

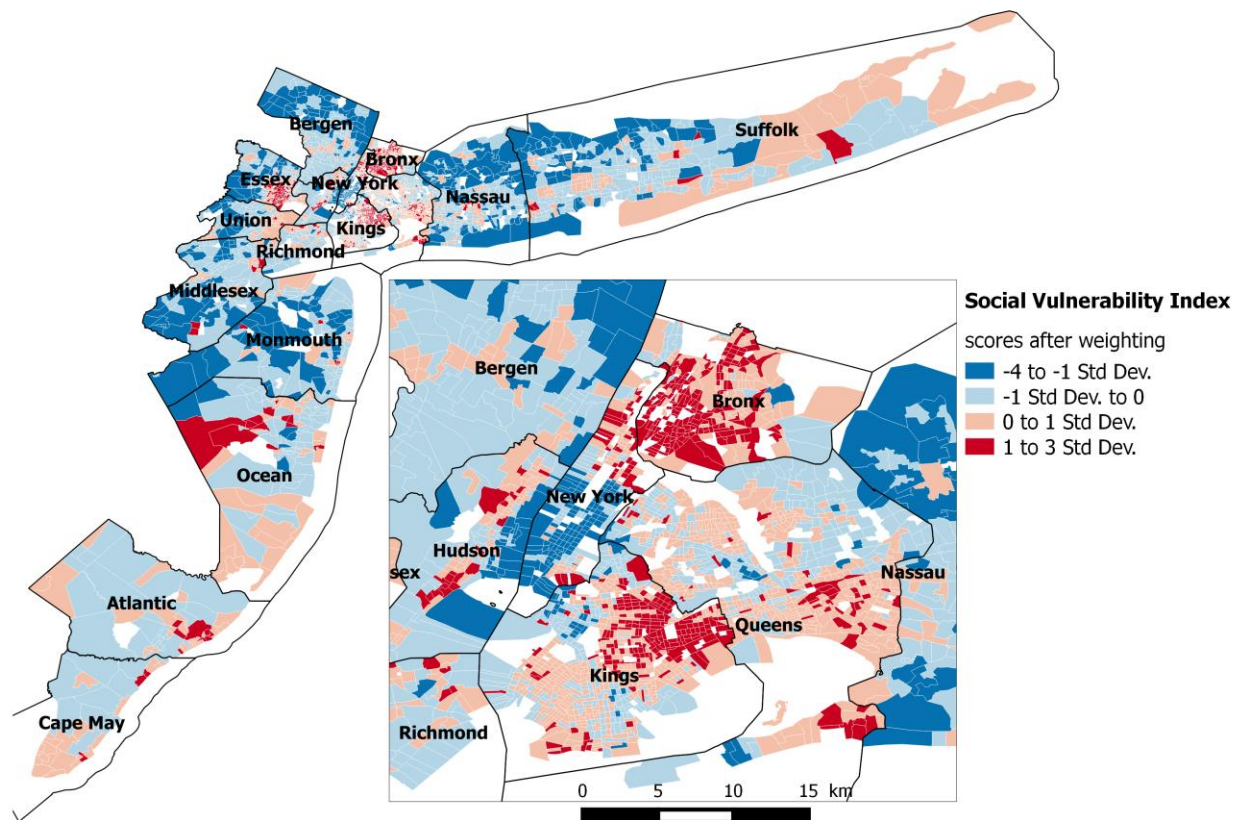


Figure 9. SoVI scores after weighting by PCA eigenvalue

For our second modeling approach, we constructed a hierarchical model of social vulnerability. To foster comparison with the inductive models, the same input variables (Table 2) were used. Individual indicators were aggregated into pillars, and the pillars were then aggregated to create the index according to a weighting scheme based on expert knowledge. The expert weights were derived from a survey of hazards and disaster professionals to derive a level of importance for individual social vulnerability indicators (Emrich 2005). The survey applied a budget allocation approach in which experts were asked to allocate a budget of 100 points among a set of indicators (Table 5).

Table 5. Expert-derived weighting scheme (Emrich 2005)

Variable	Weight %	Description	Dimension
PerCap	15.1	Per capita income	Socioeconomic status
QPoverty	14.3	% families in poverty	Socioeconomic status
MedVal	8.4	Median value of owner occupied housing	Socioeconomic status
QOld	7.5	% Elderly over 65	Age
QKids	5.7	% Children under 5	Age
QCvUn	5.1	% Civilian labor force unemployed	Socioeconomic status
QBlack	4.9	% Black	Race & ethnicity
NHRes	3.8	Nursing home residents	Special needs
QSSBen	3.4	Social security recipients	Social dependence
QRich	3.3	% Families earning > 100K	Socioeconomic status
Immig	3.2	% International migration	Migrants
RentOcc	3.1	% Renter occupied units	Home ownership
QSpanish	2.9	% Hispanic	Race & ethnicity
PPH	2.2	Persons per household	Family structure
FLFP	1.9	% Female in civilian labor force	Socioeconomic status
FHH	1.9	% Female headed households with no spouse	Family structure, gender
MedRent	1.8	Median gross rent	Socioeconomic status
Health	1.8	% Health care employment	Economic sector
Service	1.5	% Service occupations	Socioeconomic status
QIndian	1.4	% Indian	Race & ethnicity
Primary	1.3	% Primary industry	Economic sector
NoHS	1.3	% No high school education over 25 years	Socioeconomic status
LFP	1.2	% Civilian labor force participation	Socioeconomic status
Trans	0.9	% Transportation, communications, utilities	Economic sector
QAsian	0.9	% Asian	Race & ethnicity
Fem	0.8	% Female	Gender
BRate	0.4	Birth rate	Population structure

Once selected, the variables were transformed using a Min-Max scaling scheme. It is a method in which each variable is rescaled into a range of 0.0 to 1.0, with a score of 0.0 indicating the lowest social vulnerability rank and a score of 1 being the highest. All other values were scaled in between the minimum and maximum values. Similar to the inductive model, variables that rise as social vulnerability falls were adjusted by multiplying by -1 before aggregation. The twenty-seven variables were then aggregated based on the

weighting scheme. The final score was normalized by z-score (subtraction by the mean and division by SD) to create the output index score. The results are mapped in Figure 10, with high vulnerability outliers depicted in red, and low vulnerability outliers in blue.

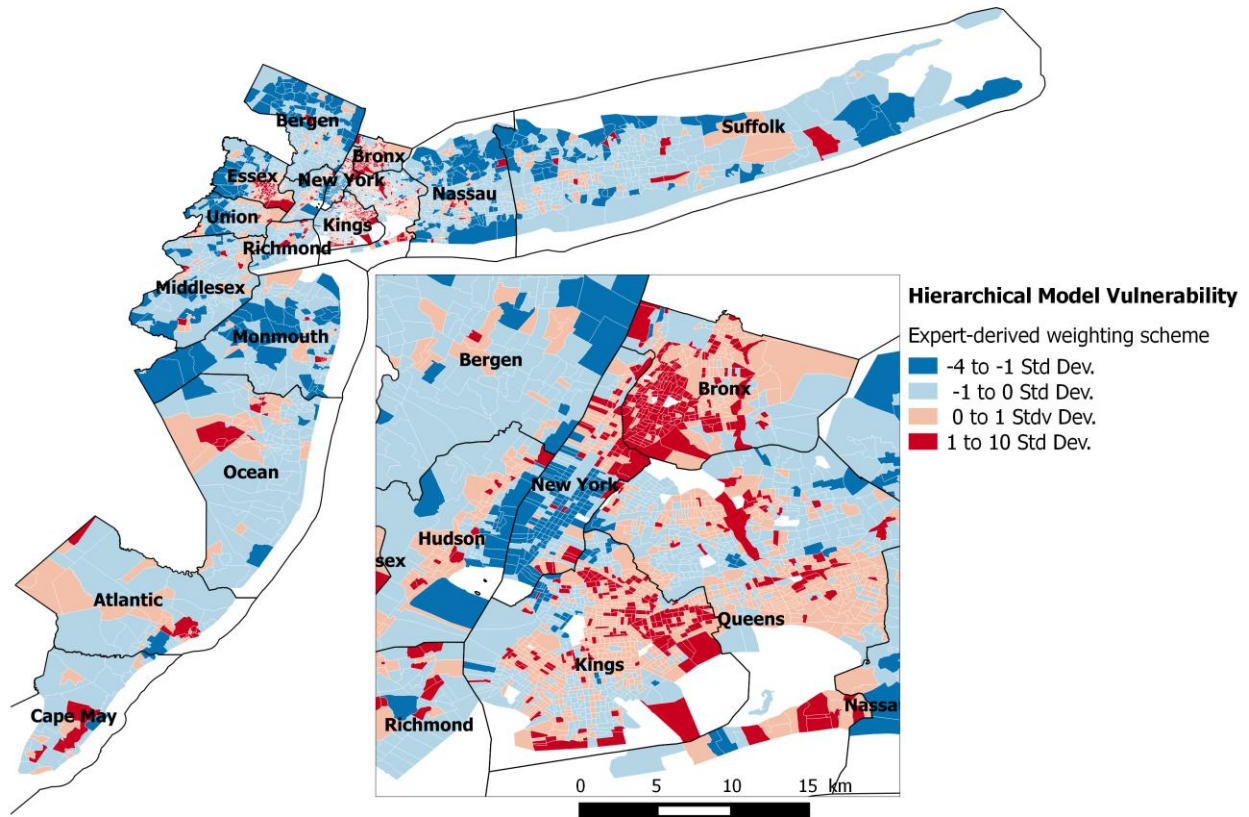


Figure 10. Hierarchical model social vulnerability scores

Vulnerability profiling is the third method we applied, using the same indicator set (Table 2). The starting point was the extraction of the most relevant vulnerability drivers for the case study. To limit colinearity, prevent implicit weighting, strengthen statistical power, and preserve a balance between the different dimensions of vulnerability, the association between variables was tested using a correlation analysis. Following the interpretation of the resulting correlation matrix, eighteen variables were utilized in the final model (Table 4) in which all 18 variables (Table 7) were input into a PCA to derive components.

Table 7. 18 remaining variables available from ACS 201

Variable Name	Description
1. POPDENS	Population density
2. AGE05	% Age under 5, over 65)
3. AGE65	% Age over 65
4. NURSRES	% Nursing Home Residents
5. FHHOLDS	% Female-Headed Households
6. NWHITE	% Pop Non White
7. ESLANG	% English as Second Language
8. EDU12LES	% Adults Completed <Grade 12
9. POVTY	% Poverty
10. UNEMPLOY	% Unemployed
11. SSBEN	% Social Security Income
12. NOAUTO	% No Automobile
13. MOHOME	% Mobile Homes
14. VACANT	% Vacant Housing
15. PERPUNIT	Persons Per Housing Unit
16. RENTERS	% Renters
17. MDGRENT	Median Rent
18. MHSEVAL	Median Home Value

All PCA components with an eigenvalue under 1.0 were omitted leaving five components that represent 70% of the total variance in the data. The corresponding factor scores for each variable were used as a distance matrix for the classification (HAC), a divisive non-spatial clustering according to Ward's method, without any weighting. The optimal partitioning was determined without *a priori* expectations: a five cluster partitioning was deemed most robust based on the Ward level index that minimizes the total within-cluster variance. For each of the 5 resulting clusters, the 18 initial variables were normalized, comparing mean and SD inside and the cluster and on the total population (Figure 11).

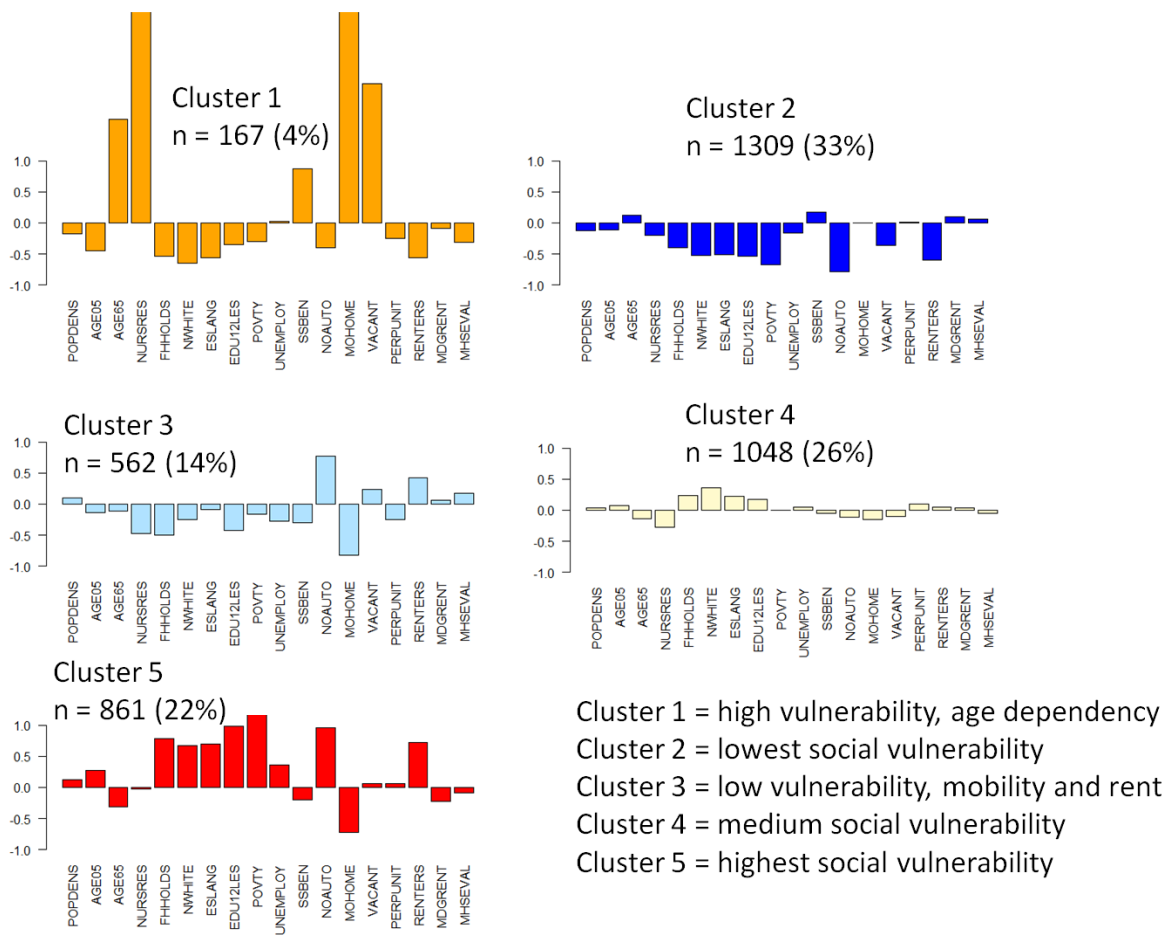


Figure 11. Vulnerability Clusters

The vulnerability profiles are interpreted as an over or underrepresentation of the different variables. Their association or mutual exclusion in each cluster are interpreted regarding the resulting impacts on the strengthening (or reduction) of vulnerability (Figure 12). The first cluster (4% of census tracts) over represents the elderly and nursing home residents, as well as people living in unsafe or mobile homes, in vacant housing, and to a lesser extent people living on social security income. This profile is associated with the combination of dependency, housing and income insecurity or deprivation, and was interpreted as high vulnerability marked by age dependency. The second cluster (33% of tracts) under represents most variables, while staying close to the mean for the others. Hence, we interpreted cluster 2 as the lowest vulnerability profile.

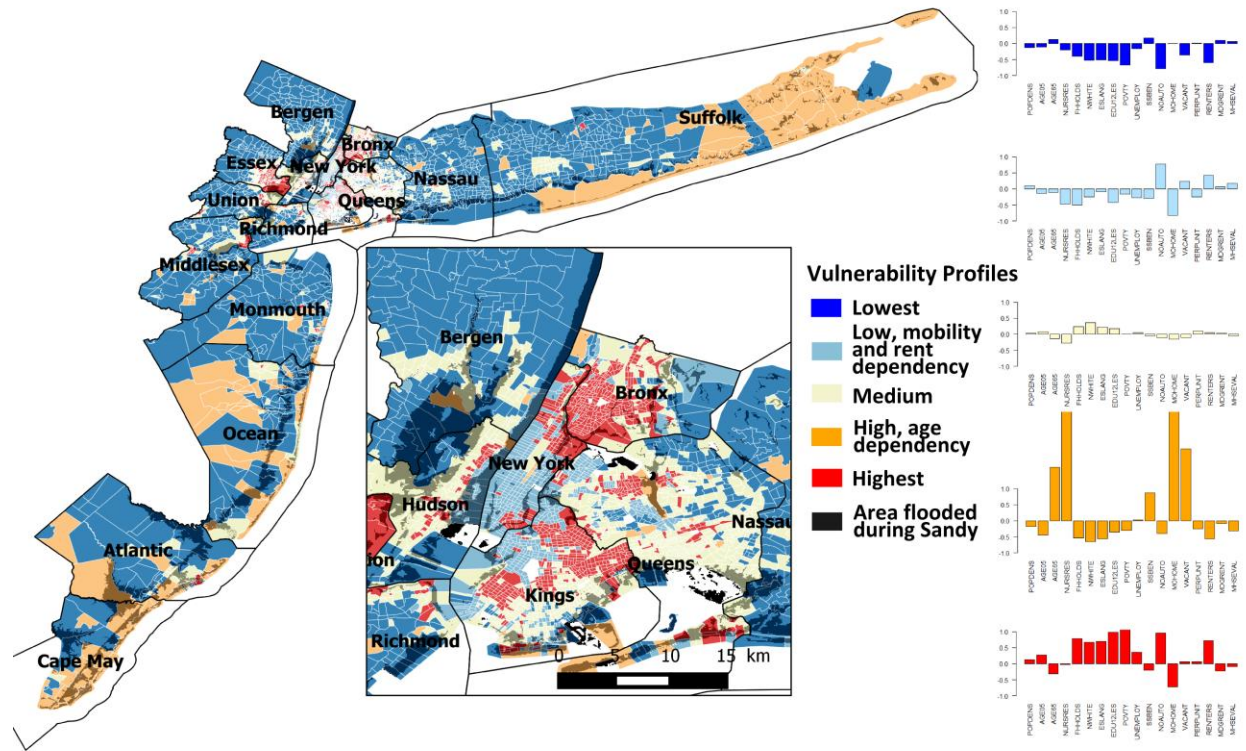


Figure 12. Vulnerability Profiles

The third cluster (14% of tracts) over represents people without an automobile, and to a lesser extent, renters and vacant housing. Meanwhile, cluster 3 under represents all other vulnerability indicators. The interactions are limited, and the cluster may therefore be interpreted as a low vulnerability profile with a public transportation and rent dependency. The fourth cluster (26% of tracts) is close to the average profile, with a minor overrepresentation of female-headed households, low educational attainment, low English proficiency, and a slight underrepresentation of the elderly, and nursing home, unsafe or mobile homes residents. We interpreted cluster 4 as a medium social vulnerability profile. The fifth and final cluster (22% of tracts) reveals the strongest overrepresentation of poverty and transportation dependency, and a stark overrepresentation of renters and most other vulnerability drivers. Despite the low underrepresentation of the elderly, people living in mobile homes or on social security income, the interactions are important

enough across all vulnerability dimensions to interpret it as the highest vulnerability profile.

The results of the comparison between social vulnerability models are somewhat convergent. On the maps, only a few places assessed as highly vulnerable by one model are quantified as least vulnerable by the others, and *vice versa*. However, when associated with Hurricane Sandy outcome indicators using multiple regression, Pearson's product-moment correlation and Kruskal-Wallis non-parametric test, their statistical power varies (the statistical significance of those tests and regressions are summarized in Table 9).

Table 9. Vulnerability Model vs. Sandy Outcomes (*p*-value)

<i>Statistical significance</i>	SOVI	Weighted SOVI	Hierarchical	Spectroscopy	
Flood Verified Loss			*	*****	
Flood Verified Loss <i>normalized by house value</i>	*	*	**	*****	
Share of affected people	*	**	***	*****	
Share of damaged houses			*	*****	
Share of uninsured renters affected			**	*****	
Flood Verified Loss <i>normalized by house value</i> controlled by flood depth	*	**	**	*****	
Share of affected people controlled by flood depth	**	***	***	*****	
Share of damaged houses controlled by flood depth			**	*****	
Share of uninsured renters affected controlled by flood depth			***	*****	
<i>p</i> -value	* 0.001	** 0.00001	*** 10 ⁻⁷	**** 10 ⁻¹⁰	***** < 10 ⁻¹⁵

When the inductive models are compared with outcome variables, the equal weights model has less statistical significance than the weighted scheme. Overall, the inductive models have a weak relationship with observed Hurricane Sandy outcomes, even when controlling for exposure measured by water depth during the flooding. The hierarchical model

performs better, with an even greater statistical power. Only the vulnerability profiles have a highly statistically significant association with all Sandy outcomes, even when normalized by population or controlled by exposure. FEMA verified losses were normalized by the average house value in each tract, the affected people, damaged housing and uninsured renters were normalized by their total population in each tract to express them as a proportion. The exposure was controlled with maximal water depth over ground during Sandy.

5.0 Summary

The measurement of social vulnerability as tool for disaster risk reduction continues to gain importance, in the face ever more exposure to risk from natural hazards. An improved understanding of how social vulnerability indicators and indices conform with real-world disaster outcomes could benefit both model development decisions and how social vulnerability indicators are interpreted during decision-making and public policy development processes.

This chapter has profiled the principal theoretical models of social vulnerability and the prominent construction approaches for defining social vulnerability models (inductive, hierarchical, profiles). Each model was harmonized to render them comparable, and statistically associated with normalized outcome measures from Hurricane Sandy. The findings highlight that the results of the model types are somewhat convergent when compared spatially. However, when the models were statistically associated with the outcome indicators, a variation in model performance was observed. The inductive model, based on the factor analytic approach, displayed the least amount of explanatory power. This may be partially due to the data reduction process in which individual variables are reduced to create uncorrelated factors. The hierarchical model statistically performs slightly better. In terms of variable selections, both models have a strong statistical association that focuses on wealth (strong negative correlation) and poverty (strong positive correlation), gender, education and race. The vulnerability profiles exhibit the highest statistical association with all outcomes measures.

Generally speaking, indicators can only explain the social vulnerability of a population to an extent and cannot explain the whole picture. Moving forward, a primary challenge is to derive a set of explanatory metrics (whether qualitative or quantitative) that is parsimonious, yet explains the phenomenon as clearly as possible. Research needs for improving social vulnerability assessments include:

- *Scale of analysis.* Our case study chapter was conducted at the U.S. Census Tract level level of analysis. It is important to consider how changes in scale might influence the results. At minimum, research should be conducted to better understand the association between social vulnerability metrics and impacts at different scales.
- *Variable selection.* The variable selection process for our case study was based on the indicator selection for the SoVI because it has become a leading methodological approach. The SoVI variable set, however, was first the result of a multivariate analysis for which the data selection was extracted from the 1990 US census. To test for consistency and the application of the SoVI variables to an ever-changing U.S. landscape it would be beneficial to derive a parsimonious data selection based on recent data.
- *Hazard Context.* Context includes the geographic setting of the disaster, pre-existing social, economic and political conditions, hazard type, degree of exposure, scale of impacts and responses, and the disaster phase. More research is needed to incorporate context into social vulnerability measures.
- *Conceptual Framework.* Another challenge to social vulnerability research is the end-to-end application of the conceptual frameworks designed to explain the topic. The application of frameworks like the PAR have been extensively documented. There is, however, limited available information of how to operationalize conceptual frameworks on social vulnerability. There is a demand for in-depth investigations of social vulnerability evidence, conceptual components, and measurement methods.

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