



Social vulnerability score: a scalable index for representing social vulnerability in virtual community resilience testbeds

S. Amin Enderami¹ · Elaina Sutley¹

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Abstract

Incorporating social systems and phenomena into virtual community resilience testbeds is uncommon but becoming increasingly important. Social vulnerability indices are a convenient way to account for differential experiences and starting conditions of the population in resilience assessments. This paper proposes a scalable index, termed Social Vulnerability Score (SVS), to serve the purpose of testbed development. The SVS overcomes two important limitations of existing indices: it is constructed using an approach that does not decrease in validity with changing spatial resolution, and it only needs to be calculated for the geographic area of interest, instead of for the entire county thereby significantly reducing computational effort for testbed developers and users. The proposed SVS aggregates the ratio of a set of demographics from U.S. Census datasets at the desired location against their national average values. The resulting scores are mapped into five levels, called zones, ranging from very low vulnerability (zone 1) to very high (zone 5). The validity of the SVS was investigated through a regression analysis of flood outcomes in Lumberton, North Carolina caused by Hurricane Matthew in 2016. The resulting correlations between the SVS zones and post-disaster outcomes of household dislocation and home repair times match the social vulnerability theory. The paper concludes with a discussion of the advantages and limitations of using the SVS.

Keywords Social vulnerability index · Community resilience · Household dislocation · Virtual testbeds

1 Introduction

Disasters occur at the intersection of hazard exposure and vulnerability, where that vulnerability can be physical or social, but is the product of society (Mileti 1999; Tierney 2014). A well-documented and fundamental canon of disaster research is that there is no such

✉ S. Amin Enderami
a.enderami@ku.edu

Elaina Sutley
enjsutley@ku.edu

¹ Department of Civil, Environmental and Architectural Engineering, University of Kansas, Lawrence, KS, USA

thing as a *natural* disaster (Squires and Hartman 2006). Rather, disasters are the direct result of society-made vulnerabilities, such as poor structural design and poor land-use planning, as well as a long history of policies distilling social inequalities, such as systemic racism (Yellow Horse et al. 2020). Social vulnerability is defined as “the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impacts of a natural hazard” (Blaikie et al. 2004). Social vulnerability thus implies an increased susceptibility to harm or negative outcomes which is based on pre-existing social characteristics stemming from race, ethnicity, income, education, disability, tenure, and their intersection.

Decades of disaster research have demonstrated that disasters do not affect all members of society equally (Fothergill and Peek 2004; Sutley and Hamideh 2020). Important social, physical, economic, cultural, and political factors drive people, households, and communities to be more or less vulnerable (Cutter 1996). Fothergill and Peek (2004) illustrate how people with different socioeconomic statuses (1) perceive, prepare for, and respond to natural hazard risks, (2) have been differentially impacted physically and psychologically, and (3) are differentially affected by the social class during different stages along the disaster timeline. The vulnerability of the low-income population in the U.S. is exacerbated by the place and type of residence, building construction, and social exclusion, providing important implications for social equity and policy. Existing disaster recovery policies have further exacerbated social inequalities after disasters by setting qualifying criteria that exclude socially vulnerable people, including renters, the poor, and some cultures, from accessing recovery resources (Kamel and Loukaitou-Sideris 2004; Sutley and Hamideh 2018; Van Zandt 2019). As Peacock et al. (2005) point out, women and ethnic minorities and individuals of low income and little education have higher perceptions of risk from natural hazards. A common theme explaining the increased risk perception is attributed to the lack of power and resources often available to people within these groups. A lack of power and resources leads to less ability to make one’s own choices, less trust in institutions, and a reduced likelihood of being in positions of relative power and control, altogether attributing to a higher social vulnerability (Link and Phelan 1995; Perry 2021). Hamideh and Rongerude (2018) point out how these very dynamics make public housing residents some of the most socially vulnerable members of communities given their lack of social and political capital. For a recent review of disaster and policy impacts on socially vulnerable populations, see Van Zandt (2019).

Historically, the focus of most hazard research resilience studies, particularly those stemming from engineering fields, has been on the built environment and reducing physical vulnerabilities; however, when communities set their resilience goals, it is imperative to consider community-specific social, human, and cultural systems, and assess social vulnerabilities along with physical vulnerability in striving for resilience (Koliou et al. 2018; Berke et al. 2023). For social vulnerability and its influence on resistance and recovery to be incorporated into community resilience analysis, there must be robust tools for quantitatively measuring social vulnerability. There is a long history of the social sciences documenting and measuring which factors, and to what extent those factors contribute to social vulnerability (Cutter et al. 2000; Eakin and Luers 2006). Geospatial social vulnerability indices are simplified powerful tools for measuring social vulnerability and are often presented via mapping (Montz and Evans 2001; Laska and Morrow 2006). This simplification has been commonly adopted in the literature to progress the state of knowledge on social vulnerability in some ways while waiting for more robust studies on the intersectionality of social vulnerability to develop. These indices serve as proxies for a community’s social vulnerability status and their mapping is sufficient for identifying geographic areas

that are quite different in abilities to respond to a natural hazard and bounce back from its impacts. The basic logic of social vulnerability mapping is to identify concentrations of populations with particular social vulnerability characteristics to identify areas within a community that will likely require special attention, planning efforts, and external support in responding to and recovering from hazards and disasters. For example, Tormos-Aponte et al. (2021) employed a geospatial social vulnerability index to assess energy inequality and clientelism in the aftermath of disasters. The strength of social vulnerability indices to properly capture a community's social status, combined with their ease of application and interpretation for non-experts, have made them a popular tool among researchers from engineering disciplines.

The tendency to use geospatial social vulnerability indices increased as the development and application of virtual testbeds for community resilience studies gained momentum. A community resilience testbed is a virtual "environment with enough supporting architecture and metadata to be representative of one or more systems such that the testbed can be used to (a) design experiments, (b) examine model or system integration, and (c) test theories" (Enderami et al. 2022, p. 031220013). As natural hazards engineering research is shifting from component- and building-level modeling into the interdisciplinary space of community-level, the application of virtual community resilience testbed is growing. Virtual testbeds enable researchers to test, verify, and validate their community resilience algorithms at different scales and spatial resolutions. For this purpose, a community's physical, social, and economic systems should be properly modeled and embedded in the associated testbed. Testbeds, however, lag behind in their ability to precisely model social and economic systems and have mainly focused on modeling buildings and physical infrastructure within a community (Enderami et al. 2022). The community's social and economic systems can be represented using either a predictive model or a static indicator such as a geospatial social vulnerability index. However, due to the complexities in modeling social systems, the use of geospatial social vulnerability indices for characterizing a community's social capacity is more common among testbed developers, particularly those with engineering backgrounds. For instance, the Gotham City (Mahmoud and Chulawat 2018) and CLARC (Little et al. 2020) testbeds use geospatial social vulnerability indices to represent the social capacity of their target communities.

Despite the advantages of existing social vulnerability indices, there are limitations regarding their application with changes in spatial resolution and geographic territory, which are commonly needs for testbed development and use. Testbeds must be capable of being scaled into different levels (such as counties, census tracts, census block groups, etc.) and jurisdictions (for example towns, cities, and metropolitan areas) to meet the requirements of the desired resilience assessment. Often, the higher the spatial resolution, the more meaningful the results can be to inform decision-makers. The current most widely used social vulnerability indices use scale-sensitive algorithms and were initially established at a county or census tract level (Cutter et al. 2003, 2013; Flanagan et al. 2011). Most testbeds are developed at a county or city-scale, and thus only being able to evaluate social vulnerability once for the entire study area does not enable investigations of how differences in social vulnerability across the geographic area of interest may influence disaster impacts and outcomes. Downscaling existing social vulnerability indices to a geographic unit finer than their original scale, regardless of challenges in obtaining high-resolution data, may lead to results that are inconsistent with their original-scale estimates (Tate 2012; Rufat et al. 2019, 2021; Spielman et al. 2020). Furthermore, any change in spatial scale, geographic domain, or temporal change often requires a full national-level analysis of the social vulnerability index (Spielman et al. 2020) extending the computational effort

required to use the index. To serve the purpose of testbed development purposes, a social vulnerability index that is not scale-sensitive and is capable of applying to other geographic territories and spatial resolutions (particularly finer than a county) is needed.

The objective of this paper is to address this gap, by developing a scalable social vulnerability index to serve the purpose of community resilience testbed development. The paper begins with reviewing the state of knowledge in social vulnerability drivers and measuring social vulnerability to disasters through assessing a selection of key studies in the literature grounded on the household and housing experience. The paper continues by introducing the Social Vulnerability Score (SVS), a scalable social vulnerability index, and describing its construction methodology and validation process. The validity of the SVS is investigated using the disaster outcomes measured following the 2016 catastrophic flooding in the city of Lumberton, North Carolina due to Hurricane Matthew. The paper concludes with a discussion on the SVS estimates and comparing them with two well-known existing social vulnerability indices.

2 Background on social vulnerability

Over the past two decades, social science studies have identified social and institutional factors that contribute to social vulnerability. These studies altogether have provided a solid foundation for developing social vulnerability assessment tools and methods. In this section, a brief review of the current state of knowledge regarding social vulnerability drivers and quantitative models for measuring social vulnerability are presented.

2.1 Social vulnerability drivers

Previous studies have shown community members with certain social characteristics are more likely to experience more severe consequences of exposure to natural hazards. These community members, known as socially vulnerable populations, face a plethora of challenges, including job losses, income gaps, and housing instability, among others. Natural hazards also exacerbate existing health disparities in socially vulnerable populations, leading to higher post-disaster morbidity and mortality rates. Disruptions to or limited access to community resources along with inadequate information due to insufficient political capital further heighten their vulnerabilities. Access to education is another casualty, often disproportionately impacting socially vulnerable communities. (Cutter 1996; Morrow 1999; Cutter et al. 2000, 2003; Montz and Evans 2001; Laska and Morrow 2006; National Research Council 2006; Myers et al. 2008; Zahran et al. 2008; Oliver-Smith 2009; Burton 2010; Dunning and Durden 2011; Flanagan et al. 2011; Van Zandt et al. 2012; Birkmann 2013; Bergstrand et al. 2015; Liu and Li 2015; Burton et al. 2018; Guillard-Gonçalves and Zêzere 2018; Dintwa et al. 2019; Drakes et al. 2021; Daniel et al. 2022).

Building on existing research on social vulnerability drivers, SVS adopts a set of most common factors, namely, households' race, ethnicity, tenure status, income, size, educational attainment, age, and disability. These social factors are selected within the U.S. context and the rationale provided for choosing each is discussed from the U.S. perspective. Importantly, there are many other factors that contribute to a household's social vulnerability in the U.S., such as being a non-native English speaker, household size, and being a female-headed household, among others. Outside of the U.S., many of these factors still contribute to social vulnerability but potentially in different ways alongside other factors.

Only considering the above six factors has three other important limitations. First, within the six factors described above are other factors that contribute to social vulnerability, such as not owning a vehicle when someone is also low-income. Second, these six factors are not necessarily independent in their influence on social vulnerability. For example, renters, those with limited education, and with disabilities are more likely to be lower income. Third, people have more than one characteristic that defines them; while the influence of intersectionality on social vulnerability is actively researched and increasingly understood, further inquiry is needed to quantify its complexities and nuances. Even though income, as an example, is a well-documented factor in research, accurately determining its impact on social vulnerability and particularly measuring its intersectionality with other factors such as race, ethnicity, and gender is still a complex methodological challenge. This difficulty largely stems from insufficient data and the shortage of longitudinal post-disaster studies as well as the social vulnerability's dynamic socio, political, and historical context. This paper acknowledges these limitations and asserts that while quantifying social vulnerability is crucial for integrating it into community resilience assessments, such quantification must be undertaken with an understanding of the inherent constraints in this research area.

Race and ethnicity have often been considered social vulnerability drivers due to longstanding systemic discrimination and racism leading to limited access to resources of all kinds, as well as lower income, and cultural and language barriers. Minority groups are more likely to occupy houses that are located in hazardous locations, and less likely to have connections to decision-makers and political capital (Cutter et al. 2003; Laska and Morrow 2006; National Research Council 2006; Myers et al. 2008; Dunning and Durden 2011; Flanagan et al. 2011). However, different racial and ethnic identities among minority populations may even differently experience exposure to disasters. For example, African Americans and Hispanics are more likely to live in areas at high risk of flooding from natural disasters than Asian people (Bakkensen and Ma 2020).

Renters tend to be more socially vulnerable than those who own their homes. Commonly referenced causes for greater social vulnerability for renters include having trouble finding shelter after a disaster, accessing or knowing about recovery financial aid programs, and having limited control over property-level hazard mitigation actions. Renters are also more likely to dislocate after a disaster with limited control over if, when, and for how long they dislocate, making them more susceptible to permanent dislocation. (Cutter et al. 2003, 2013; Dunning and Durden 2011).

Household income is directly associated with the number of financial resources that are available for households' risk mitigation and disaster recovery actions. Poor people are less likely to have savings, insurance, or social capital networks with strong financial capital to help them absorb losses and recover or political capital to lobby on their behalf for assistance. Low and very low income households have historically been excluded from accessing federal recovery resources as a result of overlooking policies that require them to demonstrate that damage is in no part due to deferred maintenance (Hamideh and Rongerude 2018; Daniel et al. 2022). Low and very low income households are also more likely to live in substandard housing in a higher-risk location and may lack resources such as having a vehicle to evacuate in an emergency (Cutter et al. 2003; Dunning and Durden 2011; Flanagan et al. 2011). In addition, the risk of post-disaster unemployment is greater for lower-wage workers (Laska and Morrow 2006).

Household size has been attributed to social vulnerability due to imposing a financial burden. Also, larger households are less likely to evacuate in an emergency because of difficulty in coordination, often being multigenerational with young children and elderly members, and difficulty in finding adequate shelter (Liu and Li 2015; Dintwa et al. 2019).

Educational Attainment is associated with the household's social, financial, human, and political capitals (Daniel et al. 2022). Higher education is associated with higher salaries, easier access to public resources for hazard preparation and recovery, and more powerful networks with local authorities. On the contrary, for low-educated people, besides lower incomes, practical and bureaucratic obstacles can make it difficult for low-educated individuals to cope with and recover from disasters (Cutter et al. 2003; Flanagan et al. 2011).

The elderly and very young are very likely to pose evacuation challenges, this is true for those with special medical needs and who live in nursing homes or hospitals, as well as for those who live in their own homes (Myers et al. 2008; Dunning and Durden 2011; Sun et al. 2017). Elderly people are more often on fixed incomes and may lack access to financial resources to help them prepare for and recover from a disaster. Elderly homeowners are more likely to have paid off any mortgage on their home and thus are less likely to opt into purchasing flood insurance (Bolin and Klenow 1982; Barbera et al. 2002). Furthermore, children also present important challenges with disasters, including evacuation decisions, and post-disaster childcare (Laska and Morrow 2006; Dunning and Durden 2011).

Disabled people face important challenges surrounding disasters, including evacuation challenges depending on the nature of their disability, as well as having access to information, potentially needing a dependent to assist in decision-making around preparedness, evacuation, and recovery, and also more likely being on a fixed income with limited resources at their disposal (Laska and Morrow 2006; Dunning and Durden 2011). The American Housing Survey data also shows a significantly higher incidence of disability among households residing in manufactured homes (Eggers and Moumen 2011). Manufactured housing has its own set of limitations that contribute to the resident's vulnerability, including being physically vulnerable to natural hazards, less likely that the resident carries insurance, and often complicated tenancy situations where the resident may own the home but rent the land and thus not be in control over dislocation and return decisions (Al-Rousan et al. 2015).

2.2 Social vulnerability measurement

Models serve an important role in understanding the intersection of humans, disasters, and the built environment. Social vulnerability is an important dynamic at this intersection that is difficult to model and validate given its multidimensional nature and inability to be directly observed and measured (Tate 2012). Although social vulnerability is complex, situational, and dynamic, past research has made incredible strides forward in measuring social vulnerability during and after disasters. Qualitative disaster studies have widely recognized that multiple dimensions of diversity can have a profound effect on pre-disaster vulnerability and preparation measures, disaster impacts, and post-disaster recovery experiences (Tierney and Oliver-Smith 2012). However, the intersection of these dimensions is poorly understood, and has not been systematically and quantitatively measured in the past. From our literature review, we found there are three types of quantitative studies on social vulnerability, those that quantify *indicators*, *indices*, and *influencers*. Indicators are quantitative variables intended to represent a characteristic of a system of interest, e.g., the percentage of African Americans in a community. Indicators can be composed of single or multiple variables, e.g., the percentage of minorities in a community. Alternatively, multiple indicators can be combined to construct composite indices, which attempt to distill the complexity of an entire system to a single measure. Lastly, influencer studies measure or model the influence that various social vulnerability indicators or composite indices have

on specific dependent variables or outcomes. Different studies use different types of data to model social vulnerability, including (a) publicly accessible data, such as census data and tax assessment data; (b) primary data collected in the field before, during, or after a disaster; and (c) social media data. The data may be collected at different spatial scales and resolutions (e.g., state-, county-, census tract-, block group-, neighborhood-, and individual-levels). Given the focus of the present article, only examples of social vulnerability indices that use various types of data at different scales and resolutions are reviewed here.

The social vulnerability index (SoVI) developed by Cutter et al. (2003) is perhaps the most frequently cited geospatial social vulnerability index. However, SoVI was built upon the groundwork laid by earlier social vulnerability studies, such as those by Morrow (1999), Cutter et al. (2000), Montz and Evans (2001), and Wu et al. (2002). The effort started with 250 variables and was reduced to 85 variables after testing for multicollinearity, but finally, 42 independent variables were used in the factor analysis. Through their principal component factor analysis, the 42 indicators were reduced to 11 independent factors accounting for 76.4% of the variance in social vulnerability across all counties examined. The 11 independent factors included per capita income, median age, number of commercial establishments per square mile, the percent of the population employed in extractive industries, percent of housing units that are mobile homes, percent of the population that is African American, percent of the population that is Hispanic, percent of the population that is Native American, percent of the population that is Asian, percent of the population employed in service occupations, and percent of the population employed in transportation, communication, and public utilities. The factor scores were incorporated into an additive model producing the social vulnerability index. The SoVI formulation has evolved over time in response to changes in the knowledge of vulnerability assessment and data collection methods. The SoVI was initiated using the U.S. 1990 decennial Census data, however, its most recent version (SoVI 2010–14) synthesizes data on 29 variables from the American Community Survey (ACS) 5-year survey (Cutter and Morath 2013). The SoVI 2010–14 was computed and mapped for all 3,141 counties and its value ranges from 9.6 (lowest) to 49.51 (highest) across the counties. The values were classified into five qualitative categories, from “Very Low” to “Very High,” using a mean and standard deviation.

The CDC/ATSDR SVI is another common geospatial social vulnerability index and was developed by the U.S. Center for Disease Control and Prevention (Flanagan et al. 2011). Public health officials use the CDC/ATSDR SVI to identify and map community members most likely to need support before, during, and after hazardous events. The most recent version of the index, CDC/ATSDR SVI (2020), is composed of 16 equally weighted variables at the census tract that are classified into four overarching themes with the same level of importance. The 16 variables include below 150% poverty, unemployed, housing cost burden, no high school diploma, no health insurance, aged 65 and older, aged 17 and younger, civilian with a disability, single-parent households, English language proficiency, racial and ethnic minority, multi-unit structures, mobile homes, crowding, no vehicle, and group quarters. The four themes include (1) socioeconomic status, (2) household characteristics, (3) racial and ethnic minority status, and (4) housing type and transportation, where each theme represents an underlying dimension of social vulnerability. A percentile rank is calculated for each census tract over each of the 16 variables. The percentile rank of variables is summed into each theme to produce a theme score. In the next step, the scores are summed, then the census tracts are ordered based on their summed scores to calculate the overall percentile ranking. Lastly, a quartile classification system is used to classify the ranked census tracts, where the highest and lowest quartiles represent the highest

and lowest socially vulnerable tracts, respectively. The CDC published social vulnerability maps and index values for the entire United States for the years 2000, 2010, 2014, 2016, 2018, and 2020.

There are multiple pieces of studies in the social vulnerability literature that attempted to refine the existing social vulnerability indices by incorporating local contextual factors to create a new index providing a more nuanced picture of vulnerability. For example, Ogie and Pradhan (2019) proposed a Strength-Based Social Vulnerability Index (SSVI) that considers the unique strengths that exist within different communities and can help minimize disaster loss along with the weaknesses that are traditionally associated with social vulnerability. This approach is built on sound sociopsychological theories of how people act during disasters and emergencies and leads to a more balanced metric. The SSVI takes several aspects of social vulnerability into account, namely, culturally and linguistically diverse communities, low-income households, children under the age of four, people living with a disability or requiring assistance in everyday life, and the elderly population.

Van Zandt et al. (2012) built a geospatial social vulnerability index on the basis of the SoVI to be used for census block-level community-based planning. At this smaller scale, only 17 out of 29 SoVI variables were available from public data sources. Through an unarticulated weighting system, each variable value was normalized to range from 0 to 1. These normalized indicators were then split into groups to form several composite indices of second-order social vulnerability measures (e.g., child care needs, transportation needs), and finally, all 17 normalized indicators were combined into a third-order hotspot index and mapped across Galveston, TX.

In another study, Collins et al. (2009) developed a social vulnerability index to combine with physical vulnerability and map the risk of natural hazards in a metropolis that straddles the Mexico-United States border. The model measures social vulnerability by assessing four related elements including population, access to resources, socioeconomic status, and institutional capacity. Each of these elements is represented by a set of sociodemographic and economic variables with a value ranging from 0 to 1. Once all variables are computed, their average is calculated to create the index. The index values are then divided into quintiles and mapped.

Before the advent of SoVI, Montz and Evans (2001) and Wu et al. (2002) also developed their own social vulnerability indices, which we review among others. According to Montz and Evans (2001), social vulnerability can be measured sufficiently by using only five socioeconomic characteristics, namely population under 15, population over 65, a single female head of household, median household income, and population density. These variables were estimated for each census block in the study area and then aggregated by three different models to produce the index. The first model assumes that each variable contributes equally to differentiating vulnerability. The second model, inversely, was built on the assumption that different variables contribute differently to determining social vulnerability, and weights are assigned to each variable, based on their relative contribution. The third model includes a scaling scheme in addition to weighting the variables. The social vulnerability maps were created individually based on each model. Montz and Evans (2001) concluded that their first two models map social vulnerability similarly, but they may overestimate vulnerability in flood plains compared to the third model. Wu et al. (2002) employed a modified version of the methodology adopted by Cutter et al. (2000) and calculated a vulnerability index using only 9 demographic variables taken from the 1990 US Census block statistics. The list of variables includes total population, housing units; the number of females, non-white residents, people under 18, people over 60, female-headed single-parent households, renter-occupied housing units, and median house

value. The model calculates the ratio of each variable's value in each census block against the maximum value for the variable in the county. The ratios range from 0 to 1; higher index values represent higher vulnerability. The arithmetic mean of these 9 variables for each census block was defined as the social vulnerability index. Then, the values were divided into quartiles, labeled respectively as low, moderate, high, and very high social vulnerability regions.

Of the indices reviewed above, the SoVI and CDC/ATSDR SVI are the most widely applied, however, they are not easily executable for testbed development purposes because (1) both the SoVI and CDC/ATSDR SVI synthesize needed data from the ACS five-year surveys, which do not provide reliable data finer than the census tract level for the demographic variables they use (Coggins and Jarmin 2021); (2) multiple SoVI-based measurements of the vulnerability of the same place can yield significantly different results using the same data (Spielman et al. 2020); (3) SoVI and CDC/ATSDR SVI are sensitive to their initial model's spatial scale and any changes in their spatial resolution may result in estimates that are inconsistent with their original-scale estimates (Rufat et al. 2019). Similar limitations exist for other available social vulnerability indices which constrain their usage for testbed development purposes. Tate (2012) examined the configurations of available social vulnerability indices to determine how each stage of the index construction process contributes to its overall reliability and internal validation. The present study leverages Tate's (2012) findings and recommendations about improving the stability of the social vulnerability indices to fill an important niche in the literature: to develop an internally robust scalable social vulnerability index for the purpose of adoption in community resilience testbeds.

3 Social vulnerability score development

This section introduces our methodology for developing the Social Vulnerability Score (SVS) and describes our rationale for its configuration. Although there is no standard procedure for developing social vulnerability indices, previous indices mostly have employed a similar multi-stage process. The process typically starts with determining the index construction method, followed by specifying the intended social vulnerability indicators, their measurement units, weights, and aggregation approach. Each of these stages involves choices between multiple plausible alternatives whose differences distinguish various social vulnerability indices. In this study, the choices have been made based on Tate's (2012) research results to produce an internally robust index.

3.1 Construction method

The index construction method is an overarching stage in building social vulnerability indices that determines the index configuration (Tate 2012). There are three common approaches in the literature for the construction of a composite social vulnerability index, namely *deductive*, *hierarchical*, and *inductive* approaches (Cutter et al. 2000, 2003; Montz and Evans 2001; Wu et al. 2002; Collins et al. 2009; Flanagan et al. 2011).

Deductive approaches linearly combine designated indicators (often less than ten) to build the composite indicator. The *hierarchical approach* consists of dividing the designated indicators into subsets that share a common dimension of vulnerability and assigning a specific normalized weight for each indicator and subset based on the experts'

knowledge. After the weighted indicators are aggregated in each subset, the subset scores are then combined to create the desired index. The CDC/ATSDR SVI is the most renowned social vulnerability index with a hierarchical structure. However, the index technically follows the deductive approach since the themes are mathematically ignored in the aggregation phase by considering equal weight for all subsets and indicators (Rufat et al. 2019). The *inductive approach* typically starts with a set of more than twenty indicators; these indicators are then reduced to a smaller set of latent factors by means of statistical methods such as Factor Analysis or Principal Component Analysis. The intended indicator is constructed by combining these factors. The SoVI is perhaps the most common index that is constructed based on the inductive approach.

Tate (2012), Rufat et al. (2019), and Burton et al. (2018) studies illuminate that each construction approach has its specific pros and cons and none of them can be argued to be inherently better or worse than the others. Evaluating the strength of the index depends on the specific situation in which it is being used. For example, the inductive approach is highly dependent on its model spatial resolution (Tate 2012), which makes it an inappropriate method for constructing a testbed-specific social vulnerability index. The deductive and hierarchical approaches are most sensitive to selected indicators' measurement units and weights, respectively (Tate 2012). Thus, the deductive approach is used for constructing the SVS as it is more feasible to define an appropriate measuring unit for selected indicators than to determine each indicator's contribution to social vulnerability and assign weights accordingly.

3.2 Indicators and their measurement units

The indicators are generally selected based on factors such as identified social vulnerability drivers and data availability. The primary motivation for introducing the SVS is to use it for developing community resilience testbeds. Given that testbeds are intended to be used for years or decades' worth of research (Enderami et al. 2022), the SVS will be grounded on the ACS five-year demographic estimates. However, ACS five-year surveys do not provide reliable data at scales finer than the census block group (Coggins and Jarmin 2021). Thus, according to common social vulnerability drivers, and constrained by the information that is available in the ACS five-year datasets, the SVS employs the set of social vulnerability indicators in Table 1.

The indicators defined in Table 1 encapsulate all common social vulnerability drivers reviewed in Sect. 2.1 but capture them by five inverse compound variables such that a higher value indicates a lower level of social vulnerability. For example, the consequences of race and ethnicity were mixed so that all races and ethnicities, except those who identify themselves as white (non-Hispanic or Latino), are considered as a minority; then, the proportion of non-minorities, who are indeed less vulnerable members, in the intended location is computed. As a result of using compound variables, a fewer number of variables are included in the SVS model, which reduces the possibility of data collection errors and uncertainty of the mean value, particularly for smaller sample sizes (Tate 2012). The use of compound variables, however, may lead to undesirable implicit assumptions. For instance, by taking the compound variable 'non-Hispanic White', the SVS inherently assumes that all minority races and ethnicities, such as Black, Native American, Asian, Hispanic, Latinx, etc., have the same influence on social vulnerability, which is not true. However, the specific differences are only partially understood, and quantifying each racial and ethnic identity individually also has its limitations by inherently assuming more is

Table 1 Social vulnerability indicators used for SVS development

Social characteristic	Social vulnerability indicator	Notation
Race and Ethnicity	Ratio of the percentage of white alone (not Hispanic or Latino) population at the intended location against its national average percentage	R_1
Housing Tenure	Ratio of owner-occupied housing unit rate at the intended location against its national average percentage	R_2
Poverty Level	Ratio of the percentage of population earning greater than official poverty threshold at the intended location against its national average percentage	R_3
Education Level	Ratio of the percentage of persons over age 25 with a high school diploma or higher education at the intended location against its national average percentage	R_4
Disability Status	Ratio of the percentage of the population between 18 and 65 years old without disability at the intended location against its national average percentage	R_5

understood than what is actually known. Furthermore, the SVS uses the poverty level that takes both household size and income into account together. Less than high school education, for those 25 and older, is taken as the cut-off for educational attainment in the SVS model since many jobs require at least a diploma or GED to qualify. The very young was defined as age 18 and younger according to the United Nations Convention on the Rights of the Child (Peek 2008).

The measuring unit characterizes how each indicator is represented in the model. The most common data presentation formats are numbers, percentages, and densities. The SVS calculates each indicator as the ratio between the non-vulnerable population percentage at the desired location and the corresponding national average percentage. The percentage of the non-vulnerable population ranges from 0 to 100, with 0 representing complete vulnerability and 100 indicating no vulnerability. Measuring a social characteristic at the desired location with respect to its national average enables analysis of relative vulnerability across the U.S.

3.3 Weighting and aggregation

The indicators are in terms of unitless ratios, so there is no need to normalize before the weighting and aggregation stages; regardless, deductive models are insensitive to weighting and aggregation approaches (Tate 2012). Thus, the indicators are aggregated while equally weighted, which implies that their relative importance is the same. The SVS calculates the arithmetic mean of the indicator values at the location of interest, expressed as

$$SVS = \frac{1}{5} \sum_{i=1}^5 R_i \quad (1)$$

The resulting values can be used directly to compare the relative social vulnerability of different communities. Of note, a higher value of SVS indicates a lower level of vulnerability given that the indicators used in the SVS development process are inversely related to social vulnerability.

For ease of interpretation, the SVS was mapped to five discrete vulnerability categories, named zones using a standard deviation classification. The zones range from very low vulnerability (zone 1) to very high vulnerability (zone 5). The zones and the criteria used to define them are shown in Table 2.

In Table 2, (*std.*) represents the standard deviation of the SVS values for the entire country. Since 99.7% of values following a normal distribution lie within 3 standard deviations of the mean (Ang and Tang 2007), (*std.*) value can be estimated as:

Table 2 Social vulnerability zones

	Vulnerability description	Criteria
zone 1	Low	$SVS > 1 + 1.5(std.)$
zone 2	Medium to Low	$1 + 0.5(std.) < SVS < 1 + 1.5(std.)$
zone 3	Medium	$1 - 0.5(std.) < SVS < 1 + 0.5(std.)$
zone 4	Medium to High	$1 - 1.5(std.) < SVS < 1 - 0.5(std.)$
zone 5	High	$SVS < 1 - 1.5(std.)$

$$\text{std.} = \frac{(SVS)_{\max} - 1}{3} \quad (2)$$

where $(SVS)_{\max}$ is the maximum possible, and one represents the mean of SVS values for the entire country. Equation (1) gives the maximum of the SVS if the percentage of the non-vulnerable population at the desired location equals 100 for all indicators in Table 1. Therefore, only the average of the reciprocal values of national average percentages of indicators in Table 1 is required for calculating the (*std*) values.

For the convenience of testbed developers, the SVS calculation is automated using a Python script. The code is open source and published on DesignSafe-CI (Enderami and Sutley 2022) for being used by other researchers to facilitate advances in current practice. The code takes the name of the intended state and county, desired spatial resolution (census tract or block group), and year as the input data. The output includes a geospatial data file (.csv) containing the SVS values and a choropleth map (.png) of the predicted social vulnerability zones. The code is only written for the spatial scales of census tract and block group given the lack of reliability in census data at higher resolutions. The SVS is capable of being applied to testbeds that require higher resolutions than the block group, including the block- and household-level, as will be demonstrated in Sect. 4.2.

4 Validation of social vulnerability score

Validation is a major challenge with community resilience analysis given that simulations cannot be performed in real life, having the appropriate data is nearly impossible, and many of the concepts (e.g., social vulnerability) are immeasurable. Social vulnerability is a multidimensional qualitative concept that is not directly observable or measurable. Researchers have resorted to the use of outcome, socio-economic, and demographic data collected from post-disaster household surveys as proxies to validate their social vulnerability models (Schneiderbauer and Ehrlich 2006). These proxies range from physical damage and economic loss to population impacts such as mortality, dislocation, and mail delivery (Gall 2007; Myers et al. 2008; Burton 2010; Finch et al. 2010; Flanagan et al. 2011; Schmidtlein et al. 2011). In addition to such external validation efforts, which have been fairly successful, multiple internal validation studies (e.g., Tate (2012); Feizizadeh et al. (2014); Spielman et al. (2020); Wilson et al. (2020)) have been conducted to explore the precision of common existing social vulnerability indices.

To externally validate how well the proposed SVS represents the social vulnerability of community members, we employed post-disaster household-level survey results on household dislocation, physical damage, and repair time of residential dwellings. The field data used in this paper are from the second wave of an ongoing longitudinal research project following the 2016 hurricane-induced riverine flooding in the city of Lumberton, NC (Sutley et al. 2021). To internally validate the SVS, Tate's (2012) findings were integrated into the SVS development to ensure internal robustness and stability, as described in Sect. 3.

4.1 Background on lumberton longitudinal field study

Lumberton is an inland city holding the county seat in predominantly rural Robeson County, North Carolina. Lumberton was one of the communities most impacted by Hurricanes Matthew (2016) and Florence (2018) due to the historic flooding of the Lumber

River. The impacts of Hurricanes Matthew and Florence were exacerbated in the areas that were deprived in terms of health, wealth, and infrastructure. The community has significant racial diversity of Black/African-American, Native American, and white populations, with a median annual income well below the national average, and a poverty rate nearly 2.5 times as high as the national poverty rate (see Table 3 for Lumberton demographics). To illustrate the community's socio-demographic makeup prior to the Hurricane Matthew flooding in comparison to the national averages, the 2012–2016 ACS 5-Year estimates were used, as presented in Table 3.

In October 2016, Lumberton was catastrophically flooded due to an intensive period of seasonal rain followed by rains by Hurricane Matthew. Many areas of Lumberton were inundated for several days, which resulted in disruption in businesses, power, communication, water, and transportation networks as well as significant building damage and lasting social impacts (van de Lindt et al. 2020).

In November 2016, a team of researchers from the Center of Excellence for Risk-Based Community Resilience Planning, alongside researchers at the National Institute of Standards and Technology's Community Resilience Group, launched a longitudinal study on the impacts and recovery of Lumberton. At the time of this writing, five waves of systematic data collection have been completed in Lumberton, each with its own goals and objectives,

Table 3 Comparison of demographics between Lumberton and U.S. based on 2012–2016 ACS 5-Year estimates

Demographics		Lumberton	United States
Population (count)		21,646	318,558,162
Race	White (%)	38.4	73.4
	Black/African American (%)	37.5	12.6
	Native American/ American Indian (%)	12.8	0.8
	Two or more races (%)	8.8	10.1
	Other (%)	2.5	3.1
Ethnicity	Not Hispanic or Latino (%)	90.6	82.7
	Hispanic or Latino (%)	9.4	17.3
Tenure	Owner occupied (%)	63.6	45.5
	Renter occupied (%)	36.4	54.5
Education	Less than high school (%)	23.0	13.0
	High school (%)	30.9	27.5
	Some college (%)	20.1	21.0
	Associate's (%)	8.4	8.2
	Bachelor's (%)	11.1	18.8
	Master's or higher (%)	6.5	11.5
Income	Median annual (USD)	31,126	55,322
	Below poverty (%)	15.1	35.1
	Above poverty (%)	84.8	64.9
Age	Under 18 years (%)	26.2	23.1
	18 to 64 years (%)	59.6	62.4
	64 years and over (%)	14.2	14.5
Disability	With at least one type of disability	15.1	12.5
	No disability	84.9	87.5

and the study continues. The first field study, denoted as Wave 1, was performed in November 2016, and collected household and housing data on initial damage and dislocation. The household and housing data were collected through door-to-door surveys across a random sample of 568 housing units (van de Lindt et al. 2018). A probability proportion-to-size random sampling procedure selected census blocks located in high-probability flooding areas over those in low-probability flooding areas at a 3-to-1 weight. Eight housing units were then randomly selected from each census block, along with two alternate housing units per block in case a unit needed replacing; ultimately, 568 housing units were visited to implement the survey.

The second field study, denoted as Wave 2 and performed in January 2018, conducted systematic surveys of the same housing units as in Wave 1 with the overall intention of documenting recovery progress (Sutley et al. 2021). This paper uses post-disaster outcome data collected from household surveys during Wave 2. The data collection has continued, including a systematic survey immediately after Hurricane Florence in September 2018, a recovery follow-up in April 2019 (Helgeson et al. 2021), a virtual data collection during the COVID-19 pandemic in Spring 2021 (Watson et al. 2022), and recovery follow-up in June 2022.

4.2 Social vulnerability score

The SVS values were calculated for each census block group within the city of Lumberton using 2016 ACS 5-year census data to correspond to the timing of Hurricane Matthew. Corresponding social vulnerability zones were then assigned, as shown in Fig. 1a. No block group was assigned a low vulnerability level. There are likely individual households who fall into the lowest vulnerability level; however, at the block group level, these households did not represent a majority in a given neighborhood and thus this outcome is consistent with field study findings. As shown in Fig. 1b, the inundated area caused by the

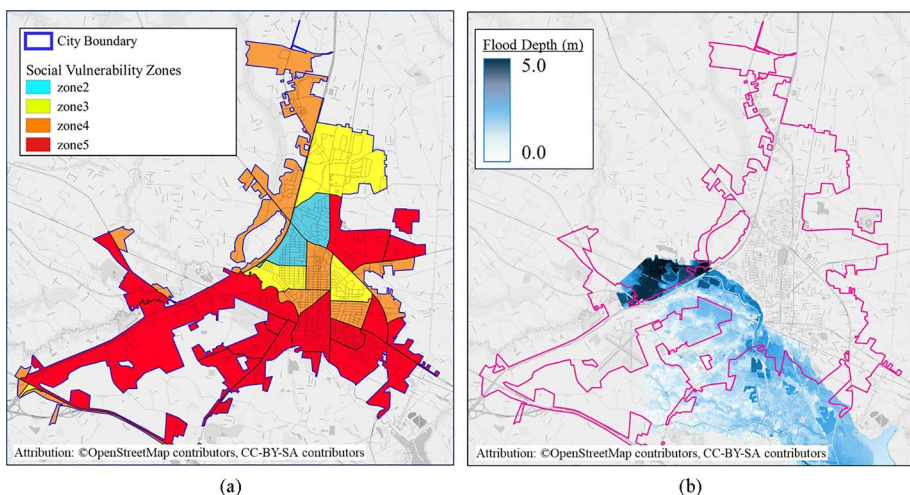


Fig. 1 **a** Mapped SVS zones at the block group level; **b** flood inundation map after 2016 Hurricane Matthew in Lumberton

2016 Lumber River flooding primarily overlaps with block groups with high social vulnerability, as is expected due to social vulnerability theory (Fothergill and Peek 2004).

To utilize the Lumberton survey results for validation, a household-level estimate of social vulnerability is required. Thus, every household within the study area was randomly assigned a value based on their corresponding SVS zone and the ranges described in Table 4. To address the consequences of spatial clustering of sociodemographic characteristics in real-world communities, each zone is assumed to have a small percentage of households with higher or lower social vulnerability. For example, in zone 2, the likelihood of households with values ranging between (0.2 to 0.4), (0 to 0.2), and (0.4 to 1.0) are 85%, 5%, and 10%, respectively. These ranges are Lumberton-specific and were chosen based on the authors' expert judgment and deep knowledge of the Lumberton community. This knowledge stems from the authors' extensive contribution to multiple waves of Lumberton longitudinal field study since Hurricane Mathew 2016 (van de Lindt et al. 2018; Helgeson et al. 2021; Sutley et al. 2021; Watson et al. 2022). Therefore, to apply these ranges to another study area, adjustments are required. These adjustments can be made based on the findings of a statistical analysis, analytical study, or expert judgment informed by a deep understanding of the target community's characteristics. In Table 4, the footnote describes the defined social vulnerability levels for households based on quantitative values.

Figure 2 displays the social vulnerability level assigned to the households occupying the 568 housing units in the study area. As can be seen, some households have been assigned a low social vulnerability level despite the block groups not being assigned zone 1.

4.3 Household dislocation

In Wave 2, 166 (of 568) households reported information on dislocation and confirmed they were living in their current home at the time of Hurricane Matthew. Approximately 28% of these respondents indicated they did not dislocate, and 60% reported that their household dislocated for at least one day. The households' self-reported dislocation time due to Hurricane Matthew was used to validate the SVS. Figure 3a illustrates household dislocation time versus SVS-based social vulnerability level for the 166 households that reported their dislocation experience. The average dislocation time for the households in each social vulnerability category is also shown in Fig. 3a. In total, the average dislocation

Table 4 Household social vulnerability values based on SVS zone

SVS Zone	Range 1*	Likelihood of Range 1	Range 2	Likelihood of Range 2	Range 3	Likelihood of Range 3
Zone 1	0.0–0.2	95%	0.2–1.0	5%	–	–
Zone 2	0.2–0.4	85%	0.0–0.2	5%	0.4–1.0	10%
Zone 3	0.4–0.6	80%	0.0–0.4	10%	0.6–1.0	10%
Zone 4	0.6–0.8	85%	0.0–0.6	10%	0.8–1.0	5%
Zone 5	0.8–1.0	95%	0.0–0.8	5%	–	–

* value < 0.2 → low;

0.2 ≤ value < 0.4 → medium to low;

0.4 ≤ value < 0.6 → medium;

0.6 ≤ value < 0.8 → medium to high;

0.8 ≤ value → high

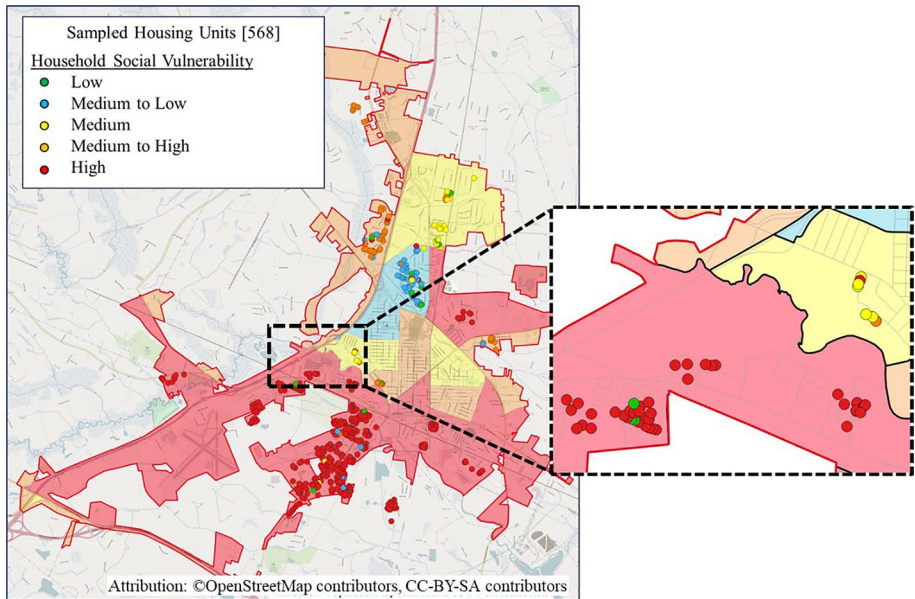


Fig. 2 Household social vulnerability levels for sampled housing units in corresponding block group-level SVS zones

time increases as social vulnerability increases. For instance, the average dislocation time for households with low, medium, and high social vulnerability is 2, 15, and 102 days, respectively.

Figure 3b provides the percentage of dislocated households in each social vulnerability level who have been dislocated for more than one week, more than one month, and more than three months. A similar trend can be observed in Fig. 3b as in Fig. 3a, where the direct correlation between households' average dislocation time and social vulnerability becomes more significant as the dislocation time increases. As can be seen in Fig. 3b, the percentage of high socially vulnerable households who were dislocated for more than one week (66%) is nearly three times more than that of medium to low vulnerable households (24%). For households who have dislocated for more than one month, the corresponding percentage consistently increases from 12% for medium to low to 15% for medium, 19% for medium to high, and 39% for high social vulnerability. In addition, only high and medium to high socially vulnerable households experienced dislocation for more than three months, at 26% and 10%, respectively. These findings are indicative of households who have different social and political capital, and thus different dislocation experiences across social vulnerability levels (Sutley and Hamideh 2020). The findings also confirm the trend detected in Fig. 3a that households with higher social vulnerability are more likely to dislocate for longer periods, thereby validating the reliability of the SVS-based estimates.

4.4 Physical damage and repair time of residential dwellings

A total of 107 households reported some initial physical damage to their homes during Wave 2; of these, 61 respondents indicated that their homes had been completely repaired

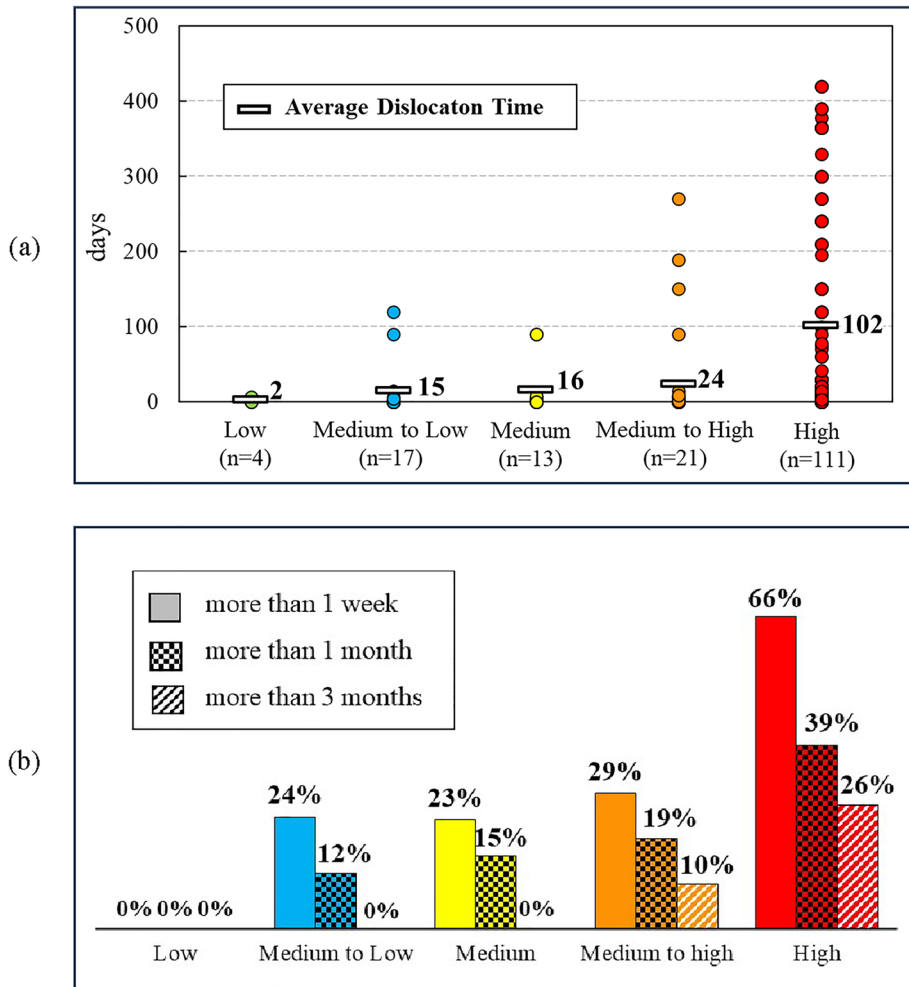


Fig. 3 **a** Household dislocation time versus social vulnerability level; **b** Percentage of households dislocated for selected durations at each social vulnerability level

at the time of Wave 2. One of the 61 households reported the highest level of damage to their home; this record has been deemed an outlier and thus removed from the present analysis. We also excluded households assigned low, medium to low, and medium levels of social vulnerability as they totaled six records only. This finally resulted in a dataset including 54 records.

The least-square linear regression model was applied to resident-reported repair time, damage level, and social vulnerability data. The number of days to repair completion was the dependent variable while damage and social vulnerability levels were used as binary independent variables. A summary of the regression analysis results is presented in Table 5.

The top two rows of Table 5 report how well the overall regression model fits the dataset by measuring the adjusted R-squared and the significance of the F-statistic. Almost 30%

Table 5 Ordinary least square regression results

R-squared:	0.336		F-statistic:	8.449	
Adj. R-squared:	0.297		Significance (F-statistics):	0.000121	
Independent Variables	Medium to High Social Vulnerability	High Social Vulnerability	Minor Damage	Moderate Damage	Severe Damage
Coefficient	86.31 *	90.97 **	-23.68	42.63 *	158.33 **

† dependent variable: repair time (days)

* p -value < 0.05

** p -value < 0.001

of the variance in repair time is accounted for by the dependent variables included in the model (adjusted $R^2 = 29.7\%$), demonstrating a moderate relationship between independent and dependent variables. This moderate relationship is plausible as several other factors also affect repair time. These factors include but are not limited to, decision-making time, time to hire a contractor or repair crew, and time to obtain a permit (Comerio 2006; Comerio and Blecher 2010). The p -value associated with the F-statistic (i.e. 0.000121) is far less than 0.001, representing a strong significant relationship. This means the model, as a whole, is likely statistically significant. The bottom row of Table 5 provides the regression coefficients and their statistical significance. On average it took 91 days longer to complete repairs for households with high social vulnerability. Moderately and severely damaged homes took 43 and 158 days longer, respectively, to be completely repaired compared to homes with minor damage net of other factors. This demonstrates how social vulnerability alongside physical damage strongly affects repair time and is aligned with Tormos-Aponte et al. (2021) findings on the relationship between social vulnerability and delayed restoration. These findings, overall, confirm the reliability of the social vulnerability index developed in this paper, at least for medium to highly vulnerable households. For further investigation of the SVS's capability to consistently interpret disaster outcomes under different circumstances, more empirical research and longitudinal post-disaster studies are required, considering a variety of places, hazard types, and temporal and spatial scales.

5 Conclusions

The concept of measuring social vulnerability using a single numeric index is a bold simplifying assumption. However, social vulnerability indices are conducive tools to advance the state of knowledge in community-related studies, while waiting for emerging more robust approaches to measure social vulnerability. Public health officials, hazard mitigation planners, community resilience researchers, and testbed developers use such indices to identify differences in social vulnerability across a population to help understand where resources may be needed to better prepare for and respond to a natural hazard and bounce back from its impact. However, the literature review presented in this paper illuminated that experts and policy-makers should be cautious in the application of these indices in some circumstances particularly based on limitations in index

construction (see Tate 2012 for more detail), and in the extreme simplification of capturing social vulnerability using factors conveniently found in census data.

While the proposed SVS is still subject to some of the same limitations in simplifying a measurement of social vulnerability, it offers important advantages to existing indices. The SVS (a) does not decrease in reliability as a function of geographic scale, so long as the data is reliable; (b) only requires calculation for the specific area of interest; (c) measures social vulnerability as a relative quantity to the national context; (d) does not yield different estimates of social vulnerability of the same place, using the same data, with changes in the geographic scope of the study area; and (e) uses fewer variables which reduces uncertainty in the influence of different factors on social vulnerability and reduces uncertainty transferred through the data itself in the final estimate. Thus, the SVS presented here addresses the need for a social vulnerability index that more consistently explains disaster outcomes, can be used at various spatial scales, and requires minimal data inputs and computational efforts making it particularly suitable for use in virtual community resilience testbeds. Nevertheless, we recognize the limitations of the SVS, which arise from using national average values in calculating indicators. Using national averages masks the actual distribution of indicators, potentially conceals any skewness in data distribution, and overlooks unique historical, cultural, and political characteristics of different communities.

This paper does not dwell on the question of whether the SVS provides more accurate and precise estimates compared to other widely used social vulnerability indices. Instead, the paper seeks to open up the discussion on the need for the construction of a scalable social vulnerability index to serve the purpose of community resilience testbed development, and introduces the SVS as a scientifically principled, yet practical, tool for this purpose. This paper further contributes by validating the SVS prediction using household-level disaster outcomes measured following the 2016 flooding in Lumberton, NC. Even still, more research is needed to understand how the SVS holds up to pre-disaster and other post-disaster outcomes beyond those evaluated here because of the dynamic nature of social vulnerability which can emerge differently depending on the context and situation. In addition to being scalable, the next generation of social vulnerability indices should account for the intersectionality of factors and explore variables outside of census data to truly understand what contributes to social vulnerability.

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Author Contributions Both authors contributed to the study's conception and design. Material preparation, data collection, and analysis were performed by *S. Amin Enderami* and *Elaina J. Sutley*. The first draft of the manuscript was written by *S. Amin Enderami* and both authors collaborated and revised the manuscript. Both authors read and approved the final revision of the manuscript.

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Data Availability All data and code that are used to calculate social vulnerability scores in this study are open sources and available in the DesignSafe-CI data repository (Enderami and Sutley 2022). The data that support the validation process in this study might be available on request from the second author, Dr. Elaina Sutley. The data are not publicly available, and its access is limited to project investigators within the Center and at NIST who have completed the Institutional Review Board (IRB) training and whose universities have signed the Interagency Agreement (IAA).

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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