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A Sensitivity Analysis of the Social Vulnerability Index

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The Social Vulnerability Index (SoVI), created by Cutter *et al.* (2003), examined the spatial patterns of social vulnerability to natural hazards at the county level in the United States in order to describe and understand the social burdens of risk. The purpose of this article is to examine the sensitivity of quantitative features underlying the SoVI approach to changes in its construction, the scale at which it is applied, the set of variables used, and to various geographic contexts. First, the SoVI was calculated for multiple aggregation levels in the State of South Carolina and with a subset of the original variables to determine the impact of scalar and variable changes on index construction. Second, to test the sensitivity of the algorithm to changes in construction, and to determine if that sensitivity was constant in various geographic contexts, census data were collected at a submetropolitan level for three study sites: Charleston, SC; Los Angeles, CA; and New Orleans, LA. Fifty-four unique variations of the SoVI were calculated for each study area and evaluated using factorial analysis. These results were then compared across study areas to evaluate the impact of changing geographic context. While decreases in the scale of aggregation were found to result in decreases in the variance explained by principal components analysis (PCA), and in increases in the variance of the resulting index values, the subjective interpretations yielded from the SoVI remained fairly stable. The algorithm's sensitivity to certain changes in index construction differed somewhat among the study areas. Understanding the impacts of changes in index construction and scale are crucial in increasing user confidence in metrics designed to represent the extremely complex phenomenon of social vulnerability.

KEY WORDS: Hazards; principal components analysis; sensitivity analyses; social vulnerability

1. INTRODUCTION

The impact of Hurricane Katrina on the Gulf Coast, and in New Orleans in particular, was perhaps the most visible recent demonstration of the need for an integrative vulnerability science approach to hazards research in the United States (Cutter, 2003). While the prehurricane evacuation from New Orleans was judged by some to be a success when measured by the volume of evacuees who were able to flee in a short timeframe and over limited highways (Wolshon *et al.*, 2006), it was a devastating failure for the socially vulnerable population that was unable to leave (Cutter & Emrich, 2006). It is estimated that some 250,000 residents in New Orleans had no access to personal vehicles; even if the regional buses had been used in the evacuation, they could have accommodated less than 10% of this number in a single trip (Wolshon *et al.*, 2005). And, these figures do not address special needs or institutionalized populations, which accounted for about 10% of the fatalities from Katrina in New Orleans (Schmidlin, 2006). These problems highlight the need to better integrate social science research concerning social vulnerability into

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emergency and risk management decision making. Such integration will allow planners to better identify what and where problems exist before an event occurs, and provide insight as to what steps may be useful in remedying them (Chakraborty *et al.*, 2005).

Toward this end, one approach for identifying the locations of populations with high levels of social vulnerability is the social vulnerability index (SoVI) (Cutter *et al.*, 2003). SoVI can be used to effectively quantify variations in the relative levels of social vulnerability over time and across space (Cutter & Finch, 2008). Yet like other comparable indicators, it is difficult to systematically assess its veracity. Because of the complex and multidimensional nature of factors contributing to vulnerability, no variable has yet been identified against which to fully validate such indices. An alternative approach to assess the robustness of the index is to identify how changes in its construction may lead to changes in the outcome. Factors that may have a large influence on the outcome of the index include changes in the set of variables used for index construction, differences in scale of analysis, and changes in the subjective decisions made in the index algorithm. When we have a greater understanding of the way the index responds to these changes, we can more confidently interpret and implement its results. The purpose of this article is to conduct such an assessment. Three research questions are asked. First, what is the impact of changes in variable set and analytical scale on the index results? Next, how robust is the SoVI to changes in its algorithmic approach? Finally, is the index sensitive to the same changes in its construction in various geographic settings? The first question will be answered by comparing indices calculated with two different variable sets and at differing scales within the State of South Carolina. The final two questions will be answered by constructing a set of social vulnerability indices calculated over varying algorithmic criteria in three locations: the Charleston-North Charleston Metropolitan Statistical Area (MSA) in South Carolina, in Los Angeles County, California, and finally in Orleans Parish, Louisiana.

2. SOCIAL VULNERABILITY

While hazards and disasters researchers have long understood that human decisions have an influence on the outcome of hazard events (Kates, 1971; Mileti, 1980), it has only been within the past decade or so that vulnerability as an explicit concept has been broadly recognized (Wisner *et al*., 2004). Although multiple definitions of *vulnerability* have been proposed (Cutter, 1996), here we define it as the likelihood of sustaining losses from some actual or potential hazard event, as well as the ability to recover from those losses.

Contributions to vulnerability can be divided into two broad categories: exposure or biophysical vulnerability, those characteristics of events and physical contexts that influence the likelihood of losses and ability of individuals or communities to recover; and susceptibility or social vulnerability, which interacts with exposure to either increase or decrease the eventual harm (Cutter, 1996). Hazards, risk, and disaster researchers in the past have focused primarily on elements related to biophysical vulnerability, perhaps because they are relatively less complex than those related to social vulnerability. Social vulnerability provides greater insight into the manner in which the decisions we make as a society influence our differential experience of hazard events. Social vulnerability stems from limited access to resources and political power, social capital, beliefs and customs, physical limitations of the population, and characteristics of the built environment such as building stock and age, and the type and density of infrastructure and lifelines (Cutter *et al.*, 2003). Others authors have discussed in much greater detail many of the important theoretical and conceptual aspects of social vulnerability and its measurements, which we only touch upon here (Adger, 2006; Birkman, 2006;Turner *et al*., 2003; Wisner *et al*., 2004; Eakin & Luers, 2006).

The antecedents of current efforts to model social vulnerability were derived from the social science research in the 1960s and 1970s on social indicators and quality-of-life indicators. Much of the research effort in the intervening years has addressed international indicators of human development and their relationship to natural hazards, but often data are not available at a subnational level (Bohle *et al.*, 1994). More recent examples of social vulnerability modeling have been based on limited representations of the social characteristics involved (Cutter *et al.*, 2000; Wu *et al.*, 2002; Wood & Good, 2004; Chakraborty *et al.*, 2005), considered only particular aspects of vulnerability (Luers *et al*., 2003), or focused on novel methodological approaches for one specific case study (Rashed & Weeks, 2003; Inter-American Development Bank, 2006)

The social vulnerability modeling approach that we assess in this article, SoVI (Cutter *et al.*, 2003), was developed to address many of these shortcomings. It originally was applied as an analysis of social contributions to natural hazard or disaster vulnerability at the county level in the United States for 1990. It was created by first finding social characteristics consistently identified within the research literature as contributing to vulnerability. These target variables were used to identify a set of 42 normalized independent variables that influenced vulnerability. The 42 variables were then entered into a principal components analysis (PCA) (Manly, 2005), from which 11 components were selected, explaining a total of 76.4% of the variance in the original data set.

These components were interpreted to identify what element of vulnerability they represented, and scaled to ensure that they contributed to the final index in an appropriate manner (positive values added to vulnerability, negative to mitigated vulnerability). The 11 factors were then summed with equal weights to create the final vulnerability index. The index was mapped, with counties shaded according to the SoVI values, to allow for identification of the spatial patterns of social vulnerability within the United States. A similar factor-analysis-based approach to characterizing social contributions to vulnerability was also used by Clark *et al*. (1998), who used a smaller enumeration unit (census block group) for one particular study area (Revere, MA).

The SoVI approach has been replicated in a number of studies in various geographic settings (Boruff & Cutter, 2007), at various spatial scales (Cutter *et al*., 2006; Borden *et al*., 2007), and in differing time periods (Cutter & Emrich, 2006; Cutter & Finch, 2008). Indeed, the method may be best viewed as an algorithm for quantifying social vulnerability, rather than as a simple numerical index. Via these approaches, SoVI has consistently illustrated its value by revealing both anticipated and unanticipated spatial patterns that conform to expert interpretations of social vulnerability. But no study to date, including the original SoVI article, has included a sensitivity analysis of the underlying PCA-based approach.

3. STUDY AREA AND SCALE

The analysis was conducted in three separate study areas: Charleston, South Carolina; Los Angeles, California; and New Orleans, Louisiana. To address changes in vulnerability across these locations, we operate at the U.S. census tract level. For Charleston, South Carolina, social vulnerability was calculated within the Charleston-North Charleston MSA, consisting of Charleston, Dorchester, and Berkeley Counties, South Carolina. Because of the much larger number of census tracts within the Los Angeles, California metropolitan area, the analysis was carried out only for Los Angeles County. Orleans Parish, Louisiana was used to represent the New Orleans study area.

While the SoVI algorithm has been applied at multiple scales in the existing literature, as noted above, there has been no explicit consideration of the impact scalar changes have on the analysis, beyond the simple visual interpretations of patterns of vulnerability. Because this analysis was conducted at the tract level, rather than at the county level as in the original SoVI index, it is important to consider how this change in scale may impact the analysis. Openshaw (1983) identified two types of problems that can occur as part of the modifiable areal unit problem when working with areally aggregated data at different scales. The first issue, termed the scale problem, is related to the ecological fallacy. As scales of analysis change, the relationships between variables aggregated to those levels may also change. Thus without access to the original, unaggregated data, it is impossible to determine how severe this problem is, although several studies indicate that correlations tend to increase with increasing scales (Clark & Avery, 1976; Openshaw, 1983). This provides a fundamental challenge to characterizing vulnerability at aggregated levels. The majority of existing research on social contributions to vulnerability has been conducted at a household or individual level (Heinz Center, 2002). This body of work was used by Cutter *et al.* (2003) to identify the characteristics that would be used to represent vulnerability for populations within particular geographic areas. While this approach seems reasonable, it is important to note that the ecological fallacy means that variables that are influential to the vulnerability of individuals or households may not have the same level or type of relationship when examining vulnerability of populations or groups. Additionally, SoVI as an areal measure of vulnerability applies only to the aggregate area as a whole, and does not represent individually based levels of vulnerability. This limitation of the ecological fallacy will remain as a challenge to all census- or demographic-based approaches to characterizing vulnerability until the relationships between particular areal descriptors for groups (i.e., percentage of population in poverty) and individual vulnerability have been determined.

To assess the impact of changes in scale between aggregation levels, Clark and Avery (1976) used an approach in which the correlations between variables were calculated for the same data and study area at multiple scales. While this did not give insight into the extent of the problem created by the initial aggregation of observation units, it did provide a method to assess the impact of the ecological fallacy on subsequent changes in aggregation scales. Combining the assessment of changing scales with an explicit limitation of the application of analytical results to the scale at which they were derived provides a simple means of addressing the impact of the scale issue on calculating SoVI at various aggregation levels. The problem then becomes one of choosing an appropriate scale of analysis. In this study, the desire was to address changes in vulnerability across a metropolitan area, so census tracts seem an appropriate level. The impact of scalar changes from the county to the tract level of aggregation was examined using an approach based on Clark and Avery's (1976) analysis, with South Carolina as the study area.

The second issue, termed by Openshaw to be the aggregation problem, is that the relationships between areally aggregated variables may result as much from the aggregation scheme as from the fundamental relationships between the variables themselves. Indeed, dramatic differences in correlations between variables may be produced by changing the aggregation scheme (Openshaw, 1983). This forces one to apply results from analyses of areal data only to the study units at which they were conducted. Short of creating new aggregation units, the problem here becomes one of determining whether the study units used in an analysis are truly meaningful.

While it would be naïve to view any preexisting areal aggregation as ideal for a given study, census tracts do seem to be a fairly meaningful spatial unit for our analysis. Tracts are defined by the U.S. Census Bureau in conjunction with local committees of census data users, and are meant to represent areas with fairly stable population sizes and to be "relatively homogeneous . . . with respect to population characteristics, economic status, and living conditions" (U.S. Department of Commerce Bureau of the Census, 2006). Additionally, it has been observed that while not complete, census tracts have provided a relevant proxy for neighborhoods within urban areas (Sampson *et al.*, 2002). Census tracts therefore seem to be a pertinent set of spatial units for modeling social vulnerability at the suburban level.

4. DATA

The list of variables from the original SoVI, created using 1990 census variables, was used to guide the selection of variables for our analysis. Changes in census variable availability at the county and tract level necessitated that a smaller set of variables be used here. Additionally, following the approach taken by Borden *et al.* (2007), built environment variables were removed from the analysis to focus more explicitly on those characteristics of the populations that themselves contributed to vulnerability. This resulted in a total of 26 variables obtained from the GeoLytics Neighborhood Change Database and U.S. Census data sources (GeoLytics, 2006; U.S. Department of Commerce Bureau of the Census, 2002), shown in Table I.

5. SOVI ALGORITHM

The algorithm used to construct indices of vulnerability in this article follows that used by Cutter *et al.* (2003), with the inclusion of data standardization for the input variables and the final index scores. The computations are carried out using the following steps:

1. Standardize all input variables to z-scores, each with mean 0 and standard deviation 1.
2. Perform the PCA with the standardized input variables.
3. Select the number of components to be further used based on the unrotated solution.
4. If desired, rotate the initial PCA solution.
5. Interpret the resulting components on how they may influence the social vulnerability and assign signs to the components accordingly. For this step, an output of the loadings of each variable on each factor was used to determine if high levels of a given factor tend to increase or decrease social vulnerability. If a factor tends to show high levels for low social vulnerability (e.g., wealth variable is strongly positive), the corresponding factor scores are multiplied by –1. In some cases, both high and low levels may increase social vulnerability (e.g., elderly is strongly negative and children is strongly positive) and in this case the absolute value of the corresponding factor score was used for calculating SoVI. Adjustments were made to the sign of components rather than to the signs of variables at the outset because of the *a priori* unpredictability of the direction of the relationships between the variables and the components: variables whose signs were adjusted prior to inclusion in the PCA may still load in a manner that indicates

Table I. Social Vulnerability Variables for Charleston, SC; Orleans, LA; and Los Angeles, CA study areas*

Civilian labor force participation	Percentage of female participation in civilian labor force
Average family income	Percentage of female-headed households
Median dollar value of owner occupied housing units	Percentage of Native American population (American Indian, Eskimo, or Aleut)
Median gross rent ($) for renter-occupied housing units	Percentage of population under 5 years
Percentage of population who are immigrants	Percentage of population 65 years or older
Percentage of institutionalized elderly population	Percentage of living in poverty
Average number of people per household	Percentage of renter occupied housing units
Percentage of employed in primary industry: farming, fishing, mining, forestry	Percentage of rural farm population
Percentage of Asian or Pacific Islander	Percentage of Hispanic persons
Percentage of black population	Percentage employed in transportation, communications, and other public utilities
Percentage of the civilian labor force unemployed	Percentage of the population living in urban areas
Percentage of population over 25 years old with less than 12 years of education	Percentage employed in service occupations
Percentage of females	Percentage of households that receive Social Security benefits

*The variables deleted from the subcounty analysis but that appeared in the original SoVI include variables relating to the built environment (percentage of housing units that are mobile homes, per capita community hospitals, number of housing units per square mile, number of housing permits per new residential construction per square mile, number of manufacturing establishments per square mile, earnings in all industries per square mile, number of commercial establishments per square mile, and value of all property and farm products sold per square mile) and social variables unavailable or less meaningful at the tract level for our study areas (median age, general local government debt to revenue ratio, number of physicians per 100,000 population, percentage of votes cast for winning presidential candidate in most recent election, birth rate, land in farms as a percentage of total land, percentage population change in last decade, percentage of households earning more than $75,000).

that the component would decrease vulnerability, and so adjusting the sign of variables before entry into the PCA would not have removed the need for this step.

6. Combine the selected component scores into a univariate score using a predetermined weighting scheme.
7. Standardize the resulting scores to mean 0 and standard deviation 1.

Because PCA is sensitive to the values of the input variables, the data standardization step is highly recommended, allowing all variables to have the same magnitude. With the standardized data set the PCA can be performed in the second step. It returns a set of orthogonal components that are the linear combinations of the original variables. By construction the first component is the linear combination that explains the greatest variations among the original variables, the second (orthogonal) component the greatest remaining variation, and so on. Based on the results of the performed PCA, it is desirable to select a parsimonious subset of components that explains the underlying features in the data as closely as possible: in the work of Cutter *et al.* (2003), the Kaiser criterion was used to select parsimonious components (Step 3). Also, a varimax rotation was used (Step 4), and the interpreted components were summed with equal weights (Step 6).

Our sensitivity analysis for this algorithm is conducted in two main stages: first, a consideration of the sensitivity to minor changes in variables used and the scale at which the analysis was applied, and secondly, the sensitivity to changes in the manner of index construction. For the sake of simplicity, the methods and results for these two stages will be presented together.

6. TEST 1: VARIABLE SET AND SCALE CHANGES

The first sensitivity test examined the role of downscaling and that of operating with a reduced variable set on SoVI construction. The first analytical step determined the impact of these two differences (scale and variable set) on the constructed indices using the subset of variables collected at the census tract level for the entire State of South Carolina. To determine the impact of using the subset of variables, these data then were aggregated to the county level. Two SoVIs were calculated at the county level, the first with the 33 social vulnerability variables used in the

Table II. County-Level Index Comparison

	Original Social Variables ($N = 33$)	Subset Social Variables ($N = 26$)
# Components selected	8	6
Pct. variance explained (6 components)	74.8	85.0
Pct. variance explained (8 components)	85.8	91.2
Component interpretation (pct. variance explained)	1. Wealth (22.2)	1. Wealth (29.5)
	2. Race & poverty (20.2)	2. Race & poverty (21.8)
	3. Age (elderly) (13.8)	3. Hispanic immigrants (10.8)
	4. Hispanic immigrants (6.7)	4. Age (9.3)
	5. Age (children) (6.1)	5. Gender (7.7)
	6. Infrastructure employment (6.0)	6. Race (6.1)
	7. Gender & nursing homes (5.9)	
	8. Community debt load (5.1)	

original SoVI, and the second with the 26 variables used instead in the tract-level analysis. The algorithm employed in this stage of the analysis followed the approach of Cutter *et al.* (2003), using the Kaiser criterion for component selection, a varimax rotation, and equal weighting to sum the collected components.

6.1. Variable Set Results

Strong similarities were found between the two indices. The PCA performed on the original set of 33 social variables led to selection of eight components, which explained 85.8 % of the variance of the original data (Table II). The PCA performed on the subset of 26 variables led to 6 components, explaining 85.0% of the data variance. The set of components derived from both PCAs had broadly similar subject interpretations.

The Spearman's rank order correlation between the two indices showed a fairly strong positive relationship ($r_s = 0.71; p < 0.01$). The average rank change between the two indices was 7, or about 16% of the total number of counties. All three of the counties identified as the highest vulnerability group (with z-scores greater than or equal to 1.5) via the original approach also exceeded this level in the 26-variable approach. Two additional counties were identified in this highest vulnerability category via the 26-variable approach, one of which was in the next lower vulnerability group (z-scores from 0.5 to 1.5), and the other from the medium vulnerability group (z-scores from −0.5 to 0.5). Overall, only 12 of the 42 counties had rank changes of 10 or greater, and only two counties experienced changes in values great enough to move them from lower to higher, or higher to lower, vulnerability status.

6.2. Scale Results

The impact of changing the level of aggregation on the analysis was assessed via the approach used by Clark and Avery (1976). These authors demonstrated that as the level of aggregation increases, the correlations between variables increase as well. Because the SoVI approach is based on PCA, which itself relies on the correlations between variables to determine the components representing the maximum dimensions of variability in the data set, it seems reasonable to suspect that decreasing the level of aggregation from the county level—the aggregation scale used in Cutter *et al.'s* (2003) original work—to the tract level would result in a decrease in the amount of variance explained by the PCA used to construct the index. To assess this, as well as to determine any other effects of downscaling the SoVI approach, social vulnerability indices were constructed at the county and tract levels for the State of South Carolina, as well as at a manually created intermediate level of aggregation. Four of the counties in the state had only three tracts, meaning that no intermediate aggregation could be created that would result in a set of units completely unique from the tract and county levels of aggregation. As such, these counties were removed from this analysis, as well as from the previous comparison of indices at the county level.

The results of the PCAs conducted at multiple aggregation scales are shown in Table III. As expected, as the level of aggregation at which the PCA was conducted decreased, the variance explained decreased, and the number of components selected using the Kaiser criterion increased. Fig. 1 shows a graph of the percentage of variance explained by the rotated components selected for each PCA. From this graph, we can see that decreasing the level of aggregation tends to flatten the displayed curve, meaning that both the

Table III. Results for County, Intermediate, and Tract Level PCAs

	County Level	Intermediate Level	Tract Level
# Components	6	6	7
Pct. variance explained	85.0	79.3	73.2
Unstandardized index variance	4.45	5.09	6.66
Unstandardized index range	10.38	11.33	29.25
Component interpretation (pct. variance explained)	1. Urban wealth (29.5)	1. Race & poverty (22.6)	1. Race & poverty (17.6)
	2. Race & poverty (21.8)	2. Urban renters (16.3)	2. Rural/urban (11.7)
	3. Hispanic immigrants (10.8)	3. Wealth (13.6)	3. Wealth (10.9)
	4. Age (9.3)	4. Age (11.3)	4. Age (elderly) (9.6)
	5. Gender (7.7.)	5. Hispanic immigrants (8.6)	5. Hispanic immigrants (8.8)
	6. Race (6.1)	6. Gender (6.9)	6. Age (kids)
			7. Gendered labor (6.8)

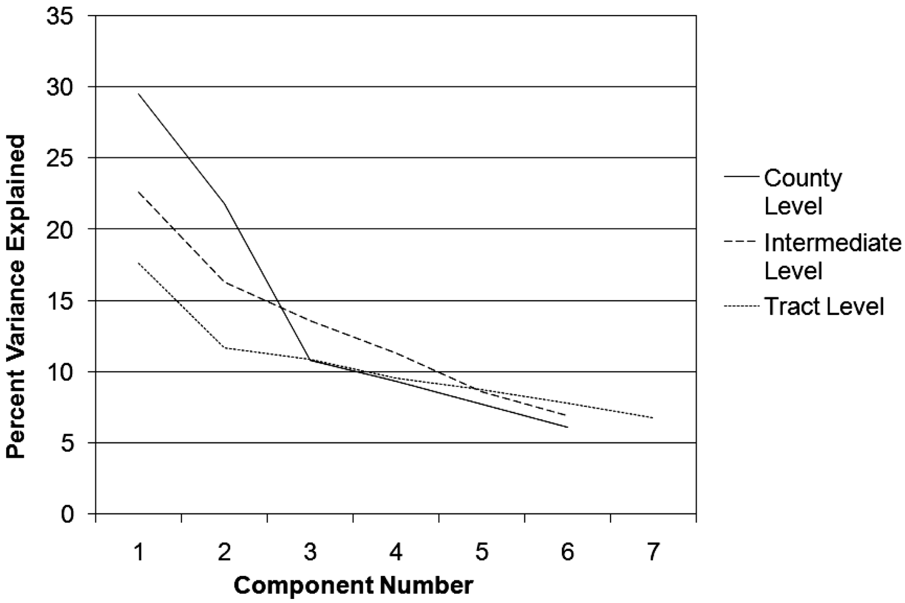

Fig. 1. Variance explained by component for three aggregation levels.

variance explained by the first rotated component is decreased, and the rate of decrease in variance explained is also reduced. Returning to Table III, we see that while there are differences among the subject interpretation of the components between the scales, they are broadly similar. The table also indicates that as the aggregation scale decreased, the variance and range of the unstandardized indices computed from the PCAs increased. Finally, Fig. 2 shows that the representations of vulnerability at the multiple levels of aggregation seem fairly stable; high vulnerability counties are composed of moderate and high vulnerability tracts, while low vulnerability counties are composed of moderate and low vulnerability tracts.

7. TEST 2: INDEX CONSTRUCTION CHANGES

The second step in our sensitivity analysis considered the influence of subjective options applied in the construction of the index. The algorithm used for constructing the original SoVI was reviewed to identify the types of subjective decisions made that seemed likely to have some influence on the assignment of index values. These fell into three categories: PCA component selection (Step 3), PCA rotation (Step 4), and the weighting scheme used to combine the components to create the final index (Step 6). Logical alternatives to each of these approaches were considered, and index values for each study area were calculated based on all possible combinations of them.

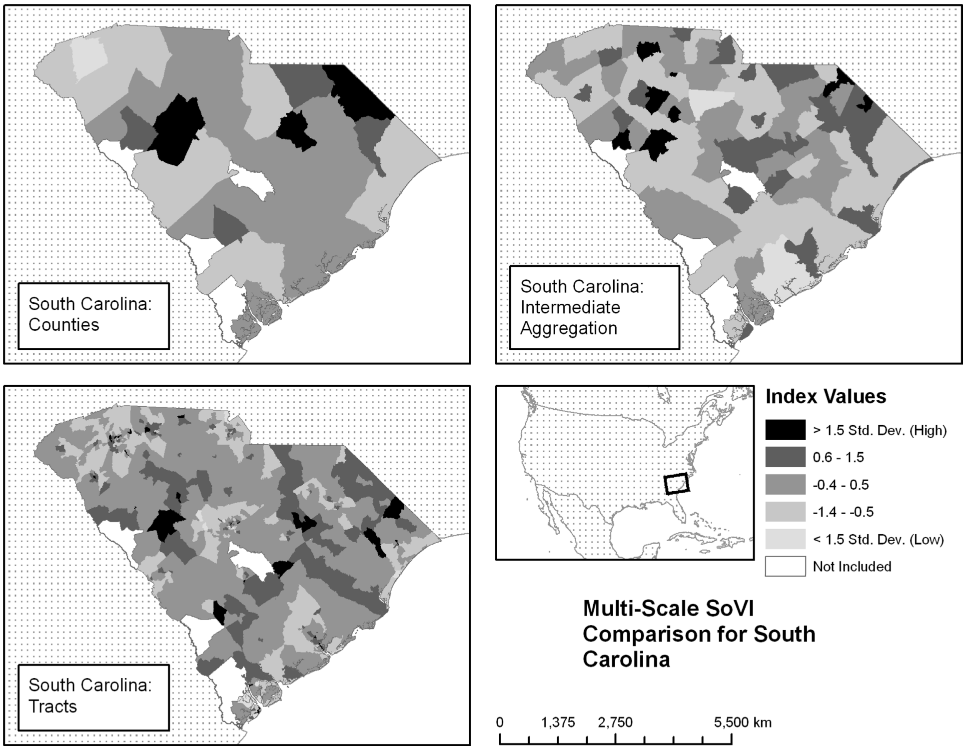

Fig. 2. Social vulnerability index value for multiple aggregation levels in South Carolina.

This approach resulted in a collection of indices for the Charleston, Los Angeles, and Orleans study areas. The values of the index could then be compared between study areas to determine if the results of the analysis remained stable across a variety of regional locations.

Within each of the three different categories for index construction, a number of options were considered. The following methods for PCA component selection were studied for calculating the SoVI index:

1. Kaiser criterion (Kaiser, 1960): Select only those components whose eigenvalues are greater than one.
2. Percentage variance explained: Retain as many components as needed in order to account for a prespecified amount of variation in the original data. For the SoVI algorithm, the fewest number of components were chosen such that at least 80% of the variation in the original data was accounted for.
3. Horn's parallel analysis (Horn, 1958): This selection criterion is similar to the Kaiser criterion. However, instead of using a fixed threshold one retains those factors whose eigenvalues are larger than the expected eigenvalue for that component. As the expected eigenvalue is arduous to compute, Horn's parallel analysis uses 100 randomly generated data sets on which a PCA is performed and then averages over the resulting eigenvalues.
4. Expert choice: Another approach for selecting components relies upon subjectively identifying a set of components that have meaningful, subject area interpretations. We term this selection criteria "expert choice."

A total of six PCA rotation methods were considered:

1. Unrotated solution: In order to use the components that explain the greatest percentage of the original variation, no rotation is applied.
2. Varimax rotation (Kaiser, 1958): This rotation tends to load each variable highly on just one component. This often leads to easier component interpretation.
3. Quartimax rotation (Neuhaus, 1954; Carroll, 1953; Ferguson, 1954; Saunders, 1953): This rotation tends to increase large loadings and decrease small ones, so that each variable will

load only on a few factors. This should lead to fewer relevant components than other rotations.

4. Promax rotation (Hendrickson & White, 1964): In contrast to the other rotations, the promax rotation represents an oblique rotation. Thus, the rotated components are no longer orthogonal. By allowing the resulting components to be correlated with each other, one may hope to achieve even easier interpretability. The promax rotation also requires specification of a power parameter, which is typically taken between 2 and 4. We chose the values 2, 3, and 4 for the algorithm.

Lastly, three approaches for weighting the selected and interpreted components were considered:

1. Sum the component scores: Since each PCA component absorbs a different aspect of social vulnerability a simple approach of combining the components is to sum the scores, thus assigning equal contributions to each component of the SoVI value.
2. First component only: Mathematically, the first extracted component from a PCA is the linear combination that explains the largest amount of variation in the original data. Therefore, selecting just the first component will give the mathematically optimal value to summarize all the input variables in a single combination.
3. Weighted sum using explainable variance to weigh each component: This is a compromise between the first two methods. Since each successive component contributes progressively less to the explainable variation, it seems reasonable to give the first PCA component the most weight and to decrease the weights accordingly for the remaining components. Thus we chose a weighting scheme where each component's weight was taken as the proportion of total variation that particular component explains.

In total, 72 different versions of social vulnerability indices were possible for each study area. In the end, only 54 unique versions were calculated because the expert choice component selection always coincided with the Kaiser criteria selection, and was therefore dropped from the analysis. The approach for this segment of the analysis was implemented using SAS Software (SAS Institute Inc., 2004).

Finally, since the computed SoVI value does not itself have any absolute interpretation, it is standardized to a z-score with mean 0 and variance 1 in order to map the values over space or to compare different methods. Positive values suggest high social vulnerability, whereas negative values suggest low social vulnerability. We considered these tracts with z-score values greater than 1.5 as being highly vulnerable, and those with values between 0.5 and 1.5 as having moderately high vulnerability. Tracts with values between -0.5 and 0.5 were considered as having moderate vulnerability. Similar, but negative ranges were used to identify moderately low and low vulnerability tracts.

7.1. Methods

To determine the impact of these subjective options on the final index values, we statistically assessed changes in SoVI using a three-way factorial analysis of the component selection, PCA rotation, and weighting scheme options. In this setting, we also accounted for the census tract by viewing the tract ID within each study area as a blocking factor, that is, an explanatory variable where tract ID represents a known source of variability. This helps to reduce residual variation and improve precision in the factorial analysis. Because the computed index values do not represent a truly random sample drawn from some broader population, this operation is not intended to make any statistical inferences. Rather, we use this calculation simply to reveal if substantial differences in the index values within each study area occurred as a result of the choice(s) of subjective option.

In the factorial analysis, we employed partial ("Type III") sums of squares to assess the importance of each subjective option. The associated p-values were treated as measures of the influence each subjective option has on the final index value. Small p-values suggest that changes in the choice of that subjective option have a large impact on the final index value, whereas large p-values suggest that choices within that subjective option do not substantially impact the final value.

For additional guidance on how changes in each specific option affected the final index values, we further assessed differences among the levels within each subjective option, using multiple comparison techniques. This was done using the all-possible-pairwise family of multiple comparisons: all possible paired differences were examined via Tukey's method (Tukey, 1994) to ensure proper multiplicity adjustment for the family of paired comparisons. Here, a difference between two choices of a subjective option that exhibits a small p-value suggests that changing from one choice of the option to the other produces quite different final index values, whereas a p-value close to 1 suggests no substantial difference in how the two choices for the option affect the final index value.

7.2. Results

Results from the factorial analysis illustrate the impact of changes in the algorithm construction on the index values for each study area. In this analysis, p-values less than 0.10 were taken to indicate substantial differences in index construction resulting from a particular set of subjective decisions (selection, rotation, and combination), or in the case of the multiplicity-adjusted results, differences between the options within a set. Table IV begins with the Type III sum of squares (SS) from the factorial analysis of the Charleston-North Charleston area. The table also includes Type III SS results for the tract ID contribution. Since ID is being employed as a blocking variable to account for the known source of variability that it represents, the analysis of those p-values is irrelevant. They are only included in the table for completeness. Next, in Table IV, we see component selection and combination method both result in substantial changes in the SoVI score for Charleston. Rotation method shows little variation. Table V and Table VI show the multiplicity-adjusted results for the options within each of these categories. The Horn and Kaiser selection criteria appear to differ substantially for Charleston, while lesser differences occur between the other selection criteria (Table V). For component combination, the weighted sum approach appears to differ substantially from the other two approaches (Table VI).

Table IV next presents the Type III SS analysis for index values in Los Angeles. Here, SoVI scores are influenced by changes in the PCA component combination and rotation criteria. As was the case in the Charleston-North Charleston study area, the

Table IV. Factorial Analysis Results for All Study Sites*

Source	DF	Type III SS	Mean Square	F Value	Pr > F*
		Charleston-North Charleston			
ID	116	2171.35	18.72	28.19	**<0.0001**
Select	2	4.90	2.45	3.69	**0.02**
Rotate	5	0.52	0.10	0.16	0.98
Combine	2	29.34	14.67	22.10	**<0.0001**
		Los Angeles			
ID	2046	45312.29	22.15	37.40	**<0.0001**
Select	2	0.20	0.10	0.16	0.85
Rotate	5	50.63	10.13	17.10	**<0.0001**
Combine	2	96.80	48.40	81.73	**<0.0001**
		New Orleans			
ID	180	3424.32	19.02	31.32	**<0.0001**
Select	2	4.21	2.11	3.46	**0.03**
Rotate	5	6.92	1.38	2.27	**0.04**
Combine	2	79.25	39.63	65.10	**<0.0001**

*Bold p values (less than 0.10) indicate substantial differences in index construction.

Table V. P-Values for Pairwise Differences in Component Selection for All Study Sites*

	Horn	Kaiser	Variance Explained
	Charleston-North Charleston		
Horn		**0.02**	0.12
Kaiser	**0.02**		0.80
Variance explained	0.12	0.80	
	Los Angeles		
Horn		0.85	0.90
Kaiser	0.85		0.99
Variance explained	0.90	0.99	
	New Orleans		
Horn		0.12	0.74
Kaiser	0.12		**0.04**
Variance explained	0.74	**0.04**	

*Bold p values (less than 0.10) indicate substantial differences in index construction.

Table VI. P-Values for Pairwise Differences in Factor Combination for All Study Sites*

	First Factor	Sum	Weighted Sum
	Charleston-North Charleston		
First factor		0.26	**<0.0001**
Sum	0.26		**<0.0001**
Weighted sum	**<0.0001**	**<0.0001**	
	Los Angeles		
First factor		0.16	**<0.0001**
Sum	0.16		**<0.0001**
Weighted sum	**<0.0001**	**<0.0001**	
	New Orleans		
First factor		1.00	**<0.0001**
Sum	1.00		**<0.0001**
Weighted sum	**<0.0001**	**<0.0001**	

*Bold p values (less than 0.10) indicate substantial differences in index construction.

Table VII. *P*-Values for Pairwise Differences in Factor Rotation for All Study Sites*

	Unrotated	Varimax	Quartimax	Promax 2	Promax 3	Promax 4
			Charleston-North Charleston			
Unrotated		1.00	1.00	1.00	1.00	1.00
Varimax	1.00		1.00	1.00	0.99	0.99
Quartimax	1.00	1.00		1.00	0.99	0.99
Promax 2	1.00	1.00	1.00		1.00	0.99
Promax 3	1.00	0.99	0.99	1.00		1.00
Promax 4	1.00	0.99	0.99	0.99	1.00	
			Los Angeles			
Unrotated		**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**
Varimax	**<0.0001**		1.00	1.00	**0.08**	0.51
Quartimax	**<0.0001**	1.00		1.00	**0.08**	0.51
Promax 2	**<0.0001**	1.00	1.00		**0.08**	0.51
Promax 3	**<0.0001**	**0.08**	**0.08**	**0.08**		0.95
Promax 4	**<0.0001**	0.51	0.51	0.51	0.95	
			New Orleans			
Unrotated		0.89	0.85	1.00	0.18	0.93
Varimax	0.89		1.00	0.99	0.93	0.40
Quartimax	0.85	1.00		0.98	0.85	0.35
Promax 2	1.00	0.99	0.98		0.44	0.73
Promax 3	0.18	0.93	0.85	0.44		**0.03**
Promax 4	0.93	0.40	0.35	0.73	**0.03**	

*Bold p values (less than 0.10) indicate substantial differences in index construction.

weighted sum combination approach appears substantially different from both of the other combination approaches (Table VI). Since rotation appears influential for the Los Angeles study area, we refer to multiplicity-adjusted results in Table VII, where the unrotated approaches appear substantially different from all other rotations, and the promax ($k = 3$) rotation appears different from all but the promax ($k = 4$) rotation.

Finally, all three subjective decision categories appear influential for Orleans Parish (Table IV). The Kaiser selection criterion appears substantially different from the variance explained approach, and also modestly different from the Horn selection criterion (Table V). As in Charleston-North Charleston and Los Angeles, the weighted sum combination approach appears substantially different from the other two approaches (Table VI). Lastly, the only substantial difference found in the rotation category was between the promax ($k = 3$) and promax ($k = 4$) rotations (Table VII).

To understand the impact of these changes on the relative rankings of individual tracts in each study area, rank changes were calculated between the vulnerability index constructed following the original SoVI approach (Kaiser selection, varimax rotation, and sum combination) and the remaining 53 index construction approaches for each study area. Histograms of these values for each study area, shown in Fig. 3, reveal that between 36–46% of the time, depending on study area, tracts experienced rank changes corresponding to 10% or less of the total range. In each study area, however, some rank changes did occur, which were large enough to move tracts from the highest to the lowest category of vulnerability.

8. DISCUSSION AND CONCLUSIONS

Based on these results, it is possible to reach a general set of conclusions regarding the sensitivity of the SoVI. The first question addresses the adequacy of the subset of variables used in the present sensitivity analysis, and the impact of scalar changes on the PCA and resulting index. We find that the employed subset of variables provided a representation of vulnerability with adequate similarity to that derived using the full set of social variables employed in the original SoVI, and that both approaches identify a similar set of highly vulnerable study units. With regard to the impact of scalar changes on the analysis, our ability to explain the variability in the data through the use of PCA decreases with decreasing levels of aggregation, but the index values themselves become more spread

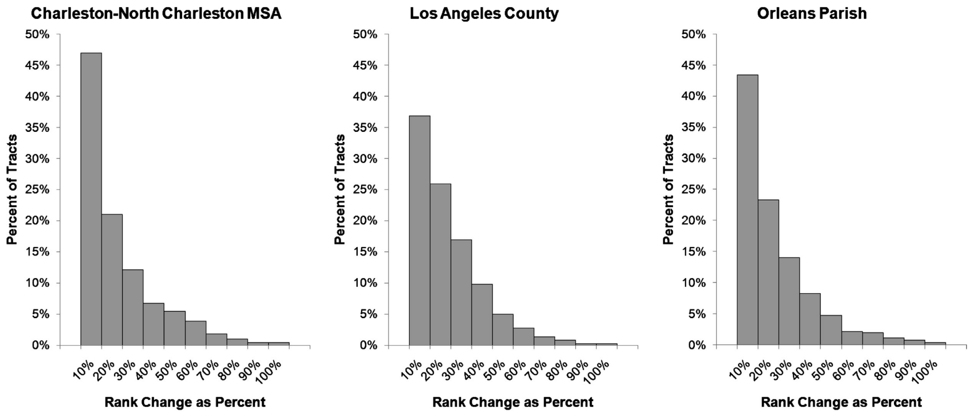

Fig. 3. Frequencies of the magnitude of rank changes. The rank changes are compared between the Kaiser criterion, varimax rotation, and sum component combination index (the original SoVI construction) and the remaining 53 variants. To allow for a more direct comparison between study areas, vertical-axis units are the percentage of total rank changes, and horizontal-axis units are rank changes as a percentage of the total number of tracts for the study area.

out. Additionally, the subjective interpretations of the PCA components remained fairly stable across scales. This suggests that while scalar changes affect the PCA analysis and the numeric properties of the index, the identification of the drivers of vulnerability within a study area, based on a constant variable set, are not strongly dependent on the scale of aggregation used to define the study area. Overall, the SoVI algorithm seems fairly robust to minor changes in variable selection, as well as to changes in the scale at which it is applied, especially downscaling from the county to census tract level.

While the performance of the SoVI algorithm does not appear to be substantially influenced by scalar changes or, more precisely, to changes in the level of aggregation to which it is applied, it is sensitive to variations in its construction. Representations of vulnerability may be substantially different based on the decisions made in index construction, including differences in the sets of tracts in the highest vulnerability group. The algorithm is also sensitive to changes in study area location, suggesting that the geographic context in which the analysis is performed has an important impact on the behavior of the index. In other words, places matter. This comes as no surprise as we would expect variation in the results from study area to study area because local places are different in their social characteristics and how they map onto the landscape. There are, however, some general conclusions that can be drawn from our analyses. First, the only procedure that had a substantial impact in all three study areas was the manner in which the components were combined to create the final index values. For all three study areas, the variance weighted approach was substantially different from the first component only and equal weights approaches. Second, when the selection criteria were important, the Kaiser criterion appeared substantially different from at least one of the others. Finally, there was no predictable pattern to the impact of the rotation methods across study areas.

What implications does this sensitivity to changes in index construction have on future attempts to create vulnerability indices? The effect of changes in index construction on the representation of vulnerability requires some method for assessing the validity of these representations, and then visualizing with maps. At present, the adequacy of the representation of vulnerability produced by the index and visualization in maps can only be determined by local expert knowledge of an area. For example, Fig. 4 and Fig. 5 show vulnerability maps for each study area using different selection criteria. The results appear quite different from one another, and without local knowledge it is unclear which map is more accurate. Local geographic knowledge of the areas suggests that Fig. 4 (constructed with the original approach of Kaiser selection, varimax rotation, and equal weighted summing of the components) is a closer approximation than Fig. 5 to real-world patterns found in the cities. Applications of the SoVI algorithm using the original SoVI approach have produced good results based on local knowledge of the study areas (Cutter & Finch, 2008; Piegorsch *et al.*, 2007; Borden *et al.*, 2007; Boruff & Cutter, 2007; Cutter *et al.*, 2006; Boruff *et al.*, 2005). Nonetheless, in light of the sensitivity of the algorithm to changes in its construction, applications of

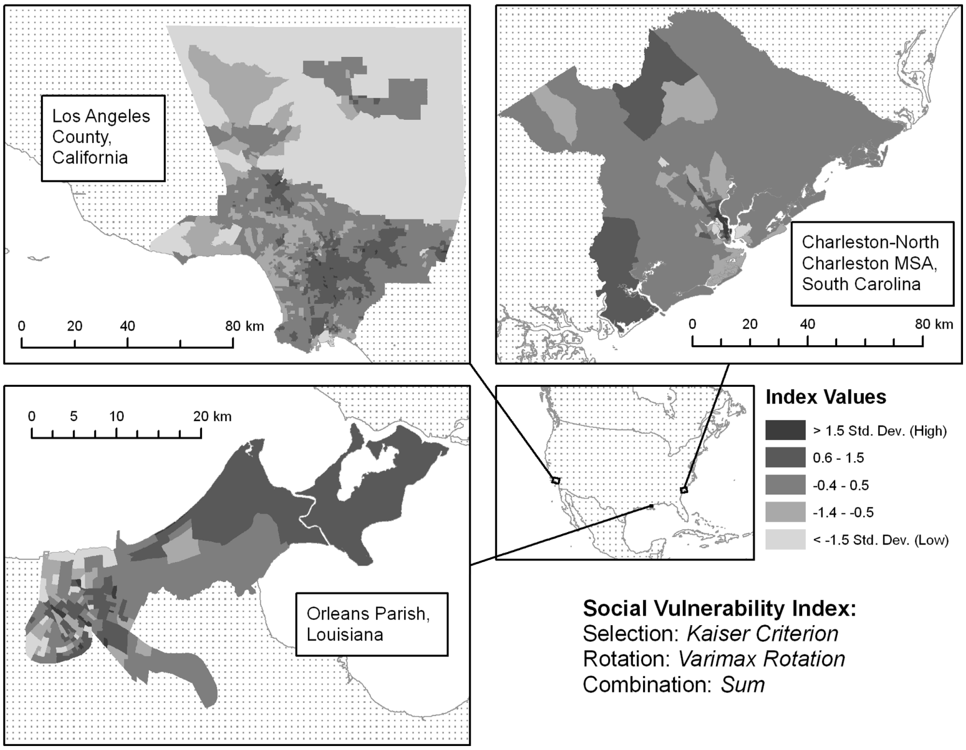

Fig. 4. SoVI values, constructed according to the original approach, using Kaiser criterion, varimax rotation, and sum component combination.

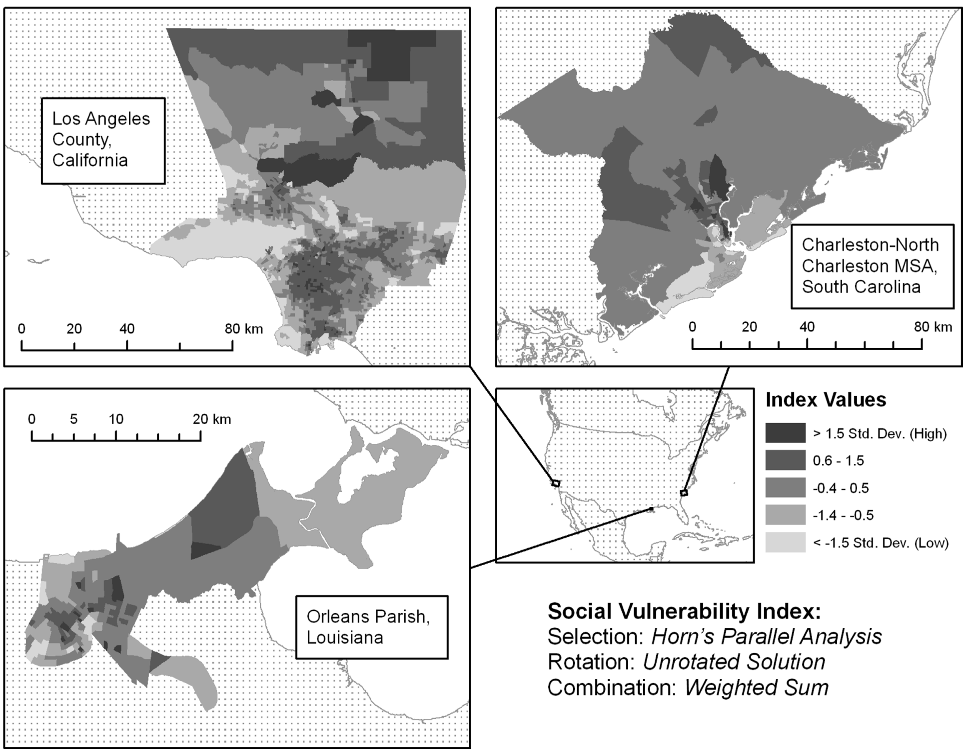

Fig. 5. SoVI values, constructed using Horn's parallel analysis, unrotated solution, and weighted sum component combination.

the SoVI should proceed cautiously and be coupled with expert guidance to ensure that the representations of vulnerability produced are reasonable and consistent with locally based geographic knowledge of the study area. The importance of expert judgment in the index creation process is not limited to validation of vulnerability representation. Expert judgment is also a critical element in the subjective interpretation of the components generated by the PCA (Step 5 of the algorithm). These components must be interpreted to determine whether they are assigned a positive, negative, or absolute value before they are combined to create the index. Future research on the SoVI algorithm could be designed to assess the impact of changes in the interpretation of components on the final index and provide more concrete guidance to this crucial element. Perhaps the same set of PCA components could be shown to a panel of local experts, and the consistency of their judgments could be measured. Input from such a panel also would be beneficial in determining not just the sensitivity of the algorithm to changes in the subjective decisions, but also the adequacy of the resulting representation of vulnerability. This could be performed by asking the local panel to "draw" a map of social vulnerability for their study area, which could then be compared to various approaches for index creation to aid in the selection of an "optimal" approach. If this were repeated for several study areas, it may be possible to reach conclusions not only about the sensitivity of the algorithm, but also to make recommendations on optimal approaches to index construction.

Our discussion on the importance of expert judgment in the creation and analysis of social vulnerability indicators also provides an opportunity for broader reflections on the ties between qualitative and quantitative approaches to the analysis of social vulnerability. Oftentimes, these two approaches to research are viewed as contradictory, but this obscures the important interplay between the two methodologies.

The creation of reliable quantitative indices of social vulnerability provides a meaningful tool that provides a comparison among places, which can assist in the allocation of preparedness resources and the selective targeting of areas that may need additional help in the aftermath of a natural or human-induced disaster. When mapped, the quantitative social vulnerability provides a useful mechanism for conveying information to nonspecialists such as policymakers, and allows them to visualize differences between the counties or between the neighborhoods within cities. By their very nature, however, indices are summary characterizations that may not always provide a complete understanding of the driving forces underlying social vulnerability or its distribution across the landscape. We must be careful when employing numerical vulnerability indices to realistically represent the underlying vulnerability, and not other hidden or related phenomena. We must also ensure that when applying these measures, any mitigation strategies will in fact decrease vulnerability (theoretically and practically), not just the value of the vulnerability index.

Where quantitative measures are weak, qualitative measures are strong. In-depth qualitative analysis, such as case studies, often proves indispensable in providing the context necessary for successful application of quantitative index constructions. As highlighted in the analysis above, the context in which quantitative indices are applied influences the way they behave. Important variables may be overlooked in practice if knowledge gained through qualitative analyses is not considered. And, in-depth case studies provide better information on the actual manner in which vulnerability manifests itself within a study area, providing information critical to the design of appropriate preparedness, response, and mitigation strategies.

Rather than solely informing quantitative analysis, however, qualitative studies are informed by them as well. The quick, broad assessments of vulnerability provided by quantitative indices are useful guides for the selection of study areas in which more intensive, qualitative analyses may be conducted.

Our analysis represents a first step toward understanding the sensitivity of the social vulnerability metric. We have demonstrated that the algorithm is robust to minor changes in variable composition and to changes in scale, but is sensitive to changes in its quantitative construction. In light of this sensitivity, we also have highlighted the need for expert guidance when constructing the index. The SoVI provides an understanding of the spatial dimensions of social vulnerability in diverse settings. Once a region's most vulnerable subareas are delineated in a systematic fashion, case-study research on the local drivers producing the pattern of vulnerability can begin, leading to reduced social vulnerabilities, and improved local resilience to environmental threats where and whenever they occur.

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