Temporal and spatial changes in social vulnerability to natural hazards

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Edited by B. L. Turner II, Clark University, Worcester, MA, and approved December 21, 2007 (received for review November 2, 2007)

During the past four decades (1960–2000), the United States experienced major transformations in population size, development patterns, economic conditions, and social characteristics. These social, economic, and built-environment changes altered the American hazardscape in profound ways, with more people living in high-hazard areas than ever before. To improve emergency management, it is important to recognize the variability in the vulnerable populations exposed to hazards and to develop place-based emergency plans accordingly. The concept of social vulnerability identifies sensitive populations that may be less likely to respond to, cope with, and recover from a natural disaster. Social vulnerability is complex and dynamic, changing over space and through time. This paper presents empirical evidence on the spatial and temporal patterns in social vulnerability in the United States from 1960 to the present. Using counties as our study unit, we found that those components that consistently increased social vulnerability for all time periods were density (urban), race/ethnicity, and socioeconomic status. The spatial patterning of social vulnerability, although initially concentrated in certain geographic regions, has become more dispersed over time. The national trend shows a steady reduction in social vulnerability, but there is considerable regional variability, with many counties increasing in social vulnerability during the past five decades.

disasters | inequality

Although significant advancements have been made in sustainability and vulnerability science, especially the conceptualization and representation of vulnerability within the human-environment system (1–6), nuanced differences in the definition of vulnerability between the risk-hazards and human-environmental research communities remain. The primary application arena also distinguishes these two communities. Human-environmental vulnerability research relates to large-scale global environmental processes, especially climate change and its local to global impacts (7, 8). Findings from natural-hazards and disasters research on vulnerability and resilience are incorporated into emergency management and hazards mitigation (9–12). Despite differences between the two research communities, both acknowledge that the composition of vulnerability is driven by exposure, sensitivity, and response (carrying capacity or resilience), and it requires measurements of both environmental and social systems, the latter being less prevalent in the literature. This paper adds to the paucity of empirical literature on the vulnerability of social systems through an examination of the historical variability in natural-hazard vulnerability, or social vulnerability.

Social vulnerability is a measure of both the sensitivity of a population to natural hazards and its ability to respond to and recover from the impacts of hazards. It is a multidimensional construct, one not easily captured with a single variable. There is ample field-based evidence for understanding the characteristics of people and social groups that make them more sensitive to the effects of natural hazards and reduce their ability to adequately respond and recover (13, 14). Race/ethnicity, socioeconomic class, and gender are among the most common characteristics that define vulnerable populations, along with age (elderly and children), migration, and housing tenure (renter or owner). For example, the literature has cited many reasons why the elderly are more vulnerable in the event of a disaster: physical limitations that influence their inability or unwillingness to comply with mandatory evacuation orders; postdisaster psychological stress that impairs recovery and increases the need for additional social services; declining cognitive abilities to process hazard information necessitating specially targeted risk communication or warning messages; and fewer economic resources to repair damaged homes, especially by elderly residents on fixed incomes (15–18). Thus, the greater the proportion of elderly in a community, the more vulnerable it is and the longer it will take for the community to fully recover from the disaster's aftermath.

There have been some notable attempts to measure vulnerability. There are many national-level hazards and disasters indicator studies that incorporate social characteristics such as population numbers and distributions as a method for defining population exposures to a variety of hazard agents (19–25). Other studies incorporating vulnerability metrics focused on human-environmental systems at different subnational spatial scales: within India (26), U.S. watersheds (27), U.S. Great Plains counties (28), and the Yaqui Valley, Mexico (29). More detailed vulnerability metrics on human-environmental systems used subcounty enumeration units within the United States: Georgetown County, SC (30); Revere, MA (31); and Hampton Roads, VA (32). Methodological difficulties, data quality and access issues, and conceptual shortcomings within social vulnerability science limit the development of consistent measures of social vulnerability to natural hazards.

Results

The shortcomings noted above led to the development of the Social Vulnerability Index or SoVI (33). The SoVI provides a county-level comparative metric of social vulnerability to natural hazards based on the underlying socioeconomic and demographic profile.

Consistency of Principal Components. The percentage of the variation among U.S. counties explained by the SoVI varies from 73% to 78% (Table 1). The number of components changes slightly from decade to decade, ranging from 9 to 12 (Table 1). In all decades, the dominant component was socioeconomic status. The remaining underlying dimensions of social vulnerability remain consistent during the decades as well. These components, broadly described as the level of development of the built environment, age, race/ethnicity, and gender, account for nearly half of the variability in social vulnerability among U.S. counties (Table 1).

A number of unique components appear only in a single decade. Suburbanization (number of building permits) assumed

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Author contributions: S.L.C. designed research; S.L.C. performed research; S.L.C. and C.F. analyzed data; and S.L.C. and C.F. wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

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Table 1. Construction of the SoVI 1960–2000

	1960	1970	1980	1990	2000
% variance explained	72.7	73.2	77.5	77.9	78.1
No. of components	9	11	12	12	11
Major components (% variance explained)	Socioeconomic status (18.4)	Socioeconomic status (15.3)	Socioeconomic status (13.9)	Socioeconomic status (13.3)	Socioeconomic status (14.7)
	Development (12.5)	Age (11.2)	Development (13.4)	Age (11.8)	Age (13.2)
	Age (8.6)	Rural (8.0)	Age (10.3)	Development (8.9)	Development (13.1)
	Age (elderly) (7.3)	Employment & gender (7.8)	Race & gender (8.8)	Rural (7.2)	Rural (8.9)
	Employment & gender (6.9)	Development (7.6)	Gender (6.4)	Race & gender (6.9)	Race & gender (8.2)

*The naming conventions for the components and representative variables include the following: Socioeconomic status (% poverty, % population with less than high school education, per capita income, median house value); Age (median age, % under 18, % over 65, % Social Security beneficiaries, birth rate); Development (commercial establishments, manufacturing establishments, housing units, new residential housing unit permits, earnings in all industries); Rural (% employed in agriculture, mining, fishing, or forestry; % rural farm population; % land area in farms); Race/ethnicity (% Asian, % African American, % Native Americans, % Hispanic); Gender (% female, % female-headed households, % female participation in the labor force); Employment (% employed in transportation, communications, and other public utilities; % employed in services; community hospitals per capita; % labor force participation).

importance in 1970. By 1980, gender, specifically high percentages of women in rural areas, emerges as a separate indicator, and extreme wealth and civic engagement (percent voting) became important as well. In 1990, the economic value of industries and value of property surfaces as a driving force of social vulnerability. In the 2000 SoVI, aspects of immigration (foreign-born residents) assumed more importance as a unique component, as did the economic dependence of counties.

Mapping Social Vulnerability. To illustrate the geographic patterns in the county SoVI scores, we classified the visualization of mapped scores using standard deviations from the mean for each decade. Because our primary focus is on the extremes of the distribution, we define social high and low vulnerability as those counties with SoVI scores greater than two standard deviations from the mean (high vulnerability $\geq +2$ SD; low vulnerability ≤ -2 SD). To determine the patterns of similarity and dissimilarity in the clustering of social vulnerability, we examined the spatial autocorrelation among the counties. For this analysis, only those counties in the conterminous United States were used (Alaska and Hawaii were deleted because of their lack of spatial contiguity). We used the GeoDa software to calculate the spatial statistics (34). The global spatial statistics measure spatial dependence based on simultaneous measurements from many locations (35). The local indicator of spatial autocorrelation (LISA or the Local Moran's I) captures the local variability (36) and identified clusters similarity (high and low social vulnerability).

Fig. 1 shows the geographic pattern of social vulnerability for each decade. In 1960, the most socially vulnerable counties are concentrated in the Southwest, north-central Great Plains, and lower Mississippi Valley, and in Florida and Hawaii. The least vulnerable counties in 1960 are in New England, the upper Great Lakes, the Pacific Northwest, and Alaska. For 1970, the pattern of high social vulnerability in the Southwest shrank, and a new area emerged along the U.S.–Mexico border regions of Texas. The lower Mississippi Valley and the Upper Great Plains retained their placement in the high vulnerability category. Interestingly, the pattern of low social vulnerability showed regional shifts, with many of the 1960 counties moving into the moderate or average range. There was strong spatial clustering in both the 1960 SoVI (Moran's $I = 0.49$) and the 1970 SoVI (Moran's $I = 0.51$) (Table 2). The 1960 decade showed the greatest number of significantly clustered counties at the extremes, high vulnerability (517 counties or 16.7%), and low vulnerability (636 counties or 20.6%) (Table 2). For the 1970 SoVI, there were fewer significant spatial clusters of high vulnerability (355 counties or 11.4%) and low vulnerability (597 counties or 19.3%).

For 1980, the extremes in social vulnerability still showed some distinct spatial patterns. For example, the areas of high social vulnerability remained along the U.S.–Mexico border; in the Native American lands in the Southwest and Great Plains, in the lower Mississippi Valley, and in Alaska and Hawaii. The distribution of least vulnerable counties in 1980 continued a westward shift, showing concentrations in the Rocky Mountain and Great Basin area (Fig. 1). A vestige of low-social-vulnerability counties remained along the eastern flanks of the Appalachians in Virginia and North Carolina. The decline in significant spatial clusters reached its low point in the 1980 SoVI (Moran's $I = 0.32$), with only 293 counties (9.4%) in the high-vulnerability cluster and 344 counties (11.2%) in the low-vulnerability cluster.

By 1990, the lower Mississippi Valley, the lower Rio Grande Valley, and the Great Plains continue to show greater social vulnerability. Most of Alaska remains in the highest category, but Hawaiian counties improve to average levels of vulnerability. There is an increase in the number of eastern counties in the least vulnerable category, and a decrease in the western counties in this same classification. The overall spatial clustering remained level (Moran's $I = 0.38$), but there were some slight increases in the local clusters of high vulnerability (344 counties or 11.1%) and low vulnerability (448 counties or 14.5%).

Finally, the 2000 SoVI shows a more dispersed pattern of social vulnerability nationally, although concentrations of high social vulnerability remain in the U.S.–Mexico border counties, the Deep South, the upper Great Plains, the Southwest, and in California (Fig. 1). The pattern of low social vulnerability appears concentrated in the Rocky Mountain counties. There was little change in the significance of the overall spatial clustering from the previous decade (Moran's $I = 0.36$), but there was a noticeable decline in the number of significant clusters locally for those high-vulnerability counties (239 counties or 7.8%) and low-vulnerability counties (342 counties or 11.1%). What this finding suggests is that the spatial clustering of social vulnerability is become less concentrated in specific regions over time (Table 2).

Three counties appeared among the top 25 most vulnerable counties in each decade: Kings (NY), New York (NY), and

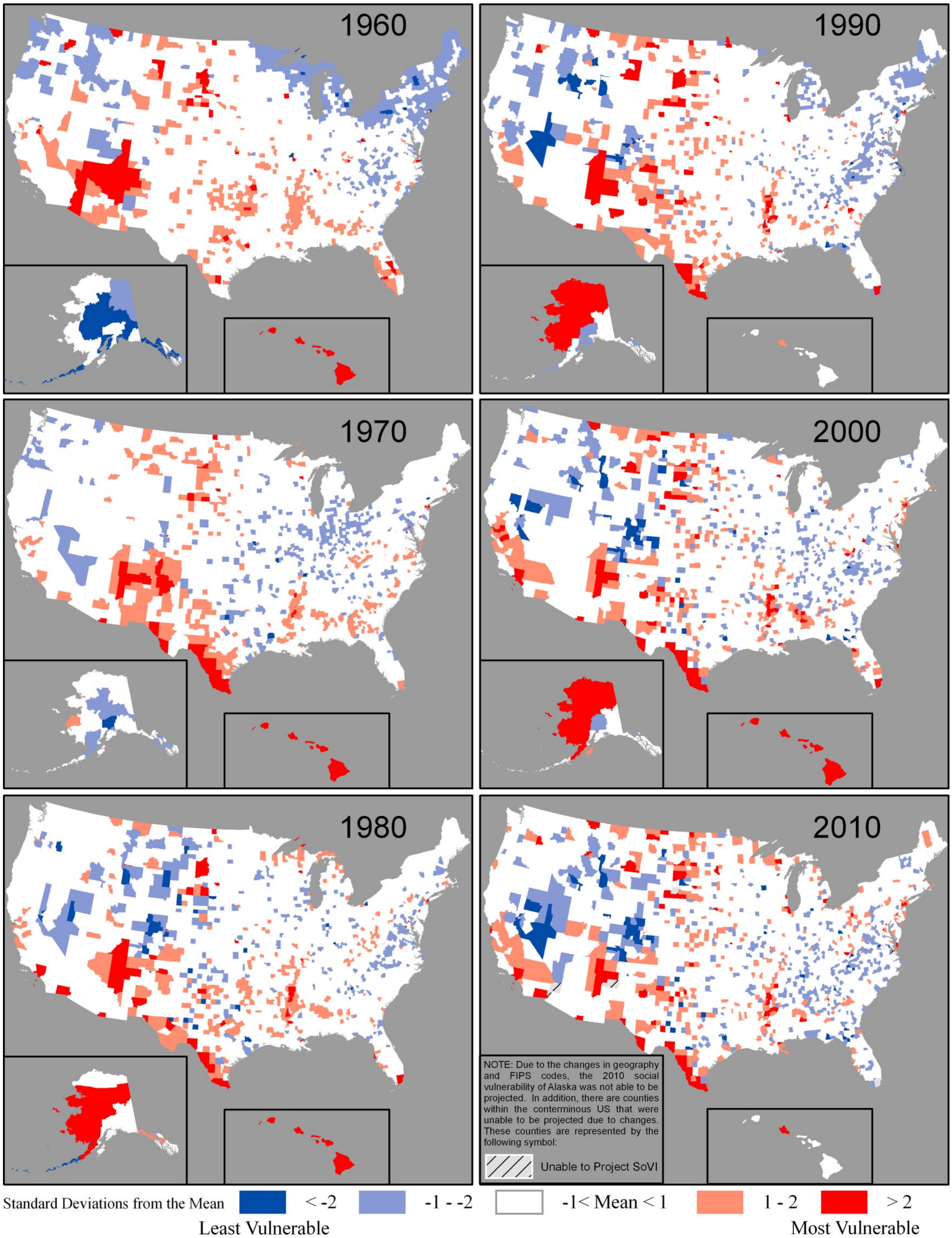

Fig. 1. Social vulnerability 1960–2010.

Shannon (SD). In fact, New York was the most vulnerable county for all decades. The components most frequently associated with areas of high social vulnerability are urban development, race and ethnicity, and low socioeconomic status. In comparison, only five counties appeared in the least vulnerable category for three decades: Gilpin, Hinsdale, Pitkin, and Summit (CO), and Teton (WY). Characteristics associated with least vulnerable counties are affluence, a relatively homogenous population (White), and a youthful population (older than 5 and younger than 65 years of age).

Local Places, Local Changes. Although it is instructive to see the national pattern and trends in social vulnerability, more localized analyses provide an understanding of those places that are experiencing significant changes in their social vulnerability and show how such changes might influence emergency preparedness and response in the future. For example, has the social vulnerability of County A increased, decreased, or stayed relatively the same historically? More importantly, on the basis of this historical trend, what level of social vulnerability might be expected in County A in 2010?

Table 2. Spatial clustering statistics and LISA cluster categories, 1960–2000

	1960		1970		1980		1990		2000	
Global Moran's *I**	0.495		0.507		0.323		0.377		0.367	
LISA cluster categories	Count	% of total	Count	% of total	Count	% of total	Count	% of total	Count	% of total
Significant local spatial clusters										
High vulnerability (high–high)	517	16.7	355	11.4	293	9.4	344	11.1	239	7.7
Low vulnerability (low–low)	636	20.5	597	19.2	344	11.1	448	14.4	342	11.0
County spatial outliers										
Low–high	25	0.8	36	1.2	55	1.8	56	1.8	60	1.9
High–low	42	1.3	46	1.5	70	2.2	60	1.9	58	1.9
No statistically significant spatial clustering										
Counties	1,880	60.7	2,073	66.7	2,347	75.5	2,203	70.8	2,410	77.5
Total	3,100	100.0	3,107	100.0	3,109	100.0	3,111	100.0	3,109	100.0

*The Moran's *I* statistic is interpreted as follows: a value close to + 1 represents strong similarity between the values of the SoVI at all pairs of locations; a value of −1 indicates dissimilarity; while a value of zero represents a random pattern.

To answer these questions, the individual SoVI scores for each county for each decade were transformed to *z*-scores (based on the national mean score per decade) to ensure comparability over time for each individual county. By using a simple linear regression, a line of best fit was calculated with each county's transformed SoVI scores from 1960 to 2000. The resulting R^2 assessed the strength of the relationship between the line of best fit and the decadal SoVI points, whereas the slope of the line of best fit assessed directionality. Thus, a positive slope indicated increasing social vulnerability, and a negative slope indicated decreasing social vulnerability. An *F* statistic was used to determine whether the strength of the relationship was considered statistically significant at a 0.01 significance level.

There were 484 counties that had statistically significant linear trends in their social vulnerability through time based on the *F* statistic; the remaining 2,657 counties showed no statistically significant linear trend. To determine the direction of the trend, these counties were classified by using the slope breaking points of 0.5. The breakpoint represents the median of the line of best fit values (range: −1.22 to +1.40) for the 484 counties with statistically significant trends. There were 46 counties with a significant slope of >0.5, thereby representing counties with an increase in social vulnerability. On the other end of the spectrum, there were 40 counties with a significant slope < −0.5, demonstrating a decrease in social vulnerability. The remaining 398 counties had a statistically significant relationship between the SoVI points and the line of best fit; however, the linear slope was not large enough to suggest an obvious temporal increase or decrease.

Population change and population density have a significant impact on the temporal trends of social vulnerability. Counties increasing in social vulnerability are doing so because of extreme depopulation or population growth. For example, the depopulation of the Great Plains had a direct influence on many components that increase social vulnerability that are evident from the mapped patterns (Fig. 1). Consider McIntosh, Towner, and Divide counties in North Dakota. All of these counties experienced a 49–59% decrease in population from 1960 to 2000. As the counties lost younger people, the remaining population aged and eventually became dependent on social services and government support for their livelihoods. With fewer people, the civilian working force decreased, influencing the economic vitality of the county, and led to reduced access to critical facilities, such as hospitals and physicians. In 2000, Divide County's population was 27.6% elderly (65+ years of age) compared with the U.S. population distribution (12.4% elderly).

The opposite influence of population change is represented in the counties that increased in social vulnerability through time. Consider Orange County, CA, which was in the moderate vulnerability category in 1960 but by 2000 was among the most socially vulnerable in the nation. Orange County experienced significant population growth because of its proximity to Los Angeles, Long Beach, and Santa Ana. Since 1960, the population of Orange County, CA, increased by ≈300%. The population increase, largely the result of an influx of recent immigrants that resulted in a more diverse population, prompted more development; both factors contribute to social vulnerability to natural hazards.

There are also examples of counties experiencing socioeconomic changes that decrease social vulnerability. In 1960, Teton County, WY, Pitkin County, CO, and Mono County, CA, were rural counties with small populations and were categorized with moderate levels of vulnerability. The counties experienced drastic increases in population over the 40-year time span, ranging from doubling to quintupling. Pitkin County's population increased by ≈525%, Teton County's increased by 496%, and Mono County's increased by 481%. Instead of increasing the vulnerability, the population growth actually reduced it because of the characteristics of in-migrants: white and wealthy individuals who helped stimulate an economic boom in the tourism sector, the predominant economic driver in the counties.

Population growth as a single variable tends to increase social vulnerability. Yet, one of the contributions of the SoVI is that it enables us to examine the multidimensionality of such growth by examining changes in the characteristics of the population and its subsequent impact on the county's overall vulnerability.

Anticipating Future Vulnerability. What might the social vulnerability of U.S. counties look like in 2010? One the basis of the linear trend for each county across the five time stamps (1960, 1970, 1980, 1990, and 2000), we expect 88 counties in the most vulnerable category, representing 2.8% of the total counties in 2010. We expect that the least vulnerable category will contain 55 counties or 1.8% of the total counties. The projected spatial pattern of social vulnerability in 2010 is similar to previous decades (Fig. 1). There will be concentrations of high social vulnerability along the lower Mississippi River, the Southwest, the Texas–Mexico border, and California. However, the most dominant area of high social vulnerability will be located in the North Central United States. The counties with increased social vulnerability in 2010 are in North Dakota, South Dakota, and Montana and are associated with Native American Reservations or the depopulation of the Great Plains. As in all other decades, New York County, NY, will be the most vulnerable county in the predicted 2010 SoVI, followed by Kings County, NY, Bronx County, NY, and San Francisco County, CA.

The least vulnerable counties in 2010 will be located in the mountainous West, especially in Colorado, Nevada, and Idaho. The dominance of Colorado counties (Summit, Pitkin, Hinsdale, and San Miguel) as the least vulnerable will continue.

Discussion

As the composition of American society changed during the past five decades, so too has our social vulnerability to natural hazards, as measured by the SoVI. Those most socially vulnerable populations were initially concentrated in the Deep South (race, gender, and socioeconomic status), the Southwest (Native American lands), and in Florida (elderly), but over time the pattern of social vulnerability to natural hazards in the United States changed. By 2000, the social vulnerability was greatest in the lower Mississippi Valley region, in South Texas border lands, in California's Central Valley, and in the upper Great Plains. Pockets of high social vulnerability remained in the Deep South and Southwest.

The driving forces behind increased social vulnerability vary between regions and across counties. For example, contributing components in the lower Mississippi Valley counties were race and socioeconomic status; along the Texas–Mexico border counties, it was ethnicity and poverty, whereas in the Great Plains counties, it was a combination of economic dependence and an aging population brought on by depopulation. The overall result was a distinct geography of social vulnerability to natural hazards based on the SoVI metric.

Many counties in the United States are experiencing a significant increase or decrease in social vulnerability, suggesting that the county's susceptibility to hazards and their potential ability to recover from them has changed. On the basis of this analysis, 46 counties had significant increases in social vulnerability and 40 counties had significant decreases in social vulnerability from 1960 to 2000. As these counties experience changes over time attributable to components such as increasing development and diversity, the driving forces contributing to the social vulnerability need to be identified in current hazard assessment and mitigation plans to make them more responsive.

The projected social vulnerability in 2010 identified priority areas that should be addressed now, to improve the resilience of communities. The SoVI of 2010 projects that high-social-vulnerability concentrations will continue along the lower Mississippi River, the Texas–Mexico border, southern California, the northern Great Plains, and in the nation's largest metropolitan areas.

Social vulnerability is born from inequality and its social and political consequences (37). In many ways, it mirrors the geography of inequality (38) and poverty (39). Within the context of natural hazards, the SoVI helps determine which places may need specialized attention during immediate response and long-term recovery after a natural hazard event, given the sensitivity of the populations and the lowered capacity to respond. Although not as readily apparent in the visualization of SoVI, metropolitan counties continue to be among the most socially vulnerable over time driven by components such as development density and large diverse populations. In a broader context of social policy, the SoVI has applicability in the identification of counties that are most in need for socially based services—health, welfare, housing, education—that would not improve the quality of life of residents but would improve their ability to respond to and recover from disaster events.

Although there is much exciting work on the development of vulnerability and resilience indices, there are serious obstacles to validating such metrics. First, the concepts of vulnerability and resilience are complex, and their meanings are often contested within their respective research communities. Thus, establishing viable metrics for measuring vulnerability and resilience and at the appropriate scale becomes problematic. Second, using natural hazard losses as validation is an oft-suggested approach, where losses would be correlated with social vulnerability. However, this approach assumes that the most socially vulnerable populations have the most to lose (economically), which is not the case. In correlating property losses with social vulnerability, we would expect an inverse relationship (high social vulnerability; low dollar losses), yet this assumes that the losses are evenly distributed throughout the nation, which they are not. Just as there is a spatial pattern of social vulnerability, there is a geographic distribution of natural hazard losses, with some regions exhibiting more hazard-proneness (e.g., coastal areas, seismic zones, and floodplains) or exposure than others (40, 41). Third, one could validate SoVI in a postevent situation such as Hurricane Katrina, where we could predict the differential recovery outcomes on the basis of the preexisting social vulnerability. This natural experiment is underway and it is too soon to judge, but such an approach could provide for a true validation of the SoVI metric. Finally, once the 2010 Census is completed and released, we will be able to test how close our projected SoVI was to the actual computation.

The identification of socially vulnerable counties and regions and the components contributing to social vulnerability is a critical element for emergency preparedness, immediate response, mitigation planning, and long-term recovery from disasters. As we have shown, social vulnerability to natural hazards is dynamic. The temporal and spatial changes in social vulnerability based on our historic assessments suggest that for future preparedness, response, recovery, and mitigation planning, a one-size-fits-all approach may be ineffective in reducing social vulnerability or improving local resilience to the impacts of hazards. Instead, a more flexible approach that nests place-specific local variability within the broader federal policy guidelines and frameworks is suggested.

Materials and Methods

SoVI. Working from the extant literature on hazard impacts and disaster response generated by field studies, a broad list of characteristics that influence social vulnerability was generated (e.g., socioeconomic status, gender, and housing tenure) (14). More than 250 variables initially were collected from 1990 U.S. Census sources for all U.S. counties. A number of statistical tests were performed to eliminate correlated variables, resulting in a set of 42 normalized (to percentages, per capita, or per square mile) independent variables (33). A principal components analysis (PCA) was used to further reduce the 42 variables into broadly based dimensions of social vulnerability (hereinafter referred to as components). To simplify the underlying structure of the dimensions and to produce more statistical independence between them, a varimax rotation was used. We used the Kaiser criterion (eigenvalues > 1.00) to generate the total number of components. These procedures reduced the 42 variables to 11 independent components accounting for 76.4% of the explainable variance in the data (in the original 1990 case). The SoVI score was created by summing all of the independent component loadings for each record, in this case the county. As noted in the original article, there is no theoretical justification for assuming the relative importance of one factor over another in the construction of the index. In the absence of such a theoretical basis, the factors were equally weighted to produce the composite SoVI score for the decade.

The SoVI is a unitless, spatial measure, and its importance is in its comparative value across geographic locations, not its absolute value. We can think of SoVI as an algorithm for quantifying social vulnerability rather than a simple numerical index that can be ground-truthed with direct observational data. For interpretive reasons, high social vulnerability is defined as those counties with SoVI scores ≥ 2 SD from the mean, whereas counties low in social vulnerability have SoVI scores ≤ 2 SD from the mean.

Historical Reconstruction of Social Vulnerability. To analyze changes in social vulnerability over time and across space, the original computation of SoVI was rerun for 1960, 1970, 1980, 1990, and 2000 by using the same variables and methodology. There were many challenges during the reconstruction of SoVI, including changes in the spatial enumeration unit and the consistency of variables throughout time.

Spatial Enumeration. The unit of analysis was the county level for the United States because it was assumed that once established, county boundaries rarely

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change with every decennial U.S. Census. The assumption was not entirely correct because there are significant changes in the county geography of the United States from 1960 to 2000 that warrant a brief discussion. In 1960, there were a total of 3,128 county entities (3,096 counties; 30 independent cities in Virginia; Baltimore, MD; and St. Louis, MO). Some of the significant changes through time include the following: the merger of Washabaugh and Jackson counties in South Dakota into a single entity, Jackson County, in 1979; the creation of Cibola County, NM, in 1981 and La Paz County, AZ, in 1982; the creation of Yakutat Borough, AK, in 1992; and the renaming of Dade County, FL, to Miami-Dade County in 1999. By 2000, there were 3,142 county units (3,097 counties; 41 independent cities in Virginia; Baltimore, MD; St. Louis, MO; and Carson City, NV). Each decadal SoVI was created and displayed by using the appropriate decadal geography.[†]

Data Comparability. One of the difficulties in examining the historical changes in vulnerability is comparability of Census variables. There is richness in the historical Census material, but often there are not exact variable matches from one decade to another. Not all of the variables were collected for all time periods, and in many instances, there was a change in the definition of the variable. There are numerous examples that illustrate this point—mostly in how the Census Bureau defines race and ethnicity (e.g., Hispanic, Asian, or Hawaiian Islanders). For example, one measure of ethnicity, Hispanics or the percentage of persons of Hispanic descent, was not always collected as such. In 1960, the measure was not available at the county level, and in 1970 it was labeled as the percentage of persons of Spanish heritage. Starting in 1980, there was an explicit variable measuring the percent of Hispanic population. In other cases, some variables simply were not collected in the earlier decades (e.g., in 1960, number of physicians per 100,000) or if collected, they were defined differently (number of physicians changed to number of people used as healthcare practitioners and technical occupations in 2000). Therefore, the equivalency of the variables over the five decades is limited by the reliance on the U.S. Census sources. In rare instances, we had to resort to closely related variables, such as the change in the threshold designator for higher income—starting with families earning more than $15,000 in 1960 to families earning more than $100,000 in 2000.

Another issue was missing values for some variables. Factor analysis in general, and PCA specifically, cannot be performed with missing values. In those counties or decades where data are missing, we substituted the mean value for the state for the missing values for that variable. This accounts for the slight difference between the original SoVI computation in 1990 (11 factors with 76.4% explained variance) and the rerun 1990 SoVI (12 factors with 77.99% explained variance). Statewide means were calculated from the variable values from the available counties within the state. We recognize that assigning a mean value for a missing variable for cases may not accurately represent the true vulnerability based on that specific variable. Although it is not a perfect solution to missing data, we felt it was more important for the research to include all U.S. counties in the analysis (a geographic consideration) and to include all years (a temporal consideration) in the overall analysis of the patterns of social vulnerability in the United States.

[†]A description of the complete county geography changes (metadata) used in the construction and mapping of SoVI can be found at www.cas.sc.edu/geog/hrl/SHELDUSmetadata.html. Alaska counties provide a unique challenge for historical analyses. Gaining statehood rather late (1959), the early census divisions were significantly altered to boroughs and census areas in the 1980s and further changed to boroughs and counties in subsequent censuses. The geographic areas were changed as were the names and identifying codes. For example, in the 1990s, Yakutat borough was formed from pieces of other divisions. These changes are noted in the U.S. Census documentation of changing geography (www.census.gov/geo/www/tiger/ctychng.html).

ACKNOWLEDGMENTS. This research has been supported by the National Science Foundation (Grant CMS0220712) and the U.S. Department of Homeland Security's Center of Excellence for the Study of Terrorism and Responses to Terrorism (START) (Grant N00140510629).

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