

1. Introduction

The goals of this research are to identify the factors that contribute to a human population's vulnerability to meteorological hazards and to locate areas in the United States that are the most vulnerable. This requires looking both at the occurrence of hazards and the socio-economic factors that contribute to vulnerability. While there are many different ways of addressing this issue, this study focuses on a quantitative approach. The results of vulnerability assessments help emergency managers and other planners identify at-risk populations and prepare for disasters.

2. Data

Socio-economic data is obtained from the U.S. Statistical Abstract, which contains data from the Census and other federal and state sources (Census 2009). Detailed results of the 2010 Census will not be available until March 2011. Although intercensal estimates of Census data are made, it is preferable not to introduce an additional source of error by using estimated data instead of the complete counts performed in the Census. For this study, the county is used as the level of analysis, and all of the contiguous United States is included. The census tract level will be used in the future, but since there are fewer counties than census tracts, using counties involves a smaller amount of data and serves as a good test for the methodology. Forty socio-economic variables identified by Cutter et al. (2003) are used in this analysis.

3. Quantitative Methods: What is the SoVI?

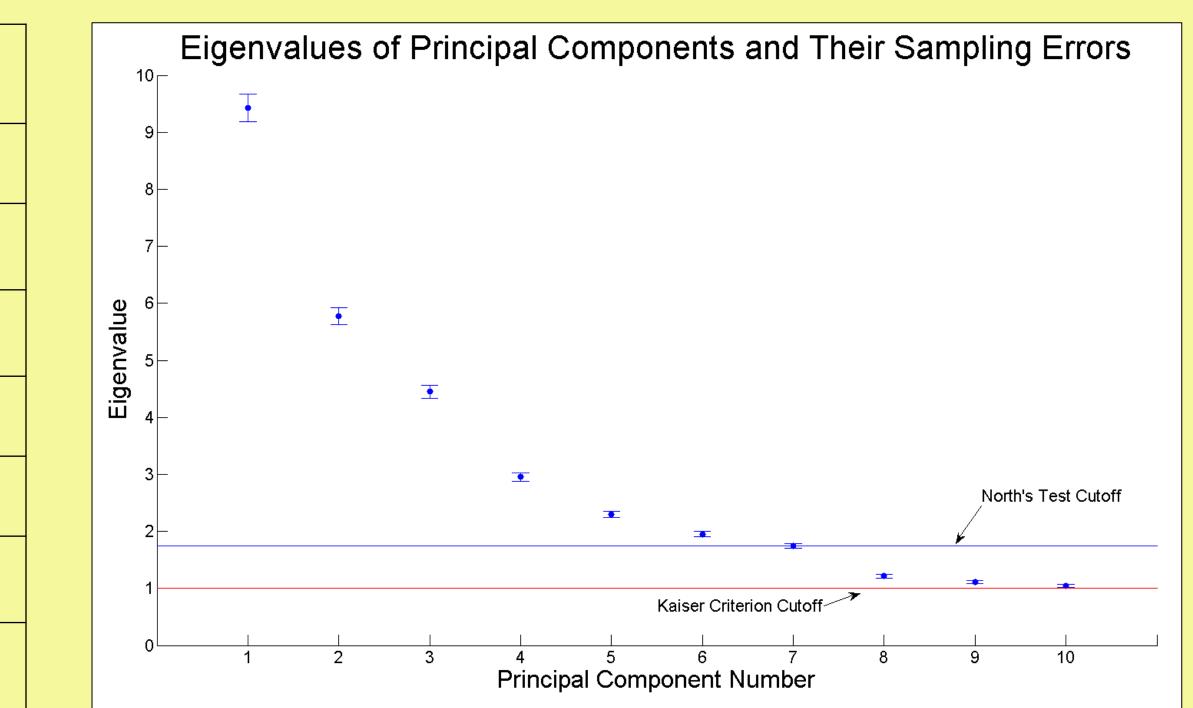
Researchers and emergency managers have employed several different quantitative models to calculate vulnerability scores. The one that is examined here is the Social Vulnerability Index (SoVI), which was developed by Cutter et al. (2003). This index is designed to quantify only the vulnerability of populations that is caused by socio-economic conditions. The SoVI uses principal components analysis (PCA), which compresses a large number of variables into a small number of components. These components are linear combinations of z-scores of the original variables, and they represent most of the variability in the data. PCA associates each component with an eigenvector and eigenvalue.

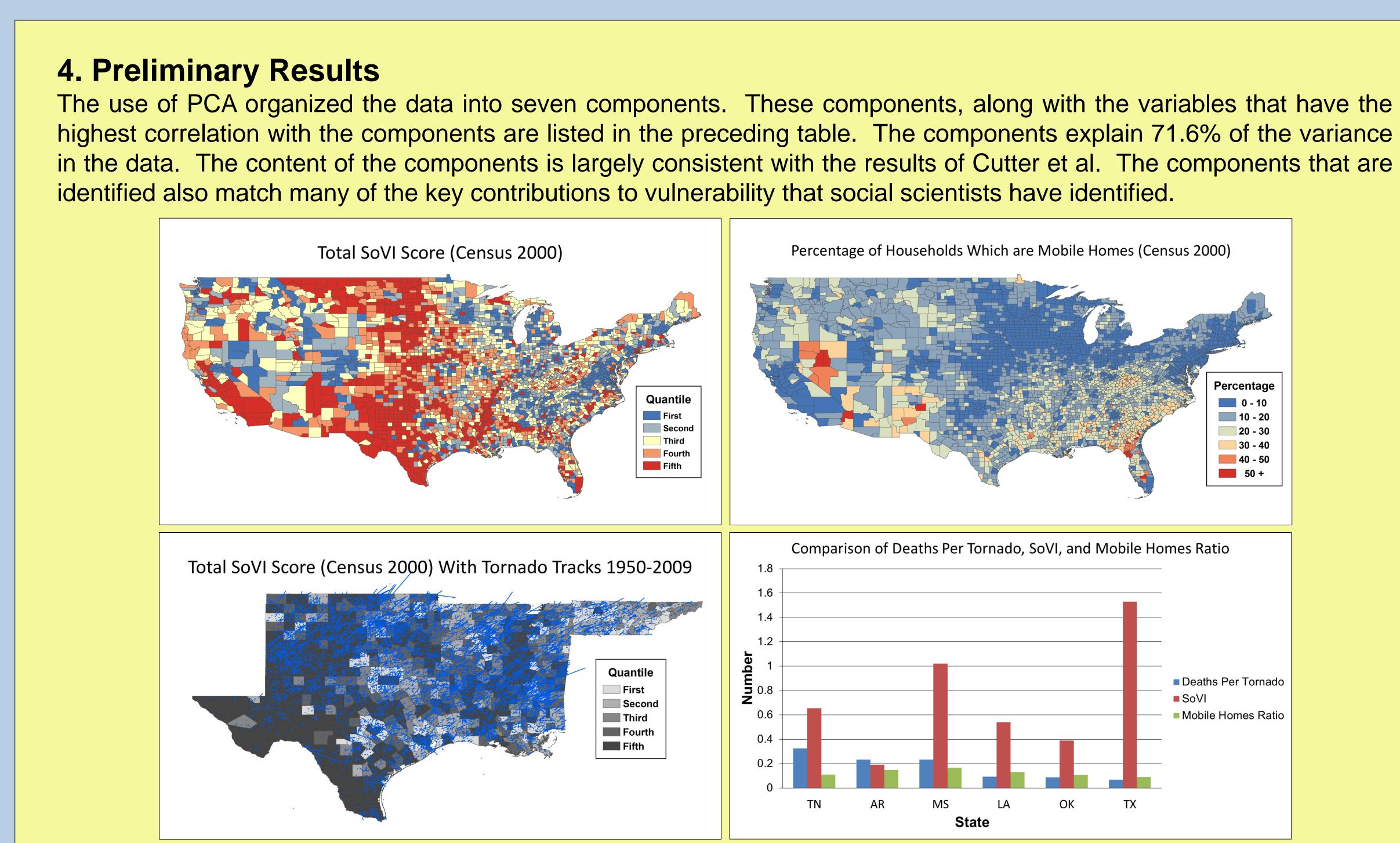
North's test is used to select the number of components that will be retained (North et al. 1982). North's test requires the retention of only eigenvalues with a small enough sampling error to be distinguished from neighboring eigenvalues. The sampling error is calculated using $\delta \lambda \sim \lambda (2/n)^{1/2}$. The use of North's test differs from Cutter et al. (2003), which used the Kaiser criterion to select the number of eigenvalues to be retained. When using the Kaiser criterion, all components with eigenvalues greater than 1 are retained. This is an arbitrary distinction that does not consider the variability among the eigenvalues. It generally retains too many components. After selecting components, A varimax rotation is used to maximize the loadings for each component onto a small number of variables. Each component is scaled so that a positive score indicates higher vulnerability (i.e. some scores are multiplied by -1). A county's SoVI score is found by taking the sum of each of its adjusted component scores.

Principal Components	First Variable	Variance Explained
Socio-economic Status	Percent pop. in poverty	23.6%
Age	Percent pop. < 5 years old	14.4%
Infrastructure	Manufacturing earning density	11.1%
Rural Agriculture	Percent pop. rural farmers	7.4%
Gender	Percent pop. female	5.7%
Growth	Net international migration	4.9%
Employment Stability	Percent pop. service industry	4.4%

Using GIS to Assess Vulnerability to Climate Hazards in the Southern United States

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Some preliminary results are presented above. The percentage of mobile homes is shown to highlight a particular vulnerability case: the inability of mobile homes to withstand tornadoes. It is well known that states such as Mississippi and Arkansas have a disproportionately high number of tornado-caused deaths. It is also known that a high percentage of deaths occur in mobile homes. Geographic Information Systems (GIS) can be used to superimpose several distinct variables, and a simple example of this is shown above. Some notable patterns are revealed by mapping the SoVI score and its components. The areas of highest vulnerability occur in large cities, the Great Plains, the lower Mississippi River Valley, and southern California. All of the areas have high SoVI scores for different reasons. The final graph shows that in the Southeast, a higher number of fatalities per tornado tend to occur in states with a higher percentage of mobile homes, but not necessarily a higher average SoVI. These simple examples demonstrate that there is future potential for the combination of social vulnerability and hazard data, but that one must be careful when drawing conclusions from the SoVI.

5. Future Work

This is work is still at a very early stage. Future additions include, but are not limited to, integration with more hazard data, the use of updated Census data, the creation of more GIS data, and an analysis of the uncertainty of vulnerability indices.

6. About SCIPP

This work is funded by the Southern Climate Impacts Planning Program (SCIPP) SCIPP is a member of the National Oceanic and Atmospheric Administration (NOAA) Regional Integrated Sciences and Assessments (RISA) program. Based at the University of Oklahoma and Louisiana State University, SCIPP conducts a variety of physical and social science research focused heavily on climate hazard preparedness across its 6-state region of Oklahoma, Texas, Arkansas Louisiana, Tennessee, and Mississippi. Visit <u>www.southernclimate.org</u> for more information on SCIPP.

7. References

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social Vulnerability to Environmental Hazards. Social Science Quarterly, 84, 242-261.

North, G. R., Bell, T. L., Cahalan, R. F., & Moeng, F. J. (1982). Sampling errors in the estimation of empirical orthogonal functions. Mon. Wea. Rev., 110, 699-706.

U.S. Census Bureau, Statistical Abstract of the United States: 2010 (129th Edition) Washington, DC, 2009; http://www.census.gov/statab/www/