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Brent Yarnal
Pennsylvania State University

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A METHOD FOR CONSTRUCTING A SOCIAL VULNERABILITY INDEX: AN APPLICATION TO HURRICANE STORM SURGES IN A DEVELOPED COUNTRY

LISA RYGEL[1], DAVID O'SULLIVAN[2] and BRENT YARNAL[3]
[1]*ESRI-Washington, D.C., 8620 Westwood Center Drive, Vienna, VA 22182;* [2]*School of Geography and Environmental Science, The University of Auckland, Private Bag 92019, Auckland, New Zealand;* [3]*Center for Integrated Regional Assessment, The Pennsylvania State University, University Park, Pennsylvania 16802 USA; (*Author for correspondence, E-mail: alibar@eesi.psu.edu; Tel: 1-814-863-4894, Fax: 1-814-863-7943)*

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Abstract. An important goal of vulnerability assessment is to create an index of overall vulnerability from a suite of indicators. Constructing a vulnerability index raises several problems in the aggregation of these indicators, including the decision of assigning weights to them. The purpose of this paper is to demonstrate a method of aggregating vulnerability indicators that results in a composite index of vulnerability, but that avoids the problems associated with assigning weights. The investigators apply a technique based on Pareto ranking to a complex, developed socioeconomic landscape exposed to storm surges associated with hurricanes. Indicators of social vulnerability to this hazard are developed and a principal components analysis is performed on proxies for these indicators. Overall social vulnerability is calculated by applying Pareto ranking to these principal components. The paper concludes that it is possible to construct an effective index of vulnerability without weighting the individual vulnerability indicators.

Keywords: vulnerability assessment, vulnerability indicators, vulnerability index, indicator weighting, Pareto ranking, social vulnerability, extreme weather events

1. Introduction

Although vulnerability has been an important theoretical topic in global change research for more than a decade (e.g., Bohle et al. 1994), vulnerability assessment has only become a noteworthy applied global change subject in the last few years (e.g., McCarthy et al. 2001). Vulnerability assessment is consequently immature, with most thematic areas and their methods still taking shape. One area of growing interest encompasses indicators of vulnerability (Alwang et al. 2001; Adger et al. 2004; Downing and Patwardhan, 2004). Vulnerability indicators are potentially useful tools for identifying and monitoring vulnerability over time and space, for developing an improved understanding of the processes underlying vulnerability, for developing and prioritizing strategies to reduce vulnerability, and for determining the effectiveness of those strategies.

Practitioners agree that the first step in a vulnerability assessment must be to determine which conceptual framework of vulnerability to use and, hence, which analytical definitions of vulnerability to use (e.g., Downing and Patwardhan 2004). For instance, Alwang et al. (2001) reviewed the vulnerability literature from economics (under which they included food security and sustainable development), sociology, anthropology, disaster management and natural hazards, environmental science (including global change), and health and nutrition. From this review, they concluded "practitioners from different disciplines [and even from different perspectives within the same disciplines] use different meanings and concepts of vulnerability, which, in turn, have led to diverse methods of measuring vulnerability" (Alwang et al. 2001, p. 2). Consequently, vulnerability indicators chosen for one context might not be appropriate for assessing vulnerability in other circumstances.

For example, in the context of national-level climate change impacts, Adger et al. (2004) defined nine categories of vulnerability indicators: economic well being; health and nutrition; education; physical infrastructure; institutions, governance, conflict, and social capital; geographic and demographic factors; dependence on agriculture; natural resources and ecosystems; and technological capacity. They also indicated potential variables for each of those categories and proxies for those variables; they then attempted to validate those proxies. For the category of economic well being, for instance, they identified national wealth, inequality, and economic autonomy as important variables and named gross domestic product (GDP) per capita, the Gini index (Yitzhaki 1979), and debt repayments as a percentage of GDP as potential proxies for those variables. In their validation exercise, they found that GDP per capita and the Gini index were good proxy indicators (i.e., they were statistically significant), but that debt repayments as a percentage of GDP was not.

Adger et al. (2004) then outlined four different approaches to developing composite indices: (1) constructing a single index by aggregating all relevant proxies, (2) a single index by defining geographical groupings, (3) separate indices representing different elements of vulnerability, and (4) vulnerability profiles for each geographical entity. Indeed, according to Alwang et al. (2001, p. 15), the first approach of Adger et al. – developing a composite index of vulnerability that reduces all variables to one number, that is comparable across time and space, and that is widely accepted by users and practitioners alike – is the "holy grail" of vulnerability assessment. There are problems with composite indices, however (Adger et al. 2004). A composite index does not indicate the structure and causes of vulnerability. A composite index can also diminish the importance of a single vulnerability factor by the process of averaging variables or indices, thereby suggesting that the area is not vulnerable when, in fact, it is extremely vulnerable on a single critical factor.

One of the more vexing problems in developing composite vulnerability indices is the method of aggregation (Adger et al. 2004). Should component variables or indices be averaged, or should some sort of weighting scheme be applied? If weights are used, how should they be determined – by quantitative methods or by expert judgment? If weights are used, how can they account for the fact that the relative importance of vulnerability indicators varies over space and time?

The purpose of this paper is to spotlight a method of aggregating indicators of relative vulnerability and, thereby, to create a context-specific composite index of vulnerability that does not suffer from the problems of averaging or weighting. To achieve that outcome, the paper will first describe the context of the study in Section 2, including the conceptual context, the regional setting, and the exposure of that region to one particular hazard: storm surges associated with hurricanes. Next, Section 3 of the paper will develop indicators of social vulnerability to this hazard. Integral to this process will be a principal components analysis. In Section 4, the paper will calculate overall (i.e., composite) vulnerability by applying Pareto ranking to these components and will present the results of this ranking, comparing it to the results obtained by simple averaging of the components. The paper concludes in Section 5 that it is possible to construct an effective index of vulnerability without weighting the individual vulnerability indicators.

2. Context of the Study

This paper is a methodological companion to a larger study conducted by Rygel et al. (2005), which investigated the vulnerability of an important United States metropolitan region to contemporary storm surges and to storm surges associated with sea-level rise. This section summarizes the conceptual context, as well as the regional setting and physical exposure sections of the larger study relevant to this paper.

2.1. Conceptual Context

The concept of vulnerability is fundamental to human-environment research (Wu et al. 2002). The word "vulnerability" is derived from the Latin word *vulnerare*, meaning "to wound." At a very basic level, vulnerability can be defined as "the capacity to be wounded" (Kates 1985; Dow 1992) or the "potential for loss" (Cutter, 1996). However, general definitions of vulnerability do not specify the type of loss or the individuals, groups, or societies experiencing loss (Cutter, 1996). Dow (1992) and Cutter (1996) provide in-depth reviews of the development of the concept of vulnerability over the last several decades.

Despite differences in the conceptualization of the term "vulnerability," two main perspectives have emerged (e.g., Wu et al. 2002; Adger et al. 2004). The first major research theme treats vulnerability as a pre-existing condition and focuses on potential exposure to hazards (Cutter 1996). Studies conducted in accordance with this perspective tend to assess the distribution of some hazardous condition, the human occupancy of the hazard zone, and the degree of loss of life and property resulting from a particular event.

The second major perspective on vulnerability suggests that not all individuals and groups exposed to a hazard are equally vulnerable; rather, affected people display patterns of differential loss (Wu et al. 2002). In addition to exposure to some stress or crisis, this differential vulnerability also depends on the *coping ability* of those affected (Anderson and Woodrow 1991; Dow 1992; Watts and Bohle 1993; Cutter 1996; Clark et al. 1998; Wu et al. 2002). Coping ability has been defined by, among others, Dow (1992), Cutter (1996), Clark et al. (1998), and Wu et al. (2002) as a combination of *resistance* (the ability to absorb the damaging impacts of a hazard and continue functioning) and *resilience* (the ability to recover from losses quickly).

Studies that follow the second approach assess the *social vulnerability* of people and communities (Adger and Kelly 1999). People living at the margins – such as those without access to social services or political power – are more vulnerable than those with better access to resources (Dow 1992). For example, poor people are more likely to live in substandard housing and suffer from malnourishment. They have fewer opportunities for education and, therefore, employment and are less likely to have health and property insurance (Anderson and Woodrow 1991). Researchers who subscribe to the second major perspective stress that vulnerability is socially constructed because of differences in complex factors such as institutional development, social relations, and political power (Cutter 1996). However, these multidimensional factors can be indicated and measured by single variables such as gender, race, age, and income (Wu et al. 2002).

Cutter (1996) asserts that a third major theme is emerging in vulnerability literature. The concept of vulnerability as a "hazard of place" combines elements of the first two perspectives. This approach – called the *vulnerability of places* framework by Wu et al. (2002) – treats vulnerability as both a biophysical risk and a social response within a specific geographic domain. Researchers such as Yarnal (1994), Clark et al. (1998), and Wu et al. (2002) have employed this approach.

This paper adopts the vulnerability of places approach. Potential exposure to a hazard and coping ability are assessed within the specific geographic region of Hampton Roads, Virginia. Storm surge flood-risk maps provide an evaluation of exposure to a particular hazard. This paper will assess social vulnerability to hazards in Hampton Roads by ranking the coping ability of census block groups based on socioeconomic characteristics. Rygel et al. (2005) determined the correspondence between exposure and social vulnerability to depict overall vulnerability to storm surge in Hampton Roads.

2.2. Regional Setting

The metropolitan region of Hampton Roads consists of ten cities and six counties in southeastern Virginia (Figure 1). The area covers approximately 7500 km^2 of low-lying coastal land at the confluence of the James, Nansemond, and Elizabeth Rivers with the Chesapeake Bay. It is home to more than 1.5 million people and has

Figure 1. The Hampton Roads, Virginia metropolitan region (Rygel et al. 2005).

intensely developed, densely populated coastal frontages, making it an appropriate case study for understanding the potential impacts of storm surges and sea-level rise. In addition, understanding the vulnerability of the region to storm-surges is crucial for economic and national security reasons: Hampton Roads is not only the second largest port on the United States eastern coast and the center of Virginia's tourism industry, but also the location of the largest naval base in the world.

Hampton Roads is entirely within the low-lying physiographic region known as the Atlantic Coastal Plain (Bingham, 1991). Elevation rises slightly across the study area from east to west – Hampton Roads reaches a maximum elevation of about

54 m above sea level along its western edge, but most of the eastern half of the study area is less than ten meters above sea level. Much of the southeastern portion of Hampton Roads is at elevations of less than five meters, including some of the most densely populated, heavily developed parts of the region. It is important to note that Hampton Roads is still experiencing subsidence in reaction to the unloading of the Laurentide ice sheet from the North American continent, thus exacerbating local sea-level rise associated with contemporary climate change. Data from the Sewells Point tide monitoring station indicates that sea level has risen by 41 cm in Hampton Roads between 1933 and 2003 (Boon 2004).

The low-lying landscape and rapid sea-level rise combines with the presence of hurricanes to make the metropolitan region particularly vulnerable to storm surge. The Virginia Department of Emergency Management (2003) reports that twenty-five hurricanes affected Hampton Roads in the twentieth century, including a hurricane in 1933 (Cobb 1991) that set the record high storm surge tide. During that storm, bay and ocean waters combined to produce a surge of 3.0 m above mean low water in the city of Norfolk, but tides may have been as much as 3.5 m above mean low water in some narrow estuaries. Most recently, in September 2003, Hurricane Isabel produced a storm tide of approximately 2.4 m and a storm surge of roughly 1.5 m (Boon 2004).

Although incomplete records exist, at least fifteen hurricanes affected the area in the seventeenth, eighteenth, and nineteenth centuries. Intensity and tide height for some of those hurricanes may have far surpassed those of recent record. A hurricane in September 1667 may have had a storm tide at least 0.6 m higher than the record 1933 hurricane. Moreover, a particularly violent hurricane in October 1749 may have had a storm tide approximately 1–5 m higher than the record high tide (Virginia Department of Emergency Management, 2003). In short, storm surge is a significant hazard in Hampton Roads.

2.3. Physical exposure of the study area

Rygel et al. (2005) used output from the SLOSH (Sea, Lake, and Overland Surges from Hurricanes) model of the National Hurricane Center to evaluate the possible exposure of Hampton Roads to storm-surge flooding. The SLOSH model was originally intended to make real-time forecasts for surge heights of approaching hurricanes (Jelesnianski et al. 1992). When the model is used to estimate surge from an actual hurricane, results are generally accurate within plus or minus twenty percent (National Hurricane Center, 2003). In recent years, the SLOSH model also has been used to determine which coastal areas are at risk of storm-surge flooding (Jelesnianski et al. 1992; see Wu et al. 2002). See Rygel et al. (2005) for details of the SLOSH model and its application to Hampton Roads to determine storm-surge risk zones for the metropolitan region.

Storm-surge flood-risk zones for various categories of hurricane are shown in Figure 2. Many locations are at risk of flooding from storm surges produced by weak

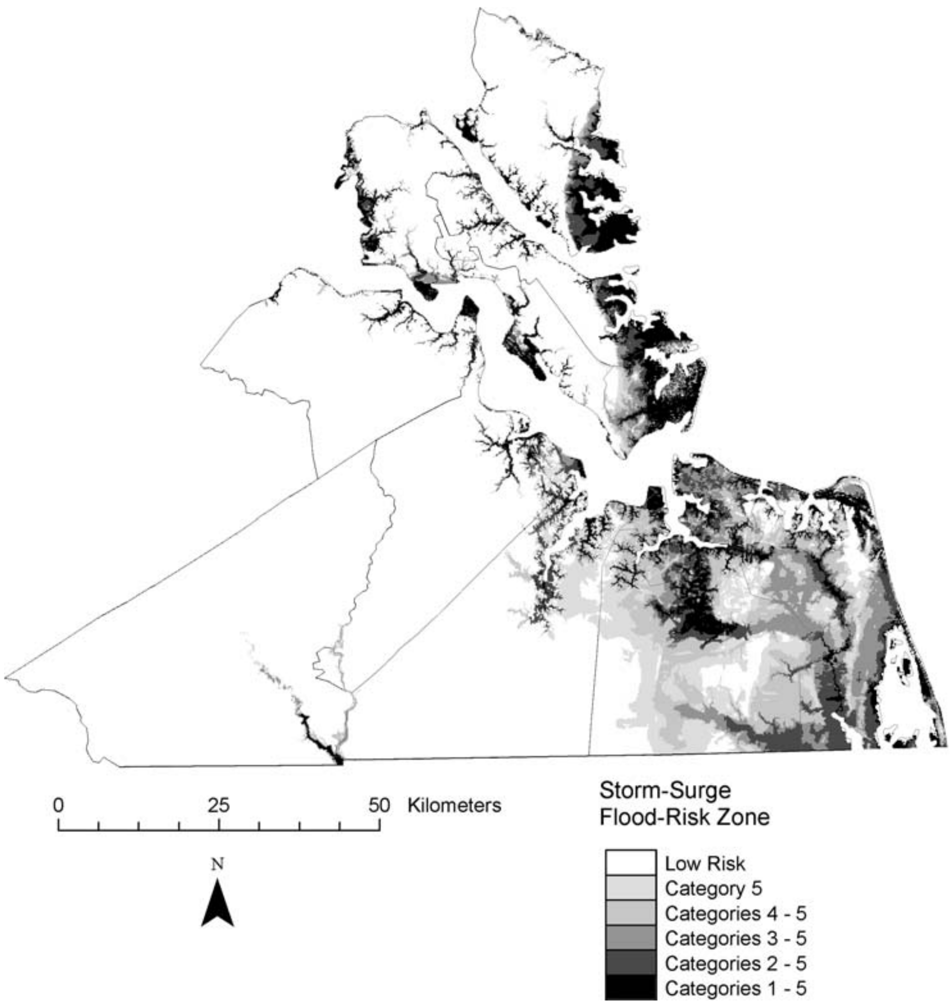

Figure 2. Storm-surge flood-risk zones at high tide in the Hampton Roads metropolitan region, by Saffir-Simpson hurricane intensity category (Rygel et al. 2005); "Categories 1–5" denotes areas influenced only by even the weakest (Category 1) storms, whereas "Category 5" denotes areas influenced only by the strongest (Category 5) storms.

or moderate hurricanes. Because slope in Hampton Roads is very shallow, storm-surge waters from stronger hurricanes can affect locations much farther inland. Nearly one third of the study area is currently at risk of storm-surge flooding from the strongest (Category 5) hurricanes. For example, in the city of Chesapeake, about 50 km^2 (roughly 6% of the city's total land area) are at risk of flooding from storm surges associated with the weakest hurricanes. For the strongest hurricanes, the storm-surge flood-risk zone occupies 708 km^2 – nearly 78% of that city.

3. Developing Social Vulnerability Indices

This section focuses on developing the component social vulnerability indices that combine to form the overall social vulnerability index in Section 4. It starts by summarizing the indicators of social vulnerability often used in vulnerability assessments such as the present study. The section then discusses several concerns that arise when constructing social vulnerability indices. Building on that information, the principal components analysis is carried out and its results are presented.

3.1. Social vulnerability indicators

Some broad indicators appear repeatedly in social vulnerability analyses, although it is possible to choose different proxies for each indicator. The vulnerability indicators used in this study – poverty, gender, race and ethnicity, age, and disabilities – are described in the following paragraphs. The emphasis of this review is on vulnerability indicators in developed countries, although most of the statements could apply equally to less-developed countries.

In general, people living in poverty are more vulnerable than the wealthy to disasters (Fothergill and Peek, 2004). Poor people have less money to spend on preventative measures, emergency supplies, and recovery efforts (Clark et al. 1998). During disasters, the poor suffer from higher mortality rates (Blaikie et al. 1994) and greater housing damage (Morrow 1999). Although the monetary value of the economic and material losses of the wealthy may be greater, the losses sustained by the poor are far more devastating in relative terms (Morrow 1999). Poor people are more likely to live in poorly built housing, which can be a major disadvantage when disasters occur. During disasters, the poor are also less likely to have access to lifelines, such as communications and transportation (Clark et al. 1998).

Gender affects vulnerability (Enarson and Morrow, 1997). Women are more vulnerable than men are to disasters, mainly because women – especially divorced mothers and never-married mothers – are more likely to live in poverty (Bianchi and Spain 1996). Women often suffer the impacts of a disaster disproportionately. For example, women are more likely than men are to hold low-status jobs or jobs in the informal economy, which often disappear after a disaster strikes (Morrow 1999). Women are also more vulnerable to disasters because of their roles as mothers and caregivers: when disaster is about to strike, their ability to seek safety is restricted by their responsibilities to the very young and the very old, both of whom require help and supervision (Fothergill 1998).

In the United States, racial minorities are more vulnerable than whites to hazards because minorities are more likely to be poor (Bianchi and Spain 1996). Discrimination also plays a major role in increasing the vulnerability of racial and ethnic minorities (Fothergill 1999). In particular, real estate discrimination may confine minorities to certain hazard-prone areas (Clark et al. 1998) or hinder minorities in obtaining policies with more-reliable insurance companies (Peacock and Girard

1997). When minorities are immigrants from non-English-speaking countries, language difficulties can greatly increase vulnerability to a disaster (Gladwin and Peacock 1997) and recovery (Yelvington 1997).

Both young and old people may be unable to respond to disasters on their own (Clark et al. 1998). Children who lack adequate family support are at a major disadvantage for disaster response (Morrow, 1999). Disruptions created by a disaster can have significant psychological and physical impacts on children (Enarson and Morrow 1997). Although not all elderly people are poor or physically weak, in general, the elderly are more likely to lack the necessary physical and economic resources to respond effectively to a disaster. They are more likely to suffer health-related repercussions and to recover more slowly (Morrow 1999). Older people also tend to be more reluctant to evacuate. In addition to the physical difficulties imposed by evacuation, older people tend to be distressed by the prospect of leaving their own homes and living in group quarters (Gladwin and Peacock 1997).

People living with mental or physical disabilities are less able to respond effectively to disasters. Disabled people require additional assistance in preparing for and recovering from disasters. Emergency managers need to target areas with high concentrations of disabled people, particularly in group-living quarters, for early evacuation and other preparatory measures (Morrow 1999).

3.2. Building Social Vulnerability Indices

Previous vulnerability analyses for the coastal United States have used data at the United States Census Bureau block-group level to build social vulnerability indices (Cutter et al. 2000; Wu et al. 2002). That approach requires the selection of proxies that indicate vulnerability. For example, Cutter et al. (2000) used the numbers of children and elderly to represent greater susceptibility to hazards due to physical weakness and the number of mobile homes to represent the level of structural vulnerability. Typically, the value of each proxy is standardized on a scale from zero to one, with higher index values indicating higher vulnerability. A composite social vulnerability score can be constructed for each spatial unit by combining the index scores for each proxy. As in Wu et al. (2002), when specific weights are not attached to each proxy, the composite index uses a simple average of the scores of all proxies.

In their attempt to measure social vulnerability, Clark et al. (1998) used a factor analysis to simplify a dataset of 34 proxies for the town of Revere, Massachusetts. The researchers recognized that many of the proxies typically chosen to represent vulnerability correlate highly and measure essentially the same themes. For example, high percentages of people living below the poverty line and having low per capita incomes both indicate poverty. Additionally, certain groups, such as racial minorities and households headed by single mothers, tend to have reduced access to resources and are more likely to be poor. Clark et al. (1998) generated five main factors that explained most of the variation in the dataset. Each factor was composed of groups of highly correlated proxies, but factors were not highly correlated with one another. Social vulnerability for each block group was calculated by combining the scores of the individual factors.

In addition to deciding which indicators to include and choosing how to devise an index or scale from the proxy list, the size and composition of each indicator must be considered. Previous vulnerability analyses have used either size or composition, but not both. For example, Cutter et al. (2000) used size – absolute numbers for each proxy – to indicate vulnerability. The logic for using absolute numbers is based on the assumption that a block group with more people, households, and housing units has a higher potential for damage than one with fewer people and structures. In contrast, Clark et al. (1998) used percentage values for each proxy to indicate vulnerability. Using this method, the composition of block groups is more important than size. This approach allows block groups with high percentages of vulnerable people, but relatively small populations, to have high vulnerability scores.

Such binary choices are arbitrary because both size and composition are important when determining vulnerability. Moreover, it is risky to use raw numbers of vulnerable people without taking into account the areal extent of each block group. For example, a hypothetical block group may have twice as many vulnerable people as its neighbor. When raw numbers are used to indicate vulnerability, the second block group appears to be half as vulnerable as the first. If, however, the first block group is twice the size of the first, the density of vulnerable people is the same, and in that respect the block groups could be considered equally vulnerable. Therefore, in this study, both percentages and areal densities of vulnerable people and households are used.

3.3. Principal component analysis

As discussed above, some broad indicators of vulnerability appear repeatedly in the vulnerability assessment literature, although different variables may be chosen to represent each indicator depending upon such factors as availability of data. This paper uses the vulnerability indicators of poverty, gender, race and ethnicity, age, and disabilities. To capture these indicators, fifty-seven variables (not shown) were chosen for inclusion in a principal components analysis of social vulnerability. All variables were derived from the 2000 United States Census and were analyzed at the census block-group level. Densities were calculated by clipping census block-group files to county boundaries and calculating the area of each block group in square kilometers. The number of people, households, or housing units in a particular category was then divided by the area of the block group.

The use of both percentages and densities did not pose a problem to the analysis because the basic aim of a principal components analysis is to reduce a complex set of many correlated variables into a set of fewer, uncorrelated components. If any radical differences between percentages and densities appeared in the analysis, a further investigation of the data structure would be warranted. For example, for any given component, if percentages of minorities had highly positive scores while densities of minorities had highly negative scores, the reason behind the disparity would be investigated. No such discrepancies appeared in the analysis.

The variables were entered into a correlation matrix and a Varimax orthogonal rotation with Kaiser normalization was applied to the solution (George and Mallery, 2003). This approach generated thirteen components with eigenvalues greater than 1.0. These thirteen components accounted for 81.01% of the variance in the dataset; however, with such a large number of components, each component was difficult to describe. After examining a scree plot, only three components were extracted for analysis. Together, the three components accounted for 50.83% of the variance in the dataset. Each component was readily described based on the raw variables that loaded most heavily on it.

Although general names – "poverty," "immigrants," and "old age/disabilities" – are used to describe the three components, more individual variables load highly onto those components than the names can express. For example, although the first component is called "poverty" because it represents low incomes and many people living in poverty, this component also includes high percentages and densities of black people and households headed by single mothers. It is important to note that no major disparities were found between the results using percentages and densities, whether they were analyzed independently or together. Thus, regardless of the chosen method of representation, the same key variables emerged as central indicators of social vulnerability.

3.4. Results of the Principal Components Analysis

Understanding the distribution of the individual social vulnerability components can be useful to planners, emergency managers, and others (Adger et al. 2004). To illustrate, Figure 3 depicts block-group scores for the "poverty" component. The 1027 block groups in the study area are sorted into five equal-interval classes. For the "poverty" component, the most socially vulnerable block groups occupy some of the metropolitan region's most intensely developed land. Only a few block groups show exceptionally high component scores. Scores are lowest in block groups that occupy forested land, agricultural land, rich coastal neighborhoods, and other wealthy communities.

Figures 4 and 5 display the "immigrants" and "old age/disabilities" components, respectively. Most block groups in the study area have low scores for the "immigrants" component; 767 block groups have scores in the lowest class. However, dozens of block groups in urban areas have high to very high scores for the "immigrants" component. For the "old age/disabilities" component, more than half of the block groups in the study area have scores in the lowest class. Very vulnerable block groups tend to be concentrated in intensely developed regions. A few block groups scattered throughout the rest of study area also have relatively high scores for the "old age/disabilities" component.

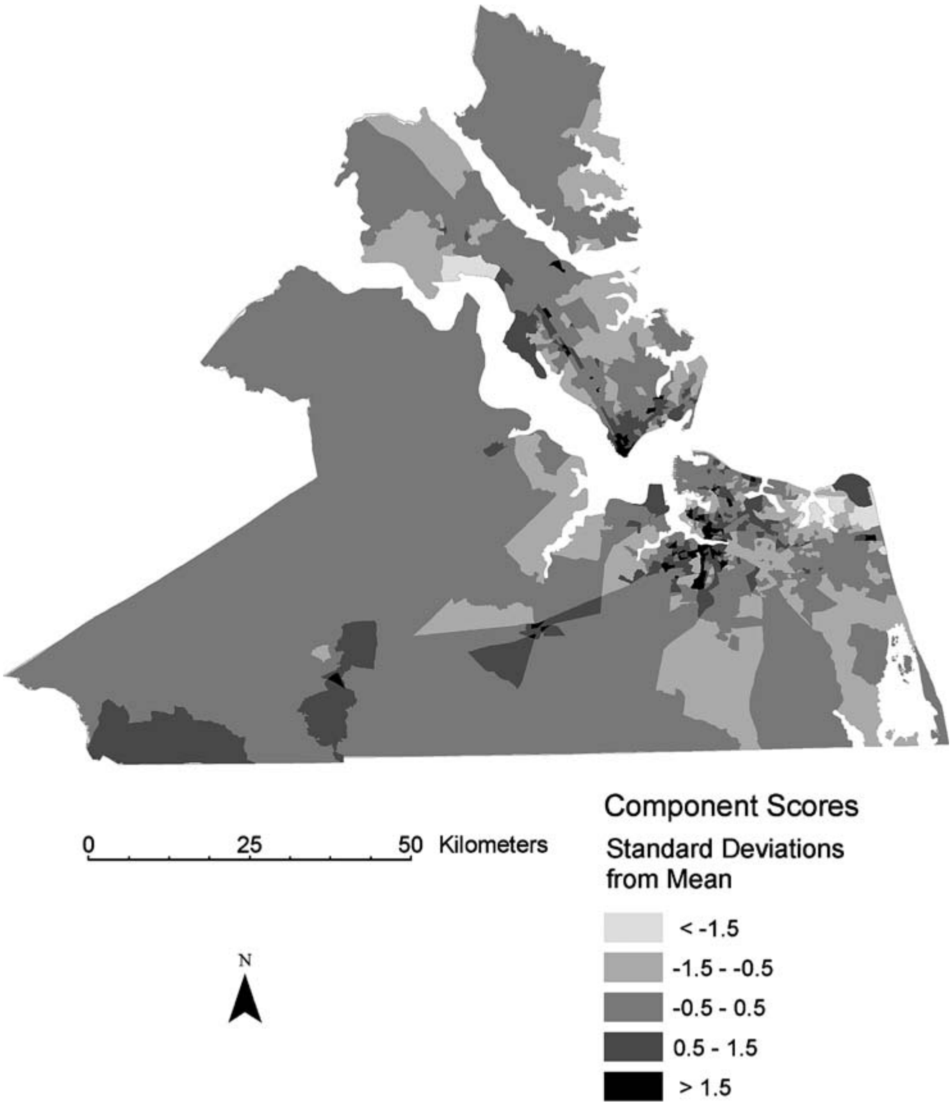

Figure 3. "Poverty" component scores, displayed as standard deviations from mean component score; negative scores load lowest on this component, indicating greater wealth, whereas positive scores load highest and indicate greater poverty.

4. Calculating Overall Vulnerability

4.1. Calculation of overall vulnerability

Although maps of individual component scores can be useful, it is easiest to assess overall social vulnerability throughout a region if the multidimensional components

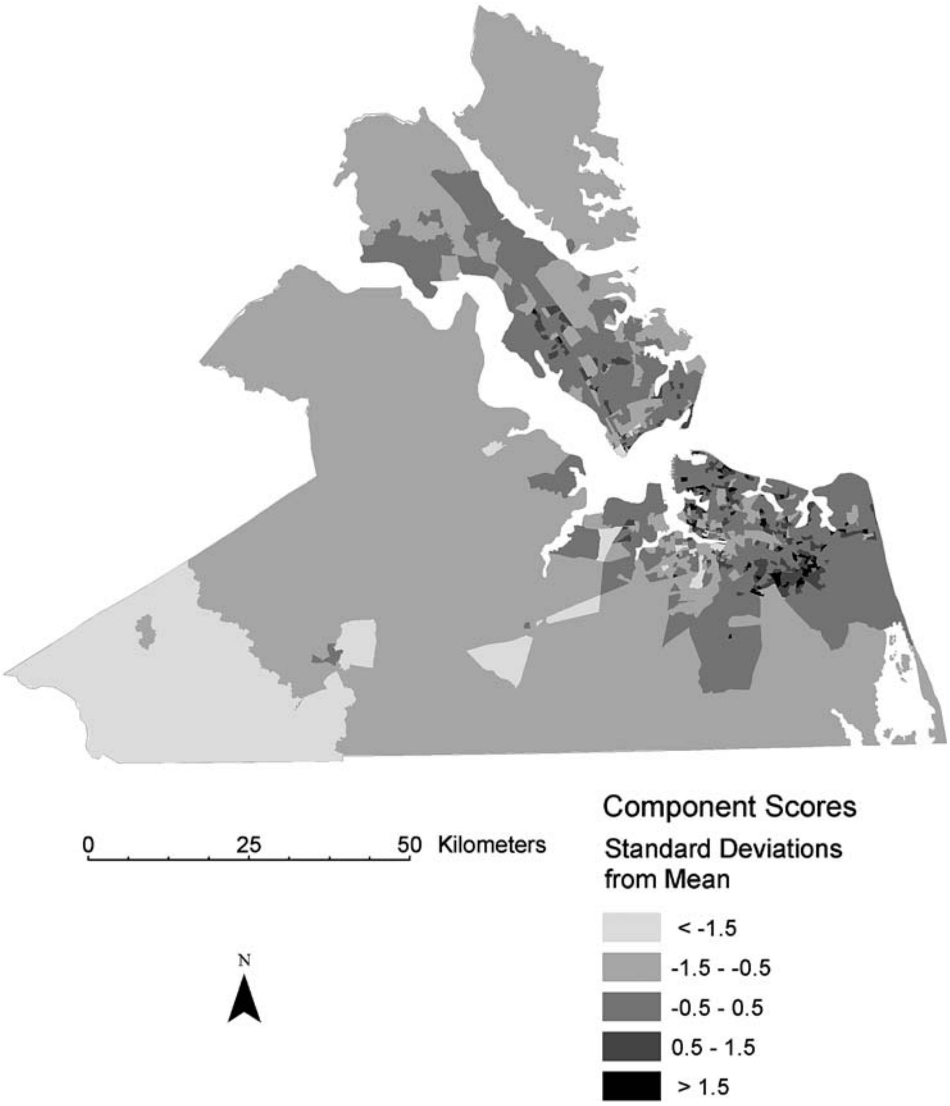

Figure 4. As in Figure 3, but for "Immigrants" component scores.

can be combined into a single measure (Clark et al. 1998). In the present case, the simplest way to combine component scores into a single measure would be to average the three component scores for each block group (Figure 8). However, averaging component scores poses two significant problems. The first problem is the construction of a weighted average. Simple averages can be used if all components contribute equally to vulnerability, but if a researcher decides that certain components contribute more to overall social vulnerability, he or she must make

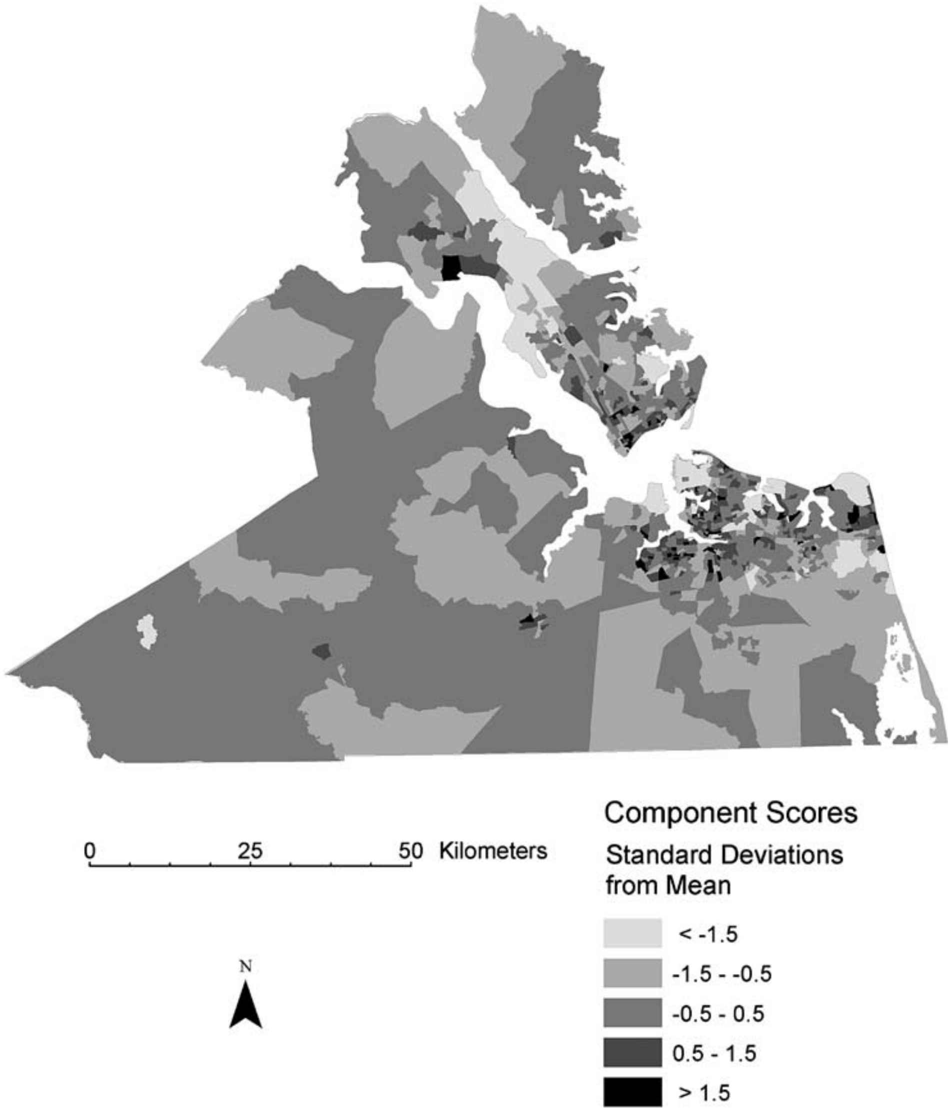

Figure 5. As in Figure 3, but for "Old Age/Disabilities" component scores.

subjective decisions to create a weighting scheme. The second problem with using averages is that they may obscure high scores on one component when averaged with low scores on the other components. However, extreme values on even one component may indicate areas particularly in need of attention.

To avoid the problems created by using component score averages to measure absolute overall social vulnerability, this study used Pareto ranking to organize the block groups into a series of ranks. Pareto ranking is a method for ordering cases on multiple criteria that has become popular in the context of genetic algorithms (see Goldberg 1989; Fonseca and Fleming 1993), where it is particularly valued because it often gives high rankings to those cases that only score heavily on one factor. Data envelopment analysis (DEA; Charnes et al. 1978) is an alternative approach from econometric analysis used by Clark et al. (1998) in vulnerability analysis that relies on many of the same underlying concepts as Pareto ranking, but is a conceptually and practically more complicated method.

The rationale behind the Pareto ranking method is as follows. Each case i is considered on the basis of a set of n component scores, $\{c_{i1}, c_{i2}, \ldots, c_{in}\}$. For simplicity, and without loss of generality, it is assumed that a higher score on any individual component indicates greater vulnerability. When two cases (block groups or other spatial units) A and B are compared, case A is more vulnerable than case B, but only if the scores for A are at least equal to those for B for *all* components and if there is at least one component on which A scores higher than B. If, for example, A has higher scores than B on the first two of three components, but B has a higher score than A on the third component, then there is no way, without assigning relative weights to each component, of determining which block group is more vulnerable.

Figure 6 illustrates the simple two-component case. The component scores for A define four regions in the 'vulnerability space.' All cases lying in the upper right quadrant with one score greater than the corresponding score for A, and the other greater than or equal to A's score, are more vulnerable than A. Scores with one score less than the corresponding score for A, and the other less than or equal to A's

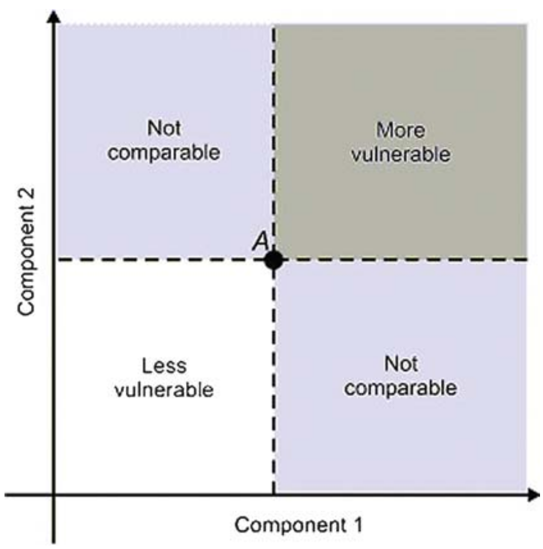

Figure 6. Vulnerability space of block group A, using two components.

score, are less vulnerable than A. All other cases are not directly comparable to A because, depending on how the relative importance of different component scores is judged, these cases may be more or less vulnerable than A. The above ideas enable a ranking of multi-component vulnerability scores that does not require researchers to judge the relative importance of different components – i.e., they do not need to develop arbitrary weights for the indicators.

Many vulnerability indices are based on determining a set of weights for additively or otherwise combining component scores, and thus require that the user decide which components are most important. The above ideas enable investigators to develop a method for ranking multi-component vulnerability scores that does not require them to judge the relative importance of different components – i.e., they do not need to develop arbitrary weights for the indicators.

To proceed, it is necessary to introduce the concept of *non-domination*. A non-dominated case is one that has no other cases in the dataset that are clearly more vulnerable than it is, by virtue of their scoring at least as high or higher on all components. A non-dominated set of cases is all the non-dominated cases in the dataset. By determining the non-dominated set of cases in the complete dataset, removing them from the dataset, determining the non-dominated cases among the remaining cases, and then repeating this process, the investigator can assign a vulnerability ranking to every block group in the dataset. The non-dominated set of cases at each repetition of this process is called the *Pareto-optimal front* (Goldberg, 1989, p. 201), a term referring to the notion of Pareto optimality from welfare economics (see Pareto, 1896, for the origins of the term; see also Johansson, 1991). Note that Fonseca and Fleming (1993) proposed a variation on this approach where the number of other cases that dominate each case is used to determine its eventual rank.

The process is illustrated in Figure 7. The first panel shows a number of block groups plotted with respect to two component scores. The second panel shows a non-dominated set of block groups (note that there are no other block groups above and to the right of each of these block groups), which are the most vulnerable locations. The top-left-most of these block groups has a lower score on component 1 than *all* other block groups. In some weighting-based schemes where component 1 was weighted sufficiently heavily relative to component 2, this condition may result in this block group not being judged among the most vulnerable. In the present scheme, its high score on component 2 means that it is not dominated by any other block group and ends up in the first Pareto rank of most vulnerable block groups. With the first Pareto rank of block groups removed from consideration, a new set of non-dominated block groups is identified in panel 3. This process continues with each rank being 'peeled away' like the layers of an onion until all block groups have been assigned a vulnerability ranking, as shown by the lines in the final panel.

While these illustrations are in two dimensions for clarity, precisely the same logic and procedure can be applied to higher-dimensional data. Note, however,

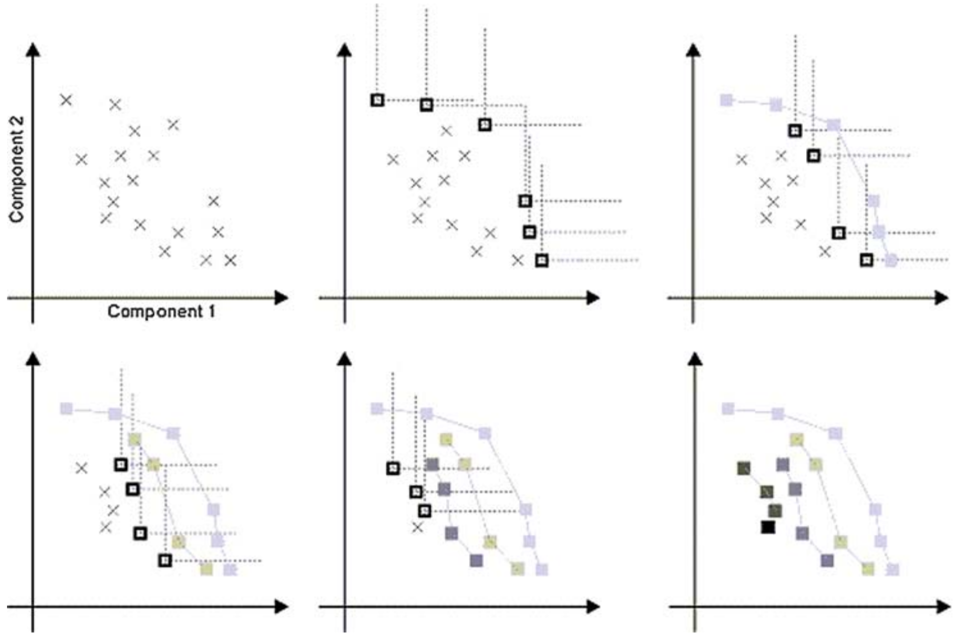

Figure 7. The Pareto ranking process.

that as the dimensionality increases (i.e., the number of component scores used to determine vulnerability increases), the number of cases in each rank will decrease until, in the most extreme case, *all* block groups are in the first rank. This situation should only occur when a large number of component scores were used to assess relative vulnerability for a small dataset.

In this study, with 1027 block groups and 3 component scores, block groups were sorted into 19 ranks. Block-group rank membership showed a normal bell-curve distribution. The middle ranks each contained approximately 100 block groups, whereas the very highest and very lowest ranks contain only a dozen block groups or less.

To assess overall social vulnerability, the 19 Pareto ranks were reassigned such that the most vulnerable block groups had a score of 19 and the least vulnerable block groups had a score of 1. The social vulnerability score of each block group was then defined as its Pareto rank. To increase interpretability, the results were rescaled from 0 to 1 and overall vulnerability zones were established by sorting the scores into four equal-interval classes.

4.2. Results

Figure 9 shows the region's overall social vulnerability as determined by the Pareto ranking technique. Largely because most of the relatively sparsely settled western

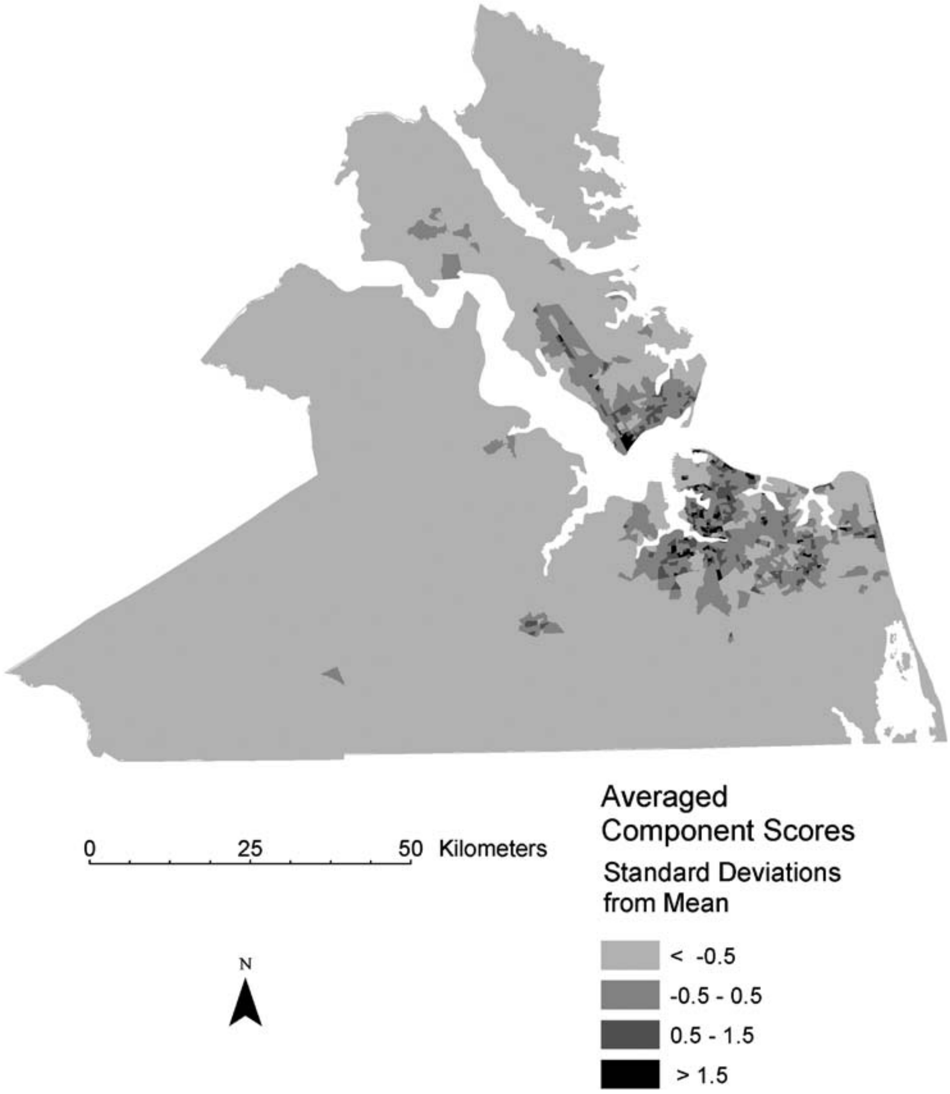

Figure 8. Overall social vulnerability in Hampton Roads, calculated using simple averaging of component scores and converted to standard deviations from the mean component score.

and northern portions of the study region have low to moderate social vulnerability, roughly 90% of the total study area has overall vulnerability scores in the lower two classes. Areas of high and very high overall vulnerability tend to be found in those portions of Hampton Roads that are most highly developed.

Looking closely at the social vulnerability of these intensely developed areas, substantial differences exist between the results of the Pareto ranking technique and simple averaging (Figure 10; in addition, compare Figures 8 and 9). The most

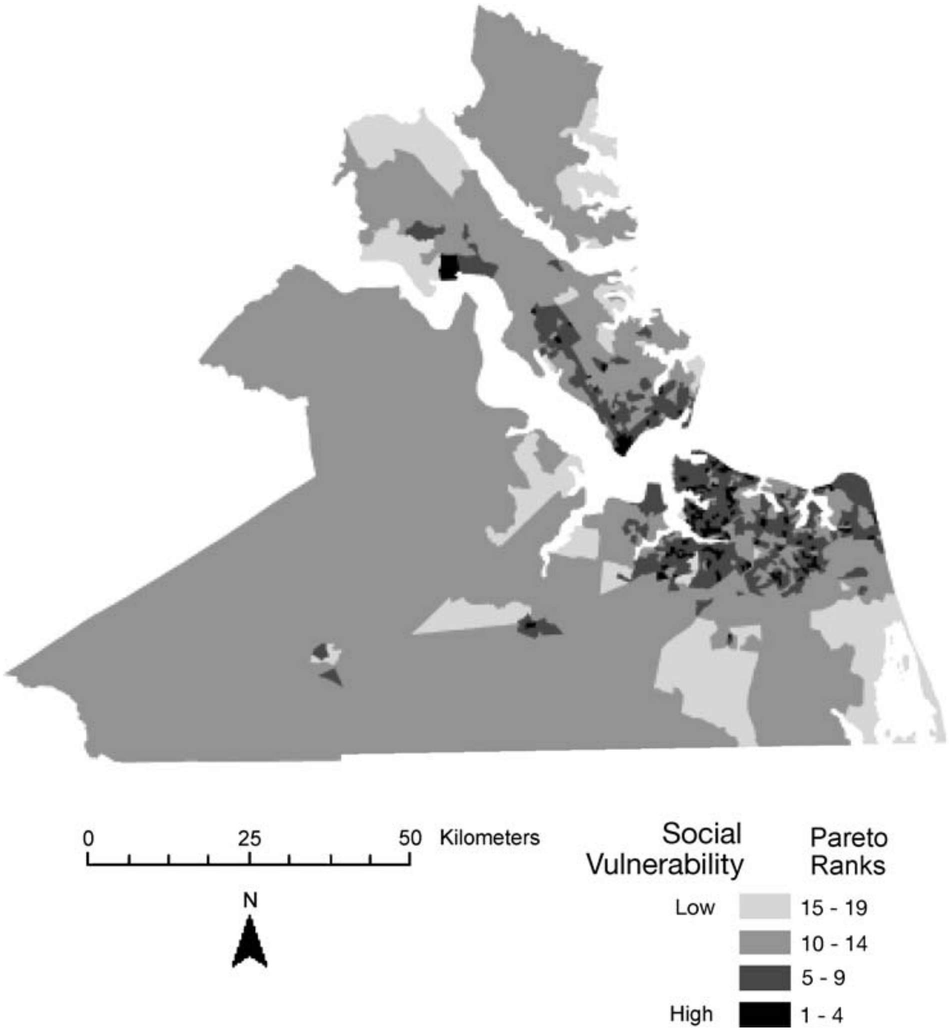

Figure 9. Overall social vulnerability in Hampton Roads, calculated using the Pareto ranking technique.

important difference is that block groups with very high scores on only one component, to which averaging tends to assign modest social vulnerability, fall into the highest Pareto ranks – i.e., the most socially vulnerable block groups. The block group labeled "A" in Figure 10 is an example. This block group has a highly positive score for the "poverty" component, but its scores on the "immigrants" and "old age/disabilities" components are lower. Because its average score obscures the high value of the first component, the block group appears to be only moderately socially vulnerable in the top panel of the figure. However, when subjected to Pareto ranking, as shown in the bottom panel, this block group sorts into the most vulnerable

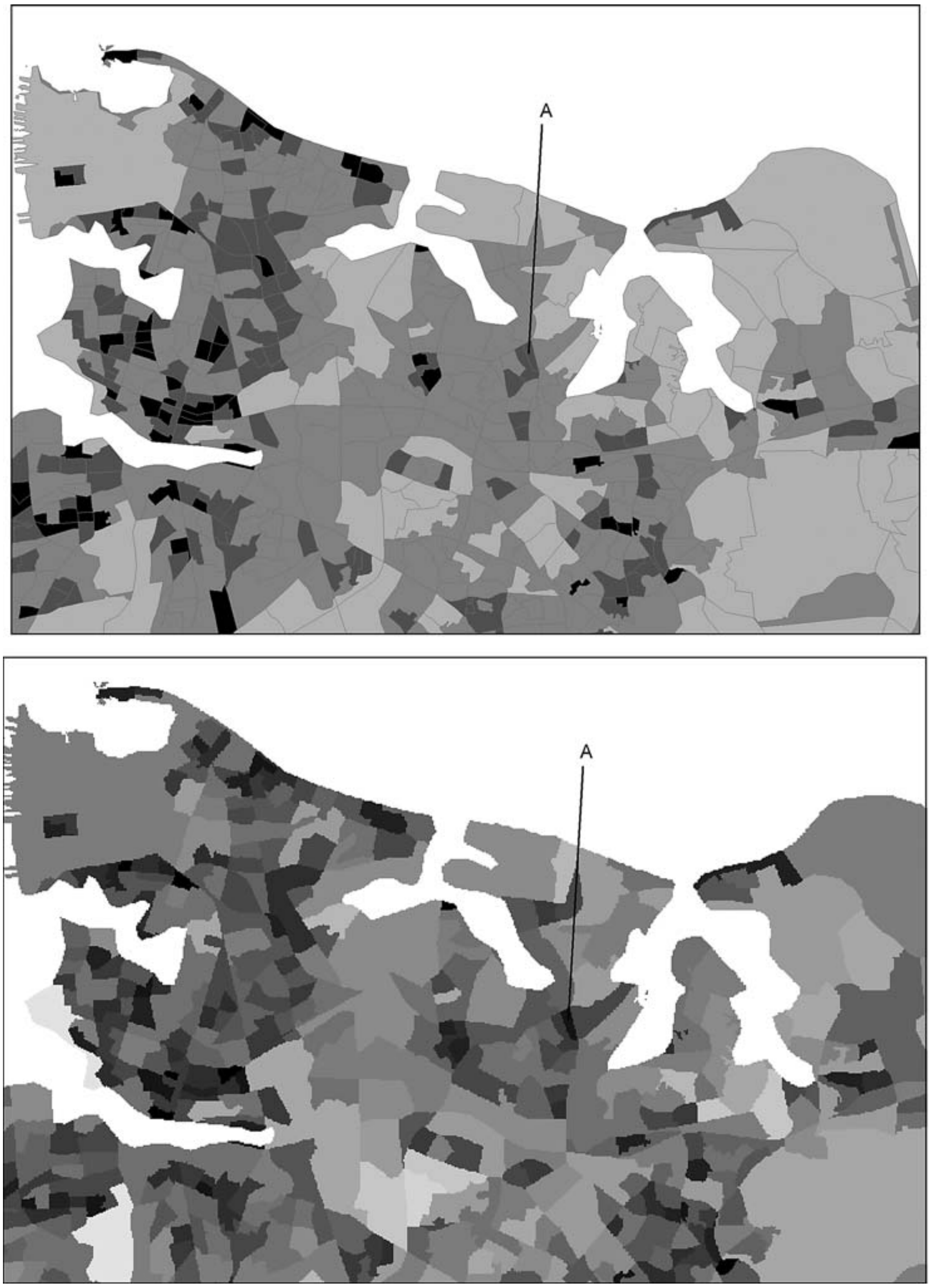

Figure 10. Overall social vulnerability in the census block groups of the urban core of Hampton Roads: top panel represents simple averaging of component scores; bottom panel represents Pareto ranking.

category. Many other block groups move up in the Pareto rankings in Figure 10. In many cases, the block groups with the lowest simple averages tend to have two moderate component scores that one extremely low component score effectively negates. These cases move up in the Pareto rankings. In contrast, block groups that occupy the lowest Pareto ranks tend to have relatively low scores on all three components.

5. Conclusions

Important tasks in vulnerability assessment are the identification of suitable vulnerability indicators and the construction of an overall vulnerability index from those indicators. Among several significant problems concerning the construction of this index is the method of aggregation: when combining indicators into a single, composite index, should the individual indicators receive weights? In some highly constrained circumstances when the vulnerability of a region is well understood, it is possible – and perhaps even desirable – to assign weights to the various indicators. In most cases, however, vulnerability is insufficiently understood, thus making it impractical to develop a weighting scheme. Moreover, in highly complex, highly dynamic biophysical or socioeconomic landscapes, assigning weights to vulnerability indicators is unwise because, especially in the face of disaster, the causes of vulnerability change quickly over time and space, rendering many indicators useless.

This paper showed that it is possible to determine the relative vulnerability of places without the difficult and problematic practice of weighting the various indicators. Consequently, the paper presented a technique based on Pareto ranking that avoids the need to weight the vulnerability indicators. It applied the technique to a highly complex, developed socioeconomic landscape in Hampton Roads, Virginia to demonstrate the advantage of Pareto ranking over simple averaging of the component indicators. Pareto ranking is a conceptually simple way to avoid the problem of assigning relative weights to multiple factors in a vulnerability index. While numerous other approaches are surely possible, this method represents a step forward in our ability to construct useful indices of vulnerability. In the end, however, the measure presented here only provides guidance for prioritizing vulnerability mitigation plans. Other factors not considered by the index, such as cost, might be important considerations when developing such plans.

It is important to return to the point that the research presented here applied the vulnerability index to a metropolitan region in a developed country. Using this approach in developing country contexts would present a challenge because of the non-availability of relevant data, but this problem would also exist for other approaches proposed in the literature. Moreover, even if similar data sets with the same variables were available to analyze the vulnerability of a developing region, because the data values themselves would differ radically, different components would probably emerge. The three components produced here – poverty, immigrants, and old age/disabilities – came from the correlations in the data for Hampton Roads. In a developing country metropolitan region, poverty and property values, for example, might not emerge as important variables because most people are poor and most property values are low. Instead, variables such as "population density" and "number of very young children" might prove to be important indicators of vulnerability. In any case, vulnerability indicators should vary with place because, as explained earlier, vulnerability represents both a biophysical risk and a social response within a specific geographic domain.

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