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A framework for the development of the SERV model: A Spatially Explicit Resilience-Vulnerability model

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A B S T R A C T

Societal assets and human populations are spread unequally across landscapes causing vulnerability and resilience to vary spatially. The spatial scale at which most traditional vulnerability assessments are conducted (the county scale), however, has limited utility in assessing and mitigating sub-county vulnerability. Traditional vulnerability studies also neglect the differential spatial distribution of indicators at the sub-county scale and disregard the influence of specific indicators on overall vulnerability. Many assessments are typically sensitivity analyses and do not consider the combined impact of exposure, sensitivity and adaptive capacity on vulnerability. These omissions can result in non-holistic vulnerability analyses.

As a response to vulnerability assessment limitations, this research presents a framework for a Spatially Explicit Resilience-Vulnerability (SERV) model that measures vulnerability at the sub-county level. The SERV model determines varying sub-county vulnerability using socioeconomic, spatial and place-specific indicators that represent exposure, sensitivity and adaptive capacity. Statistical analyses were conducted to determine the spatial distribution and differential influence of indicators on overall sub-county vulnerability. The exposure, sensitivity and adaptive capacity components were then combined to create holistic sub-county vulnerability scores. The results indicate that vulnerability varies at the sub-county level. Results also indicate that the inclusion of spatially explicit indicators in vulnerability assessments aids decision makers in identifying markers of vulnerability in specific areas. Holistic vulnerability scores can help empower decision makers in targeting mitigation efforts toward areas where vulnerability is highest and at indicators that most impact vulnerability.

Introduction

Societal assets in the form of human populations and development are often located in areas that are exposed to natural hazards. This contributes to increased vulnerability. Vulnerability is a function of exposure, sensitivity, and adaptive capacity, where exposure is the proximity of societal assets to a hazard; sensitivity is the level of impact a hazard has on societal assets; and adaptive capacity is the ability of societal assets to adjust to and cope with the effects of the hazard (Brooks, 2003; Füssel, 2007; Turner et al. 2003). Natural disasters are not preventable, but vulnerability and resilience assessments, hazard mitigation and adaptation planning can reduce the impacts of disaster events and facilitate recovery (Burby et al., 2000; Berkes, 2007; Frazier, Thompson, & Dezzani, 2013). Assessing sub-county vulnerability can be beneficial for the development of comprehensive hazard mitigation and adaptation plans because it illustrates what areas within the county are more vulnerable, thus possibly maximizing limited resources. Vulnerability assessments can also be used to estimate sub-county resilience. Resilience is a function of a community's ability to respond effectively to and recover from a disaster with minimal reliance on outside aid (Rose, 2007; Tobin, 1999; Turner et al. 2003). Lowering vulnerability can help increase overall resilience (Frazier, Thompson, Dezzani, & Butsick, 2013).

Vulnerability assessments enhance hazard mitigation and comprehensive planning because they demonstrate what areas are differentially vulnerable. For example, decision makers can use information gathered in a vulnerability assessment to provide evidence for necessary hazard mitigation funding or developing

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hazard mitigation policy and strategies. Vulnerability and resilience assessments can also aid decision makers in gathering public support that could translate to additional funding or promote policy decisions that could serve to reduce vulnerability.

Approaches to vulnerability assessments have evolved over time as new data and methodologies become available. As they currently exist, many vulnerability assessments are developed in ways that can reduce their effectiveness for hazard mitigation planning at the sub-county level (Frazier, Thompson, et al., 2013; Wood, Burton, & Cutter, 2010). Vulnerability varies spatially, making the investigation of local-scale factors important for measuring sub-county vulnerability (Fekete, Damm, & Birkmann, 2010; Frazier, Thompson, et al., 2013; Frazier, Wood, and Yarnal 2010; Morrow, 1999; Wood et al., 2010). Many existing vulnerability assessments are created for and typically rely on county (or state and national) scale data for their analysis (Cutter, Boruff, & Shirley, 2003; Wood et al., 2010), which can make their results too general for sub-county hazard mitigation planning (Frazier, Walker, Kumari, & Thompson, 2013). Vulnerability assessments used for hazard mitigation purposes also pay insufficient attention to the influences of socioeconomic factors on sub-county vulnerability (Frazier, Thompson, et al., 2013; Wood et al., 2010). Exposure to biophysical hazards alone does not necessarily indicate increased vulnerability (Frazier, Thompson, & Dezzani, 2013; Jones & Andrey, 2007). Vulnerability assessments that include both biophysical and socioeconomic factors provide a more holistic view of vulnerability, not just exposure (Burby, 1999; Cutter & Emrich, 2006; Frazier, Thompson, & Dezzani, 2013; Morrow, 1999).

Many vulnerability studies also do not typically consider the differential influence of indicators on vulnerability (Cutter, Burton, & Emrich, 2010; Jones & Andrey, 2007; Wood et al., 2010). Indicators will have variable influence on vulnerability across the landscape (Frazier, Thompson, & Dezzani, 2013; Frazier, Thompson, et al., 2013). Assessing the differential influence of indicators helps determine where specific indicators that increase vulnerability are more prevalent (Frazier, Thompson, & Dezzani, 2013; Frazier, Thompson, et al., 2013; Wood et al., 2010). Vulnerability assessments also typically do not model the effects of exposure, sensitivity, and adaptive capacity in conjunction with one another. Vulnerability assessments that do not examine the effects of all three components can potentially provide incomplete appraisals of vulnerability (Brooks, 2003; Frazier, Thompson, & Dezzani, 2013; Füssel, 2007). Despite the advantages of conducting vulnerability assessments that consider the three components of vulnerability, many communities lack the ability to conduct holistic vulnerability studies.

In consideration of the limitations in these approaches, this article presents the Spatially Explicit Resilience-Vulnerability (SERV) model as another step in the evolution of vulnerability assessment approaches. The SERV model makes it possible to incorporate place, spatial, and scale-specific indicators that are applicable for sub-county vulnerability and resilience analysis. This research is also one of the first to seek to determine vulnerability scores at the U.S. Census block level using all three components of vulnerability (exposure, sensitivity and adaptive capacity), and explores the differential importance of vulnerability indicators by determining total vulnerability scores using weighted factor scoring. The SERV model provides an improved assessment of sub-county vulnerability levels that can assist communities in allocating limited resources to vulnerable areas more effectively and developing adaptation strategies that enhance sub-county resilience. The SERV model also provides support for the development and design of more place-specific mitigation strategies and guidance on how to implement them. This model identifies indicators of preexisting social conditions that are exemplified by political economy, political ecology and structuration theory research, possibly enabling decision makers to apply resources to build adaptive capacity and reduce sensitivity where it is lacking.

The SERV model is also modifiable so that it can reflect vulnerability to different types of hazards due to the method in which exposure is considered. The sensitivity and adaptive capacity indicators are also modifiable to represent specific forms of vulnerability (i.e. economic, social, infrastructural or environmental), depending on the type of analysis being performed. As such, this research identified and examined place-specific indicators of vulnerability, using coastal inundation hazards from storm surge and inland precipitation for Sarasota County, Florida as a case study.

Evolution of vulnerability assessments

While hazard mitigation lowers hazard impacts, it is not possible to mitigate everywhere within the community when there are large numbers of societal assets (human lives and property) within a hazard zone. Understanding sub-county vulnerability can be important for comprehensive and hazard mitigation planning because it illustrates what areas in a community are more vulnerable. Communities within the same hazard exposure zone can have varying sensitivity or adaptive capacity (Frazier, Thompson, & Dezzani, 2013; Wood et al., 2010), making the inclusion of socioeconomic factors in vulnerability analysis critical for providing a complete representation of sub-county vulnerability.

Socioeconomic factors provide information about inequalities in the social structure that might increase or decrease an individual's vulnerability to hazards (Eakin & Luers, 2006; Morrow, 1999; Tierney, 2006). Political economy, political ecology, and structuration theory are theoretical frameworks that examine how underlying socioeconomic processes and social structure influence how people deal with and respond to disaster events (Bogard, 1988; Eakin & Luers, 2006; Goldman and Schurman, 2000; Miller et al. 2010). Political ecology and structuration theory are especially important to consider in vulnerability assessments because political ecology addresses multi-scalar issues and structuration theory addresses the power and agency issues that contribute to inequality. This helps identify social structures and indicators that account for the differential distribution of costs or benefits, and the structures that perpetuate those inequalities (Bogard, 1988; Eakin & Luers, 2006). For this reason, including socioeconomic factors in vulnerability assessments can depict how social variables (i.e. gender or wealth) can cause differential levels of vulnerability within a population and can highlight underlying social processes that may contribute to the differential distribution of social variables (Eakin & Luers, 2006; Miller et al. 2010).

Quantifying vulnerability

Some vulnerability assessment approaches in the past have excluded socioeconomic indicators because quantifying indicators that are inherently qualitative in nature is difficult (Cutter et al., 2003, 2008, 2010). Several recent studies have attempted to quantify vulnerability through the creation of quantification models and vulnerability indices (Cutter et al., 2003; Fekete et al., 2010; Gall, 2007; Tate, 2012; Wood et al., 2010). A common method of measuring and quantifying differential vulnerability is through geographic information systems (GIS) overlay analysis (Cutter et al., 2000; Frazier, Wood, Yarnal, & Bauer, 2010; Wu, Yarnal, & Fisher, 2002). GIS overlay analysis illustrates which areas within a study area have higher vulnerability, identifies exposed populations and societal assets and provides insight as to the socioeconomic factors that might influence that vulnerability (Frazier et al. 2010; Thompson & Frazier, 2014; Wu et al., 2002).