An Interpretable Index of Social Vulnerability to Environmental Hazards

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Abstract

Index-based measures of social vulnerability to environmental hazards are commonly modeled from composites of population-level risk factors. These models overlook individual context in communities' experiences of environmental hazards, producing metrics that may hinder spatial decision support for mitigating and responding to hazards. This paper introduces an interpretable, high-resolution model for generating an individual-oriented social vulnerability index (IOSVI) for the United States built on synthetic populations that couples individual and social determinants of vulnerability. The IOSVI combines an individual vulnerability index (IVI) that ranks individuals in an area's synthetic population based on intersecting risk factors, with a social vulnerability index (SVI) based on the population's cumulative distribution of IVI scores. Interpretability of the IOSVI procedure is demonstrated through examples of national, metropolitan, and neighborhood (census tract) level spatial variation in index scores and IVI themes, as well as an exploratory analysis examining risk factors affecting a specific sub-population (military veterans) in areas of high social and environmental vulnerability.

2012 ACM Subject Classification Information systems → Geographic information systems

Keywords and phrases Social Vulnerability, Environmental Hazard, Synthetic Population, Census, Veteran

Digital Object Identifier 10.4230/LIPIcs.GIScience.2023.74

Category Short Paper

Funding Notice: This work is sponsored by the US Department of Veterans Affairs. This manuscript has been authored by UT-Battelle, LLC, under contract DE-AC05-00OR22725 with the US Department of Energy (DOE). The US government retains and the publisher, by accepting the article for publication, acknowledges that the US government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for US government purposes. DOE will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan (`http://energy.gov/downloads/doe-public-access-plan`).

1 Introduction

Measuring and monitoring communities' social vulnerability to environmental hazards is a key consideration for planning decision support [19]. Social vulnerability (SV) broadly describes a population's collective potential for impacts from adverse events and circumstances [1], including natural hazards [3], technological hazards [10], and social determinants of health [18]. Measuring SV is complex, encompassing many conditions of everyday life, including demographics, socioeconomic status, living arrangement, housing, and mobility, that contribute to differential risk of harm or loss for communities exposed to a hazard [25].

Modeling SV often involves distilling multiple risk factors into composite indices that provide high-level characterizations of SV in an area of interest [5]. SV indices serve as entry points for more detailed analysis, including through descriptive characterizations of population risk [23] and field observations. SV modeling typically combines population-level variables (e.g., percentage in poverty, median age) into a composite score using dimensionality

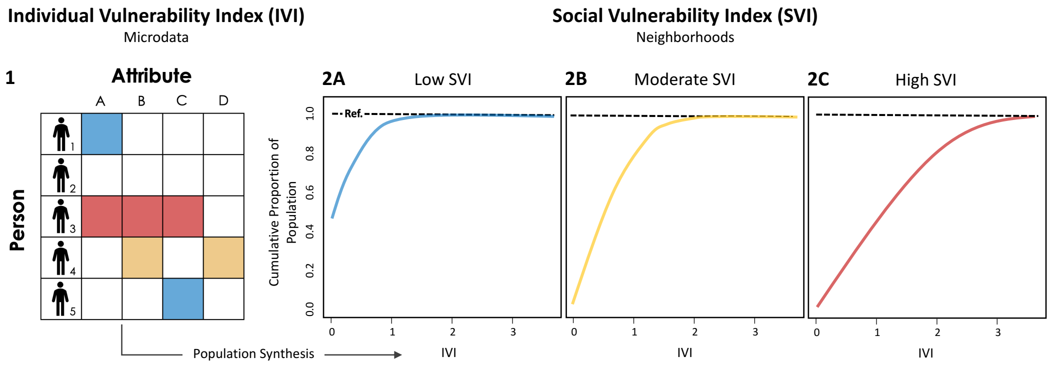

Figure 1 Conceptual illustration representing coupled Individual Vulnerability Index (IVI) scoring (Panel 1) and Social Vulnerability Index (SVI) scoring (Panels 2A - 2C).

reduction [2] or hierarchical aggregation methods [6]. A downside of these methods is that they exclusively compare areas' populations, thereby overlooking characteristics of residents who are likely to be directly impacted by hazards. In this way, ignoring individual risk factors in index construction poses challenges for the interpretability – and therefore actionability – of population-level SV models [11, 20].

This paper introduces an initial model for constructing an individual-oriented SV index (IOSVI) for the United States. The IOSVI supports greater interpretation of how individual vulnerability contributes to SV at the high spatial resolution of census tracts (1200 - 8000 people). The IOSVI is estimated from virtual or *synthetic* populations generated on public-use census microdata. Relative to model interpretability paradigms [13], the mechanisms for producing IOSVI are both *transparent* – built on open data and easily demonstrable [4] – and *decomposable* in that any one individual's level of vulnerability may be understood within the context of community SV, and vice-versa. As a result, the IOSVI is also interrogable, lending to *post-hoc analysis* (exploration, visualization) of individual/community characteristics within the context of SV.

2 The Individual-Oriented Social Vulnerability Index (IOSVI)

Individual "function-based" vulnerability is measured from intersecting *risk factors* that describe a person's daily sensitivities and may compound to affect their health and safety in adverse circumstances [17]. Common risk factors are tied to reduced socioeconomic status, living arrangement and age sensitivity, cultural sensitivity, and issues of housing and mobility [6]. Building upon the concept of function-based vulnerability, the IOSVI has two components: an Individual Vulnerability Index (IVI), which is a tabulation of the number of risk factors attributed to a member of an area's population, and the Social Vulnerability Index (SVI), which describes the cumulative distribution of the IVI within the area's population. The IVI can be a simple count of risk factors, but it can also be a hierarchical or weighted tabulation in instances where different categories of risk factors are of interest.

Figure 1 displays the cumulative distribution of resident IVI, ranked from low to high, for three hypothetical neighborhood areas. SVI can be measured as the difference in the areas under the curve (AUCs) between an area's observed cumulative IVI distribution and a reference distribution based on a hypothetical population in which no individuals are characterized by the risk factors of interest. A larger observed AUC corresponds to lower SVI, since 100% of the cumulative proportion of population occurs at a low IVI score threshold (panel 2A). The reference AUC, which equates to the total number of possible risk factors, is included in the SVI computation to ensure proper directionality of the scores (i.e., low scores $\rightarrow$ low social vulnerability; high scores $\rightarrow$ high social vulnerability).

3 Methods

The IOSVI was developed through Oak Ridge National Laboratory's (ORNL) UrbanPop project. UrbanPop uses a regularized version of the Iterative Proportional Fitting (IPF) algorithm [16] to produce attribute-rich synthetic populations matched to large volumes of variables from the American Community Survey (ACS), the U.S. Census Bureau's primary intercensal product [22]. Toward developing IOSVI, this enables creating customizable representations of individuals in census tracts across the United States with respect how they embody risk factors contributing to SV. A series of 30 replicate synthetic populations for the development of IOSVI were produced for the United States, constrained on the ACS 2019 5-Year Estimates by adapting 14 risk factors identified by the Center for Disease Control and Prevention's (CDC) [6] at the individual level: **socioeconomic variables** including income below poverty, unemployment, and less than high school educational attainment; **living arrangement variables** including age over 65, age under 18, single-adult caregiver households, and disability status; **cultural sensitivity variables** including racial/ethnic minority status and limited English proficiency; and **housing/mobility variables** including multi-unit structures, mobile homes, household crowding, group quarters residency, and lack of a personal vehicle. SVI was computed at the tract level for each synthetic population replicate, following the method presented in Section 2. The final IOSVI was then computed as the Monte Carlo estimate (mean) of the replicate SVIs.

4 Illustrations

4.1 Visualizing Spatial Variation in the Social Vulnerability Index

Figure 2 maps the spatial distribution of IOSVI across the continental United States (panel A) and demonstrates visual interpretation of IOSVI for a portion of the Houston-The Woodlands, Sugar Land, TX Metropolitan Statistical Area (Houston MSA) (panels B, C). In panel C, each census tract's SVI score breaks down to four themes, identified via Multiple Correspondence Analysis (MCA), that describe the blend of risk factors best describing each profile of individual characteristics within the Houston MSA's synthetic population.

4.2 Examining Coupled Individual-Social and Environmental Vulnerability

A case study of intersecting individual, social, and physical (environmental) vulnerabilities was developed to demonstrate post-hoc exploratory analysis of the UrbanPop model underlying IOSVI. This example, developed for the Houston MSA, concerns a specific sub-population, U.S. military veterans. In emergency and disaster scenarios, veterans may experience pronounced problems of housing and livelihood recovery that impact mental and physical health [9, 15]. ACS provides indicators of veteran status for individuals age 25 and over, which were included as constraints for the UrbanPop model, then used to produce an indicator of veteran status in the synthetic population.

The exploratory analysis examines the association between veteran risk factors used to compute the IVI in combination with residency in high IOSVI - high physical vulnerability census tracts. Physical vulnerability was represented by a composite measure of annual

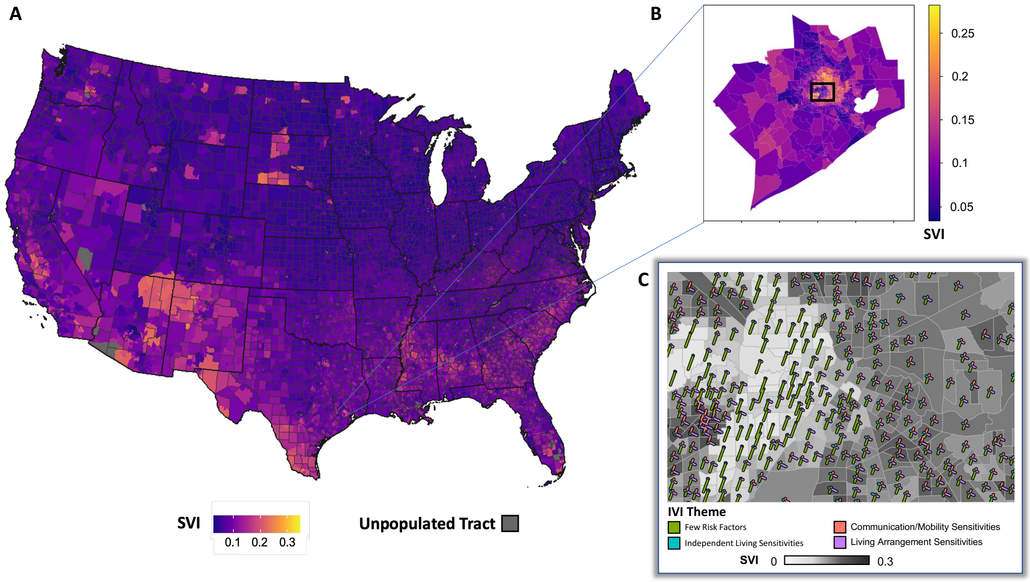

Figure 2 Mapping IOSVI to census tracts for the continental United States (Panel A), regionally (Panel B), and in neighborhood context relative to individual vulnerability index (IVI) themes (Panel C) (glyph plot methodology adapted from [14]).

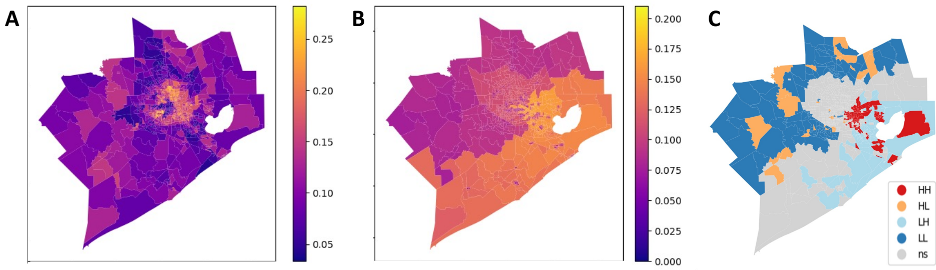

Figure 3 Overview of exploratory analysis of Individual-Oriented Social Vulnerability Index (IOSVI) for the Houston MSA. Panel A: IOSVI; Panel B: Composite annualized frequency score (AFS) of natural hazards from National Risk Index (NRI); Panel C: Bivariate Local Moran's I (BVMI) clusters for AFS by IOSVI. Abbreviations: H = High, L = Low, NS = Not Significant.

frequency of 18 hazard types for each census tract in the U.S. from the Federal Emergency Management Agency's (FEMA) National Risk Index (NRI) [26]. Bivariate Local Moran's I [12] was used to identify clusters of tracts in Houston with differing high (H) and low (L) combinations of social and physical vulnerability. For the subset of veterans in each tract's population, the association between IVI risk factors and residency in a high social vulnerability/high physical vulnerability (HH) tracts was evaluated against all other tract types, including non-significant (NS), using multinomial log-linear regression, a method specialized for dependent variables with multiple categorical labels [24].

Figure 4 reveals that risk factors frequently linked to uneven disaster recovery such as minority race/ethnicity and poverty [7, 8] were consistently associated (coefficient < 0)with veterans living in HH tracts in the Houston MSA, as were limited mobility (no car), less than high school education, disability status, single-caregiver households, and housing density (10+ units in structure).

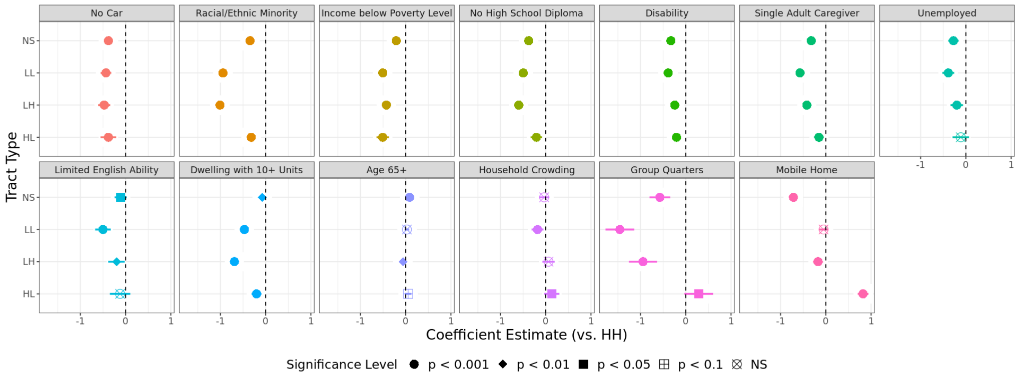

Figure 4 Multinomial regression coefficients and significances, BVMI (AFS by IOSVI) tract types by IOSVI risk factors for U.S. military veterans age >= 25 (base: high IOSVI - high AFS tracts). Abbreviations: H = High, L = Low, NS = Not Significant.

5 Conclusion and Outlook

Preliminary development of the individual-oriented social vulnerability index (IOSVI) on synthetic populations suggests enhanced interpretability (transparent, decomposible, interrogable) over existing methods that measure social vulnerability on population-level data alone.

Illustrations provided for the Houston MSA (Sections 4.1, 4.2) demonstrate the various ways that IOSVI may be examined: in national context, within census tracts, and for specific sub-populations (e.g., U.S. military veterans) in areas of high social/environmental vulnerability. Together, these insights may benefit more direct understanding of the spatial planning and policy interventions appropriate for addressing natural and technological hazards, as well as environmental determinants of health, at the neighborhood and community scales.

The primary limitation of IOSVI is the complexity of its design: large compute resources are required to generate and attribute synthetic populations, as well as estimate SV scores. This could be alleviated by developing an analytics platform for processing user requests and facilitating exploratory analysis, as well as supporting index development for custom geographies.

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