<u>NTHMP MES – Meeting Notes 10/12/2022</u>

Virtual Meeting using MS Teams

<u>Agenda</u>
1. Welcome, Introductions, and Partner Announcements
2. FEMA National Risk Index (NRI) Discussion on NRI concerns and NTHMP letter
3. Annual Work Plan - Review and discuss draft work plan
4. Closing Remarks

Attendees:

Elyssa Tappero, WA EMD; Danté DiSabatino, WA EMD; Althea Rizzo, Oregon; Emergency Management; Summer Ohlendorf, NTWC; Dave Snider, NTWC; Dave Kochevar, NWS Alaska Region Headquarters; Curtis Johnson – Alaska DHS&EM; Nate Wood, USGS; Regina Browne, VITEMA; Mario Kaipat, CNMI HSEM; Nic Arcos, NOAA/NCEI; Amanda Siok, FEMA; Ian Sears, NOAA; Victor Huerfano, PRSN; Todd Becker, Cal OES; Ed Fratto, Northeast States Emergency Consortium; Jeff Lorens, NWS Western Region HQ; Kara Sterling FEMA RX; Lewis Kozlosky NOAA; Julie Fujimoto, Hawaii EMA; John Marquis, SCEC/TsunamiZone;

1. Welcome: Todd Becker, Co-Chair of MES

No new members to introduce. No partner announcements.

2. FEMA National Risk Index (NRI) Discussion on NRI concerns and NTHMP letter

Nate Woods, USGS

Todd Becker, Co-Chair of MES

- Background and Introduction to why we are discussing the NRI tool

- https://hazards.fema.gov/nri/
- Tool developed by FEMA for mapping the potential for negative impacts as a results of hazards, including tsunami
- The NRI was discussed at the Summer Meeting
- NTHMP is working on a letter to FEMA to express some concerns and potential solutions with the letter.
- Today's discussion and presentation on the NRI is so the MES is further informed on the NRI issues and the NTHMP letter to FEMA.

- NRI overview and presentation by Nate Woods, USGS.

  (PDF slides are attached)

  - NRI mapping platform and intended use reviewed
  - Tsunami in the NRI
  - Units of Analysis (Counties and Census Tracts)
  - Calculation of Risk
  - Social Vulnerability
  - Loss estimates
  - Recommendations for NRI Revisions

- NRI Discussion
  - Not aware that any FEMA grant program is currently using the tool;
  - The intent of tool was to treat every tool the same;
  - The draft NRI letter to FEMA has already been shared with FEMA. Want to the letter out by next CC meeting;
  - The NRI should use Hazus;
  - Need to address equity issues in tool;
  - Vulnerability in tool is agnostic to the hazard and not useful;
  - Need to include territories in tool;
  - NOAA has social science committee, it would be good to involve them on this;
  - The relative scale between counties isn't useful for the local jurisdictions;

3. Annual Work Plan - Review and discuss draft work plan

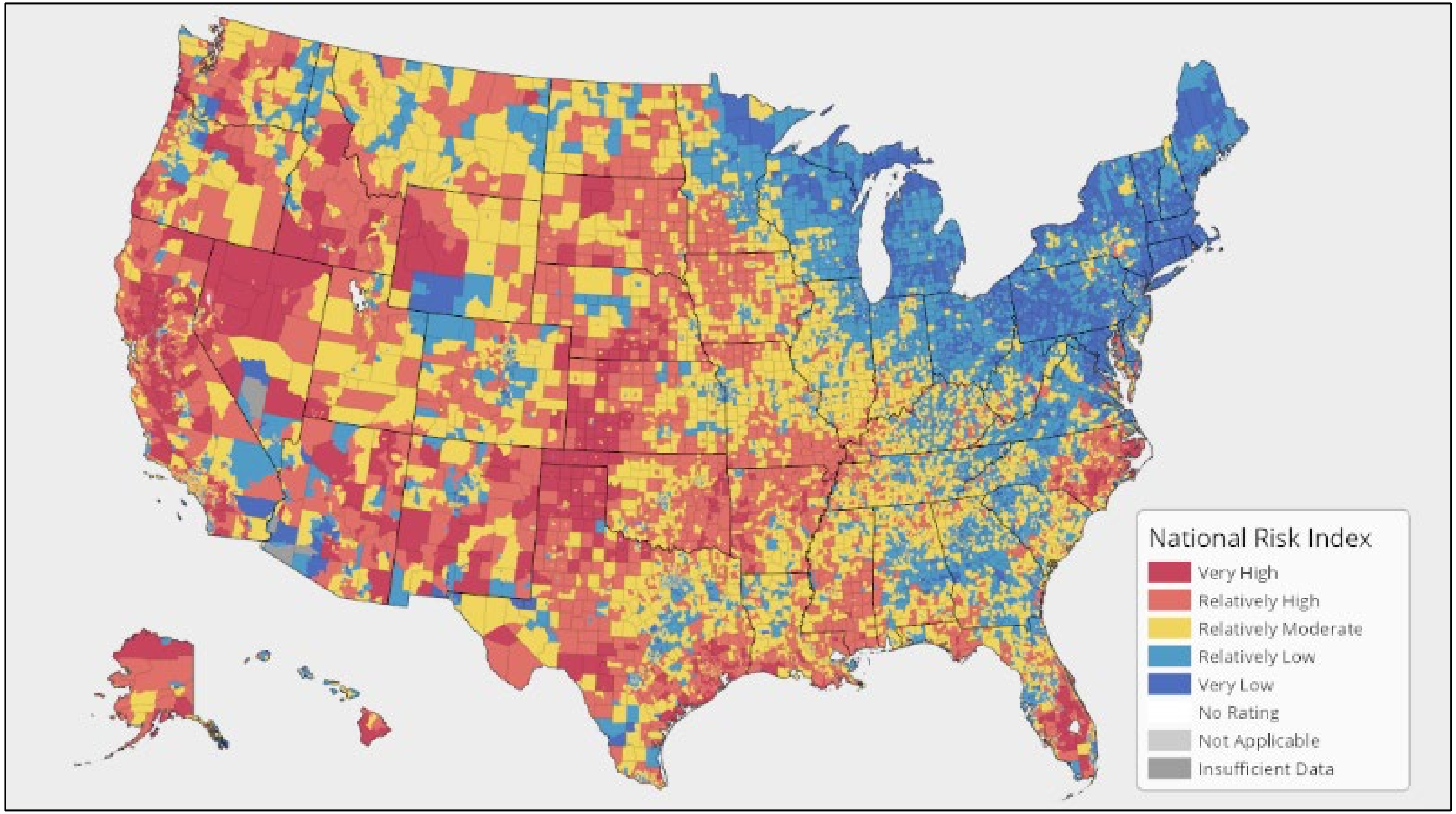
Todd Becker, Co-Chair of MES

- Review draft Work Plan developed from previous MES partner input
    - Link to work plan: https://docs.google.com/document/d/176-lkEHHaC23AEzjcrB7aKHnY2f9I5Dc/edit?usp=sharing&ouid=108818279981971996428&rtpof=true&sd=true
- Some parts of the work plan still need to be completed for some activities. MES Co-chairs will follow up with the Activity Leads (State/Agency) identified on the work plan activity to complete.
- Provide any additional comments or suggestions for work plan over next couple weeks before it is finalized.

4. Closing Remarks

- Next meeting: The next scheduled quarterly meeting falls in January just before the Winter Meeting. Co-chairs will assess if that meeting should be moved to December and send out an update.

NTHMP MES Discussion of FEMA National Risk Index



Nathan Wood, PhD
Western Geographic Science Center
nwood@usgs.gov

Overview of the National Risk Index

FEMA National Risk Index

Explore the Map | Learn More | Take Action | Get Help

- **FEMA online mapping application**
- **Visualizes “natural hazard risk metrics”**
  - 18 natural hazards
  - Expected annual losses
  - Social vulnerability
  - Community resilience
- **Intended uses for city, county, and Tribal organizations**
  - Mitigation planning
  - Hazard Mitigation Assistance Grant Application
  - Risk communication

Learn More

Learn More

The National Risk Index is a dataset and online tool to help illustrate the United States communities most at risk for 18 natural hazards. It was designed and built by FEMA in close collaboration with various stakeholders and partners in academia; local, state and federal government; and private industry.

Related

How the Risk Index Can Help

Determining Risk

Social Vulnerability

Community Resilience

Expected Annual Loss

Understanding Scores and

Tsunami Treatment in National Risk Index

- Uses historic run-up data from NCEI Global Tsunami Database Historic data to capture "tsunami threat"
- **Concerns**
    - Historic data doesn't reflect threats with geologic time scales (e.g., subduction zones)
    - Not exhaustive and biased to places that maintain tide gauges
    - Neighboring counties have different "tsunami threat" even though threat is regional (e.g., subduction zones)
    - Tsunamis are rarer than riverine flooding or other weather events, so tsunamis are under-emphasized in the "risk analysis"
    - Differences in "tsunami" threats not recognized (e.g., local vs. distant)
    - Compiling state/territorial tsunami zones creates temporal and scenario mismatches

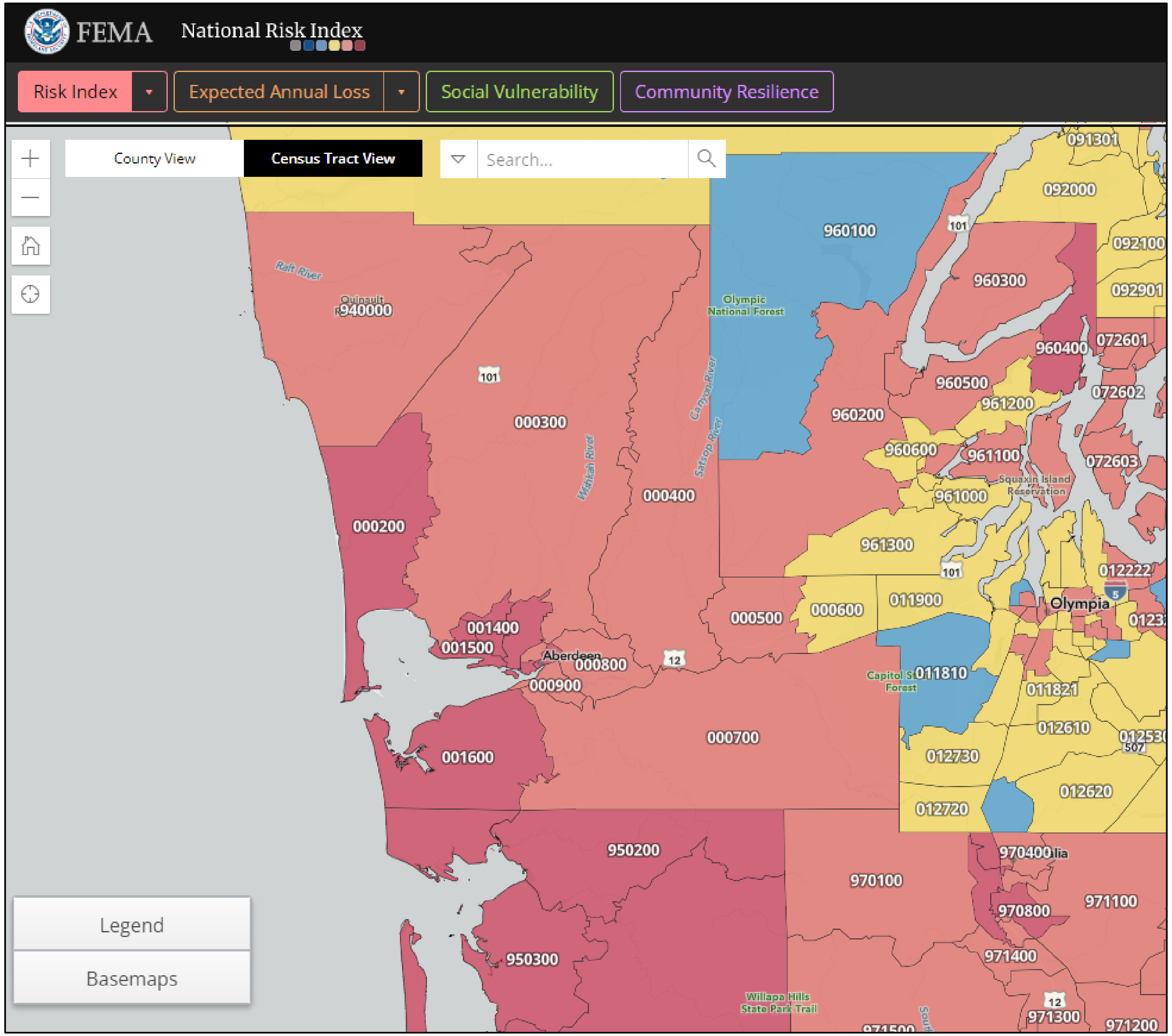
Units of Analysis in National Risk Index

NRI units

- Counties
- Census tracts

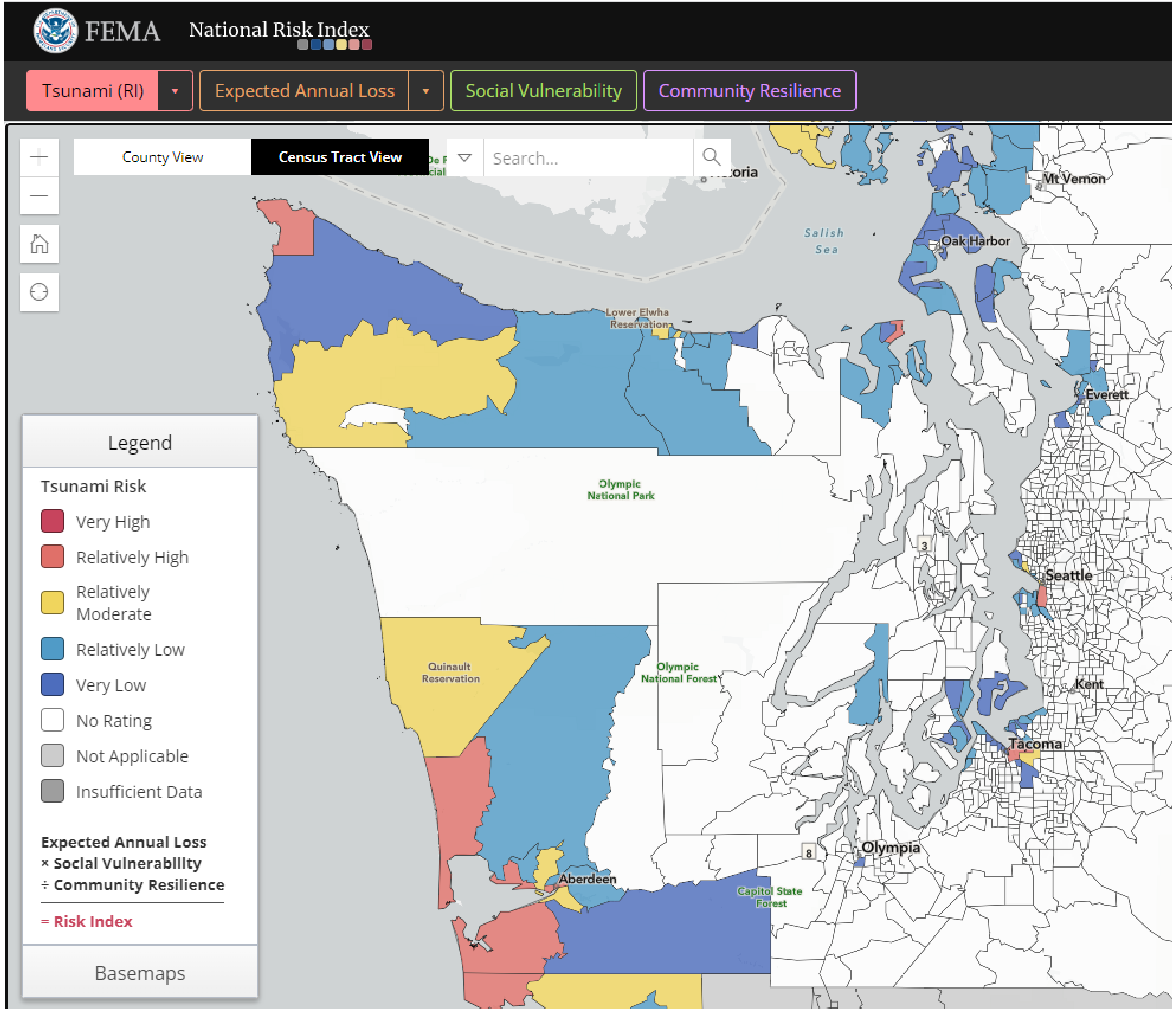
Concerns

- County-level assessments are problematic given the scale and localized, sub-county footprints of many of the hazards being addressed, such as tsunamis.
- Census tracts are also not very relevant for local planning because their boundaries are not well known to people that do not directly work with U.S. Census Bureau data.



Calculation of Risk in National Risk Index

- **Hazard-specific "risk" calculations**
  - Expected Annual Loss multiplied by Social Vulnerability Index
  - Divided by Community Resilience Score
- **Unclear NRI goals with "risk" score**
  - If NRI goal is preparedness, then why expected annual loss estimates?
  - If NRI goal is hazard mitigation, then why link expected economic losses for county to to demographically-derived social vulnerability is unclear.
  - If NRI goal is local planning, then why have relative indices that compare one county against the other ~3,000
- **Mathematically questionable** to multiply an economic loss estimate by a hazard-agnostic social-vulnerability score and then after that, divide it by a community resilience score.



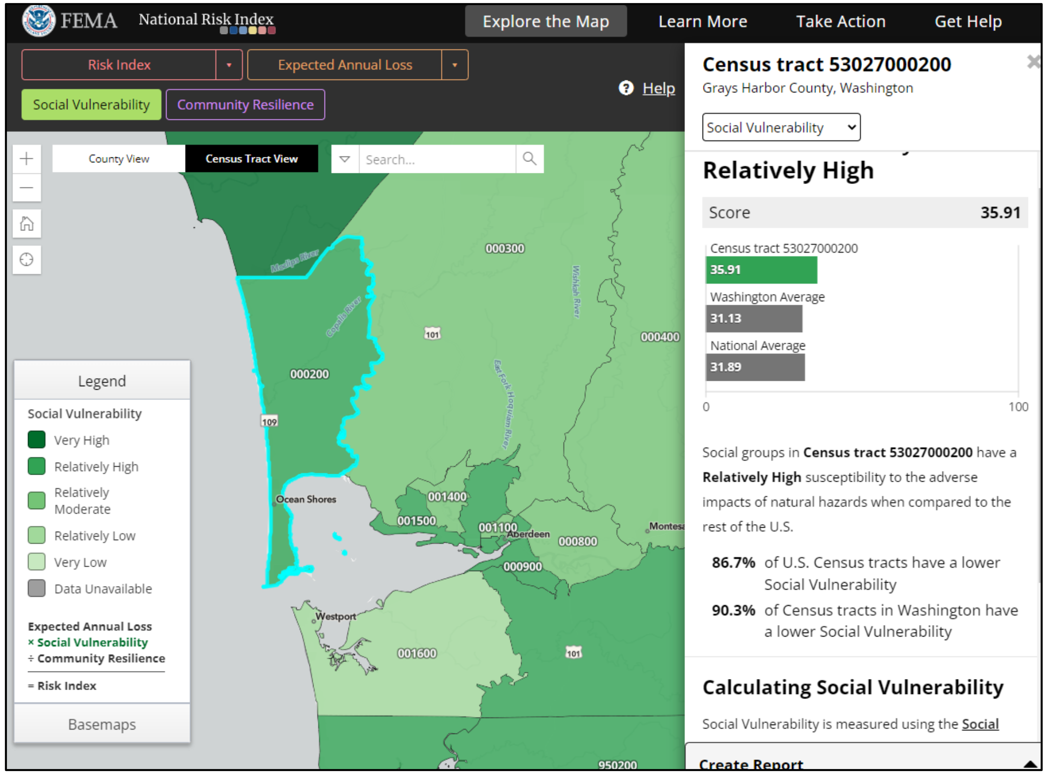
Social Vulnerability Treatment in National Risk Index

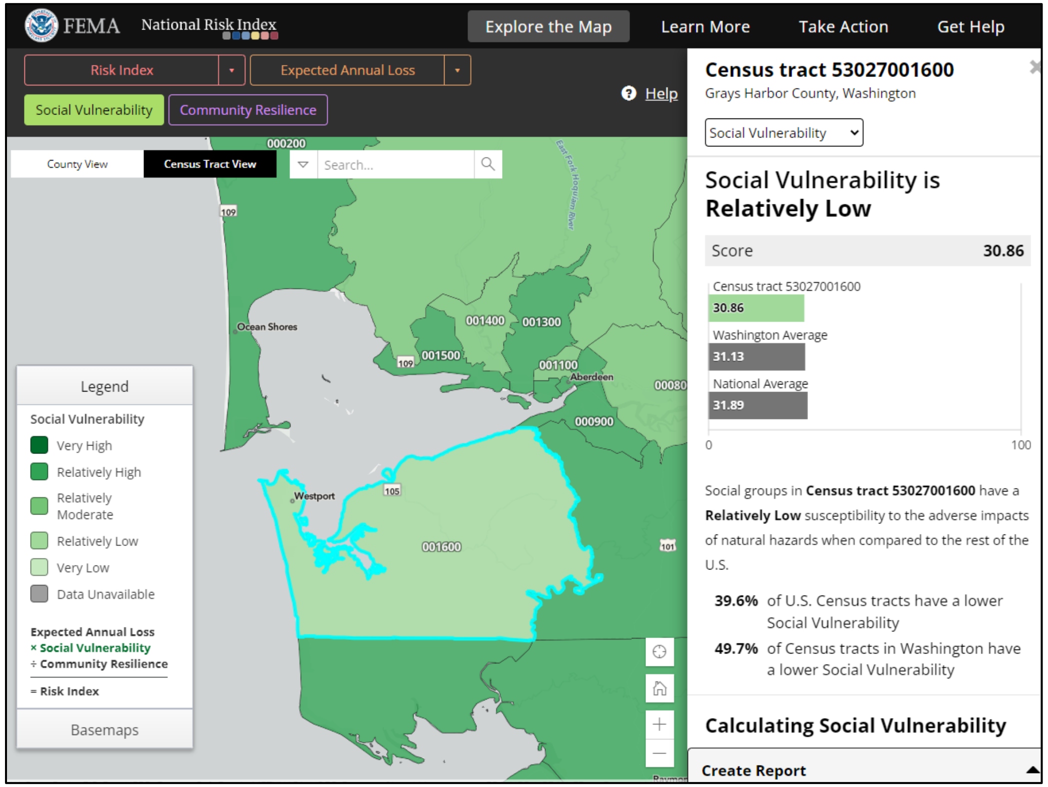
Social Vulnerability Index (SoVI) calculation

- Based on Census data at census tract and county
- Relative assessment comparing one unit to all others
- Calculation based on "principal component analysis"
- Hazard context ignored

Concerns

- Hazard context ignored. "Vulnerability" to drought is the same as to local tsunami in terms of demographic variable
- Relative assessment not relevant to local planning. So, "vulnerability" of your tract/county is a relative term comparing it to all tracts/counties in the U.S.
- Pitfall of relative assessment is that unit with "low" score thinks they don't need to plan.

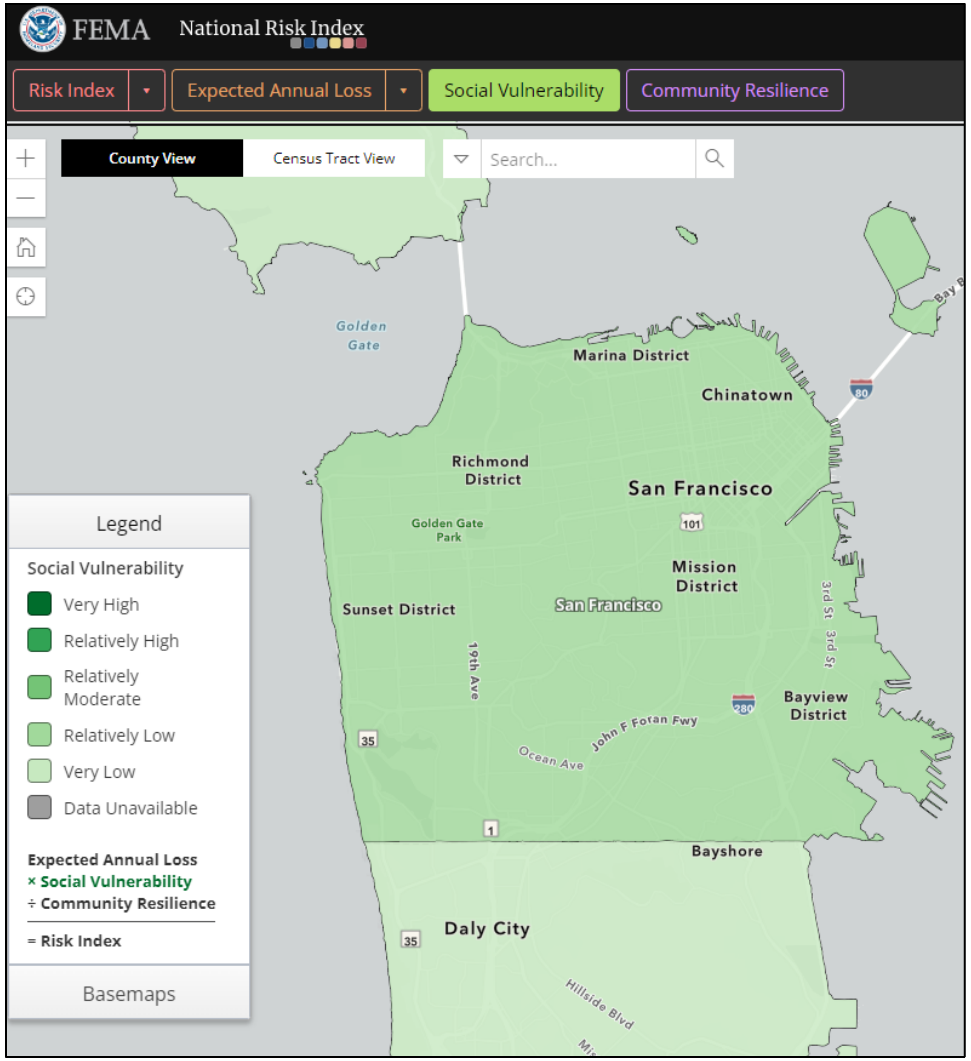


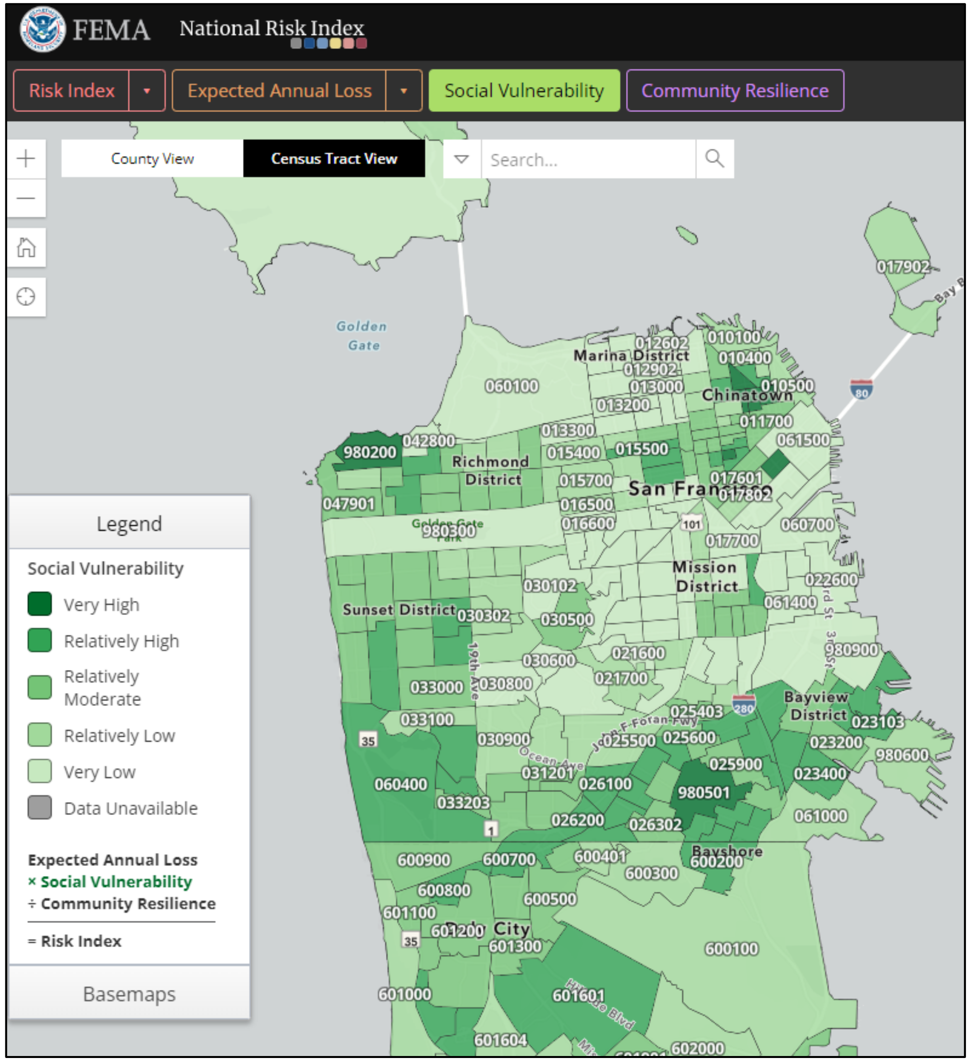


Social Vulnerability Treatment in National Risk Index

Concerns

- Index is documented as being very “volatile” and not recommended for policy/planning
- Scale discrepancies in index values between tracts and county





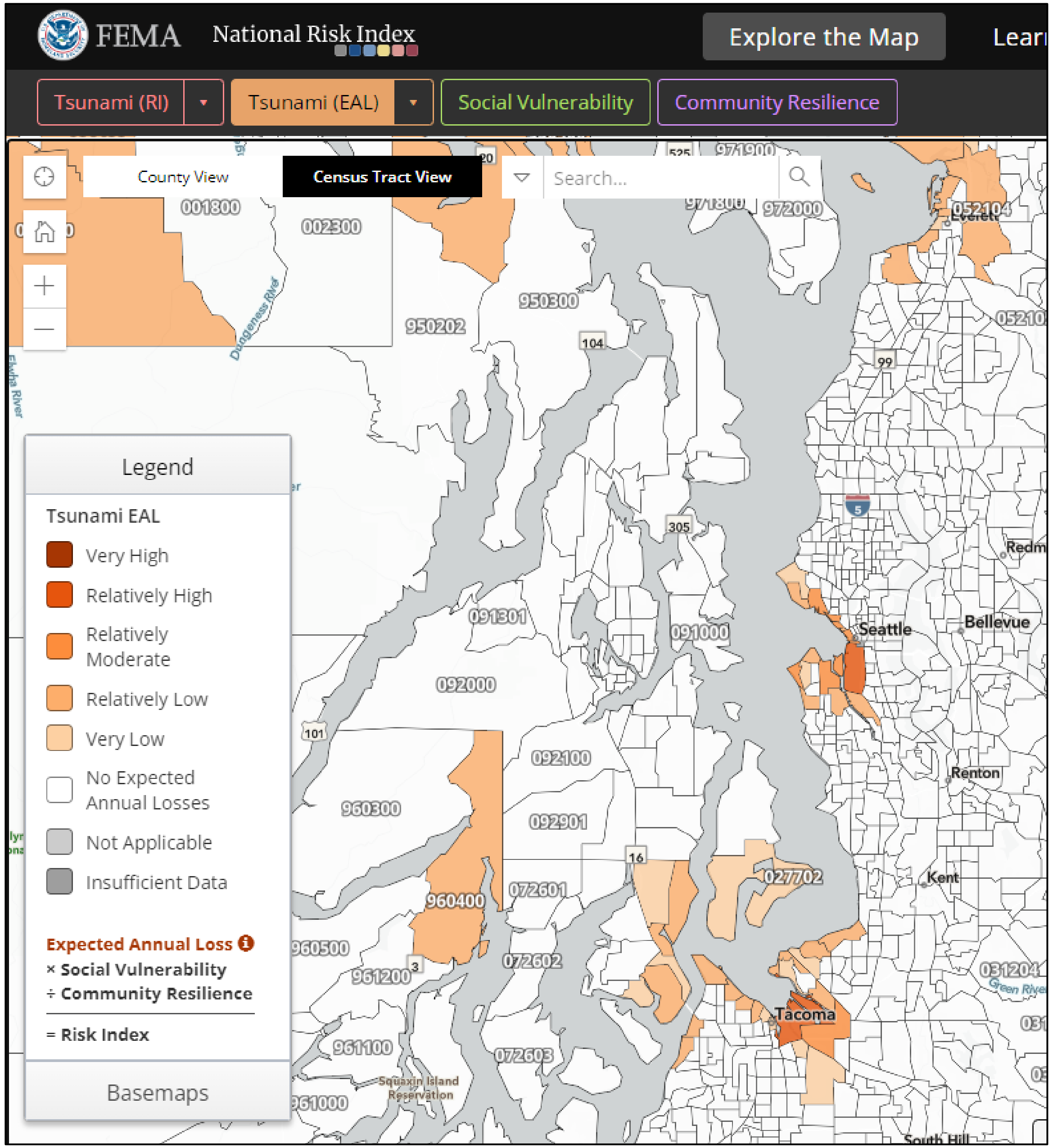
Expected Loss Estimates

Expected Annual Loss for each census block is calculated by multiplying

- Building value exposed to Tsunami events in the Census block (in dollars)
- Annualized tsunami frequency for the Census block (events per year)
- Bayesian-adjusted building Historic Loss Ratio for tsunami for the Census block (which comes from SHELDUS database)

Concerns:

- Issues with incomplete/incorrect hazard data are propagated into this calculation



Potential Recommendations for NRI Revisions

Potential recommendations

- **Tsunami hazard issue:** work with NTHMP to properly characterize tsunami threats to recognize likelihood and consequences of different tsunami sources (e.g., local vs. distant)
- **Unit of Analysis issue:** include “Census Designated Places” to identify incorporated cities, unincorporated villages
- **Social vulnerability issues:** use CDC approach which isn’t so statistically dependent or relatively assessed
- **Expected Loss Estimates:** in theory, these issues are minimized with changes to hazard characterizations
- **Risk calculations:** would require more thought and discussion

Open discussion for NTHMP MES:

- How much of this do you feel the NHTMP letter to FEMA should include?

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ORIGINAL PAPER

Evaluating social vulnerability indicators: criteria and their application to the Social Vulnerability Index

Seth E. Spielman[1] · Joseph Tuccillo[1] · David C. Folch[2] · Amy Schweikert[3] · Rebecca Davies[1] · Nathan Wood[4] · Eric Tate[5]

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Abstract

As a concept, social vulnerability describes combinations of social, cultural, economic, political, and institutional processes that shape socioeconomic differentials in the experience of and recovery from hazards. Quantitative measures of social vulnerability are widely used in research and practice. In this paper, we establish criteria for the evaluation of social vulnerability indicators and apply those criteria to the most widely used measure of social vulnerability, the Social Vulnerability Index (SoVI). SoVI is a single quantitative indicator that purports to measure a place's social vulnerability. We show that SoVI has some critical shortcomings regarding theoretical and internal consistency. Specifically, multiple SoVI-based measurements of the vulnerability of the same place, using the same data, can yield strikingly different results. We also show that the SoVI is often misaligned with theory; increases in variables that contribute to vulnerability, like the unemployment rate, often decrease vulnerability as measured by the SoVI. We caution against the use of the index in policy making or other risk-reduction efforts, and we suggest ways to more reliably assess social vulnerability in practice.

Keywords Social vulnerability · Evaluation · Social indicators

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✉ Seth E. Spielman
seth.spielman@colorado.edu

[1] Department of Geography, University of Colorado, 110 Guggenheim Hall, 260 UCB, Boulder, USA

[2] Northern Arizona University, Flagstaff, USA

[3] Colorado School of Mines, Golden, USA

[4] Western Geographic Science Center, US Geological Survey, 2130 SW 5th Avenue, Portland 97201, OR, USA

[5] University of Iowa, Iowa City, USA

1 Introduction

Who you are and where you live can have a profound impact on how you prepare for, experience, and recover from environmental shocks and extreme events (Morrow 1999; Ngo 2003; Laska and Morrow 2007). As tragically illustrated by Hurricane Katrina, the same hazard event is often experienced in different ways by different people—the short- and long-term outcomes of hazards vary across socioeconomic and geographic gradients. The social scientific literature argues that these differential experiences of, and responses to, hazards are rooted in "social vulnerability." As a concept, social vulnerability describes combinations of social, cultural, economic, political, and institutional processes that shape the differential experience of hazards (Adger 2006; Turner et al. 2003; Birkmann 2013).

Many practitioners and policymakers recognize the influence of social factors on risk management and recovery and therefore seek ways to include social vulnerability in planning efforts. Often this "inclusion" of social vulnerability is manifested through the use of data-driven tools that quantify vulnerability among diverse populations and places (Birkmann 2007; Fekete 2012; Dunning and Durden 2013; Beccari 2016). The most widely used of these tools is a quantitative indicator called the Social Vulnerability Index (SoVI) which was developed through a review of hazard case studies by Cutter et al. (2003) and now has thousands of citations (3094 according to Google Scholar 12/1/17). SoVI is frequently used when comparing geographic units in terms of their relative levels of vulnerability, where the upper and lower bounds of the index correspond to the highest and lowest vulnerability levels in a study area. SoVI's impact is not limited to the academic literature; it has been widely used in place-based assessments by governmental bodies (e.g., Dunning and Durden 2011; Flanagan et al. 2011; Emrich et al. 2014; U.S Environmental Protection Agency 2015), and charitable organizations (e.g., OXFAM America 2009). Quantitative measures of social vulnerability have had a profound impact on scholarship and practice.

SoVI was originally constructed as a general environmental hazards vulnerability measure for the USA (Cutter et al. 2003), but has since evolved to have hazard and geographic context-specific forms, including: local jurisdictions (Amec-Foster-Wheeler 2016), state-level mitigation planning (South Carolina Emergency Management Division 2008), metropolitan comparisons (Borden et al. 2007), international applications (Holand and Lujala 2013; Chen et al. 2013; Guillard-Goncalves et al. 2015; Hummel et al. 2016), preparedness for specific hazards (Kleinosky et al. 2007; Wood et al. 2010; Johnson et al. 2012), and for disaster recovery (De Oliveira Mendes 2009; Finch et al. 2010, State of South Carolina 2017).

The SoVI approach has been applied in many places throughout the world and has inspired other quantitative indicators of social vulnerability. However, there have not been sufficient efforts to critically evaluate the construction of these indices. In this paper, we provide a framework for evaluating quantitative social indicators and use the SoVI as a case study to demonstrate the framework. Previous efforts to evaluate SoVI include Cutter and Finch (2008) that illustrates geographic variability in SoVI, Tate (2012) that subjects SoVI to sensitivity analyses, and Schmidtlein et al. (2008) that uses subjective criteria. Our approach bears some similarity to Schmidtlein et al. (2008), however departs in the application of objective, rather than subjective criteria. In this article, we establish principles for objectively evaluating indicators and then evaluate SoVI against those criteria. A substantial portion of this manuscript is given over to development of these "objective" techniques for the assessment of indices.

1.1 Measuring social vulnerability

Social vulnerability is rooted in and emerges from the interaction of forces that range from macro-economic and institutional to micro-economic and situational. The notion that in spite of this complexity, social vulnerability can be quantified using a single numeric index is a bold epistemological position. More so, because social vulnerability is conceptualized as consisting of many different dimensions—sensitivity, exposure, adaptive capacity (Adger 2006)—and in practice these dimensions are collapsed into a single indicator as opposed to measured through independent indicators.

Social vulnerability is an example of a "latent" variable, something inherent to a person or a place but not directly observable. Viewing social vulnerability as a latent variable implies that from a quantitative perspective, it can only be measured indirectly through statistical procedures. That is, with sufficient information about things that can be directly measured, such as the demographic attributes of an area, a numerical quantity measuring social vulnerability can be defined. There are a number of statistical procedures for estimating latent variables; the most widespread social vulnerability indicator, the Social Vulnerability Index (SoVI), is constructed using one such latent variable method called principal component analysis (PCA) (King 1966; Rees 1970).[1]

The key thing to remember about latent variables like social vulnerability is that unlike things like educational attainment, income, or rent they cannot be directly observed and must be estimated indirectly using statistical machinery. Since social vulnerability is not directly observable, the only way to quantitatively "see" it is through statistical methods for latent variables, such as those used in composite indexes like SoVI, or the CDC's SVI (Flanagan et al. 2011). To a naïve observer, these latent variable methods might seem like voodoo, that is, via the magic of statistics, one can generate a quantitative description of something that they otherwise could not observe. While these methods are not magic, they do require a significant leap of faith. Some aspects of social vulnerability, such as adaptive capacity, may be beyond quantification, and those that are measurable, such as percent of the population that is a minority, may be context dependent such that the same value in different places has different meaning (Birkmann 2006, 2013; Fekete 2012). The use of quantitative indicators is a "leap of faith" because we cannot easily determine if the quantity provided by the index is correct. While social vulnerability indices are widely used, none have been definitively validated. Recent work has shown indicators had little explanatory power in terms of post-hurricane Sandy assistance applications (Rufat et al. 2019).

Even in the absence of robust validation, social vulnerability indicators are widely used due to the importance of including a social component in hazard planning, preparation, and response. Indicators that score or rank places reduce the cognitive burden and complexity of incorporating social and economic dimensions into such processes. Unfortunately, as we demonstrate in later sections, these indicators have some fundamental problems. While they reduce complexity, they do so at the expense of interpretability and alignment with theory.

The synthetic nature of social vulnerability indicators makes it hard to determine if a quantitative index is "right" or "wrong" by comparison to some "true" measure. Concern

[1] The SoVI is constructed using over two dozen variables; the specific formulation varies over time and application. For those familiar with principal components analysis, the index is constructed by summing the first *n* components of from PCA. This yields a continuous numeric score. The original formulation of SoVI retained 11 components retaining 76% of the variance in the original data set.

about the use of social vulnerability indicators is not new (Gall 2007; Tate 2012; Beccari 2016). Most critiques focus on technical aspects of the construction of the index itself, not its place in decision-making and governance. This technical work yields contradictory results: Some work finds the effect of changing input variables on output rankings to be limited (Schmidtlein et al. 2008), while others conclude that variable selection, among other factors, is highly influential on final scores (Holand et al. 2011; Cutter et al. 2013).

This paper does not dwell on ontological questions of whether or not the latent construct, social vulnerability, is measurable or how it should be measured. Instead, this paper attempts to lay out some criteria for the construction of indicators and assess the widely used SoVI index against these criteria using some simple evaluations in silico. Our investigation is rooted in practical and operational concerns around the utilization of SoVI in resource allocation and planning decisions. When applied in practice does the SoVI yield sensible and coherent results?

2 What makes a good indicator?

How does one determine if a measurement instrument, like a vulnerability indicator, is correct if the thing being measured is not directly observable? This question is deliberately broad because we view SoVI as an instance of a broad class of indicators—measures of poverty, resilience, collective efficacy, social cohesion are all members of the same class. For instruments designed to measure physical phenomena, like temperature or PH, well-known benchmarks can be used to calibrate and validate instruments. It is difficult to establish such benchmarks for latent social variables. This difficulty led to the then controversial, now famous, definition of measurement in the social sciences as “The assignment of numerals to objects or events according to some rule” (Stevens 1946 p. 677). Applying this inclusive concept of measurement to social indicators is useful as it allows one to enumerate a set of rules by which an index can be judged.

Through a literature review, we have developed a set of seven criteria for complex social indices, like those used to measure vulnerability:

1. *Theoretical consistency* Does the index successfully measure the thing it aims to assess? Is there clear correspondence between the index’s conceptual framework and measurable inputs? (OECD and JRC 2008)
2. *Internal consistency and robustness* Does the index produce consistent results? Does it do so under sensitivity analyses? (OECD and JRC 2008).
3. *Practicality* Does the index use readily available information? That is, can one easily obtain the necessary ingredients to make (or validate) the index (European Commission Composite Indicators Research Group (COIN) 2016).
4. *Transparency* Are construction and application methods transparent and replicable? (COIN 2016; OECD and JRC 2008).
5. *Interpretable* Does the indicator translate a complex concept into an easily communicable measure? (COIN 2016). Is it easily interpreted by experts and/or community members?
6. *Relevance* Is the indicator directly related to the problem of interest? Is the combination of input values specific to the concept that the indicator seeks to measure, or are they overly general? (Beccari 2016; Birkmann 2006; Polsky et al. 2007; Beccari 2016).

7. *Externally consistent* Does the indicator's results align with other similar measures? (Organization for Economic Co-operation and Development (OECD) and Joint Research Centre (JRC) of the European Commission 2008).

These criteria are not "rules" in the strictest sense. For example, there is no simple test to determine if an index is interpretable (criterion 5); an index might be interpretable by some audiences but not others. Nonetheless, as we demonstrate in later sections, even a partial assessment against these criteria can yield important insights into the strengths/weaknesses of an index.

2.1 Evaluating the Social Vulnerability Index

The SoVI satisfies many of these criteria. It is practical (criterion 3) because it uses readily available public domain census data. It is transparent (criterion 4) because the method used in its construction is publicly available. It is interpretable (criterion 5) because it translates the complex concept of social vulnerability into an easily communicable number. Perhaps, there is some room for investigation of criteria 5; how users comprehend the index is an open area for investigation as there are few examples of usability studies that have examined the cognitive aspects of the index such as practitioner comprehension (Fekete 2012; Oulahen et al. 2015). Relevance (criterion 6) has been the subject of some debate in the literature with some SoVI applications treating social vulnerability as detached from a hazards context (e.g., Cutter et al. 2003), whereas others argue it should be examined contextually within a specific hazard/place such that attributes of the hazard or that make certain demographic variables more meaningful than others (e.g., Wood et al. 2010; Schweikert et al. 2017; Cardona 2004; Birkmann and Weisner 2006; Birkmann 2007).

While the SoVI satisfies to varying degrees the user-facing perspectives of indicator construction (practicality, transparency, and interpretability), we focus our attention on the more conceptual aspects of index construction, namely theoretical consistency (criterion 1) and internal consistency (criterion 2). Theoretical consistency (criterion 1) is also referred to as "construct validity." A measurement instrument has construct validity if it accurately measures the thing it aims to describe. The classic reference on this topic, Cronbach and Meehl (1955) states, "construct validity must be investigated whenever no criterion or universe of content is accepted as entirely adequate to define the quality to be measured" (pg. 282). Theoretical consistency is a very broad idea; we examine it by studying how individual variables contribute to the index. Internal consistency (criterion 2) refers to consistency of the index: Do repeated measures of the same thing yield consistent results? Our evaluation of SoVI internal consistency focuses on whether or not repeated measurements of a specific place or set of places yield the same ordering of low to high vulnerability rankings. The first two criteria, theoretical consistency and internal consistency, are especially important when an index satisfies criteria around ease of construction and use; when an index is easy to construct and interpret, it becomes especially important to determine if the resulting index scores consistently measure the thing they purport to assess.

3 Methods

All code and data used in this paper are available to researchers at [https://github.com/geoss/sovi-validity]. All material in this and subsequent sections can be reproduced using the open-sourced code and data. Due to the complexity of the subsequent analyses and for the sake of readability, we omit some of the technical details and refer the reader to the published code. In the subsequent sections of this analysis, we employ U.S. County-level data from the 2008–2012 American Community Survey (ACS) 5-Year Estimates (U.S. Census Bureau 2013). The 28 input variables that we use in our evaluation are slightly different from those used by Cutter al. (2003) due to changes in how data are collected and aggregated by the U.S. Census Bureau. National-level analyses included 3007 counties and 137 county equivalents. We have validated our SOVI calculation function against a SPSS procedure provided by the Hazards Vulnerability Research Institute at the University of South Carolina on January 27, 2014.

The term "SoVI" requires some definition because it is widely used in the literature as both a framework for measuring vulnerability and a specific quantitative method. The SoVI framework begins with a well-articulated theory about what constitutes social vulnerability and then moves into a variable selection phase in which one selects quantitative indicators that map onto theory. Because SoVI is as much a process as an indicator, we do not see the specific set of variables one chooses as an existential element of SoVI, as long as the included variables are consistent with theory. In the social sciences, there are many cases where the following sequence is used: theory, variable selection, and index construction. Thus, while the analysis in the following sections centers on SoVI, it is more broadly relevant to any "SoVI-like" indicator sets, i.e. any composite measure following the progression from theory to index construction via latent variable methods like PCA.

3.1 Constructing SoVI

Principal components analysis takes a table with P input variables (columns) and n observations (rows) and returns $P \times C$ matrix, where each variable has a row and each "component" is a column. A component is a weighted combination of variables, and the values in cells of the output matrix from PCA represent weights, often called "loadings." A single component $\boldsymbol{\alpha}_\mathbf{c}$ is simply a $1 \times P$ vector of loadings. Components are sometimes manually assigned names like "race and class," "age and tenancy," or "urban vs. rural" based on the variables with the highest/lowest loadings. A noted limitation of the PCA approach is that resulting components are a complex mix of the P input variables, which makes the naming of components a highly subjective and potentially error-prone exercise[2] (Palm and Caruso 1972). Prior analyses of the SoVI, such as Schmidtlein et al. (2008), have relied on subjective interpretation of the "meaning" of components, an exercise we try to avoid in the following analyses; instead, we develop what we believe to be a more transparent and direct method for interpreting the index.

In PCA, loadings are computed for each component–variable combination ($\alpha_{c,p}$), that is, all of the variables included in the analysis make a weighted contribution to each component. For example, a statistic such as median household income makes a weighted

[2] Palm and Caruso (1972) discuss some problems that emerged in urban studies due to the use of labels applied to cities. We review this in more detail in Sect. 6.

contribution to each component of the Social Vulnerability Index. This makes it possible to calculate each variable's net contribution to the index by summing across components.

To calculate a component score for each place, one simply takes the data from a place ($\boldsymbol{x}_i$), which will include many variables ($\boldsymbol{x}_i$ is a $1 \times P$ vector), and multiplies each of the P variables with the loadings for the component of interest. This yields a place-specific component score, $\boldsymbol{\lambda}_{i,c} = \sum_{p=1}^{P} \alpha_{c,p} x_{i,p}$, where $x_{i,p}$ is the pth variable for the ith place. To build the SoVI for a place out of a PCA, one simply combines a subset m of the C components ($\mathrm{SoVI}_i = \sum_{c=1}^{m} \lambda_{i,c}$), where m is the number of components included in the index. In the subsequent sections, we estimate the loadings ($\alpha_{c,p}$) and construct the final index through the PCA procedure outlined in Schmidtlein et al. (2008, p. 1102) and validated with help from University of South Carolina Hazard Vulnerability Research Institute (HVRI). In the subsequent analyses, all variables are standardized as z-scores and combined using principal components analysis (PCA) with a varimax rotation. We then retain all components with an eigenvalue greater than or equal to 1.0.

We employ a method from Tate (2012) and deviate slightly from the original derivation in Cutter et al. (2003). After standardizing variables, we adjust directionality to align variables with their theorized contribution to vulnerability. For example, given a place where the percent of people earning more than \$200,000 is one standard deviation above the mean would have a standardized value (z-score) of $+1$. However, we flip the sign of this variable so that areas above the mean enter the index as a negative value since it is theorized to be negatively associated with vulnerability—more wealthy residents imply less social vulnerability. This ameliorates the need for a posteriori adjustment to PCA components. If a variable has positive expected contribution, then we did not adjust the signs of the standardized variables. If it is expected to reduce vulnerability, we employed the Tate adjustment. Figure 2 shows the included variables and their expected contribution to the index.

3.2 A variable-wise perspective on index construction

An interesting and under-exploited element of PCA-based indices is that one can measure the overall contribution of an individual variable to the resulting index. The SoVI is constructed "component-wise," and components are built from weighted combinations of variables and then summed to construct the final index, $\sum_{c=1}^{m} \lambda_{i,c}$. An equivalent way to build the SoVI is to take the included component-specific weights for each variable and sum them to get the "net contribution" of each variable $\gamma_p = \sum_{c=1}^{m} \alpha_{c,p}$. The index can then be constructed as $\sum_{p=1}^{P} \gamma_p x_{i,p}$.

Table 1 illustrates this idea of a variable-wise construction of SoVI by using hypothetical values for three census variables. In our hypothetical example, variable 1 (percent Asian) loads positively in each of the three components. The sum of the specific weights of the variable is $\gamma_1 = 1.5$, indicating that the variable makes a net positive contribution to the index. Variable 2 (percent homeowner) loads identically to variable 1 on the first component, but then has a mix of positive and negative loadings on other components, yielding a very weak net contribution when compared to variable 1, $\gamma_2 = 0.1$. These results imply that the influence of the percentage of Asian residents (variable 1) on the resulting index is 15 times greater than the percentage of homeownership (variable 2). The first two variables make a net positive contribution to the index, meaning that as they increase, the index increases. The third variable (percent with advanced degree) makes a negative contribution to the index, $\gamma_3 = -0.9$. Therefore, as the number of highly educated people increases, the index goes down.

In this example, a 1% increase in variable 1 yields a 1.5 point increase in the index, a 1% gain in variable 2 yields a 0.1 point gain in the index, and a 1% gain in variable 3 yields a 0.9 point decrease. Thus, one can say that in this particular example, variable 1 is the most influential variable, followed by variable 3.

Table 1 illustrates the equivalence of the variable-wise and component-wise index construction methods. Summing the net contributions of each variable and summing the components (columns) yield the same resulting index value. However, in the "component-wise" approach, one loses a sense of the net impact of each variable. We believe that to assess criterion 1, theoretical consistency, focusing on the net contribution of each variable, is essential. Traditionally, SoVI is viewed as a combination of components, which are in turn a combination of variables. This obscures the actual contribution of input variables. In the construction of SoVI-like indices, the components are sometimes weighted by their eigenvectors. One can similarly apply weights to variables to yield a weighted net contribution.

4 Evaluation of internal consistency

Internal consistency is the idea that one or more valid measures of the same thing using the same instrument should yield similar results. That is, a working thermometer measuring the same glass of water twice should register approximately the same temperature.

We conduct an evaluation similar to taking (instantaneously) repeated measurements of the same glass of water. We compute a SoVI for all counties in a state. We then recompute the index for the same state using an input file that includes all counties in that state plus all of the counties in that state's FEMA region. Finally, we again recompute the SoVI index for all counties in the state using an input file that includes all counties in the USA. In each of these indices, we use exactly the same county-level data and methods, but we vary the amount of data fed into the index. We are not varying the scale of measurement (for example using census tracts or zip codes); in each run, we simply use different subsets of US counties. Effectively, this evaluation is analogous to three measurements of the same glass of water; it yields three measurements of social vulnerability, constructed with identical data and methods, for each county of the target state.

For illustrative purposes, we use counties in the state of California to discuss the internal consistency of SoVI. The three maps shown in Fig. 1a–c depict the top five (in red) and bottom five (in blue) ranked counties in California after calculating SoVI three times (i.e., just California counties, all counties in FEMA Region IX, and all US counties and county equivalents). Figure 1d is a summary map indicating the observed range of the county ranks in the three indices. For example, Lassen County in the northern part of the state (labeled 5 in Fig. 1a) is ranked the 5th highest out of 58 counties when SoVI is calculated using an input file with only California counties (Fig. 1a), but 56th out of the 58 California counties when SoVI is calculated using an input file containing all counties in the USA (Fig. 1c).

The ranks shown in Fig. 1 are always specific to California—there is no substantive justification for a change of this magnitude. That is, Lassen County should not shift from being one of the most vulnerable places in the state to one of the least vulnerable in the state without altering any of the input data for the state of California simply because we included more counties in the input file. Similarly, San Francisco County is the 2nd most vulnerable county in California when computations are based on only state data (Fig. 1a),

Table 1 Comparison of variable-wise and component-wise approach to index construction using a hypothetical example

	Variable value	Loadings component 1 ($\alpha_{1,p}$)	Loadings component 2 ($\alpha_{2,p}$)	Loadings component 3 ($\alpha_{3,p}$)	Variable net contribution	Index score: variable contribution (γ_p)
Variable 1 (percent Asian)	10	0.5	0.5	0.5	1.5	15
Variable 2 (percent homeowner)	10	0.5	−0.5	0.1	.1	1
Variable 3 (percent w/advanced degree)	10	−0.5	0	−0.4	−0.9	−9
Component score ($\lambda_{i,c}$)	5	0	2		Total index score: 7	

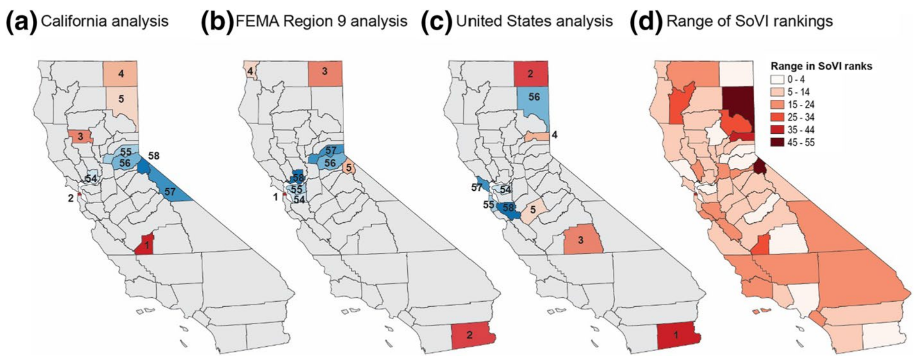

Fig. 1 The most and least socially vulnerable counties in California based on three different county-level input files (**a**) California, **b** FEMA Region IX (including Arizona, California, Hawaii, and Nevada), and **c** the entire USA. California has 58 counties. Areas labeled 1–5 (red) represent the most vulnerable counties, whereas scores 54–58 (blue) represent the least vulnerable counties. **d** The range in SoVI rankings for each California county based on the state, regional, and national SoVI analyses

the most vulnerable county in the state when calculations are based on state plus FEMA Region IX counties (Fig. 1b), and 43rd most vulnerable in the state when the calculation are based on state plus the rest of the US (Fig. 1c). Certain counties show a considerable range in SoVI ranking values among the three different input files (e.g., Lassen County), whereas other counties show little variability (e.g., Stanislaus County retains the same ranking for the state and national analyses).

Table 2 shows the spearman rank correlations comparing the association between the rankings of counties within a state when each of those rankings is constructed using progressively more data as described above. For FEMA Region 1, we combine ME, NH, MA into a single unit as states in the northeast have very few counties. If the SoVI exhibited internal consistency, then all values in Table 2 would be positive and close to 1.0. Results indicate a range of values from 0.34 (Illinois rankings when compared across FEMA Region V) to 0.94 (a composite of Main, New Hampshire, and Massachusetts across FEMA Region I), suggesting varying levels of internal consistency across the USA. Correlations are generally higher when comparing a input file containing all counties in a state to an input file containing all counties in the FEMA region containing that state (average $r=0.75$) than when comparing a state input file to US input file (average $r=0.65$). However, this is not always the case; for example, SoVI rankings for counties within Georgia (FEMA Region IV) based on the national- and state-level analyses produce a correlation of $r=0.5$. This means counties in Georgia ranked as highly vulnerable in state-level analysis ranked as less (or more) vulnerable in national- or regional-level analysis—remember we are always comparing only the counties within a single state, so the correlation of 0.5 for Georgia is based on comparing only the counties of Georgia to each other. In total, 7 out of 10 states produce correlations below 0.70. The lowest correlation was found for the FEMA region-state comparison in Illinois ($r=0.34$).

In this evaluation, one can think of each county in each target state as a "cup of water" into which we have inserted three thermometers—the thermometers in this case measure social vulnerability and are constructed with the same variables and methods but progressively larger numbers of counties. We show that despite using the same input data and methods, social vulnerability, as revealed by the SoVI, changed markedly in response to

Table 2 Spearman's rank correlation coefficient for SoVI values calculated using nested subsets of a file describing all counties in the US

	FEMA region									
	I	II	III	IV	V	VI	VII	VIII	IX	X
All US counties input file versus all counties in a state input file	0.75	0.79	0.68	0.50	0.50	0.62	0.90	0.61	0.53	0.66
All counties in a FEMA region versus counties in a state within the FEMA region input file	0.94	0.61	0.90	0.80	0.34	0.65	0.82	0.87	0.69	0.88
State used for comparison	Composite of ME, NH, MA	NY	VA	GA	IL	TX	MO	SD	CA	ID

$p < 0.01$ for all values

expanding the pool of data that informs the calculations. Our results show that SoVI lacks internal consistency. The index makes it seem that the "most" and "least" vulnerable counties in California change in response to expanding the amount of data fed into the index (Fig. 1). Furthermore, we show that this is not an isolated phenomenon and in much of the USA, the rank correlation between SoVIs computed with the same data and methods but with differing amounts of input data is low. Practically, this leaves us wondering, if SoVI is a valid representation of the latent construct social vulnerability, which one of these three divergent measures correctly captures it for a given state.

Internal consistency is a critical property for any measurement instrument. This evaluation highlights problems with the SoVI index. A model created at the FEMA region scale will lead to the targeting of different counties than the same model run at the state or national scale. Similarly, a model that omits parts of a metropolitan area (or other type of region) will yield different results than one that includes the entire area. Lack of internal consistency is not an academic curiosity; it can have real consequences for real lives when data are used to allocate resources or develop risk-reduction policies.

5 Evaluation of theoretical consistency

Theoretical consistency, which we also refer to as construct validity, is the degree to which an index measures what it claims to be measuring. With a latent variable like social vulnerability, construct validity can be especially difficult to assess. SoVI is a complex index constructed from multiple variables; in this evaluation, we use the "variable-wise" approach outlined above to examine the construct validity of the index. In the case of SoVI, we cannot assess construct validity by comparing the value of the index in a particular place to some gold standard or perfect measure of a particular place's vulnerability. However, theory and the large existing literature provide strong guidance on how most, but not all, variables should contribute to the index. For example, a variable like the unemployment rate clearly should make a net positive contribution to social vulnerability, i.e., the more unemployed people there are in an area, the more socially vulnerable it becomes. Other variables, like the percent of the population that is Asian, are more difficult to assess. Based on the literature, we have assigned each variable in the SoVI index an expected net positive or net negative contribution, and these expectations are shown in the "expected contribution" column of Fig. 2. Positive (+) implies that increases in that variable should increase social vulnerability scores and negative (−) implies that increases in that variable should reduce social vulnerability scores.

To test the expected contribution of each variable, we constructed a SoVI using all US counties and county equivalents. We then compared the expected net contribution of each variable to the actual observed net contribution (denoted in the "original contribution" column of Fig. 2). For example, the vulnerability science literature suggests that higher percentages of a population that is unemployed are expected to increase social vulnerability. However, in our national-level SoVI, we find that increasing unemployment in a county actually decreased the total indicator of social vulnerability (Fig. 2).

Figure 2 also orders the demographic variables in terms of their importance to a national-level SoVI, with highest importance shown on the highest row. High importance means that the variable makes a large net contribution to the index, and low importance means that changes to that variable have a small impact on the resulting SoVI score. A variable can have a "high impact" if its net contribution is positive or negative—the order

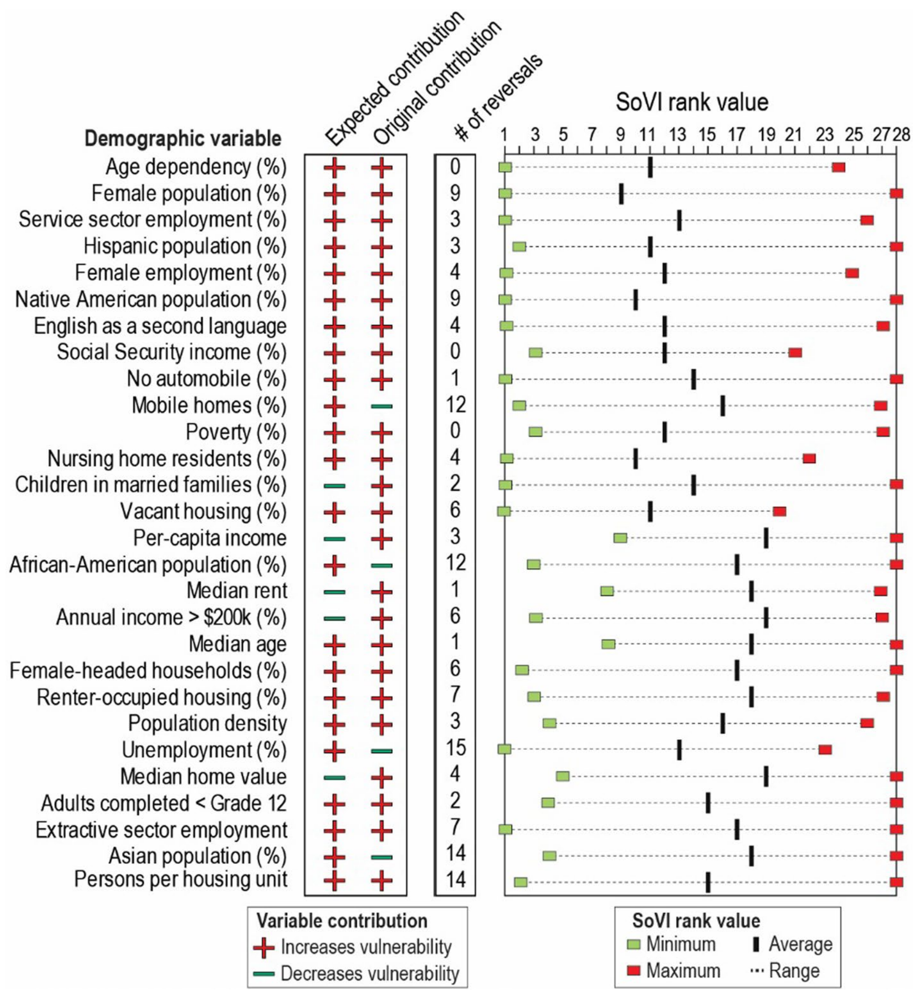

Fig. 2 Summary results for changes in variable contributions and rank values due to changes in the geographic extent of the input. Input variables are listed in descending order of importance (net contribution) to the index (when constructed using all counties in the USA). The expected contribution to social vulnerability (positive or negative) is shown, as is the actual contribution at the national level. Variable instability is shown by "# of reversals." The column counts the number of times a variable reverses its contribution to the index, from positive to negative or vice versa; the maximum number of reversals possible is 20. Instability in the relative importance of variables to the index is shown in "SoVI rank value" the observed range in ranks (from 1 being the most significant contributor to the index and 28 being the least)

in the table is based on the absolute value of the net contribution. We rank variables based on their net contribution; the most important gets rank #1 and the least important gets rank #28. In the national-level model, the age dependency ratio was the most important variable (ranked #1) and persons per housing unit was the least important (ranked #28, leftmost column of Fig. 2).

We also examined how the net contribution of each variable changed as we increased the amount of data used to calculate the index. Following the procedure used in the analysis of internal consistency, we calculated SoVI for each FEMA region and then a state within each region, yielding 21 total SoVIs (1 national model, 10 FEMA region models, and 10 state models). We find the net contributions of variables across these models with differing geographic extents to be highly unstable both in terms of sign and magnitude. Approximately, 90% (25) of the (28) variables used to construct SoVI change the sign of their net contributions as the quantity of data used to construct the index changes. For example, when SoVI is computed at the national level, the third most important variable in terms of net contribution to the index is the *Percent of the Population Employed in the Service Sector*. This variable, at the national scale, makes a strong net positive contribution to SoVI; that is, as the number of people employed in the service sector increases, a county's vulnerability increases. However, when SoVI is constructed using only the counties of FEMA Region I, the P*ercent of the Population Employed in the Service Sector* contributes in a negative way: More service sector employment decreases a county's vulnerability score.

The third column of Fig. 2 (# net reversals) counts how often a variable flipped from making a positive to negative contribution to SoVI. For example, the variable *Percent Mobile Homes* theoretically increases vulnerability—but in 12 out of 20 analyses, increasing shares of mobile homes were associated with decreasing social vulnerability scores. The net-variable-wise contribution of this variable oscillated from a positive to a negative contribution as we changed the geographic extent of the input data. Only three of the 28 input variables were consistently aligned with their theoretically expected contributions across the various geographic extents.

In addition, we examined the importance of each variable to the resulting score as the geographic extent of the input changes. We again found an enormous amount of volatility; at the extremes some variables went from being the most influential contributor to the index to being the least influential contributor. (Rightmost column of Fig. 2 shows the min, max, and average rank.)

Our results raise questions about the meaning of the SoVI index to a practitioner or policy maker because widely accepted understandings of how social and economic variables relate to vulnerability seem to be upended in the index. One can know, from theory, how different variables ought to contribute to social vulnerability. When we construct SoVI indices using data describing US counties, we find that variables often make counterintuitive contributions to the index, i.e., variables increasing social vulnerability when one anticipates they should decrease it (or vice versa). The volitality we observe suggests issues of theoretical consistency and raises questions about the interpretability of the index.

6 Discussion

There have been many efforts to quantify vulnerability, see Beccari (2016) for an overview, yet there has not been equal attention paid to examining the utility of the methods used to do so. The objective of this article was to establish criteria for the assessment of social indicators and to evaluate the Social Vulnerability Index (SoVI) against those criteria. SoVI was chosen because of its prolific application in recent years at multiple geographic scales and in many parts of the world.

Vulnerability is a complex, latent, construct; therefore, we do not believe it is possible to directly measure the "correctness" of the SoVI, i.e., its ability to correctly estimate a place's vulnerability. Instead, we evaluated the SoVI against a set of generic criteria. Such tests do not require knowing the actual vulnerability of a place yet allow us to assess the index on empirical grounds via statistical methods. In this section, we discuss the implications of our tests on index construction and on the use of index-based results by practitioners interested in understanding more about place-specific social vulnerability.

SoVI aims to provide a summary of complex social phenomena via an ensemble of variables. What does such an amalgamation of data mean in an ontological sense? How should one interpret the index? What do the numbers tell us? The act of understanding an index and its validity we believe requires an examination of its constituent parts. In this paper, we argue that these constituent parts are the variables that constitute the index. Thus, we believe that is it possible to assess construct validity by examining how individual variables contribute to the index. We find that the relative contributions of variables are highly unstable. For example, simply by changing the geographic extent of the inputs, we are able to make variables shift from being among the most important ingredient to the least important (Fig. 2).

On the other hand, it does not seem unreasonable that the meaning of social vulnerability would change with geographic context. Many contend that vulnerability is contextual to the type of hazards and potential risk-reducing options (Buckle et al. 2000; King and MacGregor 2000; Jones and Andrey 2007; Birkmann 2007). For example, the percentage of Asian individuals within a county likely has a different meaning for social vulnerability in Maui County, Hawaii (47% are Asian alone or in combination with one or more other races), than it does in Aroostook County, Maine (0.6%). The role of race in developing social capital, access to information, and other aspects of vulnerability likely varies due to place-based differences.

However, our results also demonstrated that certain demographic variables may influence SoVI rankings in ways that are counterintuitive. When we examined the net contributions of variables, we found that some which should positively affect vulnerability actually have a negative impact on SoVI scores (and vice versa). For example, as percent of total population that is African-American increases, theory posits that social vulnerability should increase in that geographic region because variables that measure potentially marginalized populations increase vulnerability. However, the percent of total population that is African-American variable decreases social vulnerability when SoVI is constructed with all counties in the USA and for several other input files. In many cases, social vulnerability scores decreased when the percentage of unemployed persons increased. These results cast doubt on the construct validity of the index.

In our analysis, the ordering of counties in the same state from most to least vulnerable changed depending on which subset of the counties in the USA were used as inputs. This volatility becomes especially salient for local practitioners (e.g., city, county, and state) hoping to use results performed by others at a regional or national scale because relative rankings for their jurisdiction of interest may change dramatically depending on the scale of analysis and inclusion of other jurisdictions to the analysis. This again raises an epistemological issue in that the meaning of vulnerability changes for an individual county or set of counties within the same state if another county in a different state is included. Others have also documented SoVI's sensitivity to scale and raised similar concerns that national indices may have limited relevance or applicability to local resource planning (Cutter et al. 2013; Tate 2012). However, our results suggest that SoVI has limited utility generally as it fails simple tests of internal consistency and construct validity.

Additional challenges exist, such as the input data itself. Specifically, this study relies on use of ACS provided by the U.S. Census Bureau and large margins of error for a single data point could drastically affect the outcome of a geographic region (Spielman et al. 2014). The authors note that this is a profound component of understanding and measuring constructs of social vulnerability, but falls outside the scope of the method itself, which is the subject of this paper.

Fundamentally, the problems we identify with SoVI are rooted in the methods used to construct the index. Principal components analysis relies on a variance–covariance matrix, which allows a change in a single variable to cascade throughout the index. Therefore, matrix structure may change drastically at varying levels of analysis, or when a variable that co-varies strongly with others is removed.

It is worth noting that there are historical parallels between the SoVI and now out of fashion line of research on urban "factorial ecology." Factorial ecology emerged as a line of inquiry in the late 1960s and continued as an active area of research through the 1970s. The term "factorial ecology" refers to the use of a method, factor analysis, to describe socioeconomic patterns within cities using census data describing the characteristics of residents (Janson 1980). Factor ecologists commonly assigned labels like "socioeconomic" or "demographic" to the factors that resulted from an analysis. A factor consisted of many variables, each one weighted differently, which is substantively similar to the common practice of naming PCA components in a SoVI analysis. The factor ecologist's subjective interpretation of factors often ignored variables, a practice that Palm and Caruso (1972) argued was a form of "speculative synthesis" and that the labels did not align with variable weights defining the factor. Their indictment of factor analysis is extensive and beyond the scope of this paper. For our purposes here, it is interesting to note that their criticism of the "crudeness of classification" in factor analysis could be extended to SoVI. That is, we find that in many cases, applying the label "vulnerability" to SoVI scores is problematic because of misalignment with theory and volatility in measurements.

7 Conclusion

We observe some substantial problems with the internal and theoretical consistency of the SoVI. However, we also recognize the importance of measuring social vulnerability in hazard planning, mitigation, and response. The next step, then, is to understand where improvements can be made so that this critical concept can continue to be utilized in ongoing planning efforts.

Social vulnerability is a complex concept, representing it on a single scale that ranges from high to low is reductionist as there are many forms of vulnerability. We believe that the best way forward is to allow experts to construct meaningful indicators by specifying variable-specific weights, without reliance on statistical techniques like PCA. Rufat et al. (2019) found that this approach performed better than existing indices in explaining Hurricane Sandy outcomes. All indices used for public policy should pass some test of their utility, whether using the criteria we outline or others. There must be a robust assessment of the quality of the measurements before an indicator is used in practice.

Variable selection plays a paramount role in index construction (Clark et al. 1974), and research shows that the process of selecting variables can be improved by the integration of qualitative methods and local expert opinion (Schmidtlein et al. 2008), as well as better recognition of the policy-relevant purpose of why an assessment is being developed (Birkmann and Wisner 2006). Holand and Lujala (2013) discuss conceptual, technical, and geographic accommodations that also would help in variable selection. Based on this previous work, more research on variable selection and its influence on social vulnerability indices would further the application of indices in risk-reduction planning.

Another area for more investigation is the potential benefit of simply communicating the covariance of variables, instead of developing composite indices composed of many variables. For example, knowing that renter-occupied households often co-occur in places where there are high percentages of populations where English is a second language can help inform outreach and preparedness planning across a state. These demographic linkages, which are somewhat hidden in the index, may help emergency managers tie vulnerability factors directly to action-oriented strategies. This objective could also be served using other analytical approaches, such as similarity indices (Chang et al. 2015) and clustering approaches (Rufat 2013, Wood et al. 2015) that focus on the commonalities in vulnerability factors.

Disaster risk-reduction efforts increasingly focus on using quantitative indicators of social vulnerability to identify vulnerable people and places, prioritize projects, and allocate resources. We have developed criteria by which these indicators can be assessed and demonstrated their application to a widely used indicator, SoVI. By many criteria, the SoVI is a success: It is easily interpreted, reproducible, and widely used. However, our examination of the index led to concerns about the index's internal and theoretical consistency. The issues we have identified here raise questions about its utility for policy making, planning, and hazard mitigation. We publish all code, and data, so that others may reproduce (or refute) our work.

While there have been other published analyses of uncertainty and scale sensitivity in vulnerability indicators, our approach is somewhat unique. We start from the position that vulnerability is a latent construct and thus hard to directly observe and validate. Rather than validating SoVI through an examination of its absolute validity (by reference to external outcome), we instead assess the index against a set of generic criteria. Our results suggest that the SoVI lacks internal consistency because relative vulnerability rankings for counties within a specific state were volatile and failed to converge when other, external counties were added to the index construction. Our results also suggest that the SoVI lacks theoretical consistency because in many instances, variable-wise contributions ran counter to expectations based on the social scientific literature (e.g., higher poverty levels counterintuitively led to lower SoVI scores). For these reasons, we question if the SoVI provides a defendable or reliable approach for understanding place vulnerability to guide risk-reduction efforts. At a minimum, practitioners need to be made aware of these significant limitations and issues if the SoVI is to be used for actual planning. For those who wish to continue with the SoVI framework, we believe that it is essential to unpack the meaning of the index by examining how each variable contributes to the final score. Doing so allows researchers to determine if the particular weighted combination of variables returned by the PCA procedure aligns with their conception of social vulnerability.

We suggest a few ways to improve the measurement of vulnerability. Ultimately, we believe that vulnerability is not a variable like temperature that runs from hot to cold, but something that manifests itself in many different forms in many different places and that any instrument used in measurement should be subject to due diligence using our (or other) criteria before it is used for risk-reduction planning. We believe place- and hazard-specific contextual measures of vulnerability are not only fruitful avenues of research but also critical in helping communities and policy makers to better prepare for, respond to, and recover from extreme events.

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ORIGINAL PAPER

Community variations in social vulnerability to Cascadia-related tsunamis in the U.S. Pacific Northwest

Nathan J. Wood · Christopher G. Burton · Susan L. Cutter

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Abstract Tsunamis generated by Cascadia subduction zone earthquakes pose significant threats to coastal communities in the U.S. Pacific Northwest. Impacts of future tsunamis to individuals and communities will likely vary due to pre-event socioeconomic and demographic differences. In order to assess social vulnerability to Cascadia tsunamis, we adjust a social vulnerability index based on principal component analysis first developed by Cutter et al. (2003) to operate at the census-block level of geography and focus on community-level comparisons along the Oregon coast. The number of residents from blocks in tsunami-prone areas considered to have higher social vulnerability varies considerably among 26 Oregon cities and most are concentrated in four cities and two unincorporated areas. Variations in the number of residents from census blocks considered to have higher social vulnerability in each city do not strongly correlate with the number of residents or city assets in tsunami-prone areas. Methods presented here will help emergency managers to identify community sub-groups that are more susceptible to loss and to develop risk-reduction strategies that are tailored to local conditions.

Keywords Social vulnerability · SoVI · Cascadia · Tsunami · Oregon · Principal component analysis

N. J. Wood (✉)
Western Geographic Science Center, U.S. Geological Survey, 1300 SE Cardinal Court, Bldg. 10, Vancouver, WA 98683, USA
e-mail: nwood@usgs.gov

C. G. Burton · S. L. Cutter
Hazards and Vulnerability Research Institute, Department of Geography, University of South Carolina, Columbia, SC 29208, USA

C. G. Burton
e-mail: burton@mailbox.sc.edu

S. L. Cutter
e-mail: scutter@sc.edu

1 Introduction

The 2004 Great Sumatra–Andaman earthquake in the Indian Ocean raised global awareness of the vulnerability of coastal populations to tsunamis. One of the most significant tsunami threats in the United States is a tsunami related to an earthquake generated within the Cascadia subduction zone (CSZ), the interface of the North American and Juan de Fuca tectonic plates extending more than 1,000 km from northern California to southern British Columbia (Fig. 1; Atwater 1987; Rogers et al. 1996; Satake et al. 1996). A future CSZ-related earthquake is capable of generating a series of tsunami waves possibly 8 m or higher that could inundate the nearby U.S. Pacific Northwest coast in fifteen to thirty minutes after initial ground shaking (Oregon Department of Geology and Mineral Industries 2008; Cascadia Region Earthquake Workgroup 2005; Walsh et al. 2003; Priest et al. 2001; Myers et al. 1999). Although much has been done to improve tsunami-hazard awareness (Bernard 2005; Oregon Department of Geology and Mineral Industries 2007; Priest et al. 1996) and tsunami-warning systems in this region (Gonzales et al. 2005; McCreery 2005), less has been done to understand community vulnerability to tsunamis, specifically the potential impacts on people and infrastructure (U.S. Government Accountability Office 2006). Given the catastrophic potential and quick arrival times of tsunamis generated by local CSZ earthquakes, emergency managers must understand who is vulnerable to tsunamis so that they can prepare realistic and effective evacuation and response procedures for individuals in tsunami-prone areas.

Vulnerability as a science involves examining the combination of physical, social, economic, and political components that influence the degree to which an individual, community, or system is threatened by a particular event, as well as their ability to mitigate these threats and recover if the event was to occur (Cutter 2001, 2003; Cutter et al. 2000; Mileti 1999; Hewitt 1997; Wisner et al. 2004). Although definitions and applications of the term vulnerability vary (Cutter 1996; Weichselgartner 2001), common elements within the natural hazard's literature include concepts of exposure, sensitivity, and resilience (Cutter et al. 2006; Cutter 2003; Dow 1992; Hewitt 1997; Turner et al. 2003). Exposure is related to hazard proximity and the environmental characteristics of a place, while sensitivity and resilience are characteristics of an individual, group, or socioeconomic system. Sensitivity refers to differential degrees of potential harm and the ability of an individual or community to protect itself from future events (Cutter et al. 2006), while resilience addresses an individual's or community's coping and adaptive capacities during and after an extreme event (Adger et al. 2005; Tobin 1999; Turner et al. 2003). Given equal exposure to external environmental threats, two groups may vary in their sensitivity and resilience due to internal societal characteristics.

Previous studies of societal vulnerability to CSZ-related tsunamis have largely focused on critical facilities (Charland and Priest 1995; Lewis 2007), perception studies (Johnston et al. 2005; Johnston et al. 2007; Wood and Good 2005), and local case studies (Wood et al. 2002; Wood and Good 2004). Regional comparisons of community exposure to Cascadia-related tsunamis on the Oregon coast (Wood 2007) and the open-ocean coast of Washington (Wood and Soulard 2008) indicate that tens of thousands of people live, work, and play in areas likely to be inundated by CSZ-related tsunamis. A significant portion of these individuals may require assistance in preparing for and responding to a tsunami. For example, 45% of the residents in the tsunami-prone areas of the City of Bandon, Oregon, are over 65 years in age (Wood 2007), and these older residents may have difficulty in evacuating, given the predicted 30 min between initial CSZ earthquake ground shaking and subsequent tsunami inundation. In addition to age, Wood (2007) identifies other

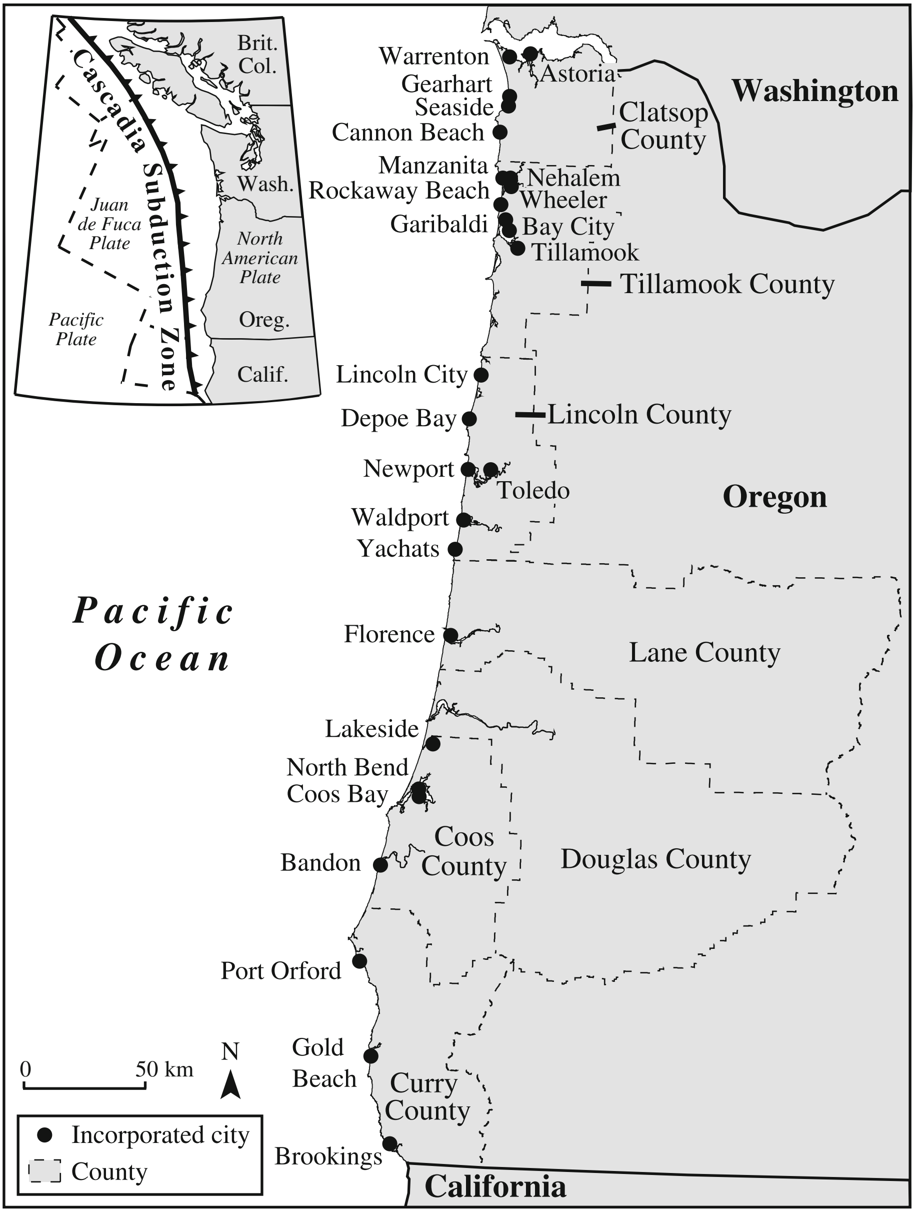

Fig. 1 Oregon cities with land in a tsunami-hazard zone related to Cascadia earthquakes plus an inset map showing the extent of the Cascadia subduction zone

demographic attributes of exposed populations considered indicators of social vulnerability, such as gender, race, and socioeconomic status (Cutter 2001; Cutter et al. 2003; Tierney et al. 2001; Wisner et al. 2004).

Assessing community vulnerability through an inventory of demographic attributes, such as those presented in Wood (2007), will help managers identify isolated issues of vulnerability (e.g., an elderly population needing assistance to evacuate quickly), but it fails to address how multiple demographic characteristics of an individual or neighborhood interact and likely amplify each other. The vulnerability of an individual who is living below the poverty level, elderly, and unable to speak the primary language is likely much larger than just the result of each attribute taken in isolation. The same can be said at the community level, where one neighborhood may be significantly more vulnerable if it contains high concentrations of single-parent, low-income, and poorly-educated populations living in close proximity to each other. Therefore, to appreciate the complex nature of social vulnerability, emergency managers need methods to understand the multivariate characteristics of individuals and communities in tsunami-prone areas.

One approach to quantify the multivariate nature of a population is the use of exploratory factor analysis, a data-reduction technique that has been widely used in human-geography research (Clark et al. 1974, 1998; Mather and Openshaw 1974; Scott 1975). Principal component analysis (PCA), one of the most common multivariate factorial approaches, uncovers the underlying dimensions of a large set of variables and mathematically transforms data into a smaller set of components based on intercorrelated variables. Specific to demographic data, the social vulnerability index (SoVI) is a spatially based descriptive tool that uses PCA to compare social vulnerability between places and has largely focused on county-level assessments (Boruff et al. 2005; Boruff and Cutter 2007; Cutter et al. 2003; Cutter and Finch 2008). Although a CSZ-related tsunami is a regional hazard that threatens thousands of people across three U.S. states and in British Columbia, Canada, a traditional county-level SoVI application is inappropriate because the majority of residents in many coastal counties are not in predicted tsunami zones; for example, only 4% of residents in Oregon coastal counties are in CSZ-related, tsunami-prone areas (Wood 2007).

In this article, we present an approach designed to describe the multivariate nature of individuals living in areas prone to CSZ-related tsunami inundation and to determine which communities have high concentrations of populations with potentially higher social vulnerability. We adjust the SoVI approach to operate at the census-block level of geography and concentrate only on residents in the tsunami-inundation zone, allowing us to examine variations in the demographic sensitivity of exposed populations. Focusing on the Oregon coast, we extend the use of the SoVI by calculating the number and percentage of total residents in each city with tsunami-prone land that are in census blocks considered to have higher relative social vulnerability, allowing us to comment on regional spatial patterns in vulnerability. Within this context, we explore several spatial properties of vulnerability including: (1) the multidimensional nature of residents in a well-defined hazard zone that spans several communities, (2) a method to determine which communities have elevated concentrations of higher socially vulnerable populations, and (3) insight into whether these concentrations relate to city attributes (e.g., total number of residents in tsunami-prone areas). Information and methods presented here further the dialogue on understanding societal risk to tsunami hazards and can be used by emergency managers to augment regional risk-reduction strategies with site-specific efforts that reflect local conditions and needs.

2 Study area

This study focuses on the seven coastal counties of Oregon, including Clatsop, Tillamook, Lincoln, Lane, Douglas, Coos, and Curry, and the 26 incorporated cities (based on 2005 city-limit boundaries) within them that intersect a statewide, potential tsunami-inundation zone (Oregon Geospatial Enterprise Office 2008) (Fig. 1). There are also 12 unincorporated towns along the Oregon coast, as delineated by census-designated place boundaries (U.S. Census Bureau 2005) that intersect the tsunami-inundation zone. Since emergency services and land-use planning for unincorporated towns are performed by county offices, results related to these towns are reported at the county level.

The tsunami-inundation zone was developed by the Oregon Department of Geology and Mineral Industries (DOGAMI) to support the implementation of a statewide ordinance (Oregon Revised Statute 455.446-447), limiting the construction of critical facilities in tsunami-prone areas (Olmstead 2003). Based on geologic evidence of past events and tsunami-propagation modeling, the tsunami-inundation zone delineates the upper limit of area expected to be covered by flood water from a tsunami caused by a magnitude 8.8 CSZ earthquake (Priest 1995). The intent of the inundation zone of Priest (1995) was to map the most likely CSZ tsunami flooding for the entire Oregon coast for use in building code enforcement. Later case studies (e.g., Witter 2008; Witter et al. 2007; Zhang et al. 2007) explored a larger range of potential CSZ tsunamis for a variety of uses, including worst-case events for evacuation planning, but these studies did not produce an inundation zone for the entire Oregon coast.

3 Methods

The purpose of this analysis is to understand relationships between the various types of residents living in the Oregon tsunami-inundation zone and to identify communities with the highest concentrations of residents that may have higher social vulnerability. Due to the limited spatial extent of the predicted tsunami-inundation zone, we adjust the SoVI, an exploratory factor analysis originally designed at the county level, to use census blocks, which are the smallest geographic units used in the decennial population count of the U.S. Census Bureau. The SoVI is based on the use of PCA to reduce a large number of census variables into a smaller set of multivariate components where variable members of each component exhibit similar variation across the study area, and each component explains a certain amount of the total variance of the entire dataset.

In the original SoVI derivation, a principal component analysis was conducted for all U.S. counties ($n = 3{,}141$) using 42 socioeconomic, demographic, and built environment variables that were selected based on empirical post-disaster research (Cutter et al. 2003). The county-level PCA produced eleven components that explained 76% of the variance, where components relating to personal wealth and age were the greatest contributors to the variance (Cutter et al. 2003). SoVI scores for each county were derived by adding PCA loadings for each component of a county and are reported in terms of standard deviations from the study area mean, where higher scores suggest higher social vulnerability. Since PCA is a data-reduction technique, components and subsequent SoVI scores are dependent on selected input variables and relevant only to the database from which the PCA was conducted (Burton and Cutter 2008).

For our adaptation of the SoVI to the census-block level, we first selected all census blocks from the 2000 U.S. Census (U.S. Census Bureau 2008) that are completely contained within or overlap the Oregon tsunami-inundation zone. Blocks with zero population would improperly distort a PCA and were therefore removed from the data, leaving 2,083 census blocks for analysis. Of the 42 census variables used in the original SoVI derivation, the following 29 variables were considered to be appropriate for a block-level PCA analysis as it relates to the ability of individuals to evacuate tsunami-prone areas before inundation (e.g., mobility) and to recover after a Cascadia tsunami (e.g., access to resources):

- *Age,* including median age, percentage under five years of age, percentage over 65 years of age, number of nursing home residents per capita, and percentage of population 25 or older with less than 12 years education;
- *Employment,* including percentage of civilian labor force participation, percentage of civilian unemployment, percentage employed in primary industry, farming, fishing, mining, and forestry, percentage employed in transportation, communication, and other public utilities, and percentage employed in service occupations;
- *Gender,* including percentage of females, percentage of households that are female headed, and percentage of female labor force participation;
- *Housing,* including average number of persons per household, percentage of occupied housing units that are renters, percentage of housing units as mobile homes, percentage of population living in urban areas, and percentage of population living on rural farms;
- *Race and ethnicity,* including percentage of population that is Black or African American, percentage of population that is American Indian or Alaska Native, percentage of population that is Asian, percentage of population that is Hispanic or Latino, and percentage of population resulting from international migration; and
- *Socioeconomic status,* including per capita income, percentage of families earning $100,000 or more, percentage of persons living in poverty, percentage of people receiving Social Security benefits, median home value, and median rent.

For variables only available at the block-group level (e.g., the percentage of civilian labor force unemployed), we assumed all blocks had the same percentage as their larger block-group. Thirteen variables from the original SoVI derivation were excluded because they define community attributes, such as (1) *local and regional economies*, including the number of manufacturing establishments per square mile, the number of commercial establishments per square mile, earnings of all industries per square mile, general local government debt to revenue ratio, and value of all non-residential property, (2) *medical services,* including the number of hospitals per capita and the number of physicians per 100,000 population, (3) *political context,* including voting records, and (4) *regional population growth,* including birth rate, the number of new housing permits, percent decennial population change, and housing density.

All data for the 2,083 blocks were then standardized through conversion to "z scores" resulting in zero means and unit variances. Z-scores are derived by subtracting the mean of the study area from the block value and then dividing this difference by the standard deviation for the study area. The use of standardized z-scores avoids potential errors resulting from the aggregation of variables with different means (Jones and Andrey 2007). A PCA was then conducted on the standardized z-scores relating to 29 block-level variables. We used the PCA procedure to minimize the number of individual variables loading high on a single component, while at the same time, increasing the differences between the components. A varimax rotation and Kaiser Criterion (eigenvalues greater than 1) were used for extracting significant loadings to minimize the number of variables that load high on a single component which, in turn, increases the percentage of variation between each component (Cutter et al. 2003). We consider component loadings for an individual census variable to be significant at 0.5 and higher or -0.5 and lower. Once the component loadings were derived, adjustments were made to their directionality with respect to their known influences on vulnerability, based on the empirical literature on what increases or decreases social vulnerability (Cutter et al. 2003). A positive directionality was assigned to all components believed to increase vulnerability (e.g., poverty), while a negative directionality was assigned to all components believed to decrease vulnerability (e.g., wealth) (Cutter et al. 2003). Component scores are then added to yield a composite SoVI score for each block. Since negative and positive components are added, resulting SoVI scores should be considered to only approximate the collective vulnerability of a block, as they implicitly assume that potentially unrelated disadvantages of one group in a block will theoretically be compensated with an advantage of another group. Although compensatory logic is assumed with metrics that use linear aggregation, more research is needed to determine whether this is a valid assumption when assessing social vulnerability (Jones and Andrey 2007).

In the original SoVI, component scores were equally weighted within its additive model. This was considered appropriate at the county levels because of the lack of justification for explicit weights or well-established relationships between variables (Jones and Andrey 2007) and because counties contained significant populations with high demographic variability. However, scale-dependent deficiencies may exist at the smaller block level when focusing on a region where the PCA-based SoVI metric may inappropriately focus on isolated anomalies or outliers within individual blocks and not on significant regional trends. This could be a function of a rotated factor analytic approach, where the varimax rotation focuses on such outliers and represents them within dimensions that explain a miniscule amount of variance. In an effort to minimize this potential deficiency and more accurately represent those components that contribute the most to demographic variability within the region, we weighted each component score by its percentage of variance explained, thereby forcing components with higher variance to contribute more to the overall SoVI score (Piegorsch et al. 2007; Schmidtlein et al. 2008). Once all blocks had a weighted SoVI score, a mean and standard deviation were calculated for the region and blocks were classified in units of standard deviation from the mean (identical to the z-score transformation described earlier). Mapping via standard deviations provides a relative representation of which blocks deviate more from regional means (Borden et al. 2007) and does not provide an absolute representation of vulnerability where we can say that block X is twice as vulnerable as block Y.

In order to compare the social vulnerability of Oregon coastal cities, census blocks with SoVI scores greater than one standard deviation from the mean were classified as having high social vulnerability and the number of residents in these blocks was summed for each of the 26 incorporated cities on the Oregon coast, as well as the unincorporated portions of the 7 coastal counties. Slivers of census-block polygons that overlap administrative boundaries and tsunami zones were omitted and final population counts are adjusted proportionately. The number of residents from census blocks considered to have high social vulnerability in each community was calculated to determine if these populations are distributed uniformly across the study area and comprise similar percentages of total population in each community. If they are not and this population is concentrated in a subset of communities, emergency managers may wish to target these communities with additional preparedness planning efforts.

These calculations are not meant to imply that we consider all individuals in census blocks with high SoVI scores to have high social vulnerability; doing so would constitute an ecological fallacy. The SoVI analysis is a relative, regional assessment based on attribute percentages (e.g., percent of individuals living in mobile homes); therefore, not all individuals within a census block with a high SoVI score may have high social vulnerability. We calculate the number of individuals in census blocks with high SoVI scores for each city only to better understand the relative magnitude of social vulnerability as it varies among cities. Like the SoVI analysis itself, these calculations are for comparative purposes only and should not be considered exhaustive inventories of individuals with high social vulnerability.

A subsequent question to knowing the number of residents in each community that is in census blocks with high SoVI scores is whether these populations correlate to certain community attributes (e.g., city size, total number of residents in the tsunami-hazard zone). If this is the case, then the level of social vulnerability within each community may simply be a reflection of the size of the exposed population or other assets. In order to test whether or not the number of residents in blocks with high SoVI scores correlate to various city attributes, simple linear regressions were conducted where the dependent variable was the number of individuals from census blocks considered to have high social vulnerability in the tsunami-hazard zone of each city and the independent variables were the total number of people, the amount of developed land, total parcel values, and total number of employees in the tsunami-hazard zone (data from Wood 2007). These attributes are chosen based on the data U.S. jurisdictions are encouraged to collect as they develop local hazard-mitigation plans (Federal Emergency Management Agency 2001), a requirement to qualify for funds under the U.S. Hazard Mitigation Grant Program in accordance with the Disaster Mitigation Act of 2000, Public Law 106-390. The null hypothesis in each test is that no statistically significant relationship exists.

All residents in the predicted tsunami-inundation zone can be considered vulnerable in some way to the tsunami threat. However, our adaptation and extension of the SoVI approach provides emergency managers with a method for determining which demographic characteristics are spatially correlated and where there are high concentrations of more vulnerable populations. Once a census block is considered to have a high SoVI score or a community is considered to have a high number of residents from blocks with high SoVI scores, emergency managers can then look at individual PCA components, as well as the original census variables, to determine where residents with potentially higher social vulnerability may exist and why they may have higher social vulnerability relative to a future tsunami.

4 Components of social vulnerability

A principal components analysis of populated census blocks in the Oregon tsunami-hazard zone results in 11 broad components that explain 64.6% of the variance (Table 1; Fig. 2). These 11 components and the census-block variables they each represent are summarized under five overarching demographic themes—wealth and education, age and tenancy, employment and housing, gender, and race. Since the analysis is based on *z*-scores (i.e., distance in standard deviations from the study-area mean), these components identify the variables that exhibit the highest amount and similar trends in variability (covariance) across the study area. The intent of this analysis is to determine which variables exhibit similar patterns of variability across the study area, and then to discuss their relevance to community vulnerability to CSZ-related tsunami hazards.

4.1 Wealth and education

The first component represents 9.7% of the database variance and captures four variables that relate to wealth and education (Table 1). Variable loadings in this component suggest

Table 1 Vulnerability components with Eigen values, the percentage variance explained by that component, and the primary census variables of each component, based on a principal component analysis with a varimax rotation

Component	Eigenvalue	% of variance	Primary census variables and component loadings
1. Wealth and education	2.814	9.704	Per capita income (0.897)
			Percent families earning $100,000 or more (0.807)
			Percent persons 25 or older with less than 12 years education (−0.550)
			Percent persons living in poverty (−0.614)
2. Age and tenancy	2.723	9.389	Percent under five years of age (0.673)
			Average number of persons per household (0.639)
			Percent renter occupied housing units (0.551)
			Percent over 65 years of age (−0.697)
			Median age (−0.875)
3. Urban/rural	2.310	7.965	Percent of the population living in urban areas (0.794)
			Percent employed in service occupations (0.548)
			Percent employed in primary industry, farming, fishing, mining, and forestry (−0.520)
			Percent rural farm populations (−0.641)
4. Housing	1.929	6.652	Percent housing units as mobile homes (0.566)
			Percent employed in transportation, communication, and other public utilities (0.553)
			Median dollar value of owner occupied housing units (−0.693)
5. Labor force participation	1.805	6.225	Percent civilian labor force participation (0.796)
			Percent social security recipients (-0.883)
6. Immigration and female workers	1.567	5.404	Percent international migration (0.688)
			Percent female labor force participation (-0.743)
7. Median rent	1.200	4.139	Median rent (0.838)
8. Females and nursing homes	1.164	4.014	Percent females (0.672)
			Nursing home residents per capita (0.612)
9. Female-headed households	1.097	3.781	Percent female headed households (0.860)
10. Race (African-American)	1.085	3.743	Percent Black or African American (0.798)
			Percent civilian unemployment (0.506)
11. Race (Asian)	1.045	3.605	Percent Asian (0.713)
			Percent American Indian or Alaska Native (−0.660)

that neighborhoods do not have a wide range of income levels (i.e., individuals with high incomes are not in the same census blocks as those living under the poverty line) and that whether an individual has attained a high-school diploma is related to personal wealth. In general, the Oregon tsunami-hazard zone can be characterized as having low- to middle-income households, based on results that indicate that the percentage of families earning $100,000 or more in this zone is approximately half the national average (5.7% compared to 10.7%, respectively) and the percentage of individuals living in poverty here approximates the national average (12.8% compared to 12.7%, respectively). The percentage of

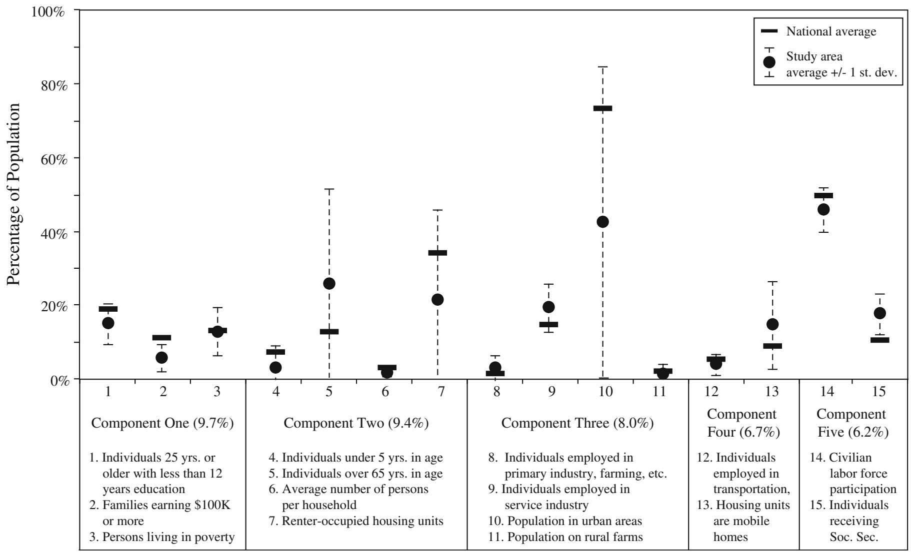

Fig. 2 Demographic characteristics of Oregon residents in the predicted tsunami-inundation zone, including study area and national averages. Demographic attributes are organized by components determined by principal component analysis, where component percentages signify the percentage of the overall study-area variance

individuals in the tsunami-hazard zone that are older than 25 years in age and lack a high-school diploma is slightly less than the national average (15.0% compared to 18.5%, respectively) (Fig. 2). The reference and comparison to national averages in this and subsequent component descriptions is meant to provide context and perspective for demographic attributes that are highlighted by the PCA because of their high variability within the study area.

With regards to social vulnerability, low-income households are often impacted greater by extreme events than high-income households. Structural maintenance and mitigation initiatives are often out of reach for low-income households, and homes may therefore sustain greater damage following a significant event due to the nature of the housing stock (Burton and Cutter 2008; Cochrane 1975; Morrow 1999; Wisner et al. 2004). In addition, low-income households often have insufficient financial reserves for buying services and materials following an event (Morrow 1999); therefore, economic recovery after a catastrophic tsunami may be more difficult.

4.2 Age and tenancy

The second component represents 9.4% of the study-area variance and includes five variables that relate to age and household tenancy (Table 1). Variable loadings on this component suggest that neighborhoods with high numbers of young children are associated with higher numbers of people per household and higher numbers of renter-occupied households, but not high numbers of older residents. Relative to national averages, the study area has low percentages of children under 5 years in age (3.17% compared to 6.8%), low percentages of renter-occupied housing (21.5% compared to 33.8%), and low numbers of individuals per household (1.6 compared to 2.59)—all indicators of relatively lower social vulnerability (Fig. 2). Although tsunami-zone percentages are low compared to national averages, the neighborhoods with children and renter-occupied households are considered to have higher social vulnerability because renters are less likely than home-owners to prepare for catastrophic events (Burby et al. 2003) and families with many dependents are likely to encounter greater obstacles when responding to an emergency due to limited financial reserves and the coupling of work responsibilities and care for family members (Cutter et al. 2003; H. John Heinz III Center for Science, Economics and the Environment 2000; Morrow 1999). The percentage of individuals 65 years in age or older in the Oregon tsunami-hazard zone is more than double the national average (25.7% and 12.4%, respectively). Research suggests the older populations may require assistance in evacuation due to potential mobility and health issues or a reluctance to evacuate, may require special medical equipment at shelters (McGuire et al. 2007), and are more apt to lack social and economic resources to recover (Morrow 1999; Ngo 2003). It may be difficult to quickly evacuate older populations from tsunami-prone areas along the Oregon coast, given their potential health and mobility issues and the limited time between earthquake ground-shaking and tsunami inundation. In addition, if a tsunami was to occur during the winter months, emergency shelters may not be equipped to adequately protect older populations from exposure to low air temperatures and high precipitation (common during winter months on the Oregon coast), causing further health complications.

4.3 Employment and housing

The third, fourth, fifth, and seventh components collectively represent variables relating to differences in employment and housing across the study area and indicate that certain occupations are associated with certain landscapes and housing arrangements across the study area (Table 1). Component 3 represents 8.0% of the study-area variance and suggests that urban neighborhoods are associated with individuals working in service industries, while rural areas are associated with individuals working in the natural resources, such as farming, fishing, mining, and forestry. Component 4 represents 6.7% of the study-area variance and suggests that neighborhoods with high percentages of mobile homes, regardless of whether they are in urban or rural settings, contain high percentages of individuals employed in transportation, communication, and other public utilities. Component 5 represents 6.2% of the study-area variance and suggests an inverse relationship between individuals in the labor-force and those receiving social security benefits. Relative to national averages, the study area has high percentages of individuals with natural resources-related occupations (3.1% in the study area compared to 0.9% for the nation), with service-related occupations (19.3% compared to 14.3%), living in mobile homes (14.7% compared to 8.4%) and receiving social security benefits (17.7% compared to 9.9%). Study-area percentages are slightly lower than national averages for civilian labor force participation (45.8% compared to 49.3%) and for employment in transportation, communication, and other public-utility sectors (4.0% compared to 4.9%) (Fig. 2). The relatively high percentages of mobile homes, recipients of social-security benefits, lower income service and natural-resource occupations, and relatively low percentage of civilian labor-force participation all indicate high socially vulnerable populations along the Oregon coast.

4.4 Gender

Several components reflect gender-related variations at the census block level (Table 1). Representing 5.4% of the study-area variance, variables in component 6 suggest areas with high international migration have low female participation in the labor force. Component 8 represents 4.0% of the study-area variance and indicates a correlation between the percentage of females and the number of nursing home residents per capita. Component 9 represents 3.8% of the study-area variance and includes a positive loading on the percentage of female-headed households. Past research of gender differences to natural hazards indicates that although women tend to have higher risk perceptions, demonstrate higher preparedness planning, and are more likely to respond to warnings than men, they are more likely to be single parents or primary care givers and have lower incomes, fewer financial resources, and less autonomy than males (Bateman and Edwards 2002; Enarson and Morrow 1998; Laska and Morrow 2007). Although gender-related variations are considered by the PCA to be moderately significant among individual census blocks in the Oregon tsunami-hazard zone, a comparison of the study-area and national averages of the original block variables suggest that gender-related variables are not significant issues for the entire region. The percentage of female-headed households in the Oregon tsunami-hazard zone is approximately one-third of the national average (3.7% and 12.0%, respectively). The percentage of international migration in the study area is approximately half of the national average (25.8% compared to 46.3%, respectively). Study-area averages are similar to national averages for the percentage of females (both 51.0%) and for the percentages of female labor force participation (47.4% and 46.9%, respectively). The comparison of study-area averages to national averages of these gender-related demographic attributes suggest that these attributes may amplify social vulnerability within individual census blocks, but are not dominant vulnerability trends for the entire study area.

4.5 Race and ethnicity

The tenth and eleventh components both relate to variations based on race and ethnicity (Table 1). Race and ethnicity influence individual sensitivity to natural hazards due to historic patterns of racial and ethnic inequalities within the U.S. that result in minority communities which lack resources to prepare and mitigate (Cutter et al. 2003), and are more likely to have inferior public services, infrastructure, and building stock (Laska and Morrow 2007), and that may be excluded from disaster planning efforts (Morrow 1999). The tenth component represents 3.7% of the study-area variance, and variable loadings suggest that neighborhoods with higher percentages of Black or African-American residents are associated with higher percentages of civilian unemployment. The eleventh component represents 3.6% of the study-area variance and variable loadings suggest that residents who classify themselves as Asian and as American Indian or Alaska Native are not associated with the same neighborhoods. Although variations based on race at the census-block level are considered moderately significant by the principal component analysis, the Oregon tsunami-inundation zone does not have high racial diversity—96% of all residents identified themselves in the 2000 Census as White, either alone or in combination with one or more other races (Wood 2007). Only 0.27% of residents in the study area classify themselves as Black or African American, compared to 12.8% for the nation. The percentage of residents who classify themselves as Asian in the study area is low and are one-third of the national average (1.32% compared to 4.4%, respectively). The percentage of residents who classify themselves as American Indian or Alaska Native is 1.24%, comparable to the national average of 1.0%. Therefore, race and ethnicity may be amplifying components within individual census blocks and for certain individuals but are not significant vulnerability trends for the entire region.

5 Geographic variations in social vulnerability

The crux of social vulnerability research is the assumption that certain groups are likely to suffer disproportionately following a damaging event due to differences in wealth, history, and sociopolitical organization (Wisner et al. 2004). In order to effectively reduce societal risks from catastrophic hazards, mitigation and emergency managers must understand (1) the social characteristics that give rise to the vulnerabilities within the communities they protect, and (2) the spatial patterns of social vulnerability across a region. Answering both questions will help managers identify the individuals and communities that may be more susceptible to loss or possibly lack the ability to recover quickly following a catastrophic event. Results of the PCA analysis in the previous section help to address the first question and suggest that although the predicted Oregon tsunami-inundation zone contains over 22,000 residents (Wood 2007), the potential impacts of a CSZ-related tsunami will likely vary among these individuals due to observed differences in wealth, education, age, etc., across the study area.

Mapping via SoVI scores allows one to determine where there are potential hotspots of social vulnerability within a community, and then determine what the primary components at a particular location are. For example, a map of census blocks classified by SoVI z-scores for the City of Seaside allows managers to quickly identify where potential hotspots may exist, including the census blocks labeled A and B (Fig. 3). Blocks A and B both contain ten individuals and may be considered to have higher social vulnerability (SoVI scores greater than 1.0) possibly due to the high percentages of residents in these blocks who are over 65 years in age (50% and 70%, respectively) and likely amplified by the high percentage of females (80% in block B) and of renters (12.5% in block A).

In order to examine spatial patterns of social vulnerability between communities, we determined how many residents in the tsunami-prone areas of each community are in census blocks with high SoVI scores. For the purposes of this case study, we define high social vulnerability populations as those residing in census blocks with transformed SoVI z-scores greater than 1.0 (i.e., greater than one standard deviation from the regional mean). Overall, there are 2,044 individuals in census blocks who are considered to have high social vulnerability, representing 9% of all residents in the Oregon tsunami-hazard zone. The number of residents in the tsunami-hazard zone from blocks considered to have high social vulnerability is not constant among Oregon communities, as 76% of these individuals come from only four incorporated cities (Seaside, Lincoln City, Waldport, and Warrenton) and the unincorporated portions of two counties (Tillamook and Coos) (Fig. 4a). At the community level, there is no discernible geographic trend for where these populations are located, as high concentrations occur on the northern (e.g., City of Seaside), central (e.g., City of Lincoln City), and southern (e.g., unincorporated portions of Coos County) sections of the Oregon coast.

There is also no apparent relationship between the number of residents considered to have high social vulnerability (Fig. 4a) and the percentage they represent of the total number of residents in the tsunami-hazard zone (Fig. 4b). For example, the City of Seaside has the highest number of residents considered to have higher social vulnerability (422), but this group only represents 9% of the in-hazard population. Similar communities with high amounts but low percentages of the total in-hazard population include the cities of Warrenton, Lincoln City, and Waldport and the unincorporated portions of Clatsop, Tillamook, and Coos counties. In these communities, emergency managers may overlook these special needs populations that are large in numbers, but represent a small fraction of the total population that could be impacted by a tsunami. Conversely, there are several

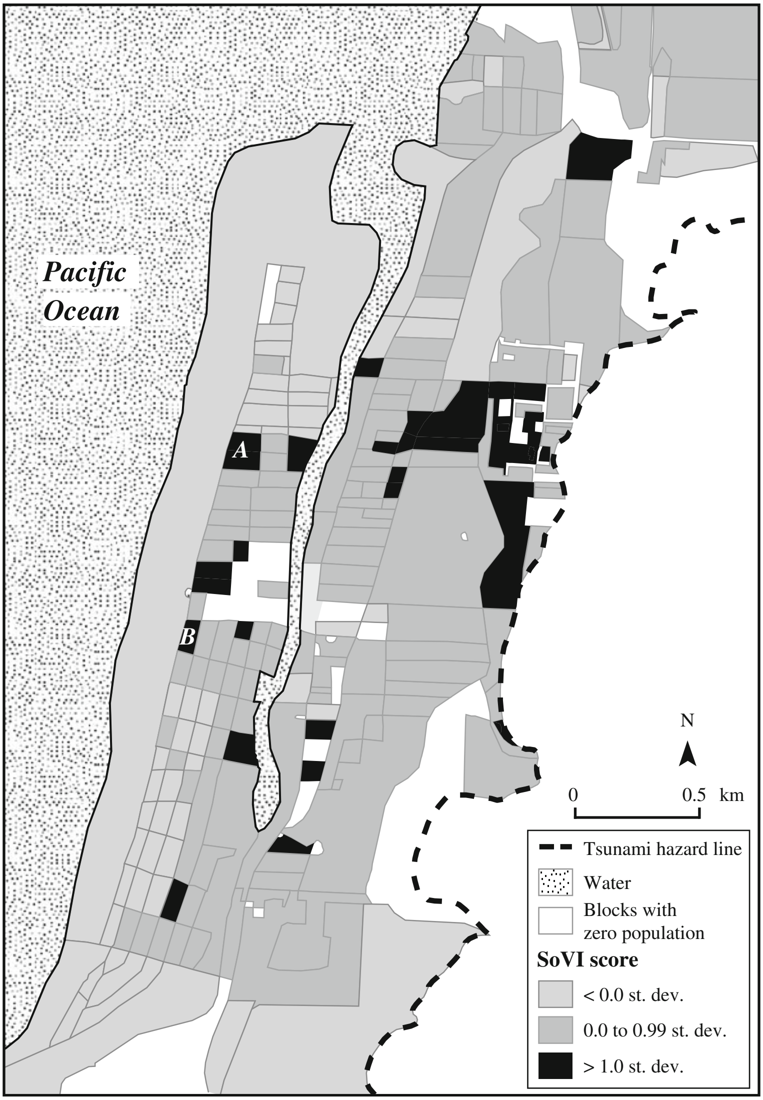

Fig. 3 Map of census blocks, classified by SoVI scores, in the City of Seaside, Oregon. SoVI scores are classified in standard deviations from the mean. Blocks labeled A and B in the figure are considered to have higher relative social vulnerability than other blocks in the study area and are further discussed in the text

communities, such as the cities of Astoria, Nehalem, Wheeler, Toledo, and Bandon, which have low numbers of residents from blocks with high SoVI scores, but these few individuals represent high percentages of the in-hazard population (Fig. 4). In these communities, emergency managers will be assisting small, but disproportionately highly vulnerable, populations.

Simple linear regressions were conducted to determine if the number of individuals from blocks considered having higher social vulnerability in each community correlates to certain city-level attributes (defined in Wood 2007). The dependent variable was the

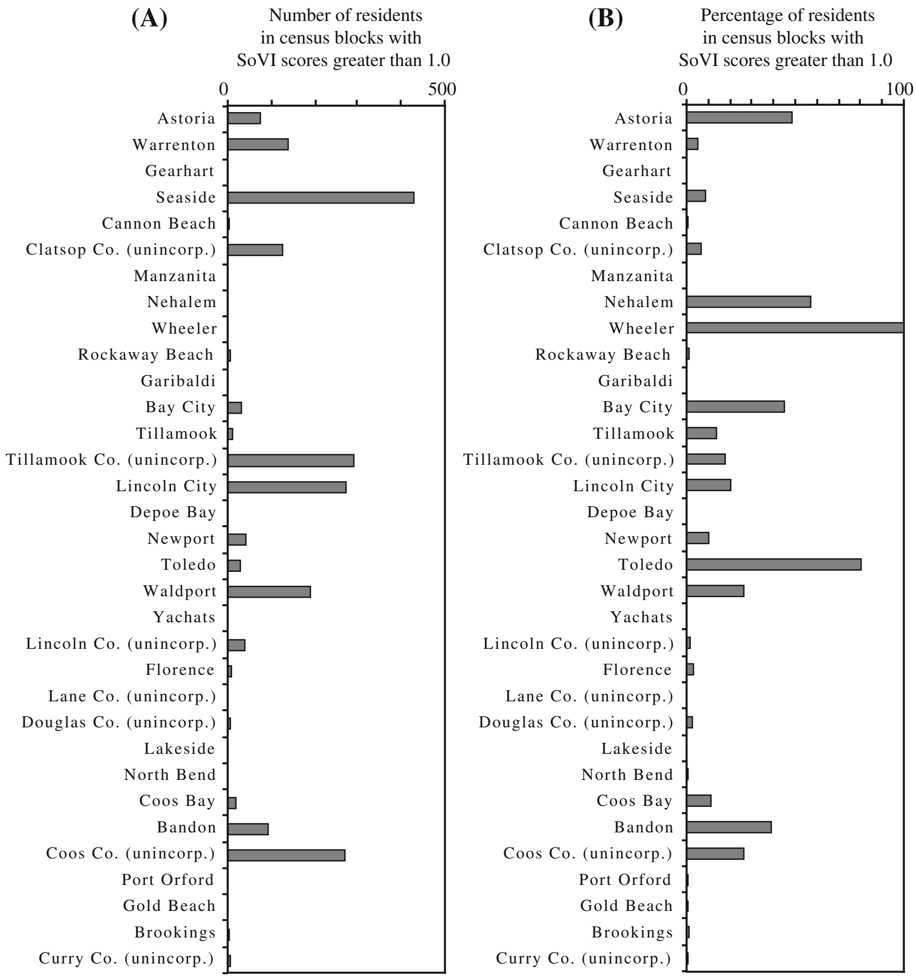

Fig. 4 The number (**a**) and percentage (**b**) of individuals in the tsunami-hazard zone from census blocks with SoVI z-scores greater than 1.0

number of residents from census blocks with SoVI scores greater than 1.0 and the independent variables were the number of residents, the amount of developed land, total parcel values, and the number of employees in the predicted tsunami-inundation zone (all from Wood 2007). All relationships are statistically significant (all have $p < 0.01$) but are not particularly strong based on moderate explained variance (r^2) values, including total amount of developed land ($r^2 = 0.594$), total number of residents ($r^2 = 0.584$), total number of employees ($r^2 = 0.409$), and total amount of parcel values ($r^2 = 0.390$) in the tsunami-inundation zone. For example, Fig. 5 graphically portrays how the number of individuals in a city's predicted tsunami-inundation zone is not a strong indicator of the number of individuals that can be considered to have high social vulnerability. Therefore, these city attributes cannot be considered a strong indicator on their own for the number of individuals in blocks who may have high social vulnerability in a community in this study area. These findings support the need for emergency managers to determine local

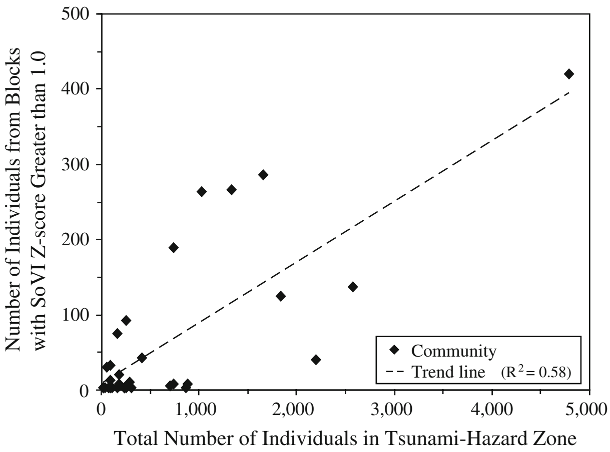

Fig. 5 Number of people in census blocks with SoVI scores greater than 1.0 compared to the total number of people in tsunami-hazard zone, summarized by Oregon city ($n = 26$)

conditions and needs, using methods like those presented, when developing risk-reduction strategies and not to implement generic strategies with the assumption that all exposed populations in different cities along the Oregon coast have similar demographic compositions.

6 Use and limitations of the SoVI approach

The SoVI is designed to be a descriptive measure of social vulnerability to hazards based on exploratory factor analysis of demographic data. As demonstrated in the previous sections, the development and mapping of relative SoVI z-scores at the census-block level provides emergency managers with a mechanism for characterizing multivariate aspects of social vulnerability and for determining where local outliers exist across a region. The use of census blocks (the smallest geographic unit used by the U.S. Census Bureau) in this analysis may also minimize potential issues of ecological fallacy, where incorrect inferences about individuals are based on characteristics of the larger group to which they belong (Jones and Andrey 2007). While the potential for ecological fallacy remains, populations may become more homogenous as census units get smaller and variables that characterize average attributes of a population in a census block (e.g., per capita income, median rent, and number of persons per household) may better reflect all members of that census block than average attributes summarized at larger census units (e.g., tract or county).

Although SoVI scores can help emergency managers to identify outliers and their location across a landscape, they should not be construed as a complete characterization of social vulnerability in an area to a specific hazard. A principal component analysis may not always capture the dominant variables contributing to vulnerability, but rather those that best explain the variation in the input data (Jones and Andrey 2007). By normalizing raw census data to z-scores, the SoVI approach ignores differences in means among the original data and therefore focuses on variances, not regional conditions, in its relative assessment of social vulnerability across a study area. All variables, regardless of their original means and variance, are transformed to have zero means and a standard deviation of one. For example, if census block A has a value of 15% for the percentage of households that are renters (mean = 10%, standard deviations = 1.5%) and census block B has a value of 95% for the percentage of residents over 65 years in age (mean = 90%, standard deviations = 1.5%), then the two blocks will have identical *z*-scores (3.33) for the different variables (i.e., 15 minus 10 divided by 1.5 equals 95 minus 90 divided 1.5). For these two variables, *z*-scores and subsequent SoVI scores may have similar patterns of data variability across a landscape, even though the second variable has a much higher mean before normalization. Therefore, the SoVI approach identifies variations in relative social vulnerability across a study and is not an exhaustive prioritized inventory of the primary causes of social vulnerability.

Since *z*-scores reflect the distance in standard deviations from the study-area mean, the distributions of two variables with drastically different standard deviations may also appear similar after their conversion to *z*-scores. For example, Fig. 6a shows a frequency histogram for the percentage of individuals in census blocks that are considered to be living in poverty (mean = 12.8%, standard deviations = 6.5%) and the percentage of individuals who are 65 years in age or greater (mean = 25.7%, standard deviations = 25.9%). Although the percentage of individuals who are 65 years in age or greater has a higher mean and a much greater range and distribution than the percentage of individuals living in poverty among the 2,086 census blocks (Fig. 2), its distribution of *z*-scores resembles those for the percentage of individuals living in poverty (Fig. 6b). Therefore, if emergency managers rely solely on results related to *z*-scores and do not also look at original data distributions, they may fail to realize that the large number of older residents may be a larger regional vulnerability issue than the smaller number of individuals living in poverty on the Oregon coast (Fig. 2).

The ability to use SoVI scores to identify hotspots of social vulnerability is immediately appealing to local managers who are responsible for site-specific risk-reduction efforts. State or regional emergency managers may want to first focus on variables that may not exhibit high variance, but that are consistently high across the region (especially those that are significantly higher than state and national averages), and then use block-level SoVI scores to find outliers. For example, Component 1 in our case study explained 9.7% of the

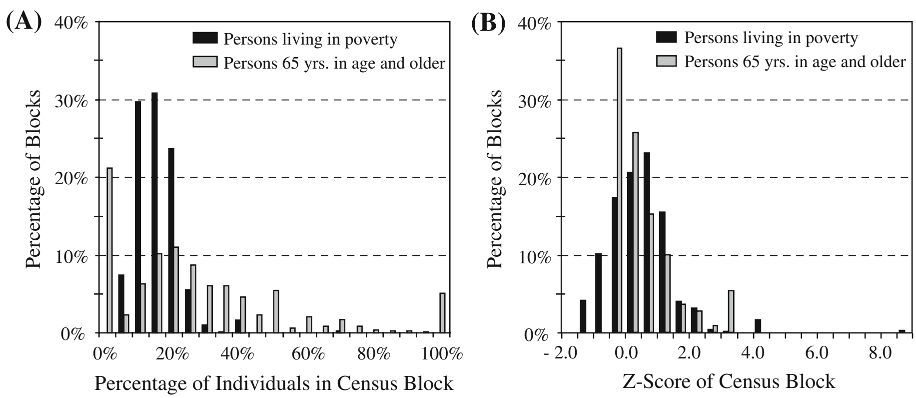

Fig. 6 Distribution of the percentage of individuals in census blocks who are considered to be living in poverty and the percentage of individuals who are 65 years in age or greater, portrayed as (**a**) the percentage of individuals in each census blocks and (**b**) the *z*-score of each census block

variance and included variables relating wealth and education (e.g., persons living in poverty, persons 25 years in age or older with less than 12 years of education, and families earning $100,000 or more), yet these variables all have means less than 15% of the population and are fairly close to national averages with standard deviations of approximately 5% (Fig. 2). Other variables, such as the percent of individuals over 65 years in age (Component 2), the percent of housing units that are mobile homes (Component 4), and the percent of individuals receiving social security benefits (Component 5), have higher regional means and standard deviations than those in Component One and these means double national averages (Table 1). However, these variables load on components that explain less variance, and therefore have less weight, in final SoVI scores (Fig. 6). Therefore, a vulnerability analysis that relies only on SoVI will identify variables with high variance but may miss the aspects of demographic sensitivity that may show less variance but high initial percentages. For our case study of social vulnerability to tsunamis on the Oregon coast, these regional sensitivities include high percentages of the population that are over 65 years in age, are employed in primary industry and service occupations, live in mobile homes, or receive social security benefits. In each of these cases, study-area percentages of these variables are double the national averages, but these variables contribute less than other variables to overall database variance and weights to SoVI scores (Fig. 2).

Place-based context is considered an important element of understanding community vulnerability (Jones and Andrey 2007). In order to appreciate and characterize social vulnerability to a hazard, emergency managers should, therefore, calculate block-level SoVI scores and interpret them within the context of the original data and relative to the hazard in question. In doing so, emergency managers can determine regional conditions, identify site-specific outliers at the block level and where they exist across a region, and then determine the individual variables that are contributing to social vulnerability at that location. Once emergency managers have targeted highly vulnerable populations with additional risk-reduction strategies, they could work with social-service providers to address the non-hazard, socioeconomic conditions that create this vulnerability (e.g., poverty and lack of education). Methods and analysis presented here can be used not only for identifying immediate response needs to a specific threat (e.g., older populations needing assistance in evacuating tsunami-prone areas) but also for non-hazard issues of resource access (e.g., populations living in poverty needing assistance to recover) germane to any catastrophic event.

7 Conclusions

The impacts from a CSZ-related tsunami will be expressed differentially across communities along the Oregon coast. Certain individuals and groups within each community are likely to suffer disproportionately due to differences in socioeconomic conditions and other demographic attributes unrelated to the natural hazard. Emergency-management officials must understand not only the physical aspects of the tsunami threat in which currently a large body of knowledge exists, but also the oftentimes undocumented, place-based characteristics of the social environment. Of utmost significance relative to Cascadia tsunamis is the ability of emergency managers to identify those areas more susceptible to loss and those hosting populations that may need assistance in evacuating tsunami-prone areas or that lack in the ability to recover quickly following an event. Results presented here demonstrate that social vulnerability to Cascadia tsunami manifests itself differently throughout the study area and that the number of individuals in census blocks with high social vulnerability is not consistent across 26 cities. Methods presented here provide emergency managers with a process for characterizing the multivariate nature of residents and for identifying which communities have significant numbers of residents that may have high relative social vulnerability. This information provides emergency managers with the means to depart from one-size-fits-all mitigation strategies that inadequately address differences in social context and, instead, to develop strategies tailored to local conditions and needs.

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