Comparing index-based vulnerability assessments in the Mississippi Delta: implications of contrasting theories, indicators, and aggregation methodologies

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Highlights

- Aggregation methodology of index-based vulnerability assessments can influence scores more than theory and indicator choice
- Improvement of aggregation methodology through validation has not kept pace with index creation
- Such assessments must acknowledge limitations in design and confidence in results to avoid misguided policy decisions

Abstract

There are many index-based approaches for assessing vulnerability to socio-natural hazards with differences in underlying theory, indicator selection and aggregation methodology. Spatially explicit output scores depend on these characteristics and contrasting approaches can therefore lead to very different policy implications. These discrepancies call for more critical reflection on index design and utility, a discussion that has not kept pace with the impetus for vulnerability assessments and respective index creation and application following the Hyogo Framework for Action 2005-2015. Comparing index outputs is an effective approach in this regard. Here, the Social Vulnerability Index (SoVI®) and the vulnerability component of the Global Delta Risk Index (GDRI) are applied at census tract level in the Mississippi Delta and visually and quantitatively compared. While the SoVI® is grounded in the hazard/risk research paradigm with primarily socio-economic indicators and an inductive principal component methodology, the GDRI incorporates advancements from sustainability science with ecosystem-based indicators and a modular hierarchical design. Maps, class rank changes, and correlations are used to assess the convergence and divergence of these indexes across the delta. Results show that while very different theoretical frameworks influence scores through indicator selection, methodology of index calculation has an even greater effect on output. Within aggregative methodology, the treatment of inter-indicator correlation is decisive. Implications include the need for an increased focus on index methodology and validation of results, transparency, and critical reflection regarding assessment limitations, as our results imply that contradictory risk reduction policies could be considered depending on the assessment methodology used.

Keywords

index design; comparison; sensitivity; SoVI®; GDRI; social vulnerability indices

1. Introduction

Index-based approaches have become increasingly recognized for their ability to spatially synthesize multi-dimensional concepts like vulnerability (Beccari, 2016). Identifying, including and emphasizing vulnerable populations is central to guidelines for the preparation and fulfillment of National Adaptation Plans (NAPs) and Nationally Determined Contributions (NDCs); the latter of which is a core element of the Paris Agreement on climate change (United Nations, 2015). Moreover, the Hyogo Framework for Action 2005-2015 (HFA; UNISDR, 2005) explicitly called for the creation of risk and vulnerability indicators and subsequent utilization of their results for informing decision-makers. Since the inception of the HFA, and continuing with the Sendai Framework for Disaster Risk Reduction (SFDRR) 2015-2030 (UNISDR, 2015), such index-based assessments have been applied in many different contexts and at different scales, each founded either implicitly or explicitly on epistemological frameworks with potentially distinct approaches (Birkmann, 2013; Schneiderbauer et al., 2017). Beccari (2016) provides a list of current relevant index-based approaches, with some of the more prominent that explicitly consider vulnerability being e.g. the World Risk Index (Heintze et al., 2018), the Disaster Risk Index (Peduzzi et al., 2009), the Index for Risk Management (InfoRM) (De Groeve et al., 2014), Social Vulnerability Index (SVI) (Flanagan et al., 2011), and the Social Vulnerability Index (SoVI®) (Cutter et al., 2003).

Along with the theories behind them, assessments also contrast on the basis of indicator selection and calculation methodology. Because the concept of vulnerability is both user-defined and latent, a range of assessment methods and variation in index results should be expected. Despite this, due to the importance of operationalizing vulnerability as a first step towards its informed reduction, research is needed to scrutinize and improve assessments. Although the HFA and the SFDRR also encourage the improvement of methods to better understand risk, including efforts to standardize assessments (UNISDR, 2005), this mandate has failed to keep pace with the plethora of new approaches to index-based assessments.

There is a lack of studies evaluating the sensitivity and validity of vulnerability and risk indexes (Beccari, 2016; Rufat et al., 2015; Rufat et al., 2019). It should be noted that while this study focuses on technical “desktop” validation, user validation is also understudied, and such feedback can provide direct information regarding index utility (Wannewitz et al., 2016). Further, there have been extensive qualitative evaluations of indexes that can contribute to validity (e.g. Gall, 2007). However, thus far, technical validation attempts have generally been carried out (1) using the data or indicators found within the same indexes by disaggregating, adjusting, and carrying out statistical tests (Cutter et al., 2013; Jones and Andrey, 2007; Schmidtlein et al., 2008; Tate, 2012; Tate, 2013); (2) by external means using impact or loss and damage data as a proxy for vulnerability (Brooks et al., 2005; Burton, 2015; Fekete, 2009; Hagenlocher and Castro, 2015; Peduzzi et al., 2009; Rufat et al., 2019; Yoon, 2012); or (3) by triangulating input or output against expert consultancy (Bohle et al., 1994; Brooks et al., 2005; Hagenlocher et al., 2013; Kienberger et al., 2009; Peduzzi et al, 2009; Polsky et al., 2007; Schmidtlein et al., 2008). While the adequacy of methods for validation is dependent on the intended scope and aim of an assessment, the approaches described carry a number of inherent limitations evidenced by past research.

An important contribution has been made by analyses that validate indexes internally (using their own component parts) (Schmidtlein et al., 2008) as well as differential weighting and indicator selection (Garriga and Foguet, 2010; Saisana et al., 2005; Tate, 2012). However, one weakness of this approach is that claims based on results must be restricted to sensitivity or reliability. Studies that equate the presence and intensity of vulnerability to figures describing loss and damage are also limited by several factors. For example, difficulties arise from the inability to account for the wide spectrum of potential negative short and long-term effects experienced from socio-natural hazards (Morrissey and Oliver-Smith, 2013; Rufat et al., 2019) resulting from the lack of relevant or reliable data (Gall et al., 2009). Such studies must also control for potential confounding factors like differential exposure that contribute to impacts (Cutter and Finch, 2008; Fekete, 2019). Finally, the use of survey data and input from experts for assessing and increasing the validity of vulnerability indexes can justifiably increase confidence in results (Emrich, 2005) but also entails inherent weaknesses. In addition to the need for sufficient resources and targeting of appropriate experts (Brooks et al., 2005), the creation of an index is itself an implicit recognition of the difficulties of making representative estimations regarding a multi-dimensional and spatio-temporally dynamic concept.

Comparing index outputs and determining the underlying reasons behind potential disparities can supplement validation efforts and avoid these shortcomings. Lacking an established external measure, identifying spatial convergence or divergence can only be regarded as a means to increase or decrease confidence in output. However, examining actual index results can also reveal index particularities and the relative importance of specific theoretical and methodological choices. There is a lack of research that analyzes hypothesized differences in high spatial resolution index outputs resulting from both contrasting epistemological frameworks and methodological construction in the same study area.

Such a comparison was carried out in the present study using United States census tract (sub-county) units in the Mississippi Delta, a region rich in history characterized by intertwined social and environmental diversity (Kemp et al., 2014). Scores from the SoVI® (Cutter et al., 2003), a well-known and widely-implemented index with an *inductive* methodology (Tate, 2012) for assessing social vulnerability, were compared to those of a hierarchically-designed index centered on social-ecological system (SES) vulnerability, the Global Delta Risk Index (GDRI) (Hagenlocher et al., 2018).

While the SoVI and GDRI conceptualize vulnerability differently, they are comparable based on their ultimate shared aim to reduce the potential negative impacts of natural hazard events by providing spatially explicit vulnerability scores to relevant stakeholders. Furthermore, they exist within the same larger research paradigm primarily concerned with risk to human well-being, although the GDRI also includes ecosystem services as a conduit in coupled social-ecological systems (Anderson et al., 2019). These particular indexes were chosen for comparison for several reasons. Firstly, their divergence in underlying theory allows for scrutiny and broader reflection across a spectrum of possible differences in such index-based approaches. Furthermore, because the contrast in theory should be reflected in index output, this divergence provides a comparative baseline for interpreting changes in scores resulting from indicator selection and aggregation methodology. The SoVI's use of PCA and the GDRI's hierarchical design represents another divide in index-based vulnerability approaches, therefore also contributing to the utility of comparing results from these indexes and determining their effects.

Lastly, differences are maximized and results more useful given that the SoVI is a well-established index while the GDRI was first introduced in Hagenlocher et al. (2018).

This study thus aims to provide a basis of empirical evidence to reflect upon theoretical and methodological choices in index-based vulnerabilty assessments while employing a comparative methodology to support index validity. It is hypothesized that the final output scores from each index show significant spatial differences resulting primarily from their contrasting conceptualizations of vulnerability. Ecosystem-based indicators from the GDRI should contribute to producing a different spatial pattern in final output scores if they are capturing a unique concept. Likewise, a high degree of similarity in purely social vulnerability scores would suggest increased confidence in output based on the concept of convergent validity. This is the idea that scores from a measure should correlate to those of another measure if the underlying construct is shared (Privitera, 2014).

However, the effect of contrasting aggregation methodologies when comparing the same vulnerability constructs in terms of output scores has also been demonstrated in previous studies (e.g. Burton, 2015; Cutter et al., 2014; Fernandez et al., 2017; Tate, 2012, 2013; Willis and Fitton, 2016). Because the GDRI employs a hierarchical and modular design for calculating scores and contains a purely social vulnerability component, the influence of theory and indicator selection can be isolated through a comparison with the SoVI. To control for theory, however, the hierarchical design of the GDRI was also applied to the SoVI indicators to create a hypothetical $SoVI^G$ index and outputs compared.

The influence of differences in conceptualization of vulnerability (affecting indicator selection) as well as aggregation methodologies between the indexes on output scores was tested primarily on the basis of changes in output rank classes of the census tracts using quantile and standard deviation classifications. Although correlations were also employed to triangulate results, differences in class rankings more directly translate to the ultimate policy messages of the indexes. By determining the influence of theory and calculation methodology in relation to output scores, the relative importance of these index design features, their implications, as well as insights into unique index characteristics are enabled.

2. Conceptualizing and operationalizing vulnerability: the SoVI and the GDRI

Contrasting theoretical underpinnings inform differences in operationalization of vulnerability, thematic indicator selection and aggregative methodology between the SoVI and GDRI (Table 1). These differences are summarized below and detailed in the following subsections in order to provide background information on the indexes (2.1 and 2.2).

Table 1. Comparison of main characteristics between the SoVI® and vulnerability component of the GDRI.

Index Characteristics	SoVI	GDRI (vulnerability)
Introduction	Cutter et al., 2003	Hagenlocher et al., 2018
Conceptual framework	Hazards-of-Place Model (Cutter, 1996)	Delta-SES Framework (Sebesvari et al. 2016)
Focus	Social System	Social-ecological system
Operationalization of vulnerability	Social vulnerability (no further disaggregation)	Vulnerability = social susceptibility + ecosystem susceptibility + lack of capacities (coping/adaptive) + lack of ecosystem robustness
Hazards considered[1]	Universal for environmental hazards	Hurricane (wind), flooding, coastal flooding (storm surge), drought, salinity intrusion (also possible to extend to other hazards)
Indicator data	Primarily Census data	Indicator library (varying sources)
Aggregative methodology	PCA with regression scores into additive model	Modular and hierarchical
Output(s)	Final SoVI scores and component scores from PCA	Disaggregation possibilities based on: single vs. multi-hazard, social vs. ecosystem, susceptibility vs. coping capacity (and combinations thereof)

2.1 The Social Vulnerability Index (SoVI)

The SoVI, introduced by Cutter et al. (2003), is built upon the theoretical background of the Hazards of Place Framework (Cutter, 1996). This framework has its roots primarily in the hazard/risk research paradigm (Cutter, 1996). From this perspective, vulnerability is seen most often as a phenomenon that, beginning with a stressor, helps determine negative impacts and human response (Adger, 2006; Eakin and Luers, 2006). Cutter et al. (2003, p. 243) describe the social context included in the framework as, “community experience with hazards, and community ability to respond to, cope with, recover from, and adapt to hazards, which in turn are influenced by economic, demographic, and housing characteristics.”

[1] Hazards considered by GDRI methodology are dependent on study area and data availability. Those shown here were included in this study.

The SoVI and its associated conceptual framework represent one of the most common sub-national vulnerability assessment approaches (Oliver-Smith et al., 2012). Although the SoVI is relevant to any hazard type because of indicators that largely represent social disadvantage (Jones and Andrey, 2007), it has also been used in numerous hazard-specific studies to assess vulnerability to drought (Emrich and Cutter, 2011; Oxfam America, 2009), flooding (Azar and Rain, 2007; Fekete, 2009), sea-level rise (Emrich and Cutter, 2011; Oxfam America, 2009), coastal erosion (Boruff and Cutter, 2007), and hurricanes (Chang, 2005; Emrich and Cutter, 2011; Myers et al., 2008; Oxfam America, 2009). The SoVI has also been applied at diverse scales in countries around the world, albeit with adjusted indicator sets (Armas and Gavris, 2013; Chen et al. 2013; Guillard-Gonçalves et al., 2015; Hummel et al., 2016). The ubiquity of the SoVI is also evidenced by the wide spectrum of specific purposes for which it has been employed. For example it has acted as a means of legally allocating disaster relief funds (Emrich et al., 2016) such as in the aftermath of unprecedented floods in 2015 in South Carolina (U.S.A.) (SCDRO, 2015), to help explain differential rates of recovery in New Orleans post-Katrina (Finch et al., 2010), and to assist the U.S. Army Corps of Engineers to consider social vulnerability in work historically centered around physical flood protection measures (Cutter et al., 2013).

Theoretical foundations are reflected in the 27 socio-economic indicators for census tract level analyses that emphasize factors such as gender, race and ethnicity, age, education, and wealth (Cutter and Morath, 2013); a full list of which is provided (Supplementary Material 1). Along with the focus on social disadvantage represented by its indicators, another defining feature and contribution of the SoVI to vulnerability research is its methodological design (Fig. 1), which has become one of the most widely used and cited in disaster risk research (Beccari, 2016; Rufat et al., 2019; Yoon, 2012).

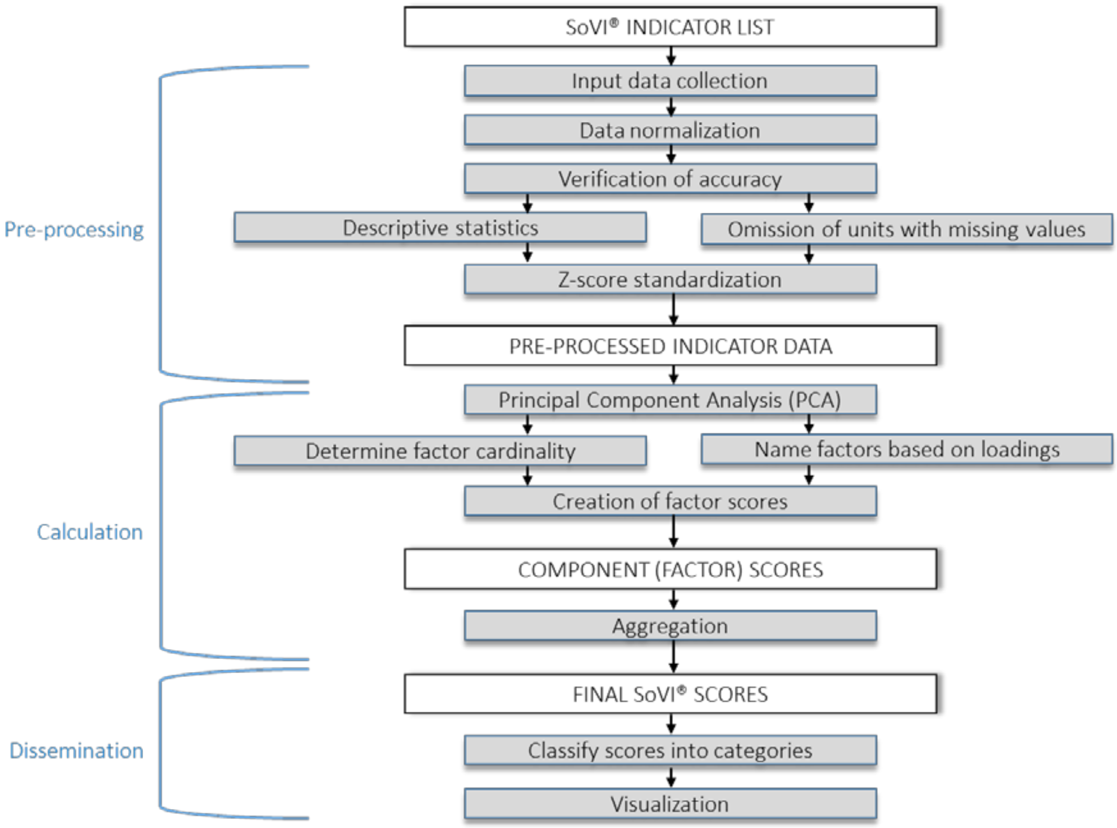


Fig. 1. SoVI design and aggregation flow from the top downwards.

Tate (2012) describes the SoVI approach as *inductive* because components emerge from input indicator data Z-scores through PCA. Z-scores standardize the data by indicating how many standard deviations an observation is either above or below the mean (Dunning and Durden, 2011). PCA reveals underlying dimensions of a large set of variables (in this case indicators) and transforms them into components (or factors) based largely on their intercorrelation (Abdi and Williams, 2010; Field, 2013). In other words, highly correlated indicators will generally be grouped within the same components. For more information on PCA specifications used in the SoVI formulation, see Schmidtlein et al. (2008). The resulting components are then named (e.g. *Poverty*, *Wealth*, *Age*, *Gender*) based on the indicators with the associated highest loadings (correlations). Adjustment to the cardinality of components is determined so that positive values equate to increases in vulnerability and negative values to decreases in vulnerability based on the underlying correlating indicators.

While PCA is used to express important latent information in a data set, factor scores are also commonly computed to allow for further analyses (DiStefano et al., 2009; Grice, 2001; Odum, 2011). For the SoVI, this means appending a unique score to each input unit (tracts in this case) based on indicators' factor loadings. Factor scores are calculated using the regression method (Thurstone, 1935), the most common of three *refined* methods in the statistical software SPSS (DiStefano et al., 2009; Odum, 2011) designed to maximize the degree of *determinacy* (Grice, 2001). Lastly, factor scores with the correct cardinality applied are summed and a final SoVI score emerges (Cutter and Morath, 2013). Scores are most often visualized using standard deviation classes, although quantiles can also be used.

2.2 The Global Delta Risk Index (GDRI)

The GDRI (Hagenlocher et al., 2018) is based on the Delta-SES Framework developed by Sebesvari et al. (2016). This is itself largely derived from the vulnerability framework created by Turner et al. (2003), an attempt to synthesize the concerns and findings from sustainability and environmental change science with those of vulnerability analysis. Turner et al. (2003) are most widely recognized for advancing the concept of vulnerability by integrating the coupled social-ecological system (SES) (Adger, 2006; Birkmann, 2006). For the GDRI, this conceptualization is merged with that of the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2014) understanding of vulnerability as the predisposition of (SES) elements and processes to be adversely affected. Although there is a general lack of recognition of SES in vulnerability analyses, the gap in research is far more critical for delta environments, as most assessments disproportionally emphasize socio-economic factors (Hagenlocher et al., 2018; Sebesvari et al. 2016). Indicators in the GDRI are based on social- and eco-system characteristics with four vulnerability domains defined as social susceptibility, ecosystem susceptibility, lack of coping and adaptive capacity, and lack of ecosystem robustness (Sebesvari et al., 2016). Because all adaptive capacity indicators were either not relevant or lacking data for this study, only coping capacity is considered. The GDRI was designed to enable the application of expert weights to indicators, but equal weighting is used in this study. While weighting can produce significant differences in results, particularly in heterogeneous study areas (Emrich, 2005), equal weighting is a standard procedure in the absence of contradictory knowledge (Rufat et al., 2015).

Data pre-processing for GDRI indicators followed the steps of outlier detection and treatment (winsorization), and multicollinearity detection, followed by Min-Max standardization and adjusting cardinality (such that all higher values equate to higher vulnerability). Outliers are first identified on the basis of the 5% trimmed mean, extreme values, and measures of skewness and kurtosis. In a further step, both the quality of indicator data and the divergence in values from spatially neighboring units were examined. Winsorization was applied to four tracts in the study area. Multicollinearity was assessed using a Pearson's r correlation matrix and Variance Inflation Factor (VIF) scores and no indicators were excluded on this basis.

Along with its theoretical contribution, the GDRI is also designed to enable flexible indicator selection based on relevance and data availability from a library of hazard-dependent and independent indicators as well as potential proxies categorized by their corresponding vulnerability domain (Hagenlocher et al., 2018). Although the GDRI is designed to calculate both hazard-specific and multi-hazard scores, only the multi-hazard feature of the GDRI is applied here for comparison purposes (see Hagenlocher et al., 2018 or Anderson et al., 2019 for details on hazard-specific calculation). Each of the four vulnerability domains can be aggregated to the higher orders of ecosystem or social vulnerability and finally to social-ecological system vulnerability using arithmetic means (Fig. 2). Aggregation is also possible on the basis of SES susceptibility and SES robustness/coping and adaptive capacity (Hagenlocher et al., 2018). In this study an alternate configuration (resulting in identical *final* scores) to explicitly assess social vulnerability is favored to enable comparison with the SoVI. Moreover, while the GDRI is designed to enable further calculation of risk scores by including spatial exposure of hazard elements (Anderson et al., 2019; Hagenlocher et al., 2018), only vulnerability is considered in this study.

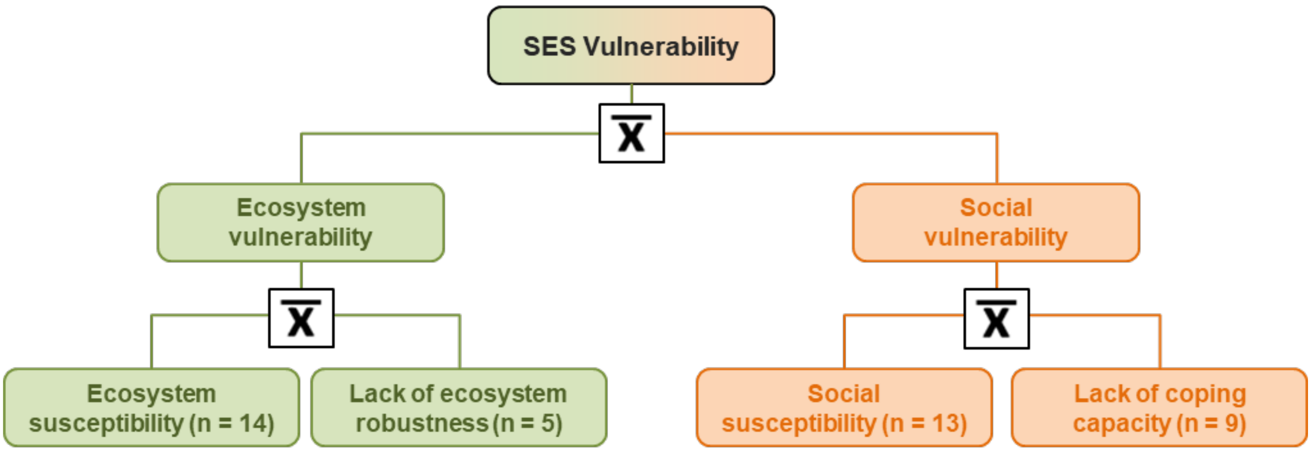


Fig. 2. Aggregative modular structure of GDRI (excluding exposure and risk) based on arithmetic means with aggregation flow from the bottom upwards (based on Hagenlocher et al. (2018)).

First, the indicators used in this study within each domain – ecosystem susceptibility (*n* = 14), lack of ecosystem robustness (*n* = 5), social susceptibility (*n* = 13), and lack of coping capacity (*n* = 9) (Supplementary Material 1) –

were aggregated using arithmetic means to derive a score for each. A further arithmetic mean is calculated for the next hierarchical step – ecosystem vulnerability and social vulnerability. Thus, e.g. both social susceptibility and lack of coping and adaptive capacity have equal influence on the social vulnerability score. This process is repeated to derive a final score of SES vulnerability. Scores are visualized using quantiles.

3. Methods: study area, index application and comparison

3.1 Study area: Mississippi Delta

The Mississippi Delta has a rich cultural, economic, social, and environmental history and is one of the most biologically productive ecosystems in the U.S. (Kemp et al., 2014). Wetlands and intact coastal ecosystems not only support livelihoods but also reduce the impacts of flooding and storm surge by acting as buffers (MEA, 2005a; Nicholls et al., 2007). The mutual dependency of human and environment, exemplified by interconnections which are particularly evident in deltaic systems (Brondizio et al., 2016; Nicholls et al., 2007; Sebesvari et al., 2016; Szabo et al., 2016), supports the consideration of a coupled SES when assessing vulnerability (Hagenlocher et al., 2018).

Increased hazard exposure has therefore been observed as a result of environmental degradation (Austin, 2006; Kemp et al., 2014) in an already highly exposed environment (Emrich and Cutter, 2011). Some of the most relevant hazards affecting the Mississippi Delta are climate-related and include drought, flooding, storm surge, hurricane winds, storms, and sea level rise, among others (Emrich and Cutter, 2011; Oxfam America, 2009). The interaction of exposure with high vulnerability has spawned many disasters in the region. Since only 2010, there have been nine major disaster declarations for the State of Louisiana (FEMA, 2018). Most of the delta falls within Louisiana and all nine of the declarations have affected counties within the delta boundary covered by this study (Fig. 3) (Tessler et al., 2015). From 1960 to 2015, Louisiana lost 86.6 billion USD and suffered 1,399 fatalities in socio-natural disasters, respectively the third and fifth highest figures of any state in the U.S. (HVRI, 2017).

Perhaps most illustrative of current vulnerability and exposure are the impacts of recent hurricanes (Finch et al., 2010; Myers et al., 2008). Hurricane Katrina in 2005 caused the loss of 212 km^2 of land in and around the Mississippi Delta (Barras, 2005), brought storm surges of over three meters spreading hundreds of kilometers, caused the deaths of more than 1500 people directly (Day et al., 2000), and resulted in federal disaster declarations covering an area roughly half the size of the United Kingdom (Freudenburg et al., 2009). Furthermore, a significant loss of estuarine marshes[2] as well as extensive forest damage were observed (Wang and Xu, 2009), eroding crucial ecosystem services. More importantly, it has been empirically proven that the poor, elderly, renters and black populations were disproportionately negatively affected (Bullard and Wright, 2009), also justifying the importance of assessing social vulnerability in the delta.

The Mississippi Delta boundary was taken from work by Tessler et al. (2015) and census tracts were used as the unit of assessment. These are relatively stable sub-county spatial units designed for collection and presentation of data from the decennial U.S. Census and other statistical programs (United States Census Bureau, 2011). Tracts contain an optimum number of inhabitants at 4,000 (United States Census Bureau, 2017), reflecting the approximate average population of tracts in the delta. Thirteen special land-use tracts (e.g. airports, water bodies, parks, etc.) were excluded from the assessments because of their capacity to skew the data standardization process and subsequent relative index scores. Thus, a remaining 736 census tracts of the original 749 total tracts were assessed that fall within counties (or *parishes* in the case of Louisiana) contained or contiguous to the delta extent (Fig. 3) (U.S. Census Bureau 2016a; 2016b).

[2] https://coast.noaa.gov/digitalcoast/stories/katrina

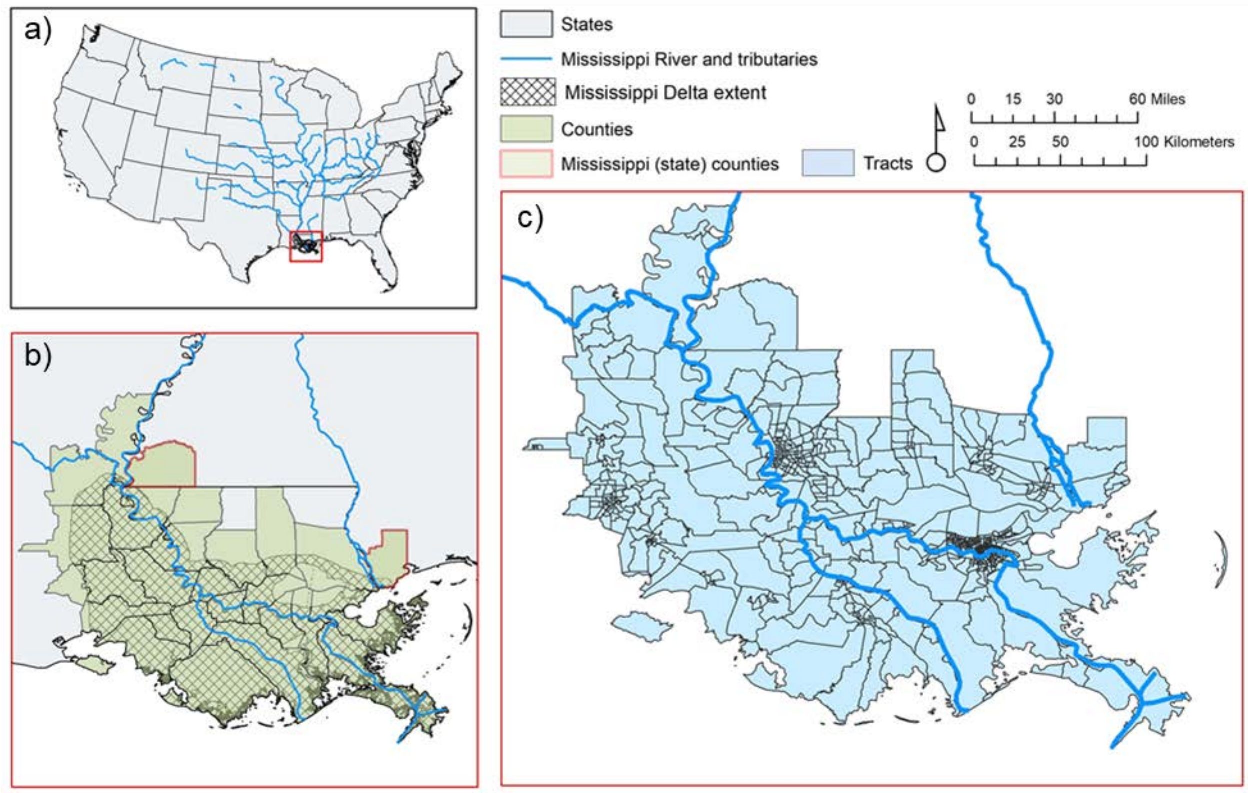


Fig 3. Map of study area –Mississippi River and tributaries flowing into the Mississippi Delta study area (a), Mississippi Delta delineation (crosshatch) (Tessler et al., 2015) with 29 intersecting counties, 27 from Louisiana and two from Mississippi (outlined in red) (b), and 749 census tracts within the study area (736 were used in the assessments) (c).

3.2 SoVI and GDRI application

The SoVI and GDRI were applied to the study area according to their respective approaches. While the SoVI application used the standard set of 27 socio-economic indicators for tract level assessments based on U.S. Census data, 41 indicators composed the GDRI. These were selected from the indicator library provided by Sebesvari et al. (2016) based on relevance to the study area as determined by spatial applicability and expert consultation when necessary. The contrasting epistemological and historical underpinnings inform differences in indicator selection between the indexes. Despite this divergence, of the 27 SoVI indicators, seven (26%) are identical to GDRI indicators applied, two (7%) share concepts but use different data, and eighteen (67%) are unique. All of the shared indicators fall within the social vulnerability component of the GDRI. Only one common indicator from the SoVI – *Percent of Housing Units with No Car* – is represented by coping capacity in the GDRI and all others by social susceptibility. Social vulnerability as defined by the GDRI is therefore expected to show high convergence with the SoVI in relation to theory and indicator selection.

A complete list of indicators applied for both indexes as well as data sources and scales are provided in Supplementary Material 1. The hazards of flooding (pluvial/fluvial), hurricanes (wind), storm surge (equivalent to coastal flooding), drought, and salinity intrusion form the basis of multi-hazard vulnerability for the GDRI. For a more detailed description of generic GDRI application steps see Hagenlocher et al. (2018). The SoVI assessment yielded seven components retained in the PCA explaining 74% of the variation in the input data (Supplementary Material 2). For a more detailed description of generic SoVI application steps see e.g. Cutter (2016), Dunning and Durden (2011), or Emrich et al. (2017).

3.3 SoVI and GDRI comparison

3.3.1 Comparing theory

In order to first compare the index outputs including their contrasting theoretical perspectives, maps of index output scores for the SoVI and GDRI final SES scores were created. The SoVI was visualized using five standard deviation classes and the GDRI on the basis of the quantile symbology (equal number of observations per class) in ArcGIS (ESRI, Redlands, U.S.A.). Because the comparison should be based on final output and classification/visualization is an important step prior to disseminating results to the public and policy makers (UNISDR, 2015), the original classification methodologies for each index were retained. However, the sensitivity of findings are tested by using matching quantile classification and matching standard deviation methods.

3.3.2 Comparing indicator selection

Maps of index output scores for the SoVI and disaggregated social vulnerability component within the GDRI were created to focus on the effects of indicator selection while controlling for theory. The extent to which tracts change classes between the SoVI and social vulnerability component of the GDRI was also mapped to interpret the degree of difference in visual message (Cutter et al., 2013; Fernandez et al., 2017; Schmidtlein et al., 2008). The absolute value of the difference in tract rankings was determined, equating to values ranging from 0 (no class change between indexes) to 4 (maximum class change). A change of three classes or more serves as a threshold for interpretation because a tract must either flip from a low vulnerability class to a high class or vice versa within the five total classes. Such a shift represents a significant discrepancy in the final message with implications for shaping policy. Pearson's r correlations using index scores were also calculated to support the visual and class-change trends.

The test for difference in indicator selection is somewhat biased given that nine indicators out of the 27 in the SoVI share the same raw data or concept with social vulnerability GDRI indicators. Because theory and indicator selection are tightly connected, truly defining the influence of either separately is not possible. However, in order to simulate the isolated influence of indicator selection in this case, social vulnerability within the GDRI was calculated using only the remaining 14 unique indicators. This was then compared to a formulation of the SoVI using the hierarchical averaging of the GDRI as described in the following subsection.

3.3.3 Comparing aggregation methodologies

The effects of the contrasting methodological approaches of each index were isolated by taking the SoVI indicators and using the GDRI aggregation methodology in an assessment. The resulting difference in the original SoVI using its inductive approach (PCA factor scores placed in an additive model) and a SoVI using the hierarchical GDRI methodology (hereafter SoVI^G) serves as a sensitivity analysis of SoVI methodology as applied in the study area. By comparing the extent of divergence between the SoVI^G and GDRI scores and the original SoVI and GDRI scores, the contribution of methodological index characteristics in explaining the overall difference in index outputs is determined.

GDRI assessment application steps were followed starting with data pre-processing for the SoVI^G. No indicators were removed following a test for multicollinearity based on variance inflation factor (VIF) scores and Pearson's r correlation coefficients. Sub-groupings of vulnerability indicators, as present in the GDRI, were not artificially created because the SoVI indicators represent social susceptibility and coping capacity. The comparison methodology of class changes and correlation was replicated as described in the prior subsection (3.3.2).

Because the SoVI's inductive approach with PCA reduces input data based on indicator intercorrelation, this characteristic of the SoVI indicator set was isolated to explain the causal influence behind differences caused by aggregative methodology in index scores[3]. This feature of PCA is particularly relevant for the SoVI construction as

[3] For more information on the intricacies of PCA related to index construction see Nardo et al. (2005) or Saisana and Tarantola (2002); or for other examples of application in this context see e.g. Clark et al. (1998), Li et al. (2012), Nicoletti et al. (2000), or Rygel et al. (2006).

many social vulnerability indicators are often highly intercorrelated (Clark et al., 1998). The aggregated intercorrelations of indicators were determined by first creating a Pearson's r correlation matrix of the 27 SoVI indicators. Absolute values were taken, and the mean ($\bar{r}$) of the 26 correlations for each indicator calculated. Absolute values are used because the strength of relationship, rather than direction, determines component loadings, interpreted as either increasing or decreasing vulnerability in the SoVI's PCA method (Schmidtlein et al., 2008). The 27 indicators were rank-ordered by intercorrelation and graphed against the average Z-scores of groups of tracts that changed four, three, two, one, and no classes between the SoVI and SoVI^{G}. Z-scores are standardized unitless scores that represent the position of distributed indicator values. Z-scores thus reveal the relative extremity of values. If divergence in scores between the indexes is a function of indicator intercorrelation, then values for the most intercorrelated indicators should have a disproportionate effect on the groups of tracts that change the most classes.

4. Results and interpretation

4.1 Influence of contrasting theories

The GDRI was classified and visualized using quantile classes while the SoVI used standard deviations (Fig. 4).

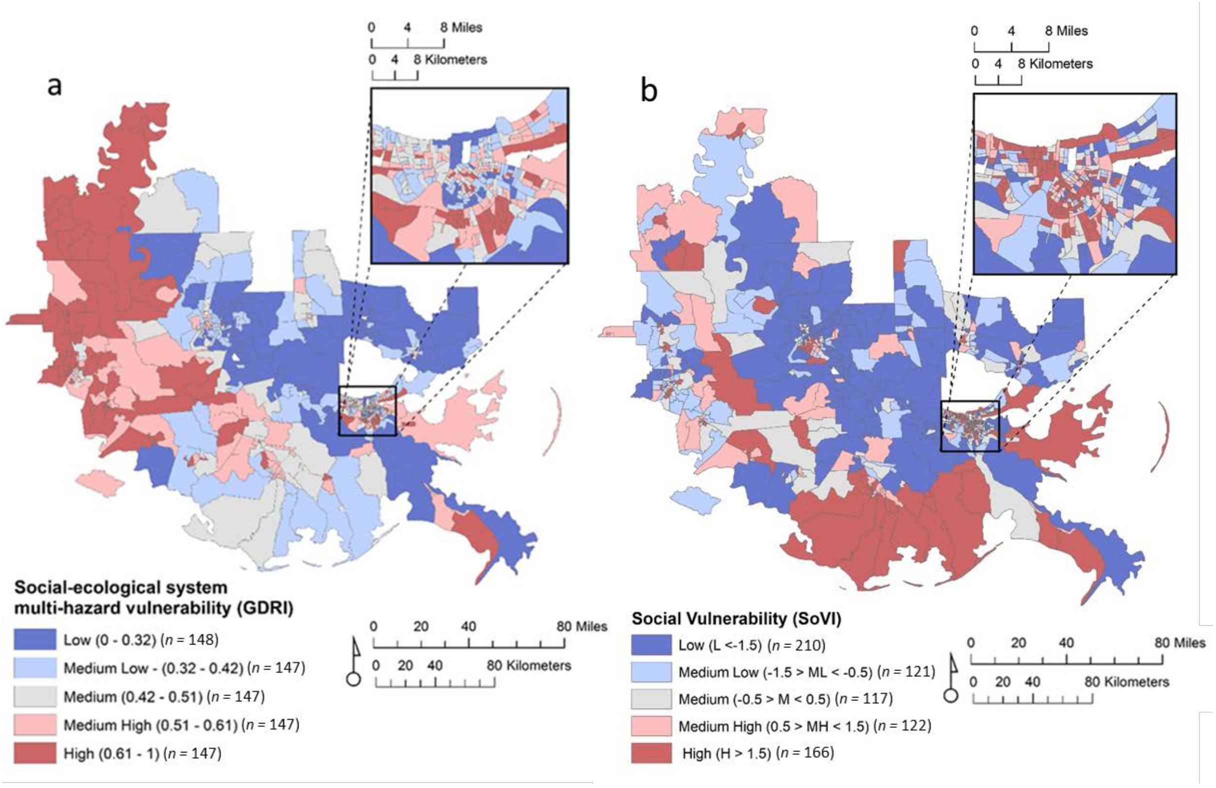


Fig. 4. GDRI final scores of SES multi-hazard vulnerability using the quantile classification (a) and final SoVI scores (b) using standard deviations with *Low, Medium Low, Medium, Medium High,* and *High* vulnerability classes.

As expected, significant disparity between the indexes using different vulnerability constructs and methods is visually evident, with the northwest portion of the study area in the GDRI showing high SES vulnerability and coastline tracts in the SoVI showing high social vulnerability. A Pearson's r correlation of r = 0.25 (α = 0.00) using final index scores triangulates the visual discrepancy. This degree of difference supports the divergent validity of each, given that the indexes are operationalizing different vulnerability constructs. The only potential concordance in terms of a general visual pattern is the band of both low SES vulnerability and low social vulnerability tracts in the eastern region of the delta. This finding warrants follow-up studies to identify the causal drivers of the pattern.

4.2 Influence of contrasting indicators

By disaggregating the GDRI and comparing on the basis of the same social vulnerability construct (controlling for different theories), overall discrepancies remain (Fig. 5).

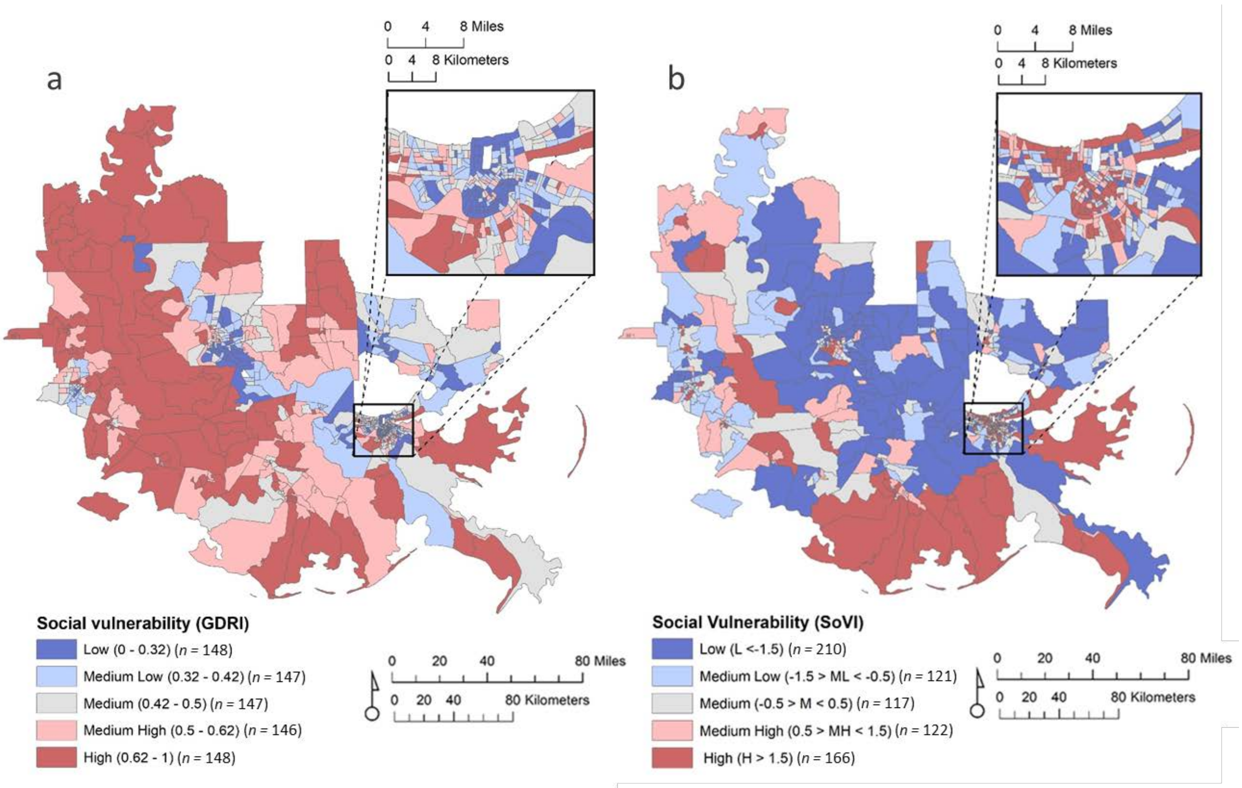
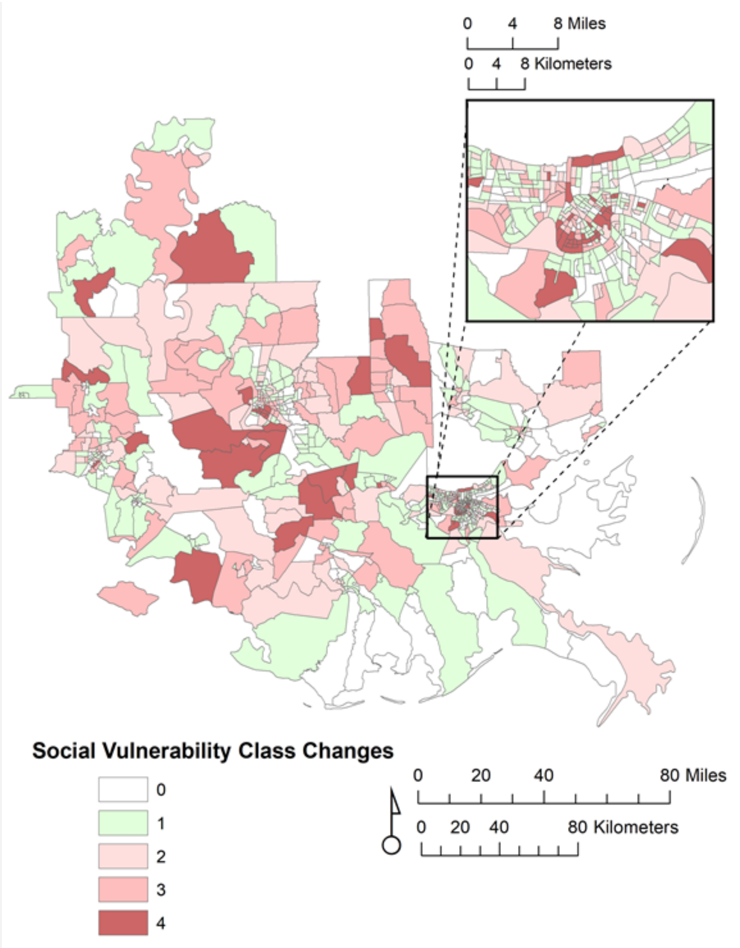


Fig. 5. Social vulnerability assessed by the GDRI using quantile classification (a) and SoVI® scores using standard deviations with *Low, Medium Low, Medium, Medium High,* and *High* vulnerability classes.

The social vulnerability domain of the GDRI identifies rural tracts as being highly vulnerable and urban tracts less so. This is an expected outcome as the rural Mississippi Delta population is comparatively disadvantaged socio-economically. The SoVI shows a less clear trend, although rural coastal tracts, generally the most isolated and sparsely populated, are attributed to the highest vulnerability class. Comparing on the basis of the same vulnerability construct *decreases* the Pearson's r correlation to r = 0.095. The increased discrepancy in results indicates that the difference in theory, namely SES vulnerability (GDRI) as opposed to social vulnerability (SoVI), may be playing less of a role than the difference in aggregation methodology used. However, using class changes is a more indicative measure of differences in results given that classification and visualization is one crucial step in index creation. Thus, the extent of class changes per tract between the indexes was first mapped and then quantitatively compared based on social vulnerability (Fig. 6).



	Divergence ⟷ *Convergence*									
Total Tracts	**4 Class**	***% Change***	**3 Class**	***% Change***	**2 Class**	***% Change***	**1 Class**	***% Change***	**No Class**	***% Change***
736	62	*8.4*	114	*15.5*	158	*21.5*	232	*31.5*	170	*23.1*

Fig. 6. Degree of class change between the SoVI (standard deviation classes) and GDRI social vulnerability (quantile classes) scores. Values of *0* indicate full agreement while *4* is a change from either *high* to *low* vulnerability or vice versa.

Close to a quarter of all tracts (23.9 %) change either three or four classes between the indexes assessing social vulnerability. This equates to a tract moving across the *medium* vulnerability axis of generally low to generally high social vulnerability or vice versa. Over half (54.6%) of tracts show general agreement, with only one or no class change.

In order to determine the influence of the differing classification methods, both indexes were classed using quantiles and both using standard deviations. Quantile classifications for both indexes yields only slight shifts in outcome, with e.g. 21.2% of tracts now changing three or four classes. Using standard deviations for both indexes leads to less divergence. This is largely due to the distribution of GDRI scores around the mean leading to more *medium* vulnerability tracts, with 17.7% now changing three or four classes. Although important, the trends in divergence and convergence are only marginally sensitive to the choice of classification method. Using the original classification methods and comparing based on shared theory (social vulnerability), the indexes are delivering a significantly different message for the 176 tracts (23.9%) that cross the axis of *medium* vulnerability, while a nearly equivalent 170 tracts (23.1%) deliver the exact same message.

However, nine indicators are shared between the indexes within the construct of social vulnerability. Thus social vulnerability in the GDRI was reassessed using only unique indicators and compared to the SoVI^G (SoVI aggregated using hierarchical averaging). The classification method of each index was retained, with the SoVI using standard deviations and the SoVI^G quantiles. This comparison results in 11.8% of tracts changing three or four classes and 64.8% changing either one or no classes.

4.3 Influence of contrasting aggregation methodologies

The influence of aggregation methodology was tested by comparing results of the newly created SoVI^G (SoVI indicators aggregated using hierarchical averaging). Based on class changes, the test for methodology is shown to have a greater effect on both the divergence and convergence in output scores than the test for indicators, with 12.6% of tracts changing three classes or more and 69% of tracts changing only one or no classes (Table 2).

Table 2. Degree of class changes and results of Pearson's r among tract scores using the SoVI, GDRI social vulnerability, and SoVI^G configurations testing the influence of indicators and methodology.

Comparison	**Divergence (>= 3 class changes)**	**Convergence (<= 1 class change)**	*r*	**Held constant**	**Test**
SoVI^G/SoVI	12.6% (n =93)	69% (n = 508)	0.56**	- Vulnerability construct - Indicators	- Methodology
SoVI^G/GDRI social vulnerability with unique indicators	11.8% (n =87)	64.8% (n = 477)	0.17**	- Vulnerability construct - Methodology	- Indicators (unique)
SoVI/GDRI social vulnerability	23.9% (n = 176)	54.6% (n = 402)	0.095**	- Vulnerability construct	- Indicators (nine shared) - Methodology

**correlation is significant to the 0.01 level (two-tailed)

Therefore, methodology is creating the largest number of both significantly different and significantly similar tract scores. For each of the tests, the influence of classification method on results was determined by also using matching standard deviation and matching quantile methods, resulting in preserved general relative patterns.

Despite recalculating social vulnerability in the GDRI using completely different indicators, methodology is exerting a slightly greater influence on whether or not output class rankings diverge or converge with the SoVI.

One difference between the SoVI's inductive method and the GDRI's hierarchical method is their distinct treatment of indicator intercorrelation (Nardo et al., 2005). In the case of tracts within the Mississippi Delta, nine out of 27 SoVI indicators have a Pearson's r correlation greater than 0.7 or less than -0.7 with at least one other indicator. The most highly intercorrelated indicator is *Percent Black*, which has a correlation of $r = 0.77$ ($\alpha = 0.00$) with the indicator *Percent Female-headed Households* and $r = -0.74$ ($\alpha = 0.00$) with the indicator *Percent of Children Living in Married Couple Families*. The next three most intercorrelated indicators among the 27 are *Per Capita Income*, *Percent Poverty*, and *Percent Education below High School*. Averaged Pearson's r values were rank-ordered, with number one representing the most intercorrelated indicator (*Percent Black;* $\bar{r} = 0.354$) and number 27 the least intercorrelated indicator (*Percent of Population Living in Nursing and Skilled Nursing Facilities;* $\bar{r} = 0.053$).

By taking the average Z-scores per indicator within the groups of tracts that change four, three, two, one, and no classes between the SoVI and SoVI^{G}, respectively, the degree of extremity in indicator data for the tracts within these groups is expressed. Plotting the average Z-scores by class change on the y-axis and ordering the indicators from 1 (most intercorrelated) to 27 (least intercorrelated) on the x-axis, it is shown that as scores converge, and tracts change fewer classes, their average Z-scores approach zero for less intercorrelated indicators (Fig. 7).

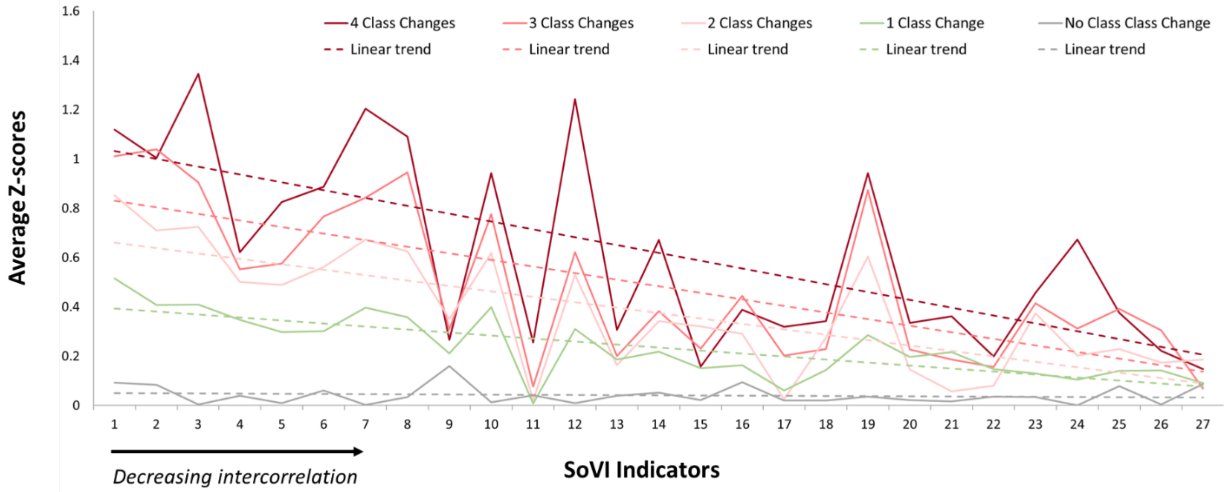


Fig 7. Averaged absolute value Z-scores by class change with linear trend lines of indicator data arranged from most intercorrelated (1) to least intercorrelated (27) among tracts that change four, three, two, one, and no class.

The tracts that flip more classes between the SoVI and SoVI^G have relatively more extreme average values for the most intercorrelated indicators. The flat linear trend line of average Z-scores for the 247 tracts that change no classes demonstrates that intercorrelation among indicator data is driving the discrepancy in index scores caused by methodology. By using PCA with regression scores, the SoVI minimizes the influence of the most intercorrelated indicators and rather computes scores based on the relationship between indicators and extracted components (Goodwyn, 2012; Marsh, 2001; Thompson, 2004). In the case of SoVI methodology and output scores in the Mississippi Delta, the extracted components have reduced the impact of the most intercorrelated indicators when compared to the hierarchical design of the GDRI. This is highly influential in determining convergence and divergence caused by aggregative methodology - the most influential index characteristic when comparing SoVI and GDRI scores in the Mississippi Delta.

5. Discussion

While the GDRI more closely represents the nature of the Mississippi Delta as a coupled SES, demonstrated throughout its long history as a subject of research (Kemp et al., 2014), the SoVI is based on years of applied practice and evidence regarding the importance of socio-economic and demographic inequalities for vulnerability. The coupled SES represented by the GDRI has roots in the concept of ecosystem services, whereby social interactions with ecosystems can improve or deteriorate these crucial services and influence risk (MEA, 2005b).

The inclusion of ecosystem-based indicators thereby also enables the consideration of ecosystem-based disaster risk reduction measures by decision makers (Renaud et al., 2016). For the SoVI, indicator selection derived from its underlying theory represents an important contribution by capturing a range of socio-economic and demographic factors. The well-documented struggles of socially marginalized population sub-groups in the aftermath of prior disasters in the Mississippi Delta like Hurricane Katrina (Bullard and Wright, 2009) have contributed to confidence in the validity of SoVI indicators in this context. In this study design, the use of convergent validity is not able to prove or disprove the degree of representativeness of actual relative vulnerability scores for either index. However, the satisfactory translation of theory into scores and policy message is tenuous given the powerful intermediary effect of aggregation methodology revealed.

The significance and extent of influence arising from methodology on output scores has been demonstrated in previous research (e.g. Burton, 2015; Cutter et al., 2014; Dunning and Durden, 2011; Fernandez et al., 2017; Tate, 2012, 2013; Willis and Fitton, 2016). Tate (2012) highlighted the importance of methodology using results of a thorough sensitivity analysis across study areas by observing similar metrics and concluding that, "…uncertainty and sensitivity of social vulnerability indices is more a function of the construction methodology of the index than differences in demographics between places" (p. 340). Similar findings were presented by Fernandez et al. (2017) regarding the impact of aggregation methods on index output and the pessimistic implications for the utility of index-based vulnerability assessments in policy contexts. Although the effect of contrasting methodologies has been established, critical research and discussion surrounding the specific implications of these findings has not been sufficient. Distinct approaches as well as advances in vulnerability theory will not be effectively operationalized and leveraged for policy without serious consideration of methodological choice.

Indeed, the influence of methodology as an intermediary between theory and output was shown here to exert more influence on the final scores than the initial theory itself. One influential driver of this is the unique treatment of indicator intercorrelation by each index. The hierarchical method does not inherently consider the interrelations among indicator data but rather assumes, if no weighting is used, that increases in values of one indicator compensate for decreases in another (Jones and Andrey, 2007; Nardo et al., 2005). The arithmetic mean within each sub-grouping is designed to capture corresponding levels of vulnerability. This implies that scores from a hierarchical index with many highly intercorrelated indicators will most closely represent the 'story' these indicators are telling.

One step of GDRI pre-processing is possible indicator exclusion based on multicollinearity, a common practice in index construction and important in order to avoid ‘double counting’ the same or similar phenomena (Nardo et al., 2005). In the case of both the original study by Hagenlocher et al. (2018) and the GDRI applied in the Mississippi Delta presented here, no indicators were excluded on this basis. However, three indicators used in this study (*Density of emergency services, Access to shelter places, and Density of transportation network*) within the social coping capacity sub-grouping had Pearson’s r intercorrelations of > 0.9 ($\alpha = 0.00$). They were justifiably retained given that they represent both separate and important concepts relevant for coping with disaster events. While indicators within the SoVI^{G} were also retained despite high correlation values, the subjective yet justifiable decision could have been reached to exclude several indicators. Findings emphasize that these decisions, particularly for the GDRI’s hierarchical approach, have implications for index output and general policy message.

Contrary to the hierarchical method, using the inductive design with PCA reduces highly intercorrelated indicators into single components. The tacit assumption is that those indicators are telling the same story and should not be ‘double-counted’ (Nardo et al., 2005). Clearly, there is no *right* or *better* answer but rather two distinct approaches. Crucial, however, is the contextual consideration of whether the method is adequately enabling the representation of a justifiably chosen theory. Cutter and Morath (2013) refer to the SoVI design and argue that not merely the proportion of a population characterized by indicators but rather the interaction between the indicators is decisive. This is theoretically sound, as vulnerability is a multi-dimensional construct and the experience of being both black and a member of a female headed household or black and impoverished is likely different than the simple summation or averaging of both traits taken together. In the case of the SoVI as applied in the Mississippi Delta, these highly intercorrelated indicators were significantly reduced in relative influence when compared to their application using the hierarchical design.

Similarly, it is necessary to consider the relative increased influence of the least intercorrelated indicators with the inductive design and relative decrease with the hierarchical design. For example, the SoVI indicator *Percent Native American* represents a specific demographic characteristic contributing to social vulnerability against the background of a unique historical trajectory in the study area. This indicator was one of the least intercorrelated in the assessment and therefore its relative influence based on the set of 27 indicators was comparatively augmented in the SoVI when compared to the SoVI^{G}. Is it sufficient to include such an indicator in an arithmetic mean or does its unique contribution to social vulnerability merit a more nuanced approach? Clearly, it should not be diminished because of low intercorrelation, but does it contribute more to vulnerability than indicators that happen to be highly intercorrelated? More research is needed along these lines of inquiry to ensure that methodological choices are proper conduits of established theory. Notwithstanding needed advancements; clearly defined assessment objectives, reflecting on the influence of methodological decisions, and a consultation of expert qualitative knowledge can inform these decisions.

This study focuses on comparing the effects on index scores manifested by general characteristics regarding contrasting theory, indicator selection, and methodology. However, there are a number of other important considerations *within* any given aggregation methodology chosen that can significantly alter results. For example, Tate (2013) showed that although selecting the indicator set is an important step for indexes using hierarchical designs, in fact decisions regarding weighting and transformation of data can more greatly impact final scores. Likewise, the many decisions within the inductive SoVI design interact to exert significant influence on final scores (Schmidtlein et al., 2008; Tate, 2013).

Given the ubiquity of the SoVI® in policy contexts and the countless potential configurations regarding initial indicator set, normalization, factor extraction, derivation of factor scores and/or weighting based on loadings, and final summation, further systematic research is warranted. The simple hierarchical method does have one advantage here in that it more easily allows analysts or end users to dissect the drivers behind final vulnerability rankings within study units. While any form of aggregation will skew original indicator data, it is difficult to trace back the influence of indicators on final vulnerability scores using the SoVI's inductive design with PCA (Dunning and Durden, 2011; Yoon, 2012). Component scores for geographic units can be presented along with final scores (e.g. Emrich et al., 2017), but are not very intuitive given that original indicator data have undergone a sophisticated statistical transformation.

Although both the SoVI and GDRI emphasize social susceptibility and coping capacity, neither index explicitly captures the concept of adaptive capacity in this study. The GDRI's indicator library does categorize 73/236 (31%) of indicators as relevant to adaptation (Sebesvari et al., 2016), but contextual data relevance and availability for the Mississippi Delta excluded these indicators from the assessment. Future research, including longitudinal studies, should more closely focus on these dimensions of vulnerability theory and dissect their dynamic nature in contexts of disaster impacts. Studies using impact metrics that are able to capture long-term recovery as well as a broader range of non-economic impacts (psychological, cultural, environmental and otherwise) would also improve validation efforts.

The current inevitability of a scarcity of necessary data (Hinkel, 2011) as well as the consequential influence of methodological choices lacking substantiation as shown by this study raise questions regarding the use of index-based vulnerability assessments in policy contexts. Findings suggest that, given the uncertainty, best practices include clear and explicit margins of confidence in results. Using fuzzy logic, observations, natural experiments and narratives (Young et al., 2006), grounded theory for inductive and deductive method development (Polsky et al., 2007), and including qualitative data (Adger, 2006) could help better support findings.

Also, the fewer ranked categories into which relative output scores are placed, the more likely their attribution is to be accurate. Quantiles could easily be consistently substituted, for example, by the use of only three categories of *low*, *medium* and *high* vulnerability as is also common practice with the SoVI (e.g. Emrich, 2017; Emrich et al., 2017; Puerto Rico, 2018; SCDRO, 2018; Oxfam America, 2009). In the context of this study, however, when comparing class changes between the SoVI and the social vulnerability component of the GDRI and using three classes for both indexes, 61 out of the 163 (44.9%) tracts in the highest SoVI standard deviation class (> 1.5) still change two classes when compared to three quantile GDRI classes, a trend that holds using matching quantile classifications. In other cases, a lower level of precision may improve accuracy and be adequate depending on the index purpose or intended use. Therefore, determining these considerations by working with decision-makers during index design, visualization and dissemination should be a fundamental part of assessment procedure.

Efforts to improve validity, including uncertainty and sensitivity analyses, can guide discussion regarding methodological choices (Beccari, 2016) and must be seen as an important step in index creation and use (Baptista, 2014). Rigorous usage by decision makers should also help with user validation efforts (Gall, 2007) if lessons from monitoring and evaluation are used as input in future best practices. Future studies should directly assess and relate index design choices analyzed in this research to actual preferences by decision-makers. In addition to the lack of refinement and associated confidence in results, indexes can represent narrow views of reality. Further, they can be interpreted as quick-fixes to complex problems if used improperly (Morse, 2013), an issue magnified by their appeal to policy makers (Barnett et al., 2008). This serves to increase the urgency with which advancements are needed. Taubenböck and Geiß (2014) rightly call for “research about research” in light of the diffusion of vulnerability concepts and subjects. Although more attention has progressively been given to methodological challenges for assessing vulnerability there remains a lack of consensus and progress has not kept pace with theoretical advancements. Critical comparison studies should be accompanied by improvements in transparency regarding the inherent trade-offs and limitations of methods and results.

6. Conclusion

While findings point to the need for general critical reflection of index-based vulnerability assessments, the importance of scrutinizing and improving existing aggregation methodologies has been highlighted. The two contrasting index-based approaches compared in this paper, the SoVI and the GDRI, represent significant divides found in vulnerability assessment literature regarding theory, indicator selection and aggregation methodology. The effect of aggregation methodologies driven by their unique treatment of intercorrelation among indicators more strongly dictates final vulnerability classes than the assessment step of theory-driven indicator selection.

Bolstered by past studies regarding the influence of aggregation methodology, generalized findings presented are likely applicable in other contexts. However, the degree of influence of theory, indicator selection, and aggregation methodology will vary based on place-specific factors and should be systematically assessed on a case-by-case basis.

Indexes can be powerful tools for synthesizing complex phenomena such as vulnerability and risk. However, the proliferation of vulnerability assessments and particularly index-based approaches has not coincided with the sufficient critical reflection and sharpening of methods needed for confidence in results. Advancements in underlying theory will only be as useful as their ability to be reliably operationalized. Efforts should not be limited to technical validation but rather rigorously consider the relation between final index scores and theoretical aims, with methodology acting as a conduit. Although it is unrealistic and misguided to search for one configuration that is normatively superior, it may be possible to create a ‘toolbox’ of approaches that transparently allows justifiable links between theory, method and output for vulnerability and risk analysts.

Rapidly changing environmental and social systems further support the need for establishing representative vulnerability baselines, confronting assumptions, and calibrating assessments. Revealing convergence or divergence in index output should be seen as one effective tool for determining confidence in results and providing insight into how vulnerability is assessed and manifested, contributing to urgently needed advancements in the field.

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Supplementary Material

1. SoVI/GDRI indicator tables and data sources (.pdf)
2. SoVI PCA Components

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