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

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ABSTRACT

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

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

Introduction

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

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

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

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

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

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

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

Evolution of vulnerability assessments

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

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

Quantifying vulnerability

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

While GIS overlay analysis is useful for quantifying vulnerability, it weights all factors equally. For this reason, the creation of vulnerability indices has become a more common practice in recent years, particularly due to their utility in hazard mitigation planning. Planners employ vulnerability indices because they provide a tangible score that can be used for guiding hazard mitigation planning (Jones & Andrey, 2007; Tate, 2012; Wood et al., 2010). Most indices measure the influence of certain physical and social factors on vulnerability at various jurisdictional and socio-political scales, the most common of which is the county level (Birkmann, 2007; Cutter et al., 2003; Jones & Andrey, 2007; Turner et al. 2003; Wood et al., 2010).

Vulnerability index indicator selection

Vulnerability indices are comprised of several socioeconomic, institutional, and infrastructure indicators that describe the spatial distribution of vulnerability across a given study area (Cutter et al., 2003, 2010; Jones & Andrey, 2007; Wood et al., 2010). Several components that comprise index creation, such as indicator selection, indicator weighting, data aggregation, the scale of analysis, and data sources, influence the outcome of the index (Jones & Andrey, 2007; Tate, 2012). Initial index creation often utilizes indicators previously identified through qualitative methods and existing literature, but those variables may not apply to places within a specific study area. For example, 67.3% of the municipality of Longboat Key in Sarasota County is aged over 65, whereas only 17.9% of the municipality of North Port is aged over 65 (U.S. Census Bureau, 2010). Therefore, elderly populations are potentially a more prominent indicator of vulnerability in Longboat Key than in North Port. In order to select variables that are applicable to place-specific study areas, place, spatial and scale-specific indicators should be determined (Frazier, Thompson, et al., 2013; Jones & Andrey, 2007).

Once place-specific indicators are identified, exploratory data analysis (EDA) can be employed to reduce indicators into a smaller set of inter-correlated variables that have the greatest influence on vulnerability (Cutter et al., 2003; Dillon & Goldstein, 1984; Jones & Andrey, 2007; Wood et al., 2010). Factor analysis and principal components analysis (PCA) are EDA data-reduction techniques used in index creation because they simplify complex relationships that exist within a set of indicators and reduce them into a more manageable list (Dillon & Goldstein, 1984). Data aggregation is used to determine a composite measure of vulnerability by standardizing the identified indicators and summing them to create a composite vulnerability score (Cutter et al., 2003; Jones & Andrey, 2007).

Socioeconomic data is readily available at the national, state and county scale, making data acquisition for county level vulnerability studies easier to accomplish. A limitation of county-level assessments (and higher-level analyses) is that indicators that are applicable at the county scale may not be applicable at the sub-county scale (Jones & Andrey, 2007). While identification of initial indicators influences index construction, statistical sensitivity analyses of vulnerability indices suggest that final indicator selection and data representation have the greater influence on index functionality (Jones & Andrey, 2007; Schmidtlein, Deutsch, Piegorsch, & Cutter, 2008). Sub-county, spatially explicit indicators provide information that can reflect unique characteristics of place, including socioeconomic and biophysical factors and spatial dependencies that may exist at the sub-county level (Cutter et al. 2008; Frazier, Thompson, et al., 2013; Füssel, 2007).

Vulnerability indicator characteristics

As vulnerability indices have evolved, the methods in measuring individual indicators have changed as more data becomes available. Past vulnerability assessments commonly use spatially homogenous indicators in their analyses, which can provide inaccurate results if vulnerability is differentially distributed within the study site. Some studies have accounted for the unequal distribution of vulnerability by using higher resolution indicator data. Wood et al. (2010) examined sub-county vulnerability using Census block-level data, while Wang and Yarnal (2012) measured vulnerability using Census block group-level data. This technique provides more information about vulnerability distributions at the sub-county scale and can lead to the creation of more accurate vulnerability assessments for local hazard mitigation.

Other studies have tried to enhance vulnerability assessments by weighting indicators based on their individual influence on vulnerability. Some studies, such as Cutter et al. (2003), Wood et al. (2010) and Wang and Yarnal (2012) have weighted vulnerability scores based on the percentage of explained variance for the indicator's encompassing factor. These studies, however, do not consider the variable influence of individual indicators that form individual factors. This technique provides an incomplete view of indicator influence on vulnerability because individual indicators may have a greater impact on the overall explained variance than other indicators within their factor. This omission is especially problematic when factors comprised of multiple indicators are equally weighted as factors comprised of one indicator (Jones & Andrey, 2007; Wood et al., 2010). For example, one factor described by multiple age groups might have the same percent variance explained as a factor described by a single land-use type. This form of data aggregation misrepresents the actual level of influence that each of the multiple age groups have on the factor in which they are grouped (Frazier, Thompson, & Dezzani, 2013). Other studies (i.e. Clark et al., 1998; Rygel, O'Sullivan, & Yarnal, 2006), have employed the Pareto ranking method to organize indicators into ranked areas instead of using weighting for additive vulnerability scores. While this method does rank groups of indicators in terms of influence, it does not examine the influence of individual indicators, nor does it provide information about which indicators are more influential on vulnerability.

One issue that few vulnerability assessments have yet to address is the spatial distribution and dependency of indicators, particularly at the sub-county level (Frazier, Thompson, & Dezzani, 2013; Jones & Andrey, 2007; Wood et al., 2010). Spatial autocorrelation describes the correlation of values in a variable over space and suggests a non-random distribution (Burt, Barber, & Rigby, 2009). If spatial autocorrelation is present in the variable datasets, then it is possible that the distribution of variables no longer exhibits an independent and identically distributed (i.i.d.) distribution (Burt et al., 2009). This violation can cause classical statistical techniques, such as principal component analysis (PCA), to provide less reliable results (Burt et al., 2009). Clustering or dispersion can skew PCA results if the rotation applied to the dataset is only applicable for data that follows i.i.d. assumptions. Thus, conducting classical statistical tests without correcting for spatial effects in the data can provide unreliable results (Burt et al., 2009).

Vulnerability index frameworks

As the importance of including socioeconomic factors in vulnerability has become more accepted, there has been an effort to include more than simply exposure studies in vulnerability assessments. County-level vulnerability assessments commonly make use of hazard exposure extents and socioeconomic data to delineate the intersection of human lives, property, and a hazard event (Eakin & Luers, 2006). While these studies advance some aspects of vulnerability assessments, they predominately conduct an exposure or sensitivity analysis and often neglect the effects of adaptive capacity on vulnerability. Communities within the same hazard exposure zone can have varying sensitivity or adaptive capacity due to several factors including socioeconomic variability, differential land use patterns and exposure of critical facilities (Frazier, Thompson, & Dezzani, 2013; Wood et al., 2010). Utilizing a model that examines all three components of vulnerability at the sub-county scale provides information that can: 1) identify exposed populations and infrastructure, 2) pinpoint preexisting conditions that exacerbate sensitivity in the absence of a hazard, and 3) identify areas where exposure is acutely felt by indicators and the available capacities to deal with the hazard. Vulnerability can be high in areas that do not necessarily have high exposure; therefore, a model of this type could account for non-exposed vulnerability indicators.

In contrast, some studies argue that exposure is a separate element and that sensitivity and adaptive capacity comprise vulnerability. The Intergovernmental Panel on Climate Change (IPCC) recently redefined vulnerability as the predisposition to be adversely affected due to existing characteristic of societal assets (sensitivity) and the ability of those assets to cope with and recover from a disaster event (adaptive capacity) (Murray & Ebi, 2012; Wisner, Blaikie, Cannon, & Davis, 2004). While this definition is useful for developing separate sensitivity or adaptive capacity analyses, it is limited in terms of targeting mitigation strategies to areas that are more likely to face hazard exposure when funding is limited. The IPCC definition assumes that exposure is a separate component of disaster risk and does not influence vulnerability directly. The simplest definition of vulnerability is the potential for loss (Adger, 2006; Cutter, 1996; Füssel, 2007; Turner et al. 2003; White, 1945), making it arguable that losses cannot occur in the absence of exposure. Therefore, studies that focus solely on individual components (i.e. just exposure) may not measure vulnerability holistically.

Many vulnerability assessments do not examine the role of adaptive capacity on vulnerability from a holistic perspective. The direct impact of adaptive capacity on vulnerability is that it reduces social vulnerability (Adger, Brooks, Bentham, Agnew, & Eriksen, 2004). While several adaptive capacity indices exist, the influence of adaptive capacity on vulnerability is rarely incorporated into vulnerability assessments (through the inclusion of a few indicators within an index) (i.e. Cutter et al., 2003), or is completely disregarded (Frazier, Thompson, & Dezzani, 2013). Cutter et al. (2010) employed a similar method in the baseline resilience indicators for communities (BRIC) model. Indicators were assigned a negative influence on the overall resilience score if they represented indicators of sensitivity or a positive influence if they represented indicators of adaptive capacity. A limitation of this method, however, is that only a small number of indicators reflect the effect of adaptive capacity on vulnerability. Many adaptive capacity indices also do not specifically measure adaptive capacity to natural hazards and often focus on adaptive capacity to climate change, drought and social and economic coping capacities (Adger et al. 2004). The lack of adaptive capacity indicators could misrepresent or neglect existing factors that may have a positive impact on adaptive capacity.

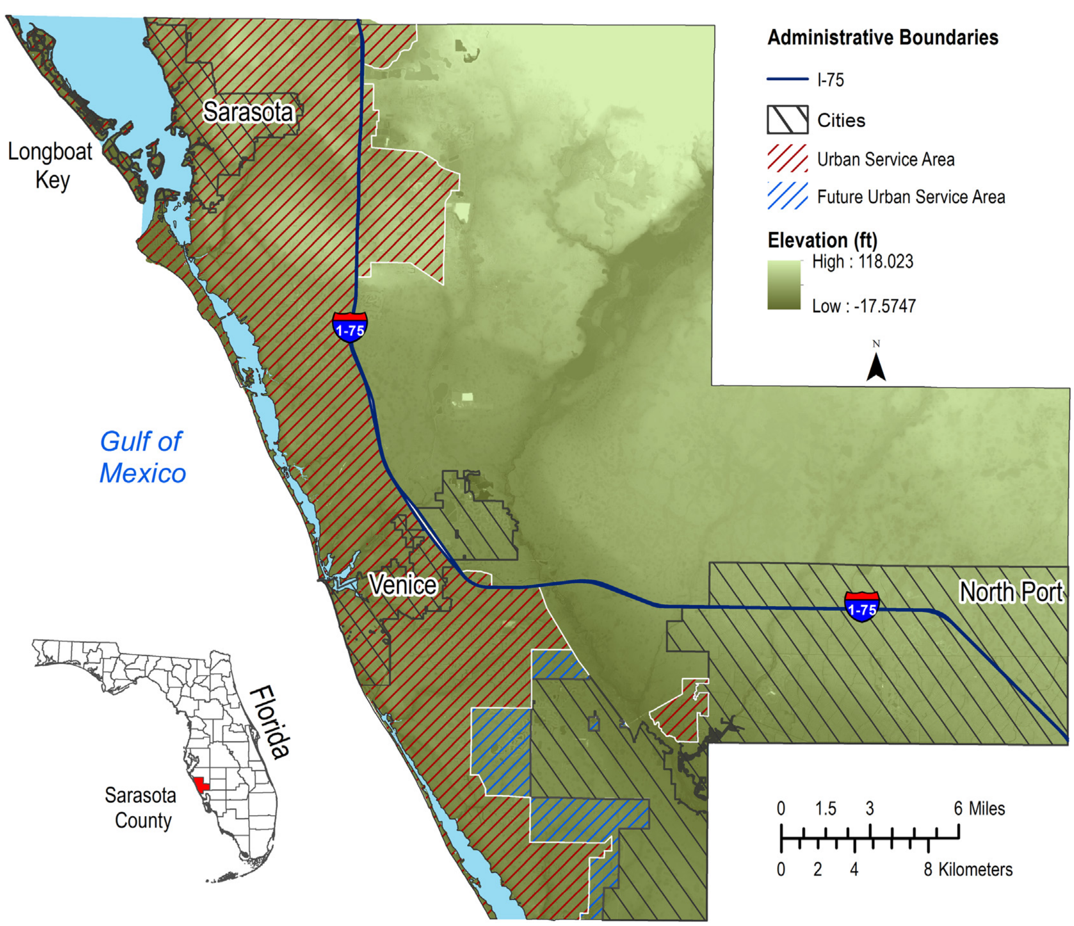

Fig. 1. Administrative boundaries of Sarasota County, FL.

Some studies have attempted to assess total risk by creating functions that regard vulnerability and adaptive capacity as separate risk components (Hahn, De León, & Hidajat, 2003; Roberts, Nadim, & Kalsnes, 2009; White et al. 2005). While these types of studies follow a similar definition of vulnerability as a function of exposure, sensitivity and adaptive capacity, their methodological design measures total risk from a hazard event, not overall vulnerability (Hahn et al., 2003; Villagrán De León, 2006; White et al. 2005). Studies like Yohe and Tol (2002), Hahn et al. (2003), White et al. (2005), and Villagrán De León (2006) often represent sensitivity as overall vulnerability and adaptive capacity serves as an entirely separate function in the formula. They also do not weight indicators based on their influence on vulnerability, possibly resulting in inaccurate estimates of vulnerability. Yohe and Tol (2002) discussed quantifying vulnerability as a function of exposure, sensitivity and adaptive capacity, where adaptive capacity is classified as a scalar variable comprised of eight location-specific determinants. A limitation of this study is that many of these determinants are unquantifiable and are described qualitatively. O'Brien et al. (2004) developed a framework that measured vulnerability to climate change and globalization in India using a composite score of sensitivity, exposure to climate change and adaptive capacity. While this model addresses all three components of vulnerability, the index was developed for the national scale and excludes factors specific to social vulnerability and natural hazards studies (O'Brien et al. 2004).

Other studies, such as Polsky, Neff, and Yarnal (2007) and Birkmann et al. (2013) have developed frameworks that attempt to holistically model vulnerability from the perspective that it is a function of exposure, sensitivity and adaptive capacity. However, these studies serve more as guides for systematic assessments and do not provide specific methodologies for measuring vulnerability. In order to advance the vulnerability field, an index that combines the capabilities of these types of studies with quantifiable indicators would be ideal for compilation of a vulnerability index that more completely describes overall sub-county vulnerability.

Methodology

Study area

Sarasota County, Florida lies along the western coast of the Florida peninsula (Fig. 1). The county has approximately 35 miles of shoreline and a low average elevation (~42 ft.), which makes it susceptible to coastal hazard inundation impacts. The county has also undergone significant population growth within the last decade, experiencing approximately 16% population increase from 2000 to 2010 (U.S. Census Bureau, 2010). The county is highly developed along the lower elevations, and future development will continue along the coast due to the location of Interstate Highway 75 and the county's choice as to where to locate an urban service

Table 1
Sensitivity indicators.

Variable	Category	Definition	Data source
Total Pop	General population	Total population	U.S. Census Bureau, 2010
HISORLAT	Race/ethnicity	Hispanic or Latino population	U.S. Census Bureau, 2010
WHITEPLUS	Race/ethnicity	White alone or in combination with one or more other races	U.S. Census Bureau, 2010
BLACKPLUS	Race/ethnicity	Black or African American alone or in combination with one or more other races	U.S. Census Bureau, 2010
AMERINPLUS	Race/ethnicity	American Indian and Alaska Native alone or in combination with one or more other races	U.S. Census Bureau, 2010
ASIANPLUS	Race/ethnicity	Asian alone or in combination with one or more other races	U.S. Census Bureau, 2010
HWPALSPLUS	Race/ethnicity	Native Hawaiian and Other Pacific Islander alone or in combination with one or more other races	U.S. Census Bureau, 2010
MEDAGE	Age	Median age	U.S. Census Bureau, 2010
AGEUNDER_5	Age	Population under 5 years old	U.S. Census Bureau, 2010
AGE_65_UP	Age	Population over 65 years	U.S. Census Bureau, 2010
FEM_POP	Female Pop	Female population	U.S. Census Bureau, 2010
HSEHOLDS	Housing	Number of households	U.S. Census Bureau, 2010
RENTER_OCC	Housing	Renter-occupied housing units	U.S. Census Bureau, 2010
SINGLE_M_H	Family type	Female-headed households, with children, no spouse present	U.S. Census Bureau, 2010
PER_CAPITA	Economic	Per capita income	American Community Survey, 5-year estimates – 2006–2011
JUST_PARCE	Economic	2012 Justified parcel value for Sarasota	Sarasota County Tax Assessors Office (2012)
CC_DEVEL, AG, CHD, CMD, CLD, COD	Land use	Gulf Coast Land Use Type (Agriculture, and high, medium, low and open intensity development)	Coastal Change Analysis Program Regional Land Cover (2006)
CRITICAL	Infrastructure	Critical facilities	InfoUSA Business Data
ESSENTIAL	Infrastructure	Essential facilities	InfoUSA Business Data
MEDICAL	Infrastructure	Medical facilities – response and health facilities	InfoUSA Business Data
ADULTCARE	Infrastructure	Adult residential care –elderly populations	InfoUSA Business Data
SCHOOLS	Infrastructure	Schools – children populations	InfoUSA Business Data
CHILDCARE	Infrastructure	Child day care center – children populations	InfoUSA Business Data
CORREC_FAC	Infrastructure	Correctional facilities –immovable populations	InfoUSA Business Data
OVERNIGHT	Tourism	Overnight tourists – tourism	InfoUSA Business Data
DAYTOURIST	Tourism	Day tourists – tourism	InfoUSA Business Data
LIBRARIES	Tourism	Libraries – tourism	InfoUSA Business Data
COLLEGES	Tourism	Colleges – tourism	InfoUSA Business Data
SHOPPING	Tourism	Shopping malls – tourism	InfoUSA Business Data
ATTRACTION	Tourism	Attractions – tourism	InfoUSA Business Data
RELIGIOUS	Religious	Religious organizations – tourism	InfoUSA Business Data
NAICS_#	Industry type	NAICS standard industrial code divisions	InfoUSA Business Data
EMPLOYEES	Economic	Employees – economic vitality	InfoUSA Business Data
SALES_VOLU	Economic	Sales volume – economic vitality	InfoUSA Business Data

boundary (Fig. 1). Development in Sarasota County is primarily limited to areas within the urban service boundary, which forces development toward coastal areas and causes population or development-related indicators to cluster along the coastline (Frazier et al. 2010; Frazier, Thompson, et al., 2013).

Indicator selection

To determine place-specific, spatial and temporal sensitivity indicators for Sarasota County, researchers conducted a PCA on the list of compiled indicators. Principal component analysis (PCA) is a data-reduction technique that identifies groups of variables that are inter-correlated and reduces the number of variables in the analysis (Johnston, 1978). Initial sensitivity indicators were compiled based on existing hazards literature (Cutter et al., 2003; Morrow, 1999) and place-specific results from studies that identify significant contributing factors to sensitivity (Frazier et al. 2010; Frazier, Thompson, et al., 2013). Many past studies identify how certain vulnerability indicators have a direct impact on vulnerability, which serve as proxies for access to resources (Cutter et al., 2003; Fothergill, Maestas, & Darlington, 1999; Morrow, 1999; Wood, Church, Frazier, & Yarnal, 2007). Specific indicators like race, age, sex, female-headed households, high tourism areas and economic vitality are all indicators of access to resources that can influence the sensitivity of a community (Cutter et al., 2003; Fothergill et al., 1999; Morrow, 1999; Wood et al. 2007). The indicators were aggregated to the census block level because it is the smallest geographic areal unit of analysis available (Table 1).

A Moran's I was conducted for each indicator to determine the average level of spatial autocorrelation between all variables within the county (Burt et al., 2009). An initial PCA was then conducted on the composite list of indicators using the following parameters: maximum of 20 components; the Kaiser Criterion (eigenvalues greater than 1) to identify significant factors; and a Gamma rotation of 0.128. A Gamma rotation was used in place of a Varimax rotation to account for spatial autocorrelation in the data (Cutter et al., 2003; Johnston, 1978; Wood et al., 2010). A Gamma (or Oblique) rotation assigns factors to sets of already inter-correlated variables and can help correct for the effects of spatial autocorrelation in a dataset (Dillon & Goldstein, 1984; Johnston, 1978).

Variables that explained <5% of the total population within the county were found to be non-significant and were either aggregated into a composite variable or were removed from the PCA. In addition, variables with multicollinearity, such as the individual North American Industry Classification System (NAICS) standard industry division were removed from the indicator list because they skewed the PCA results. Researchers then conducted an additional PCA on the reduced dataset using the same parameters to determine the reduced set of principal components. Variables with component loadings ≤ -0.45 or ≥ 0.45 were considered significant to the reduced index to ensure that weaker indicators traditionally found in vulnerability theory were identified (Cutter et al., 2003; Wood et al., 2010). The reduced dataset explained a larger percent of the variance, but many variables exhibited small levels of multicollinearity (they were too similar to or duplicated other proxies); those variables were removed and a final PCA using the final set of variables was conducted to produce the final set of sensitivity principal components.

To create the adaptive capacity component of the vulnerability index, an initial set of adaptive capacity indicators was compiled by reviewing previous adaptive capacity research and assembling traditional adaptive capacity indicators unique to the study area (Table 2). There is some duplication of indicators in both the sensitivity and adaptive capacity indices because some indicators influence both components in different ways (Cutter et al., 2003; Mustafa, Ahmed, Saroch, & Bell, 2011). For example, high economic diversity (determined through the sales volume and employees proxies) can make a community less sensitive to a hazard event, but a heavy reliance one or two economic sectors (i.e. tourism) could lower community adaptive capacity (Mustafa et al. 2011).

Due to the scale of the available data for the adaptive capacity indicators, all indicators were aggregated to the census tract level. The final set of adaptive capacity variables was determined using the same method employed for the sensitivity indicators. The PCA parameters remained the same (maximum of 20 components and a Kaiser Criterion to identify significant indicators) except for the Gamma rotation. Researchers employed a Gamma rotation of 0.264 to reflect the spatial autocorrelation of the adaptive capacity indicators (Cutter et al., 2003; Johnston, 1978; Wood et al.,

Table 2
Adaptive capacity indicators.

Variable	Category	Definition of variable	Data source
NoHighSch	Education	Percent with no high school diploma over 25	American Community Survey, 5-year estimates – 2006–2011
College	Education	Percent with college education	American Community Survey, 5-year estimates – 2006–2011
Per_Ag65	Percent age over 65	Age over 65	U.S. Census Bureau, 2010
Per_Ag5	Percent age 5	Age under 5	U.S. Census Bureau, 2010
Per_FHH	Female head of households	Percent single mother households	U.S. Census Bureau, 2010
HousCap	Housing capital	Home ownership	U.S. Census Bureau, 2010
PerEmploy	Employment (percentage)	Percent employed – over 16	American Community Survey, 5-year estimates – 2006–2011
GINI	Income and equality	GINI Index	American Community Survey, 5-year estimates – 2006–2011
Sales_Vol	Sales volume	Percent of total sales volume in the tract	InfoUSA Business Data
Employees	Number of employees	Percent of total employees in the tract	InfoUSA Business Data
SS_NOTemp	single sector employment dependence	Percent population not employed in farming, fishing, forestry, and extractive industries	American Community Survey, 5-year estimates – 2006–2011
LQ_#	Location quotient – each NAICS sector	Number of employees at a location/total employees in that sector	InfoUSA Business Data
Parc_JUST	Parcel value	Sum-get from FA file and aggregate up to tract	Sarasota County Tax Assessors Office (2012)
Churches	Religion	Percent of churches within each block	InfoUSA Business Data
Social_Ser	Social services	Percent of total social services within a community	InfoUSA Business Data
PerBePov	Poverty status	Percent population below poverty line	American Community Survey, 5-year estimates – 2006–2011
Road_sqMi	Access/evacuation potential	Principle arterial miles per square mile	U.S. Census Bureau, 2010
Utilities	Exposed utilities	Percent wellheads, substations exposed	Sarasota County Government
Schools	School	Number of schools	InfoUSA Business Data
FloodSqMi	Coastal risk	Percentage of tract within FEMA flood zones	Sarasota County Government
LISA_Ave	LISA analysis of Pop	Block-level LISA analysis	U.S. Census Bureau, 2010

2010). Variables with component loadings ≤ -0.5 or ≥ 0.5 were considered statistically significant (Cutter et al., 2003; Wood et al., 2010).

Component and vulnerability scoring

In order to determine the distribution of vulnerability, block scores were then calculated using the following static vulnerability equation:

$$V = [E + S] - AC$$

where V = vulnerability, E = exposure, S = sensitivity and AC = adaptive capacity.

In order to create the final block-level vulnerability scores, each of the equation's raw component scores (exposure, sensitivity, and adaptive capacity) were calculated. Raw exposure scores were determined through overlay analysis that utilized four deterministic hazard extents that depict inundation from a Category 1 storm surge, Category 1 storm surge with 2 inches (5.03 cm), Category 3 storm surge, and Category 3 storm surge with 4 inches (15.24 cm) of inland precipitation, developed in previous research (Thompson & Frazier, 2014). The hazard extents were overlayed with census blocks to determine the areal percentage of each block within the hazard (Frazier et al. 2010). This percentage served as the raw score for the exposure component. The raw block sensitivity scores were calculated by determining the percentage of each indicator found within each census block. This was done to identify which blocks held the greatest presence of each sensitivity indicator.

After determining the exposure percentage and the statistically significant sensitivity and adaptive capacity indicators, each vulnerability component was converted into a raw score aggregated to the census block. The sensitivity component utilized a weighted component scoring methodology that assigns sensitivity scores to each block based on the varying influence of each indicator and its factor on sensitivity or adaptive capacity. To do this, researchers first determined the percentage of each indicator within each census block. The percentage of each indicator was then multiplied by its complementing component loading found in the sensitivity PCA results, as seen in the equation below:

$$S_{ik} = \sum D_{ij} L_{ik}$$

where S_{ik} = weighted score of observation i on component k

D_{ij} = value of observation for the variable
L_{ik} = loading of variable j on component k

Directionality for each indicator component loading was assigned to reflect whether the indicator had a positive or negative influence on sensitivity based on vulnerability literature (Cutter et al., 2003; Morrow, 1999). Researchers assigned a positive directionality to variables traditionally believed to increase sensitivity and a negative directionality to variables believed to decrease sensitivity (Cutter et al., 2003; Wood et al., 2010). The resulting values are multiplied by the explained variance of the factor in which the indicator lies, using:

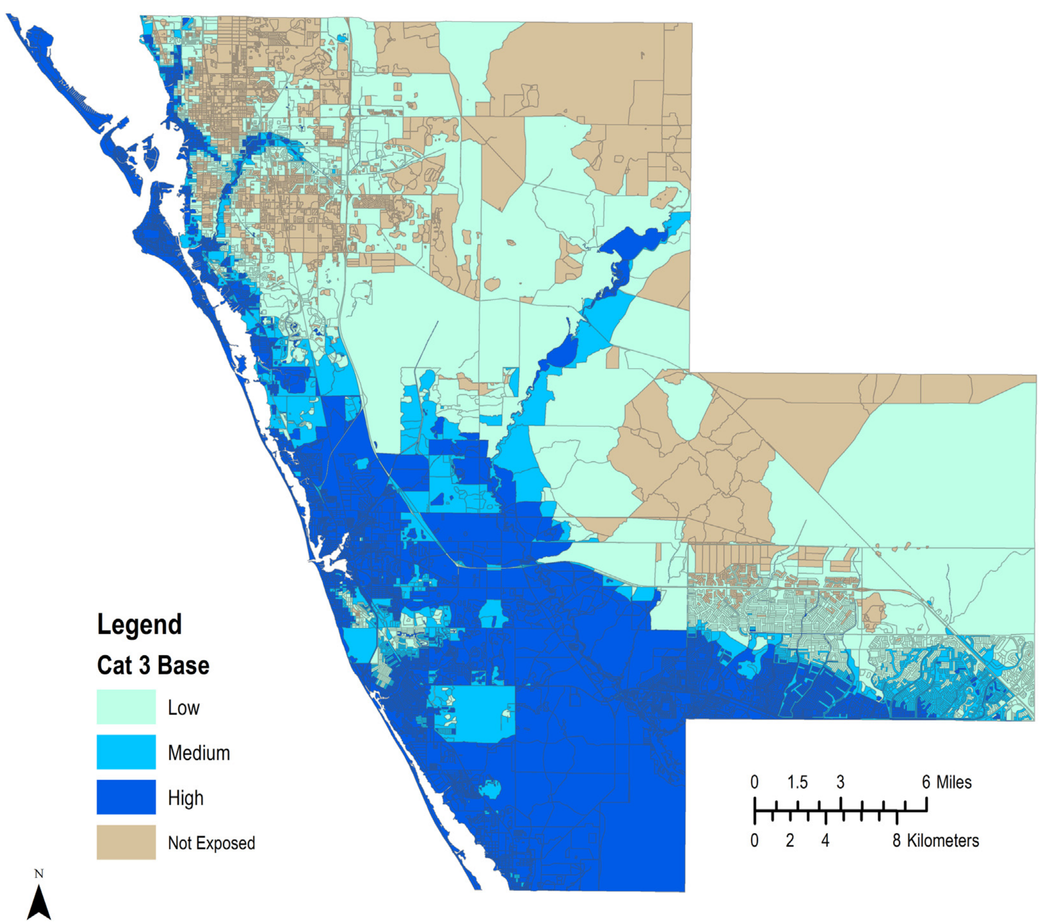

Fig. 2. Block exposure scores – Category 3 Base storm scenario.

$$B_{\mathrm{if}} = \sum S_{\mathrm{ik}} F_{\mathrm{if}}$$

where B_{if} = sensitivity score of the block

S_{ik} = weighted component score
F_{if} = amount of variance explained by factor f

This method weights the final block sensitivity scores by both the indicator's individual component loading and the total amount of explained variance of an indicator's encompassing factor (Johnston, 1978). Researchers employed this same scoring process to determine the raw adaptive capacity scores at the census tract level (the smallest unit for which the indicators were available). Once the adaptive capacity scores were calculated, researchers assigned the census tract level scores to the block level, under the assumption that all blocks have the same percentage of each variable at their aggregated tract level (Frazier et al. 2010; Wood et al., 2010).

Researchers then converted the raw scores for exposure, sensitivity, and adaptive capacity to *z*-scores to circumvent any errors that might occur during the aggregation of variables (Wood et al., 2010). Exposure, sensitivity, and adaptive capacity all describe very different processes. Therefore, it is impossible to aggregate their scores to a final vulnerability score without undergoing some form of conversion. *z*-Scores for each component were calculated by subtracting the mean raw score for each component from the block raw score and then dividing the difference by the standard deviation of each component (Wood et al., 2010). Researchers then applied the *z*-scores to the vulnerability equation to calculate block level vulnerability scores for Sarasota County.

Results

The resulting exposure *z*-scores were mapped to illustrate areas of increased exposure when the impacts of inland precipitation are included in the inundation coverage. The map illustrates the exposure scoring results using the standard deviation classification scheme (with 3 classes – Low, Medium and High), which allows scores to depict which blocks are more exposed than the mean (Figs. 2 and 3).

The SERV model exposure results indicate that hazard exposure is greatest in low-elevation areas along the coast and barrier islands (Fig. 3). This occurs because higher elevations impede the ability of storm surge to move further inland while low-elevation areas and barrier islands have fewer natural barriers that slow storm surge inundation. The results also indicate that storm scenarios that include precipitation result in greater inundation occurring further inland (Figs. 2 and 3). These blocks have notably lower levels of exposure, but there is still the possibility for low levels of inundation in those areas. This occurs because inland precipitation can cause additional flooding in areas further inland from the coast where elevation is low or drainage is poor.

The sensitivity index PCA identified principal components by determining common elements between grouped variables and vulnerability literature (Table 3).

The sensitivity index resulted in seven factors comprised of sensitivity indicators that explain 72.8% of the variance. These factors form seven main categories: base population, business and development, traditionally vulnerable populations, critical and medical facilities, low to medium development, income and

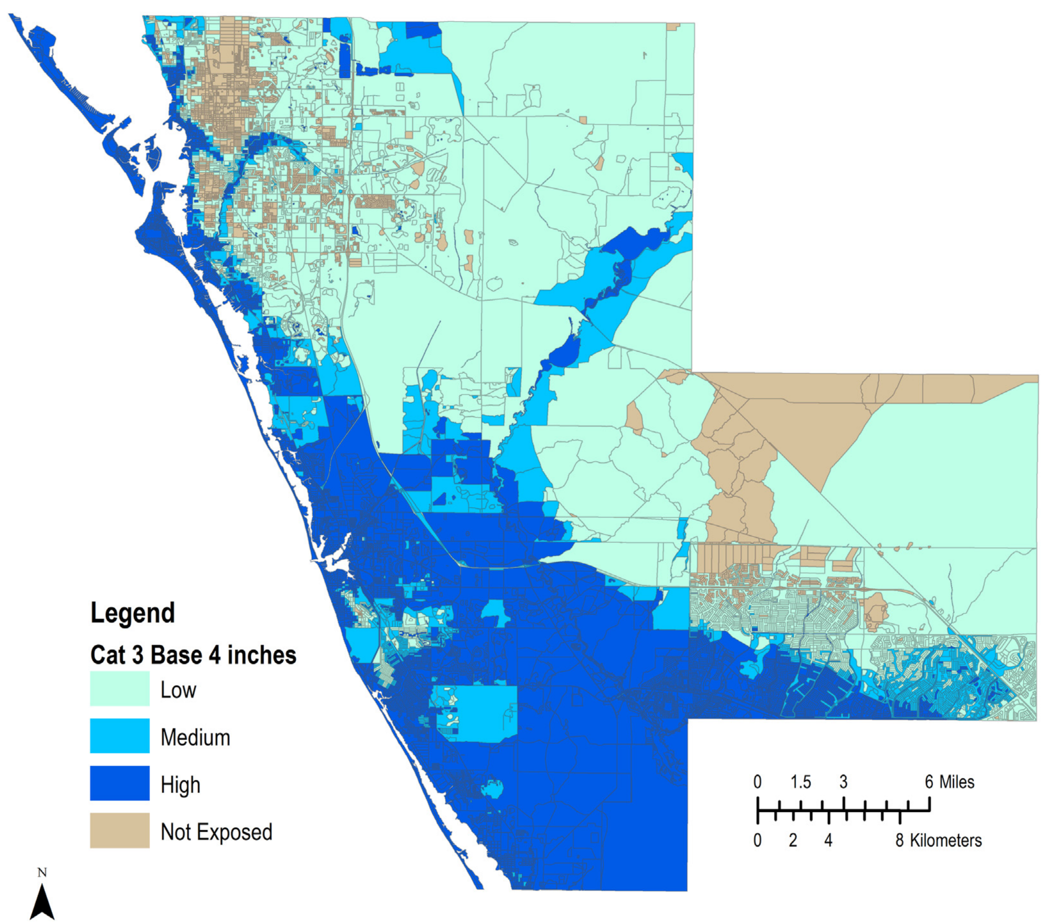

Fig. 3. Block exposure scores – Category 3 Base 4 inches storm scenario.

Table 3
Sensitivity index – final PCA results.

Component		Eigenvalue	% of variance	Variables and component loadings	
1	Base population	6.892	14.853	Percent over 65 years of age	0.805
				Median age	0.742
				Percent households	0.706
				Percent White or Caucasian	0.613
				Percent female	0.581
				Percent land cover developed, medium intensity	0.505
2	Business and development	2.495	9.55	Percent of total employees	0.915
				Percent of total sales volume	0.909
				Percent land cover developed, high intensity	0.501
				Percent essential facilities	0.481
3	Traditionally vulnerable populations	2.181	18.047	Percent female headed households	0.927
				Percent under 5 years of age	0.866
				Percent Hispanic or Latino	0.852
				Percent Black or African American	0.773
				Percent renter occupied housing units	0.685
				Percent female	0.462
4	Critical and medical facilities	1.73	8.812	Percent of medical facilities	1.001
				Percent of critical facilities	0.994
5	Low to medium development	1.397	11.266	Percent land cover developed, open space	0.954
				Percent land cover developed, low intensity	0.916
				Percent land cover developed, medium intensity	0.525
6	Income and economic base	1.034	5.83	Per capita income	0.73
				Justified parcel value	0.717
7	Tourism and agriculture	1.004	4.396	Percent land cover, agricultural	−0.888
				Percent tourism based businesses	0.463

Total variance explained: **72.75%**.

economic base, and tourism and agriculture. If an indicator has a positive component loading, this indicates that the variable is positively correlated within other variables in the factor. All of the component loadings in the second factor are positive, which indicates that there is a high correlation between sales volume, employees and medium intensity development. If an indicator is negative, this indicates that a variable is negatively correlated with another variable in that factor. The component loadings in the seventh factor (Table 3) indicate that high amounts of tourism occur in areas where there are low amounts of agriculture.

The mapped sensitivity results (Fig. 4) illustrate the distribution of sensitivity within the county (using the standard deviation classification method with 5 classes – Low, Low-Medium, Medium, Medium-High and High) to provide a relative representation of blocks that deviate from the mean sensitivity score (Cutter et al., 2003; Wood et al., 2010). Positive scores indicate higher sensitivity, while negative scores indicate lower sensitivity.

The sensitivity scoring results (Fig. 3) highlight several spatial patterns present in the distribution of sensitivity through the county. Sensitivity scores are highest along the coast and larger municipalities, such as Venice and North Port (Fig. 3), while blocks located further inland have lower sensitivity. Areas with higher percentages of traditionally vulnerable populations and low per capita income are located in and around municipalities along the coast. According to the raw model data, these areas have higher population densities, a greater presence of minorities and dependent populations and a large amount of developed land. In contrast, areas along the barrier islands have scores that are near or lower than the mean. This could occur because, while some elderly populations live along these areas, many of these residents are wealthier and are homeowners. Tourism is also very prominent in these areas, so the amount of employees, businesses and sales volume is higher.

For the adaptive capacity index, the PCA identified factors by defining common elements between grouped variables and adaptive capacity literature (Table 4).

The resulting five adaptive capacity factors explain 82.7% of the variance. These components and their explanatory variables form five main categories: age and employment, population and utilities, economic base, social services and infrastructure, traditionally vulnerable populations and housing capital and higher education and equality. Indicators with positive component loadings indicate that those variables positively correlate with other variables in the factor. All of the component loadings in the second factor are positive, which indicates that there is a high correlation between sales volume, employees and medium intensity development. Variables with negative component loadings indicate that those variables negatively correlate with other variables in that factor. The component loadings for the six variables in the third component suggest that all of the variables are negatively associated with one another. Therefore, when there are low amounts of any of these variables within a block, there are also low amounts of the correlated variables.

Fig. 5 illustrates the distribution of adaptive capacity within the county for the Category 3 storm scenario, using the standard deviation classification method with 5 classes – Low, Low-Medium, Medium, Medium-High and High (Cutter et al., 2003; Wood et al., 2010). Positive scores indicate higher adaptive capacity per storm scenario and negative scores indicate lower adaptive capacity.

The results for the adaptive capacity indicators (Fig. 4) in the Category 3 storm scenarios suggest that several census tracts along the northern and southern inland portions of the county have average or below average adaptive capacity. This might indicate areas with lower income or education, limited access to resources, or greater percentages of dependent populations. In contrast, areas that lie along the coast and barrier islands have increased adaptive capacity despite the higher percentage of exposed roads and utilities within those areas (Fig. 4). These tracts may have higher income levels, greater access to resources, and fewer dependent populations, all of which are advantages that may increase adaptive capacity despite exposed transportation and utility networks. This adaptive capacity distribution is identical to that of the Category 3 Base 4 inches storm scenario because the data is aggregated to the census tract level.

To illustrate the distribution of vulnerability within the county, the holistic vulnerability scoring results were mapped in Figs. 6 and 7. Positive scores indicate higher vulnerability, while negative scores indicate lower vulnerability.

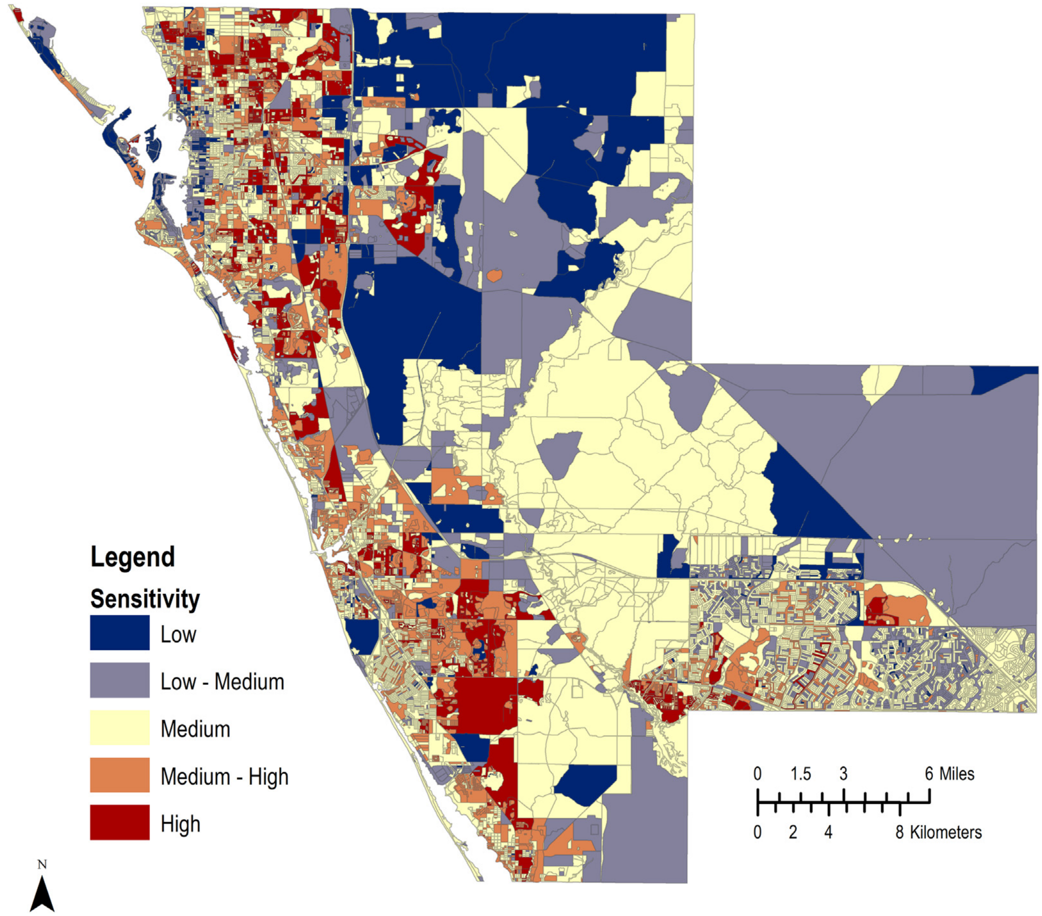

Fig. 4. Block sensitivity scores.

The results show that there is differential vulnerability across the county. Results illustrate that blocks along the coast and in the southern part of the county experience higher vulnerability scores than blocks further inland. The vulnerability scores for these communities also increase from the mean as the exposure increases by storm category.

Discussion

Assessing sub-county vulnerability is important for hazard mitigation planning because it identifies hotspots of vulnerability and factors that increase vulnerability. Sub-county vulnerability assessments could provide support for discussions and policy

Table 4
Adaptive capacity index – final PCA results.

Component		Eigenvalue	% of variance	Variables and component loadings	
1	Age and employment	6.047	19.127	Percent employed	−1.013
				Percent employed in non-primary industry, fishing, farming mining and forestry	−1.013
				Percent over 65 years of age	0.823
				Percent under 5 years of age	−0.557
2	Population and utilities	4.419	14.912	Local indicator of spatial autocorrelation in total population	0.991
				Percent utilities exposed	0.933
3	Economic base, social services, infrastructure	2.436	19.834	Percent of total sales volume	−1.016
				Percent of total employees	−0.989
				Percent of churches	−0.618
				Percent of area within flood zone	−0.612
				Percent roads exposed	−0.612
				Percent of social services available	−0.591
4	Traditionally vulnerable populations and housing capital	1.725	19.129	Percent of person below poverty line	−0.859
				Percent of persons 25 or older with less than 12 years education	−0.774
				Percent female headed households	−0.727
				Housing capital	0.716
				Percent under 5 years of age	−0.503
5	Higher education and equality	1.094	9.738	Gini coefficient of inequality	−0.87
				Percent of persons 25 or older with college education	−0.765

Total variance explained: **82.74%**.

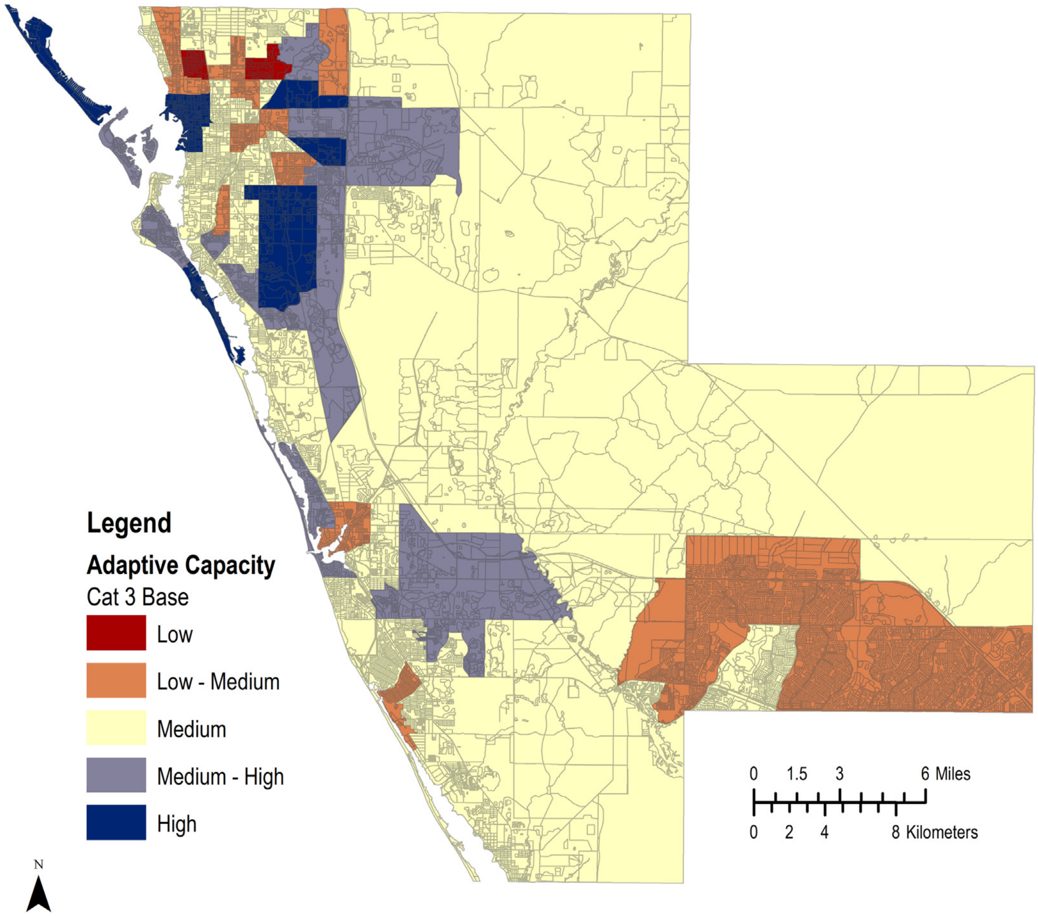

Fig. 5. Tract adaptive capacity scores – Category 3 Base storm scenario.

changes that lead to altering existing scale, structure and agency inequalities that contribute to vulnerability. Decision makers can use this information to target specific mitigation practices in areas where it will be most efficient and cost-effective for reducing vulnerability to hazards. In order to advance vulnerability analyses (Cutter et al., 2003; Frazier, Thompson, & Dezzani, 2013; Jones & Andrey, 2007; Vincent, 2007; Wood et al., 2010), this research introduces the SERV model to determine how vulnerability varies at the sub-county level from a holistic perspective.

Methodological advances

The vulnerability scoring results (Figs. 5 and 6) demonstrate the combined effects of exposure, sensitivity and adaptive capacity on vulnerability. Results indicate that areas identified as having high sensitivity and low adaptive capacity have higher vulnerability scores, no matter the level of exposure. While exposure can indicate areas where greater amounts of damage will occur, exposure does not necessarily imply that residents will be more sensitive to the hazard. Because the SERV model identifies proxies of access to resources, this causes the model to be sensitive to income and wealth data, which serve as common indicators of access to resources. Therefore, areas that have high exposure, along with high wealth, may have lower overall vulnerability scores. Wealth and access to resources often allows people to evacuate earlier and longer, and damage experienced by those individuals is easier to repair or replace (Morrow, 1999; Wood et al., 2010). It is also important to consider that areas not exposed to hurricane inundation hazards may be vulnerable to other hazards. Different hazards will have different levels of exposure for different areas, whereas the underlying sensitivity and adaptive capacity may not change.

The vulnerability scores also raise the question of the necessity for pre-disaster mitigation based predominately on exposure alone. Understanding where exposure is greatest can aid communities in mitigating against future structural losses, but these areas may not have high overall vulnerability (Frazier, Thompson, & Dezzani, 2013). The policy of targeting mitigation to areas based mostly on exposure can thus lead to insufficiently addressing needs in areas with higher numbers of exposed socioeconomically vulnerable populations. The SERV model more accurately identifies vulnerability, not exposure, in order to pinpoint areas where populations have limited power and agency, and therefore have limited ability to reduce vulnerability.

All of the sensitivity and adaptive capacity indicators demonstrate some level of spatial clustering, due largely in part to the urban service boundary and development regulations within the county. The SERV model illustrates where within the county certain sensitivity or adaptive capacity indicators are more predominant. For example, the third sensitivity component (traditionally vulnerable populations) identifies the traditionally vulnerable populations, such as minority groups and other vulnerable populations that are commonly more vulnerable to hazard events and suffer greater mortality rates. Social inequalities and lower access to resources reduce a person's ability to adapt more quickly (Cutter et al., 2003; Morrow, 1999; Wood, Soulard, and USGS 2008). The importance of identifying spatial indicators is also evident in the adaptive capacity index. The second adaptive capacity factor

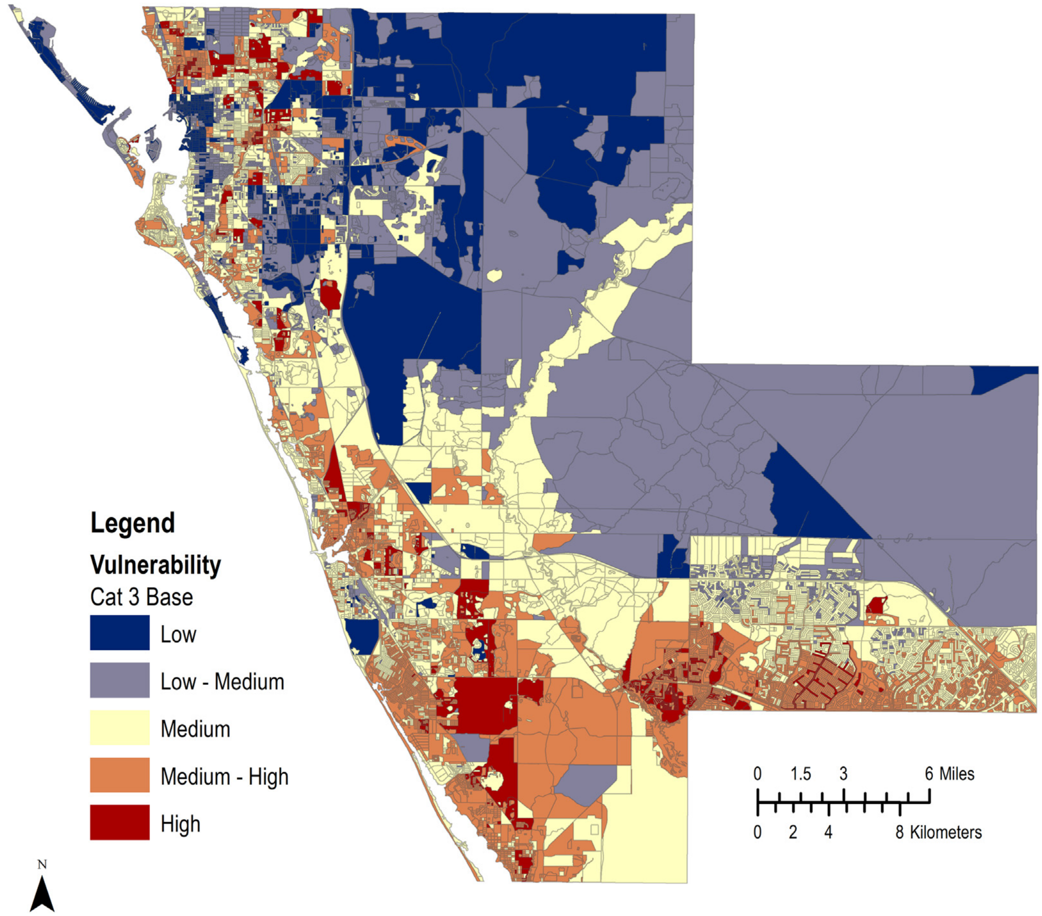

Fig. 6. Block vulnerability scores – Category 3 Base storm scenario.

(Table 4) identifies variables that describe the population and utilities. The Local Indicators of Spatial Association (LISA) analysis of the total population indicates where there is a significant presence or non-presence of people (Anselin 1995), which may help identify areas where resources are more readily available or likely to experience pressure or overuse (Brooks, Adger, & Kelly, 2005). When utility networks become exposed, there is also a greater chance that access to those amenities decreases, which reduces adaptive capacity (Brooks et al., 2005; Wall & Marzall, 2006).

Previous research supports these patterns of sensitivity and adaptive capacity (Frazier, Thompson, et al., 2013). Frazier, Thompson, et al. (2013) conducted stakeholder meetings where focus groups were asked to identify areas where resilience indicators were prevalent within the county. The groups identified areas along the barrier islands and the coast as areas of high wealth and tourism, which leads to greater economic health and higher access to resources. The groups also identified Venice and North Port as areas where a higher amount of minorities and low-income groups reside. Therefore, the sensitivity and adaptive capacity results reflect information provided by local stakeholders and follow the county's basic population and development patterns (Frazier, Thompson, et al., 2013). Understanding where vulnerability indicators are predominant may provide insight as to why certain areas experience greater vulnerability than other areas.

In addition to understanding the spatial nature of indicators, it is also important to determine which components are more influential on overall vulnerability. Specific indicators, not just their encompassing factors, may have a greater effect on overall vulnerability that is not addressed in traditional vulnerability assessments. The SERV model identifies spatial variation and differential influence of indicators on vulnerability, which can help decision makers identify where indicators are prevalent. Determining the location of these indicators can help planners target mitigation and social programs to those areas where high-sensitivity indicators (i.e. dependent populations or high poverty rates) commonly occur. Mitigation strategies that aim to improve socioeconomic conditions and vulnerable infrastructure that may increase vulnerability can help decrease the impacts of underlying socioeconomic processes that might impede people's ability to deal with and respond to disaster events (Berkes, 2007; Miller et al. 2010; Wood et al., 2010). These practices might include implementing more social services, determining where dependent populations are most dominant (i.e. elderly populations and children), relocating critical infrastructure (i.e. roads and utilities) to areas outside the hazard exposure zone, and limiting development to less exposed areas (Wood et al., 2010).

The utilization of scale-specific indicators in vulnerability assessments is also important because indicators that are found at the county level may not be as important in areas at the sub-county level. Past studies often generalize vulnerability results at the county level, which does not provide information about what areas within the county are most vulnerable. For example, existing studies assess social vulnerability at the county scale using national scale vulnerability indicators (Cutter et al., 2003; Jones & Andrey, 2007; Vincent, 2007), but they do not illustrate where within a county vulnerability is highest. A lack of spatial detail can result in

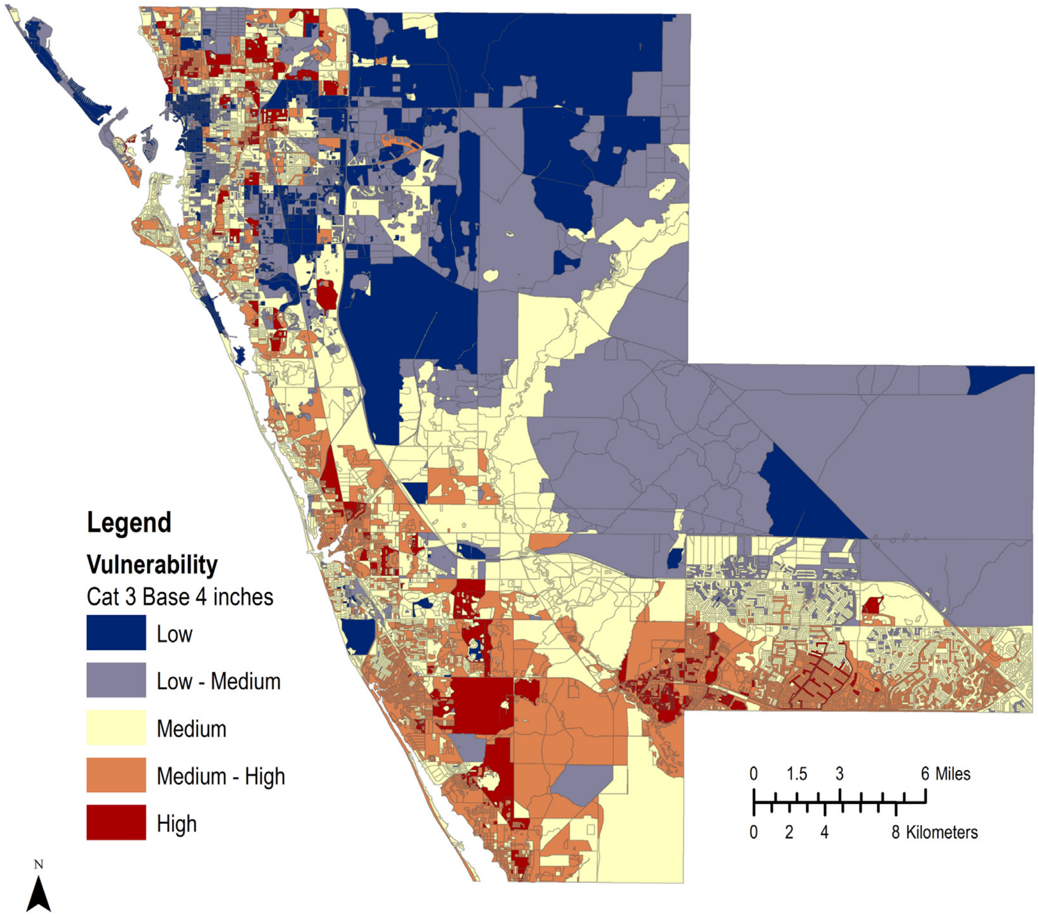

Fig. 7. Block vulnerability scores – Category 3 Base 4 inches storm scenario.

the implementation of uniform mitigation practices that do not necessarily translate to uniform vulnerability reduction.

Sensitivity analysis of existing studies also indicates that PCA factors of vulnerability are strongly associated with the scale at which indicators are measured (Cutter et al., 2003; Schmidtlein et al. 2008). If indicator distributions change at different scales, then using county level scores for sub-county vulnerability assessments may result in inaccurate assessments. Scale can also affect individual indicators. The results of the adaptive capacity scoring indicate that little change occurs between Category 1 and Category 3 storm scenarios, which could occur because the indicators were aggregated to the census tract level. The data aggregation generalizes adaptive capacity scoring for block-level analysis, which skews the results. A possible solution for this issue is to use dasymetric-mapping techniques to create census block level indicator data from census tract-level datasets.

SERV model limitations

While the SERV model provides several advances to current vulnerability assessment methodologies, it does have limitations. One limitation of the vulnerability scoring is that some areas exhibit high vulnerability in the lower storm categories, but then exhibit lower vulnerability in the higher storm categories. This pattern violates the assumption that vulnerability increases as exposure increases and could occur due to the normal distribution nature of *z*-scores. *z*-Scores can also be misleading when it comes to the distribution of certain indicators. If vulnerability scores are used to drive mitigation practices, the raw sensitivity and adaptive capacity data should be referenced to determine which indicators are most influencing the overall vulnerability in certain areas (Wood et al., 2010). Therefore, raw scores should be examined when basing mitigation strategies on the presence of specific vulnerability indicators (Wood et al., 2010).

Another limitation of the SERV model lies in the adaptive capacity component. While the adaptive capacity scores coincide with previous knowledge of the distribution of these variables (Frazier, Thompson, et al., 2013), the scoring patterns for overall vulnerability indicate that the equation may suffer from some loss of precision in its representation of block level vulnerability. Adaptive capacity in this methodology is considered static and does not account for fluctuations in adaptive capacity over time. The assumption that adaptive capacity is static may influence the level of precision in terms of accurately representing the levels of adaptive capacity experienced immediately after a disaster event. Therefore, future research will examine other methods in which to better measure and represent non-static adaptive capacity in vulnerability and resilience indices.

Another limitation of the SERV model is that the PCA weighting scheme does not consider how indicator influence might change across the county. PCA analysis is a global statistical analysis, so it does not consider that factors and components loadings will also vary at the local scale (Burt et al., 2009). Future work will examine how the influence of indicators changes across census blocks through statistical methods that correct for spatial processes, such as a geographically weighted principal component analysis (GWPCA) (Gollini, Lu, Charlton, Brunsdon, & Harris, 2013). For example, one block's vulnerability may be highly influenced by the presence of dependent populations whereas the vulnerability of the block adjacent to it may not. The results of a GWPCA would provide more accurate information about the differential influence indicators have vulnerability within the county (Gollini et al. 2013). These issues will be addressed in ongoing and future research.

Theoretical advances

The SERV model advances the field in that it provides evidence to decision makers that directly links vulnerability to policy and the implementation of hazard mitigation strategies in areas where vulnerability is highest. This advances political economy, political ecology and structuration theory frameworks in hazards research by validating the connection between economic inequalities, scale, and agency components and community vulnerability. Thus, the SERV model helps to link theory more directly to hazards research.

The SERV model also illustrates that each component (exposure, sensitivity and adaptive capacity) contributes differently to overall vulnerability, and therefore should be considered in future assessments. Vulnerability assessments that examine the impacts of exposure, sensitivity and adaptive capacity provide a more holistic representation of vulnerability and resilience. The SERV model also illustrates that the calculation of vulnerability should occur at a sub-county level in order to understand social and biophysical vulnerability at the sub-county level. This level of detail identifies which indicators have a greater influence on vulnerability at specific locations, which can guide site-specific mitigation strategies.

The SERV model also seeks to measure vulnerability more accurately in order to identify inequalities within the population that may limit the ability of communities or individuals to reduce vulnerability. Vulnerability assessments conducted at the sub-county scale can serve to steer development into areas that are less vulnerable and help guide adaptation planning strategies that could enhance resilience. The SERV model advances the evolution of vulnerability assessments by providing a holistic model that examines all three components of vulnerability at the sub-county scale that identifies exposed populations and infrastructure, pinpoints preexisting social structures or inequalities that exacerbate sensitivity or adaptive capacity in the absence of a hazard, and identifies areas where exposure is more impactful on indicators and their capacity to cope with the hazard. Vulnerability occurs in areas that are not necessarily exposed, so the SERV model accounts for those often overlooked areas.

Conclusion

Socioeconomic indicators are distributed unequally across a study site, which causes them to have differing influence on sub-county vulnerability. Understanding the uneven distribution of these factors, as well as the magnitude of the physical hazard, is important for effective sub-county hazard mitigation and adaptation planning and efficient allocation of limited resources. However, many vulnerability assessments are limited in their effectiveness for sub-county hazard mitigation because they are conducted at the county scale, they do not address spatially variable indicators and they neglect to include weighted place and scale-specific indicators in their assessments. In addition, existing studies do not calculate vulnerability as a function of exposure, sensitivity and adaptive capacity. The exclusion of adaptive capacity limits the capabilities of vulnerability assessments for adaptation planning that can increase community resilience. The exclusion of these components can hinder the effectiveness of local allocation of resources and can result in mitigation practices that assume all communities suffer uniform issues and problems.

In response to these challenges, this research advances existing work in vulnerability and resilience science by using weighted, place and scale-specific indicators to identify varying sub-county vulnerability within Sarasota County, Florida. The sensitivity and adaptive capacity PCA results suggest that different indicators have a greater influence on overall vulnerability. The SERV model results indicate that place-specific indicators help identify more influential indicators of vulnerability in different areas and the indicator weighting ascertains where certain indicators have a greater influence. This provides decision makers with the ability to identify what indicators are more influential on vulnerability and where they occur within the county. Therefore, considering all three components of vulnerability, the effect of spatial autocorrelation and differential weighting on indicators is beneficial to future analyses because these factors can influence the presence and intensity of vulnerability within the county.

Although the SERV model is beneficial to hazard mitigation and planning because it highlights areas that might require increased mitigation efforts, it does have limitations. The vulnerability scores exhibit higher vulnerability in storm categories with less exposure, which could be due to the nature of *z*-score distributions. In addition, there are limitations to the adaptive capacity component of the vulnerability equation in that it assumes that adaptive capacity is static and fully realized immediately after a disaster event.

While the SERV model has limitations, it provides a method for assessing sub-county vulnerability that may better assist communities more effectively allocate limited resources to more vulnerable, not just highly exposed, areas. Implementation of this model for sub-county vulnerability assessments could serve a critical tool for guiding land-use plans and steering development in long-range comprehensive plans and help enhance local resilience.

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