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An index of relative displacement risk to hurricanes

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Abstract Indicator and index-building activities have become commonplace for assessing and estimating social, environmental, and economic strengths and vulnerabilities of communities, regions and even countries. In the context of disasters, much of the empirical research has focused on identifying places and populations that are vulnerable to catastrophic hurricane and flood disasters. However, there have not been parallel efforts to capture measures for displacement risk. This article seeks to fill this gap by focusing on (1) a preliminary conceptualization of displacement risk; (2) a set of related indicators and measures at various scales, including indicators tapping policy capacity and commitment; and (3) development of an operational displacement risk index (DRI) and results for a snapshot year of 2007. The study area, 158 counties in the United States, was the coastal portion (an area two counties "deep") of eight states. Findings suggest that the mean levels of DRI scores were much higher for coastal counties. Clusters of the highest DRI scores are particularly evident for coastal counties of Florida, especially the South Florida counties of Miami Dade, Monroe, Palm Beach, and Broward. Florida also scores high in terms of the top ten most vulnerable counties (i.e., 7 of the top 10) as well as exposure to hurricanes (i.e., 6 of the top 10 counties with the highest probability of hurricane strikes). Despite the limitations explained in the paper, we hope that the creation of the DRI has helped to fill a gap in knowledge and will lead to higher level theoretical and research discussions on the population displacement phenomenon, its determinants and planning and policy interventions.

Keywords Index · Indicators · Hurricane · Population displacement · Risk · Resilience · Vulnerability

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1 Introduction

Catastrophic hurricane disasters such as Andrew and Katrina highlighted dilemmas of population displacement, as well as gaps in our knowledge of the magnitude and patterns of the potential displacement problem in the United States. Much of what is known about displacement causation is derived from outside the field of disaster research, and from outside the United States (Oliver–Smith 2009) and mostly in the context of conflict, development projects, or other disruptions in developing or politically unstable countries. For the purposes of this paper, we use the term displacement to mean the uprooting of people from their homes resulting from a hurricane disaster for periods of time that exceeds the typical temporary shelter timeframe of 3 months (Lin 2009; Mitchell et al. 2011; Van Zandt and Peacock 2009). Identifying those who are predisposed to displacement is a necessary first step but is not an easy task since each disaster is unique with respect to evacuation, migration, displacement, physical destruction to homes, employment centers, and critical infrastructure. Several empirical studies are useful in that regard (FEMA 1994; Smith 1996; Smith and McCarthy 1996; Peacock et al. 2000; Dash et al. 2007; Van Zandt and Peacock 2009; Henry et al. 2010; Mitchell et al. 2011). We also see the fiscal and societal impact of displacement on host/receiving communities. A second level of vulnerability and insecurity can result for both residents and displaced persons in those areas not affected by the primary event (Mitchell et al. 2011). Smith and McCarthy (1996) examined displacement after hurricane Andrew and estimated that 271,000 of displaced persons remained in Dade County, 31,900 moved north to Broward County, 32,700 moved to other parts of Florida, and 17,700 left the state altogether, totaling 82,300 persons who left Dade County at least temporarily due to the hurricane. The Houston area first experienced an influx of hundreds of thousands of Katrina displacees, followed by Ike displacees 4 years later. Therefore, some knowledge of the potential displacement problem and patterns can enhance disaster preparedness and intra-regional coordination efforts at the very least.

This highlights the second problem, which is the lack of algorithms to estimate the magnitude and spatial variation of the displaced persons problem. This is despite significant advances in the past decades to quantify measures of societal, physical, and infrastructure risk vulnerability and resilience (Bolin 1985, 1994; Clark et al. 1998; Davidson and Lambert 2001; Cutter et al. 2003, 2010; Boruff et al. 2005; Miles and Chang 2006; Jain et al. 2005; FEMA 2006; Kates et al. 2006; Simpson 2006; French et al. 2008; Zahran et al. 2008). This article reports on a research effort to fill this gap by developing an index of displacement vulnerability, referred to as the displacement risk index (DRI). This index is an attempt to measure for the first time, the risk to displacement and incorporates vulnerability, resilience, and hurricane risk probability.

The article begins by describing the study area, followed by a review of selected algorithms, models, and indices that have informed our efforts. In the next section, details are provided on our underlying conceptual framework, including a description of a set of related indicators and measures. This sets the stage for the operationalization of the displacement index and its three main components (vulnerability component, community resilience component, and hurricane exposure probability component). We conclude with the results and a discussion of the limitations and complications in the development of a displacement risk index.

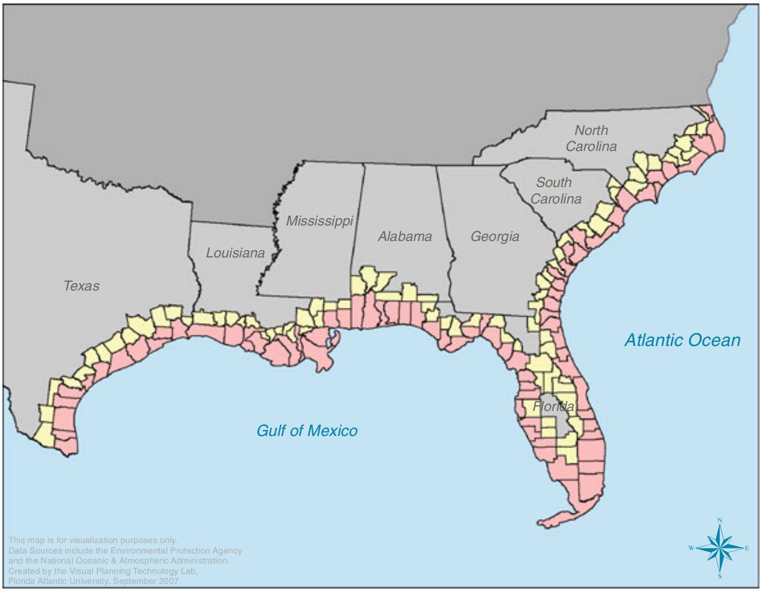

Fig. 1 Study area counties

2 Study area

Gulf Coast and Atlantic seaboard coastal communities are a large and growing part of the total economic activity of the U.S. (Murphy and Strobl 2010), but are especially at risk from hurricanes. The coastlines, once known simply as tourist attractions and resort communities, have seen tremendous growth and development pressure partly as a result of increases in permanent population (Beach 2002; NOAA 2004; Pielke et al. 2008). According to NOAA (2004), over half (53%) of all U.S. residents lived in coastal counties in 2003, and these counties comprise 10 of the 15 most populous cities. In addition to increasing densities, the character of coastal residents has changed as well from seasonal to year-round residents. According to Cutter and Emrich (2006), many of these year-round residents are elderly retirees or service industry workers who keep the tourist industry afloat, and they are more racially and ethnically diverse than in past decades.

The study area for this research is the coastal portions of North Carolina, South Carolina, Georgia, Florida, Alabama, Mississippi, Louisiana, and Texas. *Coastal portion* is defined here as the coastal counties and the counties immediately inland of them—that is, *an area two counties "deep"* (Fig. 1). These 158 counties are most likely to experience the full brunt of storm surge and strong winds, particularly for major hurricanes moving onshore, that impact areas far inland from the point of landfall.[1] These counties are those most likely to produce potentially large numbers of displaced persons. What is lacking however, are in-depth studies to test this assumption by exploring the full range of indicators and measures for displacement risk to hurricanes.

[1] Zandbergen (2009, 84) highlighted the limitations of using point of landfall for hazard evaluations given that "the effect of tropical storms or hurricanes can reach far inland and includes areas far away from the point of landfall".

3 Literature review

> Indices are attractive because of their ability to summarize a great deal of often technical information about natural disaster risk in a way that is easy for non-experts to understand and use in making risk management decisions (Davidson and Lambert 2001, p. 133).

This section is a brief summary of scholarly work that provided important insights and frames of reference for conceptualization of the Displacement Risk Index. The summary is based on three types of U.S. hazard/disaster risk indices and their applications (i.e., vulnerability and risk indices; resilience and recovery models; and population dislocation/displacement algorithms); as well as the conceptual, theoretical, statistical, and scientific underpinnings of algorithm and index construction.

3.1 Vulnerability and risk indices

Davidson and Lambert (2001) reported on the development of two variations of a hurricane disaster risk index (HDRI) which rates relative levels of hurricane disaster risk in U.S. coastal counties. The HDRI is based on the standard formulation of risk as the product of hazard, exposure, and vulnerability. The concept of risk provides a useful paradigm for evaluating complex disaster preparedness decisions as it "conjoins two basic ideas, namely, that of *adverse consequences* and that of *uncertainty*" (Shlyakhter et al. 1995, p. 1586). The adverse consequences or the impacts are associated with what is likely to happen, while the uncertainty is expressed as the probability of these circumstances to occur (Blaikie et al. 1994; Shlyakhter et al. 1995; Obellin et al. 1999; Scheraga and Furlow 2001). In the context of hurricane-related disasters, the concept of risk describes the general outcome (in terms of effects on human and natural systems) of an event of specified magnitude given inherently uncertain conditions defined as the probability of exceeding a specified intensity in any given year. While the hurricane disaster risk indices are useful in its focus on the formulation of disaster risk arising from hurricanes, other scholars (Clark et al. 1998; Cutter et al. 2003; Rygel et al. 2006) have developed broader conceptions and indices to represent relative measures of social and physical vulnerability over space. Specifically, with the development of Social Vulnerability Index (SoVI), Cutter et al. (2003) analyzed the relative social vulnerability for every county in the United States. The usefulness of that index has been amply demonstrated by its continuing evolution and utility, for example, to account for the intersection of coastal erosion and social indicators to produce a county-based index of overall coastal place vulnerability (Boruff et al. 2005). SoVI was also used for decadal comparisons of social vulnerability of Katrina ravaged coastal counties (Cutter and Emrich 2006). Other scholars have honed in on applications in various policy domains. For example, Chakraborty et al.'s (2005) work on social vulnerability index building was applied in the context of population evacuation assistance needs, and was combined with geophysical risk index, derived from probabilities of occurrence of hurricanes and floods. What we take away for our DRI is the need to account for hazard exposure, geophysical risk, and social vulnerability in determining potential displacement levels.

3.2 Disaster resilience models and indices

Simpson's (2006) index-building work on community resilience promotes the idea that a community's capacity to recover can offset its vulnerability. As such, Simpson selected factors and measures for community preparedness and vulnerability. Miles and Chang (2006) also presented the concept of resilience but from an engineering perspective (i.e., reduced failure incidence, reduced failure consequence, and reduced recovery time). The models are based on inter-related "technical, organizational, social, and economic facets" that highlight infrastructure as key to recovery. Miles and Chang (2006) use recovery time concepts similar to Pethick and Crooks (2000)—that is, an unstable system will not return to its predisturbance state. As the disaster resilience concept is increasingly applied beyond engineering to disaster risk reduction and policy formulation, scholars such as Mayunga (2007) are providing useful insights into alternative approaches and challenges with operationalizing community resilience. Mayunga (2007, p. 4) aptly cautions that "conceptualizing resilience [as the opposite of vulnerability] may not be desirable because it does not add much to our understanding". Two teams from Texas A&M University (Mayunga 2007; Peacock 2009) and University of South Carolina (Cutter et al. 2010) have ongoing projects to develop and refine baseline indicators and indices of community resilience. What we take away for our DRI is that resiliency should capture (to the extent possible) the effect of household, institutional and community capacity, resources, infrastructure, and policies; and that index-building has value in a nimble process that requires some level of experimentation with scaling methodologies (such as z-scores; linear scaling minimum–maximum transformations; linear scaling maximum value transformation), aggregation, and weighting methodologies.

3.3 Population dislocation/displacement algorithms

FEMA's Hazard U.S. MultiHazard system (HAZUS-MH) has a shelter needs module which estimates the number of displaced households and the number of short-term shelter needs, but only as a function of age, income, and home ownership (FEMA 2006). French et al. (2008) reported on a research effort that examines social and economic consequences of natural hazards as part of a four-prong comprehensive framework: (1) shelter and housing; (2) economic losses, including business interruption; (3) health, including casualties; and (4) social disruption. In that effort, French et al. (2008, 22) reported on two algorithms to estimate population dislocation: (1) a modified HAZUS approach that bases the estimation on structural damage and anticipated variations in dislocation between single and multi-family structures; and (2) a population dislocation algorithm that extends empirically-based statistical models that predict population dislocation following hurricane Andrew. These algorithms have been implemented in the MAEViz risk analysis system developed by the Mid-America Earthquake Center. The latter is an algorithm developed by Lin (2009) and is based on structural damage, housing type, and the percentages of Black and Hispanic population in block groups in Miami–Dade county, Florida. What we take away for our DRI is the need on one hand to include a broad base of household and neighborhood/community socioeconomic characteristics that impact displacement risk; on the other hand, we cannot make broad-based assumptions that traditional social vulnerability measures (race, income, age etc.,) have a positive influence on displacement risk.

3.4 Index construction

> When the objective is to design the best possible index, considerations of the most advanced statistical techniques available are important. On the other hand, if transparency and easy understanding by non-experts is equally important, the logical framework of the ESI represents a useful and valid alternative (2005 ESI, Appendix A, pp. 65–66)

Index building initiatives beyond natural hazards and disasters scholarship were worth reviewing for alternative conceptualization and computational approaches. Of particular use was the environmental sustainability index (ESI) which was developed as a comparative measure of a county's level of environmental sustainability for purposes of cross-national comparisons of environmental progress (Esty 2001, 2002; Niemeijer 2002; Esty et al. 2005). Counties are scored relative to other counties. The ESI scores are calculated as standard normal percentiles and are based on a set of five components, 22 core indicators, and a total of 67 underlying variables (Esty 2001). The various reports and articles on the ESI also provide important computational insights about data selection, standardization, scaling, weighting, and aggregation methodology. The choice of aggregation method depends on the purpose of developing the index. If one would like to know how far a particular score is from the "best" (maximum) and the "worst" (minimum), a linear scaling transformation (LST) based on the formula $(Y_{\text{obs}} - Y_{\min})/(Y_{\max} - Y_{\min})$ would be helpful. A drawback of this approach is that it is overly dominated by extreme values. Distortions related to LST arise from the influence of large variances on the composite score due to the effect of large outliers. Large variances introduce large implicit weights (Booysen 2002) and, as a result, the composite scores may become clustered at the high and low ends of the continuum. One way to avoid the relativistic bias introduced by LST is to use the standard normal percentile or z-score standardization.

The z-score approach is a method of standardization of variables with different units of measurement, scale, and range. Because of its statistical properties, it is suitable for ranking the variables in a particular dataset. The purpose of the ranking procedure is to have consistency within the entries of the dataset. A z-score is a measure of how much a particular observation deviates from the mean relative to the standard deviation. When a sampling distribution approximates a normal bell-shaped curve, the deviation from the mean would be zero, and the z-scores would be distributed roughly three standard deviations above and below the mean. The z-score standardization overcomes the relativistic bias that occurs when scores are computed in ratio to the highest (or, lowest) observation. The z-scores computation requires verification that variable sampling distributions satisfy the normality assumptions. We used the Kolmogorov–Smirnov statistic to test the hypothesis that the observed data are from a normal distribution. Data transformation and/or winsorization (i.e., trimming of the tails to the 97.5th percentile) were performed if outliers or extreme values that distort the distribution are present (Esty et al. 2005). Removing the effect of large outliers by transforming variable values to fit a standard normal distribution provides a more robust approach to meaningful ratings as it normalizes the sampling distribution in ratio to the standard deviation. Truncation is justifiable for comparative purposes because it preserves the outliers in the extreme tail of the distribution but removes their effect on the mean and the standard deviation, and thus prevents them from becoming "benchmarks for the entire population" (Samuel–Johnson and Esty 2001, p. 27). A drawback of this approach is the smoothing effect of transformation and/or winsorization on the "best" and "worst" performances as represented by the raw data values. Winsorization to the 99th percentile, however, maintains the extreme values in the tails of the distribution, allowing them to still represent "best" and "worst" practices, but reduces their undue effect on the aggregation algorithm.

Beyond development, composite indices should be internally and externally validated. According to Booysen (2002, p. 129), it is "only through continued validation and adjustment resulting from constructive debate can indices be improved." However, Simpson (2006) identified the lack of simple unified scientific validation methods as one of the shortcomings of the use of composite indices. According to Babbie (1995, p. 174), if different items are indeed indicators of the same measure, then they should be empirically related to each other. Sensitivity analysis is primarily conducted to distinguish between the importance of indicators and to identify the degree of their contribution (Saltelli et al. 2000a), with the goal being to identify relevant indicators (parsimony) because excess complexity (over-parameterization) and unimportant factors that cause no variation in the model response are signs of bad models according to Saltelli and Funtowicz (2005). This allows us to measure the importance of an input indicator is on the index's variance. For linear models, a straightforward approach for variance decomposition and sensitivity analysis involves regression techniques (Saltelli et al. 2000b, 2004) with the index indicators as regression input (independent factors) and the index score as the dependent factor.

External validity requires a selection of a variable (validator) which is not included in the index and an analysis of the relationships between the values of the validator variable and the index scores (Babbie 1995; Booysen 2002). Several methods have been advanced to externally validate indices, including in-depth cases and surveys to assess the reliability of the output, calibration with event data, and comparison to proxy measures or other indices (Babbie 1995; Booysen 2002; Simpson 2006; Gall 2007; Peacock 2009; Sherrieb et al. 2010). Single-factor analysis of variance (i.e., one-way ANOVA), Kruskal–Wallis test and Ordinary Least Squares (OLS) regression analyses are statistical techniques that have been used for examining between group variation and predictive validity as part of the process of external validation of results in various fields (Bonanno 2007; Markos et al. 2010; Gall 2007; Peacock 2009; Mitsova and Wang 2010). The single-factor ANOVA test determines if significant differences exist between two datasets. It implies approximate normal distribution, independent samples, and equal variances (Johnson and Kuby 2004). When any of these assumptions is violated or one of the datasets contains nominal/ordinal variables non-parametric tests such as the Mann–Whitney U test statistic or Kruskal–Wallis H statistic are usually applied (McDonald 2008).

Overall, what we take away for our DRI is that it should be conceptualized as an overall percentile score of displacement risk potential for the 158 counties in our study area, where a high DRI percentile score will signal that a county has a high potential for population displacement from hurricanes. Also, valuable was the consistent message by various scholars about the importance of balancing computational issues (data selection, normalization, collinearity correlations, aggregation schemes, weighting, etc.) with result accuracy and interpretation,[2] and the need for exercised caution so that indices avoid complete compensability (i.e., the possibility that a good score on one indicator can always compensate a very bad score on another indicator), which can imply substitutability between various components of the index (Munda 2003). The index must be easily transparent, reproducible, and amenable to updates as data sets are collected. Additionally, we recognize the importance of internal and external validation,and agree with Babbie's (1995) and Booysen's (2002) insights that an index should be somewhat related to any item that taps the variable even poorly given that there is no cookbook solution to selecting an objective external validator.

4 The displacement risk index: indicator and variable selection

As previously stated, the DRI is an attempt for the first time to conceptualize and quantify the risk to displacement from hurricanes that strike the US mainland. There are several

[2] See Simpson (2006) for one of the most comprehensive reviews on vulnerability and disaster risk index-building and related conceptual, methodological, and technical issues, as well as a summary of indices developed by other scholars.

intended uses of the DRI and its components. At the most basic level, percentile scores will be generated for the DRI and its sub-indices for a snapshot year of 2007. Related maps will be generated to show spatial patterns to increase awareness of planners and policy makers as well as the public about displacement risk potential of the 158 counties in the study area. This can in turn enhance mitigation efforts at various levels of government (local, regional, state levels) and inform proximate counties wishing to enter mutual agreements on issues of evacuation and hosting of displacees. The incorporation of coastal counties and the counties immediately inland of them is particularly relevant in that regard. A closer look at the vulnerability component scores can also inform policy makers as to the household and community vulnerability factors that require attention. Similarly, the community resilience component includes policy indicators tapping community capacity, institutional strength and state commitment which can affect and reduce risk, vulnerability and potential displacement.

The following sections outline the choice of variables which were driven by a consideration of the intended uses, theoretical logic and relevance to the indicator in question. Available data were collected[3] at the county level for most of the variables since displacement indices are most useful and relevant (from a policy and planning intervention perspective) at the local level. Furthermore, hurricanes and related winds generally affect spatial areas broader than alternative spatial units like census tracts or block groups. The latter are not political or administrative units and have no planning and policy authority.

4.1 Demographic, socio-economic and housing vulnerability indicators

All coastal county residents are equally at risk to a hurricane's physical impact. However, vulnerable persons with the least ability to respond and rebuild are at greatest risk to death, injury, and economic loss due to housing destruction and short-term and long-term displacement and related effects (Bolin 1985; Morrow 1999; Quarantelli 1995; Morrow and Peacock 2000; Peacock et al. 2000; Davidson and Lambert 2001; Oliver–Smith 2006; Levine et al. 2007; French et al. 2008). Koerber's (2006) study provides invaluable insights into the migration patterns and characteristics of New Orleans residents who were displaced after hurricane Katrina. According to Koerber (2006), those who moved tended to be younger, more likely to be single or separated, less likely to be fully employed or in the labor force, more likely to be in poverty, and living in renter-occupied housing. Predisaster inequities, discrimination, and exclusion emerged as important determinants on displacement (Phillips and Morrow 2007). Myers et al. (2008) also pointed out that rural households may lack the means for moving out of the path of disaster or recovering after.

Key socioeconomic vulnerability variables that are consistently documented in the literature include: population growth rate, population change/population density; income/poverty levels, density of the built environment, age (median age and/or 5 years $<$ and $>$ 65 years), race and ethnicity, educational attainment; transience, number of mobile homes, % immigrant and/or non-native speakers, race, occupations with focus on single sector economic dependence, and infrastructure dependence (Burton et al. 1993; Blaikie et al. 1994; Clark et al. 1998; Cutter et.al 2003; Dwyer et al. 2004; Chakraborty et al. 2005; Rygel et al. 2006). Specifically lacking are household indicators (such as households that rent, affordable housing demand for renters, government-assisted households), that could be used to plug gaps in the socioeconomic variables described, as well as indicators related to decisions to return or not to an area impacted by a hurricane. Peacock and Girard (2000)

[3] Most of the data was collected for the year 2007.

Table 1 Summary of socio-economic vulnerability indicators and variables

Component	Indicator (year 2007)	Normalized variables (with directional effect on vulnerability)	Data sources
Socio-economic vulnerability	Income (4)	% HHs below poverty line (+); median HH Income (−); per capita income (−); % HHs using over 30% of income for housing (+)	U.S. Census Bureau, Geolytics
	Economic (3)	% economic sector vulnerability (+); % employment gain/loss for period 2002–2007 (−); unemployment rate (+)	Bureau of Labor Statistics
	Race/ethnicity (7)	% pop White (−); % pop Latin (+); % pop African American (+); % pop Native American (+); % pop Asian (−); % pop Other (+); % pop English not well spoken (+)	U.S. Census Bureau, Geolytics
	Age (4)	% pop over 65 (+); %pop over 75 (+); %pop under 18 (+); % pop under 6 years old (+)	U.S. Census Bureau, Geolytics
	Affordable housing (2)	% HHs that Rent (+); affordable housing need as % of total HUs(+)	U.S. Census Bureau; Geolytics; HUD
	Disadvantaged (6)	% single female HHs (+); % single Parent HHs (+); % single person HHs over age 65 (+); % HHs on public assistance (+); % HHs with disabilities (+); % HHs without Cars (+)	U.S. Census Bureau, Geolytics
	Residence (1)	% pop born in State (−)	U.S. Census Bureau, Geolytics
	Education (2)	% pop with less than high school (+); % pop with less than 8th grade education (+)	U.S. Census Bureau, Geolytics

(+)/(−) signs after each variable refer to the directional effect on vulnerability; the household data are averages for the county

found that those who are economically and socially disadvantaged were more likely to reside in housing that is substandard, and more likely to be damaged. These households are more likely to be renters, mobile home occupants, and/or reside in housing with lower quality construction (Fothergill and Peek 2004; Myers et al. 2008). Further, renters face recovery problems as well, usually having no insurance and no rights to stay in the property, despite damage, as homeowners do (Fothergill and Peek 2004; Myers et al. 2008). Table 1 summarizes the socio-economic vulnerability indicators and normalized variables used for the displacement risk index.

4.2 Physical vulnerability indicators

The relationship between the physical and social aspects of vulnerability has been widely acknowledged by several scholars. Bogard (1989), Downing (1991), Dow (1992), Smith (1992), and Cutter (1993) have all noted that vulnerability is a function not only of the immediate physical conditions, but also of society's capacity to withstand disasters. Bohle et al. (1994) and Dow and Downing (1995) define vulnerability as a multi-dimensional construct captured in physical and socio-economic factors. Other research has integrated social aspects with physical risks in a wide array of spatial contexts (Wilhite and Easterling

Table 2 Summary of physical vulnerability indicators and variables

Component	Indicator	Normalized variable (with directional effect on vulnerability)	Data sources
Physical vulnerability	Built environment (5)	% HUs that are mobile homes (+); % owner occupied HUs (−); % renter occupied HUs (+); population density (+); % urbanized area (+)	U.S, Census Bureau, Geolytics, ESRI tiger files
	Flood (3)	% urban area in flood zone (+); % county in flood zone (+); coastal vulnerability index (+)	FEMA, Gecomm.com, ESRI tiger files, state/county GIS clearinghouses, USGS

(+)/(−) signs after each variable refer to the directional effect on vulnerability

1987; Mitchell et al. 1989; Lewis 1987; Liverman 1986, 1990; Palm and Hodgson 1992; Degg 1993; Longhurst 1995).

Coastal counties are especially vulnerable to flooding, overwash and storm surges, as well as huge capital investments required to reconstruct private property and public infrastructure (Platt 1994). They are also vulnerable to erosion and other short-term and long-term impacts such as sea level rise (Theiler and Hammer–Klose 1999, 2000; Boruff et al. 2005). The Coastal Vulnerability Index (CVI) listed in Table 2 represents the physical vulnerability of coastal edge/shoreline, based on six variables: mean tidal range, coastal slope, rate of relative sea level rise; shoreline erosion, and accretion rates; mean wave height; and geomorphology (Theiler and Hammer–Klose 1999).

Displacement risk is being produced (Steinberg 2000) given the increased exposure of the "expanding capital stock" (Mileti 1999) to natural hazards. This capital stock is mostly in dense urbanized areas with exposed lifeline infrastructure such as transportation networks, electrical networks, water networks, and other critical facilities (Davidson and Lambert 2001; Miles and Chang 2006); as well as vulnerable commercial and residential structures. As such, indicators are needed to capture both built and natural environment factors to convey physical vulnerability. Table 2 summarizes the physical vulnerability indicators and normalized variables used for the displacement index.

4.3 Community resiliency indicators

Individual and household displacement is intrinsically linked to pre- and postdisaster community resiliency: restoration of functioning infrastructure including schools; return of a critical mass of residents; sufficient housing repairs and replacements to accommodate returnees (Levine et al. 2007; Phillips 2009); a resurgence in school enrollments; and business recovery (Alesch et al. 2009), among others. More resilient communities will tend to have lower numbers of households that are displaced for longer time periods compared to their less resilient counterparts.

Displacement risk can therefore be reduced with increased attention to a community's resilience. Poor policies and land use planning can substantially increase risk, while well-designed policies undergirded by strong political institutions at local and state levels can increase resiliency and lead to lower levels of potential displacement (Burby et al. 1999; Burby 2006; Birkland and Waterman 2008). Norris et al. (2008) offer an important perspective of linking a network of adaptive capacities including economic development,

Table 3 Summary of resiliency and policy indicators and variables

Component	Indicator	Normalized variable (with directional effect on resilience)	Data sources
Resiliency	Economic resilience (4)	Foreclosure rate (−); % housing vacancies (+); social capital groups per 10 K pop (+); NGOs per 10 K pop (+)	HUD; USPS; Citizen Corps; National Center for Charitable Statistics; County websites
	Emergency capacity (3)	Hospitals per 10 K pop (+); medical services per 10 K pop (+); physicians per 10 K pop (+)	American Medical Association; County Business Patterns NAICS
	State performance (1)	State performance score (+)	Pew Center
	Institutional resilience (5)	% of pop covered by: existence of State Plan (+); local mandates (+); mandatory hazards element (+); geographic coverage of local mandatory hazards element (+); post-disaster recovery plan requirement (+)	Institute for Business and Home Safety (IBHS); FEMA

Variables for the state performance and institutional resilience indicators are collected at the state level

(+)/(−) signs after each variable refer to the directional effect on resilience

social capital, information and communication, and community competence. Capacities and disaster readiness can in turn be enhanced through interventions and policies (Norris et al. 2008; Sherrieb et al. 2010). As such, indicators need to be included that account for community capacity, institutional strength, recovery, and commitment to mitigation and sustainable recovery partly via plan and policy interventions at local, regional, and state levels.

Informative efforts include Cutter et al. (2010) work on baseline indicators and related social, economic, infrastructure; institutional capacity (mitigation); and community competence variables, as well as Peacock's (2009) work on a community disaster resilience index. The latter (Peacock 2009) uses a different conceptual model based on a combination of the community's capital resources (social, economic, physical, and human), and the four phases of a disaster mitigation (perceptions and adjustments); preparedness (planning and warning); response (pre- and postimpact); and recovery (restoration and reconstruction).

Using theoretical insights based on this past research, our explication of policy and resiliency indicators is presented in Table 3. We recognize that the variable list is incomplete, which is due to lack of data for the complete study area. For example, county-level long-term recovery planning and affordable housing planning factors should ideally be included to account for general pre- and postdisaster planning capacity, accelerated job recovery, accelerated school recovery, capacity to meet temporary housing needs, and capacity to provide affordable housing options in the short-term and long-term.

4.4 Hurricane return periods and probability of strikes

The return period is a measure of exposure as it reveals a statistical relationship between the magnitude of a hurricane event and its average recurrence interval (Chow et al. 1988). It describes the probability of occurrence of a hurricane crossing a particular county. The return period is therefore an important adjustment factor which describes the displacement potential due to hurricane events in terms of expected frequency. Methods for estimating return periods and hurricane strike probabilities have been presented by various scholars (Simpson and Lawrence 1971; Neumann 1987; Elsner and Kara 1999; Johnson and Watson 1999; Keim et al. 2007; Parisi and Lund 2008) who all agree that the accuracy of the return period depends on the length of the record. Elsner and Kara (1999) further added that low probability extreme events, like the occurrence of major hurricane strikes along a small stretch of coastline, are particularly sensitive to record length. Our conceptual approach is most in line with that of Zandbergen (2009) who emphasized that exposure to hurricane storm conditions should not be based solely on points of landfall. Using NOAA's historical storm tracks from 1851 to 2003, Zandbergen (2009) created a cumulative exposure factor for all counties in the continental United States to capture the full effect of hurricanes and tropical storms. We did not normalize the number of strikes by a county area because we assume that the number of strikes in each county implicitly accounts for county size. Larger counties in hurricane-prone areas receive larger number of strikes on average because of their size compared to counties of smaller size given similar frequencies of occurrence. There are other factors beyond size that are also important and have been accounted for: inland counties receive relatively smaller number of direct strikes than coastal counties; higher wind speeds are significantly correlated with more damage. NOAA's National Hurricane Center Risk Analysis Program (HURISK) has calculated return periods for given locations (e.g., cities) along the Atlantic and Gulf coasts (Neumann 1987, 1993). HURISK used a circle of 75 miles from a particular location to calculate how many category 1–5 hurricanes had passed near this location (e.g., a city). This approach is different from creating a buffer of both sides of the best-track line and then estimate what would happen to places that are at a certain distance from the track. Although there is data on wind speed near the best-track line there is no reliable data available for wind speeds at a certain distance from the track as these vary under different hurricane intensities (Jagger et al. 2001; Tartaglione et al. 2003).

5 The displacement risk index: mathematical formulation

The selection of indicators and variables, and attempts at index formulation and validation is always fraught with some problems which can be elucidated by undertaking this effort. For example, similar to the ESI presented earlier, we are hampered in creating a causal model linked to observable outcomes because the displacement risk phenomenon includes the future as well as the past and the present. Arriving at the conceptualization of the displacement risk index for the intended uses required several iterations of the index formula. We chose sub-index approach which facilitates a modular approach to index-building and makes the index more transferable (An et al. 2004). This in turn can allow users to more easily get at the questions related to factors, and their importance.

First was the ratio formula (DRI = VSI/CRSI) with differential exposure factored into the physical vulnerability sub-component using a location proxy (1 county deep vs. 2 counties deep). However, this ratio formula created some computational problems that were very difficult to solve. The main problem was with interpretation. Many different combinations of VSI and CRSI can result in the same ratio. For example, if VSI = 75 and CRSI = 50, the ratio is 1.5, the same result if VSI = 97.5 and CRSI = 65, making it difficult to have meaningful interpretations for policy recommendations. Our second iteration involved use of hurricane return period data to generate probabilities of exposure, but still lumped in with the physical vulnerability sub-component. The biggest drawback was that VSI data are all converted to *Z*-scores, and we could not find supporting evidence to transform return periods (not normally distributed) into *z*-scores. Overall, the statistical procedure for calculating the probability of occurrence is not equivalent to a *z*-score. Furthermore, the return period is an important variable for distinguishing the DRI based on various categories of hurricanes. Simply, factoring the probability of hurricanes and averaging it within the overall *z*-scores means that that variable has very little influence on the final score. It will essentially be mixed with more than 30 variables of vulnerability including age, education, incomes, etc. and will have a low implicit weight and effect. Our third iteration led us to pull out the probability value to create what we called a return period adjustment factor (RPAF), and multiply it by the product of the VSI and CRSI. However, the multiplicative approach of the sub-indices was hard to justify given that the sub-indices were derived using an averaging approach.

The displacement risk index (DRI) was finally conceptualized as a composite, multi-dimensional index based on the mathematical aggregation of a set of two sub-indices [a *Vulnerability Sub-Index* (*VSI*), and a Community *Resilience Sub-Index* (*CRSI*)], and a hurricane exposure probability component*)*; and 14 key indicators (10 vulnerability indicators; 4 resiliency indicators) derived from 50 underlying variables (37 vulnerability variables and 13 resiliency variables). The displacement index can be summarized as follows and in Fig. 2.

$$\mathrm{DRI} = ((\mathrm{VSI} + \mathrm{CRSI})/2) * \mathrm{Prob}$$

where DRI, displacement risk index; VSI, vulnerability sub-index, which includes demographic (socioeconomic and housing vulnerability indicators) and physical vulnerability indicators for year 2007; CRSI, community resiliency sub-index, which includes resiliency and policy indicators that reduce vulnerability and displacement potential for year 2007; Prob, the probability that a hurricane of category 1–5 will impact the county based on return periods derived from historical hurricane tracks for the period 1851–2008, published by NOAA. Conceptually, two locations with similar vulnerability scores and resilience factors should not score equally on the displacement risk index if one of these locations has a higher probability of hurricane strikes[4] than the other.

5.1 Vulnerability sub-index

The vulnerability component (sub-index) is the average of the physical and social vulnerability sub-components converted to a standard normal percentile. The physical vulnerability measure combines two indicators aggregating eight measures of the built and natural environments. The social vulnerability measure is derived on the basis of eight indicators aggregating 29 underlying normalized variables describing income, race/ethnicity, age, housing affordability, educational level, and household characteristics. In the strict mathematical sense, equal indicator weighting is applied since no objective mechanism or theoretical literature exists to determine the relative importance of the different aspects of displacement vulnerability for such a broad multi-state study area.

For the variables included in the VSI dataset (see Tables 1, 2) that exhibited skewed distributions, various transformations techniques were applied. When an approximation of a normal distribution) is sought, a new variable *Y* is often created as a function *f*(*X*) of the original variable *X*. This is achieved through various forms of transformation. We have applied the natural log, log-10, or square root transformations. The choice of the appropriate approach depended on the statistical properties of the random variable in question. For the variables that were approximately normally distribution, we have used graphical

[4] Hurricane strike is the exposure of the jurisdiction to hurricane force winds (Neumann 1987).

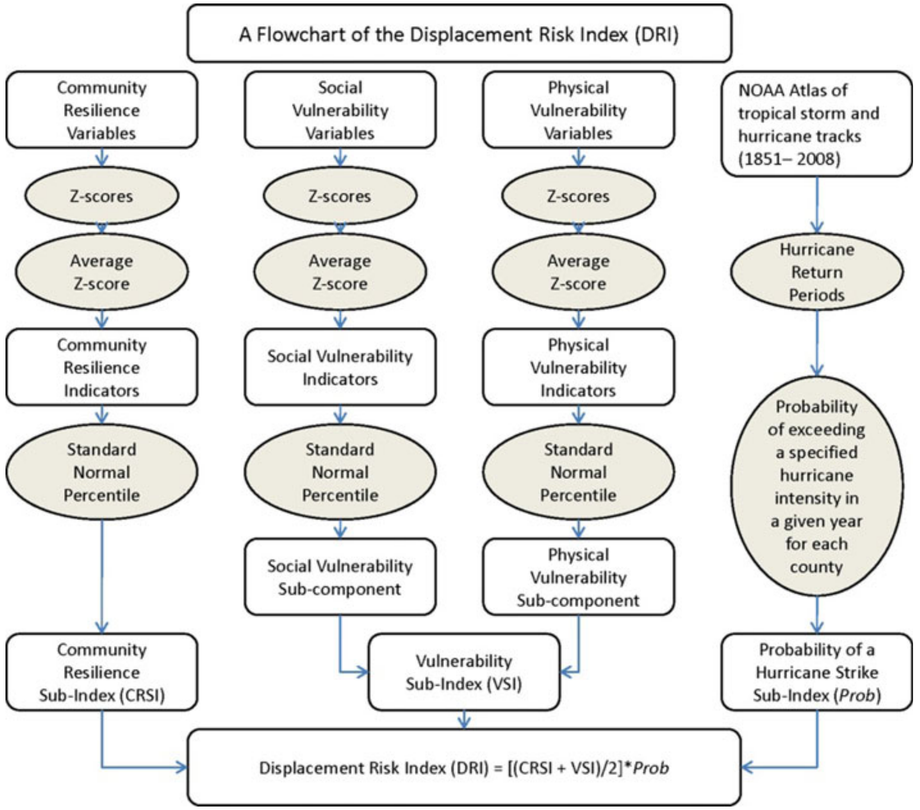

Fig. 2 Conceptual framework of the displacement risk index

techniques such as scatter plots and box plots as well as an analytical procedure based on the Grubbs statistical test to identify outliers. The Grubbs test statistic is useful for differentiating outliers in data with approximately normal distributions. It is derived from the following equation:

$$G = \frac{\max|Y_i - \bar{Y}|}{s}$$

where $\bar{Y}$ denotes the sample mean and s denotes the sample standard deviation (Grubbs 1969; Stefansky 1972). The Grubbs test statistic uses the sample standard deviation to determine the absolute value of departure from the sample mean (Grubbs 1969). The two-sided version of the test was used to determine whether the minimum or maximum values were outliers. Outlier values were recalculated and forced back into the distribution to equal the 99th percentile at both tails of the distribution following the methodology used by ESI (Samuel–Johnson and Esty 2001). Two-tailed hypothesis testing for μ_d at the 0.01 significance level for the truncated and the original distributions failed to indicate any statistically significant difference.

All variable datasets were standardized using a standard z-score calculation. The variables contributing to the composite score of the vulnerability sub-index were examined for directional effect on vulnerability. Variables with positive effect on vulnerability were

Table 4 Results of regression analysis with VSI as the dependent variable

	Unstandardized coefficients		*T* stat	Sig.
	B	SE		
Intercept	−2.347	0.503	−4.66	.000
PV	0.548	0.004	112.90	.000
SV	0.503	0.008	65.03	.000

Higher Prob values indicate higher levels of exposure to hurricanes

standardized by dividing the difference between the observed and the expected value by the standard deviation (Samuel–Johnson and Esty 2001). Variables having negative effect on vulnerability were multiplied by (−1) before using the z-score standardization approach (Samuel–Johnson and Esty 2001; Booysen 2002). Each indicator was then computed as the average of the underlying z-scores. The computation of the physical vulnerability (PV) and social vulnerability (SV) sub-components involved the average z-score of the underlying indicators converted to a standard normal percentile. Finally, the overall vulnerability component sub-index (VSI) was calculated by averaging the standard normal percentile of the two sub-components.

To check the internal validity of the VSI, ordinary least squares regression analysis was undertaken using the VSI as the dependent variable and the PV and SV as independent variables. The results of the analysis yielded a highly significant model ($F = 8{,}298.72$, p-value $= 0.000$). The adjusted R-square for the model was 0.99 which indicated that the model explained as much as 99% of the variance in the VSI scores. The intercept and the two regression coefficients were also statistically significant at virtually any significance level. Table 4 shows the results from the regression analysis using the VSI as a dependent variable.

5.2 Community resiliency sub-index

The community resiliency sub-index is the average of four sub-components: economic resilience, emergency capacity, state performance, and institutional resilience, converted to a standard normal percentile. The community resilience sub-component combines four variables: two that measure social capital (number of social capital groups and non-governmental organizations (NGOs) and two that describe housing resilience (the number of housing vacancies and the number of foreclosures). The emergency capacity indicator aggregates three underlying variables measuring emergency capacity, which are the number of hospitals, physicians, and other medical services in a county. Each of the variables in these sub-components were normalized by calculating them per 10,000 populations (for instance, number of physicians per 10,000 population). In addition to factors at the local level, we argue that state policies also affect the resilience level of communities. To capture the effects of such policies, we included two indicators tapping these variables: state performance and institutional resilience. The state performance indicator variable is a composite index (Pew Center for the States 2008) on the overall performance of a state including how well states maintain, improve and plan for physical infrastructure needs, and how well they manage employees, budgets and finance, and information. This indicator was hypothesized to have a positive effect on county resilience, reducing potential displacement.

The institutional resilience indicator is derived from five variables tapping state specified elements of local disaster planning, which are the existence of state plans and guidelines, mandating local planning, mandated natural hazard elements in local planning, geographic coverage of natural hazard elements, and mandated requirements for a post-disaster recovery plan. Dichotomous variables regarding the presence or absence of a policy were operationalized as the percent of population in the county covered by the policy. If the policy applied to the entire county, then that county's population as a percent of state population was used. This follows the same method used by Peacock (2009) and Cutter et al. (2010). Since the five variables tapping institutional resilience exhibited high correlations among each other, were theoretically related, and their inter-relationships were confirmed by a factor analysis, they were combined using factor analysis and the factor scores derived were standardized using the standard z-score calculation.

For these indicators and their underlying variables, equal indicator weighting is applied in the strict mathematical sense, since no objective mechanism or theoretical literature exists to determine the relative importance of the different aspects of displacement risk for such a broad multi-state study area. We recognize however, that we are implicitly giving some measures more weight than others due to the number of variables used (see Table 3). Most of the variables included in the CRSI exhibited skewed distributions and therefore, two approaches to process the initial data were undertaken. The square root or natural log transformation was applied (as needed) to variables in which a large number of outliers were detected. After the data processing was completed, the datasets were standardized using a standard z-score calculation. The variables contributing to the composite score of the CRSI were examined for directional effects on resilience. Variables with positive effects on resilience were standardized by dividing the difference between the observed and the expected values by the standard deviation (Samuel–Johnson and Esty 2001). Variables having a negative effect on resilience were multiplied by (-1) before using the z-score standardization approach (Samuel–Johnson and Esty 2001; Booysen 2002). Each indicator was then computed as the average of the underlying z-scores. The computation of the four CRSI sub-components involved the average z-score of the underlying indicators converted to a standard normal percentile. Finally, the overall community resilience sub-index was calculated by averaging the standard normal percentile of the four sub-component indicators.

To check the internal validity of the CRSI, an ordinary least squares regression analysis was undertaken using the CRSI as the dependent variable and the four indicators, economic resilience (ER), emergency capacity (EC), state performance (SP), and institutional resilience (IR) as the independent variables. The results of the analysis yielded a highly significant model ($F = 5{,}883.63$, p-value $= 0.000$). The adjusted R-square for the model

Table 5 Results of regression analysis with CRSI as the dependent variable

	Unstandardized coefficients		Standardized coefficients	T stat	Sig.
	B	SE	Beta		
Intercept	−4.882	.882		−5.534	.000
Emergency capacity	.311	.017	.461	18.136	.000
Community strength	.248	.012	.277	20.540	.000
State performance	.283	.010	.457	28.926	.000
Institutional resilience	.289	.017	.473	17.491	.000

was 0.99 which indicated that the model explained as much as 99% of the variance in the CRSI scores. The intercept and the four regression coefficients were also statistically significant at virtually any significance level. Table 5 below shows the results from the regression analysis using the CRSI as a dependent variable.

5.3 Hurricane probability component

A review of the work of various scholars presented in a previous section provided sufficient scientific basis for use of the hurricane return periods as a suitable proxy for differential exposure among the coastal counties in the study area. Return periods (RP) for tropical cyclone events of various magnitude were generated from the 6-hourly data obtained from the Atlantic basin dataset of historical hurricane tracks (1851–2008) obtained from NOAA Coastal Services Center. Strike frequencies were generated from maximum sustained winds and Saffir–Simpson categorization based on wind intensity at indicated time. For each county, a line output was derived by intersecting the tropical cyclone paths with the county boundary shape file. The new layer contained information about the storm paths and the county boundary they fall inside. Thus, we were able to summarize the tropical cyclone information on a county level. More specifically, five sets of counts were derived (i.e., for: (1) all tropical cyclones, (2) tropical storms, (3) category 1 and 2 hurricanes, (4) category 3–5 hurricanes, and (5) categories 1–5 hurricanes). For each dataset, return periods and probability were calculated at the county level as follows.

$$\text{RP} = 158\,\text{year period of record}/\#\,\text{of hurricane strikes}$$

Since RP is defined as the inverse of the annual probability of experiencing normalized circular winds with a speed in excess of a given intensity X (Elsner and Kara 1999; Johnson and Watson 1999; Emanuel and Jagger 2010), the probability (*Prob*) was derived as $p\ (X = x) = 1/\text{RP}$.

The probabilities allow us to distinguish counties with higher level of exposure, and therefore at higher risk for displacement, from counties with lower level of exposure, and therefore, a lowered risk of displacement. What follows are the resulting DRI scores based on the operationalization of the displacement risk index, its three components and the input indicators and variables presented above. This sets the stage for the discussion of the limitations and complications of the index construction effort in the last section of the paper.

6 Results and discussion

The resulting displacement risk scores are measures of the relative displacement risk to hurricanes of categories 1–5 for the 158 counties in the study area. In order to convert the DRI raw scores to a common scale and be consistent with the VSI and CRSI rankings, we have used the standard normal percentile rank, where a percentile of 100 denotes the maximum hurricane-related displacement risk for a county. Fig. 3 shows the spatial distribution of the DRI percentile scores, mapped as natural breaks using Jenks classification. The Gulf of Mexico coastal counties show higher displacement risk potential compared to that for the Atlantic Ocean coastal counties. What is also evident is the cluster of the highest DRI scores for the coastal counties of Florida, especially in the South Florida counties of Miami Dade, Monroe, Palm Beach, and Broward. The inland counties show a general pattern of low to moderate displacement risk.

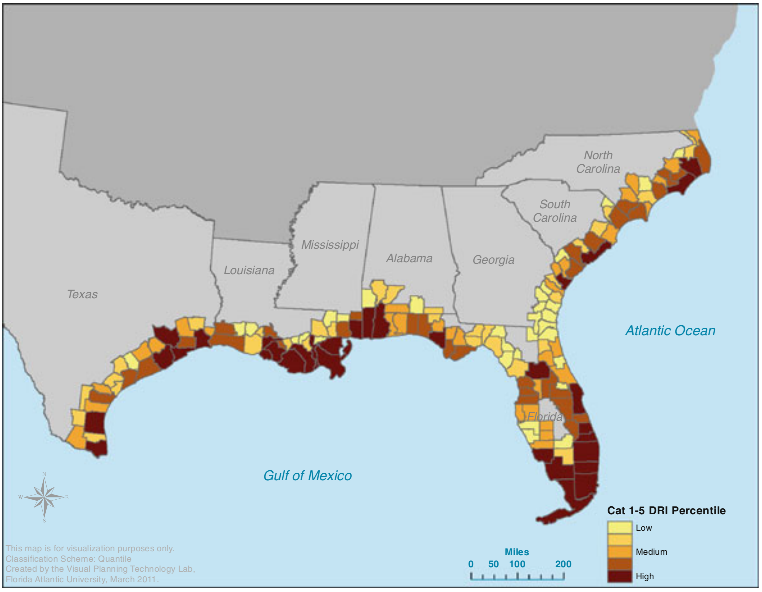

Fig. 3 Spatial distribution of the displacement index scores

Tables 6 and 7 provide additional information for the top 10 and bottom 10 DRI scoring counties respectively. Information on county depth, VSI scores, CRSI scores, and hurricane probabilities (Prob) are included. What is immediately apparent is that seven of the ten counties with top DRI scores are in Florida, and nine of them are coastal counties. One inland Texas county (Harris), ranked in the top ten DRI scores as well. Conversely, eight of the ten counties with the lowest DRI scores are inland counties in a variety of states. To check the differences in the DRI scores between coastal and non-coastal counties, we ran a paired samples t-test. The mean levels of DRI scores were much higher for the coastal counties (for coastal counties, $\mu_1 = 3.90$, for non-coastal counties, $\mu_2 = 1.82$) and the t-test results shows the difference in DRI scores as being statistically significant ($p < 0.001$). The following sections provide a closer look at the VSI, CRSI, probability components and the final DRI percentile ranks.

6.1 A closer look at the VSI and CRSI scores

Seven of the top ten most vulnerable counties are in Florida (i.e., Gilchrist, Lafayette, De Soto, Baker, George, Liberty, Levy, and Escambia). With the exception of Levy and Escambia, 8 of the top ten most vulnerable counties are also non-coastal counties. The least vulnerable counties are an even combination of coastal and non-coastal counties (5 coastal and 5 non-coastal counties). In looking at the CRSI scores, we find that five of the top ten most resilient counties are in Florida (Miami–Dade, Palm Beach, Pinellas, Orange, and Broward counties). Six of the top ten most resilient counties are also coastal counties, which may be an indication of the stronger hazard mitigation and recovery policies adopted in these counties. Of the bottom ten least resilient counties, all but two of them are non-coastal counties. Overall, the correlation between VSI and CRSI was also found to be non-significant (−0.018, p-value = 0.826).

Table 6 Top 10 DRI scores with component VSI, CRSI, and Prob values

County and state	Coastal depth	VSI score (percentile)	CRSI score (percentile)	Prob	DRI score (percentile)
Miami–Dade, FL	1	62.52	88.41	0.1835	13.85
Monroe, FL	1	35.54	66.78	0.2595	13.28
Terrebonne, LA	1	41.48	62.03	0.1709	8.84
Palm Beach, FL	1	55.21	85.73	0.1203	8.47
Broward, FL	1	53.97	81.61	0.1203	8.15
Martin, FL	1	44.01	60.61	0.1519	7.95
Sarasota, FL	1	56.93	70.28	0.1139	7.25
Harris, TX	2	67.88	95.35	0.0886	7.23
Mobile, AL	1	61.81	67.37	0.1076	6.95
Collier, FL	1	43.07	66.06	0.1266	6.91

Table 7 Bottom 10 DRI scores with component VSI, CRSI, and Prob values

County and State	Coastal depth	VSI score (percentile)	CRSI score (percentile)	Prob	DRI score (percentile)
Brantley, GA	2	31.88	36.08	0.0127	0.43
St. Johns, FL	1	46.01	63.45	0.0063	0.35
Jefferson Davis, LA	2	49.40	58.91	0.0063	0.34
Baker, FL	2	77.91	29.92	0.0063	0.34
Charlton, GA	2	52.42	40.63	0.0063	0.29
Nassau, FL	1	45.54	46.59	0.0063	0.29
Jackson, TX	2	39.85	47.98	0.0063	0.28
Dillon, SC	2	57.29	29.23	0.0063	0.27
Washington, NC	2	51.95	30.01	0.0063	0.26
St. James, LA	2	42.32	35.08	0.0063	0.24

For Tables 6 and 7: Min VSI score: Dare, North Carolina (27.31); max VSI score: Gilchrist Florida (85.5)

Min CRSI score: Washington, Alabama (11.27); max CRSI score: Harris, Texas (95.35)

Min prob: Monroe, Florida (.2595); Max Prob: Jackson, Texas (.0063)

Higher Prob values indicate higher levels of exposure to hurricanes

6.2 A closer look at the hurricane exposure (probability) component

Six of the top 10 counties with the shortest return periods (i.e., highest probabilities of hurricane strikes) for hurricanes are experienced by counties in Florida (i.e., Monroe, Miami Dade, Martin, Collier, Broward, and Palm Beach). With the exception of Collier county, Florida, these are consistent with the counties with the highest exposure factor scores reported by Zandbergen (2009). Over a period of 158 years, the study region experienced 877 tropical cyclones, out of which 484 passed through as tropical depressions and tropical storms, and 393 landed as hurricanes of various magnitudes. Among the landfalls, 292 were category 1 and 2 hurricanes, and 101 were major hurricanes of category 3–5. Among the counties in the study region, Monroe County, Florida, has experienced 94 tropical cyclones, including tropical storms and hurricanes, followed by Collier County with 69, and Miami–Dade and Palm Beach with 58 and 57 strikes, respectively. Over a period of 158 years, 37 counties had less than twenty strikes altogether (including tropical storms and hurricanes), and 48 have never been exposed to the damaging winds of a major hurricane. Another 46 counties have only had one major hurricane strike. These results indicate that there is substantial variability among counties with regard to their exposure to hurricanes.

6.3 A closer look at the DRI: internal and external validation

To support the internal validation of the DRI, we conducted a regression analysis in which the final DRI scores were used as the dependent variable and the VSI, CRSI, and probability (*Prob)* as a measure of exposure based on the hurricane return periods were the independent variables in the model. The F-statistic indicated that the model was highly statistically significant ($F = 376.49$, p-value $= 0.000$). The model explained nearly 88% of the variance (Adjusted $R = 0.878$). The intercept and the three regression coefficients were also highly statistically significant as shown by Table 8. The results indicate that a regression model using VSI, CRSI, and Prob as the independent variables can predict the DRI scores reasonably well.

For external validation, Babbie's (1995, 167) exposition about bad indices versus bad validators were especially valuable, specifically the point that "nearly every index constructor at some time must face the apparent failure of external items to validate the index" given the presumption that all the best indicators and variables have been included to construct the index, [and therefore] the validity items are second-rate indicators. We no doubt found ourselves in that dilemma in our search for an external validator that made sense for our full study area. We used available 2006 post-Katrina percent population change[5] from the Census Bureau for the following forty-eight county sample set (Table 9) which is approximately 1/3 of our study area. Our sample data set is in turn part of a subset of the 117 Gulf coast counties[6] identified by FEMA and Census Bureau as exhibiting migration and displacement in the wake of hurricanes Katrina and Rita in August and September of 2005, and eligible for individual and public assistance (Koerber 2006; US Census Bureau 2006, 2009). A cursory examination of the population changes shows drastic population decline in several Louisiana counties: >75% decrease for St. Bernard; >50% decrease for Orleans; and >20% decrease for Cameron and Plaquemine. Three of these are in the top 30 DRI percentile scores.

The Kruskal–Wallis alternative, introduced in an earlier section, can be used to test the null hypothesis that 2006 post-Katrina percent population change and the DRI ranks for the sample counties listed above come from identical distributions. If the distributions are identical, the H test statistic has approximately a chi-square distribution with $(k - 1)$ degrees of freedom (McDonald 2008). Large values of the H test statistic lead to rejection of the H_0 of similarity of distributions.

We used the sums of the ranks of k samples to compare the distributions of the percent population change and DRI ranks. The Kruskal–Wallis H statistic was adjusted for the number of ties. The calculated H statistic of 2.646 (p-value $= 0.104$) is not significant as it is less than the critical values of 2.71 (at $\alpha = 0.1$) and 3.84 (at $\alpha = 0.05$). Therefore, the proposed null hypothesis cannot be rejected at these significance levels. Consequently,

[5] The percentage change calculation was based on use of change from July 2005 (pre-Katrina) to July 2006 (post-Katrina).

[6] We only included the counties in our study area. The 117 set includes counties far inland.

Table 8 Results of regression analysis with DRI as the dependent variable

	Unstandardized coefficients		T stat	Sig.
	B	SE		
Intercept	−17.12	4.55	−3.76	.000
VSI	0.29	0.07	4.19	.000
CRSI	0.34	0.04	8.12	.000
Prob	582.55	19.98	29.16	.000

Table 9 Sample counties used for external validation

State	No. of counties	County names
Alabama	8	Baldwin, Clarke, Covington, Escambia, Geneva, Mobile, Monroe, Washington
Louisiana	20	Acadia, Assumption, Calcasieu, Cameron, Iberia, Jefferson, Jefferson Davis, Lafayette, Lafourche, Orleans, Plaquemines, St. Bernard
Mississippi	6	George, Hancock, Harrison, Jackson, Pearl River, Stone
Texas	14	Brazoria, Calhoun, Chambers, Fort Bend, Galveston, Hardin, Harris, Jackson, Jefferson, Liberty, Matagorda, Orange, Victoria, Wharton

Table 10 Results from the Kruskal–Wallis test and chi-square critical values

Kruskal–Wallis		Chi-square			
Adjusted H	2.646	Critical values	2.07	2.71	3.84
Degrees of freedom	1	Degrees of freedom	1	1	1
p-value	0.104	p-value	0.15	0.10	0.05

there is no sufficient evidence to suggest that there is a significant difference between the DRI ranks, and the 2006 percent population change for selected counties used as a proxy for the number of people displaced by Katrina and other major hurricanes in 2005. This indicates that DRI is a valid measure of the displacement risk in our study area. Table 10 presents a summary of the validation results.

7 Discussion and conclusion

We recognize that our conceptualization of the displacement phenomenon is far from perfect. Displacement is a multilayered and complex phenomenon; it is both an outcome and cause of vulnerability. There is a dynamic interplay between (1) exposure, risk, vulnerability, and resilience; (2) predisaster mitigation/preparedness and post-disaster recovery phases; (3) short-term and long-term actions and planning and policy interventions; (4) multifaceted components of community well-being (housing, businesses, schools, social services etc.); and (5) regional, state and national trends. As such, attempts at index-building are inherently complex, and have to benefit from contributions of scholars from diverse fields such as geography, sociology, anthropology, planning, science and engineering.

We also recognize that indices are reductionist by default and have been appropriately described as "reified snapshots" (Simpson 2006, p. 5). The displacement risk index is not perfect either and needs to be continually refined as data becomes available. We had identified several additional variables based on our review of the literature but were unable to locate useful or complete data for the entire study area. Some of these data include: vulnerability (BCEGS rating, owner occupied housing with wind insurance, owner occupied housing without flood insurance, extent of protective works [age, extent, and condition], surge zones, land subject to sea level rise, homelessness); resilience (existence of state housing task force, plans in place [development plans, business recovery plans, school recovery plans, housing recovery plans, affordable housing policies, and plans]; budget [per capita budget, budget surplus, public budget versus annual budget]; and emergency management capacity. Furthermore, we acknowledge that the index as conceptualized above is static and does not account for the fact that indicators will change over time. The DRI also does not account for interactions among variables, complex, and cumulative interventions (e.g., preventative mitigation actions) over short-time and long-time horizons, and cumulative impacts of sequential hurricanes. Other complicating issues include the lack of primary data, the disadvantages of using the county as a unit of analysis, and longitudinal research on migration patterns and mover characteristics caused by catastrophic hurricanes to inform variable selection. An understanding of whether there is a higher probability of evacuees becoming defacto displacees can for example provide useful information.

While problems with the use of census data for vulnerability assessments are well documented, the timing of data collection (especially economic indicators such as unemployment and foreclosure rate) is especially problematic given the current (as of 2010) economic downtown in the United States. The economic reality of most households in the United.States, also calls for an expanded definition of "displacee vulnerability" and an adaptable profile of these, given the pockets of residents who can quickly shift to vulnerable status during the process of long-term recovery and displacement. Conceptualization of a "sliding scale" social vulnerability framework can serve as a useful starting point, but was beyond the scope of this research effort.

Lack of theoretical literature was especially problematic in assessing the directional effects of individual variables on displacement risk. We encountered situations where some indicators can have both a positive and negative effect on long-term displacement. For example, the natural assumption is households with higher socio-economic status can return and rebuild. Yet, Lin's empirical analyses for Miami–Dade county and hurricane Andrew found evidence suggesting that households with higher socio-economic status have a greater tendency to leave their homes and communities following a natural disaster (Lin 2009).

Despite these limitations, we hope that the creation of the DRI has indeed helped fill a gap in knowledge, and will lead to higher level theoretical discussions on the population displacement phenomenon, its determinants and related planning and policy interventions. In that way, state and local government agencies responsible for services can develop appropriate strategies that take into account the larger numbers projected to need assistance in both impacted areas and host communities that do not have high displacement potentials. If not, there can and likely will be a ripple effect of problems that move downward to the local level, eventually trickling into communities and households least able and least responsible for bearing the social and financial costs of this burden.

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