An Investigation of a C-MIST Index to Measure Functional Needs for Disaster Risk and Its Spatial Distribution in Florida Counties

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Abstract

In the absence of a single composite measure to assess, rank, and test disability and functional needs in the context of disaster, this study undertook an interdisciplinary approach to develop a composite index based on C-MIST theory. An examination into how well the C-MIST index represents the multidimensional nature of disability and functional needs was conducted, as well as illustrating any gaps in the underlying dimensionalities of current social vulnerability indices. First, an index was constructed in accordance with the C-MIST theory for sixty-seven counties in the State of Florida, using an additive aggregation model. Second, the underlying data structure and measure validity were examined at the sub-component level of the C-MIST index, using Cronbach's coefficient alpha (C-alpha) and using exploratory factor analysis to determine the dimensionality of the sub-components. Third, the results were spatially compared with a calculated functional needs prevalence rate. Results were also compared at the index sub-component level and against another index, SoVI, in order to explore possible relationships and trends. Results indicated the C-MIST Index appeared initially to be unidimensional and a consistent and valid instrument for assessing functional needs in Florida with a high C-alpha of 0.997. However, when reviewing factor analysis and results from the functional needs prevalence rate comparison, dimensionality of underlying data structure requires further research and testing at both sub-component and individual indicator levels.

Introduction

The disproportionate risk and unique challenges that people with disabilities and functional needs face increase in the context of disaster, particularly as it relates to estimating disaster risk and disaster planning (Kailes and Enders, 2007; National Council on Disability [NCD], 2009). The importance of and interest in including disability and functional needs in the context of disaster at the research and policy levels, especially after the aftermath of Hurricane Katrina, has grown within the last decade (Kailes and Enders, 2007; NCD, 2009).

This study undertakes an interdisciplinary approach to assessing vulnerability by examining one sub-dimension of it and its dimensionality, i.e. disability and functional needs in the context of disaster. To this end, the literature surveyed examined a cross-section of the following disciplines as it relates to vulnerability and disaster: composite indices, social vulnerability,

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and disability and functional needs.

From a social vulnerability perspective, blending theoretical and methodological approaches as well as undertaking an interdisciplinary line of inquiry is encouraged to further the understanding of vulnerability and its measurement (Birkmann, 2013a, 2013c). From a disaster risk and disability perspective, according to the NCD (2009), "what emergency management and people with disabilities require is a concerted, comprehensive, interdisciplinary research effort to systematically address the full life cycle of emergency management" (p. 295).

Evolution of Social Vulnerability Indices

Composite indices are relative measures useful for representing and simplifying complex and multidimensional phenomena (Nardo and Saisana, 2008; Organization of Economic Cooperation and Development [OECD], 2008). Composite indices have been recently applied to the field of natural hazards and disaster risk and require further research and evaluation in terms of representing the multidimensional aspects of vulnerability and their root causes in general (Birkmann, 2013a, 2013b, 2013c; Tate, 2012).

Cutter (2010) defines social vulnerability as "those pre-existing characteristics of groups or conditions within communities that make them more susceptible to the impacts of hazards, in other words, those factors that shape the social burdens of risk" (p. 25). The notion of social vulnerability and developing an associated index for measurement should be in accordance with a particular vulnerability conceptual framework and using a particular viewpoint on vulnerability (King and MacGregor, 2000; Cutter, 2010; Birkmann, 2013b).

In addition to index model validation issues and the subjectivity of the index construction process (Cutter, 2010; Tate, 2012, 2013), the extent of the representation of vulnerability dimensions and indicators in an index greatly depends upon the school of thought adopted for vulnerability or the conceptual framework being modeled (Birkmann, 2013a). Within the popular Hazardousness of Place model, pioneered by Hewitt and Burton (1971) and reintroduced and improved upon by Cutter (1996), there has been some agreement on common vulnerability indicators, such as age (elderly and children), gender (women and female headed households), race (most non-white populations, especially black), poverty, etc. (Cutter, Boruff, and Shirley, 2003; Blaikie, Cannon, Davis, and Wisner, 2004; Chakraborty, Tobin, and Montz, 2005; Prasad, 2012; Flanagan, Gregory, Hallisey, Heitgerd, and Lewis, 2011; Rygel, O'Sullivan, and Yarnal, 2006). Other vulnerability indicators, such as disability and functional needs, are either inadequately represented in indices or not at all, despite recent policy changes and current research focus (NCD, 2009). This paper examines the multidimensional aspects of disability and functional needs in order to determine their representation empirically and quantitatively.

Social vulnerability literature has revealed that there are numerous opportunities for improvement in developing social vulnerability indices, as well as for modeling in disaster risk, including indicator selection, model validation, and index construction approaches (Rygel *et al.*, 2006; Simpson and Katirai, 2006; Chakraborty *et al.*, 2005; Tate, 2012, 2013; Jones and Andrey, 2007; Prasad, 2012; Flanagan *et al.*, 2011; Birkmann, 2013a, 2013b, 2013c; Cutter and Morath, 2013). Birkmann (2013c) more broadly recommended the investigation of how best to represent and measure the dynamic, causal factors of vulnerability as well as its multidimensionality. Also, in the absence of a truly comprehensive and robust instrument, Birkmann (2013a) called for interdisciplinary research and collaboration as well as the application of different theoretical and methodological combinations in order to compensate for the existing deficiencies.

Functional Needs in Disaster Risk

Disability has been conceptually presented as a complex, multidimensional phenomenon for which the best representation is a functional model in any research or policy context, in contrast to the unpopular medical model (World Health Organization [WHO], 2002, 2013; Kailes, 2005; Kailes and Enders, 2007). WHO (2002) developed a conceptual framework and classification scheme for disability and functioning and defined *functioning* as "referring to all body functions, activities and participation, while *disability* is similarly an umbrella term for impairments, activity limitations and participation restrictions" (p. 2). The functional model is broad-based and encompasses the interaction between the health context (body functions and body structures) and the environmental context (environmental factors and personal factors), and is focused on the "functioning" terminology, nomenclature, and classification scheme versus medically related terminology and classifying people (WHO, 2002, 2013). In this model, there are four underlying premises which advocate for removing any medical bias from the functioning and disability classifications: universality, parity, neutrality, and environmental factors (WHO, 2002). By contrast, according to WHO (2002) the medical model describes "disability as a feature of the person" (p. 8) resulting from a medical condition, and stimulates a strictly medical response to the problem with a "disabling" connotation (Tate and Pledger, 2003; WHO, 2013). While not entirely inapplicable to medically warranted scenarios, by definition of its limited scope and focus, it has been historically criticized for being problematic for enabling interdisciplinary research and collaboration and deemed inappropriate for use in policy-making (WHO, 2002; Tate and Pledger, 2003; NCD, 2009).

Within the interdisciplinary research and policy context of disability and disaster, the NCD (2009), asserts that "it is not sufficient or appropriate to simply state that people with disabilities are 'at risk'" (p. 37). Kailes and Enders (2007) further state a "one-size-fits-all approach" (p. 37) for disability is not a realistic approach in disaster risk planning and argue that it is a multidimensional phenomenon when viewed as functional needs and not simply and narrowly as disability (Kailes, 2005; Kailes and Enders, 2007).

At the disaster research level, and in view of the scant literature, the NCD called for more scientific research and evaluation of the functional model, so as to better inform policy (NCD, 2009). Kailes and Enders (2007) proposed C-MIST, as a functional model adaptation within a disaster context, representing the following components: communication, medical needs, maintaining functional independence, supervision, and transportation. These five functional need components translate into logistical and resource management requirements in all facets of the emergency management life cycle (Kailes and Enders). Based on the literature surveyed on disability and functional needs in the context of disasters, there has not been further research and evaluation conducted on this model.

Furthermore, the NCD (2009) expressly highlighted the need to conduct further research and evaluation of the functional model. The NCD further recommended "expanded and expedient" research as a "comprehensive interdisciplinary effort" so as to "produce practical content on the full life cycle of emergency management: preparedness, response, recovery, and mitigation" (p. 292). In addition, the NCD also highlights that there is still a gap between the research community and actually operationalizing these concepts at a practical level in emergency management activities and initiatives.

Based on the literature surveyed, there is no mention of, and a distinct absence of, a measurement instrument for functional needs in a disaster context that is useful for relative comparisons (Kailes, 2005; Kailes and Enders, 2007; NCD, 2009).

The purpose of this study is to create a composite index as an instrument to measure the multidimensionality of functional needs, based on the C-MIST functional conceptual model (Kailes and Enders, 2007). The resulting index will be compared to the relative spatial distribution of functional needs in contrast to an established, robust index, such as the Social Vulnerability Index (SoVI) (Cutter *et al.*, 2003; Schmidtlein, Deutsch, Piegorsch, and Cutter, 2008; Cutter and Finch, 2008; Cutter and Morath, 2013). Since the C-MIST functional model has not previously been tested empirically, the objective of this study is to establish groundwork for a viable measurement instrument of disability and functional needs.

In this context, this paper will examine the following research problems: (a) What is the spatial distribution of functional needs in Florida, based on a developed composite index of each county? (b) What is the underlying data structure and measure validity of the composite index developed? (c) How does the spatial distribution of functional needs compare with the spatial distribution of a baseline social vulnerability index, such as SoVI?

Methods

The OECD (2008) defines a composite index or indicator as "an aggregate of all dimensions, objectives, individual indicators and variables used" (p. 51) According to Nardo and Saisana (2008), composite indices are "a measure of similarity" (p. 1). As such, composite indices are well suited and flexible to model complex phenomena which have multiple dimensions and which according to the OECD (2008) "cannot be captured by a single indicator" (p. 13). Thus they are practical for modeling dimensions of vulnerability (Jones and Andrey, 2007; Birkmann, 2013b).

While a composite index provides benefits for the simplification of a complex phenomenon to derive meaning and interpretation, comparative analysis, and synthesis, it also can be misleading or misused if not constructed properly and if not in adherence to an adopted conceptual model (King and MacGregor, 2000; Simpson and Katirai, 2006; Jones and Andrey, 2007; Nardo and Saisana, 2008; OECD, 2008; Birkmann, 2013b). Birkmann (2013b) further asserts that "approaches for measuring vulnerability need to be based on a systematic, transparent and understandable development procedure for dealing with the indicators and criteria used to assess vulnerability" (p. 80).

Several authors have cautioned the development and usage of composite indices is not a perfect science and involves much subjectivity throughout the entire index development process (King and MacGregor, 2000; Saltelli, Nardo, Saisana, and Tarantola, 2005; Simpson and Katirai, 2006; Jones and Andrey, 2007; Nardo and Saisana, 2008; OECD, 2008). Consequently, its interpretation should be in terms of a relative measure that is not definitive or absolute, which provides a point in time estimate (Simpson and Katirai, 2006; Jones and Andrey, 2007; Nardo and Saisana, 2008; OECD, 2008; Tate, 2012, 2013).

Composite indices have been in use for a long time and have been applied to other policy domains and research disciplines such as in economics and econometric studies, for example Gross Domestic Product (GDP), Consumer Price Index (CPI), etc. (King and MacGregor, 2000; Jones and Andrey, 2007; Nardo and Saisana, 2008; OECD, 2008). Their practicality and the ability to synthesize complex phenomenon in a single metric has led to their increased usage and popularity in general (King and MacGregor, 2000; Jones and Andrey, 2007; Nardo and Saisana, 2008; OECD, 2008). In the social vulnerability research, indices have only been recently adopted and applied within the last fifteen years or so, for measuring disaster risk (King and MacGregor, 2000; Cutter *et al.*, 2003; Jones and Andrey, 2007). The theory behind vulnerability has a longer history, spanning at least fifty years (Hewitt and Burton, 1971; Cutter, 1996, 2010).

At the same time, many authors have asserted socio-economic and political conditions are multi-dimensional, dynamic and complex, and are not always well understood, easily explained and/or measured, and are spatially contextual in nature (Cutter, 1996; Blaikie *et al.*, 2004; Cutter, 2010; Birkmann, 2013c). This has further propagated the debate and research on evaluating the soundness and robustness of social vulnerability indices as an assessment tool for vulnerability (King and MacGregor, 2000; Cutter *et al.*, 2003; Chakraborty *et al.*, 2005; Simpson and Katirai, 2006; Jones and Andrey, 2007; Schmidtlein *et al.*, 2008; Cutter, 2010; Flanagan *et al.*, 2011; Prasad, 2012; Birkmann, 2013b; Tate, 2013).

C-MIST Index Construction

The first part of the study entailed constructing a C-MIST index. Based on the literature in social vulnerability (Cutter *et al.*, 2003; Chakraborty *et al.*, 2005; Simpson and Katirai, 2006; Jones and Andrey, 2007; Schmidtlein *et al.*, 2008; Prasad, 2012; Flanagan *et al.*, 2011; Tate, 2012, 2013) as well as examination of established practices in composite index development in general (Nardo and Saisana, 2008; OECD, 2008), there is a definite sequence of steps for developing a transparent and robust composite index, which are generally accepted in the research community. These include: (1) selecting a theory upon which to construct or test an index, using the definitions from the overall conceptual framework as a guide for the ensuing steps for index development, (2) selecting applicable data based on the conceptual framework and assessing data quality, (3) imputation of missing data and consideration and treatment of outliers in the dataset, (4) detecting the underlying data structure with multivariate analysis to further establish index model assumptions, such as weighting and aggregation, (5) consideration of and selection of appropriate normalization techniques that are applicable to the datasets in question and in accordance with the conceptual framework, including adjustments to scale, addressing outliers, and other data transformations, (6) weighting and aggregation considerations within the context of the underlying theory and past literature, and (7) once the index has been constructed, then conducting uncertainty and sensitivity analysis and performing applicable statistical tests to assess the overall robustness and transparency of the index (Nardo and Saisana, 2008; OECD, 2008; Birkmann, 2013b, 2013c). For the purposes and scope of this study, the first six steps toward index construction apply.

C-MIST: A Functional Model and Conceptualization For Disaster Risk

Kailes and Enders (2007) proposed C-MIST as both a functional model alternative to the limited medical model that was previously being used in disaster risk management and as a terminology replacement for "special needs." C-MIST stands for communication, medical needs, maintaining functional independence, supervision, and transportation. Definitions are provided in Appendix A; each one is a sub-component of the model (Kailes and Enders, 2007). Kailes and Enders (2007) assert that, "addressing functional limitations includes both people who identify as having a disability and the larger number of people who do not identify as having a disability but who have a functional limitation in hearing, seeing, walking, learning, language, and/or understanding" (p. 234).

A functional model perspective would also include "people who are morbidly obese, pregnant women, people on kidney dialysis, and people living in zero-vehicle households" (Kailes and Enders, 2007, p. 231) and also involve the complexity and interaction of diverse socio-economic challenges in addition to the diversity and ranges of physical limitations (Kailes and Enders, 2007).

Each sub-component of the C-MIST model (Appendix A) has wide-reaching implications for logistical and resource management throughout the emergency management lifecycle and advocates for a switch in mindset, nomenclature, and terminology of "special needs" and the medical model assumptions to that of "functional needs." Also, the model calls for inclusive and integrative approaches to incorporating people with functional needs and limitations in decision-making and problem-solving at all stages of emergency management (Kailes and Enders, 2007).

Functional Needs Indicators

According to Tate (2012), "indicator selection involves choosing specific variables to represent the vulnerability dimensions in the conceptual framework" (p. 329). Tate (2012) further states that, "choices among indicators are generally guided by factors such as data availability, desired number of indicators, statistical properties, and most importantly validity – how representative is the indicator of the underlying vulnerability dimension?" (p. 329).

According to Birkmann (2013b), various definitions exist for the term 'indicator' as it applies to disaster risk. However, Birkmann (2013b) defines it generally as a variable that has been given special meaning or significance to describe a certain phenomenon, which can also be operationalized in a "qualitative (nominal), rank (ordinal), or quantitative" form (p. 87). Simpson and Katirai (2006) define an indicator as a “value or group of values that give an indication or direction” (p. 2).

From a social vulnerability perspective, the literature indicates numerous proxy variables and combinations thereof have been used to generate vulnerability indicators, but they have varied according to each study objective (Chakraborty *et al.*, 2005; Simpson and Katirai, 2006; Jones and Andrey, 2007; Rygel *et al.*, 2006; Schmidtlein *et al.*, 2008; Prasad, 2012; Cutter and Morath, 2013; Birkmann, 2013b). There has been no definitive consensus on indicator selection, using certain proxy variables and developing vulnerability indicators to denote these characteristics (Cutter *et al.*, 2003; Chakraborty *et al.*, 2005; Rygel *et al.*, 2006; Simpson and Katirai, 2006; Jones and Andrey, 2007; Schmidtlein *et al.*, 2008; Flanagan *et al.*, 2011; Prasad, 2012; Birkmann, 2013b; Tate, 2012, 2013). Frequently used variables in social vulnerability index development studies are: poverty, population densities, housing densities, gender, age (specifically minors and the elderly), disability, ethnicity, net migration, degree of educational attainment, and many more (Cutter *et al.*, 2003; Chakraborty *et al.*, 2005; Simpson and Katirai, 2006; Jones and Andrey, 2007; Schmidtlein *et al.*, 2008; Cutter, 2010; Prasad, 2012; Cutter and Morath, 2013; Birkmann, 2013b). Also, it is widely accepted in social vulnerability research that the indicators of income or poverty are crucial in determining one’s vulnerability and susceptibility in a disaster (Cutter, Boruff, and Shirley, 2003; Chakraborty, Tobin, and Montz, 2005; Flanagan, Gregory, Hallisey, Heitgerd, and Lewis, 2011; Jones and Andrey, 2007; Simpson and Katirai, 2006; Prasad, 2012; Birkmann, 2013).

Of the social vulnerability indices examined, only that of Cutter *et al.* (2003), the SoVI index, and that of Flanagan *et al.* (2011), the SVI index, are maintained with current data, and have U.S.-wide application at local scales, using counties and census tracts respectively. In addition, the SoVI index, compared to many other recently proposed variants of social vulnerability indices, still provides the most versatile, comprehensive, robust and up-to-date vulnerability measure at a local level (Cutter *et al.*, 2003; Cutter and Finch, 2008; Schmidtlein *et al.*, 2008; Cutter, 2010; Prasad, 2012; Cutter and Morath, 2013). Therefore, in this study, the SoVI index will be used as the benchmark and point of reference in investigating a composite index measure for functional needs.

From a disability and functional needs perspective and in prior constructions of social vulnerability indices, the literature surveyed has presented no consistent way of measuring or assessing the multidimensionality of disability and functional needs, if at all (Cutter *et al.*, 2003; Chakraborty *et al.*, 2005; Simpson and Katirai, 2006; Jones and Andrey, 2007; Rygel *et al.*, 2006; Flanagan *et al.*, 2011; Kailes, 2005; Kailes and Enders, 2007; NCD, 2009; Schmidtlein *et al.*, 2008; Prasad, 2012; Tate, 2012, 2013). Chakraborty *et al.*, (2005) and Cutter *et al.* (2003) included one indicator or so in their respective index model to include the disabled but it is hardly representative of the multidimensionality of disability and functional needs.

At the time of writing this paper, the data necessary to fit the categories of functional needs was available only at the county level, and not at lesser geographic units such as census tracts. Due to this data constraint, the study area as well as the size of the data set were determined to constitute the entire state of Florida with sixty-seven counties. Another consideration was that emergency and disaster risk planning processes often occur at the local level. The county is a geographic unit that encompasses the entire state and can easily represent local planning and all populations. In addition, there was a need in this study to facilitate comparisons between the C-MIST index and another established, robust index such as SoVI, which was constructed at the county level (Figure 1 and Appendix A).

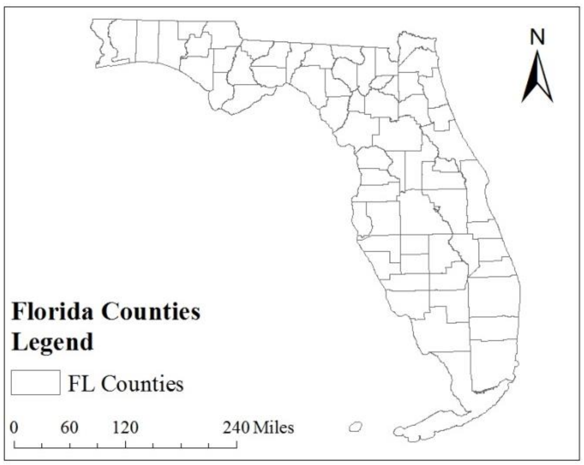

Figure 1. Study Area - sixty-seven Counties in Florida (FL). Data Source: U.S. Census Bureau (2011).

The two primary data sources used in this study were: the Functional Needs Support Services (FNSS) Demographic Resource Toolkit for Florida Counties (Appendix A), which was obtained from the State of Florida (Florida Department of Health, 2012), and the SoVI 06-10 data for the State of Florida (Hazards and Vulnerability Research Institute, 2014).

The FNSS Demographic Resource Toolkit for Florida Counties (Appendix A) is a data compilation from seven separate data sources collected in 2011, for the original purpose of conducting a shelter needs and resource gap analysis study for policy purposes (Florida Department of Health, 2012). Aside from reconstructing the dataset for functional needs, this was the most applicable, accessible, and readily available dataset of functional needs in the context of disasters at the time of writing this paper. This data was prepared for analysis and reformatted into a table format, and any extraneous data attributes that were not pertinent to the analysis were removed.

For purposes of this study, indicators in the original dataset were reorganized in accordance with the C-MIST conceptual model and in accordance with the definitions of the sub-components (Appendix A). The Florida Department of Health (2012) derived half of the indicators, six out of 13, as a percentage of the county population size, corresponding to the following C-MIST sub-components: Communication, Maintaining Functional Independence, and Transportation (Appendix A).

The decision to err on the side of the conceptual model, rather than select a more neutral and statistical method of factor extraction as in the social vulnerability literature (Cutter *et al.*, 2003; Prasad, 2012), was deliberate. Unlike social vulnerability, where the theoretical and conceptual constructs are so broad and ill-defined that there is still much debate about what dimensions, indicators, and spatial scales are the most useful and representative in a social vulnerability index (Birkmann, 2013b; Cutter and Morath, 2013; Tate, 2012, 2013), the C-MIST conceptual model is a well-defined conceptualization for functional needs and precise enough to guide the indicator selection process.

The second data source utilized was a version of the SoVI 2006-2010 index at the county level, which was specifically recalibrated for the State of Florida by the Hazards and Vulnerability

Research Institute (2014) in order to make it suitable for statewide analysis. In this study, the SoVI index was used as a comparative index and benchmark measure of robustness, and it was used to gauge the gaps and similarities between the C-MIST index and the SoVI index.

Data Transformations, Normalization, and Multivariate Analyses

Several normalization techniques exist and are generally acceptable for composite index development (OECD, 2008). Based on the social vulnerability literature, there were a few data transformation and normalization techniques that were more commonly used, such as the use of log transformations, percentages, averages, Z-scores or standardization, ranking, and percentile ranking (Cutter *et al.*, 2003; Chakraborty *et al.*, 2005; Simpson and Katirai, 2006; Jones and Andrey, 2007; Flanagan *et al.*, 2011; Prasad, 2012; Tate, 2012, 2013; Birkmann, 2013b).

For this study, index development techniques and methods described herein and that were adopted were similar to the data preparation and normalization techniques utilized by Cutter *et al.* (2003) and Prasad’s (2012) studies on social vulnerability index development. Some deviations and distinctions in indicator selection, normalization, standardization procedures, and multivariate techniques were adopted. For example, Prasad (2012) and Cutter *et al.* (2003) both began with a large dataset from a single, primary data source, such as the U.S. Census, and utilized principal components analysis or factor analysis as the primary extraction method for indicator selection and for building the index model. In this study, the dataset was much smaller and the data sources were numerous, so factor analysis or principal components analysis for extraction purposes were unsuitable. Also, compared to social vulnerability conceptual frameworks, C-MIST is a well-defined conceptual model which was precise enough to guide the indicator selection process entirely, so factor analysis was not necessary as the primary extraction method but instead used to analyze the underlying data structure of the sub-components and assess its dimensionality.

Cutter *et al.* (2003) utilized percentages and averages as the normalization methods of choice for the indicators selected, with standard deviations as the ranking method, while Prasad (2012) utilized log transformations, Z-scores, and percentile ranking as the preferred normalization and ranking methods.

In this study, due to the initial presence of outliers in the original data, a mixed presence of percentages and absolute numbers in the raw data, and conditions for normality and linearity not initially present with the original data, the indicators were first normalized using log transformations (Log10). The log transformed variables were then aggregated together in an additive model, first at the sub-component level for each county. All sub-components were then added together to create the C-MIST index for each county. The county-level C-MIST indices were then standardized, first by converting them to Z-scores, and then converting the standardized scores to P-values or cumulative percentile ranks to facilitate relative ranking, reference, and comparison.

For ease of comparison, the SoVI scores were also converted to Z-scores and then standardized into P-values or cumulative percentile ranks for this study. This differs from Prasad’s (2012) study in that the SoVI scores were not converted to percentile ranks for comparison.

Once the development of the C-MIST index was complete, the index was then assessed for measure validity and reliability, as well as for the dimensionality and underlying data structure for each sub-component. This part of the methodology is unlike prior literature, where the primary source for structure detection had been factor analysis only. Due to the suitability of the dataset and its size, an alternative method for structure detection was conducted by first performing reliability analysis using Cronbach's coefficient alpha (C-alpha), with an acceptable minimum alpha of 0.80. Prior to running C-alpha, the sub-components of C-MIST were standardized, where the mean is zero and the standard deviation is 1, as advocated by the OECD (2008). Exploratory factor analysis often accompanies C-alpha analysis, but with a different objective; instead of being used for factor extraction, the focus is on structure detection, and on the dimensionality of the data at the sub-component level, as unidimensionality is a strict assumption of C-alpha (OECD, 2008).

As a complementary analysis and in order to assess and gauge the proportion of the population that was vulnerable or having functional needs in relation to the total population, all C-MIST indicators were added together. The derived affected population counts were used to calculate a functional needs prevalence rate for each county, by dividing the total population by 100 and then using this quotient to divide the affected population percentage. The prevalence rates are reported as percentages in this study. For the prevalence rates, no part of the calculation was standardized to Z-scores or percentile ranks.

Weighting and Aggregation Methods

Based on the social vulnerability literature, there was a consistent pattern of not adopting a precise weighting method per se due to the lack of justification for one, and all weighting, if mentioned, assumed equal weighting (Cutter *et al.*, 2003; Chakraborty *et al.*, 2005; Simpson and Katirai, 2006; Jones and Andrey, 2007; Schmidtlein *et al.*, 2008; Flanagan *et al.*, 2011; Prasad, 2012; Tate, 2012, 2013). Chakraborty *et al.* (2005) adopted a geometric model, which assumes some weighting trade-offs, although none were explicitly identified in that study. Although it should be noted that based on the results of indicator extraction from factor analysis, a few authors decided to offset the impact of certain known indicators that would have a negative effect on the social vulnerability index, like income, since the higher the income the less vulnerable the population (Cutter *et al.*, 2003; Prasad, 2012). Using the factor loadings, which would be negative for income, certain authors have treated this indicator as a weight and/or re-ranked income from low to high instead of high to low to offset its impact (Cutter *et al.*, 2003; Chakraborty *et al.*, 2005; Flanagan *et al.*, 2011; Prasad, 2012).

In addition, based on the disability and functional needs literature, there was no indication to suggest weights for the functional model (Kailes, 2005; Kailes and Enders, 2007; NCD, 2009; WHO, 2002, 2013), therefore no weighting preferences were adopted for the development of the C-MIST index model per se. In fact, contrary to the medical model, the functional model assumes inclusiveness and equal importance to all who have functional needs, which can vary greatly and where people can demonstrate more than one need simultaneously (Kailes, 2005; Kailes and Enders, 2007; NCD, 2009; WHO, 2002, 2013). So it would not only be impossible to prioritize any weighting considerations but it would go against the assumptions of the functional model in the first place.

However, in the adoption of an index aggregation method itself, there is a number of associated assumptions and implied weighting considerations (OECD, 2008). The aggregation method adopted in this study is a simple, linear, additive model, whereby all normalized indicators are added at the sub-component level for each county, then each sub-component is added together to create the index of each county. The following assumptions therefore apply to it: the dataset contains no outliers and satisfies the conditions for normality and linearity, and there is full compensability or trade-offs between the dimensions, thus equal weighting (OECD, 2008). Also, the OECD (2008) further states “the use of a linear aggregation procedure implies that there are no synergies or conflicts” (p. 103). Based on the social vulnerability literature, the linear, additive aggregation model was the preferred model, with the exception of Chakraborty *et al.* who employed a geometric model (Cutter *et al.*, 2003; Chakraborty *et al.*, 2005; Simpson and Katirai, 2006; Jones and Andrey, 2007; Prasad, 2012; Tate, 2012, 2013).

Results

Affected Population Distribution

When the C-MIST indices were ranked in descending order, the affected population ranged from a low of 8,494 persons in Liberty County to a high of 2,3441,93 for Miami-Dade County (Table 1 and Figure 4). The results also indicated that the C-MIST index increased in direct proportion with the affected population as seen in Table 1. This result is not coincidental as based on the scatterplot in Figure 2, there appeared to be a near perfect, positive, linear relationship, with a correlation coefficient of 0.997, between affected population size (P-values) and the C-MIST index (P-values) (Figure 2). The near perfect, positive relationship between the affected population and C-MIST was expected, as six out of thirteen indicators were derived as percentages from the total population, as per the data collection practices conducted by the Florida Department of Health (2012). In contrast, Figure 3 illustrates a scatterplot between SoVI and the affected population size, but shows almost no relationship, with a very weak correlation coefficient of 0.011.

Table 1. Top 10 Florida counties sorted by the P-values of C-MIST Index in descending order. The P-values of the SoVI 2006-2010 index, county population, and affected population are also included. Data Source: Florida Department of Health (2012); Hazards and Vulnerability Research Institute (2014).

Counties	County Population	Affected Population	C-MIST	SoVI
Miami-Dade	2,477,658	2,344,193	98%	86%
Broward	1,742,843	1,610,918	97%	60%
Palm Beach	1,287,224	1,215,172	95%	41%
Hillsborough	1,200,754	1,203,513	95%	57%
Orange	1,112,526	1,127,779	94%	41%
Pinellas	926,217	1,012,829	94%	85%
Duval	899,820	935,039	92%	52%
Lee	618,188	625,825	88%	57%
Polk	584,058	635,036	88%	70%
Brevard	554,908	601,035	88%	41%

However, when counties were ranked according to their functional needs prevalence rates, the C-MIST rankings did not necessarily trend in accordance with the highest prevalence rates, and there is a very weak relationship between the prevalence rates and the C-MIST index, with a correlation coefficient of 0.057

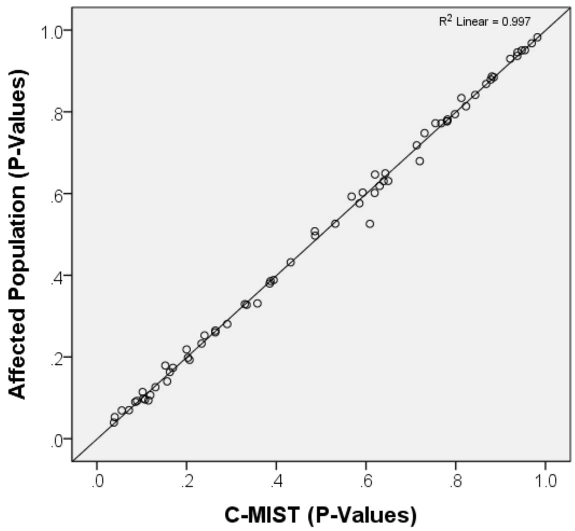

Figure 2. Scatter plot of C-MIST (P-values) and affected populations by county. Correlation coefficient (R^2) was 0.997. The linear equation was y = -1.18E-3+1*x. Data Source: Florida Department of Health (2012).

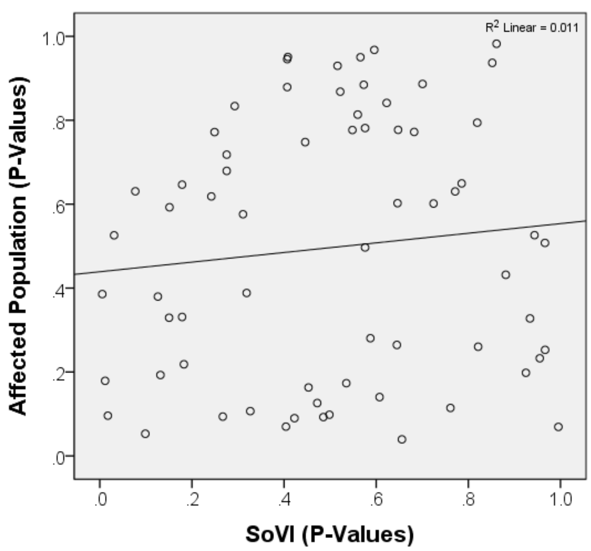

Figure 3. Scatterplot of SoVI 2006-2010 (P-values) and affected populations by county. Correlation coefficient (R^2) was 0.011. The linear equation was y = 0.44+0.11*x. Data Source: Florida Department of Health (2012); Hazards and Vulnerability Research Institute (2014).

(Table 2 and Figure 6). By contrast, SoVI, in relationship to the prevalence rates, showed a much stronger pattern with higher SoVI scores trending with higher prevalence rates, and a stronger, positive relationship with a correlation coefficient of 0.274 (Table 2 and Figure 7). Prevalence rates ranged from a low of 64.4% (St. Johns) to a high of 120.7% (Highlands) (Table 2). A majority (79%) of the sixty-seven counties showed that the affected population exceeded the actual county population size, with prevalence rates above 100% (Figure 5). As seen in Table 1, the top ten counties with highest functional needs prevalence were: Highlands, St. Lucie, Dixie, Hernando, Lake, Putnam, Gadsden, Taylor, Jefferson and Hardee (Table 2).

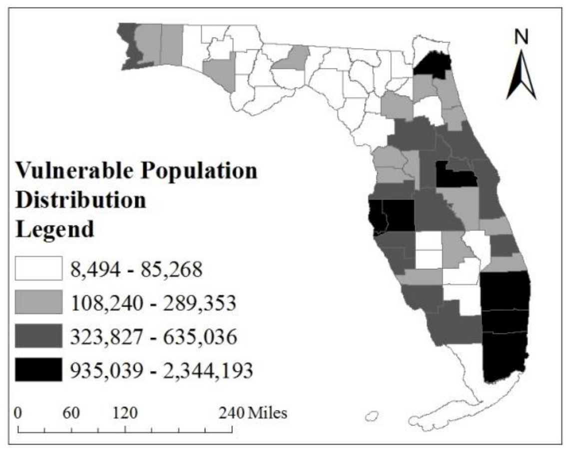

Figure 4. Map of the distribution of the affected populations with functional needs, symbolized by four classes using Natural Breaks (Jenks) Classification. Data Source: Florida Department of Health (2012); U.S. Census Bureau (2011).

C-MIST Index Results

From Table 1, the top ten highest C-MIST cumulative percentile rankings, listed in descending order, corresponded to the following counties: Miami-Dade (98.2%), Broward (96.9%), Palm Beach (95.4%), Hillsborough (94.7%), Orange (93.8%), Pinellas (93.7%), Duval (92.1%), Lee (88.5%), Polk (88.0%), and Brevard (87.8%).

The spatial distribution of the C-MIST percentile rankings can be referenced in the map in Figure 8, where the counties were symbolized by quartile ranges of the percentile ranking. To facilitate comparison, a similar map was created to illustrate the SoVI index score distribution (Figure 9).

The spatial patterns in both maps confirmed only slight similarities in terms of distribution of C-MIST and SoVI scores, particularly above the 50th percentile. This weak relationship between SoVI and C-MIST is further confirmed in the scatterplot in Figure 10, with a correlation coefficient of 0.009.

Table 2. Ranking by prevalence rates of functional needs per county (as a percentage), alongside comparative rankings of county population size, affected population and C-MIST and SoVI indices. Data Source: Florida Department of Health (2012); Hazards and Vulnerability Research Institute (2014).

County	County Population	Affected Population	Functional Needs Prevalence	C-MIST	SoVI
Highlands	99,825	120,462	120.7%	53%	94%
St. Lucie	275,298	324,156	117.7%	75%	68%
Dixie	16,205	19,017	117.4%	10%	76%
Hernando	165,758	191,399	115.5%	64%	79%
Lake	293,883	339,143	115.4%	78%	58%
Putnam	74,133	85,268	115.0%	43%	88%
Gadsden	49,810	57,209	114.9%	33%	93%
Taylor	23,132	26,269	113.6%	16%	45%
Jefferson	14,800	16,737	113.1%	10%	50%
Hardee	28,282	31,895	112.8%	20%	92%

Results for Sub-Components of C-MIST

At the sub-component level of C-MIST, the percentile rankings of the 5 individual sub-dimensions yielded varied results, and influenced the overall C-MIST index for each county differently.

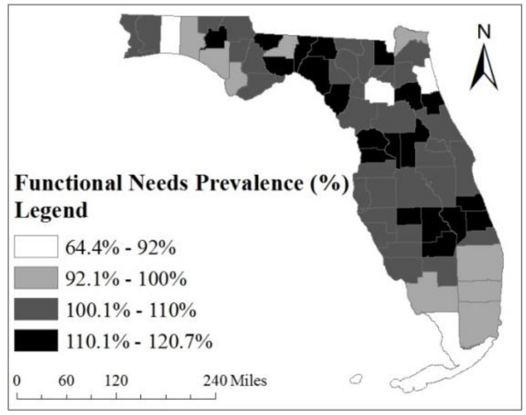

Figure 5. Map of functional needs prevalence rates by county (as a percentage), symbolized by four classes using a manual classification. Data Source: Florida Department of Health (2012); Census Bureau (2011).

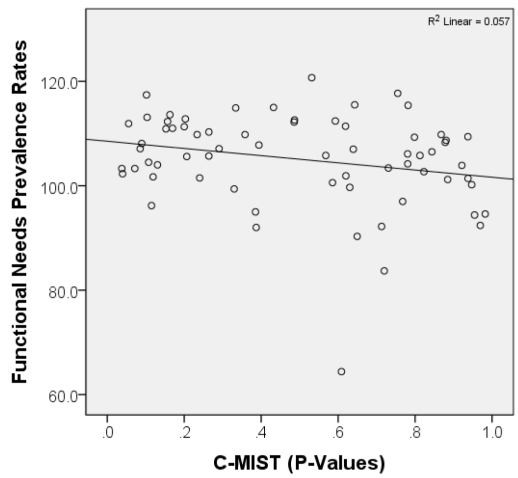

Figure 6. Scatterplot of Functional Needs Prevalence Rates and C-MIST (P-values). Correlation Coefficient (R^2) was 0.057. Linear Equation is y = 1.09E2-6.89*x. Data Source: Florida Department of Health (2012).

In the Communication sub-component, C-MIST indices ranged from 0 to 100%, with the top ten counties listed in descending order as follows: Glades (100%), Hendry (100%), Sumter (100%), DeSoto (100%), Highlands (100%), Gadsden (100%), Hardee (100%), Putnam (99.7%), Miami-Dade (99.3%), and Pinellas (99.1%) (Table 3).

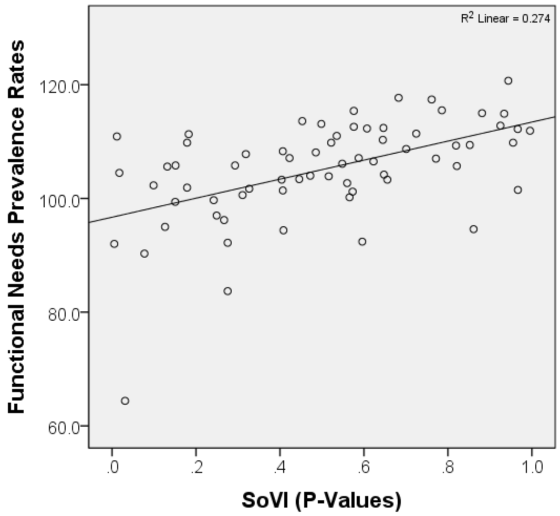

Figure 7. Scatterplot of Functional Needs Prevalence Rates and SoVI (P-values). Correlation Coefficient (R^2) was 0.274. Linear Equation is y = 96.7+16.73*x. Data Source: Florida Department of Health (2012).

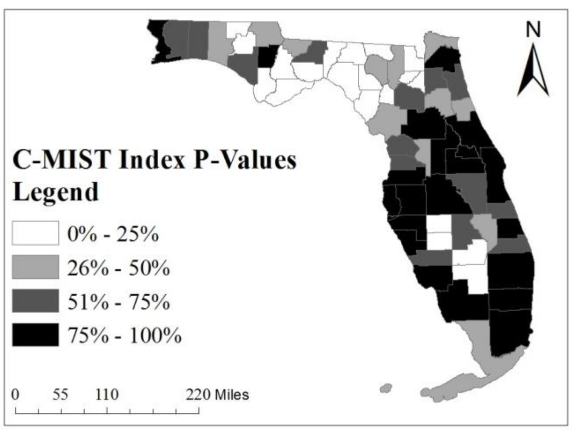

Figure 8. Map of C-MIST Index distributions using the P-values (percentile ranks), and symbolized using four manual classes to simulate quartile ranges. Data Source: Florida Department of Health (2012), U.S. Census Bureau (2011).

C-MIST indices for Medical Needs ranged from 3.8% to 98.2%. The top ten counties were Miami-Dade (98.1%), Broward (96.9%), Palm Beach (96.1%), Pinellas (93.4%), Hillsborough (92.9%), Orange (91.6%), Duval (91.5%), Brevard (88.6%), Lee (88.1%), and Polk (88.0%) (Table 4).

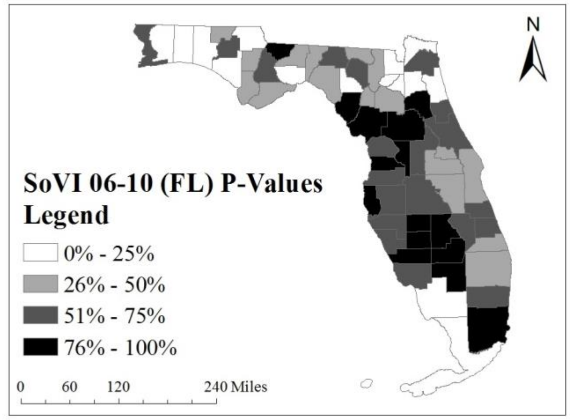

Figure 9. Map of the SoVI Index distribution mapped as P-values (percentile ranks), using four manual classes to simulate quartile ranges. Data Source: Hazards and Vulnerability Research Institute (2014); Census Bureau (2011).

Table 3. Top 10 Florida counties sorted by the P-values of the Communication sub-component of C-MIST, in descending order, and in comparison to the overall C-MIST index and its sub-components. Data Source: Florida Department of Health (2012).

Counties	C-MIST	C	M	I	S	T
Glades	6%	100%	6%	100%	52%	84%
Hendry	24%	100%	25%	97%	59%	83%
Sumter	49%	100%	48%	97%	69%	83%
DeSoto	23%	100%	25%	96%	59%	83%
Highlands	53%	100%	60%	94%	70%	83%
Gadsden	33%	100%	35%	93%	63%	82%
Hardee	20%	100%	21%	92%	58%	82%
Putnam	43%	100%	48%	88%	67%	81%
Miami-Dade	98%	99%	98%	86%	84%	81%
Pinellas	94%	99%	93%	85%	83%	80%

For Maintaining Functional Independence, the category or sub-component C-MIST indices ranged from 0.5% to 99.5%. The following counties ranked as the top ten: Glades (99.5%), Hendry (96.7%), Sumter (96.6%), DeSoto (95.5%), Highlands (94.4%), Gadsden (93.4%), Hardee (92.5%), Putnam (88.1%), Miami-Dade (86.1%), and Pinellas (85.2%) (Table 5).

Table 4. Top 10 Florida counties sorted by the P-values of the Medical Needs sub-component of C-MIST, in descending order, and in comparison to the overall C-MIST index and its sub-components. Data Source: Florida Department of Health (2012).

Counties	C-MIST	C	M	I	S	T
Miami-Dade	98%	99%	98%	86%	84%	81%
Broward	97%	57%	97%	60%	83%	72%
Palm Beach	95%	13%	96%	41%	83%	66%
Pinellas	94%	99%	93%	85%	83%	80%
Hillsborough	95%	49%	93%	57%	83%	71%
Orange	94%	13%	92%	41%	83%	66%
Duval	92%	36%	91%	52%	82%	70%
Brevard	88%	13%	89%	41%	81%	66%
Lee	88%	51%	88%	57%	81%	72%
Polk	88%	83%	88%	70%	81%	76%

Table 5. Top 10 Florida counties sorted by the P-values of the Maintaining Functional Independence sub-component of C-MIST, in descending order, and in comparison to the overall C-MIST index and its sub-components. Data Source: Florida Department of Health (2012).

Counties	C-MIST	C	M	I	S	T
Glades	6%	100%	6%	100%	52%	84%
Hendry	24%	100%	25%	97%	59%	83%
Sumter	49%	100%	48%	97%	69%	83%
DeSoto	23%	100%	25%	96%	59%	83%
Highlands	53%	100%	60%	94%	70%	83%
Gadsden	33%	100%	35%	93%	63%	82%
Hardee	20%	100%	21%	92%	58%	82%
Putnam	43%	100%	48%	88%	67%	81%
Miami-Dade	98%	99%	98%	86%	84%	81%
Pinellas	94%	99%	93%	85%	83%	80%

In the Supervision category, the C-MIST indices ranged from 51.5% to 83.7%. The top ten counties in this category were: Miami-Dade (83.7%), Broward (83.4%), Palm Beach (83%), Hillsborough (82.8%), Orange (82.6%), Pinellas (82.6%), Duval (82.2%), Lee (81.2%), Polk (81.1%), and Brevard (81%) (Table 6).

Table 6. Top 10 Florida counties sorted by the P-values of the Supervision sub-component of C-MIST, in descending order, and in comparison to the overall C-MSIT index and its sub-components of C-MIST. Data Source: Florida Department of Health (2012).

Counties	C-MIST	C	M	I	S	T
Miami-Dade	98%	99%	98%	86%	84%	81%
Broward	97%	57%	97%	60%	83%	72%
Palm Beach	95%	13%	96%	41%	83%	66%
Hillsborough	95%	49%	93%	57%	83%	71%
Orange	94%	13%	92%	41%	83%	66%
Pinellas	94%	99%	93%	85%	83%	80%
Duval	92%	36%	91%	52%	82%	70%
Lee	88%	51%	88%	57%	81%	72%
Polk	88%	83%	88%	70%	81%	76%
Brevard	88%	13%	89%	41%	81%	66%

Finally, in the Transportation category or sub-component, the C-MIST indices ranged from 50.2% to 84.0%. The top ten counties were: Glades (84.0%), Hendry (83.3%), Sumter (83.3%), DeSoto (82.7%), Highlands (82.7%), Gadsden (82.5%), Hardee (82.2%), Putnam (81.1%), Miami-Dade (80.5%), and Pinellas (80.3%) (Table 7).

Comparison of C-MIST Index and SoVI Index

The C-MIST Index and SoVI 2006-10 Index were compared on a scatterplot, which revealed a very weak, positive correlation between the two indices, with a correlation coefficient of 0.009 (Figure 10). While the relationship between the two indices was not significant, within the individual sub-components of C-MIST there appeared to be similar trends with SoVI. While the results in Table 8 only reveal the top ten counties, the counties with the highest SoVI scores also had the highest scores for Communication, Maintaining Functional Independence, and Transportation.

Table 7. Top 10 Florida counties sorted by the P-values of the Transportation sub-component of C-MIST, in descending order, and in comparison to the overall C-MIST index and its sub-components. Data Source: Florida Department of Health (2012).

Counties	C-MIST	C	M	I	S	T
Glades	6%	100%	6%	100%	52%	84%
Hendry	24%	100%	25%	97%	59%	83%
Sumter	49%	100%	48%	97%	69%	83%
DeSoto	23%	100%	25%	96%	59%	83%
Highlands	53%	100%	60%	94%	70%	83%
Gadsden	33%	100%	35%	93%	63%	82%
Hardee	20%	100%	21%	92%	58%	82%
Putnam	43%	100%	48%	88%	67%	81%
Miami-Dade	98%	99%	98%	86%	84%	81%
Pinellas	94%	99%	93%	85%	83%	80%

Table 8. Top 10 Florida counties sorted by the P-values (%) of SoVI 2006-2010, in descending order, and in comparison to C-MIST and its sub-components. Data Source: Florida Department of Health (2012); Hazards and Vulnerability Research Institute (2014).

Counties	C-MIST	SoVI	C	M	I	S	T
Glades	6	100	100	6	100	52	84
Hendry	24	97	100	25	97	59	83
Sumter	49	97	100	48	97	69	83
DeSoto	23	96	100	25	96	59	83
Highlands	53	94	100	60	94	70	83
Gadsden	33	93	100	35	93	63	82
Hardee	20	92	100	21	92	58	82
Putnam	43	88	100	48	88	67	81
Miami-Dade	98	86	99	98	86	84	81
Pinellas	94	85	99	93	85	83	80

C-MIST Index - Measure Validity Results

The reliability analysis using Cronbach's coefficient alpha (C-alpha) was run on the five, standardized sub-components of the C-MIST index, resulting in an alpha coefficient of 0.997, which suggests a relatively high internal consistency (Table 9).

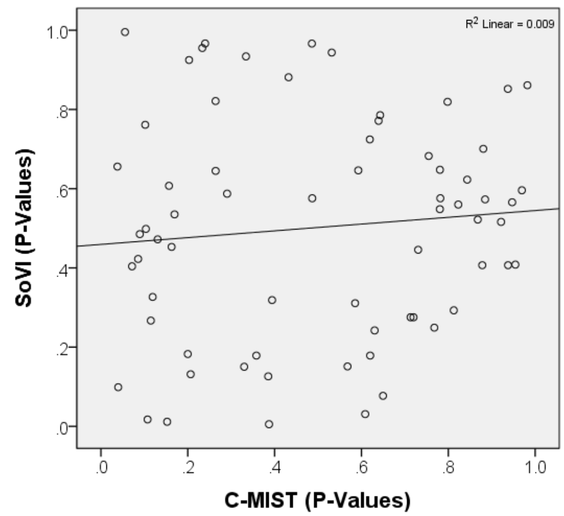

Figure 10. Scatter plot of CMIST P-Values and SoVI P-Values. The correlation coefficient (R^2) was 0.009 with a Linear Equation of y = 0.46+0.09*x. Data Source: Florida Department of Health (2012); Hazards and Vulnerability Research Institute (2014).

The C-alpha ranges from 0 to 1, with 0 signifying that there is no correlation between the sub-components or dimensions measured, and 1 signifying that they are perfectly correlated (OECD, 2008). Furthermore the OECD (2008) also specifies that a minimum alpha of 0.7 is widely considered acceptable, and that the higher the c-alpha, the more indicative it is that the "indicators are measuring the same underlying construct" (p. 72), signifying that the index is unidimensional.

While C-alpha does not measure dimensionality but assumes unidimensionality as part of the requirement for reliability analysis, it is generally recommended to also run exploratory factor analysis in order to determine the dimensionality of the underlying data structure (OECD, 2008). The OECD explains that this is because "a set of individual indicators can have a high

C-alpha and still be multi-dimensional” (p. 72).

Table 9. Results of reliability analysis conducted on the five C-MIST sub-components.

C-alpha	C-alpha Based on Standardized Items	N of Items
0.997	0.997	5

The results from exploratory factor analysis, using the principal axis factoring extraction method in order to analyze the underlying data structure, revealed that 98.8% of the variance in the sub-components can be explained by the first factor or sub-component, the Communication dimension, which has an eigenvalue greater than 1 (Table 10). This suggests that there are very high and strong inter-correlations between all five dimensions, and resulted in only one factor extracted. Therefore, a factor matrix and factor loadings of the sub-components could not be generated as part of the analysis. Based on this result, it is recommended to re-run exploratory factor analysis with a larger dataset to be certain of these results and the conclusion on the dimensionality of the data at the sub-component level and also at the indicator level.

It should be noted that based on the literature, factor analysis in social vulnerability index constructions has been previously used for factor extraction at the indicator level, not at the sub-component or dimensional level as applied here (Cutter *et al.*, 2003; Prasad, 2012). However, since C-alpha can only be conducted at the sub-component or dimensional level, factor analysis in this study was similarly applied in order to compare and assess the results at that level.

In order to assess the appropriateness of exploratory factor analysis to analyze the data structure, two additional tests were conducted: the Kaiser-Meyer-Olkin (KMO) Measure and Bartlett’s Test of Sphericity test (see Table 5).

Table 10. Part of factor analysis results using principal axis factoring extraction. The table shows the ranking of the Eigenvalues of the five dimensions of C-MIST, in the order of the highest influence on the data variance. Eigenvalues higher than 1 are extracted as factors.

Factor	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	4.94	98.807	98.807
2	0.033	0.661	99.468
3	0.014	0.289	99.757
4	0.012	0.234	99.99
5	0	0.01	100

The KMO Measure indicates that on a scale of 0 to 1, it is relatively high with a value of 0.884 (Table 11). A high value, i.e. anything above 0.50, indicates that running factor analysis may be useful and suggests that a proportion of the variance may be caused by underlying factors. The Bartlett’s Test of Sphericity also supports this conclusion, since it has a significance level of 0.000, which is smaller than 0.05 (Table 11).

Discussion

Measurement Validity of the C-MIST Index

Based on the results of the C-alpha alone, the C-MIST index appears to be a relatively unidimensional, consistent and valid instrument to assess the relative functional needs at the county level in Florida. However, caution is advised on readily accepting this conclusion given the combined results of both C-alpha (Table 9) showing a very high alpha of 0.997, and the results from factor analysis (Table 10) where only one factor, Communication, accounted for 98.8% of the variance in the data. Furthermore, it is widely accepted that a C-alpha greater than 0.90 suggests there may be redundancies, and the results from factor analysis in this study also confirm the presence of redundancies.

Table 11. Part of factor analysis results using principal axis factoring. Results from Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity are summarized to reflect the appropriateness of factor analysis on the data.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.884
Bartlett's Test of Sphericity	Approx. Chi-Square	1150.841
	Df	10
	Sig.	.000

Given the results, additional testing with C-alpha and factor analysis is recommended at the sub-component level. The OECD (2008) advises that one could observe the influence of individual indicators on the sub-components and thus the overall index, by eliminating an indicator at a time and re-running C-alpha.

Therefore, with more testing, this index may be useful in taking into account the dimensionality of functional needs as it relates to disaster risk and social vulnerability, and could then also be applied in a practical sense at the local level for disaster and emergency management and resource planning.

Multidimensionality of Functional Needs

In this study, factor analysis was applied at the sub-component level only, in support of the C-alpha analysis and to demonstrate the degree of dimensionality at that level. Therefore, further testing is still needed to adequately assess the dimensionality of the individual indicators themselves, using a larger dataset. Additionally, the OECD (2008) states that in C-alpha "correlations do not necessarily represent the real influence of the individual indicators on the phenomenon expressed by the composite indicator" (p. 27).

Instrument Limitations and Measurement Error

Limitations of the index and its analysis are inherent to the data sources available for Florida to construct the C-MIST index, the sample size, and the types of multivariate analyses undertaken, namely C-alpha and factor analysis. The data sources for the original dataset were obtained by the State of Florida from seven different sources, and thus the C-MIST index and the underlying data assume varied data collection practices and margins of error, which are not fully transparent or accessible. As a result, assessing a precise coefficient of variation for the C-MIST index would be difficult and would have to be calculated at the indicator level only. Thus, while measurement error is an important aspect of an index's reliability, it could not be confirmed, despite the very high C-alpha of 0.997.

Also, the dataset was limited to sixty-seven as the scale of the study was at the county level in Florida. Having a larger dataset or sample size would have permitted more significant multivariate analysis results, particularly with factor analysis so as to confirm the underlying data structure, inter-correlations and suitability for the index. Furthermore, the analysis for C-alpha can only be limited to the sub-component level, as this is an inherent requirement for running C-alpha.

Data Trends

Spatial Distribution of the Affected

Population

The same underlying dataset was utilized to create both the C-MIST index and the functional needs prevalence rates. This yielded significantly different rankings. In fact there was practically no relationship between the two measurements (Figure 6). When comparing the relationship between C-MIST and the affected populations, it appeared that the larger counties have a larger rate of functional needs than the smaller ones (Table 1 and Figure 8). Whereas, the functional needs prevalence rates indicates different and almost opposite trends, in that over 75% of all Florida counties have affected populations that exceed the actual population size, and that the counties with the highest prevalence rates were not the largest but small to mid-size ones (Table 2 and Figure 5). One reason for this difference could be that there was some degree of double-counting in the underlying indicators, in which case more information about the data collection practices would be needed to ascertain this. For example, more than one person could be accounted for multiple times in the underlying indicators for simply having more than one functional need. Another reason could be that the two measurements were recompiled and calculated differently, which could have had a direct impact into the rankings of both C-MIST and prevalence rates. The extent of this impact would require further testing of the C-MIST index, in order to further assess the robustness and reliability of the instrument.

On the other hand, SoVI had a much stronger, positive relationship with the functional needs prevalence rates (Figure 7). In contrast, SoVI and C-MIST barely showed any relationship (Figure 10). Further investigation of the strength of the relationship between SoVI and the underlying indicators might reveal further explanatory patterns for differences and trends.

C-MIST Index and Sub-Components

The sub-components for C-MIST that had the same top ten rankings and trended in the same order were: Communication (Table 3), Maintaining Functional Independence (Table 5) and Transportation (Table 7), as follows: Glades, Hendry, Sumter, DeSoto, Highlands, Gadsden, Hardee, Putnam, Miami-Dade, and Pinellas.

The Medical Needs (Table 4) and Supervision (Table 6) sub-components had the same counties in the top ten rankings as well, and in almost the same order, with Orange and Pinellas counties swapping their ranks depending upon which sub-component was being ranked.

Relationship Between SoVI and C-MIST

The rankings of C-MIST and SoVI, when compared to their relationship with the affected populations revealed different trends. The greater the affected population size, the higher the C-MIST Index (Table 1 and Figure 8), whereas the same did not hold true for SoVI (Table 2 and Figure 5). In fact, Miami-Dade and Pinellas counties were the only two that ended up being in both the top ten rankings for C-MIST and for SoVI (Table 8). Interestingly, Glades County, which is part of the bottom ten for C-MIST with a score of 5.5%, ended up with the highest SoVI score of 99.5% (Table 8). In contrast, Miami-Dade which ranked the highest in the C-MIST index (98.2%) only had a SoVI score of 86.1% (Table 8). Glades County also had one of the lowest index scores for Medical Needs (6.4%) while Communication and

Maintaining Functional Independence ranked at almost 100% (Table 8). Miami-Dade county ranked consistently in the top ten rankings for all sub-components of C-MIST, which certainly contributed to its index ranking as the overall highest C-MIST index score (Table 2).

Based on the scatterplot in Figure 8, SoVI and C-MIST appeared to have almost no relationship. Upon further examination in Table 8, the individual sub-components of Communication, Functional Independence and Transportation not only trended in the same direction, but also in a similar direction as SoVI, in that the higher the SoVI score, the higher these individual scores were as well (Table 7). Further analysis including scatterplots could be conducted in order to determine the strength and degree of correlation and relationship between those individual sub-components and SoVI. The fact that there is no discernible relationship or trend between SoVI and Medical Needs or Supervision dimensions suggests that there is not enough dimensionality of functional needs present in SoVI and presents an opportunity to improve and enhance either existing or future social vulnerability index constructions.

Recommendations

The evidence suggests that the exploration of the dimensionality of disability and functional needs should be continued. The dimensionality of the index could be further improved and tested by eliminating, adding, or substituting data sources and comparable indicators, as well as including demographic indicators that measure functional needs. The OECD (2008) affirms "the strength and weaknesses of composite indicators largely derive from the quality of the underlying variables" (p. 23). Transportation, for example, only had one indicator representing the dimension. Also, demographic data such as age and income, which based on the literature are considered social vulnerability indicators, would have been helpful to provide additional context and analysis as to why certain sub-components trended positively with either the C-MIST Index or SoVI Index, but not both indices at the same time. For example, it could be hypothesized that there are high concentrations of seniors in certain counties instead of others which could explain why medical needs and C-MIST indices trended together and were consistently higher relative to other sub-components, but additional demographic data would have enabled that analysis and testing.

Expanding the sample size may yield stronger statistical results and analysis, and may further confirm the underlying data structure or reveal new findings with respect to this. Sensitivity and uncertainty analyses using Monte Carlo and variance-based techniques are a logical next step in building and testing composite indices (OECD, 2008). The purpose of these techniques are to further test the transparency, robustness, and possible weighting and aggregation implications and assumptions of the instrument (OECD, 2008). Comparing the C-MIST index with another social vulnerability index that is deemed robust, other than SoVI, may also be significant as well. The simplicity, versatility, and scalability of the C-MIST index signifies that it could be adapted for other studies at any scale or paired together with other index calculations, which would foster additional research for disaster risk in the following research disciplines: disability, functional needs, and social vulnerability.

Conclusion

Disability and functional needs in the context of disaster has garnered research interest and policy changes in the past decade (NCD, 2009). Disability and functional needs has been described as a complex and multidimensional concept best described by the functional model (WHO, 2002, 2013; Kailes, 2005; Kailes and Enders, 2007). However, the functional model had been not been adequately modeled in the context of disaster (NCD, 2009). Using the broad concept of vulnerability as the underlying foundation, this study represented an interdisciplinary approach integrating the domains of social vulnerability, composite indices, and disability and functional needs in highlighting the need for an instrument to measure functional needs. Utilizing the C-MIST concept put forth by Kailes and Enders (2007), a functional model, the C-MIST index was modeled in this study.

Results indicated the C-MIST index appeared to have a strong relationship with the affected population size, whereby the greater the affected population size, the greater the functional need. Also, as far as measure validity, the index initially appeared to be a consistent and valid instrument to measure and assess affected populations who have functional needs at the county level in Florida, in the context of disaster risk. However, as far as adequately representing the dimensionality of disability and functional needs in the C-MIST index, further research and testing is advised to ensure the validity and robustness of the instrument for eventual application in disaster risk.

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Appendix A. The following table is readapted from the Florida Department of Health (2012) and the functional need population measures were reorganized to fit the C-MIST definitions and sub-components. Source: Kailes and Enders (2007); Florida Department of Health (2012).

C-MIST Components	C-MIST Description	Functional Need Category	Population Measures	Data Sources
Communication (Kailes and Enders, 2007)	Communication needs concerns the accessibility and adaptability of a variety of information receipt and delivery methods in order to accommodate "a very large and diverse population of those who will not hear, see, or understand in addition to those who cannot hear, see or understand" (Kailes and Enders, 2007, p. 234). This affected population reflects various ethnic, linguistic, cognitive and speaking, seeing or hearing limitations.	Auxiliary Aids and Services Necessary to Ensure Effective Communication for Persons with Communication Disabilities (Florida Department of Health, 2012)	Estimated number of county population functionally deaf - derived as 0.38% of total county population (Florida Department of Health, 2012)	U.S. Census Bureau Survey of Income and Program Participation (SIPP)
			Estimated number of county population hard of hearing - derived as 3.7% of the total county population (Florida Department of Health, 2012)	
		Access to orientation and way-finding for people who are blind or have low vision (Florida Department of Health, 2012)	Estimated number of county population with low vision or blind - derived as 2.3% of the total county population (Florida Department of Health, 2012)	American Foundation for the Blind
Medical Needs (Kailes and Enders, 2007)	Medical Needs, at the time of writing called for a redefinition from a medical model to a functional model perspective, and, "can include managing unstable, terminal, or contagious health conditions that require observation and ongoing treatment; managing medications, intravenous (IV) therapy, tube feeding, and/or regular vital signs; administering dialysis, oxygen, and suction; managing wounds, catheters, or ostomies; and operating power-dependent equipment to sustain life" (Kailes and Enders, 2007, p. 234).	Access to medications to maintain health, mental health, and function (Florida Department of Health, 2012)	Estimated number of county population oxygen dependent - 8.6% x 65+population (Florida Department of Health, 2012)	Florida Department of Health Vulnerable Population Profiles
			Number of dialysis clients (Florida Department of Health, 2012)	

C-MIST Components	C-MIST Description	Functional Need Category	Population Measures	Data Sources
Maintaining Functional Independence (Kailes and Enders, 2007)	Maintaining Functional Independence needs "can include replacing essential medications for blood pressure management, seizures, diabetes, and psychiatric conditions; replacing lost or adaptive equipment (wheelchairs, walkers, scooters, canes, crutches) and essential consumable supplies (catheters, ostomy supplies, padding, dressings, sterile gloves); and assisting with orientation for those with visual limitations" (Kailes and Enders, 2007, p. 235). Having supplies on hand and delivering immediate assistance to those affected have implications for not only maintaining their functional independence but also their level of health (Kailes and Enders, 2007, p. 235).	DME that assist with activities of daily living (Florida Department of Health, 2012)	Estimated number of county population with physical activity limiting disability - derived as 8.2% of the total county population (Florida Department of Health, 2012)	U. S. Census Bureau
		Availability of food and beverages appropriate for individuals with dietary restrictions (e.g., persons with diabetes or severe allergies to foods such as peanuts, dairy products and gluten) (Florida Department of Health, 2012)	Estimated number of the county that may have special dietary requirements including those with diabetes, renal, or cardiovascular disease or severe food allergies - derived as 17% of the total population (Florida Department of Health, 2012)	U. S. Census Bureau
		Access to medications to maintain health, mental health, and function	Estimated % of adult population with diabetes, asthma/lower resp. disease, diagnosed hypertension (Florida Department of Health, 2012)	U. S. Census Bureau
			Estimated number of county population (adults and children) with serious mental illness (Florida Department of Health, 2012)	Florida Department of Health Vulnerable Population Profiles
Supervision (Kailes and Enders, 2007)	Supervision needs impacts children, the elderly, prisoners, and persons who don't have or who lost family and friend support network, have cognitive and intellectual limitations, those who suffer from disorientation and/or those who are unable to cope with the unfamiliar (Kailes and Enders, 2007, p. 235).	Assistance for individuals with cognitive and intellectual disabilities (Florida Department of Health, 2012)	Number of developmentally disabled in county (Florida Department of Health, 2012)	Florida Department of Health Vulnerable Population Profiles
			Number of elders with dementia (Florida Department of Health, 2012)	

C-MIST Components	C-MIST Description	Functional Need Category	Population Measures	Data Sources
Transportation (Kailes and Enders, 2007)	Transportation needs impact a cross-section of people, impacting the poor, the elderly, those who have ambulatory issues, and zero-vehicle households, which have implications for emergency evacuation (Kailes and Enders, 2007, p. 235).	Access to transportation for individuals who may require a wheelchair-accessible vehicle, individualized assistance, and the transportation of equipment required in a shelter because of a disability (Florida Department of Health, 2012)	% of households having someone with a disability or medical condition requiring evacuation assistance - derived as 8% of the total county population (Florida Department of Health, 2012)	Florida Division of Emergency Management Regional Evacuation Surveys