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DESIGN AND USE OF COMPOSITE INDICES IN ASSESSMENTS OF CLIMATE CHANGE VULNERABILITY AND RESILIENCE

JULY 2014

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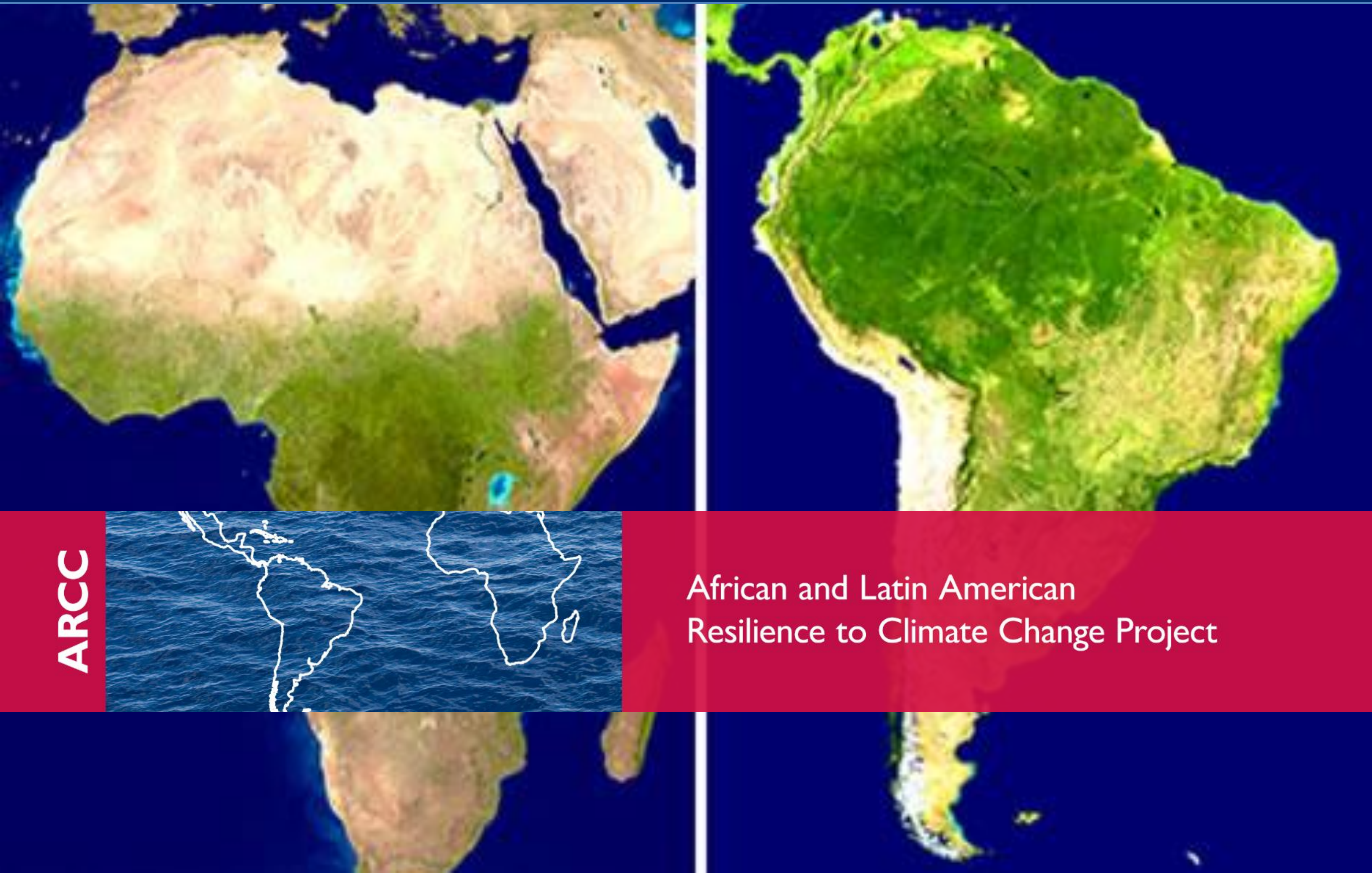

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AFRICAN AND LATIN AMERICAN RESILIENCE TO CLIMATE CHANGE (ARCC)

JULY 2014

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ACRONYMS AND ABBREVIATIONS

ARCC	African and Latin American Resilience to Climate Change
BOD	Benefit of the Doubt
CCFVI	Coastal City Flood Vulnerability Index
CIESIN	Center for International Earth Science Information Network at Columbia University
CVI	Climate Vulnerability Index
DEA	Data Envelopment Analysis
FVI	Flood Vulnerability Index
GDP	Gross Domestic Product
HDI	Human Development Index
IHE	International Institute for Hydraulic and Environmental Engineering
IPCC	Intergovernmental Panel on Climate Change
LVI	Livelihood Vulnerability Index
MCDA	Multiple Criteria Decision Analysis
OECD	Organisation for Economic Co-operation and Development
PAR	Pressure and Release Model
PCA	Principal Component Analysis
PSR	Pressure-State-Response Model
RCCI	Regional Climate Change Index
SCVI	Socio-Climatic Vulnerability Index
UNESCO	United Nations Educational, Scientific, and Cultural Organization
USAID	United States Agency for International Development
WPI	Water Poverty Index
WVI	Water Vulnerability Index

EXECUTIVE SUMMARY

Increasingly, researchers and practitioners are developing composite indices to provide multidimensional, integrated assessments and synthetic measures of climate change vulnerability and resilience. The creators of these indices design them to capture complex social-ecological systems at multiple spatial scales, ranging from national to local levels, and to support comparative analysis of climate exposure units within particular geographic areas and socioeconomic sectors. Composite indices can provide relative measures (or scores) that allow the ranking of cases from lowest to highest level of climate vulnerability or resilience.

This paper presents an overview of existing approaches to the design, use, and improvement of composite indices, with emphasis on their application in a range of efforts to better understand climate change impacts, vulnerabilities, adaptation, and resilience at different spatial and temporal scales. The goal of this paper is to provide readers with an introductory overview of composite index design and use for climate change vulnerability and resilience assessments at subnational scales, as well as guidance on the essential steps needed to construct and refine a composite index. Readers interested in learning more about how to construct climate change vulnerability and resilience indices can use this document, and the body of literature it cites, as a starting point.

Section 1 introduces the paper with background on why an understanding of indicator and composite index design and use may be of interest to professionals involved in climate change adaptation efforts. Section 2 identifies the advantages, disadvantages, and limitations of using composite indices. To provide a general framework and a set of criteria and guidelines for evaluating existing composite indices, Section 3 describes key theoretical and methodological considerations and commonalities by explaining 11 essential stages and the range of decisions involved in composite index design. Section 3 also includes an overview table to facilitate comparison of six selected composite indices according to these 11 steps. The indices were selected because they represent recent efforts at subnational levels to develop indices on climate-sensitive systems or sectors, such as water, agriculture, food, livelihoods, human health, river basins, urban areas, and coastal regions. An additional criterion for inclusion in this paper was some degree of implementation in African, Latin American, and/or Caribbean contexts. Summaries of the six selected composite indices are presented in an Annex. Section 4 discusses current best practices and key challenges. Section 5 offers concluding remarks and summarizes recommendations.

The paper concludes that a substantial body of work and expertise currently exists to provide valuable guidance on the necessary stages of composite index design and use for the purpose of climate change vulnerability and resilience assessment at subnational scales. Most of the indexing efforts for this purpose are recent, having emerged within the past decade. Few have been thoroughly verified and validated or undergone multiple iterations toward refinement. Nevertheless, they provide a substantive basis for defining best practices, recognizing limitations, and identifying remaining challenges.

Composite indices should be viewed as analytical, communication, and collaborative tools that have potential to support climate-related decision making, planning, policy development, and management systems by promoting discussions about climate change vulnerability and resilience and by facilitating scenario analysis to examine possible futures. Experts and stakeholders should be involved early in the composite index design process to inform the theoretical and conceptual framework used to define climate change vulnerability and resilience as well as to inform the structural design of the index, indicator selections, weighting schemes, aggregation methods, and the selection of visualization options for displaying results.

1.0 INTRODUCTION

Composite index methodologies have evolved to meet a wide range of purposes and to inform particular decisions or decision-making processes. Examples include assessments of human development, wellbeing, quality of life, sustainability, governance quality, gender inequality, poverty, multiple deprivation, food security, energy security, disaster risk, and disaster risk management.[1] In recent years, composite indexing efforts have begun to develop synthetic measures of relative vulnerability and resilience to climate variability and climate change at a range of spatial scales.[2] Notably, the U.S. Global Change Research Program has been coordinating activities to develop a system of physical, ecological, and societal indicators and indices to measure, monitor, and manage conditions at national and subnational spatial scales in support of ongoing U.S. National Climate Assessment efforts (Janetos et al., 2012; Kenney et al., 2012). Composite indices can be applied to analyze and compare units of analysis within particular geographic areas or socioeconomic sectors. They can provide relative measures (or scores) that allow the ranking of cases from lowest to highest level of climate vulnerability or resilience.

DEFINITION OF KEY TERMS

An **indicator** is a direct measure, an indirect measure (proxy indicator), or a calculation used to represent an attribute of a system of interest (e.g., a population, geographic region, socioeconomic sector, or coupled human-environment system). Indicator values are derived from processed data. An indicator can be a quantitative or a qualitative measure. For example, maternal mortality ratio, infant mortality rate, and life expectancy at birth can serve as proxy indicators to indirectly measure and monitor a population's access to essential health care services.

A **composite index** aggregates multiple individual indicators to provide a synthetic measure (a summary statistic) of a complex, multidimensional, and meaningful societal issue (e.g., poverty, degree of human development, level of sustainability, or capacity for disaster risk management). Individual indicators and indicator sets can be selected, arranged, and combined to produce subindices representing the main components or dimensions of the system under investigation. An education subindex might include indicators such as literacy rate, primary school enrollment, and educational attainment. A set of subindices can then be further aggregated into a final composite index. The Human Development Index (HDI), for example, organizes indicators into three main dimensions of human wellbeing: health, education, and income.[3]

1 See, for example, Andrews (1989), Booysen (2002), Cendrero et al. (2003), Molle and Mollinga (2003), Parris and Kates (2003), Birkmann (2007), Carreño et al. (2007), Van de Kerk and Manuel (2008a), Schmidt and Dorosh (2009), Kaufmann and Kraay (2007), Kaufmann et al. (2010), Noble et al. (2010), Razafindrakoto and Roubaud (2010), Cardona and Carreño (2011), Sovacool and Mukherjee (2011), Collomb et al. (2012), Magee et al. (2012), Nussbaumer et al. (2012), Emerson et al. (2012), Ravallion (2012), O'Hare and Gutierrez (2012), van Staveren (2012), and de Sherbinin et al. (2013).

2 See, for example, Vincent (2004), Sullivan and Meigh (2005), Eakin and Bojórquez-Tapia (2008), Balica et al. (2009), Confalonieri et al. (2009), Füssel (2009), Gbetibouo and Ringler (2009), Hahn et al. (2009), Jean-Baptiste et al. (2011), Sullivan (2011), Abson et al. (2012), Balica (2012b), Balica et al. (2012), Tate (2012), Torres et al. (2012), and Confalonieri et al. (2013).

3 For more information about the HDI, see Lawrence et al. (2002), Molle and Mollinga (2003), Chowdhury and Squire (2006), Heidecke (2006), Stapleton and Garrod (2007), Klugman et al. (2011), Nguefack-Tsague et al. (2011), Wolff et al. (2011), Torres et al. (2012), and Tofallis (2013).

An indicator can represent a single variable or a combination of variables. Throughout this paper, indicators representing single variables are referred to as *individual indicators,* while measures representing the integration of multiple individual indicators are referred to as *composite indices*. Once *baseline conditions* (i.e., existing conditions, which serve as a foundation for analysis) are benchmarked, an individual indicator or a composite index can be evaluated over time at regular intervals to monitor changes in system status or to track trends in system performance (Organisation for Economic Co-operation and Development [OECD], 2008; Balica, 2012b).

A composite index for climate change vulnerability and resilience assessment may serve a variety of purposes and functions. Composite indices aim to capture complex realities and multidimensional concepts that cannot be adequately represented by an individual indicator or by an unstructured, disaggregated set of individual indicators such as indicator sets presented using a basket of indicators or a dashboard approach (Kenney et al., 2012). Ideally, the *process* of designing and implementing a composite index is reflexive and serves to: raise awareness; promote debate and dialogue; and improve understanding and communication of the complex, multidimensional issue. Process-oriented composite indexing should help build consensus among stakeholders and support decision-making.

Given these multiple purposes and functions, composite index approaches may be well-suited to:

- help assess and track vulnerability and resilience to climate variability and change at national and subnational scales;
- analyze and compare units of analysis in particular geographic areas or socioeconomic sectors;
- estimate expected or possible future climate vulnerability and resilience for comparison with assessments of past and current conditions by adjusting input values according to future climate and socioeconomic scenarios and projections; and
- help guide policy decisions, set priorities, target resources, and manage progress toward climate change adaptation and resilience.

Composite indices are one method of conducting spatial vulnerability assessments, as discussed in the USAID African and Latin American Resilience to Climate Change (ARCC) Project working paper on "Spatial Climate Change Vulnerability Assessments: A Review of Data, Methods, and Issues" (de Sherbinin, 2013). Readers may also wish to refer to the ARCC report "Mali Climate Vulnerability Mapping" for an example of climate vulnerability index development and mapping (de Sherbinin et al., 2014).

Later in this paper, we make recommendations for the development of composite indices. In summary, several important issues need to be considered and some common challenges need to be addressed. The reasons, assumptions, and underlying decision-making processes behind all methodological choices should be made clear. Developers of climate vulnerability and resilience indices should strive to articulate coherent and compelling theoretical and conceptual frameworks and to select the most appropriate and credible indicators to represent key aspects of interconnected physical, social, demographic, economic, political, institutional, environmental, ecological, and resource systems. From the outset of this process, index developers should explicitly identify and communicate overarching values and principles, underlying assumptions and theories, frameworks of analysis, intended goals and audiences, available data sources, and data limitations. They must also make methodological choices about how to organize, standardize, weigh, and aggregate the selected indicators to build index components (subindices) and to arrive at the final index results. Uncertainty analysis and sensitivity analysis, essential to index development and indicator selection, are used to assess and compare the robustness of alternative index designs and rankings.

Section 2 identifies the advantages, disadvantages, and limitations of using composite indices. Section 3 describes key theoretical and methodological considerations and commonalities by explaining 11 essential steps and decisions involved in composite index design and development. This section provides a general framework and set of criteria to help guide evaluations of specific composite indices. Section 3 includes an overview table to facilitate comparison of six selected composite indices according to these 11 steps. These six examples have been designed and implemented within the past decade to assess relative vulnerability to climate variability and change at subnational levels. These indices were selected because they represent recent efforts at subnational levels to develop indices on climate-sensitive systems or sectors, such as water, agriculture, food, livelihoods, human health, river basins, urban areas, and coastal regions. An additional criterion for inclusion was some degree of implementation in African, Latin American, and/or Caribbean contexts. Summaries of the six selected composite indices are presented in an Annex to illustrate the 11 essential stages and evaluation criteria. Section 4 discusses current best practices and key challenges. Section 5 offers concluding remarks and summarizes recommendations.

2.0 COMPOSITE INDICES: ADVANTAGES, DISADVANTAGES, AND LIMITATIONS

The power of the composite index approach is in its ability to portray the results of an integrated analytical framework. While individual indicators can be informative, a well-designed and rigorously implemented composite index has the potential to capture "the bigger picture," i.e., the multidimensionality of complex systems, and to provide summary statistics that communicate system status and trends to a variety of relevant audiences (Booysen, 2002; Hahn, 2008; Zhou and Ang, 2009; Balica, 2012b; Ravallion, 2012). Therefore, a potential advantage of designing a composite index to analyze multidimensional complex systems is its understandability when results are presented as scores or rankings that key stakeholders, decision makers, and the general public can easily comprehend (Kenney et al., 2012).

In addition to benchmarking baseline conditions and tracking performance over time, composite indices offer flexibility as tools that can be shaped to meet the needs of decision makers and stakeholders (Booysen, 2002). Composite index designs can and should be adjusted and refined over time. As improved or new data sets become available, they can be used to substitute previously used data sets or added to the index. Thus, the process of composite index design often helps guide future research, data collection, and data improvement efforts by revealing weaknesses and gaps in knowledge domains and data systems.[4]

By improving understanding of social-ecological conditions and trends, climate vulnerability and resilience indices can help societies to identify priorities, establish and refine standards, develop policy guidelines, determine appropriate adaptations, set targets, and allocate resources for vulnerability reduction and resilience enhancement. To meet these goals, composite indices should be developed through participatory processes that encourage input and feedback from experts and/or that incorporate public opinion. By serving as a point of entry or a "boundary object," a composite index can help promote multi-stakeholder dialogue toward establishing common understanding and overcoming sociopolitical barriers to decision making (Preston et al., 2011: 183). In other words, if designed and used in ways that foster multi-stakeholder participation and convene experts, practitioners, policymakers, and citizens, composite indices have the potential to promote collaborative formulation of coordinated development and climate change adaptation strategies, help build consensus, and inform collective action. The range of stakeholders who should be involved in the composite index development process will depend on the goals of the particular effort.

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[4] It is worth noting that there is a trade-off between improving indices with new data and continued development of comparable indicators over time. Index creators need to determine which goal is more important: to reflect the latest science or to ensure comparability with past analyses.

It is important to be aware that the aggregation of individual indicators into a composite index to produce a summary statistic results in a loss of specificity and may mask important information about individual indicators (Molle and Mollinga, 2003; Abson et al., 2012; Kenney et al., 2012). Composite indices may fail to capture the interconnectedness of indicators, ignore important dimensions that are difficult to measure, and disguise weaknesses in some components (Molle and Mollinga, 2003; Zhou and Ang, 2009; Abson et al., 2012).

Maggino and Zumbo (2012) argue that a potential advantage of developing composite indices is that they can help to overcome problems concerning precision, reliability, accuracy, and validity that are associated with using individual indicators, i.e., a variable that is not directly observable through an individual indicator may require integration of multiple indicators, each corresponding to a particular aspect of the variable. Kaufmann and Kraay (2007) assert that indicator aggregation has the potential to reduce the influence of measurement error associated with any individual indicator. On the other hand, others warn that indicator aggregation tends to amplify the influence of measurement error and that the problems referenced above that are associated with individual indicators are propagated in the process of aggregation into a composite index (M. Gall, personal communication, August 20, 2013).

It is not necessary to model the entire system of interest to effectively measure its climate vulnerability or resilience. It may be possible to identify a parsimonious set of indicators to construct an effective and efficient measure (M. Gall, personal communication, August 20, 2013). In a recent evaluation of several social vulnerability indices, Gall (2007) found that, in most cases, the index developers over-specified their indices without increasing accuracy. Barnett et al. (2008: 107) argue that indices "should utilize fewer indicators based on widely available and robust data." However, others argue that oversimplification of a complex system risks omission of significant components and inaccurate representation of the intended condition or process (Vincent, 2007). This topic is taken up in greater detail in Section 3.4.

Index-based analyses and comparisons of climate change vulnerability and resilience can be more challenging when local geographic, ecological, and socioeconomic contexts vary widely within a given area of interest. For example, it may be more challenging to analyze countries possessing both coastal and inland districts than landlocked countries at subnational levels if the same set of indicators is not appropriate for different ecological zones within a country.

Given these and other related concerns, composite indices have the potential to misguide policy and practice if used in an indiscriminating manner or if results are misinterpreted, misrepresented, or overstated. Therefore, care and vigilance should be exercised to avoid such risks

3.0 STEPS AND DECISIONS IN THE COMPOSITE INDEX DESIGN AND DEVELOPMENT PROCESS

> *The quality of a composite indicator, as well as the soundness of the messages it conveys, depend not only on the methodology used in its construction but primarily on the quality of the framework and the data used. A composite based on a weak theoretical background or on soft data containing large measurement errors can lead to disputable policy messages, in spite of the use of state-of-the-art methodology in its construction…Whichever framework is used, transparency must be the guiding principle of the entire exercise.* (OECD, 2008: 17)

> *Far too often…indicators are developed and used without consideration of the conceptual definition of the phenomenon and a logical cohesion of the conceptual definition and the analytic tools and strategies. In our experiences, the lack of any logical cohesion is often masked by the use and application of sophisticated procedures and methods that can deform reality producing distorted results.* (Maggino and Zumbo, 2012: 202, 205)

The methodological choices made during various stages of composite index construction involve assumptions, subjectivity, and uncertainties that should be recognized, addressed, and communicated throughout the analytic process (Eriksen and Kelly, 2007; OECD, 2008; Balica and Wright, 2010; Sullivan, 2011; Balica, 2012b; Permanyer, 2012; Tate, 2012, 2013). While the steps outlined below are presented in a logical procedural sequence, in practice, several of these stages are likely to take place concurrently as participants collaborate to develop, adjust, and refine the evolving index; each stage should be revisited after the initial version of the index is created (Booysen, 2002).

The following guidelines, i.e., key steps and best practices drawn from the literature on composite indices, provide benchmarks against which to qualitatively evaluate the six examples — presented in Table 1 and the Annex — of existing indices focused on climate-sensitive systems or sectors. Table 1 in the following pages facilitates an at-a-glance comparison of the six examples, while the summaries presented in the Annex provide a more detailed examination. For example, a quick review of Table 1 shows that both the Flood Vulnerability Index (FVI) and the Coastal City Flood Vulnerability Index (CCFVI) integrate indicators of exposure (E), susceptibility (S), and resilience (R) to calculate vulnerability (V = E + S – R) and that, while the FVI is structured into four major components (social, economic, environmental, and physical), the CCFVI is structured into three major components (hydro-geological, socioeconomic, and political-administrative). The FVI and CCFVI summary in the Annex provides the reader with the specific indicators selected for each of the four major components of the FVI and at which geographic scale (see Figure 2 in the Annex). For instance, in the social component, five resilience indicators are applied at the river basin scale, sub-catchment scale, and urban area scale: 1) warning system, 2) evacuation routes, 3) institutional capacity, 4) emergency service, and 5) shelters.

TABLE 1. OVERVIEW OF SIX COMPOSITE INDICES DESIGNED TO ASSESS RELATIVE VULNERABILITY TO CLIMATE CHANGE AT SUBNATIONAL LEVELS

	Climate Vulnerability Index (CVI)	Flood Vulnerability Index (FVI) and Coastal City Flood Vulnerability Index (CCFVI)	Livelihood Vulnerability Index (LVI) and LVI-IPCC	Socio-Climatic Vulnerability Index (SCVI)	Water Poverty Index (WPI)	Water Vulnerability Index (WVI)
Purpose and Theoretical/ Conceptual Framework	Assessment of relative vulnerability to existing climate variability within a region or zone. Focuses on water-related issues. Combines social, economic, environmental, and physical factors. Builds on the WPI (Connor and Hiroki, 2005; Sullivan, 2011).	Flood vulnerability assessment for flood risk management. Initially developed to assess vulnerability to river flooding. Extended to assess vulnerability to coastal flooding. Intended to serve as a tool for policy and decision makers. The FVI and CCFVI integrate indicators of exposure (E), susceptibility (S), and resilience (R) based on the general vulnerability (V) concept: $V = E + S - R$	Assessment of household livelihood vulnerability to climate variability and change. Builds on the *sustainable livelihoods approach* (Chambers and Conway, 1992) to identify the household characteristics that contribute most to climate vulnerability.	Assessment of social vulnerability to climate change. Torres et al. (2012) do not explicitly define the conceptual framework, but it appears to combine the *risk-hazard* and *social vulnerability* approaches.	Assessment of water stress and water scarcity. Although the WPI did not initially focus on climate change, it provided a basis for the development of both the CVI and the WVI (Sullivan, 2011; Balica, 2012b). The WPI applies a *basic needs approach* and is based on the premise that access to adequate and sustained supplies of safe water and adequate sanitation are essential for social and economic development and the reduction of poverty, hunger, and disease.	Assessment of water sector vulnerability to climate change. Comparison of water vulnerability profiles and identification of main drivers at the municipal scale. Tool to support water governance, water management across heterogeneous basins, and local efforts toward integrated water resources management. Builds on the WPI (Sullivan, 2011).
Geographic Scope/ Regions and Scales Covered in Existing Studies	Focuses on West Africa at the national level. Focuses on Peru at the department and district levels.	FVI: Focuses on river basin scale (Danube, Mekong, Rhine); sub-catchment scale (Tisza, Timis, and Bega in Danube; Mun in Mekong; Neckar in Rhine); urban scale (Timisoara City, Romania; Phnom Penh City, Cambodia; Mannheim City, Germany). CCFVI: Focuses on Buenos Aires (Argentina), Calcutta (India), Casablanca (Morocco), Dhaka (Bangladesh), Manila (Philippines), Marseille (France), Osaka (Japan), Shanghai (China), and Rotterdam (the Netherlands).	Focuses on Moma and Mabote districts in Mozambique.	Focuses on Brazil at a spatial resolution of 1° x 1° latitude/ longitude grid.	Focuses on the national scale for 140 countries (Lawrence et al., 2002). Focuses on various subnational scales in South Africa (Sullivan et al., 2003; Cullis and O'Regan, 2004), Tanzania (Sullivan et al., 2003), Benin (Heidecke, 2006), Kenya (Giné Garriga and Pérez Foguet, 2010), Mexico (Fenwick, 2010), and Peru (Pérez Foguet and Giné Garriga, 2011).	Developed as an integrative tool for basin- and local-level water managers and decision makers to consider site-specific drivers and adaptation options; applied to compare 87 South African municipalities within the Orange River Basin (Sullivan, 2011).

	Climate Vulnerability Index (CVI)	Flood Vulnerability Index (FVI) and Coastal City Flood Vulnerability Index (CCFVI)	Livelihood Vulnerability Index (LVI) and LVI-IPCC	Socio-Climatic Vulnerability Index (SCVI)	Water Poverty Index (WPI)	Water Vulnerability Index (WVI)
Applicable Spatial Scales of Analysis	Applicable at multiple spatial scales. Spatially nested application recommended.	Applicable at multiple and nested spatial scales FVI: river basin, sub-catchment, urban area CCFVI: urban area	Applicable at district and community levels	Applicable at multiple and nested spatial scales.	Applicable at multiple and nested spatial scales.	Applicable at multiple and nested spatial scales.
Structural Design/Major Components	Six major components: 1) Resources 2) Access 3) Capacity 4) Use 5) Environment 6) Geospatial	Four major components of the FVI: 1) Social 2) Economic 3) Environmental 4) Physical Three major components of the CCFVI: 1) Hydro-geological 2) Socioeconomic 3) Political-administrative	Seven major components of the LVI: 1) Socio-demographic profile 2) Livelihood strategies 3) Health 4) Social networks 5) Food 6) Water 7) Natural disasters and climate variability Three major components of the LVI-IPCC: 1) Exposure 2) Sensitivity 3) Adaptive capacity	Two major components: 1) A climate change index such as the Regional Climate Change Index (RCCI), which synthesizes over 100 climate model projections; and 2) A social vulnerability index, e.g., combining demographic density (inhabitants/km^2) and HDI scores.	Five major components: 1) Resources 2) Access 3) Capacity 4) Use 5) Environment	Two major components: 1) Supply-driven vulnerability of water systems (four subcomponents; eight individual indicators) 2) Demand-driven vulnerability of water users (four subcomponents; eight individual indicators)
Indicator Selection Criteria/ Approach	• Data availability • Practicality • Locally relevant	• Deductive approach used to identify the best possible indicators • Data availability • Data accuracy • Reliability of data sources • Ease of quantification • Avoidance of redundancy • Expert opinion	• Extensive literature review on variables that affect exposure, sensitivity, and adaptive capacity to climate change • Practicality of data collection by means of household surveys	• Data availability • Indicators obtained from existing data sources only • Spatial coverage • Comparability of data sets • Strengths and weaknesses of each indicator • HDI salience and resonance with policymakers	• Data availability • Practicality • Indicators obtained from existing data sources only	• Consultation of previous qualitative research investigating local perceptions of water vulnerability • Qualitative information from interviews and workshops • Data availability • Expert opinion
Data Sources and Data Quality	Best and most recent available data at the appropriate spatial and temporal resolutions. If data gaps are identified, either use proxy data or gather new data.	Data sources vary according to spatial scale of analysis. May include government agencies (e.g., national statistical agencies), research institutes, and universities.	Primary data gathered using household surveys designed with a clearly framed theoretical, conceptual, and analytical approach.	Existing climate model projections (synthesized to calculate a climate change index); demographic census data; HDI.	Data sources vary according to spatial scale of analysis. May include government agencies (e.g., national statistical agencies), research institutes, and universities.	National statistical agency (Statistics South Africa; www.statssa.gov.za) databases and national hydrologic and meteorologic data from other relevant sources.

	Climate Vulnerability Index (CVI)	Flood Vulnerability Index (FVI) and Coastal City Flood Vulnerability Index (CCFVI)	Livelihood Vulnerability Index (LVI) and LVI-IPCC	Socio-Climatic Vulnerability Index (SCVI)	Water Poverty Index (WPI)	Water Vulnerability Index (WVI)
						Census data, population growth rates, land cover data, catchment boundaries, water management areas, local municipality boundaries, soil erodibility index (sediment yield), water demand for agriculture, domestic use, mining and industry, transfers, and power generation. Data for South Africa is well-organized, available from a variety of sources, and relatively uniform in quality (Sullivan, 2011: 630).
Data Trans-formation	Not addressed by Sullivan and Meigh (2005).	Dimensionless FVI equations developed by using fractions with indicators as part of a numerator or denominator, depending on their effect on flood vulnerability. Use of "per capita" or "per property" values to eliminate the influence of the basin's scale.	An equation previously used in the HDI methodology to calculate the life expectancy index was adapted to normalize LVI subcomponents measured on different scales.	Raster data normalized to a 1° resolution grid.	Each component is standardized to fall in the range of 0 to 100, giving a final WPI value between 0 and 100.	Nine out of 16 individual indicators normalized (Sullivan, 2011: 631).
Data Reduction and Factor Retention	Not addressed by Sullivan and Meigh (2005).	FVI: Number of indicators reduced by combining use of derivative and correlation methods with a survey of expert knowledge (Balica and Wright, 2010). CCFVI: multi-collinearity analysis applied to reduce from 30 to 19 coastal indicators (Balica, 2012a; Balica et al., 2012).	Begins with a limited set of indicators.	Begins with a small set of candidate indicators.	Principal component analysis (PCA) (e.g., Cho et al., 2010; Giné Garriga and Pérez Foguet, 2010). Cho et al. (2010) proposed two simplified WPIs, a three-component version and a two-component version, as more cost-effective and viable alternative approaches.	Begins with a small set of candidate indicators.

	Climate Vulnerability Index (CVI)	Flood Vulnerability Index (FVI) and Coastal City Flood Vulnerability Index (CCFVI)	Livelihood Vulnerability Index (LVI) and LVI-IPCC	Socio-Climatic Vulnerability Index (SCVI)	Water Poverty Index (WPI)	Water Vulnerability Index (WVI)
Weighting and Aggregation Methods	Initially, components are equally weighted (i.e., set to 1) to establish a base rate. This step is followed by experimentation with alternative weighting schemes based on participatory consultation and expert opinion. The weight for each component is context-specific.	Stakeholder involvement in weighting indicators is recommended (Balica et al., 2012).	Balanced weighted average approach where each subcomponent contributes equally to the overall index even though each major component comprises a different number of subcomponents. Weighting scheme can be adjusted.	Weighting not addressed by Torres et al. (2012). Aggregation of gridded data.	Equal or differential weights can be applied to both the components and subcomponents. Equal weights should be applied initially to calculate a baseline value. Giné Garriga and Pérez Foguet (2010) compare different aggregation methods.	Interviews and workshops held to gather additional qualitative information from the perspective of local people. These sources of qualitative data were analyzed and interpreted to evaluate the relative importance of different aspects of vulnerability and to explore differential weighting schemes.
Uncertainty and Sensitivity Analysis	Not addressed by Sullivan and Meigh (2005).	Insufficiently addressed in the available literature. There is a brief mention of sensitivity analysis in the Discussion section of Balica et al. (2009: 2579).	Not addressed in the available literature.	Not addressed by Torres et al. (2012).	Giné Garriga and Pérez Foguet (2010) apply sensitivity analysis to test the robustness of the WPI and improve its transparency.	Not addressed by Sullivan (2011).
Visualization of Results	Results are mapped (spatial vulnerability assessment).	Bar graphs, line graphs, and spider diagrams are used.	The seven component scores of the LVI are displayed using spider diagrams. The three component scores of the LVI-IPCC are displayed using triangle diagrams.	Results are mapped (spatial vulnerability assessment).	Results have been mapped, displayed in bar graphs, and displayed in spider diagrams.	Results are displayed graphically using multi-axis graphs (spider diagrams) showing component values for different municipalities and mapped (spatial vulnerability assessment) to show variation in vulnerability at municipal level across the basin.
Validation and Verification	Further work is needed to improve the methodology. Wider application and component refinement recommended.	The FVI methodology was first developed and applied at the river basin scale (Conner and Hiroki, 2005). It has since been refined and extended to other spatial scales (Balica, 2007, 2012; Balica and Wright, 2009, 2010; Balica et al., 2009, 2012). Application to additional case studies at various scales is expected to lead to further methodological improvements.	Further work and wider application needed to improve the methodology. Hahn et al. (2009) recommend refinement of the Social Networks subcomponents.	Further work and wider application needed to improve the methodology. Torres et al. (2012) recommend refinements by using higher-resolution regional climate models and more advanced statistical downscaling techniques, and by experimenting with other social vulnerability indicators.	The WPI has been applied at a variety of scales, in several different countries, and by multiple authors. A rich literature, published from 2002 to 2011, documents methodological challenges and improvements.	Further work is needed to refine the methodology and to improve its validity, for example, by including more information on water quality (Sullivan, 2011).

	Climate Vulnerability Index (CVI)	Flood Vulnerability Index (FVI) and Coastal City Flood Vulnerability Index (CCFVI)	Livelihood Vulnerability Index (LVI) and LVI-IPCC	Socio-Climatic Vulnerability Index (SCVI)	Water Poverty Index (WPI)	Water Vulnerability Index (WVI)
Transparency and Flexibility	Offers transparent methodology. Offers a flexible design.	Transparent methodology made available for public review and scrutiny in multiple publications and online at unesco-ihe-fvi.org. This website is intended to serve as a collaborative interface to create and maintain a "network of knowledge" that can support advancement of the methodology. The FVI offers a flexible design. Selection of indicators can be scale-, context-, and site-specific.	Offers transparent methodology. Offers a flexible design.	Offers transparent methodology. Offers a flexible design.	Offers transparent methodology. Offers a flexible design.	Offers transparent methodology. Offers a flexible design.
Main Citation(s)	Sullivan and Meigh (2005)	Balica (2007, 2012a, 2012b); Balica and Wright (2009, 2010); Balica et al. (2009, 2012); Connor and Hiroki (2005); United Nations Educational, Scientific, and Cultural Organization (UNESCO)-IHE (2012)	Hahn (2008); Hahn et al. (2009)	Giorgi (2006); Torres et al. (2012)	Cho et al. (2010); Cullis and O'Regan (2004); Fenwick (2010); Giné Garriga and Pérez Foguet (2010, 2011); Heidecke (2006); Lawrence et al. (2002); Molle and Mollinga (2003); Pérez-Foguet and Giné Garriga (2011); Sullivan (2002); Sullivan and Meigh (2007); Sullivan et al. (2003, 2006)	Sullivan (2011)

3.1 DEVELOPING A COHERENT AND COMPELLING THEORETICAL AND CONCEPTUAL FRAMEWORK

To develop a composite index successfully, it is important to have a clear understanding of how it will be used, i.e., the decisions the index is intended to inform, the information needed to inform those decisions, and the key elements required to make informed decisions. Therefore, the following questions should be considered during the composite index theorizing, conceptualization, and framing process:

- What is the primary motivation for composite index development and use?
- What specifically is the composite index intended to measure and monitor, and toward what goal(s)?
- Who is intended to benefit from and/or gain insights from the composite index results?
- What types of benefits and/or insights are those people expected to gain?

By clearly defining the target concepts, such as the multidimensional concepts of climate vulnerability and climate resilience, and by establishing the theoretical framework, context, purpose, and target audience(s) for the index, process participants can delineate meaningful broad themes, core index categories (often referred to as index domains or dimensions), and subcategories needed to organize and group indicators to allow for aggregation. A few examples of broad themes related to climate change are flood vulnerability, water sector vulnerability, and livelihood vulnerability. These broad themes may be broken down into core vulnerability index categories such as climate exposure, sensitivity or susceptibility, and adaptive capacity or resilience. Within a core category, individual indicators may be grouped into subcategories (and subindices) such as poverty, health infrastructure, education, access to resources and services, and quality of governance. Throughout this theorizing, conceptualization, and framing process, participants should explore meaningful variables and corresponding indicators or indicator sets to operationalize the composite index in accordance with the "fitness-for-purpose" principle (OECD, 2008; see also Hinkel, 2011: 203-205). In other words, the quality of the composite index depends on the careful and thoughtful selection and combination of variables to fit the needs of the intended users.

The initial stage of composite index development should focus on exploring and evaluating relevant theoretical approaches and key concepts, as well as conceptualizing the composition and structure of the complex system of analysis or the multidimensional issue of interest (Booysen, 2002; Nardo et al., 2005; Eriksen and Kelly, 2007; OECD, 2008; Kenney et al., 2012; Maggino and Zumbo, 2012; Ravallion, 2012). To create a robust composite index, experts and stakeholders should be involved at this stage to contribute their knowledge and experience by providing multiple viewpoints and insights regarding evolving bodies of theory, terminology and conceptual definitions, normative debates and agendas, system attributes of concern, temporal considerations, and measurement practice. As Bohle et al. (1994), Eakin and Luers (2006), Smit and Wandel (2006), Füssel (2007), Jean-Baptiste et al. (2011), Preston et al. (2011), Kienberger (2012), and others discuss, existing theoretical and conceptual approaches to vulnerability research and vulnerability assessment include, but are not limited to:

- the *risk-hazard approach* to vulnerability, which addresses biophysical exposure and sensitivity (Füssel, 2007; Costa and Kropp, 2013);
- the place-based *social vulnerability approach*, which builds on the risk-hazard approach by explicitly focusing on the demographic and socioeconomic factors that increase or reduce the impacts of hazard events on local populations (Cutter et al., 2000, 2003, 2009; Cutter and Finch, 2008; Cutter, 2010);

- the disaster *pressure and release (PAR) model,* which emphasizes the underlying (i.e., root) causes of disaster and the social production of risk (Blaikie et al., 1994; Wisner et al., 2004; Füssel, 2007);
- the *political economy approach* to vulnerability*,* which analyzes social, economic, and political processes in historical context and asks who is most vulnerable and why (Füssel, 2007);
- the *political ecology approach* to vulnerability, which builds on the political economy approach but delves deeper to examine social inequalities and social conflicts, as well as differential impacts and differential recovery, coping, and adaptation capacities;
- the *social-ecological resilience approach*, which conceptualizes vulnerability as a dynamic property of coupled human-environment systems that respond to a variety of stresses and shocks (including disturbances associated with hurricanes, floods, landslides, heat waves, droughts, and wildfires), and suggests that human-managed resource systems should allow for dynamic learning and enhance the flow of different types and sources of knowledge across multi-scale nested governance systems (e.g., Ernstson et al., 2010; Cabell and Oelofse, 2012); and
- *integrated (*or *hybrid) approaches* (Eakin and Luers, 2006; Füssel, 2007; IPCC, 2012).

If those engaged in the composite index creation process determine that previously developed approaches are insufficiently compelling or not fit-for-purpose, they may decide to develop their own theoretical and conceptual framework.

3.2 SCOPE AND SPATIAL SCALE OF ANALYSIS

Climate vulnerability and resilience are geographically and socially differentiated, reflecting conditions, processes, driving forces, and interacting factors that vary depending on spatial scale and local context. Thus, one of the major challenges of composite index development is to select indicators that are appropriately matched and most relevant to the spatial scale of vulnerability assessment, decision-making, and policy and management objectives. The overall spatial extent (scope) of the study region and the comparative units of analysis may correspond closely to standard administrative units (e.g., nations, states/provinces, counties, municipalities, districts, villages, census enumeration units, households, firms), or they may be other types of regions and exposure units (e.g., hydrologic units such as river basins, watersheds, and aquifers; coastal regions; ecosystem types; city regions; transboundary zones; communities; raster cells) (Parris and Kates, 2003; Kenney et al., 2012; Costa and Kropp, 2013).

Different patterns of vulnerability and resilience may result from applying the same index approach at different spatial scales (Cullis and O'Regan, 2004; Tate, 2012). Correlations between variables may increase with the level of aggregation (Tate, 2013). National-level indicators and indices mask higher-resolution variations in vulnerability and resilience at local scales (Sullivan, 2002; Vincent, 2004; McLaughlin and Cooper, 2010; Kenney et al., 2012). Therefore, while it may be feasible to downscale certain broad-scale composite index approaches successfully (Birkmann, 2007), it would be unwise to simply adopt a national-level index approach for a subnational- or local-scale study without adequate consideration of the potential need for modifications and adjustments; similarly, aggregation of local scale findings to estimate vulnerability and resilience at broader scales may be methodologically questionable (Vincent, 2007). Instead, the structure and composition of a composite index should take scale-dependent variations into account to be as scale-specific as possible. In some cases, it may be feasible to develop a spatially nested approach to indicator selection and index construction for coordinated assessments at micro-, meso-, and macro-scales of analysis (Sullivan and Meigh, 2005; Balica and Wright, 2010; McLaughlin and Cooper, 2010; Kenney et al., 2012).

3.3 DETERMINING THE STRUCTURAL DESIGN OF A CLIMATE VULNERABILITY OR RESILIENCE INDEX

Most social vulnerability indices adopt one of three commonly used structural designs: (a) *deductive*; (b) *hierarchical*; or (c) *inductive* (Tate, 2012, 2013). None of these architectures is inherently better or worse than another, but they may vary in robustness and performance depending on the index configuration (Tate, 2012). The deductive approach is theory-driven and typically synthesizes a relatively small set of indicators (Niemeijer, 2002; Vincent, 2007; Balica and Wright, 2010; Hinkel, 2011; Balica, 2012b). Hierarchical designs commonly synthesize roughly 10 to 20 indicators arranged into subindices representing major themes or core domains, enabling meaningful positioning of each indicator to represent distinct components of the system of analysis (Maggino and Zumbo, 2012; Tate, 2012, 2013). The inductive approach to composite index development is primarily data-driven and tends to begin with a large set of candidate indicators (more than 20 variables), which is reduced to a smaller set prior to aggregation (Niemeijer, 2002; Vincent, 2007; Balica, 2012b; Tate, 2012, 2013). All approaches must: consider how index components may be nested, consider how certain elements may fit more than one category, and use sensitivity analysis to understand how distinct indicators within or across categories influence the numeric outputs.

3.4 THE INDICATOR SELECTION PROCESS AND SELECTION CRITERIA

Generally, a composite index is developed to either measure a multidimensional concept or to describe a system. In cases where the goal is to measure a multidimensional concept, aggregation of a parsimonious set of indicators can be effective. Large sets of indicators are needed when the goal is to construct a model of a system.

While indicators are often obtained from existing data sources, they can also be sourced by planning and implementing new data collection efforts. Once a pool of potential indicators is identified, several considerations need to be addressed during the indicator selection process for integration in a composite index (Parris and Kates, 2003; Adger and Vincent, 2005; Nardo et al., 2005; Sullivan and Meigh, 2005; OECD, 2008; Van de Kerk and Manuel, 2008a; Hinkel, 2011; Kenney et al., 2012). The strengths and weaknesses of each candidate indicator should be discussed, assessed, and recorded in a summary table on data set characteristics (OECD, 2008). As stated at the beginning of this section, it is important to be aware that the variables that are easiest to measure or most readily available are not necessarily analytically sound or valid indicators. As Barnett et al. (2008: 106) recognize, indicators are sometimes "selected not because the data reflect important elements of a model of vulnerability, but because of the existence of data that are relatively easy to access and manipulate." Care should be taken to avoid this pitfall.

Decisions about whether to include or exclude indicators involve highly pragmatic criteria, as follows:

- *Data availability* from public or private sources, including the *cost, frequency*, *timeliness*, *consistency,* and *accessibility* of available data and the temporal and spatial *coverage* for a particular indicator;
- If periodic updates are planned, then it is important to ascertain institutional commitments to update and maintain constituent data sets, and to choose data accordingly;
- In situations where new data is to be collected, the *measurability* of the variable given time, labor, and budget constraints;
- *Data quality* (e.g., data accuracy; whether or not the data are adequately georeferenced and dated);
- The degree of *salience* (How relevant is the indicator to the intended users of the index?); and
- The degree of *audience resonance* (How meaningful is the indicator to the intended audience?).

Additional selection criteria may be highly subjective and shaped by theoretical choices and value judgments, including potentially contested views about indicator *relevance, suitability*, *construct validity* (i.e., whether or not the indicator measures the intended component of the index), and *representativeness* (i.e., whether or not the indicator represents underlying vulnerability or resilience). Indicator selections are often shaped by statistical issues, such as the *comparability* of available data sets and whether or not the available data samples are sufficiently large to ensure statistically significant results. All indicator data sources and methods should meet acceptable standards of *transparency, credibility, reliability,* and *legitimacy*. If any compromises are made in the indicator selection process for practical reasons (e.g., to overcome data scarcity), then these compromises should be made explicit.

Indicator selection should be an iterative rather than a linear process. That is, once a set of indicators has been selected and aggregated, the composite index must be tested using uncertainty analysis and sensitivity analysis (see Section 3.9), the index output must be evaluated, and, based on the results of these tests and evaluations, the set of indicators must be adjusted to improve the quality of the index (M. Gall, personal communication, August 20, 2013).

3.5 EVALUATION OF DATA QUALITY AND POTENTIAL SOURCES OF DATA ERROR

Evaluation of data quality during the indicator selection process should include the identification and assessment of all potential sources of data error in social, economic, political, environmental, biological, and physical data sets.[5] The margins of error of all indicators should be understood, explicitly acknowledged, and disclosed (Kaufmann and Kraay, 2007). Measurement error of input data is a source of uncertainty in index output (Tate, 2013). The combination of different data sources may amplify the influence of measurement error and thereby bias final results.

Coverage error that results in missing some important segments of the population is a common concern in the evaluation of both census (e.g., undercounts) and survey data quality (Tate, 2013). Other types of measurement error associated with surveys include sampling error, problems in survey dissemination, non-response, ambiguities in survey questions or responses, differences of opinion between respondents, and data processing errors (Kaufmann and Kraay, 2007; OECD, 2008). Missing values and errors due to data updating and formula revisions are additional concerns (Wolff et al., 2011).

When individual indicators are derived from geospatial Earth observation data, such as satellite-based remote sensing, evaluation of data quality must consider the degree of adherence to data quality standards and the level of completeness of metadata records (Yang et al., 2013). In the case of spatial data on the occurrence and distribution of climate-related hazards, data sets may have significant temporal and spatial gaps. Problems associated with climate-related station data collection systems, such as inadequate spatial coverage of hydrometeorological observation networks and weak data management capacities, can cause data error in a variety of data sets including those on rainfall, temperature, stream flow, wind speed, soil moisture, and sea level.

Daly (2006: 708) highlights issues and difficulties with assessing error in high-resolution spatial climate data sets derived from remote sensing, numerical models, and station data interpolation, including the need for "the user to have a working knowledge of what the basic spatial climate-forcing factors are; how they affect climatic patterns; where, when, and at what spatial scale they occur; and how they are handled by the major interpolation techniques." Spatial climate-forcing factors on precipitation and

5 It is admittedly difficult to ascertain sources of error or error levels in many data sets that are produced without peer review, and even in those that are peer reviewed. Many public domain data sets lack information on sources or levels of data error.

temperature patterns are physiographic features such as elevation, terrain, water bodies, and coastal proximity. Similarly, Bishop and Beier (2013) stress the trade-off between resolution and realism when using high-resolution gridded historical climate products, which are model outputs that usually have increasing uncertainty at higher resolutions.

3.6 OVERCOMING INCOMMENSURABILITY: DATA TRANSFORMATION

Once one or more indicator sets are selected, integration of the selected indicators into subindices and a final composite index may require data transformation by means of data normalization or data standardization techniques; that is, data sets measured using different scales or measurement units can be made comparable by transforming them into a common scale or measurement unit and/or by adjusting the directionality of the values by performing inverse adjustment (Booysen, 2002; Nardo et al., 2005; Cherchye et al., 2007; Barnett et al., 2008; OECD, 2008; Abson et al., 2012; Kenney et al., 2012; Tate, 2012, 2013). For example, in order to make values comparable across administrative units, values may be transformed to a fixed scale (e.g., percentages) or they may be denominated by population or land area. Inverse adjustment may be applied to data sets for attributes such as income, wealth, and access to medical care, in which higher values represent lower levels of vulnerability (Tate, 2013).

Indices adopting deductive and hierarchical designs commonly apply min-max normalization (min-max linear scaling) to transform values to a minimum-maximum scale (e.g., between 0 and 1), whereas indices using inductive designs tend to apply the z-score normalization method that produces variables with a mean of zero and a standard deviation of one (Nardo et al., 2005; Barnett et al., 2008; Tate, 2012, 2013). The z-score normalization method is preferable to min-max linear scaling when data sets contain extreme values (outliers), but in either case it may be necessary to trim the tails of the distribution (Booysen, 2002; Nardo et al., 2005; Tate, 2013). Cherchye et al. (2007) and Tate (2012) stress that the data normalization stage of composite index development deserves rigorous methodological scrutiny, since statistical artifacts may have a major effect on scores. Extreme values and skewed data sets should be identified and accounted for at this stage of the process, and log transformations may be required in order to approximate more of a normal distribution (OECD, 2008).

3.7 DATA REDUCTION AND FACTOR RETENTION

When starting with a large number of candidate indicators, it is desirable to reduce the pool by identifying the most significant indicators, removing indicators of low relevance, and minimizing the redundancy of highly correlated variables. A variety of statistical techniques and stakeholder engagement processes are available to carry out the indicator reduction process, such as exploratory factor analysis, principal component analysis (PCA), derivative method, correlation method, expert survey, and stakeholder discussion (Adger and Vincent, 2005; Balica and Wright, 2010; Balica et al., 2012; Babcicky, 2013).

A simple correlation table can help to identify which indicators are highly correlated with one another to the degree that one might safely be removed. When PCA is used to reduce a large indicator set to a smaller set of uncorrelated factors, the Kaiser criterion (i.e., eigenvalue greater than one) is usually applied to decide how many factors to retain (Deressa et al., 2008; OECD, 2008). However, as Tate (2012) points out, use of the Kaiser criterion may overestimate the number of factors to keep, and parallel analysis may be a better method for determining the number of factors to retain from a PCA.

3.8 WEIGHTING AND AGGREGATION METHODS

There are multiple approaches for weighting and aggregating components in the process of constructing a multidimensional composite index. Given the wide range of available options, analysts should make the weighting and aggregation methods they select transparent by providing clear documentation of procedures and by communicating how methodological decisions are shaped by the effort’s goals and underlying theoretical framework, conceptual definitions, the structural design of the index, the spatial scale of analysis, the properties of the data, and index dimensionality (OECD, 2008; Maggino and Zumbo, 2012). Assignment of numerical weights should be tested by sensitivity analysis.

Differential weighting, also referred to as *unequal weighting*, can be applied when there is sufficient knowledge and understanding of the relative importance of index components or of the trade-offs between index dimensions (Belhadj, 2012; Decancq and Lugo, 2013; Tate, 2013), whereas *equal weighting* is typically applied when the differences in component significance or the trade-offs between dimensions are poorly understood and therefore assignment of differential weights cannot be reliably justified, or when there is a lack of agreement about the appropriate weighting scheme (Booysen, 2002; Cherchye et al., 2007; OECD, 2008; Nguefack-Tsague et al., 2011; Belhadj, 2012; Tate, 2012, 2013; Decancq and Lugo, 2013; Tofallis, 2013). It is important to be aware that when an index synthesizes multiple dimensions, assignment of equal weights to individual indicators will lead to unequal weighting of index dimensions if the number of individual indicators in each dimension differs (OECD, 2008). If this is the case, it may be desirable to adjust the individual indicator weights, or to first aggregate subindices and then aggregate these to the overall index, so that the dimensions are equally weighted. Furthermore, as Tate (2013: 530) explains, "the existence of high correlations between indicators might introduce implicit weighting into an equal weighting scheme, as the associated dimensions could be effectively double counted."

When the decision is made to experiment with and set unequal weights to index components, these weights can be assigned by means of normative, data-driven, or hybrid approaches (Decancq and Lugo, 2013). Normative approaches include use of participatory methods — such as expert consultation, stakeholder discussion, and public opinion surveys — to inform weighting schemes on the basis of the expertise, experience, local knowledge, perceptions, value judgments, preferences, and insights of particularly relevant individuals and groups (Booysen, 2002; Chowdhury and Squire, 2006; Cherchye et al., 2007; Barnett et al., 2008; OECD, 2008; Kienberger, 2012; Decancq and Lugo, 2013). Data-driven approaches may be preferred when there is substantial disagreement among the participants or underrepresentation of key social groups as a result of participant selection bias.

Data-driven differential weighting procedures apply statistical methods to generate indicator weights. As Blancas et al. (2013) point out, use of statistical procedures to determine weights may help to counteract the influence of subjective decisions made at other stages of the index design process. Statistical methods, such as PCA and factor analysis, may be applied to test indicators for correlation, thus allowing analysts to adjust the weighting scheme by reducing the weights of correlated indicators or, as mentioned above in Section 3.7, to minimize correlation and identify a more parsimonious set by removing redundant indicators. PCA and factor analysis enable analysts to generate weighting schemes that account for as much of the variation in the data as possible with the smallest possible number of indicators (Deressa et al., 2008; OECD, 2008; Nguefack-Tsague et al., 2011; Abson et al., 2012; Tofallis, 2013). The results of a correlation-based PCA may provide justification for equal weighting (Nguefack-Tsague et al., 2011). A number of studies have used regression coefficients in linear regression or the inverse of the coefficient of variation to arrive at statistical weights (Tate, 2013).

Well-established data-driven approaches to statistical weighting and aggregation in composite index construction also include data envelopment analysis (DEA), the benefit-of-the-doubt (BOD) method, and multiple criteria decision analysis (MCDA) (Charnes et al., 1978; Nardo et al., 2005; Cherchye et al., 2007; OECD, 2008; Zhou and Ang, 2009; Hatefi and Torabi, 2010; Zhou et al., 2010; Rogge, 2012; Blancas et al., 2013; Tate, 2013; Tofallis, 2013). DEA is a flexible endogenous weighting method that eliminates the need for data normalization prior to weight setting; this facet may be seen as an important advantage in situations where normalization procedures are found to have an undesirable impact on index rankings (Cherchye et al., 2007). One of DEA's main conceptual starting points is that "(some) information on the appropriate weighting scheme for…performance benchmarking can in fact be retrieved from the…data themselves" (Cherchye et al., 2007: 117).

Commonly applied aggregation options include summation (additive aggregation), multiplication (geometric aggregation), and multicriteria analysis. It may be necessary to make the directionality (i.e., whether values are positive or negative) of the indicator set uniform before starting the aggregation process (Maggino and Zumbo, 2012). The additive aggregation method is the summation of normalized and weighted or unweighted indicators to compute the arithmetic mean (Booysen, 2002; Tate, 2012). *Compensability* can be a disadvantage of additive aggregation if a low value in one indicator or dimension masks a high value in another, i.e., a deficit in one indicator or dimension can be compensated by a surplus in another (Tate, 2013). Geometric aggregation — the product of normalized weighted indicators — is a nonlinear approach used to avoid concerns related to interaction and compensability (Tate, 2013). Both additive and geometric approaches result in a quantitative index score, while multicriteria analysis methods, such as Pareto ranking and DEA, use nonlinear aggregation methods that generate index ranks instead of scores (Tate, 2013). Zhou and Ang (2009) compare MCDA aggregation methods using the Shannon-Spearman measure. Zhou et al. (2010) analyze the data aggregation problem from the perspective of information loss and apply the minimum information loss concept. The reliability and robustness of index rankings (rank robustness) can be tested by experimenting with alternative weighting systems and aggregation techniques, and comparing the results (Booysen, 2002; Hinkel, 2011; Permanyer, 2011, 2012).

3.9 UNCERTAINTY AND SENSITIVITY ANALYSIS TO ASSESS AND IMPROVE INDEX ROBUSTNESS

Uncertainty analysis and sensitivity analysis are used synergistically and iteratively during composite index development to aid in indicator selection, add transparency to the index construction process, and explore the robustness of alternative composite index designs and rankings. These analyses inform modifications and refinements of index composition and structure to improve the accuracy, credibility, reliability, and interpretability of index results (Nardo et al., 2005; Saisana et al., 2005; Gall, 2007; OECD, 2008; Schmidtlein et al., 2008; Giné Garriga and Pérez Foguet, 2010; Permanyer, 2011; Tate, 2012; Decancq and Lugo, 2013; M. Gall, personal communication, August 20, 2013; Tate, 2013). They can help index developers to determine if there is a good fit, or a lack of fit, between the adopted theoretical model and the selected constituent indicators as well as the extent to which a different choice of inputs changes the output ranking. This step allows the developer to test if the weighting scheme is actually reflected in the output and if the index is capable of reliably detecting change over time and space. Any index that has not undergone empirical evaluation through uncertainty and sensitivity analysis remains untested and is unreliable (M. Gall, personal communication, August 20, 2013).

Uncertainty analysis "focuses on how uncertainty in the input factors propagates through the structure of the composite indicator and affects the composite indicator values" (Nardo et al., 2005: 85). That is, it serves to identify and evaluate all possible sources of uncertainty in index design and input factors including theoretical assumptions, selection of constituent indicators, choice of analysis scale, data quality, data editing, data transformation, methods applied to overcome missing data, weighting scheme, aggregation method, and composite indicator formula. Models of complex systems are associated with two general forms of uncertainty: (1) *aleatoric uncertainty* and (2) *epistemic uncertainty* (Helton et al., 2010; Tate, 2013). Aleatoric uncertainty results from "heterogeneity or the inherent randomness of input parameters and processes" and might affect the input data used in index construction (Tate, 2013: 527). Epistemic uncertainty results "from an incomplete or imprecise understanding of parameters that are modeled with fixed but poorly known values" and can be found throughout the index construction process (Helton et al., 2010; Tate, 2013: 527). The degree of epistemic uncertainty associated with each stage will vary depending on the particular index effort; for example, in the case of an index that has been designed to analyze vulnerability and resilience at a specific administrative scale of interest, there would be little to no uncertainty associated with determining the appropriate spatial scale of analysis (Tate, 2013). Uncertainty analysis can be used in the composite index construction process to determine the degree of epistemic uncertainty at each stage.

Sensitivity analysis examines the degree of influence of each input on the index output, thereby revealing which methodological stages and choices are most or least influential (Gall, 2007; Giné Garriga and Pérez Foguet, 2010; Tate, 2012) and helping to reveal "how much each individual source of uncertainty contributes to the output variance" (Nardo et al., 2005: 85). For example, modelers may wish to compare index results that are calculated by using alternative weighting schemes, within an agreed upon range of variation, to explore whether or not the overall index ranking or specific positions of interest within that ranking change substantially (Permanyer, 2012). When secondary data sets are used to construct a composite index, adequate understanding of their sources of measurement error is necessary to effectively carry out a sensitivity analysis (Hahn et al., 2009). Index sensitivity can be assessed one index construction stage at a time using *local sensitivity analysis*, or choices at multiple stages of index construction can be varied and evaluated simultaneously to assess interactions using *global sensitivity analysis*, typically applying Monte Carlo simulation to generate a frequency distribution of index ranks for each enumeration unit through the computation of reasonable alternative model configurations (Tate, 2012, 2013).

3.10 VISUALIZATION OF RESULTS

The tabular results of a composite index can be visually displayed in a variety of ways (see Figure 1 and Figures 3 through 8 in the Annex). Attention should be given to how the visualization option selected may affect the interpretation of results and ease of understanding. Spider and triangle diagrams are commonly used and offer the advantage of displaying the values of all index dimensions in a visually clear and appealing way, facilitating comparison of cases (e.g., Sullivan et al., 2003: 197; Van de Kerk and Manuel, 2008a; Hahn, 2008: 17, 39-42; Hahn et al., 2009: 84-85; Sullivan, 2011: 634, 638; Balica et al., 2012: 97). Bar graphs or line graphs can also display the values of index dimensions and overall scores; while they may be well-suited for use with indexes having two to five dimensions (e.g., Sullivan, 2011: 635; Balica et al., 2012: 93), they may not be the best option when trying to display a larger number of dimensions. The mapping of index results offers the distinct advantage of revealing geospatial relationships and patterns (Sullivan and Meigh, 2005: 75; Sullivan, 2011: 636; Torres et al., 2012: 603; de Sherbinin et al., 2014). For examples of vulnerability index mapping in this paper, see Figures 1, 5, and 7 in the Annex.

3.11 VALIDATION AND VERIFICATION

Validation of the conceptual and methodological construct of a composite index requires meaningful engagement with and significant input from stakeholders, experts on the geographic area or sector of interest, and experts on indicator and index design (Barnett et al., 2008). In data-driven inductive approaches, verification of indicators requires statistical analysis, while verification of indicators in deductive approaches "involves assessment of the goodness of fit between theoretical predictions and empirical evidence" (Eriksen and Kelly, 2007: 516). Statistical internal validation of social vulnerability indices is performed using global sensitivity analysis to examine how changes in index construction affect index results (Tate, 2012). Another way to validate a composite index is to consider an external outcome measure that is conceptually relevant, such as infant mortality, deaths from heat stress, or morbidity from a climate-related disease, and then determine whether or not the composite index helps to predict the observed spatial patterns.

4.0 BEST PRACTICES AND CHALLENGES

As emphasized above, *transparency* throughout the process of composite index design, use, and refinement is essential. First, index developers must have a clear understanding of what the composite index is intended to measure, for what purpose, and for which target users and audiences. Developers should articulate their rationale for choices made in the index construction process and explain how their choices influence index results (Tate, 2012). *Uncertainty analysis* and *sensitivity analysis* are not optional; they are essential parts of the index construction process. All methodological steps should be *scientifically and empirically defensible*, *carefully documented*, and *disseminated* along with the index results for rigorous peer review. Methodologies and results also should be communicated clearly and concisely to relevant non-technical audiences.

In addition to meeting high standards of methodological rigor, composite indices should be based on trusted, reputable, reliable, and accessible data sources. Disaggregated input data sets and metadata should be accessible to audiences, allowing them to link the summary statistics the index produced to their underlying values (OECD, 2008; Kienberger, 2012). However, common challenges in composite index construction relate to *data limitations* (Molle and Mollinga, 2003). Important index dimensions may lack time-series data. Data on variables of interest may be unavailable, collected inconsistently, or have significant gaps and biases.[6]

Ideally, composite indices and other indicator approaches should be designed to maximize their *flexibility* and *customizability* by, for instance, enabling the user to easily modify the structural design, indicator selections (e.g., from a larger "menu" of candidate indicators), the weighting scheme, and the aggregation method (Booysen, 2002; Sullivan et al., 2003; Kenney et al., 2012). The general methodology should be transferable across sites and flexible enough to allow for the development of versions that are context-specific (Rygel et al., 2006; Vincent, 2007; Below et al., 2012). If data availability and data quality permit, and if scientifically defensible, indicators and composite indices should be designed for use at multiple spatial scales from national to local (Janetos et al., 2012). Application at different scales may require modifications to make the index scale appropriate.

Construction of a composite index should not be viewed as an end goal, but rather as an analytical tool to facilitate the evaluation and interpretation of information, support decision making, promote discussion, and attract public attention to an important multidimensional subject (Blancas et al., 2013). An ongoing process should be established and maintained to *build capacity* and continually test and *refine* the overall index, its components and subcomponents, and to regularly *update* it with new data (Eakin and Luers, 2006; Balica and Wright, 2009; Maggino and Zumbo, 2012; Kenney et al., 2012). A number of authors have stressed the need for *international coordination* of data collection, data management, and analysis and international guidelines to promote global consistency and to enhance the comparability of statistics (Sullivan and Meigh, 2005; OECD, 2008; Sullivan, 2011).

Lastly, it is critical to acknowledge and address *subjectivity* and *uncertainty* at each stage of the composite index design process (Booysen, 2002; Cherchye et al., 2007; Vincent, 2007; Barnett et al., 2008; OECD,

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[6] Three general methods for dealing with missing data are case deletion, single imputation, and multiple imputation (Nardo et al., 2005: 35-43; OECD, 2008: 15, 24-25).

2008; Hahn et al., 2009; Janetos et al., 2012; Tate, 2012, 2013; Blancas, et al., 2013). As Tate (2013: 527) points out, "Although there is broad interest in the need to quantitatively model social vulnerability, there is far less consensus regarding the ideal set of methods used for the production of indexes. This lack of consensus means that uncertainty is introduced into the modeling process whenever an index developer chooses between competing viable options." Sullivan (2011: 639) suggests embracing *fuzzy approaches*, arguing that the uncertainty associated with composite index methodologies and results "should not be seen as a disadvantage of the process, but rather one which provides a more honest picture of the situation, recognizing explicitly that our understanding is not perfect, and that we need to develop policies that are adaptive and flexible in the face of such uncertainty."

5.0 CONCLUDING REMARKS AND RECOMMENDATIONS

The literature review and selected examples of composite indices examined in this paper suggest that a substantial body of work and expertise currently exists to provide valuable guidance on the necessary stages of composite index design and use for the purpose of climate change vulnerability and resilience assessment at subnational scales. Most of these indexing efforts are recent, having emerged within the past decade. Few have been thoroughly verified, validated, or gone through multiple iterations toward refinement. Nevertheless, they provide a substantive basis for defining best practices, recognizing limitations, and identifying remaining challenges. One of the challenges for those with little to no experience in this field is that with so many different methodological options available, it can be difficult to know how to choose among them or how to implement innovative hybrid and fuzzy approaches. Online communities of practice (e.g., the FVI "network of knowledge" described by Balica and Wright [2009]) and workshops led by composite index design experts who specialize in climate change vulnerability and resilience assessment, as well as participatory approaches, might be useful for sharing experiences, advancing knowledge, and encouraging meaningful dialogue about theoretical, methodological, and practical concerns.

In sum, the key steps and recommended best practices for successful composite index design and use include the following:

- View composite indices as analytical, communication, and collaborative tools that have the potential to support decision making, planning, policy development, and management systems by: raising awareness and improving understanding of a complex, multidimensional issue; promoting discussion; and facilitating scenario analysis to examine possible futures. Composite indices should be designed for distinct purposes, such as to serve as a measure for tracking and monitoring change or as a tool for system assessment.
- Consider the following questions during the design process: What is the primary motivation for composite index development? What specifically is the composite index intended to measure and monitor, and toward what goal(s)? Who is intended to benefit from and/or gain insights from the composite index results? What types of benefits and/or insights are they expected to gain?
- Invest sufficient time and effort to explore and evaluate relevant theoretical approaches, conceptual frameworks, and key concepts to determine if they are appropriate for use. However, if the existing approaches, frameworks, or concepts are not sufficiently compelling or fit-for-purpose, develop your own.
- Delineate meaningful broad themes and dimensions to determine the structural design for organizing, grouping, and aggregating indicators (i.e., the composition and arrangement of major components and subcomponents).
- Involve experts and stakeholders during the conceptualization stage to contribute their knowledge, experience, and insights early in the index design process.
- Maintain a participatory and inclusive approach during the index implementation and refinement process to encourage experts and stakeholders to build consensus and prioritize action.

- Explicitly identify and communicate overarching values and principles, underlying assumptions, subjectivities, frameworks of analysis, intended goals and audiences, available data sources, data limitations, and uncertainties.
- Select indicators that are appropriately matched and most relevant to the spatial scale of the vulnerability assessment, decision making, planning, and policy and management objectives. Determine final indicator selection and index design based on empirical evidence derived from uncertainty and sensitivity analysis.
- Discuss and assess the strengths and weaknesses of each candidate indicator, and record strengths and weaknesses in a summary table on data set characteristics.
- Identify, assess, and disclose all potential sources of data error.
- When selected data sets are measured using different scales or measurement units, overcome incommensurability by normalizing the data, i.e., transforming the data into a common scale or measurement unit and/or by adjusting the directionality of the values by performing inverse adjustment.
- When starting with a large number of candidate indicators, reduce the pool by identifying the most significant indicators, removing indicators of low relevance, and minimizing the redundancy of highly correlated variables.
- The applied weighting and aggregation methods must be made transparent by providing clear documentation of procedures and by communicating how these methodological decisions are shaped by the effort's goals and underlying theoretical framework, conceptual definitions, the structural design of the index, the spatial scale of analysis, the properties of the data, and index dimensionality.
- Uncertainty analysis and sensitivity analysis are not optional; rather, they are essential steps during index development and indicator selection that add transparency to the index construction process and aid in determining the robustness of alternative composite index designs and rankings.
- Consider different options for displaying composite index results in order to select visualization approaches that facilitate interpretation and understanding.
- To validate and verify a composite index, seek meaningful engagement with and significant input from stakeholders and experts on the geographic area or sector of interest, and experts on indicator and index design.
- Use global sensitivity analysis to perform statistical internal validation.
- Design composite indices to maximize their flexibility and customizability by enabling users to easily modify the structural design, indicator selections, the weighting scheme, and the aggregation method.
- Maintain transparency throughout the process of composite index design, use, and refinement.

ANNEX. SUMMARIES OF SELECTED COMPOSITE INDICES

To illustrate the process of composite index design and use with specific examples, this annex describes six composite indices that have been developed and implemented within the past decade to assess relative vulnerability to climate change at subnational levels. Each of the six examples focuses on one or more climate-sensitive systems or sectors (e.g., water, agriculture, food, livelihoods, human health, river basins, urban areas, and coastal regions) and has been implemented in African, Latin American, and/or Caribbean contexts. While an effort has been made to identify the methodological strengths and weaknesses of each example presented, quantitative examination and comparative evaluation of the quality and accuracy of the construction and output of these indices is beyond the scope of this paper.[7]

To the extent possible, based on the available literature and online sources of information (and, in the case of the Livelihood Vulnerability Index, personal communication with the lead development practitioner and author), each of the summaries aims to cover the following theoretical and methodological issues: the central purpose and history of index development, primary goals and audiences, analytical scope and scale, theoretical and conceptual framework, structural design, index composition, data sources, indicator selection, data transformation, data reduction, factor retention, weighting, aggregation, results, visualization, and validation.

A.1 CLIMATE VULNERABILITY INDEX

With a focus on water-related issues, the Climate Vulnerability Index (CVI) aims to combine social, economic, environmental, and physical factors to assess relative vulnerability to current climate variability (Sullivan and Meigh, 2005). The CVI approach can be applied to regions or zones representing different geographical or ecosystem types, such as small islands, developing cities, mountainous regions, semi-arid regions, over-abstracted or degraded catchments, and low-lying coastal zones (Sullivan and Meigh, 2005: 72). The CVI scores estimate vulnerability to existing climate variability. These spatial estimates of vulnerability are then used to compare exposure units within a region or zone. Patterns of vulnerability can then be examined within the region of interest (e.g., a group of countries, a country, or a subnational region) to understand spatial variations. Sullivan and Meigh (2005: 73) outline the following steps for estimating the CVI:

- Identify zones of current and potential water stress.
- Identify geographical types likely to be vulnerable, select geospatial variables for each, and select sample locations within the geographical or ecosystem types.
- Collect and collate all relevant data for the selected sample locations.
- Construct scenarios of social, economic, and environmental change to combine with estimates of change in water resources derived from climate impact assessments using global or regional climate model outputs (this step requires a high level of expertise).

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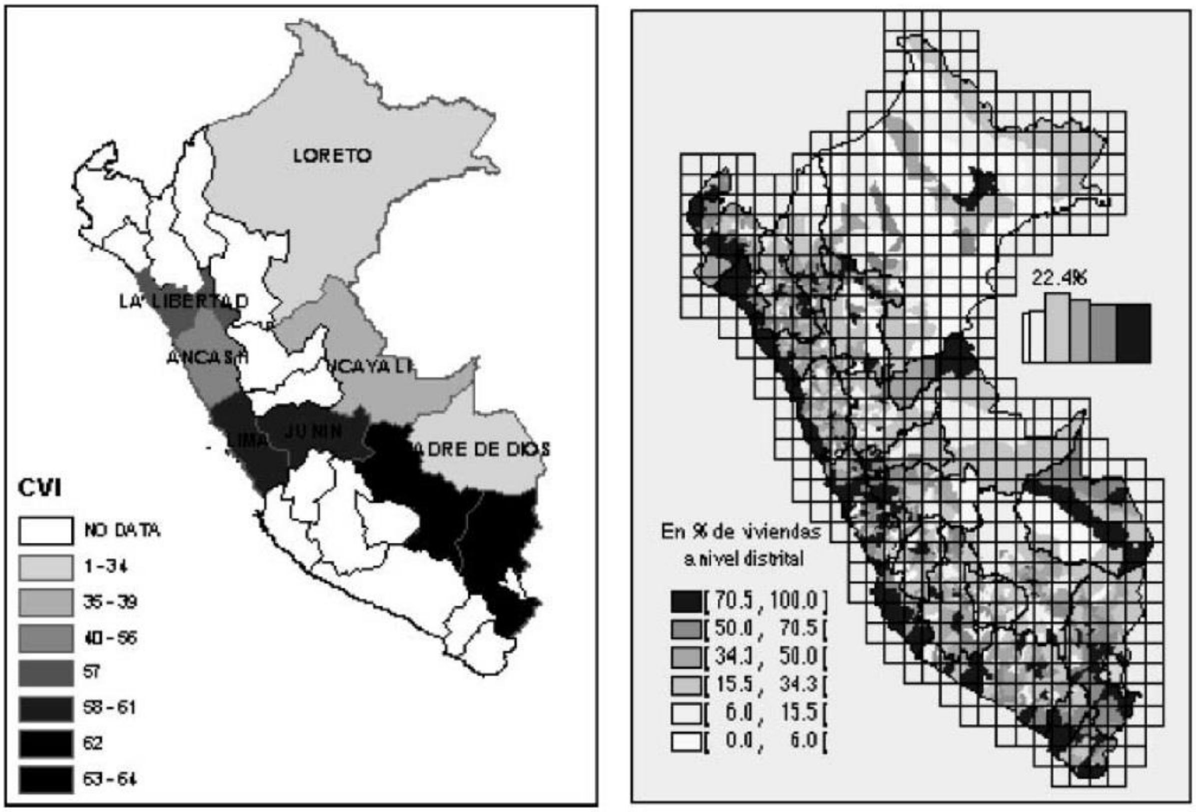
7 Gall (2007) quantitatively evaluated existing social vulnerability indices, testing them through uncertainty and sensitivity analysis to determine if and how they meet their claims, and found that most of these indices did not hold up under empirical scrutiny.

- Calculate CVI scores for the present situation and under the combined change scenarios.
- Interpret the meaning of the CVI scores in terms of impacts on people.
- Calculate results at a range of spatial scales, incorporating uncertainty.

The CVI integrates the following six major components and their subcomponents (Figure 1):

1) *Resource* (e.g., assessment of surface water and groundwater availability, evaluation of water storage capacity and reliability of resources, and assessment of water quality and dependence on imported and/or desalinated water)
2) *Access* (e.g., access to clean water and sanitation and access to irrigation coverage adjusted by climate characteristics)
3) *Capacity* (e.g., expenditure on consumer durables or income; gross domestic product [GDP] as a proportion of gross national product, and water investment as a percentage of total fixed capital investment; educational level of the population and the under-five mortality rate; existence of disaster warning systems and strength of municipal institutions; percentage of people living in informal housing; and access to a place of safety in the event of flooding or other disasters)
4) *Use* (e.g., domestic water consumption rate related to national or other standards and agricultural and industrial water use related to their respective contributions to GDP)
5) *Environment* (e.g., livestock and human population density, loss of habitats, and flood frequency)
6) *Geospatial* (e.g., extent of land at risk from sea-level rise; degree of isolation from other water resources and/or food sources; deforestation, desertification, and/or soil erosion rates; degree of land conversion from natural vegetation; and deglaciation and risk of glacial lake outbursts)

FIGURE 1. COMPARISON OF THE CVI CALCULATED FOR PERU AT THE DEPARTMENT AND DISTRICT LEVELS



Comparison of the CVI calculated for Peru at the department level (left map) and at the district level (right map) showing the percentage of households with a piped water supply, using data obtained from Peru's National Institute of Statistics and Informatics. Source: Reproduced from Sullivan, Caroline, and Meigh, 2005, with permission from the copyright holders, IWA Publishing.

The CVI is calculated on a scale from 0 (least vulnerable) to 100 (most vulnerable). Initially, the components can be equally weighted to calculate a base rate CVI. Participatory consultation and expert opinion by means of a transparent process should then be used to develop a weighting scheme. The CVI can serve as a dynamic modeling tool for developing future scenarios based on climate change projections and assumptions about future driving forces.

Developers of the CVI claim that it is applicable at multiple spatial scales and suitable for spatially nested application; however, given that application of the CVI to date has been limited, empirical evidence to support these claims is lacking. Notably, Sullivan and Meigh (2005) failed to address data transformation, data reduction, uncertainty analysis, or sensitivity analysis in the CVI methodology. They acknowledge the need for wider application of the CVI methodology and structural refinement of the index; therefore, while the CVI appears to provide a flexible design, further work is needed to improve its methodology.

Sullivan and Meigh (2005: 72) report using the following three indicator selection criteria: data availability, practicality, and degree of effectiveness at "expressing key aspects of vulnerability that are relevant locally." To date, the CVI has relied primarily on data available from existing sources, and developers have emphasized the importance of integrating the highest-quality and most recent data available at appropriate spatial and temporal resolutions. Initially, components can be equally weighted (i.e., set to one) to establish a "base rate CVI" prior to experimentation with alternative weighting schemes based on participatory consultation and expert opinion, which should also be tested with sensitivity analysis. The weight for each component is context specific, i.e., determined by the relevance of the component in a specific place. CVI scores can be mapped to facilitate comparisons across exposure units and to identify regional patterns. To assess expected or possible future climate vulnerability for comparison with scores for current conditions, input values can be adjusted according to projections or future scenarios.

A.2 FLOOD VULNERABILITY INDEX AND THE COASTAL CITY FLOOD VULNERABILITY INDEX

The Flood Vulnerability Index (FVI) is an interdisciplinary tool designed to assess flood vulnerability for flood risk management at multiple spatial scales, including river basins, sub-catchments, and urban areas (Connor and Hiroki, 2005; Balica, 2007, 2012a, 2012b; Balica and Wright, 2009, 2010; Balica et al., 2009, 2012). The FVI has been designed specifically to assess flood vulnerability due to climate change (Connor and Hiroki, 2005). It has been used to identify the main factors responsible for an exposure unit's flood vulnerability and is meant to be used in combination with other decision-making tools. It is intended to serve as an easily accessible tool for policy and decision makers. As Balica and Wright (2010: 327) note, "the ultimate aim [of the FVI] is to provide the stakeholders with a clear and flexible methodology to evaluate flood vulnerability, in order to be used at various scales and in as many case studies as possible." FVI developers seek to use the index to monitor the chronological change of flood vulnerability for specific exposure units and to show potential flood vulnerability under future scenarios, reflecting socioeconomic trends and climate change. Initially, the FVI methodology was developed to assess vulnerability to river flooding. The methodology was later extended to develop the Coastal City Flood Vulnerability Index (CCFVI), which aims to assess vulnerability to coastal flooding in urban areas.

The methodology is transparent and made available for public review and scrutiny in several publications. The use of sensitivity analysis is insufficiently addressed in the available literature on the FVI and CCFVI, indicating that this critical step has not been applied; there is only brief mention of sensitivity analysis in Balica et al. (2009: 2579). The FVI offers a flexible design. The selection of indicators is scale-, context-, and site-specific. Further methodological refinements and improvements can be achieved by applying the methodology to additional case studies at diverse scales. To support advancement of the methodology, the developers of the FVI have established a website (unesco-ihe-fvi.org) to "create a network of knowledge between different institutions and universities" and "encourage collaboration between members of the network on managing flood vulnerability information" (Balica and Wright, 2009: 2983-2984). This collaborative web interface requires each network participant to create a user account in order to log on and add data that the administrator can then review for verification.

The FVI and CCFVI standardized values fall between 0 and 1, with higher values being the most vulnerable to flood. The FVI architecture consists of four system components (social, economic, environmental, and physical) used to assess three main factors influencing flood vulnerability (exposure, susceptibility, and resilience) (Figure 2, following page). In the FVI approach, a system's vulnerability to flood events is conceptualized as:

$$\mathit{Vulnerability} = \mathit{Exposure} + \mathit{Susceptibility} - \mathit{Resilience}$$

Balica et al. (2009: 2574-2575) applied a deductive approach to identify the best possible indicators. To simplify and improve upon the original FVI methodology, Balica and Wright (2010) applied an expert survey as well as mathematical techniques (derivation and correlation methods), which helped them to identify the most significant indicators available and reduce the complexity of the FVI from an initial large set of 71 indicators to a smaller set of 28 indicators, of which 20 were selected for the river basin scale, 22 were selected for the sub-catchment scale, and 27 were selected for the urban area scale. The questionnaire that was used to survey expert knowledge is accessible on the FVI website; it asks experts to assign levels of indicator significance on a scale from 5 (very high influence) to 1 (very low influence).

The indicators considered for the river basin scale included: average rainfall per year of the entire river basin, number of days with heavy rainfall, river discharge, degraded area, land use, natural reservation, population in flood-prone area, Human Development Index, child mortality, past experience, awareness and preparation, communication penetration rate, warning system, evacuation roads, unemployment, inequality, and economic recovery. Indicators of urbanized area, rural population, proximity to river, life expectancy, and unpopulated area were only used at the sub-catchment scale, while indicators of cultural heritage, population growth, shelters, emergency services, industries, contact with river, recovery time, and the drainage system were only used at the urban area scale. The following indicators were used to assess vulnerability at the river basin and sub-catchment scales, but not at the urban area scale: land use (percent area used for industry, agriculture, and other economic activities); economic recovery; degraded area; land use (percent forested area); natural reservation; and frequency of occurrence. Other indicators were used to assess vulnerability at the sub-catchment and urban area scales, but not at the river basin scale: population density; disabled people; flood insurance; dikes and levees; water storage capacity of dams; and urban growth.

FIGURE 2. INDICATORS USED TO COMPUTE FLOOD VULNERABILITY INDICES

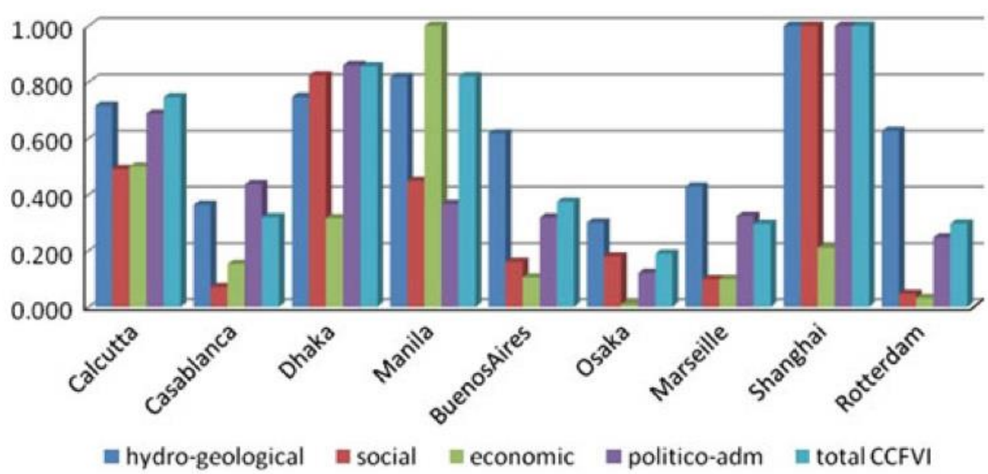
Overall Indicators Relationship between components and factors						
Flood Vulnerability =	**Exposure +**	Geographic Scale	**Susceptibility -**	Geographic Scale	**Resilience**	Geographic Scale
Social Component	Population density	R,S,U	Past experience	R,S,U	Warning system	R,S,U
	Population in flood area	R,S,U	Education (Literacy rate)	R,S,U	Evacuation routes	R,S,U
	Closeness to inundation area	R,S,U	Preparedness	R,S,U	Institutional capacity	R,S,U
	Population close to coast line	R,S,U	Awareness	R,S,U	Emergency service	R,S,U
	Population under poverty	R,S,U	Trust in institutions	R,S,U	Shelters	R,S,U
	% of urbanized area	R,S	Communication penetration rate	R,S,U		
	Rural population	R,S	Hospitals	R,S,U		
	Cadastre survey	S,U	Population with access to sanitation	R,S,U		
	Cultural heritage	S,U	Rural population w/o access to WS	R,S		
	% of young & elder	S,U	Quality of Water Supply	S,U		
	Slums	U	Quality of Energy Supply	S,U		
			Population growth	S,U		
			Human health	S,U		
			Urban planning	U		
Economic Component	Land use	R,S,U	Unemployment	R,S,U	Investment in counter measures	R,S,U
	Proximity to river	R,S,U	Income	R,S,U	Infrastructure Management	R,S,U
	Closeness to inundation areas	R,S,U	Inequality	R,S,U	Dams & Storage capacity	R,S,U
	% of urbanized area	R,S	Quality of infrastructure	R,S,U	Flood insurance	R,S,U
	Cadastre survey	S,U	Years of sustaining health life	R,S,U	Recovery Time	R,S,U
			Urban growth	S,U	Past experience	S,U
			Child mortality	S,U	Dikes/ Levees	S,U
			Regional GDP/ capita	S		
			Urban planning	U		
Environmental Component	Ground WL	R,S,U	Natural reservations	R,S,U	Recovery time to floods	R,S,U
	Land use	R,S,U	Years of sustaining health life	R,S,U	Environmental concern	R,S,U
	Over used area	R,S,U	Quality of infrastructure	R,S,U		
	Degraded area	R,S,U	Human health	S,U		
	Unpopulated land area	R,S	Urban growth	S,U		
	Types of vegetation	R,S	Child mortality	S,U		
	% of urbanized area	R,S				
	Forest change rate	R				
Physical Component	Topography (slope)	R,S,U	Buildings Codes	U	Dams & Storage capacity	R,S,U
	Geography	R,S,U			Roads	R,S,U
	Geology	R,S,U			Dikes / Levees	S,U
	Heavy rainfall	R,S,U				
	Flood duration	R,S,U				
	Return periods	R,S,U				
	Proximity to river	R,S,U				
	Soil moisture	R,S,U				
	Evaporation rate	R,S,U				
	Temperature (yearly average)	R,S,U				
	River discharge	R,S,U				
	Frequency of occurrence	R,S,U				
	Flow velocity	S,U				
	Storm surge	S,U				
	Tidal	S,U				
	Flood water depth	S,U				
	Sedimentation load	S,U				
	Coast line	S,U				
	Coastal bathymetry	S,U				

"R" represents river basin scale, "S" represents sub-catchment scale, and "U" represents urban area scale. Source: Reproduced from UNESCO-IHE, 2012, with permission from Stefania F. Balica.

Balica et al. (2012: 74) produced the CCFVI to help "identify the most vulnerable coastal cities, develop adaptation measures for them, and assess the effects of future change scenarios." The three major system components of the CCFVI are: the hydro-geological component representing the natural system; the socioeconomic component representing the socioeconomic system; and the political-administrative component representing the administrative and institutional system. The CCFVI integrates a total of 19 indicators, which were selected after using multi-collinearity analysis among 30 coastal indicators (Balica, 2012a; Balica et al., 2012). The indicators included in the *hydro-geological component* are: (1) sea-level rise; (2) storm surge; (3) the number of cyclones in the past 10 years; (4) river discharge; (5) foreshore slope; (6) soil subsidence; and (7) kilometers of coastline along the city. The indicators in the *socioeconomic component* are: (8) cultural heritage (number of historical buildings, museums, etc. in danger when a coastal flood occurs); (9) population close to the coastline; (10) growing coastal population; (11) number of shelters and hospitals; (12) percent of disabled persons (younger than 14 and older than 65); (13) awareness and preparedness; (14) recovery time; and (15) kilometers of drainage. The indicators in the *political-administrative component* are: (16) flood hazard maps; (17) existence and involvement of institutional organizations; (18) uncontrolled planning zone; and (19) flood protection.

Based on city size and physiographic setting, the CCFVI developers selected the following nine cities as case studies: Buenos Aires (Argentina); Calcutta (India); Casablanca (Morocco); Dhaka (Bangladesh); Manila (Philippines); Marseille (France); Osaka (Japan); Shanghai (China); and Rotterdam (the Netherlands). Of these nine case studies, the city of Shanghai was found to be the most vulnerable to coastal floods, and the city of Osaka was found to be the least vulnerable (Figure 3).

FIGURE 3. OVERALL COASTAL CITY FLOOD VULNERABILITY INDEX FOR NINE CASE STUDIES



Source: Reproduced from Balica, Wright, and van der Meulen, 2012, with kind permission from Springer Science + Business Media.

Balica et al. (2012) suggest stakeholder involvement in the process of weighting indicators. Bar graphs, line graphs, and spider diagrams have been used to display FVI and CCFVI results (Balica et al., 2009; Balica and Wright, 2010; Balica, 2012a; Balica et al., 2012).

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A.3 LIVELIHOOD VULNERABILITY INDEX

Drawing on the Sustainable Livelihoods Approach (Chambers and Conway, 1992), the Livelihood Vulnerability Index (LVI) was designed to support comparative assessments of vulnerability to climate variability and climate change at district and community levels (Hahn, 2008; Hahn et al., 2009). The LVI is meant to serve as "an assessment tool accessible to a diverse set of users in resource-poor settings" and "to inform resource distribution and program design" among humanitarian, development, and public health organizations (Hahn, 2008: 18; Hahn et al., 2009: 76, 86). This project was a collaborative effort that researchers at Emory University (Atlanta, GA, USA) and partners at CARE-Mozambique (Maputo, Mozambique) undertook. It was Micah Hahn's thesis project while earning her Master of Public Health at the Rollins School of Public Health at Emory University (Hahn, 2008).

The LVI was piloted in 2007 in two districts of Mozambique to assess household livelihood security, the strength of health systems, and community capacity in the context of climate change. To capture geographic variability, the Moma District (5,752 km^2, more than 329,000 inhabitants) in Nampula Province was selected as representative of Mozambique's coastal communities. The Mabote District (14,577 km^2, more than 45,000 inhabitants) in Inhambane Province was selected as representative of the country's inland communities. This study analyzed primary data collected through household surveys. Toward identifying which household characteristics contribute most to climate change vulnerability in each district, the researchers analyzed survey data collected from 200 households in each of the two districts (a total of 400 households) on household characteristics by interviewing heads of households. When the head of household was not available, the spouse was interviewed instead. Based on 1997 national demographic census data, the probability proportional to size method was applied to select 20 villages in each district. Ten households in each village were randomly selected for interviews, which lasted 30 minutes on average.

The structural design of the LVI is based on seven major components: (1) socio-demographic profile; (2) livelihood strategies; (3) health; (4) social networks; (5) food; (6) water; and (7) natural disasters and climate variability (Figure 4, following page). Hahn (2008) and Hahn et al. (2009) tested two approaches to index calculation. In the first approach, they calculated the LVI by synthesizing all seven major components. The second approach LVI-IPCC, based on the Intergovernmental Panel on Climate Change (IPCC) vulnerability framework, aggregated the seven major components into three contributing factors to vulnerability: (1) *exposure* to natural disasters and climate variability; (2) *sensitivity* (health, food, and water); and (3) *adaptive capacity* (socio-demographic profile, livelihood strategies, and social networks). These core components, their constituent indicators, and survey questions were derived from an extensive literature review focused on the variables that affect exposure, sensitivity, and adaptive capacity to climate change. They also reflect consideration of the practicality of data collection by means of household surveys.

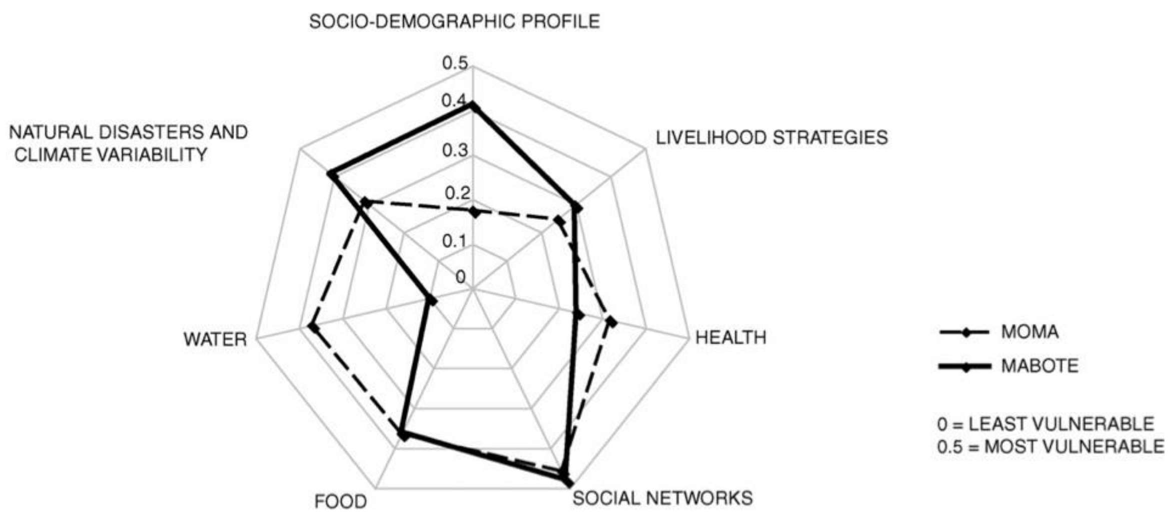
The LVI is calculated on a scale from 0 (least vulnerable) to 0.5 (most vulnerable). The LVI-IPCC is calculated on a scale from -1 (least vulnerable) to 1 (most vulnerable). The quantification methods for each of the subcomponents, the household survey questions associated with each subcomponent, the original source of each survey question, and the potential limitations and sources of bias associated with each survey question are reported in Hahn (2008: 17-33) and Hahn et al. (2009: 77-79). Several of the household survey questions were adapted either from Demographic and Health Surveys or from survey questions developed by the World Bank, the World Health Organization, and Mozambique's National Statistics Institute. Other questions were developed for the purposes of this study's questionnaire.

Adapting an equation previously used in the Human Development Index (HDI) to calculate the life expectancy index, the authors normalized the subcomponents, which had been measured on different scales (Hahn, 2008; Hahn et al., 2009). They applied a balanced weighted average approach "where each subcomponent contributes equally to the overall index even though each major component is comprised of a different number of subcomponents" (Hahn et al., 2009: 76). The weighting scheme can be adjusted as needed.

The seven component scores of the LVI are displayed using spider diagrams, while the three component scores of the LVI-IPCC are displayed using triangle diagrams. These spider and triangle diagrams are used to facilitate a comparison of vulnerability among the major components as well as across districts. Overall, Mabote (0.326) was found to have relatively greater climate change vulnerability than Moma (0.316). Mabote's vulnerability scores were higher for socio-demographic profile, livelihood strategies, social networks, and natural disaster and climate variability. Moma's vulnerability scores were higher for health, food, and water.

One of the strengths of the LVI is its use of primary data collected by using a survey instrument that was designed with a clearly framed theoretical, conceptual, and analytical approach. Studies using secondary data may be limited by problems such as mismatch of the available data with the conceptual and analytical framework of the study, missing data, inconsistent data, incompatibility of data collected at different spatial or temporal scales, and limited information about the sources of measurement error in the data sets (Hahn, 2008; Hahn et al., 2009). Another advantage of the LVI is that the index calculation method is straightforward and accessible to development practitioners (Hahn, 2008; M.B. Hahn, personal communication, October 24, 2012). LVI assessments can be repeated in the same location over time to monitor changes in the dimensions of vulnerability, and input values can be adjusted to analyze the potential change in the vulnerability of study populations under future scenarios reflecting possible program or policy shifts (Hahn, 2008). Further work and wider application are needed to improve the methodology. For instance, Hahn et al. (2009: 87) suggest "refinement of the Social Networks subcomponents in order to more accurately evaluate social bonds."

FIGURE 4. VULNERABILITY SPIDER DIAGRAM OF THE SEVEN MAJOR LVI COMPONENTS FOR MOMA AND MABOTE DISTRICTS, MOZAMBIQUE



Source: Reproduced from Hahn, Riederer, and Foster, 2009, with kind permission from Elsevier.

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A.4 SOCIO-CLIMATIC VULNERABILITY INDEX

The Socio-Climatic Vulnerability Index (SCVI) is designed to assess social vulnerability to climate change in order to enable comparisons across regions and locations and to help target and prioritize adaptation policies and actions by identifying socio-climatic hotspots (Torres et al., 2012). It has been developed to provide spatially explicit assessments of social vulnerability to climate change for countries and regions. It is intended as a synthetic and socially relevant tool for improving dialogue and communication between climate scientists, social scientists, policymakers, and other stakeholders. The SCVI relies on existing and salient data sources, i.e., climate data from known climate models, demographic census data, and HDI data sets. The SCVI appears to combine the *risk-hazard* and *social vulnerability* approaches, although Torres et al. (2012) do not explicitly state that this is the adopted conceptual framework.

The SCVI integrates two major components: (1) a climate change index such as the Regional Climate Change Index (RCCI) developed by Giorgi (2006), which synthesizes more than 100 climate model projections; and (2) a social vulnerability index, e.g., combining demographic density (inhabitants/km^2) and HDI scores (integrating measures of health, education, and poverty). The SCVI is applicable at multiple and nested spatial scales of analysis. Index results are mapped to reveal geospatial relationships and patterns. The authors illustrate the use of the SCVI by applying it to analysis of the spatial distribution of socio-climatic vulnerability in Brazil.

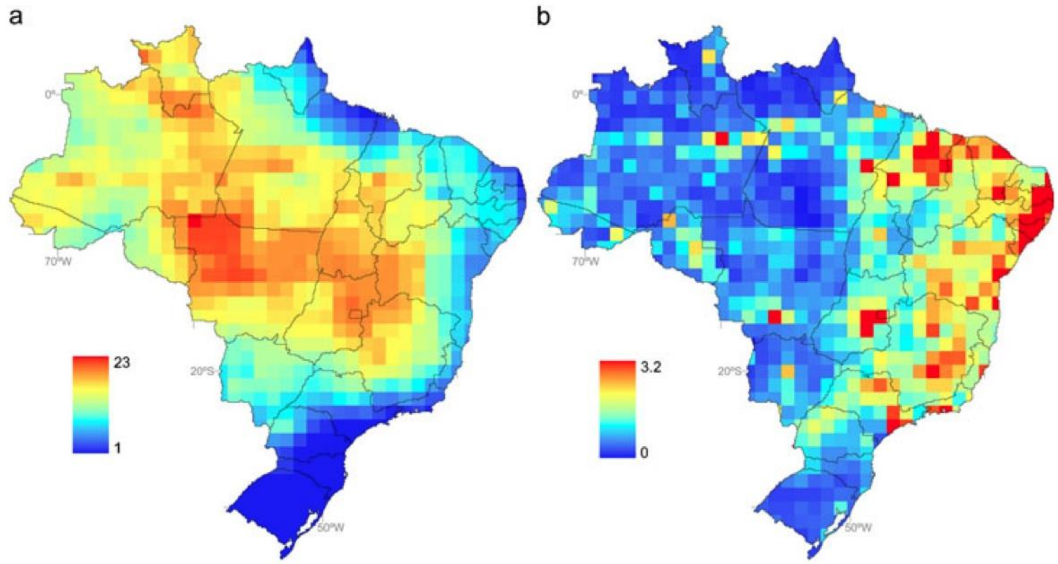
The RCCI synthesizes more than 100 climate model projections to summarize a large body of information about the expected magnitude of climate change in specific regions. Other climate change indices can be used instead of or in addition to the RCCI to calculate the SCVI. The SCVI is a relative index of climate change vulnerability, i.e., high or low socio-climatic vulnerability scores are intended to enable comparisons across regions and locations. It can be applied at multiple spatial scales and can synthesize multiple social vulnerability indicators as long as sufficient data is available. The SCVI is not intended to substitute the RCCI, but rather to serve as an auxiliary index. In other words, together these indices can serve as useful tools for exploratory purposes as well as for improving dialogue and communication between climate scientists, social scientists, policymakers, and other stakeholders seeking to collaboratively target and prioritize adaptation efforts.

The specific social vulnerability indicators used in this study of Brazil are demographic density (inhabitants/km^2) and the inverse of the HDI for all Brazilian municipalities in the year 2000. This selection of indicators is based on the assumption that social vulnerability to climate change is likely to be higher in regions with higher demographic density and lower HDI scores. Indicator selection criteria include data availability, spatial coverage of data, and comparability of data sets.

Using ArcGIS®, the authors applied the following steps to normalize these two input variables to a 1° resolution grid. The initial demographic density gridded (raster) data set resolution was five arc-minutes. The municipal-level HDI data were transformed from a vector data set (polygons) into a five arc-minute raster layer. Next, both five arc-minute raster layers were converted into 1° resolution raster layers using mean neighborhood block statistics.

Mapping of the RCCI and SCVI analyses revealed distinct spatial patterns (Figure 5). Torres et al. (2012: 604) explain that "low RCCI values should not be interpreted as indicating 'no change' or 'no impact,' but rather as a smaller change relative to other regions." The SCVI analysis revealed major socio-climatic hotspots in Brazil's semi-arid Northeast region, which is characterized by low-to-medium RCCI values, relatively high demographic density, and the country's lowest HDI levels. The SCVI results also revealed several punctual socio-climatic hotspots in several of Brazil's major metropolitan regions — areas expected to be impacted by climate-related events such as floods, landslides, and heat waves — including Manaus, Belo Horizonte, Brasília, Salvador, Rio de Janeiro, São Paulo, and most of the northeastern state capital cities. Manaus, Belo Horizonte, and Brasília were found to have high or very high RCCI values.

FIGURE 5. MAP DISPLAYING (A) THE RCCI AND (B) THE SCVI FOR BRAZIL



Source: Reproduced from Torres, Lapola, Marengo, and Lombardo, 2012, with kind permission from Springer Science + Business Media.

Torres et al. (2012) present a transparent methodology but do not address weighting, uncertainty analysis, or sensitivity analysis. The SCVI provides a flexible design. Both of its major components can be modified and updated as new data sets become available. Other climate change indices can be used instead of or in addition to the RCCI, and users can explore alternatives to HDI data sets for integration in the social vulnerability component. Wider application and refinements are needed to improve the SCVI methodology. Torres et al. (2012) recommend refinements of SCVI index calculation in future studies by using higher-resolution regional climate models and more advanced statistical downscaling techniques to calculate the RCCI, and by experimenting with other social vulnerability indicators to capture direct and indirect climate change impacts (e.g., high resolution data on climate-driven agricultural losses, epidemiological impacts, and susceptibility to a variety of hazards and risks).

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A.5 WATER POVERTY INDEX

The Water Poverty Index (WPI) is designed to assess water stress and water scarcity. It is built on the premise that access to adequate and sustained supplies of safe water along with adequate levels of sanitation are essential for social and economic development and for the reduction of poverty, hunger, and disease (Sullivan, 2002; Molle and Mollinga, 2003; Sullivan et al., 2003; Giné Garriga and Pérez Foguet, 2011). The conceptualization of poverty in the WPI is derived from the basic needs approach as developed by Amartya Sen and others. Access to sufficient quantities of safe water is necessary for an individual, a household, or a community to be effective and productive. Failure to meet this basic condition has negative repercussions for human health given that food production, personal and food hygiene, pathogen exposure, and time available for activities other than collecting water are affected by water availability, quality, and access. Furthermore, inadequate water supply is likely to have negative impacts on the condition of the local environment, with additional harmful consequences for the inhabiting human population.

Although the WPI did not initially focus on climate change, it provided a basis for the development of both the CVI and the Water Vulnerability Index (WVI) (Sullivan, 2011; Balica, 2012b). The Resources component of the WPI, which includes measures of water quantity and water availability, reflects hydrometeorological factors.

The WPI is intended to serve as a holistic monitoring, policy, and management tool in support of collaboration among stakeholders seeking to address the complexities of water resource issues toward equitable water provision and allocation. The index links human wellbeing and poverty to critical water-related variables within physical, social, economic, and environmental dimensions. Similar to the LVI, the WPI applies an interdisciplinary approach and adopts concepts from the Sustainable Livelihoods Framework (Carney, 1998; Scoones, 1998; Sullivan et al., 2003), which assesses development outcomes in terms of the distribution of livelihood assets (i.e., natural, physical, financial, social, and human capital). If developed using a participatory, inclusive, and transparent approach, the WPI can help stakeholders build consensus and prioritize action (e.g., decide how to target assistance for water provision to specific areas or populations).

The WPI methodology takes into account spatial and temporal variability within a country or region, and it can be applied at a range of spatial scales from local (e.g., district) to intermediate (e.g., river basin) to broad scale (e.g., national-level comparisons) using a variety of data sources (Sullivan et al., 2003, 2006; Sullivan and Meigh, 2007; Balica, 2012b). A rich supply of literature published from 2002 to 2011 documents methodological challenges and improvements. At local scales, the WPI has been applied as follows: Sullivan et al. (2003) at the community scale in South Africa, Tanzania, and Sri Lanka; Fenwick (2010) at the community scale in Mexico; Giné Garriga and Pérez Foguet (2010, 2011) at the district scale in Kenya; and Heidecke (2006) at the commune scale in Benin. Lawrence et al. (2002) and Cho et al. (2010) applied the WPI at the national scale to draw international comparisons. Analysts have georeferenced variables to link macro-level hydrological data on water availability and micro-level data such as household-, community-, and district-level information on water stress, time spent collecting water, and the ability to use water for productive purposes. Studies applying the WPI should be updated at regular intervals (e.g., every three to five years) to monitor progress. International coordination of locally generated data and data management would help to advance multiscalar analysis.

The WPI is calculated on a scale from 0 (the highest level of water poverty) to 100 (the lowest level of water poverty). Each component is standardized to fall within this range. Equal weights or differential weights can be applied to both the components and the subcomponents. Equal weights initially should be applied to calculate a baseline value. Giné Garriga and Pérez Foguet (2010) compare different aggregation methods.

Sullivan et al. (2003) used the following five WPI components and their subcomponents for pilot sites in South Africa, Tanzania, and Sri Lanka (Figure 6, following page):

1) **Resources** (assessment of surface water and groundwater availability using hydrological and hydrogeological techniques, quantitative and qualitative evaluation of the variability or reliability of resources, quantitative and qualitative assessment of water quality);

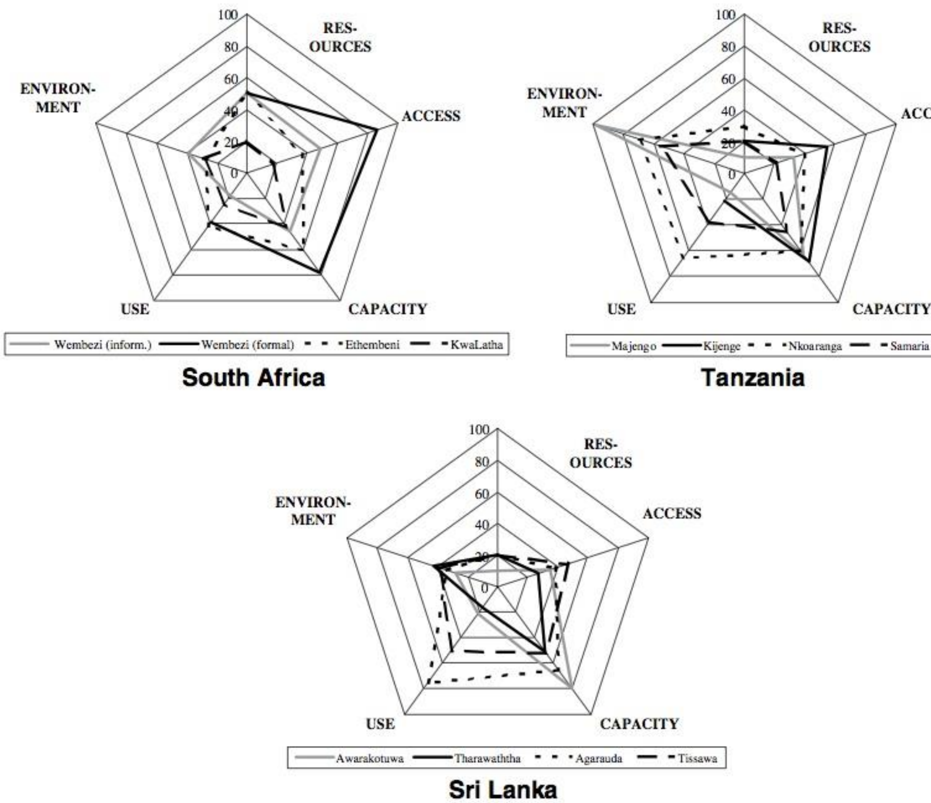
2) **Access** (access to clean water as a percentage of households having a piped water supply; reports of conflict over water use; access to sanitation as a percentage of population; percent of water carried by women; time spent in water collection, including waiting; access to irrigation coverage adjusted by climate characteristics);

3) **Capacity** (wealth proxied by ownership of durable items, under-five mortality rate, education level, membership of water users associations, percent of households reporting illness due to water supplies, percent of households receiving a pension/remittance or wage);

4) **Use** (domestic water consumption rate; agricultural water use, expressed as the proportion of irrigated land to total cultivated land; livestock water use, based on livestock holdings and standard water needs; industrial water use [purposes other than domestic and agricultural]); and

5) **Environment** (people's use of natural resources, reports of crop loss during the past five years, percent of households reporting erosion on their land).

FIGURE 6. SPIDER DIAGRAM OF THE FIVE WPI COMPONENTS FOR PILOT STUDY SITES IN SOUTH AFRICA, TANZANIA, AND SRI LANKA



Source: Reproduced from Sullivan et al., 2003, with kind permission from John Wiley and Sons.

An advantage of the WPI is that it can be easily adapted to local needs and local data availability. It can be calculated even if some of the data are unavailable, although this step may weaken comparability between study sites. Cho et al. (2010) proposed two simplified water poverty indices as more cost-effective and viable alternative approaches; they test an unequally weighted, three-component index integrating access, capacity, and environment and an equally weighted two-component version combining capacity and environment.

PCA has been used by WPI developers to reduce the number of input indicators (e.g., Cho et al., 2010; Giné Garriga and Pérez Foguet, 2010). Giné Garriga and Pérez Foguet (2010) apply sensitivity analysis to test the robustness of the WPI and improve its transparency. WPI results have been mapped (Cullis and O'Regan, 2004; Heidecke, 2006; Sullivan et al., 2006; Giné Garriga and Pérez Foguet, 2010, 2011; Pérez Foguet and Giné Garriga, 2011), displayed in bar graphs (Lawrence et al., 2002; Sullivan et al., 2003), and displayed in spider diagrams (Sullivan et al., 2003; Cullis and O'Regan, 2004; Heidecke 2006; Sullivan et al., 2006; Sullivan and Meigh, 2007).

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A.6 WATER VULNERABILITY INDEX

The Water Vulnerability Index (WVI) assesses current and future water sector vulnerability to climate change. It has been developed as an integrative multidimensional tool for use by basin- and local-level water managers and decision makers to support water governance and local efforts toward integrated water resources management (Sullivan, 2011). The WVI is intended to help guide the development of climate adaptation strategies and to prioritize investments by enabling comparison of water vulnerability profiles and identification of site-specific drivers of vulnerability at the municipal scale. While the WVI methodology can be adapted for use at multiple spatial scales, to date it has been used at the municipal scale to understand how water vulnerability varies across municipalities within a river basin.

The WVI structural design consists of two major components: (1) *supply-driven vulnerability of water systems;* and (2) *demand-driven vulnerability of water users* (Sullivan, 2011). Each of the two major components integrates four subcomponents and eight individual indicators. This structure allows the user to consider adaptation options based not only on the information that the overall comparative WVI scores provide, but also on the more detailed information that the subcomponent and individual indicator values provide. To assess expected or possible future water vulnerability for comparison with scores for current conditions, input values can be adjusted, for example, by increasing current values of the demand-driven indicators and/or decreasing current values of the supply-driven indicators according to projections or future scenarios.

Relying on existing data, Sullivan (2011) applied the WVI to compare supply- and demand-driven water vulnerability across 87 South African municipalities within the Orange River Basin (Figures 7 and 8). The WVI is calculated on a scale from 0 (the least vulnerable) to 100 (the most vulnerable). In this pilot study, supply-driven water system vulnerability was calculated using the following four subcomponents and eight individual indicators:

- Resource vulnerability (mean annual run-off including upstream contributions; annual groundwater exploitation potential);
- Extreme event vulnerability (number of days per annum where rainfall = 0 mm; days per annum with rainfall >25 mm);
- Land cover vulnerability (percentage cover of urbanization upstream; percentage cover of irrigated land); and
- Storage vulnerability (dam coverage; coefficient of variation of mean annual precipitation).

Demand-driven water user vulnerability was calculated using the following four subcomponents and eight individual indicators:

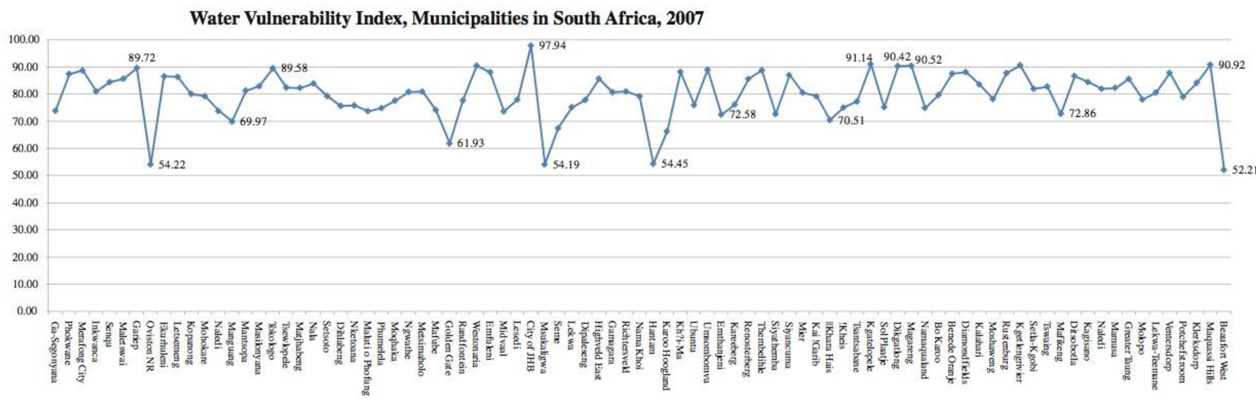
- Demographic vulnerability (total population; population density);
- Household vulnerability (percentage of economically vulnerable households; percentage of households using water from direct resource);
- Economic vulnerability (percentage of employment in water-dependent sectors, e.g., agriculture, manufacturing, and mining; percentage gross value added in water-dependent sectors); and
- Bulk demand vulnerability (total annual water demand; evaporative demand).

Identification and selection of appropriate indicators began with consultation of previous qualitative research by Romero (2007) on local perceptions of vulnerability of water supplies and water users in the study region. Interviews and workshops were then held to gather additional qualitative information from the perspective of local people. These sources of qualitative data were analyzed and interpreted to evaluate the relative importance of different aspects of vulnerability and, thus, to explore possible differential weighting schemes for calculating index scores. Data availability concerns and expert opinion shaped the final selection of indicators and organization into subcomponents. According to Sullivan (2011: 630), data for South Africa is well-organized, available from a variety of sources, and relatively uniform in quality. Coverage of the entire Orange River Basin was limited by insufficient data availability and the lack of data consistency from Lesotho, Botswana, and Namibia. Data sources included databases of the national statistical agency, Statistics South Africa (www.statssa.gov.za). Other relevant sources including South Africa's Department of Water and Forestry provided national hydrologic and meteorologic data. The qualitative information was used to evaluate the relative importance of different vulnerability indicators and to consider possible unequal weighting schemes.

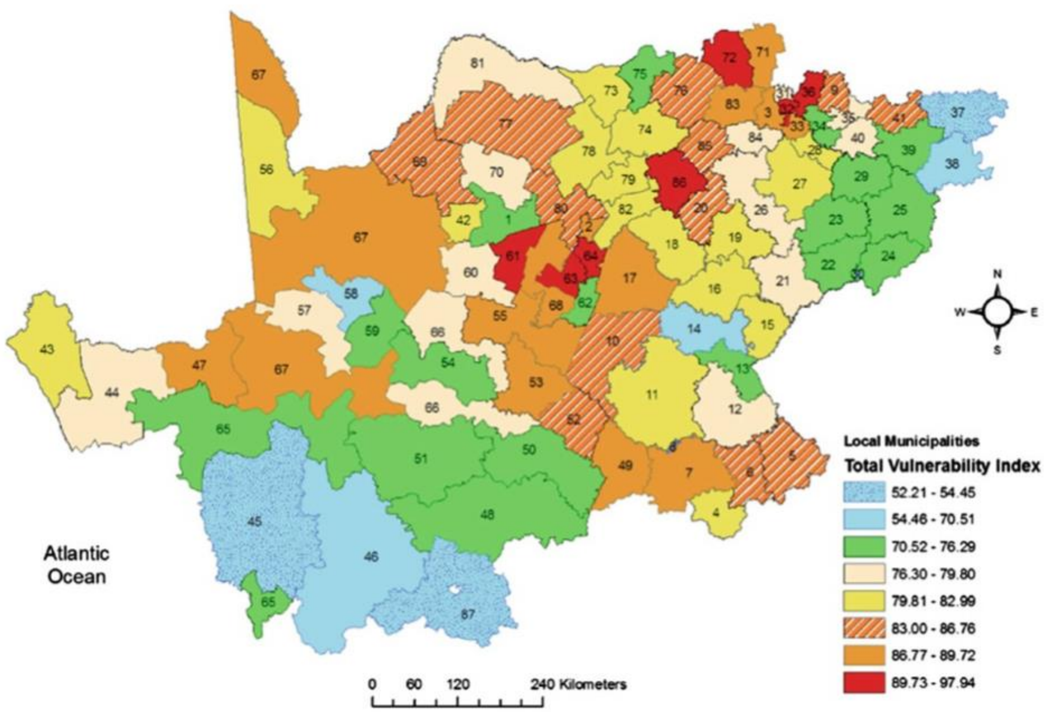
Sullivan (2011) does not include uncertainty or sensitivity analysis but recognizes that there is uncertainty associated with the values generated by the WVI approach. Sullivan (2011) also acknowledges that more work is needed on order to refine the WVI methodology and recommends including more information on water quality as a way to improve the validity of the WVI.

FIGURE 7. (A) WVI SCORES FOR 87 MUNICIPALITIES IN SOUTH AFRICA AND (B) WVI SCORES AT THE MUNICIPAL SCALE MAPPED ACROSS THE ORANGE RIVER BASIN

(a)



(b)



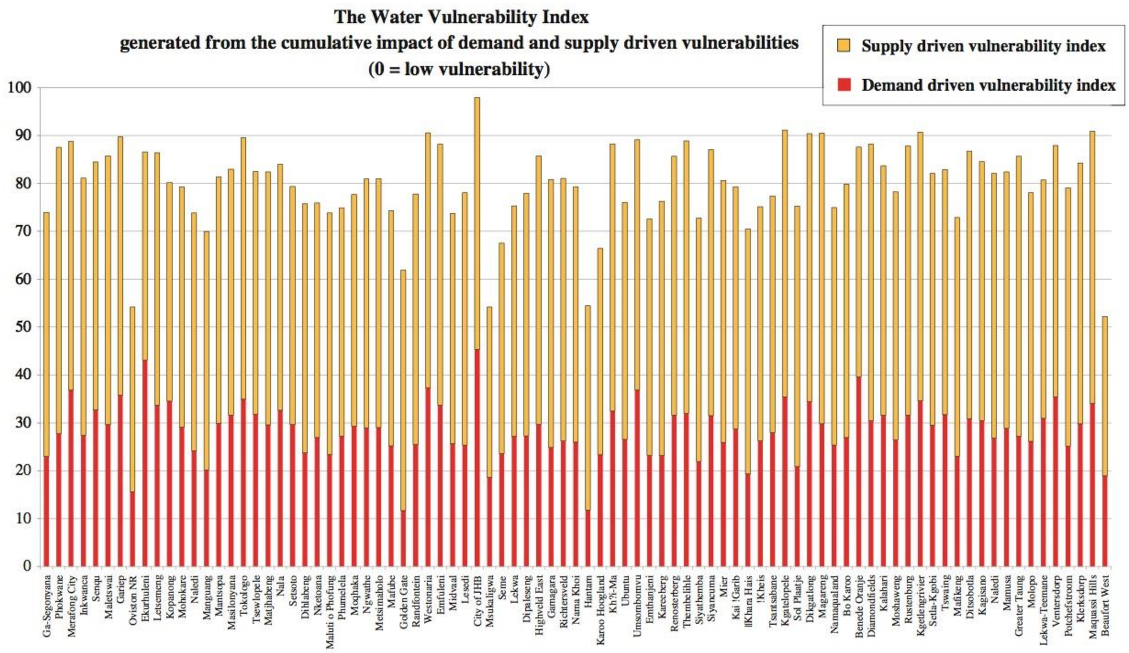
(continued on following page)

Municipality ID	Name	Municipality ID	Name	Municipality ID	Name	Municipality ID	Name	Municipality ID	Name
M 1	Ga-Segonyana	M 21	Setsoto	M 41	Highveld East	M 61	Kgatelopele	M 81	Molopo
M 2	Phokwane	M 22	Dihlabeng	M 42	Gamagara	M 62	Sol Plaatje	M 82	Lekwa-Teemane
M 3	Merafong City	M 23	Nketoana	M 43	Richtersveld	M 63	Dikgatlong	M 83	Ventersdorp
M 4	Inkwanca	M 24	Maluti o Phofung	M 44	Nama Khoi	M 64	Magareng	M 84	Potchefstroom
M 5	Senqu	M 25	Phumelela	M 45	Hantam	M 65	Namaqualand	M 85	Klerksdorp
M 6	Maletswai	M 26	Moqhaka	M 46	Karoo Hoogland	M 66	Bo Karoo	M 86	Maquassi Hills
M 7	Gariep	M 27	Ngwathe	M 47	Kh?i-Ma	M 67	Benede Oranje	M 87	Beaufort West
M 8	Oviston NR	M 28	Metsimaholo	M 48	Ubuntu	M 68	Diamondfields	The municipalities across the portion of Orange Basin that falliing within South Africa are very variable, and include desely populated areas, such as the City of Johannesburg, as well as remote mountain and desert areas.	
M 9	Ekurhuleni	M 29	Mafube	M 49	Umsombomvu	M 69	Kalahari		
M 10	Letsemeng	M 30	Golden Gate	M 50	Emthanjeni	M 70	Moshaweng		
M 11	Kopanong	M 31	Randfontein	M 51	Kareeberg	M 71	Rustenburg		
M 12	Mohokare	M 32	Westonaria	M 52	Renosterberg	M 72	Kgetlengrivier		
M 13	Naledi	M 33	Emfuleni	M 53	Thembelihle	M 73	Setla-Kgobi		
M 14	Manguang	M 34	Midvaal	M 54	Siyathemba	M 74	Tswaing		
M 15	Mantsopa	M 35	Lesedi	M 55	Siyancuma	M 75	Mafikeng		
M 16	Masilonyana	M 36	City of JHB	M 56	Mier	M 76	Ditsobotla		
M 17	Tokologo	M 37	Msukaligwa	M 57	Kai !Garib	M 77	Kagisano		
M 18	Tsewlopele	M 38	Seme	M 58	||Khara Hais	M 78	Naledi		
M 19	Matjhabeng	M 39	Lekwa	M 59	!Kheis	M 79	Mamusa		
M 20	Nala	M 40	Dipaleseng	M 60	Tsantsabane	M 80	Greater Taung		

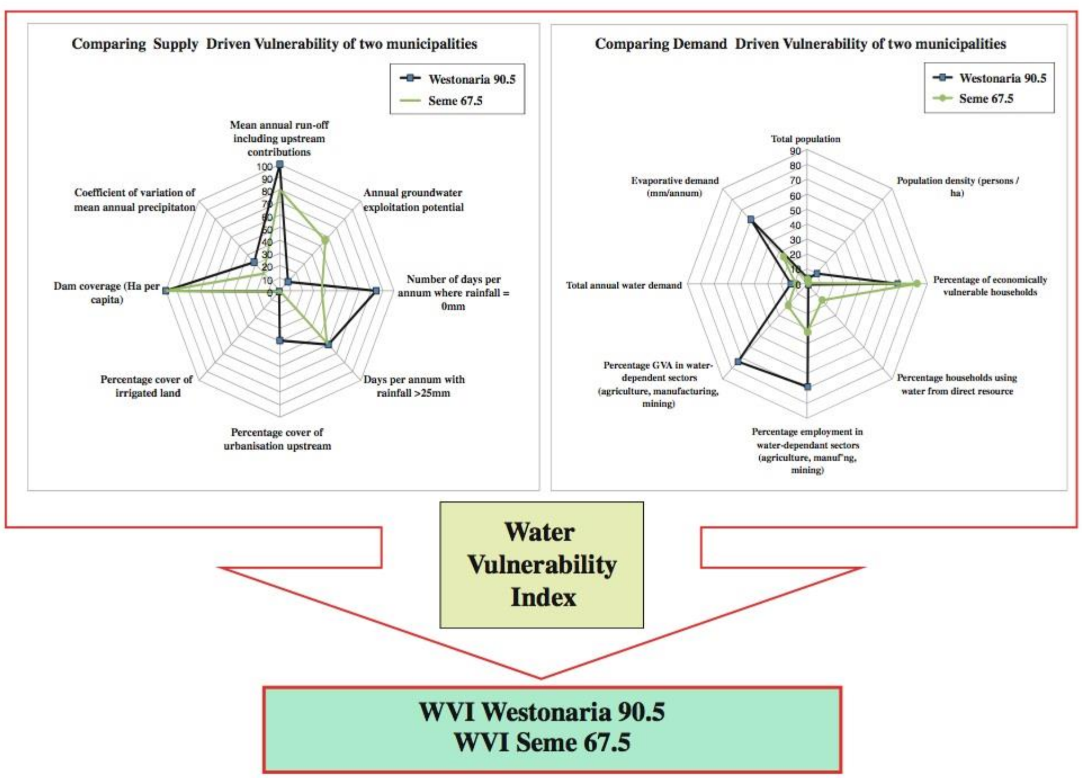
Source: Reproduced from Sullivan, 2011, with kind permission from Springer Science + Business Media.

FIGURE 8. (A) WVI COMBINED SUPPLY AND DEMAND DRIVER VALUES FOR 87 MUNICIPALITIES IN SOUTH AFRICA AND (B) CURRENT CONDITIONS OF WATER VULNERABILITY IN TWO MUNICIPALITIES IN SOUTH AFRICA (WESTONARIA AND SEME)

(a)



(b)



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